Comparison of two assimilation methods of radar derived surface rain rate over Northern Italy

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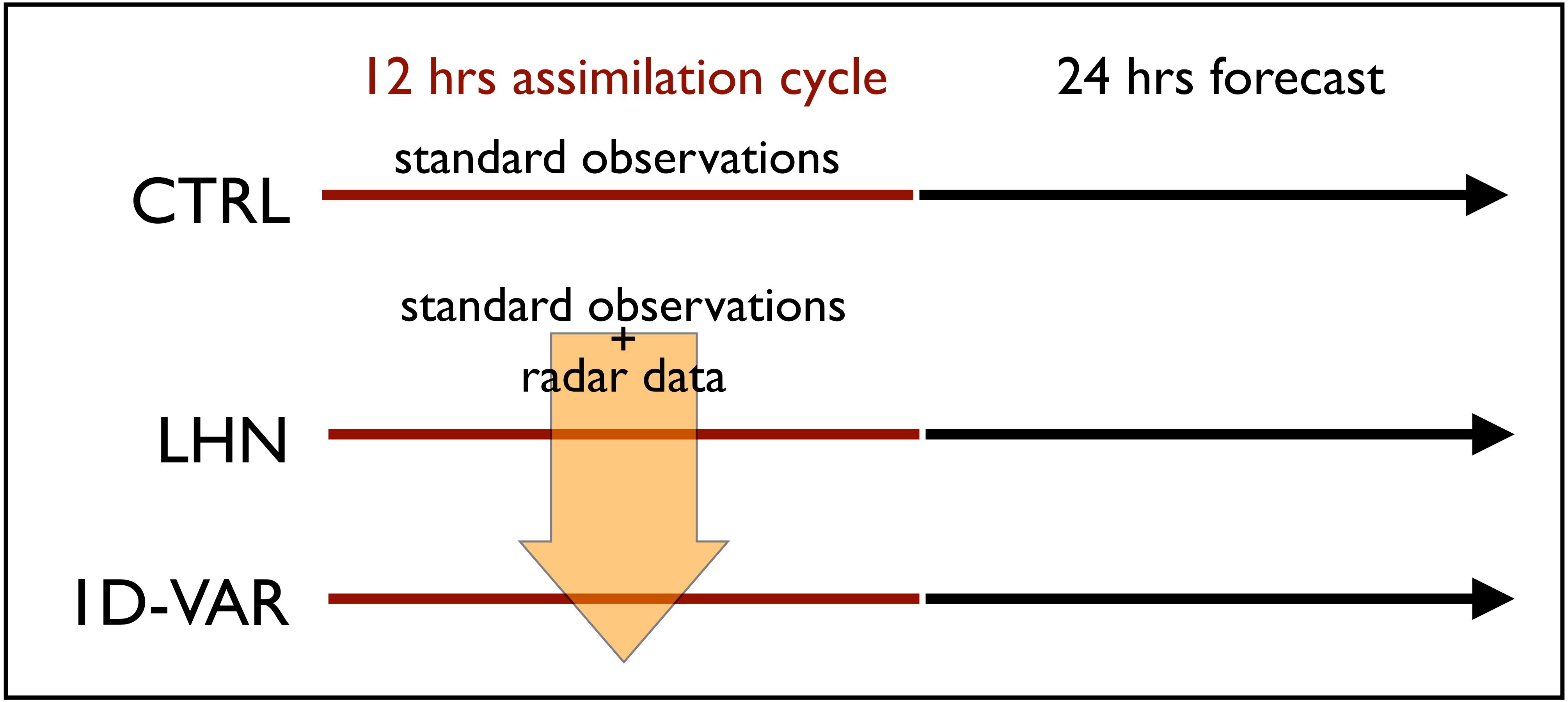
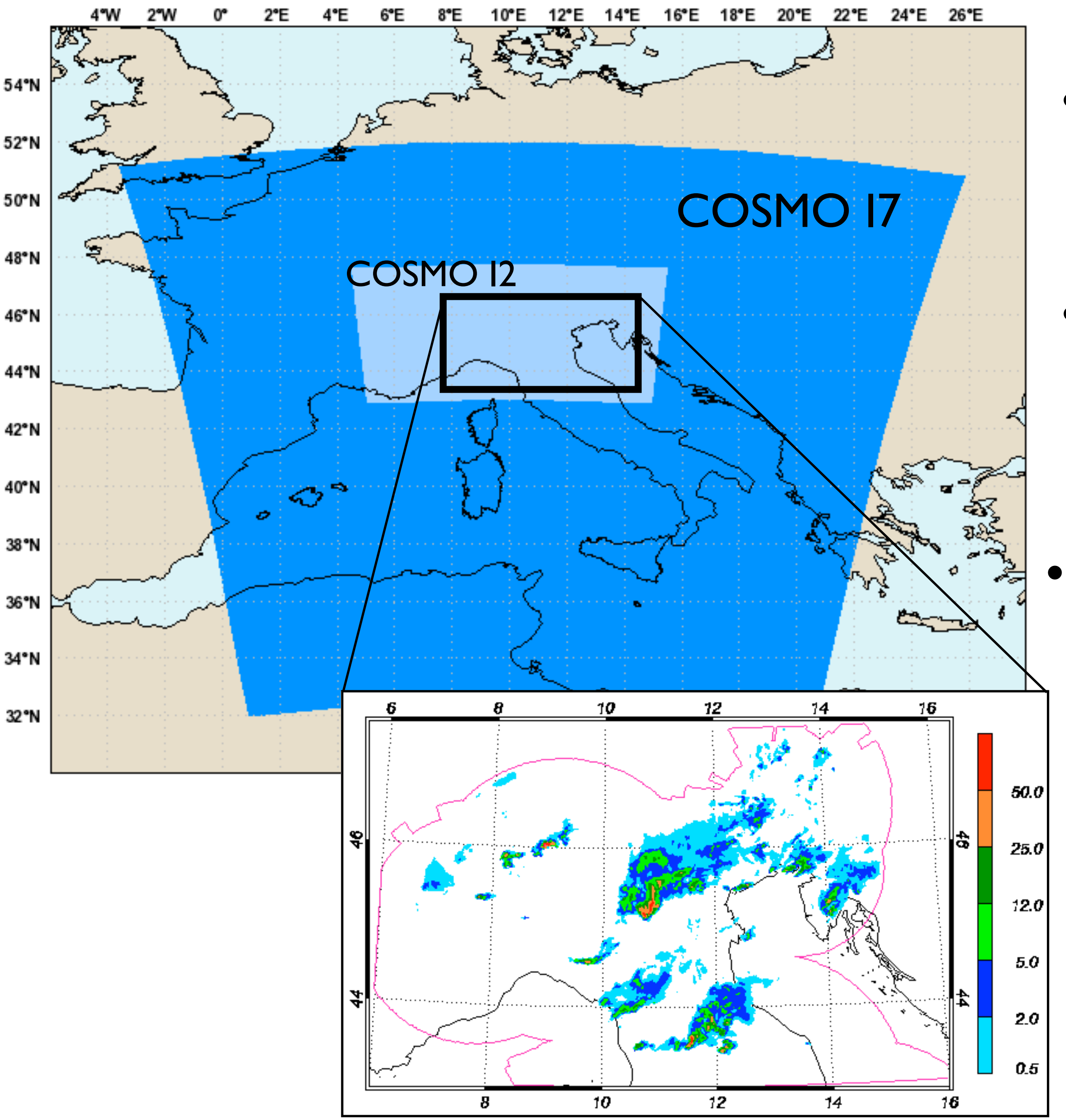
Motivation

A requirement of the assimilation of high resolution observations into numerical weather prediction is the improvement of the storm-scale precipitation forecasts. As a matter of fact the use of very high spatial and temporal data resolution should guarantee a better initial condition knowledge.



