

Overview of Data Assimilation Activities in COSMO

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current DA method: nudging

radar-derived precip:
• latent heat nudging

PP KENDA for (1 – 3) km-scale EPS:
LETKF

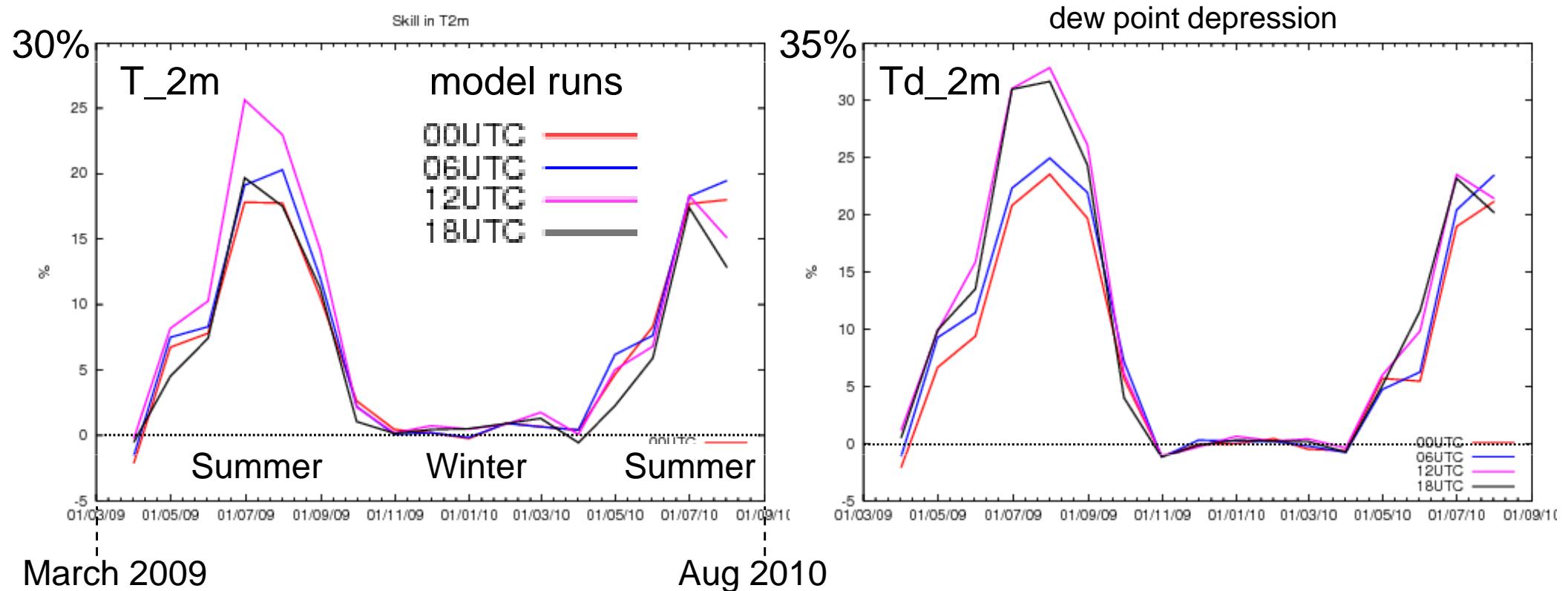
LETKF for HRM
(28 km → 10 km, opr)

Long-term impact of LHN assimilation on soil moisture ?

Experiment: 18 months (April 2009 – August 2010) COSMO-DE without LHN
→ compare with operational COSMO-DE with LHN
(COSMO-DE: no soil moisture analysis)

impact of LHN on soil moisture: impact on surface parameters

monthly relative forecast skill $(1 - \text{rmse(LHN)} / \text{rmse(noLHN)})$

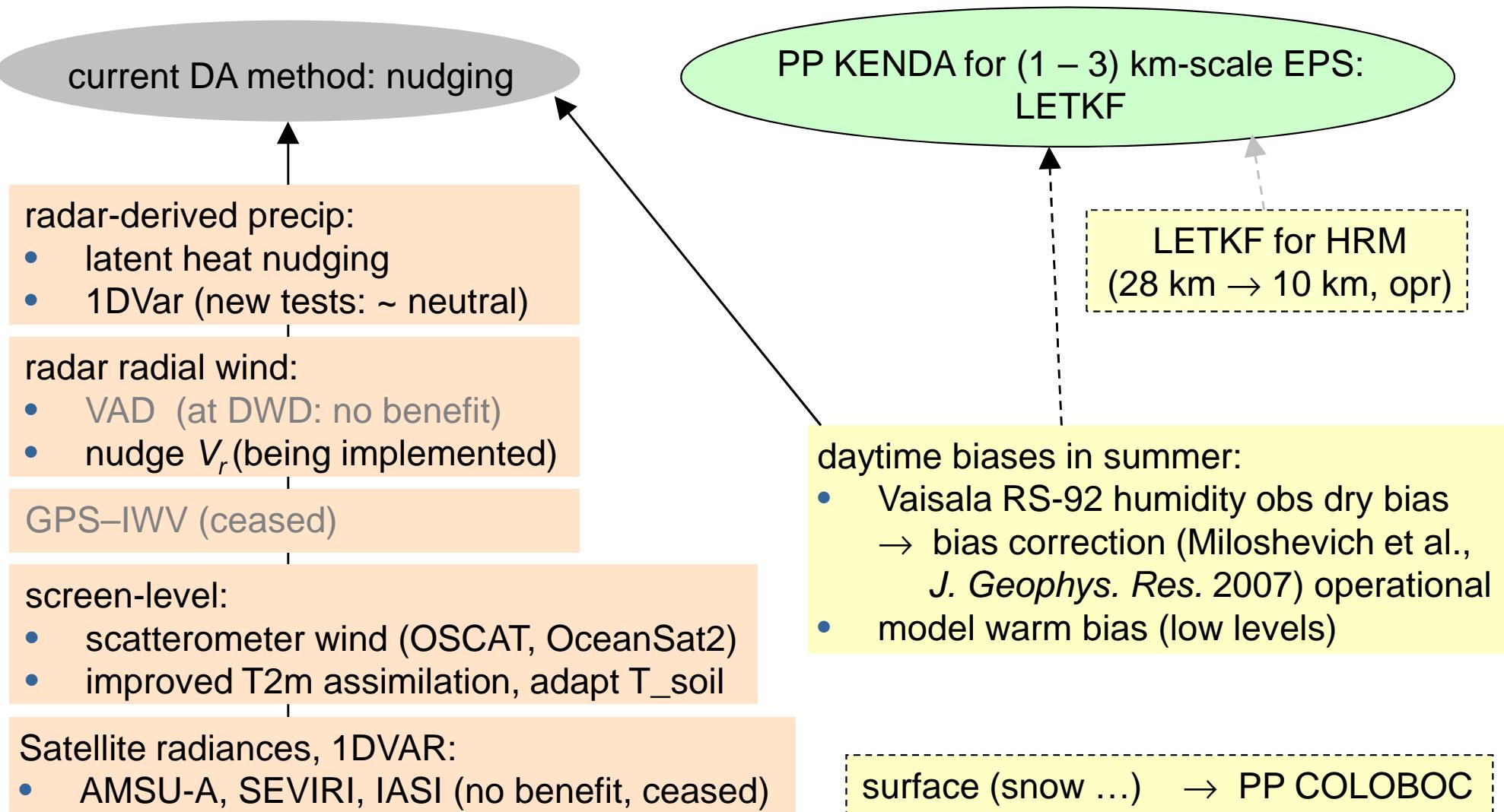


→ LHN → higher soil moisture content → improved T-2m , Td-2m forecasts,
benefit lasts over whole forecast time

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Status Overview of PP KENDA

Km-scale ENsemble-based Data Assimilation

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Contributions / input by:

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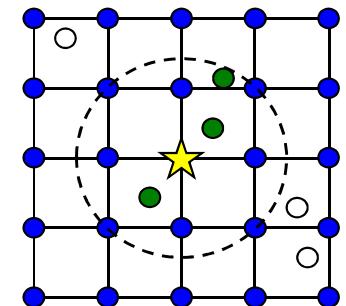
Mikhail Tsyrulnikov, Vadim Gorin (HMC)

Lucio Torrisi (CNMCA)

Amalia Iriza (NMA)

focus: development of **LETKF** (Local Ensemble Transform Kalman Filter)

- implementation following Hunt et al., 2007
- basic idea: do analysis in the space of the ensemble perturbations
 - computationally efficient, but also restricts corrections to
subspace spanned by the ensemble
 - **explicit localization** (doing separate analysis at every grid point,
select only obs in vicinity)
 - analysis ensemble members
are locally **linear combinations**
of first guess ensemble members

