

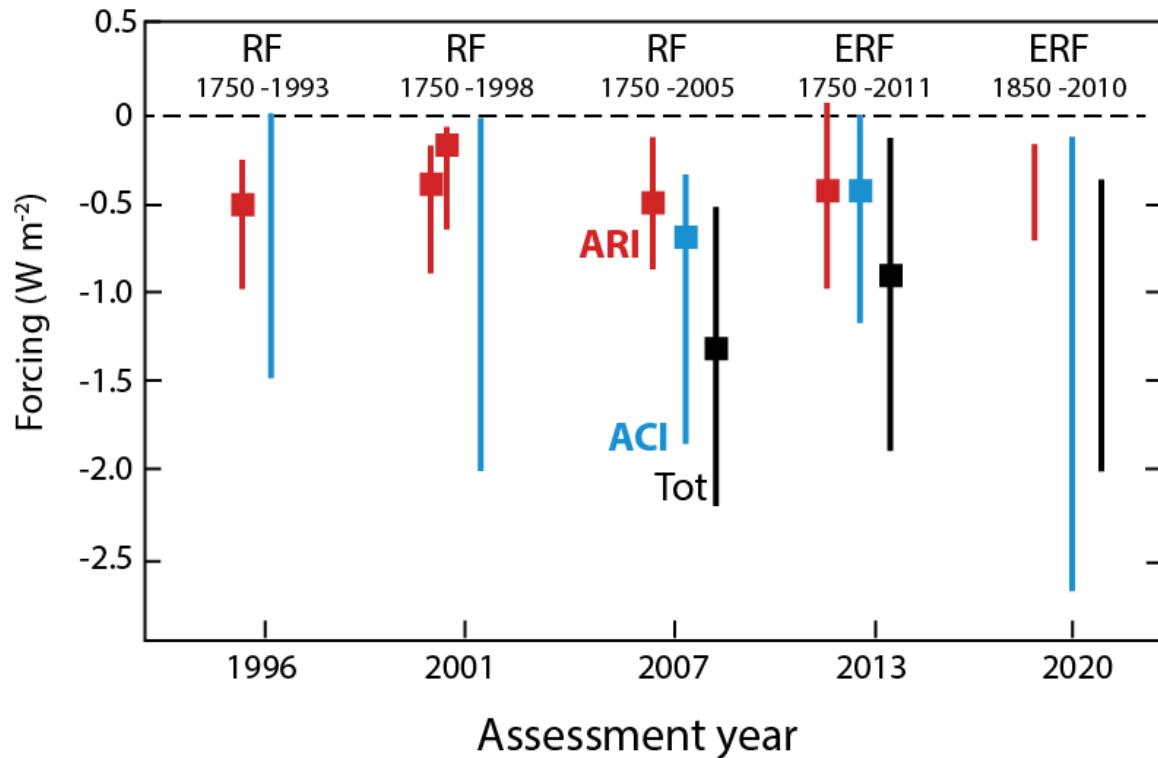
# Perturbed parameter ensembles as a way to improve models and understand system behavior

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Funding gratefully acknowledged from



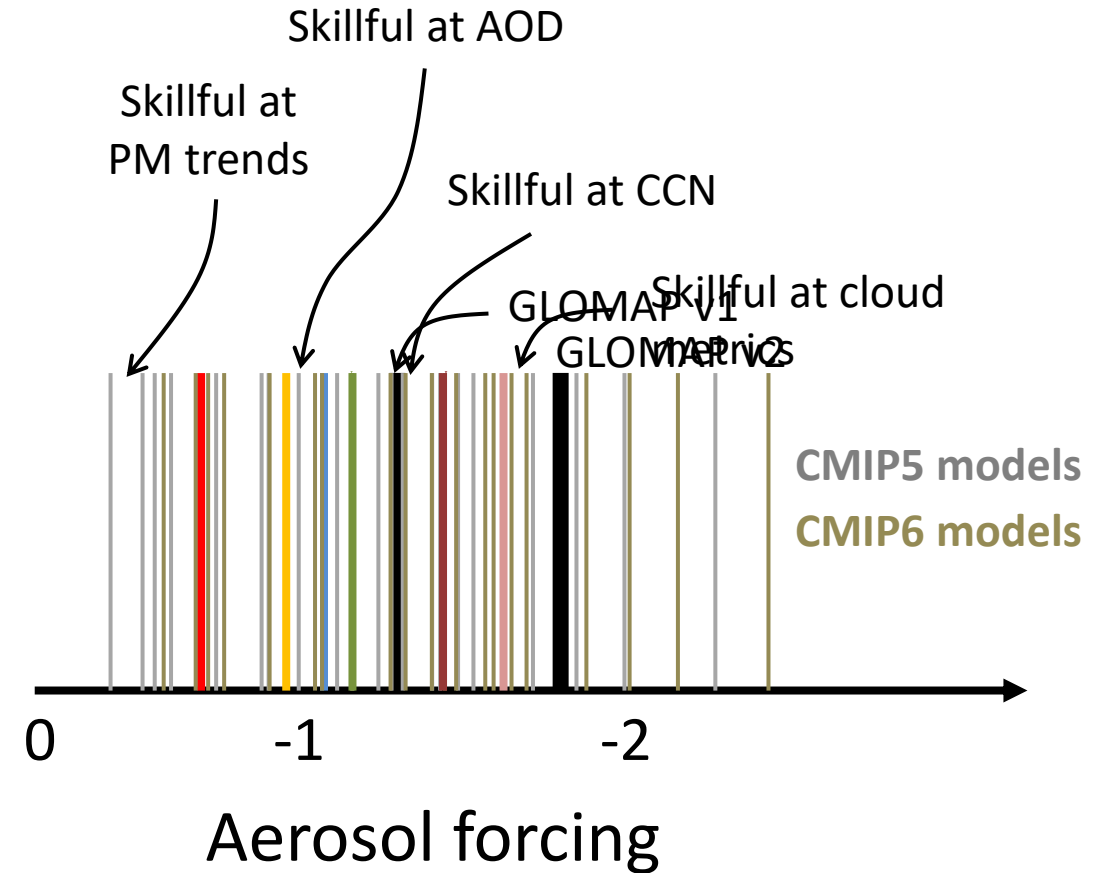


## How do we reduce uncertainty?

**Constraining models** – e.g., using observations to constrain dozens of uncertain model parameters

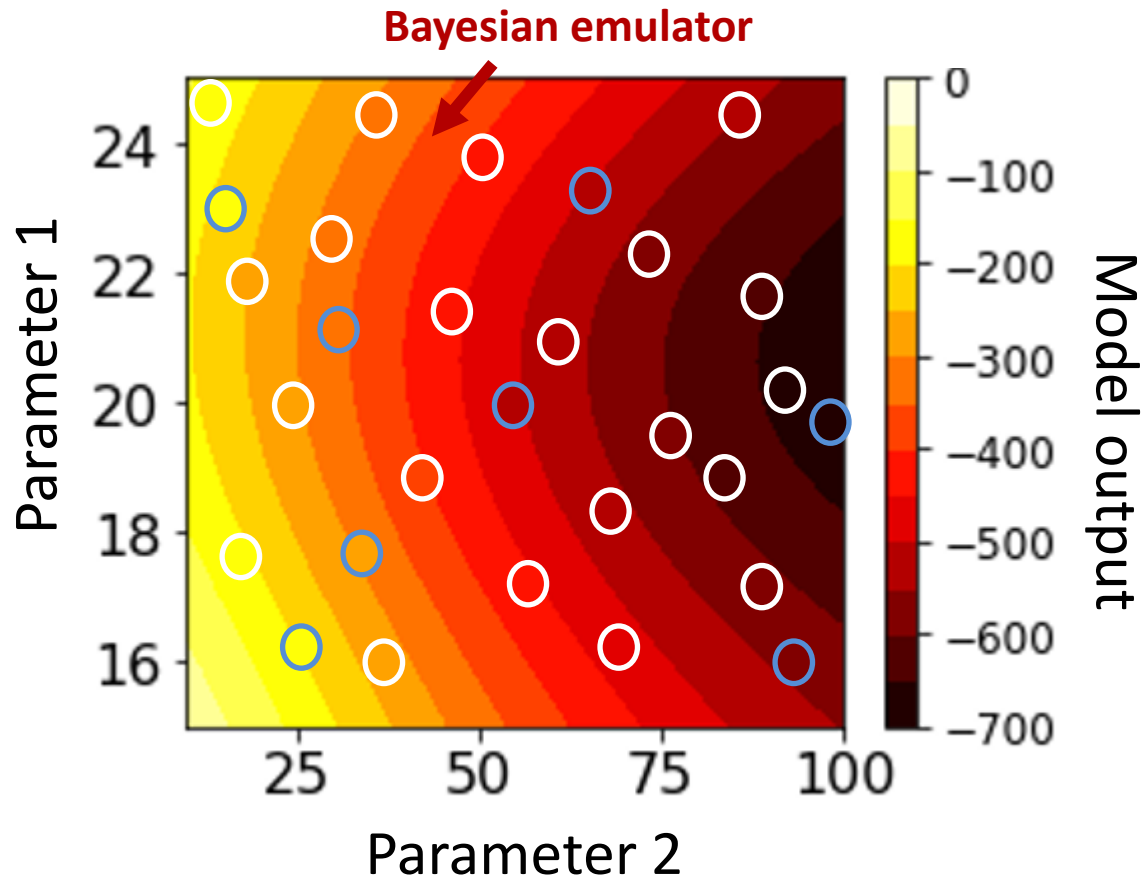
**Making models better** – detecting and attributing structural deficiencies

**Understanding processes** – e.g., how clouds respond to aerosols in an environment with many confounding factors



Different parameterizations (structural uncertainty)  
Different parameter settings (parametric uncertainty)

