A flexible Bayesian approach for parameterization of warm microphysics

Kaitlyn Loftus (Columbia / LEAP NSF STC)

Marcus van-Lier Walqui (Columbia / NASA GISS)

Hugh Morrison, Kamal Kant Chandrakar, Trude Eidhammer (NSF NCAR)

Sean Santos, Po-Lun Ma (PNNL)

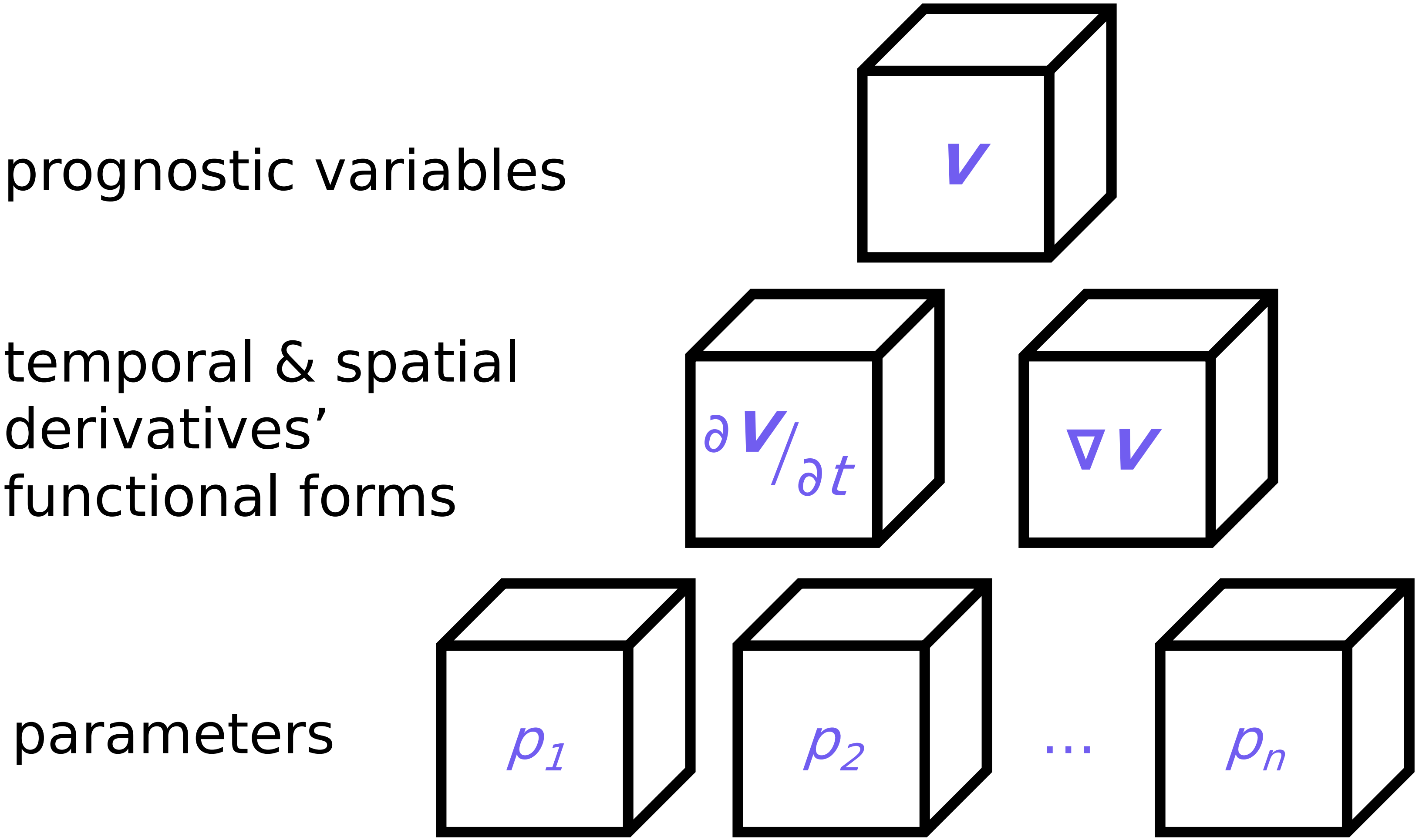
BOSS is a framework to flexibly configure micro-physics parameterizations via Bayesian inference.

Morrison et al. (2020a), van Lier-Walqui et al. (2020; in prep), Santos et al. (in prep)

Bayesian
Observationally constrained
Statistical–physical
Scheme

logo: Matthew Kumjian / Marcus van Lier-Walqui

BOSS approach to building a parameterization.

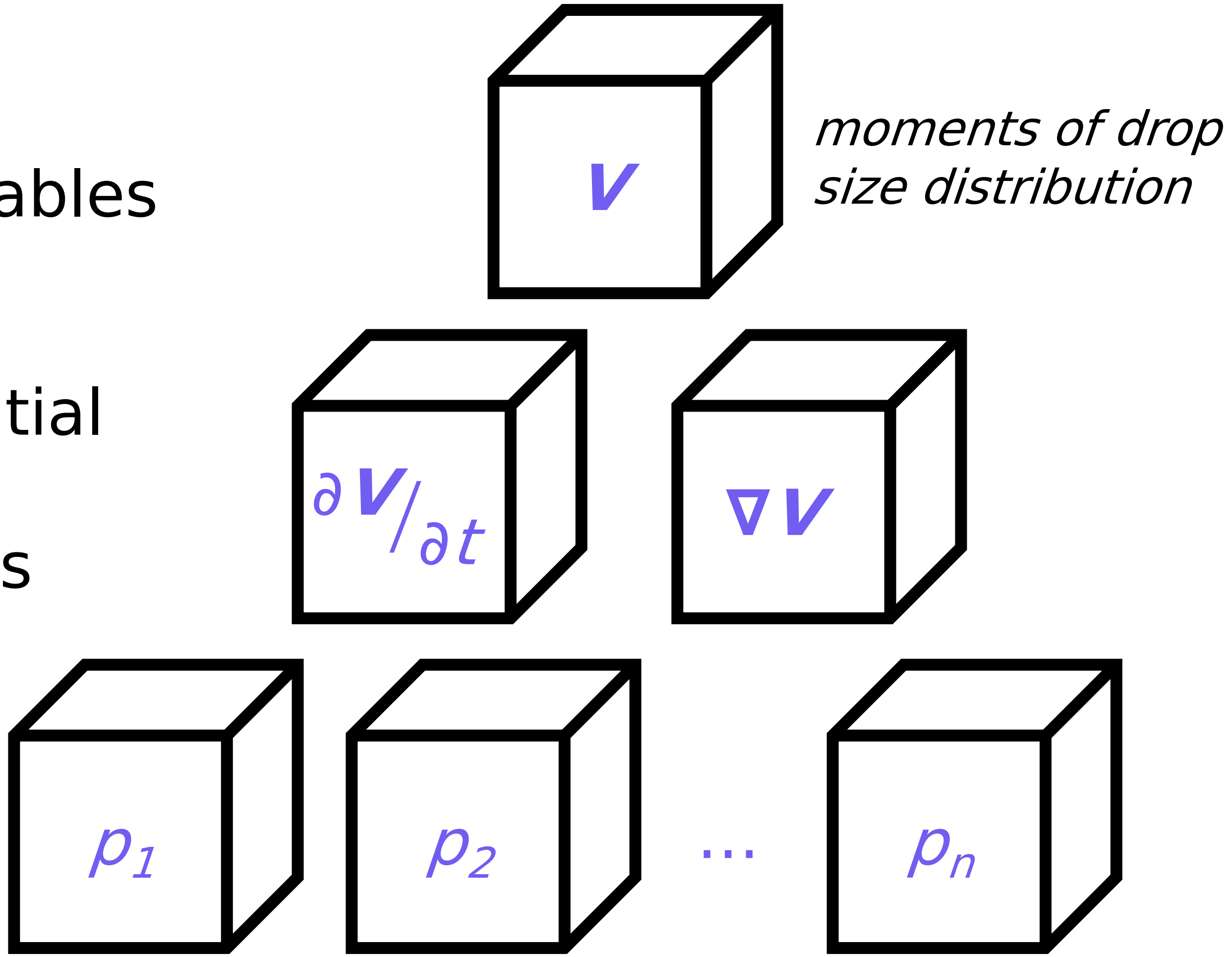


BOSS approach to building a parameterization.

prognostic variables

temporal & spatial derivatives’ functional forms

parameters



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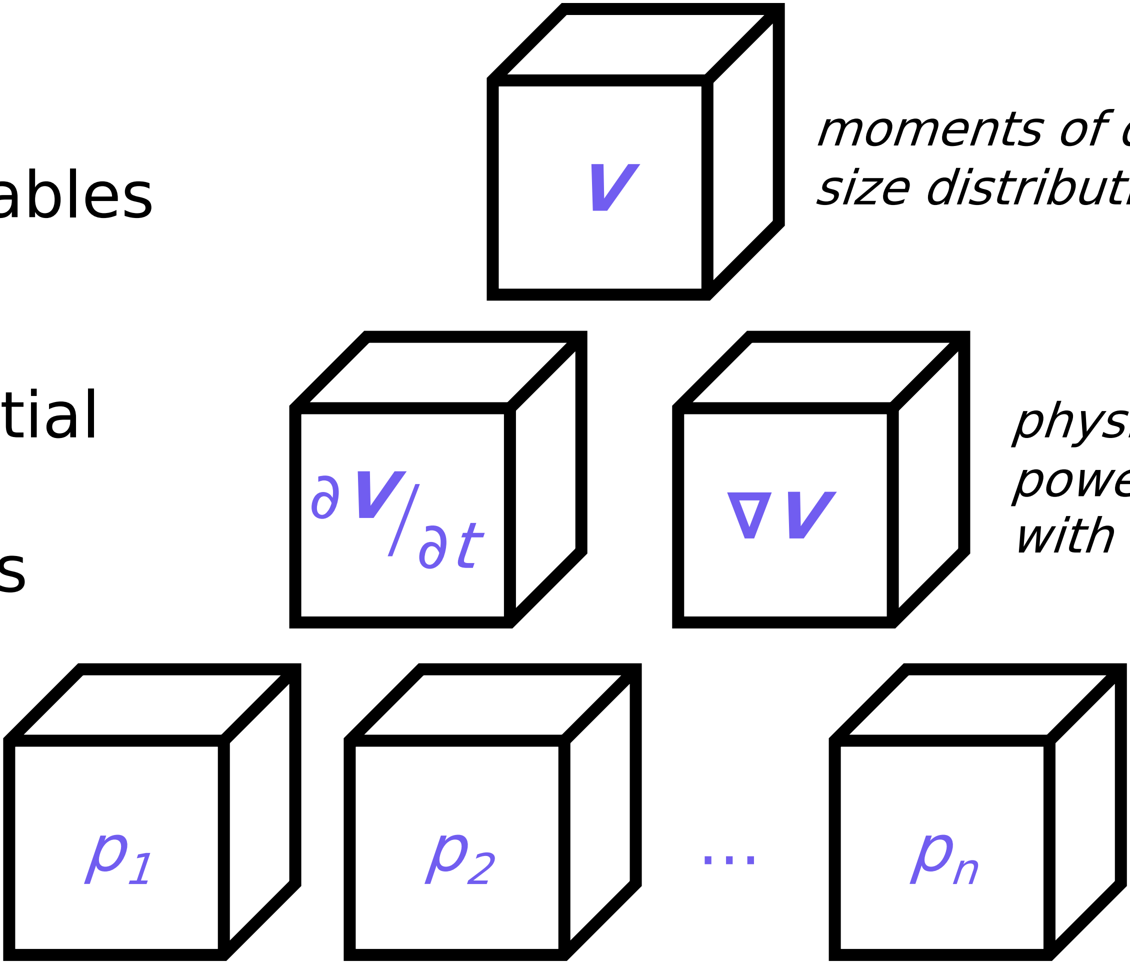


