Two ways to account for the dependence of microwave observations of precipitation on uncertain microphysics

Z.S.Haddad (JPL), J. Steward (UCLA), S. Kacimi (JPL), J. Munchak (GSFC), H.-C. Tseng (UC Davis), S. Hristova-Veleva (JPL), S.-H. Chen (UC Davis),

Explicitly account for habit and size distribution assumptions, making sure that **additional simplifying assumptions are consistent** with observations

or

Try to **smooth over habit and size assumptions** to make sure that analysis does not try to adjust poorly modeled parameters (and that it adjusts prognostic variables consistently with covariances)

⇒ Assume closed-form diameter distributions (e.g. Γ):

$$N(D) = N_0 \; D^{\mu} \; e^{-\Lambda D}$$

Let's try to interpret the parameters in terms of physically meaningful quantities:

$$D_m = \frac{\int D \; D^3 N(D) \; dD}{\int D^3 N(D) \; dD} = \frac{\mu + 4}{\Lambda}$$

$$q = \int \frac{4}{3}\pi \left(\frac{D}{2}\right)^3 \rho \; N(D) \; dD = \frac{\pi}{6} \frac{\rho \; \Gamma(\mu+1) \; D_m^{\mu+1}}{(\mu+4)^{\mu+1}} \; N_0$$

$$\sigma_m = \left(\frac{\int (D - D_m)^2 \; D^3 N(D) \; dD}{\int D^3 N(D) \; dD} \right)^{1/2} = \frac{D_m}{\sqrt{\mu + 4}}$$

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$\Rightarrow$ Assume closed-form diameter distributions (e.g. Γ):

In the models, typically assume N_0 constant and $\mu = 0$.

What that implies is:

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$$= \frac{\pi\rho}{24} N_0\ D_m$$

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What that implies is: $$D_m = \frac{24}{\pi \rho N_0} q$$

In particular,

- D_m/q = constant, and
- max(D_m)/min(D_m) = max(q)/min(q)

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In particular,

- D_m/q = constant, and
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But 3.5 mm / 0.5 mm ≠ max($R^{0.9}$)/min($R^{0.9}$) ≈ 100 mm/hr / 0.1 mm/hr

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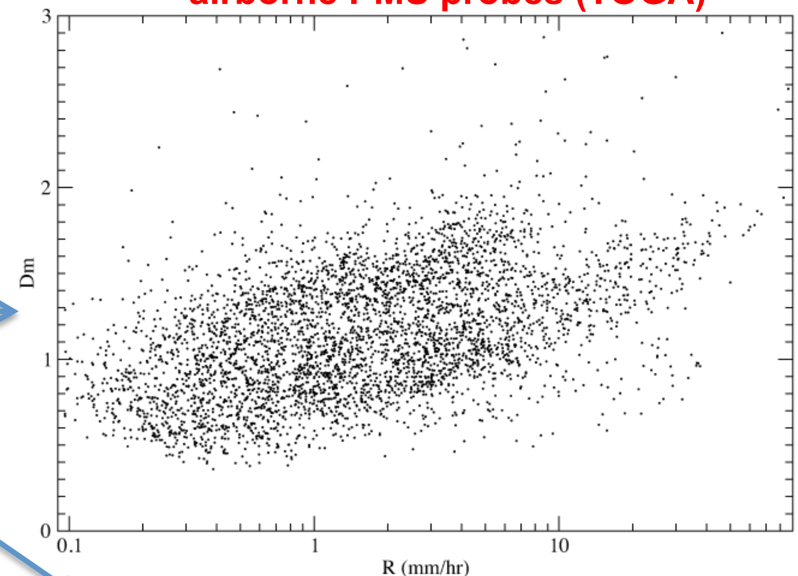
$\Rightarrow$ In fact, hydrometeor data suggest $D_m \sim q^{0.2}$ ± white noise

$D_m \sim q^{0.2}$ behavior in profiler data

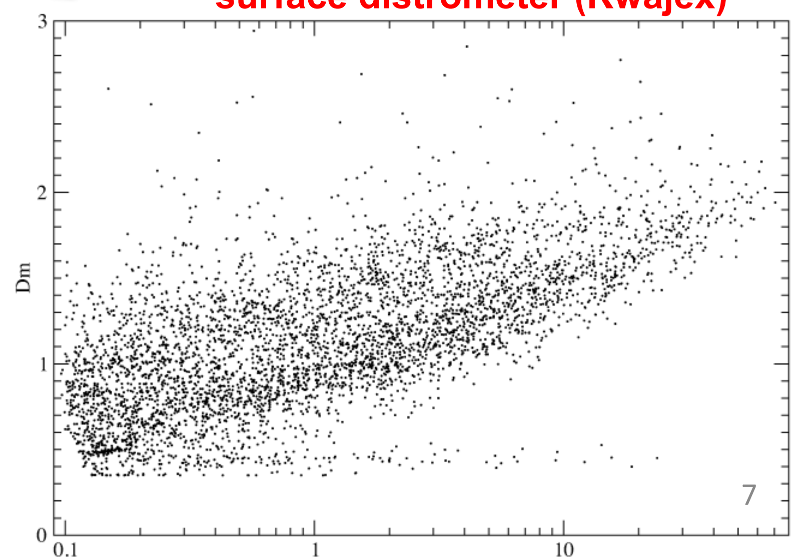
is consistent with TOGA-COARE

and Kwajex data …

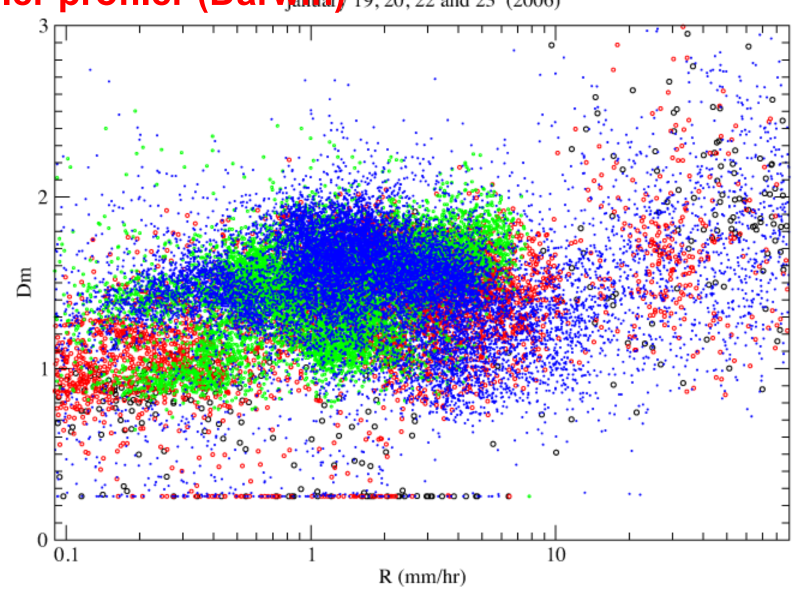
airborne PMS probes (TOGA)



surface distrometer (Kwajex)



Doppler profiler (Darwin)



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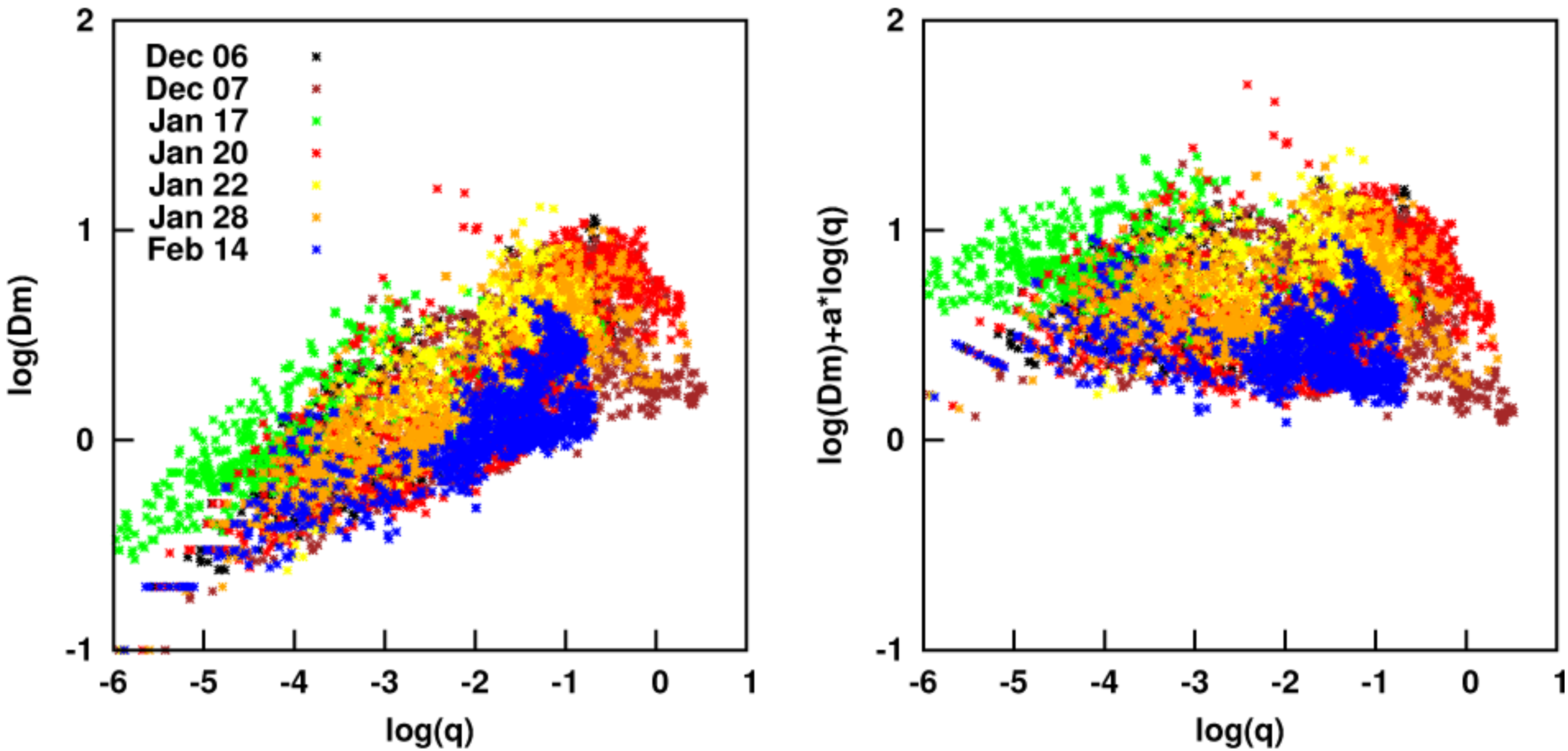
⇒ In fact, hydrometeor data suggest $D_m \sim q^{0.2}$ ± white noise

2D video Distrometer (King City, ON – thanks to Environment Canada)



⇒ Assume closed-form diameter distributions (e.g. Γ):

$$N(D) = N_0 \, D^{\mu} \, e^{-\Lambda D}$$

Fixing Λ is at least as problematic:

$$D_m = \frac{\int D \, D^3 N(D) \, dD}{\int D^3 N(D) \, dD} = \frac{\mu + 4}{\Lambda}$$

$$\sigma_m = \left(\frac{\int (D - D_m)^2 \, D^3 N(D) \, dD}{\int D^3 N(D) \, dD} \right)^{1/2} = \frac{D_m}{\sqrt{\mu + 4}}$$

The above imply:

$$D_m = \frac{D_m^2 / \sigma_m^2}{\Lambda} \Rightarrow \frac{D_m}{\sigma_m^2} = const \quad \text{, i.e.} \quad \sigma_m = const \; D_m^{0.5}$$

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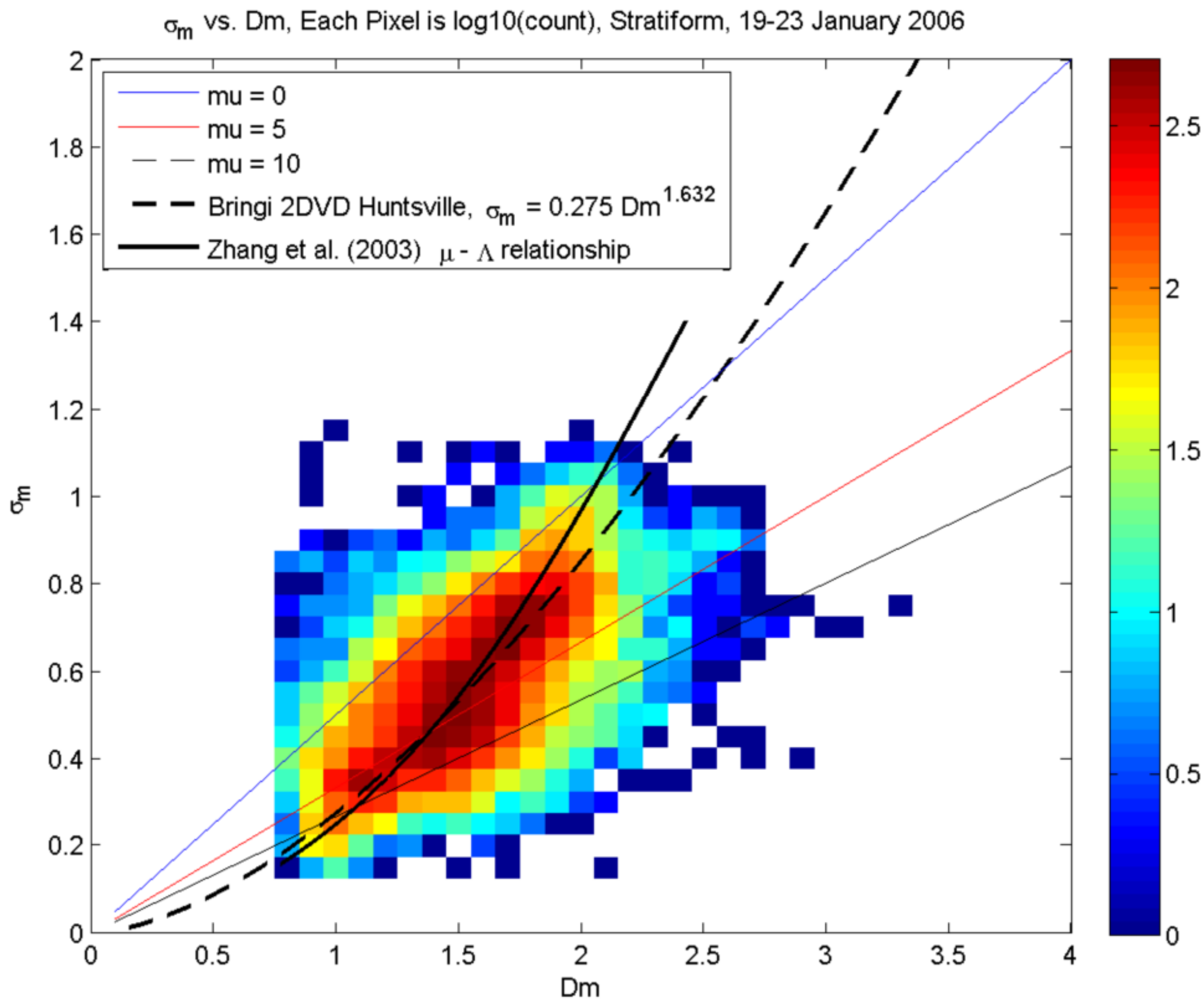

$$\sigma_m \neq const\ D_m^{0.5}$$

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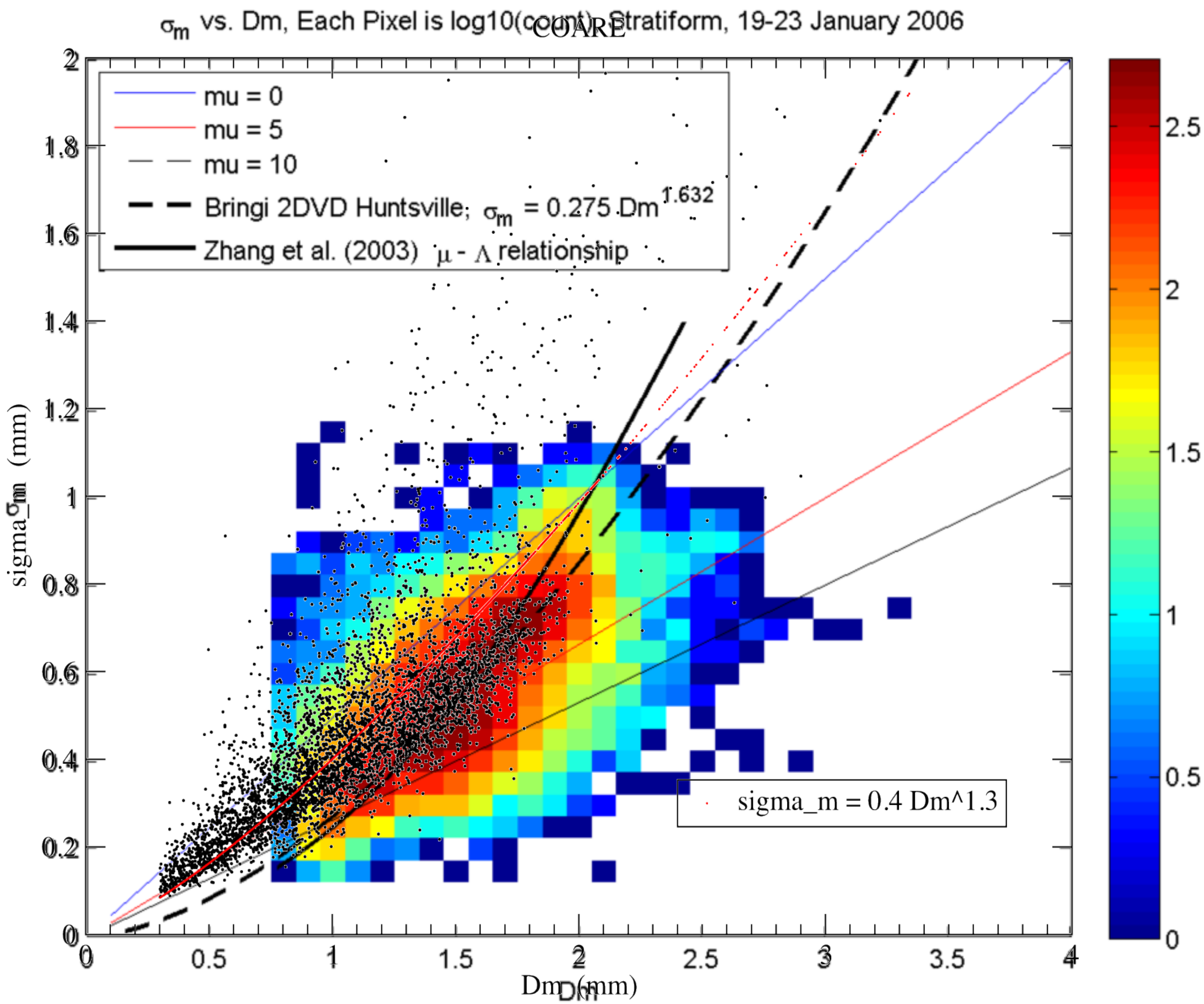

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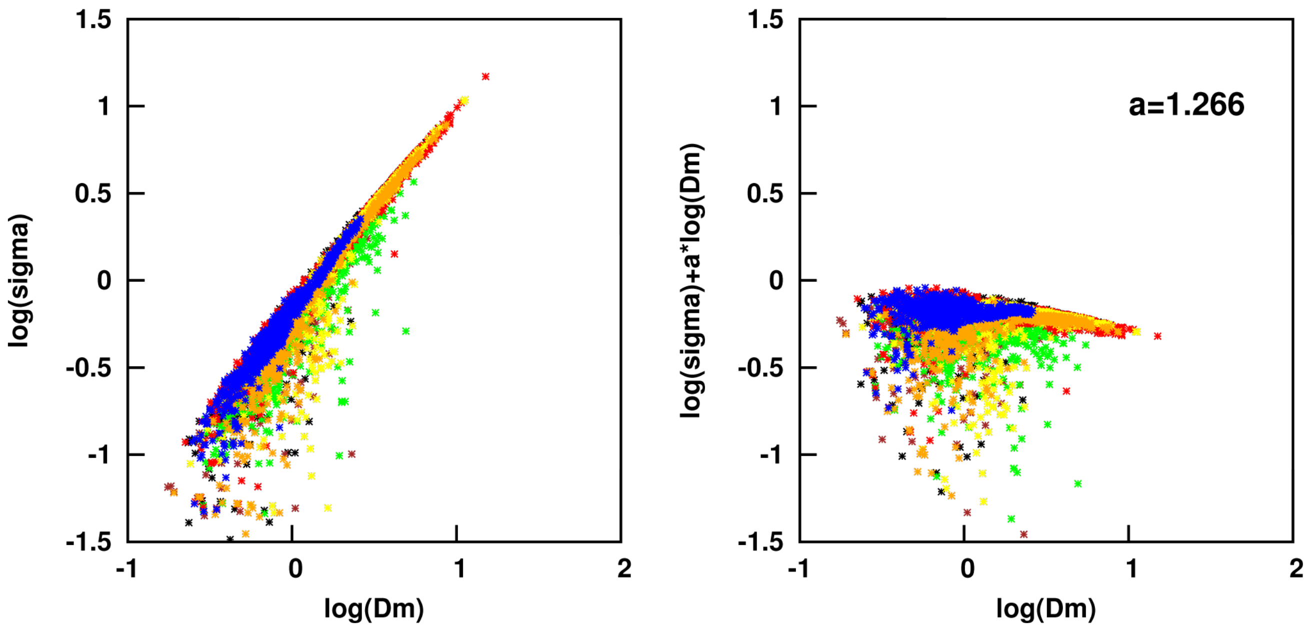

