Use of Remote Sensing coupled with Models in Agricultural Decision Making

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Satellite Data to Propel a new Era in Agriculture?

- Interest of agricultural decision makers in remote sensing data fuelled by economic pressures, fears about a coming “food gap”, and visions on autonomous farming

Autonomes Fahren

Das Monster auf dem Acker

Autonom fahrende Traktoren sollen helfen, die Ernährungsprobleme der Welt zu lösen. Noch kosten die Maschinen ein Vermögen.

Von **Dietmar H. Lamparter**

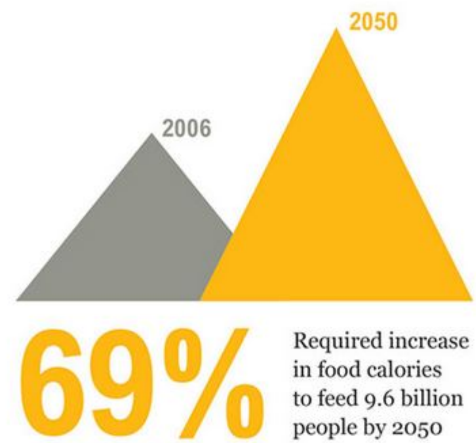
30. März 2017, 11:11 Uhr / Editiert am 15. April 2017, 15:32 Uhr / 38 Kommentare

AUS DER ZEIT NR. 14/2017

Der Prototyp eines fahrerlosen Traktors von Case © Hersteller

The Food Gap

Taking into account a growing population and shifting diets, the world will need to produce 69 percent more food calories in 2050 than we did in 2006.

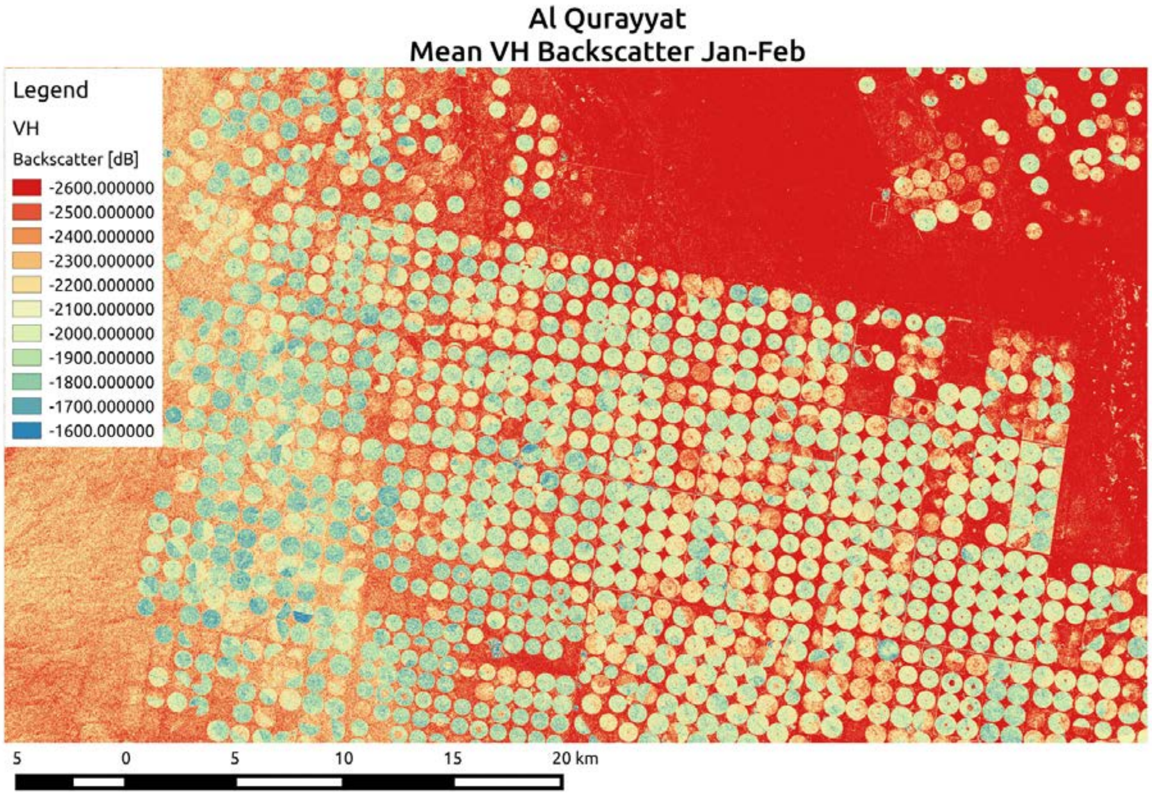


WORLD RESOURCES INSTITUTE

Sources: http://ow.ly/rpfMN

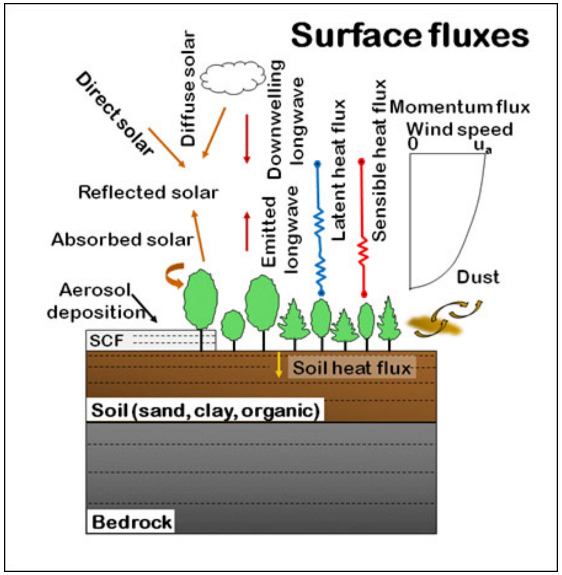
Food Production in the Desert

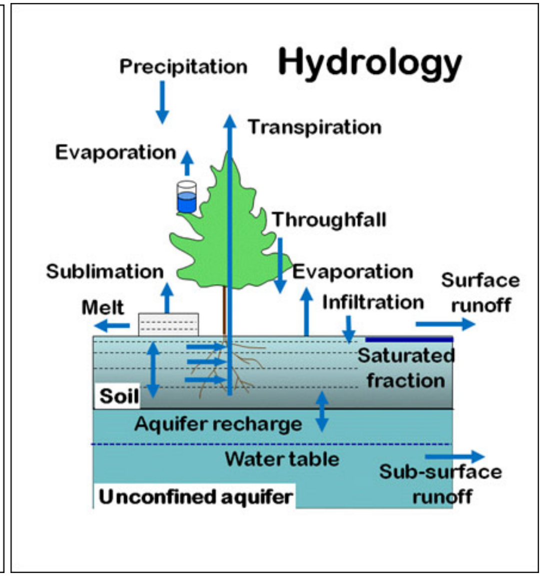
- Saudi Arabia uses center pivot irrigation to grow crops like wheat and alfalfa

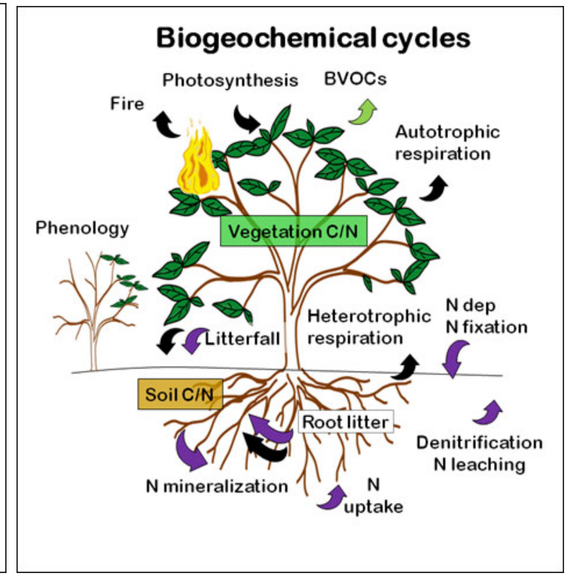


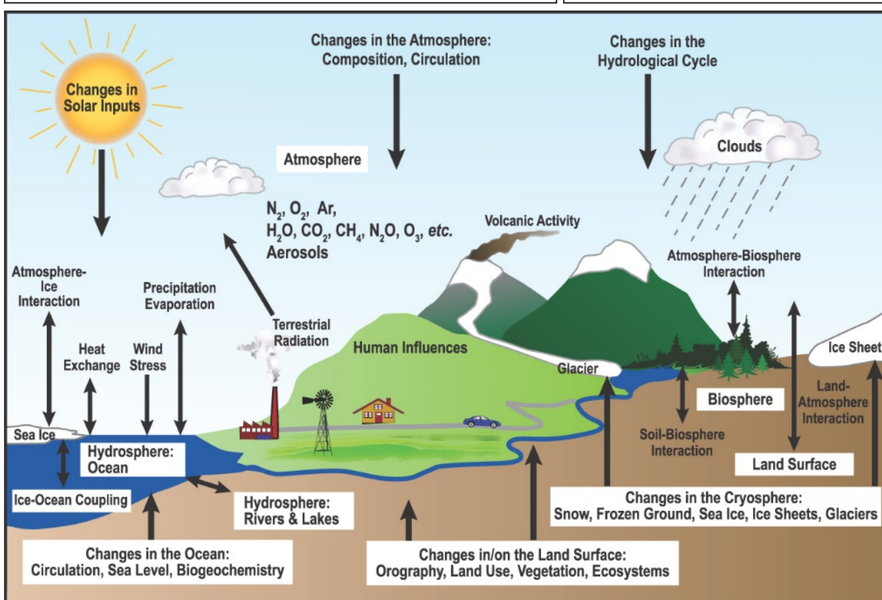
Bi-monthly Sentinel-1 VH image mosaics for 2016

Agricultural Monitoring Requires a Holistic View







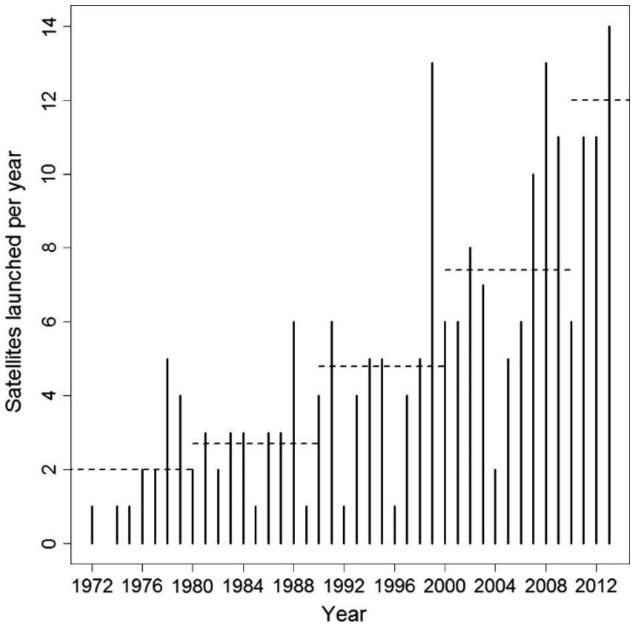


Schematic diagram depicting processes represented in the Community Land Model (http://www.cesm.ucar.edu/models/clm/)

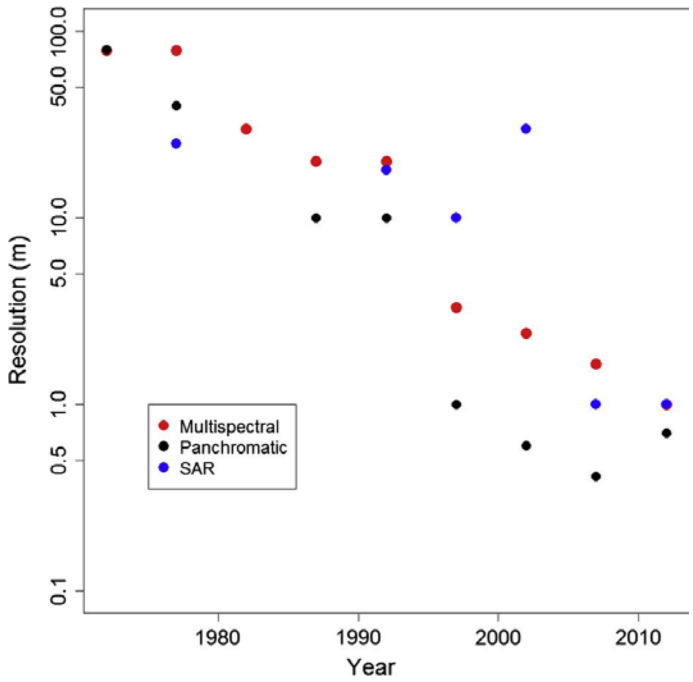
Lawrence and Fisher (2013) The Community Land Model Philosophy: model development and science applications. iLEAPS Newsletter, 13, 16-19.

Earth Observation

- More satellites than ever and better than ever



Number of individual near-polar orbiting, land imaging civilian satellites launched per year



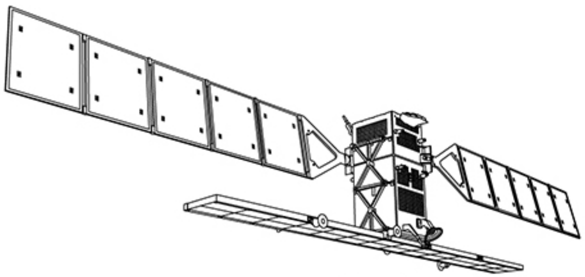
The highest resolution (meters) achieved from any panchromatic, multispectral and/or SAR sensor onboard a near-polar orbing, land imaging civilian satellite

Belward and Skøien (2015) Who launched what, when and why; trends in global land-cover observation capacity from civilian earth observation satellites. ISPRS Journal of Photogrammetry and Remote Sensing, 103, 115-128.

