



# Long time series of soil moisture obtained using neural networks: application to AMSR-E and SMOS

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# Need for long time series of soil moisture



◉ Global Climate Observing System has endorsed soil moisture (SM) as an Essential Climate Variable



◉ 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

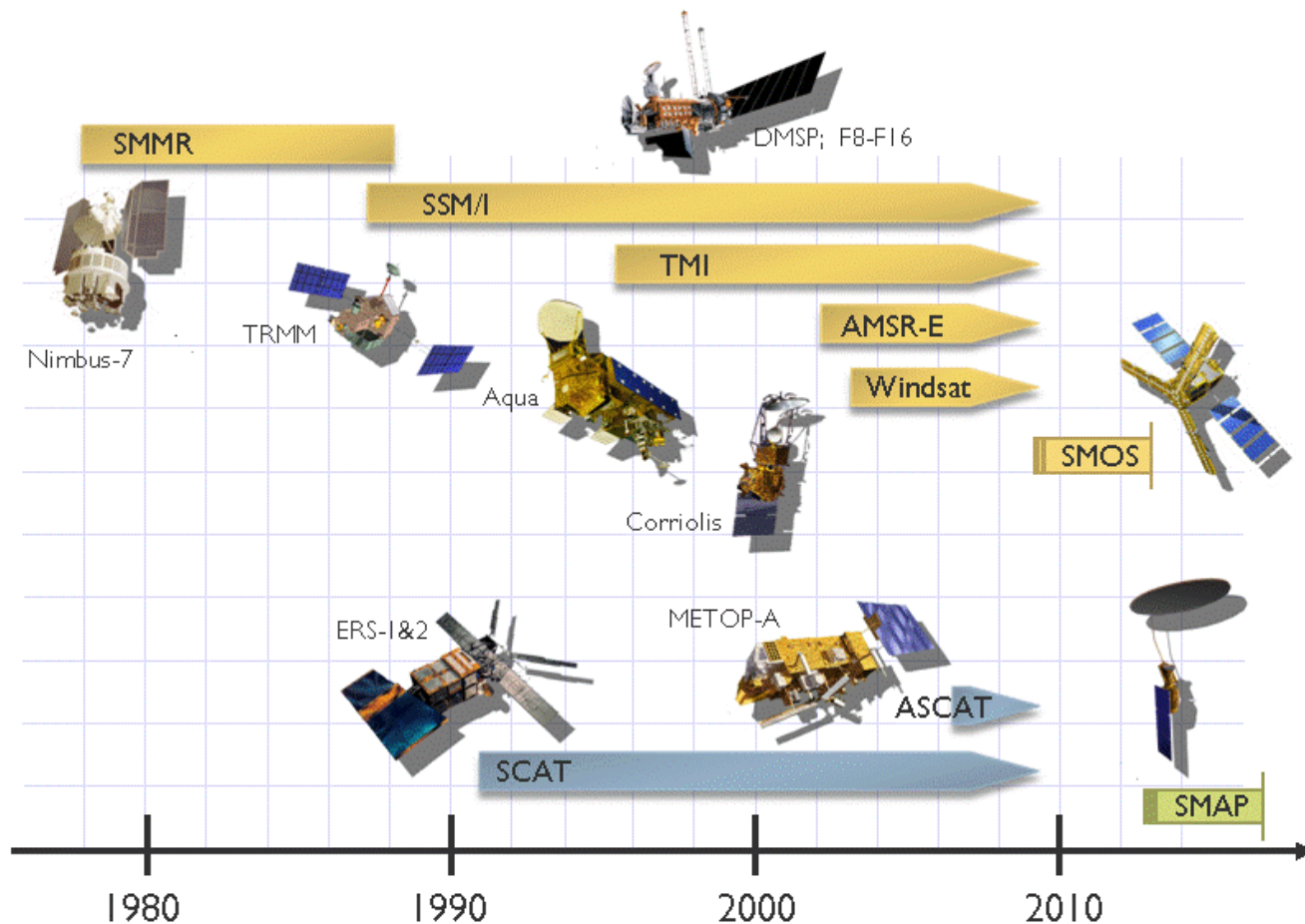


◉ Wagner et al. 2012.

- Windsat added, Reference GLDAS and ERA-Interim models



# New devoted sensors: SMOS, SMAP



## SMOS

- Full polarization
- Multi-angular (0-60°)
- L-Band (1.4 GHz) : lower sensitivity to vegetation

Best strategy to add SMOS to a long term SM record?  
First step: the **ESA AMSR-E / SMOS fusion project**.



# The “SMOS/AMSR-E fusion project”



- “From ASMR-E to SMOS” : optimizing the **LPRM** algorithm and apply it to SMOS data (led by VUA) → poster 17, van der Schalie et al.

Van der Schalie et al. (in press)

- “From SMOS to ASMR-E” : Local multi-linear regression equations (led by INRA) poster 15, Al Yaari et al.

Al Yaari et al. (in press)

$$\ln(SSM) = b_2 \ln(\Gamma_{pH}(\theta)) + b_1 \ln(\Gamma_{pv}(\theta)) + b_0(\theta) \quad \Gamma_p(\theta) : \text{Soil reflectivity}$$

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

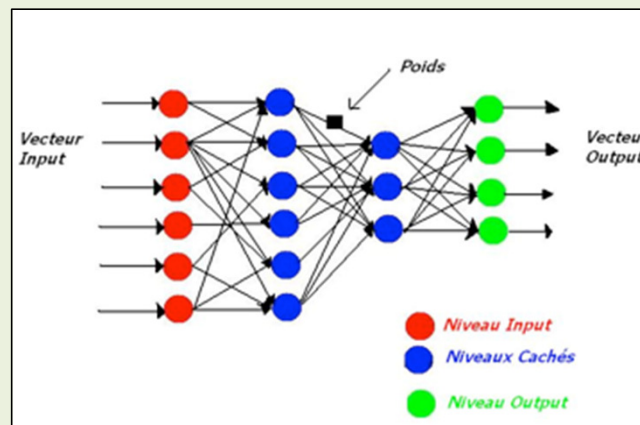
$$v_j^{L1} = \tanh\left(\sum_{i=1}^{n_{in}} W_{L1}^{ij} v_i^{norm} + B_{L1}^i\right), \quad \forall j = 1 \dots n_{L1}$$

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

Rodriguez-Fernandez et al. (in prep)

DATA DRIVEN METHODS

AMSR-E  
Brightness  
temperatures



SMOS-like  
Soil Moisture



# Application of LPRM to SMOS observations

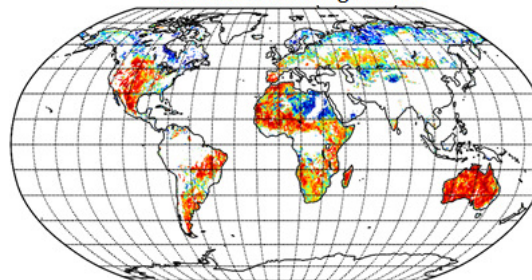


Goal: To apply the Land Parameter Retrieval Model (LPRM) to the SMOS L-band observations and update the C- and X-band LPRM parameters (See poster ID:196, by Robin van der Schalie)

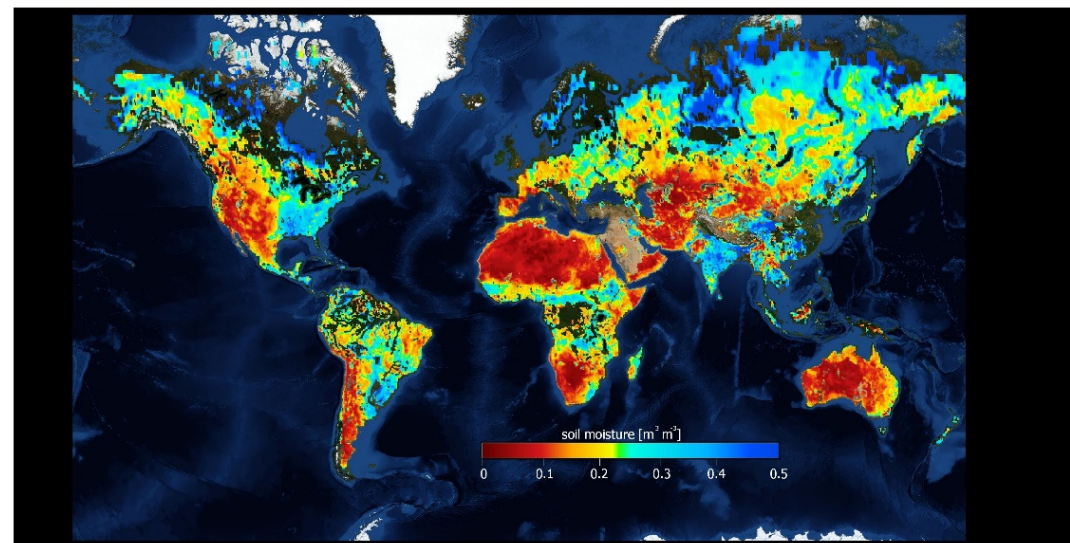
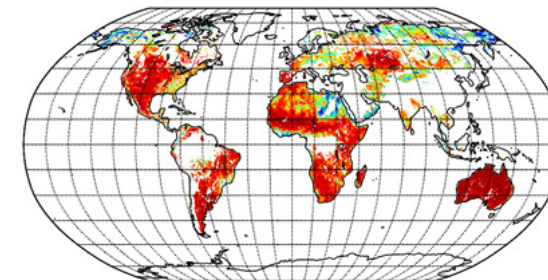
Advantage of LPRM: intensely tested and evaluated method that uses a single parameterization globally and minimizes the use of ancillary data inputs

First results show high correlations between SMOS LPRM against AMSRE LPRM, SMOS Level 3, MERRA soil moisture and ERA-land soil moisture over all area's except for: Dense tropical forest and boreal areas

