Testing a hybrid ensemble-variational data assimilation system in convective-scale NWP model AROME over Austria

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Variational Data Assimilation

- Cost function (J) is minimized iteratively by a gradient method to get Initial Conditions (ICs).

$$\mathbf{J}(\mathbf{x}) = \frac{1}{2}\overbrace{(\mathbf{x}-\mathbf{x}_b)^{\mathrm{T}}\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b)}^{\text{(squared deviation from background)}} + \frac{1}{2}\underbrace{[\mathbf{y}_\mathbf{o}-\mathbf{H}(\mathbf{x})]^{\mathrm{T}}\mathbf{R}^{-1}[\mathbf{y}_\mathbf{o}-\mathbf{H}(\mathbf{x})]}_{\text{(squared deviation from observation)}}$$

$\mathbf{x}$ = model state vector
$\mathbf{x}_b$ = background state vector
$\mathbf{y}_\mathbf{o}$ = observation state vector
H = forward observation operator
B = background error covariance matrix
R = observation error covariance matrix

- Correct estimation of error statistics (***B*** and ***R***) leads to accurate ICs.

- ***B*** determines weightage to the background and spread information (physical consistency).

- Sampled from climatology and contains seasonal variations.

- Homogeneous and isotropic.

- Non-linear error growth of convective processes is not well represented.

$$\boldsymbol{B} = \begin{pmatrix} \sigma_1^2 & cov(\sigma_2\sigma_1)\ldots & & \\ cov(\sigma_1\sigma_2) & \sigma_2^2 & & \\ \vdots & & \ddots & \\ cov(\sigma_1\sigma_m) & & \cdots & \sigma_m^2 \end{pmatrix}$$

Ensemble-Variational Data Assimilation

- Errors statistics are sampled from an ensemble of forecasts

$$\boldsymbol{B_e} = \frac{1}{N-1}\sum_{k=1}^{N}(\mathbf{x}^k - \bar{\mathbf{x}})(\mathbf{x}^k - \bar{\mathbf{x}})^{\mathsf{T}}$$

N = number of ensembles
x^{k}= k^{th} ensemble member
$\bar{\mathrm{x}}$ = ensemble mean

- Incorporates non-linear error growth & daily variations (flow-dependency)
- Small ensemble *O(50-100)* introduces sampling errors in $\boldsymbol{B_e}$

Hybrid Data Assimilation

- A weighted combination of the climatological and ensemble error statistics

$$\boldsymbol{B} = \alpha\boldsymbol{B_e} + (1-\alpha)\boldsymbol{B_s}$$

$$\alpha\ [0\,;1]$$

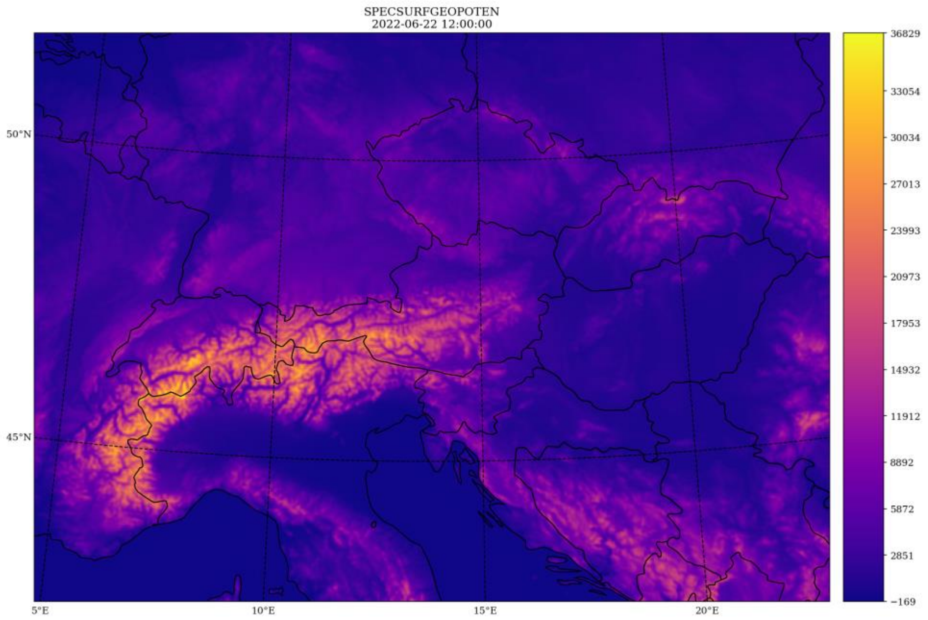
α = weight given to $\boldsymbol{B_e}$
$\boldsymbol{B_e}$= ensemble error covariance matrix
$\boldsymbol{B_s}$= climatological error covariance matrix

Research question?

- Can initial conditions be improved by using ensemble error statistics in data assimilation?