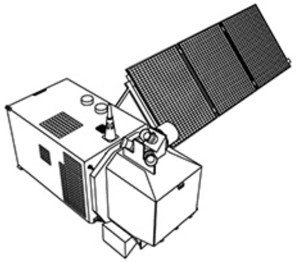
eodc TU WIEN GEO

Sentinel Satellites

Fleet of European
Earth Observation Satellites

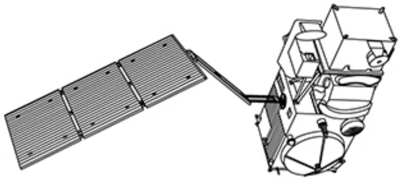


sentinel-1

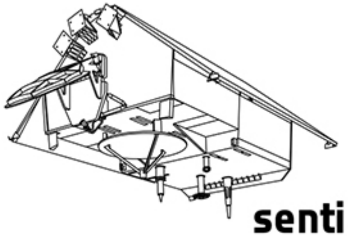


sentinel-2

Data are
free & open!



sentinel-3

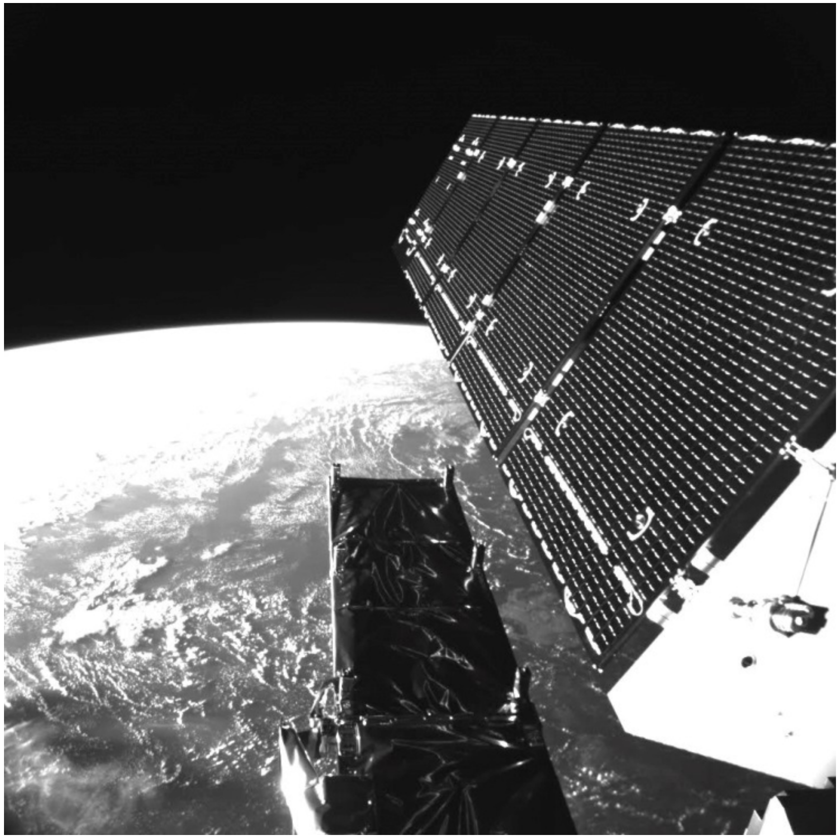


sentinel-6

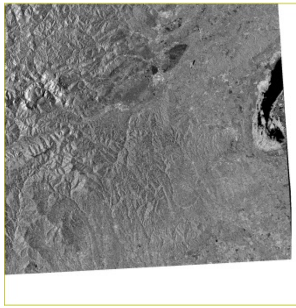
Sentinel-1 – A Game Changer

- C-band SAR satellite in continuation of ERS-1/2 and ENVISAT
- High spatio-temporal coverage
  - Spatial resolution 20-80 m
  - Temporal resolution < 3 days over Europe and Canada
    - with 2 satellites
- Excellent data quality
- Highly dynamic land surface processes can be captured
  - Impact on water management, health and other applications could be high if the challenges in the ground segment can be overcome

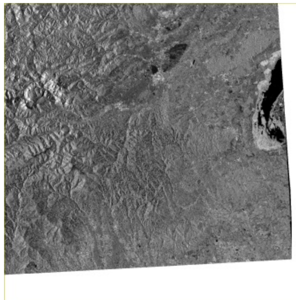
Solar panel and SAR antenna of Sentinel-1 launched 3 April 2014. Image was acquired by the satellite's onboard camera. © ESA



Sentinel-1 Time Series



2014-11-08



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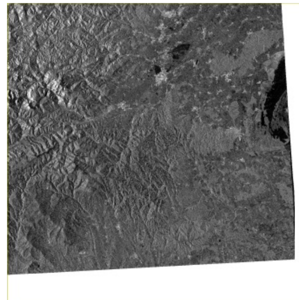

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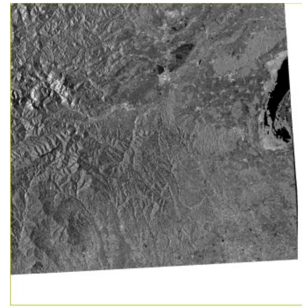

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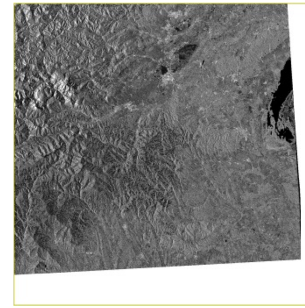

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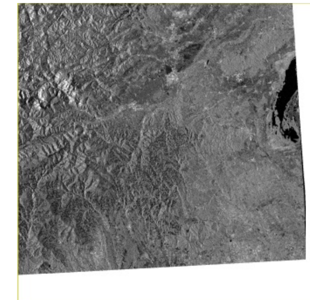

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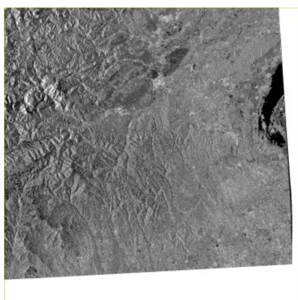

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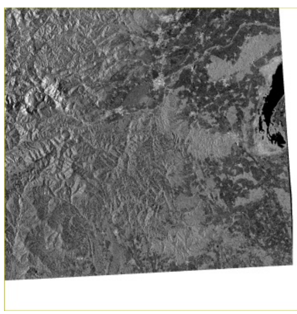

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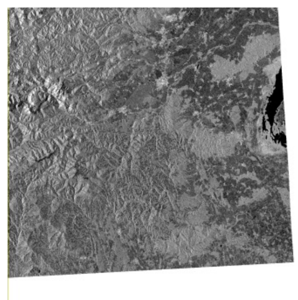

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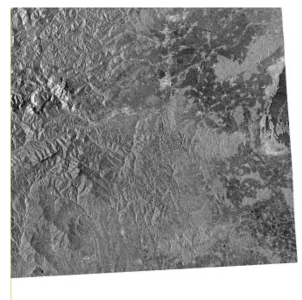
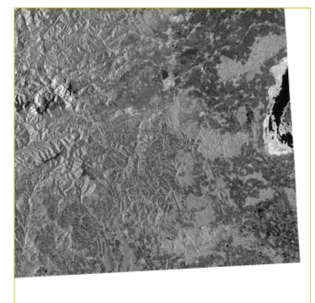


2015-04-01



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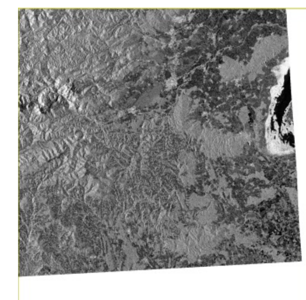

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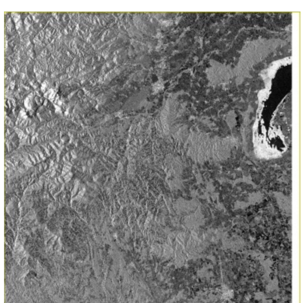

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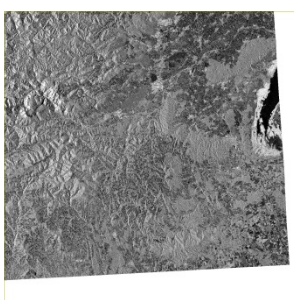

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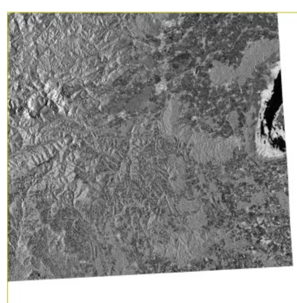

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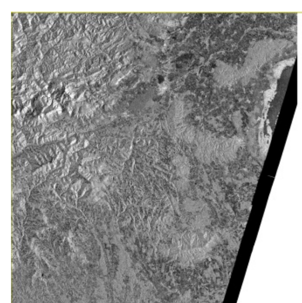
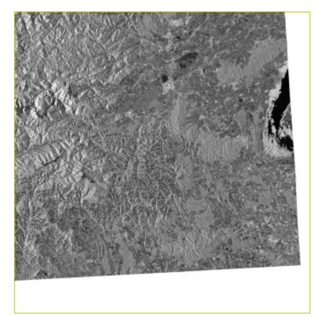


2015-06-04



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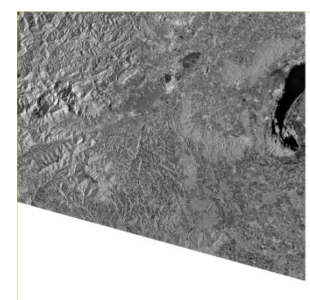
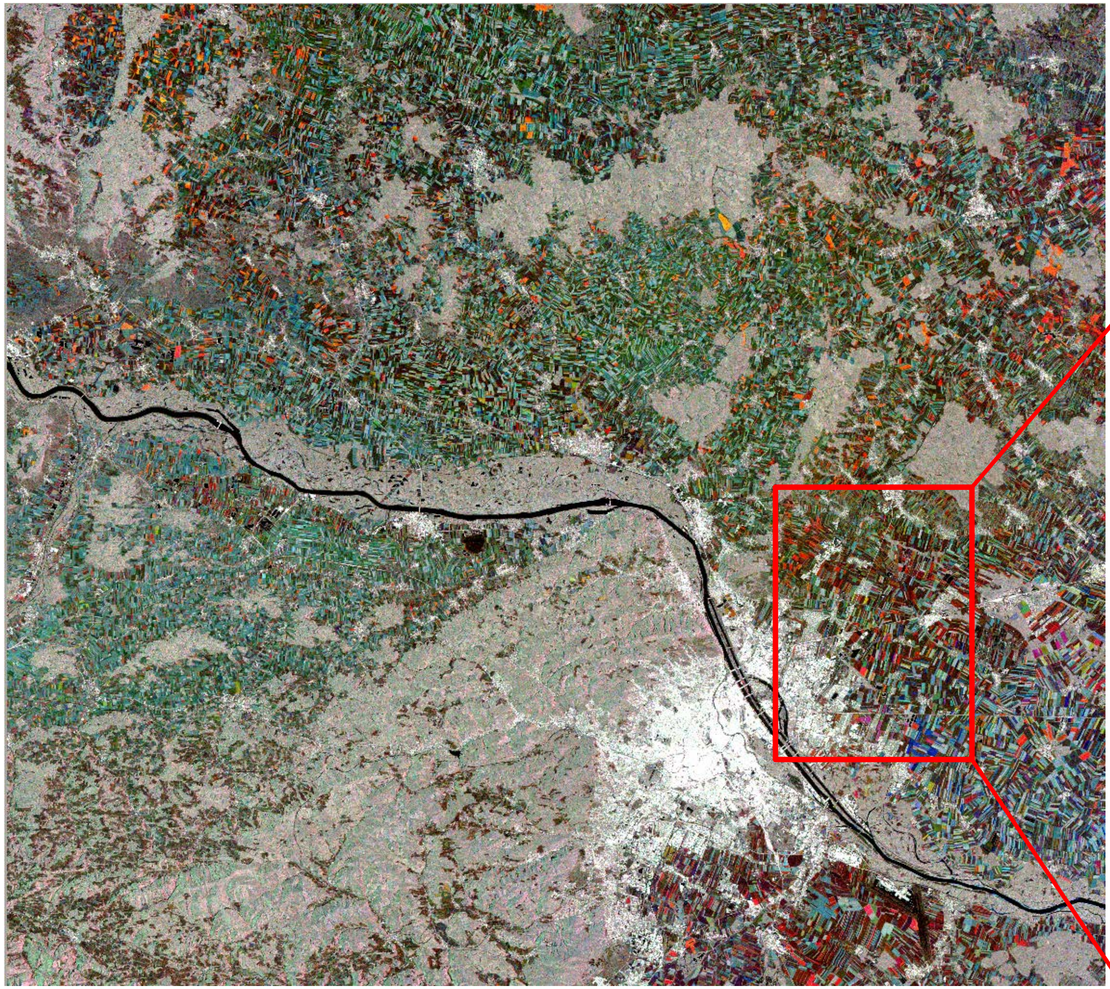


