

# Investigating the Scale Dependence of SCM Simulations by Using 3D Forcing

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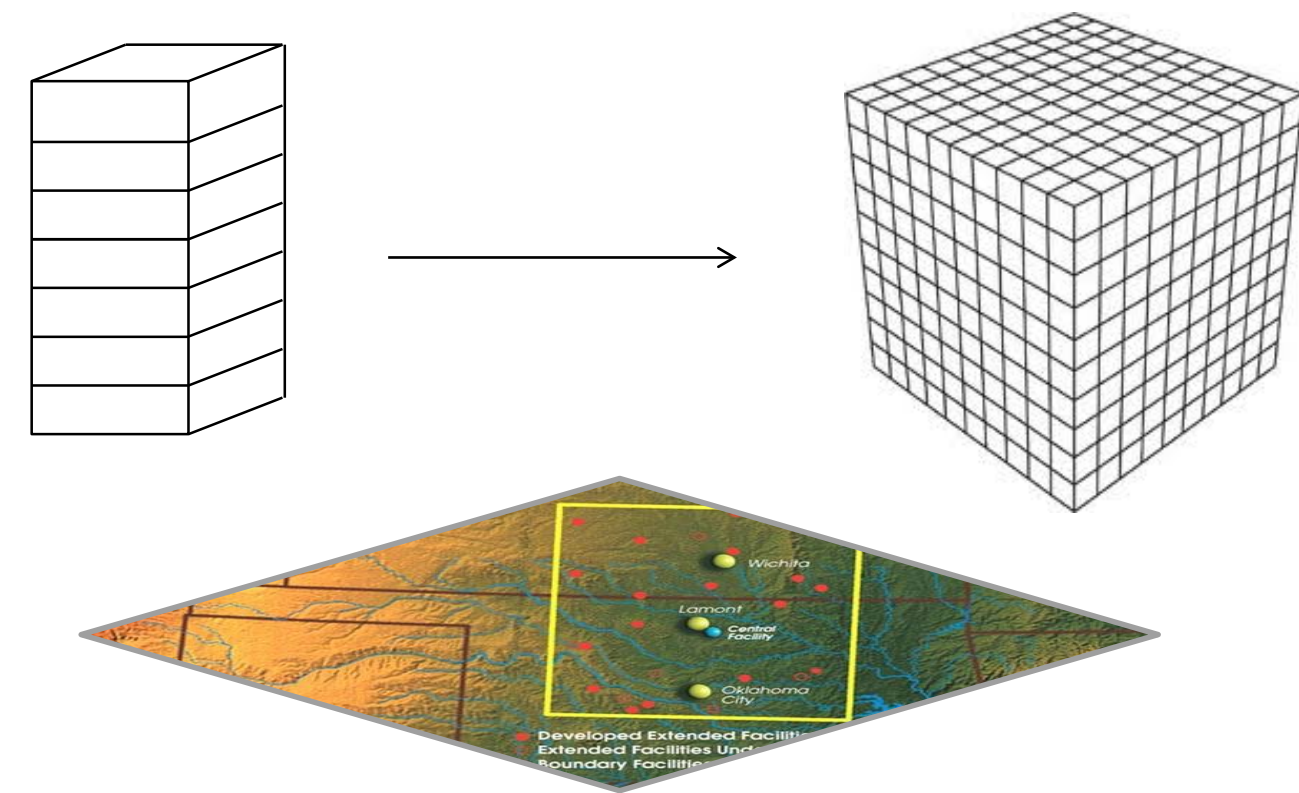
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## Introduction

- Previous studies (e.g., Xie et al., 2005) have indicated that SCM/CRM simulation errors might be partially attributed to the **lack of spatial variability** in the domain-mean large-scale forcing fields.
- The spatial variability of the large-scale forcing can be described in the gridded forcing data from a 3D constrained variational analysis (3DCVA) method (Tang and Zhang 2015).
- This study will use this gridded large-scale forcing data to investigate the benefits of including spatial variability and to explore its impacts on SCAM5 simulations of clouds and precipitation.

## Gridded Large-Scale Forcing

### 1D Forcing vs 3D Forcing



$$\langle \nabla \cdot \vec{v} \rangle = -\frac{1}{g} \frac{dP_s}{dt}$$

$$\frac{\partial \langle q \rangle}{\partial t} + \langle \nabla \cdot \vec{v} q \rangle = E_s - P_{rec} - \frac{\partial \langle q_i \rangle}{\partial t}$$

$$\frac{\partial \langle s \rangle}{\partial t} + \langle \nabla \cdot \vec{v} s \rangle = R_{TOA} - R_{SRF} + LP_{rec} + SH + L \frac{\partial \langle q_i \rangle}{\partial t}$$

