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EUMETrain Week

Webinar 17/12/2020

Integration of rainfall data for improving hydrological modelling

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Part1: Modified Conditional Merging

F. Pignone

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INTRODUCTION

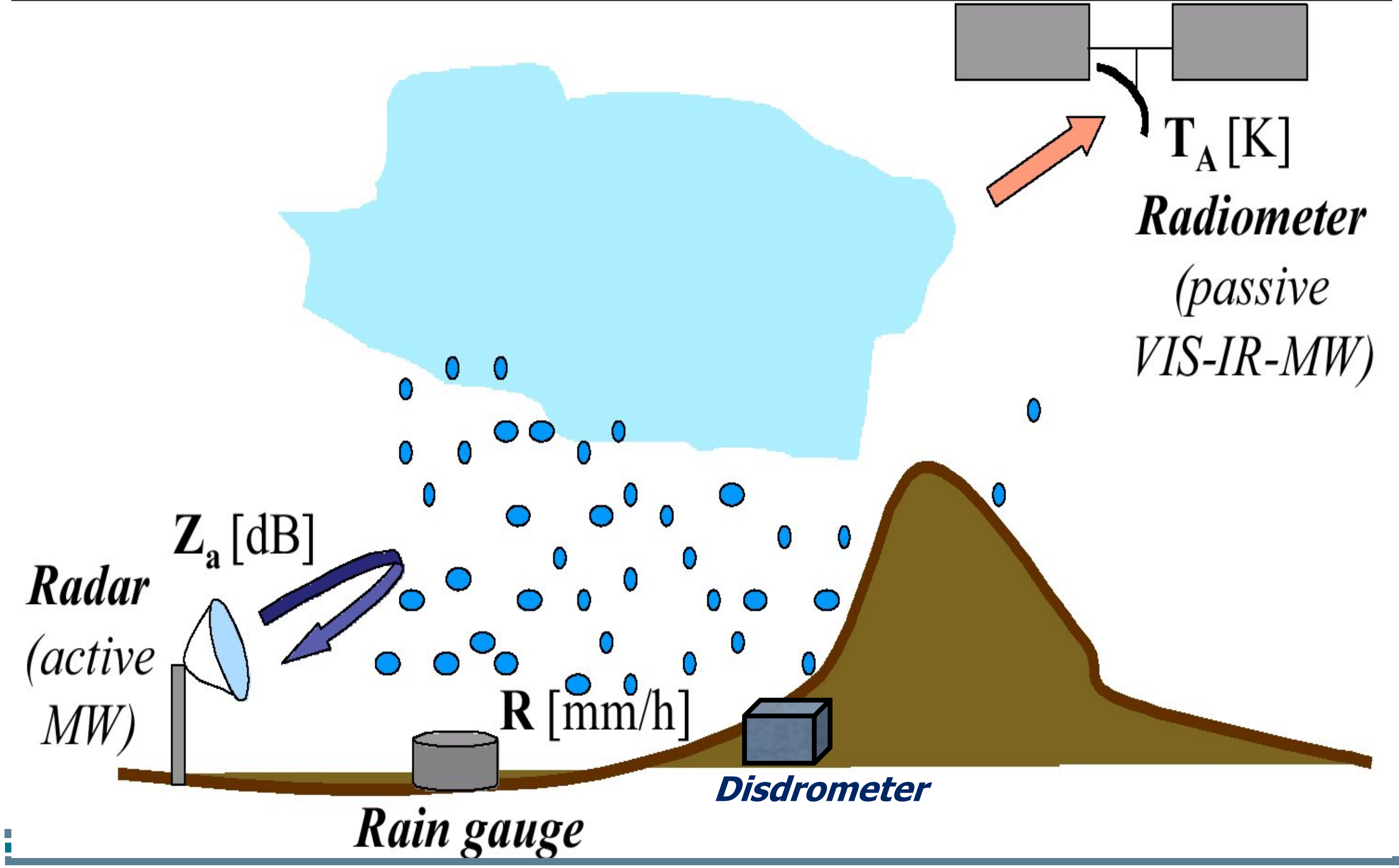
“The Mediterranean coastal cities, both on southern and northern borders, are used to sudden and disastrous rainfall. The interaction between convective processes originating on the warm sea and sudden orographic lifting very close to the coast produces heavy rainfalls. It rains very often in one hour the monthly average and in a day the yearly average.”

Genoa flood, 1970

Genoa flood, 2011

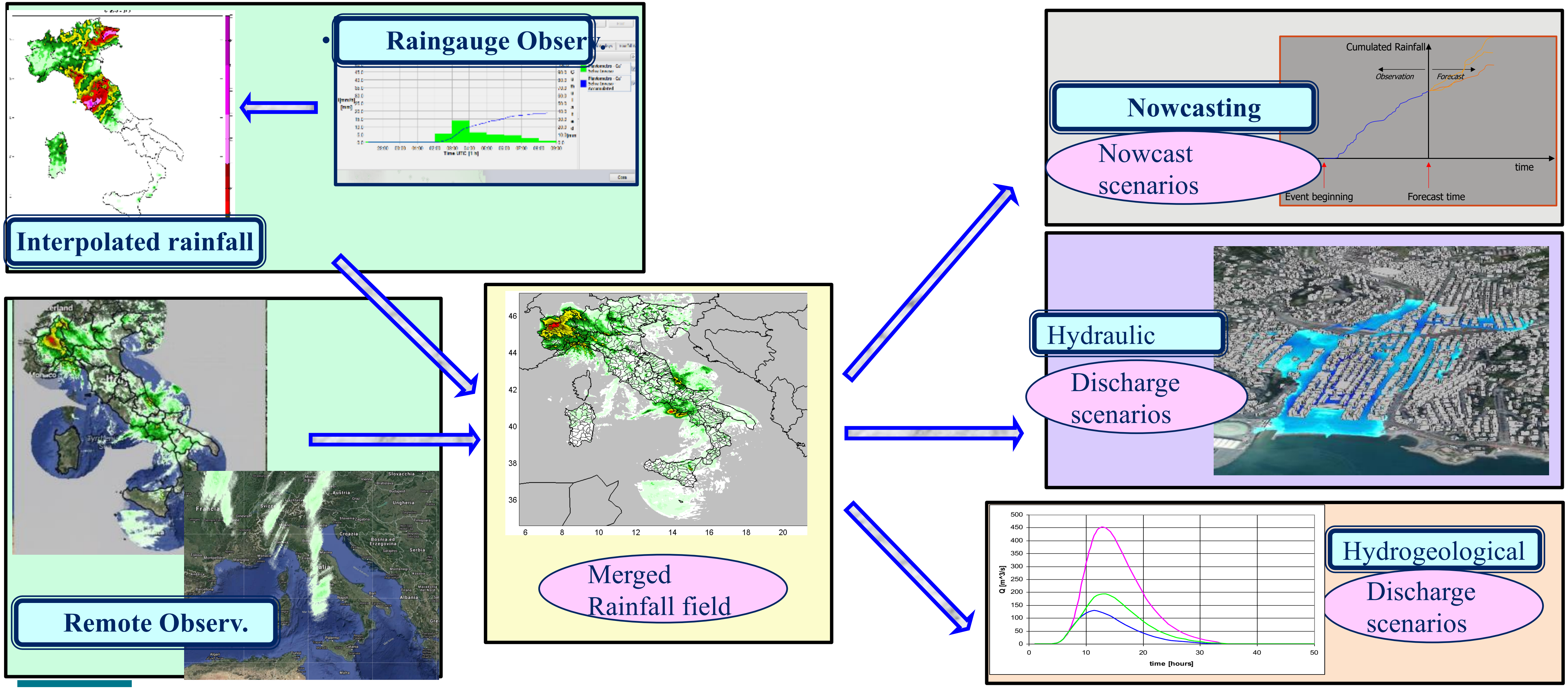
INTRODUCTION

The **estimation of rainfall fields**, especially its **spatial distribution and position** is a crucial task both for rainfall nowcasting and for modeling catchment response to rainfall.



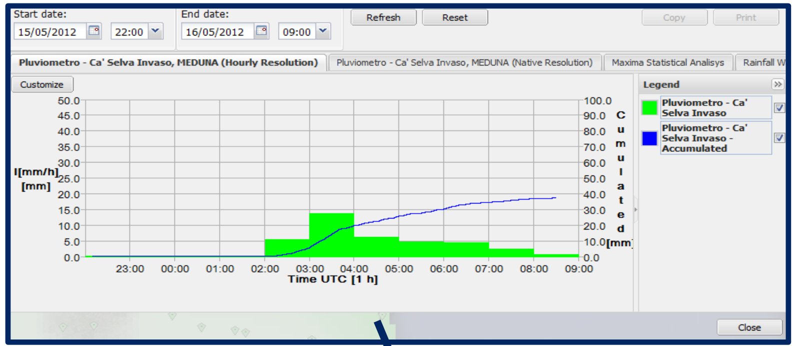
A lot of studies have suggested that **discharge estimations are improved when data from multisensors** are combined to estimate input rainfall fields.

PROBABILISTIC HYDROLOGICAL NOWCASTING CHAIN FOR FACING FLOOD OR FLASH FLOOD

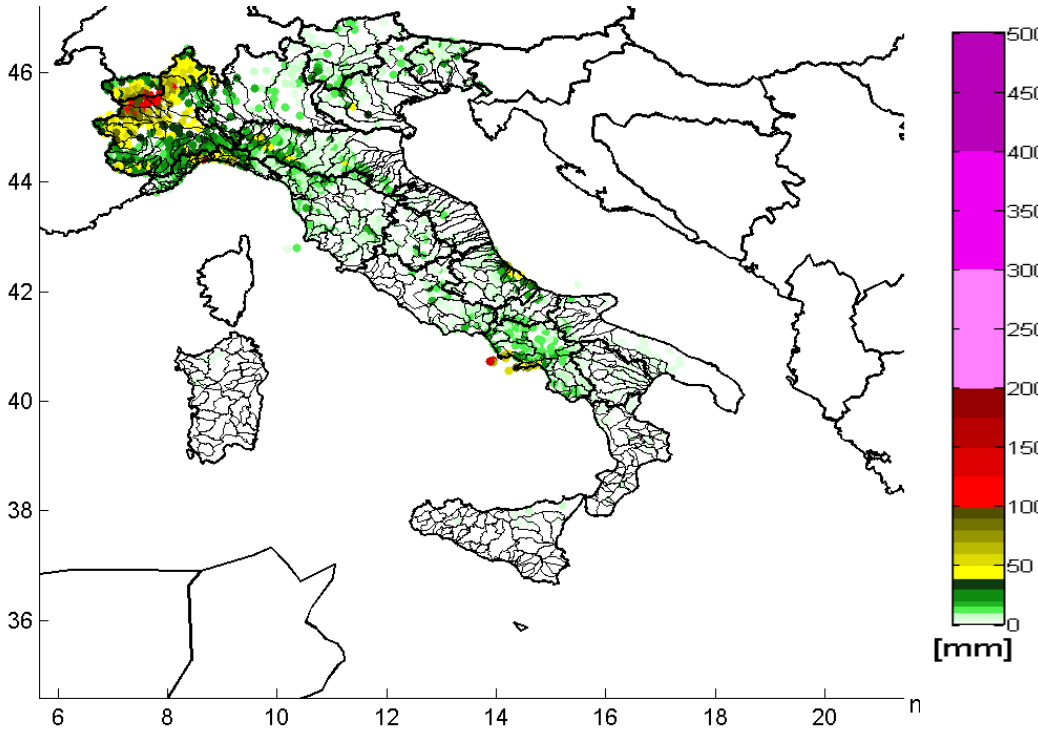


Data available: raingauges

Supplier:	Department of Civil Protection
Temporal availability data:	10 mins
Temporal resolution:	5 mins
Number of sensors:	Approx. 4000
Average density network:	1/100 km²



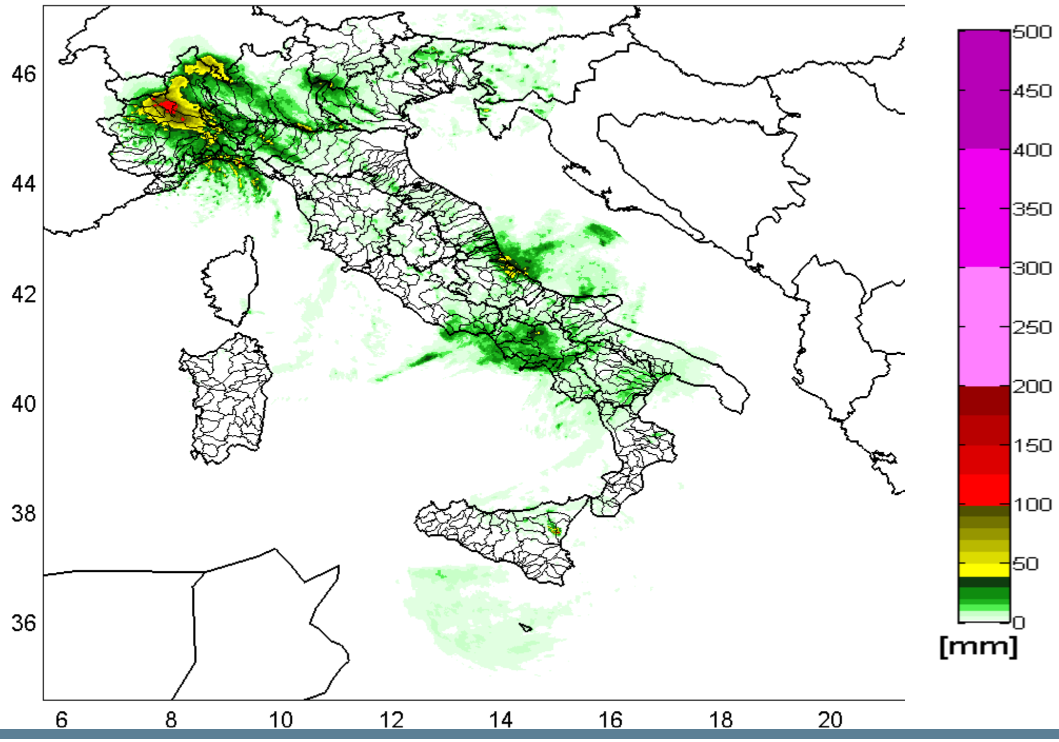
National raingauge network

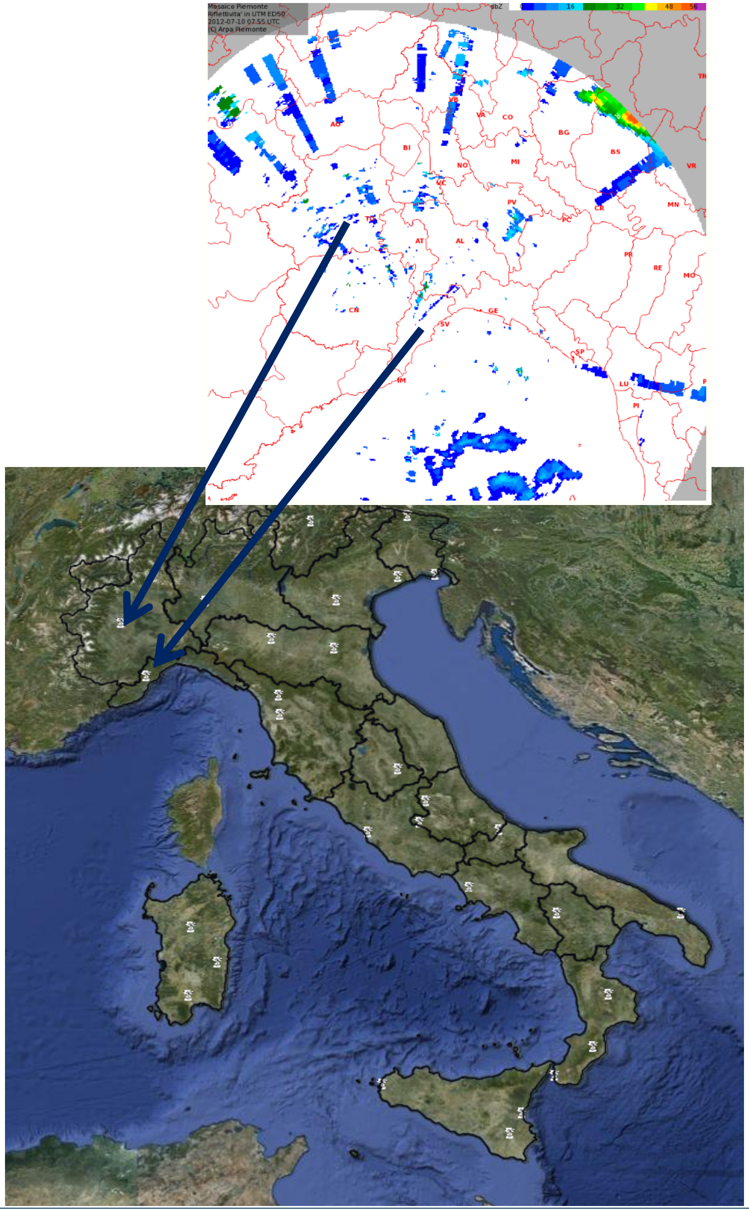


Data available: radar

Supplier:	Department of Civil Protection
Temporal availability data:	10 mins
Temporal resolution	10 mins
Spatial resolution:	1 km
Output:	SRT, SRI, CAPPI Z, Polar volume

National radar network

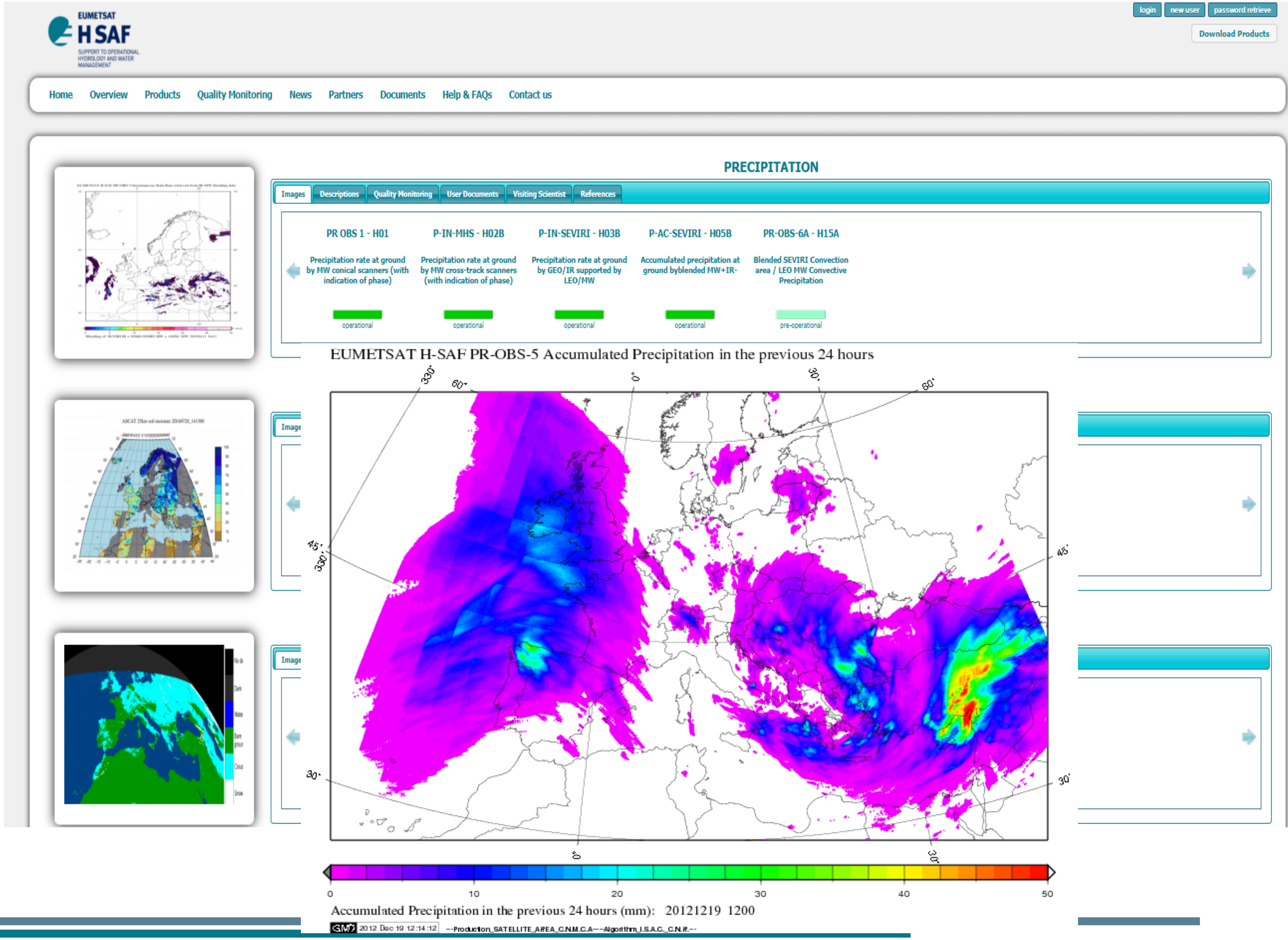




Data available: satellite

H-SAF Satellite products: P-IN-SEVIRI (H03B) and P-AC-SEVIRI (H05B)

Supplier:	Department of Civil Protection
Temporal availability data:	minuntes
Temporal resolution	H03B 15 mins H05B 3hours
Spatial resolution:	3 km near the sub-satellite point to 8 km on average



OVERVIEW OF LITERATURE

All of the methods in the literature can be classified according to the following approaches:

- **Geostatistic /Adjustment** (e.g.: Krajewski, 1987; Sinclair and Pegram, 2005; Velasco-Forero,2008; Germann,2009; Gabella, 2001; Koistinen and Puhakka, 1981)
- **Bayesian** (e.g.: Castelli,2009; Todini, 2001; Fiorucci)
- **Recursive Multiscale** (e.g.: Bocchiola 2007, Ebtehaj and Foufoula-Georgiou 2011).
- **Neural network** (e.g.: Xiao and Chandrasekar, 1997; Liu and Chandrasekar2001).

At the time, despite the availability of various methods **was not clear which approach was the best** or if there is one unique way to estimate the optimal rainfall precipitation field. A **comparative analysis of the various methods of merging has never been done**, so the advantages and disadvantages of the different algorithms are not yet explored.

The availability and the quality of data, the need of stable and quick results suitable for operational civil protection case, leaded to the choice of geostatistical method

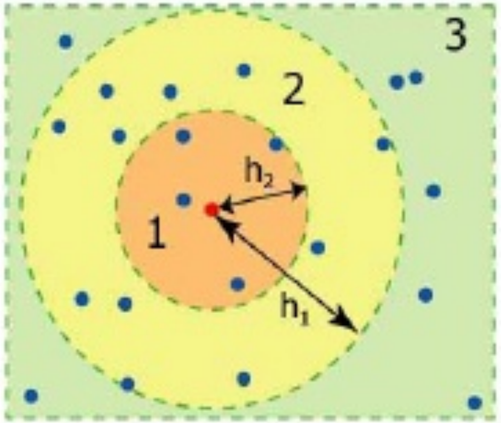
METHOD DESCRIPTION: geostatistic

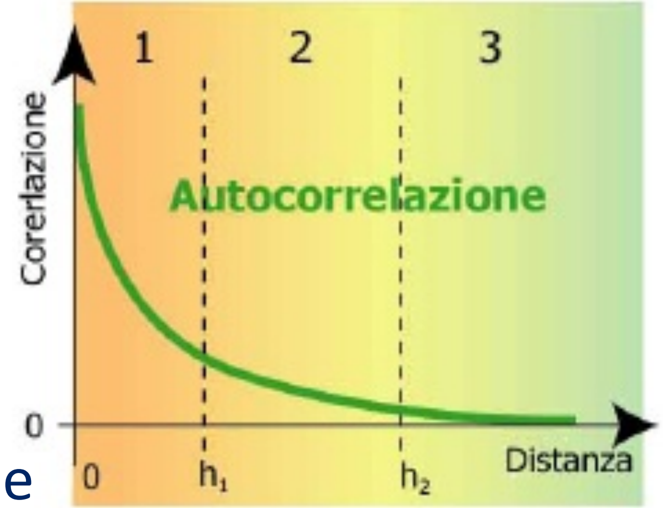
Geostatistic methods

Geostatistic is a branch of statistics focusing on spatial or spatio-temporal dataset.

What they do?

The idea is to verify if and how observation close to another is similar, while observation far from other present bigger variability.





The goal is evaluate the observations variability due to the position of the Gauge whitin network and use this information for build the interpolated field.

Advantages: The interpolated field in the gauge location is forced to reach the observed value

Disadvantages: In case of poor gauge density network there are less checkpoint.

:

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METHOD DESCRIPTION: GRISO interpolator

GRISO – Geostatistic Rainfall Interpolator of Scattered Observations

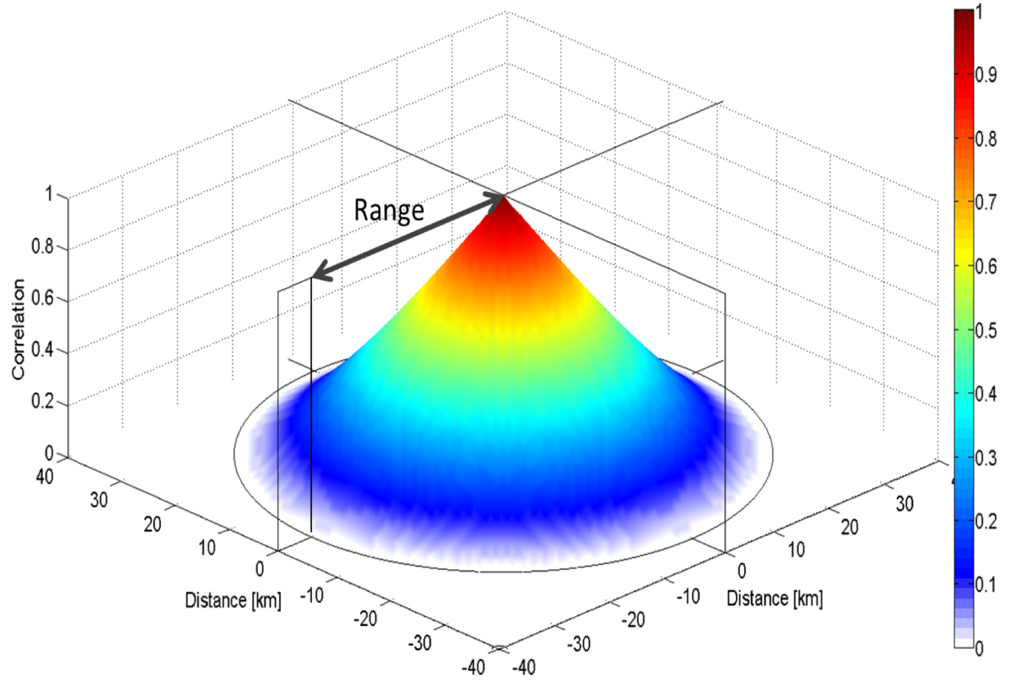
The GRISO interpolated field presents two main constraints:

•Passing throughout the observations. It means that on the gauges location the output field maintain the values measured.

•Tendency to a fixed value. The interpolated field far from the gauge locations and their influence assumes a specific imposed value.

To obtain the aforementioned characteristics it is necessary to define or estimate a couple of parameters:

- covariance kernel function (shape of cone)
- correlation length (range of influence)



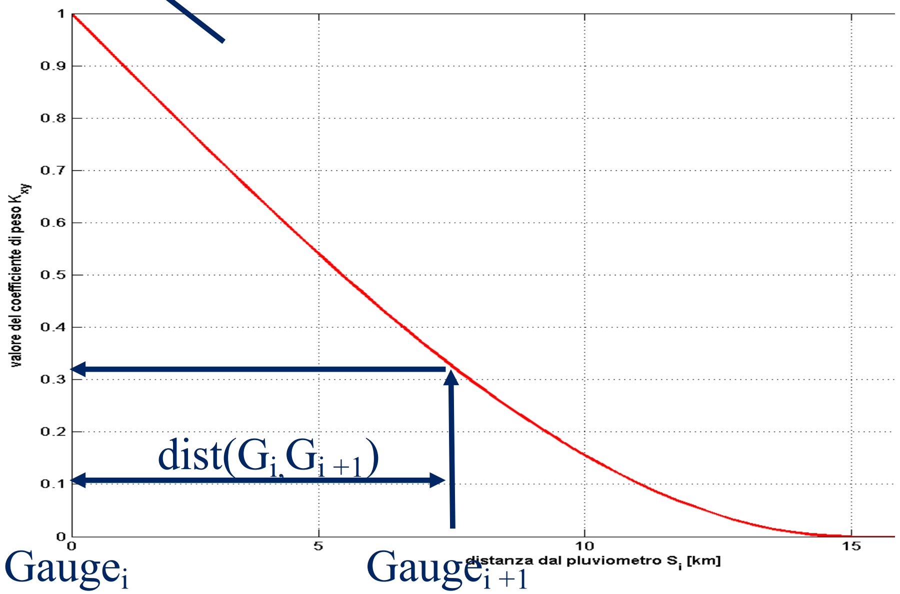
METHOD DESCRIPTION: GRISO interpolator

Linear equation system :

$$\begin{pmatrix} K_{11} & K_{21} & \dots & K_{1N} & 1 \\ K_{12} & K_{22} & \dots & K_{2N} & 1 \\ \dots & \dots & \dots & \dots & 1 \\ K_{1N} & \dots\dots & \dots & K_{NN} & 1 \\ \mu_{K_1} & \mu_{K_2} & \dots & \mu_{K_N} & 1 \end{pmatrix} \begin{pmatrix} W_1 \\ W_2 \\ \dots \\ W_N \\ W_{N+1} \end{pmatrix} = \begin{pmatrix} V_1 \\ V_2 \\ \dots \\ V_N \\ Tend_V \end{pmatrix}$$

Where:

- Kxy weights depending on the kernel and the distance between raingaguges
- μKi areal mean of single raingauges depending on kernel used
- Vi raingauges observations of the N-gauges
- TendV tendency values



Depending on the distance between the gaugei and the gaugei +1 is evaluated the correlation on the kernel covariance (red line)

METHOD DESCRIPTION: GRISO interpolator

Linear equation system :

$$\begin{pmatrix} K_{11} & K_{21} & \dots & K_{1N} & 1 \\ K_{12} & K_{22} & \dots & K_{2N} & 1 \\ \dots & \dots & \dots & \dots & 1 \\ K_{1N} & \dots. & \dots & K_{NN} & 1 \\ \mu_{K_1} & \mu_{K_2} & \dots & \mu_{K_N} & 1 \end{pmatrix} \begin{pmatrix} W_1 \\ W_2 \\ \dots \\ W_N \\ W_{N+1} \end{pmatrix} = \begin{pmatrix} V_1 \\ V_2 \\ \dots \\ V_N \\ Tend_V \end{pmatrix}$$

Where:

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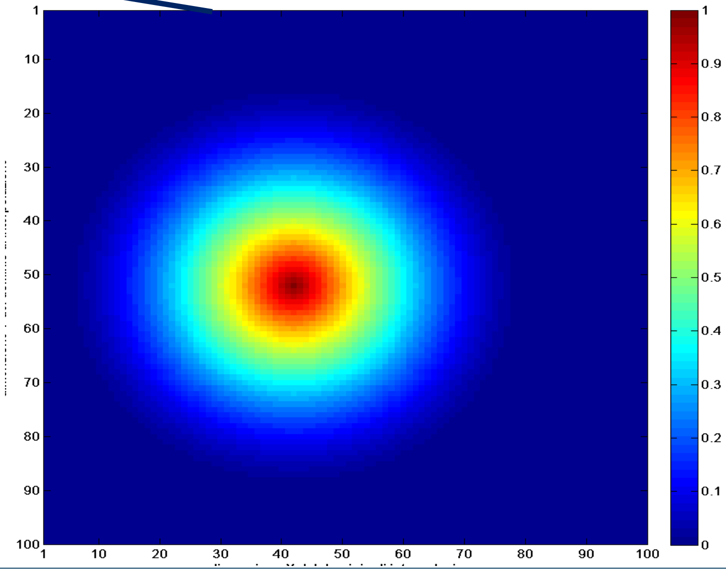

Depending on the kernel covariance and length of correlation adopted is evaluated the areal mean of the single raingauge

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METHOD DESCRIPTION: GRISO interpolator

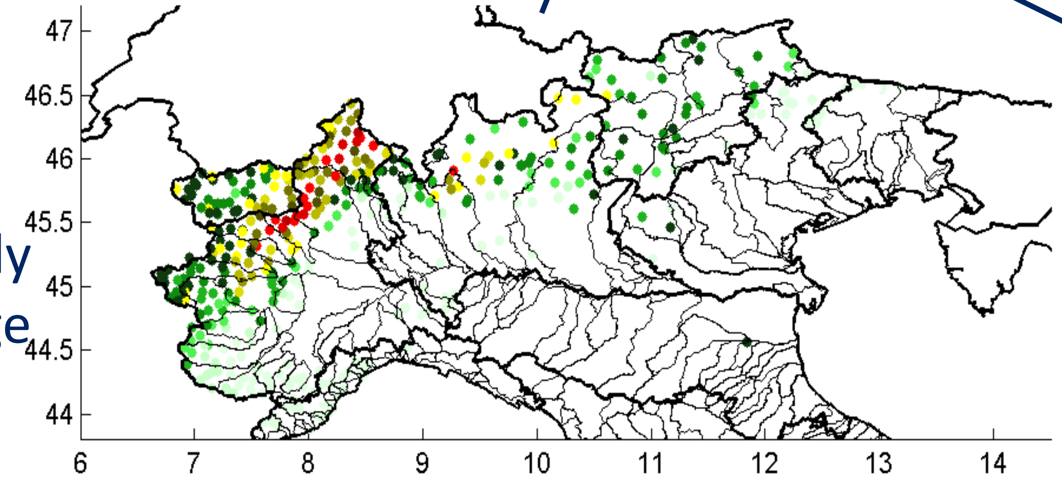
Linear equation system :

$$\begin{pmatrix} K_{11} & K_{21} & \dots & K_{1N} & 1 \\ K_{12} & K_{22} & \dots & K_{2N} & 1 \\ \dots & \dots & \dots & \dots & 1 \\ K_{1N} & \dots\dots & \dots & K_{NN} & 1 \\ \mu_{K_1} & \mu_{K_2} & \dots & \mu_{K_N} & 1 \end{pmatrix} \begin{pmatrix} W_1 \\ W_2 \\ \dots \\ W_N \\ W_{N+1} \end{pmatrix} = \begin{pmatrix} V_1 \\ V_2 \\ \dots \\ V_N \\ Tend_V \end{pmatrix}$$

Where:

- Kxy weights depending on the kernel and the distance between raingaguges
- µKi areal mean of single raingauges depending on kernel used
- Vi raingauges observations of the N-gauges
- TendV tendency values

Is used directly the raingauge observations



Is defined a tendency values of the rainfall field. This value is the one that is reach far from gauge and their influence

METHOD DESCRIPTION: GRISO interpolator

Linear equation system :

$$\begin{pmatrix} K_{11} & K_{21} & \dots & K_{1N} & 1 \\ K_{12} & K_{22} & \dots & K_{2N} & 1 \\ \dots & \dots & \dots & \dots & 1 \\ K_{1N} & \dots. & \dots & K_{NN} & 1 \\ \mu_{K_1} & \mu_{K_2} & \dots & \mu_{K_N} & 1 \end{pmatrix} \begin{pmatrix} W_1 \\ W_2 \\ \dots \\ W_N \\ W_{N+1} \end{pmatrix} = \begin{pmatrix} V_1 \\ V_2 \\ \dots \\ V_N \\ Tend_V \end{pmatrix}$$

Where:

- Kxy weights depending on the kernel and the distance between raingaguges
- µKi areal mean of single raingauges depending on kernel used
- Vi raingauges observations of the N-gauges
- TendV tendency values

Once the linear system is solved are evaluated the weights **Wi**.

The **interpolated rainfall field F0** is obtained simply **summing the product of covariance kernel used with the weights W** of every raingague and rescaling with the tendency value according to the following formula:

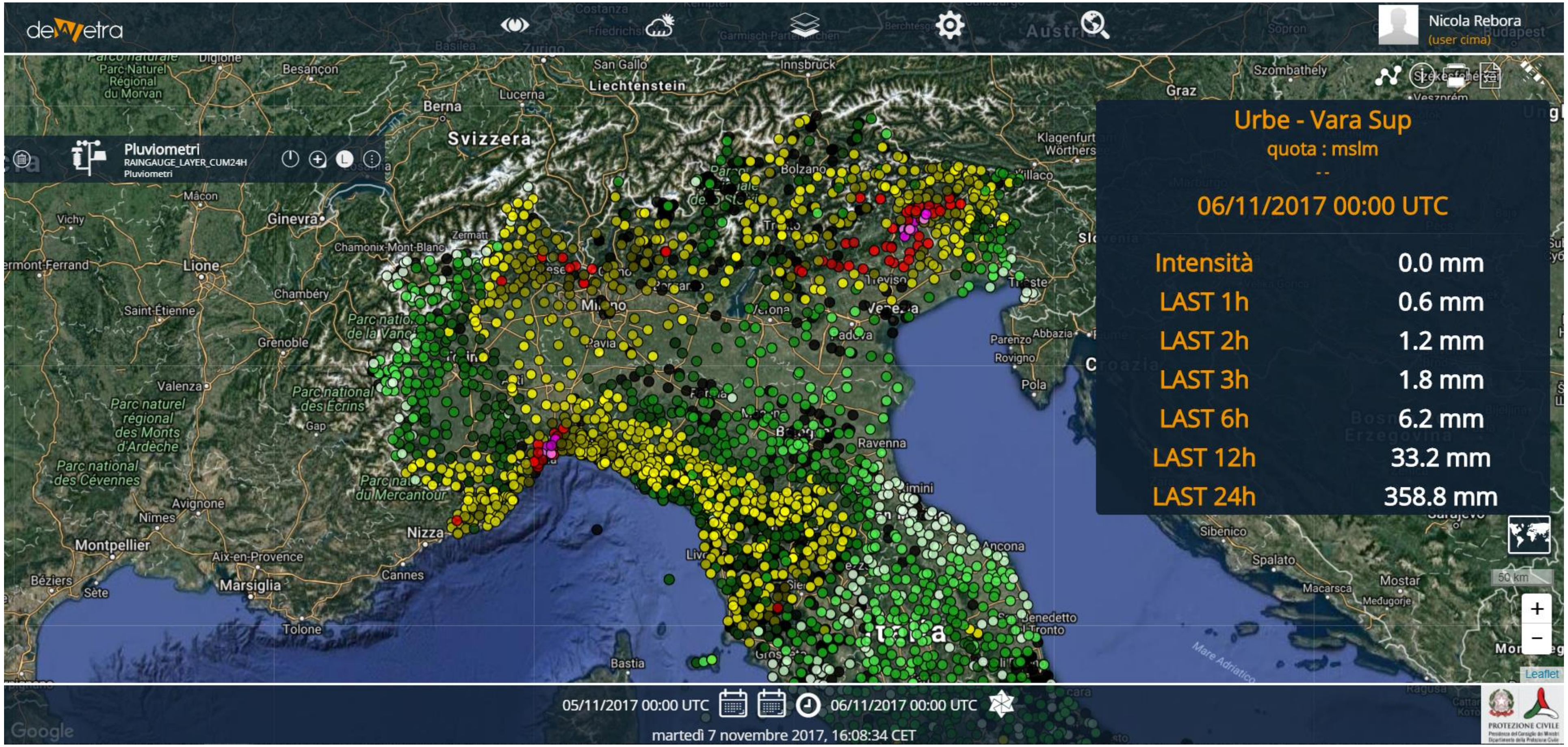
$$F_0(x, y) = Tend_V + \sum_{i=1}^{N} W_i K_i(x, y)$$

METHOD DESCRIPTION: GRISO interpolator example

GRISO – Geostatistic Rainfall Interpolator of Scattered Observations

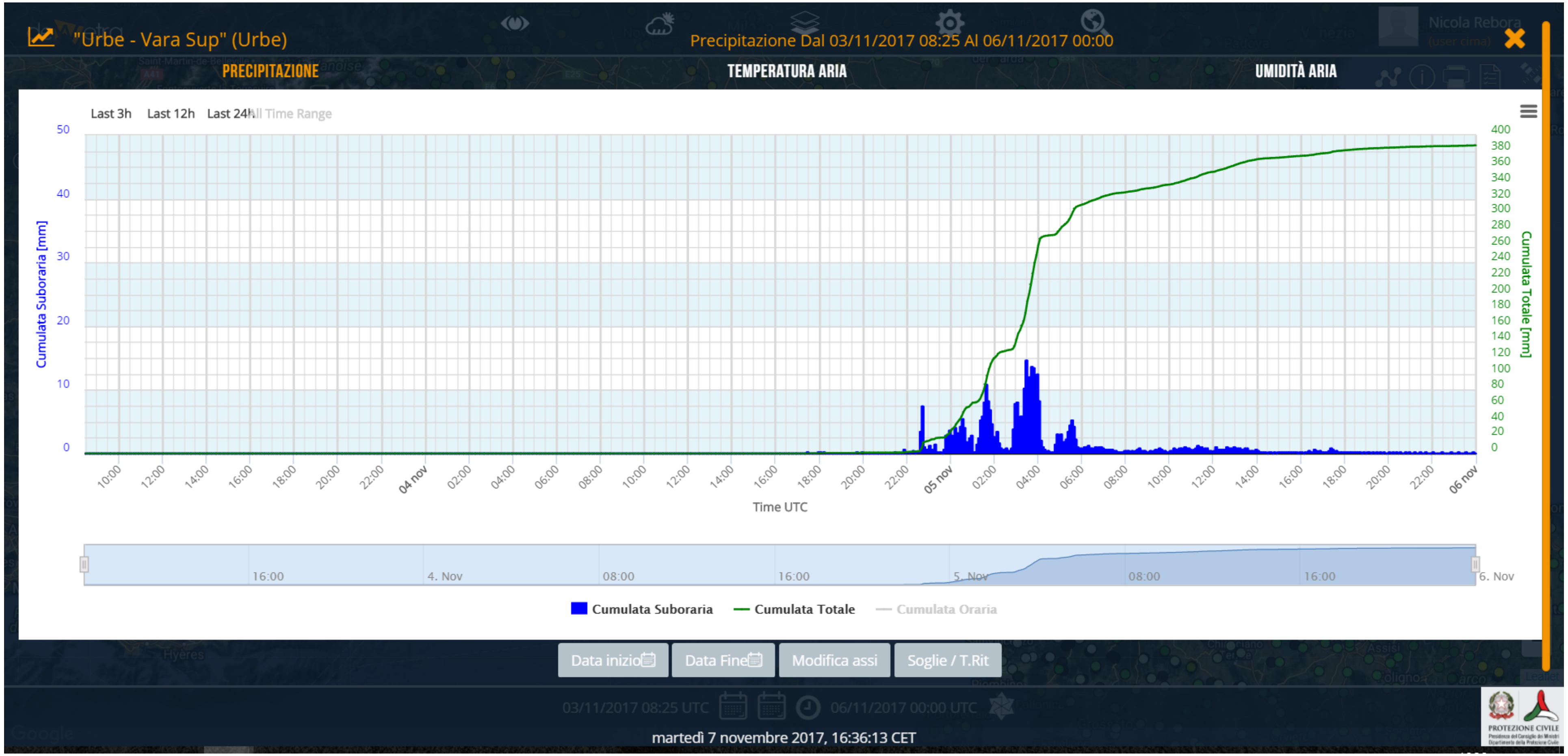
METHOD DESCRIPTION: GRISO interpolator example

GRISO – Geostatistic Rainfall Interpolator of Scattered Observations



METHOD DESCRIPTION: GRISO interpolator example

GRISO – Geostatistic Rainfall Interpolator of Scattered Observations



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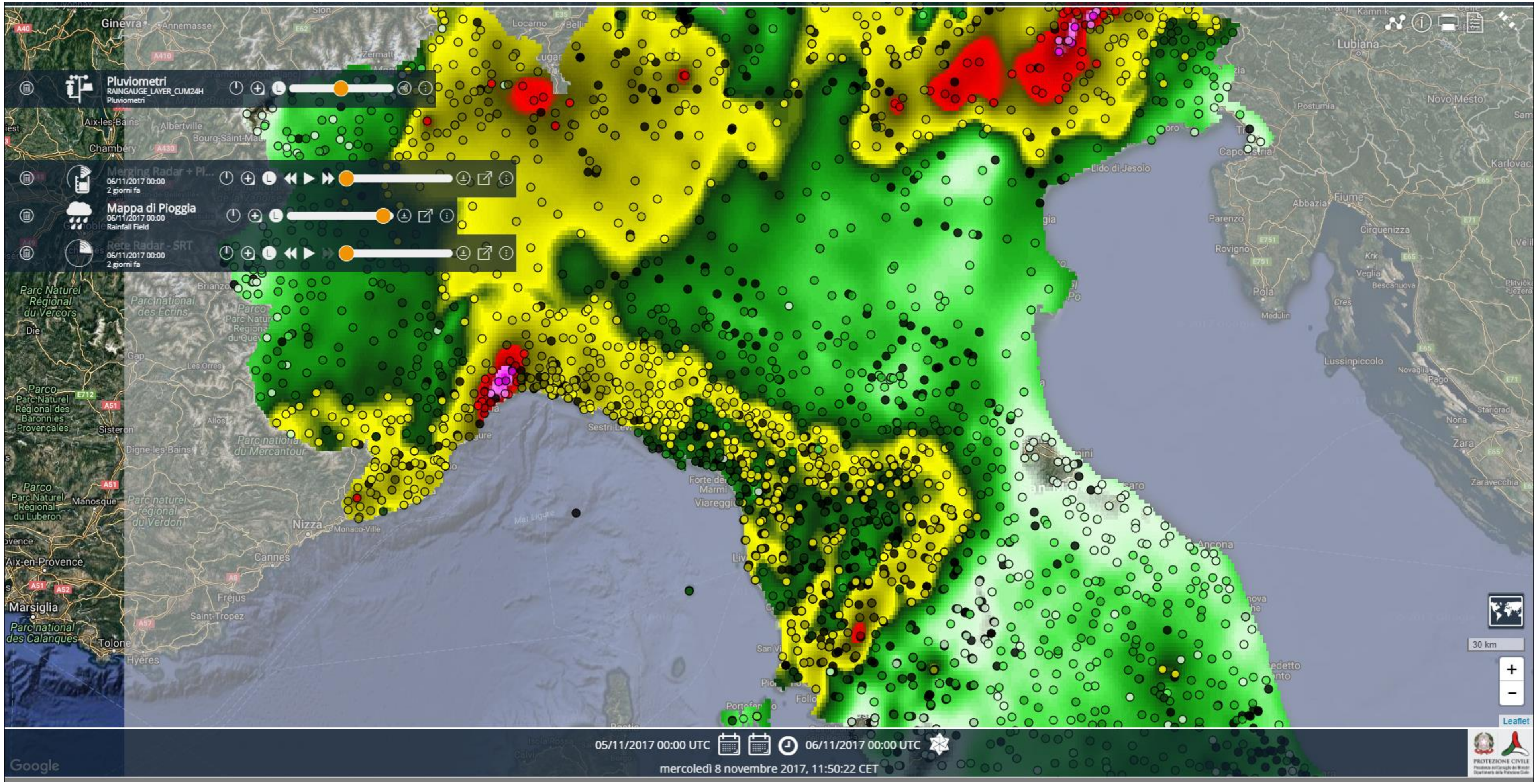
METHOD DESCRIPTION: GRISO interpolator example

GRISO – Geostatistic Rainfall Interpolator of Scattered Observations



METHOD DESCRIPTION: GRISO interpolator validation

The validation was done by:

1. **Identification of** a cospicuos number of **event** with different characteristic of duration and position
2. Identification of **different spatial density** for the generation of the rainfall interpolated field
3. Use the **radar map of the same spatial and temporal domain** as input of the validation
4. **Sampling the radar input map with the density specified** (in this way is possible to obtained different “raingauge” network). For evey density a number of replica are generated so it is possible to have a strong statistical information
5. **Using GRISO** for make the interpolated field.
6. **Application of different statistical score** on the new fields (RMSE, power spectra, ecc)
7. **Comparison with Kriging** statistic

METHOD DESCRIPTION: GRISO interpolator validation

1. Identification of a cospicuos number of event with different characteristic of duration and position

In the table are reported location and duration of some examples.