2015-06-23

Sentinel-1 Cross-Pol (VH) Images

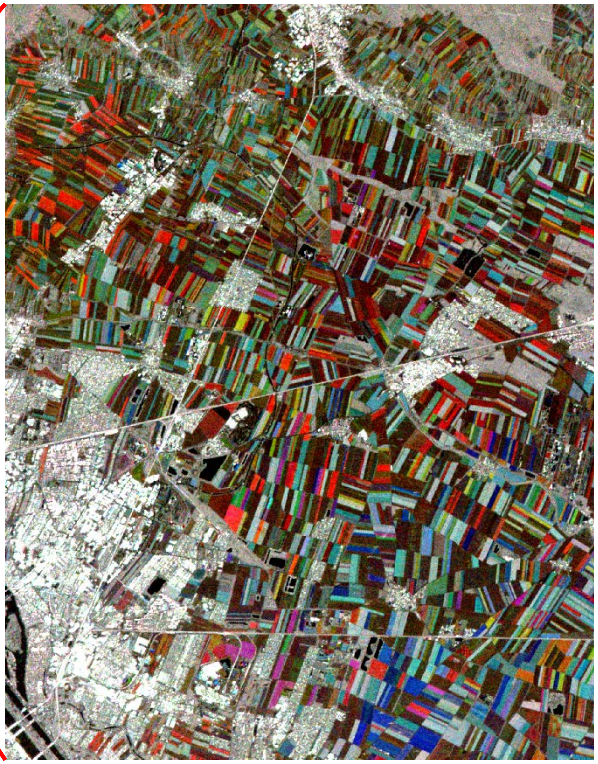


False-colour image of Sentinel-1
VH monthly image mosaics

Red – June

Green – July

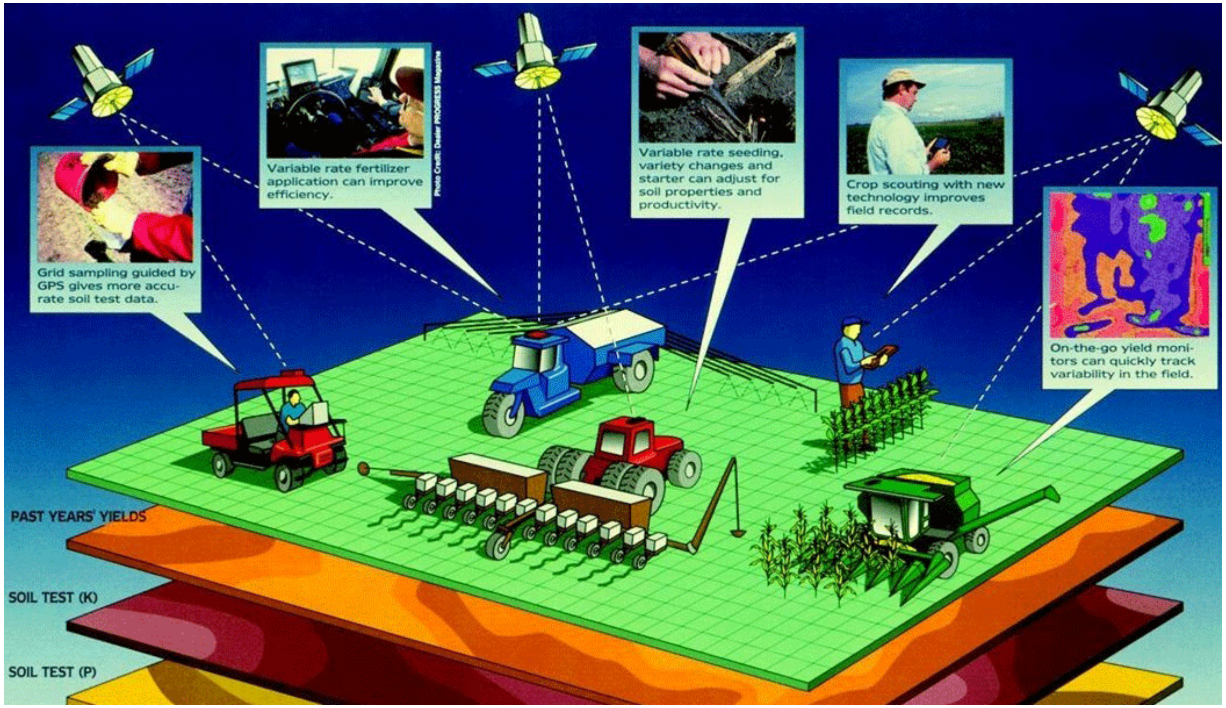
Blue – August



Operational EO Data Services

Impact on Agrometeorological Applications

- Remarkably, the proliferation of earth observation technology has had only modest impacts on agrometeorological applications yet
- Simple indices such as the Normalised Difference Vegetation Index (NDVI) continue to be the main EO data type
  - Quantitative applications (e.g. assimilation of biogeophysical variables in crop yield models) still rare



When will EO-powered *Precision Agriculture* become a reality?

Rodericks Oisebe (2012) Geospatial Technologies in Precision Agriculture, GIS Lounge, https://www.gislounge.com/geospatial-technologies-in-precision-agriculture/

Hurdles to Using EO Data

- Added value of using EO data in agrometeorological applications often difficult to demonstrate
  - What is the unique information provided by the EO data? For whom?
- EO data services are often not fit for purpose
  - Using EO data should be simple, not requiring expert knowledge
  - Consistency between near-real-time and historic off-line data
  - Parallel data streams for operations and testing
  - Spatiotemporal uncertainty estimates and quality flags
- Complexity of problem
  - Relationship between EO data and crop yield not straight forward
  - Existing agrometeorological models have not been built for using EO data
  - Data assimilation schemes are complex and costly
  - Lack of high quality reference data
  - Understanding scaling and representation problems

Specific Concerns about Satellite Soil Moisture Data

CONCERNS

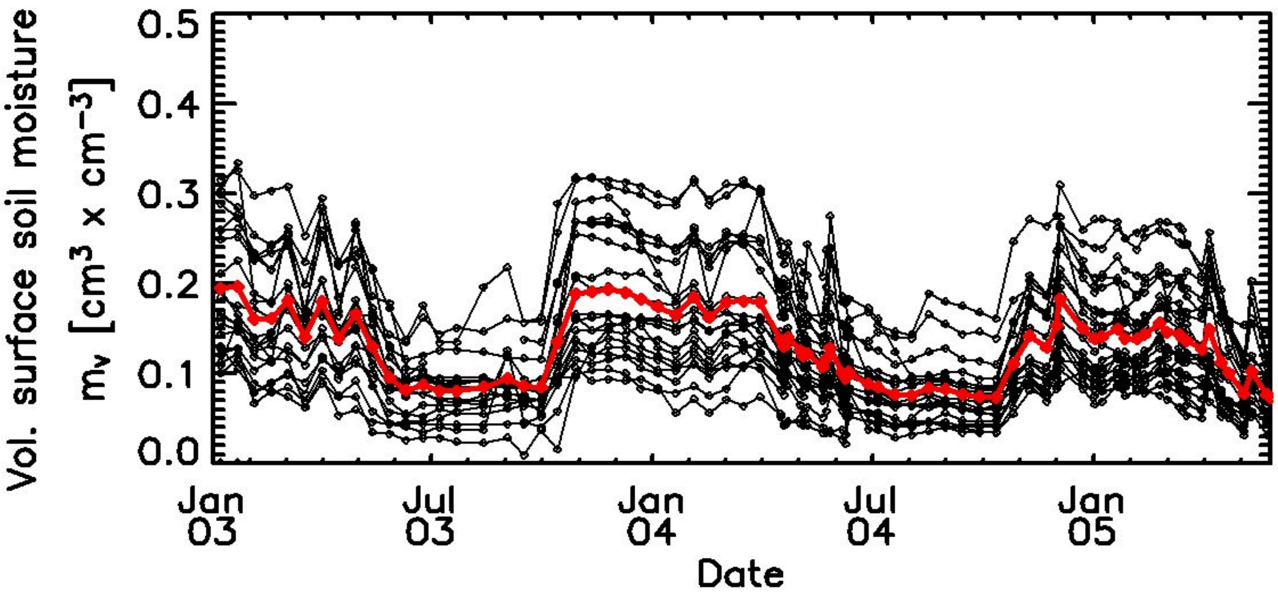
- Coarse spatial resolution
  - 25-50 km for current operational data services
- Only thin surface layer is sensed
  - A few centimetres under growing conditions
- Does not penetrate dense vegetation

WHY IT STILL WORKS

- Temporal Stability
  - Soil moisture dynamics can be compared across spatial scale
- Dense temporal sampling
  - Allows to predict profile soil moisture content
- Retrieval accuracy best over agricultural areas and grasslands

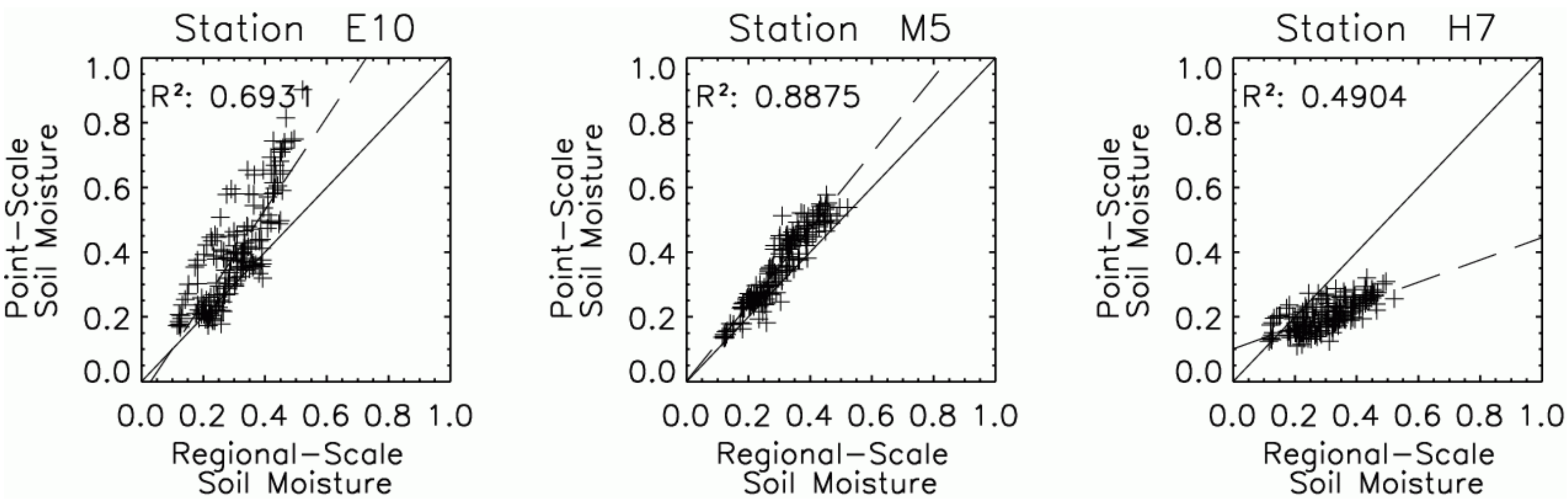
Temporal Stability

- Temporal stability means that spatial patterns persist in time
  - Vachaud et al. (1985)
    - Practical means of reducing in-situ soil moisture network to few representative sites
  - Vinnikov and Robock (1996)
    - Large-scale atmosphere-driven soil moisture field
    - Small-scale land-surface soil moisture field



Mean (red) and station (black) in situ soil moisture time series from the REMEDHUS network operated by University of Salamaca.

Time-Invariant Linear Relationship



Regional scale soil moisture

$$\theta_r(t) = \frac{1}{A_r}\iint_R \theta_p(x', y', t)\,dx'dy' = c_{rp}(x, y) + d_{rp}(x, y)\,\theta_p(x, y, t)$$

Local scale soil moisture

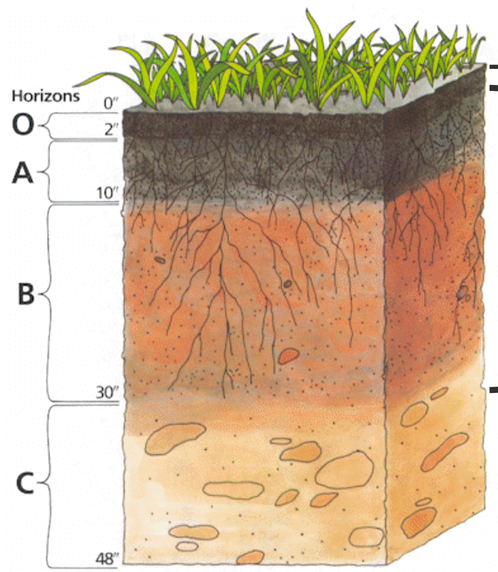
Linear scaling coefficients

Model Error ≅ 5 %

Estimation of Profile Soil Moisture

- Our method rests upon simple differential model for describing the exchange of soil moisture between surface layer (Θ_s) and the “reservoir” (Θ)
  - T … characteristic time

$$\frac{d\Theta}{dt} = \frac{1}{T}(\Theta - \Theta_s) \quad \Longrightarrow \quad \Theta(t) = \frac{1}{T}\int_{-\infty}^{t} \Theta_s(t') \exp\left[-\frac{t-t'}{T}\right] dt'$$



Thin, remotely sensed soil layer with Θ_s

Root zone with Θ : layer of interest for most applications

Soil profile

Wagner, W., G. Lemoine, H. Rott (1999) A Method for Estimating Soil Moisture from ERS Scatterometer and Soil Data, Remote Sensing of Environment, 70, 191-207.

"Red-Noise" Infiltration Model

- Mathematically, this model corresponds to a first-order Markov process, where
  - $\Theta(t)$ is the process variable
  - $\Theta_s(t)$ is the external forcing
  - *T* is the response time of the system

- The autocorrelation function of $\Theta(t)$ is given by
  - First suggested theoretically for soil moisture by Delworth and Manabe (1988)
  - Confirmed with observations by Robock, Vinnikov, and collaborators

$$r(\tau) = e^{-t/T}$$

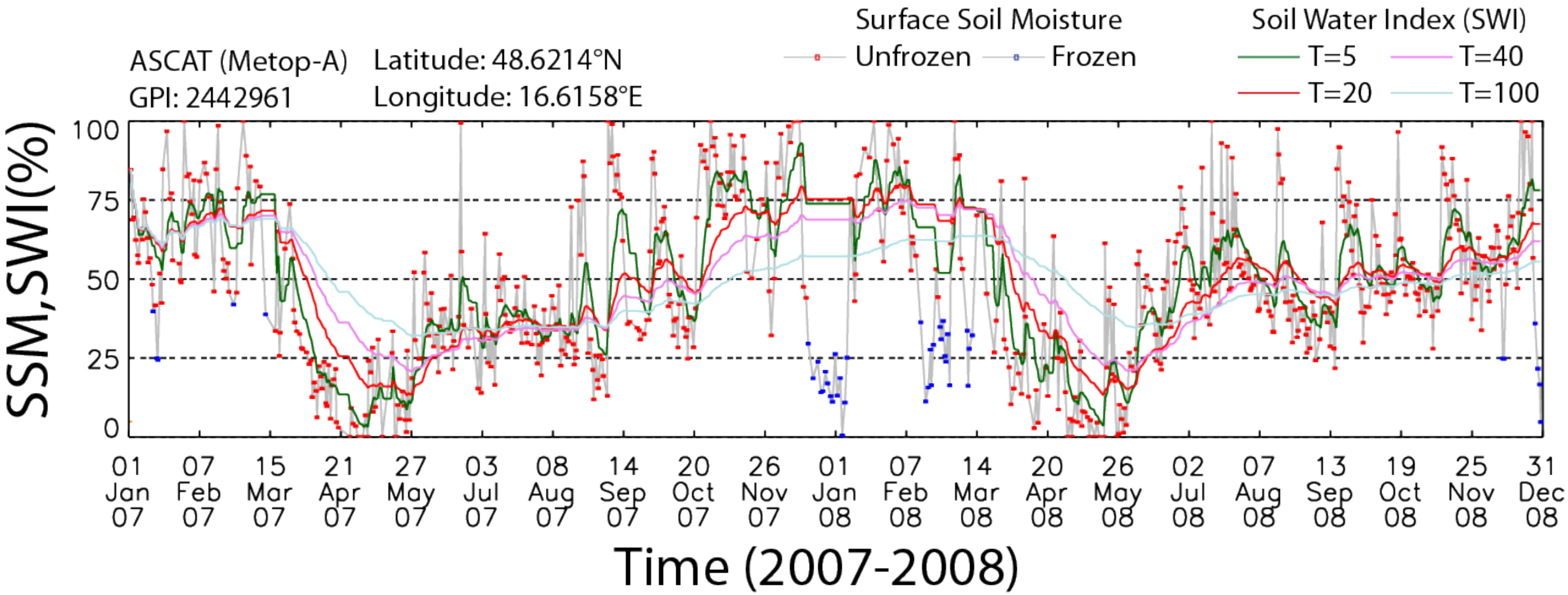
- Effects of convolution integral
  - Retarded and smoothed time series

Ceballos, A., K. Scipal, W. Wagner, J. Martínez-Fernández (2005) Validation of ERS scatterometer-derived soil moisture data over the central part of the Duero Basin, Spain, Hydrological Processes, 19, 1549-1566, doi: 10.1002/hyp.5585.

