Estimation of key parameters in cloud microphysics using ensemble Kalman filter

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Introduction

Toward the improvement of weather prediction

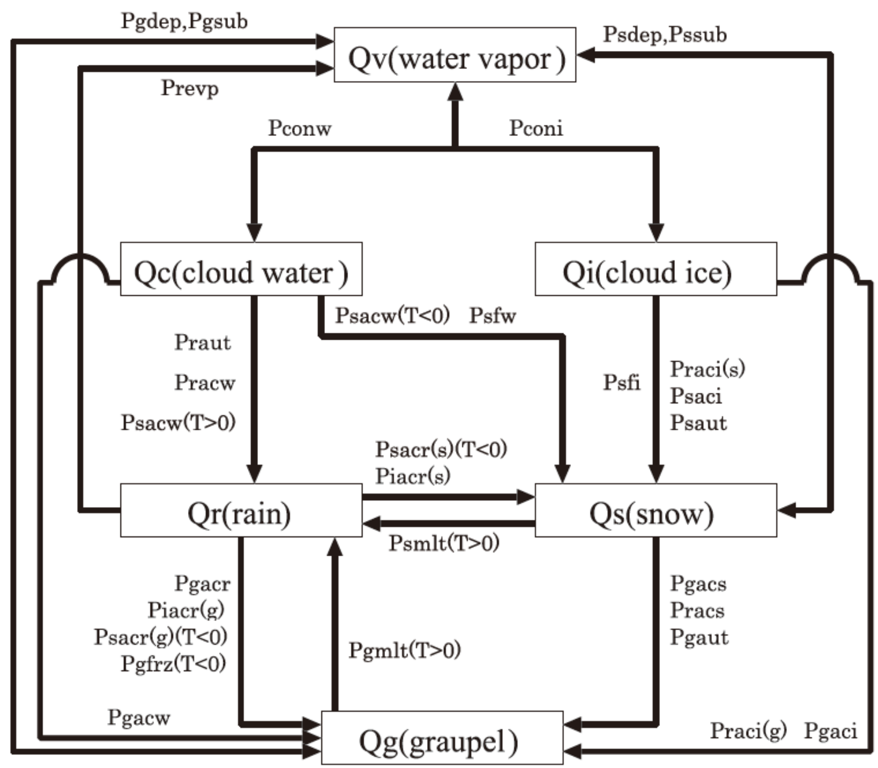
- ✓ **Better model** ← Using data science
- ✓ Better observation
- ✓ Better data assimilation method

Using data science

Introduction

More specifically…

- Components of atmospheric model
  - ➢ Dynamical core, cloud microphysics, turbulence, radiation, …
- In the precipitation forecast, performance of cloud microphysics scheme is particularly important
- Simple bulk microphysics schemes are widely used
  - ➢ Many "tunable" parameters
    - ✓ Terminal velocity,
    - ✓ Auto-conversion rate,
    - ✓ Collection efficiency, …



Tomita (2008), JMSJ, Fig. 1

Introduction

"Optimal" parameter values depend on the situation

- Space and time scales to be simulated
  - ➢ Short-term weather forecast ↔ Long-term climate prediction
- Metrics of interest
  - ➢ Rainfall amount, radiation budget, …

We focus on short-term heavy rainfall prediction

- Need good representation of lifecycle and organization of deep convective clouds

Introduction

But how?

—Parameter estimation using ensemble Kalman filter (EnKF)

- **Tong and Xue (2008), MWR**
  - ✓ **Target**: Size distribution of hail, etc
  - ✓ **Observation**: Radar reflectivity calculated from cloud simulation with known parameter values

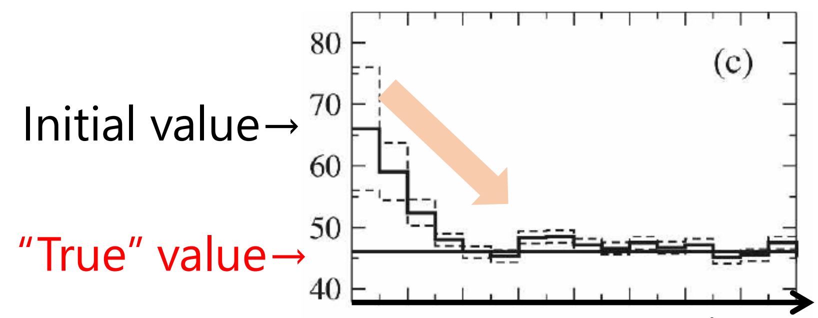


Fig. 1c

- **Kotsuki et al. (2018), JGR**
  - **Target**: Conversion rate of cloud water to rain
  - **Observation**: Global precipitation distribution

