Statistical analysis of atmospherical components in ERS SAR data

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Rationale

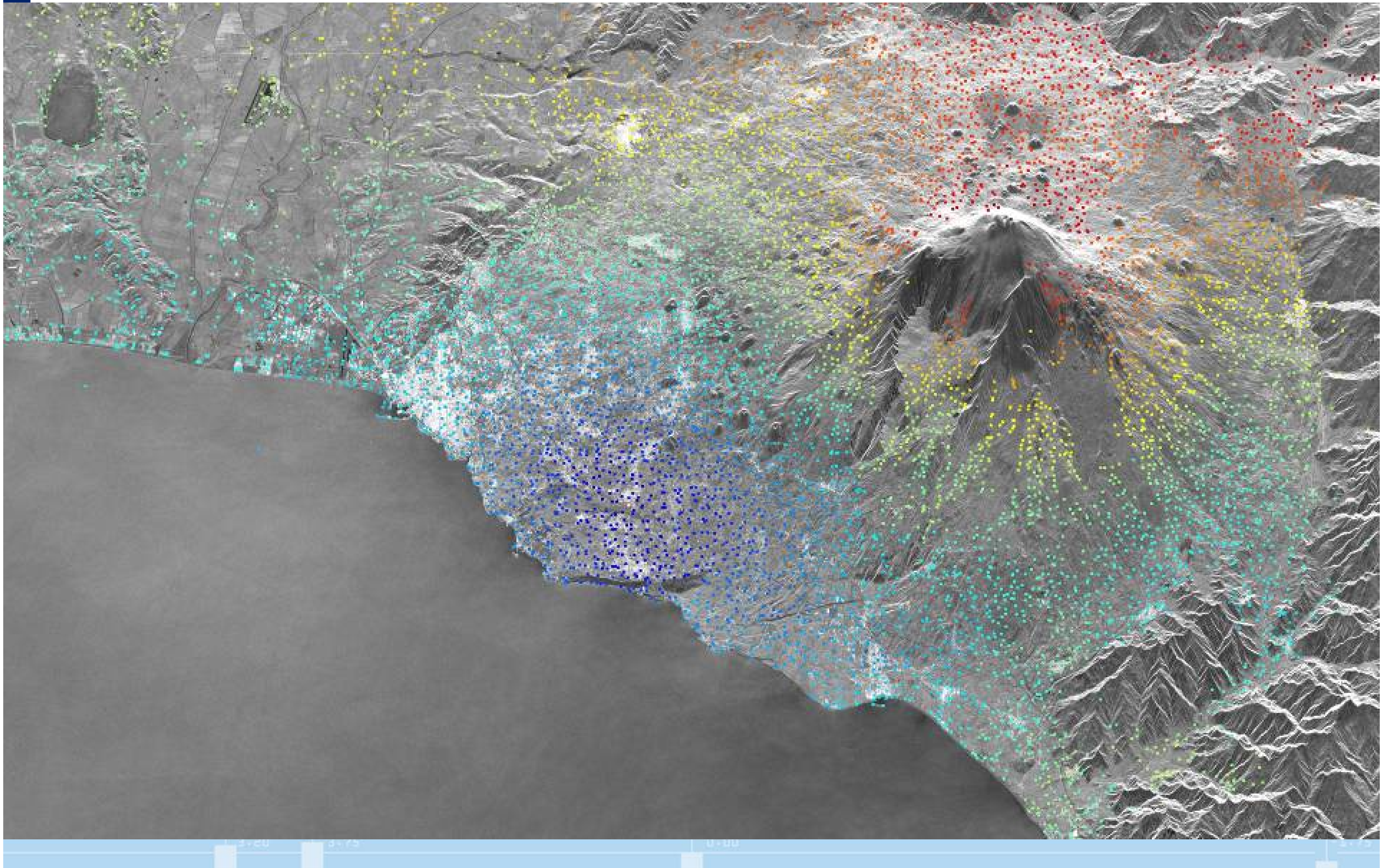
- **Lately, PSInSAR (and similar multi-interferogram techniques) has been widely used as a geodetic technique since it allows to infer precise information on possible variations of the sensor-to-target distance.**

- **The assessment of the impact of atmospheric disturbances on phase data, as well as the identification of possible mitigation strategies, has become more and more important.**

- **The number of data available at TRE (>9,000 ESA, >800 RADARSAT scenes) allows us to start a statistical analysis of the Atmospheric Phase Screen (APS).**

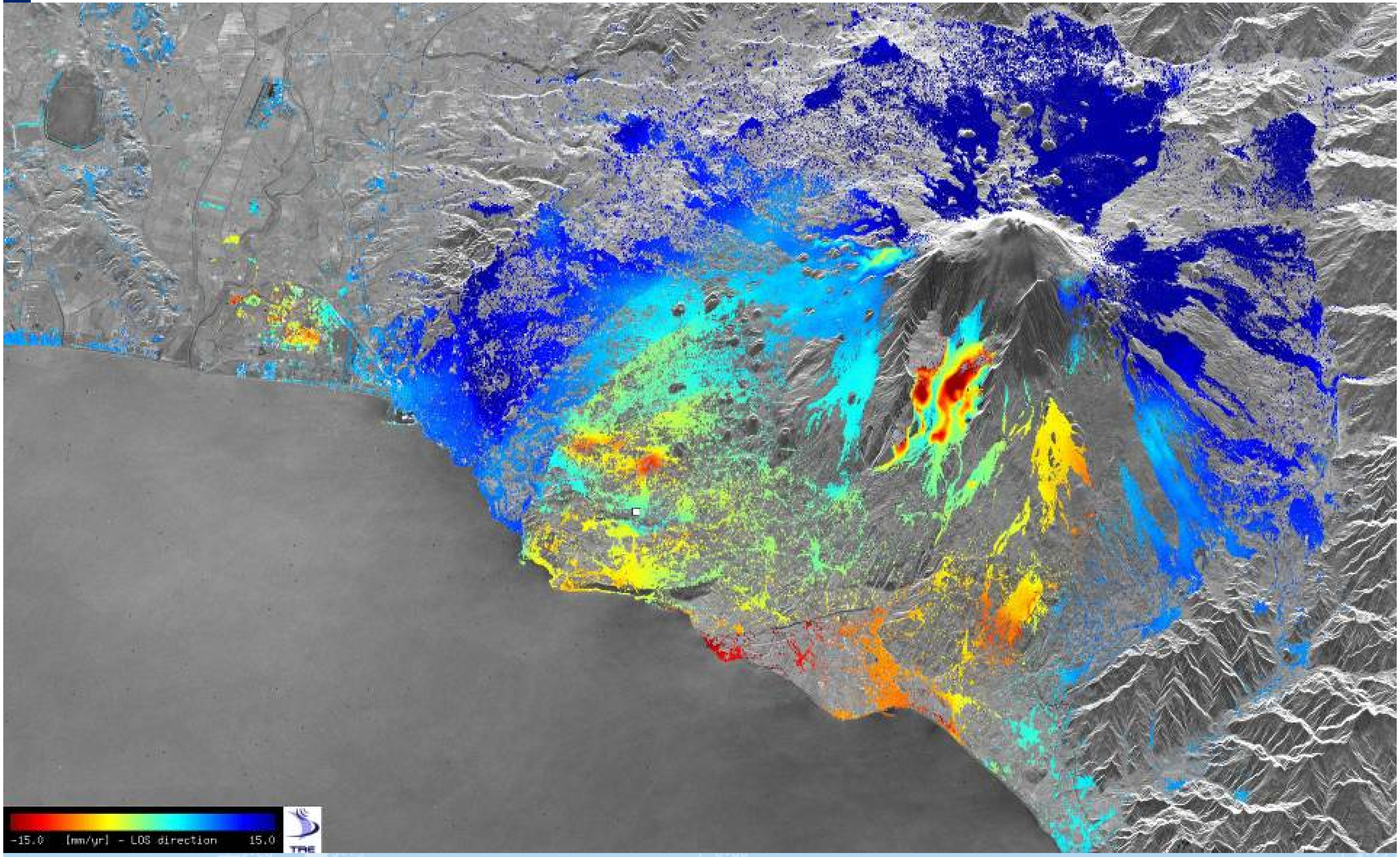
- **Results presented here should be consider as preliminary, since they refer to ~250 ERS scenes.**

PSInSAR: a 2-step algorithm (PSC vs. PS)



Final PS grid

Velocity field [mm/yr] of Etna volcano estimated from 55 ESA-ERS data (95-00)



Aims of the study

- **FACT:** **Estimation and removal of atmospheric disturbances (APS) is a <u>key-step</u> in PSInSAR**

- **QUESTIONS:**

  1. **How can we characterize APS? APS is a white process?**
  2. **Is it possible to improve PS results by better estimating APS?**
  3. **How can we take advantage of the data available in the ESA archive?**
  4. **What, if no auxiliary information (e.g. meteo-radar, GPS) is available?**
  5. **Can easy-to-access meteo data help in APS estimation?**

Estimation and Interpolation

Q: What is the best algorithm to interpolate the APS estimated on the sparse PSC grid?

$$\Delta\alpha = \tau_{turbulence} + \tau_{topography} + \varsigma$$

- **Turbulence phenomena can be described by a variogram (ie a structure function) exhibiting a "power law" behavior:**