AIM: Comparison of 2 different assimilation methods of radar derived precipitation

Numerical model and radar data



- COSMO I2, version 4.10
  - horizontal resolution=2.8 km
  - 45 vertical levels
- Nested in COSMO I7
  - horizontal resolution=7 km
  - 40 vertical levels
- Radar data from the radar network of italian Department of National Civil Protection
  - Horizontal resolution: 1km
  - Temporal resolution: 15 min
  - Selected domain: Northern Italy
  - Data are interpolated on COSMO I2 grid before their assimilation

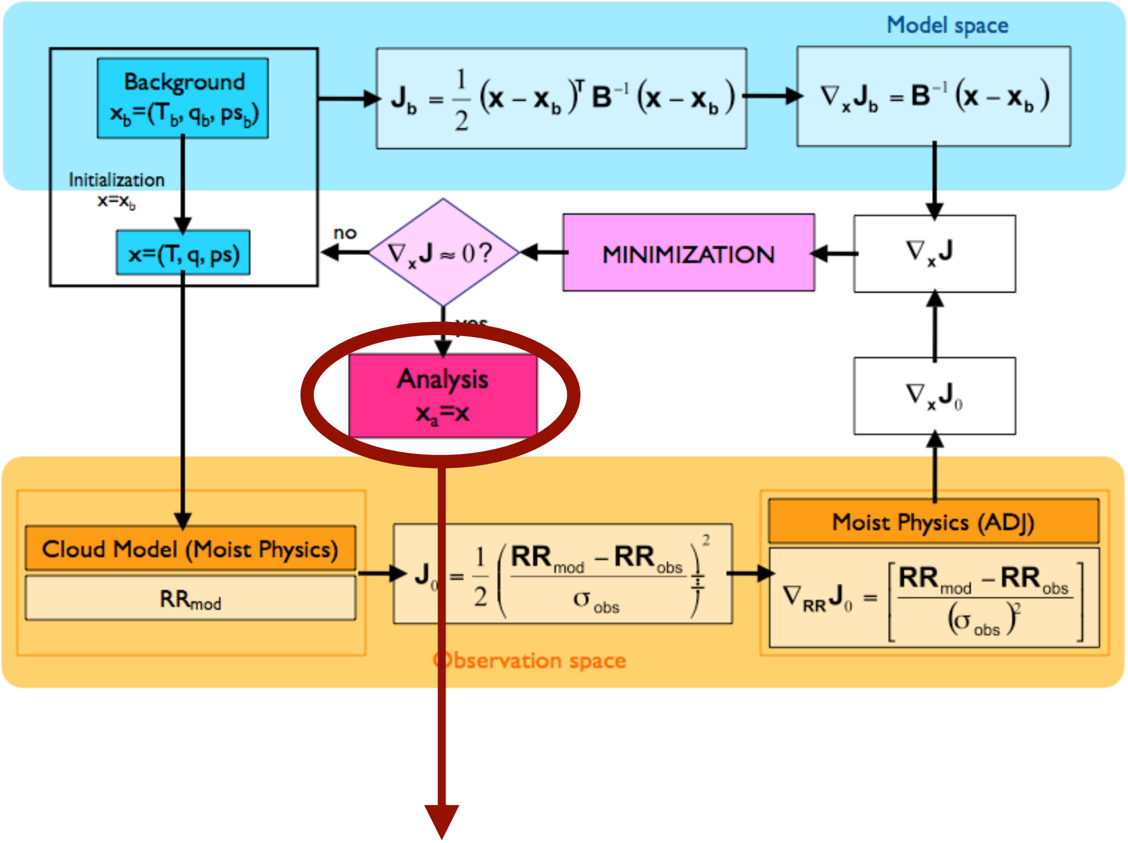
Variational assimilation

The goal of the variational assimilation is to find the optimal model state, the analysis, that simultaneously minimizes the distances to the observations and a background model state, usually coming from a previous short-range forecast.

1D-Var:

- is applied off-line

  A first COSMO run (doubling the assimilation cycle) is made in order to get, every 15 minutes, the parameters needed by 1D-VAR (temperature profiles, humidity profiles...)
- is applied to each grid point of the model with its matching radar derived rain rate
- Only point with $RR_{fg} \geq 0$ are considered for minimization



Retrieved analysed profile of T and Q are then nudged into COSMO

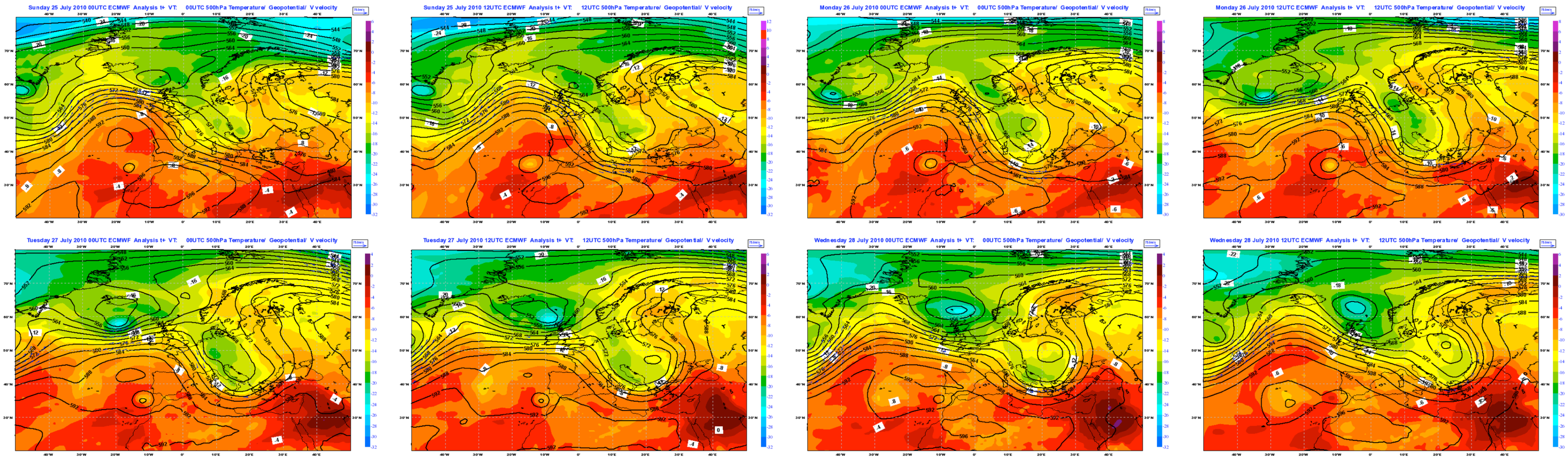
Critical points

- 1D-Var:
  - definition of the model error covariances matrix:
    at the moment a climatological B matrix has been calculated with the NMC method.
    12 hrs and 36 hrs forecasts are compared at the same nominal time. The atmospheric fileds at 12 hrs are considered as the best estimate of the real state of the atmosphere, while the 36 hrs forecasts provide an estimate of model uncertainties.
  - definition of the observation error covariance matrix R
  - definition of observation operator H:
    the link between prognostic model variables and precipitation has to be modeled employing linearized parameterization of large scale condensation and also convection. There are nevertheless large uncertainties in the various formulations of these models and inverting these relations poses fundamental problems.

