Institute for Climate & Atmospheric Science
SCHOOL OF EARTH AND ENVIRONMENT

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Towards maximum feasible reduction in aerosol forcing uncertainty

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Centre for Environmental Data Analysis
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“Maximum feasible reduction” in uncertainty

When you can’t tell, within observational uncertainty, that the model has deficiencies

- **Deficiencies** = **inappropriate** structural design or inadequately tuned
- **Inappropriate** = incorrect, incomplete, too simple

Topics

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- Using Perturbed Parameter Ensembles (PPEs) and observations to expose model structural deficiencies
- Causes of uncertainty and how they change as the model is constrained priority observations
- “Process-based” model PPEs

An introduction to perturbed parameter ensembles (PPEs)

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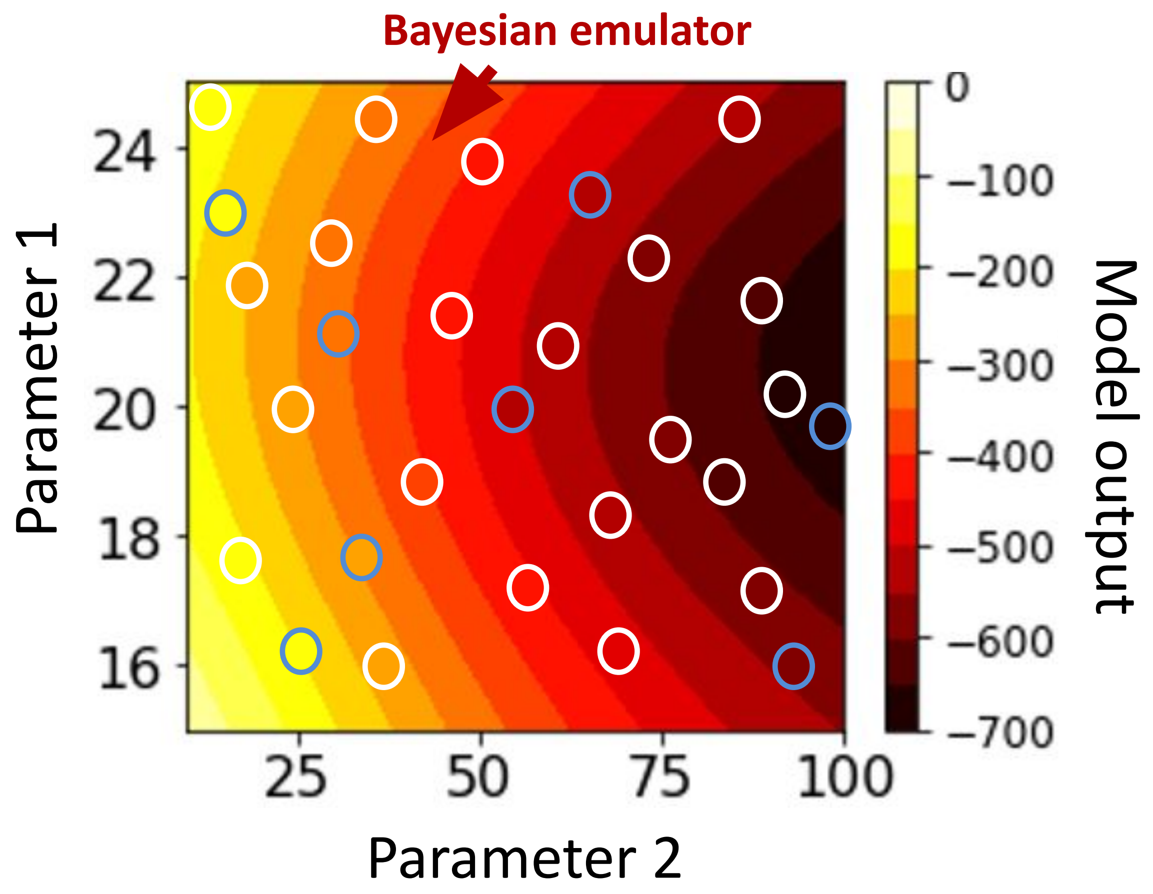

Oakley and O'Hagan, Probabilistic sensitivity analysis of complex models: A Bayesian approach, J. Roy. Stat. Soc. B (2004).

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

- A **perturbed parameter ensemble** (PPE) is a set of model simulations that samples combinations of model inputs – any "simulation-controlling factor"
- Optimally designed to train a **statistical emulator**
- Typically need 5-10 simulations per parameter

 Can then generate **~millions of "model variants"**

Using PPEs to "constrain" a model

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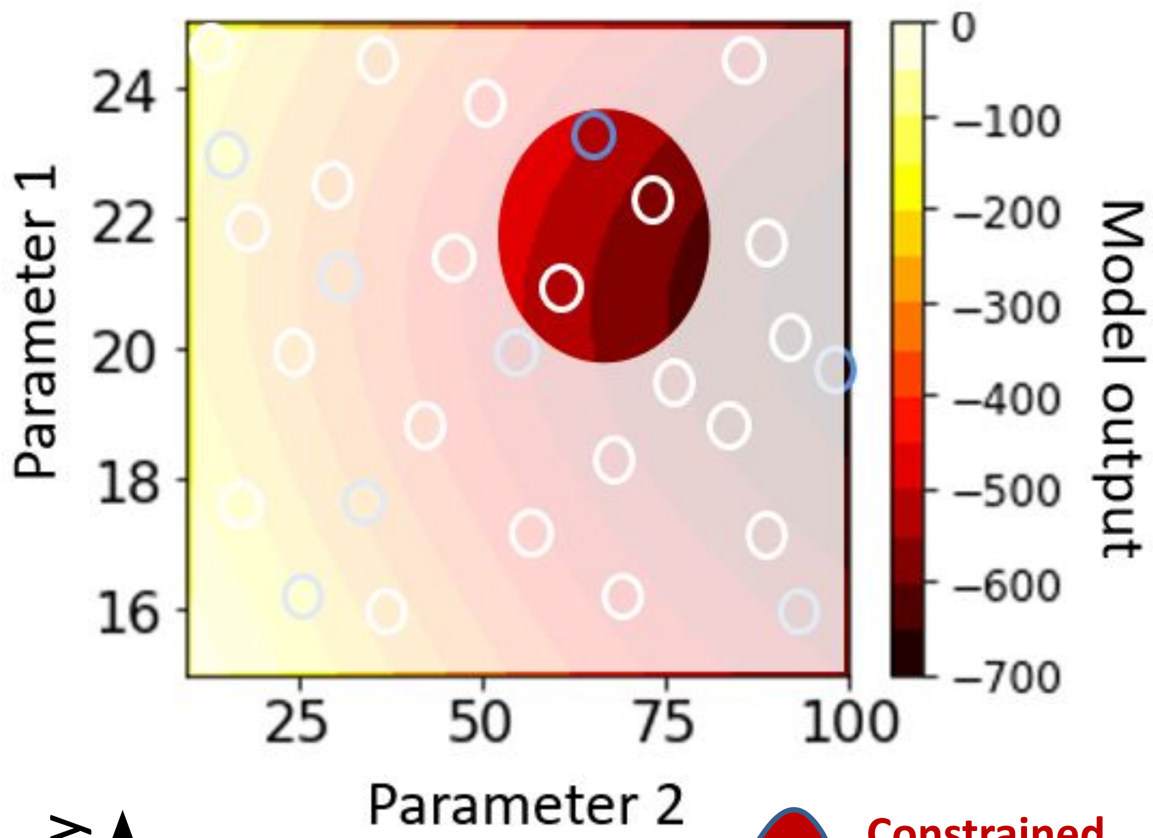

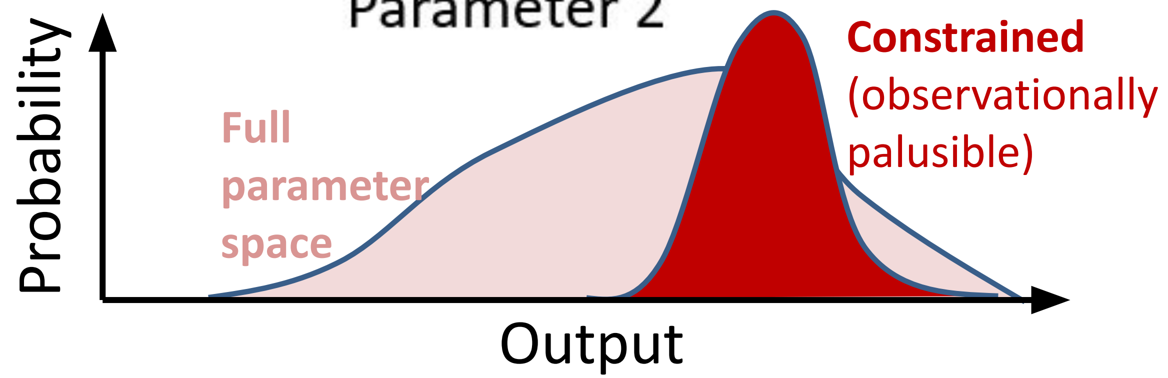

Identify the **observationally plausible** parameter space
(lots in here about obs. uncertainty!)

- Constrains the joint parameter ranges

- Constrains the range of **unobservable quantities** (e.g., forcing, cloud feedback)

Approach to model development and tuning

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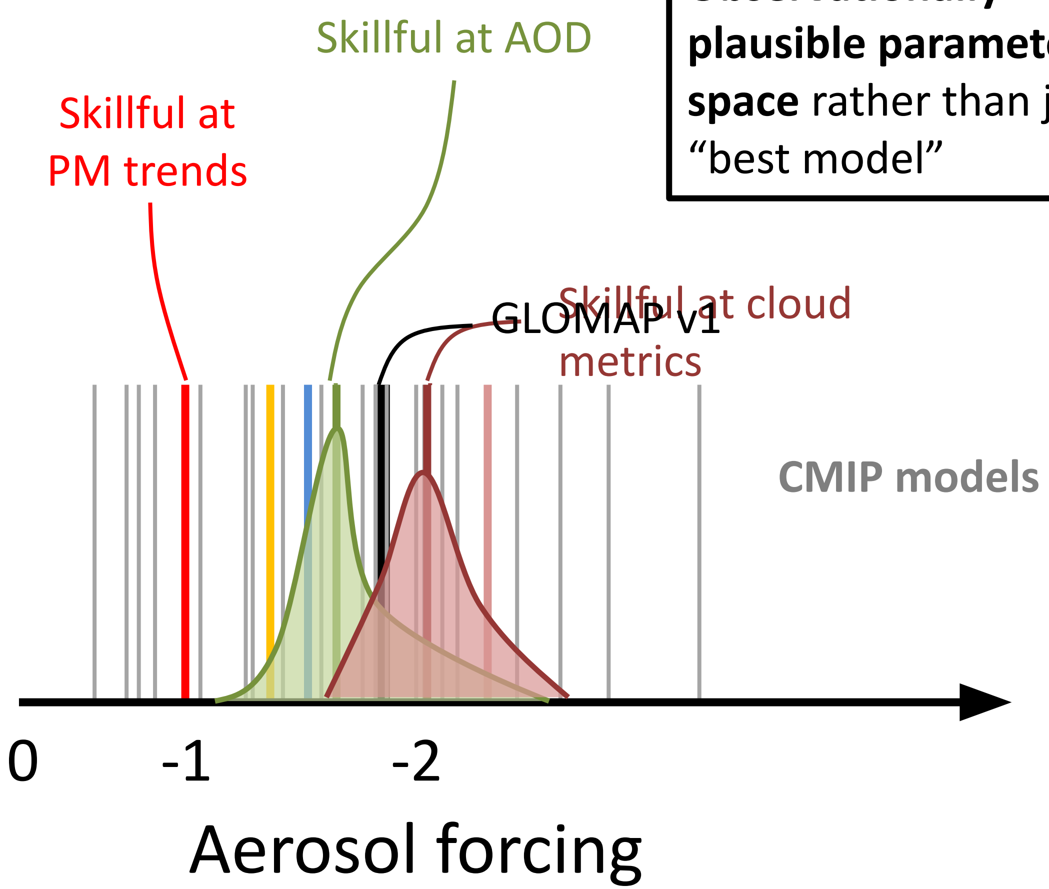

Observationally plausible parameter space rather than just "best model"

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

Balloon-squeezing problem:

Can't reduce its size (constrain it) without changing the balloon

It's structurally not the best balloon

The balloon-squeezing problem implies structural errors

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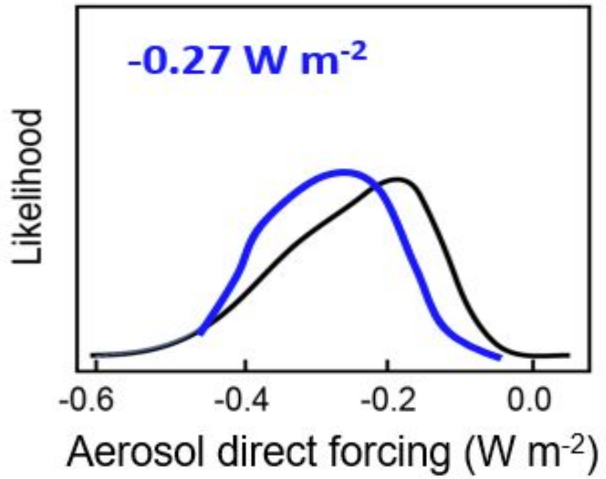
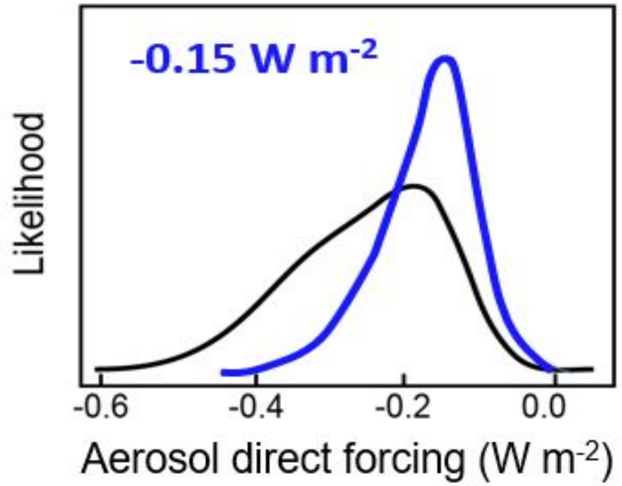
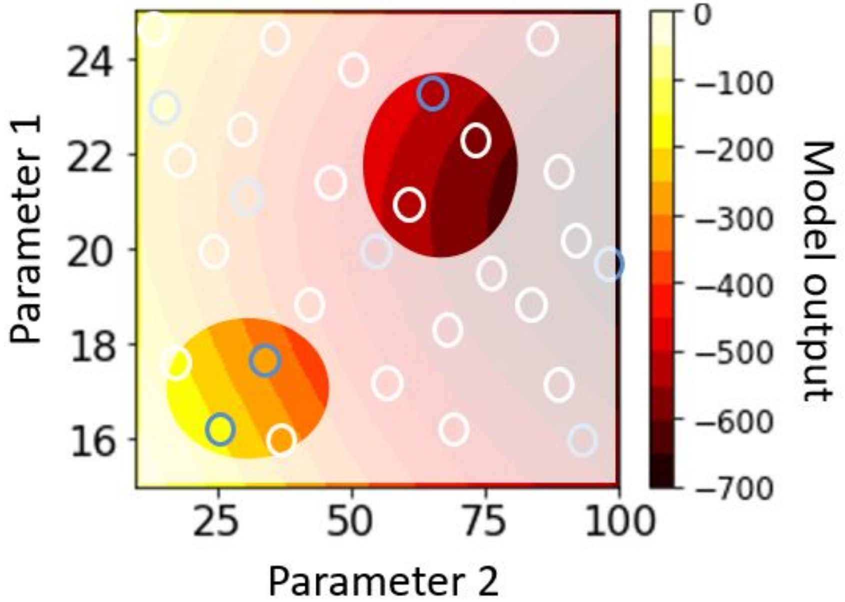
Forcing constrained by **$PM_{2.5}$**



Forcing constrained by **Sulphate**



HadGEM climate model PPE perturbing 26 aerosol parameters **(Johnson et al., 2020)**



The model doesn't include nitrate aerosol, so constraining $PM_{2.5}$ forces sulfate to be too high, resulting in too-high a forcing

Note, you don't *need* a PPE to expose potential structural deficiencies, but it helps because you have explored all possible other explanations (full parameter space)

"… I can't retune my model, it must have a structural error."