1. Correlation SMOS LPRM vs C-band LPRM using AMSRE



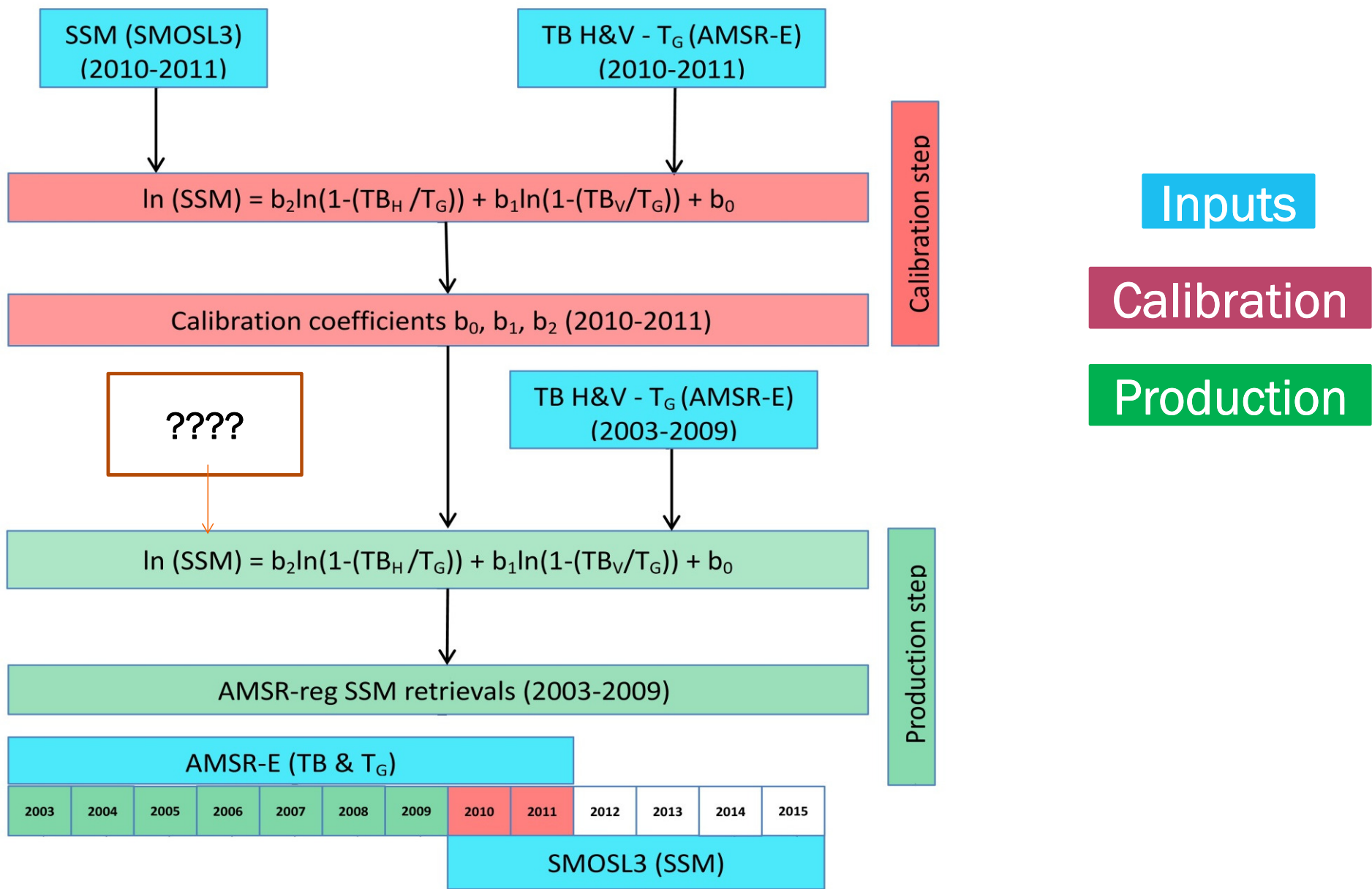
2. Correlation SMOS LPRM vs SMOS Level 3



Mean soil moisture - SMOS LPRM (Asc)



# Local multi-linear regressions: Methodology



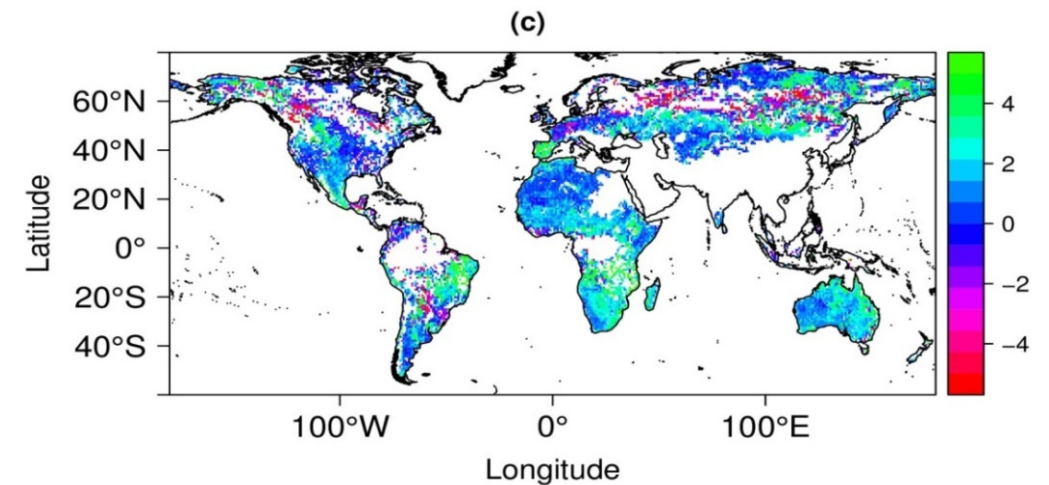
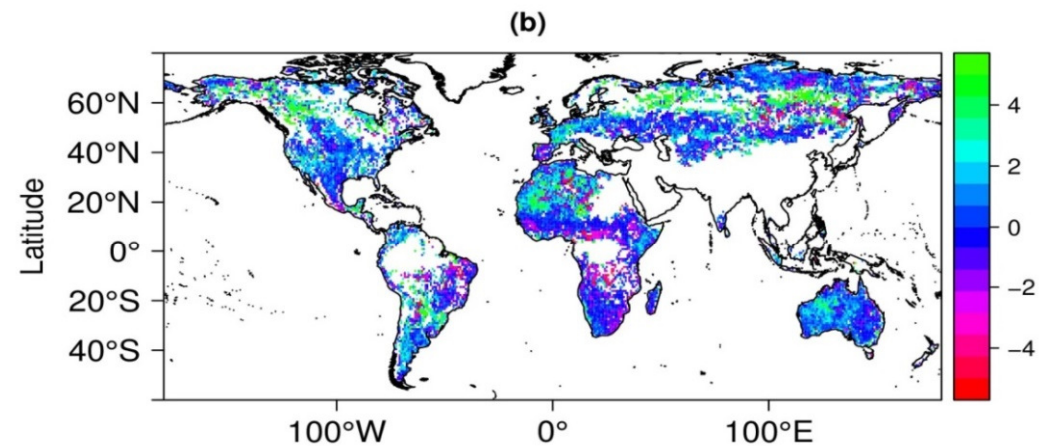
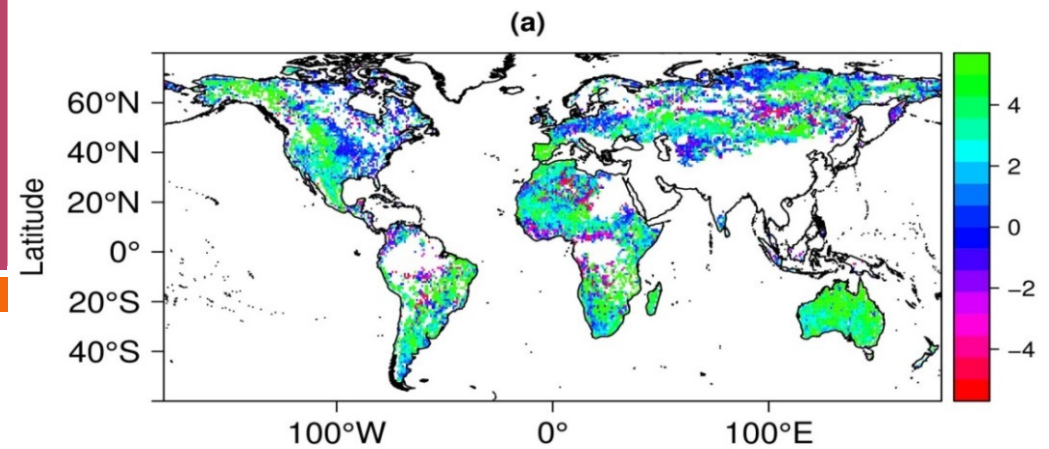
# Results (Calibration)

Regression coefficients:

$b_0$ ,  $b_1$ ,  $b_2$  (Oct2010-Sept2011)

- ∞ The spatial patterns of the coefficients can be distinguished
- ∞ In agreement with land cover type!

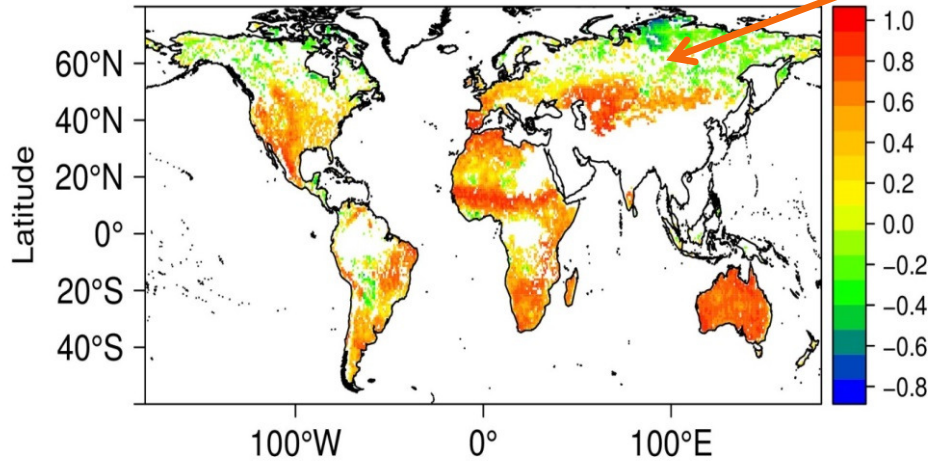
White areas:  $N < 50$



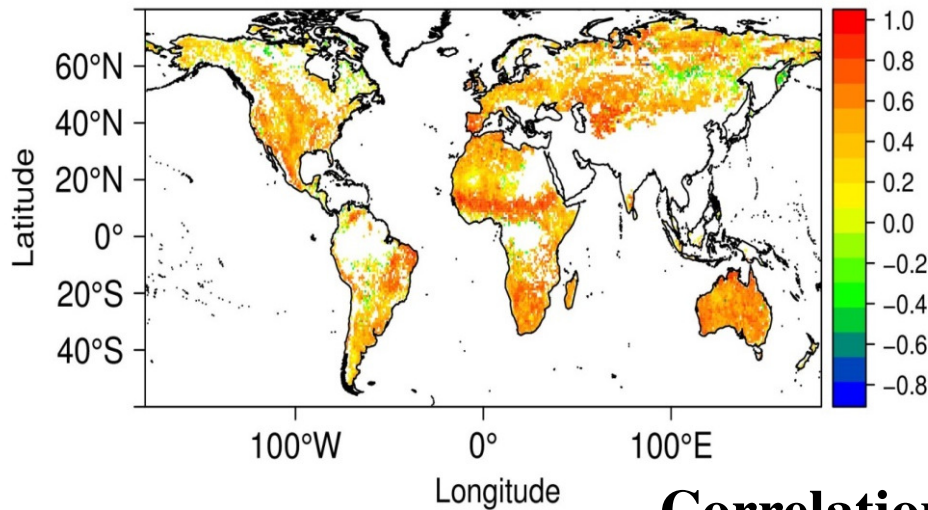
# Results

(AMSR-reg product evaluation against model 2003 - 2009)

