

Using satellite data assimilation techniques to exploit infrasound measurements

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NCEO/DARC training course
Applications lecture

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Data Assimilation
Research Centre



University of
Reading

(Infra)sound paths

Sound propagation

Sound waves propagate away from the source. They can find **obstacles**, and/or suffer **attenuation** in a medium.



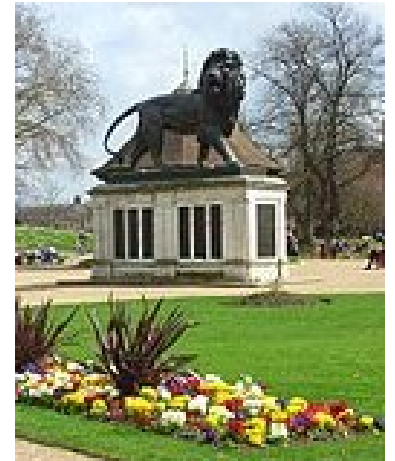
I can hear the music



I can't hear the music

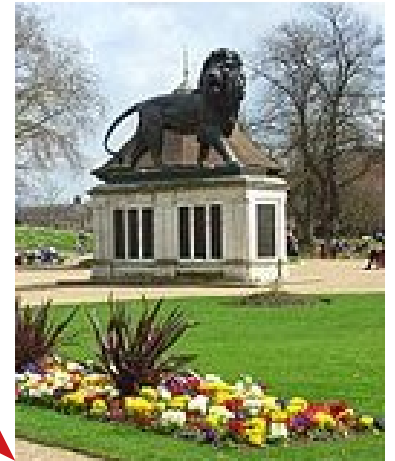
$$\text{attenuation} \propto \text{frequency}^{\alpha}$$

Finding paths



I can actually hear
the music!

Finding paths



I can actually hear
the music!

Don't forget other
directions.



The ARISE project (infrasound)

ARISE

Atmospheric dynamics Research
InfraStructure in Europe




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ARISE Project

The ARISE2 project is a collaborative infrastructure Design Study project (2015-2018) funded by the H2020 European Commission. It includes 24 institutes and universities, belonging to 10 European member states, 3 associated countries, 1 international organization and 3 African countries.

[> more on the Arise European project](#)



Technologies

Infrasound IMS network and European infrasound network (atmospheric waves and inversions in the stratosphere).

LIDAR of the NDACC network (stratospheric wind and temperature).

The project will also use complementary stations including **radars, wind radiometers and ionospheric sounders**. It also use **satellite observations**.

[> more about technologies](#)

Highlights



ARISE meetings

Thanks to the ARISE support by the French MRSEI ANR program, the following ARISE meetings were organized to ensure the project continuation:

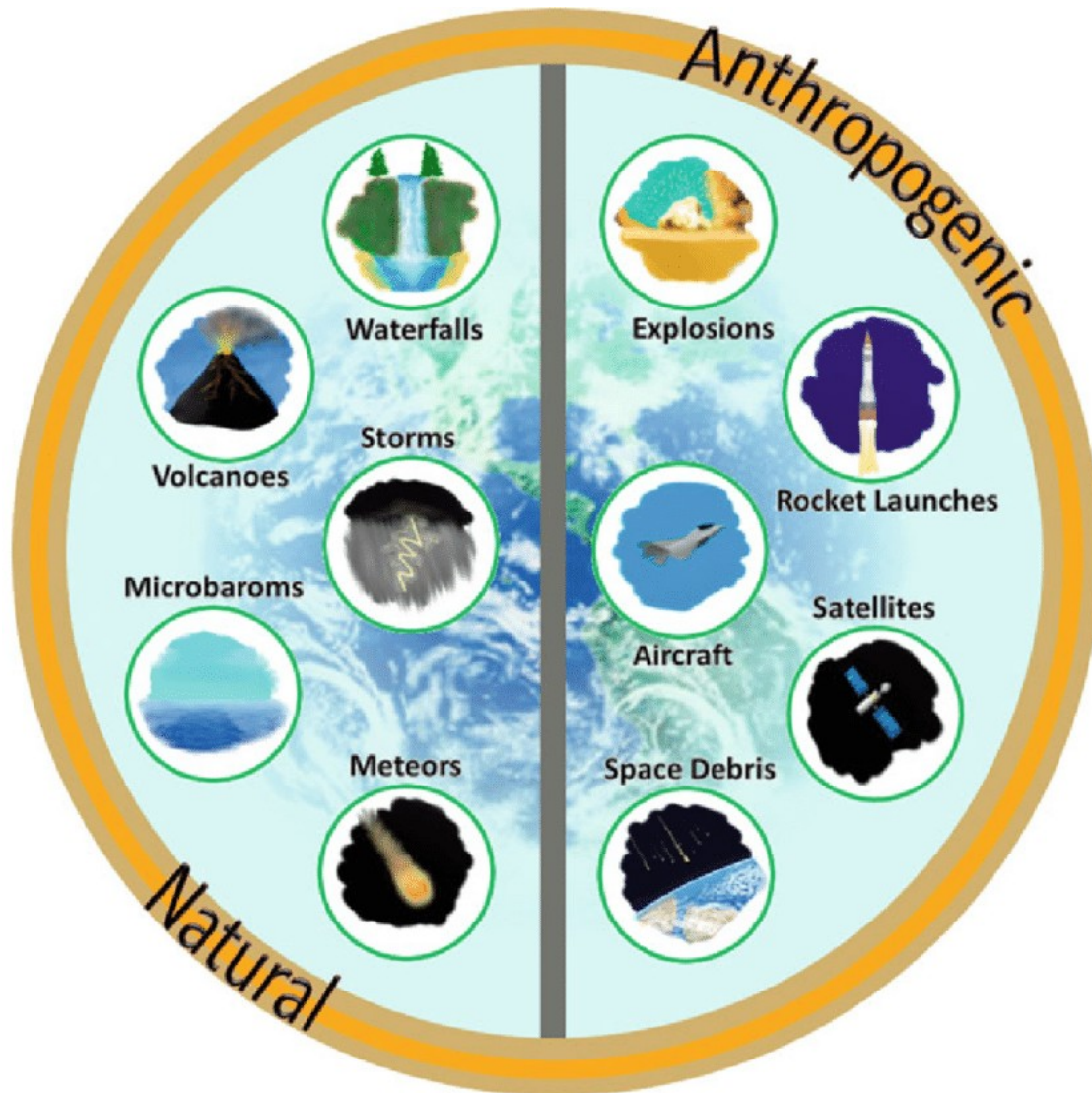
January 24-25, 2019 : Paris (France), organized by Versailles University (UVSQ) and CEA

April 10, 2019 Vienna (Austria) during the EGU2019 meeting

June 5-6, 2019 Budapest (Hungaria) organized by CSFK

September 10-11 Paris (France) organized by

Infrasound



0.1-1 Hz

It can travel long distances.

attenuation \propto frequency $^{\alpha}$

It is affected as it travels through an atmospheric slab.

Sources of infrasound waves

RUOTUVÄKI

UUTISET

ARTIKKELIT

KOLUMNIT

TOIMITUS

DIGILEHDET

puolustusvoimat.fi



29.8.2019 8.00

Massaräjätysleirillä korostuu yhteishenki

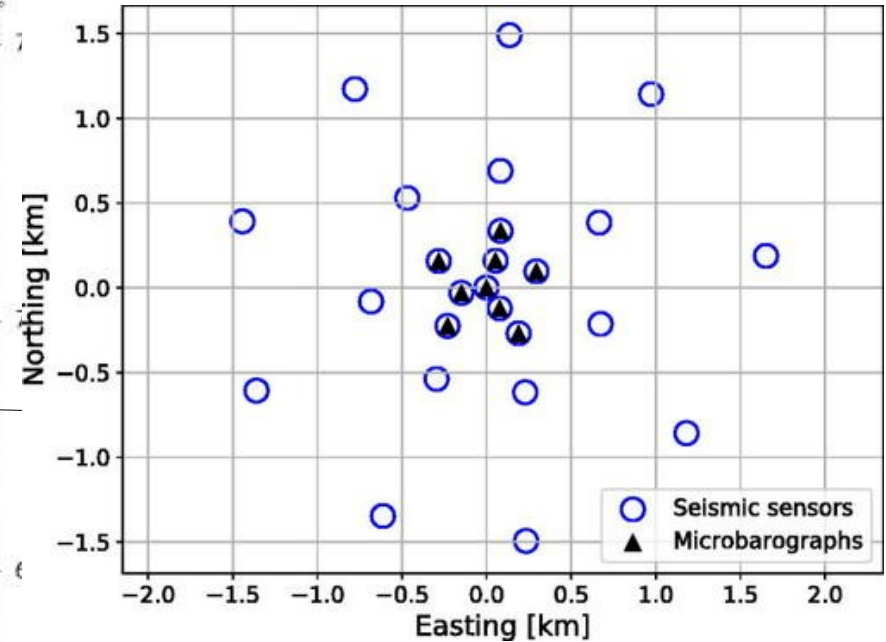
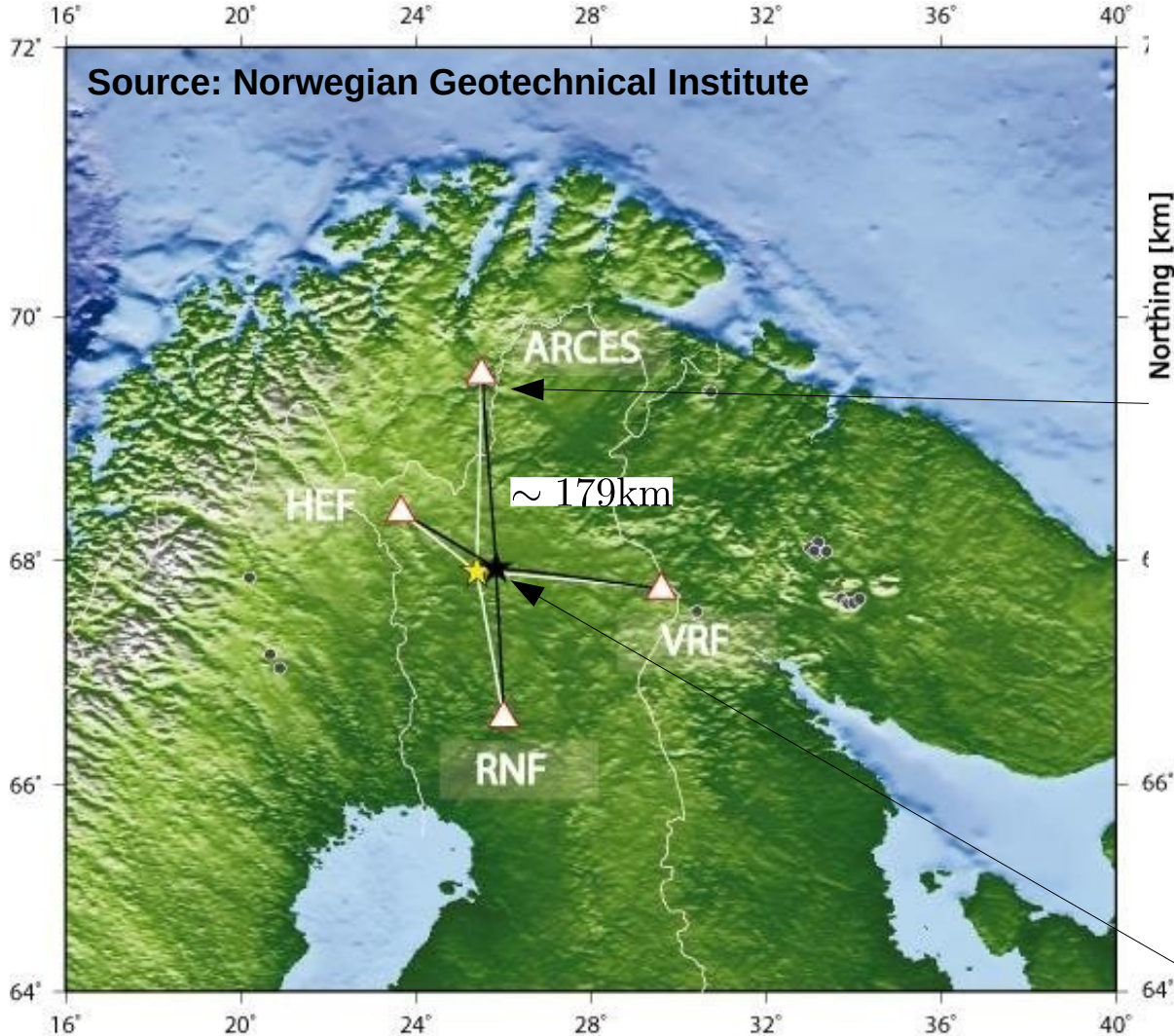
TEKSTI: LEILA KAUPPILA KUVAT: SAMULI PÖNTINEN

