Challenges Propagating Innovations on Precipitation and Cloud to Other State Variables

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4th Workshop on Assimilating Satellite Cloud and Precipitation Observations for NWP – Reading, UK – 5 February 2020

Context: Conditions of Success for Data Assimilation

1) Accurate simulation of expected observations

Sessions 1-3

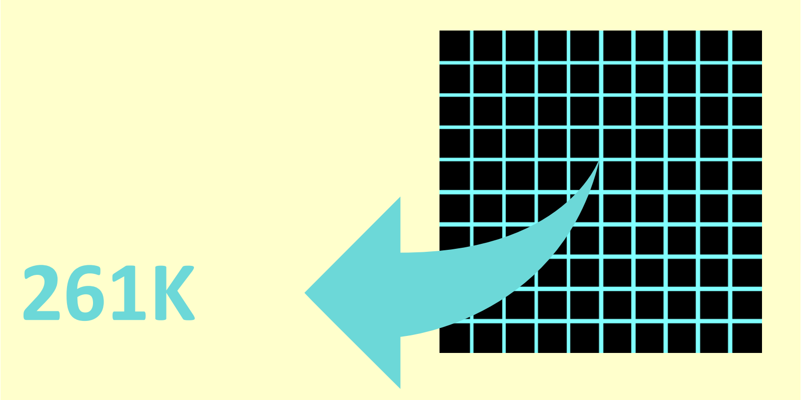
2) Non-trivial information from observations

3) Proper statistical description of unbiased errors

4) Usability of mismatch to correct relevant state variables

5) Propagability of the information via error relationships

6) Usefulness of the added information for forecasting



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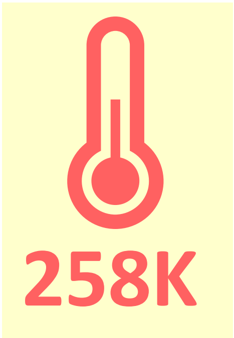
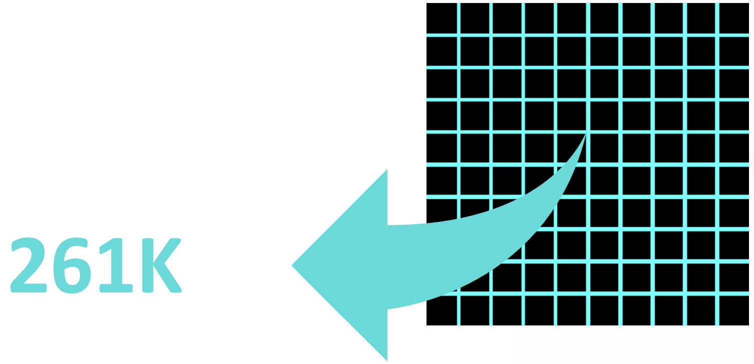
Session 1





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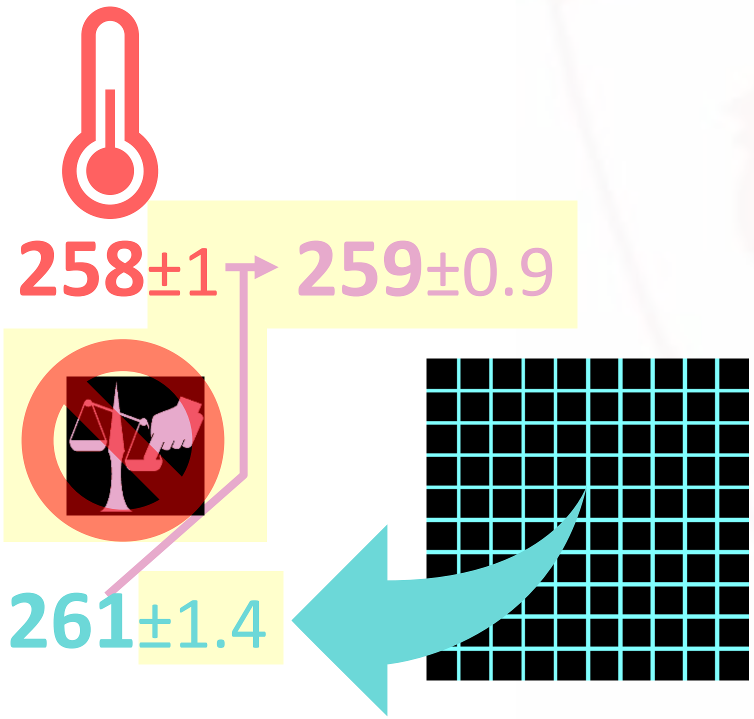
4.1, 4.2,…



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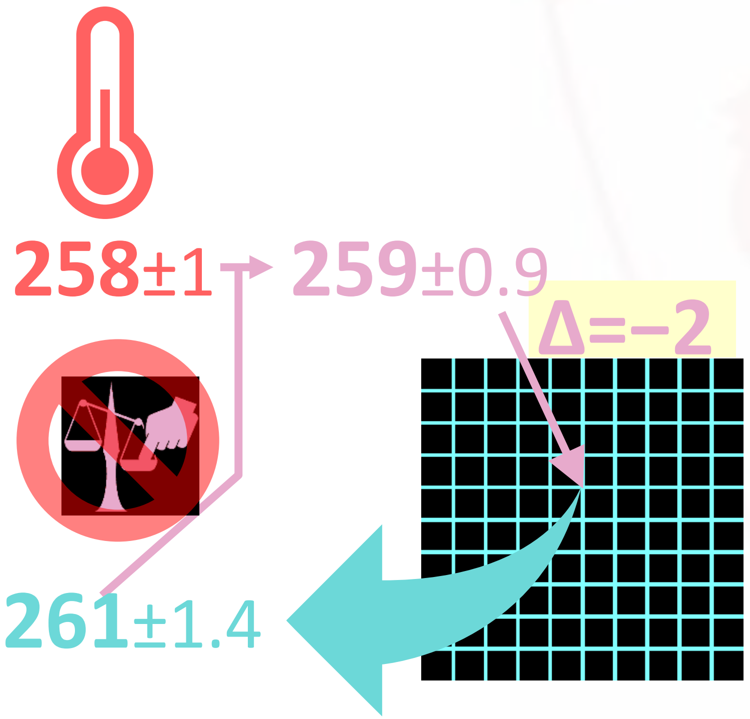
4.3, non-linearity



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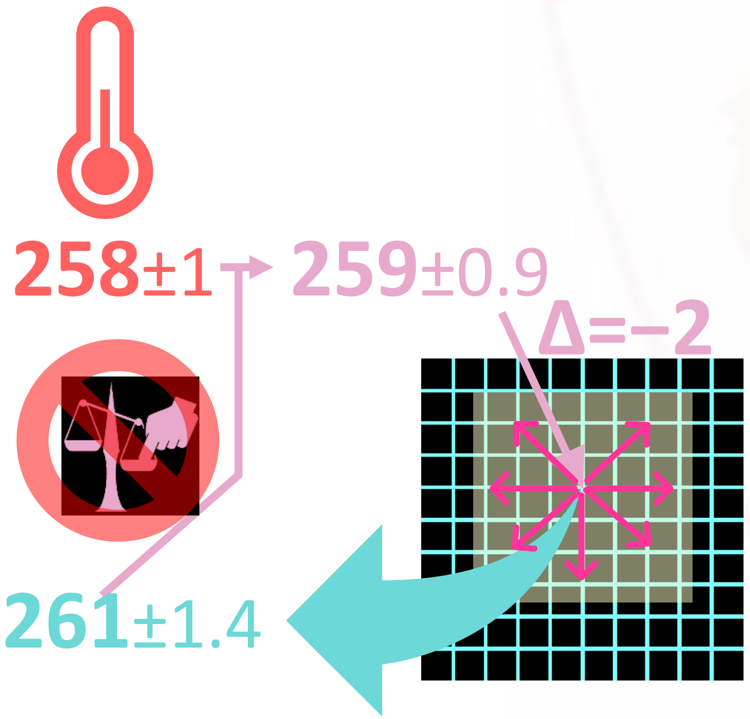

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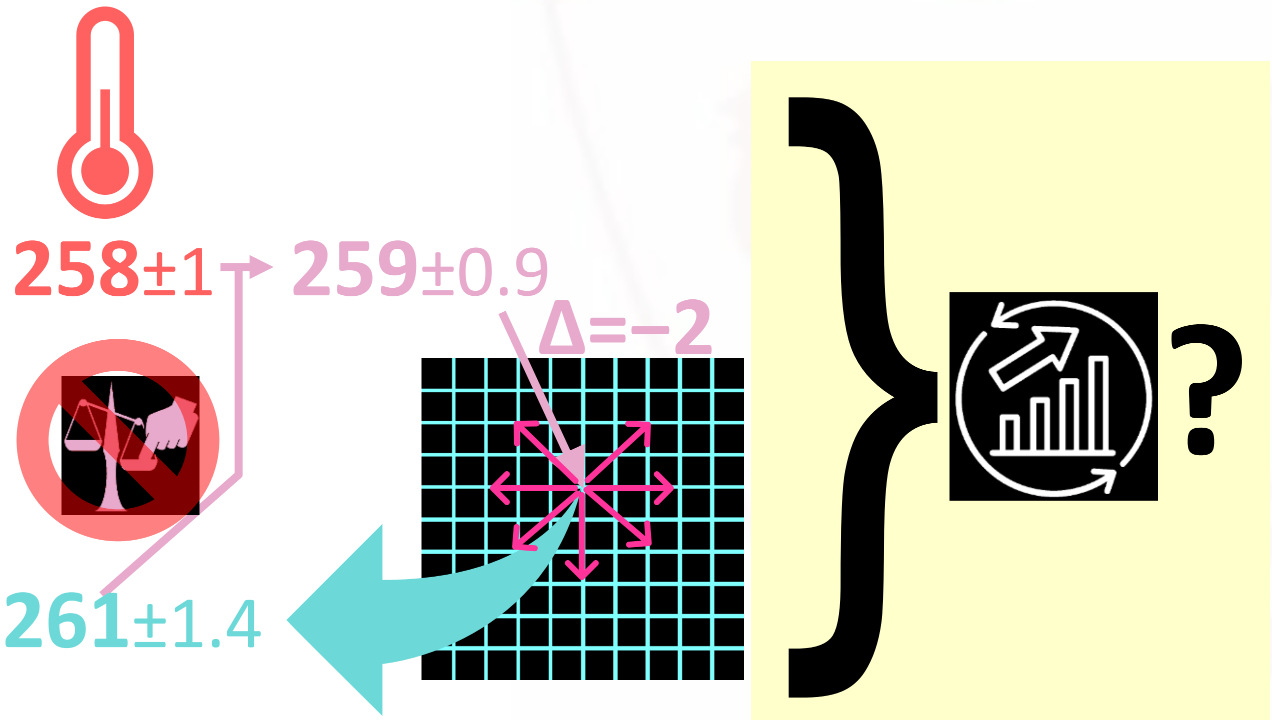


Focus of this Talk and Rationale

1) Accurate simulation of expected observations 2) Non-trivial information from observations 3) Proper statistical description of unbiased errors 4) Usability of mismatch to correct relevant state variables	Obvious satellite-specific issues
5) Propagability of the information via error relationships 6) Usefulness of the added information for forecasting	**Focus of this talk**

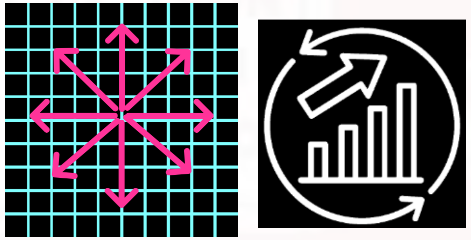
Rationale for focus:

A) **Assimilating satellite** precipitation and cloud **observations** for NWP **is more than** simply **obtaining an analysis for cloud and precipitation** fields;

B) **Clouds and precipitation** have properties that **hinder the effectiveness of** many data **assimilation** approaches.

Why Worry About Information Propagation and Usefulness?

5) Propagability of the information via error relationships
6) Usefulness of the added information for forecasting



?