HadGEM PPE spread

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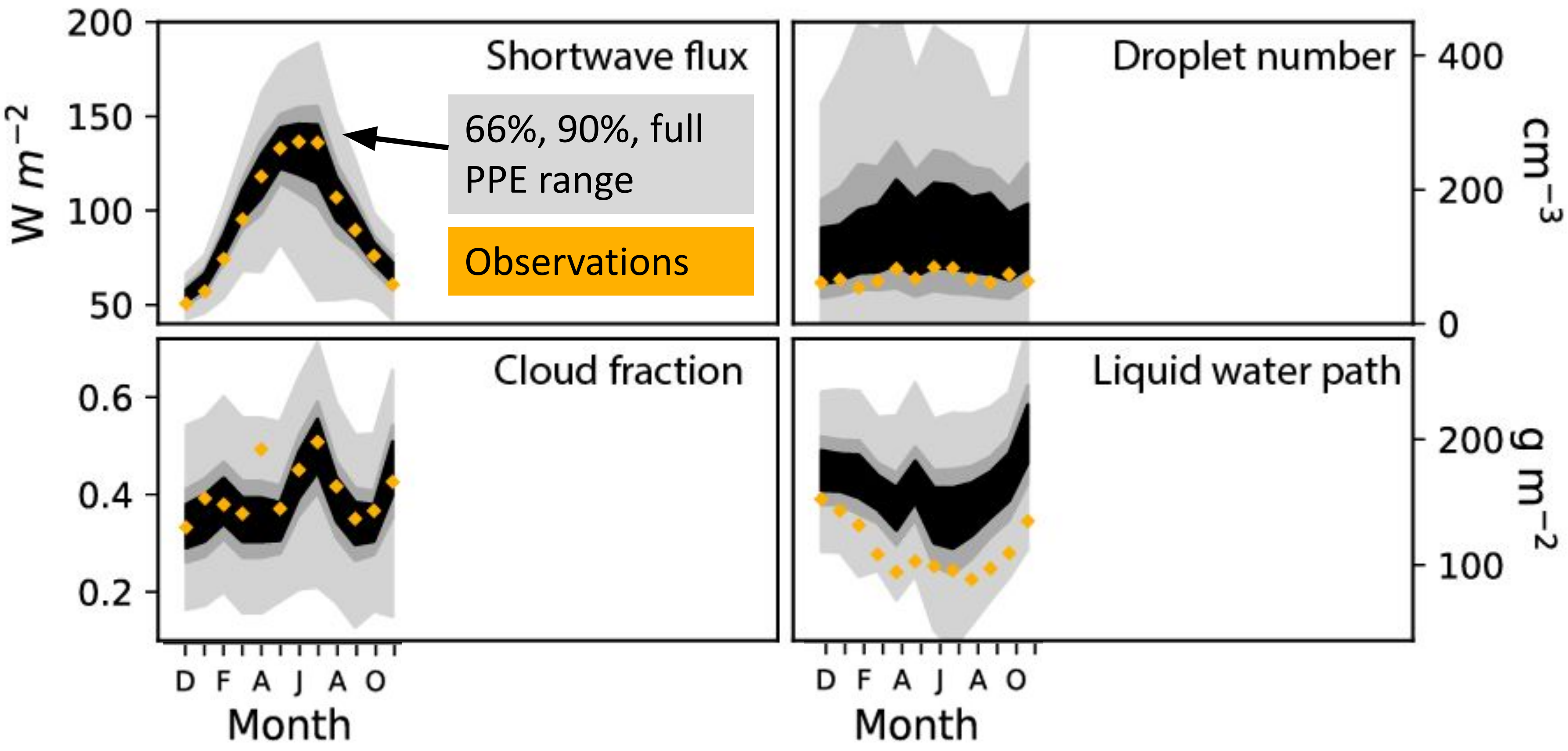
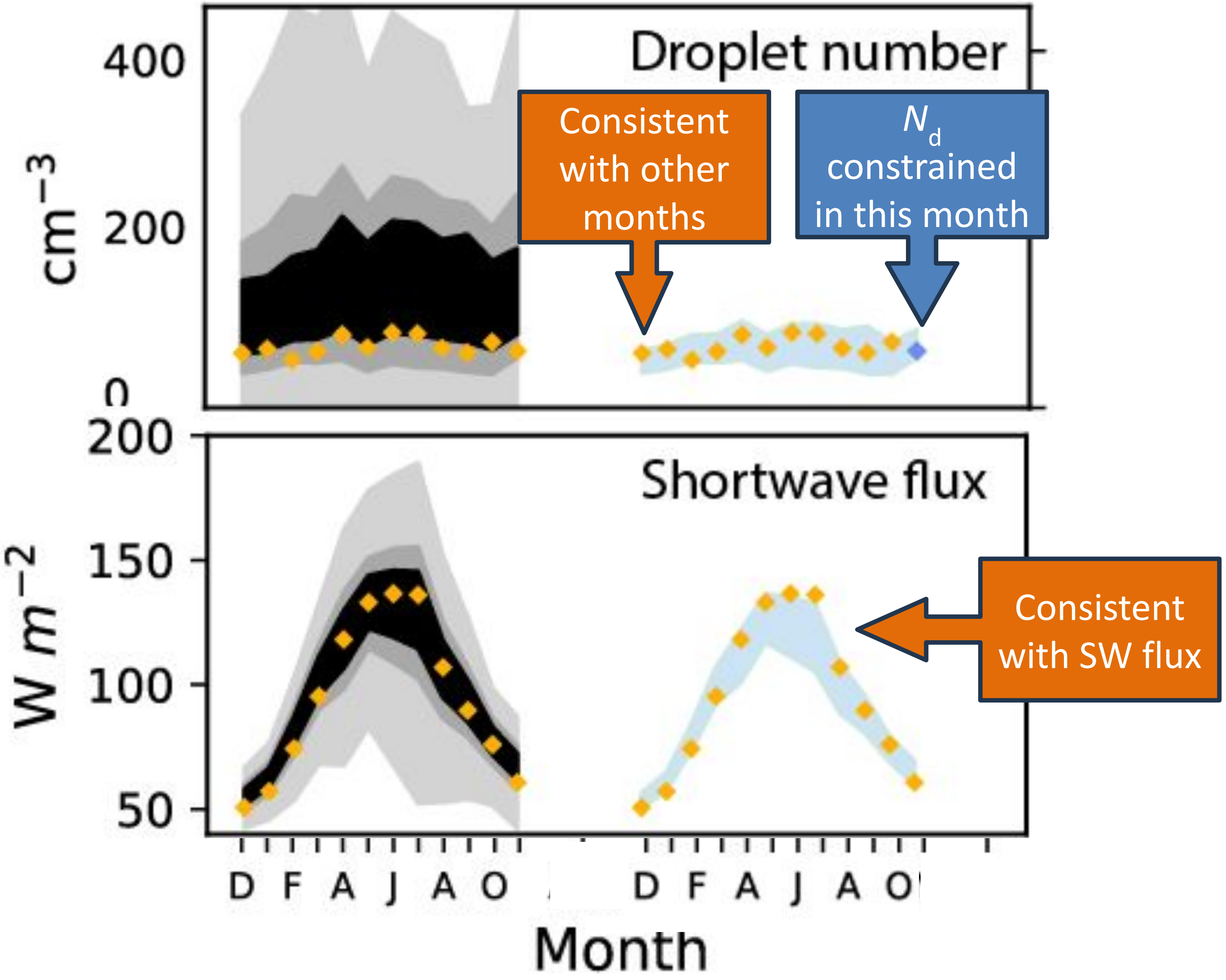
UKESM1 climate model PPE perturbing
37 aerosol, cloud & physical model parameters
(Regayre et al., 2023)



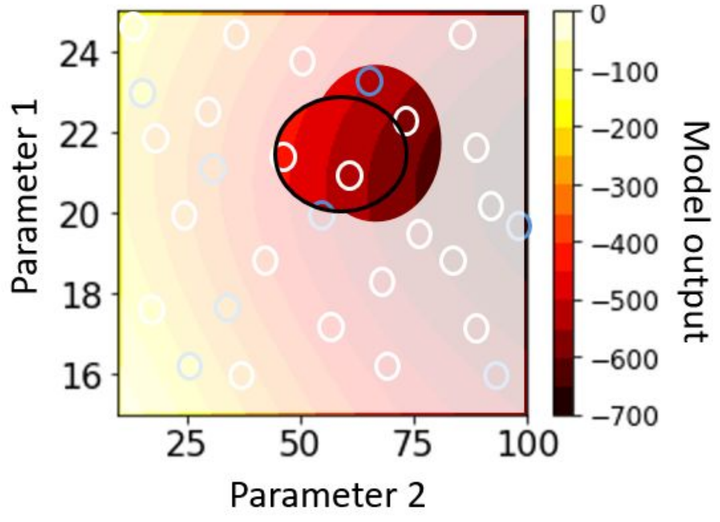
N Atlantic shallow cloud properties

MODIS, CERES and Multisensor Advanced Climatology

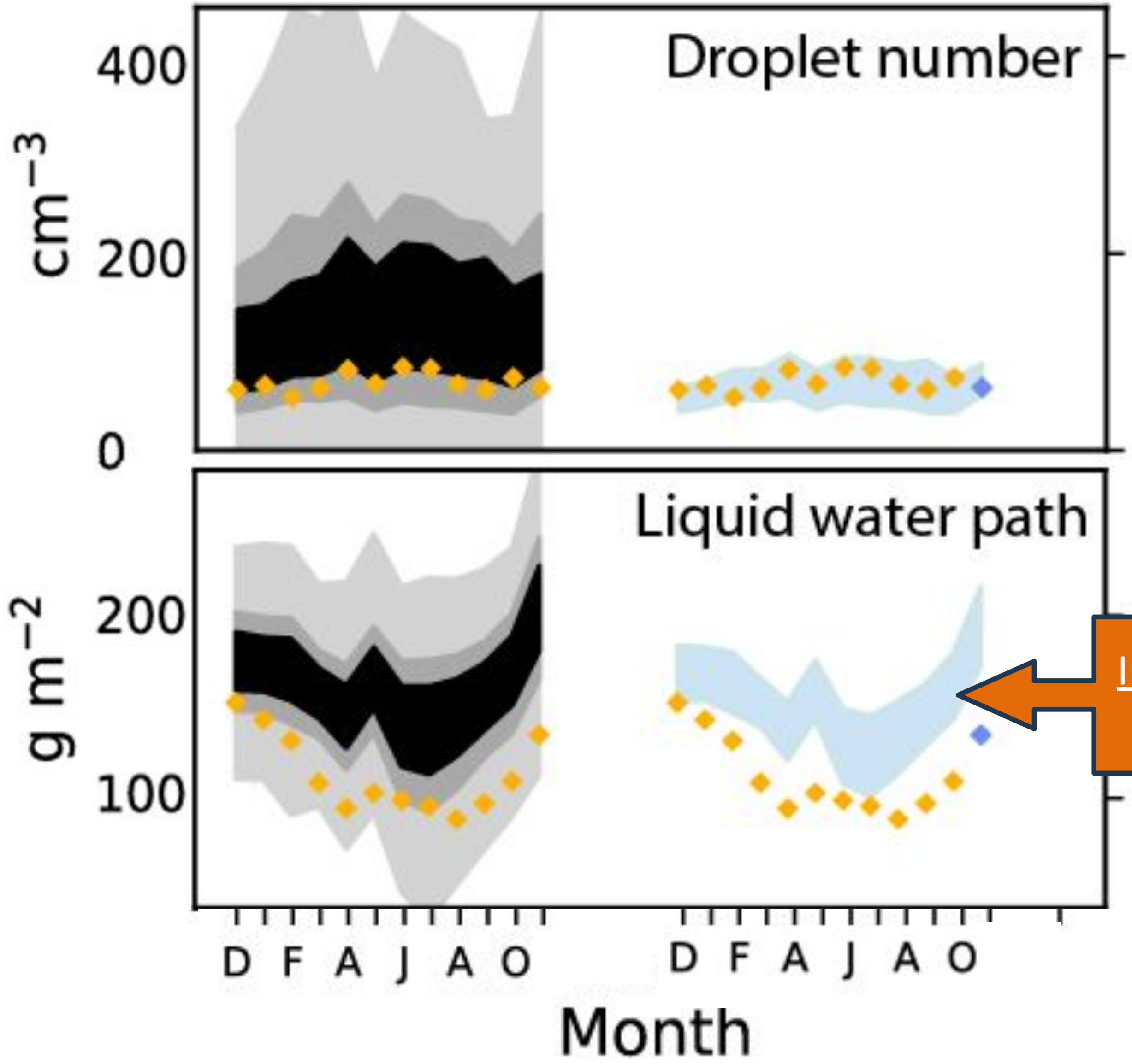
Constraint of droplet number



Constraining droplet number constrains **shortwave flux**

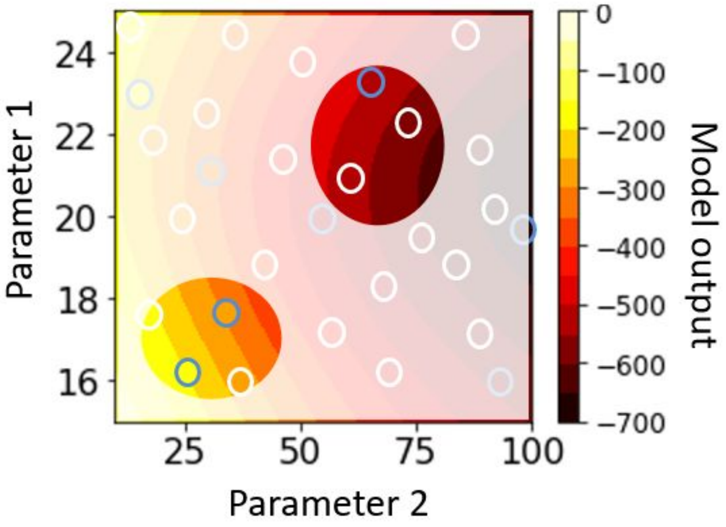


Constraint of droplet number



Structural error? In a single-moment cloud model, rain doesn't reduce LWP and droplet number consistently

