NN retrieval of soil moisture

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and co-authors…

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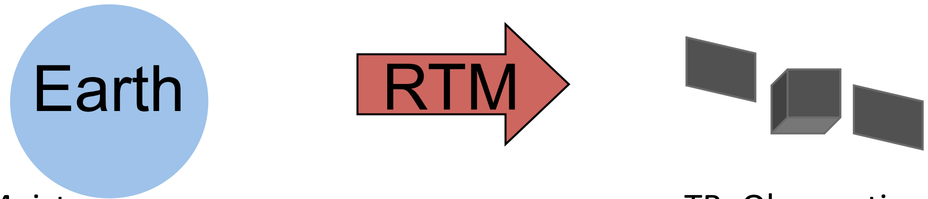
CNRS

Estellus

Physical retrieval algorithm

- **Inverse problem:**



SM=Soil Moisture
Z=other geophysical parameters:
veg., soil prop., Ts, *etc.*)

TB=Observations
SMOS, ASCAT, AMSR-E…)

➔ For each observation TB, we search SM such that: RTM(SM,Z) = TB
where RTM is Radiative Transfer Model

- **Classical approaches:** Iterative, Optimal Interpolation, Bayesian, etc.

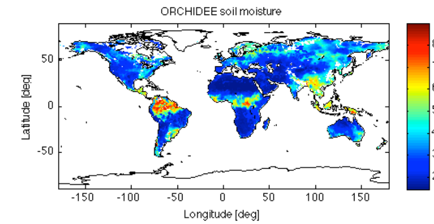
$$SM^* = SM_{fg} + [A^t S_\varepsilon^{-1} A + S_{fg}^{-1}]^{-1} \; A^t S_\varepsilon^{-1} (TB_\varepsilon - A \,.\, SM_{fg})$$

- **Limitations:** requires simulations RTM(X,Z) but uncertainties on:
  - *A priori* information on surface parameters Z
  - Radiative Transfer Model (RTM)

- **Question:** RTM modeling not satisfactory. Other solution?

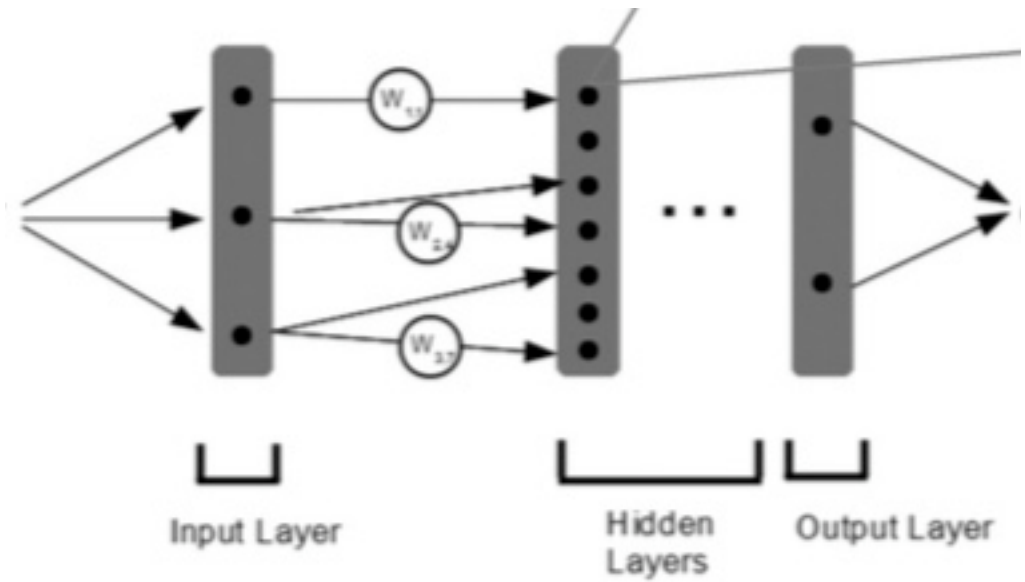
Neural networks retrieval

It is a parametric nonlinear regression model



Satellite Observ.

Pre-processing



SM Retrieval

Remark: The NN model is applied at pixel level, not as image processing (≠deep learning)

Advantages/inconvenients

Advantages of NNs:

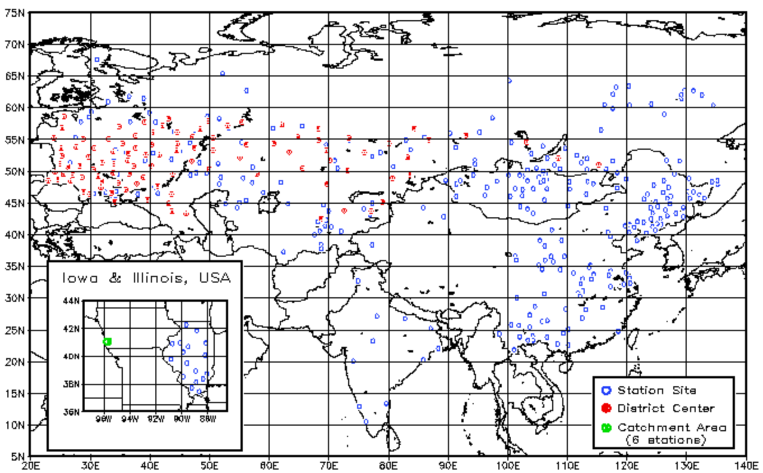
- *Fast* in operational mode, low memory required
- Multivariate, *high-dimension* space
- *Nonlinear*: situation-dependent, saturation effects
- *Flexible*: No rigid assumptions, can take realistic and complex specifications (FG, instr. noise, model errors, etc.) and various ways to introduce *a priori* information
- Global inversion model, no need for further inversion scheme
- Exploit *synergy*
- *Information content* tool to quantify the impact of: FG, noise, regime-dependence, number and location of channels, compression errors, fusion of information, *etc.*

Limitations of NNs:

- Needs to be *re-trained* if conditions change (new instrument, noise characteristics, etc.)
- Need a high-quality *learning dataset*

Building a learning dataset: *in situ* solution

In situ measurements



Global Soil Moisture Data Bank
(Robock et al., BAMS, 2000)