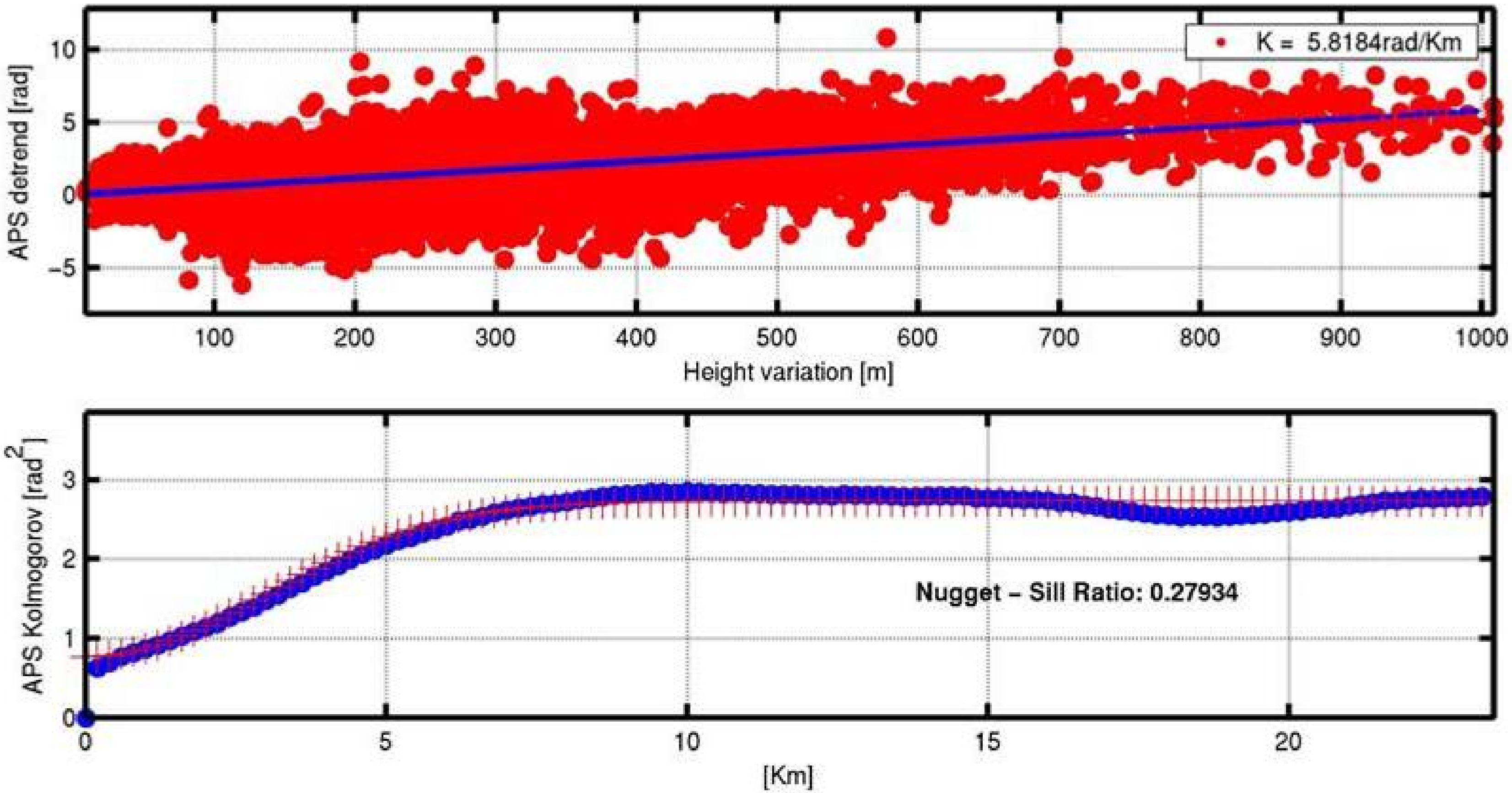
$$E\left[(\tau(\mathrm{P})+\tau(\mathrm{P,d}))^2\right] = \mathrm{C}\cdot\mathrm{d}^{\beta} \quad \text{with } 2/3 < \beta < 5/3$$

- **Topography dependent components are related to different atmospheric profiles at the time of the acquisitions. Different models are available (e.g. Saastamoinen model used in dGPS)**

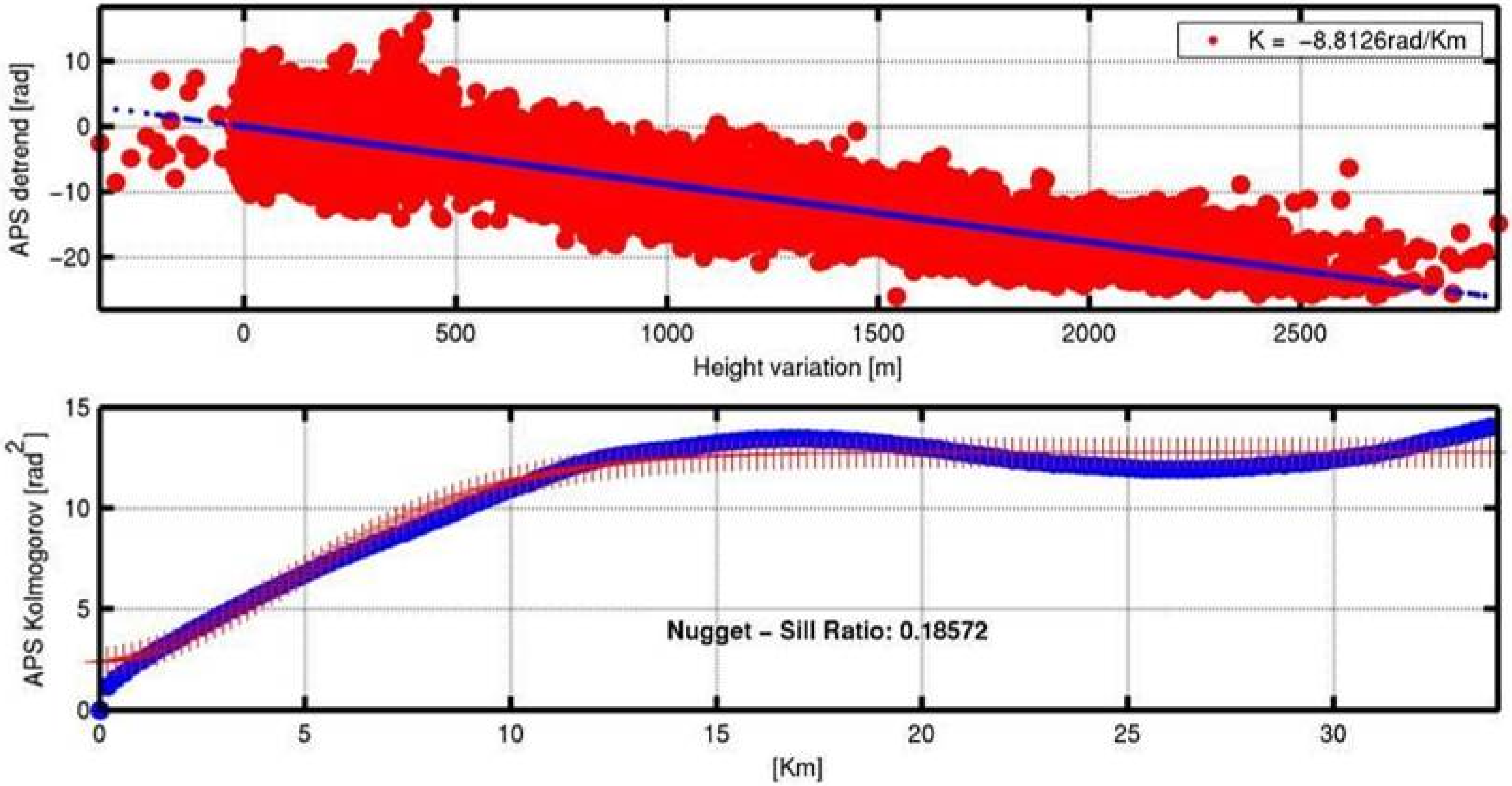
- **Ionospheric/orbital effects ζ can be easily estimated by fitting a low order polynomial to the estimated APS**

Data analysis (Gardanne - France)

APS values estimated by the PS processing on the sparse PSC grid, compensated for ionospheric/orbital components



Data analysis (Etna - Italy)



A mathematical model for APS

$$APS(x,y) = \tau_{turbulence}(x,y) + K \cdot z(x,y) + Ax + By + C$$

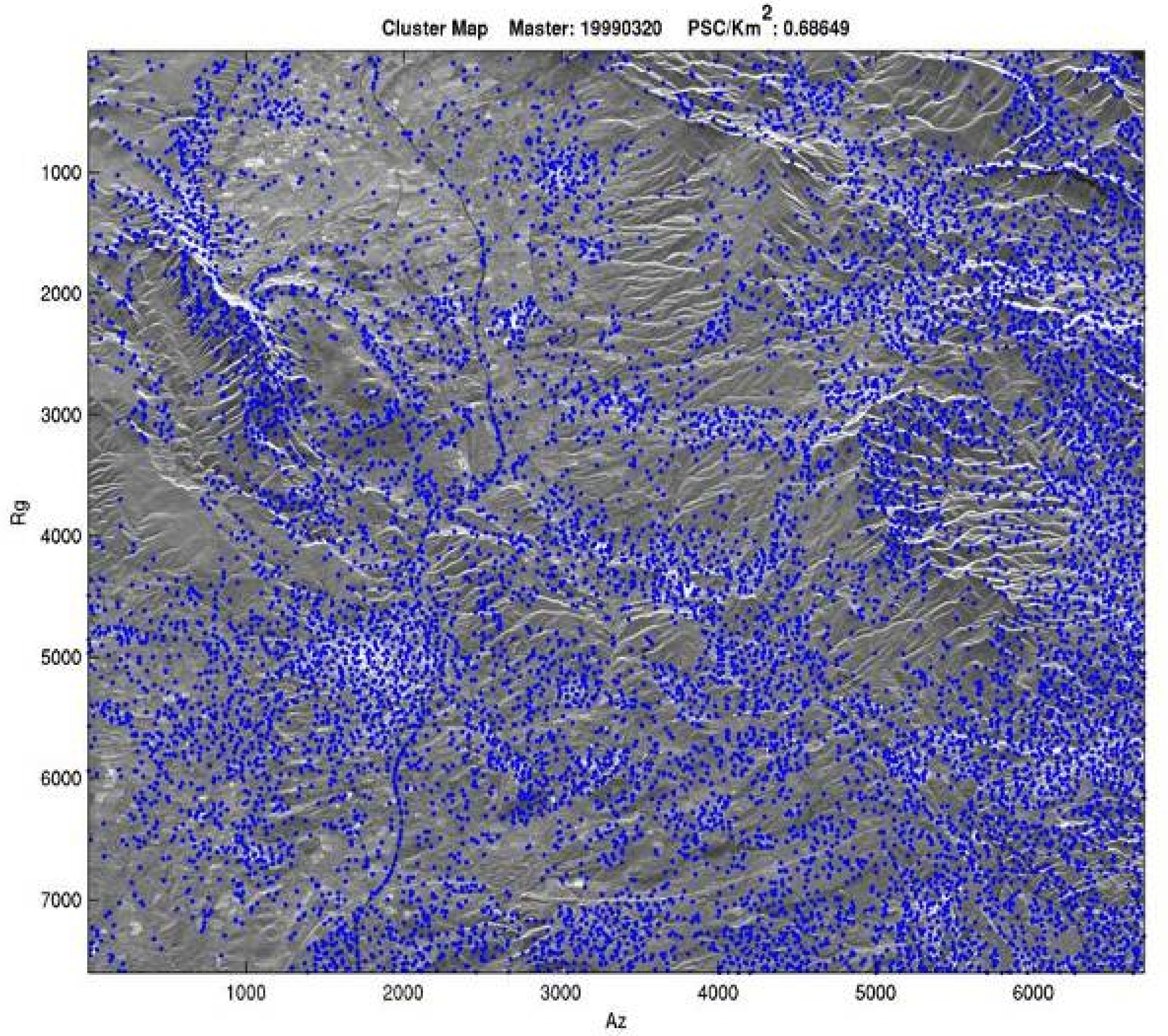
Kriging interpolation
after variogram estimation