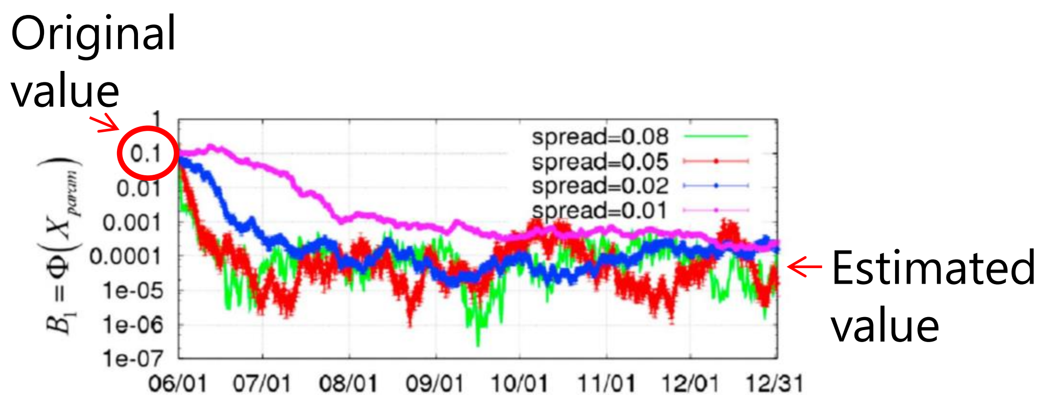


Fig. 4b

Introduction

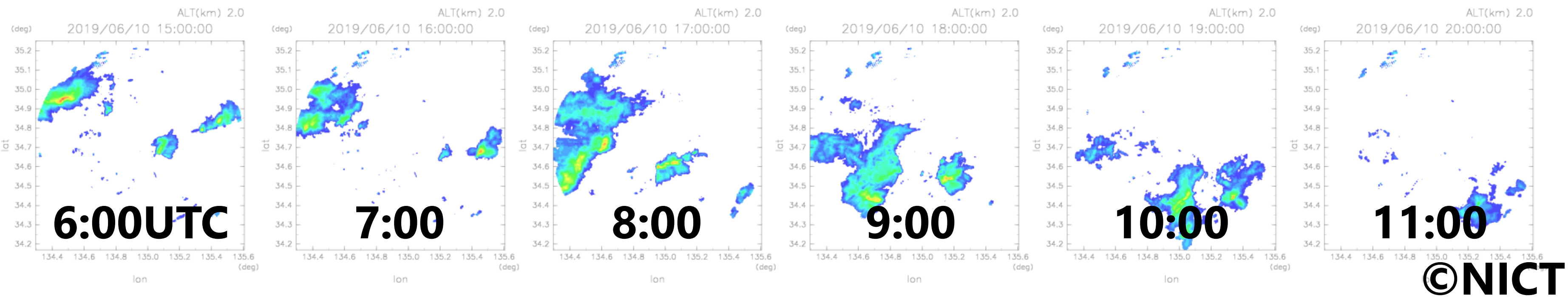
- **Final goal**:
  Find optimal parameters of cloud microphysics scheme focusing on short-term heavy rainfall prediction

- **Present study**:
  Test parameter estimation using the EnKF based method with radar reflectivity data

Today, I introduce our resent efforts to estimate optimal parameters of cloud microphysics scheme

Real data experiments

Case study: Thunderstorm on 10 July 2019



- Well captured by phased array weather radar (PAWR) in Kobe city
  - ➢ 3D reflectivity and doppler velocity, every 30 second

