Assimilation of SMOS neural-network-retrieved soil moisture for numerical weather prediction at ECMWF

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Goal: assimilation of soil moisture from remote sensing observations

Analysis Background Observations Observation operator

$$\mathbf{x}^{\mathrm{a}}(t_i) = \mathbf{x}^{\mathrm{b}}(t_i) + \mathbf{K}_i \left[\mathbf{y}^{\mathrm{o}}(t_i) - \mathcal{H}_i(\mathbf{x}^{\mathrm{b}}) \right]$$

Observation operator:

- Spatial interpolation
- radiative transfer
- Bias correction

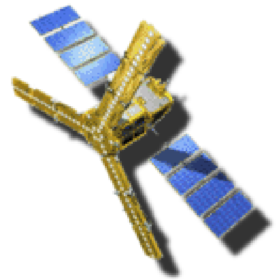
Soil moisture is not measured by any satellite. The observables are Brightness temperatures or backscattering coefficients. Needed in Near-Real-Time

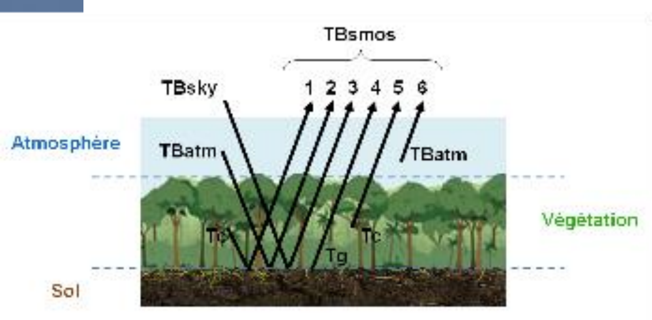
$$\mathrm{K}_i = \left[\mathrm{B}^{-1} + \mathrm{H}_i^{\mathrm{T}}\mathrm{R}^{-1}\mathrm{H}_i\right]^{-1} \mathrm{H}_i^{\mathrm{T}}\mathrm{R}^{-1},$$

R: need well defined errors of the observations

Direct models

SMOS





Brightness temperature

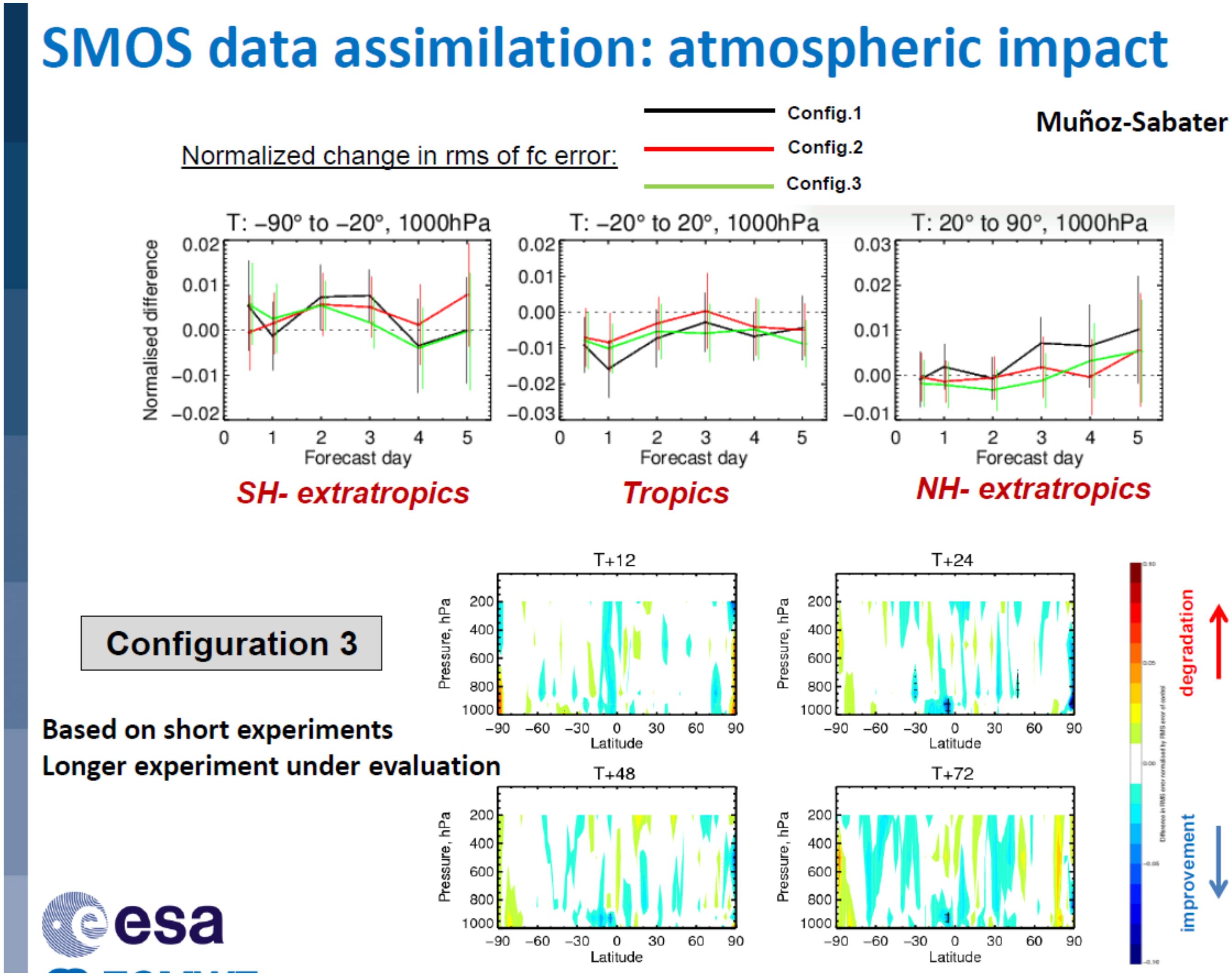
$$\mathrm{TB_P} = (1-\omega_\mathrm{p})(1-\gamma_\mathrm{p})(1+\gamma_\mathrm{p} r_\mathrm{gp})T_\mathrm{c} + (1-r_\mathrm{gp})\gamma_\mathrm{p} T_\mathrm{g}$$

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

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

Soil moisture

Assimilation of SMOS **brightness temperatures**

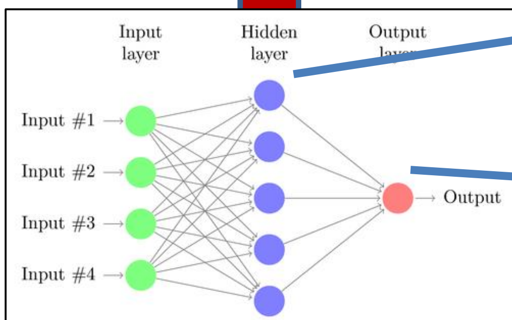


Alternative for operational users: SMOS SM in Near-Real-Time

- Operational Level 2 Soil Moisture cannot be available in near-real-time
  - Computing time to invert locally and iteratively the observations
- Solving the inverse problem with neural networks gives a fast retrieval and with similar quality to the L2 SM

