Neural networks retrievals and applications: what we learnt from SMOS

N.J. Rodriguez-Fernandez
CESBIO (CNRS, CNES, IRD, Université de Toulouse)

Acknowledgements (in alphabetical order): F. Aires, C. Albergel, A. Al Yaari, M. Drusch, R. de Jeu, Y. Kerr, J. Muñoz-Sabater, C. Prigent, P. Richaume, P. de Rosnay, R. Van der Schalie, J.P. Wigneron

Outline

- Training NNs with radiative transfer data
  - Operational application: ESA near real-time SMOS SM
- Training NNs with land surface models
  - Research application: SM assimilation at ECMWF
- Purely data driven approach: linking remote sensing observations and in situ measurements
- Disaggregation (downscaling), root zone soil moisture
- Multi-sensor synergy and climate records

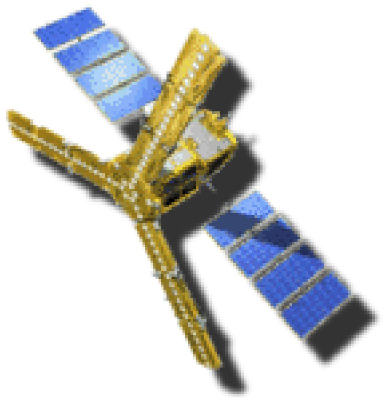
Neural networks and SMOS : a long story

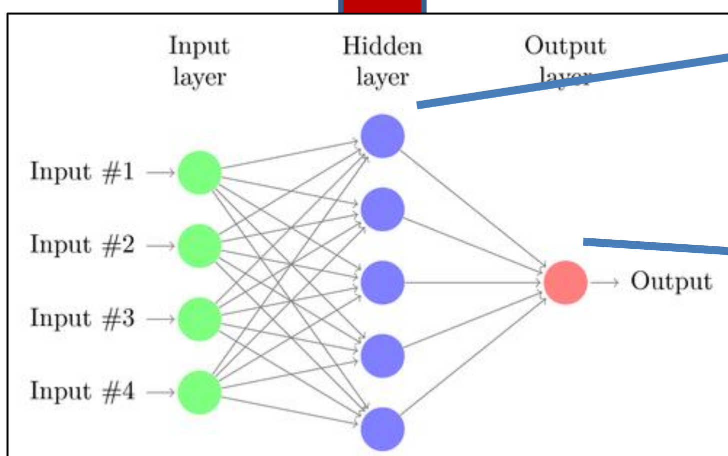
• Neural networks to retrieve soil moisture and salinity were planned since the late 90's / early 2000's (see ATBD, Kerr et al.)
• Several preliminary evaluations were done : local studies, mainly based in simulating TBs

• **Liou** et al, "*Retrieving soil moisture from simulated brightness temperatures by a neural network*," **2001**, IEEE TGARS
• **Liu** et al., "*Retrieval of crop biomass and soil moisture from measured 1.4 and 10.65 GHz brightness temperatures,* **2002**, IEEE TGARS
• **Berthelot**, "*Inversion de l'humidite des sols en utilisant une approche neuronale*," Noveltis report NOV-3050-NT-1965, Oct. **2004**
• **Berthelot** et al. *"Estimation of soil moisture from SMOS SEPSBIO simulated dataset using neural network*," in Poster seesion, 7th SMOS Workshop, ESA ESRIN Frascati, Italy October 29- 31, **2007**,
• **Ammar** et al., "*Sea Surface **Salinity** Retrieval for the SMOS Mission Using Neural Networks,* **2008**, IEEE TGARS
• **Angiuli** et al., *"Application of Neural Networks to Soil Moisture Retrievals from L-Band Radiometric Data,"* IGARSS **2008**
• **Chai** et al. "*Explicit inverse of soil moisture retrieval with an artificial neural network using passive microwave remote sensing data* IGARSS **2008**. pp. II–687.
• **Chai** et al, "*Use of Soil Moisture Variability in Artificial Neural Network Retrieval of Soil Moisture*," **2010**, Remote Sensing

The ESA near-real-time SM product

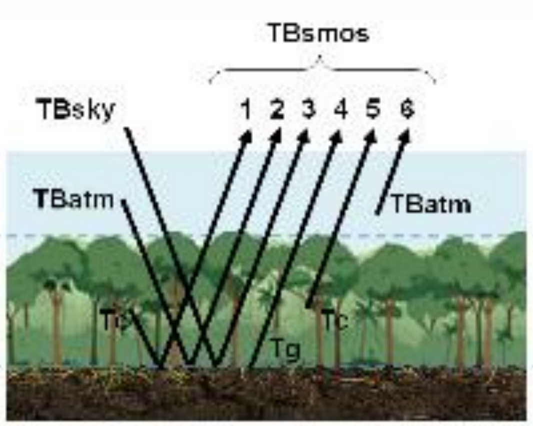
- SMOS Near Real Time Tbs 30º-45º
- Normalization with local extreme SM
- ECMWF Tsoil





$$v_j^{L1} = \tanh\left(\sum_{i=1}^{n_{in}} W_{L1}^{ij}\, v_i^{norm} + B_{L1}^{i}\right),\ \forall j = 1...n_{L1}$$

$$v^{L2} = \sum_{j=1}^{n_{L1}} W_{L2}^{j} v_j^{L1} + B_{L2}$$



Soil moisture

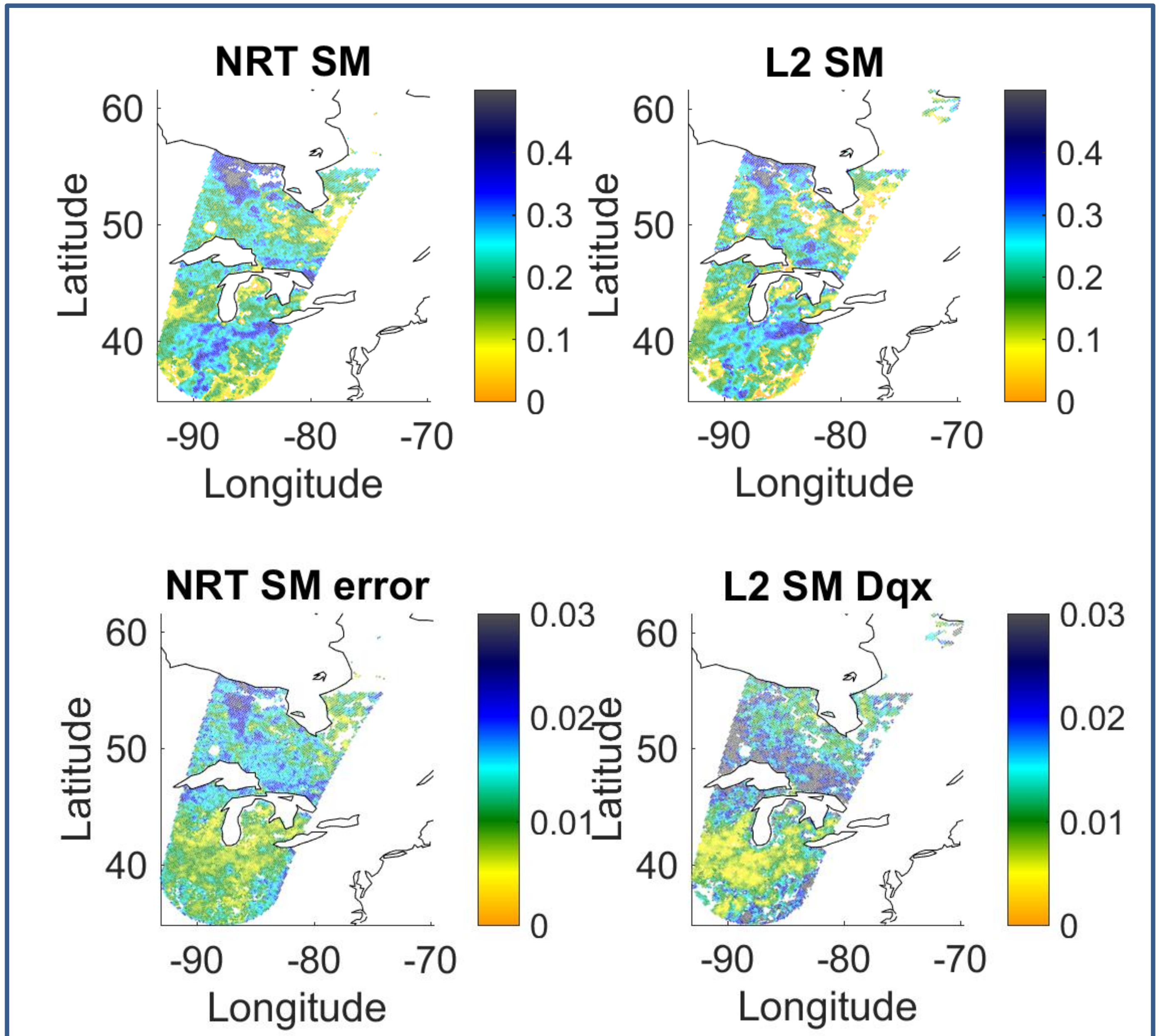
Training with two years of SMOS Level 2 soil moisture

- The neural network gives a global retrieval and very fast to apply

- Errors of SM computed from errors of the input data (NN weights assumed error free)

The ESA Near Real Time SMOS SM product

- Similar performances to L2 SM (slightly better indeed)
- Much faster ! Less than 3.5 hours after sensing
- Available from April 2016



Implemented by : ECMWF

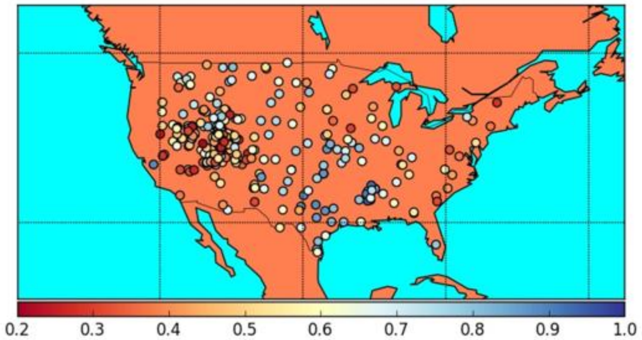
With support by : CESBIO

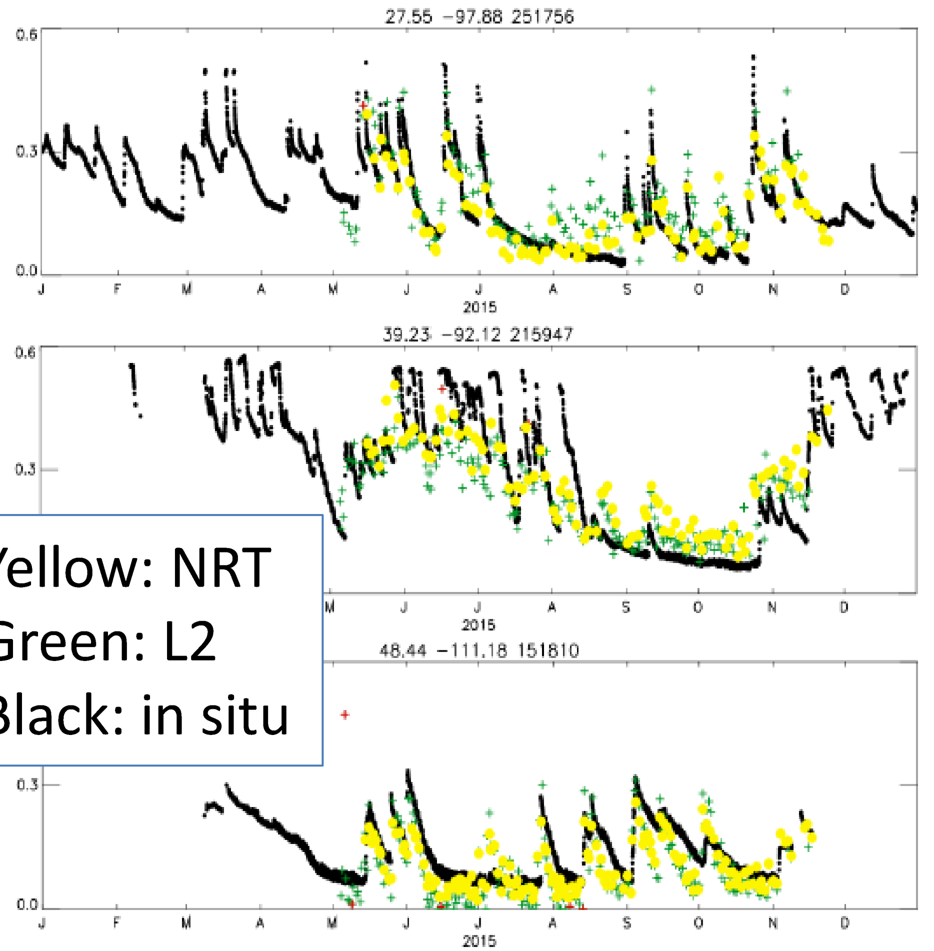
Delivered to : esa

Disseminated by: EUMETSAT

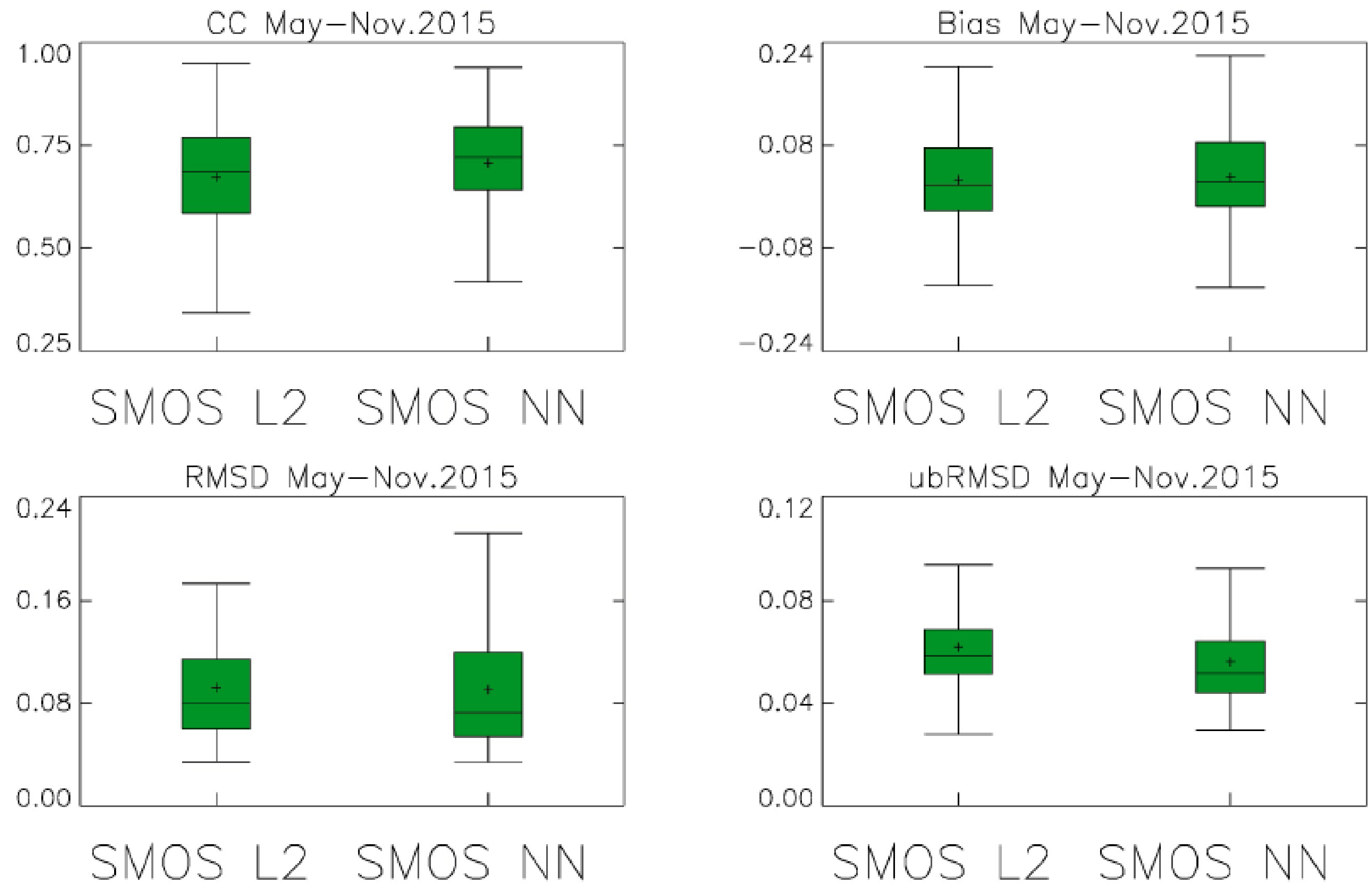
Rodriguez-Fernandez et al. (2017, HESS)

Evaluation against SCAN and USCRN *in situ* measurements





Yellow: NRT
Green: L2
Black: in situ

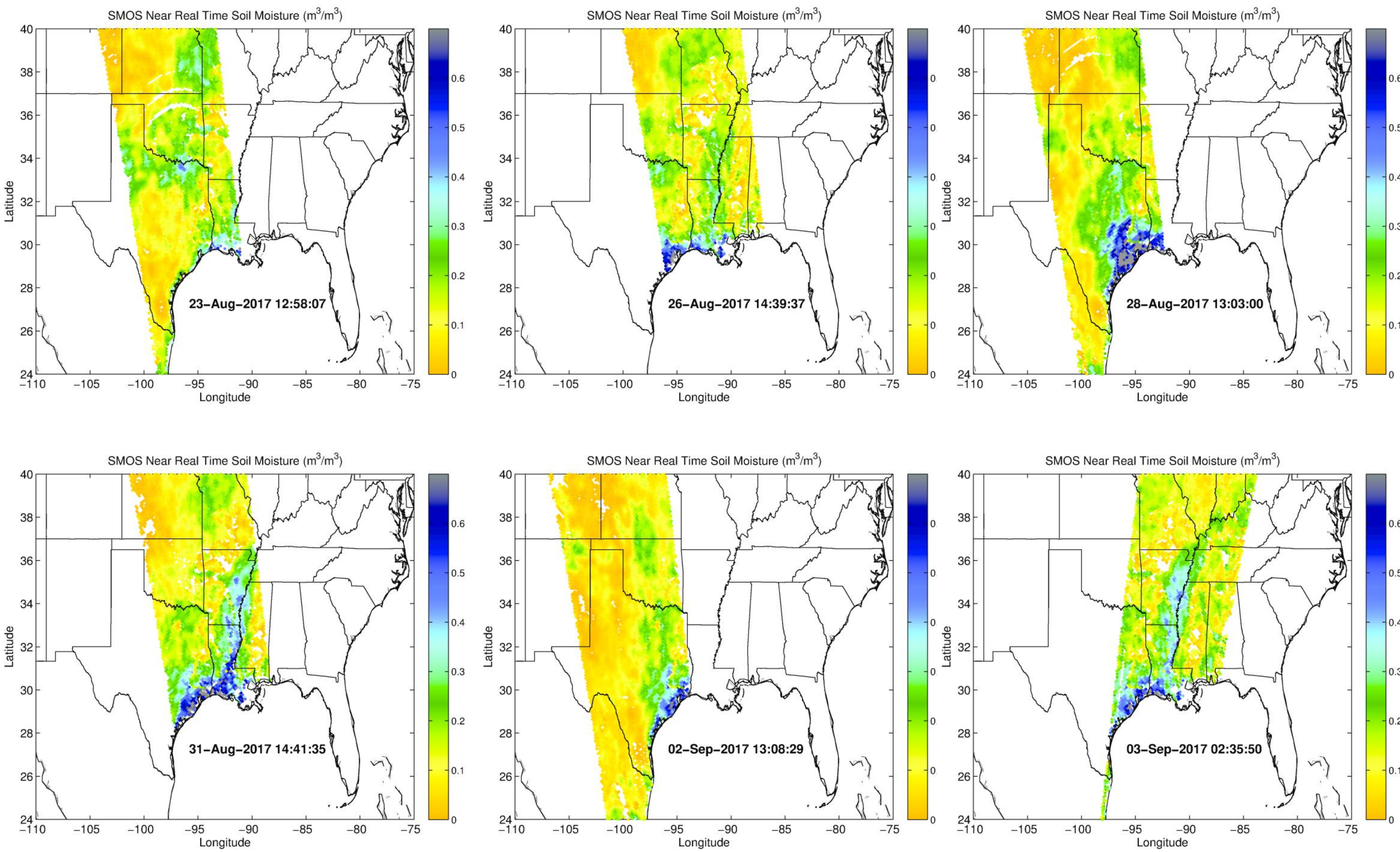


The NRT SM and the L2 SM **give similar statistics** with respect to in situ measurements **for the global set of sites**

Rodríguez-Fernández, Muñoz-Sabater et al (2017, HESS)

Monitoring

• **The NRT SM has captured well an extreme event such as the Harvey floods in Texas**



What would have been the performances of the NN if trained on synthetic data before launch ?

