

# Bin, bulk, or BOSS?

## Producing bulk microphysics schemes that emulate bin microphysics using Bayesian inference

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### Summary

- A bulk microphysics scheme consisting of a set of simple power law formulae can be tuned to emulate the behavior of a bin scheme.
- Traditionally, empirical fitting of bulk schemes is performed on a process-by-process basis in the context of a 0-D (box) model, but we also use Markov-chain Monte Carlo (MCMC) methods to fit an entire fully-coupled, time-evolving 1-D model.
- Fitting the 1-D model significantly improves skill over directly fitting process rates.

### An Idealized 1-D Driver

The 1-D model used in this study is an idealized finite volume model with 20 vertical levels, each 100 m in height, which is advanced using a time step of 20 s. Vertical advection and sedimentation of particles use a first-order upwind scheme.

Initial conditions are calculated to be in rough equilibrium based on moist adiabatic ascent, with a surface temperature of 20 °C and a uniform relative humidity of 90 %. The atmosphere is horizontally uniform, and is exposed to the oscillating vertical velocity

$$w = w_0 \cos(2\pi t/T) \sin(\pi z/2000 \text{ m}) \quad (1)$$

where  $w$  is vertical velocity,  $w_0$  and  $T$  are respectively the amplitude and period of oscillation, and  $z$  and  $t$  are the vertical and time coordinates. A constant latent heat flux is also applied to every level at each time step.

### The Bin Model

The reference bin scheme is the 2-moment TAU microphysics bin model. For diagnostic purposes, bins containing particles of sizes below 79.3 microns are considered to be “cloud”, while larger bins are considered to be “rain”.