$s \equiv C_p T + gz$

## Methodology

### March 2000 IOP at SGP:

- Analysis domain: 5° × 4.5°
- Sub columns: 0.5° × 0.5°

### SCAM5 settings:

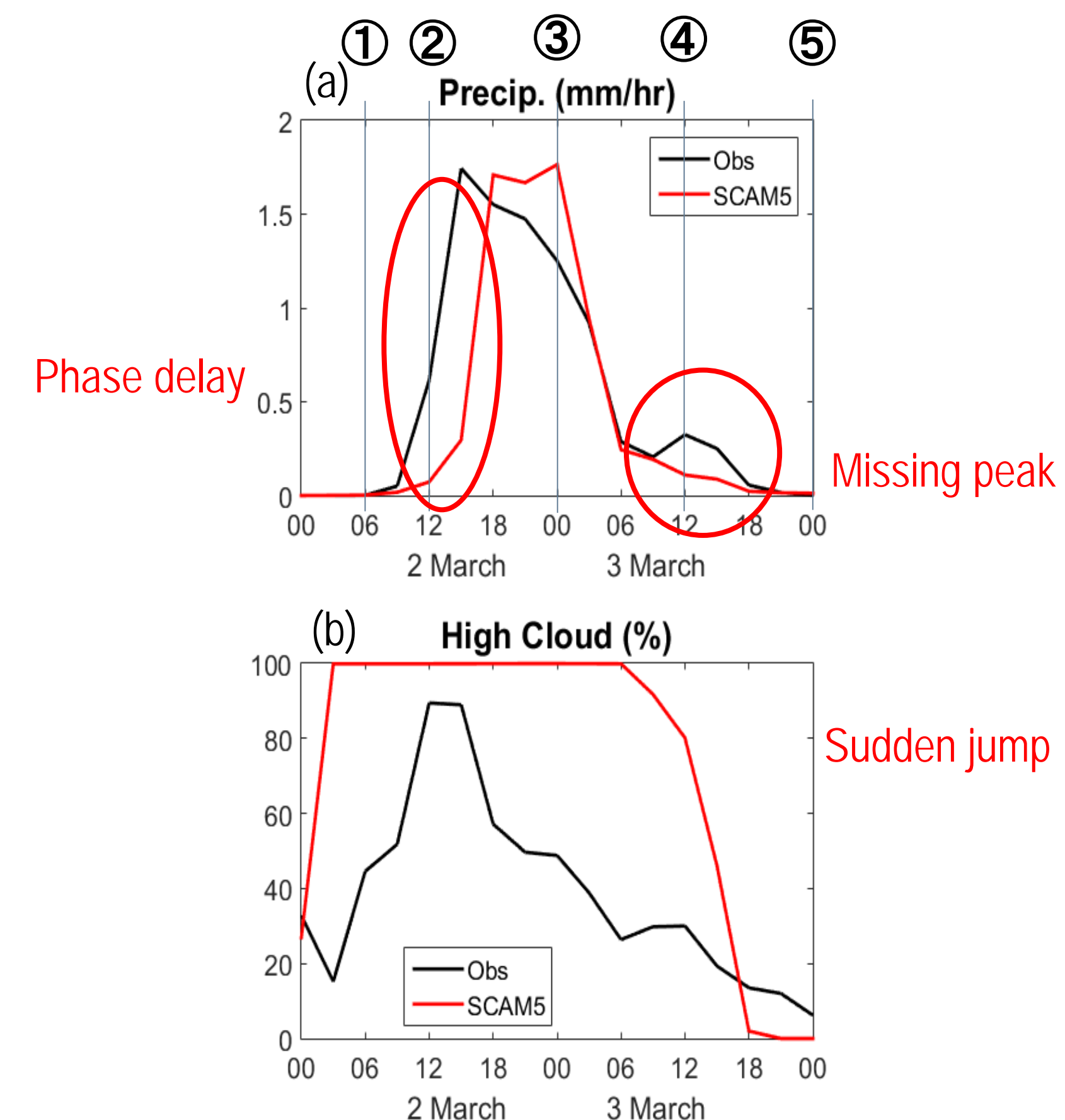
- Model started every 3 hr and simulations from 6 – 9 hr are used
- Prescribed surface turbulence fluxes
- No nudging

