Microwave Remote Sensing of natural surfaces: experimental and modeling results

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CNR-IFAC

Commission F: Wave propagation and remote sensing

Introduction

- This speech is focused on the investigation of natural surfaces using microwave remote sensing sensors: experimental equipment and satellite data from both microwave radiometers and SAR systems
- Observations on agricultural-forest surfaces and snow-covered soils carried out from IFAC Microwave REMOTE Sensing Group
- Analyzing experimental data and implementing electromagnetic models for simulating surface responses
- Implementing inversion algorithms for estimating surface parameters by integrating data from different sensors

Experimental Results

Soil Moisture Content (SMC)

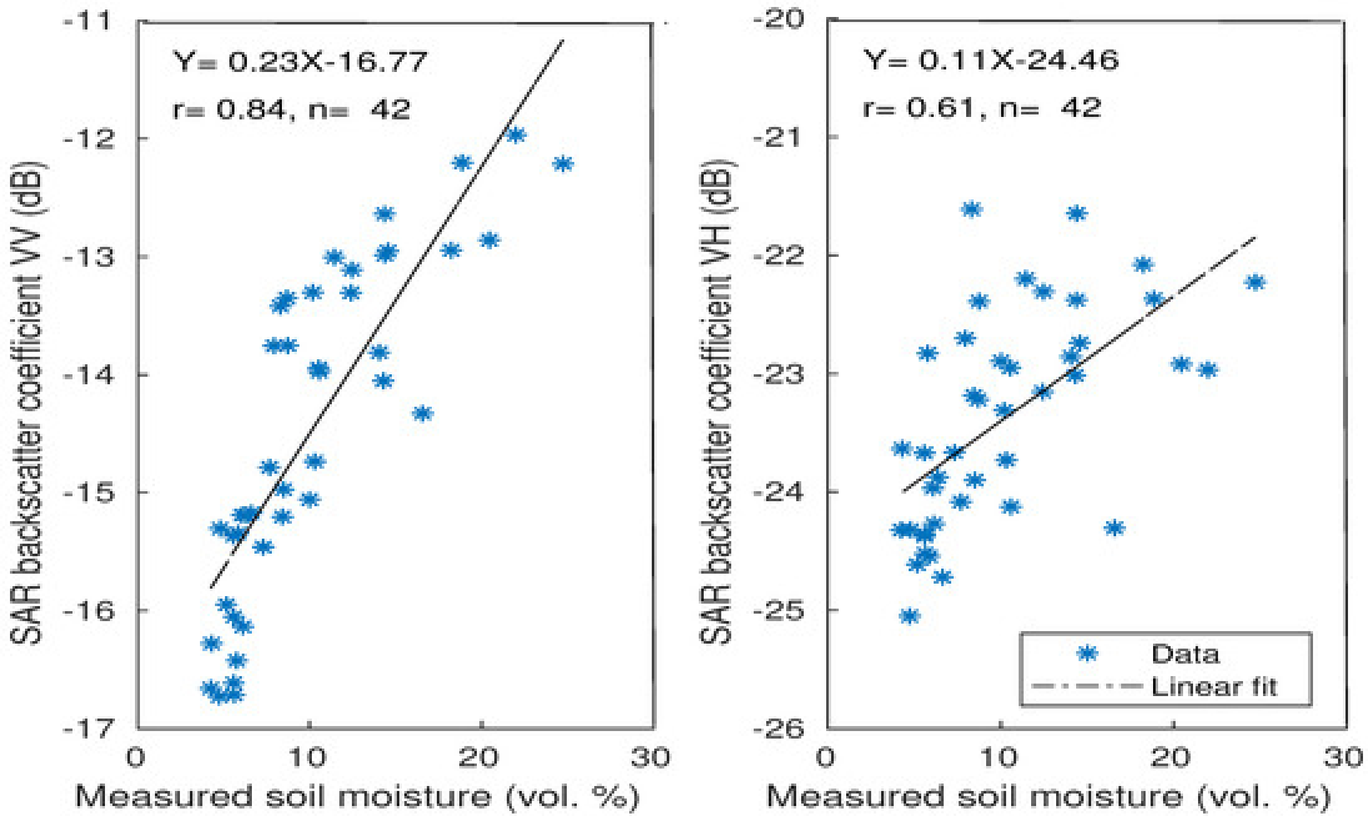
Vegetation Biomass (PWC/LAI)

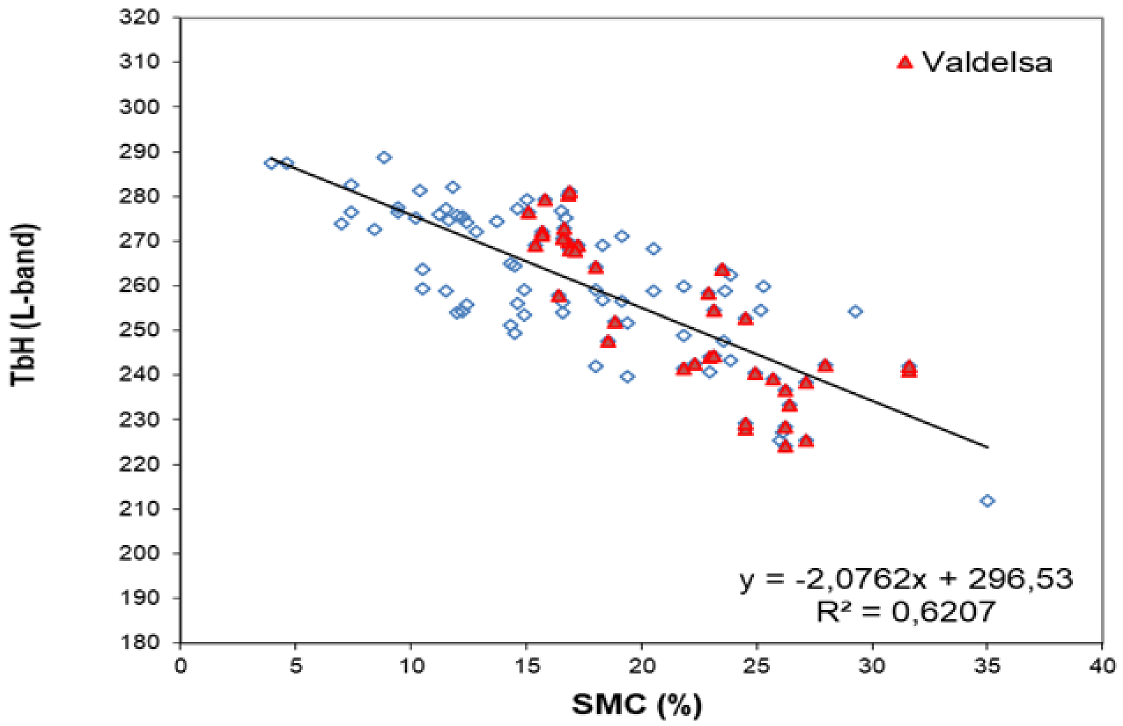
Snow water equivalent (SWE/SD)

Soil Moisture Content (SMC)

Typical SAR σ° sensitivity to soil moisture (SMC) - Sentinel-1

- Sentinel-1 σ° at VV pol. is significantly correlated with SMC compared to the VH pol. which showed more dispersion.
- The correlation coefficients (r) were 0.84 and 0.61 for the VV and VH polarizations, respectively.
- The sensitivity of σ° to SMC was 0.23 and 0.11 dB/vol.% for VV and VH polarizations, respectively.
- An increase in SMC of approximately 5% generates an increase in σ∘VV of 1.15 dB and 0.55 dB in σ∘VH



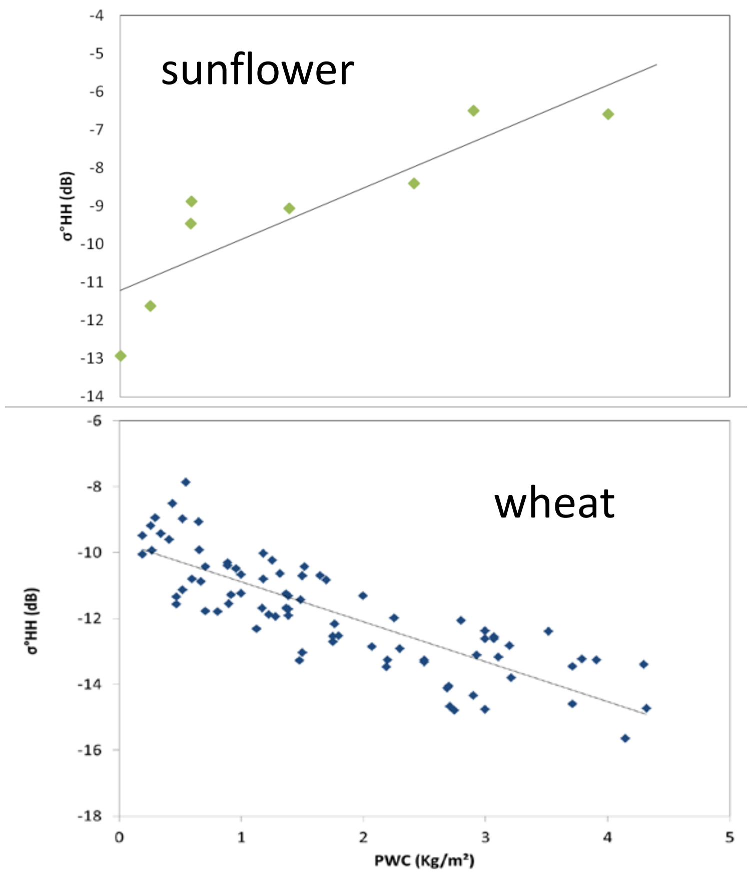


Typical sensitivity of Tb at L-band to soil moisture (SMC) – IFAC MW radiometers

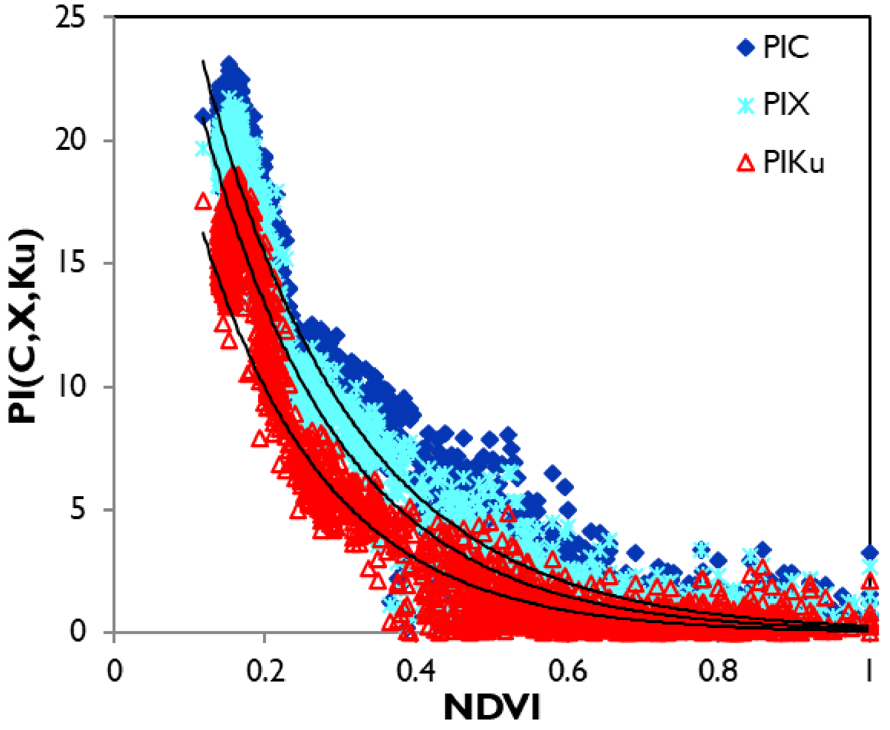
(Airborne data gathered on different agricultural fields at different dates)

Biomass of agricultural and forest crops (PWC)

Sensitivity of σ° (CSK-X band) & PI (AMSR2-C, X and Ku bands) to crop biomass (PWC/NDVI)



