Stochastic and machine learning assisted models of population dynamics of convective clouds and their applications to parameterization

Samson Hagos, Jingyi Chen, Katelyn Barber, Koichi Sakaguchi, Zhe Feng, Heng Xiao and Bob Plant

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

April 8, 2021

Objective:

How do we represent the interaction among clouds and resulting evolution of cloud populations in models? populations in models?

A brief history

General energy cycle

(Arakawa and Schubert 1974)

$$\frac{dA_i}{dt} = -\sum_{j=1}^{N} \gamma_i M_{Bj} + F_i$$

Work function tendency

Forcing

1970

Progress since Arakawa and Schubert (1974)

- Quasi-equilibrium assumption

2000

- Stochastic variations about quasi-equilibrium

  (Craig and Plant 2008, Wang et al. 2016, Wang et al. 2021)

2010

- Cloud population models

  (Wagner and Graf 2010)

A machine Learning Assisted cloud population Model-based Parameterization (LAMP)

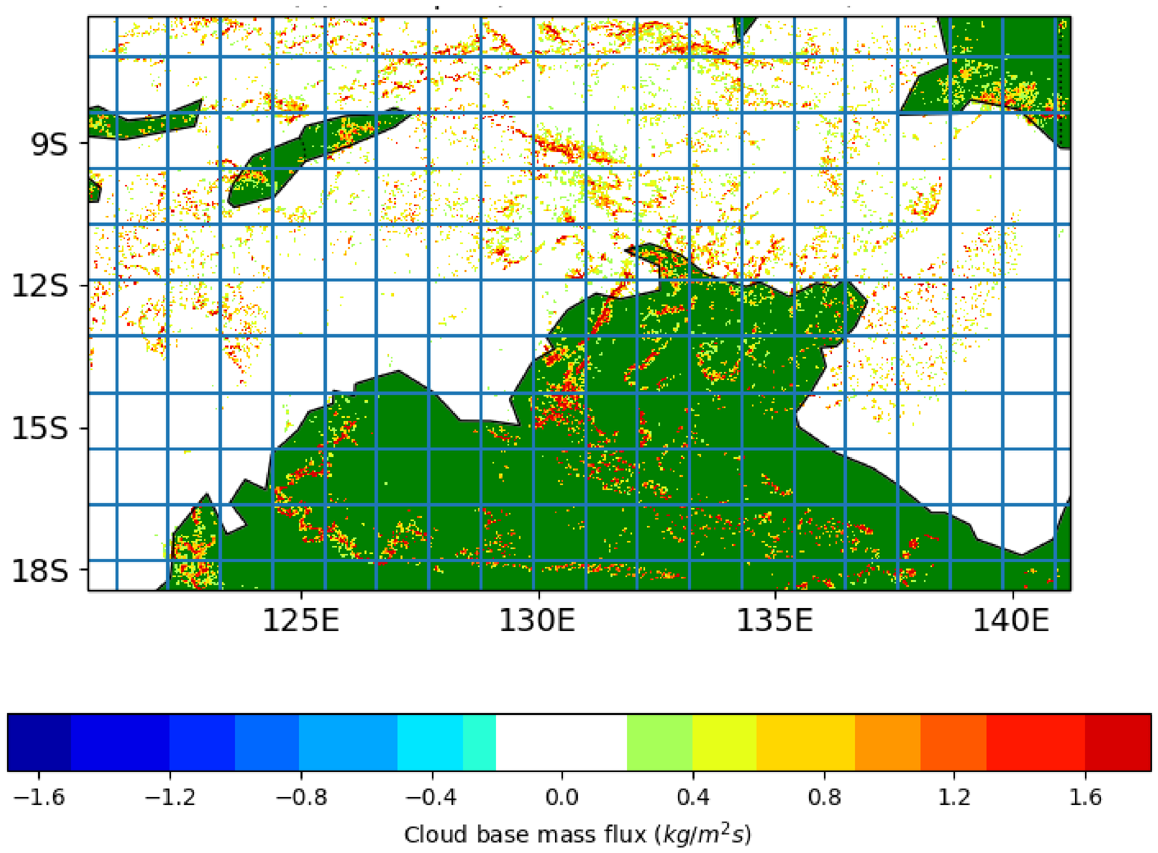
(a) Development

Transition function.

$$dc = f(c)dA_c$$

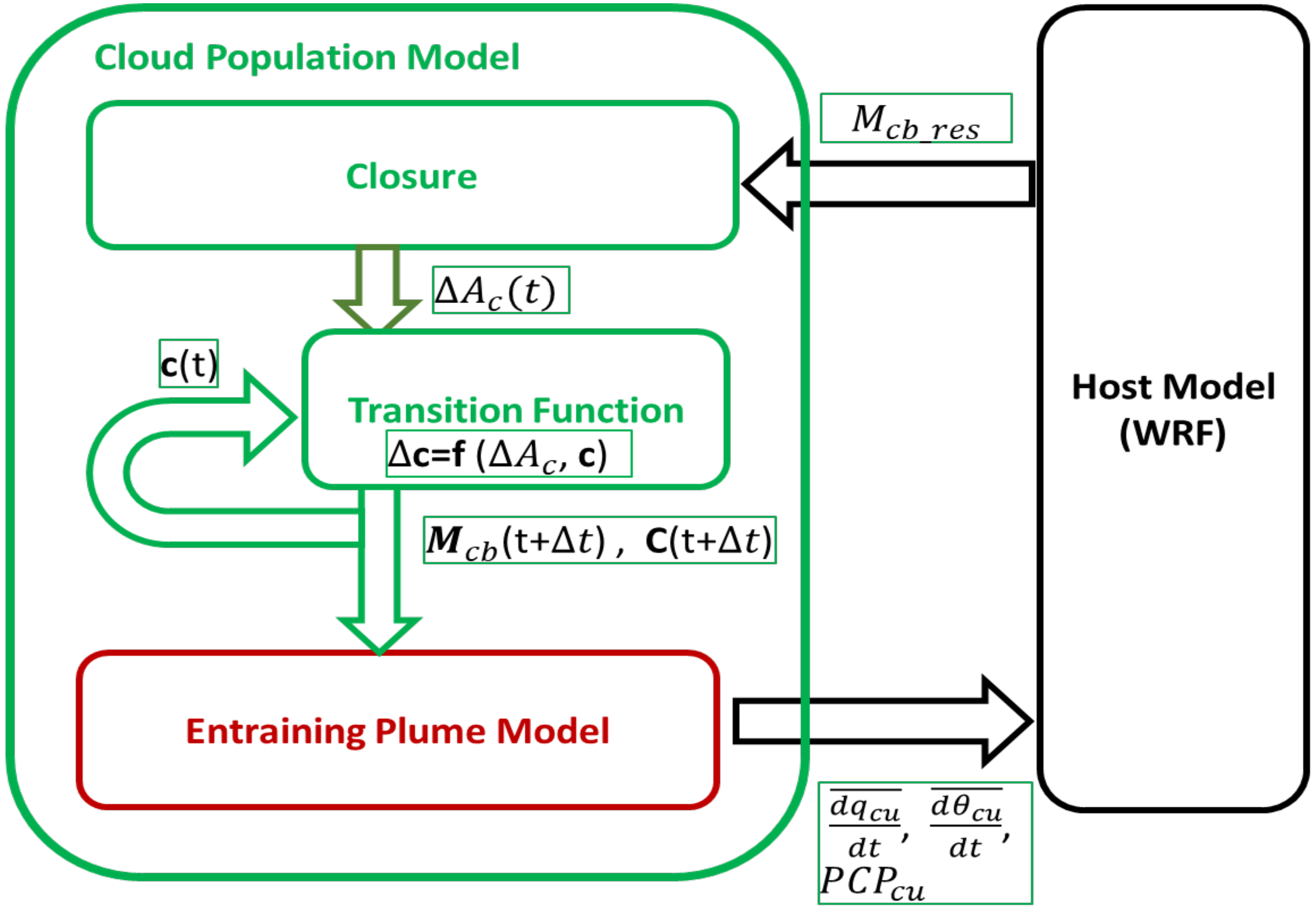
Change in the total convective area in the grid box.

Change in the area contributed by cells of size c.