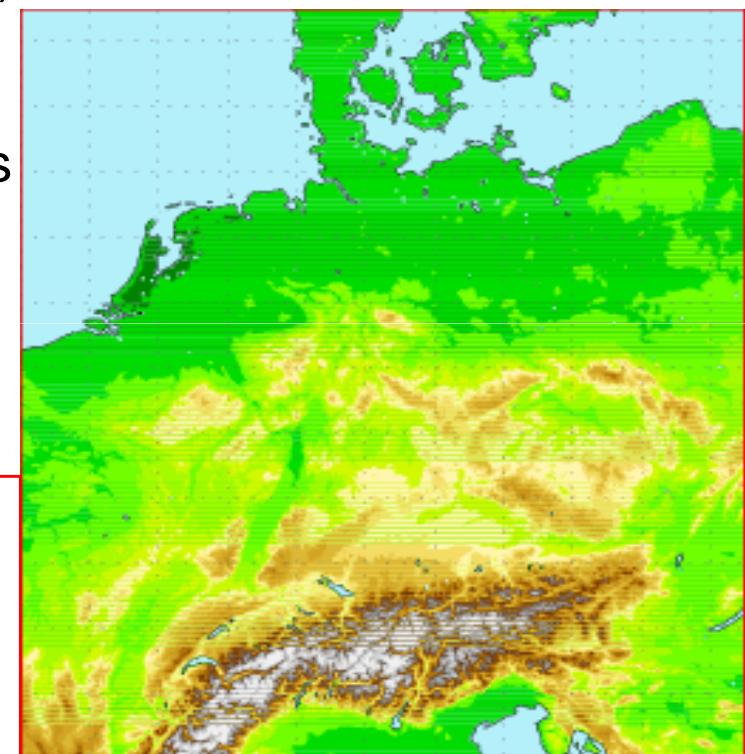


- use **conventional obs** (TEMP, AIREP, SYNOP, Wind Profiler)
- **3-hourly** cycles (and only up to 2 days: 7 – 8 Aug. 2009: quiet + convective day)
→ (near) future: 1-hourly / 30-min / 15-min cycles
- lateral (and upper) boundary conditions (BC)
 - **ensemble BC** from COSMO-SREPS (3 * 4 members),
→ future: ens. BC from global LETKF (GME/ICON)
- ensemble size: **32** (→ near future: ~ 40)
- ‘deterministic run’ verified against nudging ana / obs
(det. analysis by applying EnKF Kalman Gain
to obs increments of det. f.g.)

COSMO-DE: $\Delta x = 2.8 \text{ km}$

(deep convection explicit,
shallow convection param.)

domain size : ~ 1250 x 1150 km



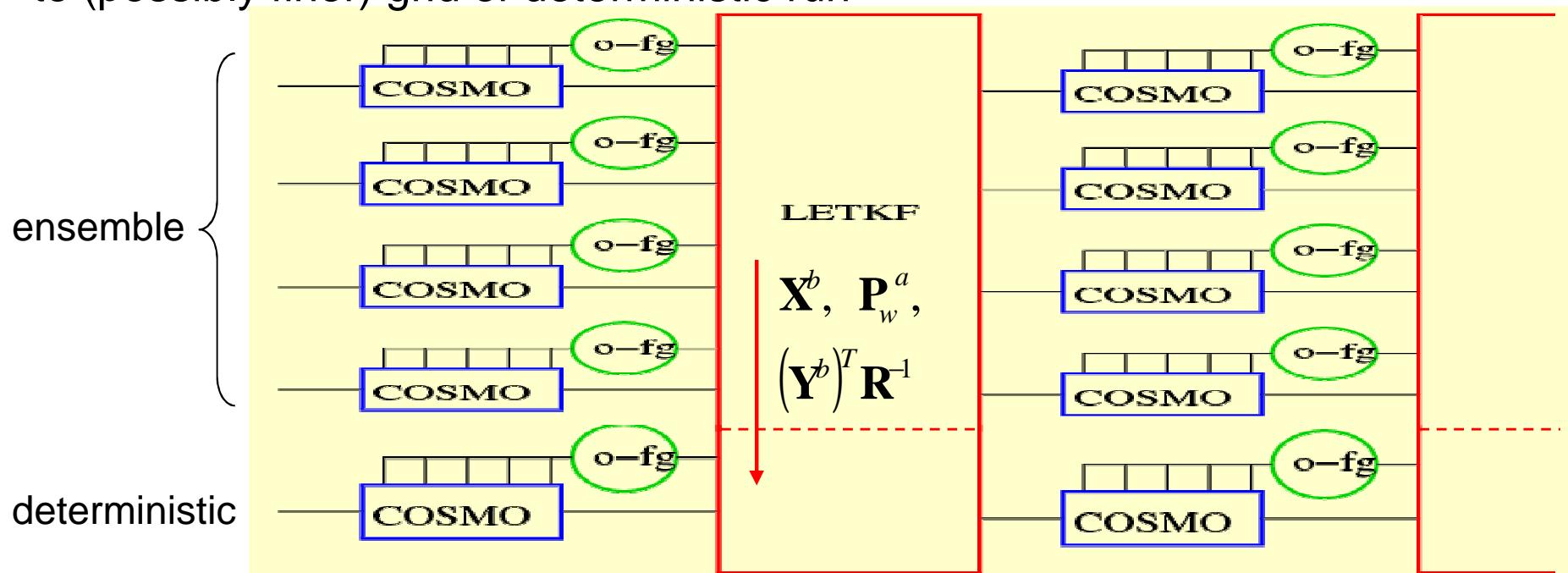
Analysis for a deterministic forecast run : use Kalman Gain \mathbf{K} of analysis mean

$$\mathbf{x}^A = \mathbf{x}^B + \mathbf{K} [\mathbf{y}^o - H(\mathbf{x}^B)] , \quad \mathbf{K} = L \mathbf{X}^b (\mathbf{P}_w^a)^{-1} (\mathbf{Y}^b)^T \mathbf{R}^{-1}$$

$$\mathbf{P}_w^a = (k-1) \mathbf{I} + (\mathbf{Y}^b)^T \mathbf{R}^{-1} \mathbf{Y}^b$$

deterministic analysis
recently implemented

L : interpolation of analysis increments from grid of LETKF ensemble
to (possibly finer) grid of deterministic run



- deterministic run must use same set of observations as the ensemble system !
- Kalman gain / analysis increments not optimal,
if deterministic background \mathbf{x}^B (strongly) deviates from ensemble mean background

- lack of spread: (partly) due to model error and limited ensemble size which is not accounted directly by the algorithm

to account for it: covariance inflation, what is needed ?

- **multiplicative** $X_b \rightarrow \rho \cdot X_b$ (tuning, or adaptive ($y - H(x) \sim R + H^T P_b H$))
- **additive** : perturbing the NWP model
 - fixed perturbations of model physics parameters : no
 - stochastic physics (being implemented, Torrisi CNMCA)
 - statistical 3DVAR-B → hybrid schemes !
 - additive inflation which reflects model error as estimated by statistics (comparing forecast tendencies with observed tendencies, Gorin & Tsyrulnikov)

- **adaptive multiplicative** covariance inflation ρ :
 - compare ‘observed’ quantities (errors) with ‘expected’ ones:
(Desroziers et al., QJRMS 2005; Li et al., QJRMS 2009)

$$\begin{aligned}
 1. \quad & \langle (y - H(x_b))(y - H(x_b))^T \rangle = \mathbf{R} + \rho \mathbf{H} \mathbf{P}_b \mathbf{H}^T \\
 2. \quad & \langle (H(x_a) - H(x_b))(y - H(x_b))^T \rangle = \rho \mathbf{H} \mathbf{P}_b \mathbf{H}^T
 \end{aligned}$$

aim: satisfy statistics

problem: 1. depends heavily on \mathbf{R} , 2. found to give too small values ρ

- relaxation to prior spread (RTPS) :
(Whitaker et al., 2010)

