Assessing the *non-linear* cloud susceptibility to N_d using Machine Learning: differences between GCMs and observation

A framework for model evaluation?

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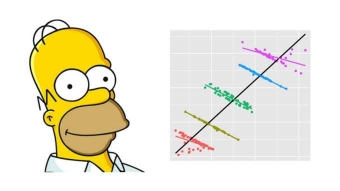
Quantifying cloud susceptibility to N_d using observations and GCMs presents challenges

- ❑ Large scale (top-down) satellite-based assessments (e.g., Wall et al. 2022,2023) have difficulties in
  - ❑ Removing **confounding effects**: co-varying cloud controlling factors *(Simpson's paradox)*
  - ❑ **Causal** attribution



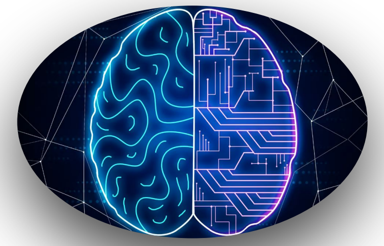
- ❑ Bottom-up approaches that establish causality (e.g., Yuan et al. 2023, Manshausen et al. 2022) face challenges in **scaling-up** *(or generalization to all clouds all conditions)*

- ❑ GCM studies have demonstrated ***correlation ≠ causality*** in the context of ACI (e.g., Mülmenstädt et al. 2024, Mahfouz et al. 2024)

- ❑ GCM perturbation experiments that deduce causality (e.g., PD-PI) face limitations in:
  - ❑ Parameterized processes
  - ❑ Insufficient grid-resolution *(esp. in the vertical) to resolve process (esp. microphysical)*
  - ❑ Reliance on knob tuning which may improve certain aspects of the model while degrading others

We propose a **Machine Learning** framework that can integrate OBS and GCMs

- ❑ Capture the ***non-linear*** relationship between **MET-aerosol (N_d)-cloud**
- ❑ Designed to **avoid confounding effects**
- ❑ Taking model evaluation to the next level by evaluating cloud **sensitivities** to MET/N_d, instead of cloud property themselves.



A Machine Learning approach to capture the co-variability between MET-N_d-Cloud

1°x1°, monthly

60°S - 60°N, 10-years (2005-2014)

CERES-ERA5
CESM2-CAM6
E3SMv2

LHF
CWV
ω_{500}
RH_{850}
RH_{925}
θ_{700}
θ_{850}
θ_{1000}
N_d

→

3 Neural Networks
with 10 hidden layers
50 nodes per layer

→

low-cloud fraction (LCF)
liquid water path (LWP)
SW albedo

R^2 values	LCF	LWP	SW Albedo
CERES-ERA5	0.90	0.81	0.92
CESM2	0.96	0.92	0.95
E3SMv2	0.95	0.90	0.93

A Machine Learning approach to capture the co-variability between MET-N_d-Cloud **& deriving cloud susceptibilities**

LHF

CWV

ω_{500}

RH_{850}

RH_{925}

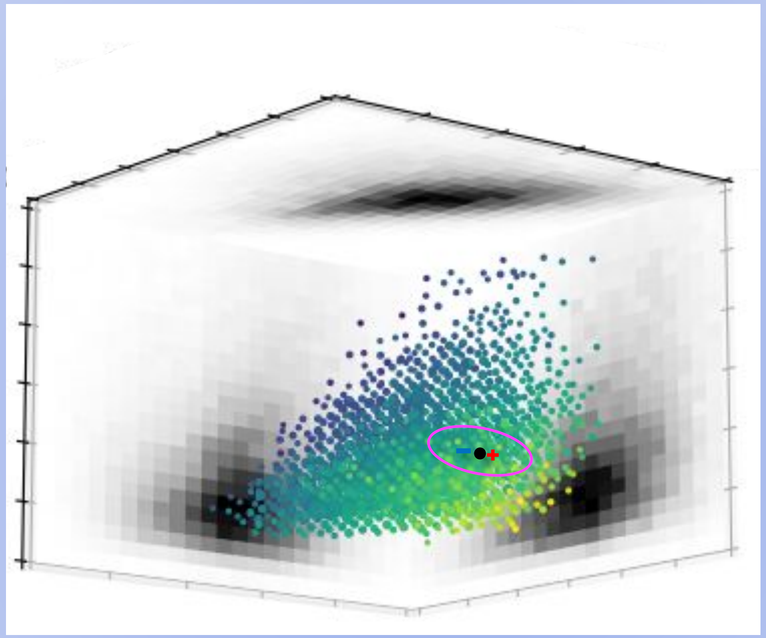
θ_{700}

θ_{850}

θ_{1000}

– N_d +

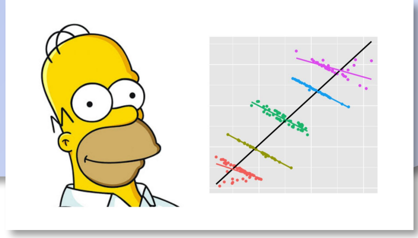
A 3-d illustration of local susceptibility



