Deutscher Wetterdienst
Wetter und Klima aus einer Hand

DWD Systems II: COSMO

Hendrik Reich

DWD-HErZ winterschool on data assimilation, Offenbach

13-17. February 2012

outline

- COSMO consortium
- HErZ
- LAM's at DWD
- current DA system: nudging, observation network
- KENDA project: LETKF
- LETKF: first results
- LETKF: next steps
- outlook, open questions

COSMO consortium

COSMO countries: D, CH, I, RO, RU, GRE, PL

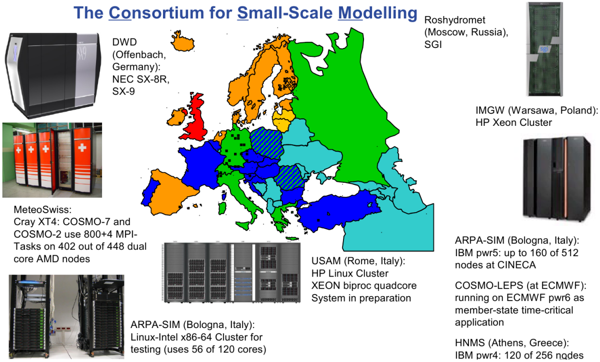

Fig.1: COSMO countries (green), super computers

Research environment: HErZ

HErZ: Hans-Ertel Zentrum
Data assimilation: LMU Munich, DLR

- projects:
  - Observation impact studies
  - use of satellite data
  - uncertainties in EPS
  - DA algorithms for the convective scale

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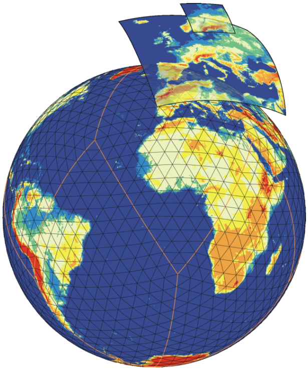
LMU Ludwig-Maximilians-Universität München, Fakultät für Physik, Meteorologie

Deutsches Zentrum für Luft- und Raumfahrt e.V. in der Helmholtz-Gemeinschaft

DWD systems: model hierarchy



COSMO-DE
COSMO-EU

GME/(ICON)

Fig.2: DWD models: GME, COSMO-EU and COSMO-DE

DWD systems: local models

- COSMO-EU
  - region: Europe
  - 7km horizontal resolution, 40 vertical levels
  - 665*657*40 grid points; forecast range up to 78h
  - time step 66 sec.
- COSMO-DE
  - region: Germany and parts of neighbouring countries
  - 2.8 km horizontal resolution, 50 vertical levels
  - 421*461*50 grid points
  - forecast range 21h, forecast every 3h (00,03, ... UTC)
  - time step 25 sec.
  - nonhydrostatic model

COSMO-DE EPS

developed at FE15, preoperational

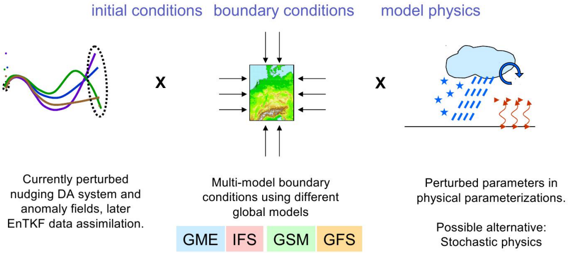


Fig.3: COSMO-DE EPS setup

operational schedule

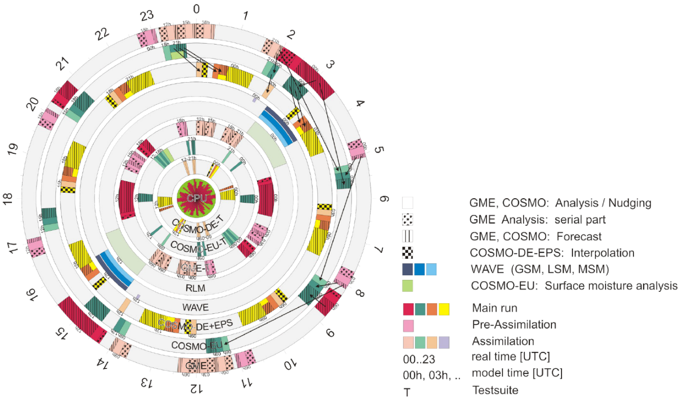


Fig.4: “Modell-Uhr”, model-clock

experimental system: NUMEX

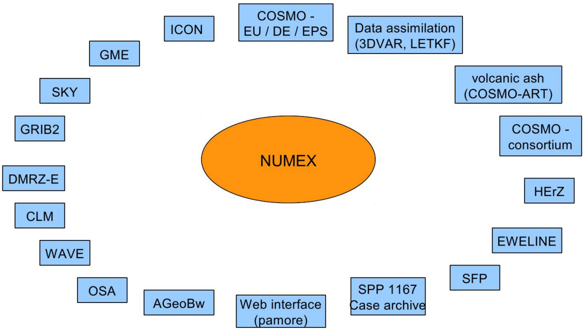


Fig.5: programs/models in NUMEX, now with LETKF!