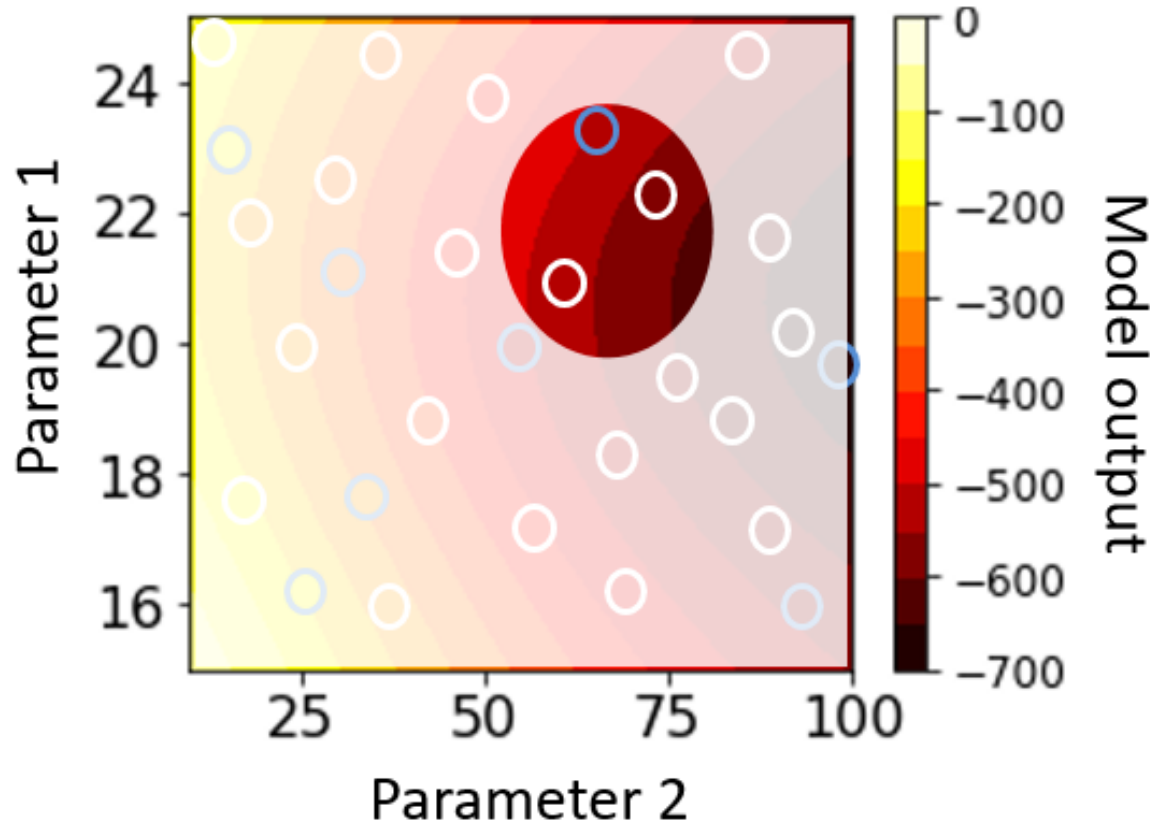
- Our models and our natural systems of interest are **controlled by many factors** (many structures, parameters and environmental conditions)
- Models are expensive to run
- We therefore usually only sample tiny parts of the ‘parameter space’



- A **perturbed parameter ensemble (PPE)** is a set of model simulations designed to optimally sample combinations of model inputs
- Designed to train a statistical emulator
  - Can then generate **~millions of “model variants”**

Oakley and O’Hagan, Probabilistic sensitivity analysis of complex models: A Bayesian approach, J. Roy. Stat. Soc. B (2004).

Lee et al. Emulation of a complex global aerosol model, ACP (2011)



Compare PPE/emulator results against observations

→ Constrains the parameter ranges (to a joint observationally plausible range)

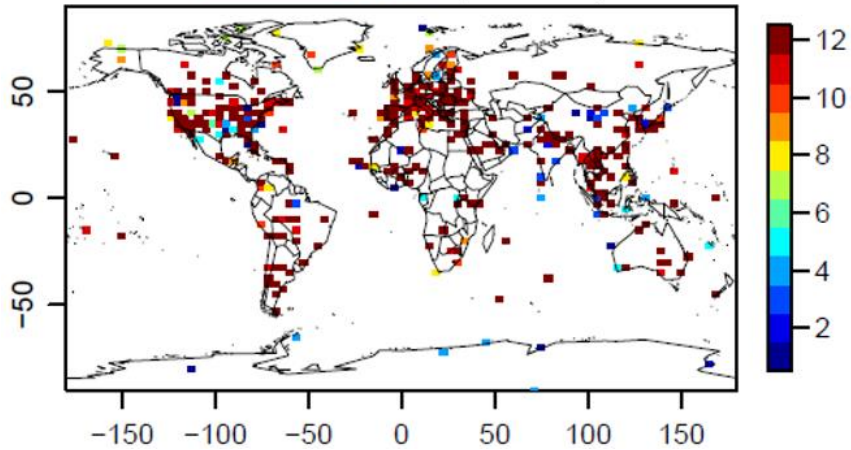
→ Constrains range of model outputs (e.g., reduces uncertainty in forcing)

A PPE of the HadGEM GCM with **26 aerosol-related parameters**  
(emissions, aerosol processes, removal rates, chemistry, etc.)

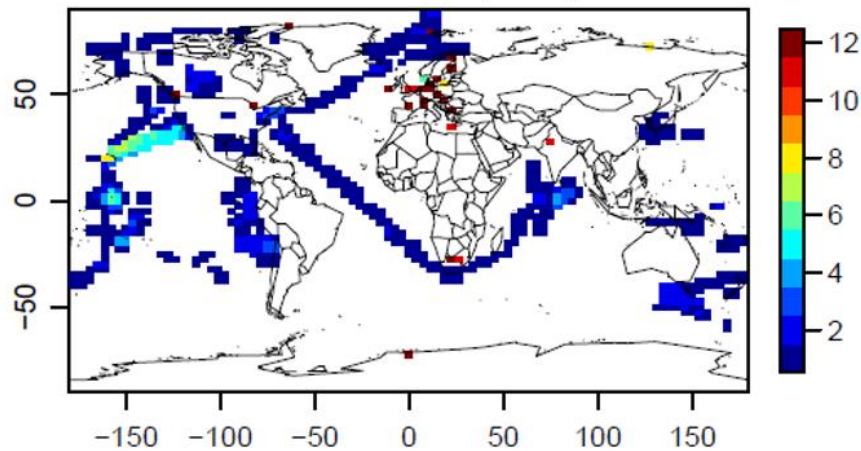
**Johnson et al. (ACP 2020)**

Robust observational constraint of uncertain aerosol processes and emissions  
in a climate model and the effect on aerosol radiative forcing

Aeronet AOD (440nm)



GASSP N50 (cm<sup>-3</sup>)



~9000 grid-point aggregated measurements of:

- Aerosol optical depth
- PM<sub>2.5</sub>
- Aerosol concentration ( $N_{>3\text{nm}}$ )
- ~CCN concentration ( $N_{>50\text{nm}}$ )
- Sulphate mass
- Organic carbon mass



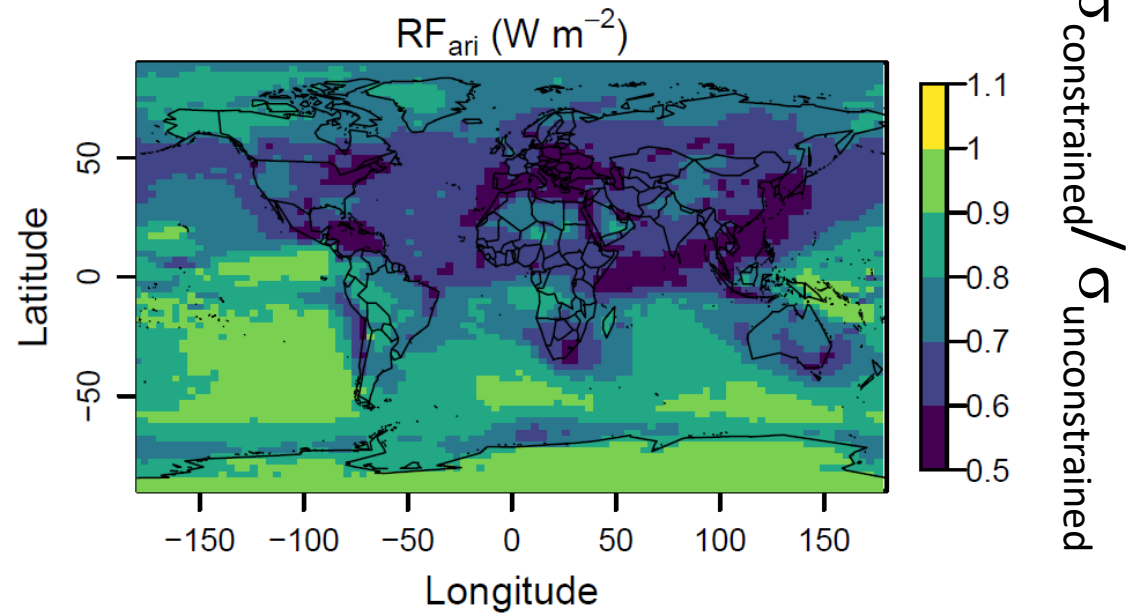
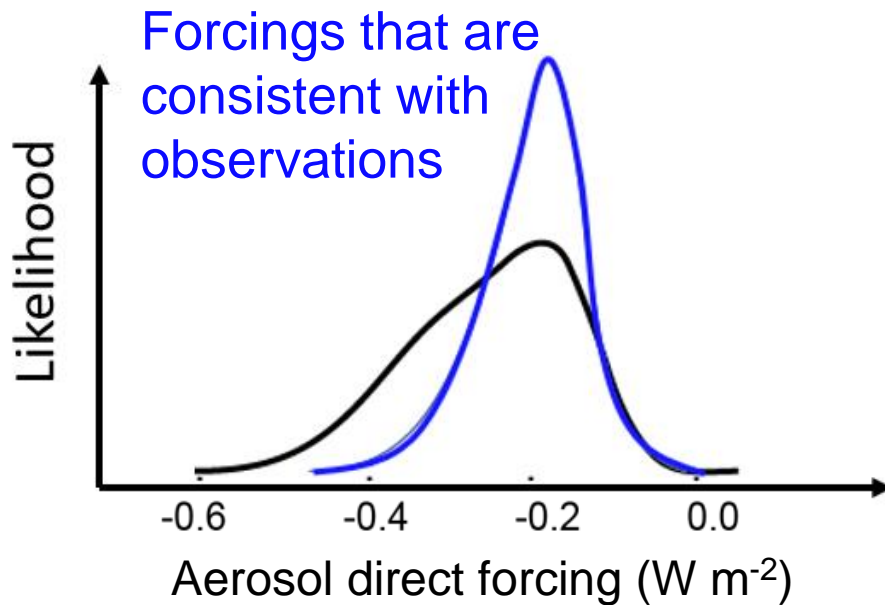
Observations



