

LACE data assimilation: recent activities

Gergely Bölöni, Edit Adamcsek, László Szabó, Alena Trojáková, Patrik Bénácek,
Antonin Bucanek, Xin Yan, Florian Meier, Tomislav Kovacic, Antonio Stanesic,
Michal Nestiak, Jure Cedilnik, Benedikt Strajnár, Mirela Pietrisi



Outline

1. Progress in DA implementations
2. Case studies
3. CANARI surface assimilation developments for mountains
4. Developments related to background error simulation
5. Plans

Progress in DA implementations

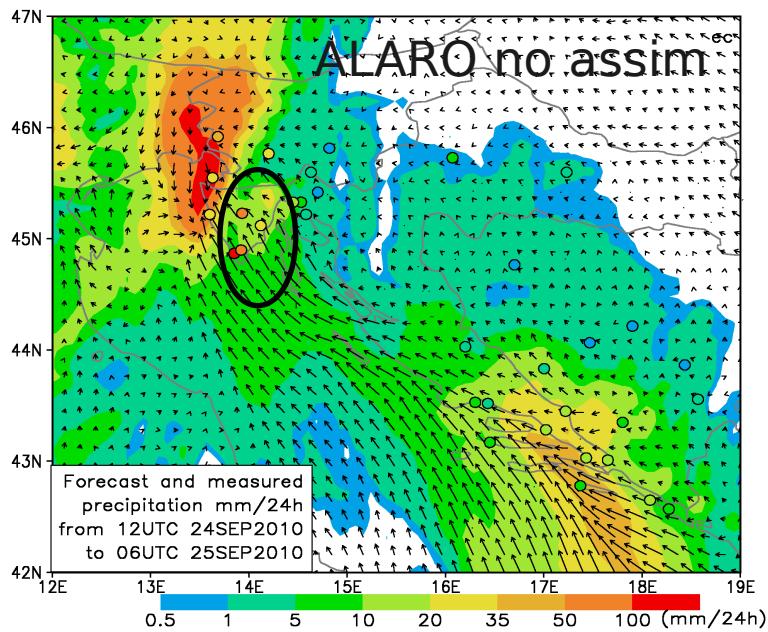
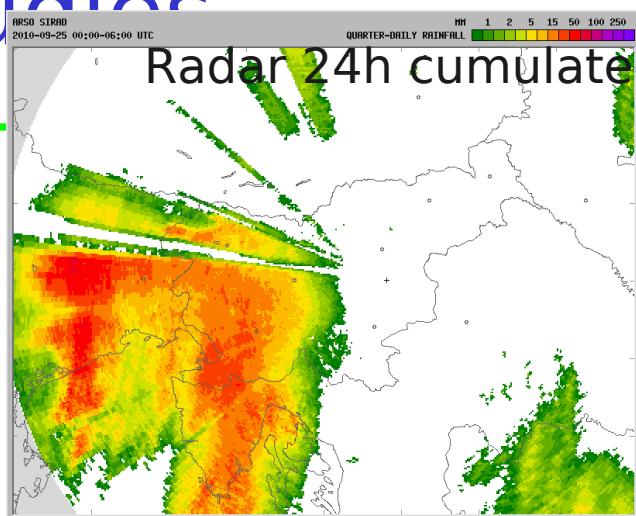
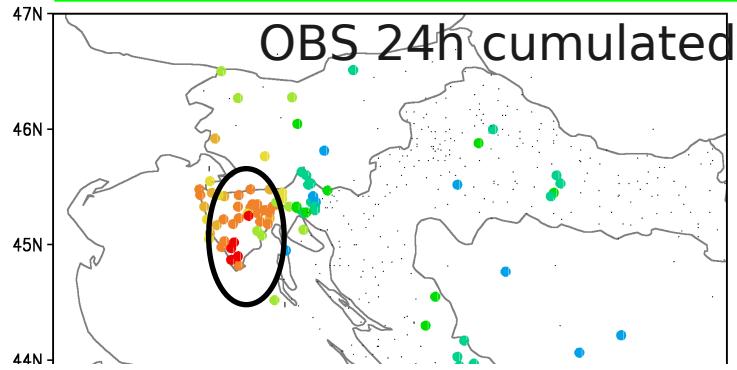
- All LACE members are running regular/test data assimilation suites (surface or upper air)
- Austria implemented operational surface assimilation (CANARI) in the high resolution ALARO 5km runs
- Slovenia implemented operational surface + upper air assimilation (CANARI + 3DVAR) in the high resolution ALARO 4.4km runs → positive feedback from forecasters

Progress in DA implementations

- Croatia showed improvements by data assimilation in terms of classical scores. Also case studies are found with improvements by assimilation. Although no operational implementation yet mainly because Tmin and Tmax at 2m are degraded by assimilation in summer.
- Collection and redistribution of national (non-GTS) surface data is on the table (starts soon with CZ data)
- OPLACE extended to METOP/IASI data

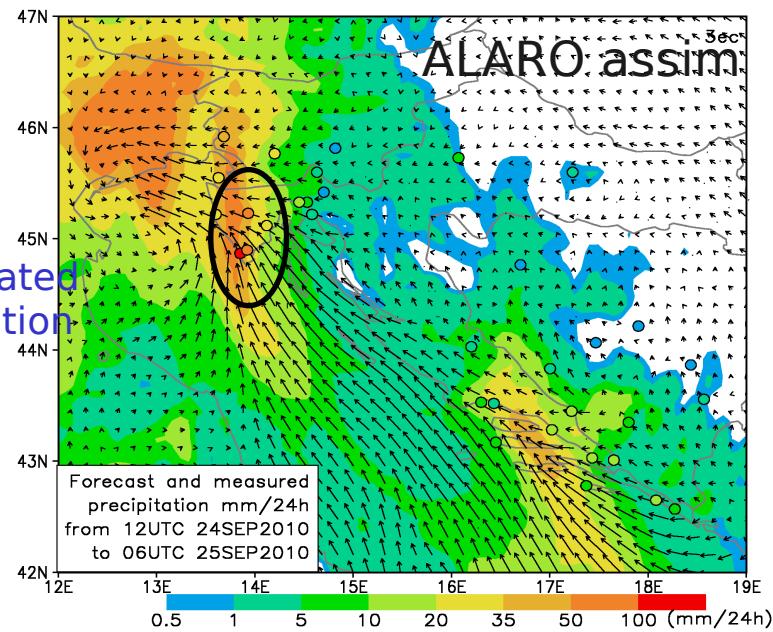
Istria flood 25 September 2010 (Croatia)