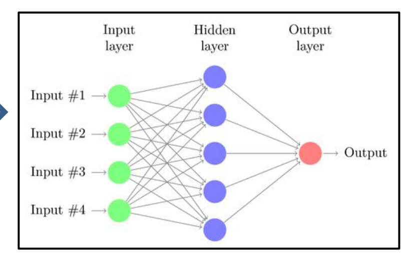
Neural network training

Synthetic TBs

noise

L-MEB

Realistic SM fields, LAI climatology, soil texture maps…



Neural network application

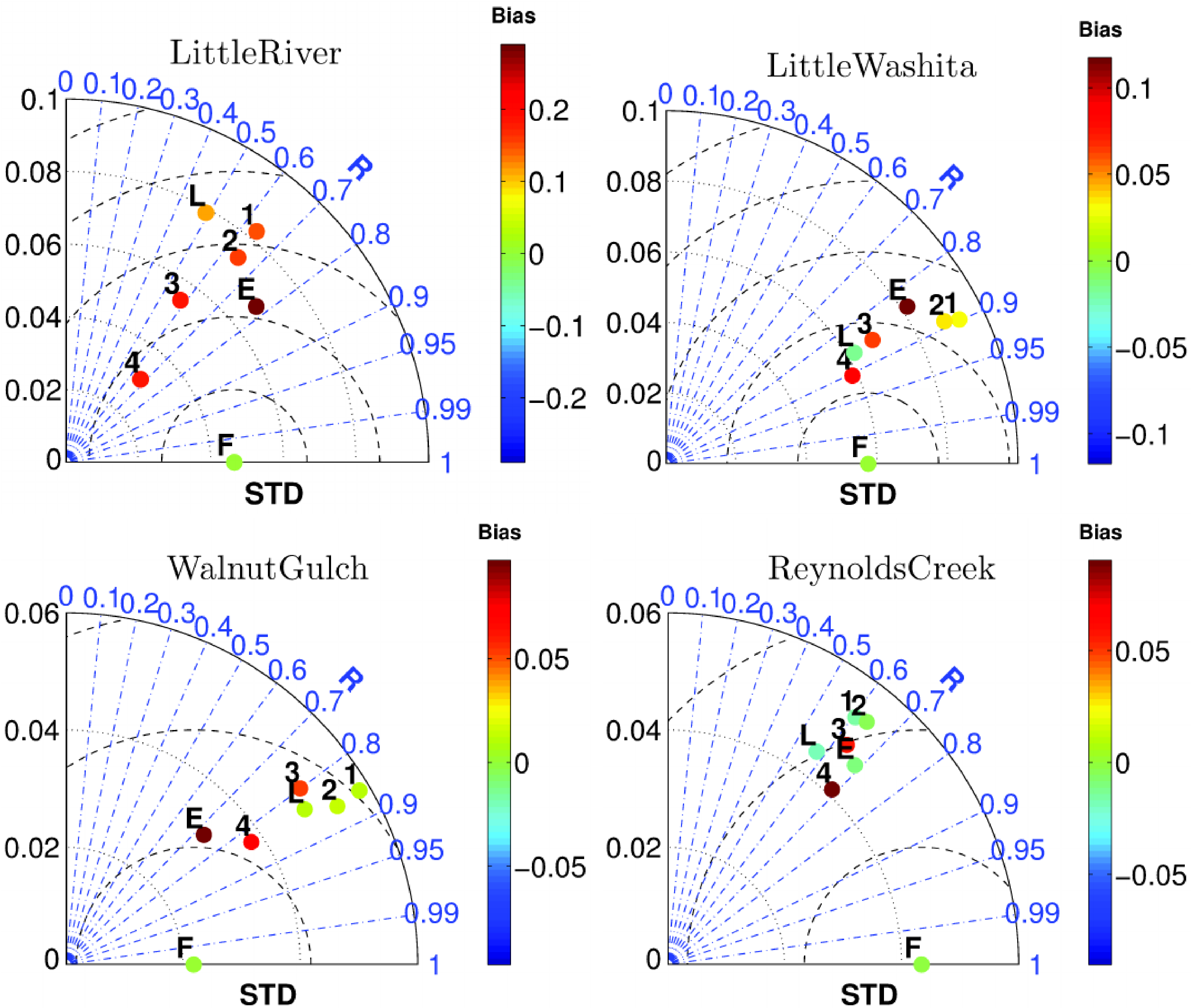
SMOS TBs

Soil Moisture

Rodriguez-Fernandez et al. (2017, IGARSS)

Evaluation: USDA-ARS watersheds

Rodriguez-Fernandez et al. (2017, IGARSS)



1 Bayesian regularization
2 LM
3 SCG
4 SCG with regularization

E ECMWF
L SMOS L3

F in situ measurements

The NN trained on synthetic data with regularization shows higher R and lower SEE than SMOS L3

Towards a new generation of satellite surface products ? Soil moisture, skin temperature,...

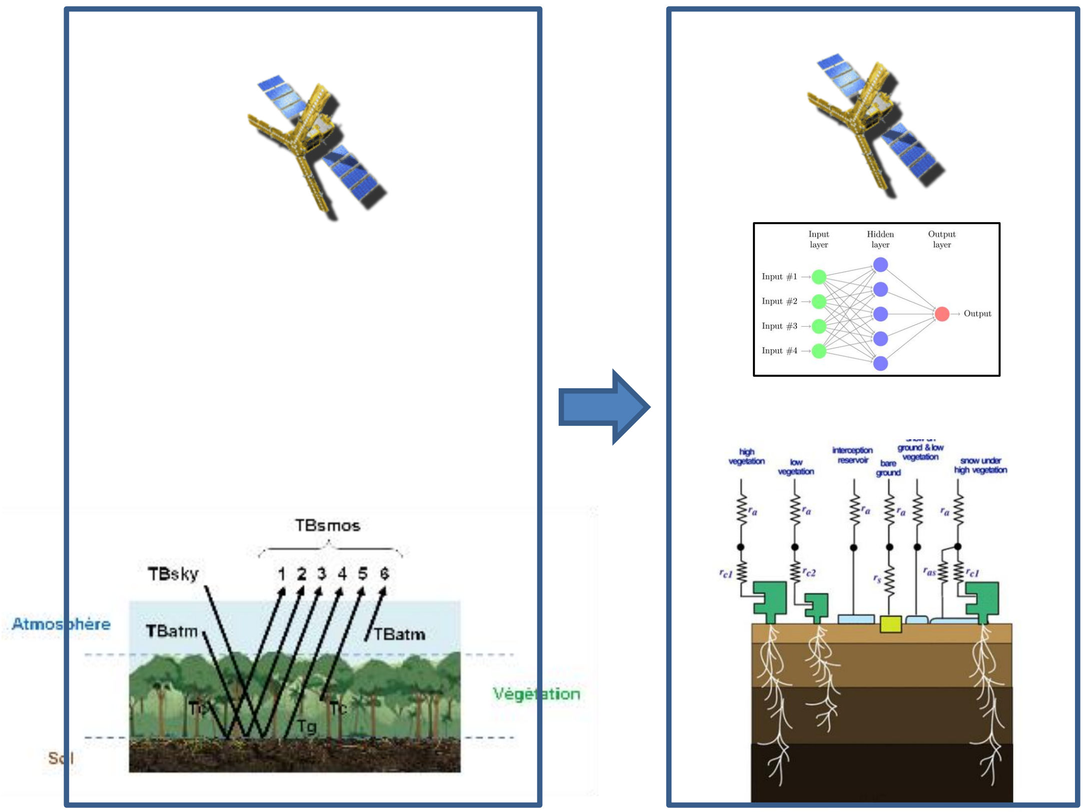
Land surface models within NWP models show good performances when comparing to in situ measurements of SM

Albergel et al. (2012), Kerr et al. (2016), Dorigo et al. (2013), Rodriguez-Fernandez et al. (2016)

Instead of computing the complex radiation transfer trough the biosphere why not linking directly the best remote sensing observations to the best NWP models ?

Prigent & Aires 2006, JGR; Prigent, Aires, et al. 2005, JGR

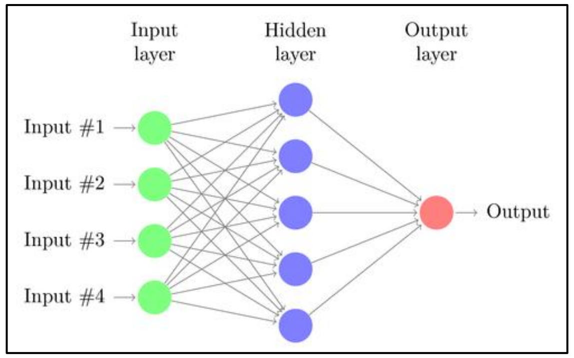
- **One interesting application will be efficient Data Assimilation.** The retrieved datasets are similar to the model fields, by construction, but they are driven by the remote sensing input data *Aires, Prigent, Rossow 2005, JGR*



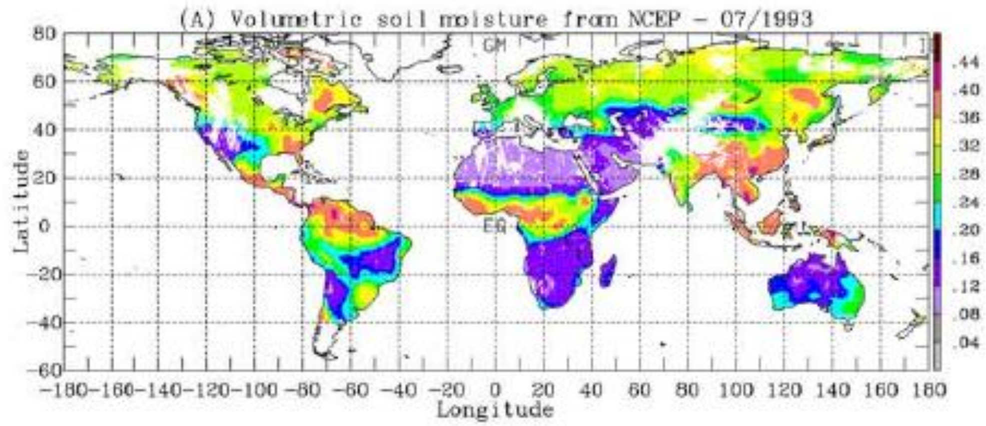
An alternative: using land surface models for the training

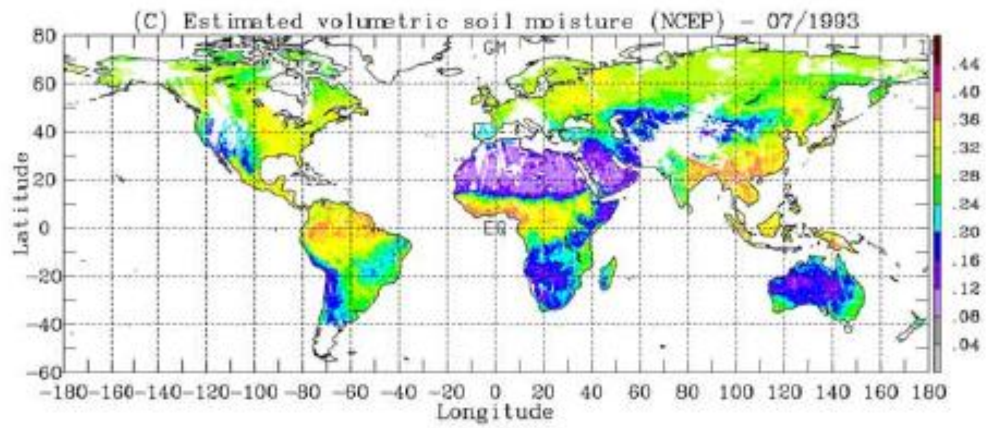
Neural networks can also be used to develop a new retrieval algorithm linking remote sensing observables to global soil moisture simulated fields from NWP models.

***Monthly means of*: ERS, SSM/I, NDVI (AVHRR), Tskin (ISCCP)**



Soil moisture





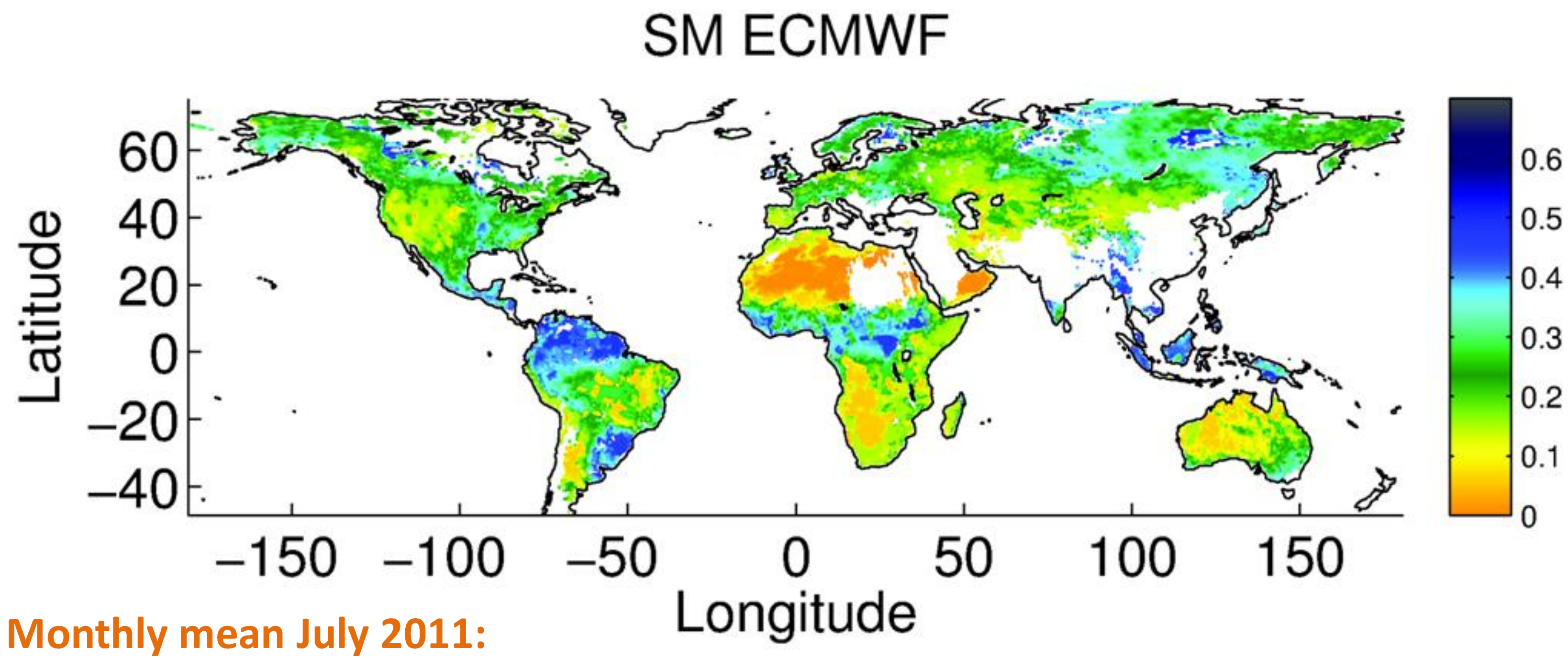
Prigent, Aires, et al. 2005, JGR
Aires, Prigent, Rossow 2005, JGR

Training with NCEP or ECMWF models

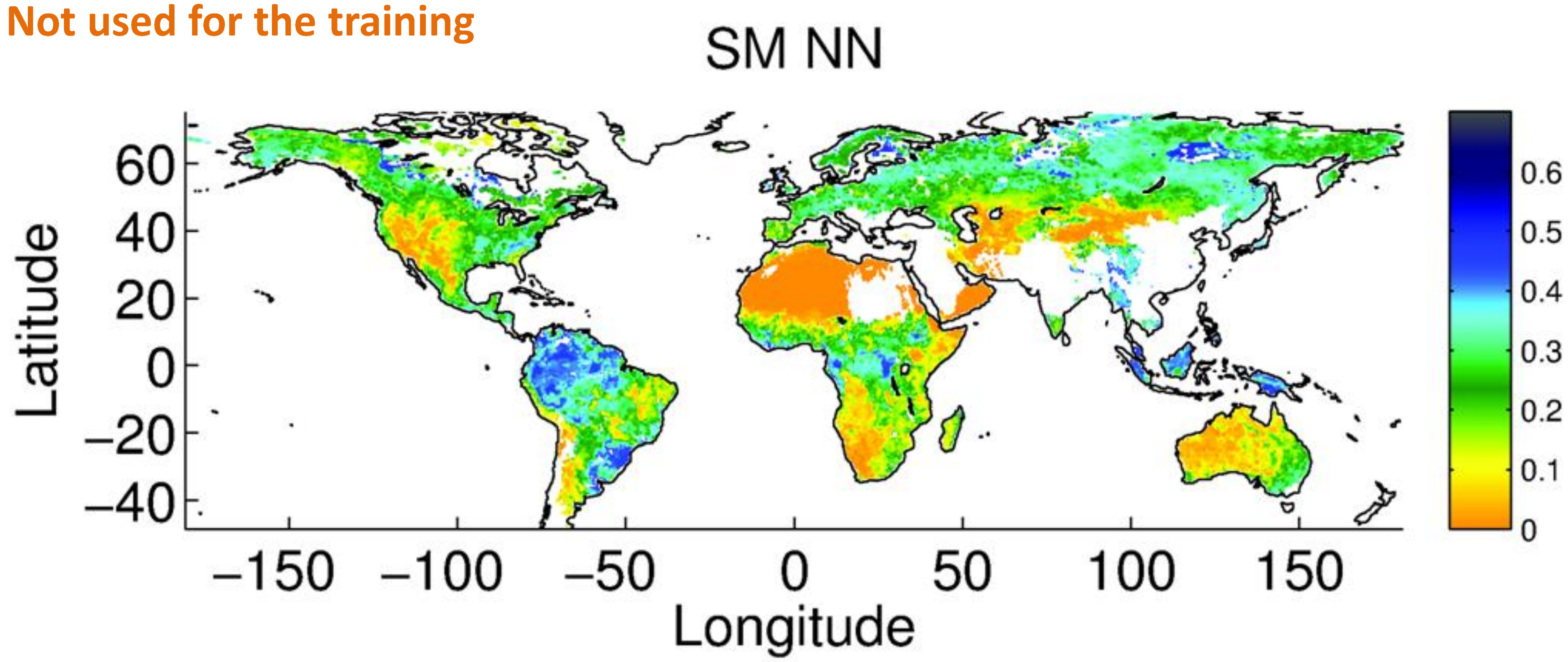
Founded (2012-2013) by:

N. Rodríguez-Fernández, P. Richaume, Y. Kerr

F. Aires, C. Prigent



Monthly mean July 2011:
Not used for the training



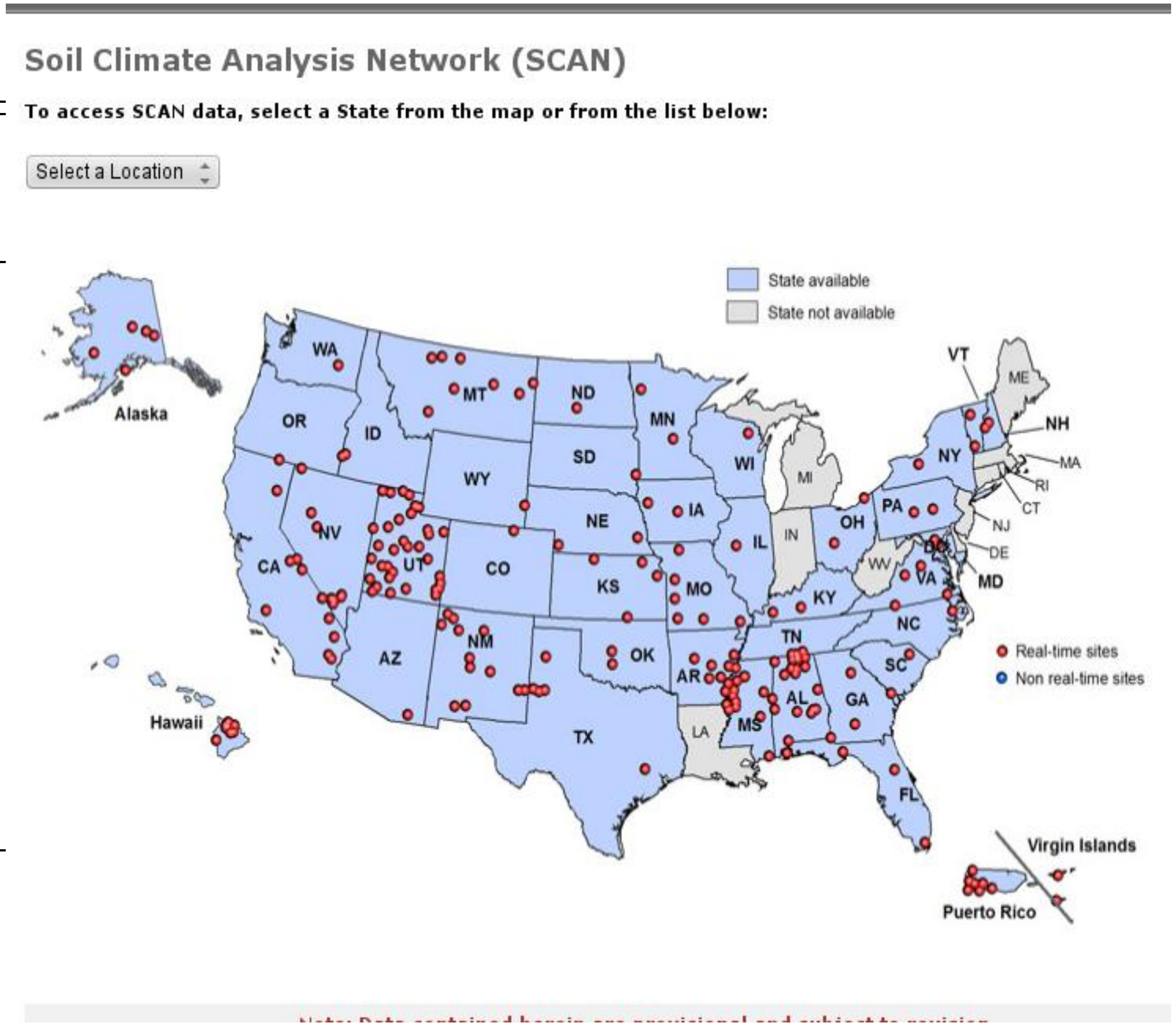
No need to average in time the data for the retrieval
Average of the figure is just for comparison purposes

Rodríguez-Fernández et al. IEEE TGARS, 2015

Evaluation with respect to SCAN in situ measurements

SM product	Asc. Orbits STDD	R	Bias
14Tb+NDVI+tex+T	0.046	0.52	0.076
14Tb+14I_1+NDVI+tex	0.049	0.60	0.075
14Tb+NDVI+tex+σ_{40}	0.044	0.61	0.067
8I_2+NDVI	0.029	0.61	0.054
14I_2+$I_{2\sigma 40}$	0.027	0.60	0.052
14Tb+14I_1	0.055	0.55	0.092
ECMWF SM_1	0.049	0.59	0.050
SMOS L3	0.060	0.52	-0.021

Rodríguez-Fernández et al. IEEE TGARS, 2015



SMOS NN SM DA experiment

ESA CONTRACT REPORT

Contract Report to the European Space Agency

SMOS Neural Network Soil Moisture Data Assimilation

N.J. Rodríguez-Fernández, P. de Rosnay, C. Albergel, F. Aires, C. Prigent, P. Richaume, Y.H. Kerr, J. Muñoz-Sabater

Progress report for ESA contract 4000101703/10/NL/FF/fk

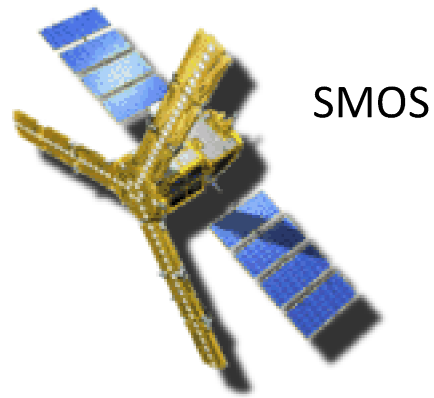
European Centre for Medium-Range Weather Forecasts
Europäisches Zentrum für mittelfristige Wettervorhersage
Centre européen pour les prévisions météorologiques à moyen terme

Funded by :

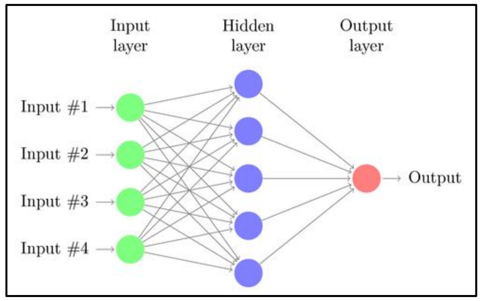
Done in 2016 by :

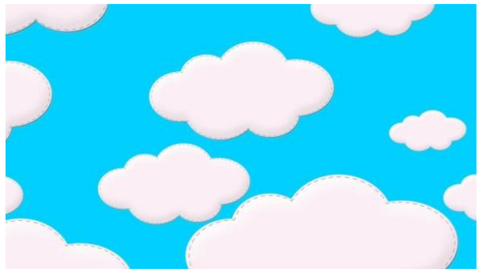
With support from :

NN SM for the DA project



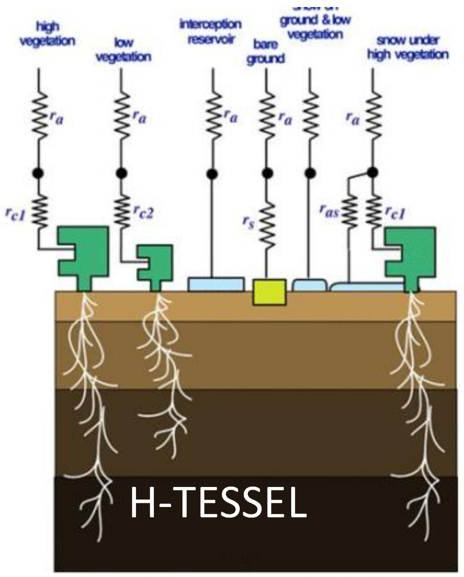
- SMOS L3 Tbs, polarization H &V , angles 30º-45º
- Local linear estimators of SM computed from extreme values of Tbs and SM





NN soil moisture and associated uncertainties

Ready for DA!



