3D wind retrievals for the analysis of hailstorm dynamics in Germany and the USA

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Funded by DFG Deutsche Forschungsgemeinschaft German Research Foundation

ECSS European Conference on Severe Storms

Motivation and objectives

Primary goal is to improve our understanding of large hail formation and trajectory models (e.g. HailTrack; Brook et al., 2021)

→ because large hail growth is more likely in stronger and wider updrafts (e.g. Fischer et al., 2025; Kumjian and Lombardo, 2020) precisely retrieved wind fields are crucial

- 3D wind retrievals → minimizing the sum of various cost functions (e.g. via 3D variational method; Potvin et al., 2012; Shapiro et al., 2009) to optimize trajectory models

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- Applying the open-source Pythonic Direct Data Assimilation (PyDDA; Jackson et al., 2020) algorithm

→ obtain the best weighting parameter set for convective events in Germany

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PyDDA algorithm

Cost Function	Symbol	Equation
Total	$J(V_{\text{proj}})$	$J(V_{\text{proj}}) = C_{mass} J_{\text{mass}} + C_O J_O + C_r J_r + C_{sm} J_{sm} + \dots$
Radar observations	J_O	$J_O = \sum_{\text{radar}} [V_{\text{obs}} - V_{\text{proj}}]^2$
Mass continuity	J_{mass}	$J_{\text{mass}} = \sum_{\text{domain}} \left[\nabla \cdot V_{\text{proj}} + w_{\text{proj}} \frac{d\rho}{dz}\right] \frac{1}{2}$
Vertical vorticity	J_v	see e.g. Potvin et al. (2012), their Eq. 10
Radiosonde (background)	J_r	$J_r = \sum_{\text{background}} [V_{\text{sounding}} - V_{\text{proj}}]^2$
Smoothness	J_{sm}	$J_{sm} = \sum_{\text{domain}} \left[\nabla^2 V_{\text{proj}}\right]$
Model (e.g., ERA5)	J_m	$J_m = \sum_{\text{domain}} [V_m - V_{\text{proj}}]^2$
Point (obs. from stations)	J_{point}	$J_{\text{point}} = \sum_{\text{region}} \left((u_{\text{proj}} - u_{\text{point}})^2 + (v_{\text{proj}} - v_{\text{point}})^2\right)$

see e.g. Potvin et al. (2012); Shapiro et al. (2009); Jackson et al. (2020); Brook (2023)

- The weighting parameters (e.g. C_O, C_{mass}) have a large influence on the wind retrievals
- Appropriate tuning is crucial for balancing the effects of the constraints

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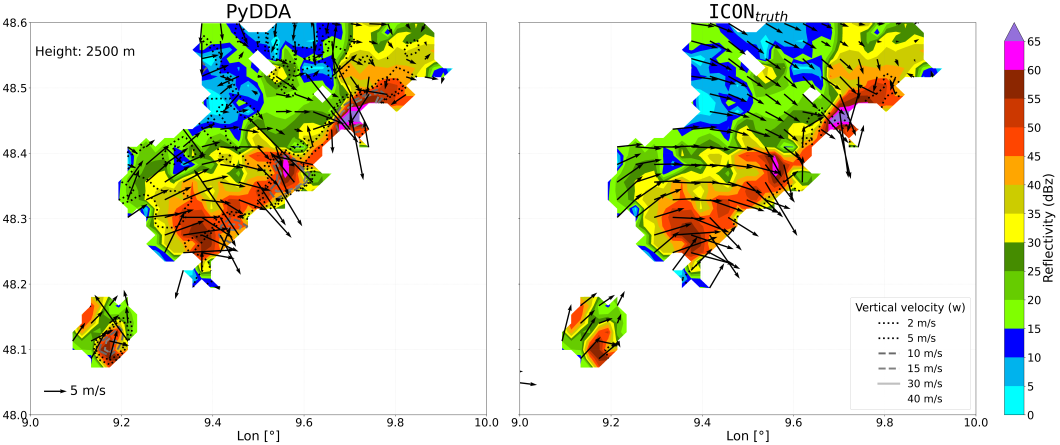
Example: 2023-08-17 12:30



with example setting $\rightarrow C_0 = 1, \; C_{mass} = 15000, \; C_m = 0$

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Sensitivity study of PyDDA weighting parameters

Observations C_O	0	0.01	0.1	1	10	100	—	—	—	—	—
Mass continuity C_{mass}	0	0.01	0.1	1	10	100	1000	10000	15000	20000	25000
Model C_{m}	0	0.01	0.1	1	10	100	—	—	—	—	—
Smoothness C_{sm}	0	0.01	0.1	1	10	100	1000	—	—	—	—

