Numerical and Physical Sensitivities in Large Eddy Simulations of Plume Lofting and Spread

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Warm Boundary Layer Process

October 27, 2022

PNNL is operated by Battelle for the U.S. Department of Energy

Near-surface PINACLES plume tracers overlaid on vertical velocity field

Motivation

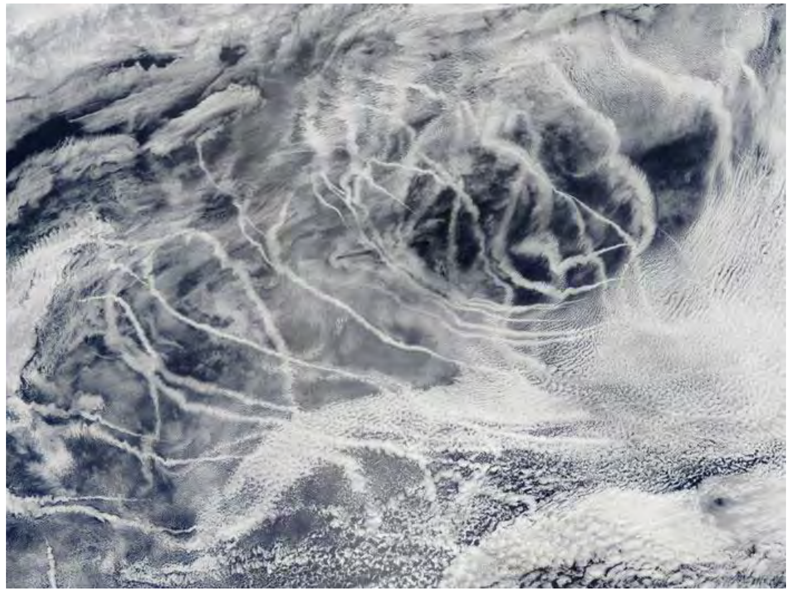
- Inject salt-water plumes at the ocean surface
  - Droplets evaporate to leave sea salt aerosol
  - Turbulent mixing lofts the aerosol to cloud base
  - Increase cloud albedo and longevity

- Limited opportunities for controlled field experiments
  - **Numerical Experiments**

- PINACLES: **P**redicting **IN**teractions of **A**erosol and **C**louds in **L**arge **E**ddy **S**imulation

- Similar simulations of stratocumulus cloud test case for sensitivity studies

- 3 plumes injected a few km apart just above the surface with identical properties



"Ship tracks" are brightened cloud areas that result from aerosol particles in ship exhaust. They are an inadvertent example of the same cloud responses MCB seeks to use. Credit: NASA

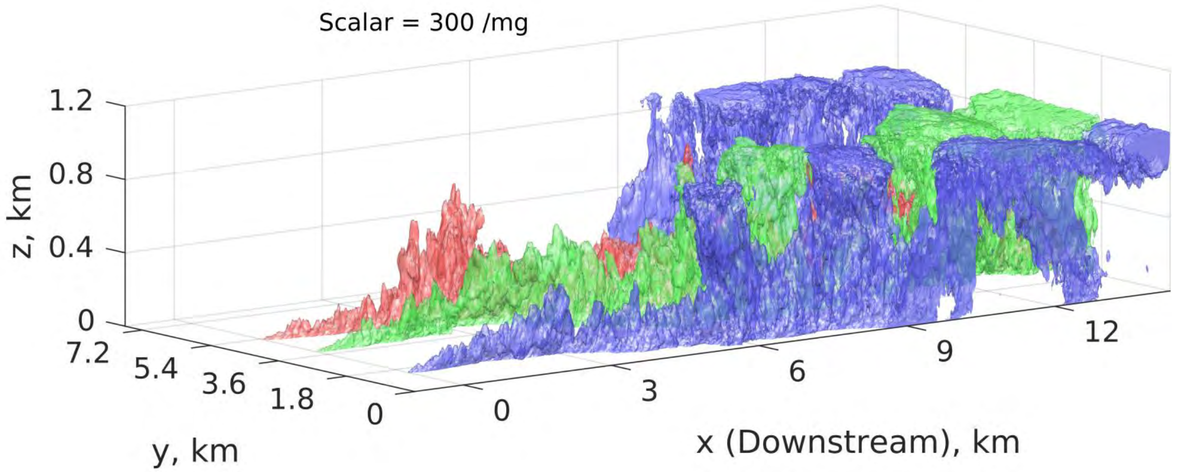
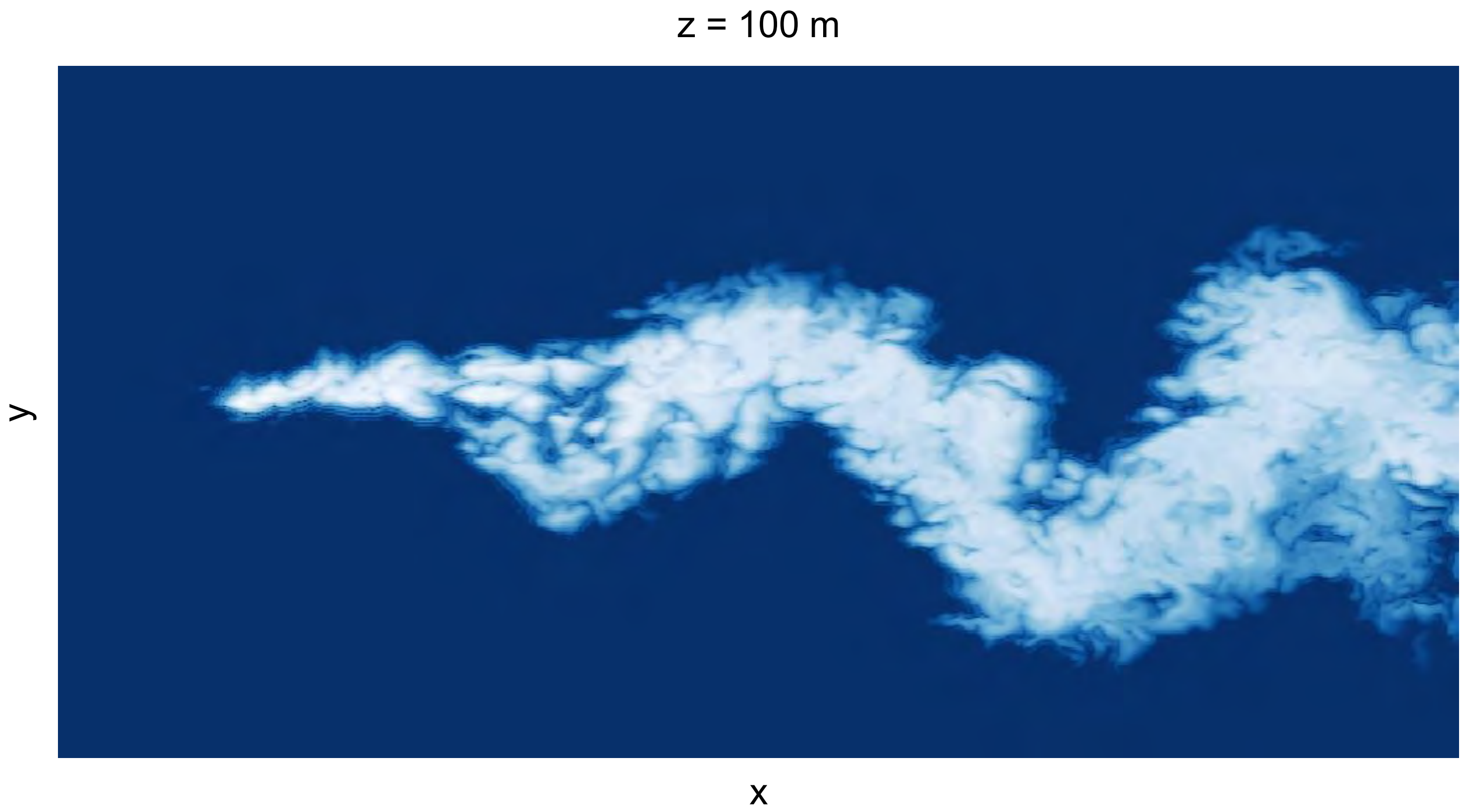


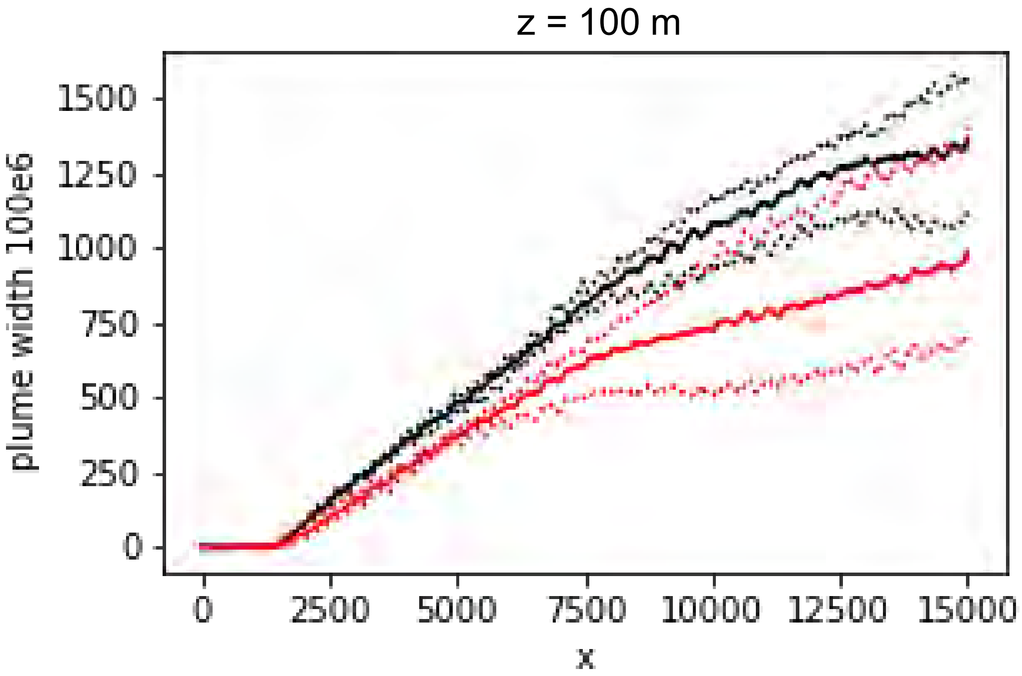
Image credits: Peter Blossey

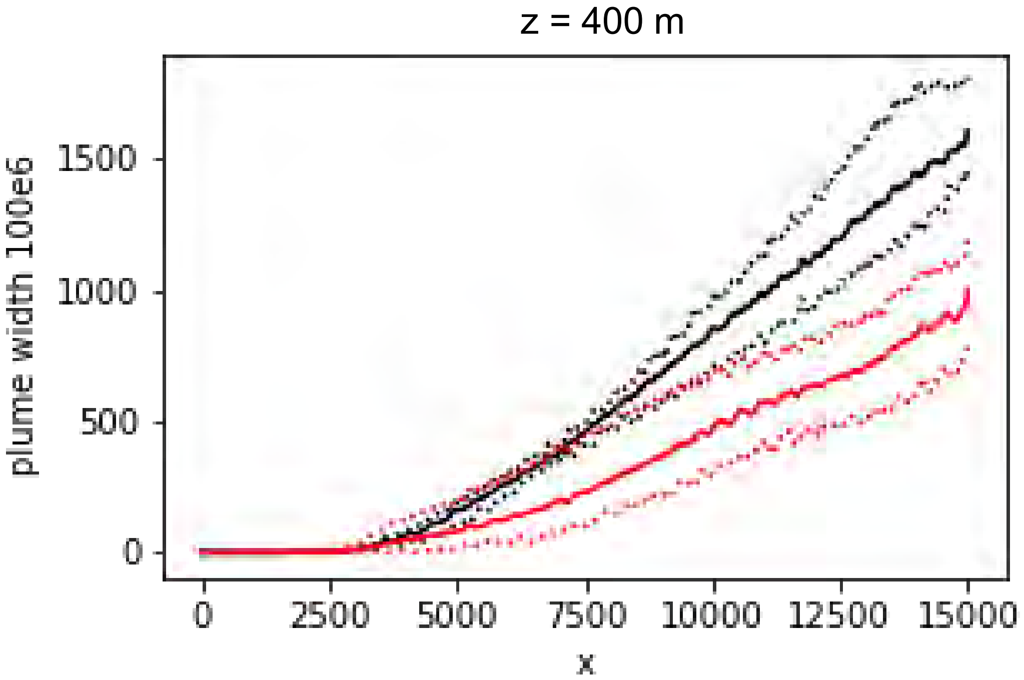
Results – Microphysics schemes

- P3 vs Morrison[1,2] microphysics schemes



Plume tracer contours from simulation using Morrison (black) microphysics scheme, z = 100 m





Plume width calculated from simulations in PINACLES using P3 (red) and Morrison (black) microphysics schemes

[1] *Morrison et al., Journal of the Atmospheric Sciences (2005)*
[2] *Wyant et al., Journal of Advances in Modeling Earth Systems (2022)*

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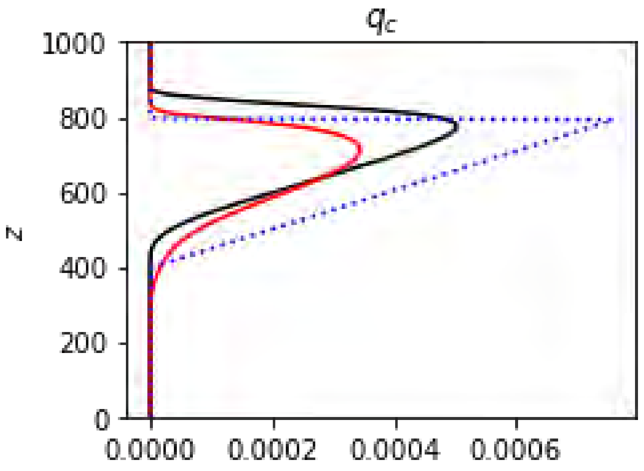
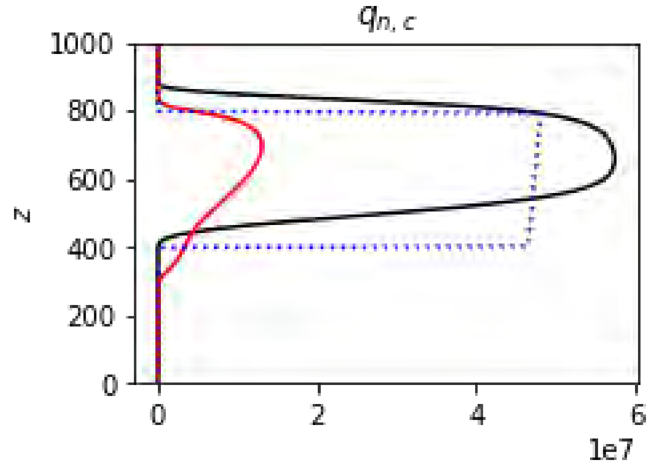
Pacific Northwest

Results – Microphysics schemes

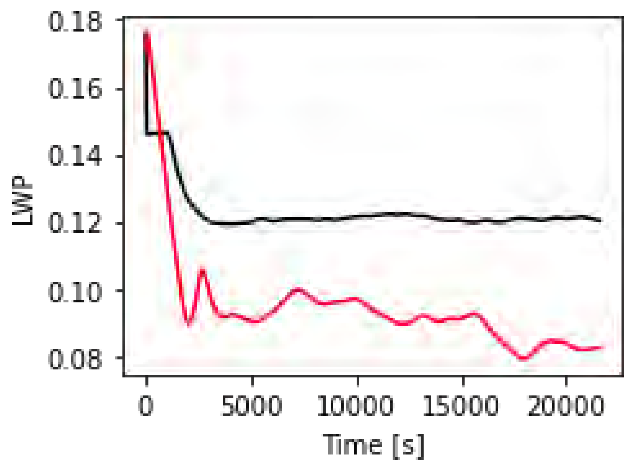
Cloud water mixing ratio



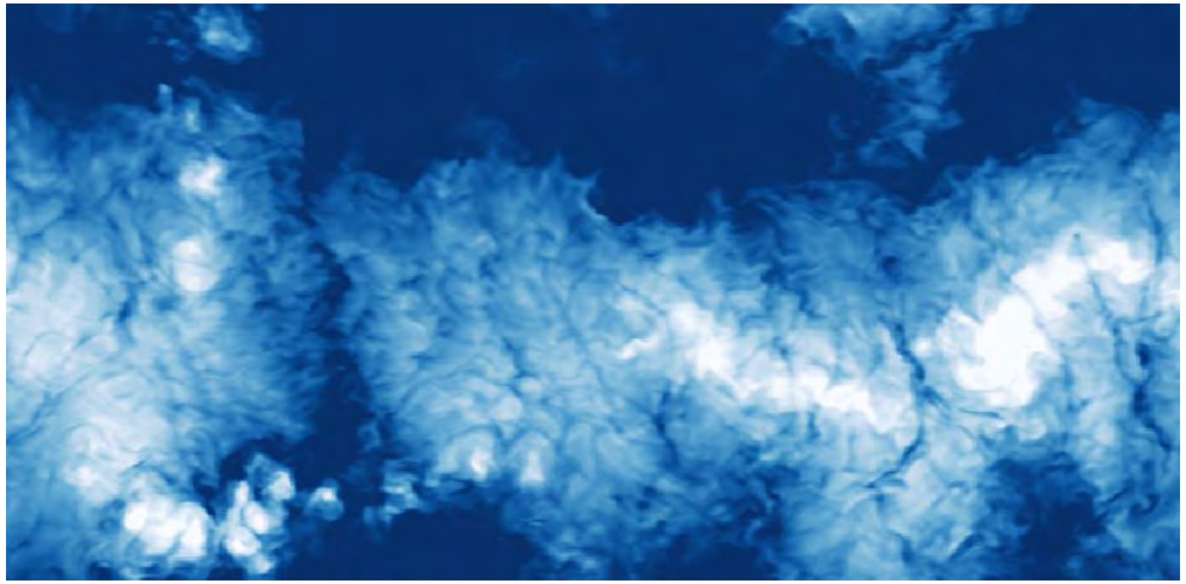
Cloud number concentration



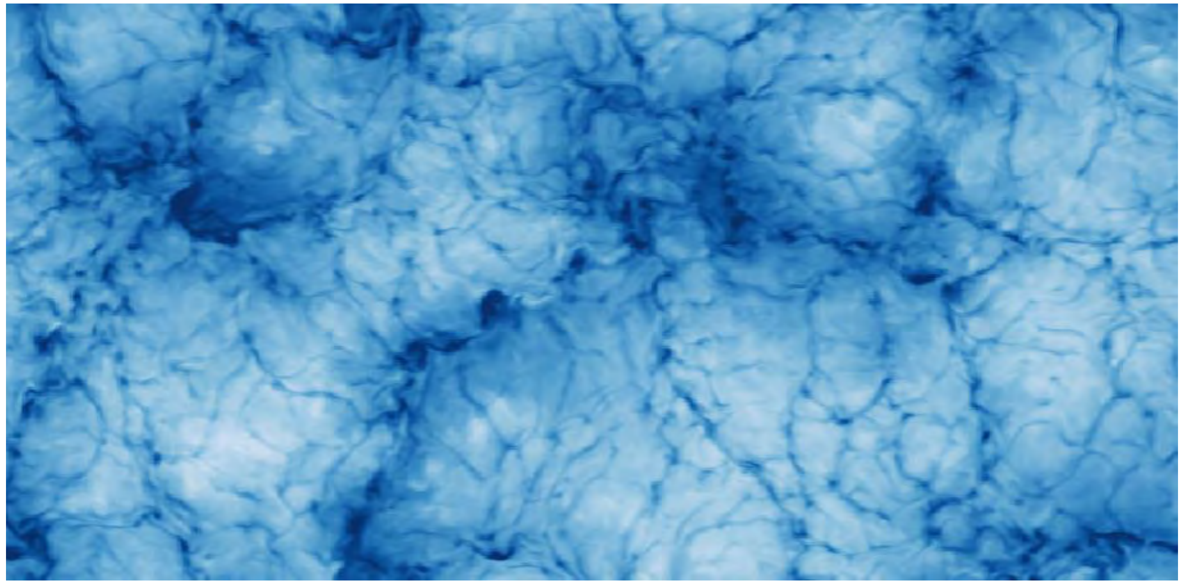
Liquid Water Path



Mean vertical profiles and time evolution calculated from simulations using P3 (red) and Morrison (black) microphysics schemes



P3 (red)

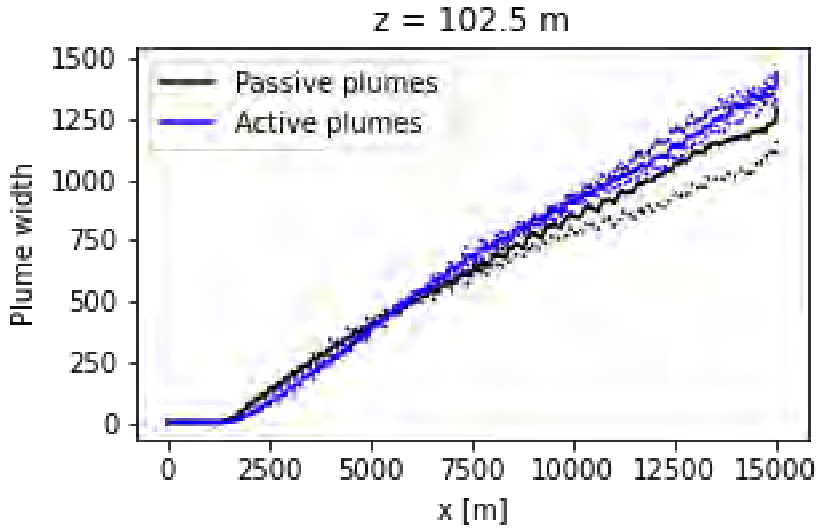


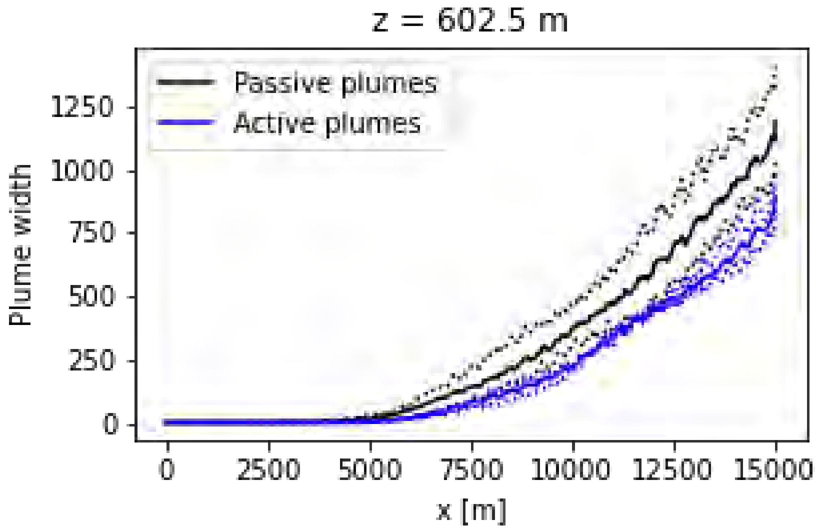
Morrison (black)

Results – Passive and active plumes

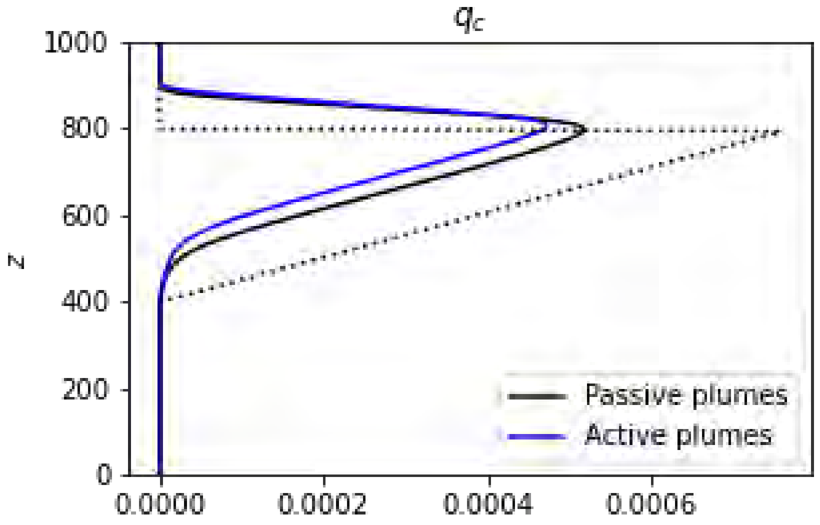
- Passive vs active plumes
- Little difference in plume lofting, with our current resolution
- Aerosol in the plumes result in much smaller cloud droplets
- Aerosol in the plumes lower liquid water path

Plume width calculated from simulations in PINACLES using passive (black) and active (blue) plumes

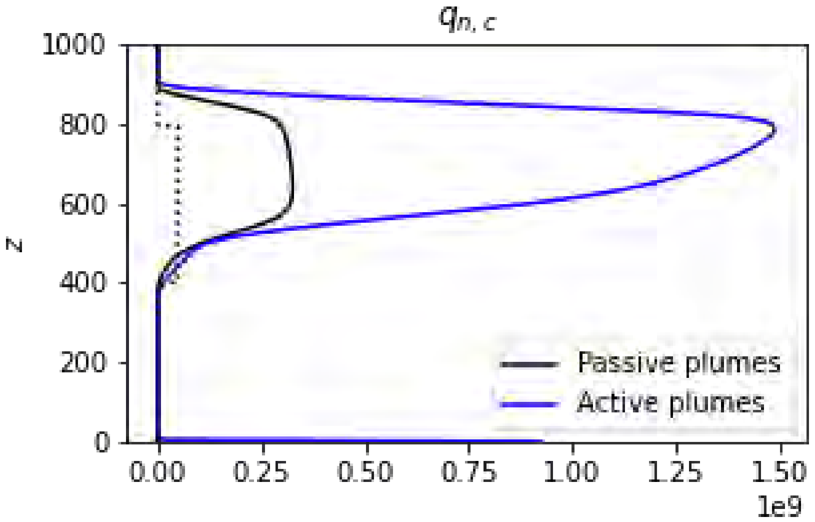




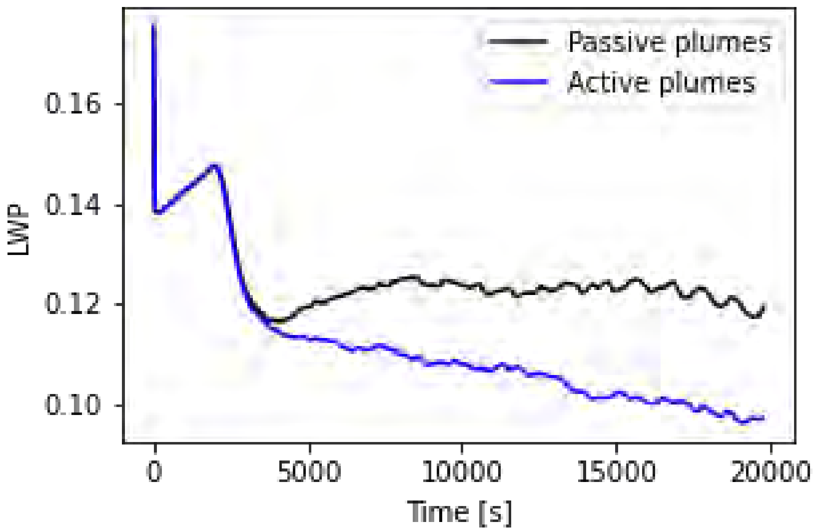
Cloud water mixing ratio



Cloud number concentration



Liquid Water Path



Mean vertical profiles and time evolution calculated from simulations using passive (black) and active (blue) plumes

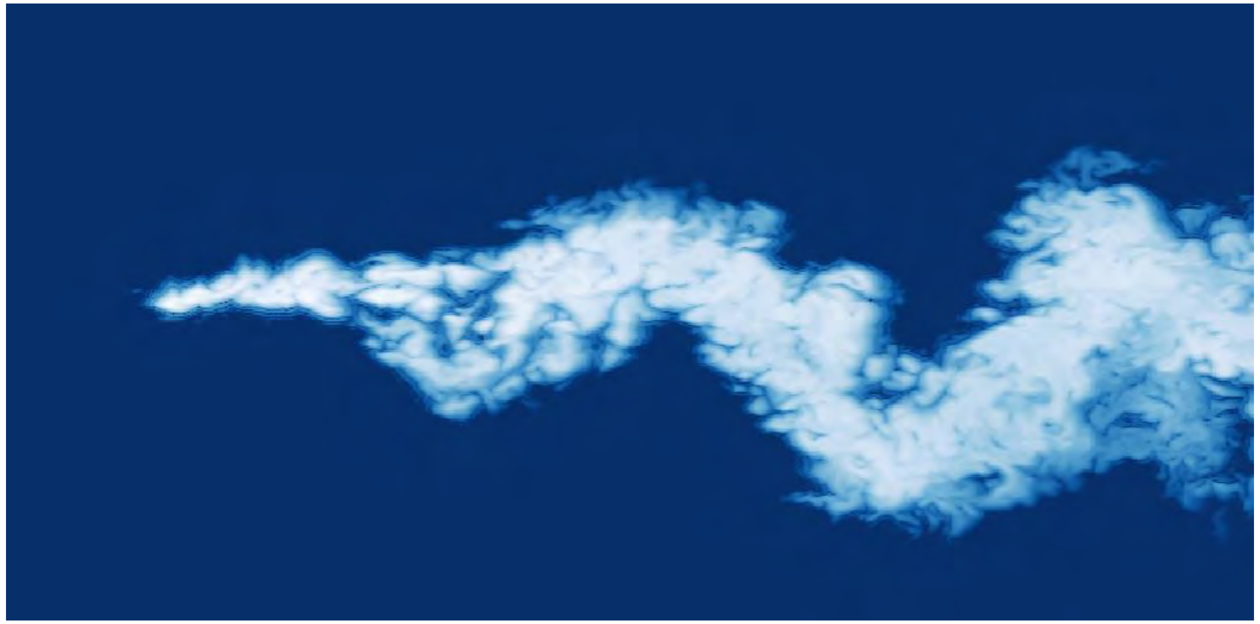
Conclusions

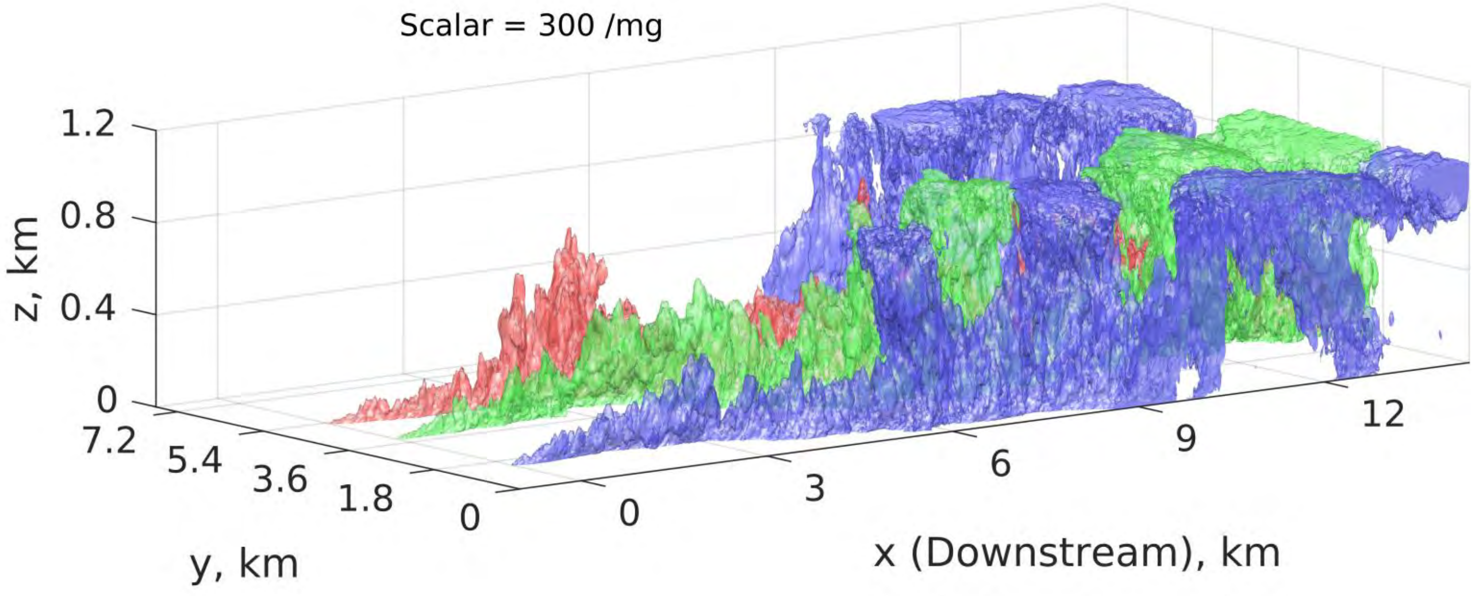
- Sea salt plumes introduced at the ocean surface spread and loft to the clouds
- Microphysics schemes have significant impact on the clouds and plume spread
- Active plumes modify cloud coverage, but have little effect on plume spread
- Different scalar and momentum advection schemes also result in differences of the same order

Future Work

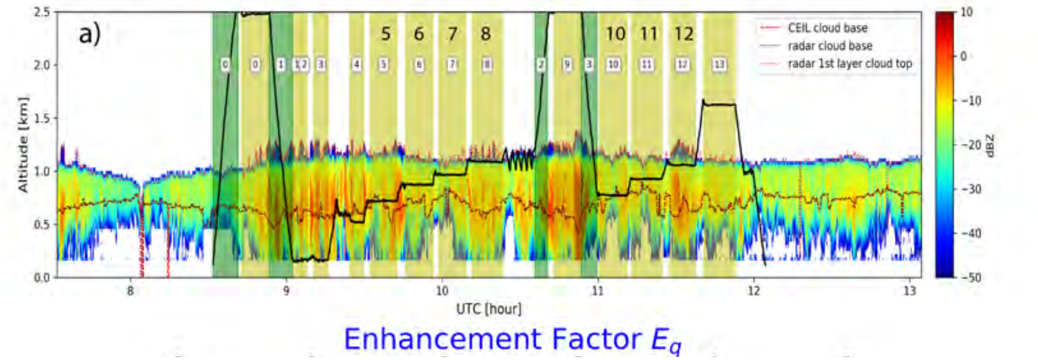
- Simulations with higher grid resolution
- Simulations of different types of stratocumulus cloud setups

More info: Poster session 3, number 45





The impact joint variability of liquid water and droplet concentration on grid-mean autoconversion and enhancement factor



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Warm Boundary Layer Process Working Group Breakout
2022 Joint ARM User Facility and ASR PI Meeting
27 October 2022

We gratefully acknowledge support from the Department of Energy Office of Science.

Impact of subgrid-scale variability on grid-mean process rates

- Neglect of SGS variability can produce biases in microphysical process rates
- Some ESMs account for via a simple "enhancement factor" multiplier *E*

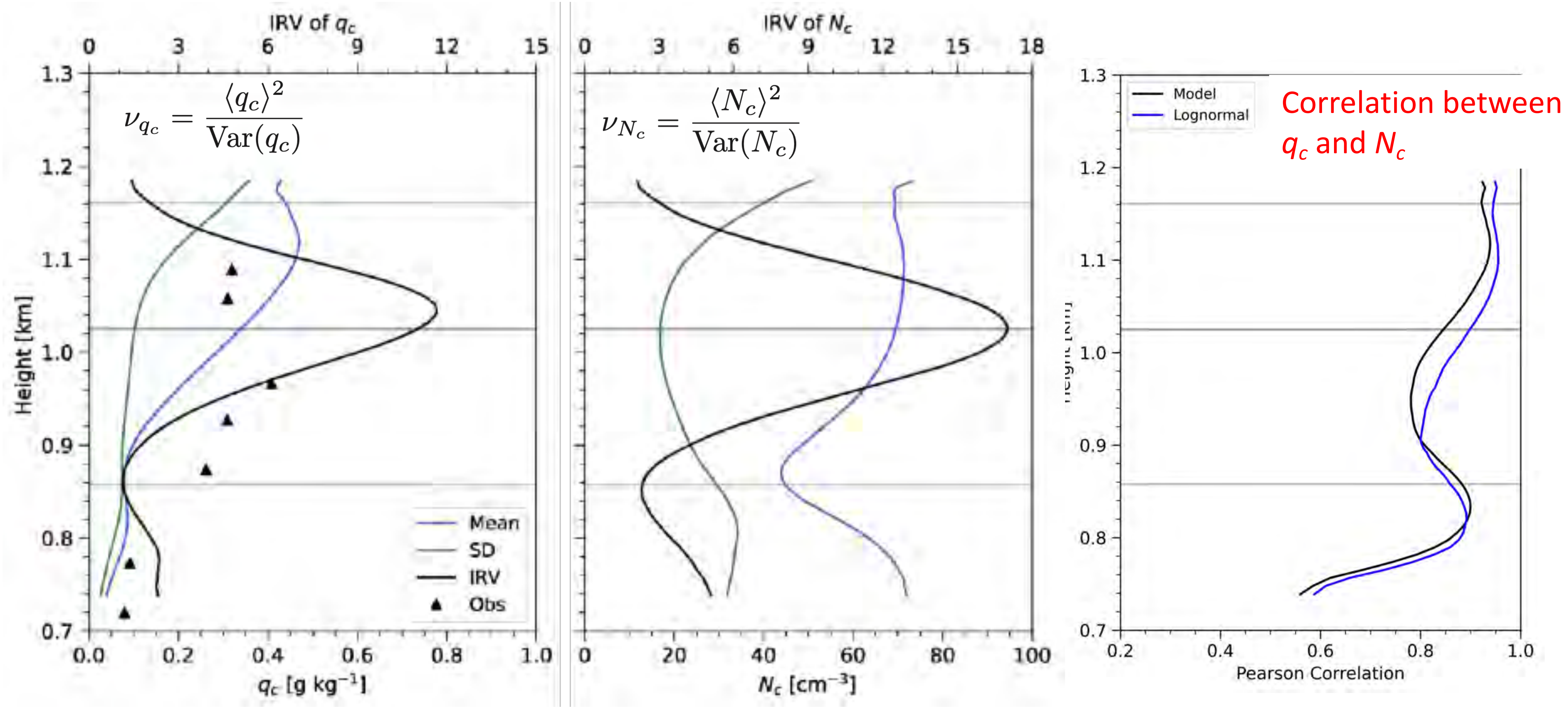
For a bivariate lognormal distribution $P(q_c, N_c)$, E can be written as

$$E = \underbrace{E_q(\nu_{q_c}, \beta_q)}_{(1)} \cdot \underbrace{E_N(\nu_{N_c}, \beta_N)}_{(2)} \cdot \underbrace{E_{\mathrm{COV}}(\rho_L, \beta_q, \beta_N, \nu_{q_c}, \nu_{N_c})}_{(3)}$$

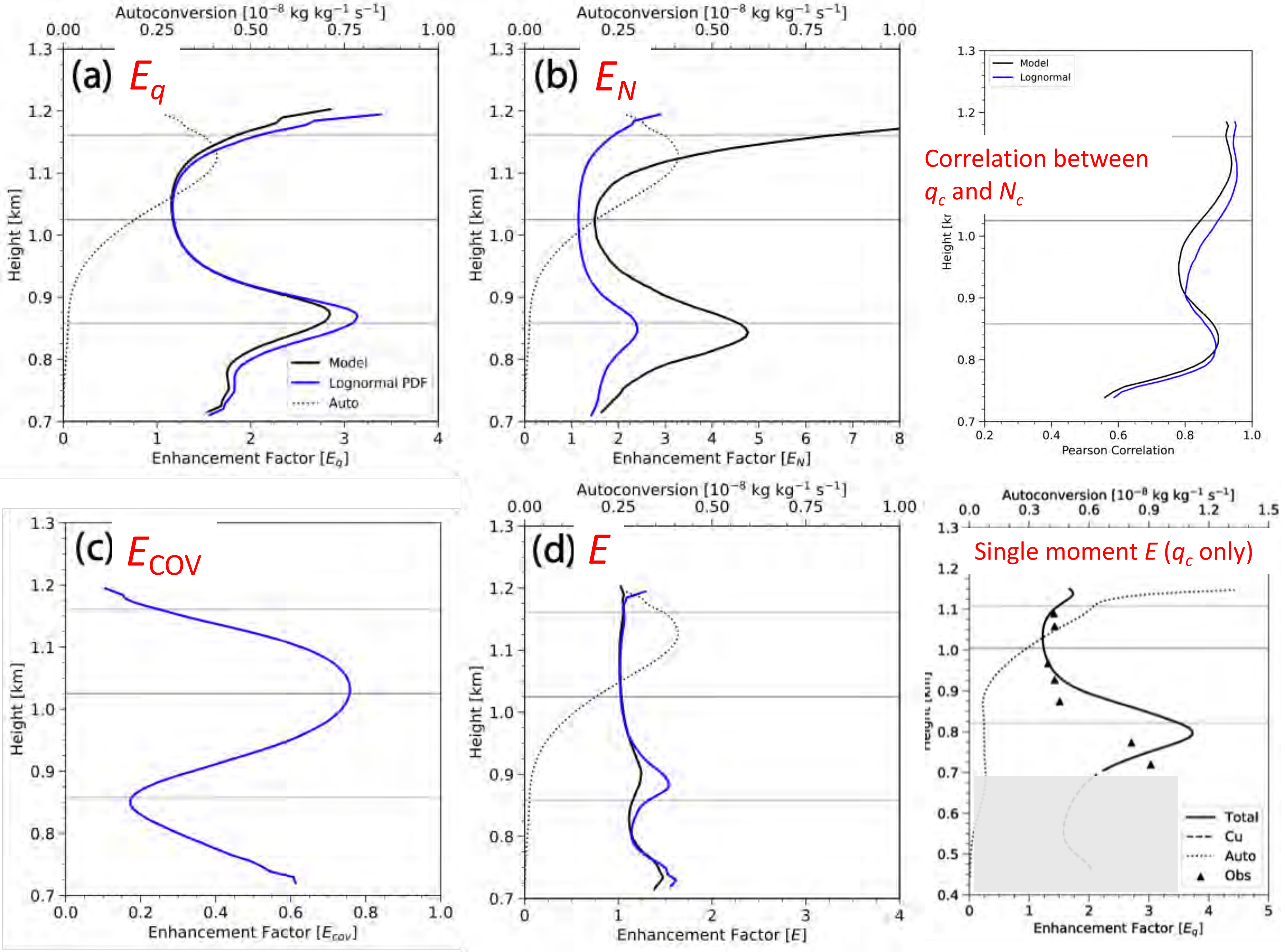
(1) Contribution to E from variability of cloud water mixing ratio (q_c)
(2) Contribution to E from variability of cloud droplet concentration (N_c)
(3) Contribution to E from the covariance between q_c and N_c

- Here we present results from large-eddy simulation (LES) with bin microphysics to analyze the impact of the co-variation of cloud water q_c and cloud droplet concentration N_c on SGS variability and enhancement factor E

Impact of subgrid-scale variability on grid-mean process rates



Contributions to E from variability in q_c, N_c, and COV(q_c, N_c)



Conclusions

- Both bulk and bin simulations suggest that E should be lower than the 3.2 value commonly used
- Covariance between q_c and N_c responsible for the reduction in E
- Large correlation between q_c and N_c near cloud top suggests inhomogeneous mixing

Washington University in St. Louis
James McKelvey School of Engineering

Maximum Supersaturation in the Marine Boundary Layer Clouds Over the Eastern North Atlantic

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[1]*Washington University in St. Louis, St. Louis, MO, USA*

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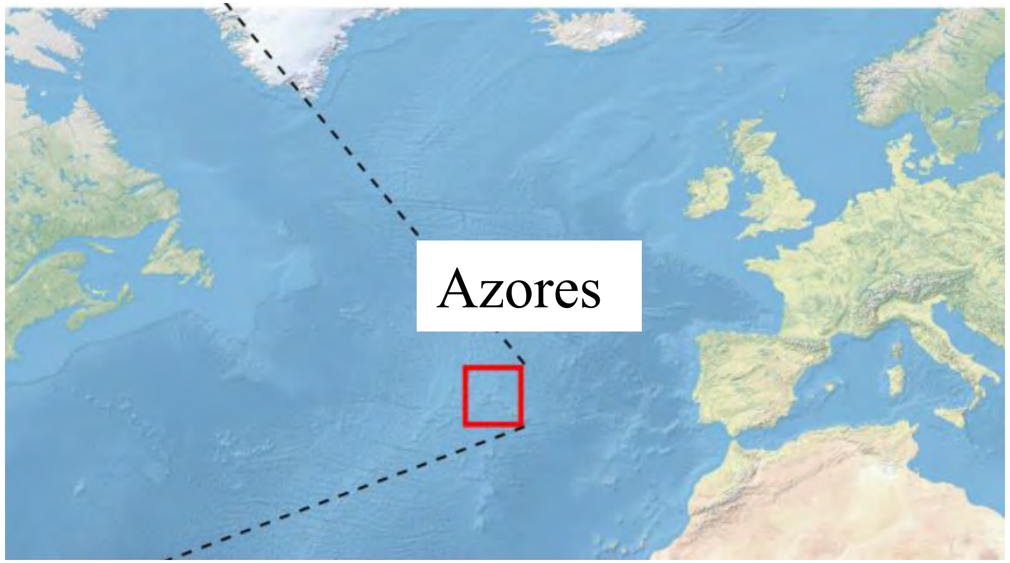
center for aerosol science and engineering

Aerosol and Cloud Experiment in Eastern North Atlantic (ACE-ENA)