TAKE HOME MESSAGES

Thesis #1: For reasons of remote sensing and atmospheric instabilities, **the need to propagate information below cloud** tops **is more pressing**;

Thesis #2: Cloud and precipitation fields have large areas of zero values, smaller-scale structures, and considerable errors, all **reducing our ability to propagate information** using traditional assimilation approaches;

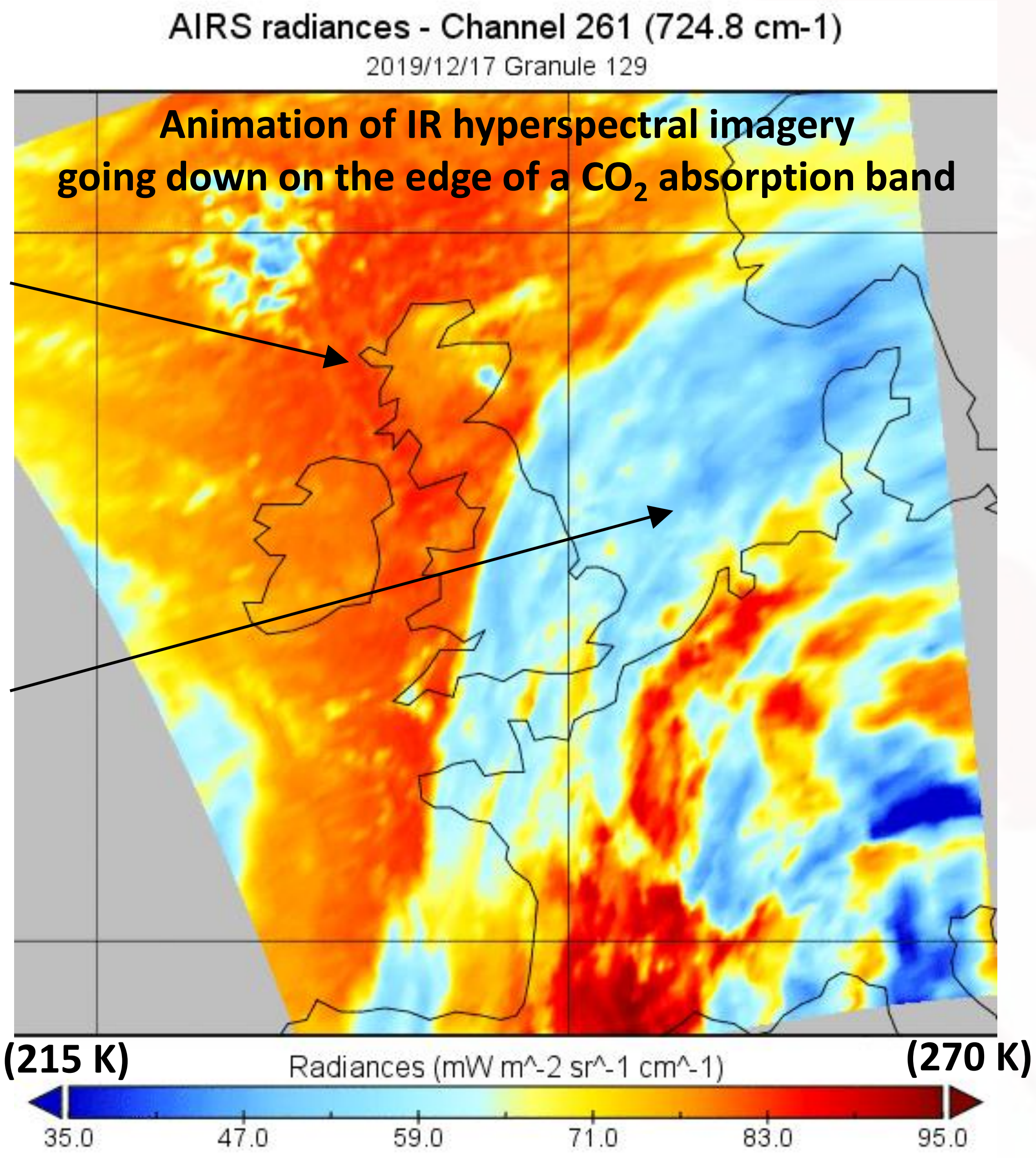
Thesis #3: Knowing precipitation fields better has small forecasting value.

→ To improve the quality and forecasting use of analyses, I believe **these issues must be <u>explicitly</u> confronted**.

Assimilation, Remote Sensing, and Clouds

Clear area: Remote-sensed information is available down to the surface

Cloudy area: Remote-sensed information is limited below cloud top



Clouds are largely opaque at infrared wavelengths and scatter strongly visible and high-frequency microwaves.

→ Available information for assimilation is considerably reduced below thick clouds.

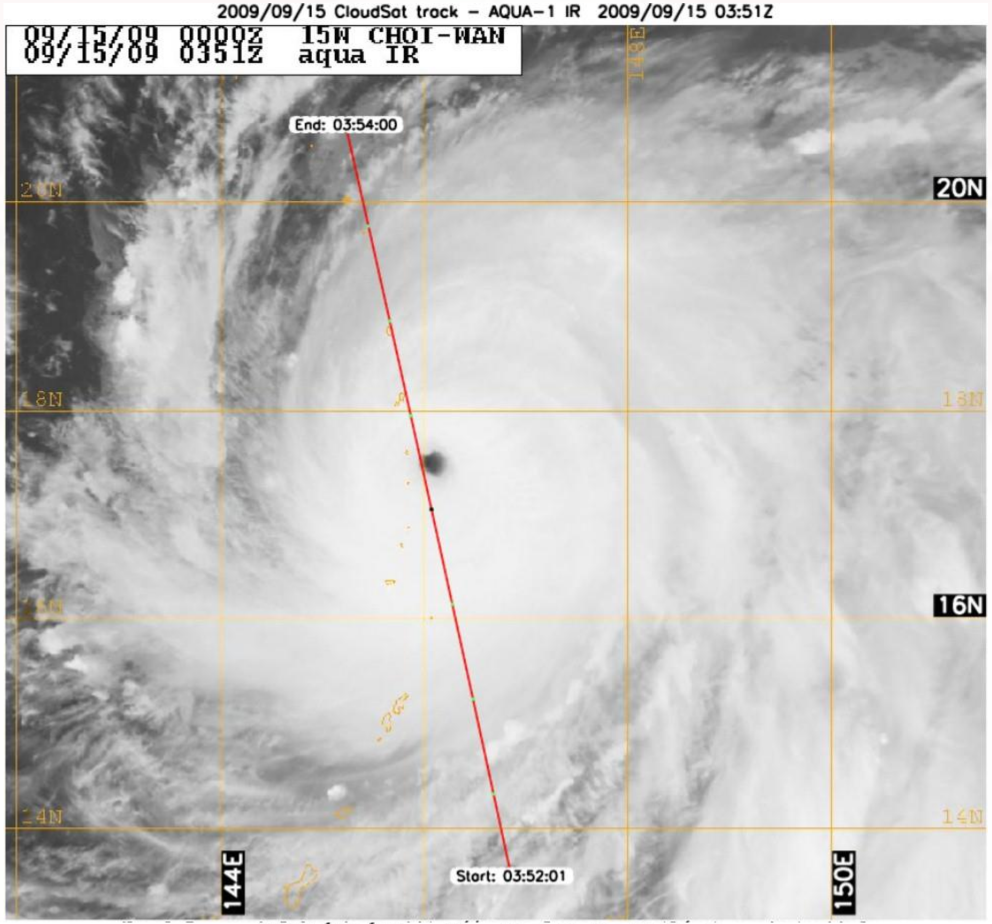
Cloudy Areas, Instabilities, and Forecasting

Clouds are generally in updraft areas, often triggered by atmospheric instabilities.

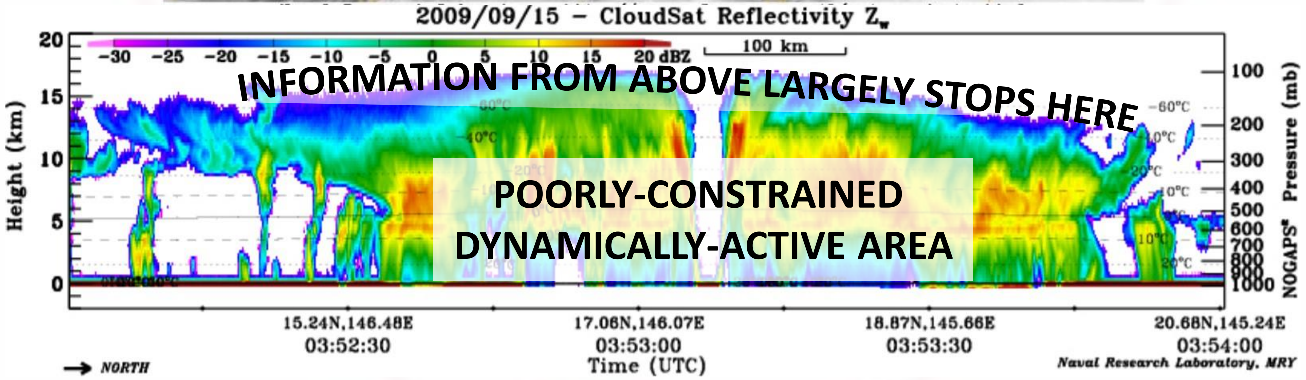
Unstable regions are also where initial condition errors will grow most rapidly.

→ Information is needed most acutely where it is most difficult to obtain by remote sensing.

→ **Greater necessity to propagate the information** from the sides and from above.



Images courtesy of JPL



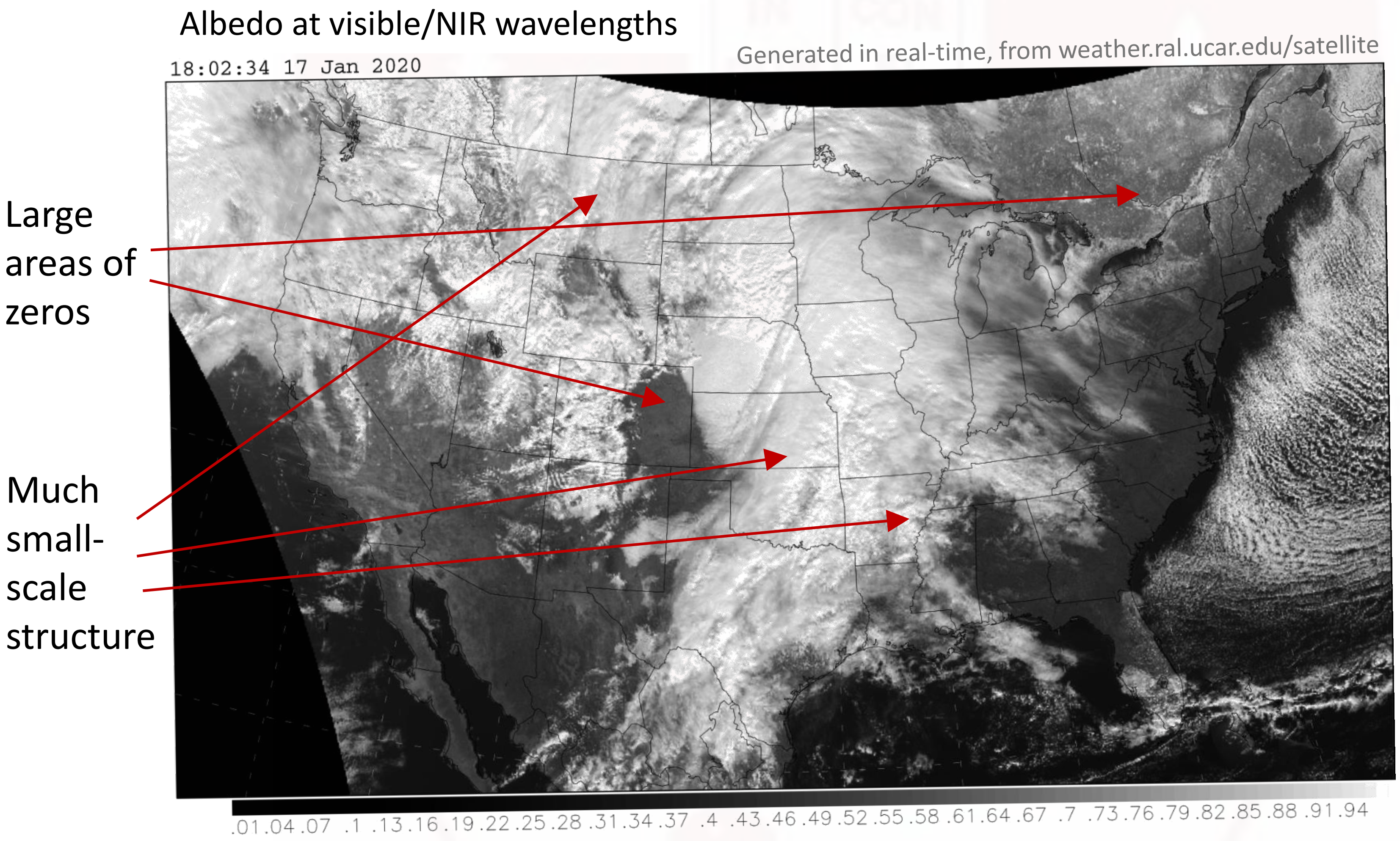
The Unusual Structure of Clouds and Precipitation

Compared to more usual fields (e.g., pressure), clouds and especially precipitation have:

1) Large areas of zeros, much of which is already in the background

→ No mismatch between background and observations

→ No innovation from these areas.