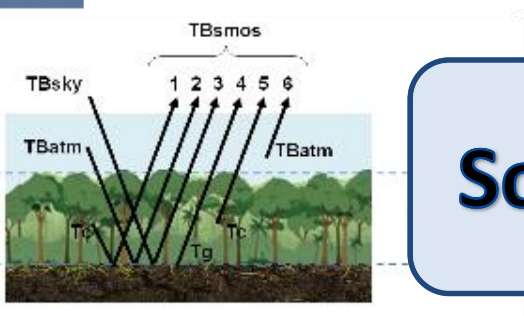
Fast inversion with neural networks

- **SMOS Tbs 30º-45º**
- **Normalization with local extreme SM**
- **ECMWF Tsoil**



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

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



Soil moisture

- Training with two years of SMOS Level 2 soil moisture
- The neural network gives a global retrieval and very fast to apply

NRT soil moisture errors

$$\Delta I_{1_{\lambda\phi}}(t) = \frac{1}{T_{D_{\lambda\phi}}}\left[\Delta T_{b_{\lambda\phi}}(t)^2 + \left(\frac{T_{m_{\lambda\phi}}(t)}{T_{D_{\lambda\phi}}}\Delta T^{max}_{b_{\lambda\phi}}\right)^2 + \left\{\left(-1+\frac{T_{m_{\lambda\phi}}(t)}{T_{D_{\lambda\phi}}}\right)\Delta T^{min}_{b_{\lambda\phi}}\right\}^2\right]^{1/2}$$

$$\boxed{T_{m_{\lambda\phi}}(t) = T_{b_{\lambda\phi}}(t) - T^{min}_{b_{\lambda\phi}}} \qquad \boxed{T_{D_{\lambda\phi}} = T^{max}_{b_{\lambda\phi}} - T^{min}_{b_{\lambda\phi}}}$$

$$I_{2_{\lambda\phi}}(t) = SM^{T_b^{min}}_{\lambda\phi} + [SM^{T_b^{max}}_{\lambda\phi} - SM^{T_b^{min}}_{\lambda\phi}]I_{1_{\lambda\phi}}(t)$$

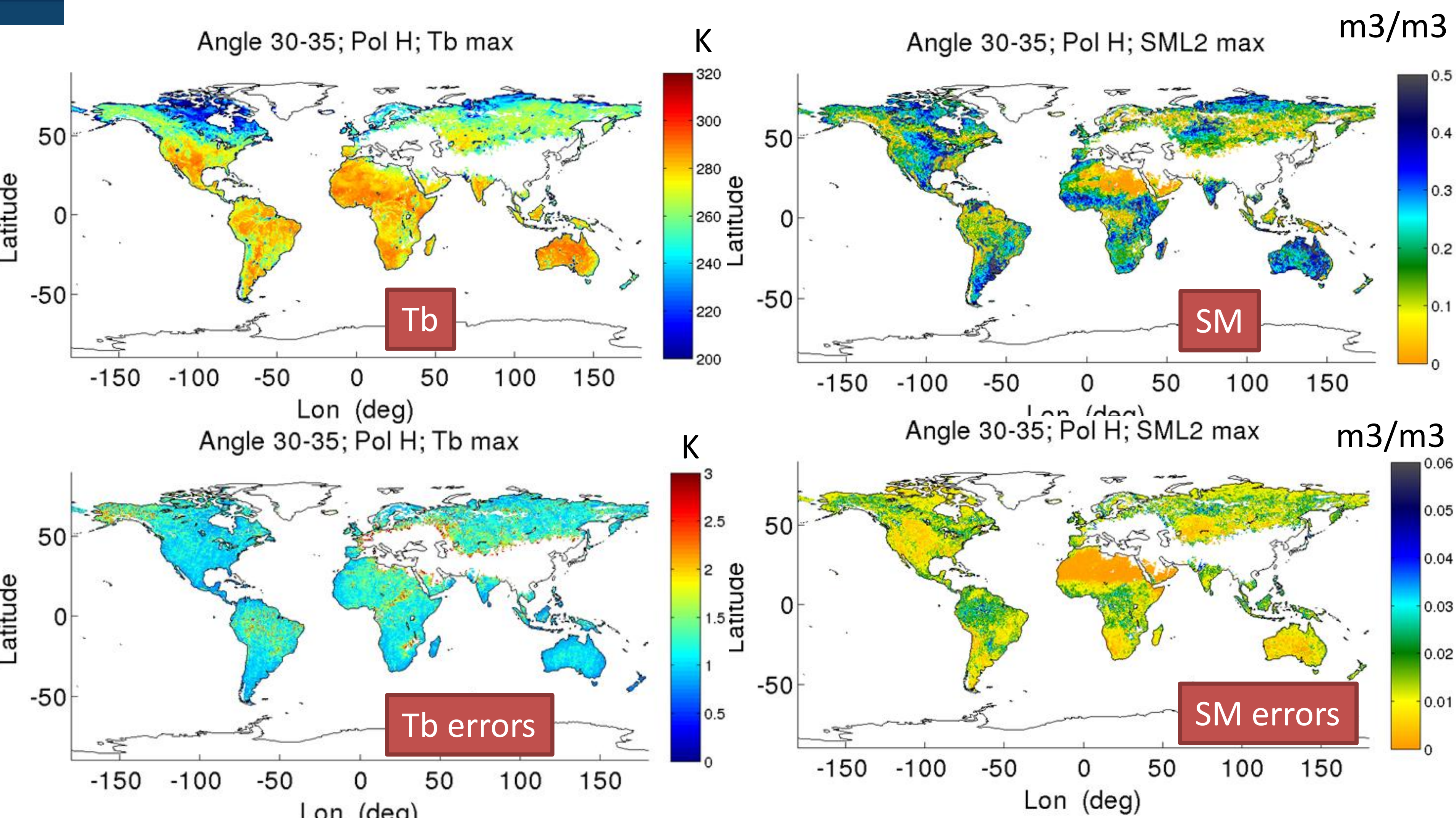
$$\Delta I_{2_{\lambda\phi}}(t) = \left\{[SM^{T_b^{max}}_{\lambda\phi} - SM^{T_b^{min}}_{\lambda\phi}]^2(\Delta I_{1_{\lambda\phi}}(t))^2 + [1 - I_{1_{\lambda\phi}}(t)]^2(\Delta SM^{T_b^{min}}_{\lambda\phi})^2 + [I_{1_{\lambda\phi}}(t)]^2(\Delta SM^{T_b^{max}}_{\lambda\phi})^2\right\}^{1/2}$$

$$(\Delta v^{L2})^2 = \sum_{i=1}^{n_{in}}\left\{(\Delta v_i^{norm})^2\left(\sum_{j=1}^{n_{L1}} W^j_{L2} W^{ij}_{L1}\sigma^j\right)^2\right\}$$

$$\sigma^j = 1 - \tanh^2\left(\sum_{i=1}^{n_{in}} W^{ij}_{L1} v_i^{norm} + B^j_{L1}\right)$$