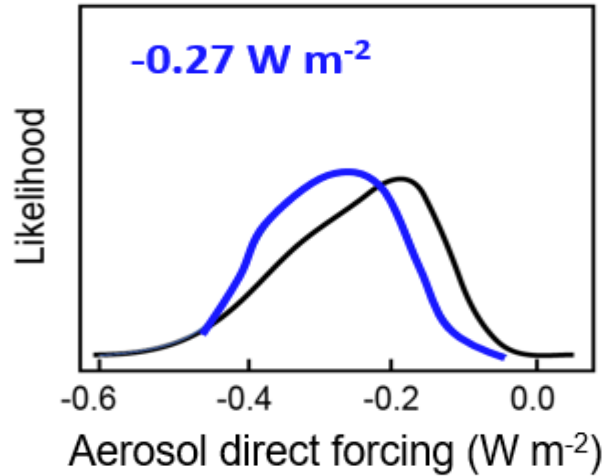
Constrained parameter space



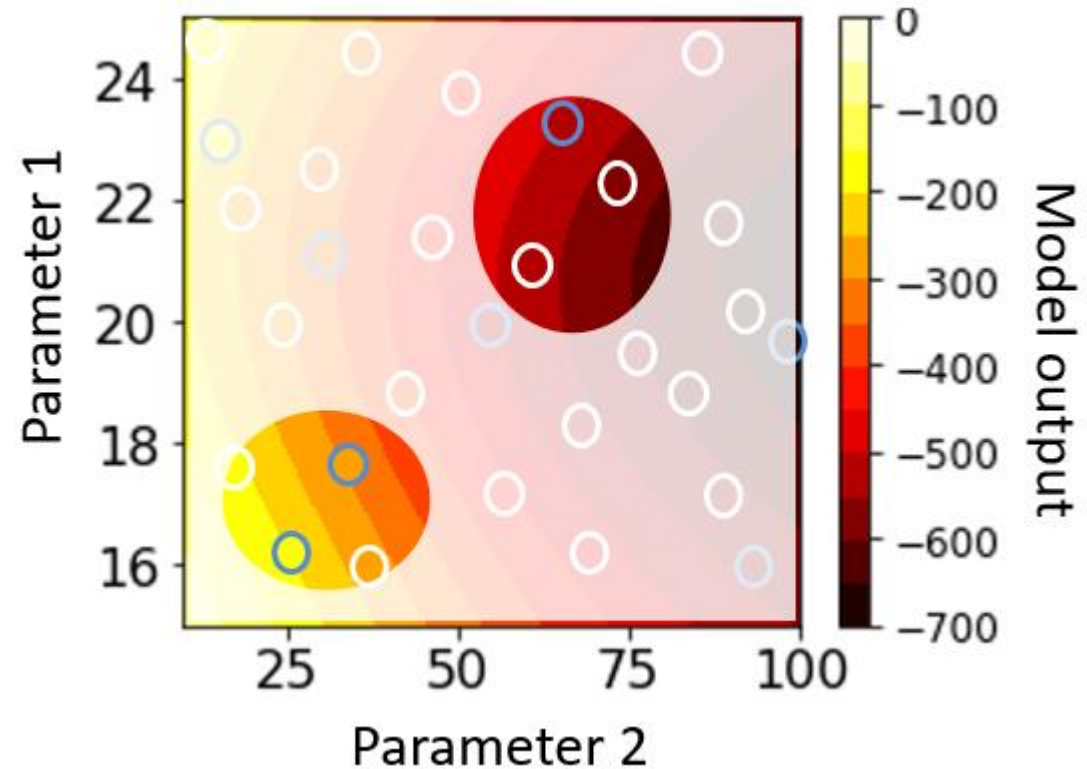
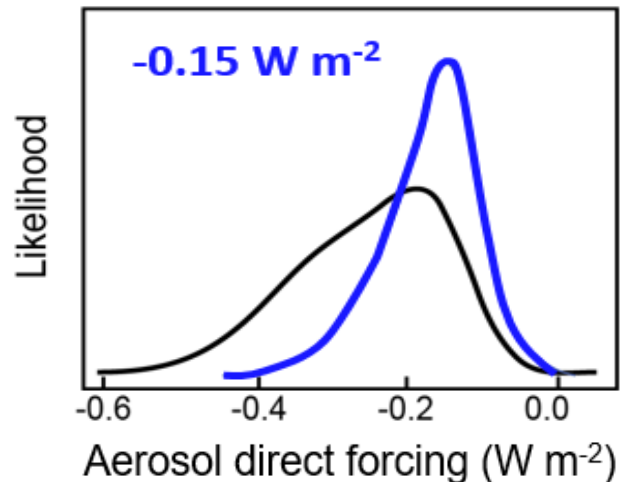
Constrained Forcing



Forcing constrained by **PM<sub>2.5</sub>**



Forcing constrained by **Sulphate**

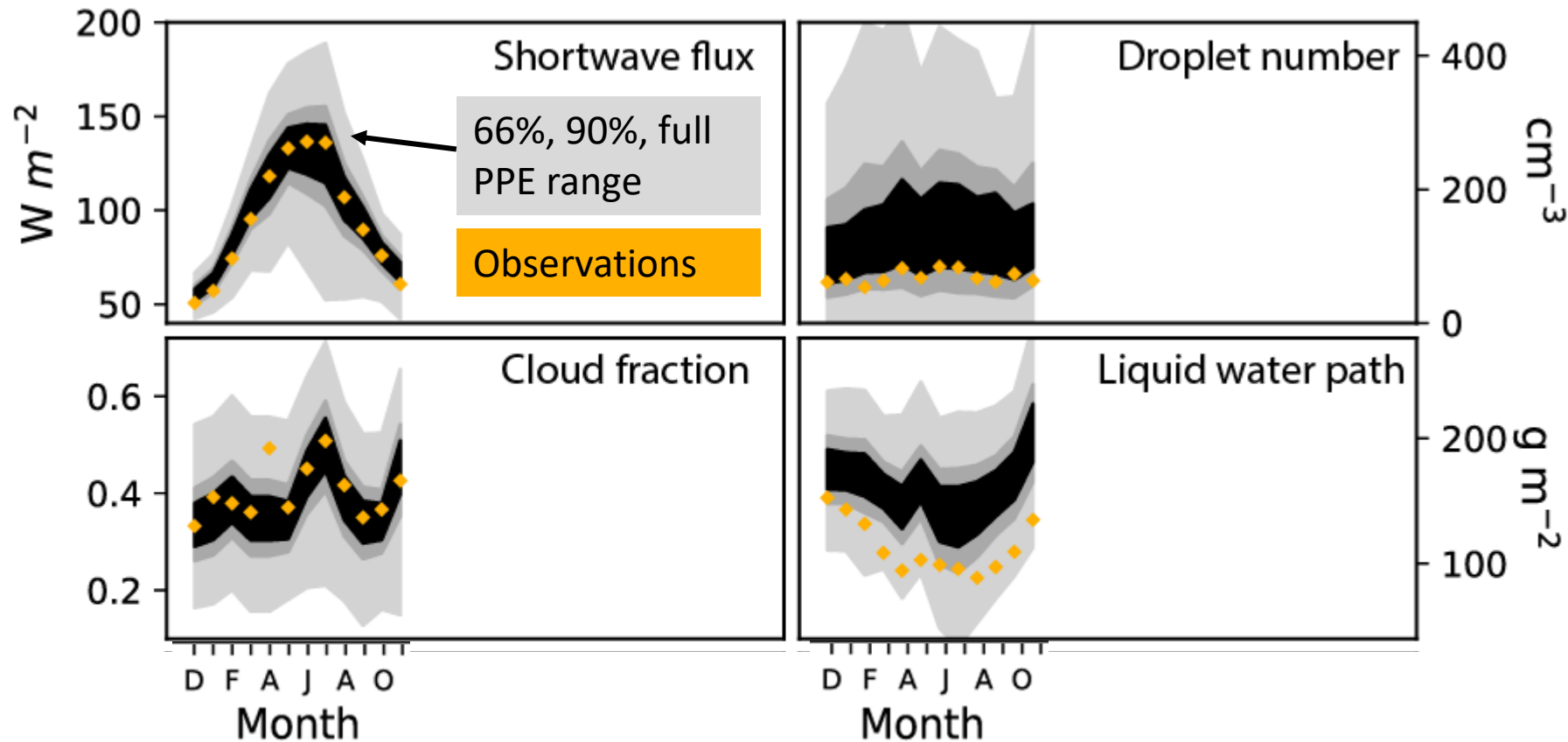


The model doesn't include nitrate aerosol, so constraining PM<sub>2.5</sub> forces sulfate to be too high

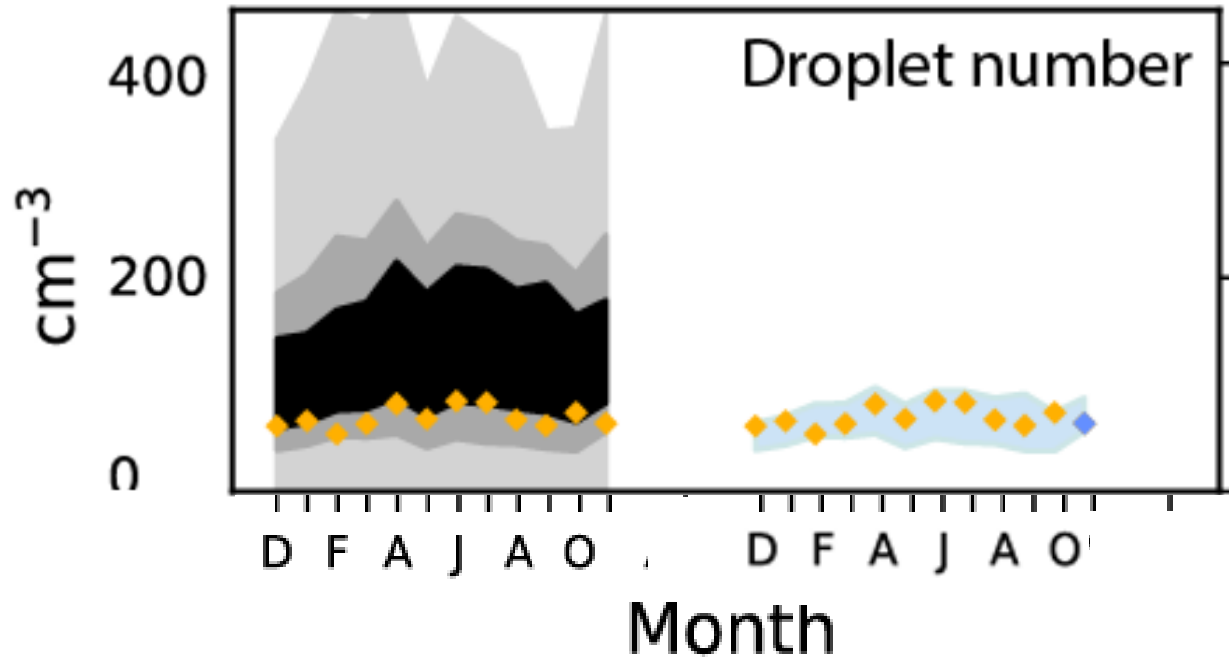
A PPE of the HadGEM GCM with **37 aerosol, cloud and physical climate parameters**  
(emissions, aerosol processes, radiation, cloud processes, aerosol-cloud interaction, etc.)