20110316	201103160000	201103170000	45,42	46,56	11,76	13,42
20111122	201111221200	201111230000	37,94	39,08	15,12	16,78
20121104	201211040000	201211050000	43,66	44,8	9,4	11,05
20130120	201302200000	201302210000	43,72	44,86	9,54	11,2
20130318	201303180000	201303190000	43,49	45,78	9,4	12,74
20130519	201305190000	210305200000	45,12	46,27	8,5	10,17

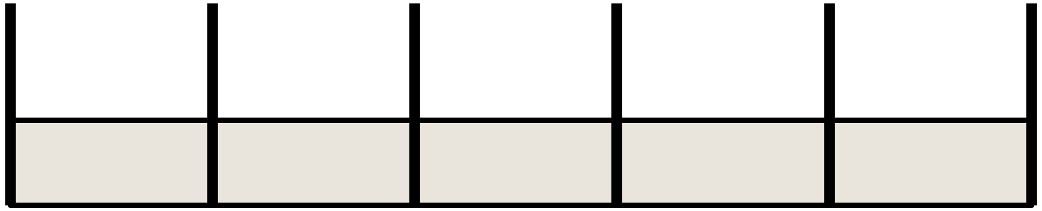
METHOD DESCRIPTION: GRISO interpolator validation

2. Identification of different spatial density for the generation of the rainfall interpolated field

Min network density≈ 1/200 km^2
Max network density≈ 1/20 km^2
Mean network density ≈ 1/100 km^2

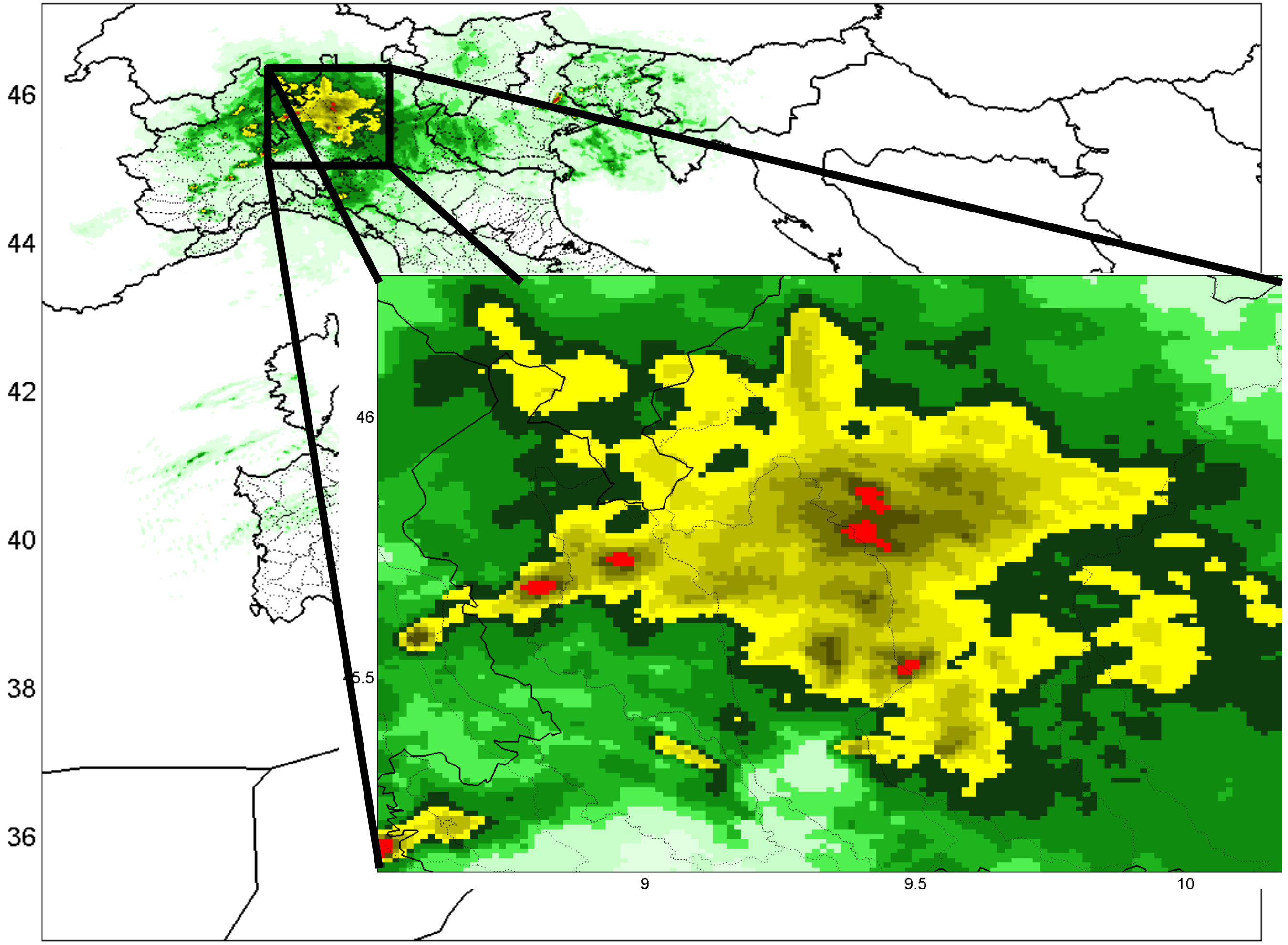
Sampling density:

1/2000 km^2 | 1/1000 km^2 | 1/500 km^2 | 1/200 km^2 | 1/100 km^2 | 1/25 km^2



METHOD DESCRIPTION: GRISO interpolator validation

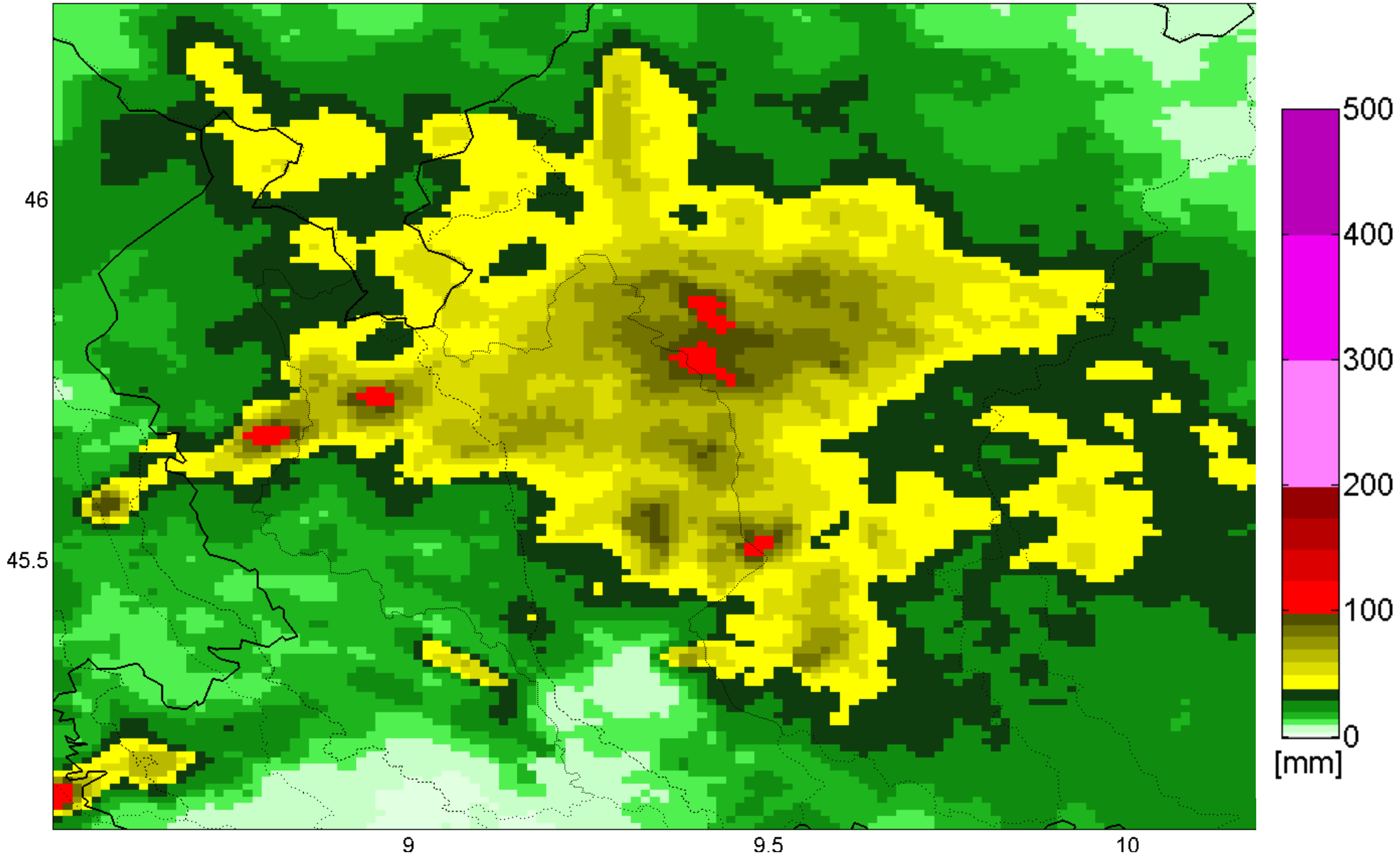
3. Use the radar map of the same spatial and temporal domain as input of the validation



Event on
19 May, 2013 on
Piedmont region

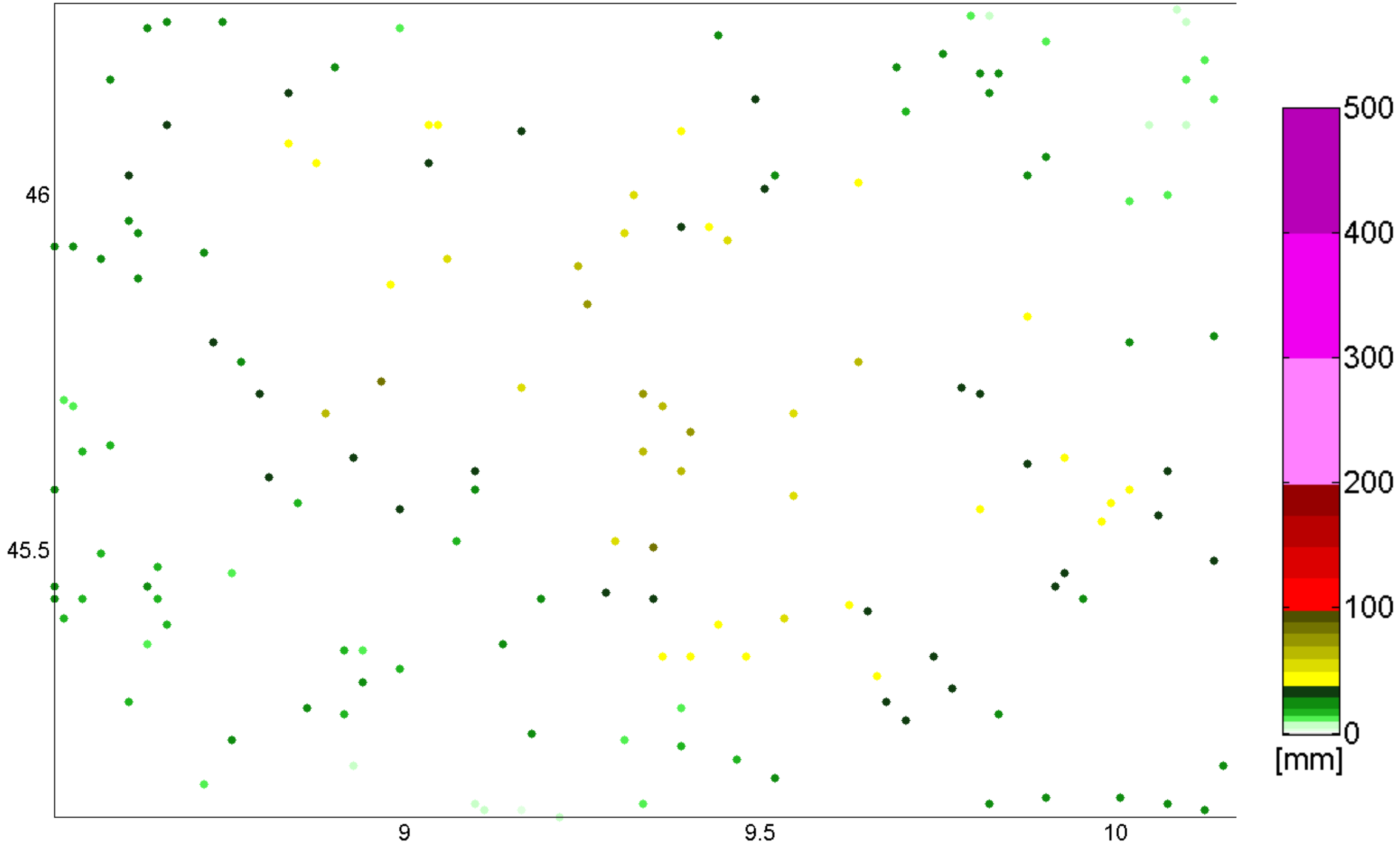
METHOD DESCRIPTION: GRISO interpolator validation

3. Use the radar map of the same spatial and temporal domain as input of the validation



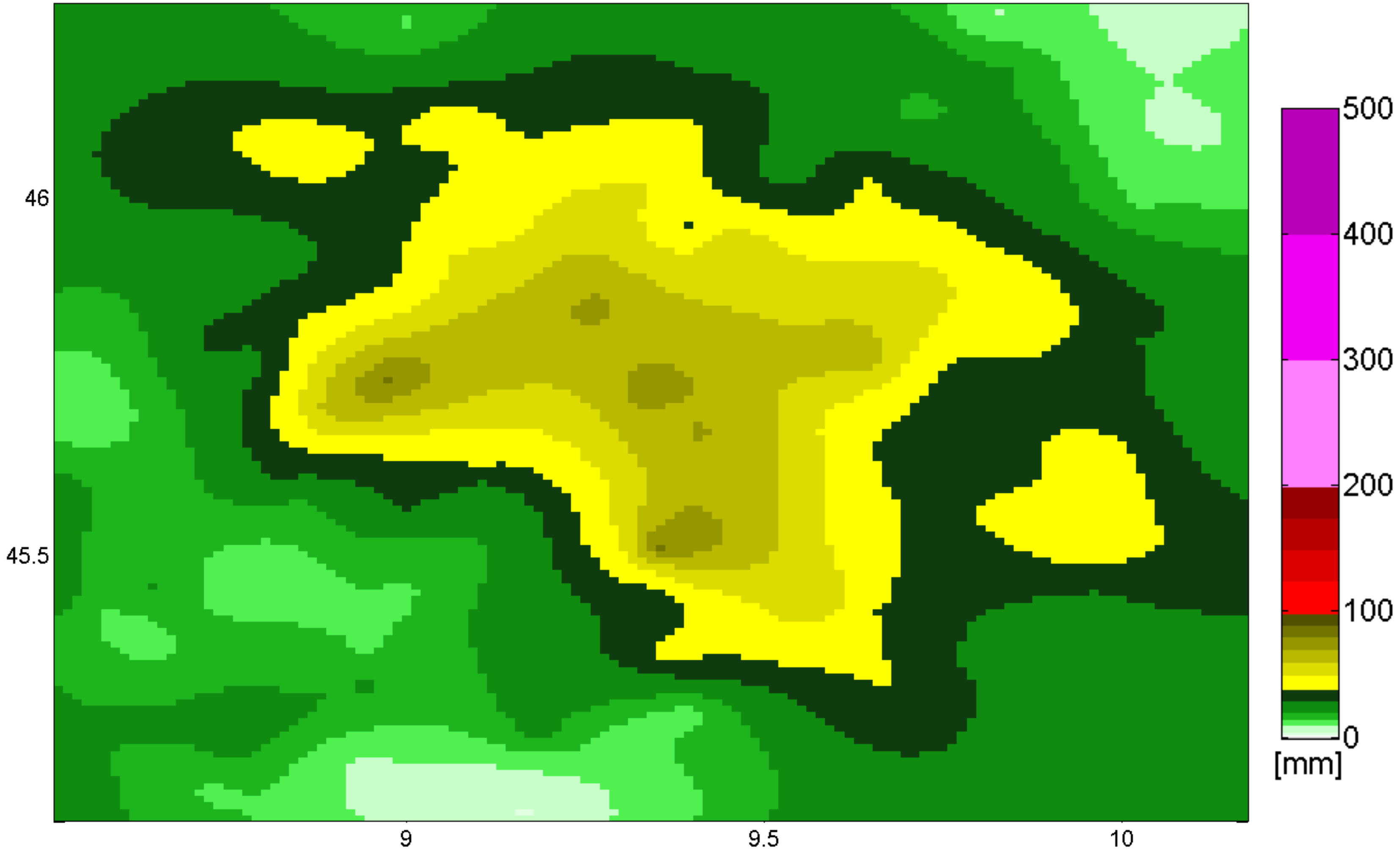
METHOD DESCRIPTION: GRISO interpolator validation

4. Sampling the radar input map with the densities specified



METHOD DESCRIPTION: GRISO interpolator validation

5. Using GRISO and KRIGING to obtain the interpolated rainfall field.



METHOD DESCRIPTION: GRISO interpolator validation

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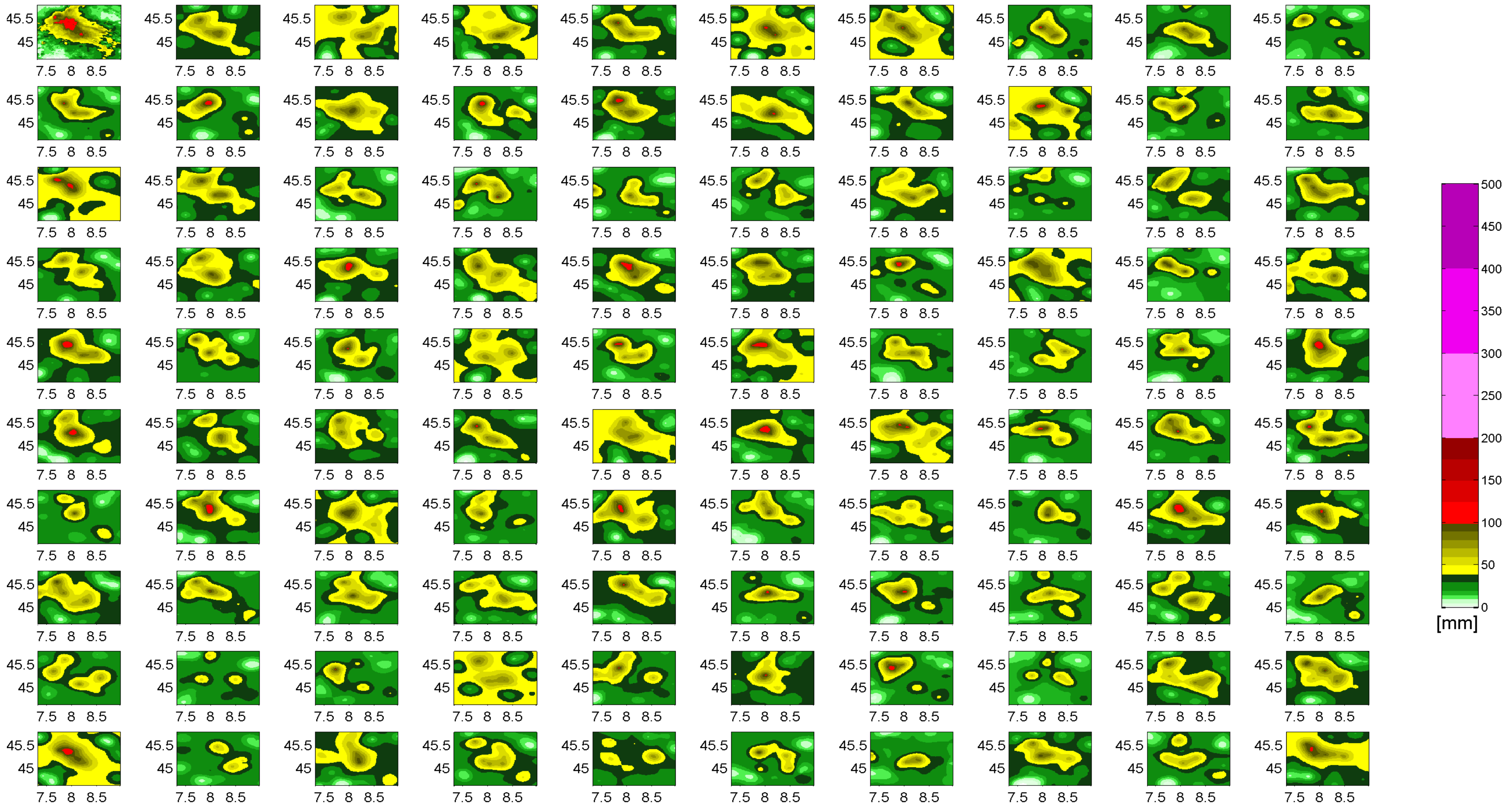
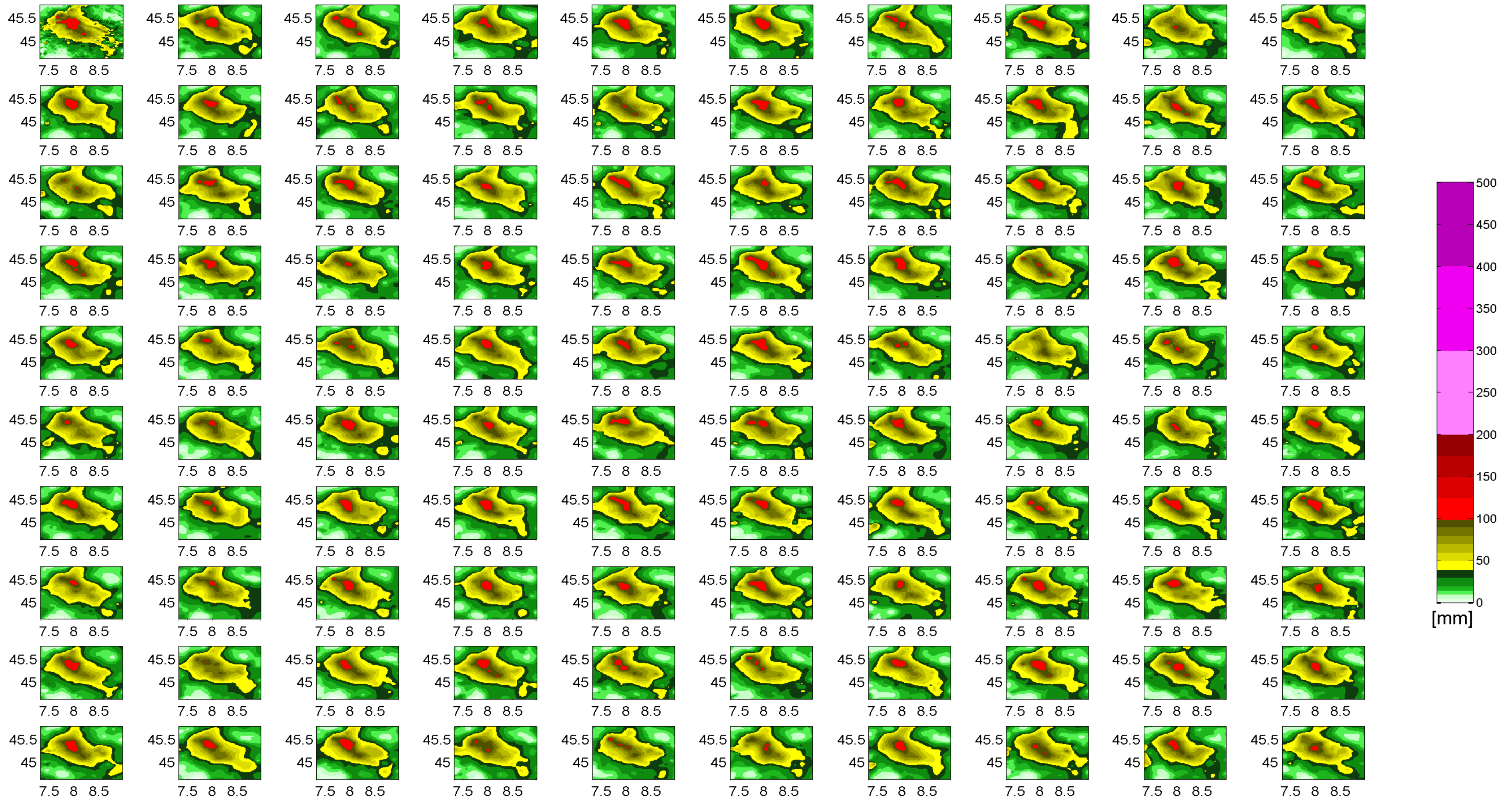
100 GRISO replicas starting from 1/2000 km² random density network



METHOD DESCRIPTION: GRISO interpolator validation

100 GRISO replicas starting from 1/500 km² random density network



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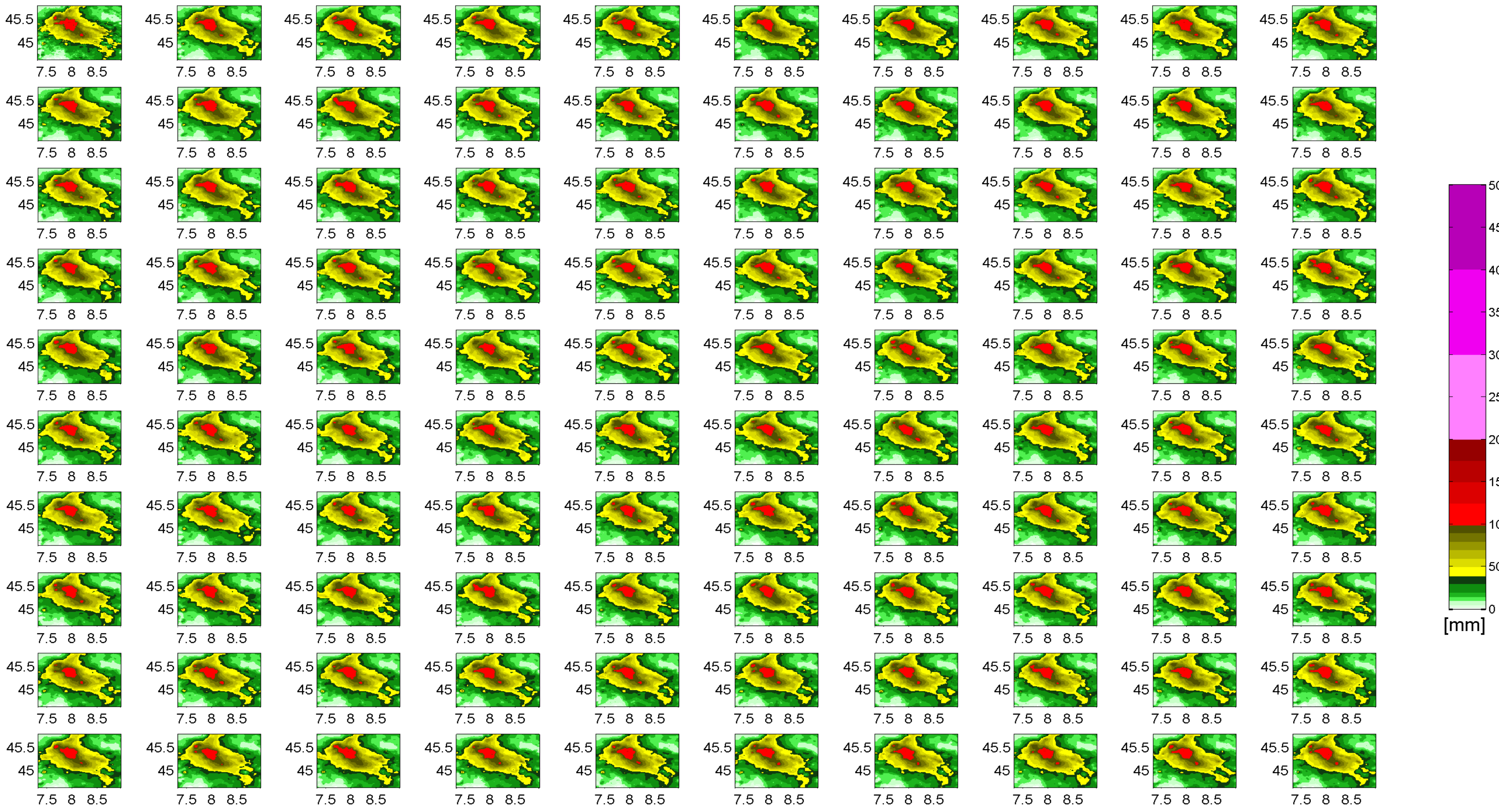
METHOD DESCRIPTION: GRISO interpolator validation

100 GRISO replicas starting from 1/25 km^2 random density network



METHOD DESCRIPTION: GRISO interpolator validation

6. Application of different statistical score on the new fields

- Statistical score (mean, variance, ecc)
- PDF e CDF
- Power spectra
- NSE,RMSE, PBIAS
- PDF of differences between interpolated fields and radar input map

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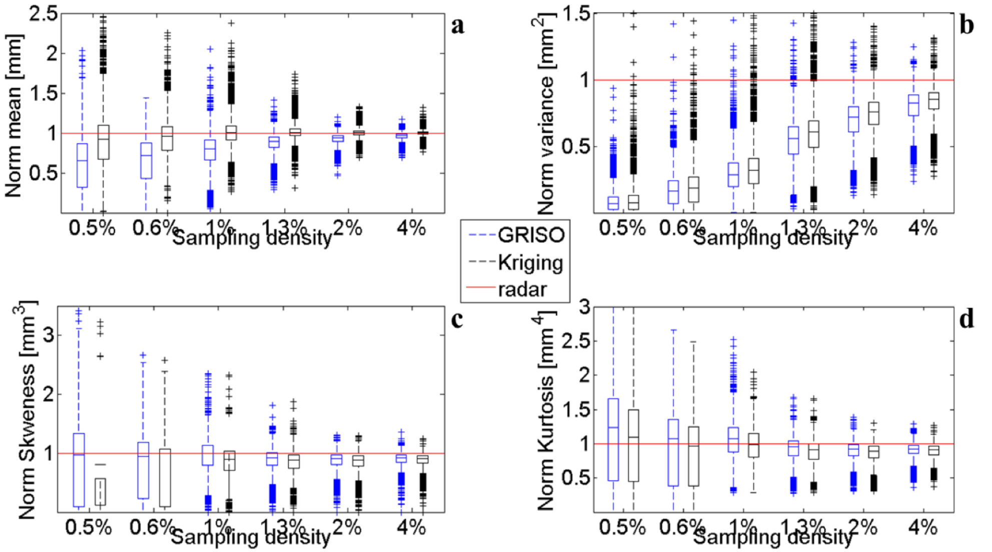
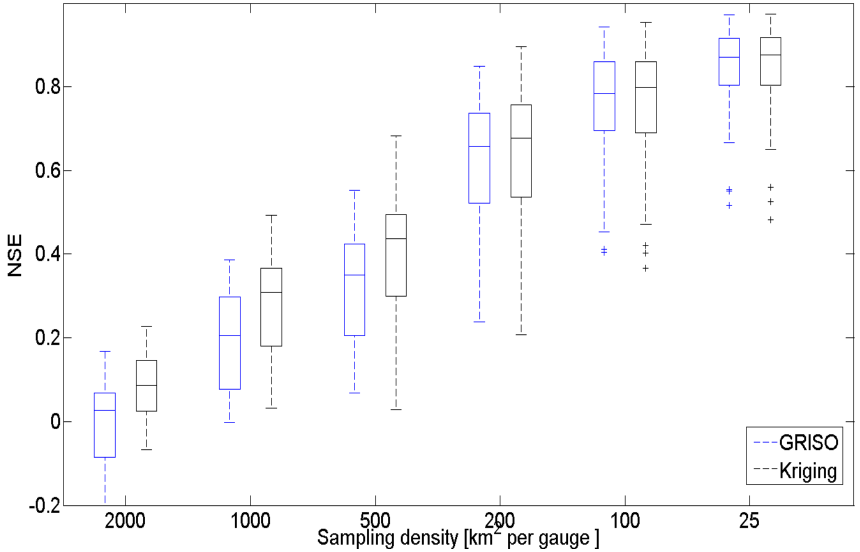
METHOD DESCRIPTION: GRISO interpolator validation

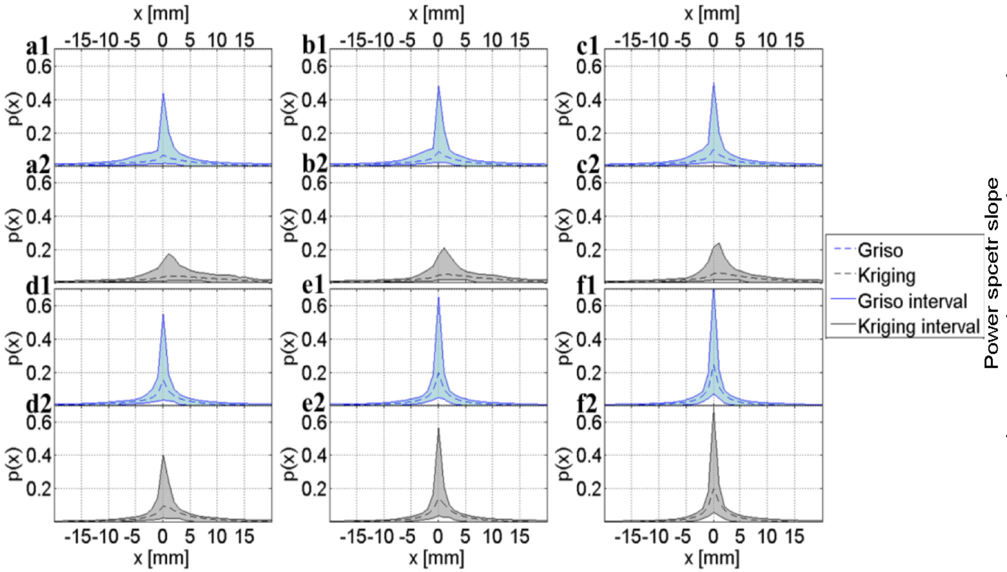
Ensemble of statistical moments



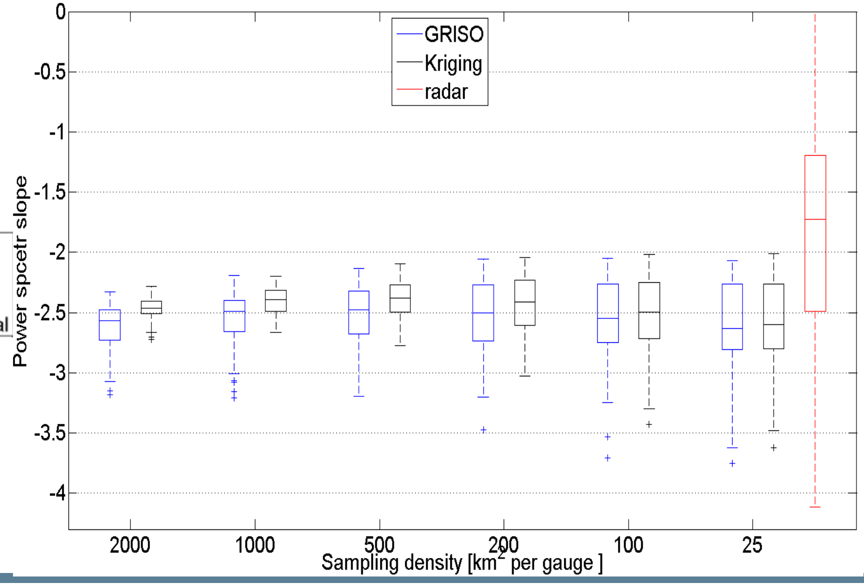
Ensemble of NSE



Ensemble of PDF differences



Ensemble of power spectra slope

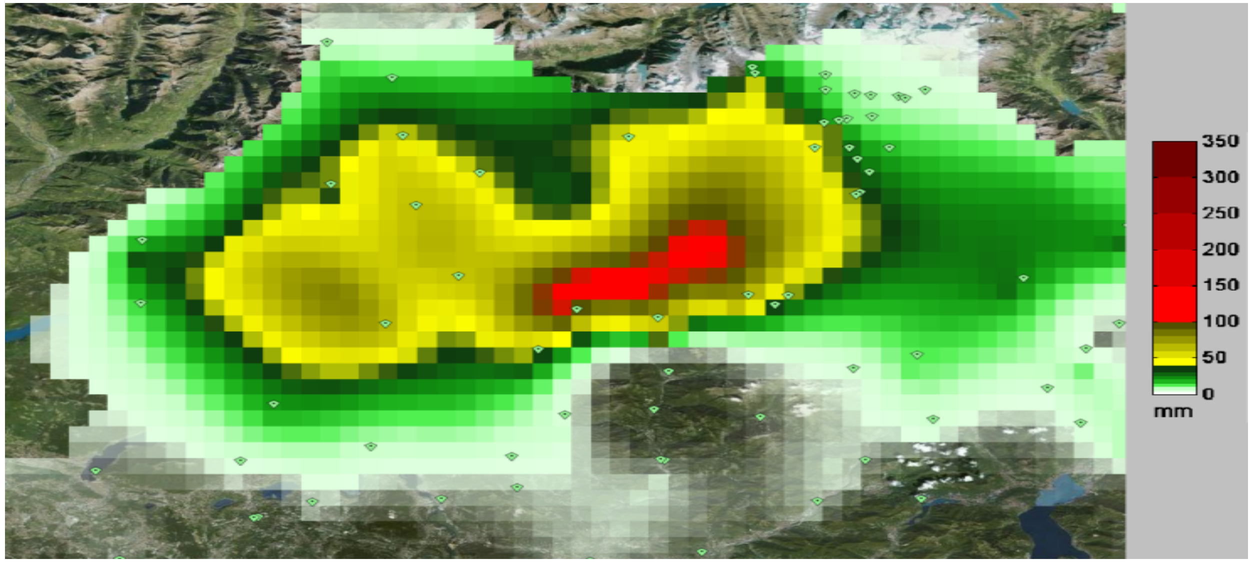


METHOD DESCRIPTION: GRISO interpolator conclusion

According to the previous results GRISO and KRIGING have generally similar statistical score.

But the GRISO method have few advantages respect to Kriging that are not negligible:

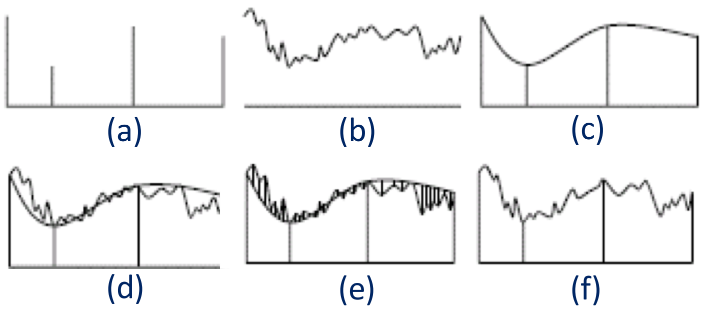
1. reducing the computational time for operational purposes
2. Possibility of using different covariance structures for the spatialization of the rainfall, for each raingauge.
3. Possibility of using a covariance structure that is based on high-resolution, spatial-temporal, observations (e.g. from Radar)
4. Center of showher should be located between Raingauges and not necessarily on one of it



METHOD DESCRIPTION: CONDITIONAL MERGING

The information from the radar can be used to inferred the pattern to the spatially limited information obtained by rain gauges interpolation and produce an estimation of the rainfall field that contains the correct spatial structure while being constrained to the rain gauge data.

1D example of Conditional Merging



Reproduction of Sinclair and Pegram method

a) **PUNCTUAL OBSERVATION OF CUMULATIVE RAINGAUGE PRECIPITATION HEIGHT**

↓

b) **$R(s)$**
OBSERVATION OF THE RADAR PRECIPITATION FIELD

↓

c) **$G_K(s)$**
INTERPOLATION OF RAINGAUGE OBSERVATIONS ON THE STUDY REGION

↓

d) **$R_K(s)$**
INTERPOLATION OF RADAR OBSERVATIONS (ON RAINGAUGE POSITIONS)

↓

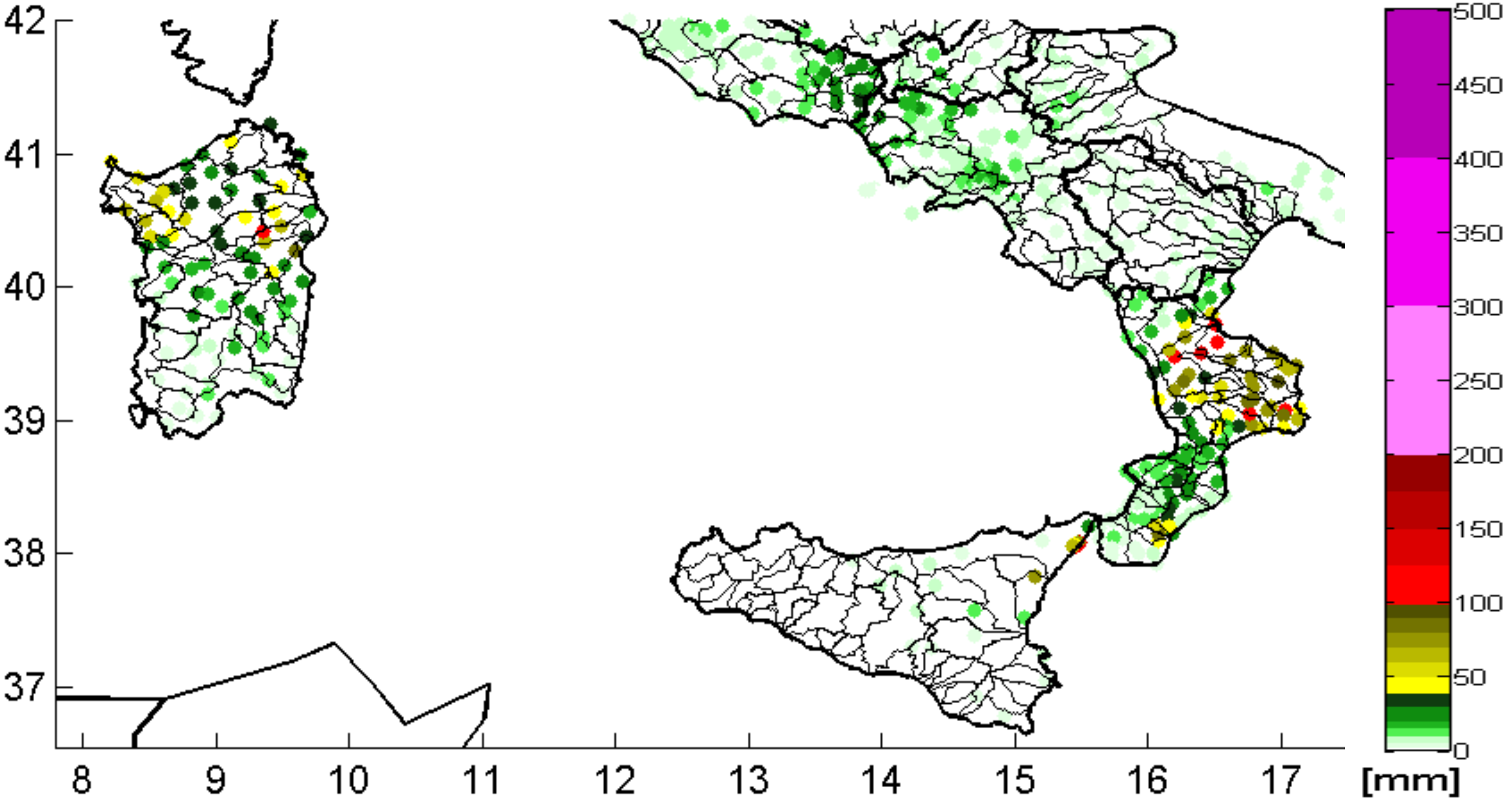
e) **$\Delta R = R(s) - R_K$**
DIFFERENCE BETWEEN RADAR OBSERVATION FIELD AND INTERPOLATION OF RADAR OBSERVATION FIELD

↓

f) **$Z = G_K + \Delta R$**
SUM OF THE DIFFERENCE FIELD WITH INTERPOLATION OF RAINGAUGE OBSERVATIONS FIELD

METHOD DESCRIPTION: CONDITIONAL MERGING

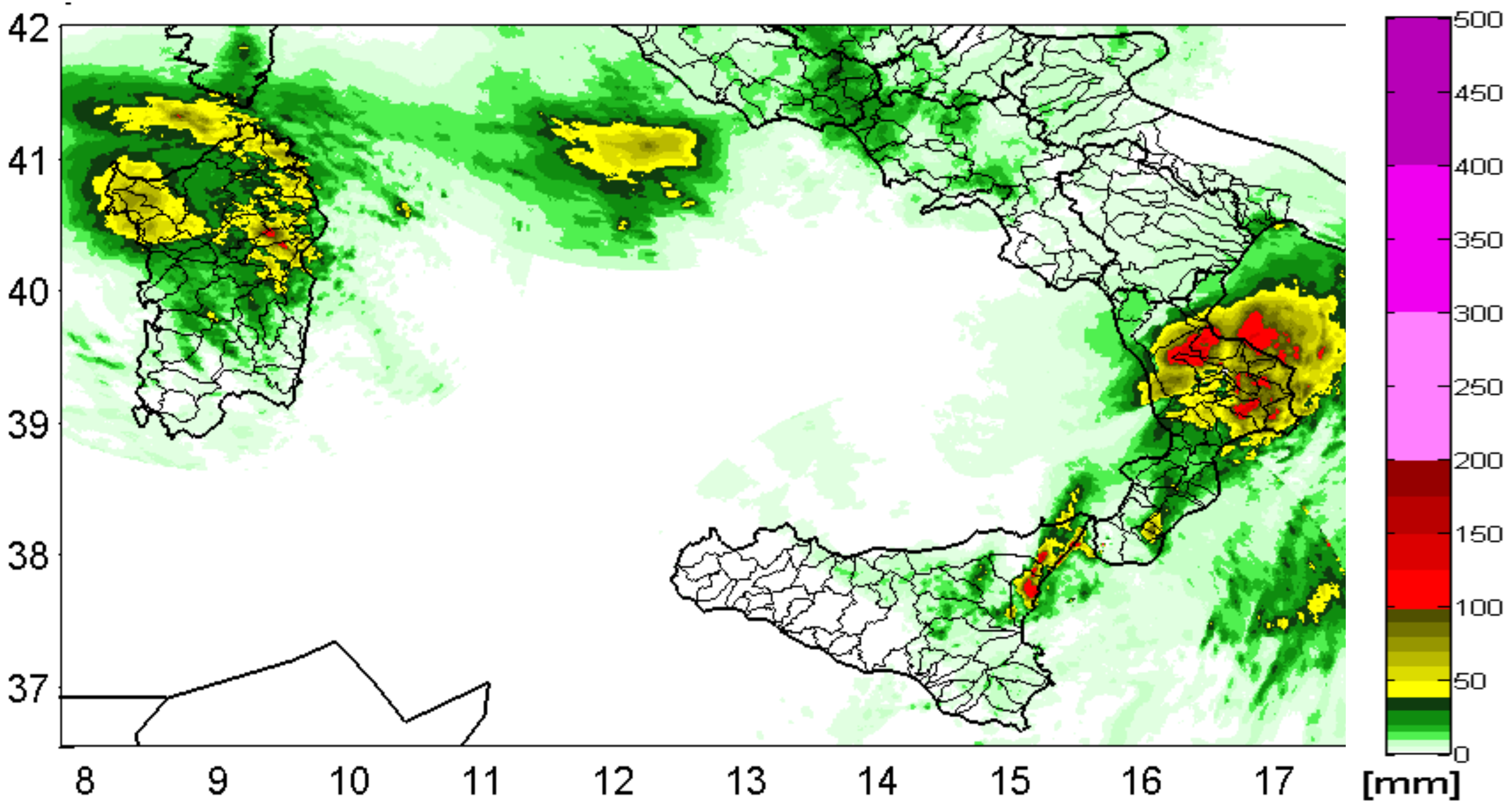
1) RAINGAUGES OBSERVATIONS



Based on Conditional Merging: Sinclair and Pegram, 2005

METHOD DESCRIPTION: CONDITIONAL MERGING

2) RADAR RAINFALL MAP



Based on Conditional Merging: Sinclair and Pegram, 2005

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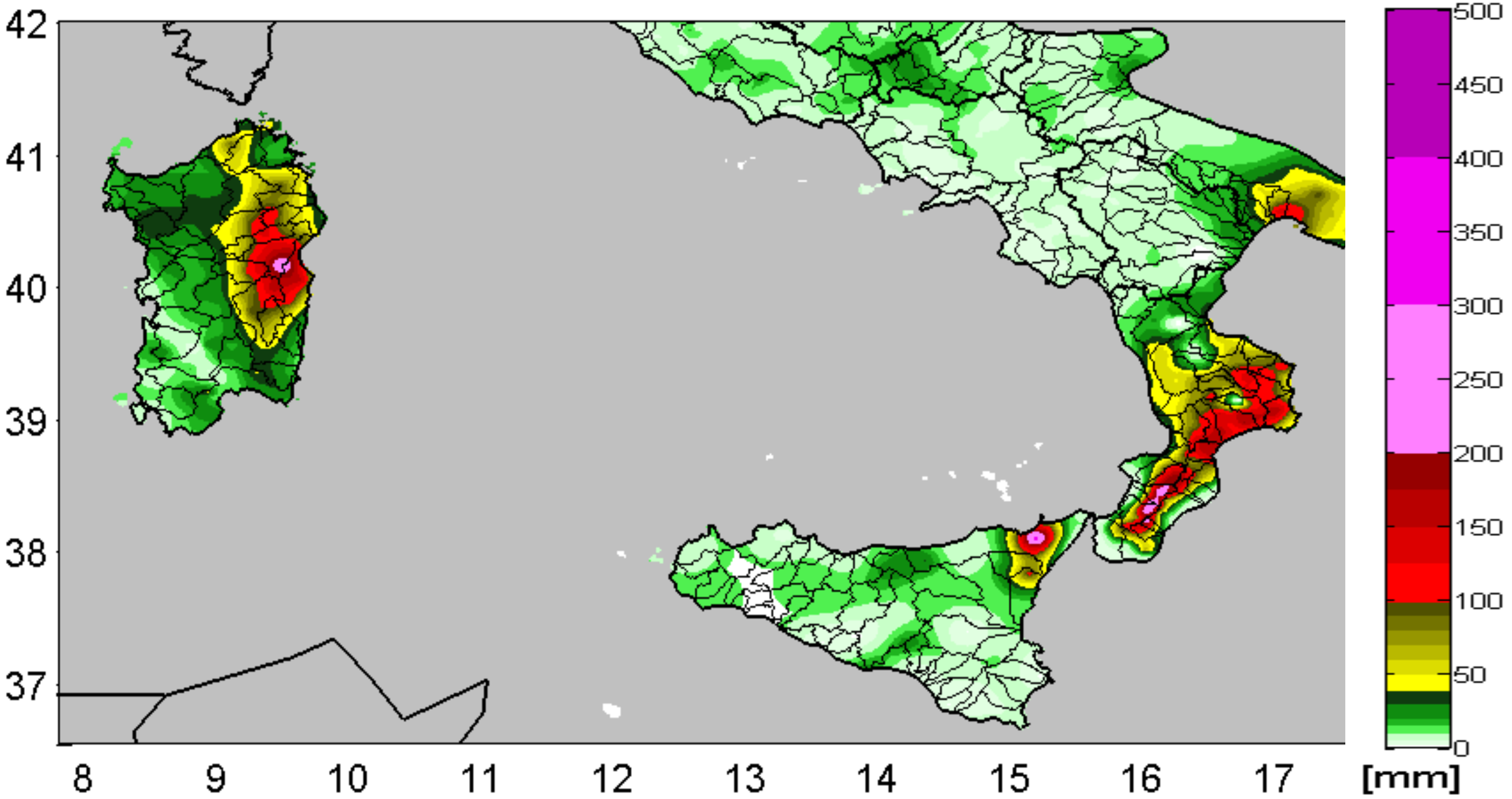
METHOD DESCRIPTION: CONDITIONAL MERGING