COSMO DA: observation network

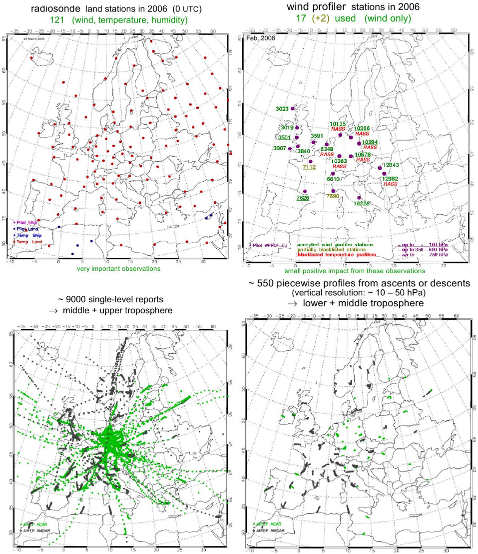


Fig.6: radiosondes, wind profiler, aircraft reports; SYNOP stations not shown here

radar network

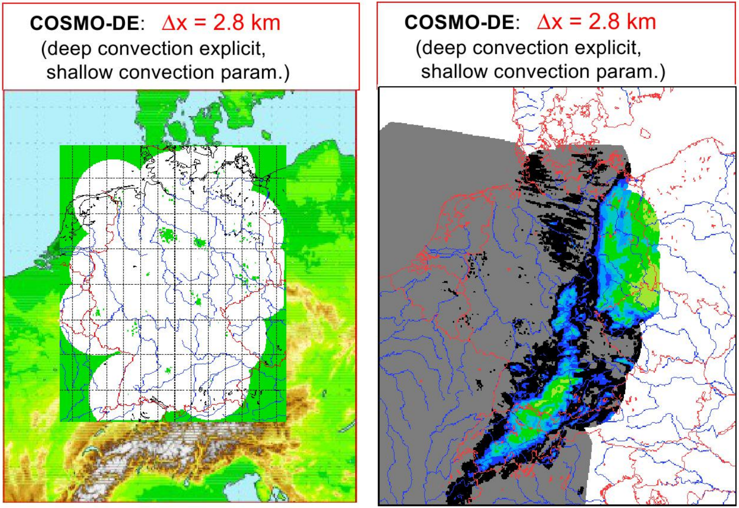


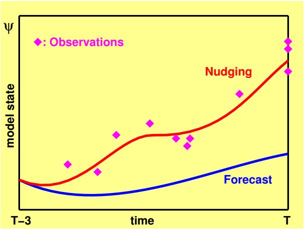
Fig.7: radar network; area covered by radars (left), snapshot (right)

nudging

Method: dynamic relaxation against observations

$$\frac{\partial}{\partial t}\Psi(\underline{x}, t) = F(\underline{\Psi}, \underline{x}, t) + G_\Psi \cdot \sum_{k_{(obs)}} W_k \cdot [\Psi_k - \Psi(\underline{x}_k, t)]$$

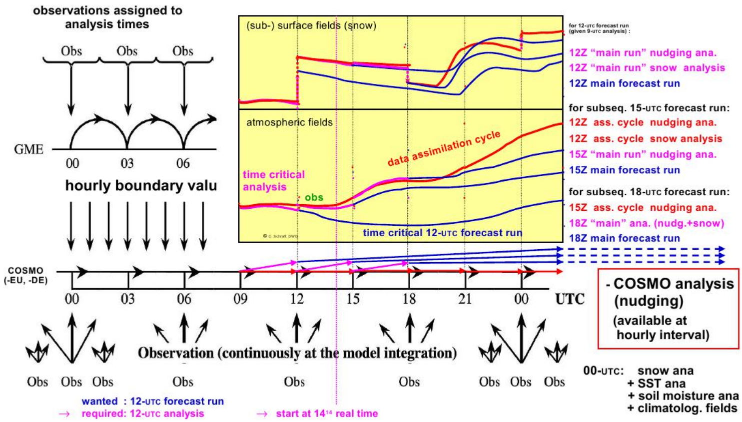
- G_Ψ determines the characteristic time scale for relaxation
- The weight W_k for the model grid point $(\underline{x}, t)$ depends on:
  - time difference to observation (w_t)
  - spatial distance to observation $(w_{xy},\ w_z)$
  - observation and model errors (q_k)



$$W_k = \frac{w_k}{\sum_j w_k} \cdot w_k$$

$$w_k = w_t \cdot w_{xy} \cdot w_w \cdot q_k$$

nudging ctd.

