Application of ANN techniques for the soil moisture retrieval from active and passive microwave satellite acquisitions

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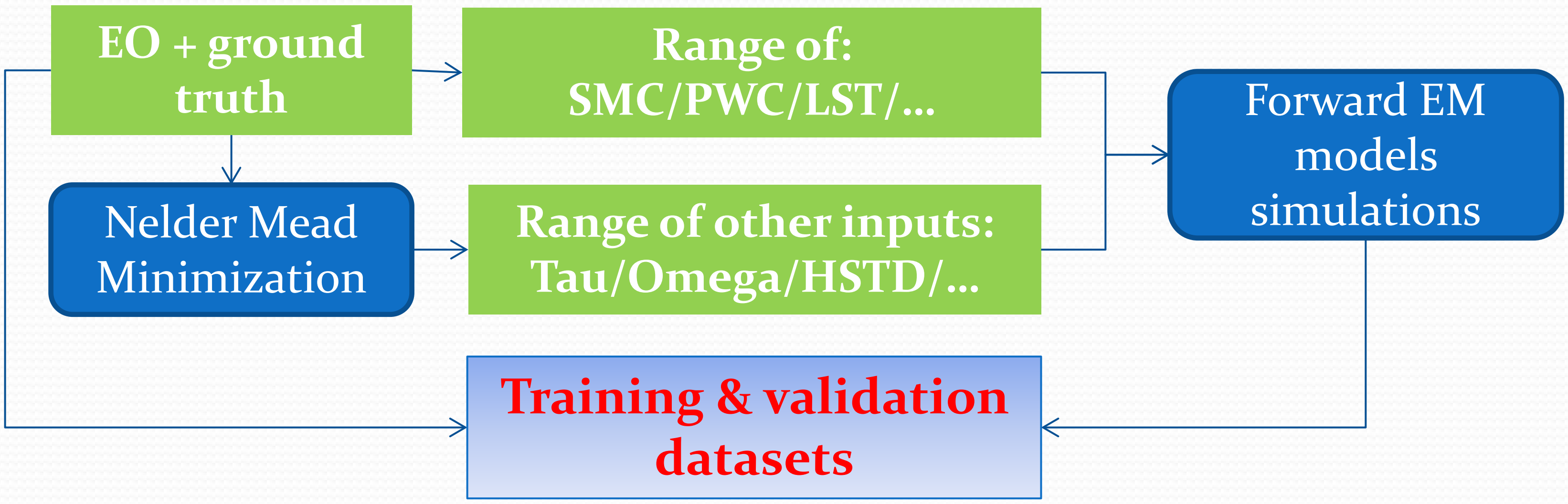
Introduction

- The **moisture of soil (SMC)** is the chief-factor affecting the hydrological cycle: a systematic and timely monitoring of this parameter is of primary importance for managing environmental resources as well as natural disasters.
- the **possibility of observing soil moisture** from space is therefore extremely attractive for the most part of the applications related to the environmental disciplines, such as climatology, meteorology, hydrology and agriculture.
- The retrieval of soil moisture from EO microwave measurements is however an **ill posed problem** because, in general, more than one combination of surface parameters has the same electromagnetic response.
- in order to minimize the uncertainties and enhance the performance of the retrieval of soil parameters from remote sensing data, **statistical approaches are widely adopted**
- In this framework the **Artificial Neural Network** (ANNs) represent **a good compromise** between **retrieval accuracy** and **computational cost** respect to other statistical approaches based on Bayes theorem and Nelder-Mead iteration (Paloscia et al. 2008).
- **4 ANN based algorithms** for SMC retrieval from **AMSRE, SMAP, ASCAT** and **C-band SAR** from **ENVISAT/RADARSAT** will be presented here.

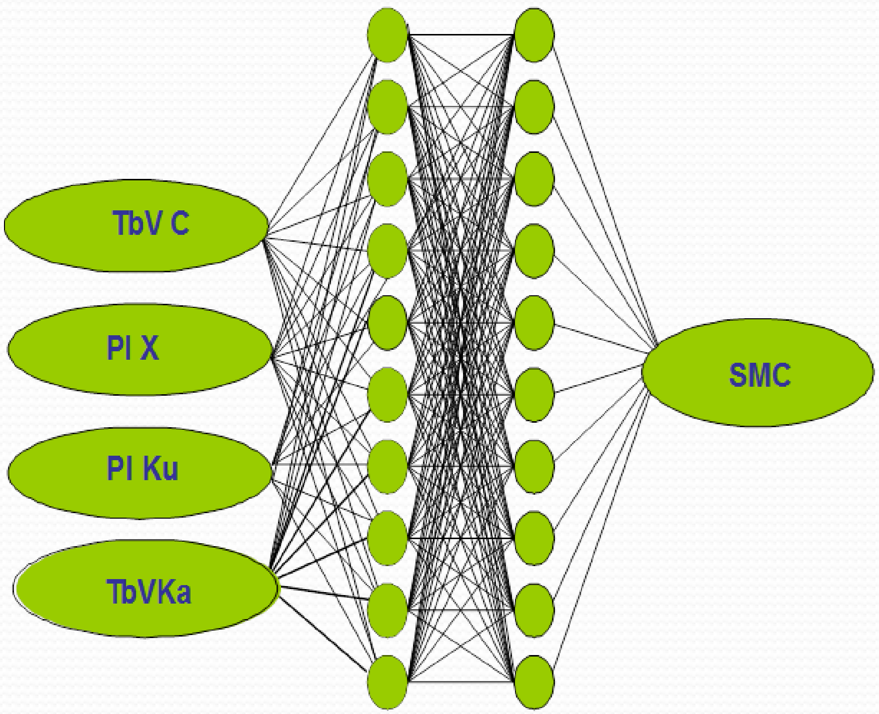
ANN training

- The main constraint for obtaining a good accuracy with ANN approaches is the "**robustness" of the training**, that has to be representative of a variety of surface conditions as wide as possible.
- The datasets derived from experiments are not enough for training ANNs for large scale/global monitoring.
- Training set is therefore obtained by **combining experimental data and electromagnetic forward models** simulations based on RTT.
- The consistency between experimental data and model simulations is obtained by deriving the range of input parameters from the experimental data.



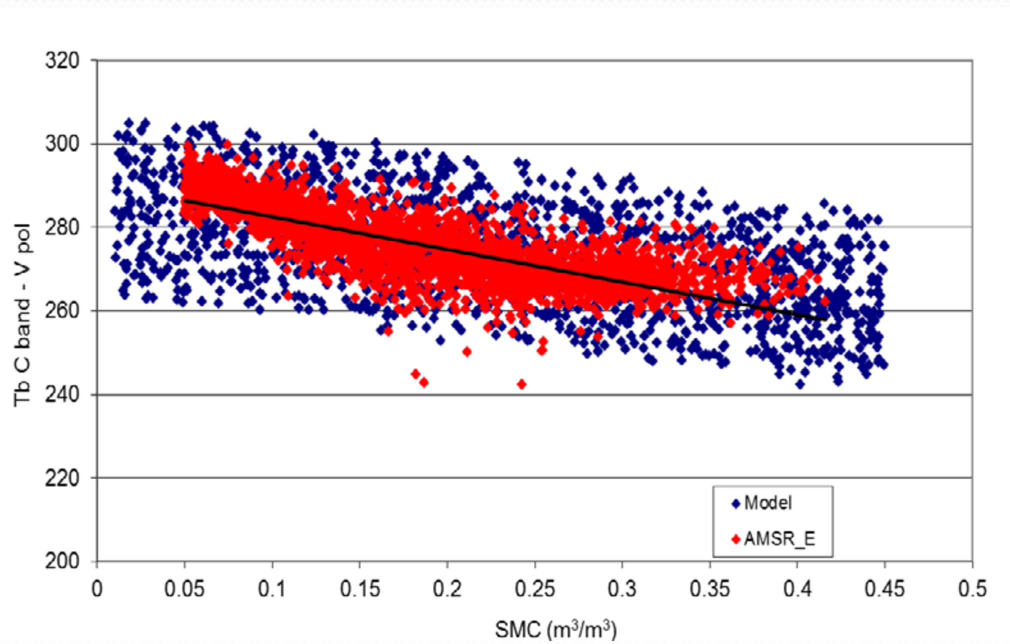
ANN algorithm for AMSR-E (HydroAlgo)