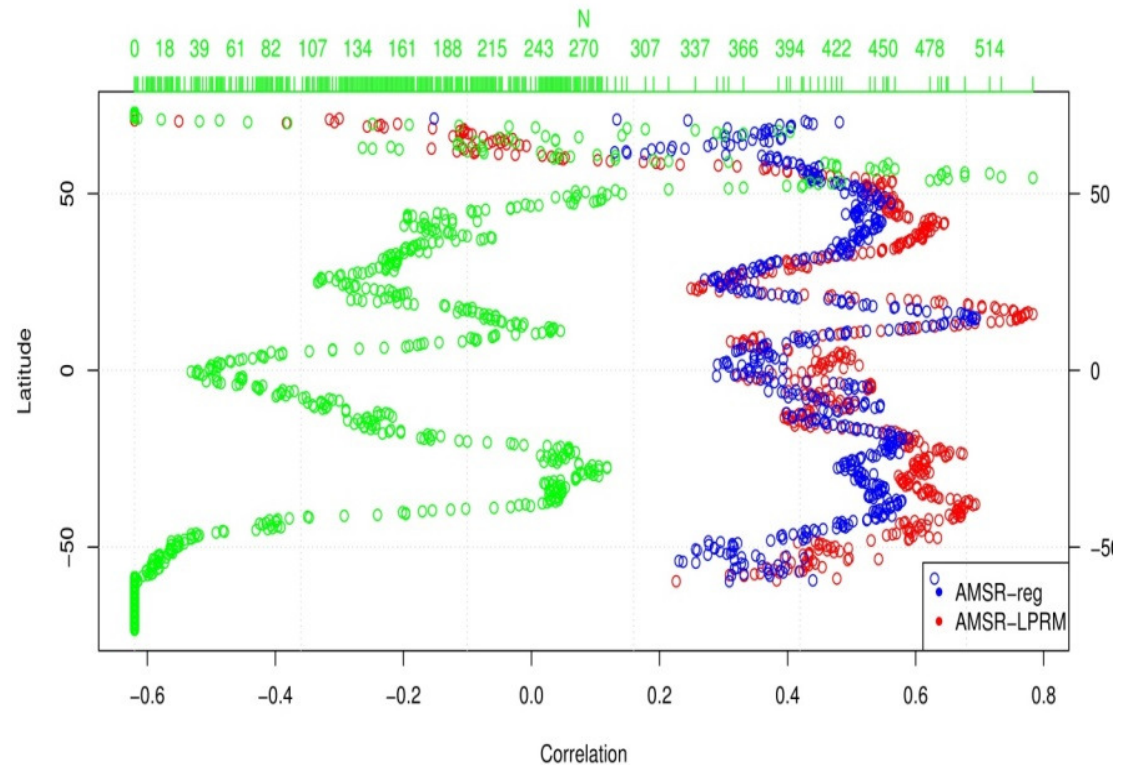
AMSR\_LPRM/MERRA-Land



AMSR\_reg /MERRA-Land



● AMSR-LPRM  
● AMSR-reg



Latitudinal plots

Correlation coefficient R (2003 - 2009)





# Non-linear global regression using neural networks



## ◉ Neural networks are powerful non-linear regression tools:

- Universal approximators (Cybenko 1989)
- Can correct the reference data (Jimenez et al. 2013)
- They use the synergy of multi-sensor data (Aires et al. 2006)

## ◉ NN tested to invert SM from radiometer observations at **small scale**

- Liou et al. 2001, Del Frate et al. 2003, Angiuli et al. 2008,
- AMSR-E : Inversion of SM in the North of Italy, Uses the polarization ratio as input. Santi et al. 2014

## ◉ NNs have shown good performances in previous **global studies**

- SSM/I, ERS, AVHRR : Aires et al. 2005, Kolassa et al., Jimenez et al. 2013
- SMOS (MODIS and ASCAT): Rodriguez-Fernandez et al. 2015



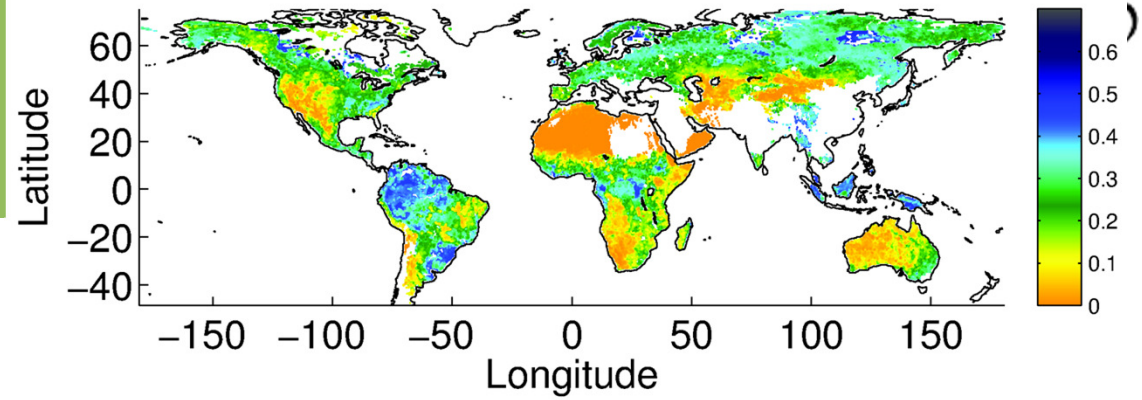
**smos+**  
**neural net**

support to science element

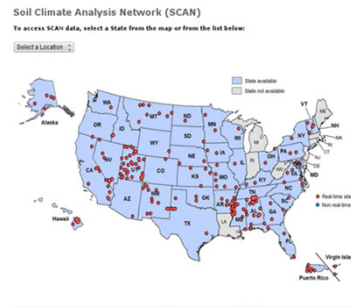
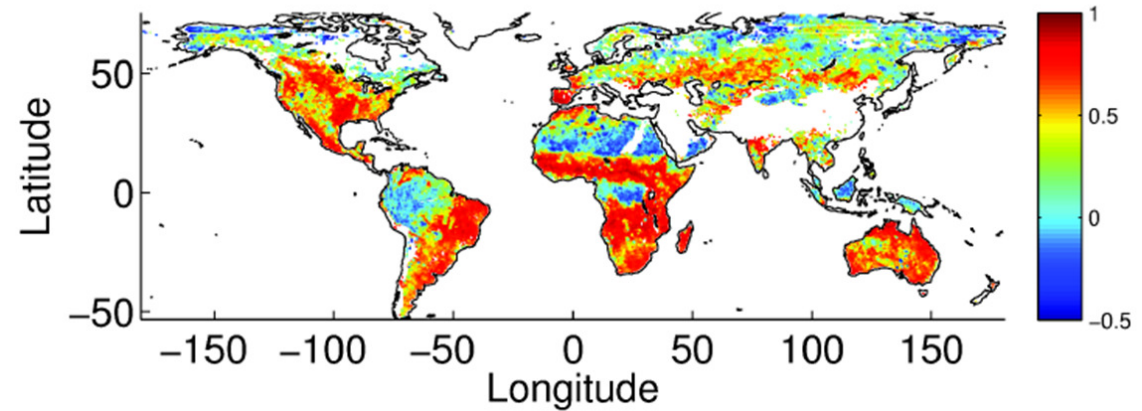
- The NN captures the temporal variability of SM in ECMWF models or SMOS L3 data
- A NN retrieval can be done in daily bases
- The temporal dynamics are best reproduced when adding passive (SMOS) and active data (ASCAT) or a local normalization of the TBs (in agreement with Kolassa et al. 2013)
- The NN SM exhibit good statistics when compared to in situ measurements

**Rodriguez-Fernandez et al. (2015, TGARS)**

SM NN July 2011



NN (SMOS,ASCAT,MODIS) versus ECMWF 0-7 cm Rtemp June 2010-Dec 2012



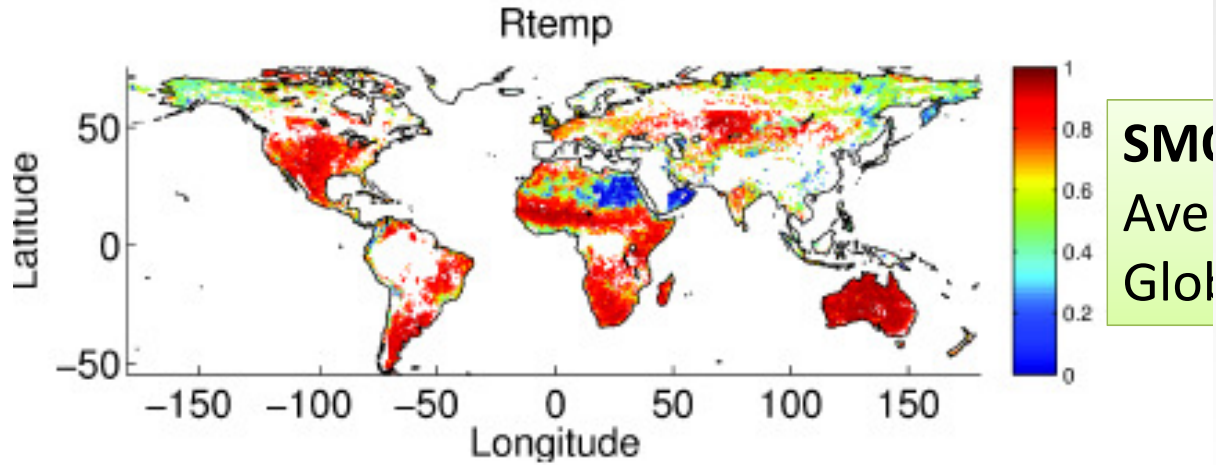
SM product	Asc. Orbits		
	STDD	R	Bias
14Tb+NDVI+tex+T	0.046	0.52	0.076
14Tb+14I <sub>1</sub> +NDVI+tex	0.049	0.60	0.075
14Tb+NDVI+tex+σ <sub>40</sub>	0.044	0.61	0.067
8I <sub>2</sub> +NDVI	0.029	0.61	0.054
14I <sub>2</sub> +I <sub>2</sub> σ <sub>40</sub>	0.027	0.60	0.052
14Tb+14I <sub>1</sub>	0.035	0.55	0.092
ECMWF SM <sub>1</sub>	0.049	0.59	0.050
SMOS L3	0.060	0.52	-0.021



# An official ESA Near-Real-Time product based on Neural Networks



Under development: collaboration ES



Input	STD	R	Bias
NN	<b>0.049</b>	<b>0.55</b>	-0.024
ECMWF	0.049	0.59	0.056
SMOS L3	0.064	0.50	-0.026

## New : near-real-time SMOS soil moisture product

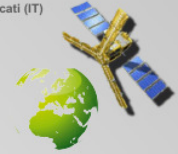
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- (2) European Centre for Medium-Range Weather Forecasts, Reading, UK
- (3) Estellus, Paris, France
- (4) European Space Agency, ESTEC, Noordwijk (NL) and ESRIN, Frascati (IT)

### Introduction

Numerical weather prediction and hydrological applications such as flood risk assessments need estimations of soil moisture (SM) as soon as possible after sensing. This poster presents a new SM dataset produced and disseminated in Near-Real-Time (NRT, ~ 3hours after sensing).