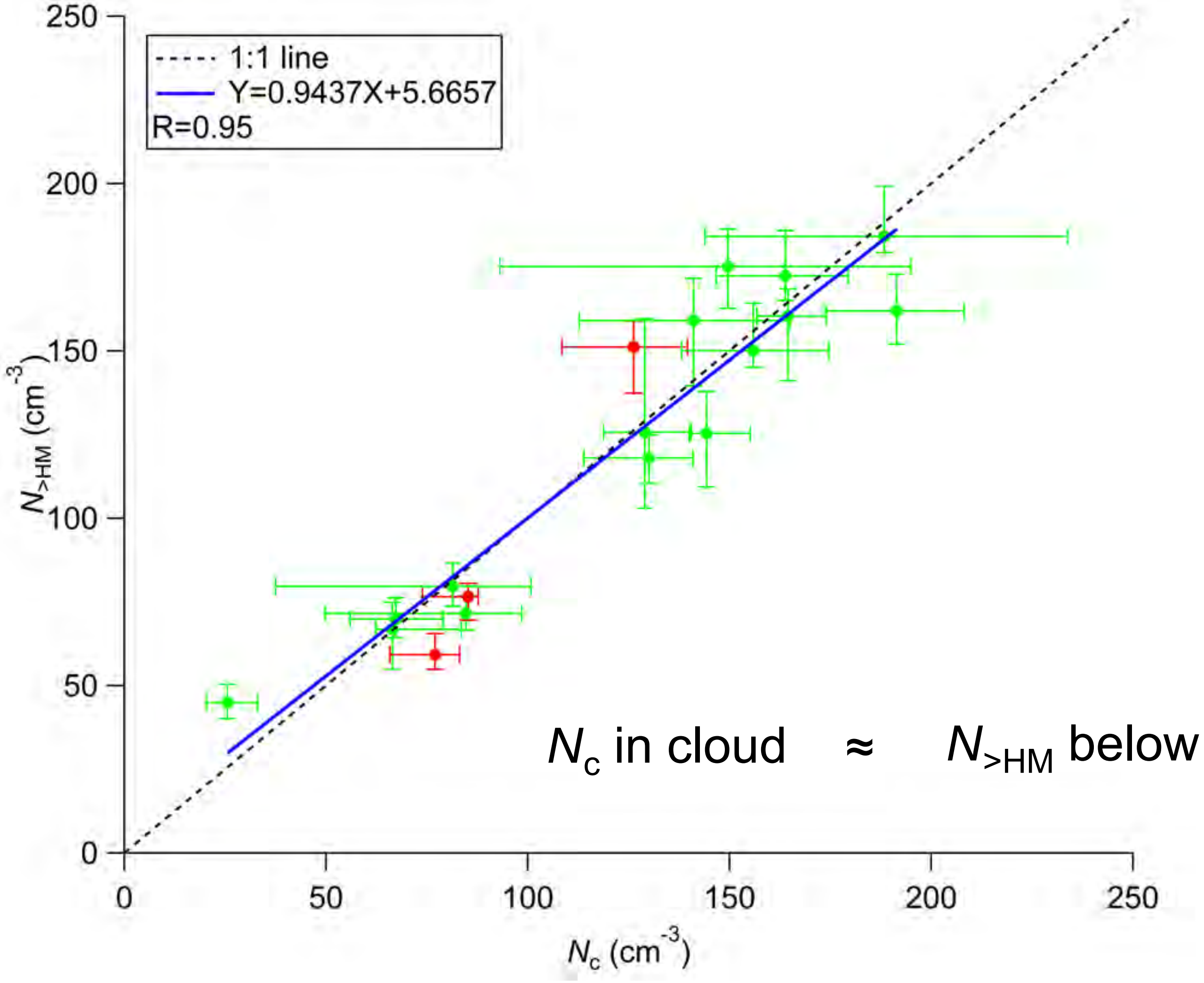


ENA site: Particle number size distribution, CN, N_{CCN}, particle hygroscopicity (κ_{CCN})

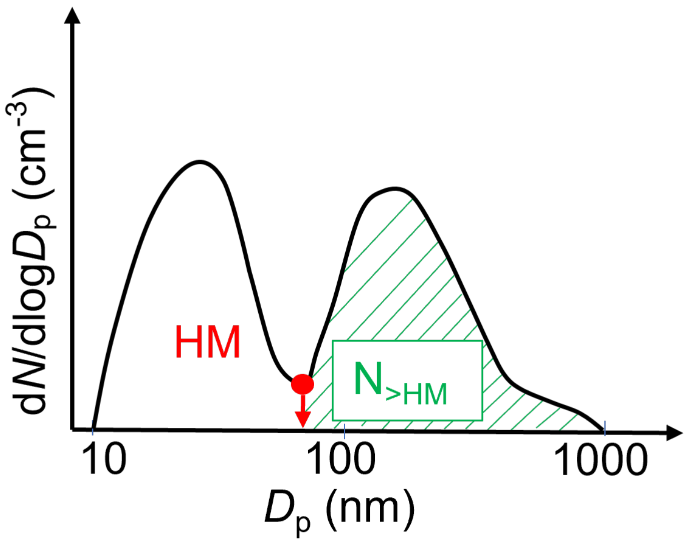
Aircraft measurements: aerosol properties and cloud microphysics

Wang et al., 2022, BAMS

Hoppel Minimum and Maximum Supersaturation



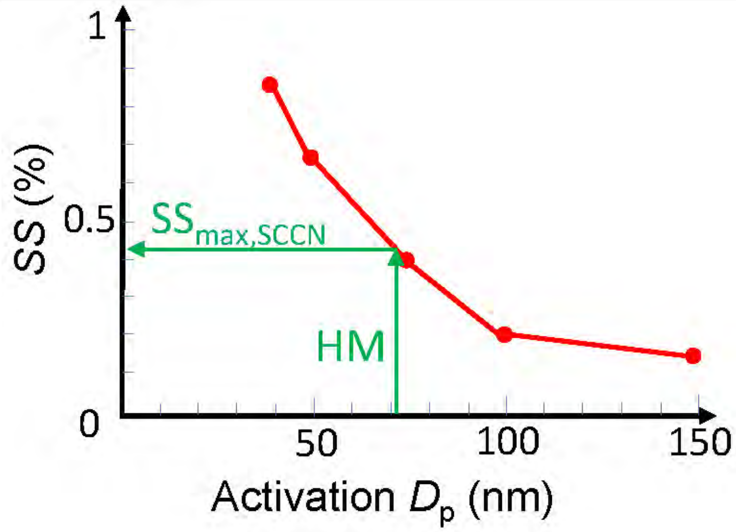
N_c in cloud ≈ $N_{>HM}$ below cloud



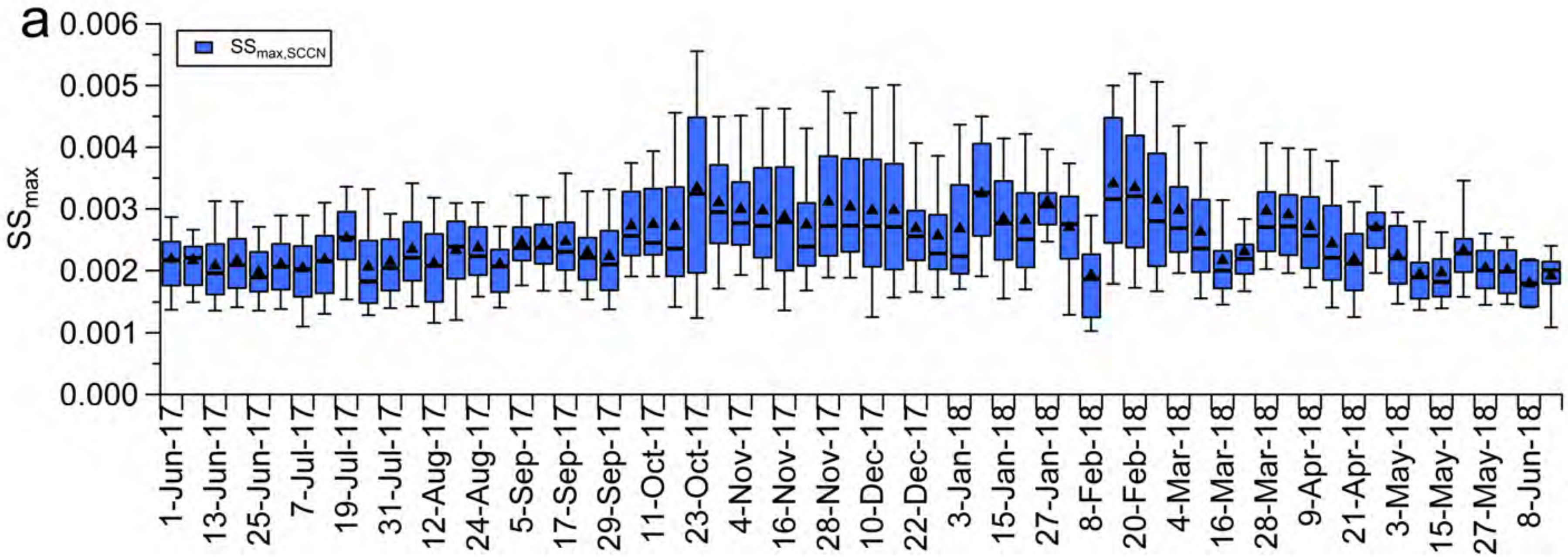
$N_{>HM}$: particle number concentration in the size larger than HM

N_c: cloud droplet number concentration

Maximum Supersaturation in the Clouds

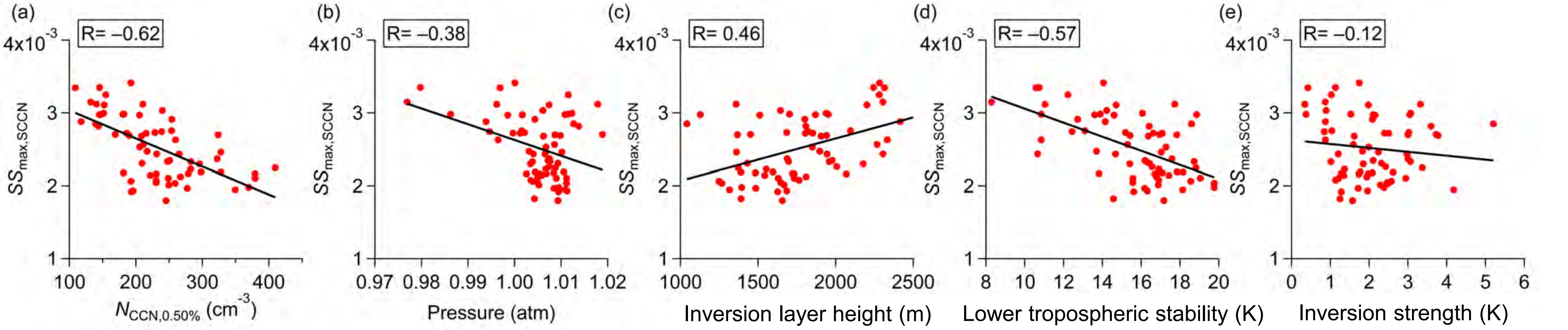


SCCN measured particle activation spectrum + Hoppel Minimum → $SS_{max,SCCN}$



Clear seasonal variations with high values in winter

Dependence on CCN Concentration and Meteorological Parameters



Suppression of SS_{max} by increased condensation sink of water vapor at high N_{CCN}.

Stronger convection as cold air advects over warm ocean following the passage of fronts

The strong updrafts are associated with strong radiative cooling on cloud top, and stronger latent heat release, which scales with the cloud thickness. Thicker clouds are often formed in deeper MBL. Lower static stability allows for deeper MBL, as does reduced subsidence.

MLR
R^2=0.57

Summary

- Hoppel Minimum in the marine boundary layer is the result of processing by non-precipitation clouds.
- SS_{max} in the cloud is derived from Hoppel Minimum and aerosol activation measurements at the ENA site.
- SS_{max} over the Eastern North Atlantic shows a clear seasonal variation.
- SS_{max} variation is related to CCN number concentration, pressure, lower tropospheric stability, and inversion layer height.

Acknowledgements

ASR Atmospheric System Research

U.S. DEPARTMENT OF ENERGY

Office of Science

ARM

Lawrence Livermore National Laboratory

ENA Warm Boundary Layer Clouds from ARM Observations and Geostationary Satellite Cloud Retrievals

Xue Zheng, Shaoyue Qiu

Lawrence Livermore National Laboratory

David Painemal

NASA Langley Research Center

Science Systems and Applications Inc.

2022 ARM/ASR Joint User Facility and PI Meeting

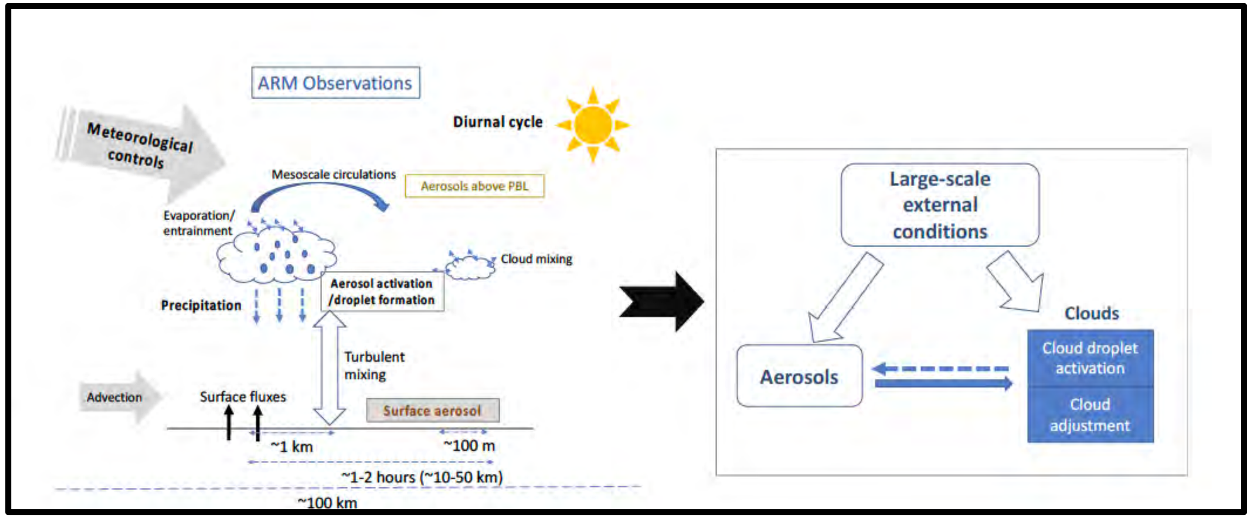
Rockville, MD
Oct. 26, 2022

Acknowledgement: *This work is supported by the DOE Office of Science Early Career Research Program and the ASR Program. This work was performed under the auspices of the U.S. DOE by LLNL under contract DE-AC52-07NA27344. LLNL-PRES-841669*

ASR Atmospheric System Researc

Scientific Objectives

- Better detect and understand the liquid-phase cloud response to aerosol perturbations in observations through constraining large-scale meteorological factors
- Reduce the related uncertainty in the DOE Energy Exascale Earth System Model with an emphasis on the process-level understanding



We started this project with the marine boundary layer clouds over the ENA region

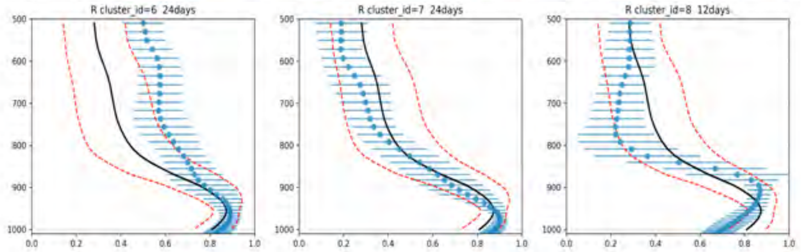
Lawrence Livermore National Laboratory

Constrain meteorological controlling factors

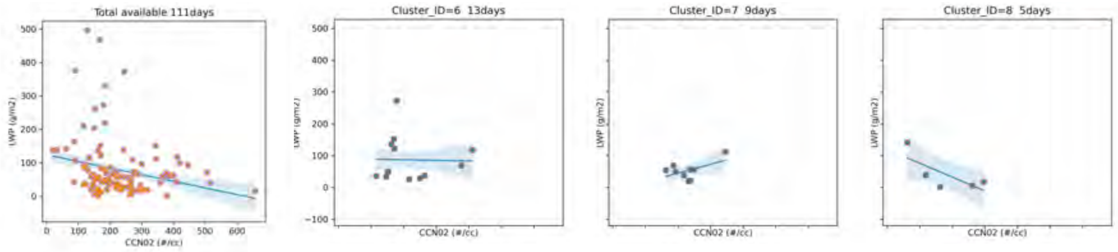
- Multiple meteorological variables clustering
  - Daily U, V, T, Q, Relative humidity profiles (7 pressure levels for now)
  - ECMWF analysis for the ARM ENA site: 2015-2020 JJA. **276** no-deep-convection days in total
  - Unsupervised clustering algorithms (MiniBatchKMeans, DBSCAN, Spectral Clustering)
- Analyze ARM observed cloud and surface CCN for each cluster
  - Daily LWP and surface CCN (SS0.2%): 2016-2019 JJA, **111** days from ARM Best Estimate Data Products (ARMBE)
- Advantages and challenges
  - The approach is applicable to model analyses
  - Limited observed variables and data samples
- Future work
  - Optimize the clustering process
  - Expand the sample size through including different ARM sites
  - Case study based on the clustering result

Calendar of clusters

Relative humidity in three clusters as an example

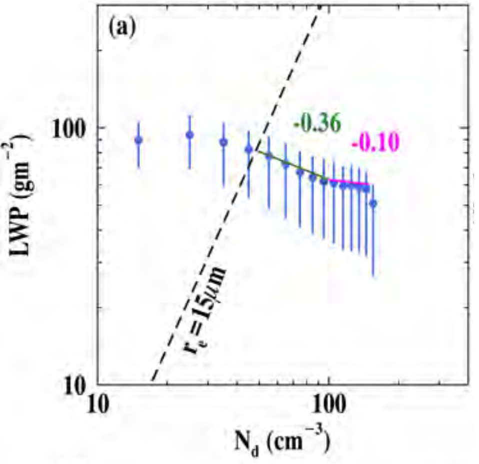


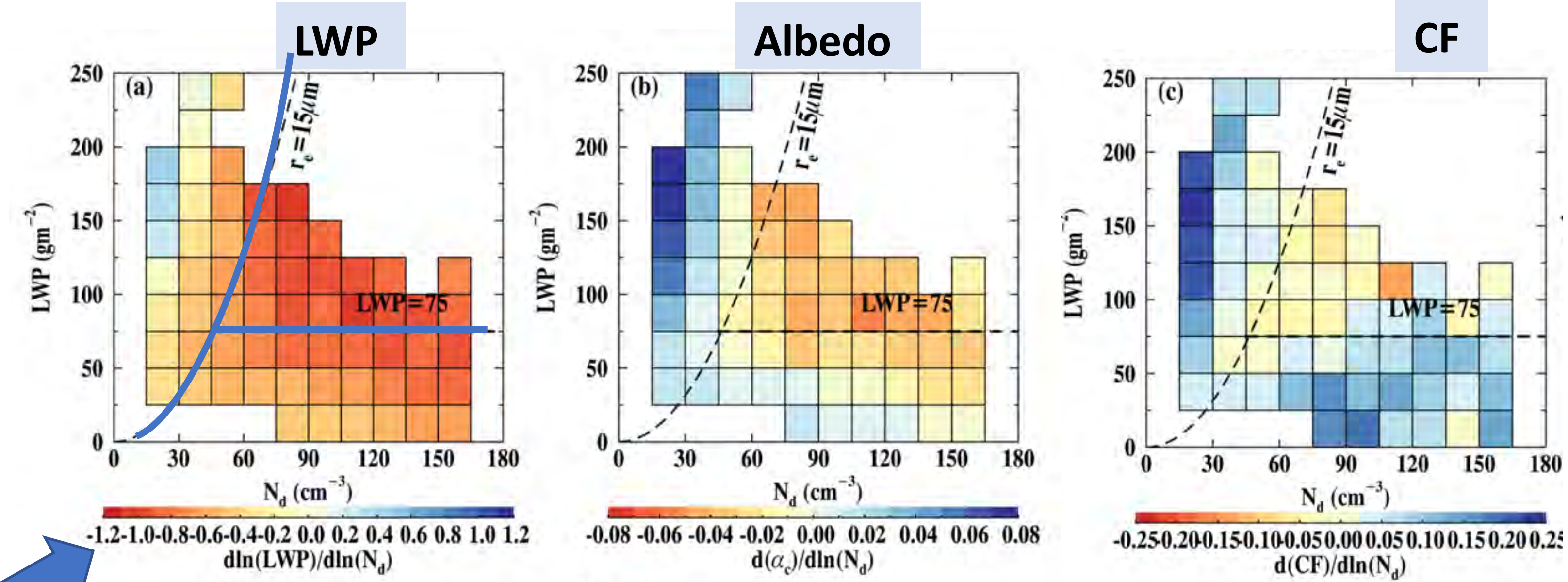
ENA Obs CCN_{surf} SS0.2% vs. LWP



Cloud susceptibilities over the ENA region from Meteosat retrievals

LWP-N_d climatology

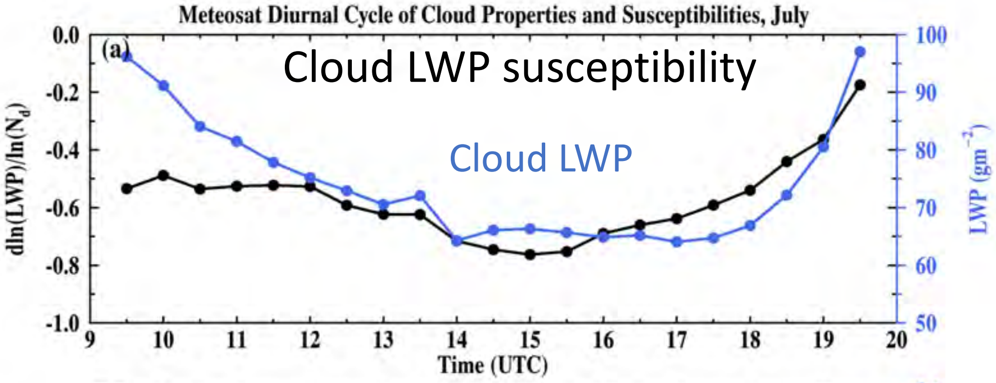




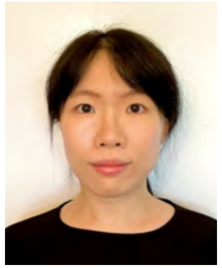
Meteorological conditions *are **better constrained** in the instantaneous spatial correlation within each 1°x1° grid*

Different cloud regimes including broken clouds

Diurnal variability



Daytime half-hourly data during July 2018-2021: ~ 8x10^4 samples for the region (33-43°N, 23-33°W)



Shaoyue Qiu
LLNL

Shaoyue Qiu's virtual poster for more information

Understanding the microphysical control and spatial-temporal variability of **warm rain probability** using CloudSat and MODIS observations

Zhibo Zhang (UMBC)
Lazaros Oreopoulos (NASA GSFC), Matthew D. Lebsock (NASA JPL), David B. Mechem (Univ. of Kansas), Justin Covert (Univ. of Kansas)

This research is supported by the DOE-ASR and NASA-CCST programs

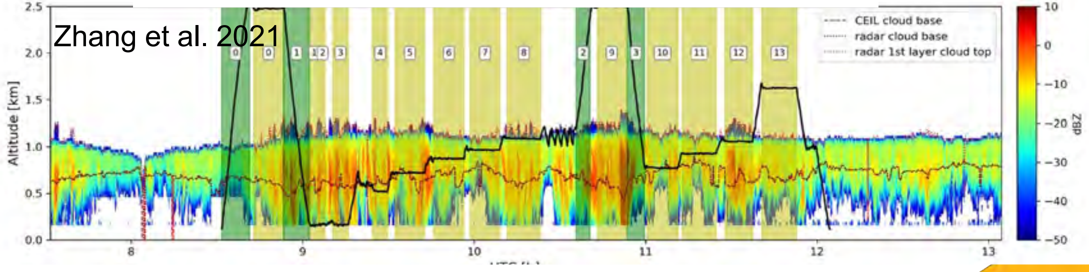
Warm rain in marine low clouds (MLC)

- Warm rain is generated by the collision coalescence process and prevalent in MLC
- Warm rain is important for
  - Water budget in MLC (important sink of water)
  - Lifetime of MLC
  - Radiative effects of MLC
  - Aerosol-cloud interactions (lifetime effects)
- Measurements of warm rain
  - Intensity/precipitation rate
  - Fraction/probability (e.g., PoP)

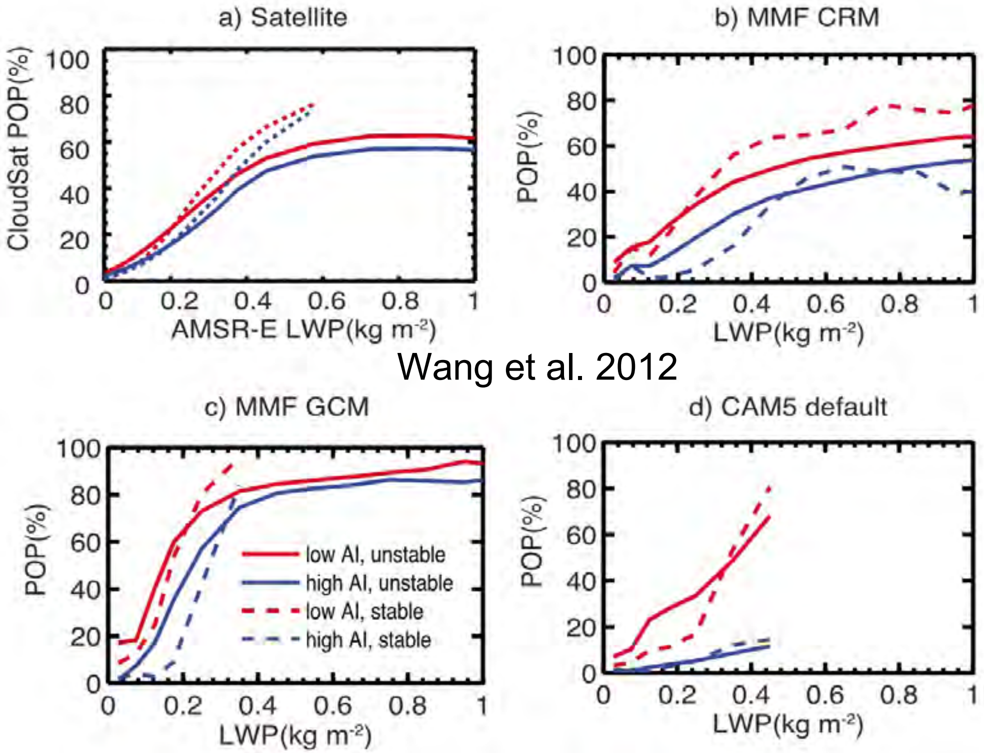
Precipitation rate is difficult to quantify from remote sensing observations

Many previous studies used the PoP to study warm rain. (Lebsock et al. (2008) and L’Ecuyer et al. (2009) Wang et al. 2012; Mann et al. 2014; Song et al. 2018, Mülmenstädt et al. 2020)

Ground-based w-band radar reflectivity

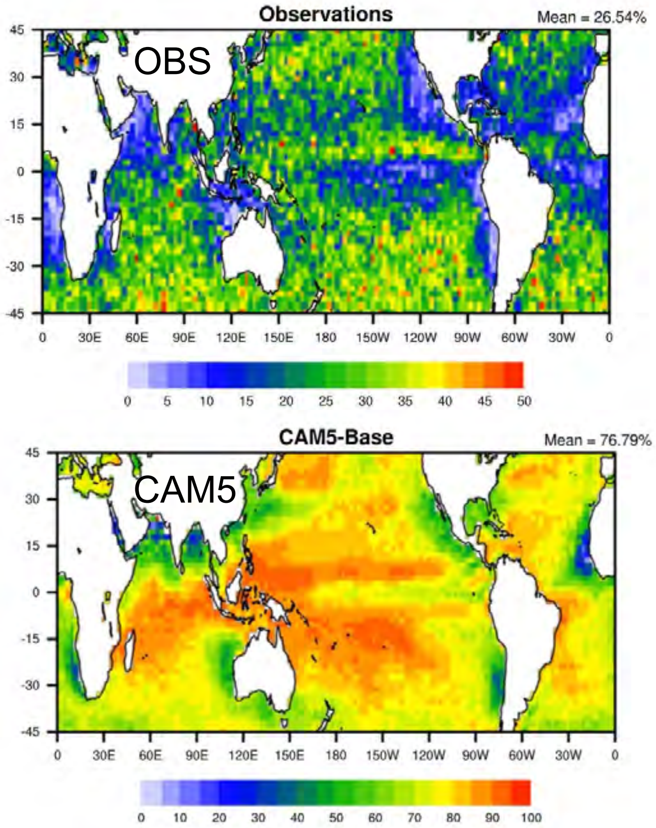


PoP is important and useful



Wang et al. 2012

Song et al. 2018



Motivation and Objectives

- Derive the warm rain probability (i.e., PoP) from the observation (MODIS+CloudSat)
- Investigate the dependence on PoP on cloud properties
  - Cloud liquid water path (LWP)
  - Cloud Droplet Number Concentration (CDNC)
- Understand the spatial-temporal variability of PoP
  - Transition of PoP from stratocumulus to cumulus cloud regimes
  - Seasonal variation of PoP in stratocumulus cloud regions

Key Hypothesis

$$\langle PoP \rangle = \iint PoP(LWP, CDNC)\, PDF(LWP, CDNC)\, dLWP\, dCDNC$$

Grid mean PoP

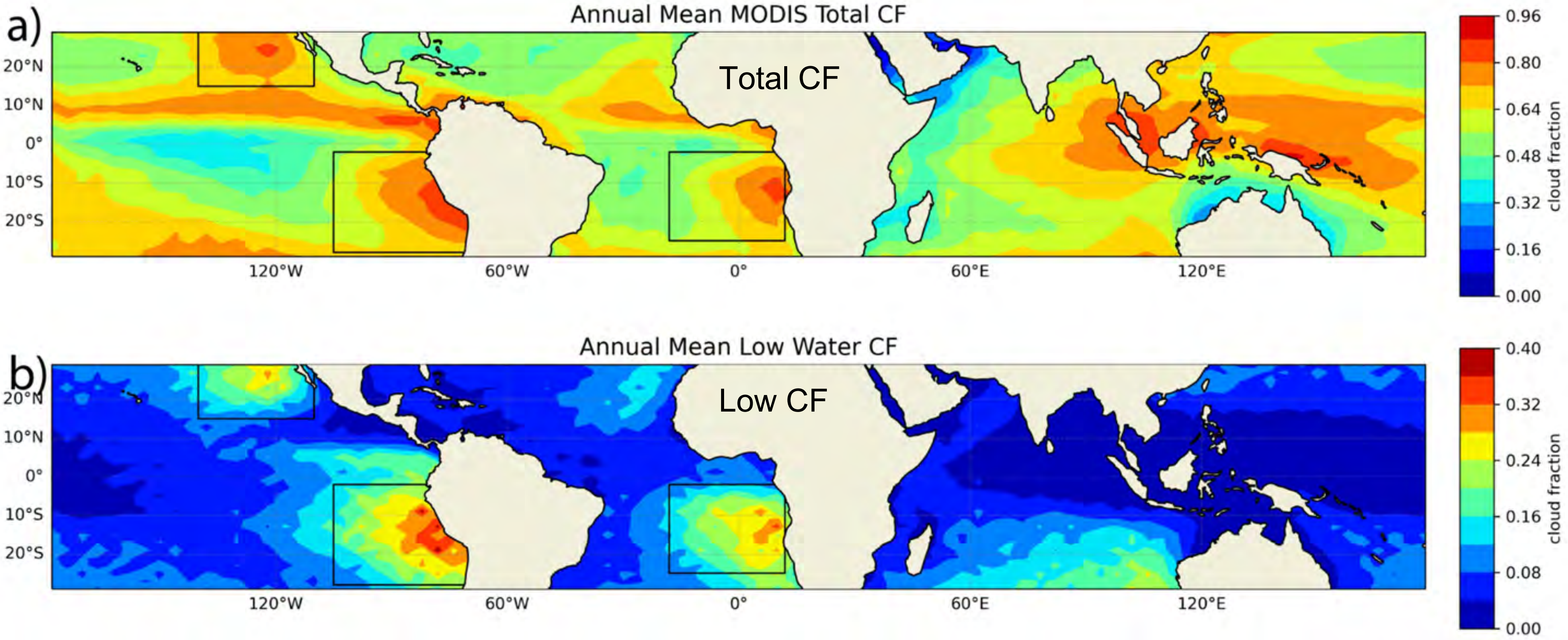
Universal
microphysical control

PDF
of cloud properties

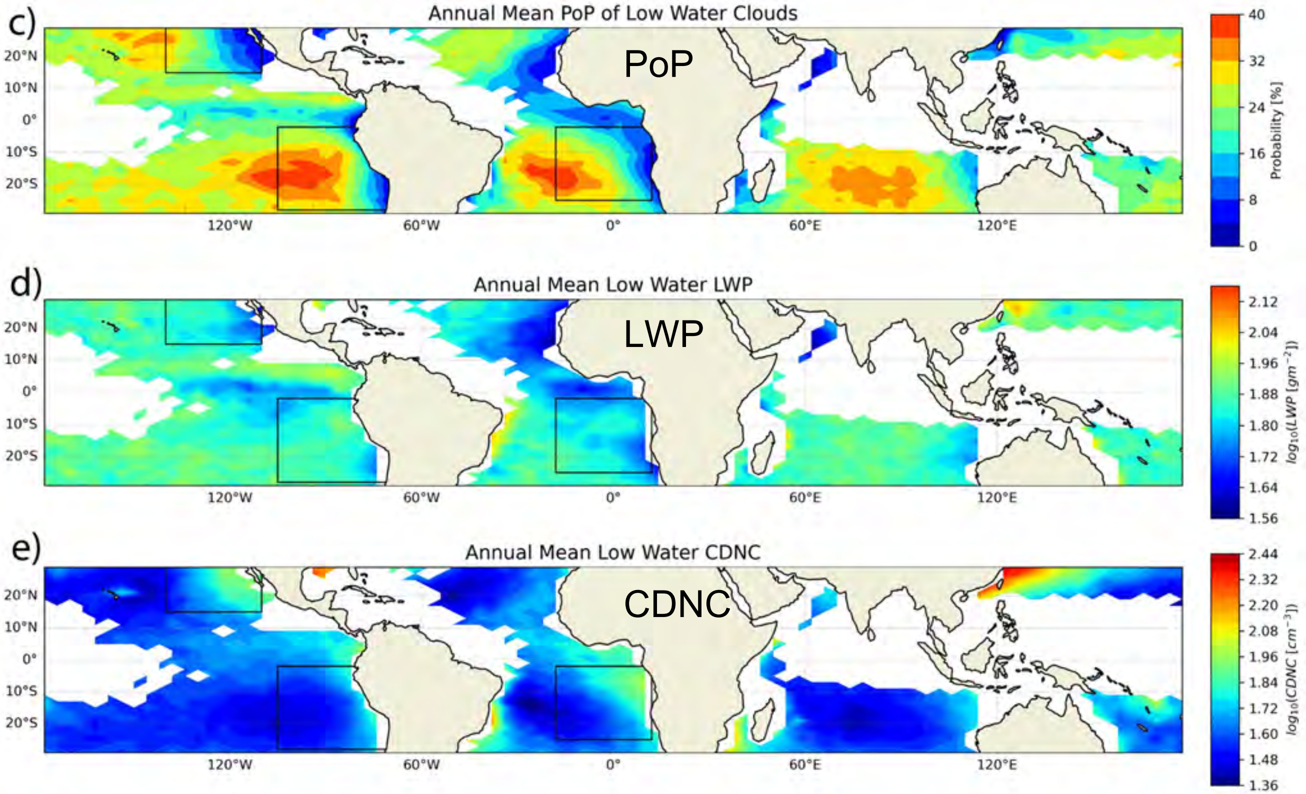
Data and Methodology

- MODIS-CloudSat collocated product
  - **Identify MLC** from MODIS and CloudSat data
    - "Cloudy" and "Liquid-phase" based on MODIS observation
    - Cloud top < 3km based on CloudSat/CALIOP
  - **Identify precipitation from** CloudSat data
    - Maximum radar reflectivity in the column dBZ_max > -15
- Definition of PoP
  - **PoP = Number of precipitation MLC clouds / Number MLC clouds** in an area (grid, region) and over certain period (monthly, seasonal, annual)

Properties of MLC in Tropics



Properties of MLC in Tropics

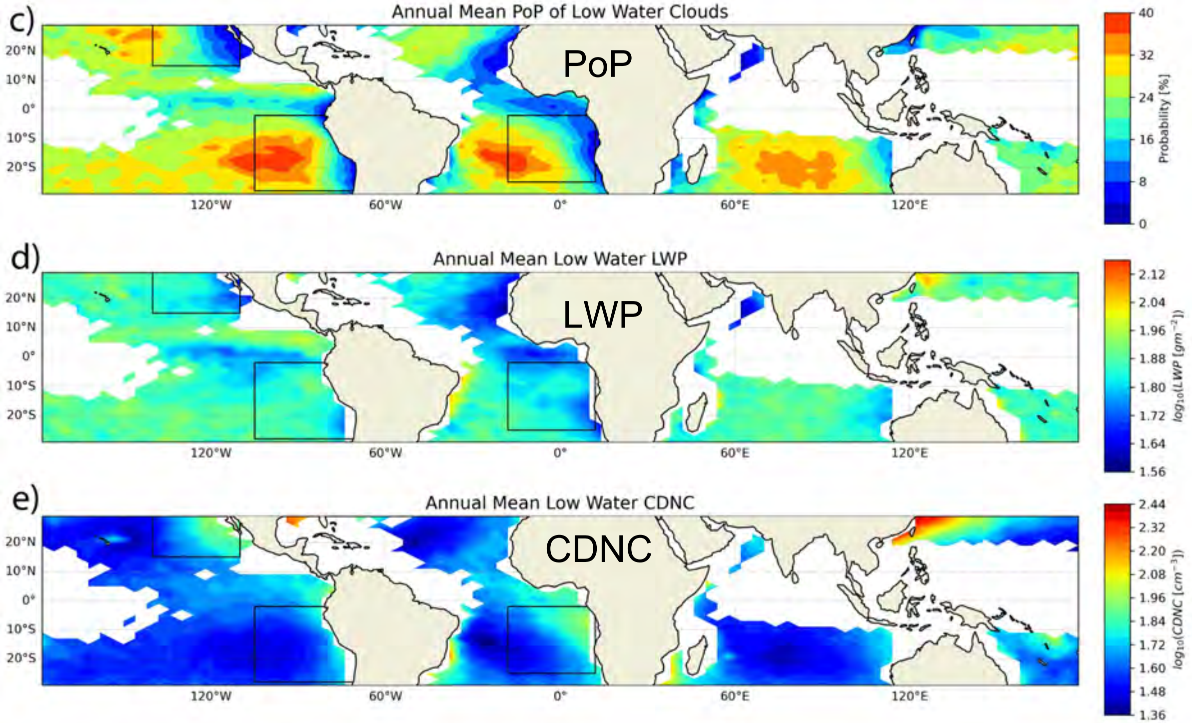


PoP = Number of precipitation MLC clouds / Number MLC clouds

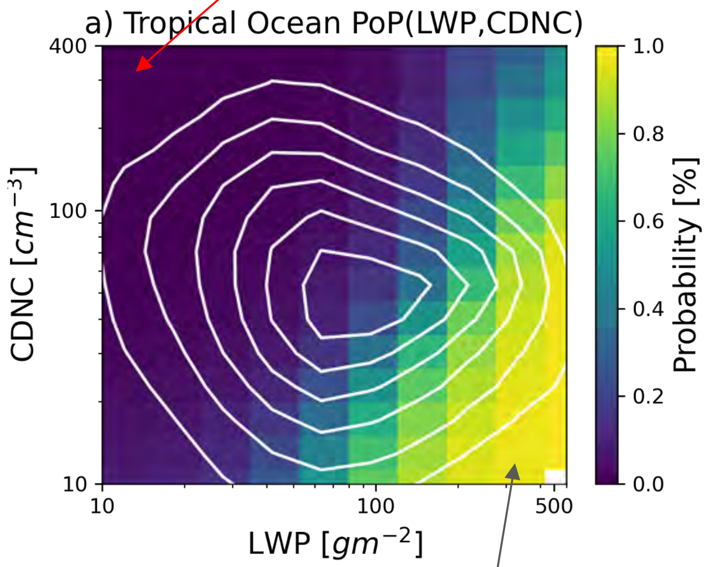
LWP: integrated total water in clouds

CDNC: Number of droplet in clouds

Properties of MLC in Tropics

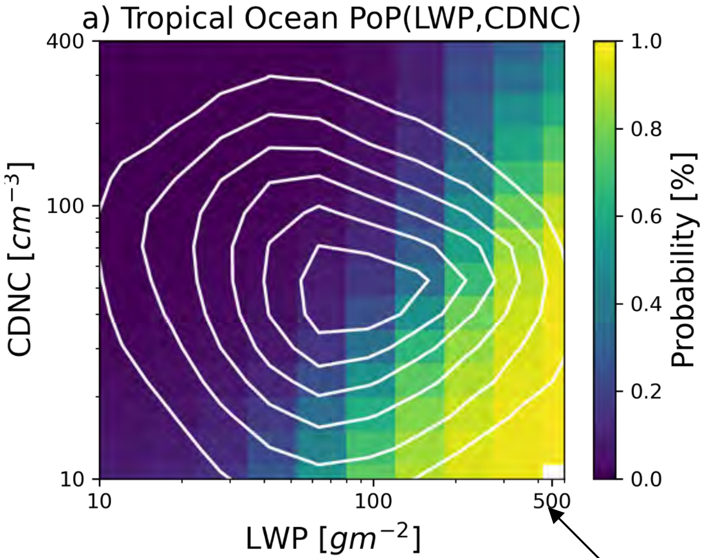


small LWP + large CDNC -> small PoP



Large LWP + small CDNC -> large PoP

Parameterization of PoP



Logistic function

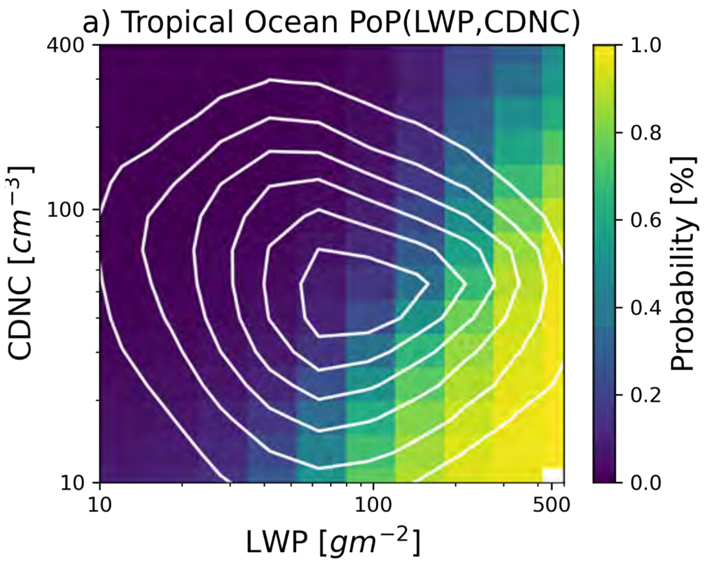
$$PoP(x,y) = \frac{1}{1+\exp[-(c_o+c_1x+c_2y)]}$$

$$x = \log_{10}\left(\frac{LWP}{1gcm^{-2}}\right) \text{ and } y = \log_{10}\left(\frac{CDNC}{1cm^{-3}}\right)$$

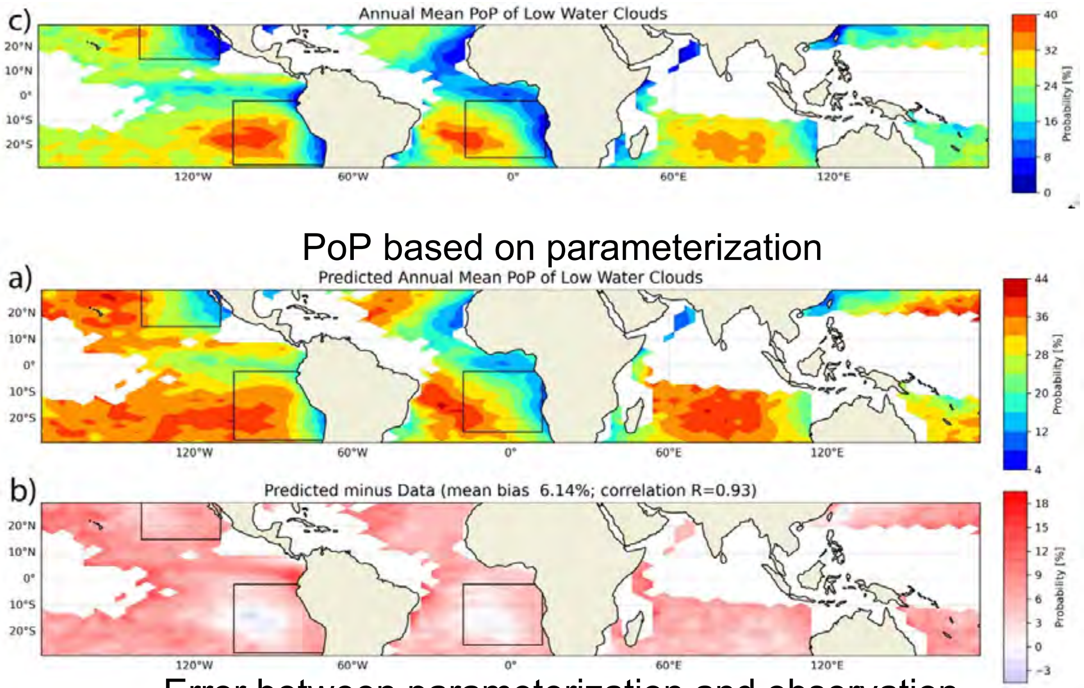
$$c_0 = -6.9, c_1 = 5.7, c_2 = -3.2$$

$$\langle PoP \rangle = \iint PoP(LWP, CDNC) PDF(LWP, CDNC) dLWP dCDNC$$

Parameterization of PoP



PoP based on observation

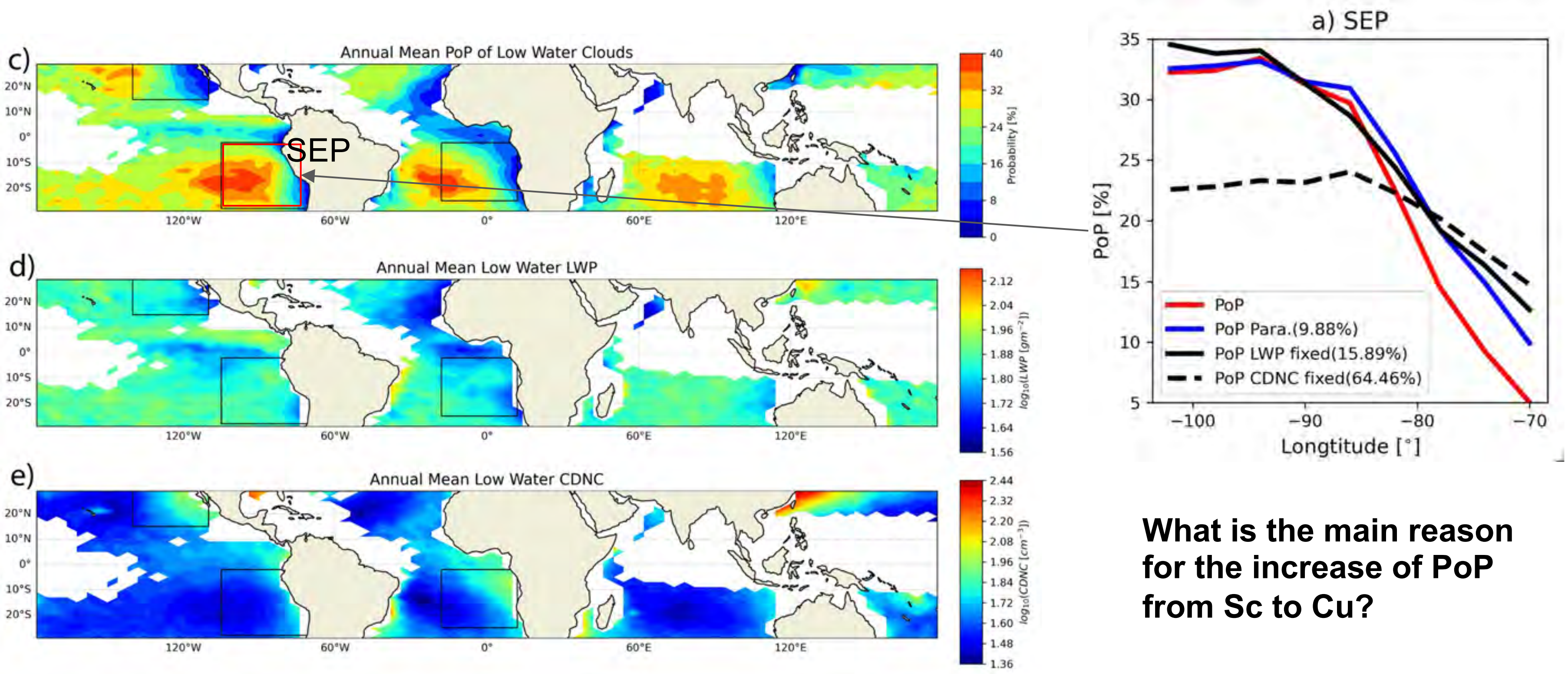


Error between parameterization and observation

✓ Universal microphysical control

$$\langle PoP \rangle = \iint PoP(LWP, CDNC)\, PDF(LWP, CDNC)\, dLWP\, dCDNC$$

Understanding the St to Cu transition of PoP



What is the main reason for the increase of PoP from Sc to Cu?

