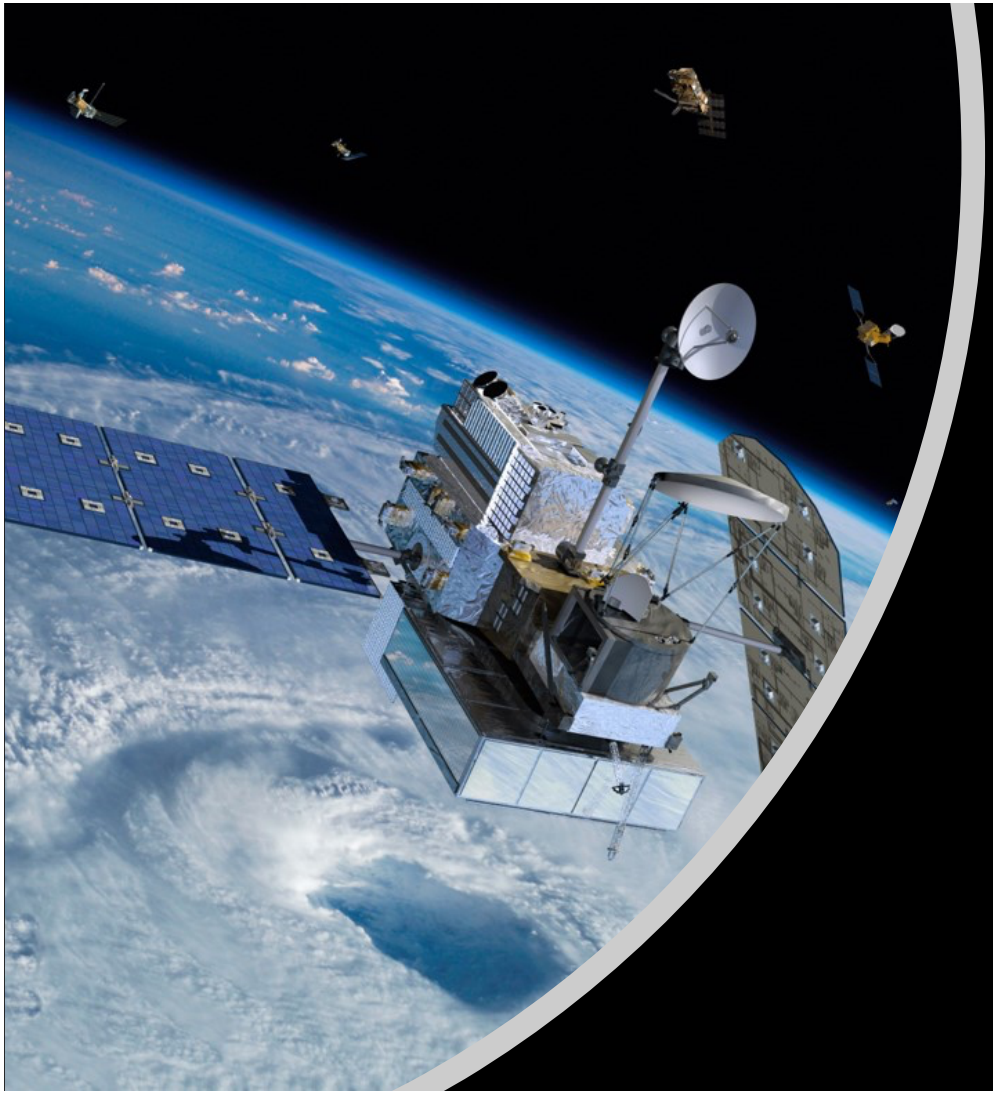


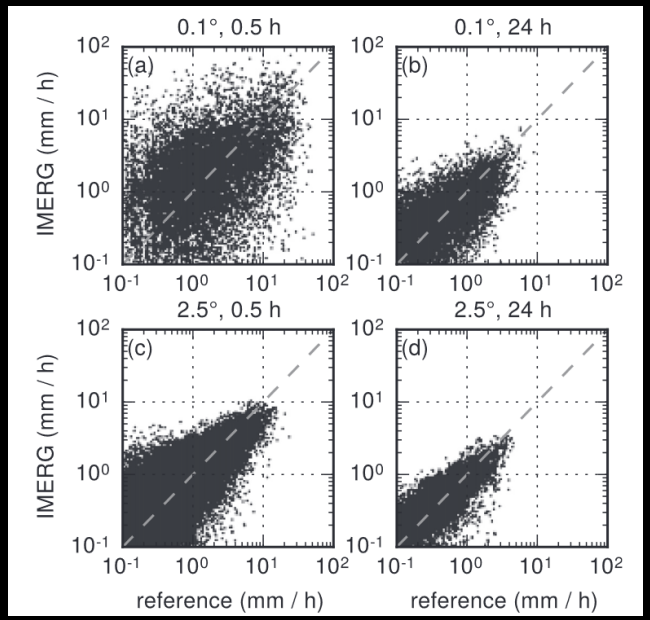
BEYOND THE PIXEL:

Using pattern-oriented approaches for improving and validating precipitation retrievals

Efi Foufoula-Georgiou and Clement Guilloteau
University of California, Irvine
PMM meeting, November, 2019

Part I: Effective Resolution

THE CLASSICAL APPROACH IN COMPARING/VALIDATING PRODUCTS



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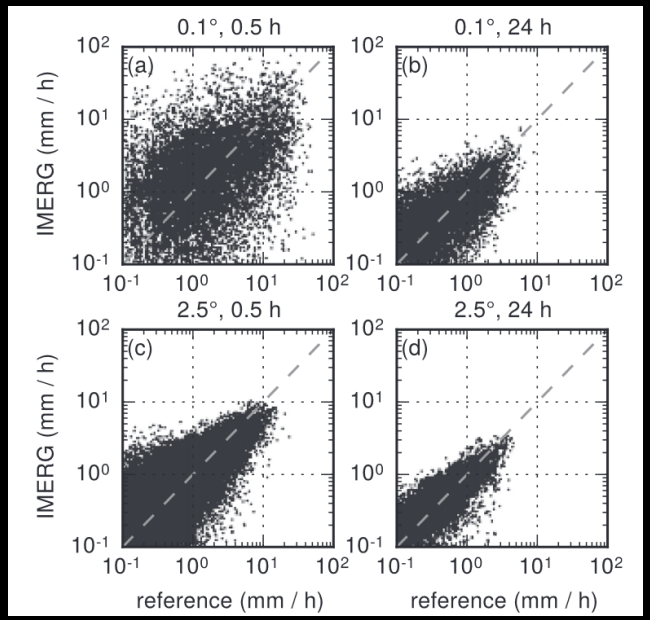

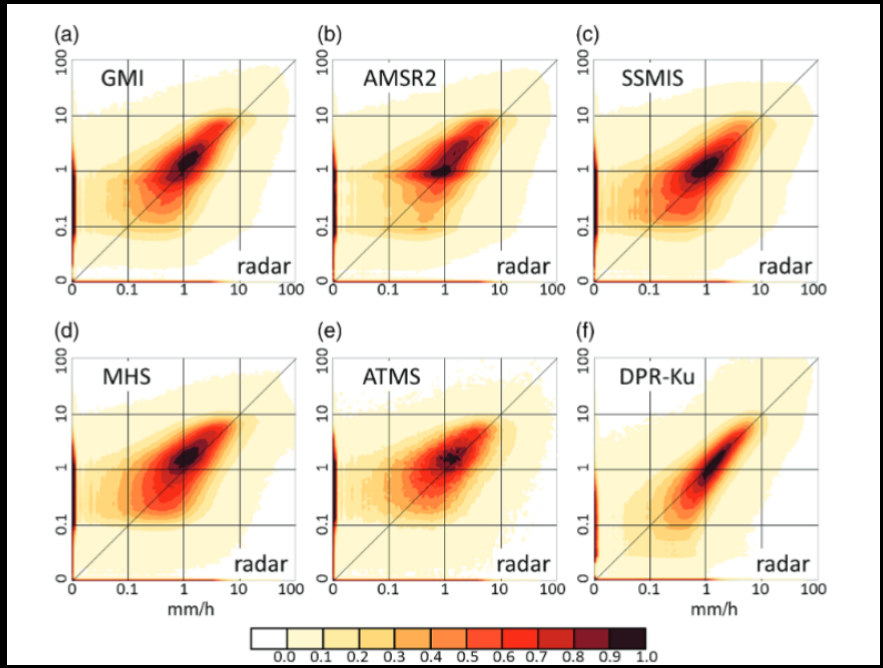

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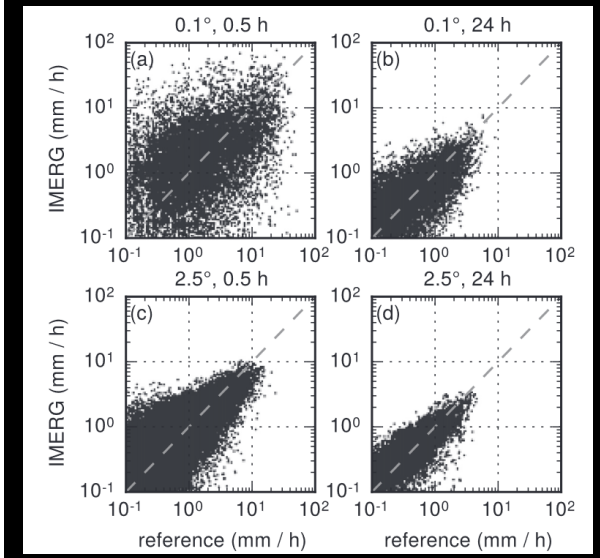

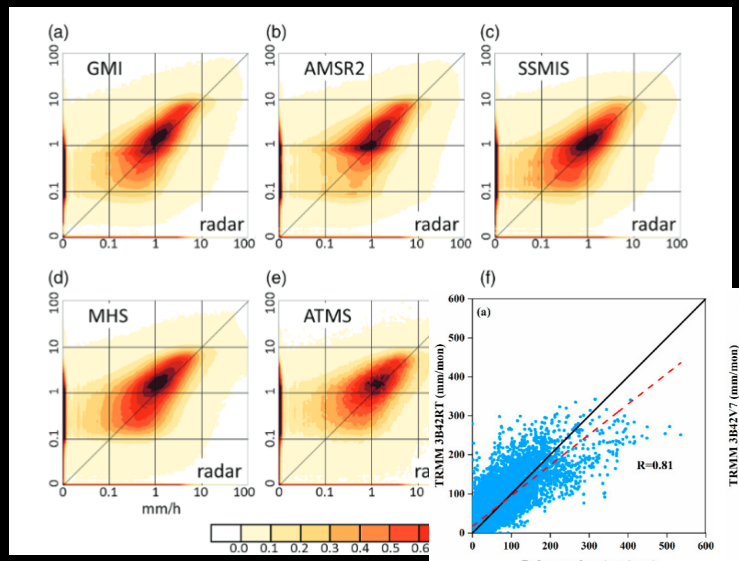

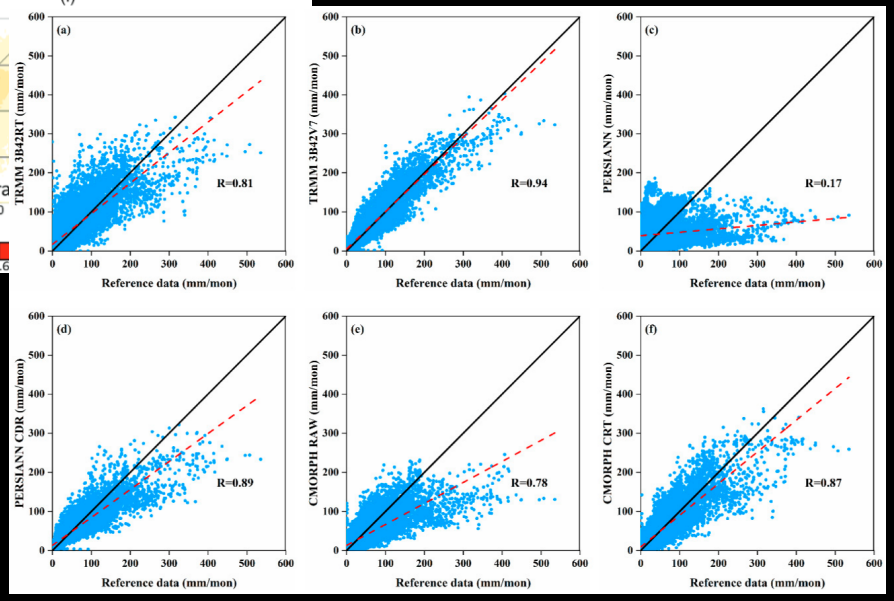

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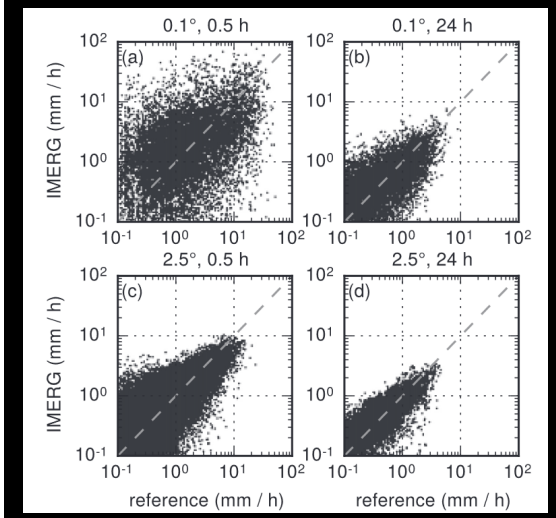

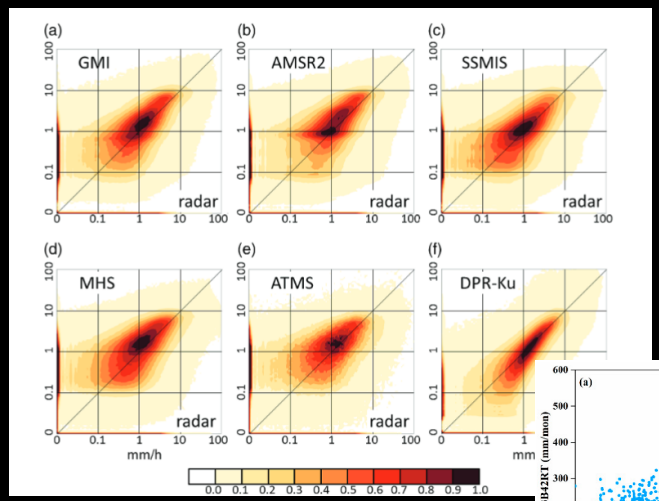

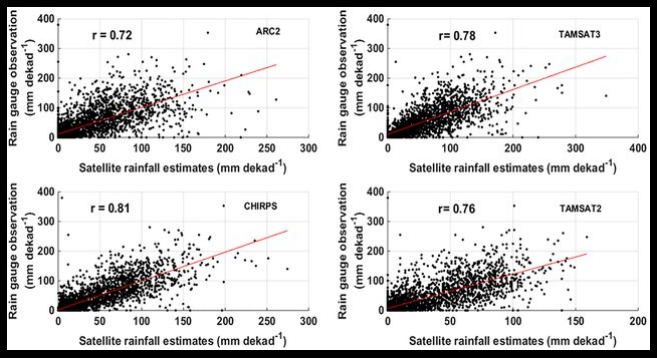

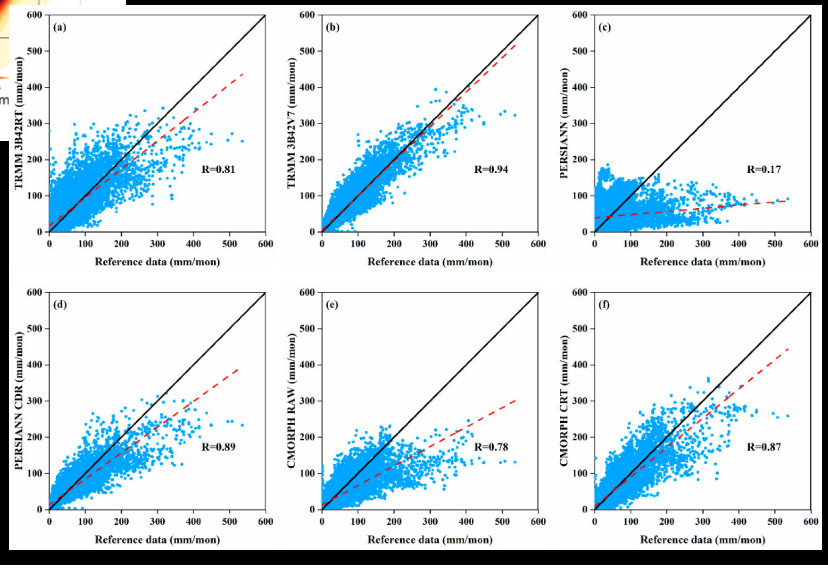

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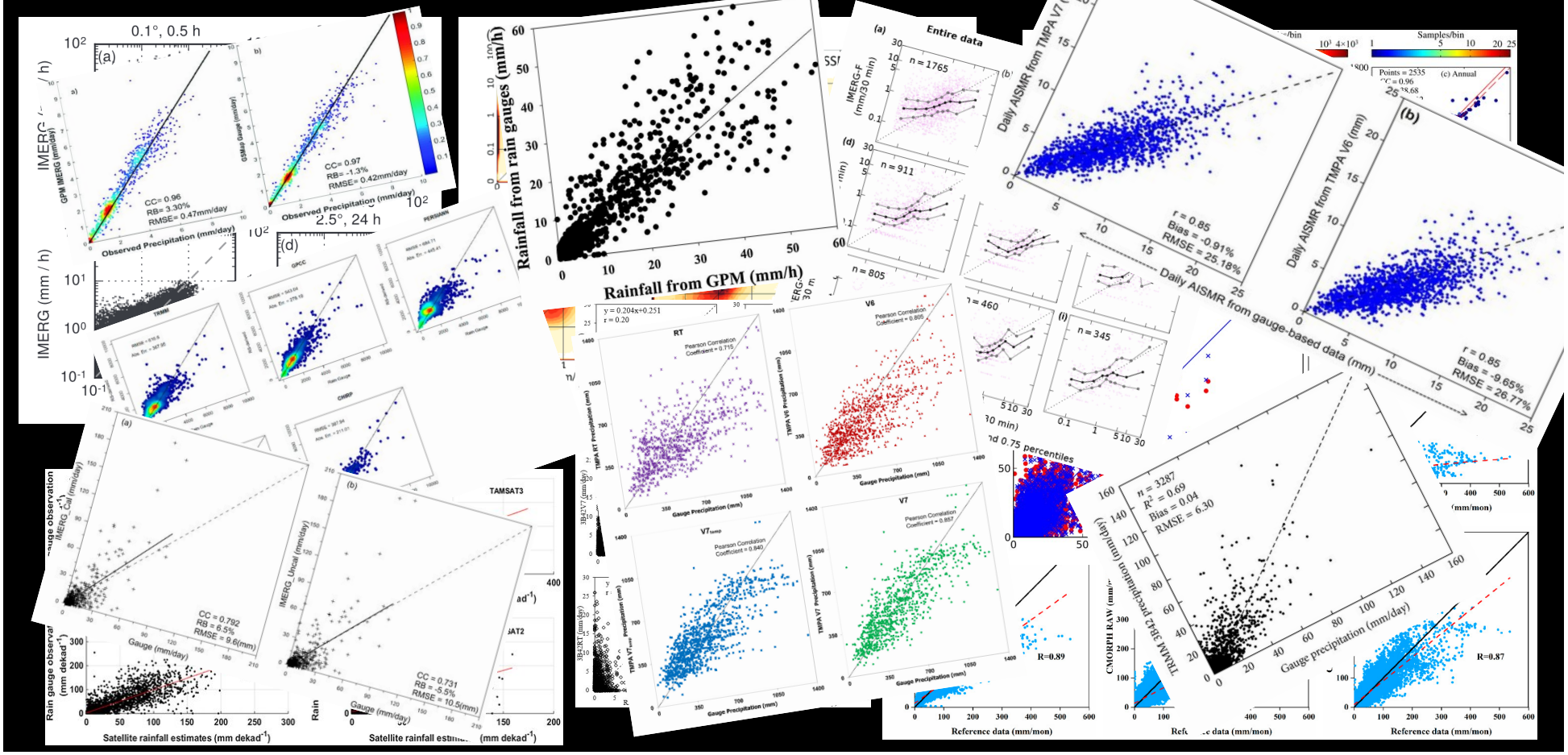