Hukkakeron massaräjätysleirillä 27 000 kiloa käytöstä poistuvaa räjähdemateriaalia katoaa kirjaimellisesti savuna ilmaan. Elokuun lopulle ajoittuva leiri kerää yhteen eri alojen asiantuntijoita ja osaajia.



Finland's summer pastime is to detonate excess ammunition in the summer.

Ammunition explosions in Finland

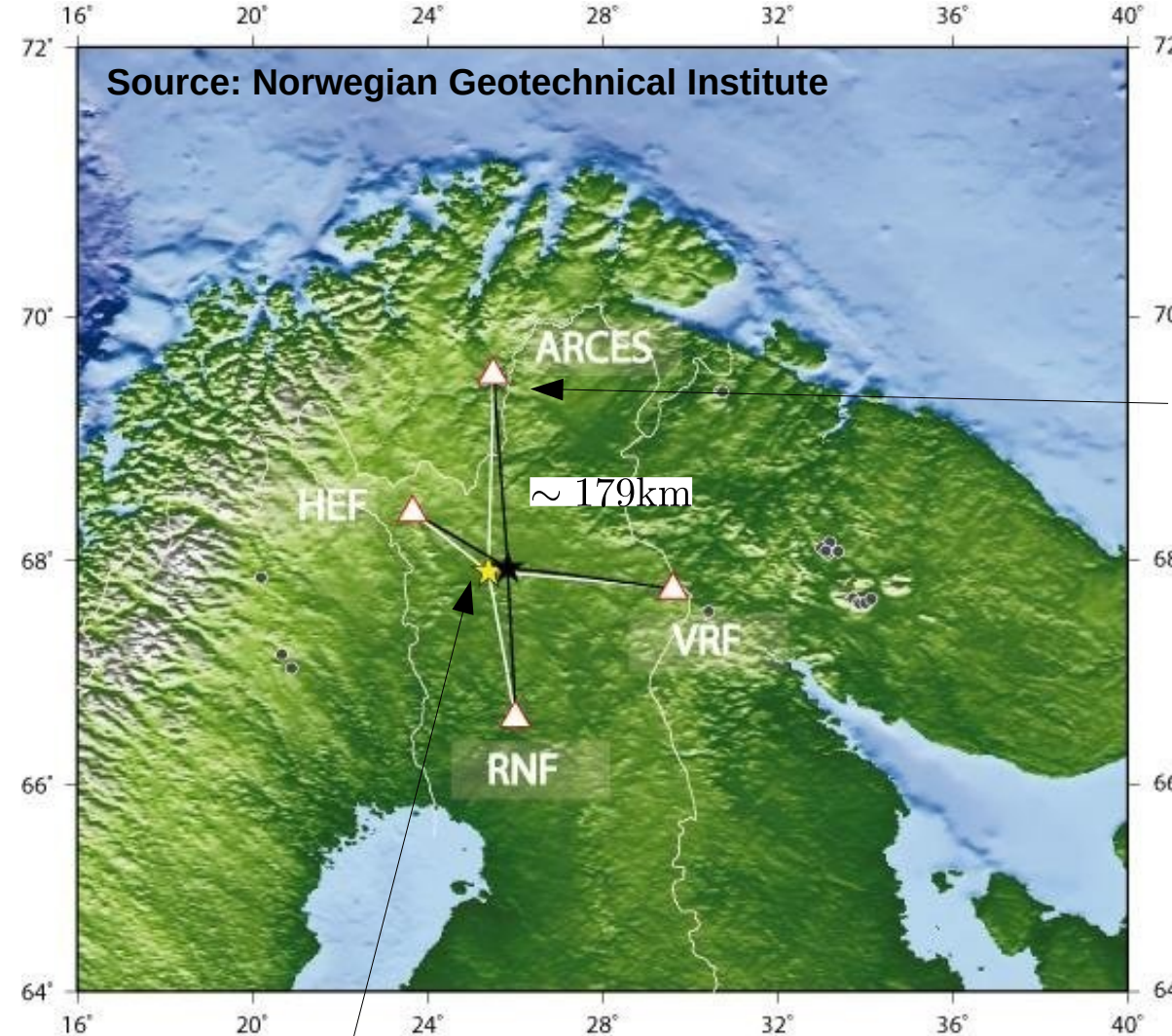


From Blixt et al 2019.

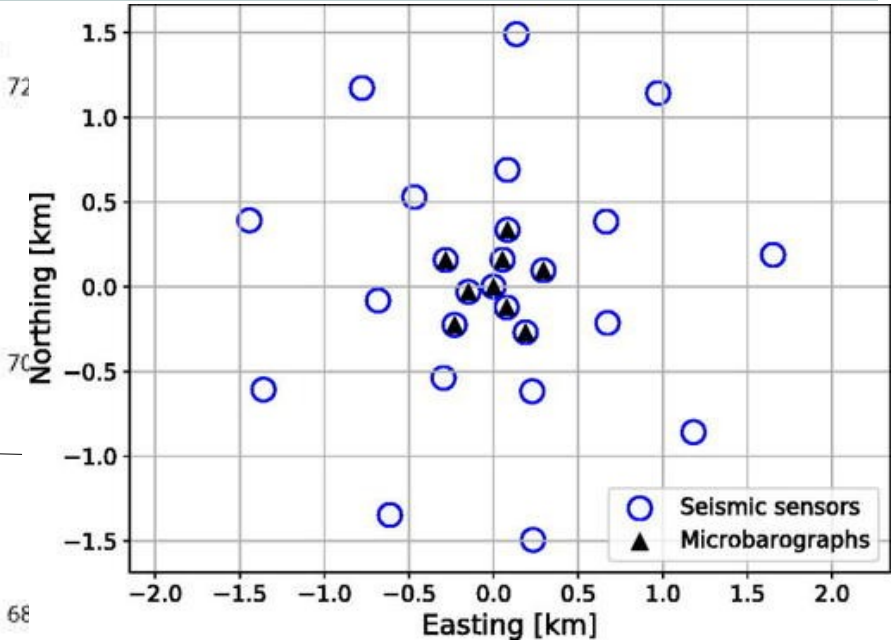
Hukkakero

Ammunition explosions in Finland

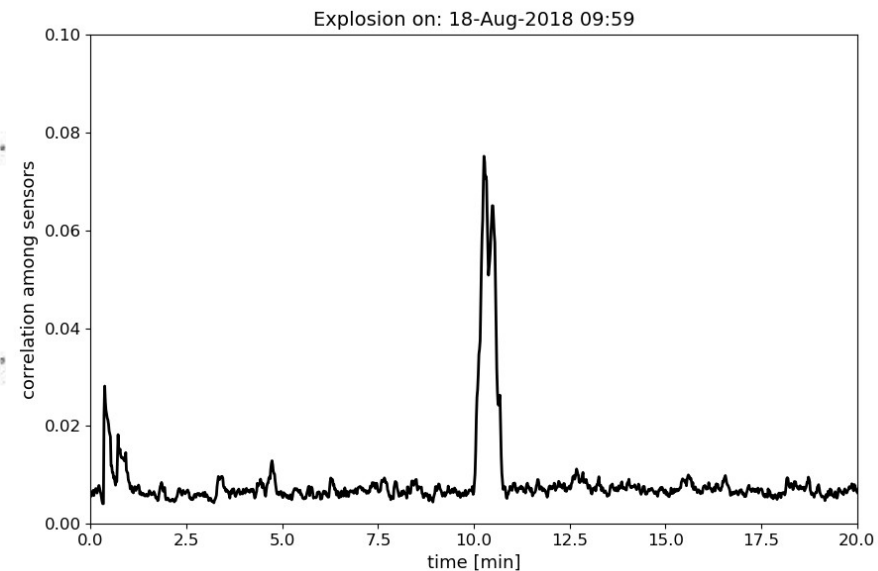
Source: Norwegian Geotechnical Institute



Hukkakero



From Blixt et al 2019.