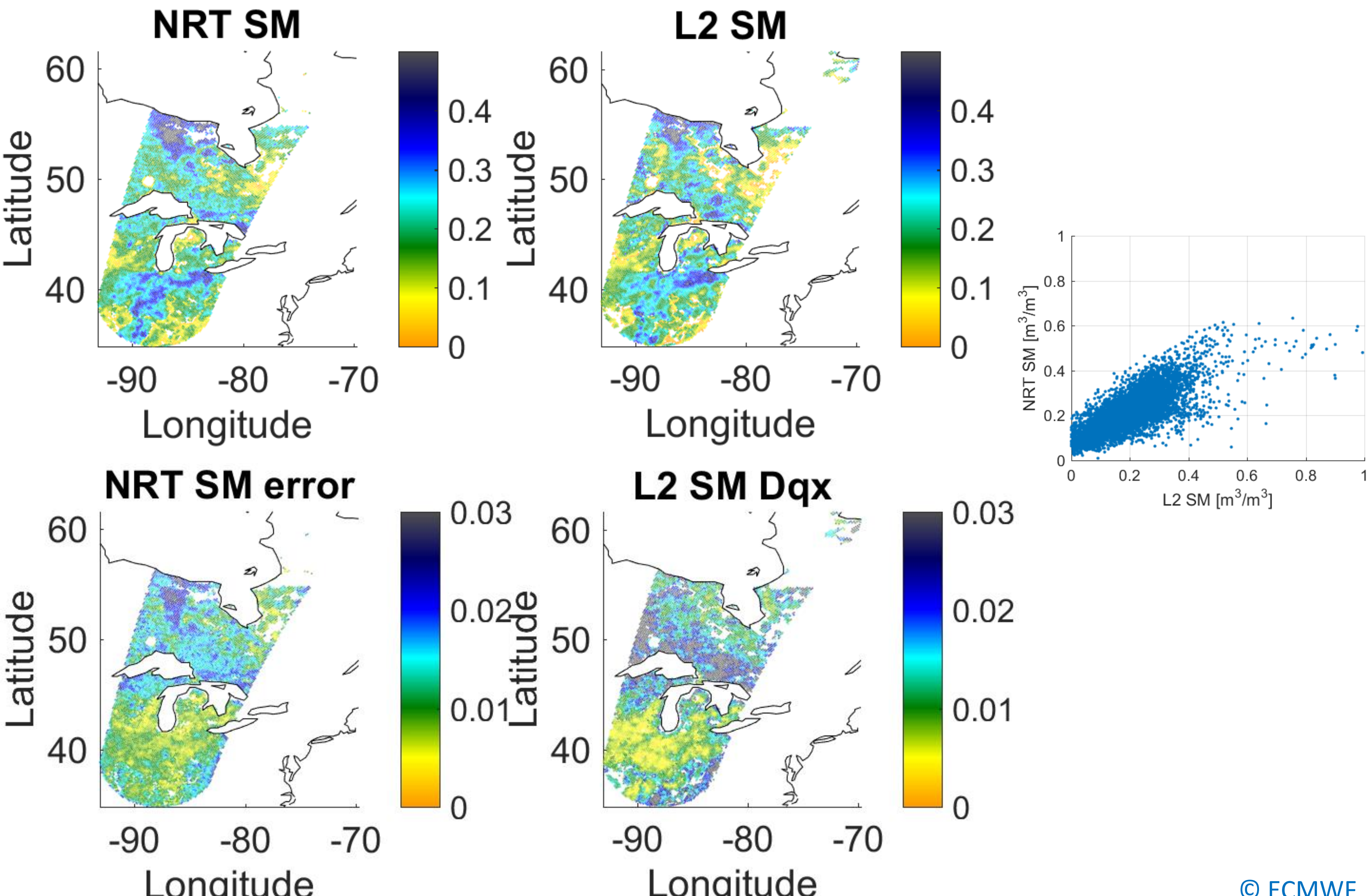
Takes into account uncertainties in the input data but not uncertainties
In the neural network weights (W): lower limit to the actual total errors but errors
In the training data are taken into account via errors in I2