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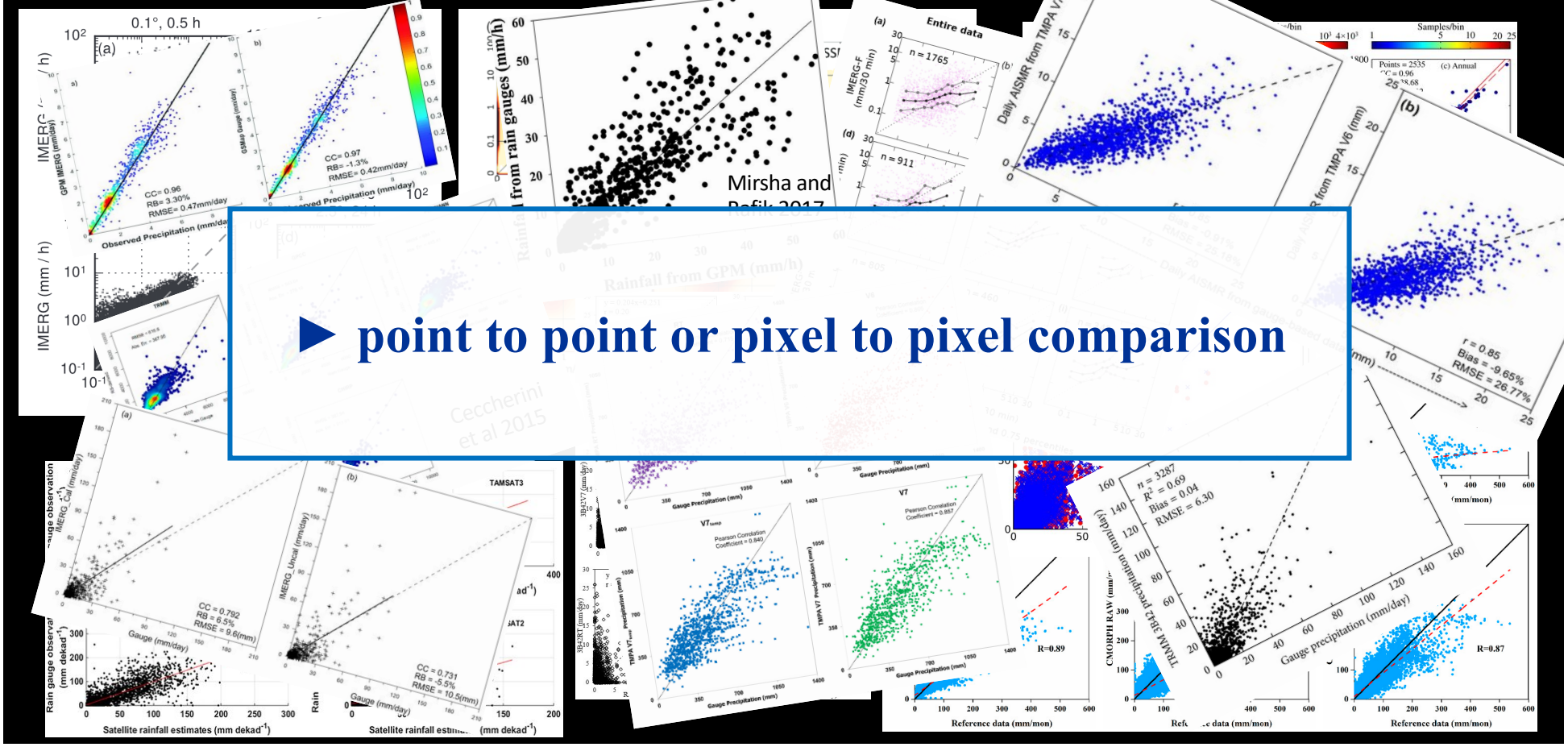
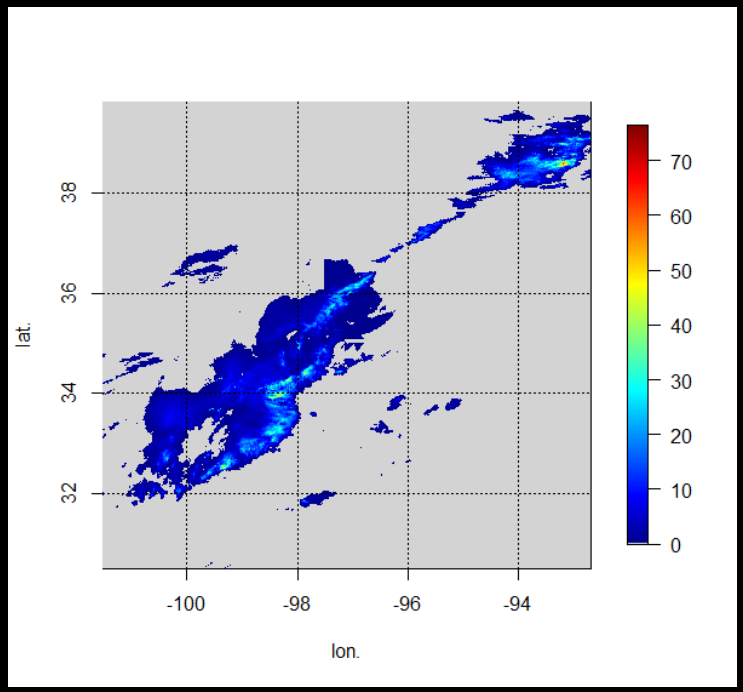
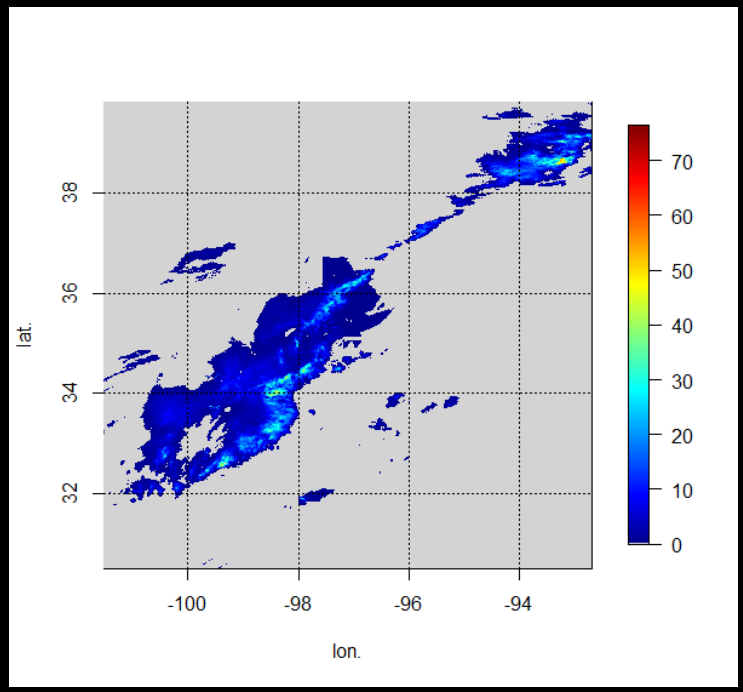


► **point to point or pixel to pixel comparison**

THE CLASSICAL APPROACH IN COMPARING/VALIDATING PRODUCTS

How different are these two fields?

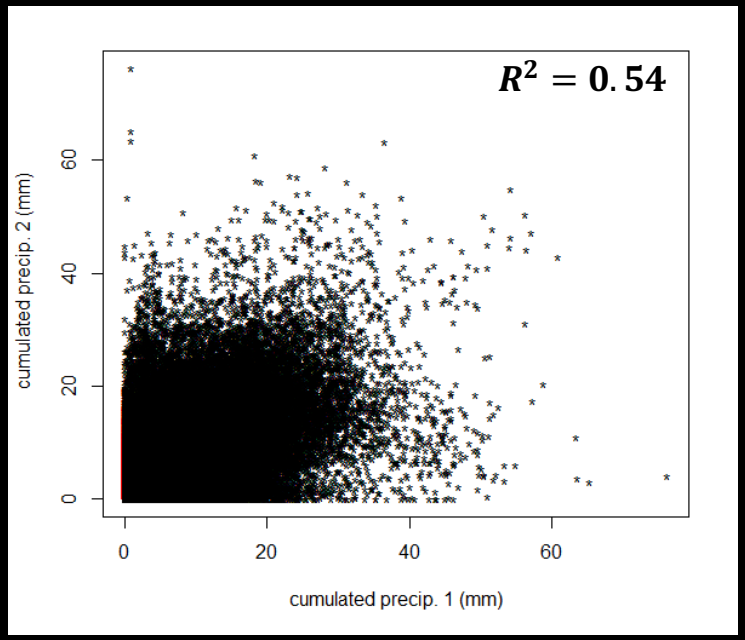




MRMS hourly at 1 km shifted by 7 km

THE CLASSICAL APPROACH IN COMPARING/VALIDATING PRODUCTS

How different are these two fields?



=> Quite different at the pixel level!

Effective Resolution

1. What is ***"The finest scale at which retrievals accurately reproduce the <u>local</u> spatial variability of a reference product"?***

2. Proposed a method to compute ER

3. Used ER as diagnostic tool

Global multiscale evaluation of satellite passive microwave retrieval of precipitation during the TRMM and GPM eras: effective resolution and regional diagnostics for future algorithm development

Clement Guilloteau[1,*], Efi Foufoula-Georgiou[1], *and* Christian D. Kummerow[2]
[1] *Department of Civil and Environmental Engineering, University of California, Irvine*
[2] *Department of Atmospheric Science, Colorado State University, Fort Collins*

https://doi.org/10.1175/JHM-D-17-0087.1
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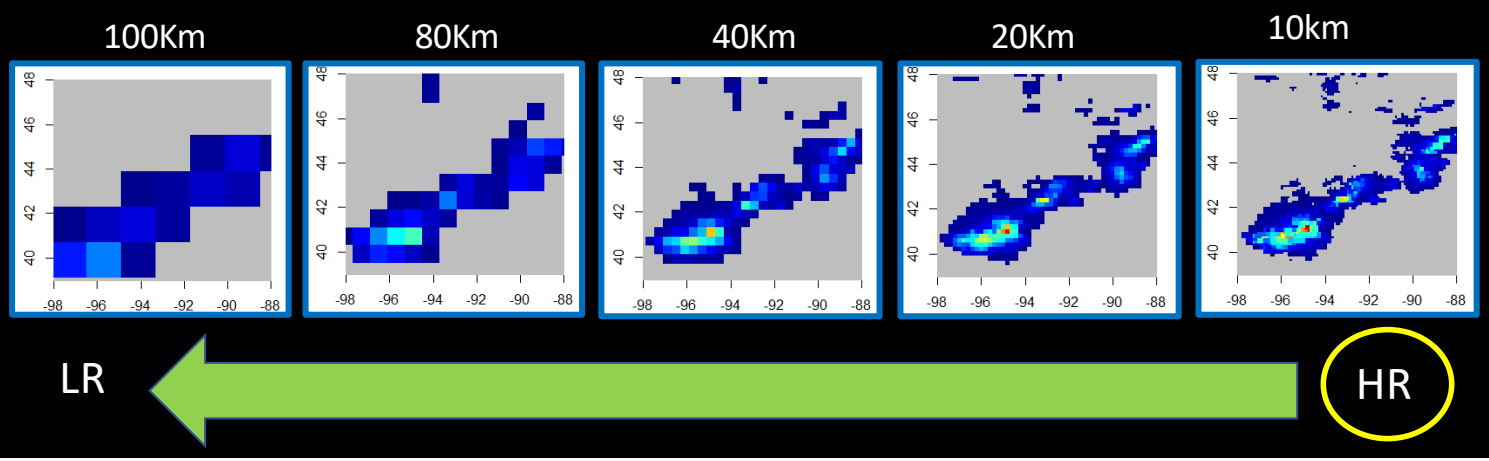
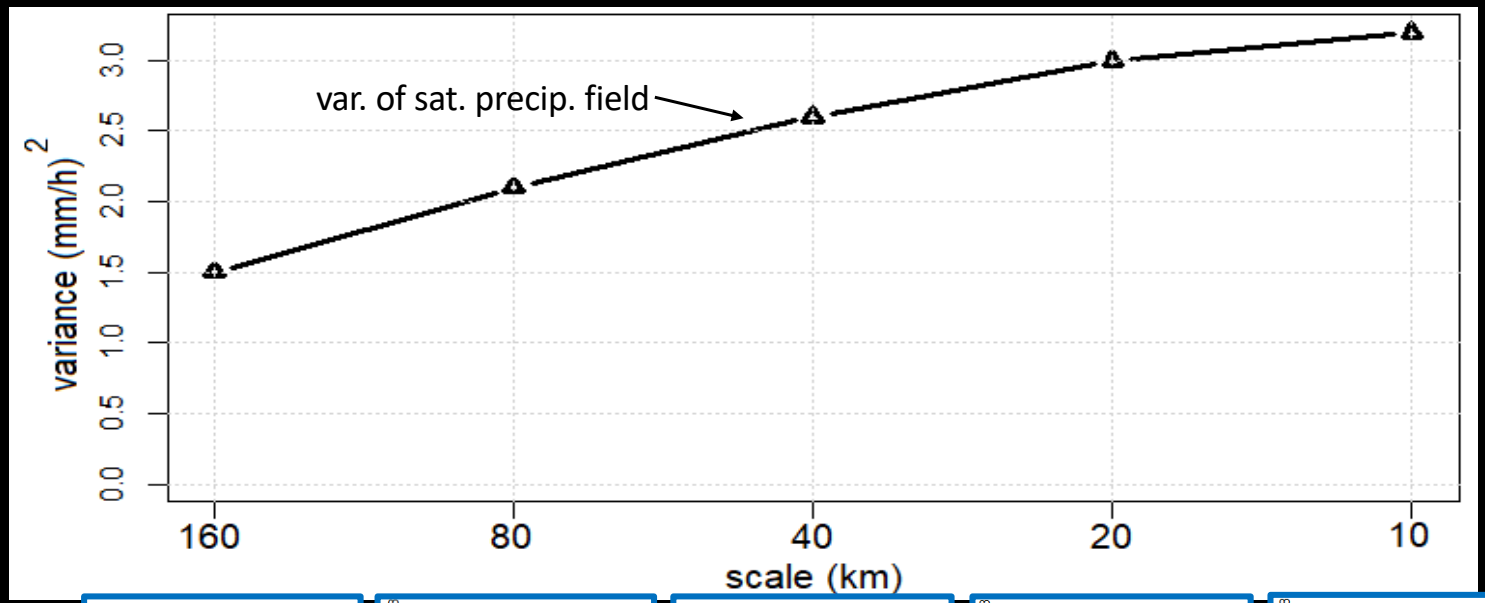
Variance as a function of the scale

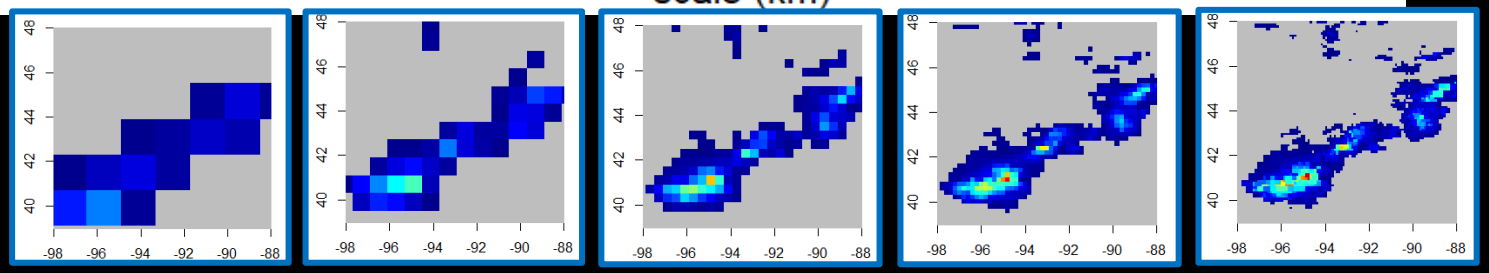
satellite precipitation field



Variance as a function of the scale



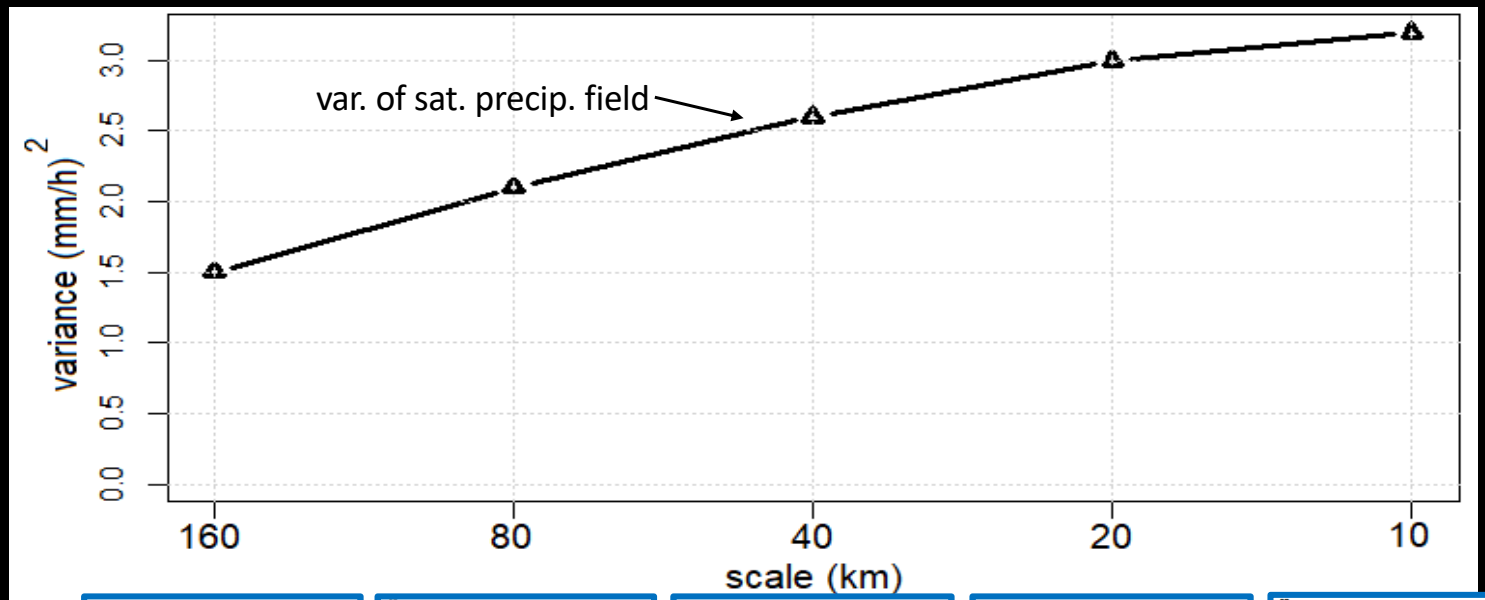
satellite precipitation field



LR

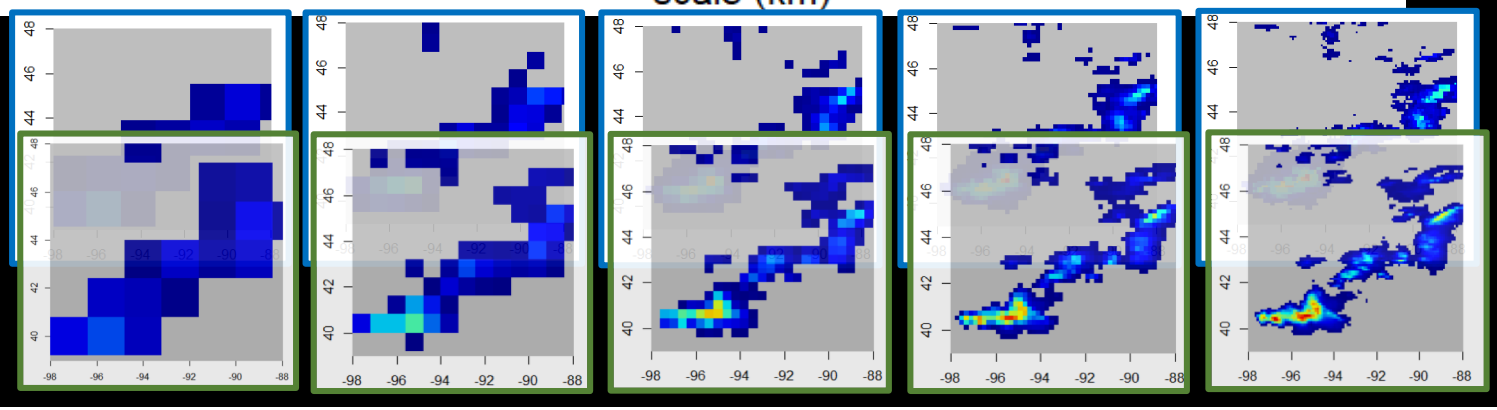
HR

Variance as a function of the scale



satellite precipitation field

radar precipitation field



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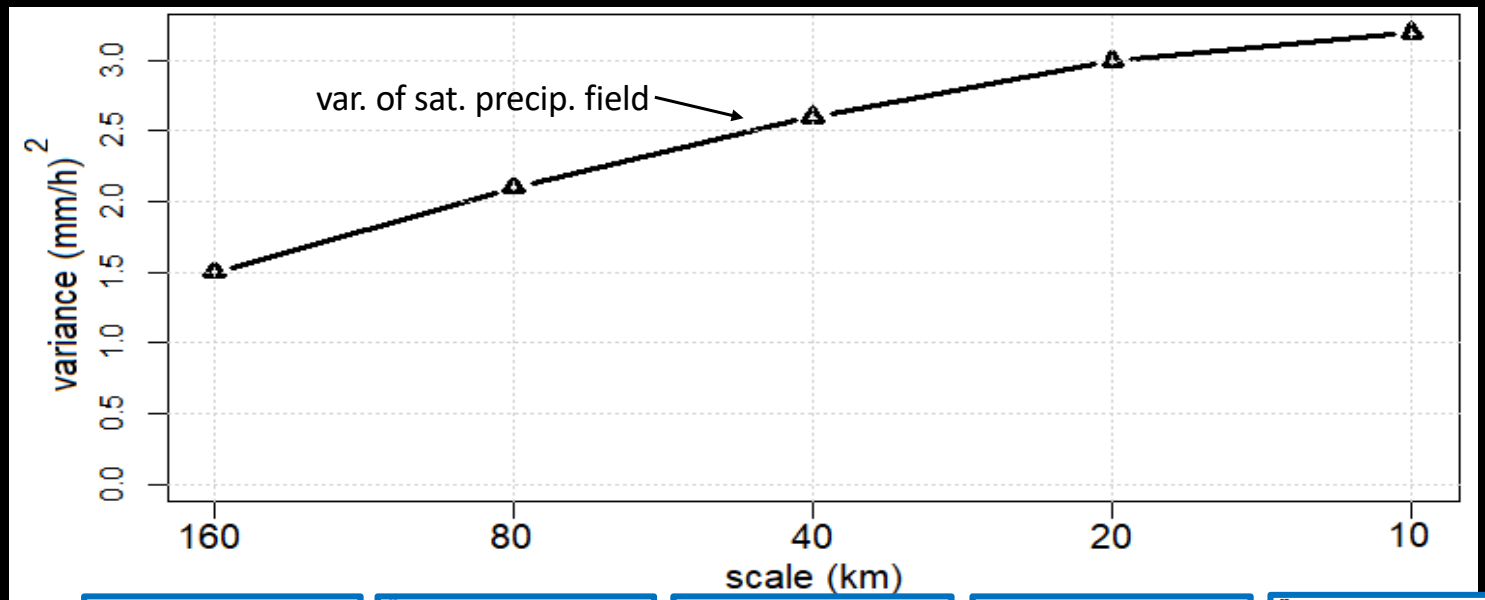

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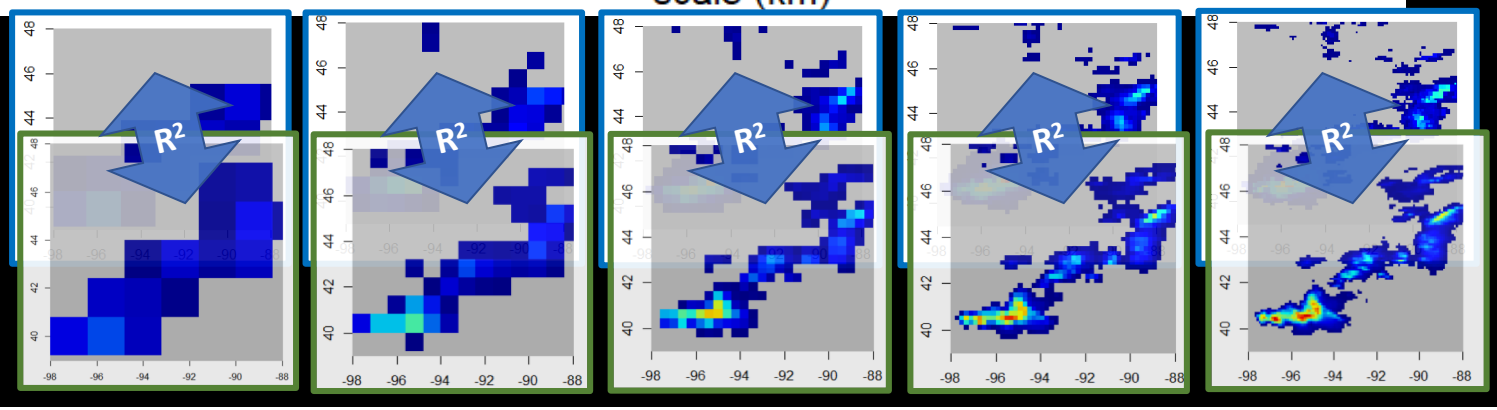
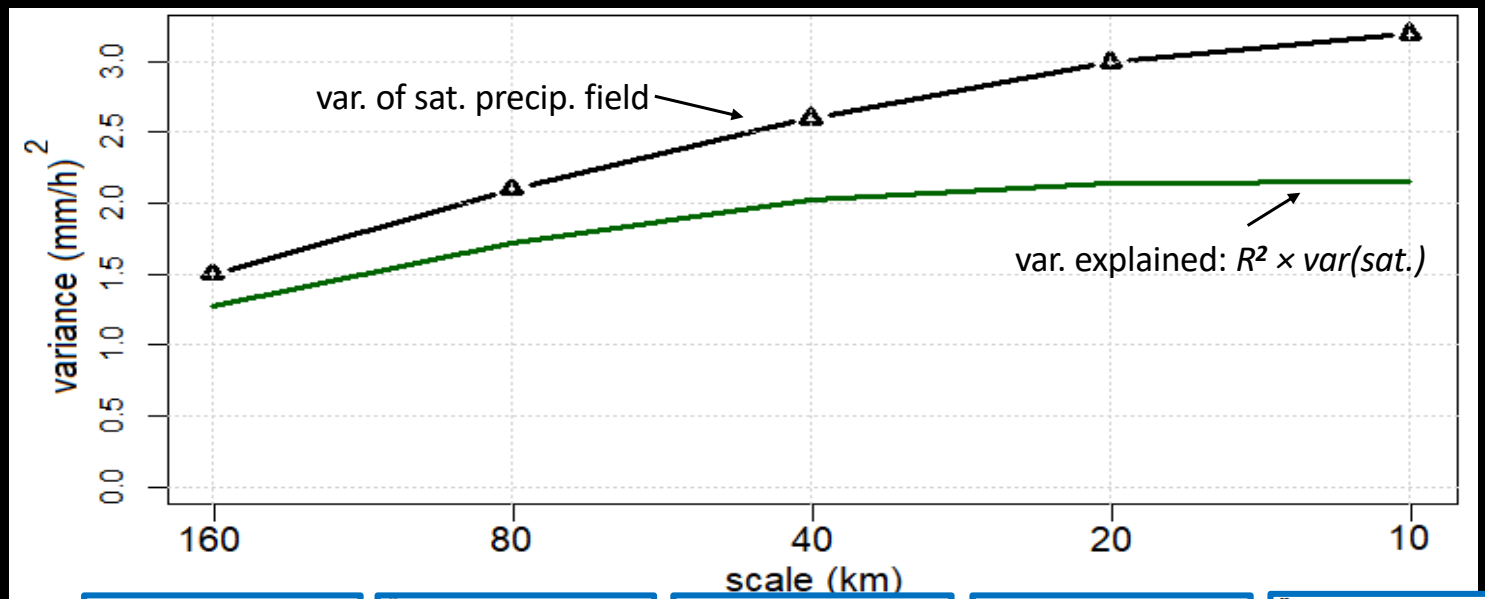
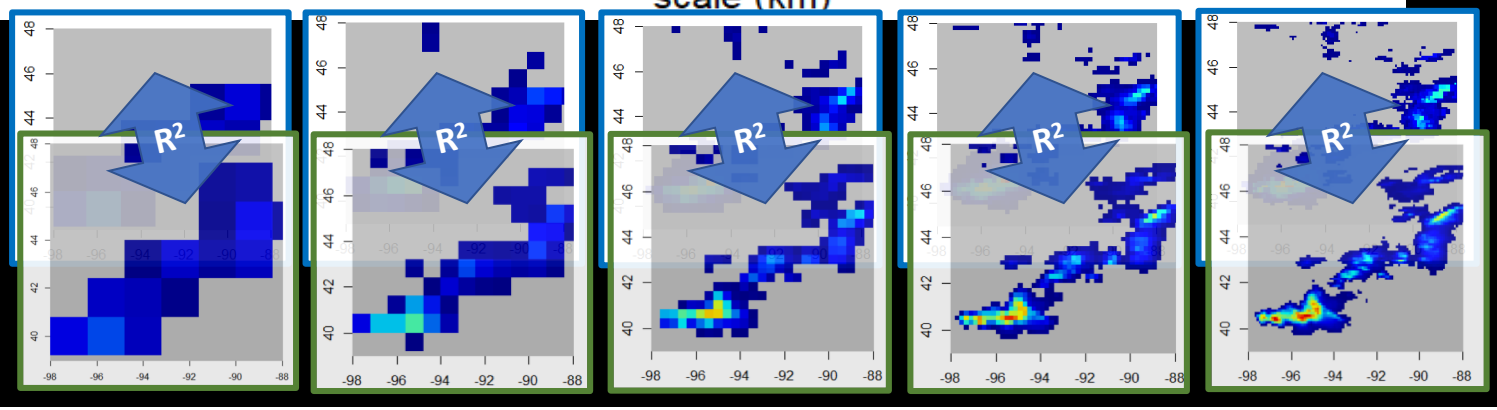