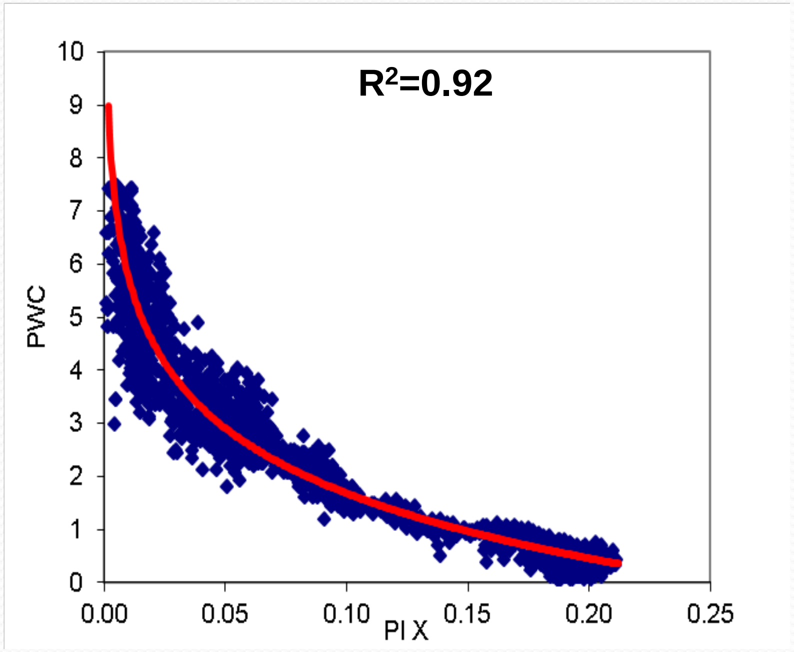
- **feed-forward multi-layer perceptron (MLP)**, with 2 hidden layers of neurons between the input and output.
- **The algorithm chosen for the training phase was the back-propagation (BP) learning rule**, an iterative gradient descent algorithm designed to minimize the mean square error between the desired target vectors and the actual output vectors.
- **Architecture** is defined after **optimization** process.



ANN algorithm for AMSR-E (HydroAlgo)

- The algorithm has been developed and tested using in situ observations over Mongolia and Australia and radiative transfer model ($\tau-\omega$) simulations (total about 10.000 samples).
- Surface temperature is estimated from the Tb at 37GHz in V pol.
- The spatial resolution at C- and X- band is improved using high frequency AMSR-E observations (37 GHz) and a decorrelation technique (SFIM).
- Vegetation effects are accounted by using the polarization index (PI) at X and Ku bands. **PI=2 (TbV-TbH)/(TbV+TbH)**