$$N + S \cdot \left(1 - e^{-\left(\frac{d}{L}\right)^{\alpha}}\right)$$

4-parameter model

K,A,B,C LMS from the data
Z from a DEM

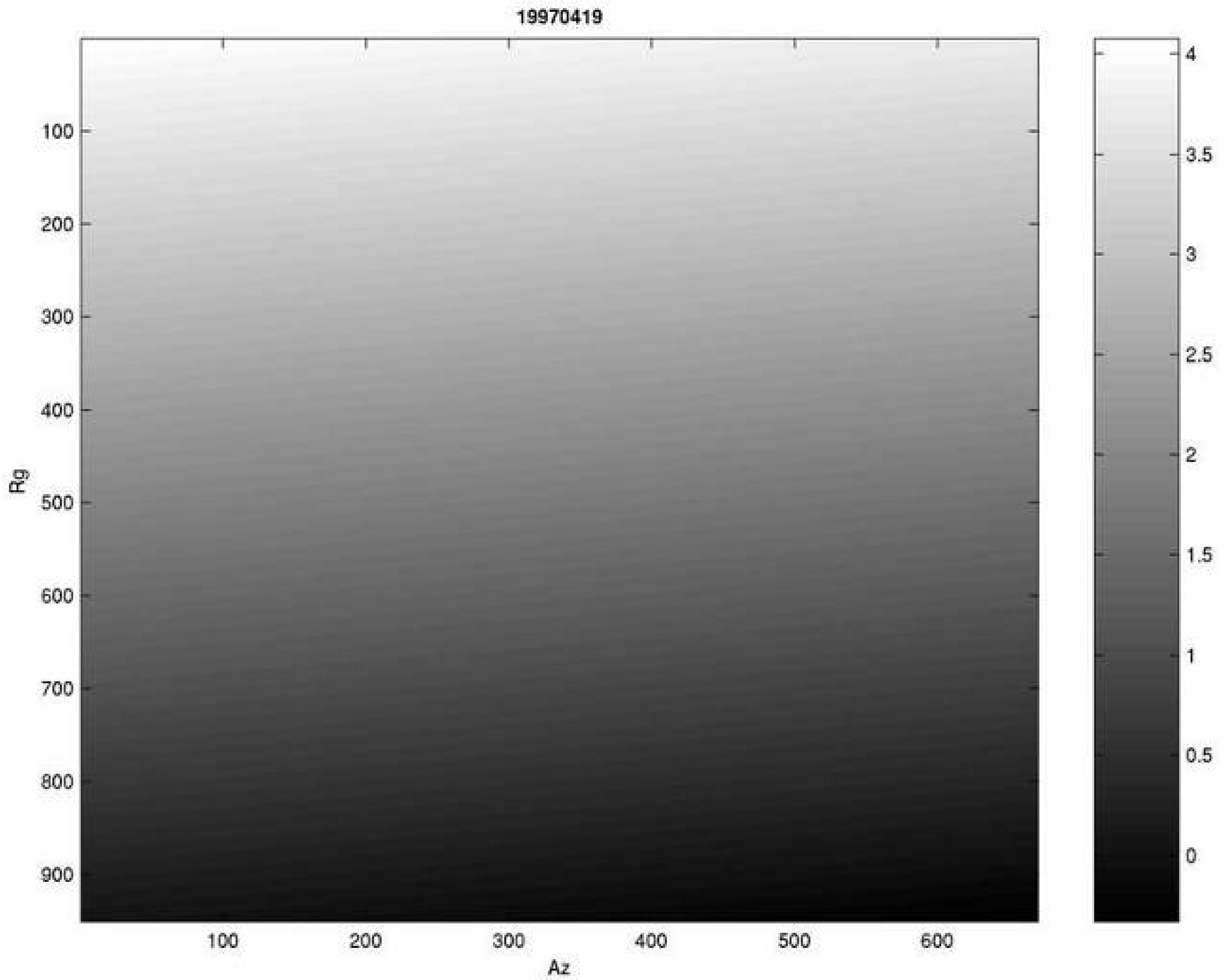
Application (Gardanne- FR)