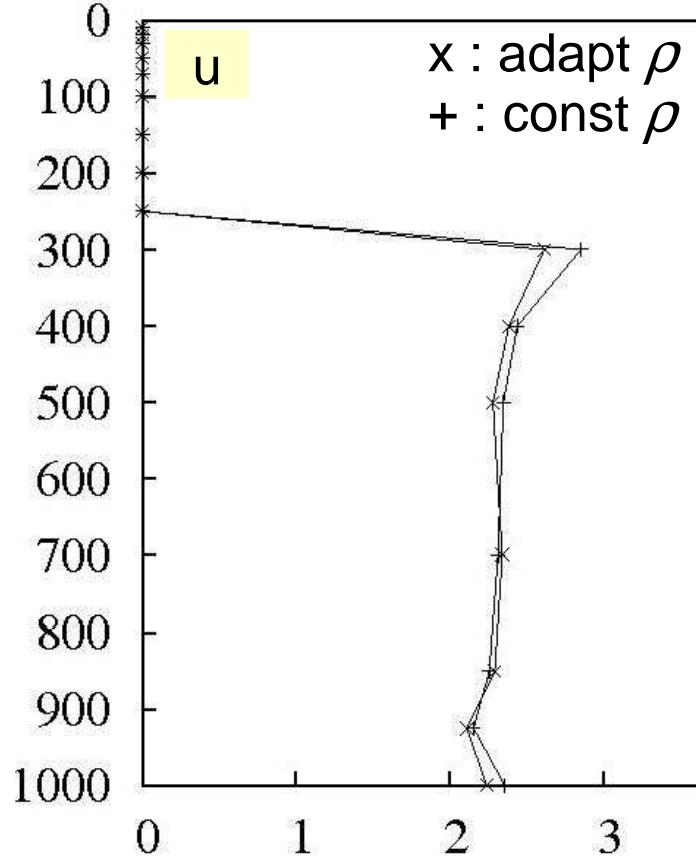
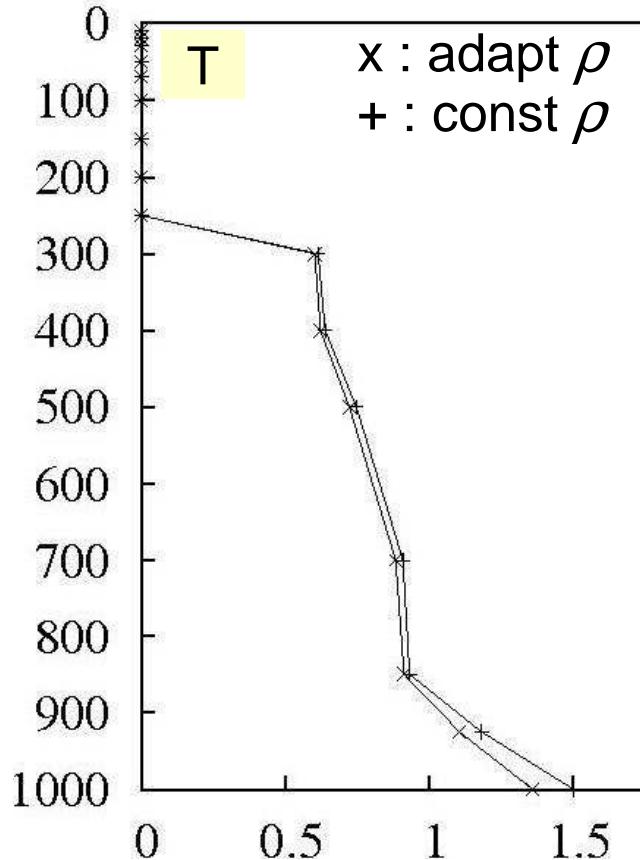
$$\rho = \sqrt{\alpha \frac{\sigma_b - \sigma_a}{\sigma_a}} + 1, \quad \alpha \leq 1$$

aim: compensate reduction of spread due to assimilation of obs

potential problem: long-term drift ; implemented in ensemble space
instead of model space → ρ too small

adaptive covariance inflation ρ , by statistical method

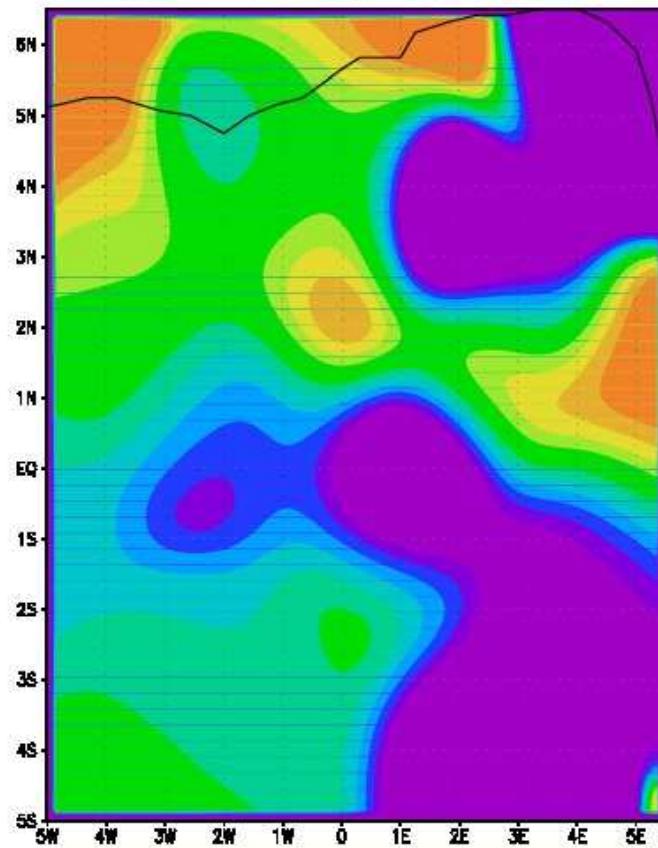
f.g. rmse against AMDAR



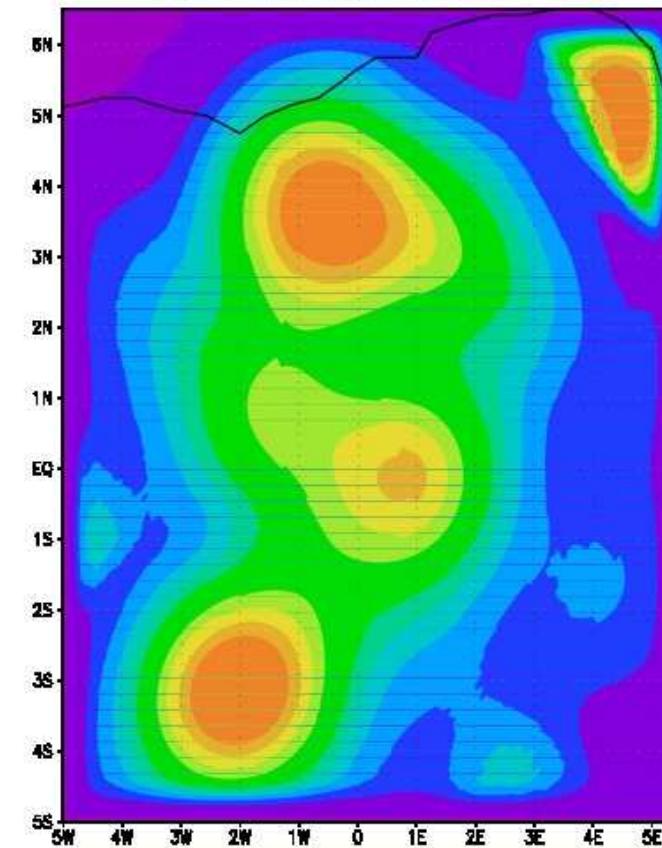
- rmse : slight positive impact
- spread : increased

adaptive covariance inflation ρ

statistical method 1. (obs space)



relaxation method (ens space)



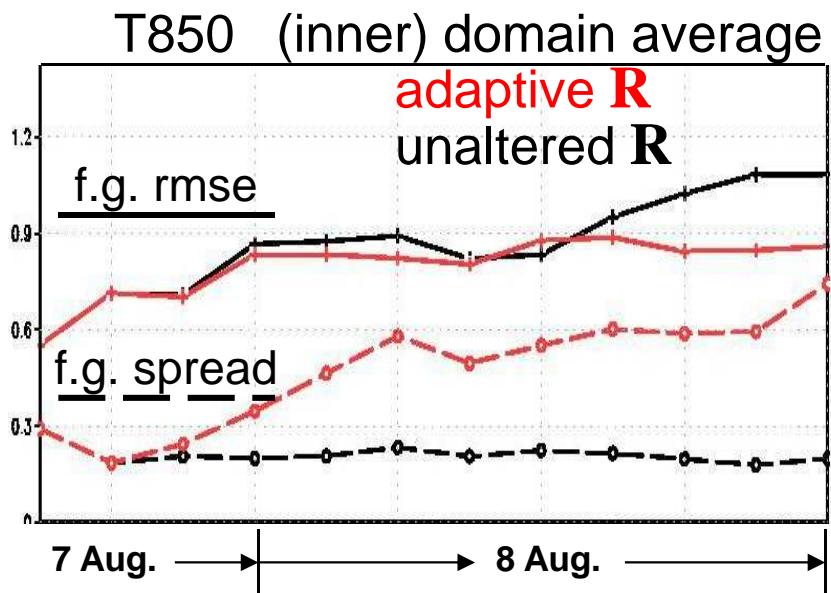
- very different spatial patterns of ρ
- similar results (area avg. rmse / spread), preliminary !

- adaptive estimation of obs error covariance \mathbf{R}
(Li, Kalnay, Miyoshi, QJRMS 2009) , but our implementation: in ensemble space !