3) RAINFALL MAP INTERPOLATED FROM RAINGAUGES



Based on Conditional Merging: Sinclair and Pegram, 2005

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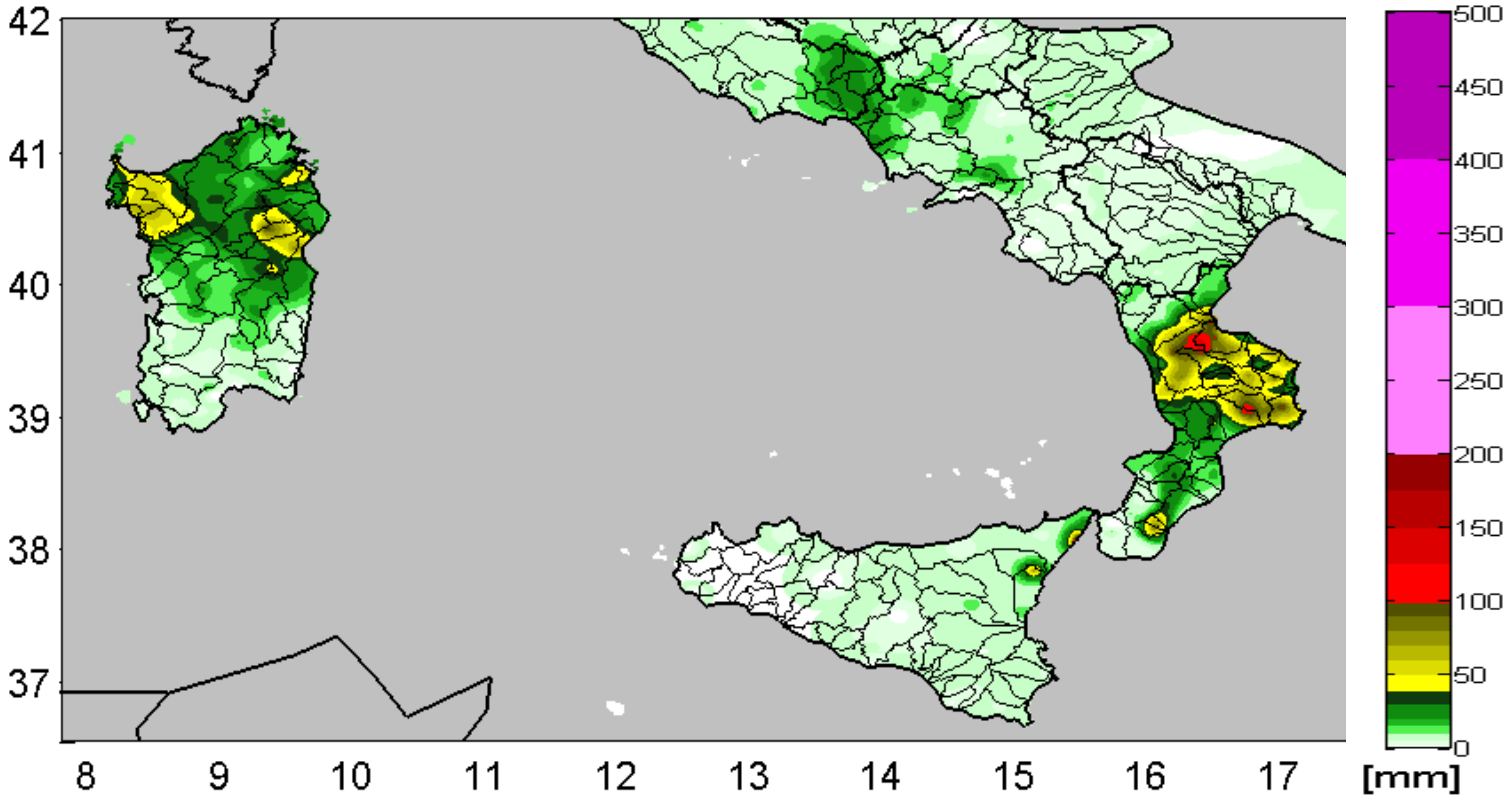
METHOD DESCRIPTION: CONDITIONAL MERGING

4) RAINFALL MAP INTERPOLATED FROM RADAR



Based on Conditional Merging: Sinclair and Pegram, 2005

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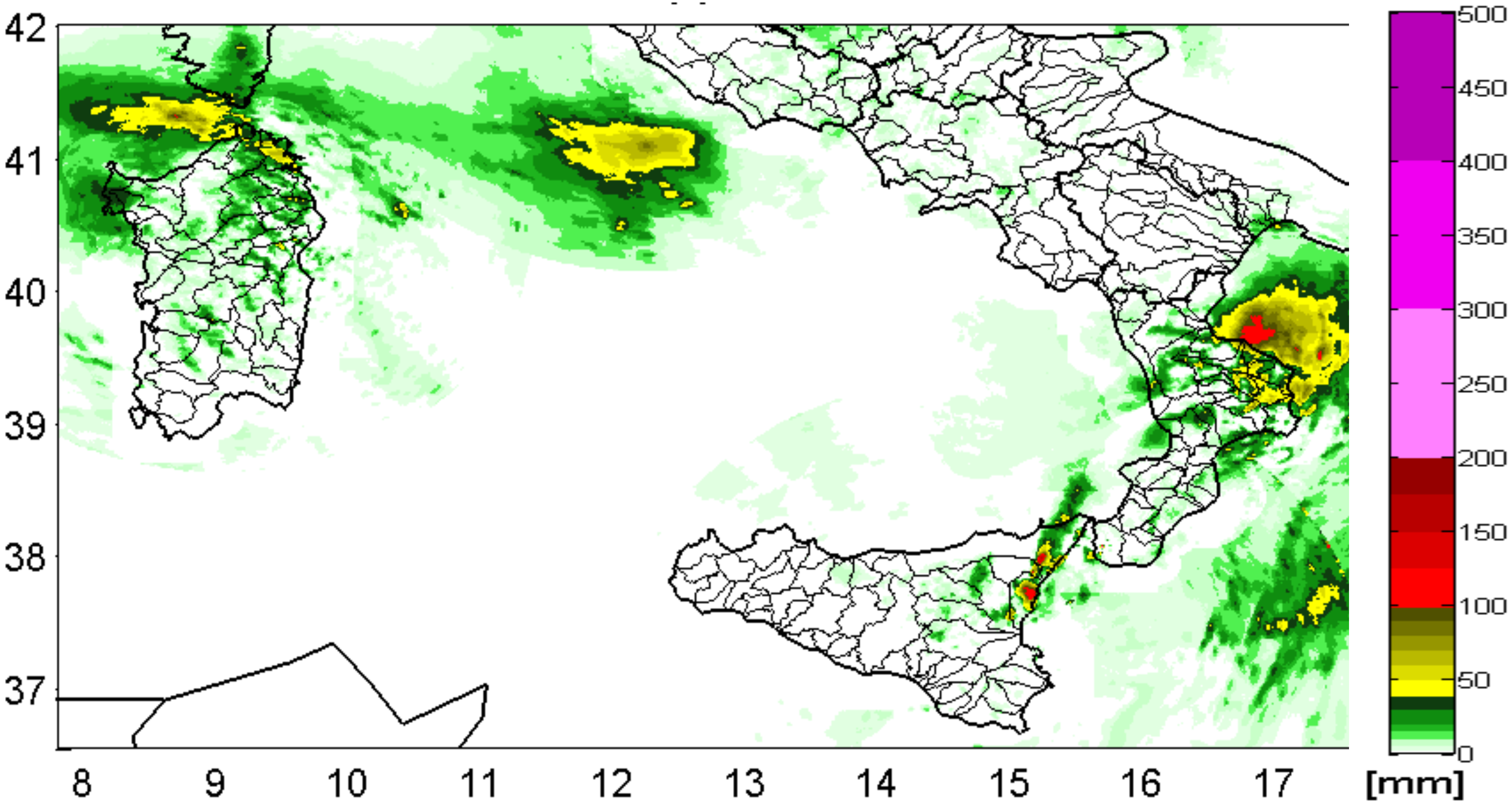
METHOD DESCRIPTION: CONDITIONAL MERGING

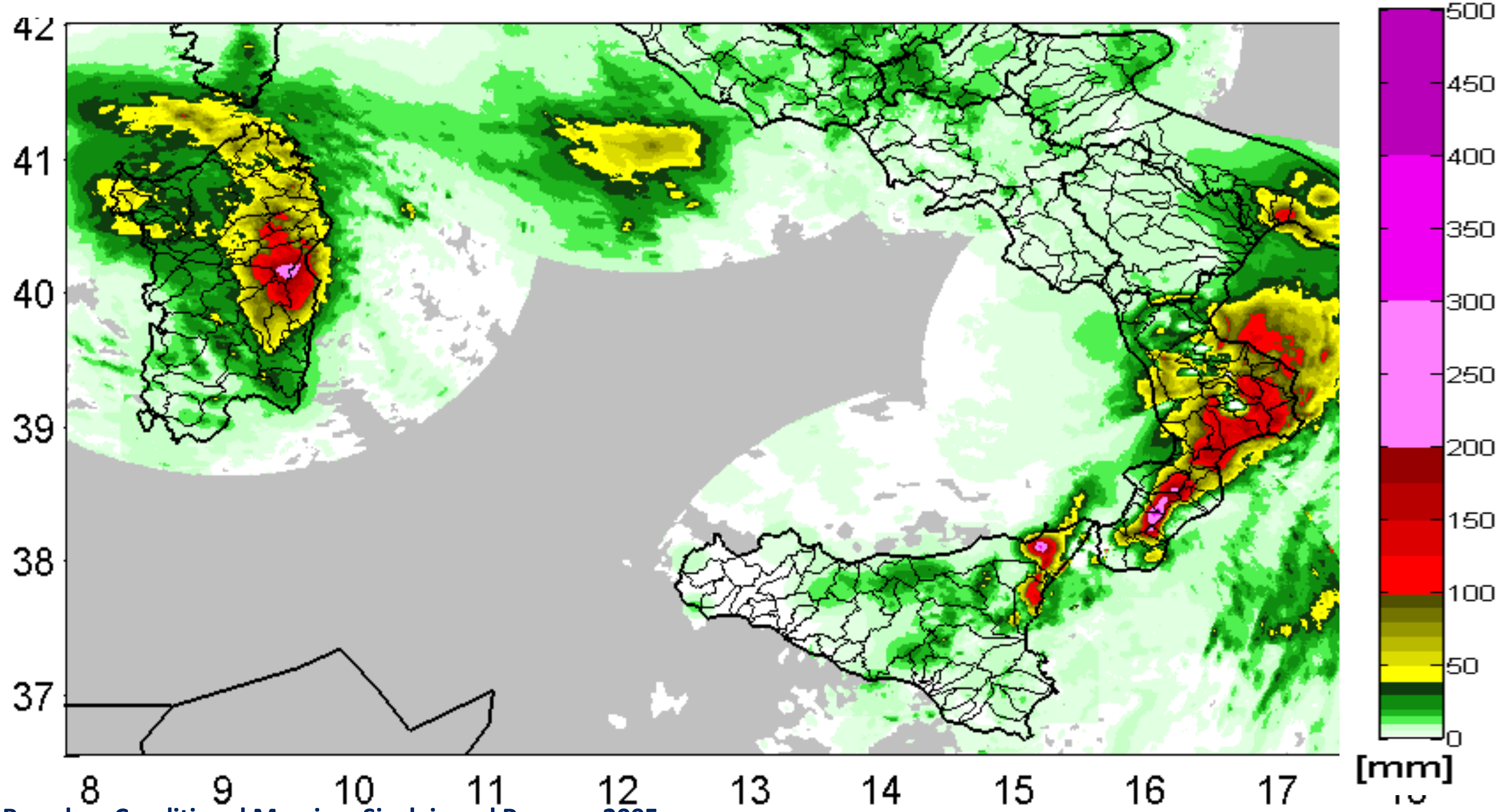
5) MAP OF DIFFERENCES



Based on Conditional Merging: Sinclair and Pegram, 2005

METHOD DESCRIPTION: CONDITIONAL MERGING

6) SUM OF INTERPOLATED MAP FROM GAUGES AND MAP OF DIFFERENCES



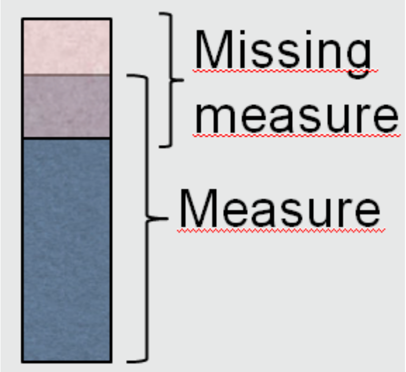
Based on Conditional Merging: Sinclair and Pegram, 2005

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING

Innovation: preprocess of raingauge data

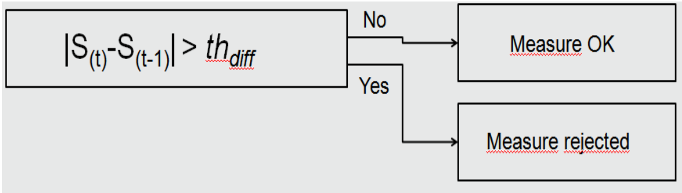
According to WMO guide the amount of precipitation measured in a gauge is less than the actual precipitation reaching the ground due to:

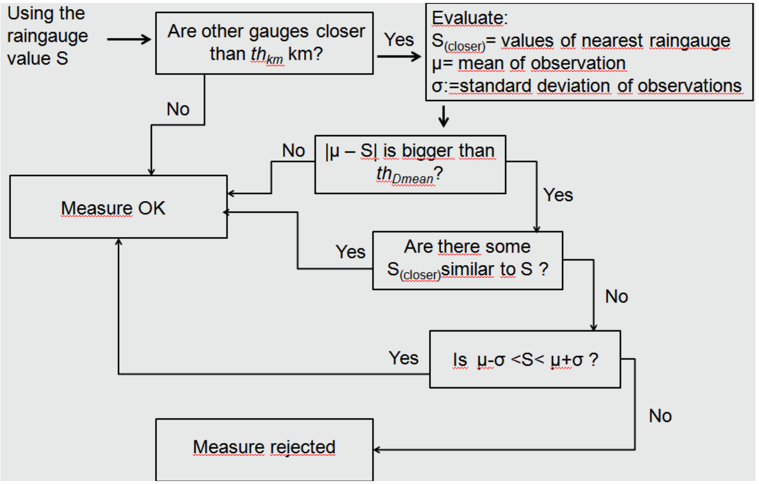
- **wind field**
- **wetting**
- **evaporation**
- **trace precipitation error**
- **mechanical errors**
- **in- and out-splashing**



In the interpolation methods GRISO the raingauges values used as input are pre-preprocessed with two different filter based on:

- **Spatial** comparison with closer gauges
- **Temporal** behavior of the single raingauge



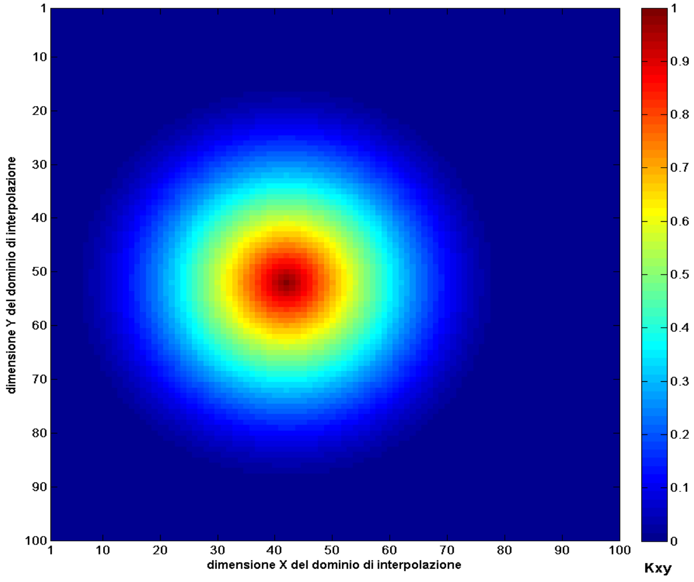


METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING

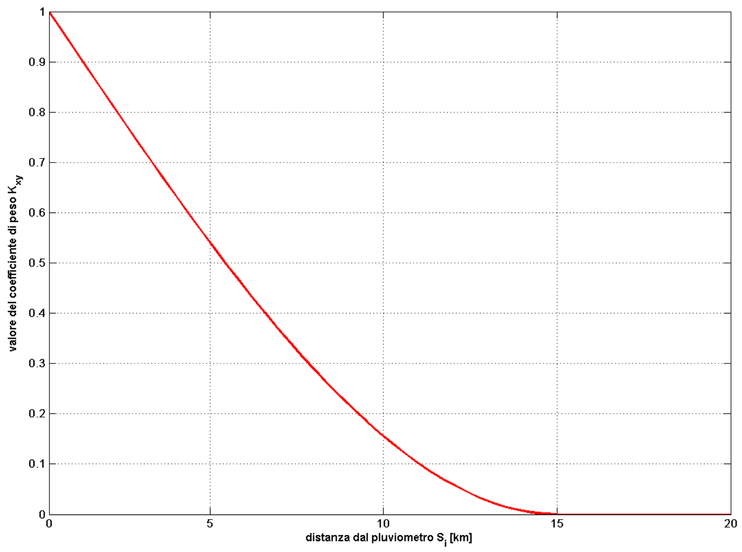
Innovation: Use of GRISO as interpolation algorithm

The interpolation algorithm allows us **to build a continuous precipitation field F(x,y) from the punctual observation data, (Vi).** It is based on:

- **The kernel of covariance K(x,y,λ)**
- **Length of correlation (λ) between observations**



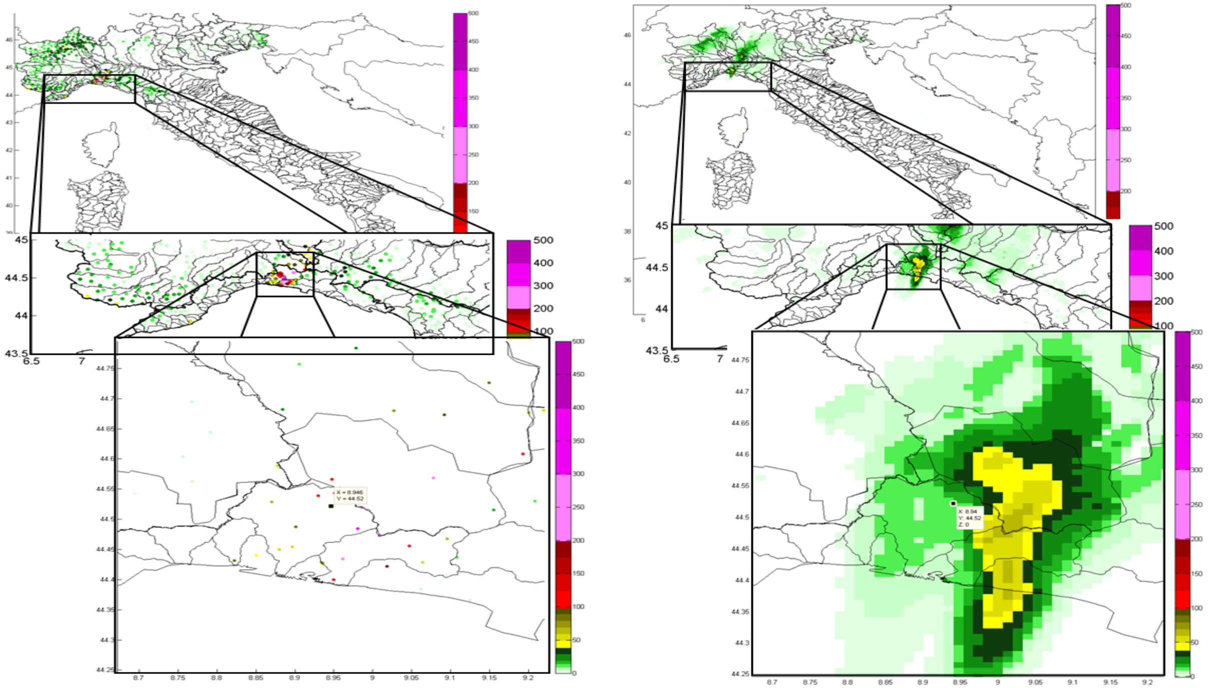
Examples of 2D and 1D variation of the covariance structure with the distance.

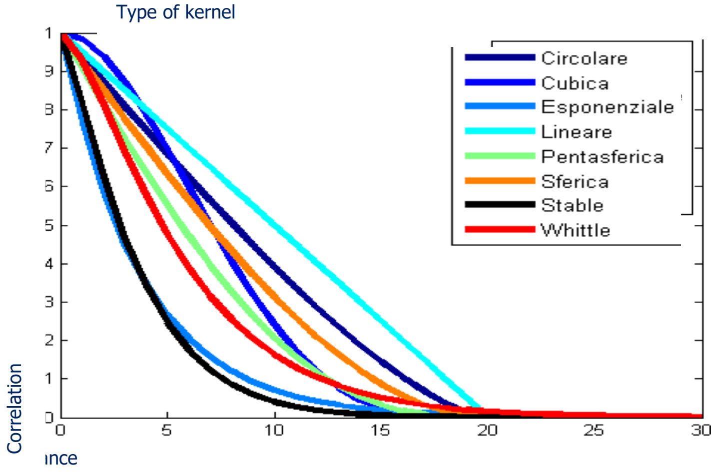


METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING

Innovation: Estimation of correlation length and kernel function of all raingauges using radar observation

The use of a length of correlation value and a kernel function **defined a priori does not allow for the proper capturing of fine scale changes** in the correlation structure of the rainfall field.



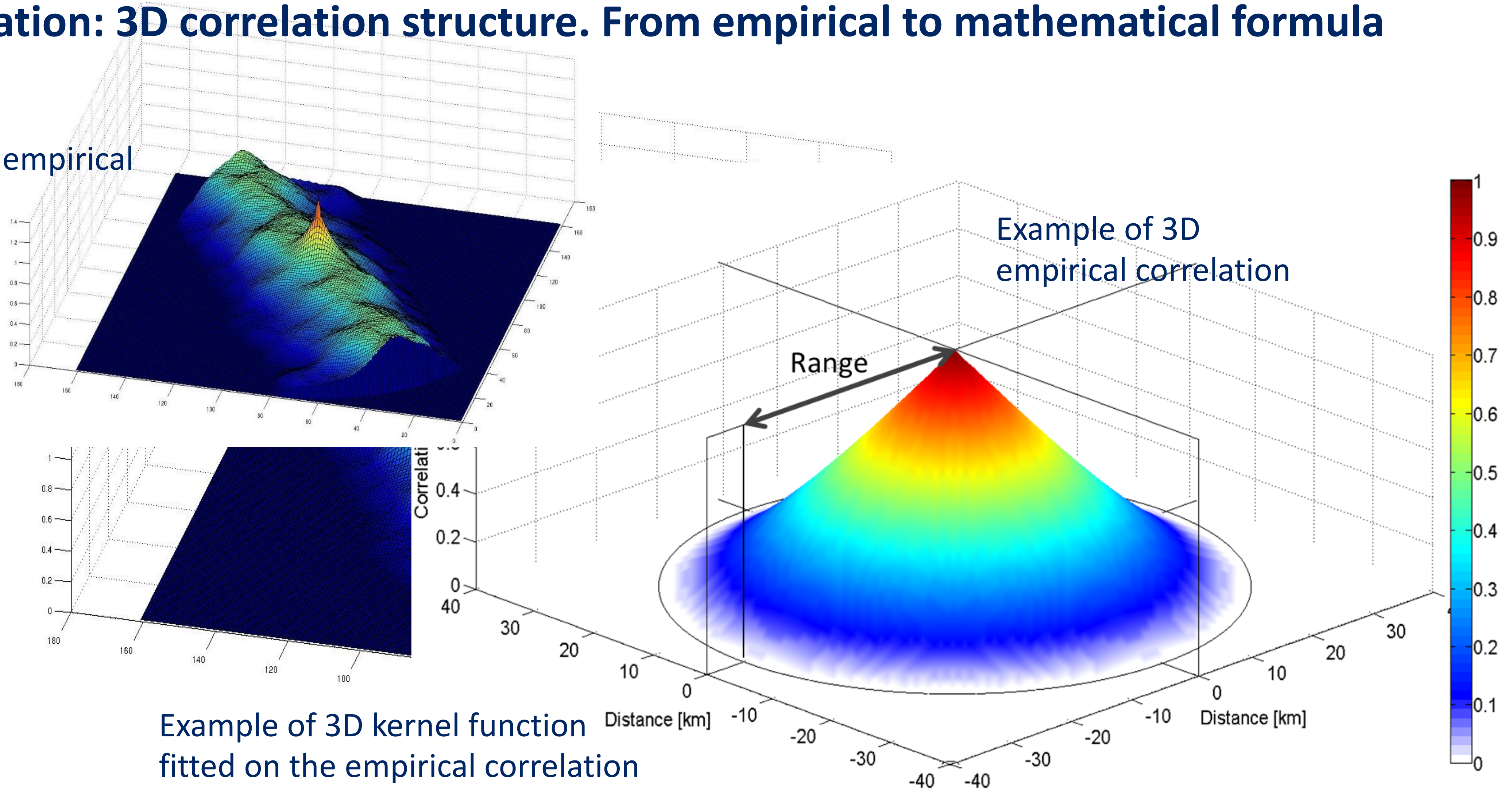


Example of covariance function

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING

Innovation: 3D correlation structure. From empirical to mathematical formula

Example of empirical correlation



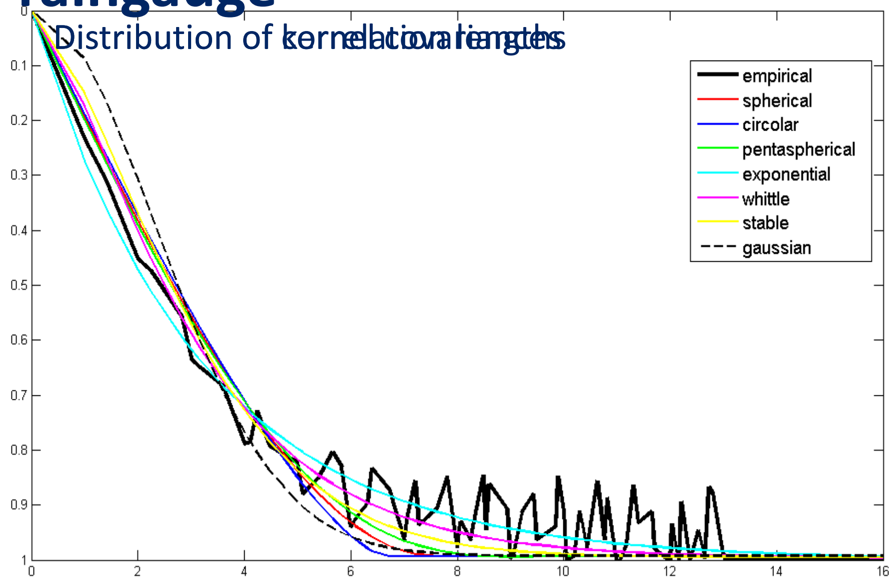
Example of 3D kernel function fitted on the empirical correlation

EUMETSAT H SAF

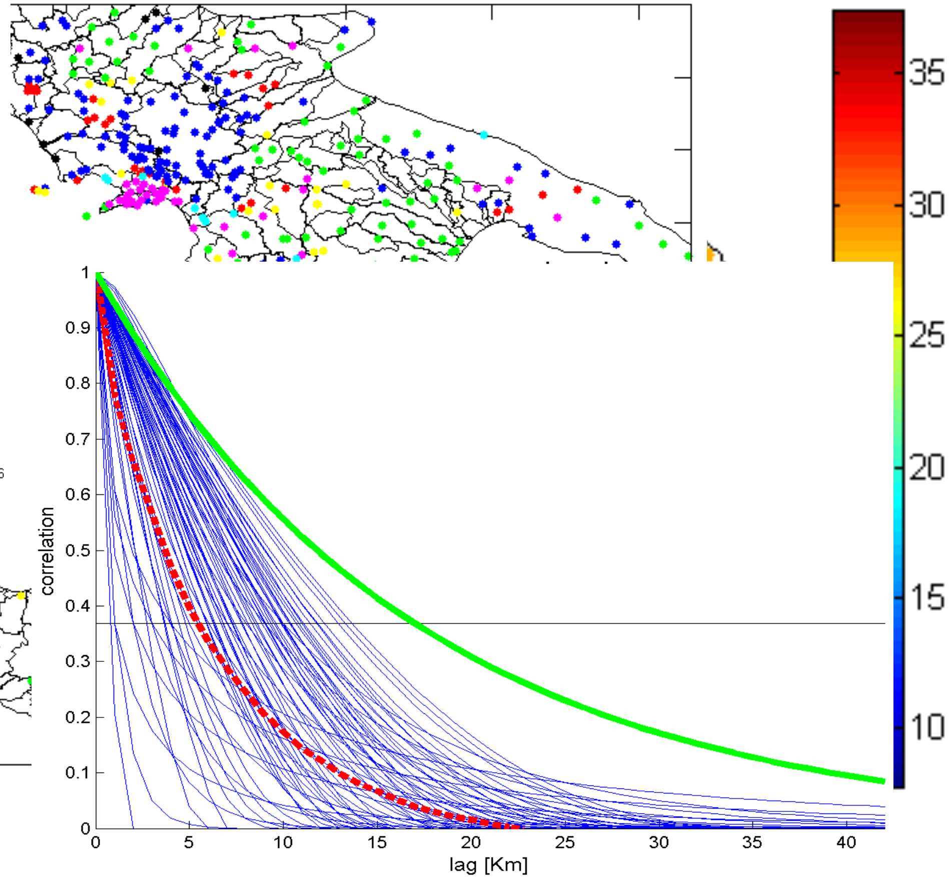
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING

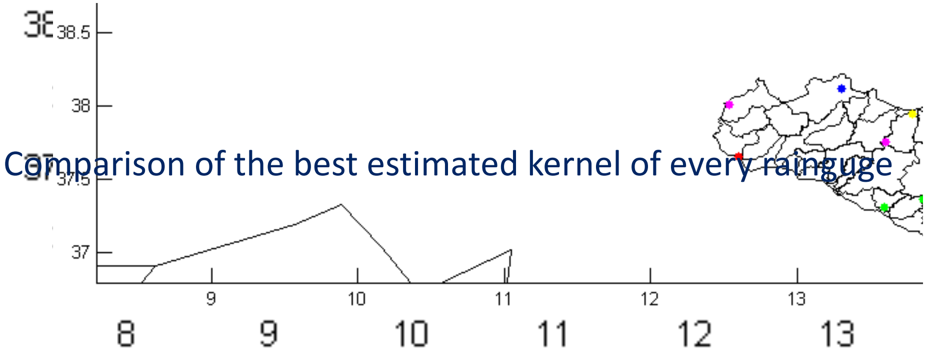
Innovation: Estimation of length of correlation and kernel from radar map for single raingauge

Distribution of correlation lengths



Best estimation of different kernel for single rainguge



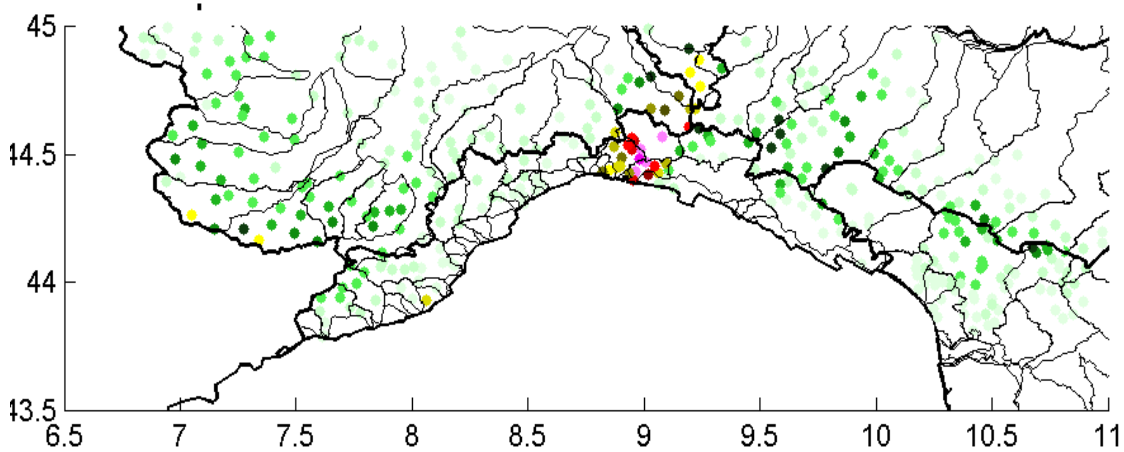


Comparison of the best estimated kernel of every raingauge

EUMETSAT H SAF

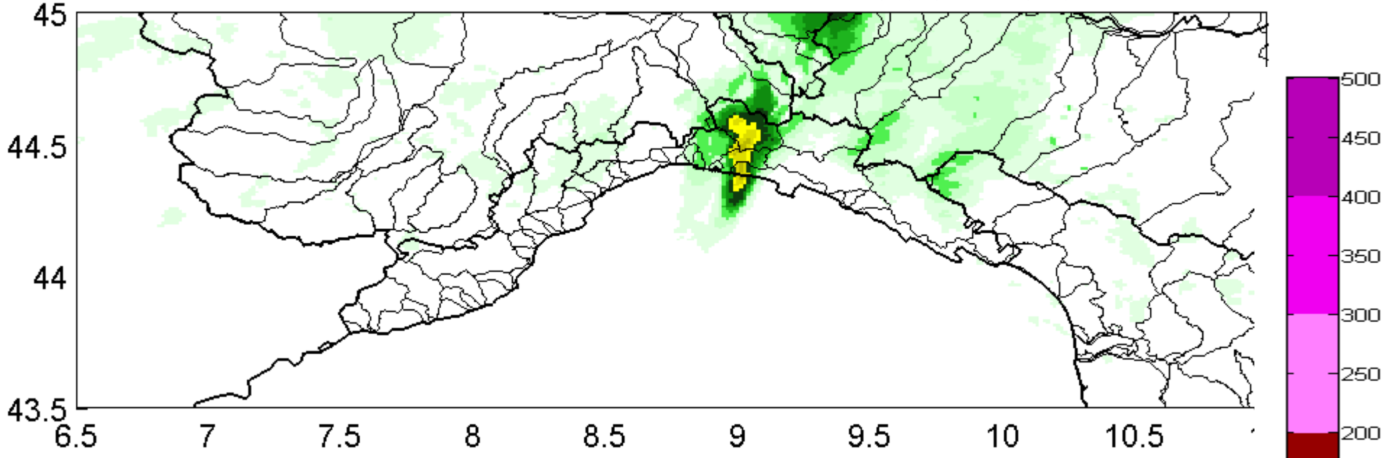
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING example event on 4 November, 2011 (6h accumulated)

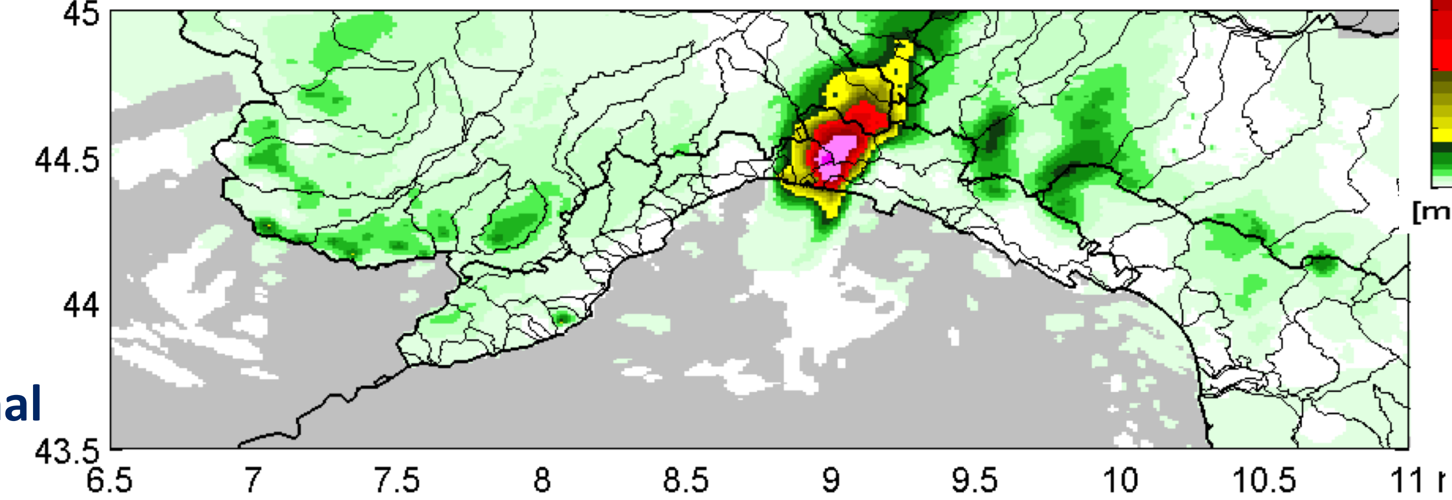
In this case the radar field had a large rainfall underestimation



Raingauge observations

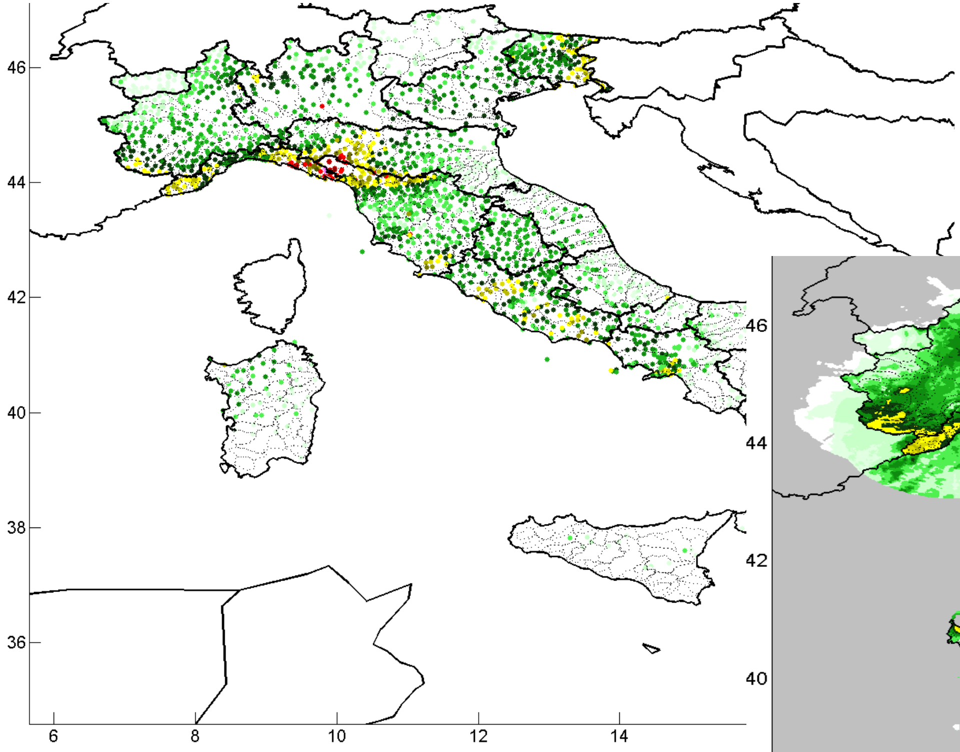
Radar field



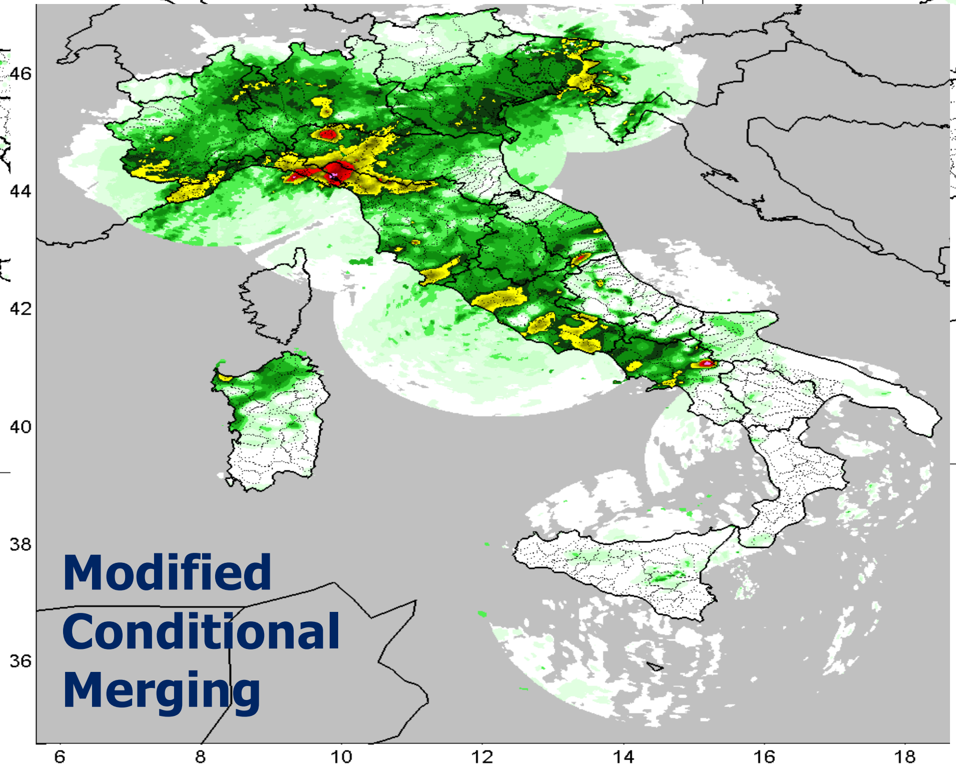


Modified Conditional Merging

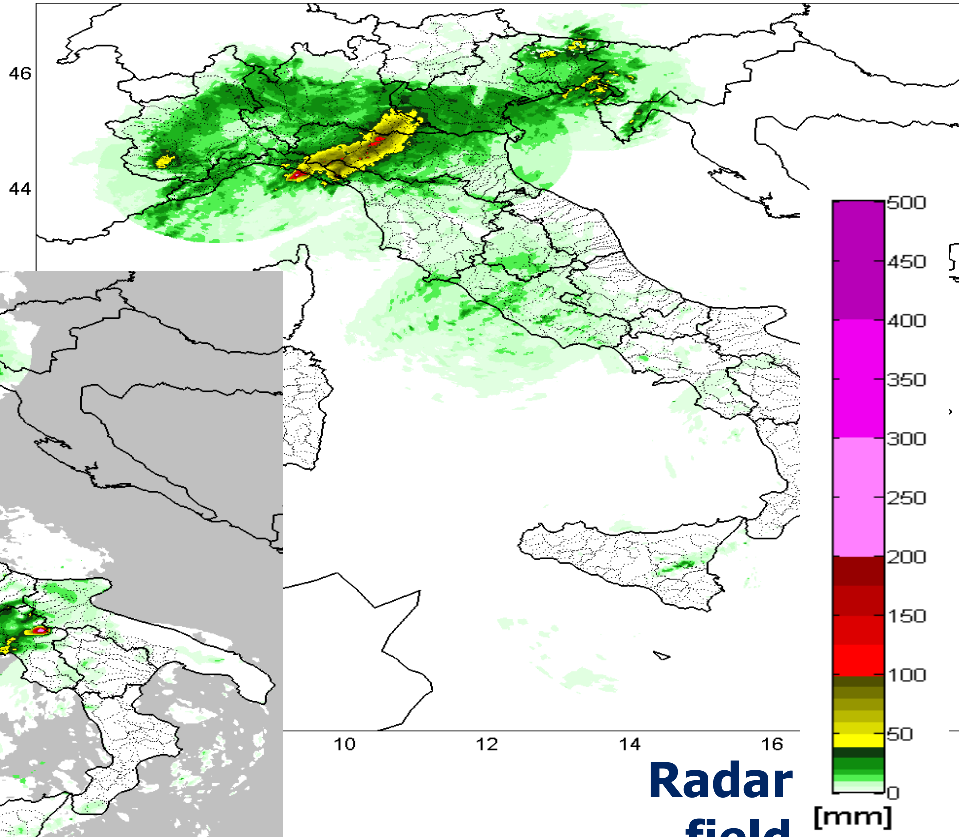
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING
example event on 22 November, 2011 (24h accumulated)