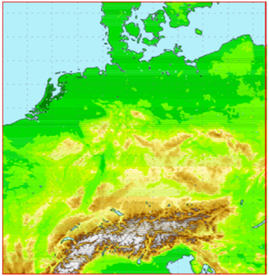


analysed variables: horizontal wind (u, v), temperature (T), relative humidity (rh), 'near-surface' pressure (pp)

LETKF/KENDA

- LETKF: *Local Ensemble Transform Kalman Filter*
  - GME (ICON): very basic setup available
  - hybrid version with 3dVar planned (following *Buehner et al.*)
- *KENDA*: **K**ilometerscale **En**semble **D**ata **A**ssimilation
  - priority project within COSMO consortium
  - LETKF for the nonhydrostatic COSMO-DE model of DWD

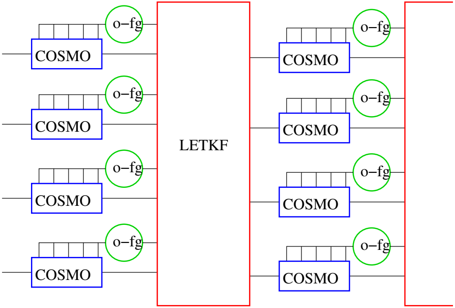
COSMO-DE domain
(≈ 1200 km x 1200 km)



LETKF basics

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

LETKF setup (COSMO)



technical setup of COSMO-LETKF:

obs-fg (netcdf) and grib files written during integration by COSMO, LETKF reads these files, computes analysis, start COSMO again...

LETKF experiments

- technical implementation of experiments (up to now):
  - stand-alone LETKF script environment to run COSMO-DE LETKF + diagnostics / plotting
  - toy model (Lorenz-96,40 grid points) to test LETKF components
- experiments with successive LETKF assimilation cycles (32 ensemble members, drawn from 3dVar B-Matrix)
  - 3-hourly cycles, up to 2 days (7-8 Aug. 2009: quiet + convective day)
  - lateral boundary conditions (LBC) from COSMO-SREPS (3 * 4 members)
  - old experiments: use obs from GME NetCDF feedback files (sparse density)
  - new experiments: use obs from NetCDF files written by COSMO-model during integration (same obs set as nudging)
  - option for *deterministic analysis* has been implemented
  - Now in NUMEX!

LETKF experiments

- experimental settings:
  - 3h update (later $\approx$ 15 min)
  - observations used: TEMP, AIREP, PILOT, SYNOP
  - 2 day period
- $\rightarrow$ characteristics:
  - highly inhomogenous observation density
  - observation density $\approx$ 10 times larger as in old setup
- experience (GME): LETKF works best (in terms of rms/spread ratio) with low number of observations
- keep localization scales unchanged to test adaptive methods within a setup where problems can be expected

LETKF experiments

- analysed variables are $u, v, w, T, pp, qv, qcl, qci$
- analysed means that linear combination is applied to these variables (other variables taken from first guess ensemble / ensemble mean)
- localization done with Caspari-Cohn function: similar to Gaussian, but identical to zero at finite distances
- localization weights are computed on coarse grid, then interploated to model grid
- verify LETKF *det run (mean)* against
  - nudging analysis (u, v, w, T, pp)
  - observations (u, v, T, rh)
- verification tool (deterministic/ensemble scores) is currently under development

spread (ens BC)

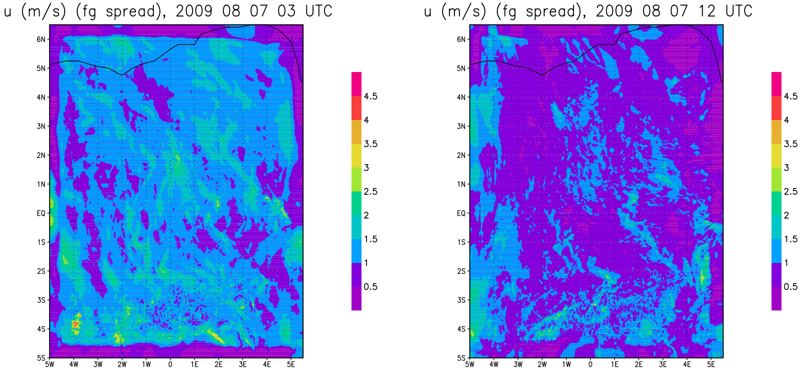


Fig.8: spread (wind component u in m/s) of first guess on 7 Aug. 2009 at 03 UTC (after 1 LETKF analysis with 3DVAR-B) (left) and at 12 UTC (after 4 analysis cycles) (right)