IFS (0-7cm) soil moisture

- ESA SMOS auxiliary files
- Spatial averaging to SMOS resolution (~43 km)
- Temporal interpolation to the time of SMOS acquisitions

Surface only experiments

- Whole year **2012**
- Land surface only assimilation forced with ERA-Interim
- Comparison of:
  - Control: open loop
  - ASCAT SM
  - SMOS NN SM
  - T2m, RH2m, ASCAT SM
  - T2m, RH2m, SMOS NN SM
- Different relative weights of observations with respect to the model were tested by assuming that *the real observation error can larger than the radiometric error*

Increments as a function of SM error

$x_a^t = x_b^t + K\,(y_0^t - \mathcal{H}[x_b^t])$

(a) Mean increments SMOS1

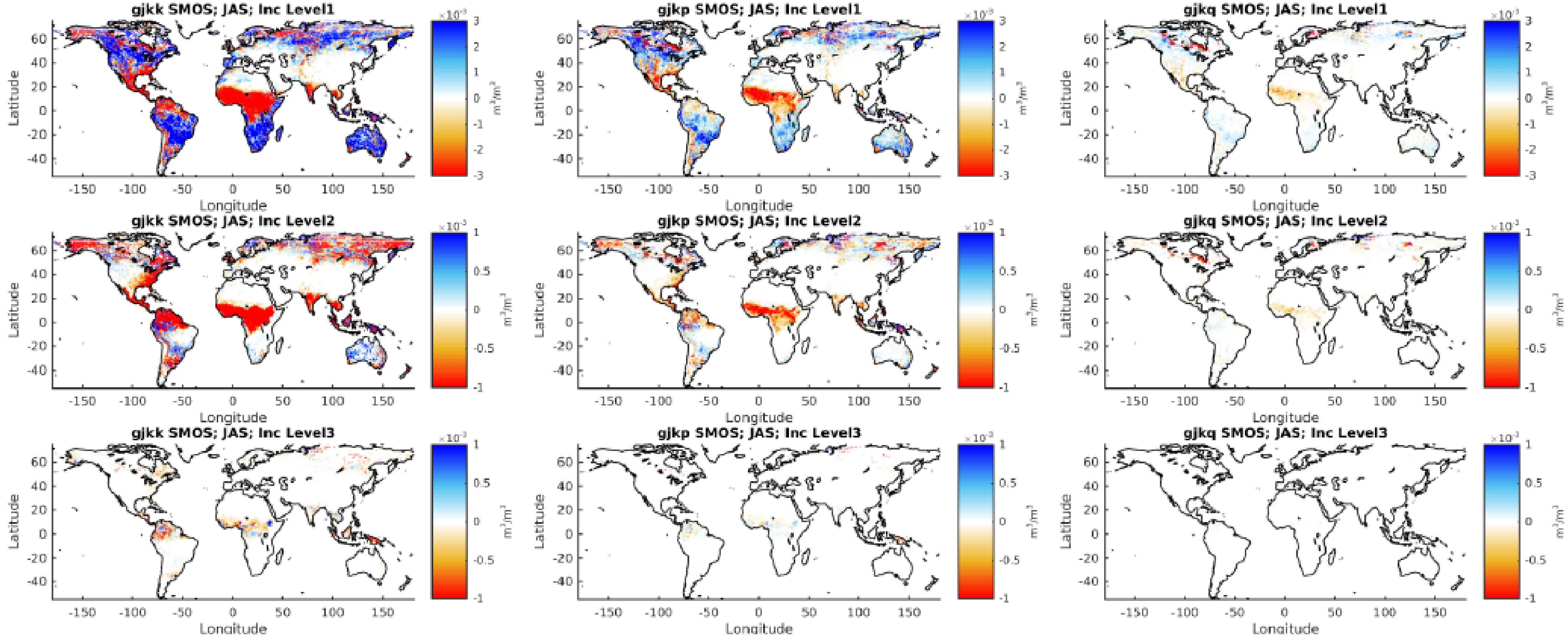
(b) Mean increments SMOS3

(c) Mean increments SMOS9

Layer 1
(0-7cm)

Layer 2
(7-28cm)

Layer 3
28-100cm



Increments: SMOS vs ASCAT

$x_a^t = x_b^t + K\,(y_0^t - \mathcal{H}[x_b^t])$

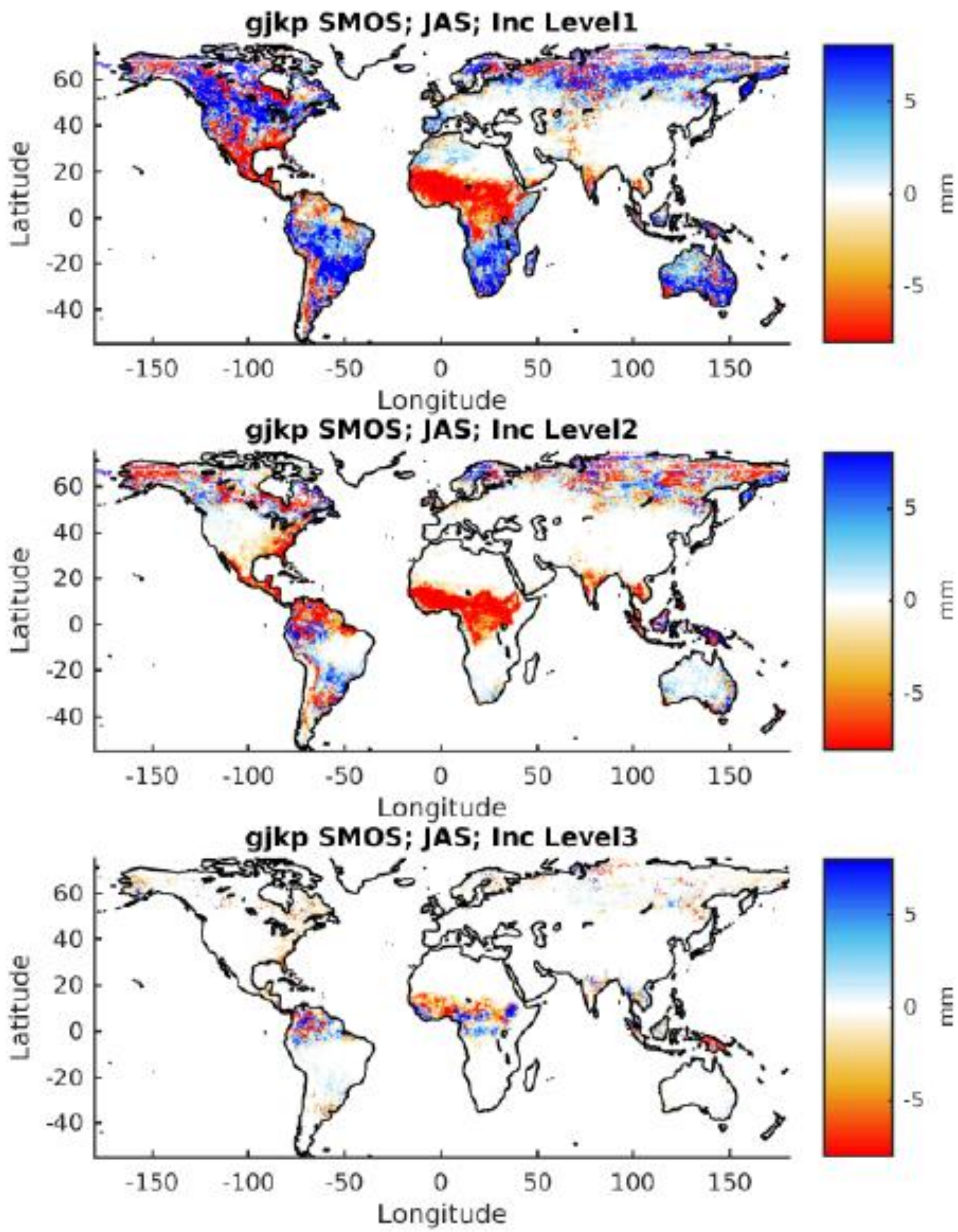
SMOS NN

(c) July-September

Layer 1
(0-7cm)

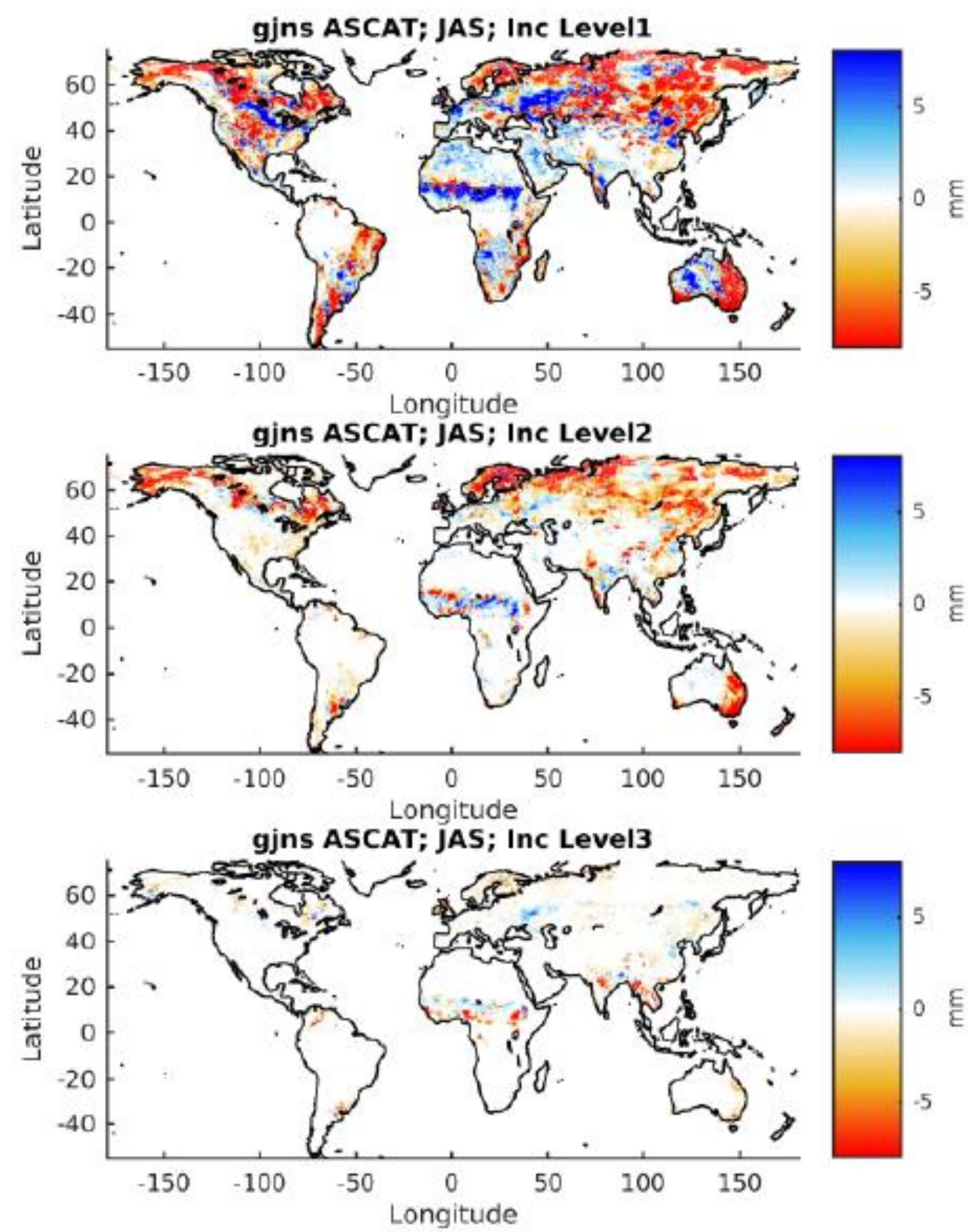
Layer 2
(7-28cm)

Layer 3
28-100cm

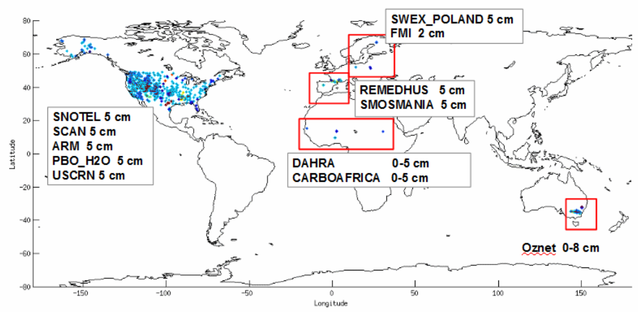


ASCAT

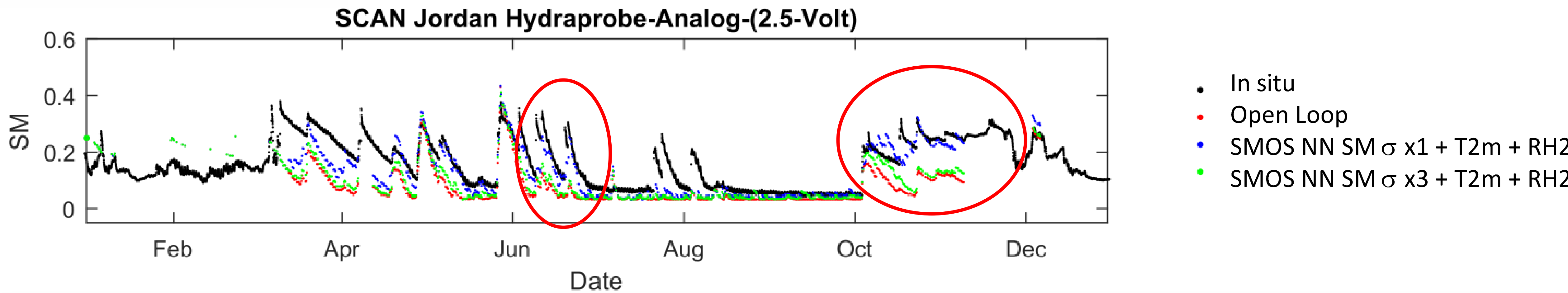
(c) July-September



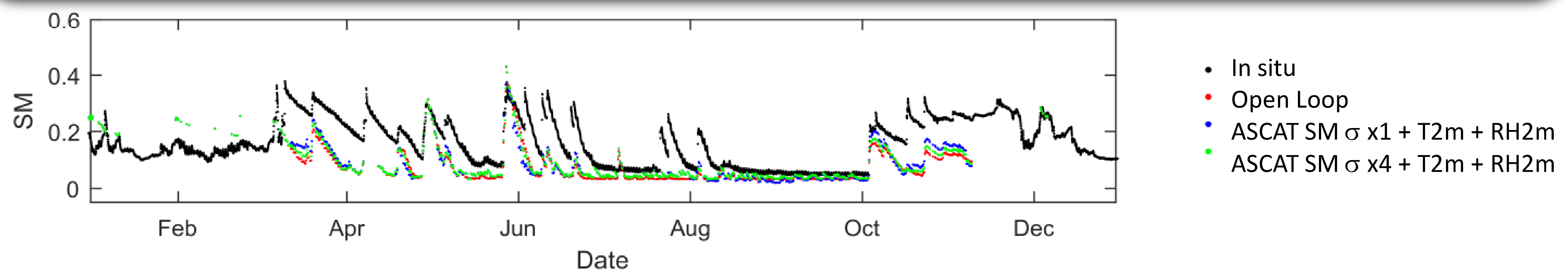
Evaluation against in situ measurements



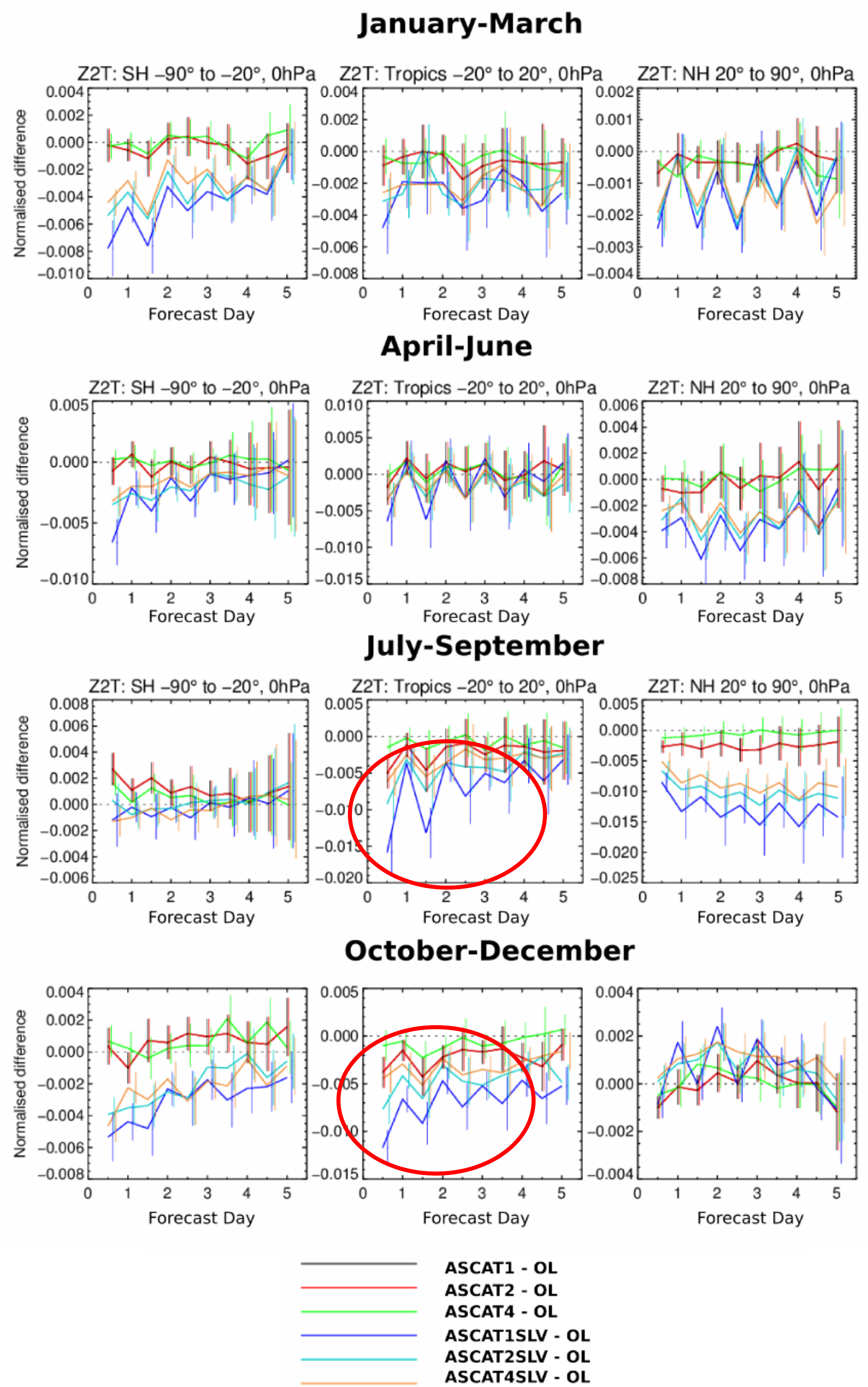
Rodriguez-Fernandez, de Rosnay, Albergel, et al. 2017, ECMWF ESA report
Rodriguez-Fernandez et al. (in prep.)