The NRT SM product is obtained from Soil Moisture and Ocean Salinity (SMOS) satellite observations and it is based on a neural network algorithm.

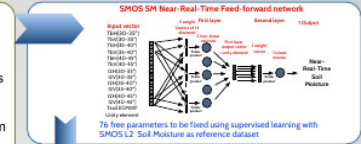


### Methods

The NRT retrieval algorithm is based in the approach discussed by Rodríguez-Fernández et al. (IEEE TGARS 2015). The neural network uses as input SMOS brightness temperatures (Tbs) for incidence angles from 30° to 45° and vertical and horizontal polarizations. In addition, for each latitude λ and longitude Φ, a local normalized index I/2, has been computed from the local maximum and minimum Tb and the associated soil moisture values as follows :

$$I_{max}(t) = \frac{SM_{max}^{L3} + [SM_{min}^{L3} - SM_{max}^{L3}]I_{22}(t)}{T_{max}(t) - T_{min}(t)} \quad I_{22}(t) = \frac{T_{bs}(t) - T_{min}}{T_{max} - T_{min}}$$

Finally, the soil temperature estimation in the 0-7 cm depth layer from ECMWF models is also used as input.

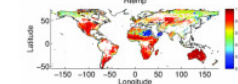


**Results**  
Using NRT Tb measurements at incidence angles from 30° to 45° the resulting swath width is 920 km (see Figure).

### Evaluation

#### Comparison to SMOS L3 SM

The map below shows the temporal correlation Rtemp of the NRT SM product (trained on SMOS L3 data) with respect to the SMOS L3 SM data obtained for time series for each grid node from June 2010 to December 2013. The average temporal Pearson correlation coefficient is 0.8, with significant differences found at high latitudes or regions with large RFI probability. The global Pearson correlation of the NRT and L3 SM is 0.92.



#### Evaluation with respect to *in situ* measurements

The table below gives the average statistics for the NRT SM product trained on SMOS L3 and the SMOS L3 SM data itself with respect to *in situ* measurements at 5cm depth from the USDA/SCAN network (shown in the map).

Input	STD (m3/m3)	R	Bias (m3/m3)
SMOS NRT	0.049	0.55	-0.024
SMOS L3	0.064	0.50	-0.026

### Summary

- The NRT SM product is very similar to the SMOS operational SM but available in less than 3hrs after sensing
- The results presented here have been obtained training the NRT neural network with SMOS L3 SM from CATDS. The neural network for the official ESA product is trained with the operational SMOS L2 SM
- The implementation is in progress at ECMWF in collaboration with CESBIO
- The SMOS NRT SM product will be available in 2015 in NetCDF format
- It will be distributed by GTS and EUMETCast

A SM product very similar to the current operational one but in near-real-time



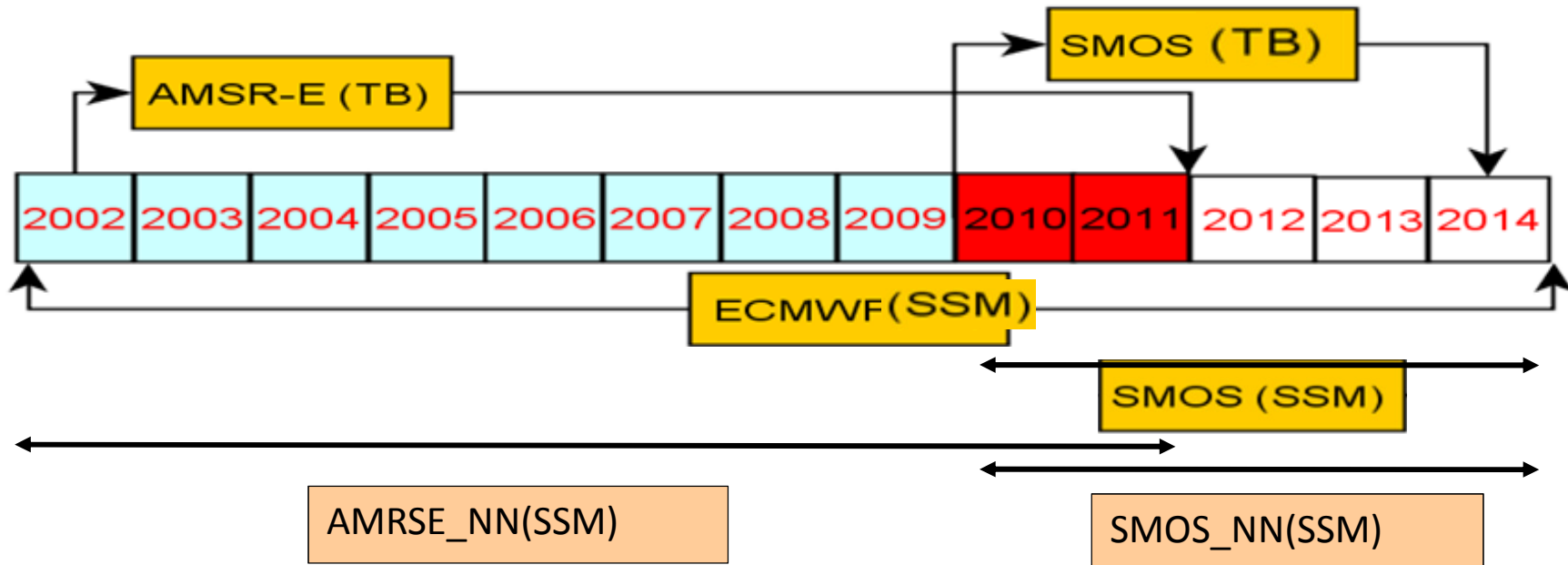
# Long time series: SMOS + AMSR-E



◉ Instead of merging a posteriori different SM datasets, one can create a new SM dataset using neural networks (NN)

◉ Two approaches

- Using a common soil moisture reference for both instruments
- Using SMOS L3 SM as reference to train the AMSR-E NN

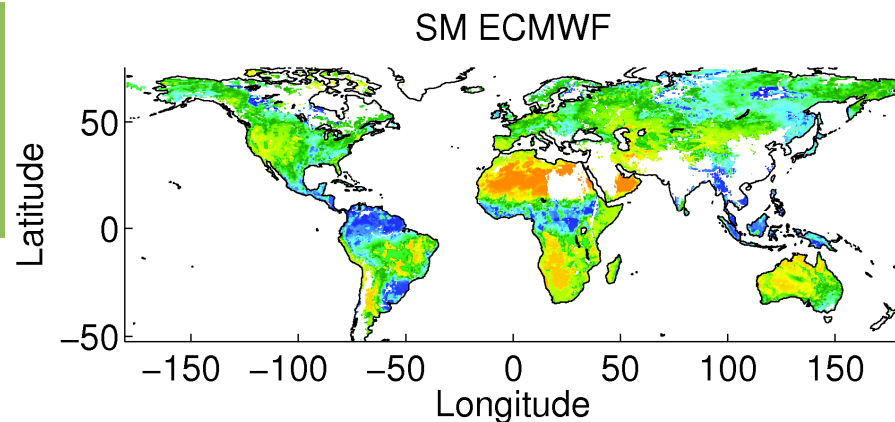




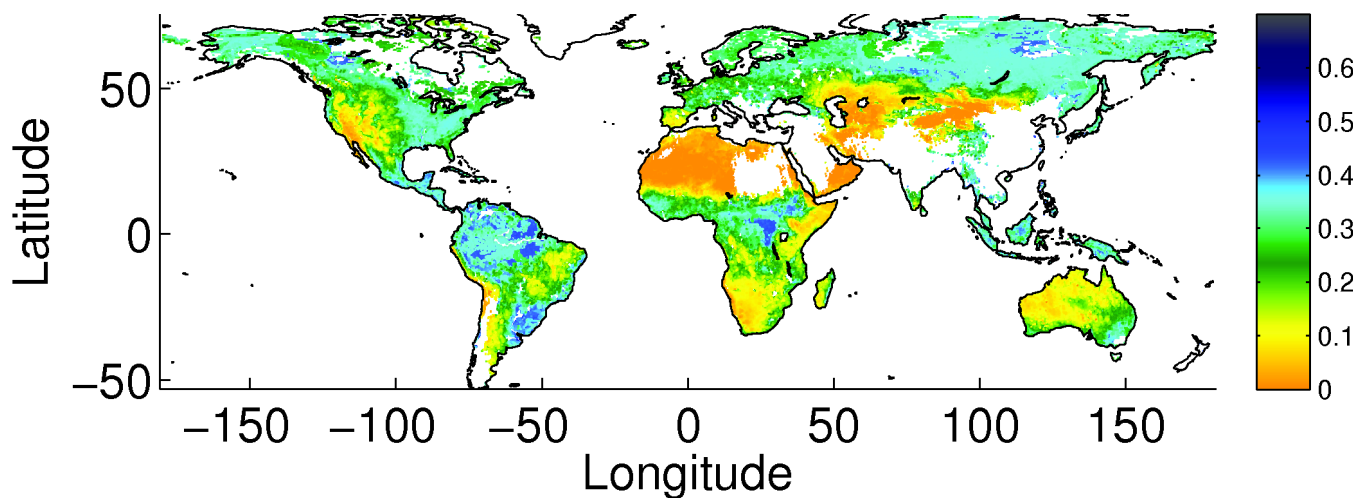


# SMOS and AMSR-E NN (reference ECMWF)

Monthly average  
July 2010



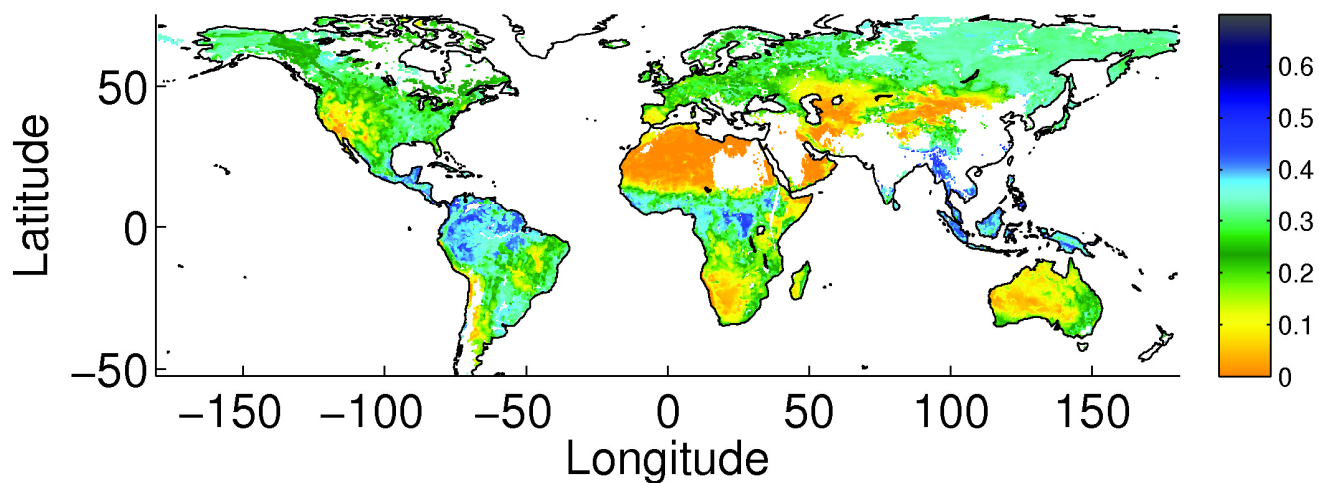
## SM NN **SMOS**



Input :