	Maximum iterations	**Vertical wind tolerance**	**Filter window**
Setting	1000	0.1	4

$\rightarrow$ All wind components are only compared in regions where $Z_H > 0$ dBZ and between beam crossing angles of $> 30^\circ$ and $< 150^\circ$

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Sensitivity study of PyDDA weighting parameters

- Applying ICON-RUC wind fields as ground truth ($\texttt{ICON}_{truth}$)

  $\rightarrow$ one event in Germany: 2023-08-17

  $\rightarrow$ same event as the hailsonde launch in real observations
- Initialization of PyDDA with $V_{\text{proj}} = 0$ m/s
- Retrieved PyDDA wind fields using various combinations of weighting parameters are compared with $\texttt{ICON}_{truth}$ via:
  - VRMSE (horizontal)
  - VRMSE (horizontal + w)
  - Directional-RMSE (DRMSE; RMSE based on the angle θ between horizontal vectors)
  - RMSE of the w components
  - Pearson correlation (ρ) of the vector magnitudes (horizontal + w)
  - Fractional skill score (FSS)

    $\rightarrow$ using horizontal max/min of w in height-columns for Updraft/Downdraft map

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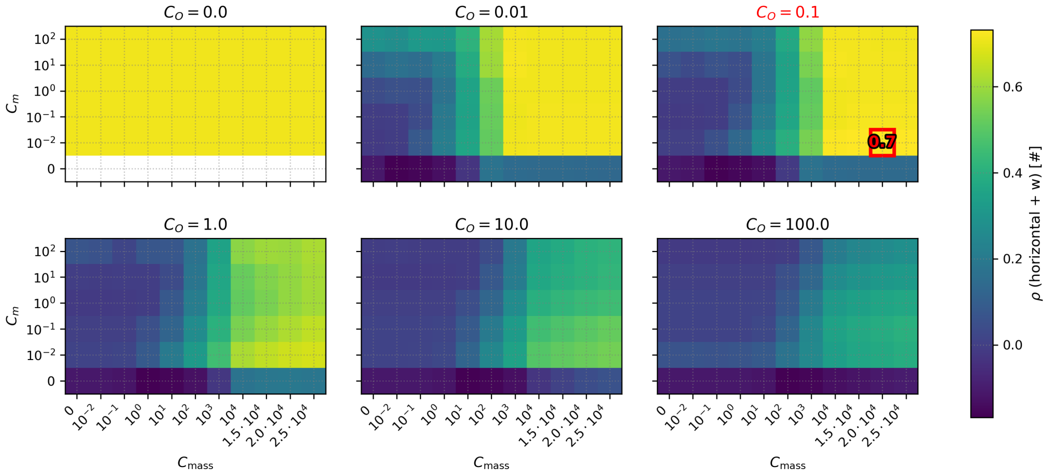
Error analysis over full domain



Sensitivity study of PyDDA weighting parameters

Observations C_O ✓	0	0.01	0.1	**1**	10	100	—	—	—	—	—
Mass continuity C_{mass} ✓	0	0.01	0.1	1	10	100	1000	10000	15000	20000	**25000**
Model C_{m} ✓	0	**0.01**	0.1	1	10	100	—	—	—	—	—
Smoothness vertical C_V	0	0.01	0.1	1	10	100	1000	—	—	—	—
Smoothness horizontal C_H	0	0.01	0.1	1	10	100	1000	—	—	—	—

	Maximum iterations	**Vertical wind tolerance**	**Filter window**
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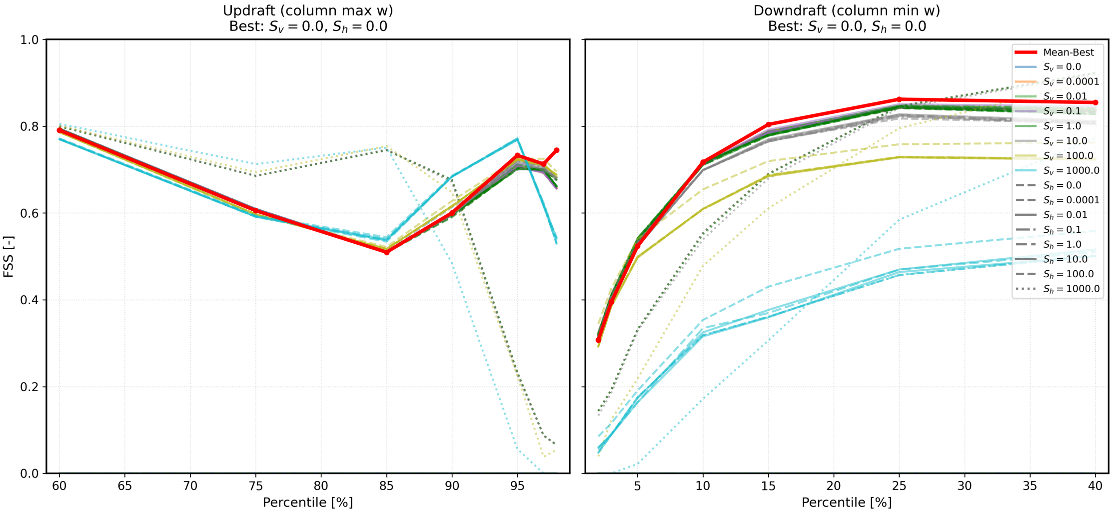
FSS as mean over timesteps – Smoothing