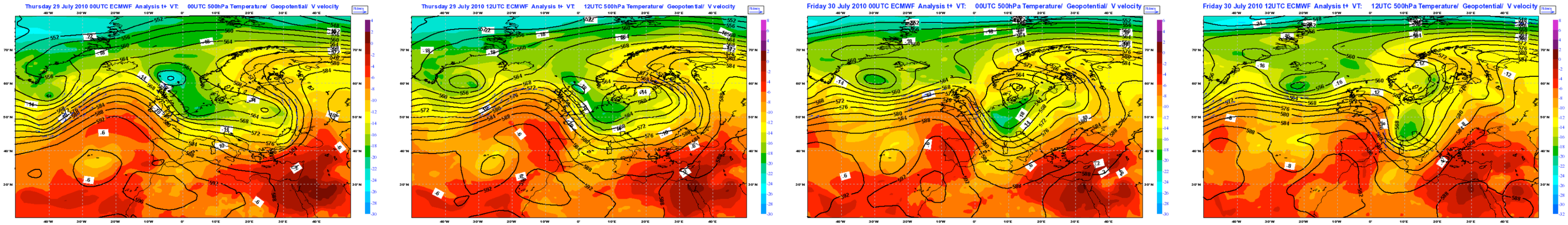
- Radar data:
  - amount of data very large (57491 profiles every 15 minutes)
  - no clever data thinning available

  ➡ Minimization made only if $|RR_{fg} - RR_{obs}| \geq 5$ mm h^{-1}

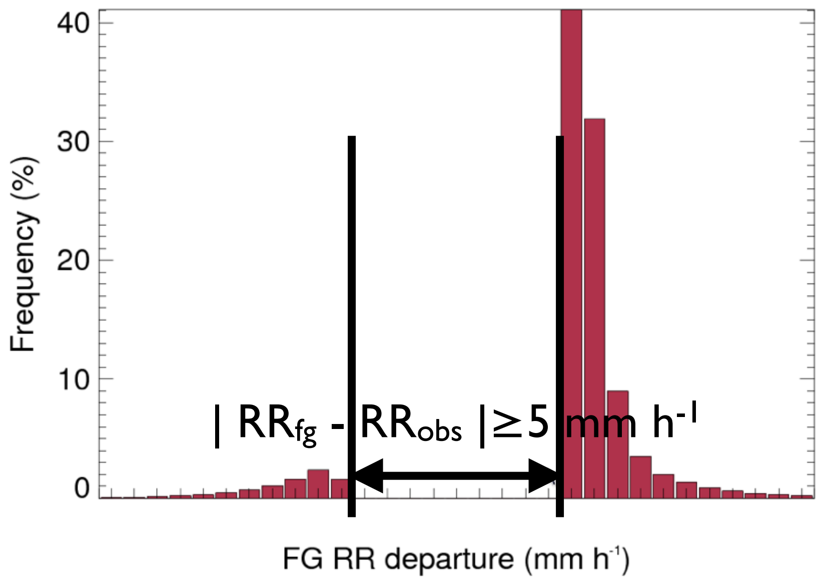
Case study



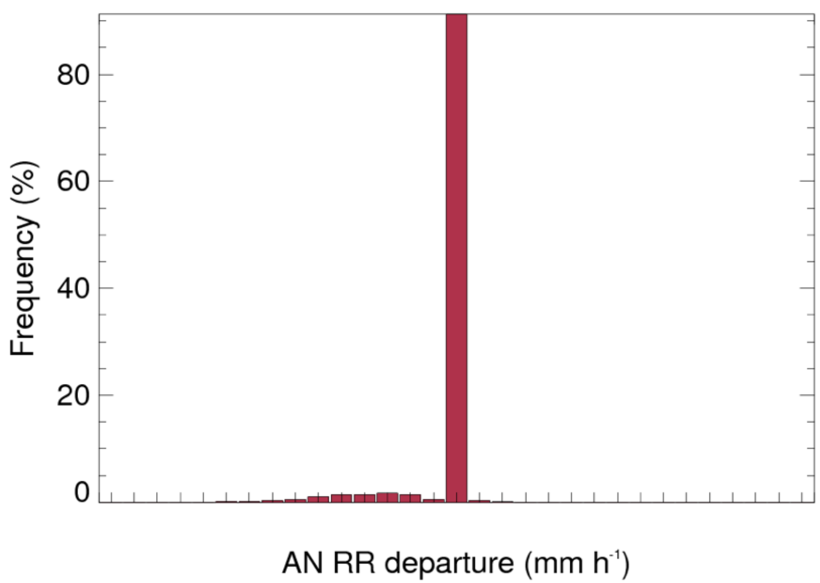
- from 25 May to 31 May 2010
- squall lines and organized convective events

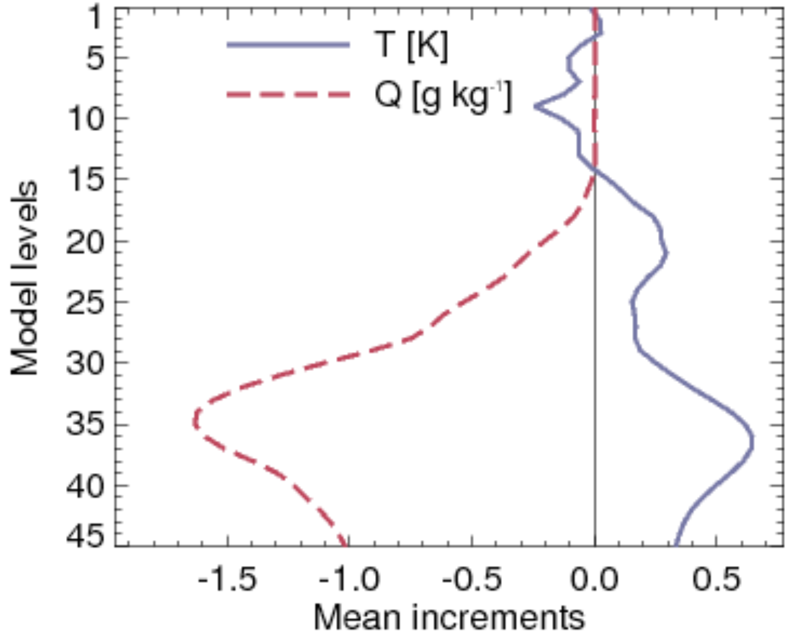


Variational assimilation: statistics on 1D-Var outputs



- On average convergency of 64% of analyzed points
- A reduction of deviation respect to the observation
- Increments in specific humidity indeed larger of those expected