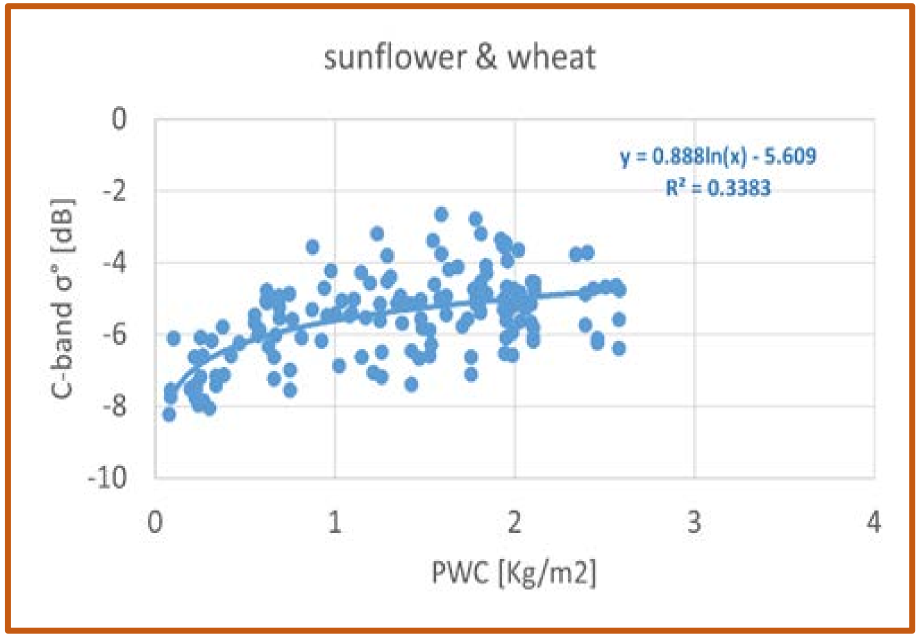
- The regression equations are:
  σ°_{HH} = 0.67PWC - 11.21 (R^2 = 0.76)
  σ°_{HH} =-1.21*PWC - 9.68 (R^2 = 0.68)



PI=(TbV-TbH)/(Tbv+Tbh)/2

Sensitivity of σ°VV/HVat X-band (CSK) to (PWC)

WHEAT SUNFLOWER

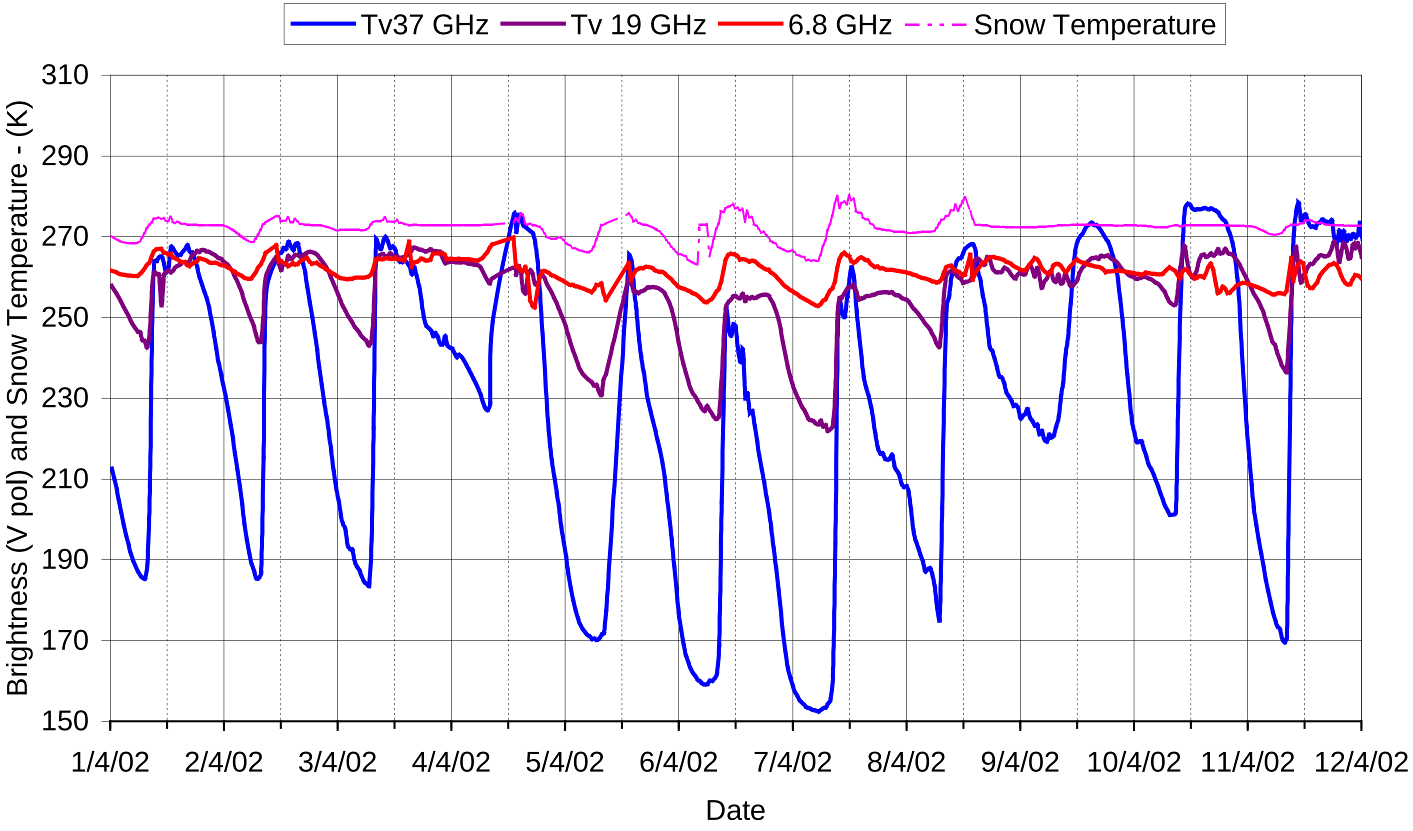


- If the ratio VV/HV is used the correlation get worse, however the trend is similar for all crop types

Sensitivity to dry/wet conditions and SD/SWE of snow cover

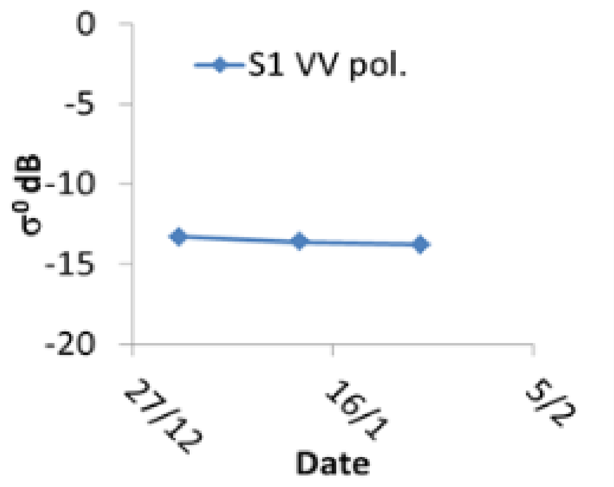
Microwave Radiometers

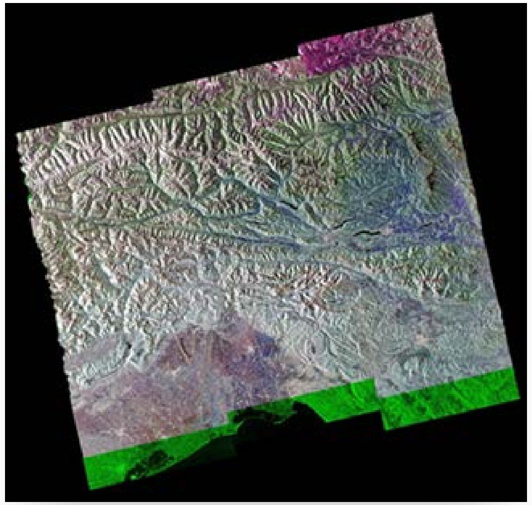
Melting/refreezing cycles of snow cover (1-12 Aprile)



- Ka band
- Ku band
- C band
- Snow temp.

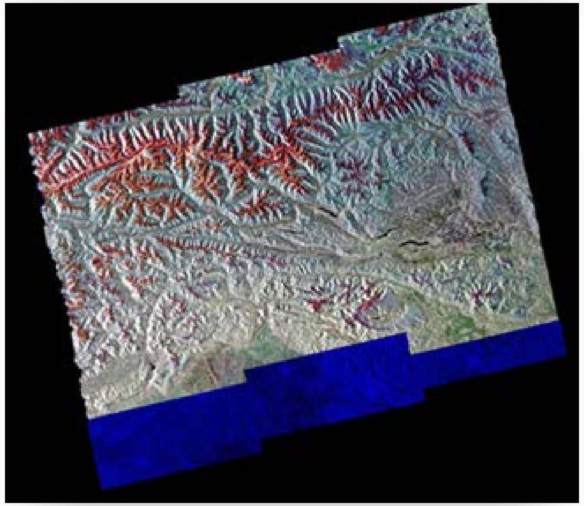
Macelloni et al., 2005, IEEE TGRS

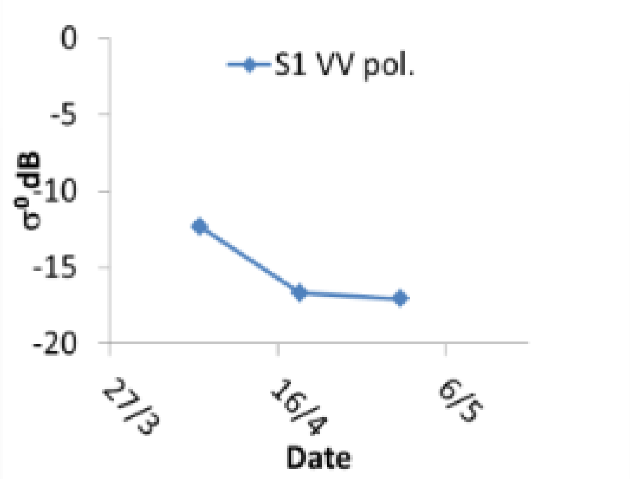




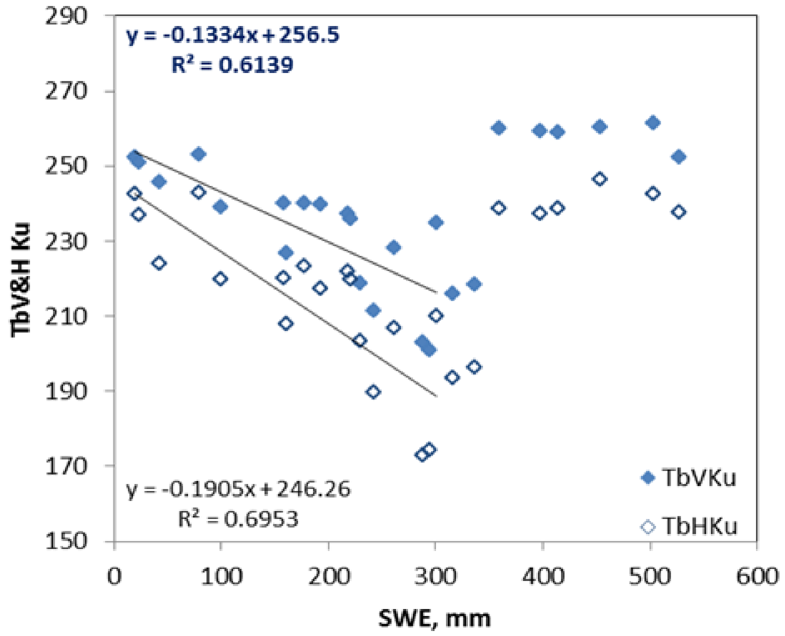
SAR sensitivity (Sentinel-1) to dry/wet snow conditions

- **Mappe RGB da dati Sentinel-1 per diverse condizioni della neve:**
- **Asciutto = R: 31 Dec 2014, G: 12 Jan 2015, B: 24 Jan 2015**
- **Bagnato = R: 6 Apr 2015, G: 18 Apr 2015, B: 30 Apr 2015**
- **I diagrammi mostrano il trend temporale di σ° in VV pol**