moments of drop size distribution

physics-informed power series process rates with adjustable complexity

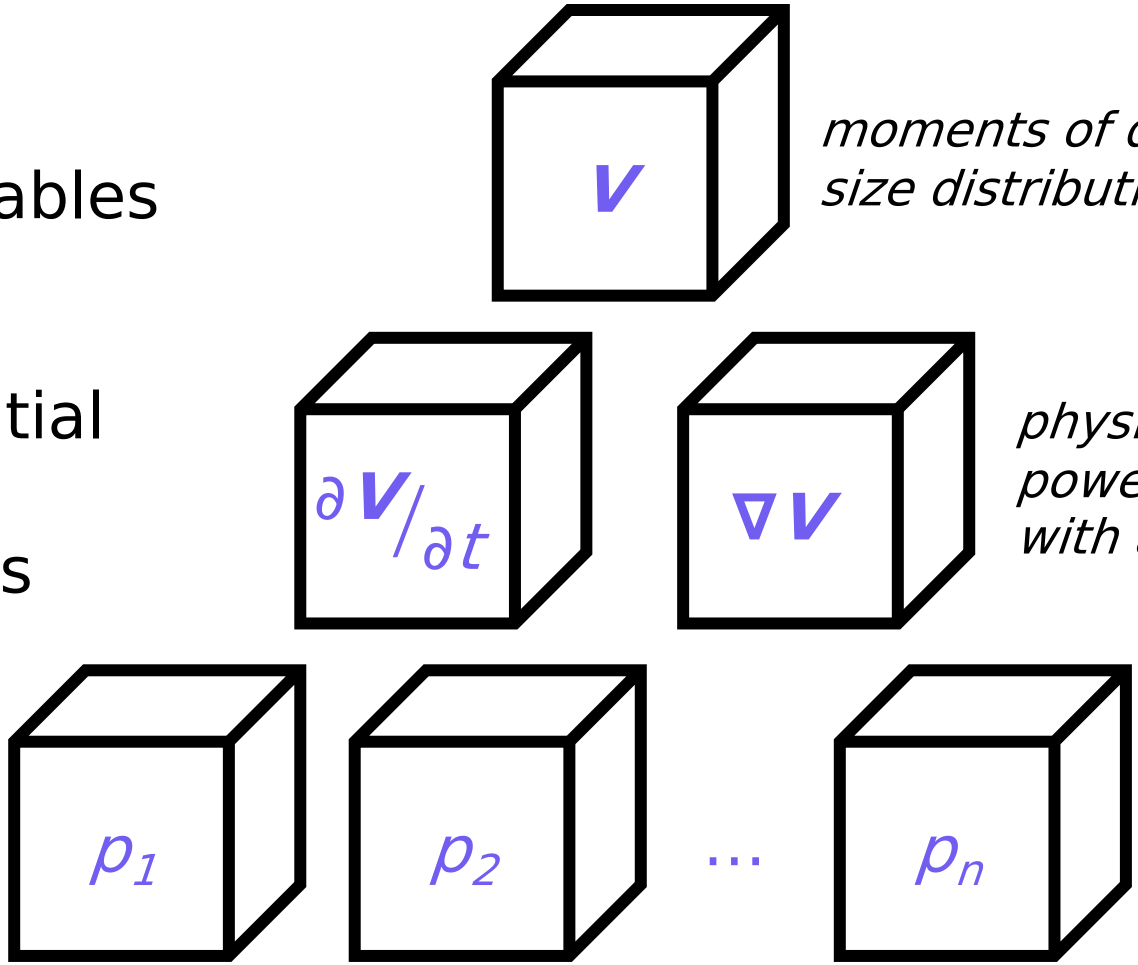
BOSS approach to building a parameterization.

flexible structure

prognostic variables

temporal & spatial derivatives' functional forms

parameters



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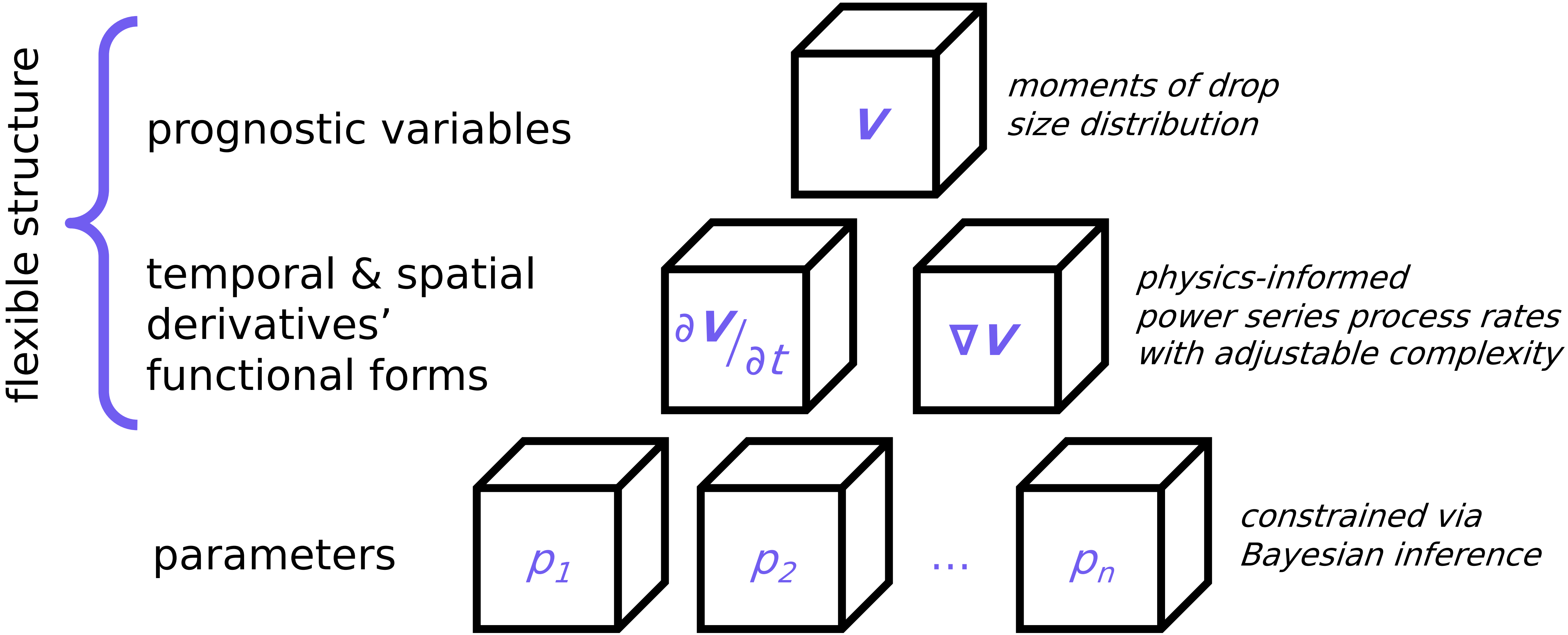
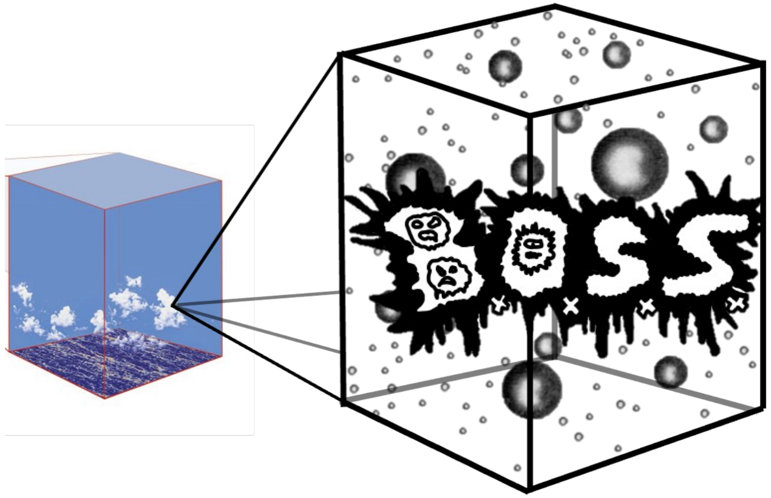


Development of BOSS in 3D models.