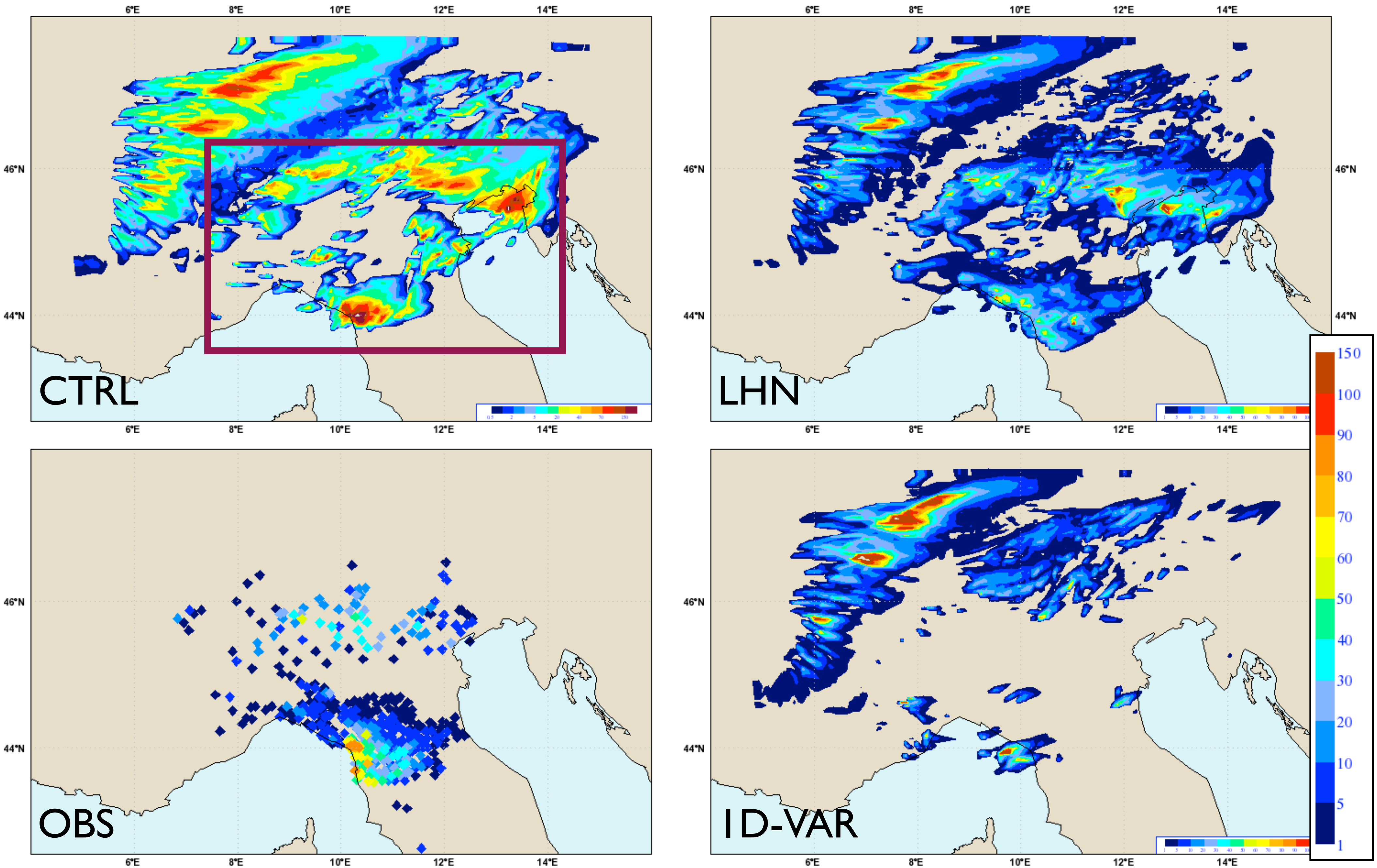




Results - Assimilation cycle - Run 00

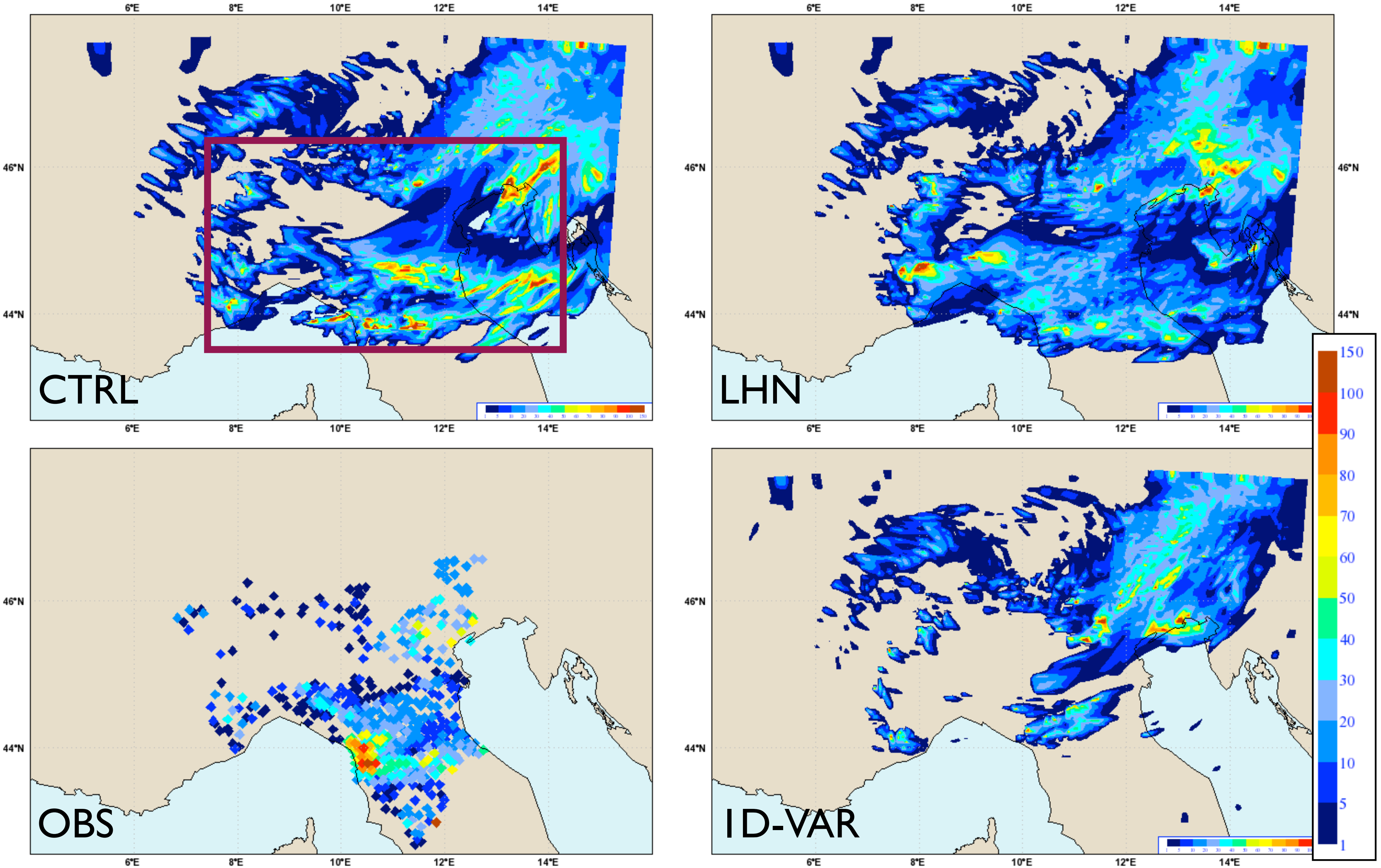
12 hrs accumulated precipitation

29 May 2010 - 00-12 UTC