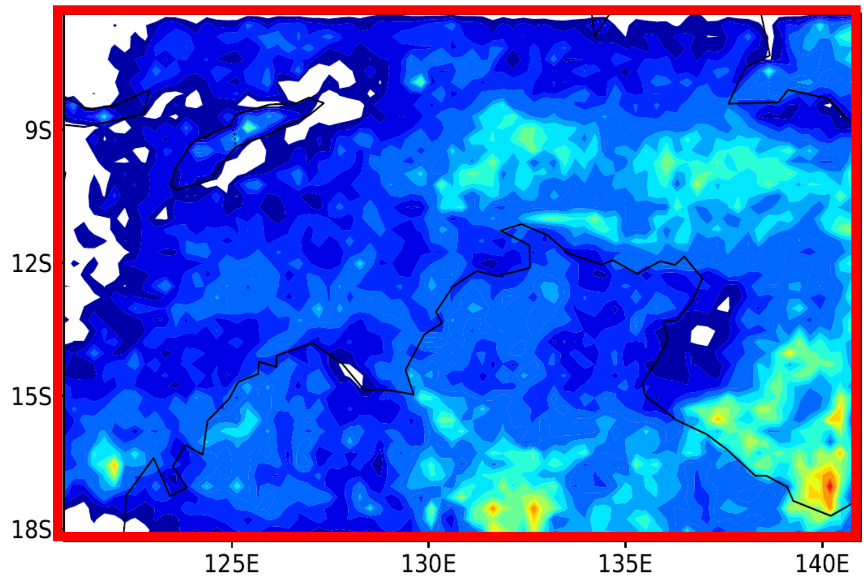
Design

- Determine $f(\boldsymbol{c})$ from a high-resolution simulation using machine learning
- Determine dA_c from the host model (WRF)
- Develop a cloud model
- Couple and optimize

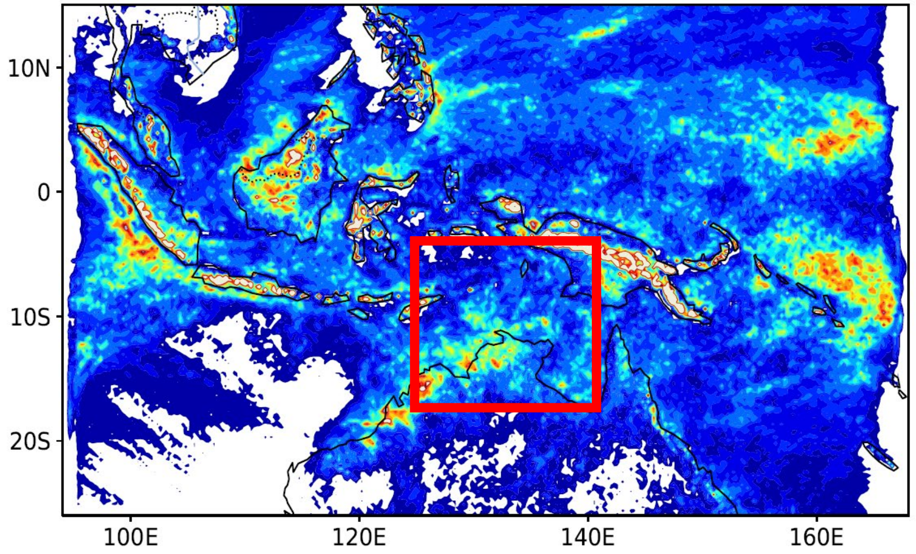


Training and Control Simulations

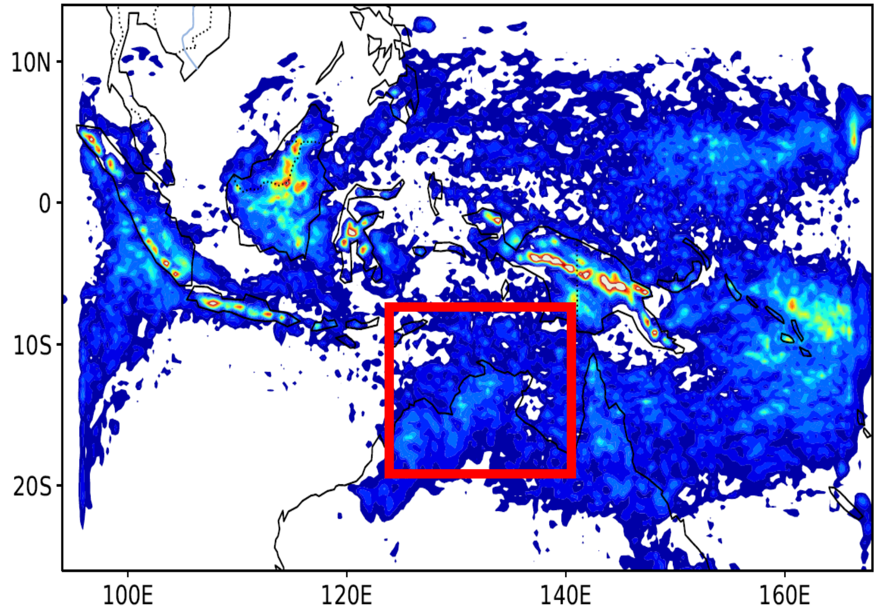
WRF-CPM (1km) Training simulation

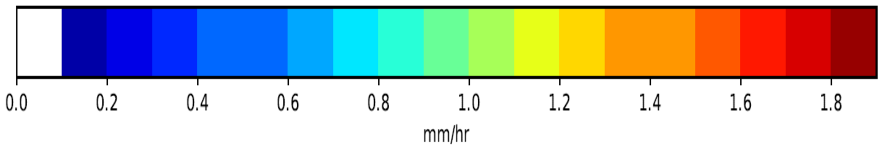


WRF-CTL (8km) Control simulation



WRF-CTL (25km) Control simulation





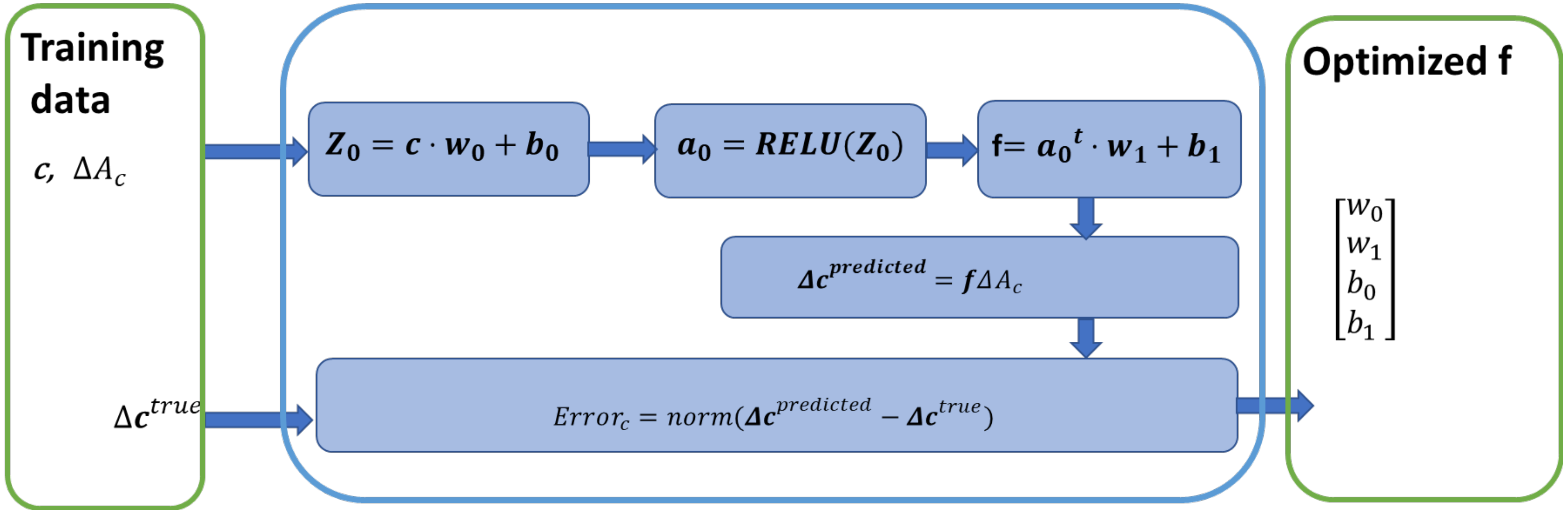
Simulation design

- No cumulus parameterization
- ERA5 SST and lateral boundary conditions
- Thompson microphysics scheme
- MYJ PBL scheme

Determining $f(c)$ from a high-resolution simulation using machine learning

c_i area in a 100km grid box covered by cloud base mass flux in m_{cbi} bin.