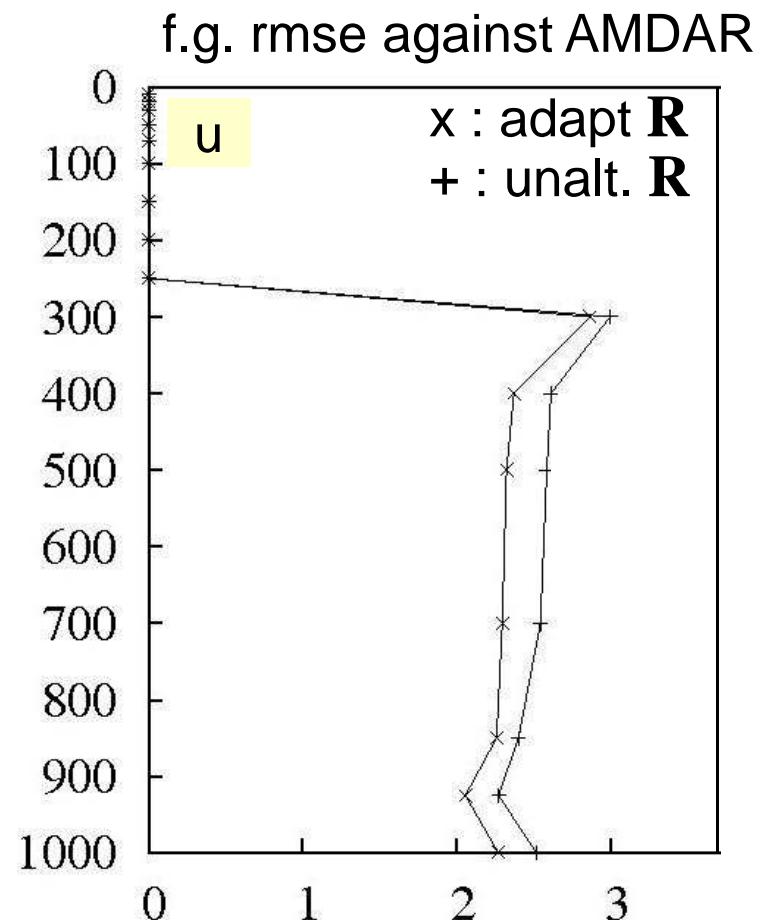
add obs, if already $N_{obs} > N_{ens}$:

- cannot be fitted well, improve analysis only slightly
(rank deficiency problem)
 - decreases analysis error !
- $$\mathbf{P}_w^a = \left[(k-1) \mathbf{I} + (\mathbf{Y}^b)^T \mathbf{R}^{-1} \mathbf{Y}^b \right]^{-1}$$
- adaptive \mathbf{R} in ensemble space takes rank deficiency problem into account and increases \mathbf{R}

adaptive obs error covariance \mathbf{R}

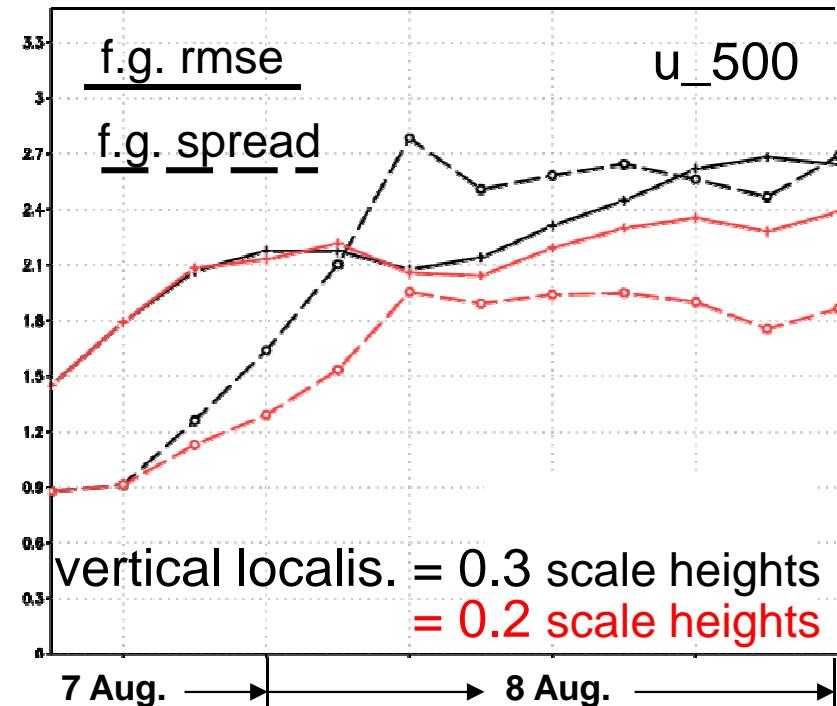


(exp. done with 'old setting'
for pre-specified \mathbf{R})



- rmse : positive impact in most levels / variables
- spread : strongly increased

- adaptive methods important when N_{obs} large
(strongly increasing N_{obs} degraded results, if previous setting used !)
- need to optimise setup of adaptive methods :
 - + need for careful specification / tuning of obs errors
 - large N_{obs} : adaptive increase of \mathbf{R} indicates non-optimal use of obs
- localisation !

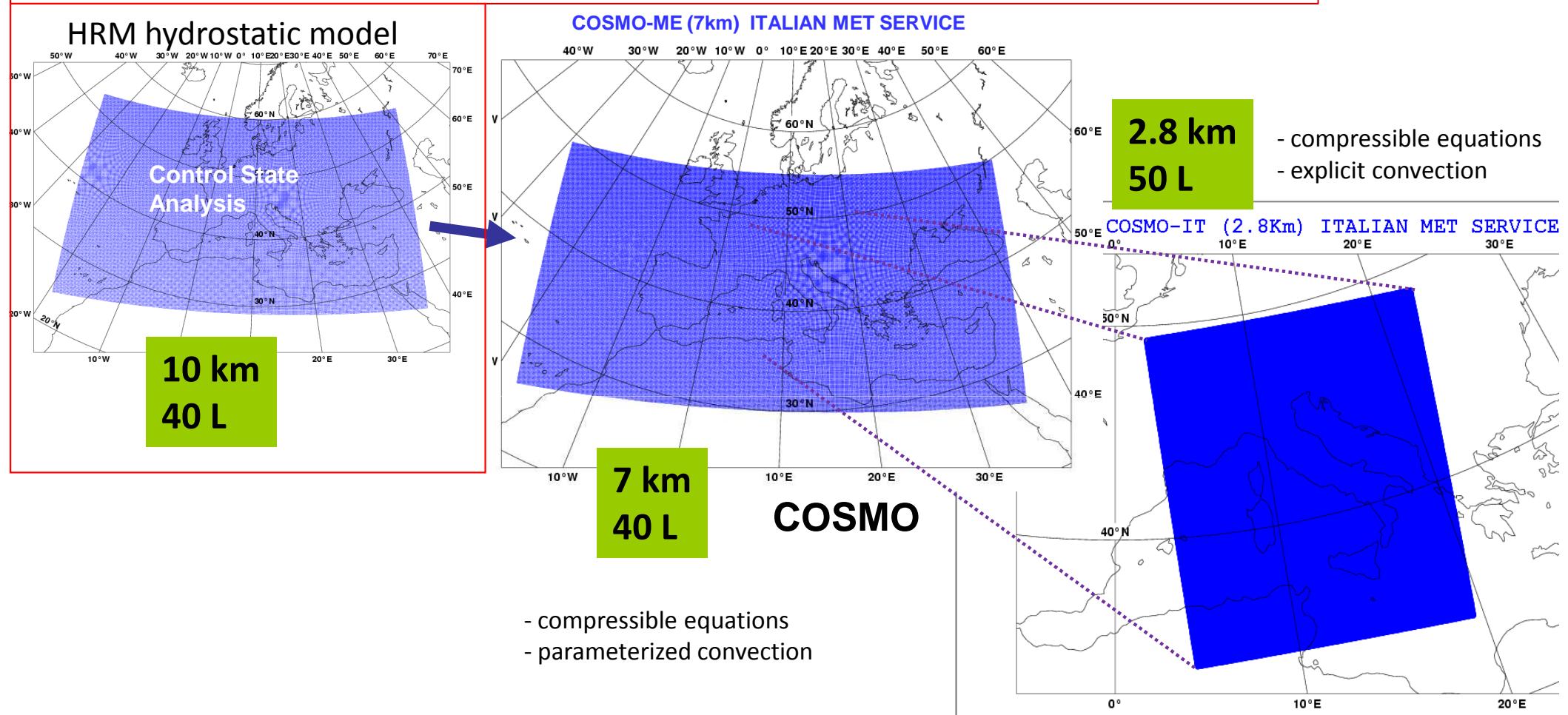


- **localisation** (multi-scale data assimilation,
successive LETKF steps with different obs / localisation ?
adaptive , dep. on obs density ?)
- **update frequency** $\Delta_a t$? $1 \text{ hr} \geq \Delta_a t \geq 15 \text{ min}$
non-linearity vs. noise / lack of spread / 4D property ?
- perturbed lateral BC , noise control ?
- non-linear aspects, convection initiation (outer loop , (latent heat nudging) ?)
- (technical aspects: efficiency, system robustness)

