A Near-Real-Time soil moisture product from SMOS observations

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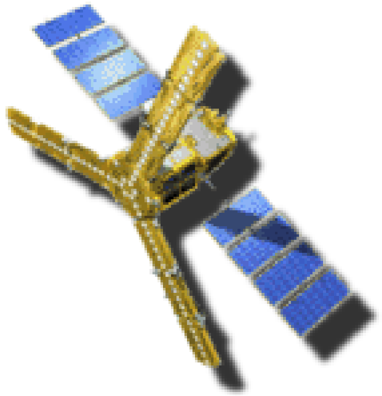
Outline

- SMOS: more than five years of observations to test data-driven statistical inversion methods: **Neural Networks**

- Direct and inverse models
- Retrieving SM from SMOS using Neural Networks
- A Near-Real-Time Soil Moisture
- Summary

Direct models

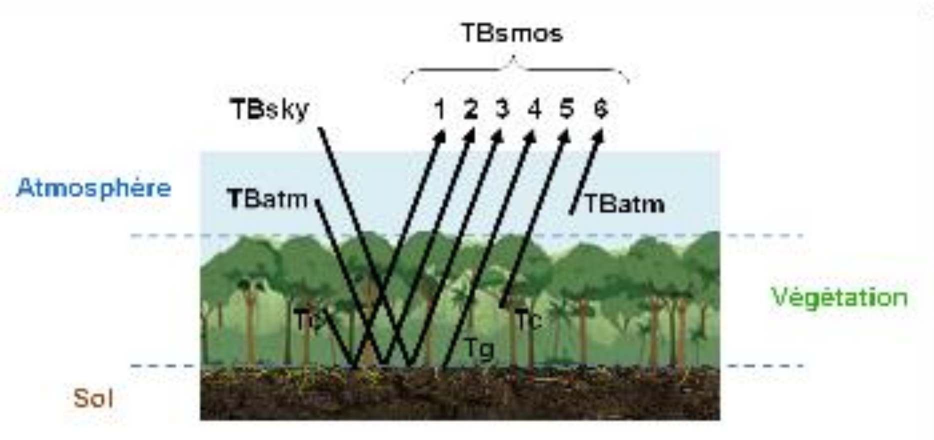


Observation

$\text{Tb} = \boldsymbol{F}(\text{SM}, \tau, \text{T}, \ldots)$

Geo-physical variables

F is given by a physical model, for instance the tau-omega model

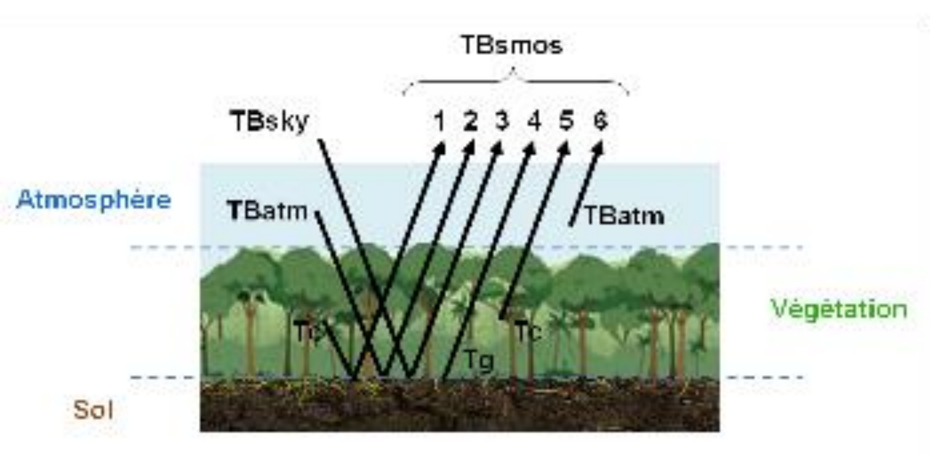


$$r_V = \frac{\epsilon \cos\theta - \sqrt{\epsilon - \sin^2\theta}}{(\epsilon \cos\theta + \sqrt{\epsilon - \sin^2\theta})}$$

$$\gamma_{\mathrm{p}} = \exp(-\tau_{\mathrm{p}} / \cos\theta)$$

$$\mathrm{TB}_{\mathrm{P}} = (1-\omega_{\mathrm{p}})(1-\gamma_{\mathrm{p}})(1+\gamma_{\mathrm{p}} r_{\mathrm{gp}})T_{\mathrm{c}} + (1-r_{\mathrm{gp}})\gamma_{\mathrm{p}} T_{\mathrm{g}}$$

Solving the inverse problem (I)



Observation

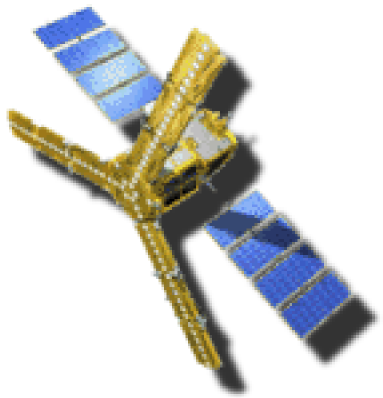
$Tb = \boldsymbol{F}(SM, \tau, T, \ldots)$

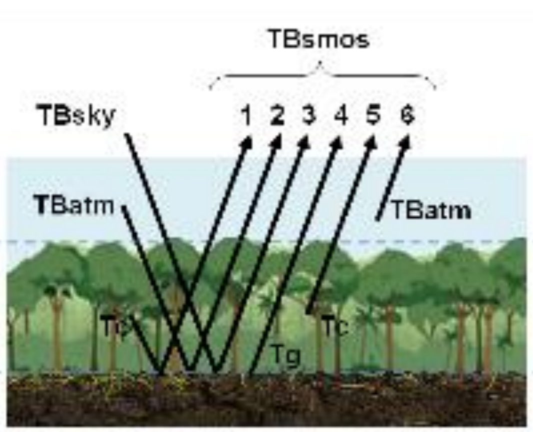
Geo-physical variables

Local method

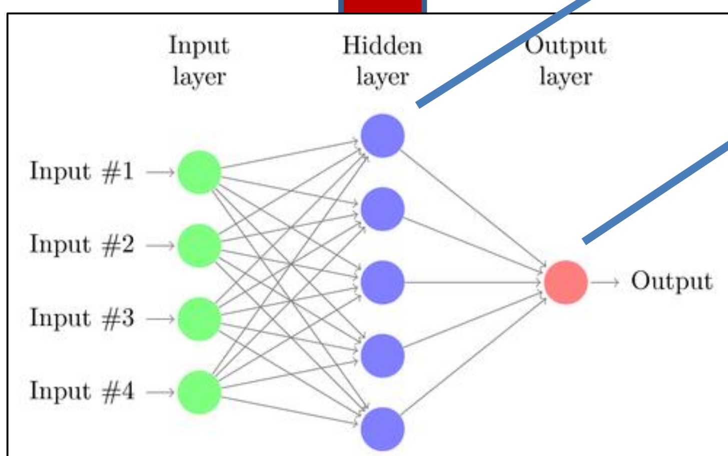
- Using the direct model "many times" for different input variables values and compare with the observations
- Iteratively get the *optimal estimation* of the variables values
- Approach of the SMOS operational algorithm
  - Kerr et al. 2012, TGRS

Solving the inverse problem with neural networks





Observation



Geo-physical variables

Global method

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

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

- The optimal weights W_{L1} and W_{L2} are obtained by minimizing the difference of the NN output and a reference SM dataset used for the training

- NNs are universal approximators, parsimonious, and fast to apply

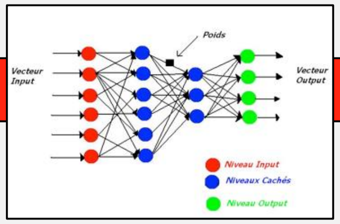
- NNs use the synergy of multi-sensor data : multivariate and non-linear nature (Aires et al. 2012)

Training the neural network

- Training data base containing typically 100 days of global data
- Avoiding over-learning : evaluating performances during training on a validation data subset and stopping training if needed
- Evaluate performances on test data subset not used for the training: different period, in situ measurements grid points removed from the training dataset

New algorithm using SMOS-independent SM data as training dataset

SMOS Tbs
NDVI …

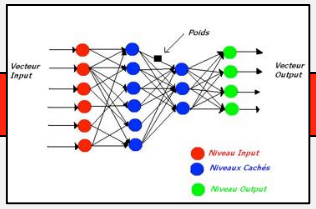


SM from global simulations (ECMWF IFS)

NN SM can be the base of and efficient *data assimilation* strategy (Aires et al. 2005)

Inversion of the SMOS operational algorithm

SMOS Tbs
NDVI …



SMOS L2/L3 SM

NN algorithm is global and faster ! → *Near Real-Time SM product*

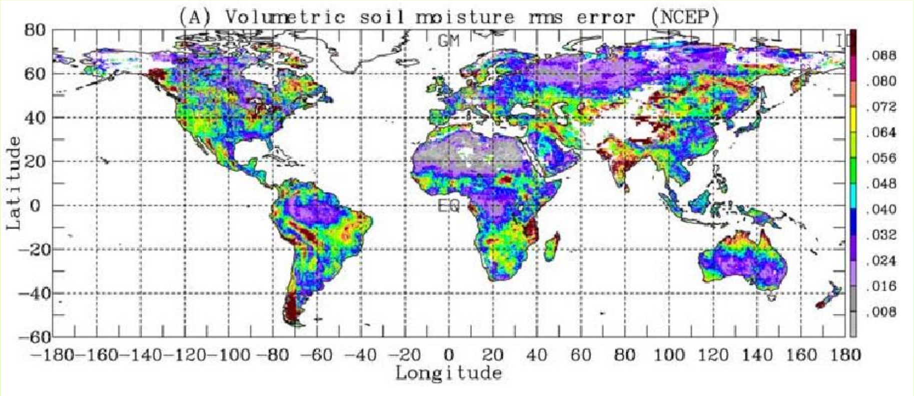
Previous works

Local applications of NNs to retrieve SM in agricultural fields:

• **SAR**: used to invert backscatterring models (IEM, Oh,…): Notarnicola et al., Paloscia et al. **Radiometers**: using an electromagnetic emission model and simple radiative transfer: Liu et al. 2001 , Liou et al. 2002, Chai et al. 2010, Angiuli et al. 2008

Global applications of NNs to retrieve SM

- Multisensor data (active and passive microwaves, visible, IR) and NNs trained with numerical weather prediction models: Aires et al. 2005, Kolassa et al 2013, Jimenez et al. 2013
  - Tested with monthly averages
  - Input: SSM/I, ERS, AVHRR



- The NN can be used to check the consistency of the weather models and as the base for assimilation (Aires et al. 2005)
- The NN can correct the reference model data (Jimenez et al. 2013)

The SMOS + Neural Network project

smos+ neural net

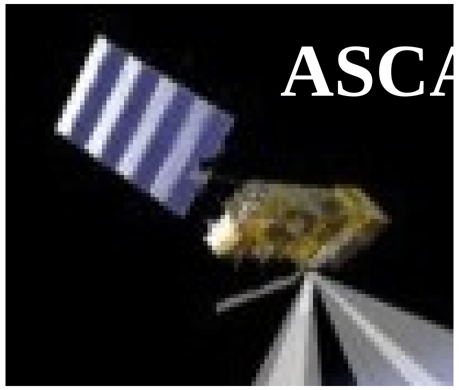
support to science element

N. Rodriguez-Fernandez[1], P. Richaume[1], F. Aires[2], C. Prigent[2], Y. Kerr[1], J. Kolassa[2], C. Jimenez[2], F. Cabot[1], A. Mahmoodi[3]