Raingauge observations

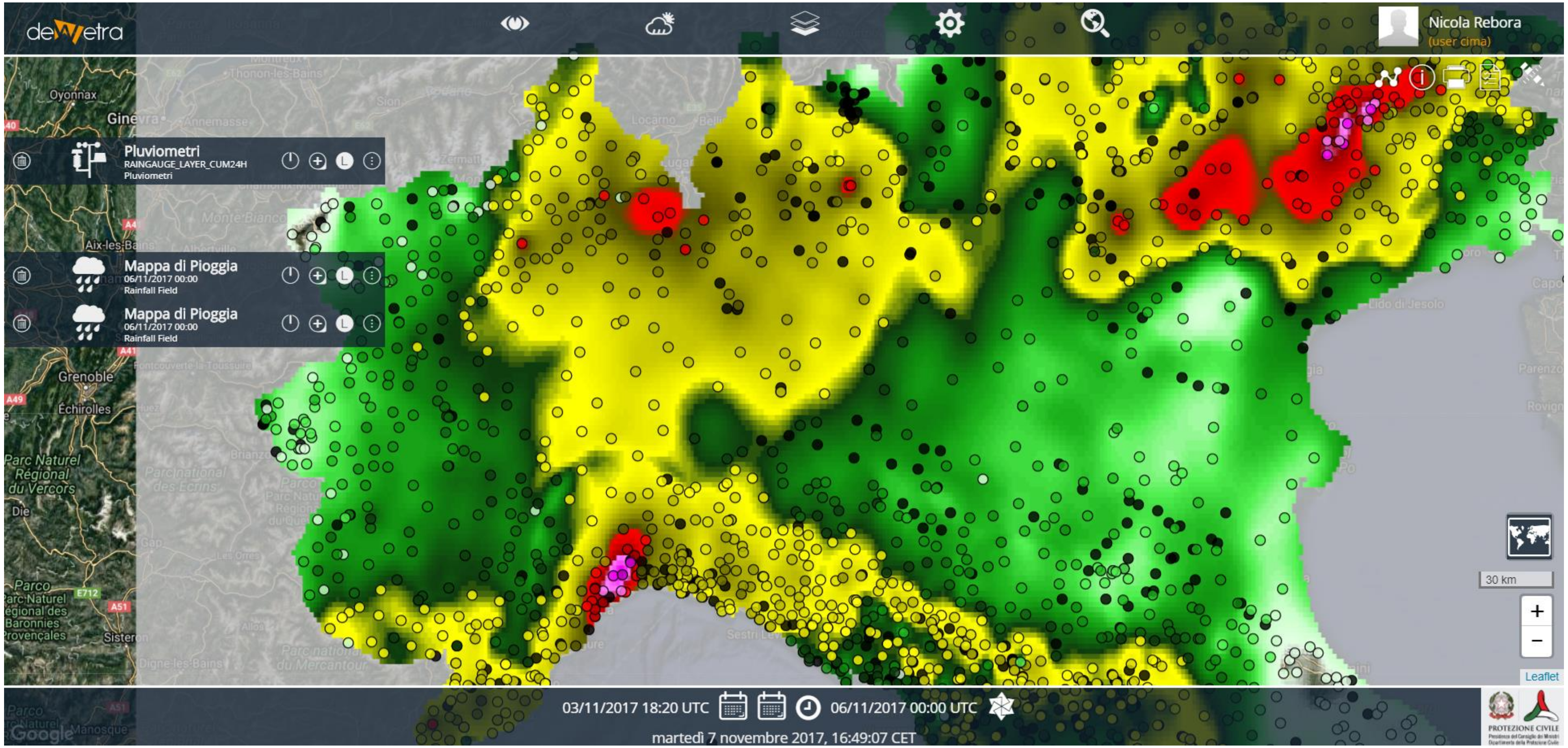


Modified Conditional Merging



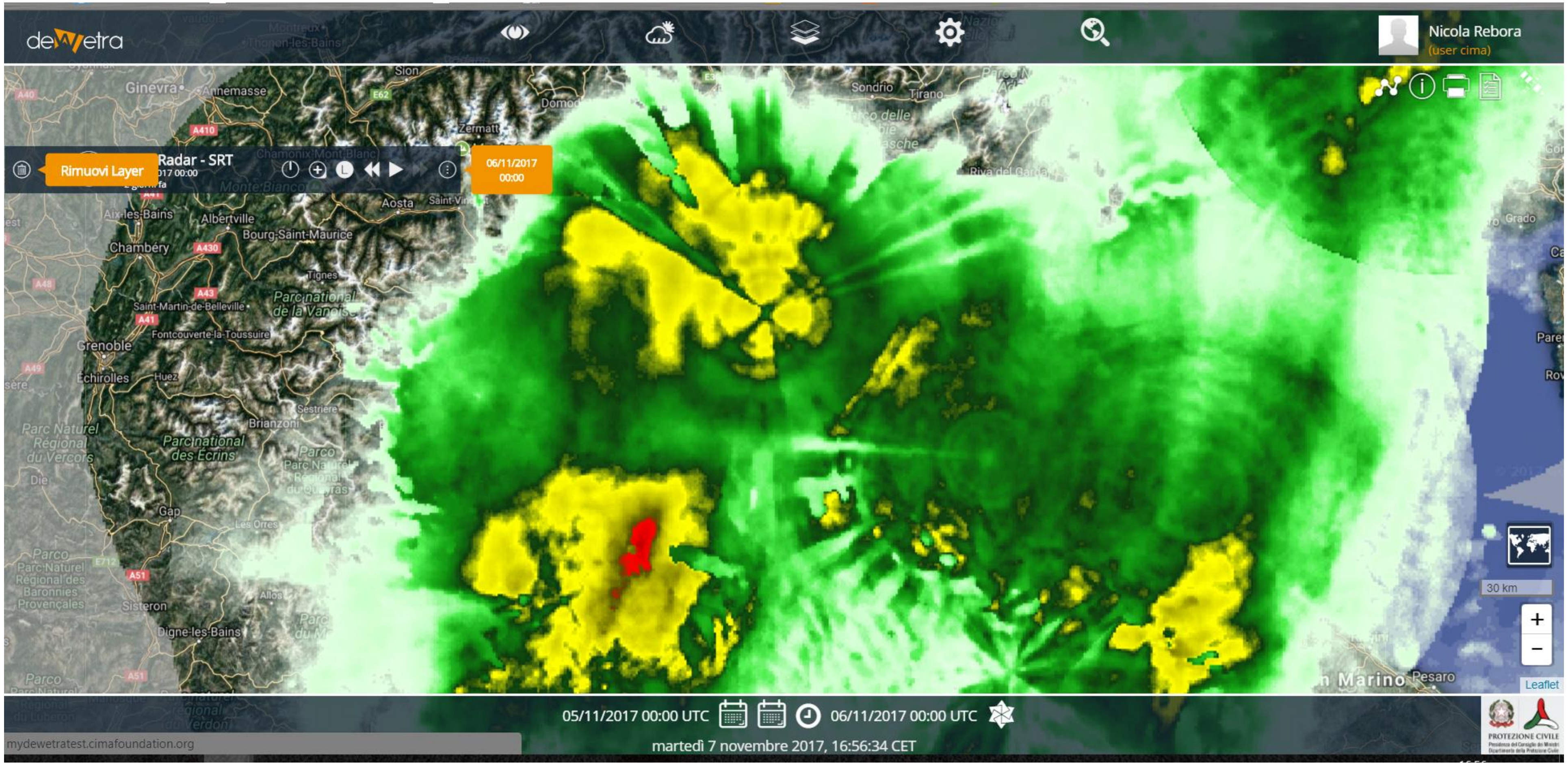
Radar field

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING example

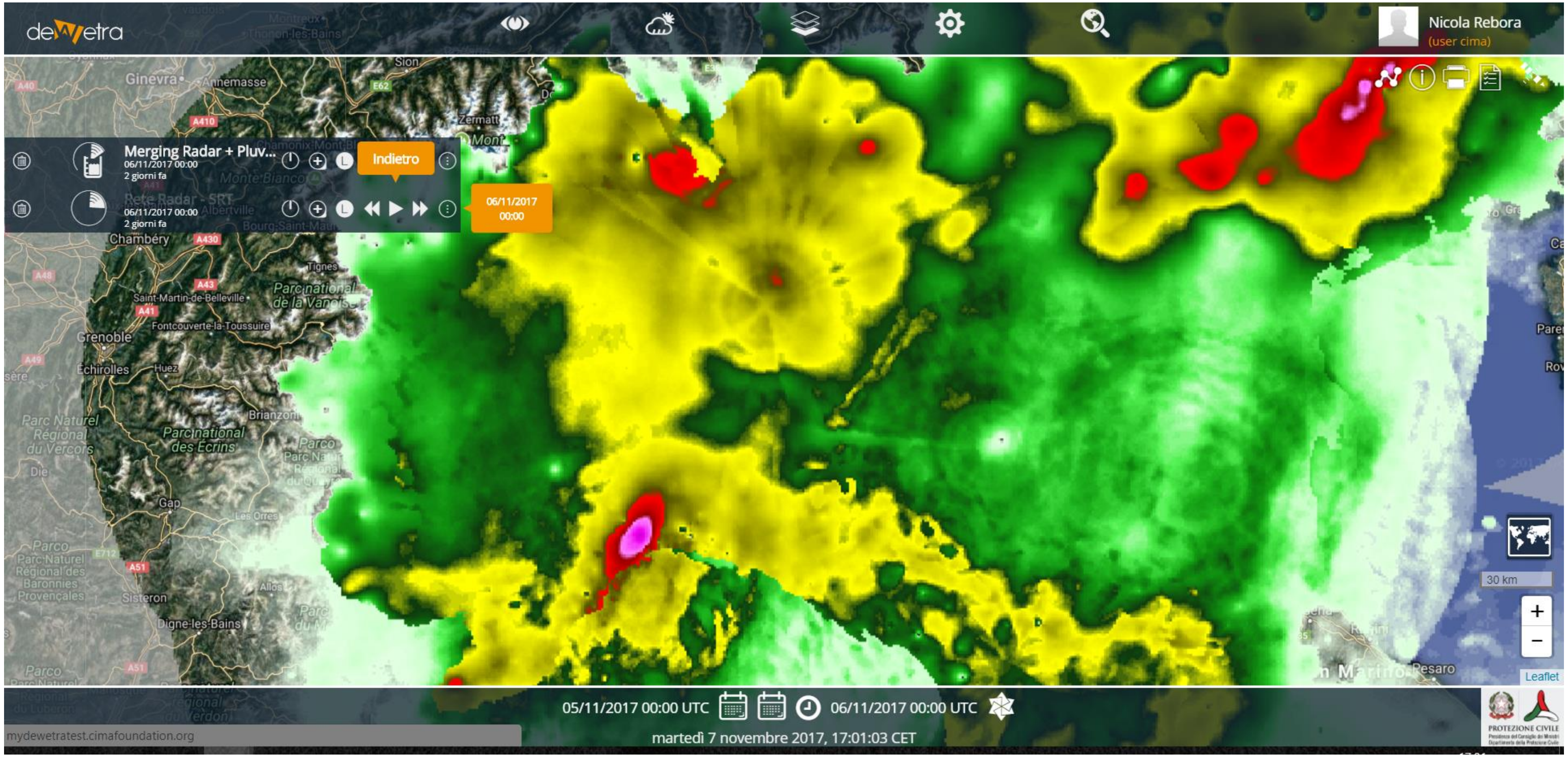


EUMETSAT H SAF

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING example



METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING example



METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING validation

The validation is made by:

1. **Identification of** a large number of **event** with different characteristic (duration and location)
2. Identification of **different spatial densities** for the generation of the rainfall merged field
3. **Apply MCM radar-raingauge** using different spatial densities and temporal accumulation within the domain (n times per configuration)
4. **Apply the original CM with Kriging** using the same configuration used for MCM
5. **Application of different statistical score** on the new fields (RMSE, power spectra, ecc)
6. **Compare** the output **maps and statistics of MCM and CM**

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING validation

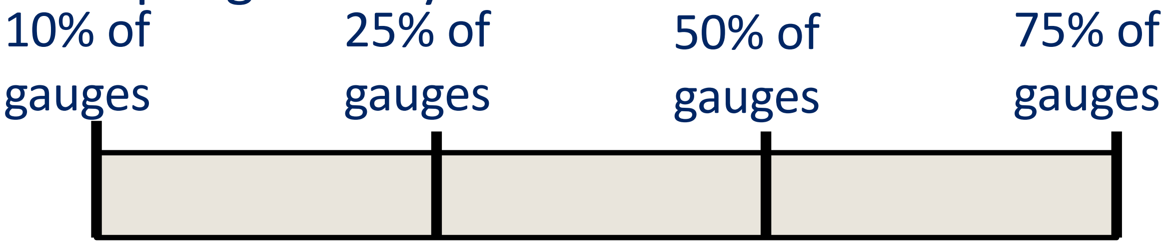
1. Identification of a large number of event with different characteristic (duration and location)

YEAR	# events
2011	17
2012	13
2013	29
2014	13

From the 1st january 2011 till today are individuated more than 70 events.
In the table are reported location and duration of some examples.

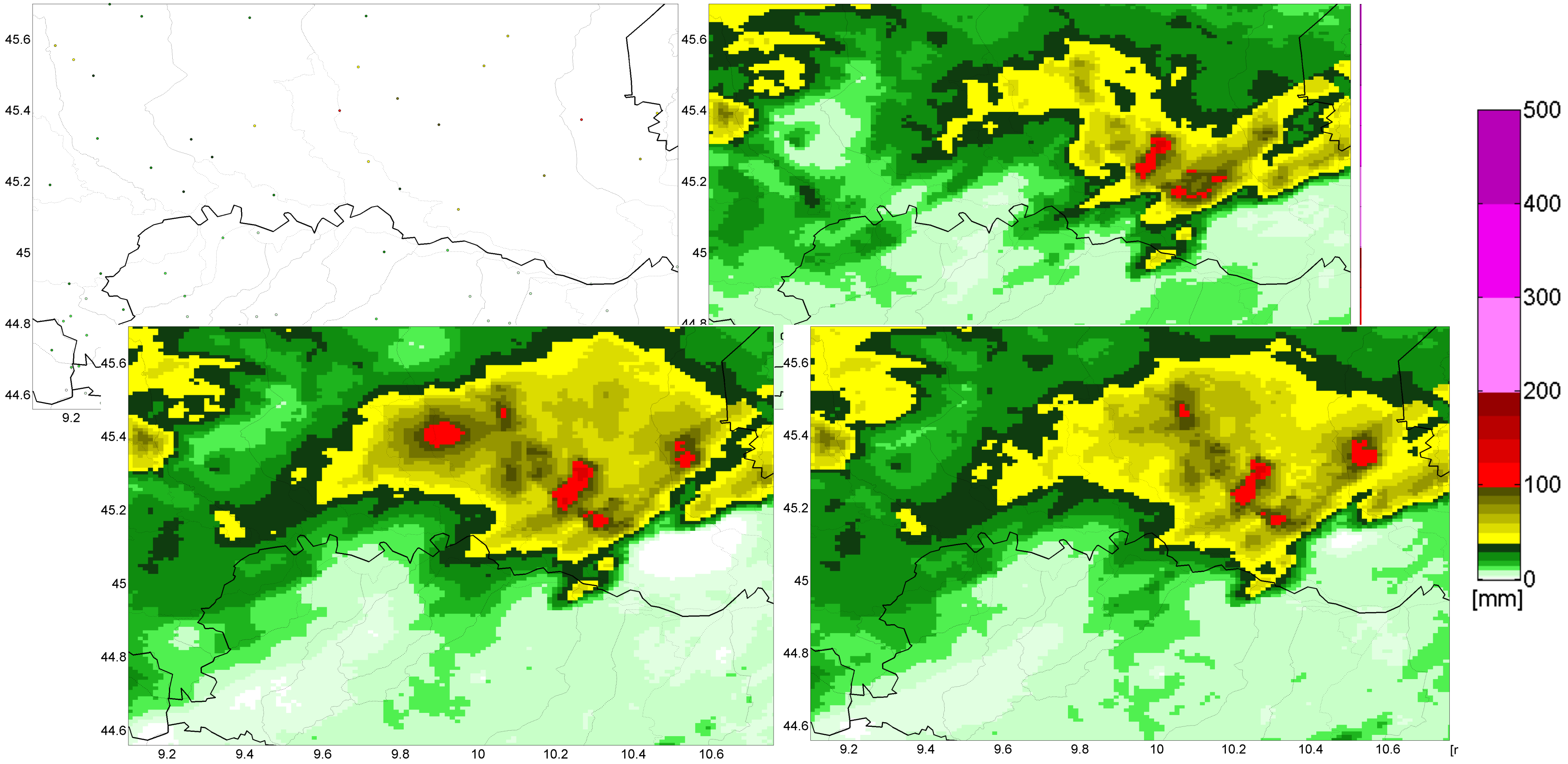
2. Identification of different spatial densities for the generation of the rainfall merged field

Sampling density:



METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING validation

3. **Apply MCM radar-raingauge** using different spatial density and temporal accumulation within the domain (n times per configuration)
4. **Applyt the original CM with Kriging** using the same configuration



METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING validation

5. Application of different statistical score on the new fields

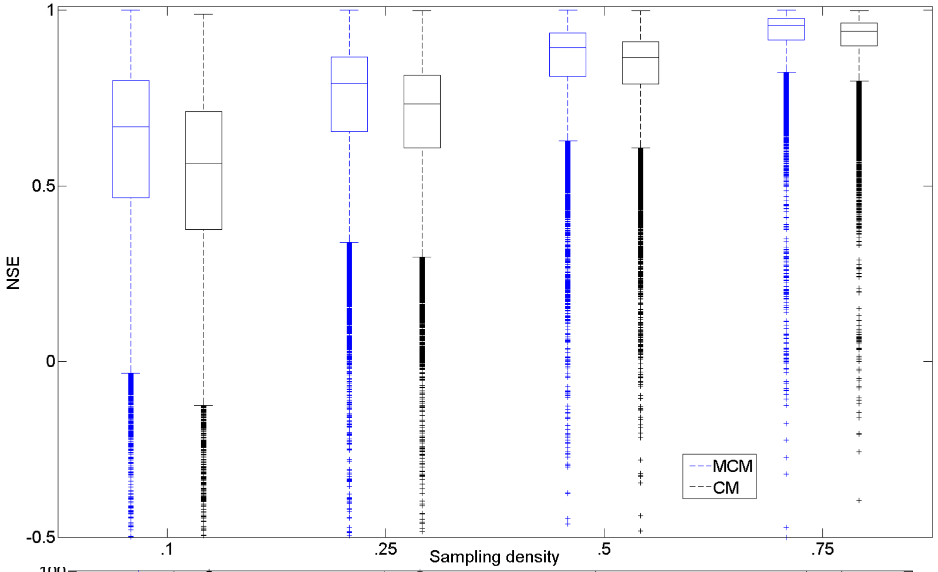
- Statistical score (mean, variance, ecc)
- PDF and CDF
- Power spectra
- NSE,RMSE, PBIAS
- PDF of differences between interpolated fields and radar input map

6. Compare the output maps and statistics of MCM and CM

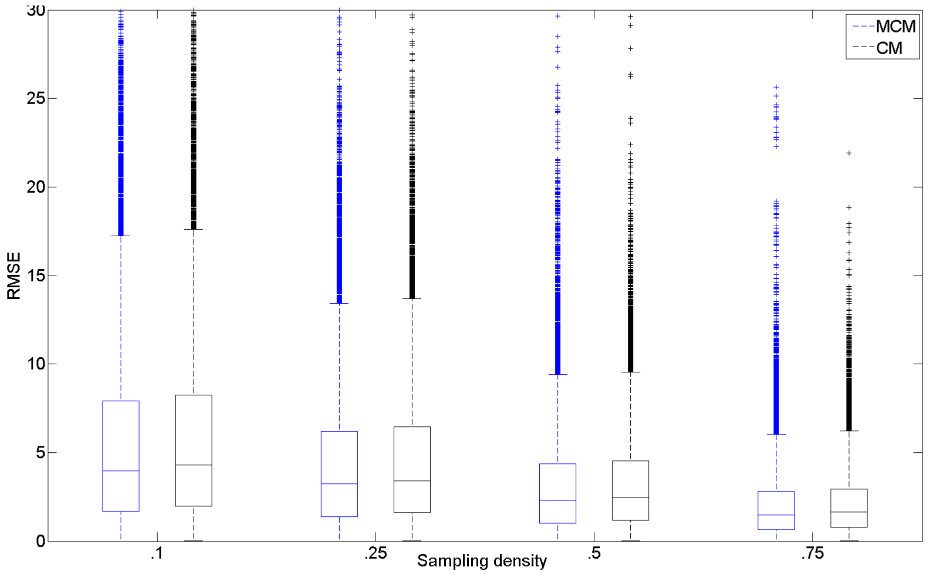
EUMETSAT H SAF

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING validation

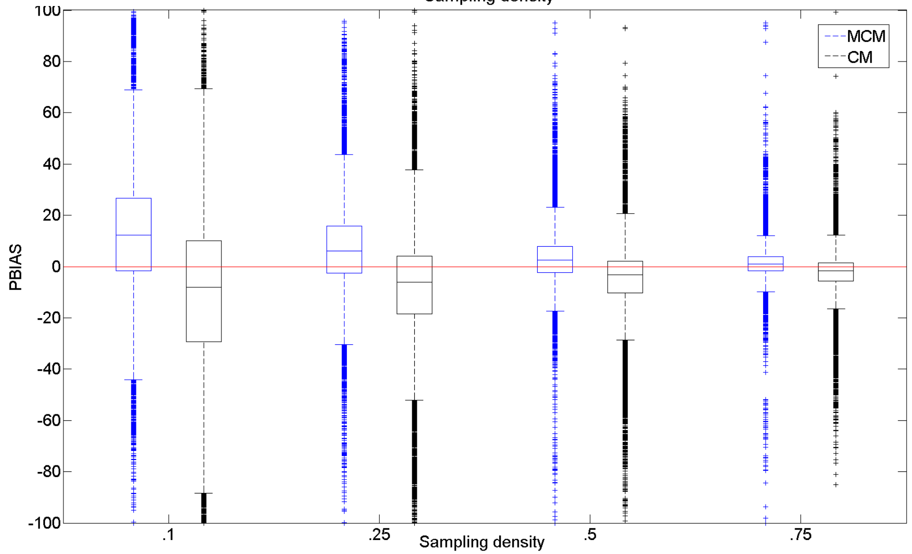
Ensemble of NSE



Ensemble of RMSE



Ensemble of PBIAS



$$RMSE=\sqrt{\frac{\sum_{i=1}^{m}(Q_{ref}(t_i)-Q_{t_i-\tau}(t_i))^2}{m}}$$

Values of the RMSE closer to zero are an indication of good comparison between model and observations

$$NSE=1-\frac{\sum_{t_i=t_{1+\tau}}^{t_n}\left[Q_{ref}(t_i)-Q_{t_i-\tau}(t_i)\right]^2}{\sum_{t_i=t_{1+\tau}}^{t_n}\left[Q_{ref}(t_i)-\overline{Q}_{ref}\right]^2}$$

NSE = 1.0 corresponds to a perfect match of modeled to the observed data.

NSE = 0 indicates that the model predictions are as accurate as the mean of the observed data

Values of NSE < 0 occurs when the observed mean is a better predictor than the model.

$$PBIAS=\left(\frac{\sum_{t_i=t_{1+\tau}}^{t_n}\left[Q_{ref}(t_i)-Q_{t_i-\tau}(t_i)\right]}{\sum_{t_i=t_{1+\tau}}^{t_n}\left(Q_{ref}(t_i)\right)}\right)\times 100$$

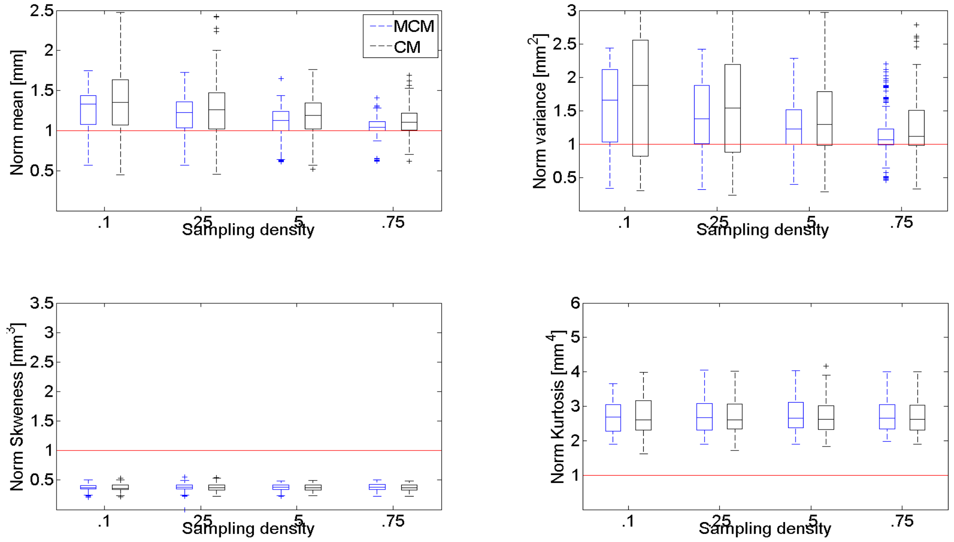
PBIAS>0 indicate that the model has an underestimation bias

PBIAS<0 indicate a model bias towards overestimation

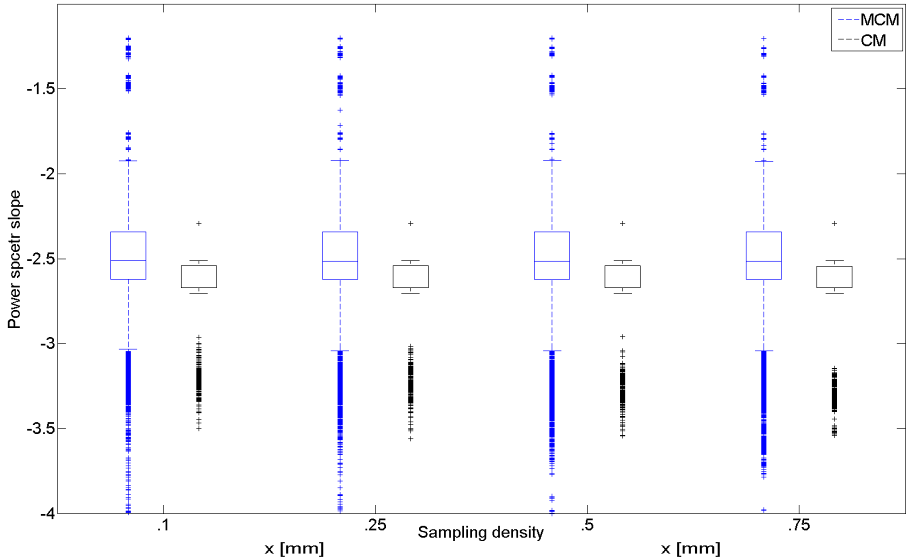
EUMETSAT H SAF

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING validation

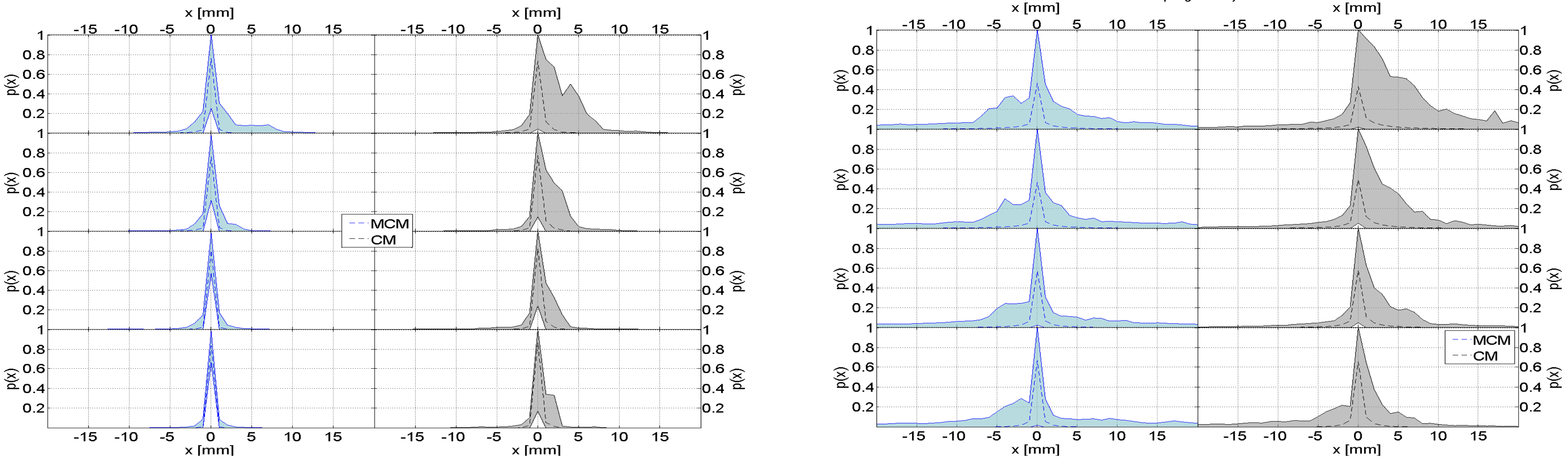
Ensemble of statistical moments



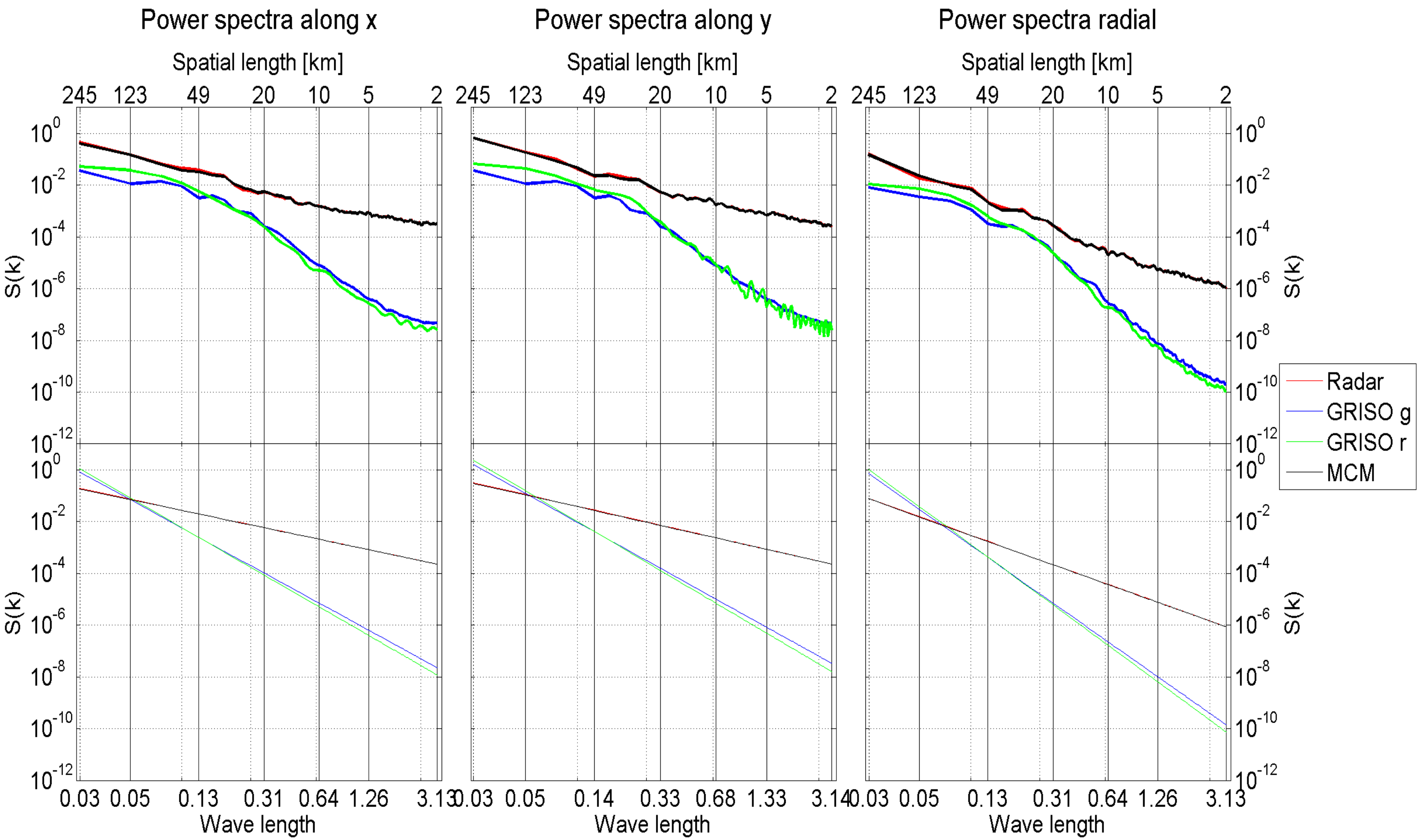
Ensemble of power spectra slope



Ensemble of PDF differences



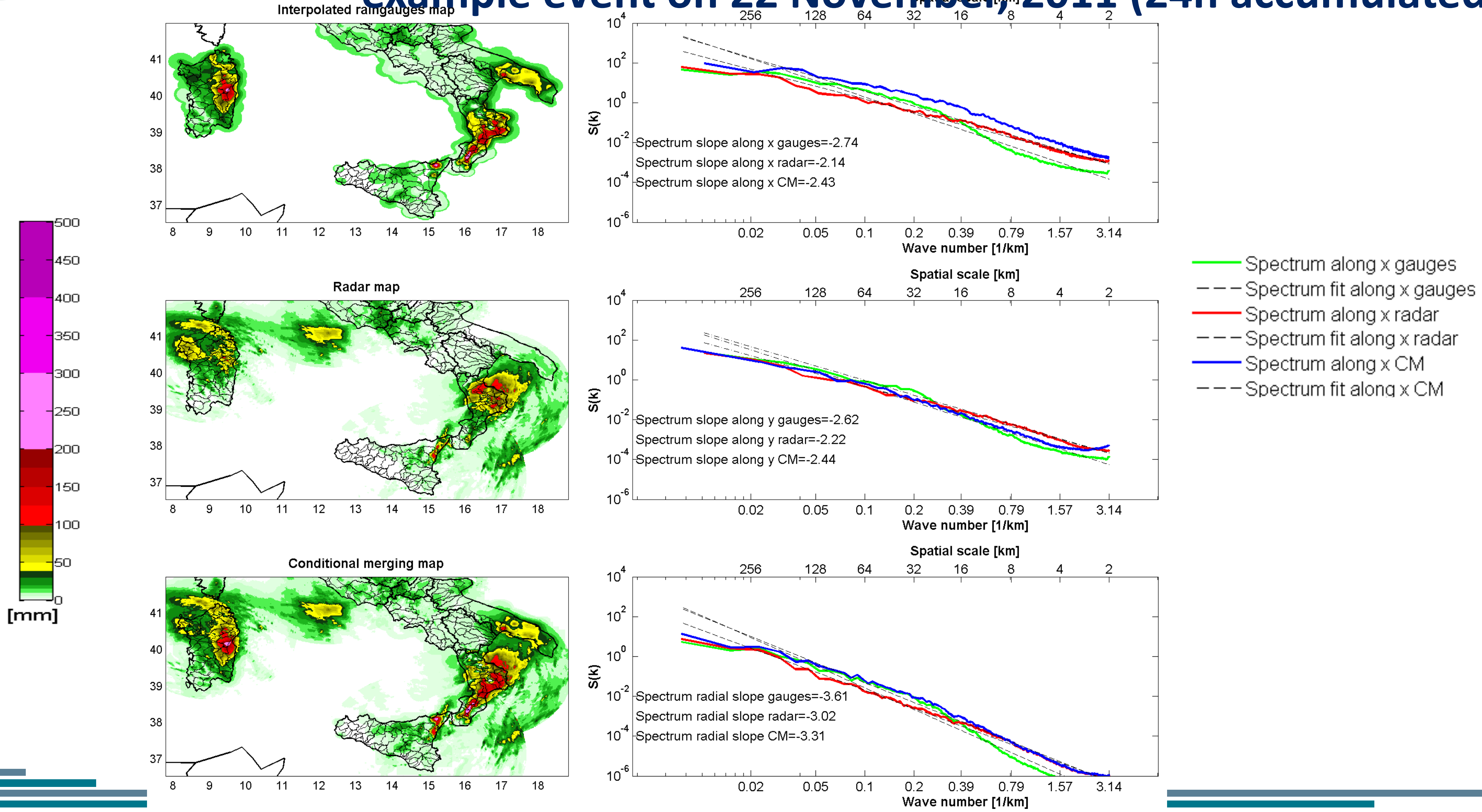
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING validation



EUMETSAT H SAF

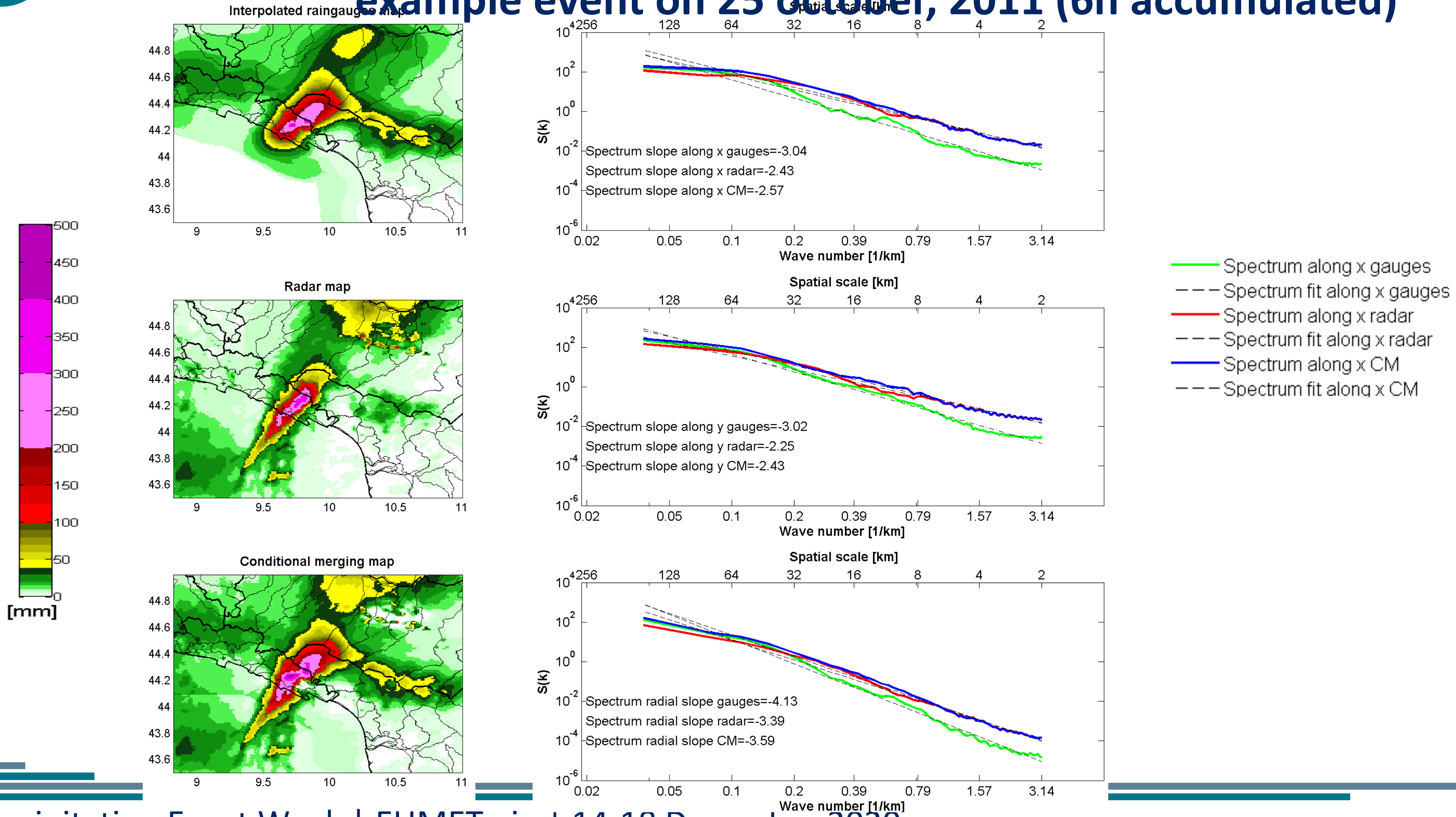
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING

example event on 22 November, 2011 (24h accumulated)

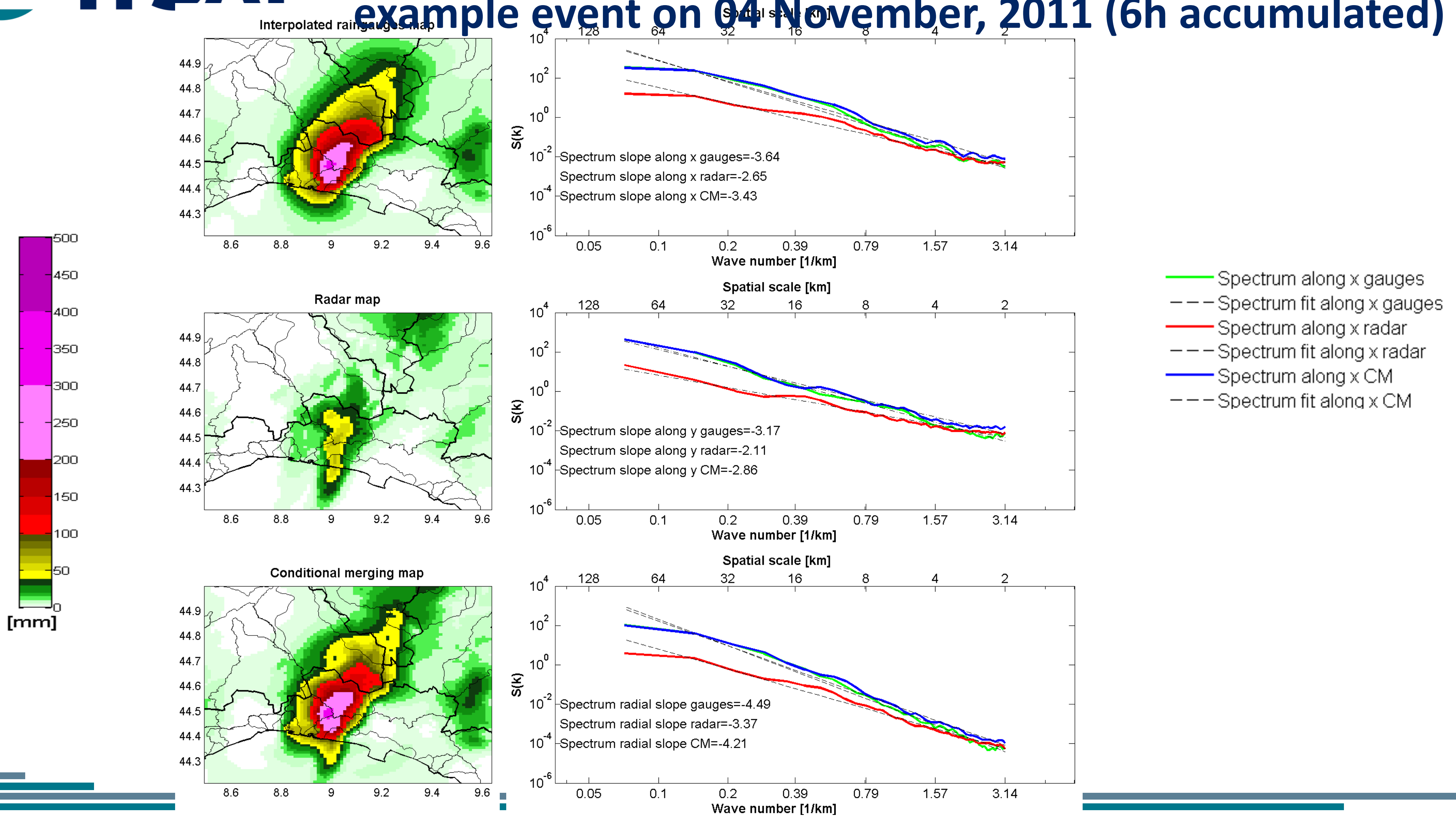


METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING

example event on 25 october, 2011 (6h accumulated)



METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING example event on 04 November, 2011 (6h accumulated)



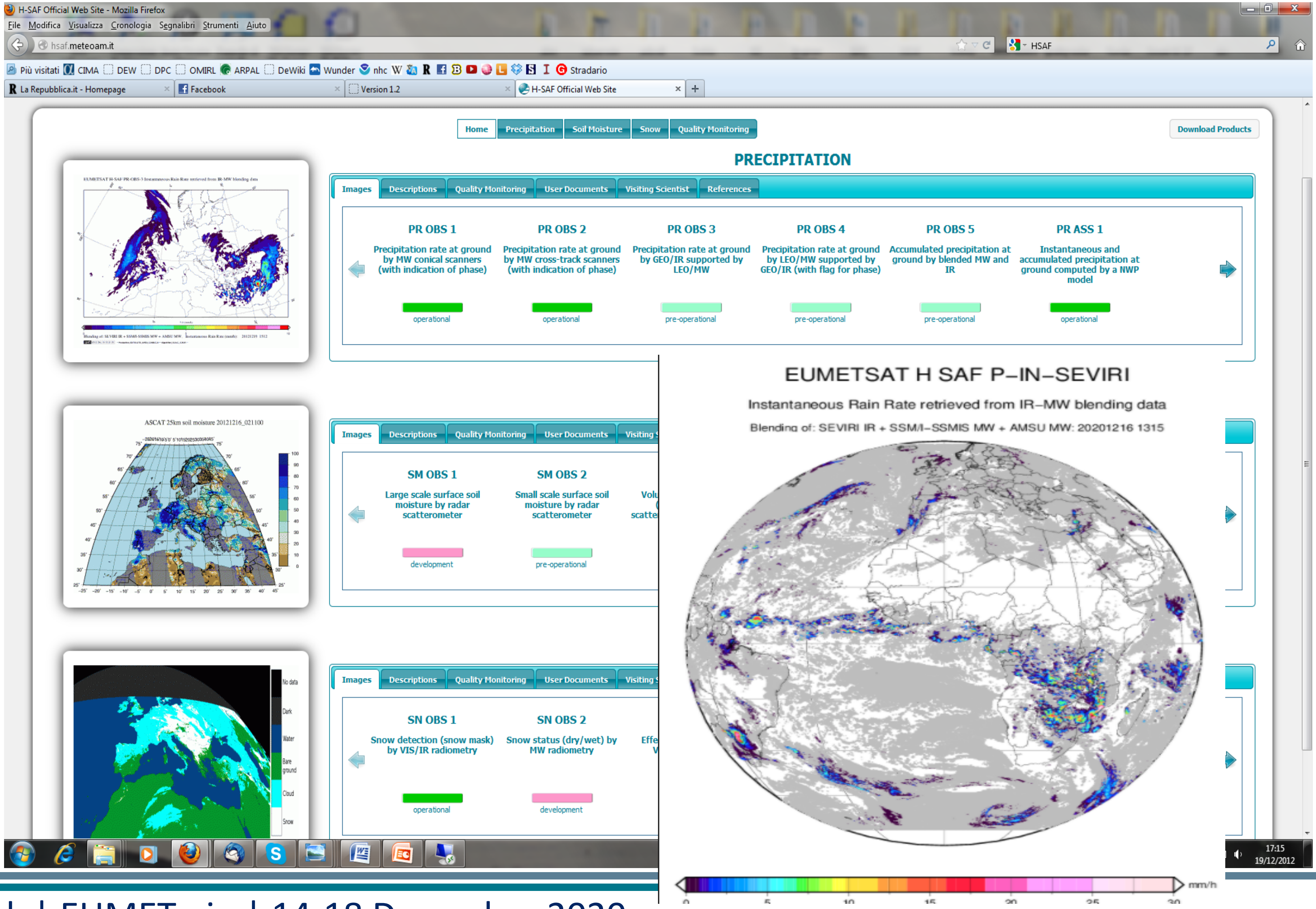
EUMETSAT H SAF

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING

Applciation on H-SAF Precipitation Product

In particular:

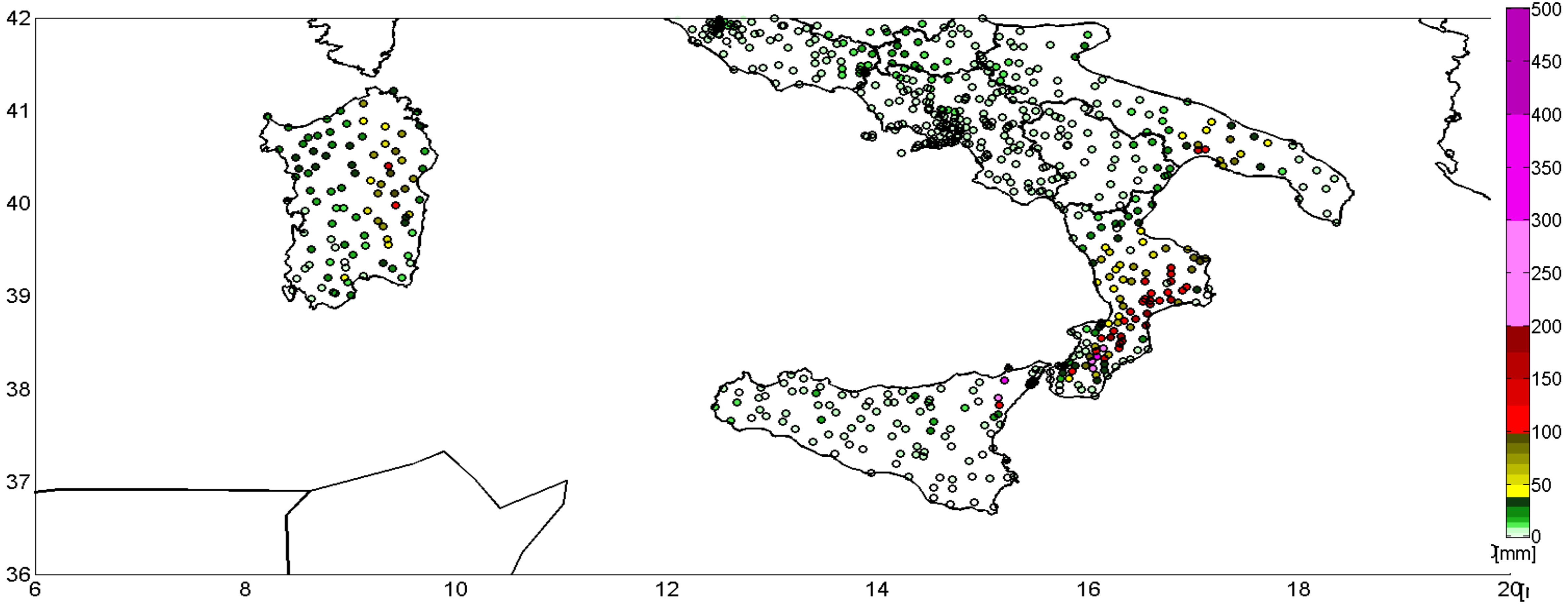
P-IN-SEVIRI (H03B) and P-AC-SEVIRI (H05B)