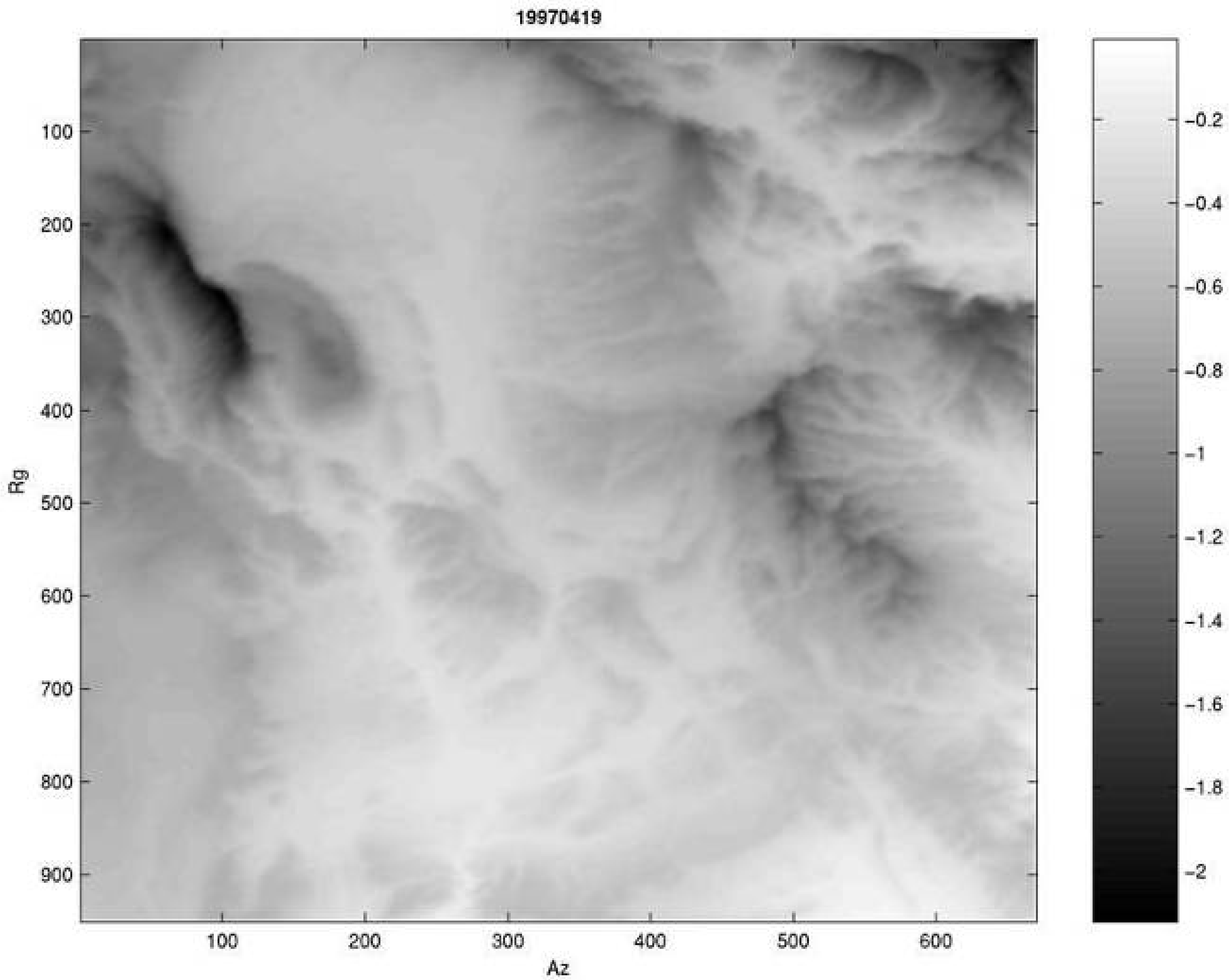
Estimated ionospheric/orbital fringes

σ =1.2 rad

From
LMS of
A,B,C



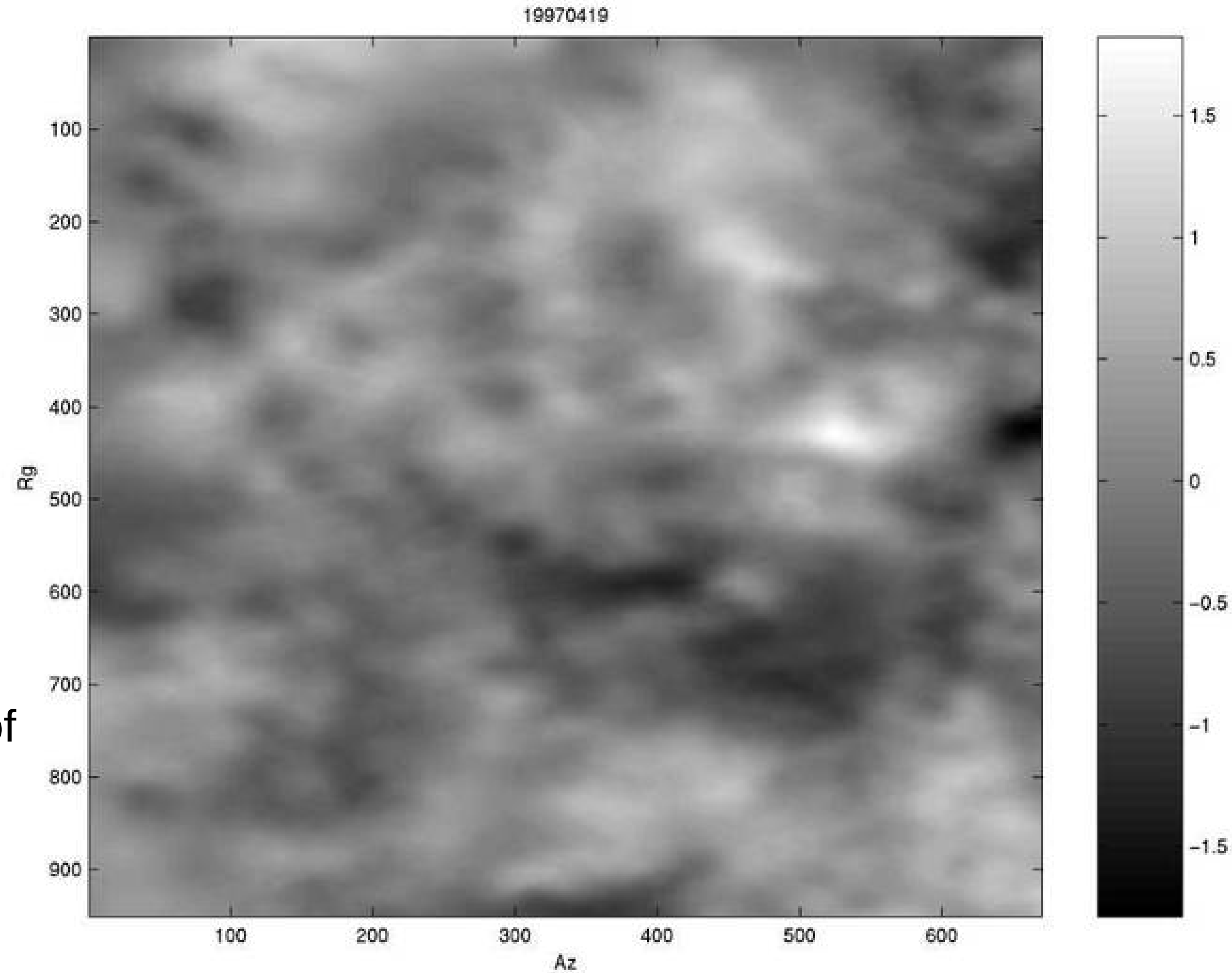
Topography dependent components



σ =0.5 rad

From SRTM data + LMS of K

Turbulent components

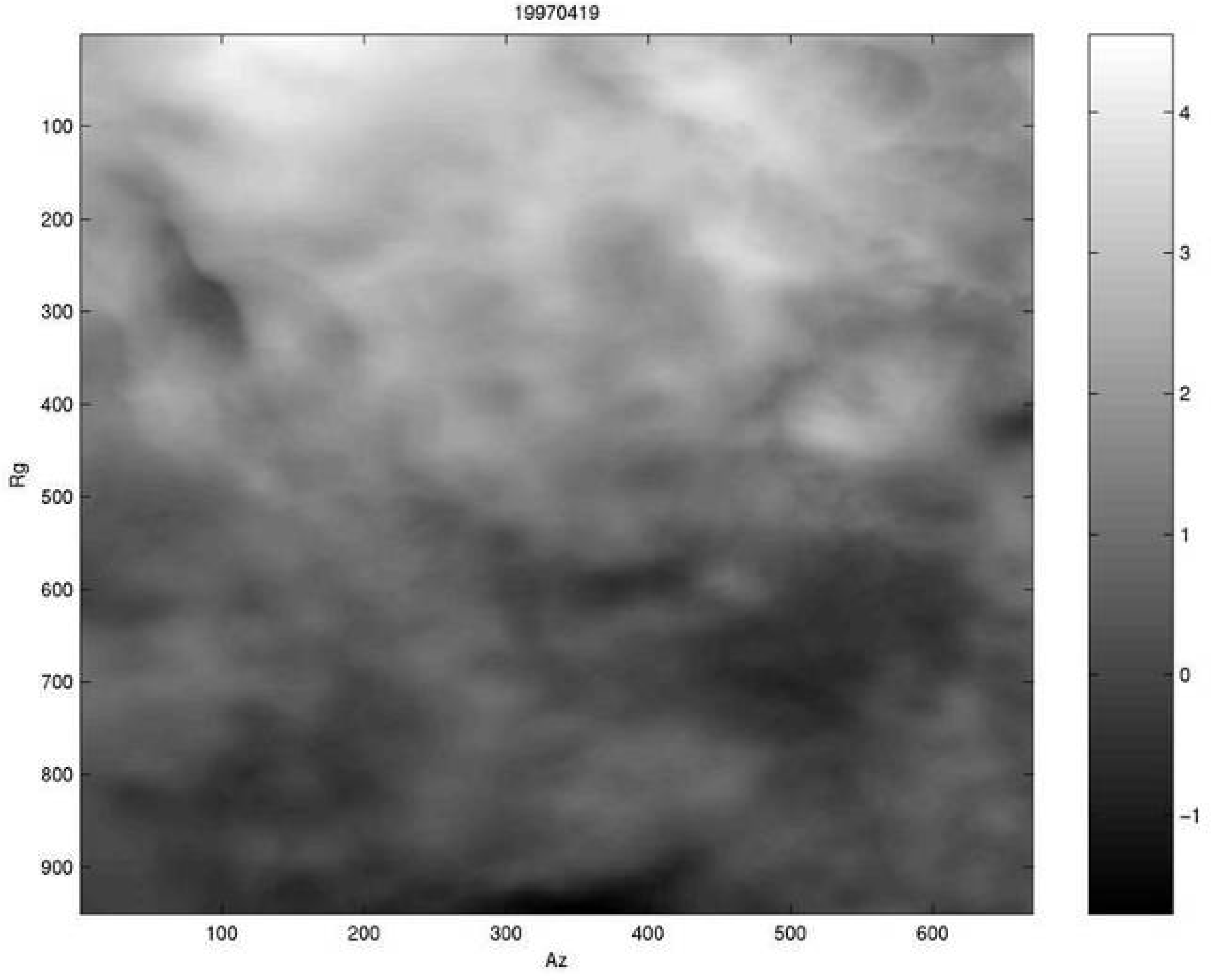


σ =0.7 rad

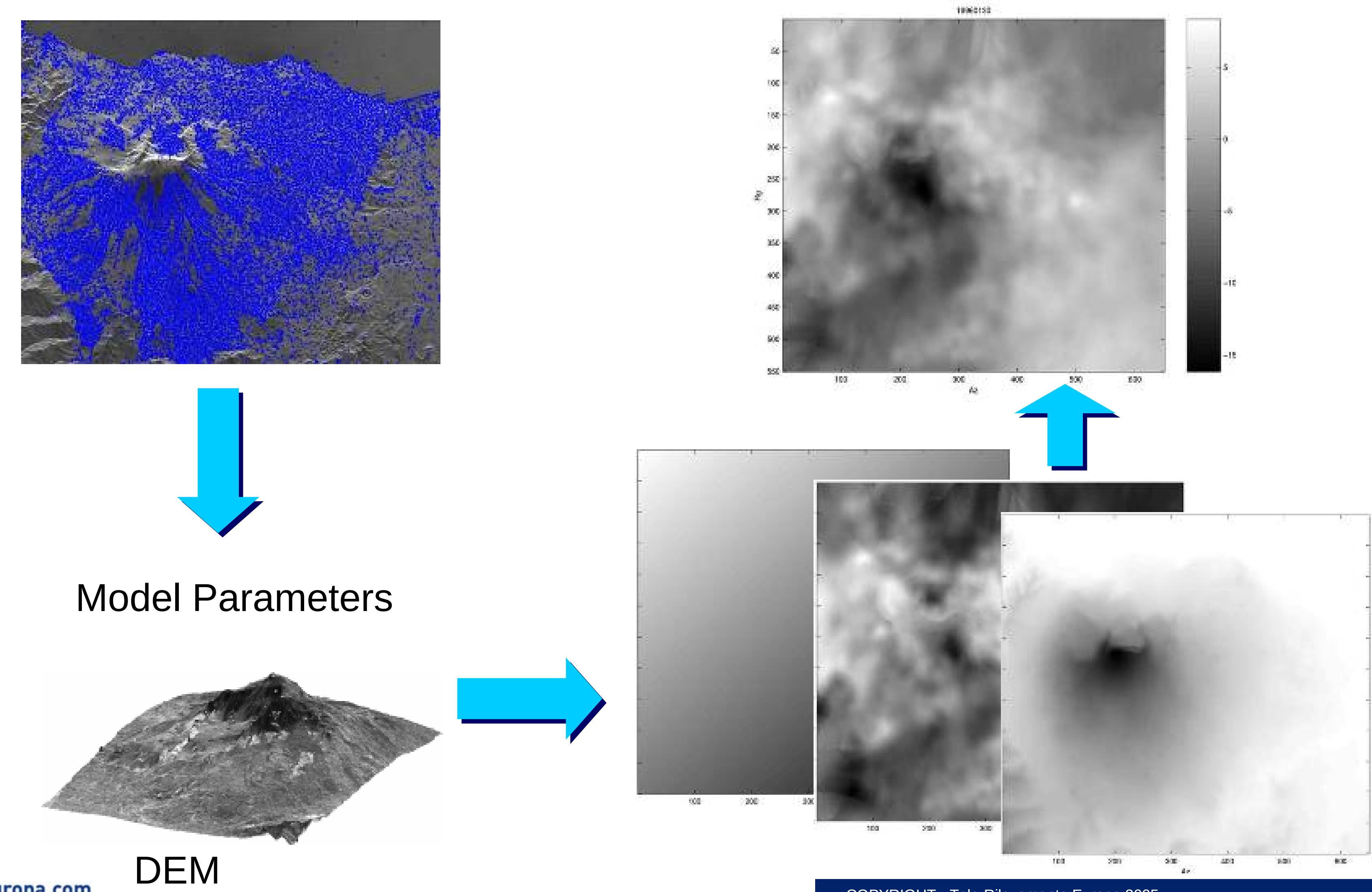
From kriging interpolation of the residual phase components