Caveat: However, as seen two slides before, information from IR emission bands around clouds more than compensate the lack of innovation from cloud-free areas. This unexpected help does not occur around precipitating areas.
→ Personal belief to verify: Regions under clouds and without precipitation are the hardest to innovate by satellite-based remote sensing.

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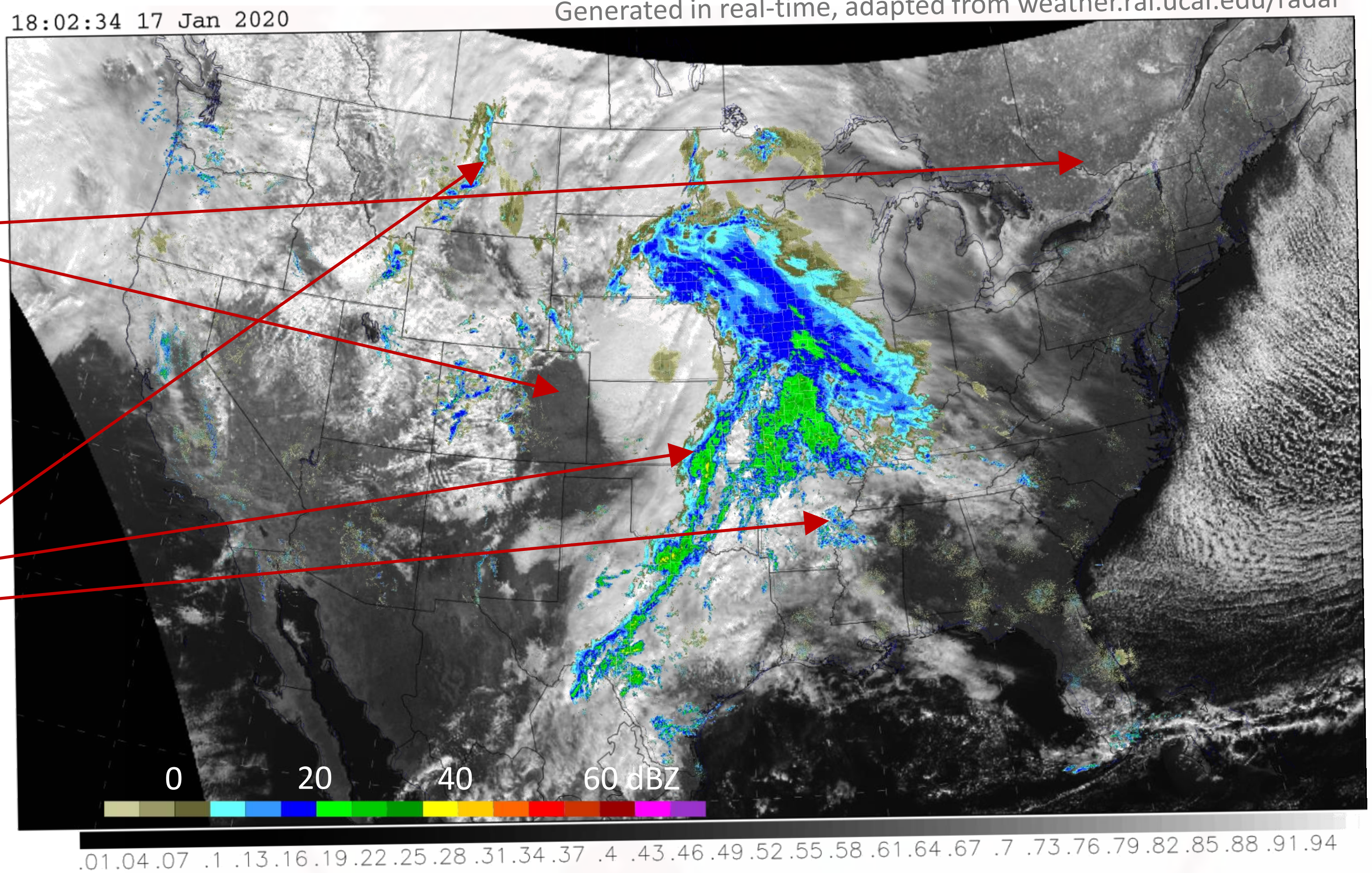
Albedo at visible/NIR wavelengths with radar reflectivity overlaid

Large areas of zeros

Much small-scale structure



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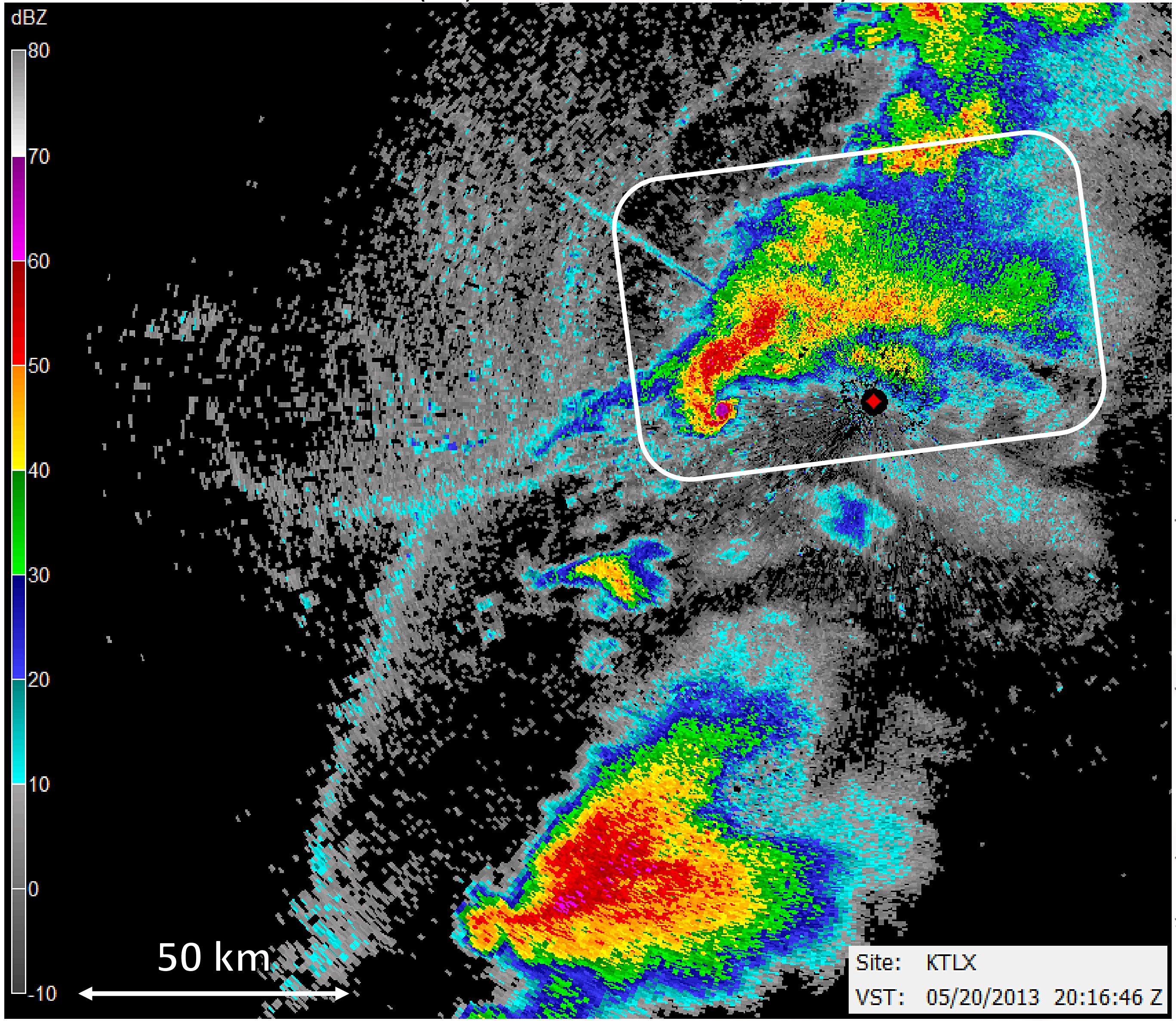
Limited Areas of Innovation: Example of a Consequence

Illustration in the context of convective-scale radar data assimilation:

Consider a large tornadic supercell storm we aim to warn for.

Suppose we had tried to forecast this tornadic supercell storm an hour before.

Moore (OK) 2013 tornado event, 20 May 2013



Adapted from Fabry and Meunier (2020), MWR

Limited Areas of Innovation: Example of a Consequence

Illustration in the context of convective-scale radar data assimilation:

Let us first replace the storm echo by a cartoon…

(courtesy of Markowski and Richardson 2010's book)

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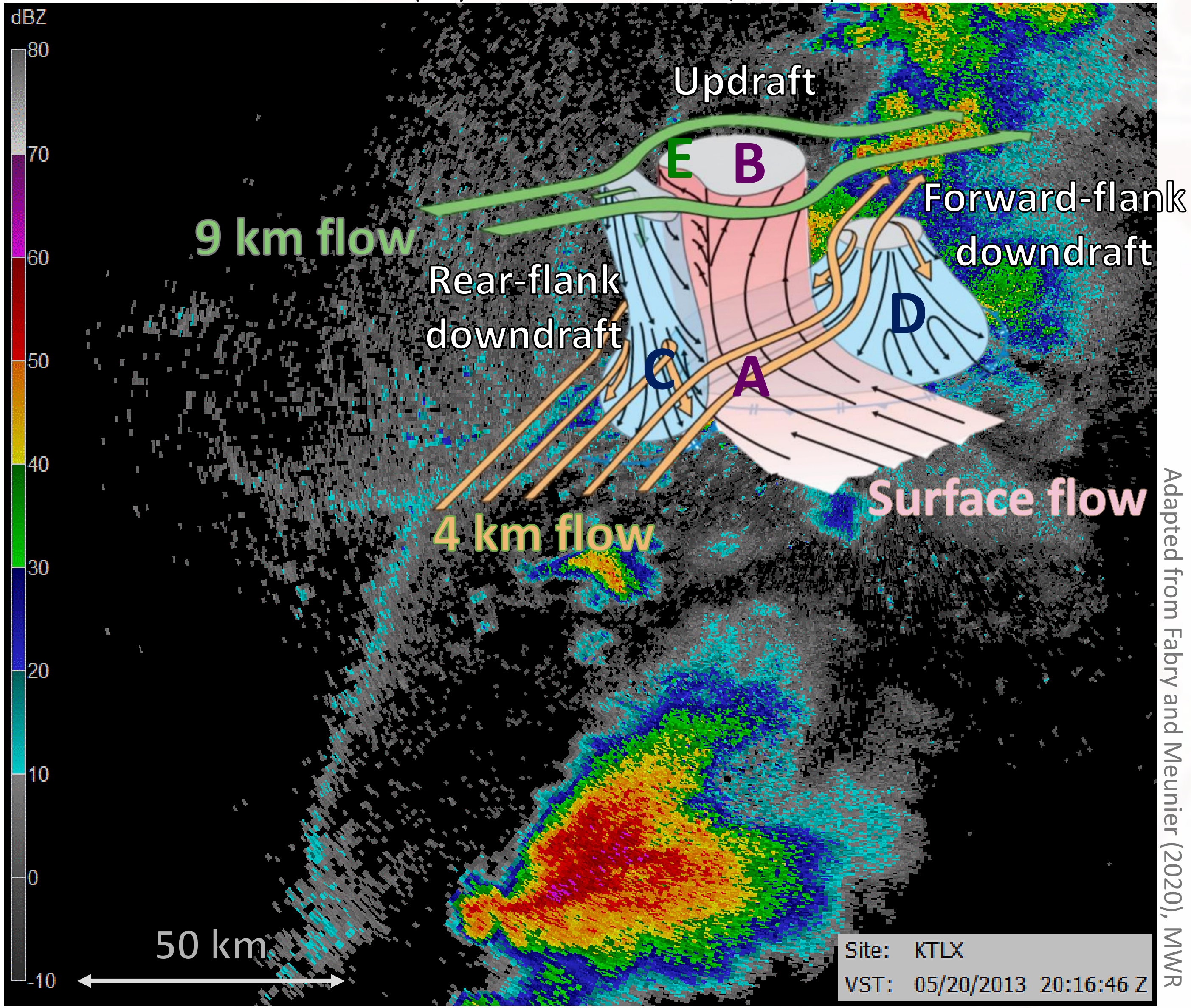