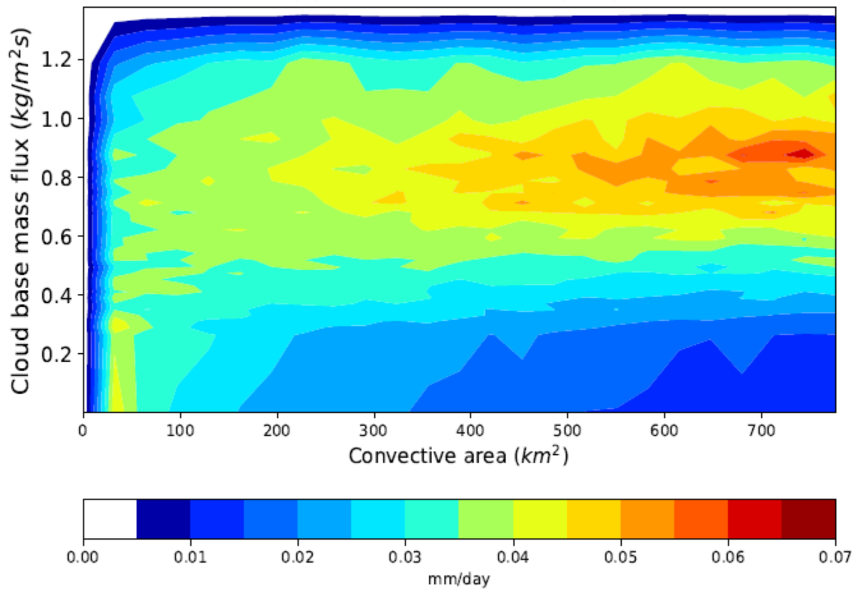
The algorithm



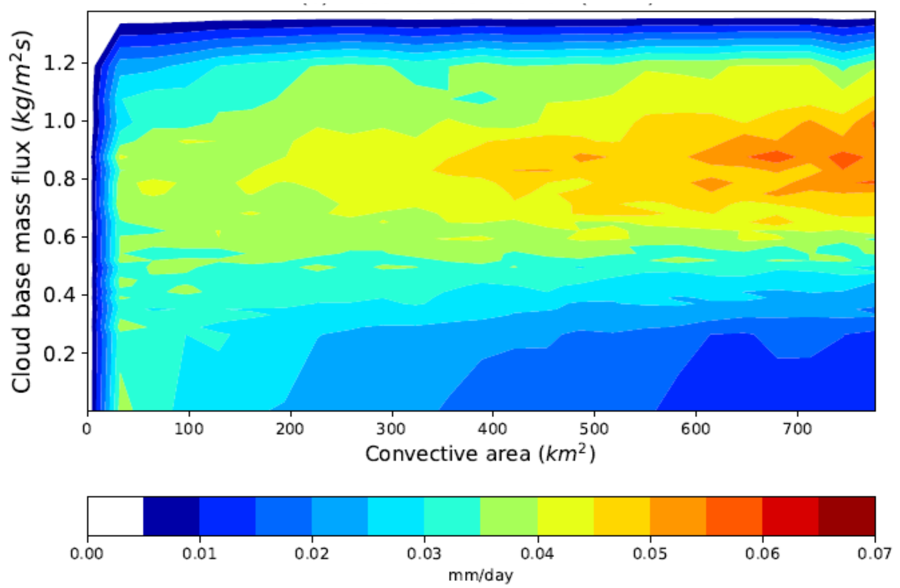
- Successive c and A_c are extracted from the 1km grid spacing training CPM simulation.
- 40,000 pairs of 10-minute frames are used for training. The machine learning code is written in TensorFlow™

Evaluation

Cloud base mass flux distribution (CPM)



Cloud base mass flux distribution (LAMP)