Combination: final result

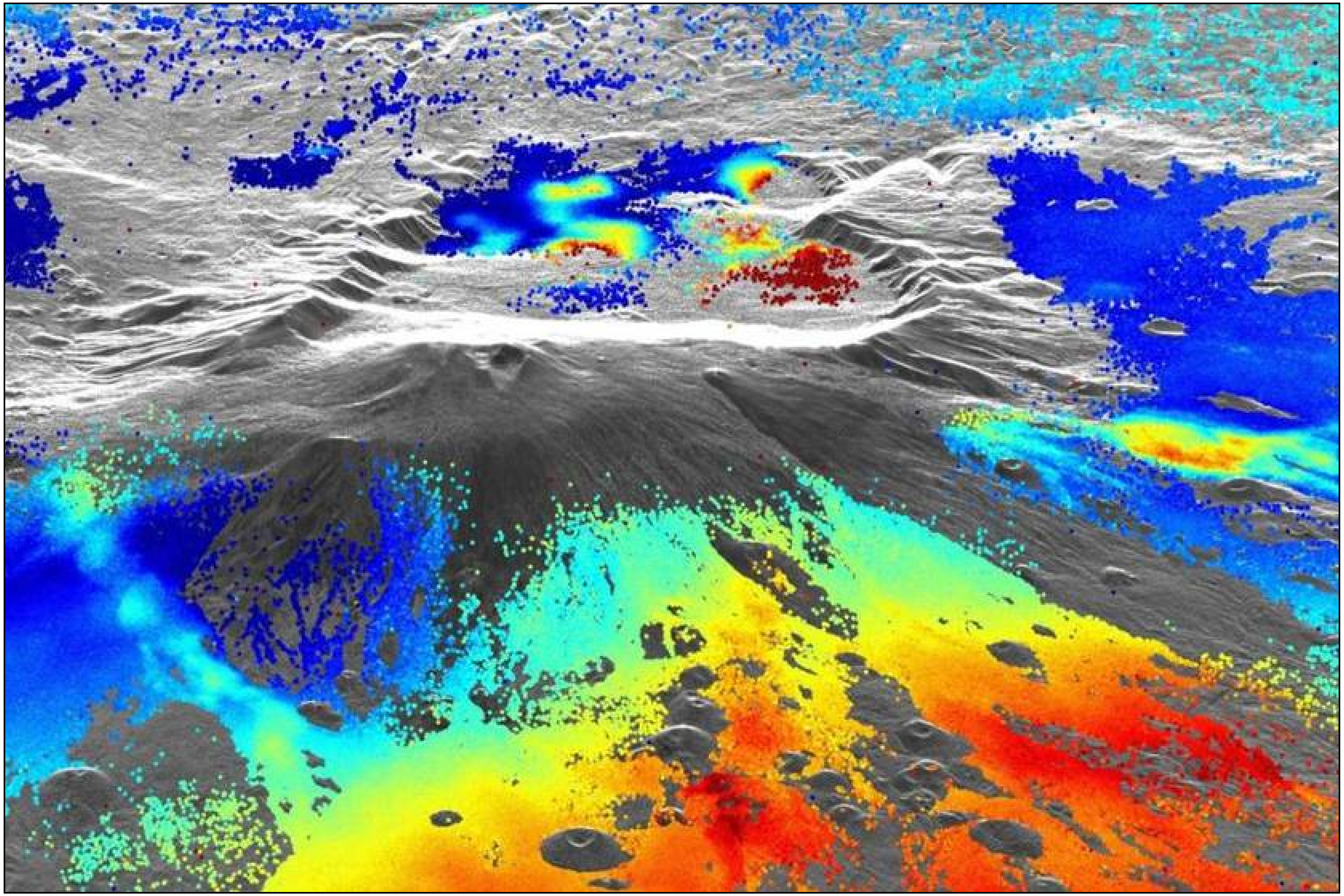
σ =1.5 rad



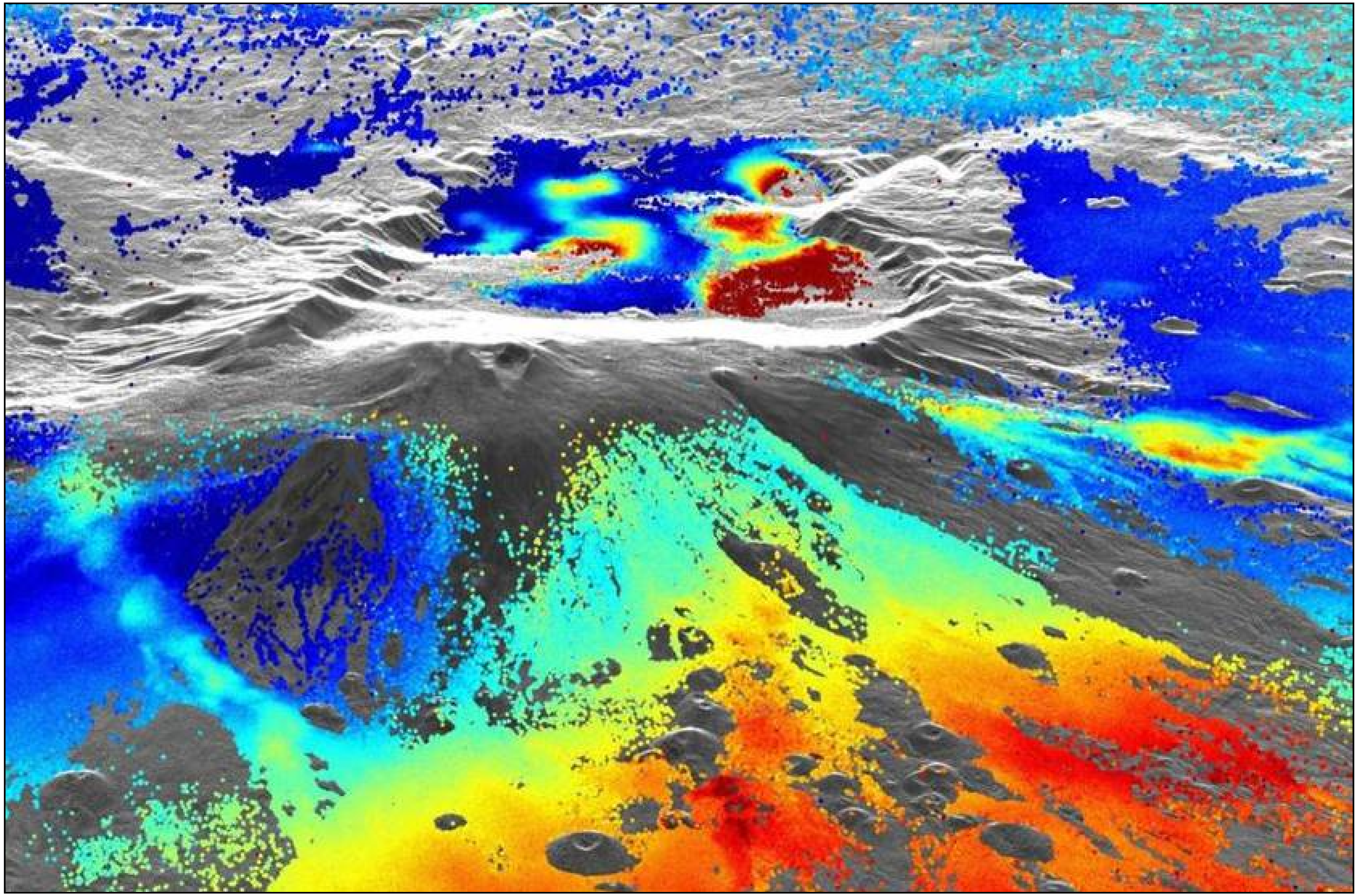
APS estimation procedure



Does it work? ➔PS results – Etna



PS results – Etna (new algorithm for APS)

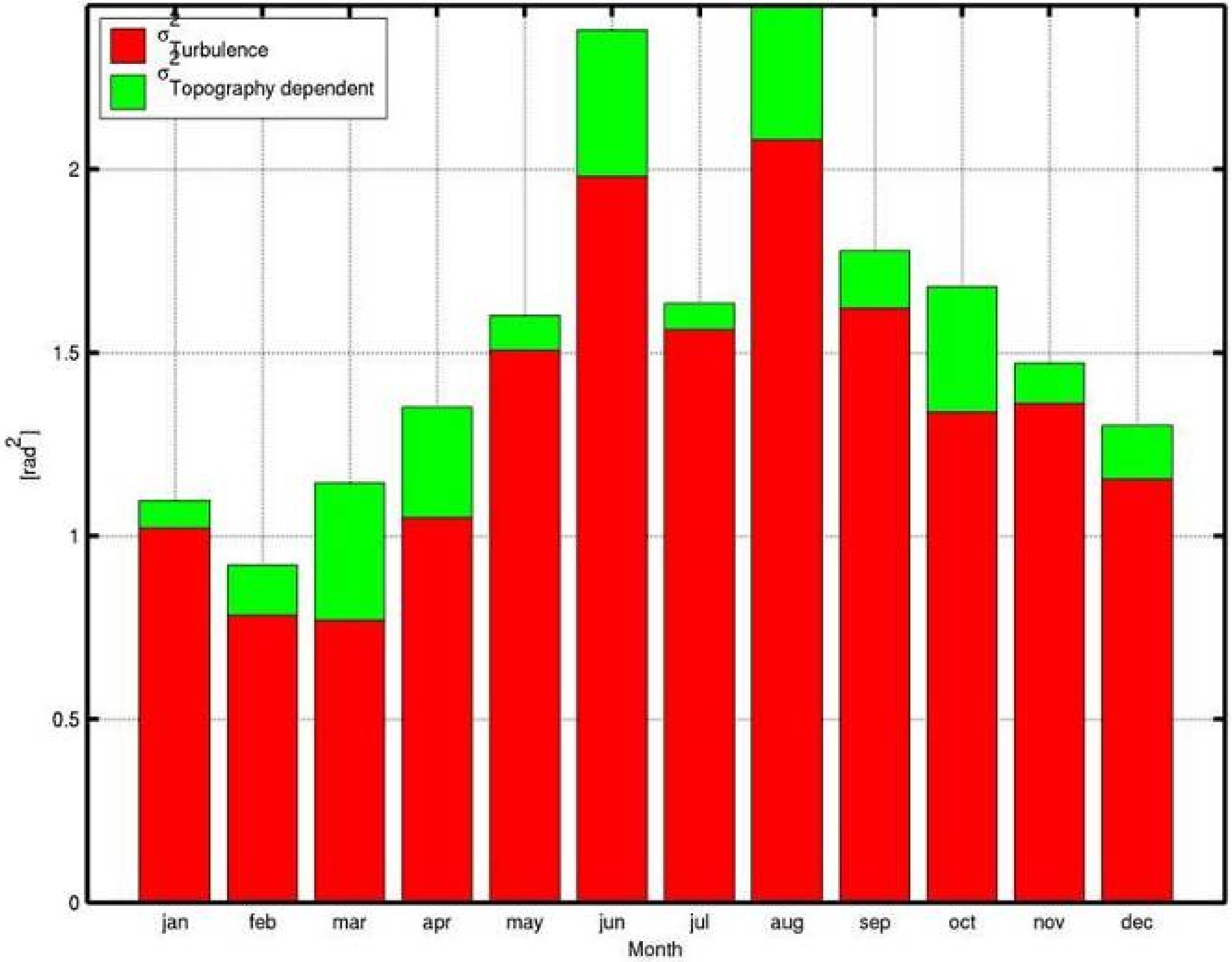


Seasonal behavior of APS power (1)