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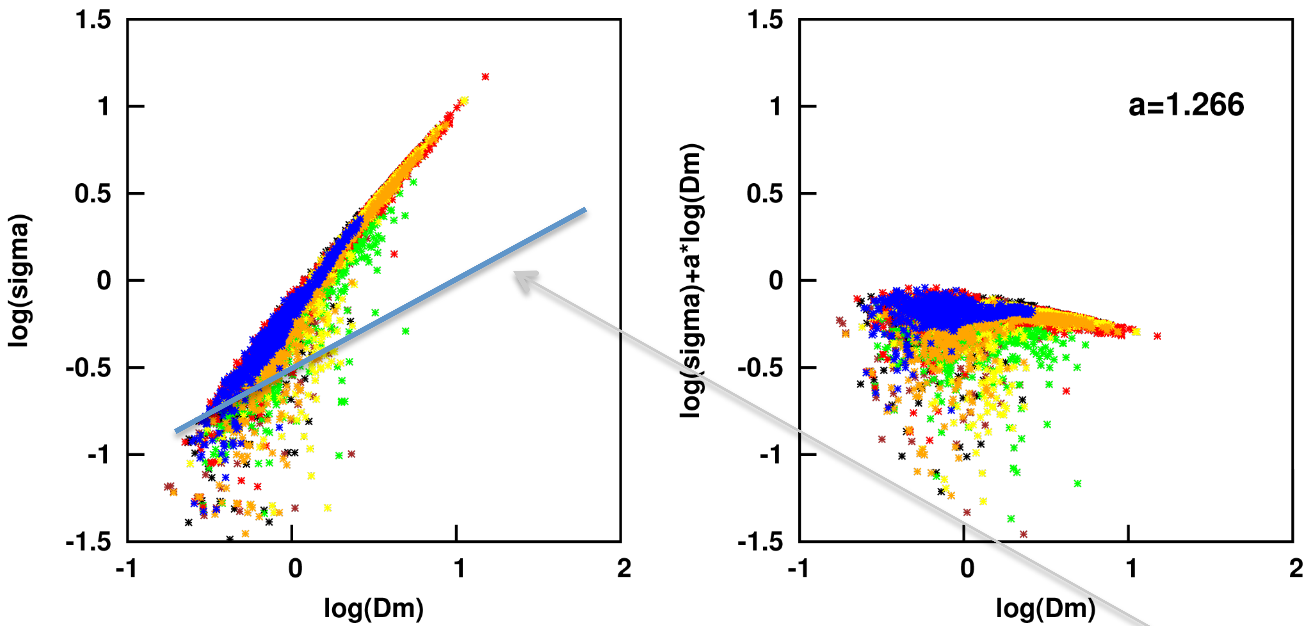

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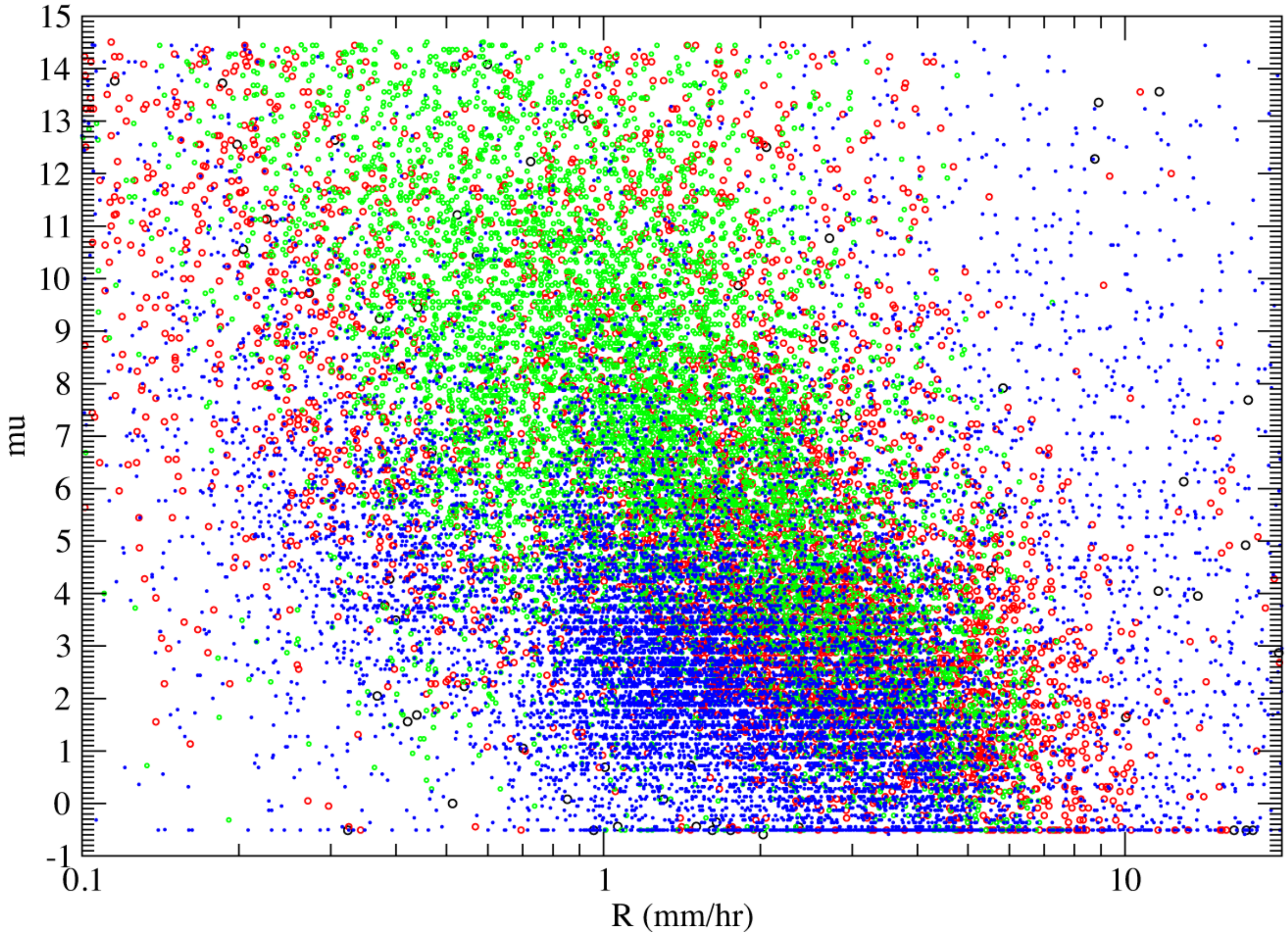
Darwin profiler, January 19+20 (blue), 22 (red) and 23 (green), 2006



Coup de grâce:

$$\frac{\partial \mu}{\partial t} + V \cdot \nabla \mu = ? \qquad \frac{\partial \sigma_m}{\partial t} + V \cdot \nabla \sigma_m = ?$$

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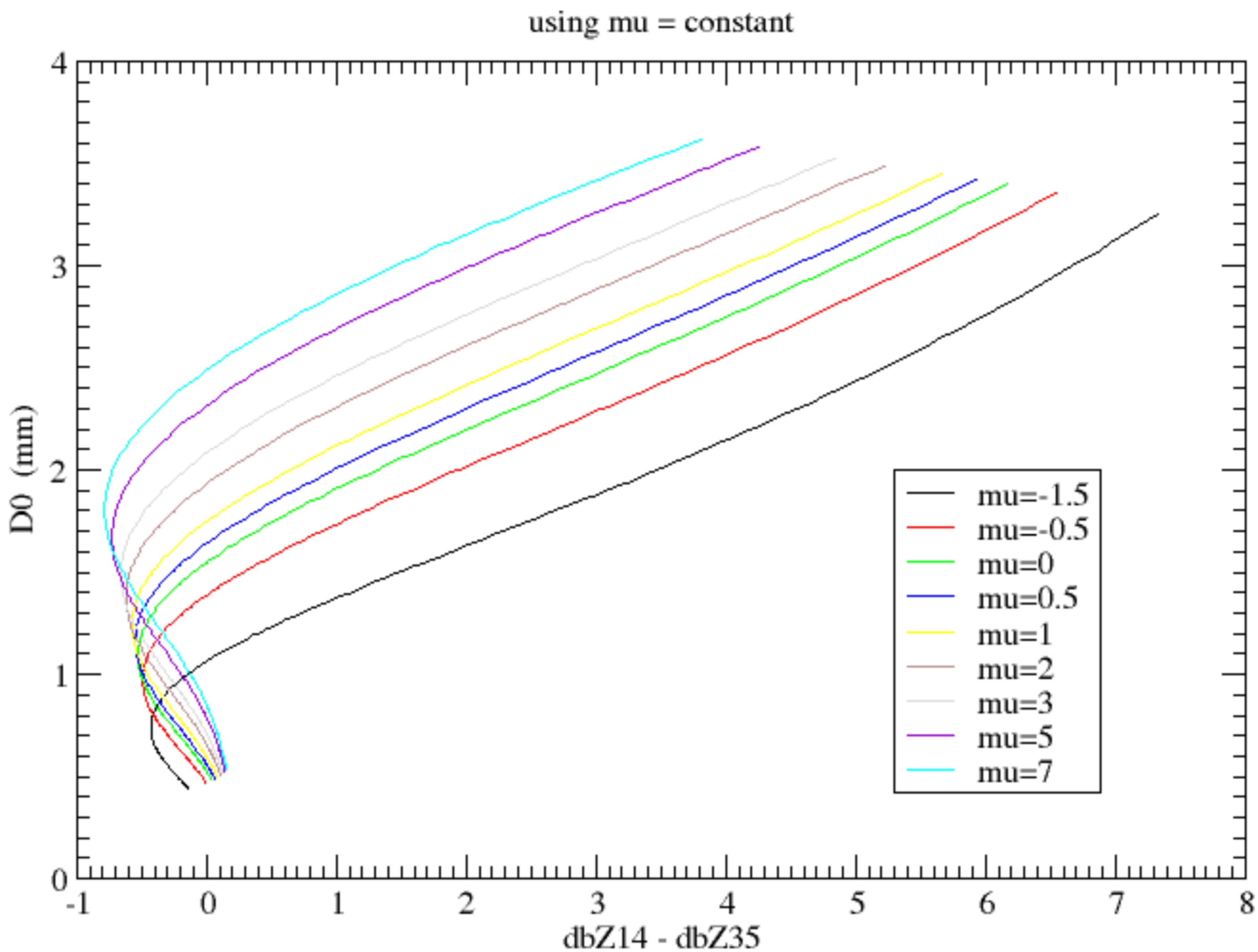

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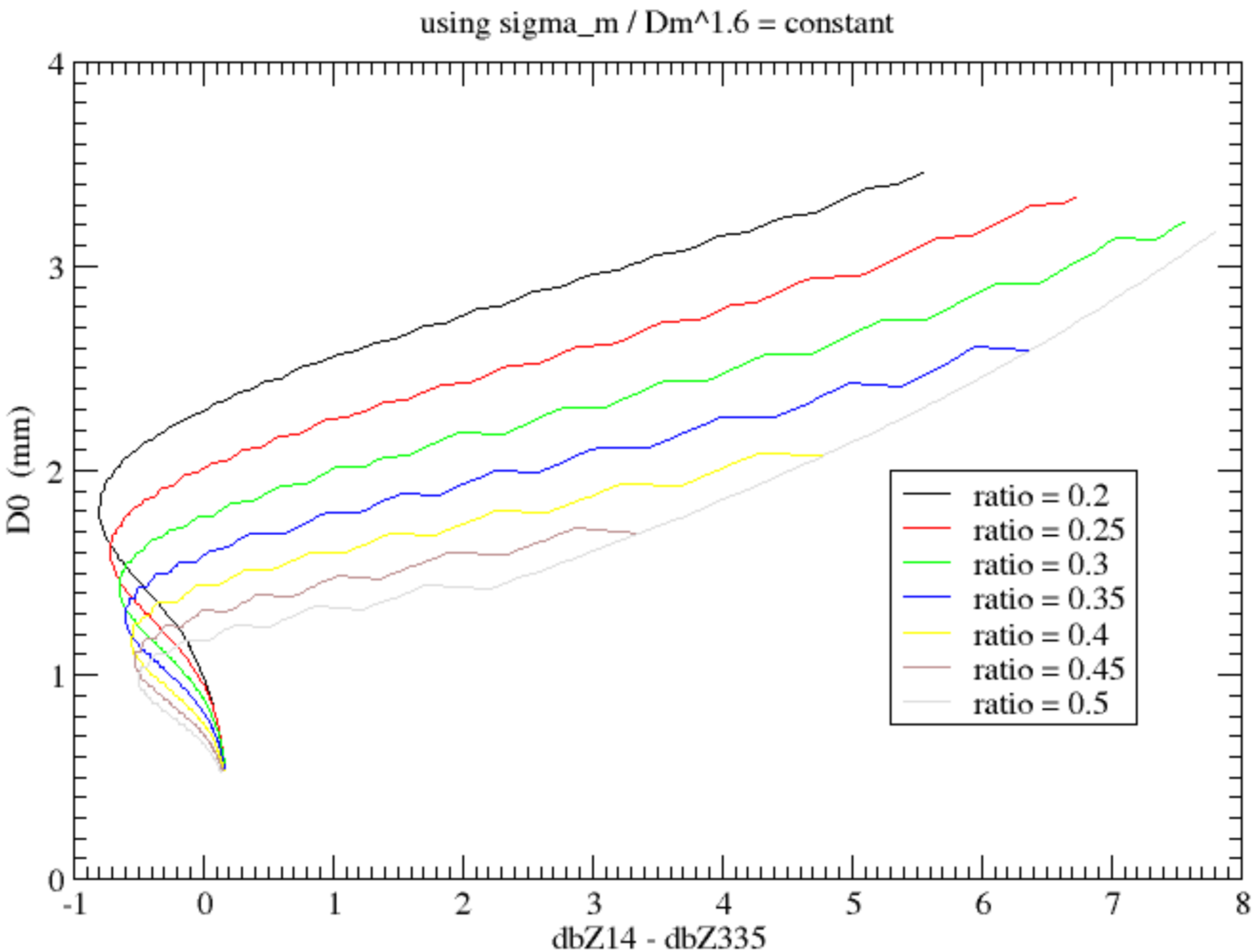

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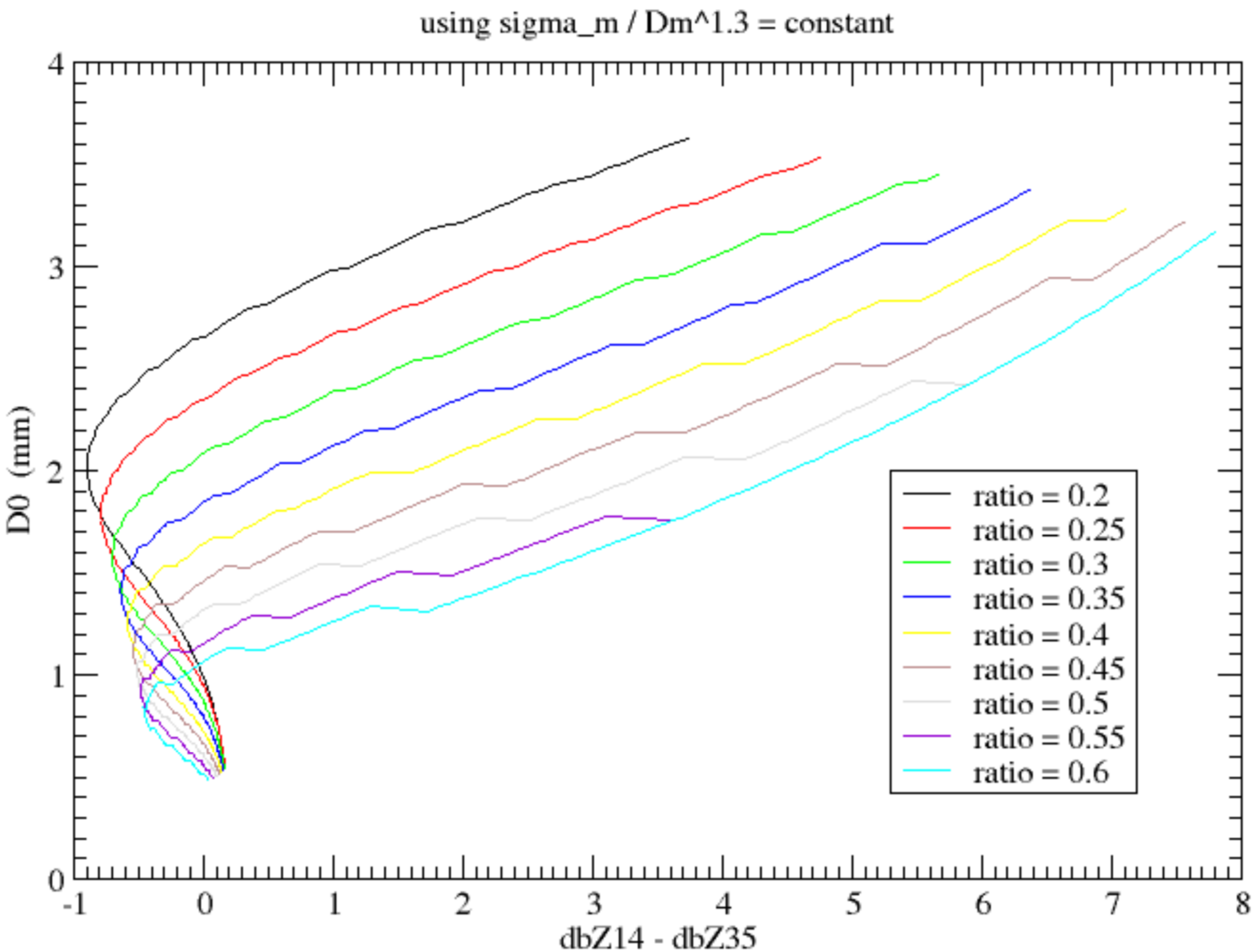