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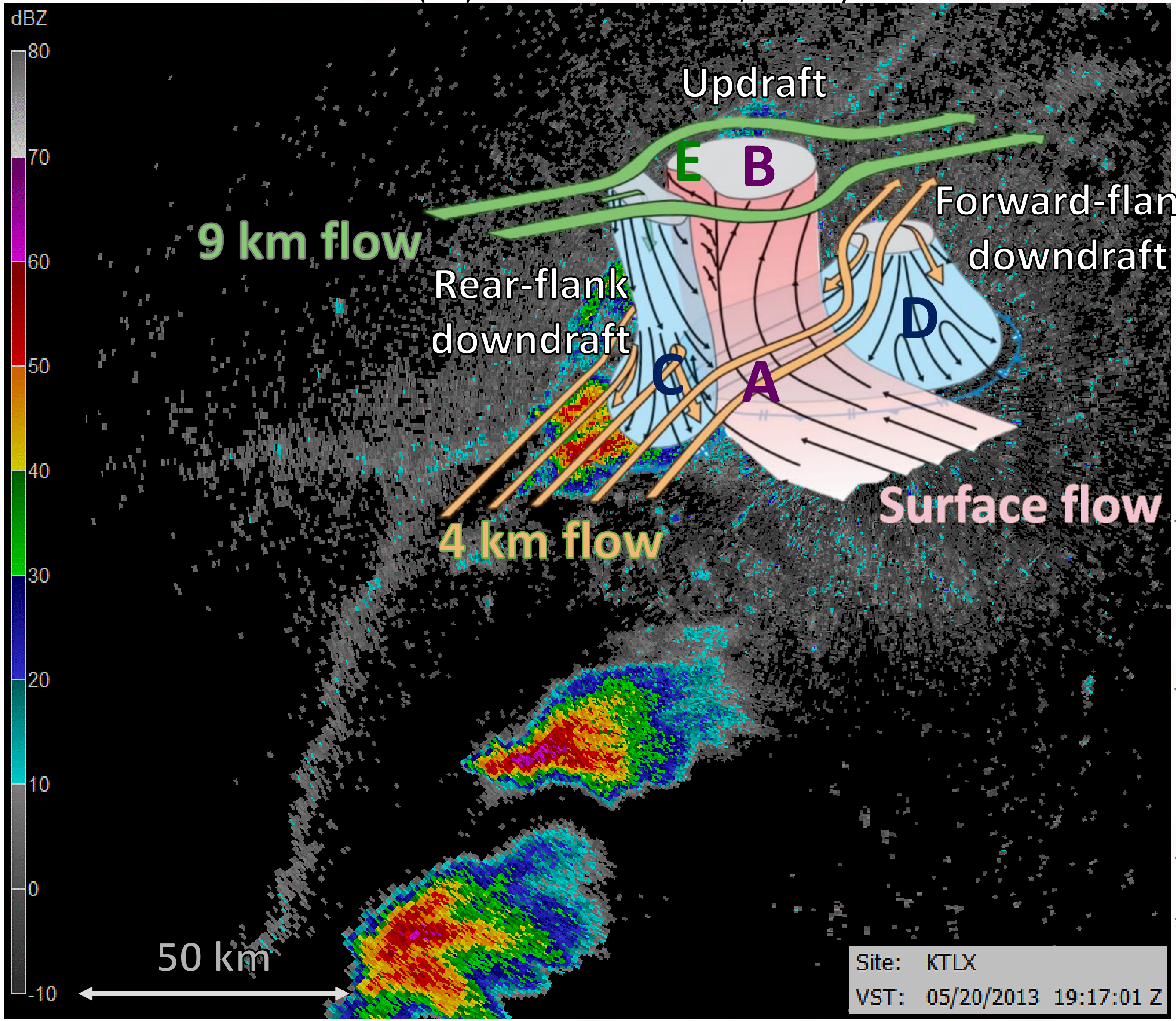
Limited Areas of Innovation: Example of a Consequence

Illustration in the context of convective-scale radar data assimilation:

Let us first replace the storm echo by a cartoon, and then go back in time one hour.

Q: What areas must be better constrained to improve the 1-hr forecast for that storm?

Moore (OK) 2013 tornado event, 20 May 2013



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Limited Areas of Innovation: Example of a Consequence

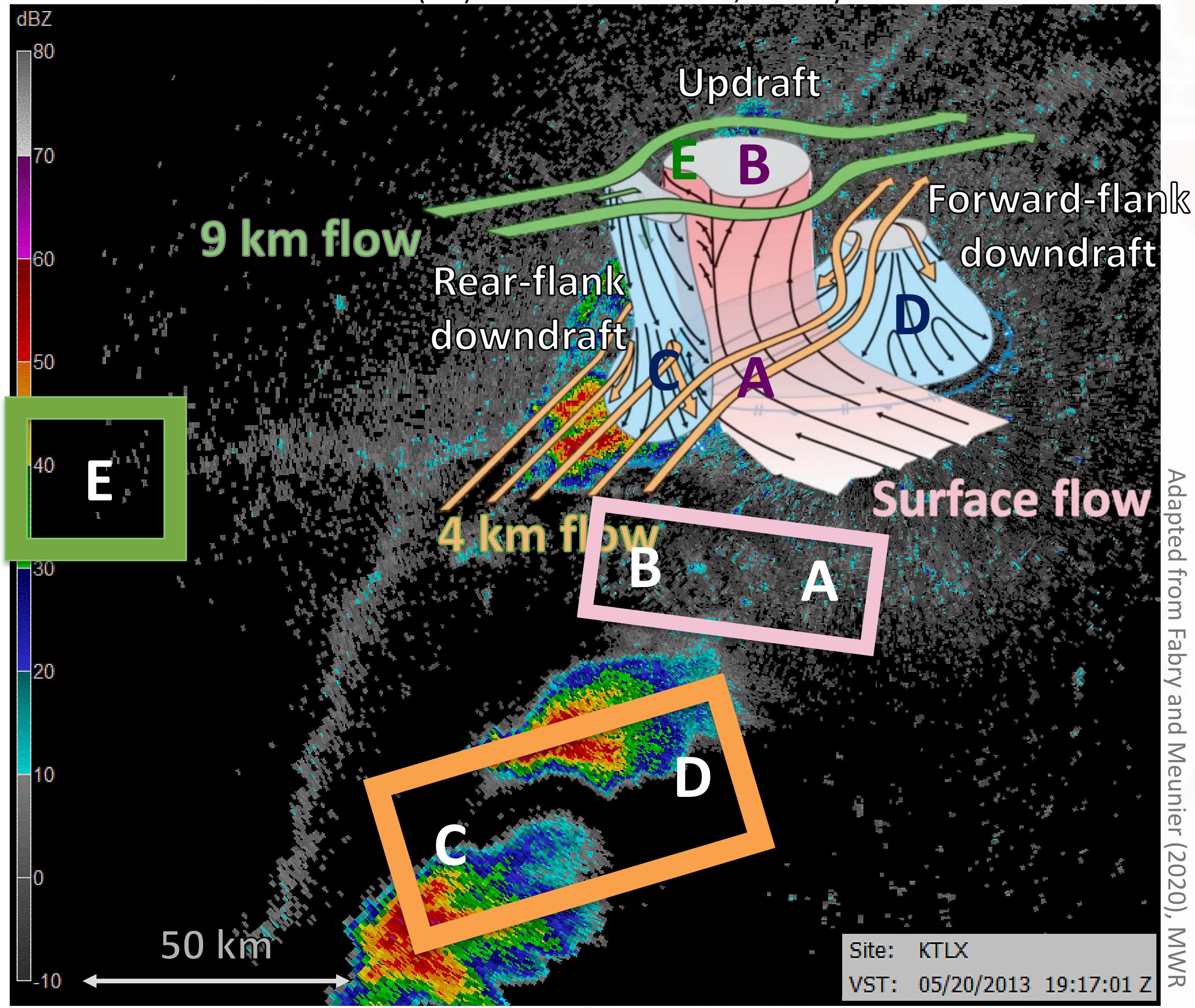
A: Many with no constraints besides "*no precipitation*", an information largely known already by the background.

→ To correct state variables in those areas, **innovation must come via relationships with errors from "distant" echoes**

(>>10 grid-points away).

In passing, this entire region is covered by high clouds.

Moore (OK) 2013 tornado event, 20 May 2013



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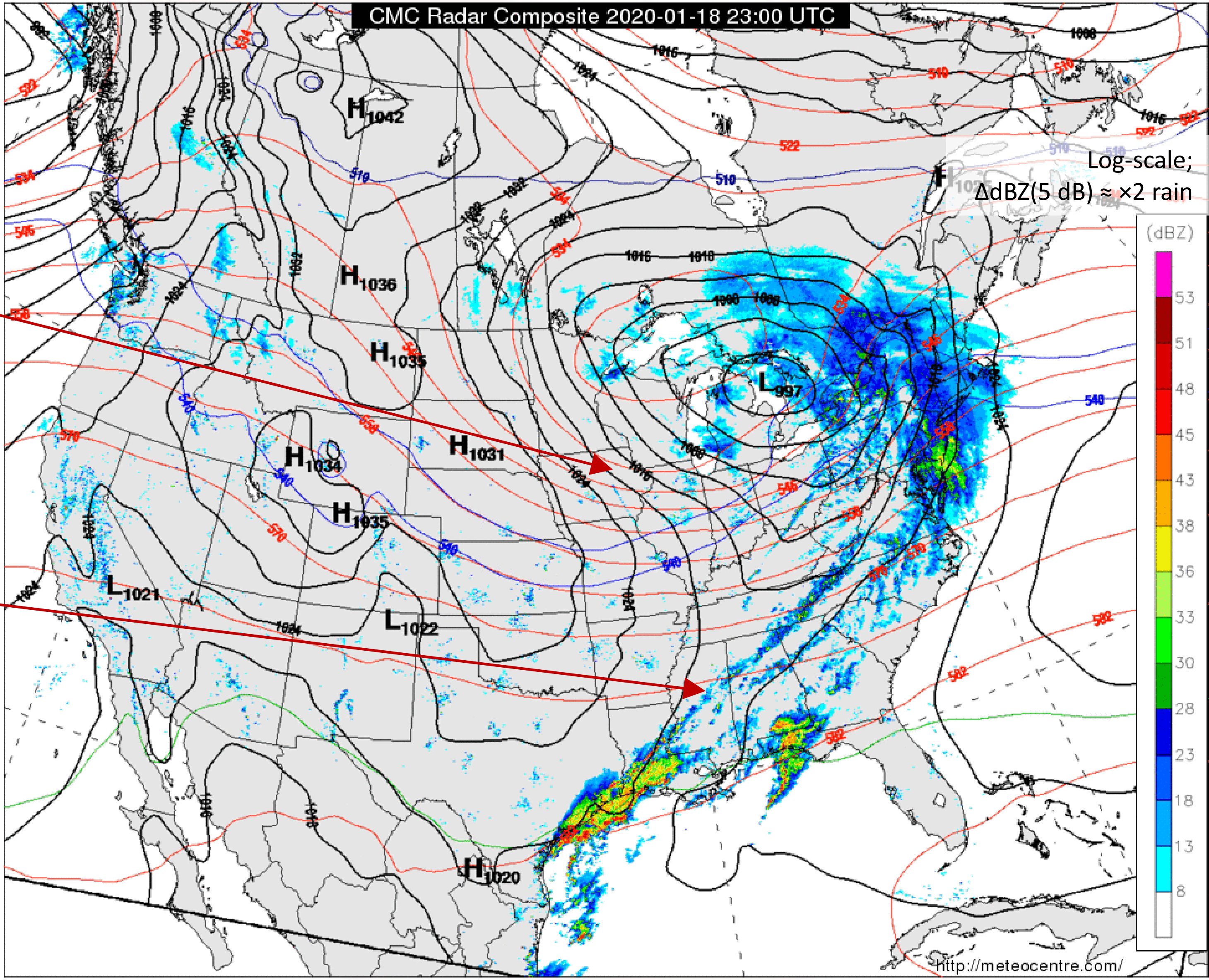
The Unusual Structure of Clouds and Precipitation