The data assimilation process

Data Assimilation

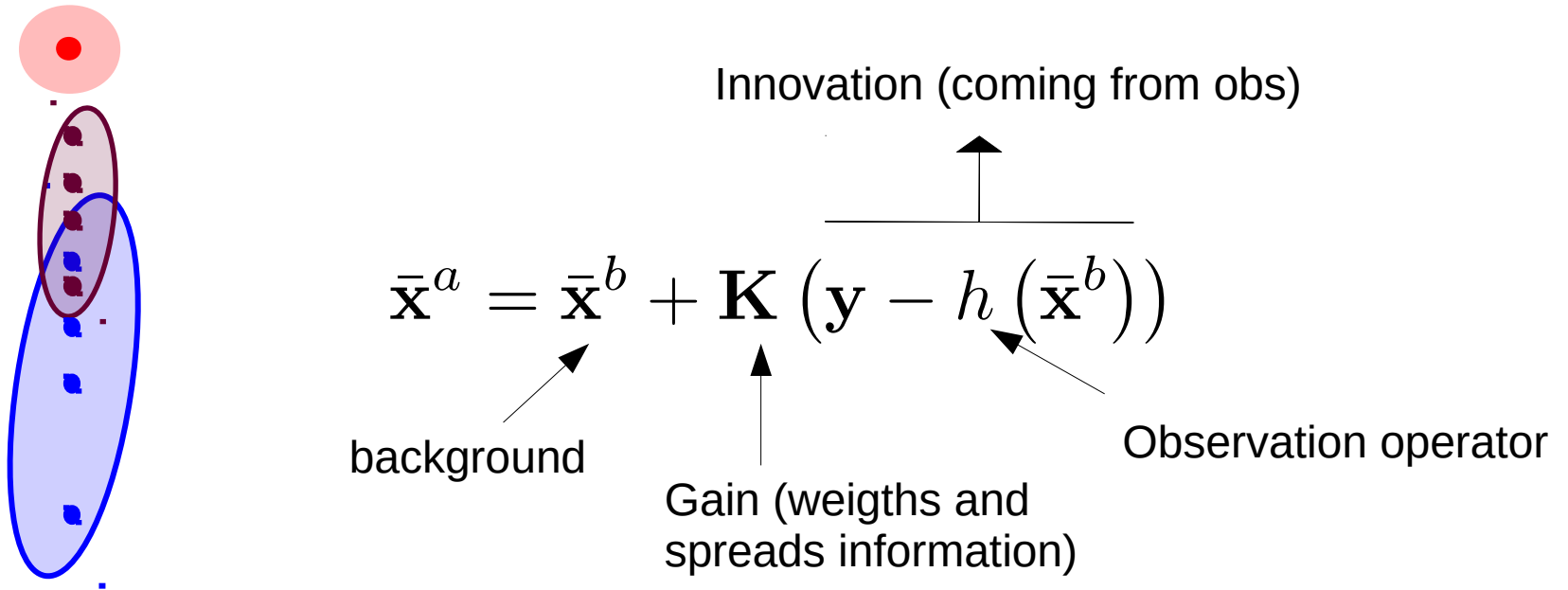
DA is the process of **combining information** from different sources in an **optimal** way. Generally, these sources are **models** and **observations**.

This has the aim of getting a **better estimate** of the state of a **system**.

Optimal includes –among other things- to **consider the uncertainty** (or conversely, the precision) of the sources.

Analysis step in Kalman methods

The KF is a particular case of **Bayesian estimation**, based on the first **two statistical moments**.



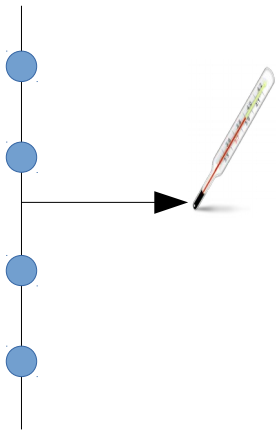
K contains information about the background error covariance **B**

This simple **linear equation** is **optimal** in the presence of **Gaussian errors** and **linear operators**. Otherwise it can still be useful, but it can need extra steps (e.g. linearisations and iterations).

Examples with different observational settings

How to observe?

Radiosonde



h: interpolator

Direct observations are the easiest.

Location of observation and grid points may not be the same. May need **interpolation**.

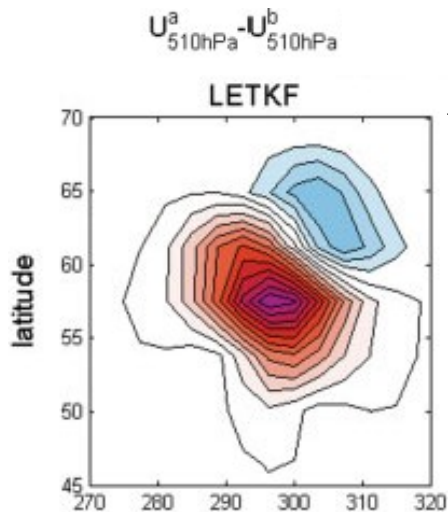
The **information** is spread through **covariances**.

A simple DA process

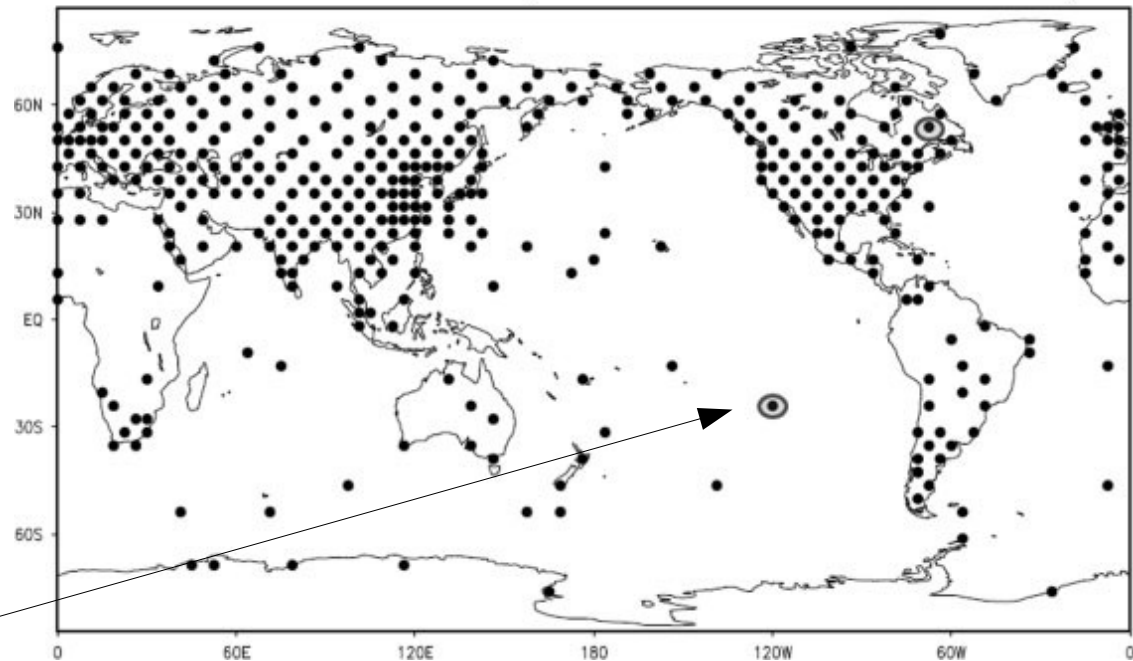
Background: atmospheric variables on a lat-lon grid.

Observation: radiosonde measuring a variable at a given height.

Analysis: updated atmospheric variables on a lat-lon grid.



OBSERVATION STATIONS (REALISTIC NETWORK NOBS=415)



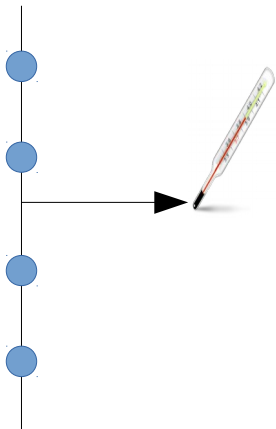
Analysis increment for zonal wind in the middle atmosphere.
Red is positive, blue is negative.

The **quality of the background covariance** is vital.

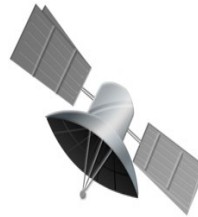
For **small ensembles** may need to **artificially ignore long-distance correlations**.

How to observe?