Results - Assimilation cycle - Run 12

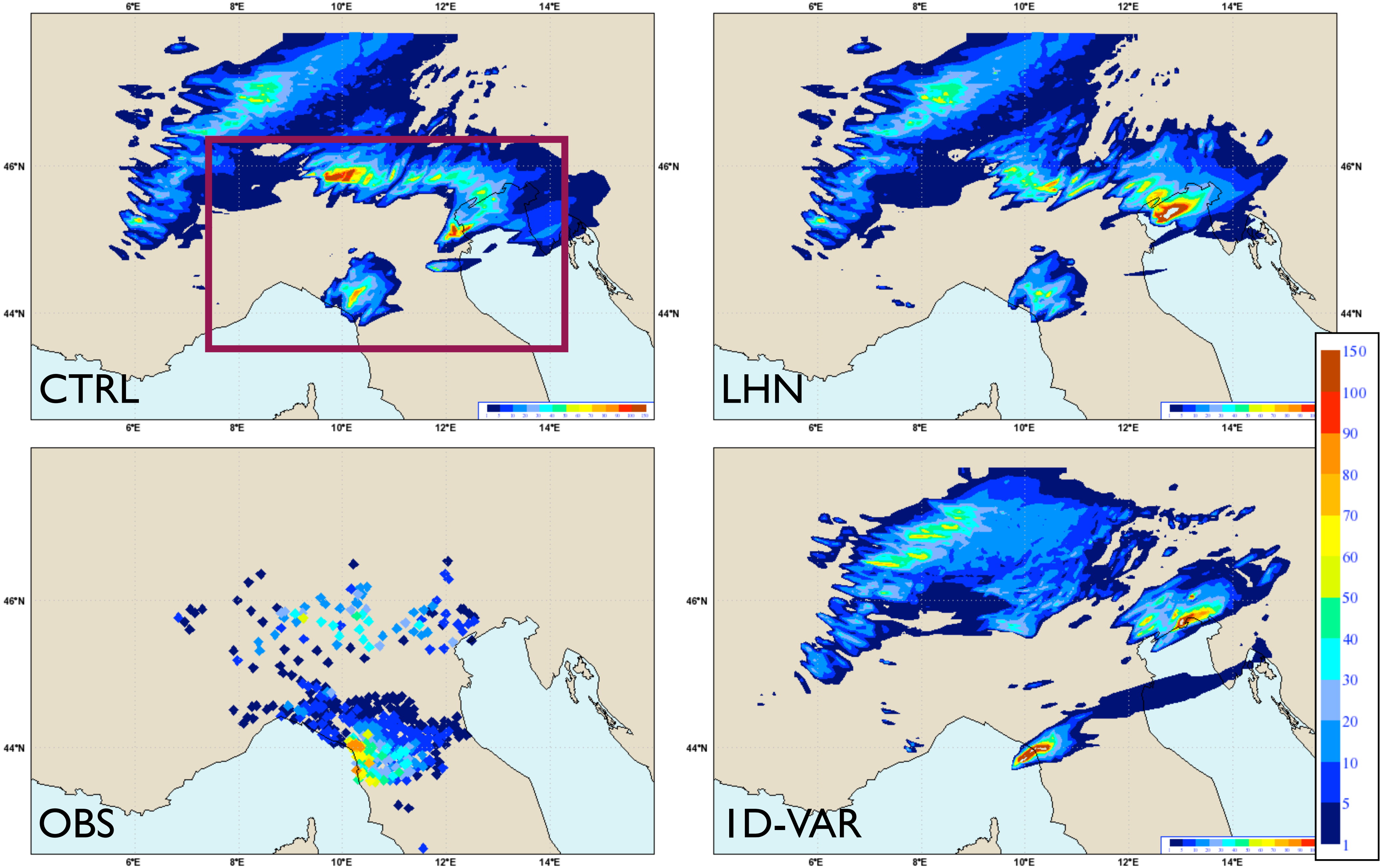
12 hrs accumulated precipitation from 29 May 2010 - 12 UTC to 30 May 2010 - 00 UTC