Examples of input errors

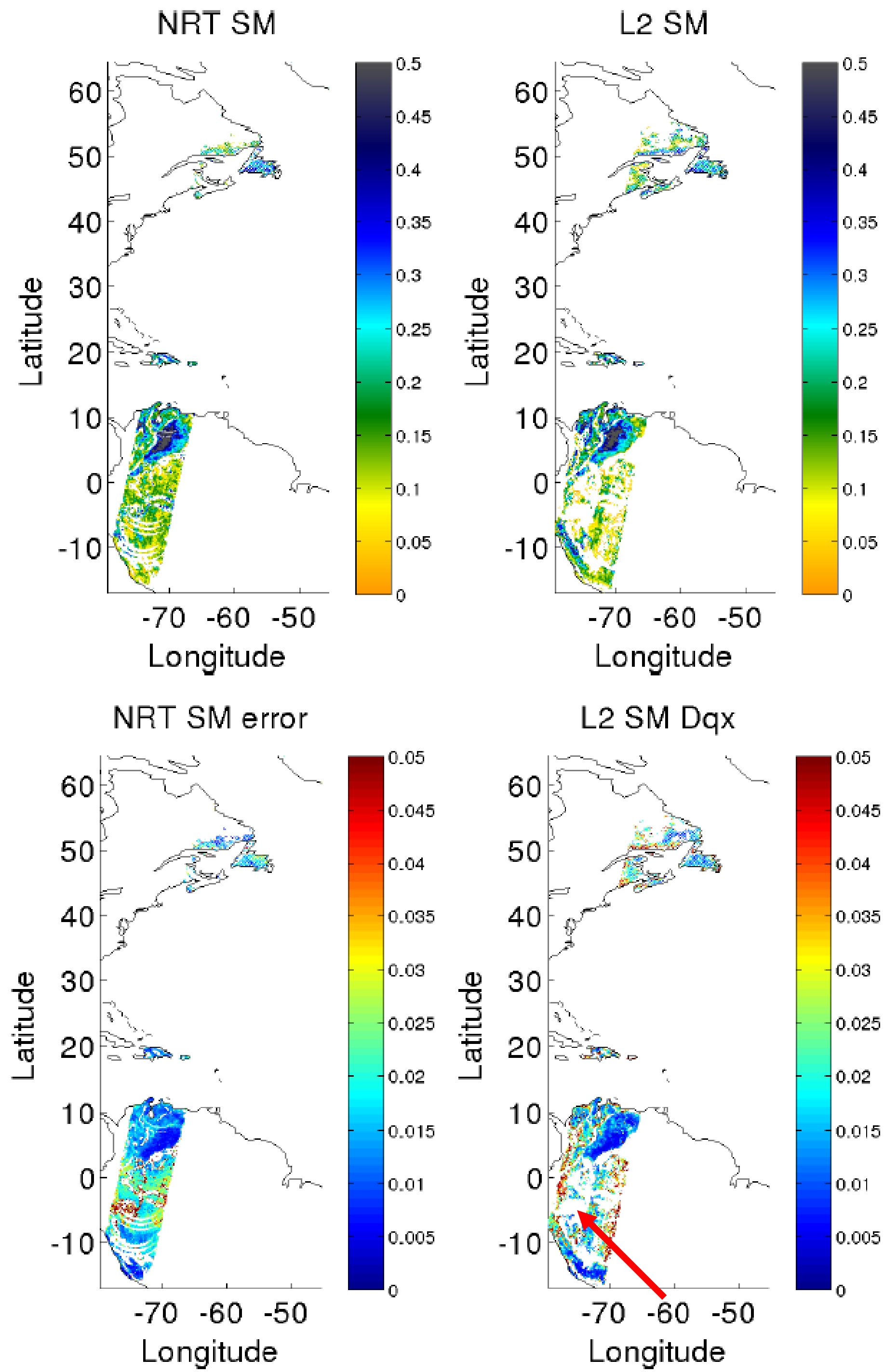


Maximum values maps from June 2010 to June 2012 and associated errors

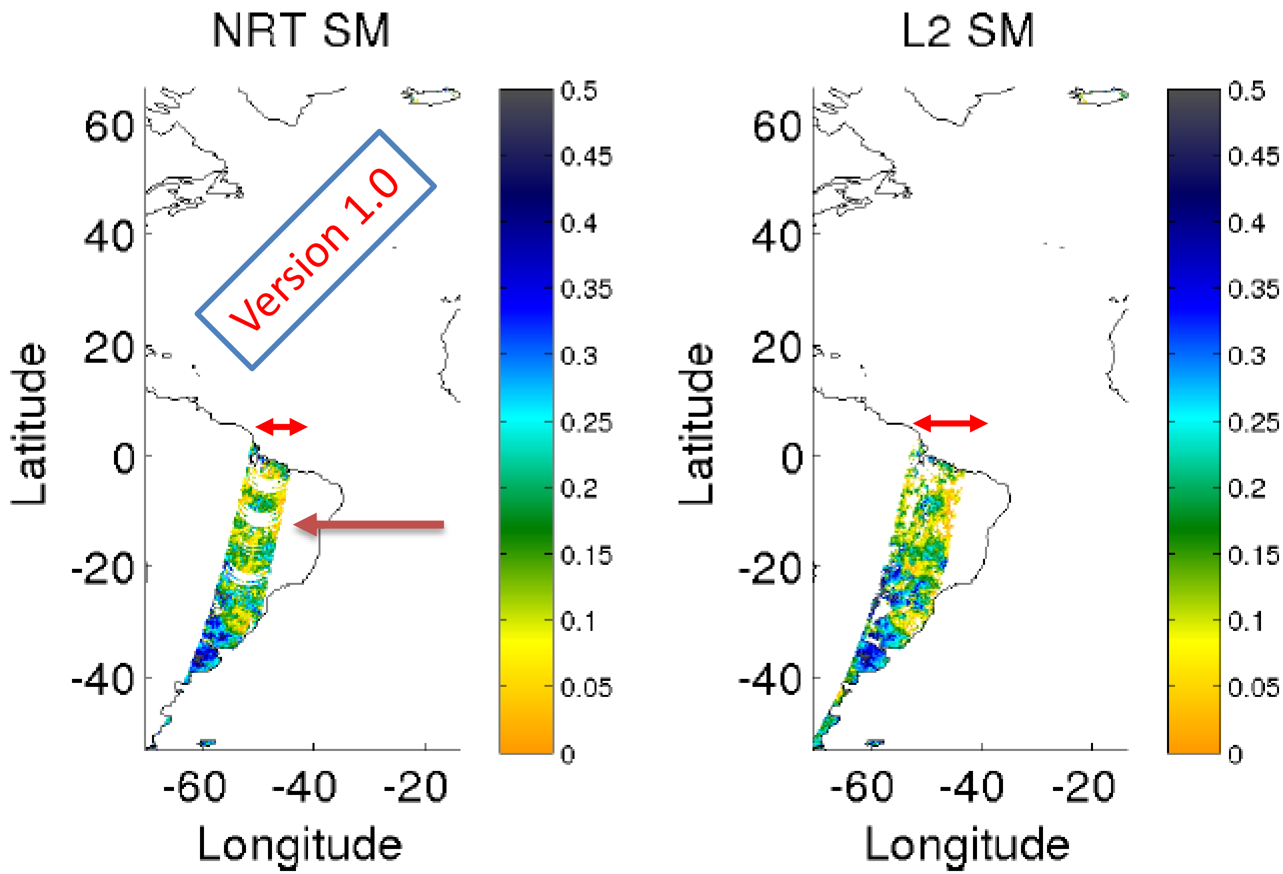
SMOS NRT SM: comparison to L2SM



SMOS NRT SM: comparison to L2SM

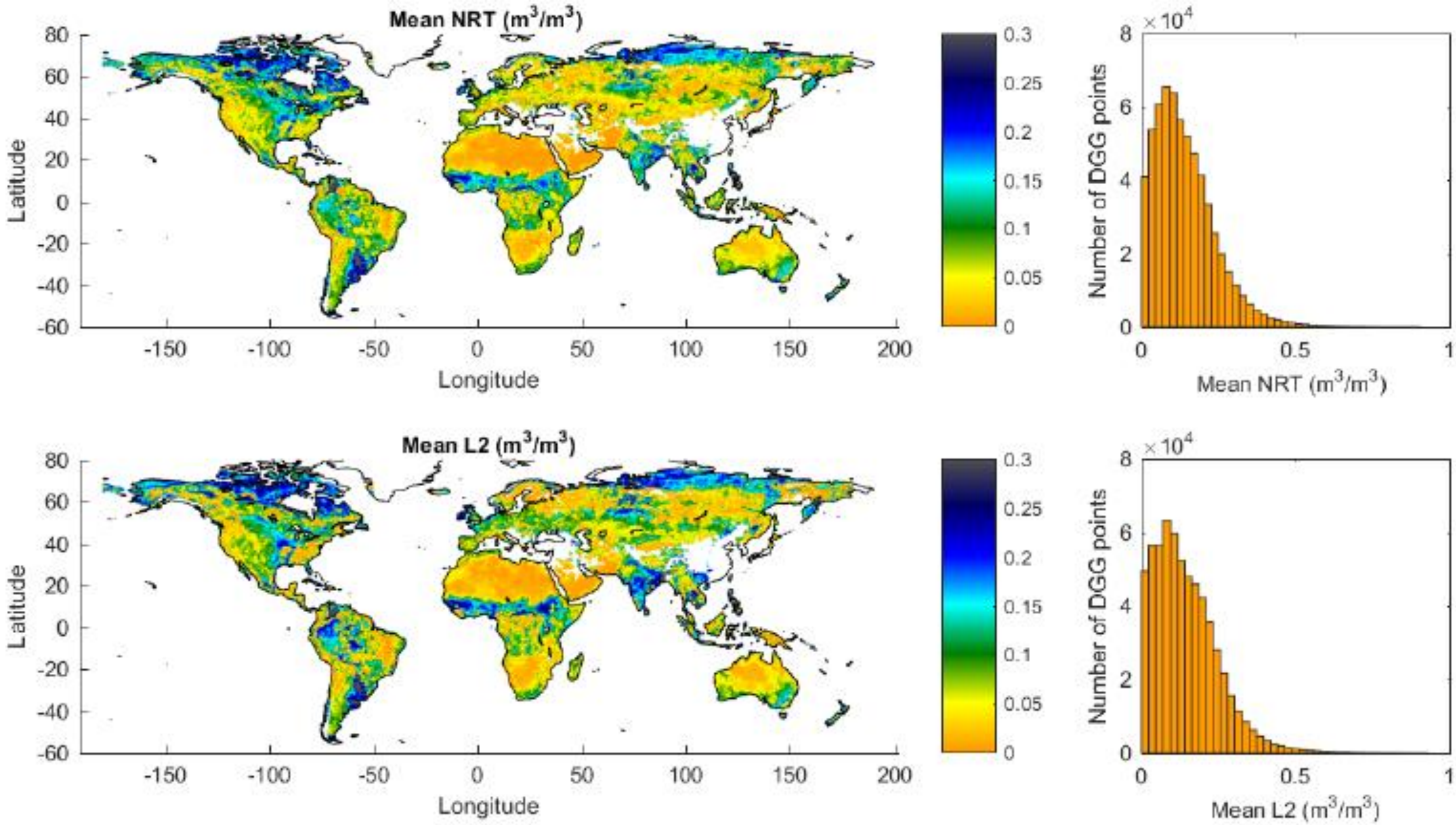


NRT SM limitations



- The NRT can show some circular gaps if not all the Tbs from 30º to 45º are available for a given observation
- The swath width of the NRT retrieval is ~915 km while it is ~ 1150 km for operational L2