1 CESBIO 2 Estellus 3 ARRAY

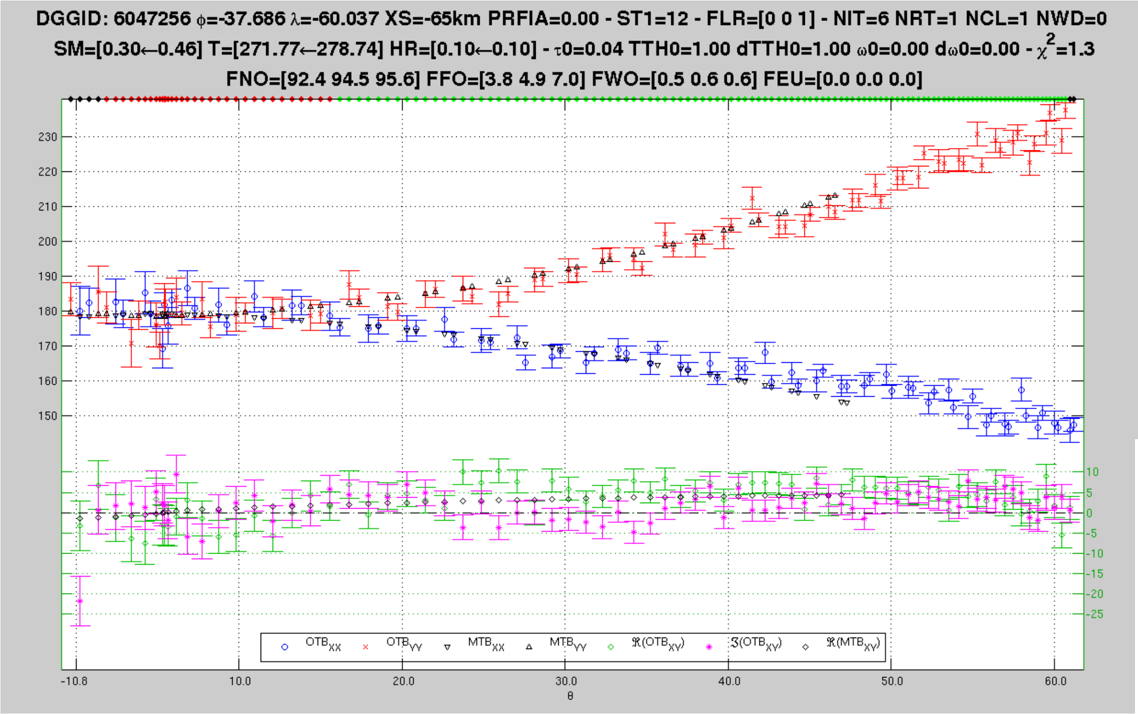
Also supported by : cnes CATDS

The synergy of SMOS with other sensors has also been studied

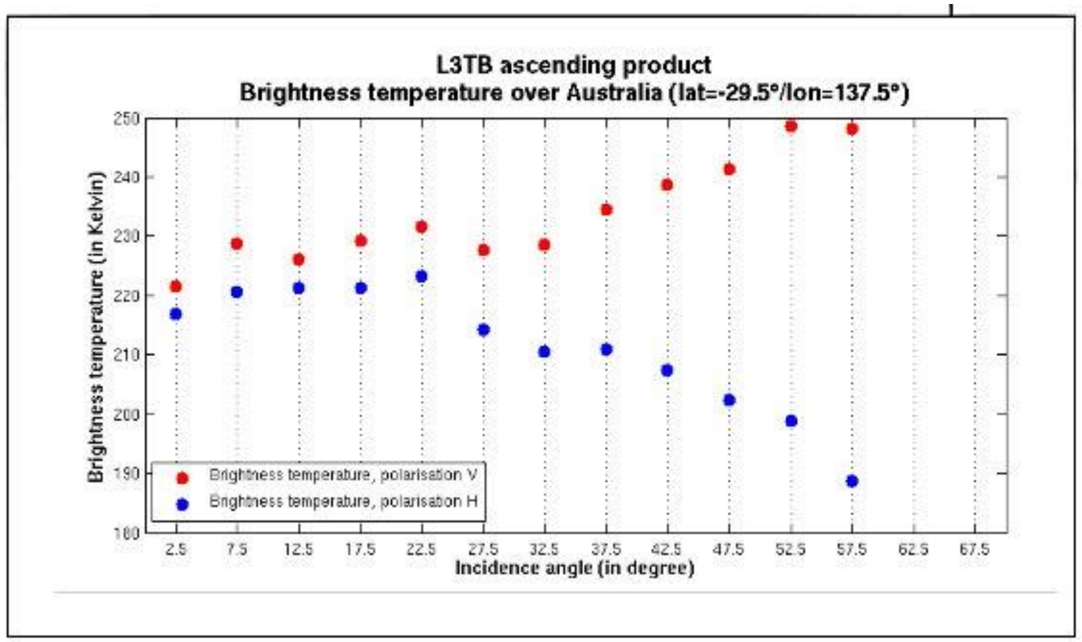


SMOS brightness temperatures

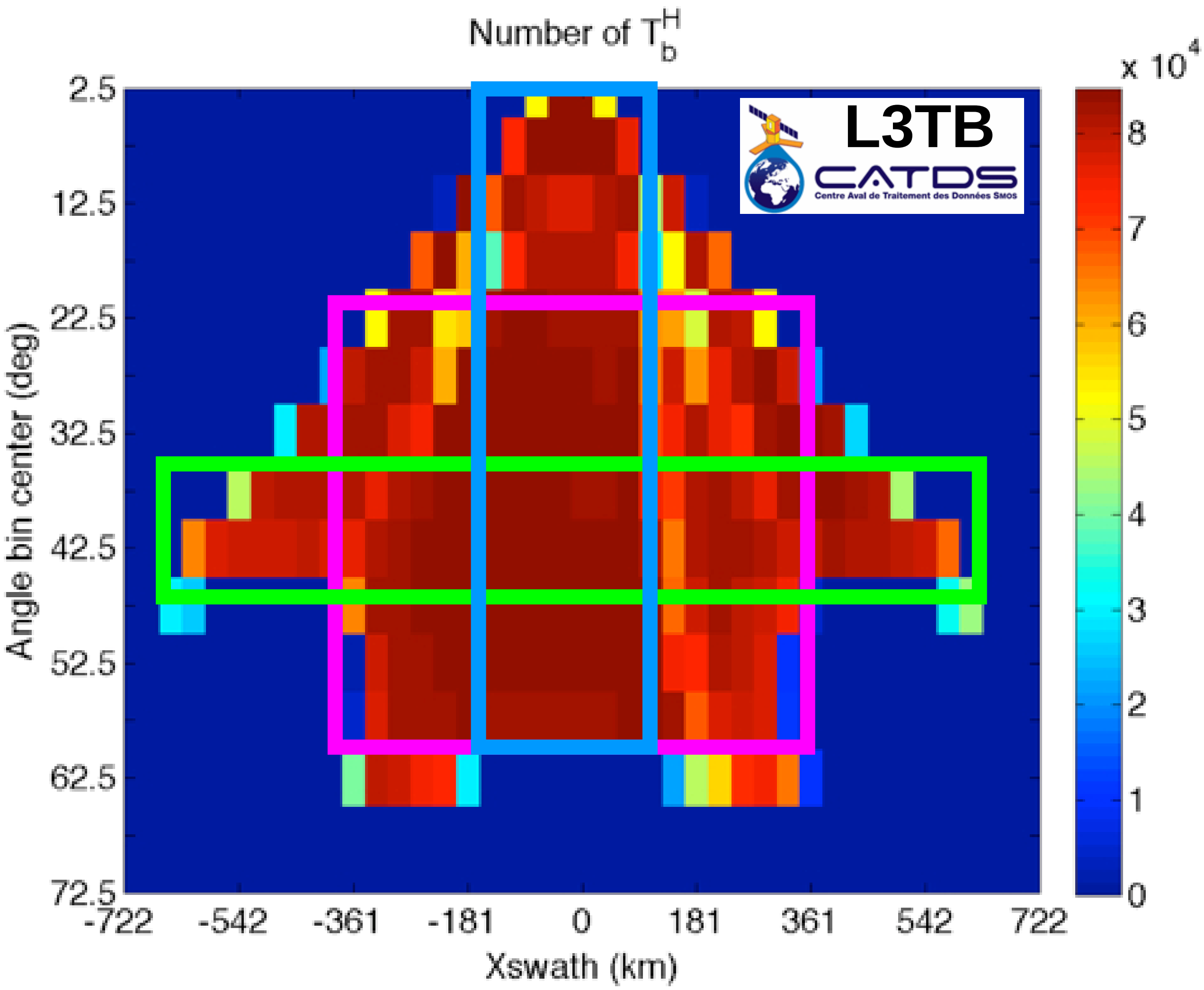
- L1C
  - No angle binning
  - XY polarization reference frame
  - ISEA grid