What is the main reason for the PoP transition?

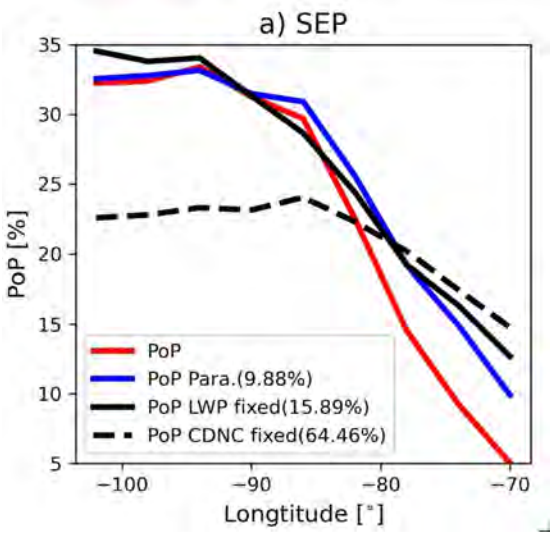
- PoP increases from Sc to Cu region
- LWP increases slightly and CDNC decreases significantly

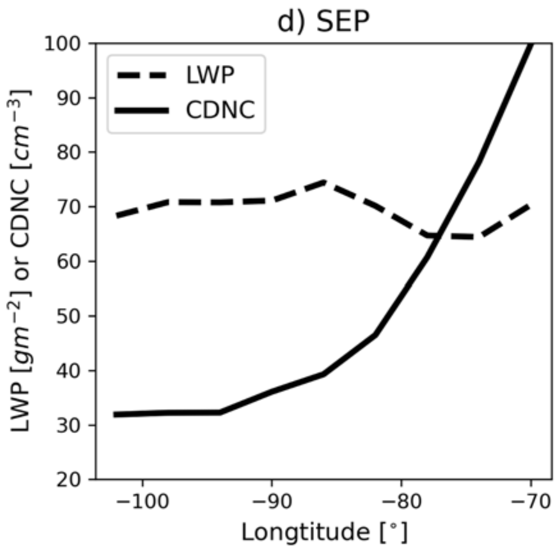
To understand the relative role of LWP and CDNC, we did the following test

We derived the following two sets of <PoP>

- LWP fixed PDF(<LWP>, CDNC)
- CDNC fixed PDF(LWP, <CDNC>)

The idea is to keep one factor fixed and allow the other to vary from Sc to Cu





$$\langle PoP \rangle = \iint PoP(LWP, CDNC) PDF(LWP, CDNC) dLWP dCDNC$$

Understanding the St to Cu transition of PoP

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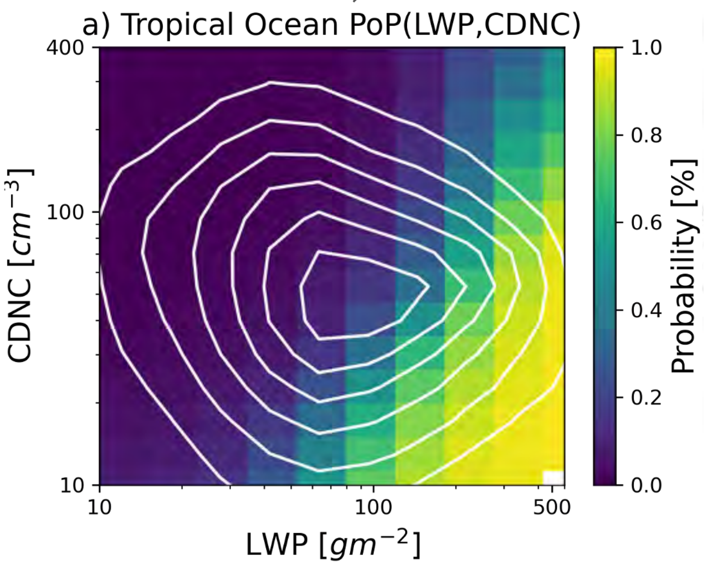
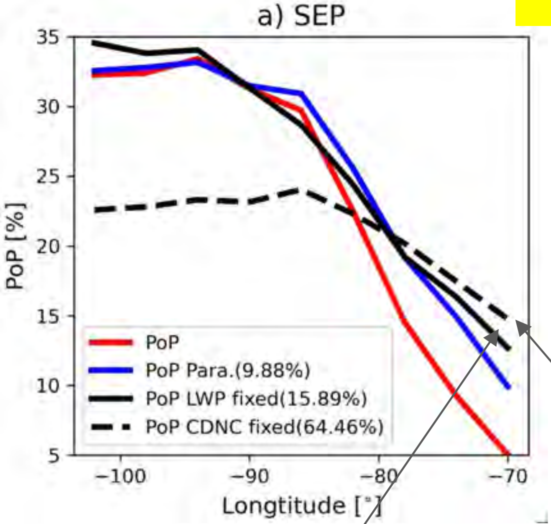
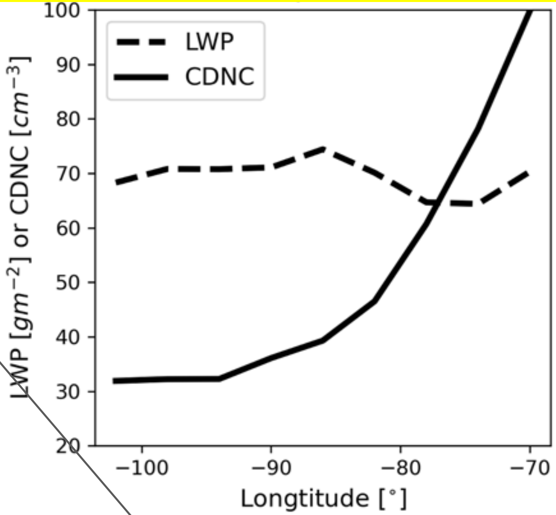
Decreases of CDNC dominates





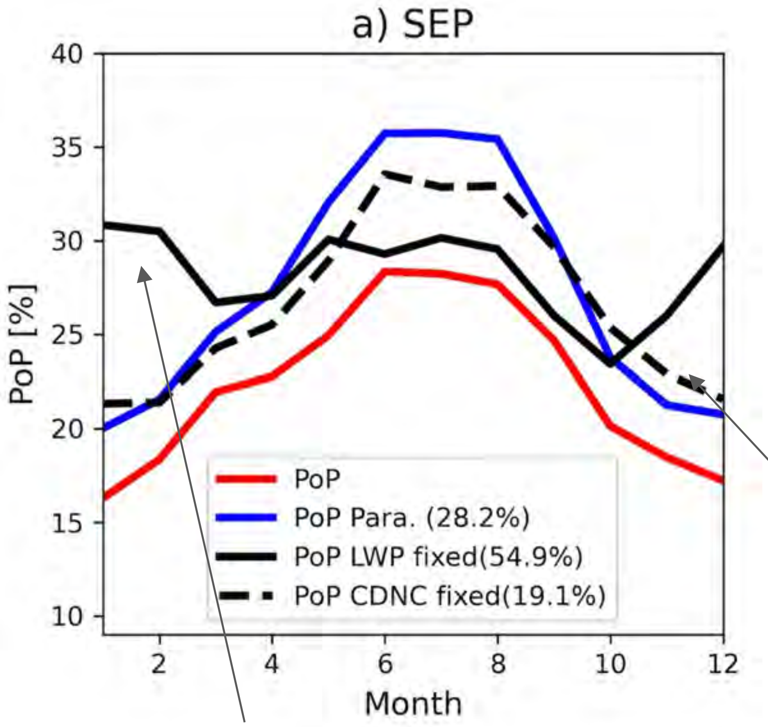


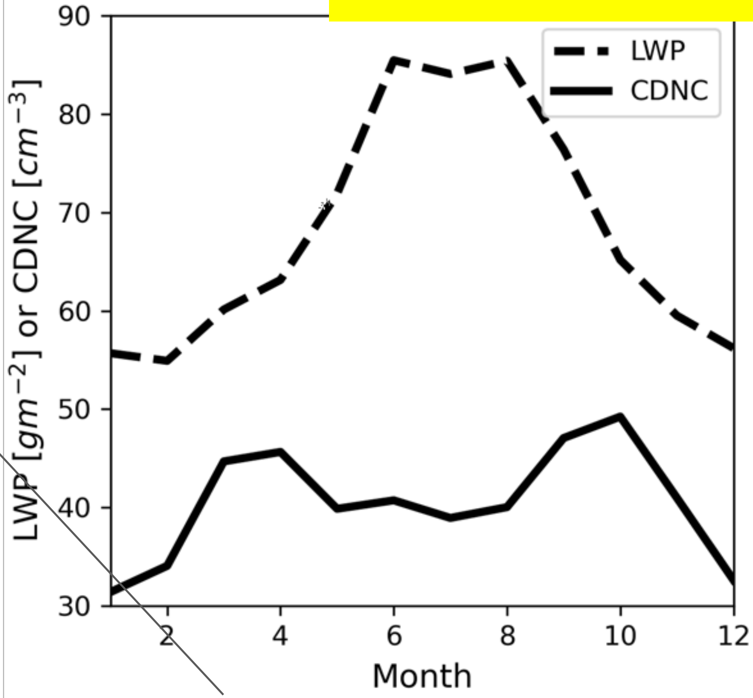
LWP fixed PDF(<LWP>, CDNC)

CDNC fixed PDF(LWP, <CDNC>)

Understanding the Seasonal variation of PoP

Seasonal variation of LWP dominates





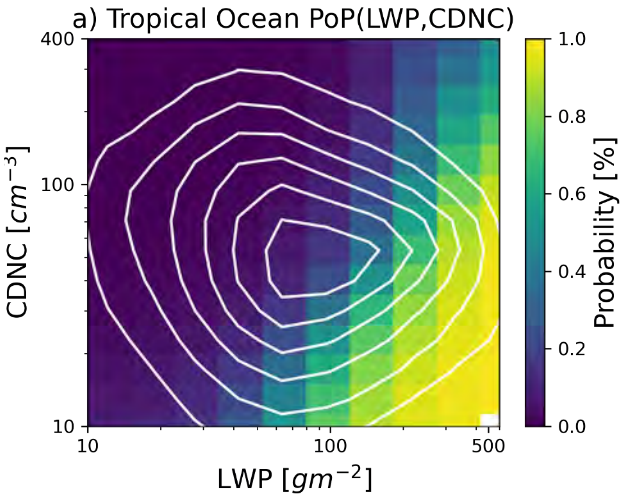
LWP fixed PDF(<LWP>, CDNC) CDNC fixed PDF(LWP, <CDNC>)

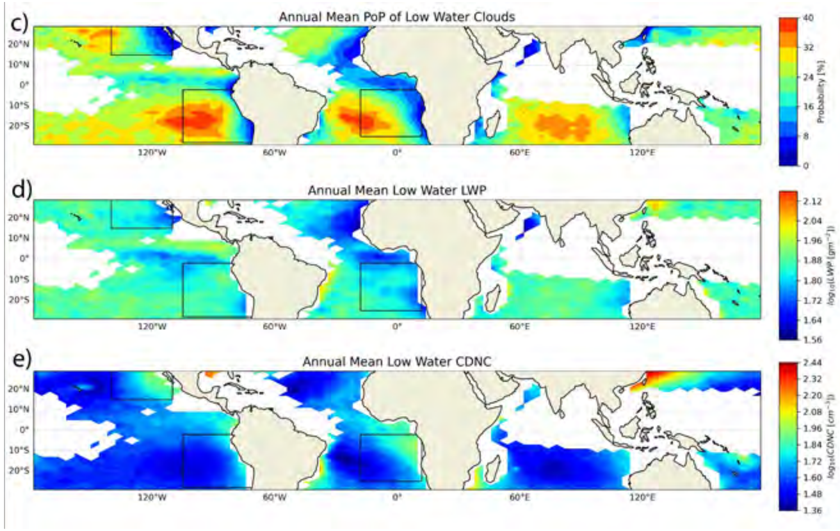
Summary

- PoP of MLC over tropical oceans is derived from the collocated MODIS and CloudSat products
- A logistic function based parameterization scheme is developed to quantify the dependence of PoP on LWP and CDNC
- The parameterization can be used to understand the the spatial-temporal variation of PoP
    - Sc to Cu transition is mainly caused by the decrease of CDNC.
    - The seasonal variation of PoP is mainly caused by the seasonality of LWP.

Outlook

- The PoP parameterization scheme can be used to evaluate the warm rain simulations on the GCMs
  - The PoP(LWP, CDNC) (color) can be used to evaluate the warm rain scheme
  - The PDF(LWP, CDNC) (line) can be used to evaluate the cloud scheme





Addressing structural errors in warm-rain microphysics with BOSS, a Bayesian data-driven physically-based bulk scheme

Marcus van Lier Walqui — CCSR Columbia University @ NASA/GISS
mv2525@columbia.edu
Sean Patrick Santos — Pacific Northwest National Laboratories
Hugh Morrison — National Center for Atmospheric Research
Karly Reimel — (prev.) Penn State University
Adele Igel — University of California Davis

ASR PI Meeting — Oct 27th 2022

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- Wealth of natural cloud and precipitation observations but difficult to measure process rates directly, only net effects on hydrometeors —> an indirect constraint of bulk schemes

Overview of the warm rain microphysics problem

The BIG question: How to use these various data sources — each with their own uncertainties — to constrain bulk schemes?

- As more complex bulk schemes are developed this makes indirect constraint (i.e., tuning) even more difficult...
- Simply stated: we want to incorporate uncertain "observations" (or process model data) in a parameterization with basic cloud physics knowledge in a rigorous way.
  - This is a Bayesian problem, and we can therefore use Bayesian statistics to address it rigorously...

Thomas Bayes (1701-1761)

$$P(\mathbf{x}|\mathbf{y}) = \frac{P(\mathbf{y}|\mathbf{x})P(\mathbf{x})}{P(\mathbf{y})}$$

BOSS

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Bayesian (we treat uncertainties robustly, uncertainties reside in parameters)

Observationally-constrained (scheme is informed by comparison to observations)

Statistical-physical (we don't just want a statistical scheme, but we will use statistics)

Scheme — bulk microphysics parameterization scheme (so far rain & cloud only)

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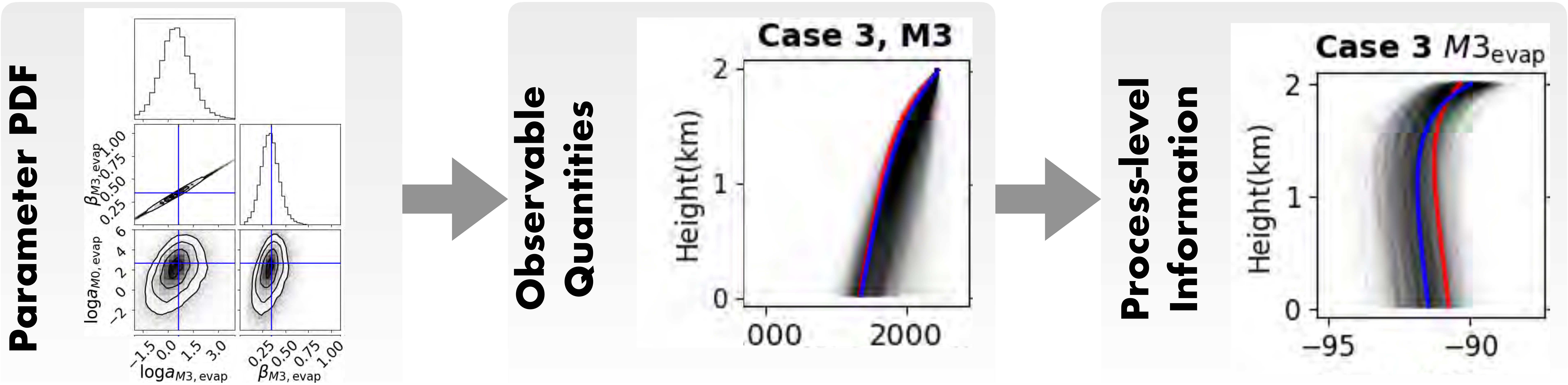

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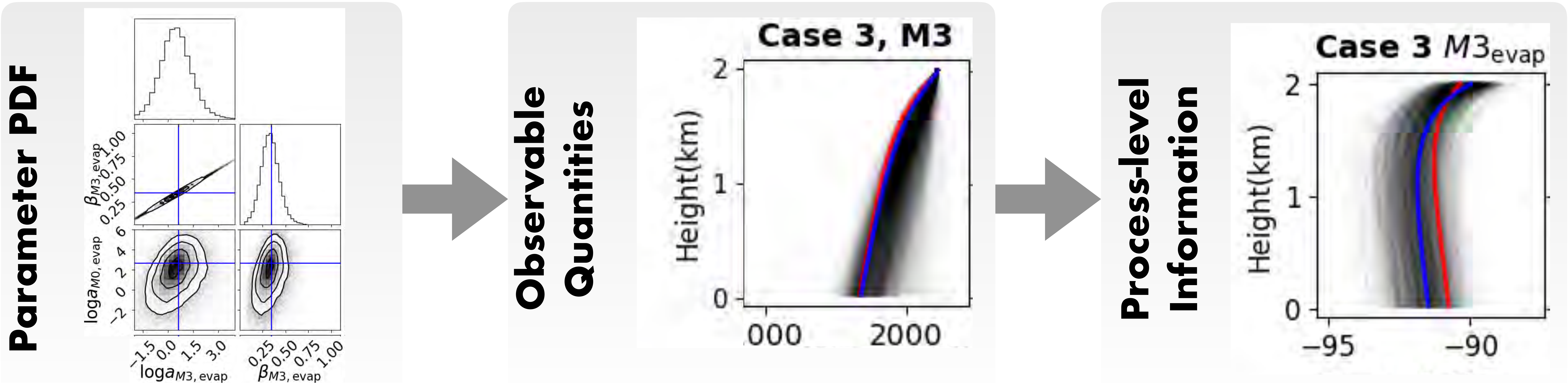

We can match performance of a traditional microphysics scheme, plus we have uncertainty estimates!

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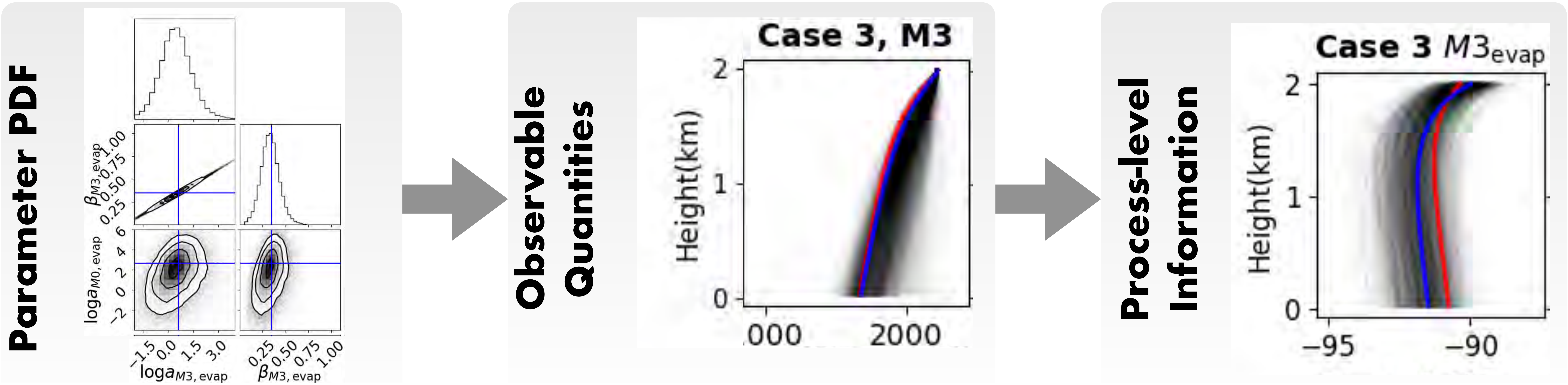

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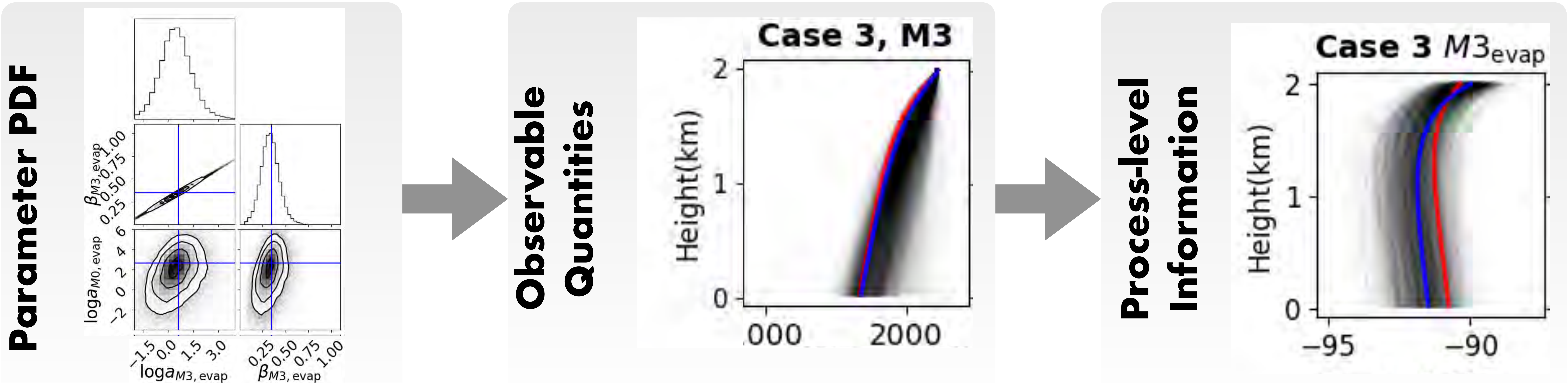

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Morrison et al. JAS 2020; van Lier-Walqui et al. JAS 2020, Morrison et al. JAMES 2020, Reimel et al. (in prep)

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No assumed DSD functional form

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Predict *moments* of the DSD $M_k = \int_{D_{min}}^{D_{max}} D^k (\partial N / \partial D) dD$

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Choose whatever moments are "best"

Get rid of fixed process rate functions

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Use a flexible (but sensible) functional basis set

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$$\frac{dM_k}{dt} \approx F(T,p,q)\sum_{l=1}^{L} a_{l,k} M_{p_1} \prod_{n=1}^{N-1} \left(\frac{M_{p_{n+1}}}{M_{p_n}}\right)^{\beta_{p_n,l,k}}$$

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Use Bayesian inference to estimate a,β,δ

Structural error estimation and parsimony

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Example of theoretical constraints on parsimony

A third moment (e.g. M6) can be used as a measure of DSD variance:

$$\sigma^2 = \frac{1}{M_{c0}} \int_0^\infty N(D)(D^3 - m_c)^2 dD = \frac{M_{c6}}{M_{c0}} - m_c^2$$

Constraint on the possible values of DSD variance enforces a structural form on the process rate for cloud self-collection (. . . some math. . .)

$$b_{6m,csc} = b_{0m,csc} + 2 \qquad a_{6,csc} \geq a_{0,csc} \tag{1}$$

Similar arguments reduce the total number of BOSS parameters from 60+ to 37 for 3-moment cloud BOSS

Directly fitting process rates to a Bin model

Autoconversion rates: bin vs. BOSS fits

Direct process fits with BOSS

- Directly fit BOSS parameters to match existing TAU bin scheme autoconversion process rates
- Test 1-term process rate formulation vs. 2-term
- Test 2-moment cloud/rain vs. 3-moment cloud, 2-moment rain
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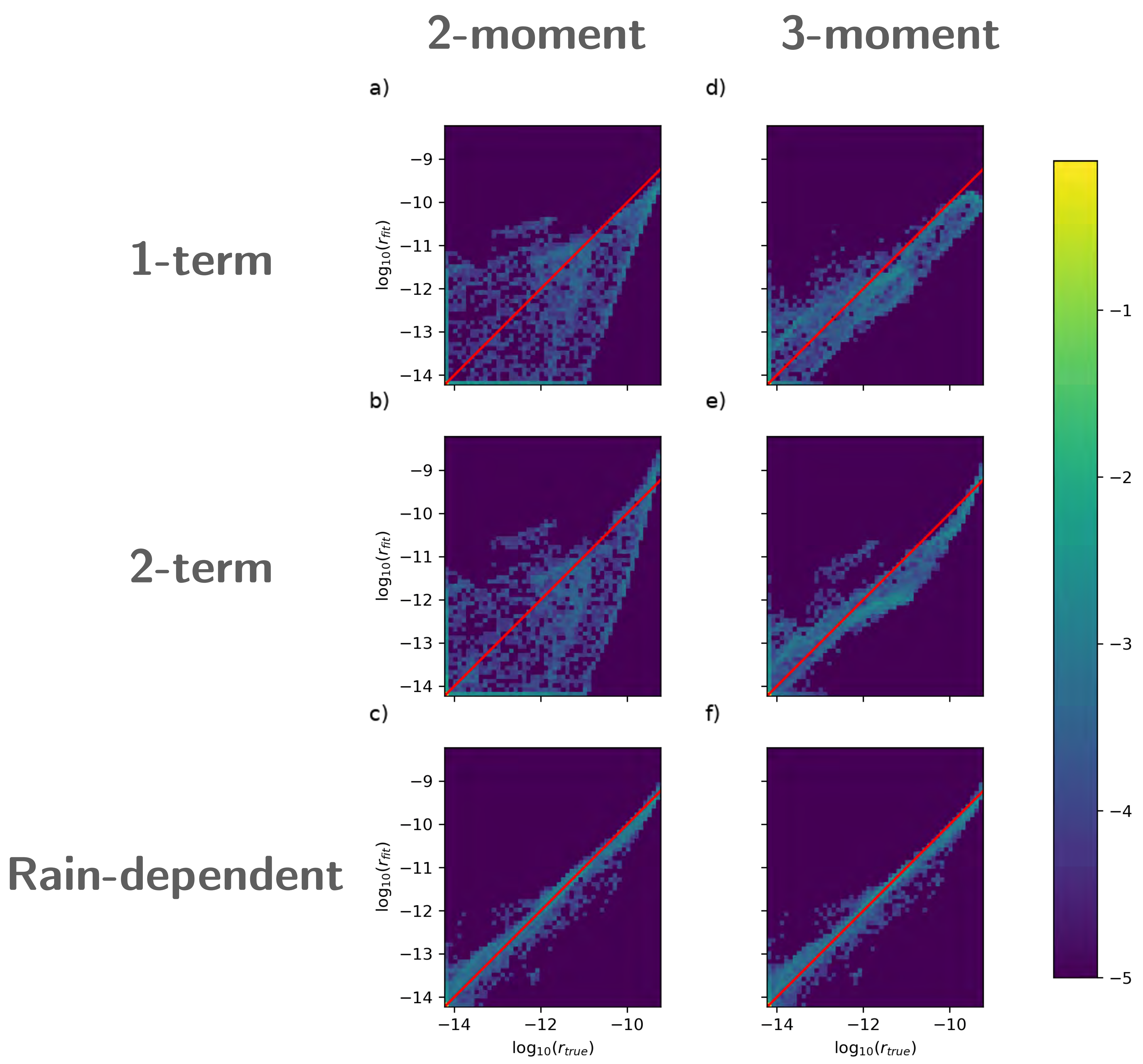
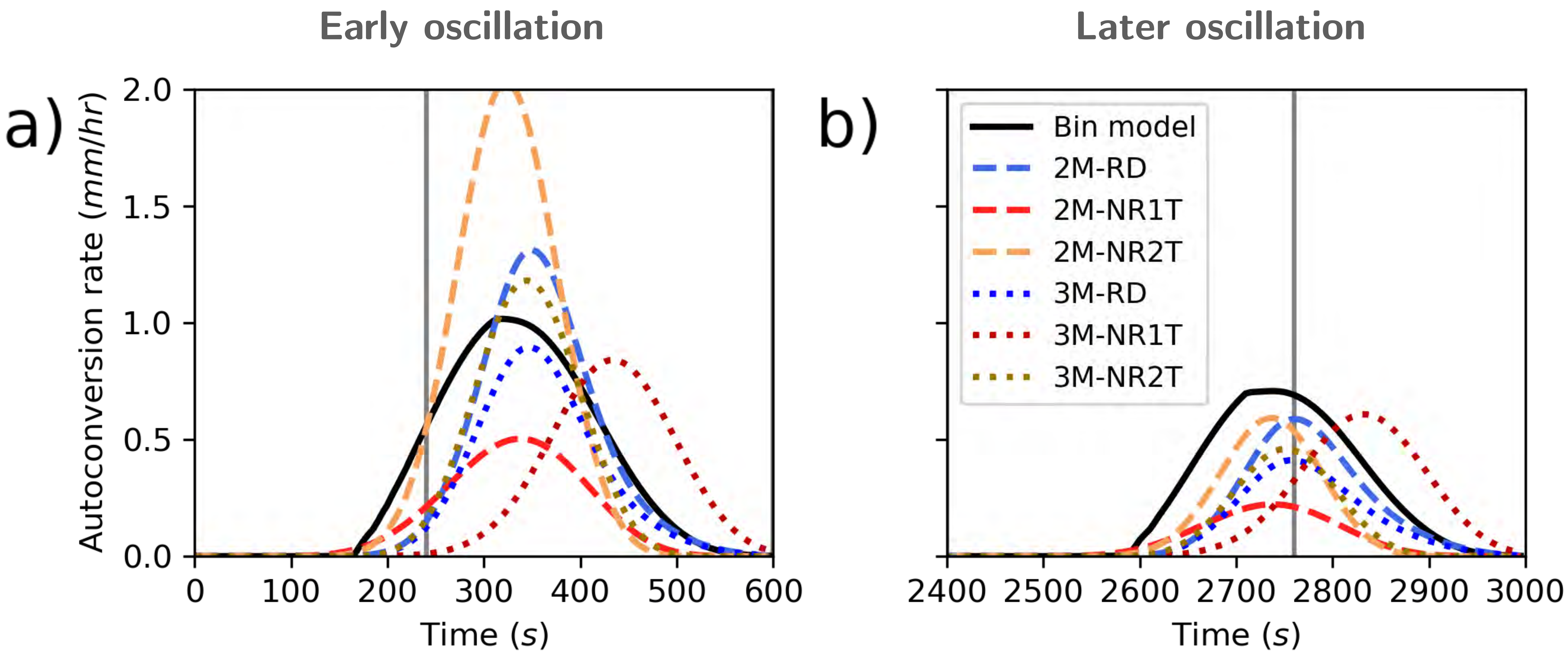


Testing direct fits in time-evolving 1D model

Looking at autoconversion rates tuned via direct fitting in 1D model simulations



Testing direct fits in 1D model (2M vs 3M)

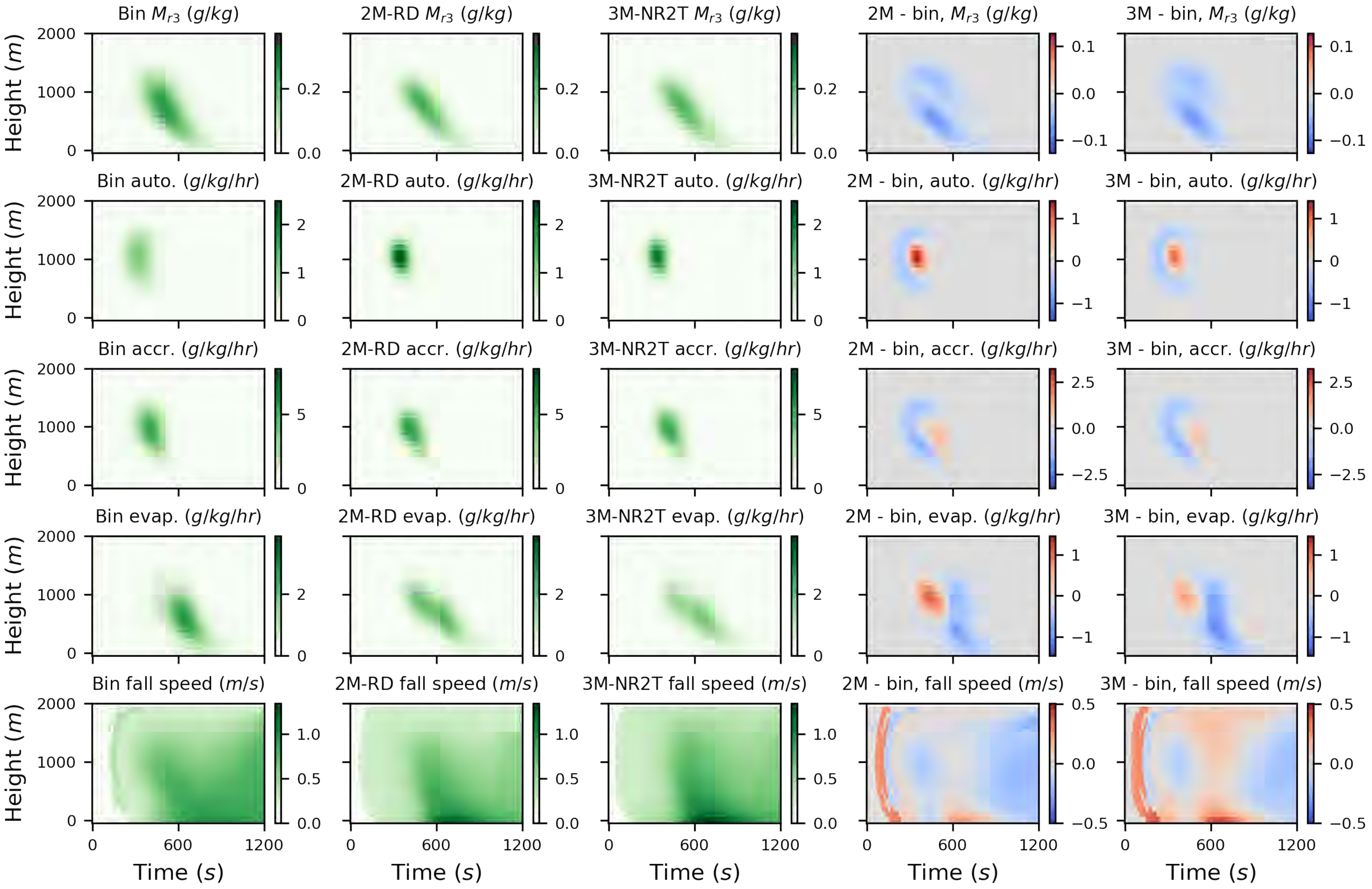
Rain M3

Autoconversion

Accretion

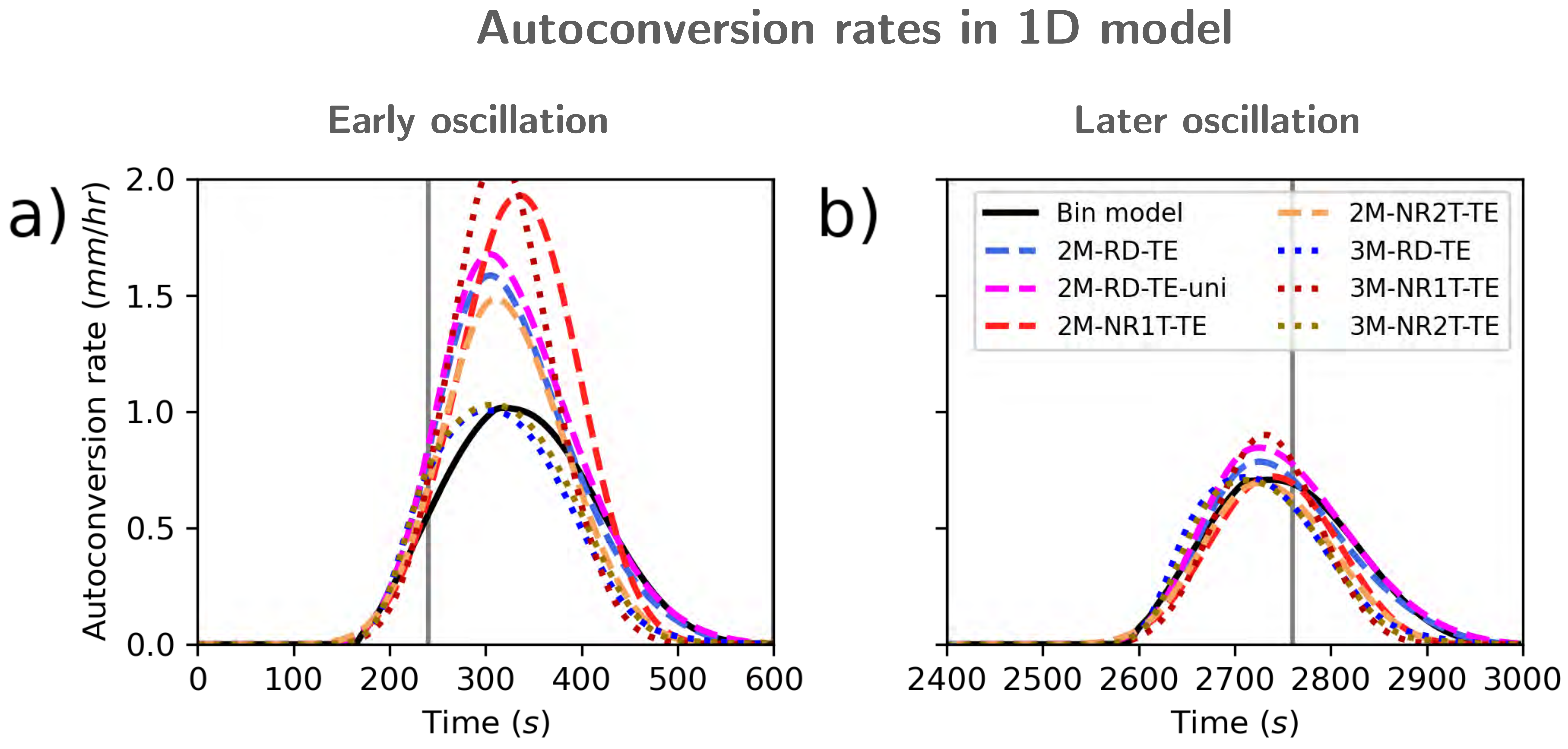
Evaporation

Fall speed

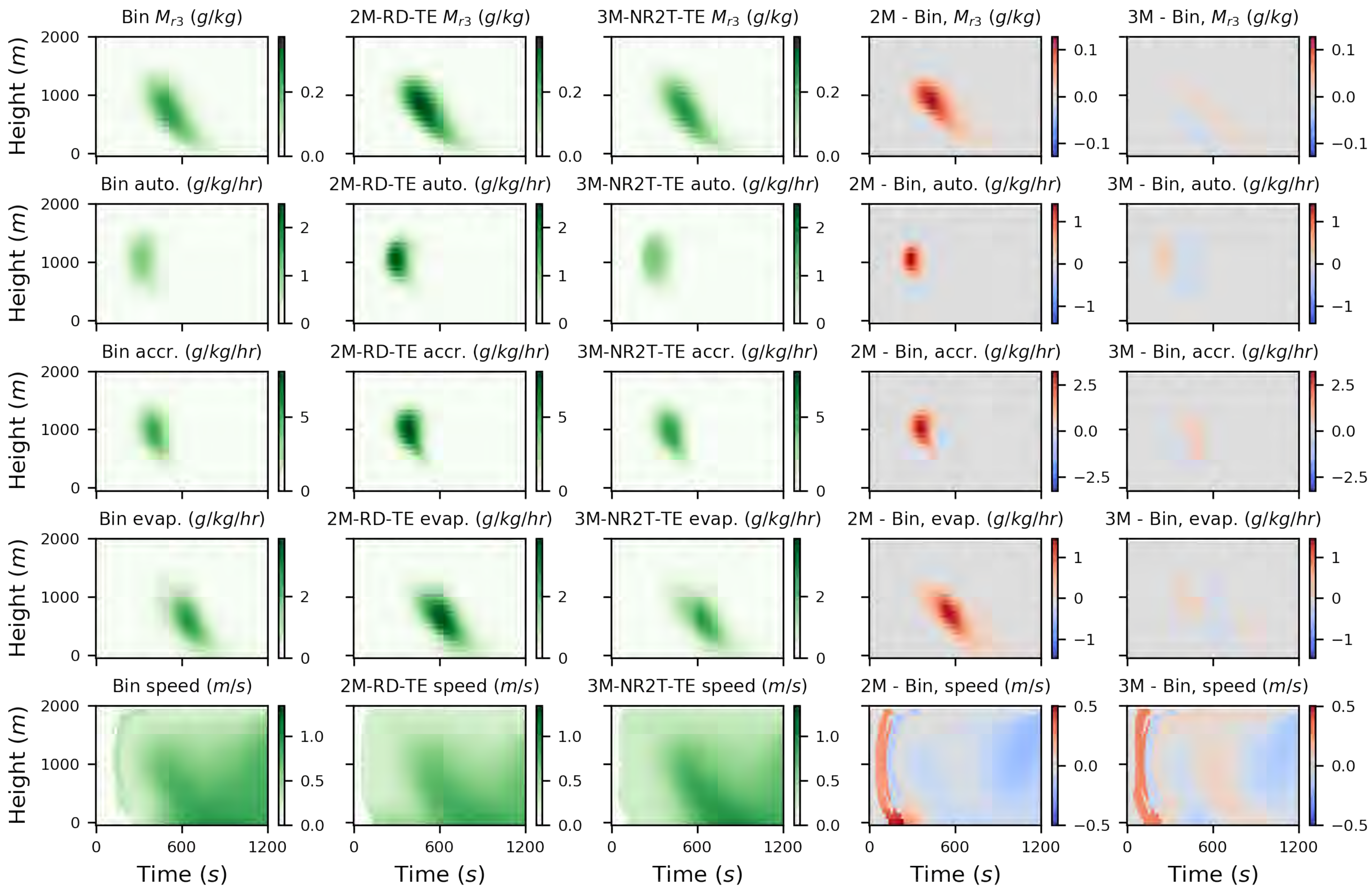


Instead use direct fits as a (Bayesian) prior

Refine the prior with a likelihood using observations from *time-evolving sim'n



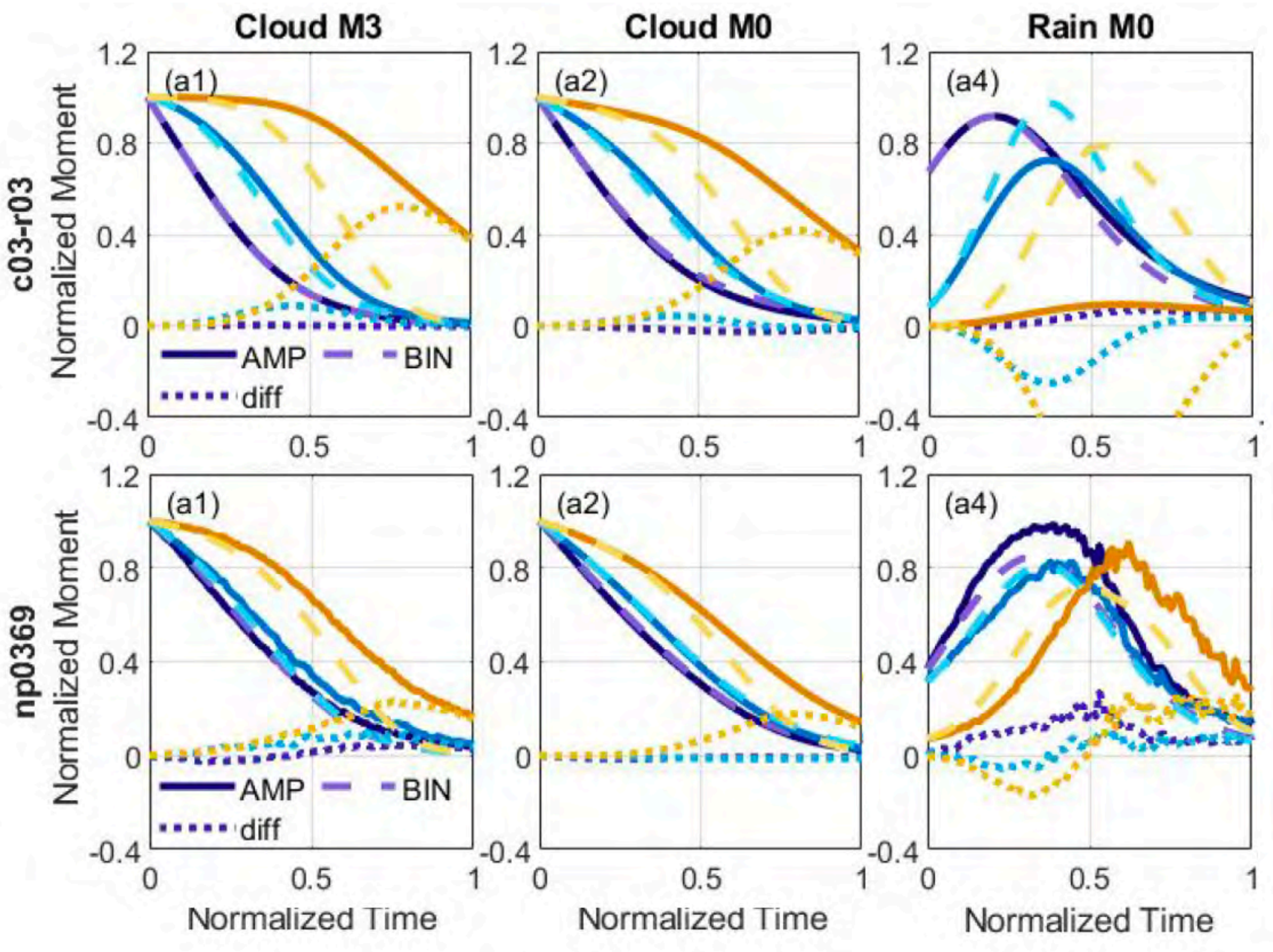
Testing direct/1D fits in 1D model (2M vs 3M)



Structural choices must be evaluated in the context of adequate parameter constraint!