Components of state and parameter estimations

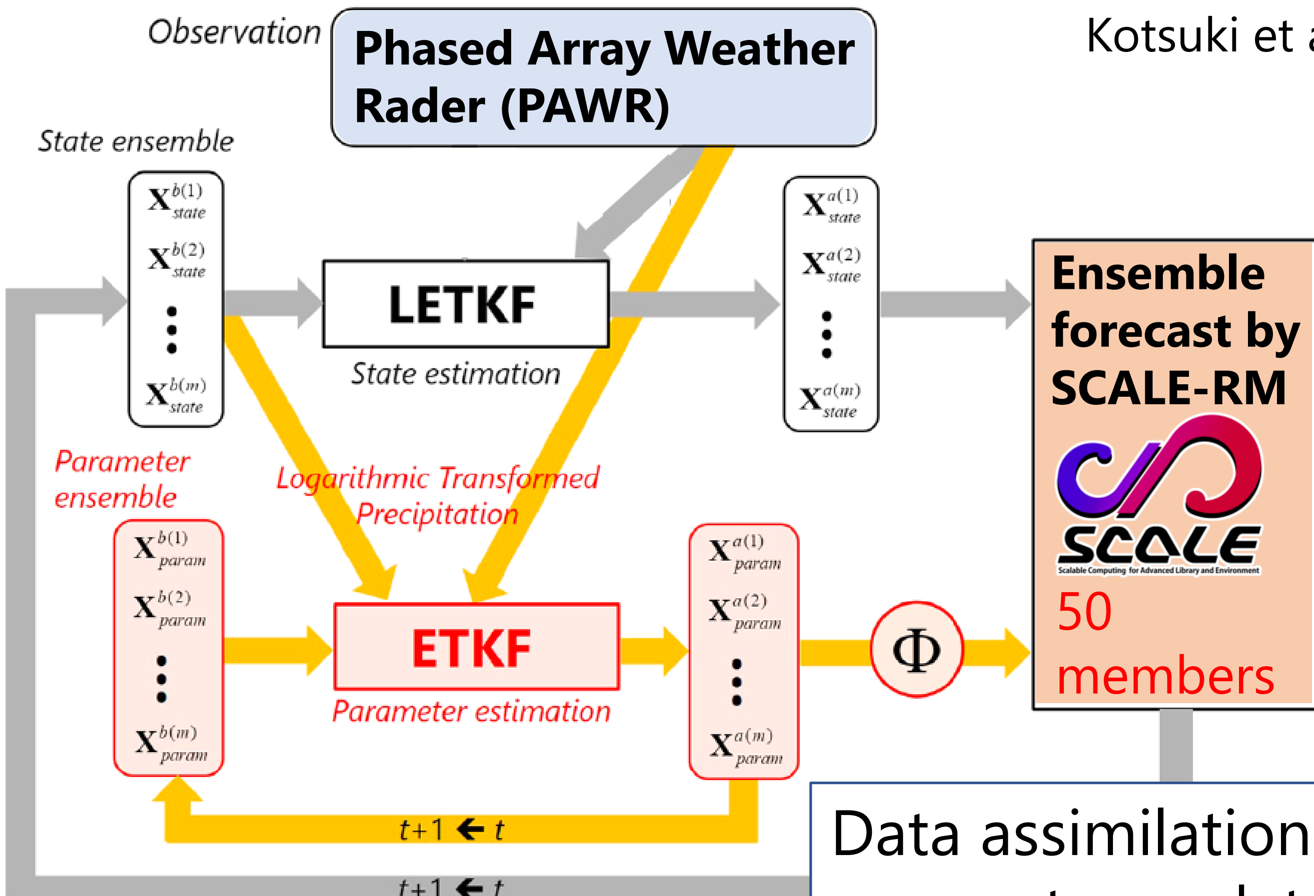
- **Forecast model**: SCALE-RM (Nishizawa et al. 2015; Sato et al. 2015)
- **Observation**: PAWR
- **State estimation**: Local ensemble transform Kalman filter (LETKF; Hunt et al. 2007) (SCALE-LETKF system; Lien et al., 2017)
- **Parameter estimation**: No-localized ETKF

Real data experiments

Schematics

- The figure from Kotsuki et al. (2018)

Modification of Fig. 1 in Kotsuki et al. (2018), JGR



Regional downscaling forecast
Δx = 1 km

Data assimilation and parameter update every 30 s

Real data experiments

Target parameter

- **Scheme**: One-moment bulk microphysics (Tomita 2008)
  - ➢ Choose coefficient of terminal velocity of rain (Cr) as the first test case

$$V_R = \mathrm{Cr}\left(D_R \frac{\rho_0}{\rho}\right)^{1/2}$$

$V_R \propto \mathrm{Cr}$
(Default value: Cr = 130)