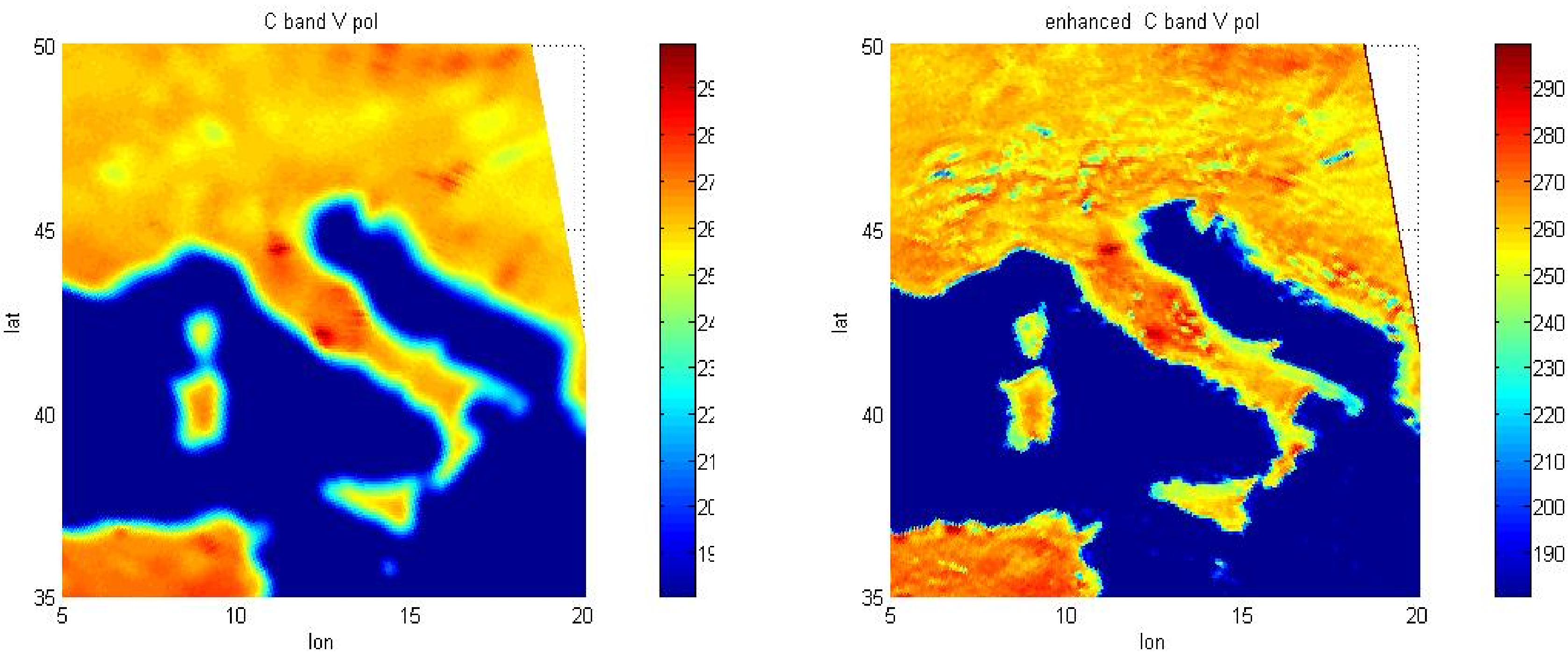


Santi et al. 2012

Spatial resolution enhancement

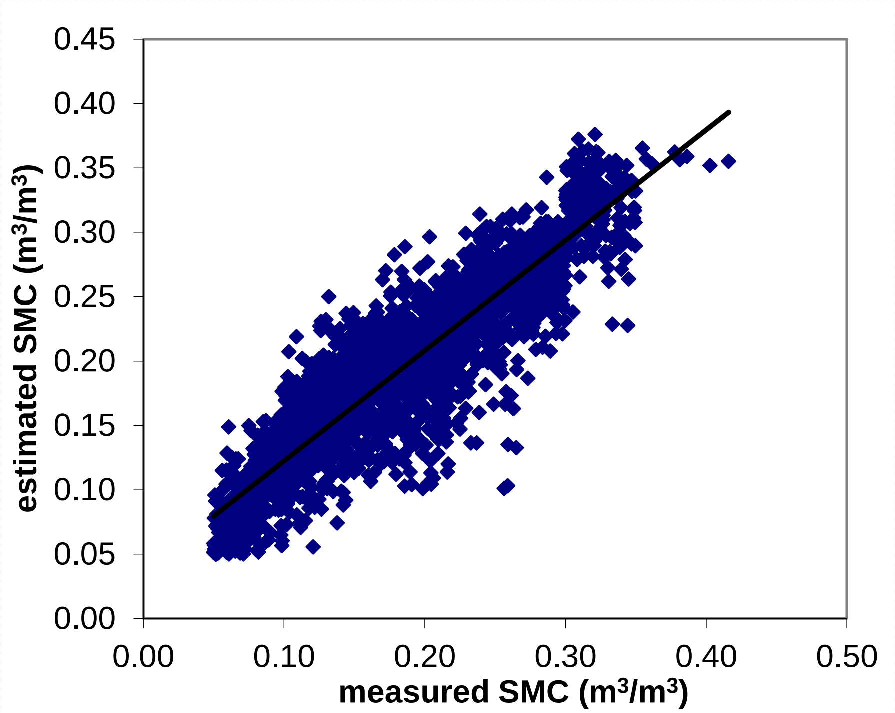
The AMSR-E sampling rate from C- to Ka- band is of about 10x10 km², however, the IFOV of the antenna, ranges between 70x40 km² at C- band and 14x8 Km² at Ka- band

- disaggregation derived from the smoothing filter-based intensity modulation technique - SFIM
- Ka band was used as reference "high resolution" image
- The enhanced image preserves the information contained in the original low-resolution image.



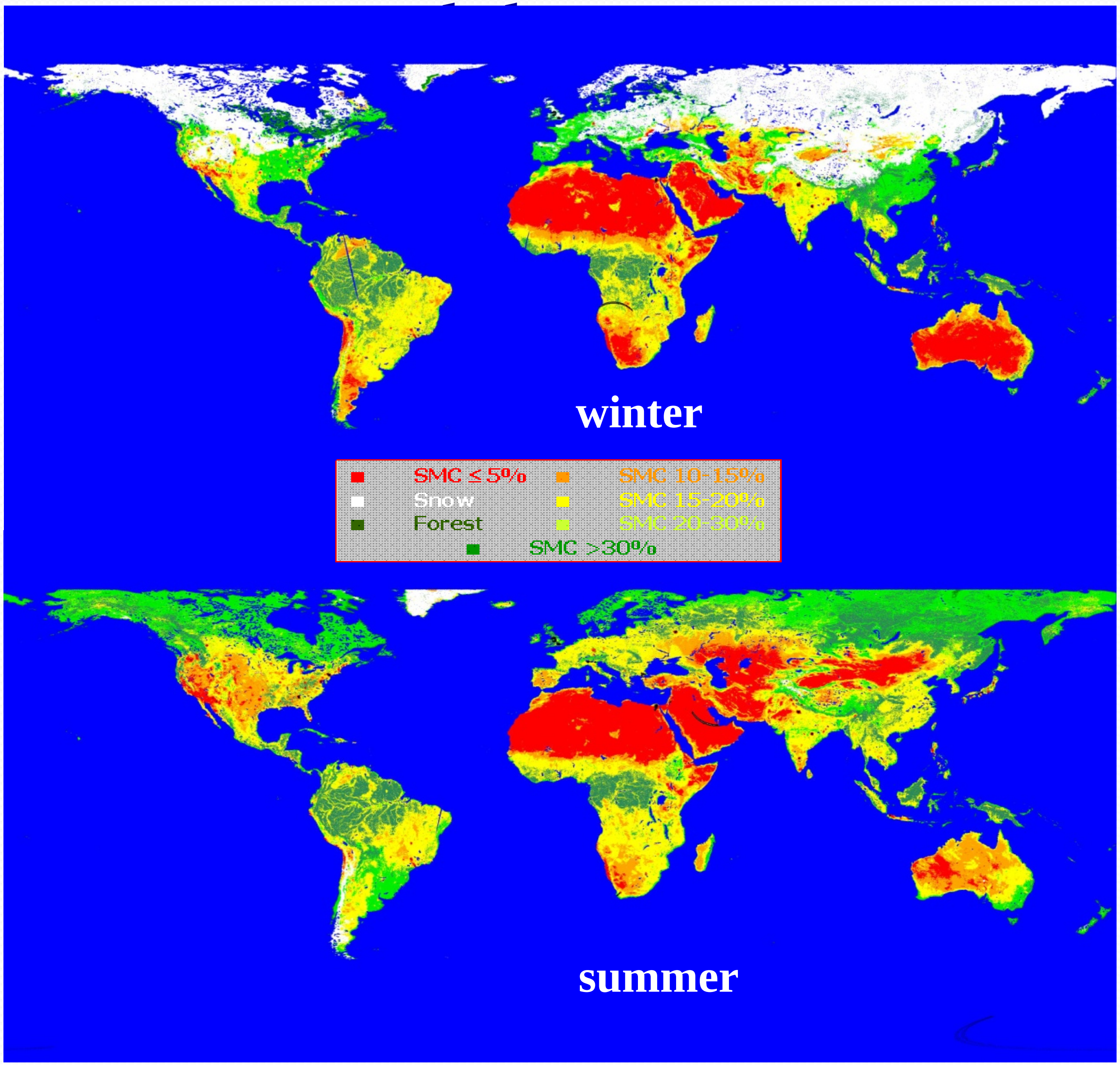
(Liu et al., 2000; Santi, 2010)