Region	Stations	Surface	Frequency	Period	Depth
Illinois	19	grass	1-3/m	All year	10cm
Iowa	6	corn	2/m	Growing	7.8cm
Russia	171	cereal	3/m	All year	20cm
India	11	grass	4/m	All year	xxcm
Mongolia	42	Pasture Weat	3/m	Spring summer	10cm

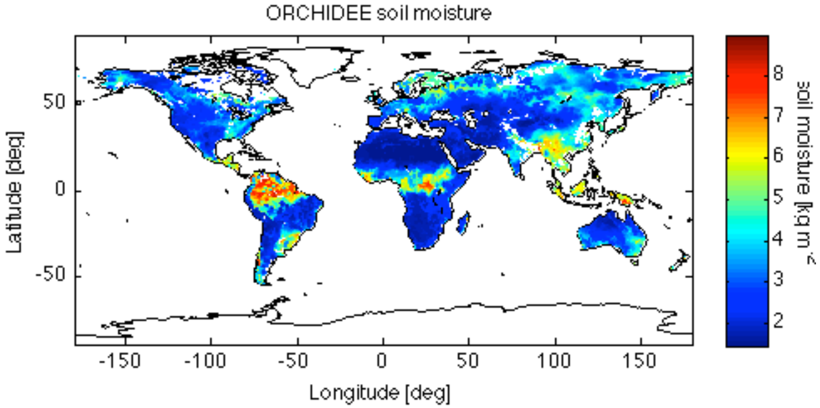
Real satellite observations

Problems:

- not enough *in situ* observations to represent well the spatial and temporal variability of soil moisture
- Spatial coherency of *in situ* data
- The measured SM might not be the same as what the satellite observes
- After launch only

Building a learning dataset: RTM simulations

Global SM from model



- Multiple years
- Global coverage
- We choose the SM we want from the model

RTM

Simulated Observations

Advantage:

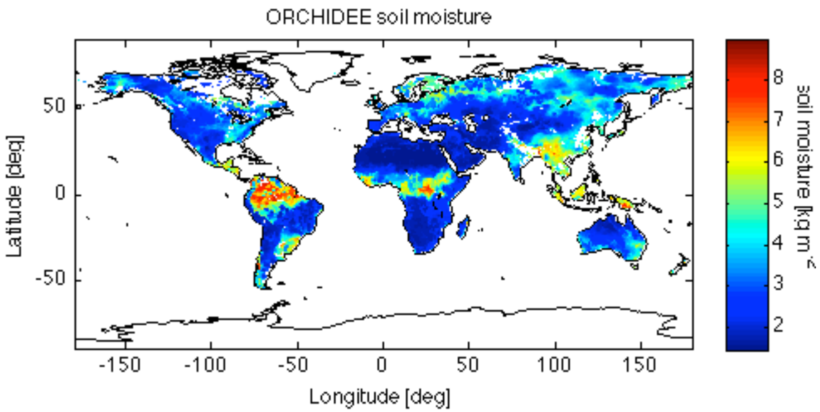
- Can be done before launch

Problem:

- What is our confidence on the Radiative Transfer Model?

Building a new learning dataset for historical measurements

Global SM from retrieval



- Multiple years
- Global coverage

Real SMOS observations

Advantage:

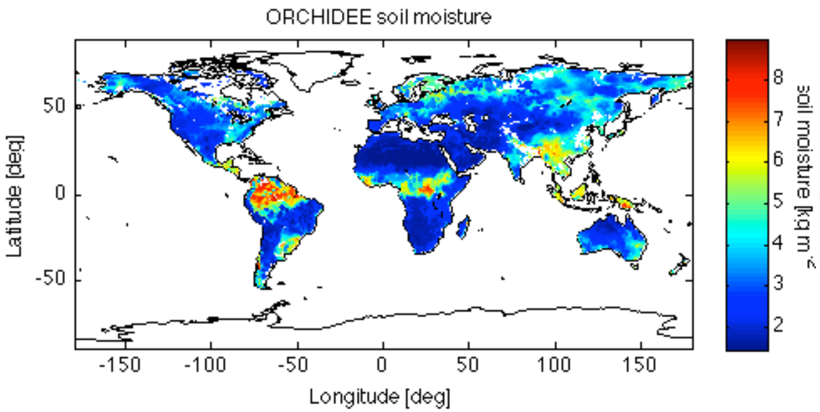
- Independent from Surface Model

Problem:

- Need to rely on an *a posteriori* retrieval, which is based on a RTM

Building a learning dataset: Our approach

Global SM from model



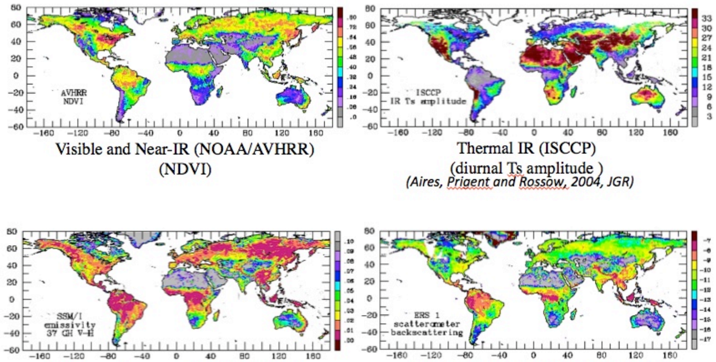
- Multiple years
- Global coverage
- We choose the SM we want from the model

Real satellite observations

Problems/questions:

- Is the land model SM good enough?
- Are the SM really related to the Obs?
- Are we just reproducing the SM from the model when teaching the retrieval with this dataset?
- After launch only

NN approach



Visible and Near-IR (NOAA/AVHRR) (NDVI)

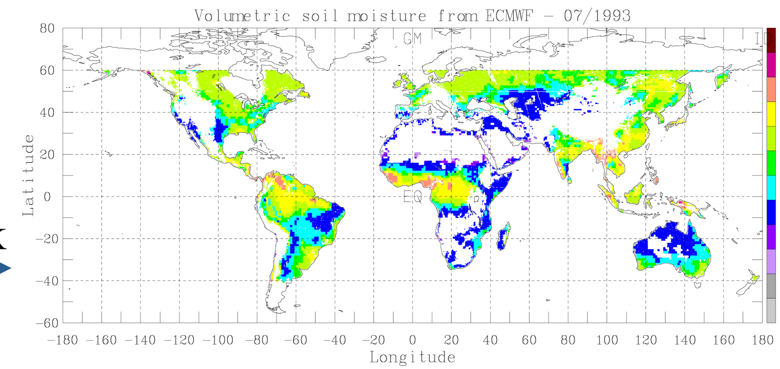
Thermal IR (ISCCP) (diurnal Ts amplitude) *(Aires, Prigent and Rossow, 2004, JGR)*