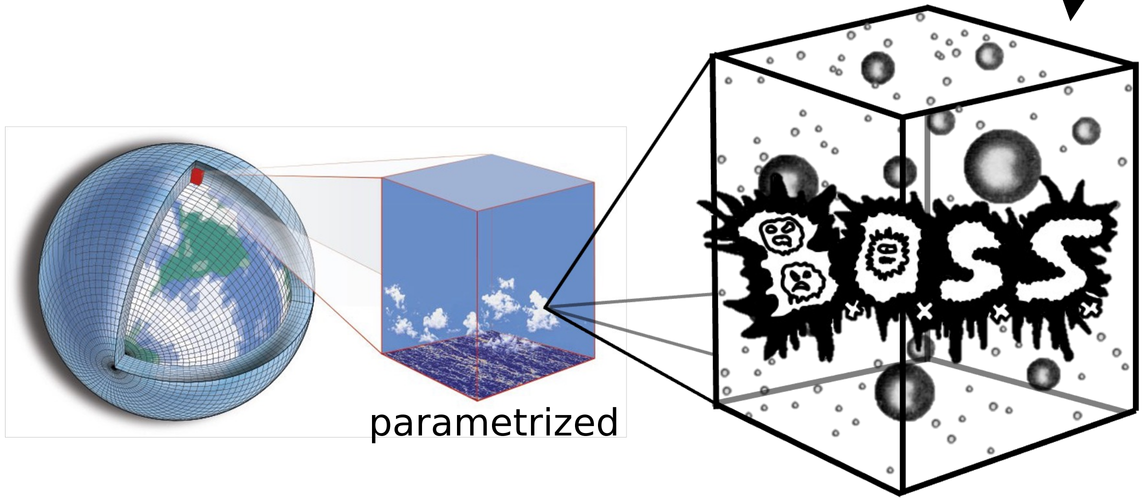
LES



parameter constraint source:
more complex microphysics schemes

BOSS in LES informs which structures to implement in ESMs

ESM



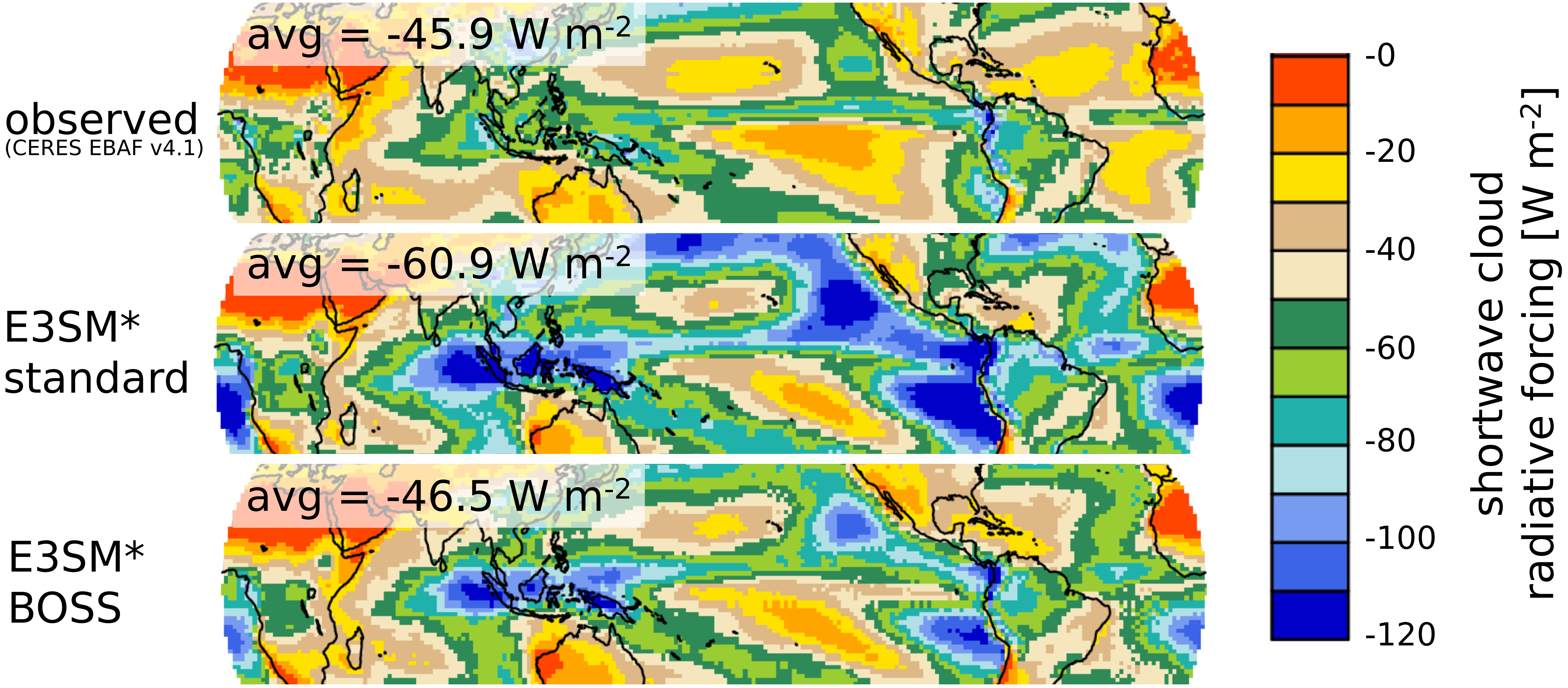
parameter constraint sources:
satellite observations,
historical record,
single column ESM experiments (?)

adapted from Tapio Schneider/Kyle Pressel/Momme Hell/Caltech + Pruppacher & Beard (1970)

Completed steps toward development of BOSS in 3D models.

- ✓ implement BOSS in LES
  - ✓ CM1 (Kaitlyn Loftus, Hugh Morrison)
- ✓ implement BOSS in ESM
  - ✓ CESM (Trude Eidhammer)
  - ✓ E3SM (Po-Lun Ma, Hugh Morrison)

BOSS E3SM simulation with "standard" structure & parameters from 1D kinematic driver constraint.



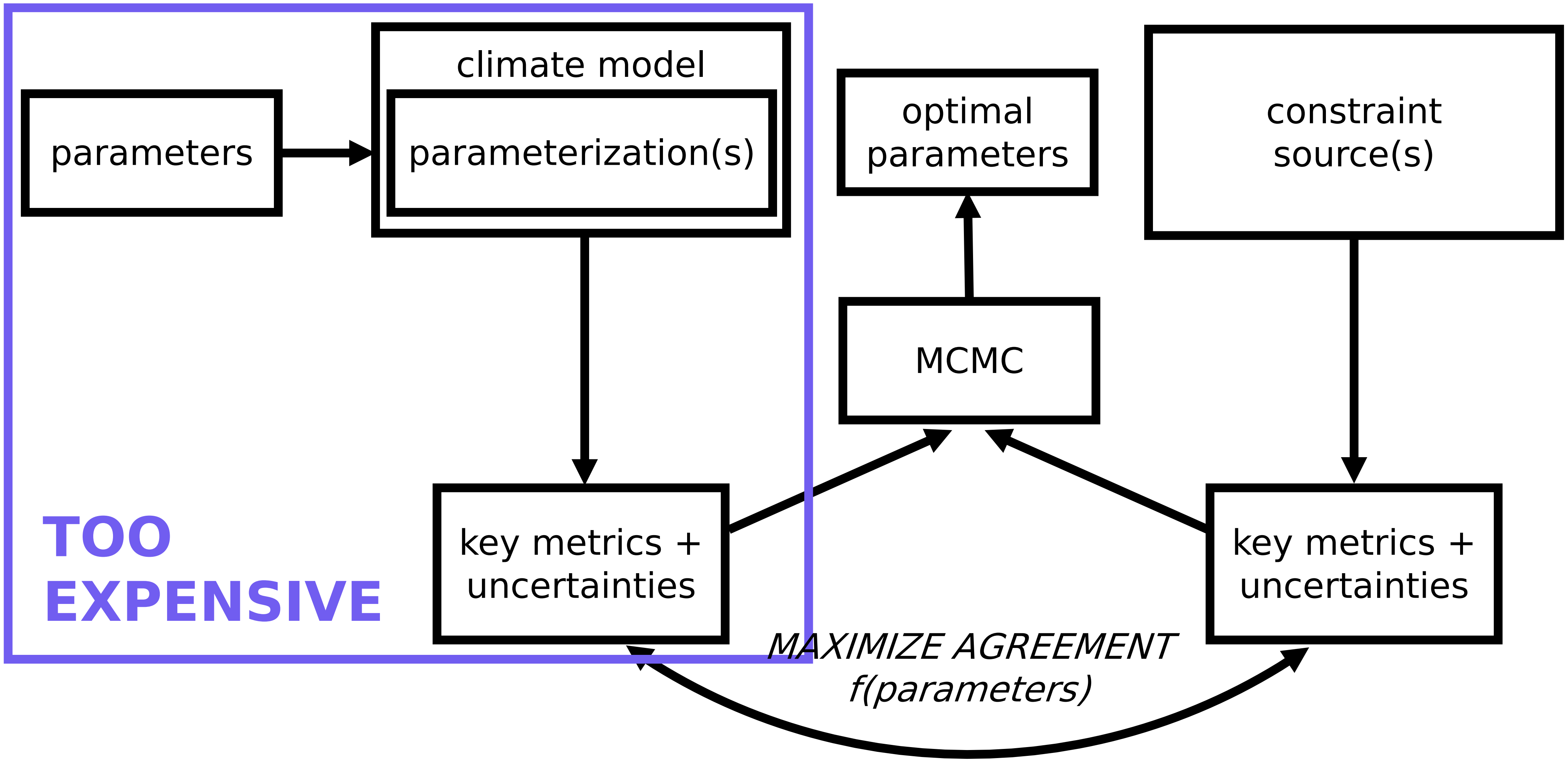
**untuned, development version (~v4)*

adapted from Po-Lun Ma

Completed steps toward development of BOSS in 3D models.

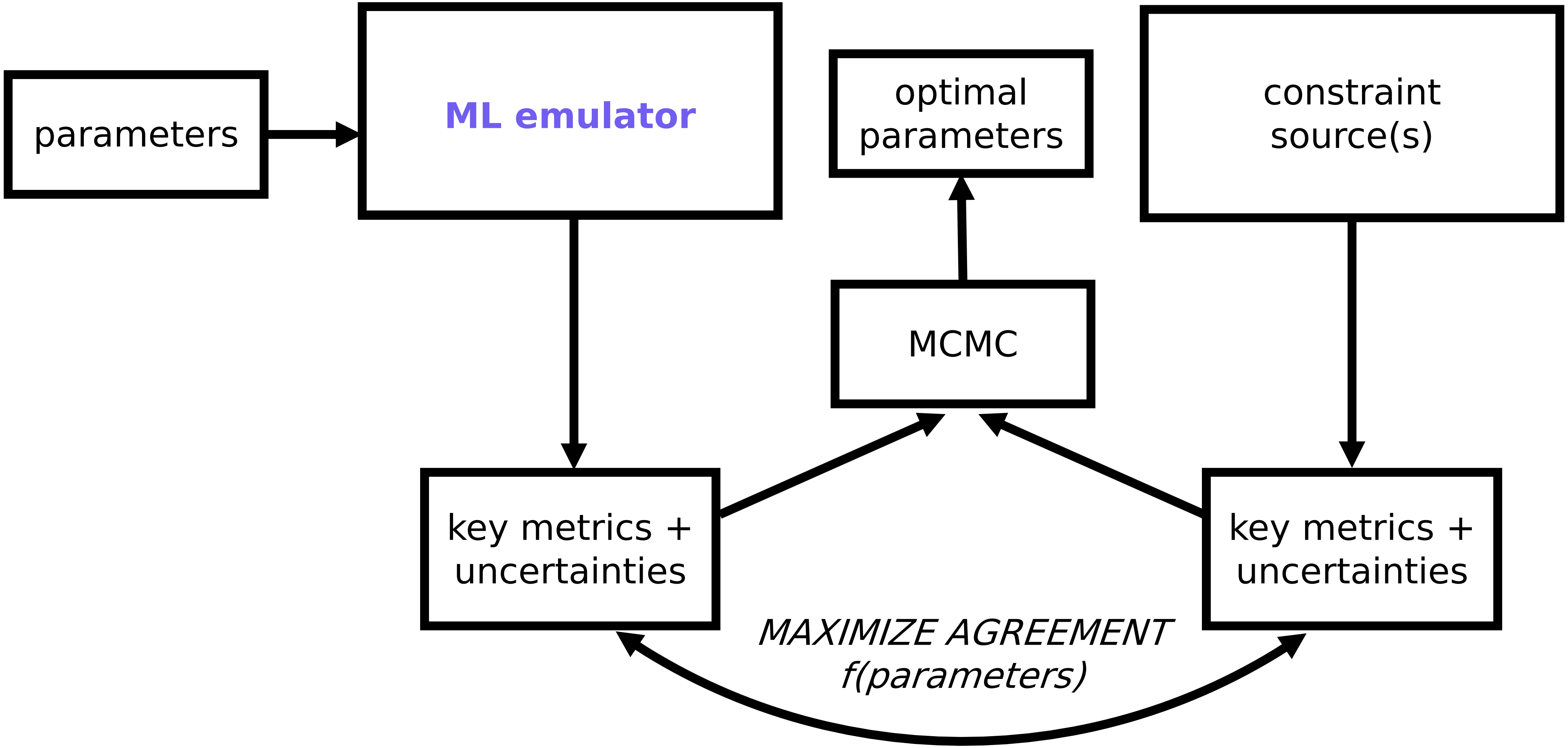
- ✓ implement BOSS in LES
  - ✓ CM1 (Kaitlyn Loftus, Hugh Morrison)
- ✓ implement BOSS in ESM
  - ✓ CESM (Trude Eidhammer)
  - ✓ E3SM (Po-Lun Ma, Hugh Morrison)
- ✓ implement machine learning-enabled Bayesian parameter inference (Kaitlyn Loftus, Marcus van-Lier Walqui)

We enable Bayesian parameter inference in expensive 3D models with machine learning.