Case studies



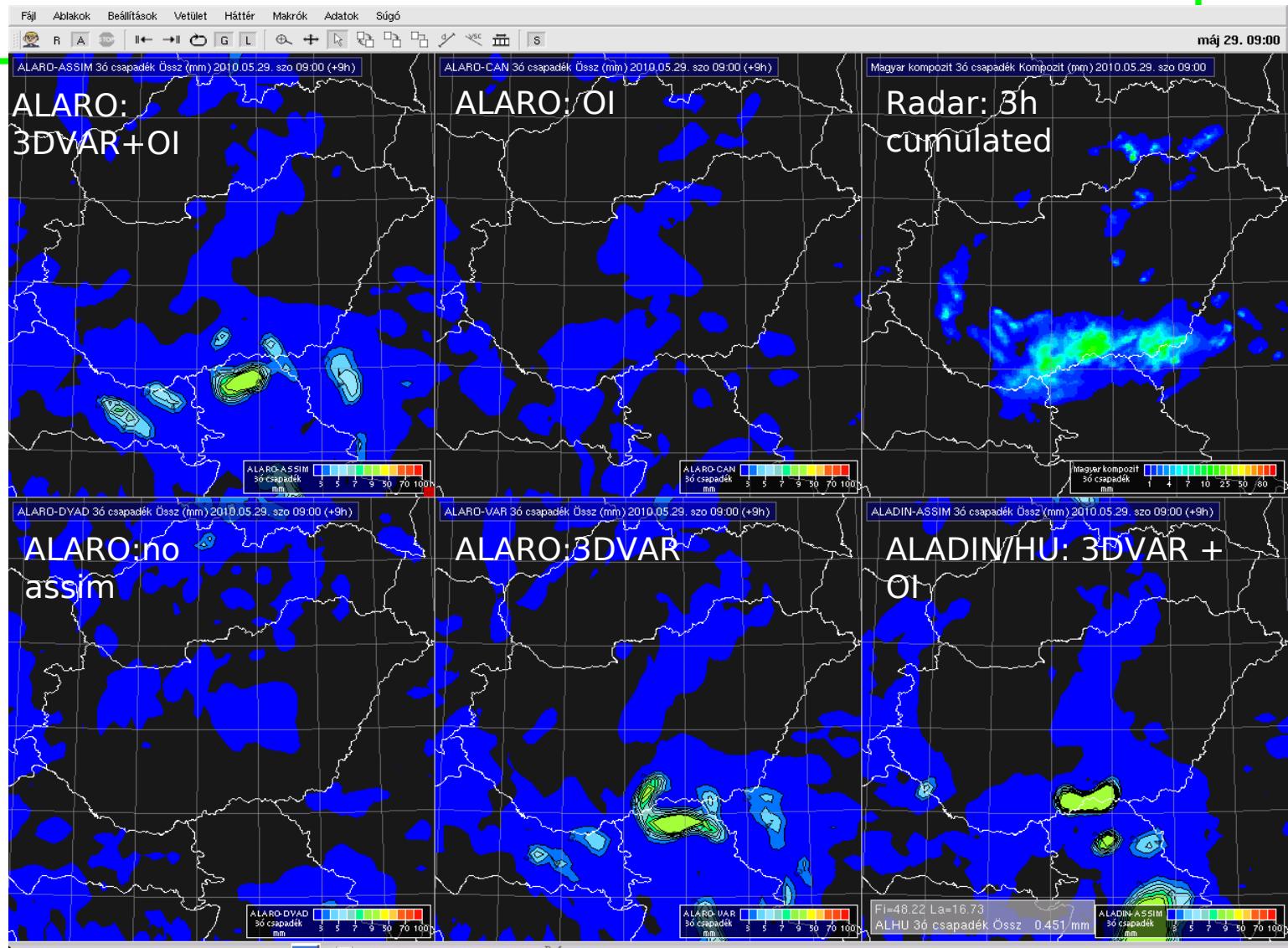
24 hours
accumulated
precipitation

iii



Convective case 29.05.2010 (Hungary)

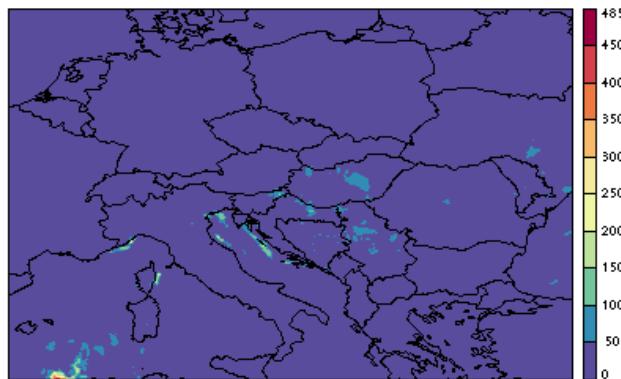
Case studies



Case studies

SURFCAPE.MOD.XFU
2010/5/29 20:00 +6h

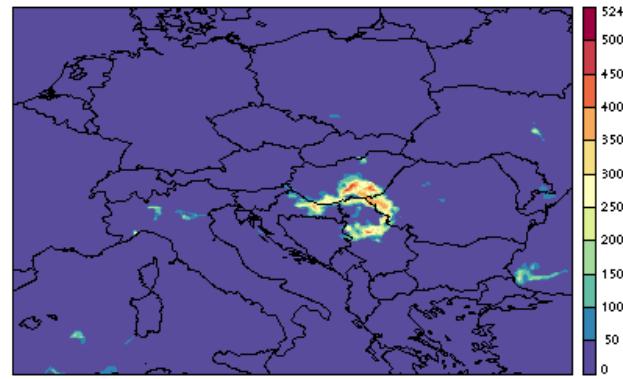
CAPE: ALARO-NOASSIM



+6h

SURFCAPE.MOD.XFU
2010/5/29 20:00 +6h

CAPE: ALARO-ASSIM



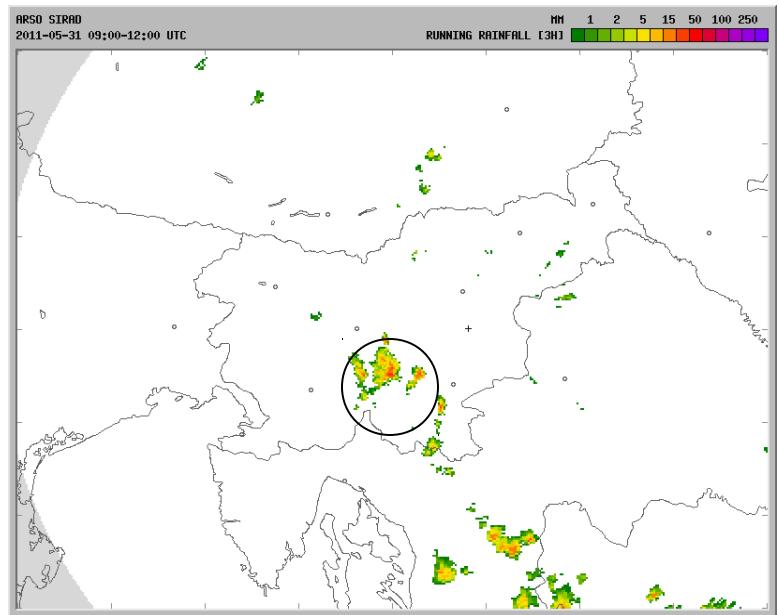
Some conclusions:

- Assimilation (mostly 3DVAR) has increased the low level humidity → improved CAPE
- The impact mostly came from SYNOP RH
- ALARO physics propagates the system more realistically (compared to old ALADIN/HU physics)

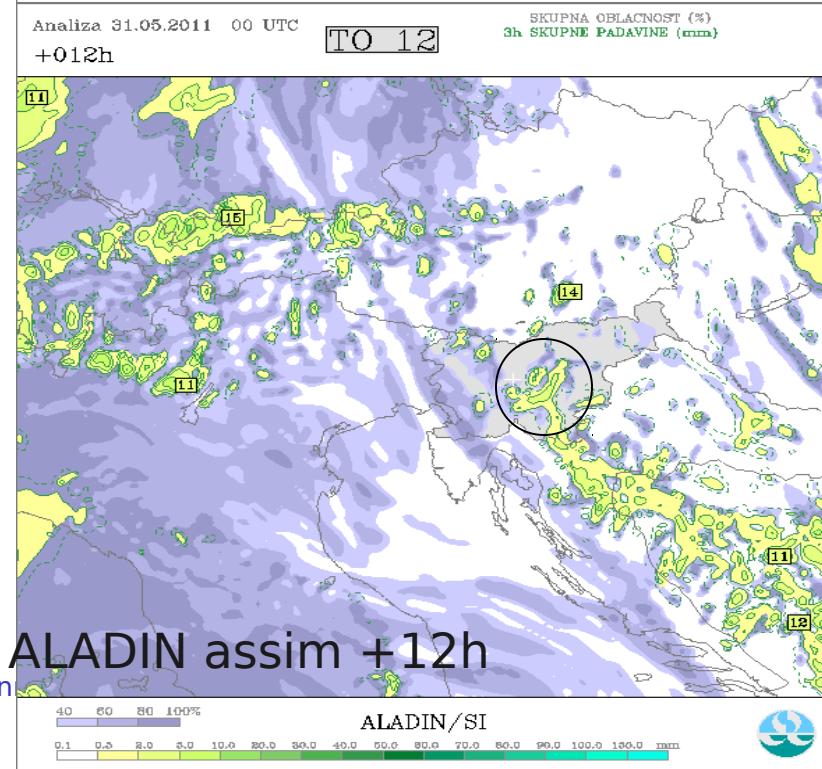
Convective case 31.05.2011 (Slovenia)

Case study

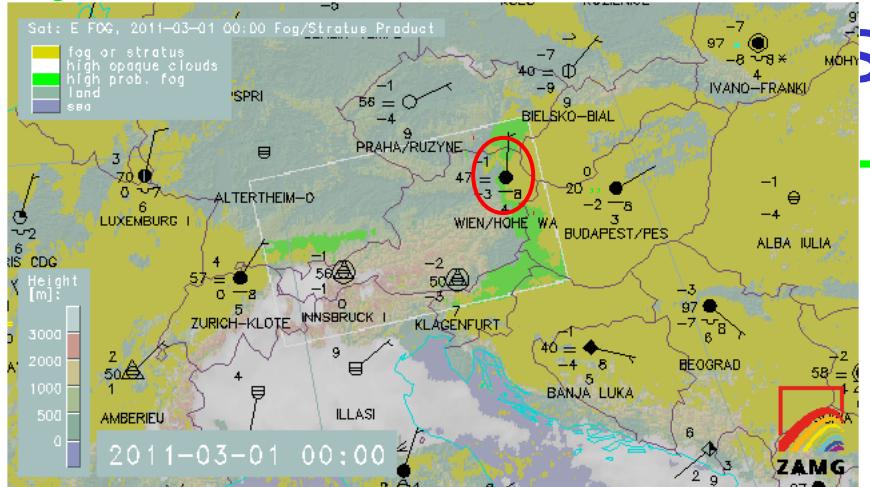
Improved location and time of the first thunderstorm



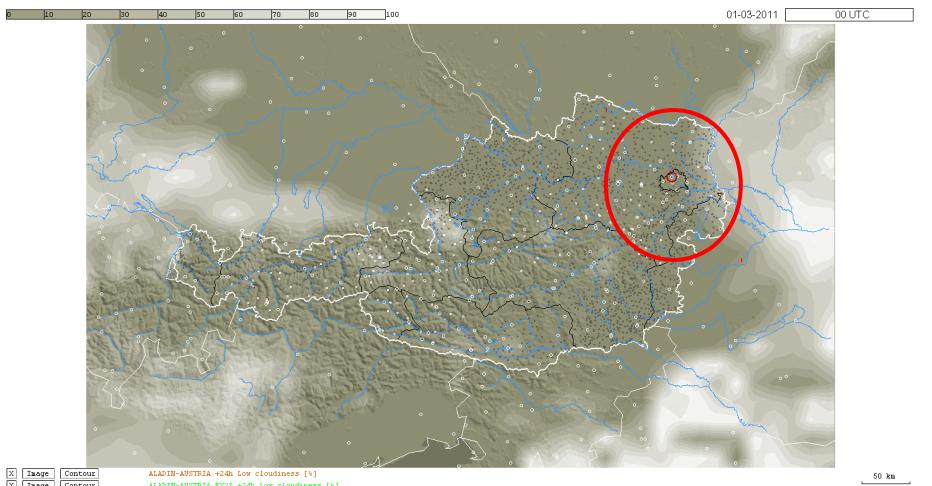
EWGLAM/SRNWP, Tallinn



Low stratus case 01.03.2011 (Austria)