Compared to more usual fields (e.g., pressure), clouds and especially precipitation have:

2) Considerable small-scale structure and larger background (and simulation) errors;

Smooth pressure fields

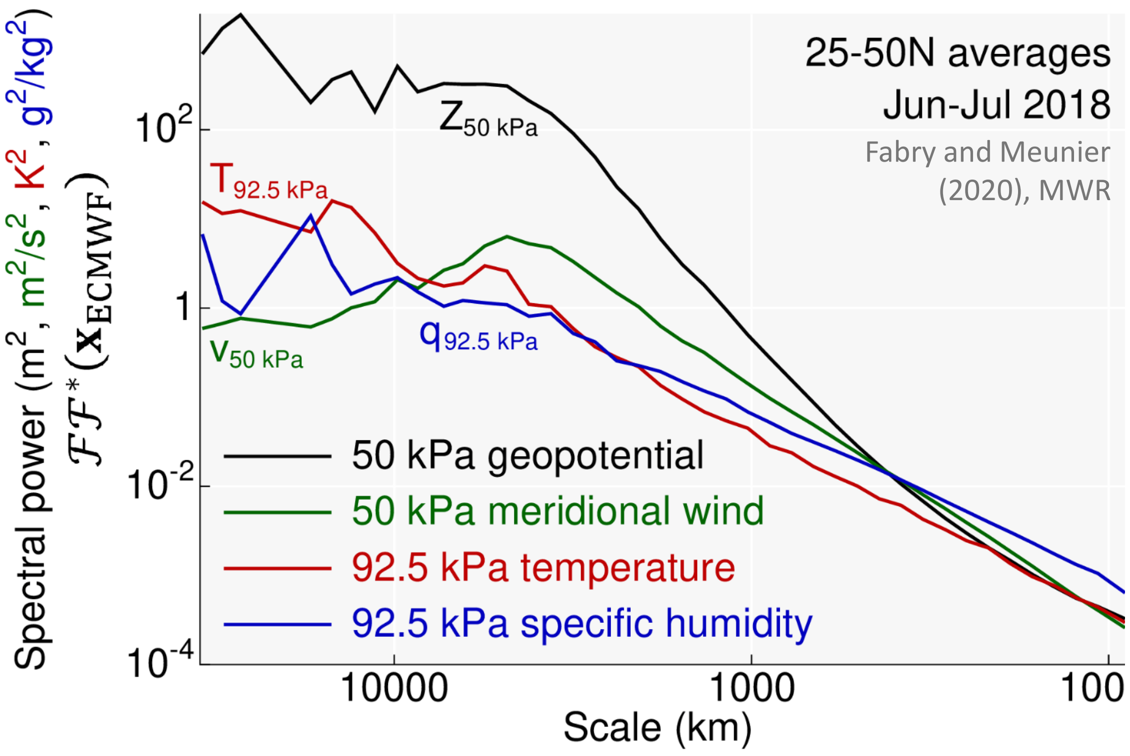
Much small-scale structure in rain



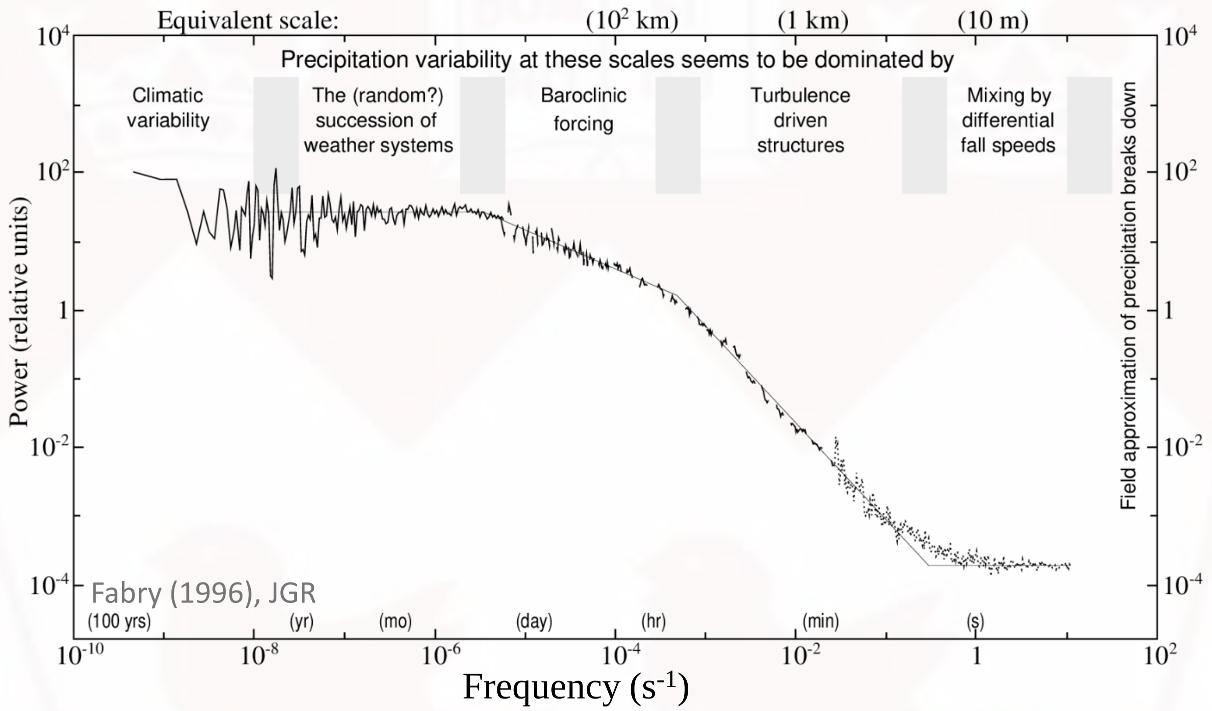
Contrast in structure between fields of pressure and radar echoes of precipitation

The Unusual Structure of Clouds and Precipitation…

a) Spectral decomposition of the ECMWF control



b) Power spectrum of precipitation rate



Attempt to contrast the structure of dynamical and thermodynamic fields (left) with that of precipitation (right). Beware of the different scales plotted.

Compared to more usual fields (e.g., pressure), clouds and especially precipitation have:
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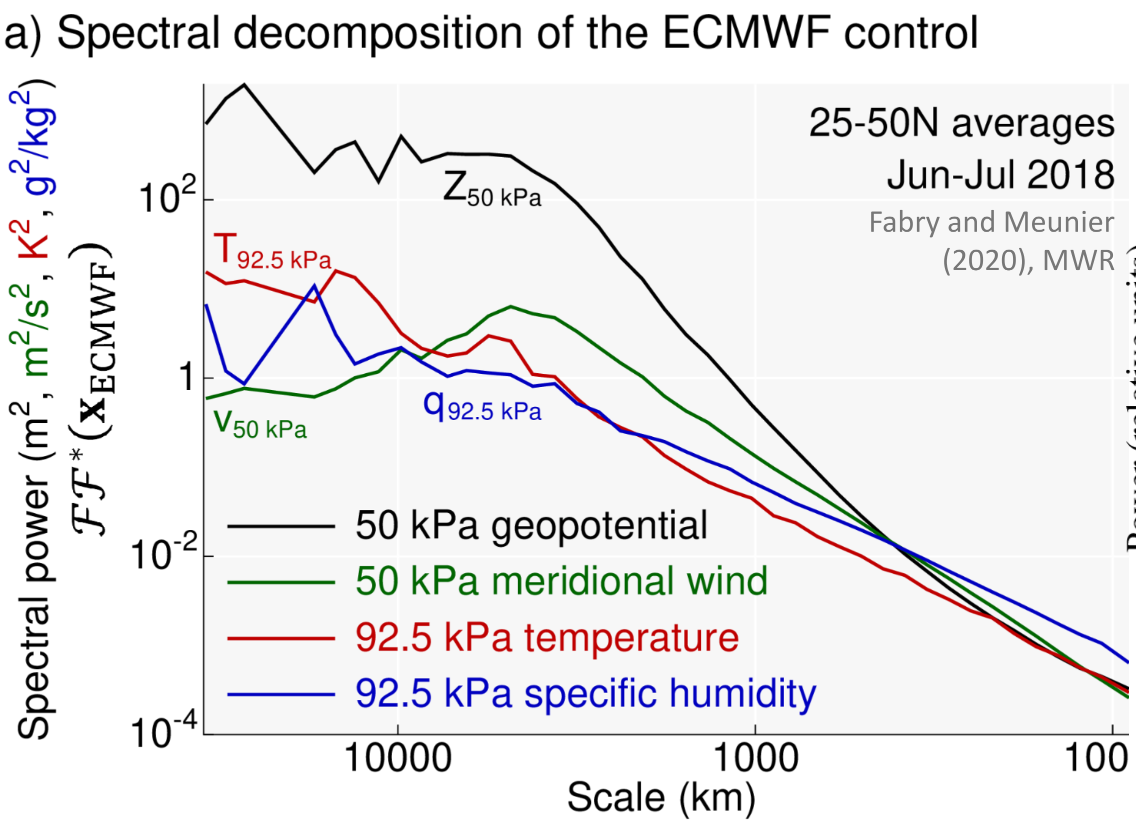
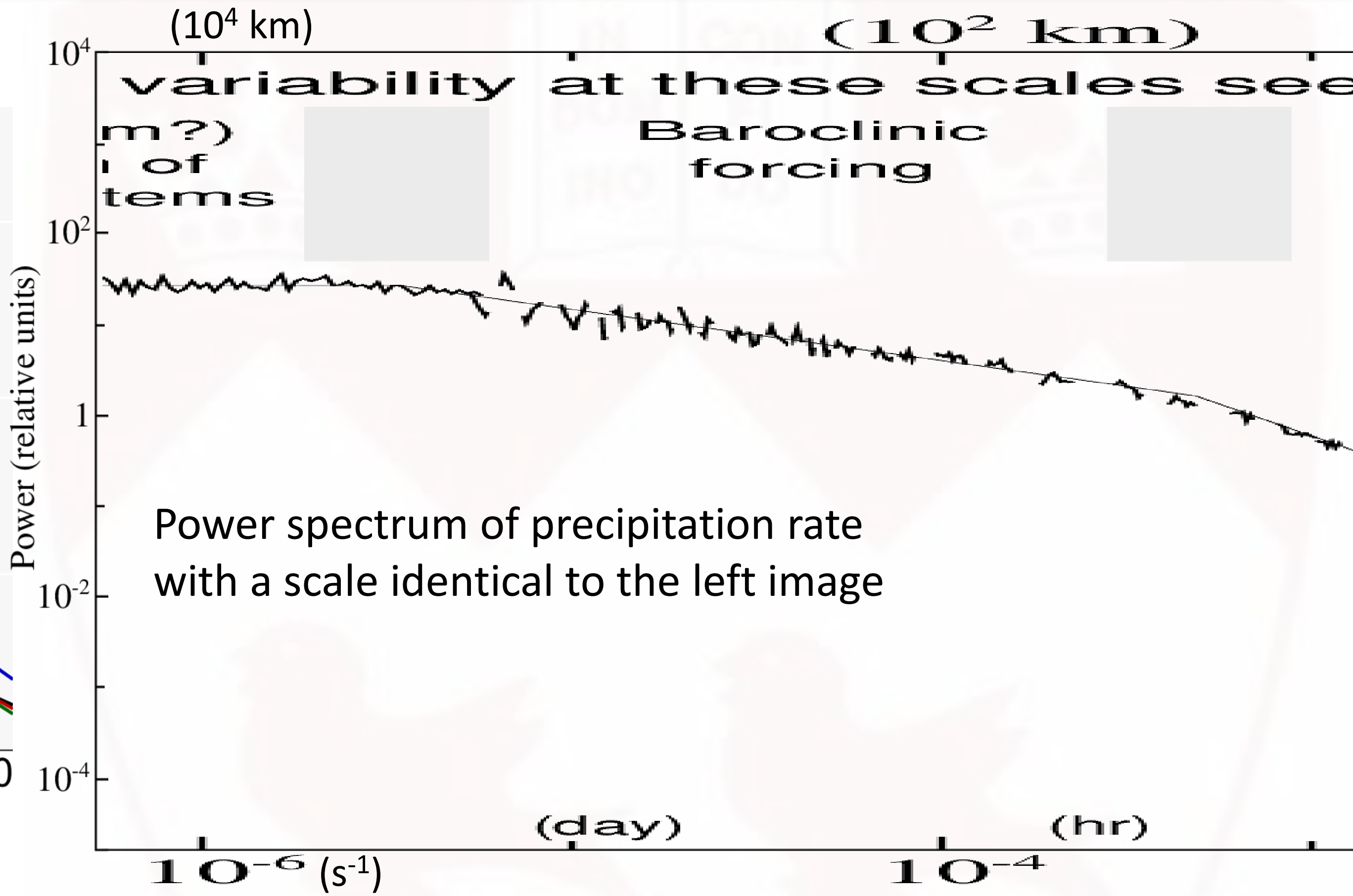
[Multi-slide explanation in progress…]