Radiosonde



h: interpolator

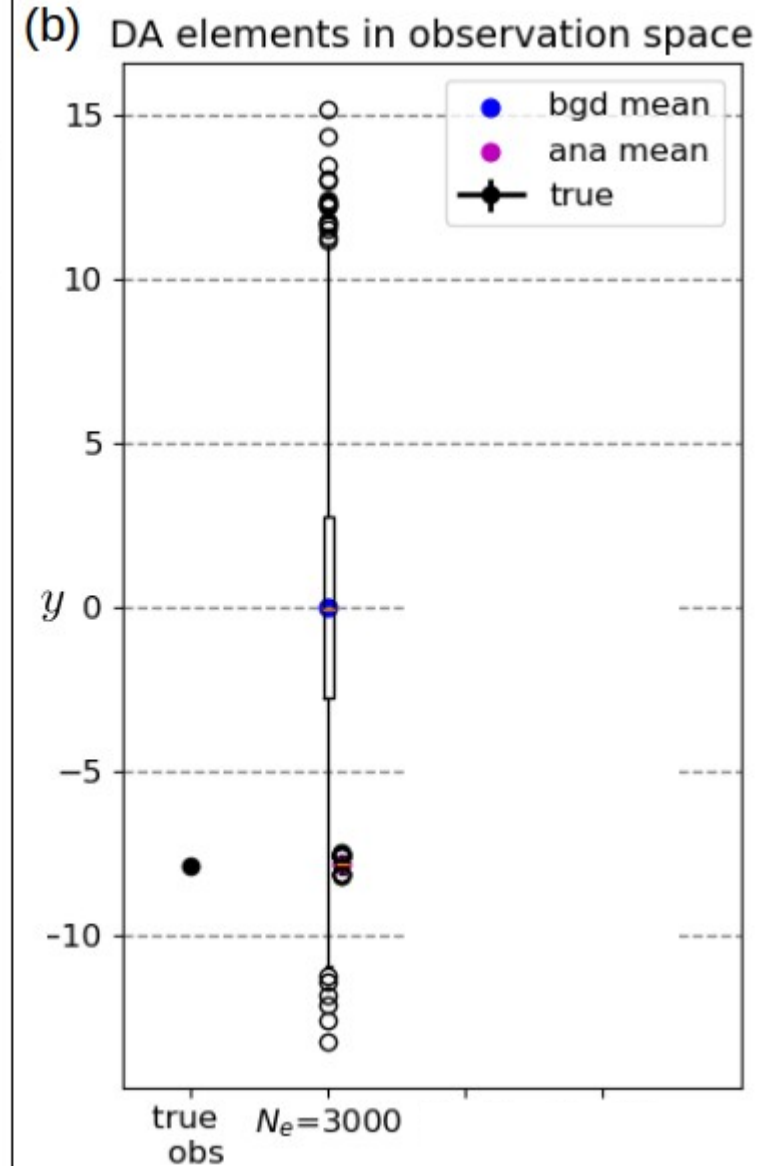
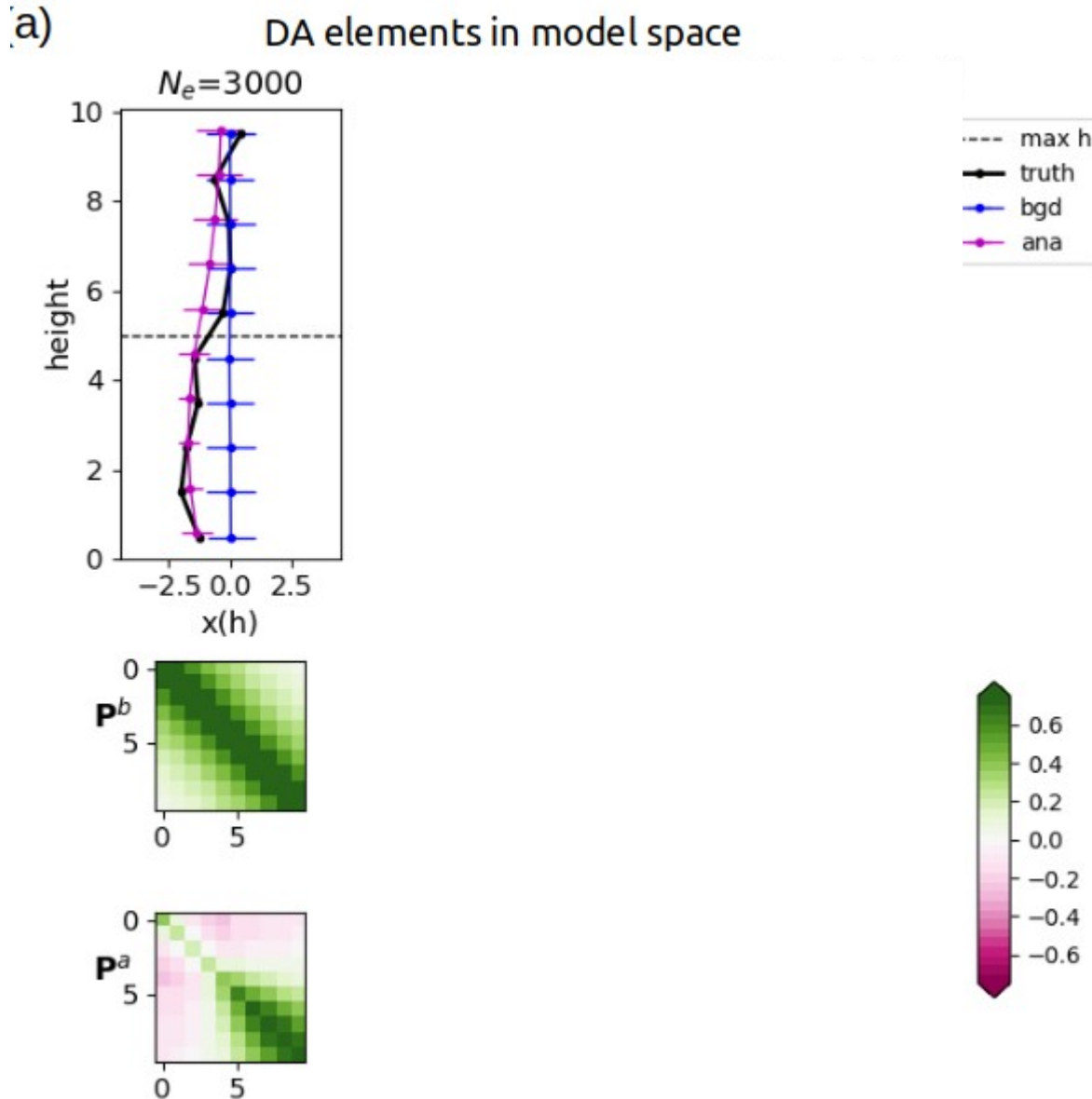


h: radiative transfer
model

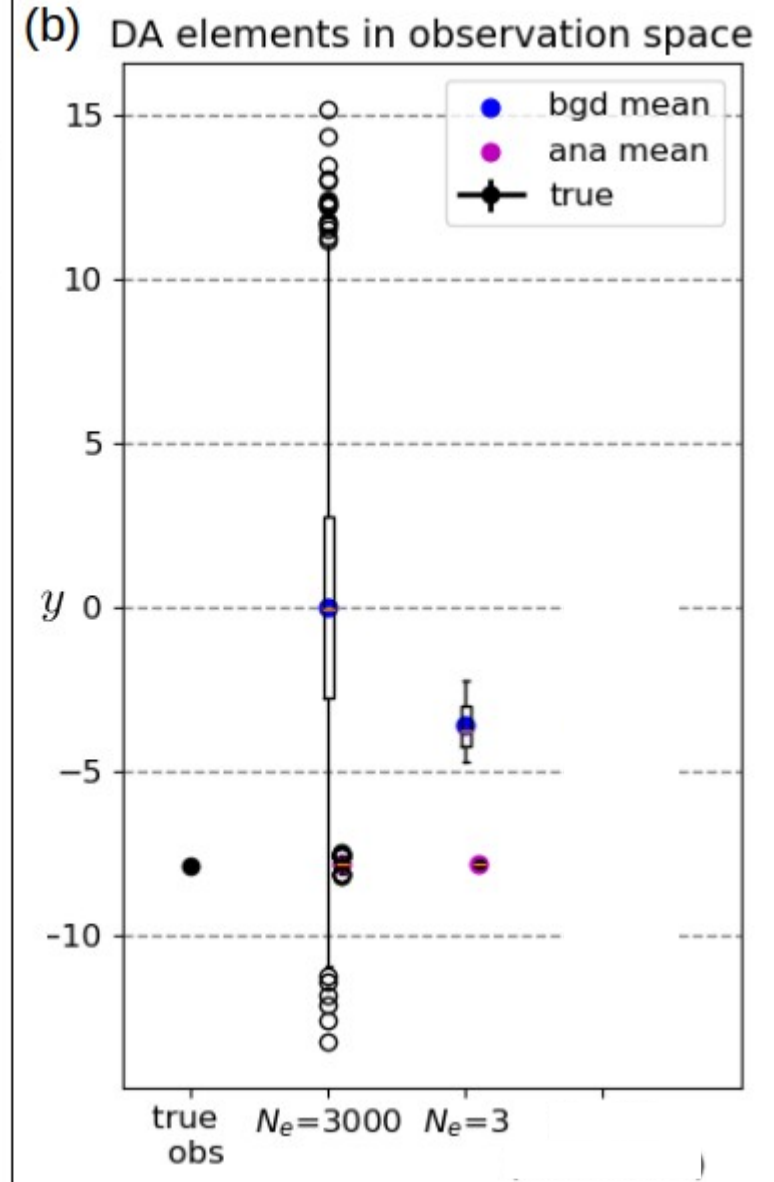
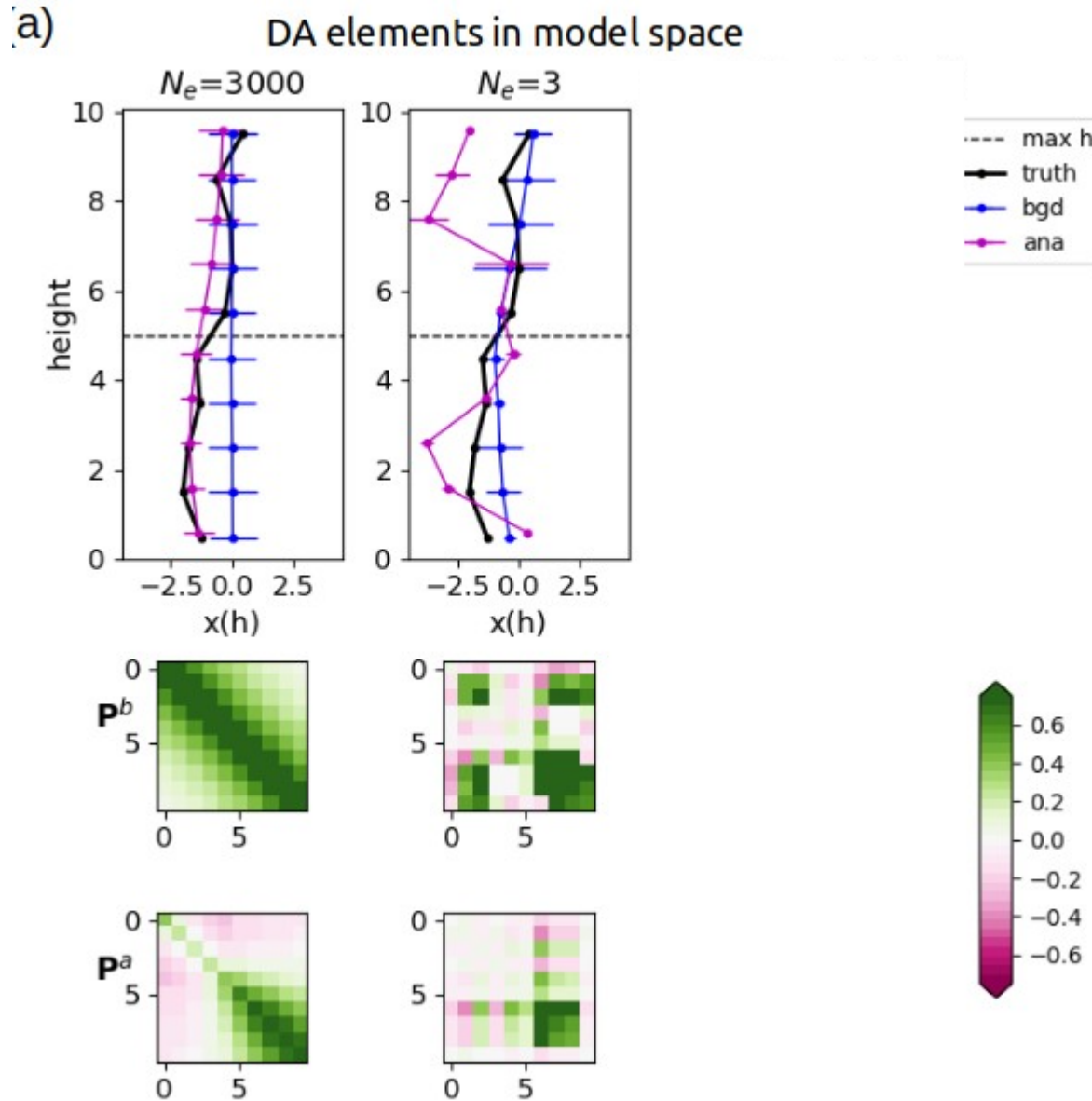
With integrated observations, it is more **difficult to 'clean' the background covariance**.
How can we define 'distances' between variables and observations?

We exploit the techniques coming from **satellite data assimilation**. In particular the **Modulated Ensemble Kalman Filter** (Bishop and Hodyss, 2017).

