Ambiguity and Nonlinearity in the Assimilation of Visible and Infrared Satellite Observations

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25 October 2024

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Introduction

Previous Talks on assimilation experiments in idealized OSSEs

- EAKF can utilize satellite observations despite nonlinear observation operators
- Visible and infrared observations: high potential impact comparable to 2D radar assimilation
- Highest impact when state errors are horizontal location errors and can be seen on a 2D satellite image

⇒ Kugler, Anderson, Weissmann (2023), QJRMS

EGU General Assembly 2023

ISDA Bologna 2023

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Content today:

1) Combined assimilation of visible and infrared radiances
2) Nonlinearity of observation operators

Comparison of visible and infrared observations

Channel is sensitive to …	Infrared 6.2 µm	Infrared 7.3 µm	Visible 0.6 µm
Tropospheric water vapor			
Cloud top height			
Cloud thickness (liquid/ice water path)			
Clouds below thin ice clouds			
Clouds below ~600 hPa			

Comparison of visible and infrared observations

Channel is sensitive to …	Infrared 6.2 µm	Infrared 7.3 µm	Visible 0.6 µm
Tropospheric water vapor	✅		
Cloud top height	✅		
Cloud thickness (liquid/ice water path)	❌		
Clouds below thin ice clouds	❌		
Clouds below ~600 hPa	❌		

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Cloud top height	✅	✅	
Cloud thickness (liquid/ice water path)	❌	❌	
Clouds below thin ice clouds	❌	❌	
Clouds below ~600 hPa	❌	✅ ~850 hPa	

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Cloud top height	✅	✅	❌
Cloud thickness (liquid/ice water path)	❌	❌	✅
Clouds below thin ice clouds	❌	❌	✅
Clouds below ~600 hPa	❌	✅ ~850 hPa	✅

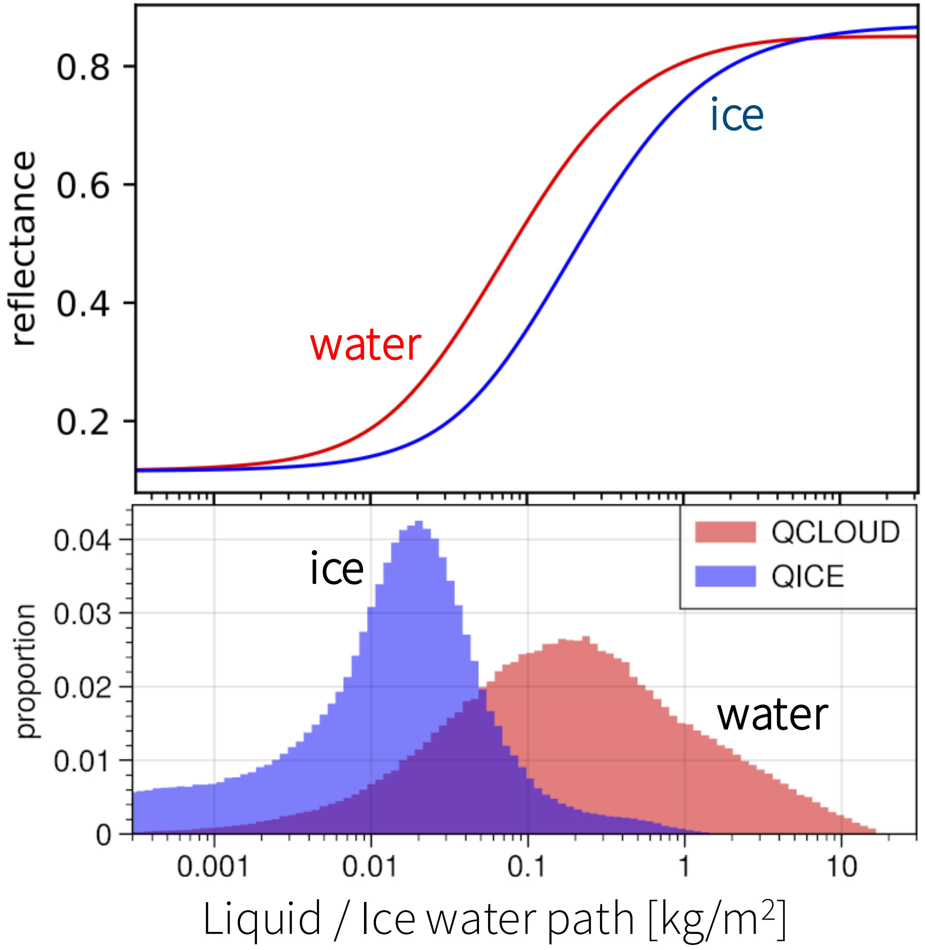
Sensitivity of visible reflectance to water and ice

How does it see through ice?

Figure: Sensitivity of visible reflectance to water and ice

Reasons:

upper panel from Geiss et al. (2021), first in Scheck et al. (2020)



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Reasons:
•Ice water path < liquid water path [kg/m^2]
Lower ice mass ⇒ reduced reflectance

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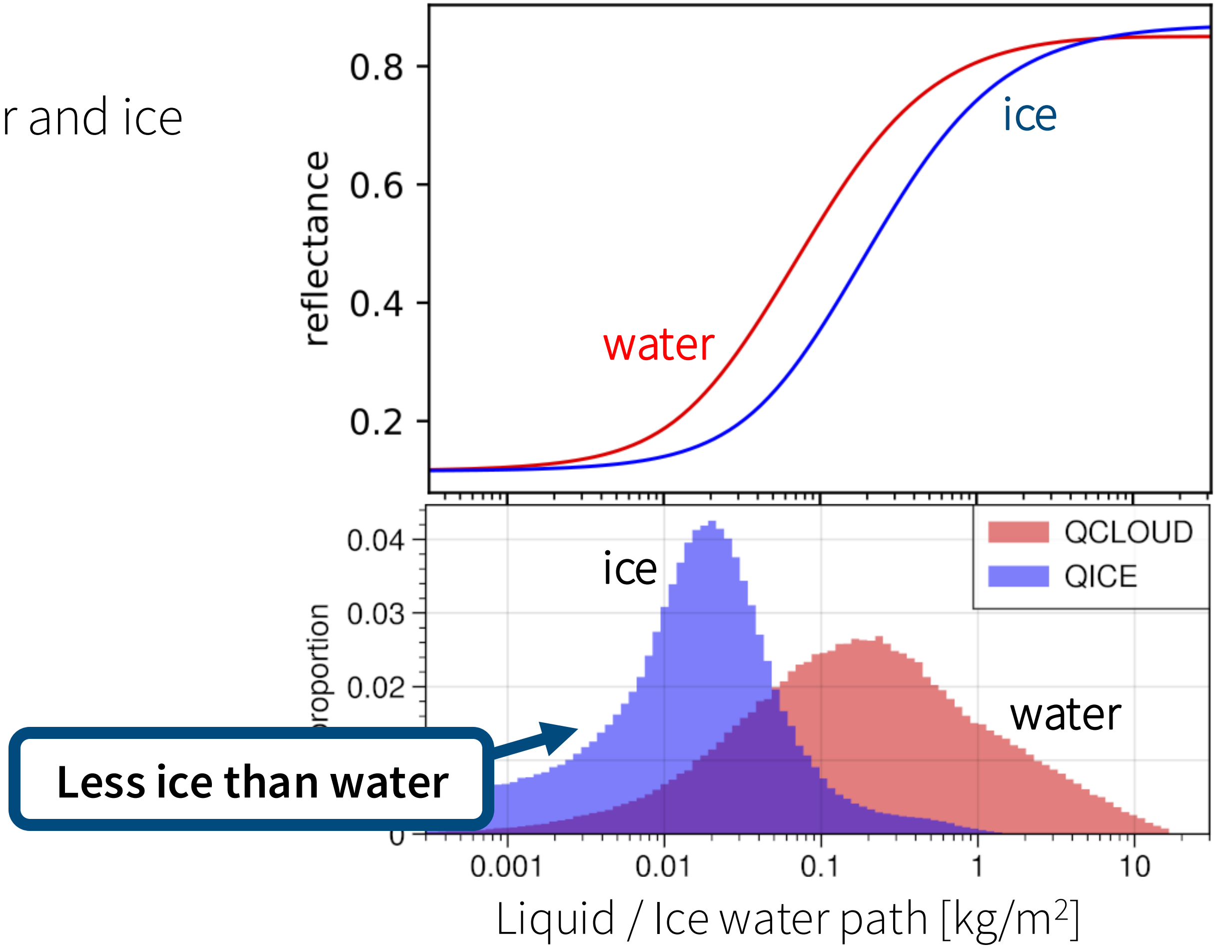

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Fewer particles ⇒ reduced reflectance

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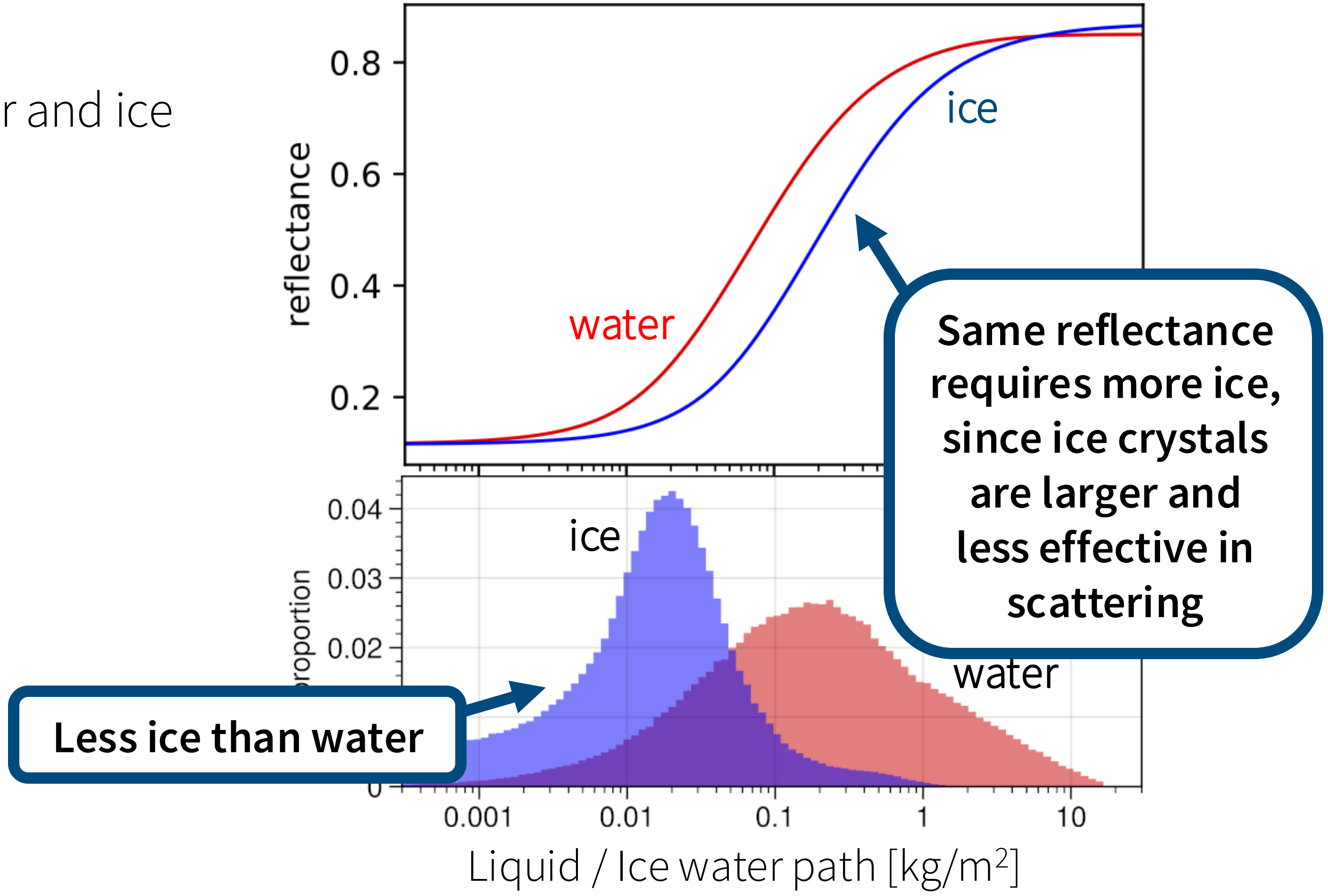

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⇒ Ice clouds tend to be translucent in the visible channel

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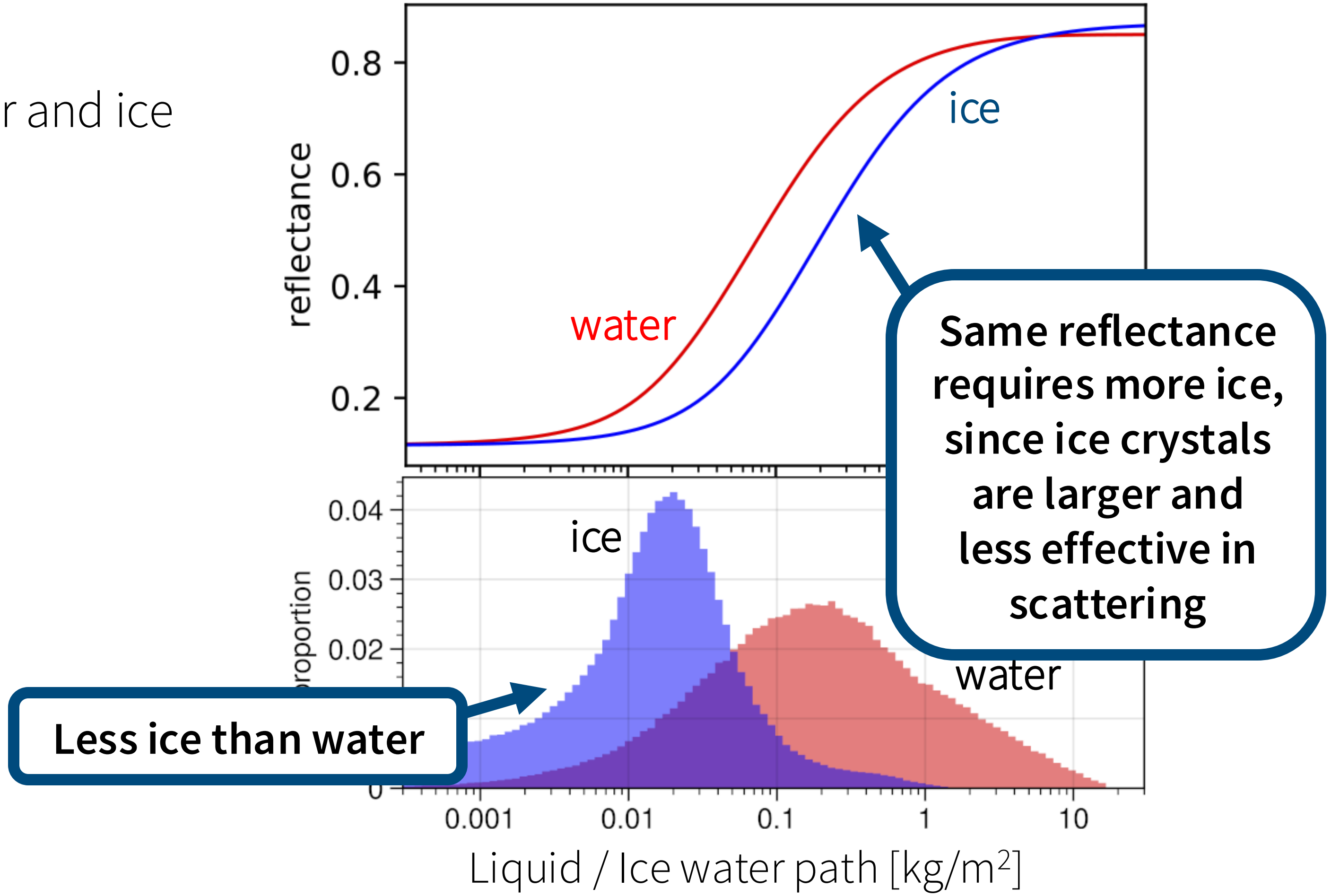

