

# Modular, unified, robust and validated: chasing the dreams of a climate model parameterization developer

Anna Jaruga,  
Sajjad Azimi,  
Zhaoyi Shen,  
Tapio Schneider,

Olivia Alcabes,  
Amy Lu,  
Jordan Benjamin,  
Costa Christopoulos,

Gabriele Bozzola,  
Charles Kawczynski,  
Dennis Yatunin,  
Nat Efrat-Henrici

Caltech



DA/ML techniques offer a way of calibrating parameterizations and reducing model uncertainty. They can't reduce structural errors stemming from individual parameterizations or the coupling, and rely on access to high quality data.

Process-level understanding can inform model design. But if unconstrained by observations, it can lead to unnecessary complexities.

## Parameterization stack

$$\frac{\partial \langle \phi \rangle}{\partial t} + \nabla_h \cdot (\langle \phi \rangle \langle \mathbf{u} \rangle) = - \frac{\partial}{\partial z} (\langle w \rangle \langle \phi \rangle) - \frac{\partial}{\partial z} \langle w^* \phi^* \rangle + \langle S_\phi \rangle$$

$$\frac{\partial (\rho a_i \bar{\phi}_i)}{\partial t} + \frac{\partial (\rho a_i \bar{w}_i \bar{\phi}_i)}{\partial z} + \nabla_h \cdot (\rho a_i \langle \mathbf{u}_h \rangle \bar{\phi}_i) = \underbrace{- \frac{\partial (\rho a_i \bar{w}'_i \bar{\phi}'_i)}{\partial z}}_{\text{Turbulent transport}} + \underbrace{\rho a_i \bar{w}_i \left( \sum_j \epsilon_{ij} \bar{\phi}_j - \delta_i \bar{\phi}_i \right)}_{\text{Entrainment/detrainment}} + \underbrace{\rho a_i \bar{S}_{\phi,i}}_{\text{Sources/sinks}}$$