**Regayre et al. (ACP 2023)**

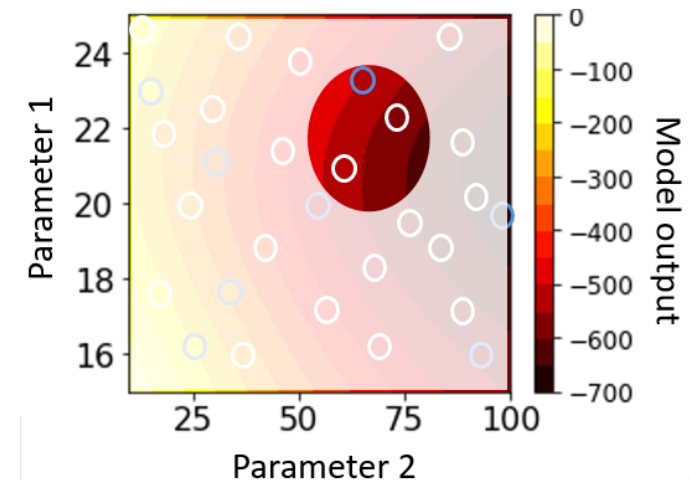
Identifying climate model structural inconsistencies allows for tight constraint of aerosol radiative forcing

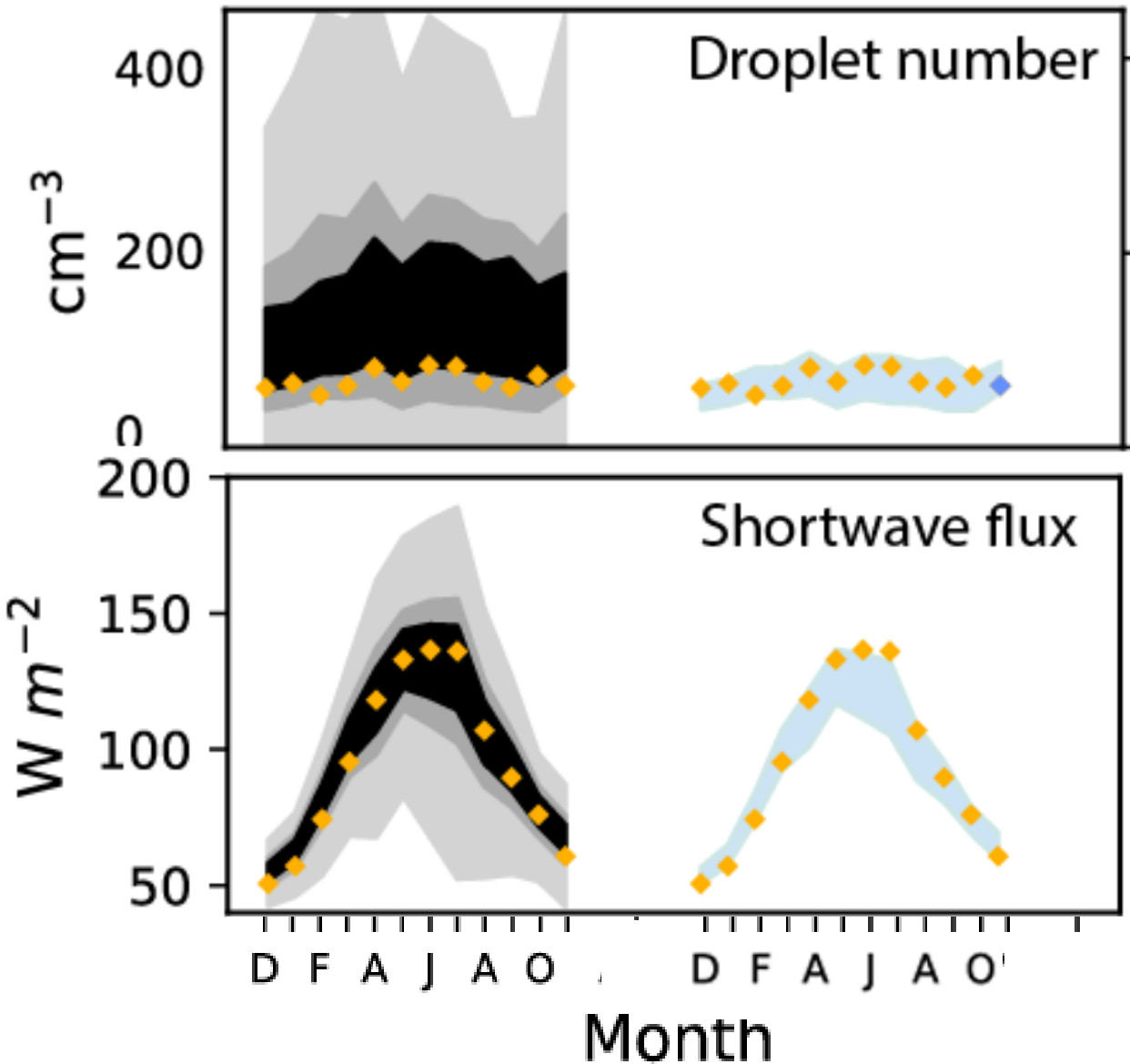


N Atlantic  
shallow cloud  
properties

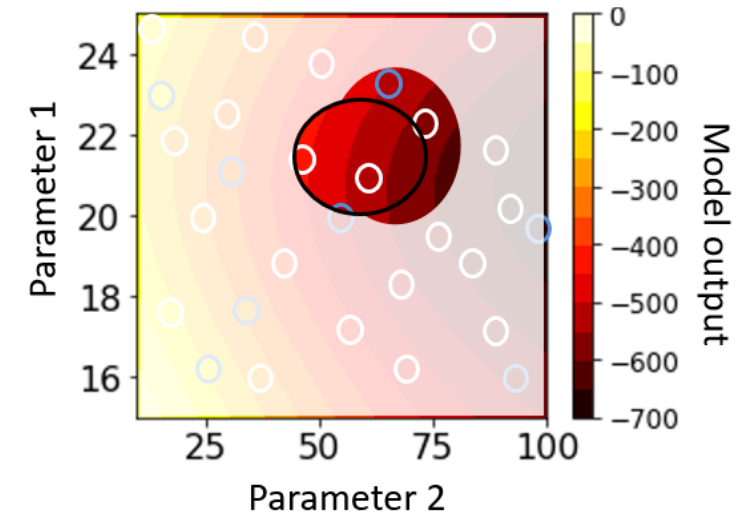


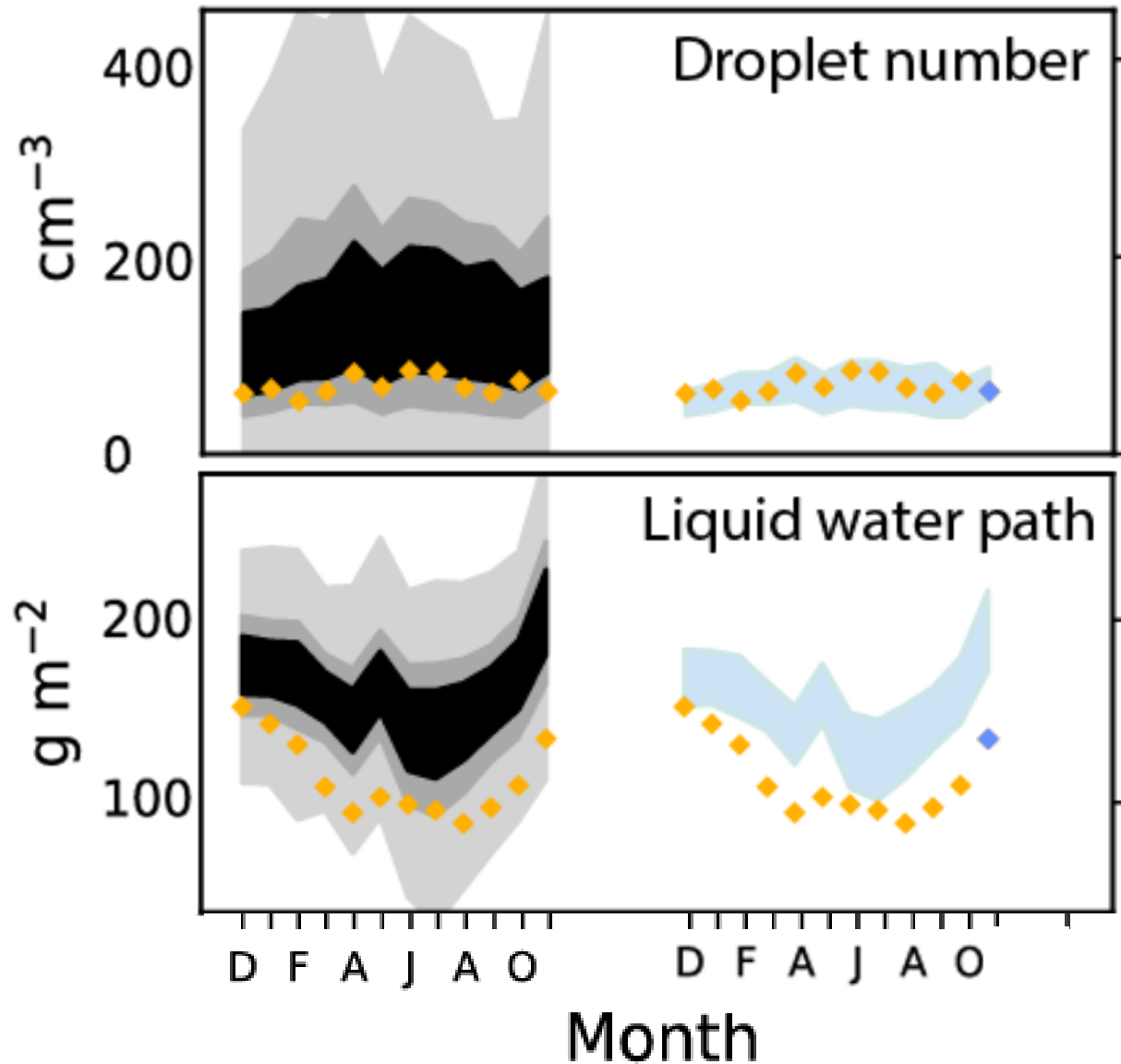
Constraining droplet number in 1 month (November) constrains all other months consistently