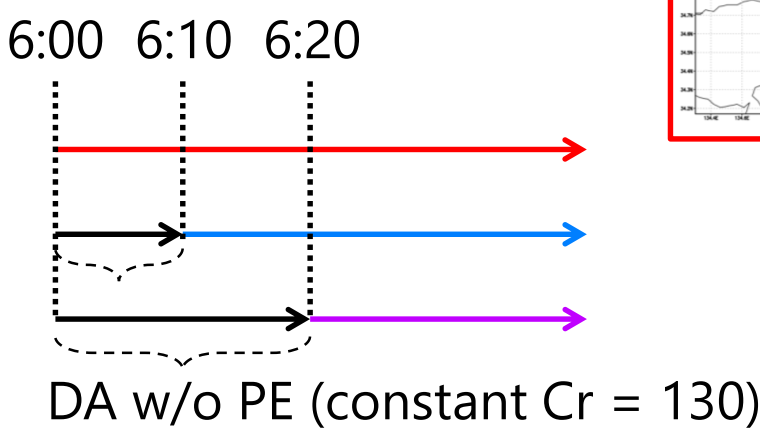
  - ➢ Why "Cr"?
    - ✓ Directly changes the radar reflectivity distribution
    - ✓ Greatly impacts the rainfall amount

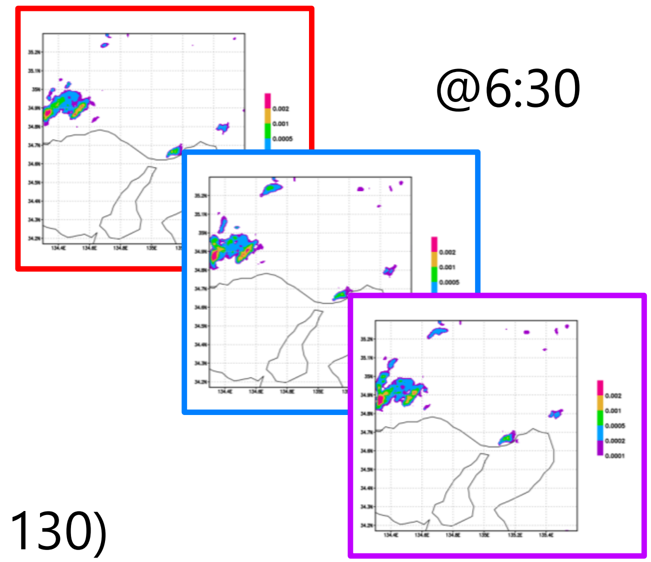
Real data experiments

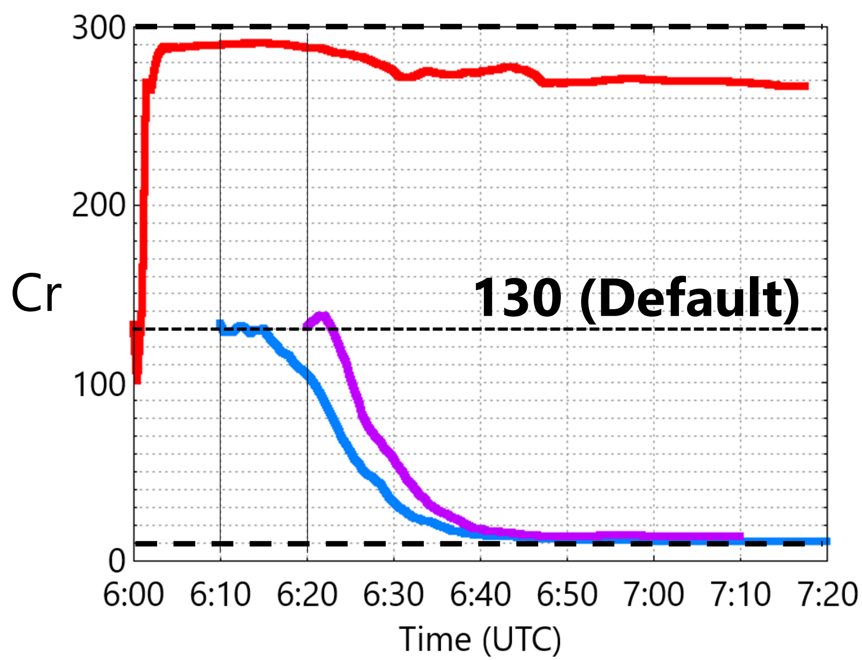
Results

- Different initial time

PE from 06:00UTC
PE from 06:10UTC
PE from 06:20UTC







- Converged value depends on the initial time
- The value approaches to the preset maximum or minimum

Hmm…
It's difficult

Real data experiments

Many challenges in achieving parameter estimation using radar observation of real clouds