The large scale spread decreases and “new” spread comes in from the west due to the lateral boundary fields.

spread (det BC)

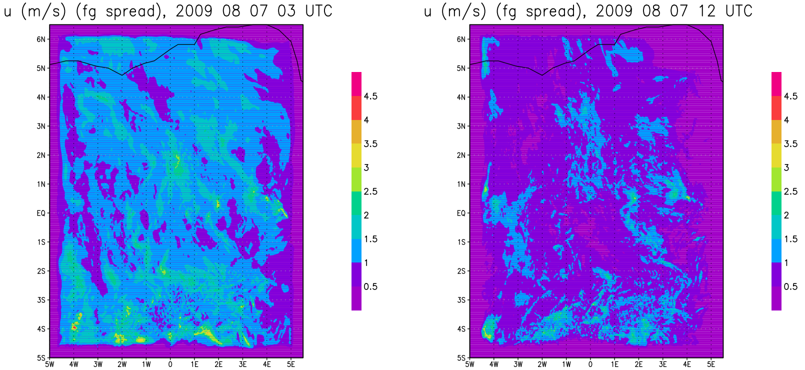


Fig.9: same as Fig.1 but with *deterministic* boundary conditions

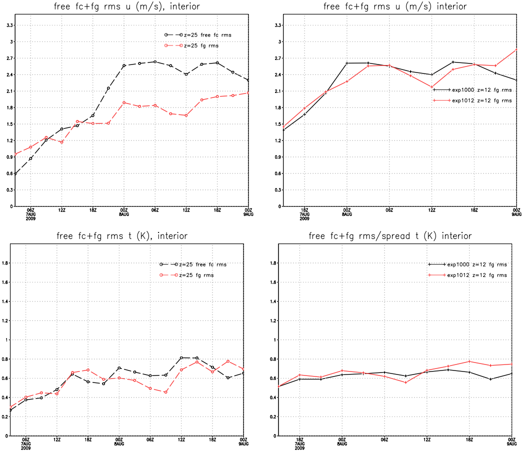
The large scale spread decreases faster as no "new" spread comes in from the lateral boundary fields.

comparison with free fc, old and new setup

free fc rmse

first guess rmse,

old setup



free fc rmse

first guess rmse,

new setup

Fig.10: upper row: *u* (m/s) at 500 hPa; lower row: *t* (K) at 500 hPa.

more obs do not lead to better results...

adaptive methods

- lack of spread is (partly) due to model error which is not accounted for so far
- one (simple) method to increase spread is multiplicative covariance inflation:
    - $X_{ens} \rightarrow \rho X_{ens}$ with $\rho > 1$
- adaptive method to estimate ρ preferable
    - (*Desroziers et al.*): describes methods to estimate (co)variance of background or analysis $\rightarrow$ estmation of ρ
    - (*Li et al.*) used two of these methods for online estimation of ρ within a toy model
    - (*Bonavita et al.*): ρ is computed at every gridpoint, tested in CNMCA LETKF

adaptive methods ctd.

two different ideas to estimate ρ have to be distinguished:

- idea (1): compare "observed" quantities with "expected" ones:

$$\left\langle (y - H(x_b))(y - H(x_b))^T \right\rangle = \mathbf{R} + \rho \mathbf{H P_b H^T}$$
$$\left\langle (H(x_a) - H(x_b))(y - H(x_b))^T \right\rangle = \rho \mathbf{H P_b H^T}$$

- idea (2): "relaxation" methods:
  - e.g. relaxation to prior spread (RTPS)
  - $\rho = \sqrt{\alpha \frac{\sigma_b - \sigma_a}{\sigma_a} + 1}$, $\alpha < 1$
- (1) works in observation space; tries to increase/decrease spread to fulfill statistical relations
- (2) works in model space; "corrects" reduction of spread due to assimilation of observations
- it would be preferable to compute ρ in *ensemble space* because this is where the LETKF works (but up to now not successful...)

adaptive methods ctd.

- obs errors / **R**-matrix probably assumed incorrectly, correction desirable
  - compare observed obs (co)variance with assumed one and correct **R** automatically if necessary
  - this is done in *ensemble space*
- both methods (est. of inflation factor / **R** matrix) have been tested with reasonable numerical cost and success within the toy model, and have been implemented in the LETKF (COSMO and GME)
- old setup: slightly postitive impact of inflation factor ρ, impact of estimation of **R** neutral
- new setup: much more observations, but worse results; can adaptive methods help?