- H and V Tb's from 25° to 60°
- Soil texture
- NDVI
- R wrt ECMWF : 0.9

## SM NN **AMSR-E**



**AMSR-E**

Input :

- H and V Tb's at 6.9, 10.7, 18.7, 23.8, 36.5 GHz
- Soil texture
- R wrt ECMWF : 0.9



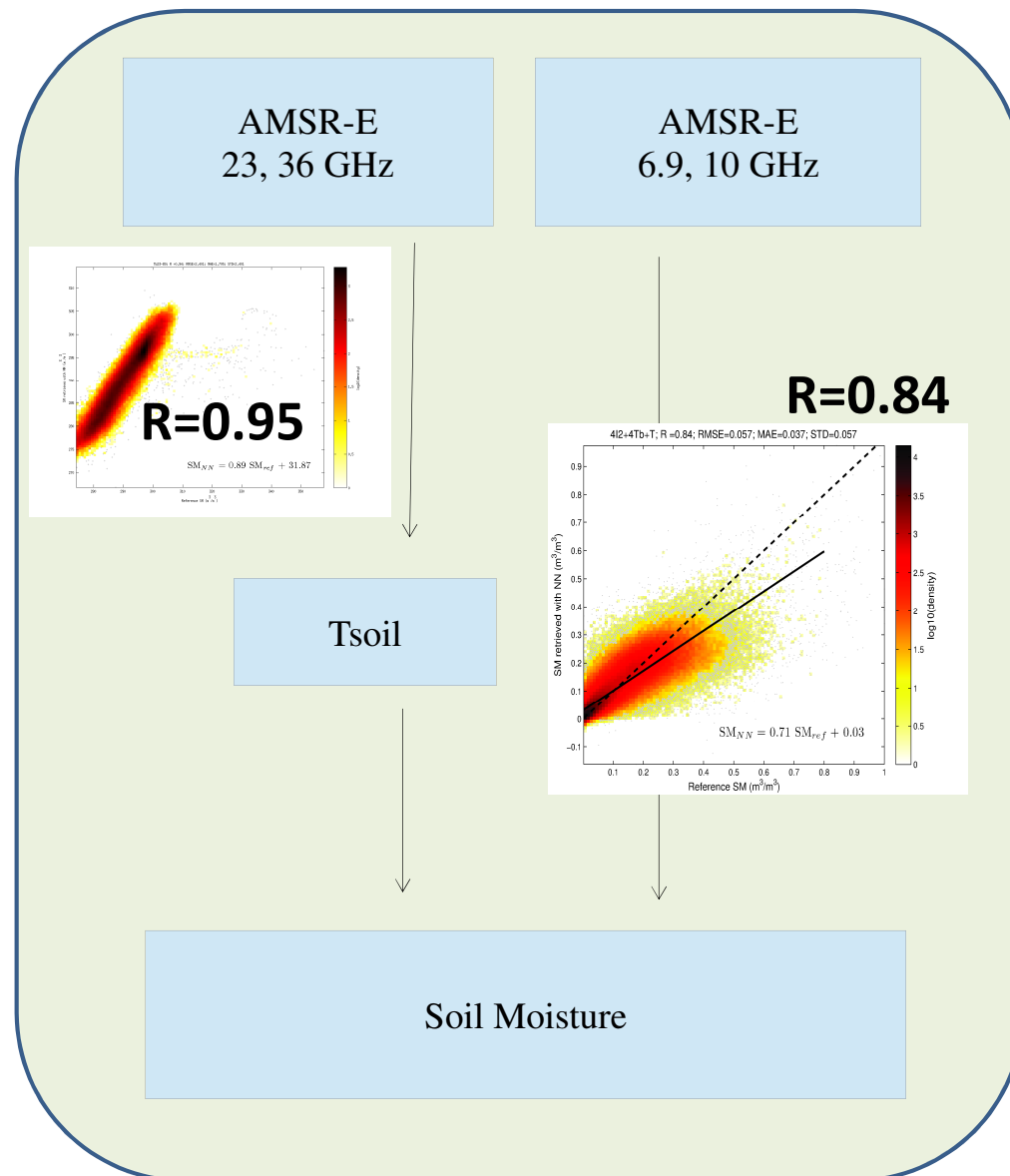
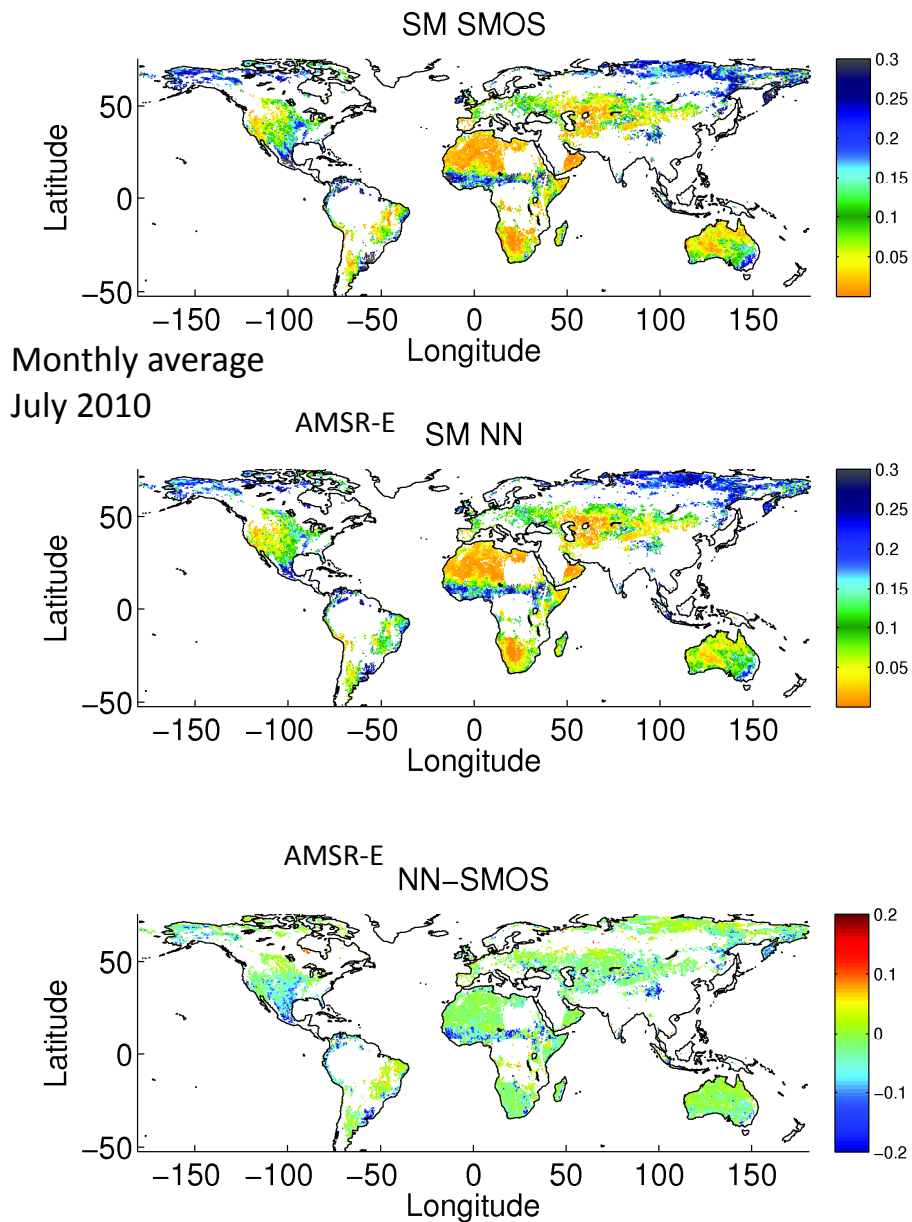
# Training the NN with SMOS L3 SM ?



- ◉ Training the NN on a model can be a problem for some applications
  - If using as reference the model from someone else is a problem for you, the same method can be used with your own model
- ◉ The SMOS operational algorithm :
  - has been developed specifically for the first satellite designed to measure soil moisture: SMOS
  - is independent of land surface models
  - has been extensively validated against other global datasets and in situ measurements (Albergel et al. 2012, Jackson et al. 2010, Albitar et al. 2012, Al Yaari et al. 2014, Leroux et al. 2012...)