Inconsistent with LWP



Many observations, many model inconsistencies

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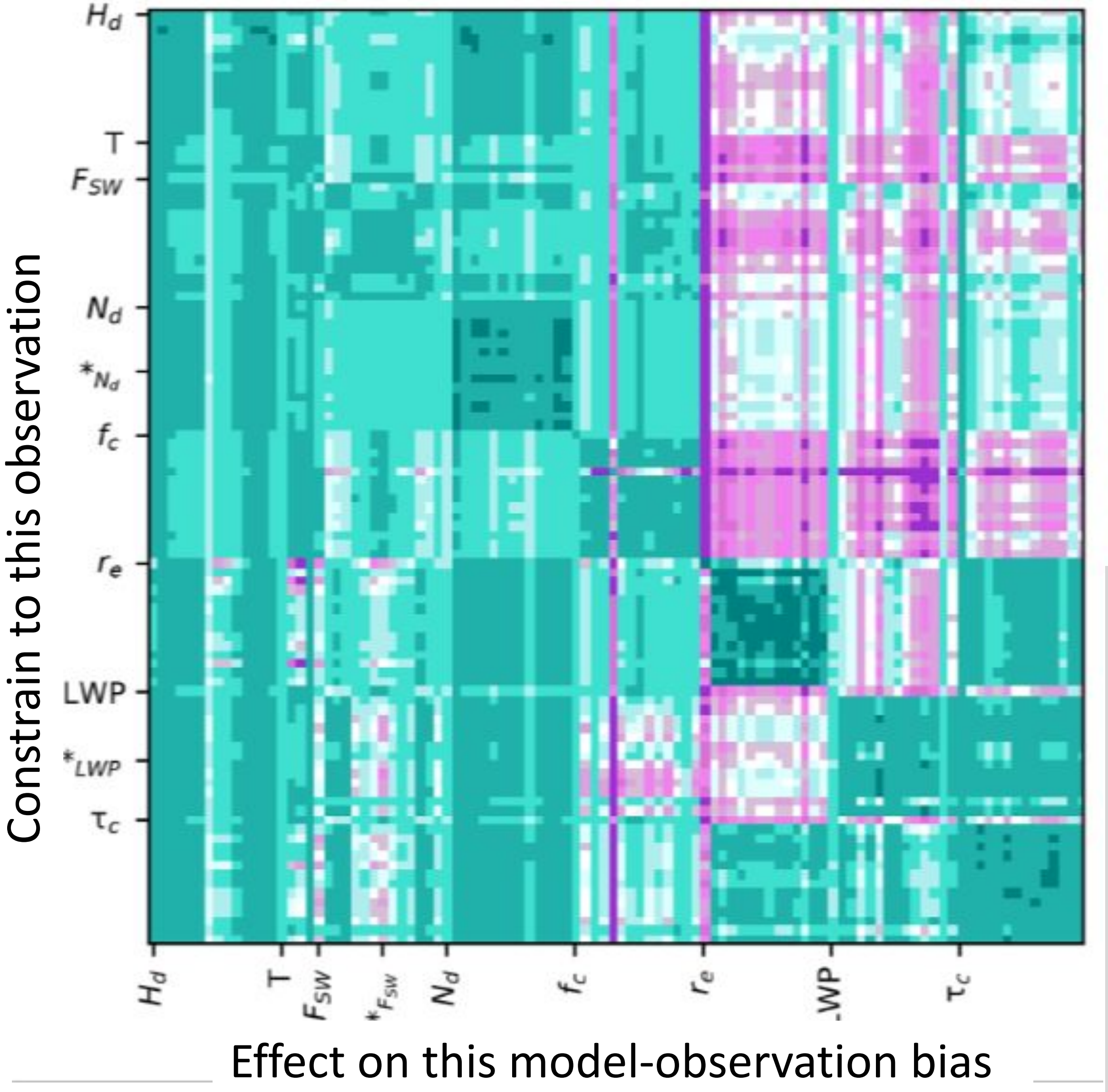
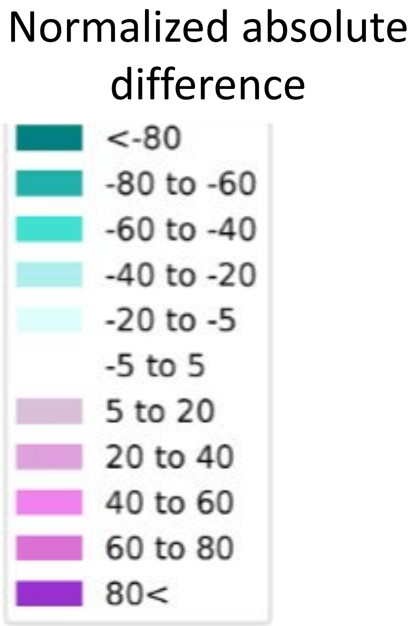
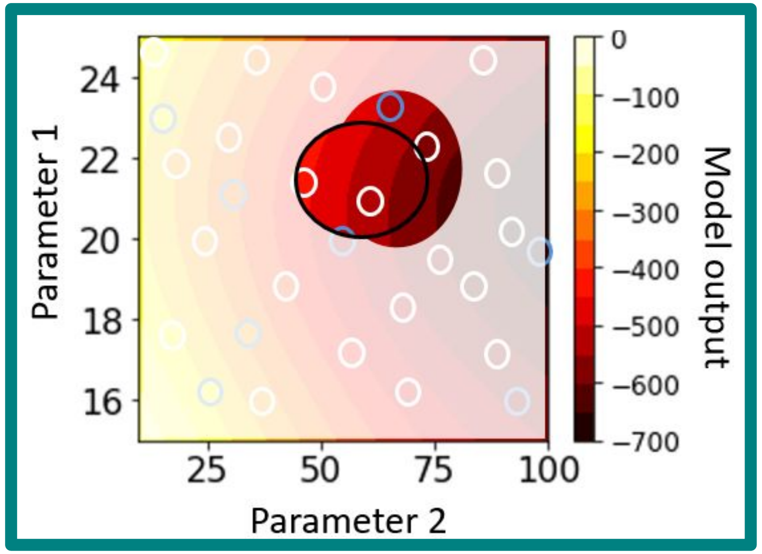
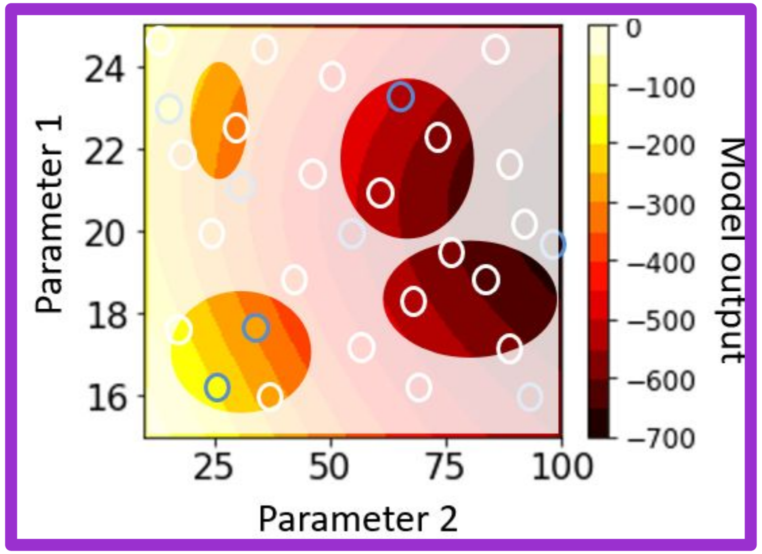








H_d Hemispheric N_d contrast

T: Sc to Cu Transects (e.g., $dN_d/dLWP$)

F_{sw}: SW flux

f_c cloud fraction

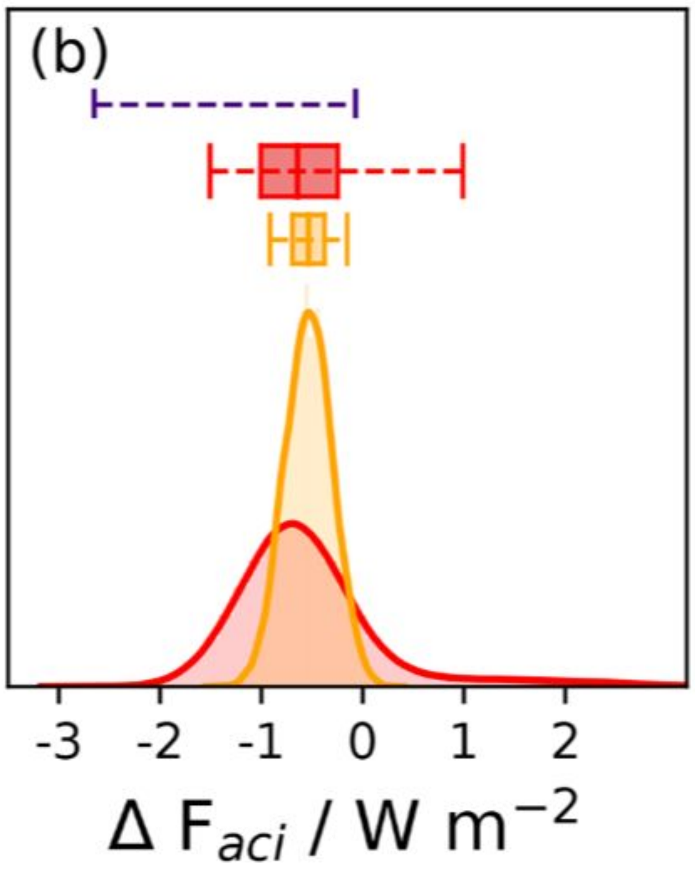
N_d Droplet number

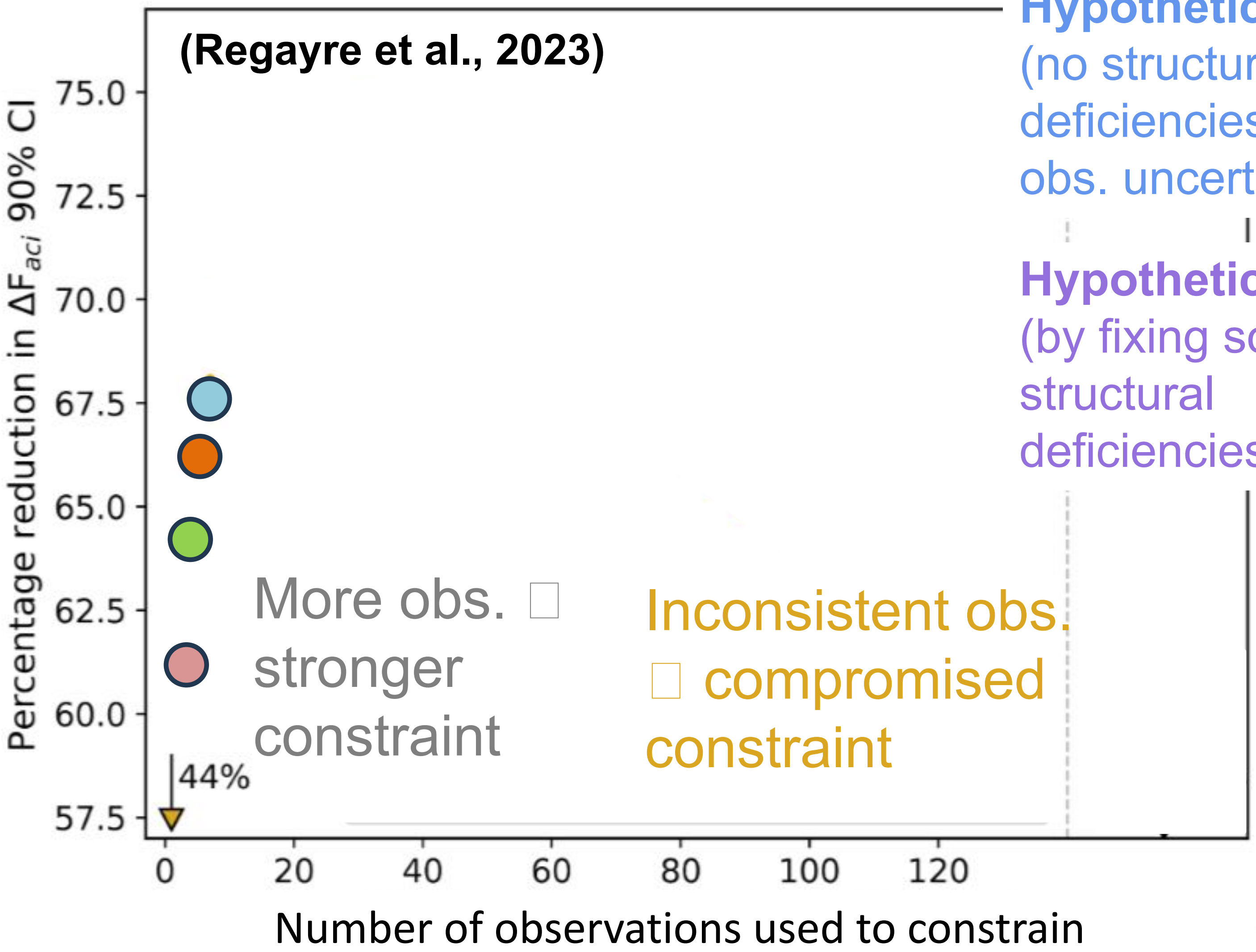
r_e Effective radius

τ_c Optical depth

Model-observation inconsistencies compromise the constraint

(Regayre et al., 2023)





Hypothetical
(no structural deficiencies, limited by obs. uncertainty)