Simple example: observation is the sum of lower layers



Simple example: observation is the sum of lower layers



Cleaning covariances with integrated observations

Article Type: [Research Article](#)

Vertical Covariance Localization for Satellite Radiances in Ensemble Kalman Filters

[William F. Campbell](#)¹, [Craig H. Bishop](#)¹, and [Daniel Hody...](#)

[View More](#) +

Print Publication: [01 Jan 2010](#)

DOI: <https://doi.org/10.1175/2009MWR3017.1>

Page(s): [282–290](#)

Article Type: [Research Article](#)

Gain Form of the Ensemble Transform Kalman Filter and Its Relevance to Satellite Data Assimilation with Model Space Ensemble Covariance Localization

[Craig H. Bishop](#)¹, [Jeffrey S. Whitaker](#)², and [Lili Lei](#)³

[View More](#) +

Print Publication: [01 Nov 2017](#)

DOI: <https://doi.org/10.1175/MWR-D-17-0102.1>

Small ensemble sizes

When using few ensemble members, we need **localisation**.

When using the geometric model, we could directly use **model space localisation**. For products, we **had the TLM**.

$$\mathbf{P}_{loc} = \mathbf{P} \circ \mathbf{L}_{model}$$

$$\mathbf{P}_{loc} \mathcal{H}^\top = (\mathbf{P} \circ \mathbf{L}_{model}) \mathcal{H}^\top$$

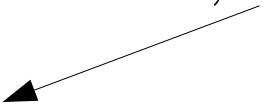
Directly applying localisation in observation space is not easy. No natural distances!

$$\left(\hat{\mathbf{X}}^b \hat{\mathbf{Y}}^{b\top} \right) \circ \mathbf{L}_{mixed}$$

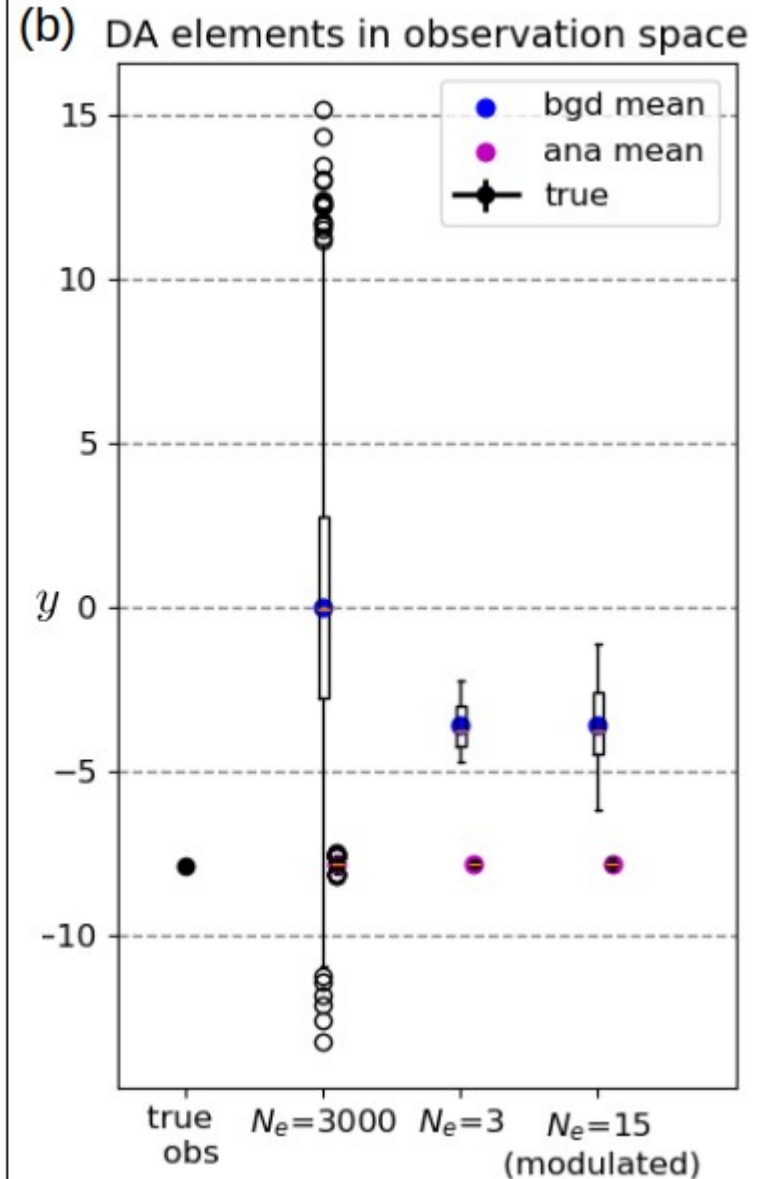
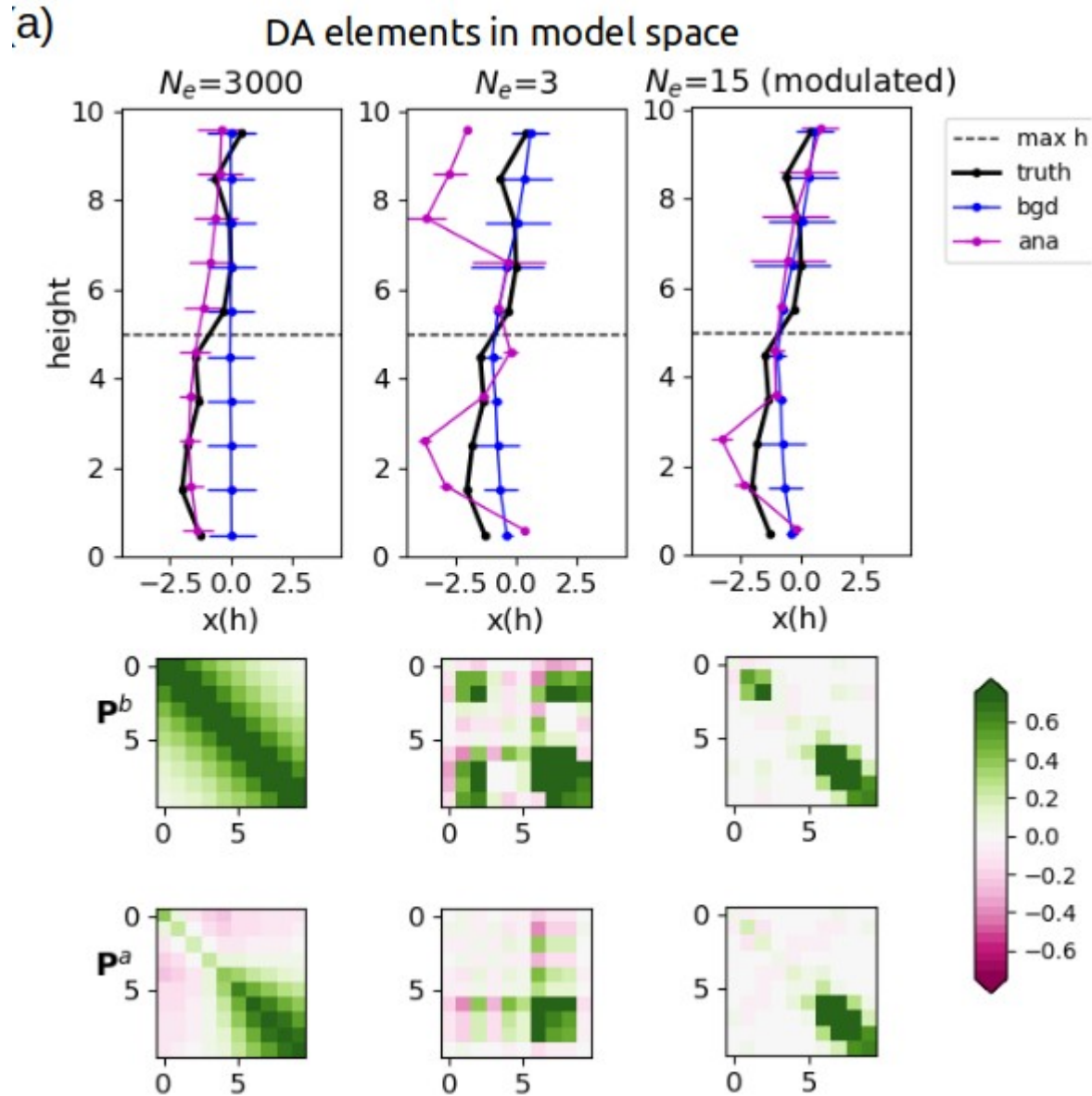
$$\left(\hat{\mathbf{Y}}^b \hat{\mathbf{Y}}^{b\top} \right) \circ \mathbf{L}_{obs}$$

In this case I use the Modulated ETKF (Bishop et al, 2017) which uses a **modulated ensemble**.

$$\mathbf{X}^b : \quad \bar{\mathbf{x}}^b, \hat{\mathbf{X}}^b$$


$$\hat{\mathbf{U}}^b = \left[\left(\mathbf{l}_1^{\frac{1}{2}} \circ \hat{\mathbf{x}}_1^b, \dots, \mathbf{l}_1^{\frac{1}{2}} \circ \hat{\mathbf{x}}_{N_e}^b \right), \left(\mathbf{l}_2^{\frac{1}{2}} \circ \hat{\mathbf{x}}_1^b, \dots, \mathbf{l}_2^{\frac{1}{2}} \circ \hat{\mathbf{x}}_{N_e}^b \right), \dots, \left(\mathbf{l}_{N_\lambda}^{\frac{1}{2}} \circ \hat{\mathbf{x}}_1^b, \dots, \mathbf{l}_{N_\lambda}^{\frac{1}{2}} \circ \hat{\mathbf{x}}_{N_e}^b \right) \right]$$

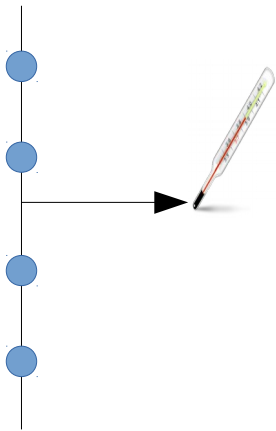
Modulated ETKF removes sampling errors



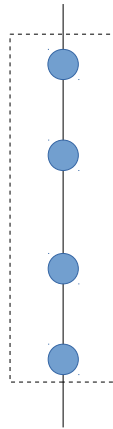
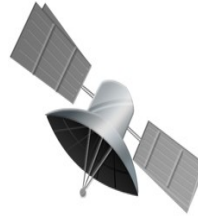
Doing DA with infrasound observations