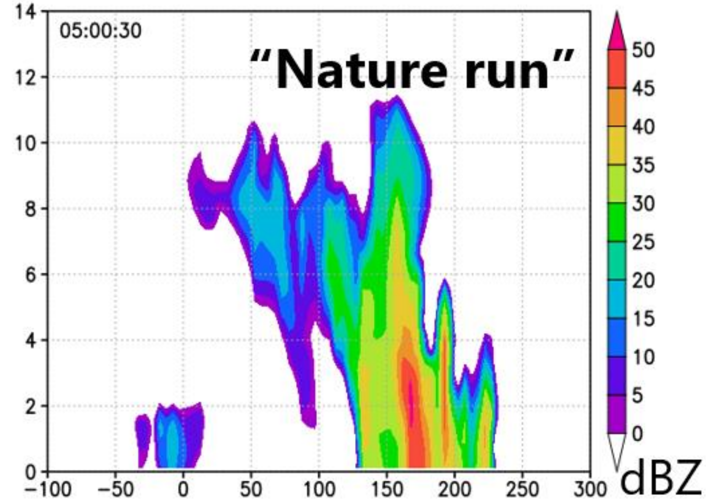
- Large time fluctuation,
- Inconsistency between "nature" and model resolution,
- In addition, the experiments are computationally costly, …

➢ Back to simpler "idealized" experiments

Idealized experiments

Idealized 2D (x-z) squall line simulation

- Δx = 5 km, Δz = 250 m
- Tomita (2008) microphysics (Cr = 130)
- Horizontally homogeneous initial condition (Same as Weisman and Klemp 1982)

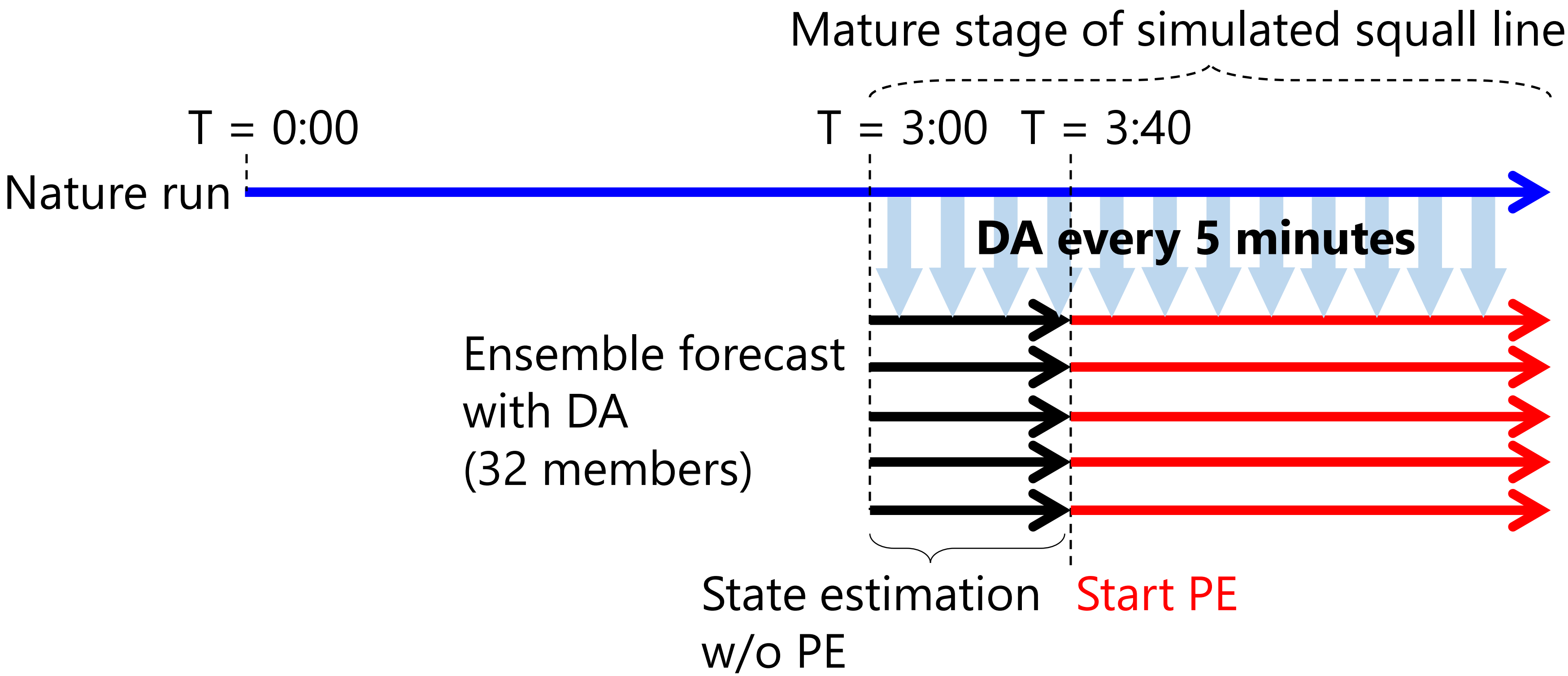


Observation

- State estimation by LETKF
- Parameter (Cr) estimation by ETKF
  - ✓ Same model setup as nature run except the parameter to be estimated
  - ✓ 32 ensemble members
  - ✓ 5 minutes DA cycle
  - ✓ Observation error assumption: 1 dBZ