### Experiment design:

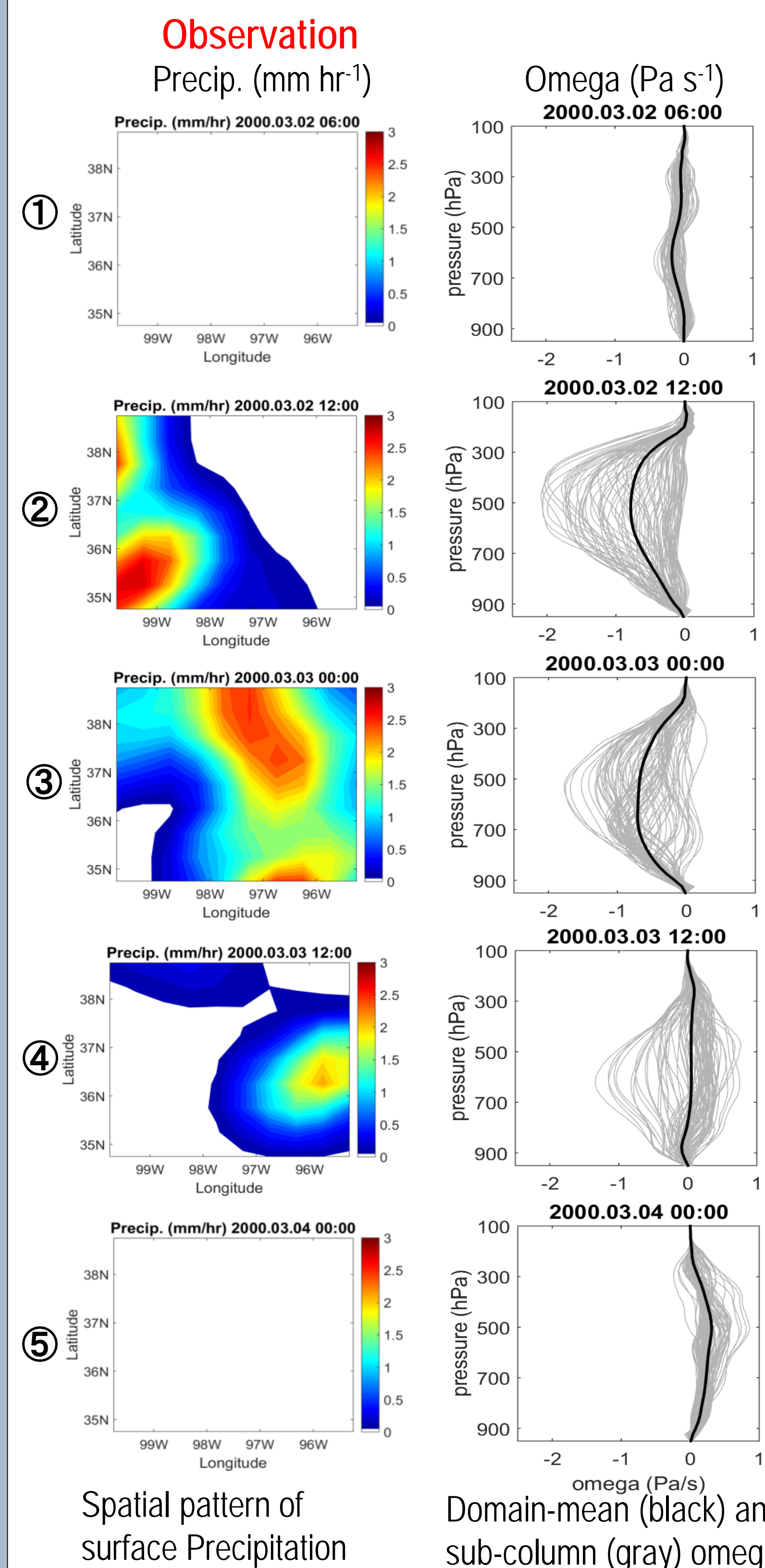
1. SCAM5 with domain-mean forcing (1D Forcing)
2. SCAM5 with each sub-column of the 3D Forcing, and the results are averaged over the domain for comparison

## SCAM5 with 1D Forcing

Time series of surface precipitation (a) and high cloud (b)