Infrasound observations

Radiosonde

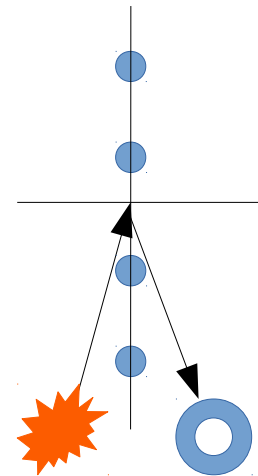


h: interpolator



h: radiative transfer
model

Infrasound

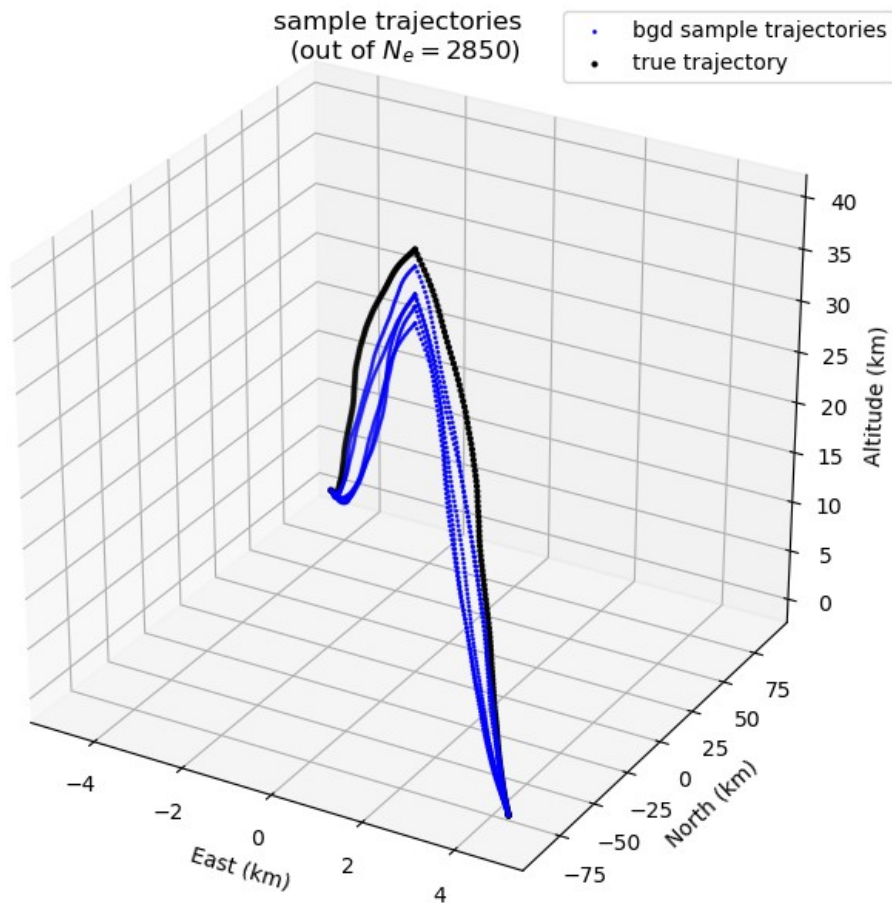


h: ray tracing
model

Infrasound observations are not too different from satellite observations.

Differences: the trajectory is more complicated, the speed of sound is slower than the speed of light.

Our problem



State variables

Observations

$$\mathbf{x} = \begin{bmatrix} \mathbf{u}(r, z, t) \\ \mathbf{v}(r, z, t) \\ \mathbf{T}(r, z, t) \\ Z_{max} \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} \delta_{ba} \\ t_{travel} \\ v_{app} \end{bmatrix}$$

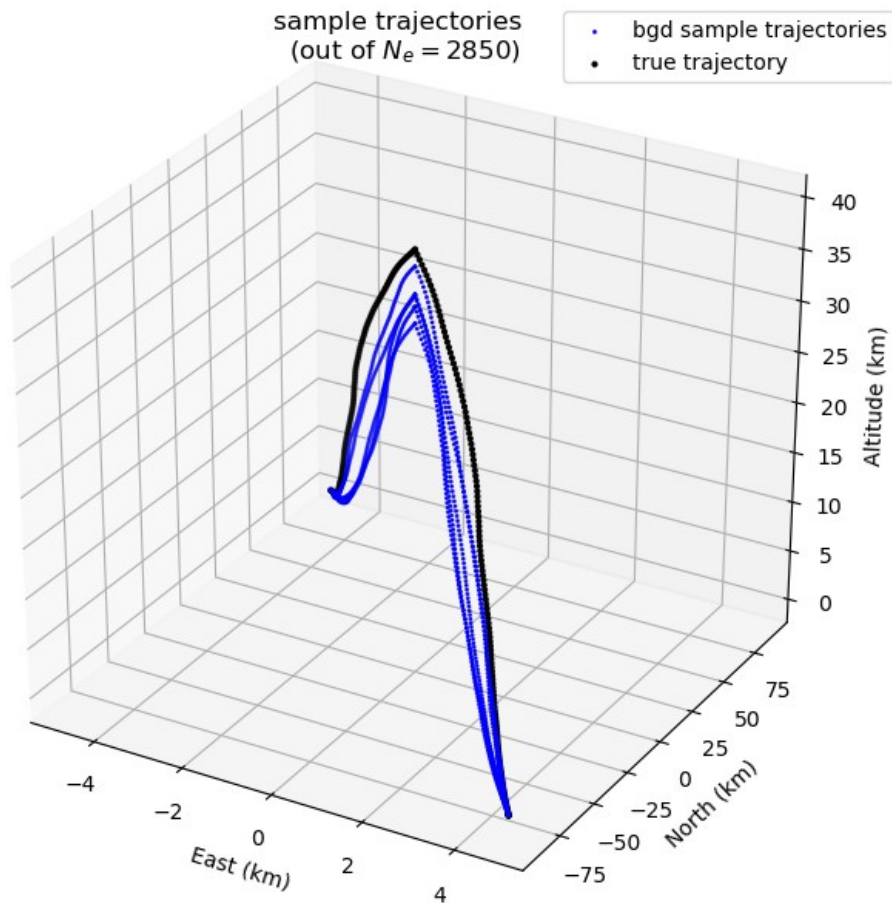
The exact problem is quite difficult.

We try to infer fields from three scalars.

The small scale features causing reflections are not well resolved in models.

We need simplifications.

Simplified



State variables

Observations

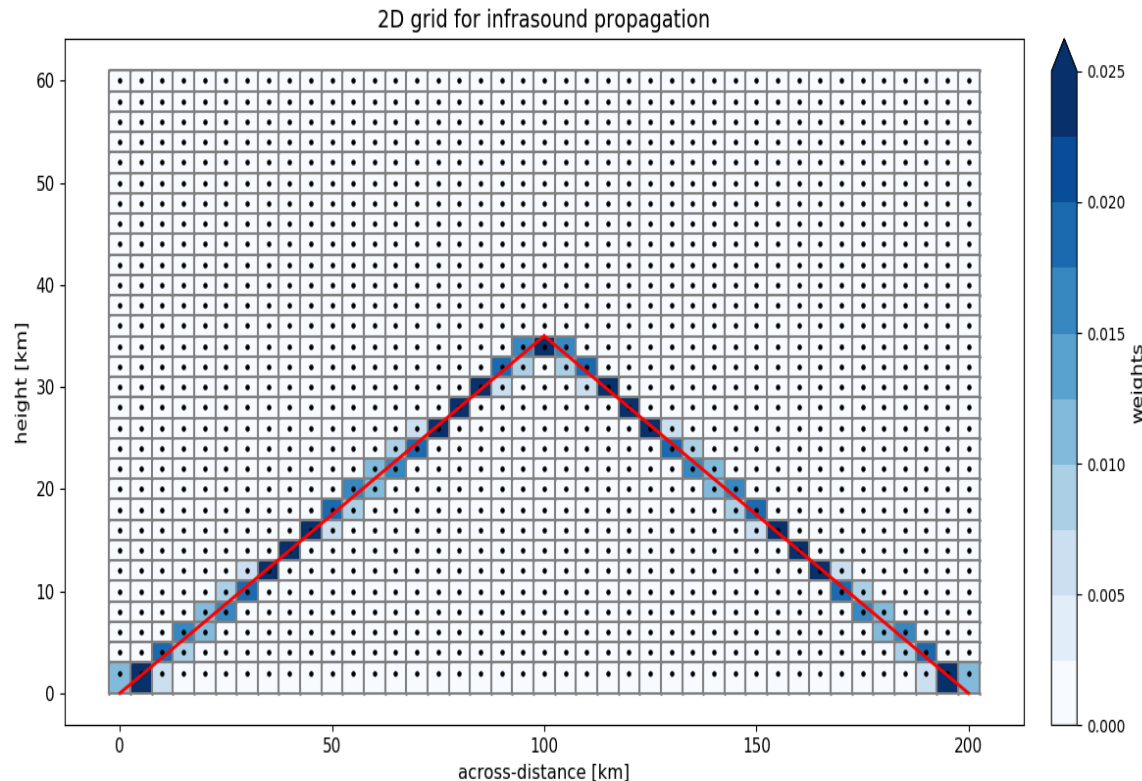
$$\mathbf{x} = \begin{bmatrix} \mathbf{u}(z) \\ \mathbf{v}(z) \\ \mathbf{T}(z) \\ Z_{max} \end{bmatrix} \quad \mathbf{y} = \begin{bmatrix} \delta_{ba} \\ t_{travel} \\ v_{app} \end{bmatrix}$$

Approximations:

– Distance ~180 km, travel time ~10 min,
so the **atmospheric fields are
considered static while the wave
travels.**