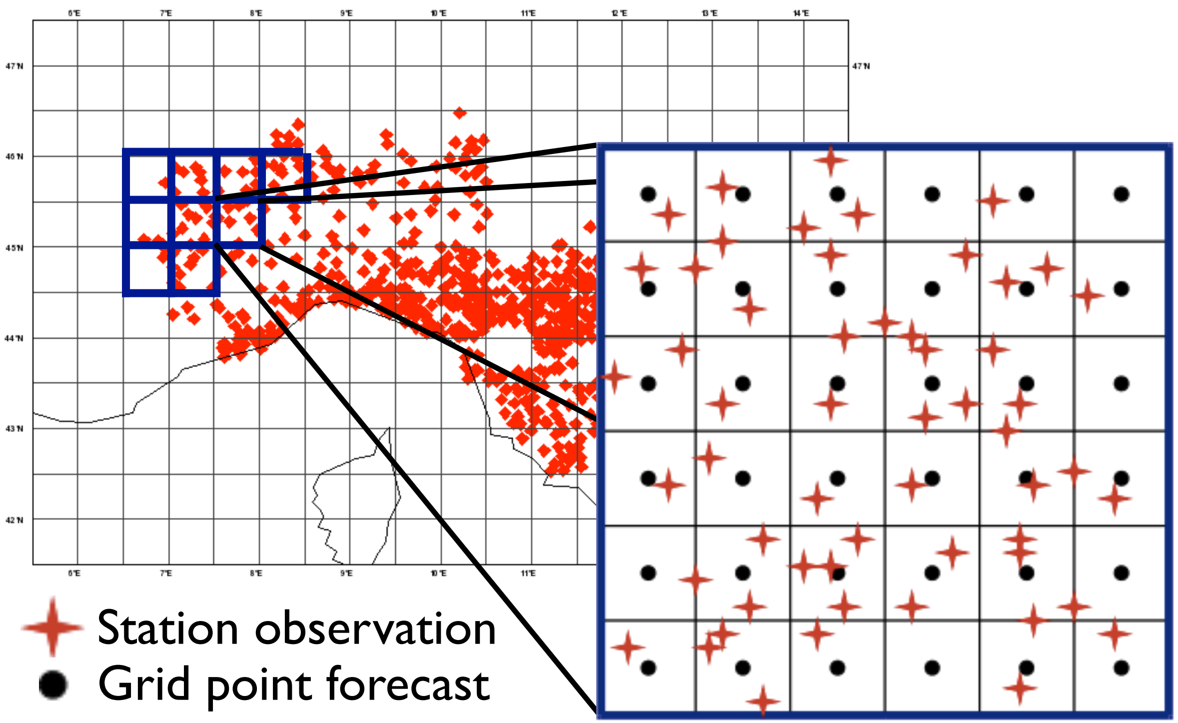
Results - Forecast cycle - Run 00

6 hrs accumulated precipitation

29 May 2010 - 6-12 UTC



Verification methodology



DISTRIBUTION

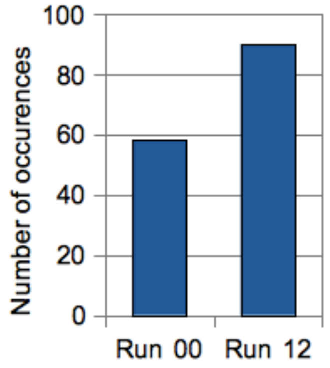
- Average value
- Maximum value

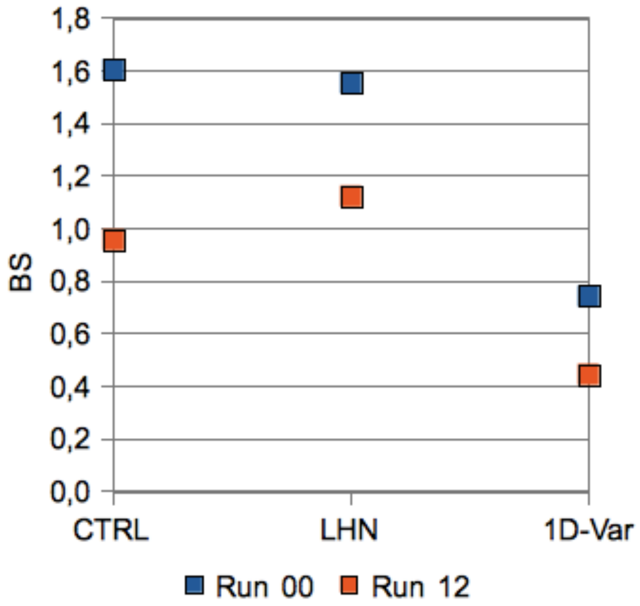
in a box

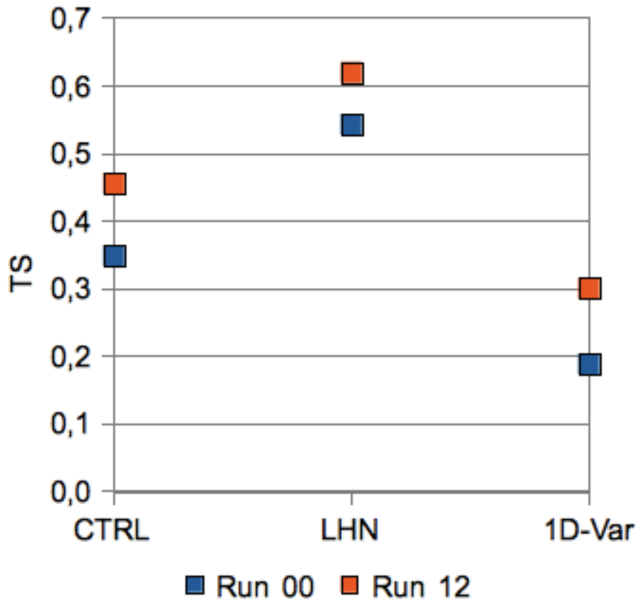
- 700 stations over north-central Italy (COSMO data-set)
- Domain covered with boxes: 0.5 X 0.5 degrees
- Precipitation accumulated over 6 and 12 hrs
- Verification of 12 hrs accumulated precipitation in the assimilation cycle
- Verification of 0-24 hrs forecast ranges
- 00 and 12 UTC runs have been compared separately

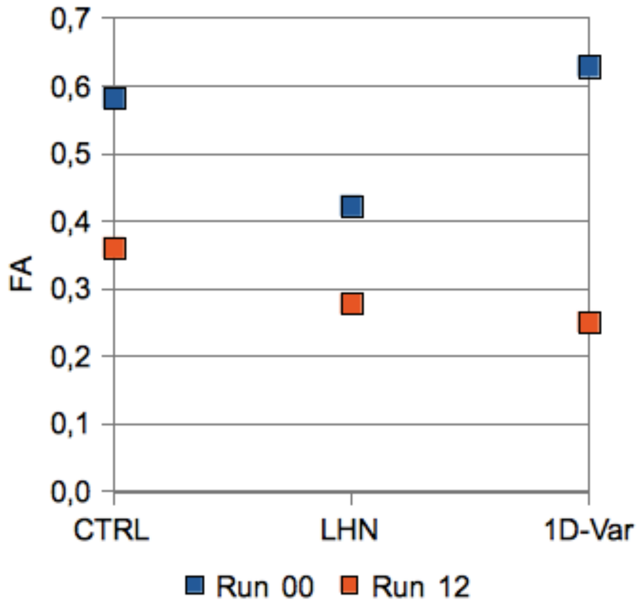
Verification scores: assimilation

Assimilation cycle
12 hrs accumulated precipitation
Average - 0.5 X 0.5 degrees
Threshold=1 mm