comparison of adaptive ρ inflation methods

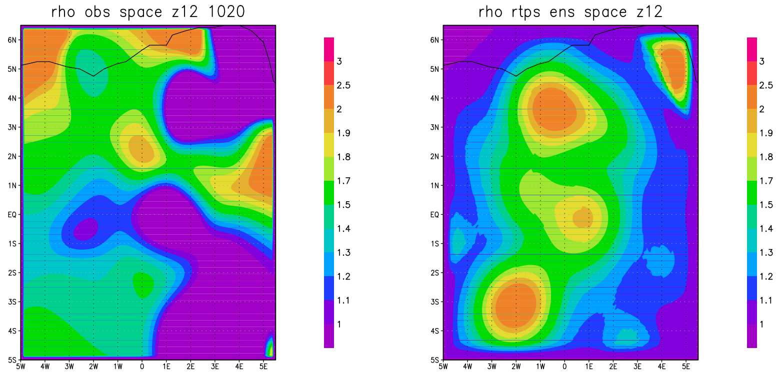


Fig.11: both plots: 2009080812 UTC, 500 *hPa*; ρ in obs space (left); ρ in ens space (RTPS) (right)

different spatial structures with obs-space/RTPS method!

adaptive **R** correction

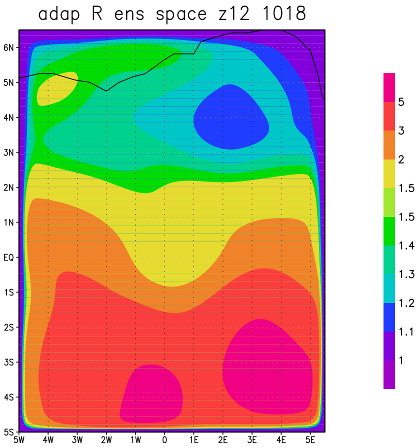


Fig.12: square root of adaptive **R**-correction factor; 2009080812 UTC, 500 *hPa*

large values in some areas → retuning of obs error necessary?

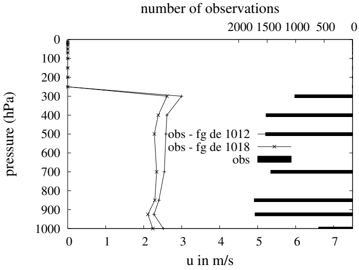


Fig.13: impact of all methods on fg rms / spread results for *u* (left), *t* (right), AIREPS

adaptive methods, changing vertical localization length scale, retuning specified observation errors; positive impact on all levels

Localization

- horizontal/vertical localization required
- vertical localization already changed (slightly positive impact)
- first test: reduce horizontal localization length scale from 100 $\rightarrow$ 50 km
- adaptive method preferable: primitive adaptive horizontal localization implemented
- results follow ...

Localization, weight grid and noise

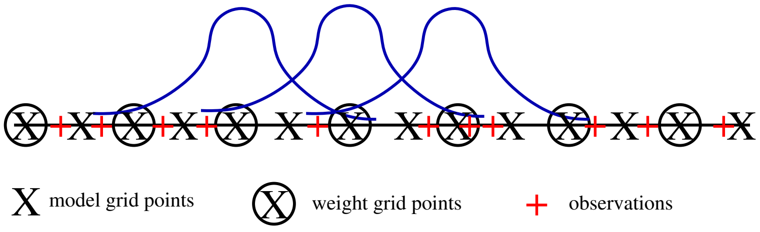


Fig. 14: localization function, observations, model and weight gridpoints

- length scale of localization function > distance between weight grid points
- "smooth" localization function to reduce effect of changes in observation sets
- but in any case localization induces noise!

hydrostatic balancing

- diagonal elements of weight matrix are larger than off diagonal elements
- $\rightarrow$ analysis ensemble k gets largest contribution from first guess ensemble member k plus (smaller) corrections from members $i \neq k$
- thus, the difference between analysis and first guess ensemble member k (the analysis increment) is small compared to the full fields
- apply hydrostatic balancing to this increment; this leaves the full fields nonhydrostatic as it should be in a nonhydrostatic model

weight matrices

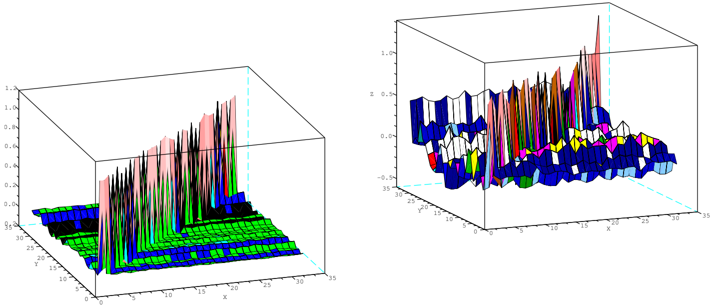


Fig.15: weight matrices (the matrix the first guess ensemble is multiplied with), for a case with "normal" number of observations (left) and with many observations (or small obs. errors; right).