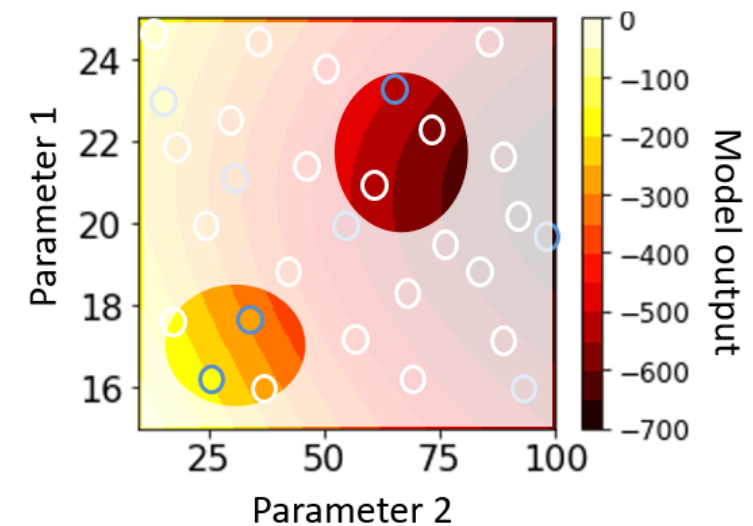


Constraining droplet number  
constrains **shortwave flux**





Constraining droplet number causes a large bias in **liquid water path**



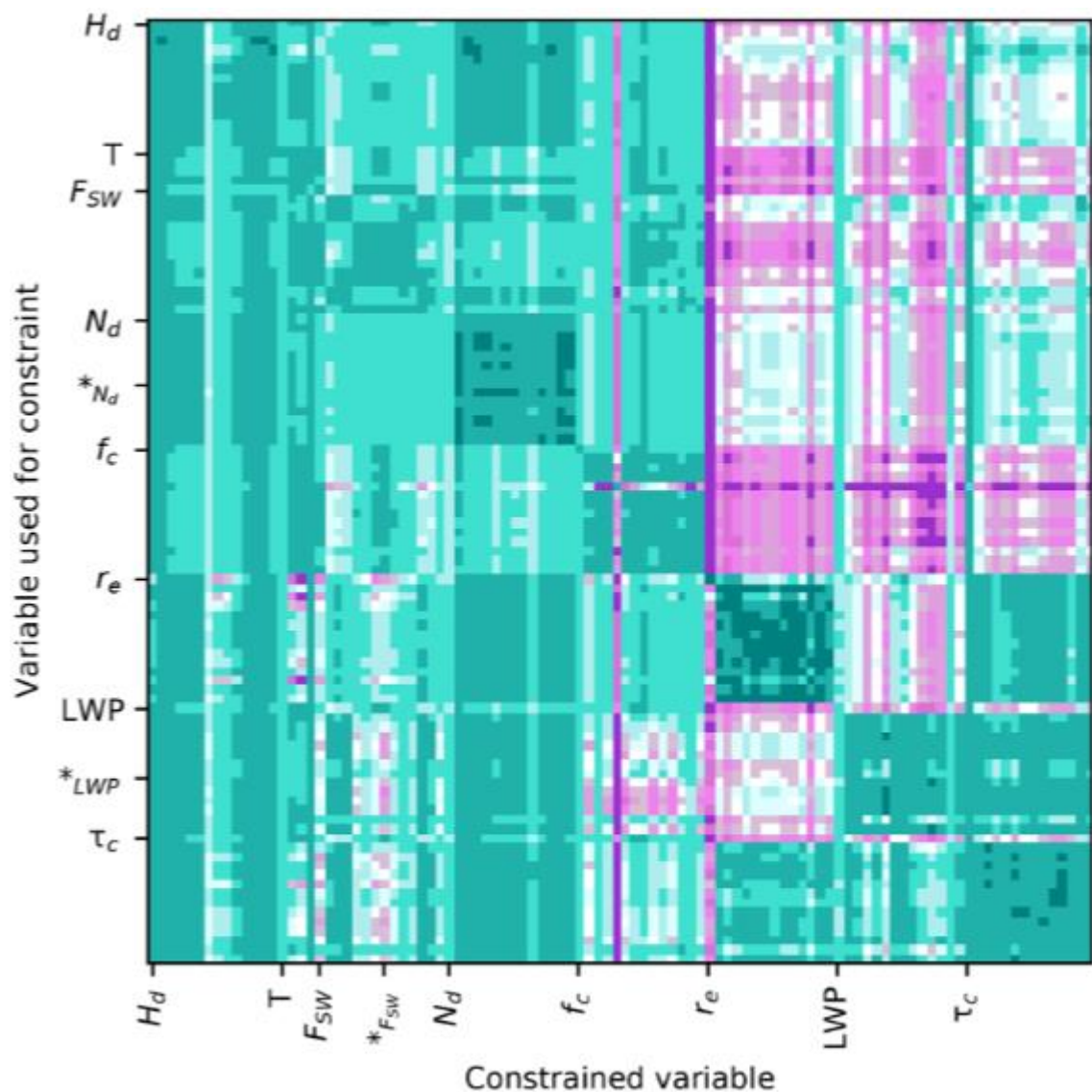
- Liquid water path and droplet number are inconsistent (constraining one creates a bias in the other)

Why?

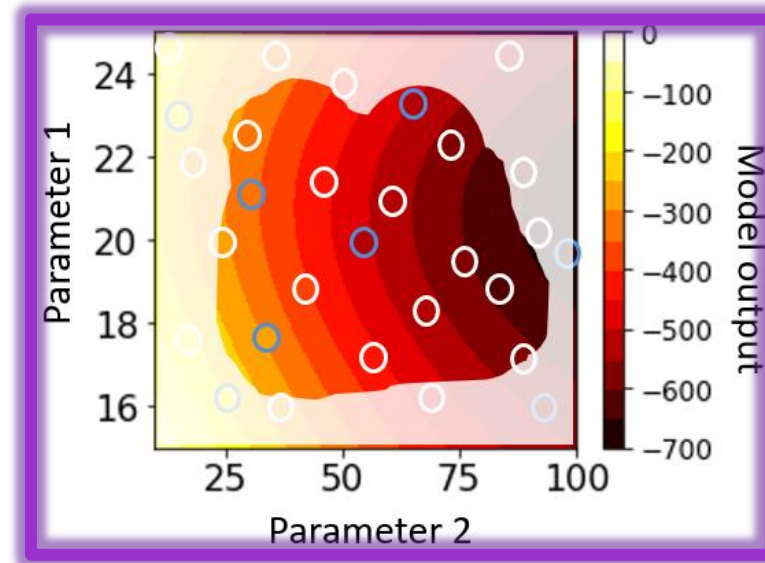
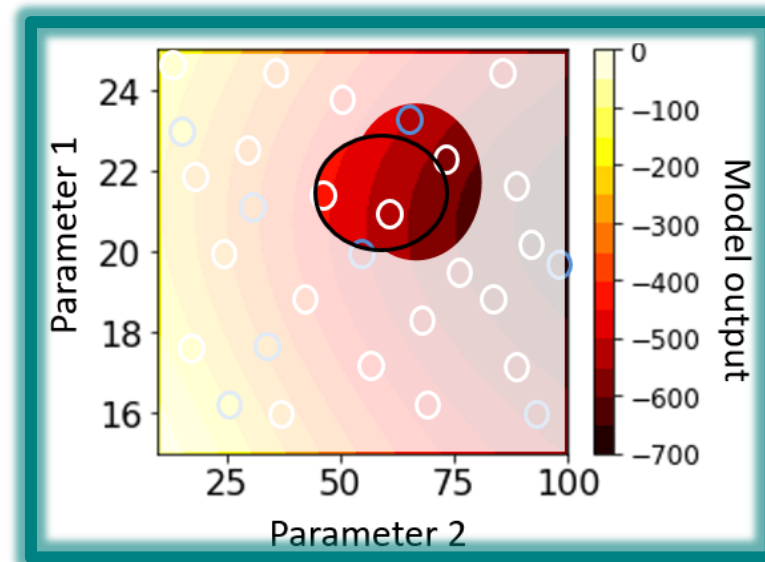
- The model has single-moment cloud microphysics
- Removal of cloud water (LWP) doesn't affect droplet number