Hypothetical
(by fixing some structural deficiencies)

Workflow for uncertainty reduction

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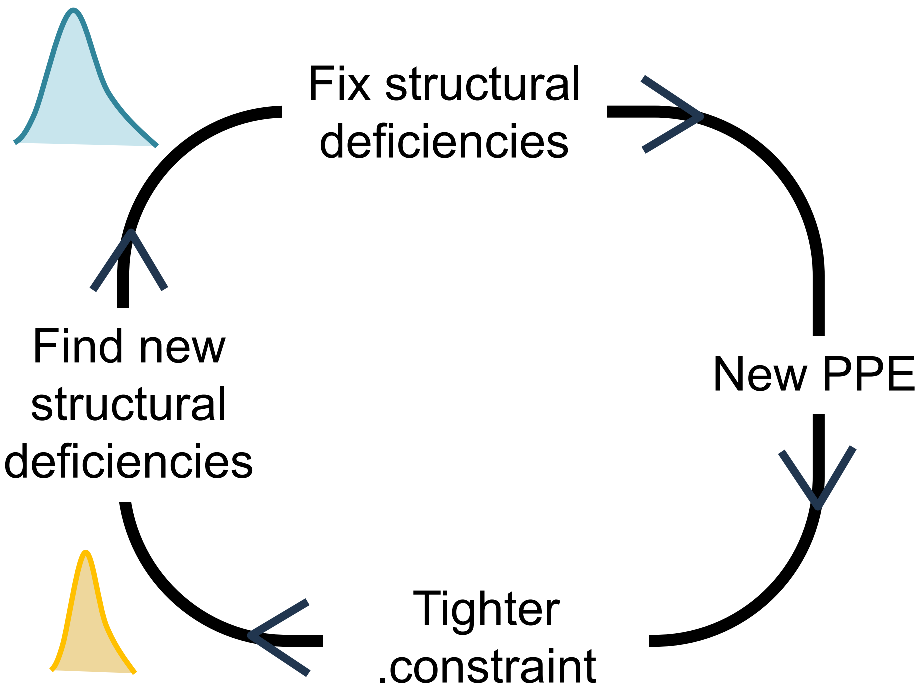

If we can reduce structural deficiencies then we can make rapid progress with observational constraint…

Remaining causes of uncertainty after constraint

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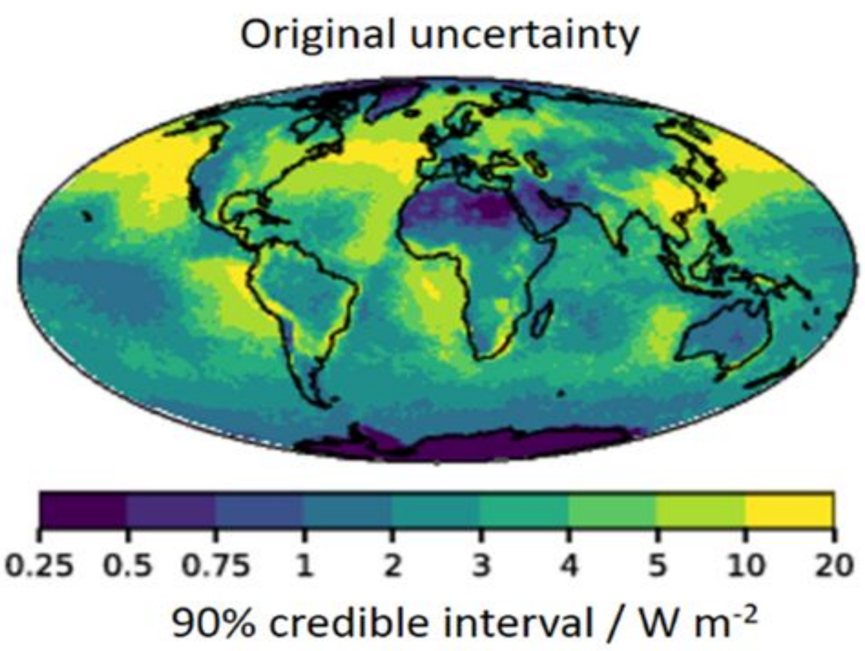

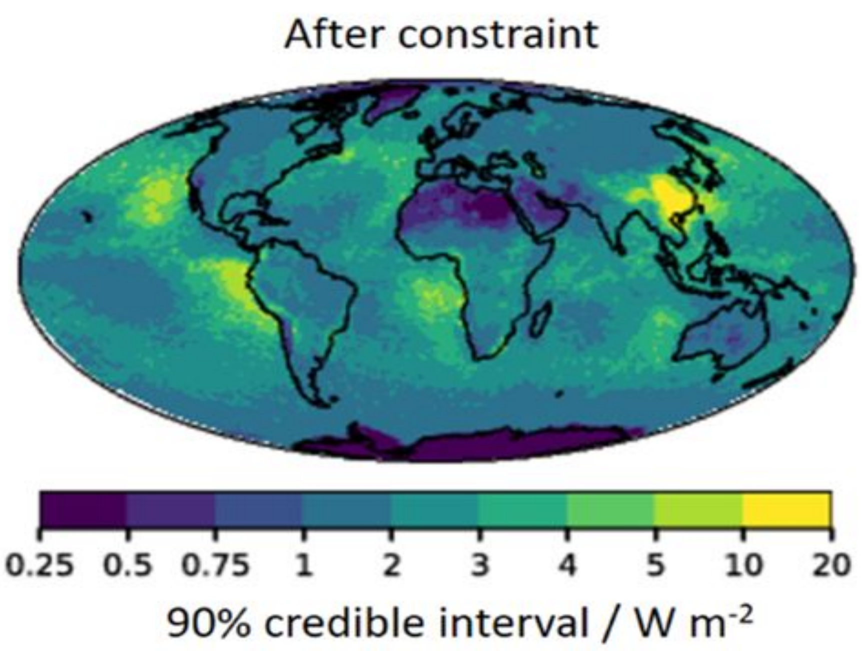

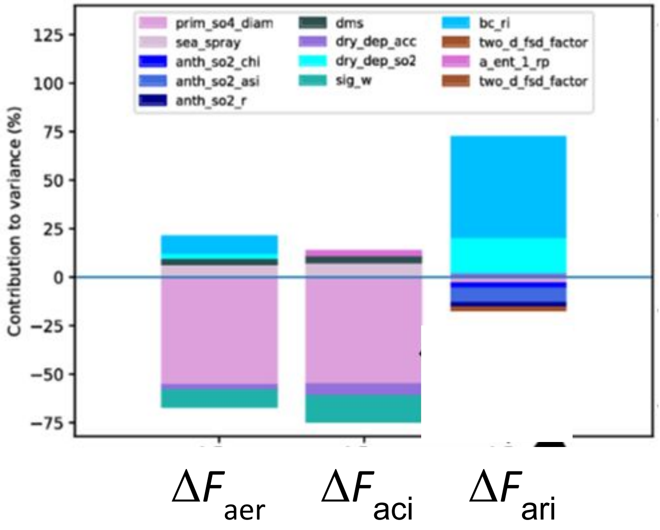

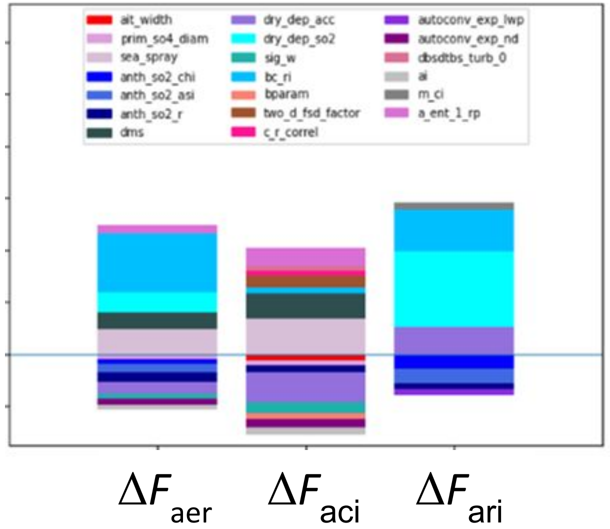

(Regayre et al., in prep.)

Remaining causes of uncertainty after constraint

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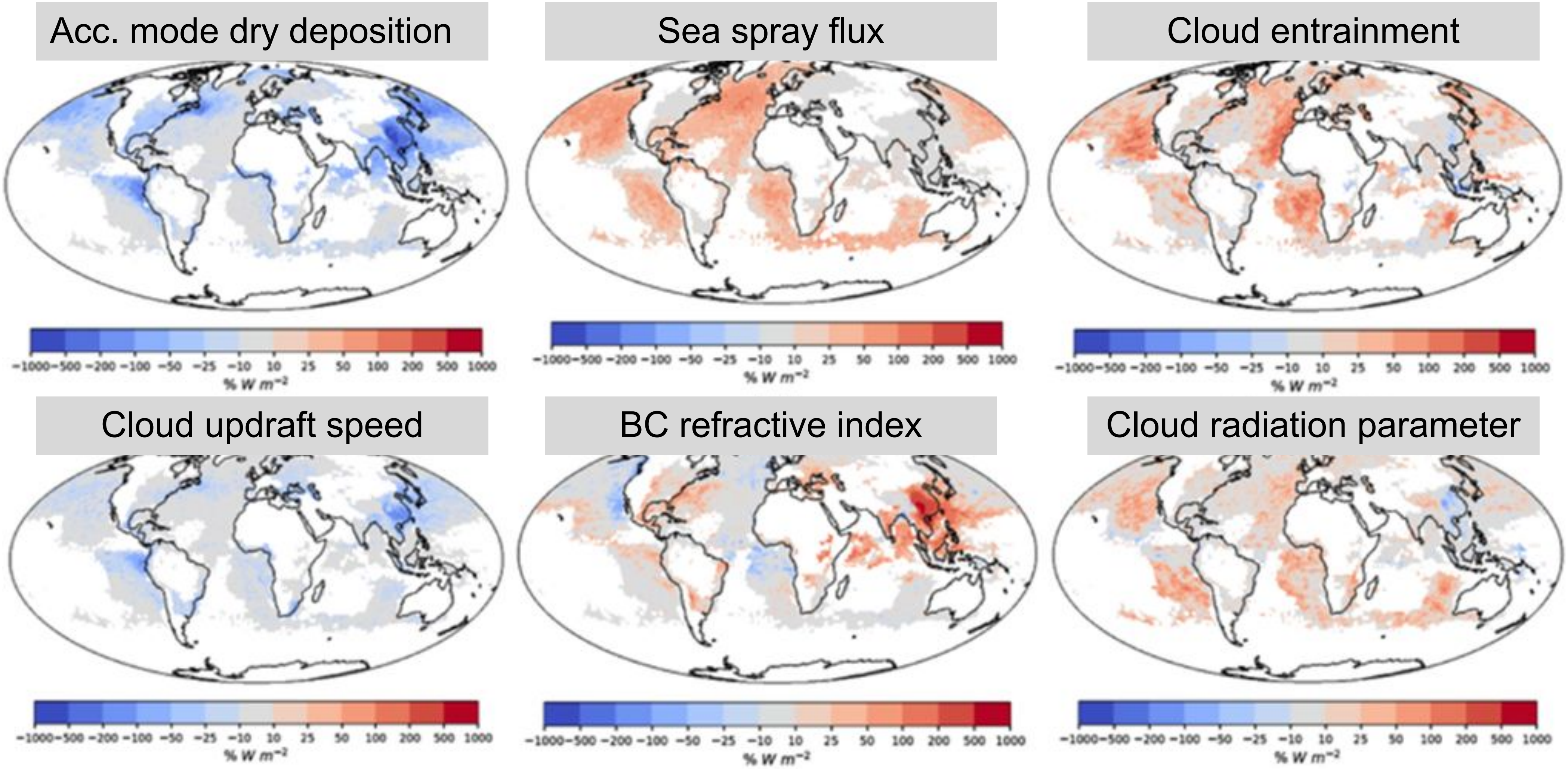


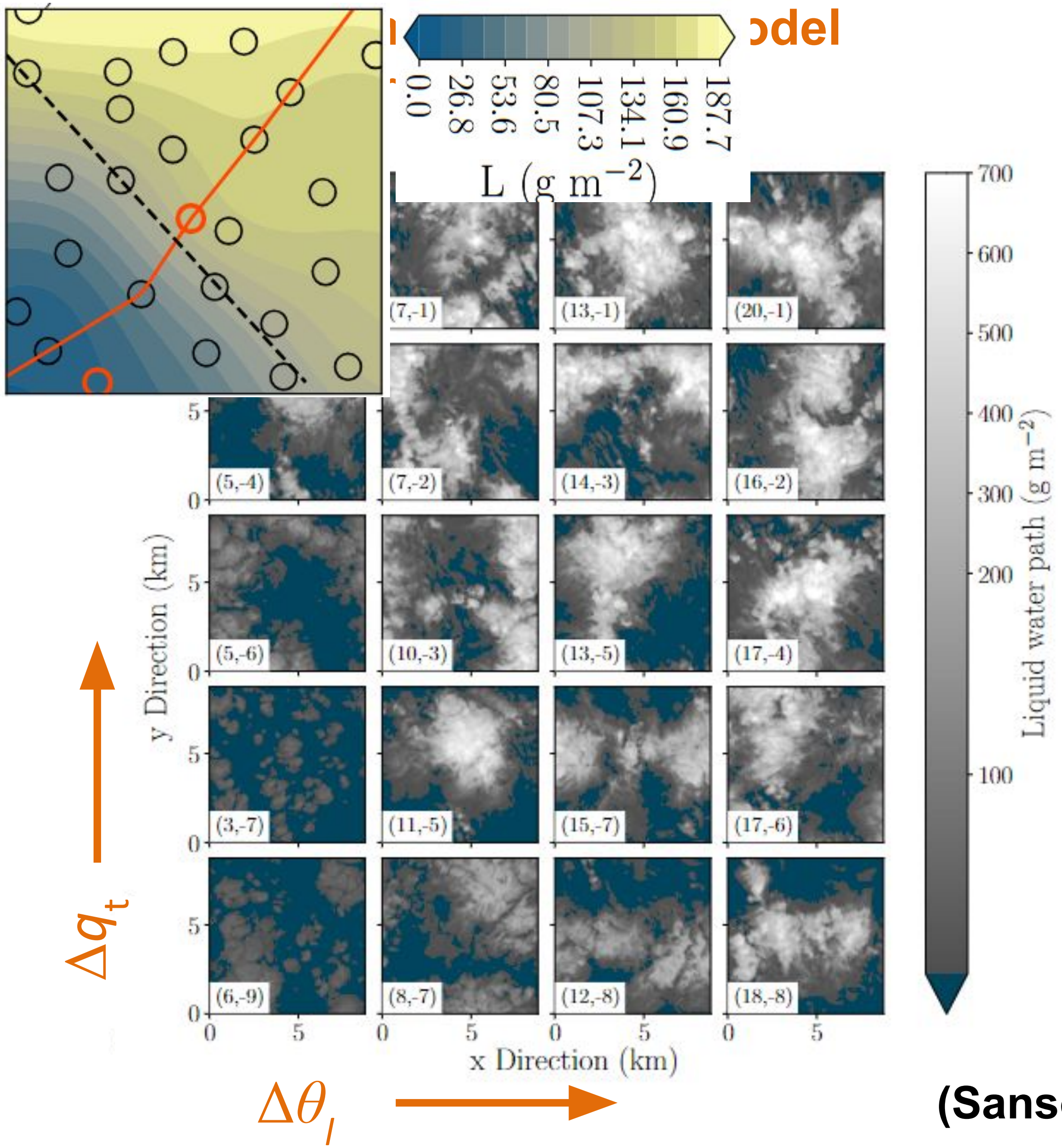
Makes ACI more negative ← → Makes ACI less negative