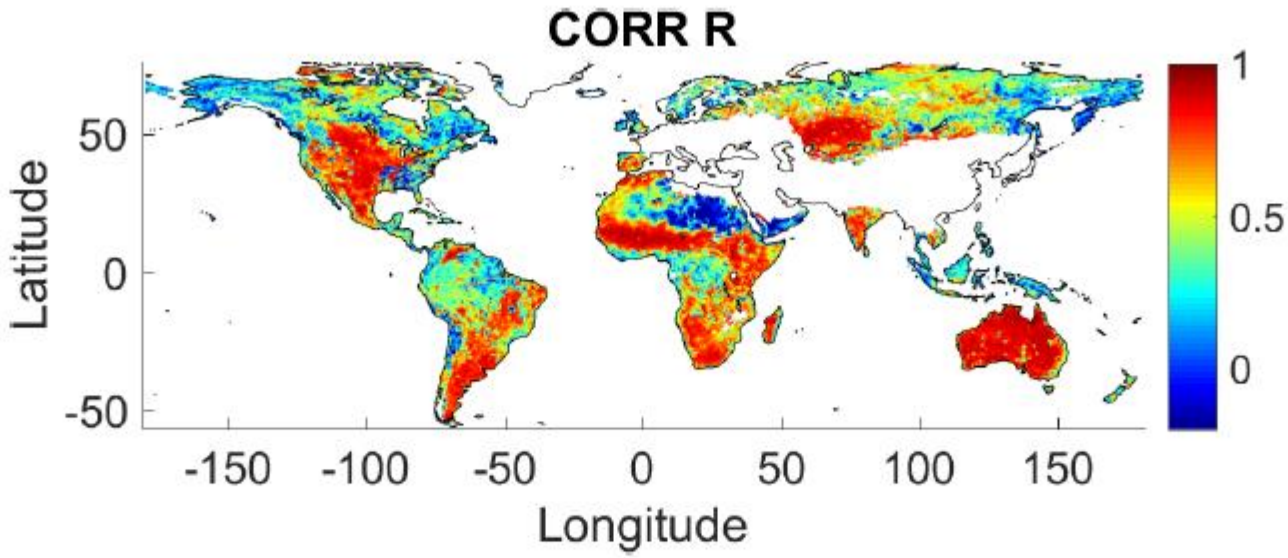
Global comparison to L2 SM



From May to November 2015

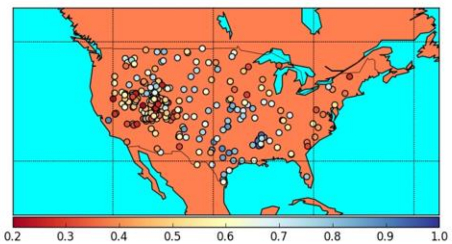
Rodríguez-Fernández, Muñoz-Sabater et al (in prep)