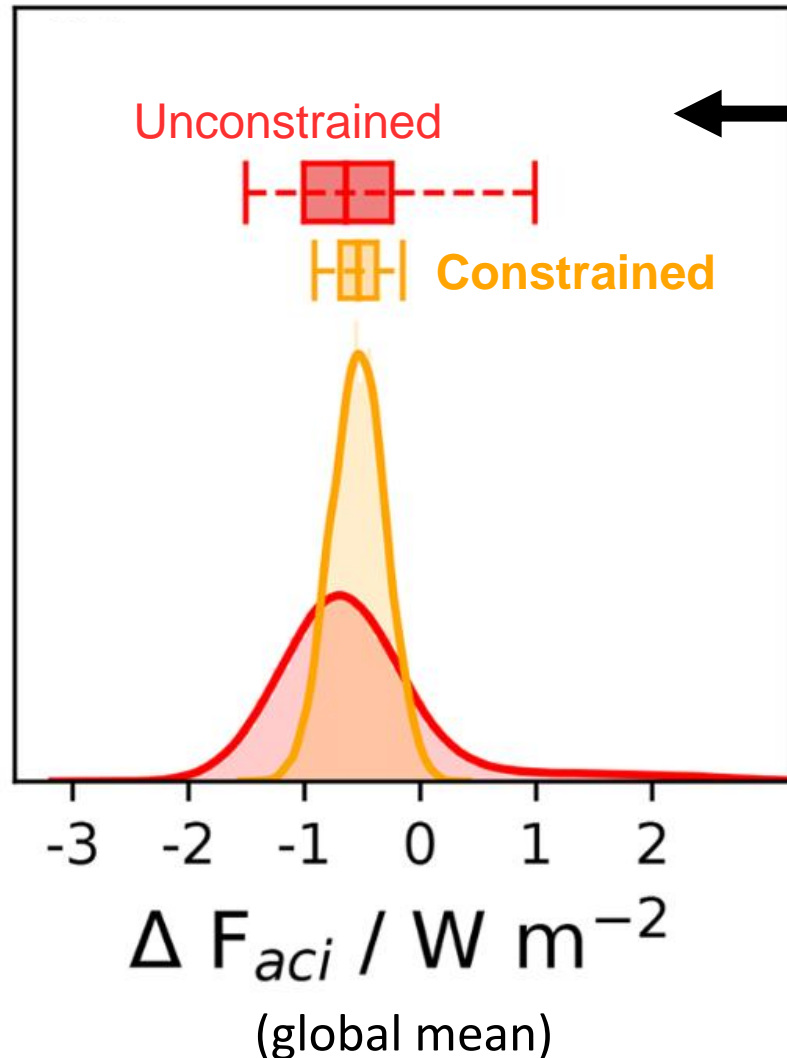


# Testing all pairs of variables



Normalized absolute difference

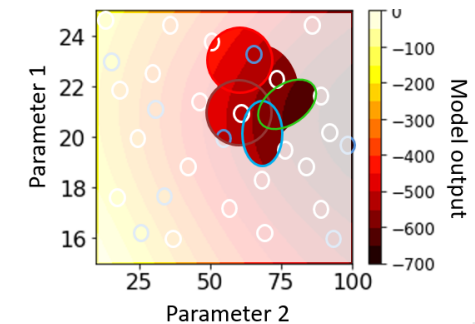
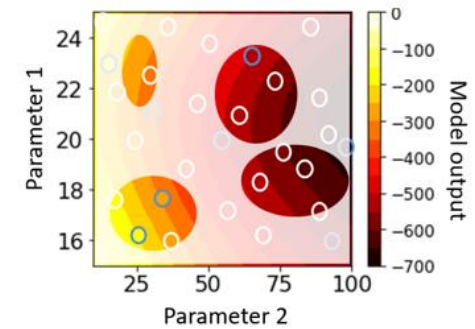
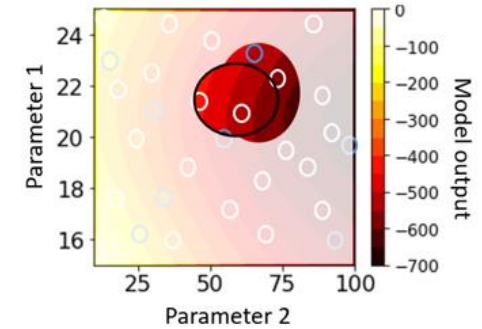




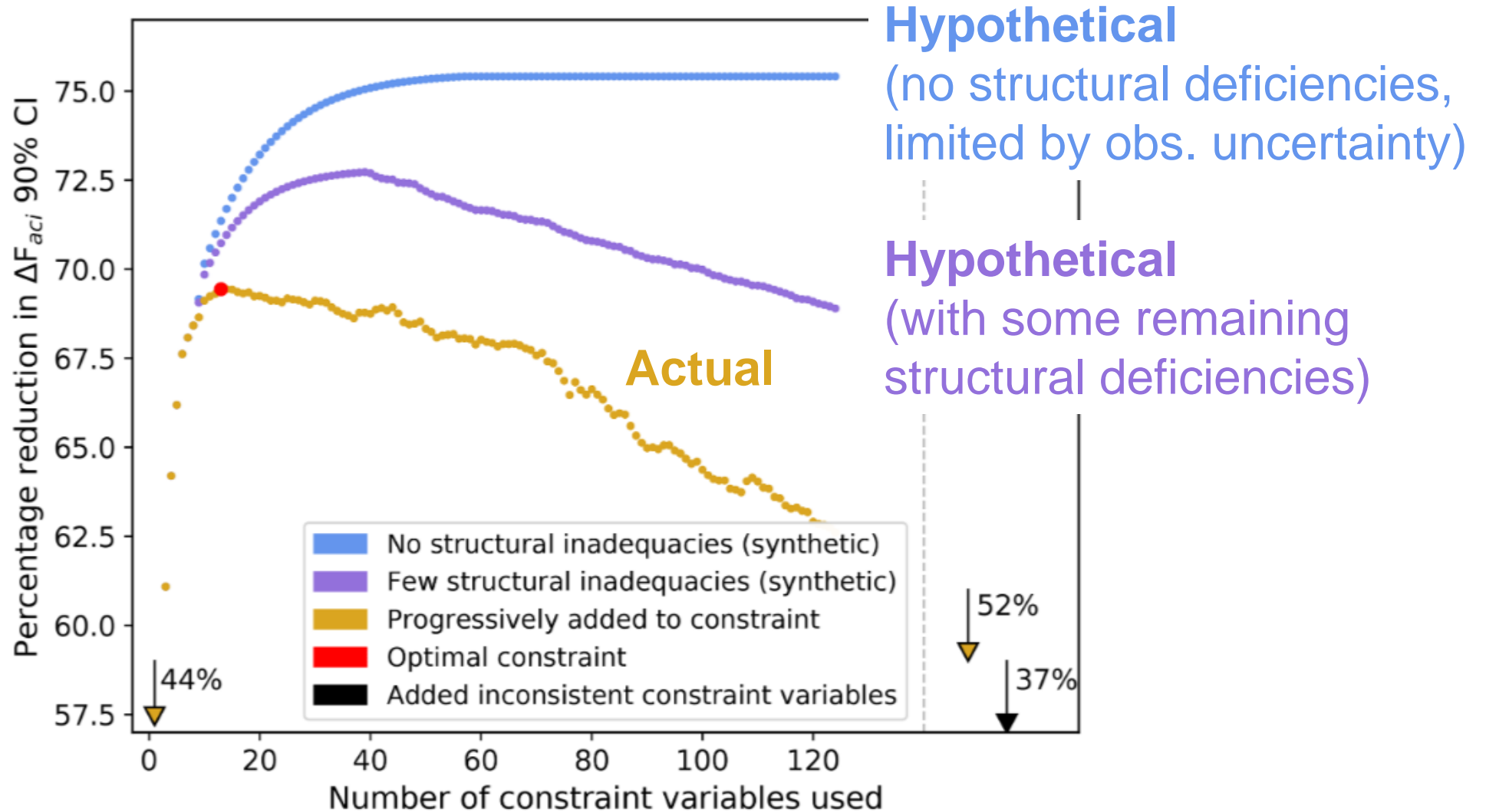
This is the forcing constraint when we use the most consistent set of observations

Adding more (less consistent) observations weakens the constraint

Tighter constraint? Find ways to eliminate the inconsistencies



# Potential for improved constraint



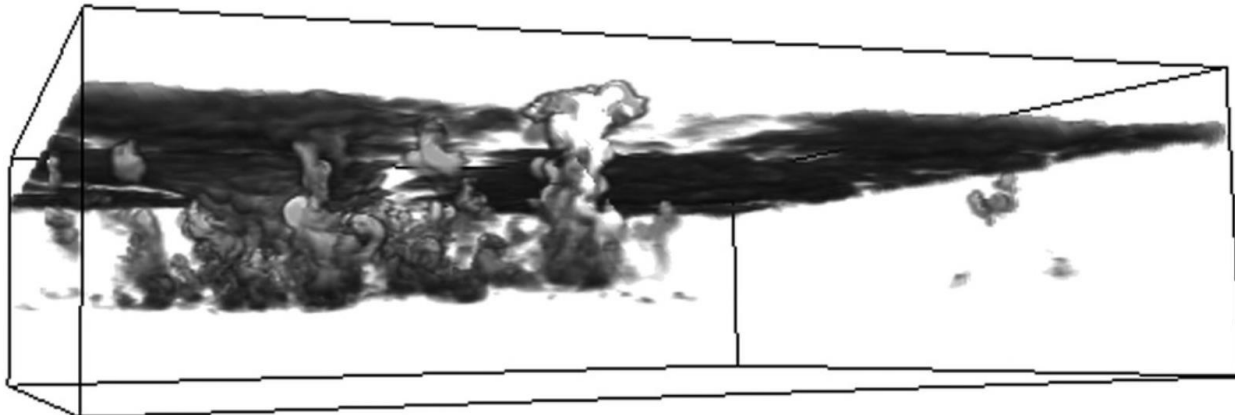
## Visualizing cloud behavior

A PPE of stratocumulus to cumulus transition using the MONC large eddy 2-moment cloud microphysics model