Soil Water Index (SWI)

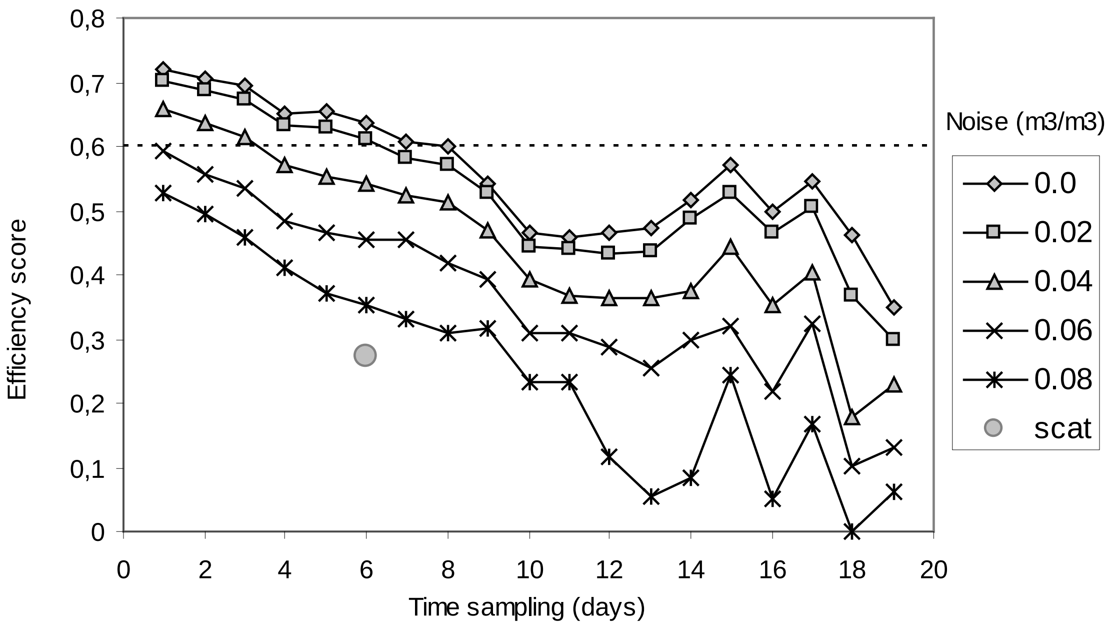
$$SWI(t) = \frac{\sum_i m_s(t_i) e^{-\frac{t-t_i}{T}}}{\sum_i e^{-\frac{t-t_i}{T}}}$$

T = 1,5,10,15,20,40,60,100



Quality of SWI

- The quality of SWI depends critically upon
  - Density of time series
  - Regular sampling
  - Removal of erroneous data (frozen and snow covered soil)



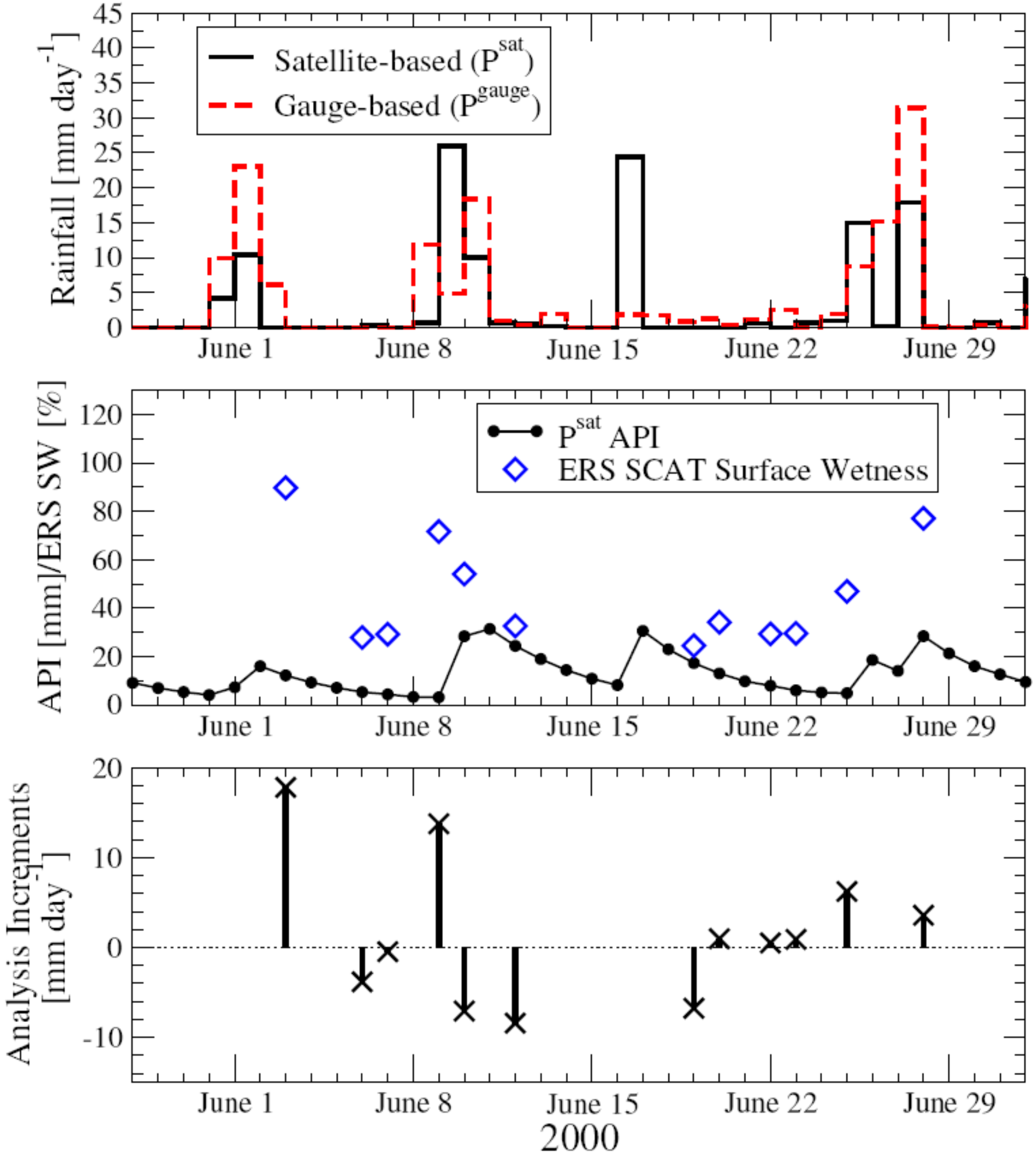
Efficiency based
on Model Simulations

Pellarin, T., J.-C. Calvet, W. Wagner (2006) Evaluation of ERS Scatterometer soil moisture products over a half-degree region in Southwestern France, Geophysical Research Letters, 33(17), L17401.

Assimilation

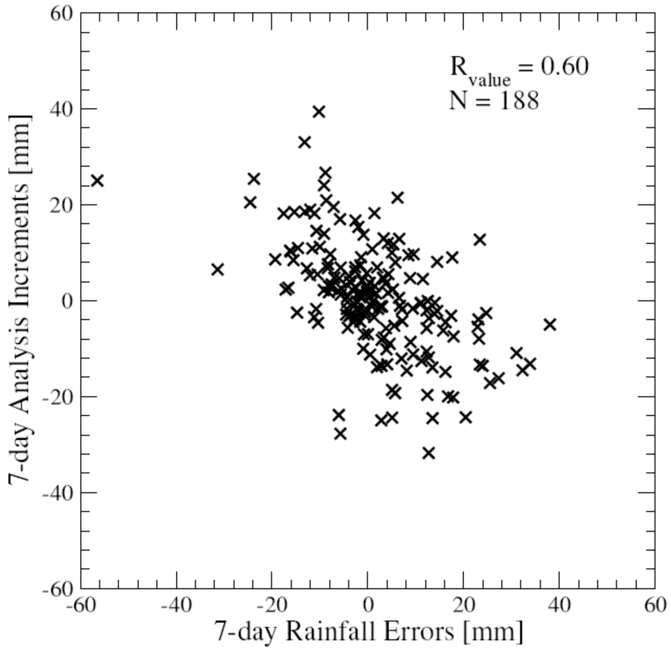
- Models and data are imperfect
- Improve outputs by data assimilation

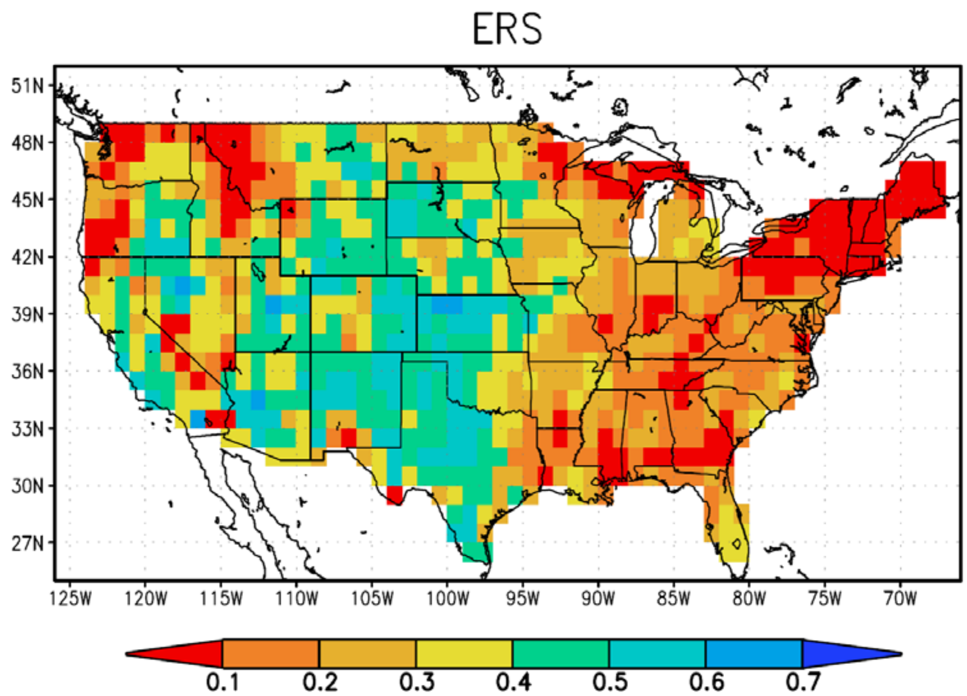
- Satellite soil moisture data can help to correct impact of erroneous precipitation data
  - Wade Crow (2007) Journal of Hydrometeorology



Crow, W.T., and X. Zhan, "Continental-scale evaluation of remotely-sensed soil moisture products," IEEE Geoscience and Remote Sensing Letters, 4(3), 451-455, 2007.