Passive microwave (DMSP / SSM/I) (surface emissivities) *(Prigent, Aires, and Rossow, 2006, JGR)*

Active microwave (ERS scatterometer) (backscattering coefficient)

All available SM- information: visible, passive and active MW, thermal IR

Neural Network



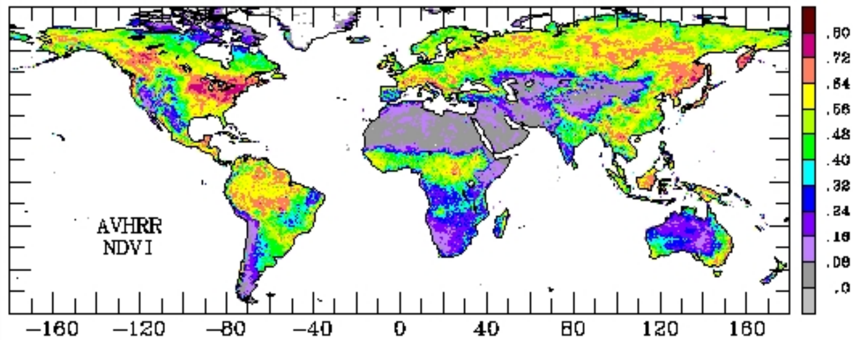
Soil moisture from model (NCEP or ECMWF)

Applications:

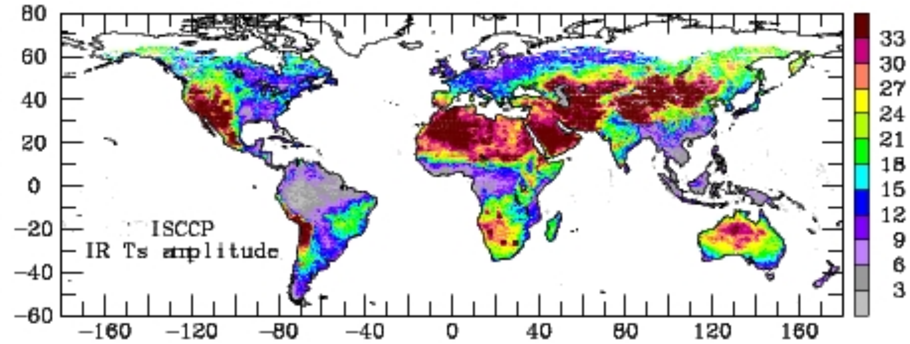
1) **Information content analysis, and synergy**
2) **Remote sensing**: No need of RTM, or *in situ* measurements
3) **Consistency checking method:** Check consistency of model output with satellite observations, help model development
4) **Variational assimilation applications:** Define a link between observations and model (link coherent with model) but need to specify uncertainties

(Aires, Prigent, Rossow, Soil moisture at a global scale. II – Global Statistical relationships, JGR, 2005)

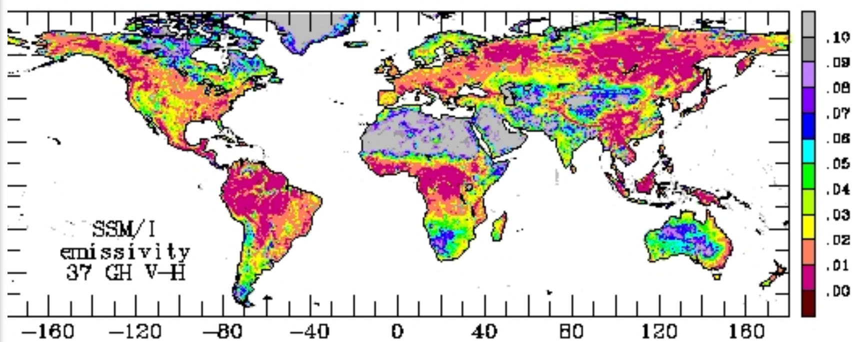
Application 1) – Information content & synergy



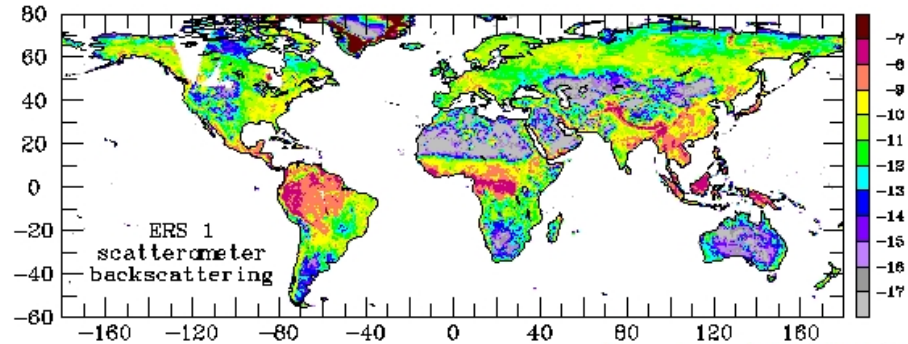
Visible and Near-IR (NOAA/AVHRR)
(NDVI)



Thermal IR (ISCCP)
(diurnal Ts amplitude)
(Aires, Prigent and Rossow, 2004, JGR)



Passive microwave (DMSP / SSM/I)
(surface emissivities)
(Prigent, Aires, and Rossow, 2006, JGR)



Active microwave (ERS scatterom
(backscattering coefficient)