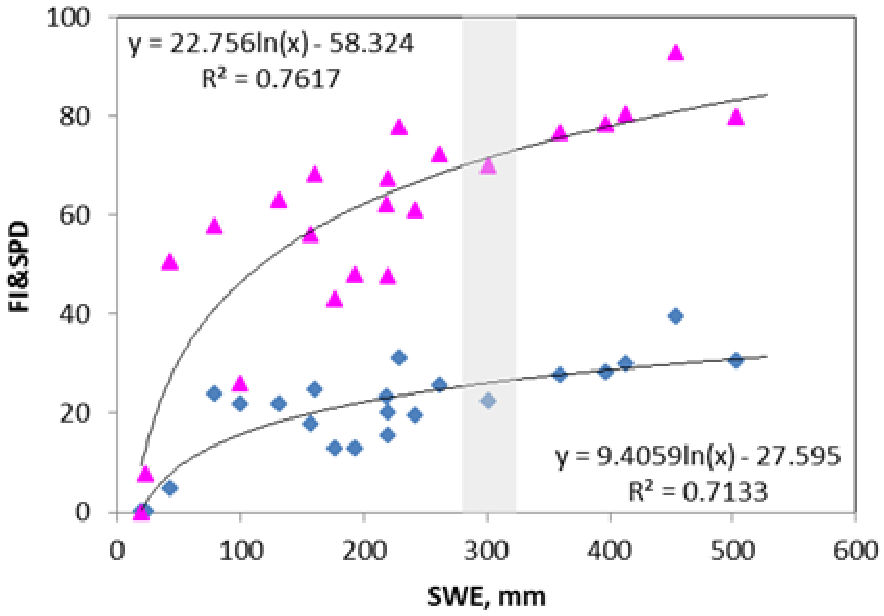


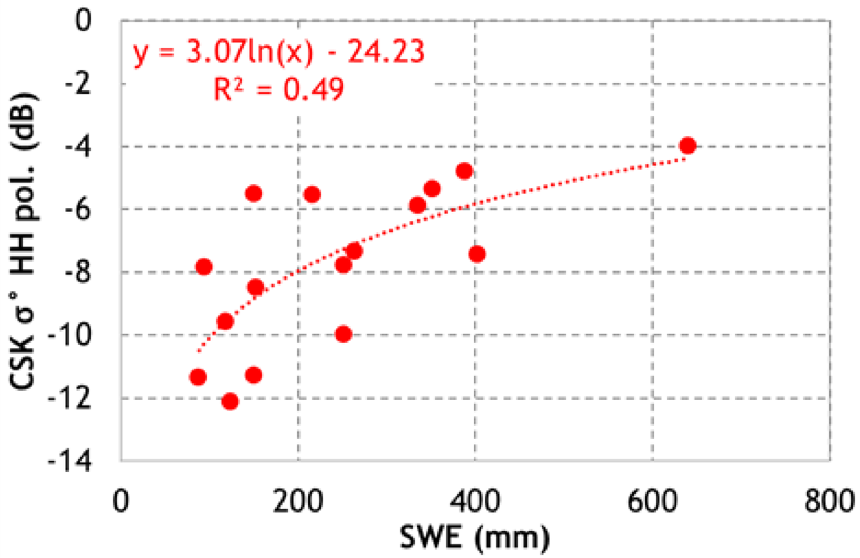
Tb (Ku band) & MW indices (Ku-Ka bands) vs SWE



As SWE increases, Tb decreases to a minimum, (300mm). At higher values, Tb tends to increase again due to emission from the snowpack itself

Dual-polarization observations (FI&SPD) allow for a better investigation of snow properties, even beyond theobserved threshold





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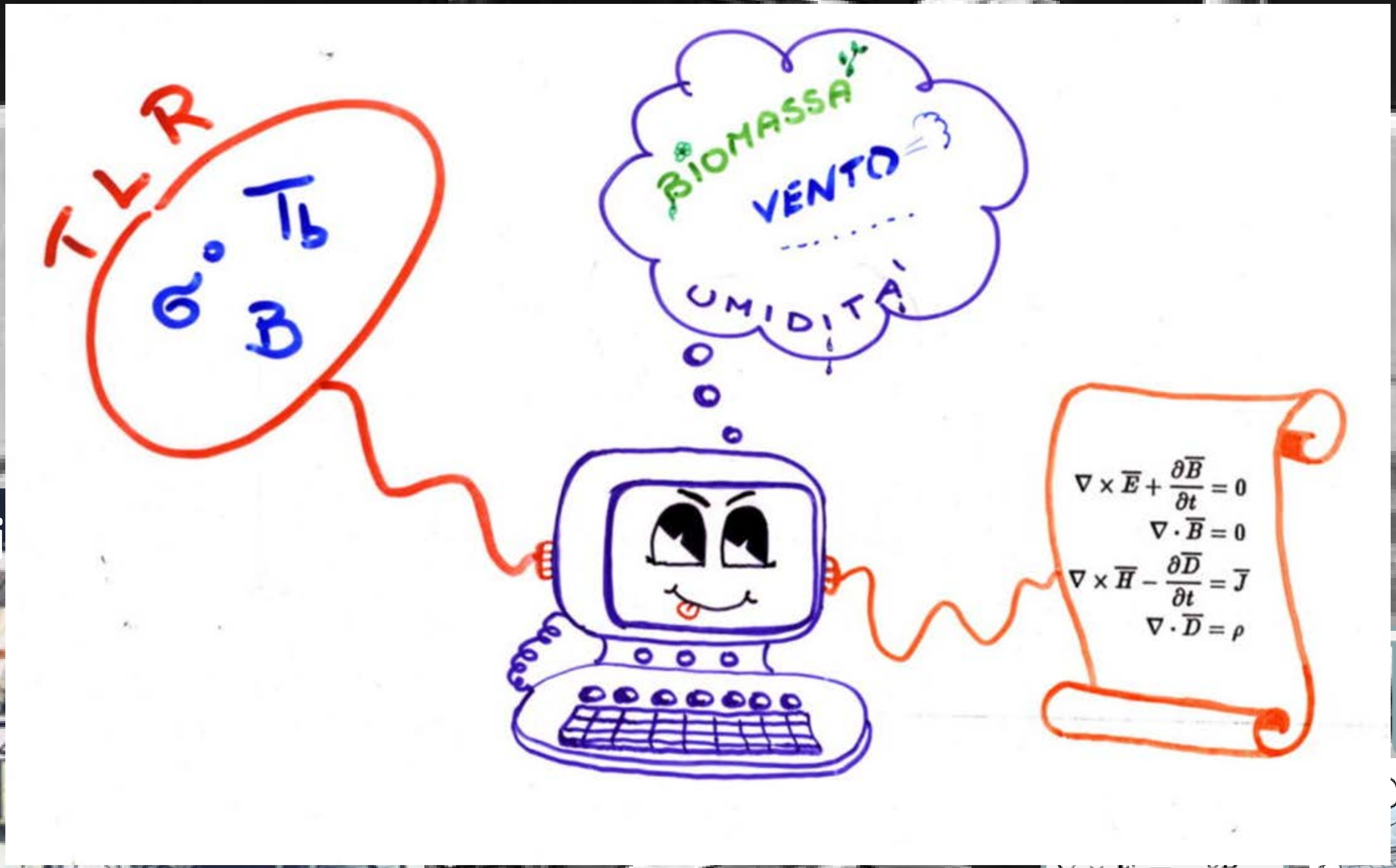
Backscattering σ° sensitivity at X band to SWE COSMO-SkyMed

- **Confronto diretto fra CSK σ° (banda X, HH pol.) e i valori a terra di SWE corrispondenti (orbite ascendenti).**
- **$\sigma° = 3.07 * \ln(SWE) - 24.23$**
- **($R^2 = 0.49$)**

“Sensate esperienze e certe dimostrazioni”

Experi



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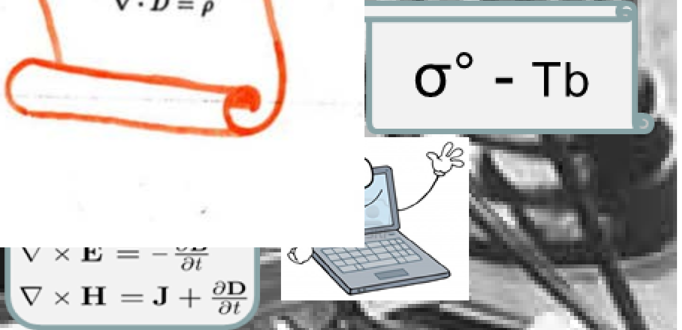
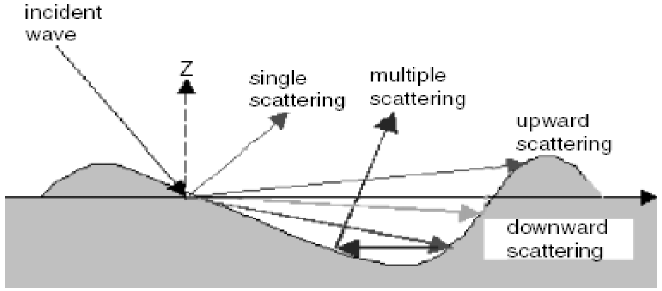
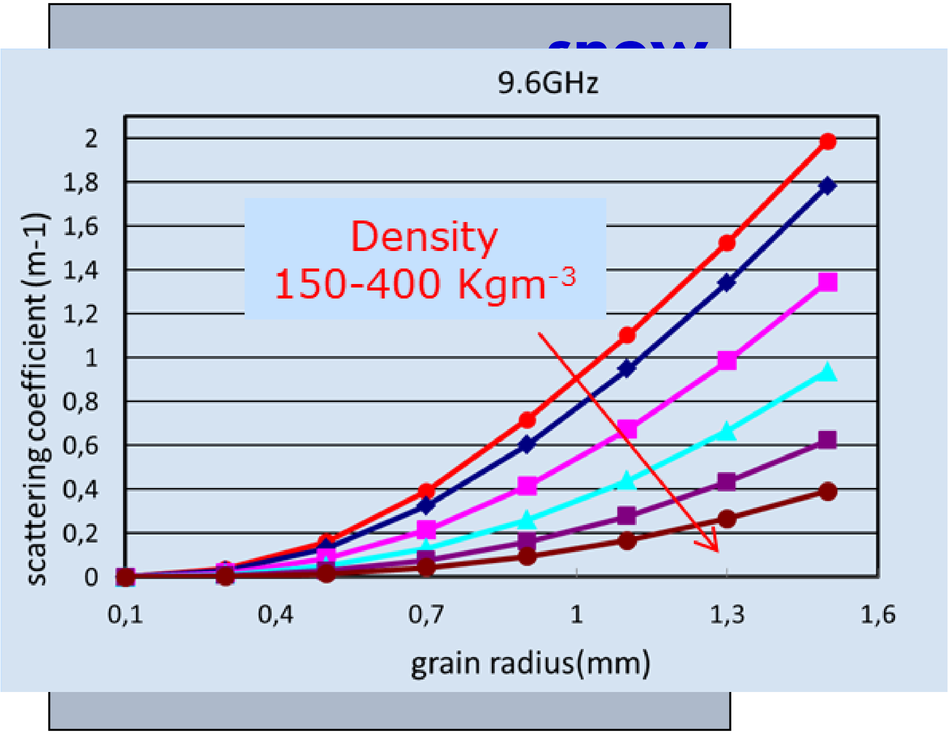


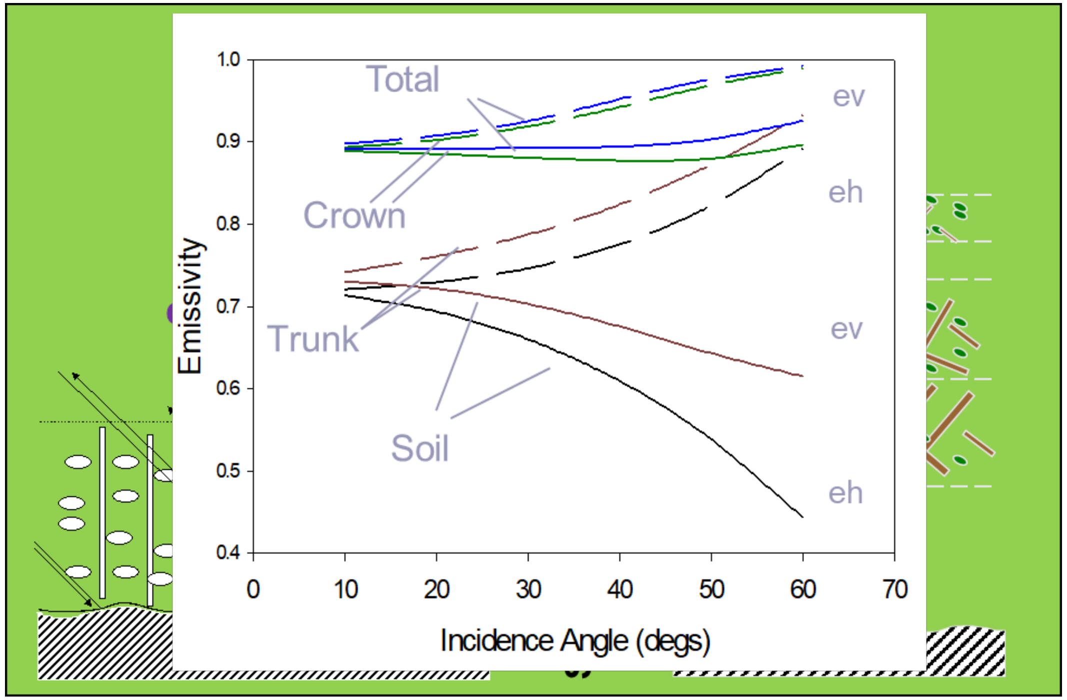
Electromagnetic models for simulating experimental data