A larger structural error?

Are separate cloud and rain categories the correct approach for bulk warm microphysics?



Adele L. Igel, H. Morrison, S. P. Santos, and M. van Lier-Walqui. *Limitations of separate cloud and rain categories in parameterizing collision- coalescence for bulk microphysics schemes.* JAMES, 2022.

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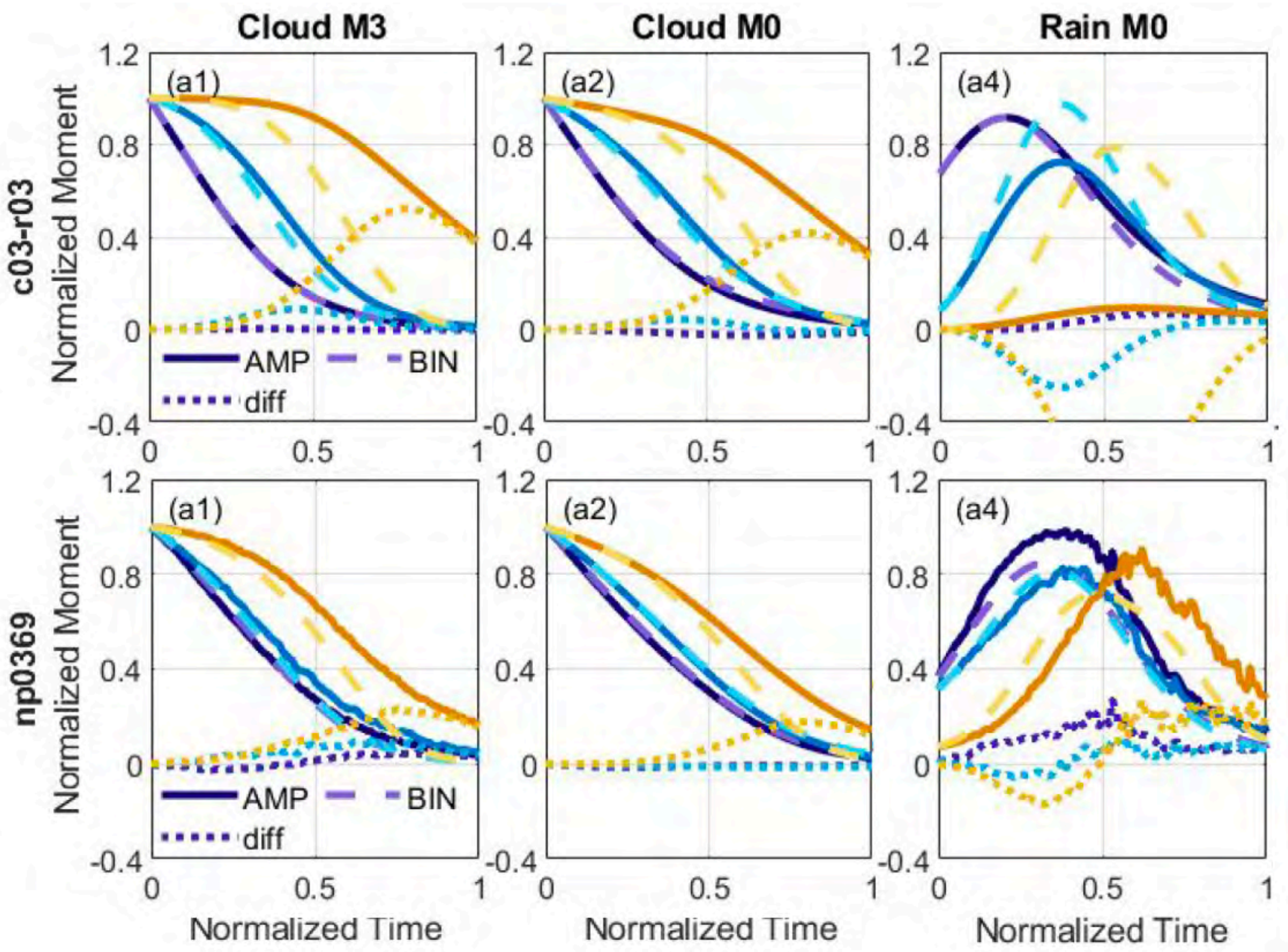

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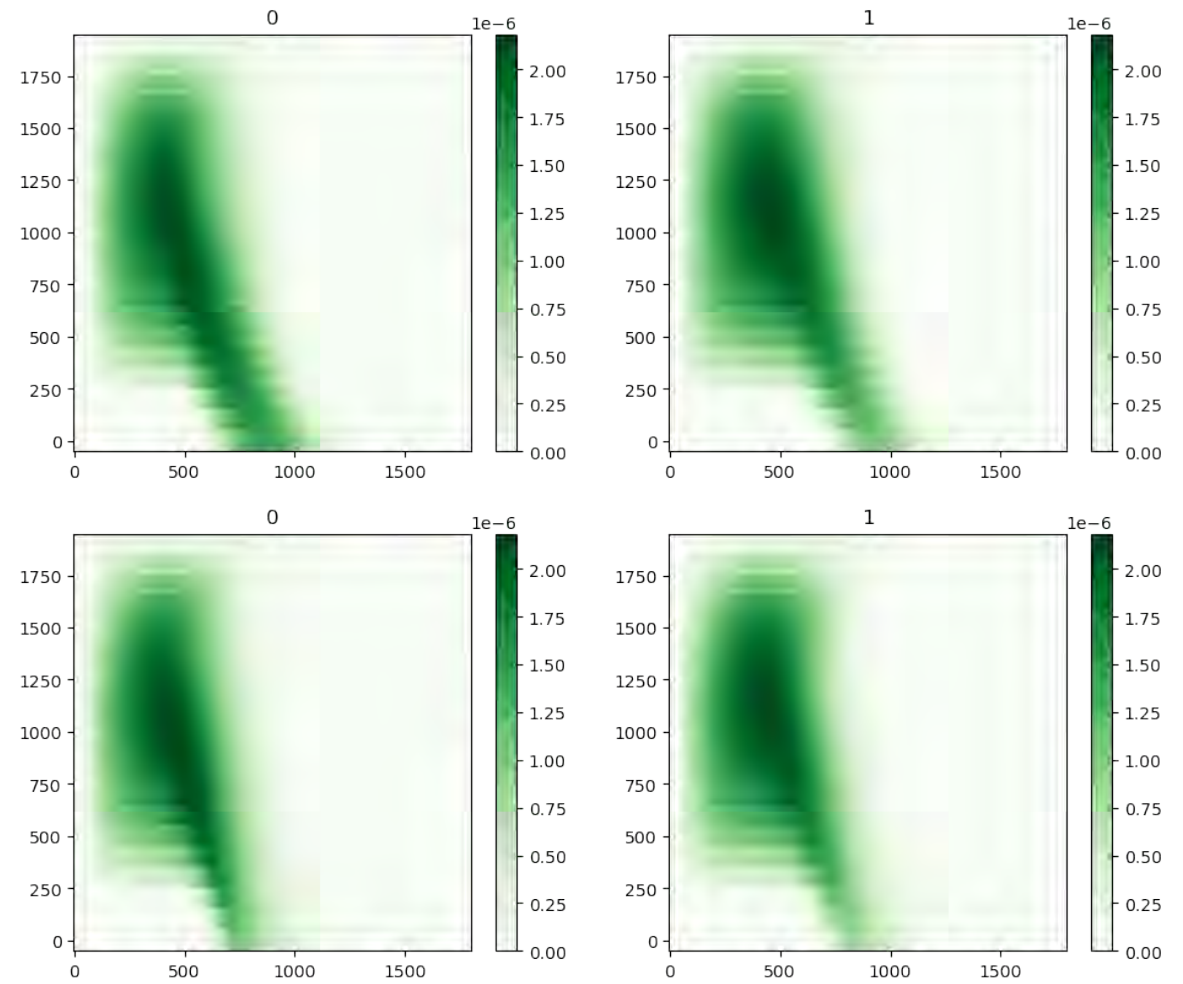
This is something we are currently testing with BOSS!

Bin model ->

BOSS single-category 4M—>



A spectrum of data and ways to constrain/inform BOSS

Less expensive,
less realistic

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Less expensive, less realistic → *More expensive, more realistic*

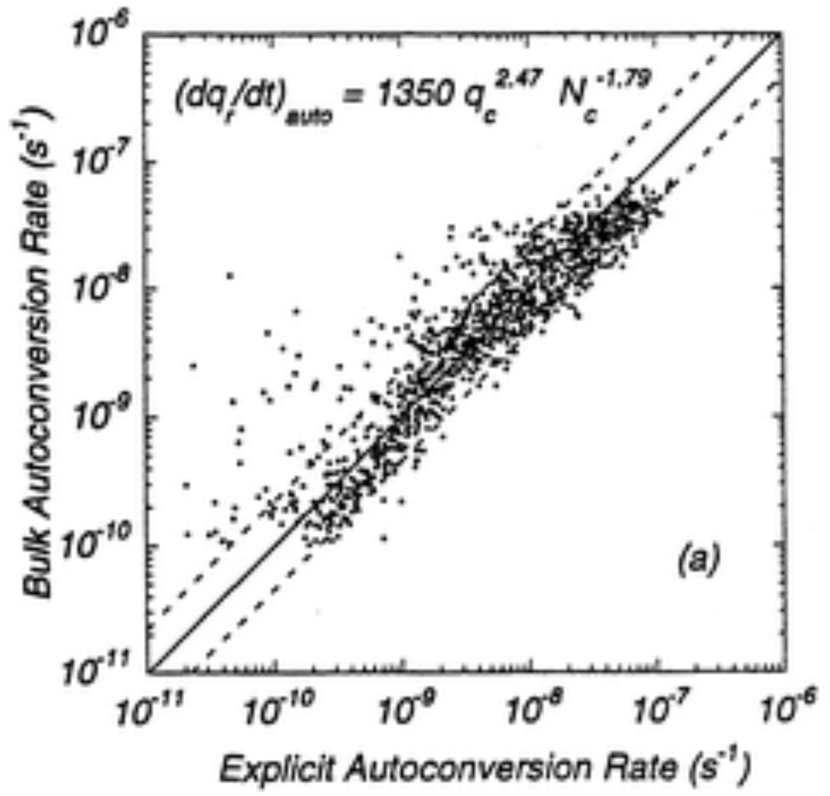
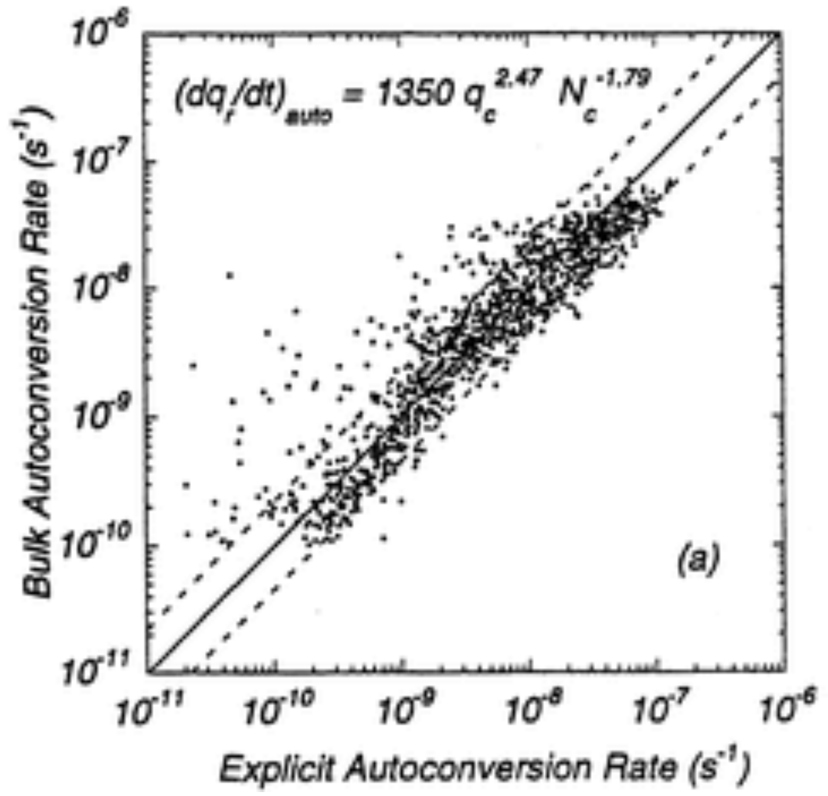


Figure 1: Regression used to produce the KK autoconversion formula, excerpted from Khairoutdinov and Kogan (2000)[2] (`https://doi.org/10.1175/1520-0493(2000)128<0229:ANCPPI>2.0.CO;2`).

Directly fitting process rates to some "reference" scheme

A spectrum of data and ways to constrain/inform BOSS

Less expensive, less realistic → *More expensive, more realistic*



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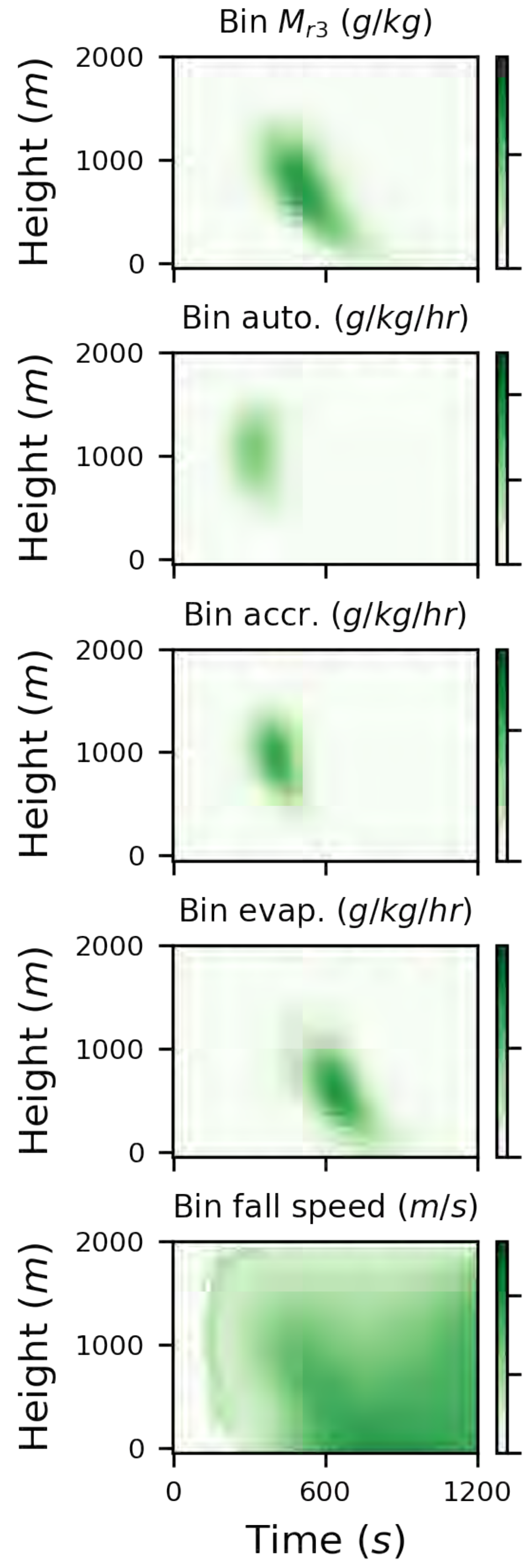

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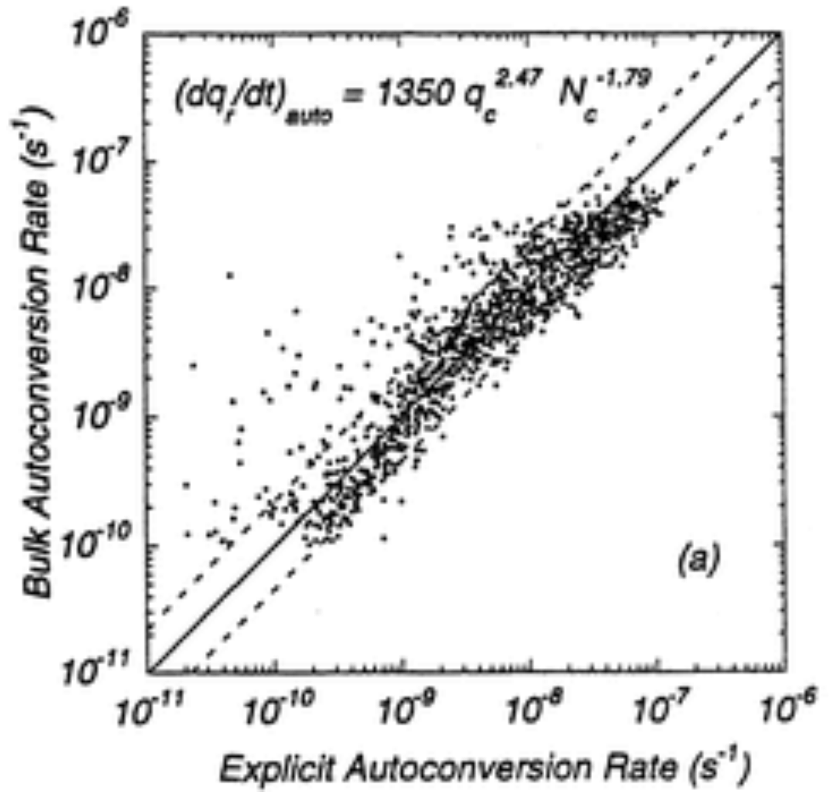

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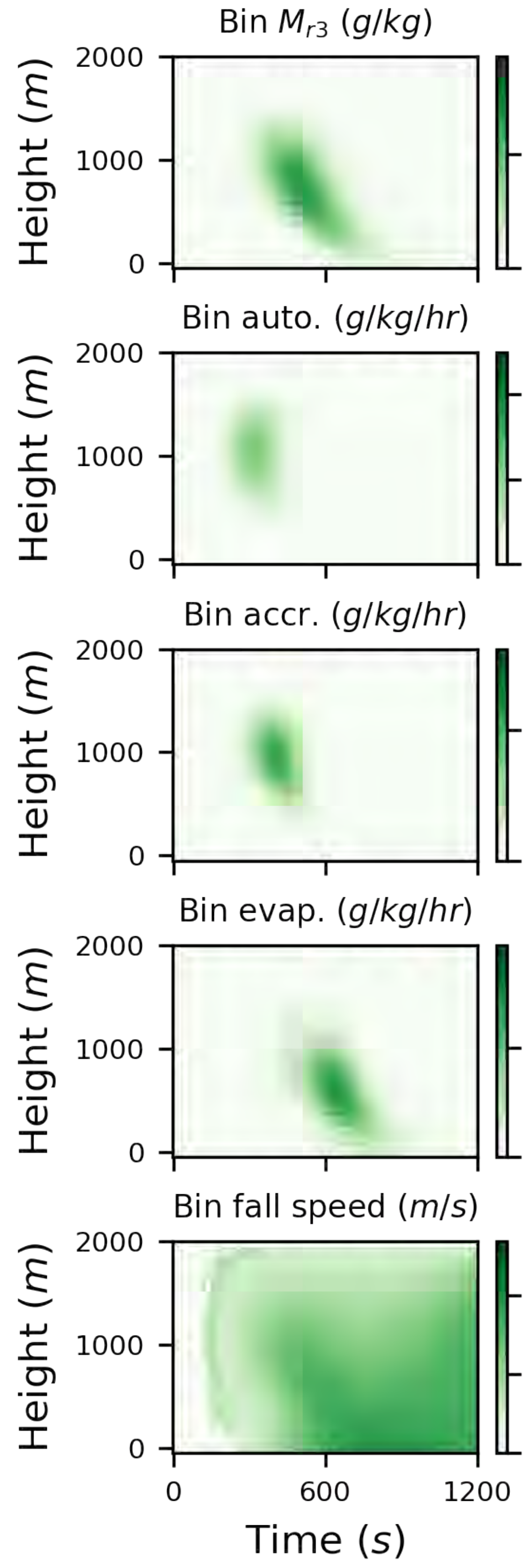

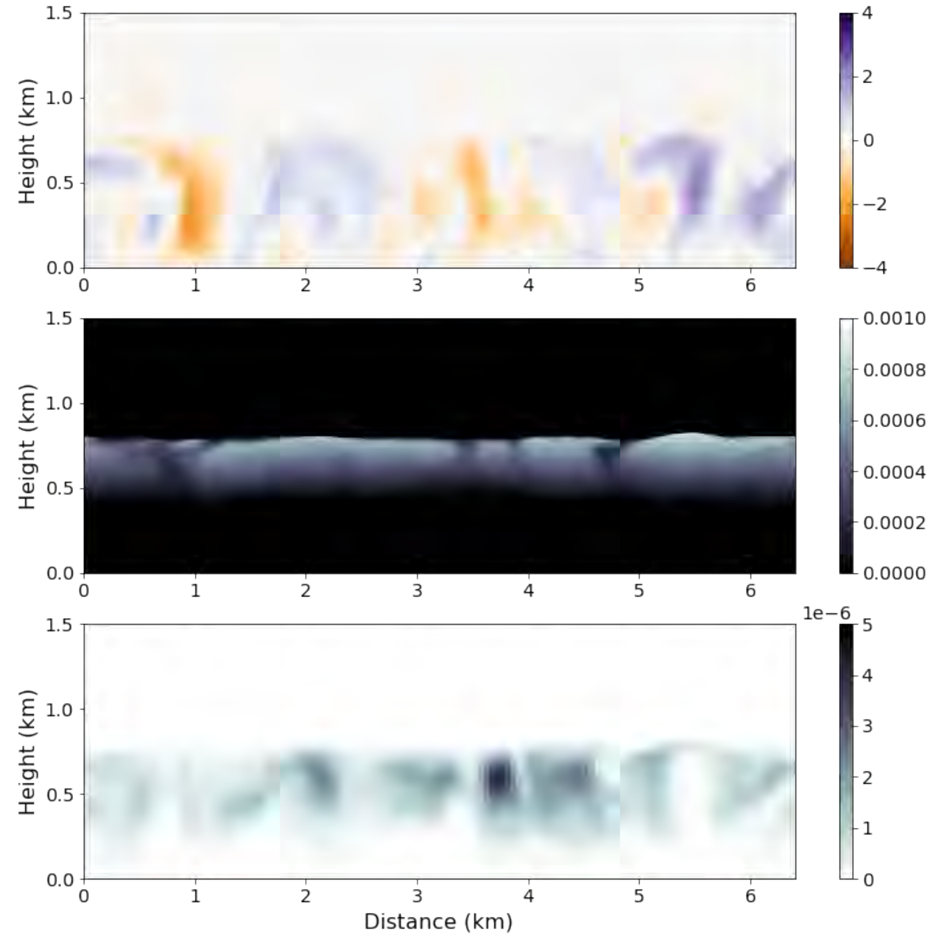

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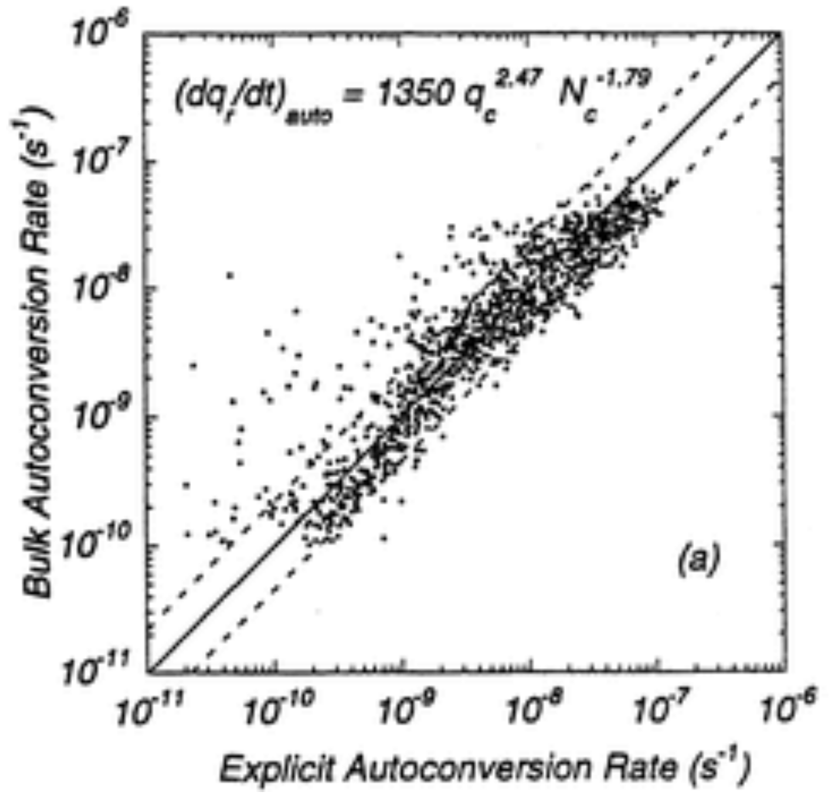

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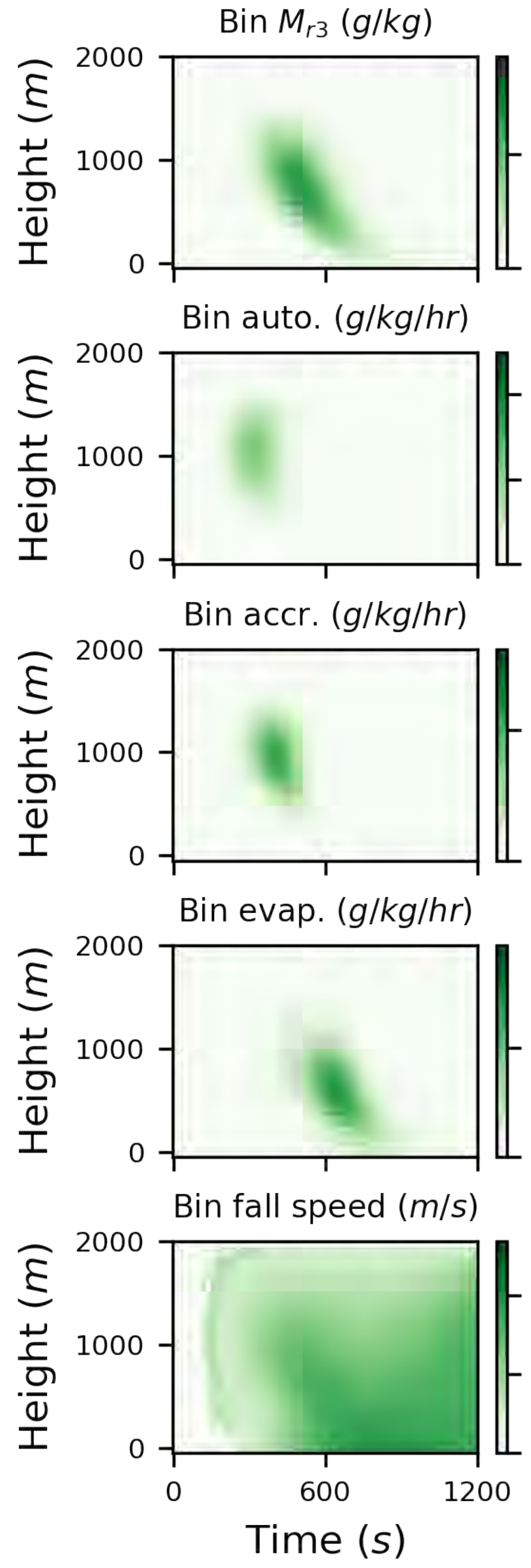

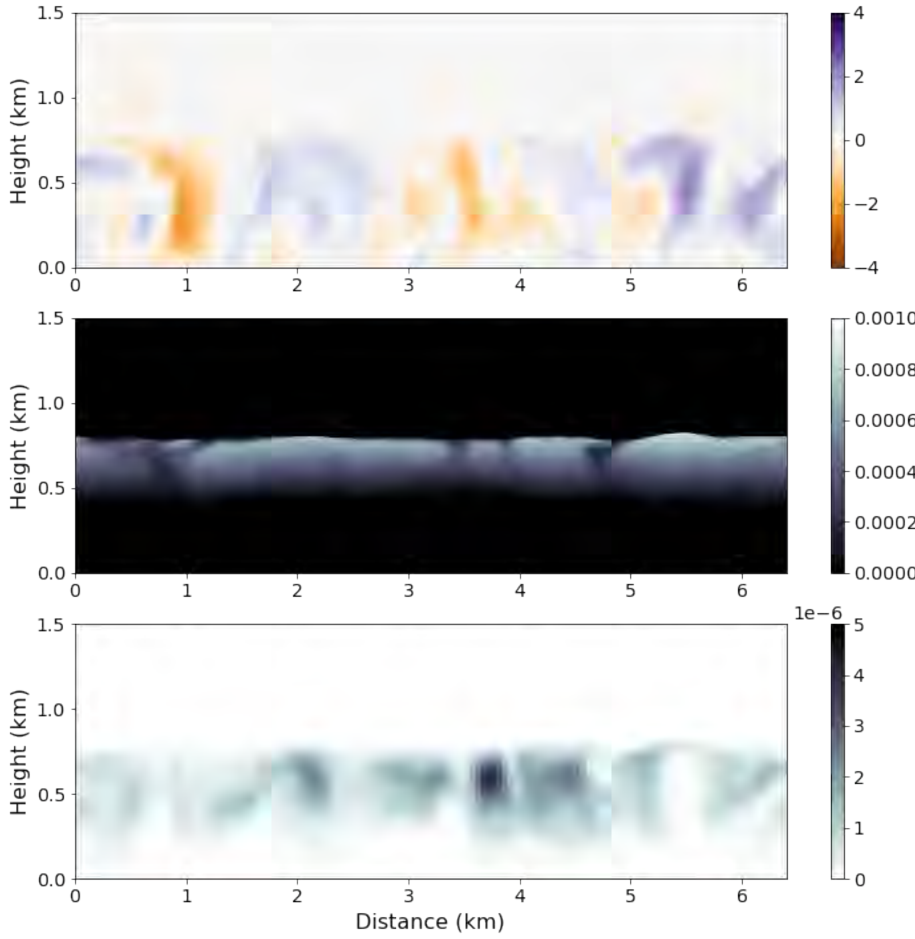

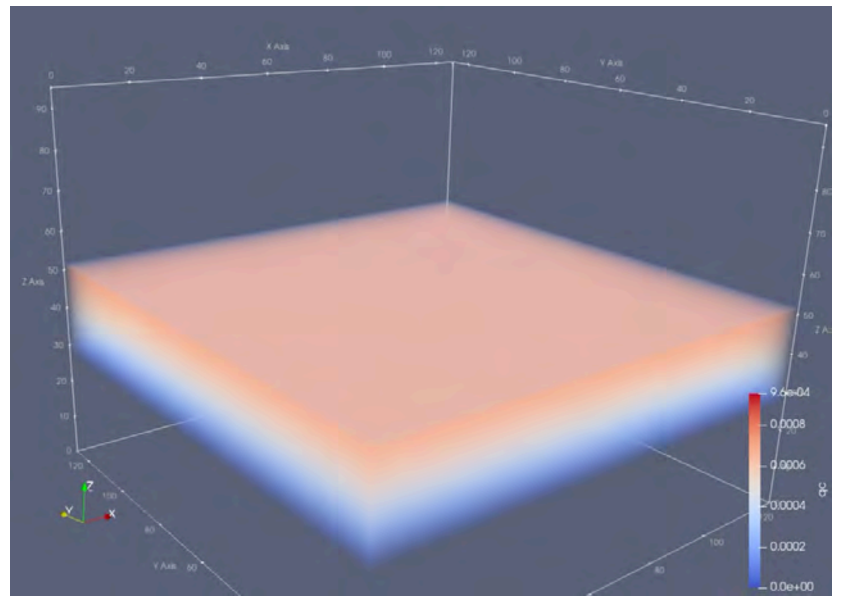

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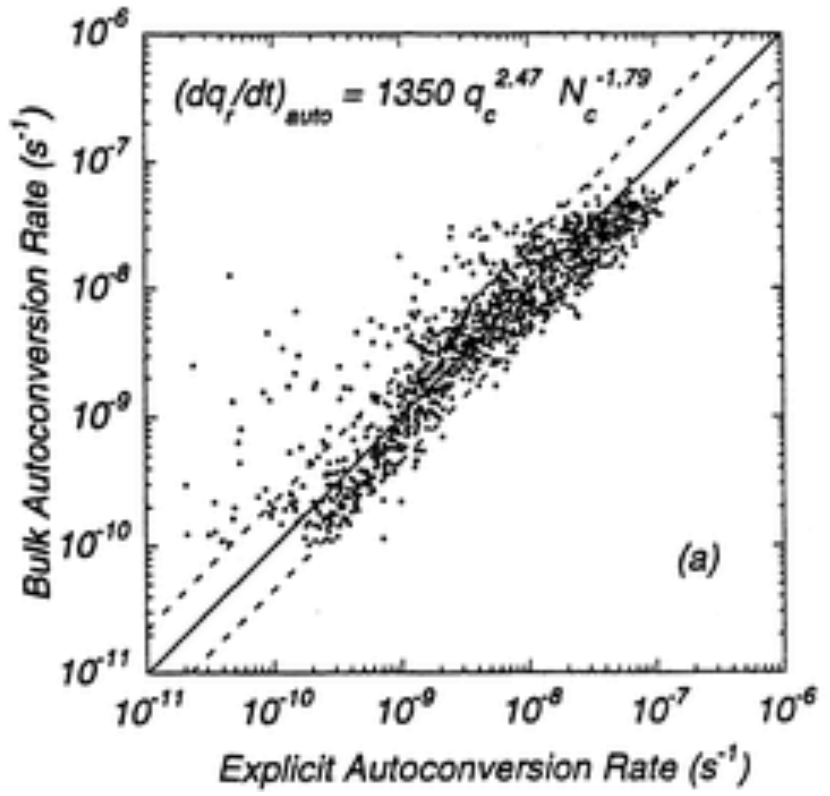

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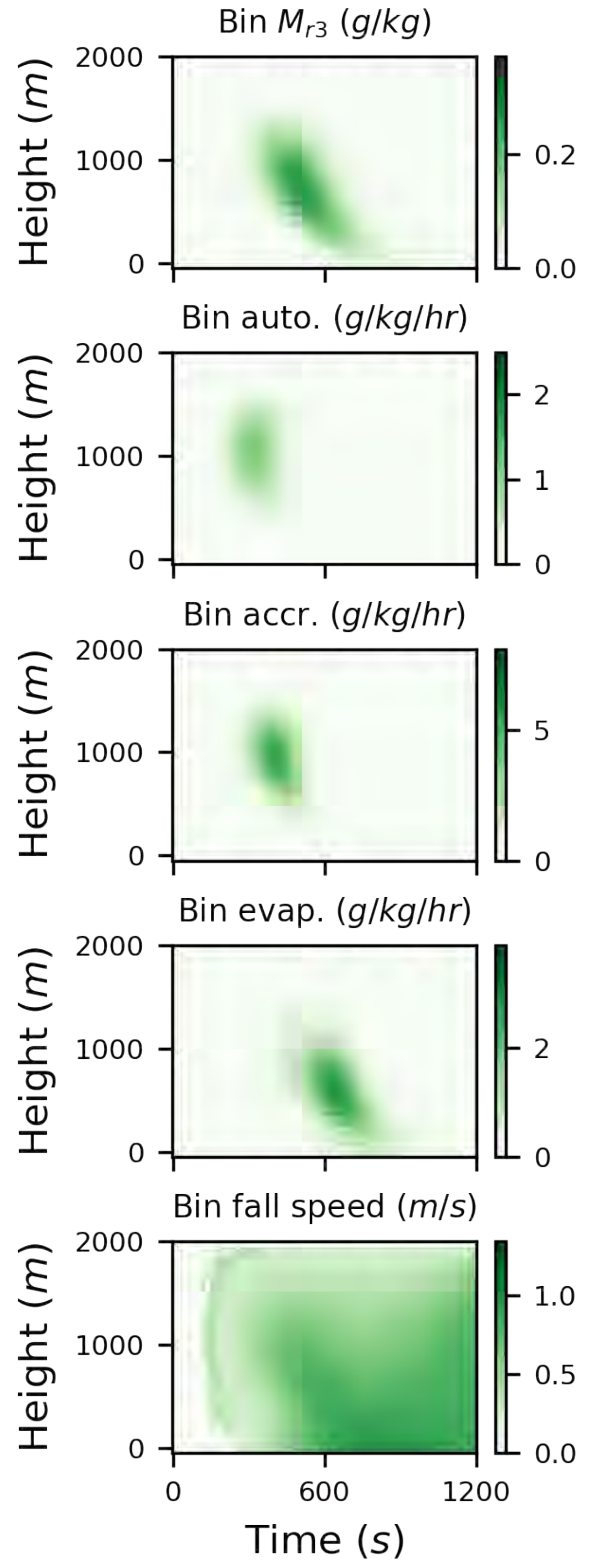

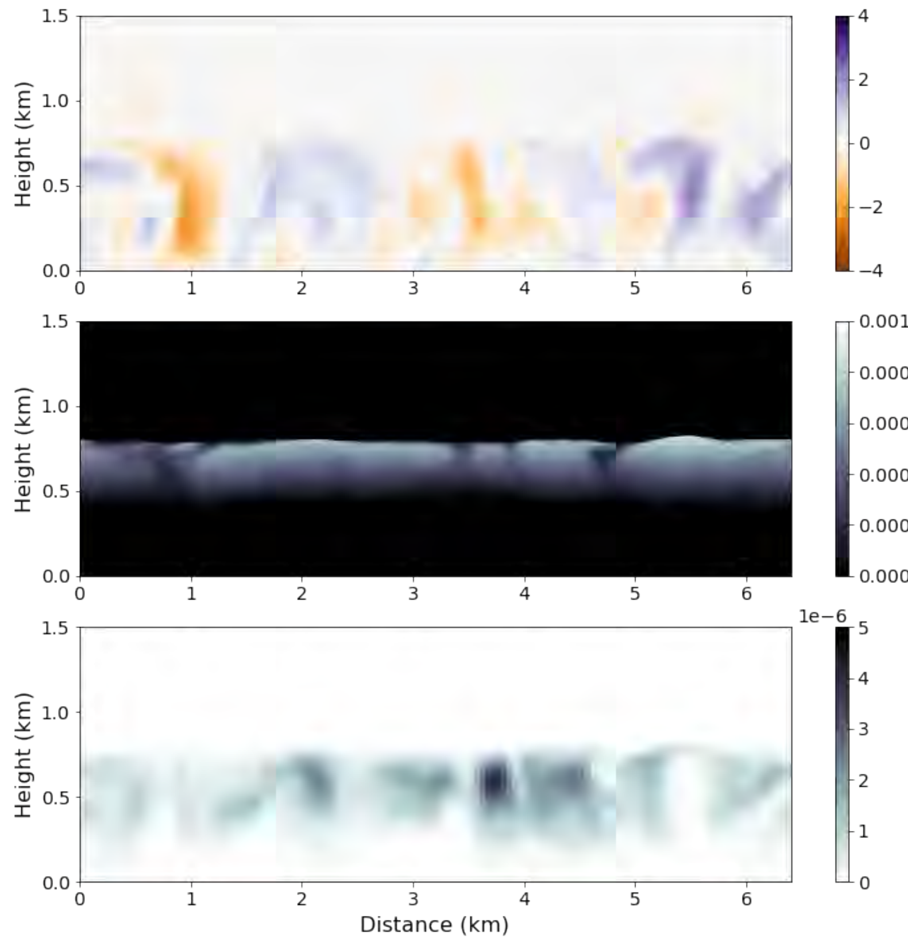

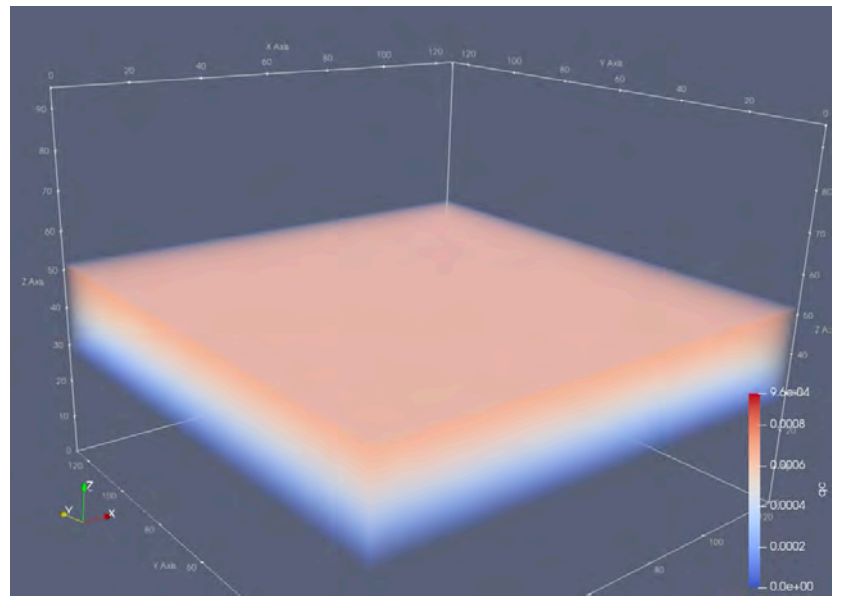

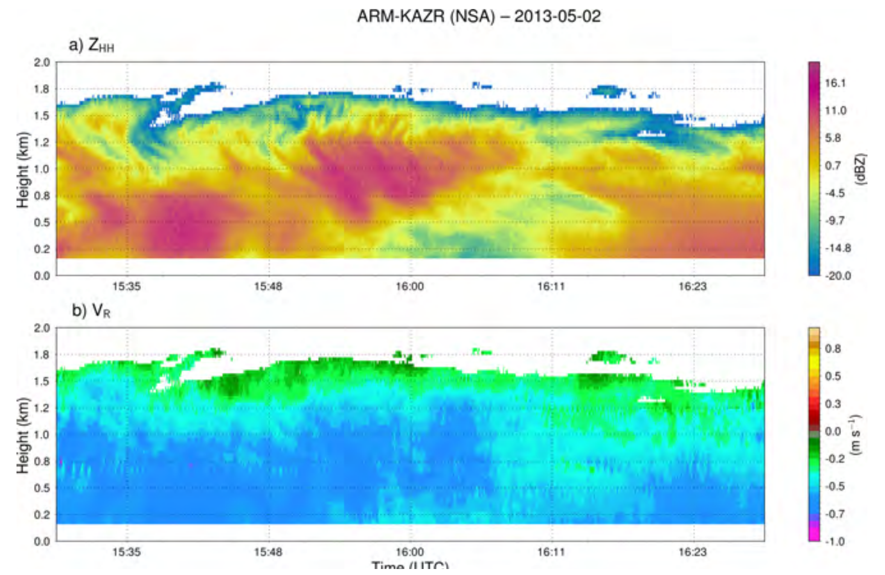

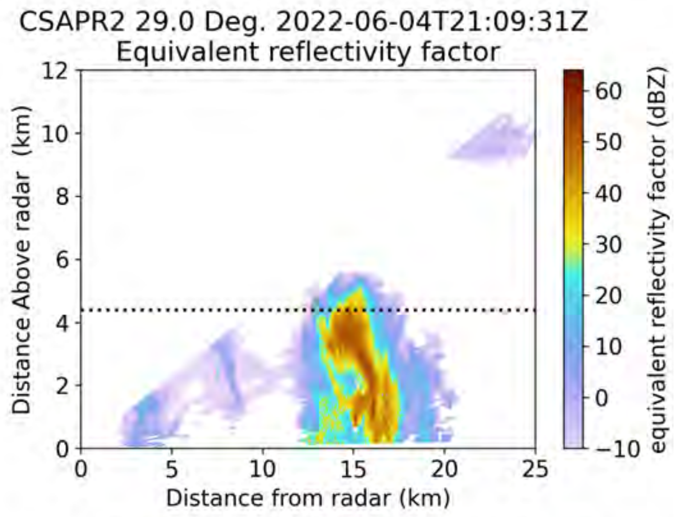

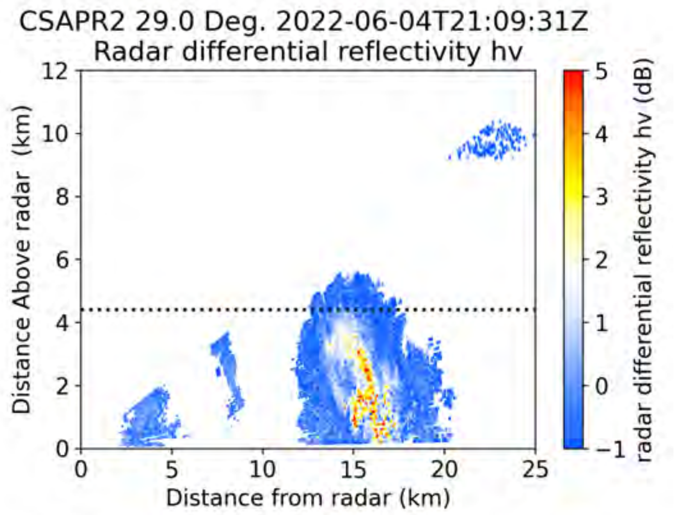

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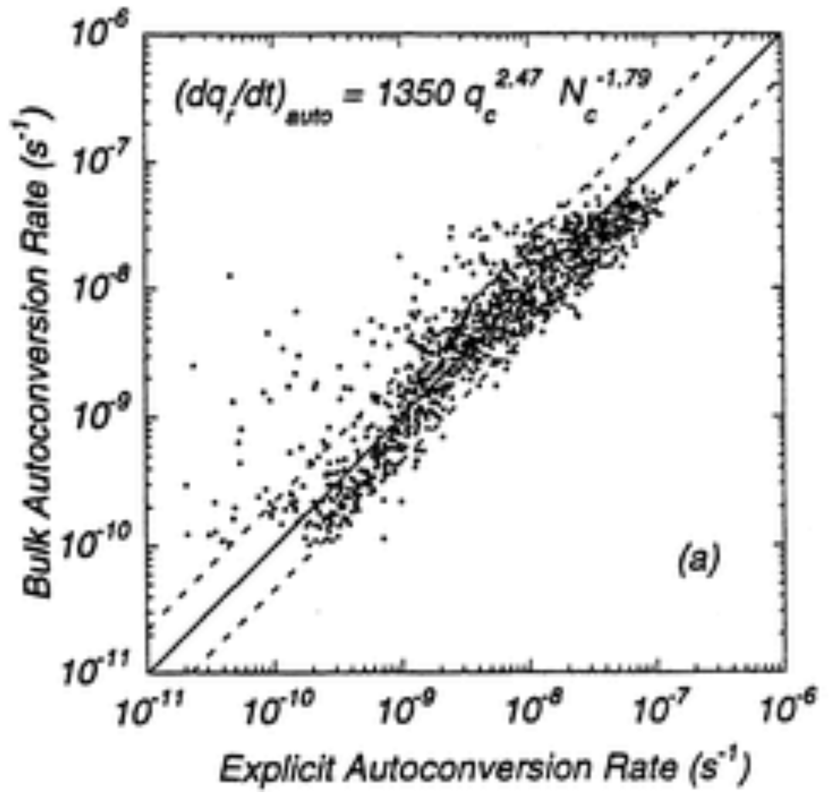