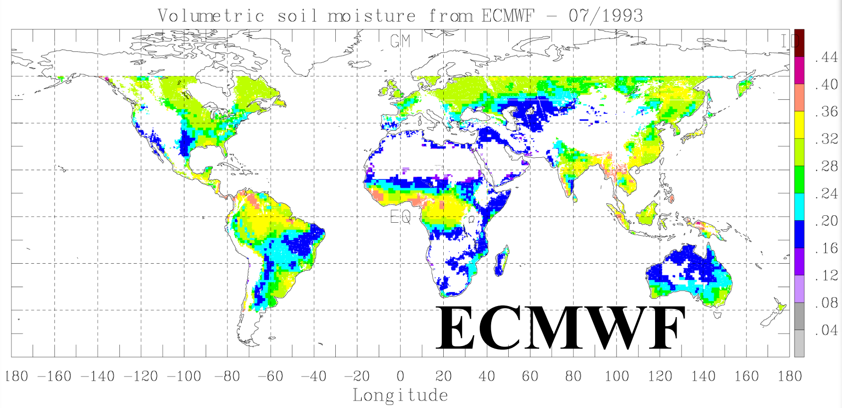
Accumulating Predictors	RMS NCEP	CORR. NCEP	RMS ECMWF	CORR. ECMWF
IR Norm Ts Amp.	0.059	0.753	0.057	0.633
ERS small ang.	0.055	0.792	0.054	0.676
NDVI	0.052	0.819	0.052	0.704
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
ERS large ang.	0.050	0.830	0.051	0.724
SSMI E37V-H	0.050	0.832	0.050	0.735
SSMI E19V-H	0.050	0.832	0.050	0.737
SSMI E19V	0.050	0.833	0.050	0.738
SSMI E85V-H	0.050	0.833	0.050	0.739

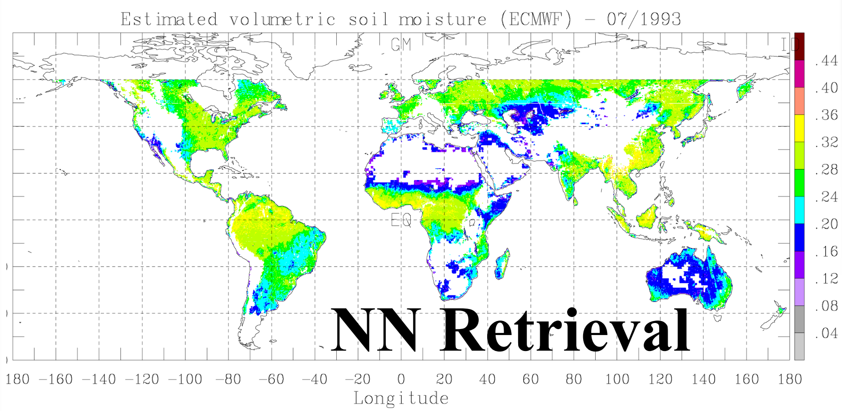
- **Information content**
- **Data fusion and synerg**

- **Soil moisture at a global scale** I, Prigent, Aires, Rossow, JGR, 2005
- Soil Moisture retrieval from multi-instrument observations: information content and retrieval methodology, Kolassa, Aires, Polcher, Prignet, Jimenez, Pereira, JGR, 2013
- Soil moisture retrieval from **AMSR-E and ASCAT** microwave observations synergy Part 1: Satellite data analysis, Kolassa, Gentine, Prigent, Aires, RSE, 2016

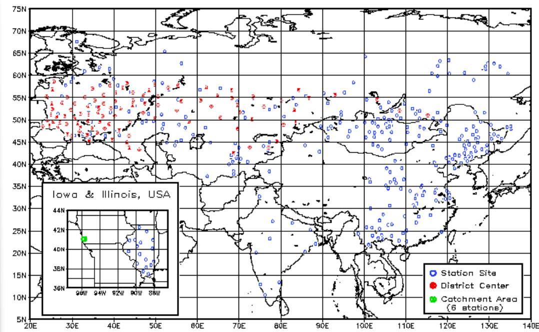
Application 2) - Soil moisture retrieval

Evaluation

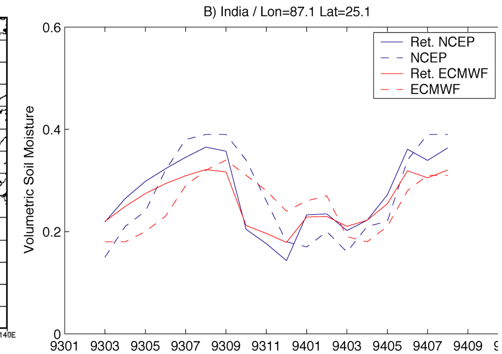




- Spatial and temporal variability of the retrieval is based on the observations
- The NN retrieval does not reproduce the model patterns, it can even correct it!



Global Soil Moisture Data Bank, Robock et al., 2000



Local temporal variability assessed

Network	spatial			temporal		
	NN	WACMOS	HTESSEL	NN	WACMOS	HTESSEL
ARM	0.65	0.59	0.48	0.09	0.49	0.71
CHINA	-	-	-	0.60	0.55	0.67
ICN	-	-	-	-0.46	0.50	0.70
MONGOLIA	0.62	0.14	0.50	0.51	0.43	0.46
SCAN	0.51	0.56	0.67	0.19	0.64	0.72
SNOTEL	-	-	-	0.46	0.61	0.70

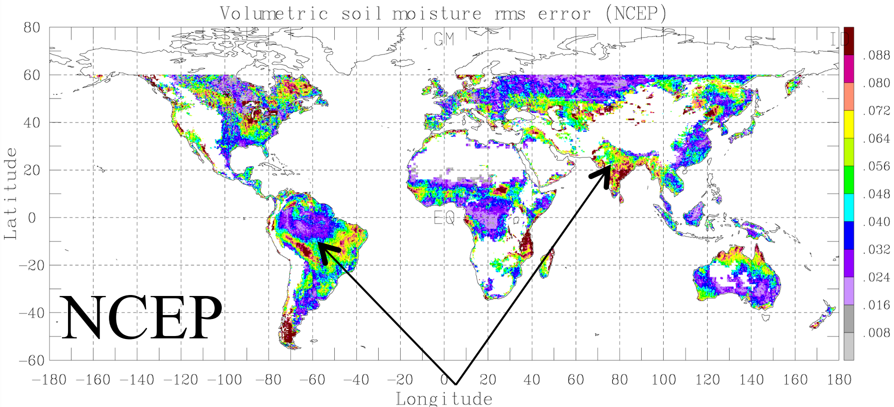
Local temporal variability assessed

Dataset	RMSE [kg m^{-2}]	σ [kg m^{-2}]	$\rho_{spatial}$	$\rho_{seasonal}$	$\rho_{interannual}$
σ_{40}	**0.95**	1.07	0.76	**0.66**	**0.56**
T_S	0.96	**1.1**	**0.79**	0.64	0.47
e_h ,e_v	1.00	1.14	0.74	0.46	0.39
NDVI	1.05	1.25	0.68	0.54	0.38
BTI	1.22	1.59	0.39	0.68	0.57