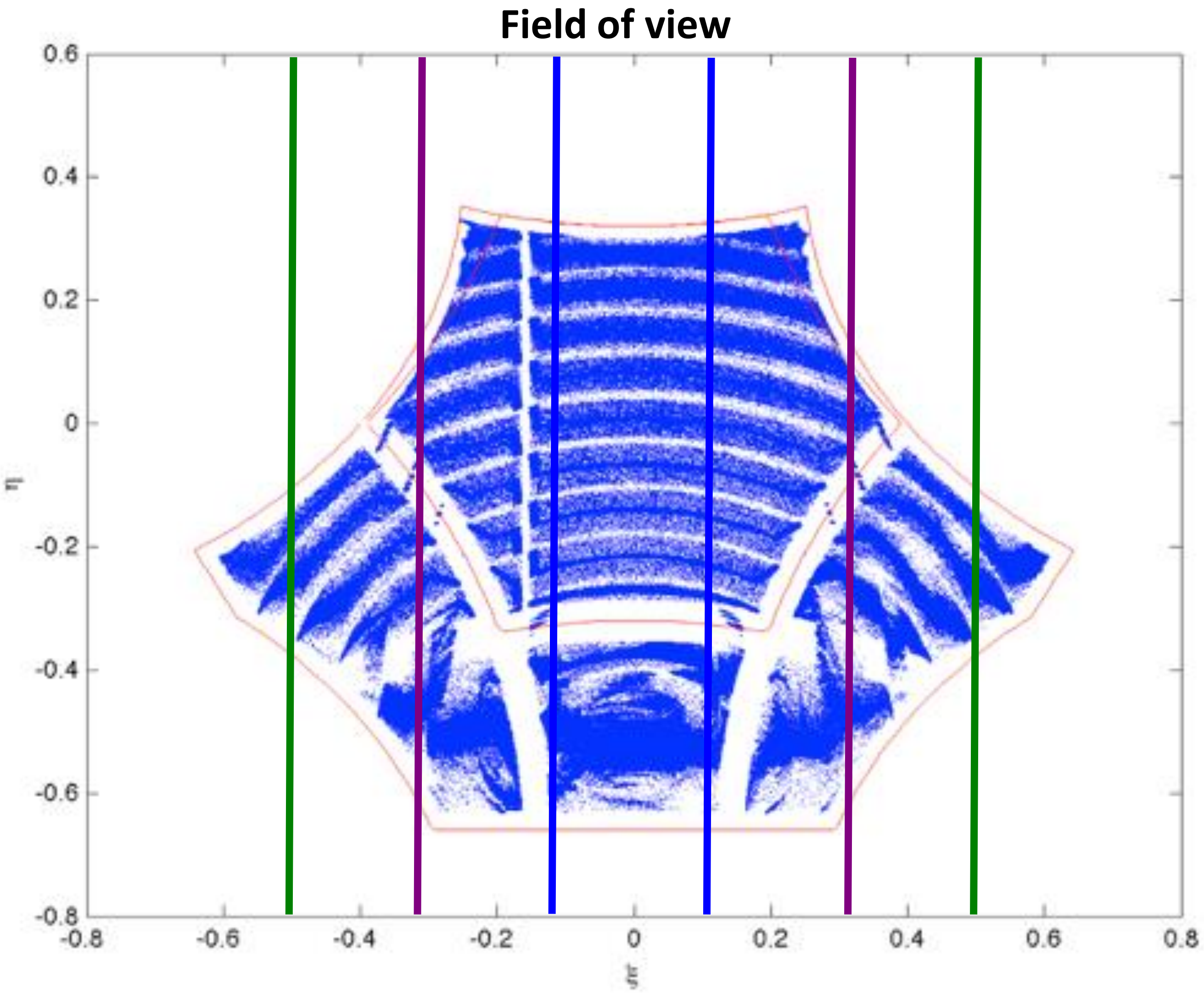


- L3TB
  - angle bins of 5º
  - HV polarization
  - EASE grid



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

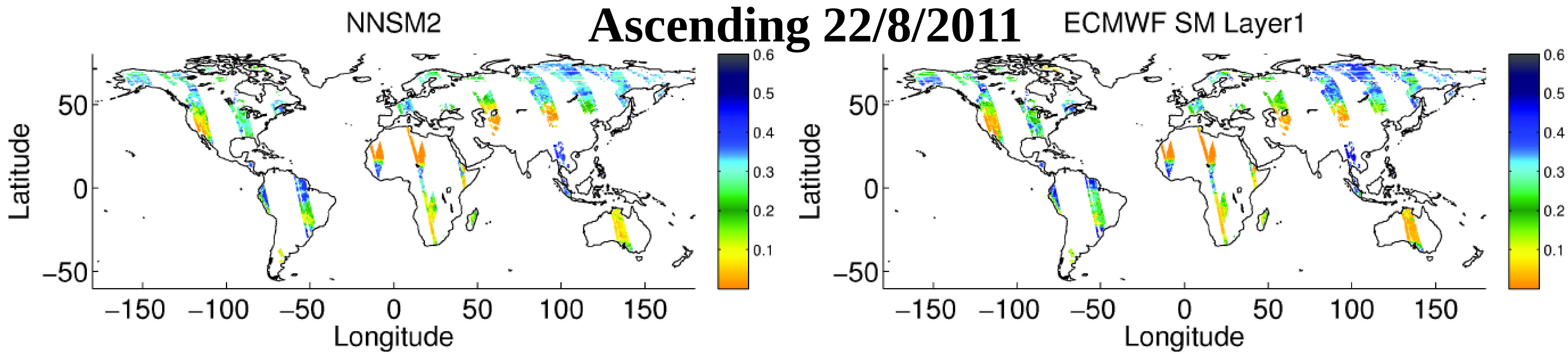




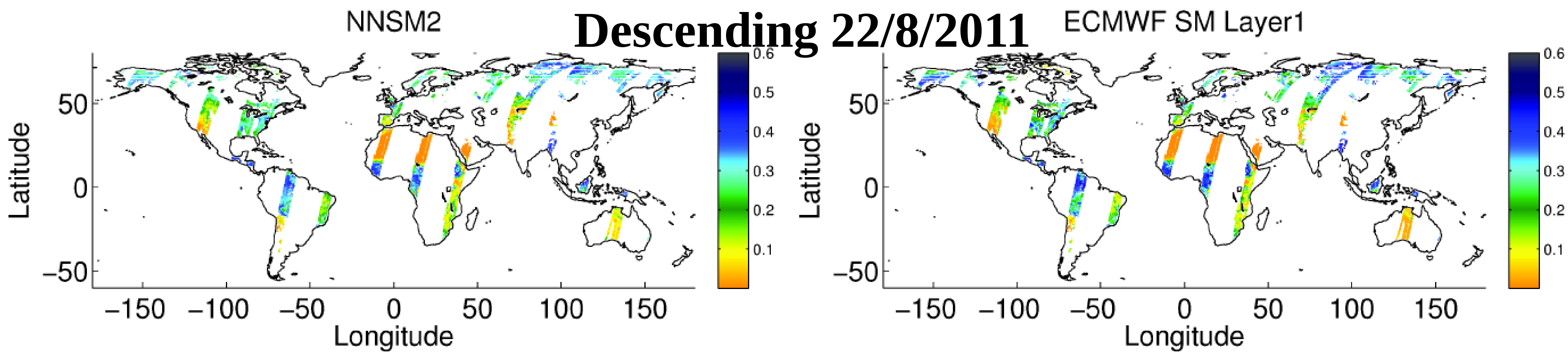
- Best option for just one NN covering as much of the swath as possible and making use of as many Tb's as possible?
  - Angles from 25 to 60 (correlation NN SM wrt ECMWF SM R=0.8).
  - Thus we have the angular signature, we can improve correlation with SM ...
  ... and we cover the **central ~700 kms** of the swath

Daily NN retrievals

Ascending 22/8/2011



Descending 22/8/2011



NN SM	input data
$NNSM_1$	14Tb+NDVI+tex+T
$NNSM_2$	14Tb+14I_1+NDVI+tex
$NNSM_3$	14Tb+NDVI+tex+σ...

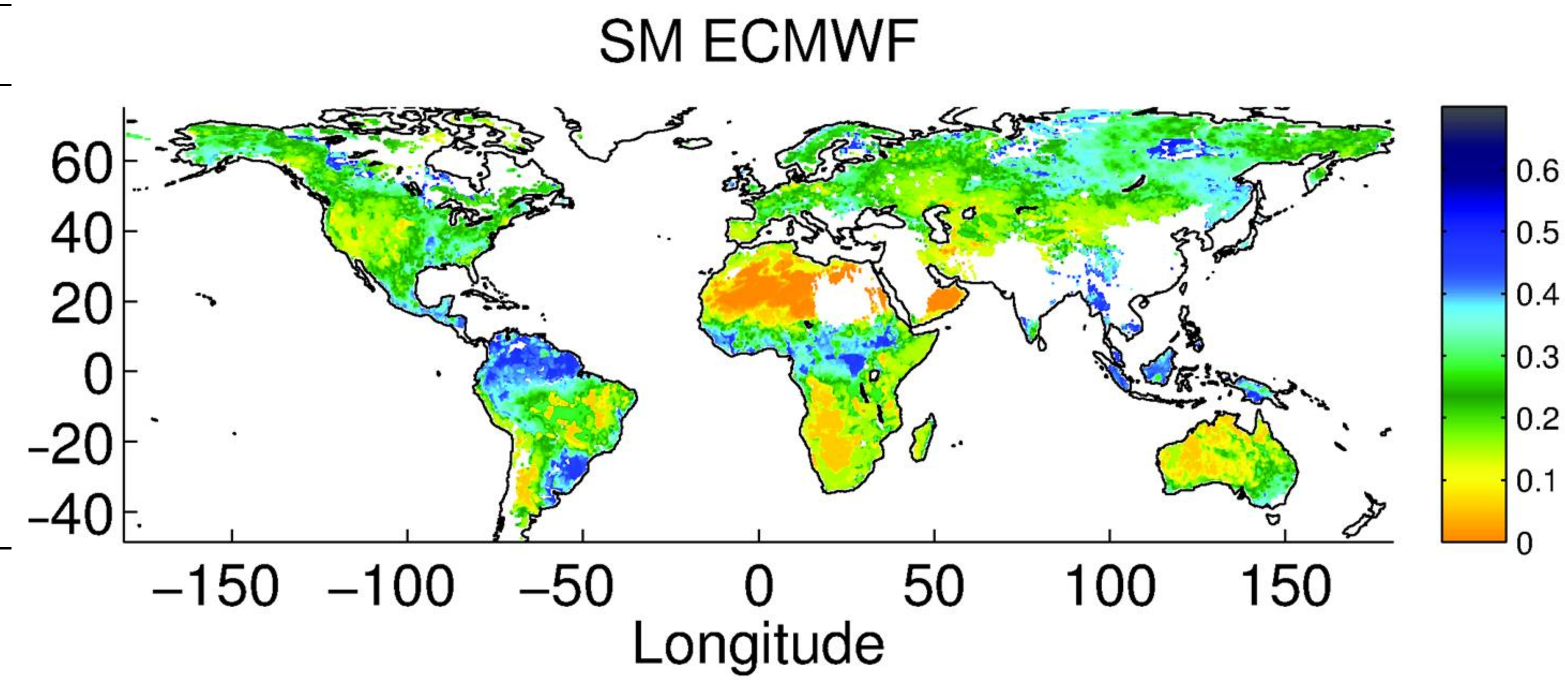
smos+ neural net

support to science element

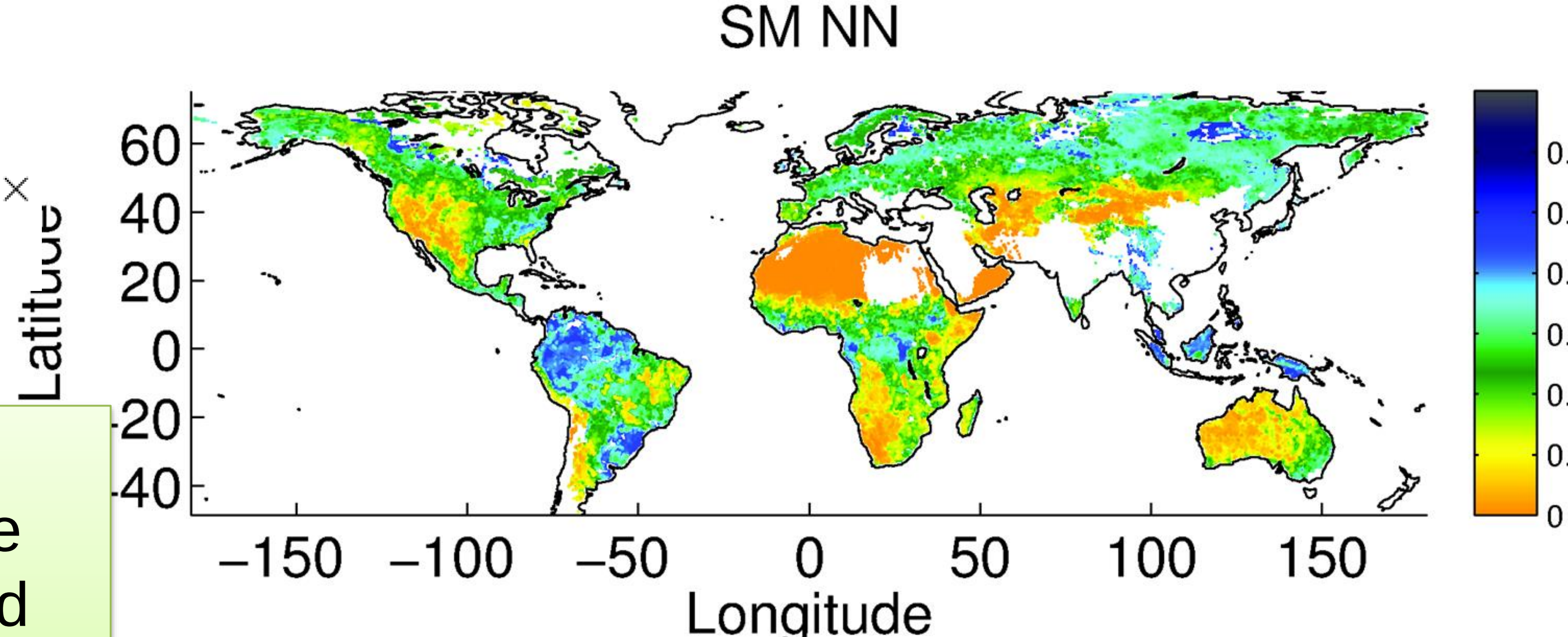
input data	R	RMSE	MAE
14Tb+NDVI+tex+T	0.91	0.067	0.050
14Tb+14I_1+NDVI+tex	0.92	0.065	0.048
14Tb+NDVI+tex+σ_{40}	0.92	0.065	0.048
8I_2+NDVI	0.95	0.052	0.037
14I_2+$I_{2_{\sigma 40}}$	0.95	0.053	0.037
14Tb+14I_1	0.83	0.086	0.066

$$I1(\mathbf{t},i,j) = \frac{T_b(\mathbf{t},i,j) - T_b^{min}(i,j)}{T_b^{max}(i,j) - T_b^{min}(i,j)}$$

$$\begin{aligned} I2(\mathbf{t},i,j) \quad = \quad & SM^{T_b^{min}}(i,j) + \\ & +[SM^{T_b^{max}}(i,j) - SM^{T_b^{min}}(i,j)] \times \\ & \times I_1(\mathbf{t},i,j) \end{aligned}$$