Gardanne
78 ERS data

Δh = 1100m

σ = 300 m

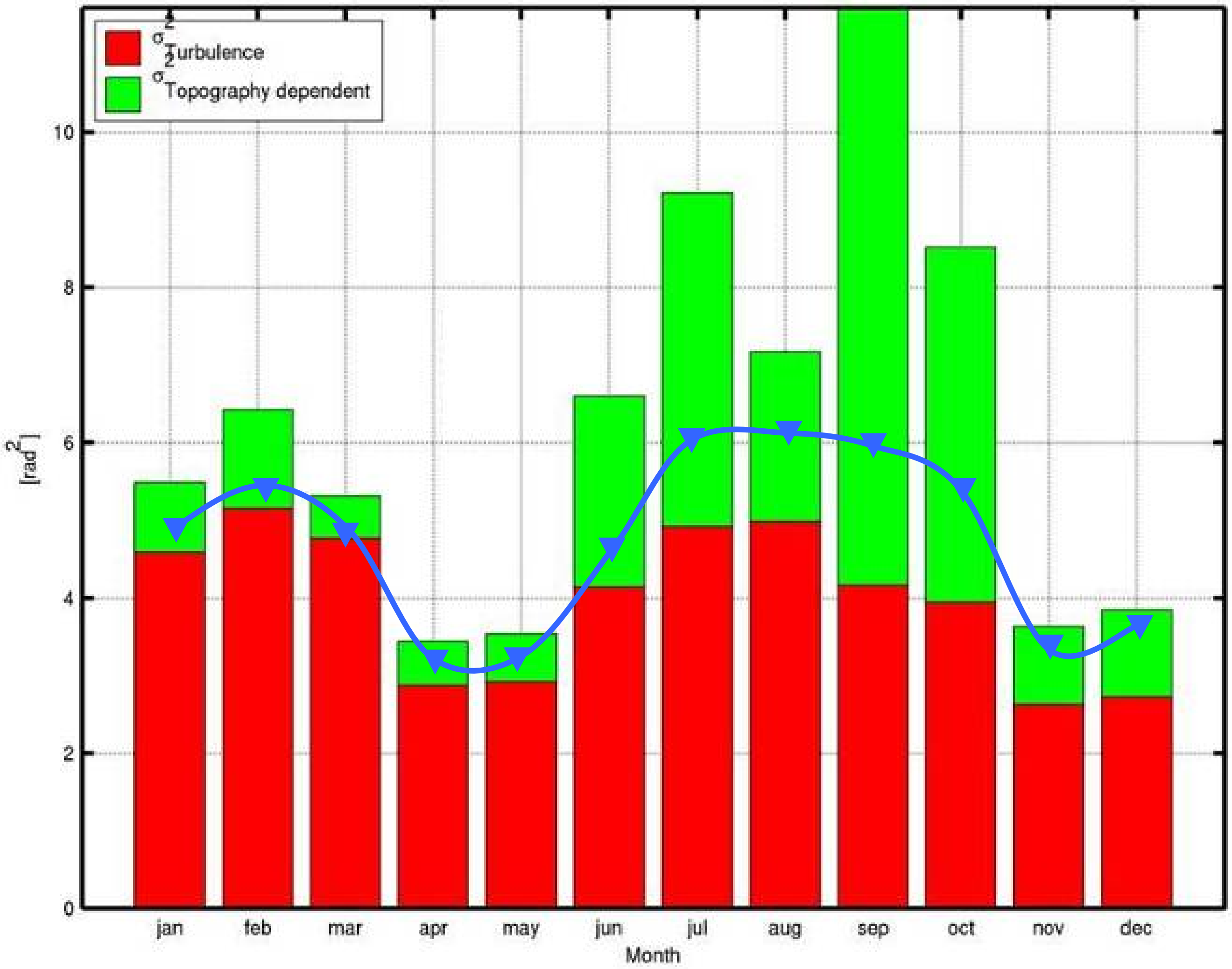


Seasonal behavior of APS power (2)

Etna
55 ERS data

Δh = 3300m

σ = 720 m



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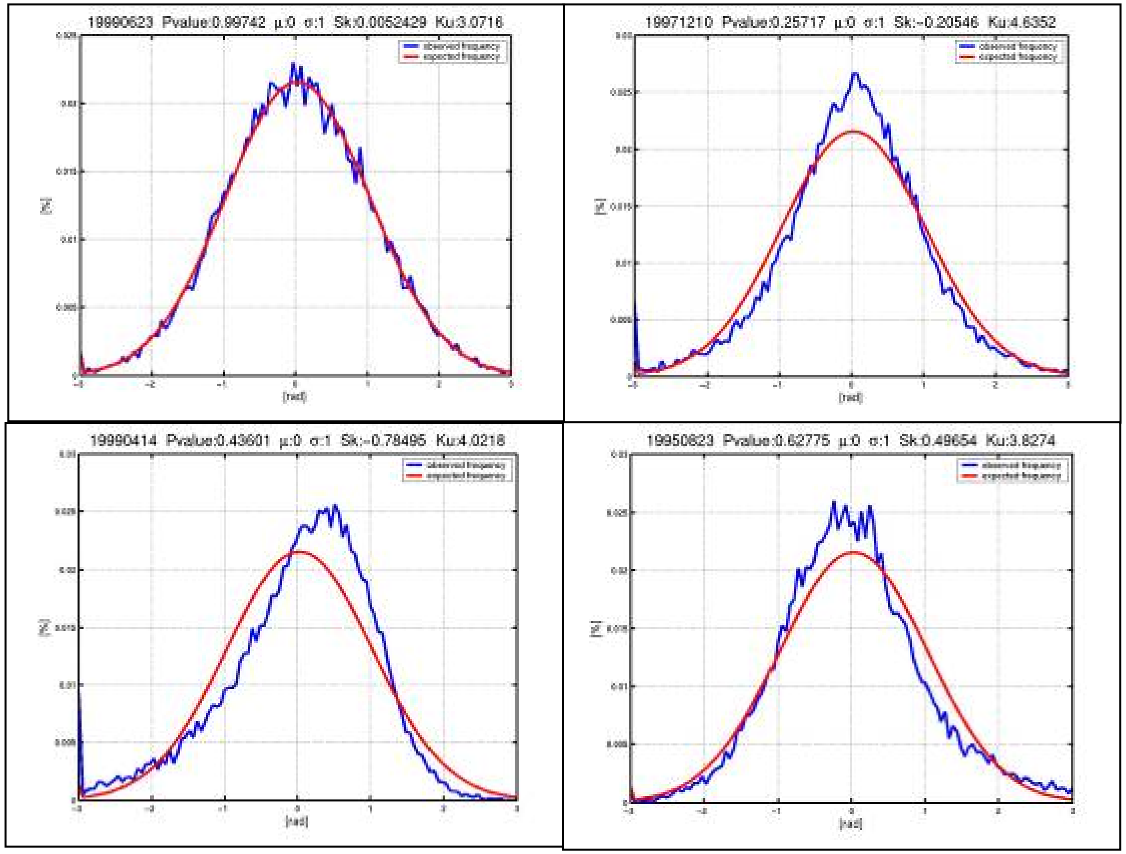
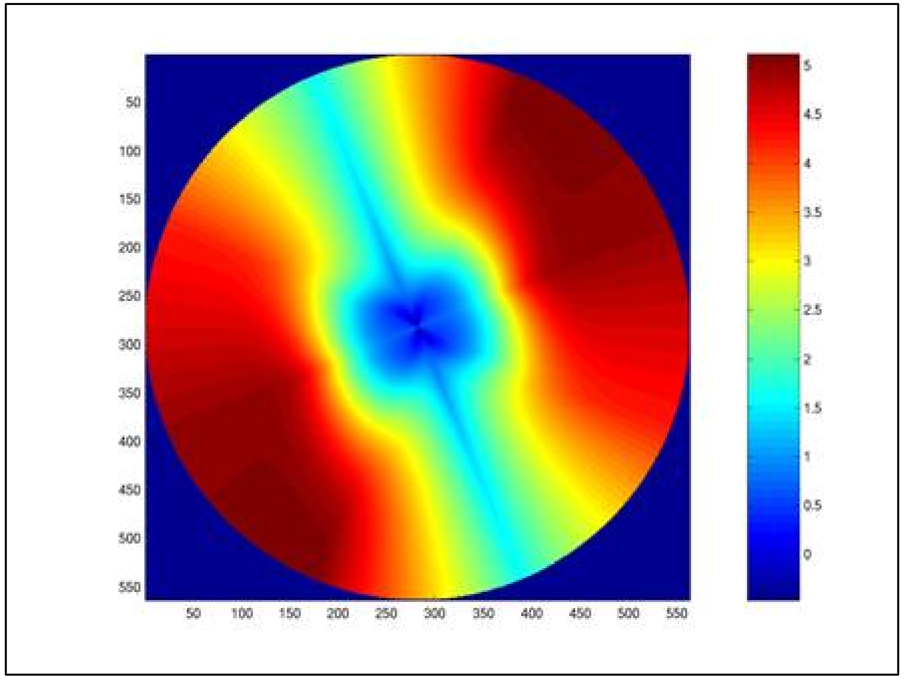
Gaussianity Test