We enable Bayesian parameter inference in expensive 3D models with machine learning.

framework from Elsaesser, van Lier-Walqui et al. (in prep)



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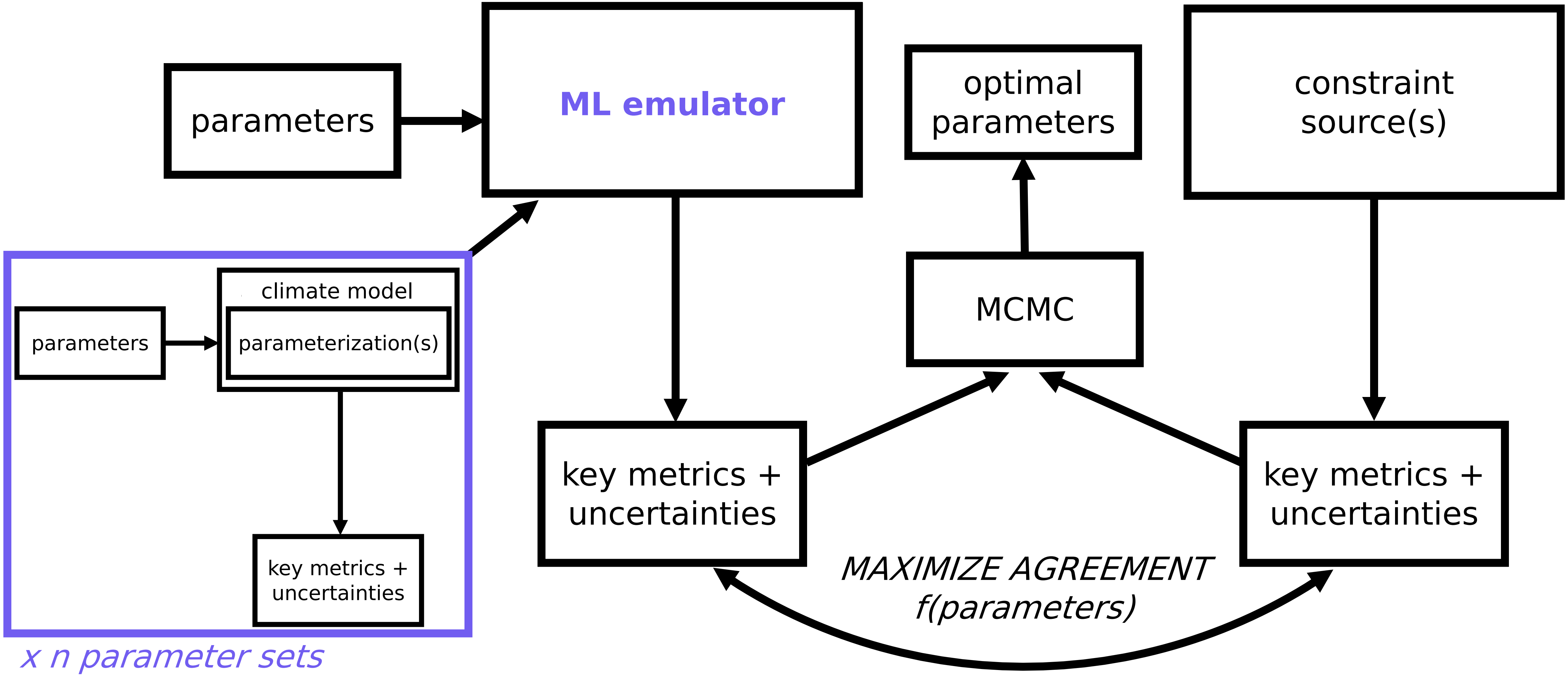
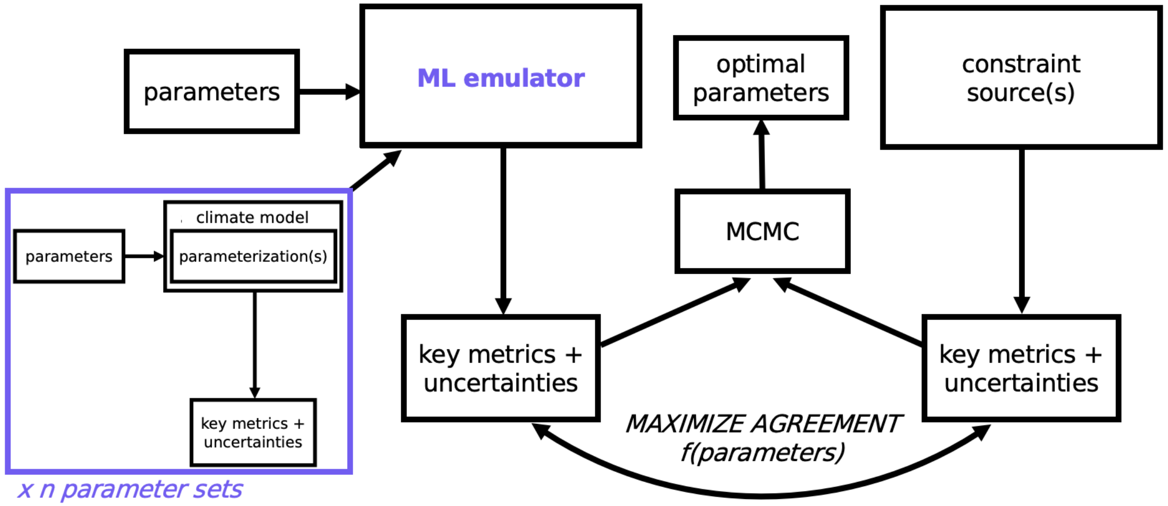


Here, we constrain 16 BOSS parameters in LES with a more complex bin microphysics scheme.

- **climate model:** LES (CM1)
  Bryan & Fritsch (2002)
- **parameterization:** BOSS
  - 2 moment, cloud & rain categories
  - power laws for collision coalescence & sedimentation velocity, other processes follow P3 *Morrison & Milbrandt (2015)*
- **parameters:** 16 microphysics
- **constraint source:**
  CM1 + TAU bin microphysics
  Tzivion et al. (1987,1989), Feingold et al. (1988)
- **setup:** marine stratocumulus (DYCOMS-II RF 2) *Ackerman et al. (2009)*
- **key metrics:** spatiotemporal avgs

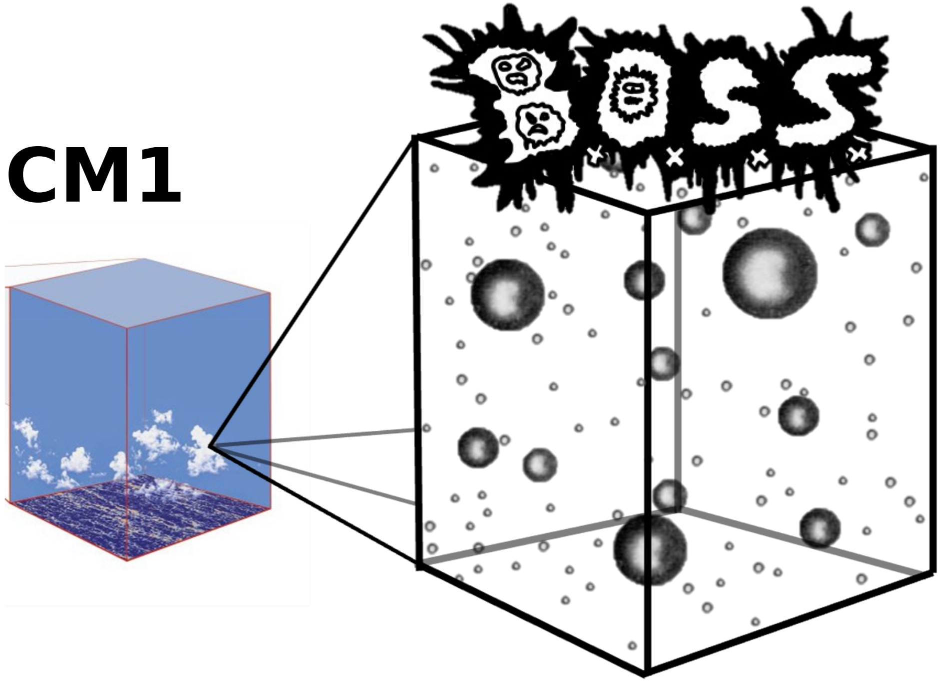


- **uncertainties:** emulator uncertainty & dynamical variability
- **ML emulator:** ensemble of RPNs trained on BOSS + CM1 runs
  Osband et al. (2018), Bhouri et al. (2023)

Here, we constrain 16 BOSS parameters in LES with a more complex bin microphysics scheme.