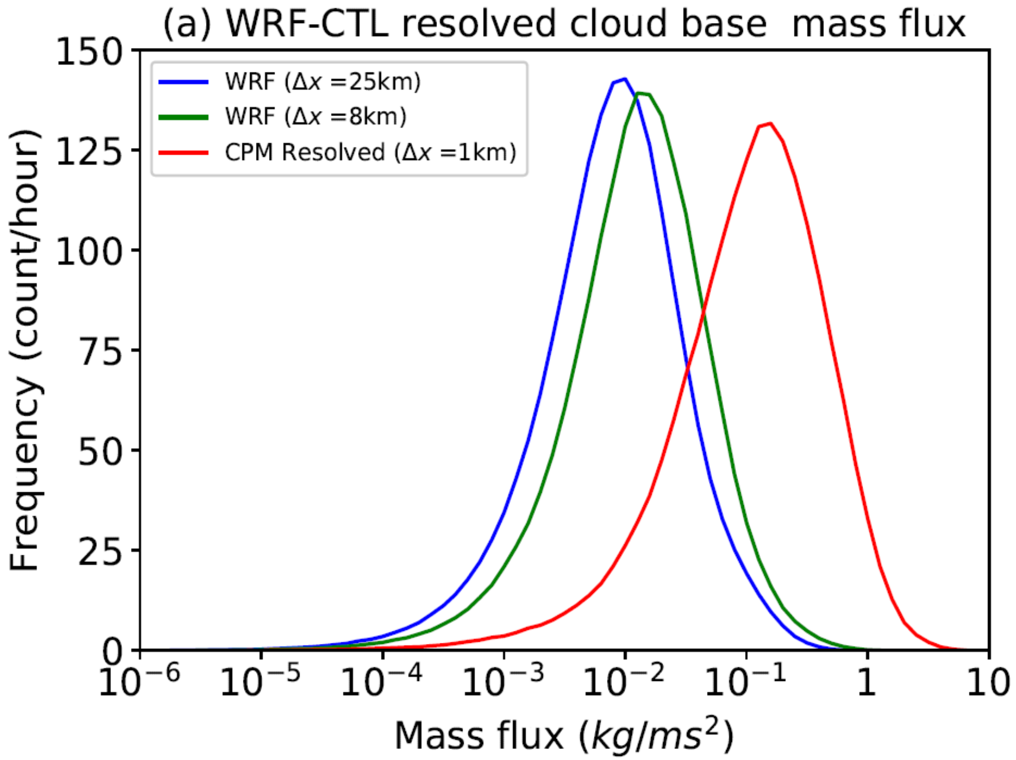


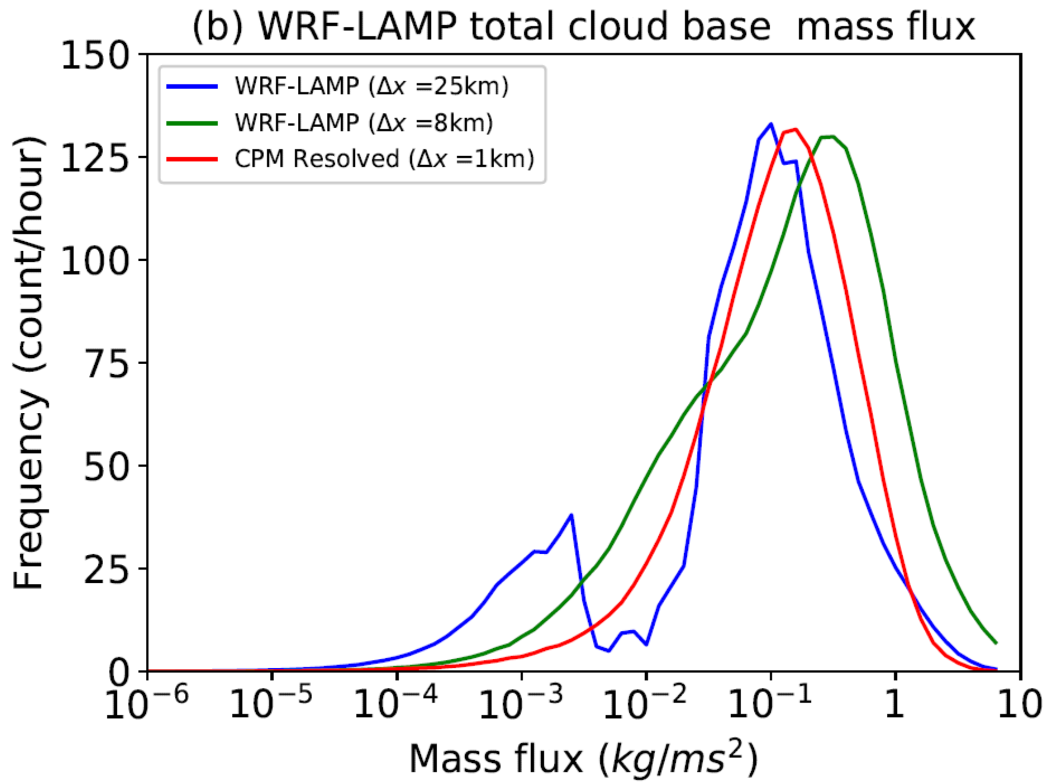
- The machine learning assisted model captures the relationship between cloud base mass flux statistics and convective area, particularly the transition to organized convection.

Closure

The convective area tendency is set to be proportional to resolved cloud base mass flux

$$A_c = \alpha(\Delta x) M_{cb\_res} \qquad \alpha(\Delta x) = \beta_{25km}\left(e^{\left(\frac{\Delta x - 1km}{25km - 1km}\right)} - 1\right)$$

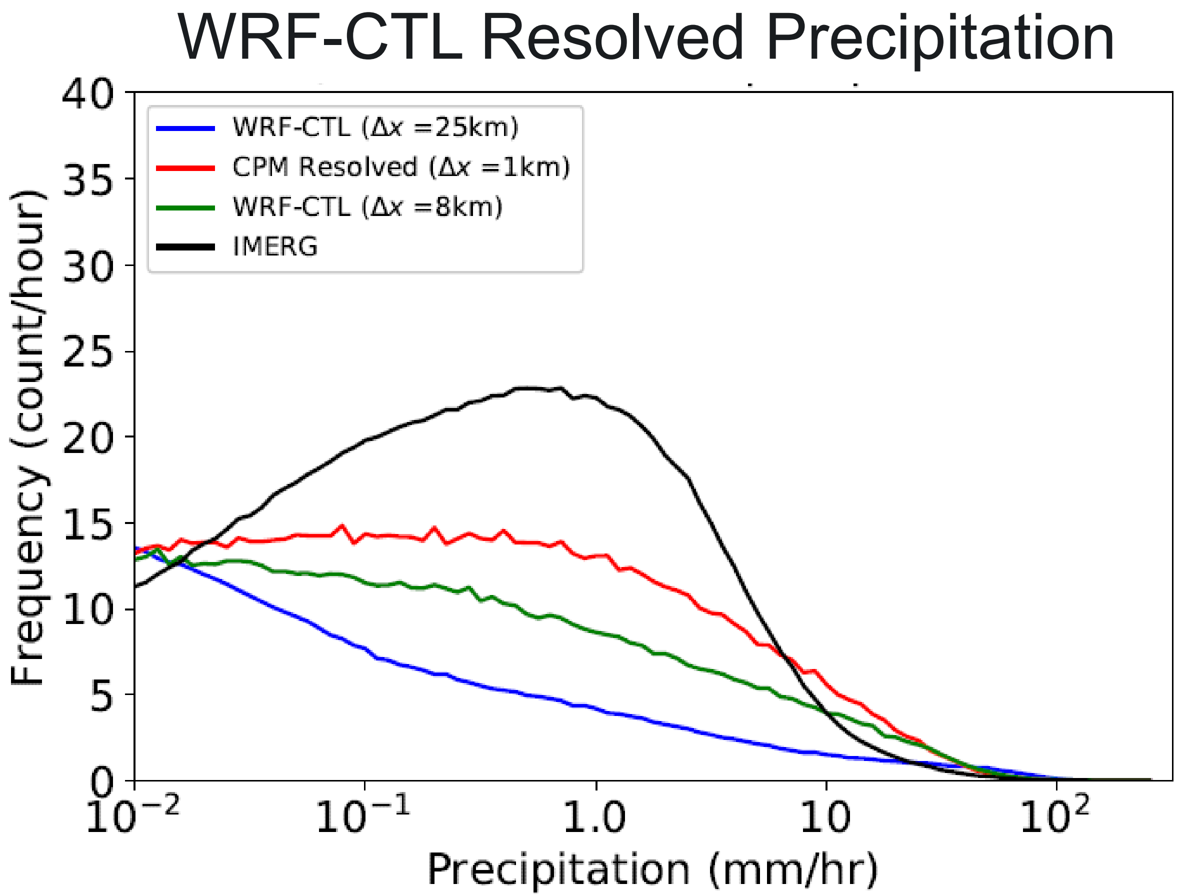


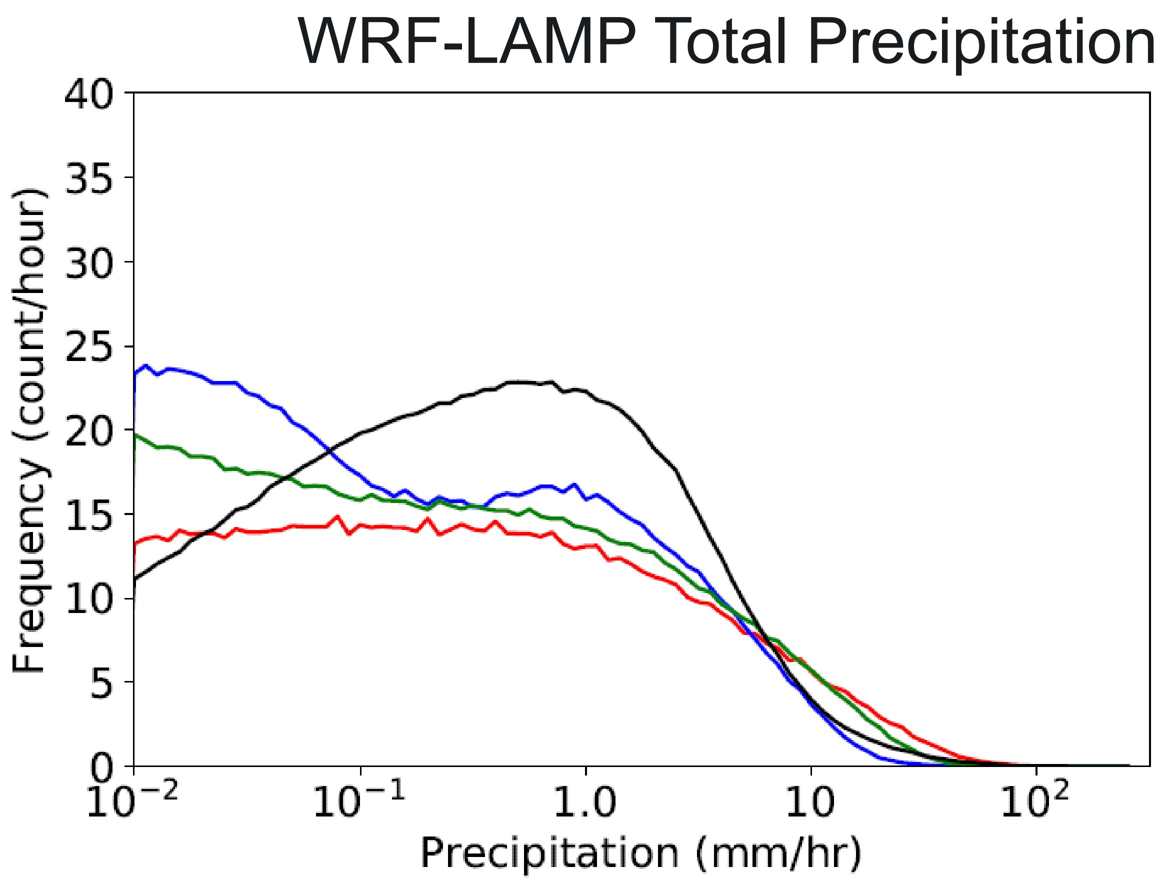


- The artificial separation between “large-scale” and “convective scale” is replaced by the requirement that **the sum of the resolved and parameterized cloud base mass flux be insensitive to grid spacing**.