EUMETSAT H SAF

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING with HSAF data

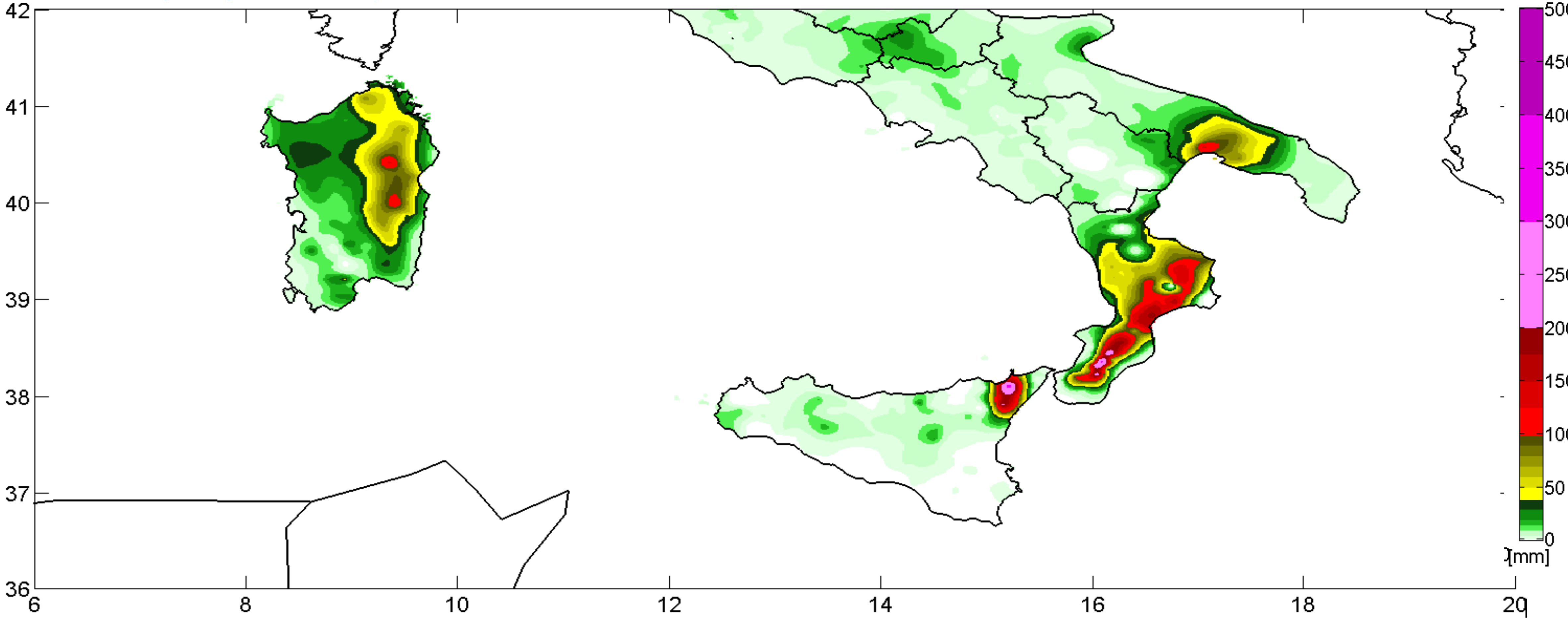
1) RAINGAUGES OBSERVATIONS



EUMETSAT H SAF

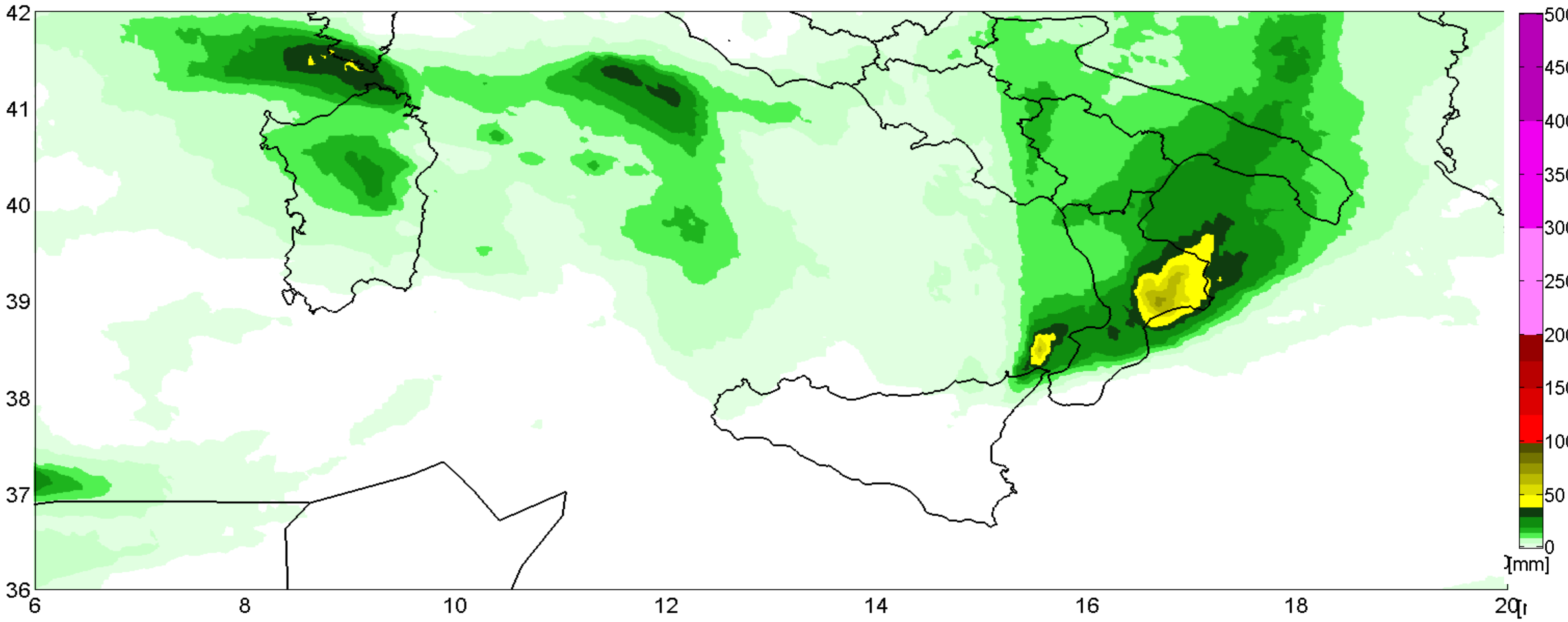
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING with HSAF data

2) Raingauges interpolation field



METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING with HSAF data

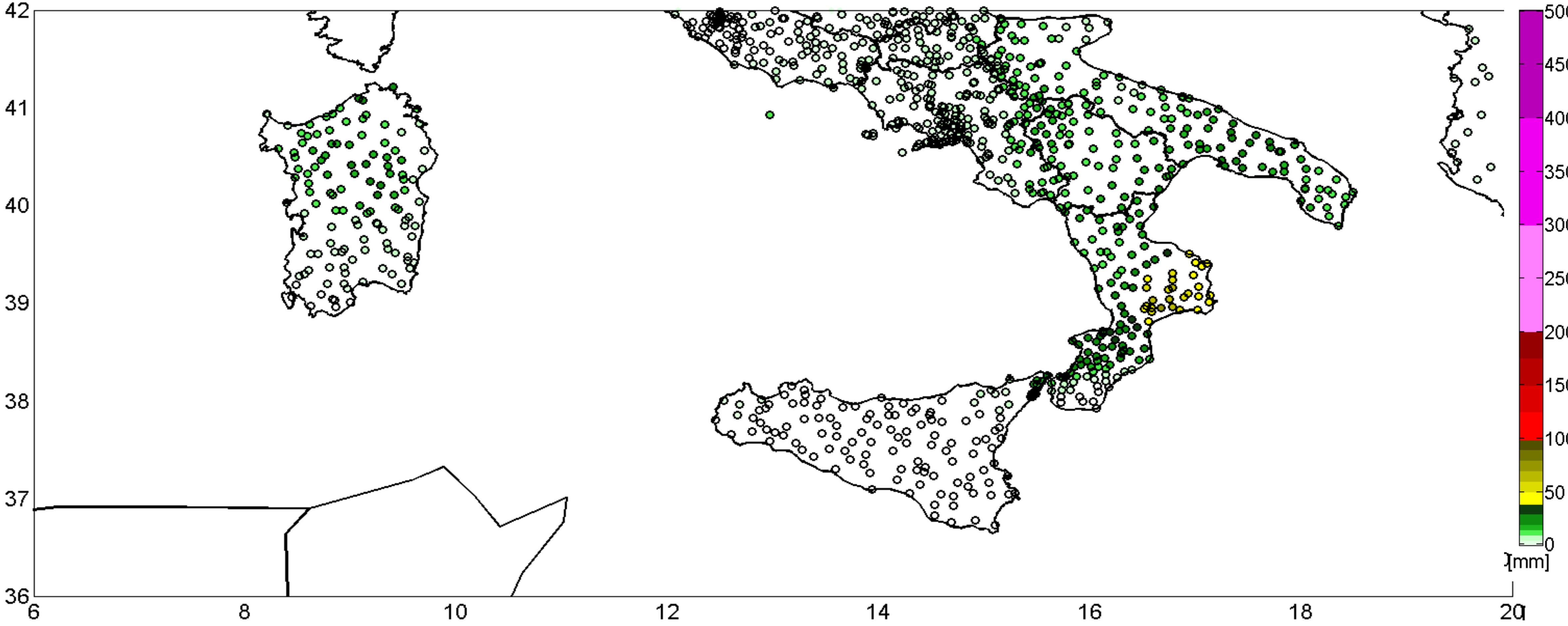
3) HSAF rainfall map from P-AC-SEVIRI (H05B)



EUMETSAT H SAF

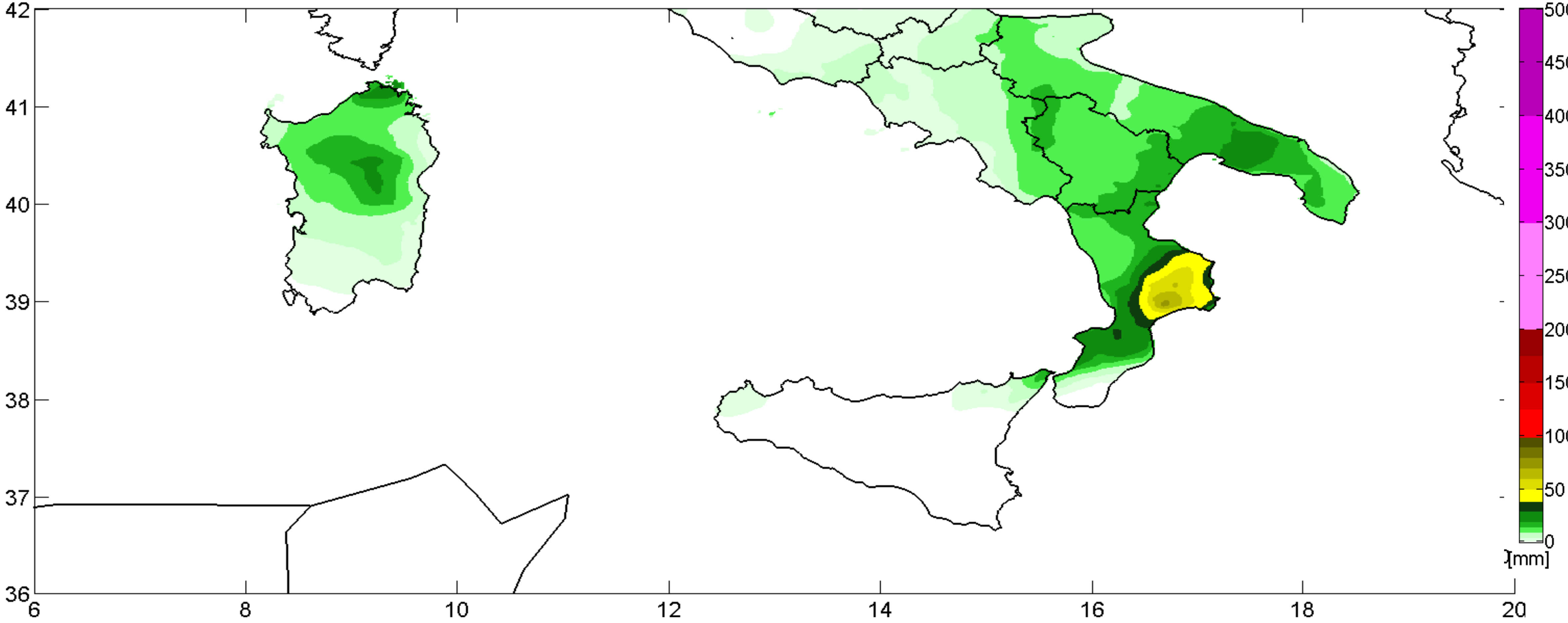
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING with HSAF data

3) HSAF rainfall map sampling on gauges location



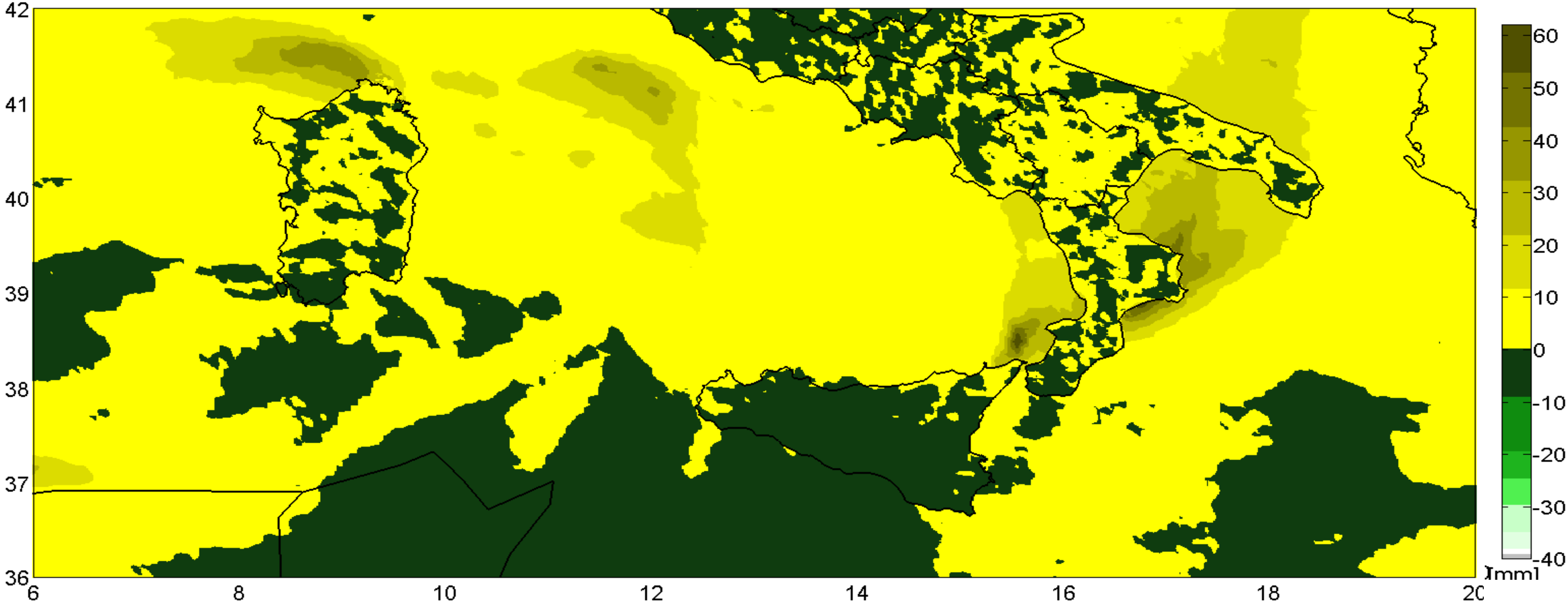
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING with HSAF data

4) HSAF Raingauges interpolation field



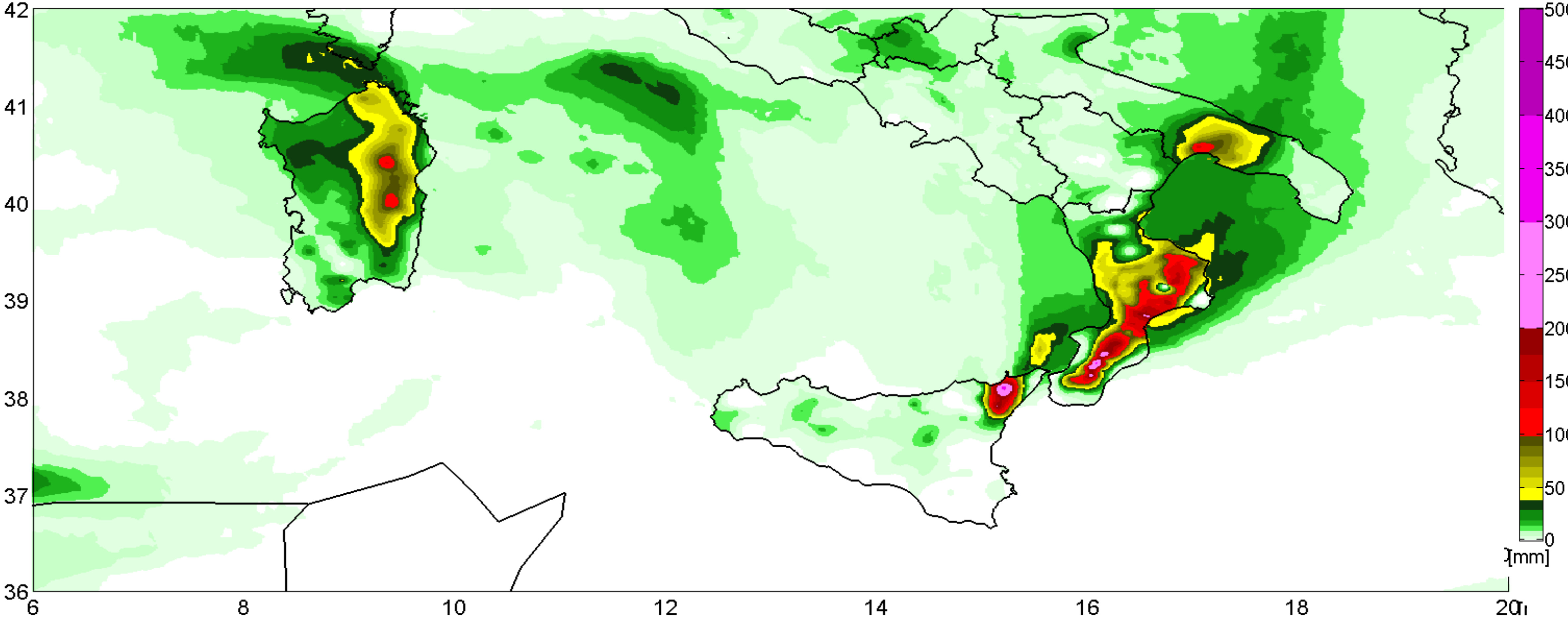
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING with HSAF data

5) Differences between interpolated maps



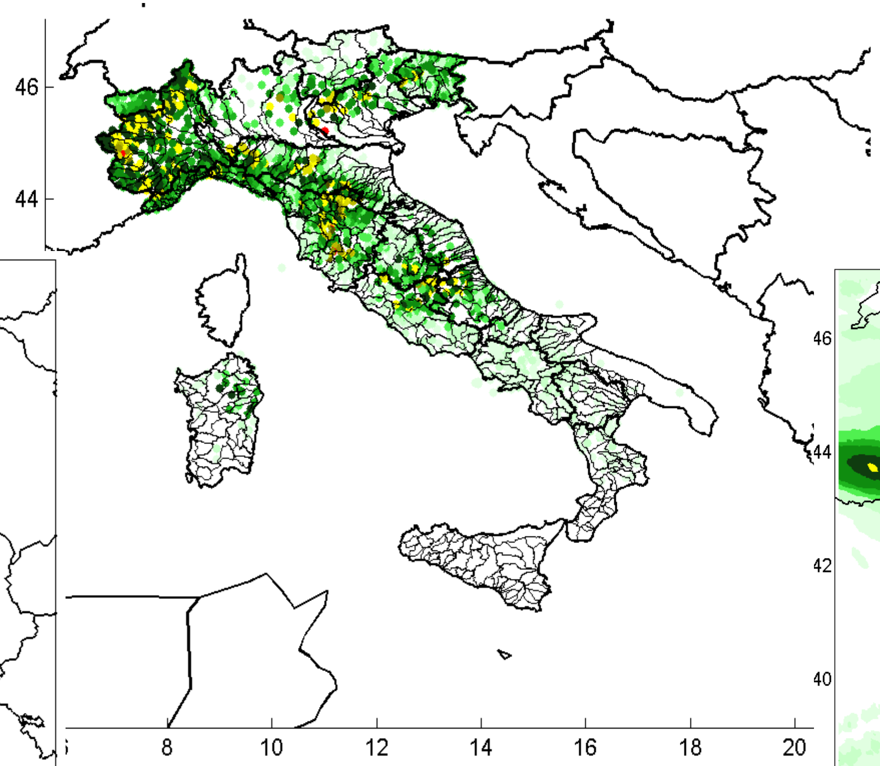
METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING with HSAF data

6) Modified conditional merging with HSAF products

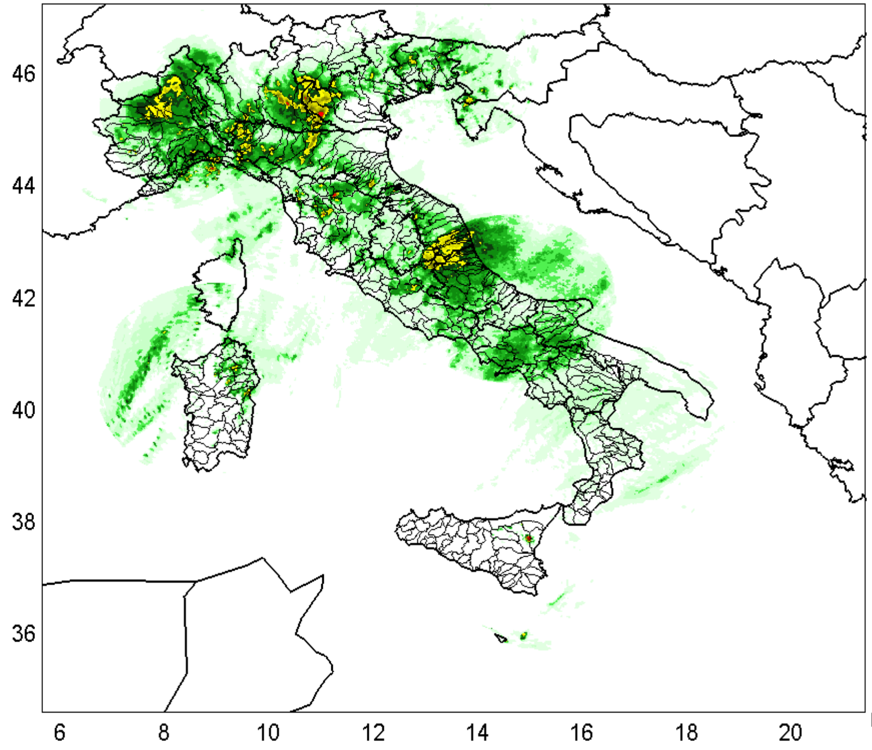


METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING
example event on 05 June, 2011 (24h accumulated)

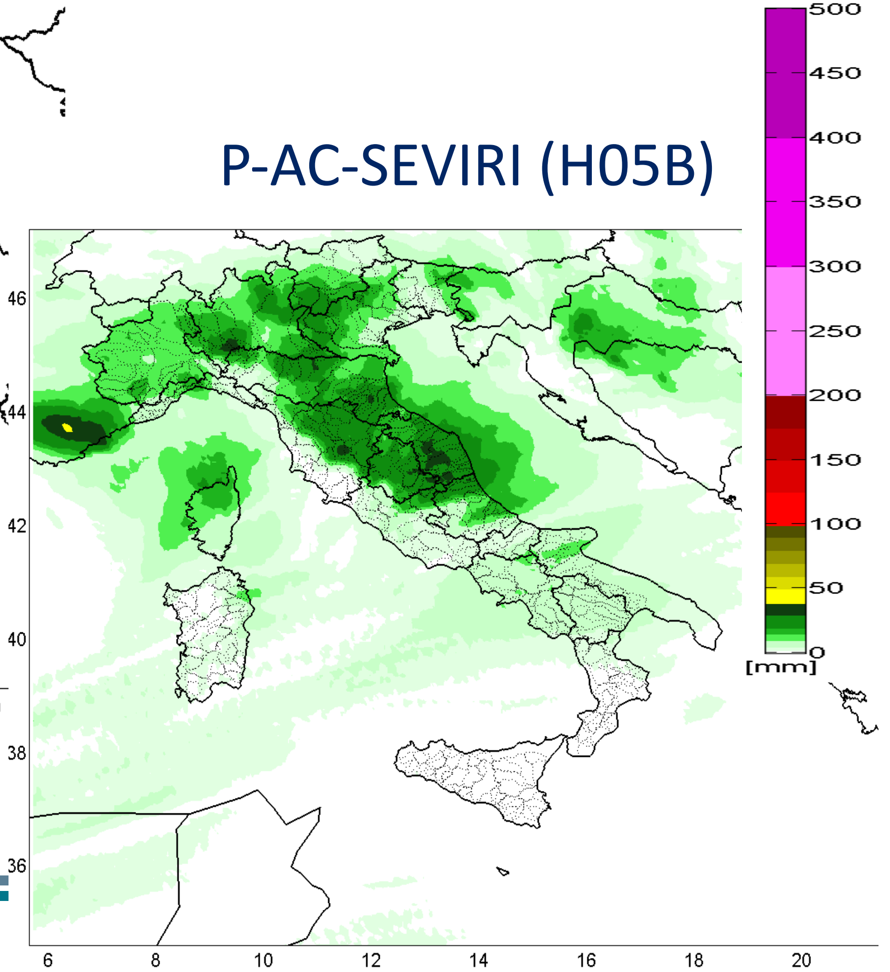
Pluviometri



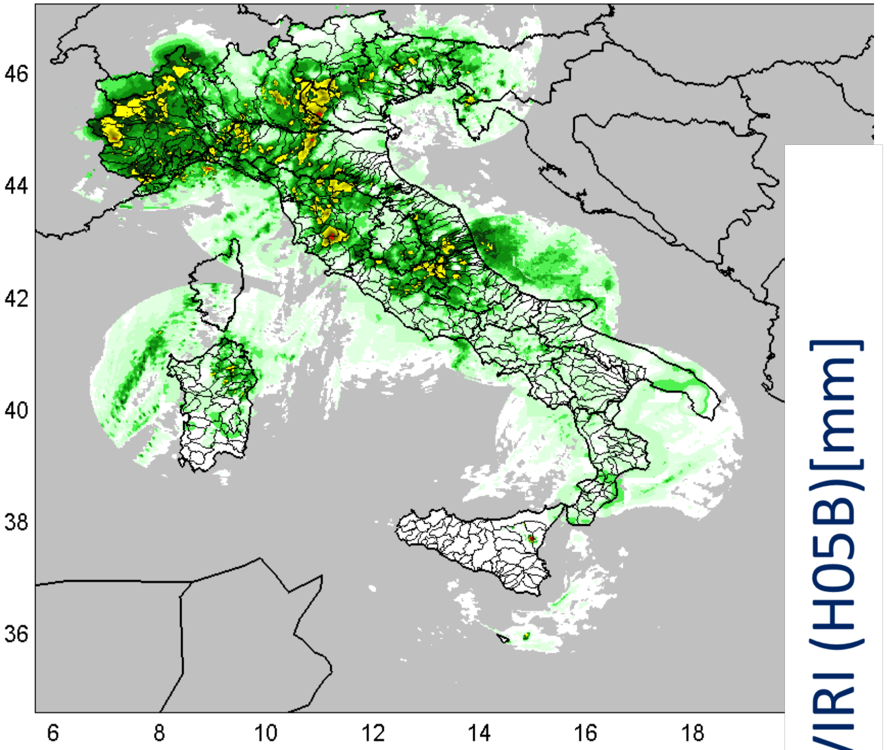
Mosaico
radar



P-AC-SEVIRI (H05B)

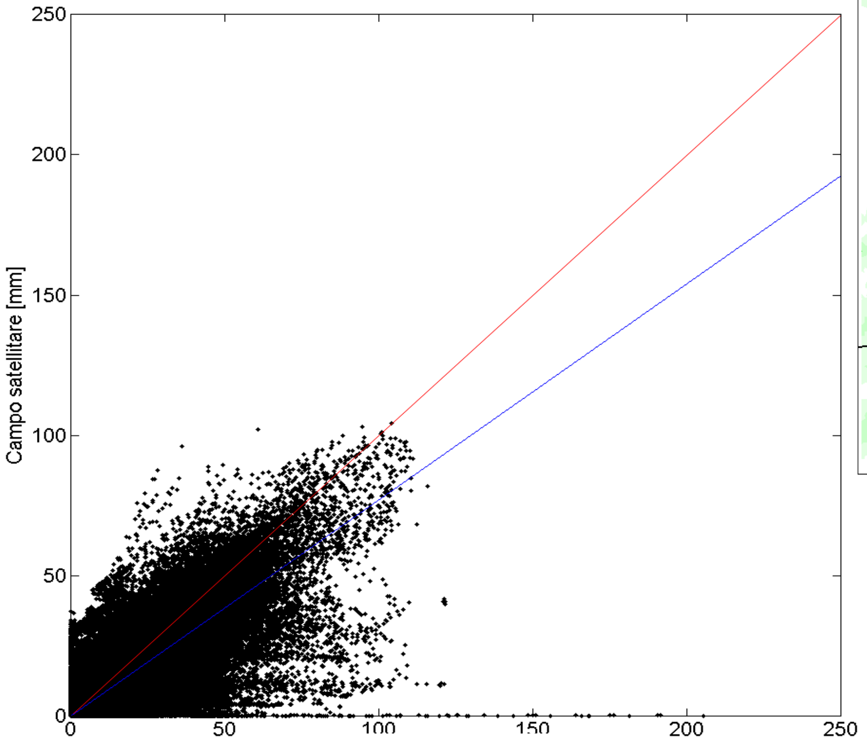


METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING
example event on 05 June, 2011 (24h accumulated)

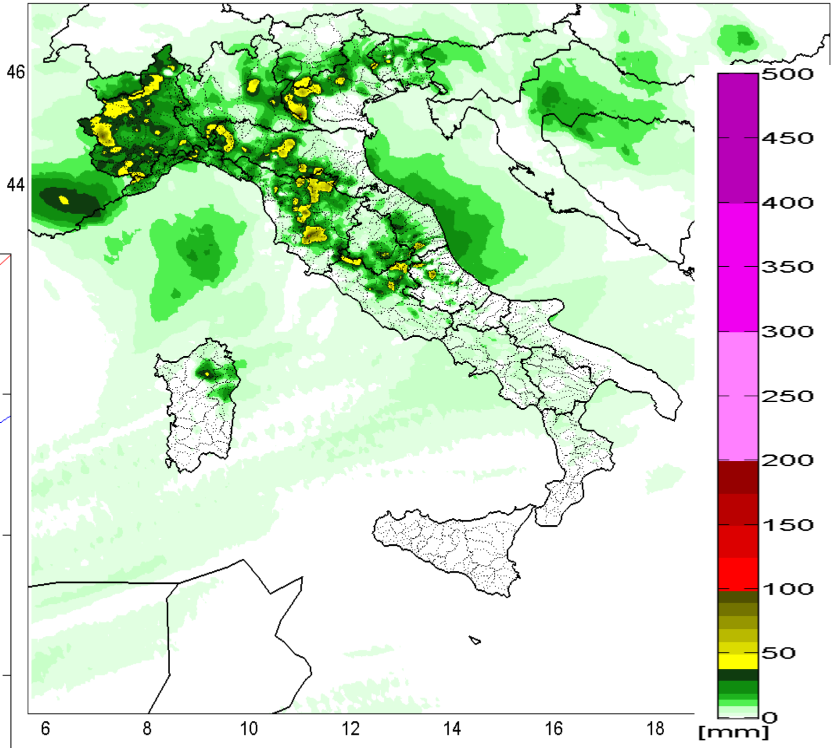


Merging
Pluviometri
radar

P-AC-SEVIRI (H05B)[mm]



Radar [mm]

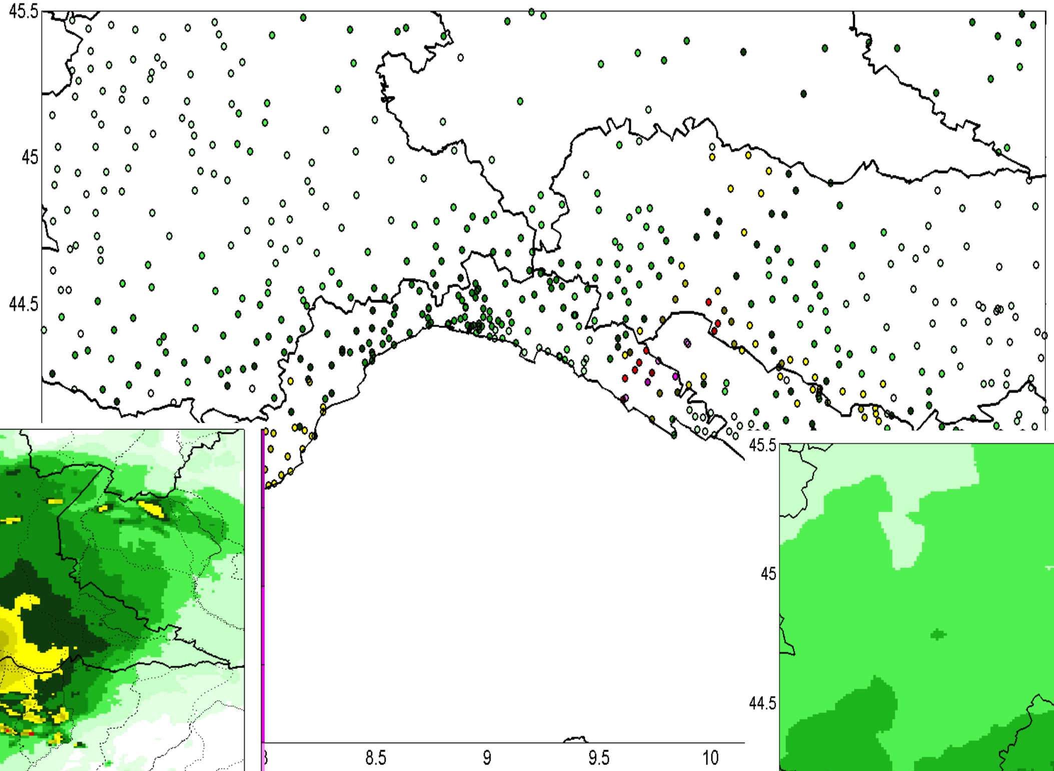


Merging
Pluviometri
P-AC-SEVIRI (H05B)

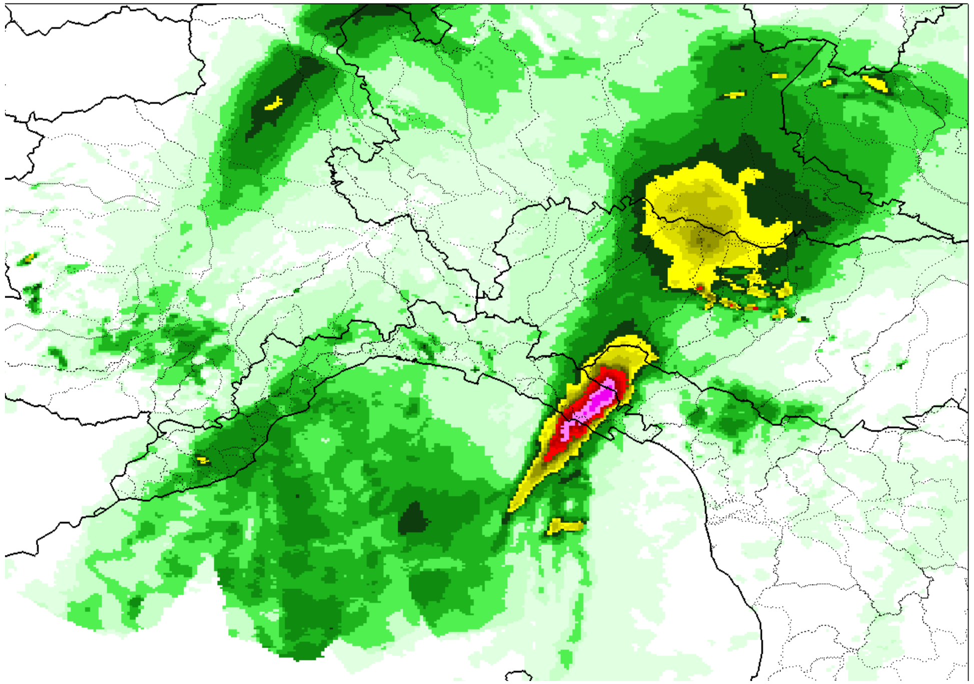
EUMETSAT H SAF

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING
example event on 25 October, 2011 (6h accumulated)

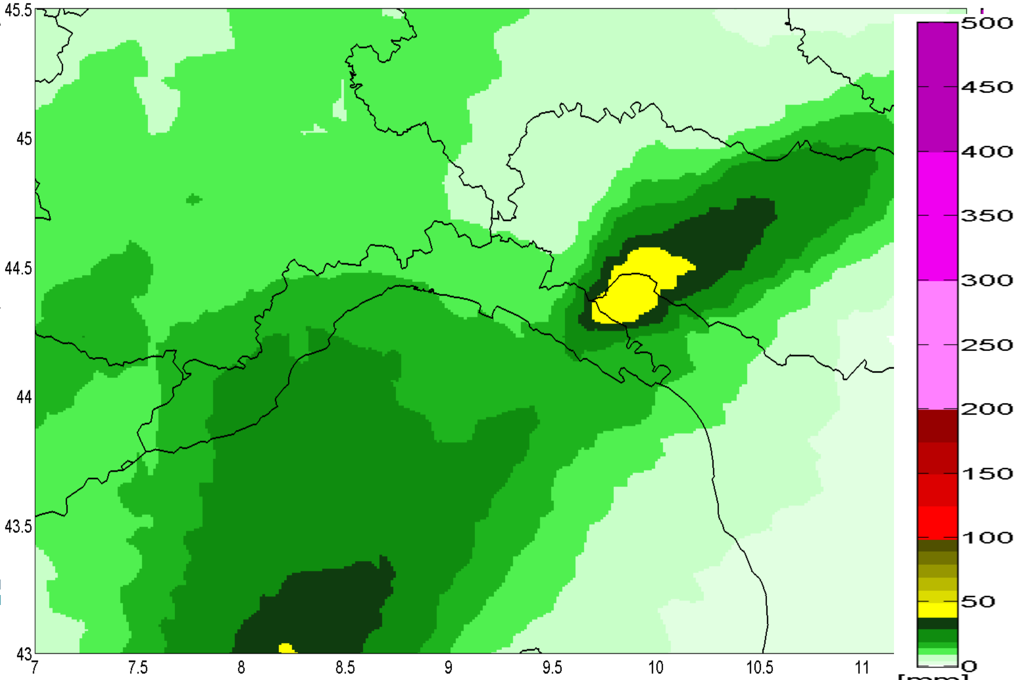
Pluviometri



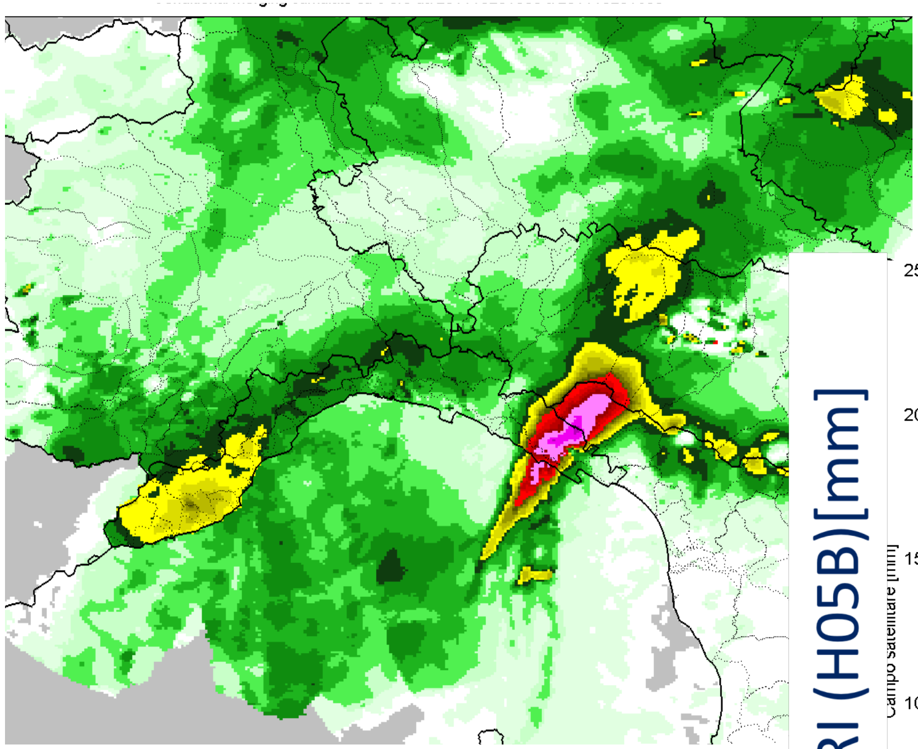
Mosaico radar



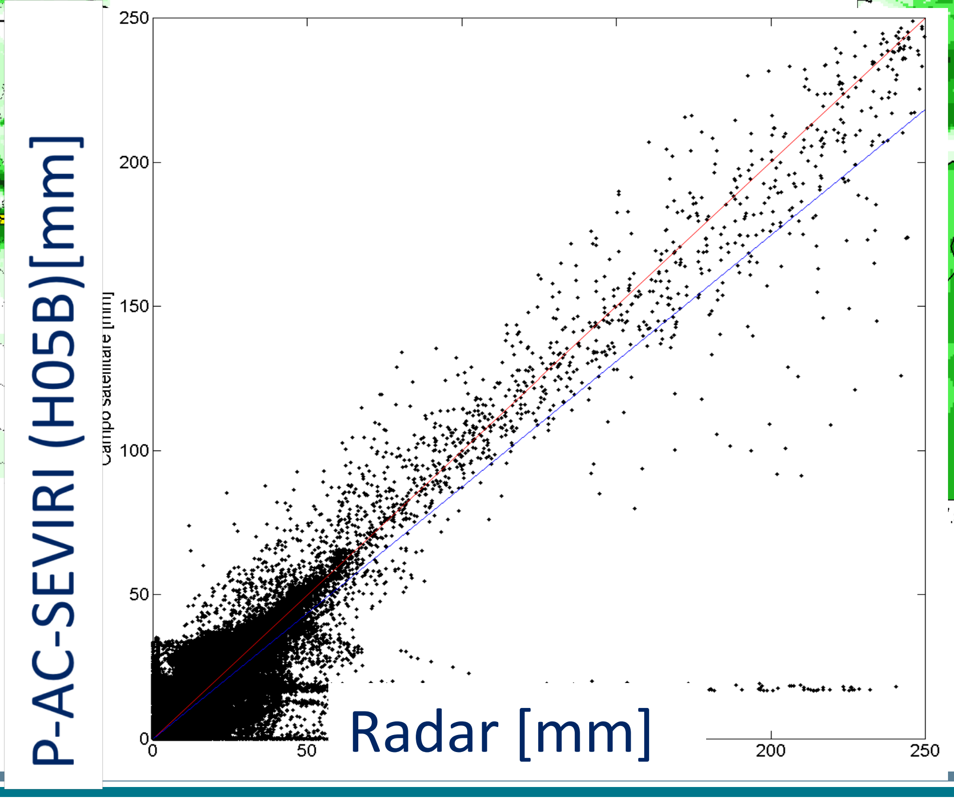
P-AC-SEVIRI (H05B)

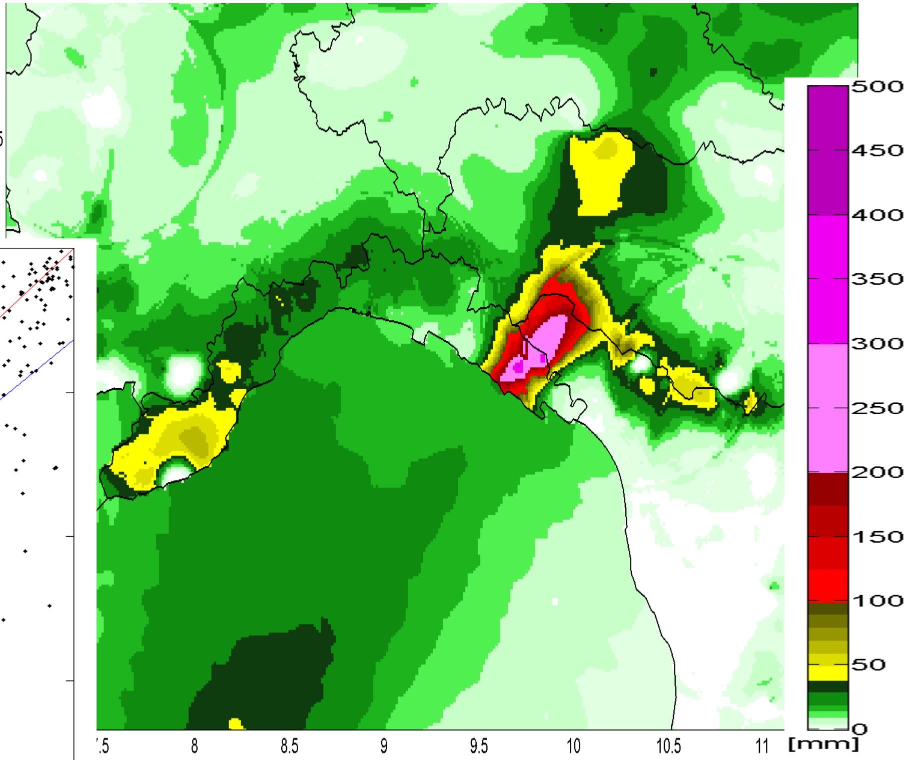


METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING
example event on 25 October, 2011 (6h accumulated)



Merging
Pluviometri
radar



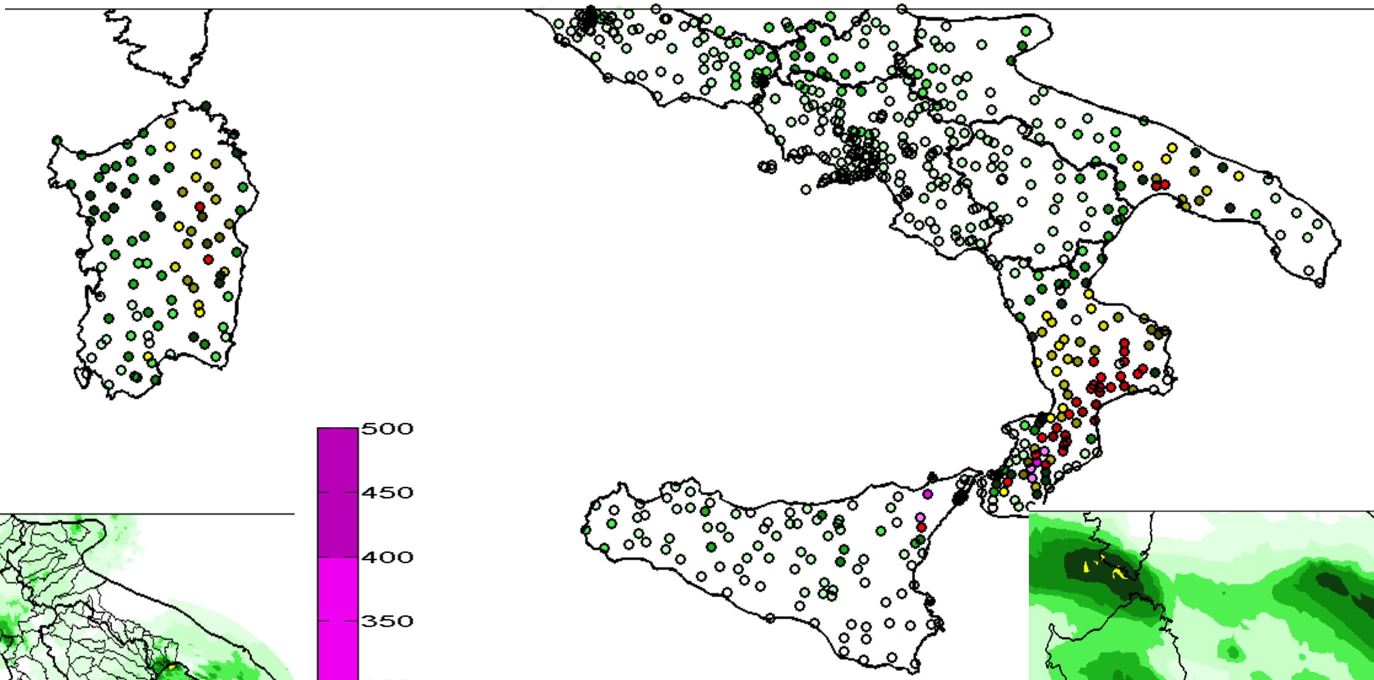


Merging
Pluviometri
P-AC-SEVIRI (H05B)

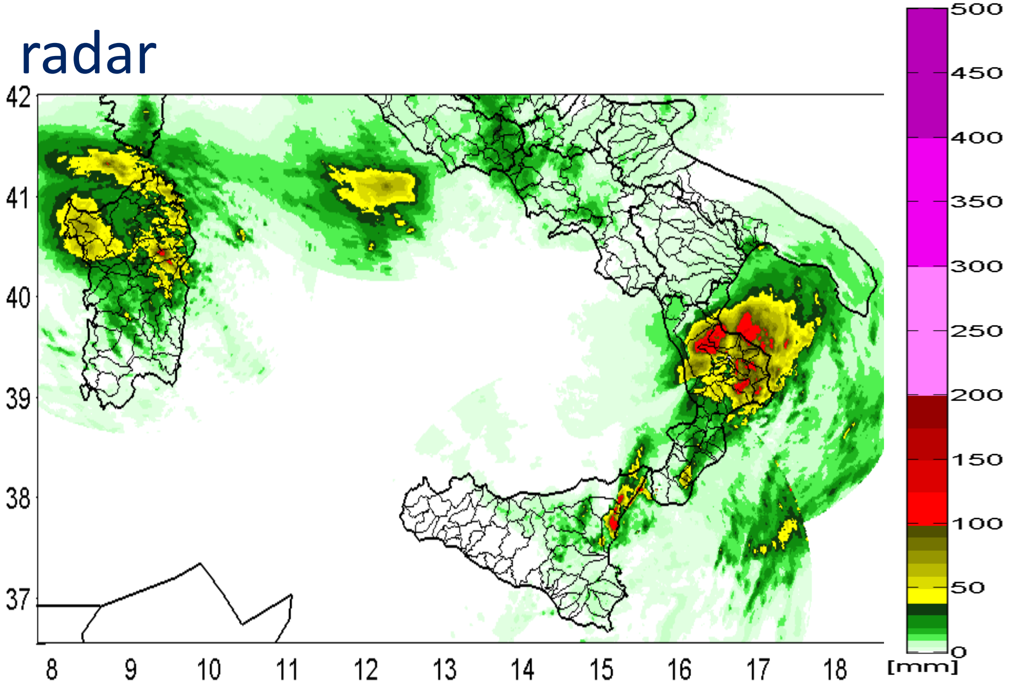
Cumulata 24h

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING
example event on 22 november, 2011 (24h accumulated)

