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


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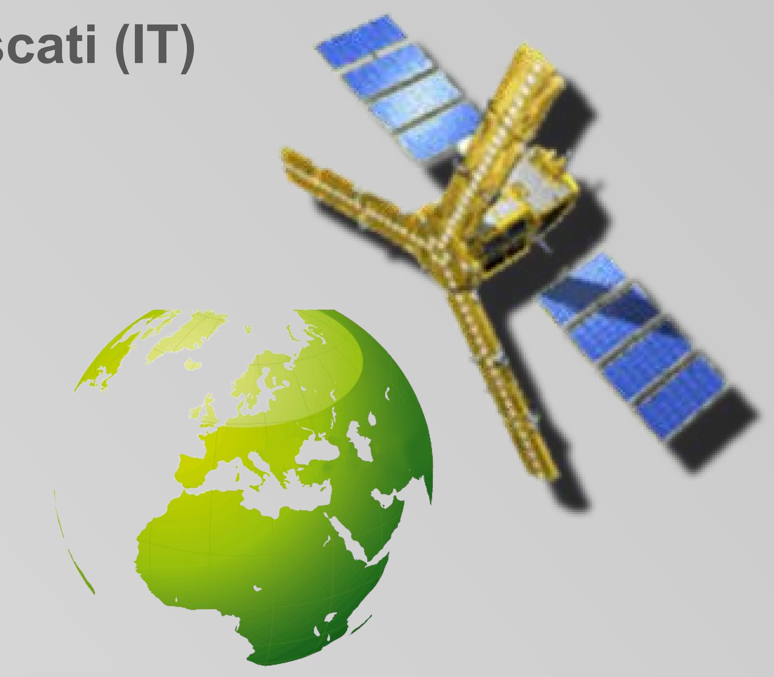


## Introduction

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 dissaminated in Near-Real-Time (NRT, ~ 3hours after sensing).

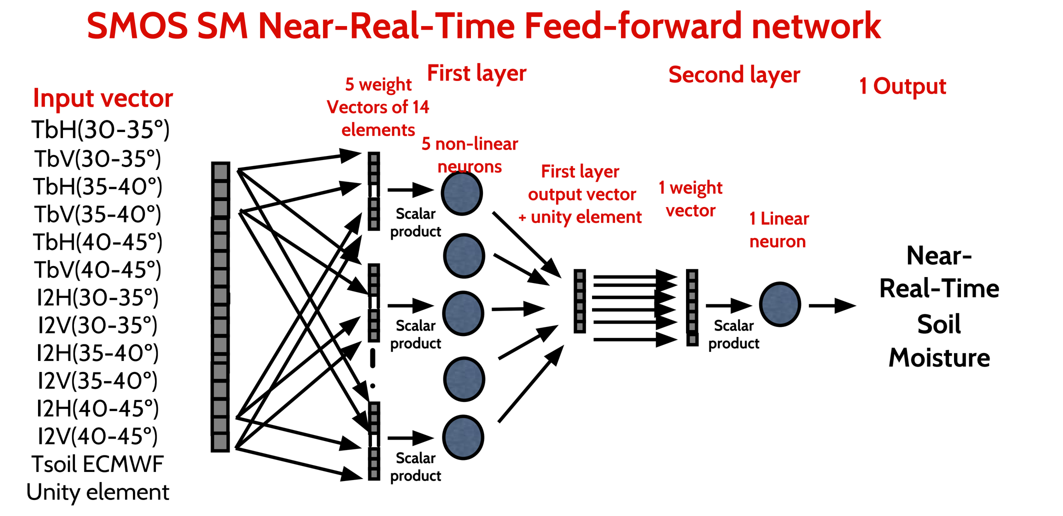
The NRT SM product is obtained from Soil Moisture and Ocean Salinity (SMOS) satellite observations and it is based on a neural network algorithm.