# Training the ASMR-E NN on SMOS L3 SM

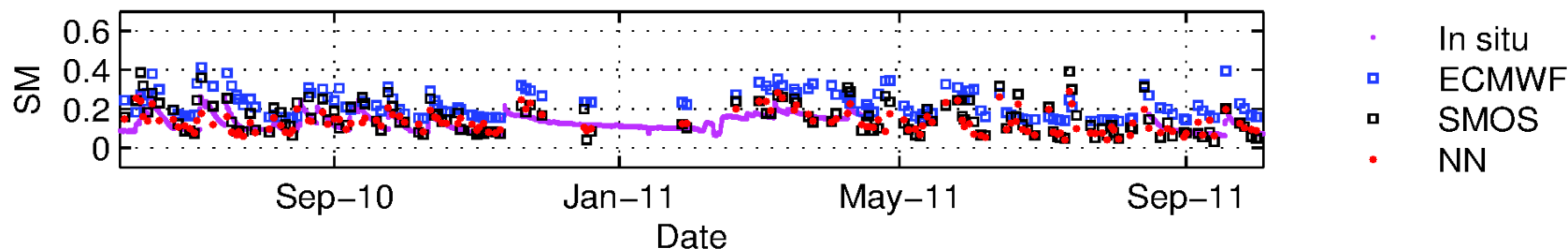




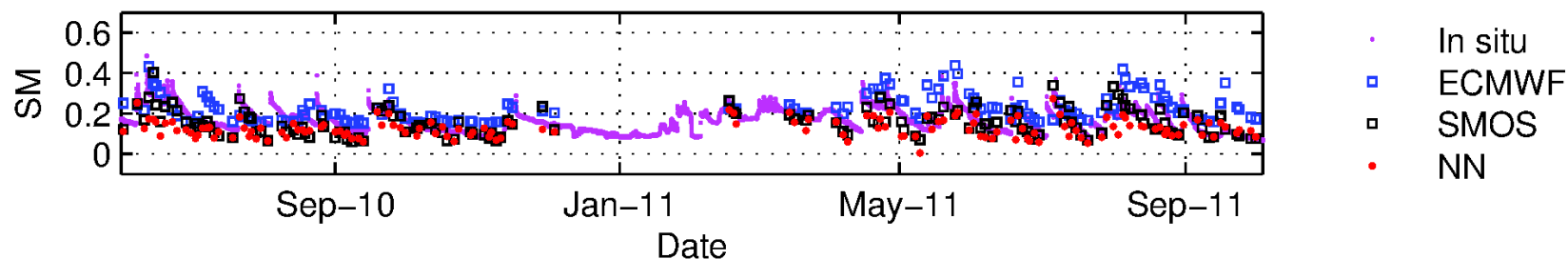
# AMSR-E NN SM vs SMOS L3 SM: consistent datasets !



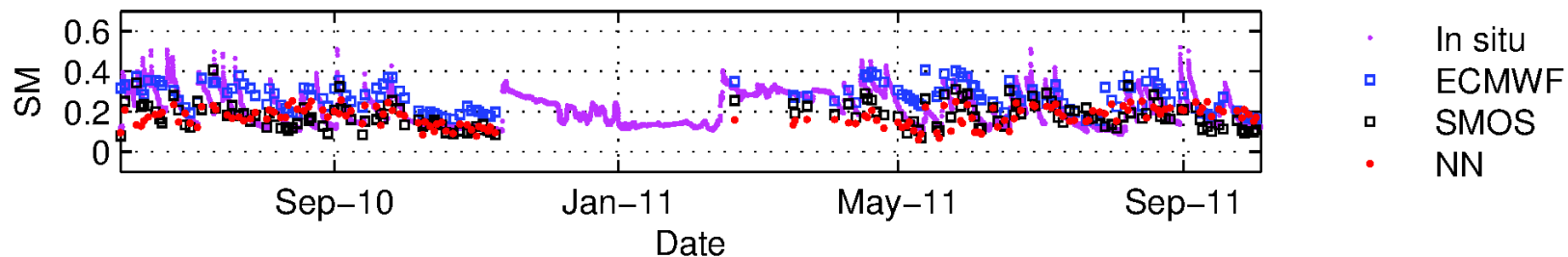
4I2+4Tb+T; TrainL3; Site: SCAN<sub>0.05\_0.05\_A</sub>brams<sub>H</sub>hydraprobe-Analog-(2.5-Volt); Pt:186819



4I2+4Tb+T; TrainL3; Site: SCAN<sub>0.05\_0.05\_P</sub>hillipsburg<sub>H</sub>hydraprobe-Analog-(2.5-Volt); Pt:181555



4I2+4Tb+T; TrainL3; Site: SCAN<sub>0.05\_0.05\_R</sub>ogersFarm#1<sub>H</sub>hydraprobe-Analog-(2.5-Volt); Pt:188005







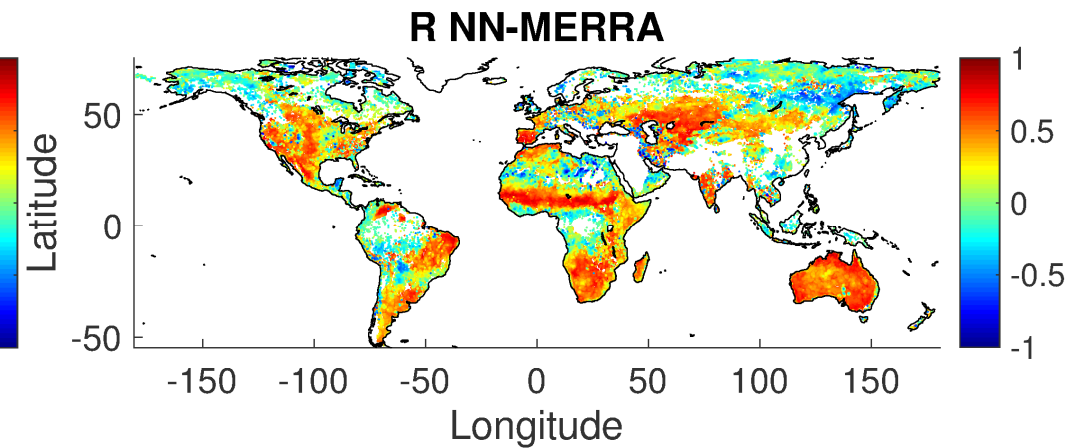
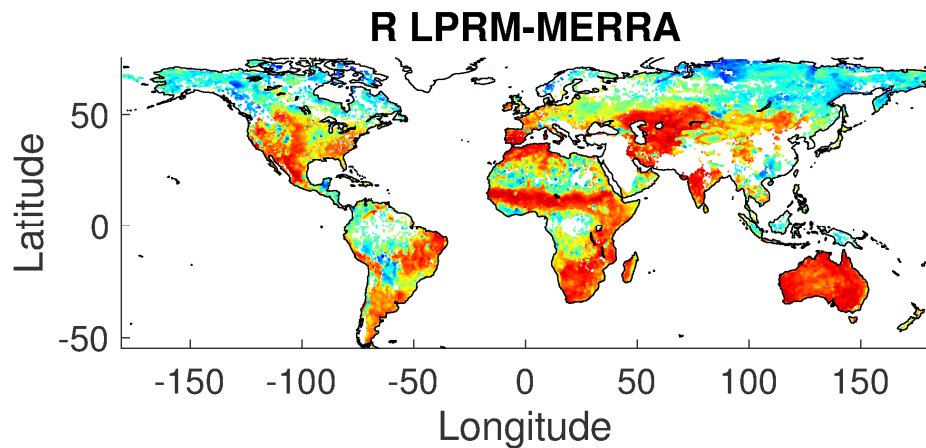
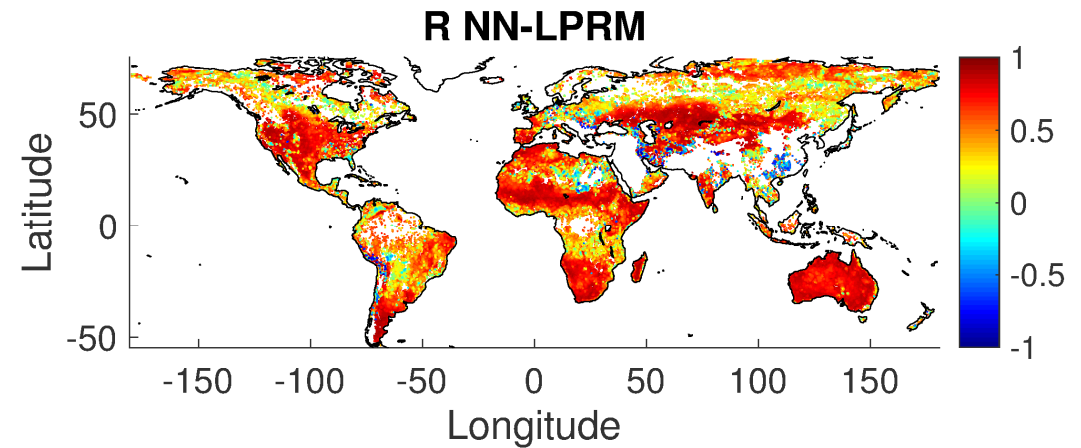
# **Inversion of the AMSR-E data in the 2003-2010 period**



# Maps of local temporal correlation



- ◉ The AMSR-E NN trained on SMOS shows high correlation with AMSR-E LPRM
- ◉ The correlation of NN and LPRM wrt MERRA show similar spatial patterns and values

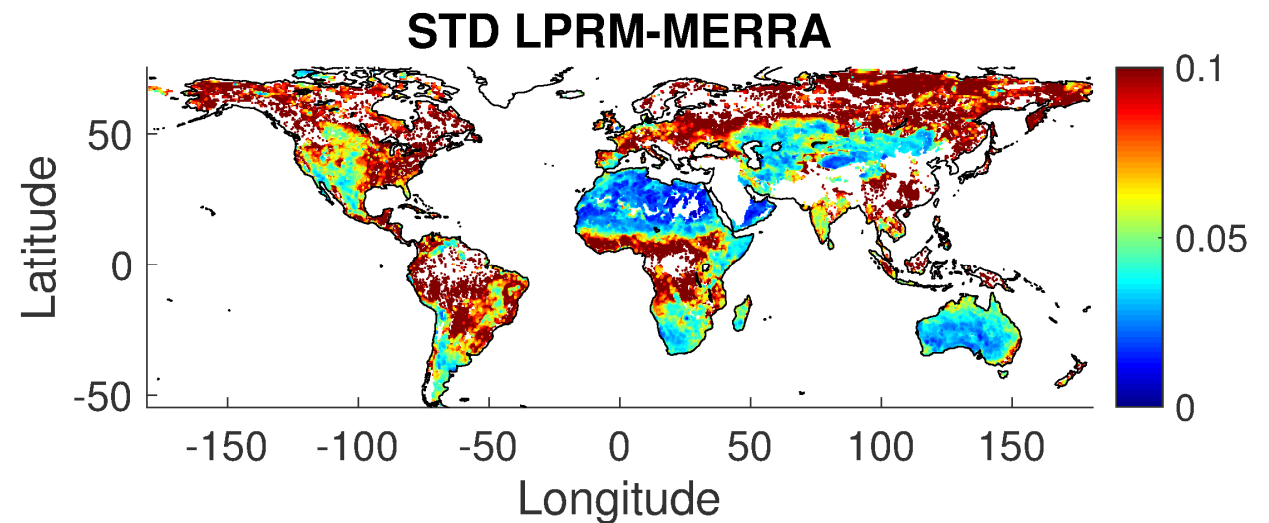
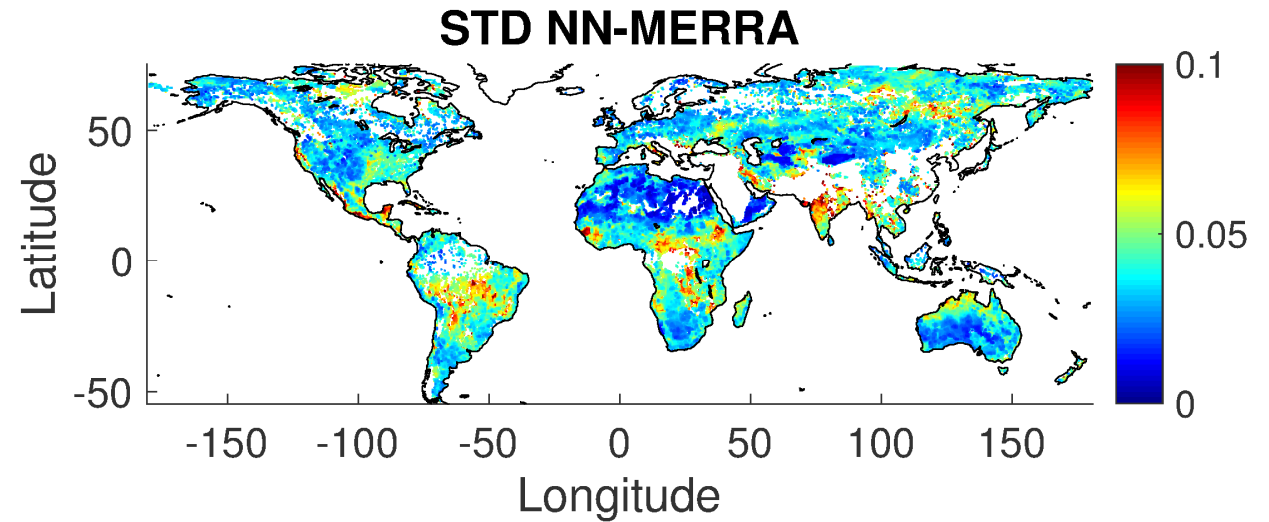