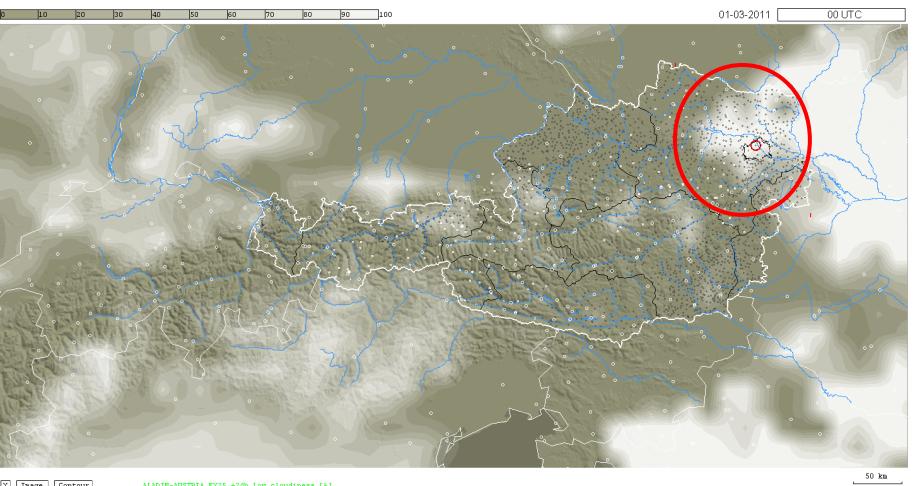


ALARO5 +24h



ALADIN-Austria +24h

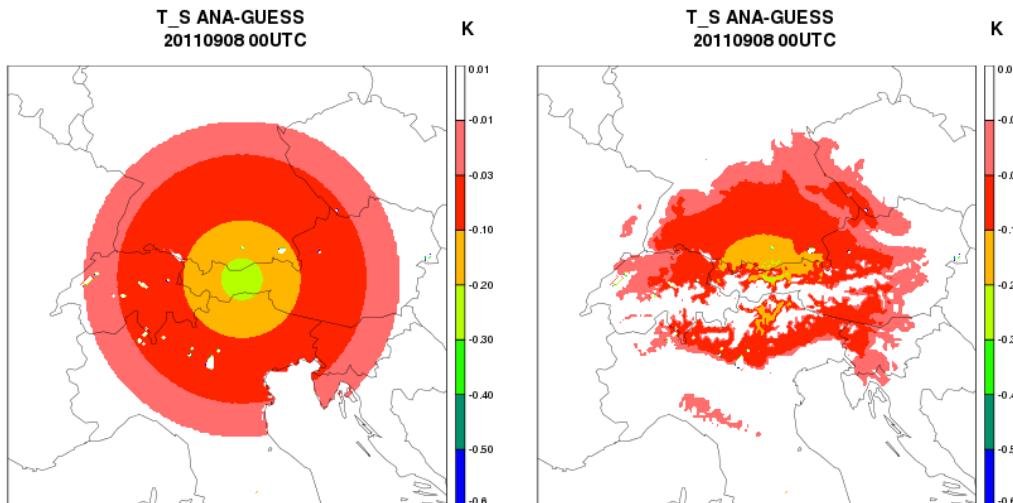
EWGLAM/SRNWP, Tallinn, 10 - 14 Oct 2011



ALADIN assim +24h

CANARI developments for mountains (Austria)

CANARI increments are quite smooth especially in Alpine areas and even in ALARO5 -> reduction of background horizontal correlation length and introduction of vertical correlation function as already existing for snow analysis also for T2m, RH2m in „catrma“ and „cacova“ (LCORRF=.TRUE.)



Ts standard CANARI

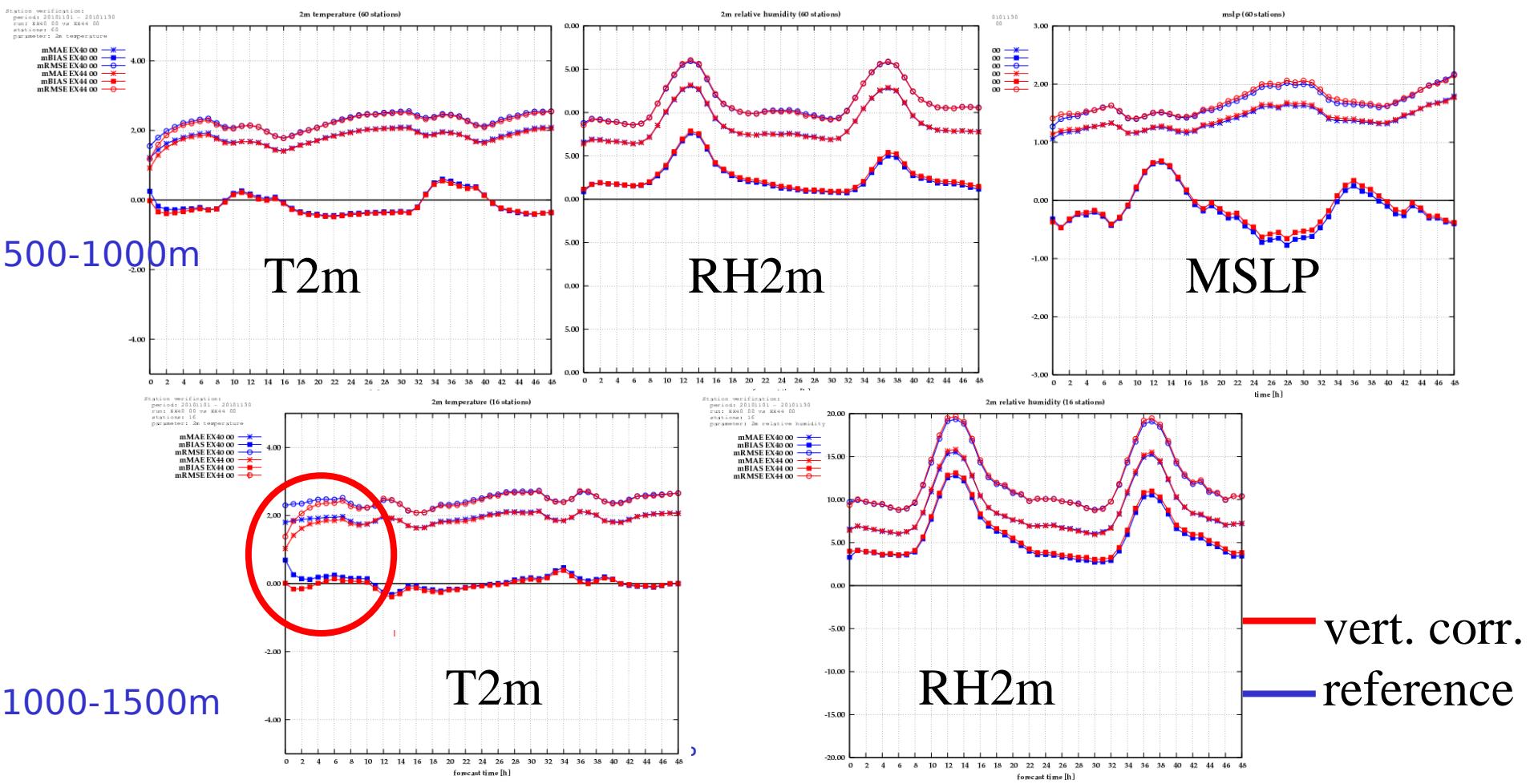
Ts CANARI +vert. corr.