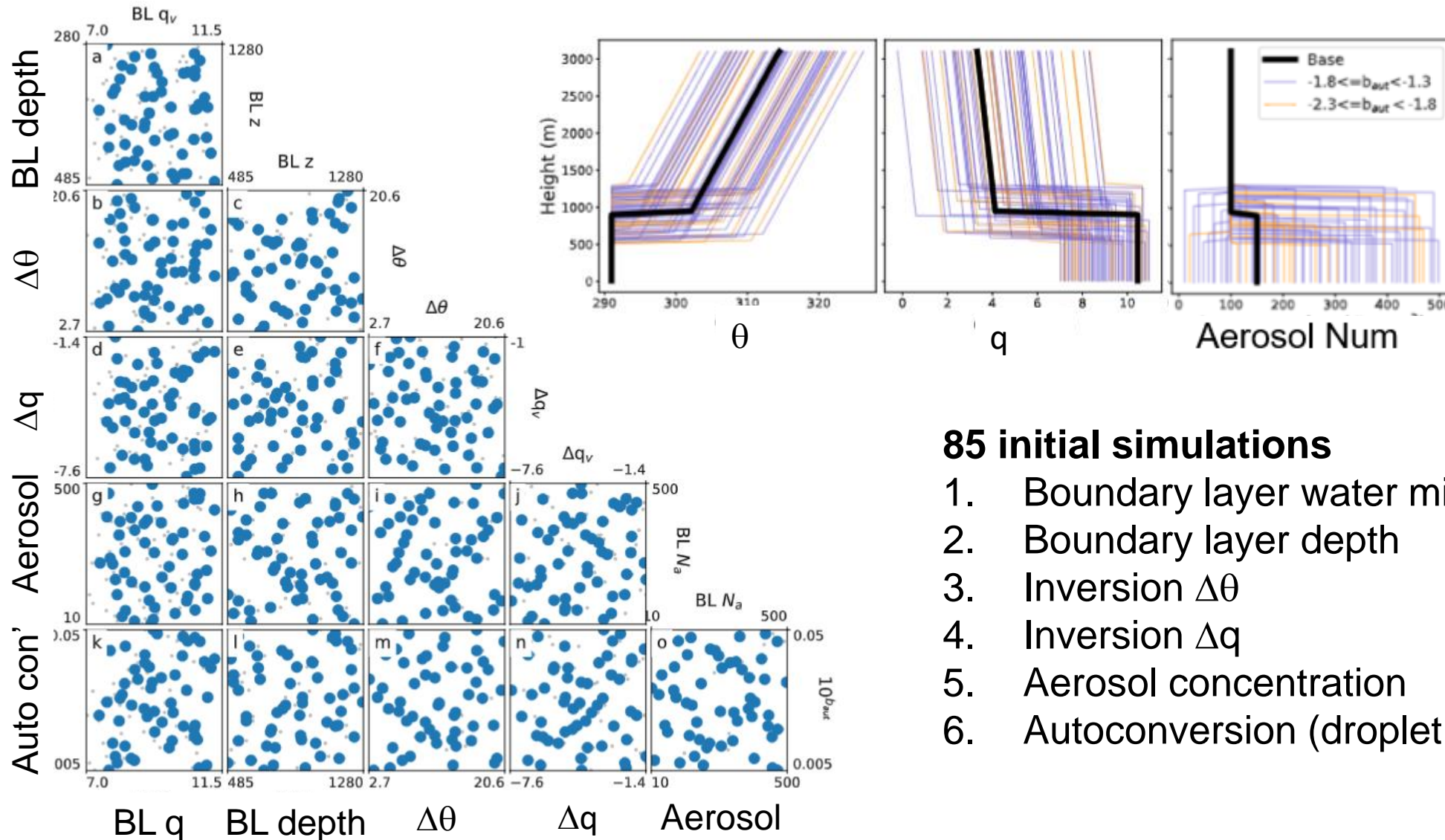
Sandu and Stevens (2011)  
 On the Factors Modulating the  
 Stratocumulus to Cumulus  
 Transitions

- Reference
- Δ SST
- Δ droplet number
- Δ divergence
- Δ LW radiation
- Δ stability
- Δ inversion strength
- Δ inversion humidity

Simulation	Domain	$\overline{CC}_{0-48h}$ (%)	$\overline{MaxCF}_{3^{rd}night}$ (%)	$\Delta A$ (%)
REF	Reference	94	83	51
CST-SST	Small	99	98	20
PP	Reference	86	40	72
DIV	Reference	94	88	38
RAD	Small	90	64	68
SLOW	Reference	97	87	44
FAST	Reference	91	33	81
DTH	Small	75	57	54
DTHQT	Small	95	94	26



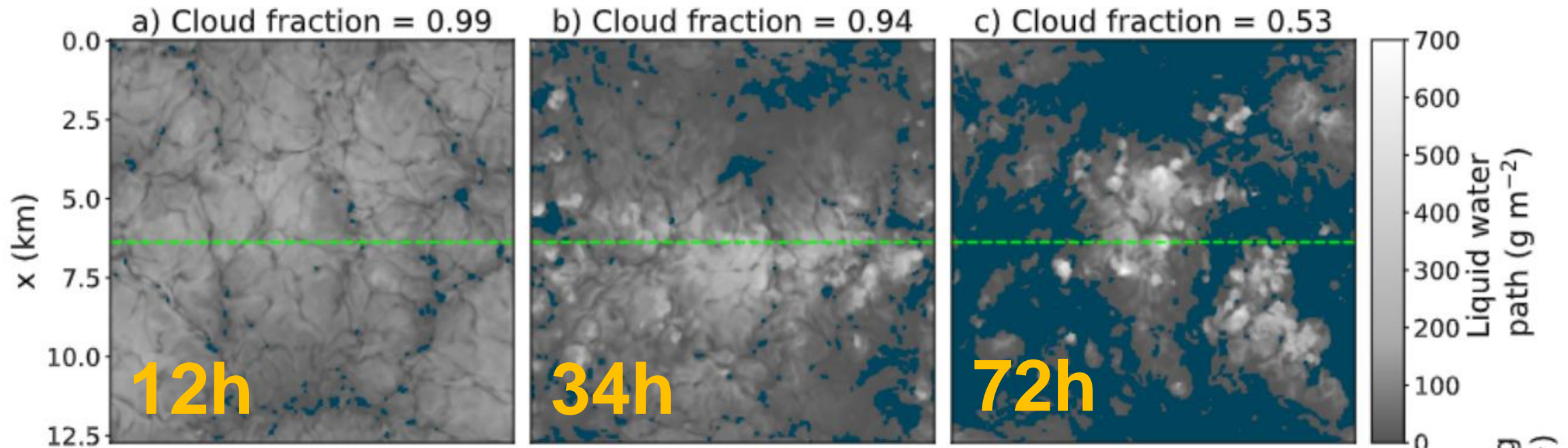
Can use PPEs to understand how multiple cloud-controlling factors affect cloud behavior



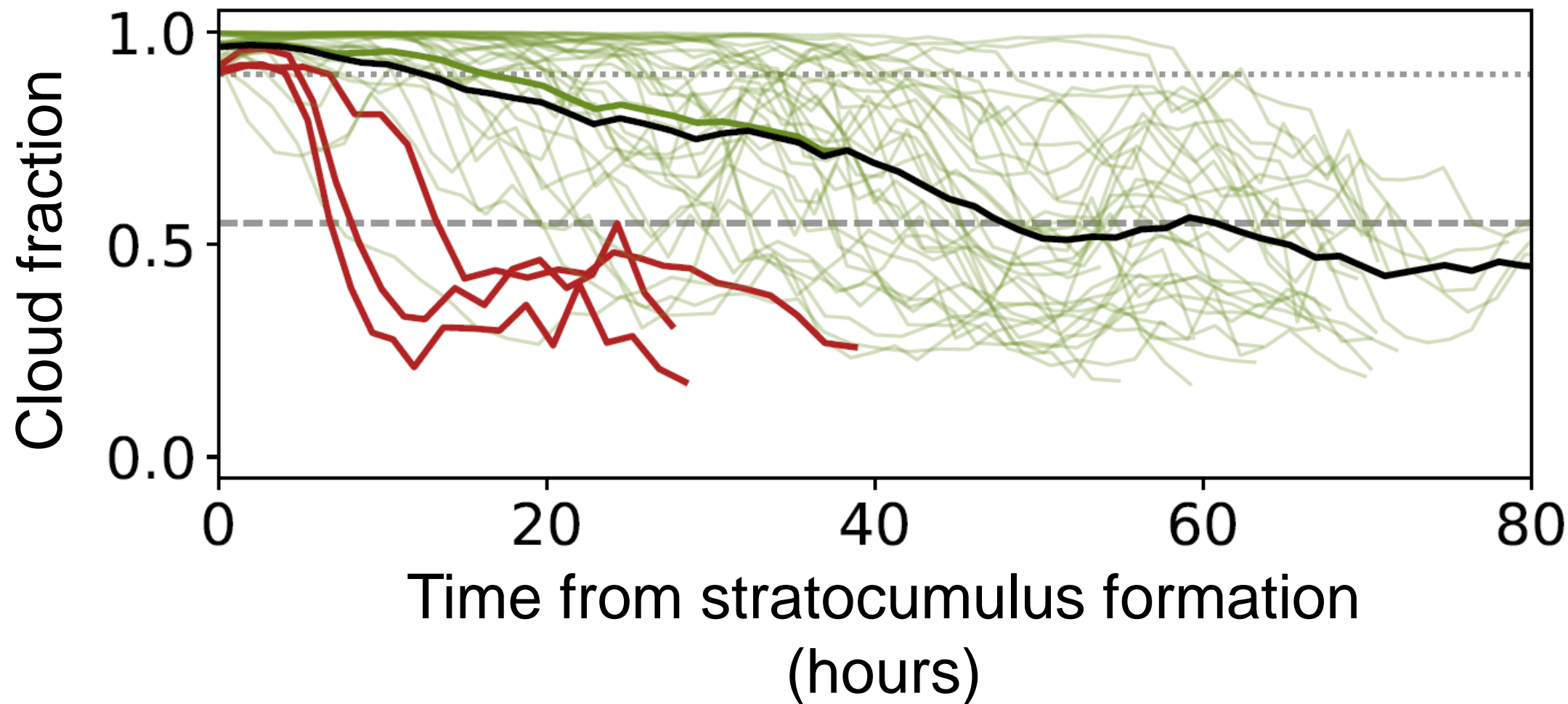
## 85 initial simulations

1. Boundary layer water mixing ratio
2. Boundary layer depth
3. Inversion  $\Delta\theta$
4. Inversion  $\Delta q$
5. Aerosol concentration
6. Autoconversion (droplet  $\rightarrow$  rain) rate