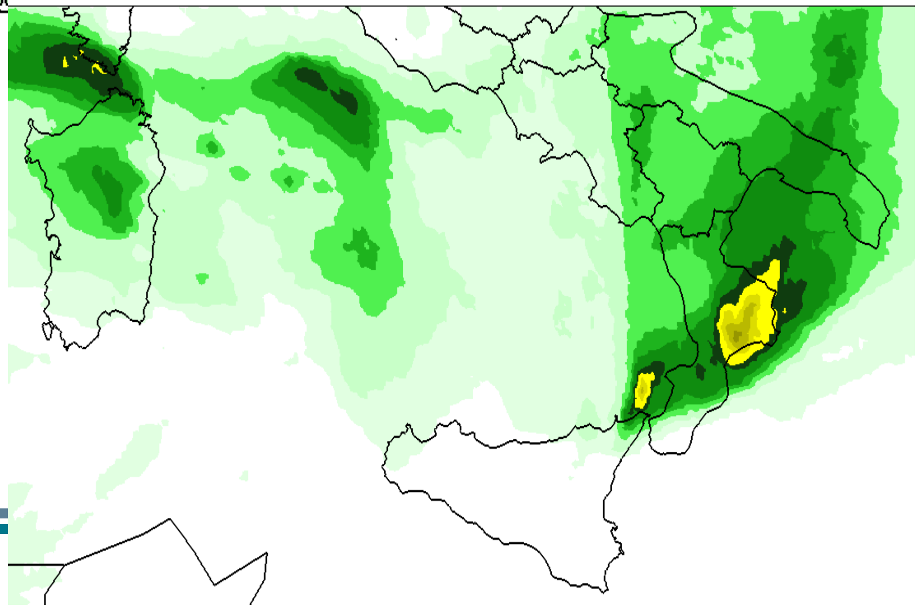
Pluviometri



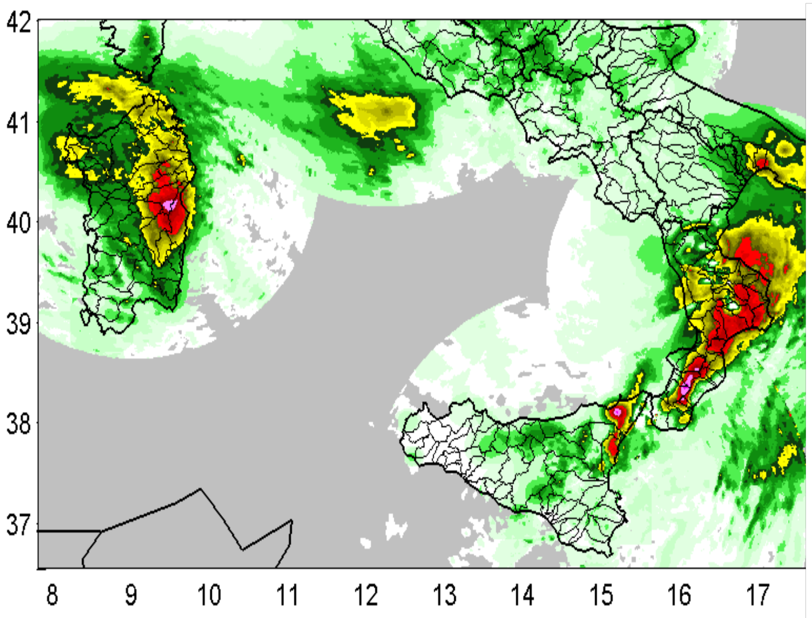
Mosaico radar



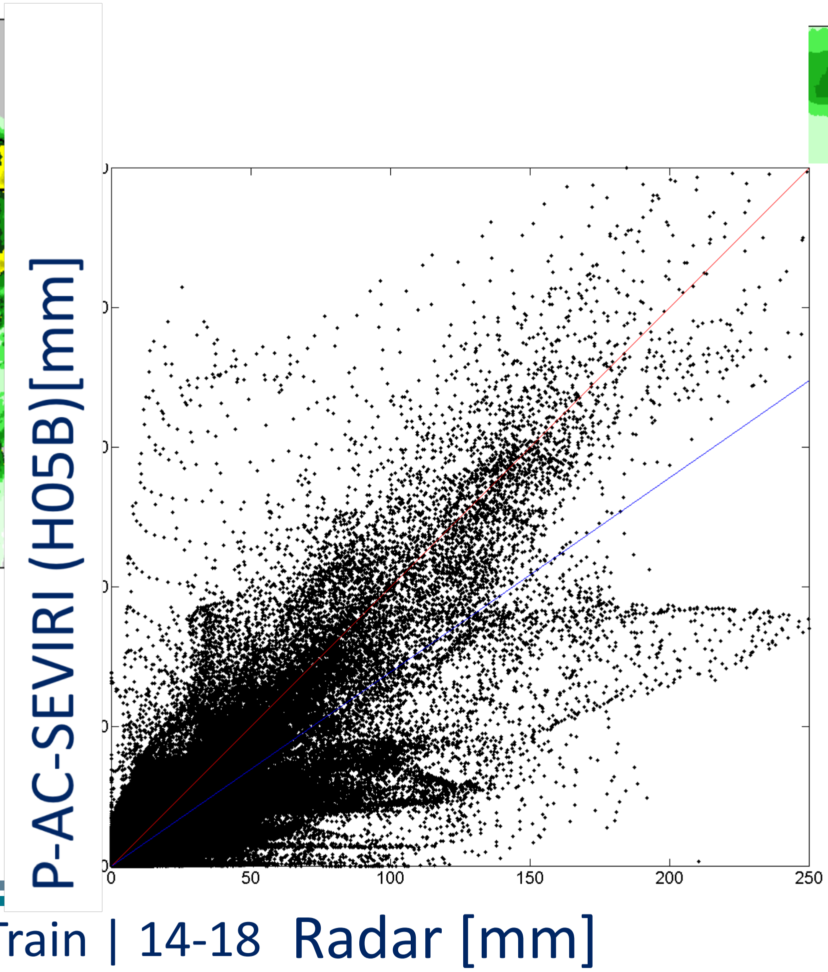
P-AC-SEVIRI (H05B)

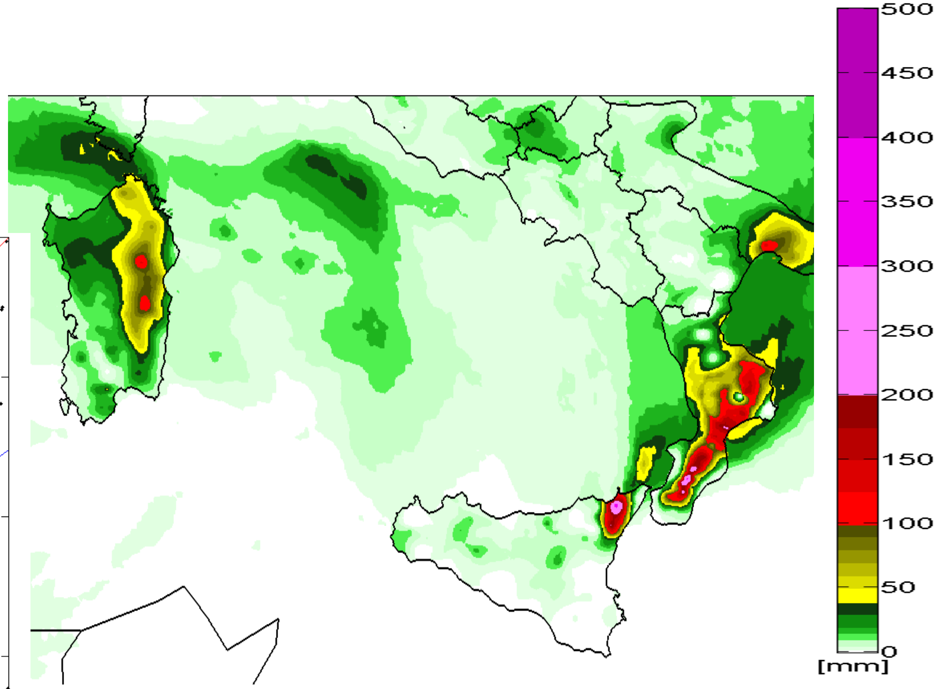


METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING
example event on 22 november, 2011 (24h accumulated)



Merging
Pluviometri
radar



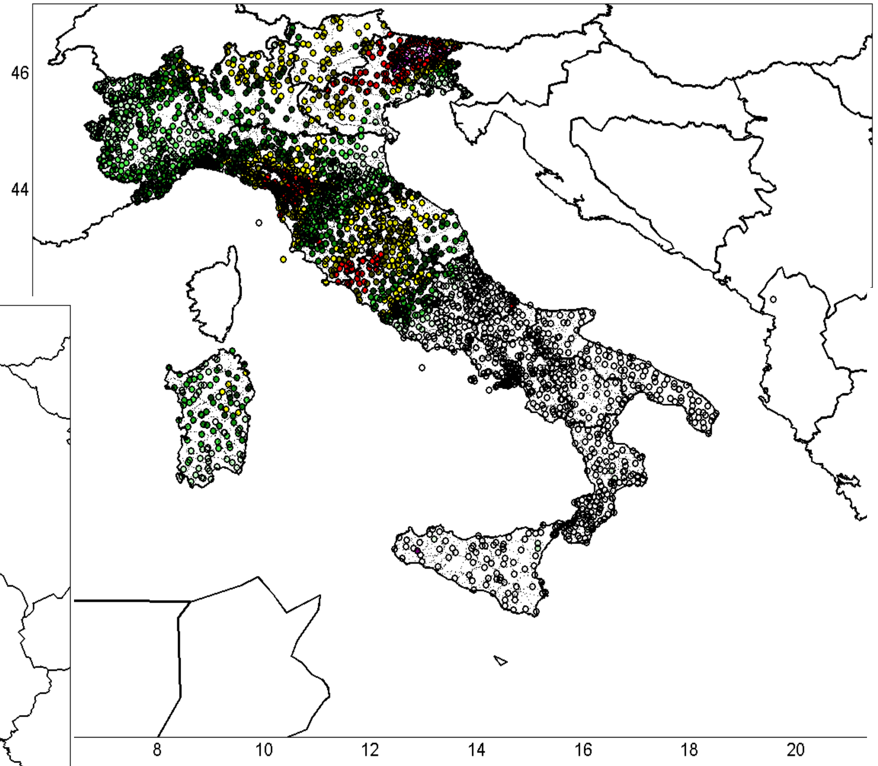


Merging
Pluviometri
P-AC-SEVIRI (H05B)

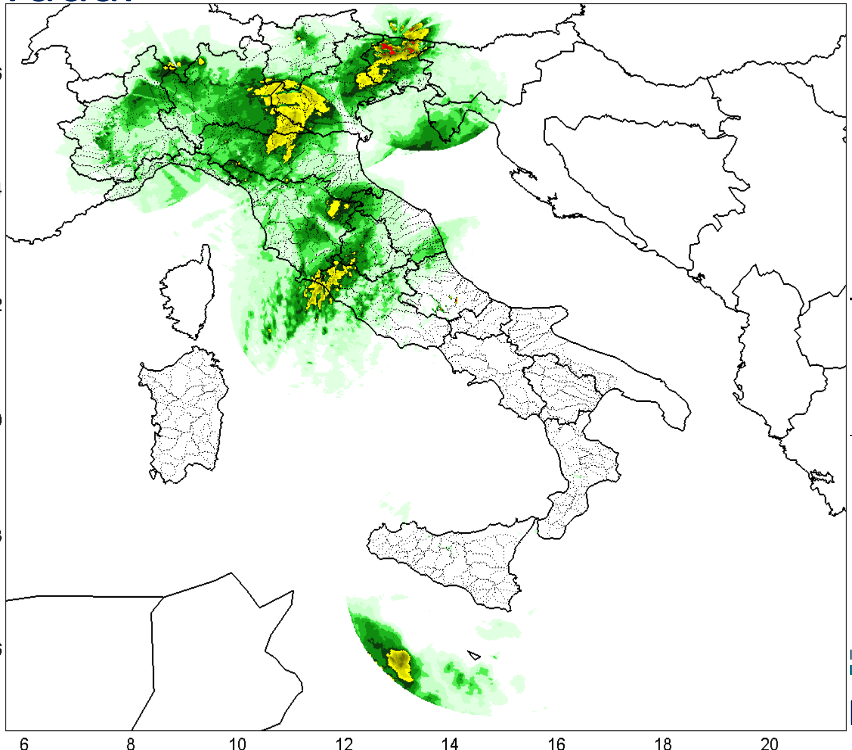
EUMETSAT H SAF

METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING
example event on 11 november, 2012 (24h accumulated)

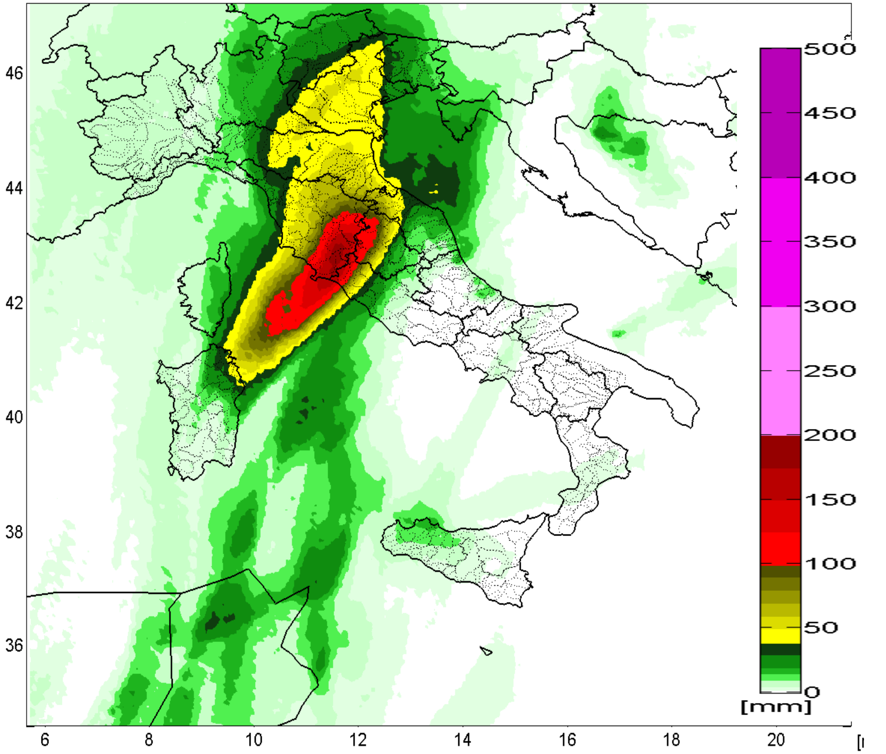
Pluviometri



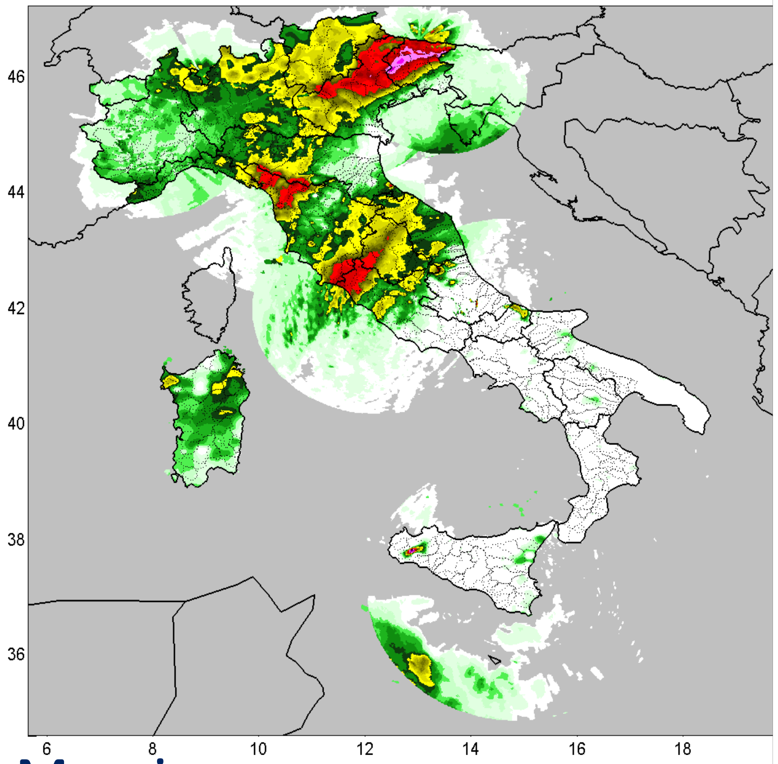
Mosaico radar



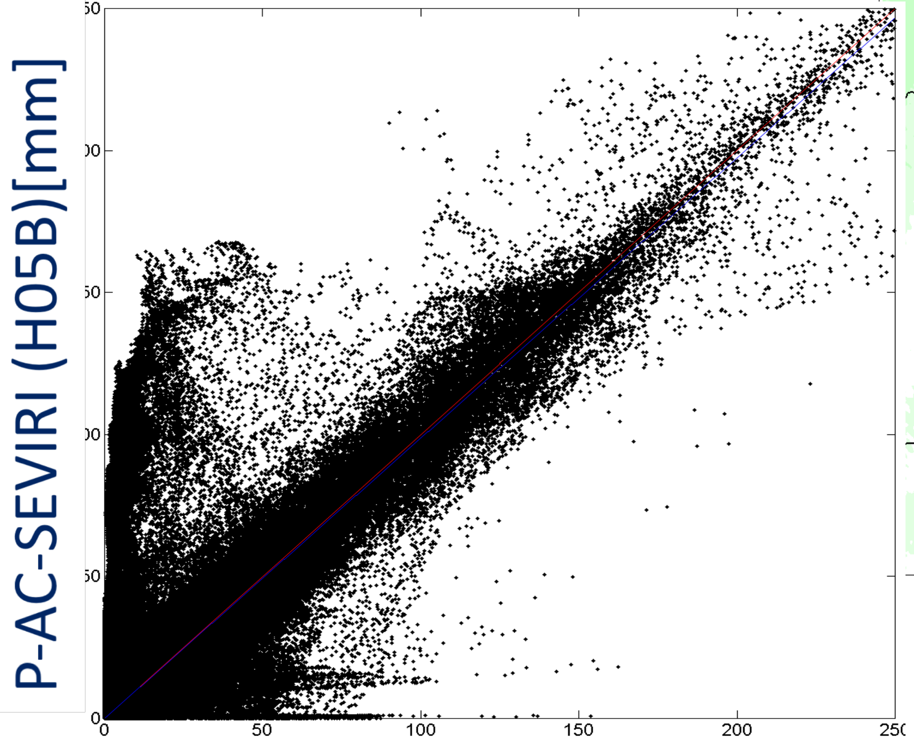
P-AC-SEVIRI (H05B)

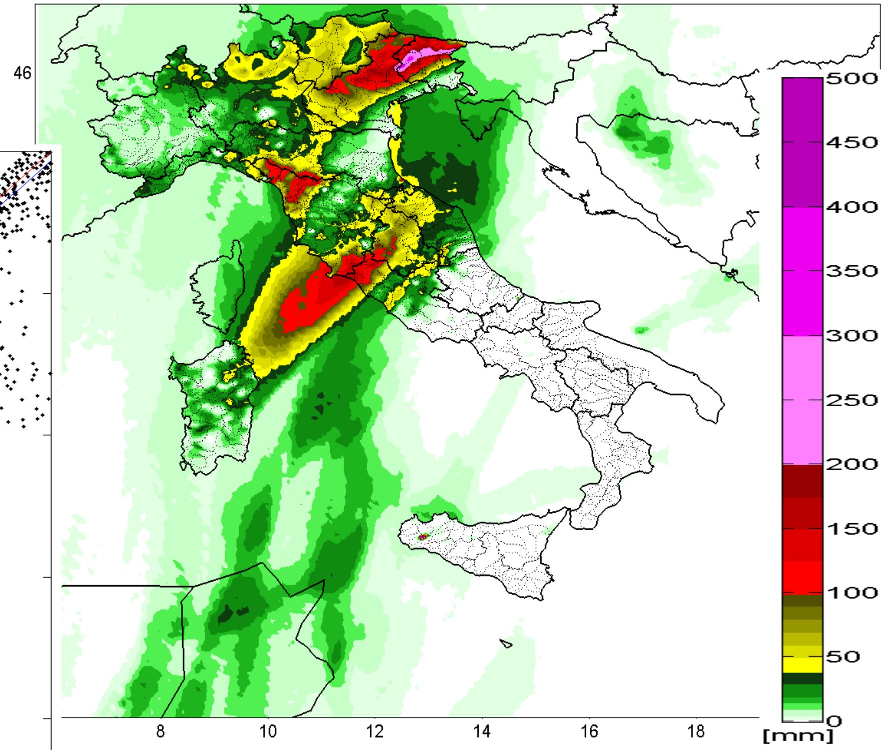


METHOD DESCRIPTION: MODIFIED CONDITIONAL MERGING
example event on 11 november, 2012 (24h accumulated)



Merging
Pluviometri
radar





Merging
Pluviometri
P-AC-SEVIRI (H05B)

CONCLUSIONS

GRISO bring some Advantages as:

- use different covariance kernel structure that better reproduce the small locale scale
- computational velocity

MCM has strong ability to merge data from multisensor and gives in output a more reliable solution of QPE problem.

Advantages of the method are:

- Better estimation of the local structure
- Operationally implemetation
- Application in any contest of data (spatial or temporal)

Part2: Impact on hydrological modelling

S. Gabellani

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Hydrovalidation → annual validation of the HSAF products using them (directly as input or assimilating them) in hydrological models

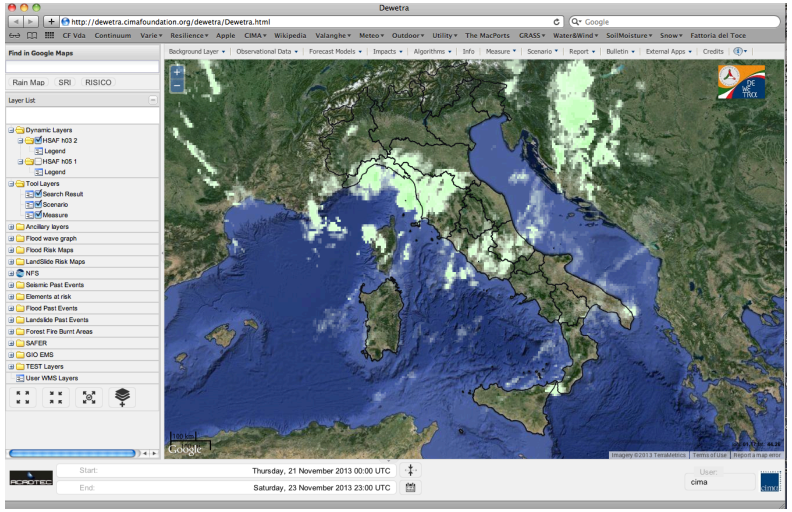
Use of P-IN-SEVIRI (H03B) and P-AC-SEVIRI (H05B) in a distributed hydrological model

EUMETSAT
H SAF

H-SAF Precipitation products

- **P-IN-SEVIRI (H03B)**

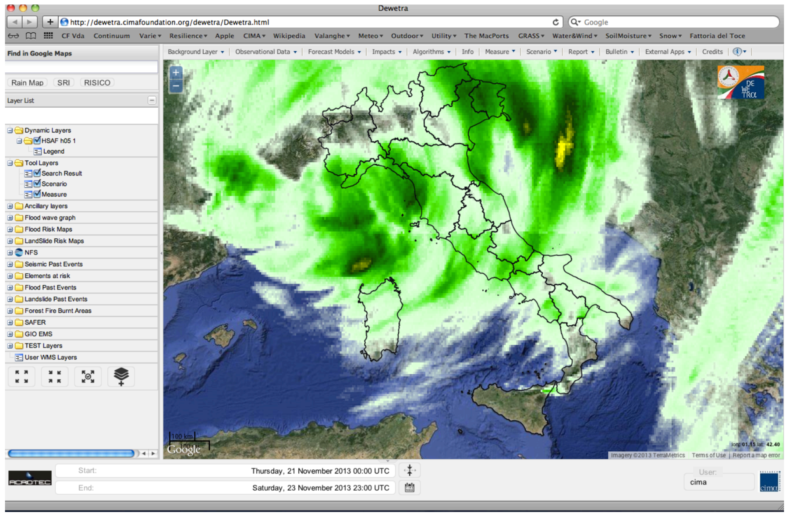
Precipitation rate at ground by GEO/IR supported by LEO/MW



Time frequency: 15 minutes
Spatial coverage: H SAF area extended to Africa and southern Atlantic
Resolution: Average over Europe 8 km (controlled by the IR pixel size)

- **P-AC-SEVIRI (H05B)**

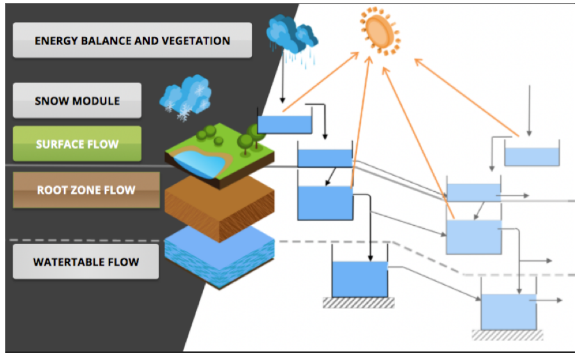
Accumulated precipitation at ground by blended MW and IR



Time frequency: Each 3 hours: MW+IR integrated over the previous 3, 6, 12 and 24
Spatial coverage: H SAF area with extension to Africa and southern Atlantic
Resolution: Average over Europe: 8 km intended as sampling, ~ 30 km effective (controlled by the resolution of MW data)

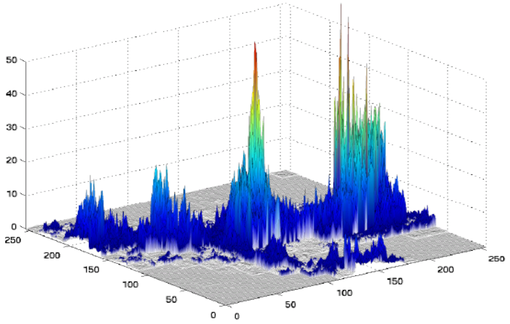
Continuum Hydrological model

A complete and distributed model that allows to simulate the main hydrological processes with a simple but robust processes schematization.

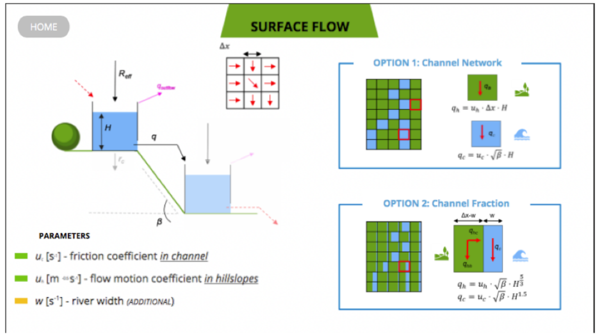


Simple & complete description of the hydrological cycle

- Schematization of vegetation interception and water table
- Tank-like schematization of overland and channel flows

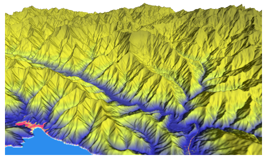


Mass and Energy Balance are both completely solved



Fully distributed

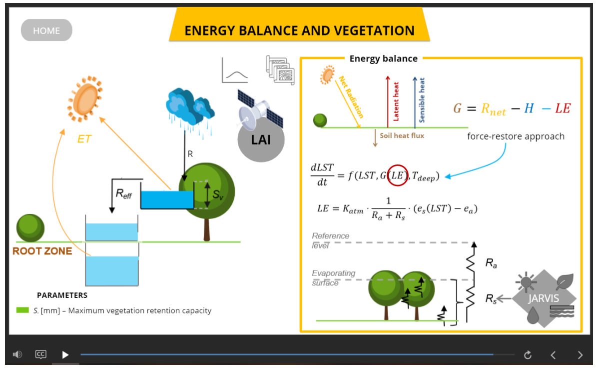
River network derived from a DEM



Spatial-temporal evolution of:

- Streamflow
- Evapotranspiration
- Land surface temperature
- Soil moisture
- Water table
- Snow Water Equivalent

https://github.com/c-hydro/



(Silvestro et al., 2013, 2015; Laiolo et al. 2016; Corral et al.2019, Parodi et al 2020)

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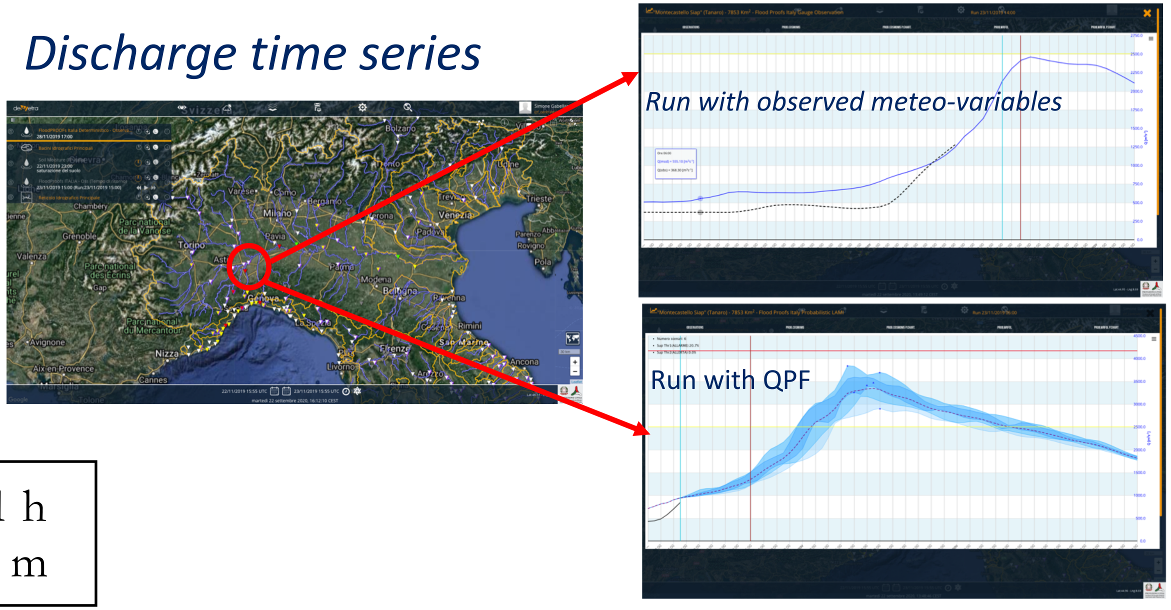
Example of operative outputs of the hydrological model

FLOOD-PROOFS
FLOOD PROBABILISTIC OPERATIVE FORECASTING SYSTEM

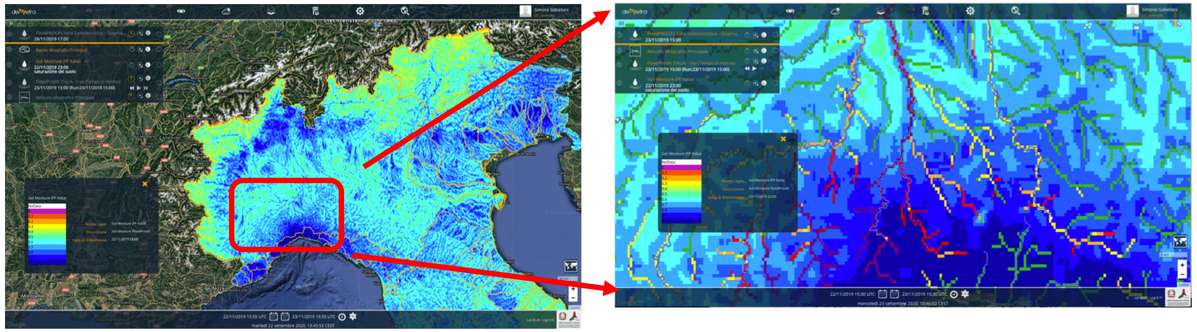
myDEWETRA

Discharge time series

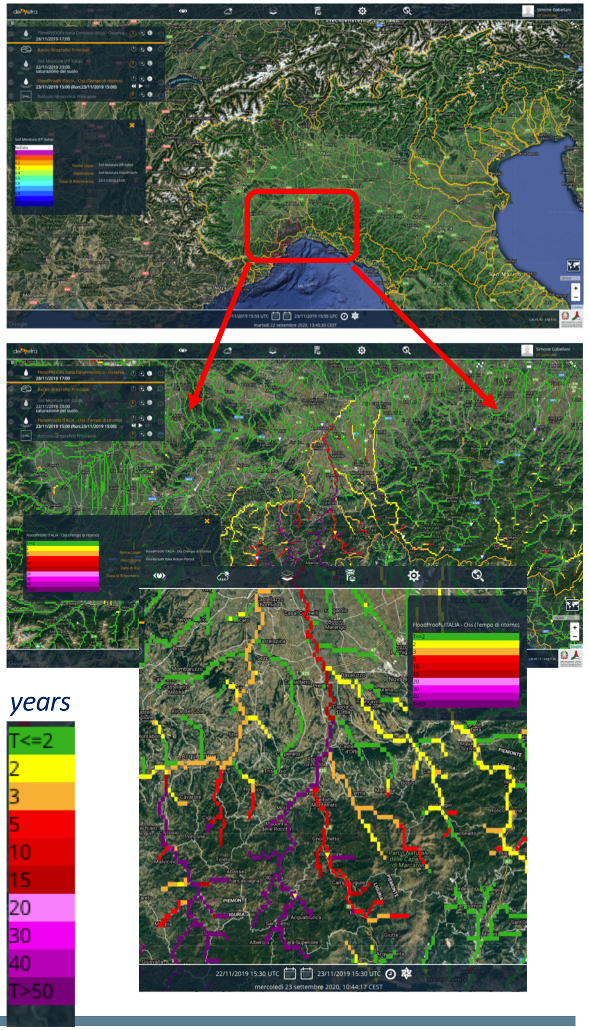


Temporal res.: 1 h
Spatial res.: 500 m

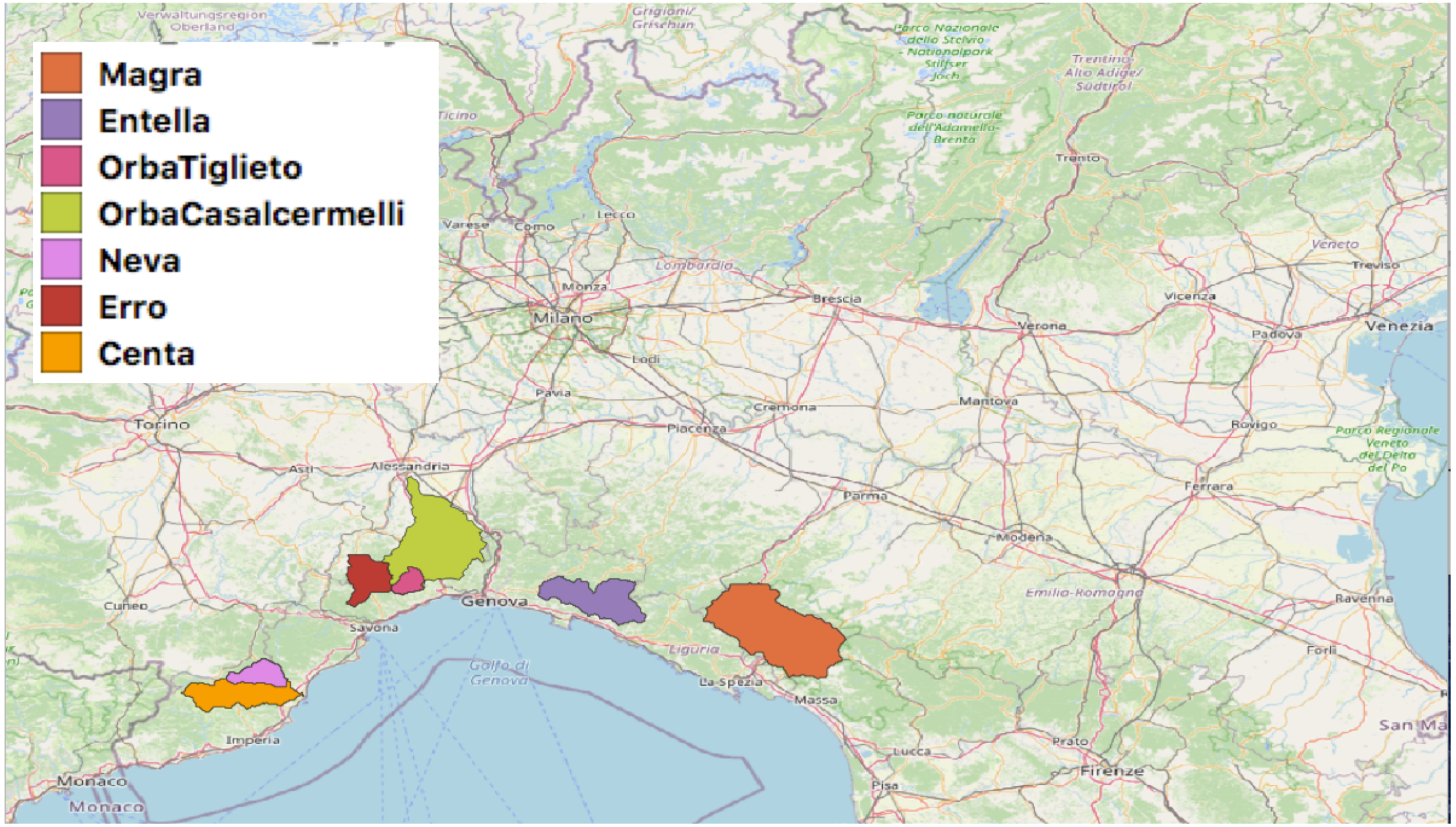
Soil Moisture Map



Magnitude (return period)



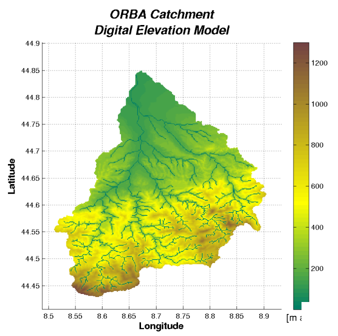
Italian test basins for HSAF hydrovalidation



Magra (Calamaza): 960 km²
Entella (Panesi): 364 km²
Orba (Tiglieto): 75 km²
Orba (Casalcermelli): 800 km²
Erro (Cartosio): 195 km²
Neva (Cisano): 123 km²
Centa (Molino Branca): 432 km²

Hydrological validation P-IN-SEVIRI-H03B

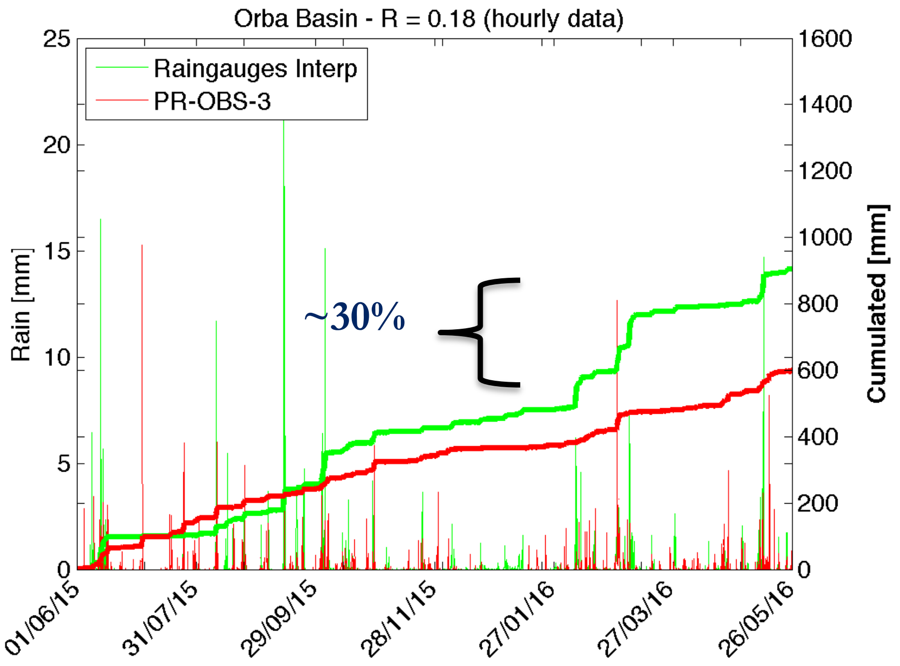
June 2015 – May 2016

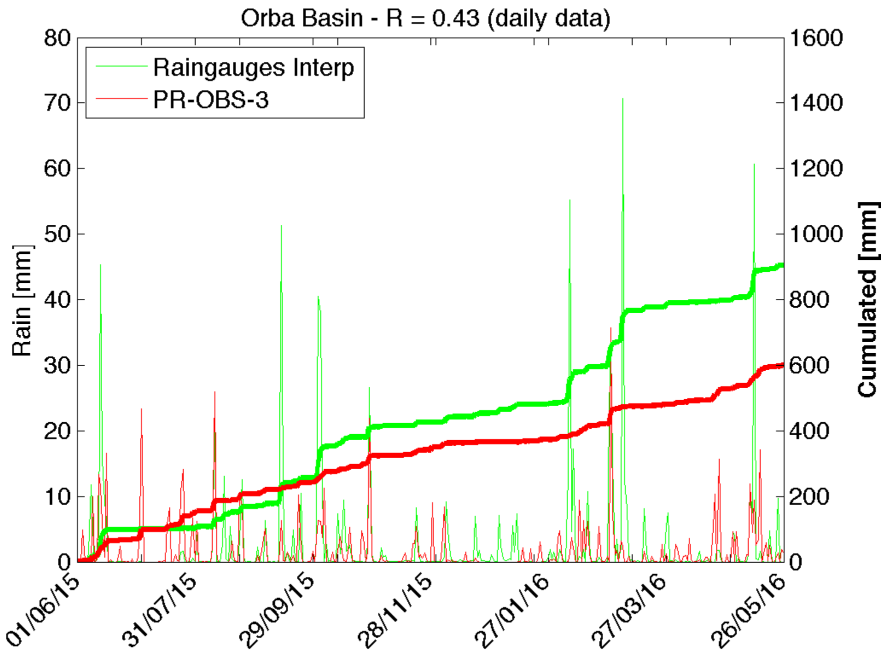


15 min. → 1 hour

15 min. → 1 day

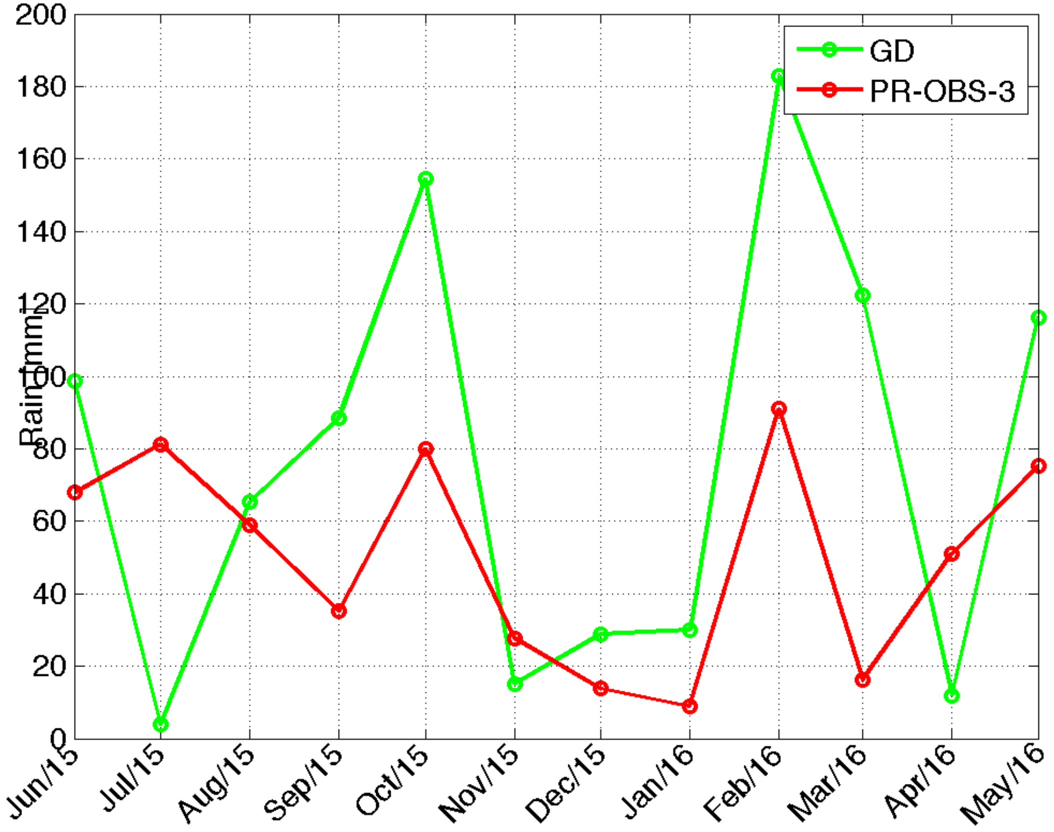
catchment average values





Hydrological validation P-IN-SEVIRI-H03B

June 2015 – May 2016



Monthly cumulated values at catchment scale

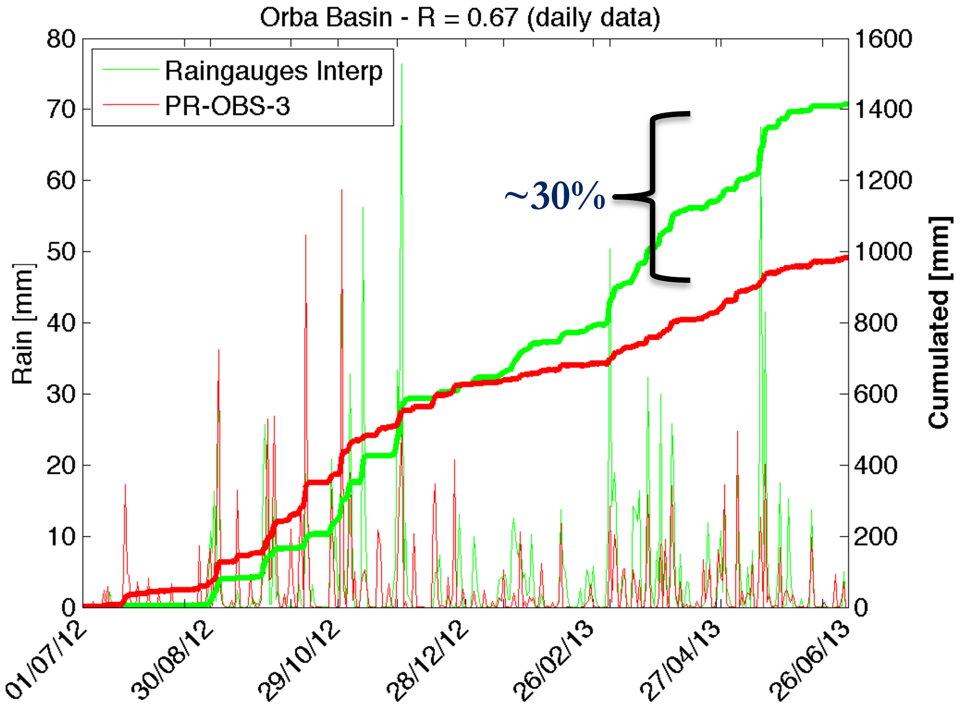
Hydrological validation P-IN-SEVIRI-H03B