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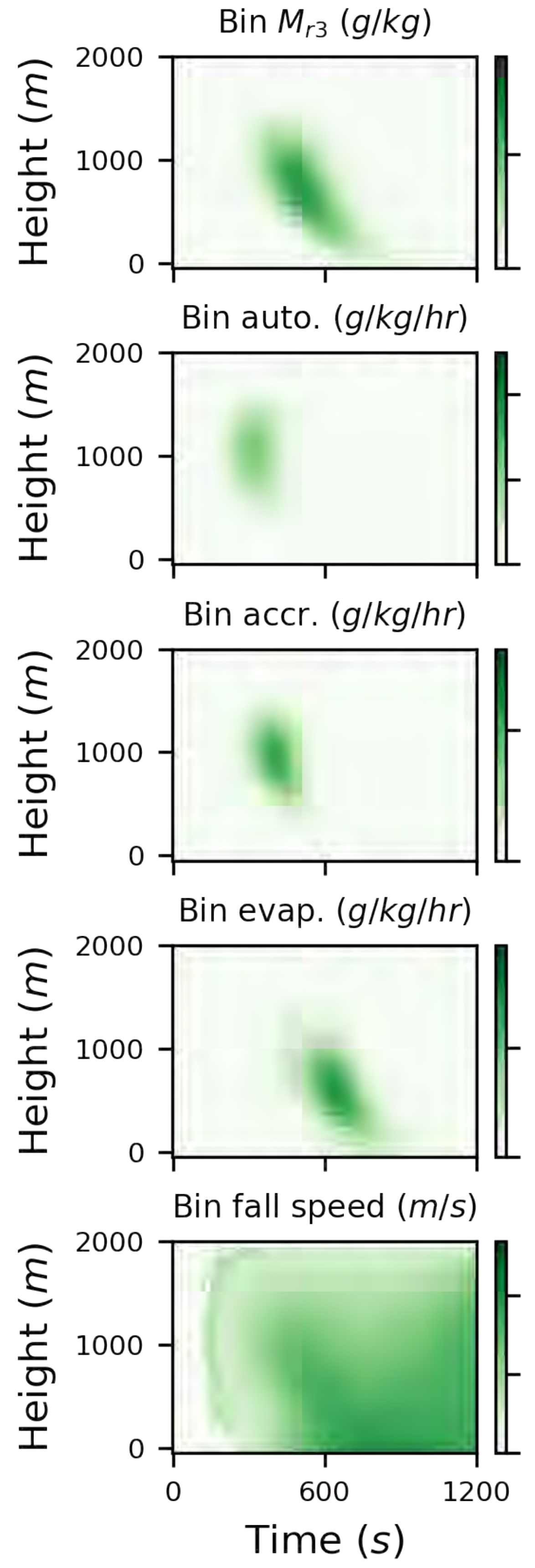
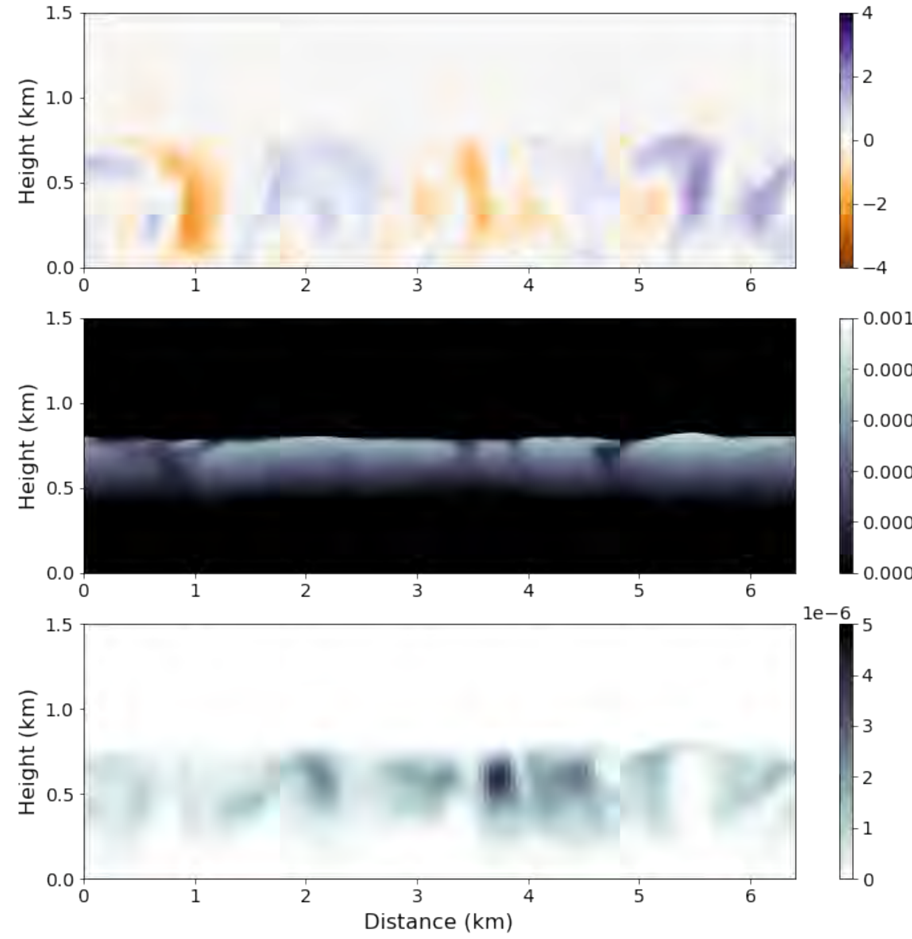
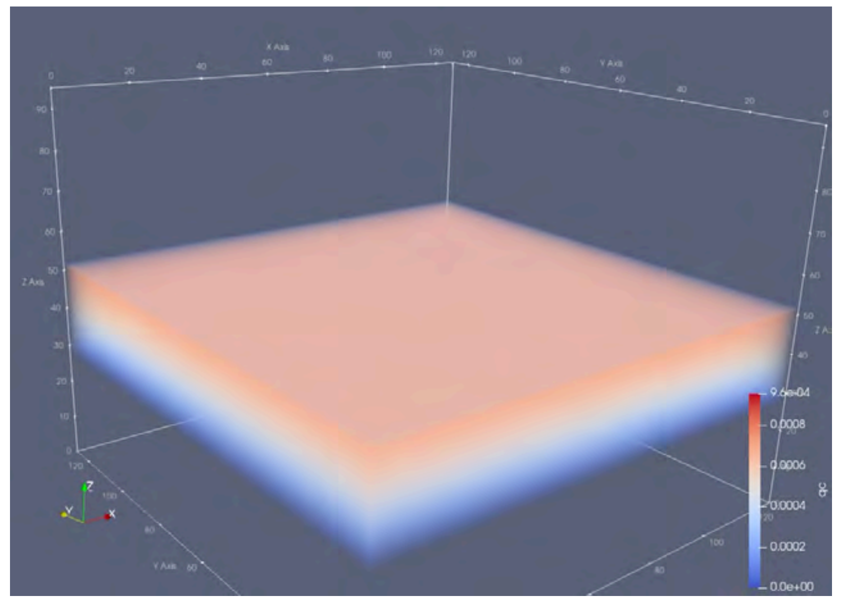
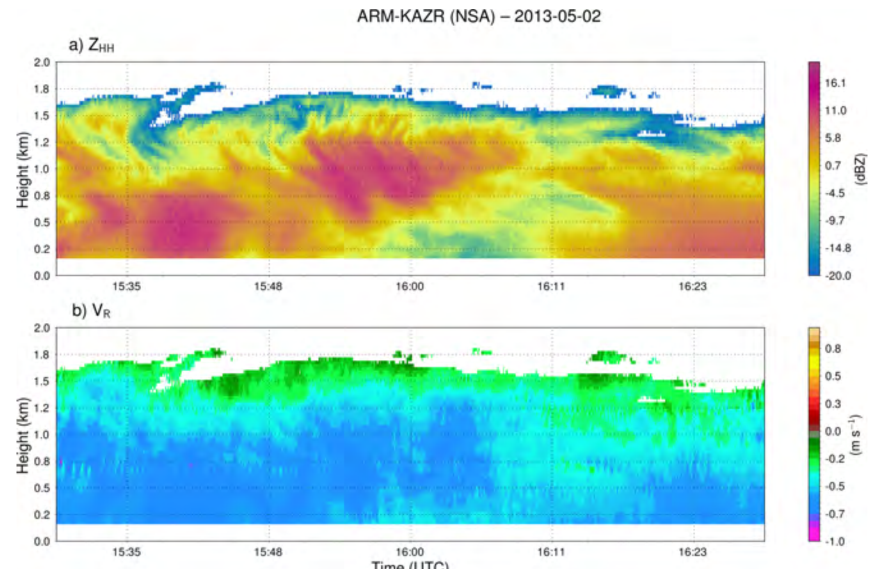
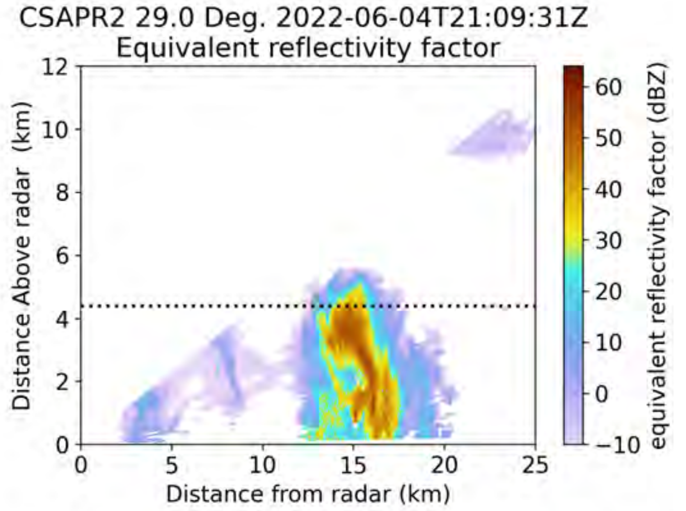
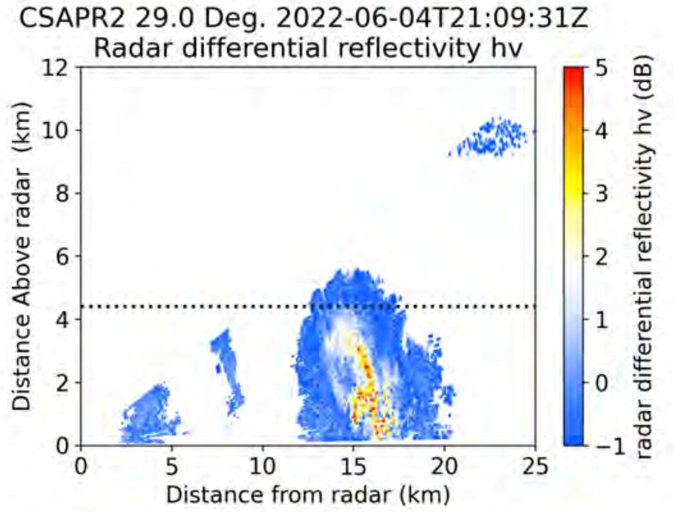




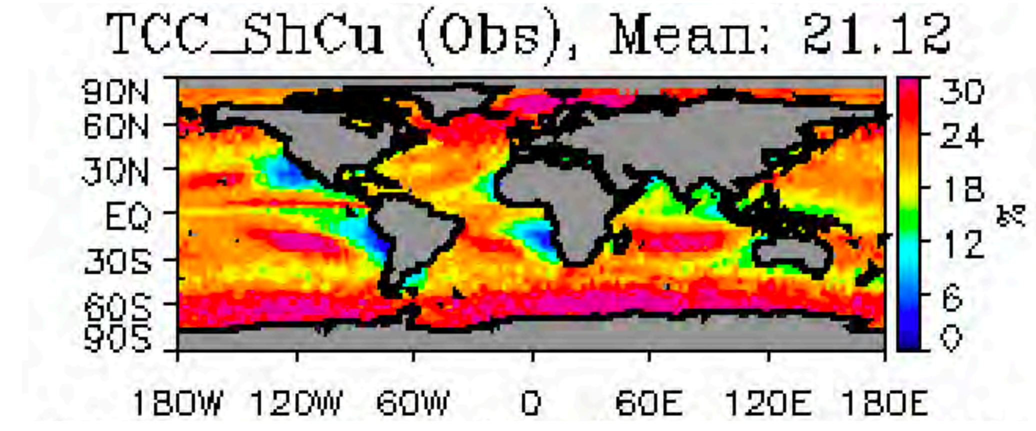




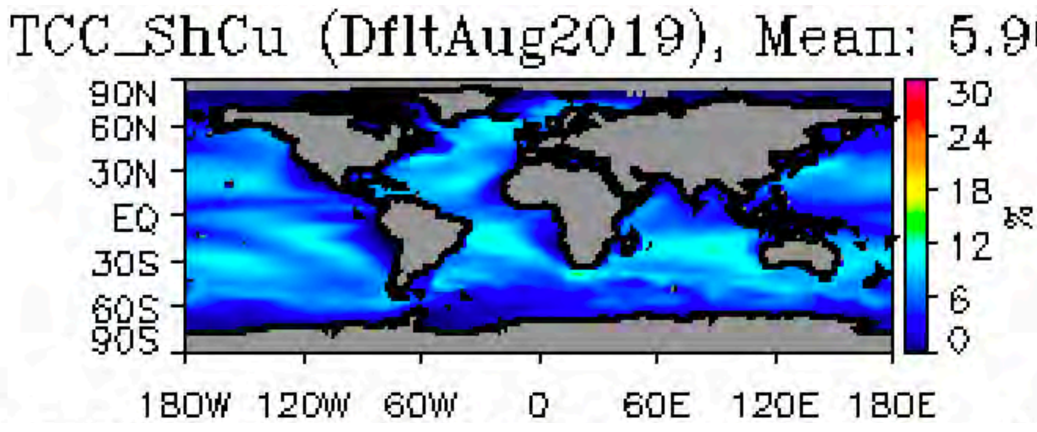




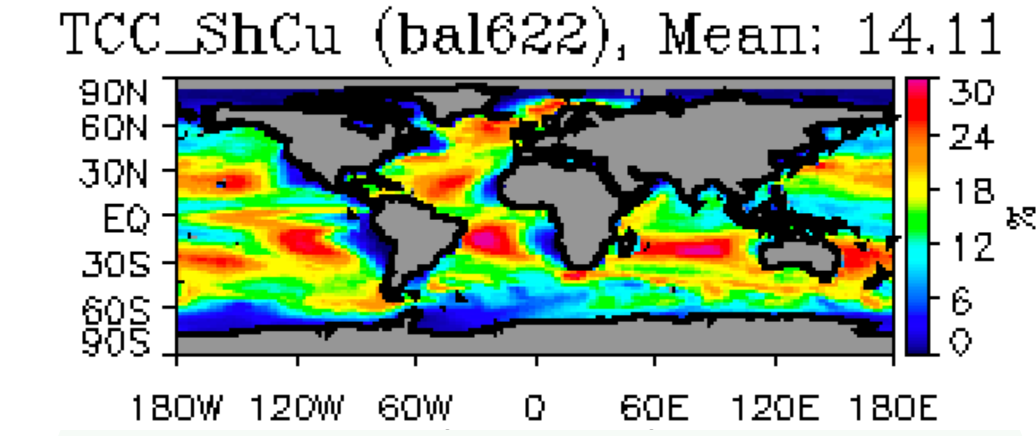
Observed Shallow Cu



Default Parameters



Tuned Parameters



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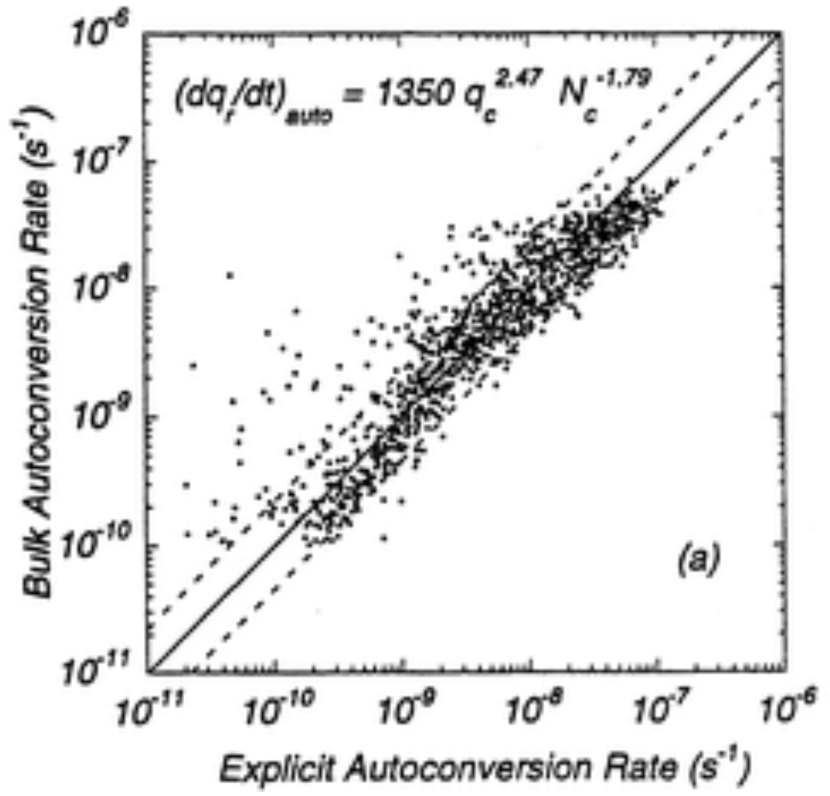

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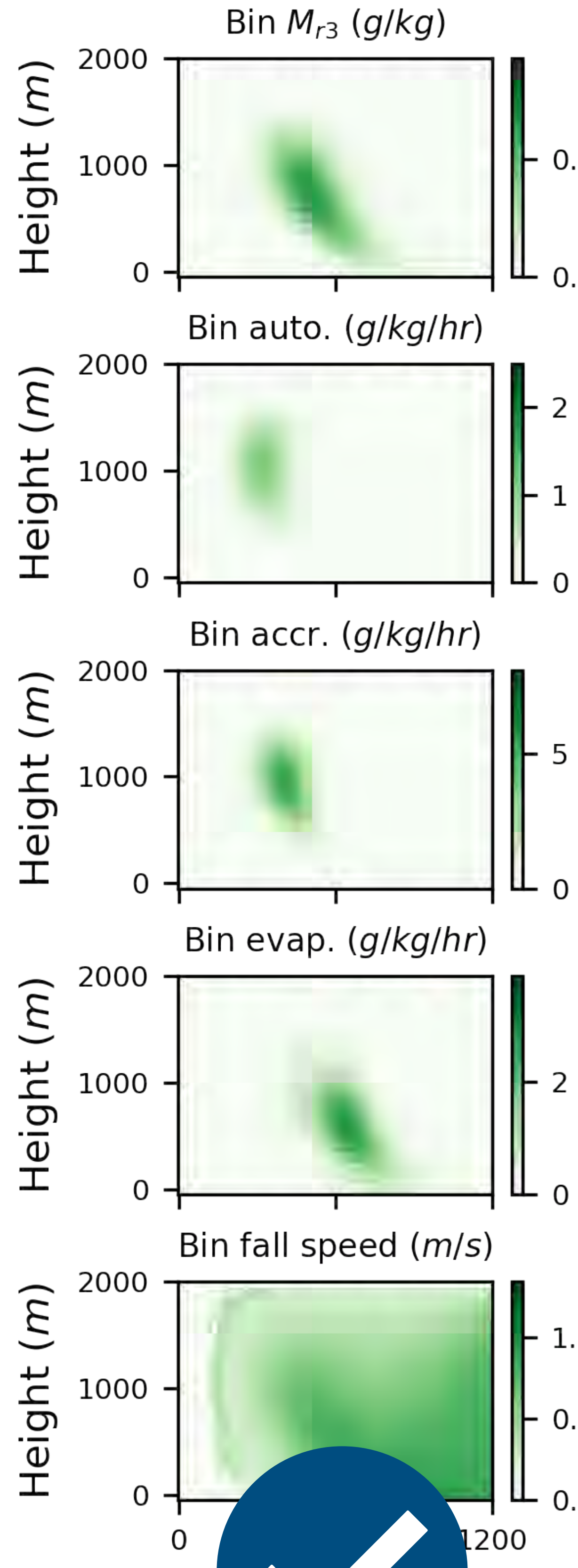

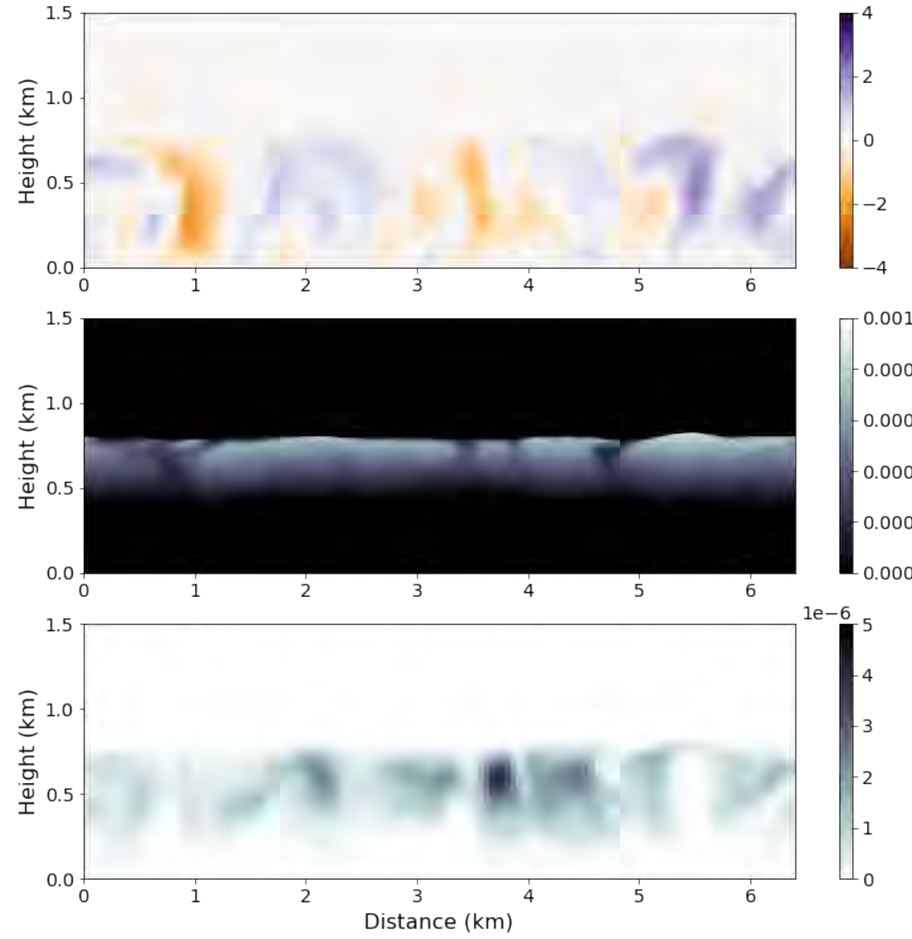

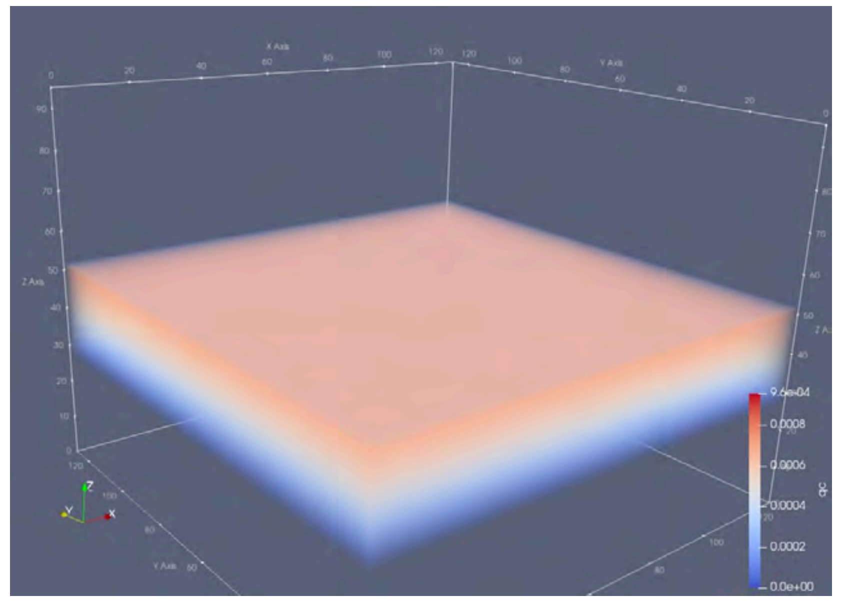

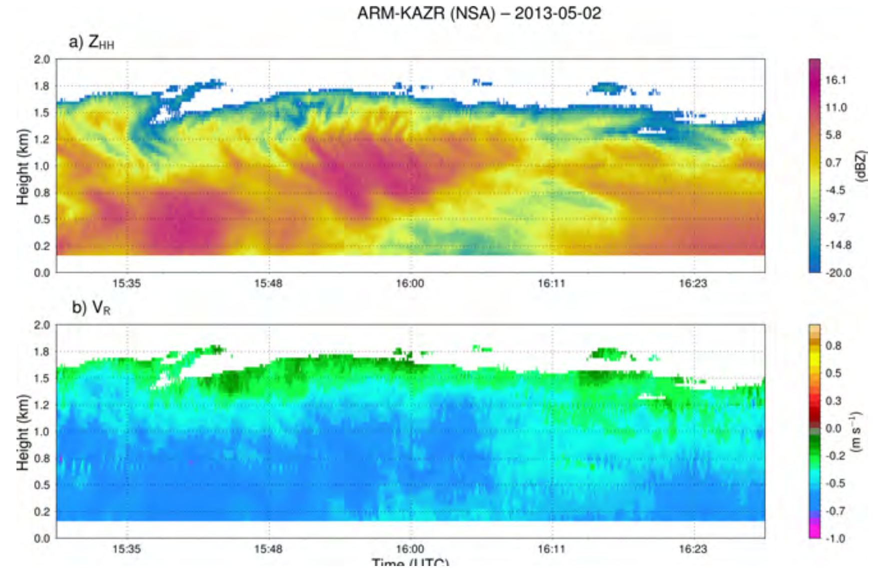

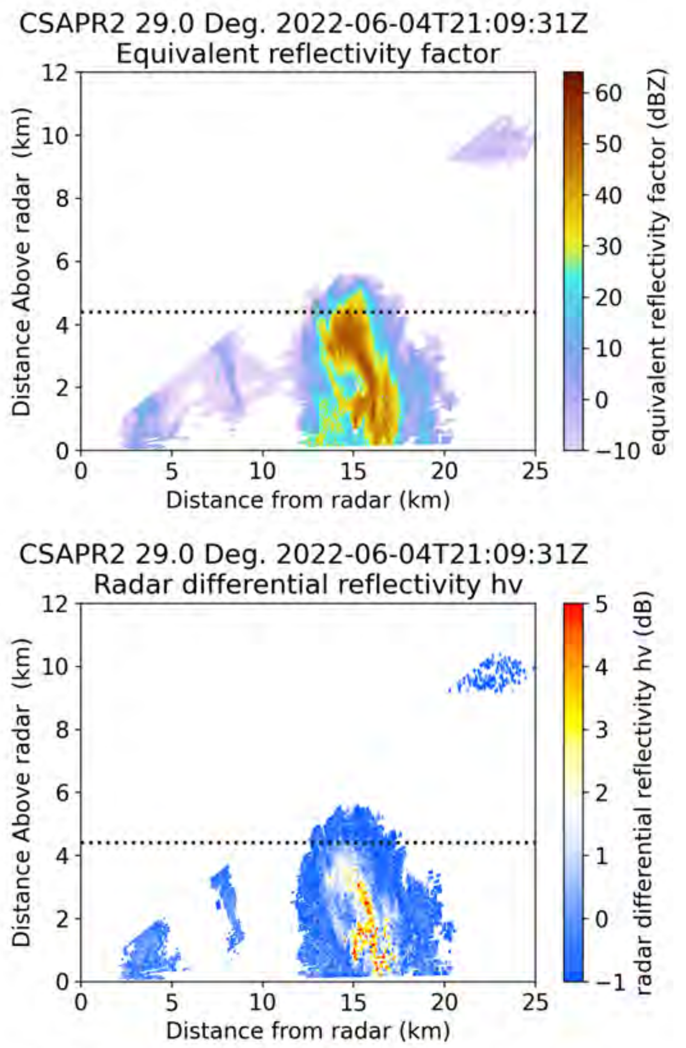

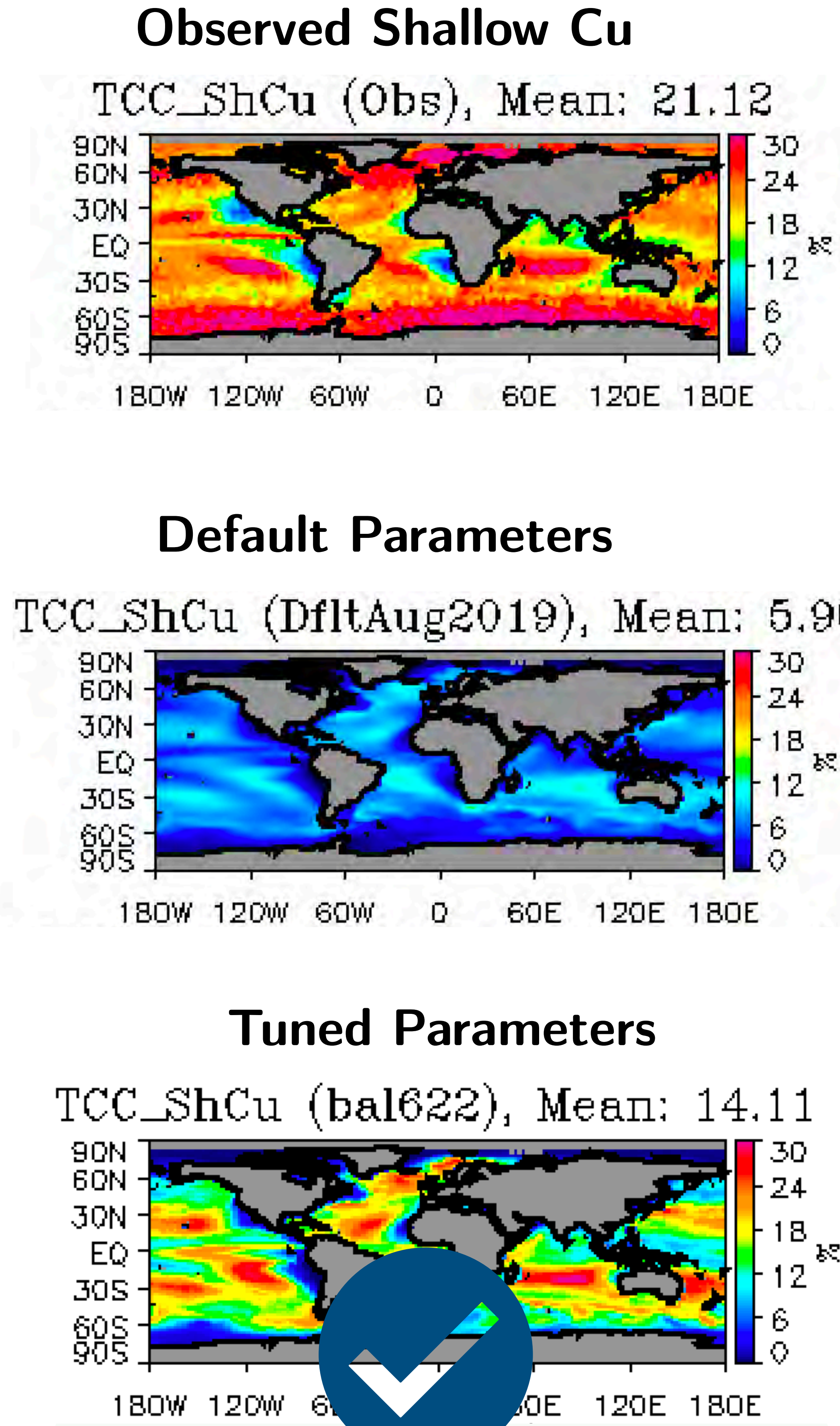

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ASR
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Extra Slides

JEFE (Sean P. Santos)

JEFE: Measuring Predictability

JEFE: Jacobian Evaluation of Functional Error

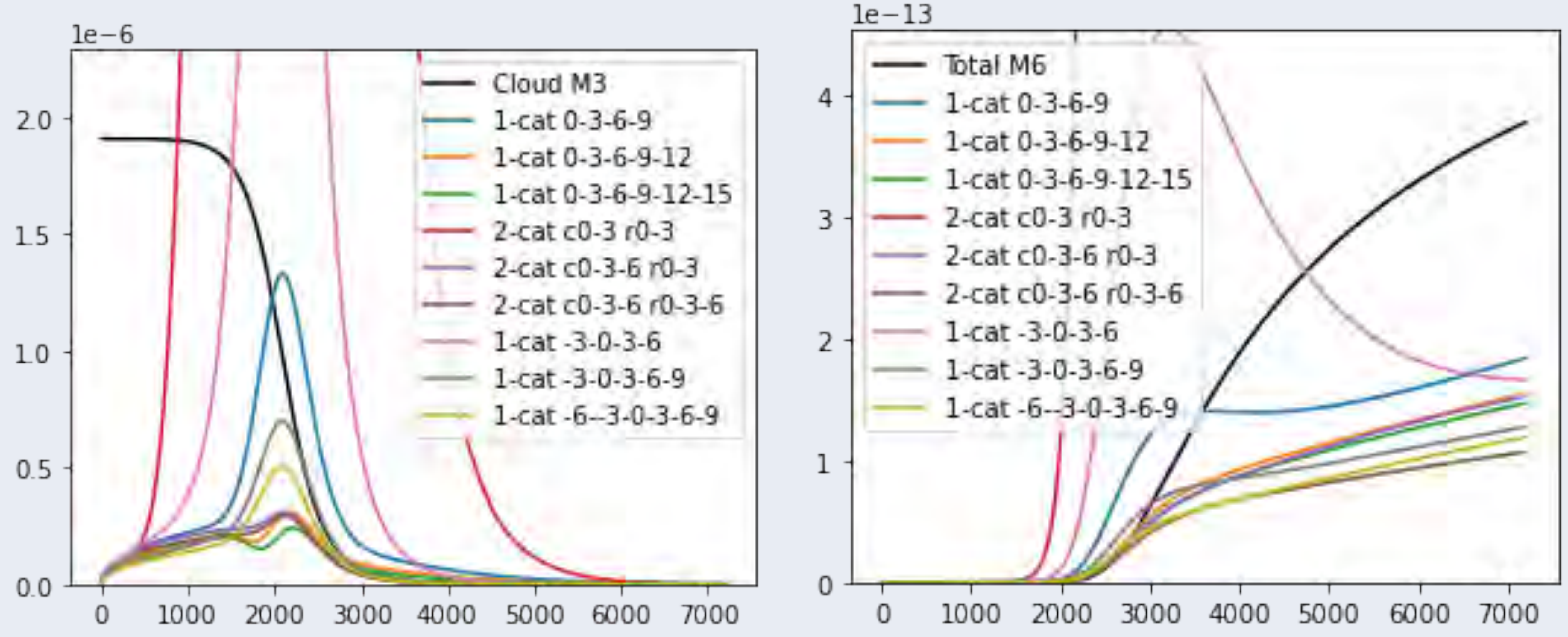

Figure 3:Adjoint-model-derived estimates of relative error of highly-accurate bulk schemes for cloud mass (left) and radar reflectivity (right).

A Challenge: inference complicated by state errors, initial & boundary condition uncertainty

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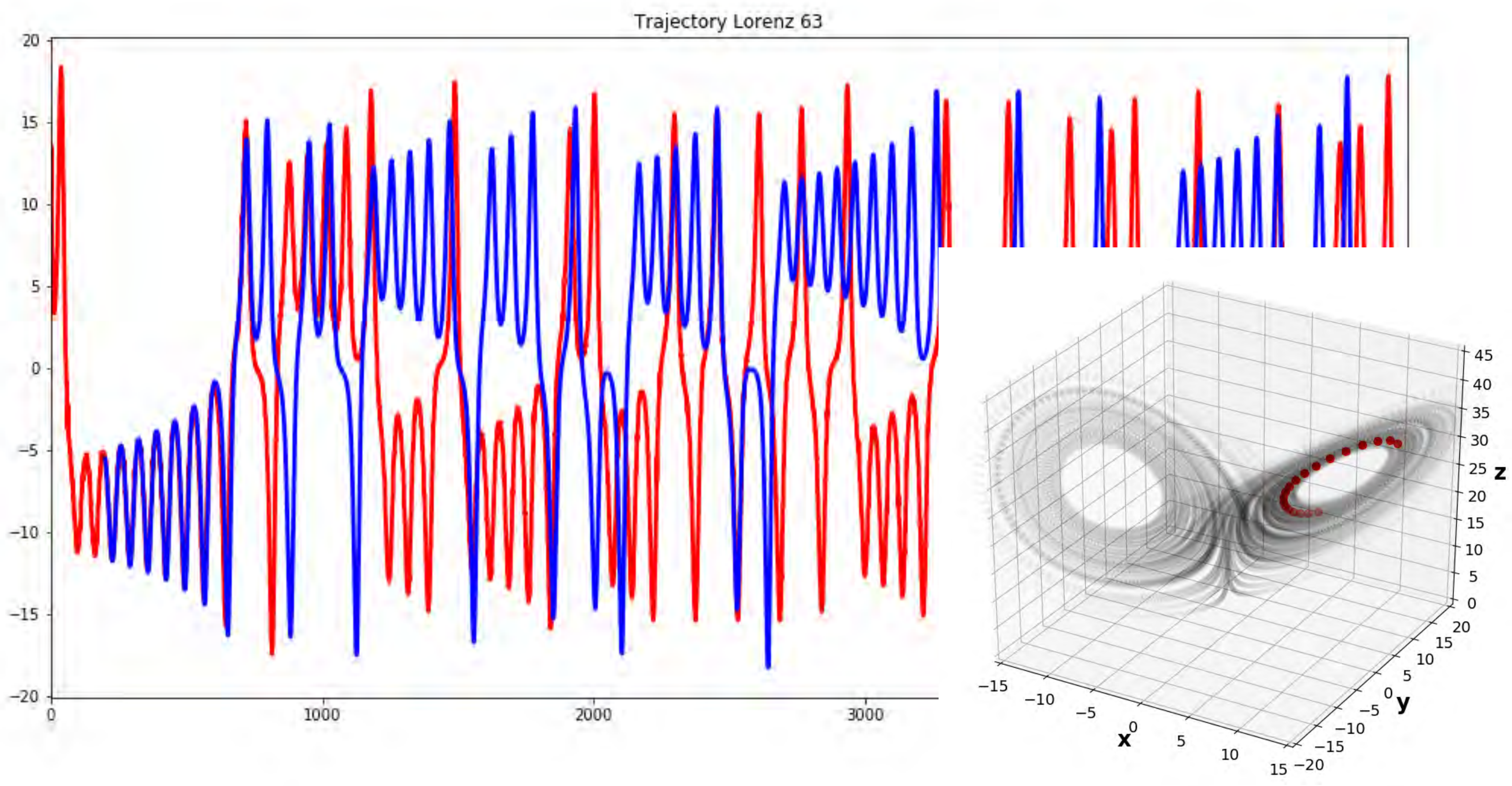
Some aspects of the atmosphere behave chaotically: errors grow nonlinearly from small perturbations, reducing predictability



Lorenz (1963)

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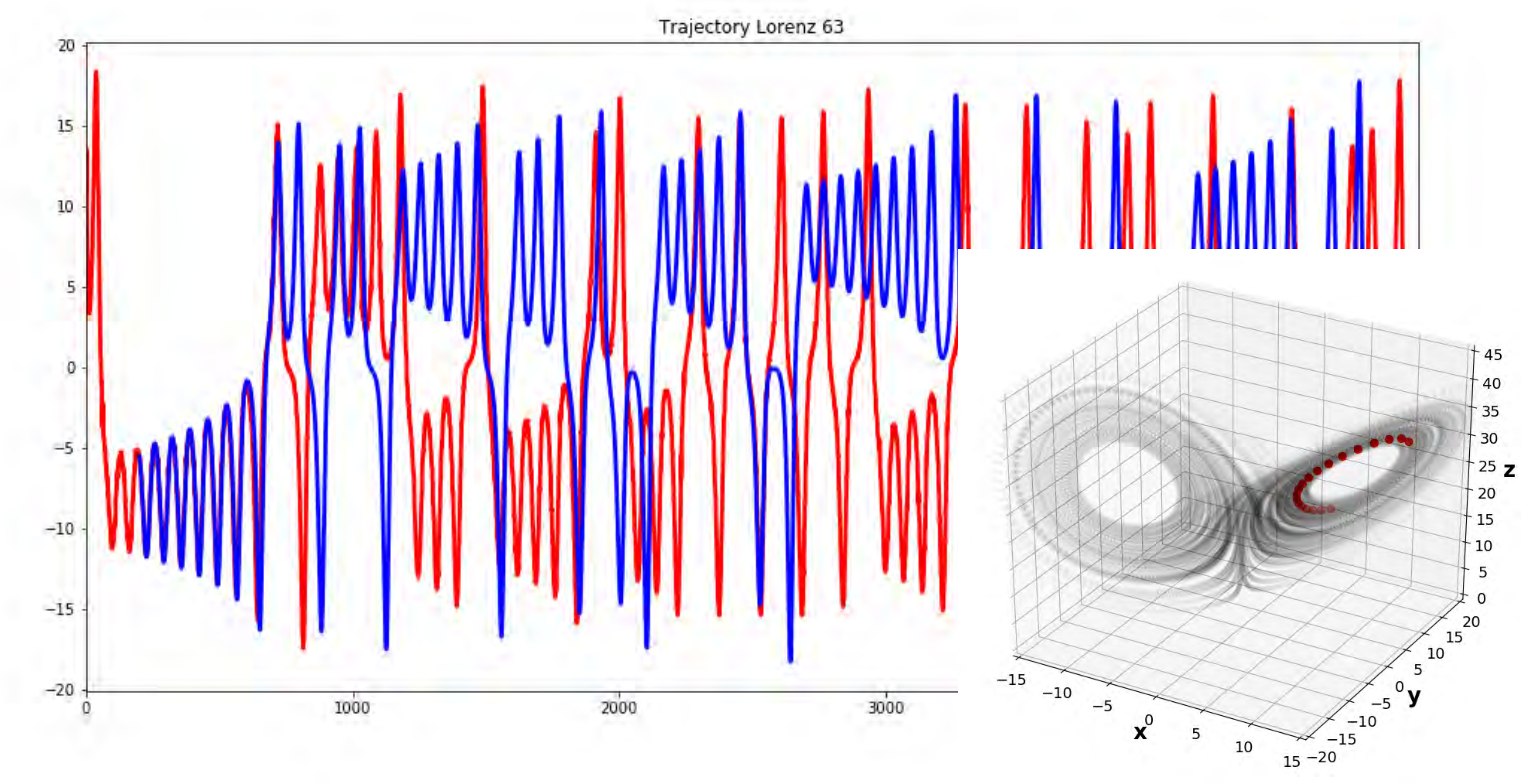

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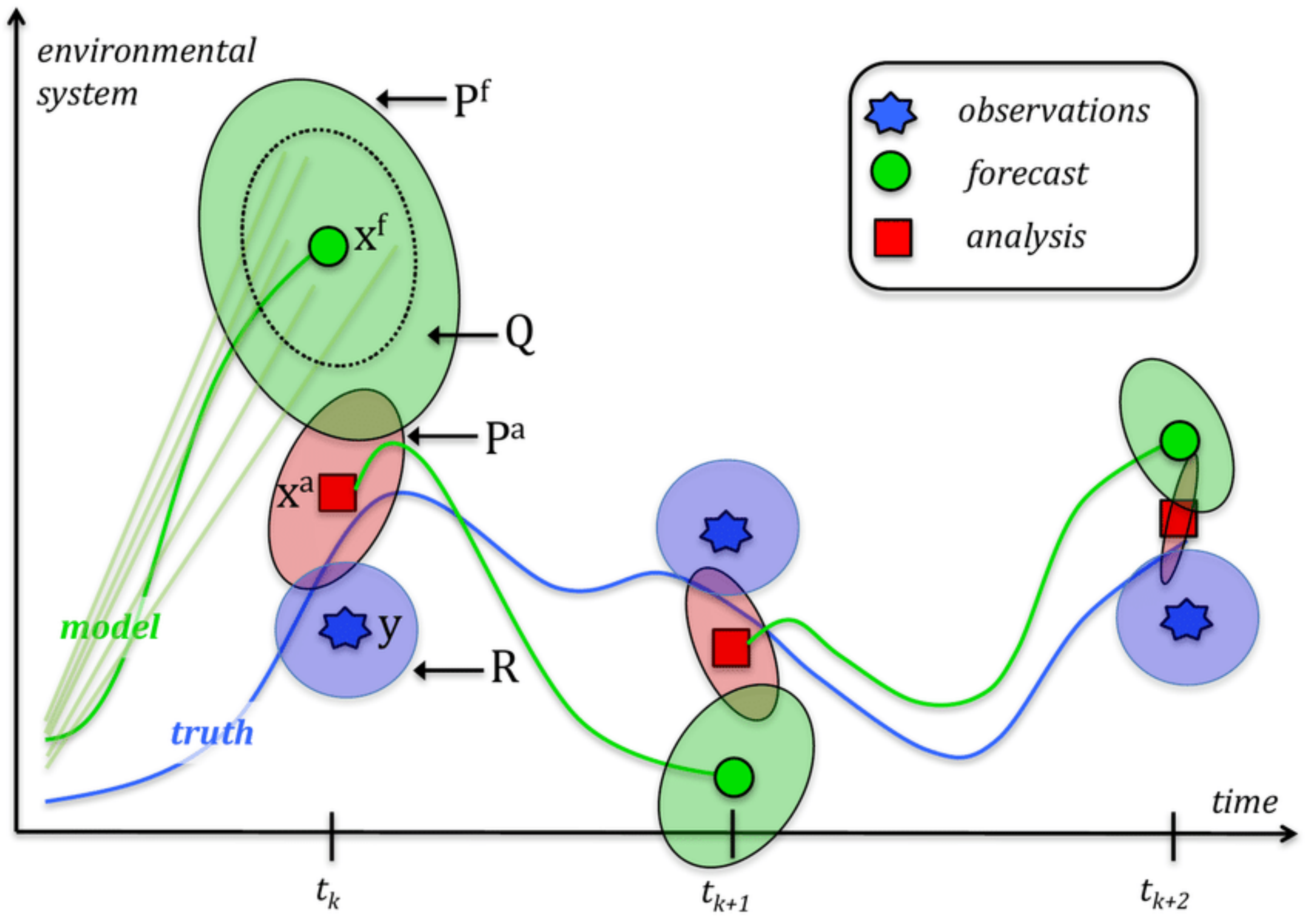
"Data Assimilation" — correcting the state of a model forecast with observations