– Consider only **height dependence.**

Side note



State variables

$$\mathbf{x} = [\mathbf{u}(x, z)]$$

Observations

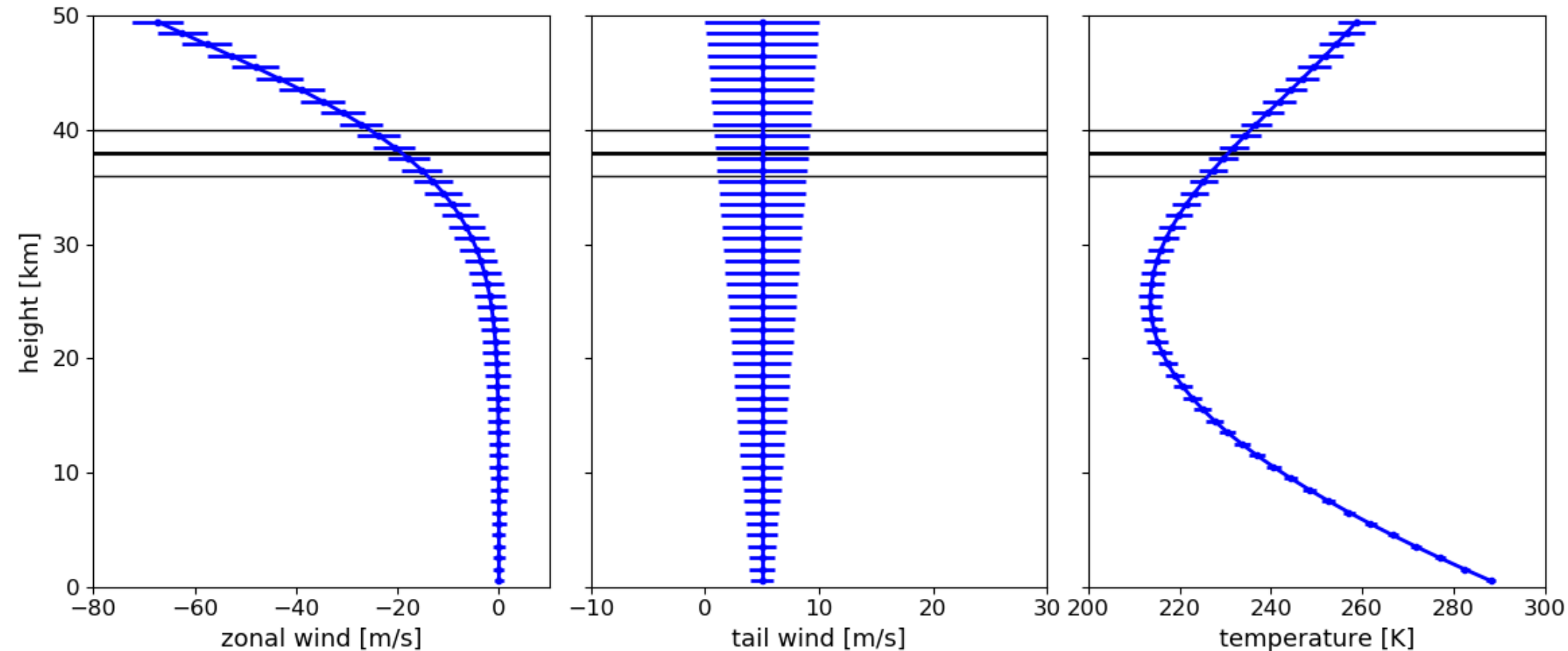
$$\mathbf{y} = [\delta_{ba}]$$

Consider height and along-track dependence.

In the past we did 2D problems with a **simple geometric model** (Blixt et al, 2019) with 1 field and 1 observation.

The reflection height was considered given.

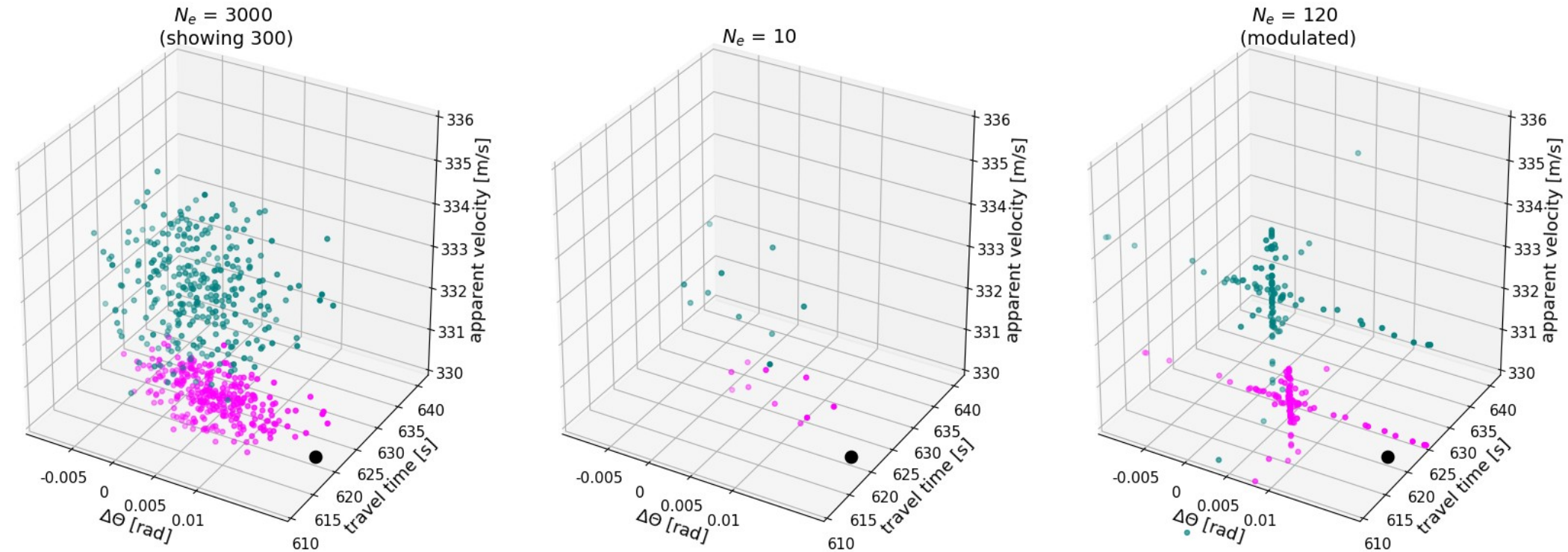
Current synthetic experiments



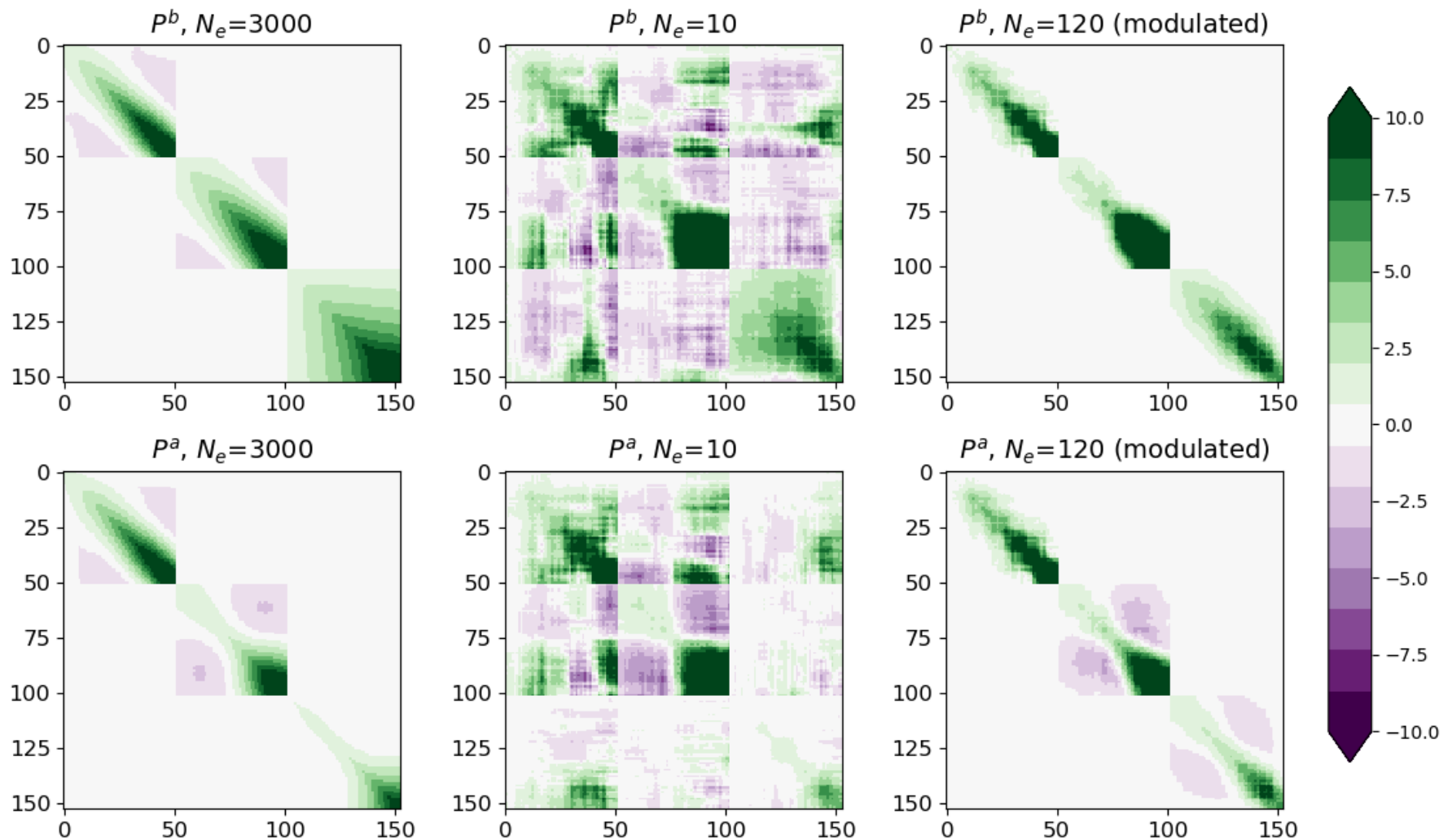
We generate $N_e + 1$ atmospheric profiles and maximum heights coming from a given distribution.

Results in observation space

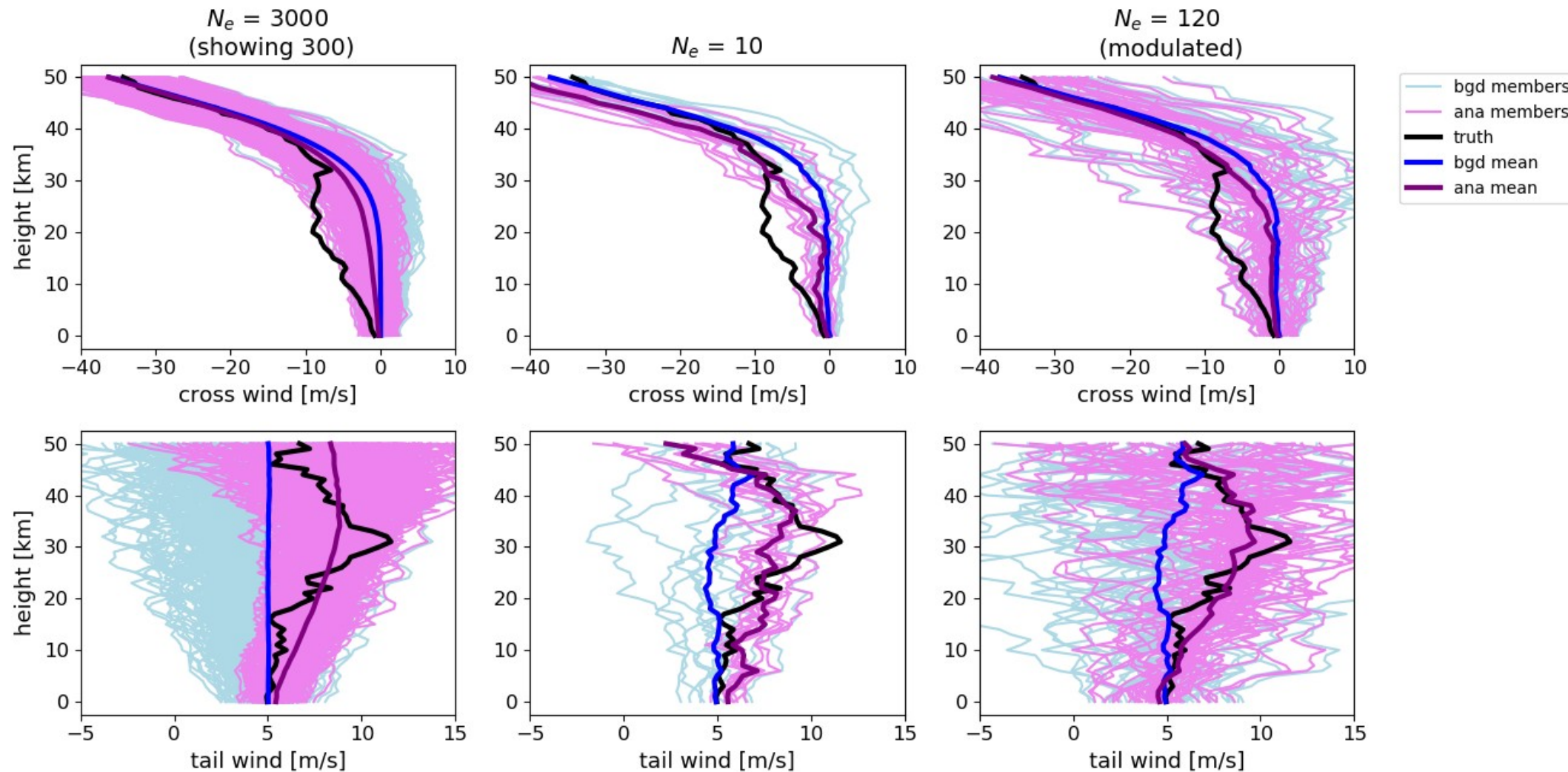
The ray-propagation algorithm is applied to every ensemble member.