off diagonal elements even for large number of obs ≤ 0.5 and diagonal elements > 0.5

noise

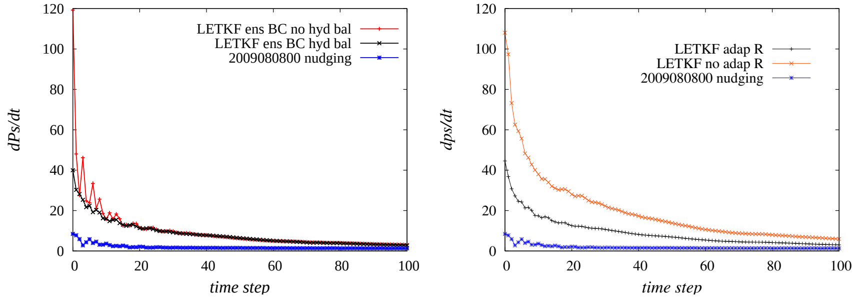


Fig. 16: noise (as measured by dps/dt) for old obs setup (left), new obs setup (right)

old setup: hydrostatic balancing reduces noise significantly; new setup: also with hydrostatic balancing applied high noise level; use of adaptive R correction reduces noise

noise: area plots

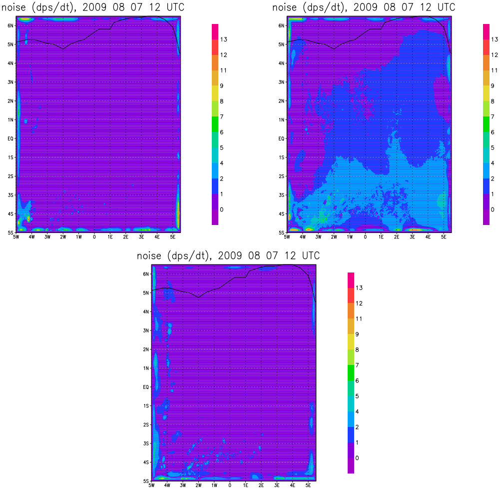
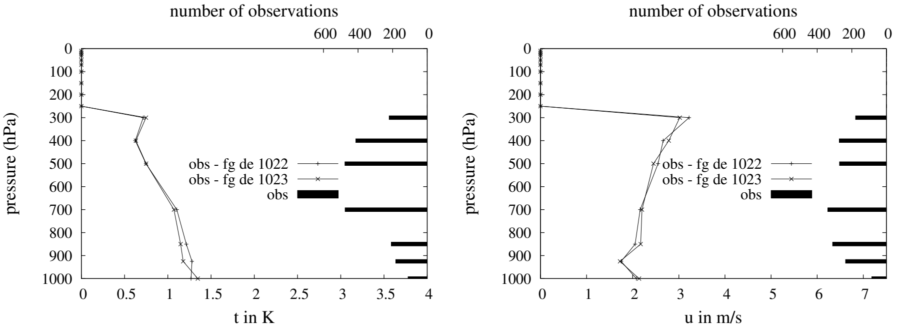


Fig.17: area plots of dPs/dt, 1st. time step; *analysis* with det. BC first guess, integration with ens BC; ens. BC first guess and ens BC integration; ens. BC first guess and ens BC integration, but hydrostatic balancing applied.

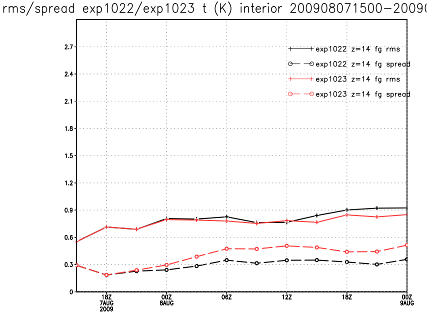
hydrostatic balancing reduces noise in the interior, no effect at the boundaries

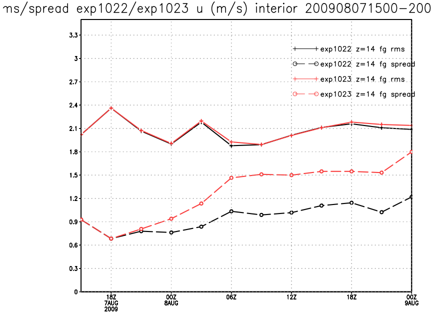
experiments: horizontal localization



exp1022: horizontal localization length scale 100 km, exp1023: horizontal localization length scale 50 km