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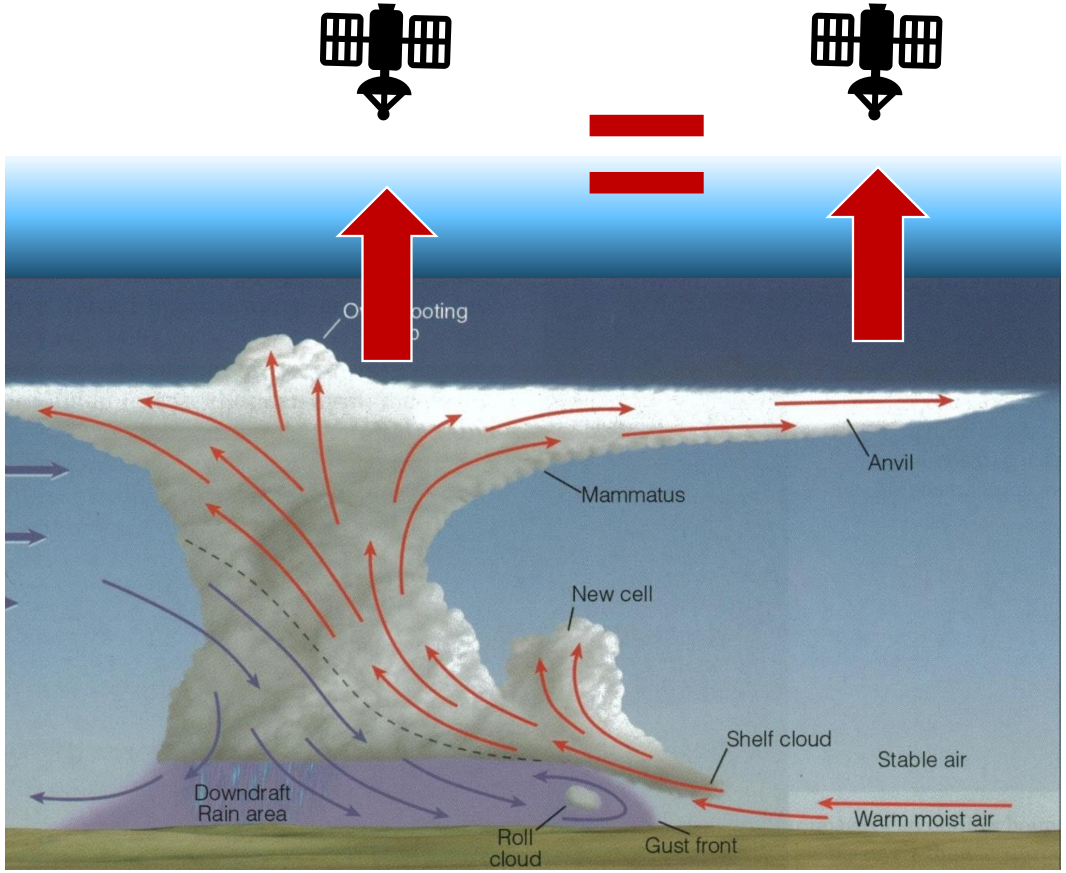
Combination can mitigate ambiguity

- Different clouds can yield the same observation
  - Infrared: Cumulonimbus and cirrus clouds
  - Visible: Shallow cumulus and cumulonimbus



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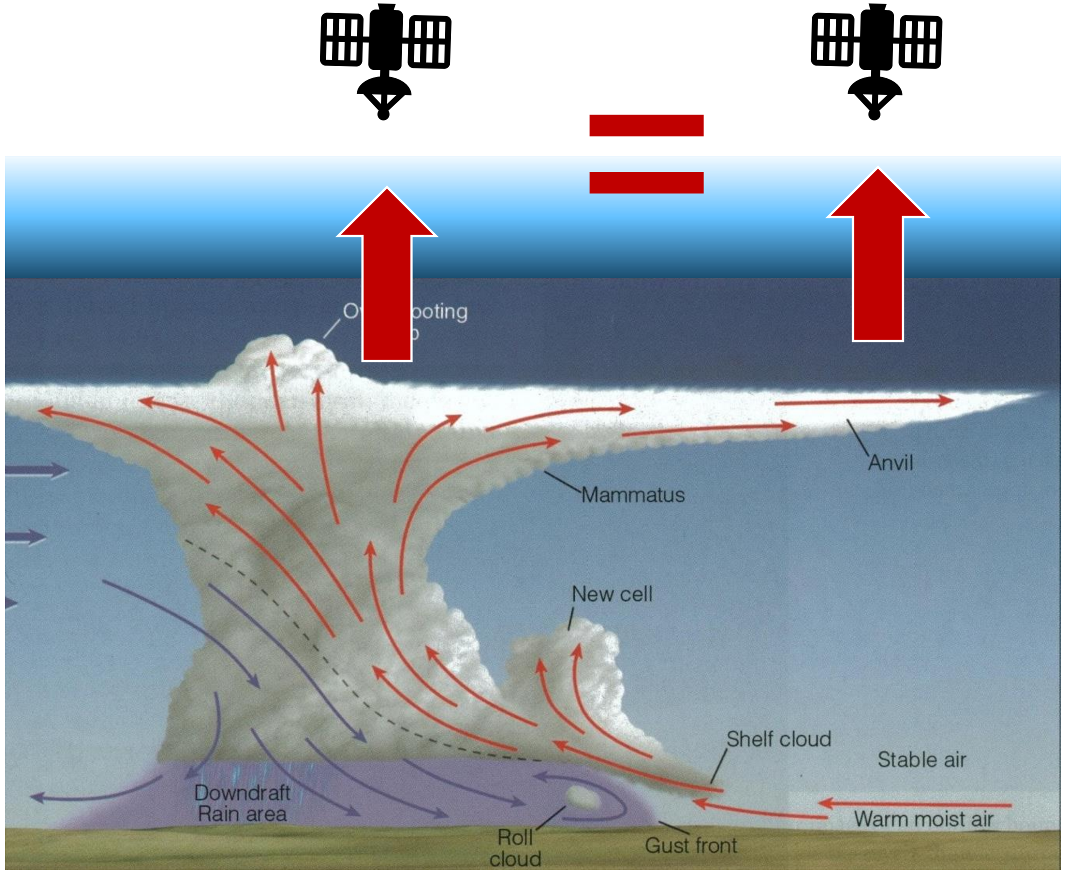

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  - Infrared: Cumulonimbus and cirrus clouds
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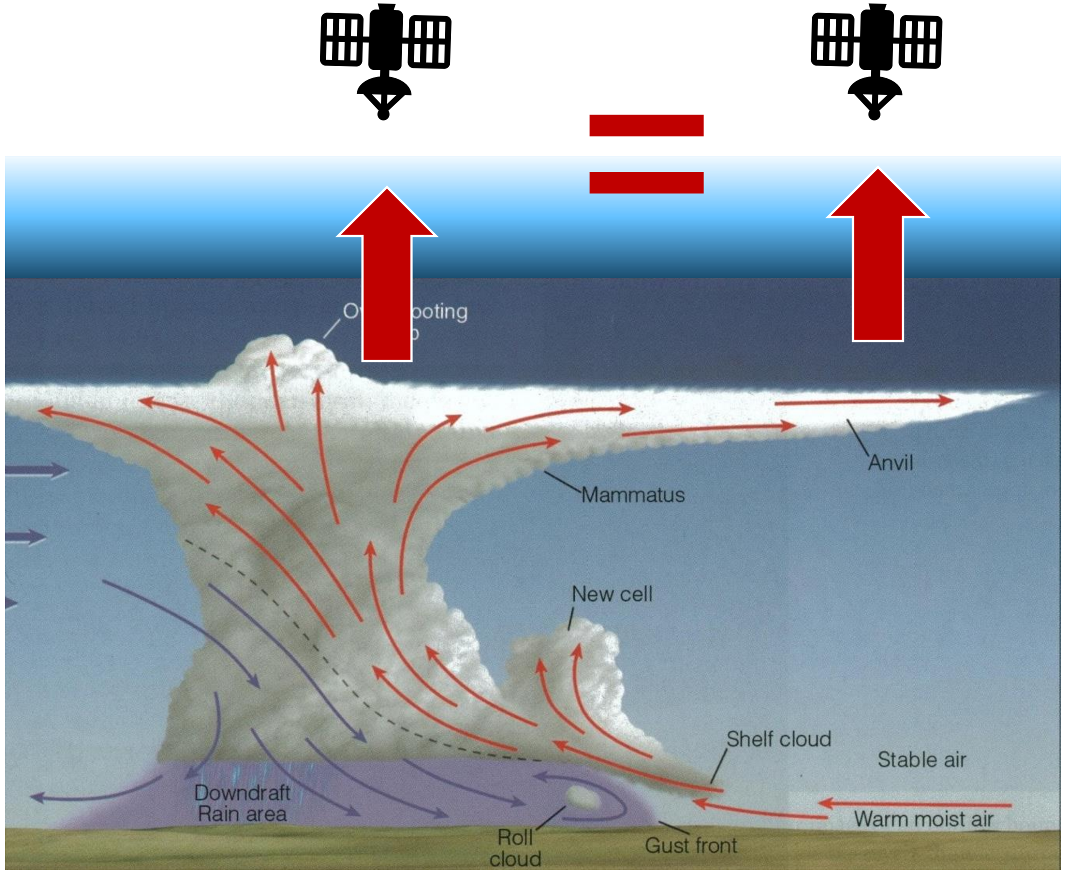
Proposed solution

- Assimilate visible reflectance additionally because ice clouds tend to be translucent in the visible



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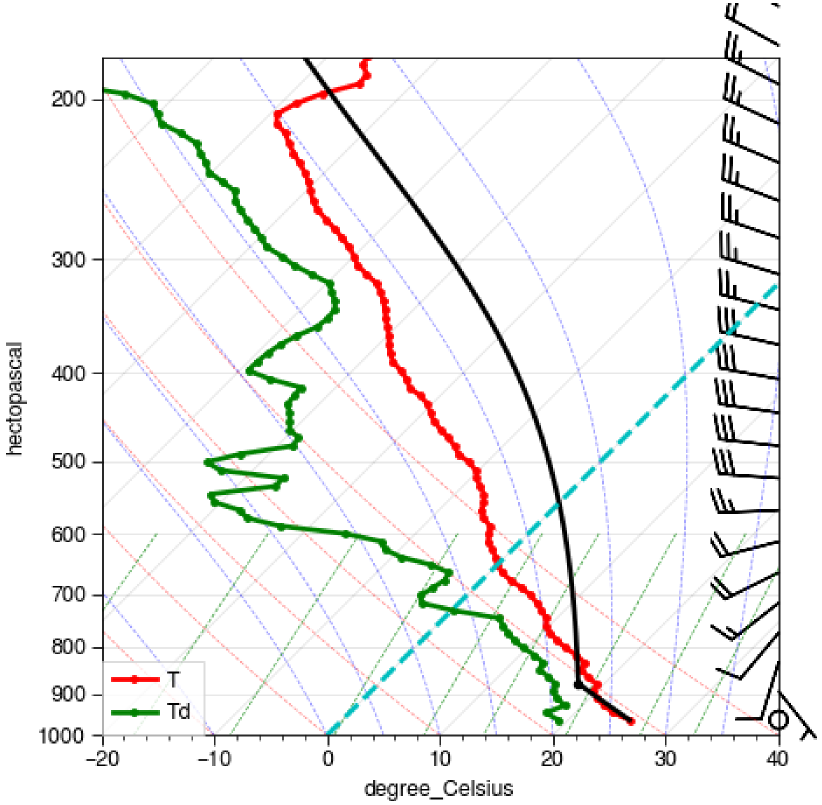
Methods: Observing-system simulation experiments

We conducted

- Idealized OSSEs
  - Perfect model and observation operator
  - Periodic boundary conditions
  - Flat and homogeneous terrain
  - Chosen initial conditions for supercells with random prior errors



Initial conditions Skew-T diagram (temperature-dewpoint-wind)

Methods: Observing-system simulation experiments

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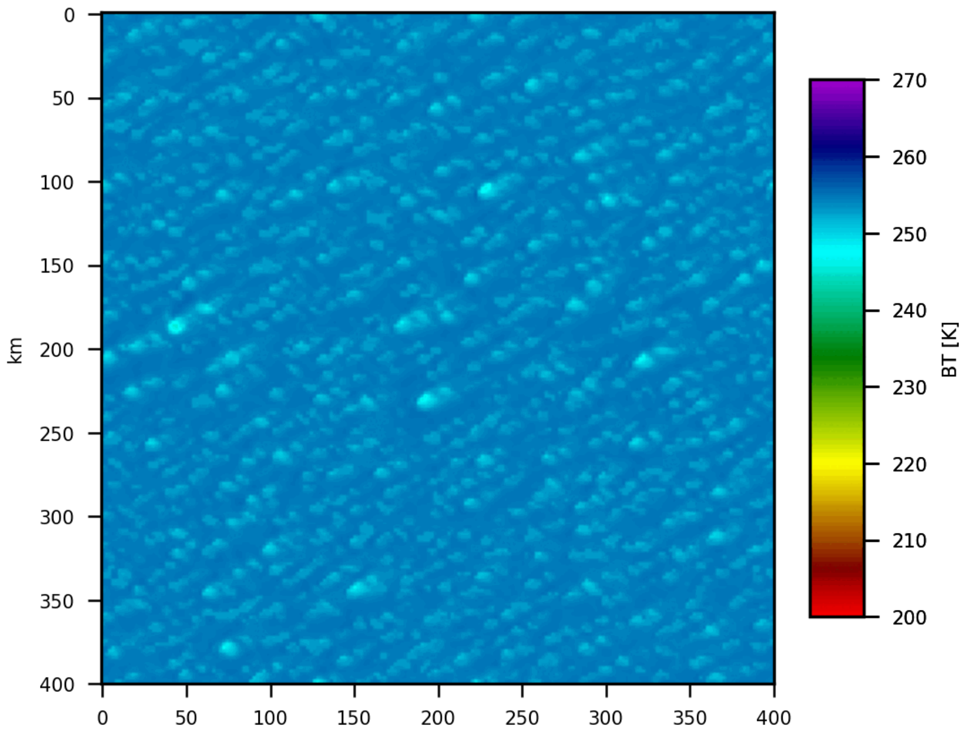
Using

- WRF model domain of size 400 x 400 km, $\Delta x = 2$ km
- RTTOV/MFASIS for visible radiances (Scheck et al., 2016)
- Ensemble Adjustment Kalman Filter (Anderson, 2001) as implemented in DART (NCAR, http://dart.ucar.edu)
  - 25 configuration settings explored (obs.-types, inflation)