AMSR-E Algorithm validation



R^2=0.83, RMSE = 0.03, BIAS = 0.02

AMSR-E Algorithm: examples of global maps

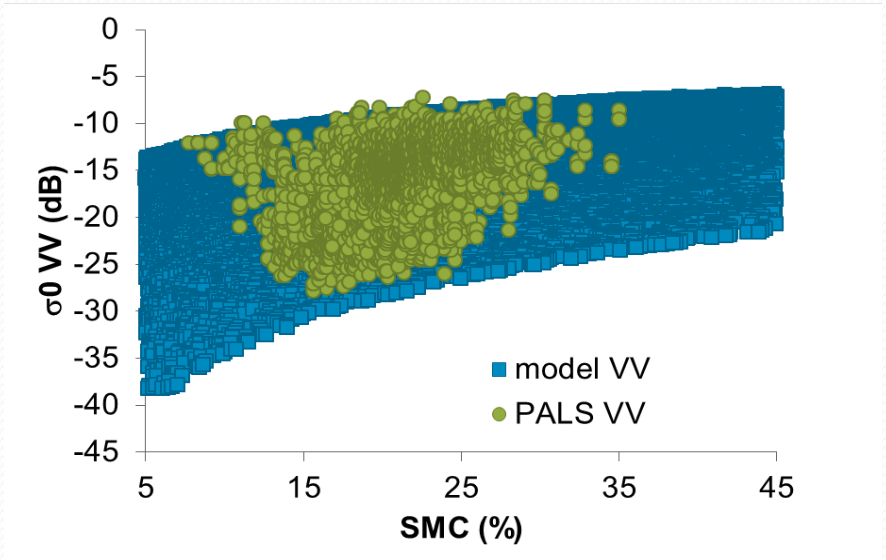


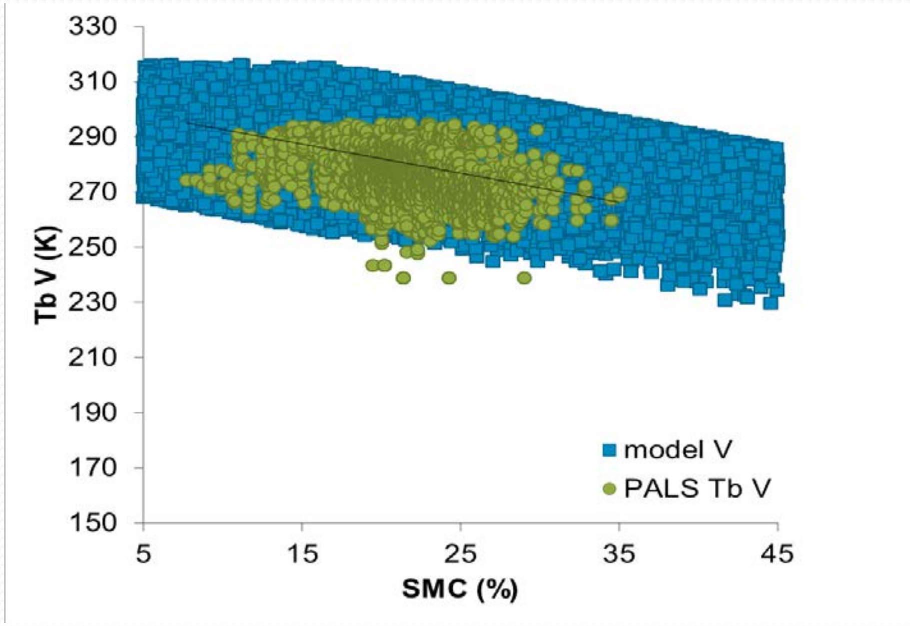
ANN algorithm for SMAP

ANN training

- Training based on the **SMEX02 dataset**
  - **L- band radar/radiometer from PALS**
  - **C- and X- band radiometer from PSR**
  - **ground truth SMC, PWC ….**

  → total ≅ 70,000 samples ←
- Training set improved adding 30.000 simulated values of Tb and σ° at L band from Mo Model and VWC model simulations (Attema, Ulaby).
- the range of surface parameters (SMC, LST, PWC, tau, omega, HSTD…) was derived from SMEX02 database.
  - **TRAINING → simulated + ½ experimental (approx. 65,000 samples)**
  - **VALIDATION → remaining ½ experimental (approx. 35,000 samples)**