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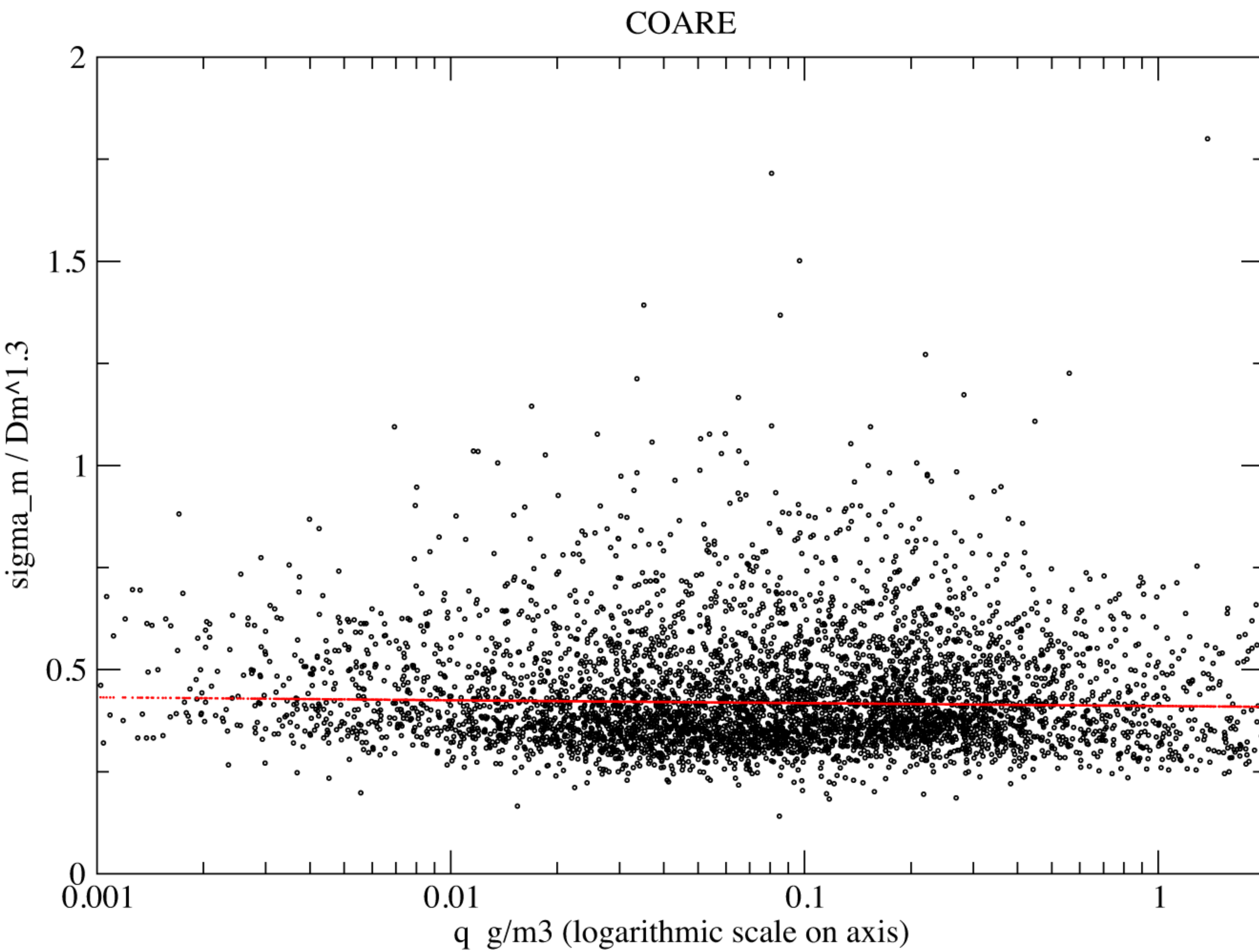

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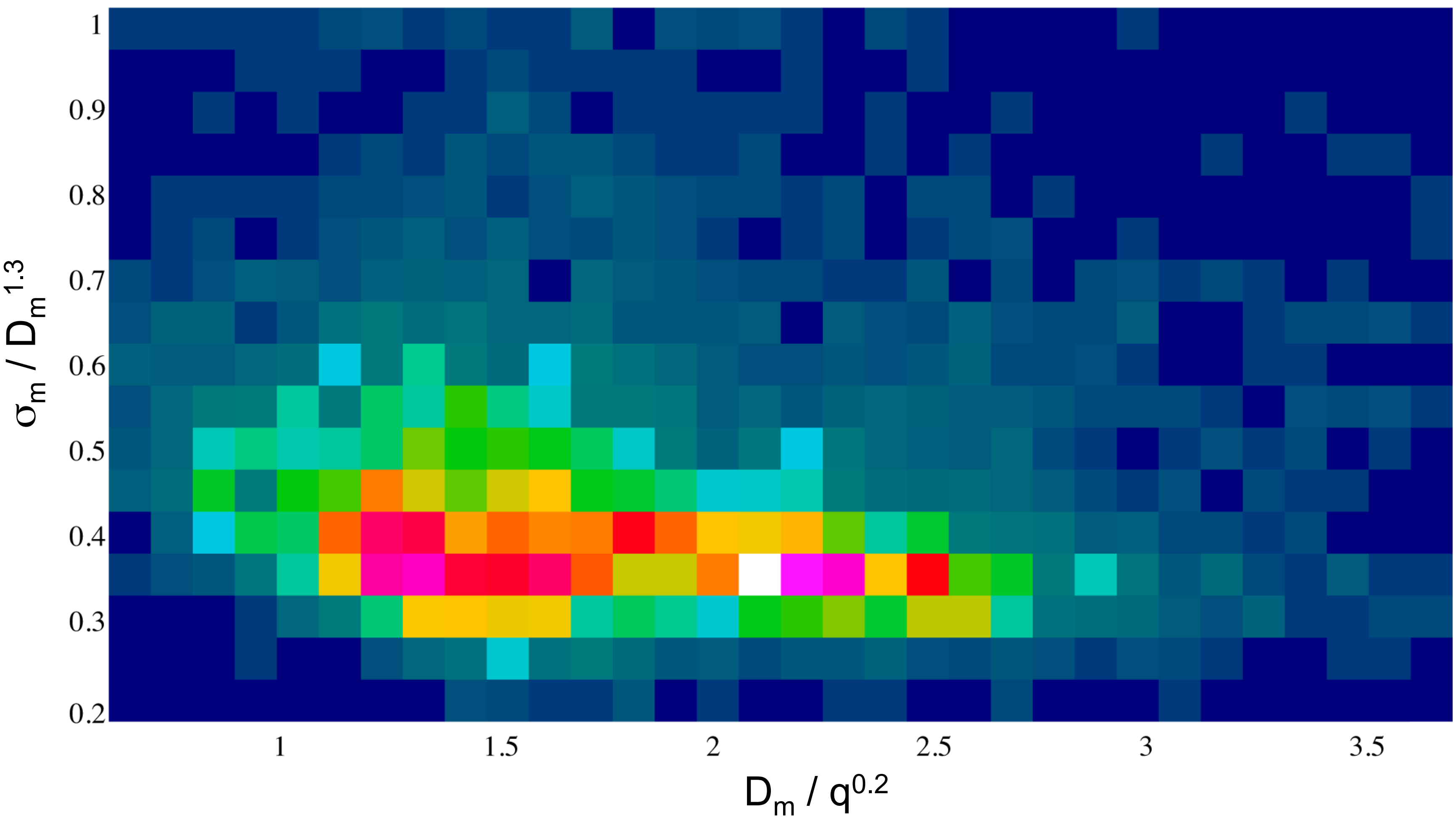
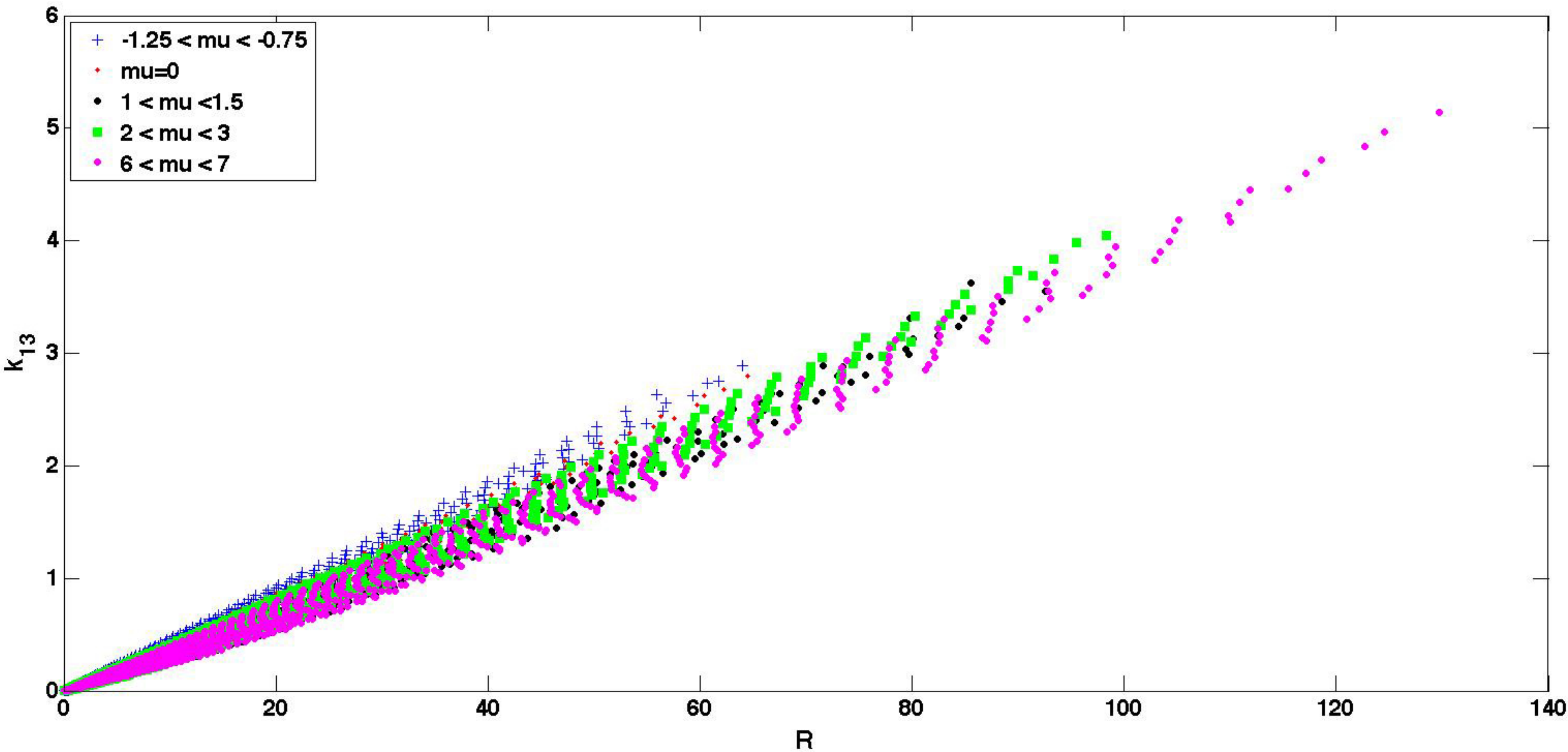
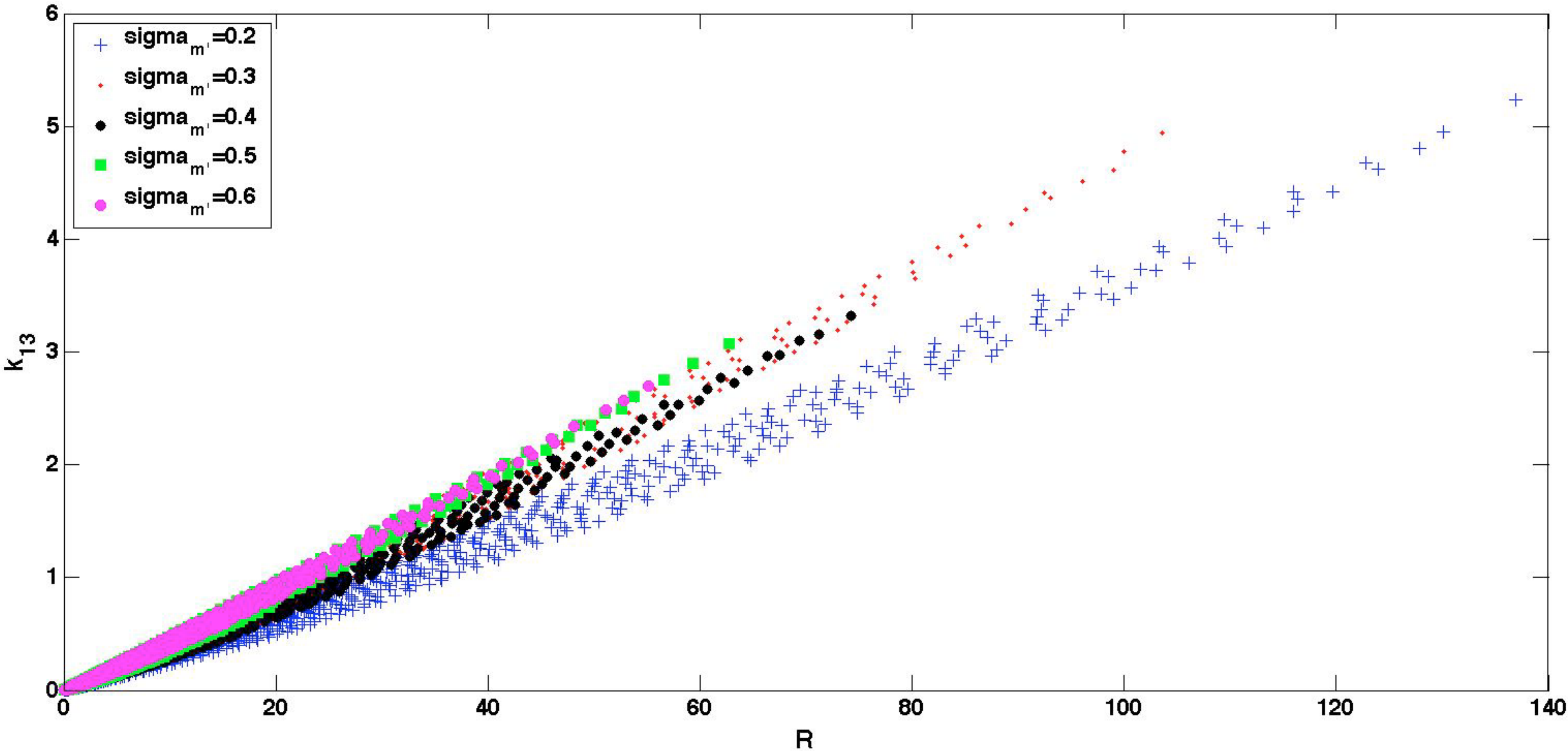


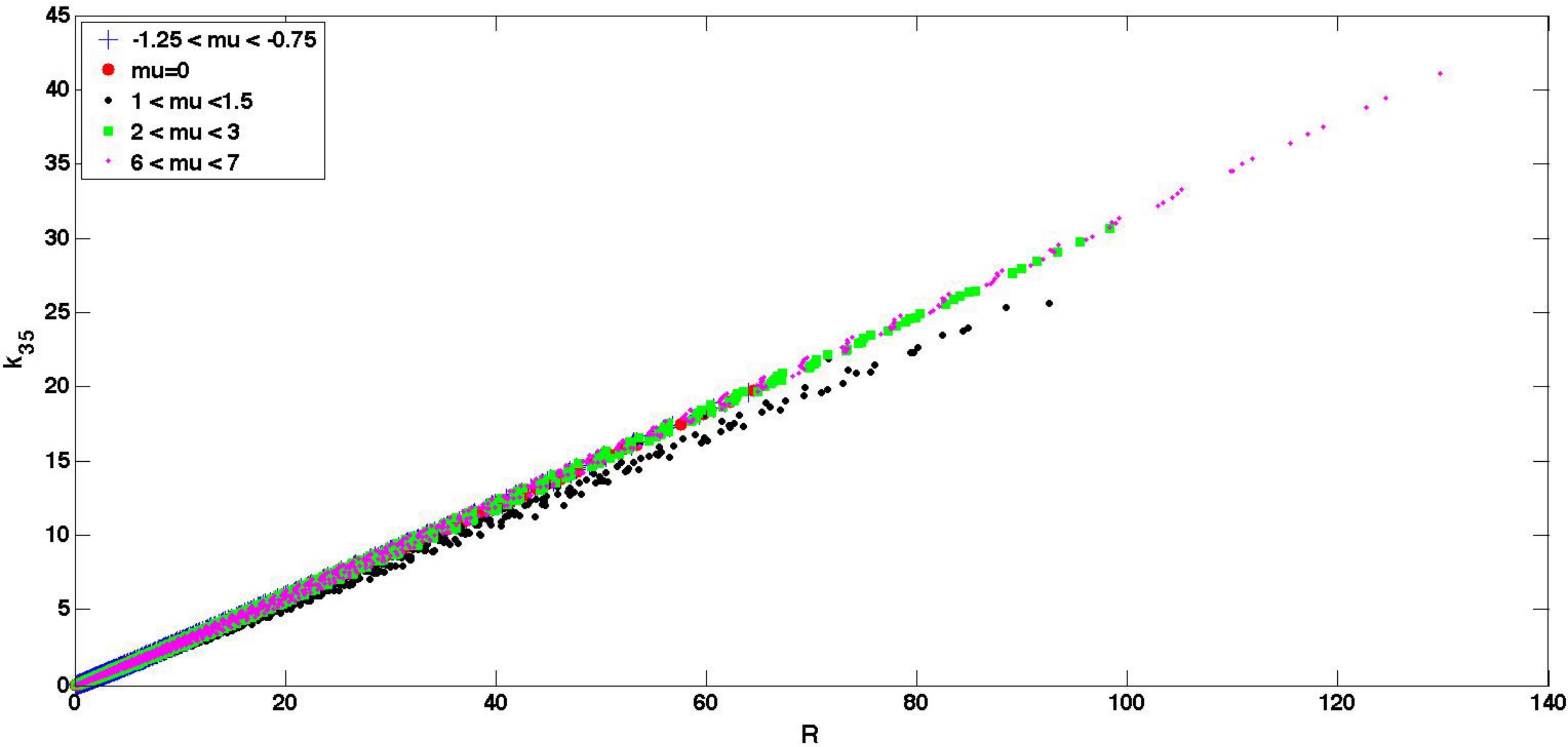
14GHz attenuation vs Rain rate -- μ constant assumption)



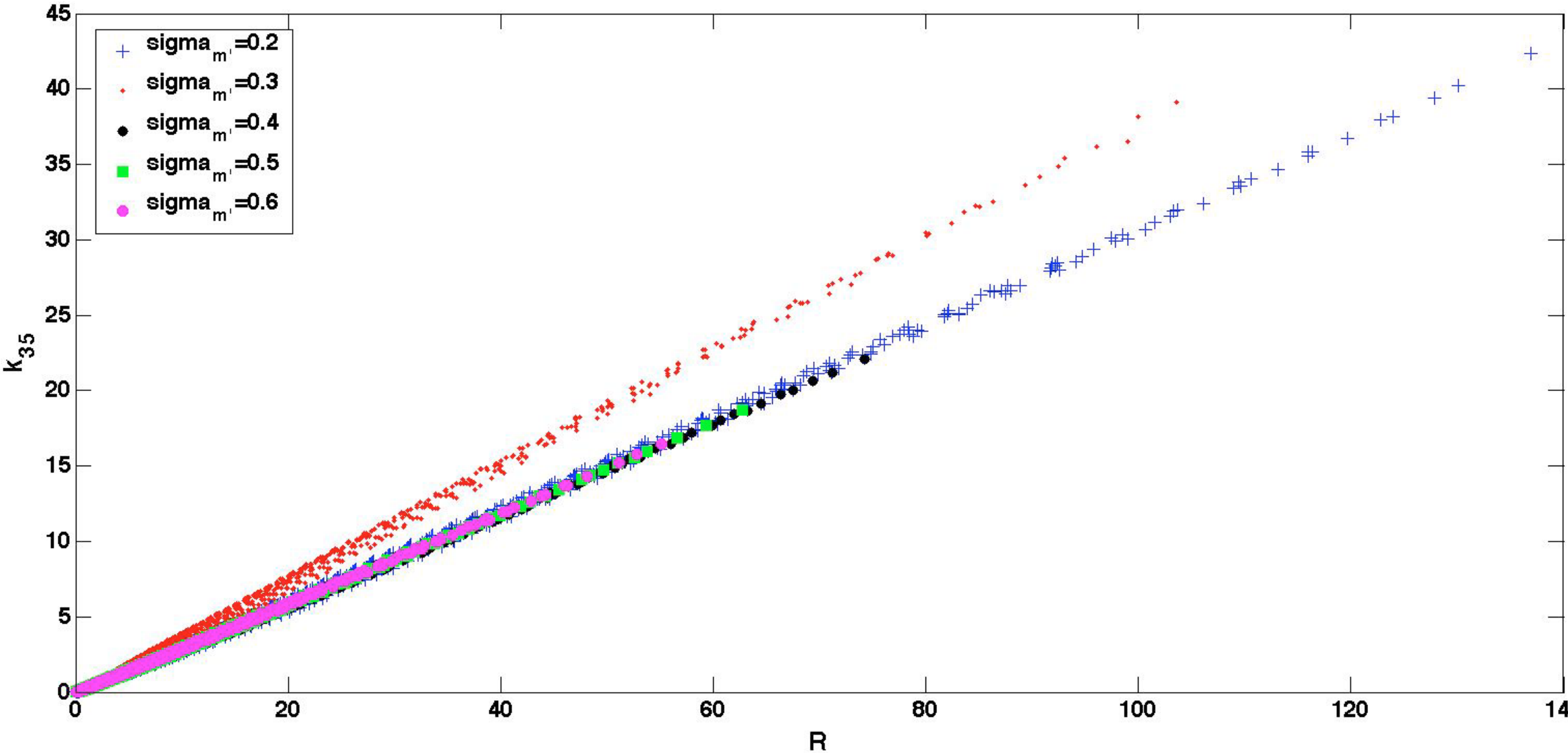
14GHz attenuation vs Rain rate -- $\sigma_m/D_m^{1.3}$ constant assumption)