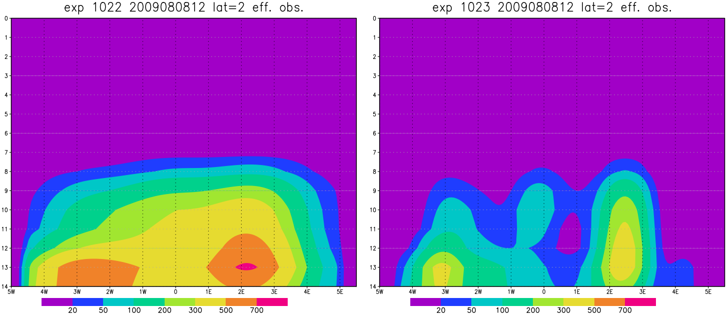
experiments: horizontal localization





exp1022: horizontal localization length scale 100 km, exp1023: horizontal localization length scale 50 km

experiments: horizontal localization

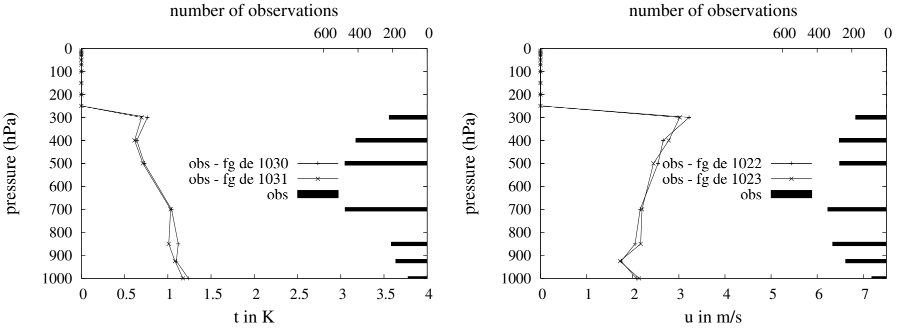


exp1022: horizontal localization length scale 100 km, exp1023: horizontal localization length scale 50 km

adaptive horizontal localization

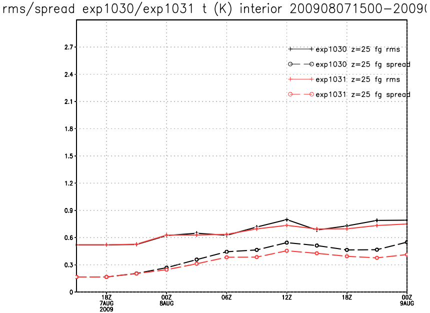
- localization length scales depend on weather situation, observation density ...
- simple adaptive method: keep number of *effective observations* fixed, vary localization radius
- *effective observations*: sum of **observation weights**
- up to now only implemented in horizontal direction
- one has to define minimum / maximum radius, number of *effective observations*
- ideal number of effective observations depends on ensemble size!
- again we have some tuning parameters ...

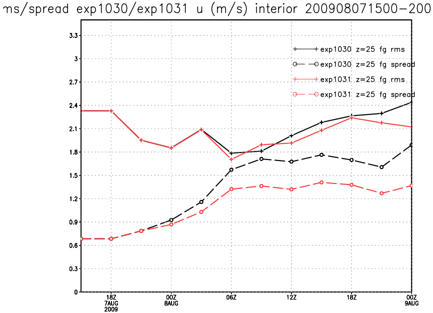
experiments: adaptive horizontal localization



exp1030: adaptive horizontal localization not used, exp1031: adaptive horizontal localization used

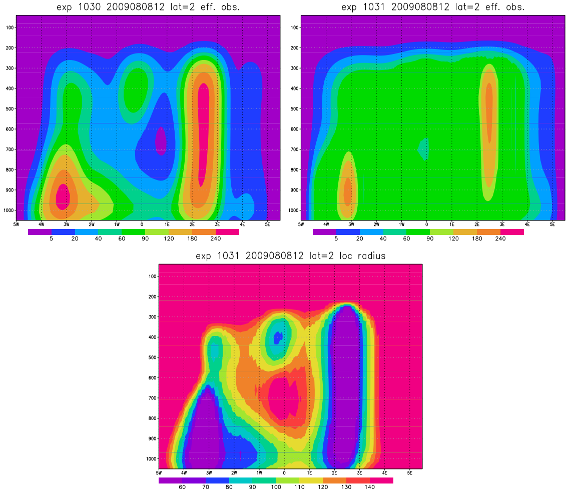
experiments: adaptive horizontal localization





exp1030: adaptive horizontal localization not used, exp1031: adaptive horizontal localization used

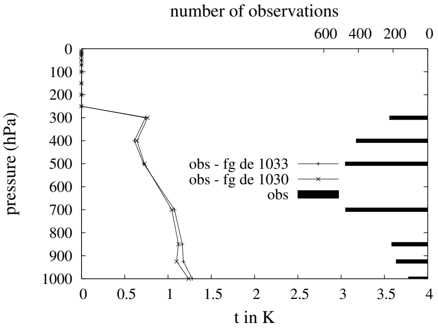
experiments: adaptive horizontal localization