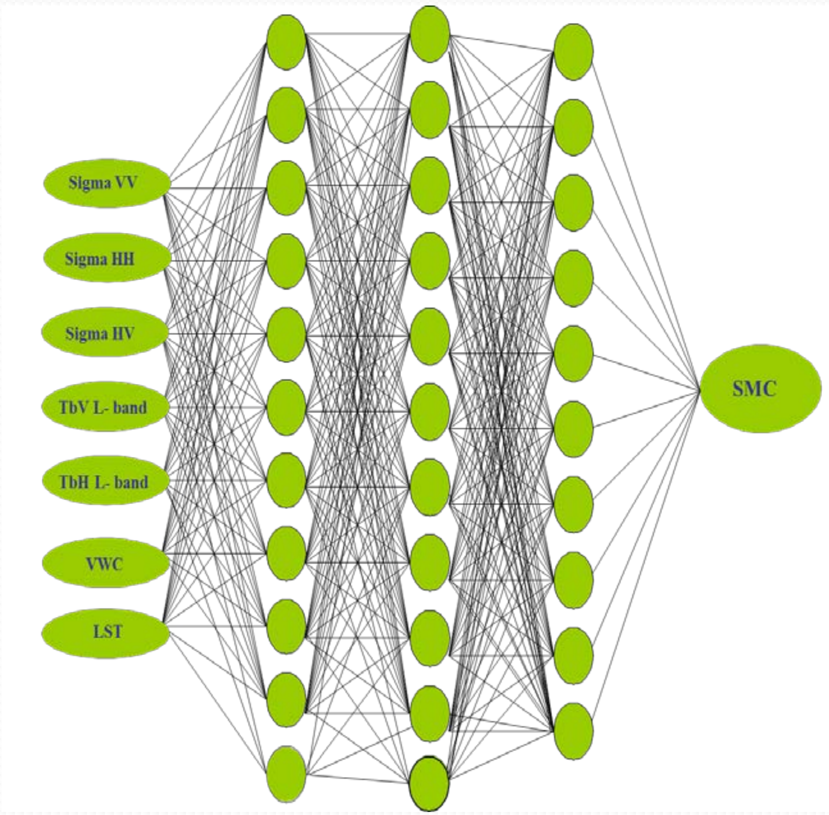


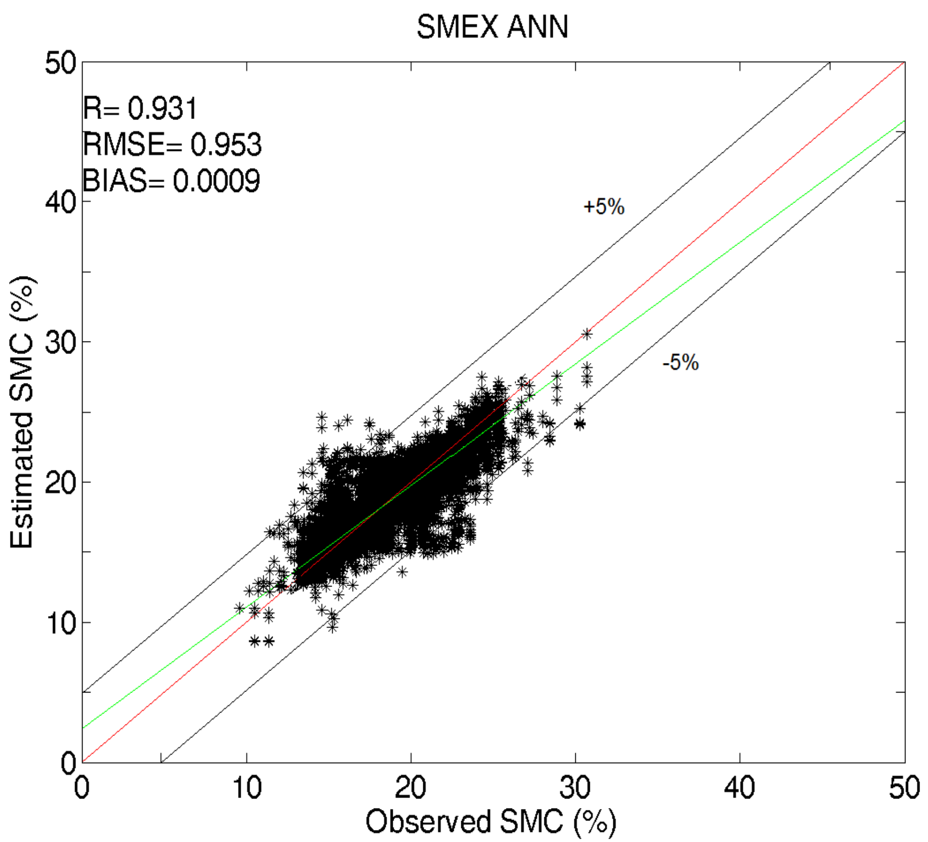


ANN validation on SMEX02

approx. 35.000 samples

<u>radar and radiometer data from PALS + PWC from PIX (PSR) + LST</u>

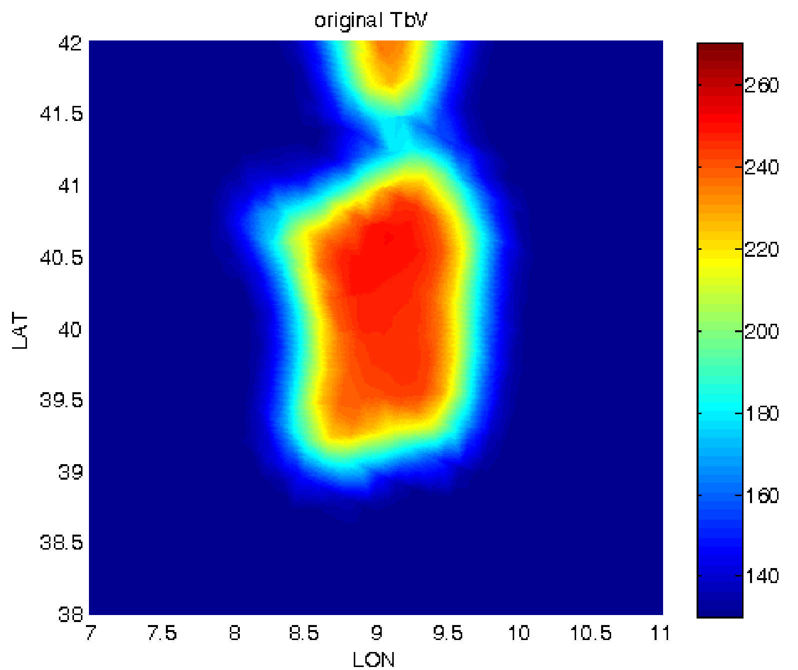


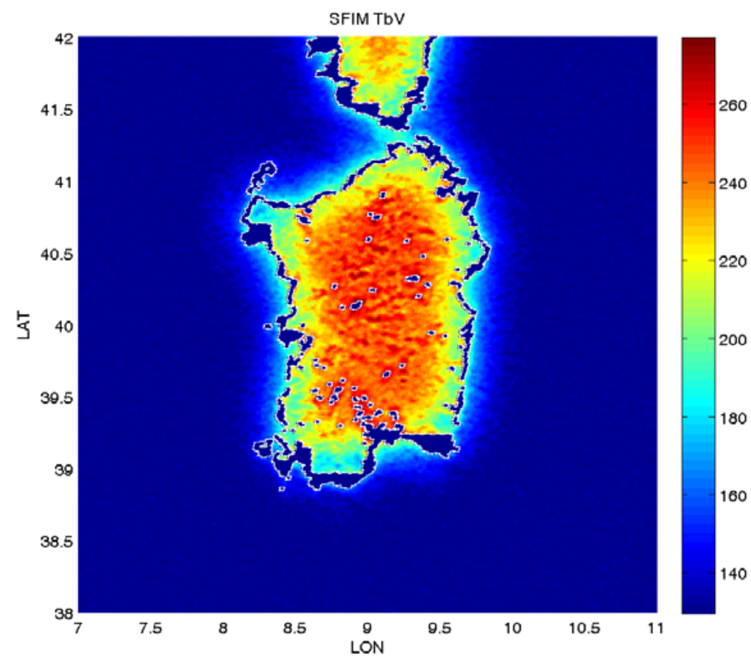


Applying to SMAP data

different ground resolutions between radar (1-3 km) and radiometer (36 km)

→Application of SFIM ←



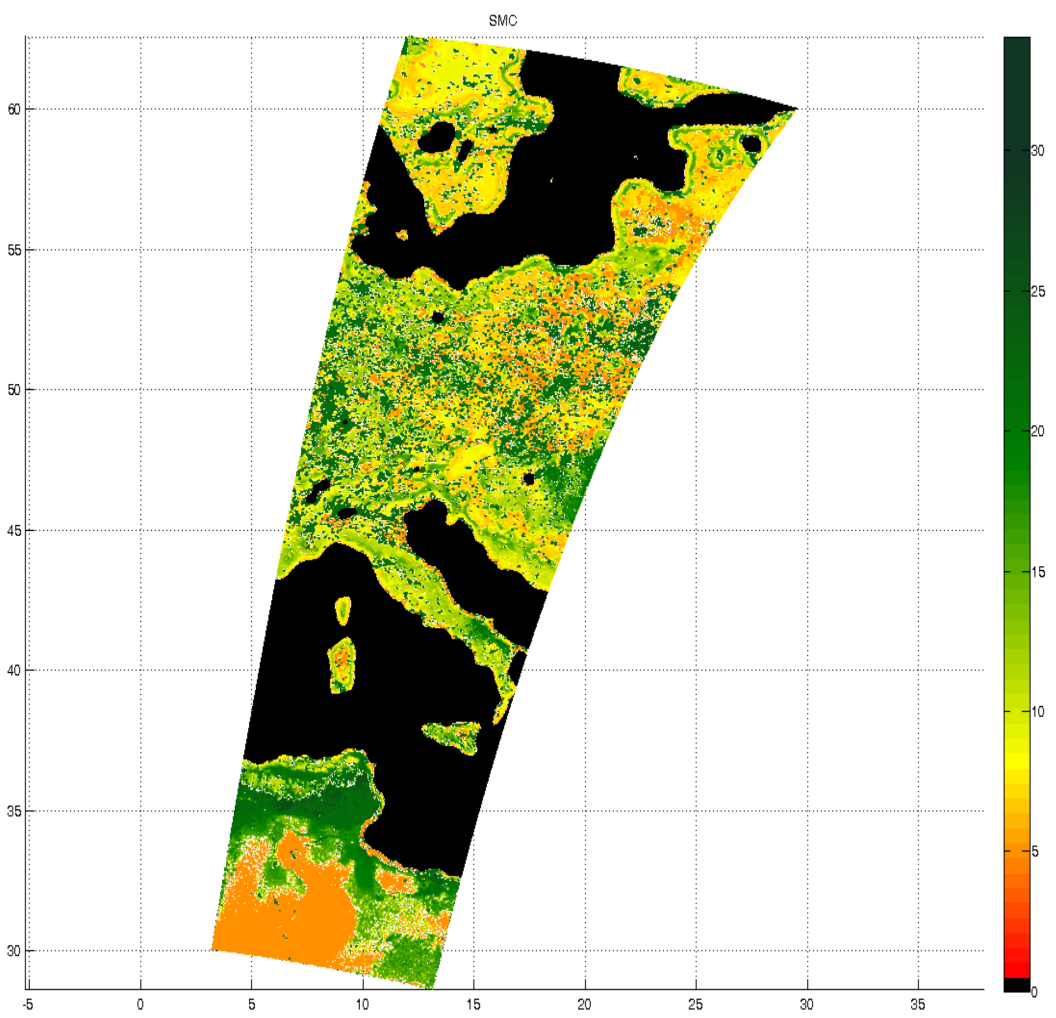


SARDINIA (ITALY)

Santi et al. 2014

Example on global scale:

SMC from ANN and simulated SMAP data



Santi et al. 2014

ANN algorithm for C- band SAR

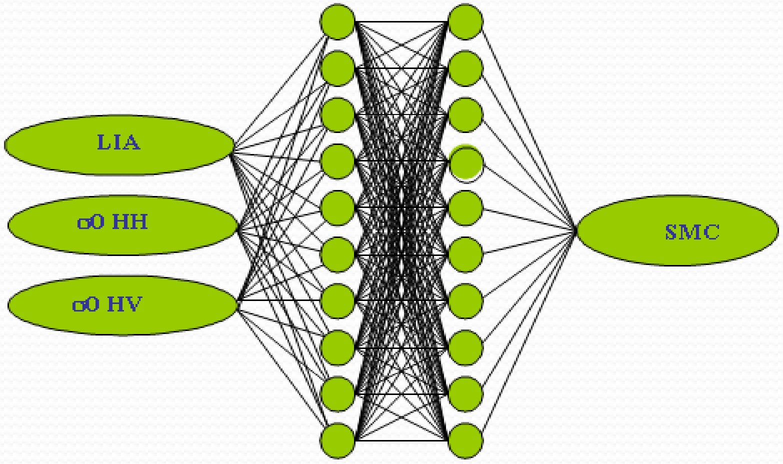
(Envisat/Radarsat/Sentinel 1)

ANN

- 6 ANN were developed depending on the S1 acquisition modes and the availability of ancillary information
- Inputs of ANN were σ° at various polarization and NDVI if available.
- Training set was composed by experimental data and forward e.m. model (AIEM + Oh + Water Cloud Model) simulations.