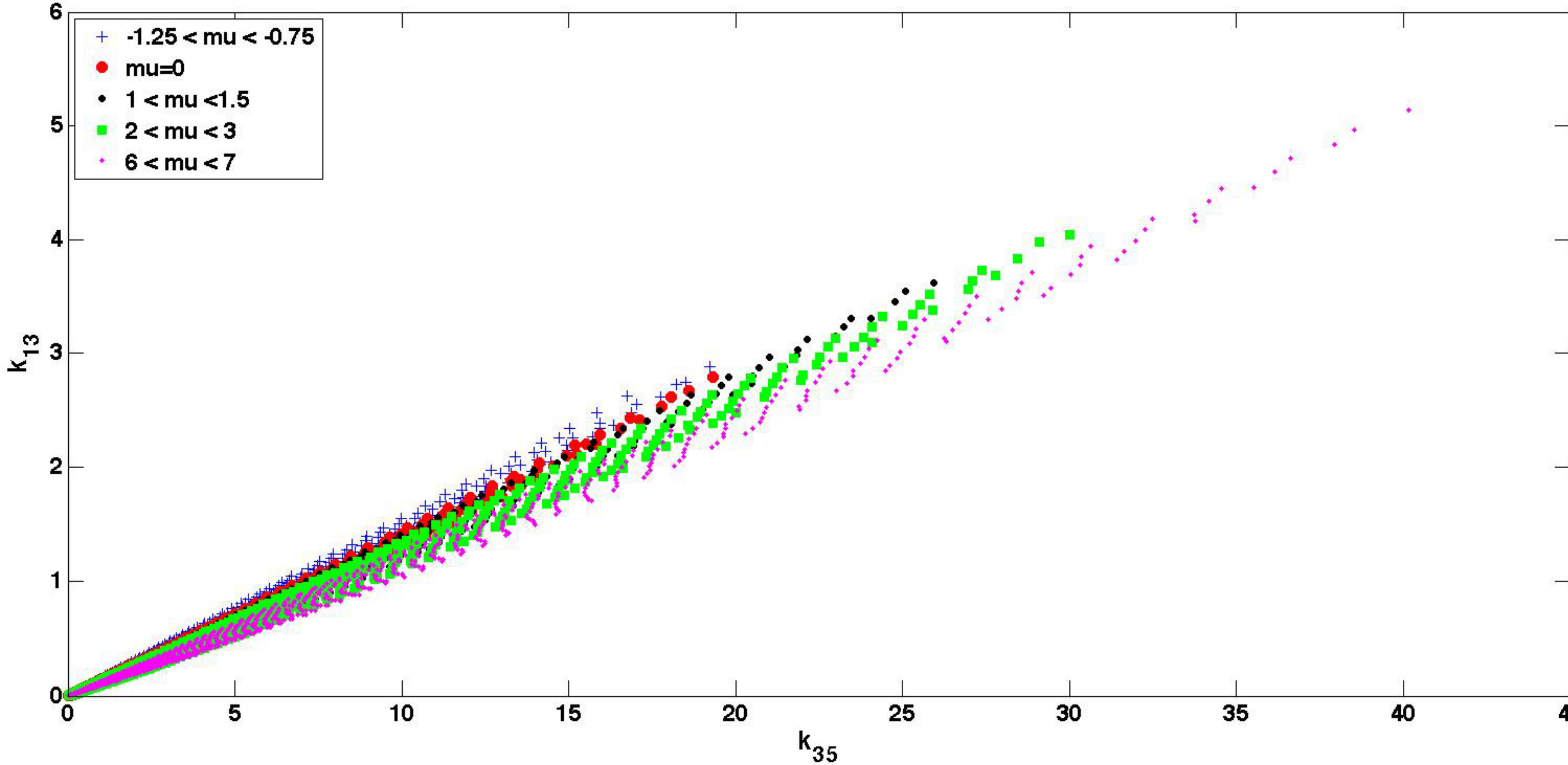
35GHz attenuation vs Rain rate -- μ constant assumption)



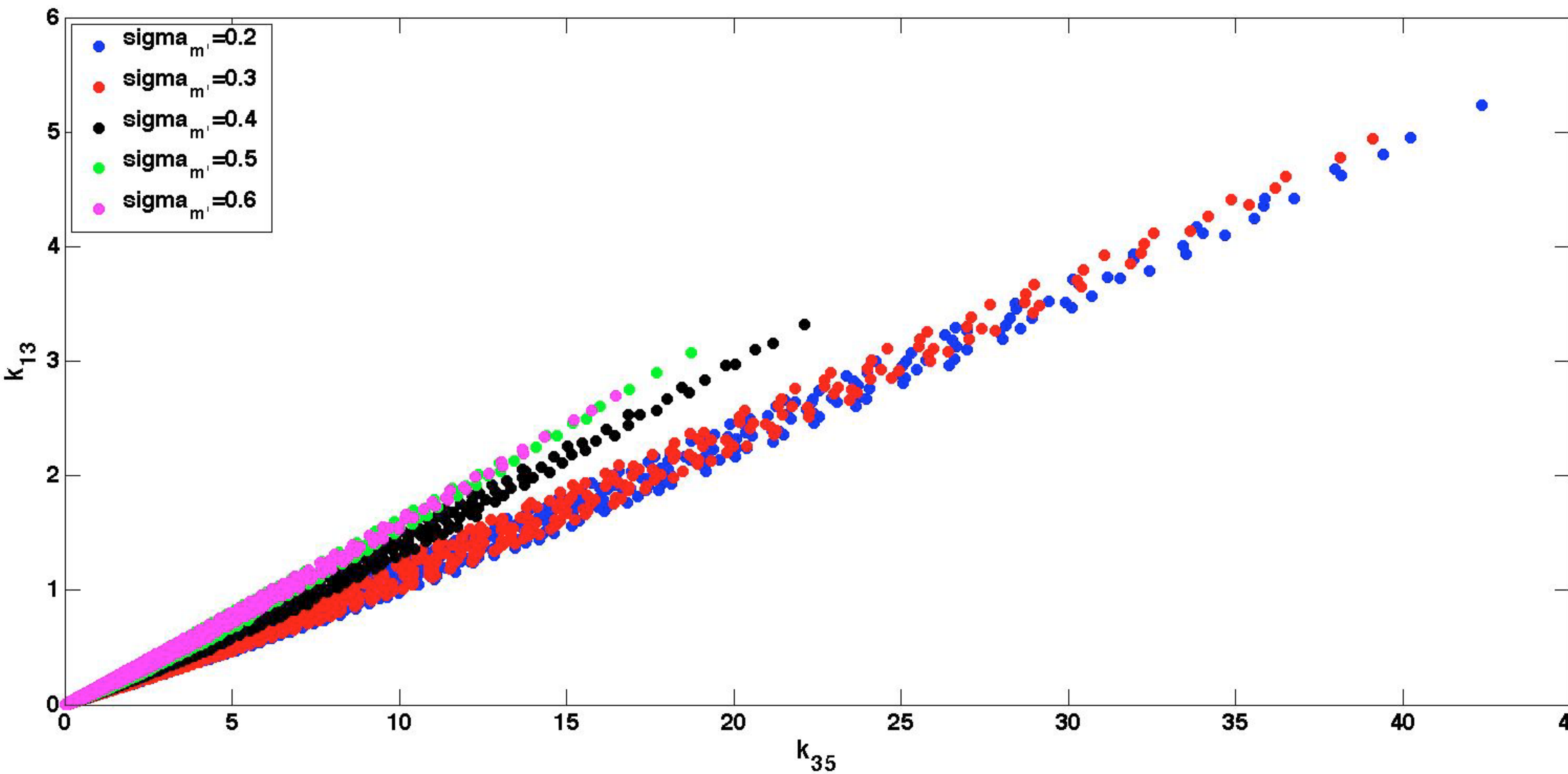
35GHz attenuation vs Rain rate -- $\sigma_m/D_m^{1.3}$ constant assumption)



14GHz attenuation vs 35GHz attenuation -- μ constant assumption)



14GHz attenuation vs 35GHz attenuation -- $\sigma_m/D_m^{1.3}$ constant assumption)



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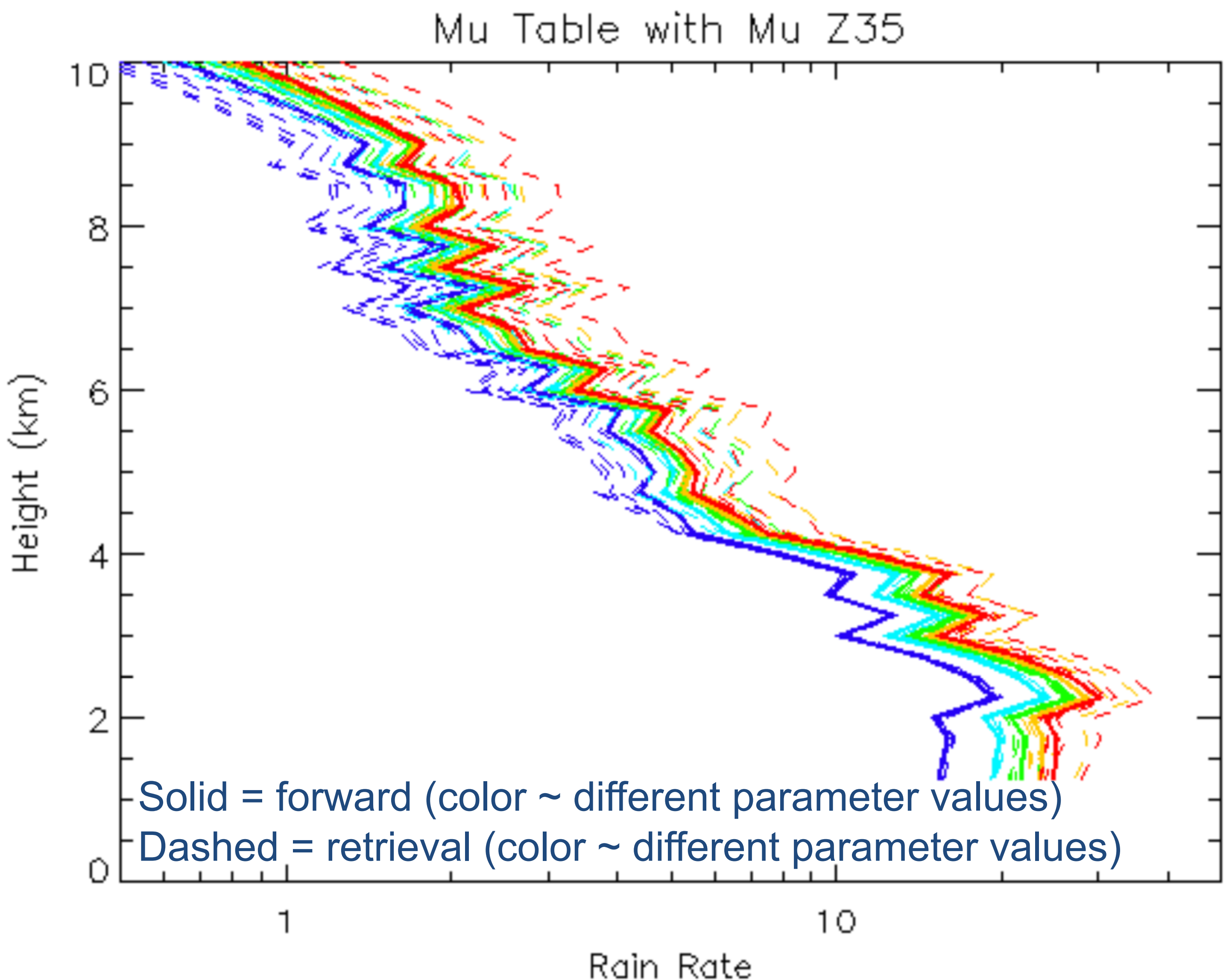
Algorithm testing: Start with TRMM, inject DSD (μ or $\sigma_m/D_m^{1.3}$) to generate Z35, then retrieve with DSD assumptions (μ or $\sigma_m/D_m^{1.3}$)



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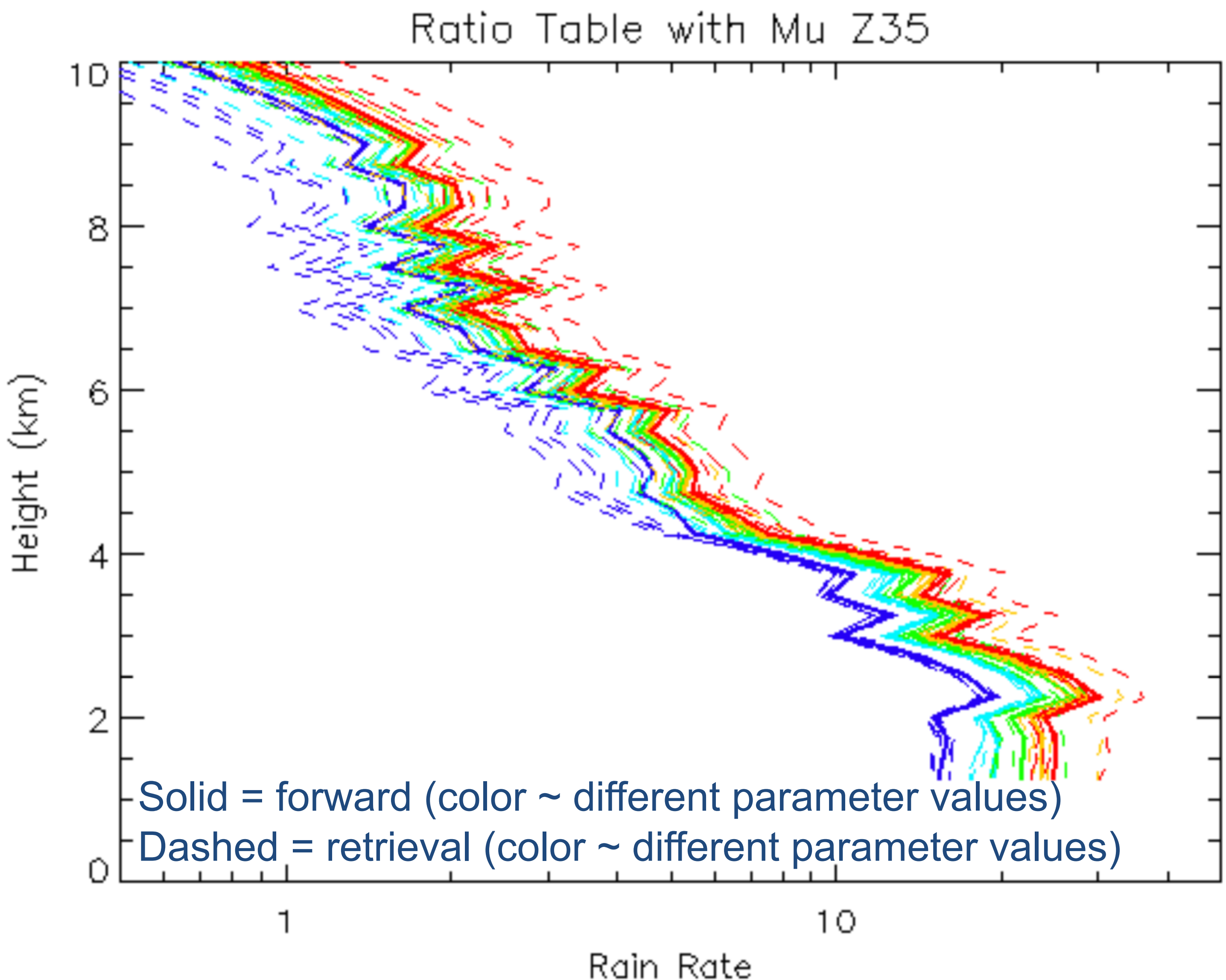

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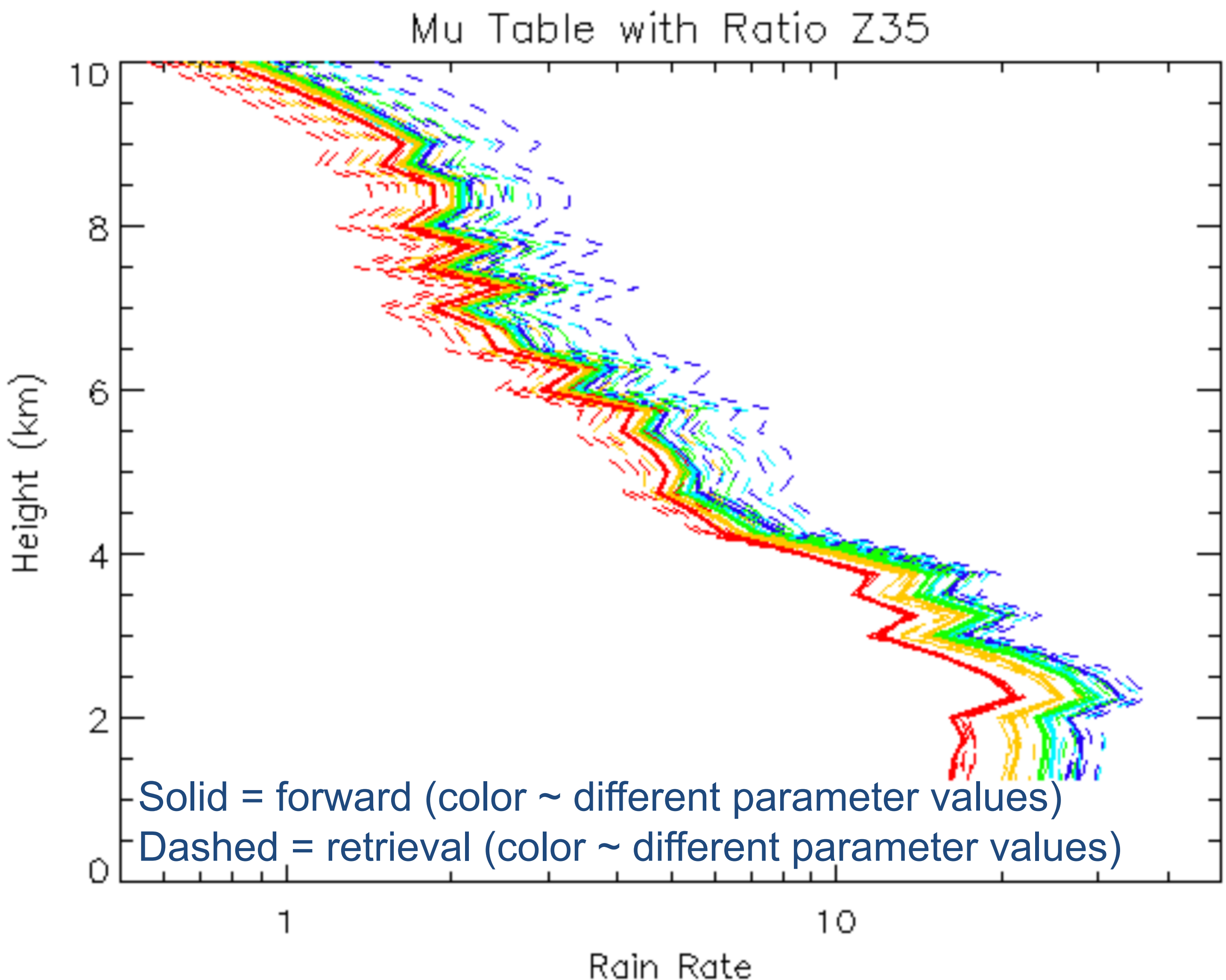