Infrared satellite observations simulated from the nature run

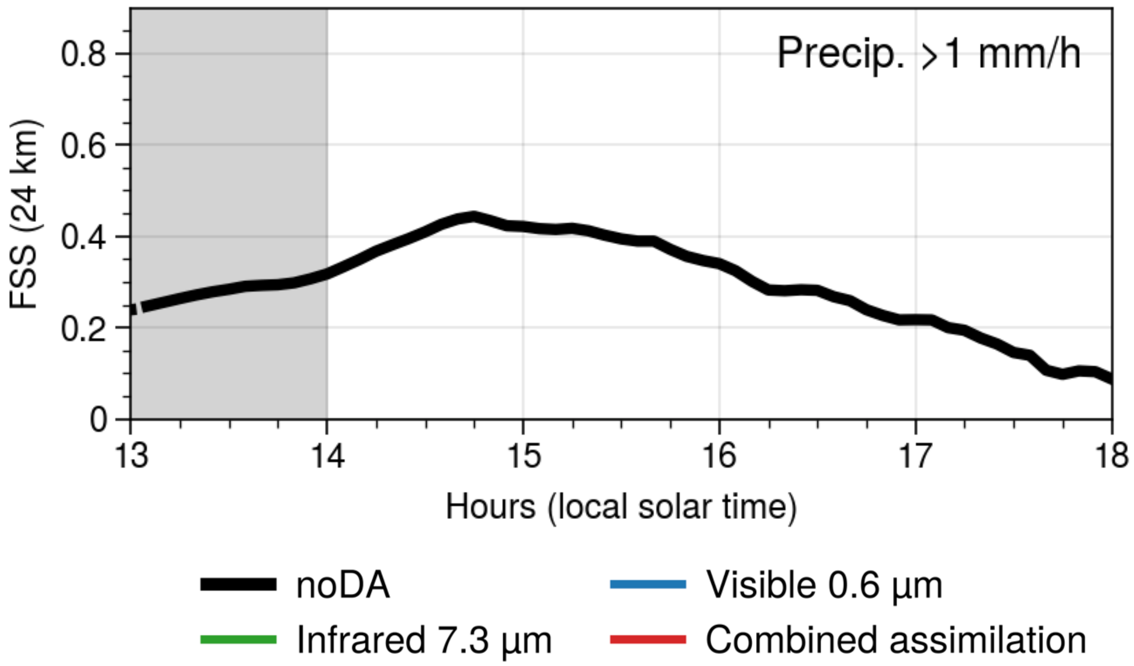
Results: Combined assimilation of visible and infrared

To combine the strengths of individual channels

- We assimilated visible and infrared radiance

<u>Result:</u>

- Improved forecasts of precipitation and cloudiness over individual assimilation



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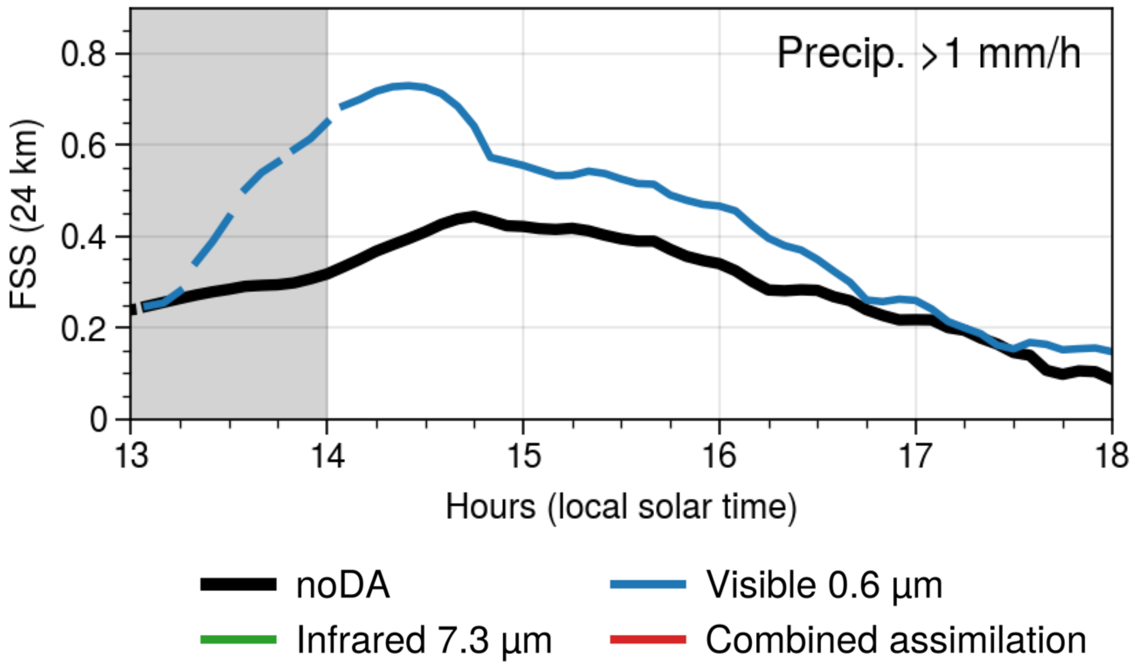

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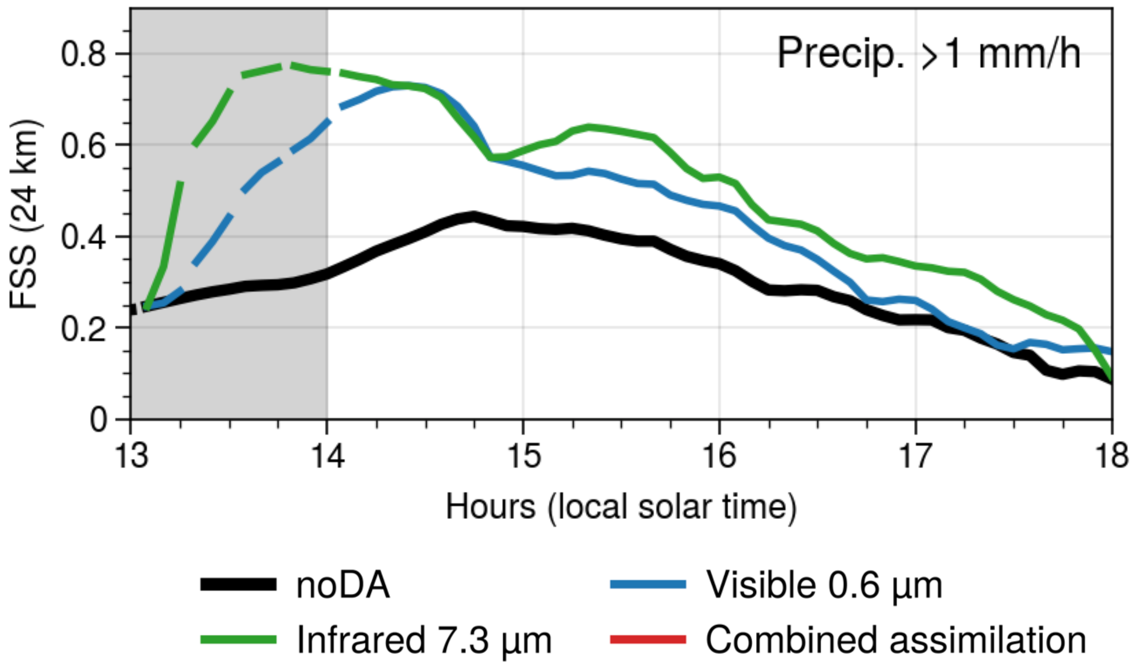

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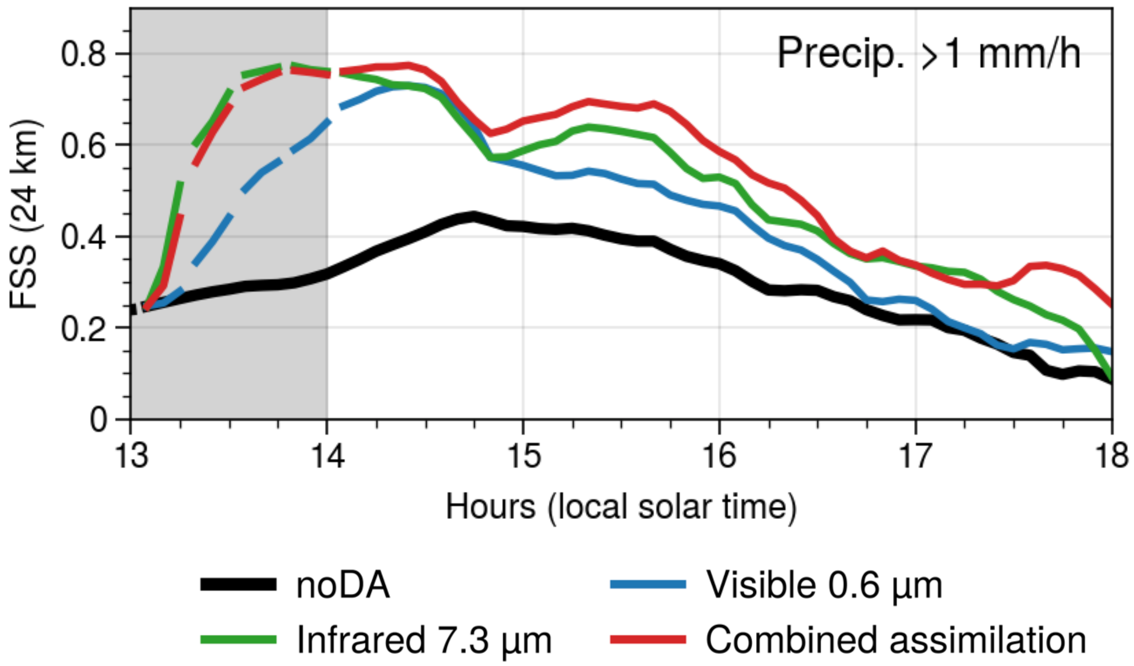

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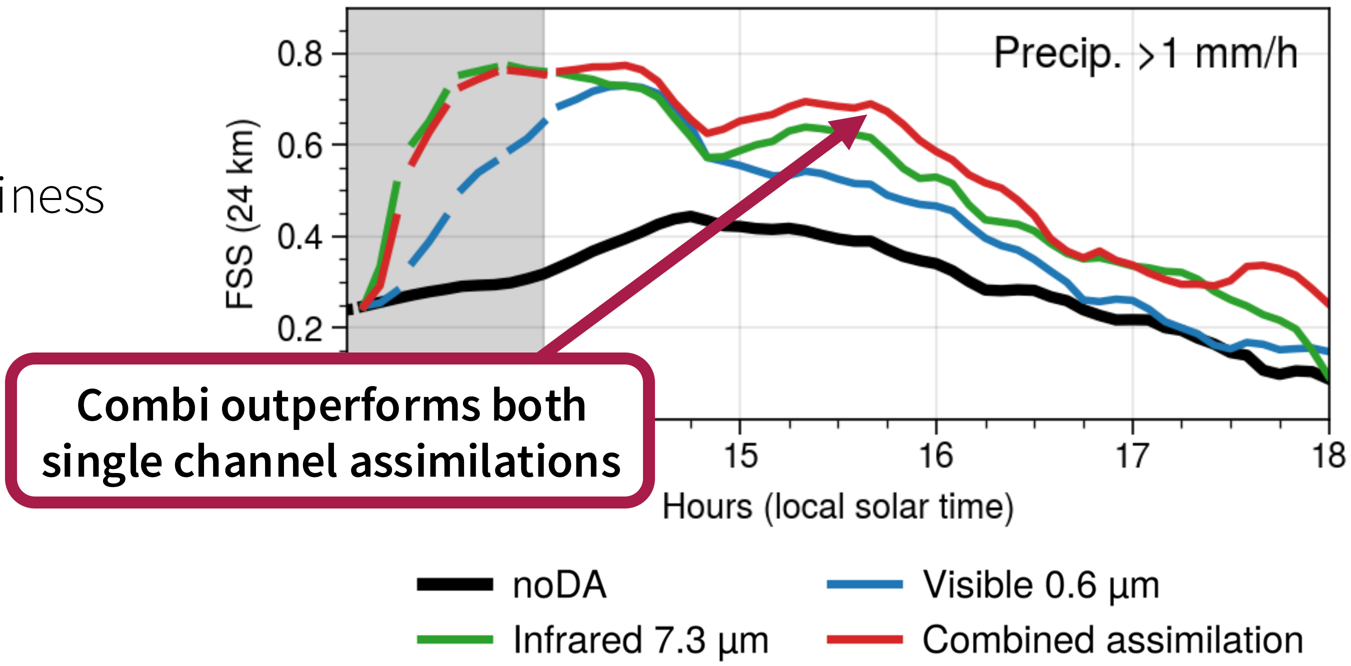

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Results: Combined assimilation of visible and infrared

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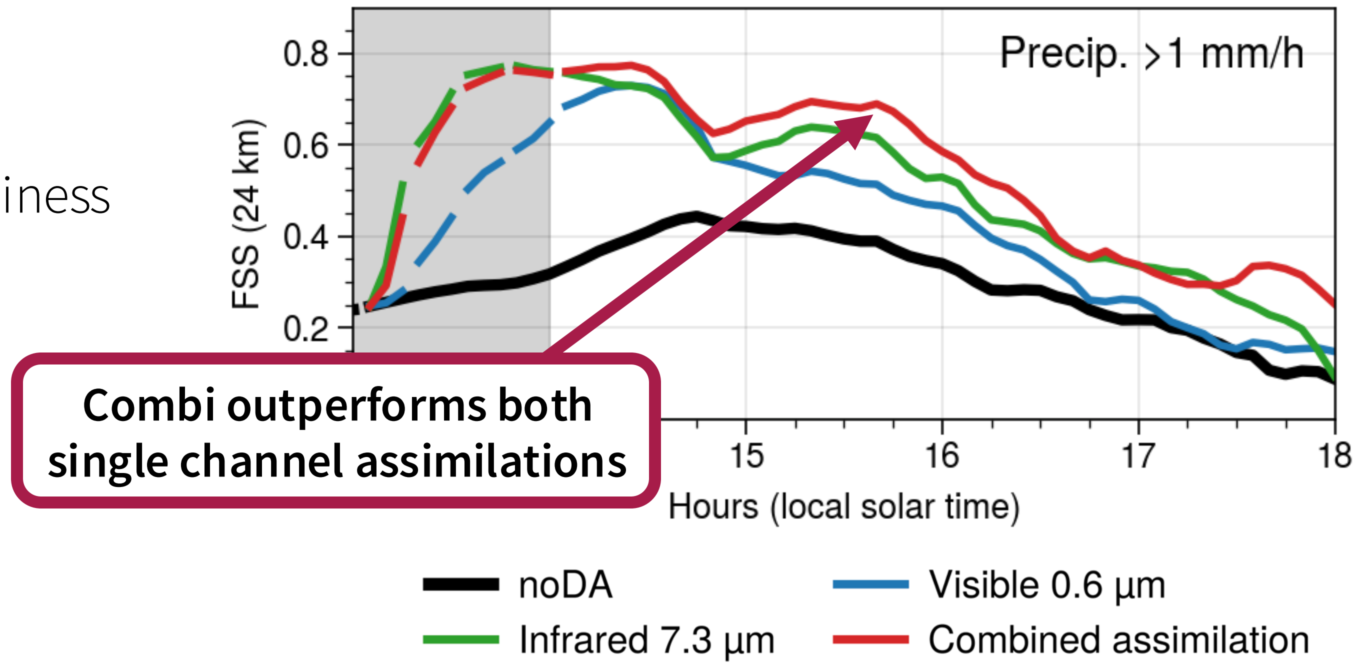
Result:

- Improved forecasts of precipitation and cloudiness over individual assimilation
- Comparable skill as radar assimilation



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Results: Combined assimilation

Impact on the analysis of cloud variables

- Evaluated different cloud categories

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Category 1:
Columns in which the nature run has only ice clouds

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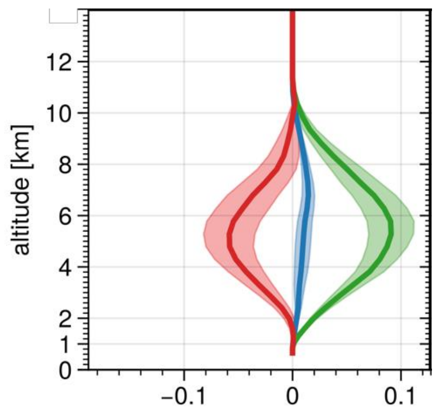
Vertical profiles of analysis error reduction



ΔMAE of
cloud water (g/kg)

noDA
Visible 0.6 µm
Infrared 7.3 µm
Combined assimilation

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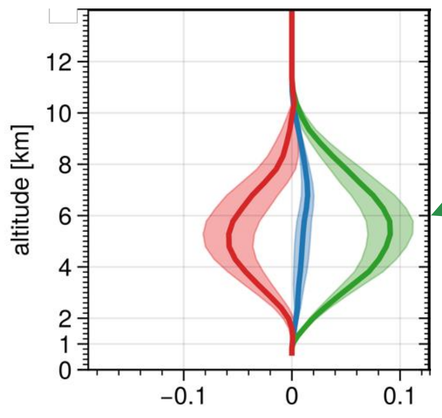

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Infrared adds wrong cloud water

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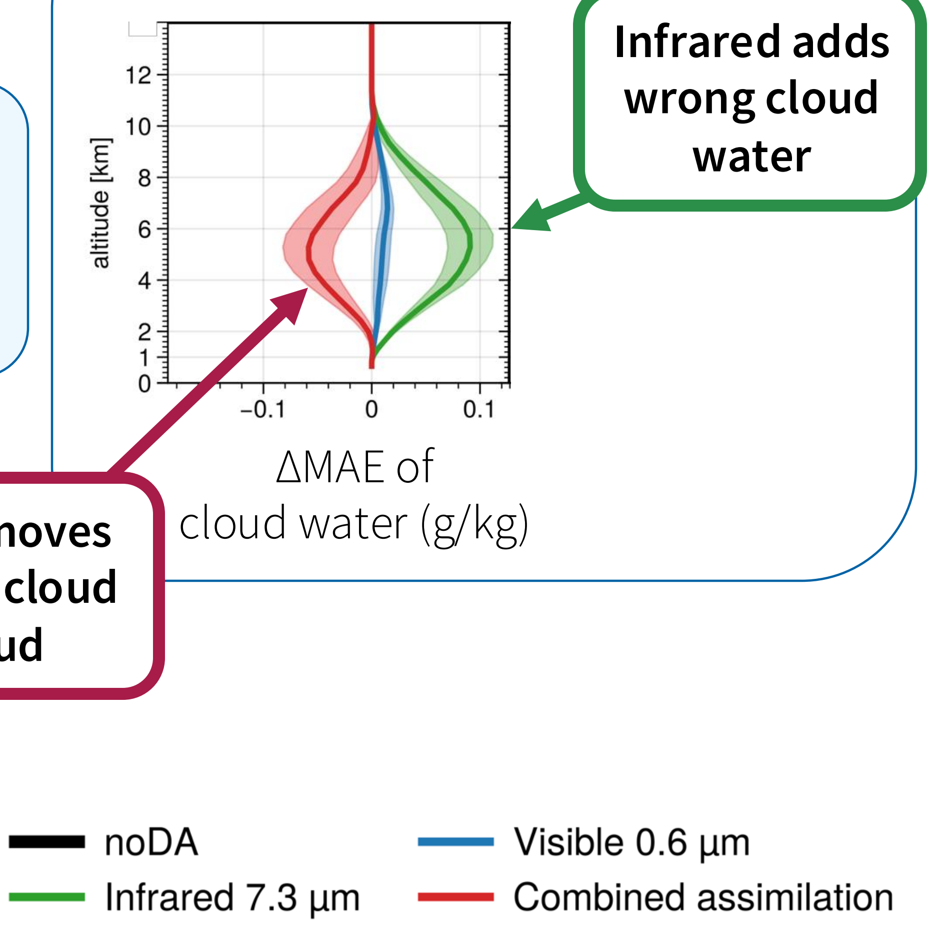

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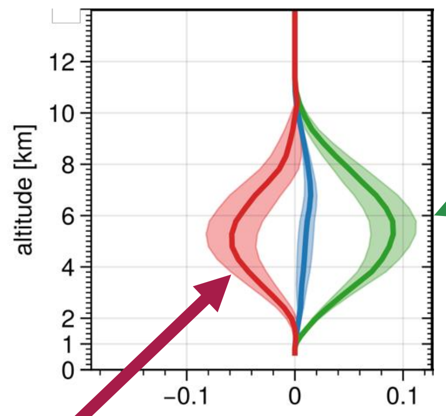

ΔMAE of
cloud water (g/kg)

Infrared adds wrong cloud water

Combination removes erroneous water cloud below ice cloud

<u>Result:</u>

- Combination outperforms single channels for cases with only ice clouds in nature
- Combined assimilation mitigates ambiguity

noDA
Visible 0.6 µm
Infrared 7.3 µm
Combined assimilation

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Results: Combined assimilation

Impact on the analysis of cloud variables

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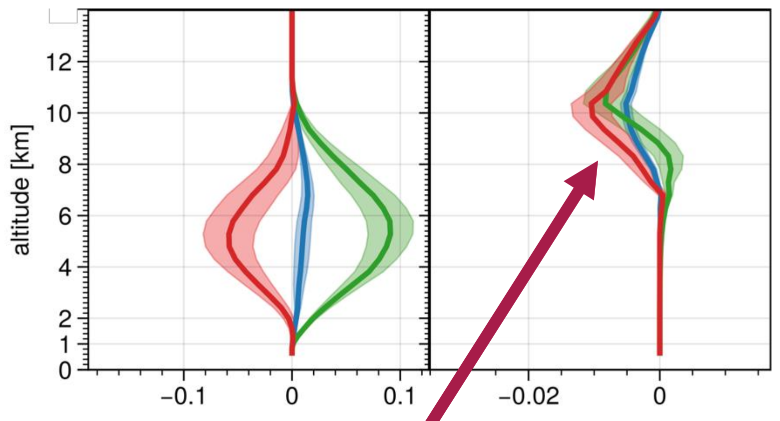
Vertical profiles of analysis error reduction



ΔMAE of cloud water (g/kg)

ΔMAE of cloud ice (g/kg)

Combination better than single channel assimilations

noDA
Visible 0.6 µm
Infrared 7.3 µm
Combined assimilation

⇒ Kugler & Weissmann (2024a), submitted to QJRMS

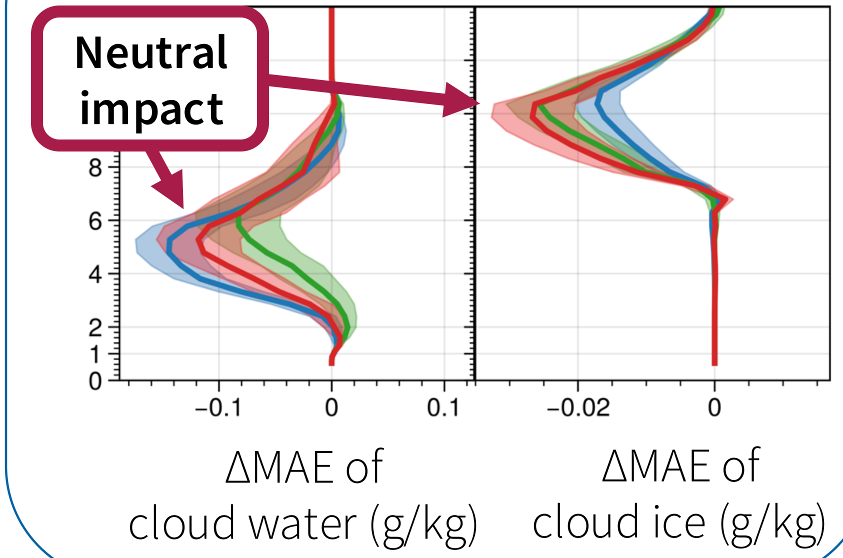
Results: Combined assimilation

Impact on the analysis of cloud variables

- Evaluated different cloud categories

Category 2:
Columns in which the nature run has <u>water & ice </u>clouds

Vertical profiles of analysis error reduction



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Part 2: Effect of Nonlinear Observation Operators

We see that

- The nonlinear observation operator causes **deviations of the posterior** from the expectation with a linear observation operator

⇒ Kugler & Weissmann (2024b), submitted to QJRMS

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We see that

- The nonlinear observation operator causes **deviations of the posterior** from the expectation with a linear observation operator

Goal:

- Understand and quantify deviations for visible reflectance and infrared brightness temperature

⇒ Kugler & Weissmann (2024b), submitted to QJRMS

Definition of the Nonlinearity Deviation

Linear posterior

→ theoretical expectation

$$\overline{y^a_{\text{linear}}} = \overline{\mathcal{H}(x^b_{ij})} + \frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2}\left(y^o - \overline{\mathcal{H}(x^b_{ij})}\right)$$

Definition of the Nonlinearity Deviation

Linear posterior $$\overline{y^a_{\text{linear}}} = \underline{\overline{\mathcal{H}(x^b_{ij})}} + \frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2}(y^o - \underline{\overline{\mathcal{H}(x^b_{ij})}})$$

ensemble member i = 1, …, N
model space variable j = 1, …, M

→ prior ensemble mean (averaged in observation space)

Definition of the Nonlinearity Deviation

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→ observation

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Nonlinear posterior

→ actual analysis

$$\overline{y^a_{\text{nonlinear}}} = \overline{\mathcal{H}\left(x^b_{ij} + \delta x_{ij}\right)}$$

Definition of the Nonlinearity Deviation

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→ observation space increments

Definition of the Nonlinearity Deviation

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→ regression coefficient from observation to model space

Definition of the Nonlinearity Deviation

Linear posterior

→ theoretical expectation

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Nonlinear posterior

→ actual analysis

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$$y^a_i = \overline{y^a_{\text{linear}}} + \sqrt{\frac{\sigma_o^2}{\sigma_o^2 + \sigma_b^2}}\left(\mathcal{H}(x^b_{ij}) - \overline{\mathcal{H}(x^b_{ij})}\right)$$

→ prior ensemble perturbations

Definition of the Nonlinearity Deviation

Linear posterior

→ theoretical expectation

$$\overline{y^a_{\text{linear}}} = \overline{\mathcal{H}(x^b_{ij})} + \frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2}\left(y^o - \overline{\mathcal{H}(x^b_{ij})}\right)$$

Nonlinear posterior

→ actual analysis

$$\overline{y^a_{\text{nonlinear}}} = \overline{\mathcal{H}\left(x^b_{ij} + \delta x_{ij}\right)}$$

$$\delta x_{ij} = \frac{\text{Cov}(x^b_{ij}, \mathcal{H}(x^b_{ij}))}{\text{Var}(\mathcal{H}(x^b_{ij}))}\left(y^a_i - \mathcal{H}(x^b_{ij})\right)$$

$$y^a_i = \overline{y^a_{\text{linear}}} + \underbrace{\sqrt{\frac{\sigma_o^2}{\sigma_o^2 + \sigma_b^2}}}_{\text{variance adjustment factor}}\left(\mathcal{H}(x^b_{ij}) - \overline{\mathcal{H}(x^b_{ij})}\right)$$

Definition of the Nonlinearity Deviation

A nonlinear observation operator introduces a deviation of the posterior in observation space.

Linear posterior

→ theoretical expectation

$$\overline{y^a_{\text{linear}}} = \overline{\mathcal{H}(x^b_{ij})} + \frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2}\left(y^o - \overline{\mathcal{H}(x^b_{ij})}\right)$$

… expectation

Nonlinear posterior

→ actual analysis

$$\overline{y^a_{\text{nonlinear}}} = \overline{\mathcal{H}\left(x^b_{ij} + \delta x_{ij}\right)}$$

… applying the operator to the updated state

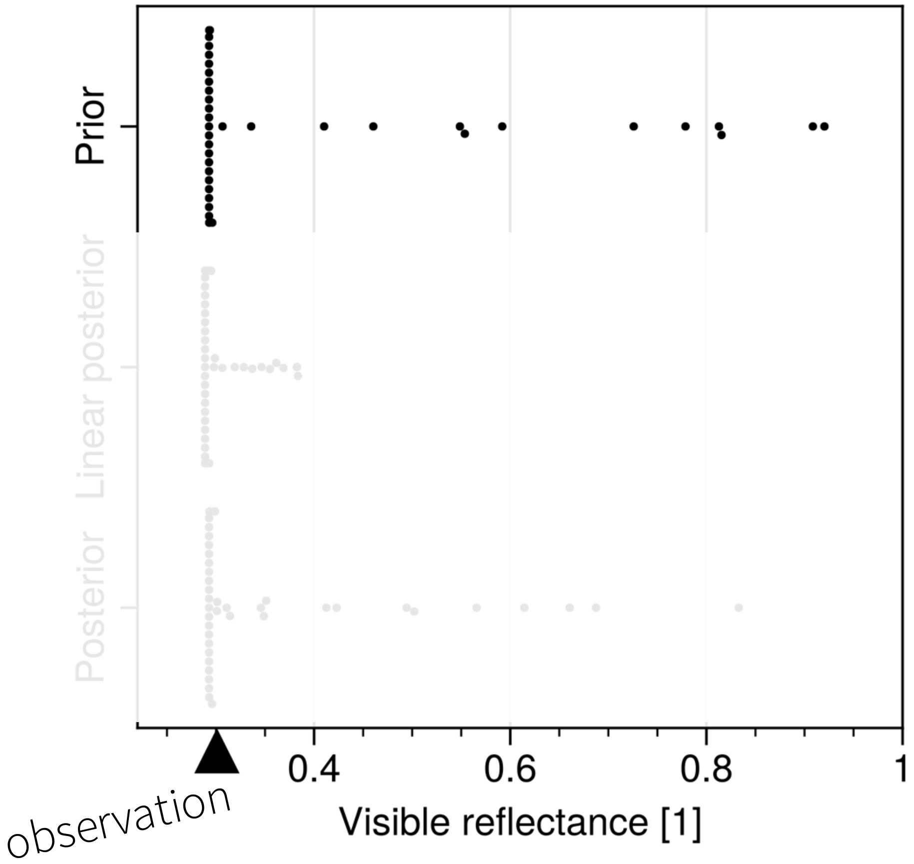
$$\delta x_{ij} = \frac{\mathrm{Cov}(x^b_{ij}, \mathcal{H}(x^b_{ij}))}{\mathrm{Var}(\mathcal{H}(x^b_{ij}))}\left(y^a_i - \mathcal{H}(x^b_{ij})\right)$$

⇒ The actual posterior deviates from our expectation!

$$y^a_i = \overline{y^a_{\text{linear}}} + \sqrt{\frac{\sigma_o^2}{\sigma_o^2 + \sigma_b^2}}\left(\mathcal{H}(x^b_{ij}) - \overline{\mathcal{H}(x^b_{ij})}\right)$$