Variance as a function of the scale

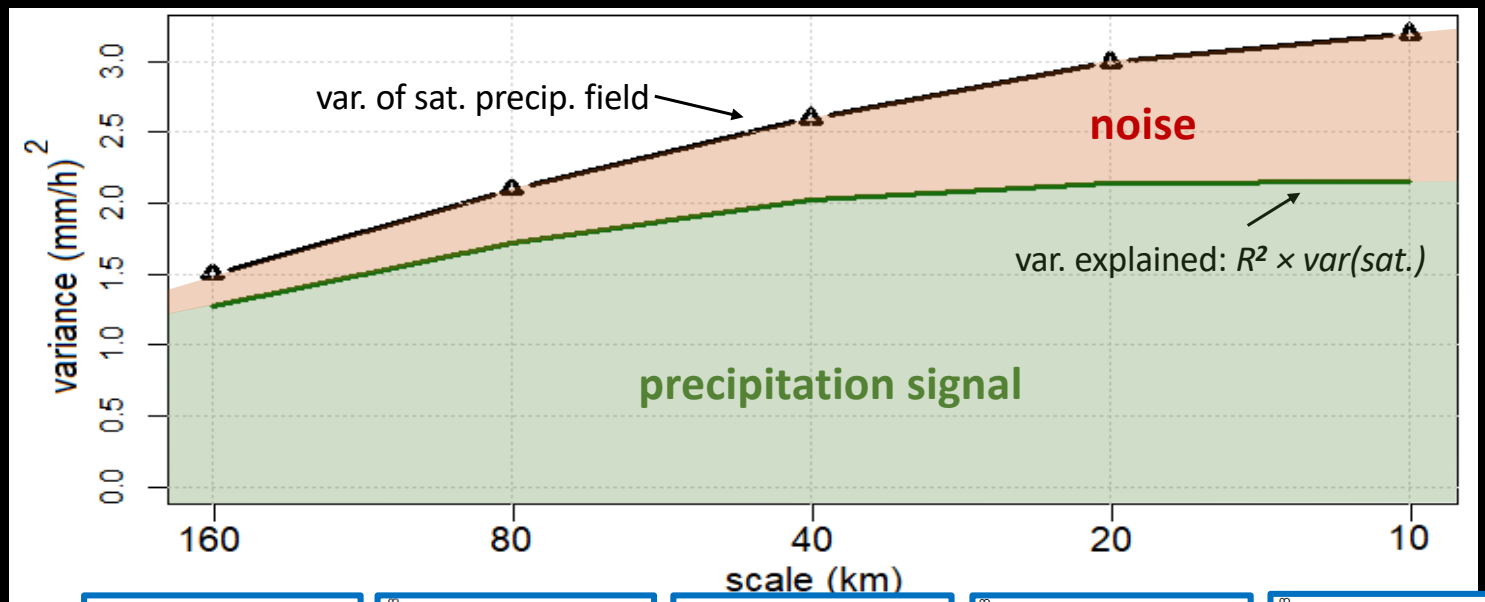


satellite precipitation field

radar precipitation field

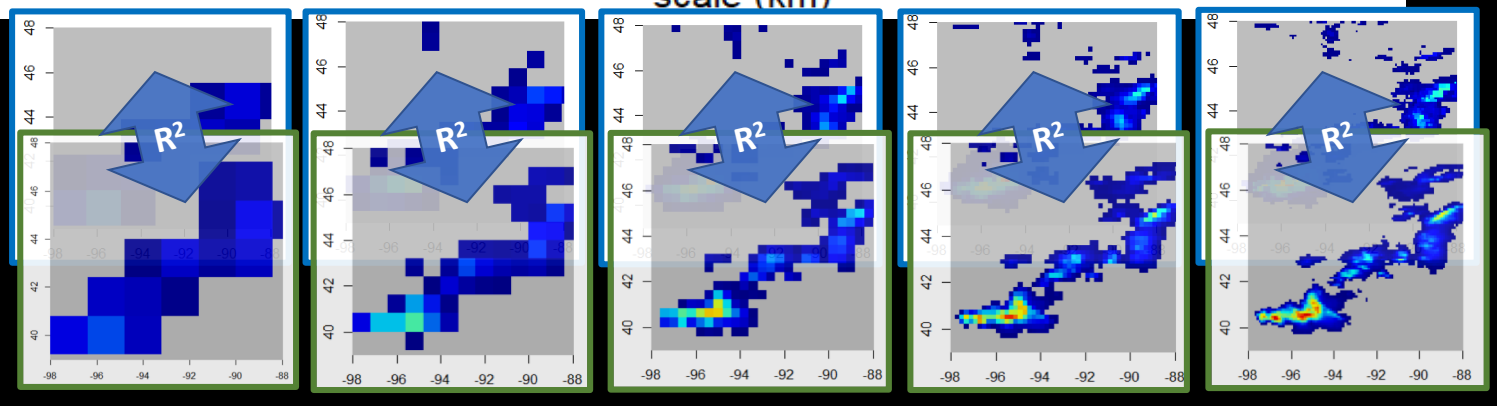


Precipitation signal or noise?



satellite precipitation field

radar precipitation field



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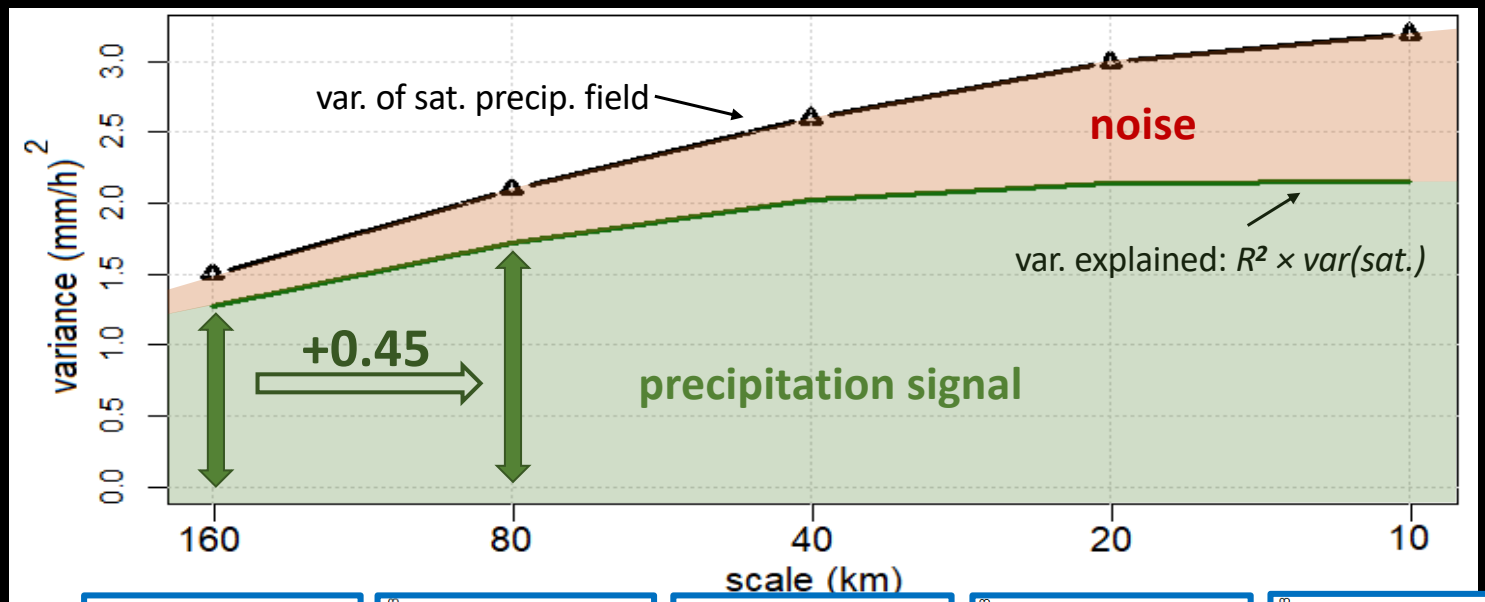
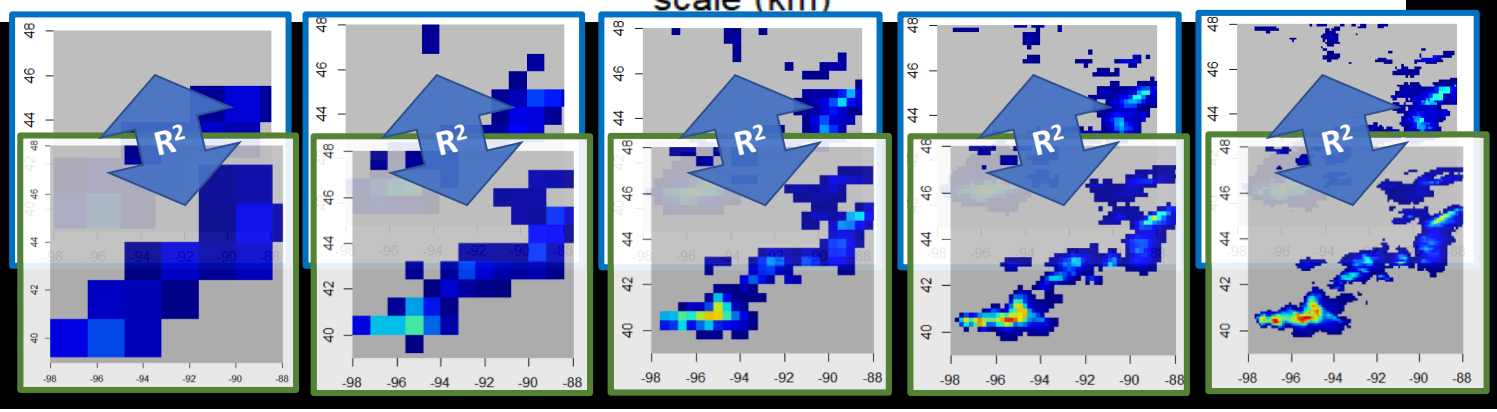


satellite precipitation field

radar precipitation field



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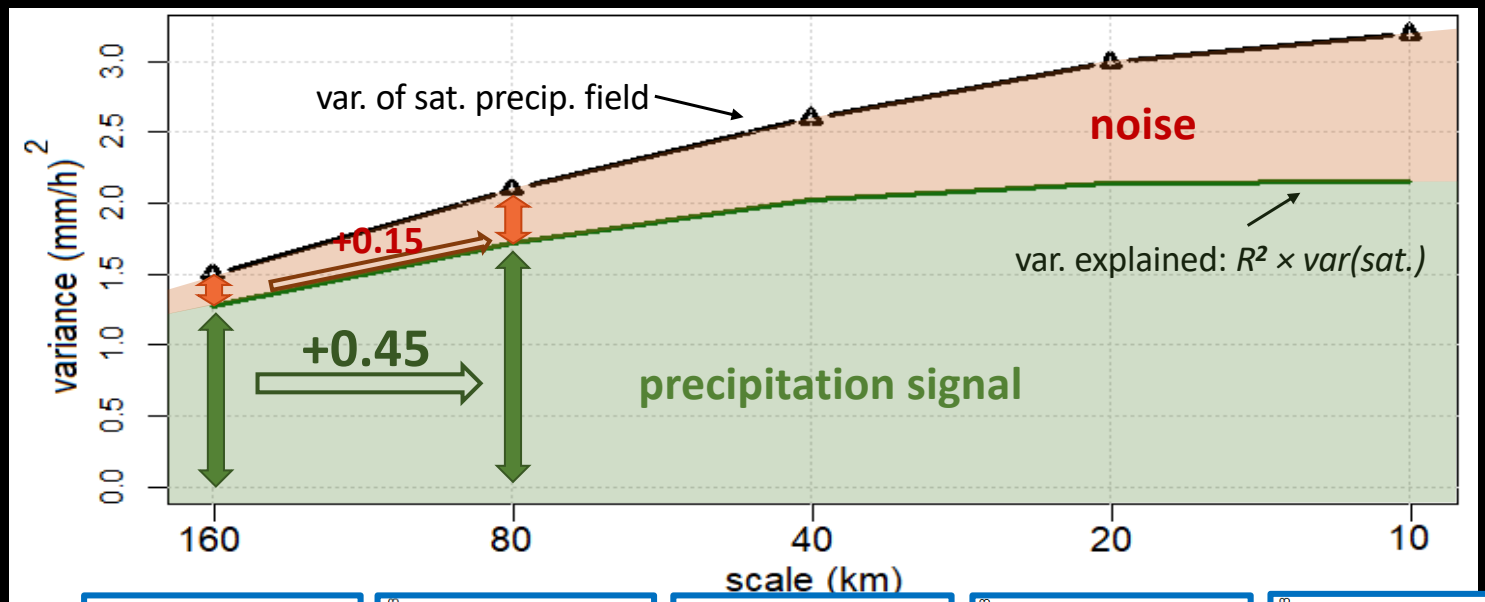
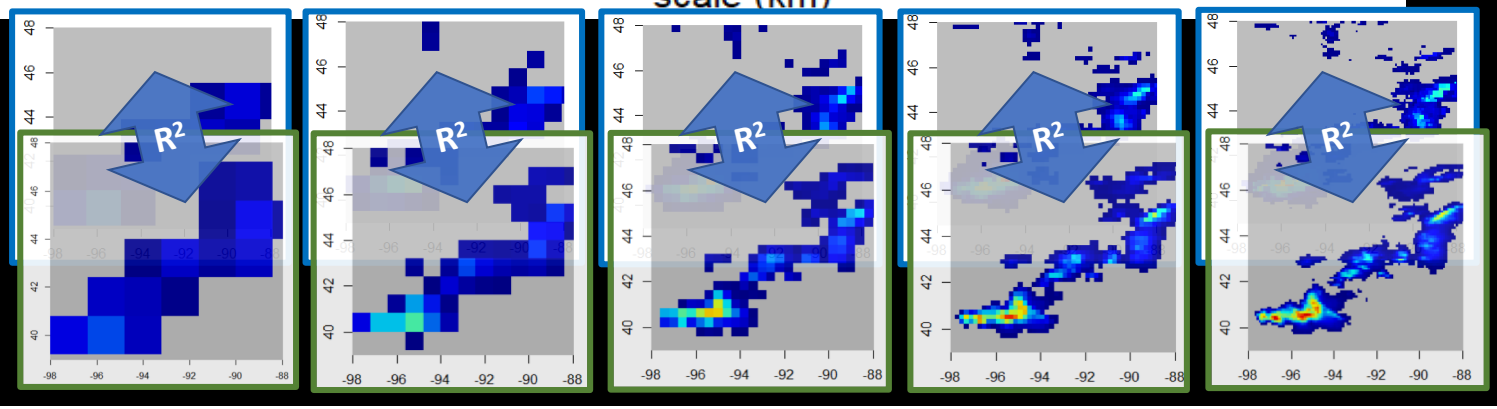


satellite precipitation field

radar precipitation field



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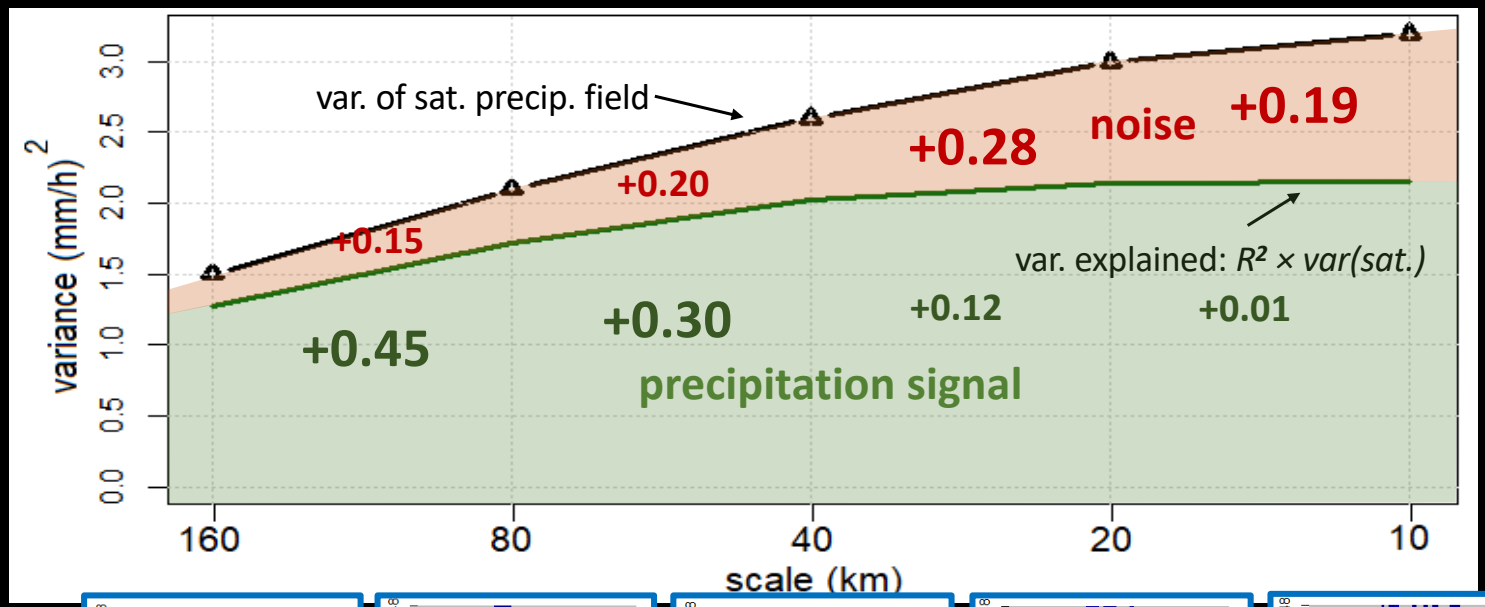

satellite precipitation field

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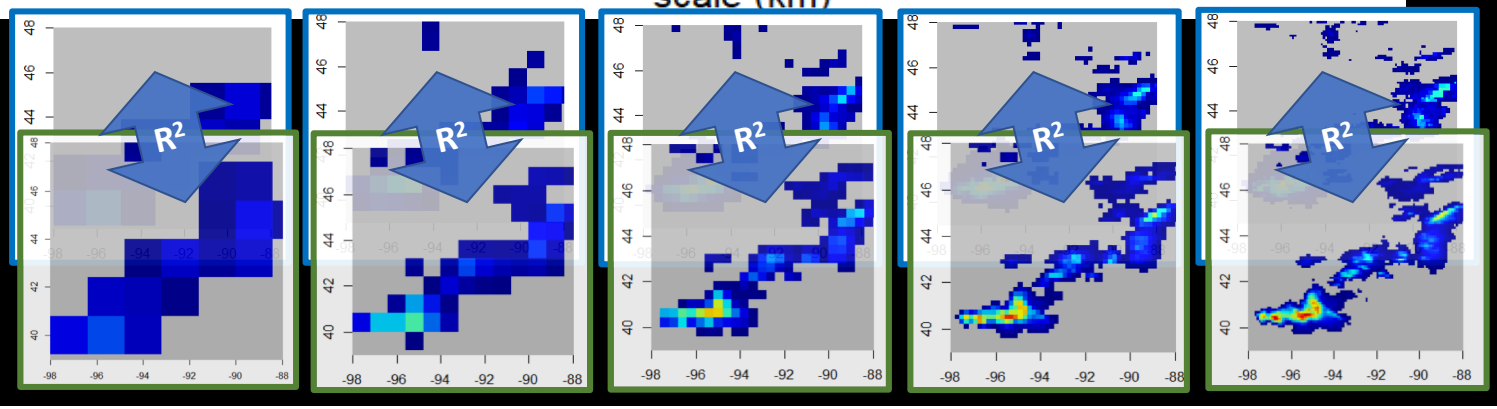