July 2010: Period not seen during training

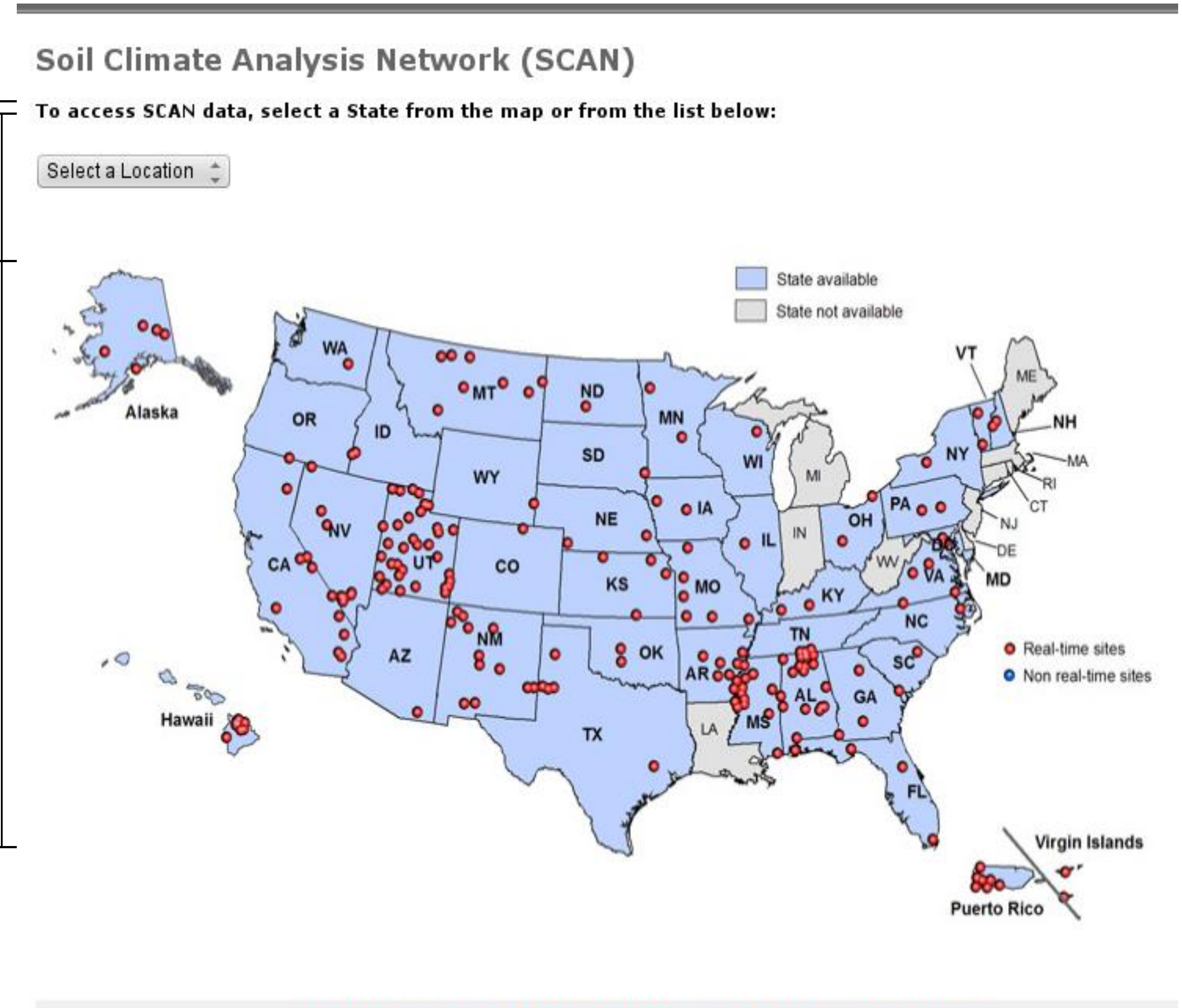


-NDVI improve the results by 10%
- Models with active MW or I1 improve the temporal correlation of NN SM and ECMWF SM

Rodriguez-Fernandez, Aires, Richaume et al. 2015 (TGRS, in press)

Comparison 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



Rodriguez-Fernandez, Aires, Richaume et al. 2015 (TGRS, in press)

Application to a Near-Real-Time product

- Once trained, the NNs are very fast to apply
  - One year of SMOS observations can be inverted in a few minutes

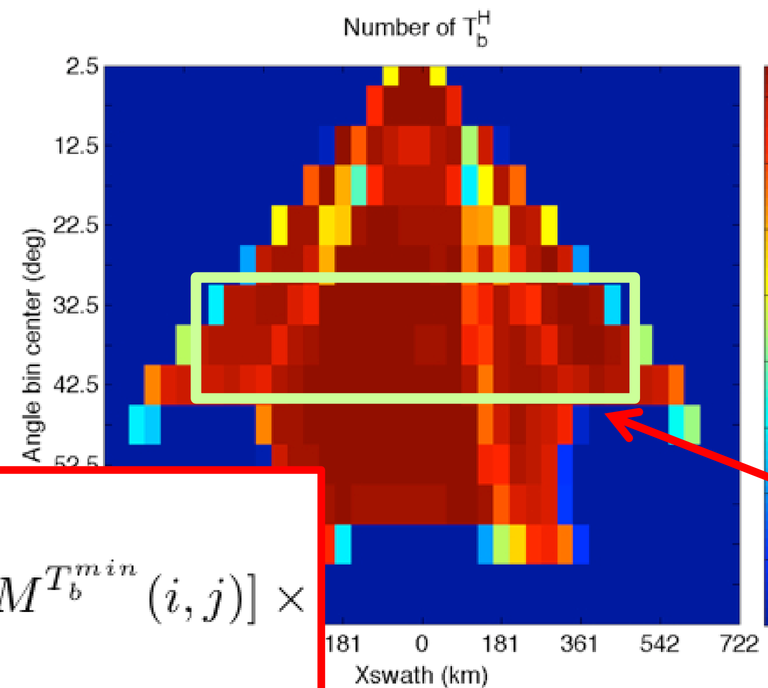
- It is possible to do a Near-Real-Time (NRT) SM product
  - Applications go from meteorology to operational hydrology (floods prediction…)

- Specifications and operational constrains for a NRT SM product
  - Available in less than 3 hours after sensing
  - Swath as large as possible
  - Better to use as little auxiliary data as possible
  - It should be as similar as possible to the current operational L2 SM

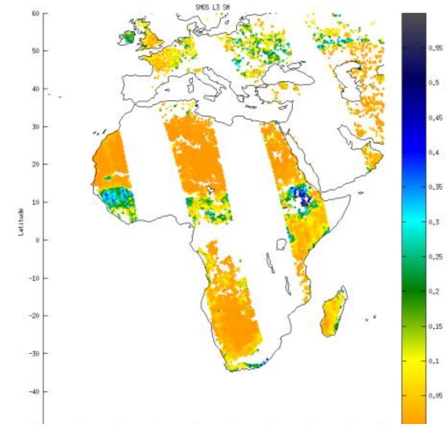
Choice of Neural Network configuration

$$I1(\mathbf{t},i,j) = \frac{T_b(\mathbf{t},i,j) - T_b^{min}(i,j)}{T_b^{max}(i,j) - T_b^{min}(i,j)}$$

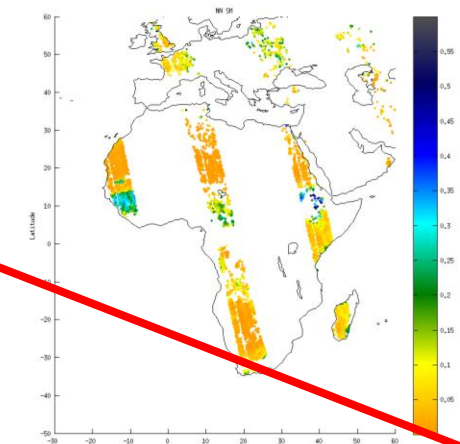
$$\begin{aligned} I2(\mathbf{t},i,j) \quad = \quad & SM^{T_b^{min}}(i,j) + \\ & +[SM^{T_b^{max}}(i,j) - SM^{T_b^{min}}(i,j)] \times \\ & \times I_1(\mathbf{t},i,j) \end{aligned}$$



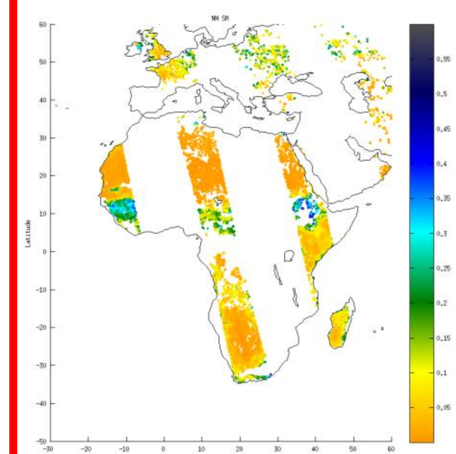
- Using I2 as input to maximize correlation with the operational SM
  - Adding the soil temperature as input improve results by 4 %
- Number of angles:
  - Quality decreases significantly with less than 3 angle
- NDVI not needed when using 30º-45º range