LETKF (km-scale COSMO) : some important observations at km scale

- **radar : direct 3-D radial velocity & 3-D reflectivity**
sufficiently accurate and efficient observation operators soon available
- **ground-based GPS slant path delay** (start Jan. 2012)
direct use in LETKF, or tomography
- **cloud information based on SEVIRI and conventional data**
(Annika.Schomburg@dwd.de , DWD / Eumetsat, start 2011-03)

LETKF analysis ensemble (40 members) every 6h
 using TEMP, PILOT, SYNOP, SHIP, BUOY, Wind Profiler, AMDAR-ACAR-AIREP,
 MSG AMV, METOP/ERS2 scatt. winds (soon: NOAA/METOP AMSUA radiances)
 + Land SAF snow mask, IFS SST analysis once a day



CNMCA LETKF: covariance inflation

In the CNMCA LETKF implementation, model errors and sampling errors are taken into account using:

- state dependent **multiplicative** inflation according to Whitaker et al (2010)

ana. perturb. $\mathbf{x}'_a = \mathbf{x}'_a \sqrt{\alpha \frac{\sigma_b^2 - \sigma_a^2}{\sigma_a^2} + 1}$

$\alpha = 0.95$
 $\sigma^2 = \text{variance}$

- climatological **additive** noise

ana. member $\mathbf{x}_i^a \leftarrow \mathbf{x}_i^a + \alpha \mathbf{x}_i^n, \quad \alpha \mathbf{x}_i^n \sim N(0, \mathbf{Q})$ α : scale factor

\mathbf{x}_i^n randomly selected, 48-24h forecast differences

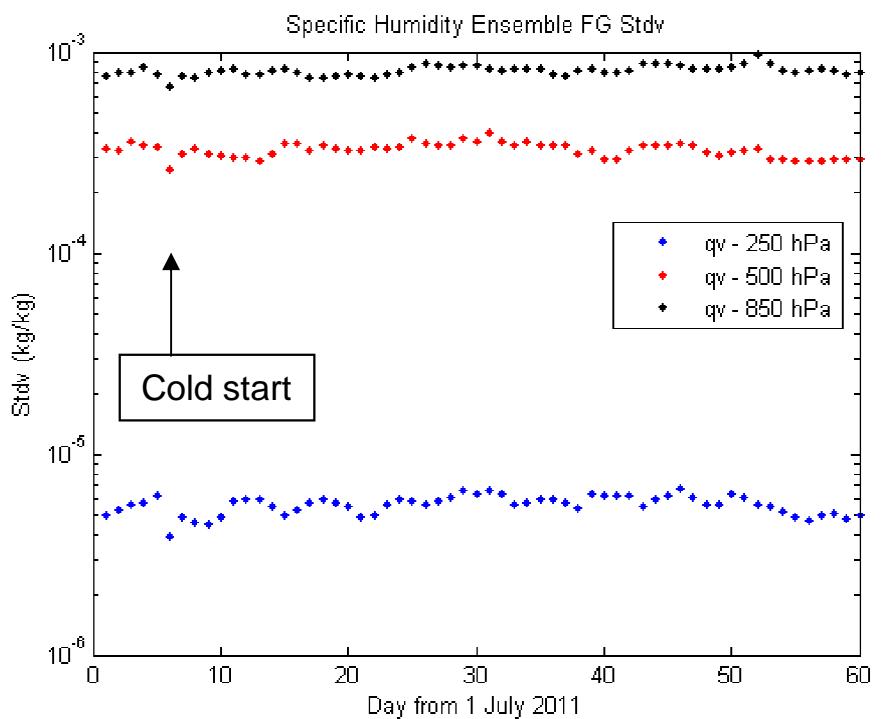
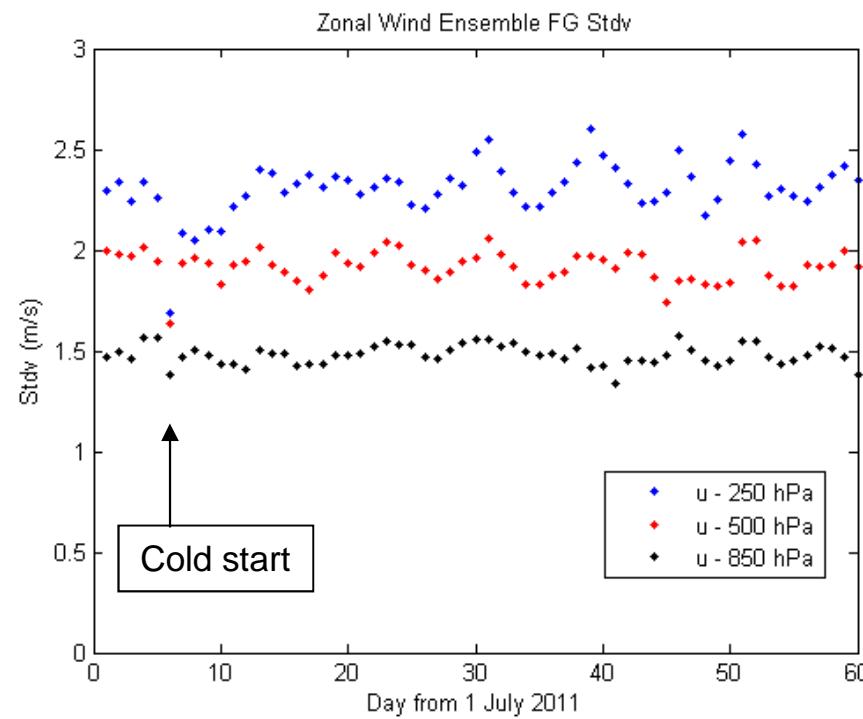
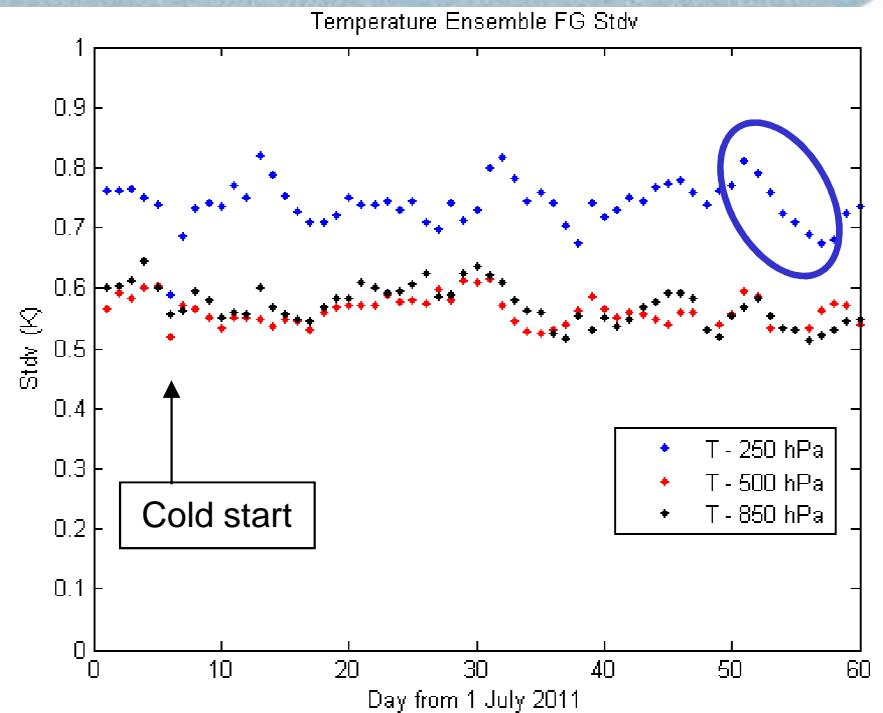
- lateral boundary condition perturbation using EPS
- climatologic perturbed SST