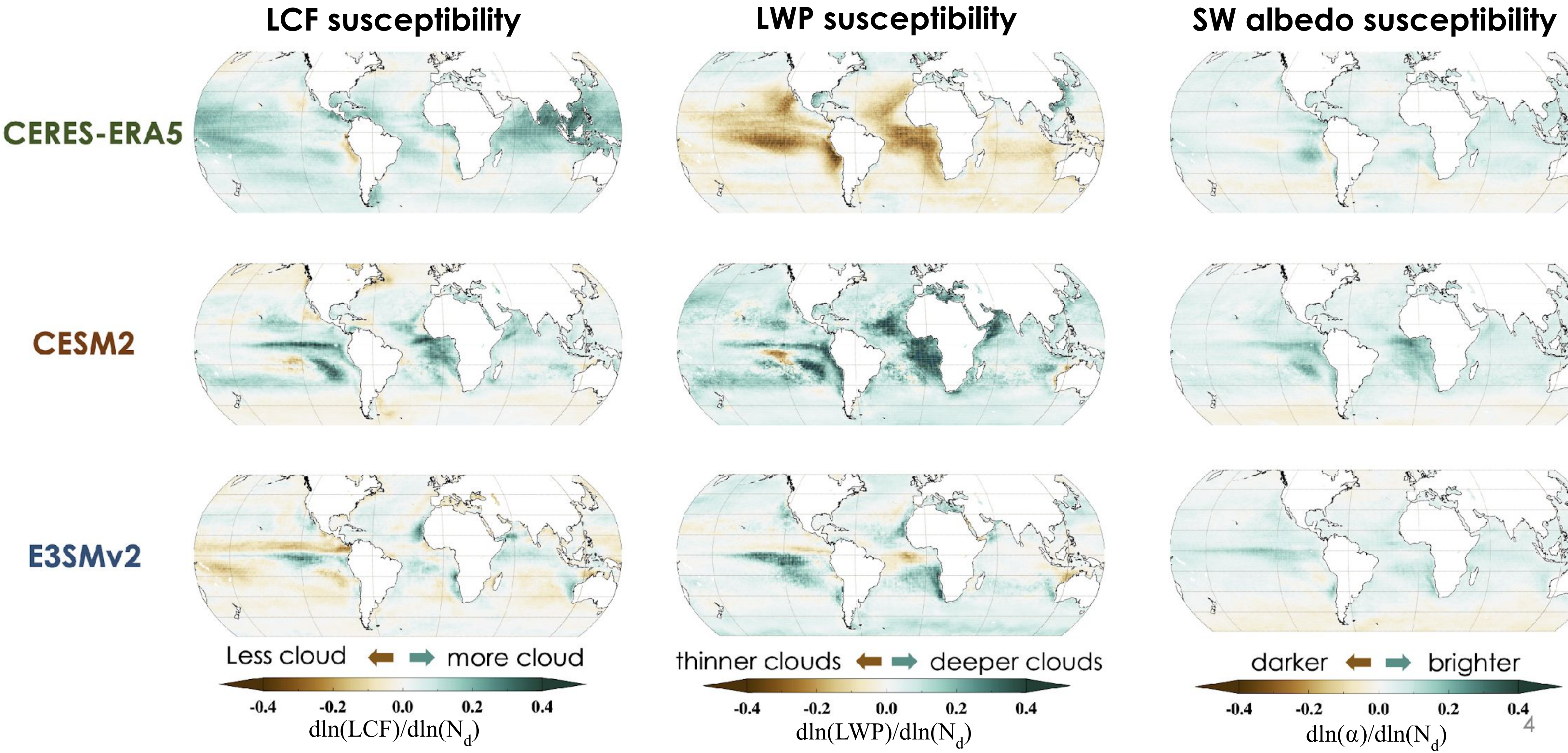
$$N_d \text{ susceptibility} = \frac{\partial \ln(X)}{\partial \ln(N_d)} \Big| \text{ all else equal}$$

