

Gianluca Palermo (Sapienza – Università di Roma)

gianluca.palermo@uniroma1.it

Project supported by ESA Network of Resources Initiative

Objectives of the project:

- Retrieve snow properties in the Italian Central Apennine with Differential Interferometric spaceborn SAR data, using some auxiliary data.
- Estimate snow cover extension and classify snow (dry snow, wet snow).
- Estimate snow depth.
- Validate estimates with in-situ data obtained with measurement campaigns.
- Provide useful information in terms of avalanche warning, monitoring of climate change evolution, flood forecasting and water volumes expected for the hydric supply.











SWE: Snow Water Equivalent (m)

DInSAR snow retrieval method

The signal delay caused by snow refraction can be measured **if snow permittivity is known**.

Therefore snow depth variation between two dates can be estimated by calculating the SAR signal phase difference between two satellite passes.



Snow Permittivity

- Snow permittivity depends on snow water fraction and snow density values.
- Different models are available to estimate snow permittivity.
- A very simple model can be used as a rough approximation:

$$\in$$
 snow = \in dry-snow (1-f_w) + \in water f_w

More complex models are available in the literature

For water fraction and snow density values two options have been explored:

· a synthetic scenario with uniform distributions of values;

• a realistic scenario (shown below) made of estimates calculated by a dynamic snow-mantle evolution model (Alpine3D).



SNOW CLASSIFICATION: identification of dry snow and wet snow cover areas.

• A first approach has been adopted for the snow classification problem which employed the backscattering-coefficient thresholdbased algorithm proposed by Nagler-Rott for the dry-wet snow classification task.

$$r_{vv}(x, y) = \frac{\sigma_{vvm}^{0}(x, y)}{\sigma_{vvmref}^{0}(x, y)} = \begin{cases} \leq r_{0wet} & Wet \ snow \\ > r_{0wet} & Dry \ snow \end{cases}$$

This approach showed poor results on the considered AOI (Italian Central Apennines) Another approach based on an Artificial Neural Network (ANN) is currently being experimented.





SNOW ESTIMATION: retrieval of snow depth and snow density.

• The PAI algorithm, which is obtained by inverting the DInSAR equation with $\Delta h_s = \Delta Z_s$:

$$\Delta \hat{h}_{s}(x,y) = \frac{\Delta \Phi_{ppsm}(x,y)}{2 k_{i} \left(\sqrt{\varepsilon_{Rrs} - sin^{2} \theta_{l}} - cos \theta_{l} \right)}$$

The main limitation of the PAI inversion algorithm is that it requires ρ and f_w values to be known in order to perform the inversion; since ρ and f_w are, in general, not known, they need to be assigned estimated values, potentially resulting in a poor accuracy of the model.

• The LRI algorithm which is based on the statistical linear-regression approach and is described by the following equation:

$$\Delta \hat{h}_s(x, y) = a_{h0} + a_{h1} \, \Delta \Phi_{ppsm}(x, y)$$

•The MLI algorithm which uses a statistical approach where the error probability density function is maximized, under a Gaussian hypothesis its negative argument is minimized.

 $\begin{bmatrix} \Delta h_s(x, y) \\ \hat{\rho}_s(x, y) \end{bmatrix} = argmin\left\{ \left[\Delta \Phi_{ppsm}(x, y) - \Delta \Phi_{pps}(x, y) \right]^2 \right\}$

PAI inverse model -
$$\mu_{an} \approx 250 \text{ kg/m}^3$$

PAI inverse model - $\mu_{an} \approx 250 \text{ kg/m}^3$
PAI inverse model - $\mu_{an} \approx 250 \text{ kg/m}^3$
PAI inverse model - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI inverse model - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI inverse model - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI inverse model - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI inverse model - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI inverse model - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ kg/m}^3$
PAI error analysis - $\mu_{an} \approx 500 \text{ k$

CONCLUSIONS

Main achievements:

- We have implemented some dielectric models for snow permittivity estimation.
- We have used a realistic scenario based on a snow-mantle evolution model (Alpine-3D)
- We have implemented and tested a threshold-based algorithm which uses the backscattering-coefficient as input. This algorithm showed poor results on the Italian Central Apennine AOI.
- We have implemented and tested three different inverse models for snow depth estimation. They use differential SAR phase as input. MLI showed better performances.

Future developments:

- Multiband/multimission integrated analysis: combine C-Band (Sentinel-1), L-band (SAOCOM), and X-band (Cosmo SkyMed 1st and 2nd generation) data to take advantage of the different characteristics of each band.
- Implementing Artificial Neural Network based models to improve accuracy.
- Validation of the results with in-situ data.

Advantages derived from using tools and data within cloud environments sponsored by NoR:

- High-performing computing virtual machine allows a substantial reduction of processing times especially on time series
- The availability of the Sci-Hub Catalog products directly on the virtual machine as a mounted local disk make the process of dat acquisition smoooth and seamless.
- High network speed is available for external data transfer.

Potential benefits to society derived from this project:

 Provision of useful information in terms of avalanche warning, monitoring of climate change evolution, flood forecasting and water volumes expected for the hydric supply.