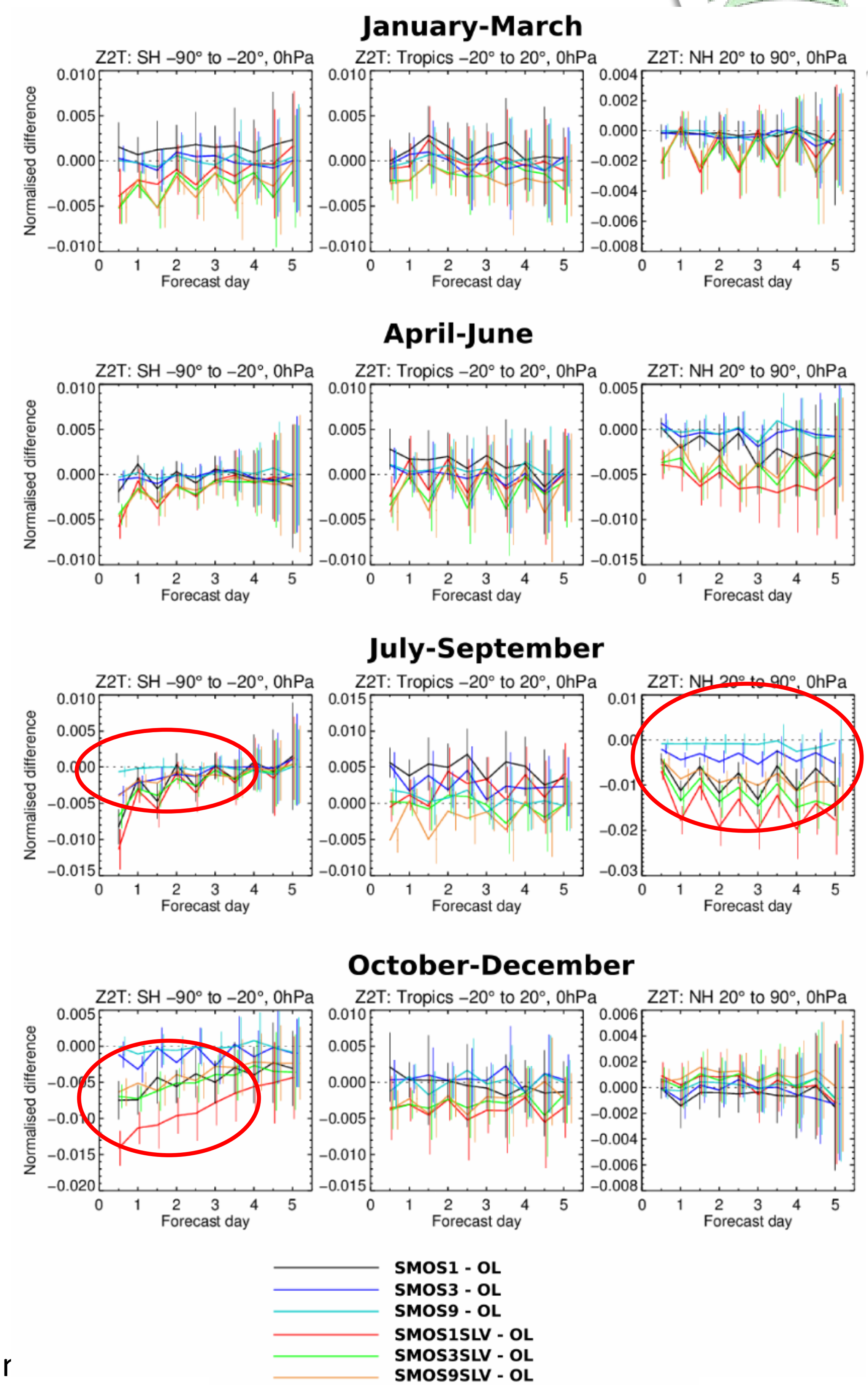


Results: On average, for more than 400 in situ sites, the performances of the analysed soil moisture fields are close (within 2-3 %) to those of the open loop experiment



Atmospheric impact (41r1, T511)





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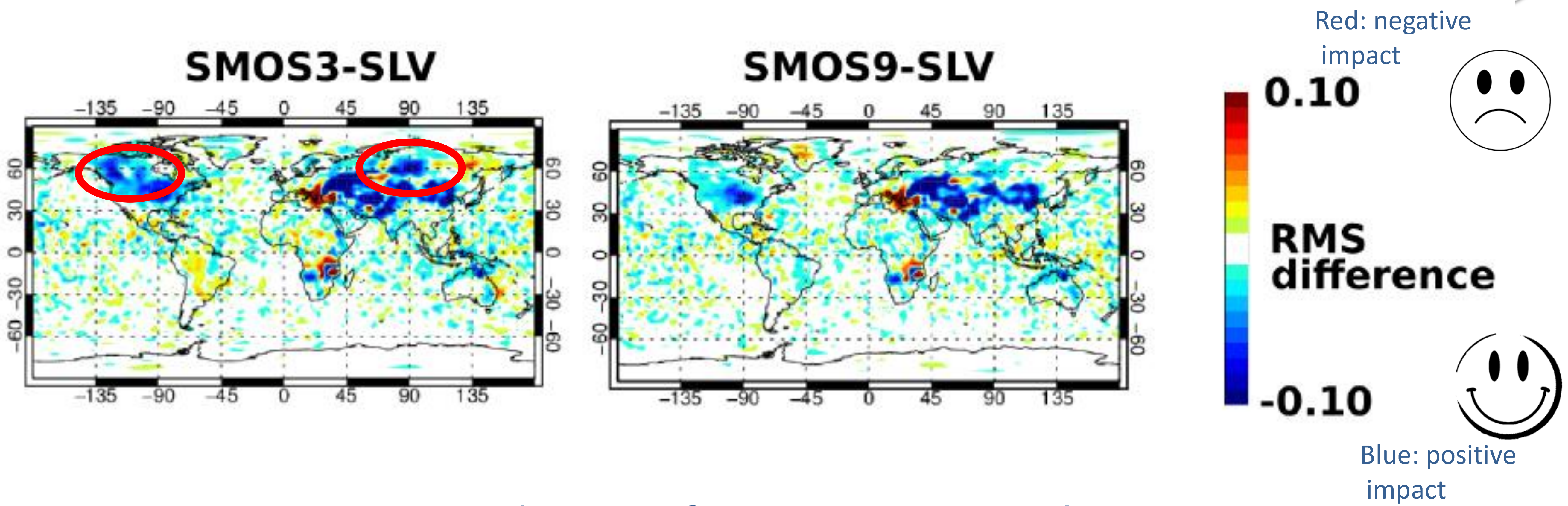


T air 850 hPa, forecast 36 hours July-September

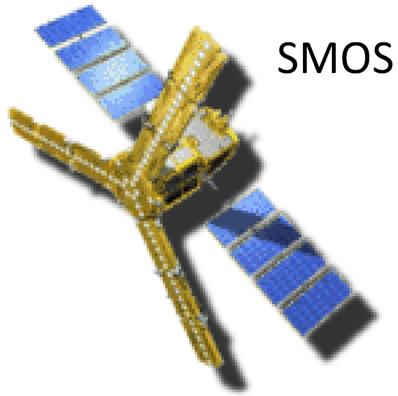
Rodriguez-Fernandez, de Rosnay, Albergel, et al. 2017, ECMWF report
Rodriguez-Fernandez et al. (in prep.)

Towards an operational assimilation

- Neural network SM can be produced **in near-real-time** and **with associated errors**
  Rodriguez-Fernandez, Muñoz-Sabater et al. (2017, HESS)
- Offline SM NN SM assimilation gave promising results
  Rodriguez-Fernandez, de Rosnay et al. (2017, ECMWF report)

- **Operational assimilation of SMOS NN SM at ECMWF**
  - **Training on ECMWF Layer 1 SM**
  - **Data-assimilation-specific near real-time processing chain**

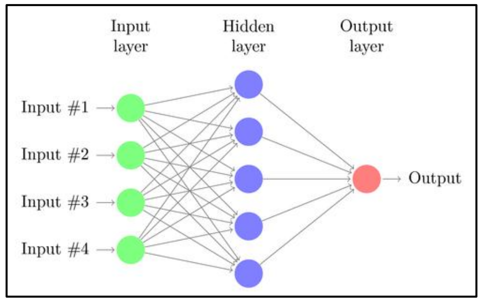
Purely data driven retrieval: training the NN on in situ measurements



- SMOS L3 Tbs, polarization H &V

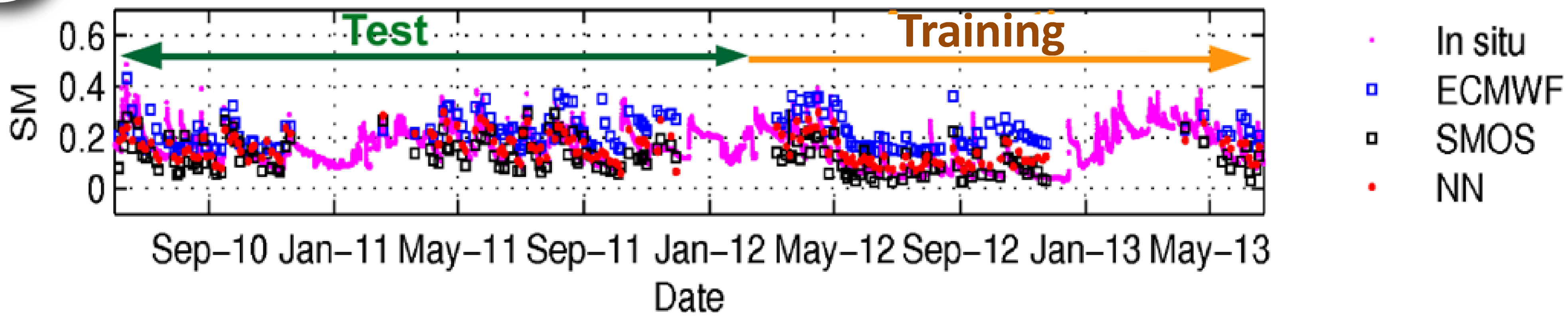
NN soil moisture

In situ soil moisture sensors (0-5cm)

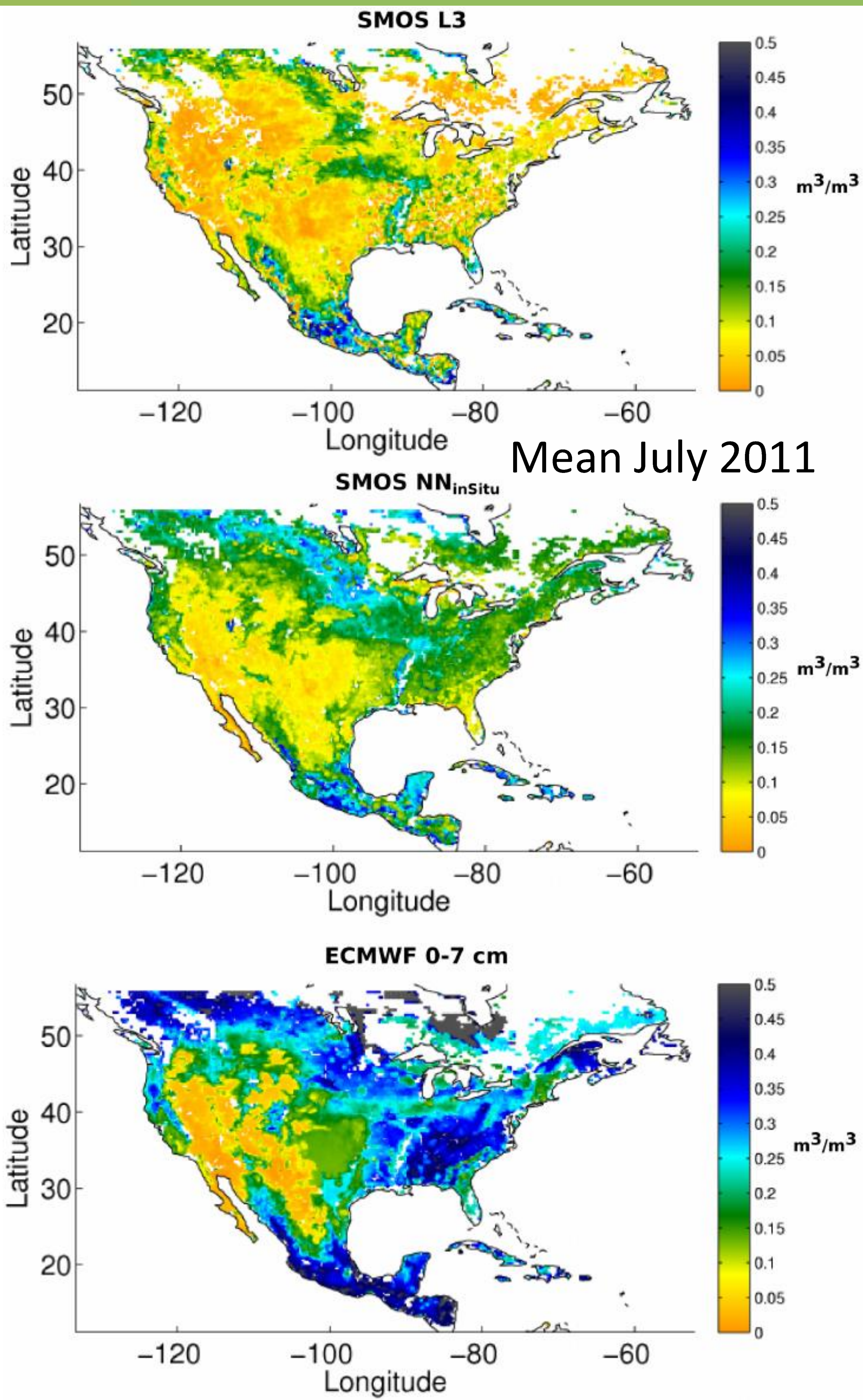


- Training using all in situ sites at once! Not site by site !

- Period: Jan 2012-June 2013



North America Maps



- **Intermediate values in between SMOS L3 and ECMWF**
- **Wetter than SMOS in the east coast**

Rodriguez-Fernandez et al. (2017, IGARSS)

Other studies using SMOS and NNs

JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION
Vol. 53, No. 1 AMERICAN WATER RESOURCES ASSOCIATION February 2017

ESTIMATING ROOT ZONE SOIL MOISTURE AT CONTINENTAL SCALE USING NEURAL NETWORKS[1]

Xiaojun Pan, Kurt C. Kornelsen, and Paulin Coulibaly[2]

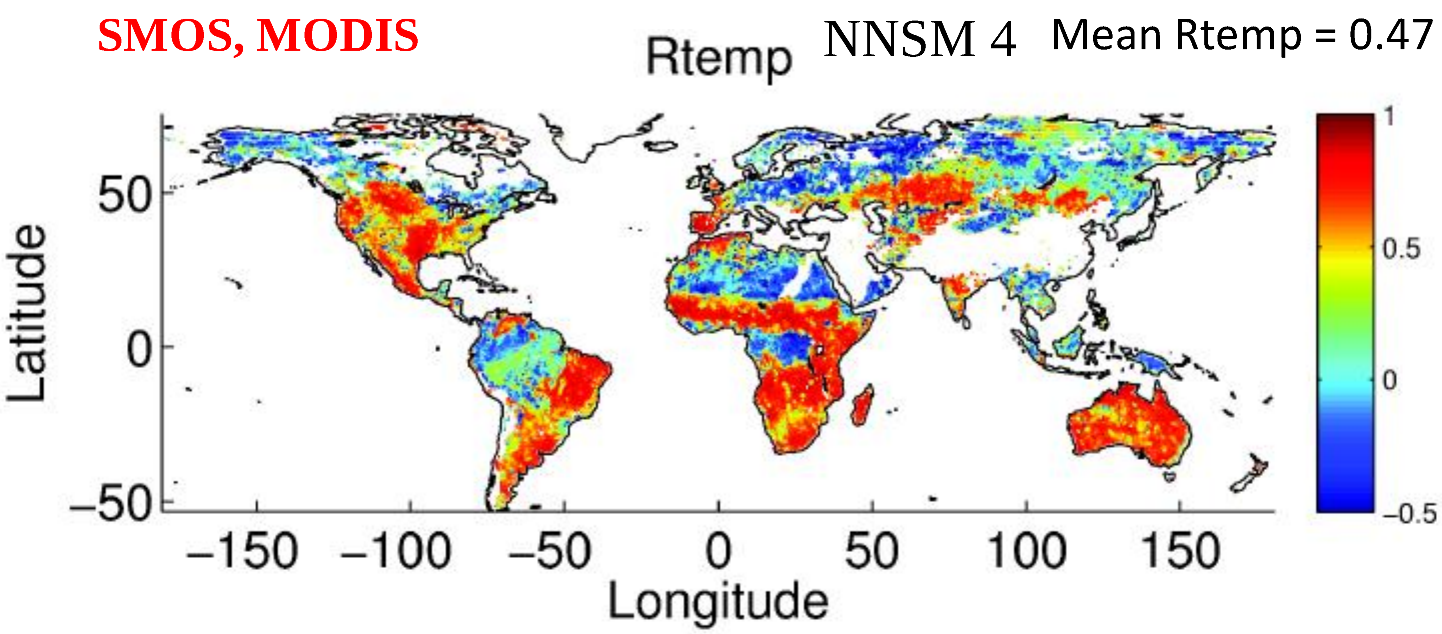
Water Resour Manage (2013) 27:3127–3144
DOI 10.1007/s11269-013-0337-9

Machine Learning Techniques for Downscaling SMOS Satellite Soil Moisture Using MODIS Land Surface Temperature for Hydrological Application

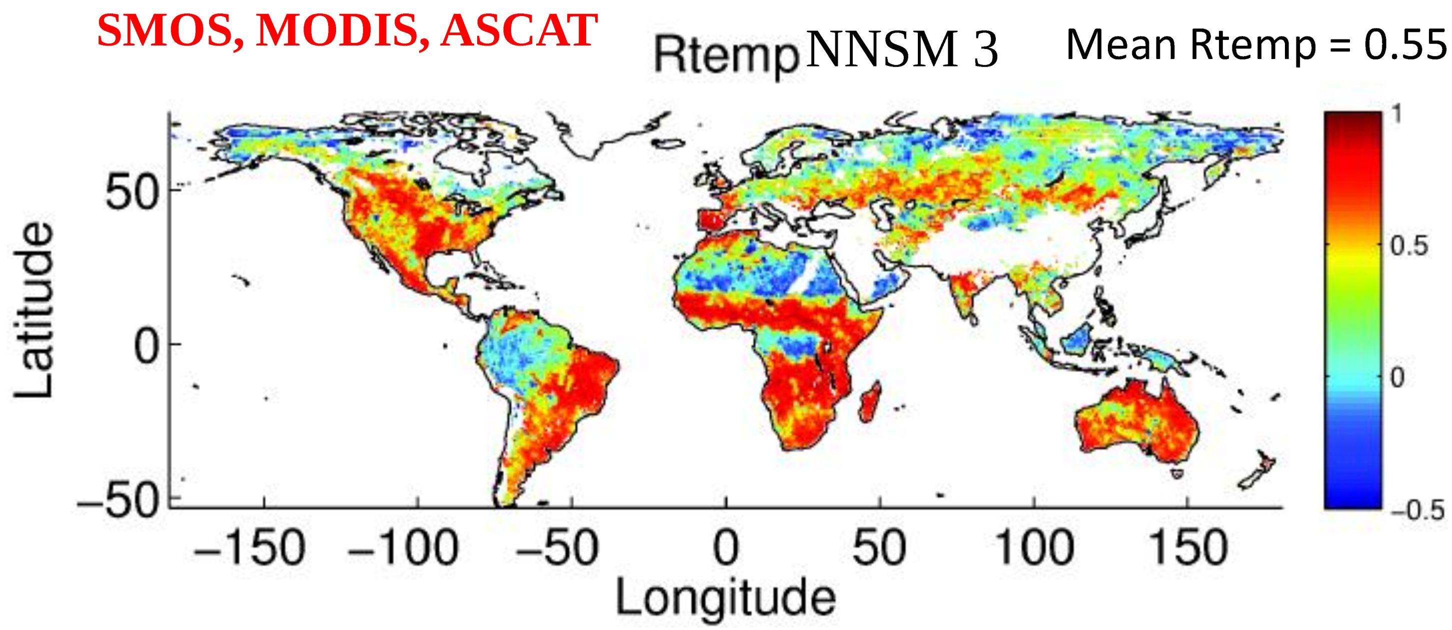
Prashant K. Srivastava • Dawei Han • Miguel Rico Ramirez • Tanvir Islam

Multi-sensor synergy

SMOS, MODIS



SMOS, MODIS, ASCAT



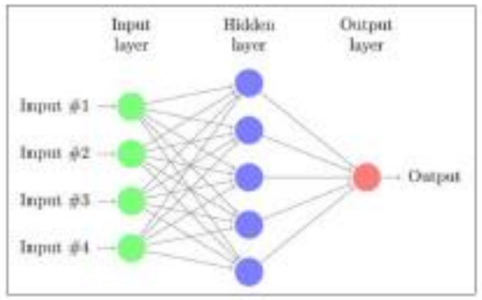
Rodriguez-Fernandez et al. (2015, TGARS)

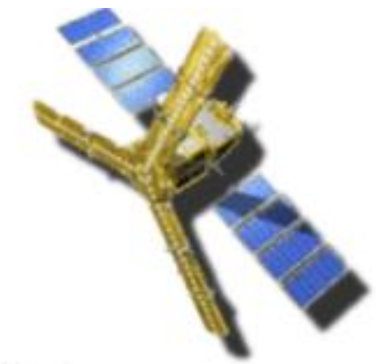
- MODIS NDVI improve the retrievals
- Active microwaves (ASCAT) improve the NN ability to capture the time dynamics (in agreement with Kolassa et al. 2013)

A multi-sensor retrieval algorithm becomes possible even when a multi-wavelength physical algorithm is not available

Using NNs to build longer SM records

Tb's AMSR-E





1st step

Supervised learning
Best input data configuration
Neural Network weights determination

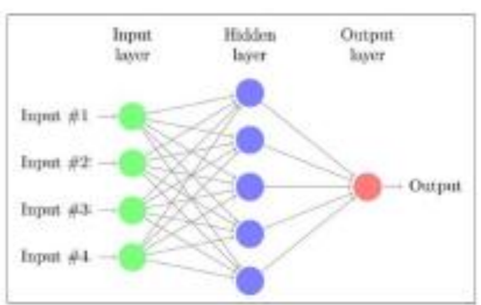
SMOS Level 3 SM

2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015

Tb's AMSR-E: HV C and X bands, H 23GHz and HV 35GHz

2nd step

Application of the trained
Neural network



AMSR-E NN SM

Feedback to ESA SM CCI ?