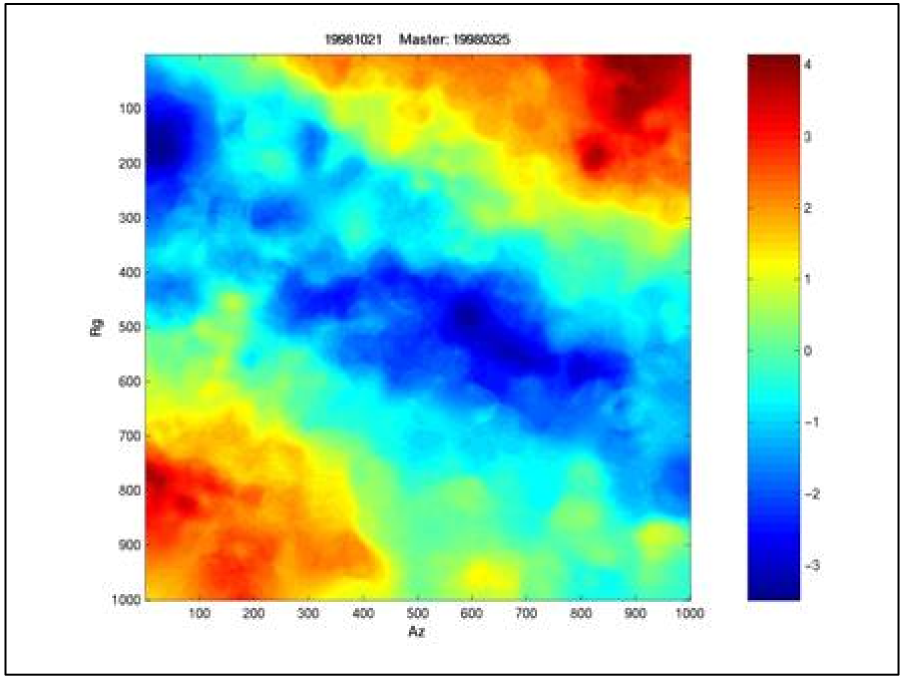
- **Only <u>33%</u> of the data pass the test for normality** (D’Agostino-Pearson - 90% confidence level)



Signal anisotropy (1/2)

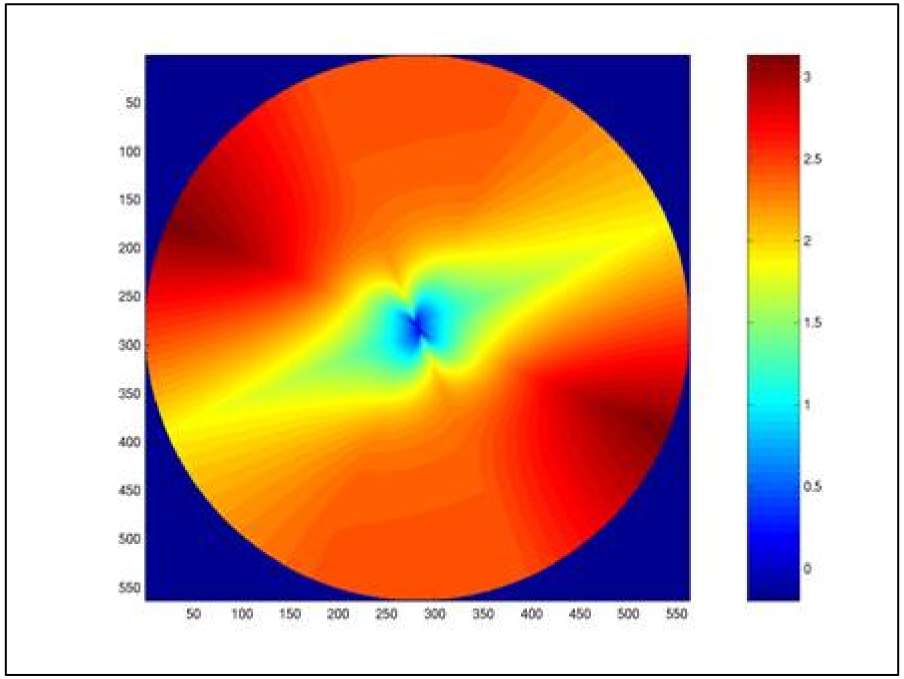
- **A statistical analysis carried out by a 2D spatial variogram shows that more than 50% of the APS exhibit anisotropic behavior, even on a full scene (100x100 km)**

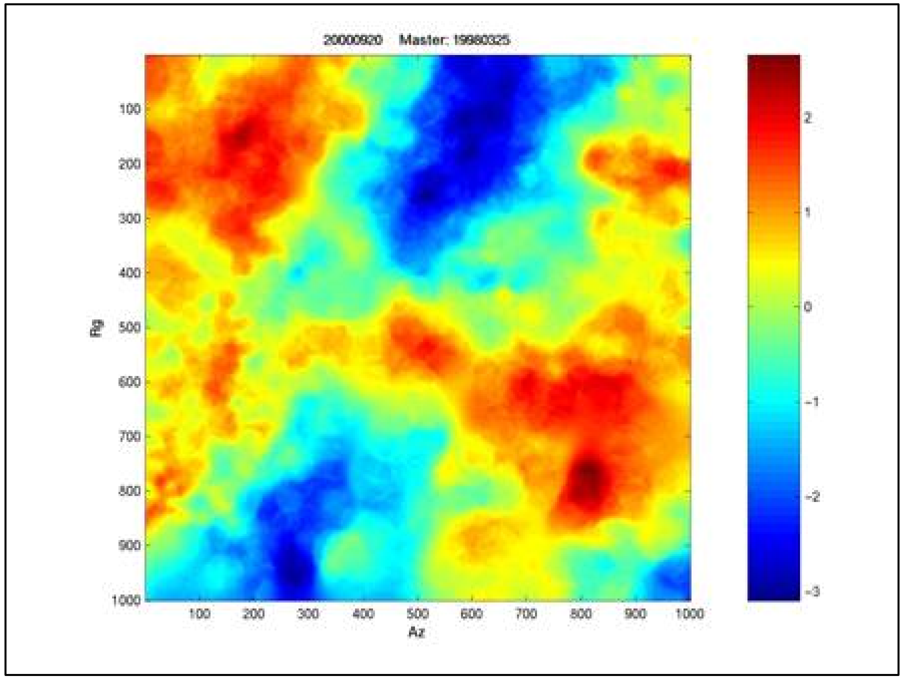




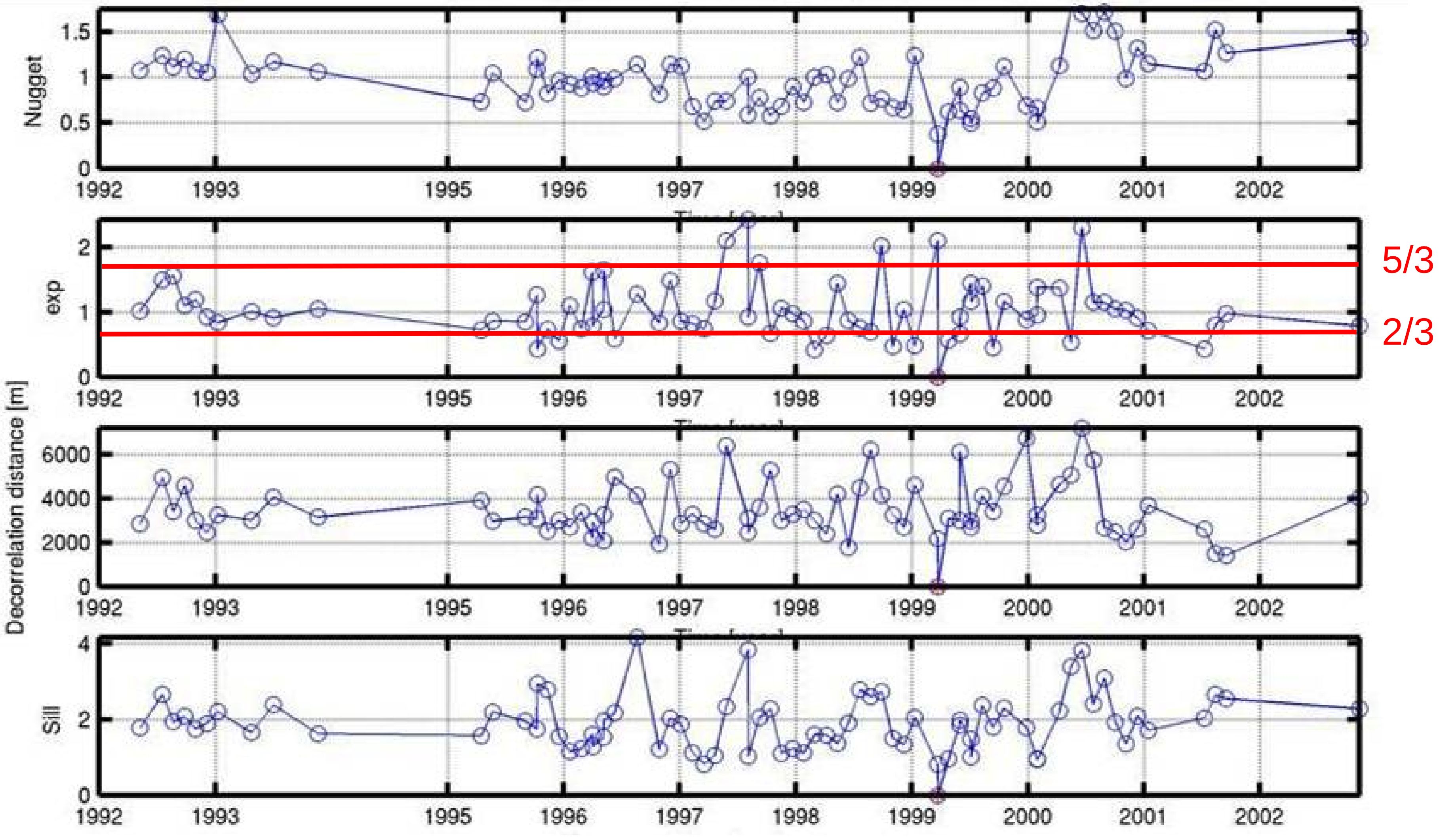
Signal anisotropy (2/2)

- **Although a quantitative analysis is still in progress, the adoption of 2D variograms in the kriging interpolation does not increase the final PS density significantly**