Results: Examples of Nonlinearity-induced Deviations

Example 1: Clear-sky observation



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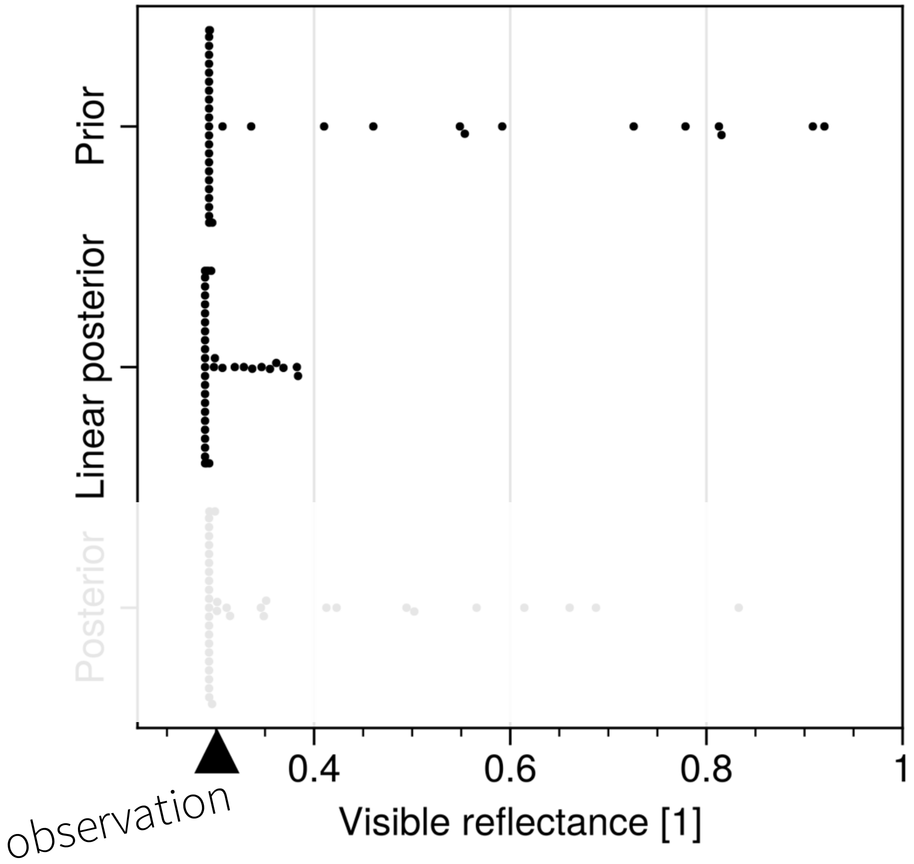

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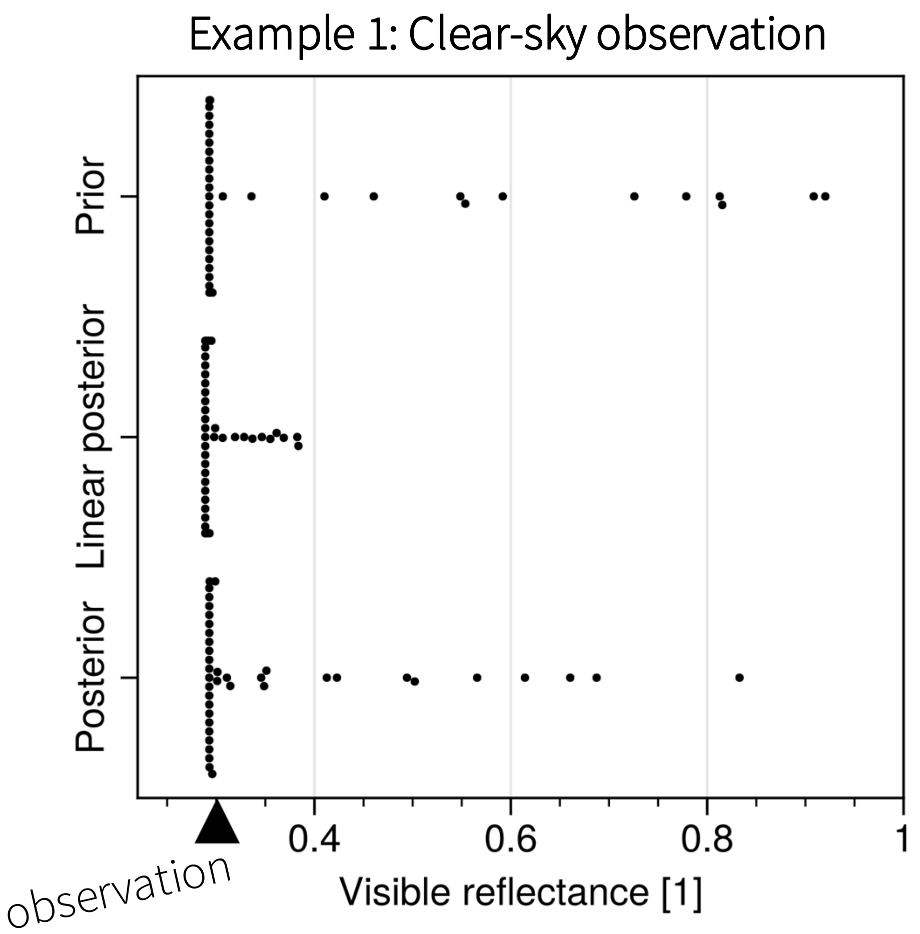

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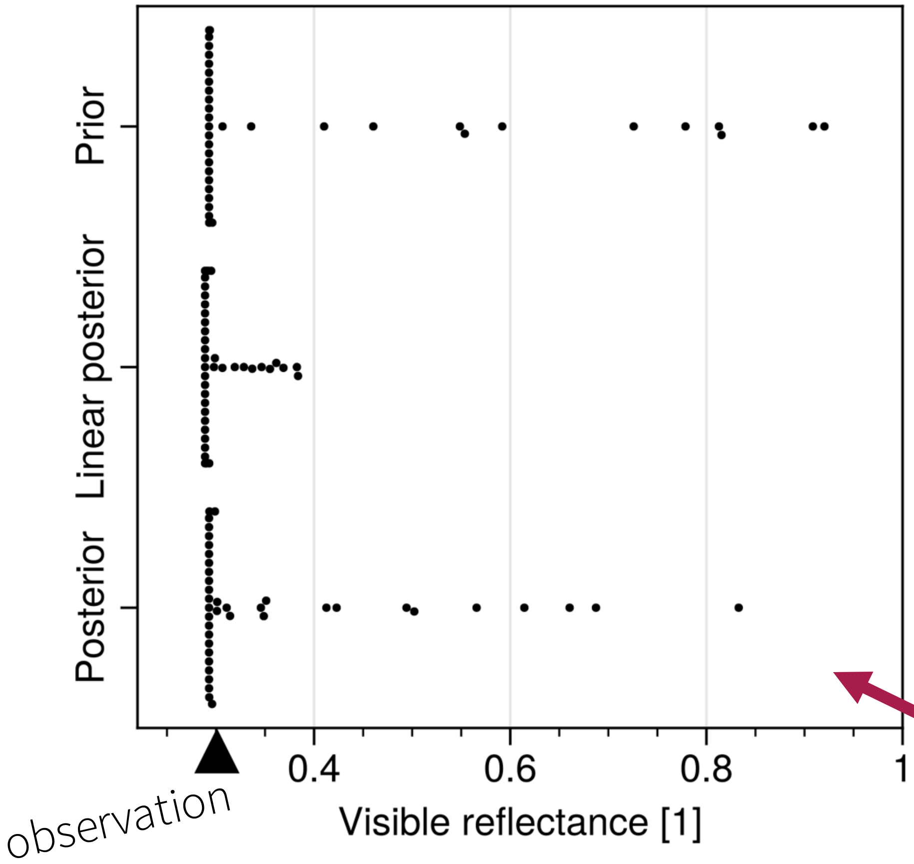

ens.-mean and spread adjustment smaller than expected

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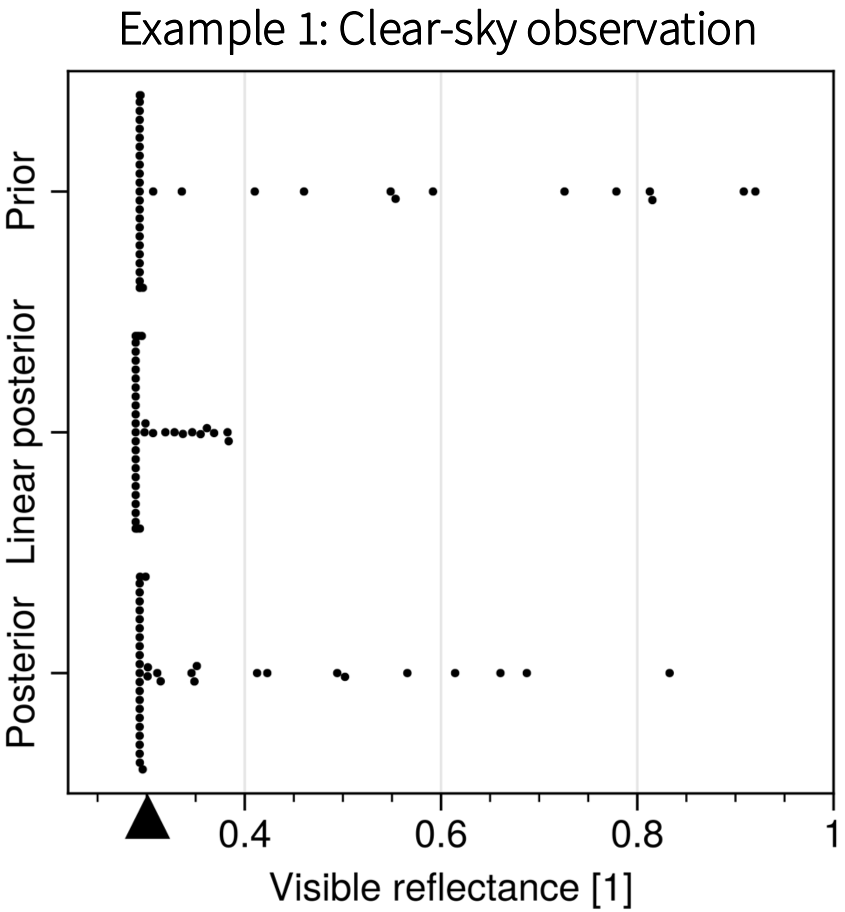
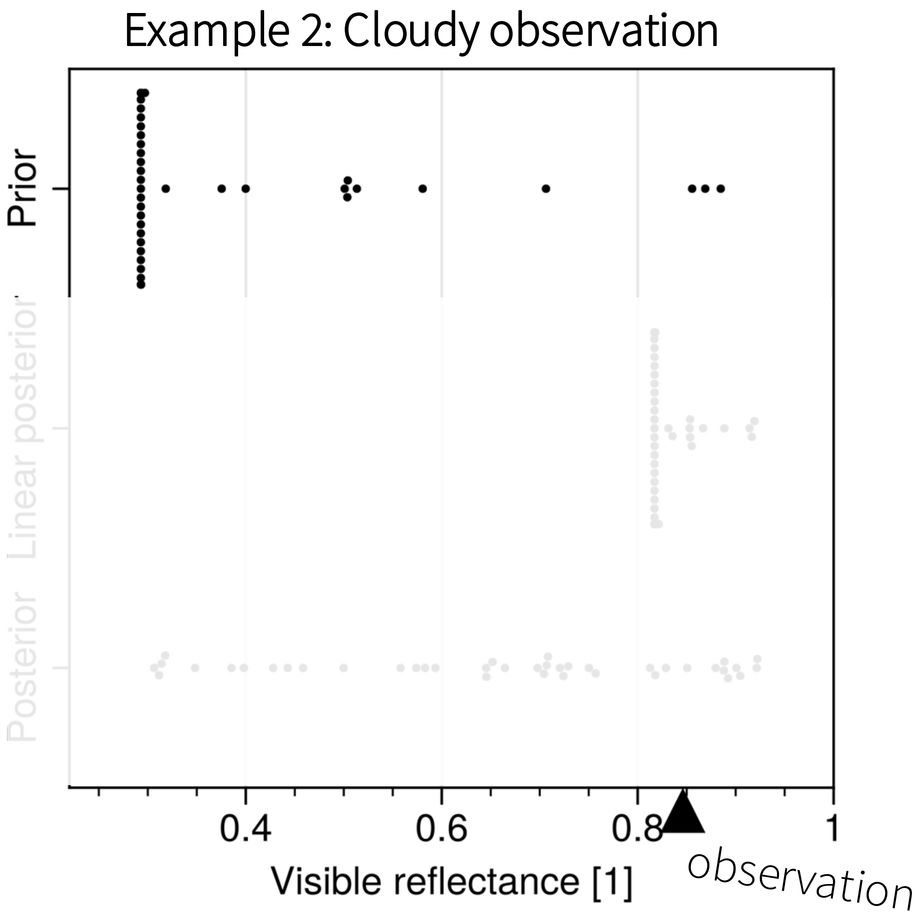
Results: Examples of Nonlinearity-induced Deviations