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Spatial verification using Wavelets

- Point-wise scores (RMSE: double penalty) and threshold based scores (FSS) can be misleading for displaced features
- Wavelet transforms can decompose atmospheric fields into localized scale bands (distributions of scale and location)

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  → Usage of the Dual-Tree Complex Wavelet Transform (DTCWT; Buschow, 2022) to derive **structural** error components between PyDDA and ICON using amplitude and phase information

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Spatial verification using Wavelets

$$
\begin{aligned}
d_z &= z_c^{(\mathrm{PyDDA})} - z_c^{(\mathrm{ICON})} && \text{scale error (too large / too small)} \\
d_\rho &= \rho_c^{(\mathrm{PyDDA})} - \rho_c^{(\mathrm{ICON})} && \text{anisotropy error (too elongated / too round)} \\
d_\varphi &= \mathrm{wrap}_{[-90^\circ,\,90^\circ]}\left(\varphi_c^{(\mathrm{PyDDA})} - \varphi_c^{(\mathrm{ICON})}\right) && \text{orientation (angle) error} \\
d_{\mathrm{disp}} &= \mathrm{RMSE}\ \left\|\boldsymbol{\delta}\right\| && \text{displacement error (average shift magnitude)}
\end{aligned}
$$

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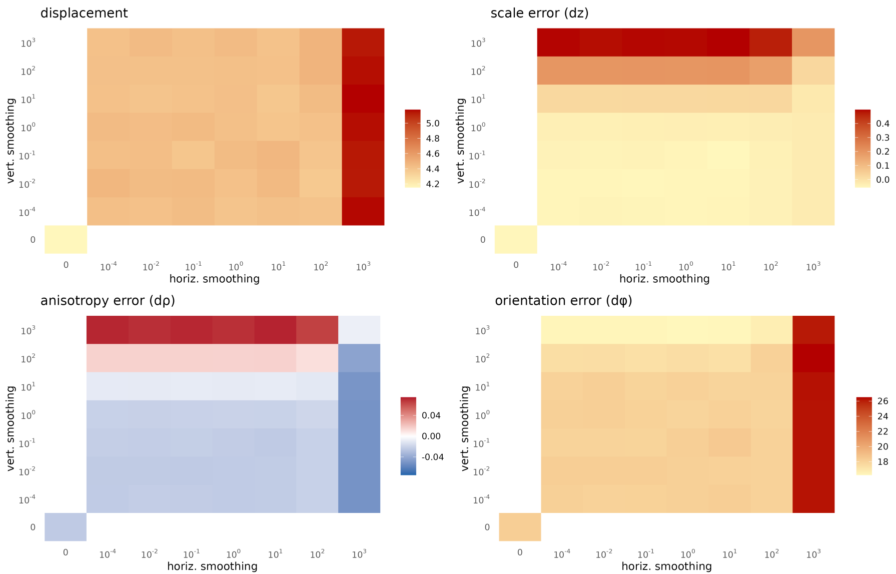
Error analysis over full domain - smoothing