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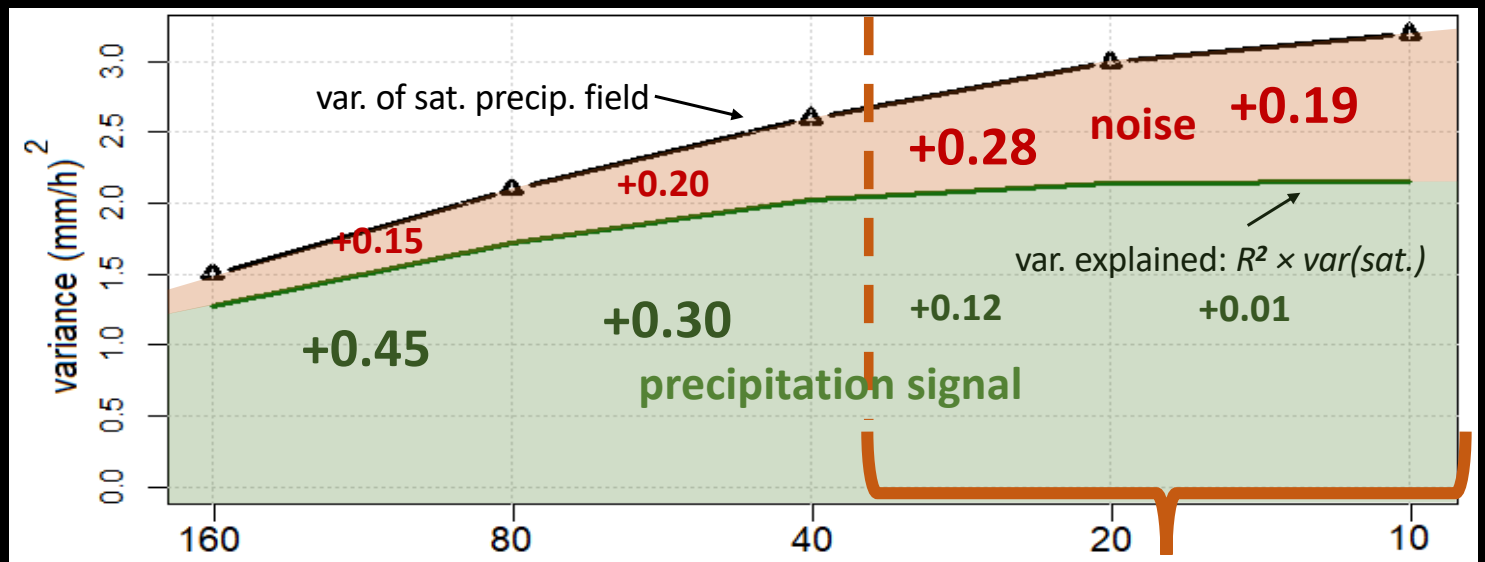
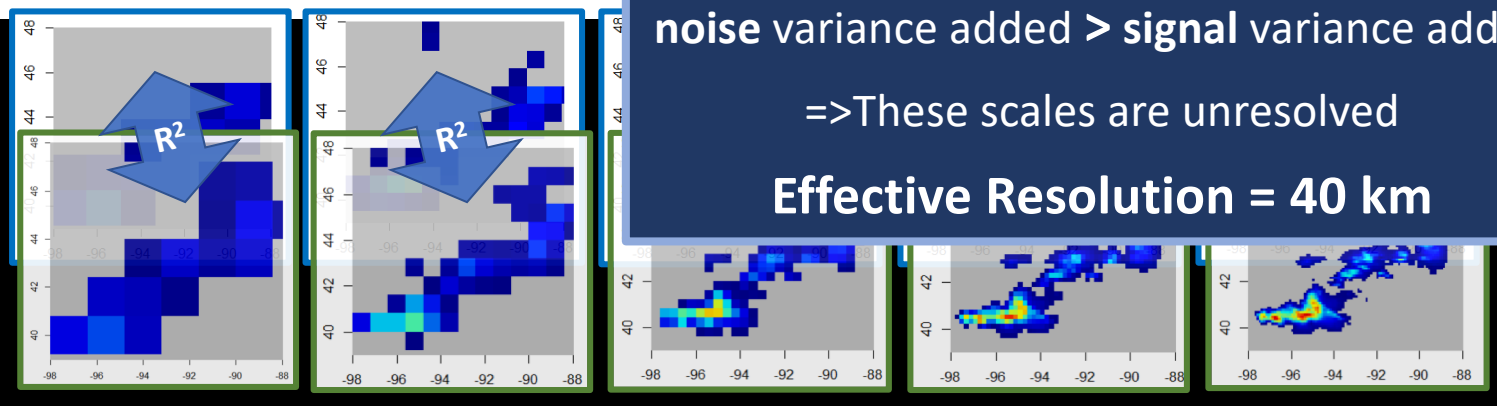


satellite precipitation field

radar precipitation field

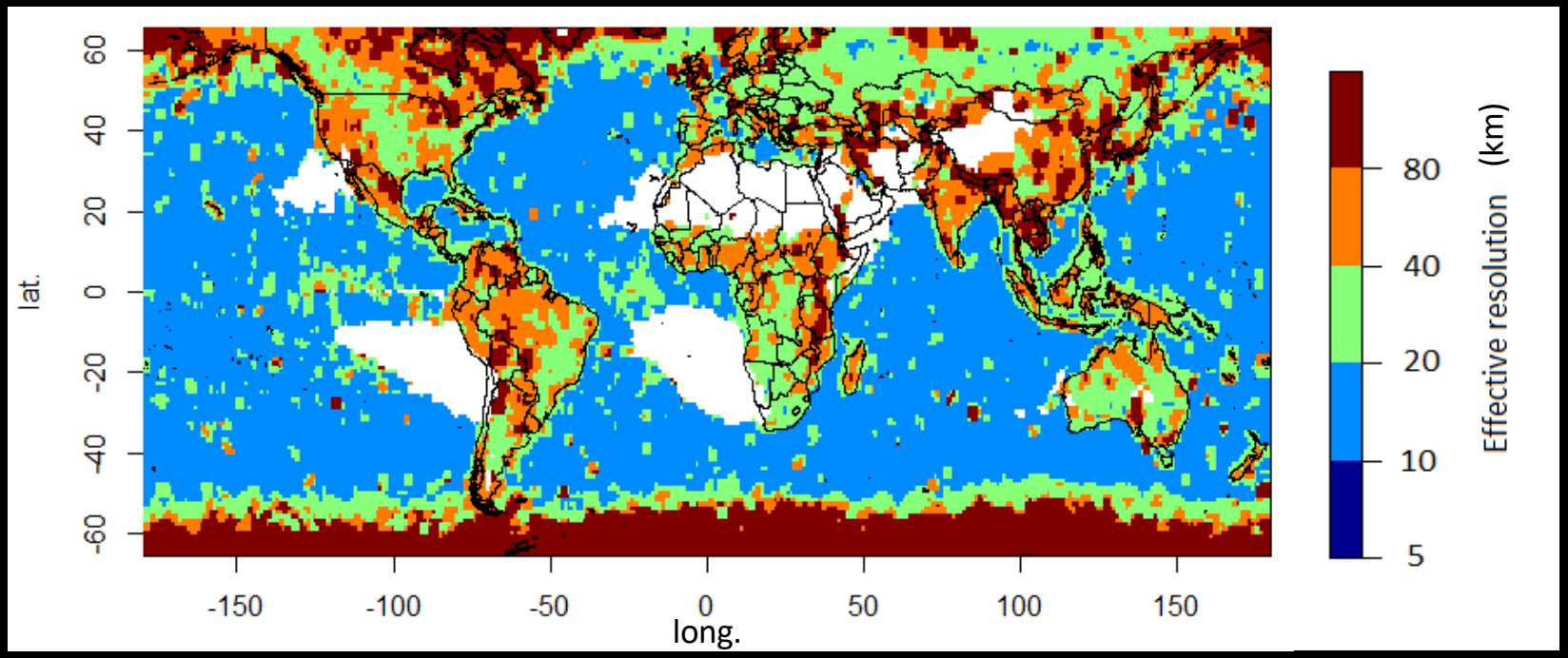


noise variance added **> signal** variance added

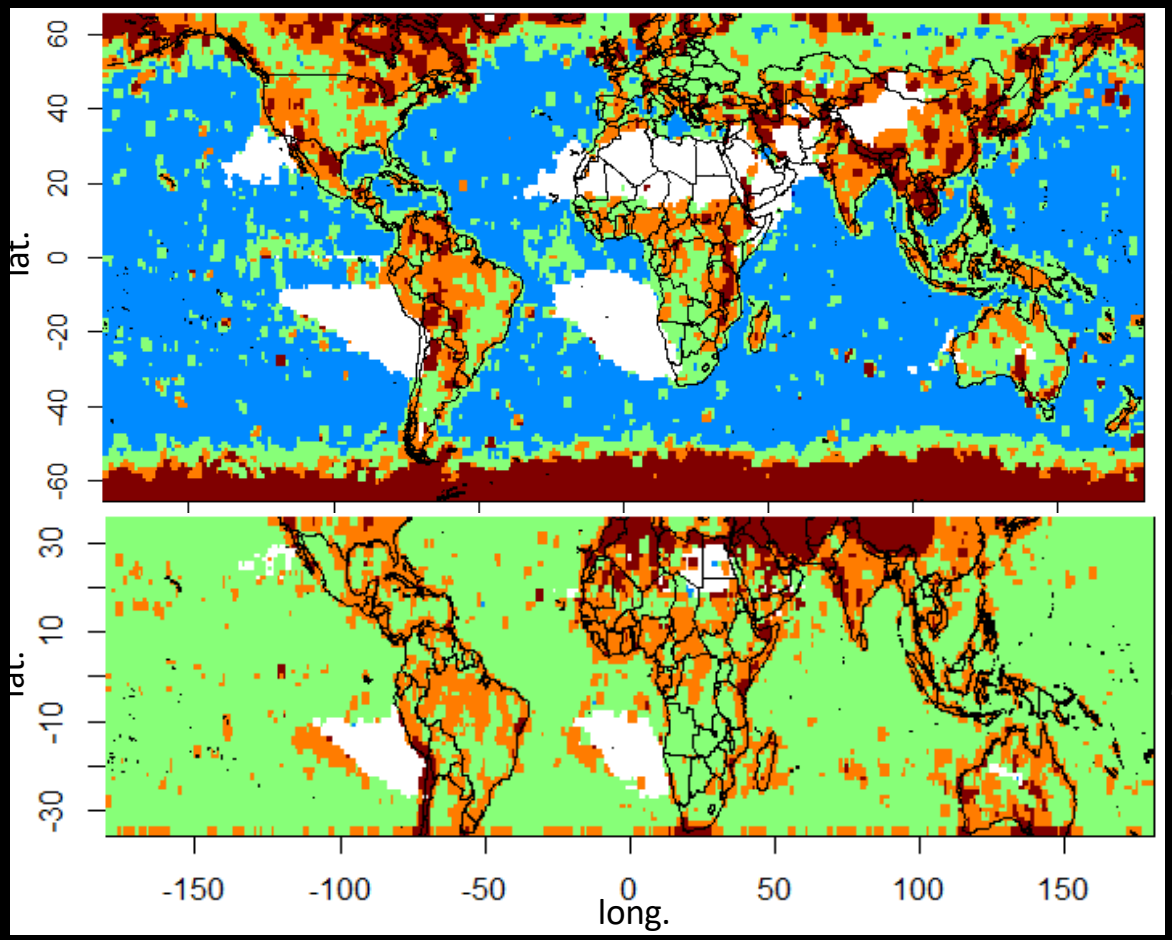
=>These scales are unresolved

Effective Resolution = 40 km

Global map of the effective resolution of GPROF-GMI vs KuPR

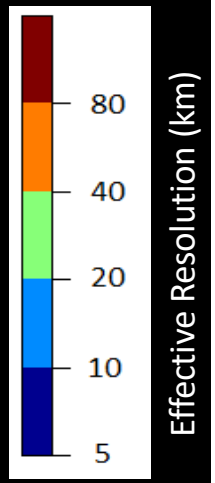


- Local values computed from all observations in 3°×3° boxes.
- March 2014 to February 2017: 16500 GPM orbits



GPM era (2014-2017):
GMI GPROF V05 vs KuPR

TRMM era (2002-2013):
TMI GPROF V03 vs PR

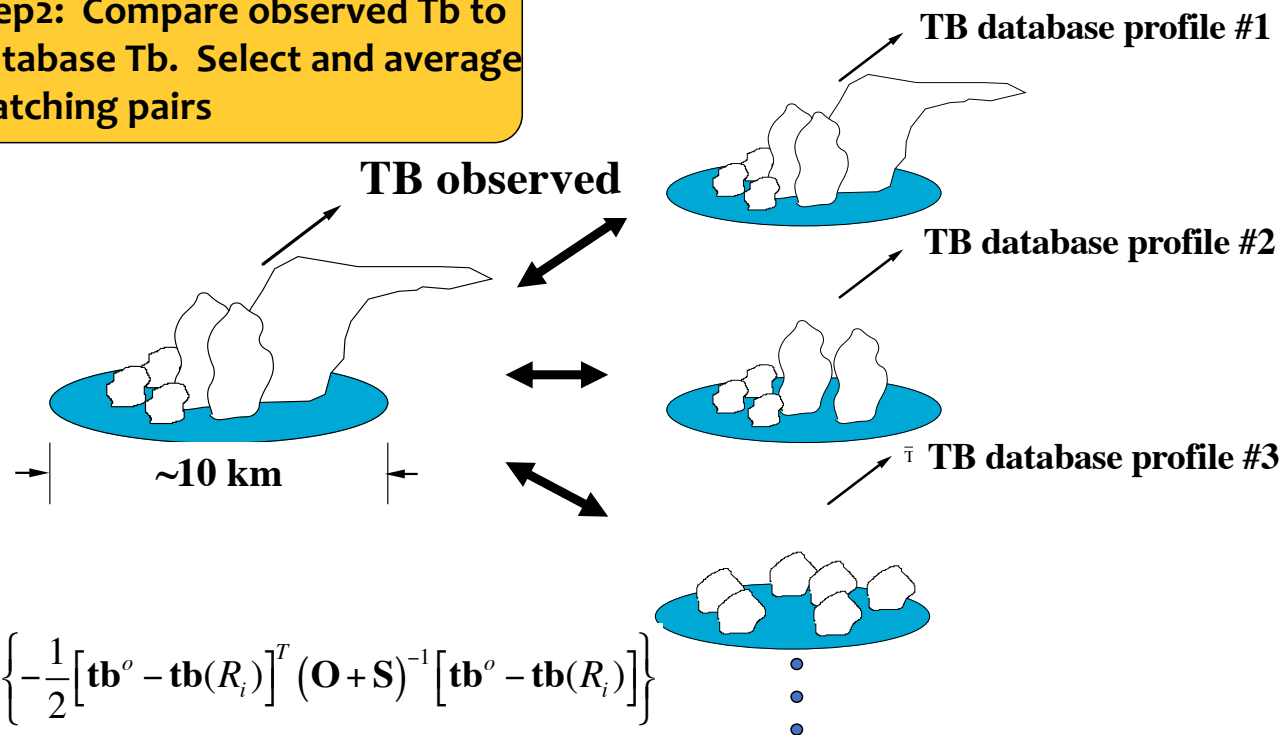


Part II: Nonlocal information to improve PMW retrievals

The GPM radiometer algorithm

Step 1: Use GPM Satellite to derive set of "Observed" profiles that define an a-priori database of possible rain structures.

Step2: Compare observed Tb to Database Tb. Select and average matching pairs

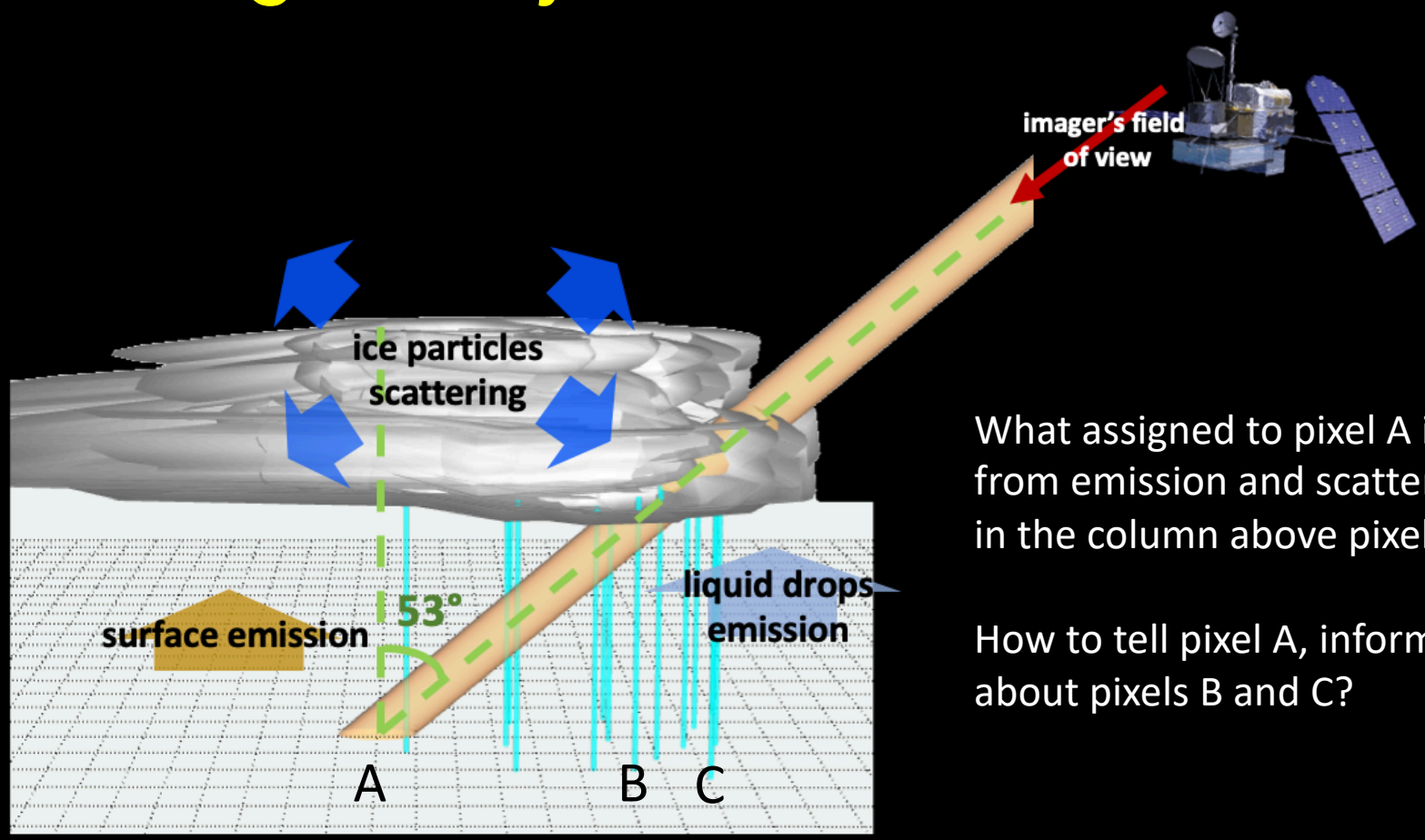


$$J_i = \exp\left\{-\frac{1}{2}\left[\mathbf{tb}^o - \mathbf{tb}(R_i)\right]^T \left(\mathbf{O}+\mathbf{S}\right)^{-1}\left[\mathbf{tb}^o - \mathbf{tb}(R_i)\right]\right\}$$

Performing retrieval at the pixel-level ignores the 3D structure of rain and does not account for sensor geometry (53 incidence angle)

=> Need to”look beyond the pixel”

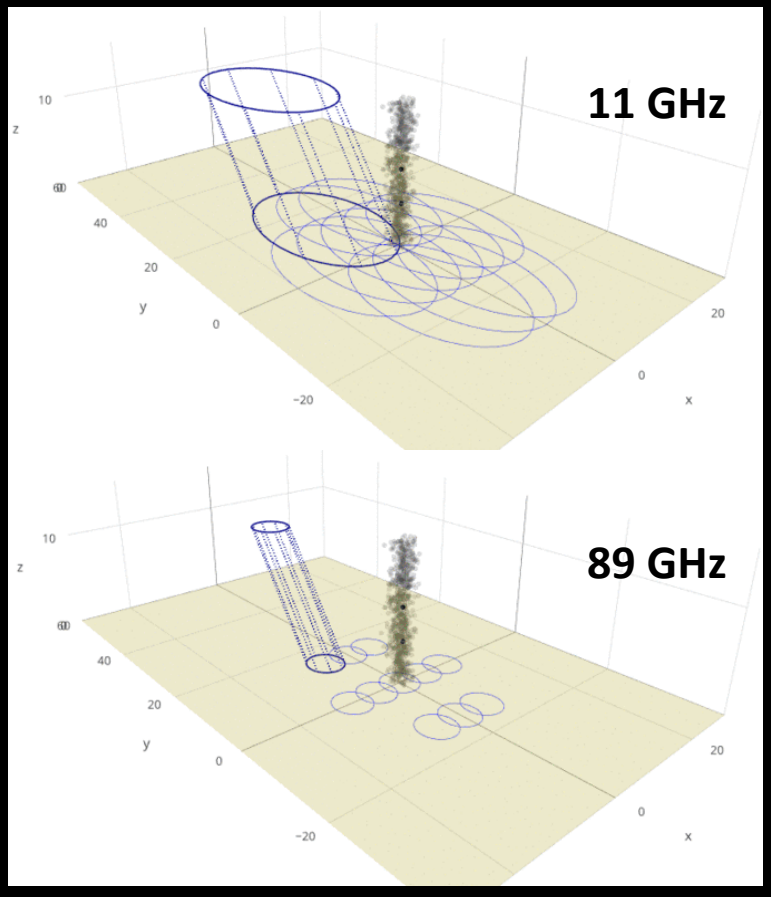
Sensor geometry



What assigned to pixel A is influenced from emission and scattering in the column above pixels B and C

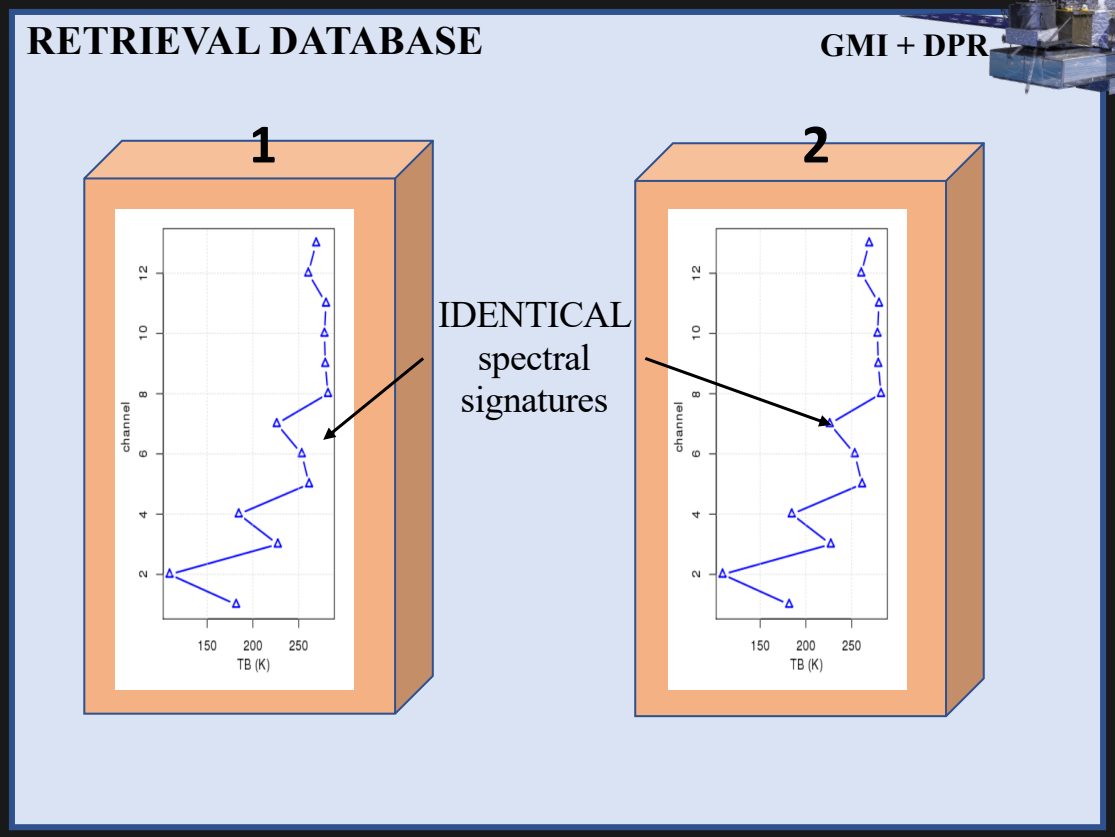
How to tell pixel A, information about pixels B and C?