Surface scattering: Soil

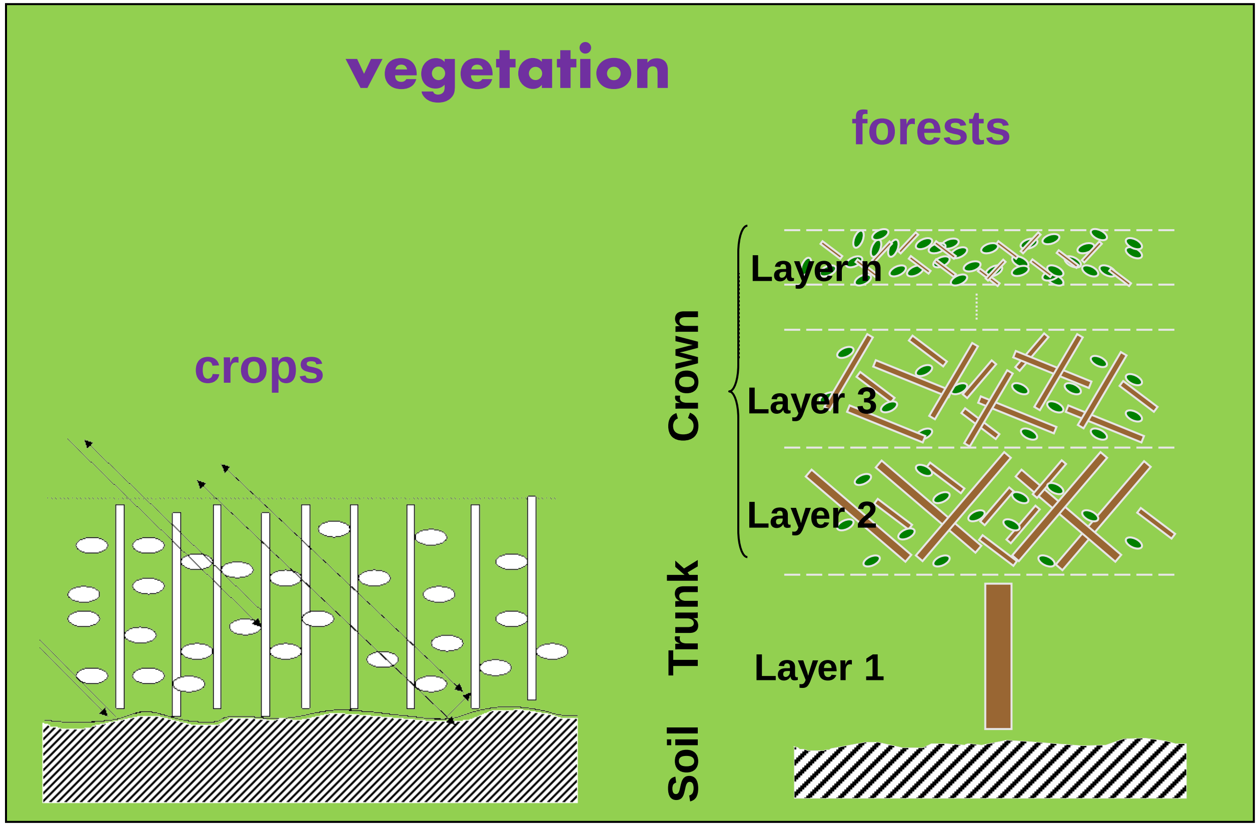


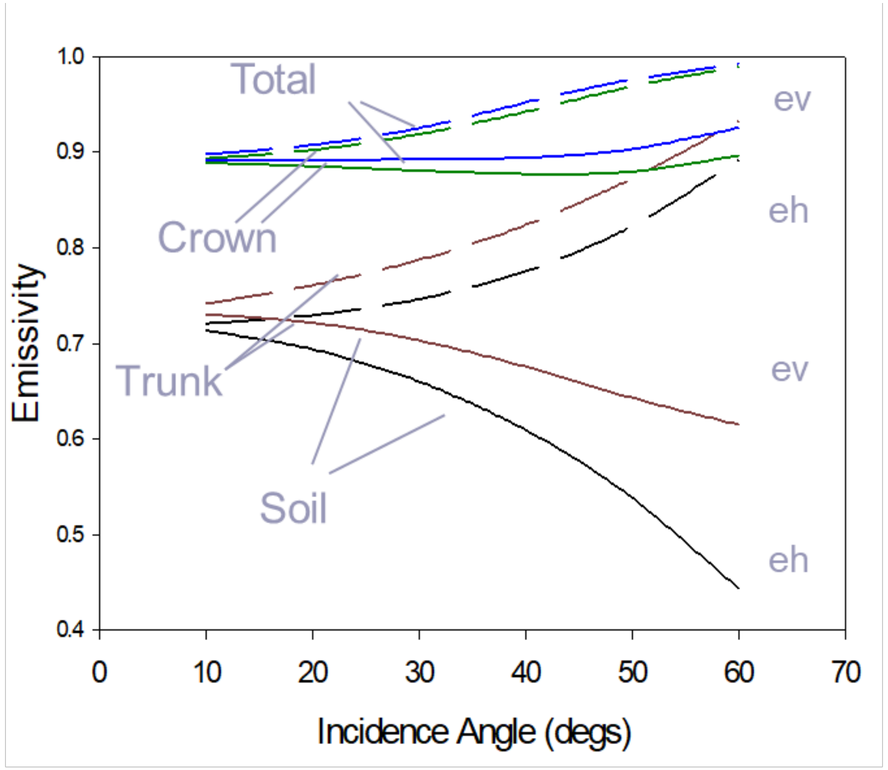
Volume scattering: SNOW and VEGETATION





Volume Scattering - Vegetation



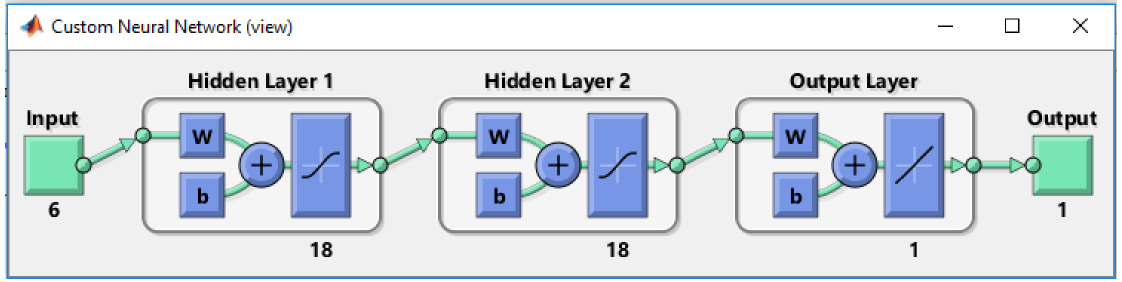


Inversion Algorithms

- Semi-empirical models
- **Machine learning approaches: Artificial Neural Networks, ANN, or Random Forests, RF (best compromise between computing time and accuracy)**
- **One main advantage of these methods is the possibility of integrating data coming from different sources**

Why ANN?

ANN aren't black boxes: the input–output relationship can be written in a close way



Pros:

- ANN can be trained to represent arbitrary input-output relationships
- ANN can **easily merge data from different sensors** (e.g MW sensors, both SAR and radiometers + optical/IR).
- Training can be updated without modifying the algorithm
- <u>Training only is time consuming</u>: application to new datasets is near real time

Cons:

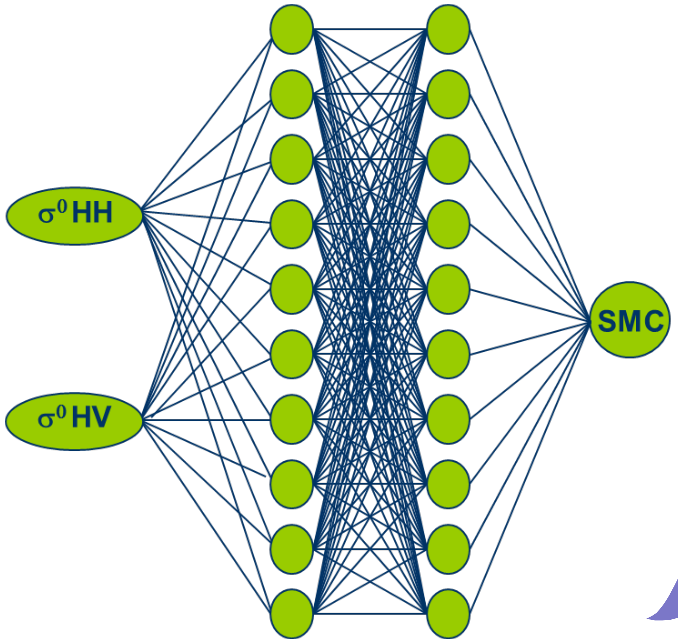
- ANN are prone to outliers→ large errors if testing data have not been properly accounted for in the training

The main constraint is represented by the statistical significance of the training set: all the observed surface conditions have to be represented.

ANN based inversion algorithms

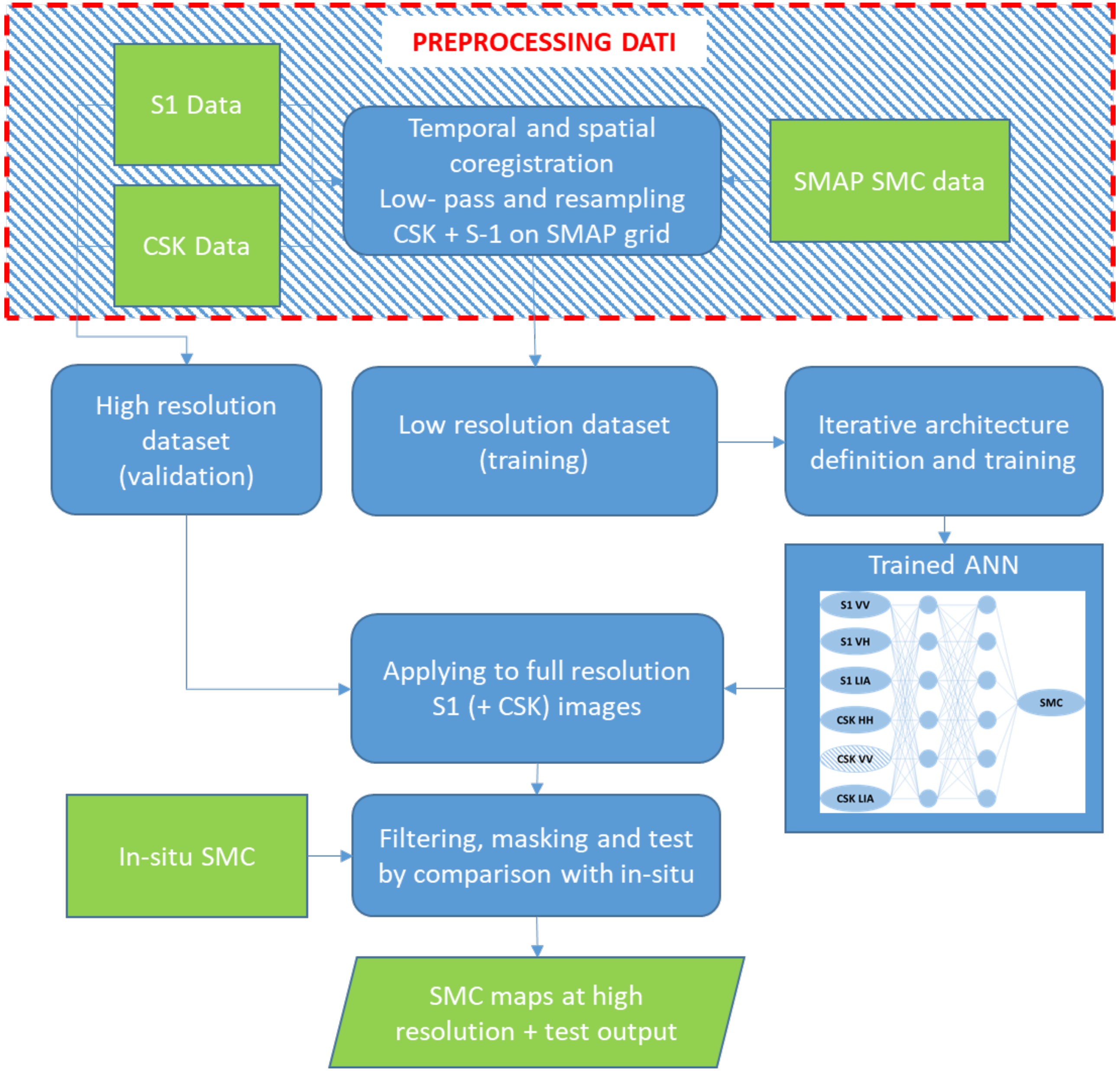
- The considered ANN are feed-forward multi-layer perceptron (MLP), with some layers of hidden neurons between input and output.
- The algorithm for the training pahase is the back-propagation (BP) learning rule.
- Usually, the ANN are trained with both experimental and e.m. model data.
  - SMC → AIEM+Oh(+WCM)
  - SWE → AIEM+Oh+DMRT-QCA+WCM
  - PWC → AIEM+Oh+RTT