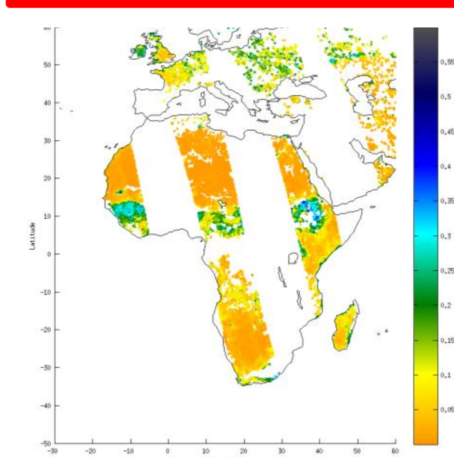
SMOS L3
R (NN-SCAN) = 0.53



NN 25º-60º
Swath : 660 km
R (NN-L3) = 0.95
R (NN-SCAN) = 0.55

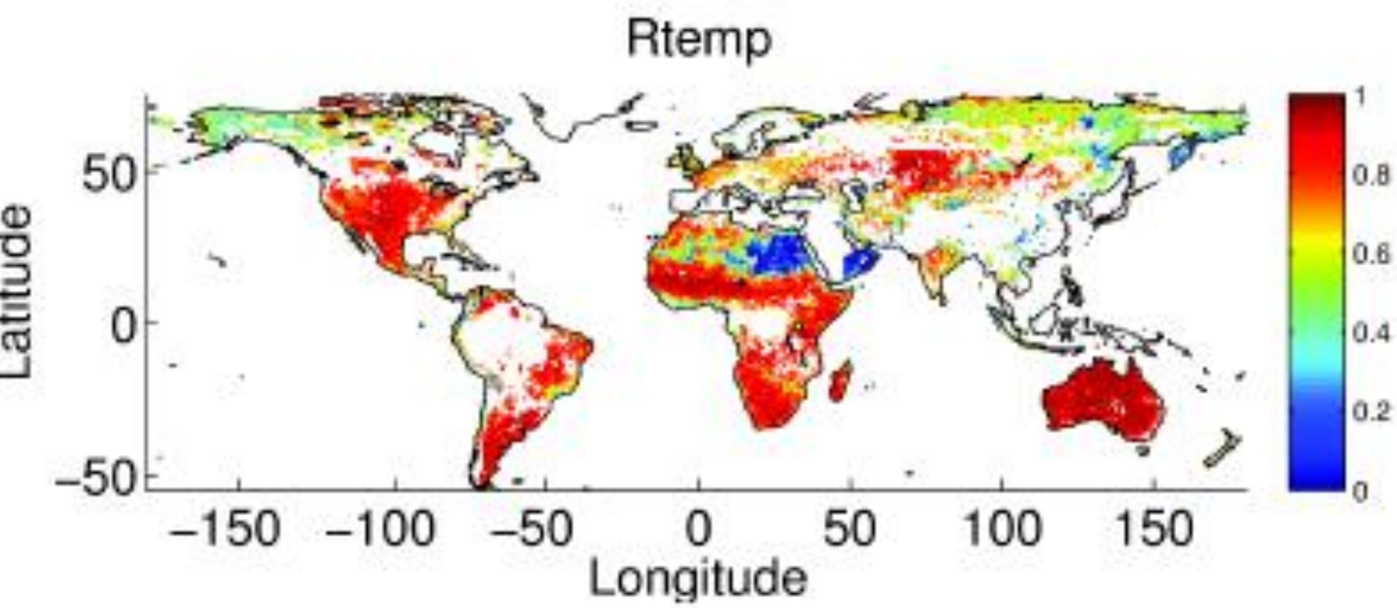


BEST CHOICE
NN 30-45º
920 km
R (NN-L3) = 0.92
R (NN-SCAN) = 0.55



NN 40º-45º
1160 km
R (NN-L3) = 0.87
R (NN-SCAN) = 0.50

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



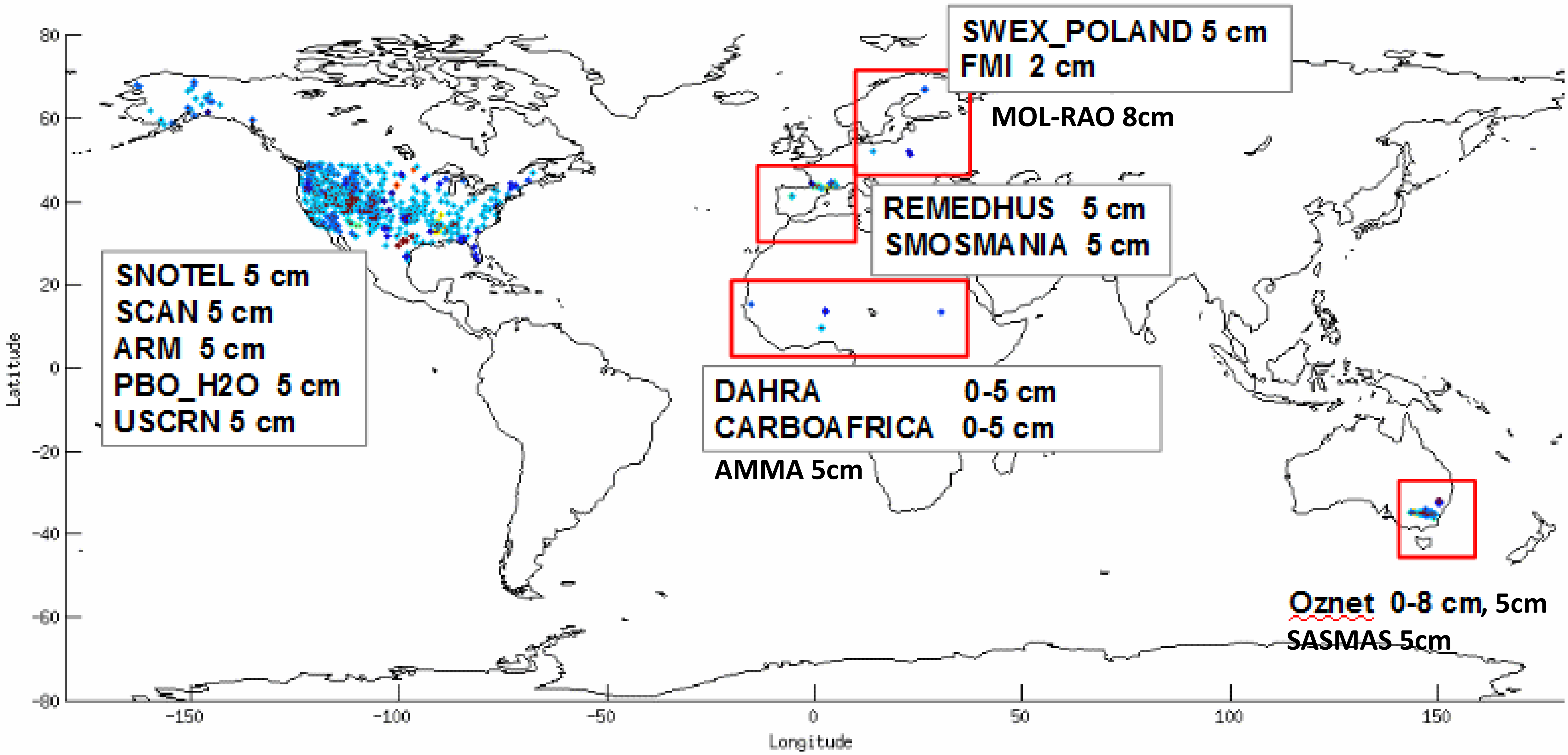
SMOS NRT SM vs SMOS L3 SM:
Global correlation R = 0.92
Average temporal correlation Rtemp= 0.8
- Main differences: high latitudes & desert

Input	STD	R	Bias
NN	**0.049**	**0.55**	-0.024
ECMWF	0.049	0.59	0.056
SMOS L3	0.064	0.50	-0.026

Average stats wrt USDA SCAN sites better than SMOS L3

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

Evaluation with respect to in situ measurements



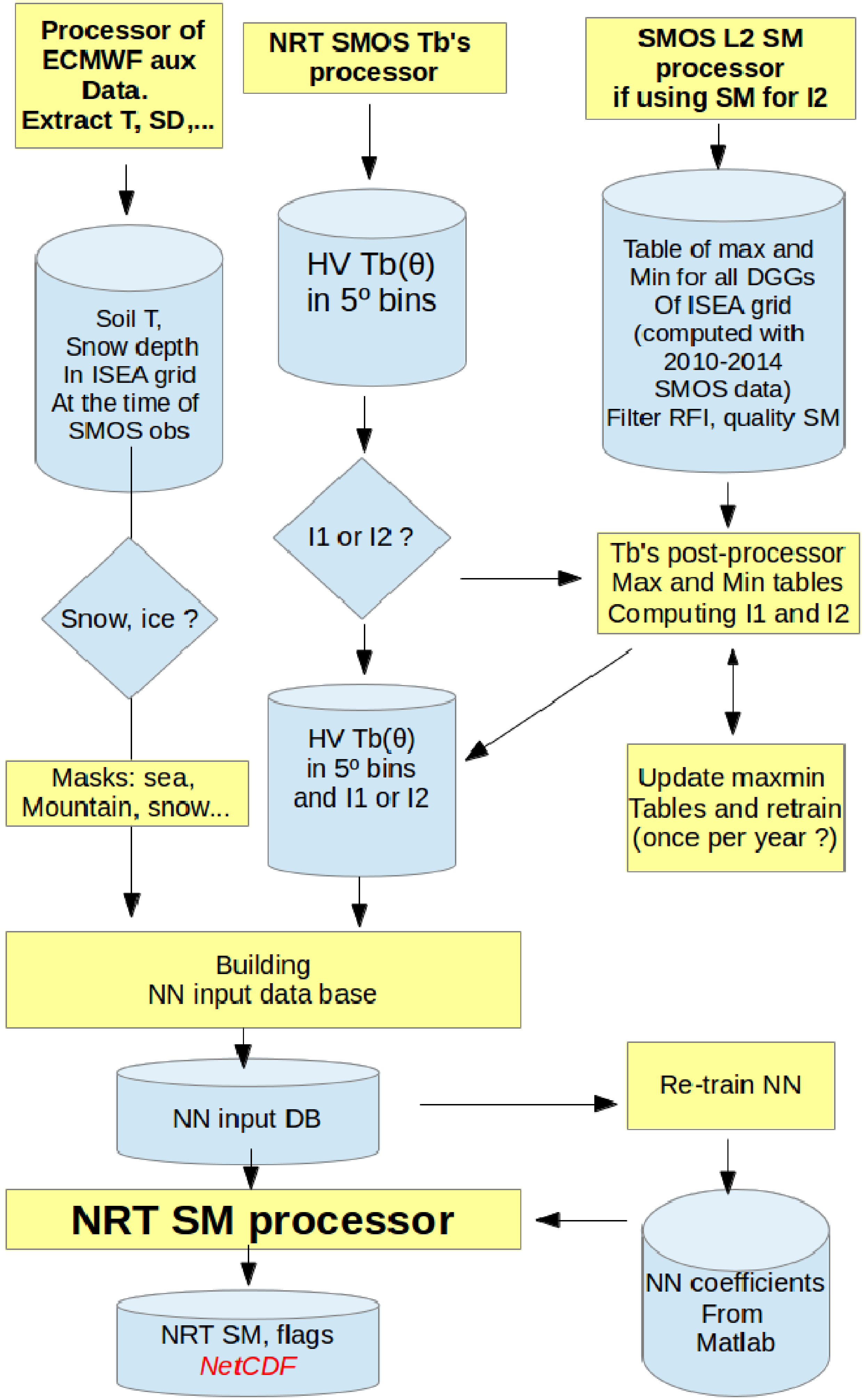
Evaluation from June 2010 to June 2013

Table 9: Evaluation of the proposed NN, ECMWF IFS and SMOS L3 SM against *in situ* measurements. NRT SM has been obtained using (6I2,6Tbs,T) as input and 5 neurons in the hidden layer.

SM	$< STD >$	$< R >$	$< Bias >$
AMMA 0.05 0.05 : Sensors: 6; $< N_p >= 53$			
NRT	0.061	0.566	0.009
ECMWF	0.027	0.601	0.044
SMOS L3	0.069	0.476	0.003
ARM 0.025 0.025 : Sites 9; $< N_p >= 124$			
NRT	0.064	0.750	-0.062
ECMWF	0.074	0.715	0.078
SMOS L3	0.084	0.679	-0.045
ARM 0.05 0.05 : Sensors: 16; $< N_p >= 128$			
NRT	0.068	0.676	-0.158
ECMWF	0.074	0.615	-0.051
SMOS L3	0.082	0.603	-0.143
HOBE 0.00 0.05 : Sensors: 42; $< N_p >= 58$			
NRT	0.053	0.470	-0.083
ECMWF	0.044	0.617	0.026
SMOS L3	0.075	0.500	-0.107
OZNET 0.00 0.05 : Sites 8; $< N_p >= 36$			
NRT	0.080	0.734	-0.022
ECMWF	0.054	0.638	0.073
SMOS L3	0.082	0.756	-0.051
OZNET 0.00 0.08 : Sensors: 6; $< N_p >= 43$			
NRT	0.074	0.706	-0.016
ECMWF	0.061	0.595	0.107
SMOS L3	0.082	0.611	0.001
PBO-H2O 0.00 0.05 : Sensors: 6; $< N_p >= 111$			
NRT	0.048	0.718	-0.063
ECMWF	0.049	0.615	0.057
SMOS L3	0.059	0.616	-0.057
REMEDHUS 0.00 0.05 : Sensors: 4 $< N_p >= 173$			
NRT	0.052	0.696	0.014
ECMWF	0.098	0.665	0.173
SMOS L3	0.063	0.682	0.026

Table 10: Evaluation of the proposed NN, ECMWF IFS and SMOS L3 SM against *in situ* measurements. NRT SM has been obtained using (6I2,6Tbs,T) as input and 5 neurons in the hidden layer.