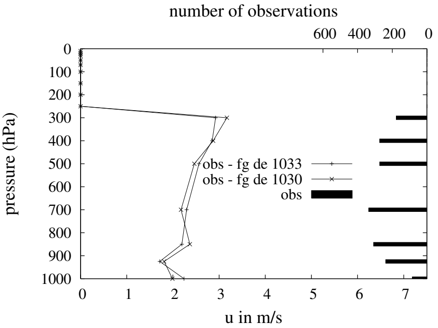


exp1030: adaptive horizontal localization not used, exp1031: adaptive horizontal localization used

experiments: vertical localization

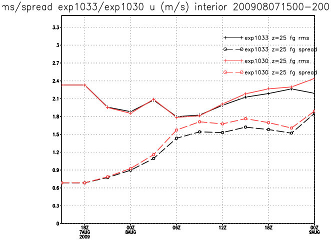
up to now: vertical localization length scale same at all levels
better: increase length scale with height to account for decreasing obs density

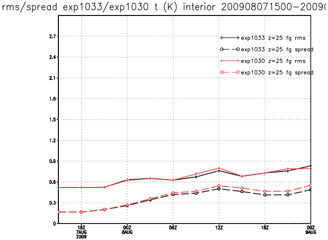


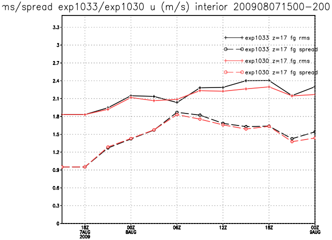


exp1030: vertical localization length scale constant, exp1033: vertical localization length scale variies

experiments: vertical localization







exp1030: vertical localization length scale constant, exp1033: vertical localization length scale variies

next steps

next steps:

- status: all methods together reduce rmse, but still work to do on adaptive methods / observation errors
- increase update frequency, use NUMEX (now ready for LETKF)
- tuning of parameters , e.g. localization length scales
  - localization: extend adaptive method to vertical localization
- compare det/mean run
- runs with BC from global LETKF

Outlook:

- model error (model perturbations): 2 projects within COSMO to account for model error; (stochastic) physics perturbations
- additional observations: radar data (radial winds, reflectivity), GPS, ...

LETKF Theory

- let $\mathbf{w}$ denote gaussian vector in k-dimensional ensemble space with mean 0 and covariance $\mathbf{I}/(k-1)$
- let $\mathbf{X}^b$ denote the (background) ensemble perturbations
- then $\mathbf{x} = \bar{\mathbf{x}}^b + \mathbf{X}^b\mathbf{w}$ is the corresponding model state with mean $\bar{\mathbf{x}}^b$ and covariance $\mathbf{P}^b = (k-1)^{-1}\mathbf{X}^b(\mathbf{X}^b)^T$
- let $\mathbf{Y}^b$ denote the ensemble perturbations in observation space and $\mathbf{R}$ the observation error covariance matrix

LETKF Theory

- do analysis in the k-dimensional ensemble space

$$\bar{\mathbf{w}}^a = \tilde{\mathbf{P}}^a (\mathbf{Y}^b)^T \mathbf{R}^{-1} (\mathbf{y} - \bar{\mathbf{y}}^b)$$
$$\tilde{\mathbf{P}}^a = [(k-1)\mathbf{I} + (\mathbf{Y}^b)^T \mathbf{R}^{-1} \mathbf{Y}^b]^{-1}$$

- in model space we have

$$\bar{\mathbf{x}}^a = \bar{\mathbf{x}}^b + \mathbf{X}^b \bar{\mathbf{w}}^a$$
$$\mathbf{P}^a = \mathbf{X}^b \tilde{\mathbf{P}}^a (\mathbf{X}^b)^T$$

- Now the analysis ensemble perturbations - with $\mathbf{P}^a$ given above - are obtained via

$$\mathbf{X}^a = \mathbf{X}^b \mathbf{W}^a,$$

where $\mathbf{W}^a = [(k-1)\tilde{\mathbf{P}}^a]^{1/2}$

LETKF Theory

- it's possible to obtain a *deterministic run* via

$$\mathbf{x}_a^{det} = \mathbf{x}_b^{det} + \mathbf{K}\left[\mathbf{y} - H(\mathbf{x}_b^{det})\right]$$

  with the *Kalman gain* **K**:

$$\mathbf{K} = \mathbf{X}_b\left[(k-1)\mathbf{I} + \mathbf{Y}_b^T\mathbf{R}^{-1}\mathbf{Y}_b\right]^{-1}\mathbf{Y}_b^T\mathbf{R}^{-1}$$

- the deterministic analysis is obtained on the same grid as the ensemble is running on; the *analysis increments* can be interpolated to a higher resolution