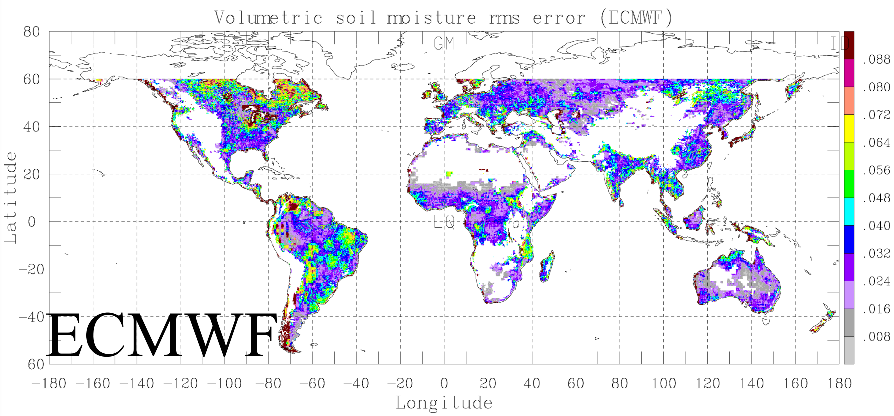
Several spatial/temporal **metrics** are used

SM retrieval from AMSR-E & ASCAT MW observation synergy Part 2: Product evaluation, Kolassa, Gentine, Prigent, Aires, Ale., RSE, 2017

Application 3) – Consistency checking



Higher incoherencies model/observations

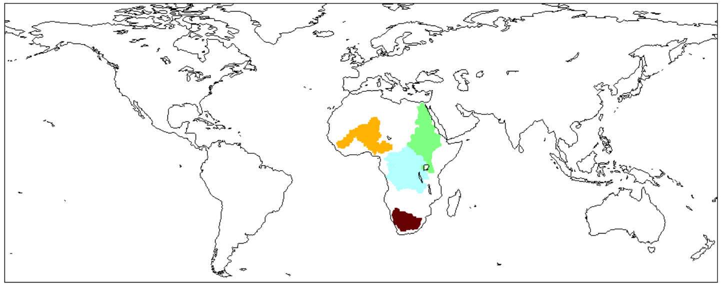


➔Consistency checking between model output and satellite observations:

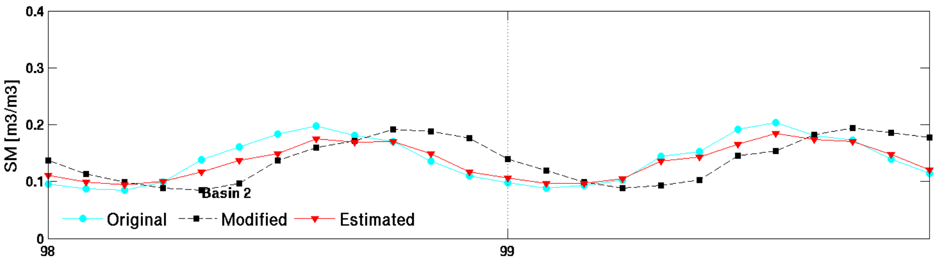
- ECMWF closer to EO observations
- This tool can help model development

Aires, Prigent, Rossow, Soil moisture at a global scale. II – Global Statistical relationships, JGR, 2005)

Synthetic tests:



Shifting the SM seasonal cycle in some basins



➔NN retrieval is able to correct season where necessary

Jimenez, Clark, Kolassa, Aires, Prigent & Blyth, A joint analysis of modelled SM fields and satellite obs., JGR,2013.

Application 4) - Variational assimilation

- Assimilation in NWP centres of:
  (1) Raw observations: need a RTM, good auxiliary parameters
  ➔ Ask to the system to "perform" the retrieval, data fusion
  (2) Retrieved SM: need uncertainty characterization Ri

- Solution (1) has been privileged because easier to specify errors in raw observations (supposed to be constant) than on retrieved products (state-dependent). But difficulty to rely on the RTM…

(2)

$$J(x_0) = \frac{1}{2}(x_0 - {x_0}^b)^T \boldsymbol{B}^{-1}(x_0 - {x_0}^b)$$
$$+ \frac{1}{2}\sum_{i=0}^{n}(x(t_i) - {x_i}^r)^T \boldsymbol{R}_i(x(t_i))^{-1}(x(t_i) - {x_i}^r)$$

Advantages of (2):

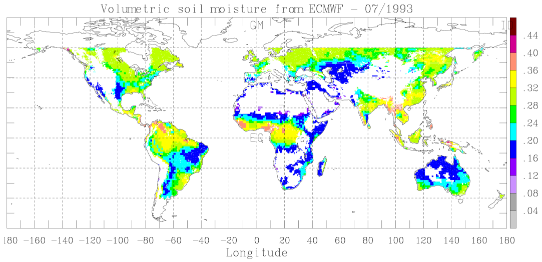
- Retrieval is coherent with model SM
- We can "help" the retrieval when necessary
- No need for aux. parameters

Aires, F., et al. (2005), Sensitivity of satellite microwave and infrared observations to SM at a global scale: 2. Global statistical relationships, JGR.

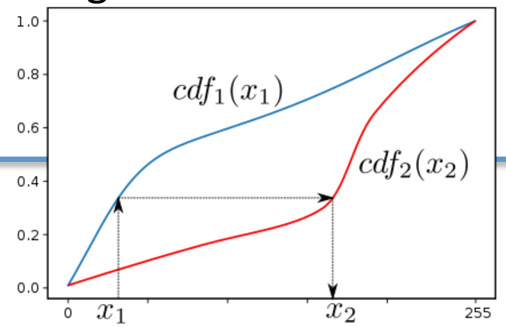
Application 4) - Variational assimilation

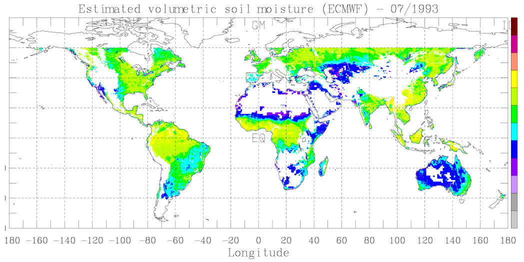
- Is NN retrieval independent enough from the model?