Tandeo et al. (2018)

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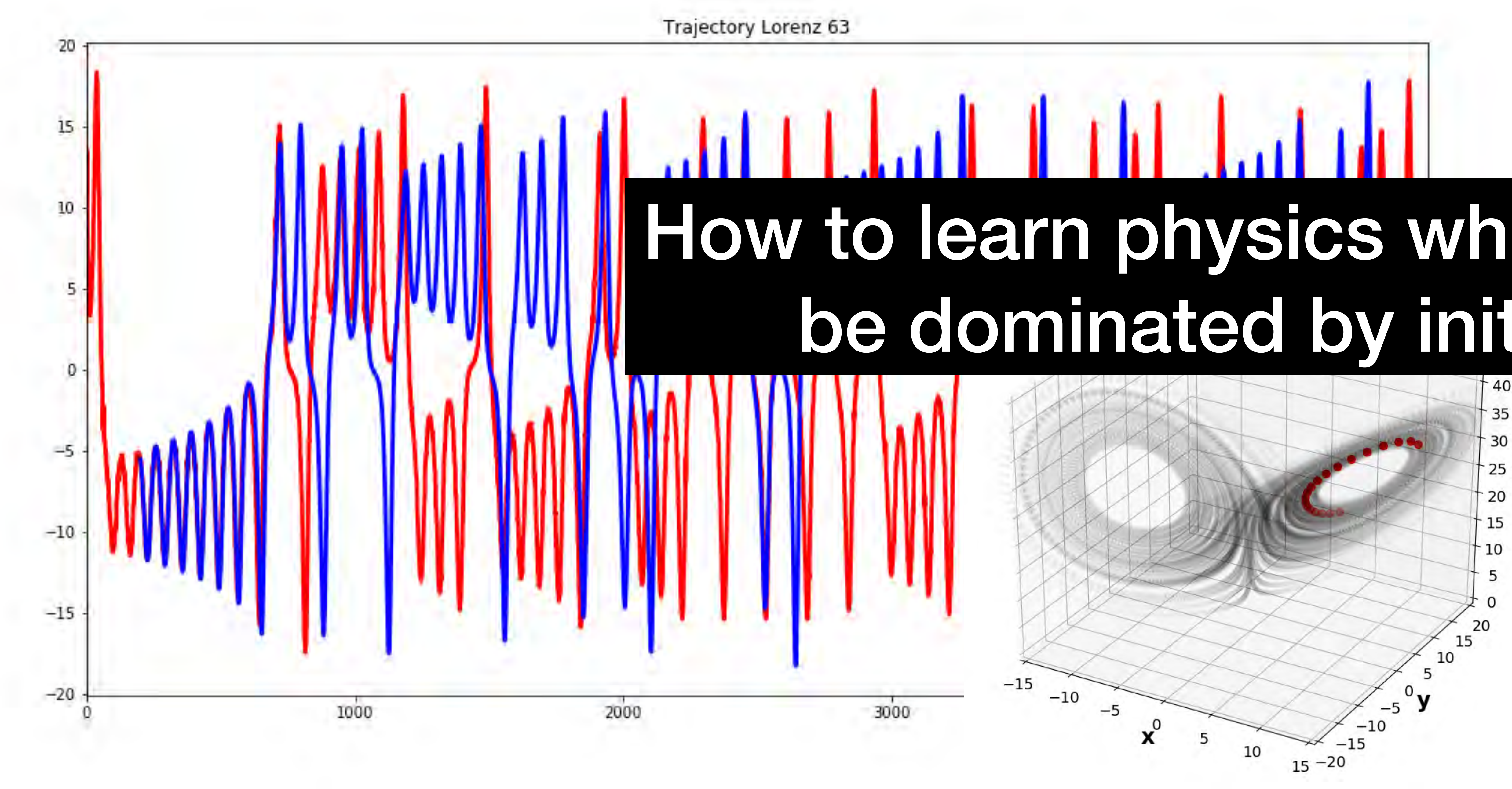

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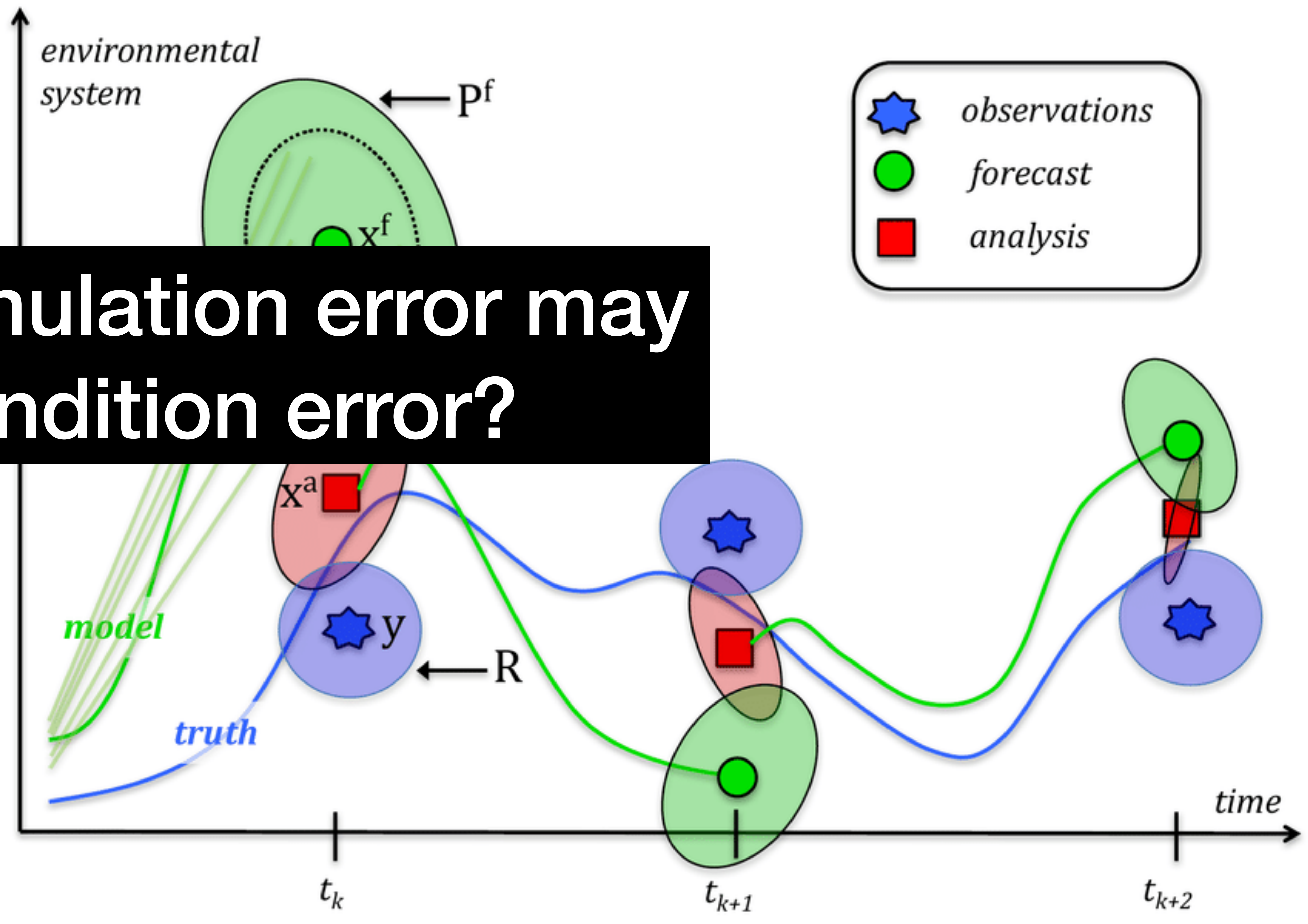

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How to learn physics when simulation error may be dominated by initial condition error?

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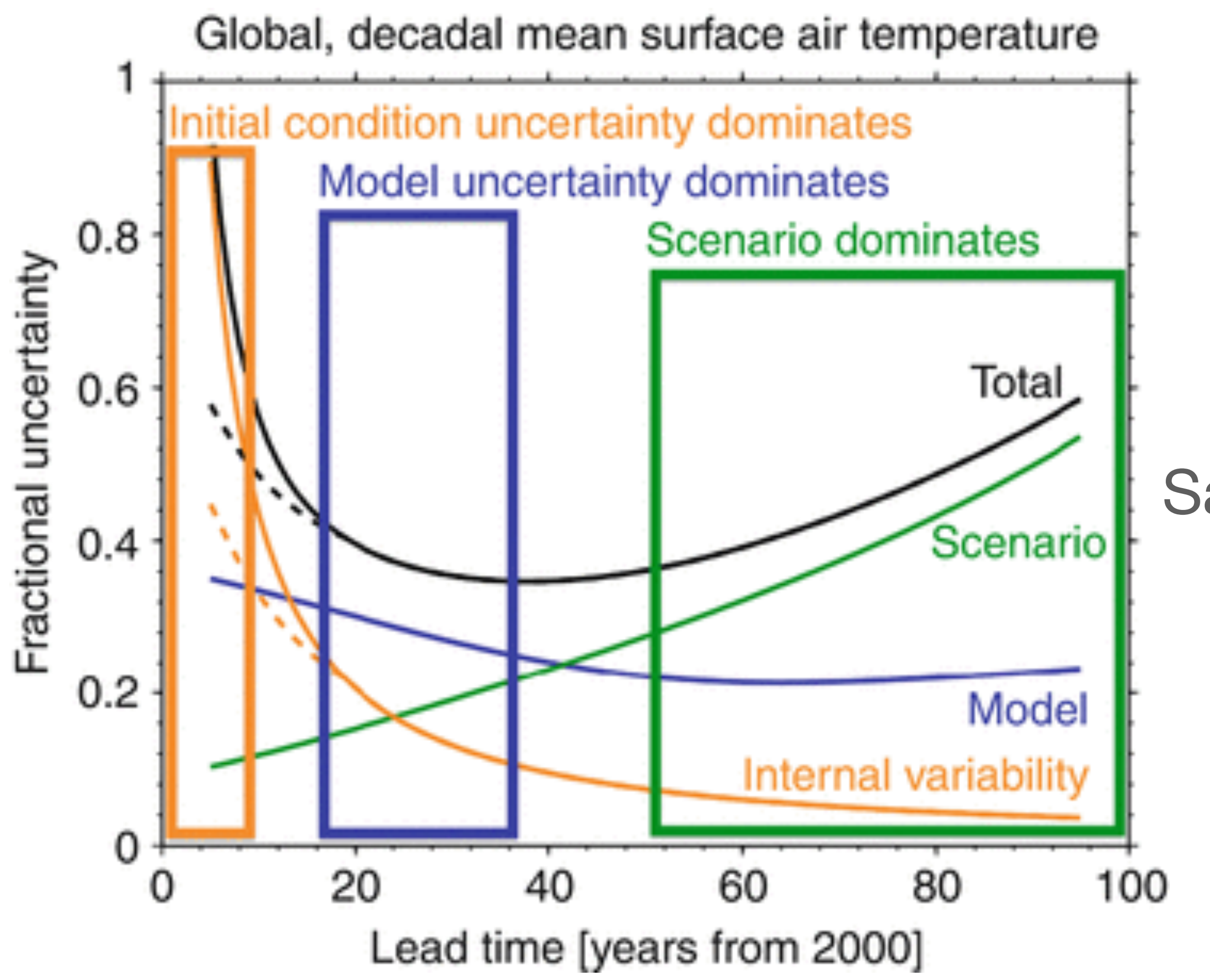

Sanderson & Knutti (2012)

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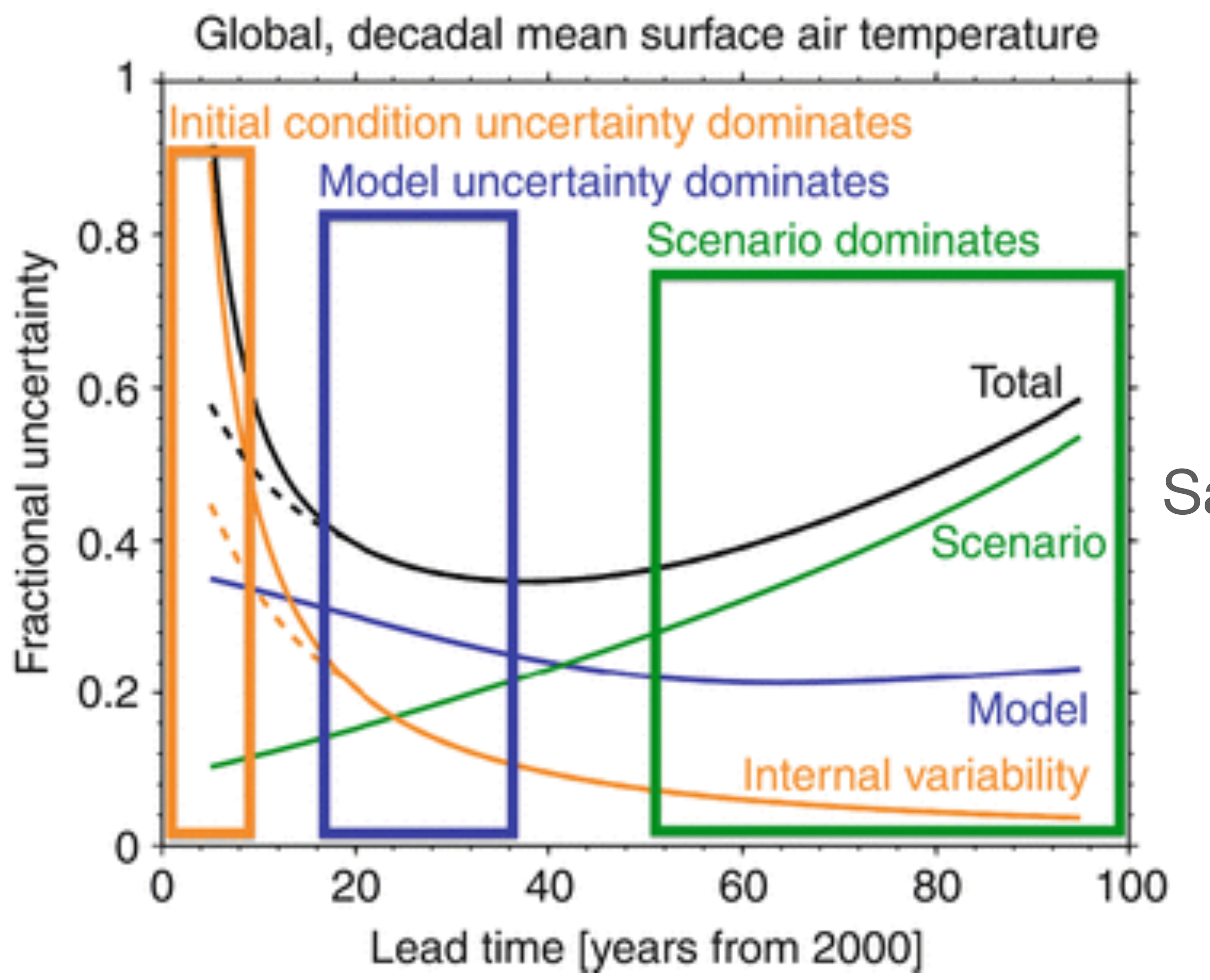

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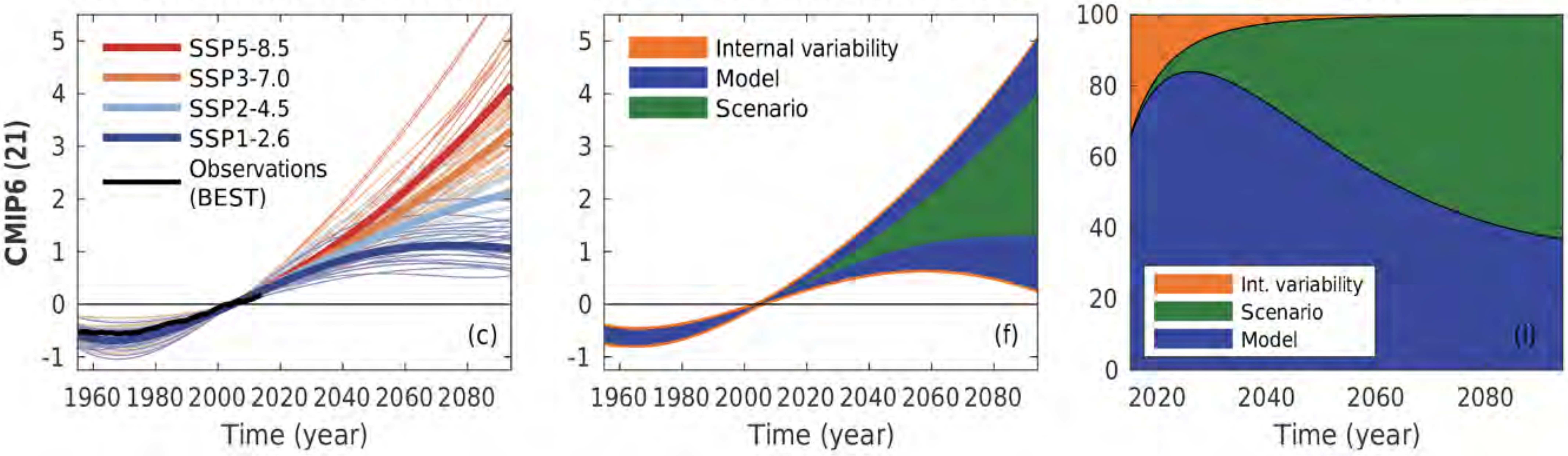

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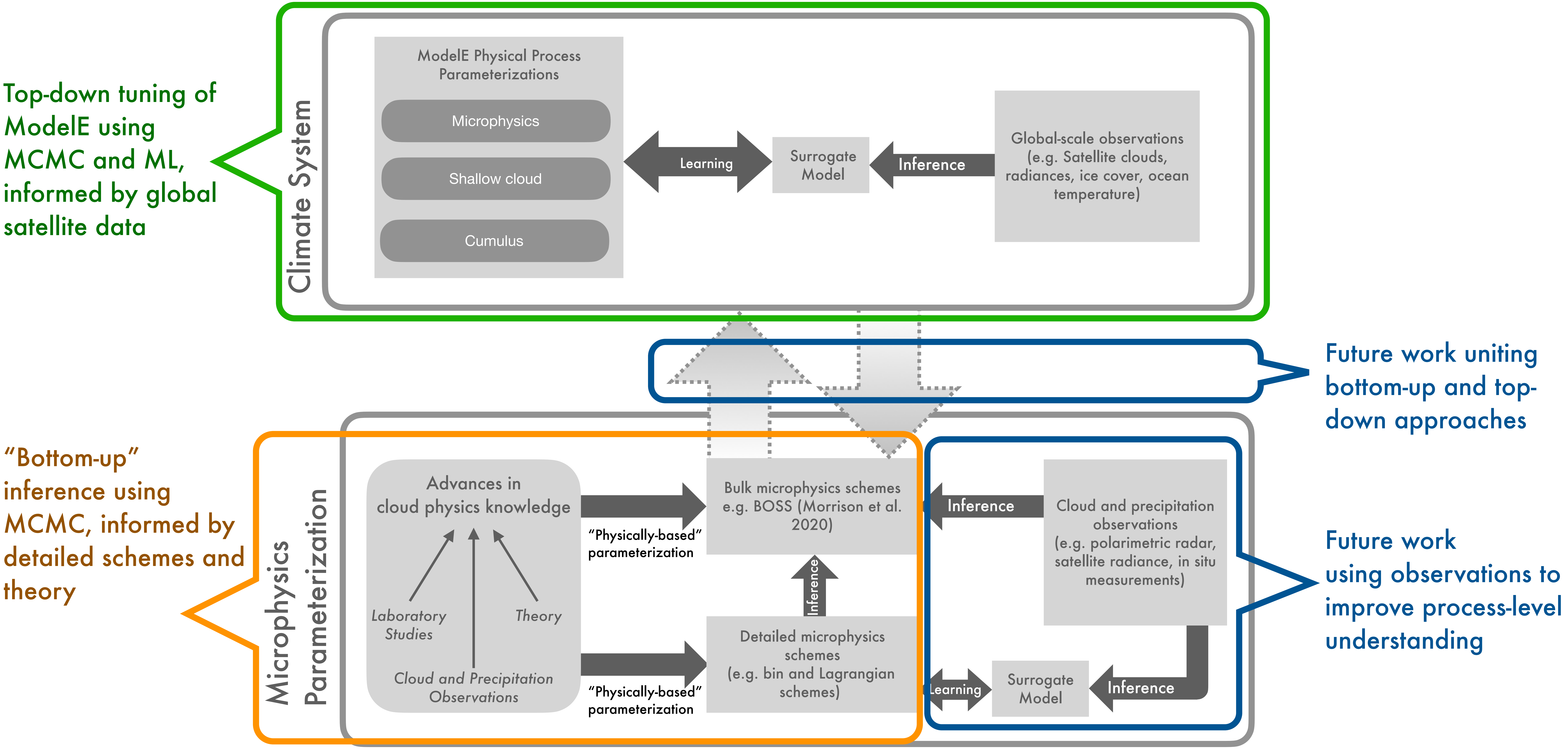
Top-down tuning of ModelE using MCMC and ML, informed by global satellite data
Climate System
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Shallow cloud
Cumulus
Learning
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Future work uniting bottom-up and top-down approaches
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Advances in cloud physics knowledge
Laboratory Studies
Theory
Cloud and Precipitation Observations
"Physically-based" parameterization
Bulk microphysics schemes e.g. BOSS (Morrison et al. 2020)
Inference
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Future work using observations to improve process-level understanding

Addressing structural errors in warm-rain microphysics with BOSS, a Bayesian data-driven physically-based bulk scheme

Marcus van Lier Walqui — CCSR Columbia University @ NASA/GISS mv2525@columbia.edu
Sean Patrick Santos — Pacific Northwest National Laboratories
Hugh Morrison — National Center for Atmospheric Research
Karly Reimel — (prev.) Penn State University
Adele Igel — University of California Davis

ASR PI Meeting — Oct 27th 2022

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- Wealth of natural cloud and precipitation observations but difficult to measure process rates directly, only net effects on hydrometeors —> an indirect constraint of bulk schemes

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The BIG question: How to use these various data sources — each with their own uncertainties — to constrain bulk schemes?

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Thomas Bayes (1701-1761)

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BOSS

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Bayesian (we treat uncertainties robustly, uncertainties reside in parameters)

Observationally-constrained (scheme is informed by comparison to observations)

Statistical-physical (we don't just want a statistical scheme, but we will use statistics)

Scheme — bulk microphysics parameterization scheme (so far rain & cloud only)

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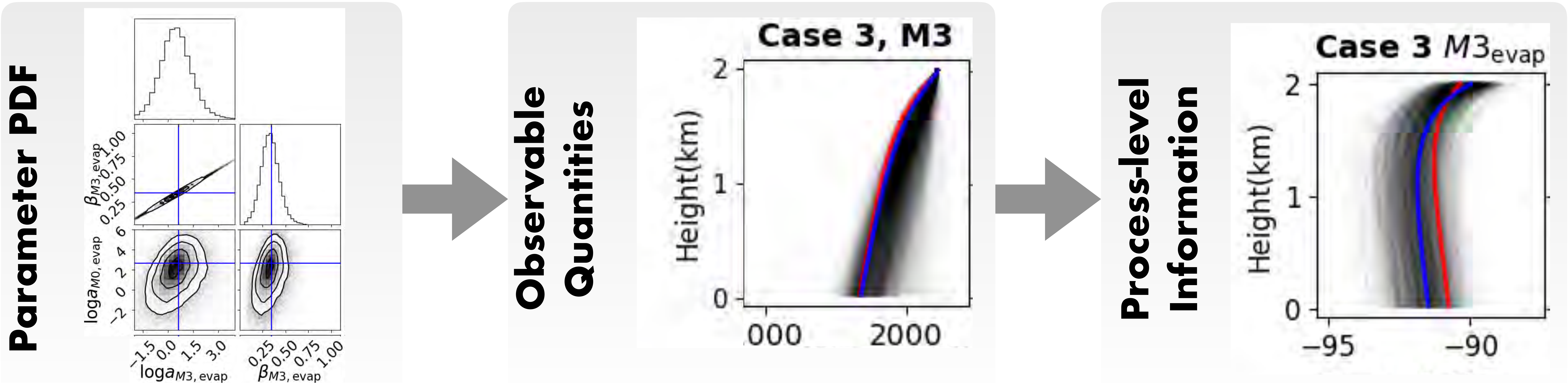

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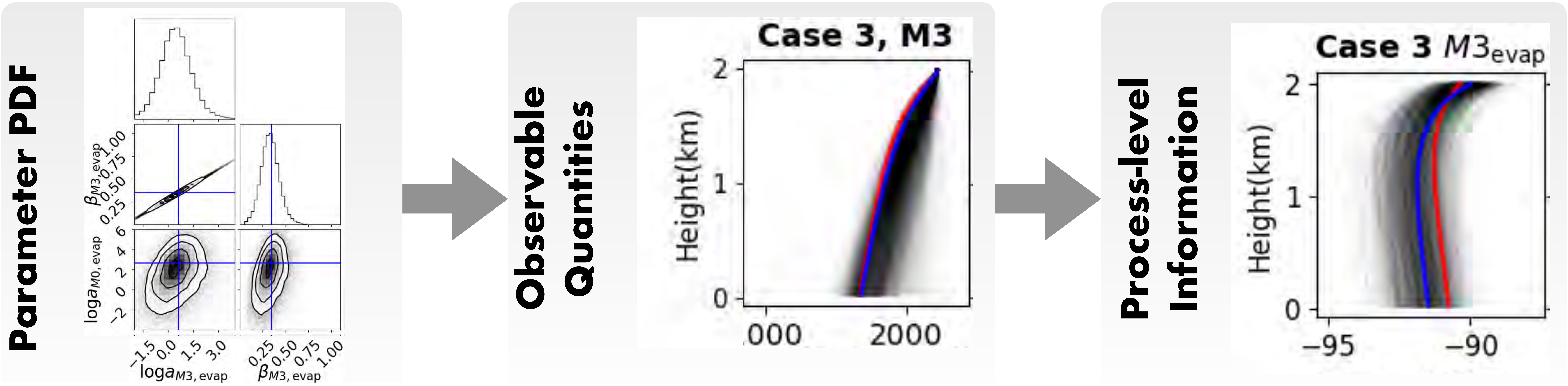

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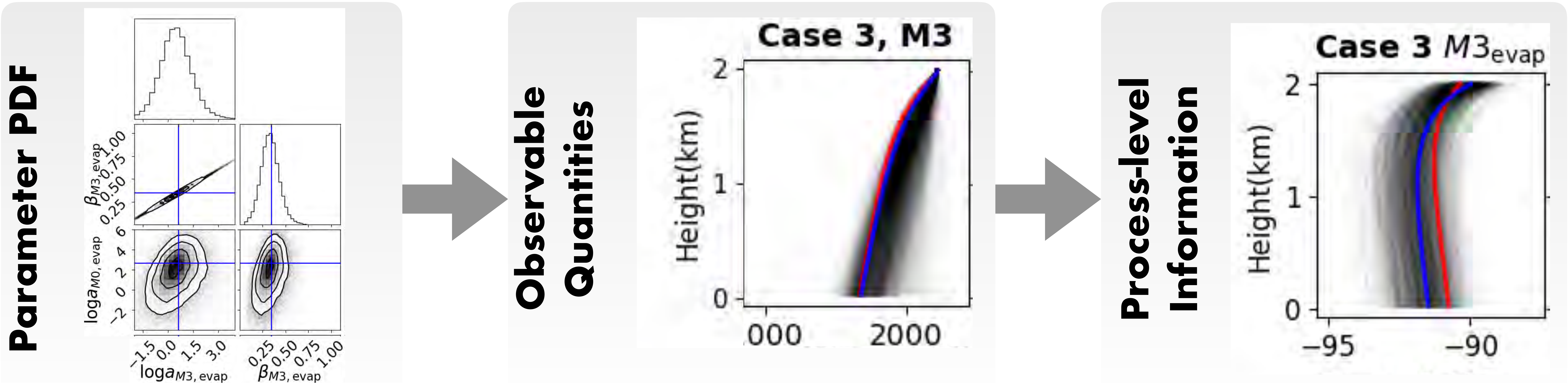

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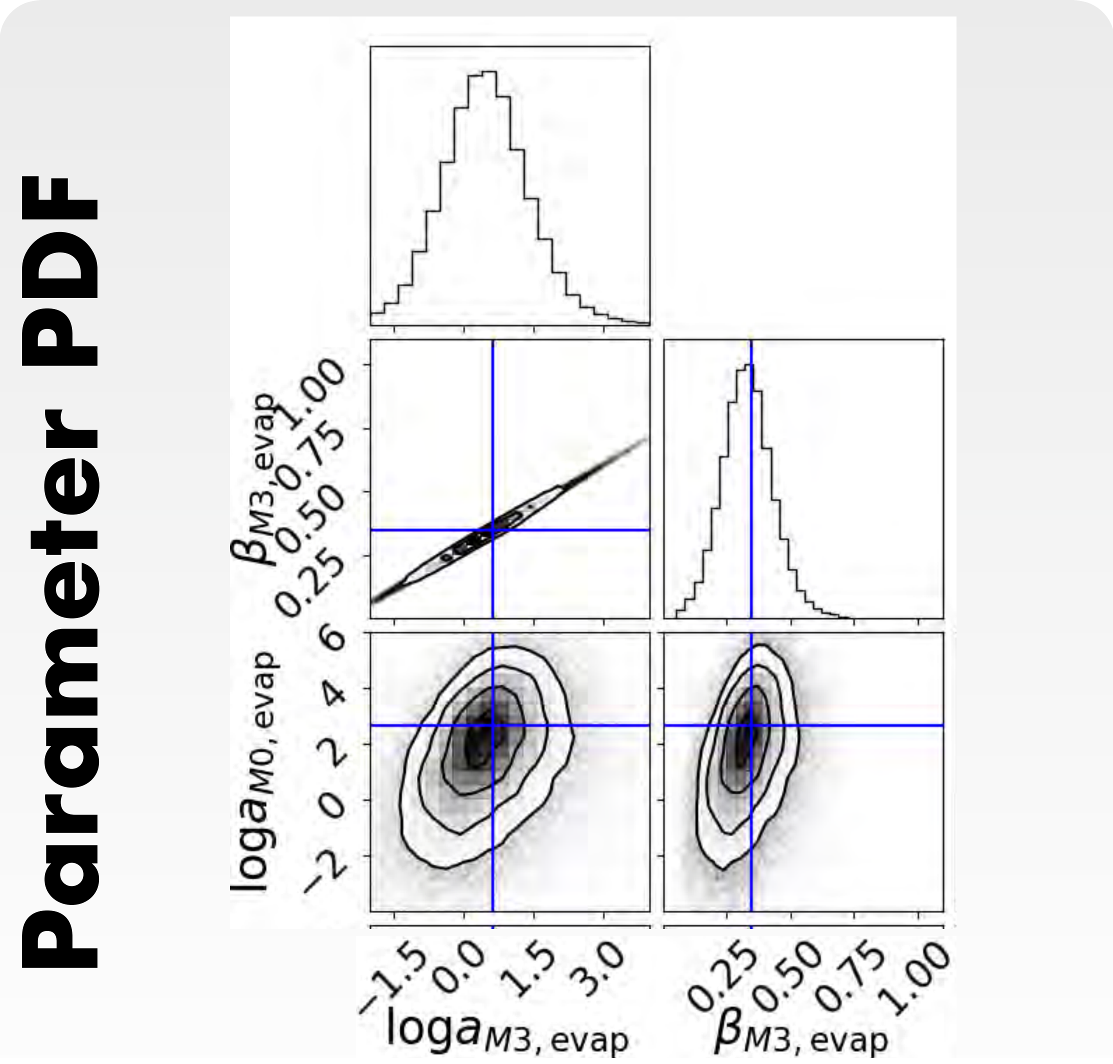

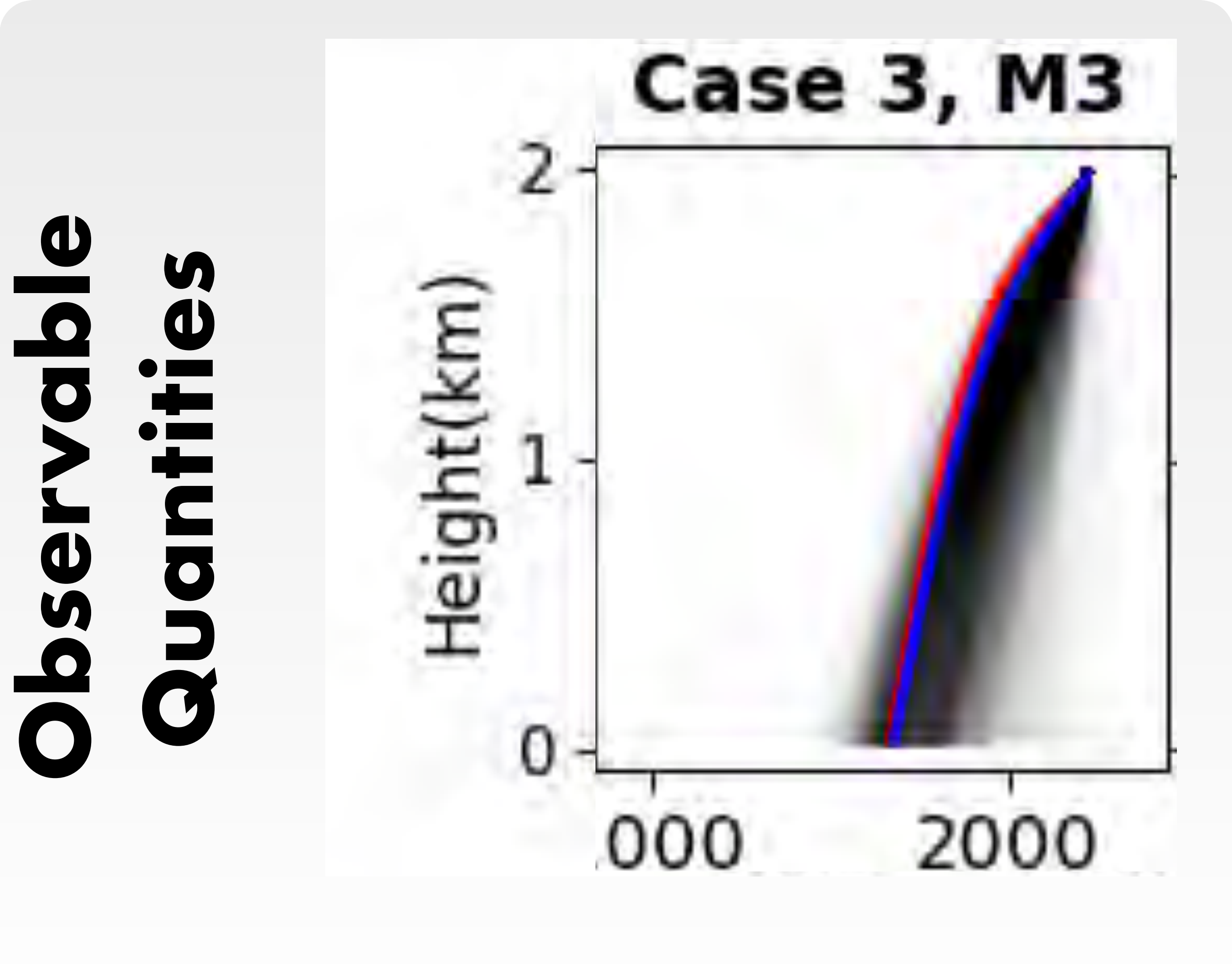

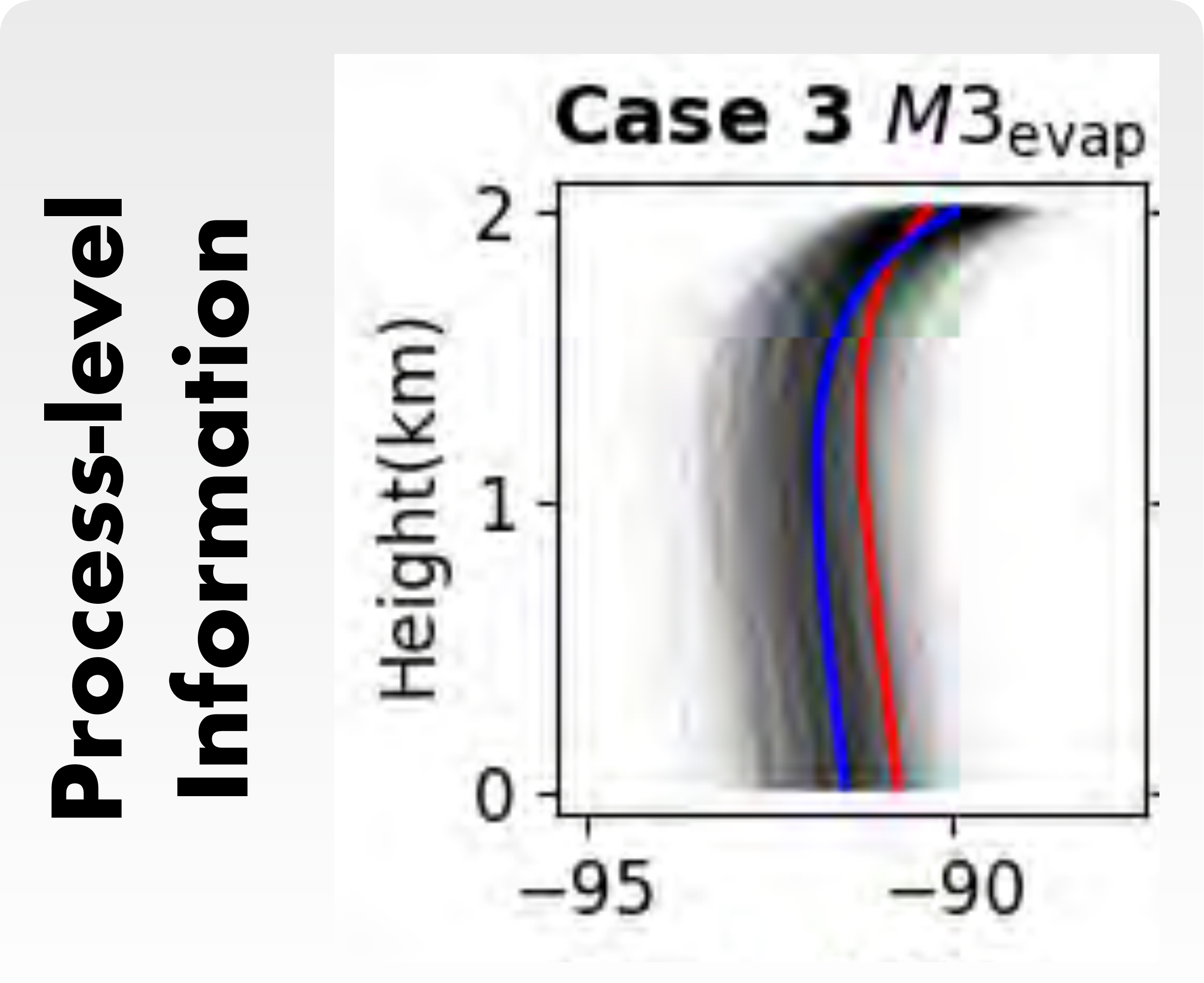

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Morrison et al. JAS 2020; van Lier-Walqui et al. JAS 2020, Morrison et al. JAMES 2020, Reimel et al. (in prep)

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Predict *moments* of the DSD $M_k = \int_{D_{min}}^{D_{max}} D^k(\partial N/\partial D)dD$

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Choose whatever moments are "best"

Get rid of fixed process rate functions

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Use a flexible (but sensible) functional basis set

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$$\frac{dM_k}{dt} \approx F(T,p,q) \sum_{l=1}^{L} a_{l,k} M_{p_1} \prod_{n=1}^{N-1} \left(\frac{M_{p_{n+1}}}{M_{p_n}} \right)^{\beta_{p_n,l,k}}$$

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Use Bayesian inference to estimate *a*,*β*,*δ*

Structural error estimation and parsimony

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Example of theoretical constraints on parsimony

A third moment (e.g. M6) can be used as a measure of DSD variance:

$$\sigma^2 = \frac{1}{M_{c0}} \int_0^\infty N(D)(D^3 - m_c)^2 dD = \frac{M_{c6}}{M_{c0}} - m_c^2$$

Constraint on the possible values of DSD variance enforces a structural form on the process rate for cloud self-collection (…some math…)

$$b_{6m,csc} = b_{0m,csc} + 2 \qquad a_{6,csc} \geq a_{0,csc} \tag{1}$$

Similar arguments reduce the total number of BOSS parameters from 60+ to 37 for 3-moment cloud BOSS

A spectrum of data and ways to constrain/inform BOSS

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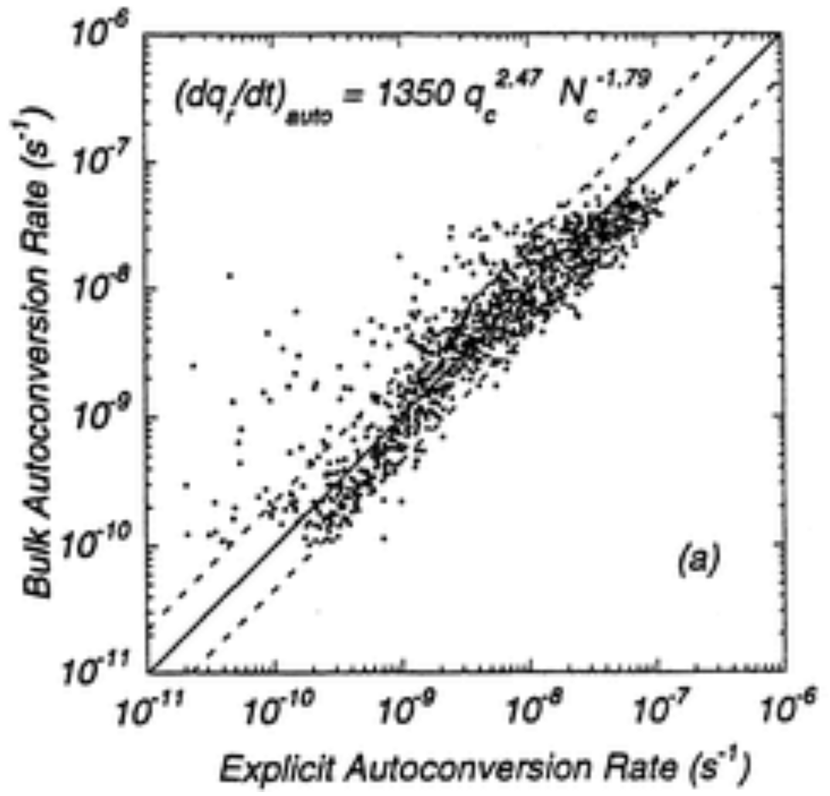

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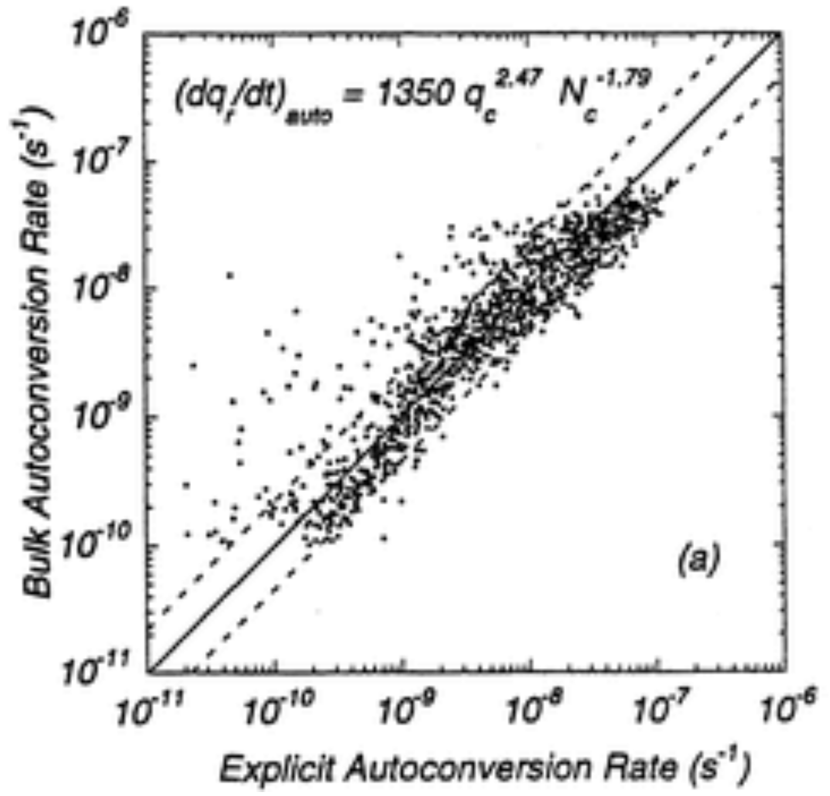