Added Value of SCAT Soil Moisture

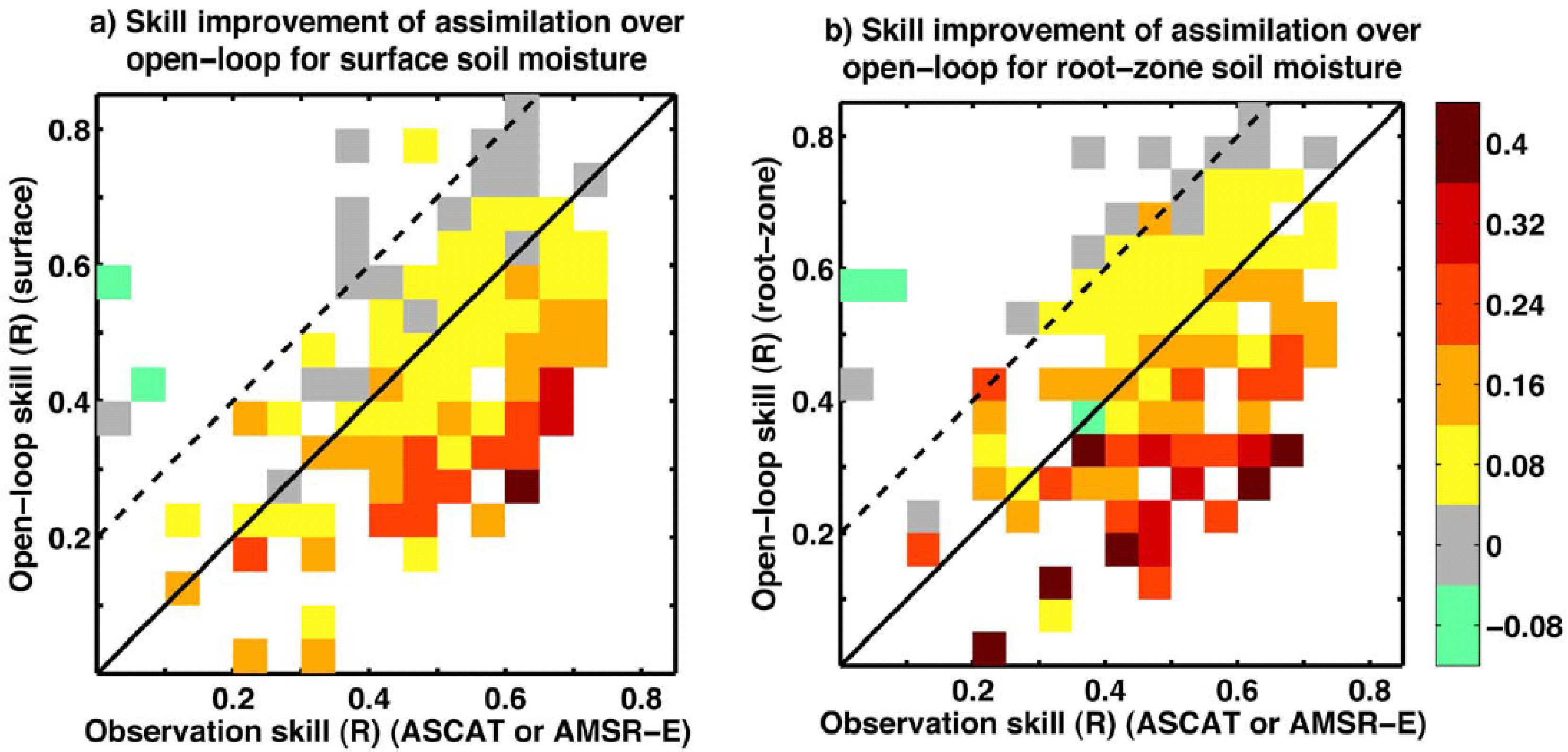




Positive Impact →

Results kindly provided by Wade Crow, USDA

Improved Soil Moisture Estimates through Assimilation



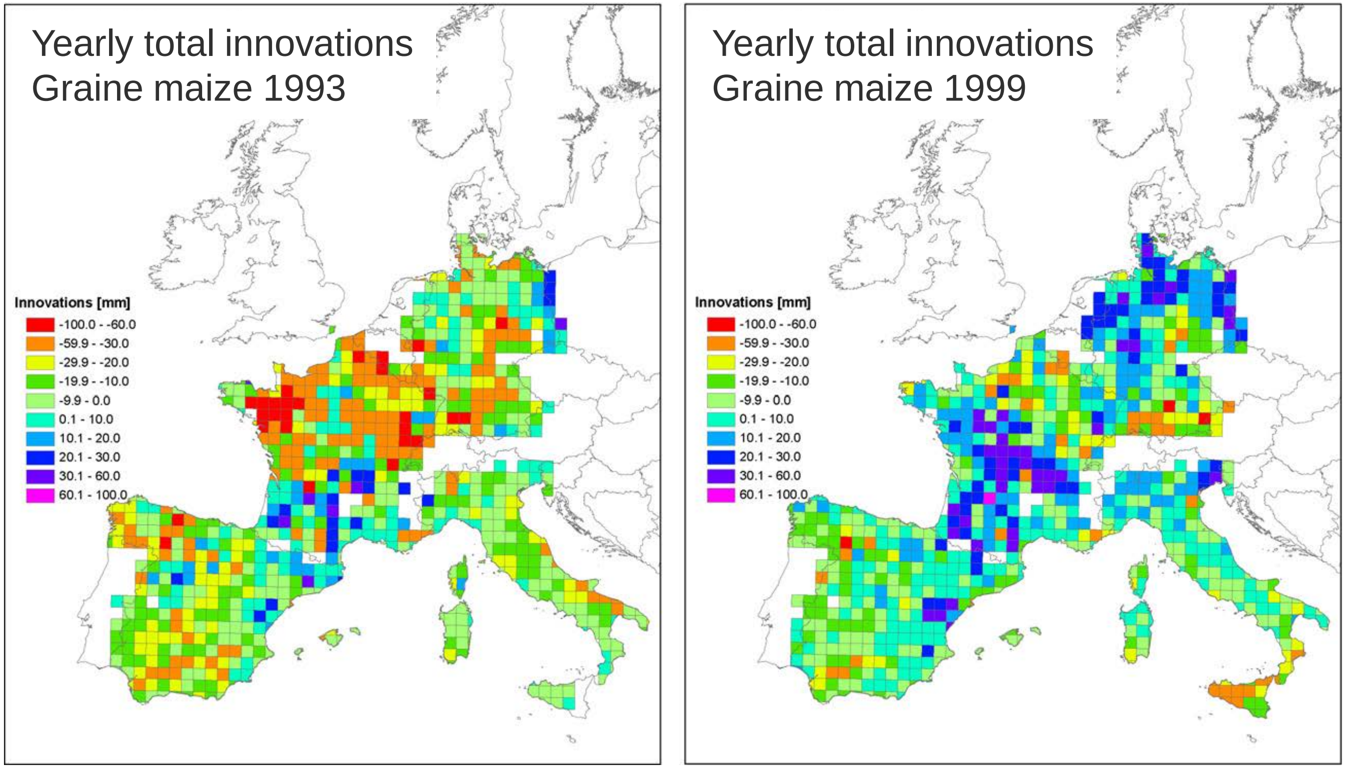
Draper, C.S., Reichle, R.H., De Lannoy, G.J.M., & Liu, Q. (2012). Assimilation of passive and active microwave soil moisture retrievals. Geophysical Research Letters, 39, L04401

Yield Modelling using Scatterometer SWI Data

- Assimilation of SWI in crop model WOFOST
  - Crop model data assimilation with the Ensemble Kalman filter with the goal of improving regional crop yield forecasts

Model was wetter than SWI

Model was drier than SWI



de Wit and van Diepen (2007) Crop model data assimilation with the Ensemble Kalman filter for improving regional crop yield forecasts, Agricultural and Forest Meteorology, 146(1-2), 38-56.

Rainfall derived from satellite soil moisture: SM2RAIN

Water balance model:

$$Z\frac{ds(t)}{dt} = p(t) - r(t) - e(t) - g(t)$$

Z ... soil water capacity (= soil depth * porosity)

s ... relative saturation

p ... precipitation

r ... surface runoff

e ... evapotranspiration

g ... drainage

Inverting for *p(t):*

$$p(t) = Z\frac{ds(t)}{dt} + r(t) + e(t) + g(t)$$

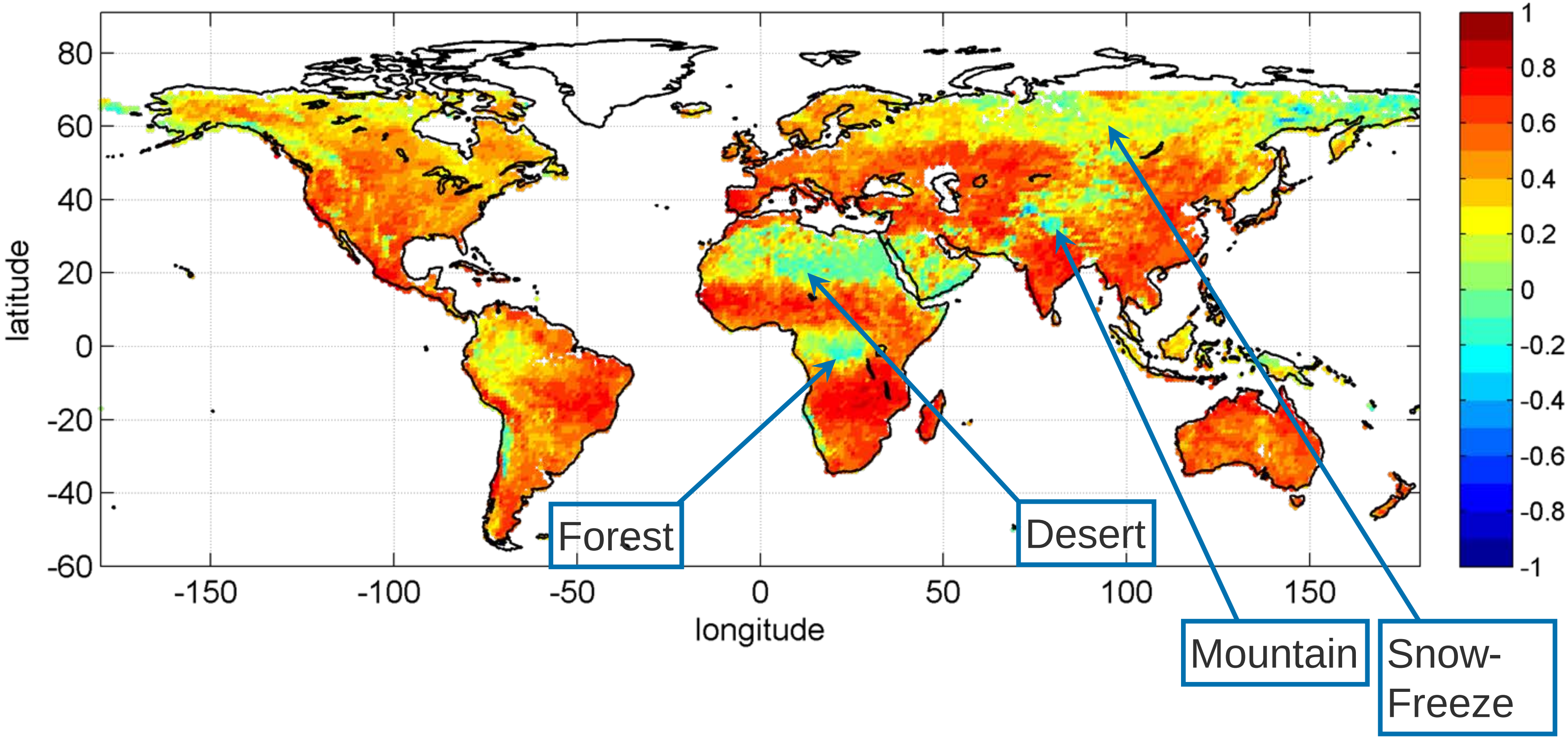
Assuming during rainfall:

$$g(t) = a\, s(t)^b \quad + \quad e(t) = 0 \quad + \quad g(t) = 0$$

$$\Rightarrow \quad p(t) \cong Z\, ds(t)/dt + a\, s(t)^b$$

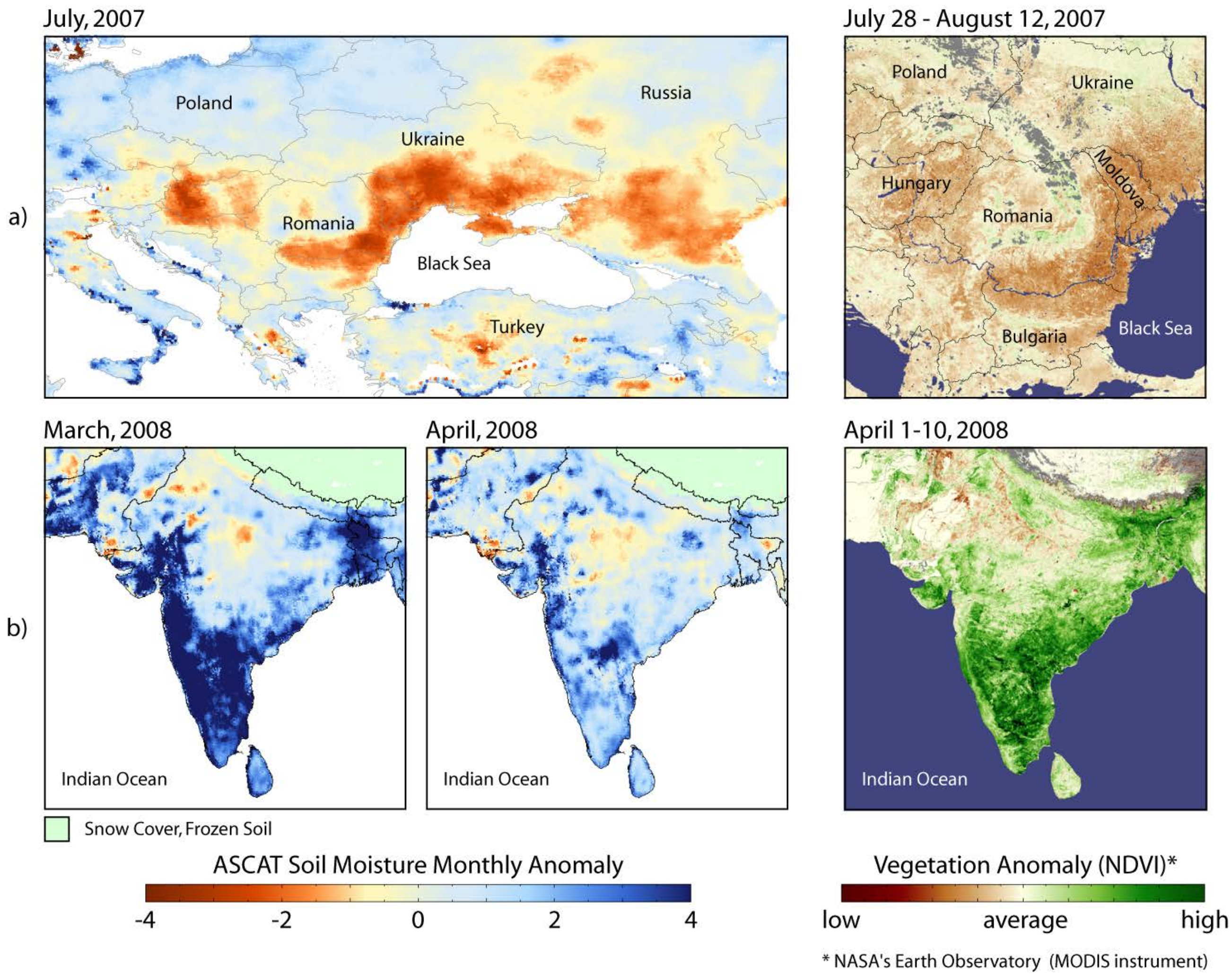
Brocca, L., Ciabatta, L., Massari, C., Moramarco, T., Hahn, S., Hasenauer, S., Kidd, R., Dorigo, W., Wagner, W., & Levizzani, V. (2014). Soil as a natural rain gauge: Estimating global rainfall from satellite soil moisture data. *Journal of Geophysical Research: Atmospheres*, *119*(9), 5128-5141.