Methodology: model setup

Forecast System	Application of Research to Operations at Mesoscale **(AROME)**
Domain	600 x 432 x 90 grid-points **(The Alps at the center of the domain)**
Resolution	Horizontal - 2.5 km **(explicit convection)** vertical - 90 hybrid pressure coordinates
Ensembles forecasts	50 members, **Convection-Permitting** Limited-Area Ensemble Forecasting (C-LAEF) at 2.5km.
Observations	Radiosonde and aircraft **T and UV**
Boundary conditions	Global model ARPEGE



AROME domain with topography (Geosphere Austria)

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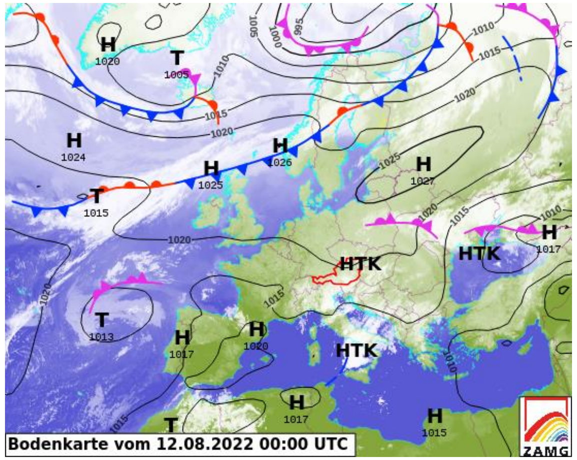
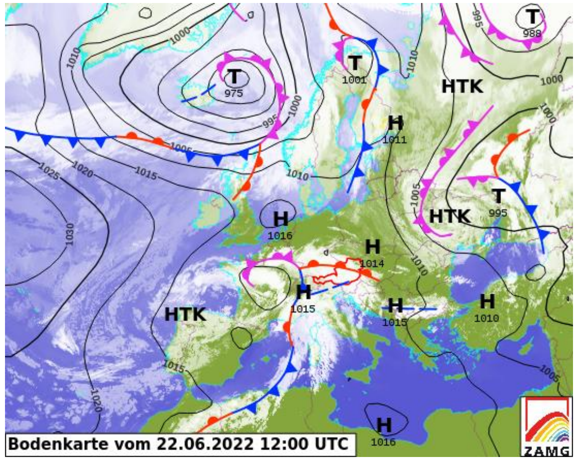
Methodology

a) 12-08-2022



- Local convection
- Weak pressure gradient

b) 22-06-2022



- convection and warm front

Experimental setup:

- 50 Ensemble members
- T and UV from radiosonde and aircraft are assimilated
- ICs are verified with non-assimilated observation

Exp.	Ensemble weight (**α**)	Ensemble member
3DVAR	0	0
ENVAR	1	50
HYB_XX	0.1 to 0.9	50

α = weight given to $\boldsymbol{B_e}$

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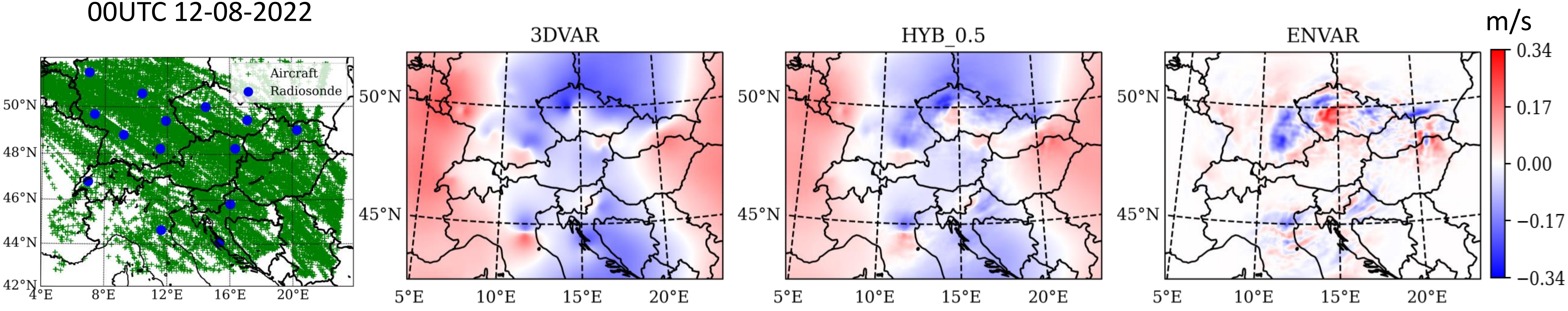
Results

UV assimilated at
00UTC 12-08-2022

Radiosonde S013WIND (~ 200hPa)



Increment = analysis - background

Climatological B:

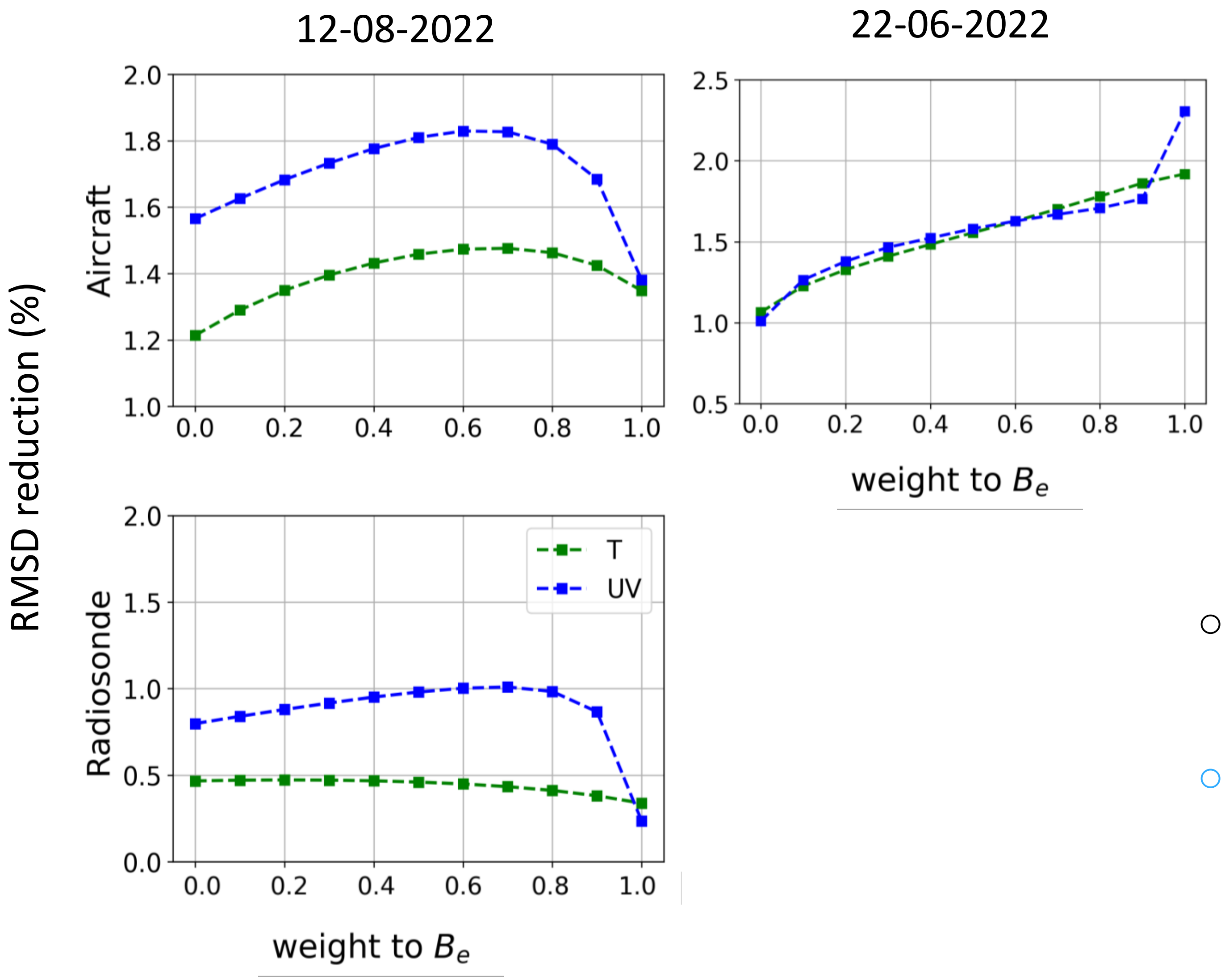
- Smooth
- Large scale increment

Ensemble B ($\boldsymbol{B_e}$):

- Spatial variability
- small scale variations

- Different B provides different increments.

Results



RMSD reduction (%) = $\left(\dfrac{RMSD_{bg} - RMSD_{anl}}{RMSD_{bg}} \right)$ X 100

- Overall using $\boldsymbol{B_e}$ improves ICs compared to the operational system. Ecmwf&123
- Hybrid has potential of most benefits yet optimal weight to $\boldsymbol{B_e}$ differs for weather scenarios, and observation assimilated.

Conclusions

1. Accurate representation of error statistics is a key factor of DA.
2. Successfully tested hybrid ensemble-variational data assimilation method at convective-scale over Austria.
3. Incorporating ensemble error statistics in data assimilation showcases potential advantages compared to the operational system, wherein the Hybrid configuration can lead to substantial benefits.
4. Optimal weights to $\boldsymbol{B_e}$ depend on various factors and differ for assimilated observations and weather scenarios.

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