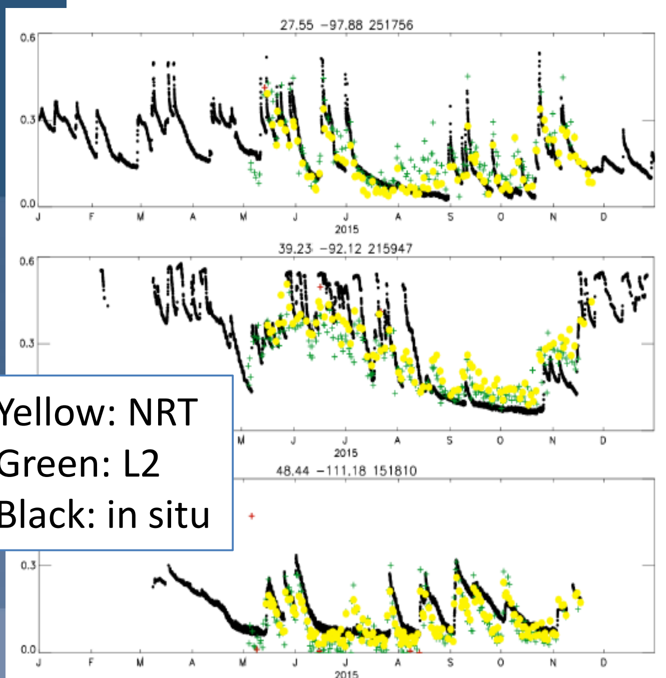
Global comparison to L2 SM



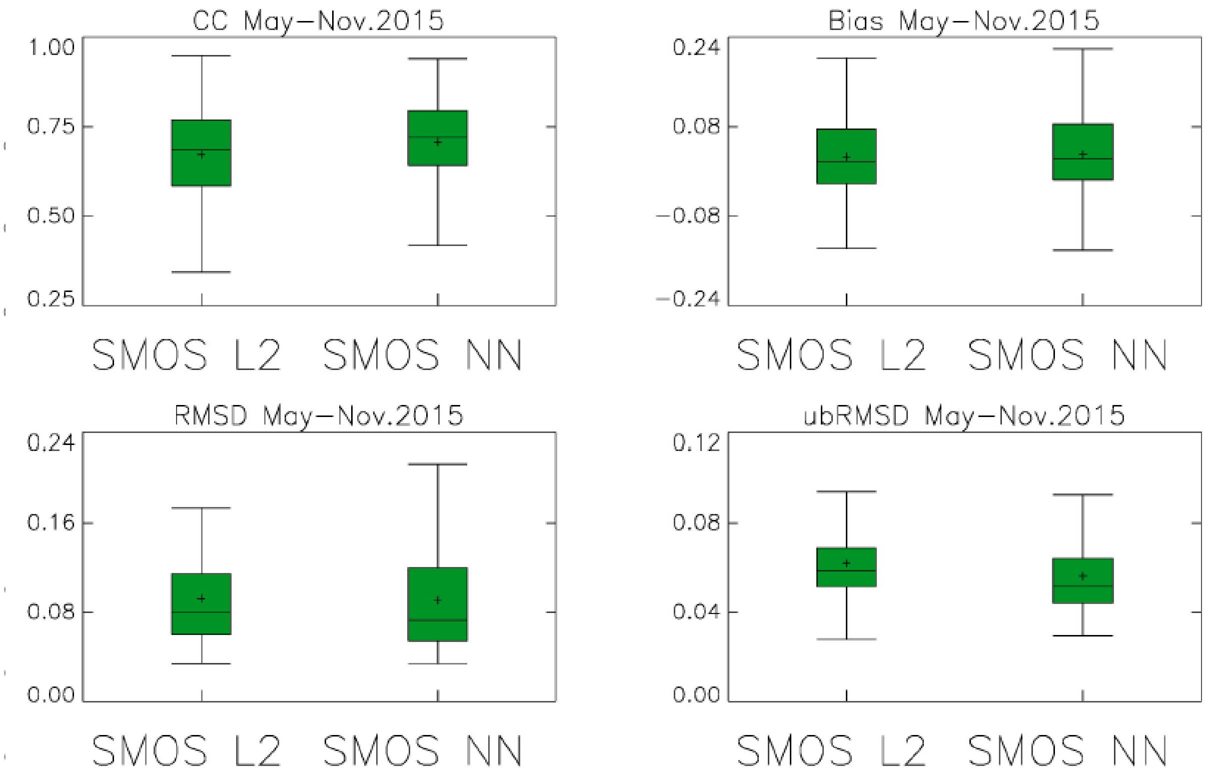
From June 2010 to June 2012

Evaluation against SCAN and USCRN *in situ* measurements





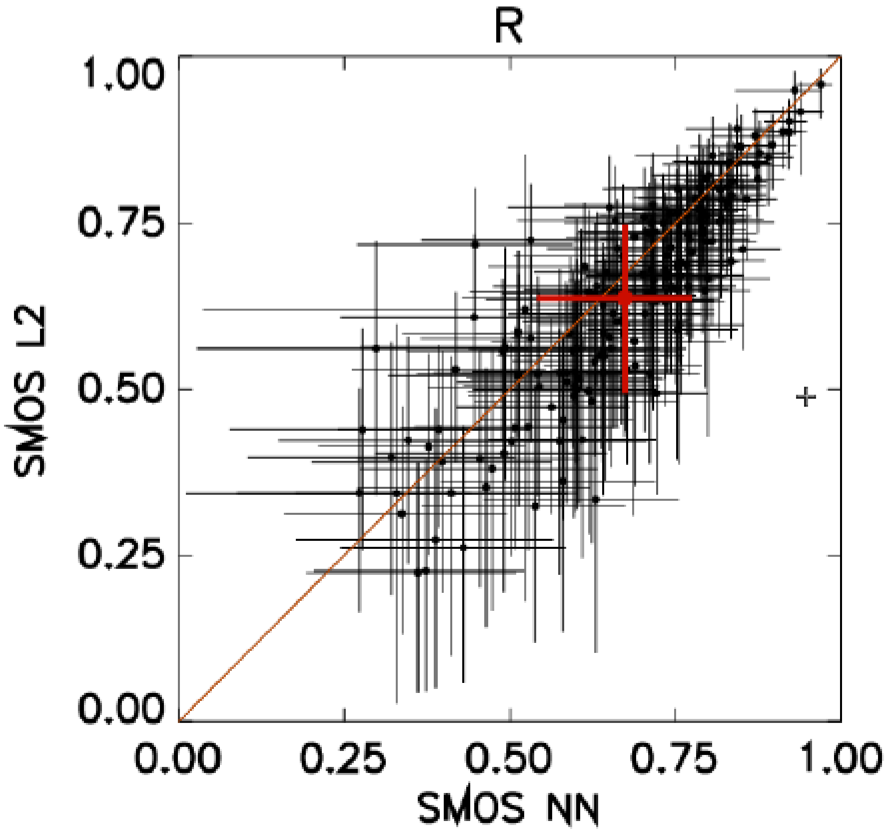
Yellow: NRT
Green: L2
Black: in situ



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 (in prep)

Evaluation against SCAN and USCRN *in situ* measurements



The NRT SM and the L2 SM **give similar correlation** with respect to in situ measurements **site per site**

Rodríguez-Fernández, Muñoz-Sabater et al (in prep)

SMOS NRT SM product

A new esa official product

Follow up of : smos+ neural net support to science element

CESBIO Estellus

Rodríguez-Fernández et al. 2015, IEEE TGRS

Implemented by : ECMWF

With support by : CESBIO

- Similar characteristics to current SMOS Level 2 Soil Moisture
- Available in less than 3.5 hours after sensing
- Disseminated via GTS and EUMETcast

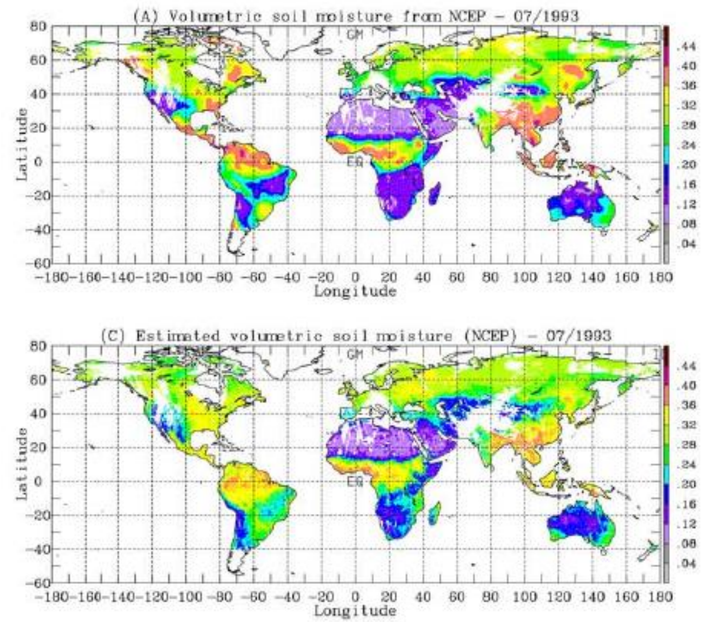
A new type of satellite surface products

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)
- The NNs were trained with NCEP or ECMWF models

Towards a new generations of satellite surface products ?