# Maps of local standard deviation

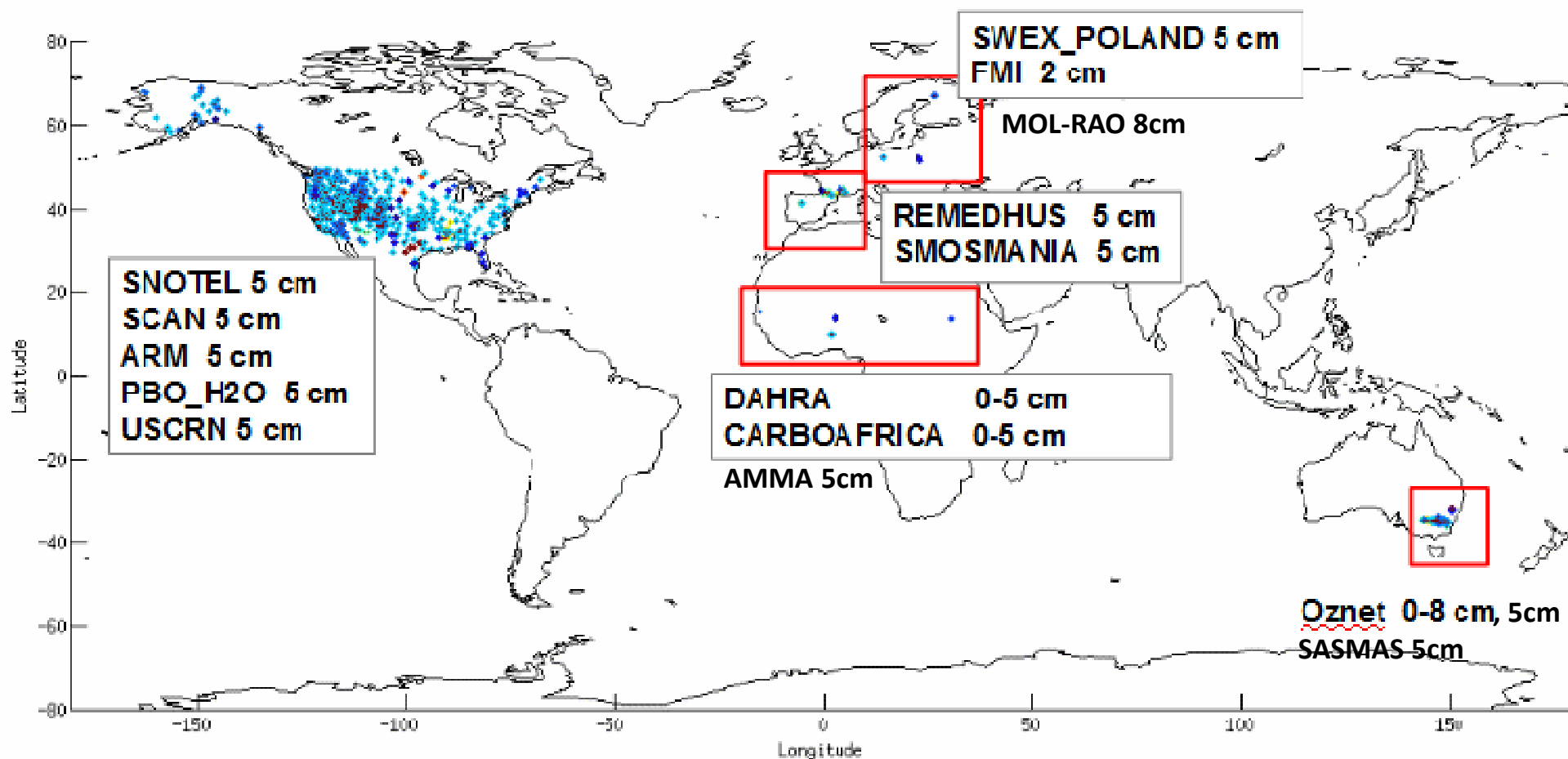


- ◉ The AMSR-E NN trained on SMOS SM shows a lower STD with respect to MERRA model simulations than AMSR-E LPRM





# Evaluation with respect to in situ measurements



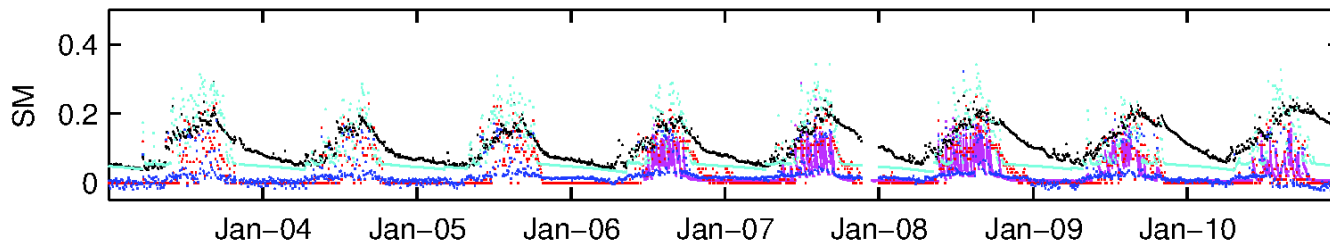




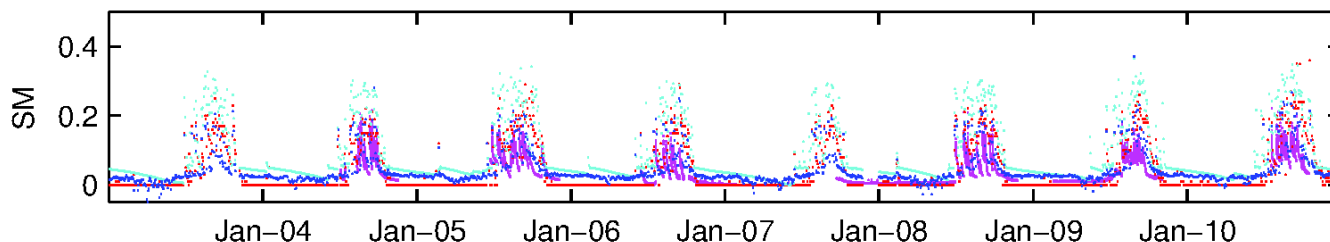
# Some examples: Africa and Australia



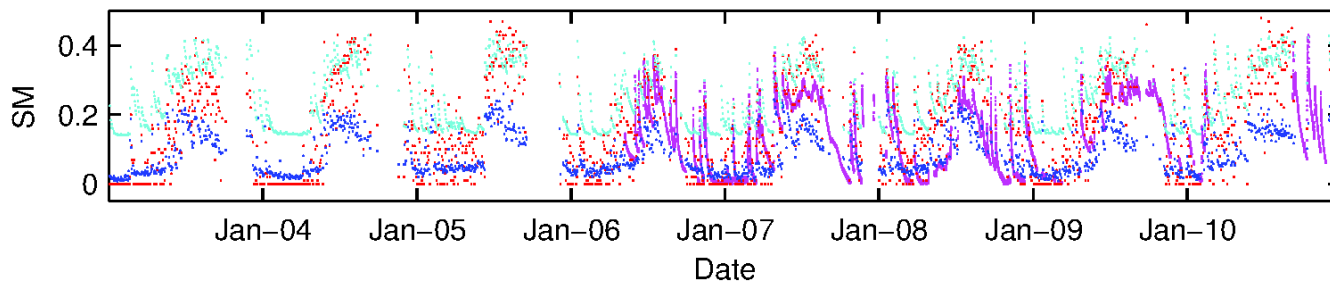
AMMA 0.05 0.05 Banizoumbou



DAHRA 0.05 0.05 DAHRA



OZNET 0.00 0.05 Alabama



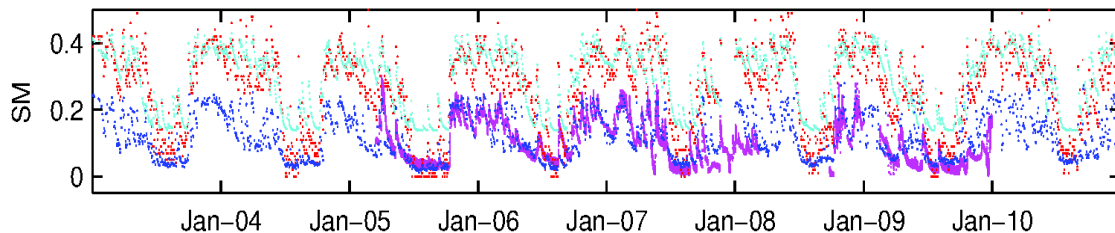
	SM	STD m <sup>3</sup> /m <sup>3</sup>	R	Bias m <sup>3</sup> /m <sup>3</sup>
AMMA-0.05-0.05 N <sub>pt</sub> = 672				
In situ	NN	0.028	0.760	0.011
LPRM	ERA	0.053	0.765	0.134
MERR	LPRM	0.049	0.804	0.031
ERA	MERRA	0.049	0.556	0.125
CARBOAFRICA-0.05-0.05; N <sub>pt</sub> =				
NN	NN	0.019	0.652	-0.016
ERA	ERA	0.059	0.787	0.104
LPRM	LPRM	0.027	0.786	0.001
MERRA	MERRA	0.033	0.670	0.049
DAHRA-0.05-0.05; N <sub>pt</sub> = 706				
In situ	NN	0.032	0.793	0.022
LPRM	ERA	0.070	0.801	0.083
MERR	LPRM	0.057	0.796	0.033
ERA	MERRA	0.051	0.681	0.082
NN	MERRA	0.051	0.681	0.082
OZNET-0.00-0.05; N <sub>pt</sub> = 747				
	SM	STD m <sup>3</sup> /m <sup>3</sup>	R	Bias m <sup>3</sup> /m <sup>3</sup>
In situ	NN	0.058	0.755	-0.035
LPRM	ERA	0.055	0.785	0.107
MERR	LPRM	0.069	0.756	0.046
ERA	MERRA	0.060	0.743	0.069
NN	MERRA	0.060	0.743	0.069