constrain 16 parameters of

CM1

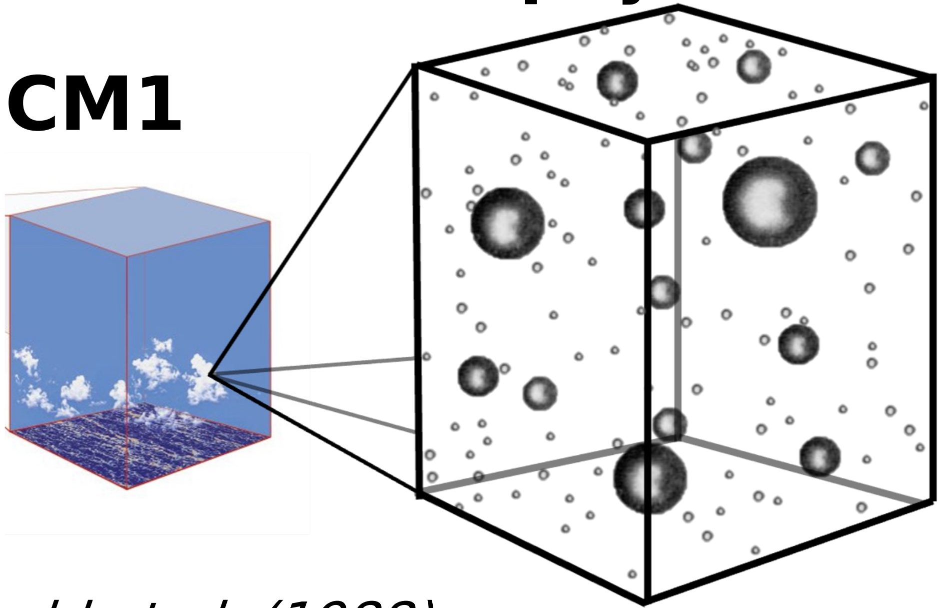


~**20**× microphysics variables, more detailed process rate calculations

based on

bin micro-physics

CM1

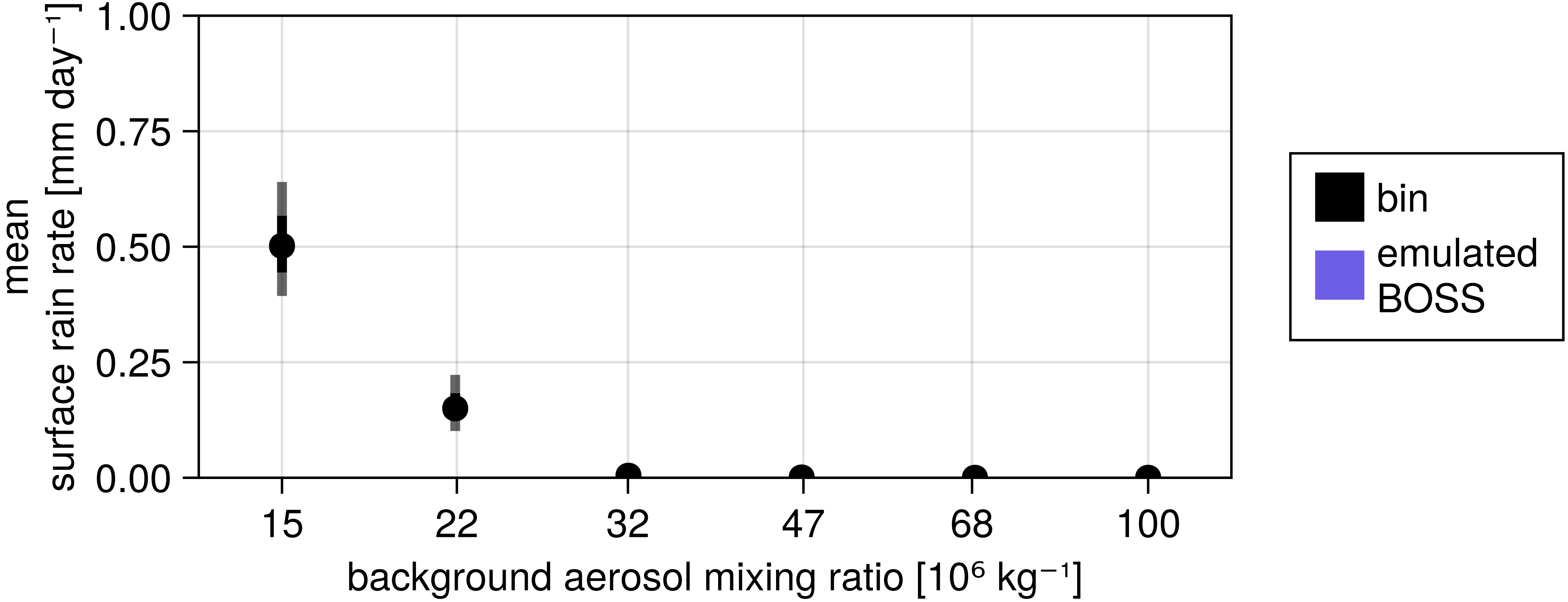


LES CM1 *Bryan & Fritsch (2002)*
bin microphysics TAU *Tzivion et al. (1987,1989), Feingold et al. (1988)*

Experiment 1: constraint with 6 different aerosol conditions.

- background aerosol varies
- 850 BOSS + CM1 runs to train emulator

We use the emulator to evaluate BOSS parameter sets' performances against the bin scheme's.



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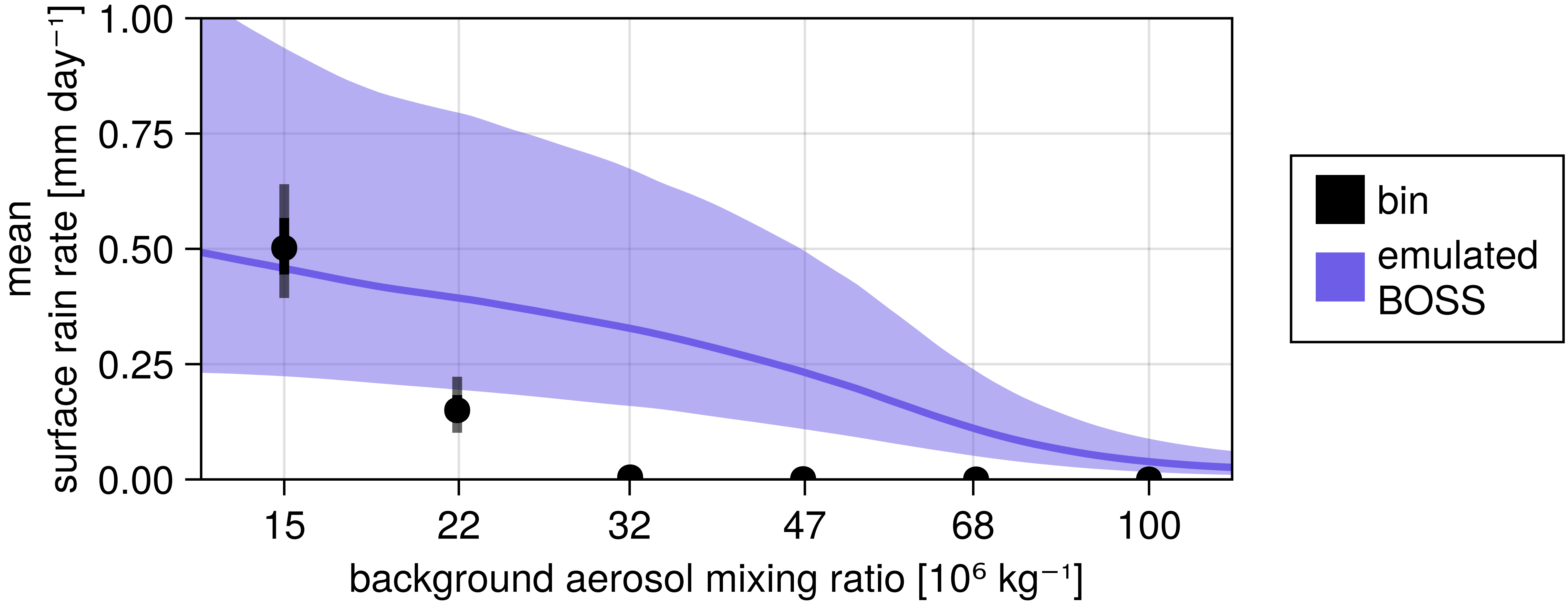

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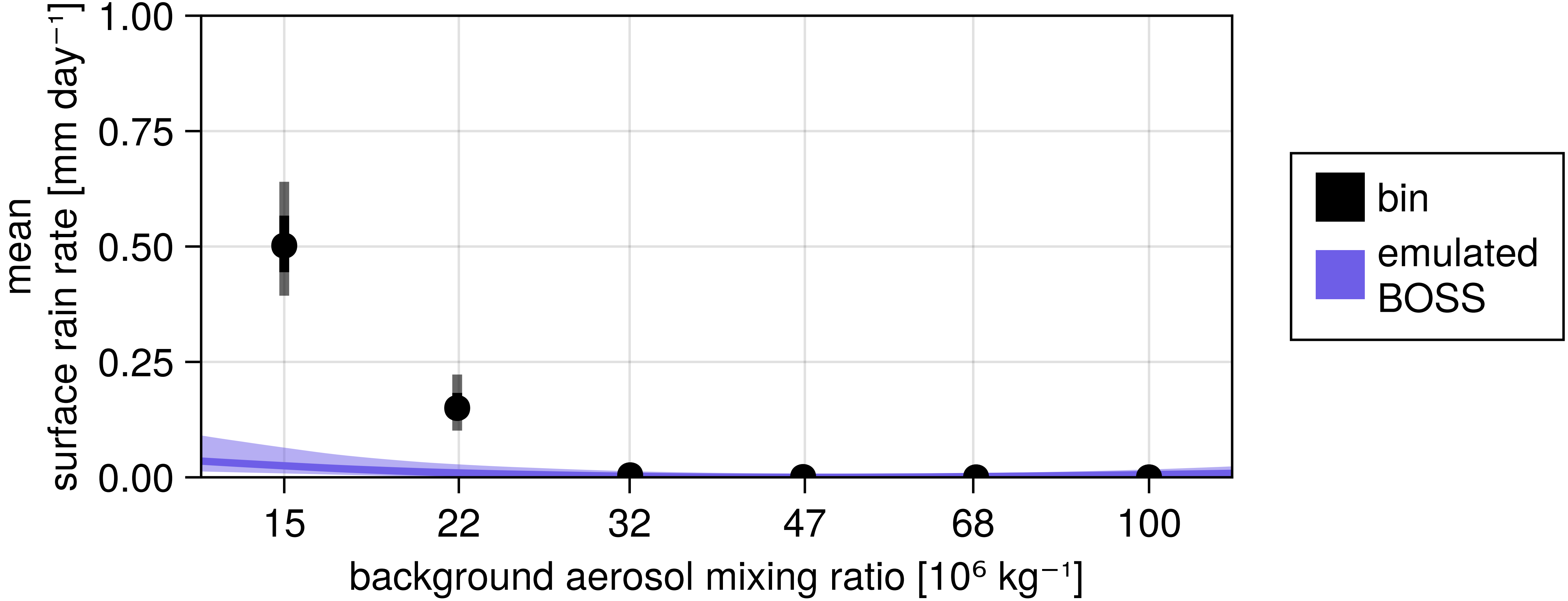