ASCAT Rainfall



Correlation between 5-day rainfall from GPCC and the rainfall extracted from ASCAT data through SM2RAIN

Soil Moisture and Vegetation



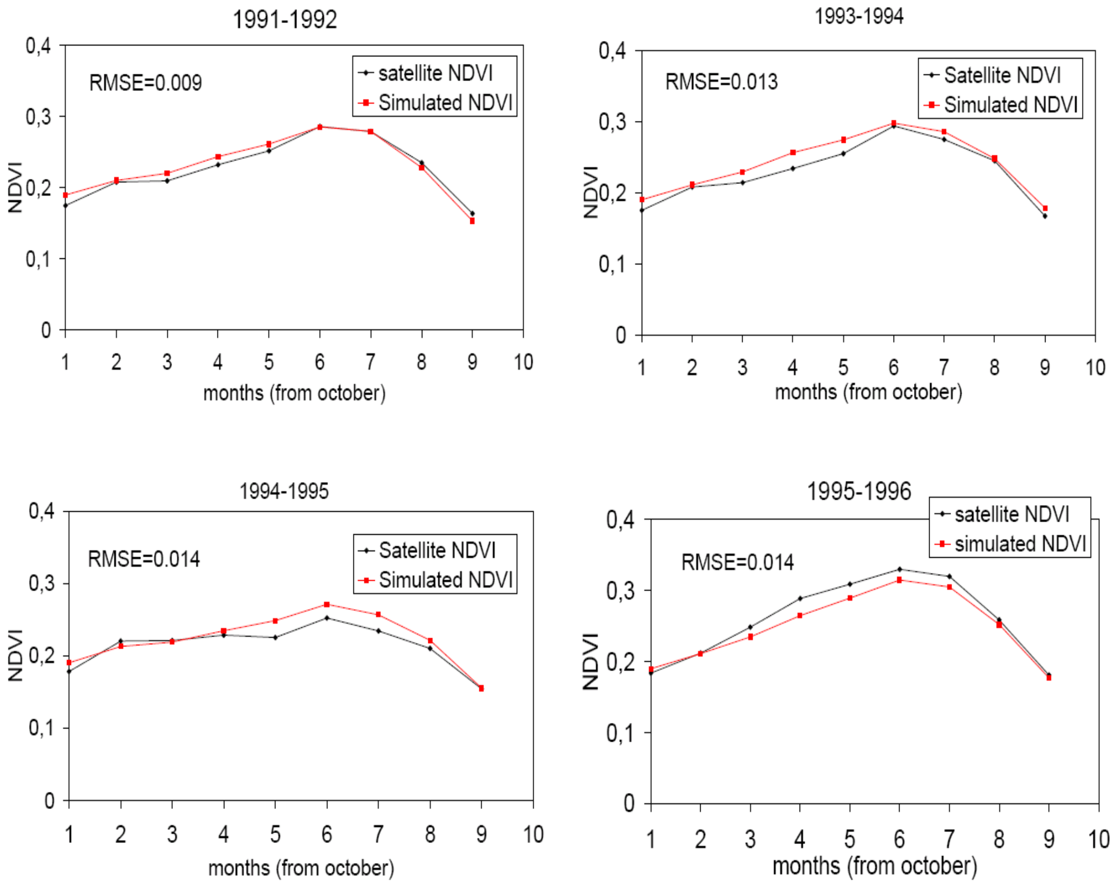
Drought
Eastern Europe
2007

Heavy Rainfall
India
2008

Naeimi, V., W. Wagner (2010). C-band Scatterometers and their Applications, Chapter 13 of "Geoscience and Remote Sensing New Achievements", Pasquale Imperatore and Daniele Riccio (Ed.), INTECH, Vukovar, Croatia, 230-246.

Prediction of NDVI using SWI

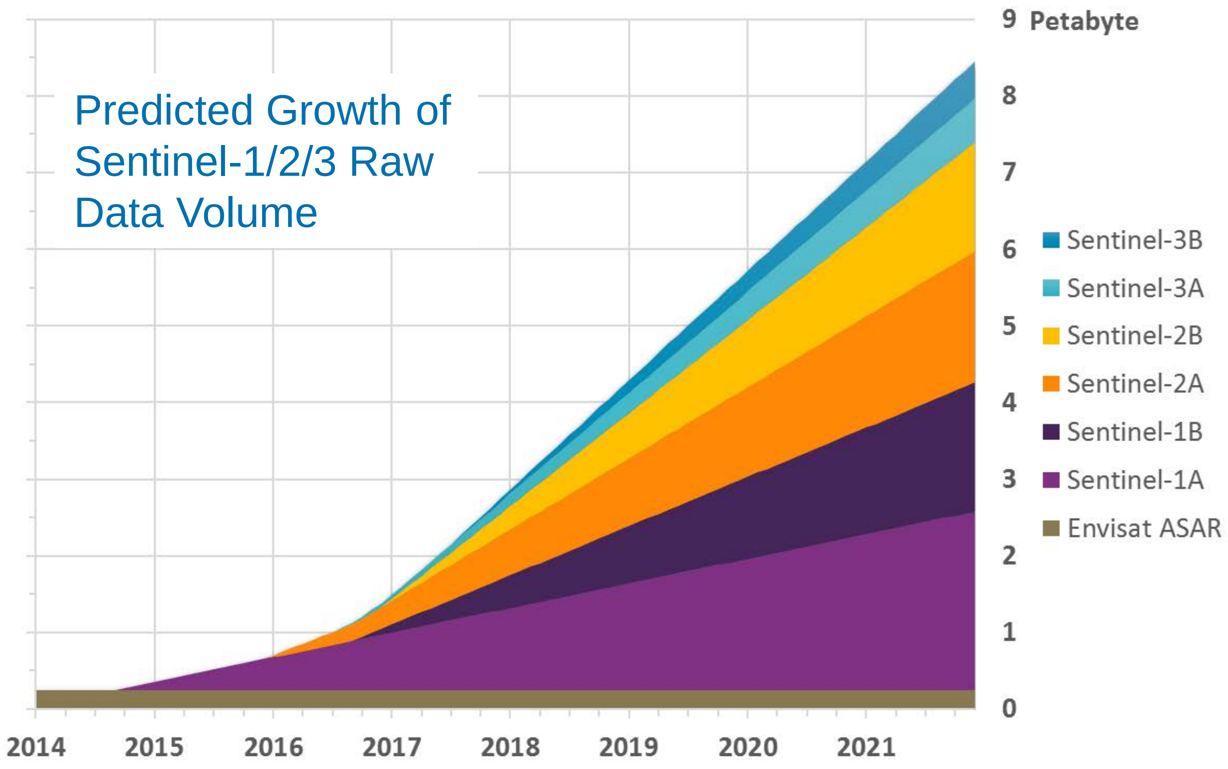
- Modelling next month's NDVI using SWI



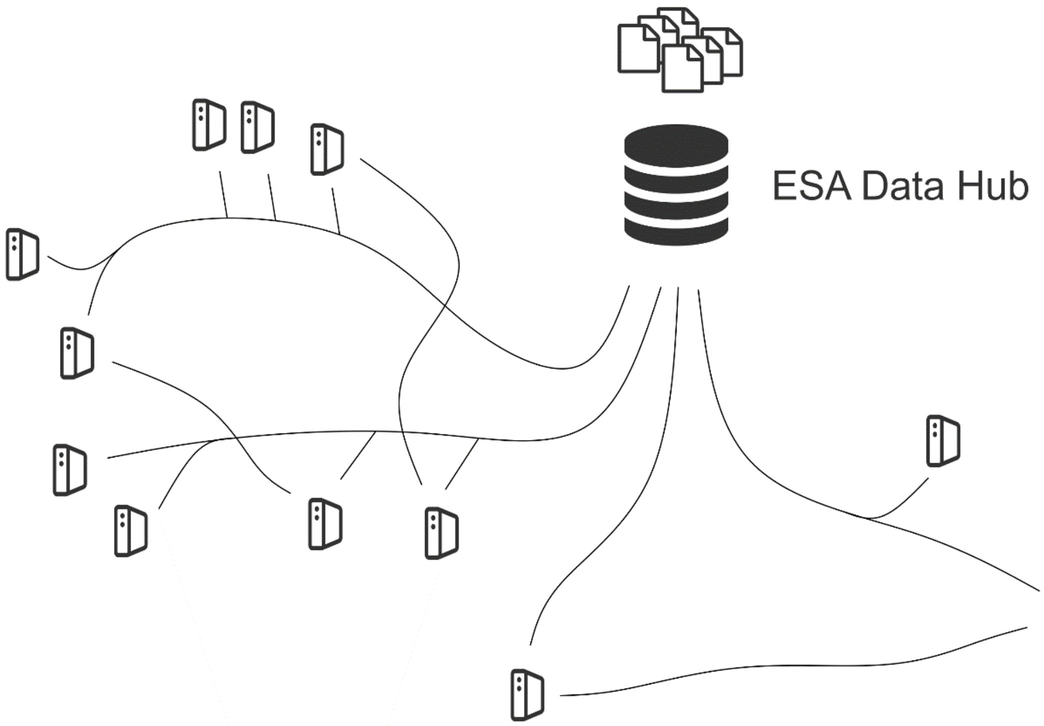
Zribi, M., T. Paris Anguela, B. Duchemin, Z. Lili, W. Wagner, S. Hasenauer, A. Chehbouni (2010) Relationship between soil moisture and vegetation in the Kairouan plain region of Tunisia using low spatial resolution satellite data, Water Resources Research, 46, W06508, 13 p.

Earth Observation in the Era of Big Data

- Volume and diversity of EO data is growing fast
- Bringing the users and their software to the data rather than vice versa becomes inevitable