Evaluation

Frequency distribution of precipitation over Australian monsoon region

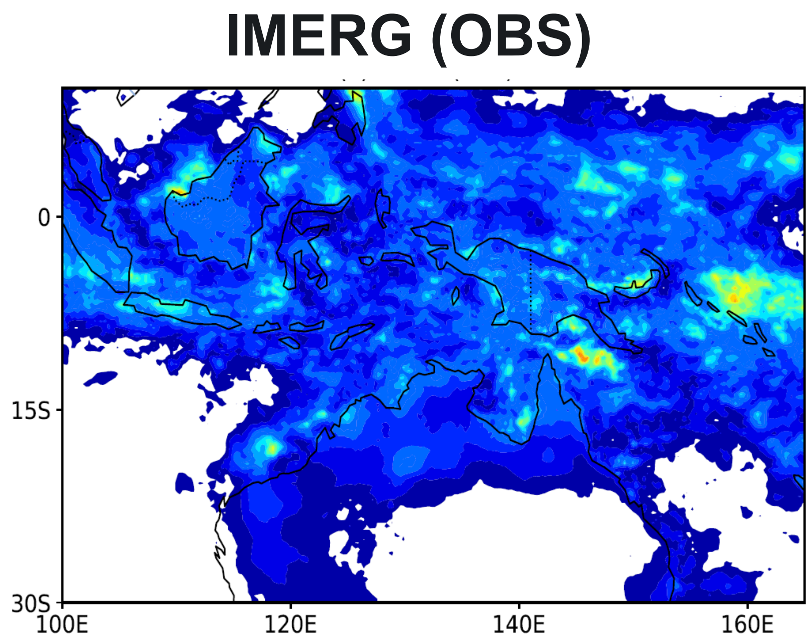


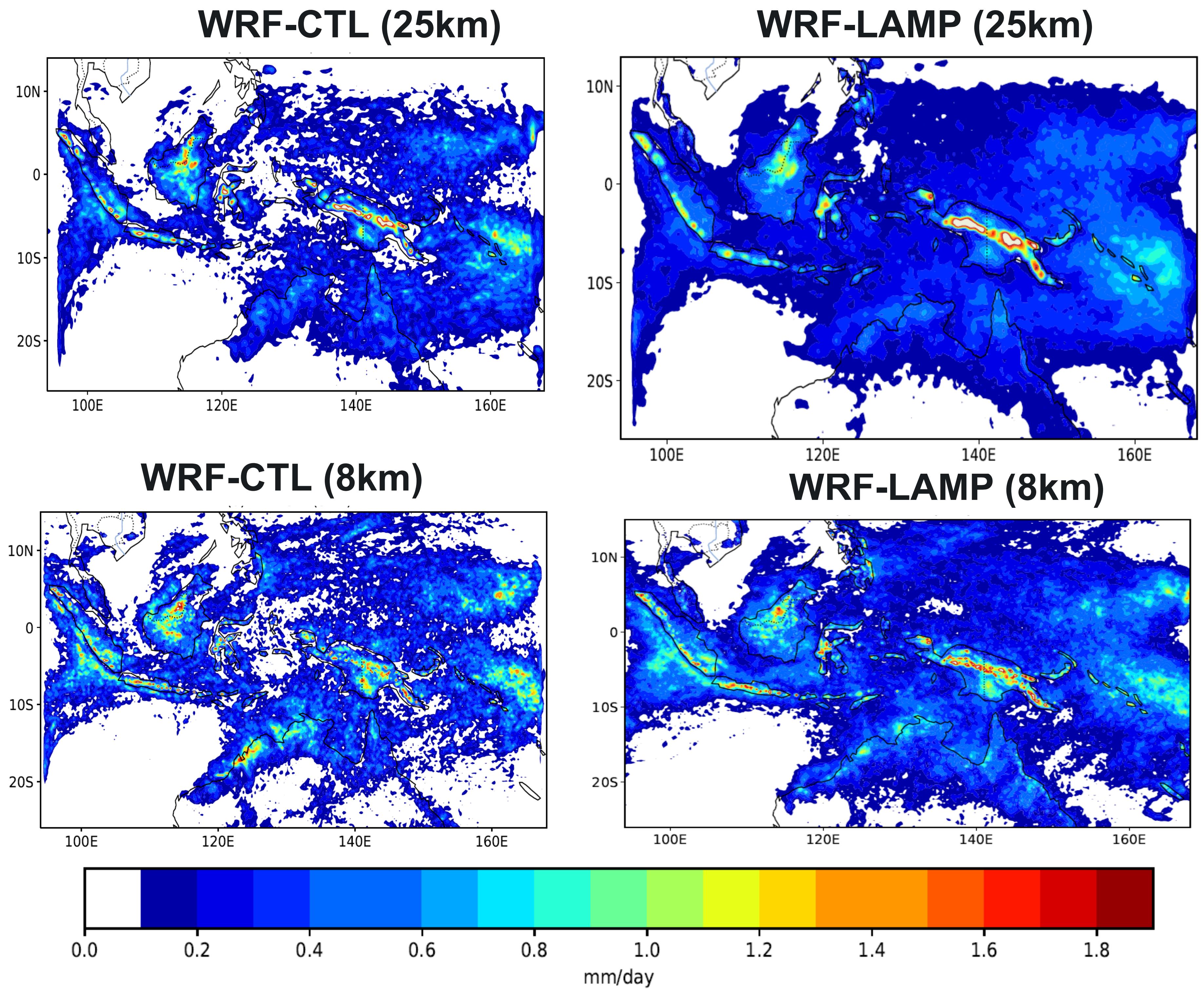


- Frequency of moderate precipitation increases
- That of high intensity precipitation decreases