The Unusual Structure of Clouds and Precipitation…





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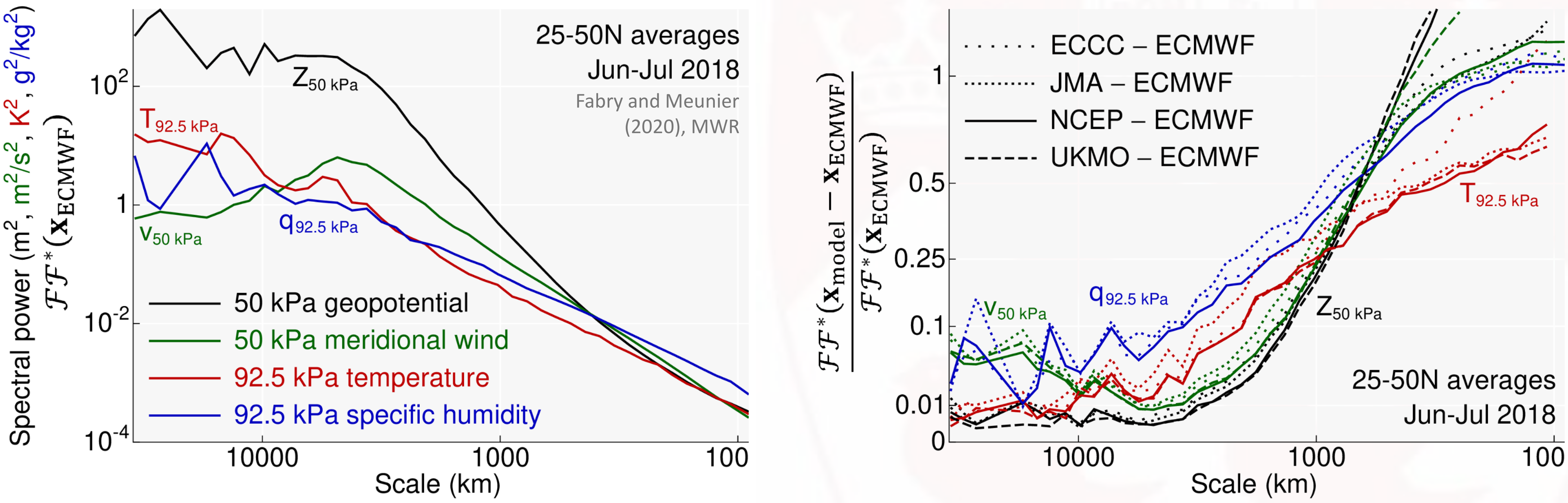
… And the High Uncertainty of Small-Scale Patterns

a) Spectral decomposition of the ECMWF control

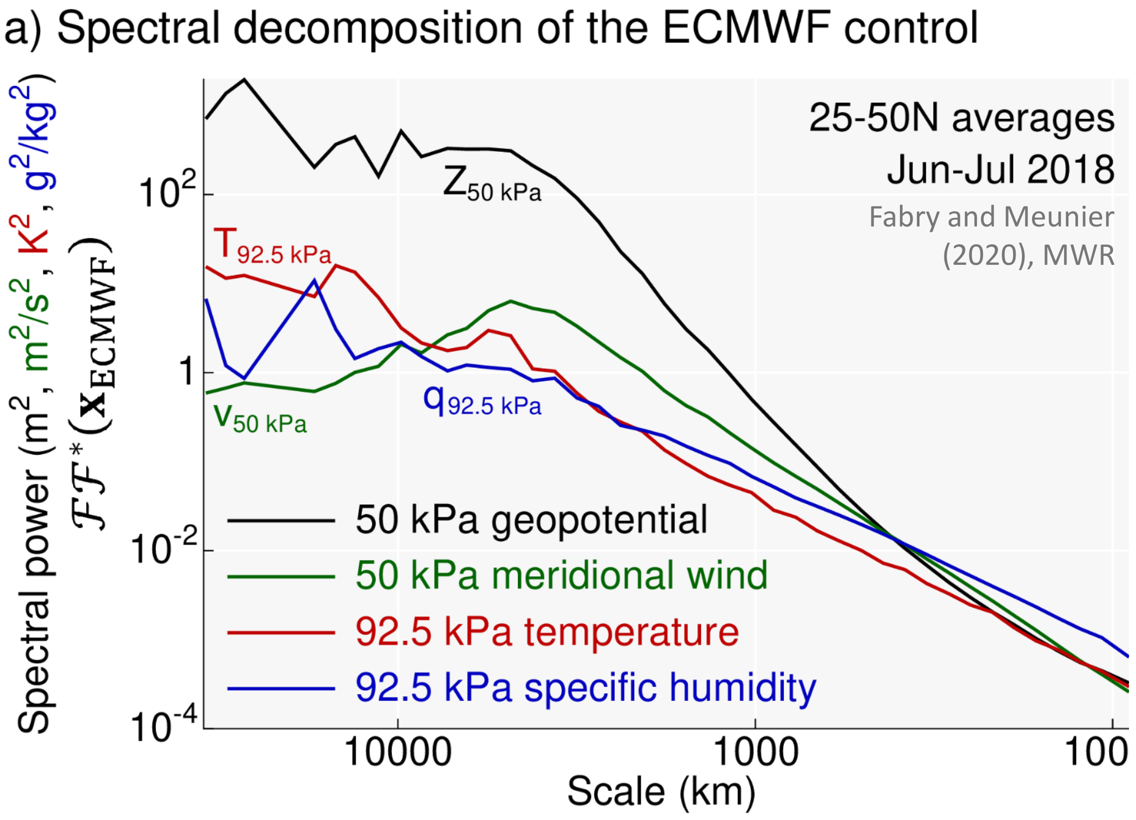
b) Control-to-control inconsistency in spectral variability

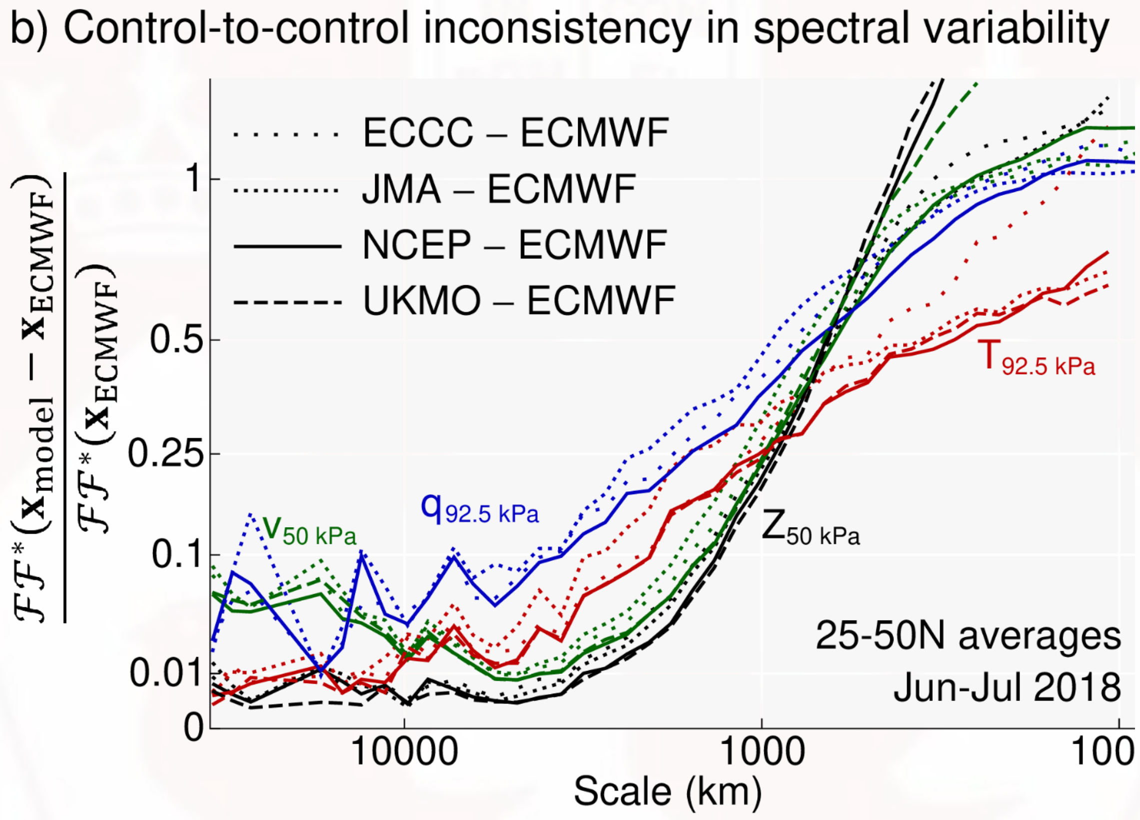


Analyses of different weather centers largely disagree for most atmospheric properties for scales below 500 km, where much of the variability in precipitation and clouds resides.

→ Cloud and precipitation errors A) are comparatively large, and B) have shorter auto-correlation and cross-correlation distances than other errors.