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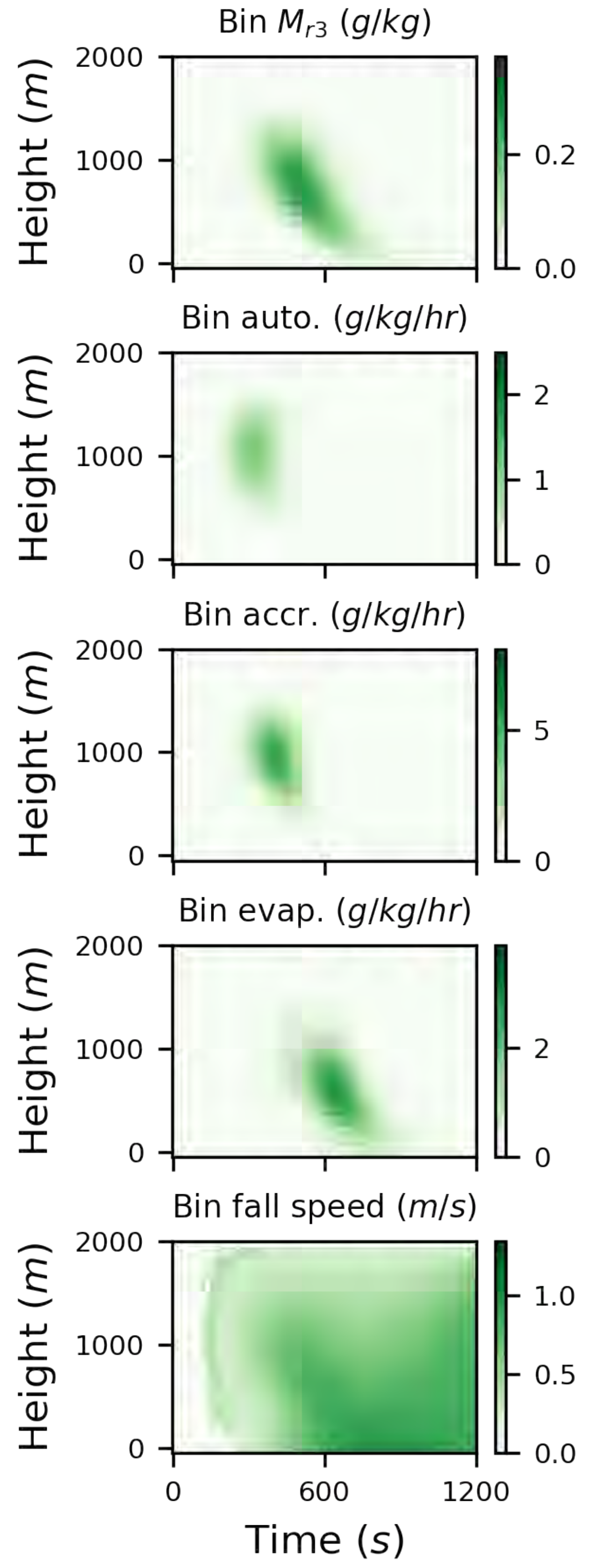

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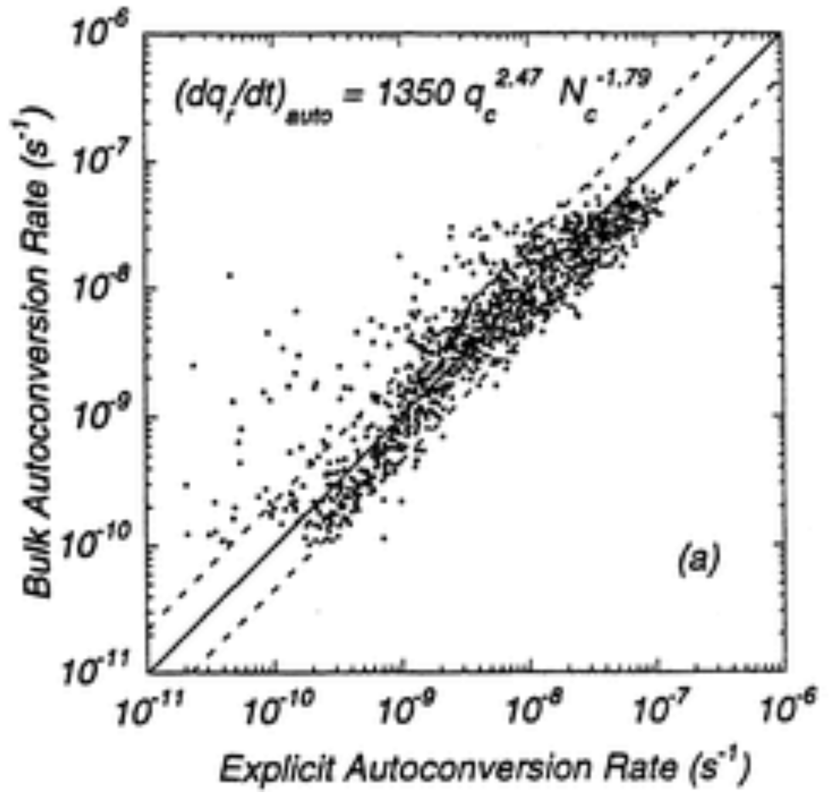

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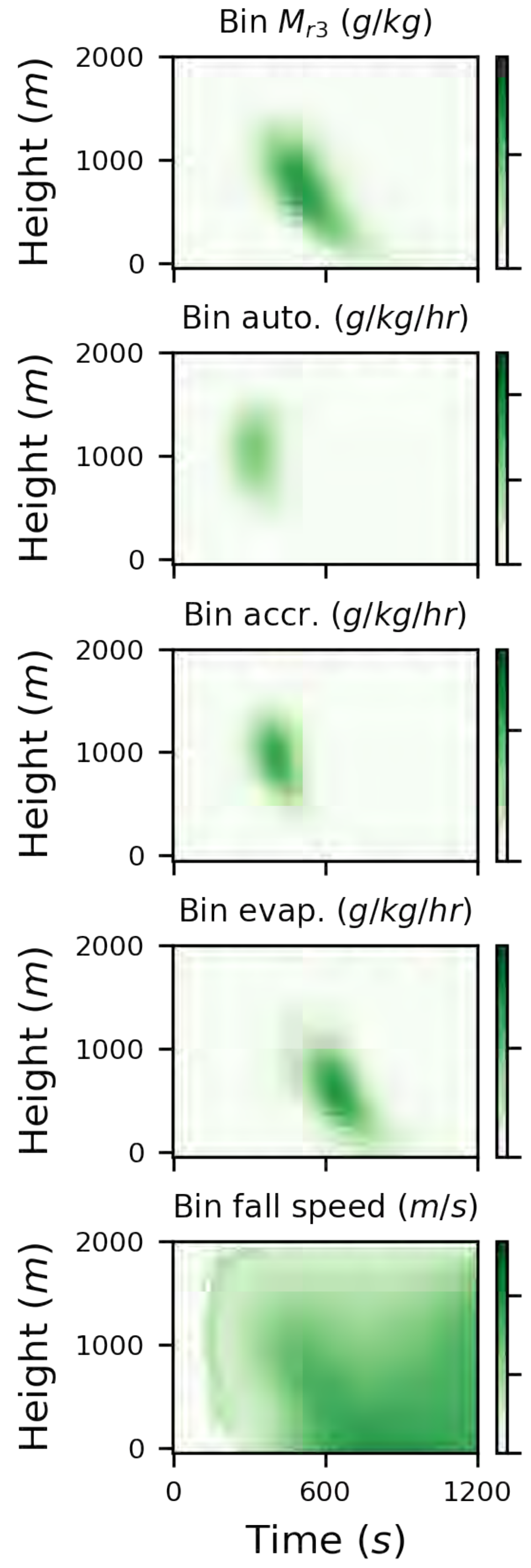

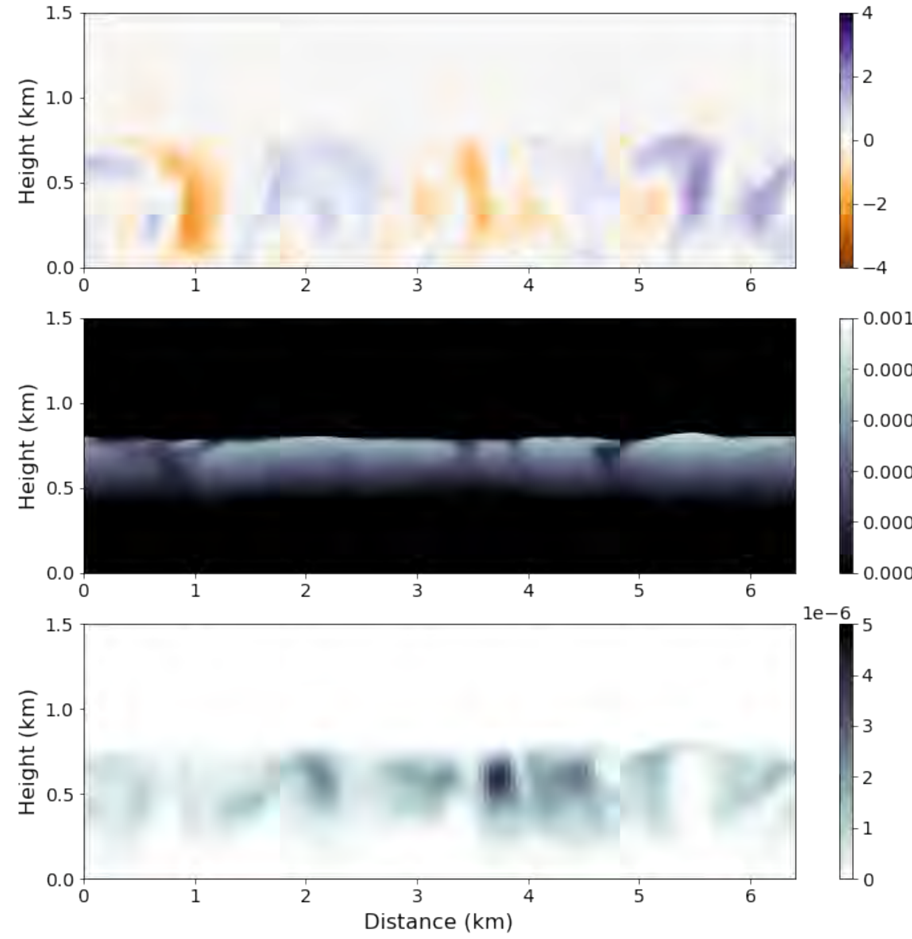

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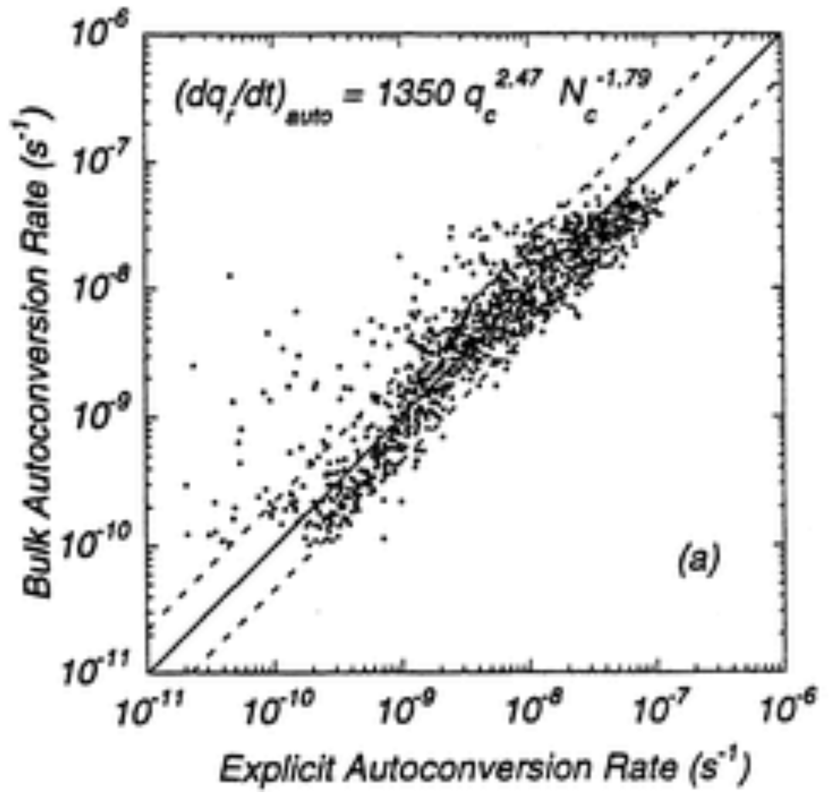

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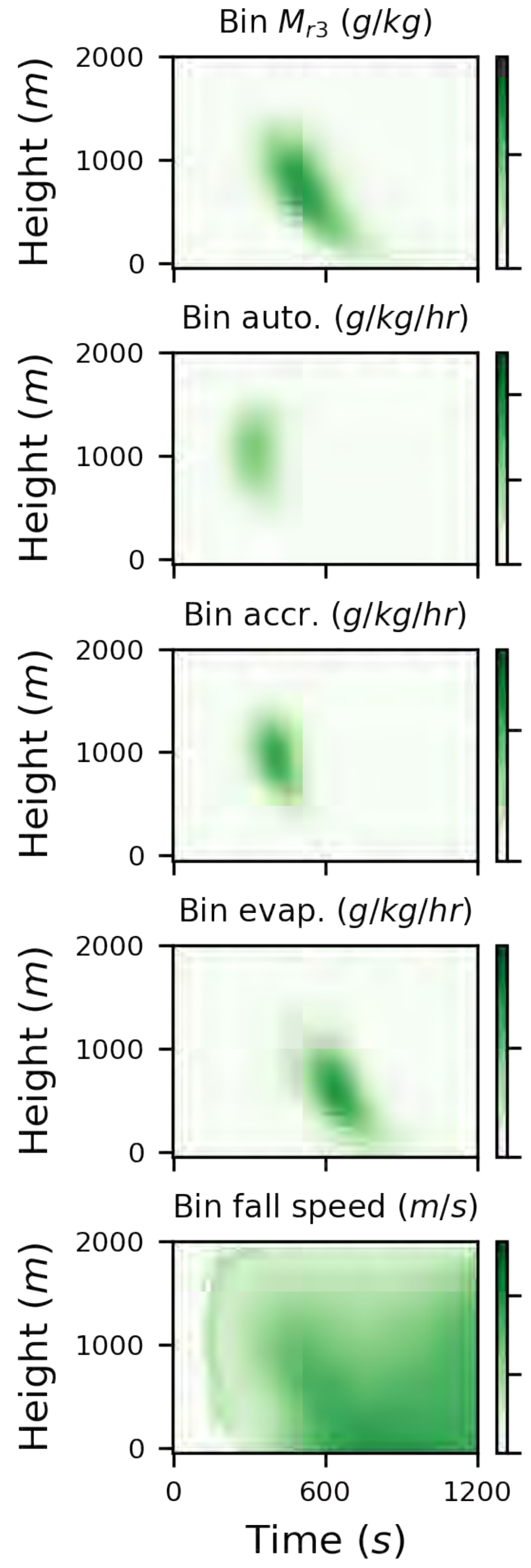

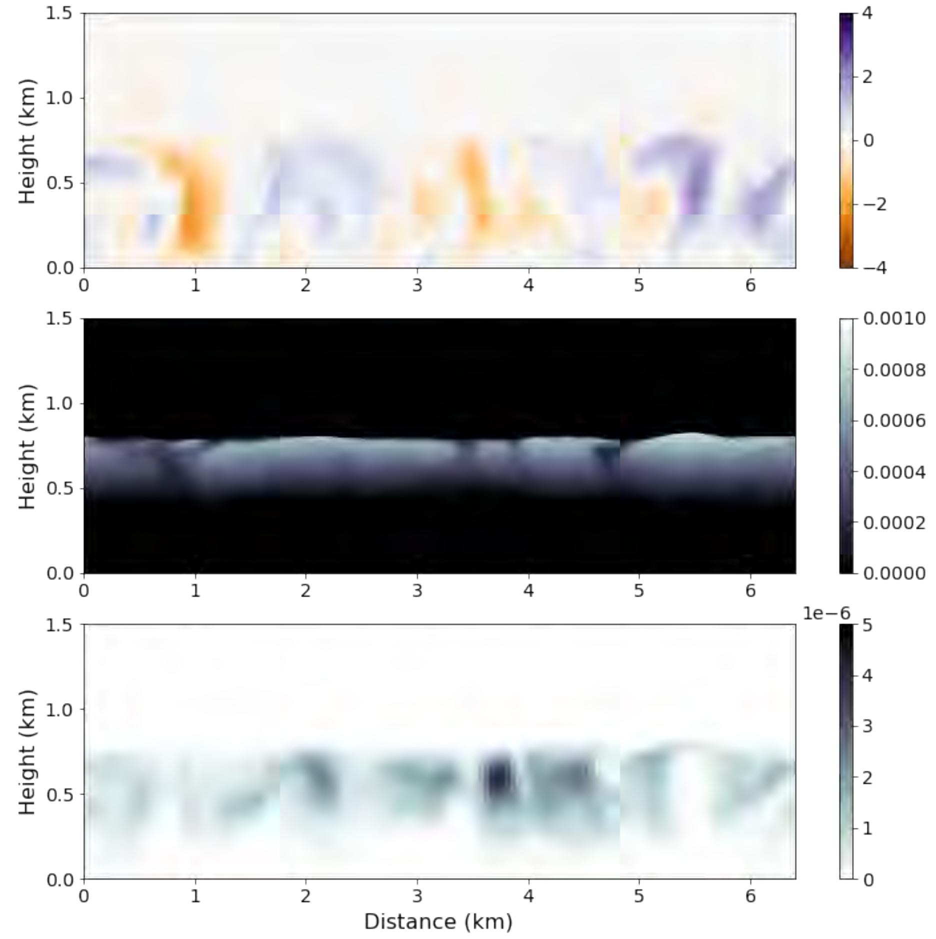

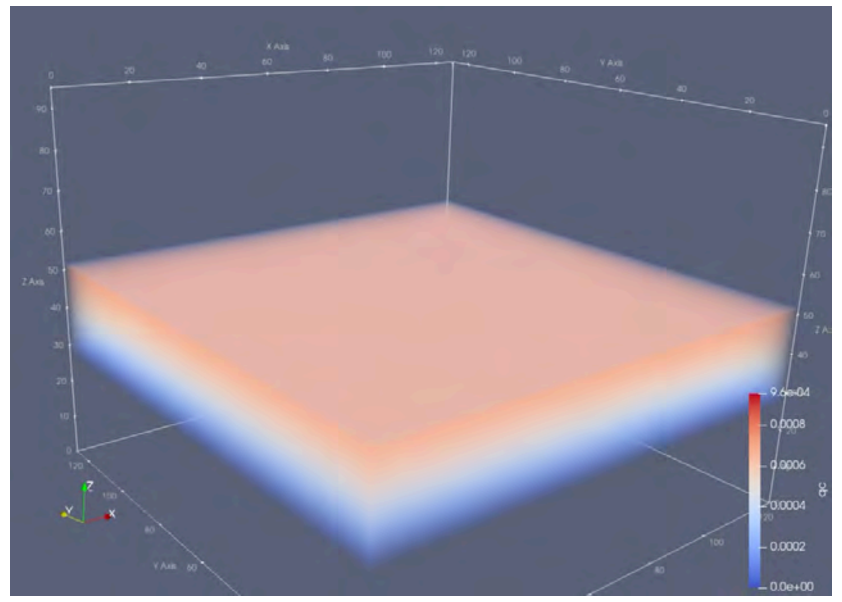

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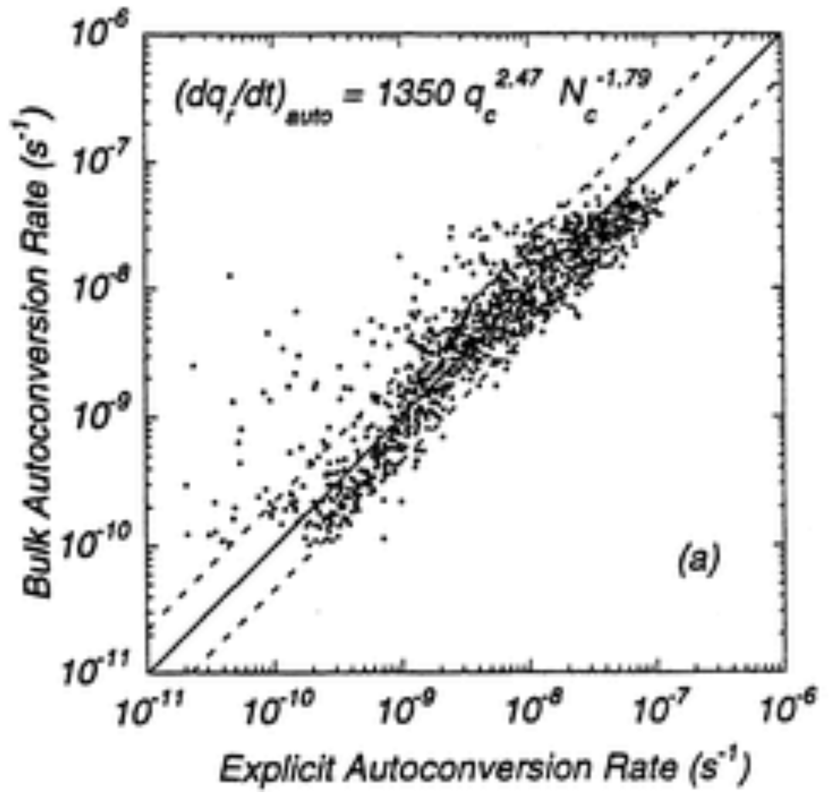

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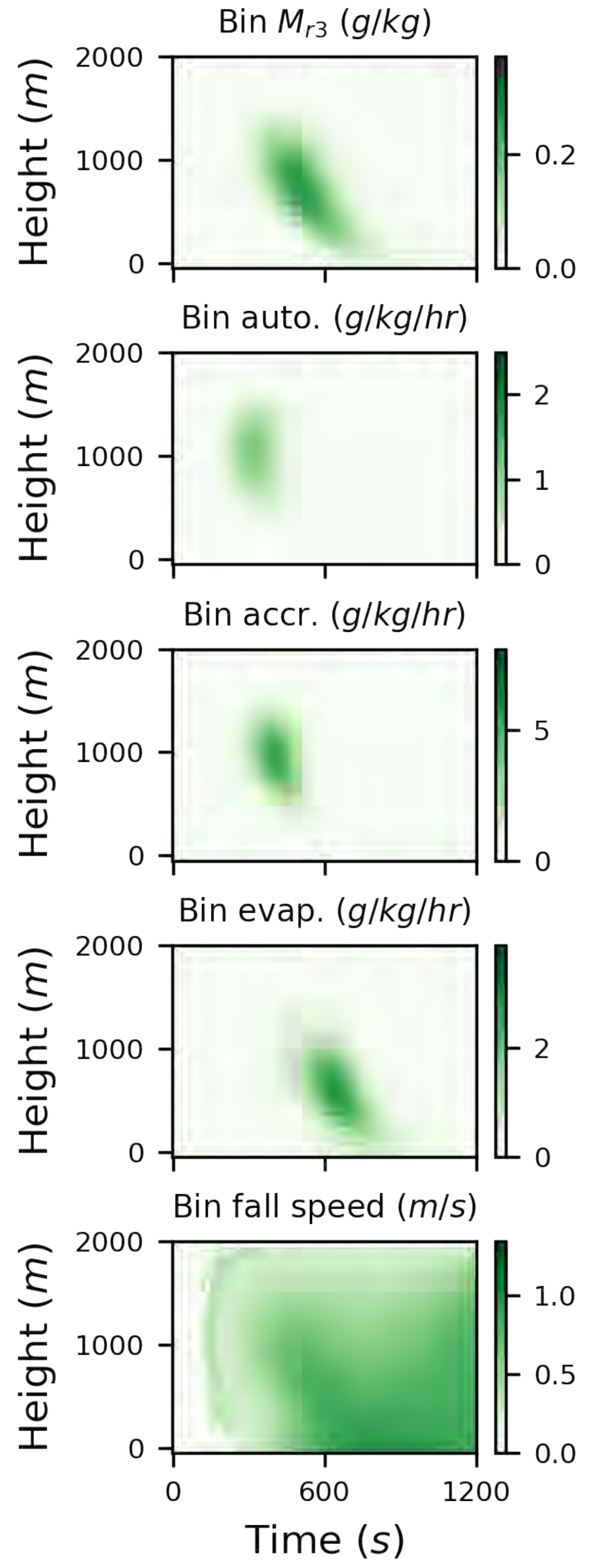

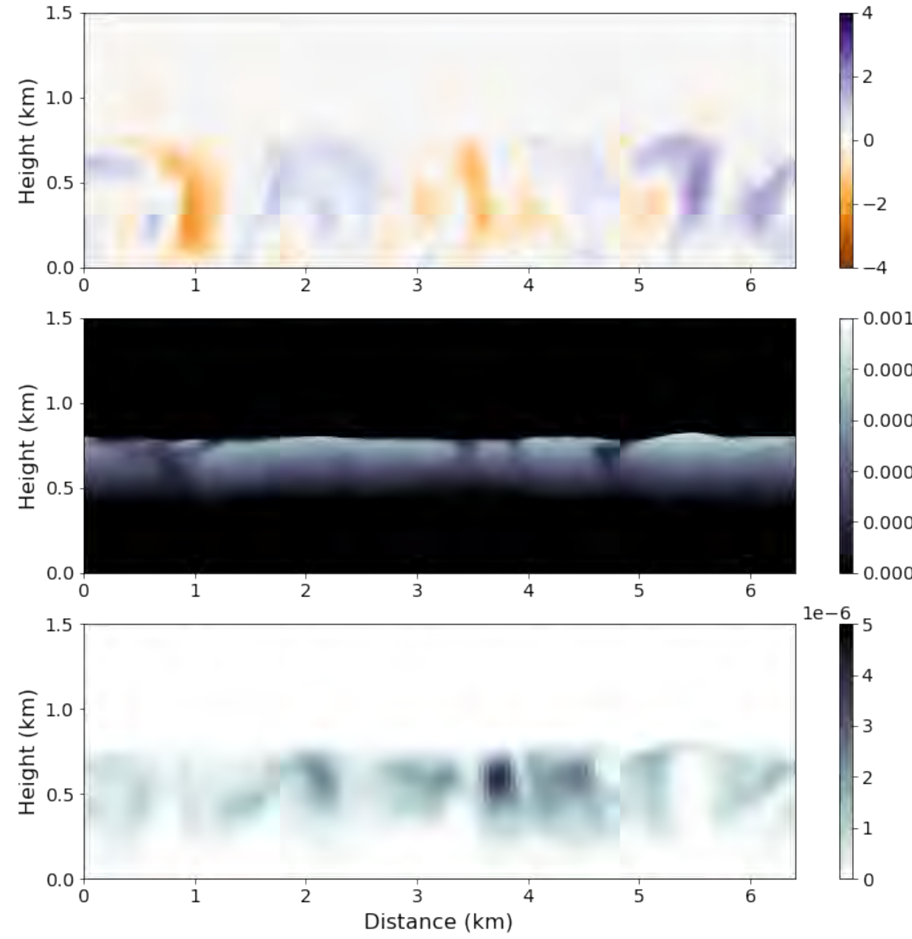

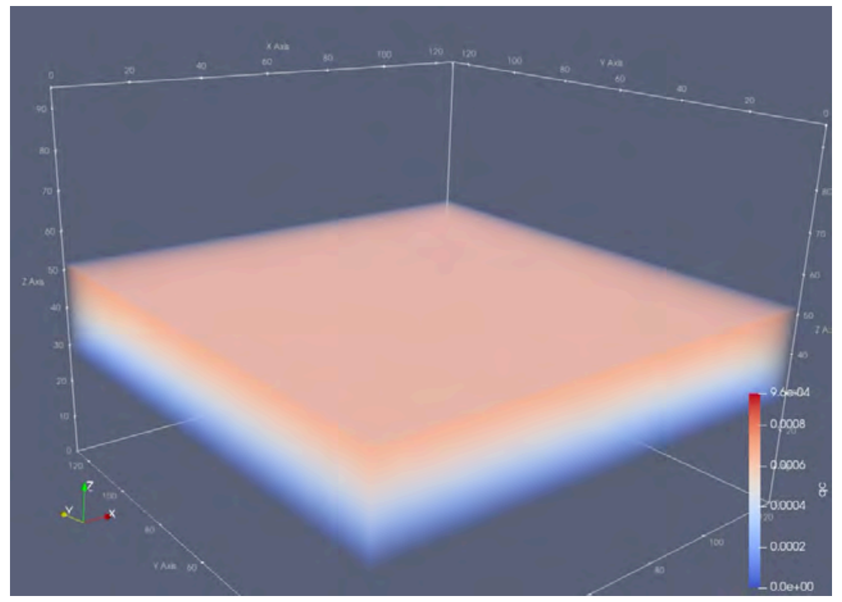

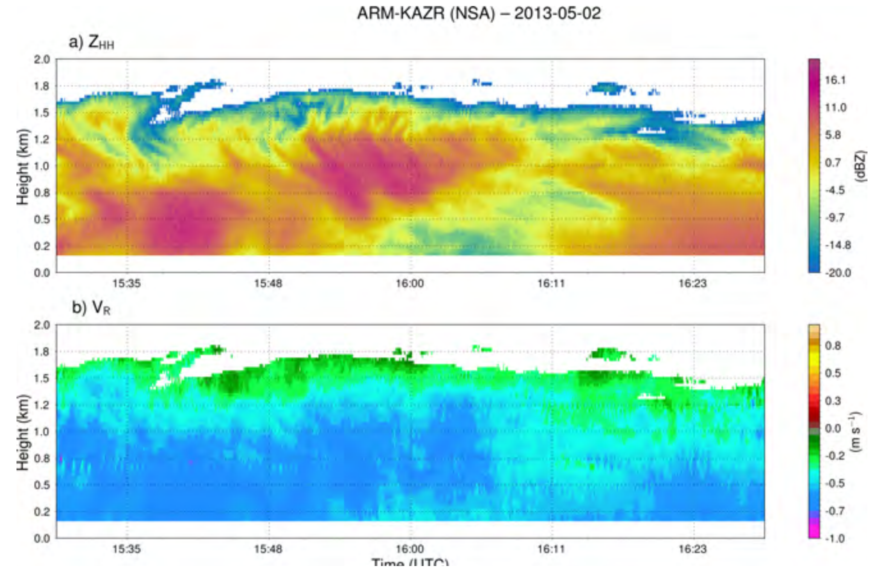

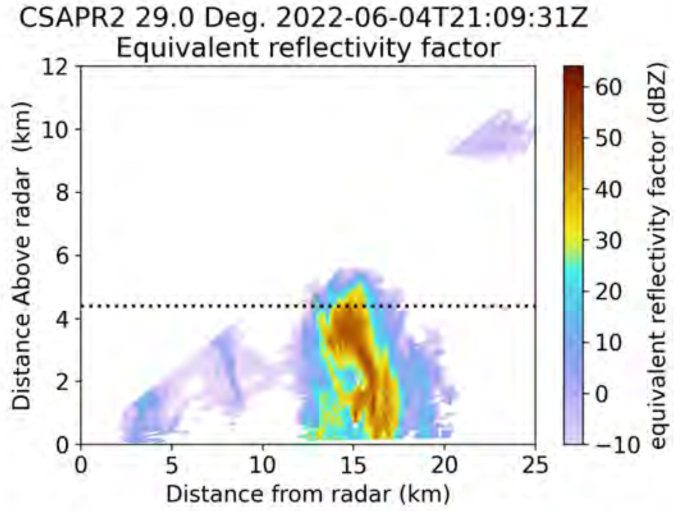

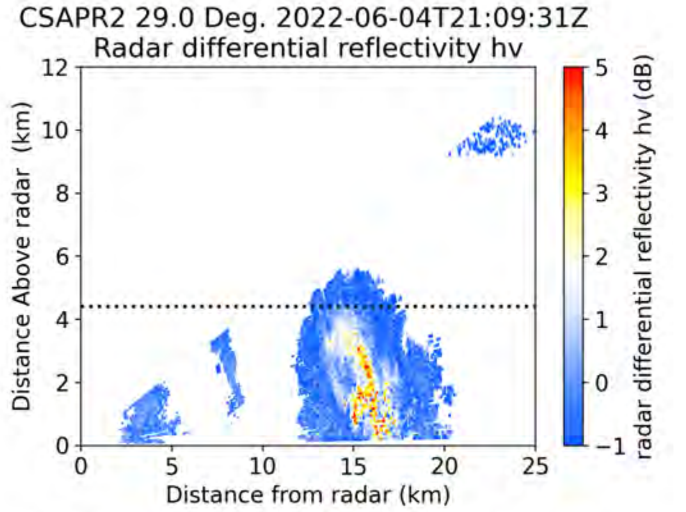

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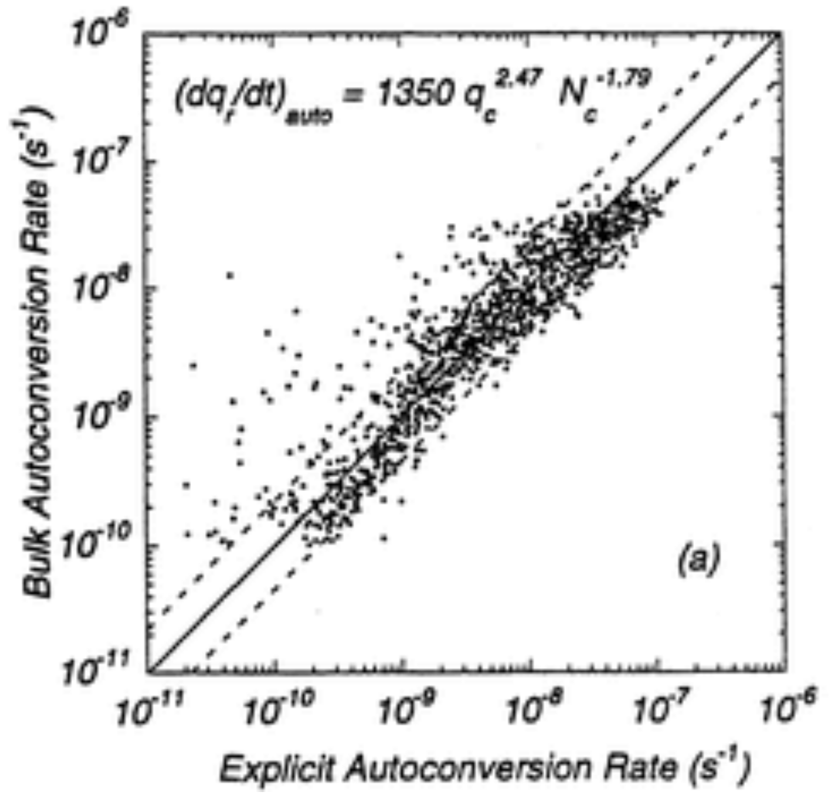

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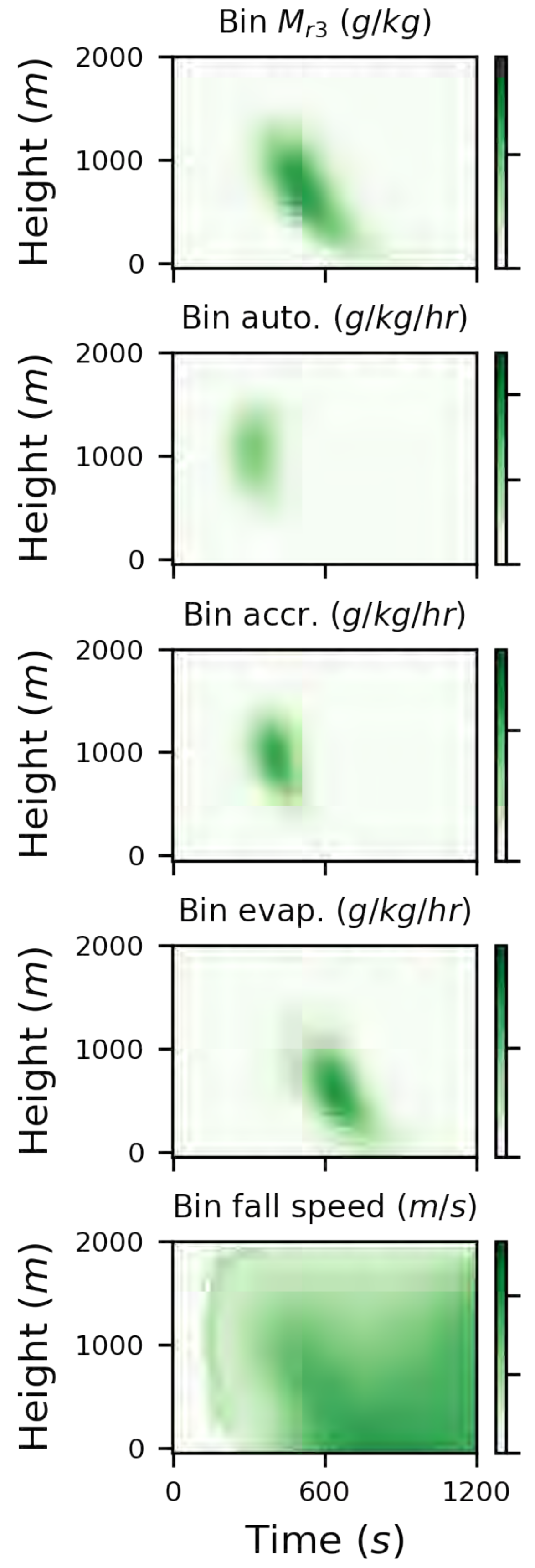
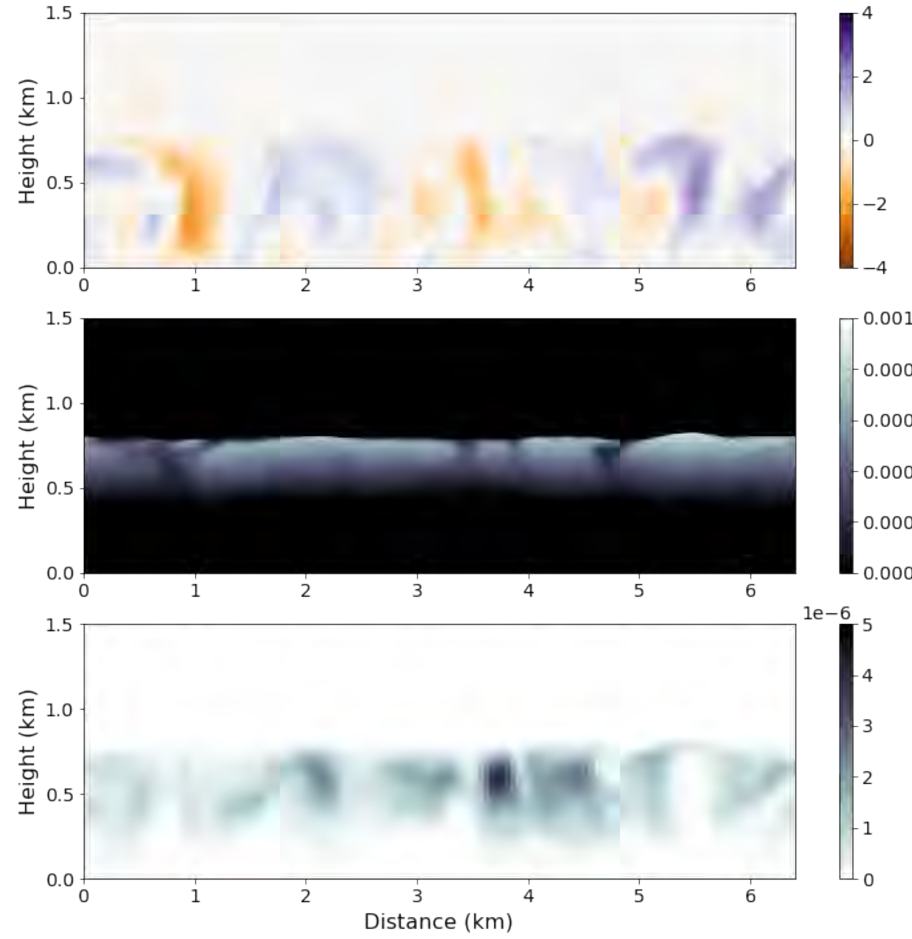
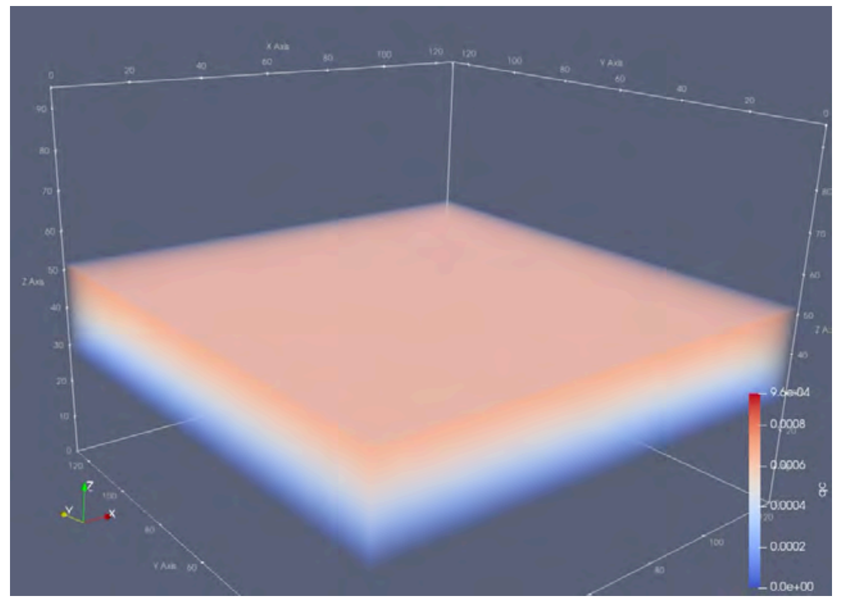
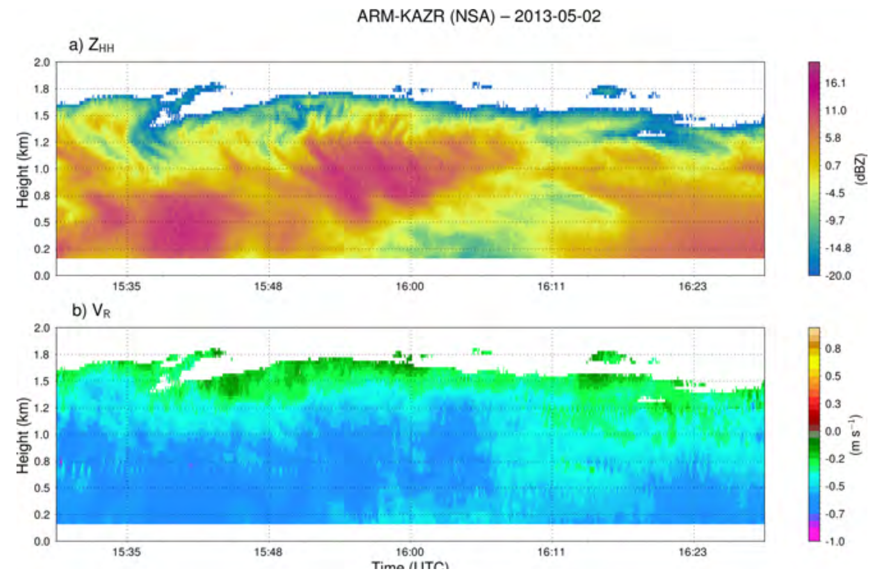
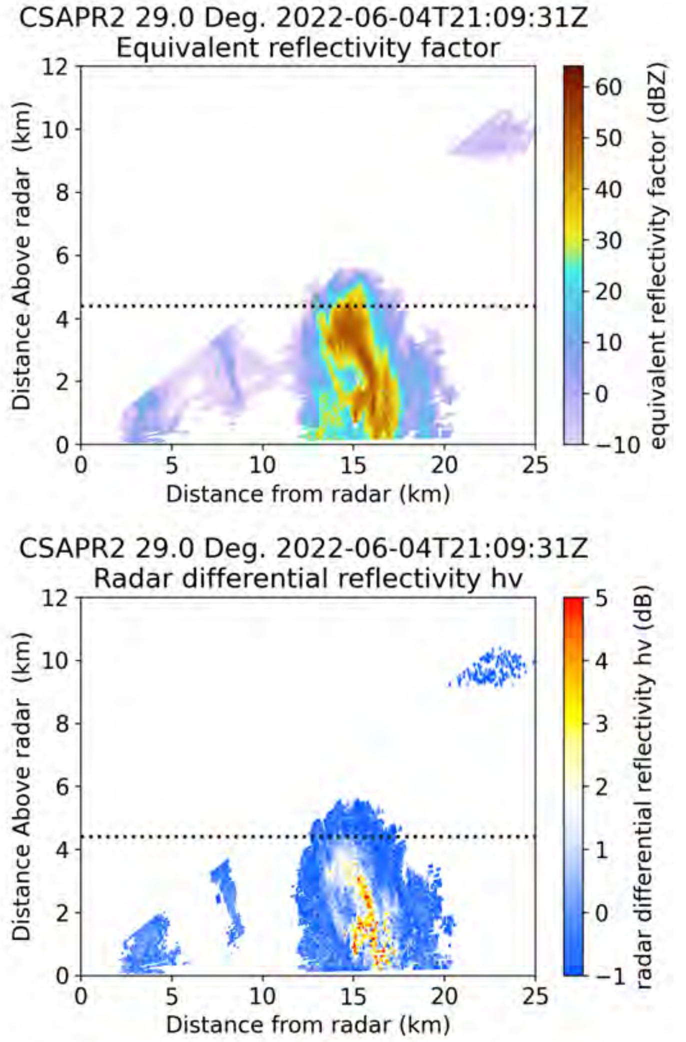