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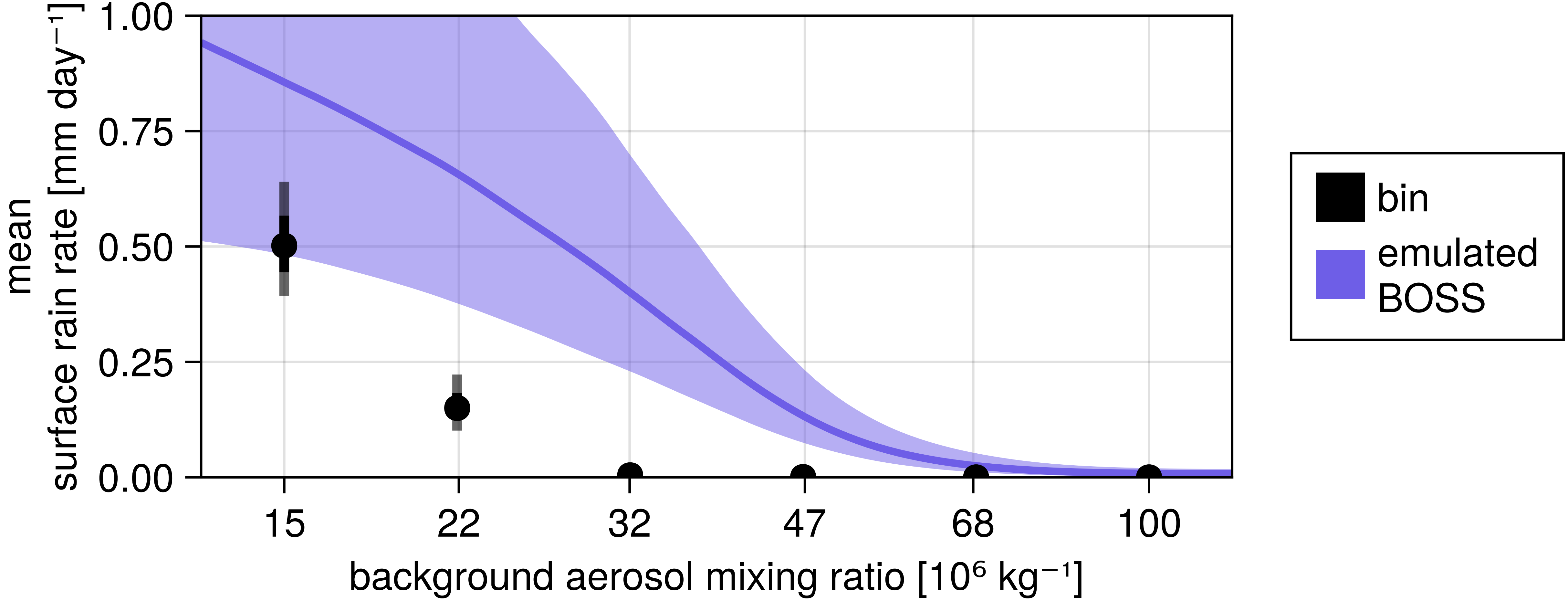
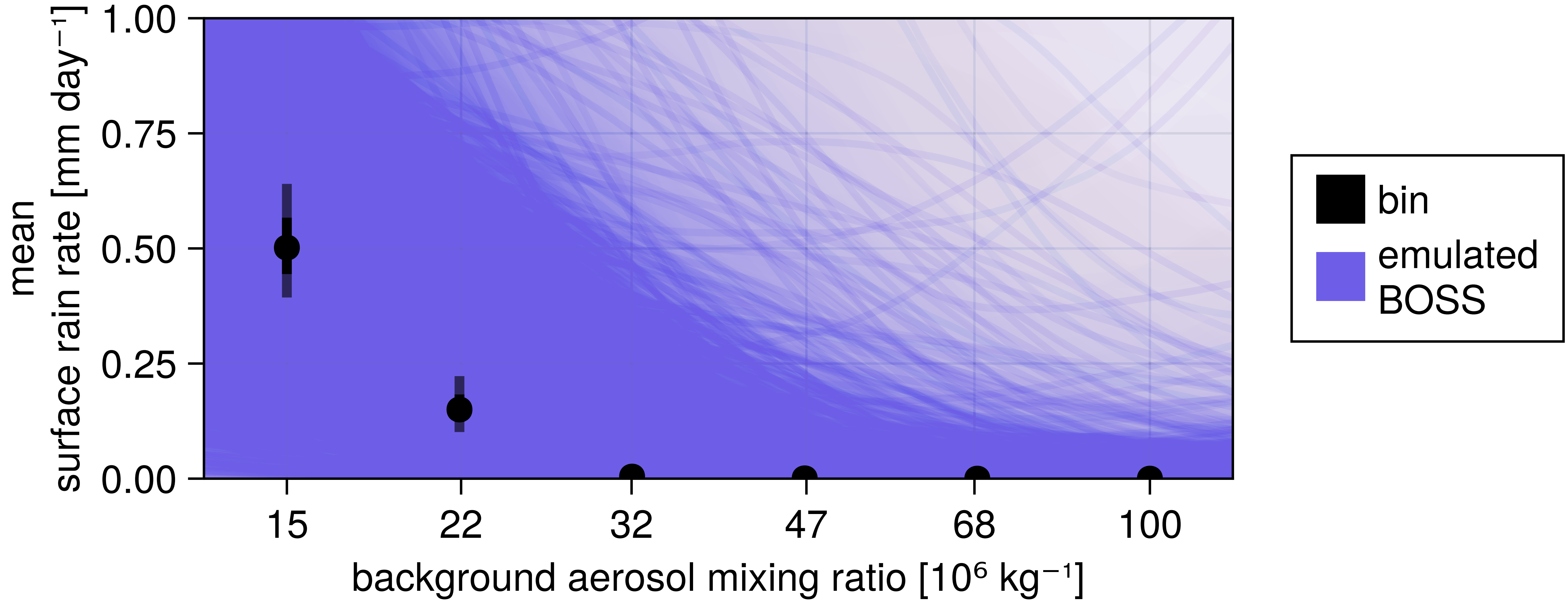
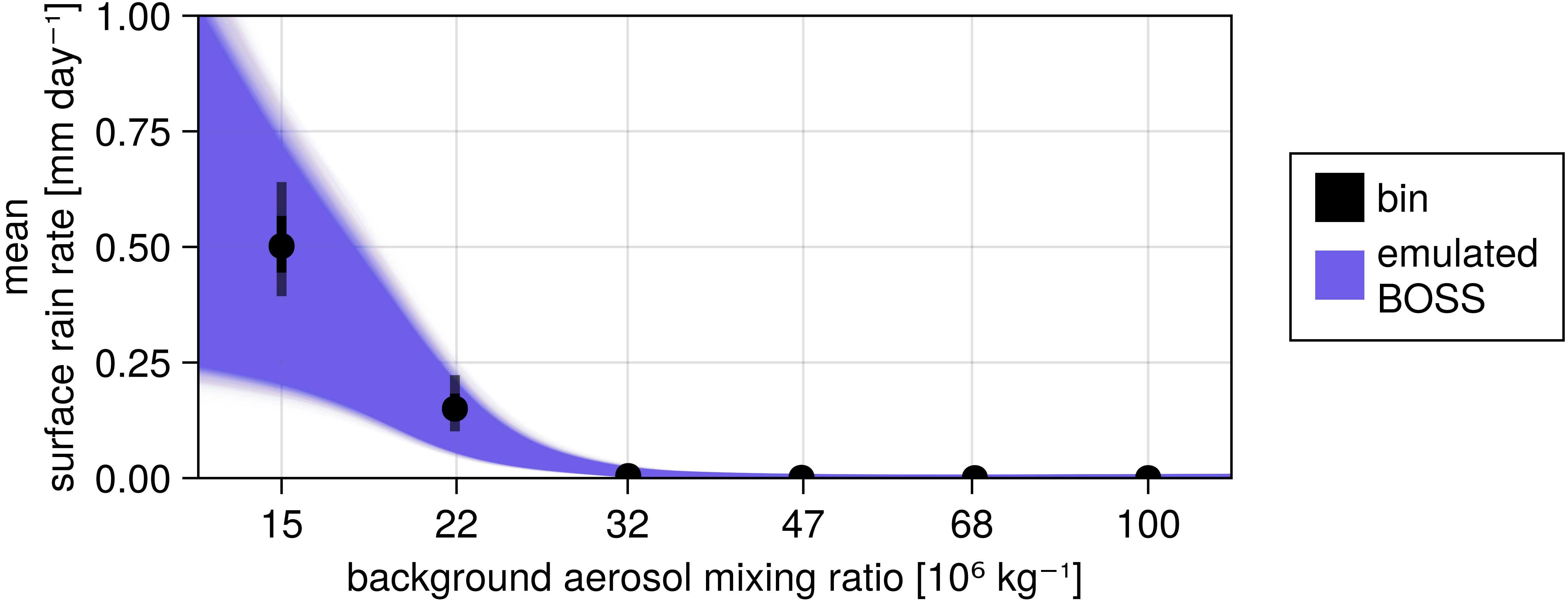


Emulated BOSS metrics with prior parameter distribution (from process rate fitting) span but don’t agree with the bin metrics.



500 prior parameter sets

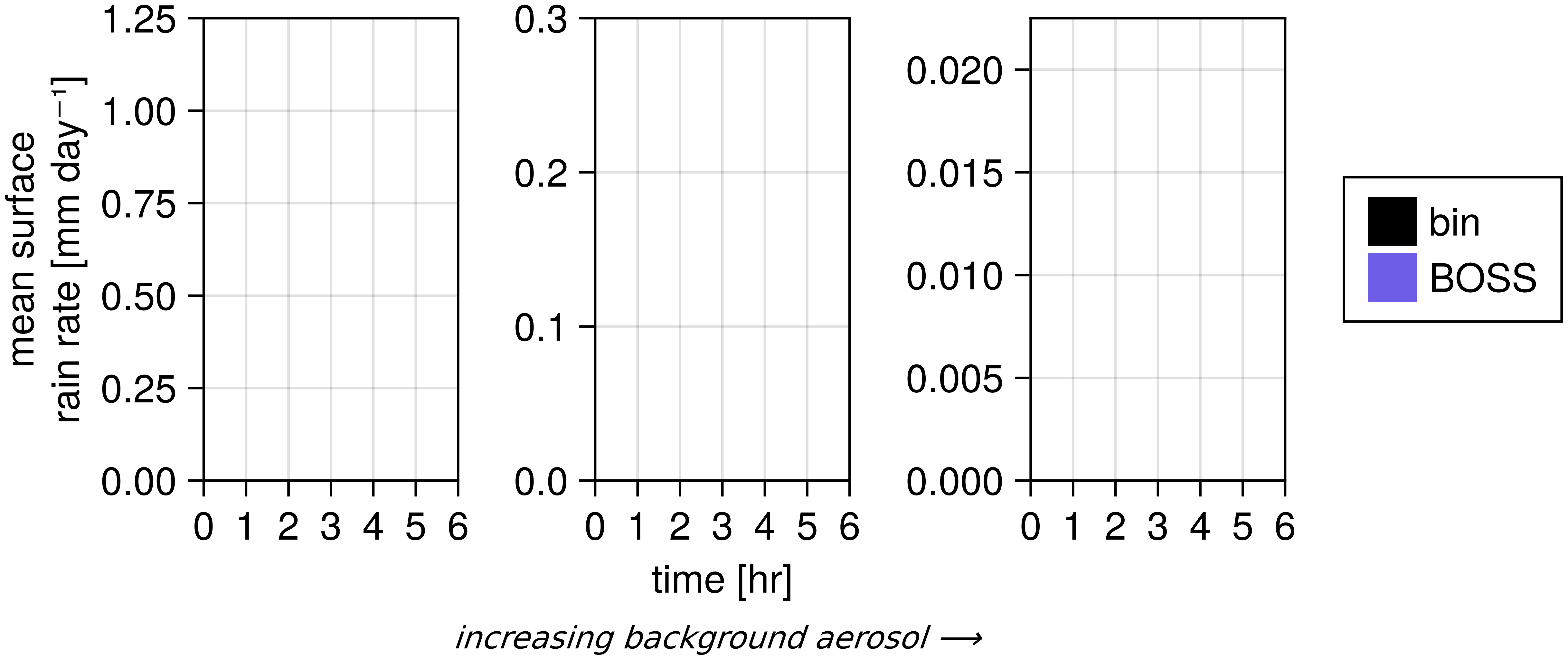
Emulated BOSS metrics with posterior parameter distribution (from Bayesian inference) agree with bin metrics.*



*** where structurally possible**

500 posterior parameter sets

Emulated posterior parameter sets maintain skill in full LES simulations.