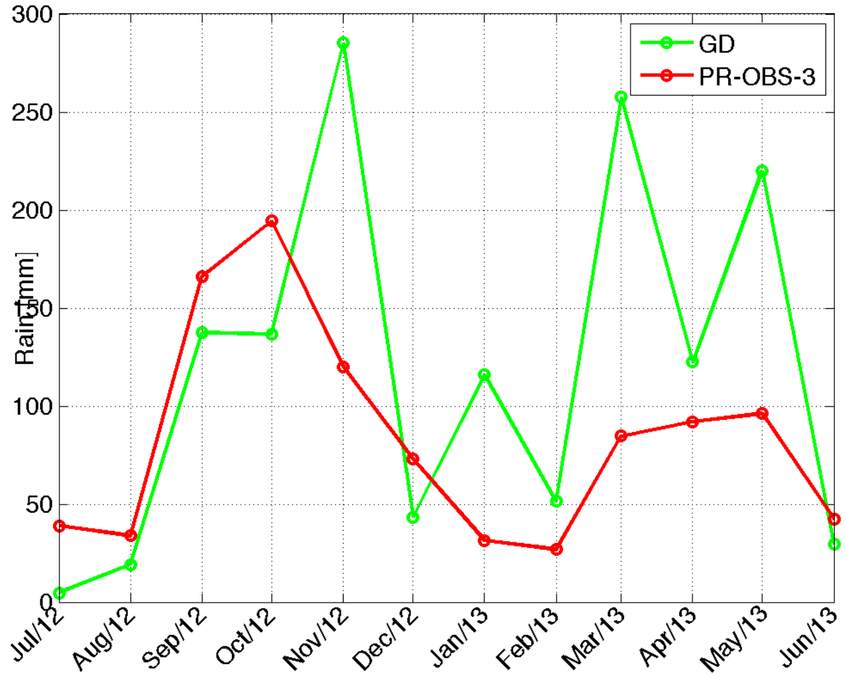
June 2012 – July 2013

catchment average

values

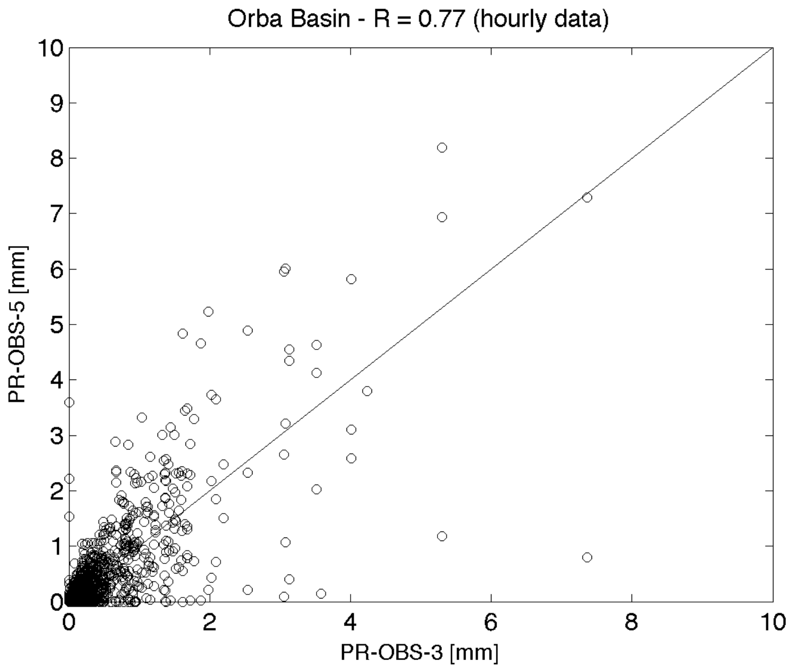
15 min. → 1 day

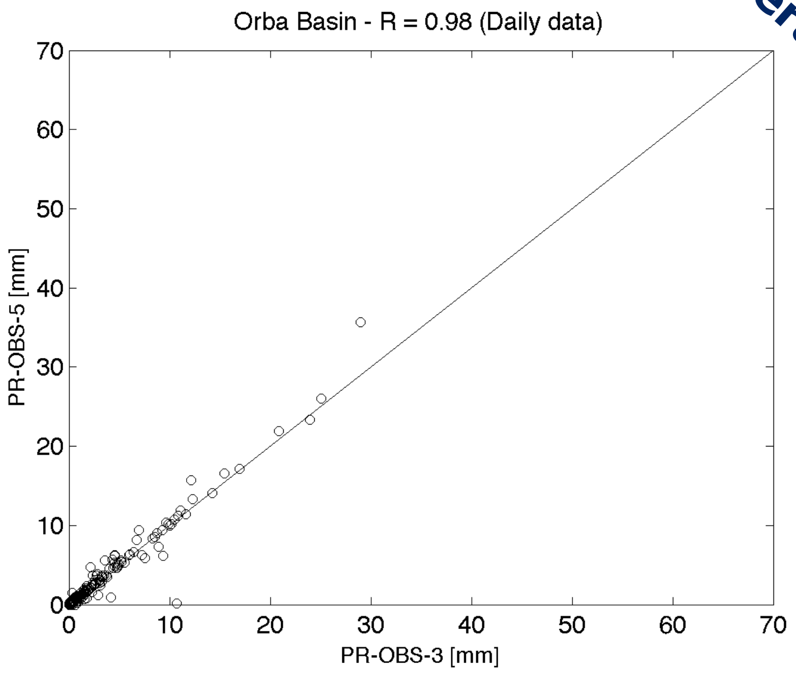




P-IN-SEVIRI (H03B) vs. P-AC-SEVIRI (H05B)

catchment average values



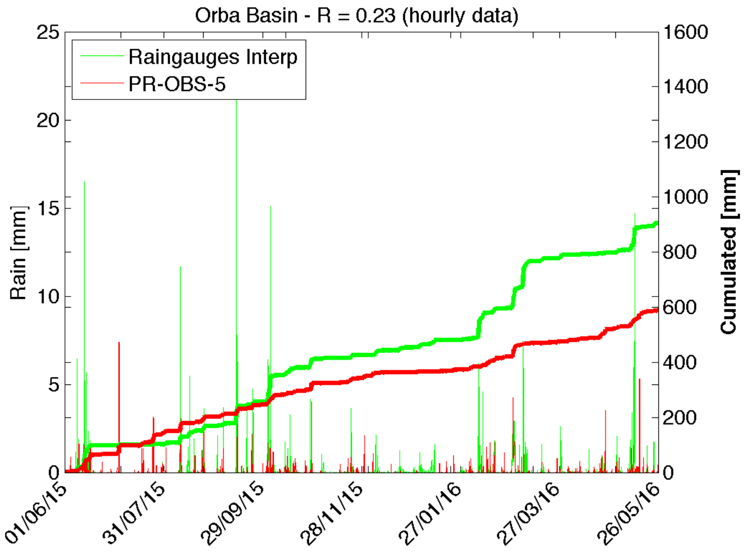


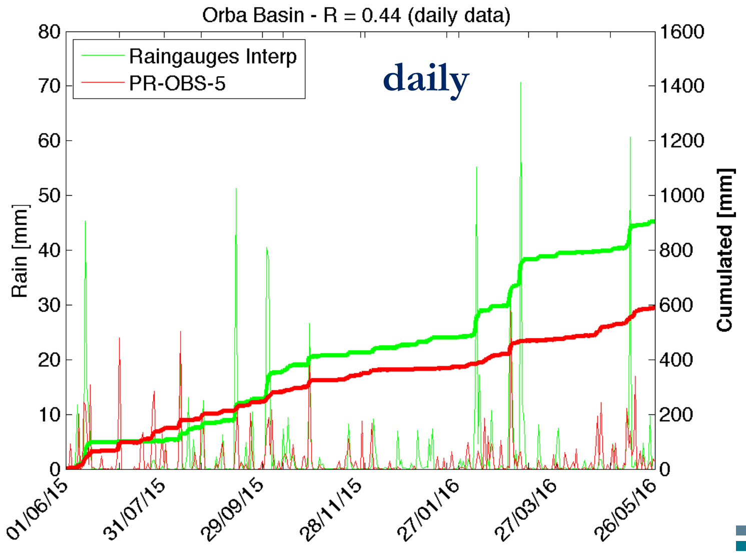
Hydrological validation P-AC-SEVIRI-H05B

catchment

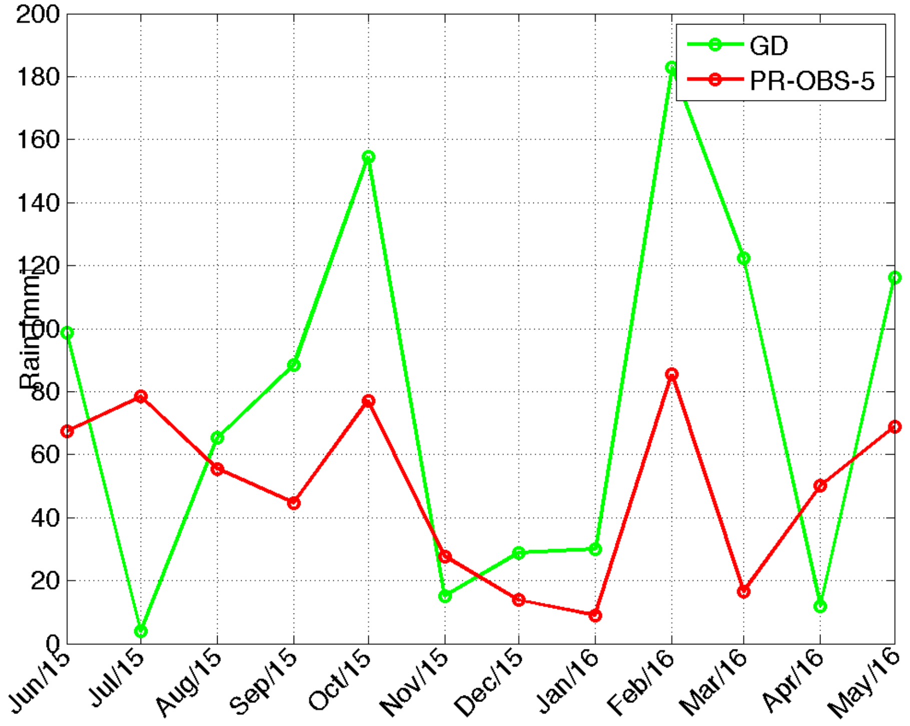
average values

June 2015 – May 2016





Monthly cumulated values at catchment scale (Orba)

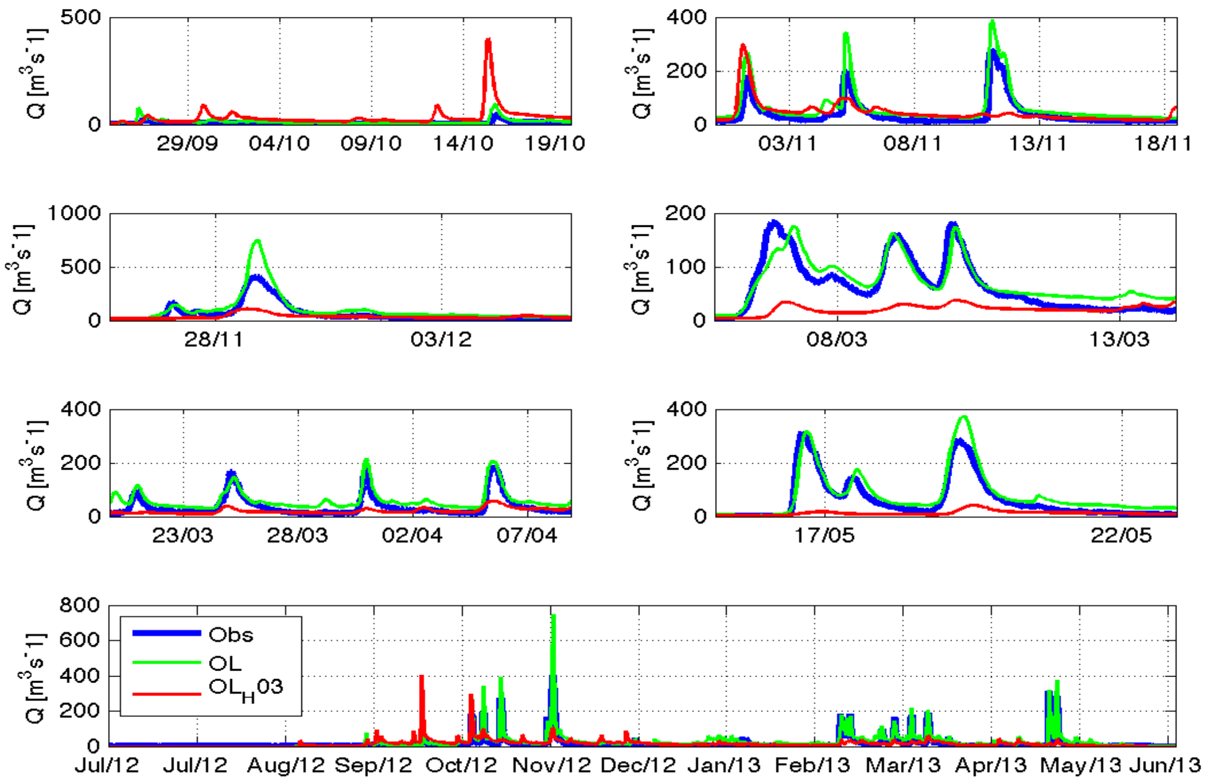


Hydrological validation P-IN-SEVIRI-H03B

Direct use of satellite P as input

June 2012 – July 2013

Orba at Casalcermelli – E = 0.63 E_{H03B}=0.02

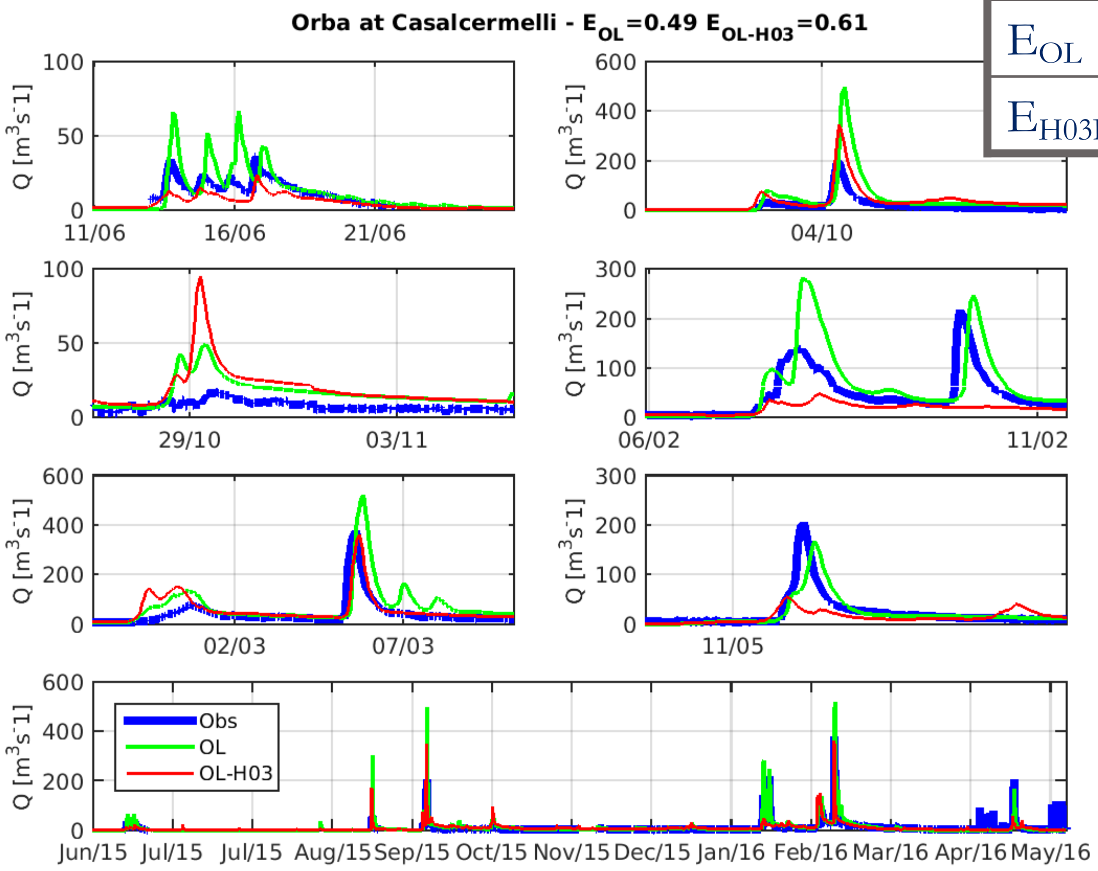


Nash and Sutcliffe's efficiency coefficient	
E	0.63
E_{H03B}	0.12

Hydrological validation P-IN-SEVIRI-H03B

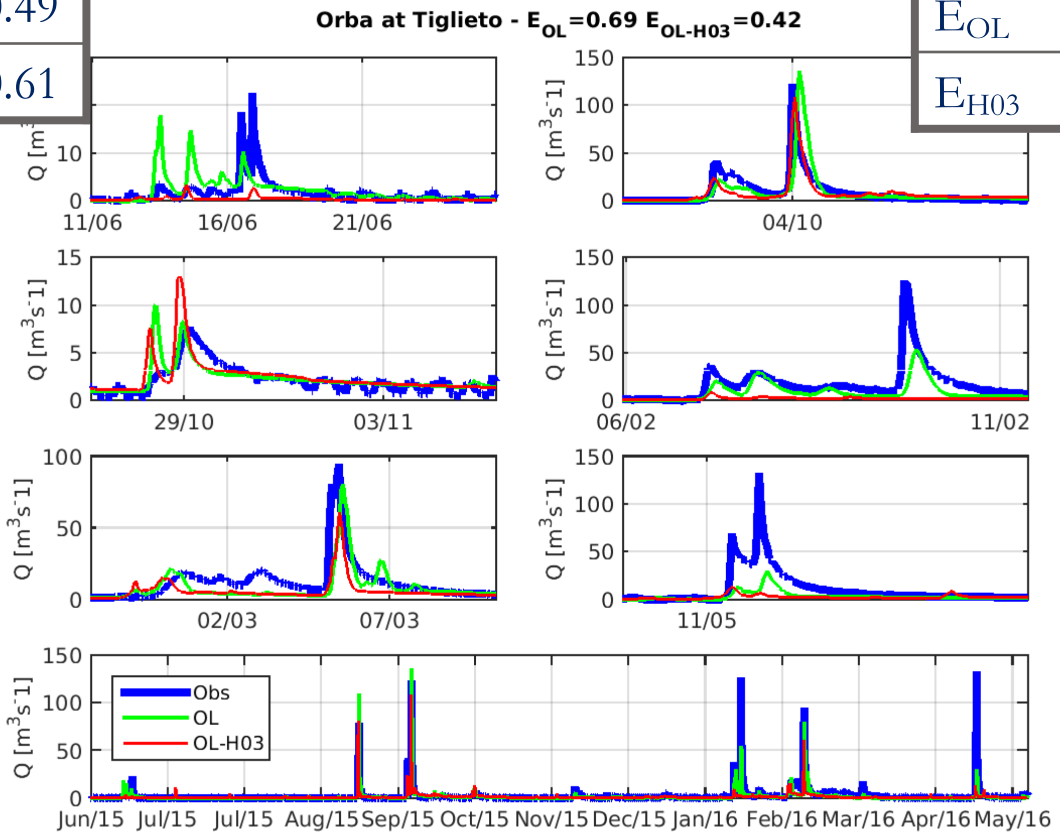
Direct use of satellite P as input

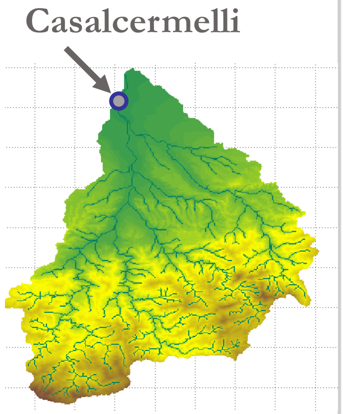
Nash and Sutcliffe's efficiency coefficient	
E_{OL}	0.49
E_{H03B}	0.61

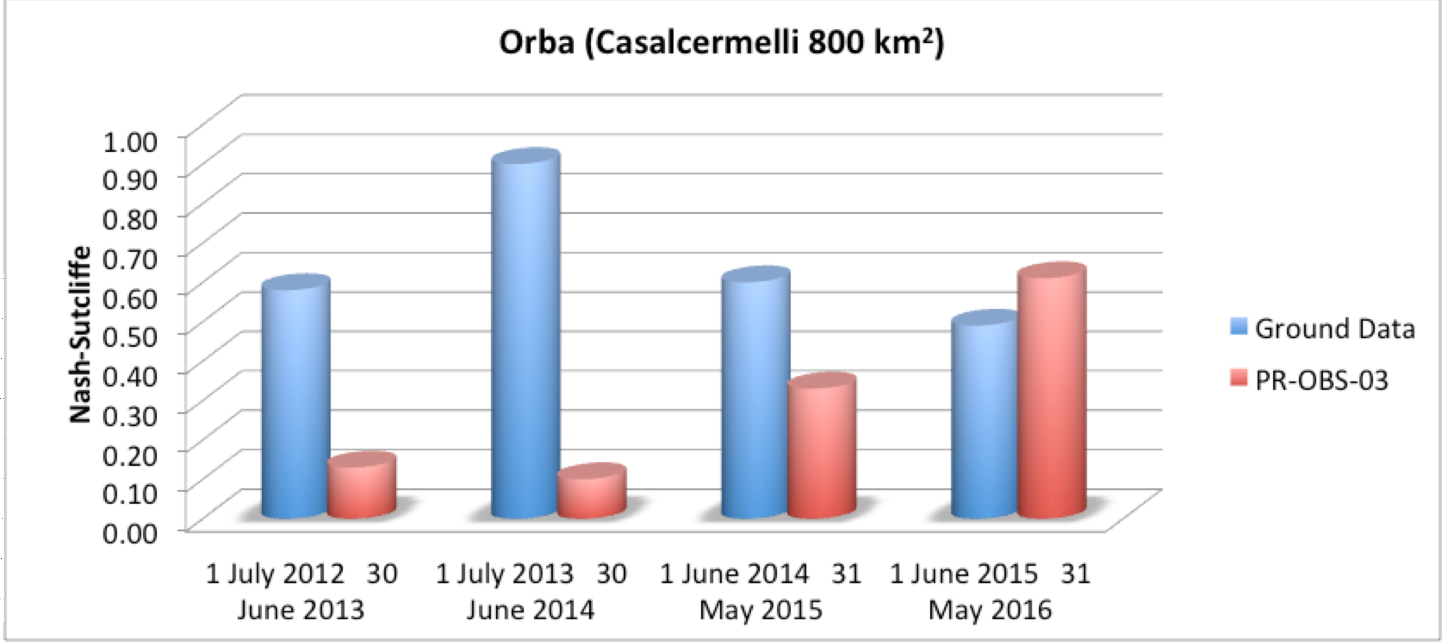


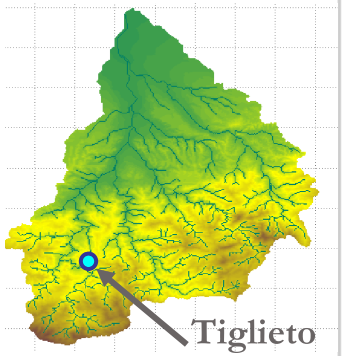
June 2015 – May 2016

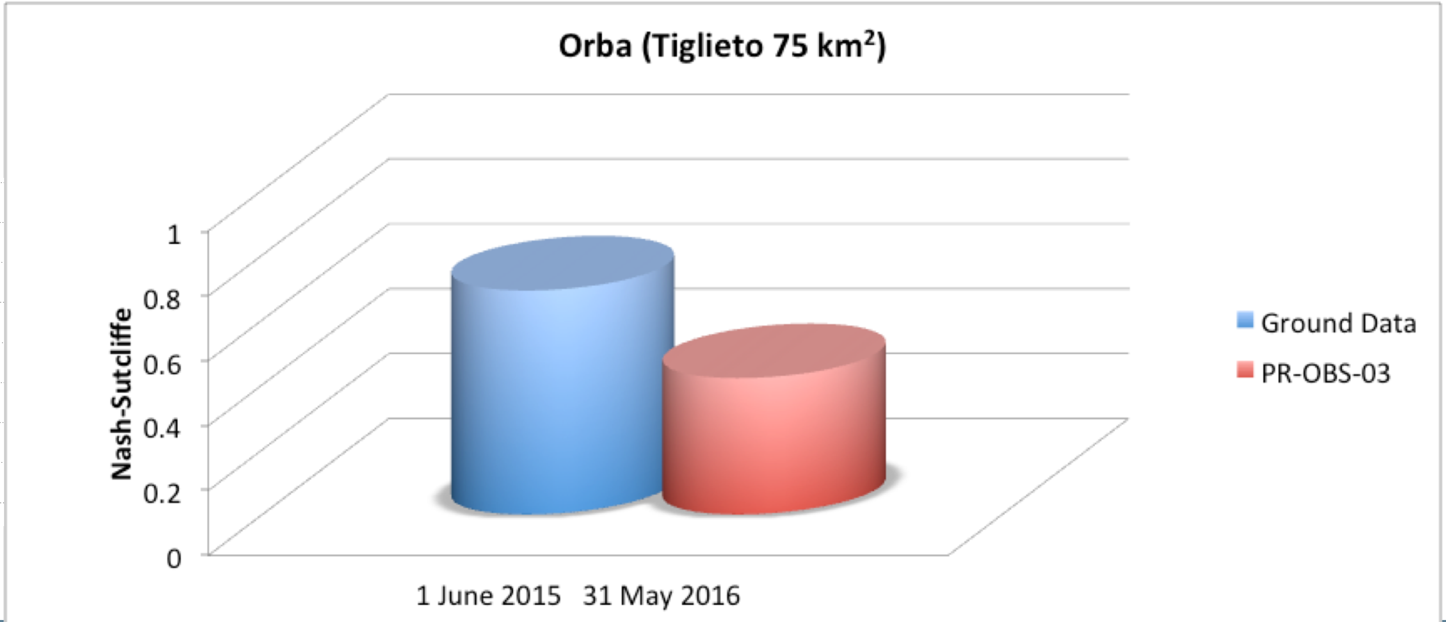
Nash and Sutcliffe's efficiency coefficient	
E_{OL}	0.69
E_{H03}	0.42




Casalcermelli

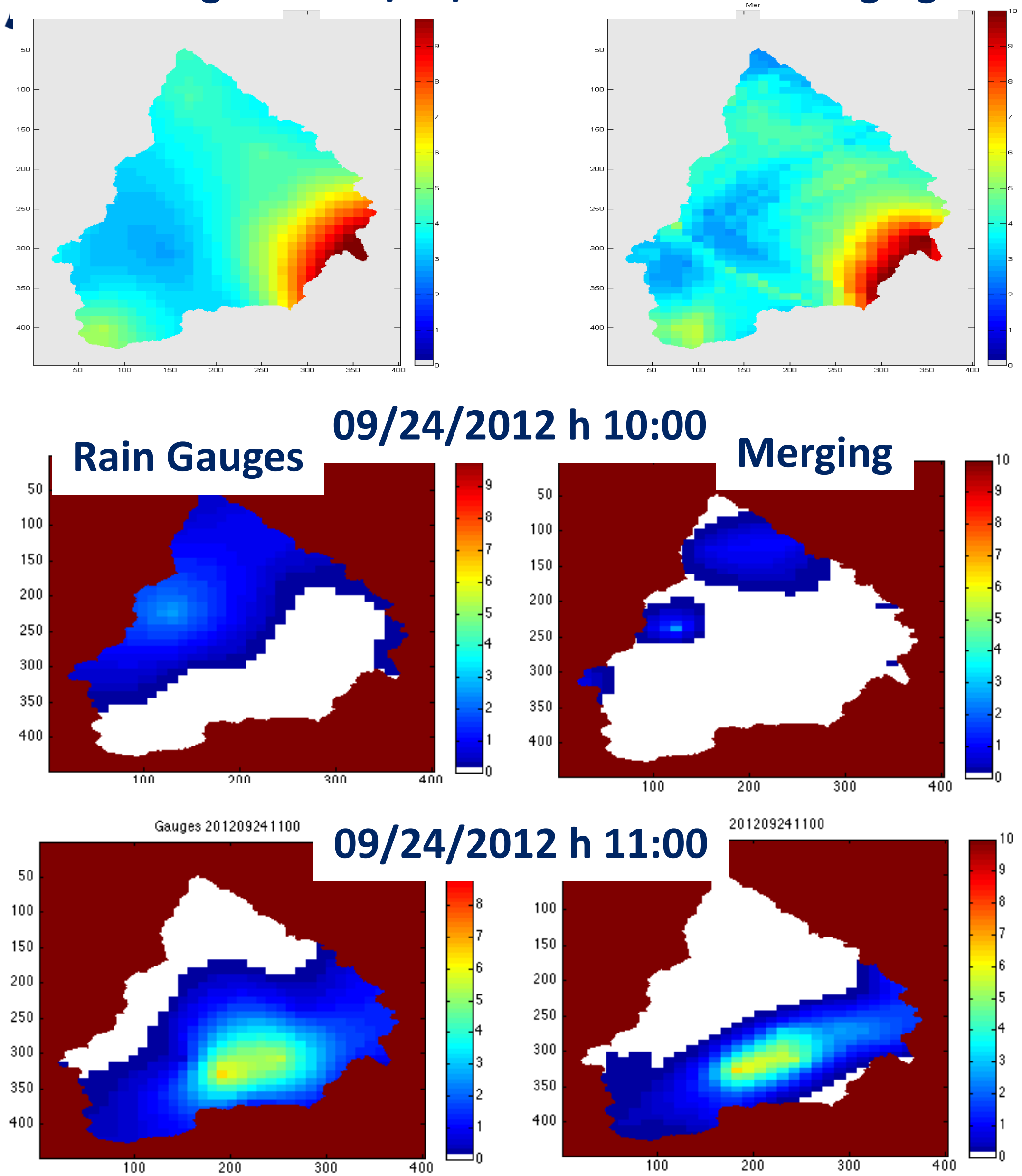

Orba (Casalcermelli 800 km²)
Nash-Sutcliffe
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
1 July 2012 30 June 2013
1 July 2013 30 June 2014
1 June 2014 31 May 2015
1 June 2015 31 May 2016
Ground Data
PR-OBS-03

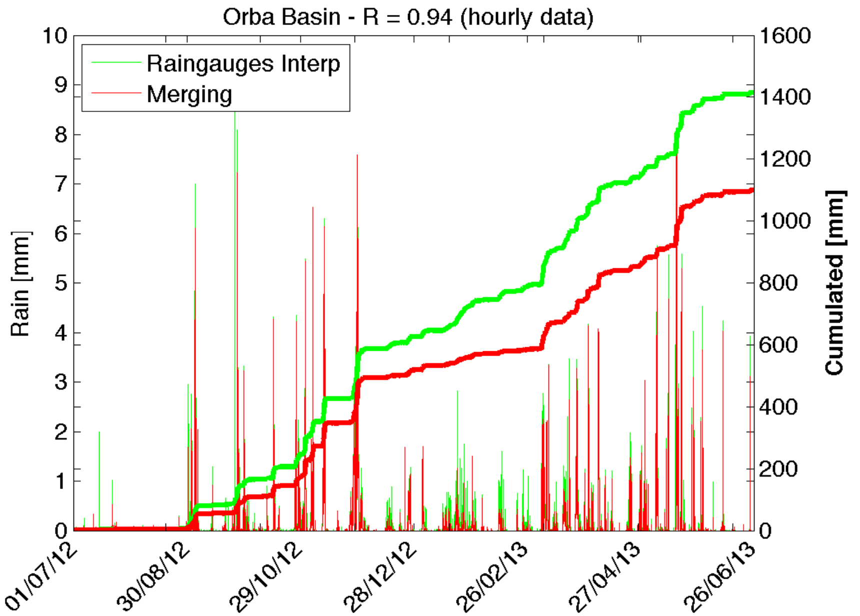

Tiglieto


Orba (Tiglieto 75 km²)
Nash-Sutcliffe
1
0.8
0.6
0.4
0.2
0
1 June 2015 31 May 2016
Ground Data
PR-OBS-03

Conditional Merging

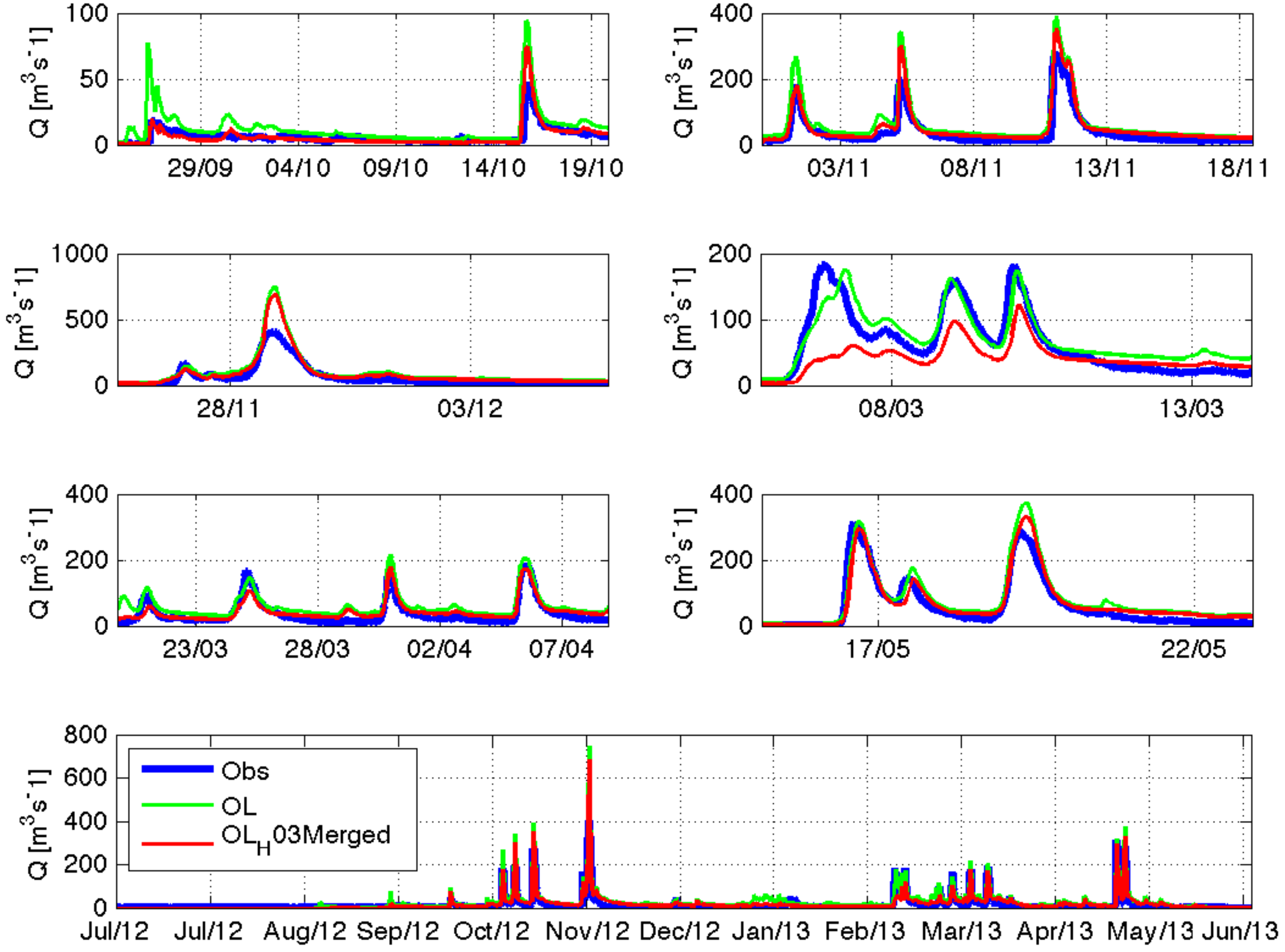
Rain Gauges + P-IN-SEVIRI H03B





Hydroval. Merging P-IN-SEVIRI (H03B)

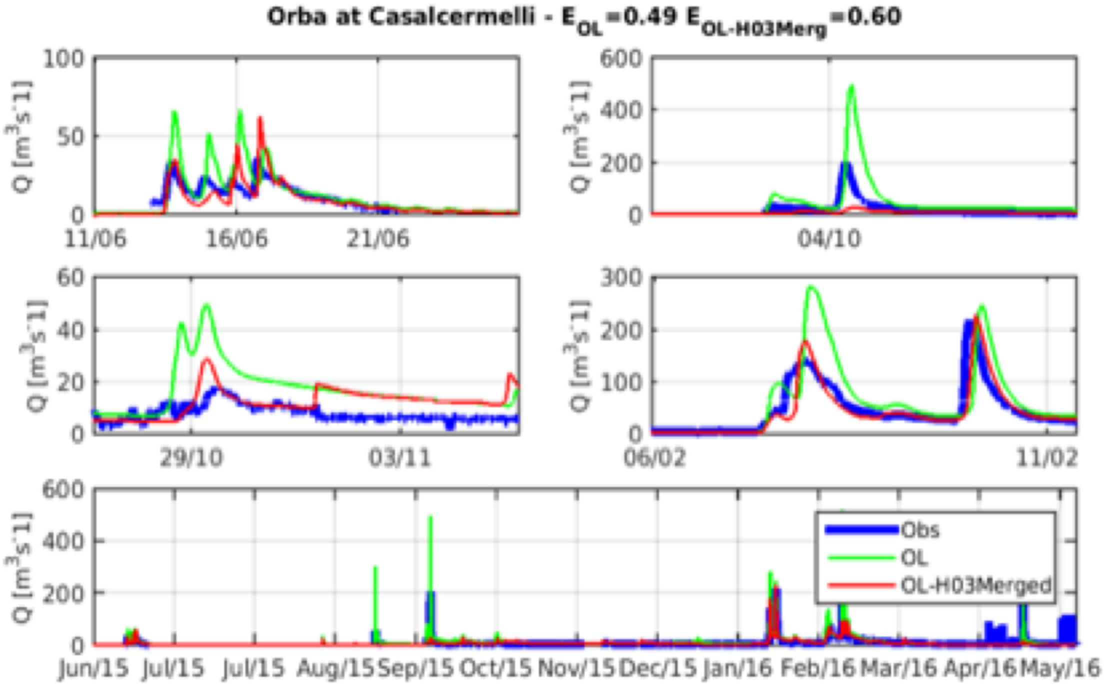
Orba at Casalcermelli – E_{OL} = 0.63 $E_{OL\text{-}Merging\_H03}$=0.77



June 2012 – May 2013

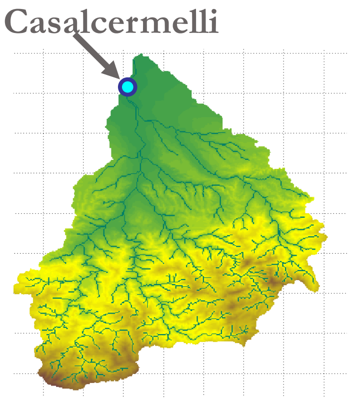
Nash and Sutcliffe's efficiency coefficient	
E_{OL}	0.63
$E_{MergH0B}$	0.77

Hydroval. Merging P-IN-SEVIRI (H03B)

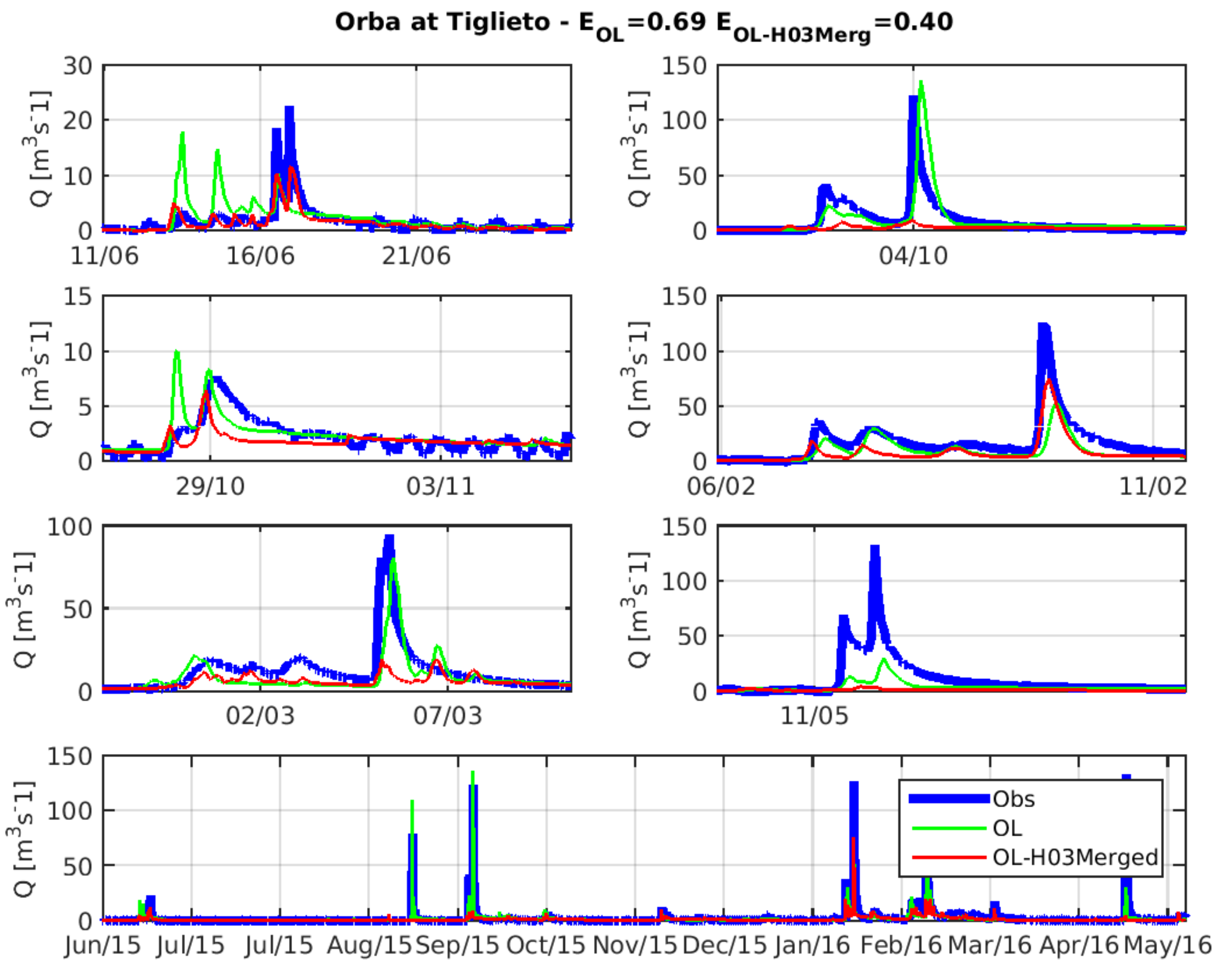


June 2015 – May 2016

Nash and Sutcliffe's efficiency coefficient	
E_{OL}	0.49
$E_{MergH03B}$	0.60

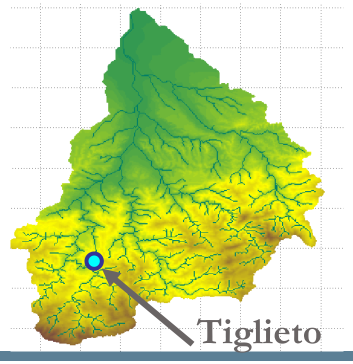


Hydroval. Merging P-IN-SEVIRI (H03B)



une 2015 – May 2016

Nash and Sutcliffe's efficiency coefficient	
E_{OL}	0.69
$E_{H03Merg}$	0.40



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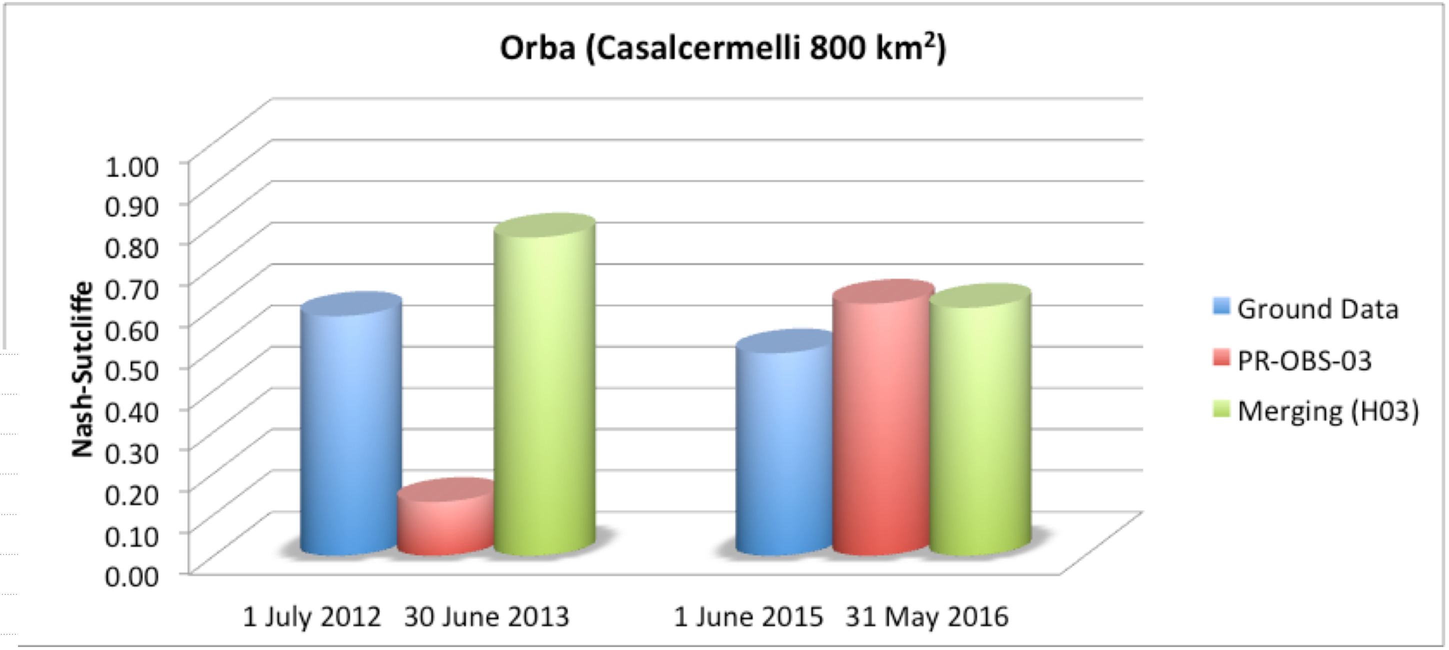
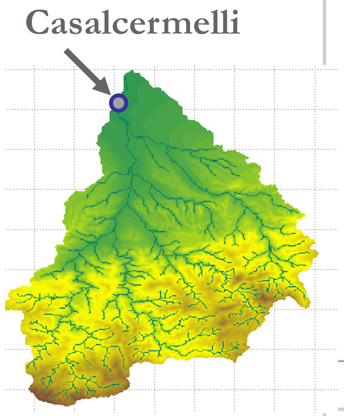
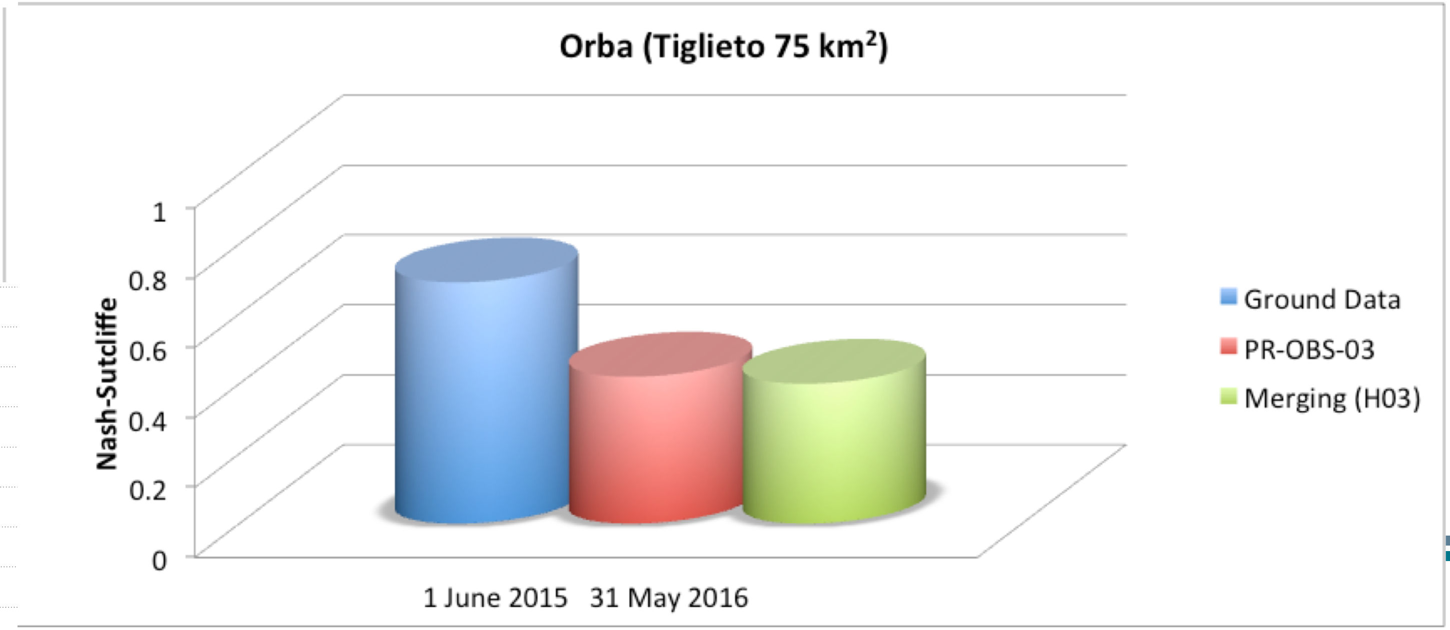
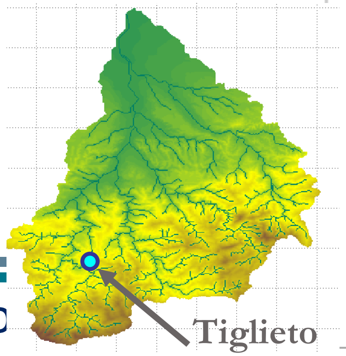