Evaluation

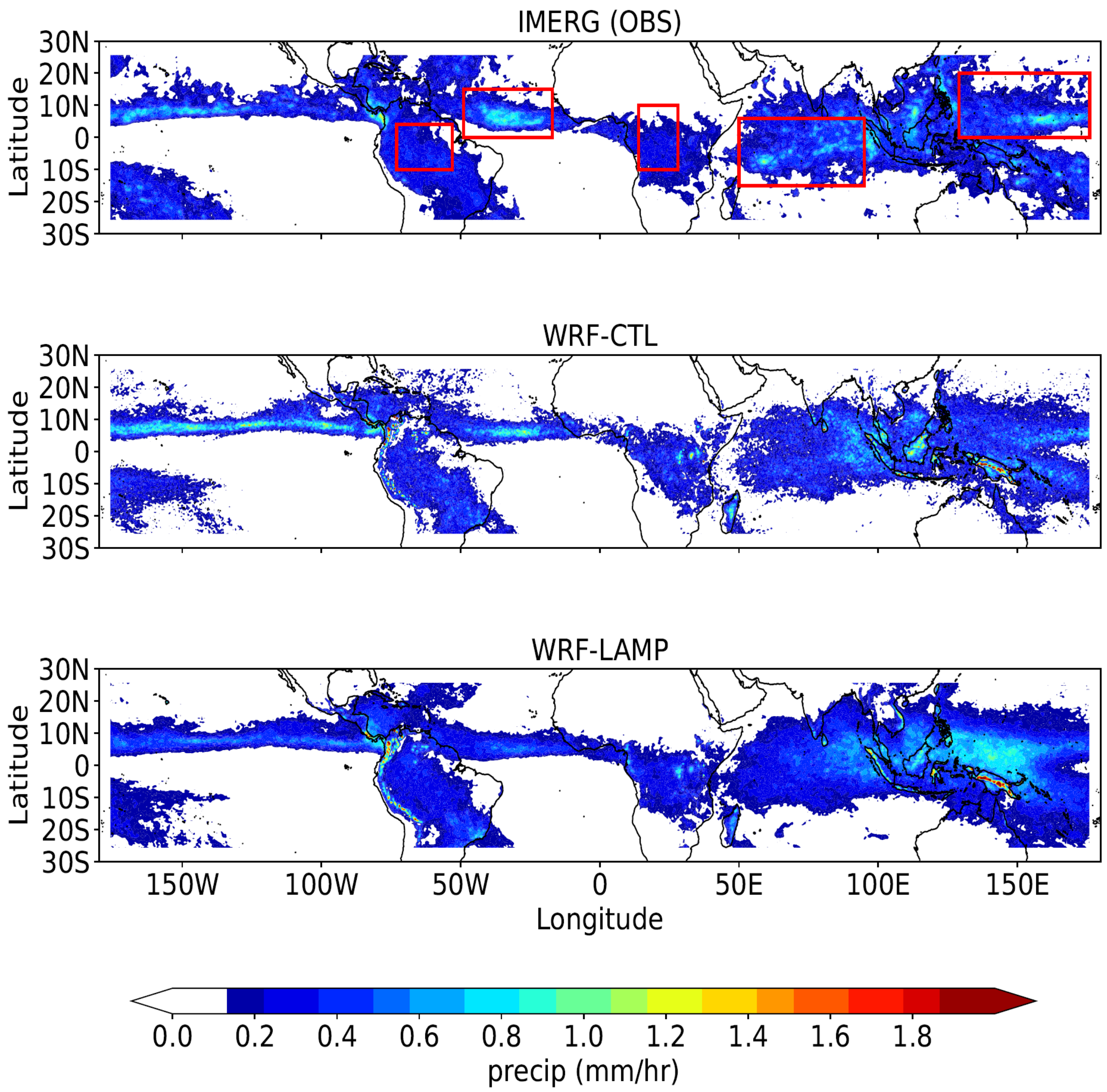
Australia and MC region (Jan-Feb 2006)

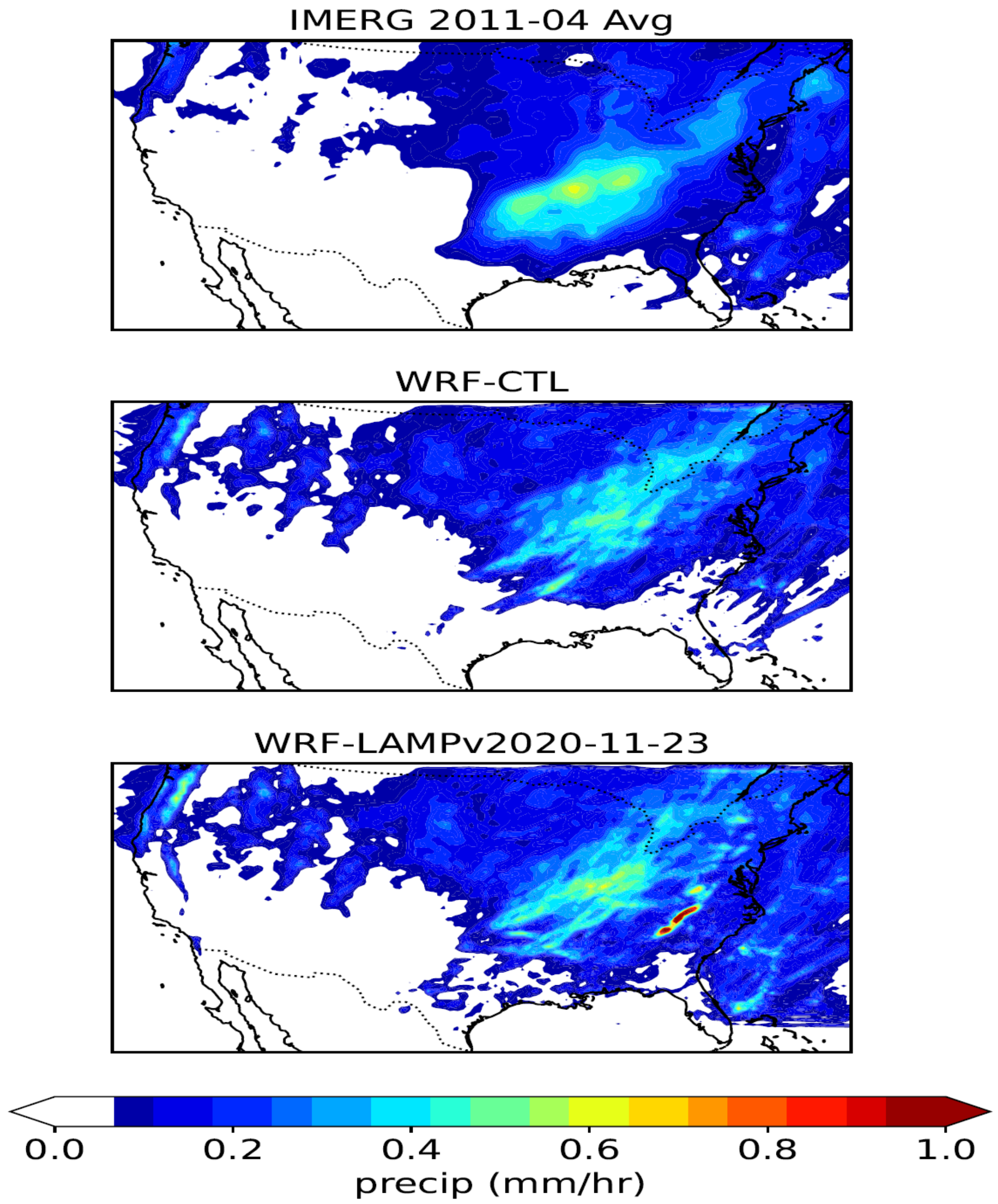




- WRF-LAMP increases precipitation both over water and land correcting the dry bias over water but overestimating precipitation over orography.