- Our approach:



One general “CDF matching”

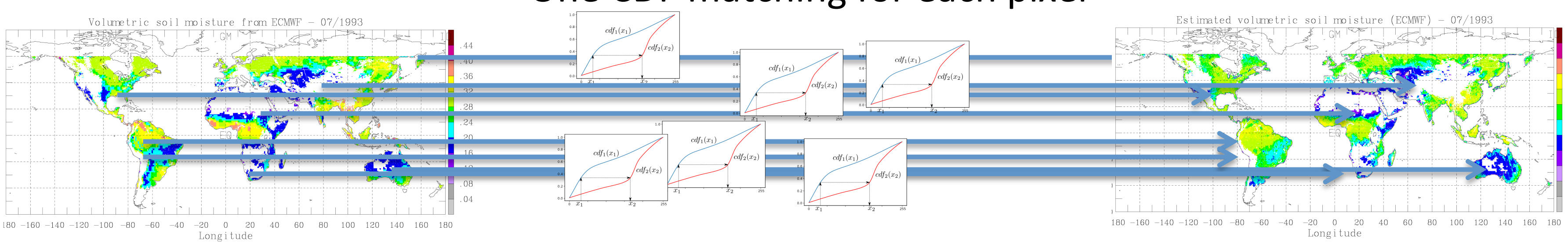




The NN retrieval is less model-dependent

- Classical approach:

One CDF matching for each pixel



Data assimilation to extract soil moisture information from SMAP observations, Kolassa et al., RS, 2017.

➔ Global bias-calibration better than localized ones for assimilation!

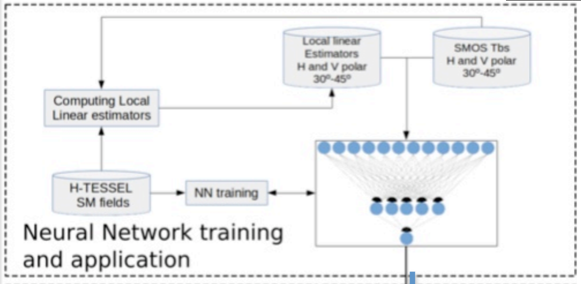
- Spatial pattern of EO data is changed
- Dynamic behaviour too

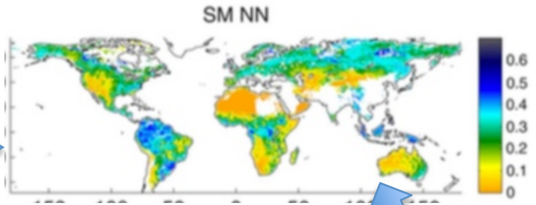
Assimilation experiments at ECMWF with SMOS

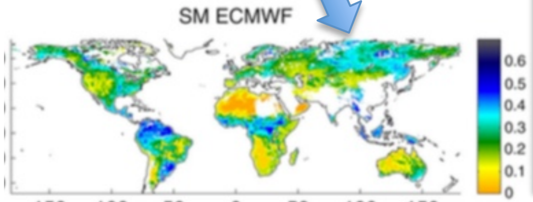
■First retrieval:

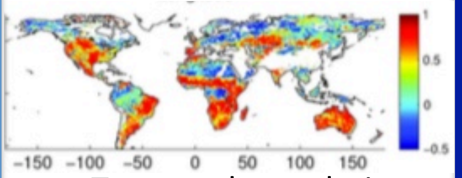
NN

SMOS data
NDVI
Soil texture…





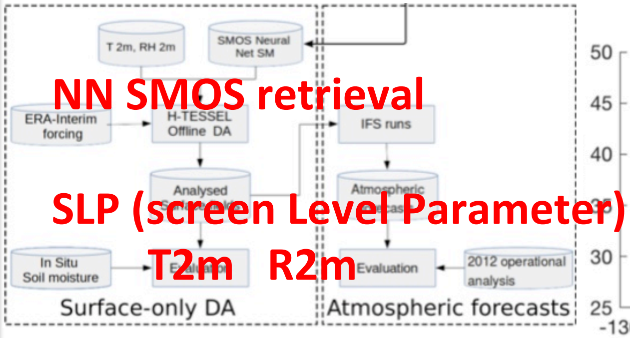




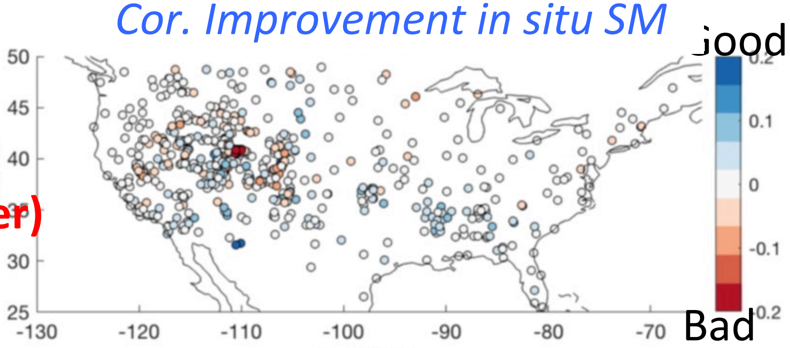
- Temporal correlation
- Spatial evaluation
- *In situ* measurements

SM retrieval using NN: Application to SMOS, Rodriguez-Fernandez, Aires, Richaume, Ker, Prigent, Kolassa, Cabot, Jimnenez, Mahmoodi, Drush, IEEE TGRS, 2015

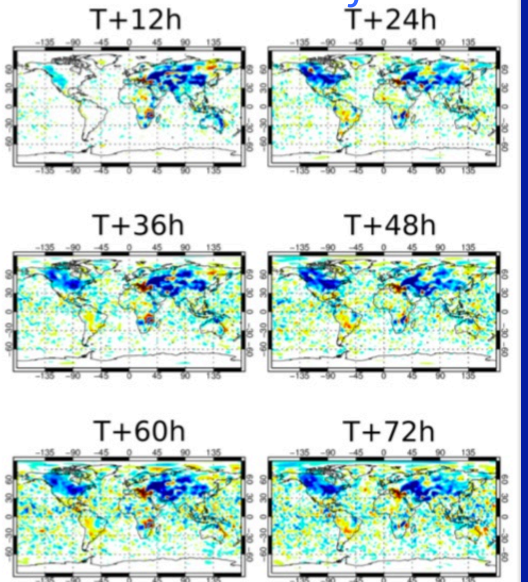
■Assimilation:



Cor. Improvement in situ SM



Forecast skills of T850



SMOS NN SM data assimilation in a land surface model& atmospheric impact, Rodriguez-Fernandez, de Rosnay, Albergel, Richaume, Aires, Prigent, Kerr, RS, 2019

■In parallel, SMAP assimilation at NASA:

- Data assimilation to extract soil moisture information from SMAP observations, Kolassa et al., RS, 2017.
- Merging active & passive MW observations in SM data assimilation, Kolassa, Reichle, Draper, RSE 2017.