… And the High Uncertainty of Small-Scale Patterns





Compared to more usual fields (e.g., pressure), clouds and especially precipitation have:
2) Considerable small-scale structure and larger background (and simulation) errors;

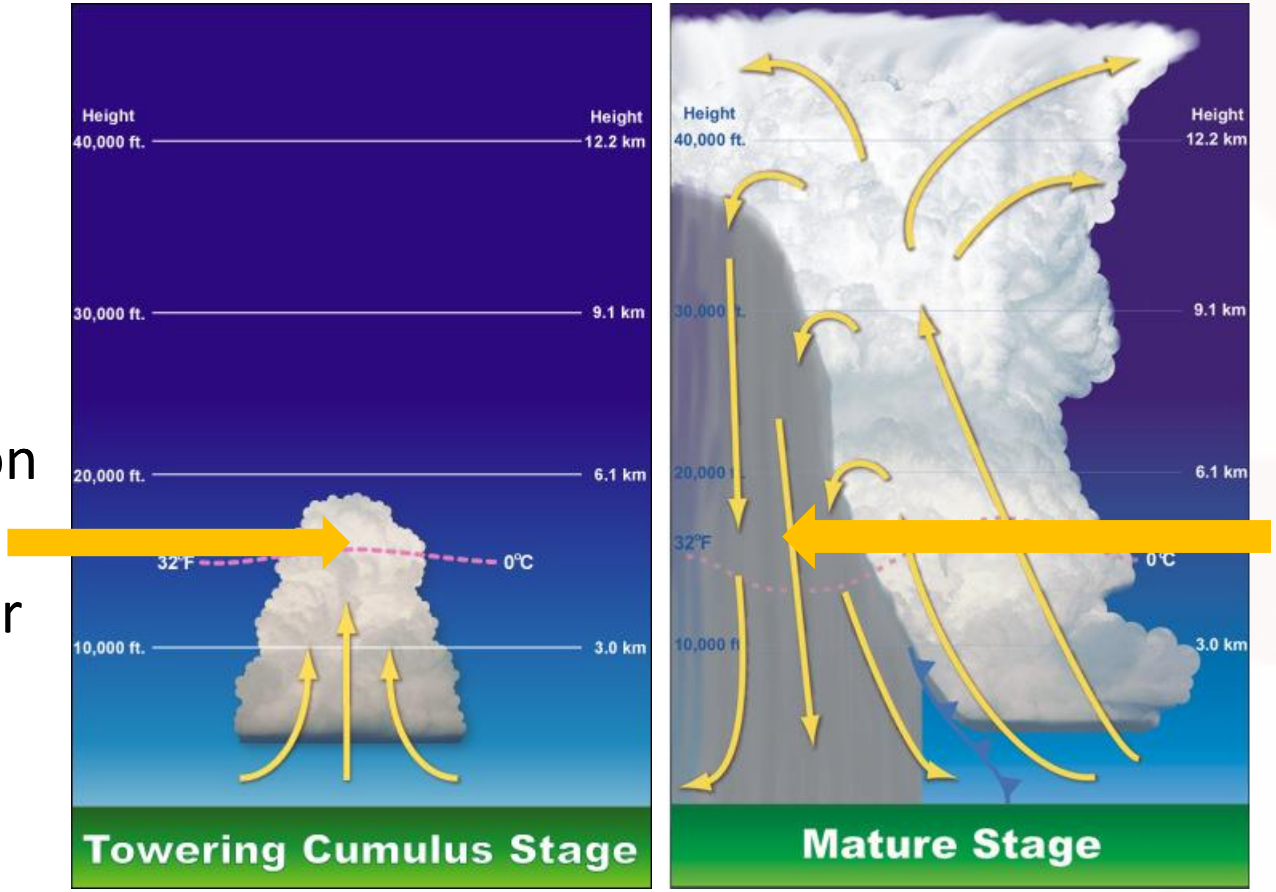
→ **Errors do not covary** (linearly) **well with errors in other fields** within and around clouds and precipitation → **Information propagation is reduced just when it is most needed**.

Large Errors and the Breakdown of Error Covariances: An Example

Scenario: Assimilation of precipitation given an error in the timing of convective storms

Situation 1:

Stronger precipitation = Stronger and warmer updraft



Situation 2:

Stronger precipitation = Stronger and cooler downdraft

When background errors are large, scenarios like these are not uncommon.

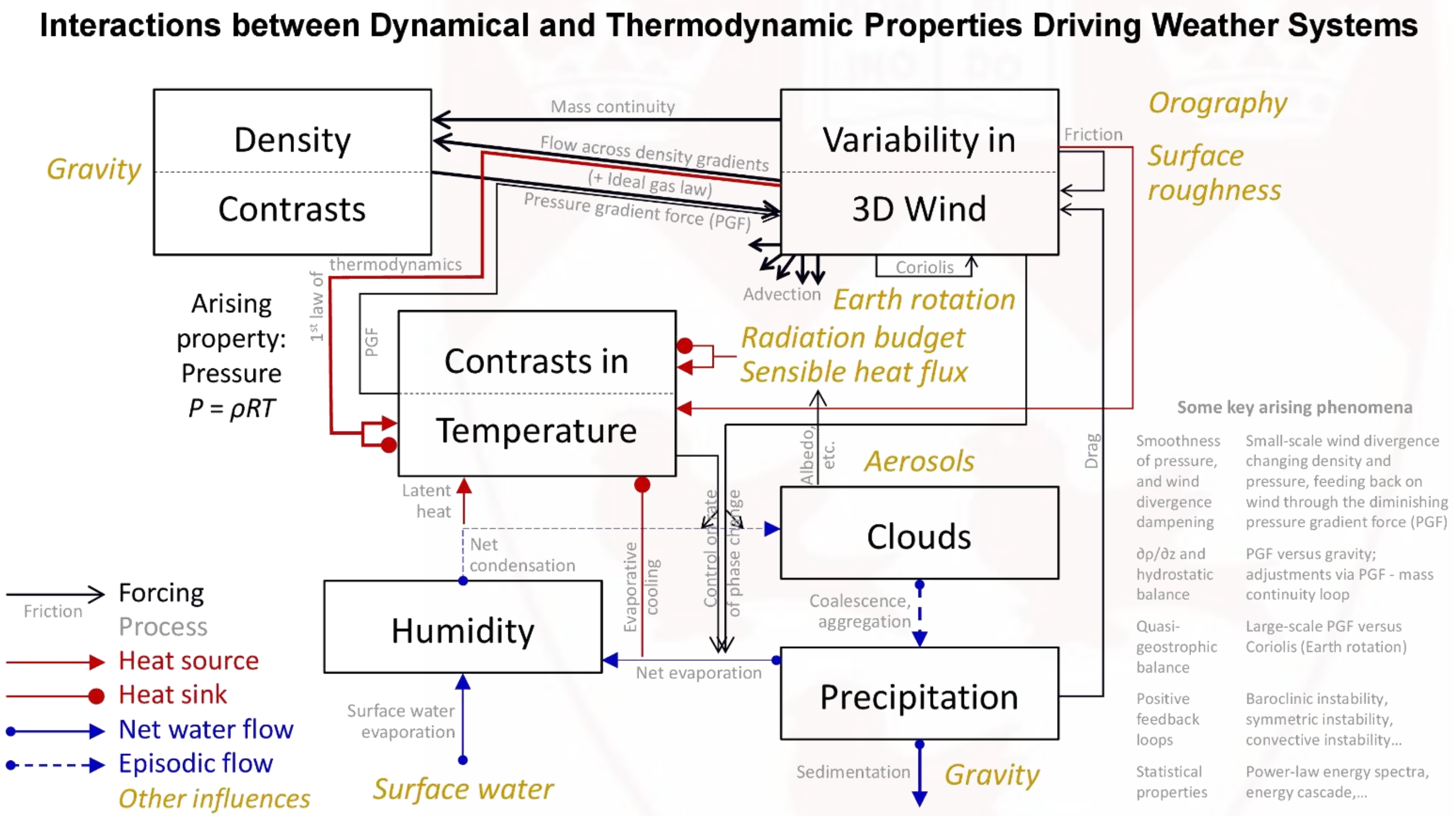
What Happens to the Added Innovation?

Thought experiment (1):

Precipitation is added to the analysis; nothing else is changed. What changes occur in the forecast?

Little: Rain will fall out, without significantly affecting other fields.

Modifying precipitation (without other changes) has the littlest value for forecasting, even if it may be the most important to forecast.



Adapted from Fabry and Meunier (2020), MWR

What Happens to the Added Innovation?

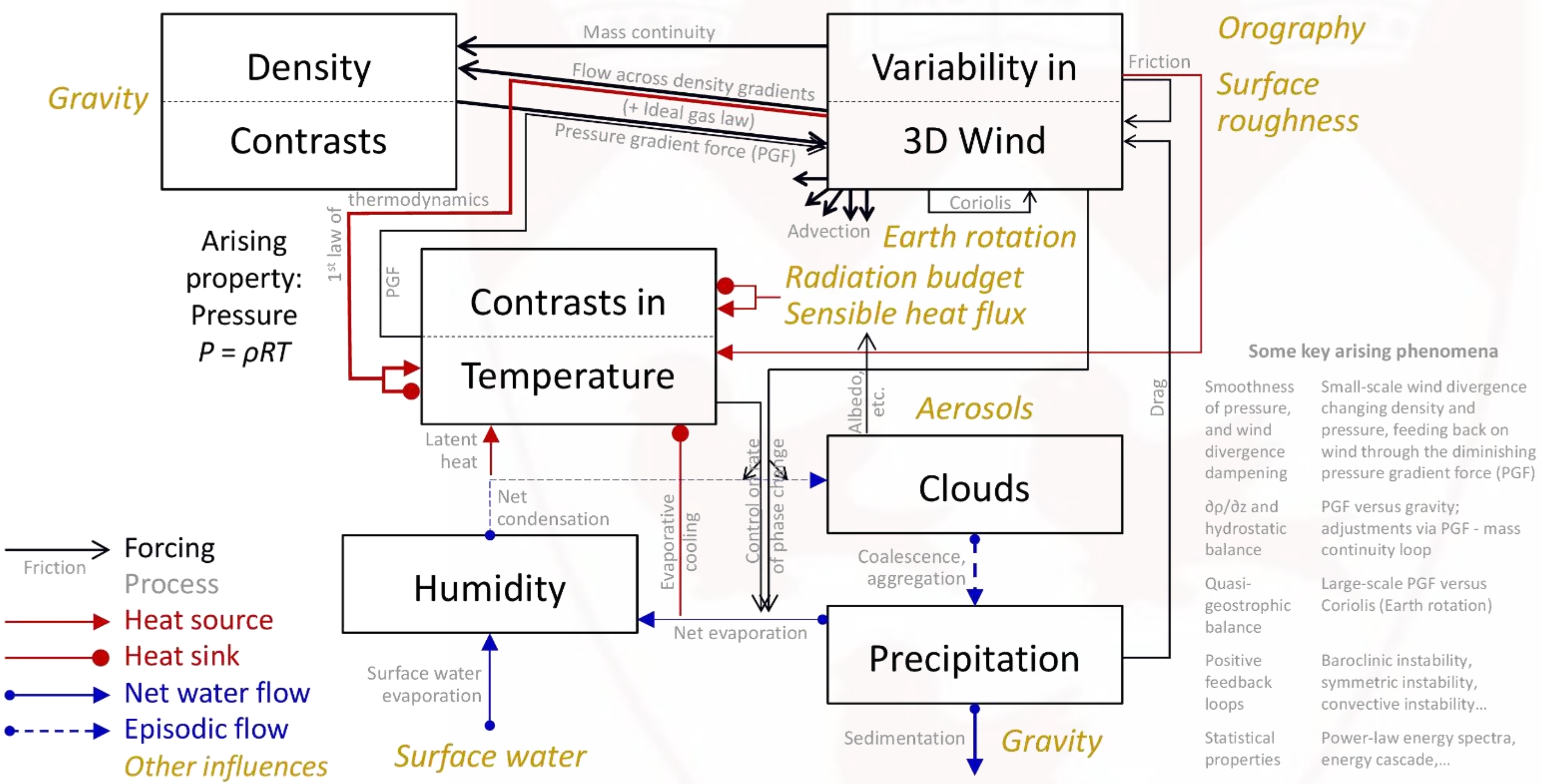
Thought experiment (2):

Modifying precipitation has the littlest value for forecasting.

How about clouds?

Modifying clouds has more impacts, primarily thanks to the clouds' forcing on temperature, the root of the thermodynamics cycle, but only if they can be properly maintained.