### Dynamical core numerics

ClimaTimesteppers.jl  
ClimaCore.jl

### Sub-grid scale dynamics (turbulence, convection)

ClimaAtmos.jl

### Sources (microphysics, radiation, ...)

CloudMicrophysics.jl  
Cloudy.jl  
KinematicDriver.jl

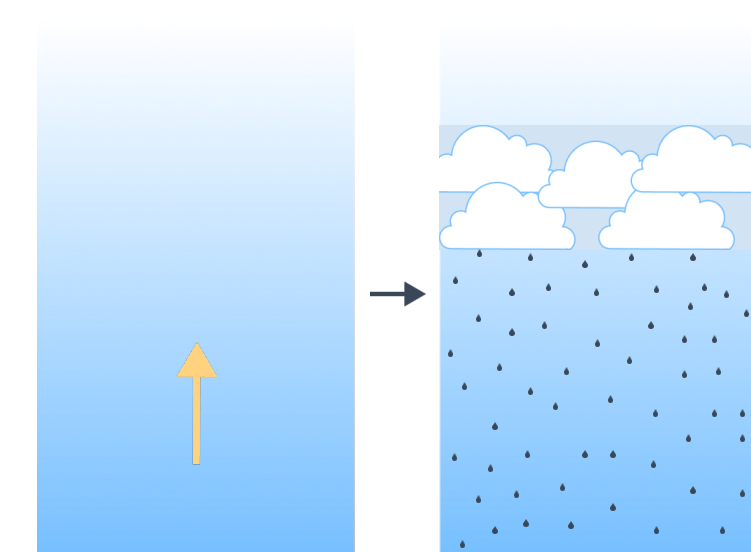
### Machine learning

EnsembleKalmanProcesses.jl  