Downscaling of SM

NN downscaling scheme

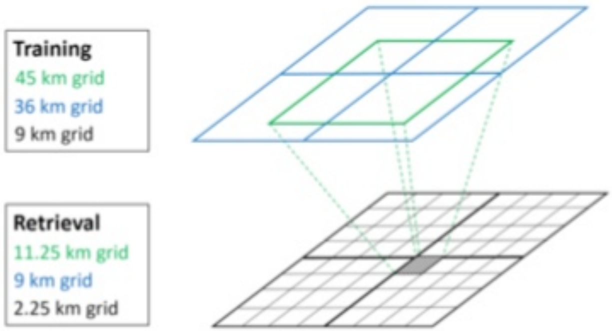
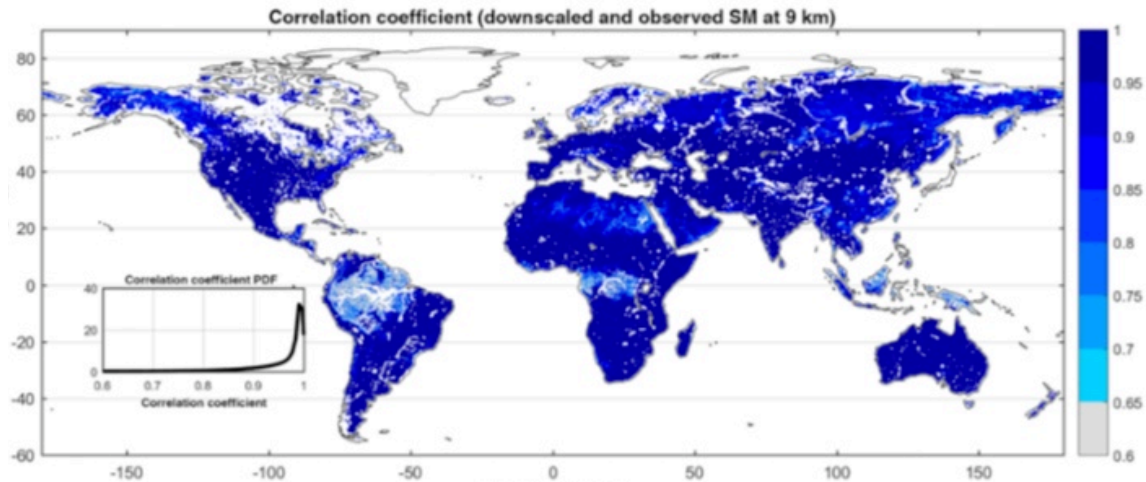


Figure 1. Two levels of spatial grids used for training and retrieval steps in the NN algorithm. While both steps have similar grid structures, the spatial resolutions are different as listed here.

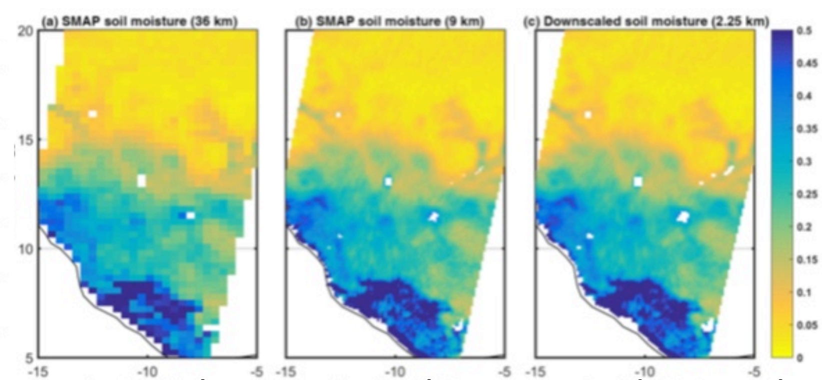


Cor. SMAP-observed SM at 9 km & NN-downscaled SM at 9 km.

Inputs using in each of the downscaling scheme:

No.	Usage	Input 1	Input 2	Input 3	Input 4	Input 5	Input 6
R1	Training	SM at 45 km	NDVI at 45 km	NDVI at 9 km for target pixel			
	Retrieval	SM at 11.25 km	NDVI at 11.25 km	NDVI at 2.25 km for target pixel			
R2	Training	SM at 45 km	NDVI at 45 km	NDVI at 9 km for target pixel	σ_{NDVI} at 45 km for all pixels at 9 km	–	–
	Retrieval	SM at 11.25 km	NDVI at 11.25 km	NDVI at 2.25 km for target pixel	σ_{NDVI} at 11.25 km for all pixels at 2.25 km	–	–
R3	Training	SM at 45 km	NDVI at 45 km	NDVI at 9 km for target pixel	TI at 45 km	TI at 9 km for target pixel	–
	Retrieval	SM at 11.25 km	NDVI at 11.25 km	NDVI at 2.25 km for target pixel	TI at 11.25 km	TI at 2.25 km for target pixel	–
R4	Training	SM at 45 km	NDVI at 45 km	NDVI at 9 km for target pixel	TI at 45 km	TI at 9 km for target pixel	σ_{NDVI} at 45 km for all pixels at 9 km
	Retrieval	SM at 11.25 km	NDVI at 11.25 km	NDVI at 2.25 km for target pixel	TI at 11.25 km	TI at 2.25 km for target pixel	σ_{NDVI} at 11.25 km for all pixels at 2.25 km