ANN 2/3 inputs



Soil Moisture Content (SMC)

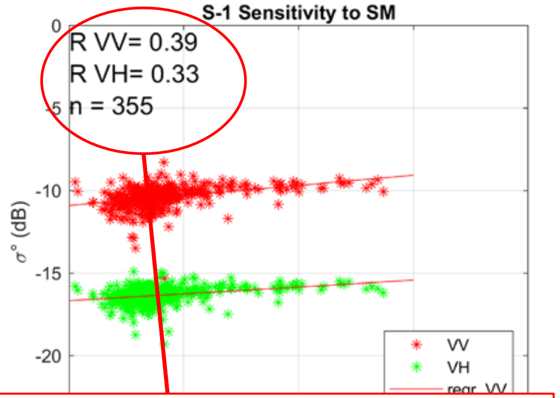
Algorithm Concept



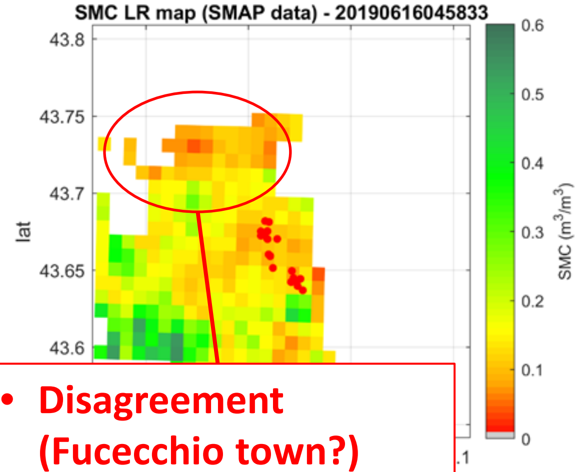
- «**Data driven**» approach, only based on **EO data**
- **Algorithm inputs:**
  - Backscattering: 2 pol + 2 freq.: C&X bands (CSK+S-1)
  - Local Incidence Angles (LIA).
- ANN is **trained on LR dataset** (SMAP radiometere)
- After training, the **ANN is applied to the HR dataset (**S-1 + CSK images at 10m resolution) to generate high resolution SMC maps
- Iterative architecture definition and training to avoid overfitting and underfitting

Output examples + some comments

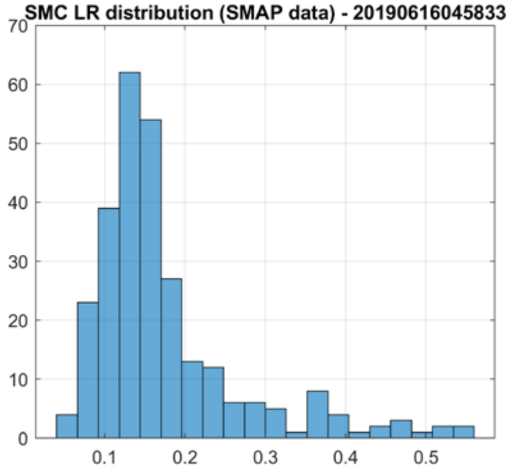
- **SMC HR map generated from one of the 37 combined SMAP/S-1/CSK acquisitions**

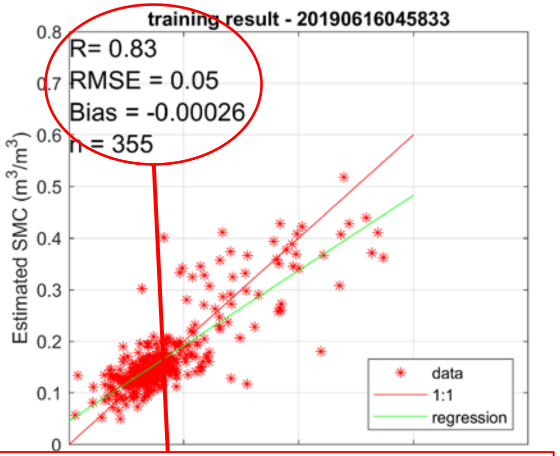


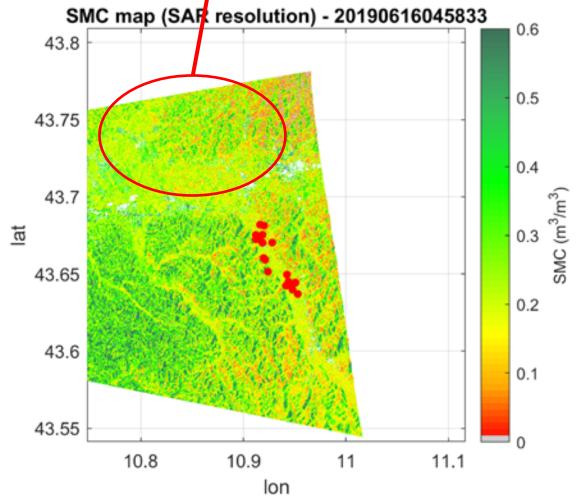
- **R <= 0.55 at all dates for S-1**
- **Even lower for CSK**

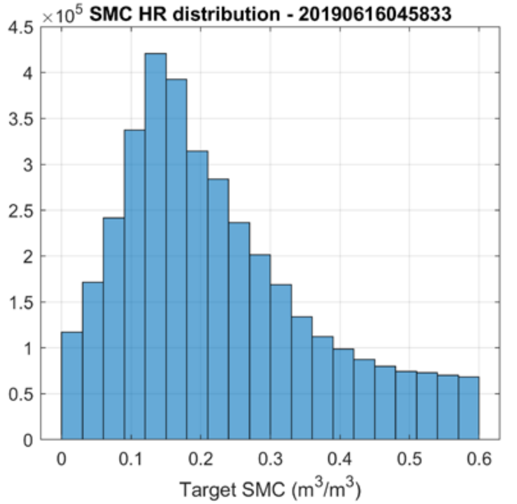


- **Disagreement (Fucecchio town?)**
- **Red bullets=in-situ**







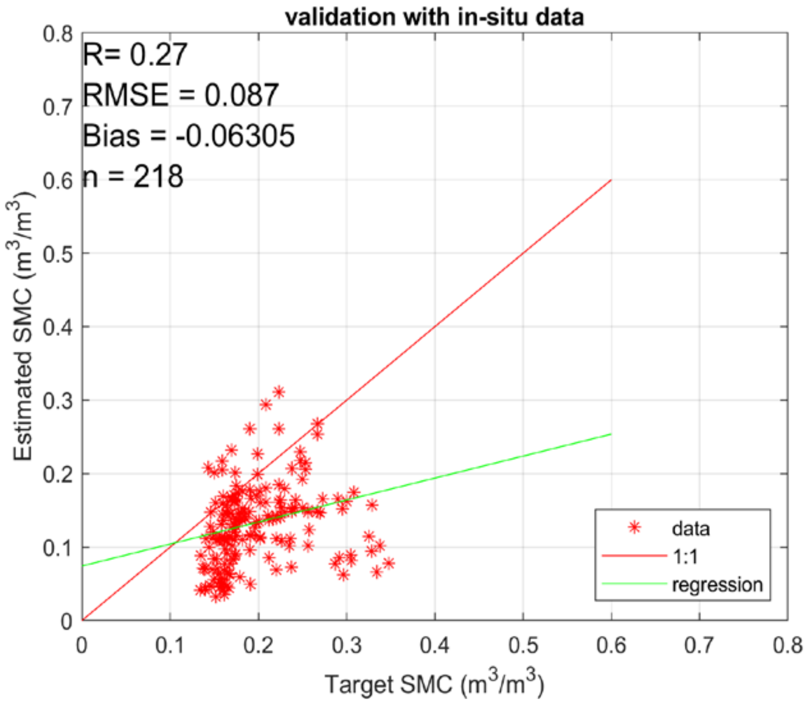


However training result is good: frequency + polarization sinergy

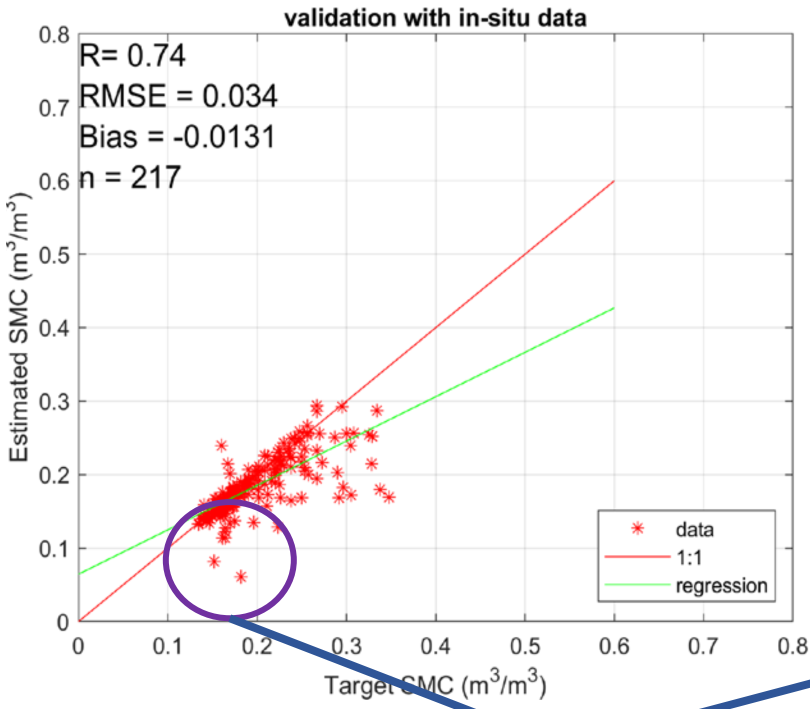
Algorithm validation with in-situ

Results of the overall validation: best SMC by ANN in a 3x3 window (30m x 30m) vs. in-situ

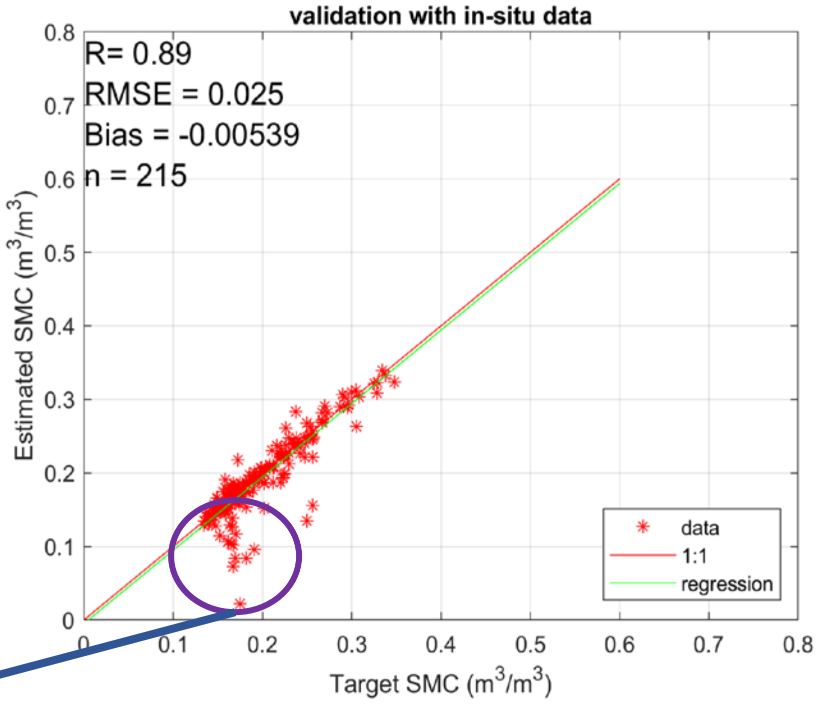
SMAP/Sentinel-1 L2 SM 3 Km



ANN SM (S-1 only)