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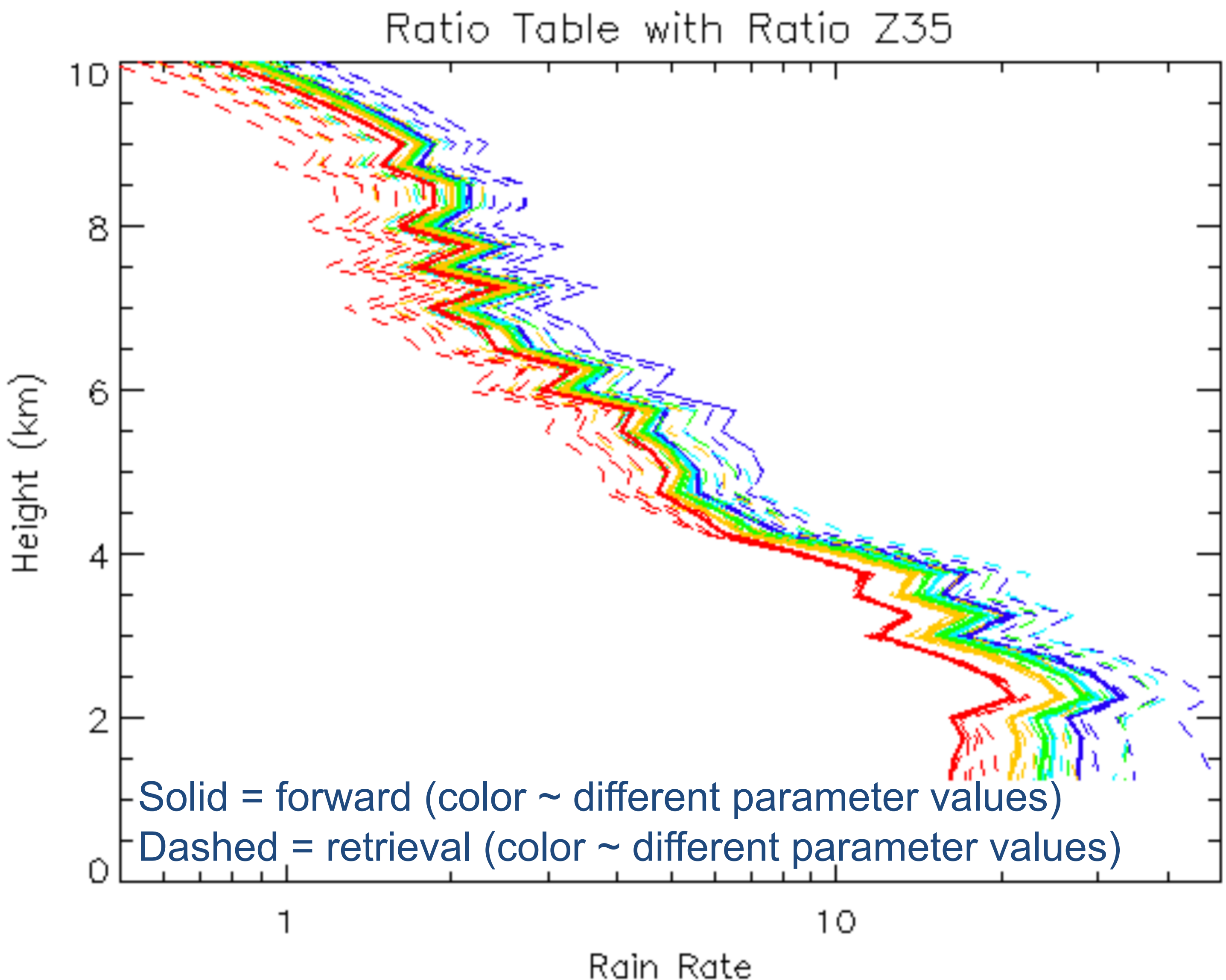

Smoothing Methodology (case of Tropical Cyclones):

• Start with WRF simulations (say HEDAS Earl 2010 h3vk, 2010-08-29-12Z to 2010-09-03-18Z), using stream ψ, potential χ, P, T, RH, W, q_{cliq}, q_r, q_{cli}, q_s, q_g, q_h at 42 vertical levels for a total of 504 variables $x_1, \ldots, x_{504}$

• for each of these 12million columns, forward-calculate $T_{b1}, \ldots, T_{b9}$

• find the principal components $x_1', \ldots, x_{504}'$ (each is a linear combo of $x_1, \ldots, x_{504}$) and the principal components $T_1', \ldots, T_9'$ (each a linear combo of $T_1', \ldots, T_9'$)

• Then we will have to find combos of $x_1',\ldots, x_{504}'$ that correlate most with combos of $T_1',\ldots, T_9'$

• Say these combos are x_1'', x_2'', x_3'' and T_1'', T_2'', T_3'': we finally need to express the latter in terms of the former, in a differentiable way (to be able to compute derivatives)

Smoothing Methodology (case of Tropical Cyclones):

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- for each of these 12million columns, forward-calculate T_{b1} , … , T_{b9}

- Step 1: find the principal components x_1', … , x_{504}'
- Step 2: find the principal components T_1', … , T_9'

- Step 3: find combos of x_1',…, x_{504}' that correlate most with combos of T_1',…, T_9'

Smoothing Methodology (case of Tropical Cyclones):

- Start with HWRF simulations (say HEDAS Earl 2010 h3vk, 2010-08-29-12Z to 2010-09-03-18Z), using stream ψ, potential χ, P, T, RH, W, q_{cliq}, q_r, q_{cli}, q_s, q_g, q_h at 42 vertical levels for a total of 504 variables $x_1, \ldots, x_{504}$
- for each of these 12million columns, forward-calculate $T_{b1}, \ldots, T_{b9}$

- Step 1: find the principal components $x_1', \ldots, x_{504}'$
- Step 2: find the principal components $T_1', \ldots, T_9'$

- Step 3: find combos of $x_1',\ldots, x_{504}'$ that correlate most with combos of $T_1',\ldots, T_9'$

and express T_1'', T_2'', T_3'' differentiably in terms of x_1'', x_2'', x_3''

$$T_i''(x_1'', x_2'', x_3'') = \sum T_i''^{(n)} \exp(-[x_1''-x_1''^{(n)}]^2 -[x_2''-x_2''^{(n)}]^2 -[x_3''-x_3''^{(n)}]^2)$$

where the weighted sum over n runs over the 12million training points

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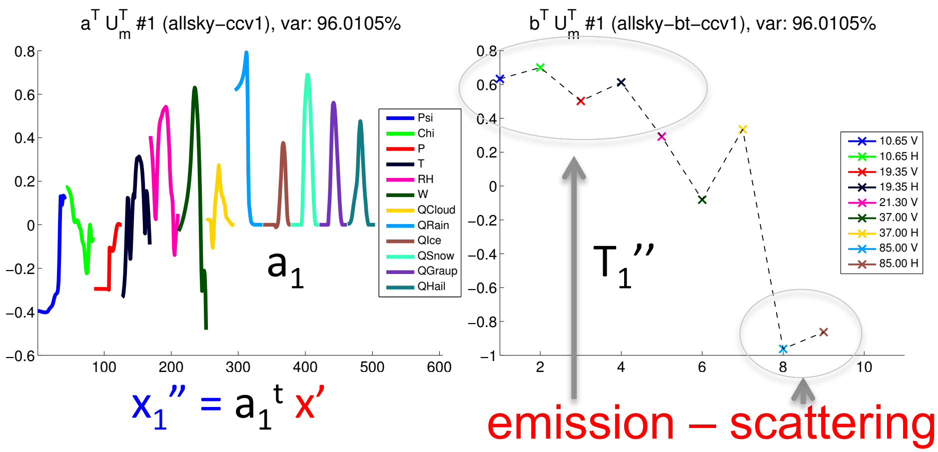
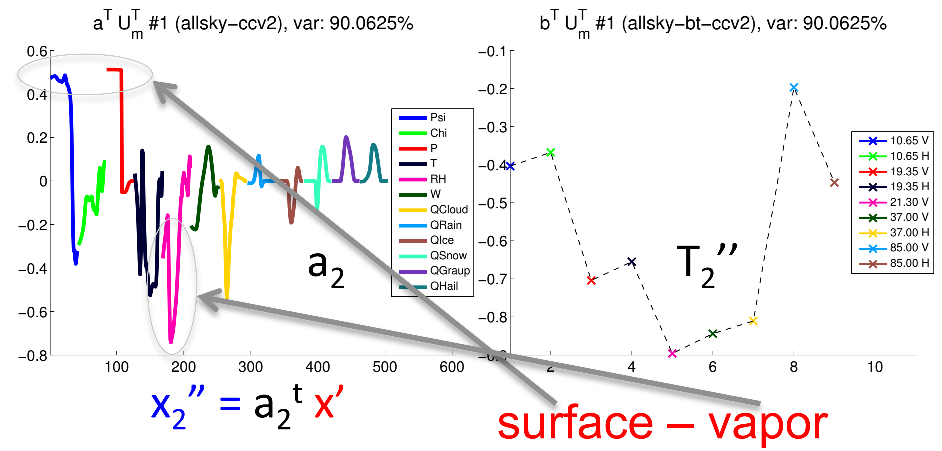
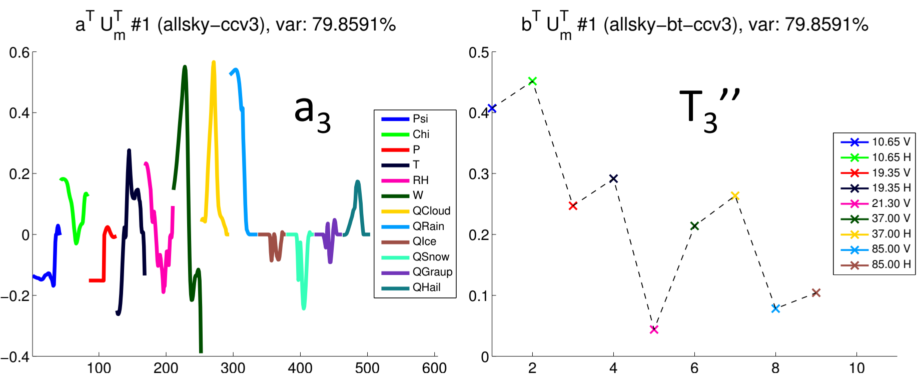
First part of step 3: here are the first 3 x'' and T''



$x_1'' = a_1^t x'$



$x_2'' = a_2^t x'$



$x_3'' = a_3^t x'$ $T_3'' = b_3^t T'$

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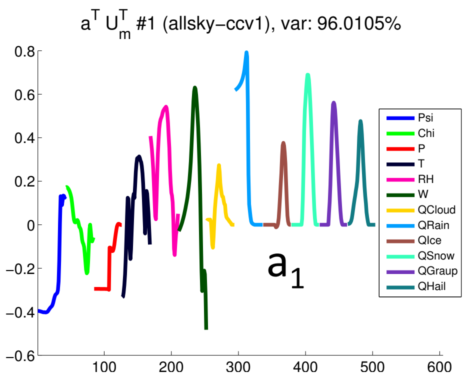
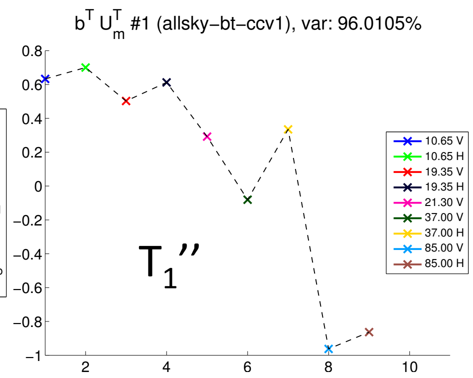
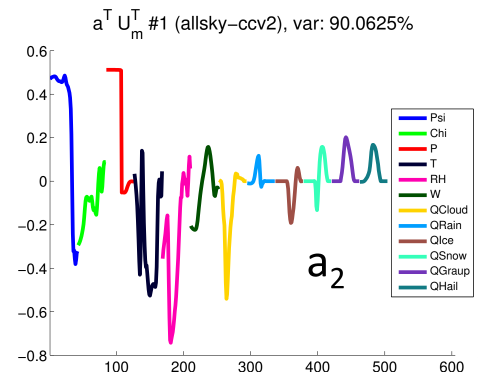
First part of step 3: here are the first 3 x” and T”



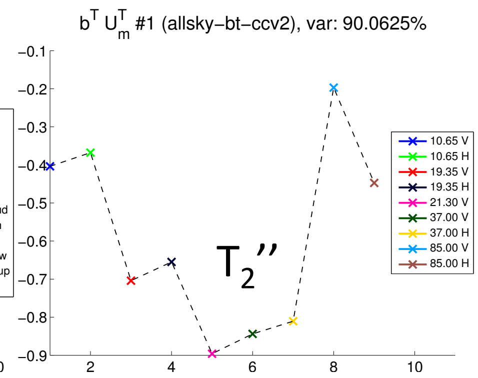
$x_1'' = a_1^t\, x'$



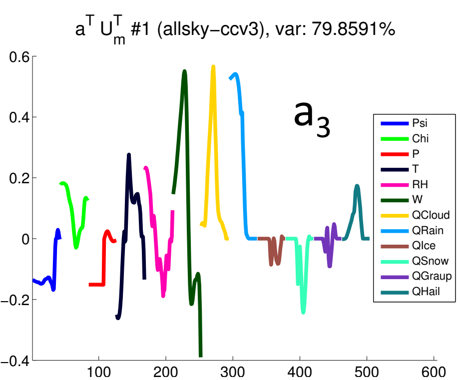
emission – scattering



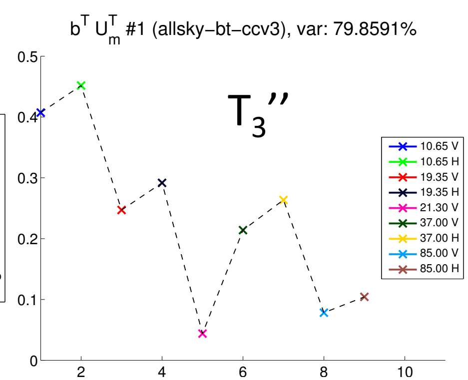
$x_2'' = a_2^t\, x'$



surface – vapor



$x_3'' = a_3^t\, x'$



$T_3'' = b_3^t\, T'$

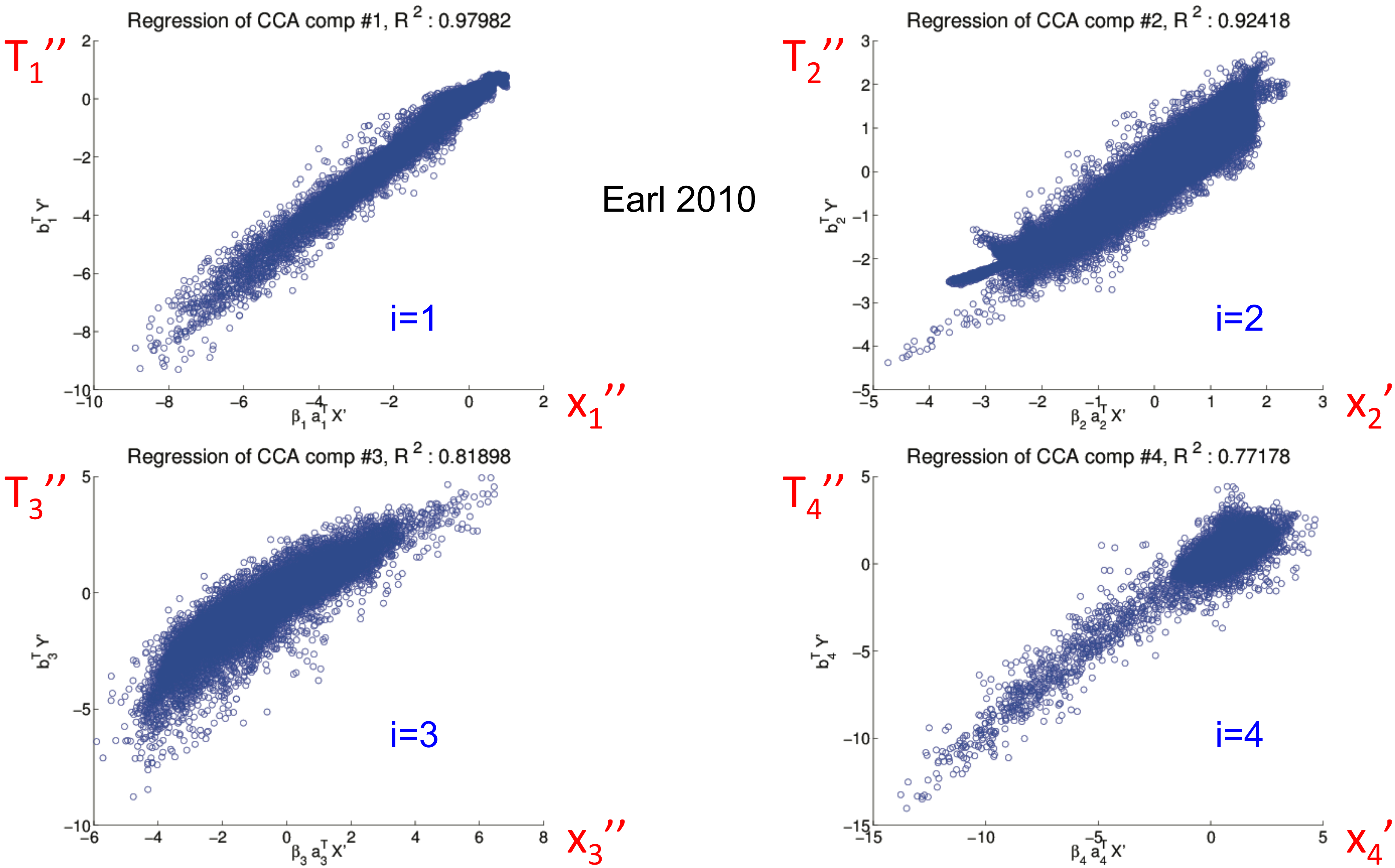
Most remarkable:

the operators H_1, H_2 , H_3 giving

$$T_1'' = H_1(x_1'', x_2'', x_3'')$$
$$T_2'' = H_2(x_1'', x_2'', x_3'')$$
$$T_3'' = H_3(x_1'', x_2'', x_3'')$$

are not so nonlinear:

First part of step 3: T_i'' (vertical) vs x_i'' (horizontal)

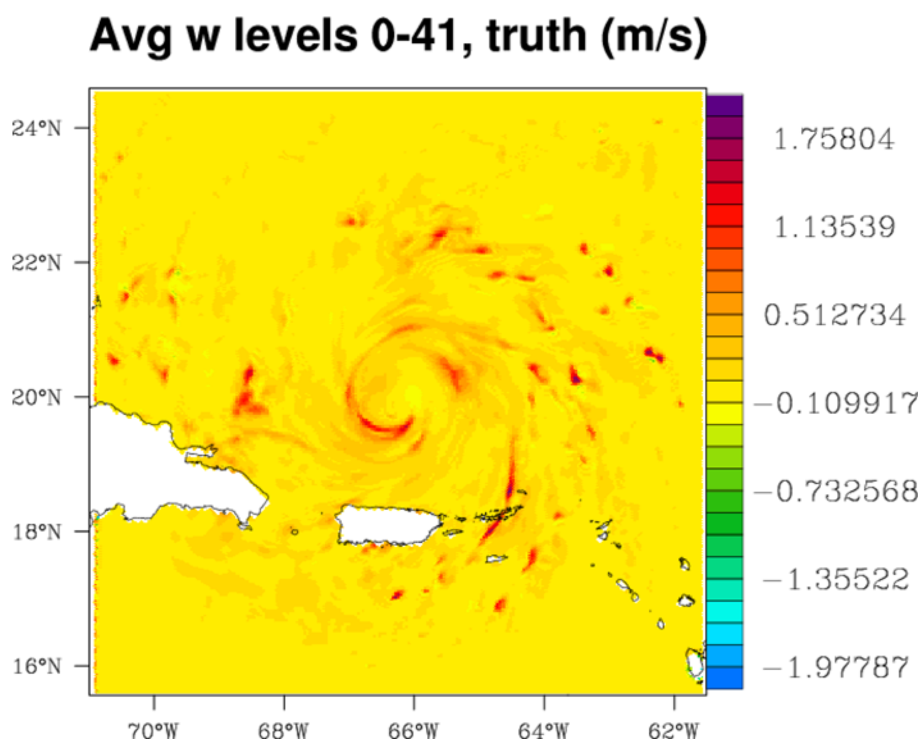


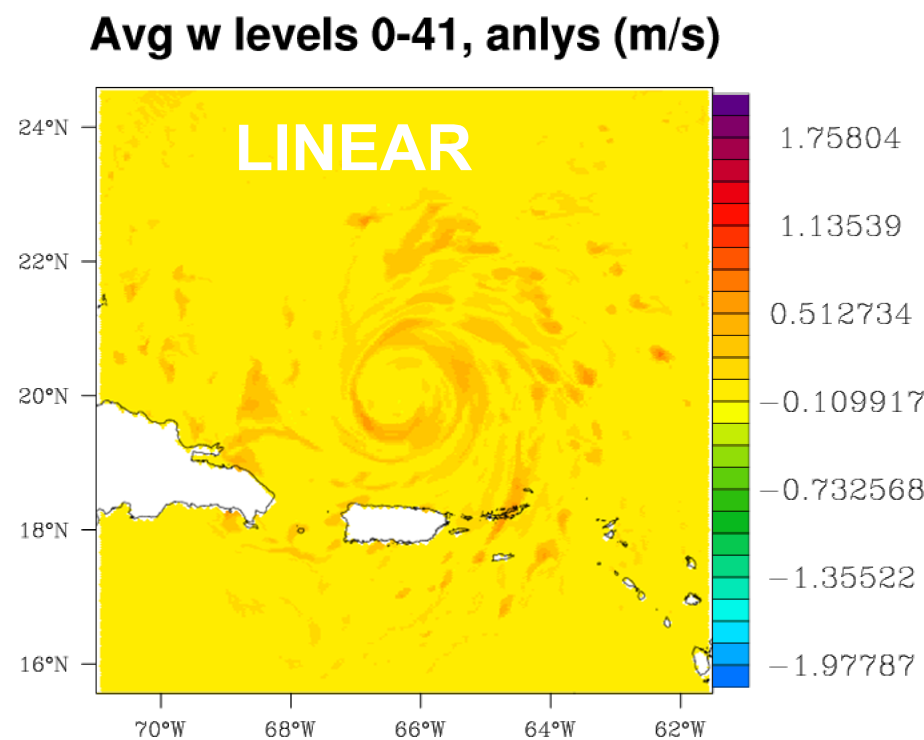
Second part of step 3: use nonlinear expression

$$T_i''(x_1'', x_2'', x_3'') = \sum T_i''^{(n)} \exp(-[x_1''-x_1''^{(n)}]^2 -[x_2''-x_2''^{(n)}]^2 -[x_3''-x_3''^{(n)}]^2)$$