Idealized experiments

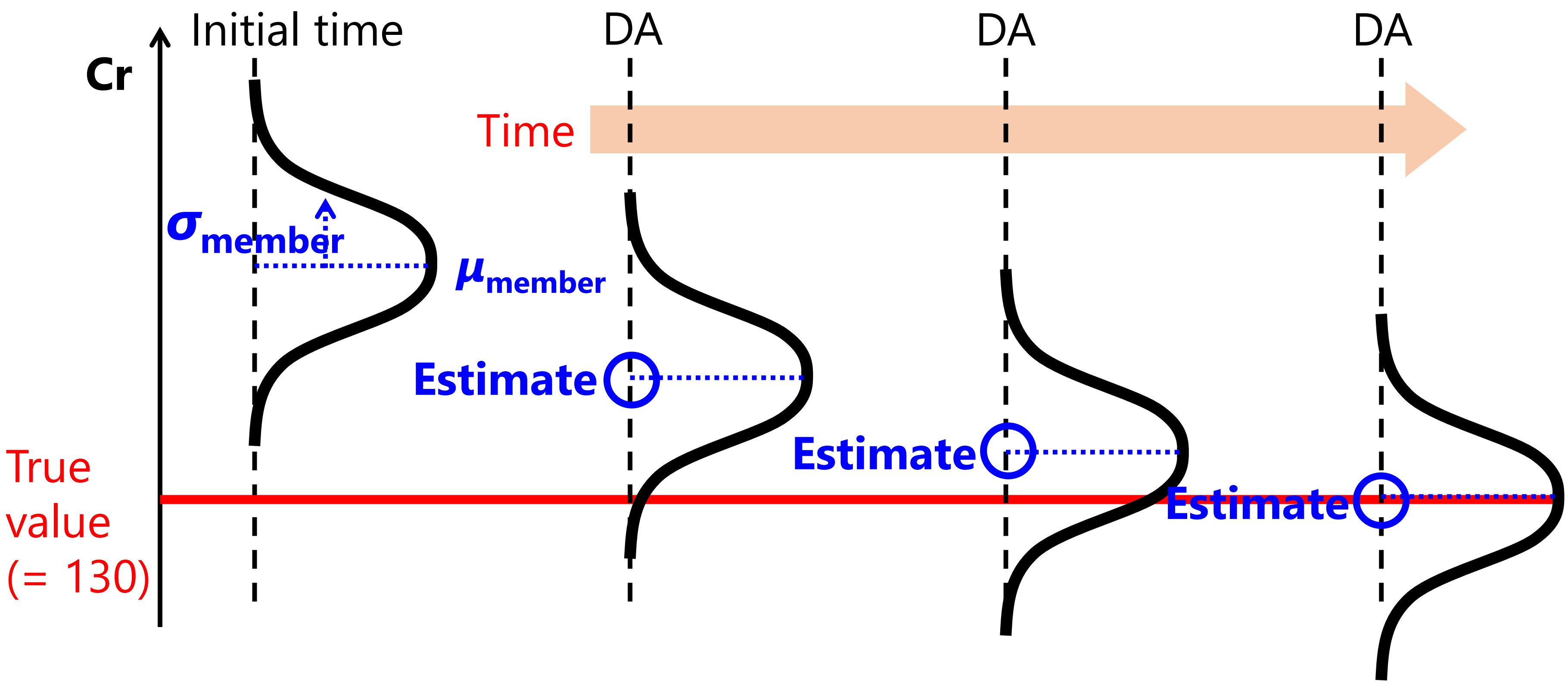
Timeseries



Idealized experiments

Concept

- Test the **feasibility** of parameter estimation for cloud microphysics

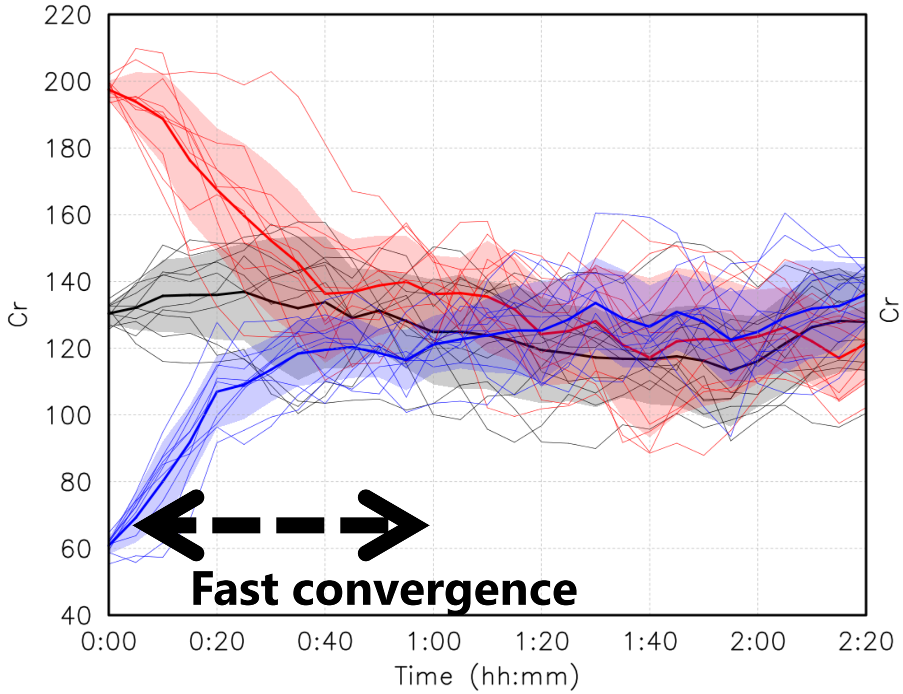


- Initial Cr distribution for 32 ensemble members (**Gaussian**)