Radiometric information is split across pixels

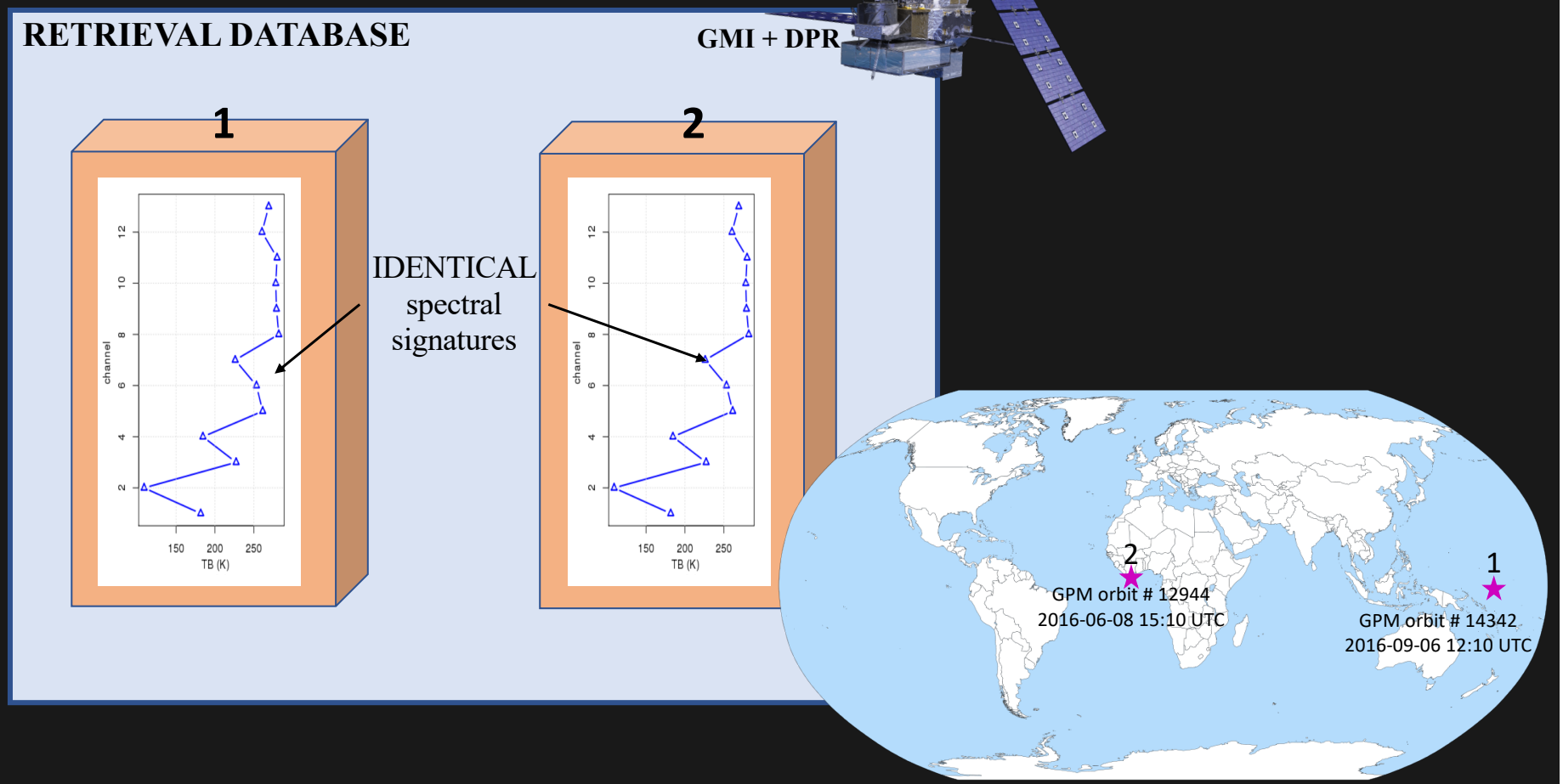


- **Low Frequencies:** (<40 GHz)**:** Significant overlapping of the fields of view
- **High Frequencies:** 53° Earth incident angle => a vertical atmospheric column always intercepted by at least two different fields of view
- Different channels respond to different altitude levels

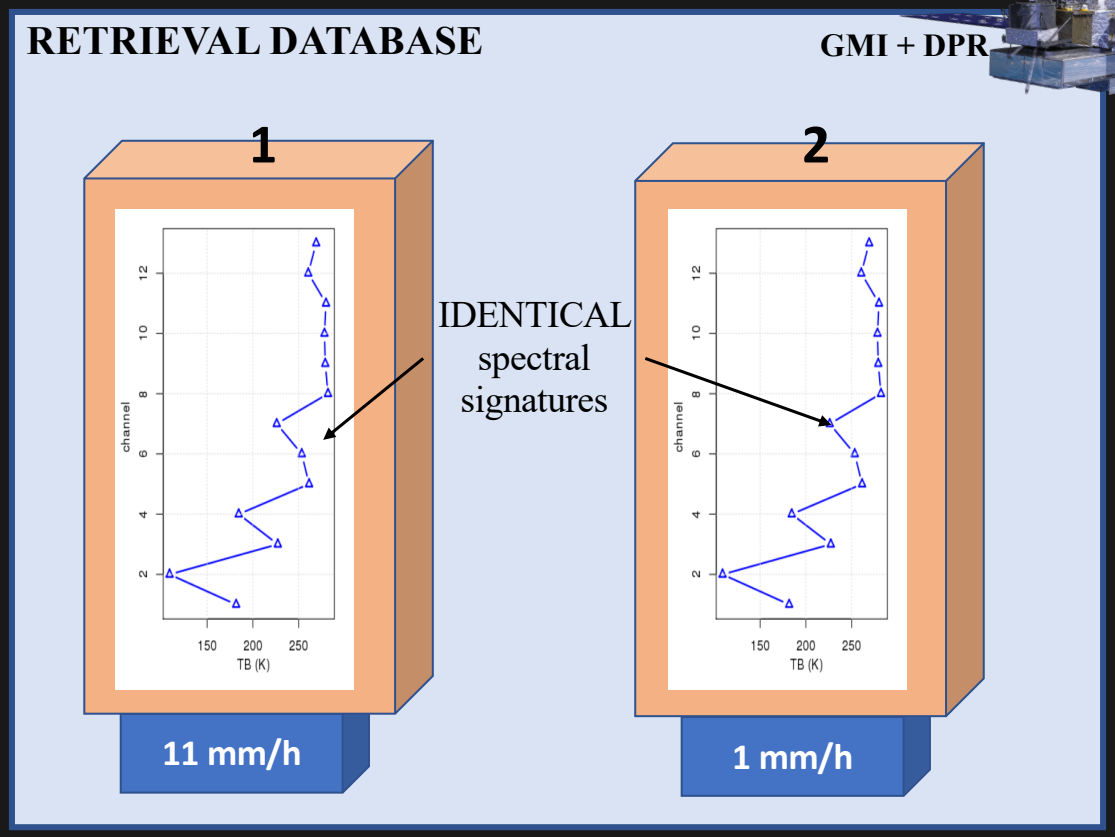
Highly Underdetermined Inverse problem



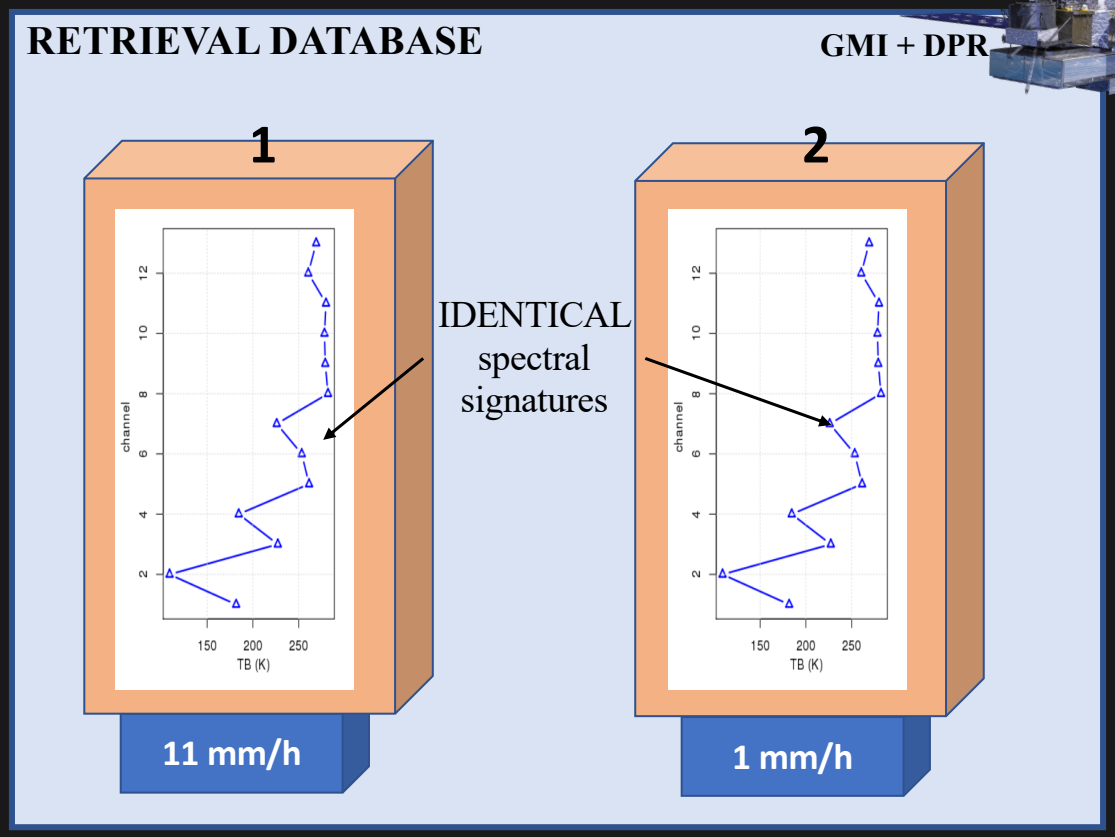
Highly Underdetermined Inverse problem



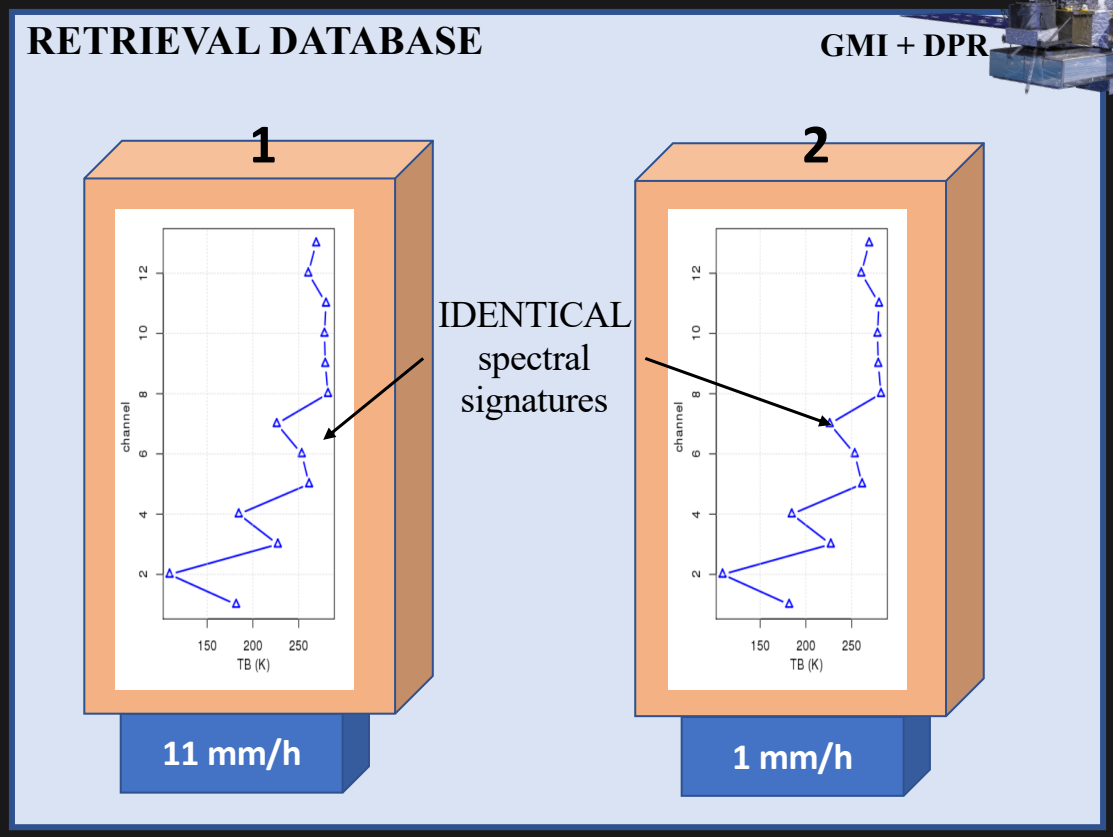
Highly Underdetermined Inverse problem

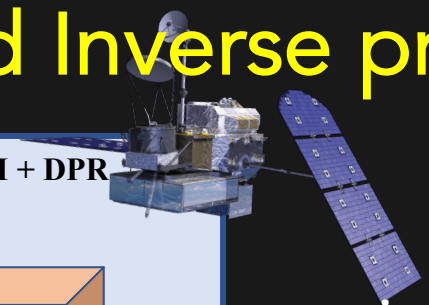


Highly Underdetermined Inverse problem

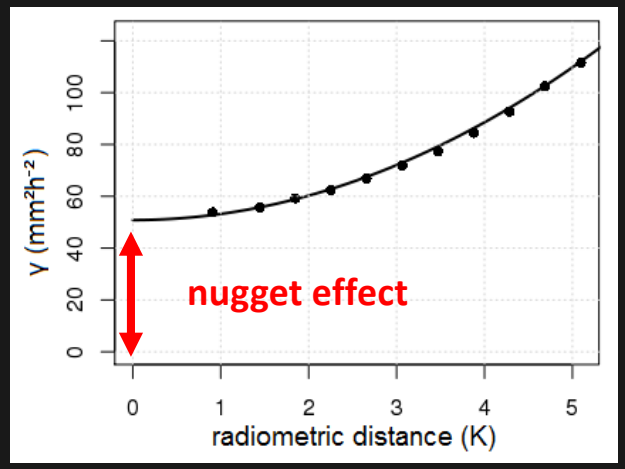


Highly Underdetermined Inverse problem



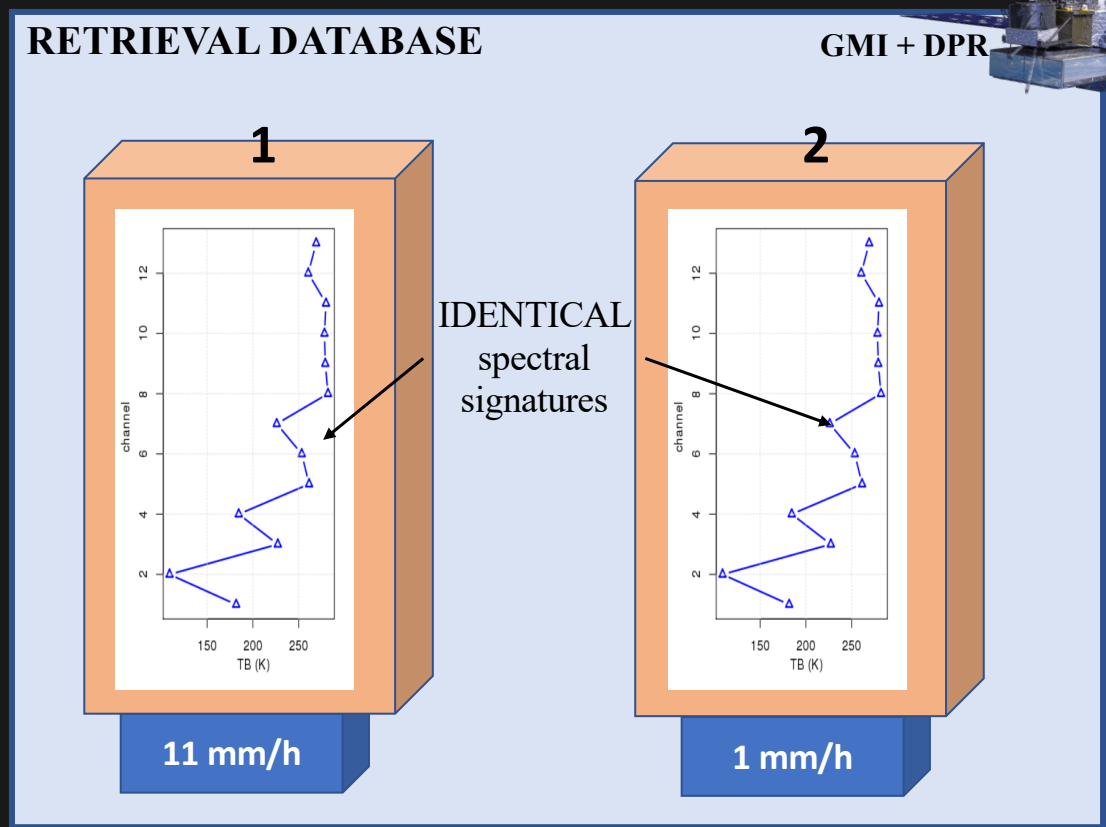


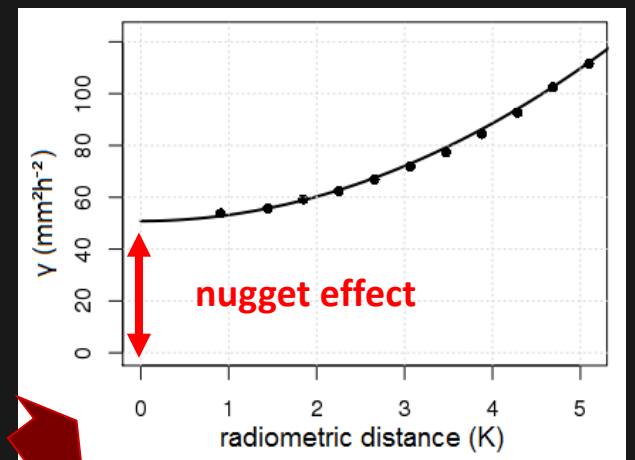
variogram of the rain rate $R(\overrightarrow{TB})$ in the 13D TB space



4,000 closest TB pixels
(from an 8M database)

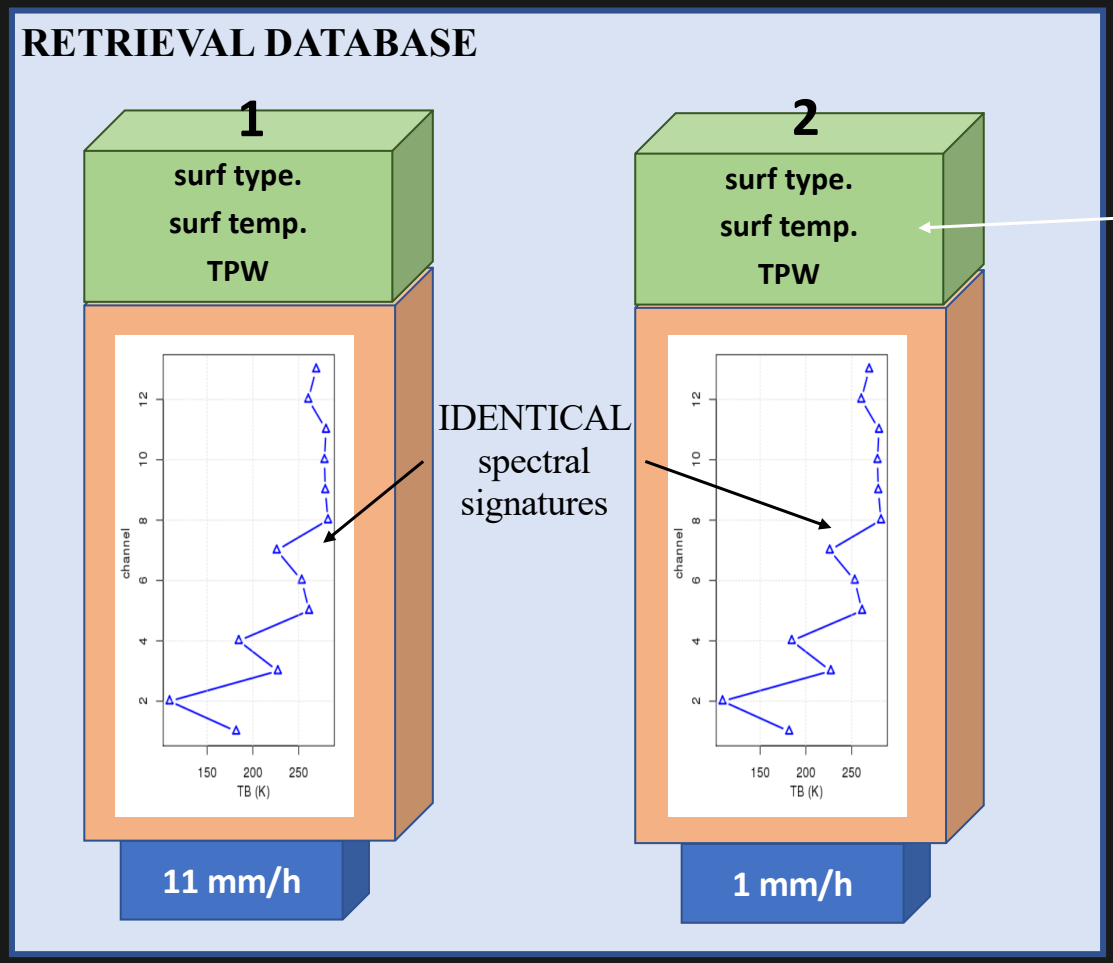
Highly Underdetermined Inverse problem



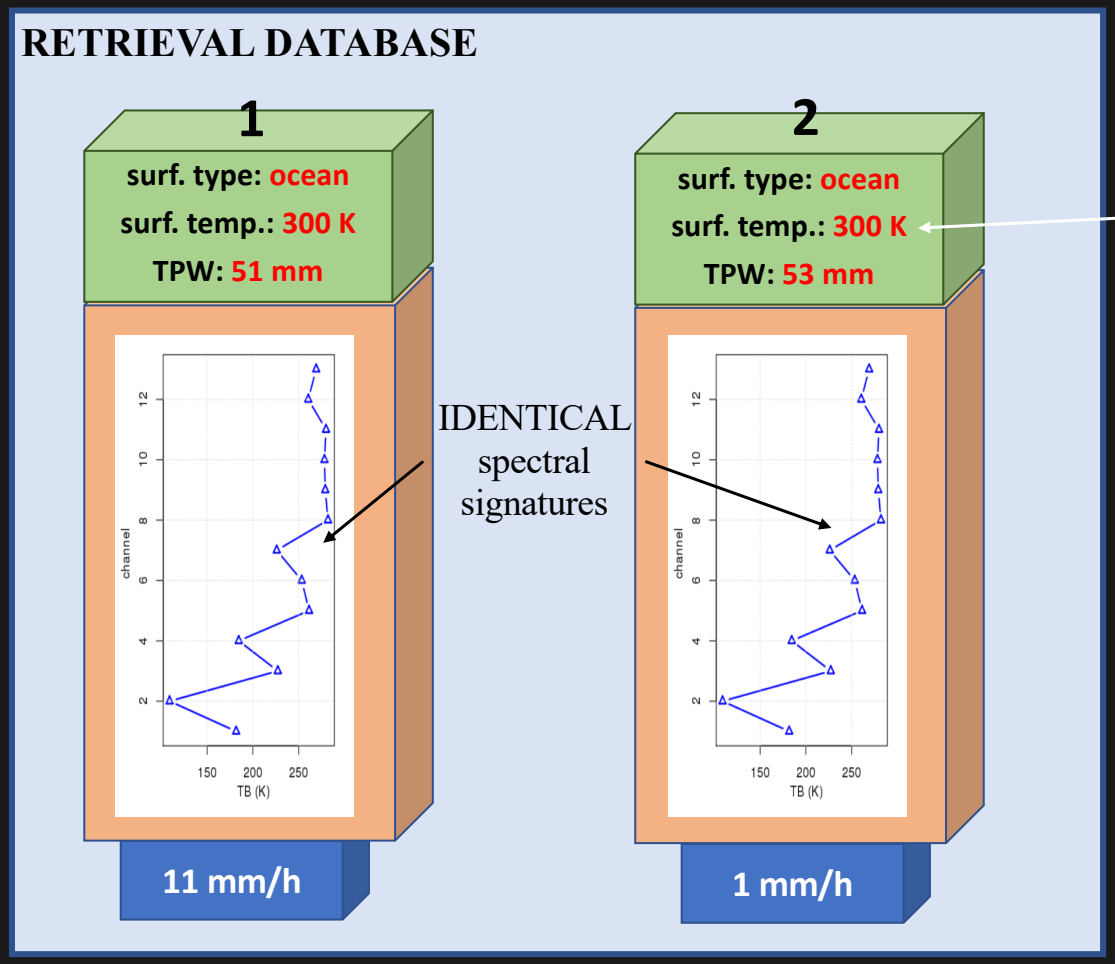


Increasing the database size does not help

4,000 closest TB pixels
(from an 8M database)