So let's try an assimilation using this observation operator:
(start with 1D-var – not quite a "retrieval", because of the covariances)

Having started with a horizontally uniform background, each variable having the global mean value at that height level:





vertical component of wind

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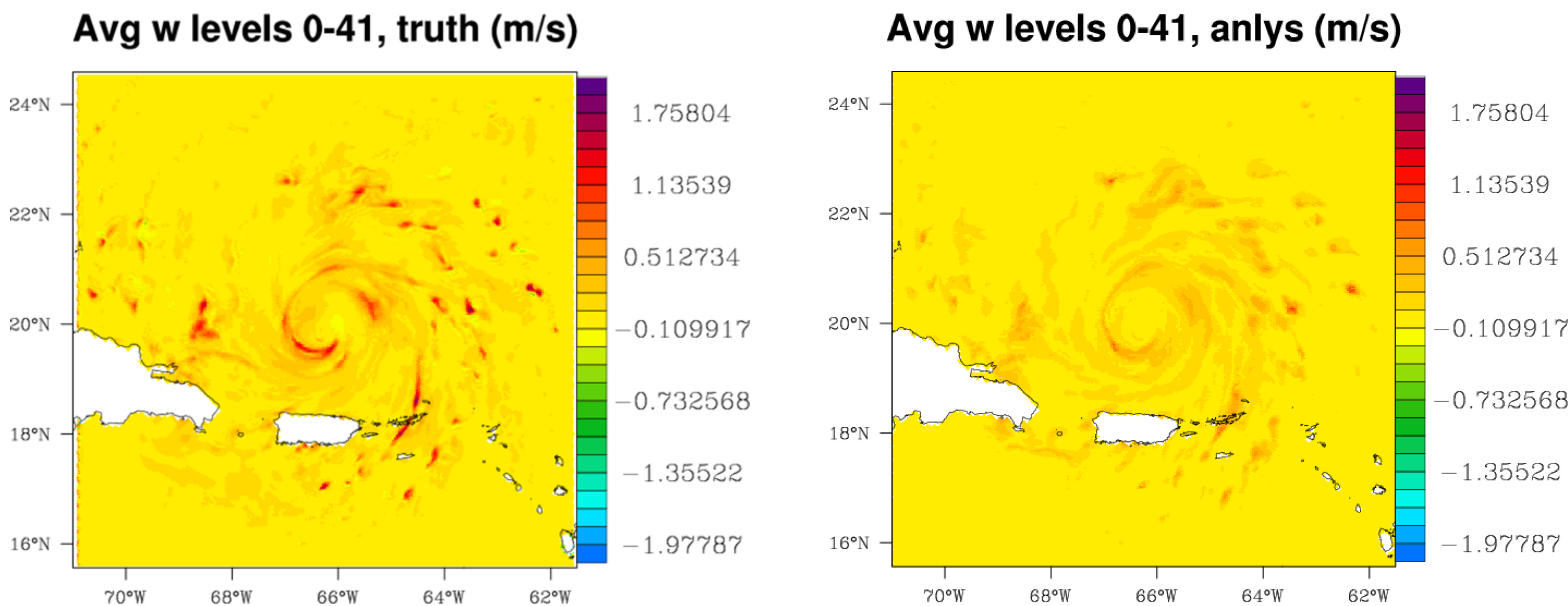

vertical component of wind

Second part of step 3: use nonlinear expression

$T_i'' \sim x_i''$

So let's try an assimilation using this observation operator:
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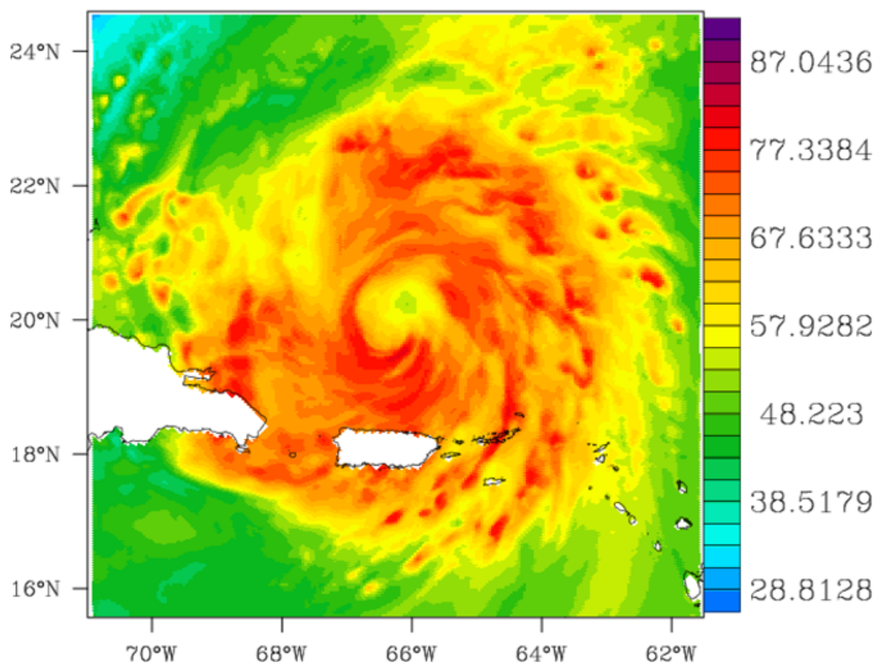
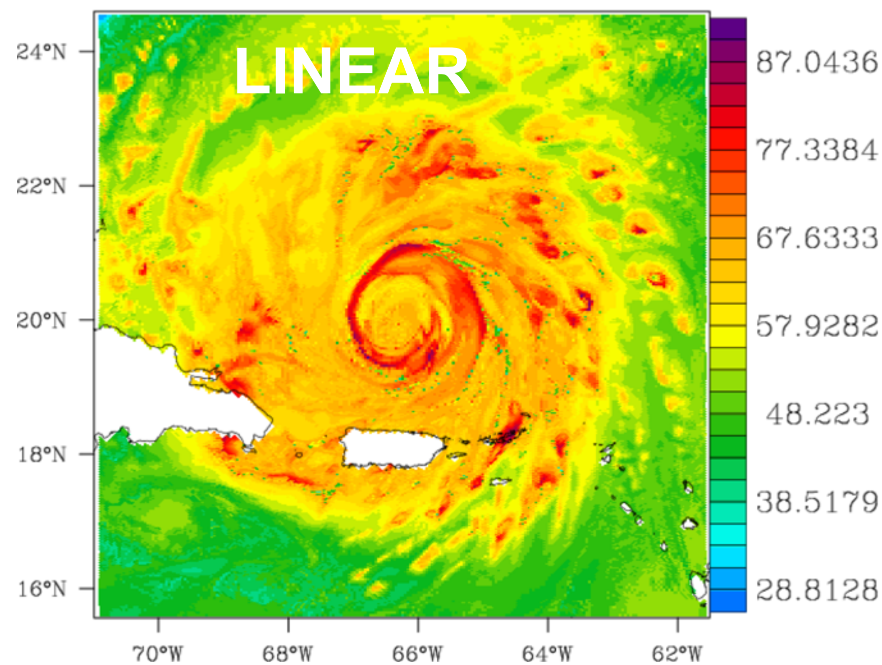
Having started with a horizontally uniform background, each variable having the global mean value at that height level:

Avg rh levels 0-41, truth (%)



Avg rh levels 0-41, anlys (%)



water vapor

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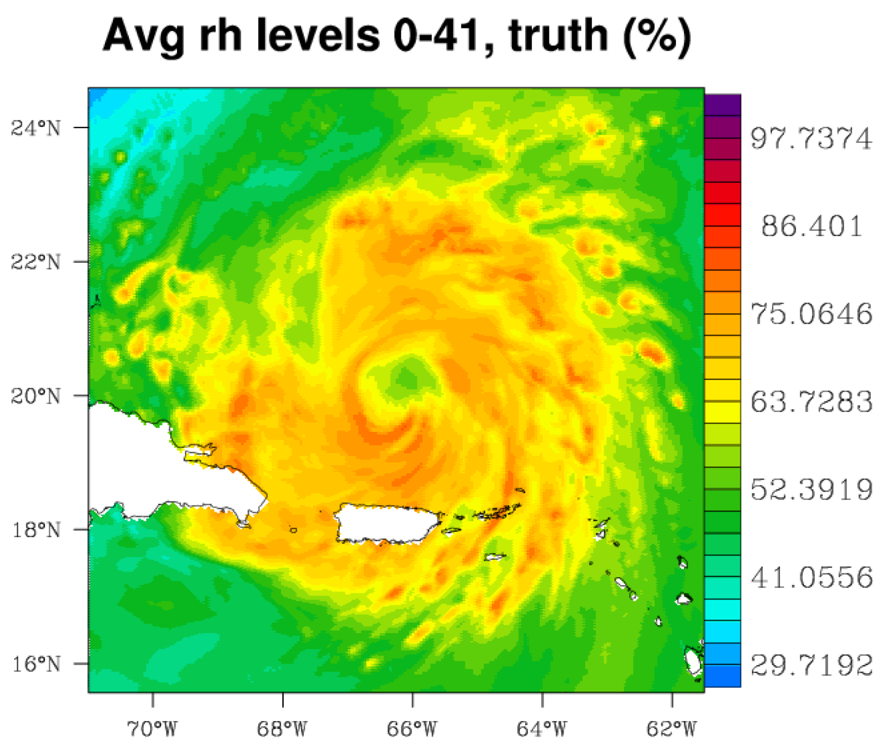
Second part of step 3: use nonlinear expression

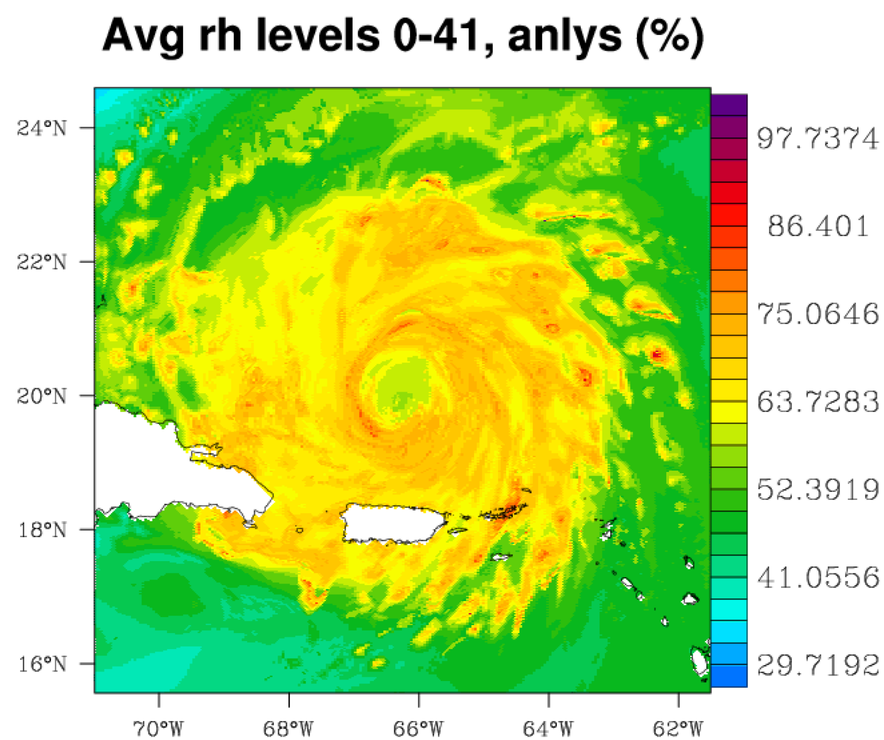
$$T_i''(x_1'', x_2'', x_3'') = \Sigma \; T_i''^{(n)} \exp(-[x_1''-x_1''^{(n)}]^2 -[x_2''-x_2''^{(n)}]^2 -[x_3''-x_3''^{(n)}]^2)$$

So let's try an assimilation using this observation operator:

(start with 1D-var – not quite a "retrieval", because of the covariances)

Having started with a horizontally uniform background, each variable having the global mean value at that height level:





water vapor

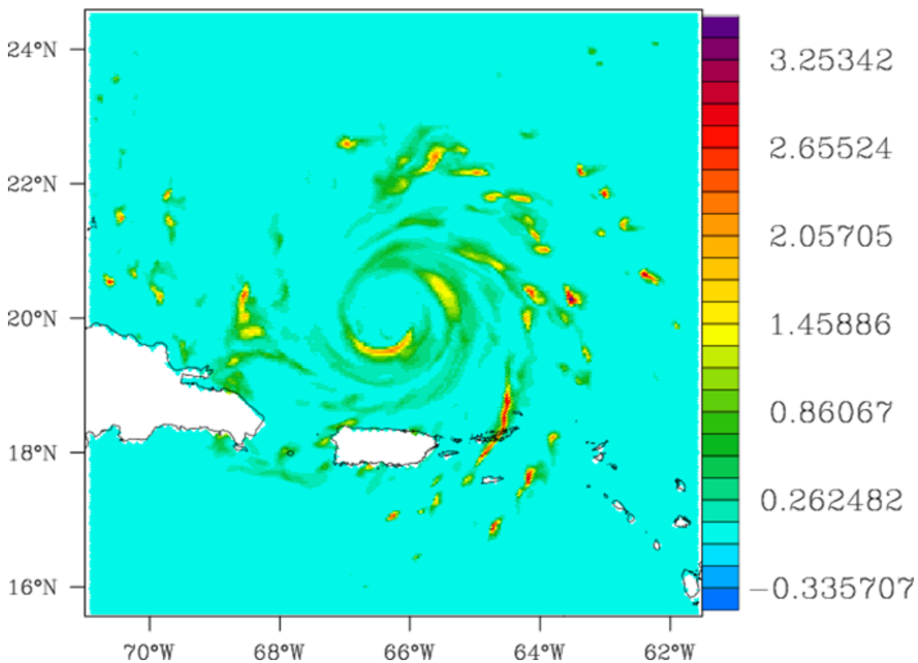
Second part of step 3: use nonlinear expression

$T_i'' \sim x_i''$

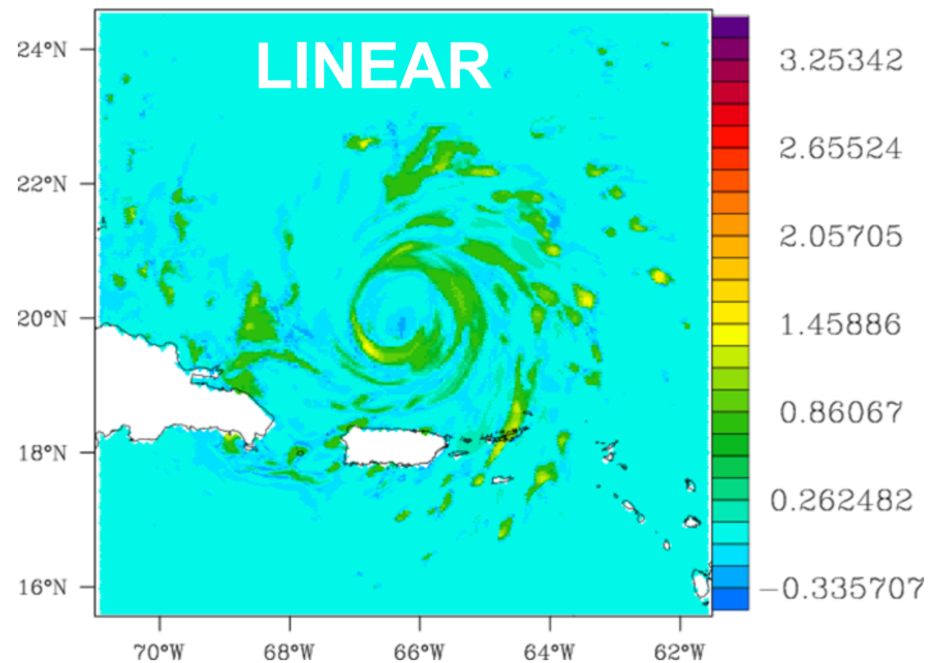
So let's try an assimilation using this observation operator:
(start with 1D-var – not quite a "retrieval", because of the covariances)

Having started with a horizontally uniform background, each variable having the global mean value at that height level:

Avg qrain levels 0-41, truth (g/kg)



Avg qrain levels 0-41, anlys (g/kg)



RAIN

Second part of step 3: use nonlinear expression

$$T_i''(x_1'', x_2'', x_3'') = \Sigma \; T_i''^{(n)} \exp(-[x_1''-x_1''^{(n)}]^2 -[x_2''-x_2''^{(n)}]^2 -[x_3''-x_3''^{(n)}]^2)$$

So let's try an assimilation using this observation operator:
(start with 1D-var – not quite a "retrieval", because of the covariances)

Having started with a horizontally uniform background, each variable having the global mean value at that height level:

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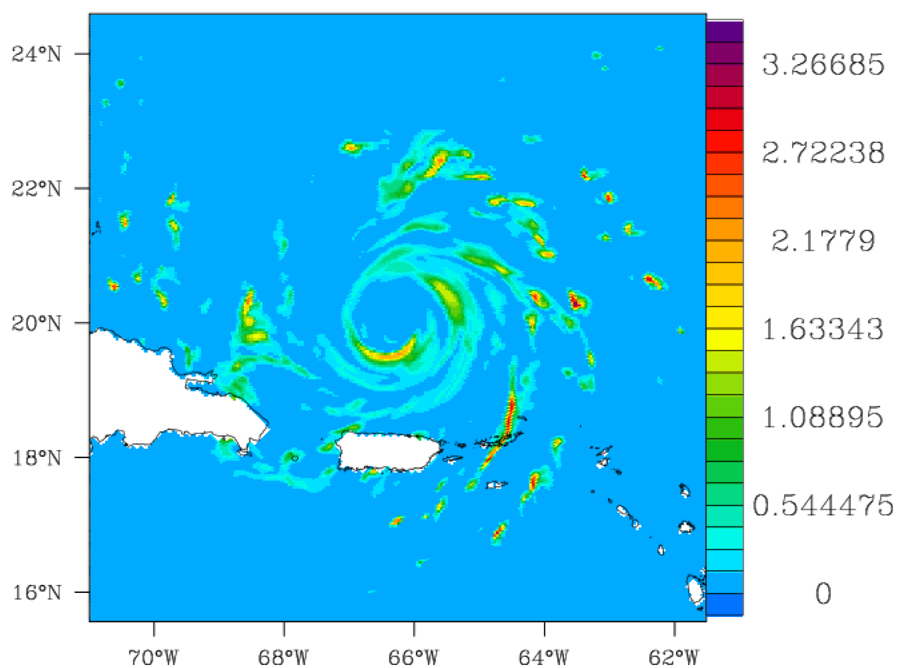
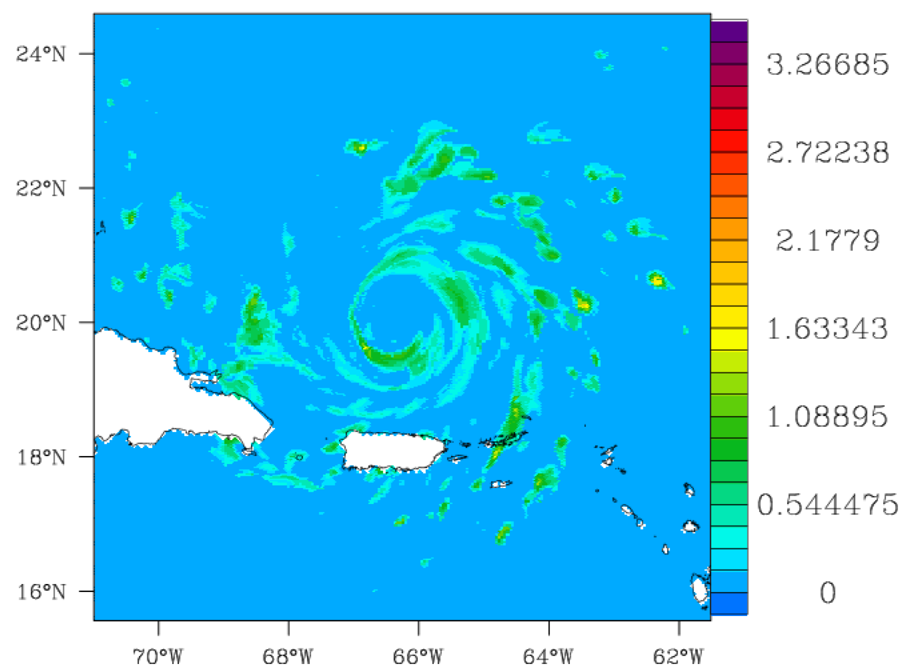