Interactions between Dynamical and Thermodynamic Properties Driving Weather Systems



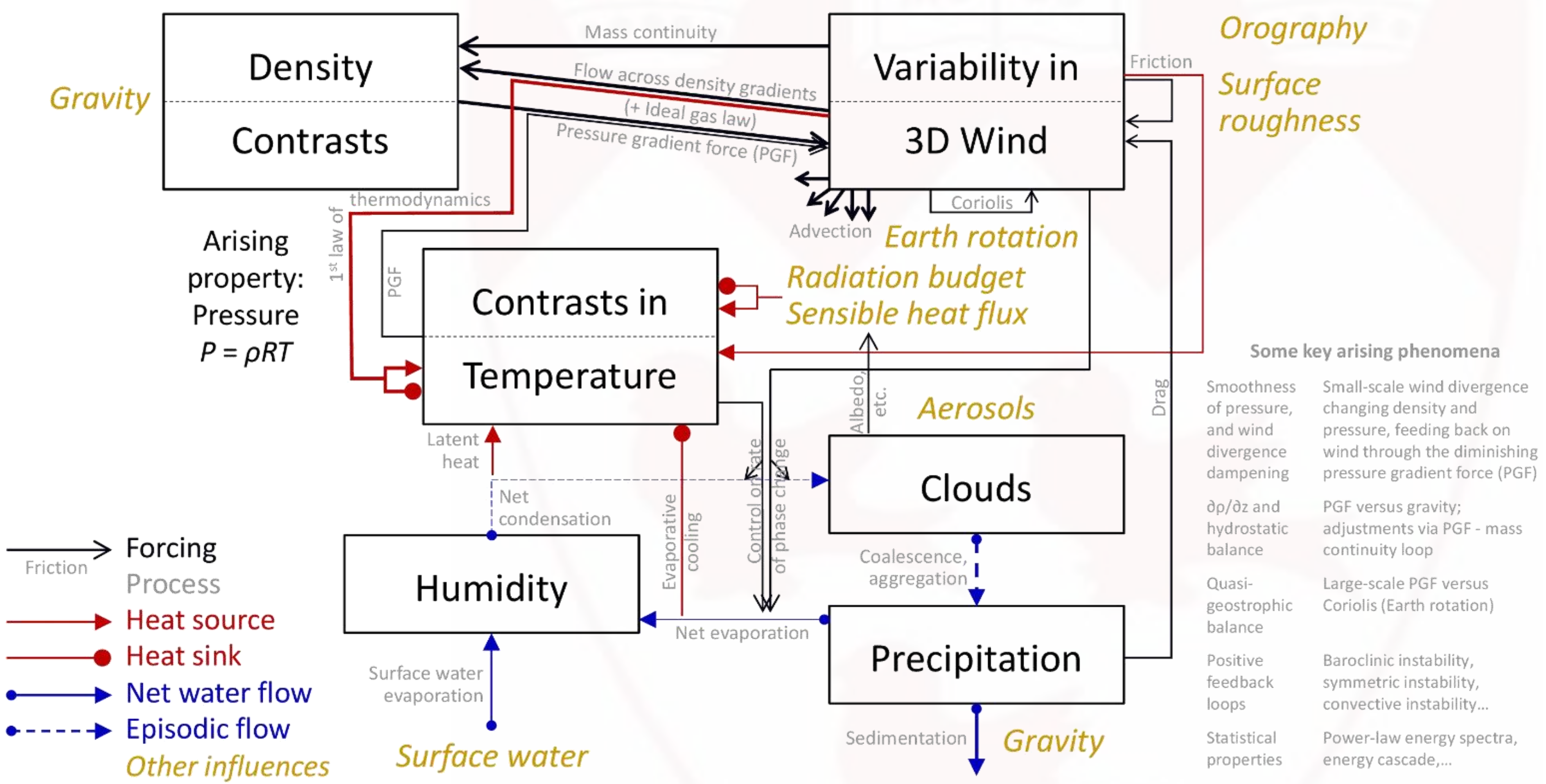
Adapted from Fabry and Meunier (2020), MWR

Assimilation and the Meteorology of Clouds and Precipitation

Clouds and precipitation are the **end products of interacting and often threshold-triggered processes** driven by other fields, usually in the context of the release of an **instability**.

Relating errors in clouds and precipitation to those in other fields is hence generally difficult.

Interactions between Dynamical and Thermodynamic Properties Driving Weather Systems



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Time to Reflect…

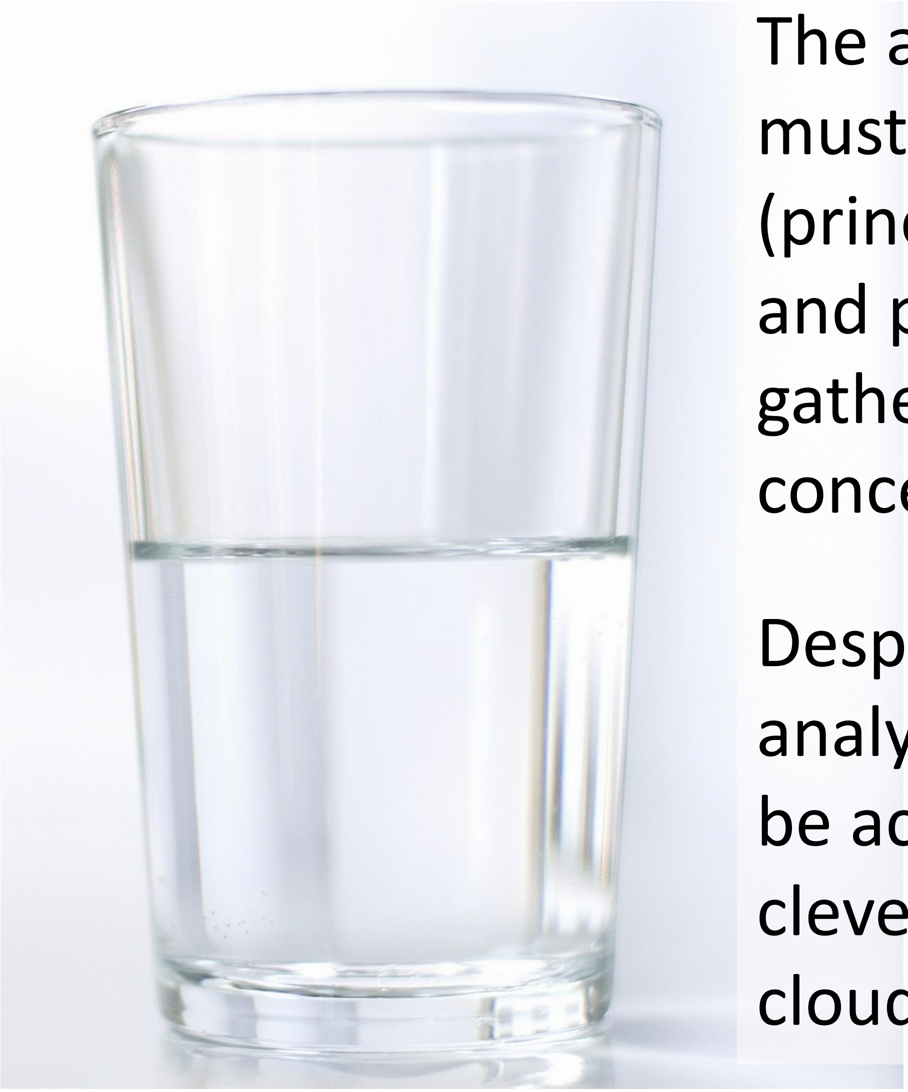


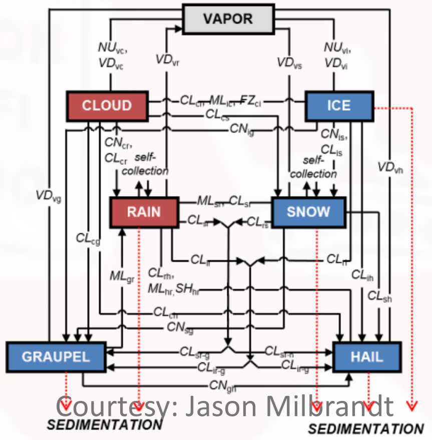
Image from The Independent

The assimilation of cloud and precipitation information must not only fix the mass of condensates, but also (principally?) other errors ($\mathbf{u}$, Φ, T, e). However, clouds and precipitation both obscure the information gathering and complicate the retrieval of information concerning other key properties.

Despite these problems, much of the error reduction in analyses come from satellite data. Imagine what could be achieved if we faced the challenges posed and more cleverly took advantage of the opportunities offered by cloud and precipitation information.

Suggestion: Set Aside the Small Scales; Focus on Larger Scales

Whereas the **small-scale patterns** of clouds and precipitation **are difficult to model** accurately in terms of 1) process, 2) observation simulation, 3) error estimations (background, measurements, and especially their simulation);

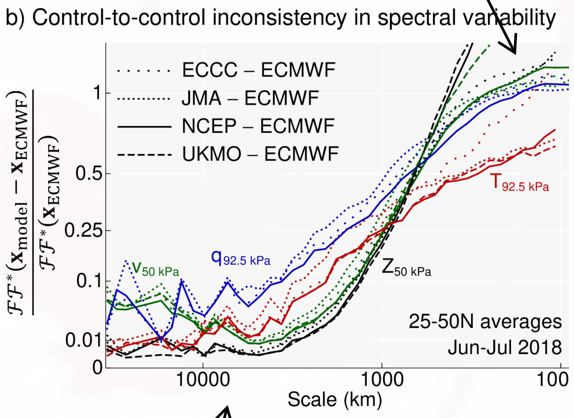


Courtesy: Jason Milbrandt

+
CRTM,
RTTOV,
+
R(H(**x**))
+ …

Whereas the **small-scale patterns are poorly known**, and their errors will grow quickly (in the context of multi-day forecasts) even if we could characterize them correctly;

Whereas the considerable **errors of small-scale cloud and precipitation** patterns **are difficult to associate with** the **errors in other fields** that created them;



Whereas the process of predictability loss is **1) growth of small-scale errors**, **2) migration** of errors **to synoptic scales**, followed by **3) growth of large-scale errors**, and **assimilation starts somewhere between steps 2 and 3**;

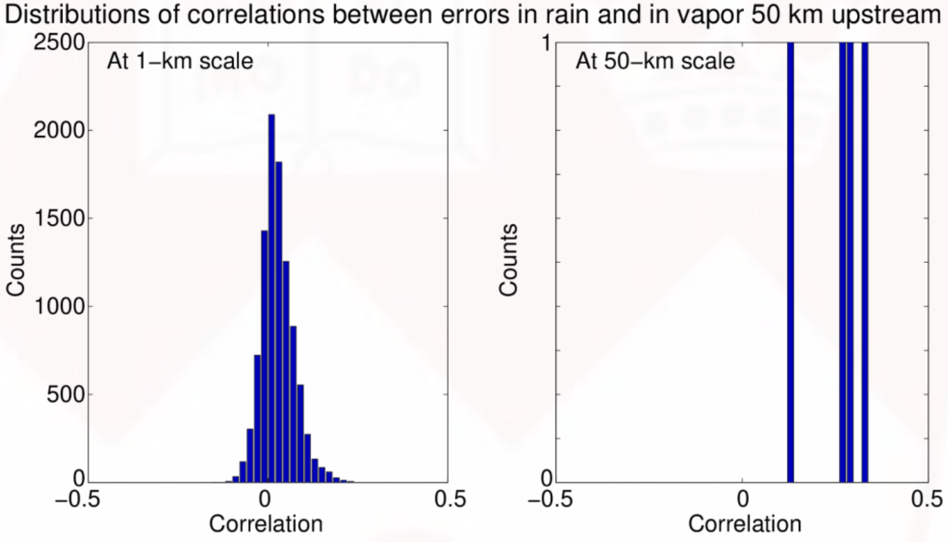
It is proposed that our **efforts should <u>at first</u> focus** on using satellite data to **reduce larger-scale errors**.

The Case to Set Aside the Small Scales, Focus on Larger Scales

Larger-scale patterns of clouds and precipitation:

- Are easier to model accurately;
- Have easier-to-characterize errors;
- Have errors whose relationship with larger-scale errors in other atmospheric properties is more linear;
- Have errors whose correlation extends to much larger distances (information is easier to propagate to poorly-observed areas);
- Allow us to better correct the relevant fields that caused those errors initially;

→ **Can be more effectively assimilated** to improve forecasts.



Smoothing increases correlation,
and hence our ability to reduce large-scale errors.
Image from Fabry and Meunier (2020) in a convective-scale context

If there is information remaining to fix the considerable errors of smaller-scale patterns, **assimilation methods that do not rely on linear covariance** of errors should be considered (particle filters perhaps, **other ideas needed**).

References

Fabry, F., 1996. On the determination of scale ranges for precipitation fields. *Journal of Geophysical Research*, **101**, 12819–12826, doi:10.1029/96JD00718

Fabry, F., and V. Meunier, 2020. Why are radar data so difficult to assimilate skillfully? *Monthly Weather Review*, in review, doi:10.1175/MWR-D-19-0374.1 (when published)