10000 Model simulations repeated varying randomly the input parameters :

- Incidence angle = 20° to 50°,
- Hstd= 1 to 3 cm,
- Lc = 4 to 8 cm,
- SMC = 5% to 45%
- NDVI =0.2-0.8

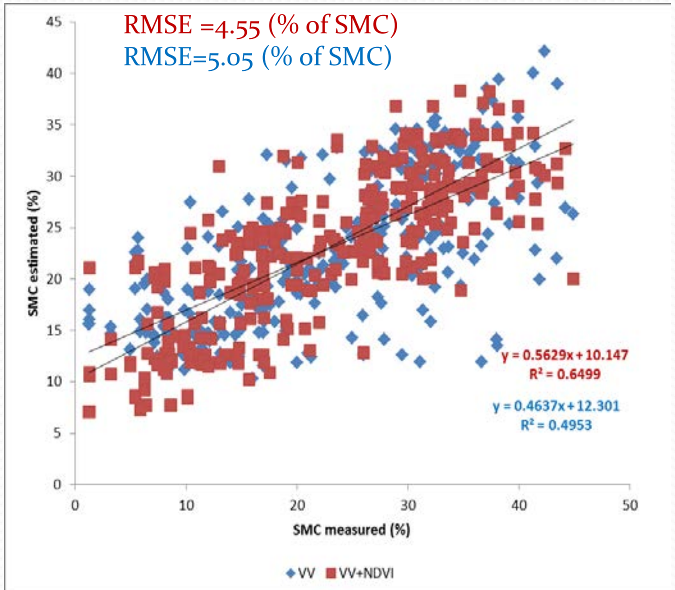


- After the training, the ANN were tested on a different dataset obtained iterating again the model simulations.
- The use of a pseudorandom function prevents a correlation between these two datasets.

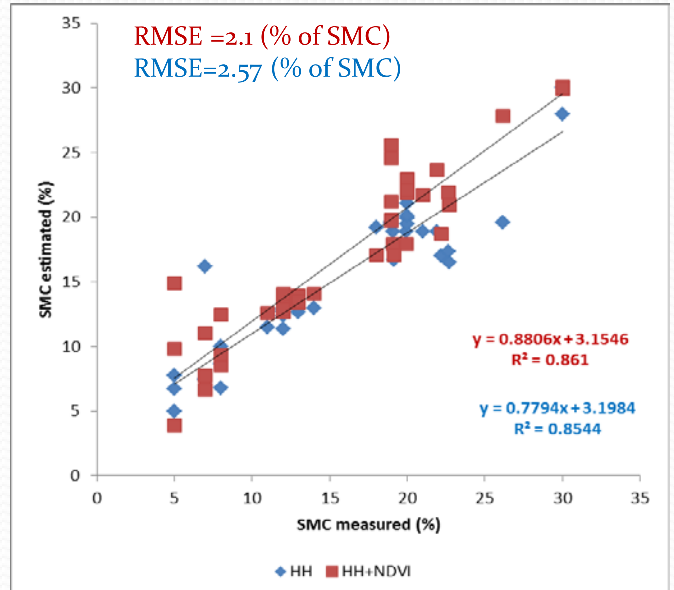
Paloscia et al. 2013, Santi et al. 2013

ANN validation

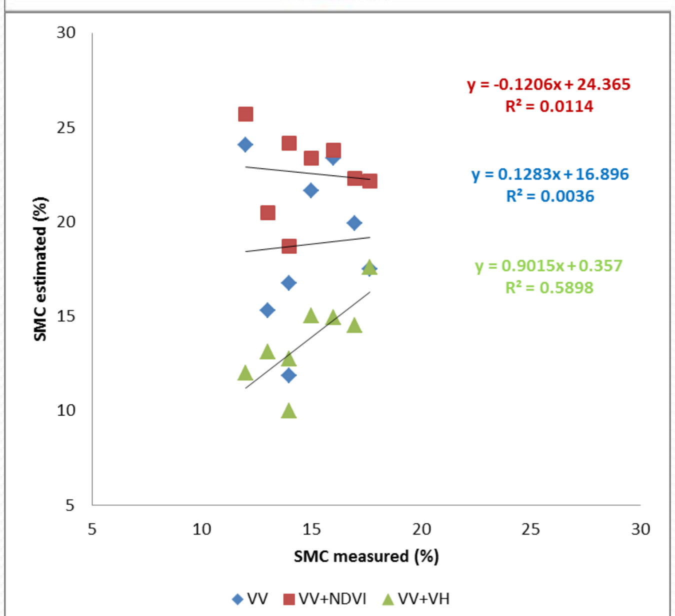
The ANN algorithm was validated on 6 test areas in Italy + Australia + Spain (> 700 ground truth points)