Avg qrain levels 0-41, anlys (g/kg)



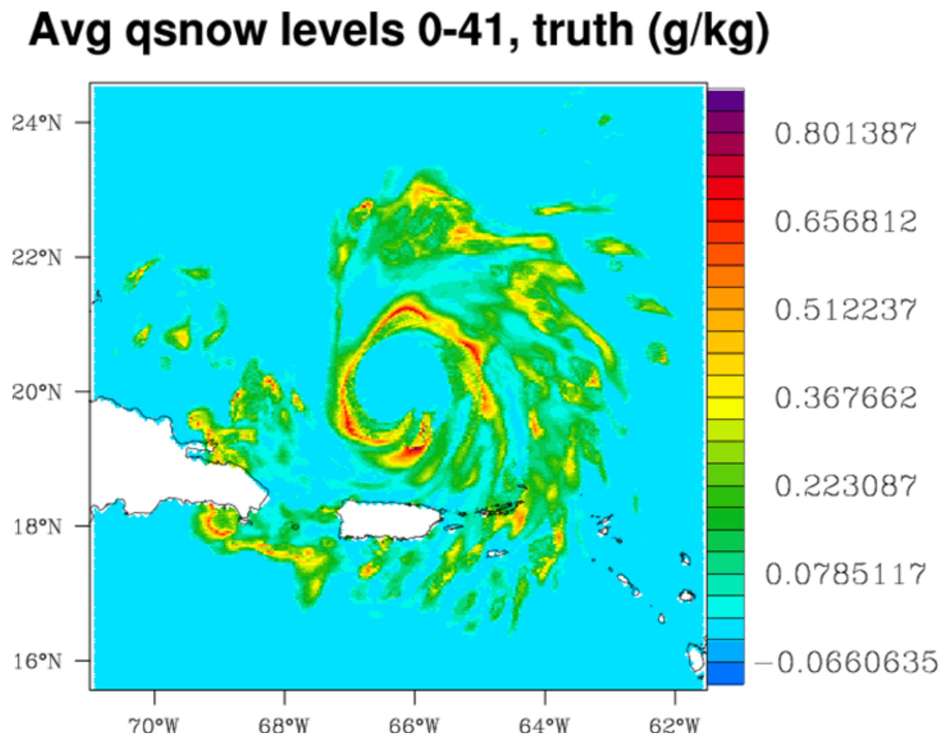
RAIN

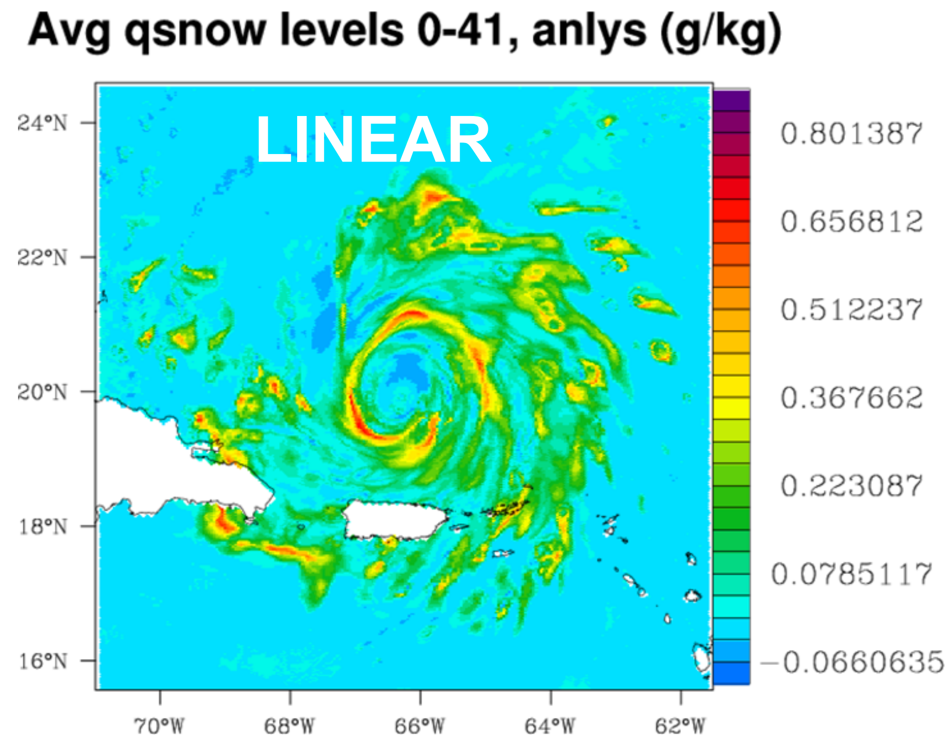
Second part of step 3: use nonlinear expression

$T_i'' \sim x_i''$

So let's try an assimilation using this observation operator:
(start with 1D-var – not quite a "retrieval", because of the covariances)

Having started with a horizontally uniform background, each variable having the global mean value at that height level:





SNOW

Z.S. Haddad et al

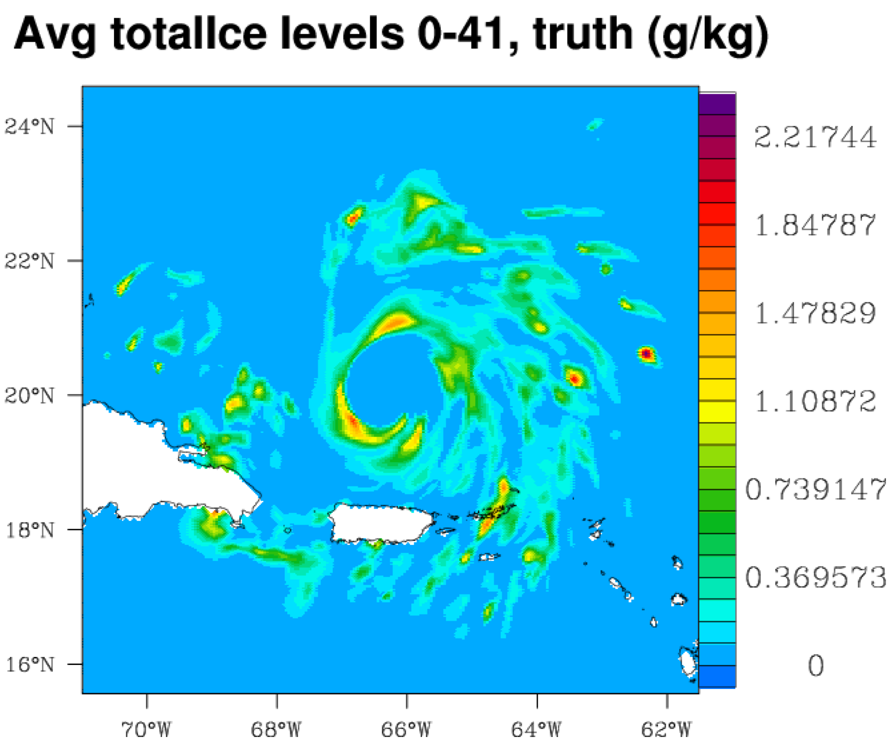
Second part of step 3: use nonlinear expression

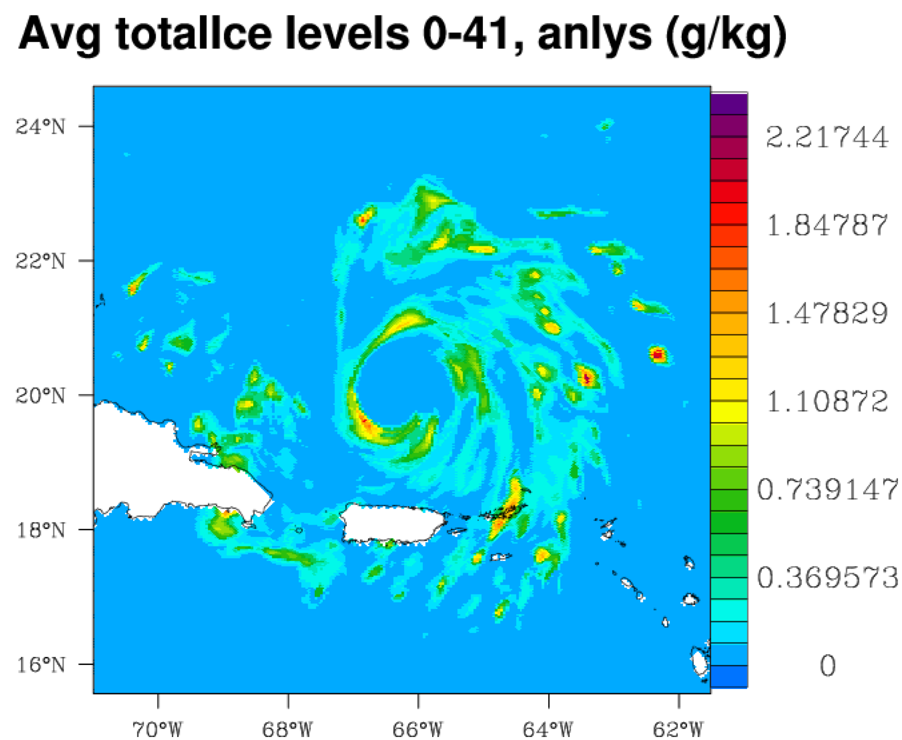
$$T_i''(x_1'', x_2'', x_3'') = \sum T_i''^{(n)} \exp(-[x_1''-x_1''^{(n)}]^2 -[x_2''-x_2''^{(n)}]^2 -[x_3''-x_3''^{(n)}]^2)$$

So let's try an assimilation using this observation operator:

(start with 1D-var – not quite a "retrieval", because of the covariances)

Having started with a horizontally uniform background, each variable having the global mean value at that height level:





TOTAL ICE

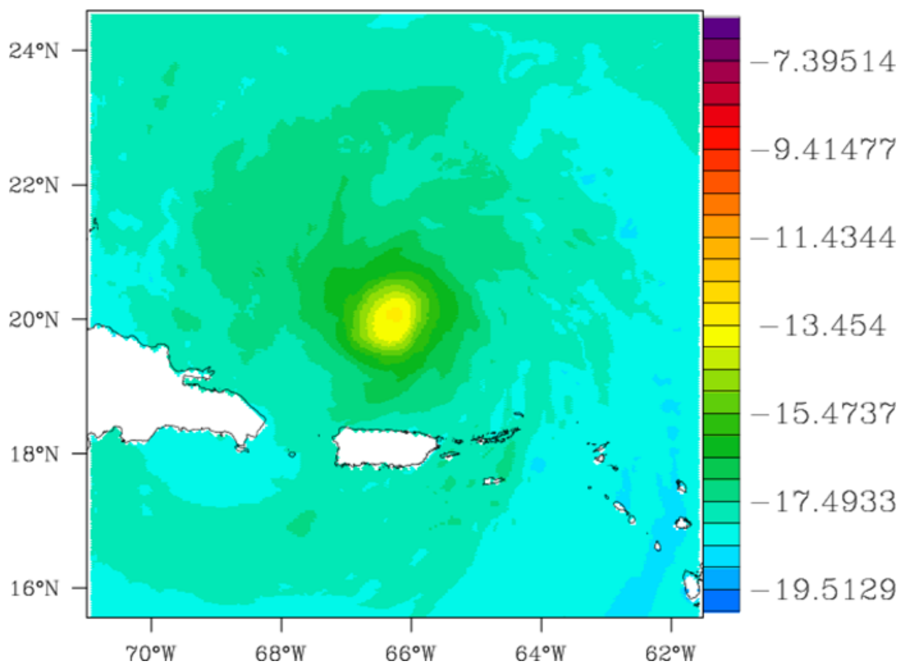
Second part of step 3: use nonlinear expression

$T_i'' \sim x_i''$

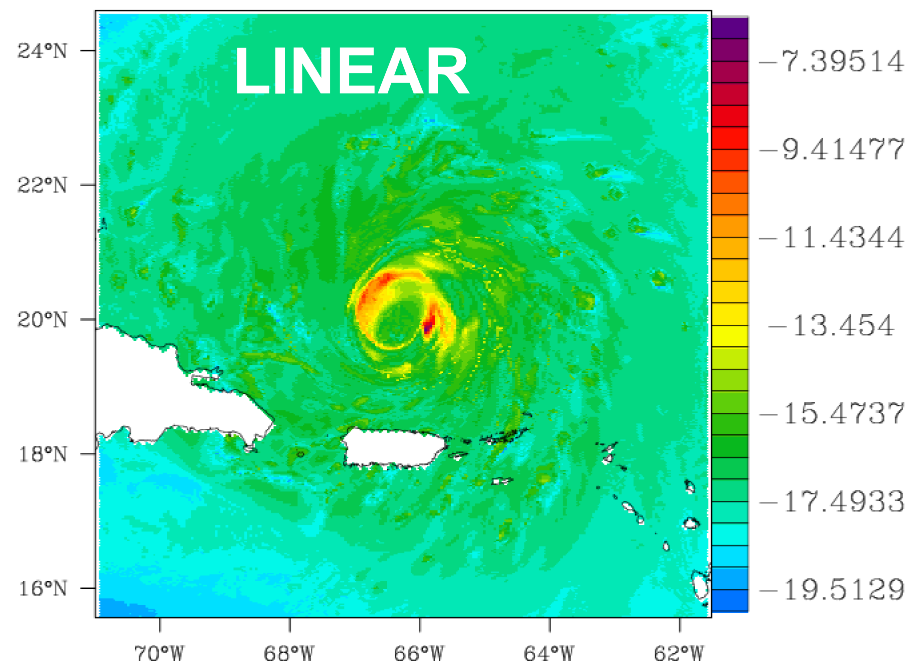
So let's try an assimilation using this observation operator:
(start with 1D-var – not quite a "retrieval", because of the covariances)

Having started with a horizontally uniform background, each variable having the global mean value at that height level:

Avg temp levels 0-41, truth (C)



Avg temp levels 0-41, anlys (C)



temperature

Second part of step 3: use nonlinear expression

$$T_i''(x_1'', x_2'', x_3'') = \Sigma \; T_i''^{(n)} \exp(-[x_1''-x_1''^{(n)}]^2 -[x_2''-x_2''^{(n)}]^2 -[x_3''-x_3''^{(n)}]^2)$$

So let's try an assimilation using this observation operator:

(start with 1D-var – not quite a "retrieval", because of the covariances)

Having started with a horizontally uniform background, each variable having the global mean value at that height level:

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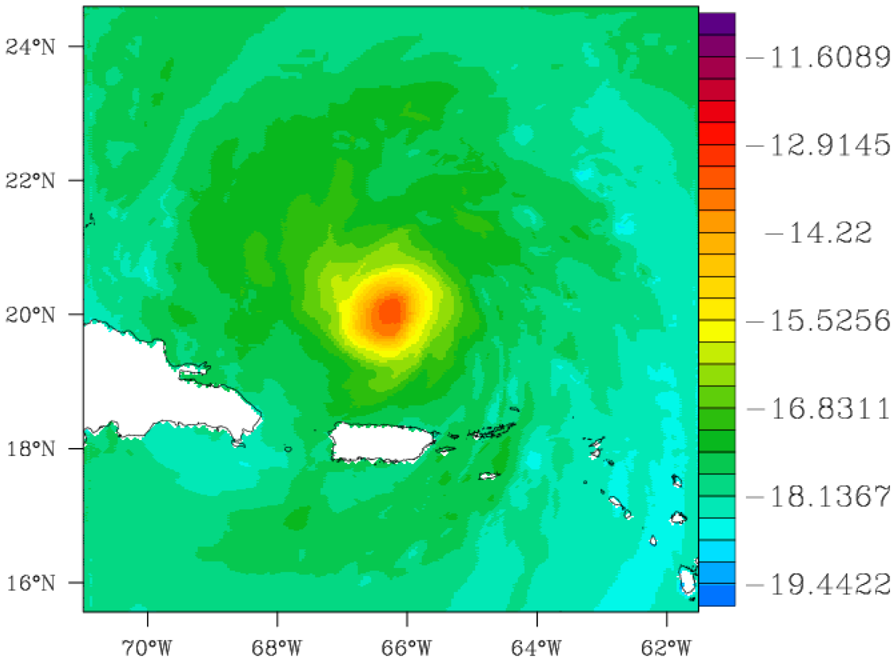
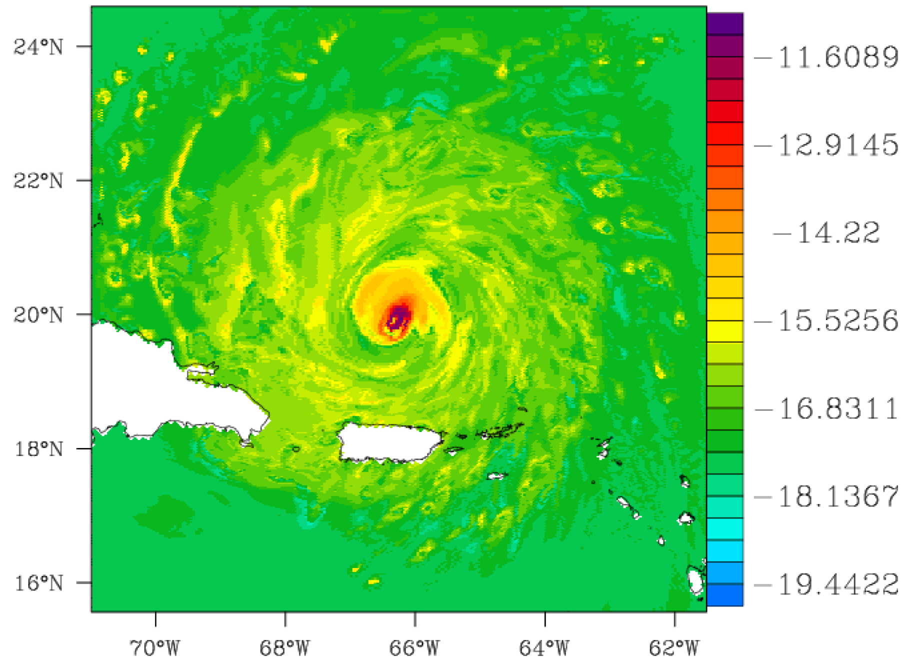


Avg temp levels 0-41, anlys (C)



Look P/Ma! a warm core!