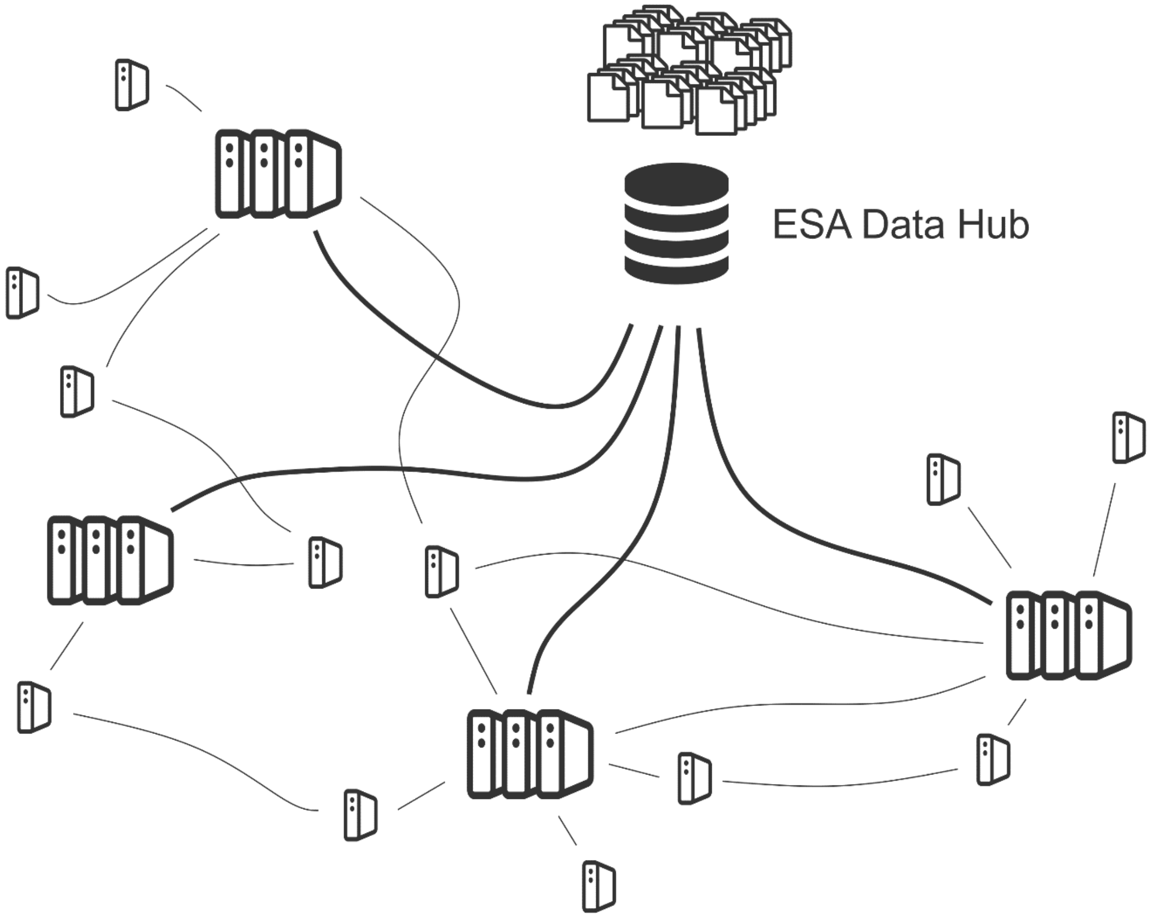


Earth Observation Ground Segment



Present

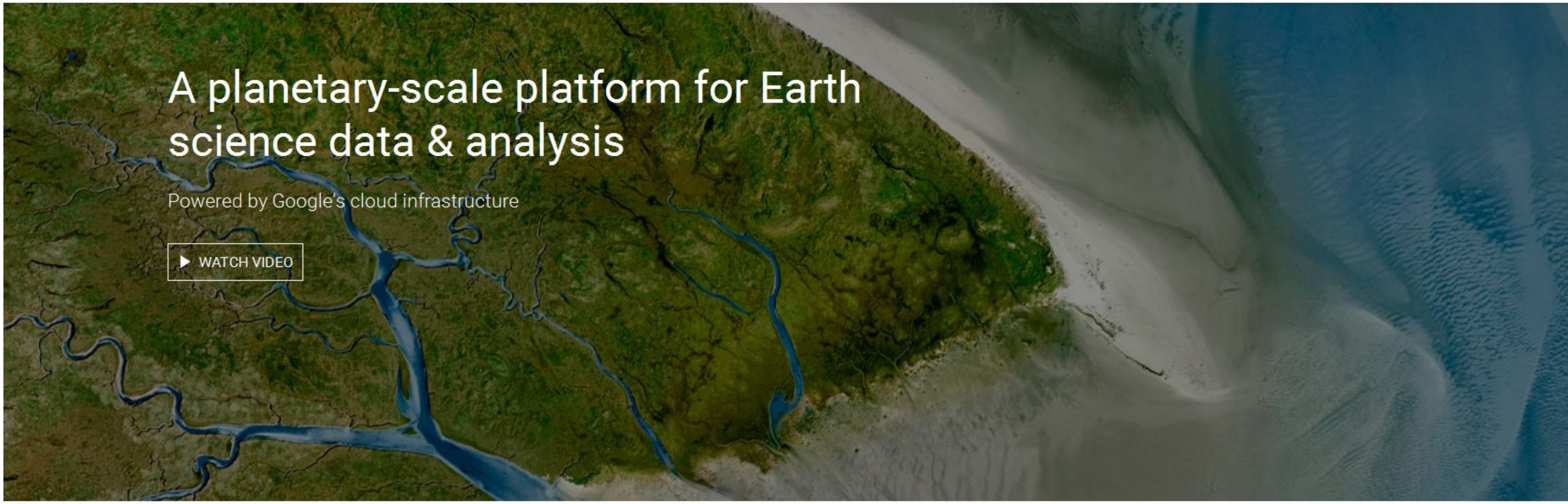
Earth Observation Ground Segment



Future

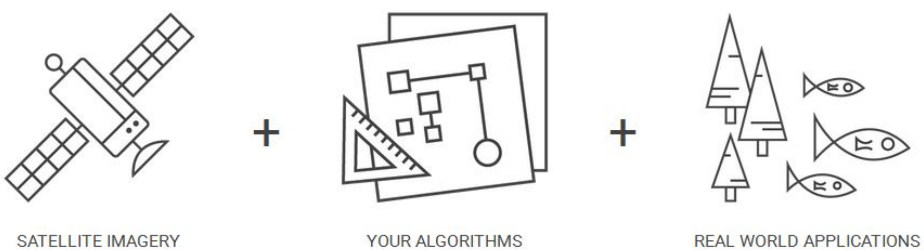
Google Earth Engine

FAQ | TIMELAPSE | DATASETS | CASE STUDIES | PLATFORM | SIGN UP



Meet Earth Engine

Google Earth Engine combines a multi-petabyte catalog of satellite imagery and geospatial datasets with planetary-scale analysis capabilities and makes it available for scientists, researchers, and developers to detect changes, map trends, and quantify differences on the Earth's surface.



https://earthengine.google.com/

Earth Observation Data Centre

- EODC works together with its partners from science, the public- and the private sectors in order to foster the use of EO data for monitoring of water and land
- Central Goals
  - Bring users and their software to the data
  - Organise cooperation & enable specialisation
- Facilitate Joint Developments
  - Cloud infrastructure, platform services, data services, software, etc.
- Processing of Big Data
  - From satellite raw data to biogeophysical data products up to model forecasts
    - Sentinel-1, Sentinel-2, etc.
- Organisation
  - The EODC GmbH was founded in May 2014 as Public Private Partnership
  - Interested organisations can join the EODC Partner Network by becoming Principal- or Associated Cooperation Partners

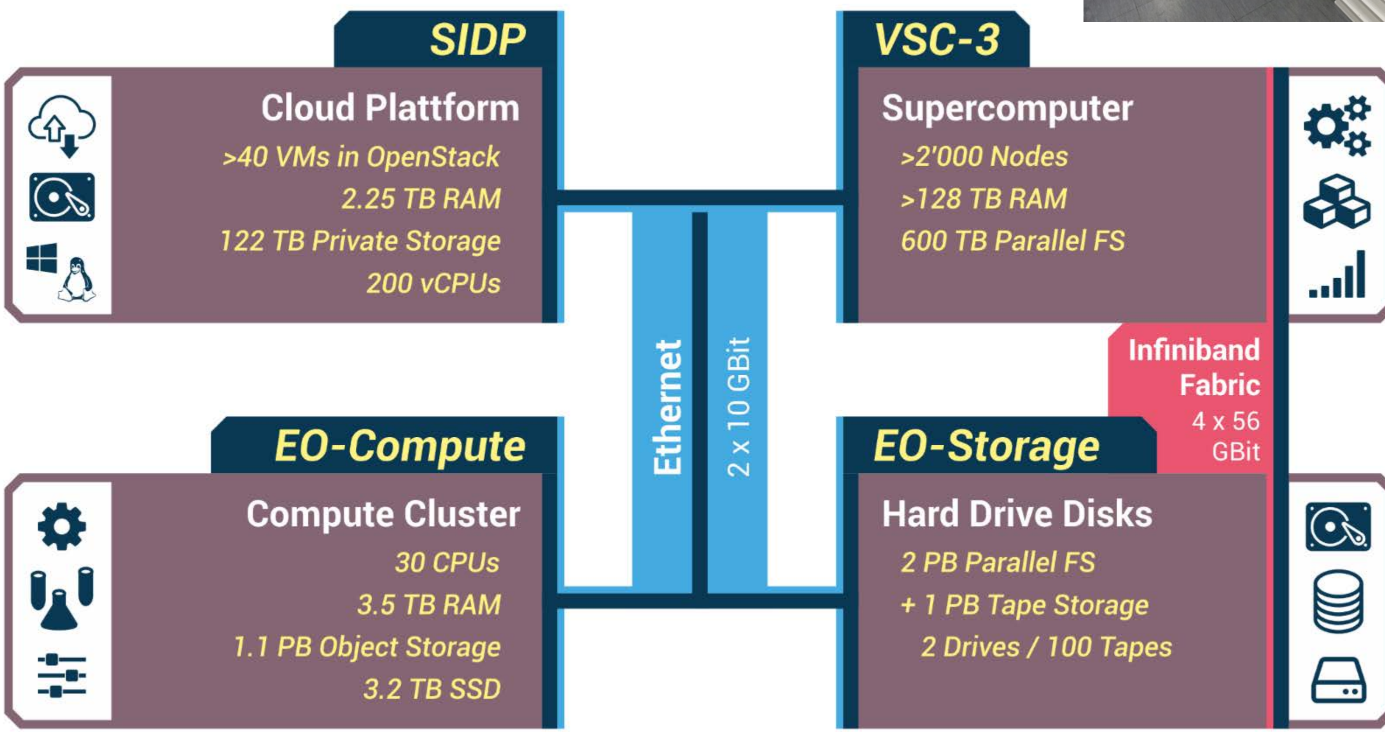
EODC Infrastructure @ TU Wien's Science Centre

- Shared, multi-owner infrastructure

TOP 500 The List.

Rank 165
(June 2016)

Science Integration and Development Cloud Platform



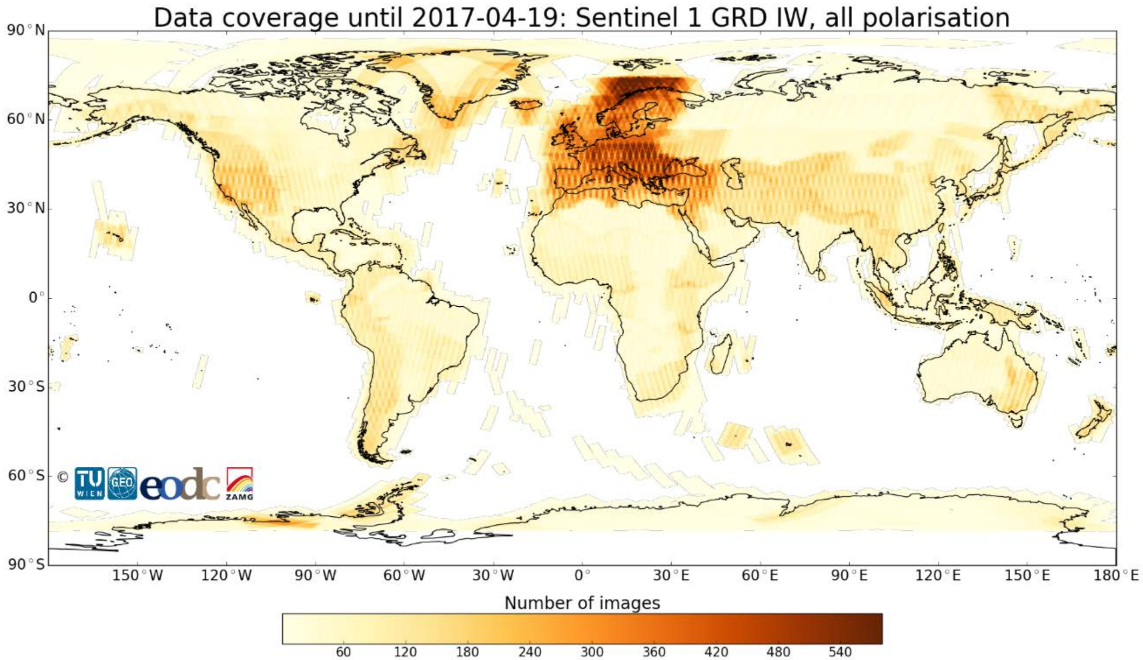
Petabyte-Scale Disk Storage (Disks & Tapes)

Dedicated EO Data Processing Cluster

Data Availability @ EODC

- Data are received via the Sentinel National Mirror Austria
- EODC aims to store complete Sentinel data record
  - Sentinel-1
  - Sentinel-2
  - Sentinel-3

> 1.4 PB of Raw Data
(Status March 2017)



Up-to-date coverage maps:
https://www.eodc.eu/sentinel-1a-coverage-maps/

Sentinel-1 Processing Times

	Global	*Europe*
Monthly data volume	15.546 TB	3.976 TB
Preprocessing time (10m) on single computing node	9,056.2 hrs (~377.3 days)	2,316.2 hrs (~96.5 days)
Monthly preprocessed data volume (*2.5 x raw data*)	38.865 TB	9.94 TB
Automatic quality check	93.2 hrs (3.8 days)	23.8 hrs (~1 day)
Parameter Estimation (10m)	1378.8 hrs (~57.5 days)	352.6 hrs (~14.7 days)
Flood Mapping (10m)	391.7 hrs (~39.1days)	100.2 hrs (~4.2 days)
Total processing time	~479 days	~118 days

Processing time for monthly Sentinel-1 (A&B) Level-1 IW GRDH (10 meters sampling) data. The table shown only automatic processing times, i.e. not including the reprocessing time and man power for running/checking/managing the processing.

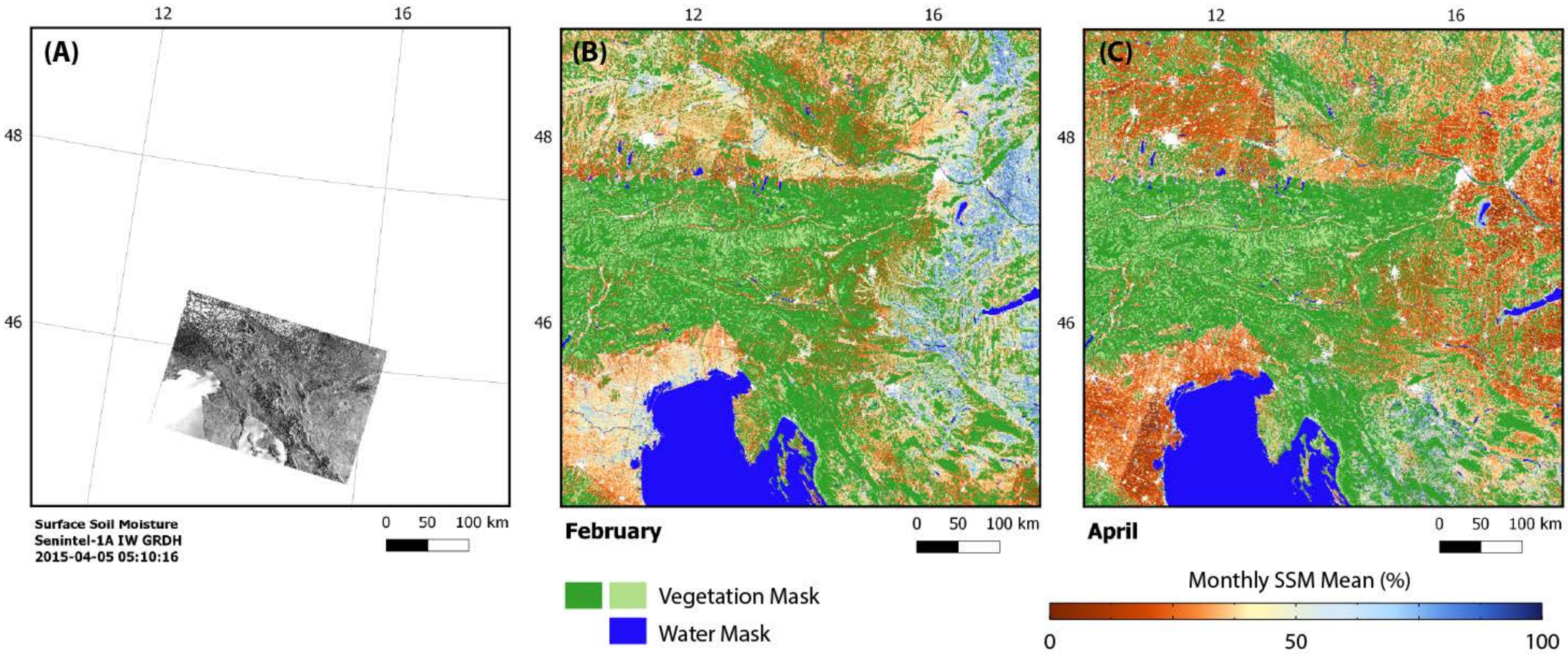
Numbers are based on 4 month Sentinel-1 data from October 2016 to January 2017