X = LCF, LWP, SW albedo

- **9-dimensional manifold** *(gradient in individual dimension is non-linear)*
- Linear approximation is used to infer 'local' susceptibility (quantified as local derivative)
- Therefore, **perturbations need to be really small**
- Nd susceptibility is quantified at each location and time (**for a given MET condition**)
- $\sum\left(\frac{\partial \ln(X)}{\partial \ln(N_d)}\Big|_{MET}\right) \neq \frac{\partial \ln(X_{all})}{\partial \ln(N_{d\,all})}$



Maps (60S – 60N) of cloud **susceptibility** to N_d at ***monthly*** timescale (NN derived)



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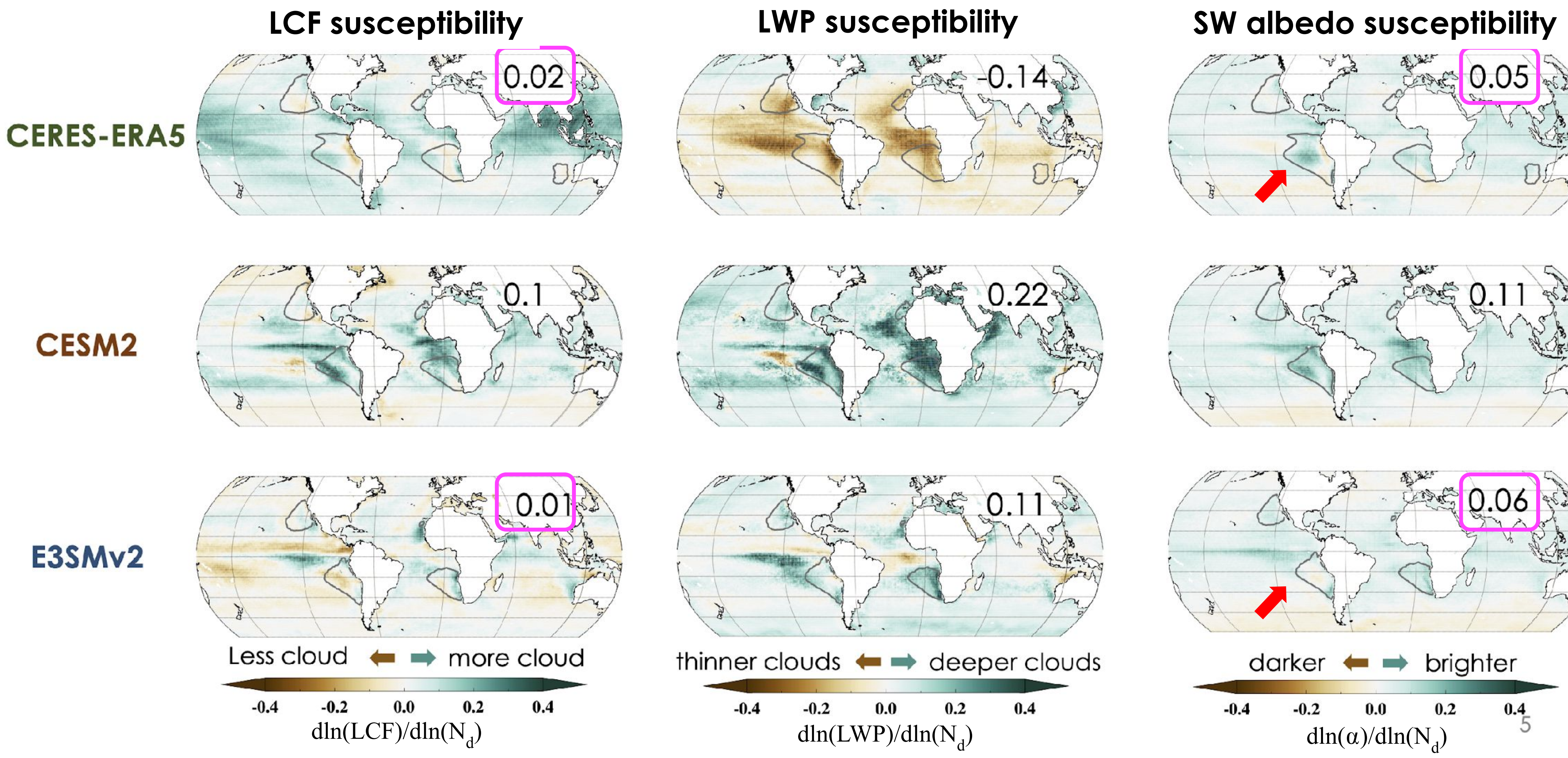
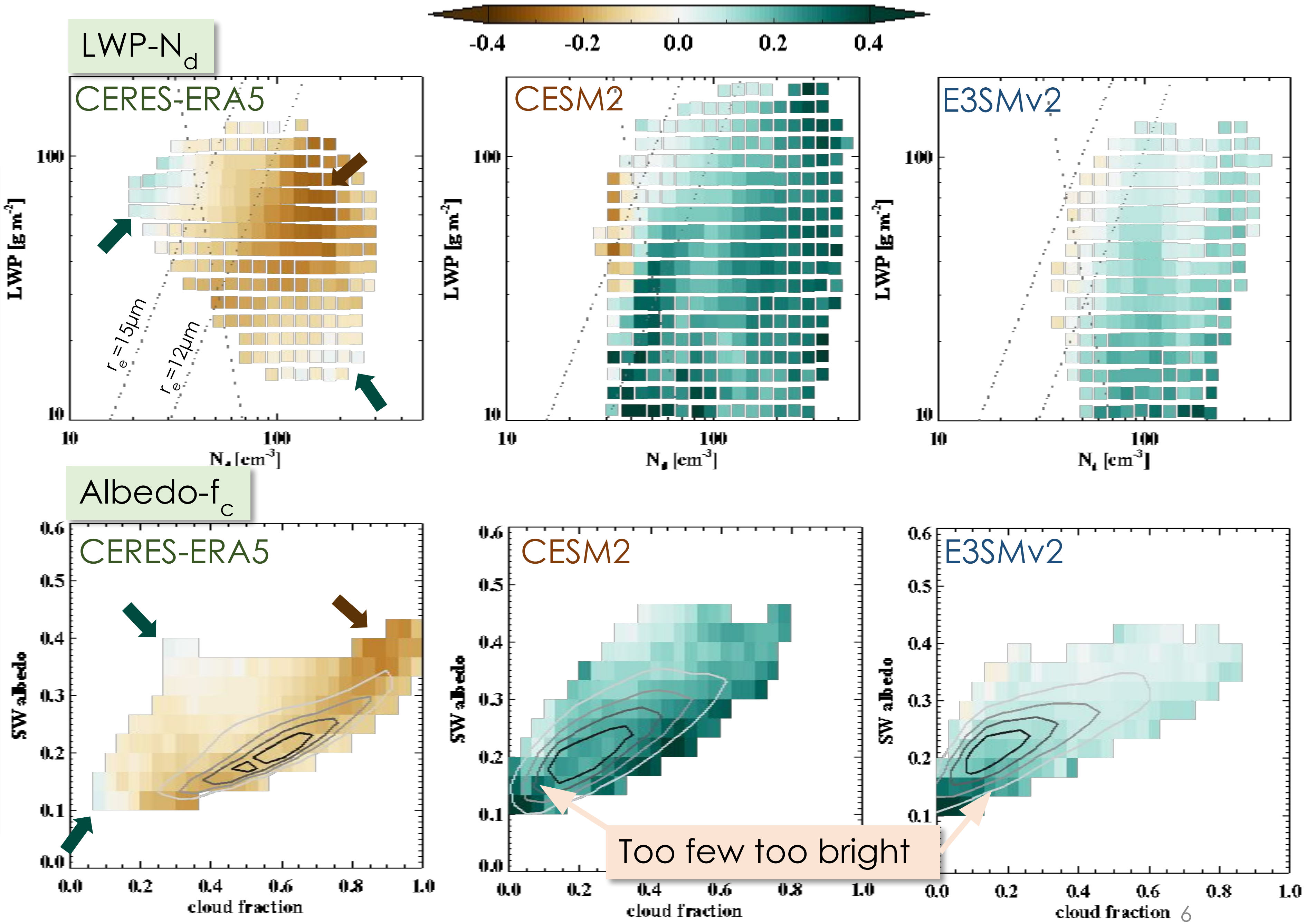


LWP susceptibility

- OBS results agree with process understanding *(precip-suppression & entrainment feedback)*
- +ve LWP-adj is evident in thin and low coverage clouds and in deep broken clouds *(cumulus regime with weak inversion)*
- -ve LWP-adj is the strongest when conditions favor entrainment-feedback mechanism *(thick overcast clouds)*
- Susceptibility distribution is flipped in GCMs *(also shown in Mahfouz et al. 2024)*