CNMCA LETKF:

time series (60 days, 0 UTC) of ensemble background spread

→ spread remains stable



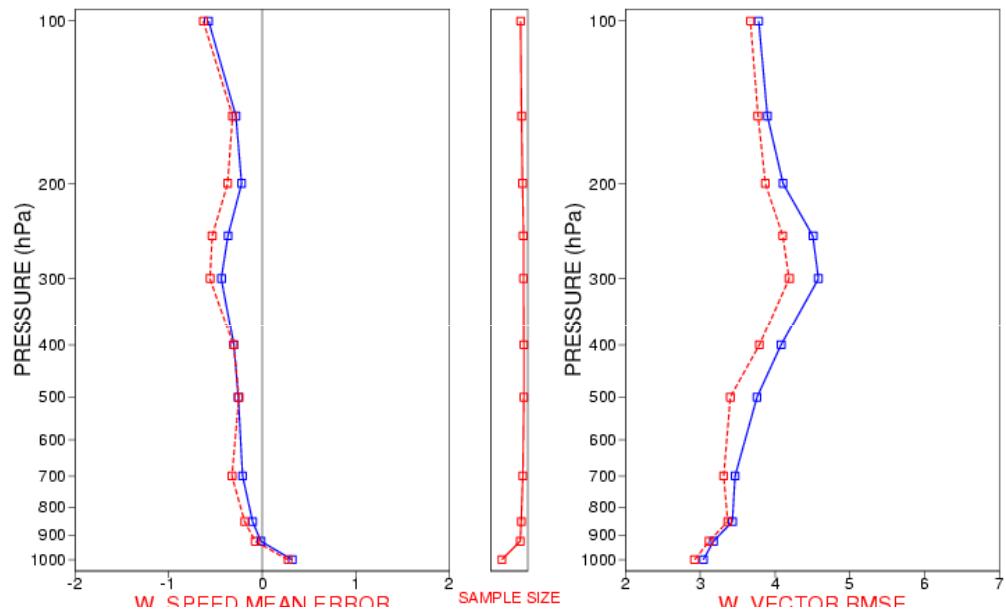


CNMCA LETKF

comparison of forecasts from interpolated
LETKF (10 km) vs. 3DVAR (14 km)
analyses

can we improve on our operational 3DVar
without the complications of 4DVar ?
→ yes !

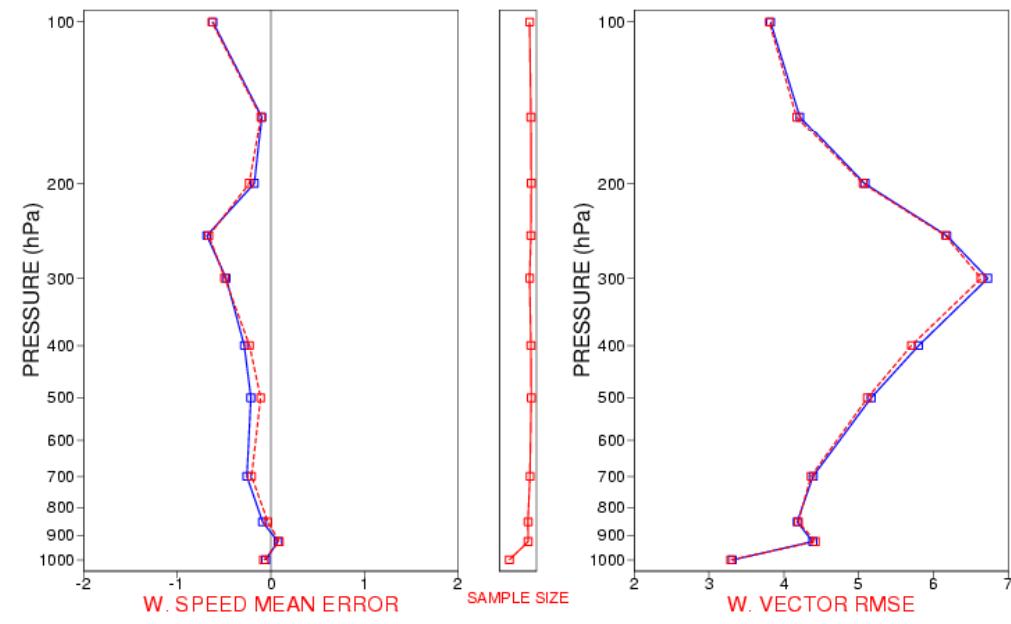
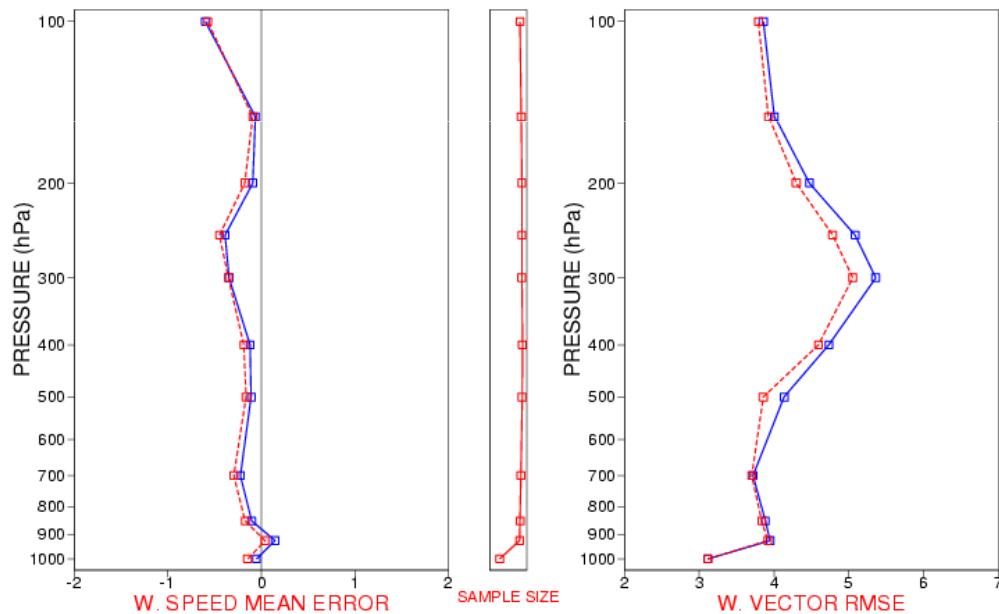
WIND (m/s) 00 UTC FC + 12 h
Verification from 04/04/11 to 03/05/11
COSMO-ME_3DV: Blue COSMO-ME_LETKF: Red



WIND (m/s) 00 UTC FC + 24 h
Verification from 04/04/11 to 03/05/11
COSMO-ME_3DV: Blue COSMO-ME_LETKF: Red

European stations
April and May 2011

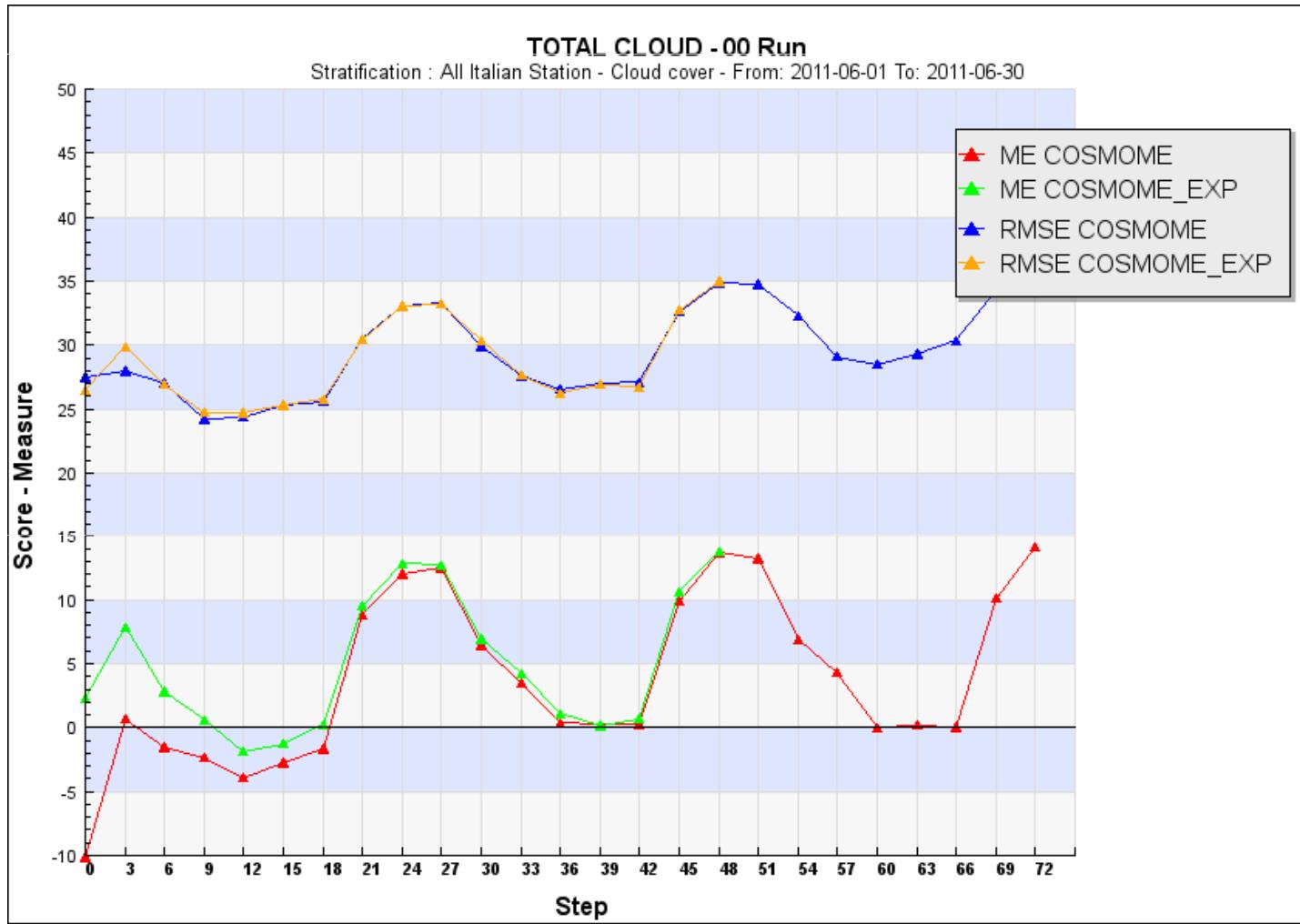
WIND (m/s) 00 UTC FC + 48 h
Verification from 04/04/11 to 03/05/11
COSMO-ME_3DV: Blue COSMO-ME_LETKF: Red