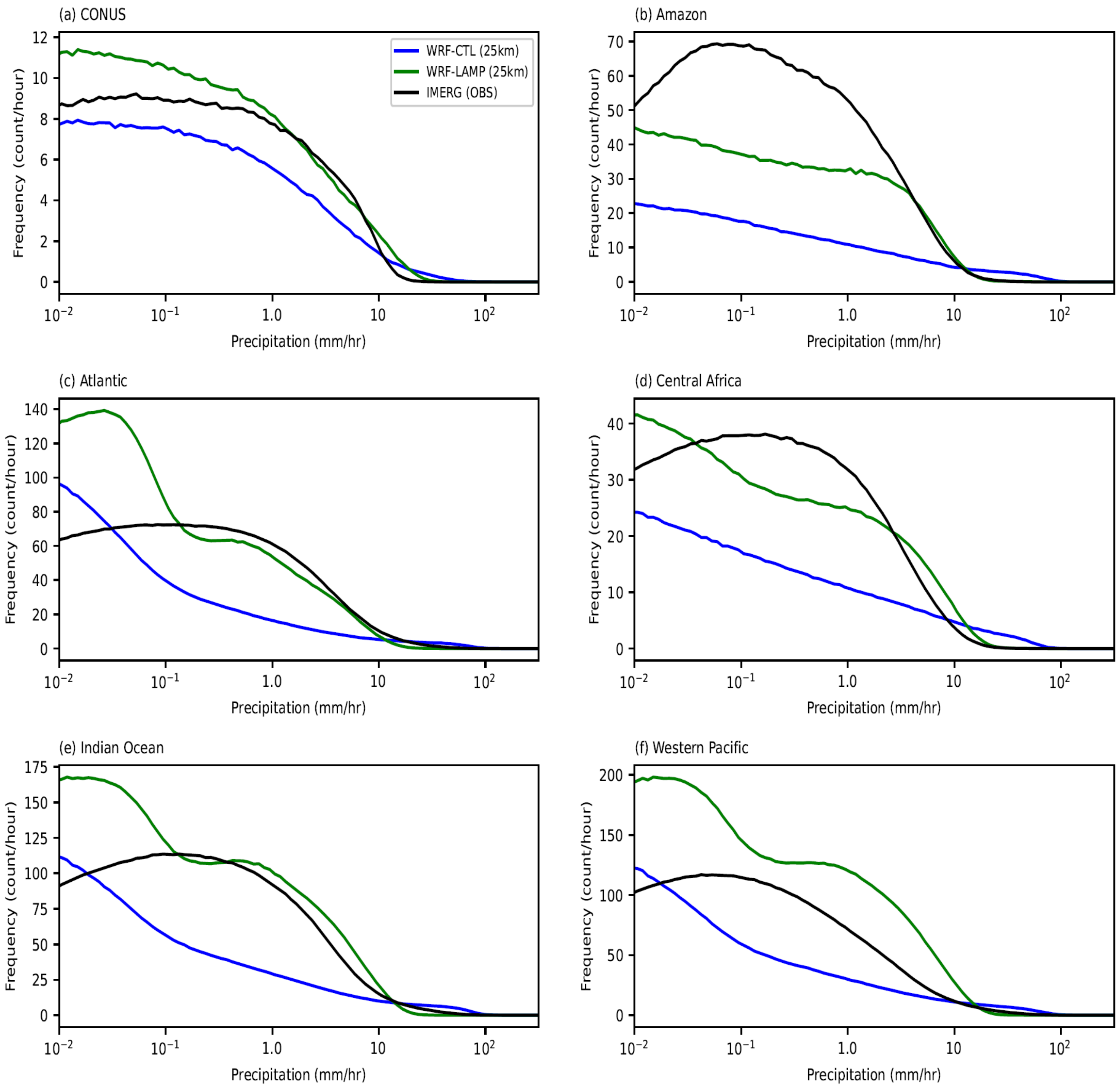
Domains of evaluation simulations





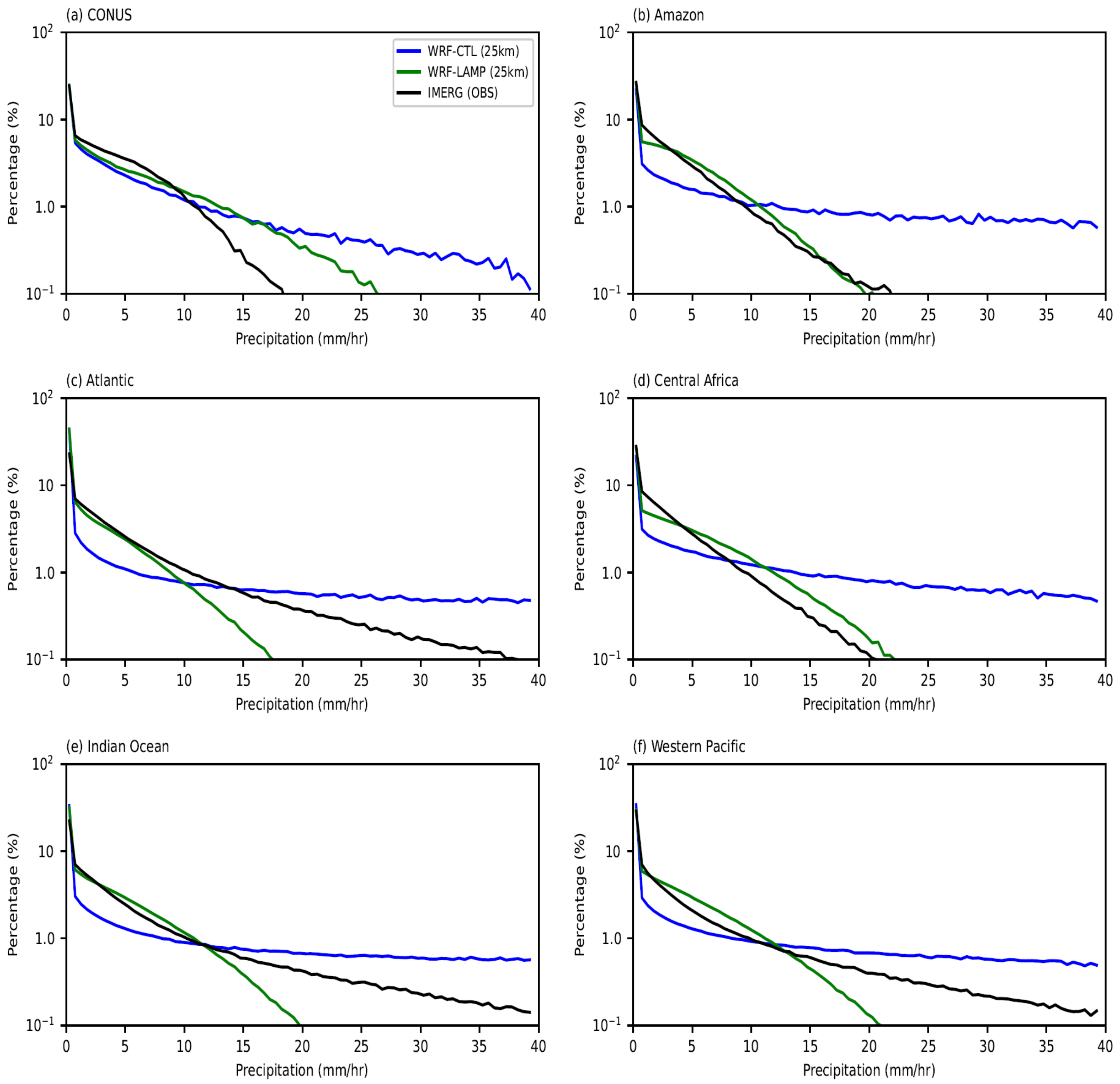
- Too much precipitation over the tropical ocean.
- The propagation of the Oct –Nov 2011 events reasonably well captured.

Precipitation statistics



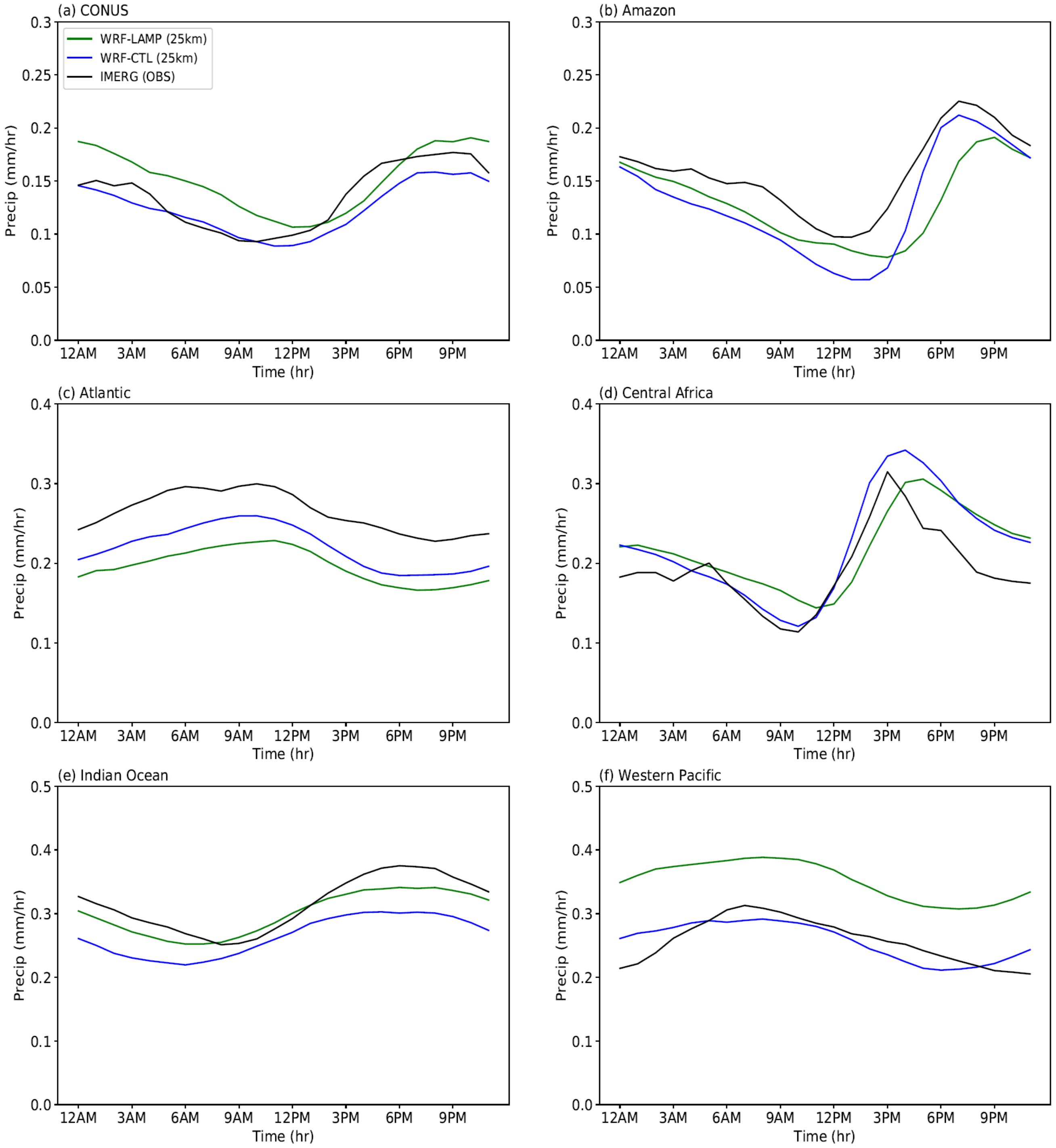
- The statistics of precipitation shows a varying degree of improvement over WRF-CTL.