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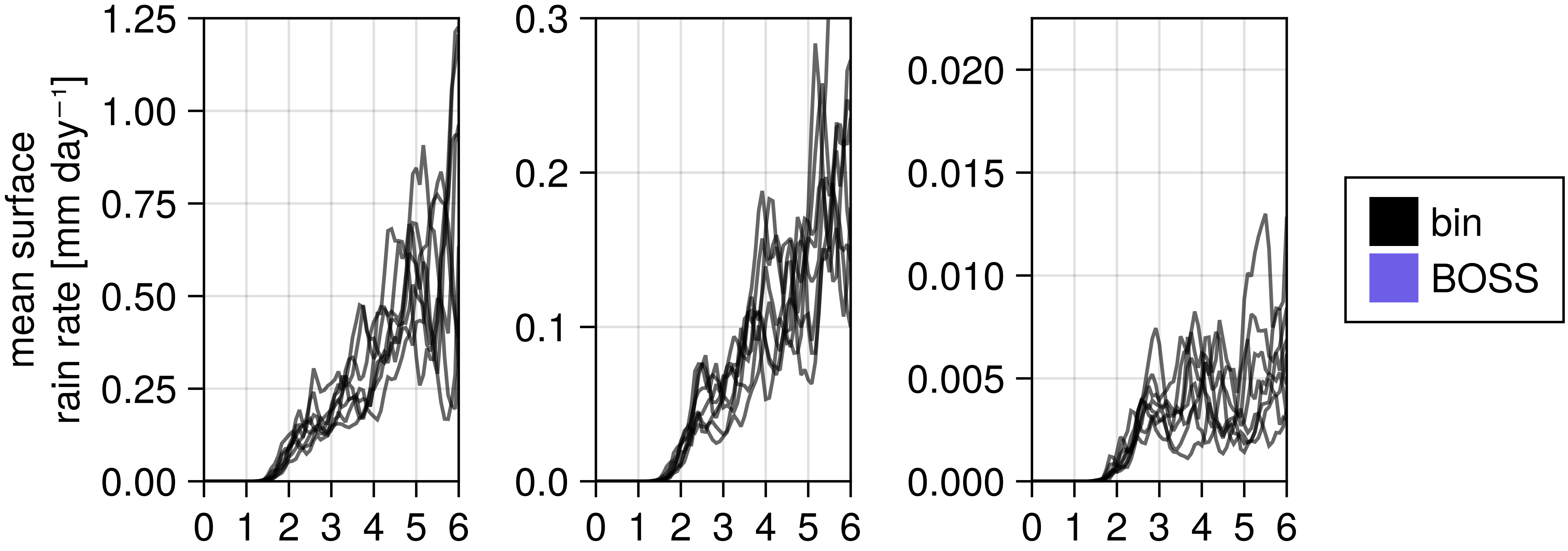

increasing background aerosol ⟶

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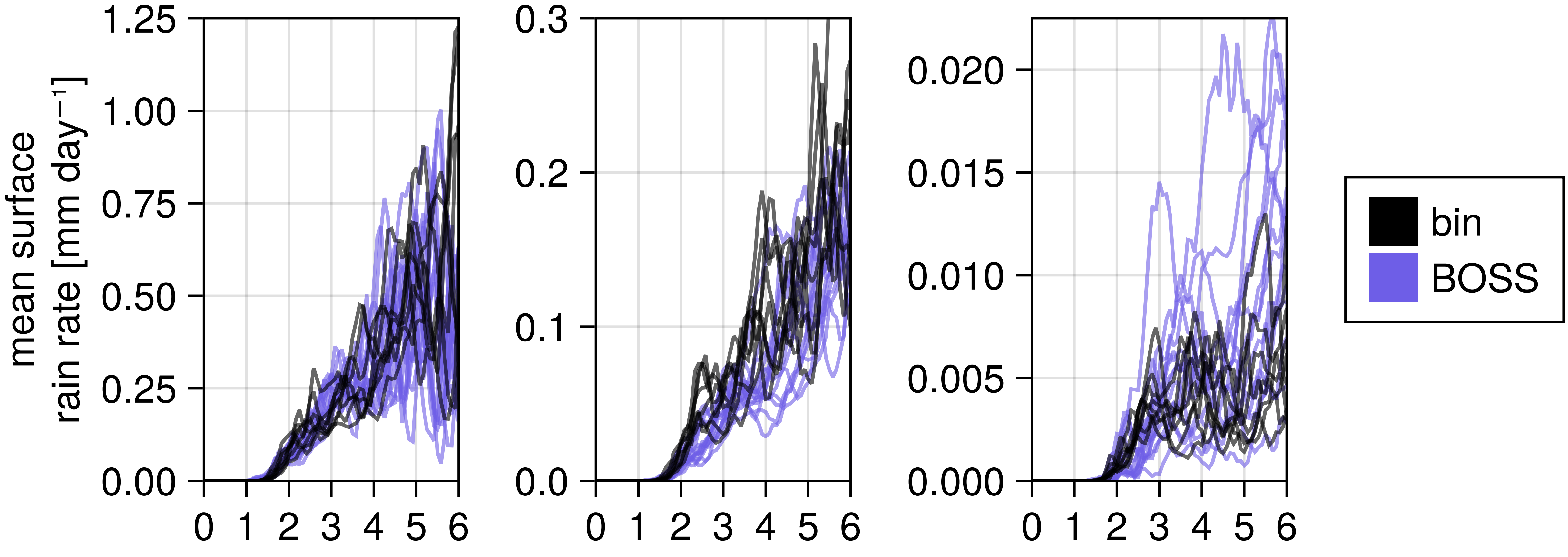

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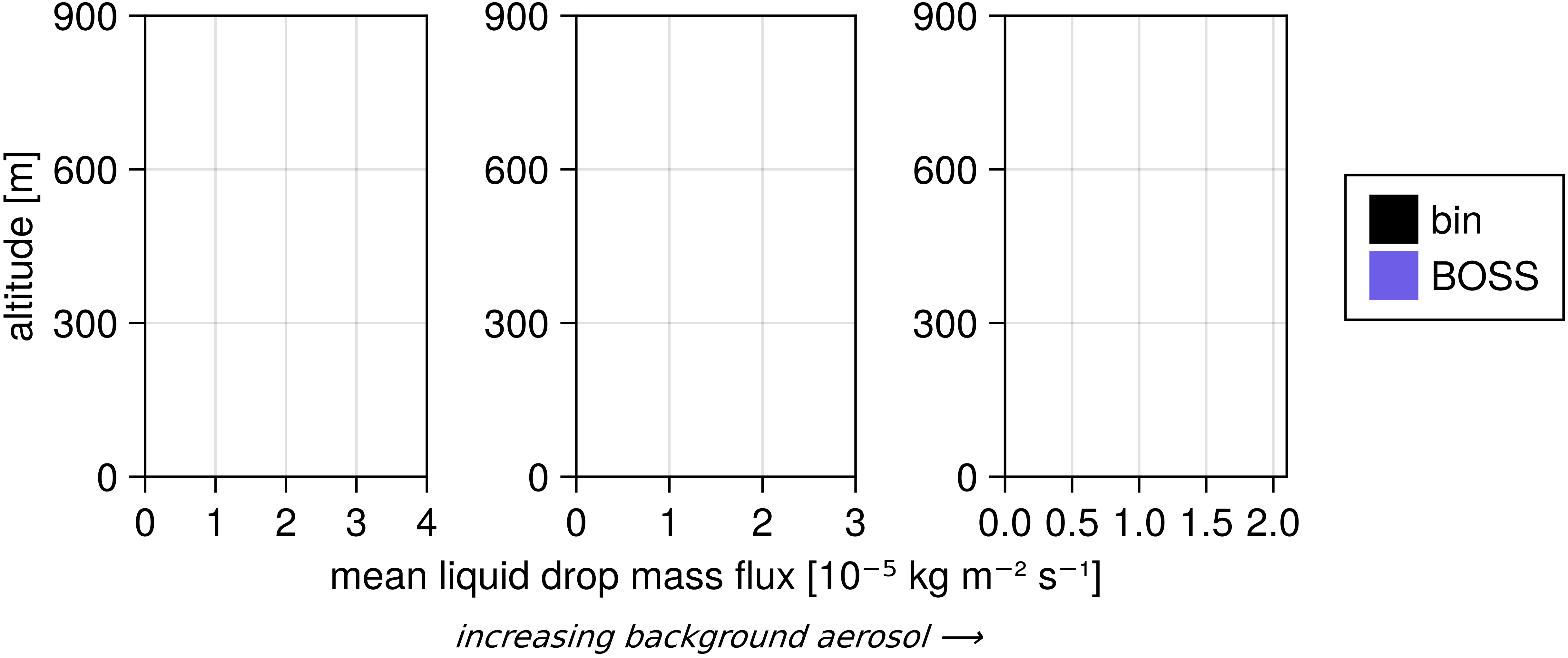

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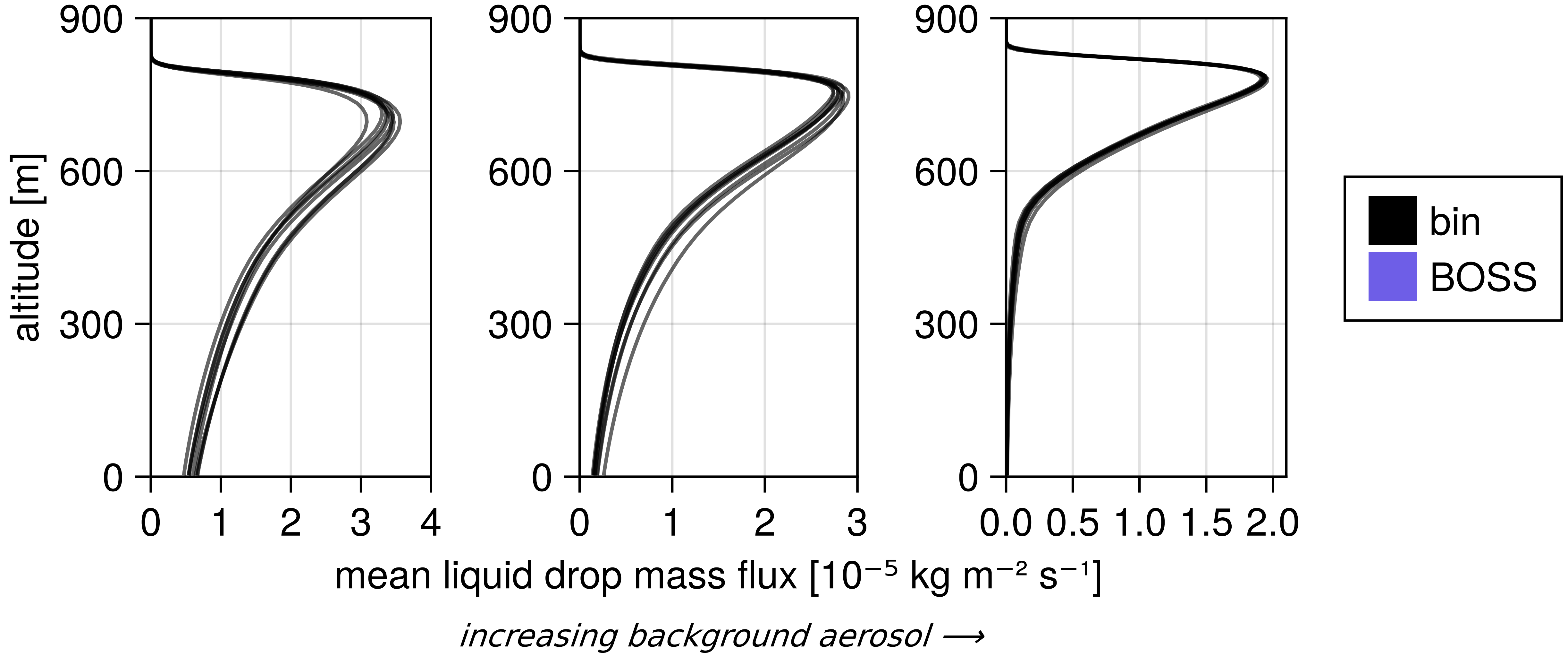