Using ancillary data may help …



Using ancillary data may help …

… but it is often insufficient

RETRIEVAL DATABASE

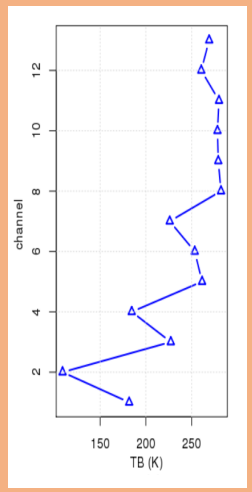
TB patterns around the pixel of interest can contain useful information

1

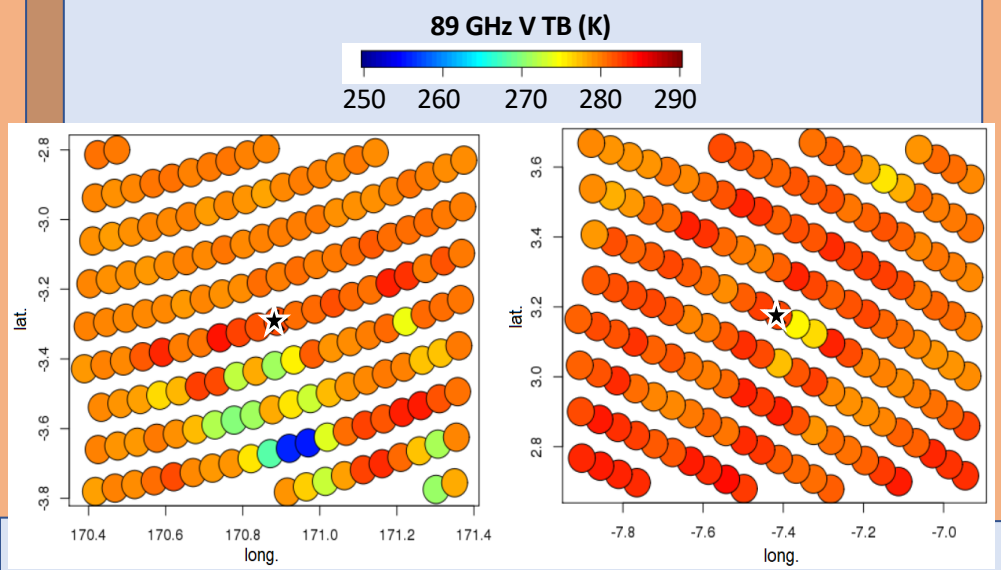
surf. type: ocean

surf. temp.: 300 K

TPW: 51 mm



11 mm/h

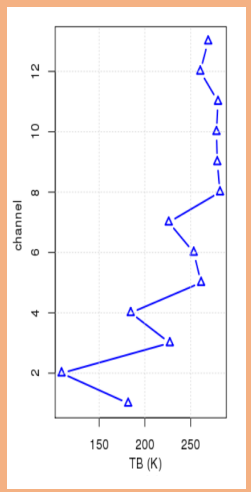


2

surf. type: ocean

surf. temp.: 300 K

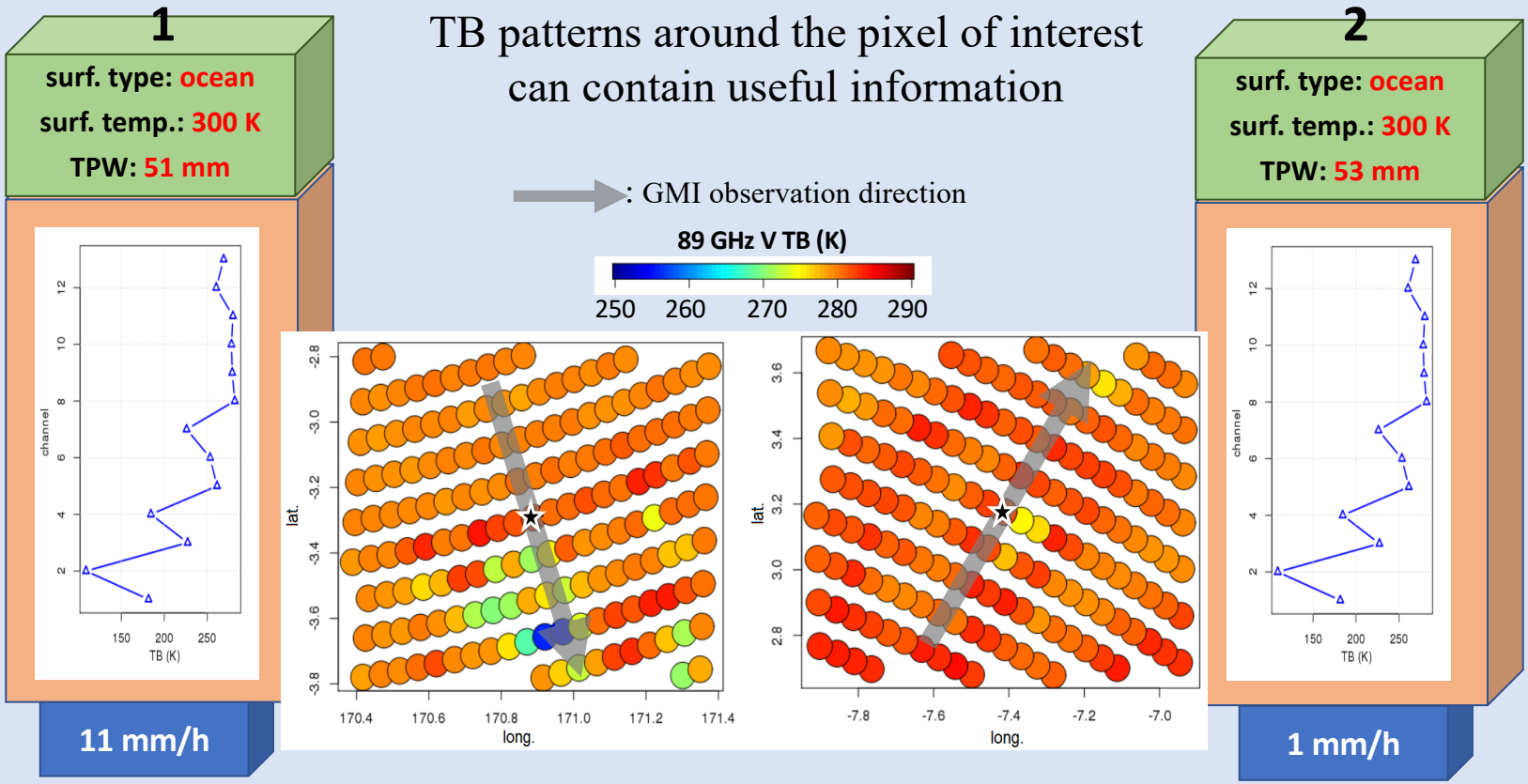
TPW: 53 mm



1 mm/h

RETRIEVAL DATABASE

TB patterns around the pixel of interest can contain useful information



RETRIEVAL DATABASE

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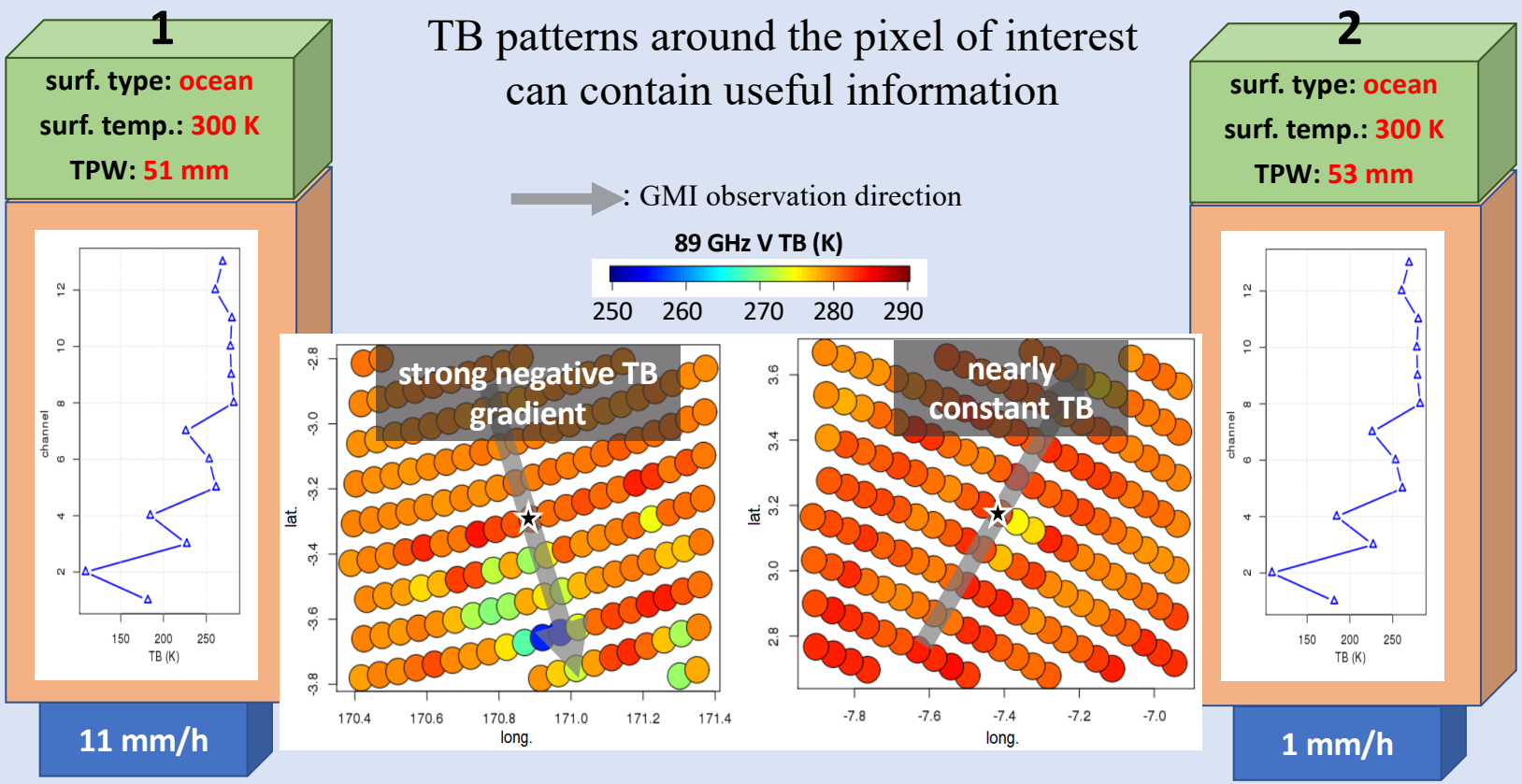
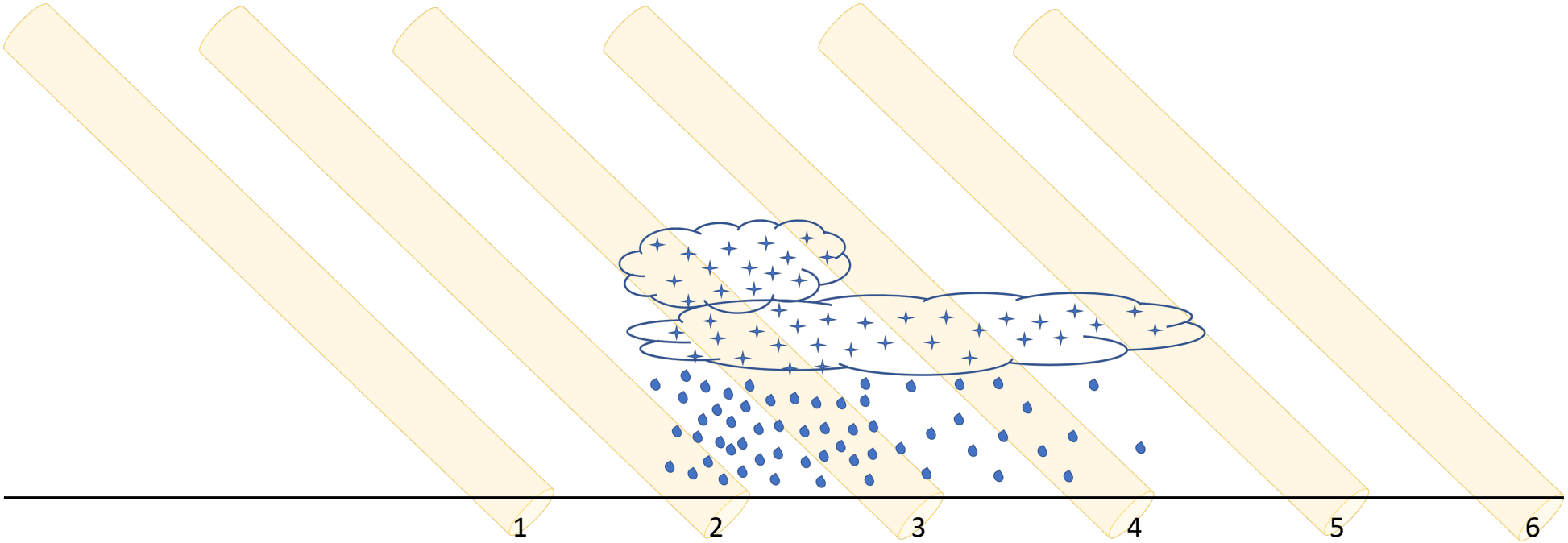


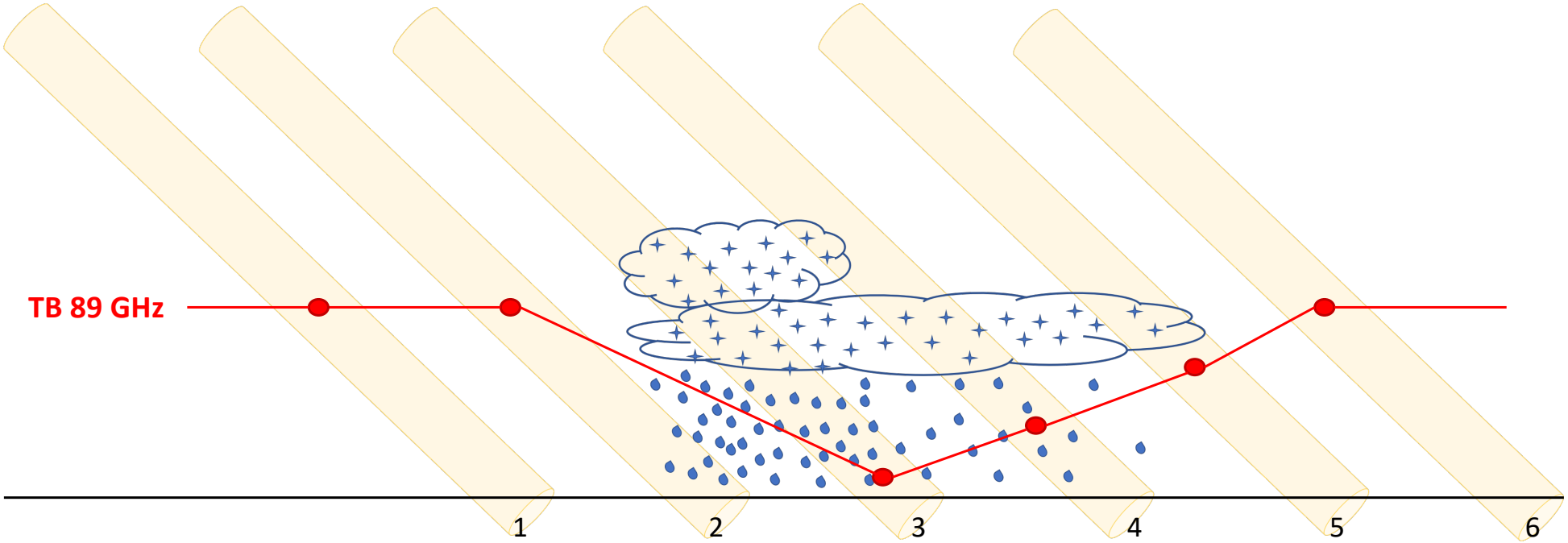
The challenge becomes:

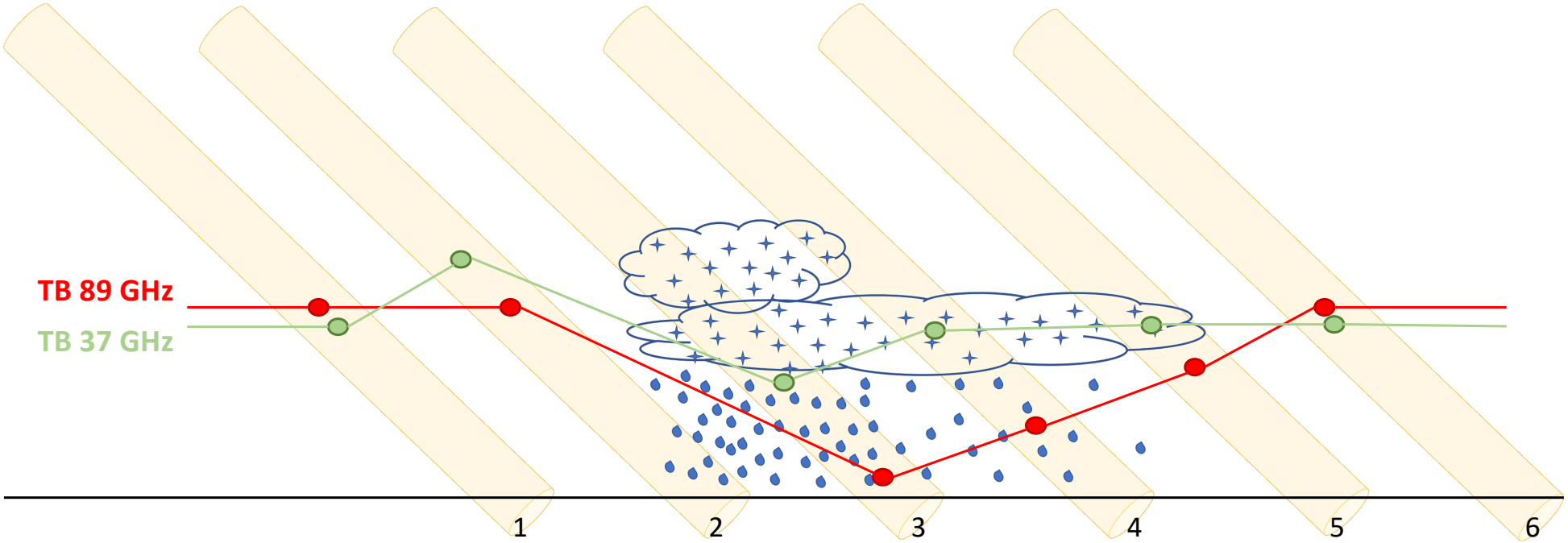
How to extract:

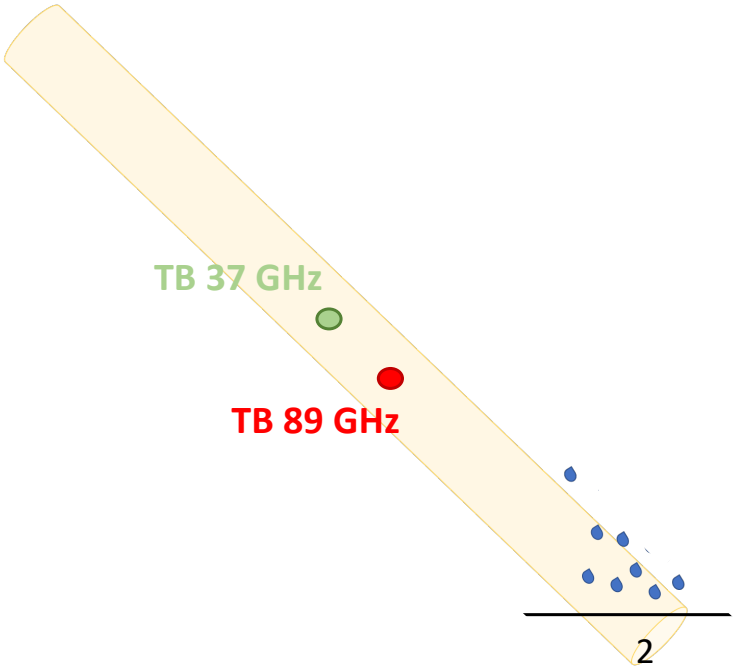
-- the most informative non-local parameters from the TB patterns

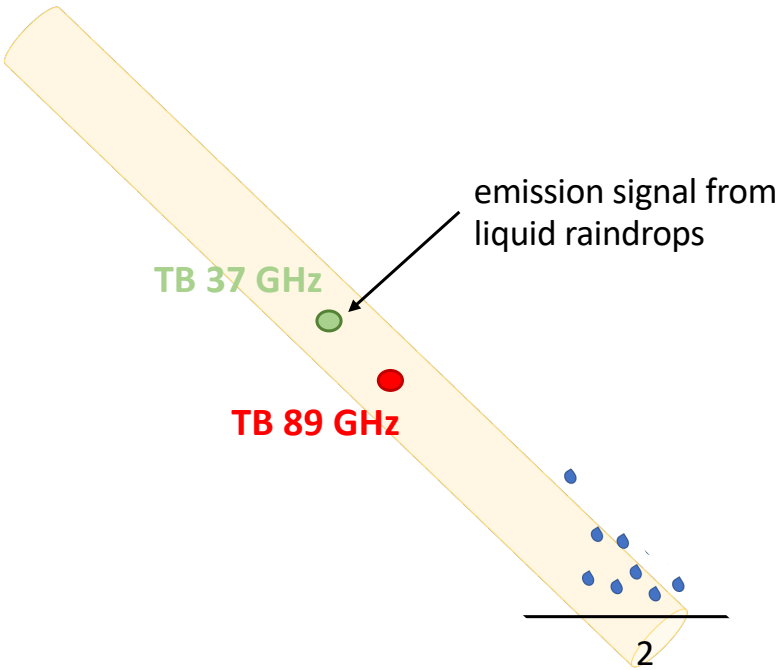
-- to increase identifiability and reduce retrieval uncertainty?