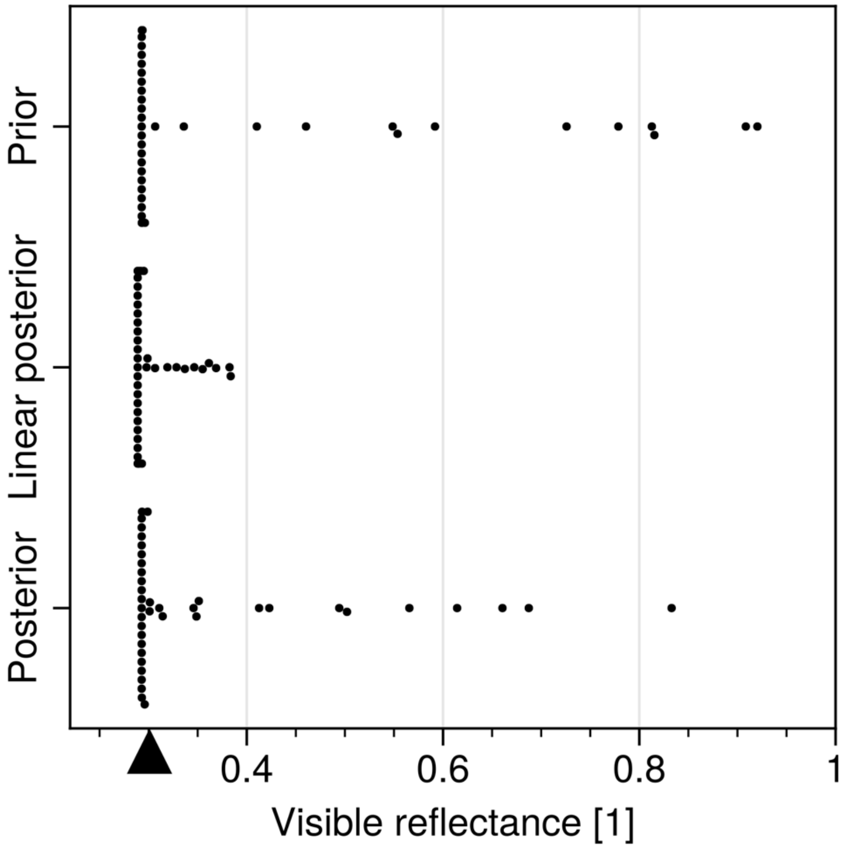




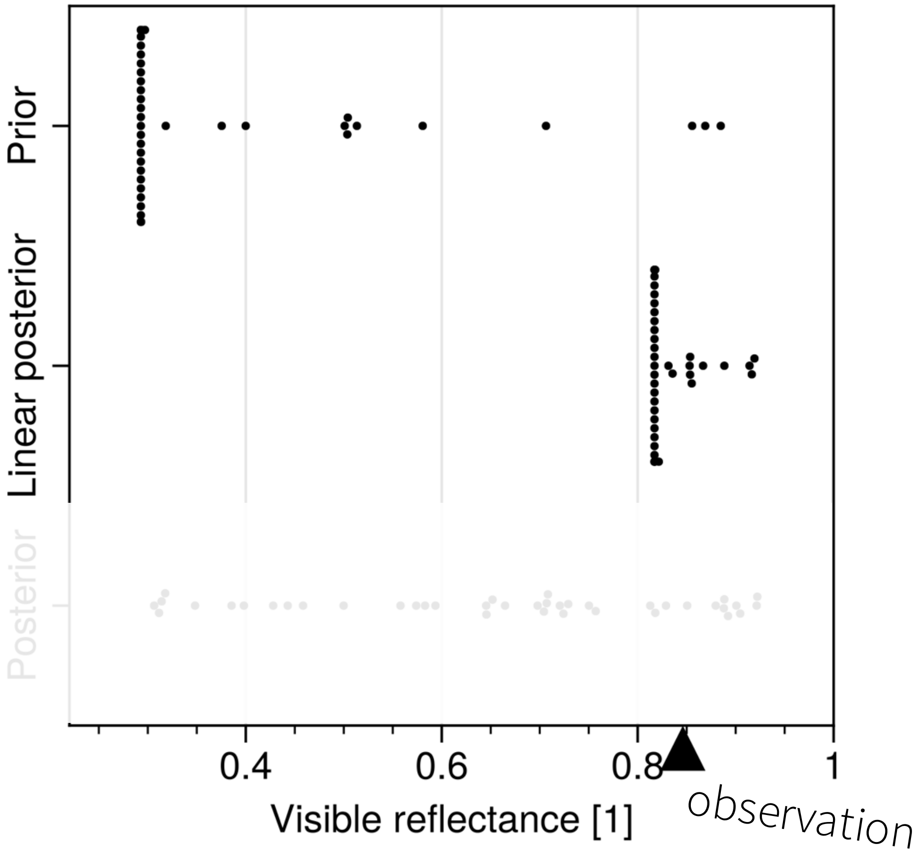
⇒ [Kugler & Weissmann (2024b), submitted to QJRMS]

Results: Examples of Nonlinearity-induced Deviations

Example 1: Clear-sky observation



Example 2: Cloudy observation



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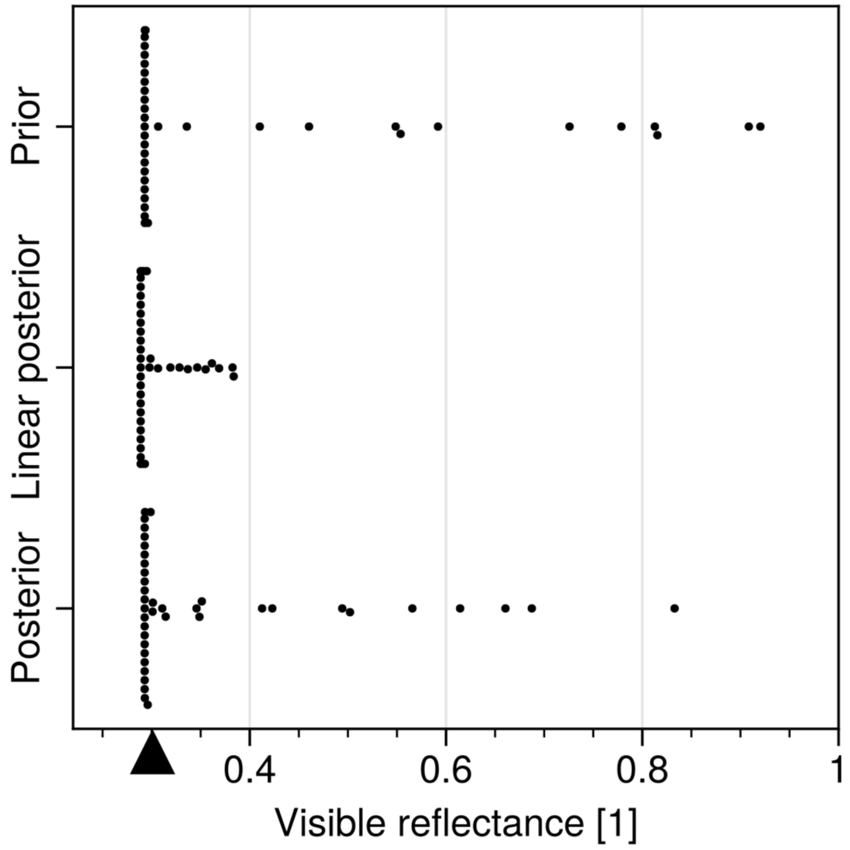
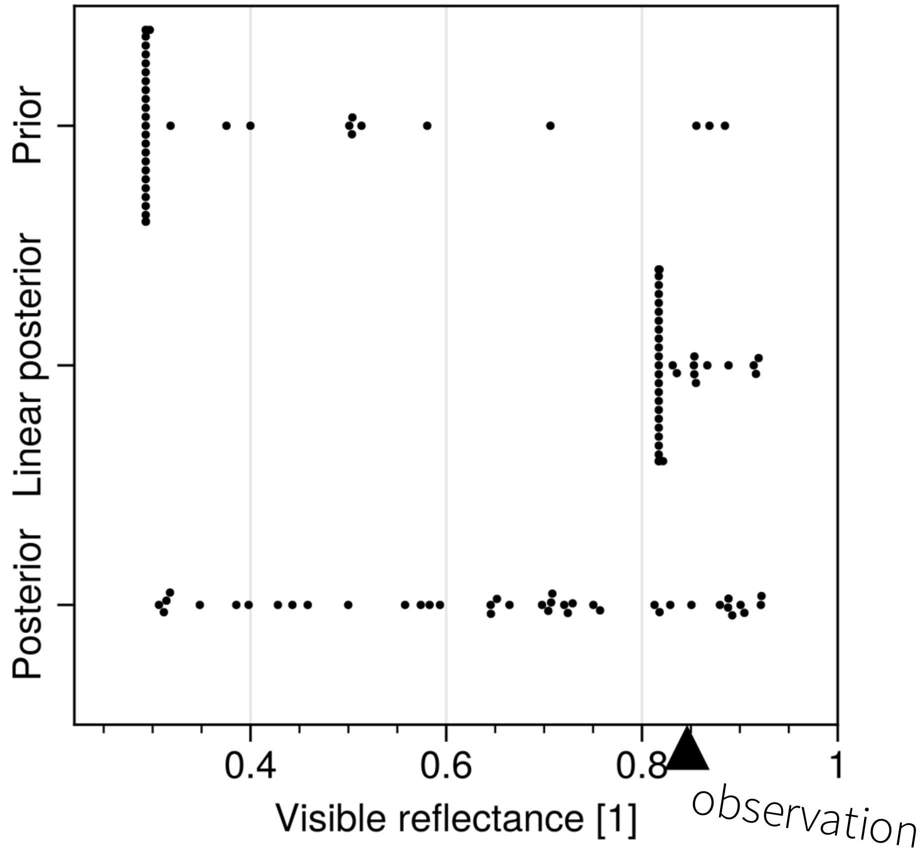


Example 2: Cloudy observation



⇒ Kugler & Weissmann (2024b), submitted to QJRMS

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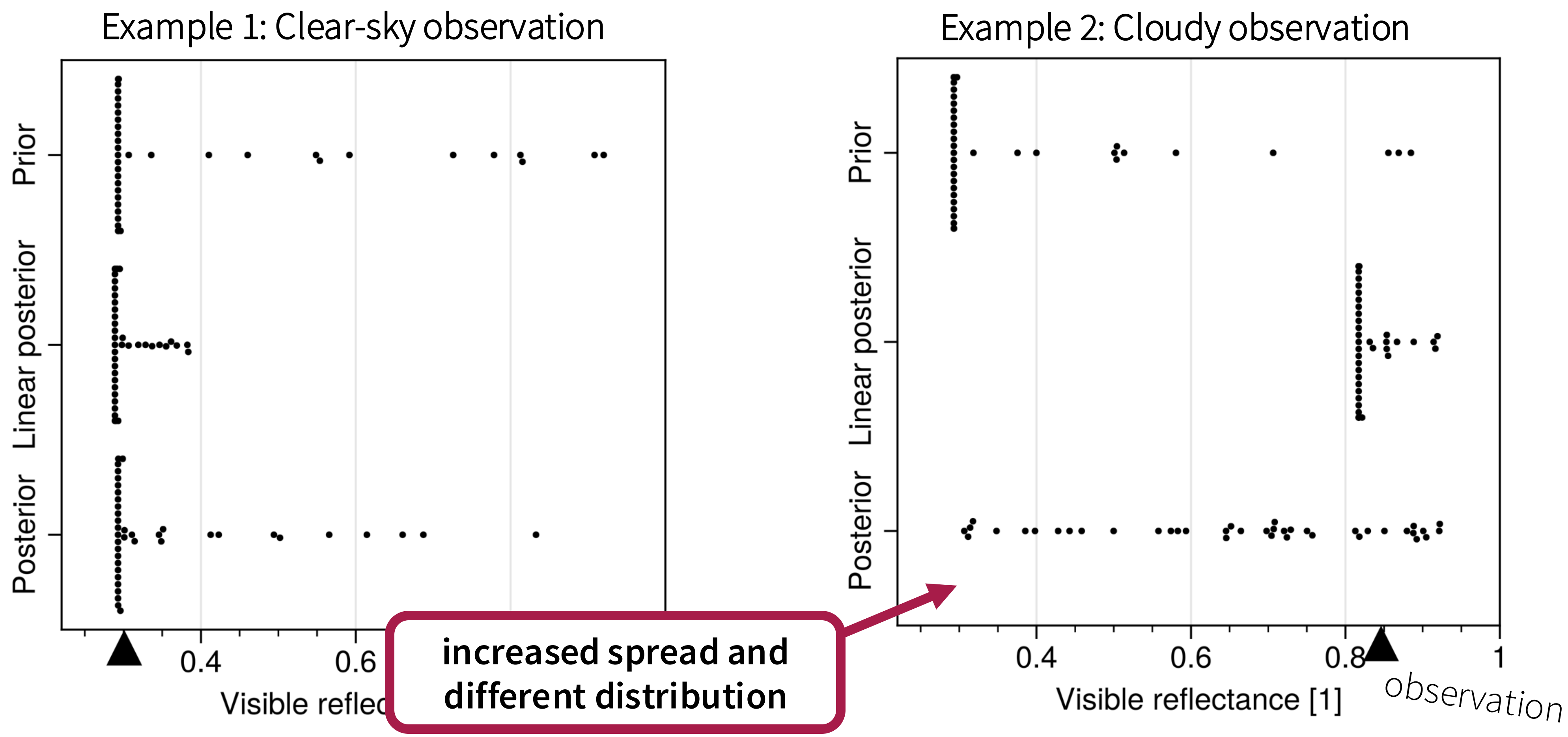
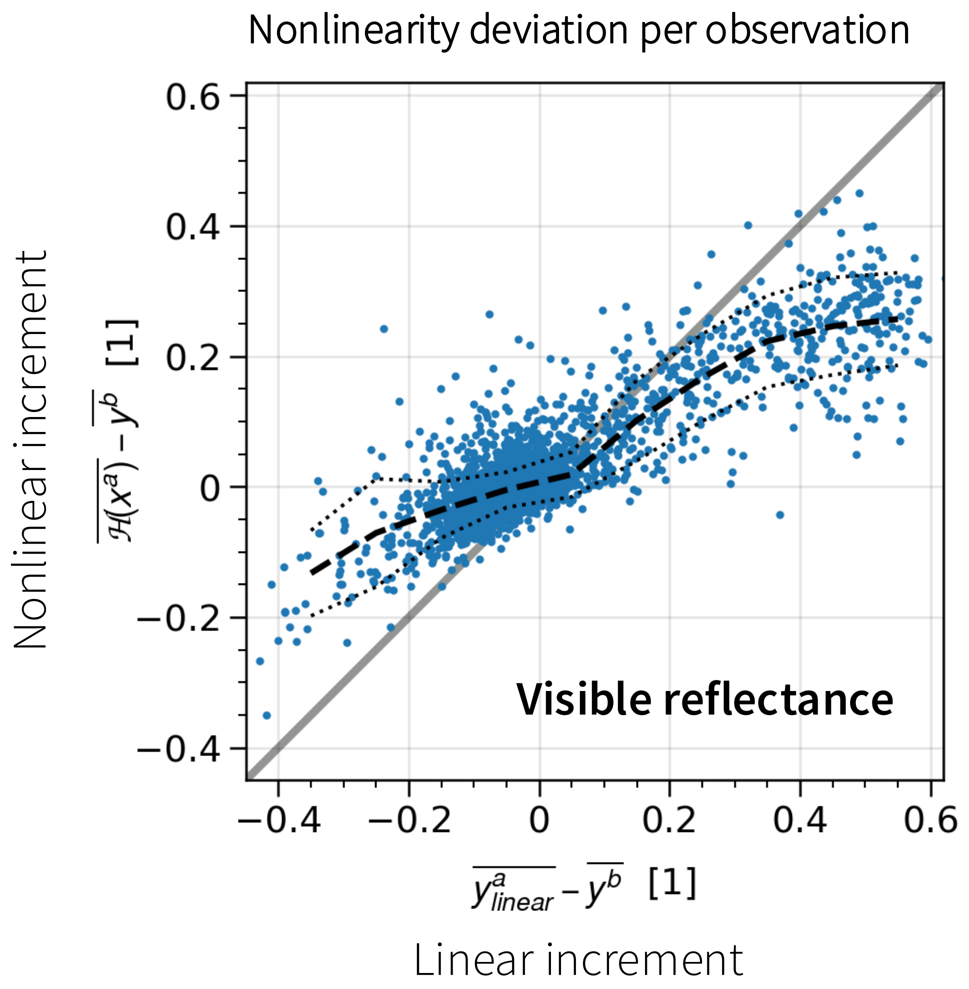


⇒ Kugler & Weissmann (2024b), submitted to QJRMS

Results: Nonlinearity Deviations

<u>Evaluation</u> for visible and infrared radiance assimilation

- ⇒ Actual increments differ from theoretical expectation
- ⇒ Systematic and random deviations



⇒ [Kugler & Weissmann (2024b), submitted to QJRMS]