Quantifying remaining causes of uncertainty after constraint will enable us to identify **priority observations or approaches** to further increase constraint

Needs to be done in parallel with structural improvements

“Process model” PPEs and emulators

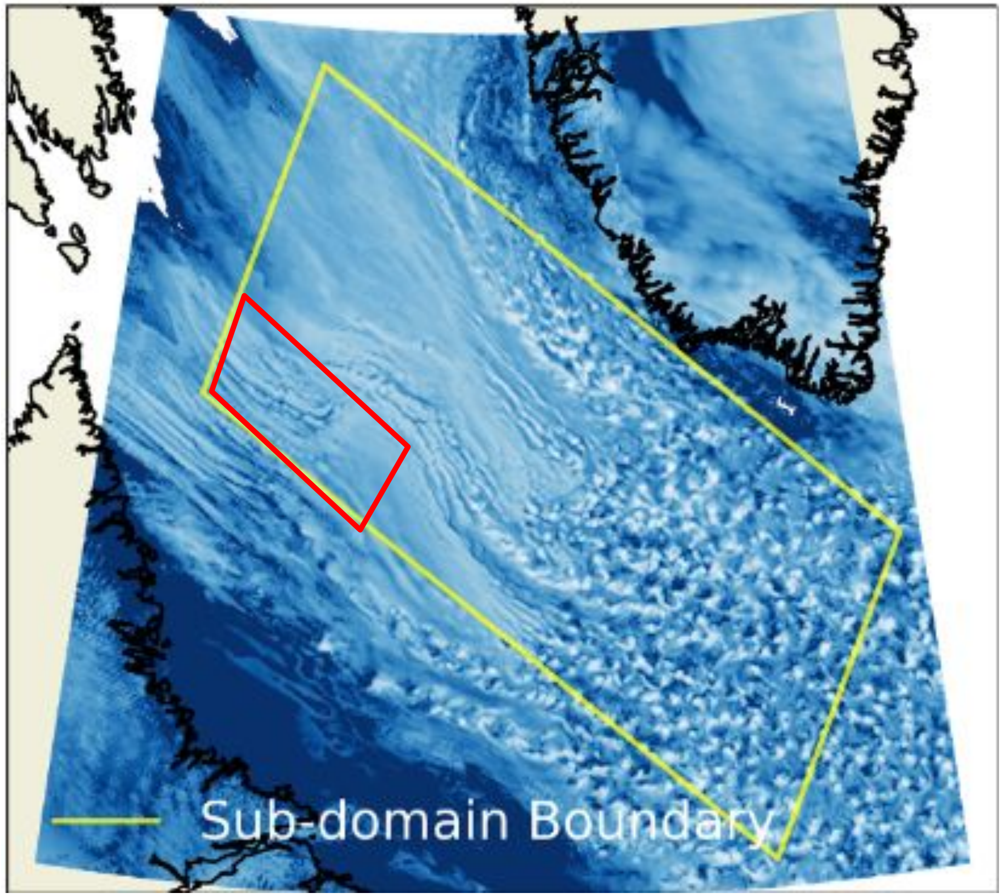
Emulator of cloud response to these two cloud-controlling factors



(Sansom et al., JAMES, 2024)

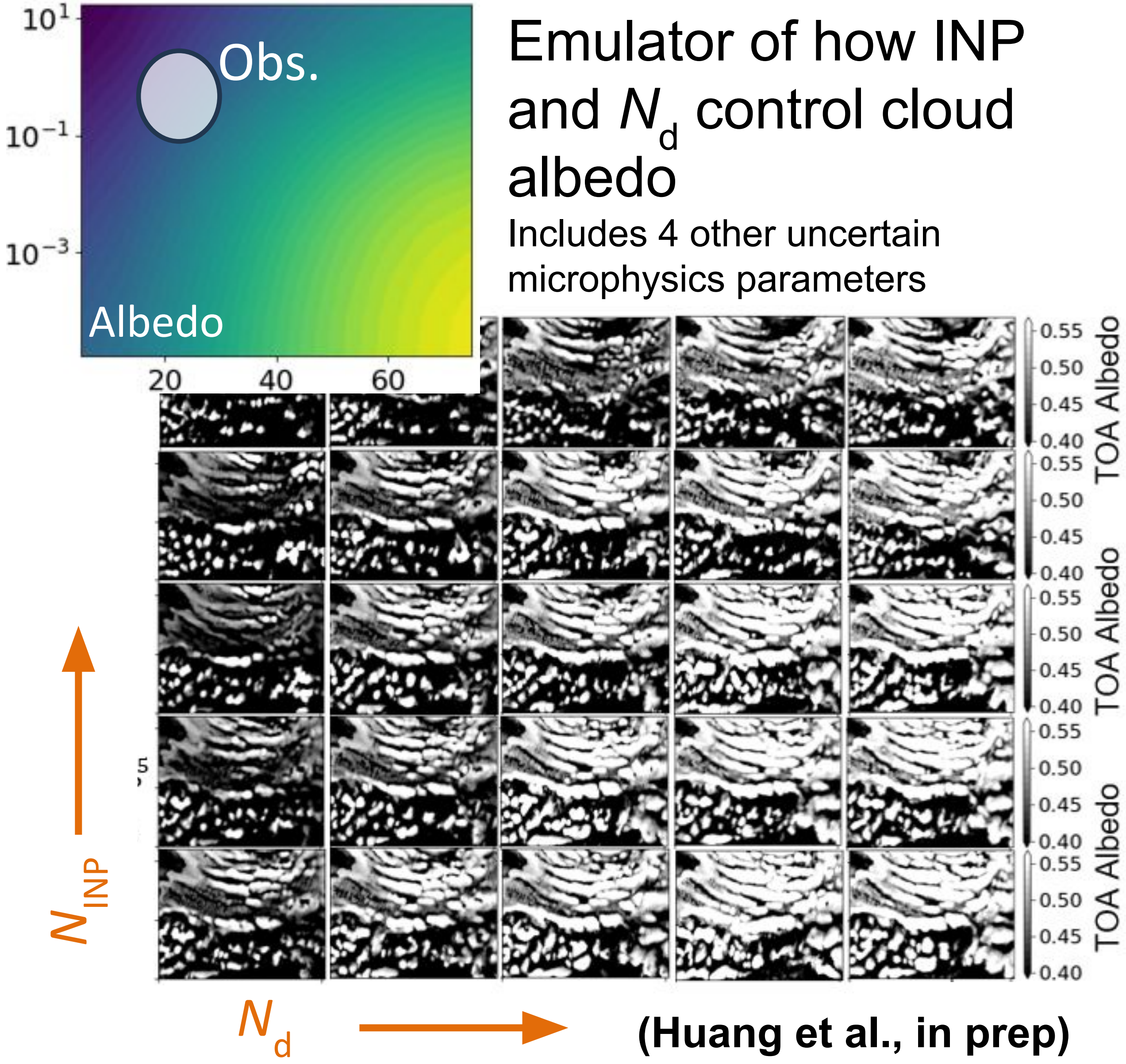
"Process model" PPEs and emulators

1.5km UM nested simulation
(mixed-phase cold air outbreak)



Emulator of how INP and N_d control cloud albedo

Includes 4 other uncertain microphysics parameters



(Huang et al., in prep)

Summary

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- Observational constraint (calibration, multi-variate tuning) of a model is fairly straightforward
  - Challenges are obs. uncertainty, representation error and inconsistencies.

- Attempts to constrain a PPE to multiple observations reveals model structural deficiencies, which limit overall constraint
  - They prevent constraint to consistent parts of parameter space
- Remaining causes of uncertainty after each constraint is applied could guide us to regions and obs. to focus on
- PPEs and emulators of high-resolution “process models” potentially very powerful

What should we do?

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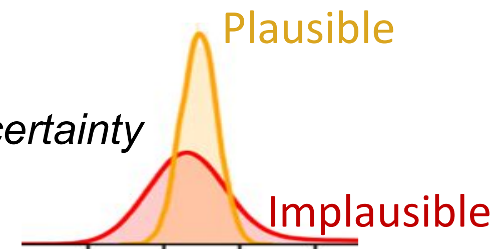
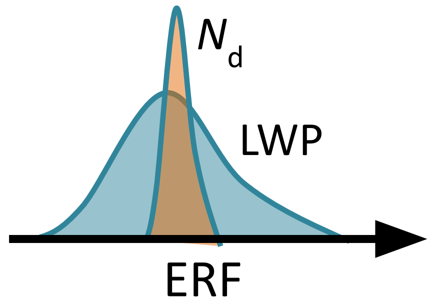
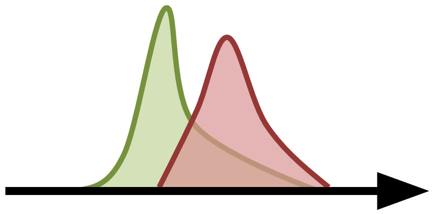
1. Define **"constraint"** (not goodness of fit)
   - *Finding all model variants (structures and parameters) that are consistent within obs uncertainty*



2. Determine the **"constraining power"** of observations (and combinations): Constraint of output variables □ constraint of forcing
   - Do "process-related" obs. have better constraining power? What are they?
   - What is the effective observational uncertainty? □ affects strength of constraint

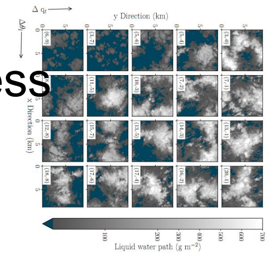


3. Expose and investigate **multi-observation inconsistency** with models
   - How do we identify deficient *processes* when we find inconsistencies
   - Are there some inconsistencies with a direct/obvious process connection?



4. Set up "process model" **multi-model PPEs.**

5. Organise uncertainty reduction as a **long-term collaborative activity** alongside process research



Observations used for constraint

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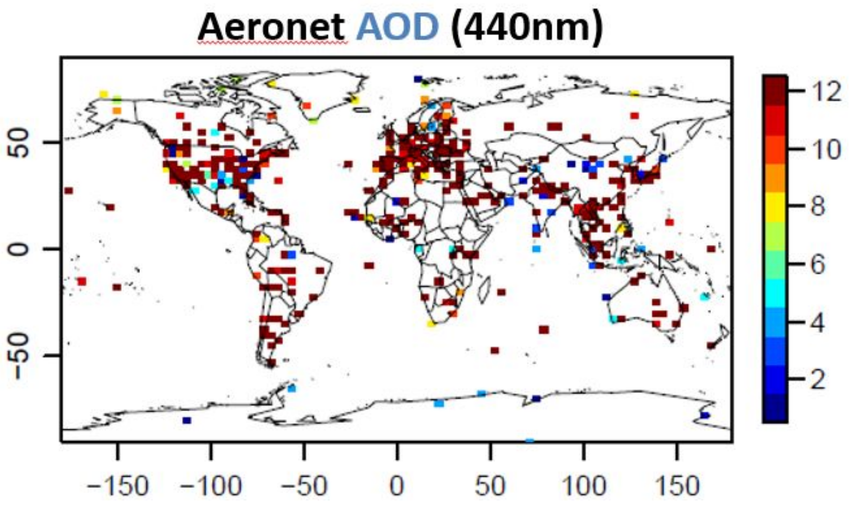
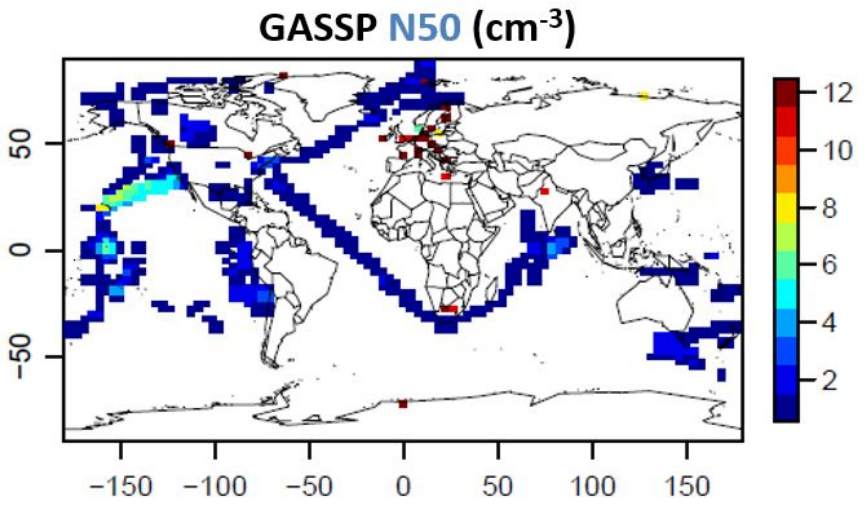




~9000 grid-point aggregated measurements of:

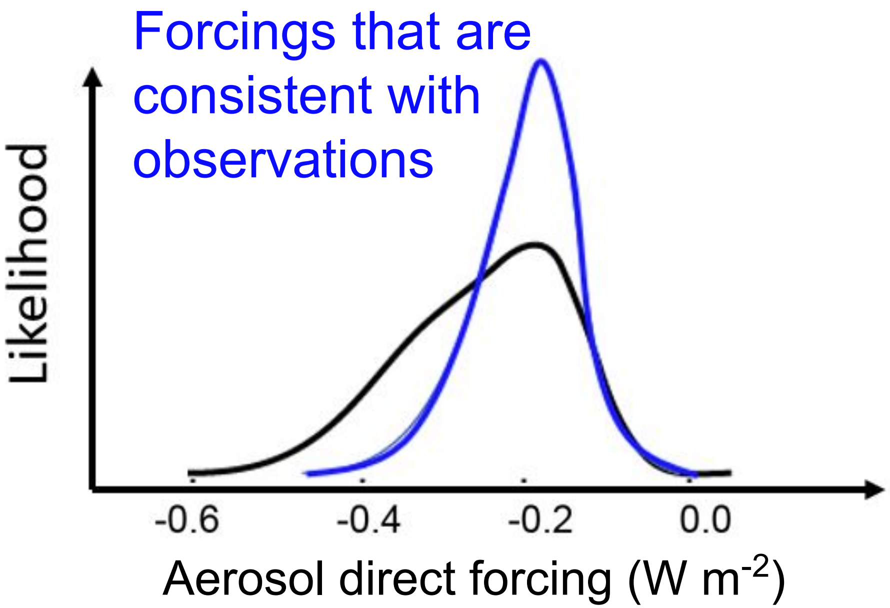
- Aerosol optical depth
- $PM_{2.5}$
- Aerosol concentration ($N_{>3nm}$)
- ~CCN concentration ($N_{>50nm}$)
- Sulphate mass
- Organic carbon mass