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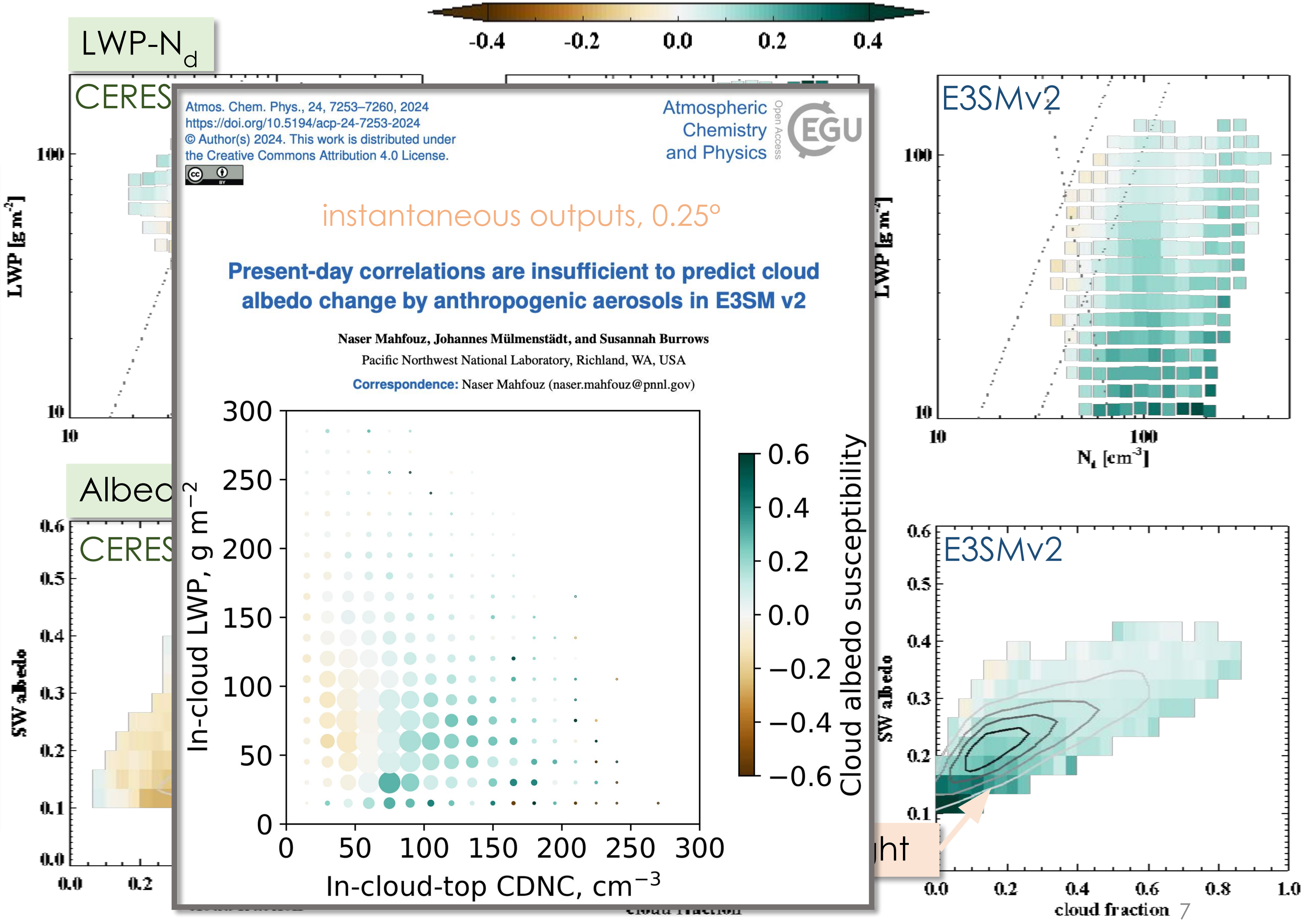
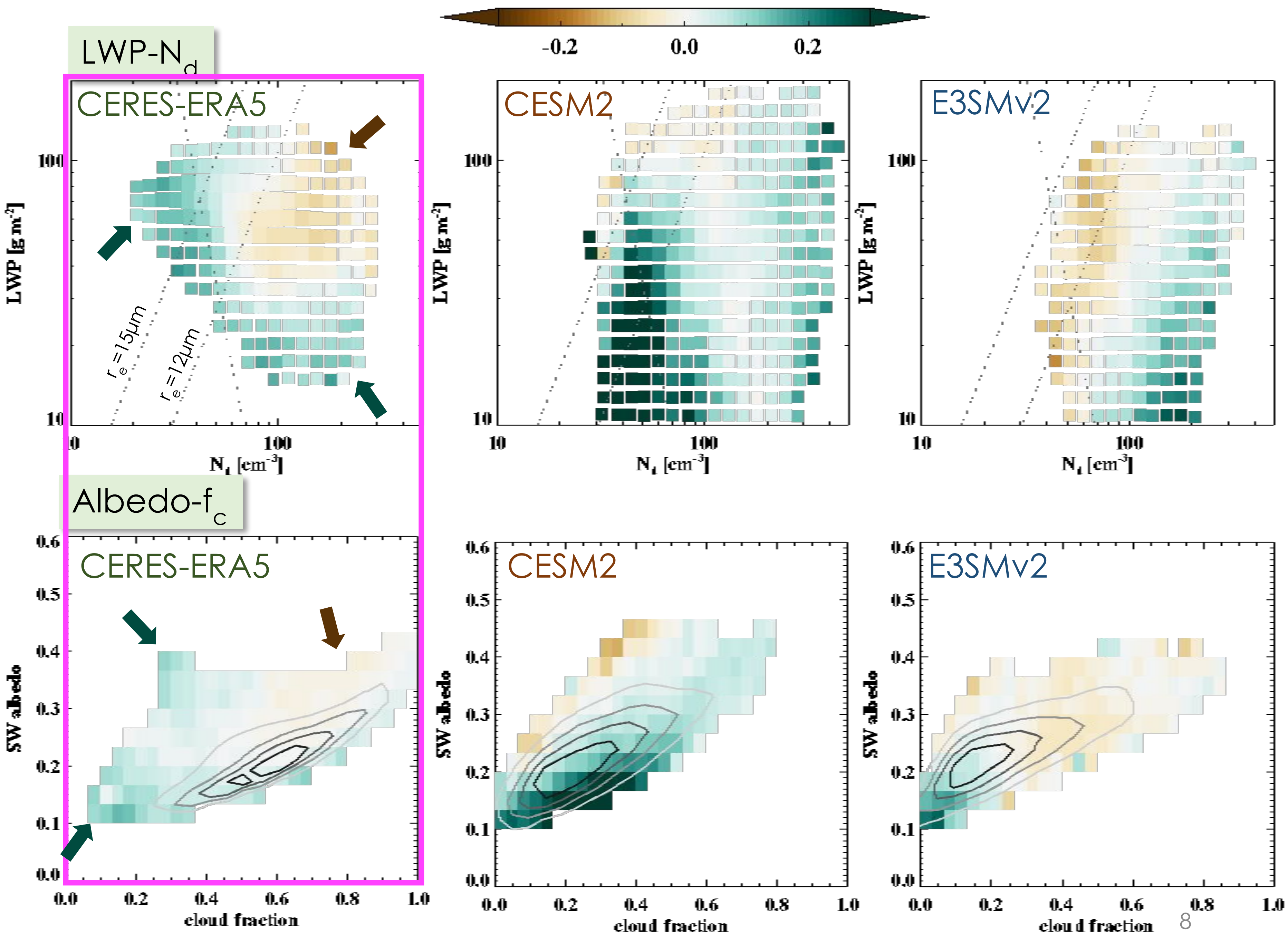