ASCAT SM (45 or 11 km)
NDVI (45 and 9km)
σ_{NDVI}
Time index

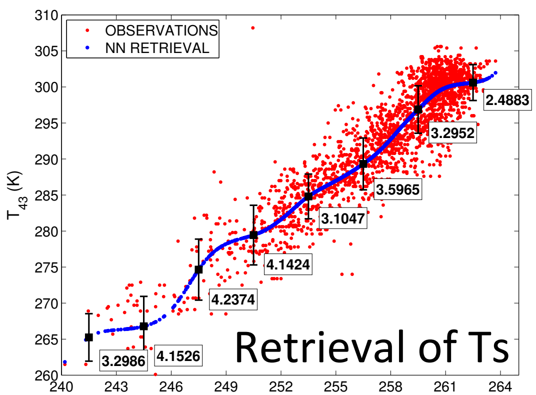


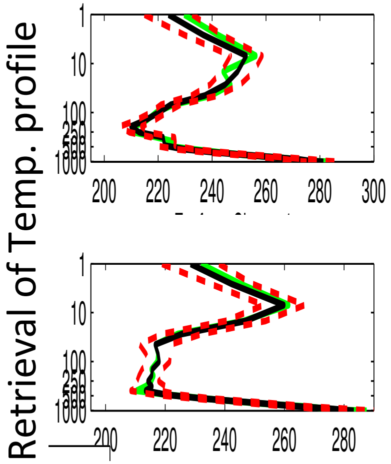
SMAP 36km SMAP 9km SMAP-downscaled

Global downscaling of remotely sensed SM using NN, Alemohammad, Kolassa, Prigent, Aires, Gentine, HESSS, 2018.

Conclusion/Perspectives

- What we learned:
  - This is perfect technique to **build long-term record of SM**
    - Calibration over long time record
    - Technique flexible enough for all kind of instruments
    - Exploit synergy for better SM retrieval
  - Good approach for **SM assimilation** (& other surface products?)
- Assimilation in NWP centres:
  - ECMWF
  - NASA
- **Uncertainty characterization** to improve usability of SM product & facilitate assimilation

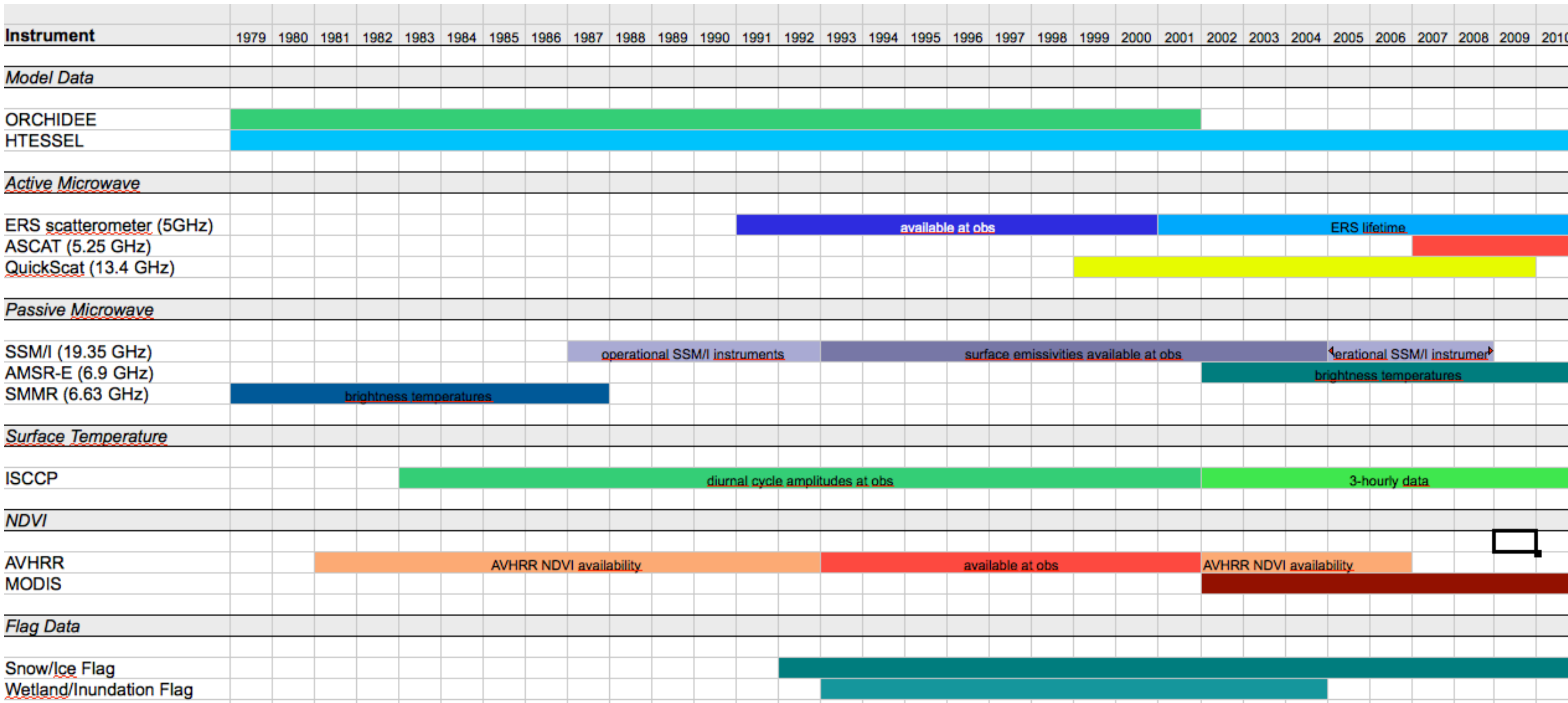




- State-dependency of retrieval errors
- Similar work should be done for SM

Perspectives

- Build long-term record of SM using all the available EO:



Data fusion better synergy than *a posteriori* combination:

- Aires, Aznay, Prigent, Paul, Bernardo, JGR, 2012
- SM retrieval from AMSR-E & ASCAT MW observations synergy Part 1: Satellite data analysis, Kolassa, Gentine, Prigent, Aires, RSE, 2016
- Merging active & passive MS observations in SM data assimilation, Kolassa, et al., RSE 2017.

➔ Merging EO data *a priori* better than *a posteriori* combination of a SM products

Thank you!