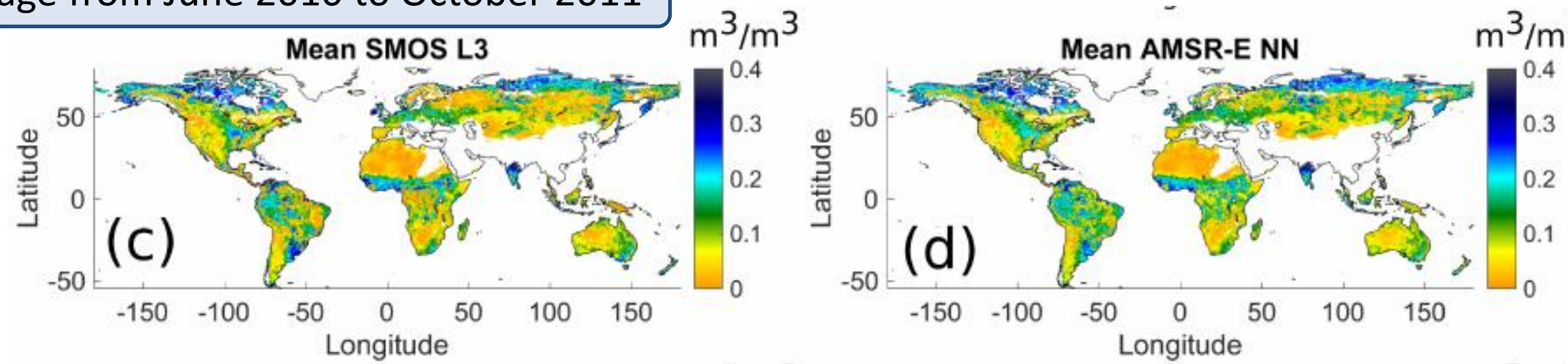
esa climate change initiative

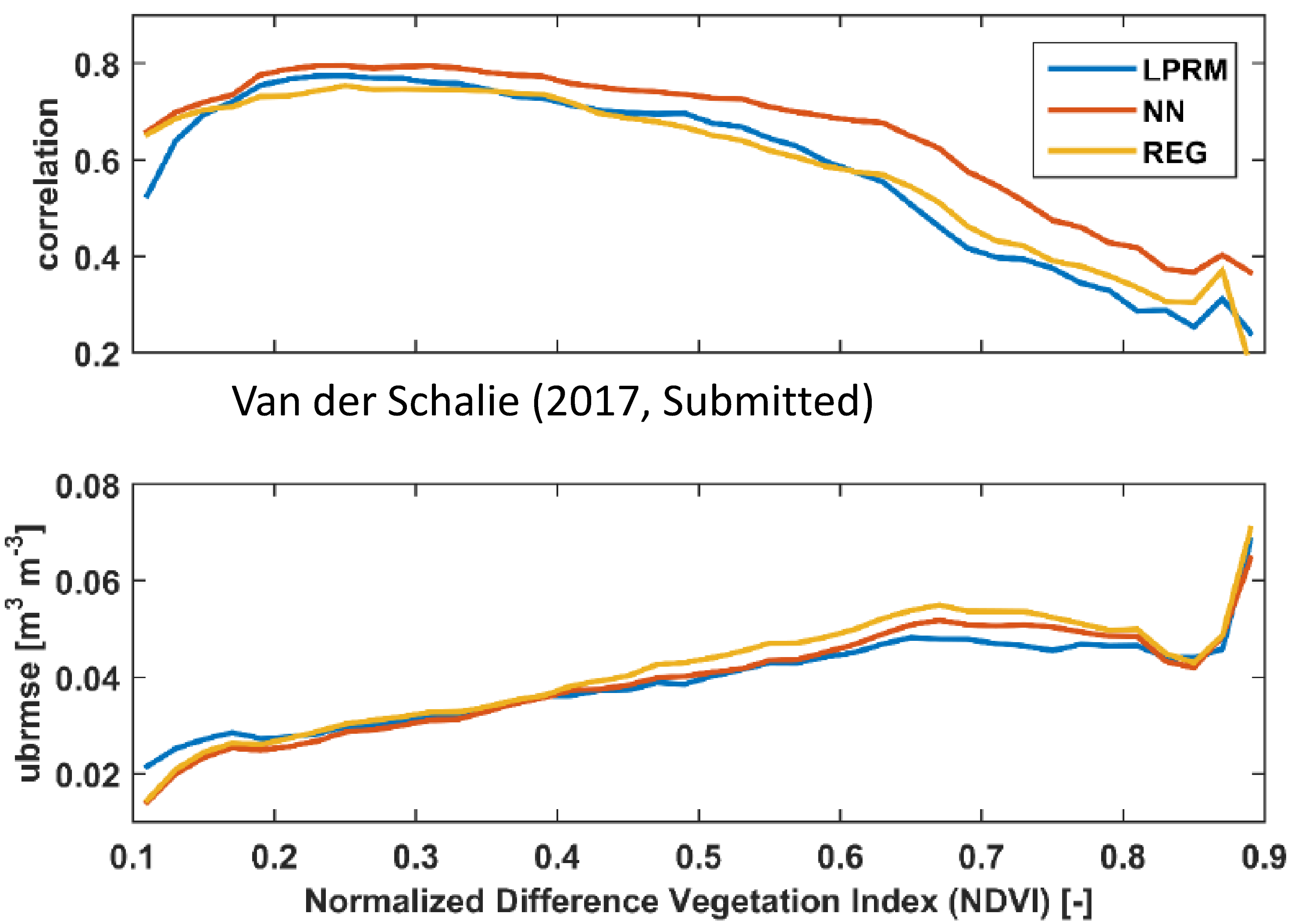
Rodriguez-Fernandez et al. (2016, Remote Sensing)

AMSR-E NN SM vs SMOS L3 SM: consistent datasets !

Average from June 2010 to October 2011

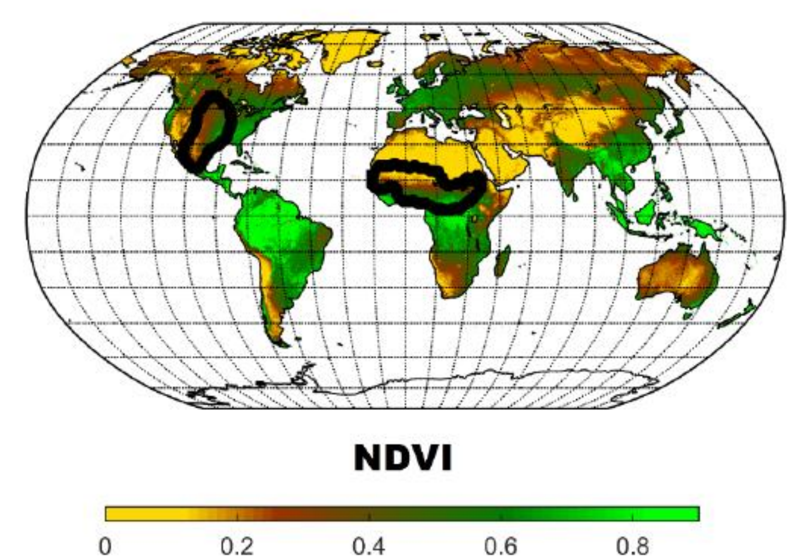
Rodriguez-Fernandez et al. (2016, Remote Sensing)





Van der Schalie (2017, Submitted)

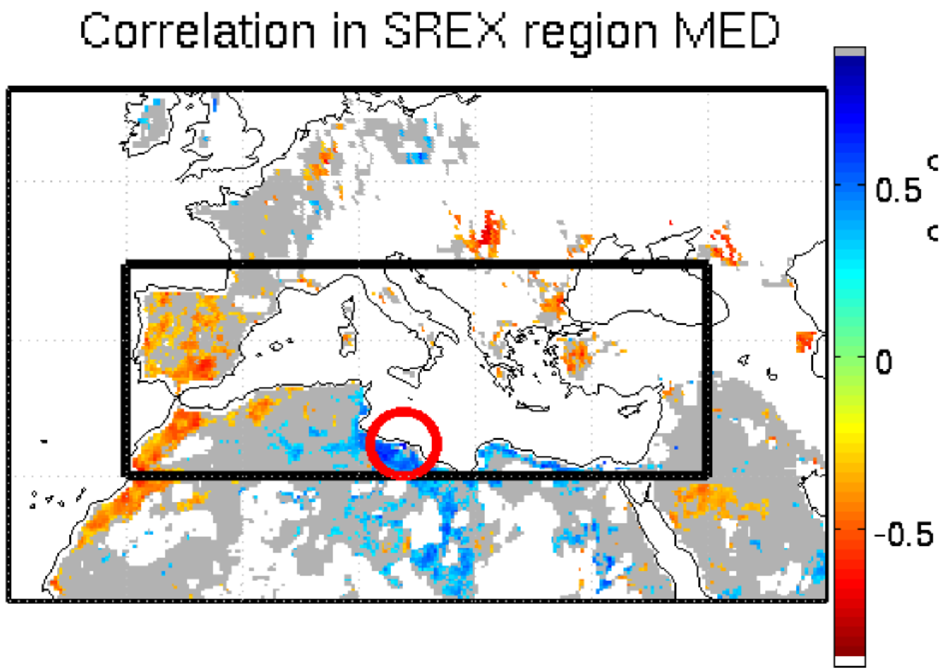
Stats with respect to SMOS SM



Correlation of SM anomalies and NAO

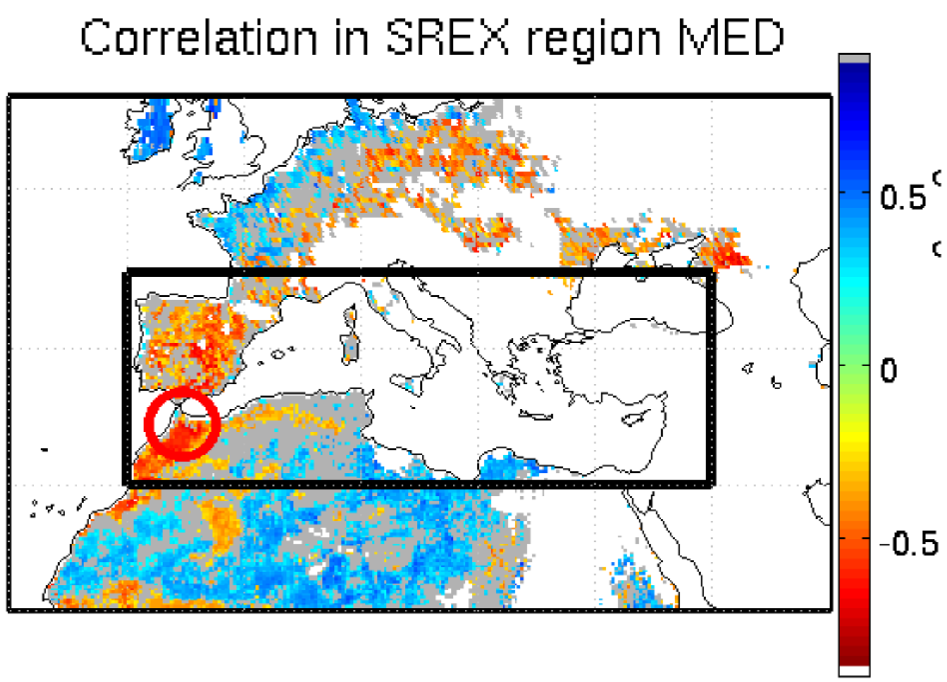
a)

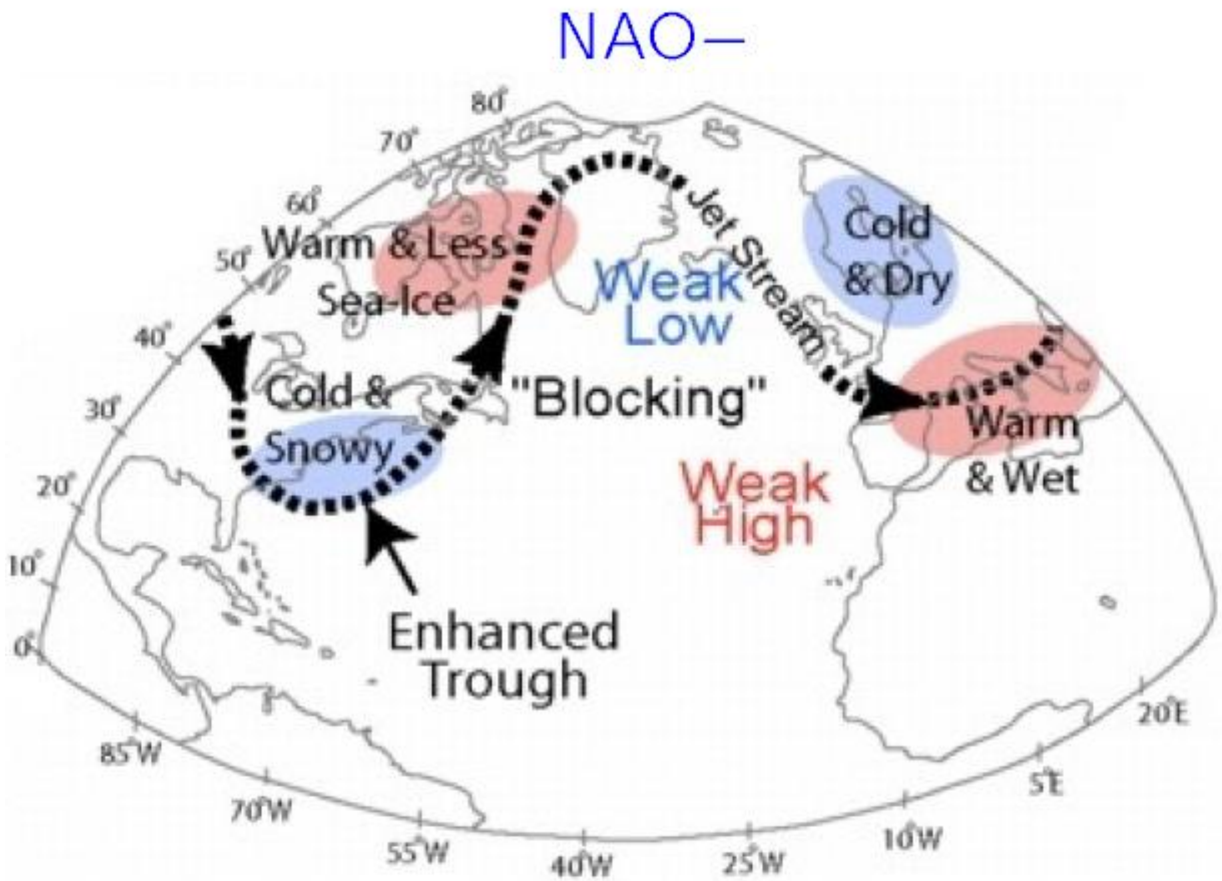
CCI



c)

NN





Source: University of Michigan

Cluzet (2017, Master thesis)

CESBIO SMOS support to the CCI

ESA SMOS/AMSR-E fusion project

- Neural networks are a promising approach
- SMOS should be inserted into the CCI framework using LPRM
- SMOS can be used as reference for re-scaling other instruments

CESBIO : extraction and pre-processing of SMOS and ECMWF auxiliary data for their use by the CCI team

SMOS now taken into account in CCIv3 (Dorigo et al. 2017)

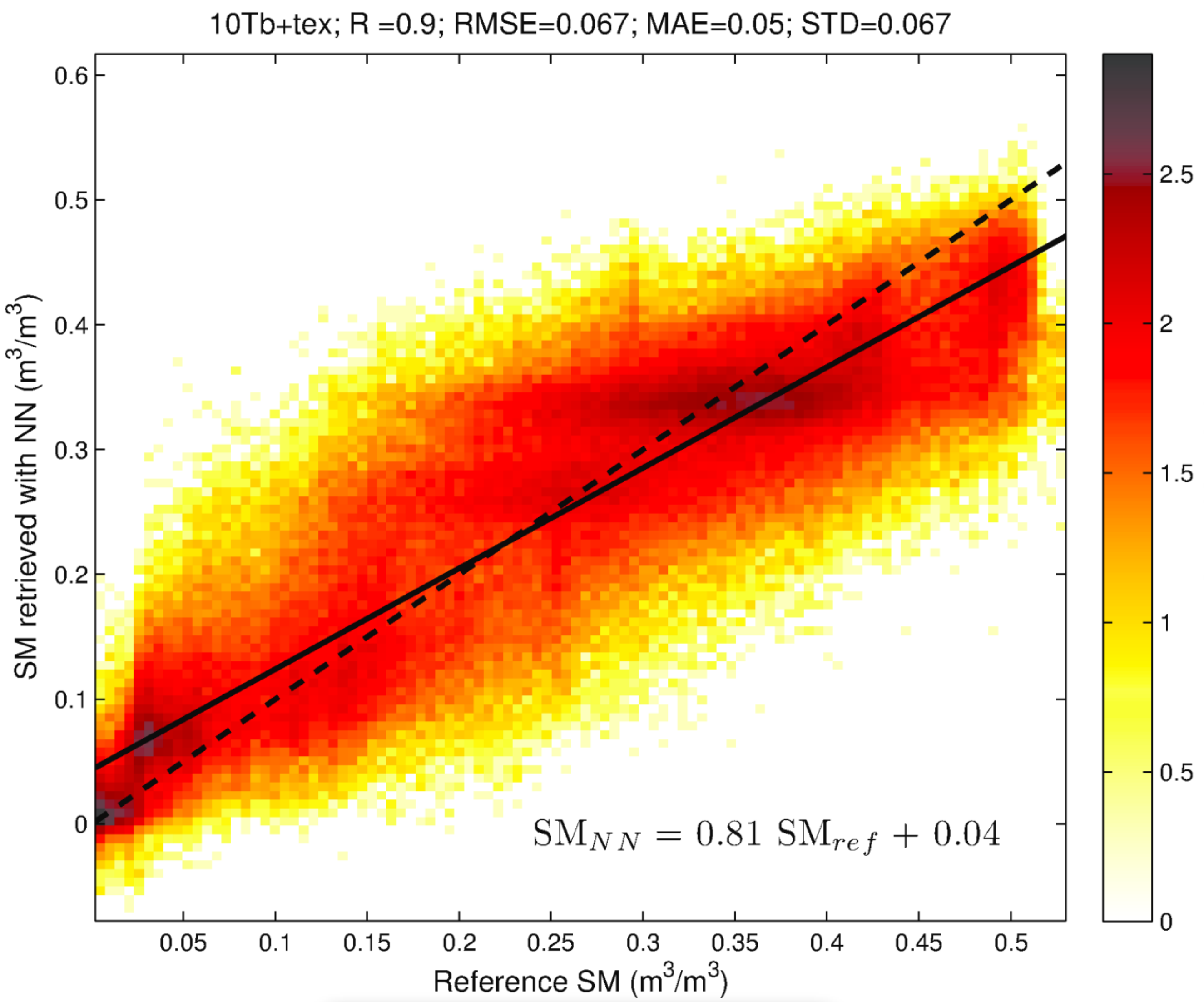
ESA CCI Soil Moisture for improved Earth system understanding: State-of-the art and future directions

Wouter Dorigo [a,*], Wolfgang Wagner [a], Clement Albergel [b], Franziska Albrecht [c], Gianpaolo Balsamo [d], Luca Brocca [e], Daniel Chung [a], Martin Ertl [f], Matthias Forkel [a], Alexander Gruber [a], Eva Haas [c], Paul D. Hamer [g], Martin Hirschi [h], Jaakko Ikonen [i], Richard de Jeu [j], Richard Kidd [k], William Lahoz [g], Yi Y. Liu [l], Diego Miralles [m,n], Thomas Mistelbauer [k], Nadine Nicolai-Shaw [h], Robert Parinussa [j], Chiara Pratola [o,p], Christoph Reimer [a,k], Robin van der Schalie [j], Sonia I. Seneviratne [h], Tuomo Smolander [i], Pascal Lecomte [q]

Different SM: instruments or algorithms ?

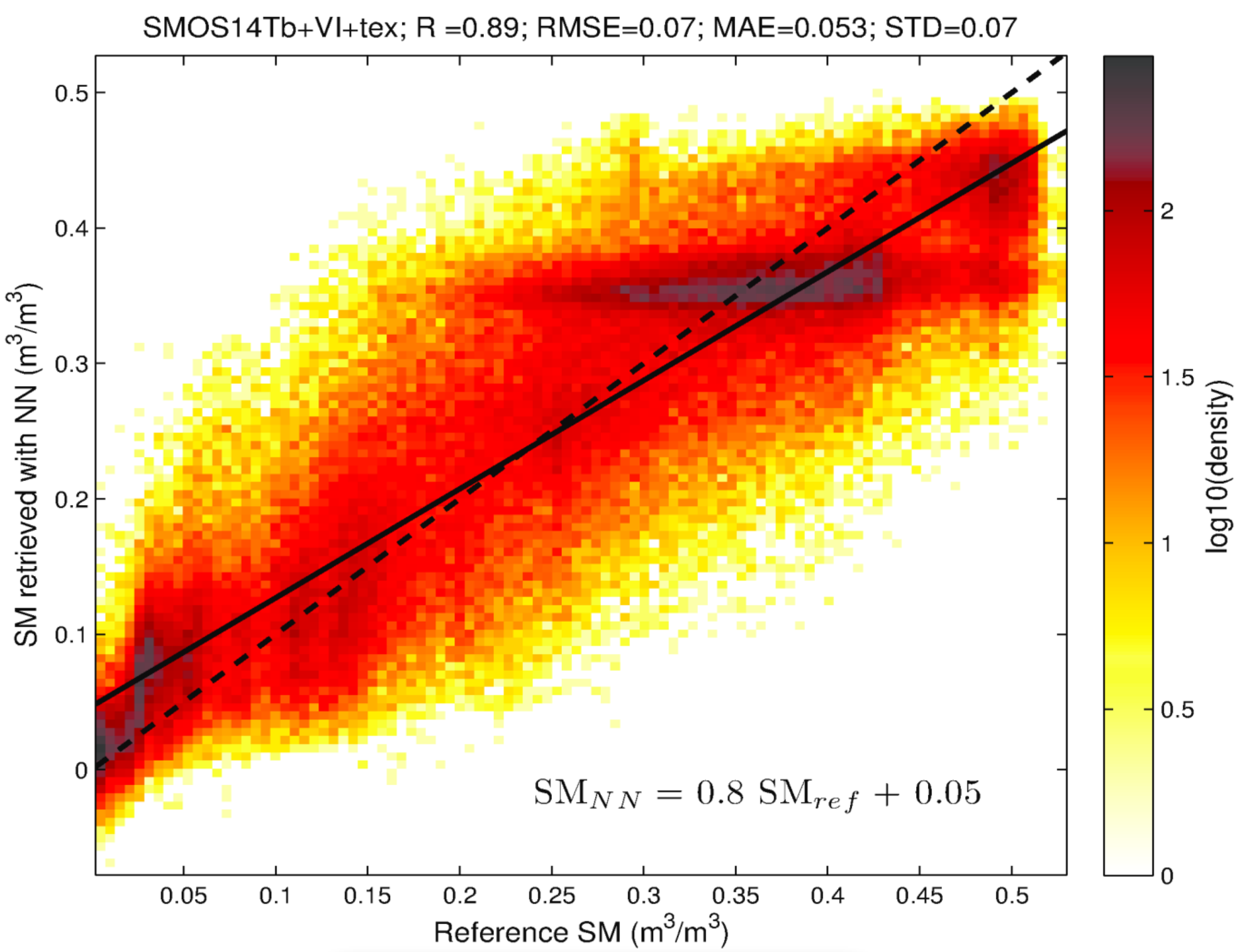
• Neural networks as a statistical consistency analysis tool

ASMR-E HV: 6, 10, 18, 23, 36 GHz
Ecoclimap sand and clay fraction



ECMWF SM (0-7 cm)

SMOS HV: 27, 32, 37, 42, 47, 52, 57 deg
MODIS NDVI
Ecoclimap sand and clay fraction



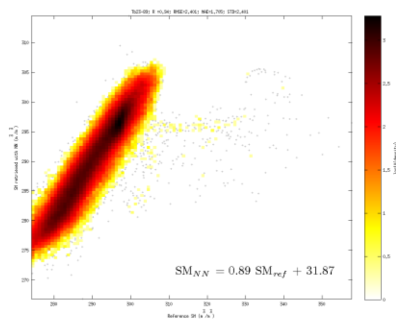
ECMWF SM (0-7 cm)