SM	$< STD >$	$< R >$	$< Bias >$
SMOSMANIA 0.05 0.05 : Sensors: 13; $< N_p >= 62$			
NRT	0.047	0.613	-0.132
ECMWF	0.074	0.792	0.085
SMOS L3	0.069	0.611	-0.107
SCAN 0.05 0.05 : Sensors: 106; $< N_p >= 100$			
NRT	0.048	0.533	-0.030
ECMWF	0.059	0.525	0.058
SMOS L3	0.063	0.504	-0.023
SNOTEL 0.05 0.05 : Sensors: 173; $< N_p >= 82$			
NRT	0.041	0.454	-0.065
ECMWF	0.045	0.471	0.040
SMOS L3	0.058	0.391	-0.054
UDC-SMOS 0.00 0.10 : Sensors: 1; $< N_p >= 34$			
NRT	0.045	0.336	-0.266
ECMWF	0.025	0.529	-0.051
SMOS L3	0.077	0.275	-0.196
UDC-SMOS 0.05 0.05 : Sensors: 4 $< N_p >= 32$			
NRT	0.046	0.301	-0.241
ECMWF	0.025	0.289	-0.027
SMOS L3	0.078	0.297	-0.171
USCRN 0.05 0.05 : Sensors: 53; $< N_p >= 115$			
SM	$< STD >$	$< R >$	$< Bias >$
NRT	0.053	0.603	-0.032
ECMWF	0.057	0.629	0.060
SMOS L3	0.066	0.549	-0.026


Processor of ECMWF aux Data. Extract T, SD,...
NRT SMOS Tb's processor
SMOS L2 SM processor if using SM for I2
Soil T, Snow depth In ISEA grid At the time of SMOS obs
HV Tb(θ) in 5º bins
Table of max and Min for all DGGs Of ISEA grid (computed with 2010-2014 SMOS data) Filter RFI, quality SM
I1 or I2 ?
Tb's post-processor Max and Min tables Computing I1 and I2
Snow, ice ?
HV Tb(θ) in 5º bins and I1 or I2
Update maxmin Tables and retrain (once per year ?)
Masks: sea, Mountain, snow...
Building NN input data base
NN input DB
Re-train NN
NRT SM processor
NN coefficients From Matlab
NRT SM, flags
NetCDF

SMOS NRT SM product

A new product

Designed by :

Implemented by :

Distributed by GTS and EUMETCAST (second half of 2015)

Summary

• NN are an efficient tool to merge multi-sensor data
• Using global models as reference is a promising method to retrieve SM from remote sensing observations → interesting dataset for data assimilation

• These techniques can be applied to link SMOS Tbs to you own surface model
• NN datasets can be distributed on demand

• A new **Near-Real-Time SM** based on NNs is under development
  • Similar to current L2 SM but on near-real-time
  • Soon available for your near-real-time applications
  • Good statistics against in situ measurements
  • Will be distributed via GTS and EUMETcast

Thank you for your attention !

Acknowledgements

- Funding
- Data

More information

@SMOS_satellite

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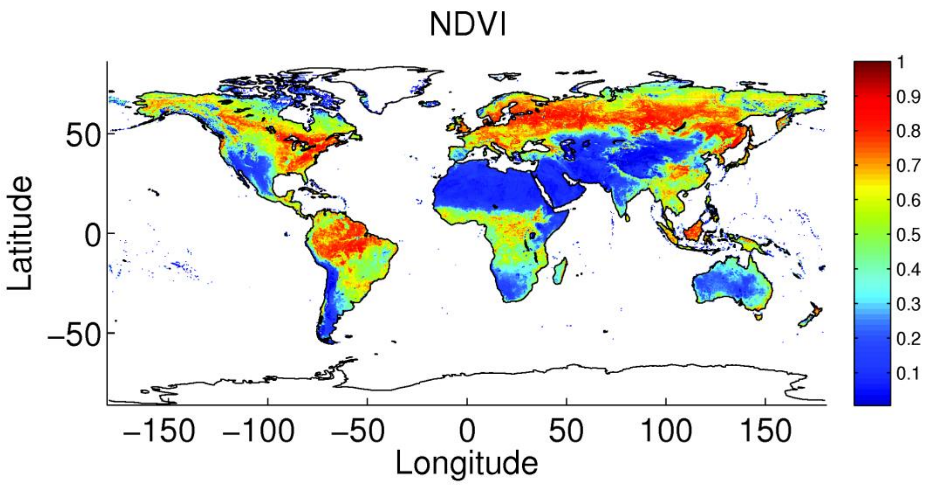
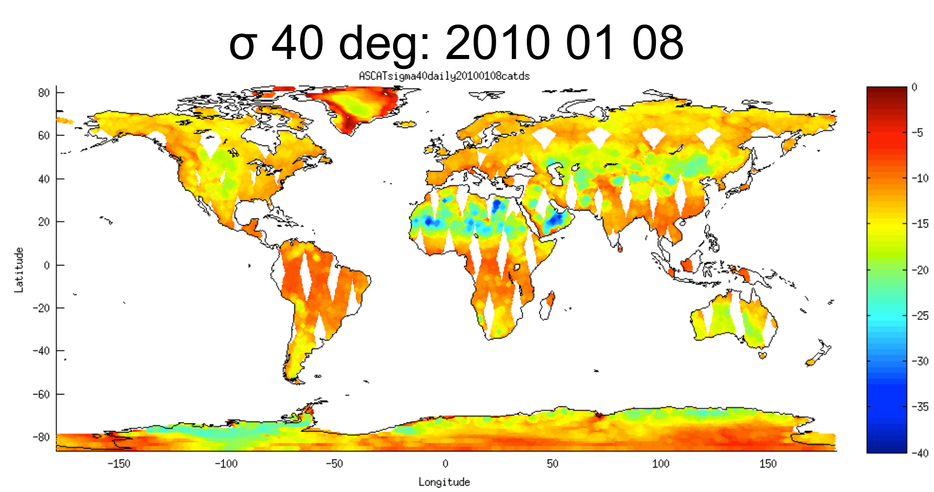
Input data sets

- SMOS L3TB (angle bins of 5º, HV polarization, EASE grid)
- NDVI MODIS (1 every 16 days)
- Soil texture Ecoclimap FAO, Masson et al. 2003
- Wetlands, 1993-2007 monthly averages, Prigent et al. (2012)
- ECMWF IFS models Soil temperature (0-7 cm), snow depth
- ASCAT L1B backscattering coefficients. Estimation of a daily σ(40º): linear regression using a 7 days window



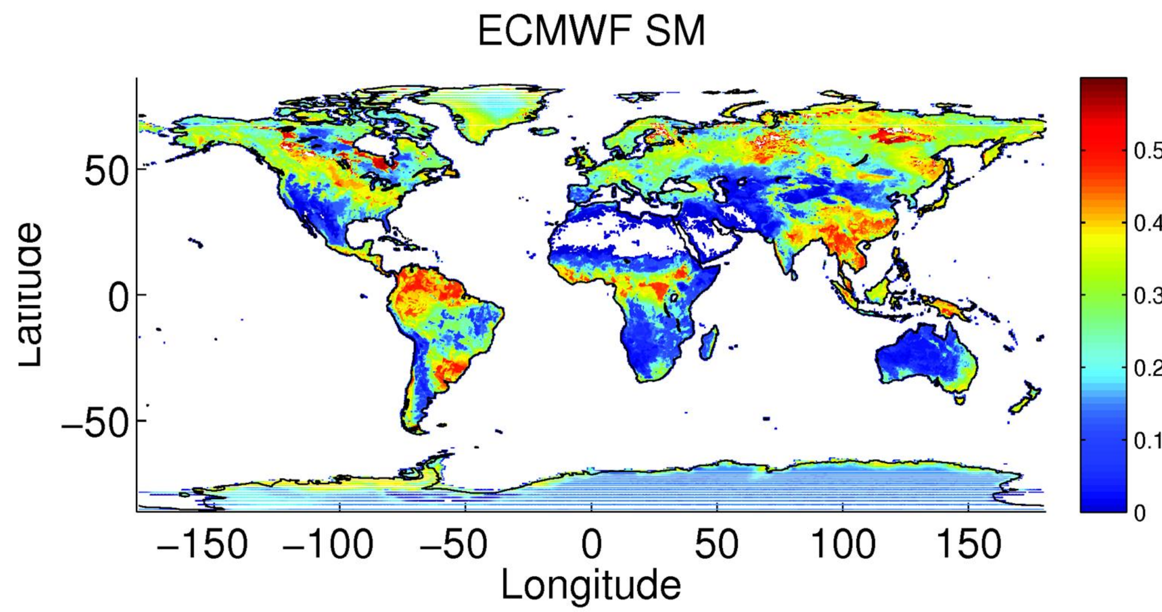


Reference SM data sets

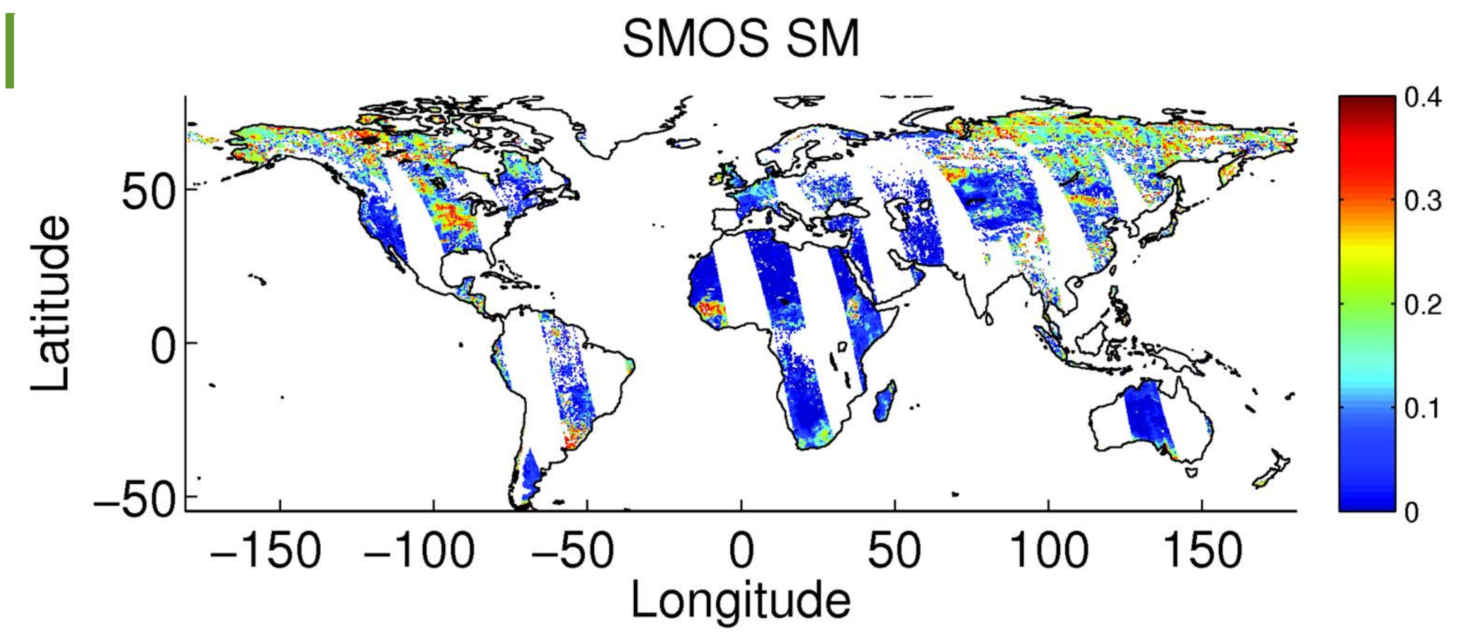
◉ECMWF IFS models (36r1-37r3)