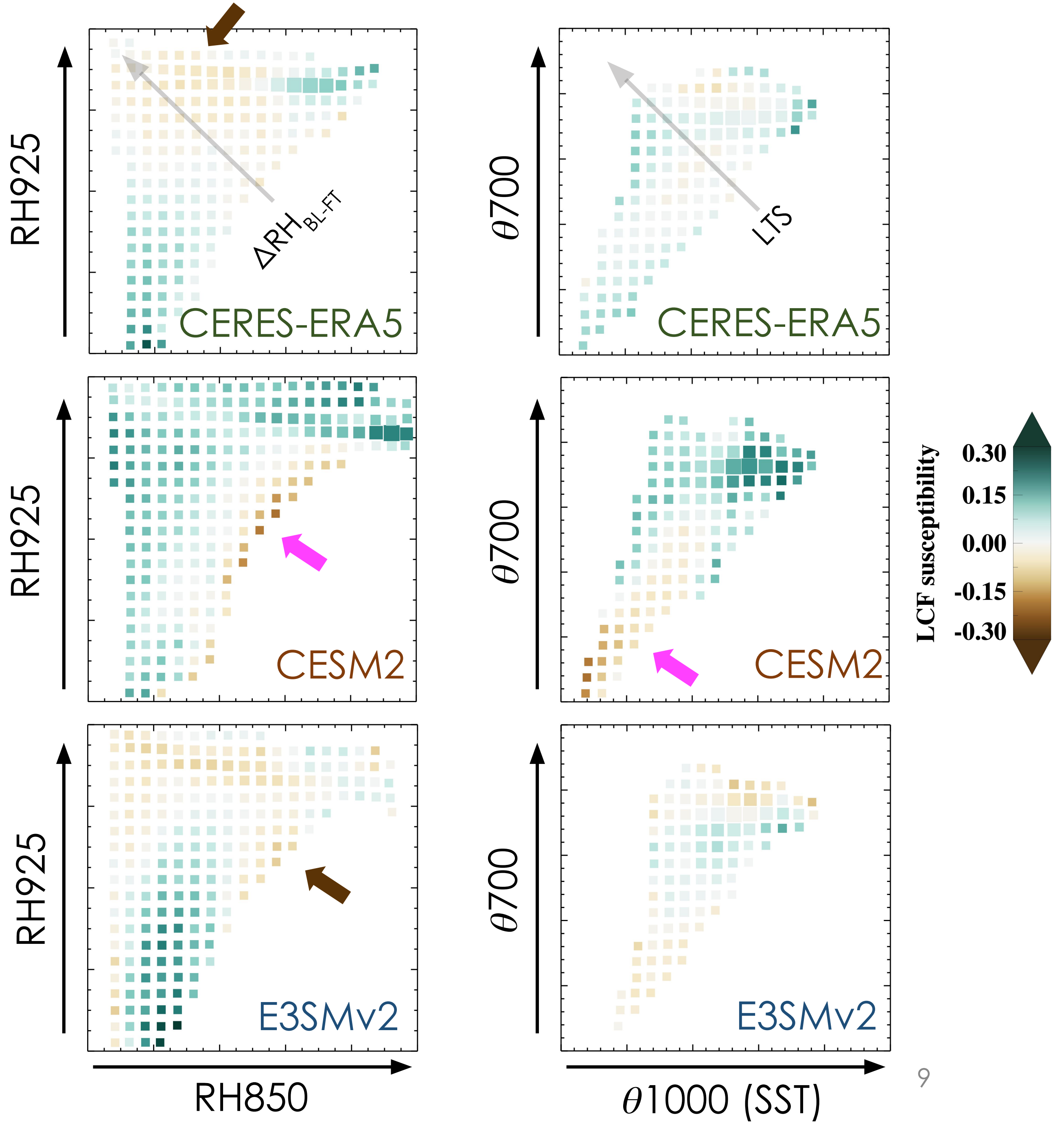
LCF susceptibility

- LCF susceptibility distribution in LWP-N space follows that of LWP susceptibility
- Thin clouds or broken cumulus *(especially under weaker inversion)* is the most susceptible to LCF increase *(or longer cloud lifetime)*
- Deep high-fc clouds *(mostly non-raining)* are subject to cloud dissipation with increasing N_d
- The NN-framework captures robust manifestation of small-scale ACI mechanisms at monthly scale
- GCMs, again, associate LCF susceptibility to clouds states differently