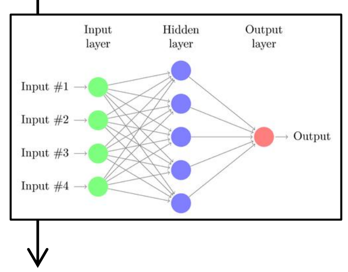
Multifrequency soil temp from AMSR-E

AMSR-E
H23, HV36 GHz

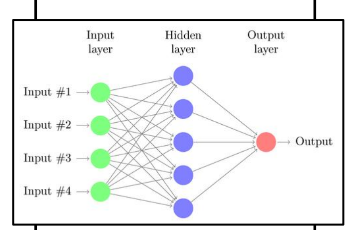
AMSR-E
6.9, 10 GHz

R=0.95





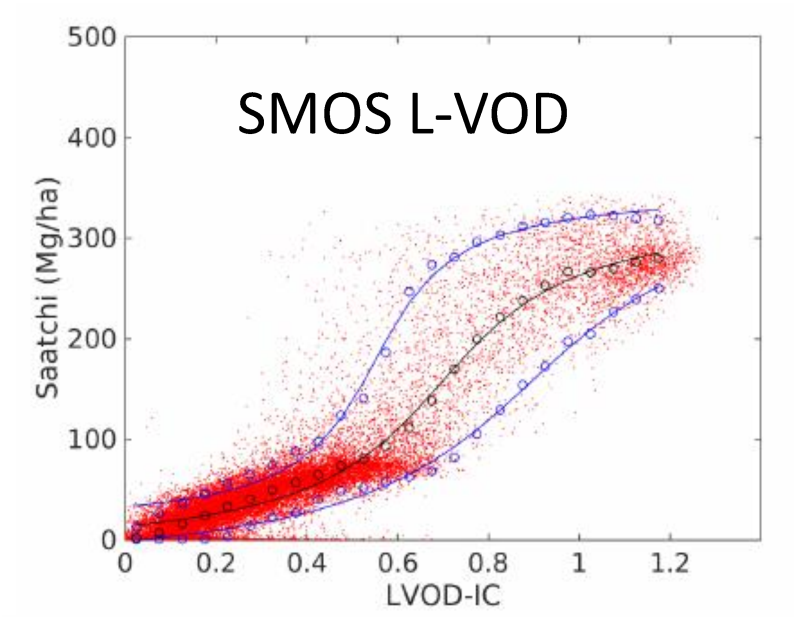
Tsoil

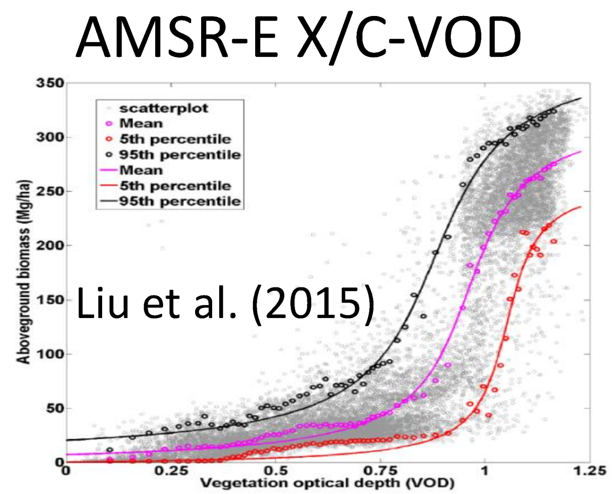


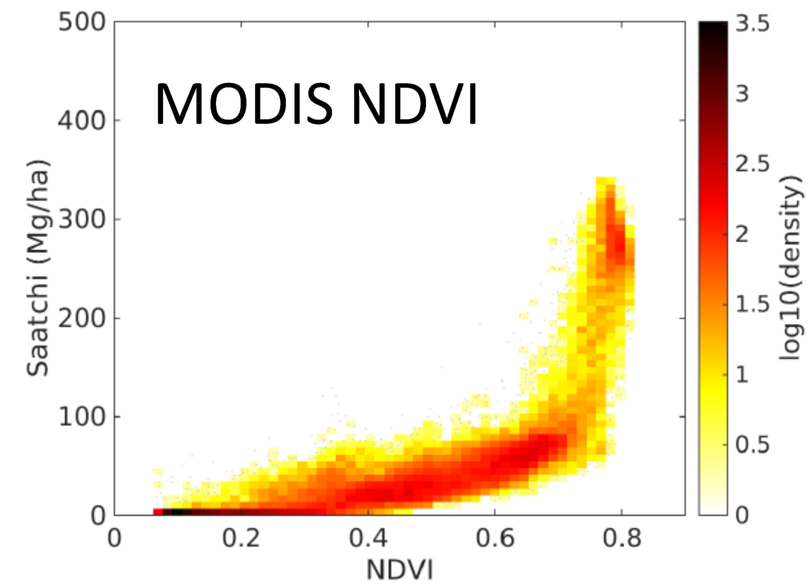
Soil Moisture

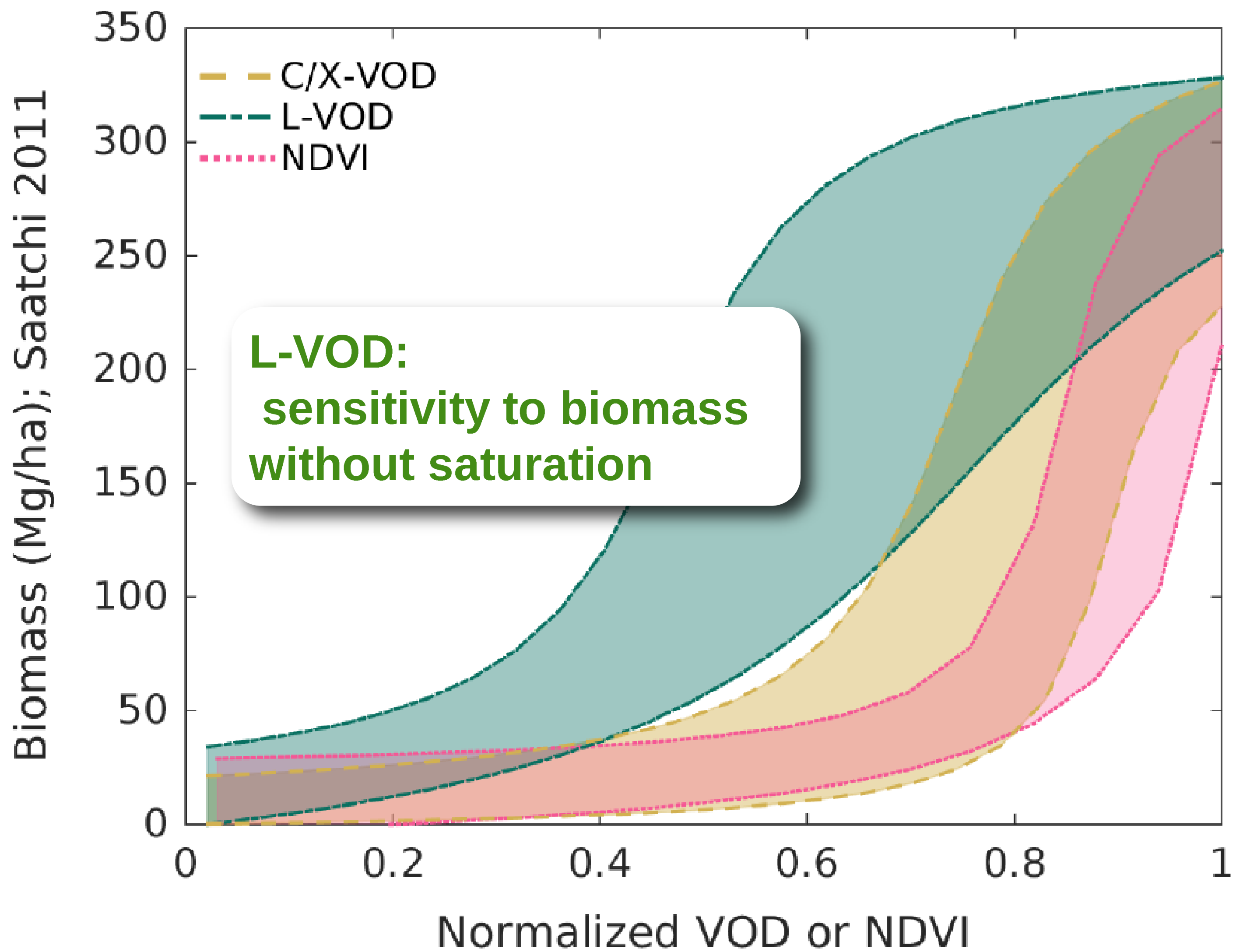
Rodriguez-Fernandez et al. (2016, Remote Sensing)

The added value of L-Band to monitor biomass









Rodriguez-Fernandez et al.

Summary and conclusions

- NNs can be used to invert a radiative transfer model : application ESA Near-Real-Time SMOS soil moisture disseminated by EUMETCast
- An alternative is to use land surface models to train the NN
  - This approach was tested with SMOS and ECMWF
  - Assimilation of SMOS NN SM into ECMWF model
    - Similar performances with respect to in situ measurements
    - Atmospheric forecasts with the analyzed fields : promising results, SMOS N positive impact in the northern and southern hemisphere
    - C-band scatterometer show complementary results
- A pure data-driven approach can be used with in situ measurements
- NNs can be used efficiently for multi-sensor retrievals
- NNs have been found to be useful to construct long time series using different sensors (C/X band, L-band)

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twitter @SMOS_satellite

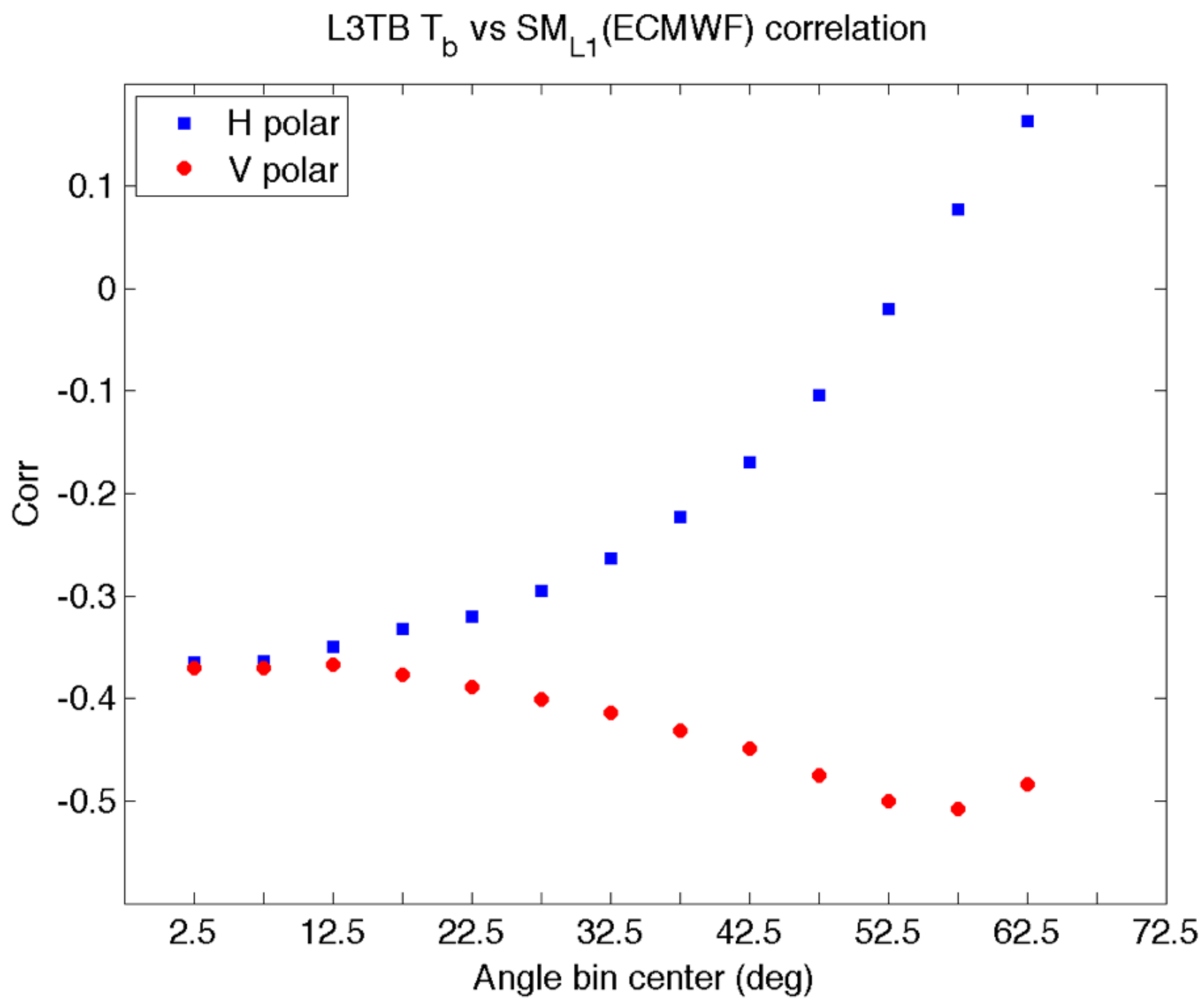
The SMOS+NN project

smos+ neural net
support to science element

N. Rodríguez-Fernández, F. Aires, P. Richaume, Y. Kerr, C. Prigent,…

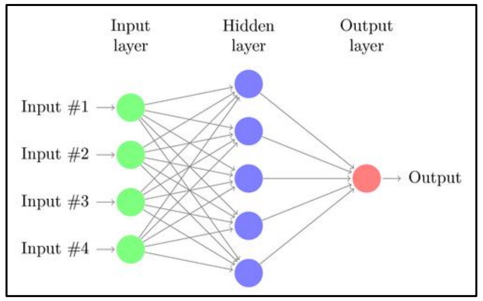
Started in mid-2012, with more of two years of SMOS data

- **Starting point: linear correlations or BTs and ECMWF SM**
- **Looking at this, the problem does not look trivial ...**



Statistical inverse model using Neural Networks

Input data



NN soil moisture

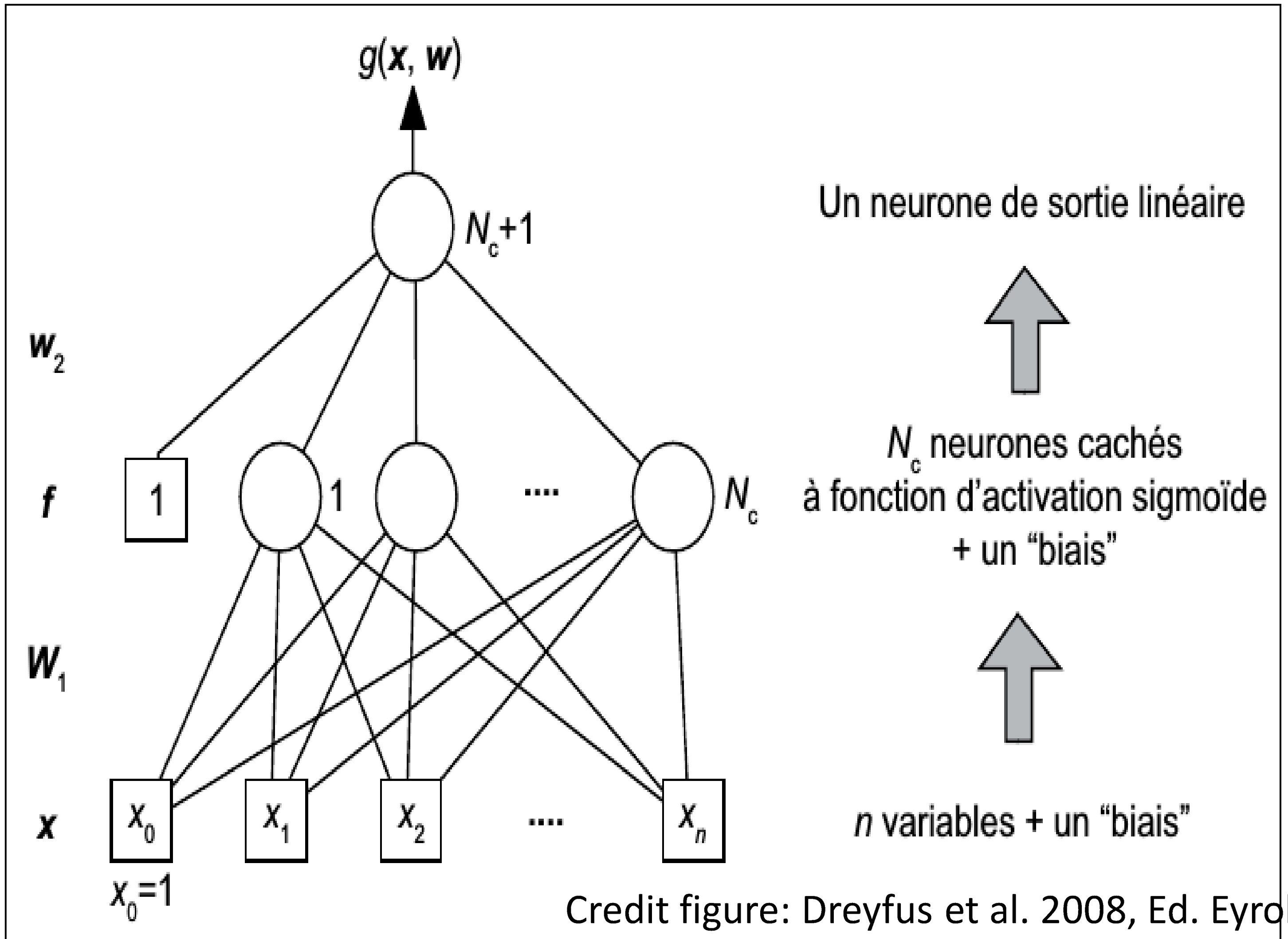
Training: comparison and new modeling step if needed

Soil moisture examples

Test different input data

Adapt NN weights

Feed-forward networks, multilayer perceptron

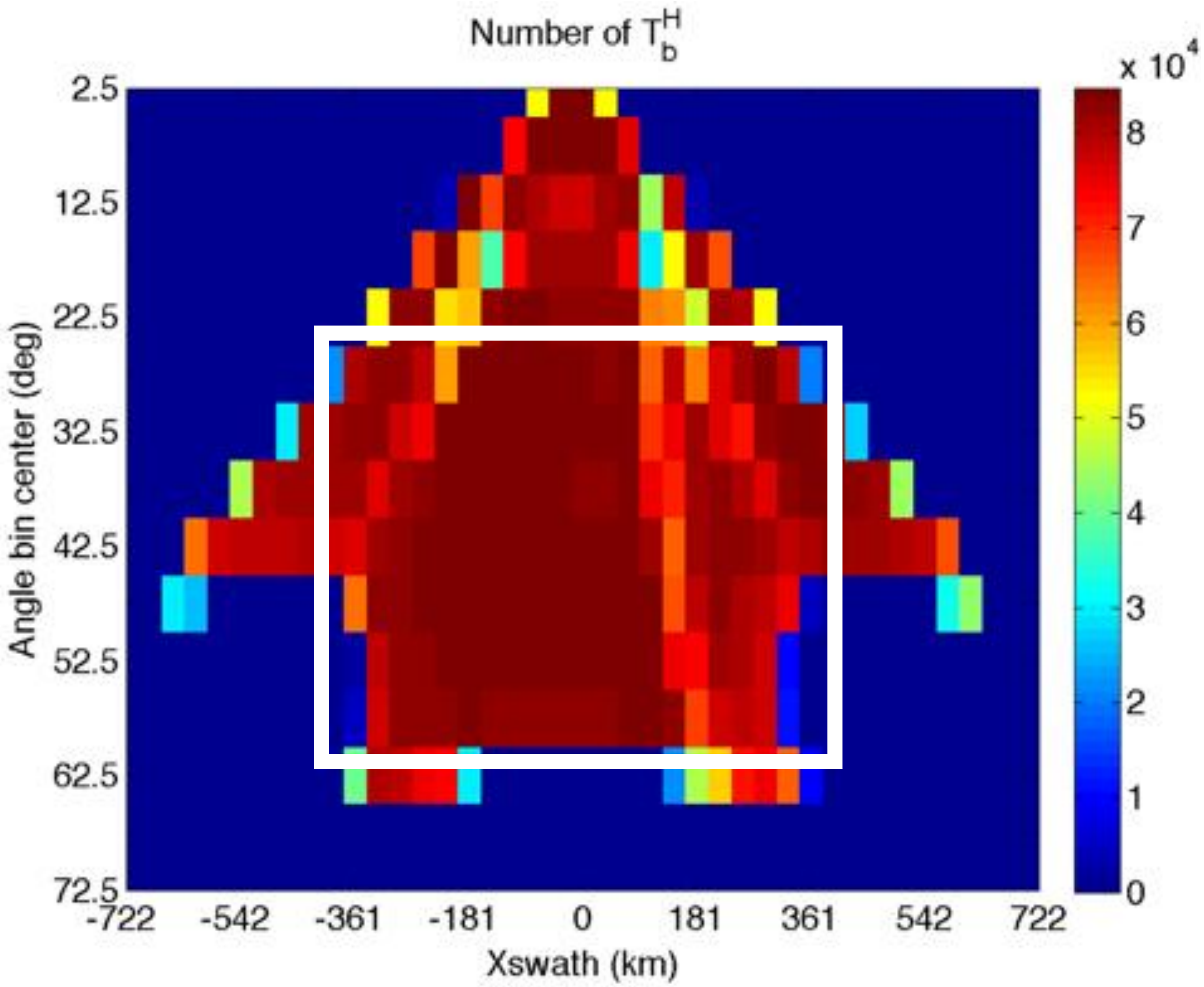


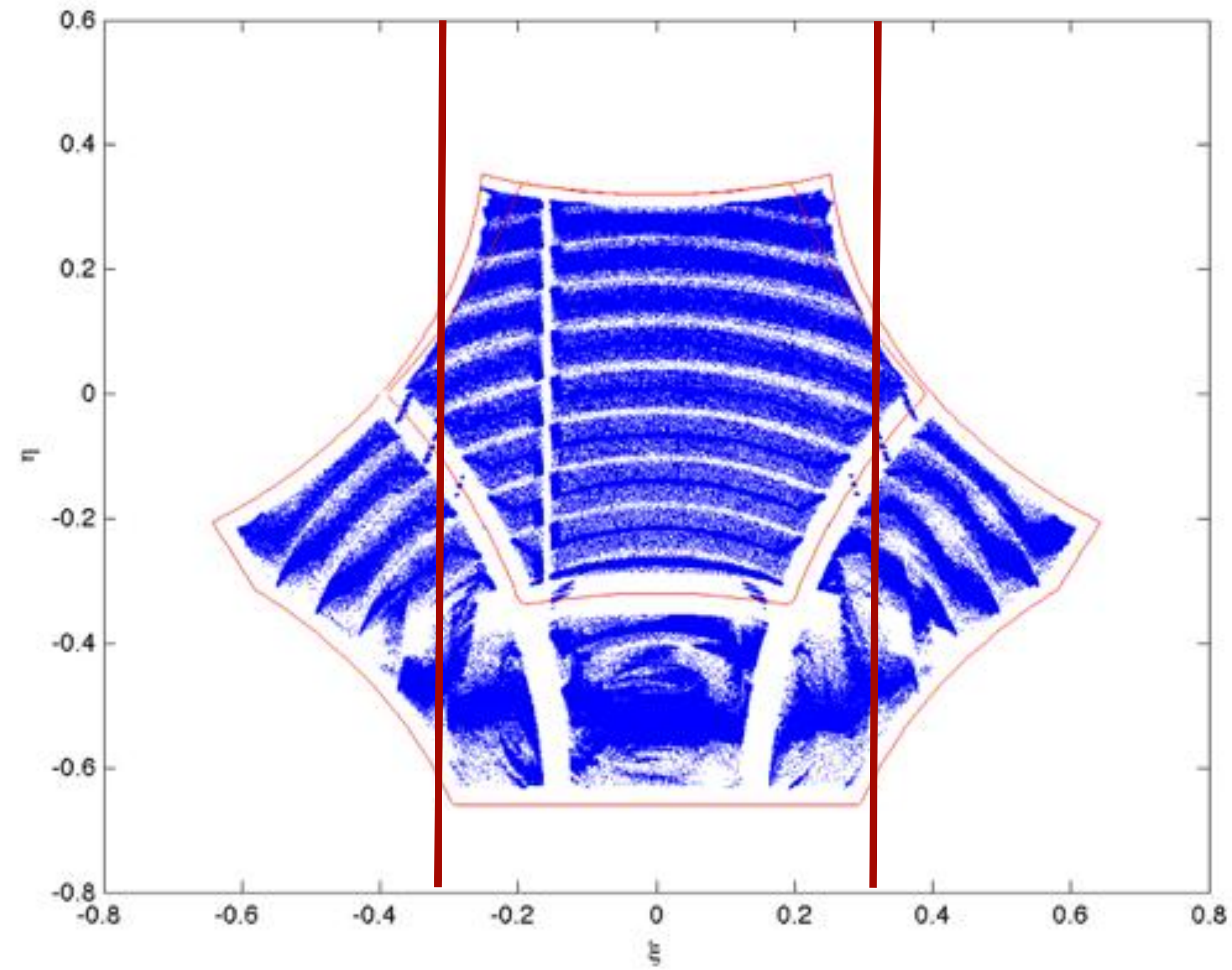
Credit figure: Dreyfus et al. 2008, Ed. Eyrolles

$$g(\boldsymbol{x},\boldsymbol{w}) = \sum_{i=1}^{N_c}\left[w_{N_c+1,i}\,\mathrm{th}\left(\sum_{j=1}^{n} w_{ij}x_j + w_{i0}\right)\right] + w_{N_c+1,0}$$
$$= \boldsymbol{w}_2 \cdot \boldsymbol{f}\left(\boldsymbol{W}_1\boldsymbol{x}\right)$$