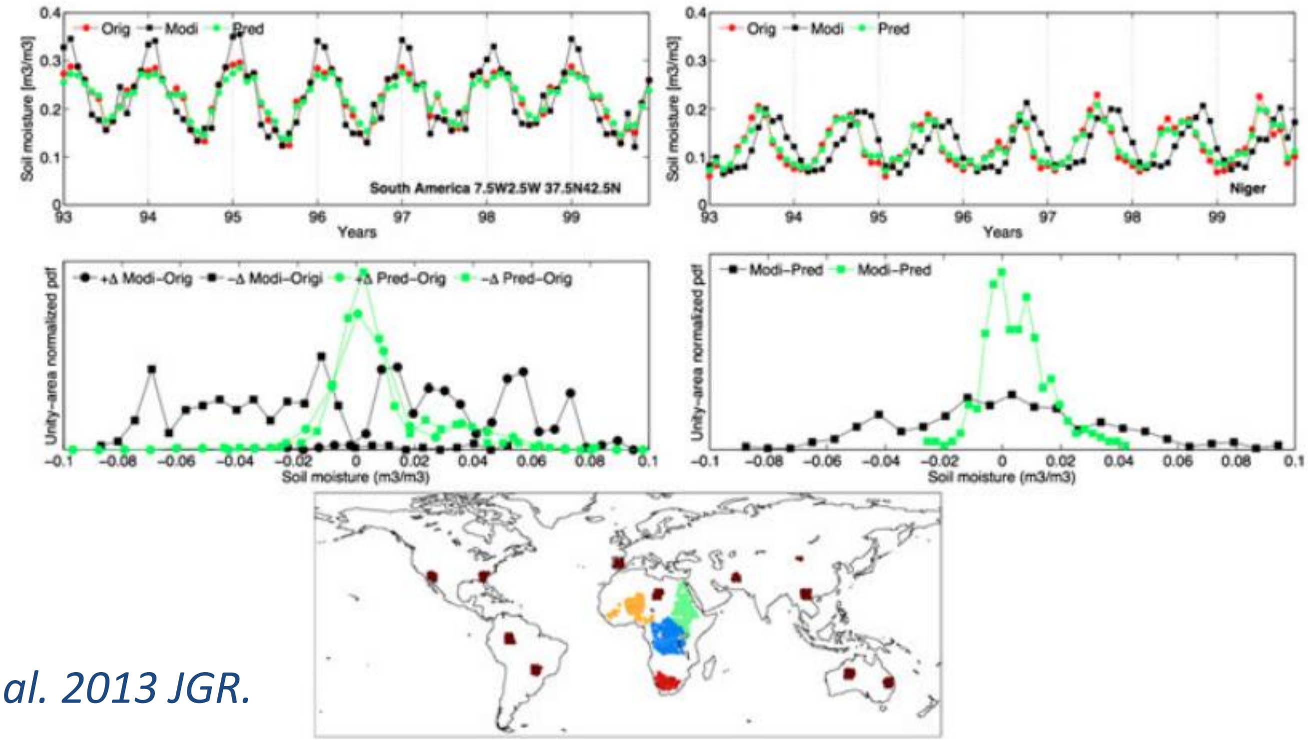
- Soil moisture, Skin temperature
  Prigent & Aires 2006, JGR



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

- **One interesting application will be efficient Data Assimilation. Since the retrieved data sets are similar to the model fields, by construction, while they are driven by the remote sensing input data**

The retrieval is driven by the input data



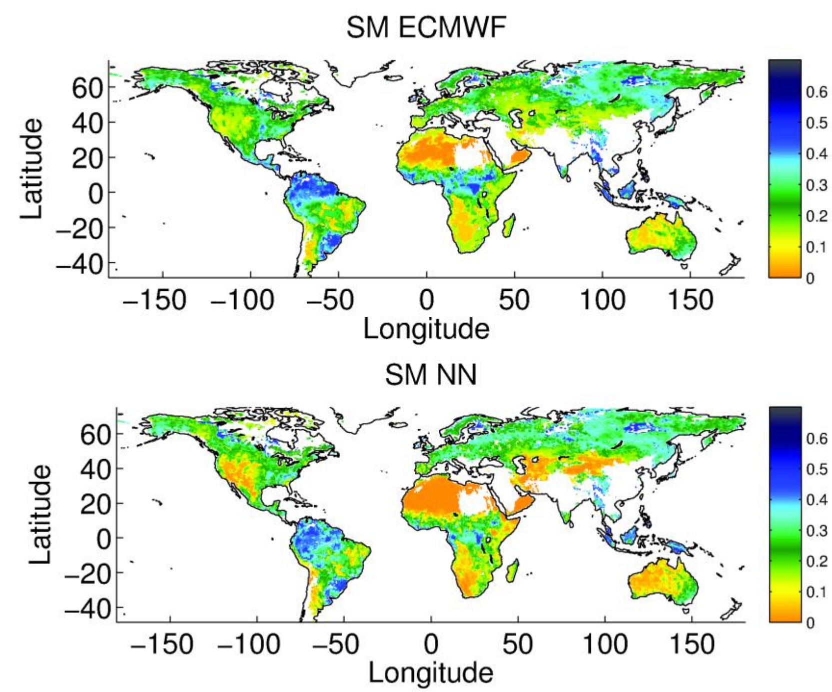
Jimenez et al. 2013 JGR.

Training on artificially modified JULES soil moisture fields

The NN gives the good result even when a small fraction of the training data is incorrect

Assimilation of SMOS neural network soil moisture at ECMWF

- Same methodology of Aires et al 2004 but applied to SMOS
- Specific SM dataset **training on ECMWF** SM (0-7 cm)
- No temporal averaging is needed thanks to the high sensitivity of SMOS to soil moisture



Rodríguez-Fernández et al 2015, IEEE TGARS

SMOS NN Data Assimilation

- Land surface only assimilation forced with ERA-Interim
- Forecast experiment with the surface analysis
- Comparison of:
  - Control
  - T2m, RH2m, ASCAT
  - T2m, RH2m, SMOS NN
  - T2m, RH2m, SMOS NN + ASCAT

- Project just started: stay tuned !

Thank you for your attention:

SMOS blog: http://www.cesbio.ups-tlse.fr/SMOS_blog/

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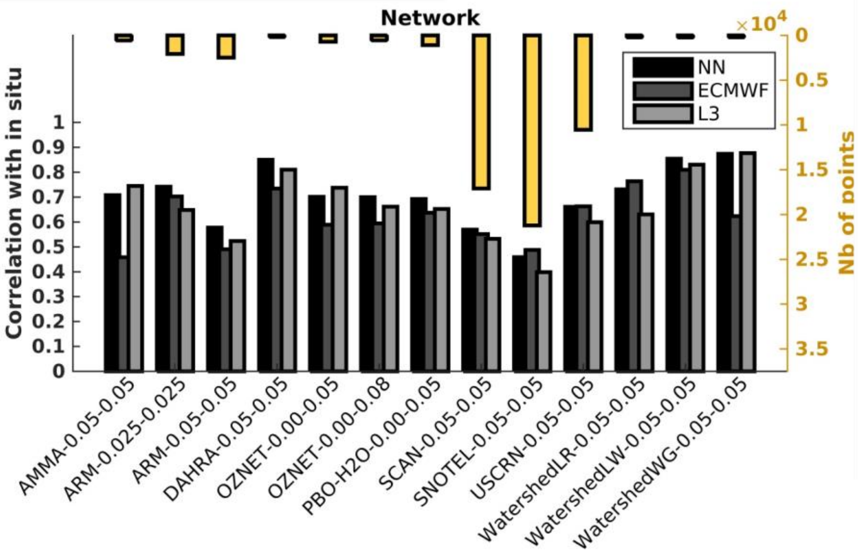
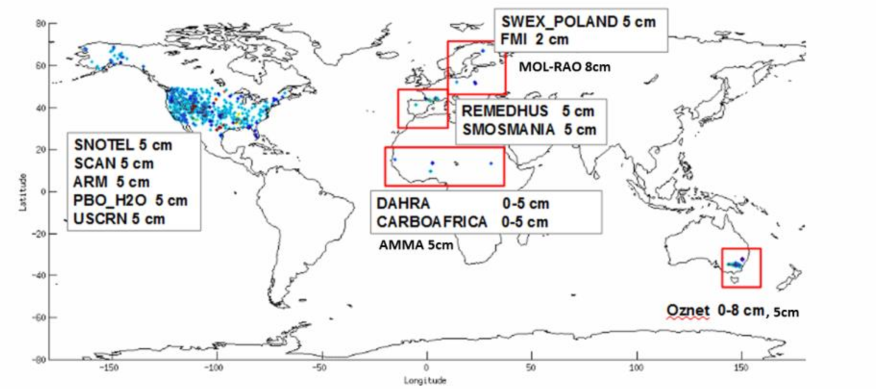
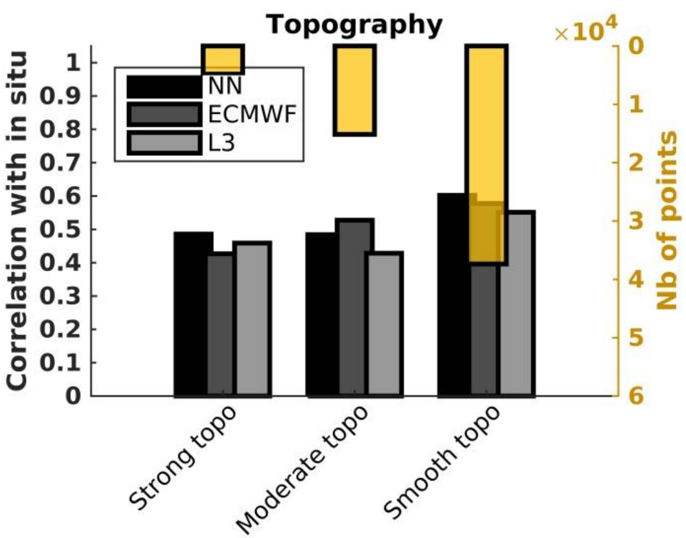
Evaluation against in situ measurements as a function of other parameters