Results: Nonlinearity Deviations

Evaluation for visible and infrared radiance assimilation

⇒ Actual increments differ from theoretical expectation

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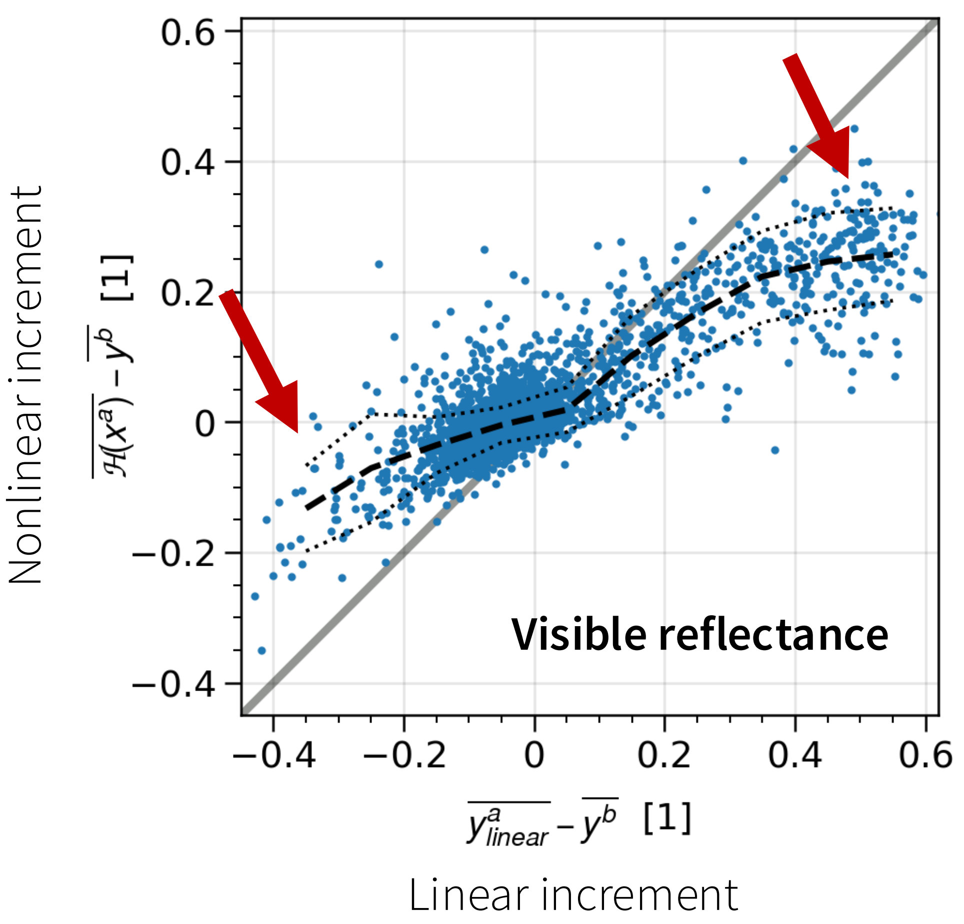
Results:

1) The ensemble mean **increment is** mostly **lower** than expected
   - **Effectiveness** of assimilating nonlinear observations **is lower** than for linear observations

Nonlinearity deviation per observation



⇒ [Kugler & Weissmann (2024b), submitted to QJRMS]

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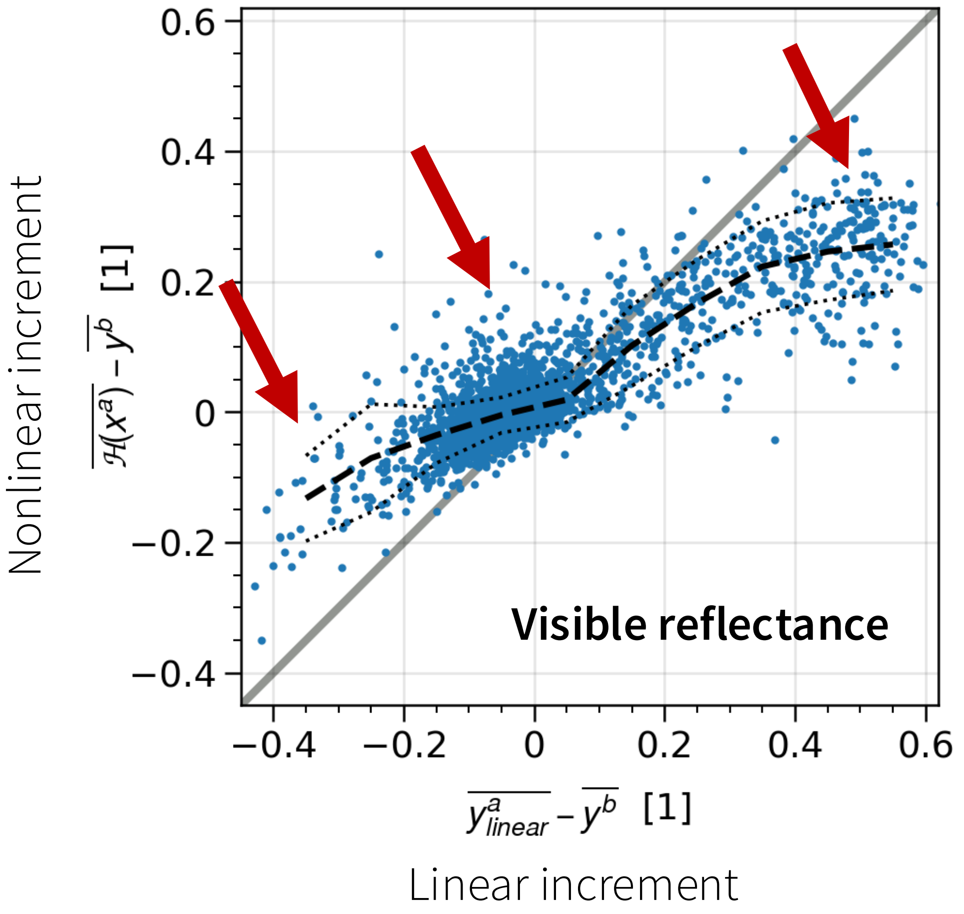

⇒ Kugler & Weissmann (2024b), submitted to QJRMS

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For infrared results, check out the preprint!

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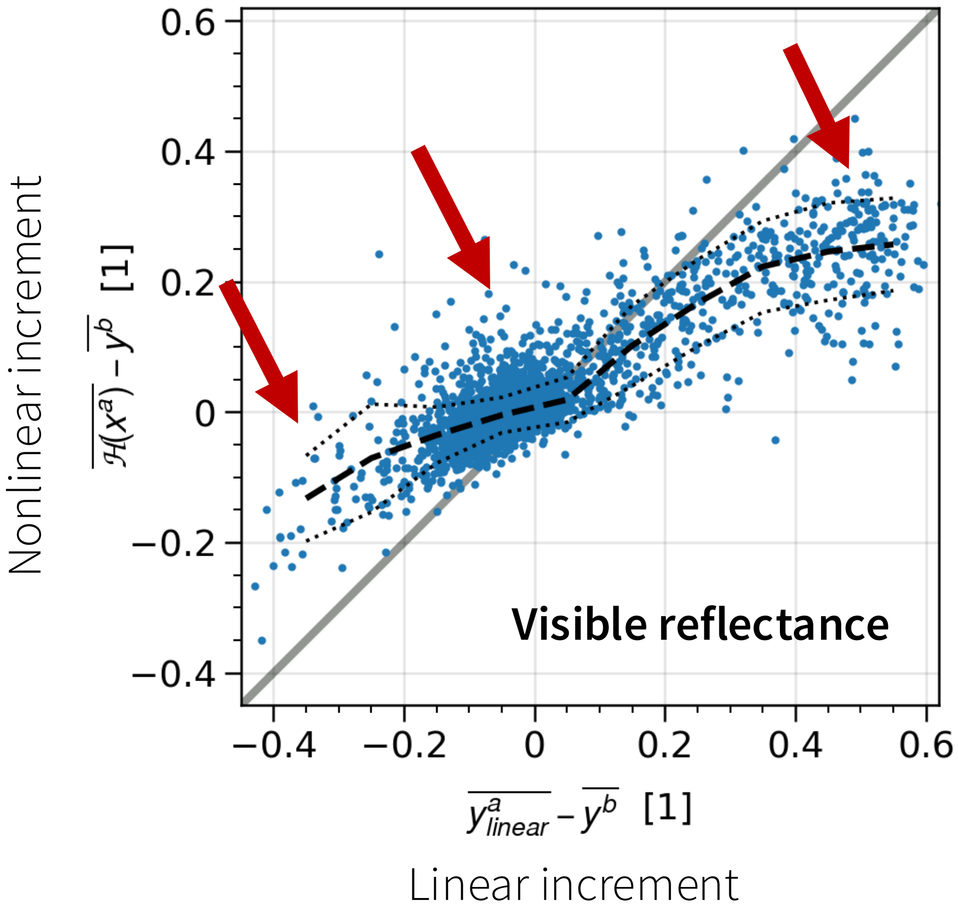


⇒ Kugler & Weissmann (2024b), submitted to QJRMS

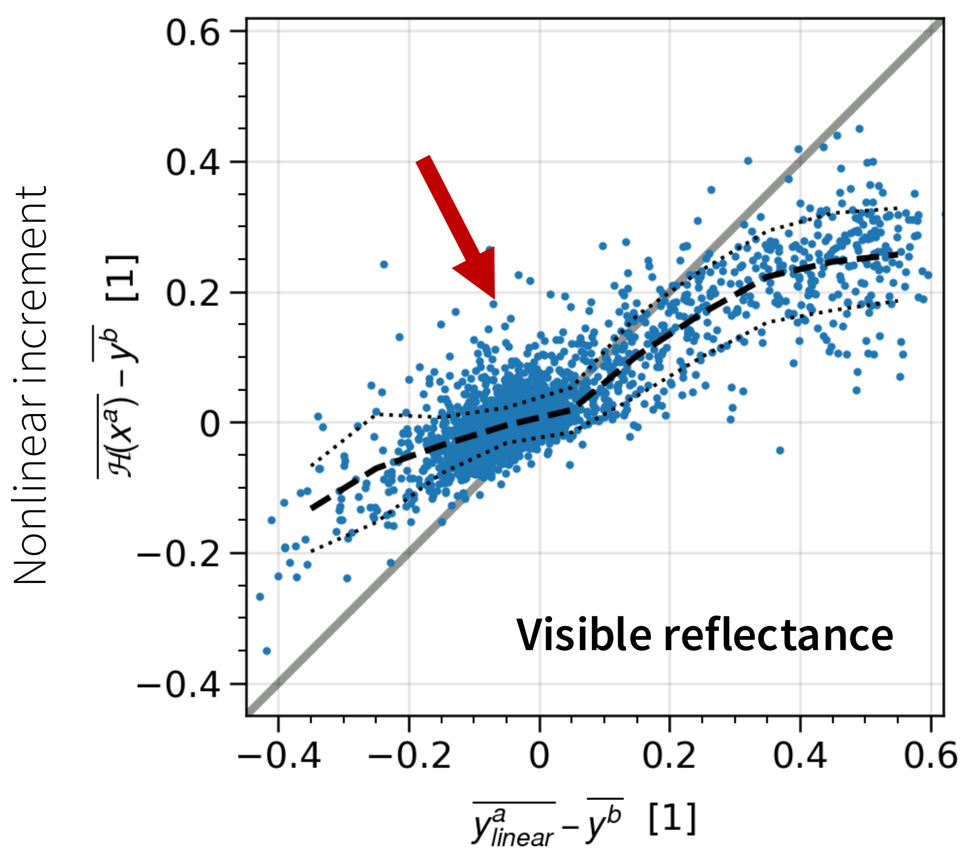
Results: Large Relative Nonlinearity Deviations

We saw, as Scheck et al. 2020:

- Large relative nonlinearity associated with observations that are close to the prior
- Nonlinear posterior partly worse than prior

<u>Hypothesis</u>: Rejecting these observations improves forecasts

Nonlinearity deviation per observation



Linear increment

⇒ [Kugler & Weissmann (2024b), submitted to QJRMS]

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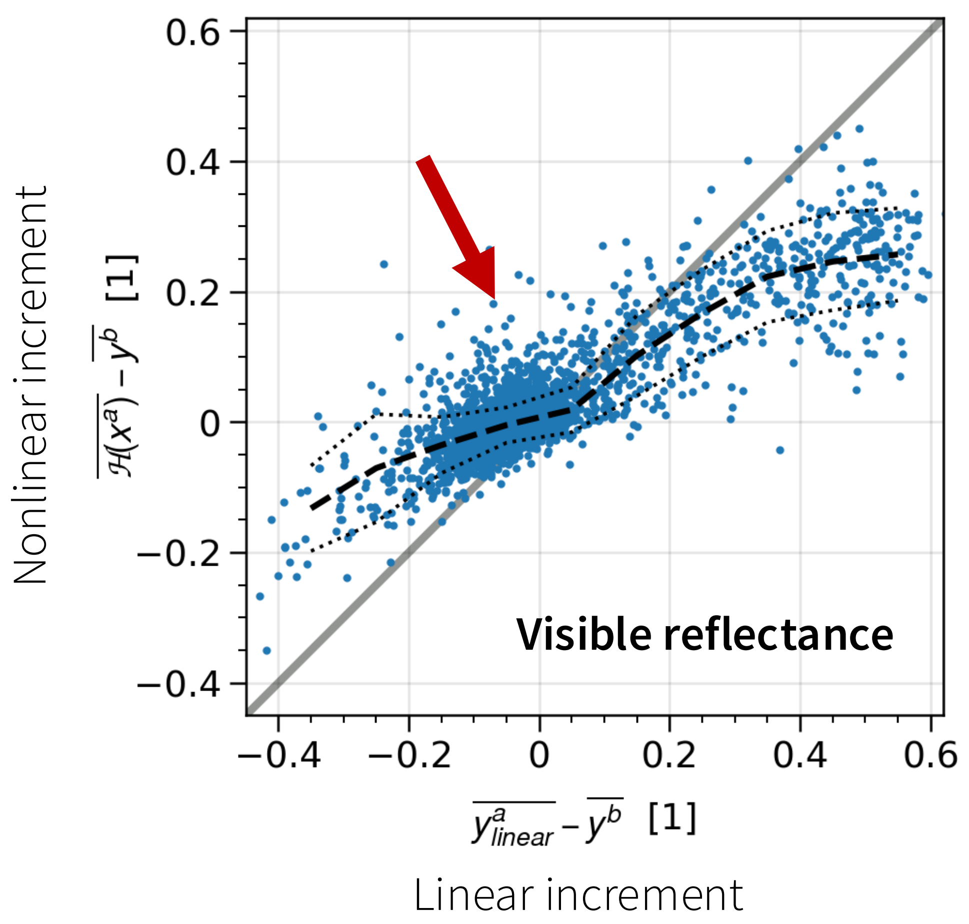
Nonlinearity deviation per observation