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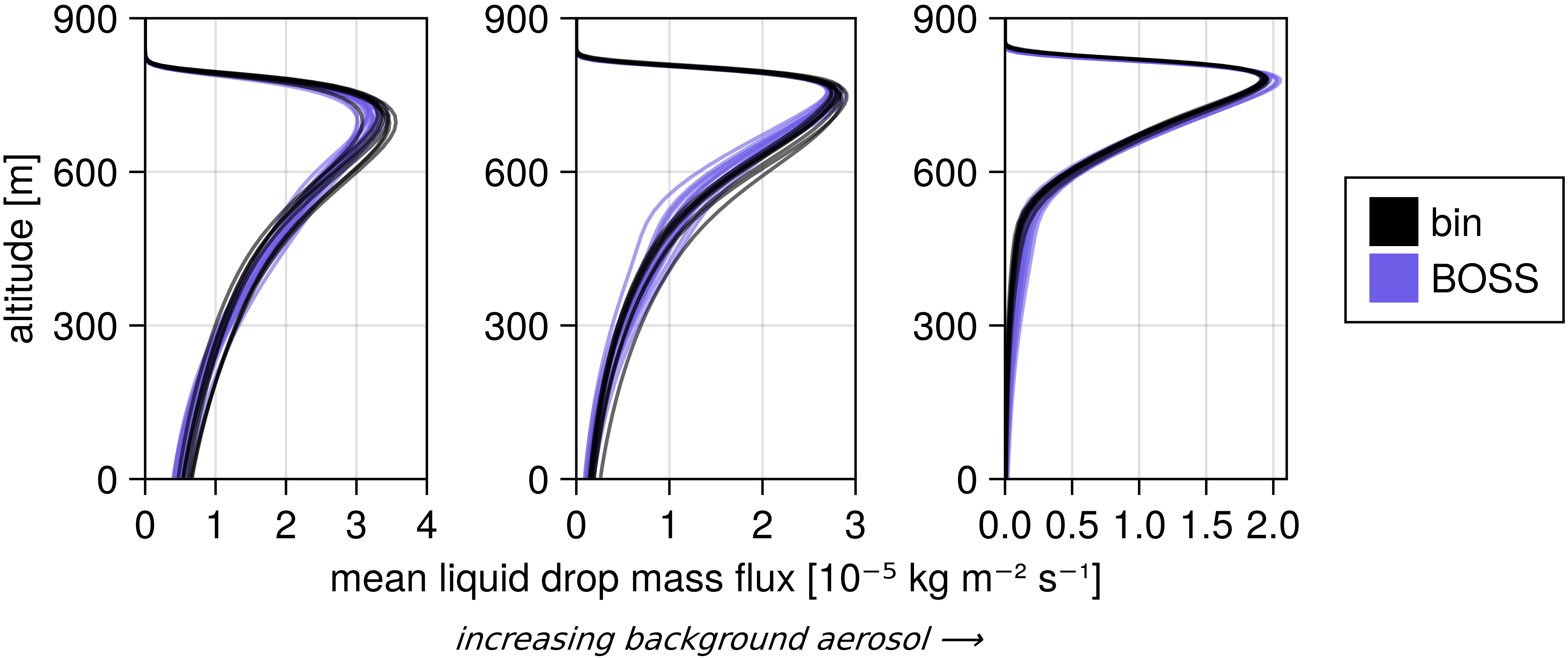
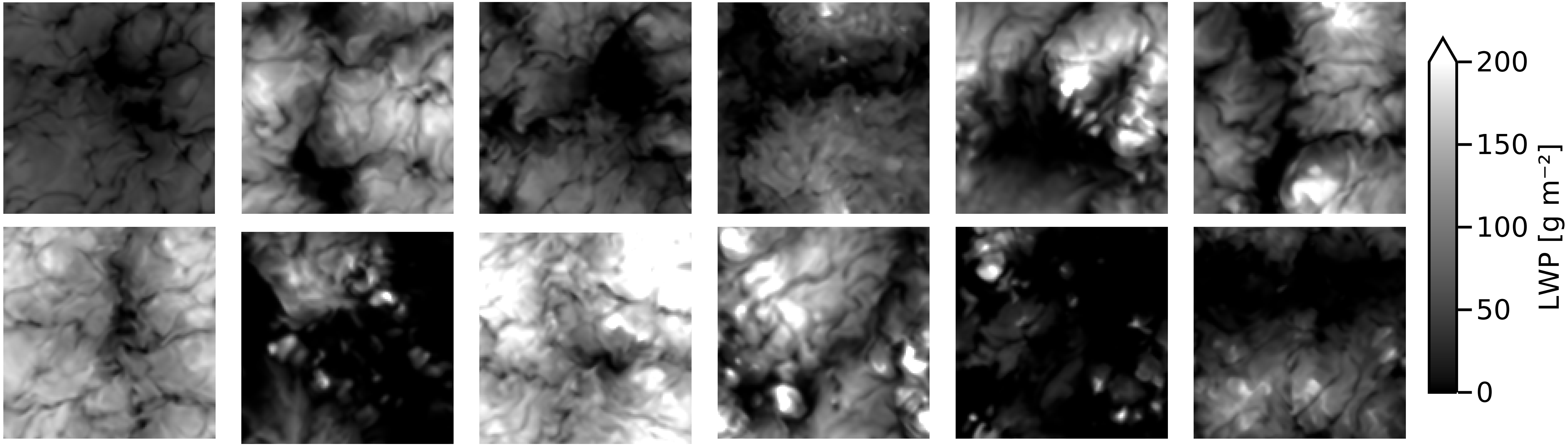
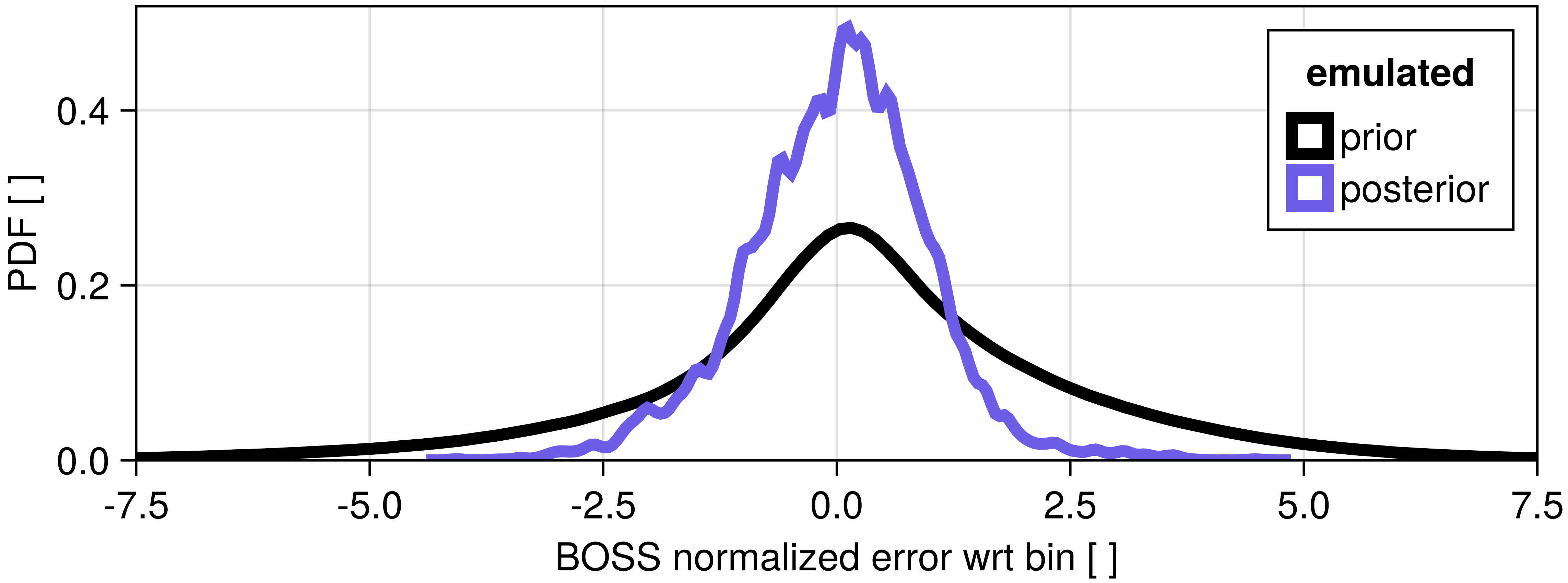


Experiment 2: constraint with 135 different environmental conditions.

- background aerosol + water & temperature profiles vary *Feingold et al. (2016), Glassmeier et al. (2019)*
- 900 BOSS + CM1 runs to train emulator

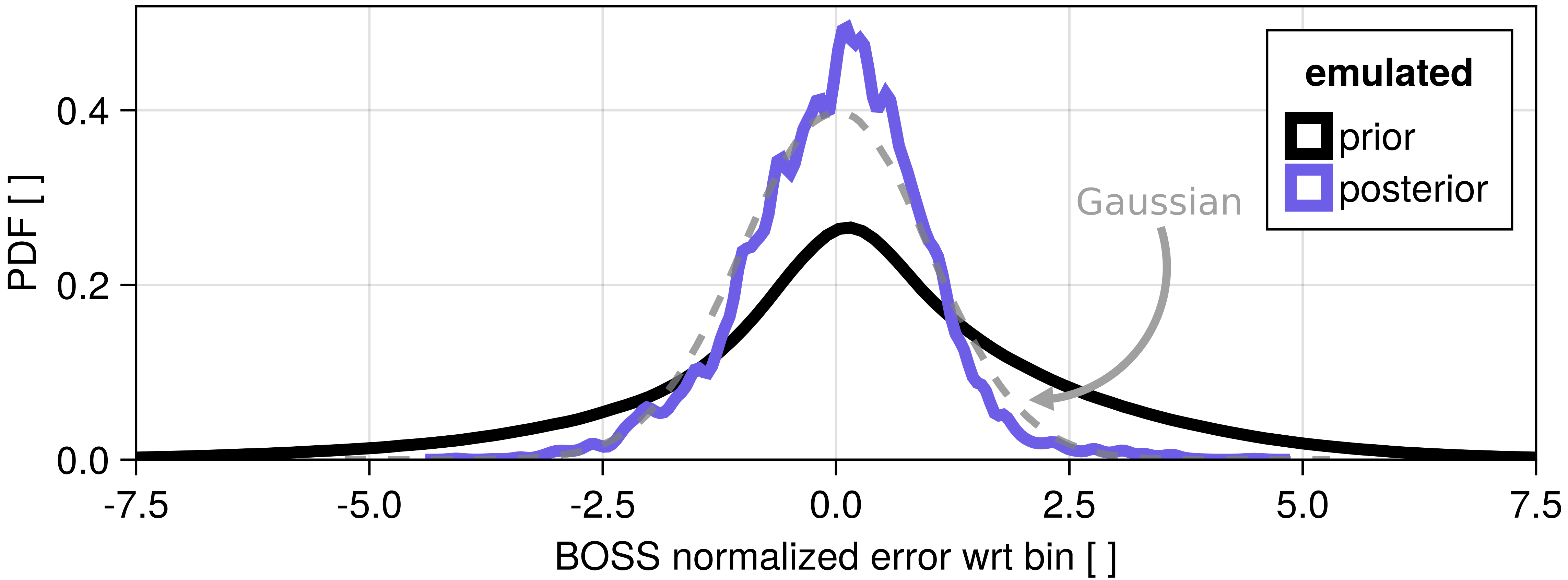


Preliminary constraints across more diverse environmental conditions show promise.



135 environmental conditions × 31 constraining metrics × 1000 parameter sets

Preliminary constraints across more diverse environmental conditions show promise.



135 environmental conditions × 31 constraining metrics × 1000 parameter sets

BOSS is a flexible Bayesian approach for parameterizing (warm) microphysics.

- We are extending BOSS to 3D models (LES, ESM)
- ML-enabled Bayesian parameter inference is a quantitative method to
  - select parameters
  - characterize parametric uncertainty
  - distinguish parametric and structural error

in parameterizations

- We present examples of its successful implementation for a cloud microphysics parameterization in LES
  - 16 parameters constrained by bin microphysics scheme in same LES

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