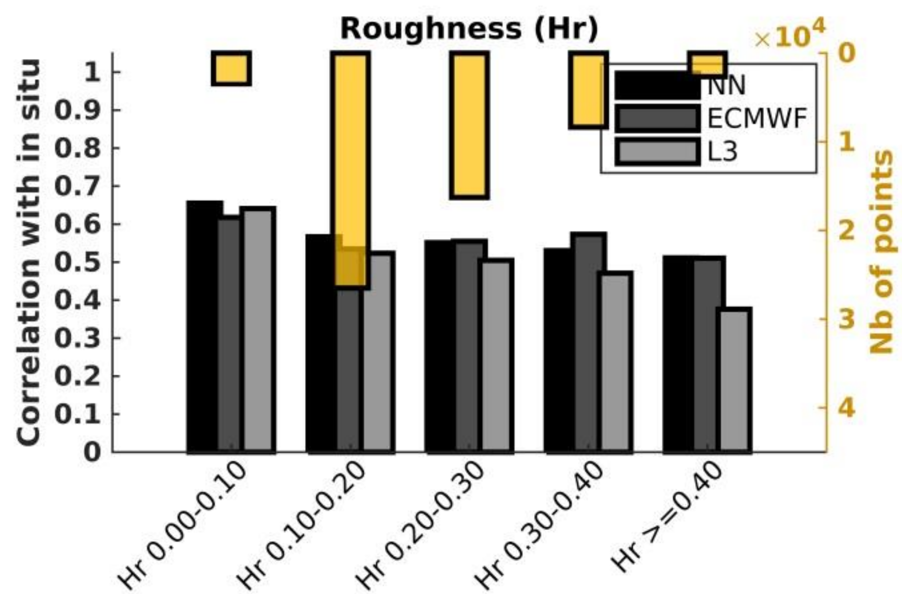
June 2010 - June 2013

Kerr et al. 2016 (submitted, RSE special issue)



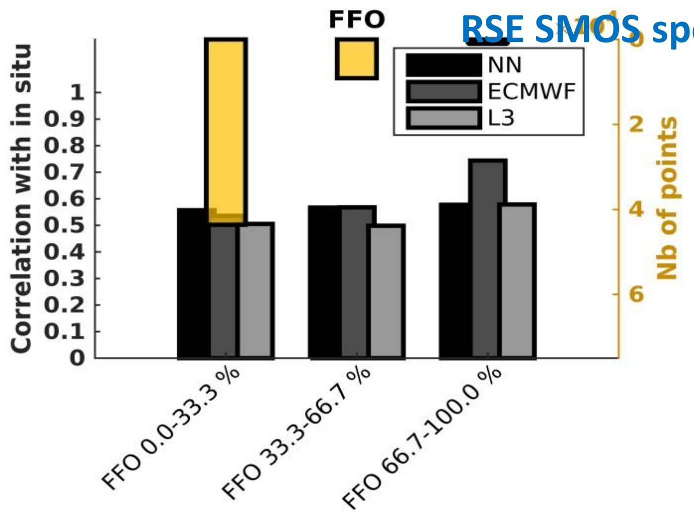


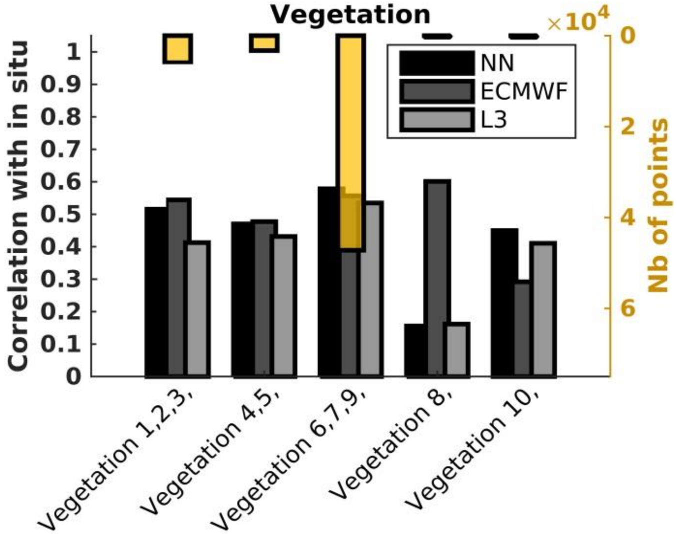


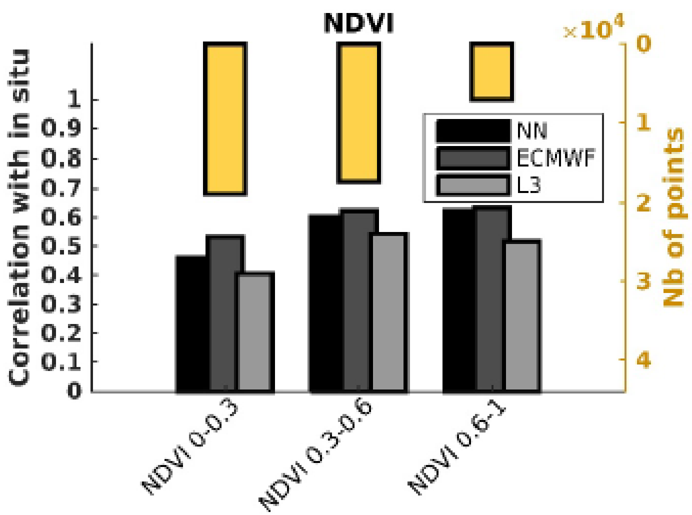


Evaluation against in situ measurements as a function of other parameters

Kerr, Al Yaari, Rodriguez-Fernandez et al. 2016, RSE SMOS special issue







1= rain forest
2= evergreen forest
3= deciduous forest
4=evergreen woodland
5=deciduous woodland
6=cultivation
7=grassland
8=tundra
9=shrubland
10=desert