Fractional contribution to total precipitation



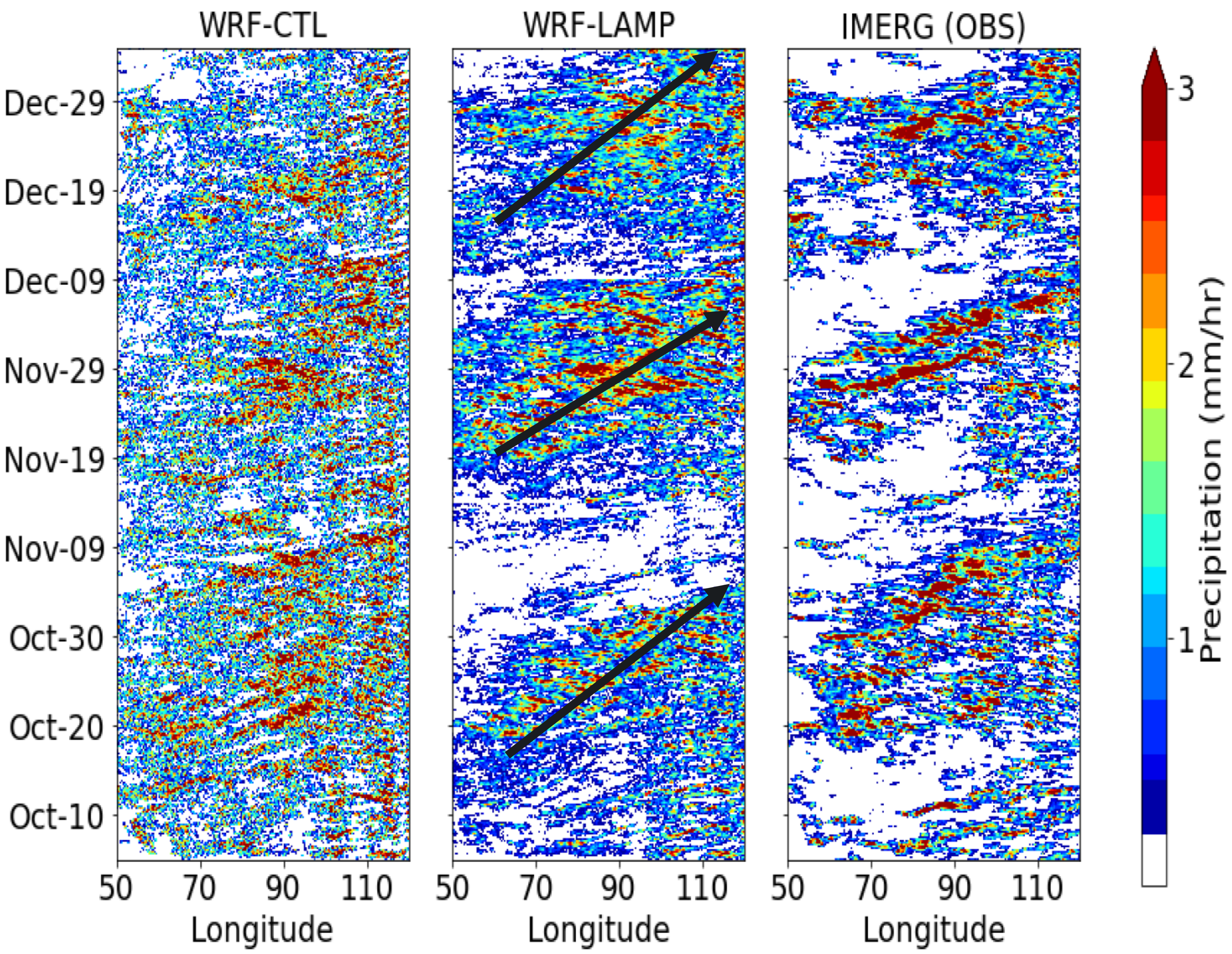
- The contribution to total precipitation of various intensities show a varying degree of improvement over WRF-CTL.

Diurnal Cycle

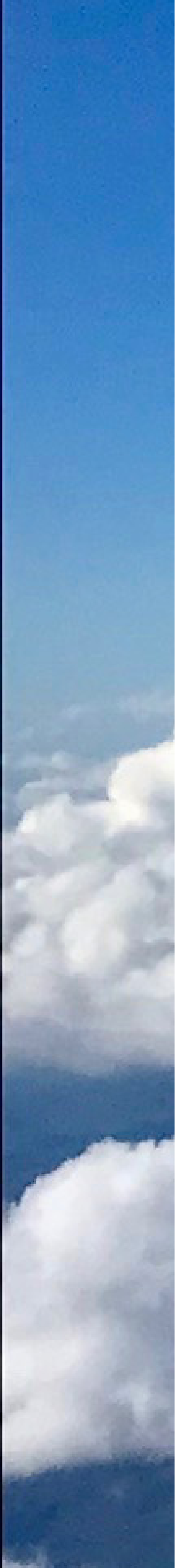


- Because of the closure, the diurnal cycle of precipitation in WRF-LAMP is in good agreement with observations.

MJO Propagation

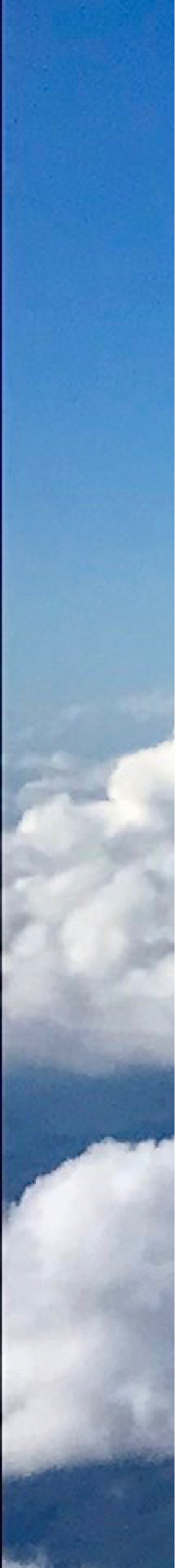


- The excess drizzle during the suppressed phases of the MJO is reduced in WRF-LAMP.



Summary

- A framework for modeling population dynamics of convective clouds is developed. A specific model in this framework is defined by the representation of **transition functions that represent lifecycles of and interactions among clouds**.
- **Application of cloud population model as parameterization** shows promise in addressing long-standing issues associated with the representation of precipitation statistics, diurnal cycle and MJO propagation associated with traditional cumulus parameterizations.
- Machine learning can be used **as a tool for constructing simple models** from observations process level understanding.



Thank you!

Acknowledgement

This work is supported by the U.S. DOE’s ASR Program via the ICLASS SFA and the ARM Climate Research Facility.