$$\mu(r, p) = e^{(-0.5 * \sqrt{\frac{r_{ij}^2}{d^2}}) * e^{(-0.5 * \ln(\frac{p_i}{p_j}) * \frac{1}{P_c})}}$$

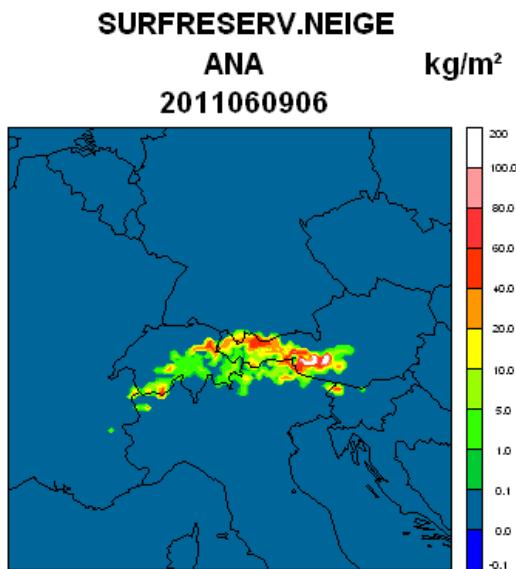
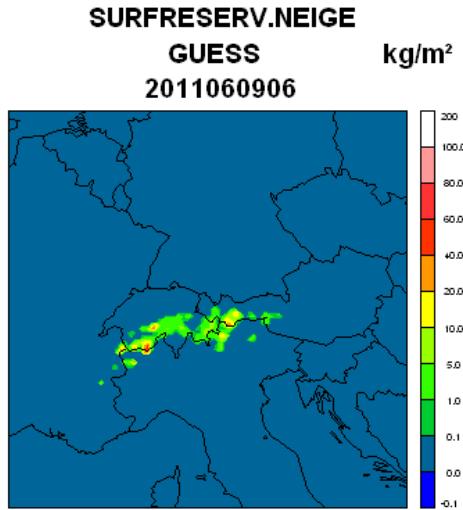
One month verification (Nov 2010): positive effect on T2m for very short range, especially for stations between 1000-1500m, otherwise rather neutral impact

CANARI developments for mountains

(Austria)



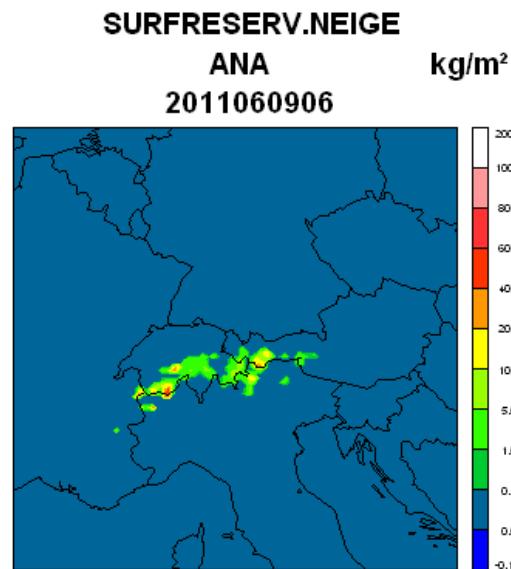
Snow analysis in CANARI



RCSNSY=200.

RI developments for mountains (Austria)

Problem: too strict O-G rejection for snow → almost no snow observation accepted in the Alps



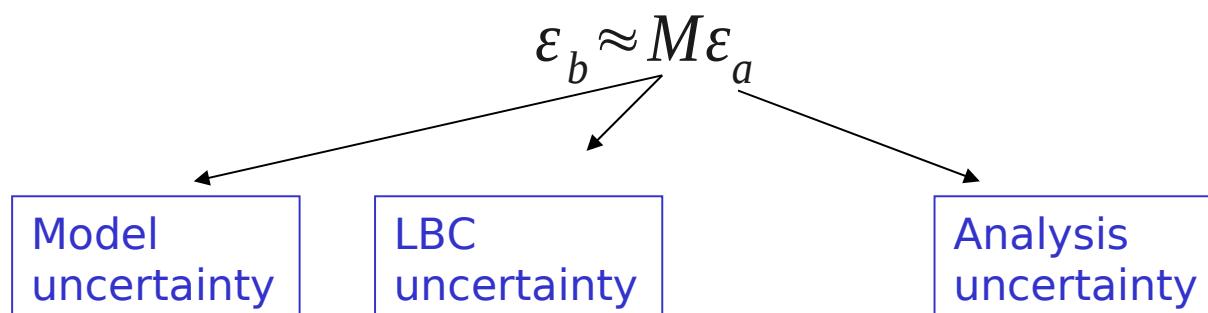
RCSNSY=2.5 (default)

LAM background error simulation

Aim: simulation of background errors (ε_b) in order to generate a statistical sample for the computation of the background error covariance matrix (B) in the variational analysis:

$$B = E(\varepsilon_b \varepsilon_b^T)$$

$$J_b(x) = \frac{1}{2}(x - x_b)^T B^{-1} (x - x_b)$$



- What is the relative importance of the different uncertainties?
- How to represent these different uncertainties?