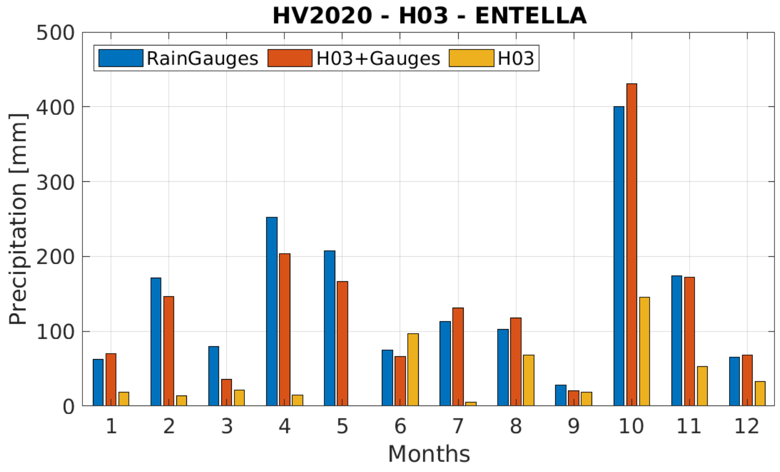


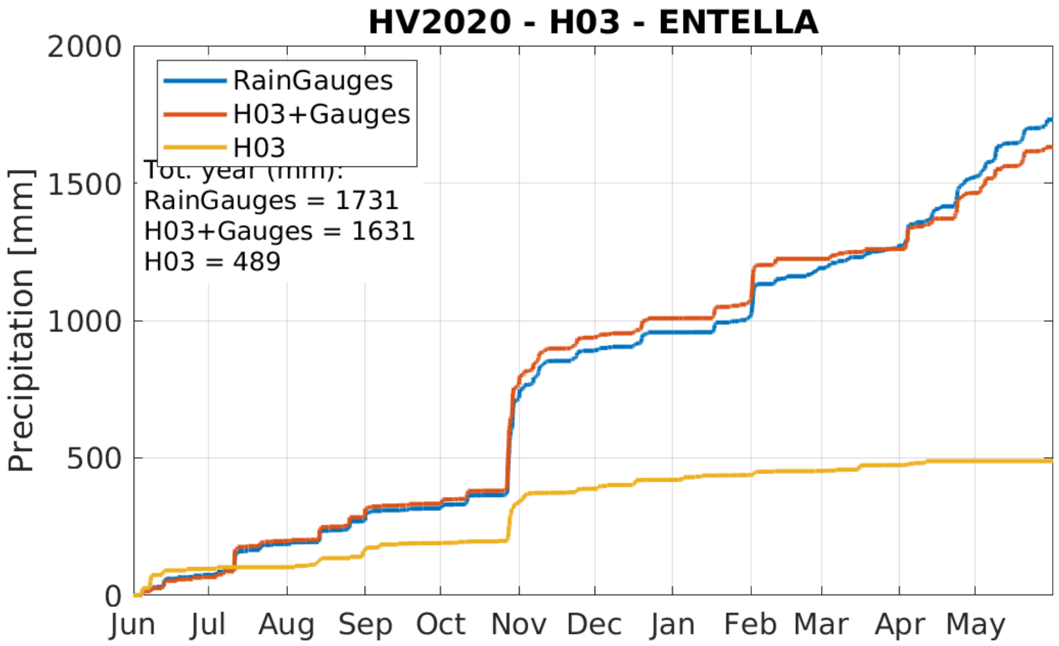


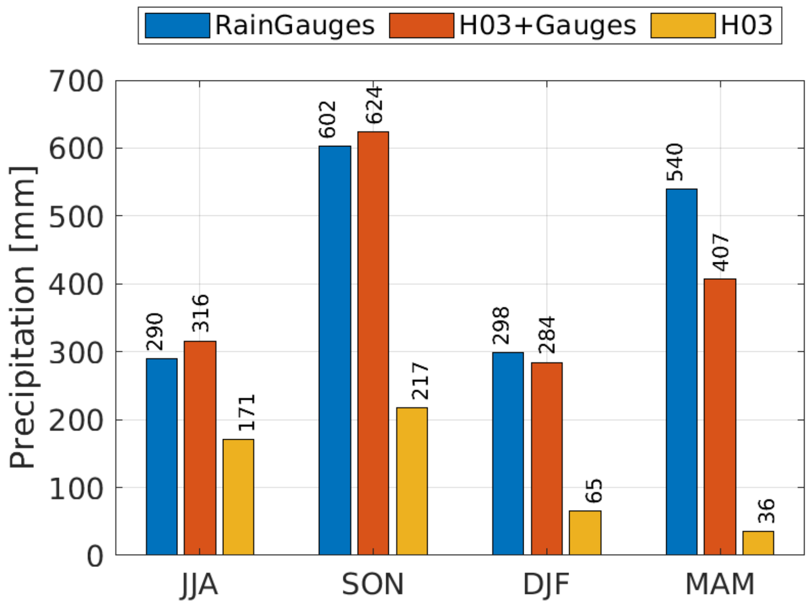


Hydrological validation P-IN-SEVIRI-H03B

June 2018 – July 2019

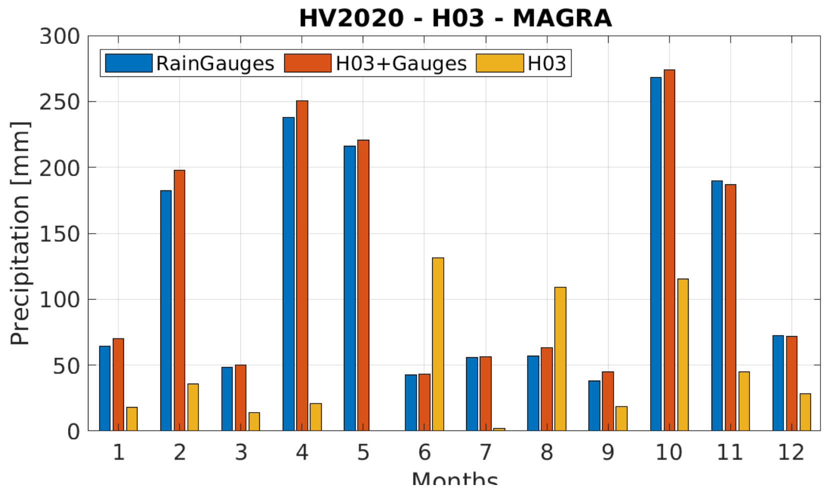


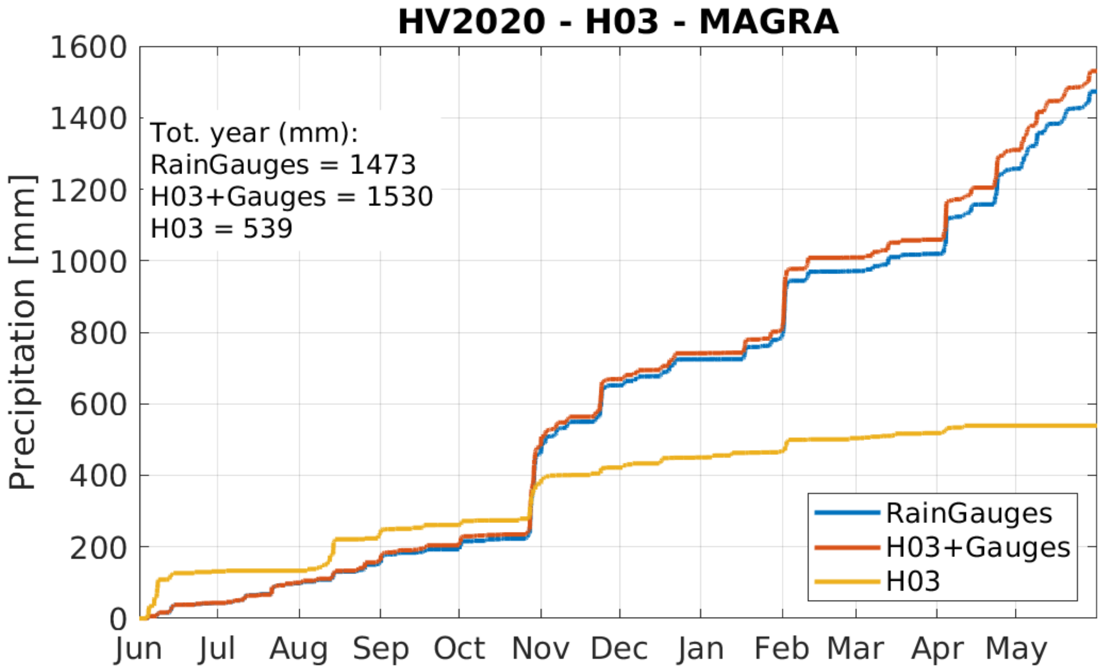


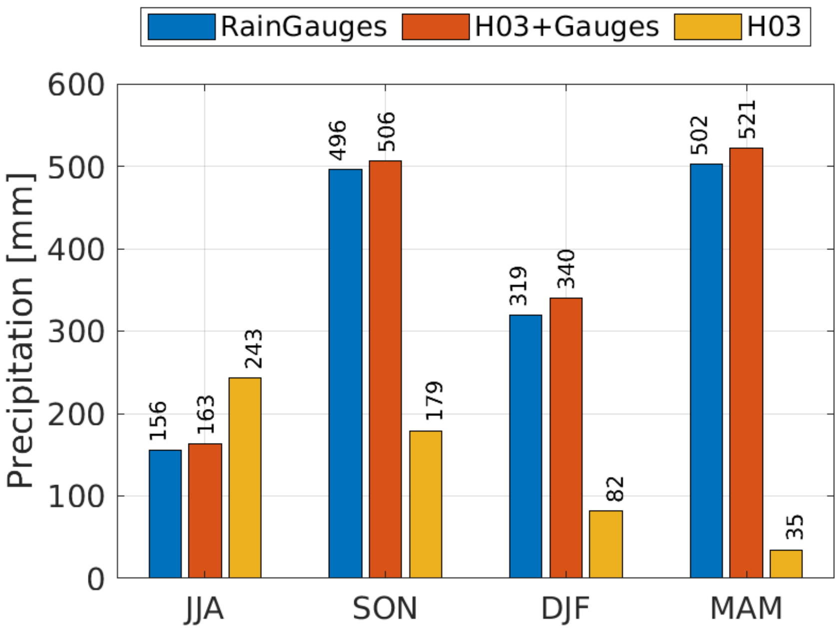


Hydrological validation P-IN-SEVIRI-H03B

June 2018 – July 2019







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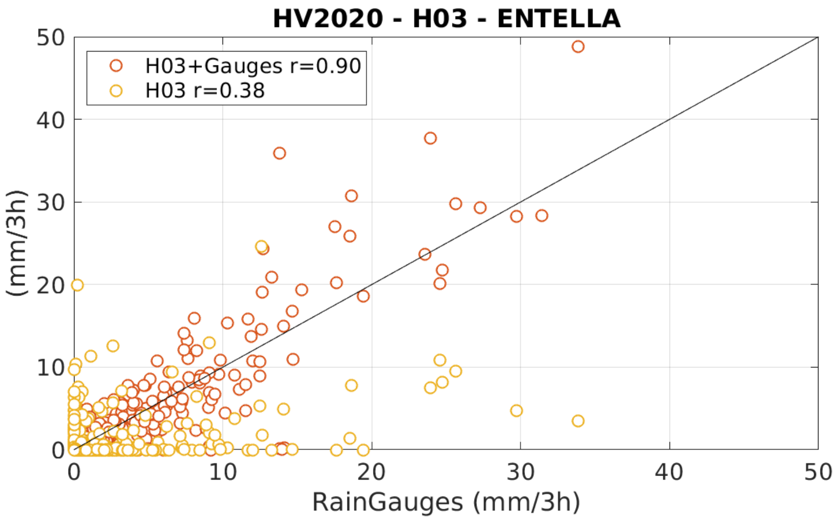
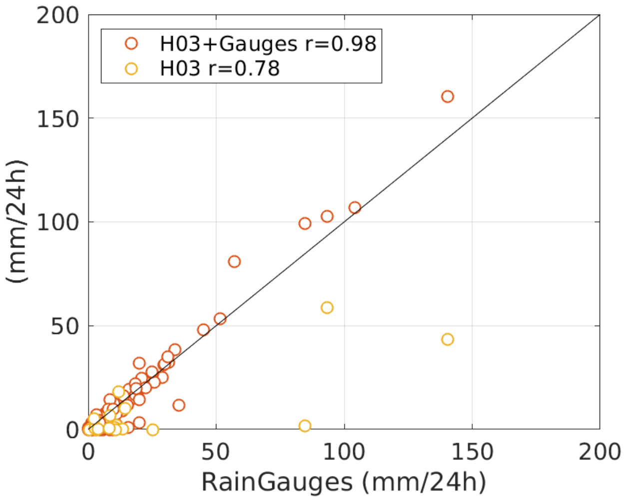
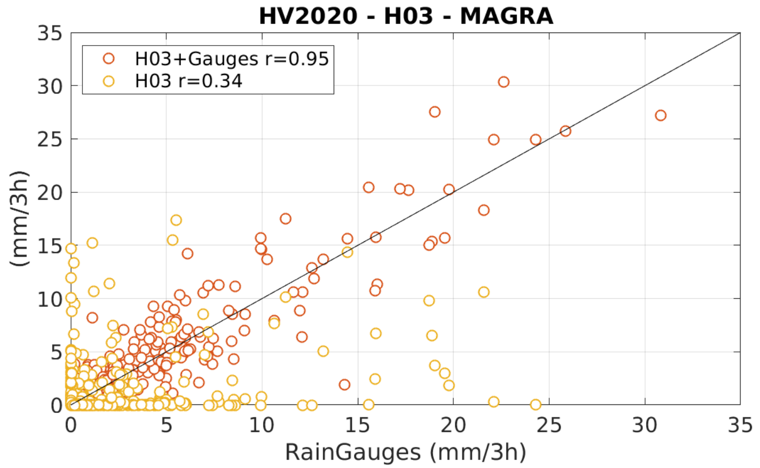
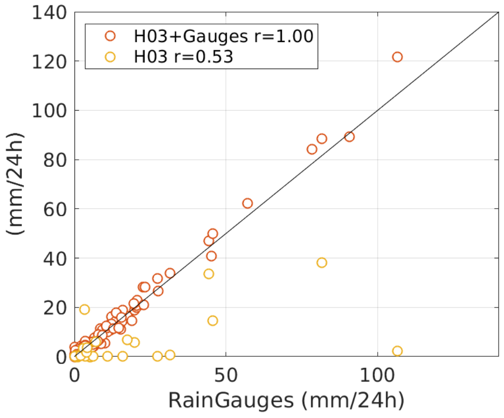
Hydrological validation P-IN-SEVIRI-H03B

June 2018 – July 2019



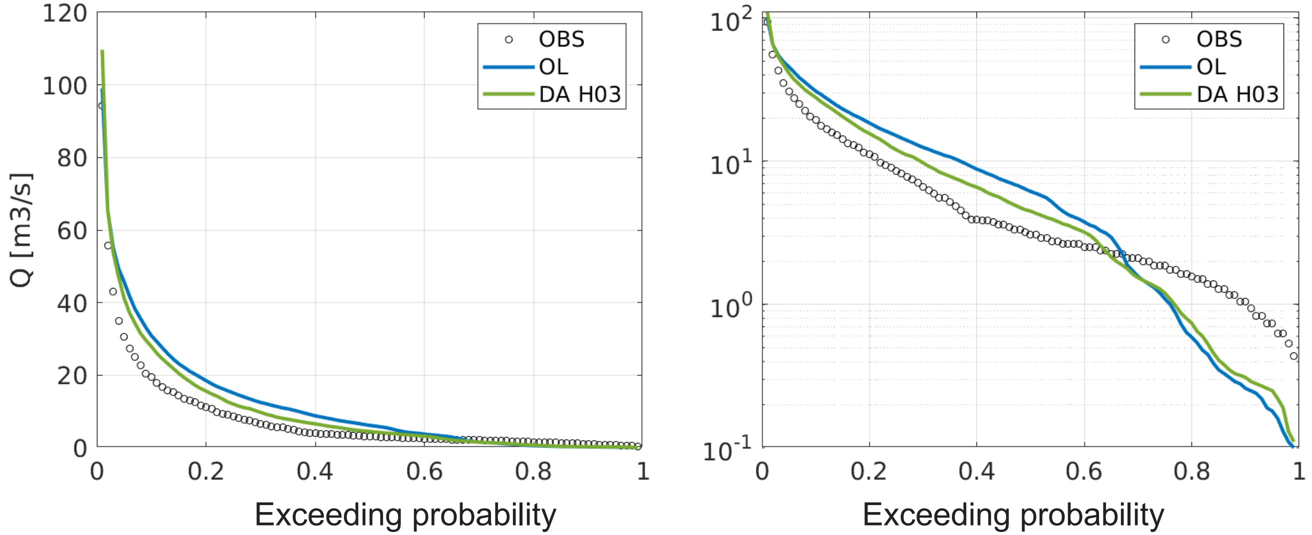






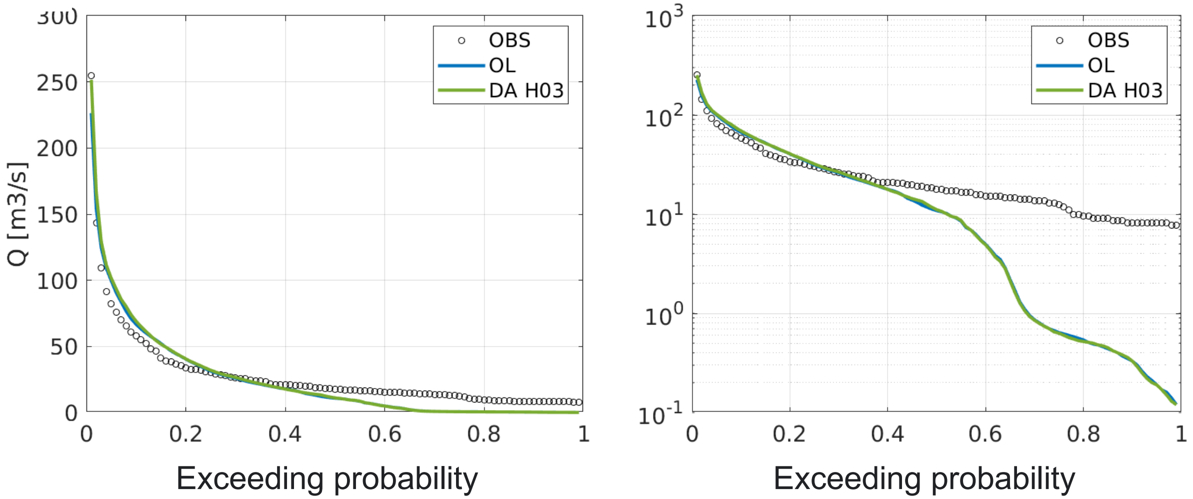
Hydrological validation P-IN-SEVIRI-H03B

HV2020 - H03 - ENTELLA



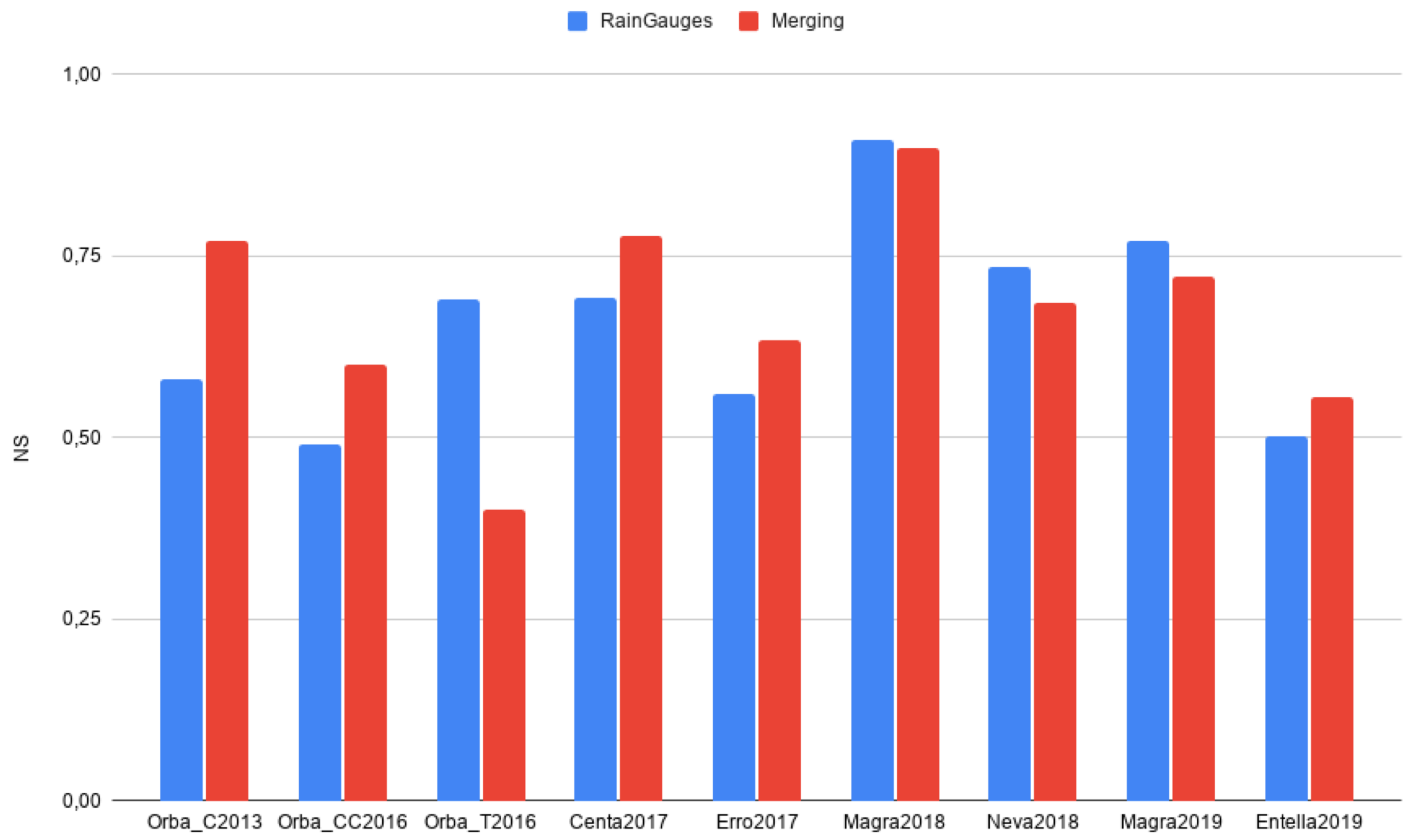
June 2018 – July 2019

HV2020 - H03 - MAGRA



OBS → Observed discharge
OL → model with raingauge data
DA H03 → model with merging (raingauge+satellite)

Hydrological validation P-IN-SEVIRI-H03B



EUMETSAT H SAF

Conclusions

In the analyzed hyrovalidation periods and basins

- P-IN-SEVIRI (H03B) and P-AC-SEVIRI (H05B) usually underestimate precipitation at catchment scale
- Direct use of P-IN-SEVIRI (H03B) and P-AC-SEVIRI (H05B) usually leads to a deterioration of the performances of the hydrological model in reproducing observed discharge due to the underestimation of satellite
- Use of Merging (raingauges + satellite product) can leads to benefit in reproducing discharge (5 cases on 9); if the performances of the model decreases this decrease is small for annual statistics

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Part3: Exercise session

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EUMETSAT H SAF

OVERVIEW

AIMS

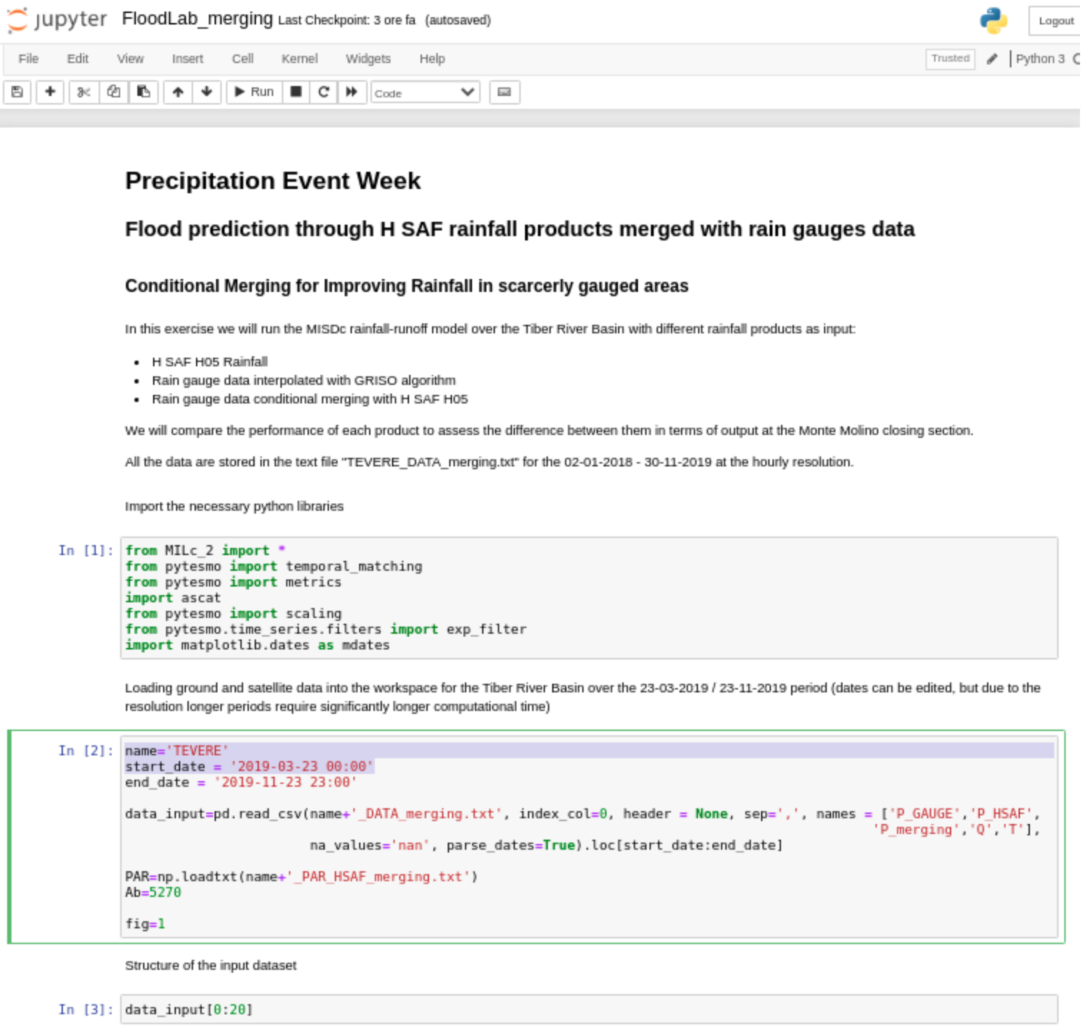
Assessing the added value of integrating satellite product and ground stations for improving flood estimation

HOW

Jupyter-Notebook FloodLab

For comparing the differences in the outputs of the MISDc[1] lumped rainfall-runoff model by using:

- H SAF H05B precipitation product
- Rain gauge data interpolated with GRISO algorithm
- H SAF H05B product conditional merging with rain gauges



jupyter FloodLab_merging Last Checkpoint: 3 ore fa (autosaved)

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Precipitation Event Week

Flood prediction through H SAF rainfall products merged with rain gauges data

Conditional Merging for Improving Rainfall in scarcerly gauged areas

In this exercise we will run the MISDc rainfall-runoff model over the Tiber River Basin with different rainfall products as input:

- H SAF H05 Rainfall
- Rain gauge data interpolated with GRISO algorithm
- Rain gauge data conditional merging with H SAF H05

We will compare the performance of each product to assess the difference between them in terms of output at the Monte Molino closing section.

All the data are stored in the text file "TEVERE_DATA_merging.txt" for the 02-01-2018 - 30-11-2019 at the hourly resolution.

Import the necessary python libraries

In [1]:
```
from MILc_2 import *
from pytesmo import temporal_matching
from pytesmo import metrics
import ascat
from pytesmo import scaling
from pytesmo.time_series.filters import exp_filter
import matplotlib.dates as mdates
```

Loading ground and satellite data into the workspace for the Tiber River Basin over the 23-03-2019 / 23-11-2019 period (dates can be edited, but due to the resolution longer periods require significantly longer computational time)

In [2]:
```
name='TEVERE'
start_date = '2019-03-23 00:00'
end_date = '2019-11-23 23:00'

data_input=pd.read_csv(name+'_DATA_merging.txt', index_col=0, header = None, sep=',', names = ['P_GAUGE','P_HSAF',
                                                                                              'P_merging','Q','T'],
                       na_values='nan', parse_dates=True).loc[start_date:end_date]

PAR=np.loadtxt(name+'_PAR_HSAF_merging.txt')
Ab=5270

fig=1
```

Structure of the input dataset

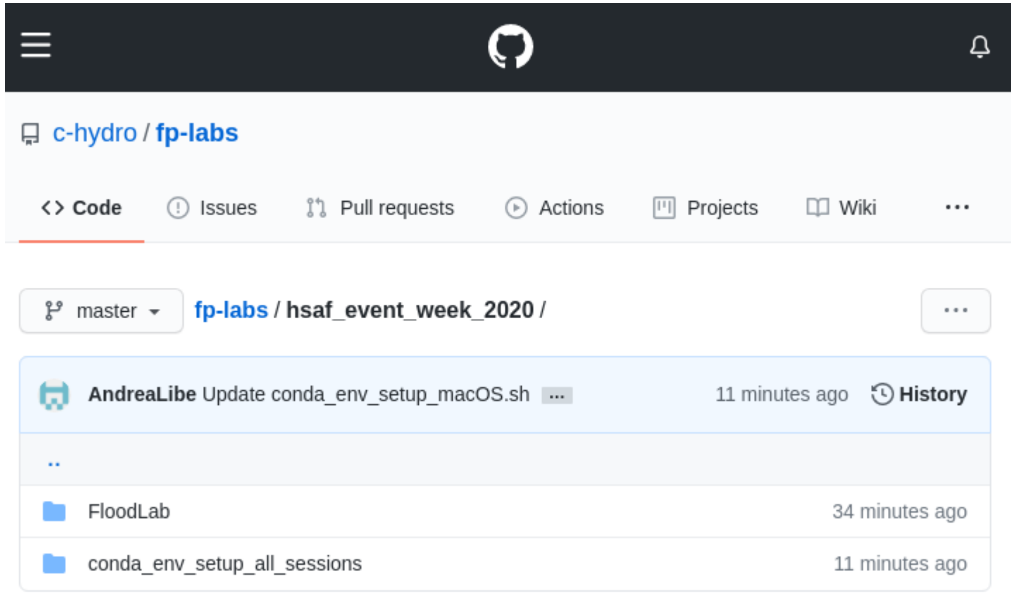
In [3]:
```
data_input[0:20]
```

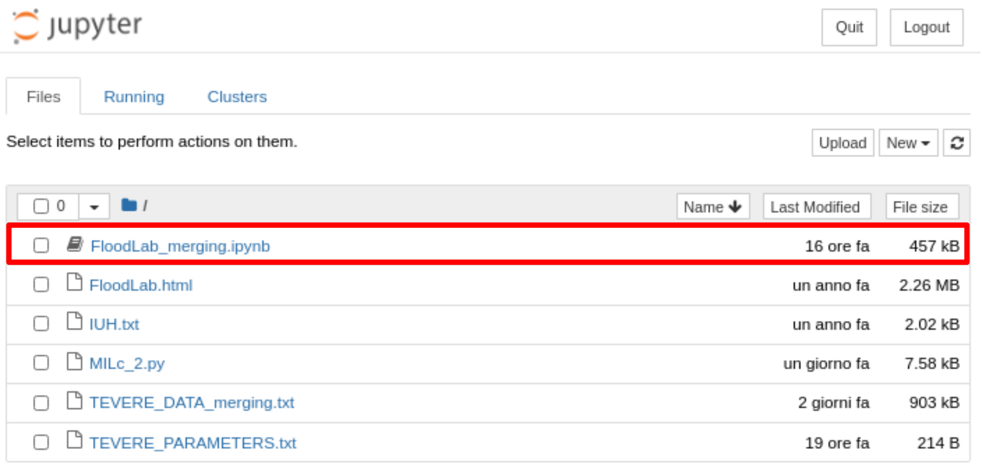
[1] *Brocca et al. (2010), Brocca et al. (2011)*

FLOODLAB SET-UP

SET UP THE JUPYTER-NOTEBOOK

- Download the FloodLab material at:
  https://github.com/c-hydro/fp-labs/tree/master/hsaf_event_week_2020
  git clone https://github.com/c-hydro/fp-labs.git --branch v1.0.0 --single-branch
- Install the conda virtual environment using the **conda_env_setup** bash scripts in the folder **conda_env_setup_all_sessions**
- Activate the conda virtual environment
  conda activate hsaf_env
- Navigate to the **FloodLab** folder and launch:
  jupyter-notebook
- A browser window will open. Select the **FloodLab_merging.ipynb** file.





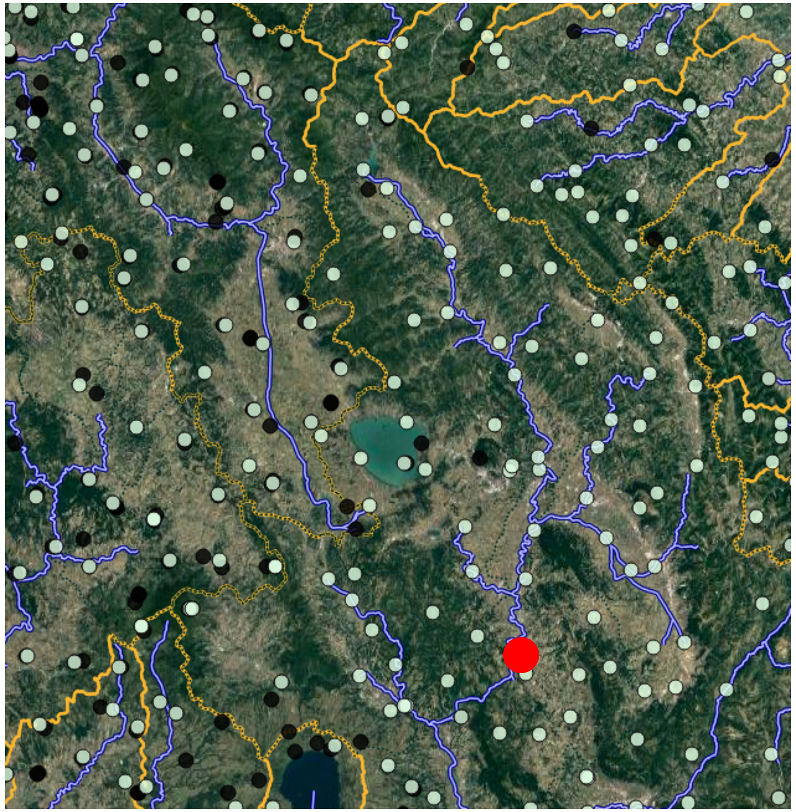
EUMETSAT H SAF

CASE STUDY

BASIN

Tiber river basin closed at Monte Molino (ITALY)

Area: about 5500 km^2



EUMETSAT H SAF

INPUT DATA

DATA AVAILABLE in the FloodLab

TEVERE_DATA_merging.txt

For the 02/01/2018-30/11/2019 period with hourly resolution

Averaged on the basin area:
- Precipitation interpolated with GRISO algorithm (P_GAUGE)
- H SAF H05 precipitation (P_HSAF)
- Conditional merging H SAF H05-Rain gauge precipitation (P_merging)
- Temperature (T)

Point data:
- Discharge at the Monte Molino gauging station (Q)

	P_GAUGE	P_HSAF	P_merging	Q	T
2019-03-23 00:00:00	0.0	0.0	0.0	6.659481	6.6
2019-03-23 01:00:00	0.0	0.0	0.0	6.659481	6.4
2019-03-23 02:00:00	0.0	0.0	0.0	5.807709	6.0
2019-03-23 03:00:00	0.0	0.0	0.0	5.807709	5.8
2019-03-23 04:00:00	0.0	0.0	0.0	6.659481	5.5
2019-03-23 05:00:00	0.0	0.0	0.0	5.807709	5.2
2019-03-23 06:00:00	0.0	0.0	0.0	6.659481	5.8
2019-03-23 07:00:00	0.0	0.0	0.0	7.089644	8.8

TEVERE_PARAMETERS.txt

Calibrated parameters for the MISDc model

EUMETSAT H SAF

STEP 1

IMPORT AND VISUALIZATION OF THE DATA

Data are imported directly in the notebook.

The study period can be specified by changing the start and end dates.

WARNING: Long periods can require large computational time!

```
name='TEVERE'
start_date = '2019-03-23 00:00'
end_date = '2019-11-23 23:00'

data_input=pd.read_csv(name+'_DATA_merging.txt', index_col=0, header = None, sep=',', names = ['P_GAUGE','P_HSAF',
                                                                                               'P_merging','Q','T'],
                       na_values='nan', parse_dates=True).loc[start_date:end_date]

PAR=np.loadtxt(name+'_PARAMETERS.txt')
Ab=5270

fig=1
```

EUMETSAT

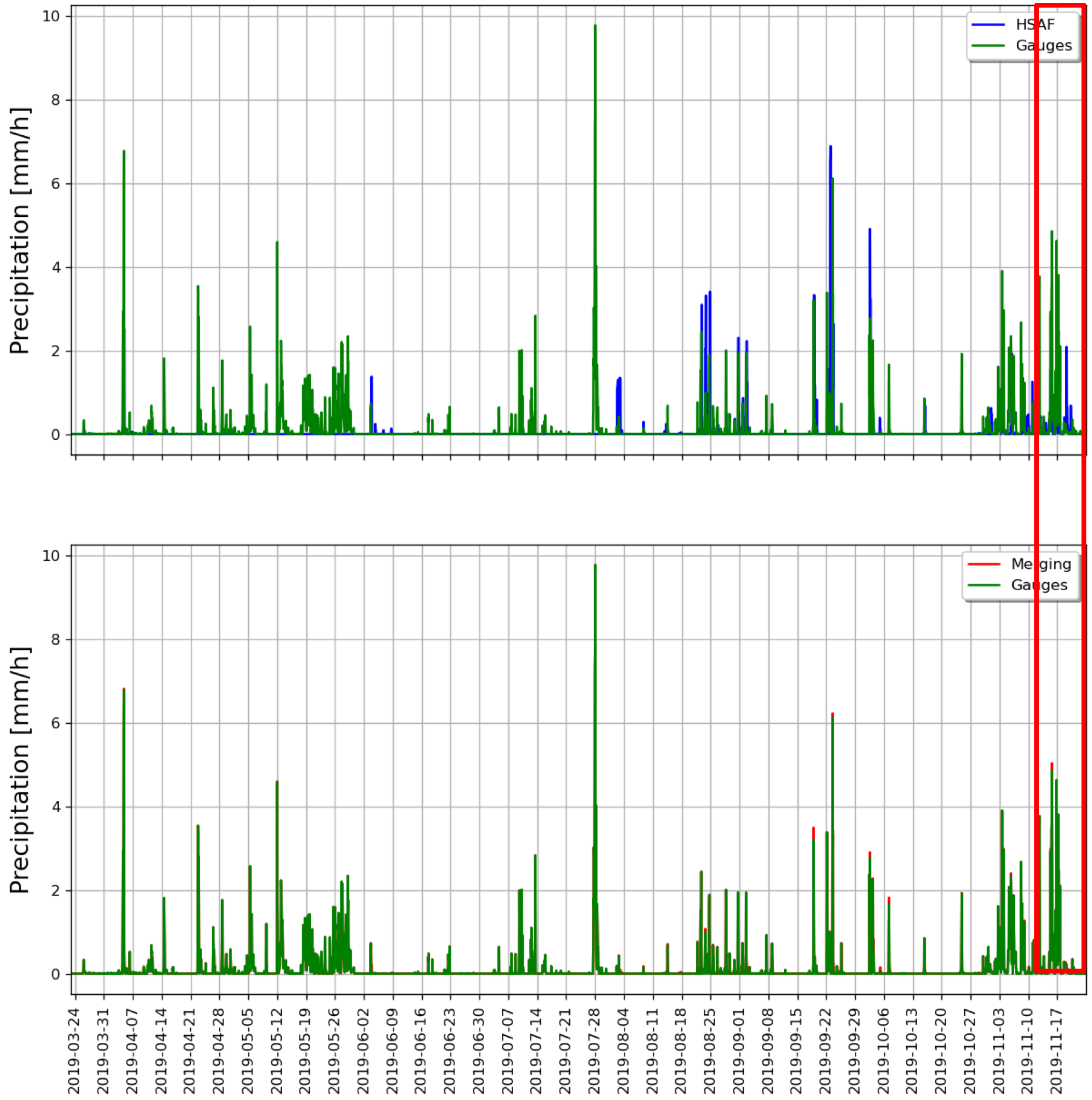
H SAF

STEP 1

INPUT COMPARISON

- H SAF H05 seems to underestimate the rainfall amounts
- The merged product shows intensities similar to the interpolated one, but slight differences arise (the rain gauge density in the area is very high).

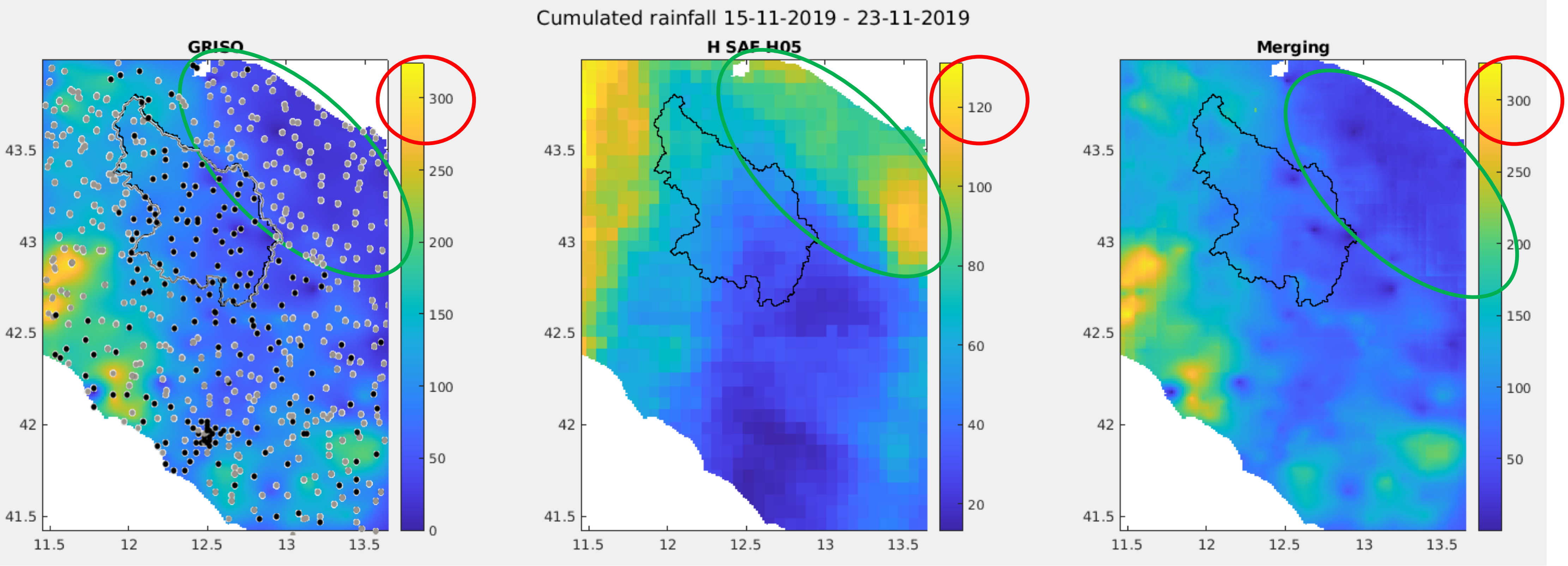
15-23 November 2019



STEP 1

SPATIAL ANALYSIS

Active rain gauges on 17-18 November 2019



EUMETSAT
H SAF **STEP 2**

MODEL RUN

Model runs are performed with the same set of parameters for all the products (they can be changed by uncommenting the commented line and providing different sets).

The variable named "P" is the one that is used as input in the model.

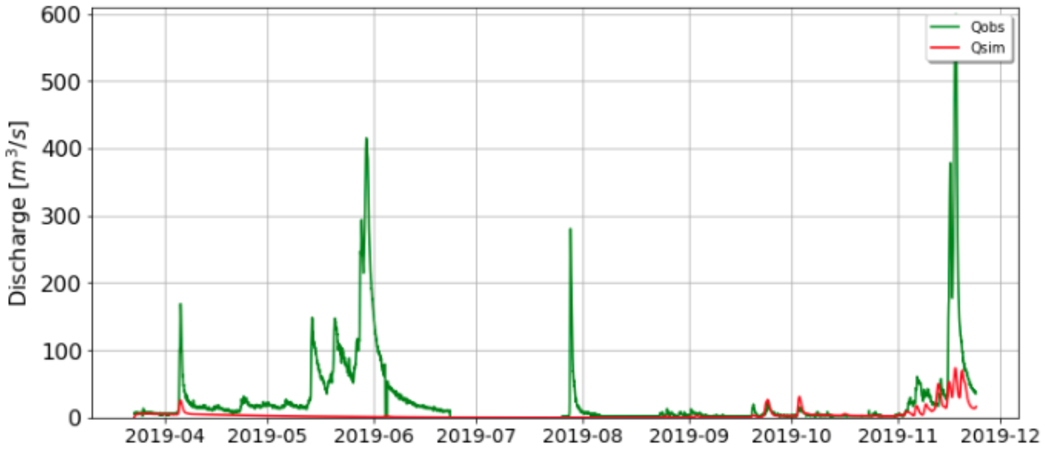
```
name_run='TEV_HSAF'
data_input1=pd.read_csv(name+'_DATA_merging.txt', index_col=0, header = None, sep=',', names = ['P_GAUGE','P',
                                                                                                       'P_merging','Q','T'],
                        na_values='nan', parse_dates=True).loc[start_date:end_date]
#PAR=np.loadtxt(name+'_PAR_HSAF_merging_2.txt')
QobsQsim,data_HSAF=MILC(name,data_input1,PAR,Ab,1)
```

EUMETSAT

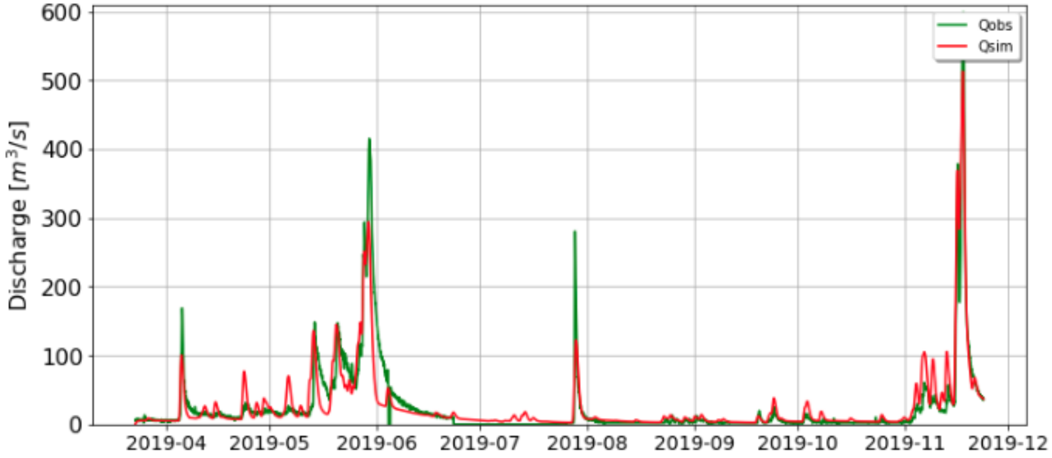
H SAF

STEP 2

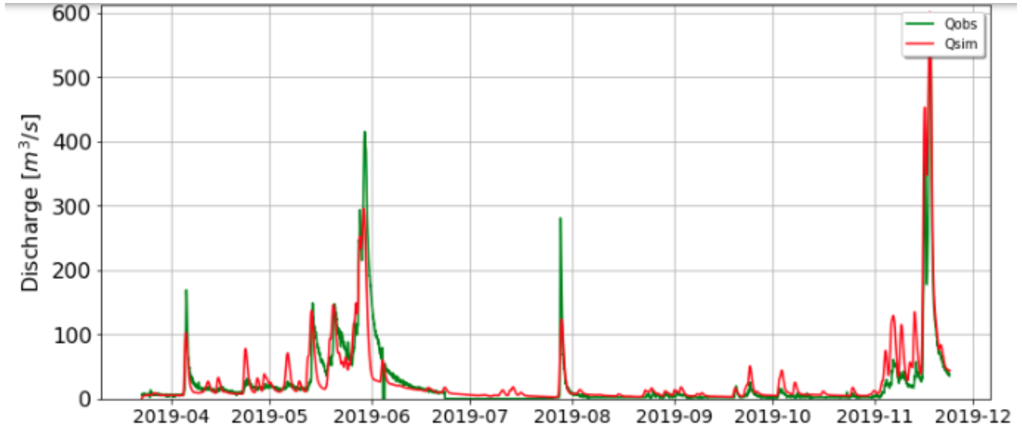
H SAF H05B



Rain Gauges with GRISO



H SAF H05B Conditional Merging



MODEL OUTPUT COMPARISON

Model output can be compared by overlapping in the last step.

By selecting an excerpt of the whole computational period specifying "start zoom" and "end_zoom" dates, the differences between the results at the event scale arises.

```
f, ax = plt.subplots(1,figsize=(12, 12))

start_zoom = '2019-11-15 00:00'
end_zoom = '2019-11-23 23:00'

ax.fill_between(data_input.index, data_input['Q'].values,label='Qobs',facecolor=(0, 1, 0))
ax.plot(data_HSAF.index, data_HSAF['S'].values,label='HSAF',color='r',linewidth=3.0)
ax.plot(data_GAUGE.index, data_GAUGE['S'].values,label='GAUGE',color='b',linewidth=3.0)
ax.plot(data_merging.index, data_merging['S'].values,label='merging',color='k',linewidth=3.0)
ax.set_xlim(pd.Timestamp(start_zoom),pd.Timestamp(end_zoom))
ax.set_ylim(0,np.max(np.append(data_input['Q'].values.max(), data_merging['S'].values.max()))+10)
ax.set_ylabel('Discharge [$m^3/s$]', fontsize=16)
ax.grid(True)
ax.tick_params(axis='y', labelsize=16)
ax.legend(loc='upper right', shadow=True)

f.savefig('Qsim_zoom', dpi=120)
```

STEP 1

OUTPUT COMPARISON ON THE 15-23 November 2019 EVENT