- Soil Moisture first layer (0-7 cm)
- Spatial and temporal interpolation to the SMOS CATDS grid

SM_L1 21/06/2011

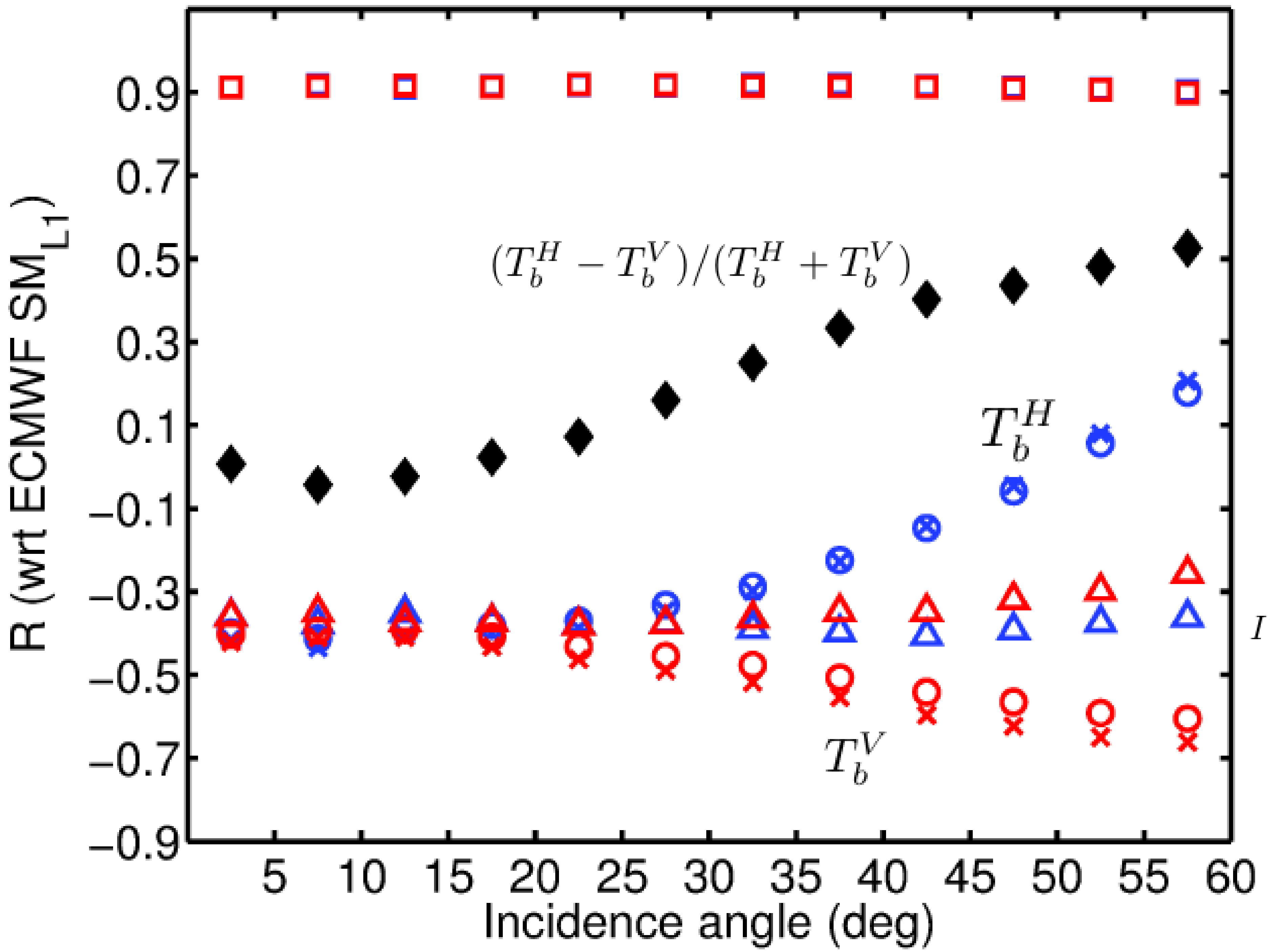


◉SMOS L3 CATDS dail SM product



Tb's sensitivity to SM

$$I2(\mathbf{t},i,j) = SM^{T_b^{min}}(i,j) + [SM^{T_b^{max}}(i,j) - SM^{T_b^{min}}(i,j)] \times I_1(\mathbf{t},i,j)$$

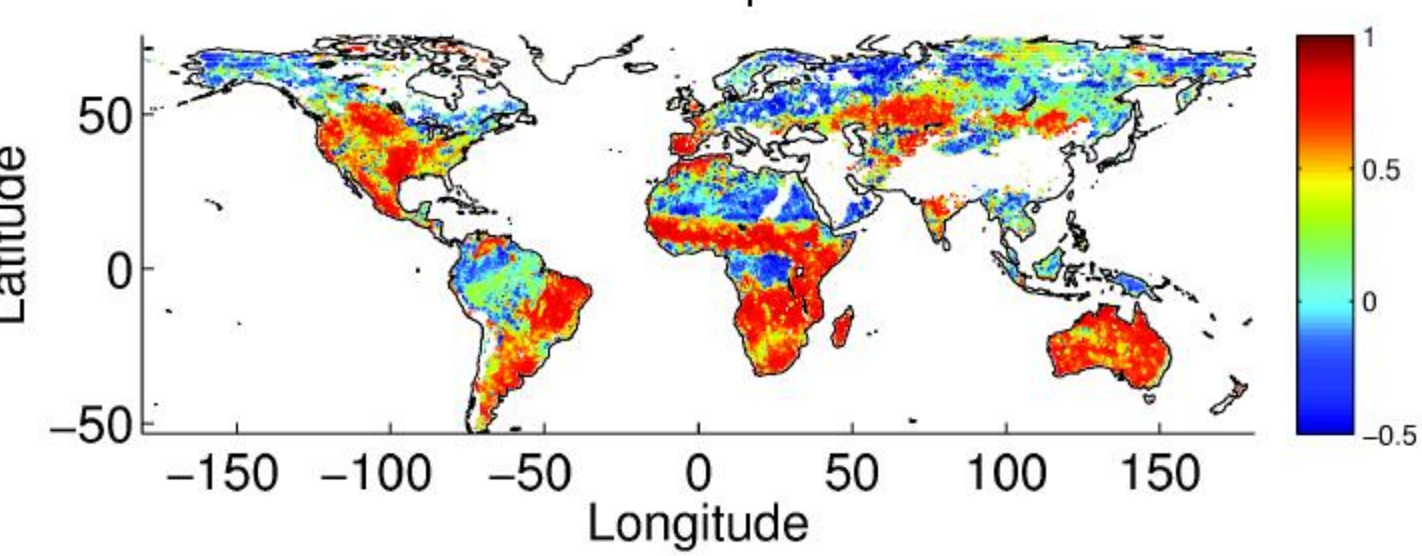


Obs	R
Ts	-0.17
NDVI	0.80
sand	-0.33
clay	0.41
σ_{40}	0.62
I_1^σ	0.24
I_2^σ	0.87

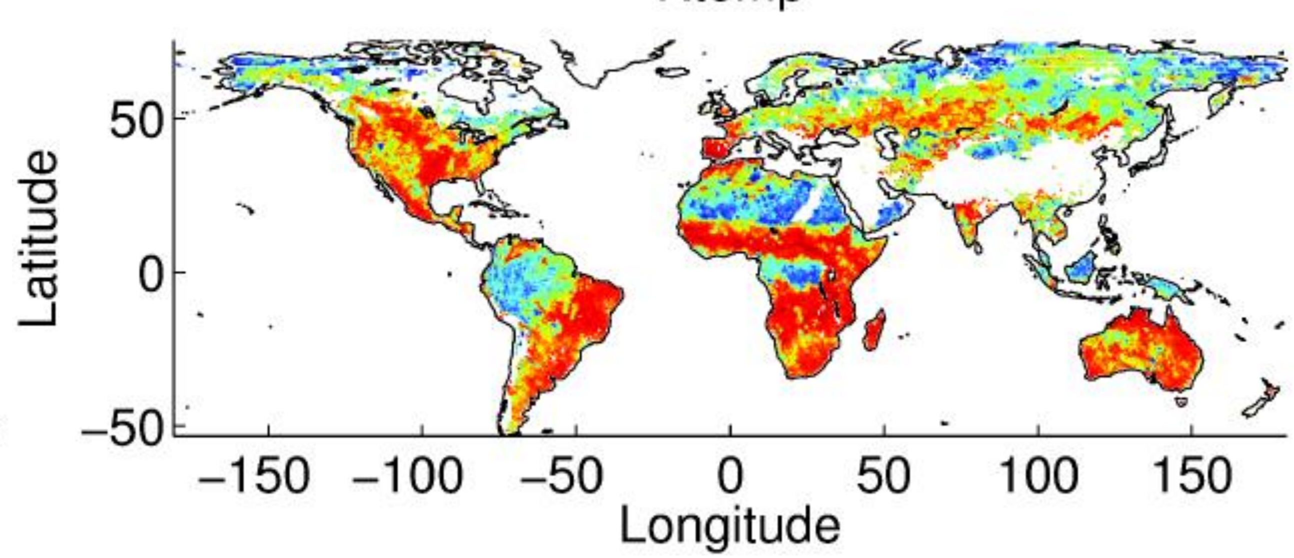
$$I1(\mathbf{t},i,j) = \frac{T_b(\mathbf{t},i,j) - T_b^{min}(i,j)}{T_b^{max}(i,j) - T_b^{min}(i,j)}$$

Maps of temporal correlation

Without active MWs



With active MWs



The neural networks that capture the best the temporal correlation are those using one of:

- Active microwaves (in agreement with Kolassa et al. 2013)
- A local normalization of the passive microwaves data (no swath intersection: more retrievals)

Retrieval	A orbits	D orbits
14Tb+NDVI+tex+T	0.47	0.49
14Tb+$14I_1$+NDVI+tex	0.54	0.57
14Tb+NDVI+tex+σ_{40}	0.55	0.56
$8I_2$+NDVI	0.52	0.52
$14I_2$+$I_{2\sigma_{40}}$	0.58	0.57
14Tb+$14I_1$	0.48	0.53