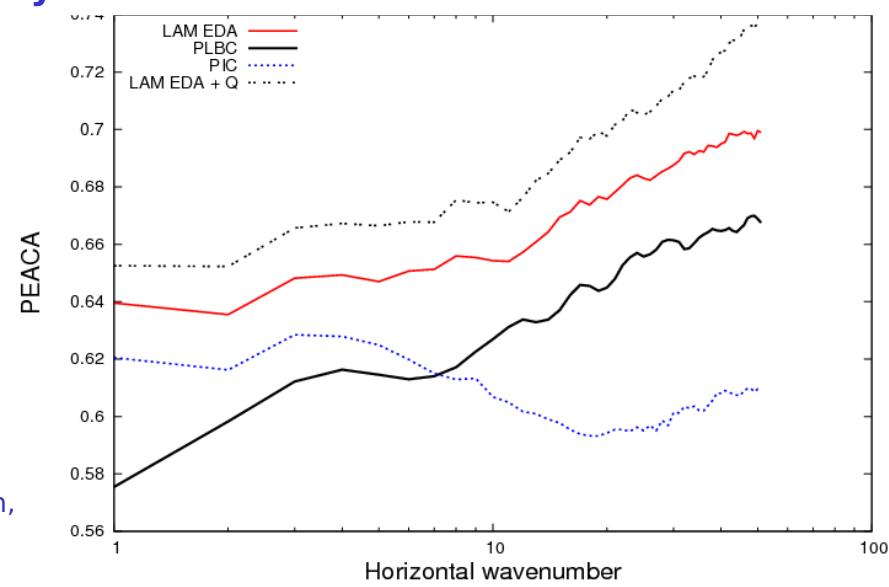
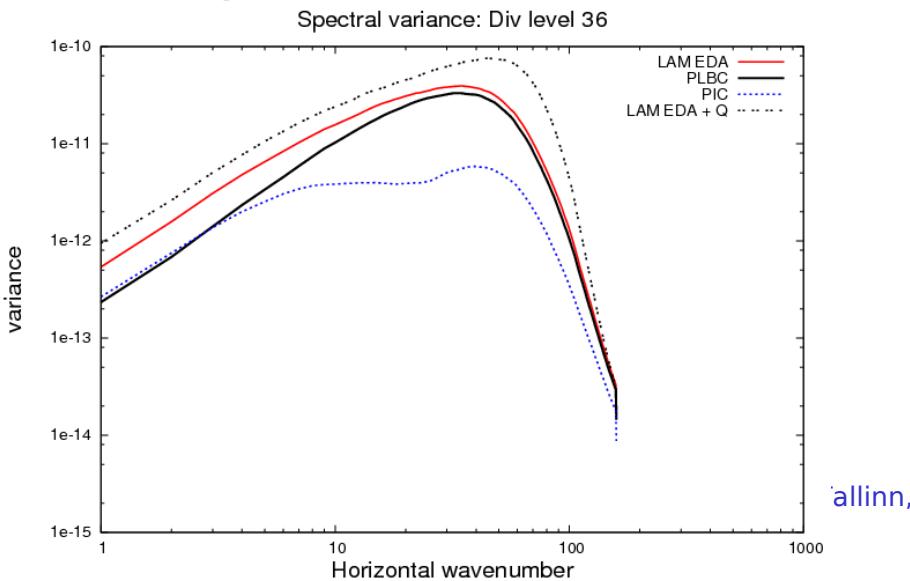
LAM background error simulation

PIC: „Perfect Initial Condition framework“ – same initial condition (oper DA) for all members but different LBCs used from an IFS EDA run (Isaksen et al., 07/2007, 4DVAR T255/L91) →**accounting for LBC uncertainty**

PLBC: „Perfect LBC framework“ – same LBCs used for all members but perturbed analyses used as Ics (normalized random perturbation of observations) →**accounting for IC uncertainty**

LAM EDA: both IC and LBC perturbations applied as explained above →**accounting for IC + LBC uncertainty**

LAM EDA +Q: additional physics perturbations added (ALARO vs operational ALADIN/HU physics)
→**accounting for IC + LBC + model uncertainty**



LAM background error simulation

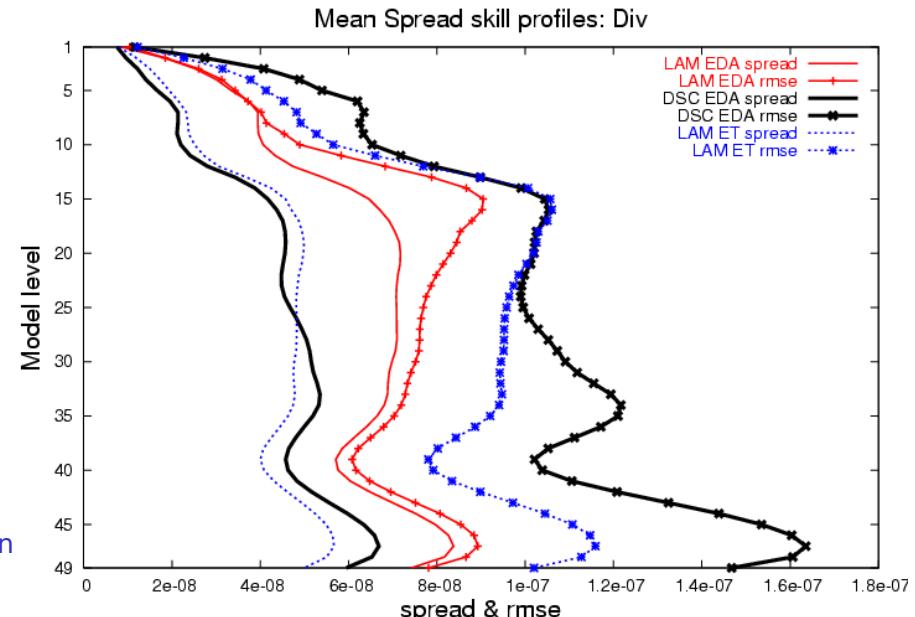
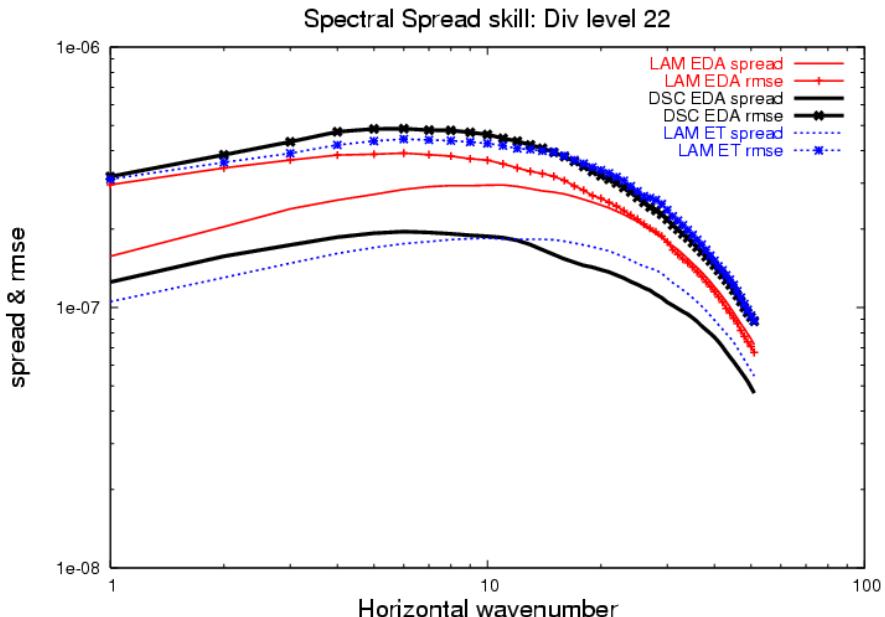
What representation of analysis uncertainty to use?