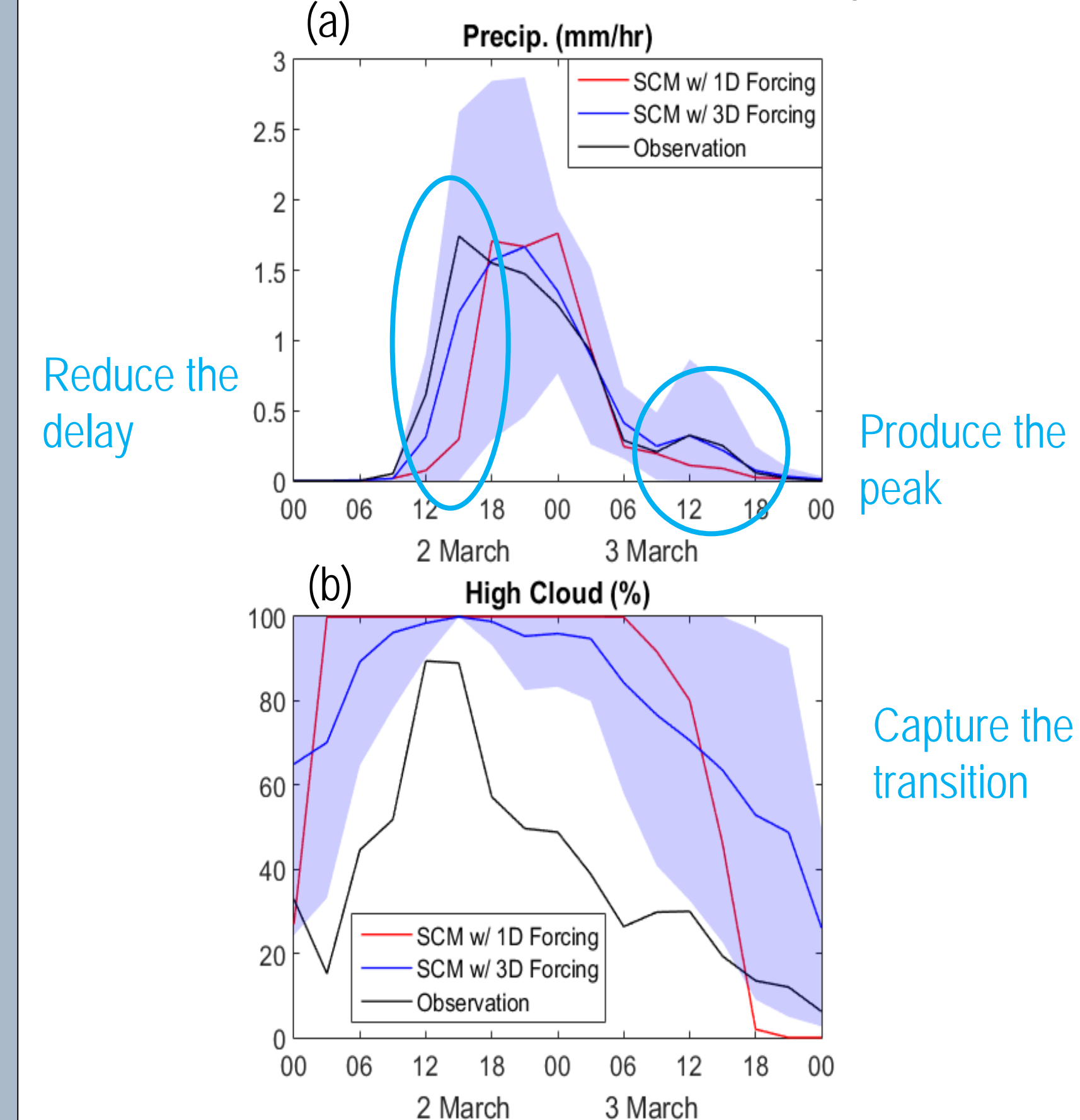


## Spatial Variability of Forcing Fields



## SCAM5 with 3D Forcing

Time series of surface precipitation (a) and high cloud (b)



### SCAM5

Precip. (mm hr <sup>-1</sup> )	Domain-mean Precip.		
	Obs.	With 1D Forcing	With 3D Forcing
	0.01	0.00	0.01
	0.69	0.07	0.31
	1.24	1.76	1.35
	0.30	0.11	0.32
	0.00	0.01	0.01

## Statistics

RMSE of domain-mean fields for the whole March 2000 IOP (2-20 March).

	PREC	LWP	LWT	SWT	LWS	SWS
SCM w/ 1D Forcing	0.174	0.107	20.6	23.1	26.3	27.7
SCM w/ 3D Forcing	0.085	0.094	16.8	19.3	25.4	28.8

	CLDT	CLDH	CLDM	CLDL
SCM w/ 1D Forcing	38.4	40.7	37.1	52.4
SCM w/ 3D Forcing	32.3	33.0	29.1	44.6

- For most of variables SCAM5 with sub-column forcing has smaller RMSE than SCAM5 with domain-mean forcing.
- This RMSE difference is larger during frontal systems with larger spatial heterogeneity, but smaller in more homogeneous conditions.

## Summary

- With the spatial variability of the large-scale forcing, SCAM5 better capture the characteristics of the frontal system with large spatial heterogeneity.

## Potential Application

- Obtain a probability distribution function (PDF) of the large-scale forcing based on its spatial variability, and implement it in SCMs to allow the investigation of its nonlinear response of model physics on the large-scale dynamics.
- Average (interpolate) the gridded large-scale forcing data into different grid sizes to evaluate scale-aware parameterizations.
- Apply in CRM/LES to study the impact of spatially heterogeneous large-scale forcing.

## Acknowledgement

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## References

Xie, S., et al. (2005), JGR: A, 110(D15),  
Tang, S., and M. Zhang (2015), JGR: A, 120(15)  
Tang, S., et al., (2017), JGR: A, submitted