Supercomputing Experiment: SAR Geocoding

Test	n. 1	n. 2	n. 3	n. 4
SAR product mode	ASAR GM	ASAR WS	ASAR WS	S-1 IW GRDH
Spatial resolution	1 km	150 m	150 m	20 m
Total number of data files	189,621	31,199	31,199	1,075
Number of images for job / Total Number of jobs	8 / 23,703	2 / 15,600	2 / 15,600	1 / 1,075
Input data file size range	1 - 73 MB	12 - 692 MB	12 - 692 MB	0.8 – 1.7 GB
Total input data files size	1.579 TB	5.401 TB	5.401 TB	1.2 TB
Max. number of simultaneous running nodes	417	454	612	396
Number of cores used by Sentinel-1 Toolbox	4	8	8	8
Input data caching on node	False	False	True	True
Output data caching on node	True	True	True	True
Averaged processing time (seconds/MB)	9.18	5.65	2.39	2.69
Elapsed time including SLURM queueing	**≈ 3.5 days**	**≈ 4 days**	**≈ 8 hours**	**≈ 3.5 hours**
Estimated elapsed time using only 1 node	**≈ 167 days**	**≈ 353 days**	**≈ 353 days**	**≈ 37 days**

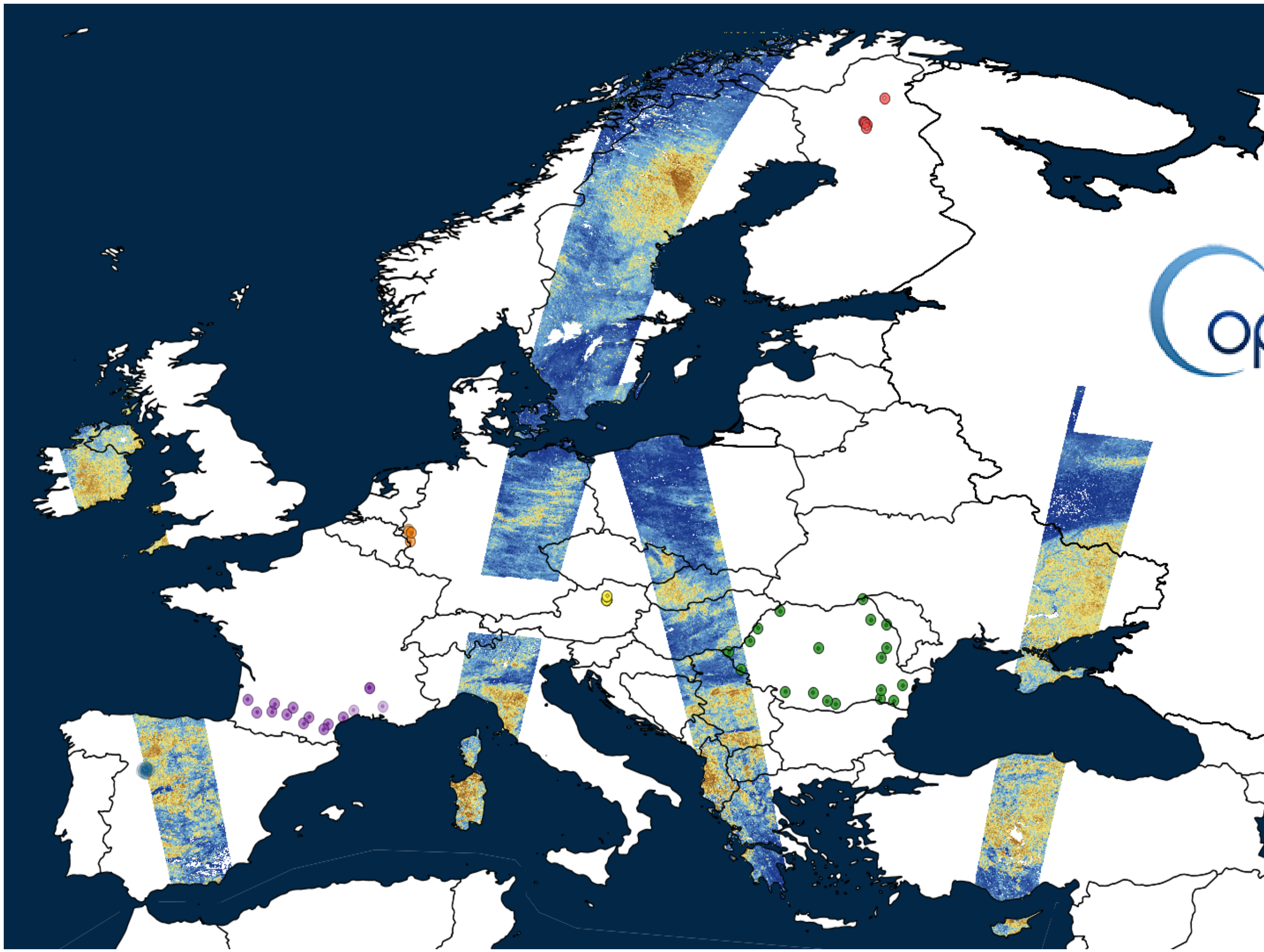
Elefante et al. (2016) High-performance computing for soil moisture estimation, BiDS'2016, EUR 27775 EN, 95-98.

Sentinel-1 Surface Soil Moisture



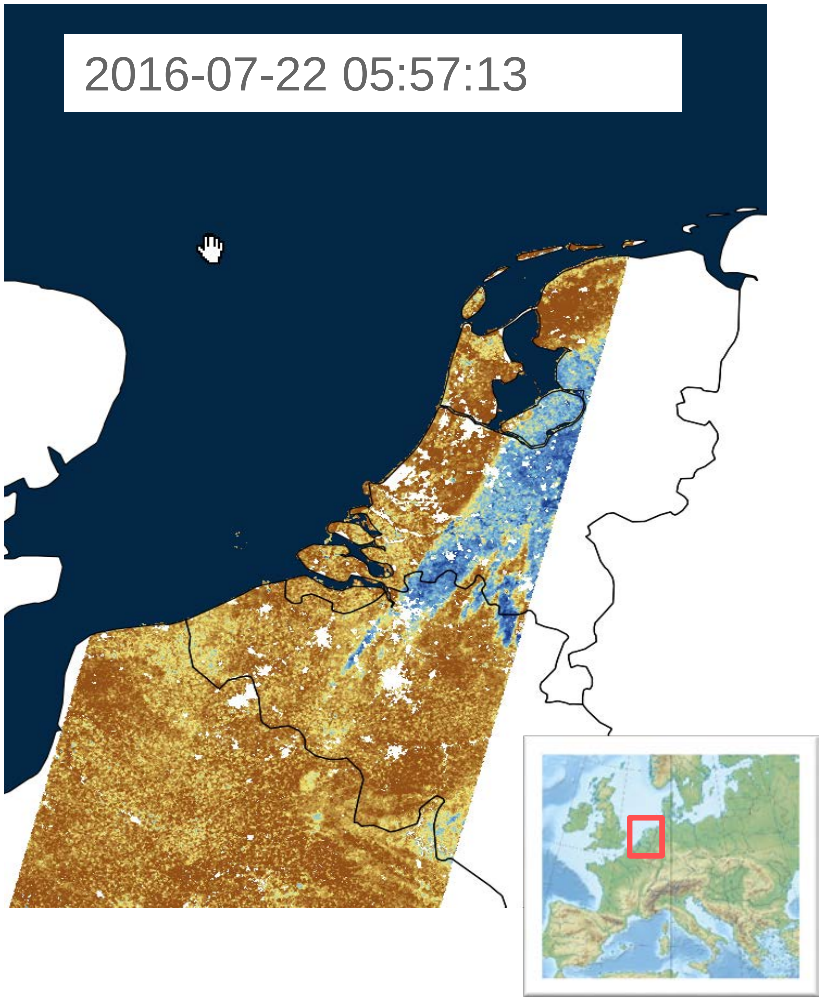
A) Sentinel-1 SSM product, 2015-04-05 05:1:15
B) Monthly average of SSM, February
C) Monthly average of SSM, April.

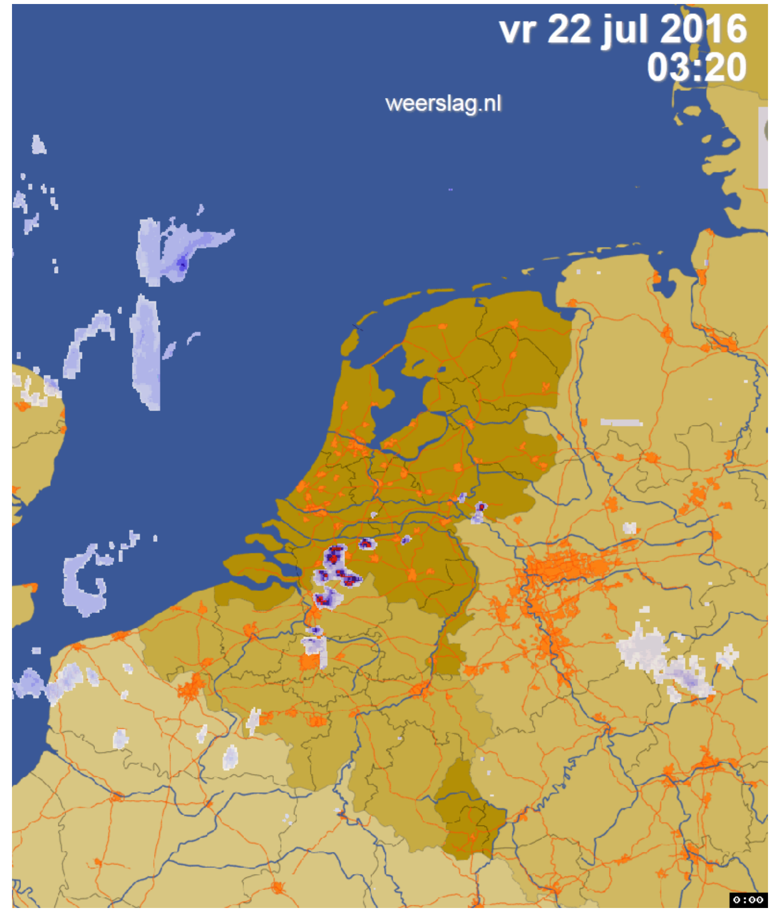
1 km Sentinel-1 SM Data



SSM1km on 2015-09-06 with ISMN stations used for validation

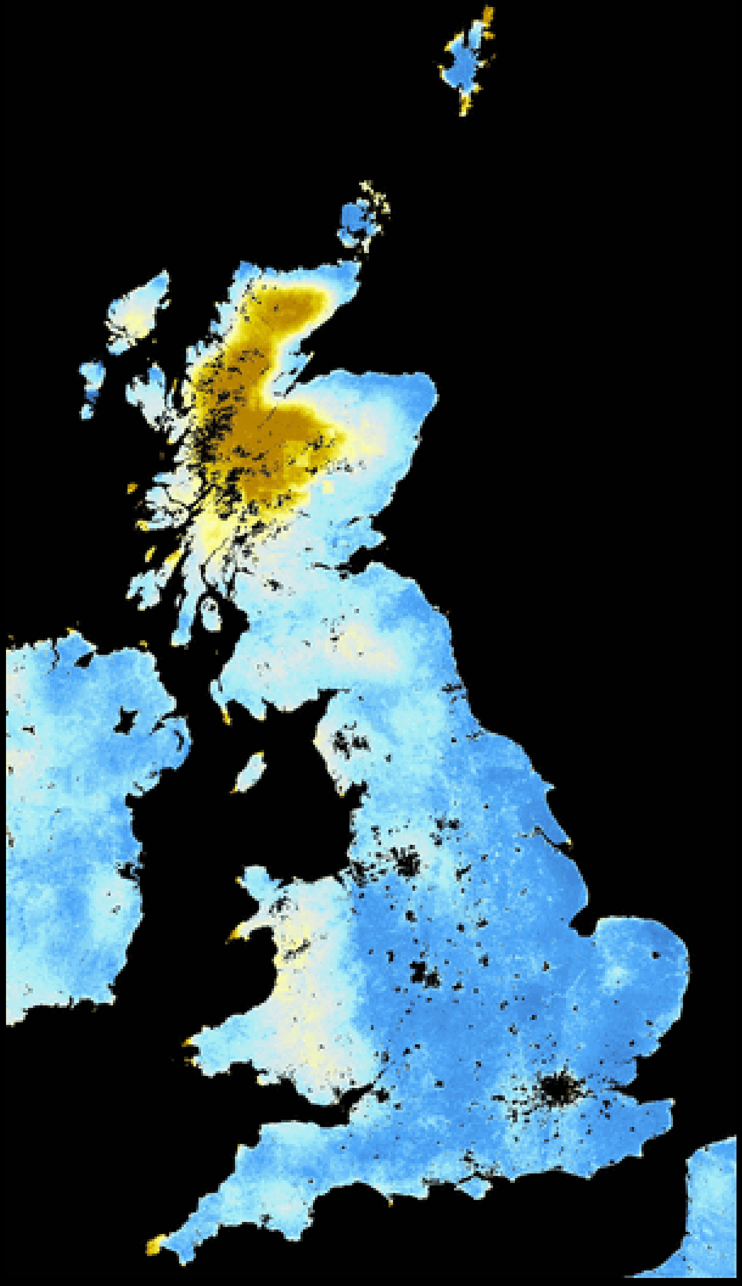
Precipitation Fronts seen in Sentinel-1 Soil Moisture





Sentinel-1 SSM 20150620_D

SCATSAR SWI T20   20150216



Conclusions & Outlook

- Scientific, technical and organisational challenges for building EO-based agrometeorological services are often underestimated
- Cooperation is essential
  - if one wants to avoid becoming 100 % dependent on a handful of big commercial ITC companies
  - to build processing chains covering all steps from raw EO data to final app interface for agrometeorological users
- Several EODC Partners are developing applications in support to agricultural decision making
  - E.g. agricultural drought apps based upon multi-sensor soil moisture and vegetation data products

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Austrian Space Application Programme: 854030 “EOP-Danube”
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European Commission JRC: Framework contract 388533 “Copernicus Global Land”
EUMETSAT: H-SAF CDOP2