DSC EDA: downscaling of the IFS EDA initial perturbations (no local assimilation involved)

LAM EDA: local EDA (normalized random perturbation of observations)

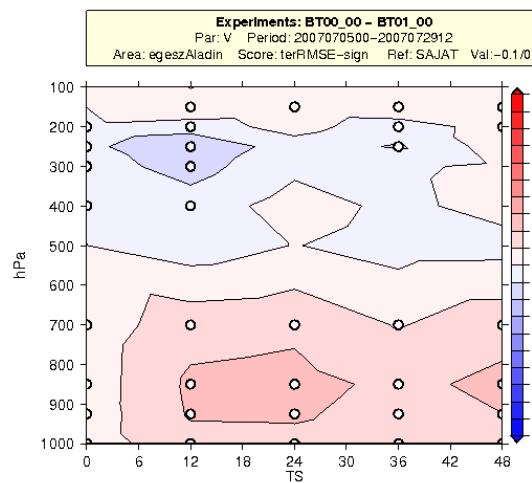
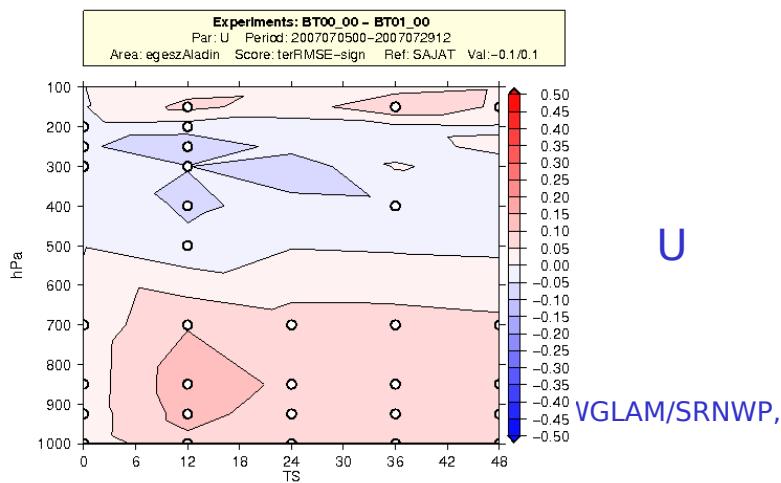
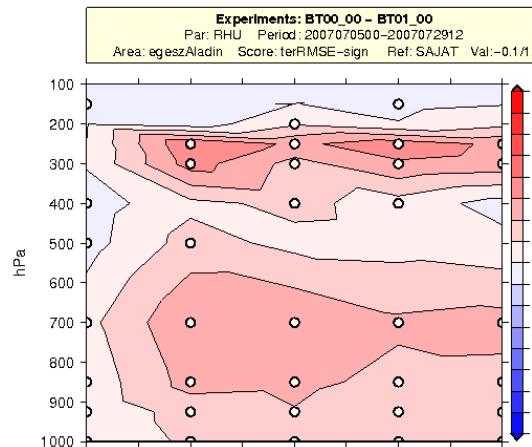
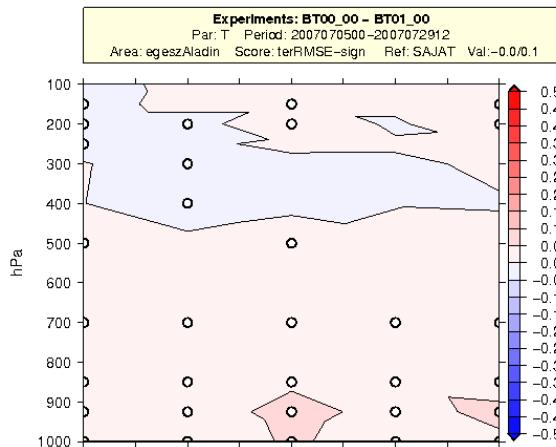
LAM ET: local perturbations by the Ensemble Transform

(LBCs are perturbed in all the simulations above)



LAM background error simulation

RMSE against analysis (each experiment against its „own”



Plans

Finalize operational 3DVAR and CANARI implementations

Maintain OPLACE

- National SYNOPs
- E-GVAP
- LandSAF albedo

High resolution (AROME and ALARO) assimilations to set up with

- Rapide update frequencies (3-1 hours)
- Include radar data
- Include IASI data
- Include GPS data (ZTD and RO)

Improve surface assimilation with

- External EKF for LandSAF albedo (snow)
- CANARI + OI_main

Plans

Ensemble Data Assimilations for:

- Estimation of background errors (climatological and flow-dependent)
- Contribution to LAMEPS IC perturbations (LAEF, HUNEPS)

Thank you for your attention!

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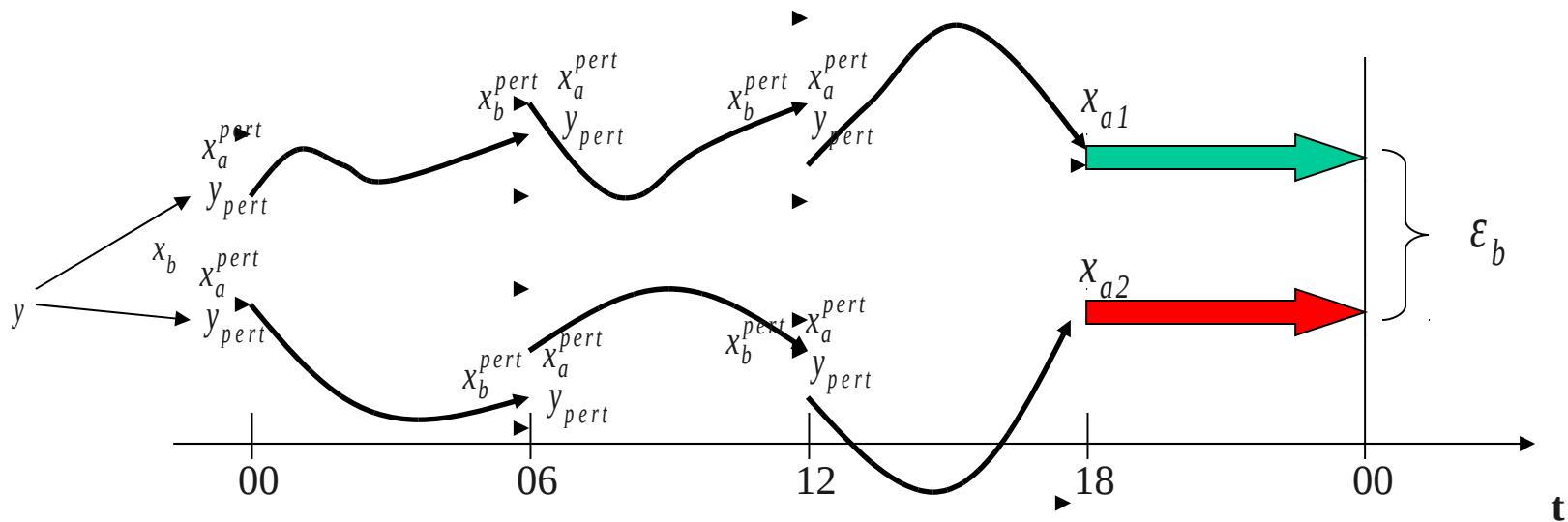
The simulation techniques in play