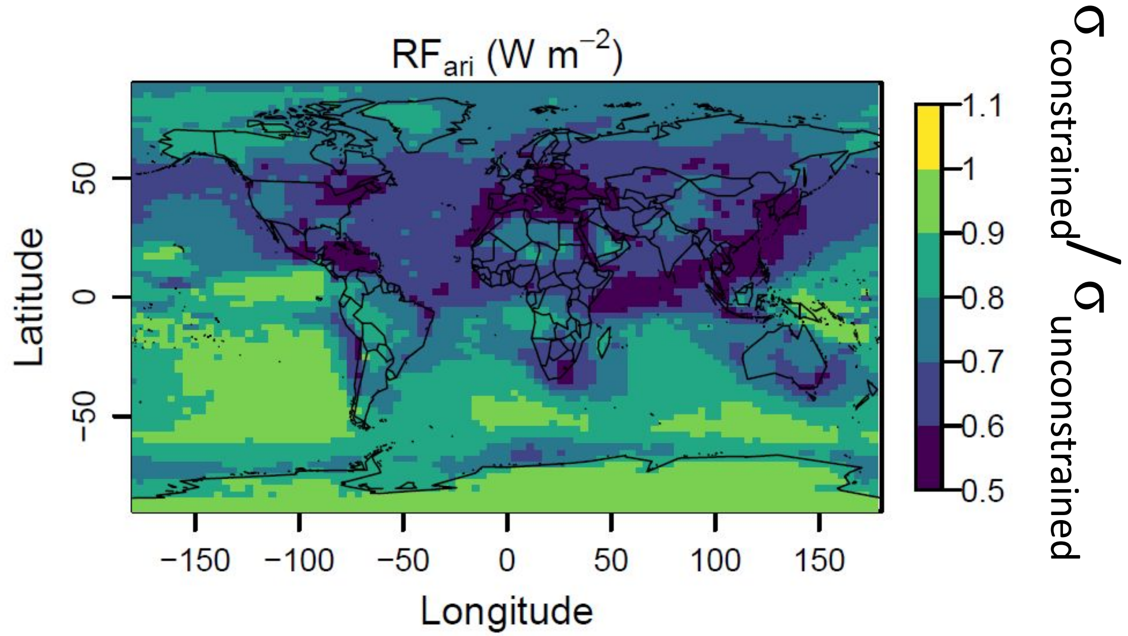
Observational constraint of aerosol forcing

Observations

Constrained parameter space

Constrained Forcing





Approach to process understanding

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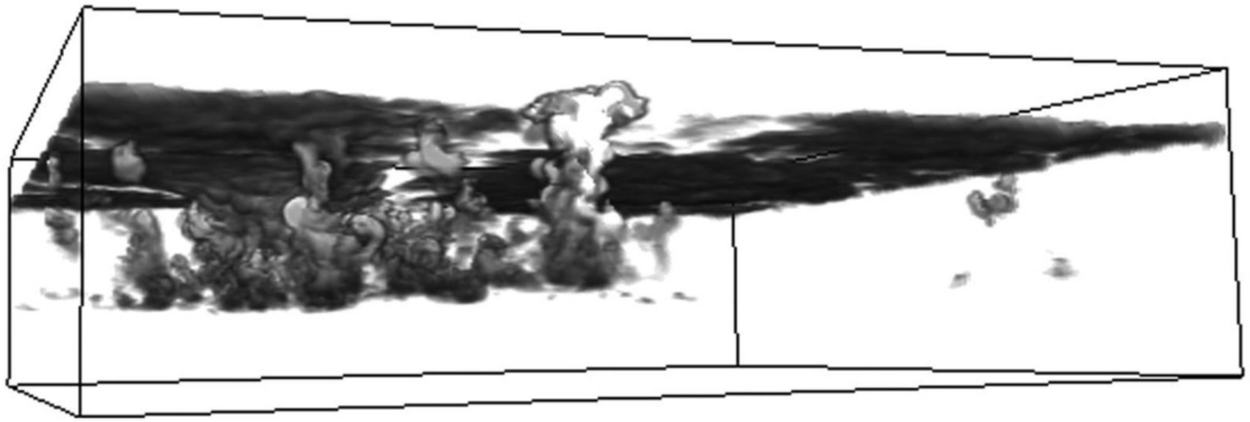
Sandu and Stevens (2011)

On the Factors Modulating the Stratocumulus to Cumulus Transitions

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



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

6-parameter large eddy cloud PPE

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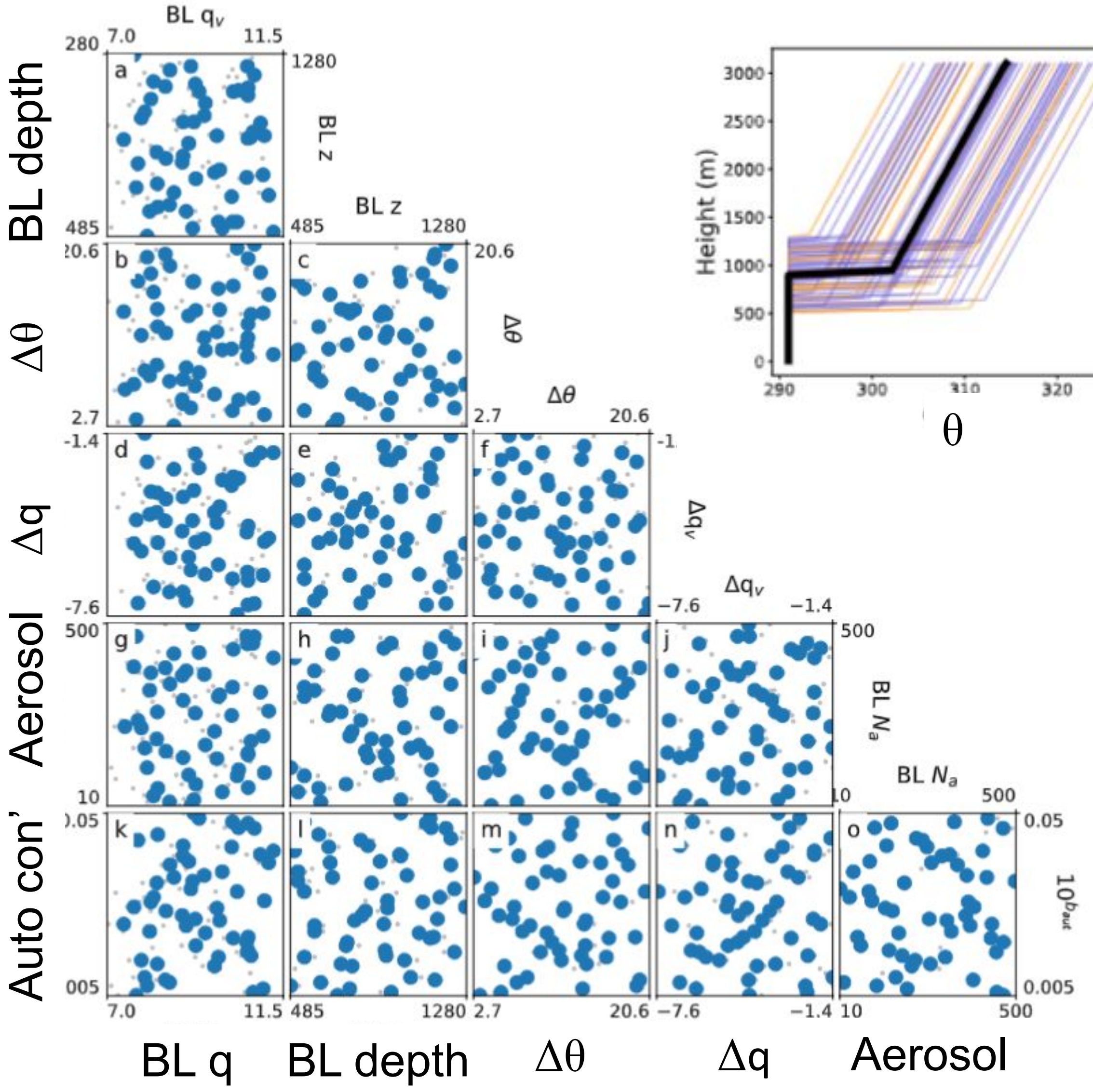
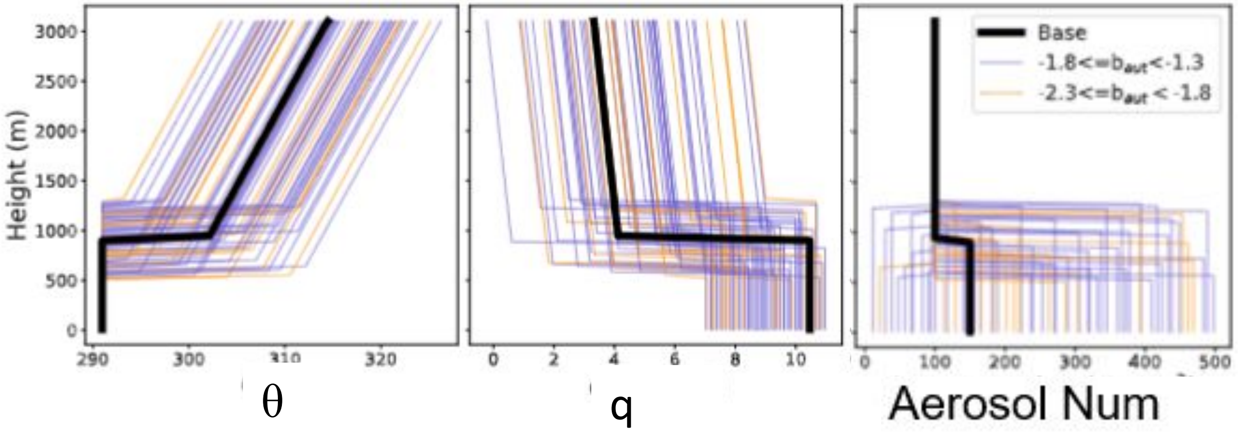
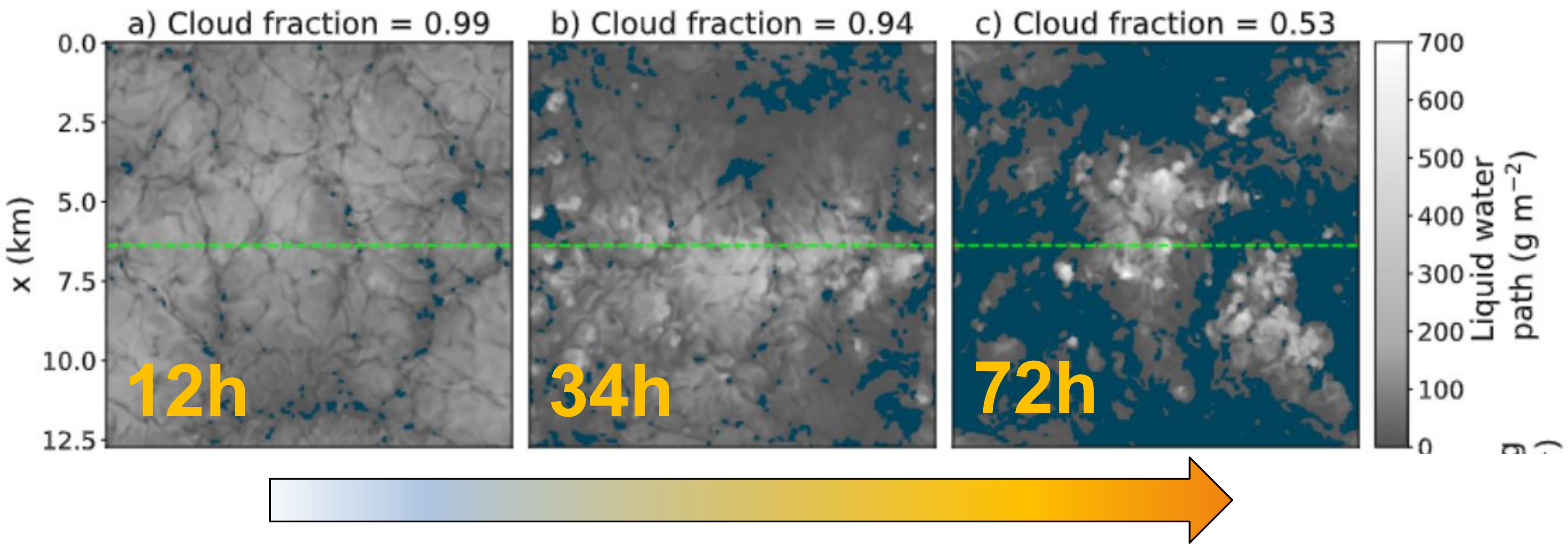




85 initial simulations

1. Boundary layer water mixing ratio
2. Boundary layer depth
3. Inversion Δθ
4. Inversion Δq
5. Aerosol concentration
6. Autoconversion (droplet□rain) rate