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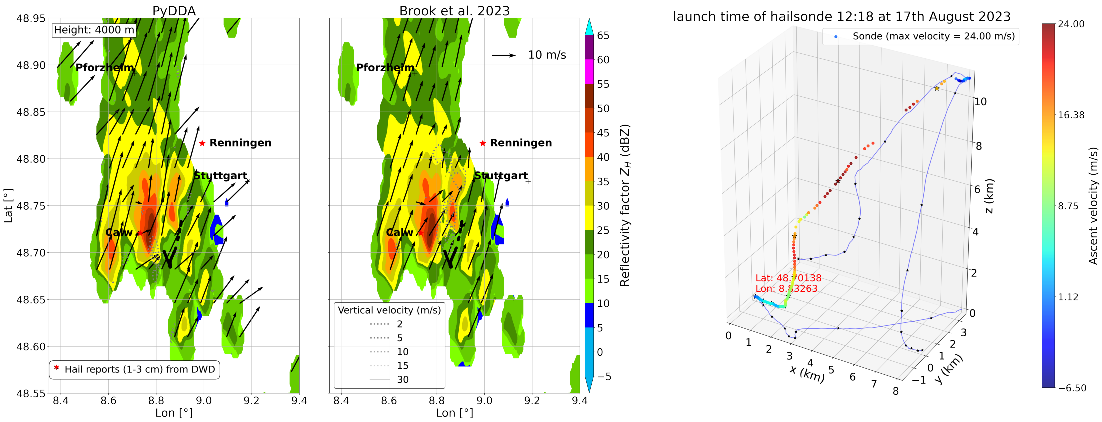
Best combination of weighting parameters in PyDDA

Final best combination for PyDDA in Germany with smoothing parameters:
$C_O = 1,\ C_{\text{mass}} = 25000,\ C_m = 0.01,\ C_V = 0,\ C_H = 0$

Comparison of PyDDA and Brook et al. 2023 retrieved wind fields



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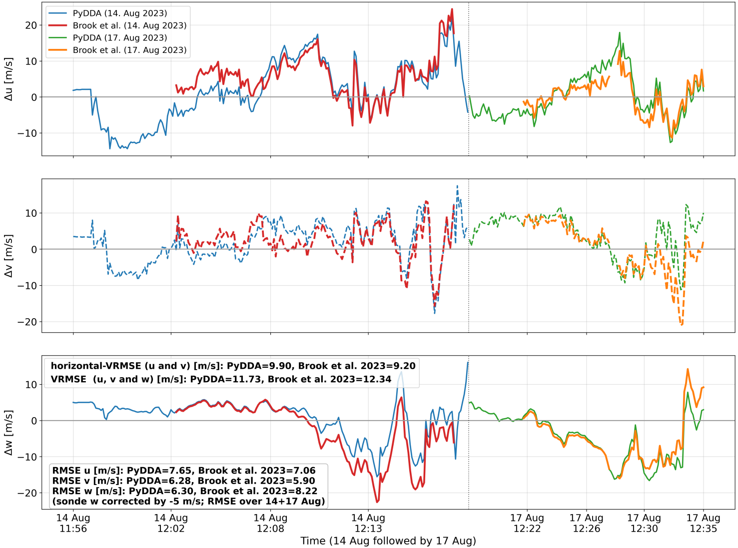
Comparison of PyDDA and Brook et al. 2023 retrieved wind fields – Differences



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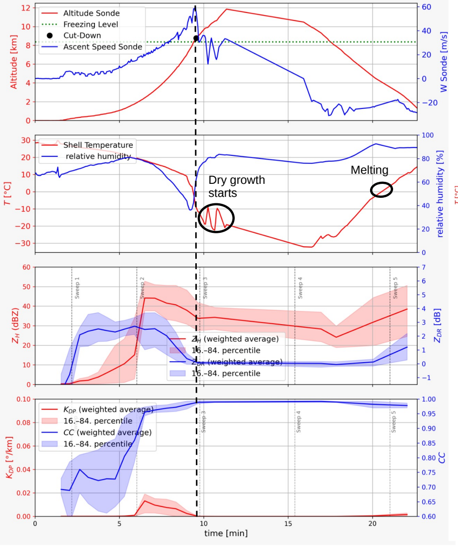
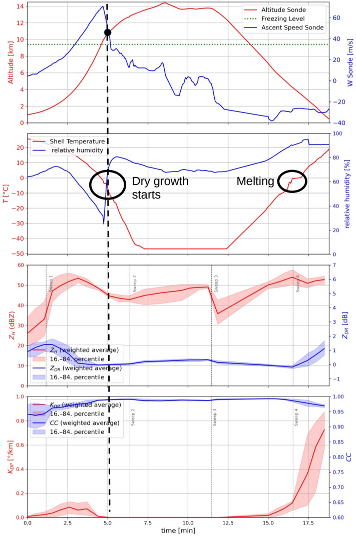
ICECHIP campaign hailsonde launches at 25th of May 2025 near Afton, Texas

21:13 UTC



21:14 UTC



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Summary and future steps

- Sensitivity study using ICON-RUC to get best weighting parameters combination of PyDDA applying different error quantities (including displacement from wavelet transform)
- PyDDA and Brook et al. 2023 retrieved wind fields in compairson to hailsonde trajectories for the 8.14.2025 and 8.17.2025 looking quite similar

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