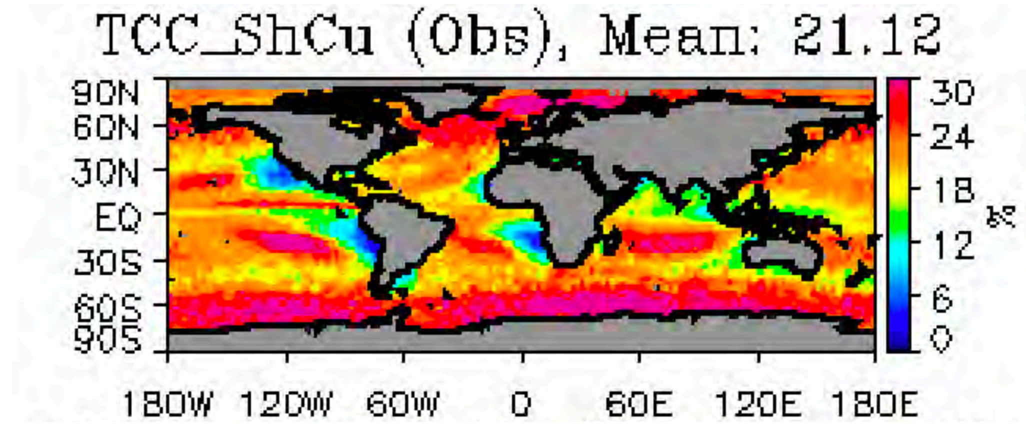




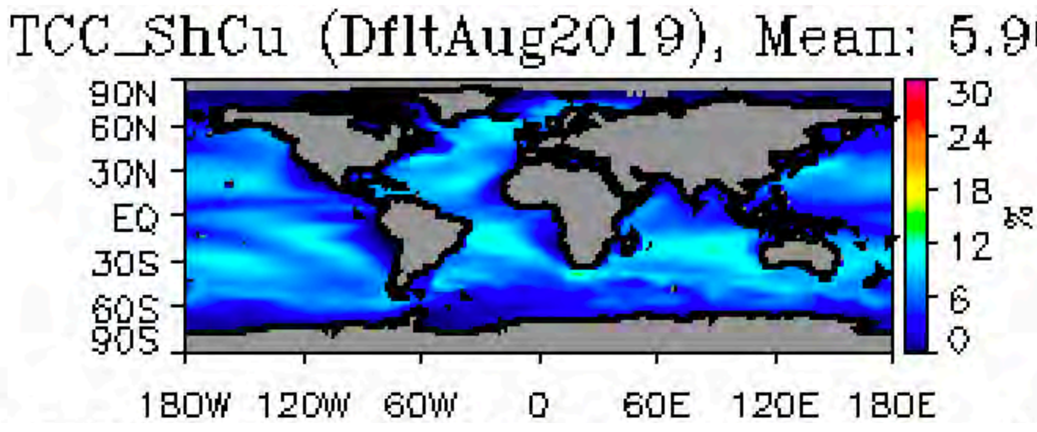




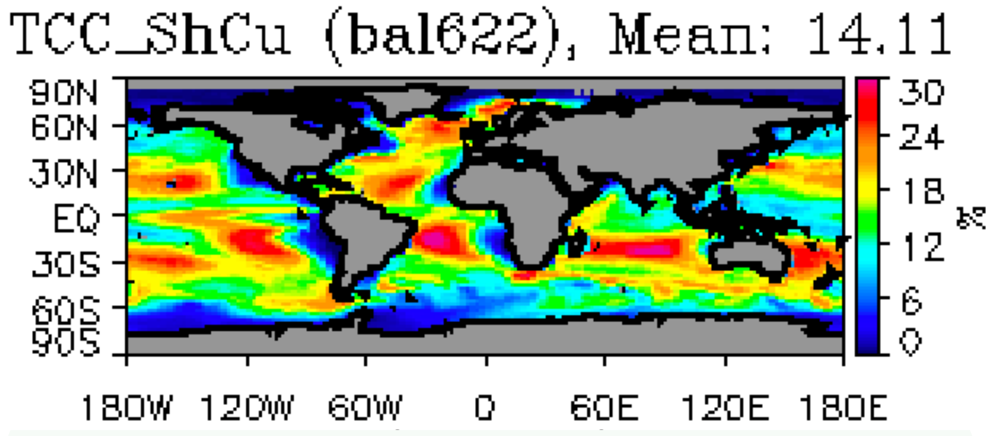
Observed Shallow Cu



Default Parameters



Tuned Parameters



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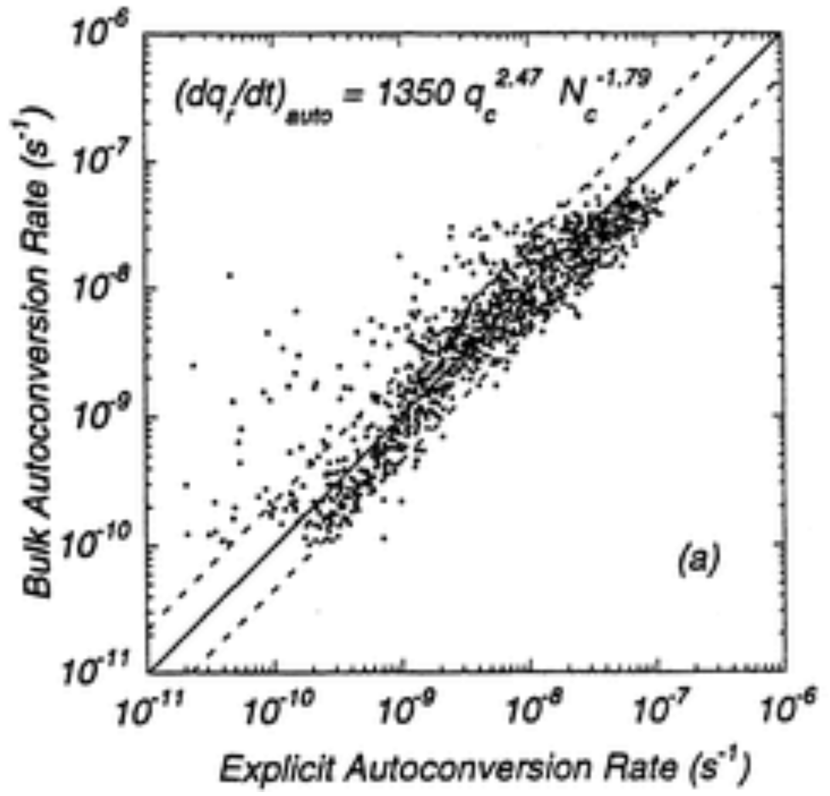

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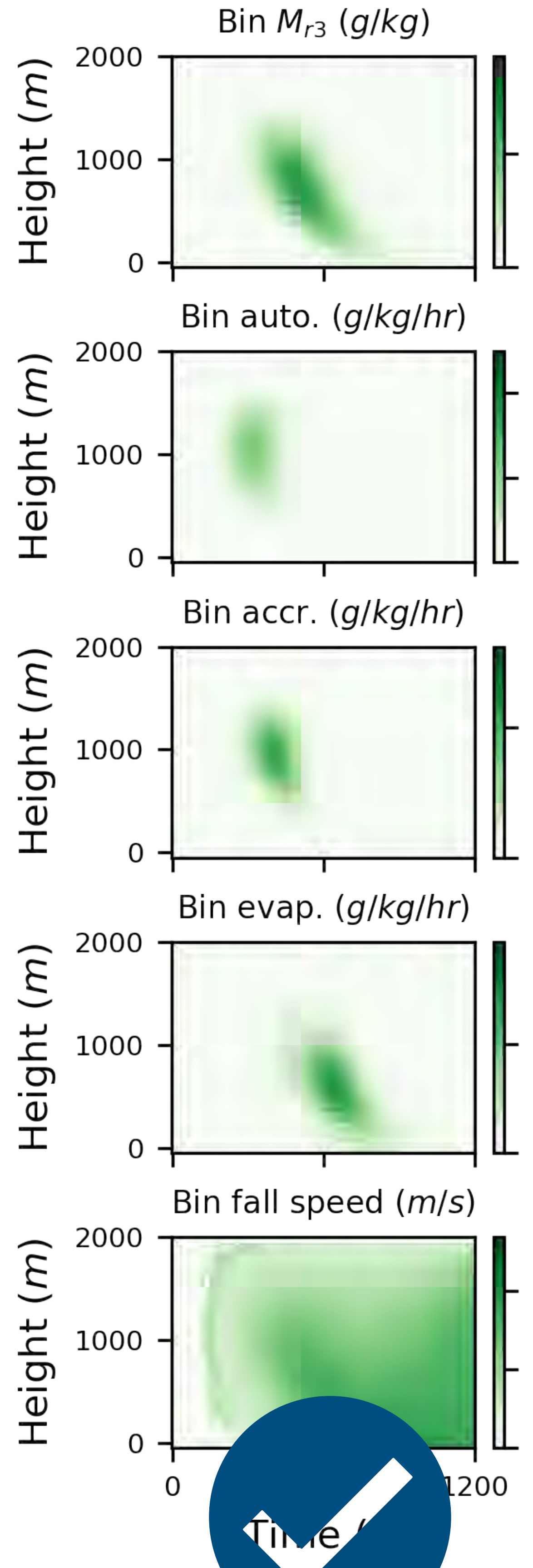
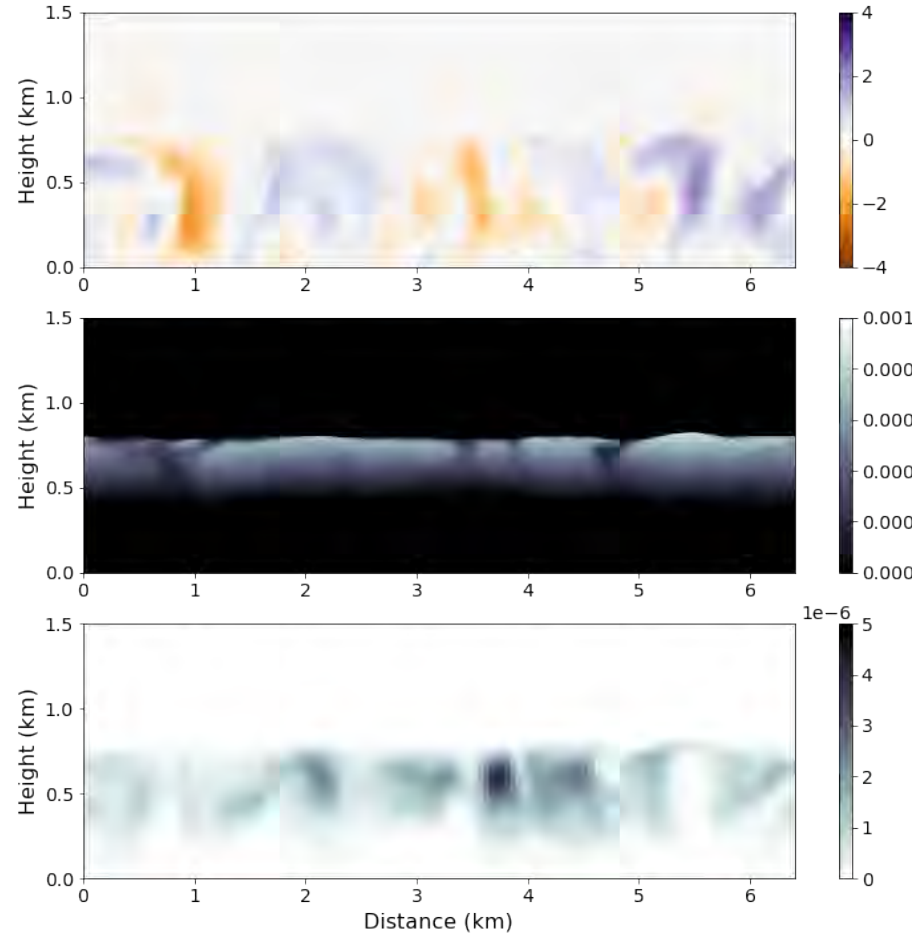
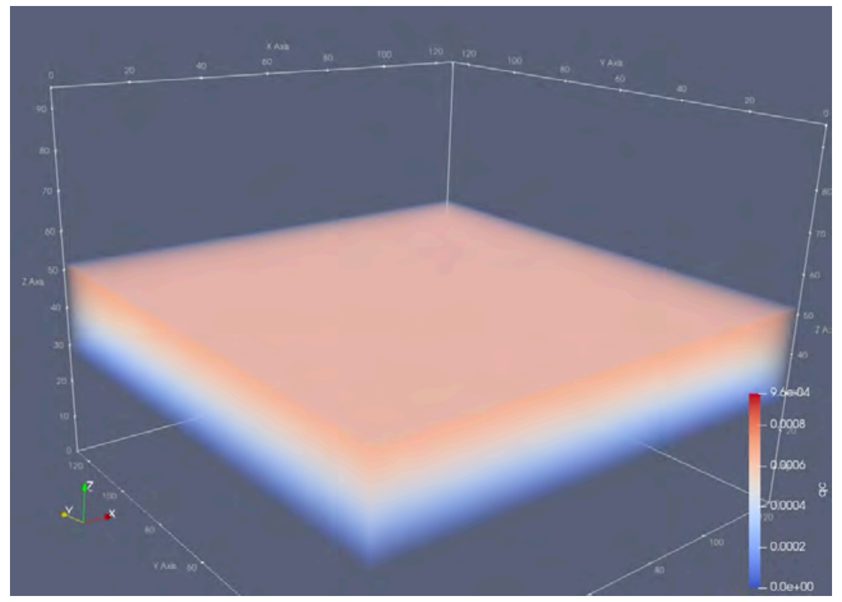
Directly fitting process rates to some "reference" scheme

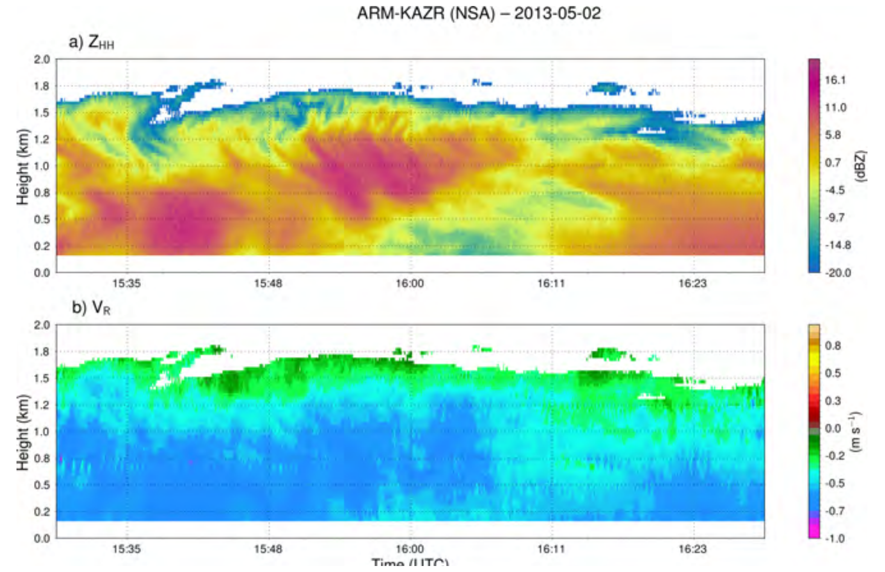


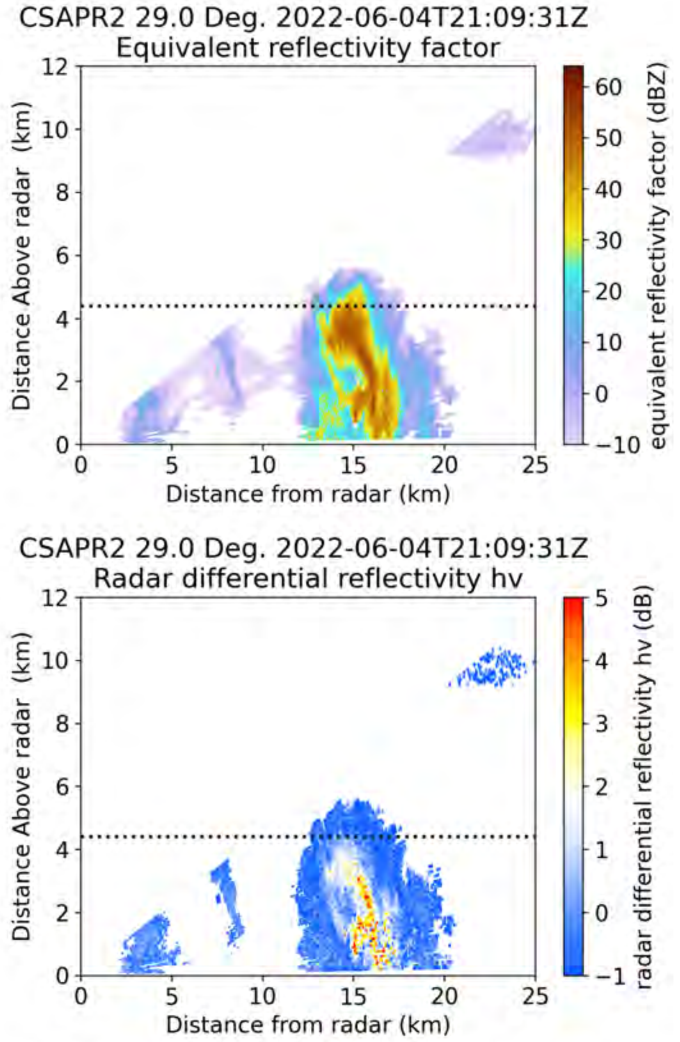
Fit using a time-evolving kinematic 1D column model w/ reference scheme





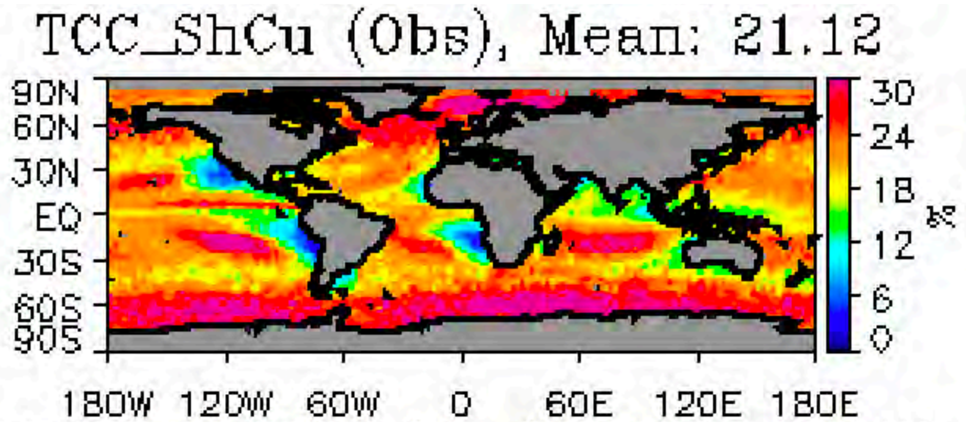
Fit using "observations" from well-studied LES test cases (e.g. DYCOMS RF02) w reference scheme



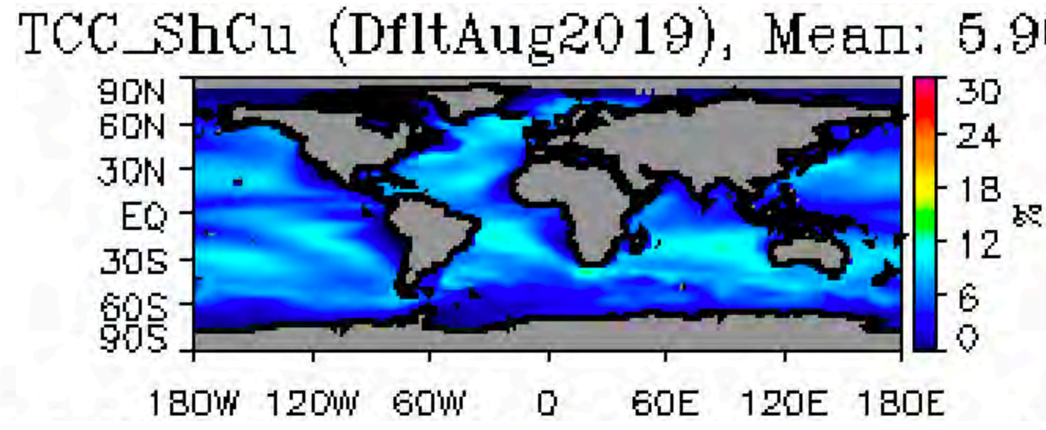


Fit using observational "weather-scale" data, e.g. from DOE ARM cloud radars & LES

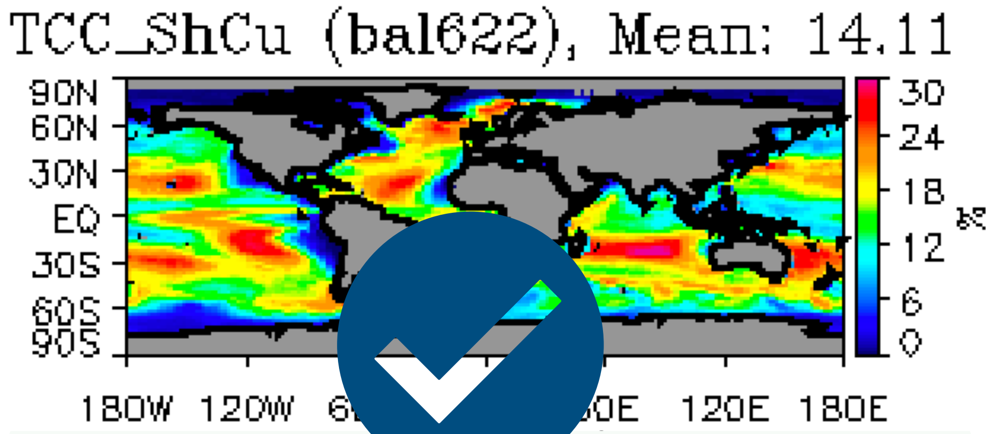
Observed Shallow Cu



Default Parameters



Tuned Parameters



Fit within GCM global simulations, satellite data using ML and perturbed parameter ensembles

Directly fitting process rates to a Bin model

Autoconversion rates: bin vs. BOSS fits

Direct process fits with BOSS

- Directly fit BOSS parameters to match existing TAU bin scheme autoconversion process rates
- Test 1-term process rate formulation vs. 2-term
- Test 2-moment cloud/rain vs. 3-moment cloud, 2-moment rain
- Test rain-dependent autoconversion term
- Observational uncertainty is treated as an unknown (using conjugate prior)

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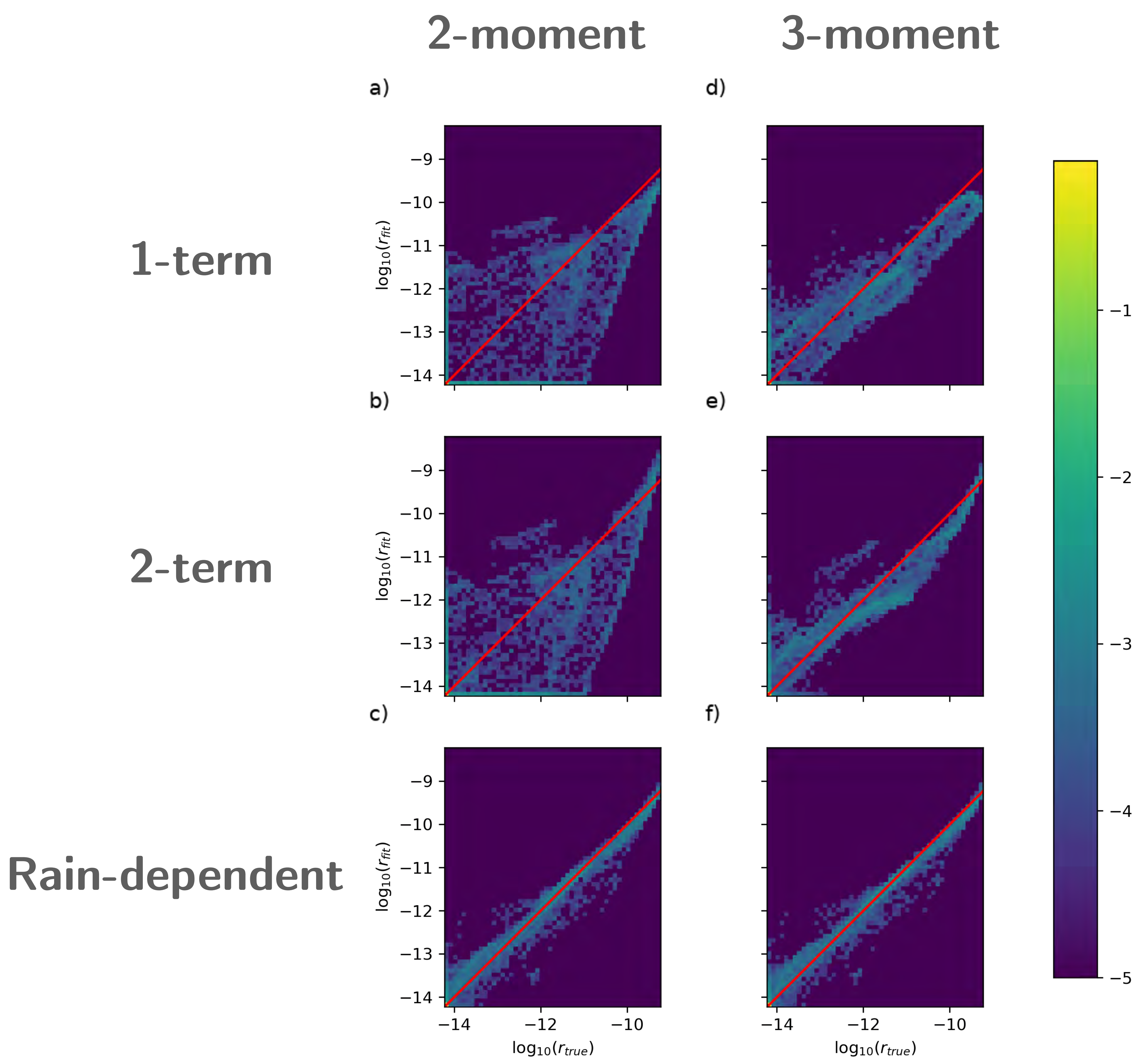
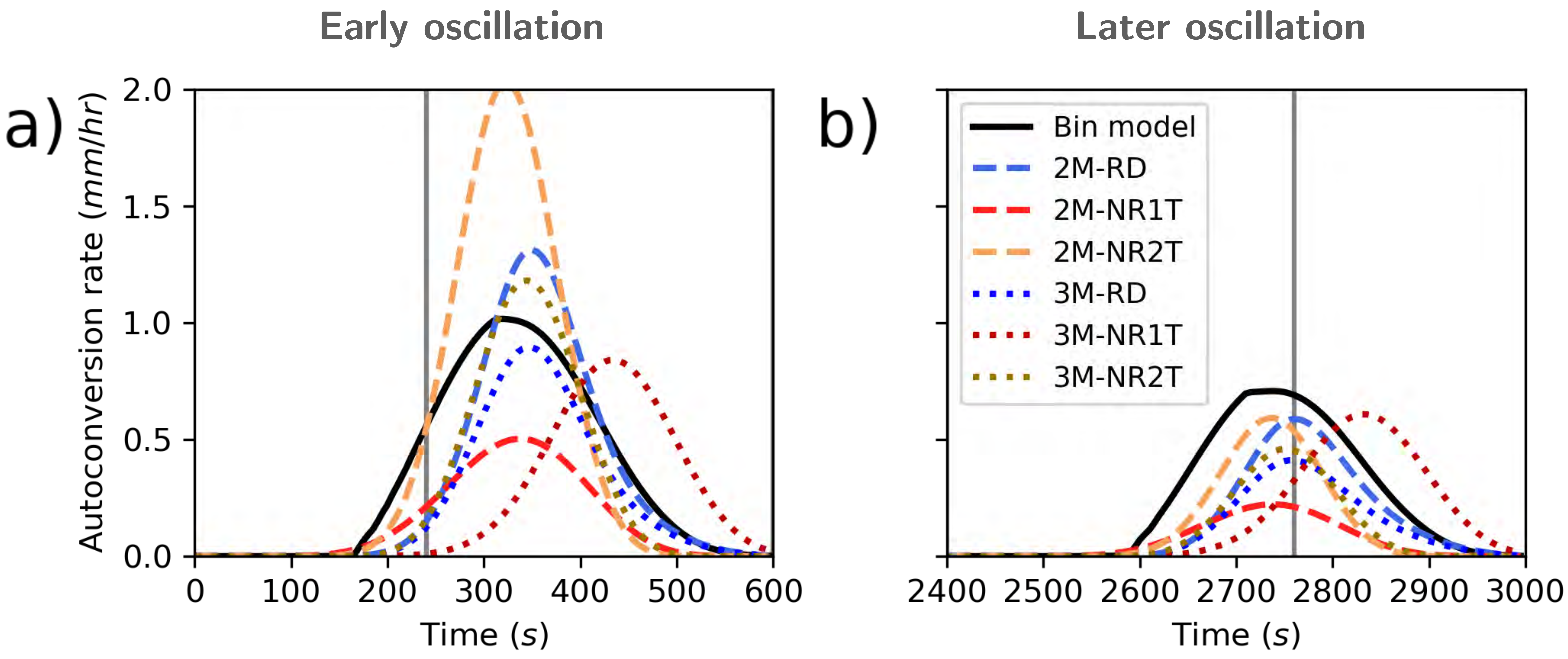


Testing direct fits in time-evolving 1D model

Looking at autoconversion rates tuned via direct fitting in 1D model simulations



Testing direct fits in 1D model (2M vs 3M)

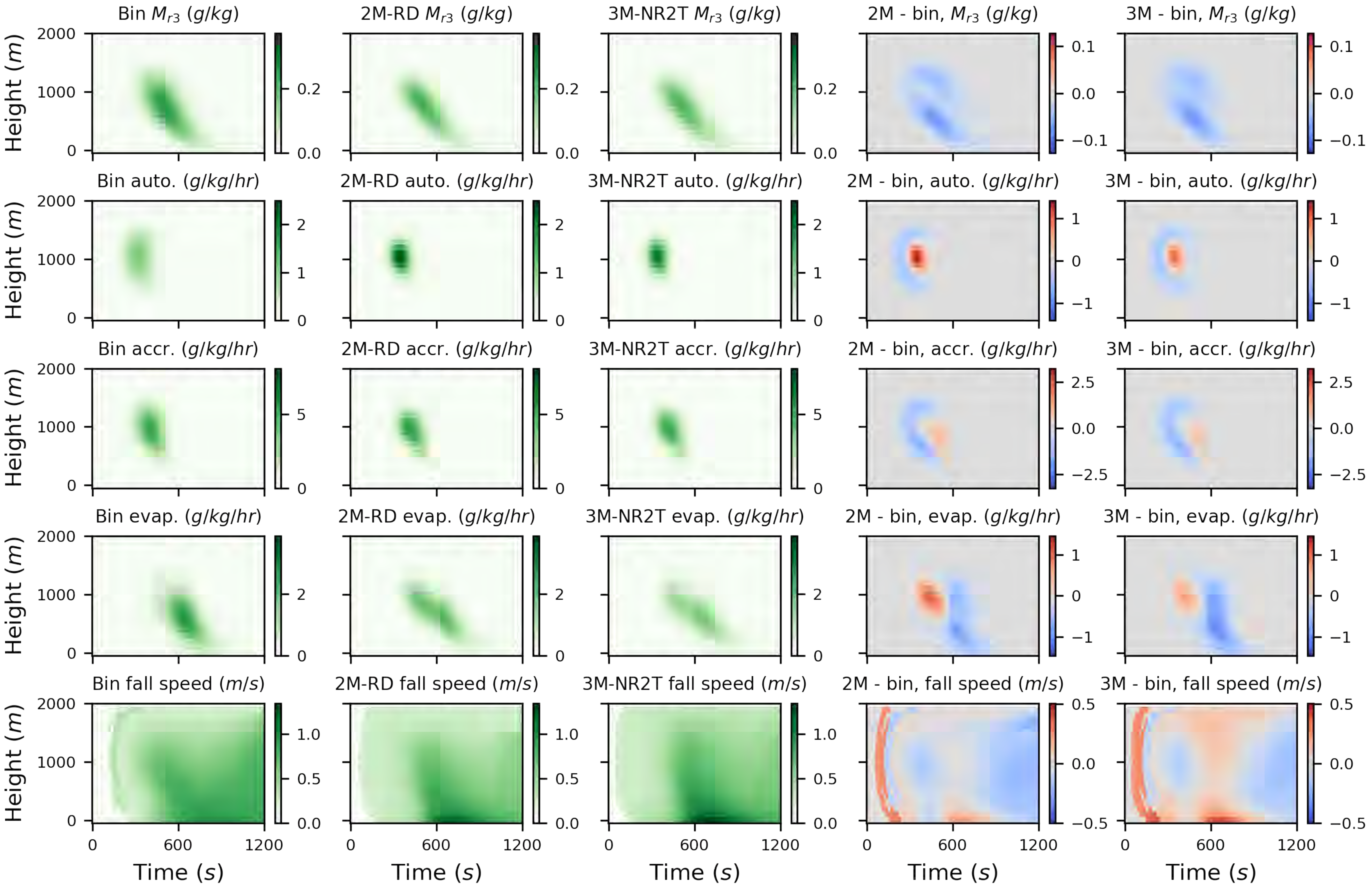
Rain M3

Autoconversion

Accretion

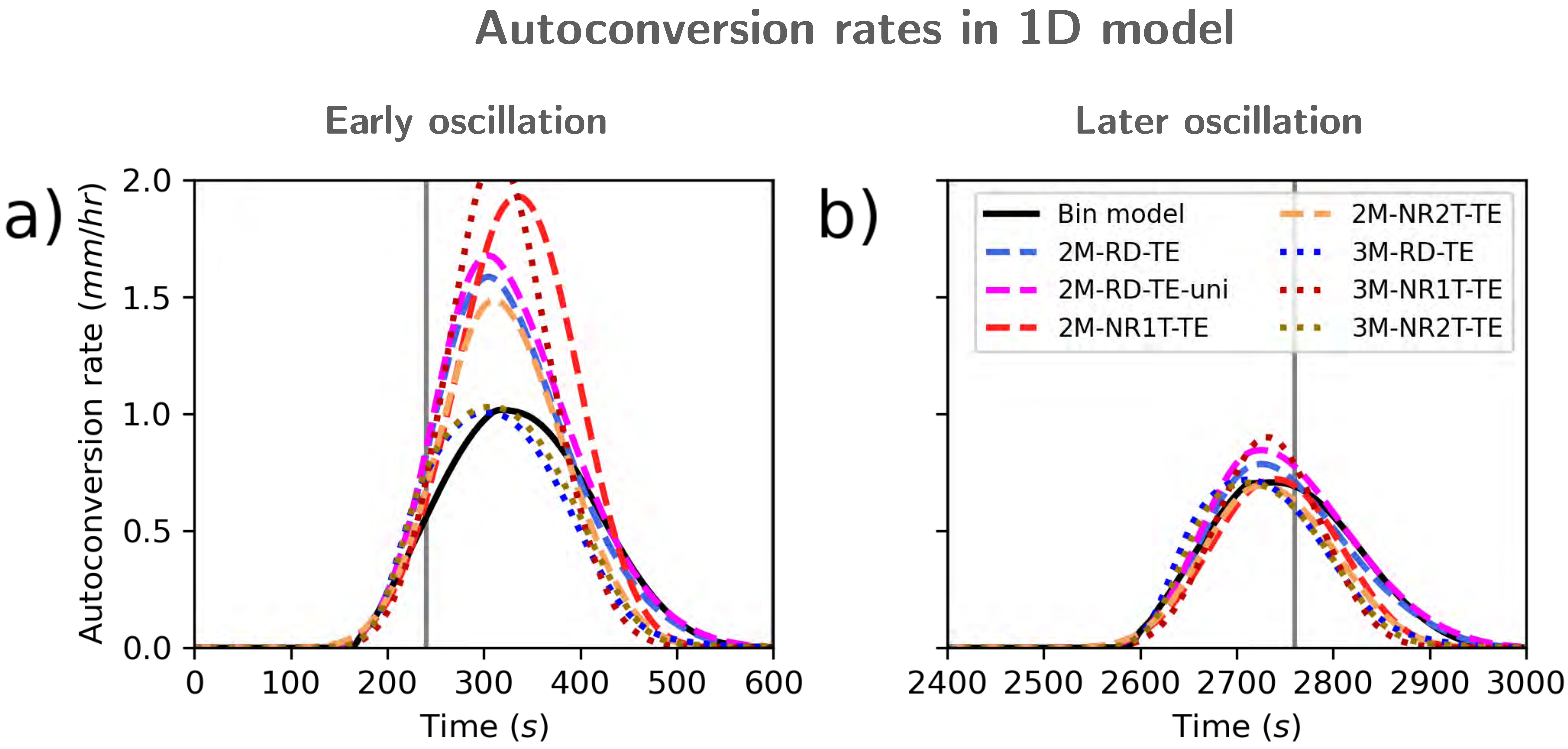
Evaporation

Fall speed

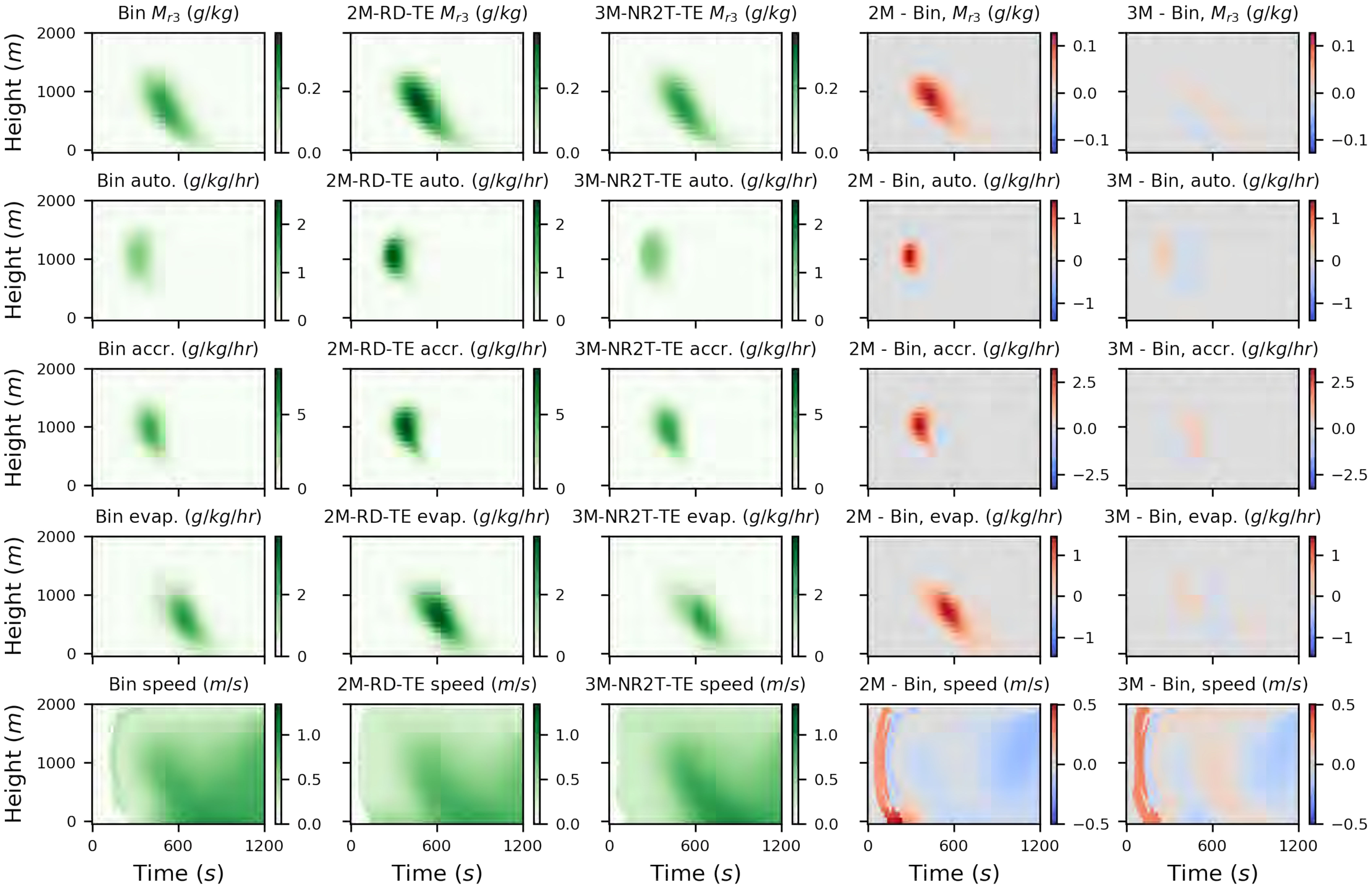


Instead use direct fits as a (Bayesian) prior

Refine the prior with a likelihood using observations from *time-evolving sim'n



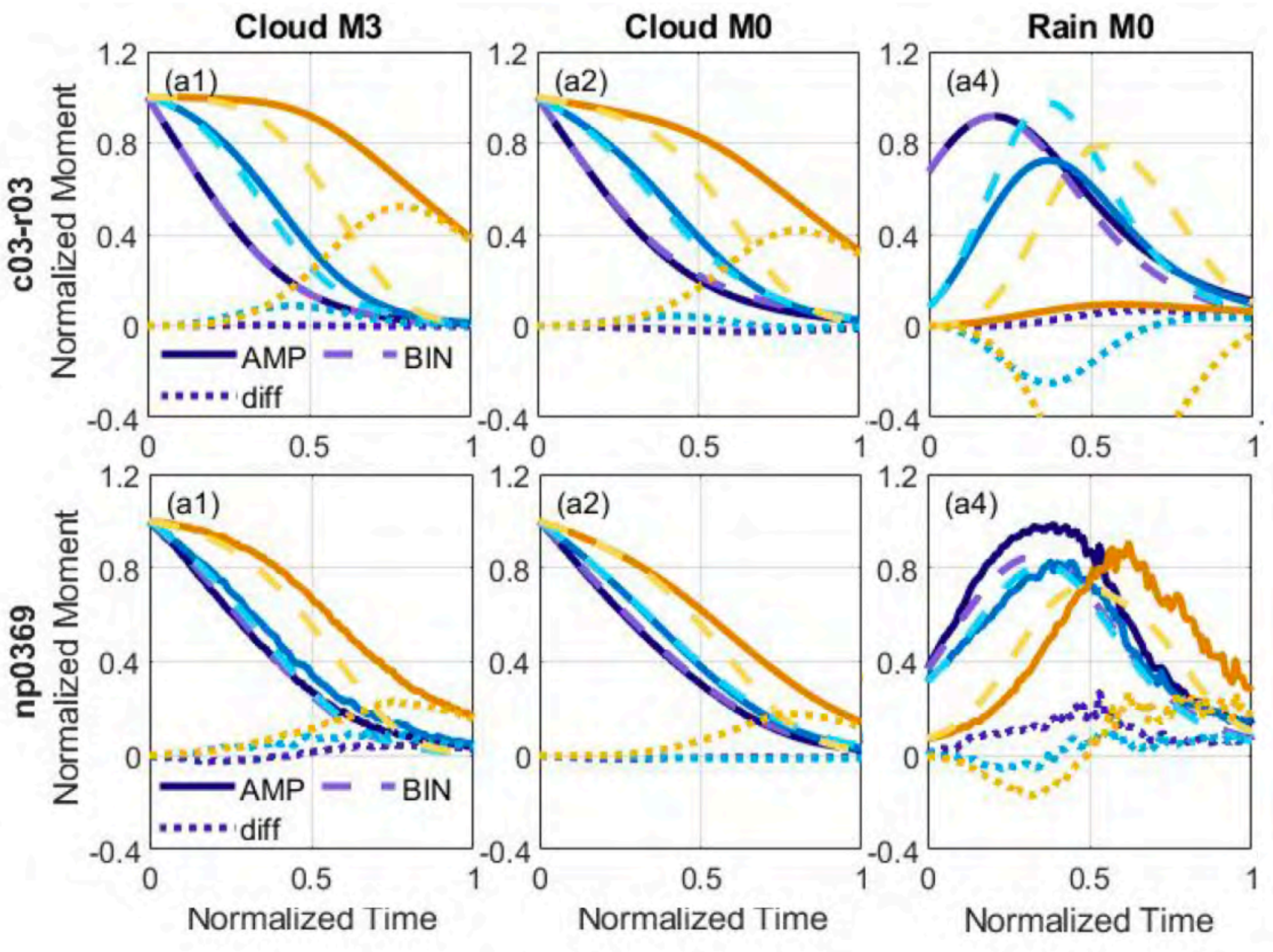
Testing direct/1D fits in 1D model (2M vs 3M)



Structural choices must be evaluated in the context of adequate parameter constraint!

A larger structural error?

Are separate cloud and rain categories the correct approach for bulk warm microphysics?



Adele L. Igel, H. Morrison, S. P. Santos, and M. van Lier-Walqui. *Limitations of separate cloud and rain categories in parameterizing collision- coalescence for bulk microphysics schemes.* JAMES, 2022.

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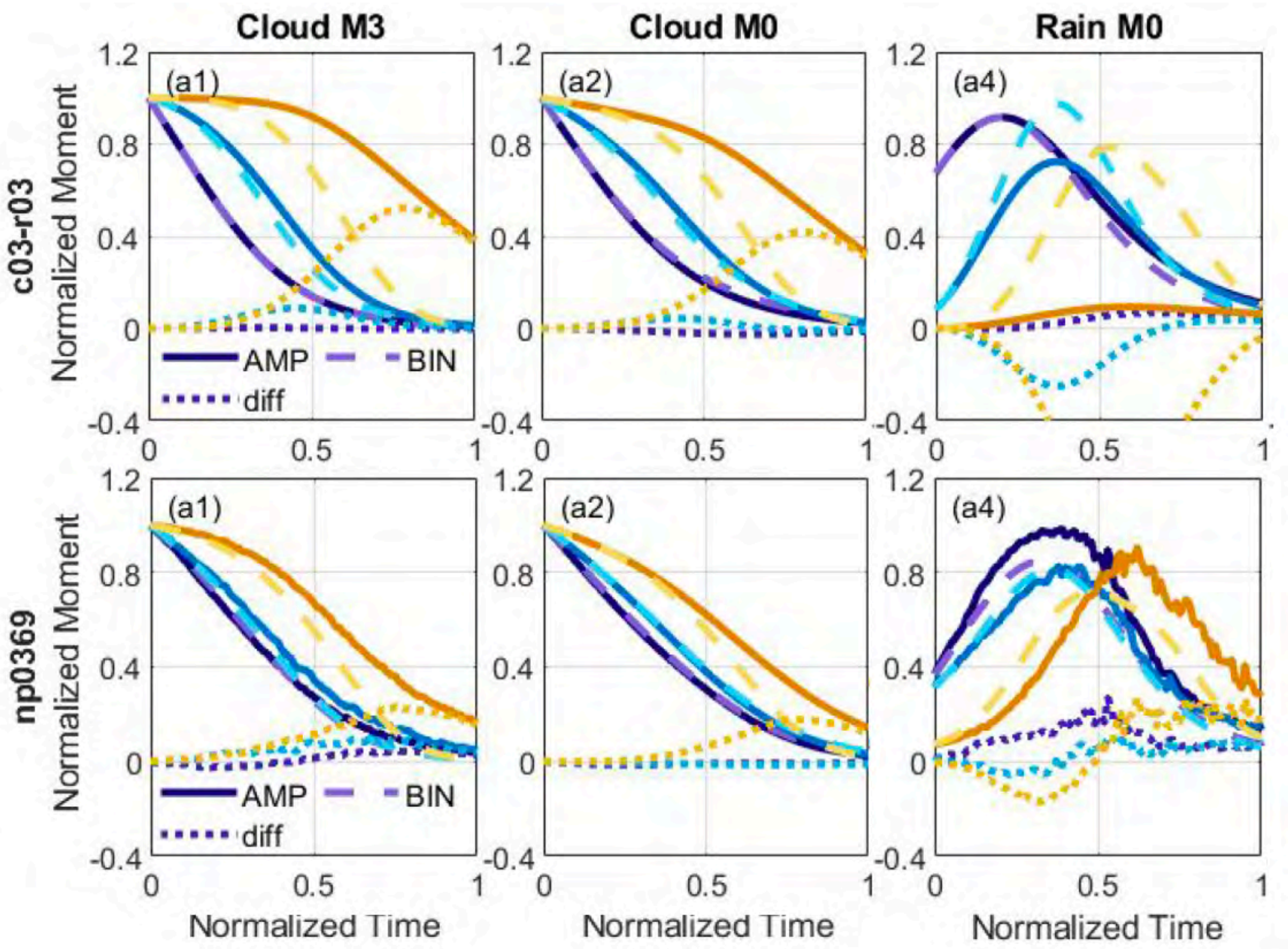

Adele L. Igel, H. Morrison, S. P. Santos, and M. van Lier-Walqui. *Limitations of separate cloud and rain categories in parameterizing collision- coalescence for bulk microphysics schemes*. JAMES, 2022.

This is something we are currently testing with BOSS!

Bin model ->

BOSS single-category 4M—>