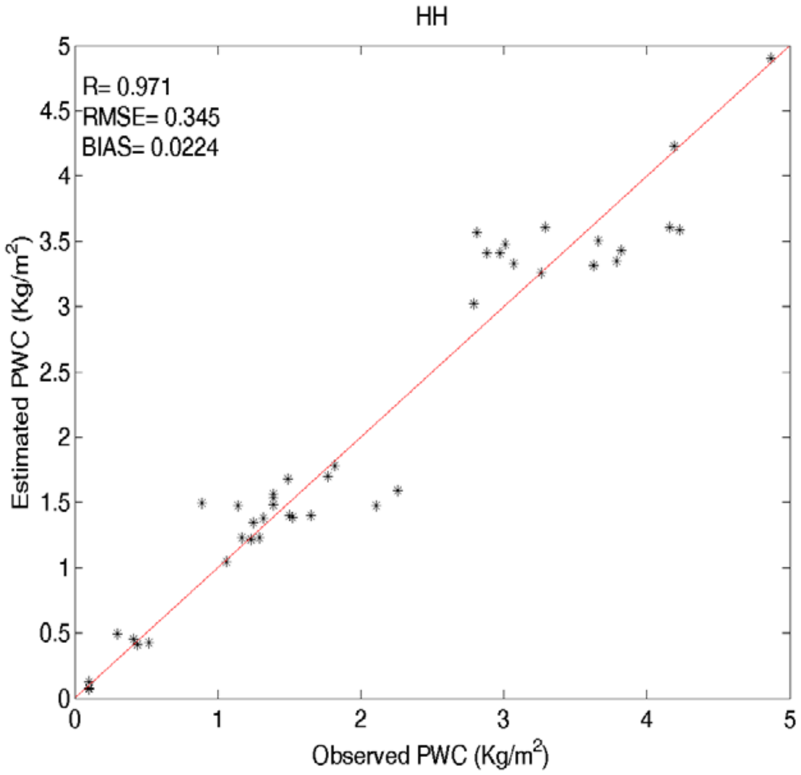


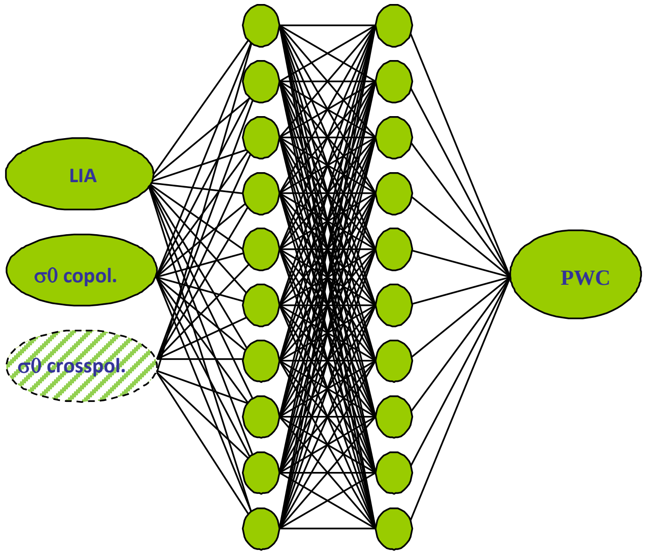
ANN SM (S-1 + CSK)



All these points come from the same date: possibly issues with the EO data

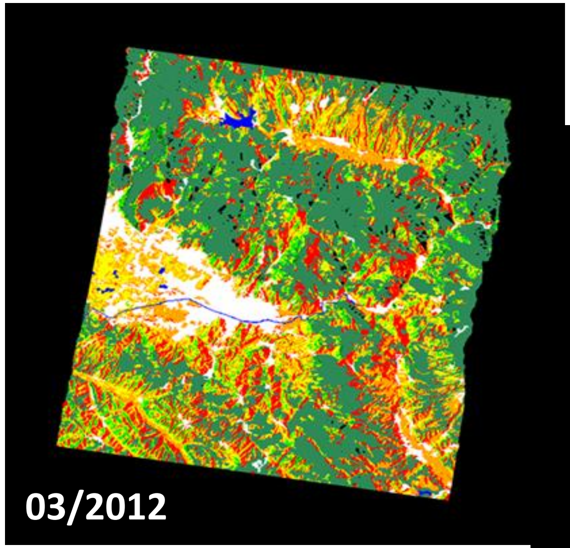
ANN algorithm validation on Firenze area

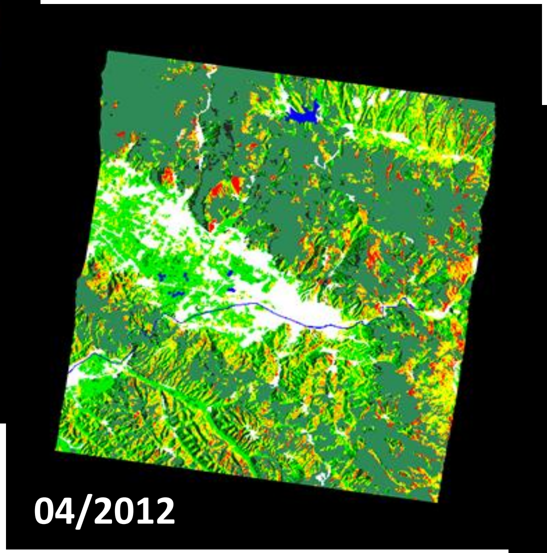


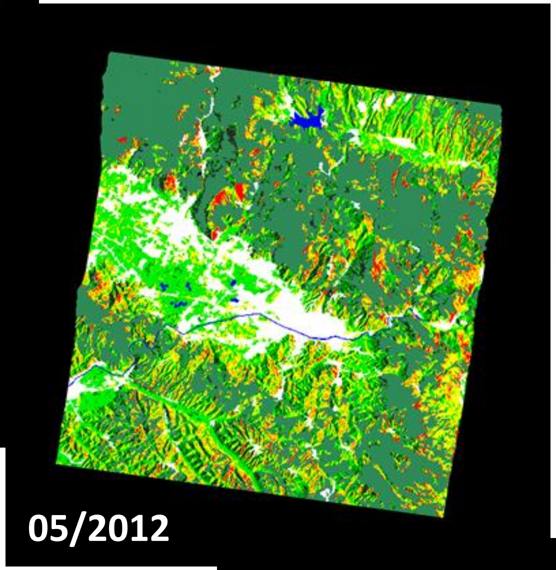


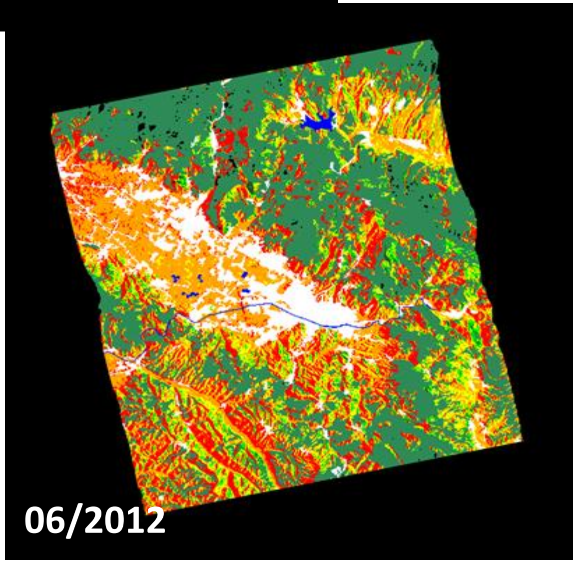
Examples of PWC Maps

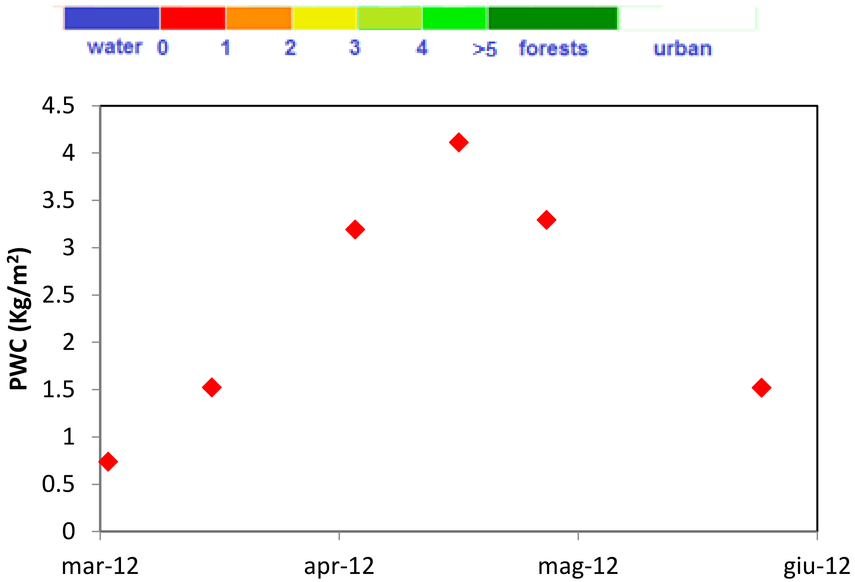
Sesto Fiorentino 2012 (COSMO-SkyMed, banda X)





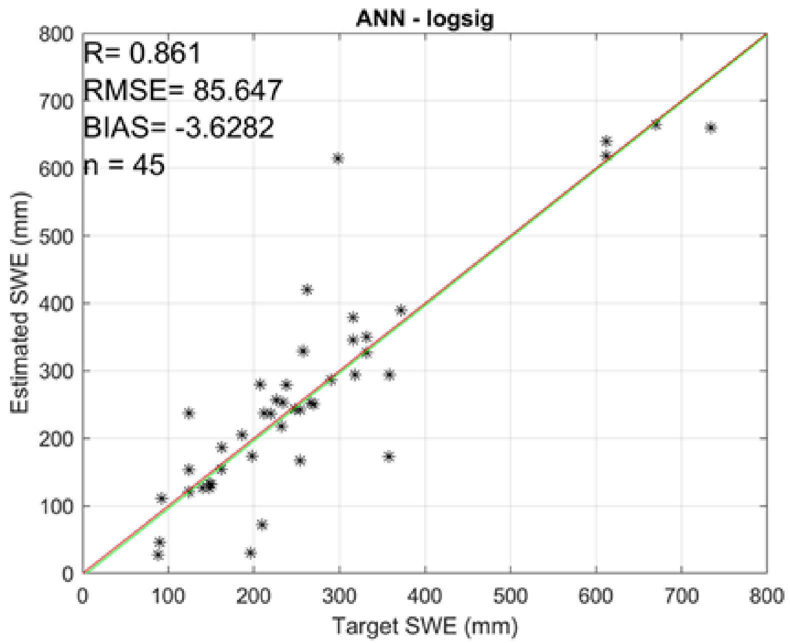






ANN IFAC results for estimating SWE

On the basis of experimental results and model simulations an approach based on ANN algorithm for estimating SWE from X-band COSMO-SkyMed data was implemented