temperature

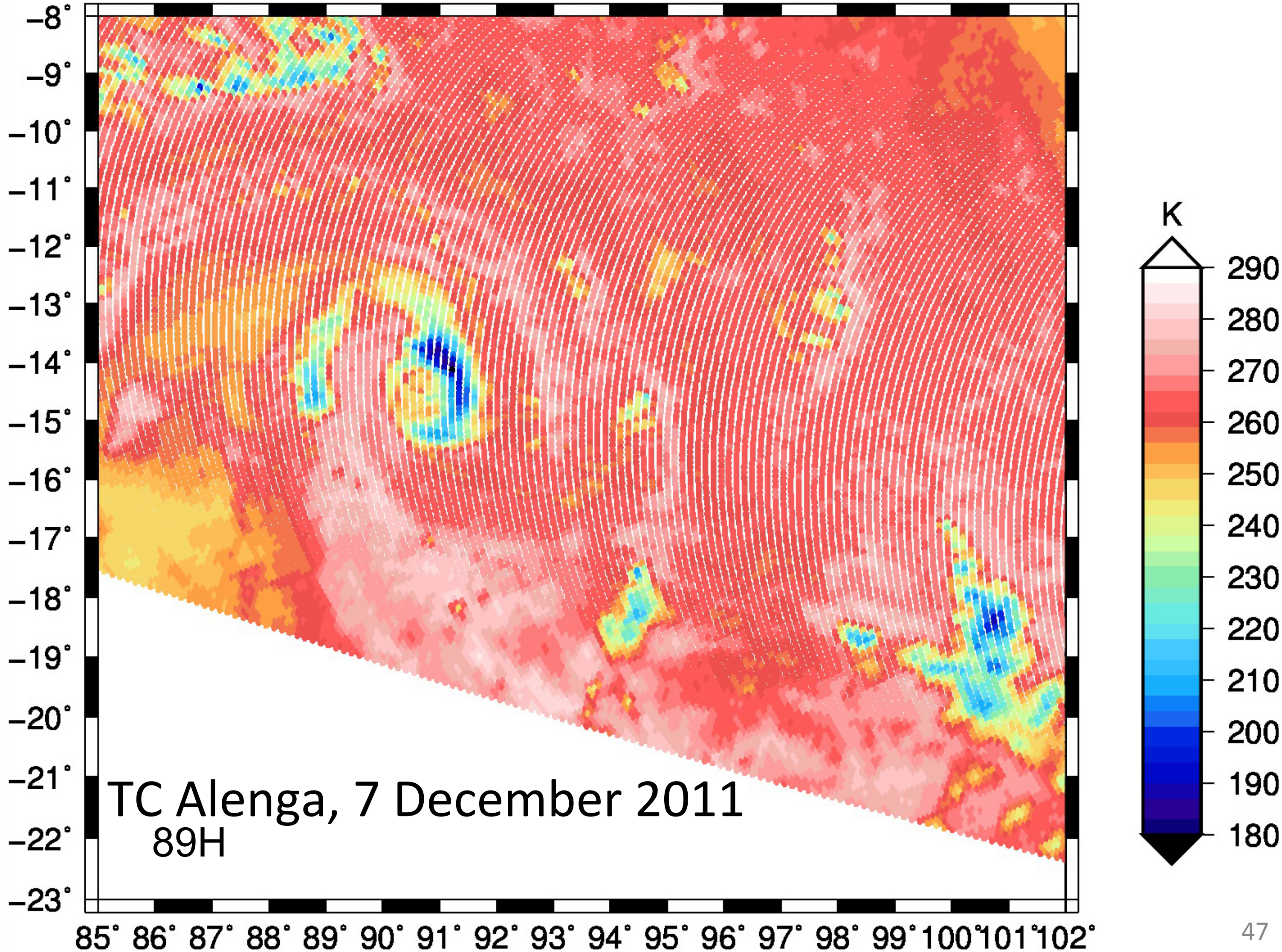
Cast:

Z.S. Haddad (JPL)
Jeff Steward (UCLA)
Joe Munchak (GSFC)
Sahra Kacimi (JPL)
Hsiao-Chieh Tseng (UC Davis)
Svetla Hristova-Veleva (JPL)
Shu-Hua Chen (UC Davis)

Two ways to account for the dependence of microwave observations of precipitation on uncertain microphysics

Z.S. Haddad et al

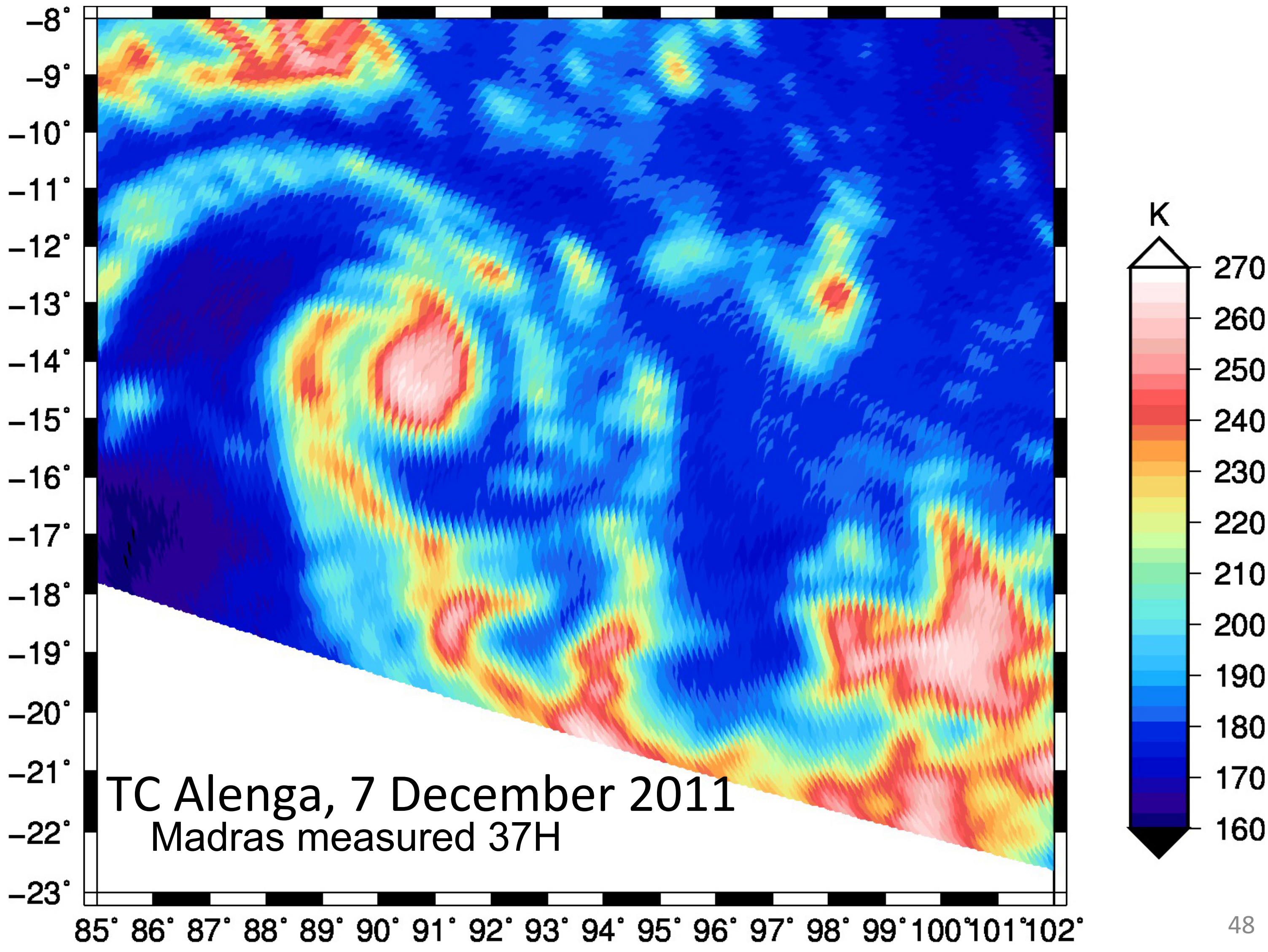
$$T_{hiRes} = t(89_{hiRes}) + (1 + C\,P^t E^{-1} P)^{-1}\, C\,P^t E^{-1} [\,T_{loRes} - P\,t(89_{hiRes})\,]$$



Two ways to account for the dependence of microwave observations of precipitation on uncertain microphysics

Z.S. Haddad et al

$$T_{hiRes} = t(89_{hiRes}) + (1 + C\,P^t\,E^{-1}\,P\,)^{-1}\,C\,P^t\,E^{-1}\,[\,T_{loRes} - P\,t(89_{hiRes})\,]$$



Two ways to account for the dependence of microwave observations of precipitation on uncertain microphysics

Z.S. Haddad et al

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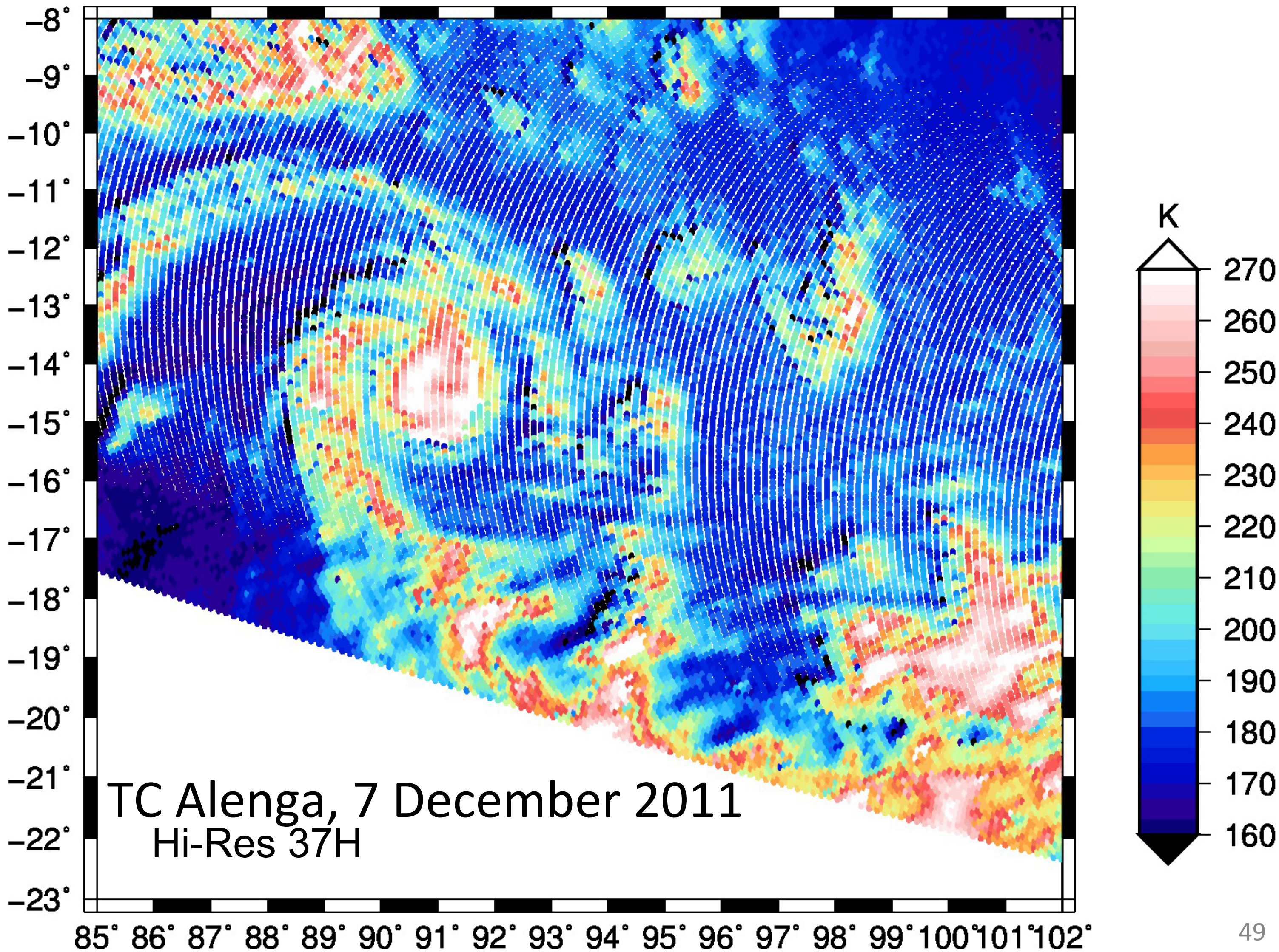


Z.S. Haddad et al

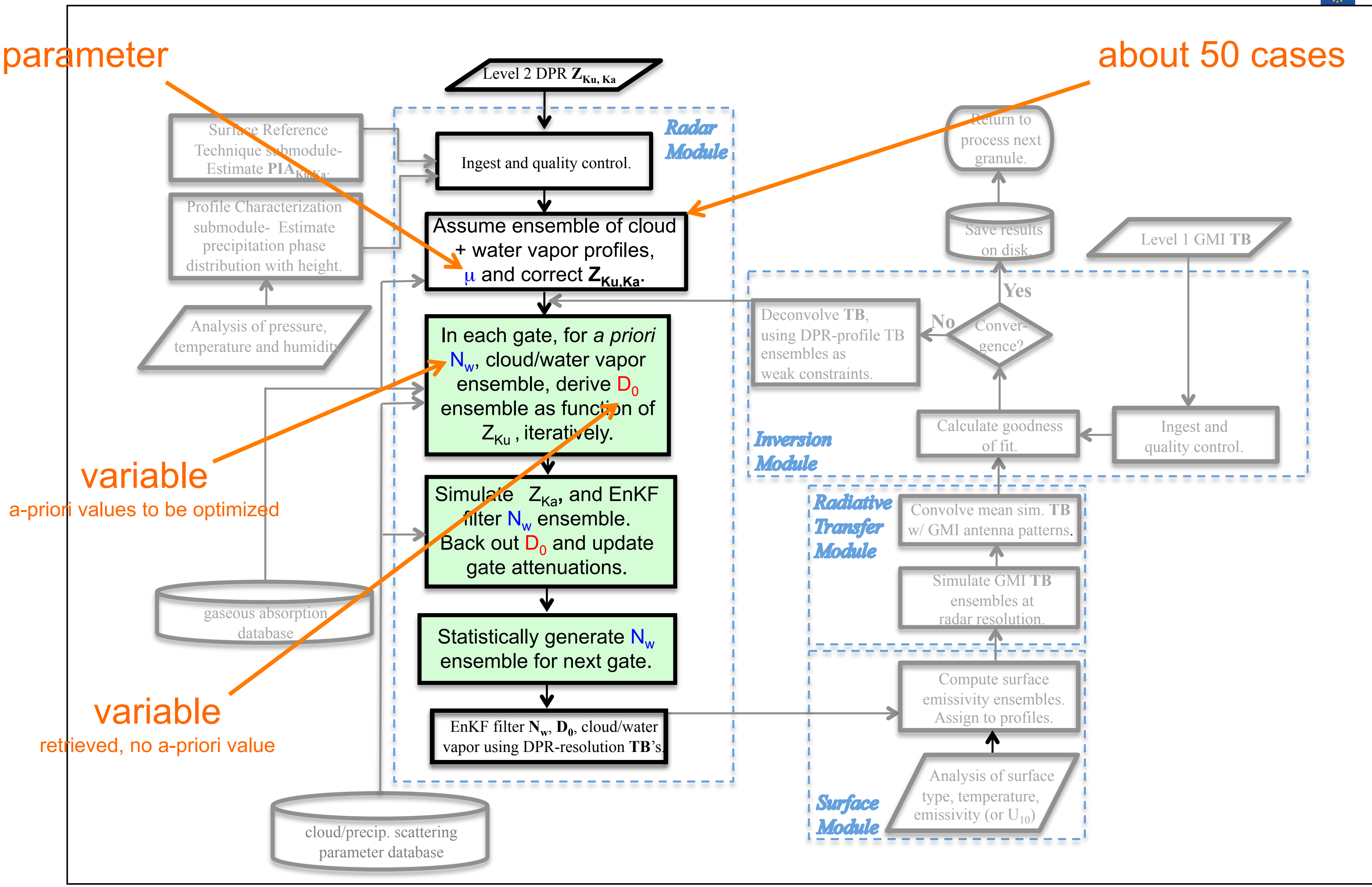
$$T_{hiRes} = t(89_{hiRes}) + (1 + C\, P^t\, E^{-1}\, P\,)^{-1}\, C\, P^t\, E^{-1}\, [\, T_{loRes} - P\, t(89_{hiRes})\,]$$

We now need to analyze the dependence on

1. the pixel classification conditioned on T89V, T89V,
2. the derived mean relations (t) between (T89V, T89V) & the lower-frequency brightness temperatures (at same resolution),
3. the quantification of the covariance around (*C*) the mean relations
4. the allowable error on the deconvolution portion (*E*)
5. the size of the domain

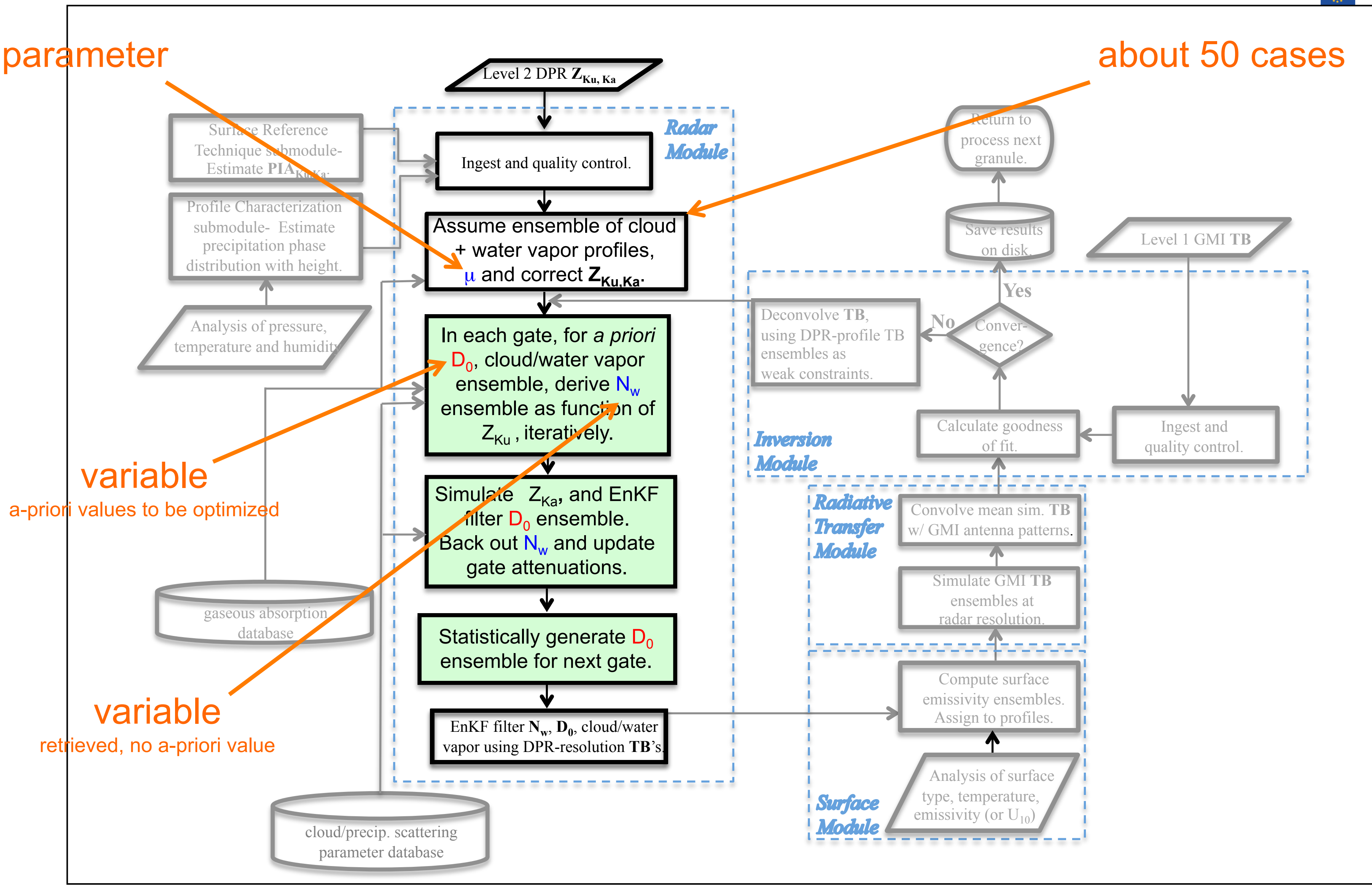
Two ways to account for the dependence of microwave observations of precipitation on uncertain microphysics

Algorithm Theoretical Basis (“Default Algorithm”)



Two ways to account for the dependence of microwave observations of precipitation on uncertain microphysics

Algorithm Theoretical Basis (“Default Algorithm”)



Two ways to account for the dependence of microwave observations of precipitation on uncertain microphysics

Test alternative