ClimaParameters.jl

## Example parameter calibration

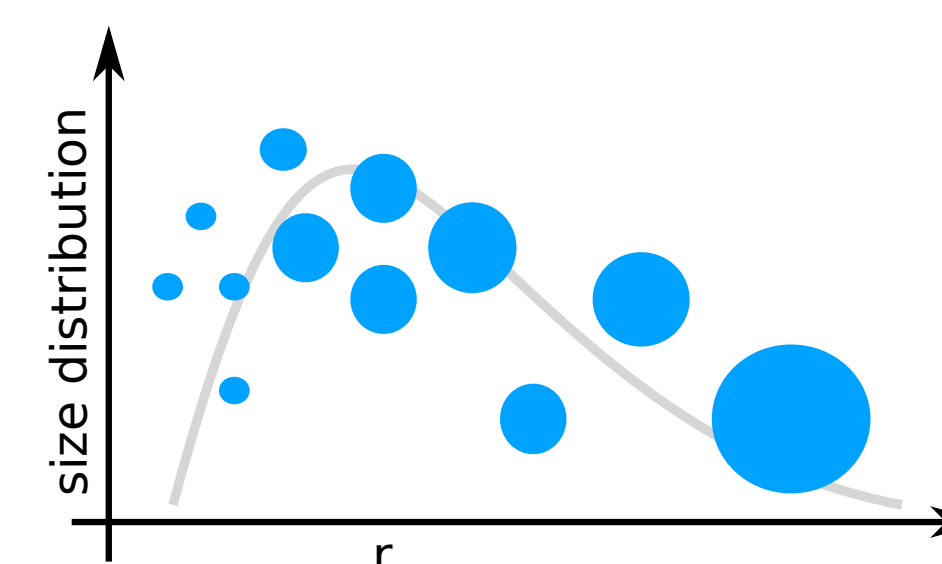
### Model

Prescribed flow 1D  
(KinematicDriver.jl) coupled  
to 1-moment and 2-moment  
bulk microphysics schemes  
(CloudMicrophysics.jl)



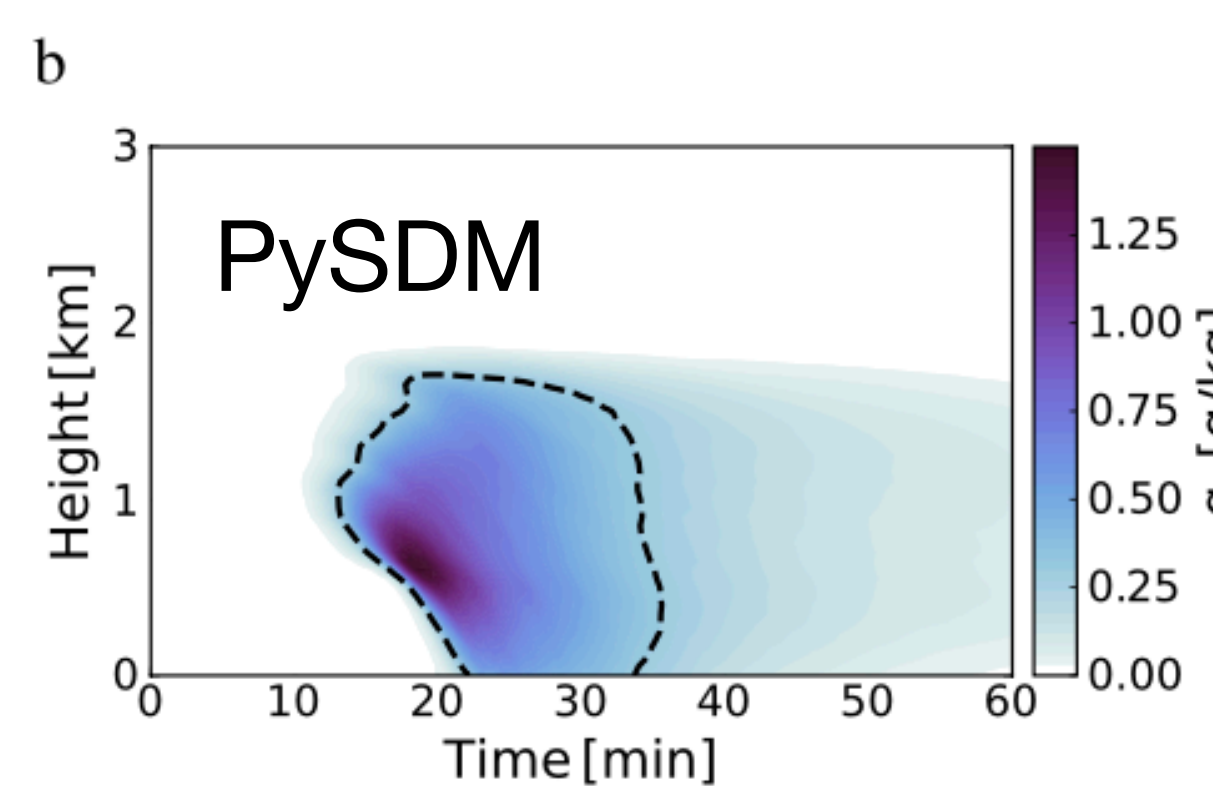
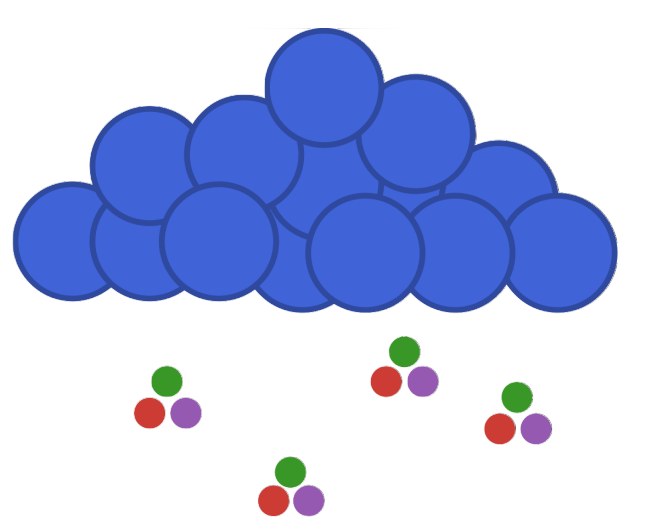
### Data