Background error simulation with EDA

$$\begin{aligned}x_{b1} &= Mx_{a1} \\x_{b2} &= Mx_{a2}\end{aligned}$$

$$\varepsilon_b \approx x_{b1} - x_{b2}$$

(EDA: Ensemble Data Assimilation)



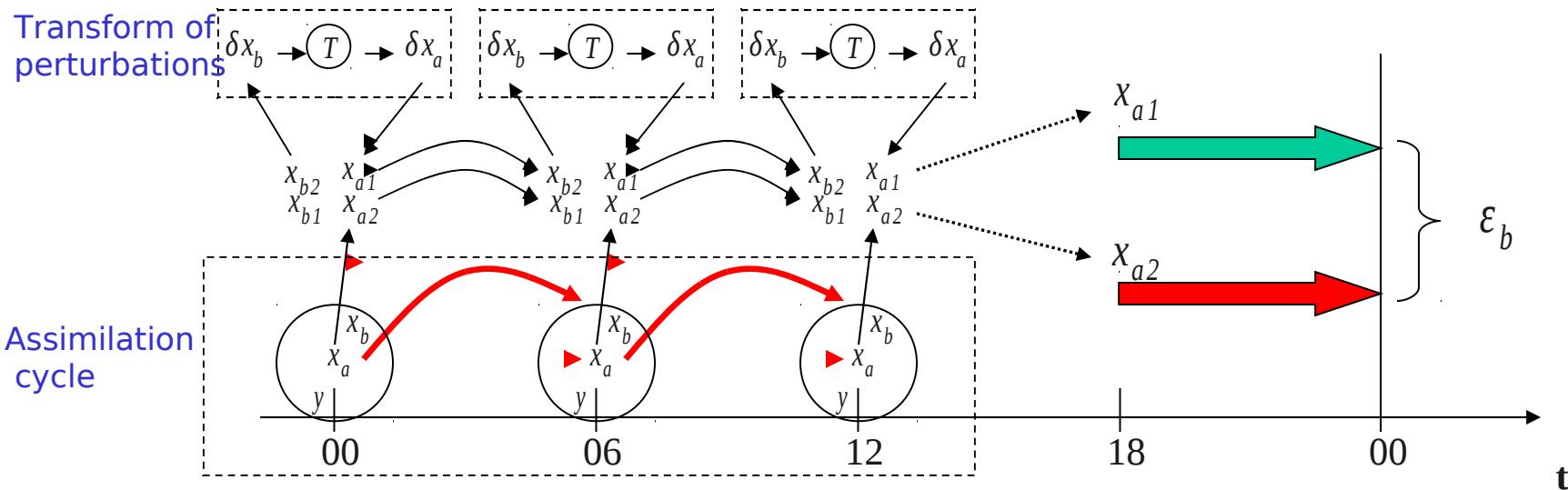
The simulation techniques in play

Background error simulation with ET

$$x_{b1} = Mx_{a1}$$
$$x_{b2} = Mx_{a2}$$

$$\varepsilon_b \approx x_{b1} - x_{b2}$$

(ET: Ensemble Transform)



Diagnostics

PEACA (Perturbation vs. Error Amplitude Correlation Analysis):

$$\text{Corr}\left(|\varepsilon_b|, |\varepsilon_b^{\text{ref}}|\right) = \frac{\text{Cov}\left(|\varepsilon_b|, |\varepsilon_b^{\text{ref}}|\right)}{\sigma(\varepsilon_b)\sigma(\varepsilon_b^{\text{ref}})} = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N \left(|x_b^j - \bar{x}_b| \right) \left(|x_a^{\text{verif}} - \bar{x}_b| \right)}}{\sqrt{\frac{1}{N} \sum_{i=1}^N \left(x_b^j - \bar{x}_b\right)^2} \sqrt{\frac{1}{N} \sum_{i=1}^N \left(x_a^{\text{verif}} - \bar{x}_b\right)^2}}$$

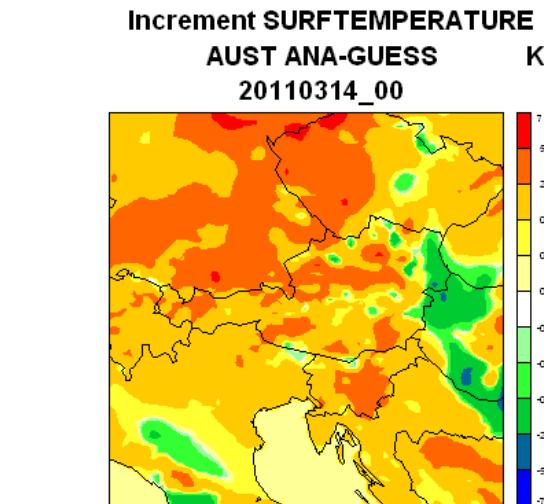
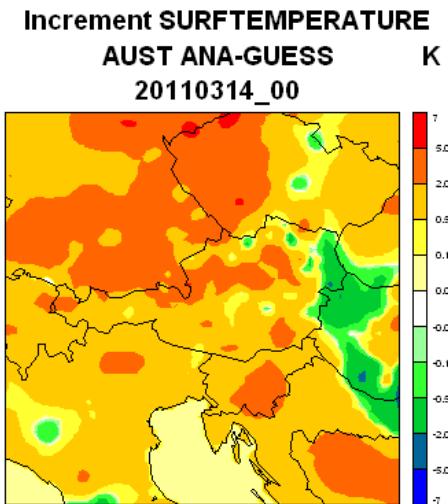
$$\varepsilon_b = \bar{x}_b - x_b^j \quad \text{simulated background error}$$

$$\varepsilon_b^{\text{ref}} = x_a^{\text{verif}} - \bar{x}_b \quad \text{„real” background error } (x_a^{\text{verif}} \textcolor{red}{\dot{\wedge}} x_t)$$

N= member size + time realizations

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