  - ✓ Mean (μ_{member}): **200** (= true + 70), **60** (= true – 70), and **130** (= true)
  - ✓ Standard deviation (σ_{member}): **7.5**, **15**

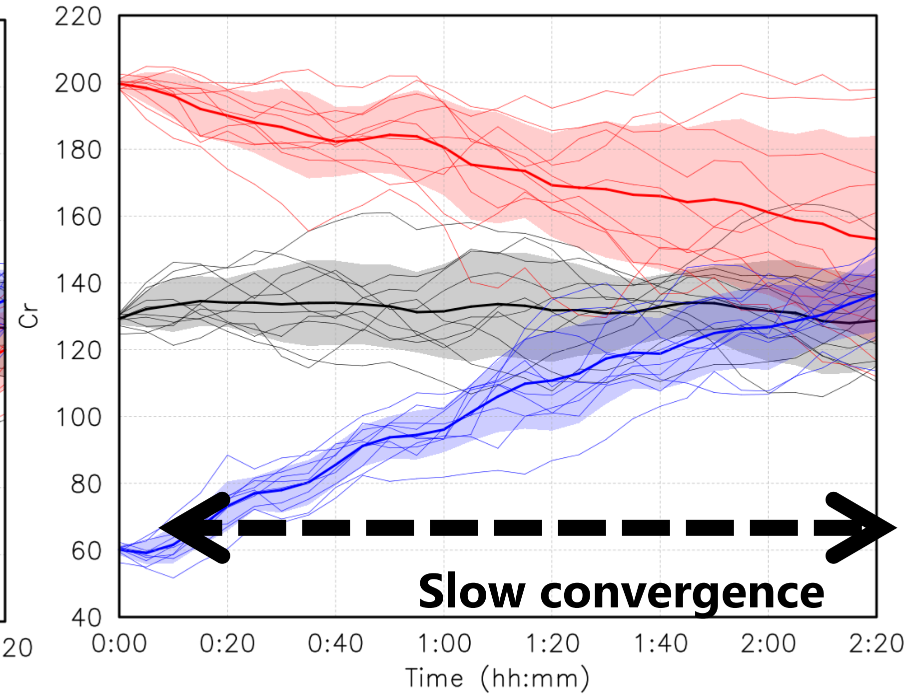
Idealized experiments

Results 1: Convergence speed to true value

Larger variance (σ = 15.0)



Smaller variance (σ = 7.5)