PySDM (particle based Lagrangian  
microphysics) coupled to the same  
modeling setup. Generated size  
distributions of aerosol cloud and  
precipitation particles.

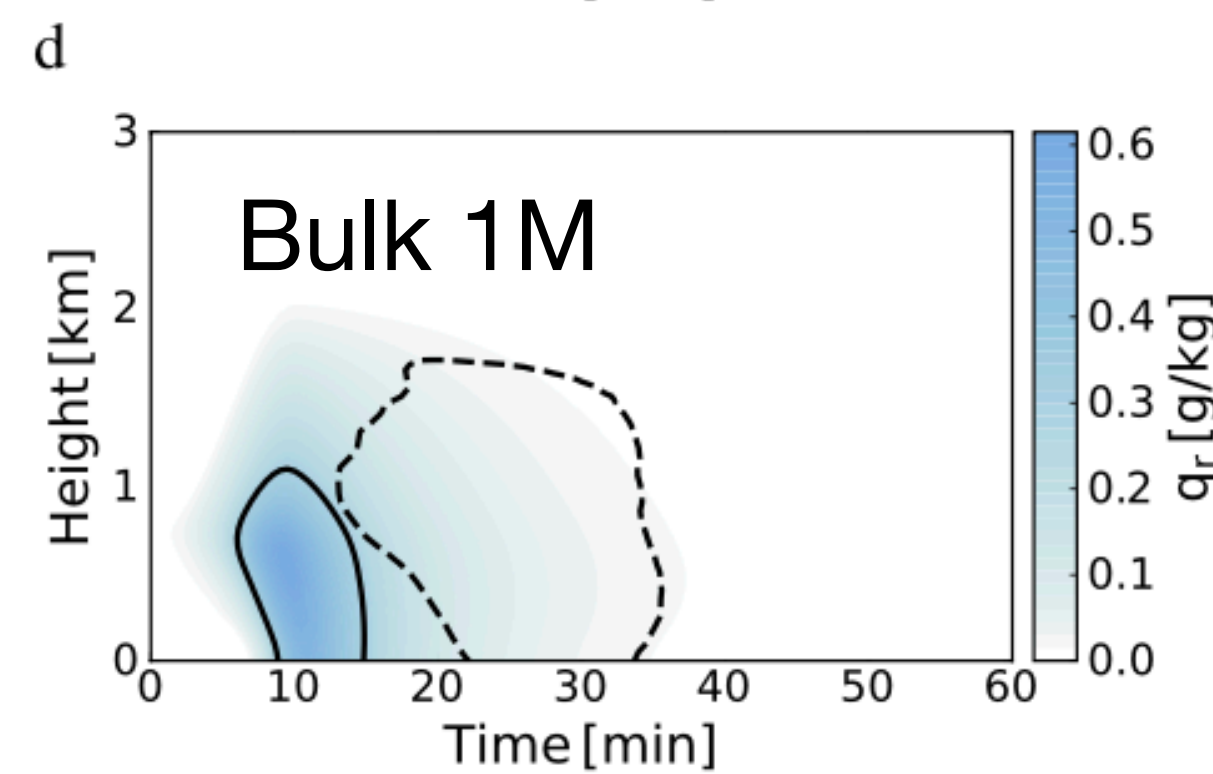


### Calibrated parameters

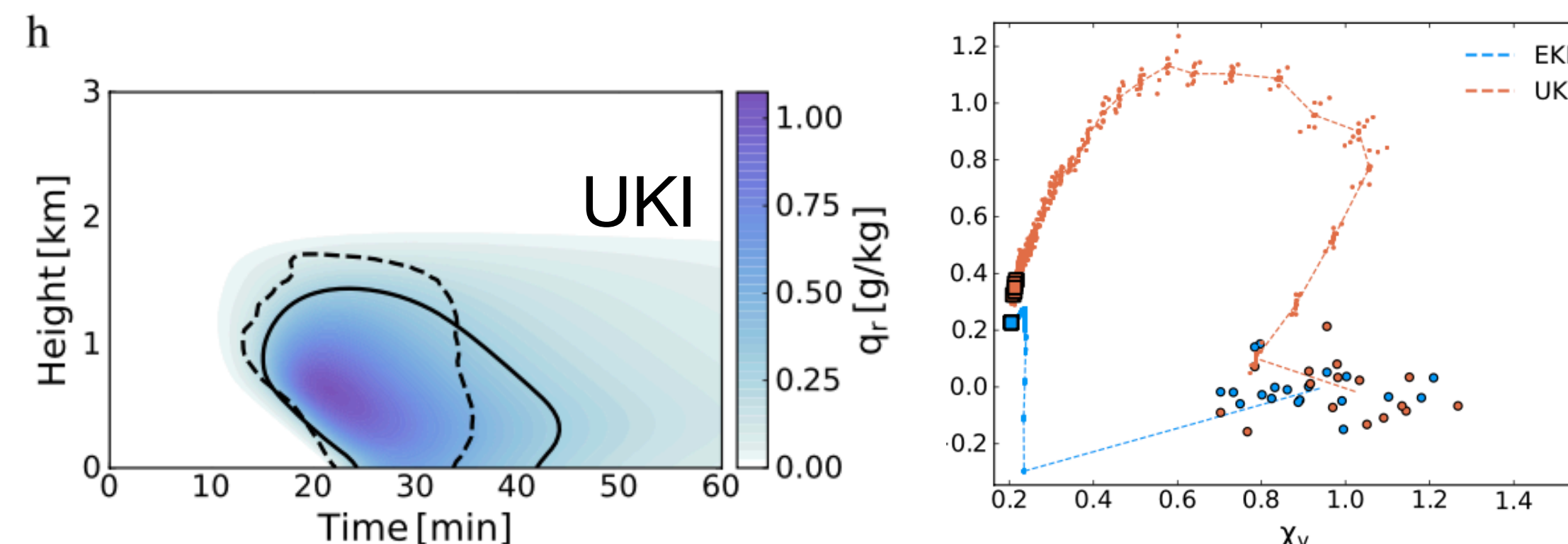
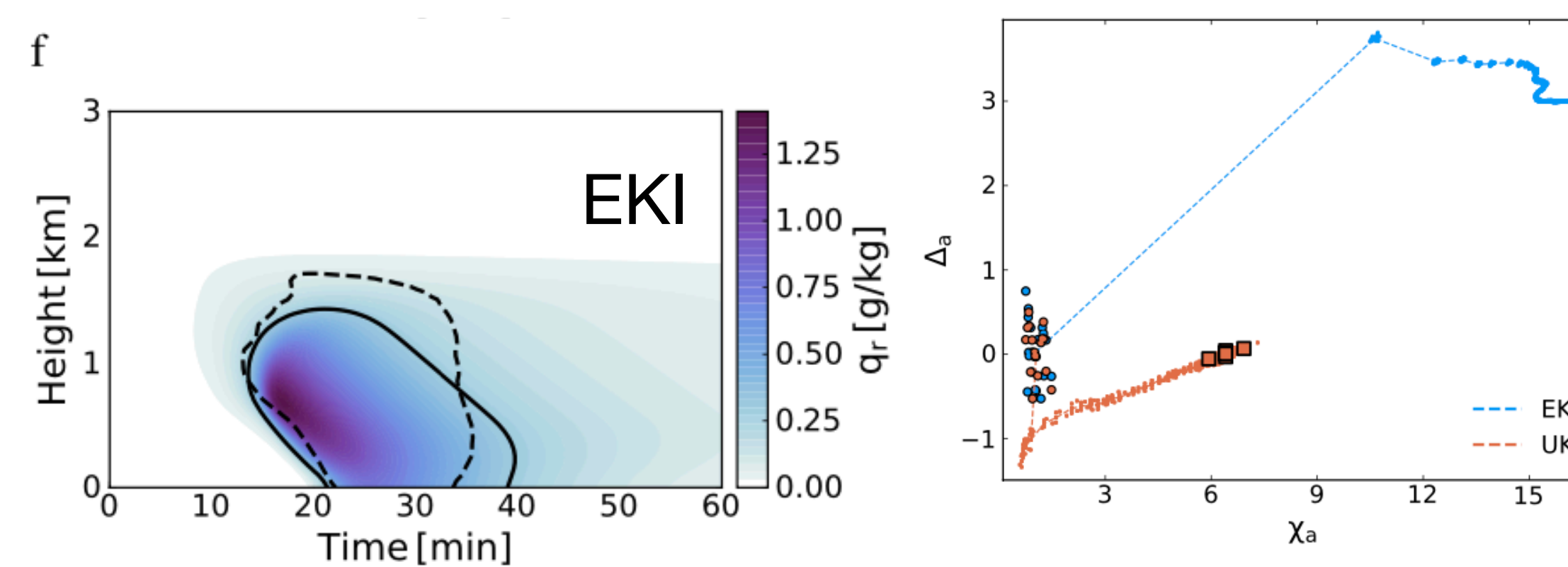
Bulk microphysics scheme parameters  
from Abdul Razzak and Ghan (ARG)  
aerosol activation and 1-moment rain  
formation parameters.



Left panels show the time evolution  
of precipitation in PySDM and in the  
uncalibrated 1-moment bulk scheme  
from the 1D kinematic model.



Right panels show the time  
evolution of precipitation in the bulk  
1-moment scheme after calibration  
using two optimization algorithms  
EKI and UKI. We also show the  
evolution calibrated parameter  
values for EKI and UKI.



- Documentation online for each of the packages
- A hierarchy of tests (unit tests, performance tests, CPU/GPU, integration, reproducibility)
- Tutorials and use examples

[github.com/CliMA](https://github.com/CliMA)

**Microphysics calibrations:** Azimi et al. 2024: Training warm-rain bulk microphysics schemes using super-droplet simulations

**Ensemble Kalman methods:** Huang et al. 2022: Iterated Kalman methodology for inverse problems.

**EDMF:** Tan et al. 2018: An extended eddy-diffusivity mass-flux scheme for unified representation of subgrid-scale turbulence and convection.

**Kinematic driver:** Shipway and Hill 2012: Diagnosis of systematic differences between multiple parametrizations of warm rain microphysics using a kinematic framework.

**Cloud microphysics:** [clima.github.io/CloudMicrophysics.jl/dev/](https://clima.github.io/CloudMicrophysics.jl/dev/)