# Some examples: Europe

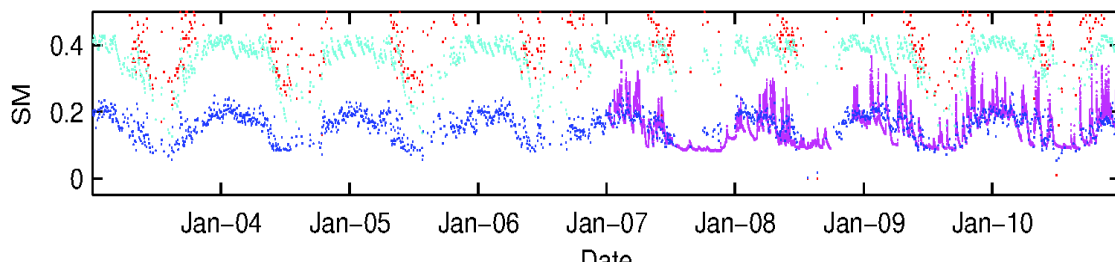


REMEDHUS 0.00 0.05 LaAtalaya



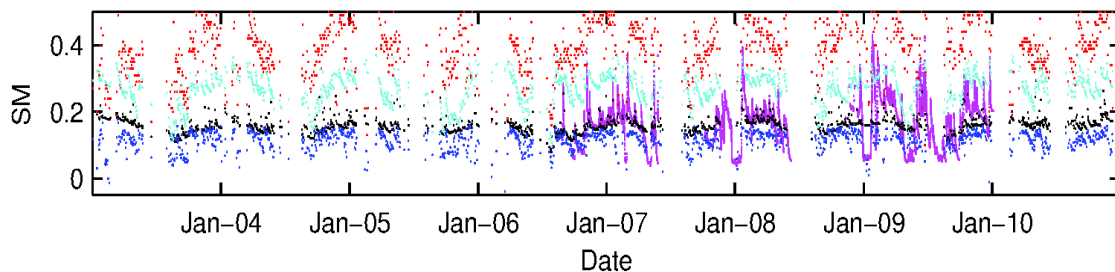
- In situ
- LPRM
- MERRA
- ERA
- NN

SMOSMANIA 0.05 0.05 CreondArmagnac



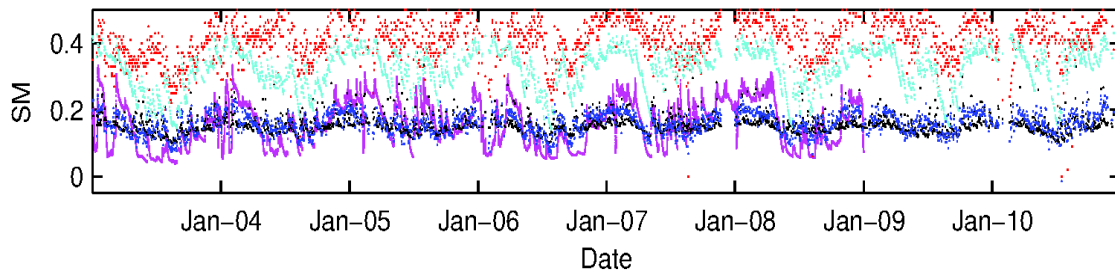
- In situ
- LPRM
- MERRA
- ERA
- NN

SWEX-POLAND 0.00 0.02 Trzebieszow,Podlasie



- In situ
- LPRM
- MERRA
- ERA
- NN

MOL-RAO 0.08 0.08 Falkenberg



- In situ
- LPRM
- MERRA
- ERA
- NN

In Europe models perform better than remote sensing retrievals

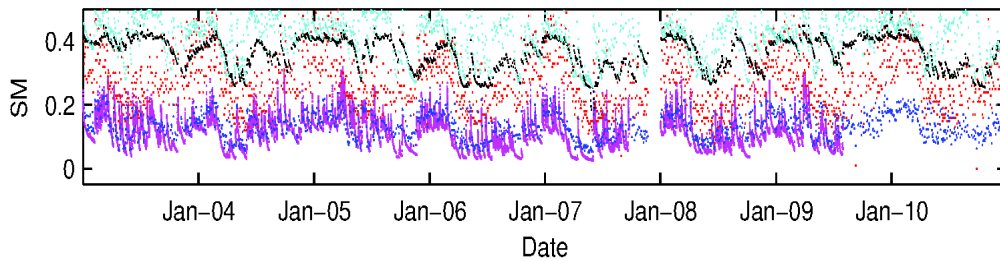
SM	STD	R	bias
MOL-RAO-0.08-0.08; N <sub>pt</sub> = 1885			
NN	0.051	0.648	0.002
ERA	0.043	0.776	0.165
LPRM	0.069	0.498	0.261
MERRA	0.048	0.693	0.086
REMEDHUS-0.00-0.05; N <sub>pt</sub> = 111			
NN	0.066	0.622	-0.003
ERA	0.079	0.674	0.158
LPRM	0.098	0.627	0.133
MERRA	0.057	0.633	0.107
SMOSMANIA-0.05-0.05; N <sub>pt</sub> = 60			
NN	0.073	0.550	-0.096
ERA	0.061	0.681	0.081
LPRM	0.108	0.566	0.223
MERRA	0.061	0.689	0.036



# Some examples: USDA-ARS watersheds

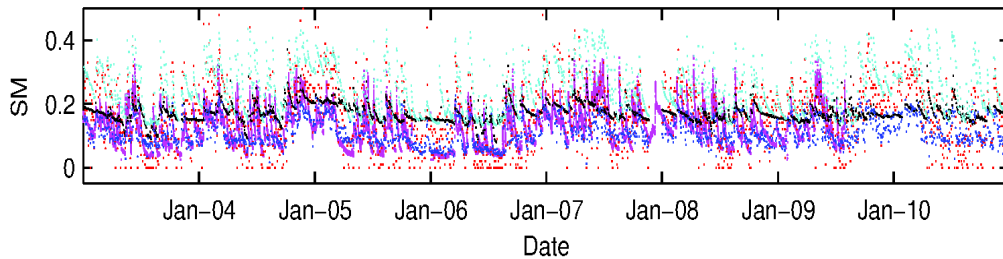


USDA-ARSare 0.00 0.05 LittleRiver



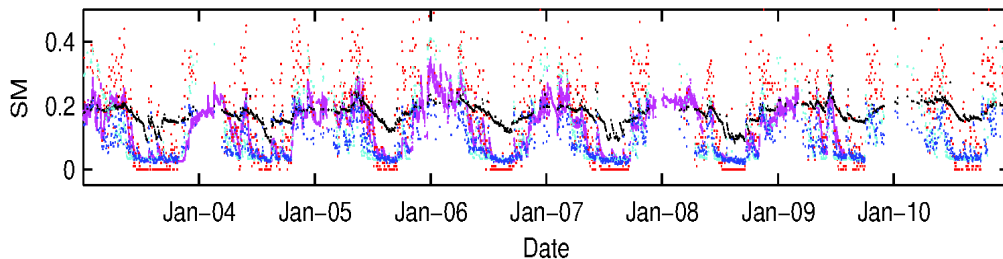
- In situ
- LPRM
- MERRA
- ERA
- NN

USDA-ARSare 0.00 0.05 LittleWashita



- In situ
- LPRM
- MERRA
- ERA
- NN

USDA-ARSare 0.00 0.05 ReynoldsCreek



- In situ
- LPRM
- MERRA
- ERA
- NN

SM	STD $m^3/m^3$	R	Bias $m^3/m^3$
LittleRiver-0.00-0.05; Npt= 1398			
NN	0.031	0.74	0.028
ERA	0.040	0.73	0.30
LPRM	0.078	0.59	0.17
MERRA	0.048	0.64	0.20
LittleWashita-0.00-0.05; Npt= 113			
NN	0.040	0.69	-0.01
ERA	0.048	0.77	0.13
LPRM	0.076	0.57	0.05
MERRA	0.040	0.69	0.08
ReynoldsCreek-0.00-0.05; Npt = 13			
NN	0.047	0.75	-0.02
ERA	0.056	0.80	-0.005
LPRM	0.090	0.77	0.06
MERRA	0.046	0.81	0.07



# Summary



- Two methods:

- Training on ECMWF a NN for SMOS and another for AMSR-E
  - If a SM dataset trained with a land surface model from someone else is a problem for you, it is possible to use this method training the NNs with your own model !
- Training a NN with AMSR-E Tb's as input and SMOS L3 SM as reference

- Coherent results in the SMOS / AMSR-E common period (2010-2011)

- Good results in the AMSR-E period (2003-2010) with respect to in situ measurements





# Thank you for your attention !



## Acknowledgements

### Funding



### Data



## More information



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# North America



SM	STD $\text{m}^3/\text{m}^3$	R	Bias $\text{m}^3/\text{m}^3$
ARM-0.05-0.05; N <sub>pt</sub> = 1308			
NN	0.054	0.459	-0.182
ERA	0.071	0.493	-0.039
LPRM	0.097	0.429	-0.086
MERRA	0.049	0.447	-0.074
SCAN-0.05-0.05; N <sub>pt</sub> = 573			
NN	0.060	0.506	-0.067
ERA	0.063	0.585	0.071
LPRM	0.103	0.471	0.086
MERRA	0.055	0.575	0.057
SNOTEL-0.05-0.05; N <sub>pt</sub> = 524			
NN	0.085	0.298	-0.082
ERA	0.087	0.428	-0.009
LPRM	0.120	0.255	0.031
MERRA	0.073	0.618	0.022
USCRN-0.05-0.05; N <sub>pt</sub> = 144			
NN	0.070	0.577	-0.092
ERA	0.070	0.615	0.063
LPRM	0.103	0.493	0.070
MERRA	0.065	0.702	0.042