Evolution of one ensemble member



Sea surface temperatures increase 1.5 K per day

Cloud evolution across the PPE

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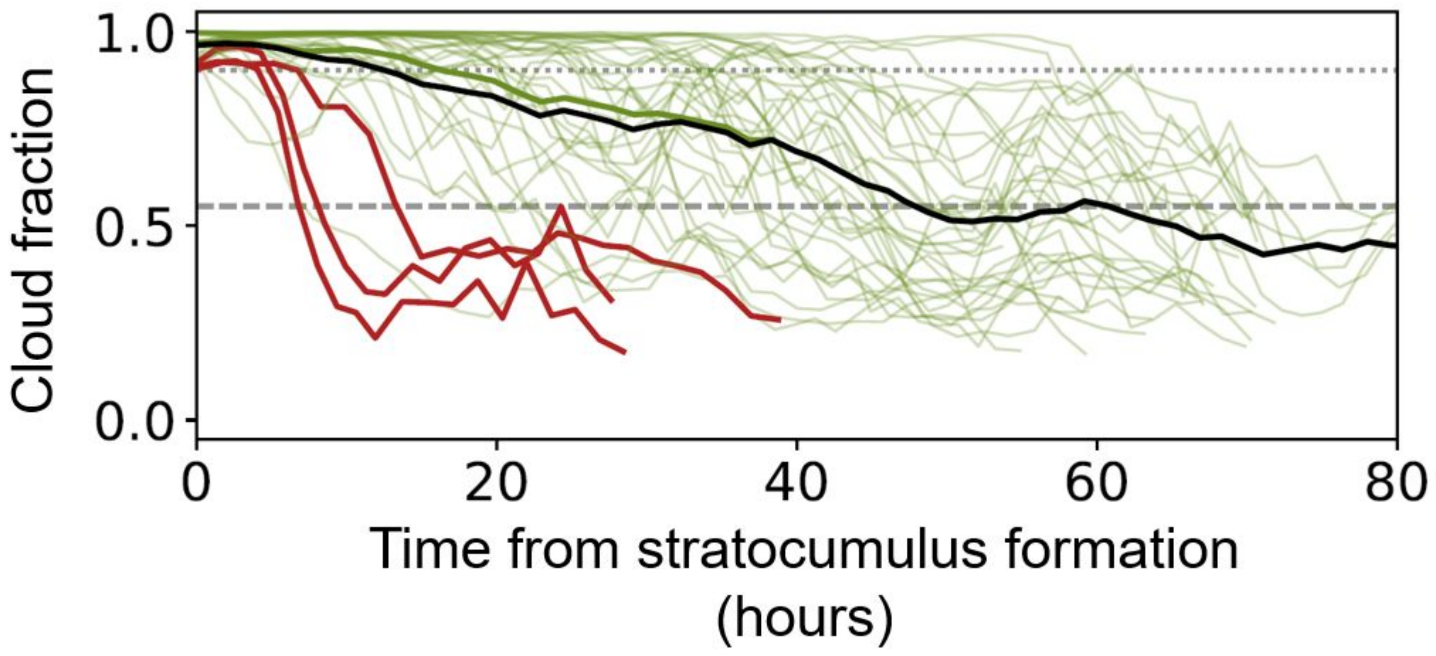
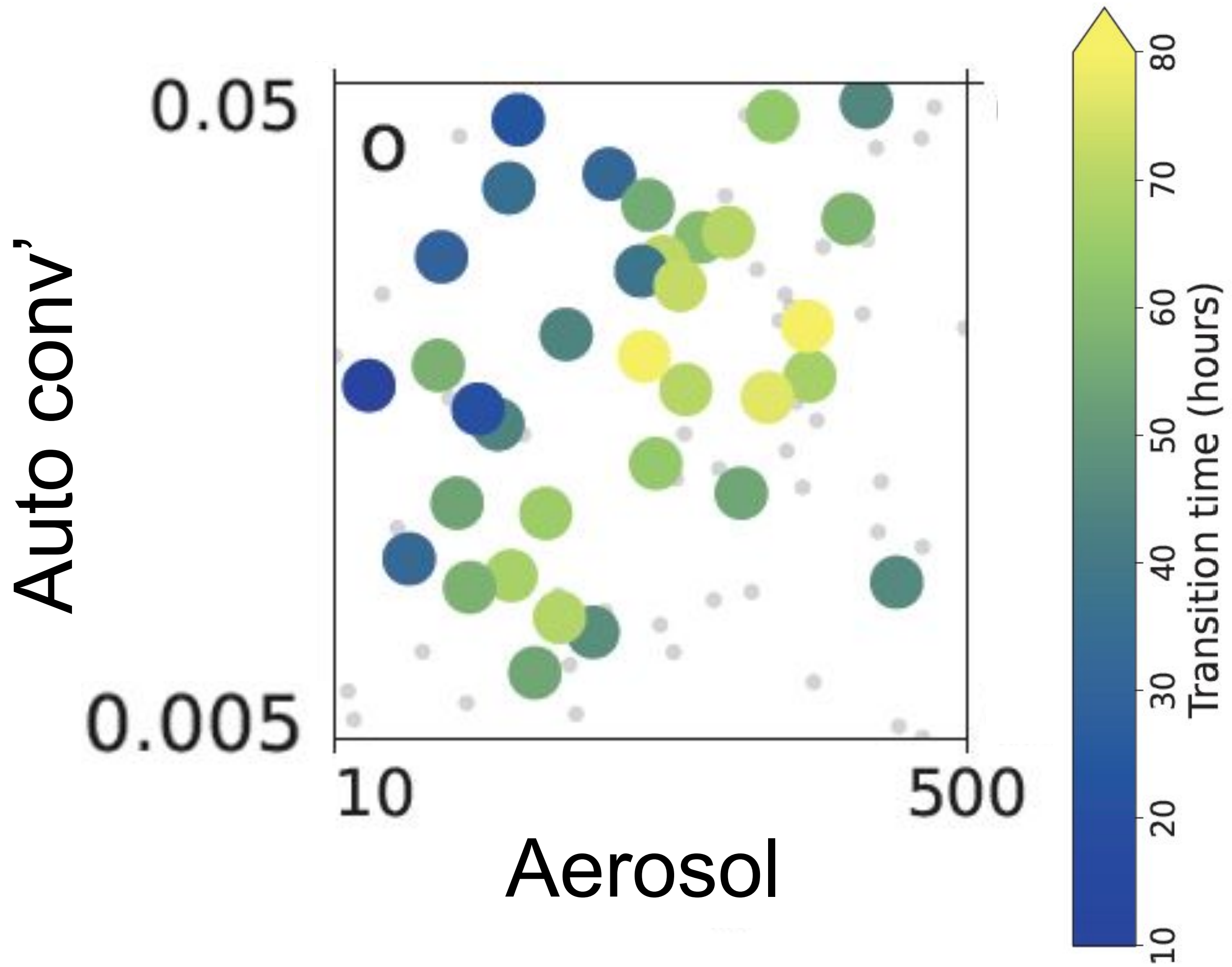
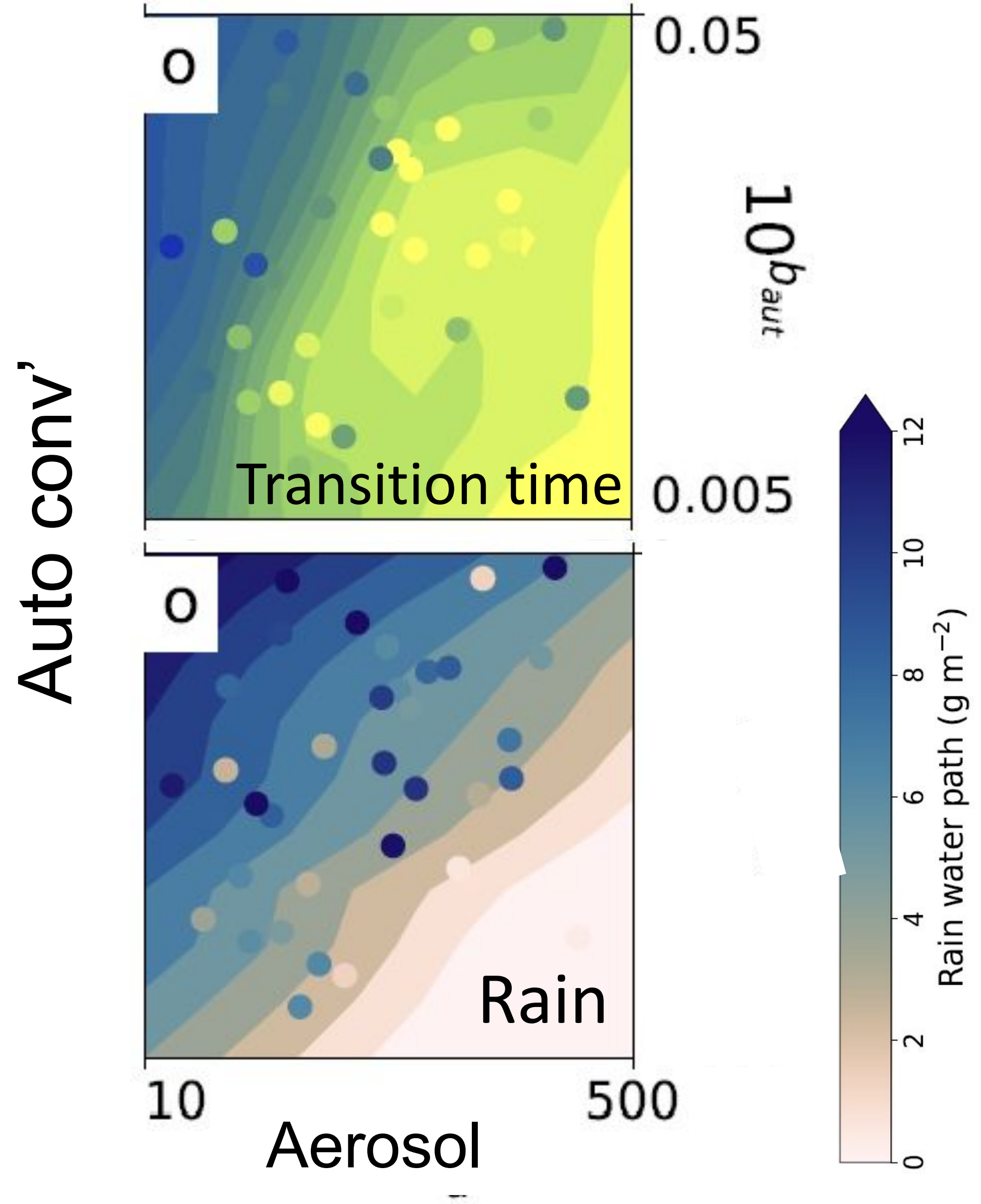


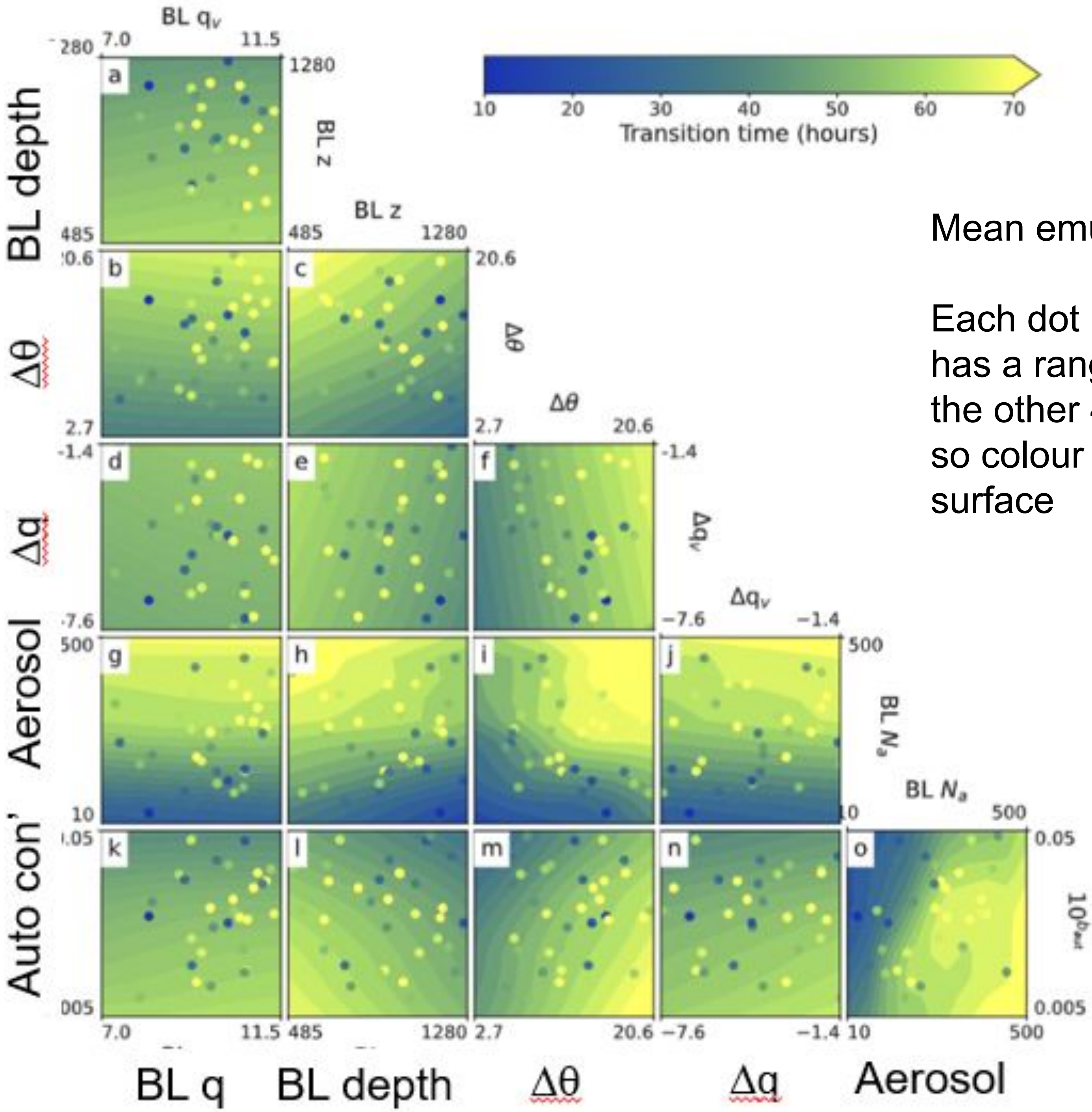
Challenges:

- Defining consistent “transition time” from Sc to Cu to emulate
- Dealing with awkward runs (no cloud, no transition)
- Accounting for natural variability (emulators describe deterministic behaviour) – subm. JAMES