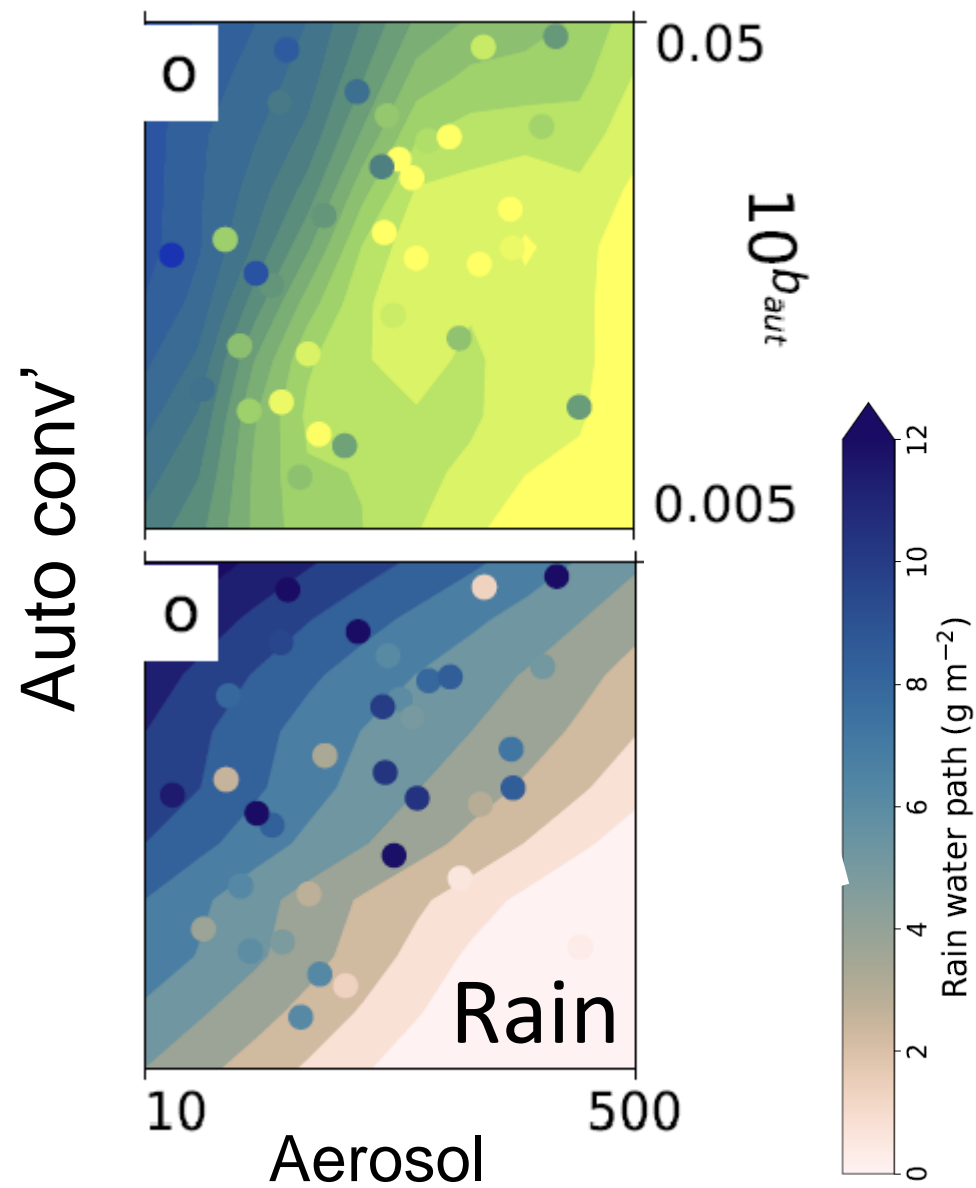
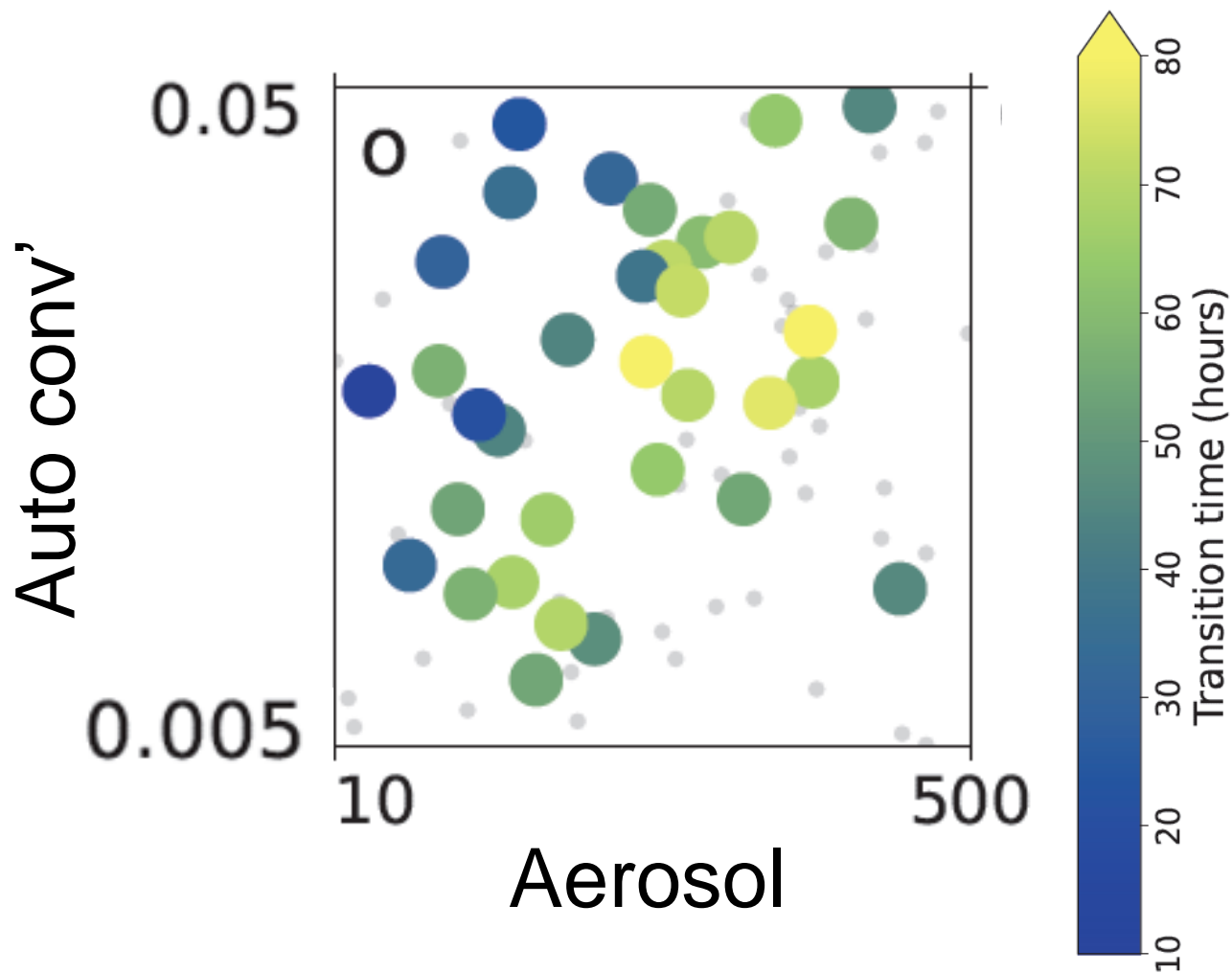
# Evolution of one ensemble member

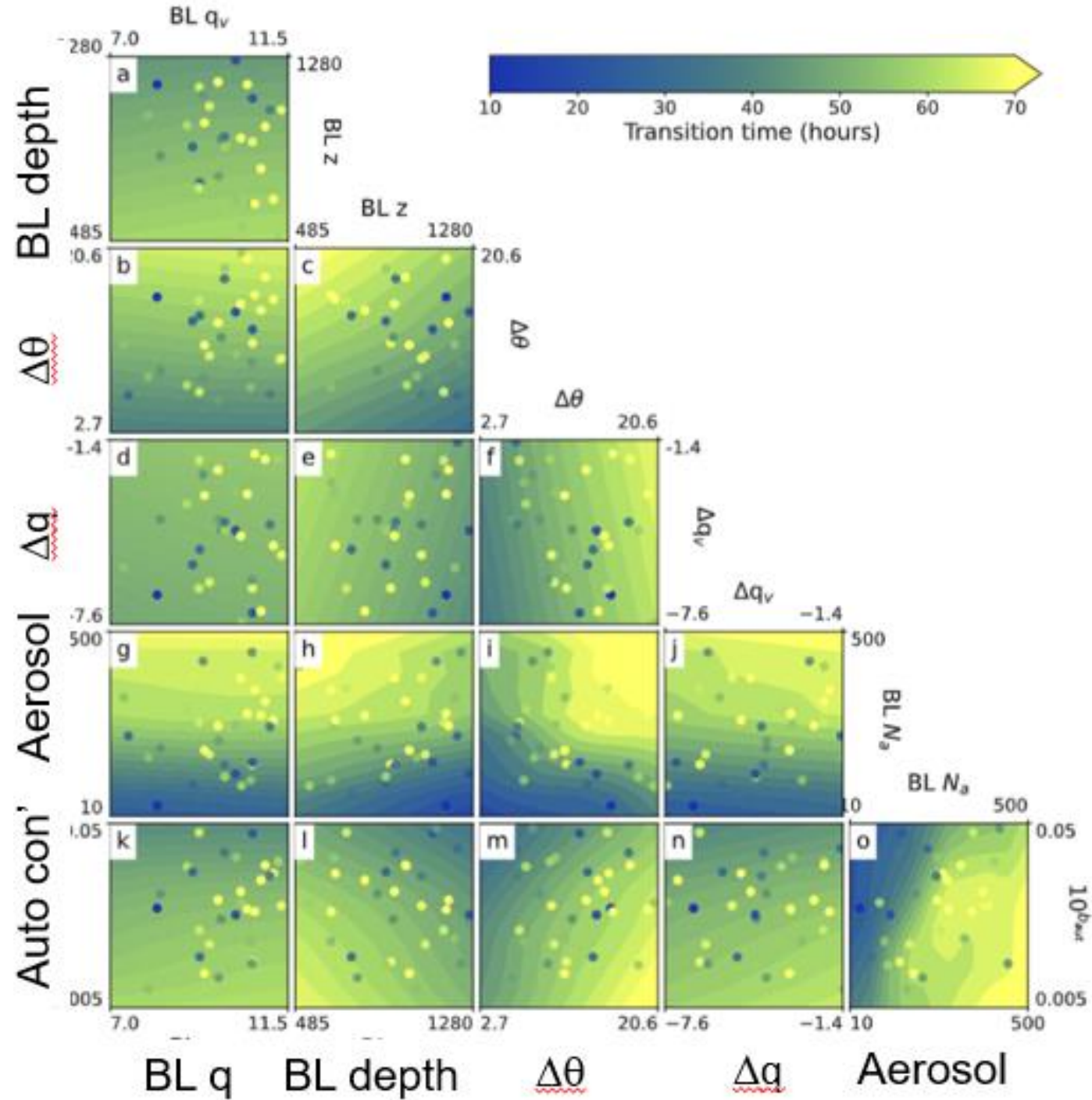


Sea surface temperatures increase 1.5 K per day









- Perturbed parameter ensembles can be used to train emulators, enabling multiple factors in models to be explored
- Provide physical insight rather than just a trained ML model
- PPEs can be analysed to expose potential structural deficiencies in models when different observations constrain the model to inconsistent regions of parameter space
  - Can apply to multiple observation types, regions and time periods
- ‘Parameters’ can also be environmental drivers – e.g., cloud controlling factors
- If interested, join the **APPEAR network** – Analysis of PPEs in Atmospheric Research (aerosols, chemistry, clouds, climate, meteorology from LES to ESM)