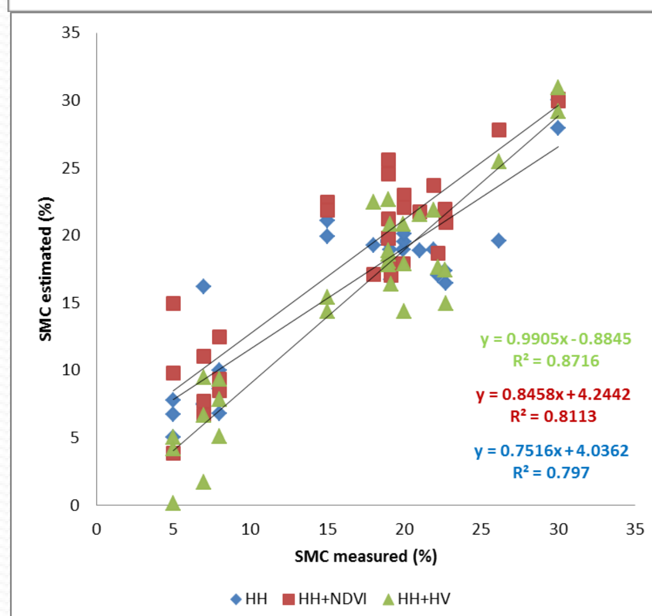
VV



HH



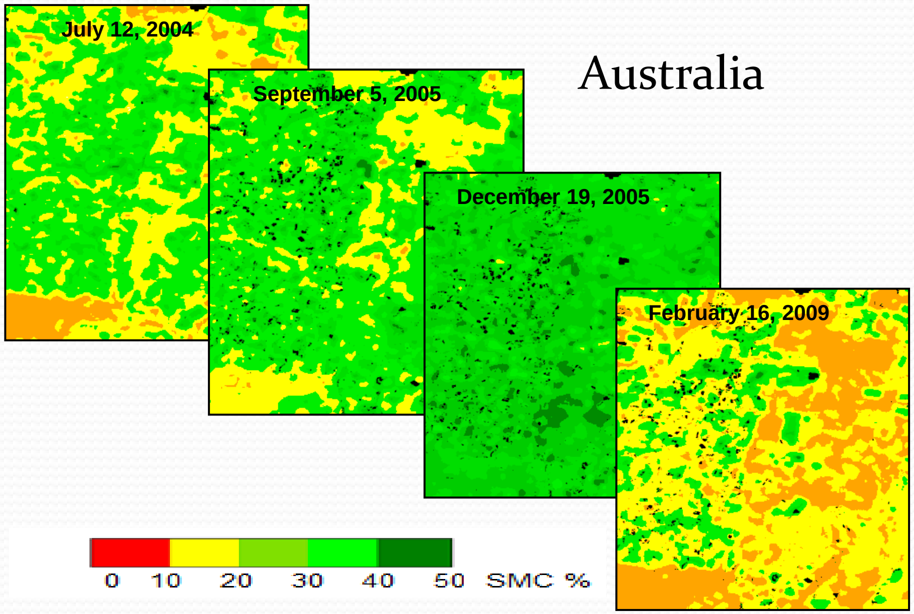
VV+VH



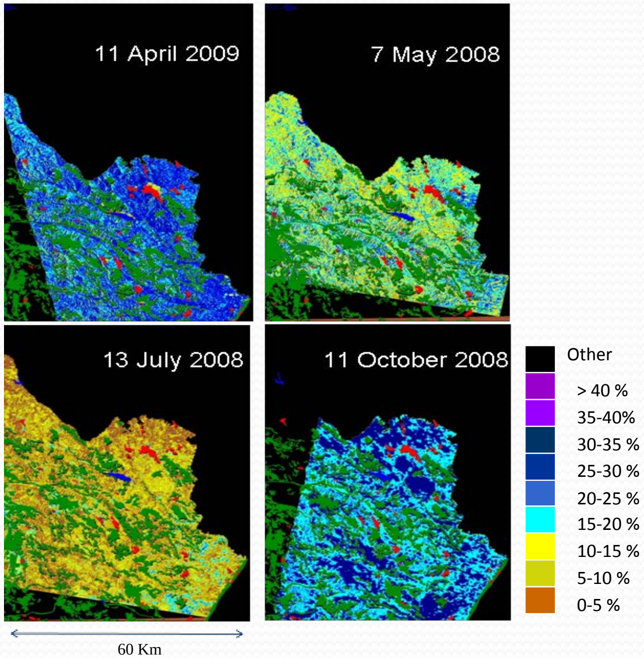
HH+HV

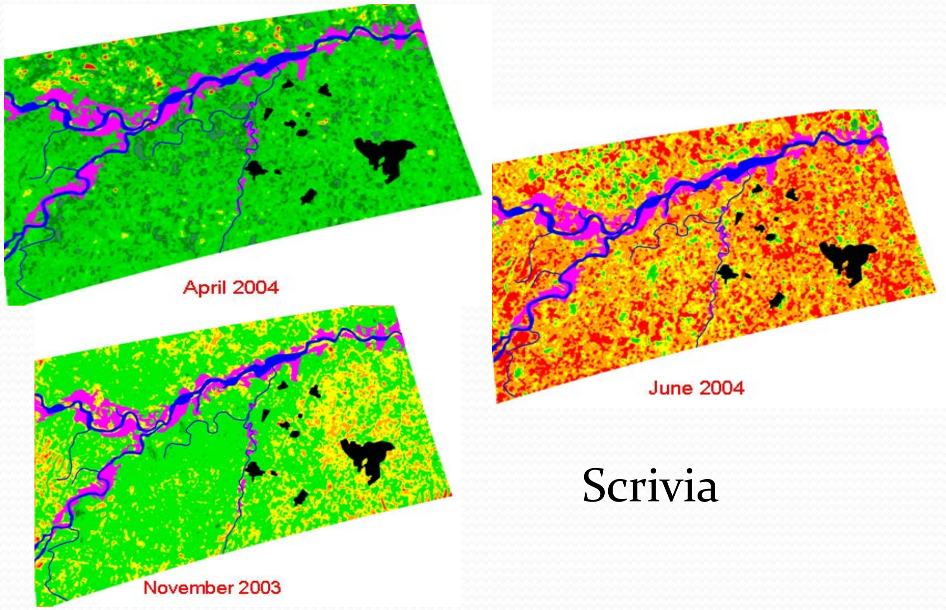
SMC maps: ANN

Australia

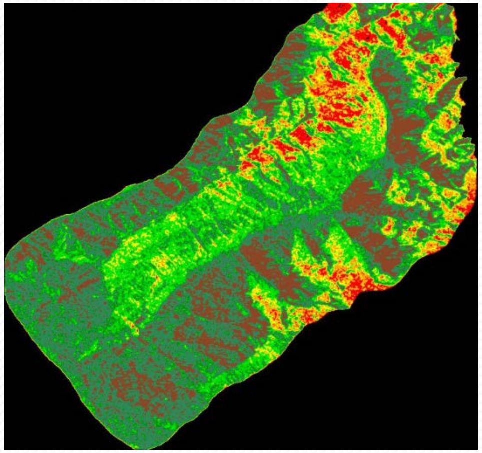


Matera





Scrivia

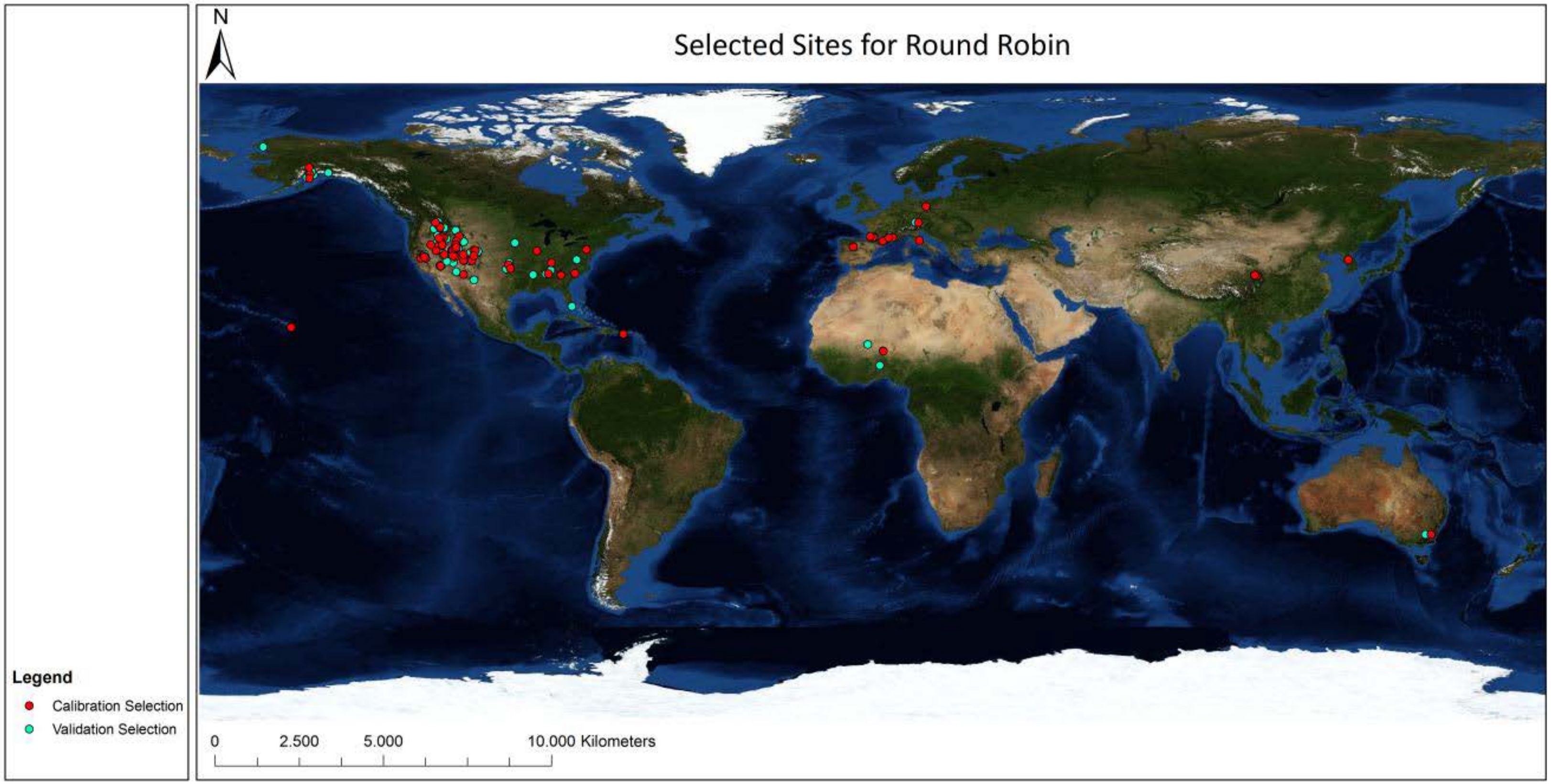


Alto Adige

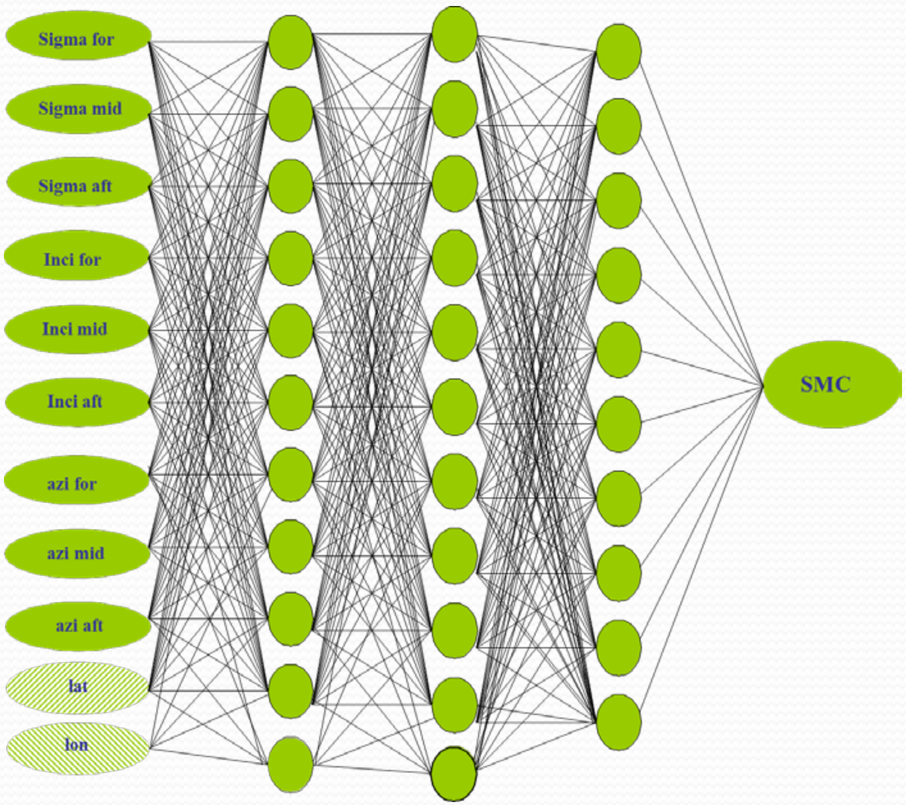
ANN algorithm for ASCAT (Round Robin)

ASCAT Round Robin Data Package (RRDP)

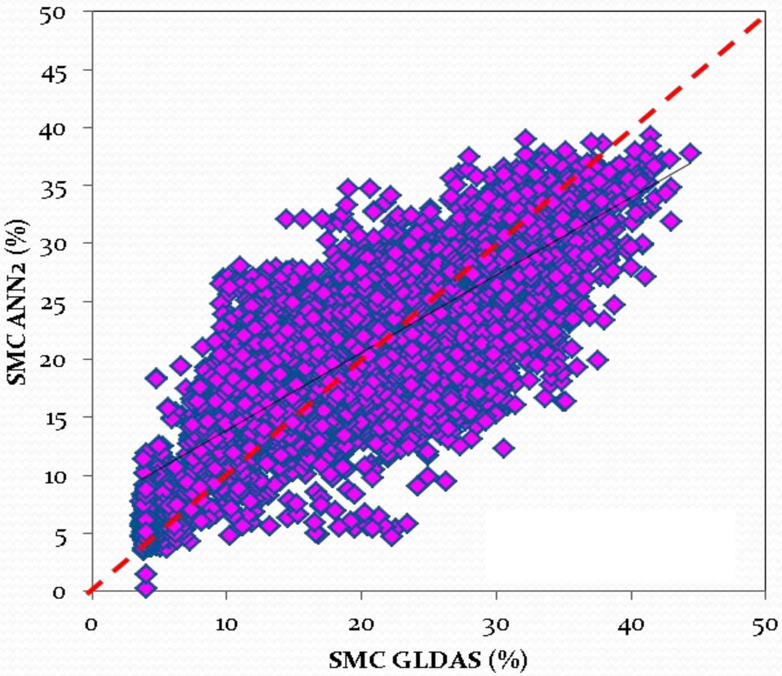
- ASCAT σ° measurements (2007-2011) resampled over 150 sites (75 training + 75 validation sites) from ISMN (20000 + 20000 samples)
- Top soil layer (0 – 10 cm) SMC measurements over 75 training sites.
- Global Land Data Assimilation System (GLDAS) simulated 10 cm soil temperature, surface temperature, precipitation, and snow water equivalent for the 75 training sites.



ANN ASCAT algorithm



σ° (3 looks)
inci. angles (3 looks) → SMC
azimuth (3 looks)



R= 0.82; RMSE= 4.24

- **ANN** trained with the GLDAS «training» set composed of σ° and direct measurements of ground parameters.
- 3 layers of neurons (11+11+10).

Santi et al., 2013

Conclusions

- An application of Artificial Neural Networks (ANN) techniques for retrieving the SMC from the active and passive microwave acquisition from satellite has been presented here.
- Four ANN based algorithms have been developed and tuned for working with **AMSRE/AMSR2, SMAP, ASCAT** and **C- band SAR** from **ENVISAT/RADARSAT /SENTINEL**….
- Experimental data and forward EM models simulations have been considered for training the ANNs
- Test of the algorithms returned accuracy values of about 0.04 m^3/m^3 of SMC or better, making these applications compliant with the usual accuracy requirements for SMC products from space.
- The possibility of repeating the training with new datasets in order to improve the retrieval accuracy makes this technique adaptable and flexible.
- The main constraint for accurate retrievals is due to the training process: the retrieval error may be large if the ANN is tested with data not properly accounted for in the training.

Thank you