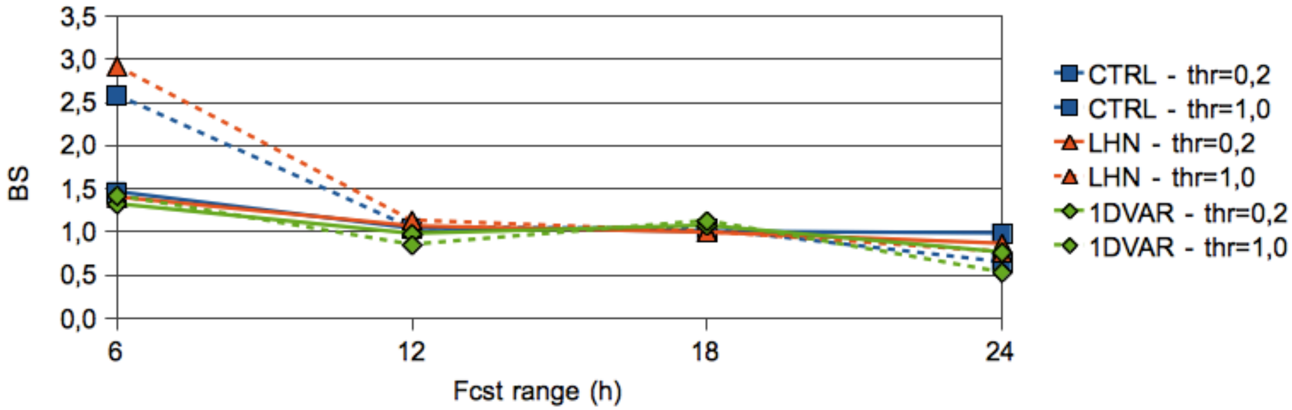


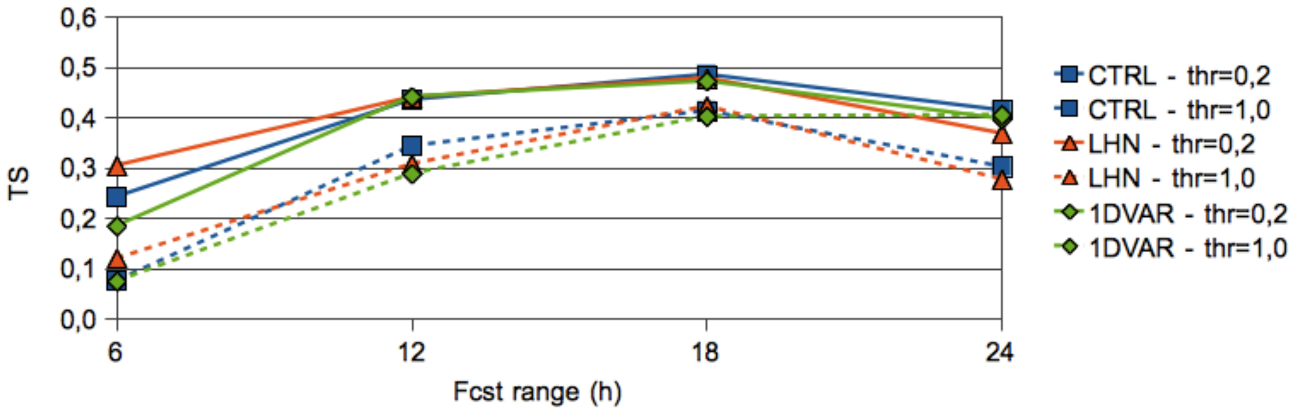


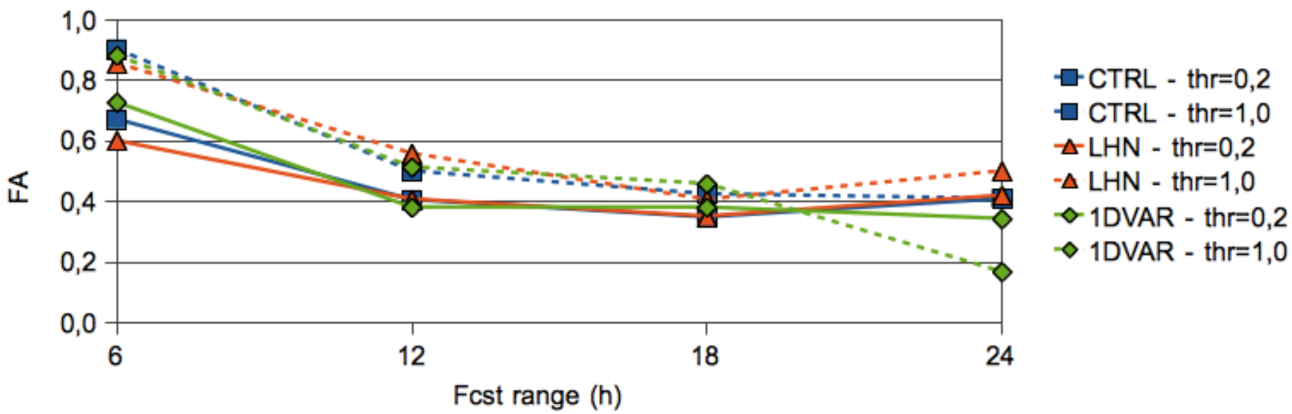


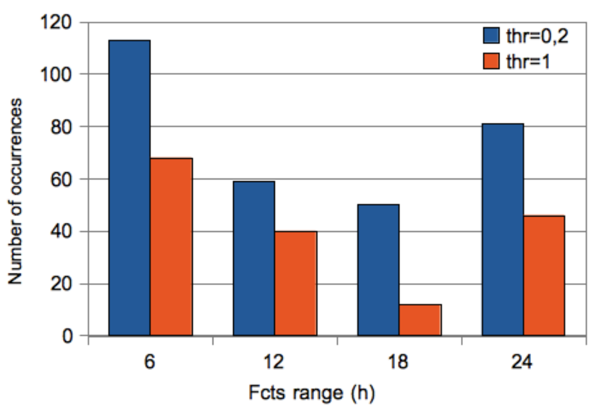


Verification scores: forecast - run 00



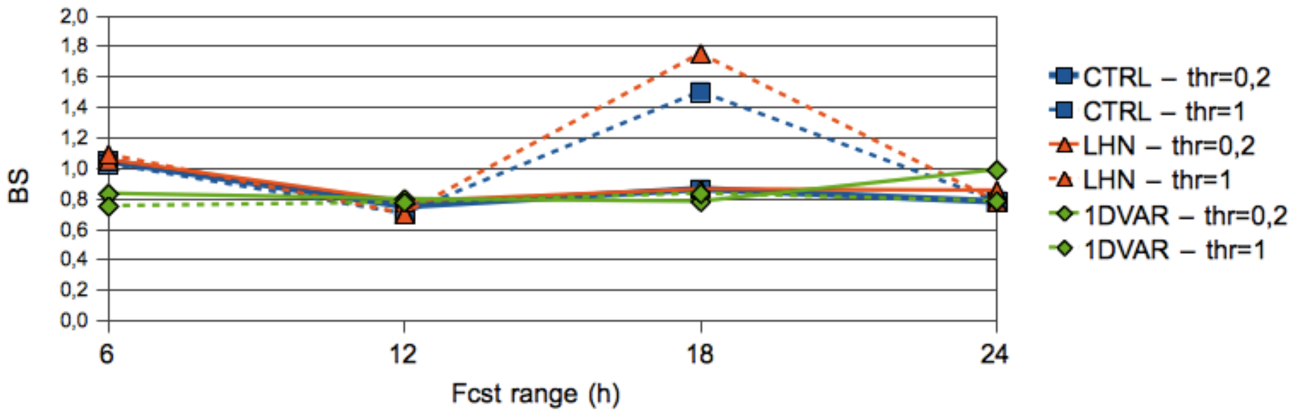


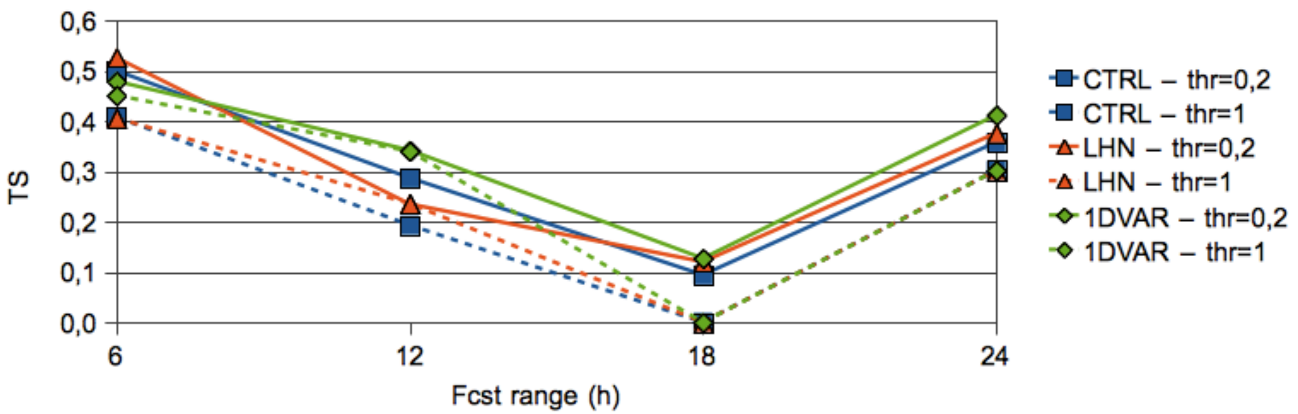


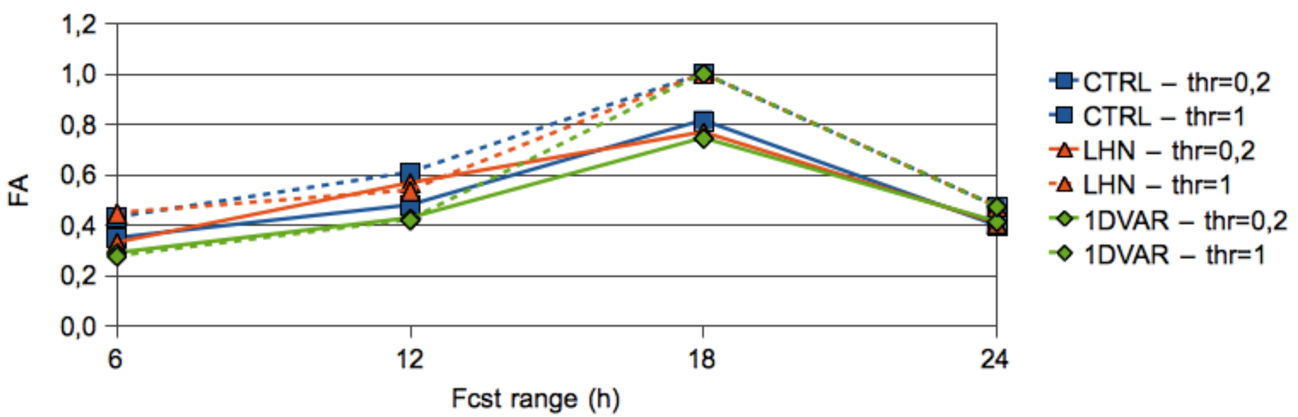


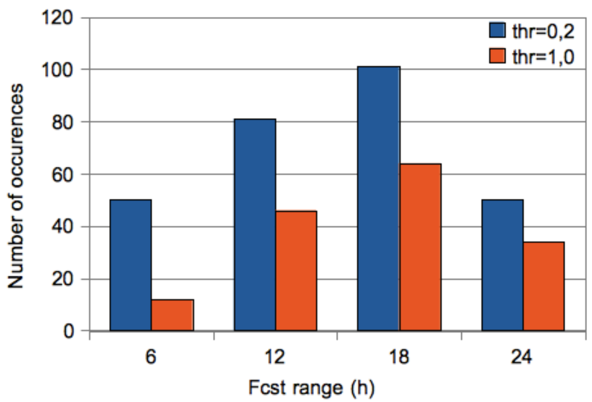
Forecast cycle - RUN 00
6 hrs accumulated precipitation
Average - 0.5 X 0.5 degrees

Verification scores: forecast - run 12









Forecast cycle - RUN 12
6 hrs accumulated precipitation
Average - 0.5 X 0.5 degrees

Conclusions and open issues

We tried to assess the supposed benefits of high resolution observations by using both a 1D-Var+nudging and a LHN approach.

The proposed methodology did not give the expected results.

Use of 1D-Var off-line

COSMO fields used as 1D-Var input are not taken out run-time. This implies:

- a double assimilation cycle
- the use of non-updated profiles

To overcome this limitation 1D-Var algorithm will be placed in an operational implementation.

Tuning of nudging coefficients

Analyzed profiles, coming from 1D-Var and nudged into COSMO, are spread in space as defined by the nudging coefficients.

Some sensitivity runs will be made to tune properly these coefficients taking care of the high resolution of observations.

Conclusions and open issues (II)

Data thinning

The use of data with very high spatial and temporal resolution should guarantee improvements in the initial condition knowledge. Moreover a spatial and/or temporal high density violates the assumption made in the most of operative models and experimental schemes in which observational errors are independent.