Parametrical, purely-mathematical model
Can approximate any continuous and discontinuous function (finite number of discontinuities)
They are parsimonious in the number of free parameters

Number of Tb's per angle and distance to the satellite track

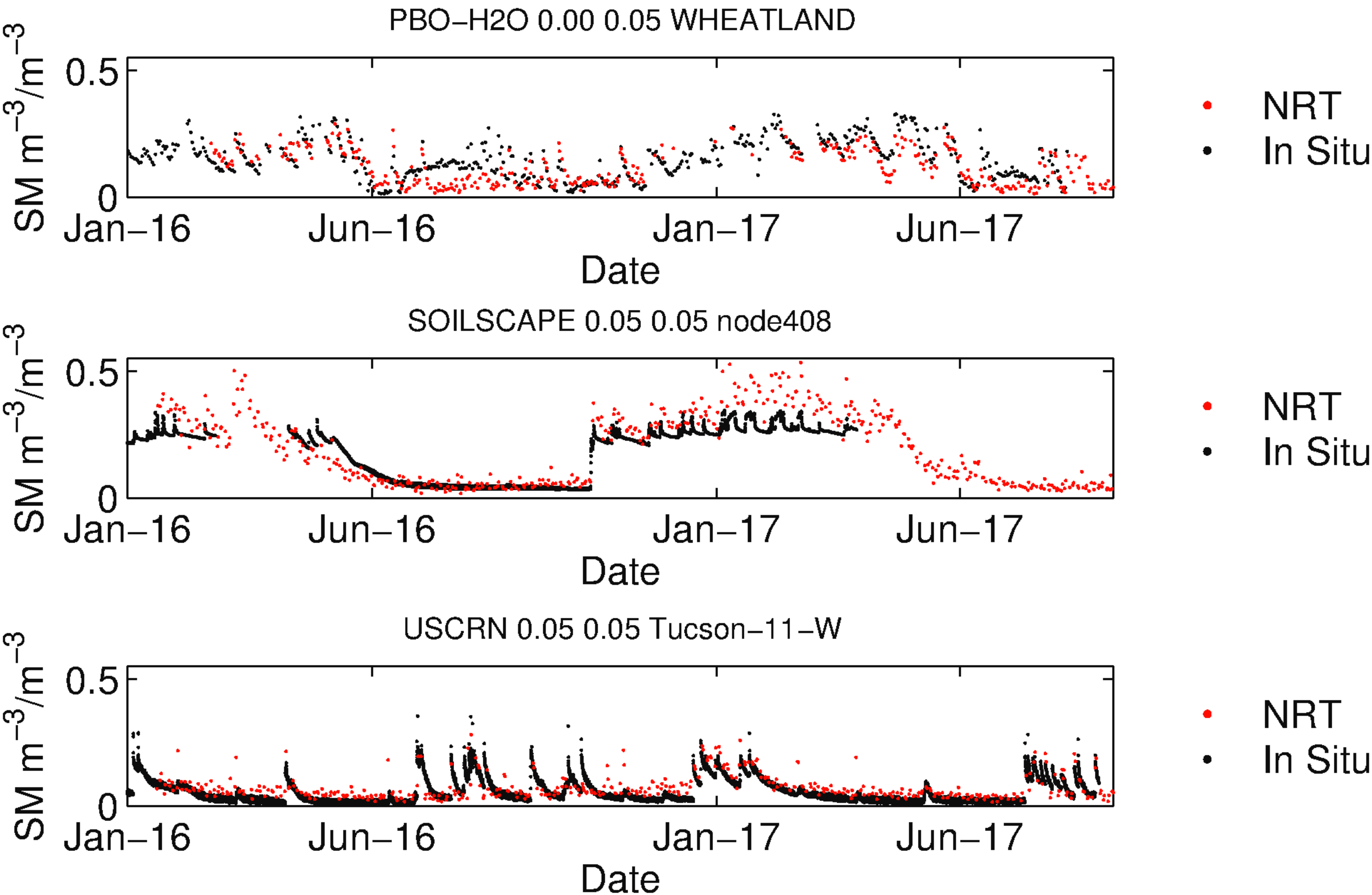




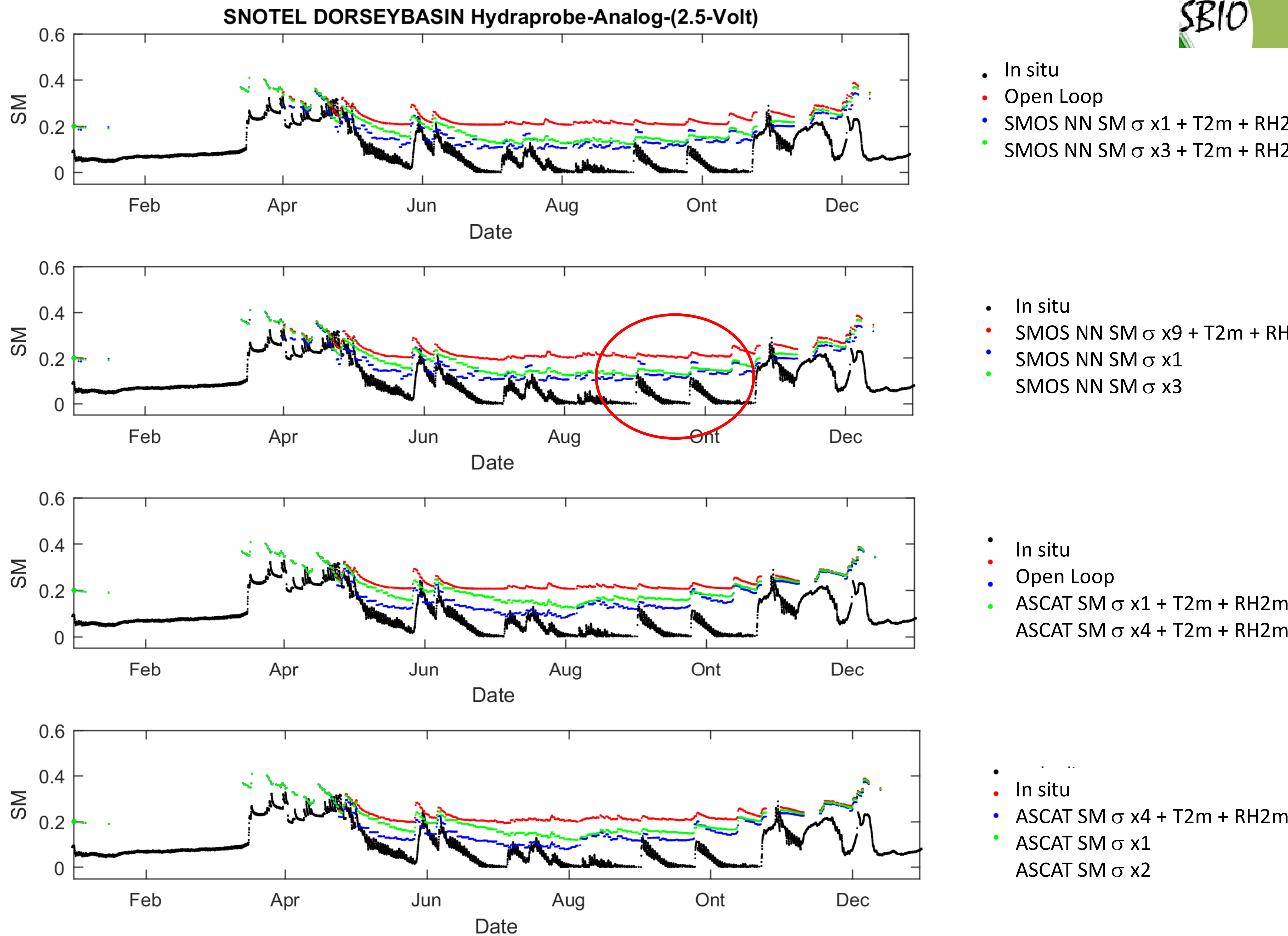
- Best option for just one NN covering as much of the swath as possible
and making use of as many Tb's as possible?
  - Angles from 25 to 60.
  - Thus we have the angular signature, we can improve correlation with SM ...
  ... and we cover the central ~700 kms of the swath

40

Results



PBO–H2O 0.00 0.05 WHEATLAND
SM m−3/m−3
0.5
0
Jan–16
Jun–16
Jan–17
Jun–17
Date
NRT
In Situ
SOILSCAPE 0.05 0.05 node408
SM m−3/m−3
0.5
0
Jan–16
Jun–16
Jan–17
Jun–17
Date
NRT
In Situ
USCRN 0.05 0.05 Tucson–11–W
SM m−3/m−3
0.5
0
Jan–16
Jun–16
Jan–17
Jun–17
Date
NRT
In Situ

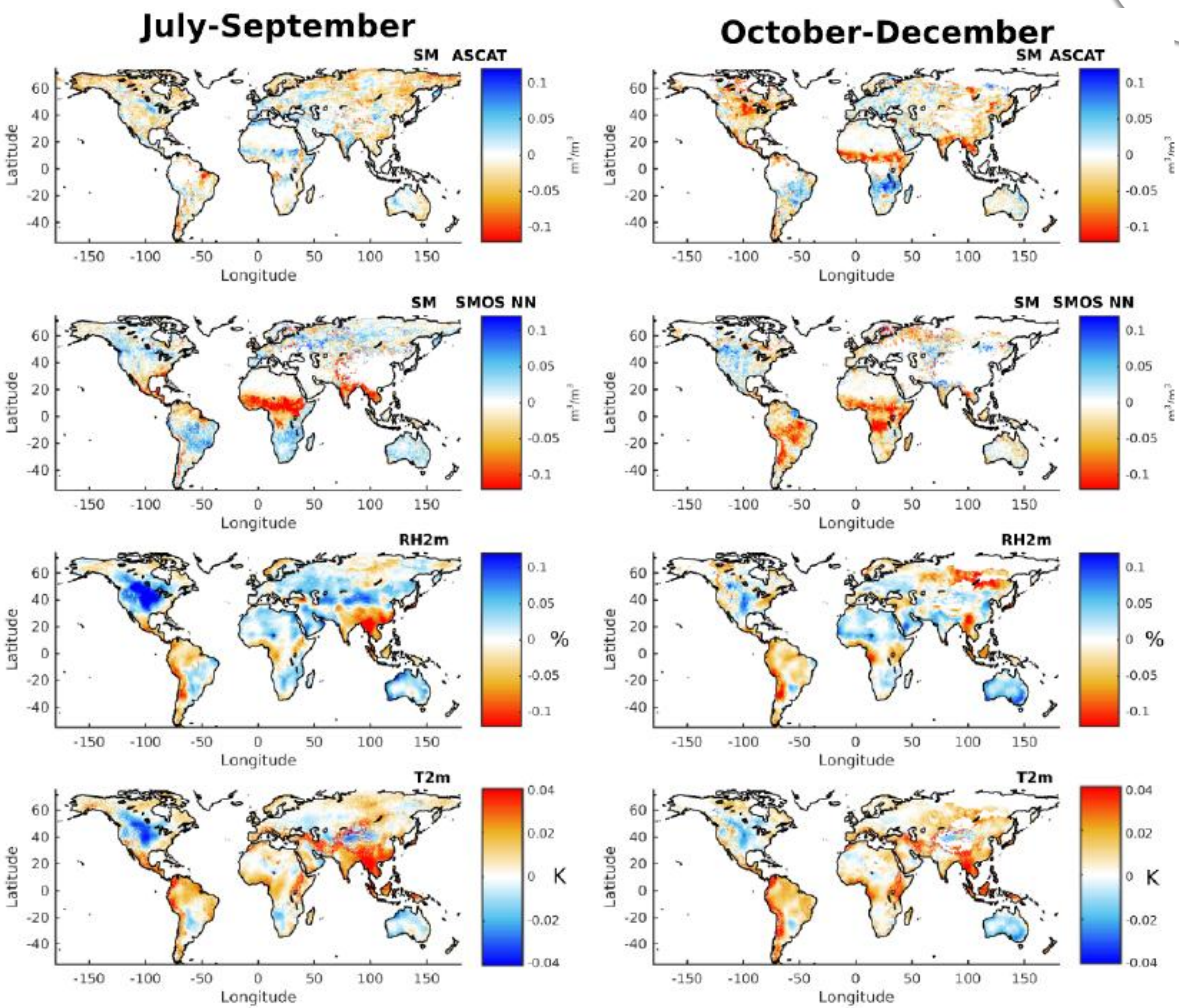

SNOTEL DORSEYBASIN Hydraprobe-Analog-(2.5-Volt)
SM
Date
0.6
0.4
0.2
0
Feb
Apr
Jun
Aug
Ont
Dec
In situ
Open Loop
SMOS NN SM σ x1 + T2m + RH2
SMOS NN SM σ x3 + T2m + RH2
In situ
SMOS NN SM σ x9 + T2m + RH
SMOS NN SM σ x1
SMOS NN SM σ x3
In situ
Open Loop
ASCAT SM σ x1 + T2m + RH2m
ASCAT SM σ x4 + T2m + RH2m
In situ
ASCAT SM σ x4 + T2m + RH2m
ASCAT SM σ x1
ASCAT SM σ x2

SM	Mean STD	Mean R	Mean Bias	Mean STD	Mean R	Mean Bias	Mean STD	Mean R	Mean Bias
	ARM Sensors= 31; Npt= 717			HOBE Sensors= 46; Npt= 687			SCAN Sensors= 240; Npt= 816		
SMOS NN SM σ x1	0.058	0.64	0.040	0.037	0.68	-0.002	0.054	0.54	0.043
SMOS NN SM σ x3	0.061	0.63	0.034	0.038	0.71	-0.010	0.055	0.55	0.038
SMOS NN SM σ x9	0.064	0.61	0.030	0.039	0.71	-0.013	0.056	0.54	0.036
SMOS NN SM σ x1 + T2m + RH2m	0.058	0.64	0.040	0.037	0.68	-0.002	0.054	0.54	0.043
SMOS NN SM σ x3 + T2m + RH2m	0.060	0.63	0.035	0.038	0.71	-0.009	0.055	0.55	0.038
SMOS NN SM σ x9 + T2m + RH2m	0.064	0.60	0.031	0.038	0.71	-0.012	0.056	0.54	0.036
ASCAT SM σ x1	0.064	0.63	0.029	0.043	0.67	-0.016	0.056	0.54	0.032
ASCAT SM σ x2	0.063	0.62	0.030	0.040	0.70	-0.015	0.055	0.54	0.034
ASCAT SM σ x4	0.064	0.61	0.029	0.039	0.71	-0.014	0.056	0.54	0.035
ASCAT SM σ x1 + T2m + RH2m	0.063	0.62	0.031	0.043	0.66	-0.016	0.056	0.53	0.033
ASCAT SM σ x2 + T2m + RH2m	0.063	0.61	0.031	0.040	0.70	-0.014	0.055	0.54	0.035
ASCAT SM σ x4 + T2m + RH2m	0.064	0.60	0.031	0.039	0.71	-0.013	0.056	0.54	0.035
Open loop	0.065	0.60	0.029	0.039	0.71	-0.014	0.056	0.54	0.035
	CTP-SMTMN Sensors= 33; Npt= 365			HYDROL-NET-PERUGIA Sensors= 2; Npt= 719			SMOSMANIA Sensors= 19; Npt= 1009		
SMOS NN SM σ x1	0.048	0.53	0.114	0.057	0.79	0.078	0.053	0.79	0.066
SMOS NN SM σ x3	0.048	0.53	0.114	0.057	0.79	0.079	0.053	0.80	0.063
SMOS NN SM σ x9	0.048	0.53	0.114	0.057	0.79	0.079	0.054	0.80	0.062
SMOS NN SM σ x1 + T2m + RH2m	0.048	0.53	0.113	0.057	0.79	0.074	0.053	0.79	0.065
SMOS NN SM σ x3 + T2m + RH2m	0.048	0.53	0.113	0.057	0.79	0.075	0.053	0.80	0.062
SMOS NN SM σ x9 + T2m + RH2m	0.048	0.53	0.113	0.057	0.79	0.075	0.053	0.80	0.060
ASCAT SM σ x1	0.047	0.57	0.113	0.056	0.78	0.067	0.054	0.79	0.059
ASCAT SM σ x2	0.048	0.54	0.114	0.057	0.79	0.075	0.053	0.80	0.060
ASCAT SM σ x4	0.048	0.53	0.114	0.057	0.79	0.078	0.054	0.80	0.061
ASCAT SM σ x1 + T2m + RH2m	0.047	0.57	0.113	0.056	0.78	0.064	0.054	0.79	0.059
ASCAT SM σ x2 + T2m + RH2m	0.047	0.55	0.113	0.057	0.79	0.072	0.053	0.80	0.060
ASCAT SM σ x4 + T2m + RH2m	0.048	0.54	0.113	0.057	0.79	0.075	0.053	0.80	0.060
Open loop	0.048	0.53	0.114	0.057	0.79	0.079	0.054	0.80	0.062

SM	Mean STD	Mean R	Mean Bias	Mean STD	Mean R	Mean Bias	Mean STD	Mean R	Mean Bias
	DAHRA Sensors= 1; Npt= 1137			PBO-H2O Sensors= 101; Npt= 206			SNOTEL Sensors= 347; Npt= 537		
SMOS NN SM σ xl	0.044	0.68	0.109	0.047	0.62	0.045	0.076	0.42	0.050
SMOS NN SM σ x3	0.048	0.71	0.112	0.047	0.63	0.038	0.074	0.47	0.037
SMOS NN SM σ x9	0.052	0.71	0.116	0.048	0.62	0.036	0.074	0.48	0.033
SMOS NN SM σ x1 + T2m + RH2m	0.046	0.68	0.111	0.047	0.62	0.046	0.076	0.42	0.050
SMOS NN SM σ x3 + T2m + RH2m	0.050	0.72	0.115	0.047	0.63	0.040	0.074	0.46	0.038
SMOS NN SM σ x9 + T2m + RH2m	0.054	0.72	0.118	0.047	0.62	0.038	0.074	0.48	0.035
ASCAT SM σ xl	0.059	0.71	0.097	0.047	0.63	0.031	0.076	0.45	0.025
ASCAT SM σ x2	0.057	0.73	0.098	0.047	0.63	0.033	0.074	0.47	0.029
ASCAT SM σ x4	0.057	0.74	0.102	0.048	0.62	0.034	0.074	0.48	0.031
ASCAT SM σ x1 + T2m + RH2m	0.059	0.71	0.098	0.047	0.62	0.033	0.076	0.45	0.027
ASCAT SM σ x2 + T2m + RH2m	0.058	0.73	0.099	0.047	0.62	0.035	0.075	0.47	0.032
ASCAT SM σ x4 + T2m + RH2m	0.058	0.75	0.103	0.047	0.62	0.037	0.074	0.47	0.034
Open loop	0.053	0.72	0.117	0.048	0.62	0.036	0.074	0.48	0.032
	FMI Sensors= 8; Npt= 245			REMEDHUS Sensors= 23; Npt= 1016			USCRN Sensors= 122; Npt= 931		
SMOS NN SM σ xl	0.030	0.49	0.114	0.065	0.79	0.114	0.053	0.66	0.081
SMOS NN SM σ x3	0.026	0.36	0.134	0.064	0.80	0.115	0.052	0.68	0.076
SMOS NN SM σ x9	0.023	0.59	0.109	0.064	0.79	0.115	0.053	0.67	0.073
SMOS NN SM σ x1 + T2m + RH2m	0.031	0.41	0.116	0.065	0.79	0.113	0.053	0.66	0.082
SMOS NN SM σ x3 + T2m + RH2m	0.026	0.36	0.134	0.064	0.80	0.113	0.052	0.68	0.076
SMOS NN SM σ x9 + T2m + RH2m	0.023	0.59	0.109	0.064	0.80	0.112	0.053	0.67	0.074
ASCAT SM σ xl	0.023	0.54	0.128	0.065	0.78	0.110	0.053	0.67	0.068
ASCAT SM σ x2	0.023	0.58	0.115	0.064	0.79	0.113	0.052	0.68	0.071
ASCAT SM σ x4	0.024	0.60	0.107	0.064	0.79	0.115	0.053	0.68	0.072
ASCAT SM σ x1 + T2m + RH2m	0.023	0.54	0.128	0.065	0.78	0.110	0.052	0.67	0.069
ASCAT SM σ x2 + T2m + RH2m	0.023	0.57	0.115	0.064	0.80	0.112	0.052	0.68	0.072
ASCAT SM σ x4 + T2m + RH2m	0.024	0.60	0.107	0.064	0.80	0.113	0.053	0.68	0.074
Open loop	0.024	0.61	0.103	0.065	0.79	0.115	0.054	0.67	0.073