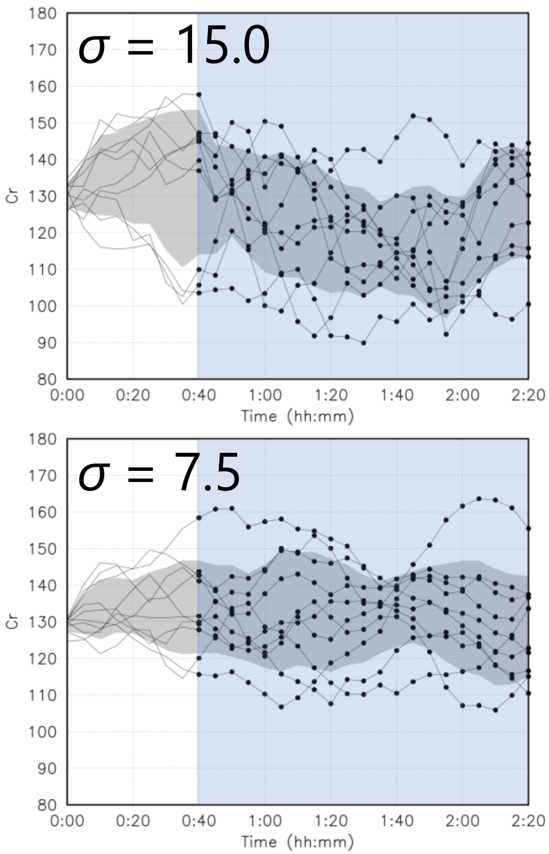


*10 trials with slightly different initial Cr values for each experiment

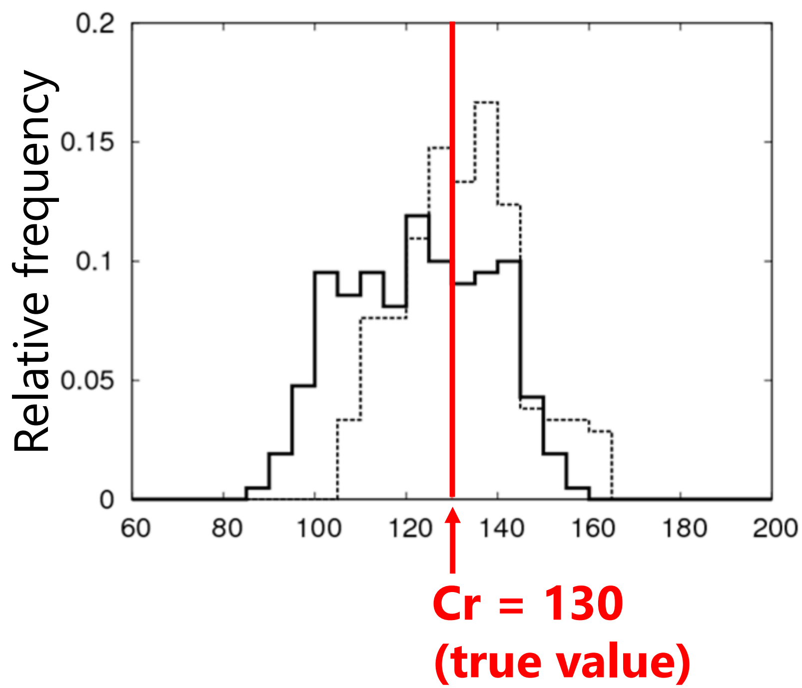
- Estimations start from μ_{member} = 200 and 60 approach the true value
  - ➢ If the model is perfect, estimation of Cr from radar data is possible!
- Ensembles having larger variance converge quickly

Idealized experiments

Results 2: Estimation accuracy



Distribution of estimated Cr values after 40 minutes



Solid line:

$\boldsymbol{\sigma_{member}}$ **= 15.0**

- Mean = 122.6
- Standard deviation = 15.6

Broken line:

$\boldsymbol{\sigma_{member}}$ **= 7.5**

- Mean = 131.9
- Standard deviation = 13.0

- Comparison of the uncertainty: 15.6 > 13.0 by the F test
  - Ensembles having smaller variance provide smaller uncertainty of the estimation

Summary

- We have started the efforts to estimate the optimal parameters for cloud microphysics scheme by using the EnKF based method
- Parameter estimation based on real radar observation is challenging at present
- Idealized experiments show the feasibility of parameter estimation for cloud microphysics
- We found that estimation speed and accuracy are trade-off

On going research

- Clarify the optimal ensemble variance for estimating the true value with the highest accuracy
- Discuss relationships between the accuracy of parameter estimation and deep convection dynamics
- Test other key parameters such as terminal velocity of snow, graupel, and evaporation rate of rain