CNMCA LETKF

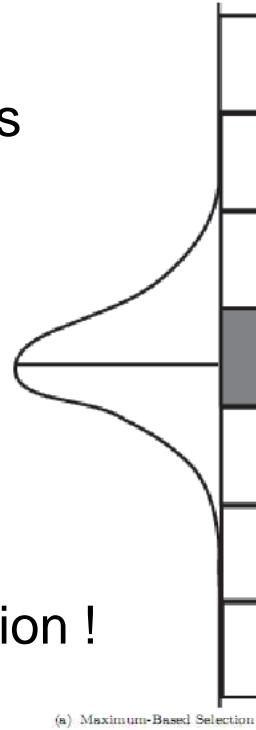
comparison of forecasts starting from
deterministic analysis (control) vs. ensemble mean analysis
→ spin-up





CNMCA LETKF : impact of AMSU-A radiances (EURO-HRM, 28 km)

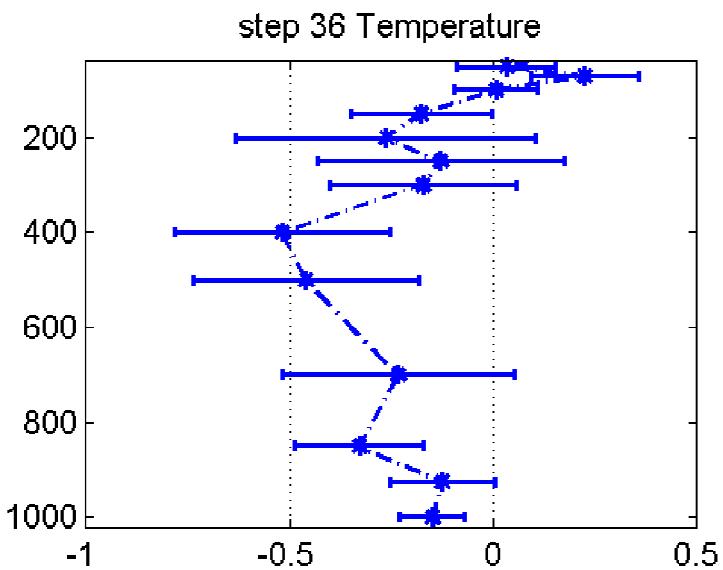
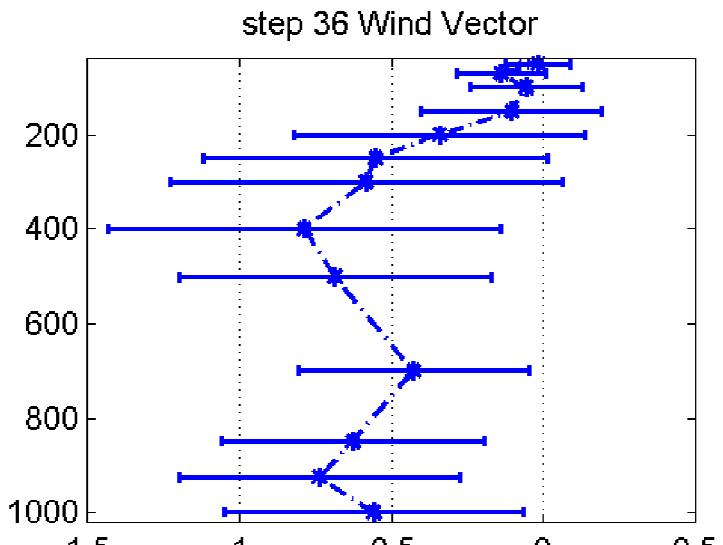
- AMSU-A treated as “single-level” obs
- assign radiance obs model level for which magnitude of weighting function (wf) is largest (maximum-based selection, Fertig et al., 2007)
- Use wf shape as vertical covariance localization function !



(a) Maximum-Based Selection

00 UTC
EuroHRM runs
(28km)
11-10 to 10-11-2009

relative difference (%) in RMSE
computed against IFS analysis





CNMCA LETKF

- as far as we know, CNMCA is the first meteorological centre which uses operationally a pure ensemble DA (LETKF) to initialize a deterministic NWP model (COSMO-ME)
- deterministic forecast started from 'det. analysis' (not ensemble mean ana.)
- AMSU-A improves LETKF analysis (28 km, large domain !)

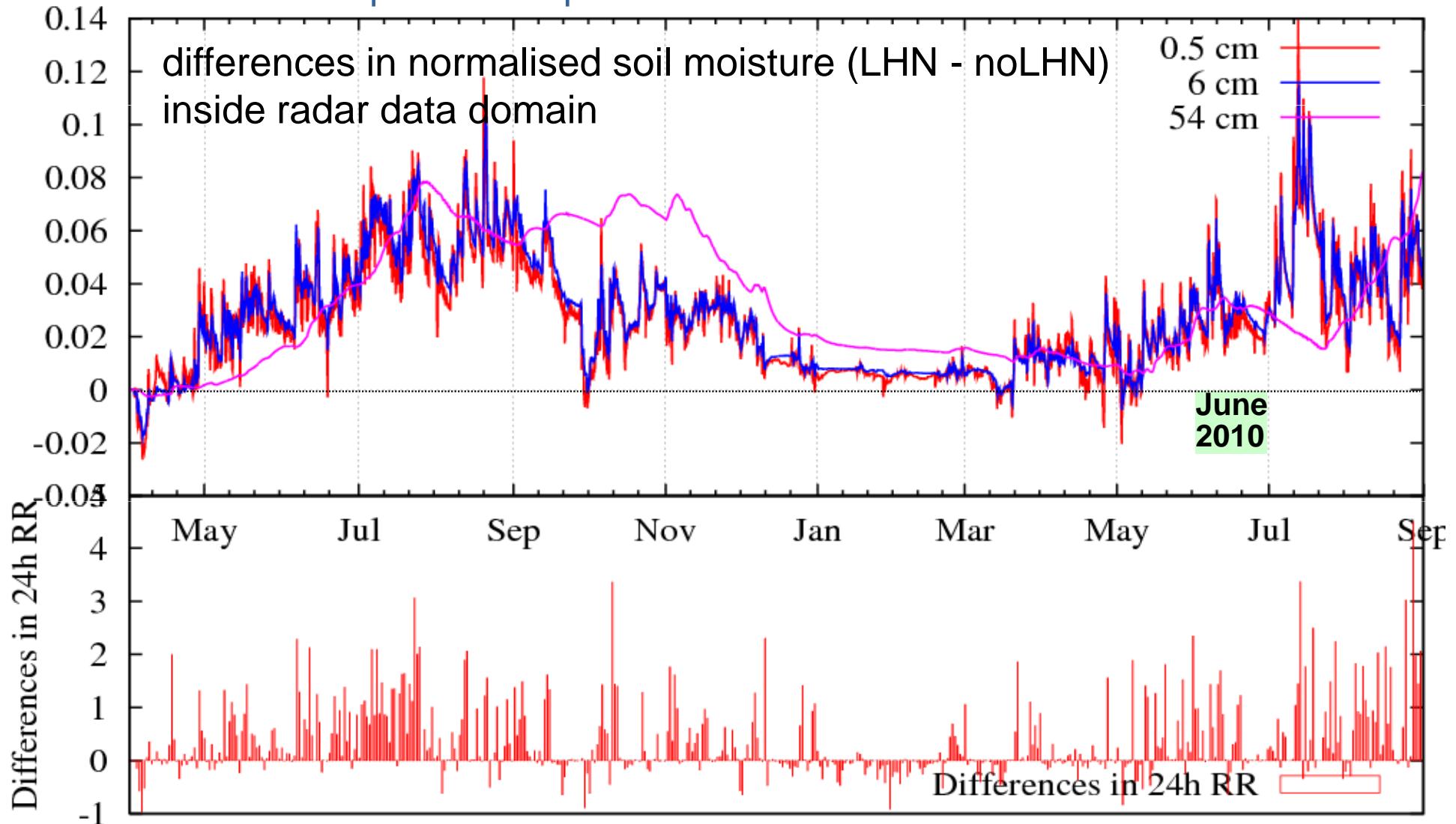
outlook

- AMSU-B/MHS and IASI retrievals: investigate soon
- balancing and non-linearities to be addressed (outer loop / RIP not beneficial)
- further tuning of model error representation
(tuning of cov. localization, evolved additive noise, bias correction, etc.)
- tests with COSMO
- implement short-range EPS based on LETKF