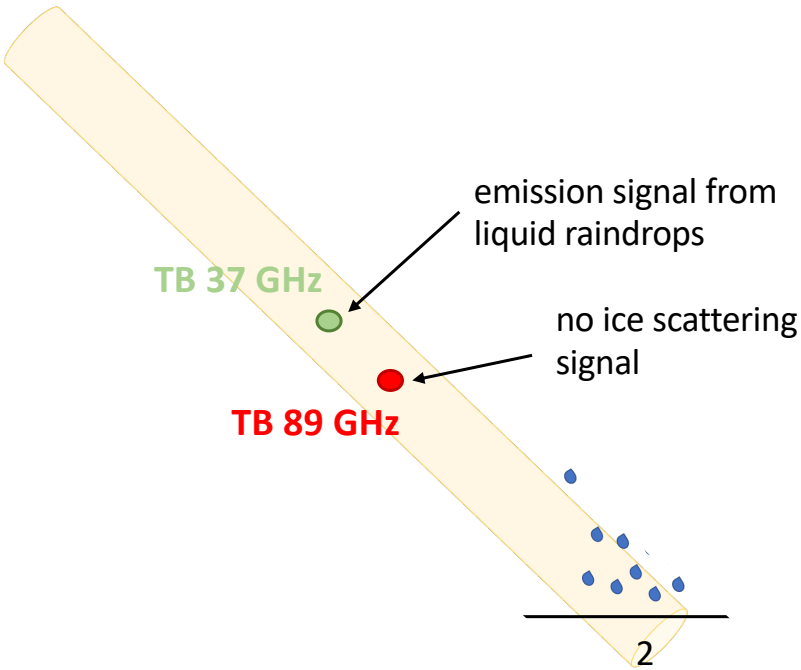

1
2
3
4
5
6

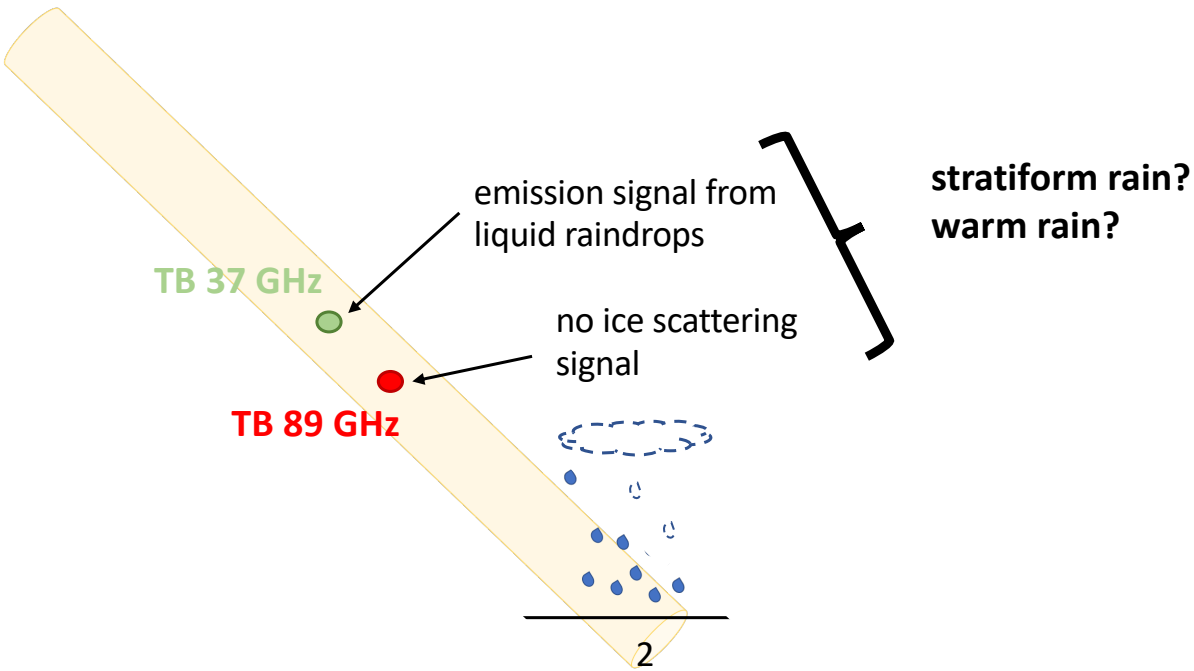

TB 89 GHz
1
2
3
4
5
6

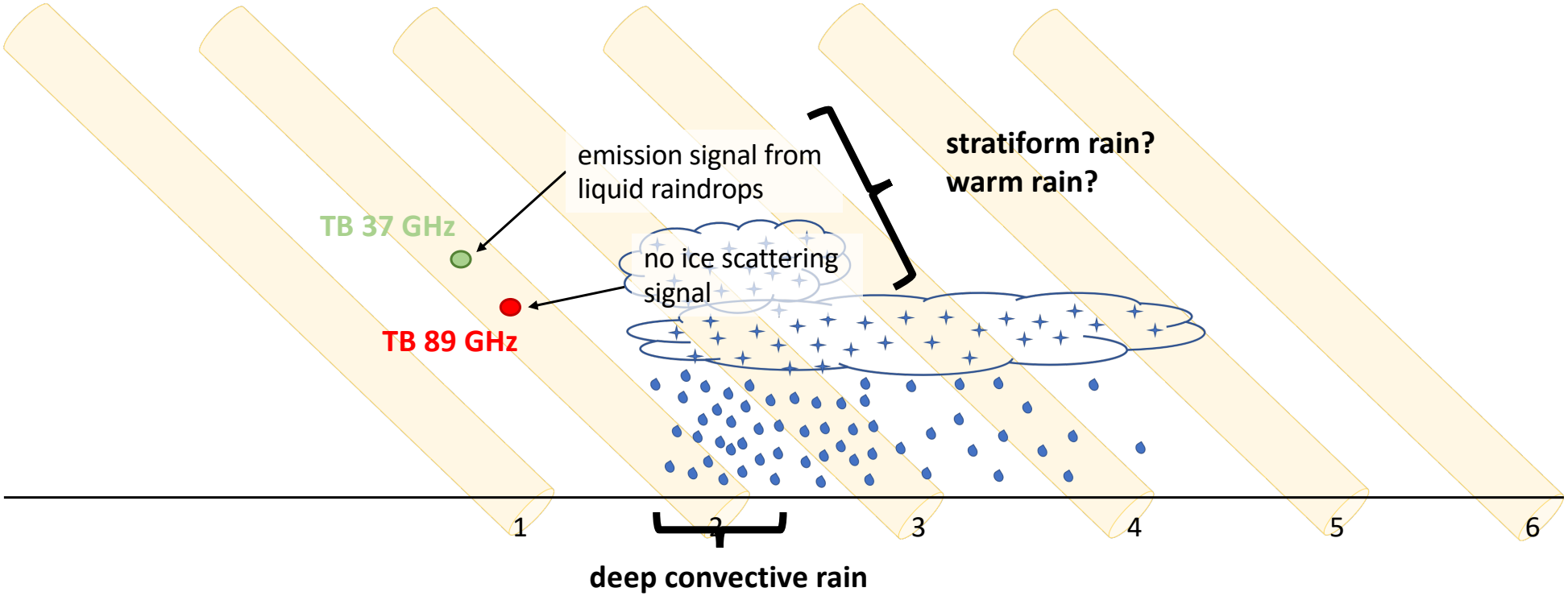

TB 89 GHz
TB 37 GHz
1
2
3
4
5
6

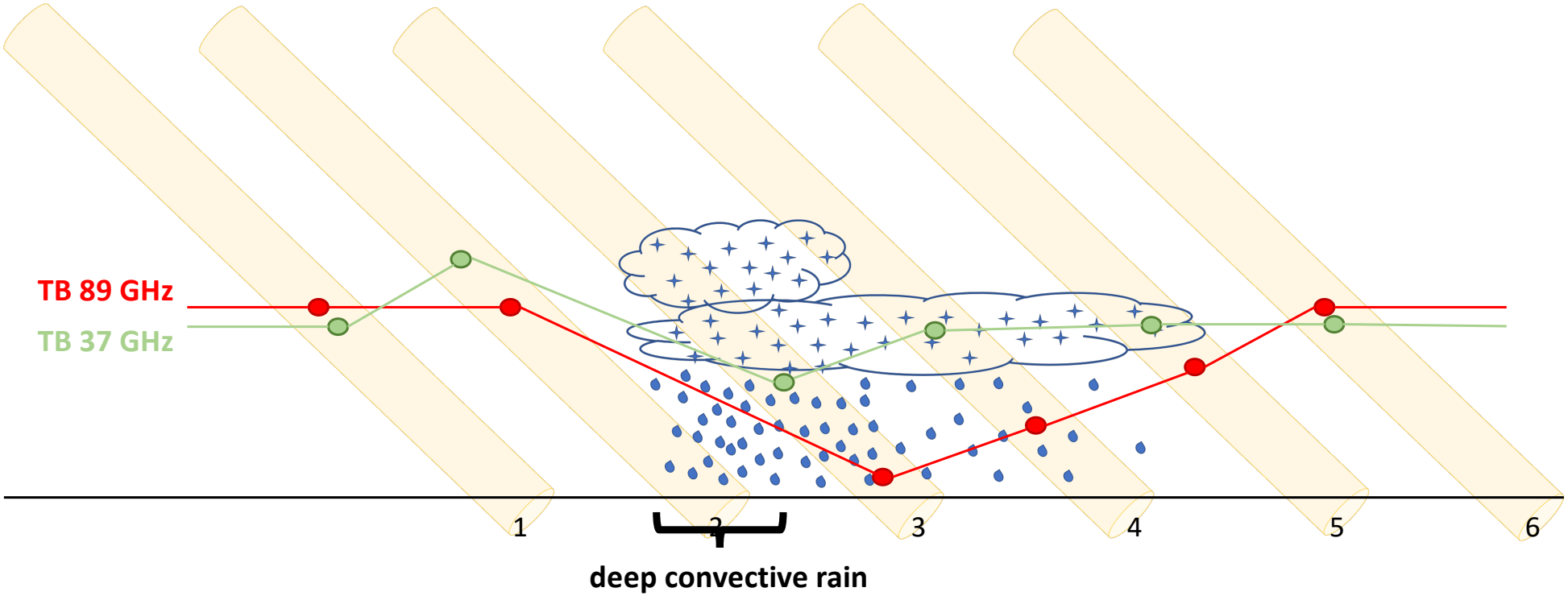

TB 37 GHz
TB 89 GHz
2

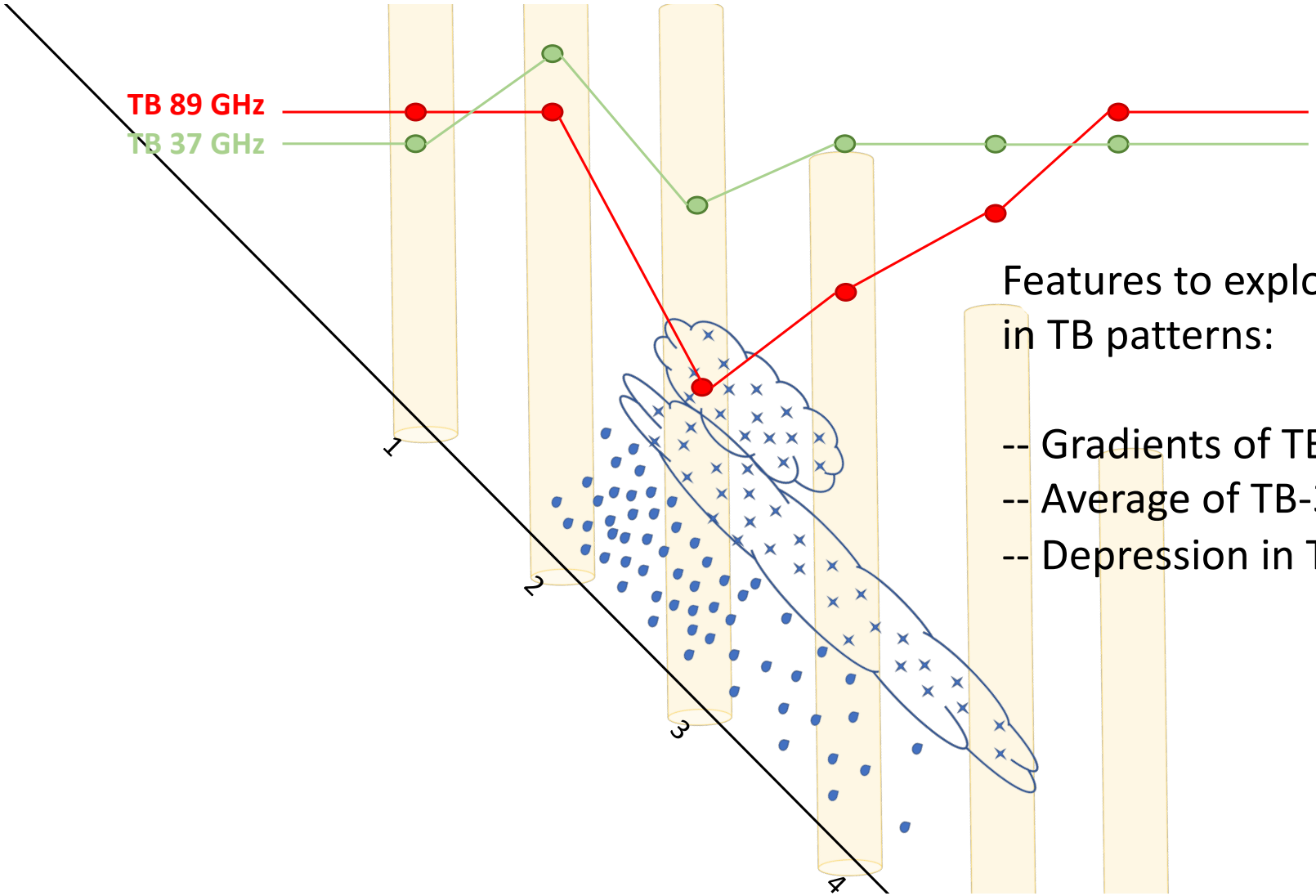

emission signal from
liquid raindrops
TB 37 GHz
TB 89 GHz
2


emission signal from
liquid raindrops
TB 37 GHz
no ice scattering
signal
TB 89 GHz
2


emission signal from
liquid raindrops
TB 37 GHz
no ice scattering
signal
TB 89 GHz
stratiform rain?
warm rain?
2


emission signal from
liquid raindrops
TB 37 GHz
TB 89 GHz
no ice scattering
signal
stratiform rain?
warm rain?
1
2
3
4
5
6
deep convective rain

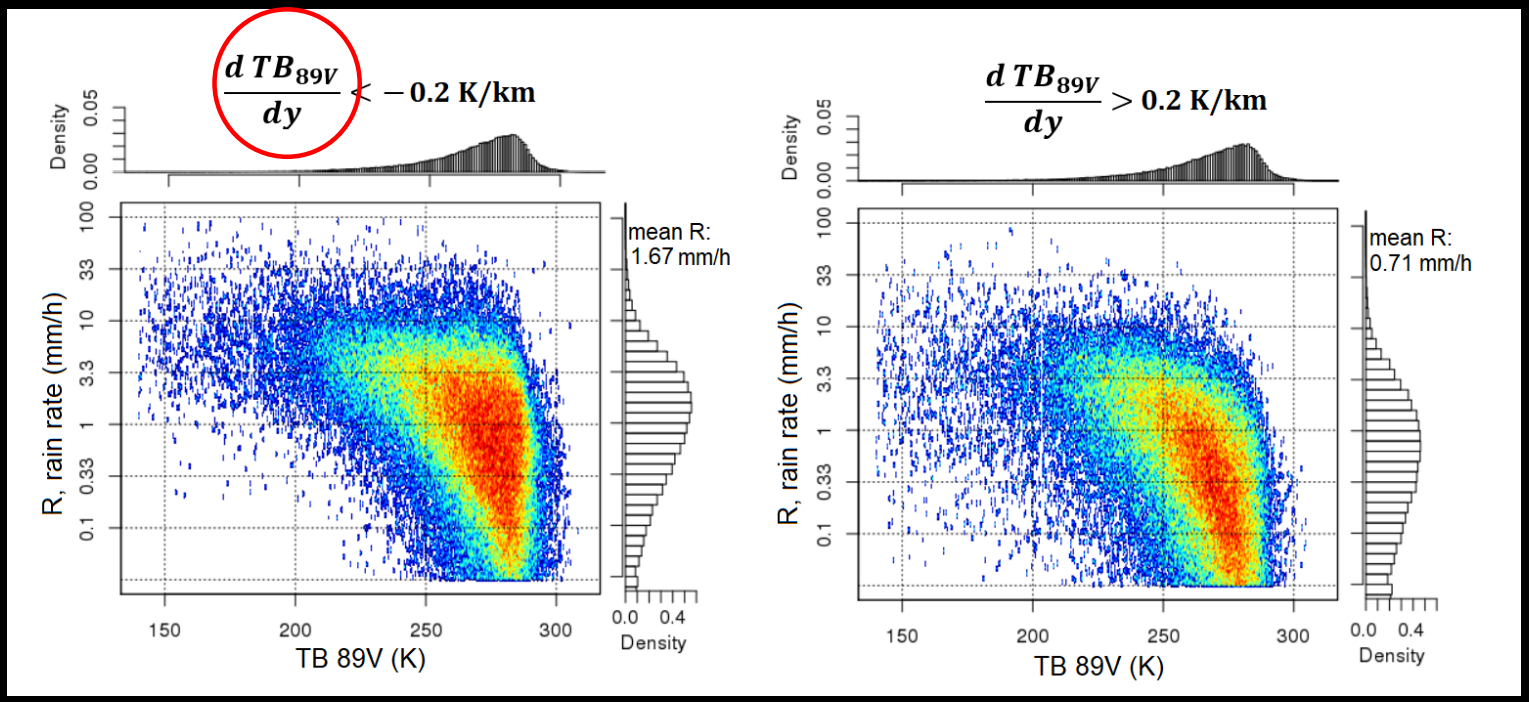

TB 89 GHz
TB 37 GHz
1
2
3
4
5
6
deep convective rain



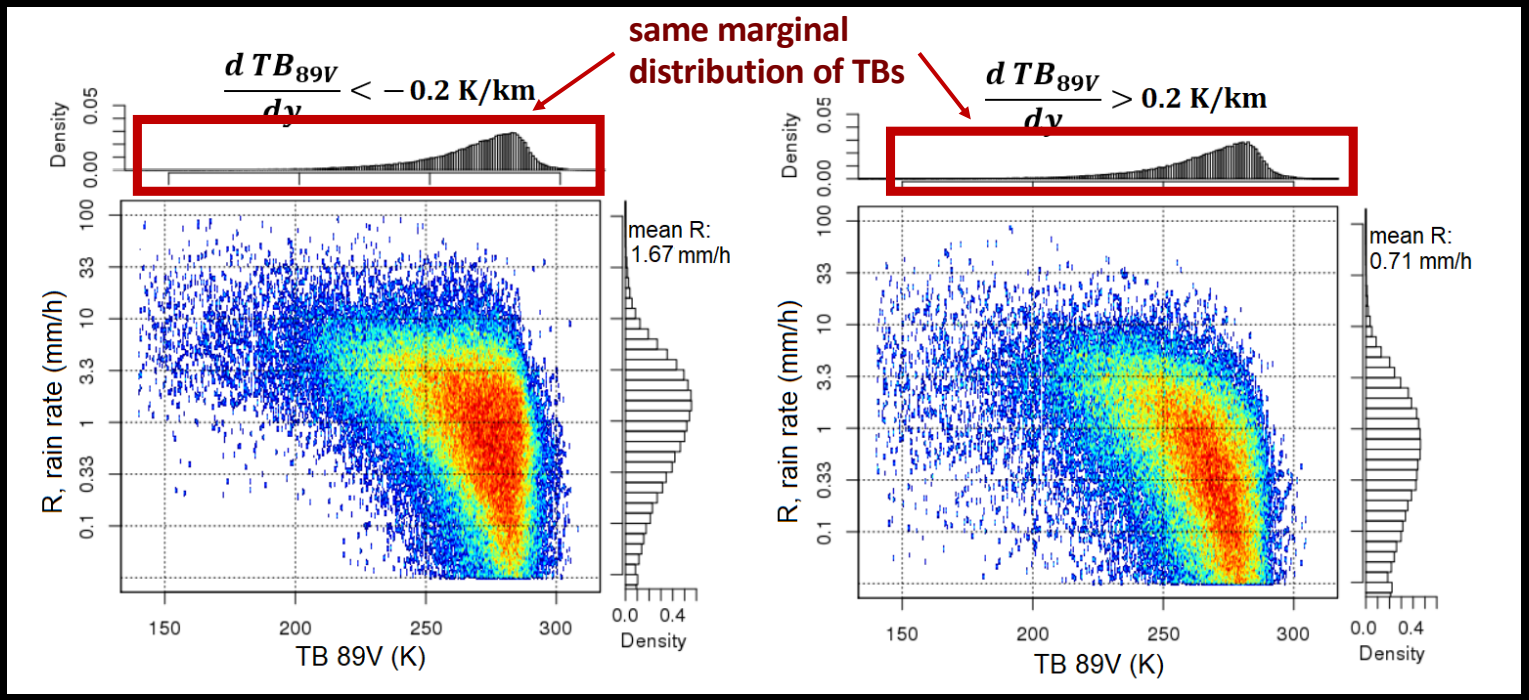
Features to explore
in TB patterns:

-- Gradients of TB-89, TB-37
-- Average of TB-37
-- Depression in TB-89

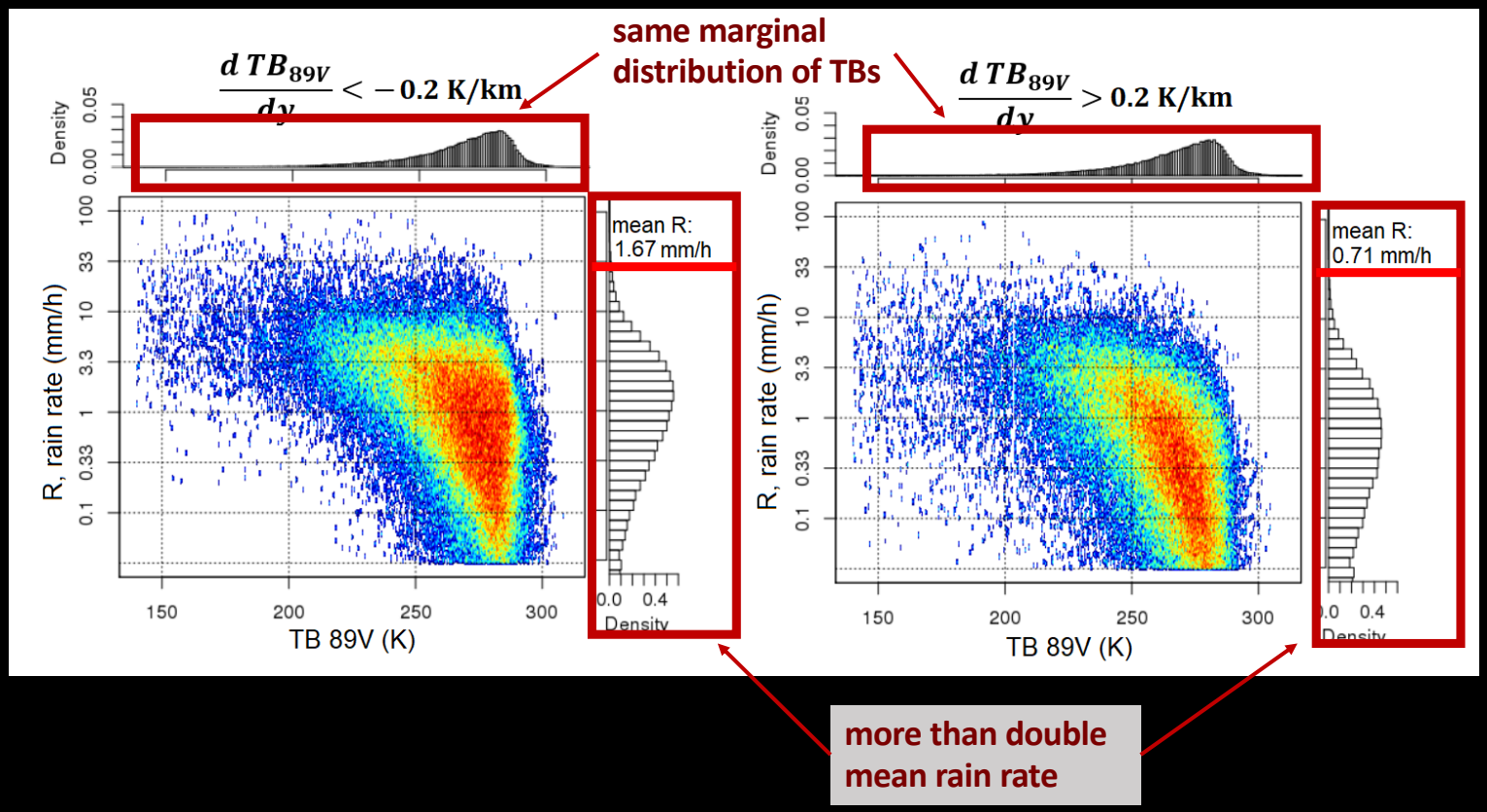
For ice-scattering sensitive TBs (TB_89) the gradient along the observation direction is a predictor of the rain rate (independently from the TB value)