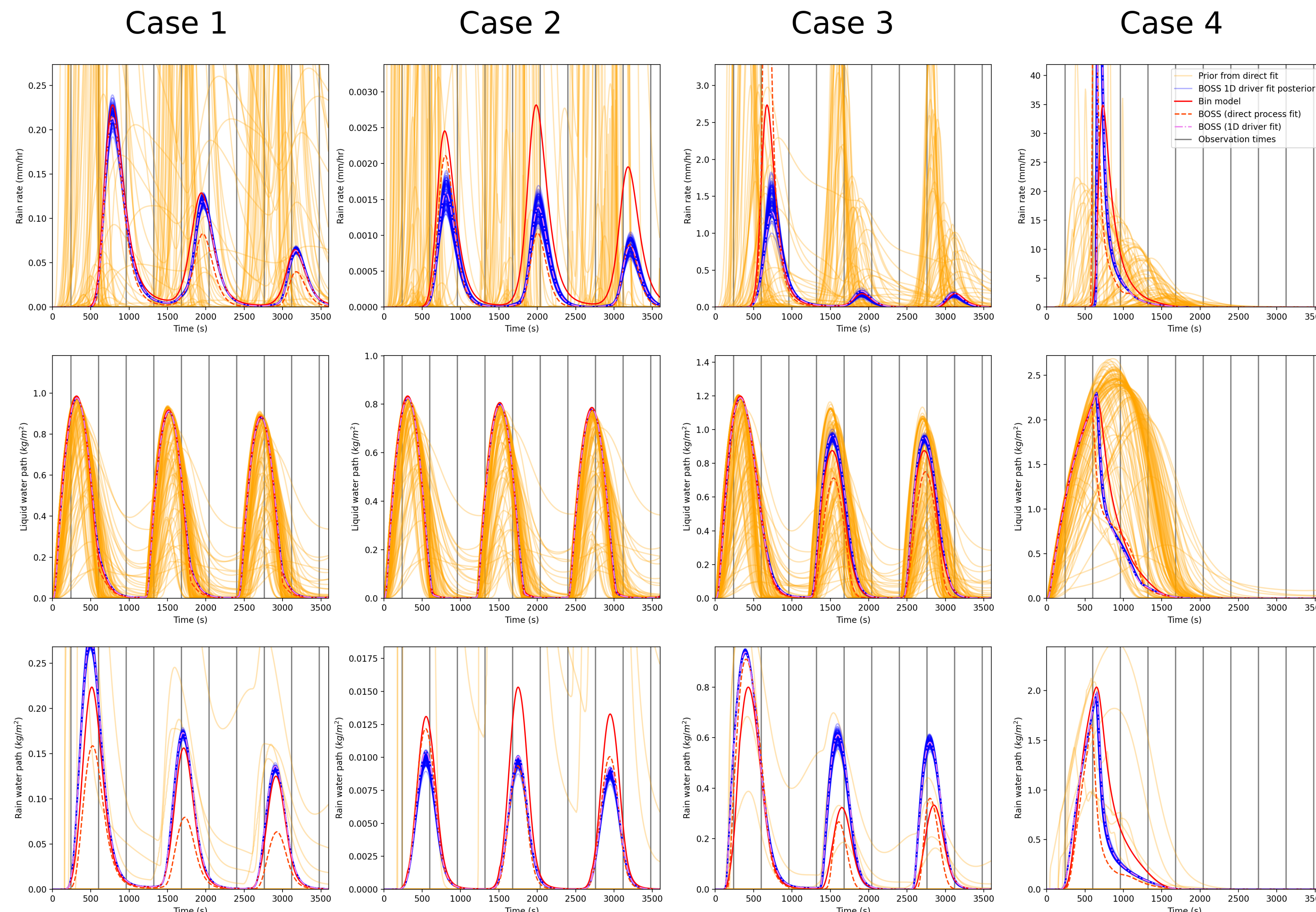


Figure 1: Surface precipitation rate (top), combined cloud and rain water path (middle), and rain water path alone (bottom) for cases covering a number of different forcing conditions. Case 1 is one of the cases used for fitting. Case 2 contains conditions in the same range of values used for fitting, but is not in this “training” set. Cases 3 and 4 contain conditions well outside the drizzling regime.

### BOSS Process Rates

If the  $n$ -th moment of cloud is  $M_{nc}$  and  $n$ -th moment of rain is  $M_{nr}$ , then a process rate  $r$  is

$$r = af(s)M_{0x}^n(M_{3x}/M_{0x})^b \quad (2)$$

Here  $f(s)$  depends on the model state, and  $n$  is a fixed integer.  $a$  and  $b$  are model parameters.

The autoconversion rate has two terms, a “triggering” term and a rain-dependent term, of the form:

$$r = a_1 M_{0c}^2 (M_{3c}/M_{0c})^{b_1} + a_2 M_{0c}^2 (M_{3c}/M_{0c})^{b_{2c}} (M_{3r}/M_{0r})^{b_{2r}} (M_{0r}/M_{0c})^{b_{2n}} \quad (3)$$

Accretion has the form:

$$r = a M_{0c} (M_{3c}/M_{0c})^{b_c} M_{0r} (M_{3r}/M_{0r})^{b_r} \quad (4)$$

### Bayesian Fitting Of Processes

Eight different sets of boundary/forcing conditions producing drizzle or non-precipitating cloud were run for 1 h in the bin model to generate input data. First we used conventional “direct” process rate fitting, matching BOSS’s process rates to diagnosed rates from the bin model. MCMC was also used to produce a prior distribution of parameter values for the next step.

We used MCMC with adaptive Metropolis sampling to perform Bayesian inference using the full 1-D driver. The bin and BOSS model *states* were compared at certain “observation” times and vertical levels, with no direct use of process rates.

### Results

The direct process rate fit was reasonably effective for non-precipitating cloud (not shown), but in drizzling cases, autoconversion was concentrated in a much smaller portion of the vertical range and time period than in the bin model. Too little rain was produced, and too much of that rain reached the surface rather than evaporating, reducing the available moisture for later oscillations. The sedimentation also produces excessive size sorting in the rain (a common problem in 2-moment models).

The fit using the 1-D driver produced better surface precipitation and liquid water path for the training data containing drizzle (Case 1 of figure), as well as when the dynamical forcing was adjusted to produce heavier rain (Cases 3 and 4), although there was no improvement for non-precipitating cloud or cases with negligible rain (Case 2).

These improvements are due to an increase in the autoconversion rate throughout the cloud, coupled with adjustments to rain evaporation and sedimentation. More rain is produced, which then behaves in a more “cloud-like” manner. The 1-D driver fit therefore performs better overall, but partitions mass between rain and cloud less accurately (e.g. compare middle and bottom plots of Case 3). The adjusted rain fall speeds also produce less excessive sorting.

A 3-moment version of BOSS is currently under evaluation to determine if the autoconversion rate can be further improved.

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