Comparison between ANN estimated SWE with SWE measured on ground

ANN IFAC results for estimating SWE

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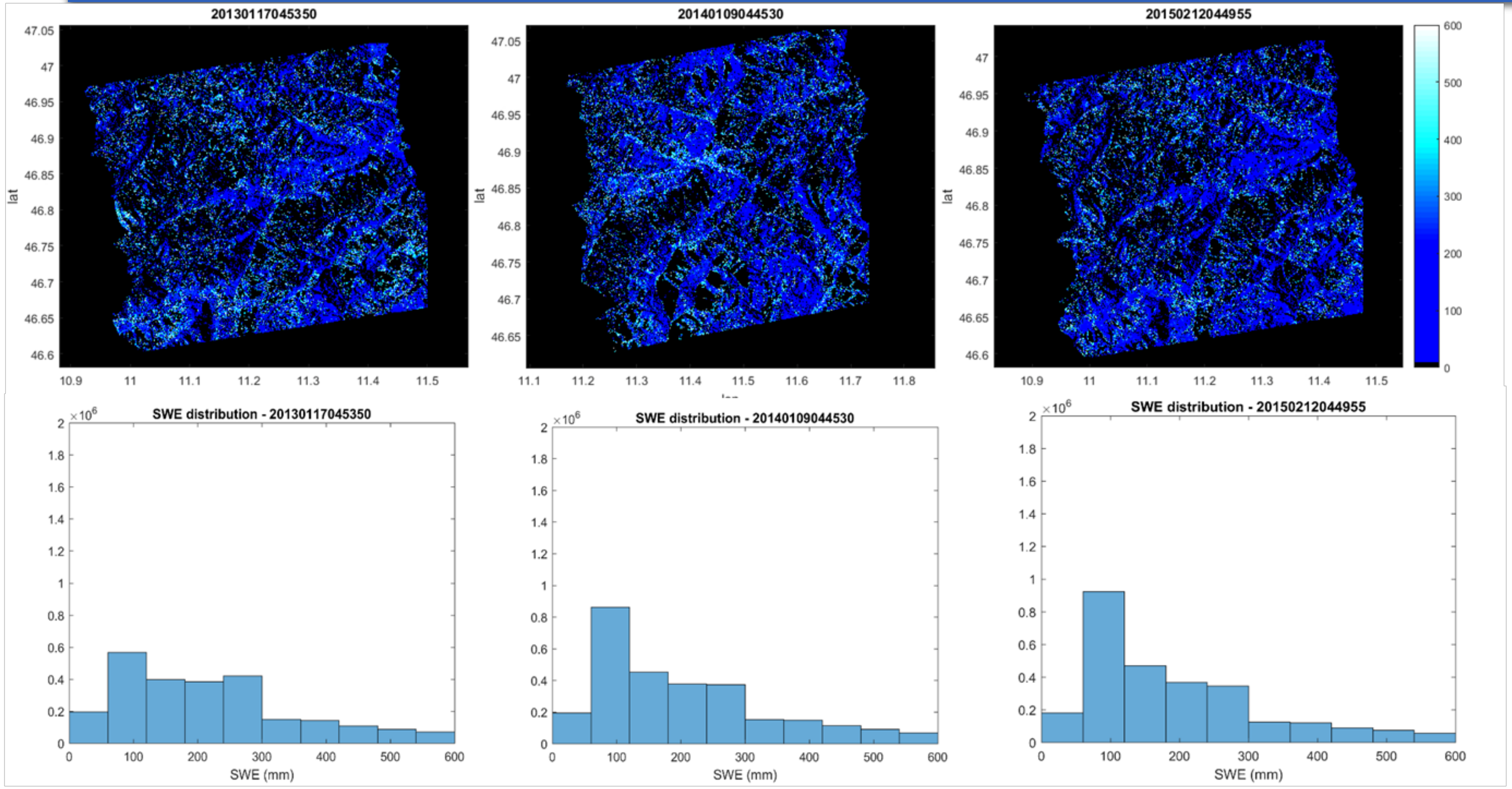
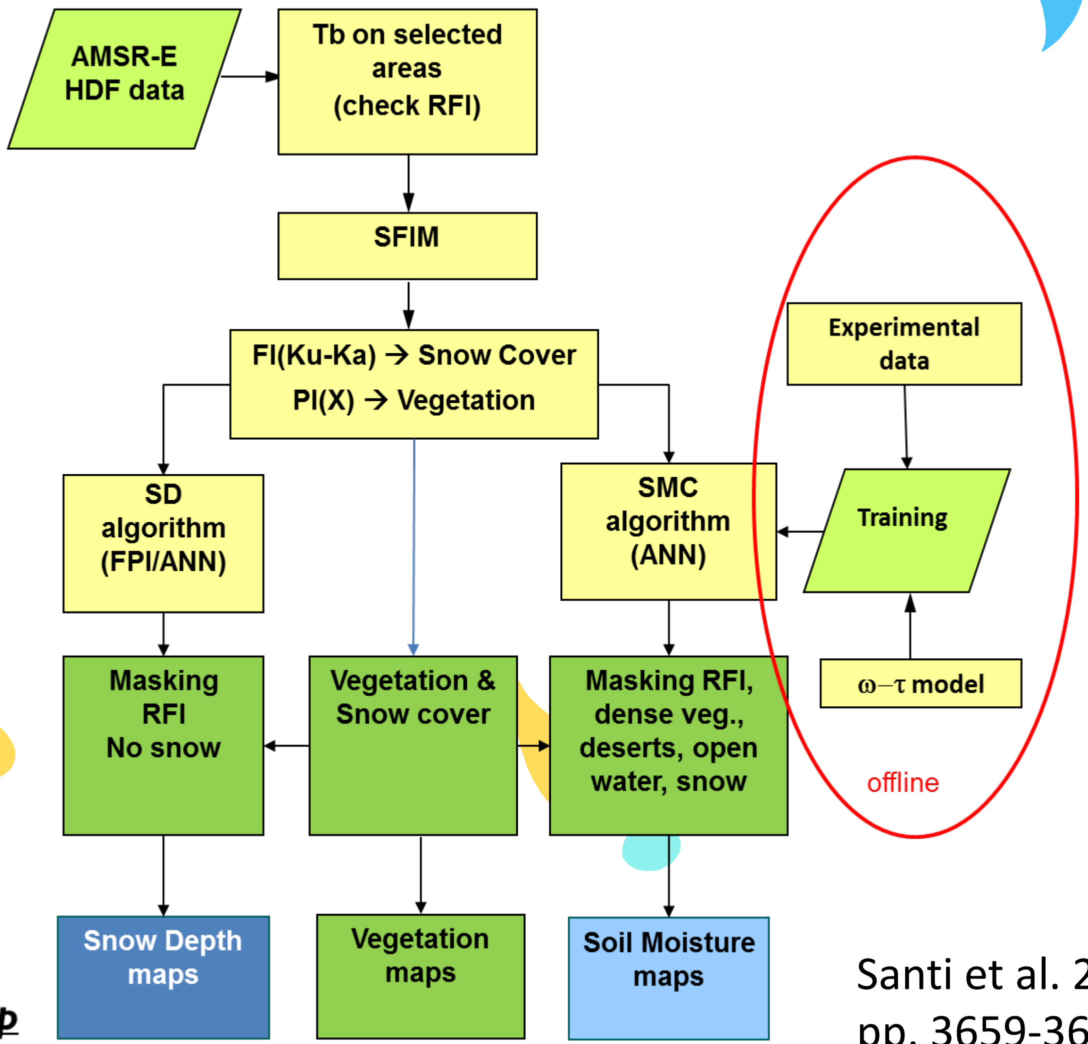


COSMO-SkyMed HIMAGE
January/Feb 2013-2015
South-Tyrol area
On the bottom: snow distribution hystograms

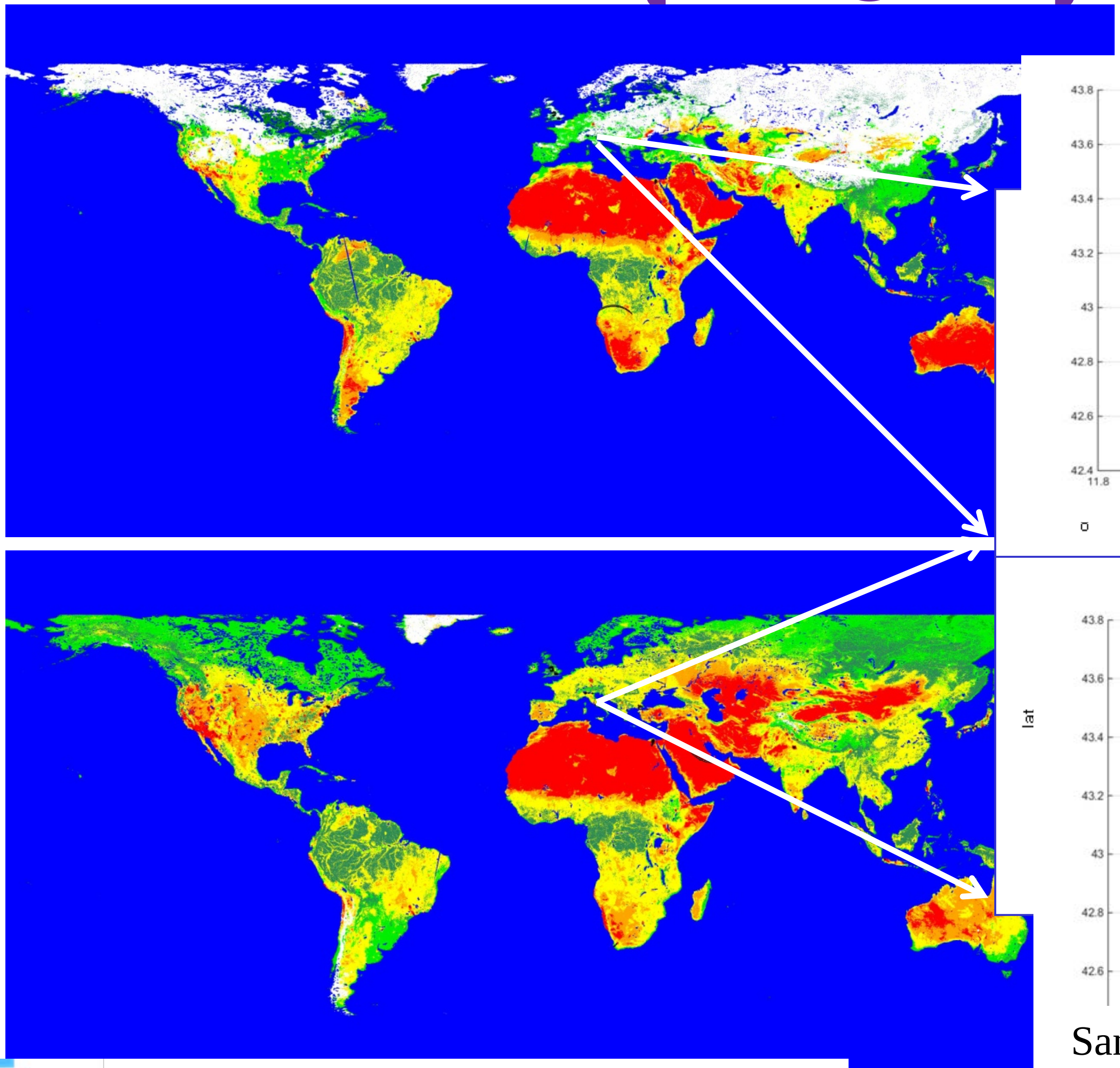
HydroAlgo
Algoritmo per la stima di SMC, PWC e SWE/SD da dati AMSR-E/2

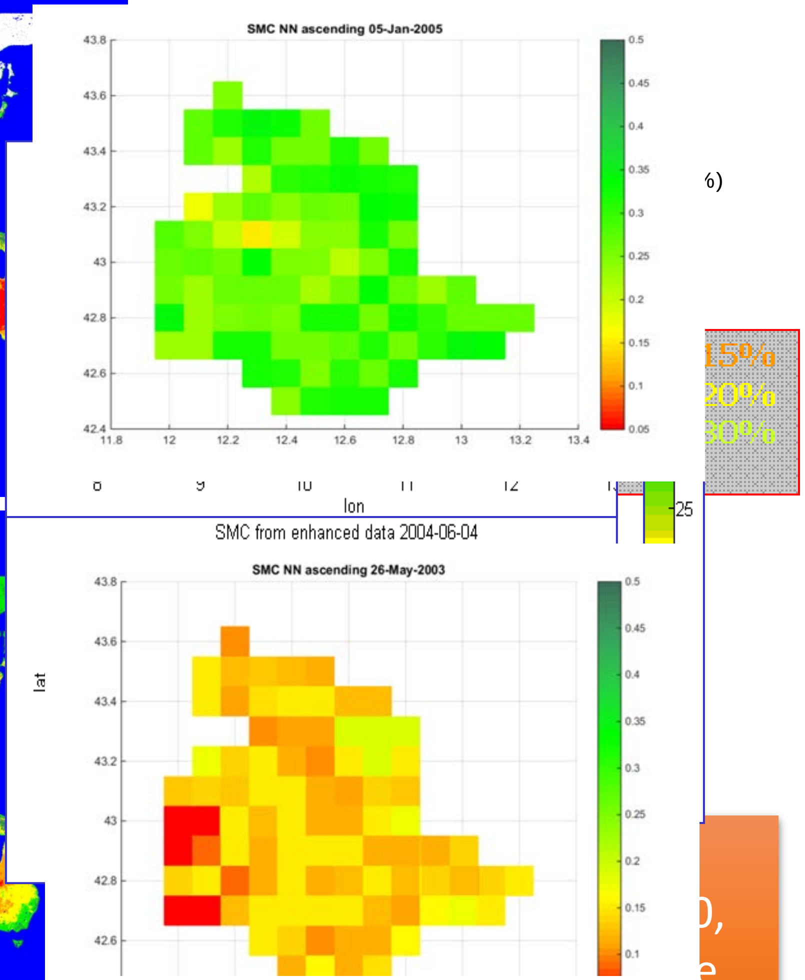


Microwave Remote Sensing Group

Santi et al. 2012, HESS, 16, pp. 3659-3676

Stima di SMC a scala globale (AMSR-E)