Covariances

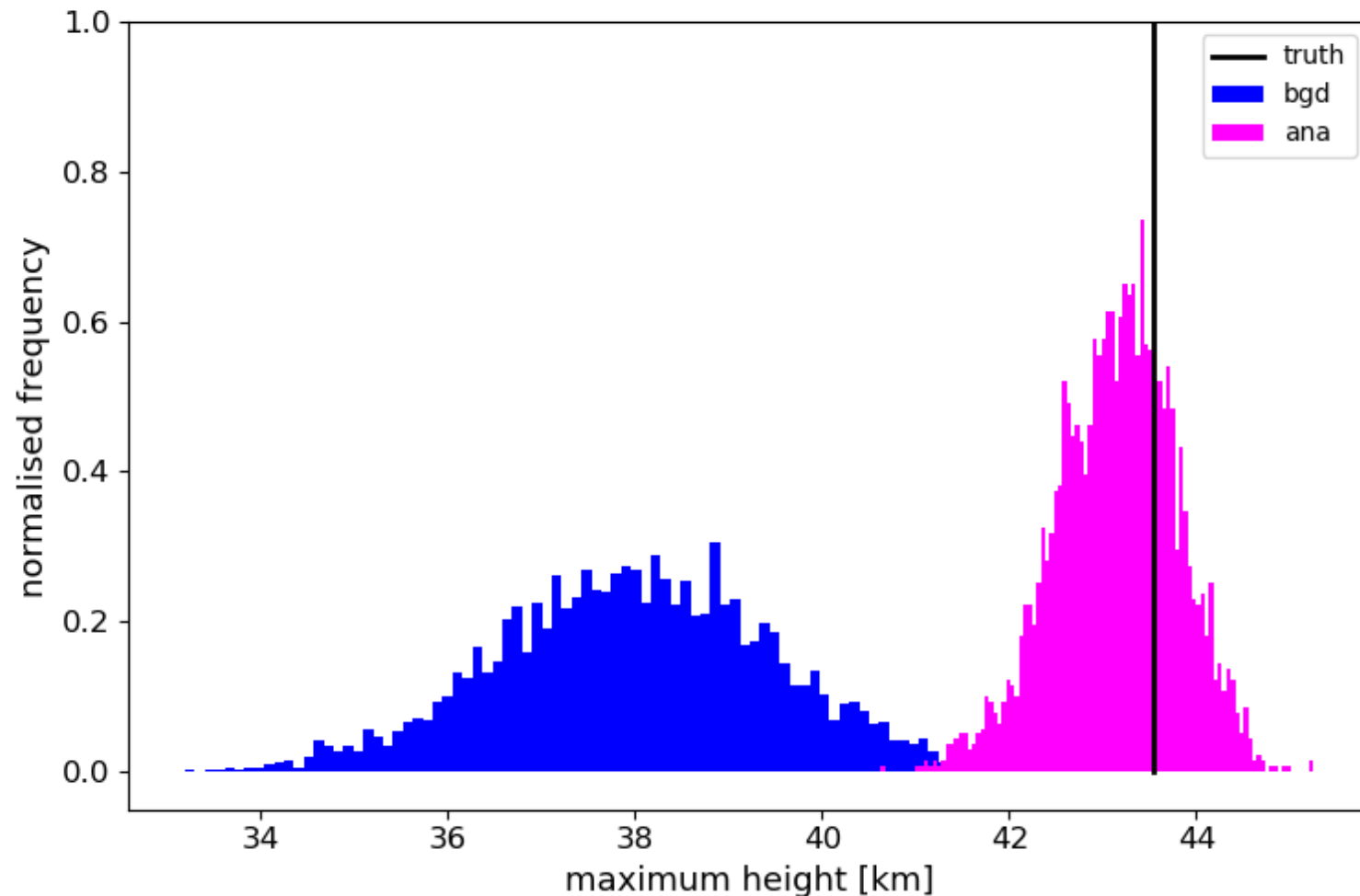


Results in model space



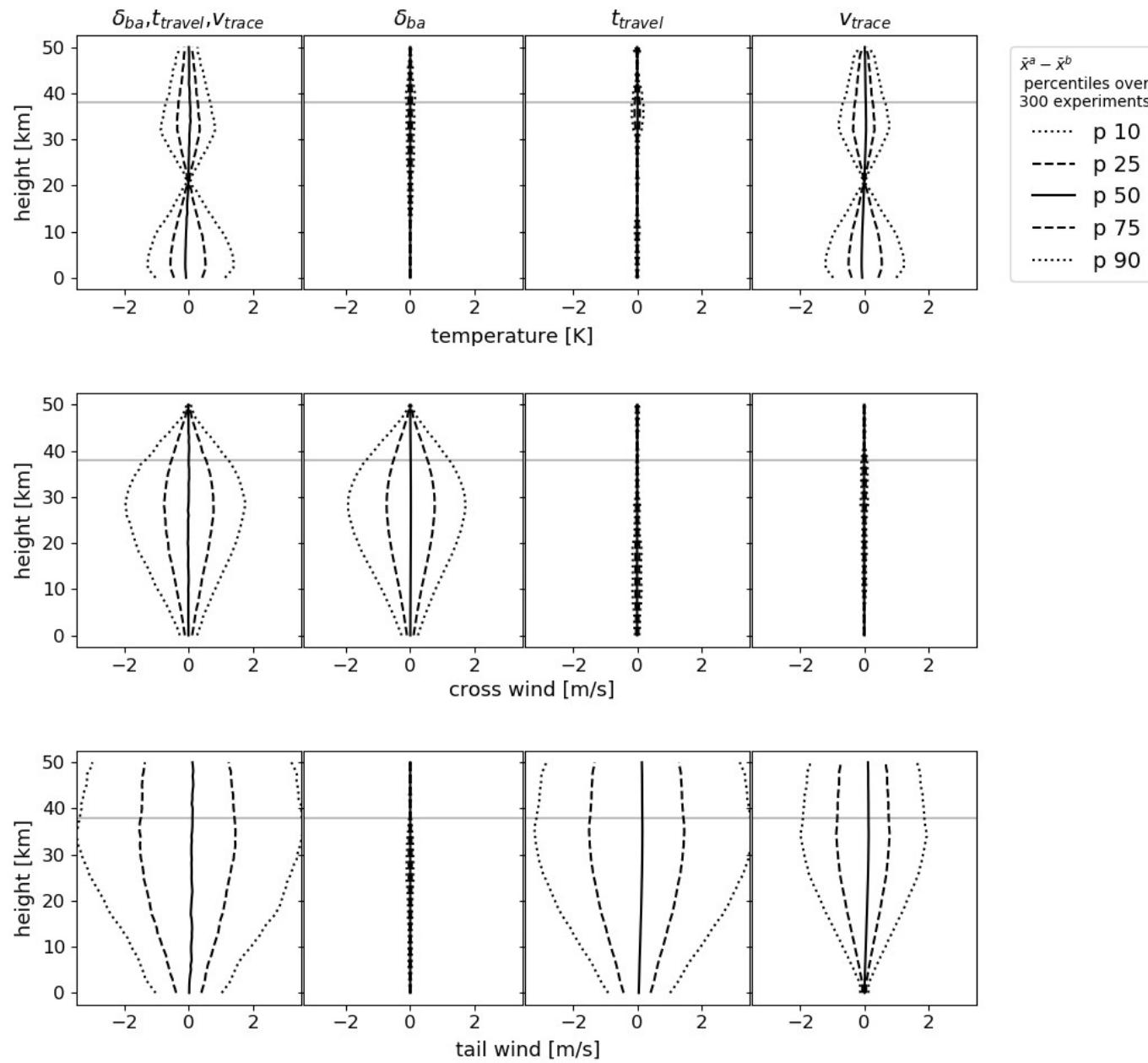
In model space, the quality of the background covariance is vital.

Results in model space



The heights are also updated (only large ensemble results shown).

Observation impact



Summary

Infrasound-related measurements contain **integrated information** of **atmospheric variables**. This can be exploited for poorly-observed regions.

Doing **DA with integrated quantities** and **small ensembles** can be difficult.

The **satellite DA** community has experience on this. We borrow a technique from them to solve our problem.

Next step: **assimilate ocean microbaroms**. More difficult since it is continuous emission and long-distance propagations.

Works:

– Amezcua, J, Näsholm, S, Blixt, EM, Charlton-Perez, AJ. (2020) Assimilation of atmospheric infrasound data to constrain tropospheric and stratospheric winds. QJR Meteorol Soc. 2020; 146: 2634– 2653.

<https://doi.org/10.1002/qj.3809>

– Amezcua, J. & Barton, Z.(2021) Assimilating atmospheric infrasound data to constrain atmospheric winds in a two-dimensional grid. QJR Meteorol Soc, 147, 3530–3554. Available from: <https://doi.org/10.1002/qj.4141>

– Amezcua, J, Näsholm, S, Vera-Rodriguez (2022). Using satellite data assimilation techniques to assimilate infrasound observations into a full ray-tracing model. The Journal of the Acoustical Society of America. *In preparation*.