Locally normalized brightness Temp

Active Microwaves

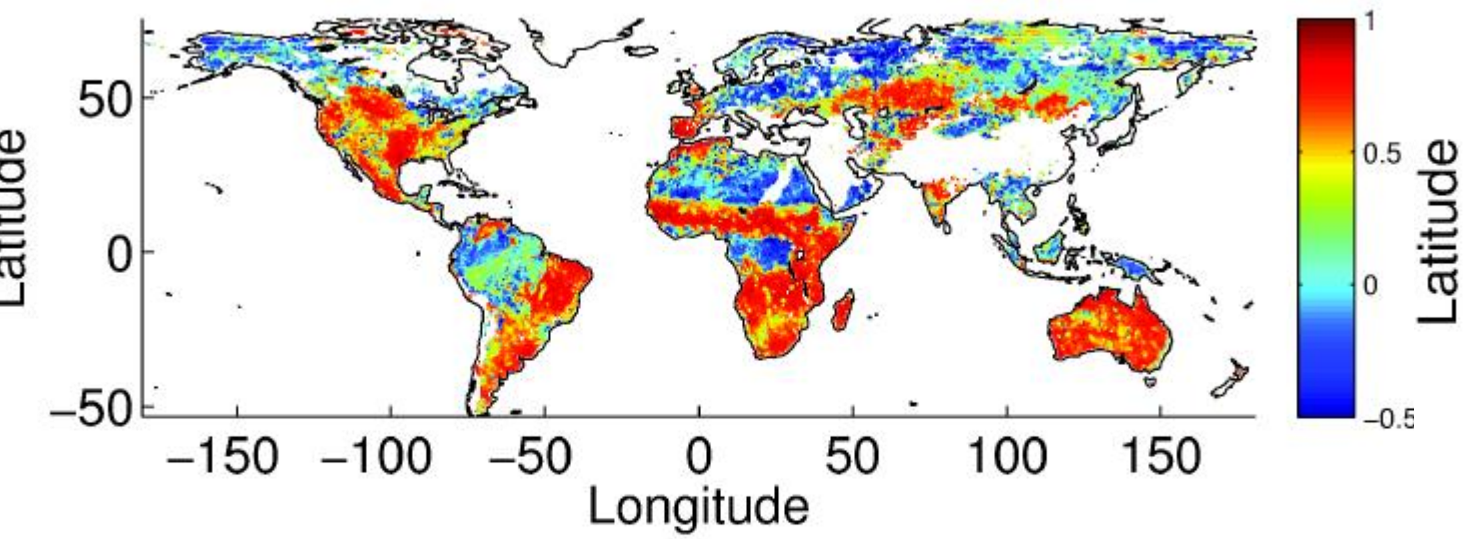
SMOS only

Monthly retrievals Kolassa et al. 2013
R = 0.54-0.67

Maps of temporal correlation

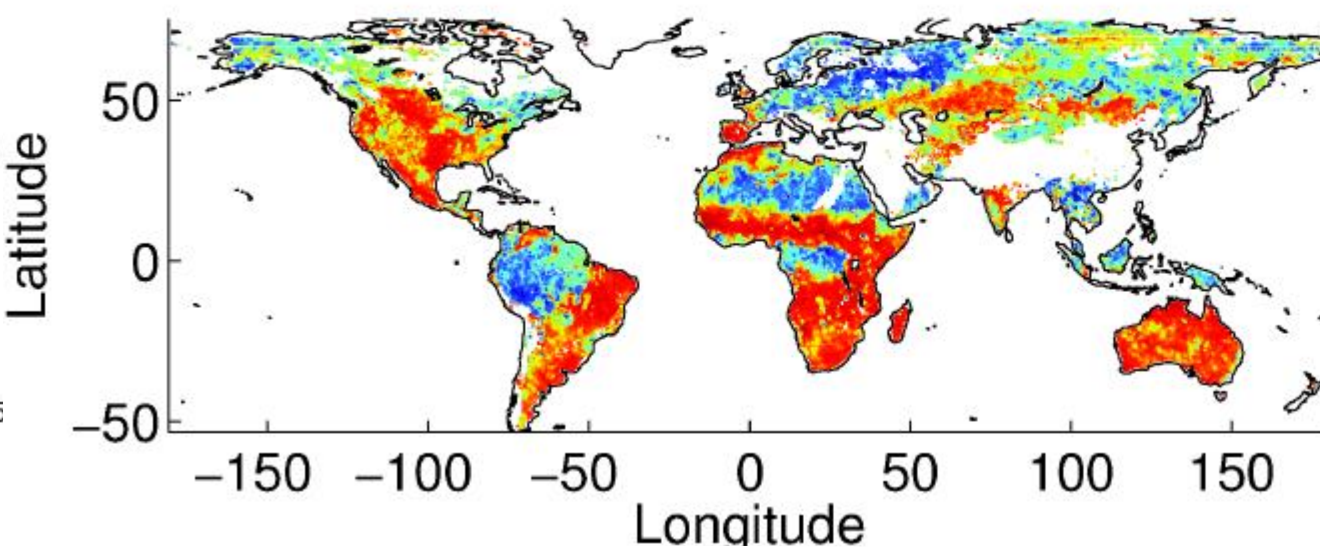
Without active MWs

NNSM 4 Rtemp



With SMOS I1

Rtemp NNSM 2



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Monthly retrievals

Kolassa et al. 2013

R = 0.54-0.67

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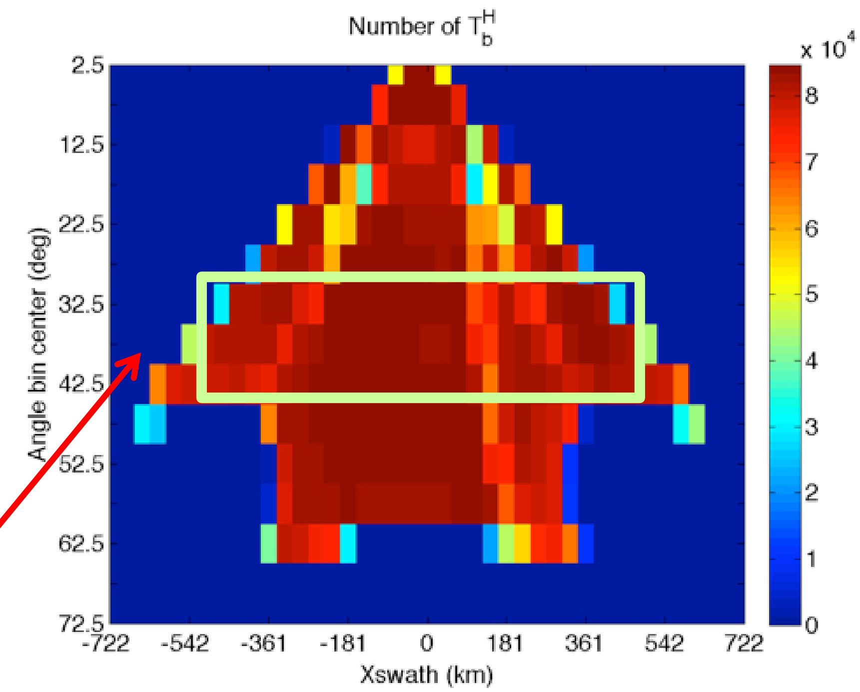
Choice of the best NN configuration ?

input	R	RMSE	MAE	STD	R	Bias	Mean R_{spa}	Mean R_{temp}
Using only Tb's								
T_b(H,V,30°-45°),T	0.81	0.065	0.041	0.052	0.50	-0.028	0.77	0.70
T_b(H,V,30°-45°),tex,VI	0.78	0.068	0.044	0.046	0.54	-0.025		
T_b(H,V,30°-45°),T,VI	0.81	0.063	0.040	0.048	0.51	-0.027		
T_b(H,V,30°-45°),T,tex	0.82	0.063	0.039	0.052	0.50	-0.025	0.78	0.70
T_b(H,V,30°-45°),tex,VI,T	0.83	0.061	0.038	0.049	0.51	-0.026	0.81	0.76
T_b(H,V,25°-60°),VI,T	0.85	0.052	0.032	0.051	0.57	-0.031		
T_b(H,V,25°-60°),T,tex	0.86	0.051	0.031	0.050	0.56	-0.028	0.82	0.79
T_b(H,V,25°-60°),VI,T,tex	0.86	0.051	0.031	0.050	0.57	-0.026	0.82	0.78
Using local normalization of T_b's (I_1)								
I_1&T_b(H,V,30°-45°),T	0.81	0.064	0.041	0.054	0.52	-0.028	0.77	0.73
I_1&T_b(H,V,30°-45°),T,tex	0.83	0.061	0.039	0.054	0.51	-0.027	0.78	0.74
I_1&T_b(H,V,30°-45°),VI	0.78	0.068	0.045	0.051	0.54	-0.026		
I_1&T_b(H,V,30°-45°),VI,T	0.82	0.062	0.039	0.050	0.53	-0.030	0.79	0.77
I_1&T_b(H,V,30°-45°),VI,tex	0.79	0.067	0.044	0.050	0.56	-0.027		
I_1&T_b(H,V,30°-45°),VI,T,tex	0.83	0.061	0.038	0.051	0.53	-0.026		
I_1&T_b(H,V,25°-45°),T	0.83	0.060	0.037	0.054	0.53	-0.030		
I_1&T_b(H,V,25°-45°),VI	0.79	0.066	0.043	0.052	0.57	-0.029		
I_1&T_b(H,V,25°-45°),VI,T	0.83	0.059	0.037	0.052	0.55	-0.030		
I_1&T_b(H,V,25°-60°),T	0.85	0.051	0.032	0.050	0.56	-0.030	0.82	0.79
I_1&T_b(H,V,25°-60°),VI	0.81	0.058	0.037	0.049	0.58	-0.030		
I_1&T_b(H,V,25°-60°),VI,T	0.86	0.051	0.031	0.052	0.57	-0.029	0.82	0.79
Using local normalization of T_b's with SM extreme values (I_2)								
I_2&T_b(H,V,40°-45°)	0.83	0.060	0.039	0.045	0.51	-0.024		
I_2&T_b(H,V,40°-45°),T	0.85	0.056	0.036	0.043	0.49	-0.025	0.86	0.71
I_2&T_b(H,V,40°-45°),VI	0.85	0.057	0.037	0.038	0.54	-0.024		
I_2&T_b(H,V,40°-45°),VI,T	0.87	0.054	0.034	0.039	0.50	-0.024	0.87	0.74
I_2&T_b(H,V,35°-45°)	0.86	0.055	0.036	0.048	0.52	-0.021		
I_2&T_b(H,V,35°-45°),T	0.89	0.050	0.031	0.045	0.51	-0.022	0.87	0.72
I_2&T_b(H,V,35°-45°),VI	0.88	0.052	0.033	0.042	0.54	-0.022		
I_2&T_b(H,V,35°-45°),VI,T	0.89	0.048	0.030	0.042	0.52	-0.021	0.88	0.74
I_2&T_b(H,V,30°-45°)	0.89	0.048	0.032	0.051	0.54	-0.023		
I_2&T_b(H,V,30°-45°),T	**0.92**	**0.043**	**0.027**	**0.049**	**0.55**	**-0.024**	**0.89**	**0.79**
I_2&T_b(H,V,30°-45°),VI	0.90	0.047	0.030	0.046	0.56	-0.022		
I_2&T_b(H,V,30°-45°),VI,T	0.92	0.042	0.026	0.047	0.55	-0.022	0.91	0.79
I_2&T_b(H,V,25°-45°)	0.91	0.044	0.029	0.052	0.55	-0.027		
I_2&T_b(H,V,25°-45°),T	0.93	0.038	0.023	0.050	0.55	-0.028		
I_2&T_b(H,V,25°-45°),VI	0.92	0.042	0.027	0.047	0.58	-0.030		
I_2&T_b(H,V,25°-45°),VI,T	0.94	0.037	0.023	0.048	0.56	-0.029		
I_2&T_b(H,V,25°-60°),VI	0.93	0.037	0.024	0.047	0.56	-0.033		
I_2&T_b(H,V,25°-60°),T	0.95	0.033	0.021	0.046	0.54	-0.031		
I_2&T_b(H,V,25°-60°),VI,T	0.95	0.032	0.020	0.048	0.55	-0.033	0.92	0.83

$$\boxed{I1(\mathbf{t},i,j) = \frac{T_b(\mathbf{t},i,j) - T_b^{min}(i,j)}{T_b^{max}(i,j) - T_b^{min}(i,j)}}$$



$$\boxed{\begin{aligned} I2(\mathbf{t},i,j) \quad = \quad & SM^{T_b^{min}}(i,j) + \\ & +[SM^{T_b^{max}}(i,j) - SM^{T_b^{min}}(i,j)] \times \\ & \times I_1(\mathbf{t},i,j) \end{aligned}}$$