Innovations

$x_a^t = x_b^t + K\,(y_0^t - \mathcal{H}[x_b^t])$

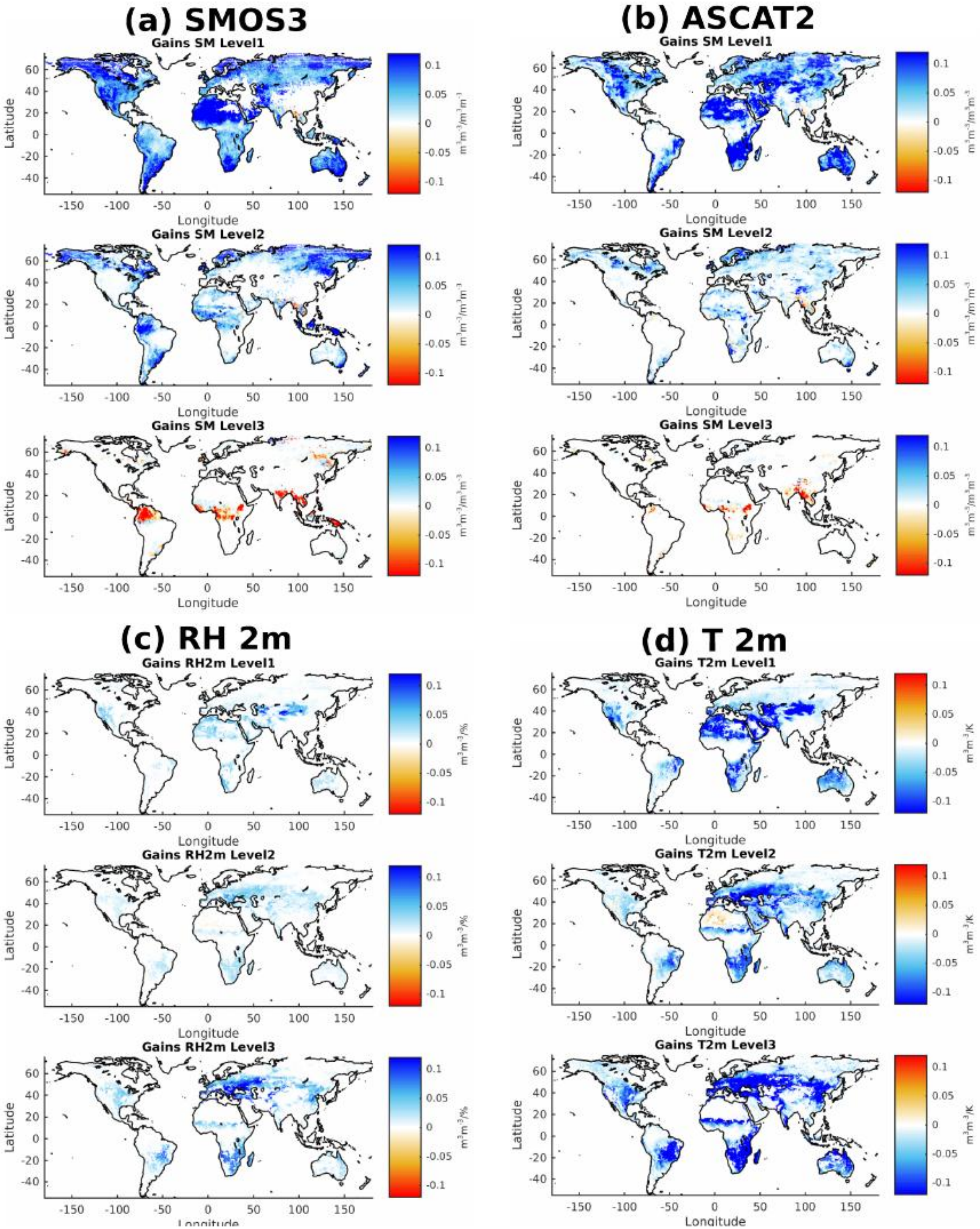


Low fr

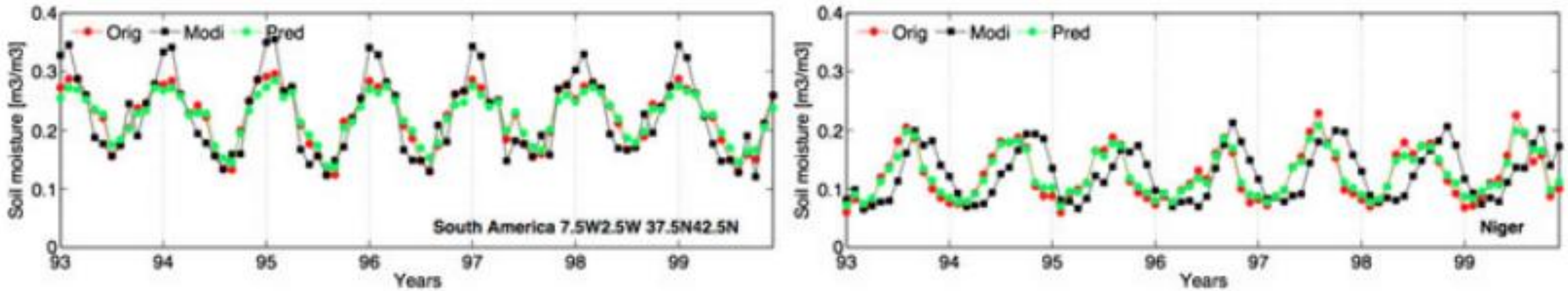
Kalman Gains

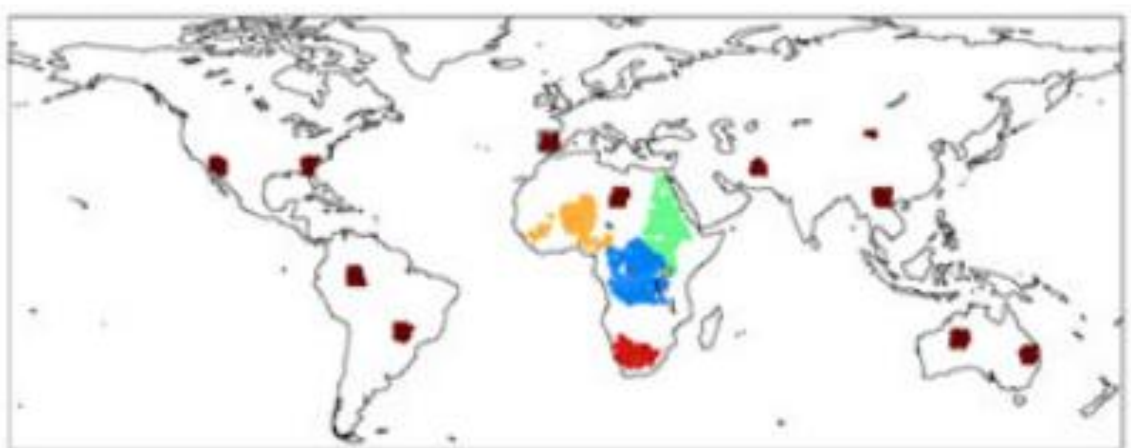
$$x_a^t = x_b^t + \mathbf{K}\,(y_0^t - \mathcal{H}[x_b^t])$$

$$\mathbf{K} = \mathbf{BH}^{\mathbf{T}}(\mathbf{HBH}^{\mathbf{T}} + \mathbf{R})^{-1}$$



“Incestuous” approach ? No, the retrieval is driven by the input observations, not by the model used as reference…





• Training on artificially modified JULES (UK Met Office) soil moisture fields

• The NN retrieval is close to the original one

Jimenez et al. 2013 JGR.

- In any case, the DA will show if the new observations dataset is adding information with respect to the model or not …

The “SMOS/AMSR-E fusion project”

– **“From ASMR-E to SMOS”** : optimizing the **LPRM** algorithm and apply it to SMOS data (led by VUA)

Van der Schalie et al. (2017)

– **“From SMOS to ASMR-E”** : Local multi-linear regression equations (led by INRA)

Al Yaari et al. (2016)

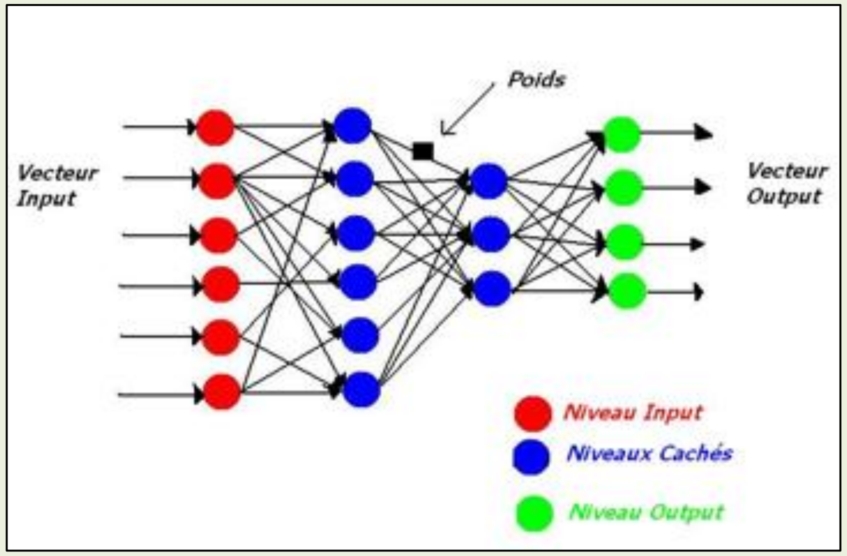
$$\boxed{\ln(SSM) = b_2 \ln(\Gamma_{pH}(\theta)) + b_1 \ln(\Gamma_{pv}(\theta)) + b_0(\theta)}$$

$\Gamma_p(\theta)$: Soil reflectivity

- **“From SMOS to ASMR-E”** : Global non-linear regressions using neural networks (led by CESBIO)

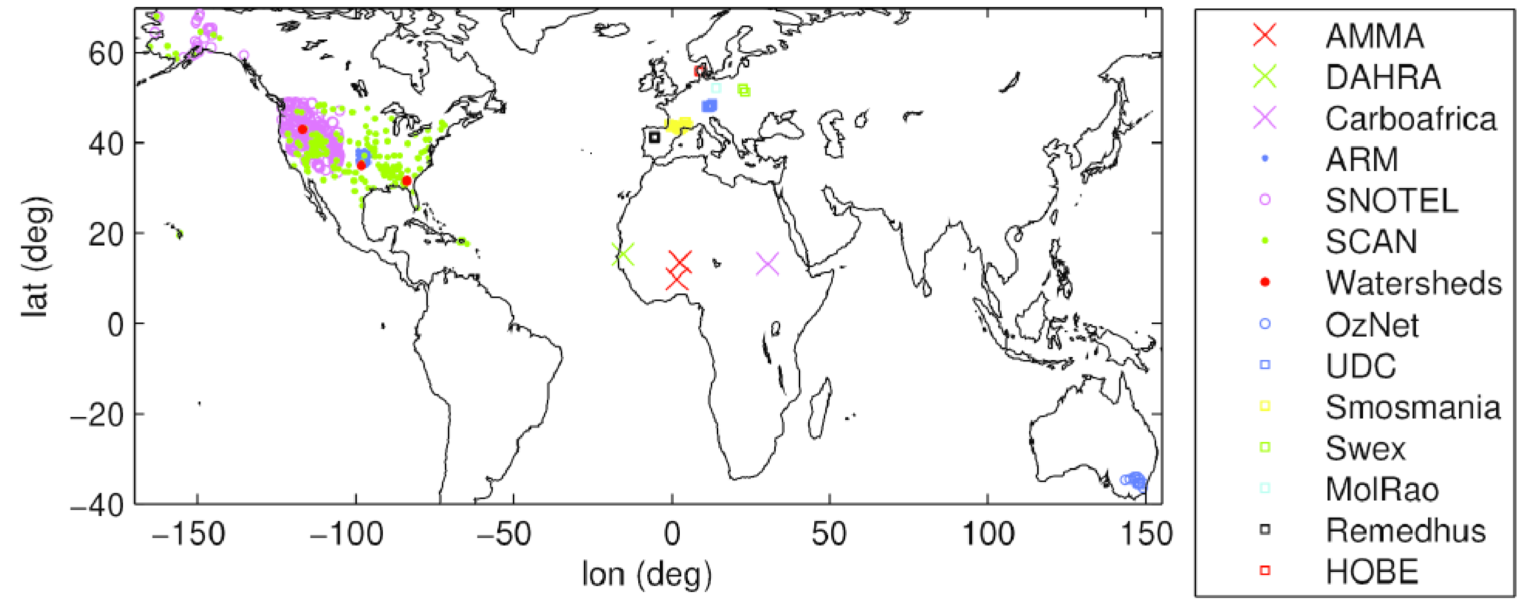
Rodriguez-Fernandez et al. (2016)

AMSR-E Brightness temperatures

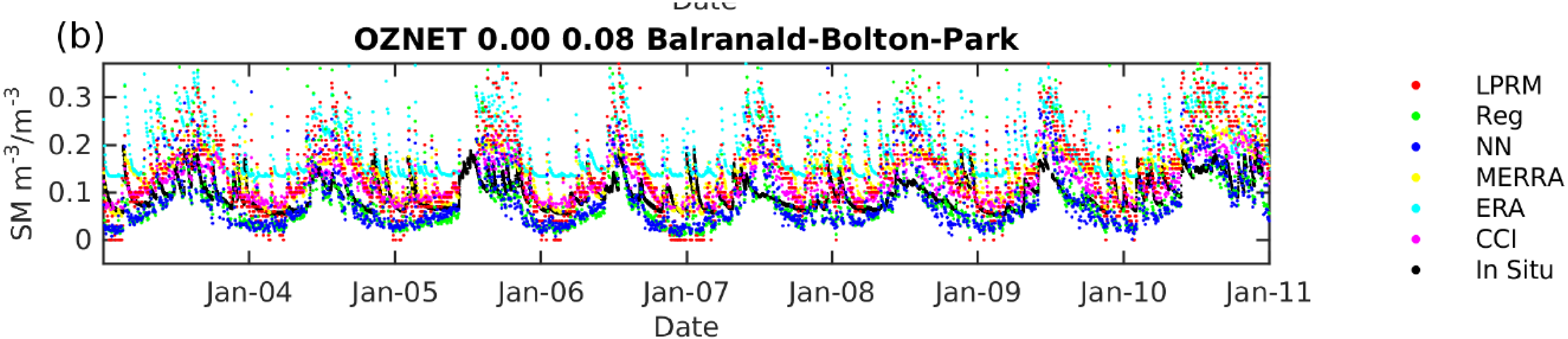


SMOS-like Soil Moisture

Evaluation against in situ measurements



Rodriguez-Fernandez et al. (2016, Remote Sensing)



Europe : models perform better than remote sensing retrievals*: residual RFI* ?
North America: models better in mountain regions, remote sensing good in the plains
Australia: similar good performances of models and remote sensing
Sahel: best performance of remote sensing data

Evaluation: SMOS Level 3, ECMWF

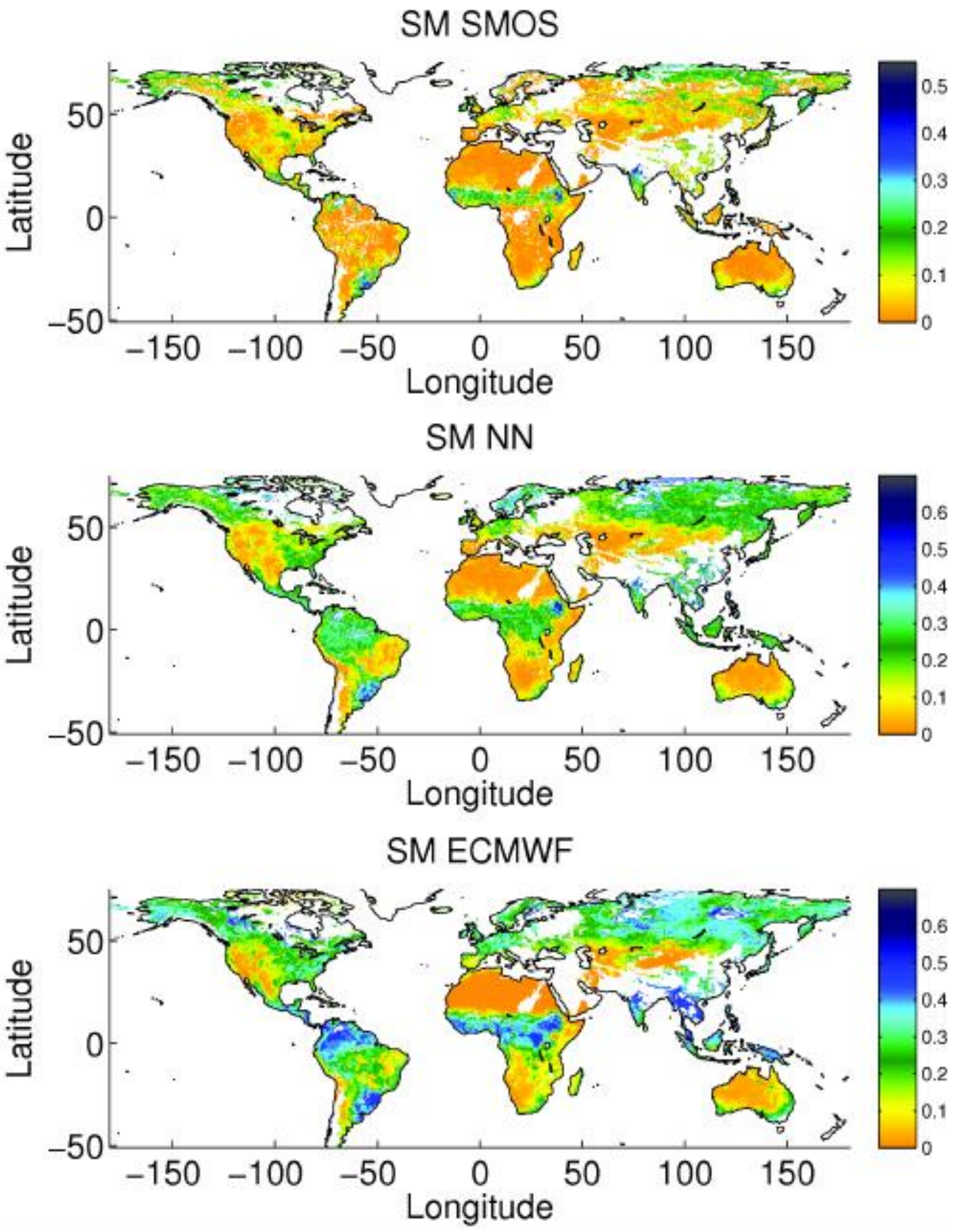
Is the minimization of SMOS L2/L3 "drying" the results ?

Mixed footprints: initialization with ECMWF?

Goals of SMOS-IC

Fernandez-Moran et al. (2017)

Mean August 2011



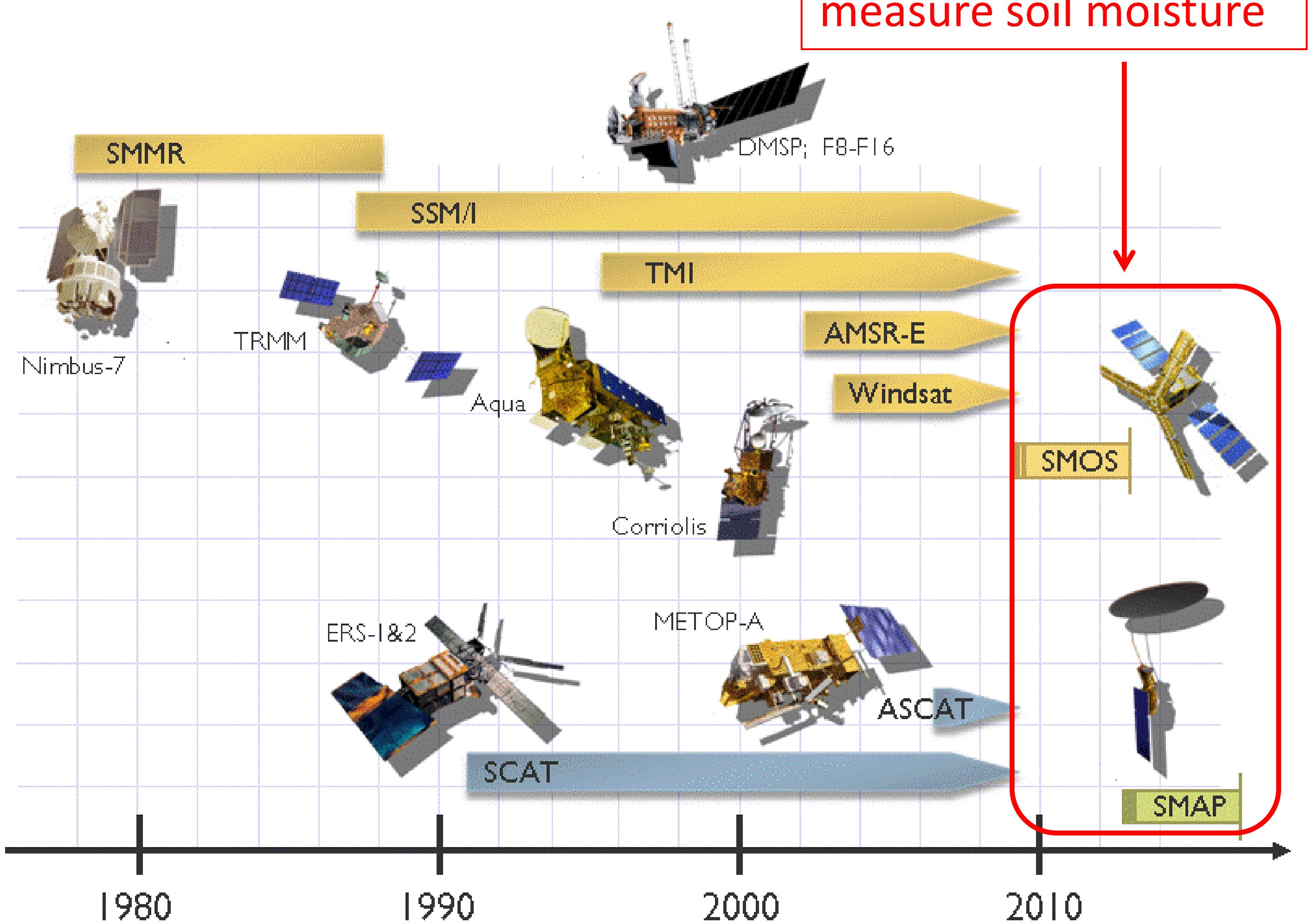
Rodriguez-Fernandez et al. (2017, IGARSS)

A climate record of soil moisture

Remote sensing from space gives access to global SM maps… but long time series are needed …

And merging data from different instruments is not trivial

New instruments specifically designed to measure soil moisture



- Liu et al. 2011,
  - AMSR-E and ASCAT rescaled using GLDAS-Noah model
- Liu et al. 2012:
  - SMMR, SSM/I, TMI scaled to AMSR-E
  - ERS scaled to ASCAT
  - Active and passive rescaled using GLDAS-Noah
- Wagner et al. 2012.
  - Windsat added, Reference GLDAS and ERA-Interim models