Sc to Cu transition time

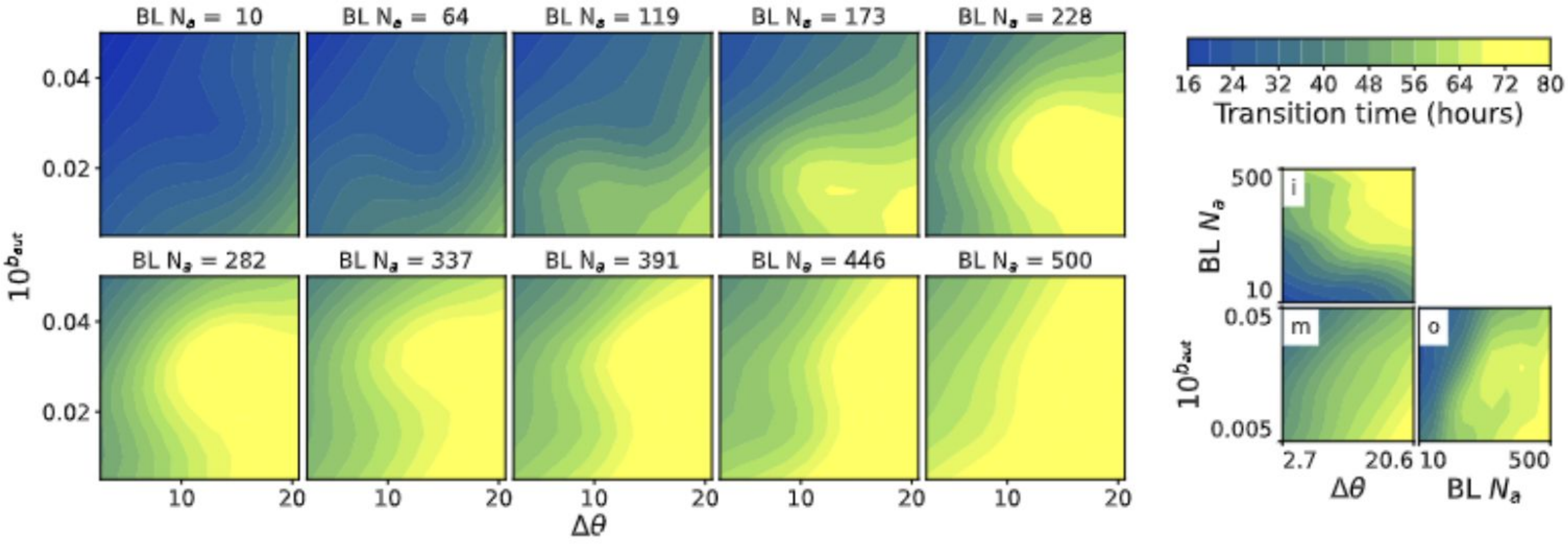






Mean emulator surfaces

Each dot (training run) has a range of values of the other 4 parameters, so colour doesn't match surface



BL N_a = 10
BL N_a = 64
BL N_a = 119
BL N_a = 173
BL N_a = 228
BL N_a = 282
BL N_a = 337
BL N_a = 391
BL N_a = 446
BL N_a = 500
0.04
0.02
10^{b_aut}
10
20
Δθ
16 24 32 40 48 56 64 72 80
Transition time (hours)
i
m
o
500
10
BL N_a
0.05
0.005
2.7
20.6

Future: PPEs of mixed-phase clouds (PhD Xinyi Huang)

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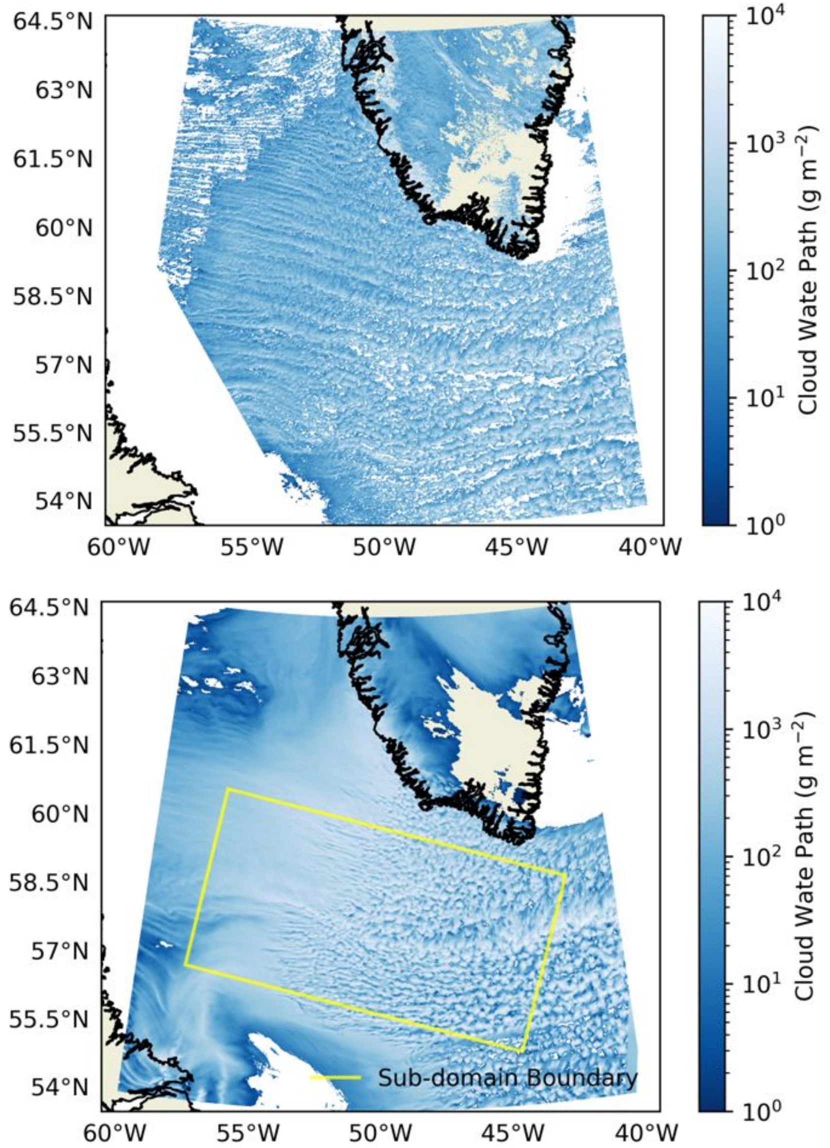
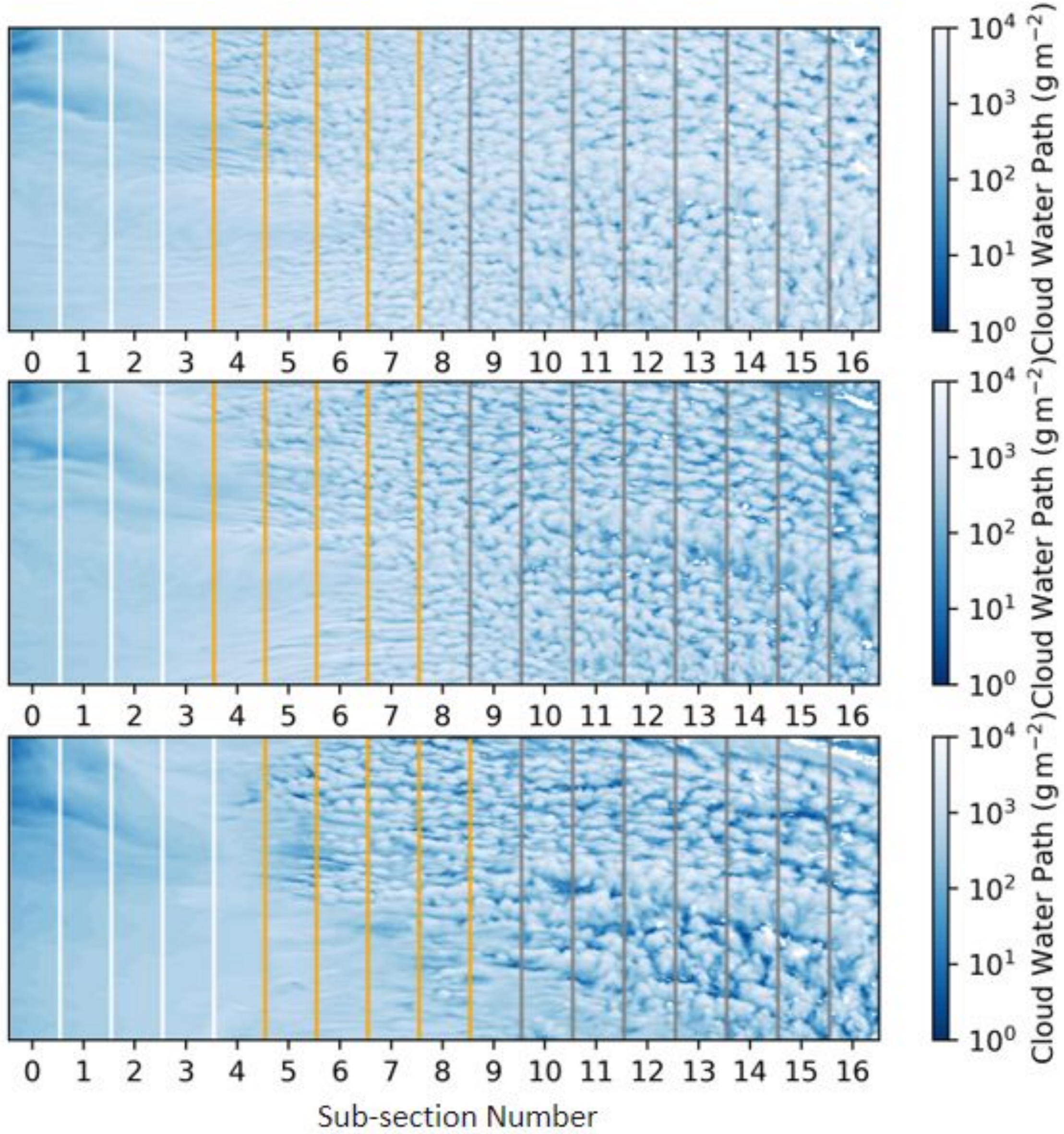
MODIS

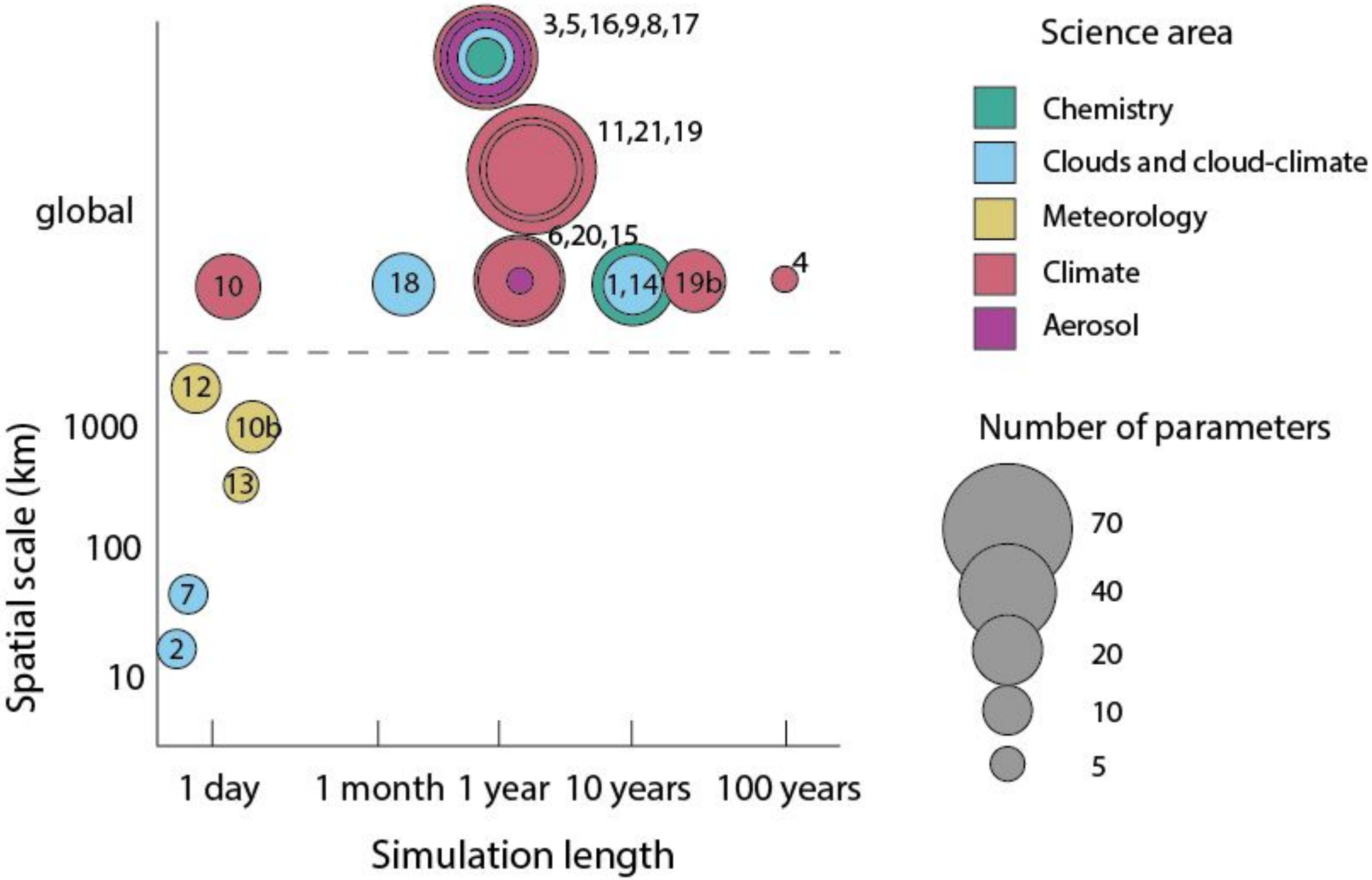
Nested UM



Increasing INP



Atmospheric PPEs at the APPEAR workshop



1. MOZART Chemistry, 28p, 13 years x global
2. LES clouds, 6p, 2h x 12km Sansom
3. GISS, climate, 45p, 1y x global Elsaesser
4. E3SM climate, 3p, 100y x global Tebaldi
5. UKESM aerosol, 37p, 1y x global Regayre
6. CAM climate, 45p, 3y x global Gettelman
7. SAM LES cloud 6p, 48km x 12h Yao-Sheng Chen
8. ECHAM simplification, 14p, 1y x global Proske
9. GLOMAP aerosol ERF, 26p, 1y x global. Johnson

0. E3SM, 18p. 5 days x global Qian (also WRF for wind/solar energy, 9 and 11p, regional (1000 km?), 24h and 6 days
1. HadGEM GA, 47,71,73p, 5y x glob, Rostron
2. RAMS meteorology, 10p, 1500km x 24 h Park
3. ICON-NWP meteorology, 5p, 3 days x 450km (nested), Oertel
4. CESM1.2 convection/microphysics, 15p, 10y x global, Sui
5. HadGEM/UKCA volcanic, 3p, 3y x global
6. FRSGC/UCI CTM chemistry, 36p, global x 1 year
7. GLOMAP SOA chemistry, 6p, global x 1 year, Carslaw
8. CAS FGOALS cloud-climate, 16p, 2 months x global, Yang
9. CAS-FGOALS-g3 climate mean state, 34p 5y x global and 16p 1 and 40y x global, Guo

0. CNRM-CM-6-1 climate feedbacks, 30p, 3y x global, Peatier
1. HadGEM3 climate feedbacks, 71p, 5y x global, Tsushima