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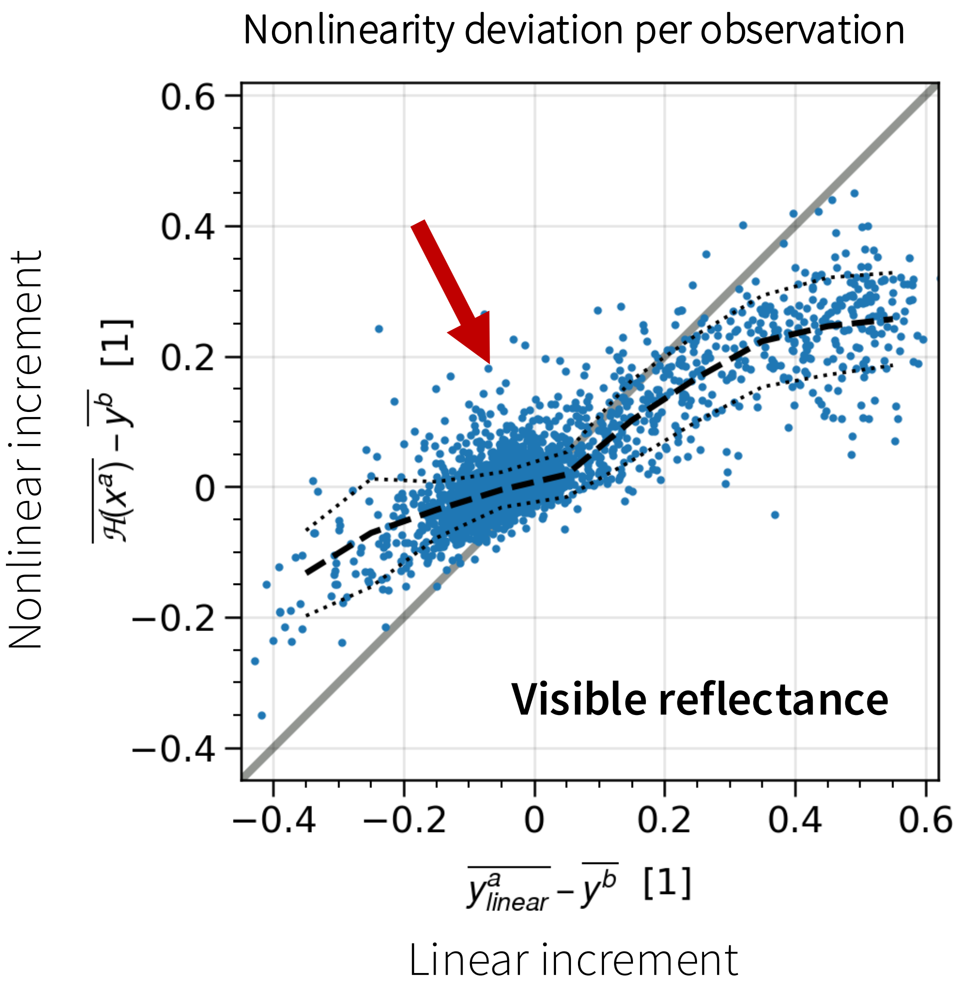
Results:

1) Rejecting increases bias and MSE at these locations
2) Assimilating affirms the prior (mostly reduces spread) and avoids that other observations pull the ens.-mean away from its already accurate first-guess



⇒ Kugler & Weissmann (2024b), submitted to QJRMS

Summary: Nonlinearity Deviations

- Nonlinear observation operators cause deviations* in the posterior
  - Despite this, the ensemble mean improved on average.

*from the expectation with a linear observation operator

⇒ Kugler & Weissmann (2024b), submitted to QJRMS

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- Nonlinearity is relatively large, when the prior is close to the observation or almost clear sky
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Moreover, shown in paper:

- **Spread reduction** is **smaller than expected*** and smaller than MSE reduction
  - **Reduced overconfidence** of the prior ensemble

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For more, see preprint

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⇒ Kugler & Weissmann (2024b), submitted to QJRMS

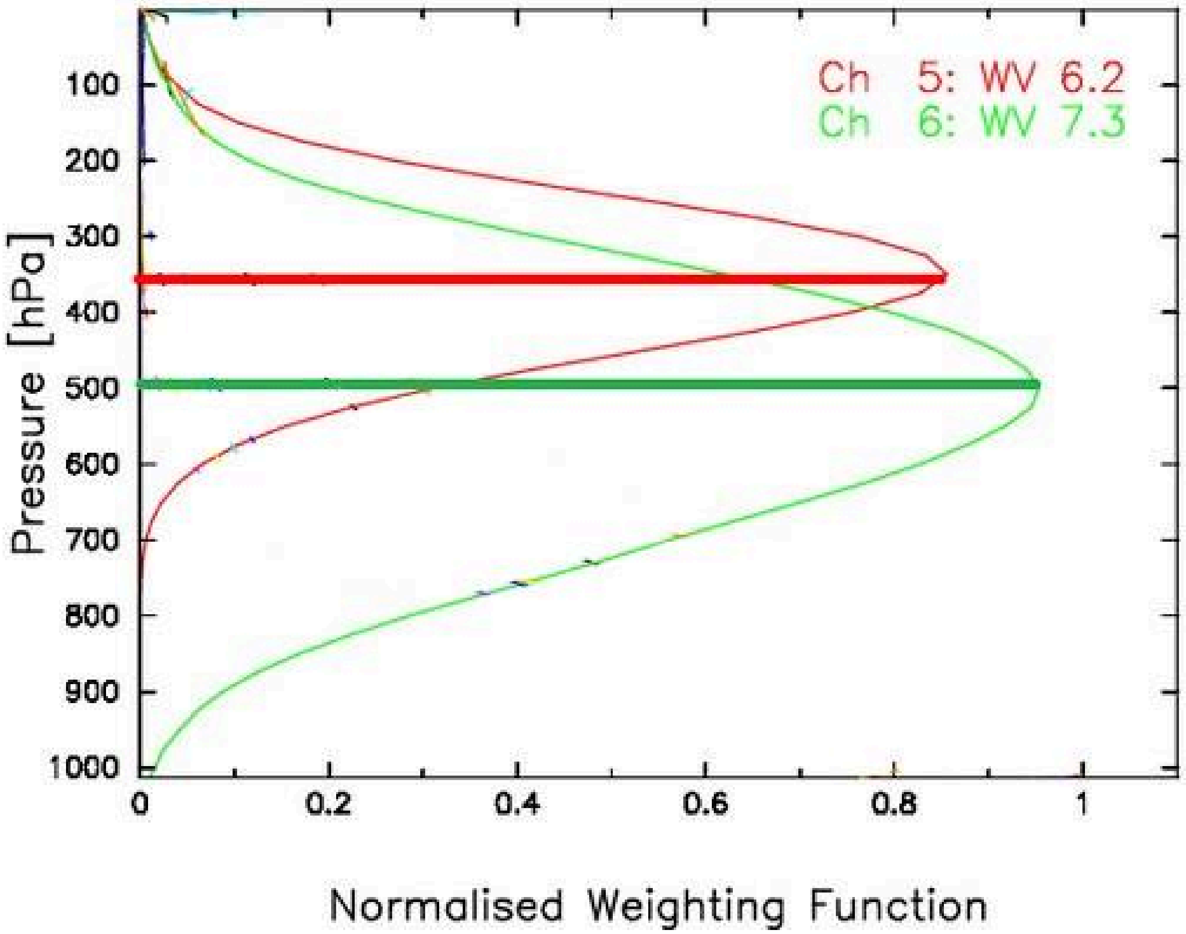
Conclusions

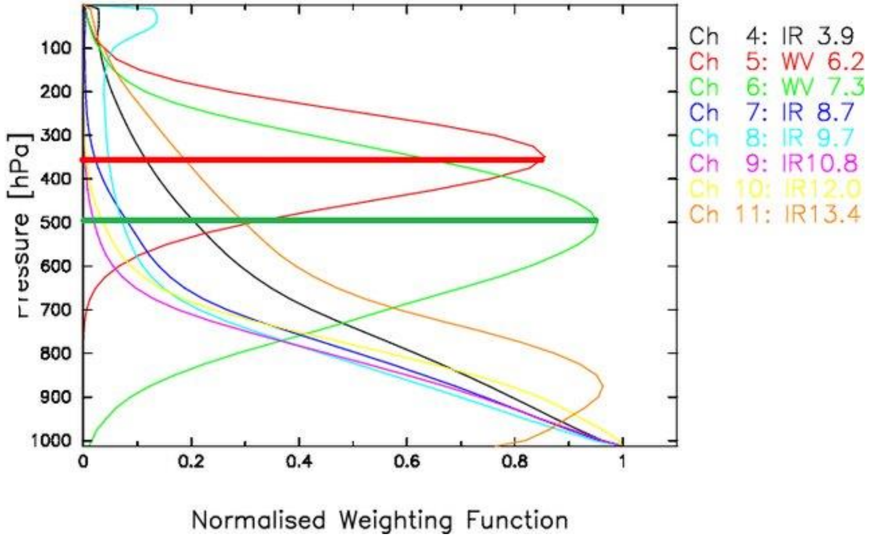
1) Kugler, Anderson, Weissmann (2023), QJRMS (open access)
    - High potential impact of assimilating visible and infrared observations that can be comparable to 2D radar assimilation

2) Kugler & Weissmann (2024a), QJRMS, submitted (preprint online)
    - Combined assimilation reduces the ambiguity regarding vertical cloud structure

3) Kugler & Weissmann (2024b), QJRMS, submitted (preprint online)
    - Understanding nonlinearity deviations
        - Smaller ensemble-mean adjustments
        - Less spread reduction (or even increase)
        - Nonlinearity relatively strong for observations with small first-guess departures but beneficial since they mostly reduce spread (which avoids potential deterioration by other observations)

Weighting functions





Results: Nonlinearity Deviations

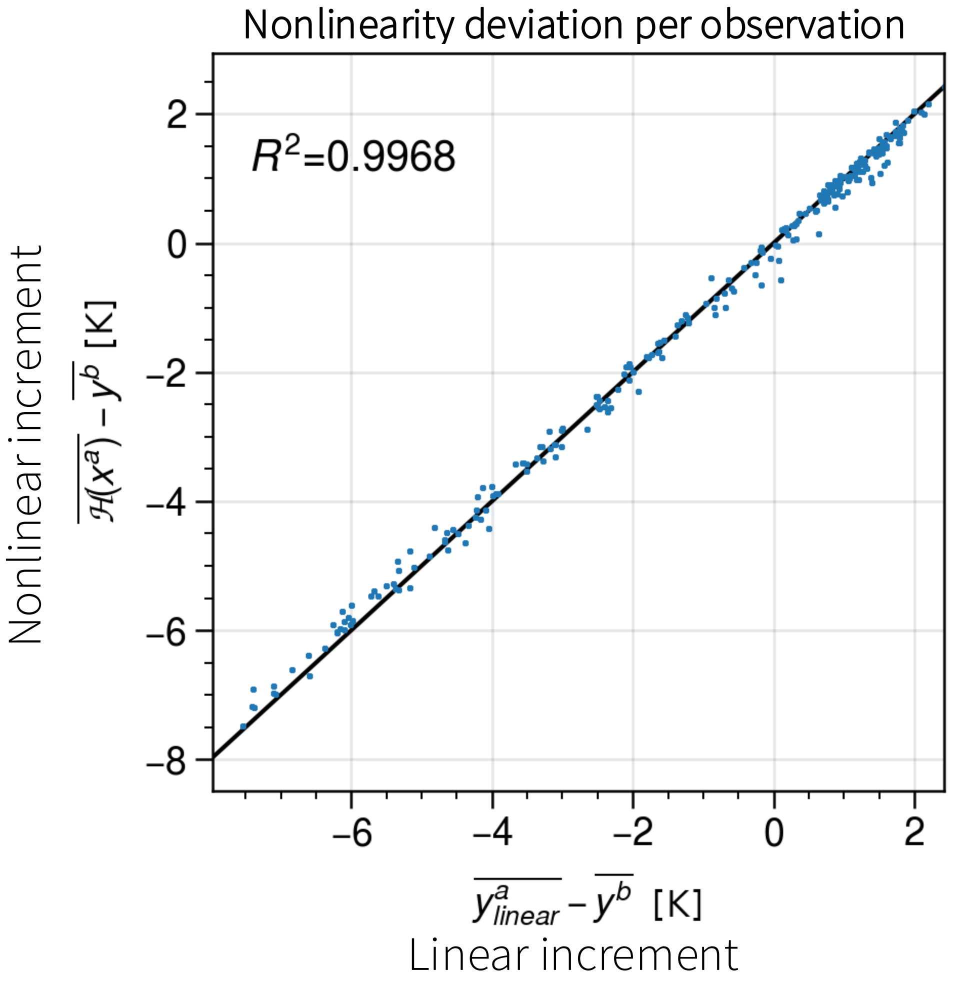
- Test case with an almost linear observation operator: 2m-temperature observations

<u>Result:</u>

- Minimal differences

→ Deviations are really due to nonlinearity

- Small differences since the observed variable „sensible temperature“ is a slightly nonlinear function of the state variable „potential temperature“



Kugler & Weissmann (2024b), under review

Results: Nonlinearity Deviations

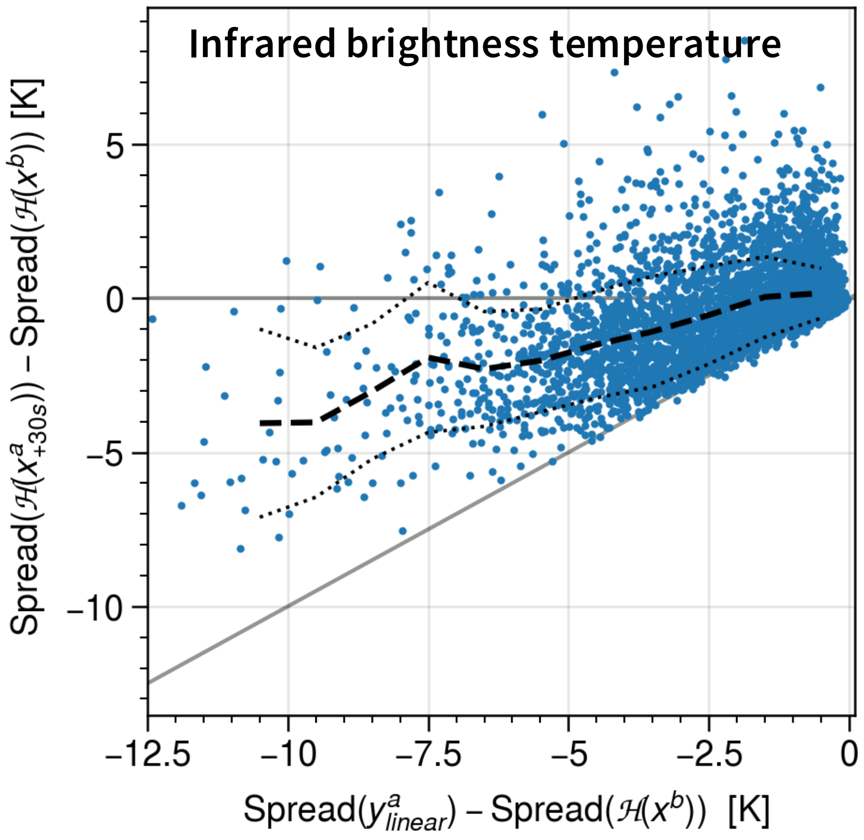
- The ensemble-variance adjustment
  is also affected by systematic and random deviations

<u>Result:</u>

1) Variance adjustment can be positive (larger variance)
2) Variance adjustment nearly always lower than in the linear case
3) Variance adjustment tends to be lower than MSE reduction

Nonlinearity deviation per observation

Nonlinear spread adjustment



Linear spread adjustment

Kugler & Weissmann (2024b), under review

Localization for infrared / visible observations

- Poster ISDA Kobe 2024: P5-01 (just before)
- Talk at ISDA Bologna 2023

Slides:https://eventi.unibo.it/isda2023/contributions/necker_tobias_empirical_optimal_vertical_localization_derived_from_large_ensembles.pdf/@@download/file/Necker_Tobias_Empirical_optimal_vertical_localization_derived_from_large_ensembles.pdf

- Citeable as EGU abstract:

Necker, T., Honda, T., Griewank, P., Miyoshi, T., and Weissmann, M.: *Situation-Dependent Localization for All-Sky Satellite Observations*, EGU General Assembly 2024, Vienna, Austria, 14–19 Apr 2024, https://doi.org/10.5194/egusphere-egu24-8868, 2024.