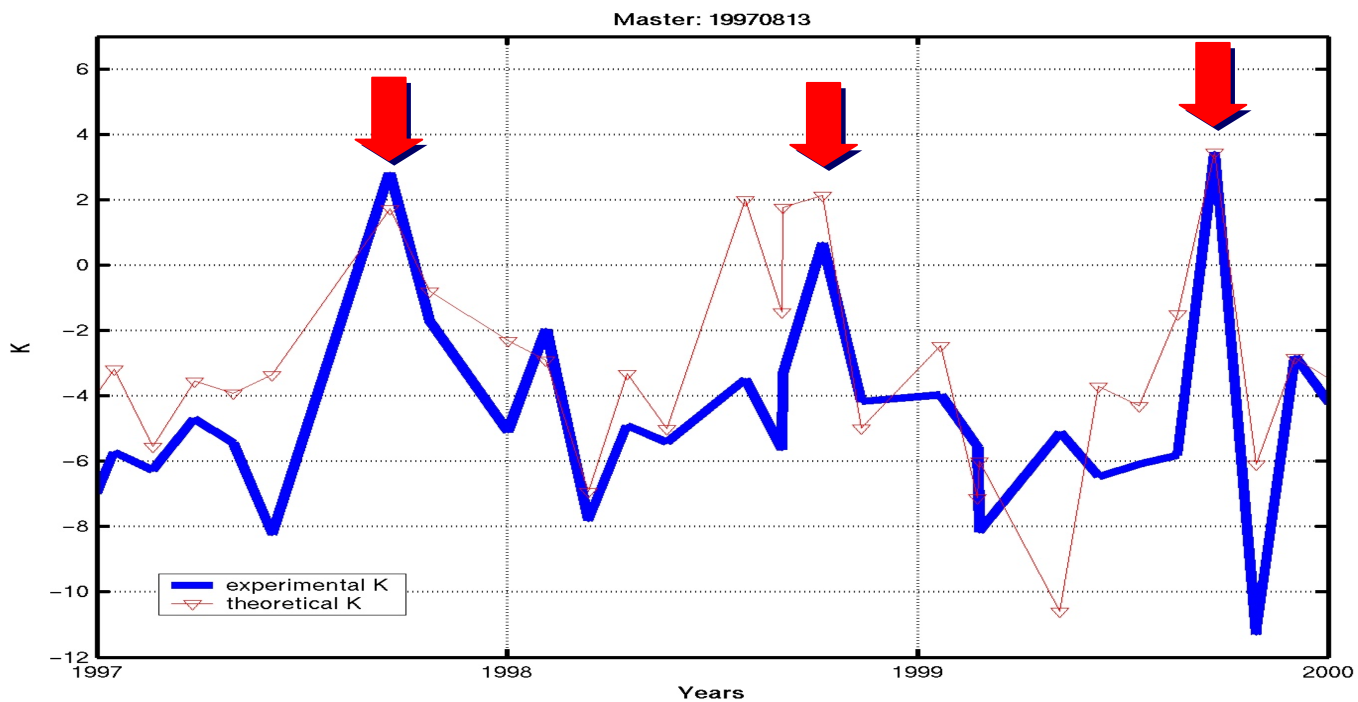


Variogram parameters



Exploitation of meteo-data

- **Topography-dependent APS components can be correlated in time (since they exhibit a seasonal behavior). This can prevent the application of the standard PS approach. The exploitation of meteo-data can mitigate this phenomenon acting as a “whitening filter”.**



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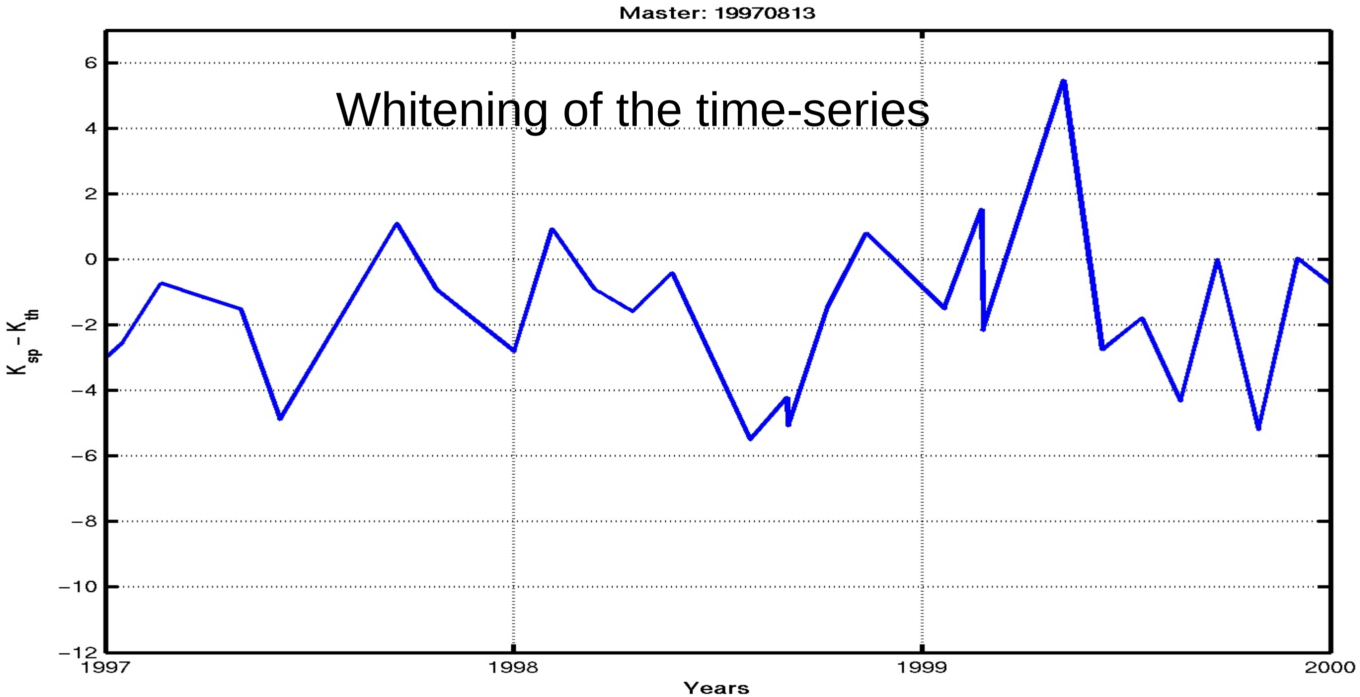
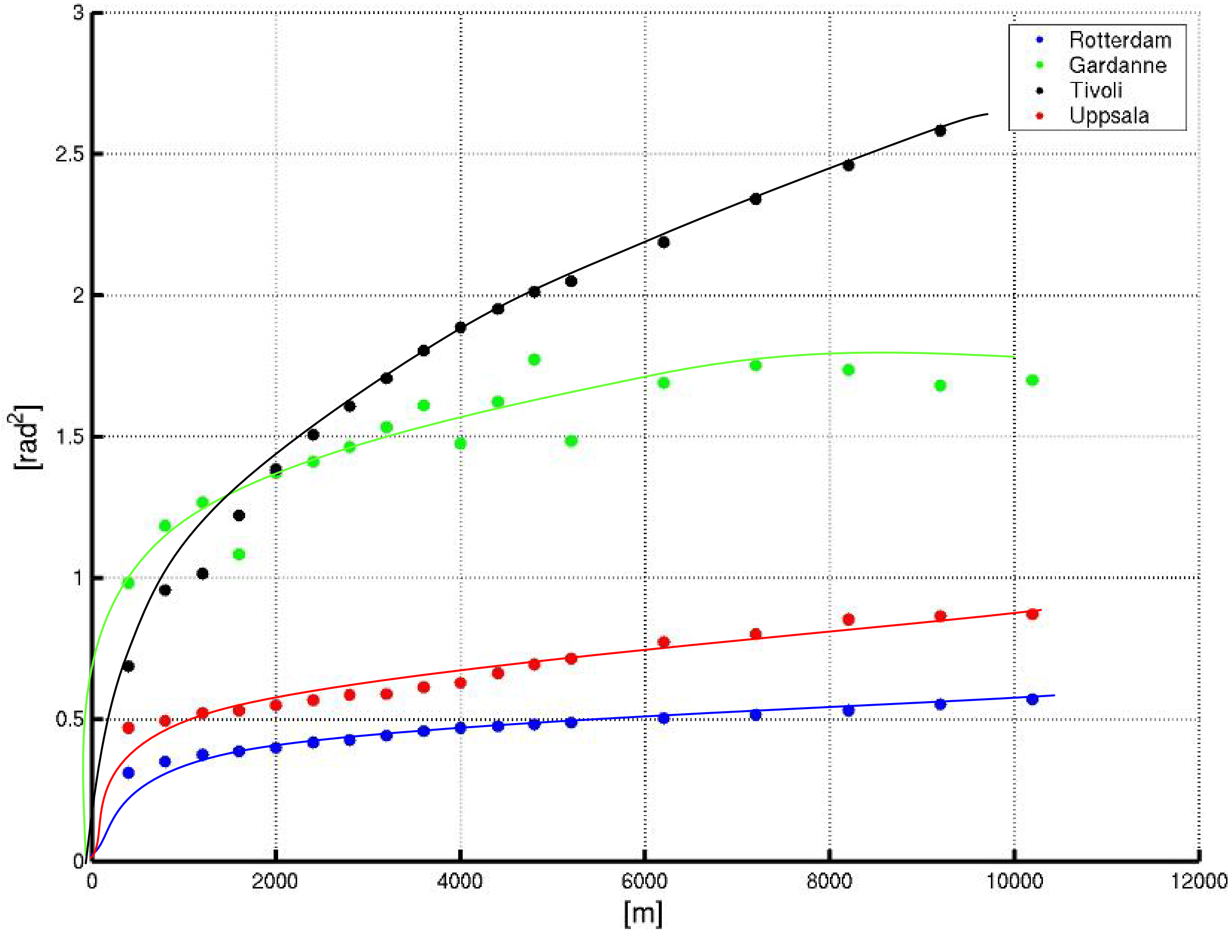


Mean variograms at different latitudes



Conclusions

- Apart from ionospheric components and orbital fringes, both topography dependent and turbulent tropospheric components have to be taken into account in DInSAR and PSInSAR.

- Data show that, as a first approximation, a linear model can be applied to fit topography dependent components. SRTM data can be successfully exploited to better interpolate APS data sampled on a sparse PS grid.

- APS RMS values can exceed 2π rad in areas of rough topography at mid-latitudes. Mean power and variogram is latitude-dependent.

- APS components usually do not exhibit a gaussian statistics.

- 10-30% reduction in APS power can be obtained using (P,T,h) information (even for moderate topographic profiles).