For ice-scattering sensitive TBs (TB_89) the gradient along the observation direction is a predictor of the rain rate (independently from the TB value)

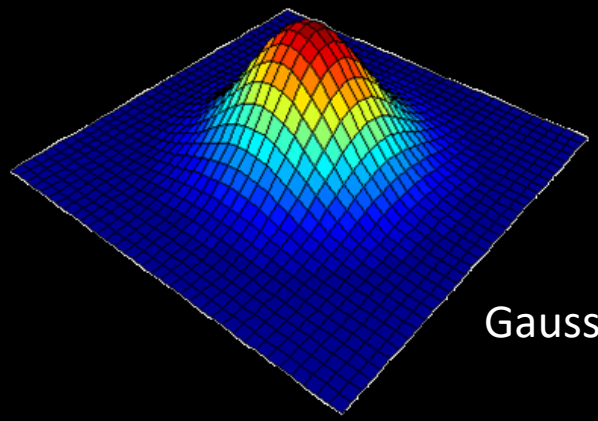


For ice-scattering sensitive TBs (TB_89) the gradient along the observation direction is a predictor of the rain rate (independently from the TB value)

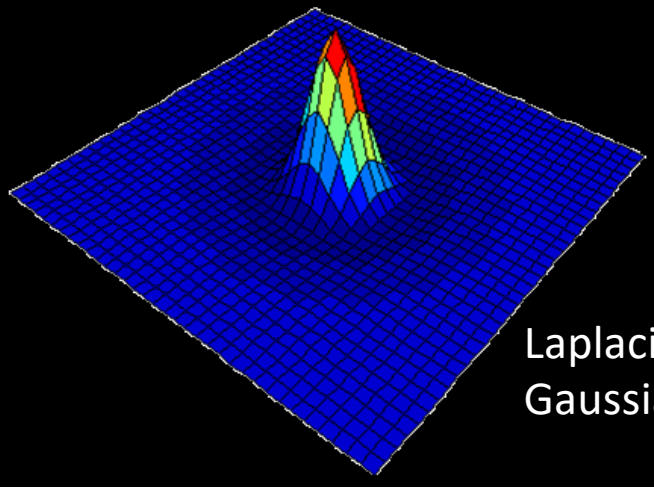


Convolution filters to extract spatial information from fields of TB

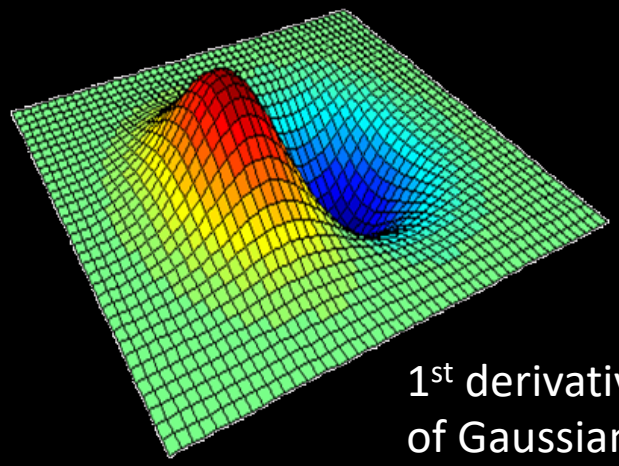
- Pattern extraction
- Spatial averaging / smoothing
- Spatial differentiation / edge detections / gradients extraction
- Multiscale decompositions (wavelets)



Gaussian



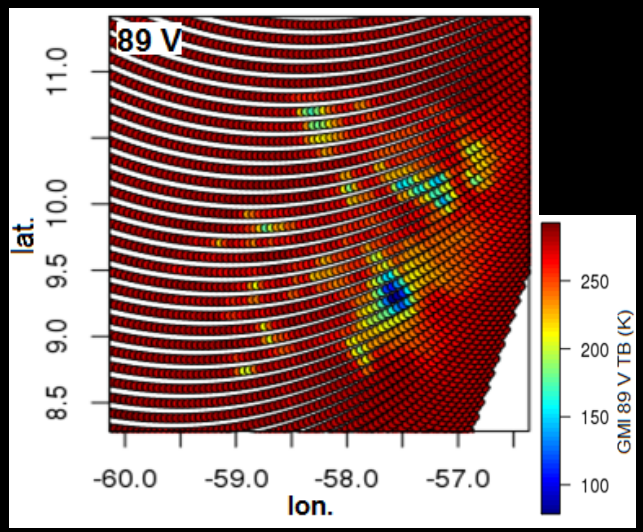
Laplacian of Gaussian



1st derivative of Gaussian

Convolution filters to extract spatial information from fields of TB

"nonlocal" parameter



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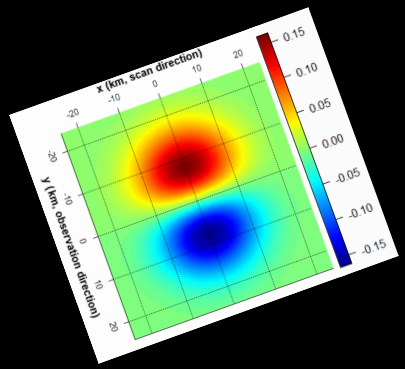

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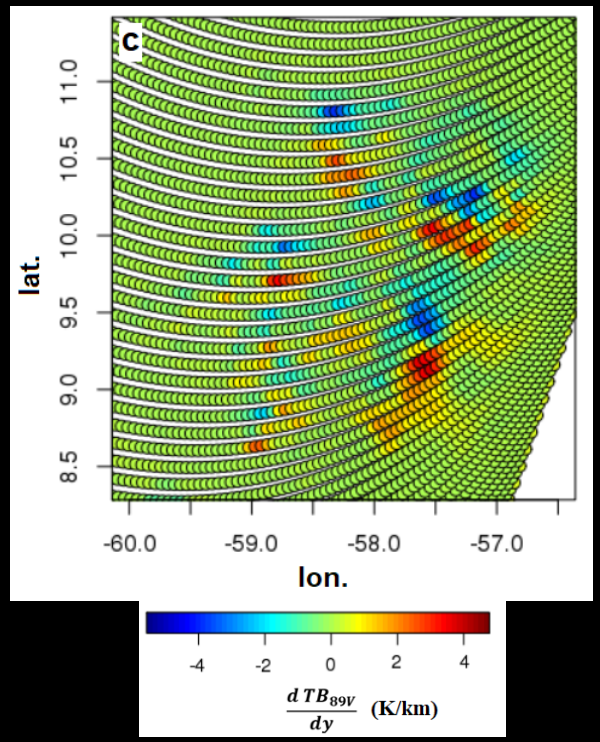
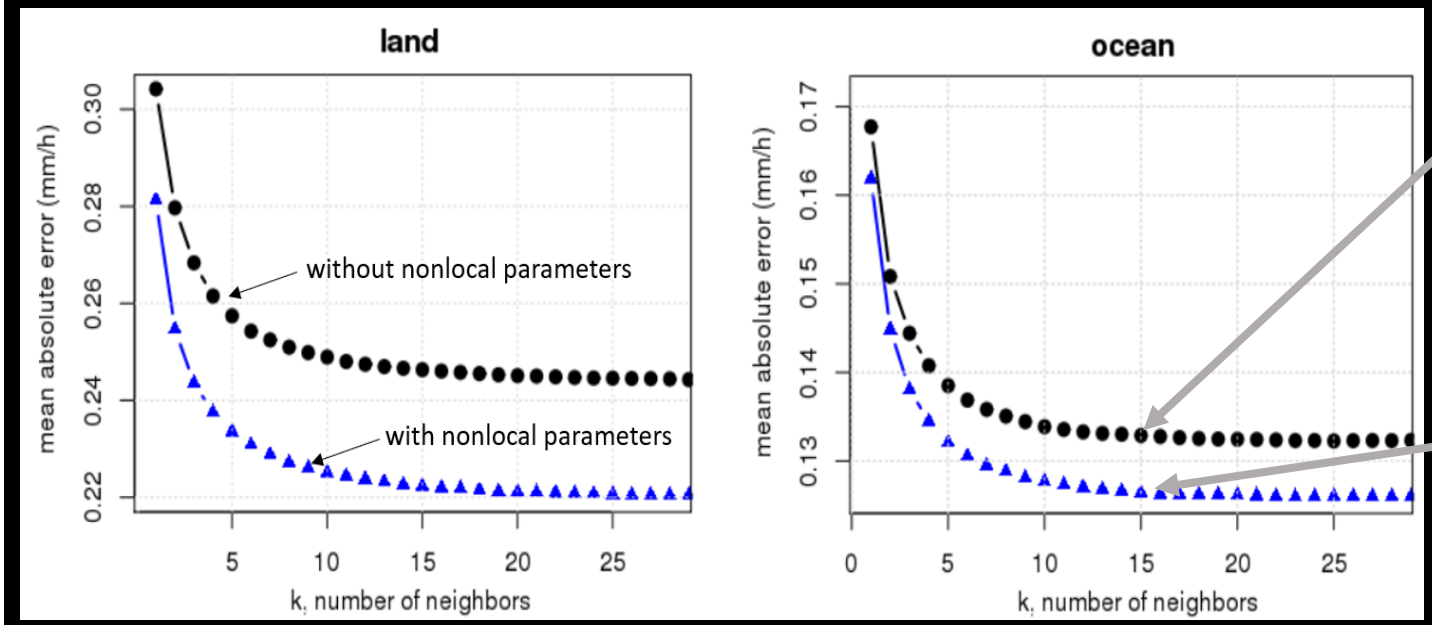


KNN retrieval from GMI over land with a 700 000 - profile database:

MEAN ABSOLUTE ERROR



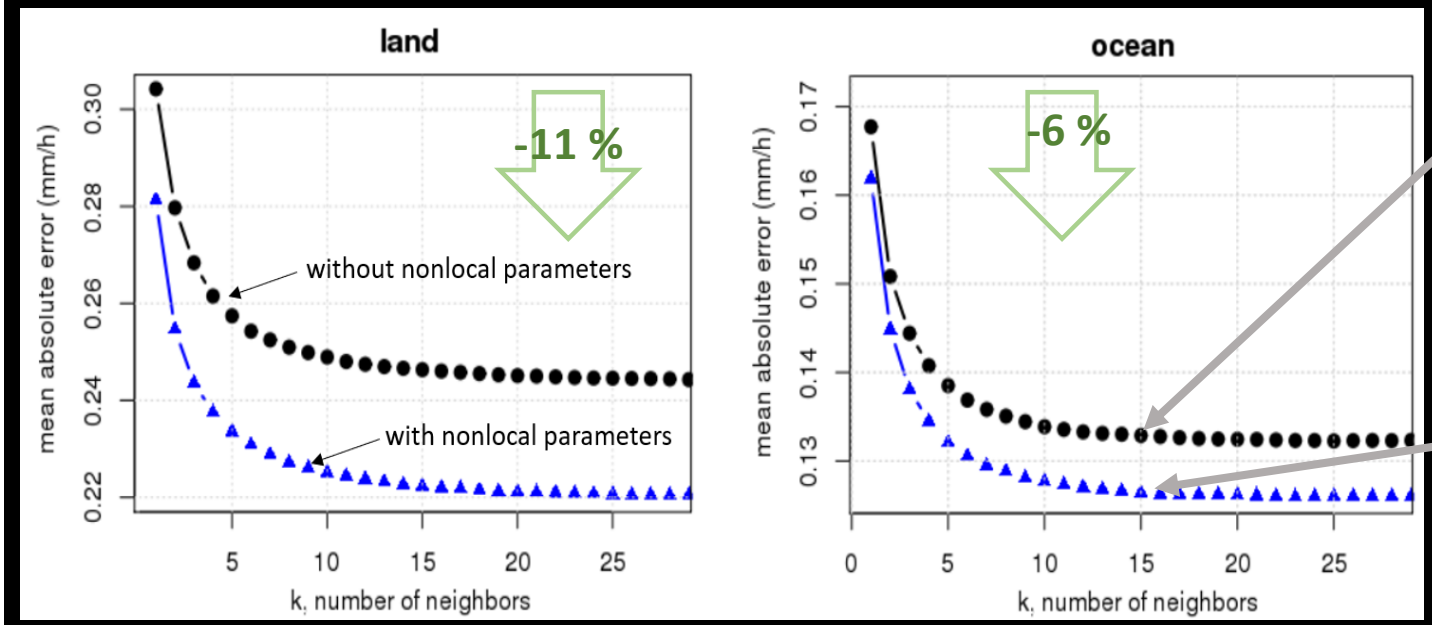
13 "pixel" TBs
+ 2m temp. + surf. type

13 "pixel" TBs
+ 2m temp. + surf. type
+ 3 nonlocal param. (at 37 and 89 GHz)

- Along-track spatial derivative of 37 GHz V TB
- Along-track spatial derivative of 89 GHz V TB
- Low-pass filtered 37 GHz V TB (Gaussian σ = 20 km)

KNN retrieval from GMI over land with a 700 000 - profile database:

MEAN ABSOLUTE ERROR



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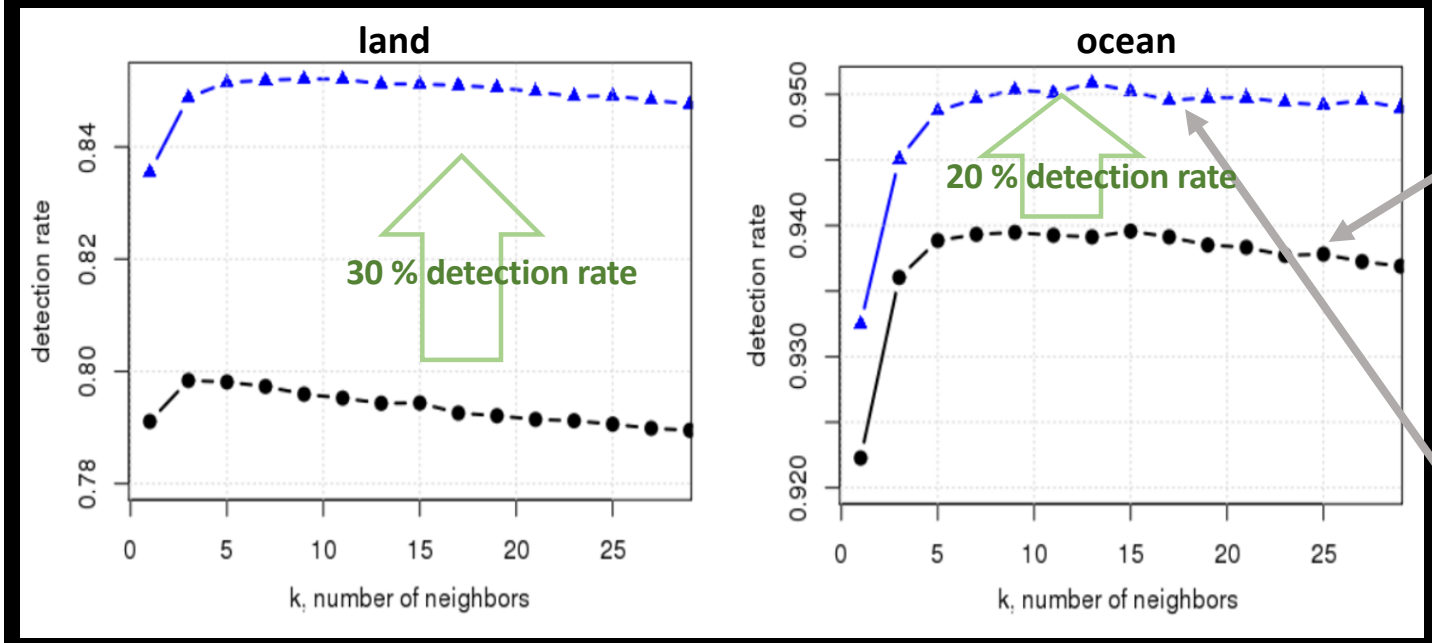
KNN retrieval from GMI over land with a 700 000 - profile database:

DETECTION RATE



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13 "pixel" TBs
+ 2m temp. + surf. type
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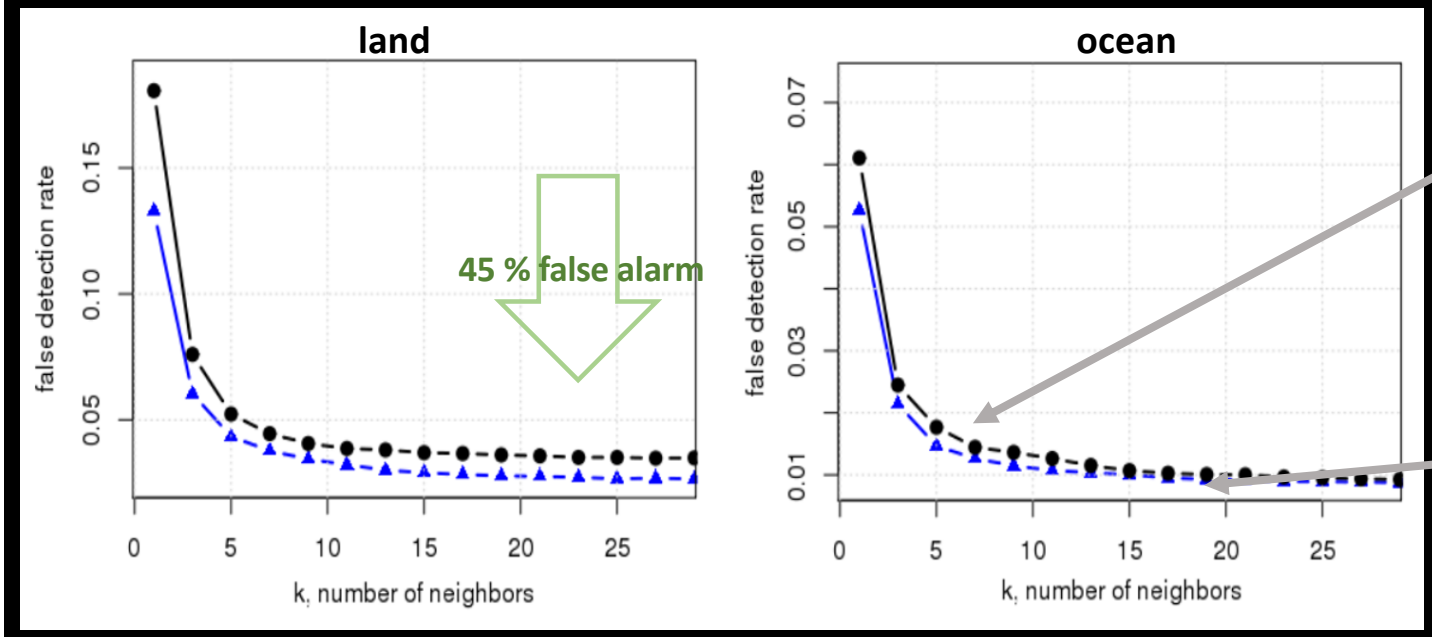
KNN retrieval from GMI over land with a 700 000 - profile database:

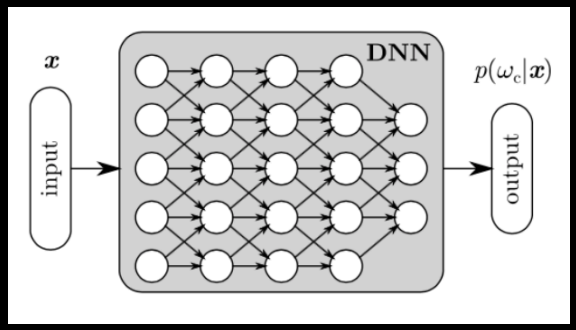
FALSE DETECTION RATE



13 "pixel" TBs
+ 2m temp. + surf. type

13 "pixel" TBs
+ 2m temp. + surf. type
+ 3 nonlocal param. (at 37 and 89 GHz)

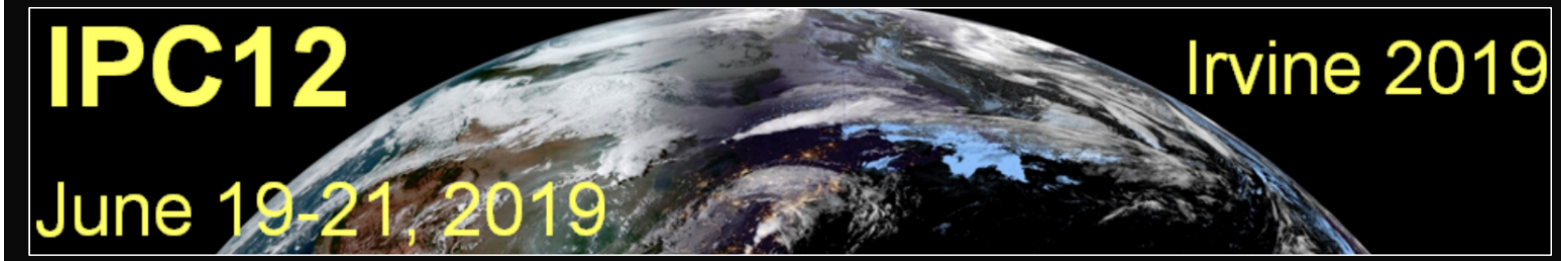
What's next?



- Is Machine Learning (ML) the solution?
- Eventually maybe, but not without physically-based dimensionality reduction first
- Train Convolutional Neural Networks (CNNs) and by backwards methods see what patterns were retained in the training (attribution methods)
- Could work on specific storm systems, e.g., snowstorms and learn patterns that "detect snow", etc.

- Guilloteau, C., and E. Foufoula-Georgiou, Beyond the pixel: using patterns and multi-scale spatial information to improve the retrieval of precipitation from space-borne passive microwave imagers, *J. Atmos. Oceanic Technol.,* in final revision, 2019.

- Guilloteau, C., E. Foufoula-Georgiou, Multiscale evaluation of satellite precipitation products: effective resolution of IMERG, Chapter 3.5, in Satellite Precipitation Measurement, Springer, to appear, 2019



http://ipc12.eng.uci.edu

Efi Foufoula-Georgiou, Christa Peters-Lidard, Joe Turk, Vincenzo Levizzani, Witold Krajewski, Remko Uijlenhoet, Terri Hogue

efi@uci.edu

Special collection of papers – March 2020

Precipitation estimation and prediction: Advances in hydroclimatology and impact studies (IPC12)

- Journal of Hydrometeorology (JHM),
- Journal of Climate (JCLI),
- Journal of Atmospheric and Oceanic Technology (JTECH),
- Journal of Applied Meteorology and Climatology (JAMC), and
- Weather Climate and Society (WCAS)