## Methods

The NRT retrieval algorithm is based in the approach discussed by Rodriguez-Fernandez et al. (IEEE TGARS 2015).
The neural network uses as input SMOS brightness temperatures (Tbs) for incidence angles from 30º to 45º and vertical and horizontal polarizations. In addition, for each latitude λ and longitude Φ, a local normalized index *I2*, has been computed from the local maximum and minimum Tb and the associated soil moisture values as follows :

$$I_{2_{\lambda\phi}}(t) = SM_{\lambda\phi}^{T_b^{min}} + [SM_{\lambda\phi}^{T_b^{max}} - SM_{\lambda\phi}^{T_b^{min}}] I_{1_{\lambda\phi}}(t) \qquad I_{1_{\lambda\phi}}(t) = \frac{T_{b_{\lambda\phi}}(t) - T_{b_{\lambda\phi}}^{min}}{T_{b_{\lambda\phi}}^{max} - T_{b_{\lambda\phi}}^{min}}$$

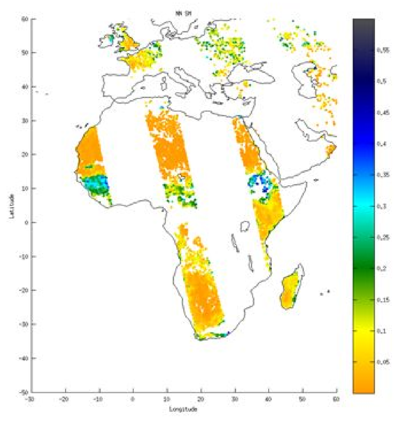
Finally, the soil temperature estimation in the 0-7 cm depth layer from ECMWF models is also used as input.




76 free parameters to be fixed using supervised learning with SMOS L2 Soil Moisture as reference dataset

## Results

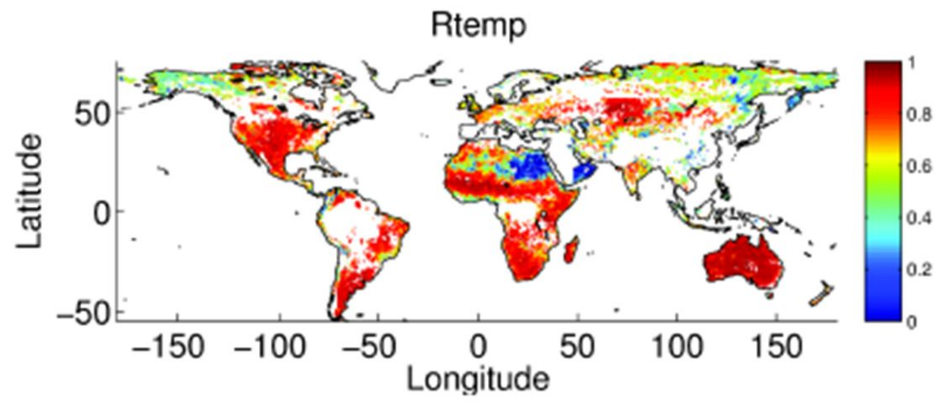
Using NRT Tb measurements at incidence angles from 30º to 45º the resulting swath width is 920 km (see Figure).



# Evaluation

## Comparison to SMOS L3 SM

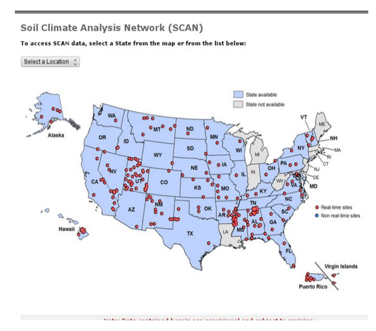
The map below shows the temporal correlation Rtemp of the NRT SM product (trained on SMOS L3 data) with respect to the SMOS L3 SM data obtained for time series for each grid node from June 2010 to December 2013.The average temporal Pearson correlation coefficient is 0.8, with significant differences 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**