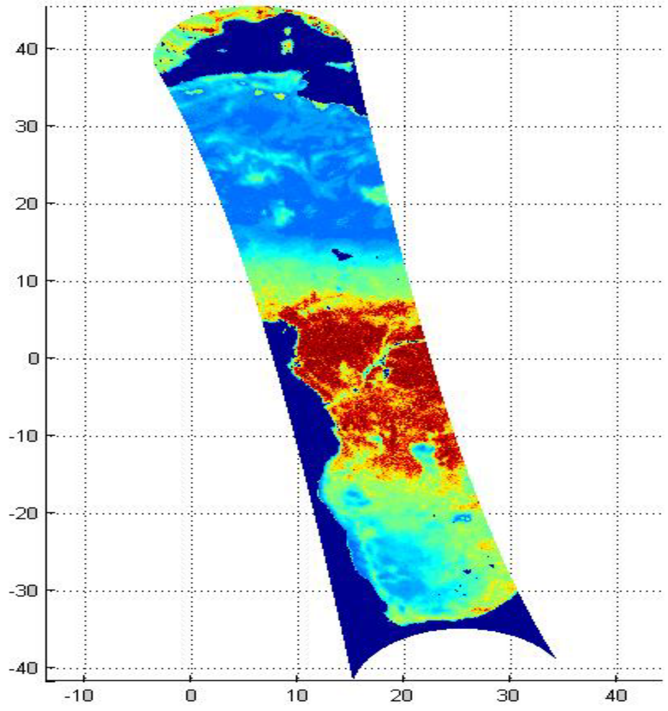


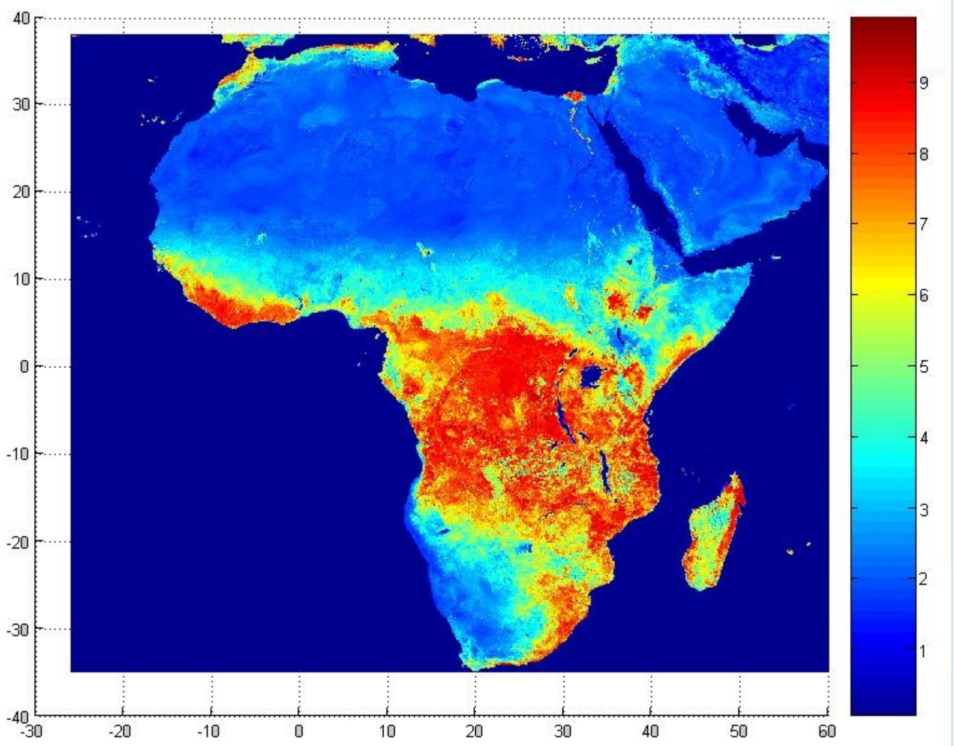


Santi et al., 2016, IEEE JSTARS

Mappe di biomassa (PWC) per l' Africa derivate da HydroAlgo

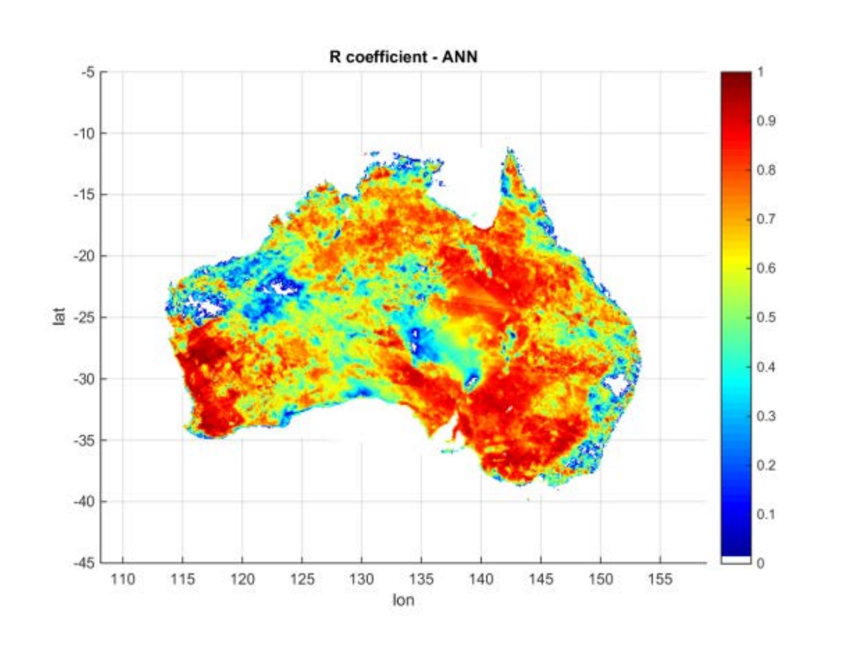
Da PI at X band e da NDVI

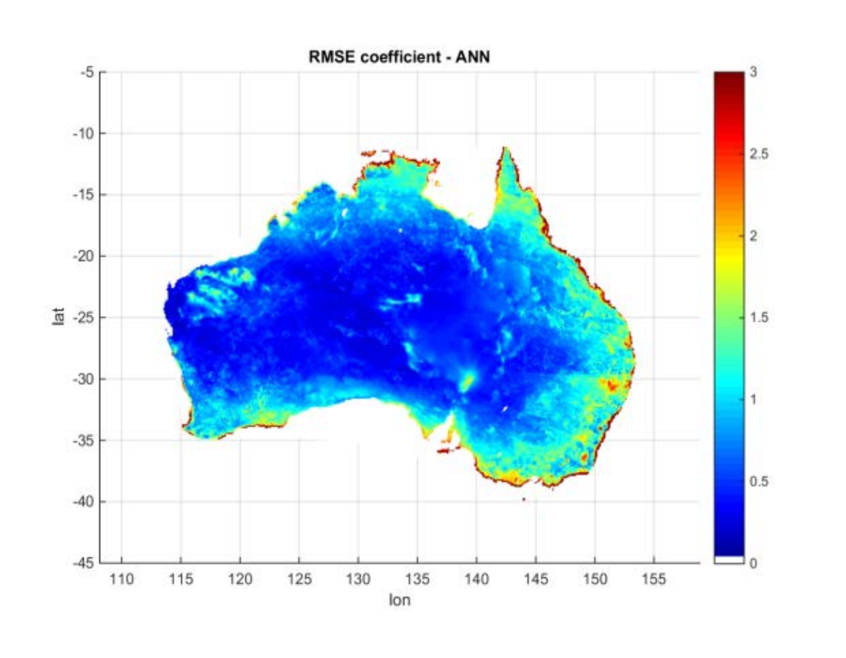




ANN PWC algorithm validation in Australia

Mappe di R and RMSE





Santi et al. 2017 IEEE JSTARS

(IEEE GRSS 2018 JSTARS Prize Paper Award)

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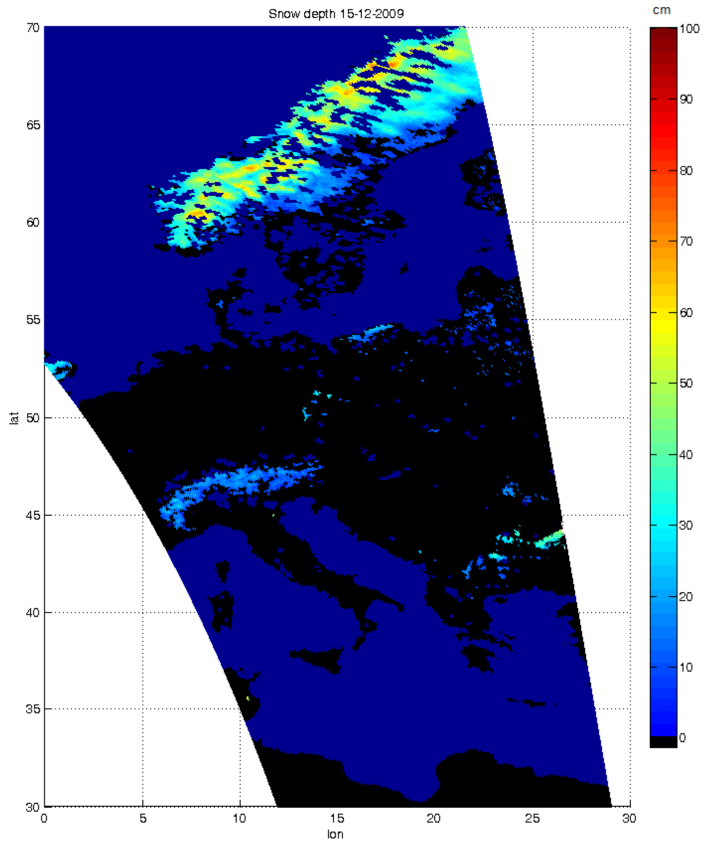
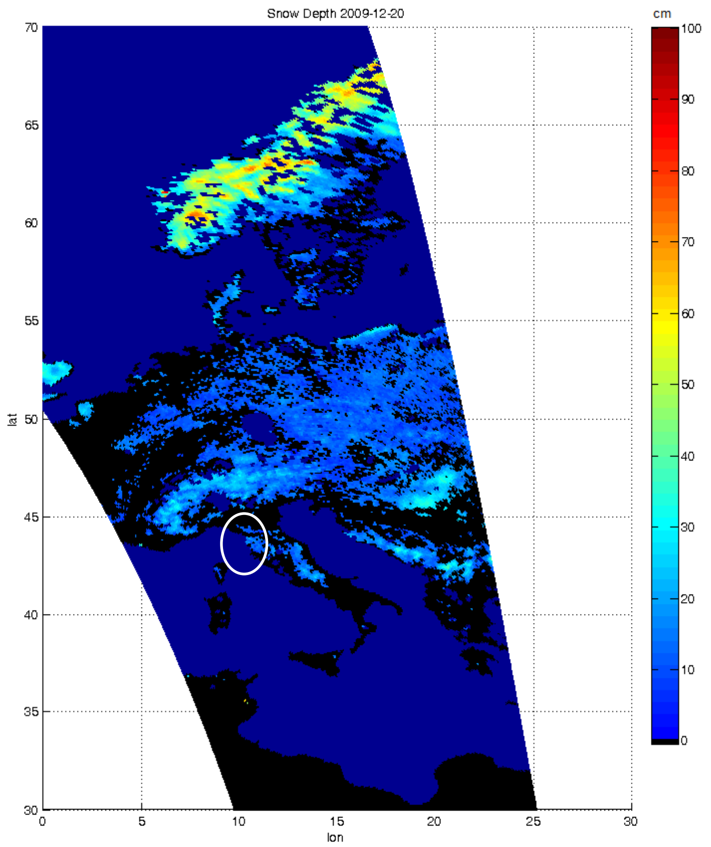
Mappe di spessore della neve da HydroAlgo e dati AMSR-E



15 Dicembre 2009



20 Dicembre 2009

CONCLUSIONS

- IFAC research confirmed the capability of multi-frequency microwave (SAR and radiometers) sensors in retrieving the main parameters of soil, snow and vegetation with good accuracy and improved spatial resolution with respect to single-frequency approaches.
- The use of retrieval algorithms based on machine-learning (ANN) allowed integration of data collected from different sensors and new inversion algorithms have been implemented for estimating SMC, PWC and SWE
- The training of the ANN was based on experimental data only (data-driven approach) and e.m. model data too
- **SMC**: CSK+S-1 and SMAP data were integrated, pointing out the algorithm capability in improving the correlation between estimated and in-situ SMC and the spatial resolution (<100m). R =0.82 and RMSE 0.046 m3/m3.
- **SWE**: The experimental sensitivity of SAR (CSK) to SWE was assessed using the DMRT and AMUNDSEN snow model and the ANN algorithm provided R=0.86 and RMSE 85mm
- PWC: only a preliminary algorithm was developed using CSK images. The preliminary results, for wheat only, are nevertheless encouraging.

CONCLUSIONS - II

- Radiometric microwave data at low resolution have been used for implementing only one algorithm ANN based (HydroAlgo), which is able to estimate SMC, SD and PWC using the different frequencies and polarizations of AMSR-E/2 sensors
- SMC was estimated at both global and local scales (10km resolution) with good accuracy although the validation is difficult
- PWC estimated was validated in Australia thanks to the support of JAXA team using MODIS NDVI as ground reference
- SD