High density observations with correlated errors can produce a degradation of the analysis because of the potential spreading of error in correlated neighboring pixels.

- The choice of using only those points with differences between RR_{fg} and RR_{obs} greater than 5 mm h^{-1} probably goes in the wrong direction inserting a bias and highlighting the drying effect.
- It is necessary to find methods which reduce the total amount of data and which extract essential content of information preserving or even improving the quality of the analysis.

A reduction of the number of data is also necessary, in this case, to speed up the algorithm (minimization process is time consuming)

Conclusions and open issues (III)

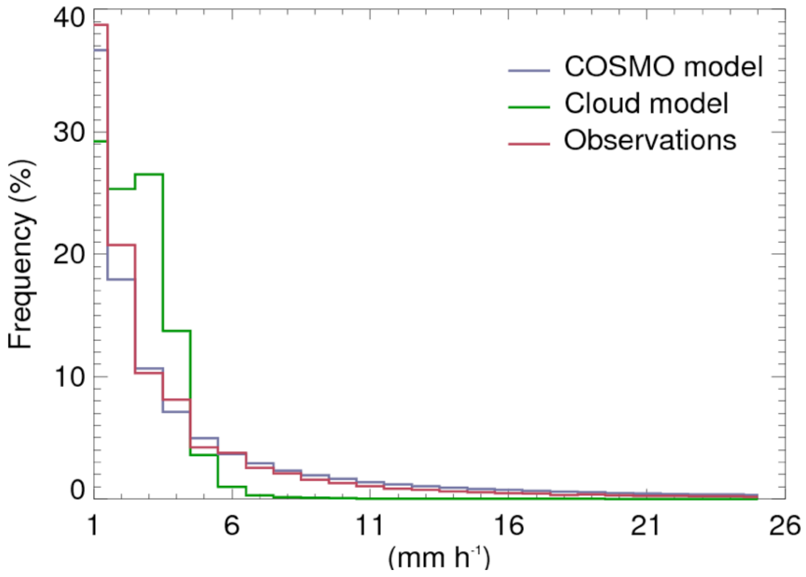
Bias removal

The variational approach works in a statistically optimal way if observations and model errors are unbiased.

In our system, the forward operator H, which is a simplified version of the cloud scheme implemented in the ECMWF forecast model, has a different physics with respect to the actual one implemented into the COSMO model.

To quantify the difference between the two models the instantaneous surface rain rate has been analyzed.

Given a set of temperature and humidity profiles the mean properties of the cloud model generated precipitation field diverges from the ones which would be produced by the COSMO model. Precipitation is not only determined by the "physical" balance of the total water contained in a 1D column but it also depends on dynamical driven processes. The simplified cloud model cannot take these effects into account.



A bias removal depending on the considered event has to be implemented.