thank you for your attention

- **objective estimation and modelling of model (tendency) errors**
(not to be confused with forecast errors)
M. Tsyrulnikov, V. Gorin (HMC Russia)
 1. set up a (revised) stochastic model (parameterisation) for model error (ME)
MEM : $e = \mu * F_{phys}(\mathbf{x}) + e_{add}$
 - involves stochastic physics ($\mu * F_{phys}(\mathbf{x})$) and additive components e_{add} and includes multi-variate and spatio-temporal aspects
 - model error model parameters: $(E(\mu), D(\mu), D(e_{add}))$
 2. develop MEM **Estimator** : estimate parameters by fitting to statistics from real forecast (COSMO-RU-14) and observation (radiosonde) tendency data, using a revised (maximum likelihood based) method (tested using bootstrap)
 3. develop ME **Generator** embedded in COSMO code
 4. develop MEM **Validator**: exactly known ME in OSSE set-up, retrieve with MEM Estimator
→ The reproducibility of the MEM parameters is not yet established !

Experiment: 18 months (April 2009 – August 2010) COSMO-DE without LHN
 → compare with operational COSMO-DE with LHN



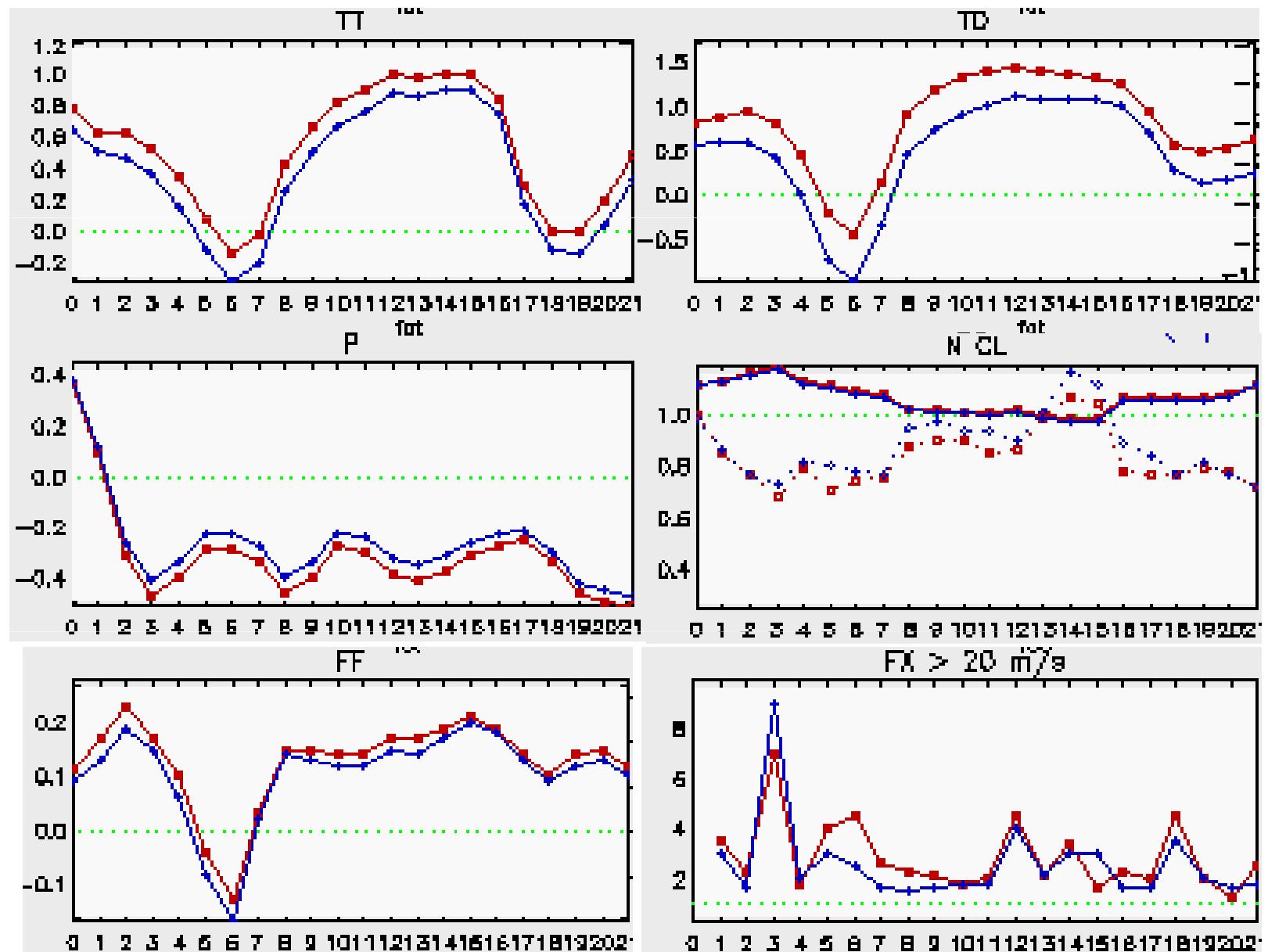
impact of LHN on soil moisture: impact on surface parameters

June 2010,
12 UTC runs

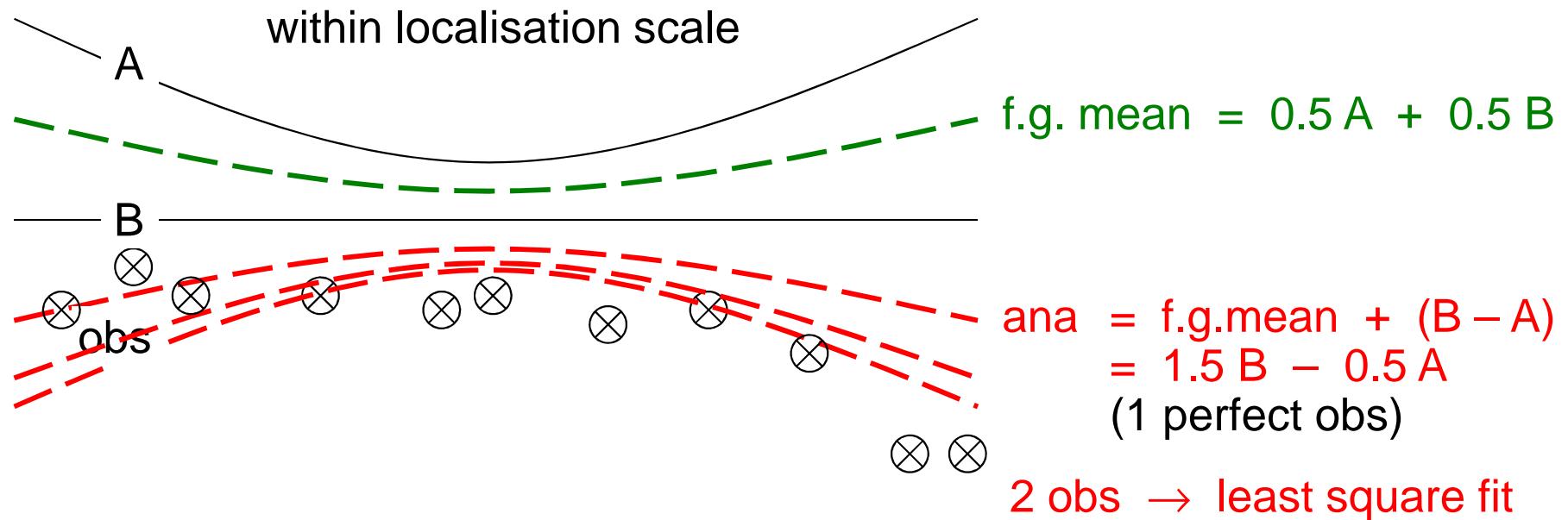
BIAS

LHN
noLHN

bias reduced
for different
parameters



- adaptive estimation of obs error covariance \mathbf{R}
(Li, Kalnay, Miyoshi, QJRMS 2009) , but our implementation: in ensemble space !



add obs, if already $N_{obs} > N_{ens}$:

- cannot be fitted well, improve analysis only slightly
 - decrease analysis error !
- $$\mathbf{P}_w^a = [(k-1)\mathbf{I} + (\mathbf{Y}^b)^T \mathbf{R}^{-1} \mathbf{Y}^b]^{-1}$$
- adaptive \mathbf{R} takes rank deficiency into account and increases \mathbf{R}