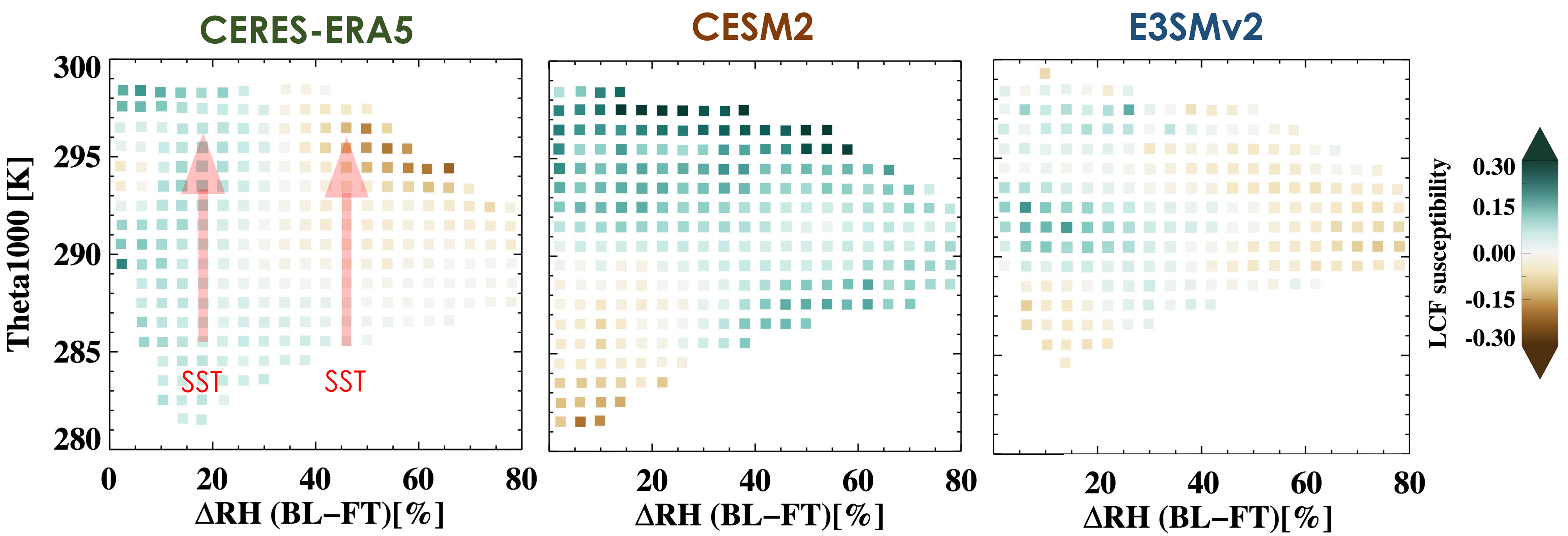


LCF susceptibility in MET spaces reinforces contrasting association between OBS and GCMs

- OBS suggest –ve cloud fraction adjustment under strong RH gradient between BL and FT *(entrainment drying favored condition)*.
- E3SMv2 captures this feature, to some extent.
- CESM2 suggests the reverse is true: more cloud dissipation when RH gradient is the weakest (θ and θ gradient is low as well).



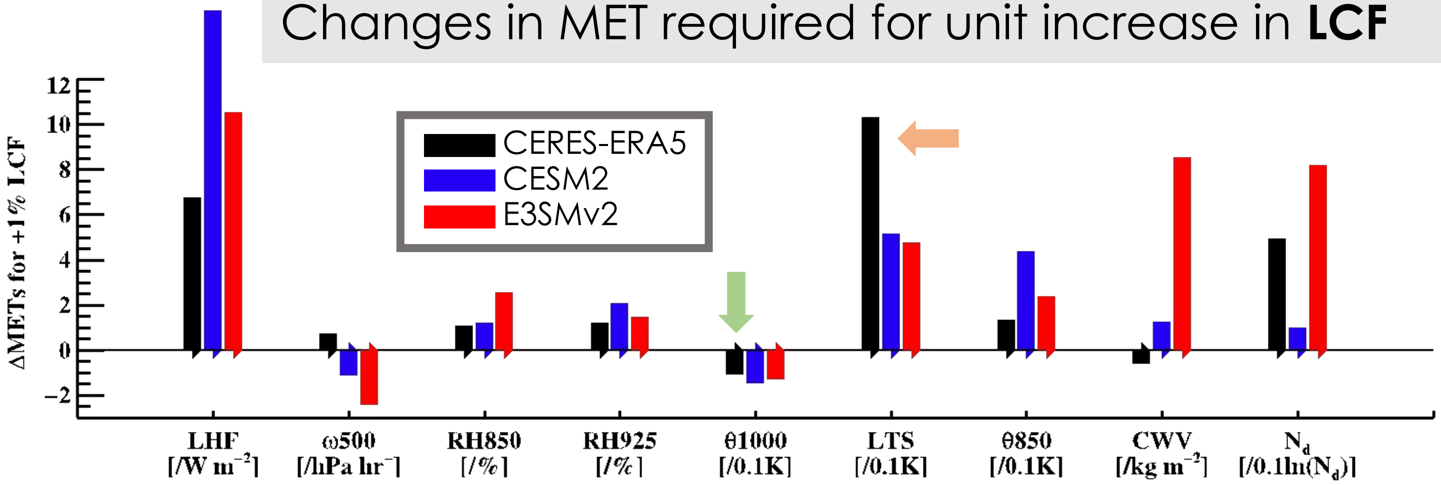
ACI in a warmer climate (constant $\Delta RH_{BL\text{-}FT}$) is base-state dependent



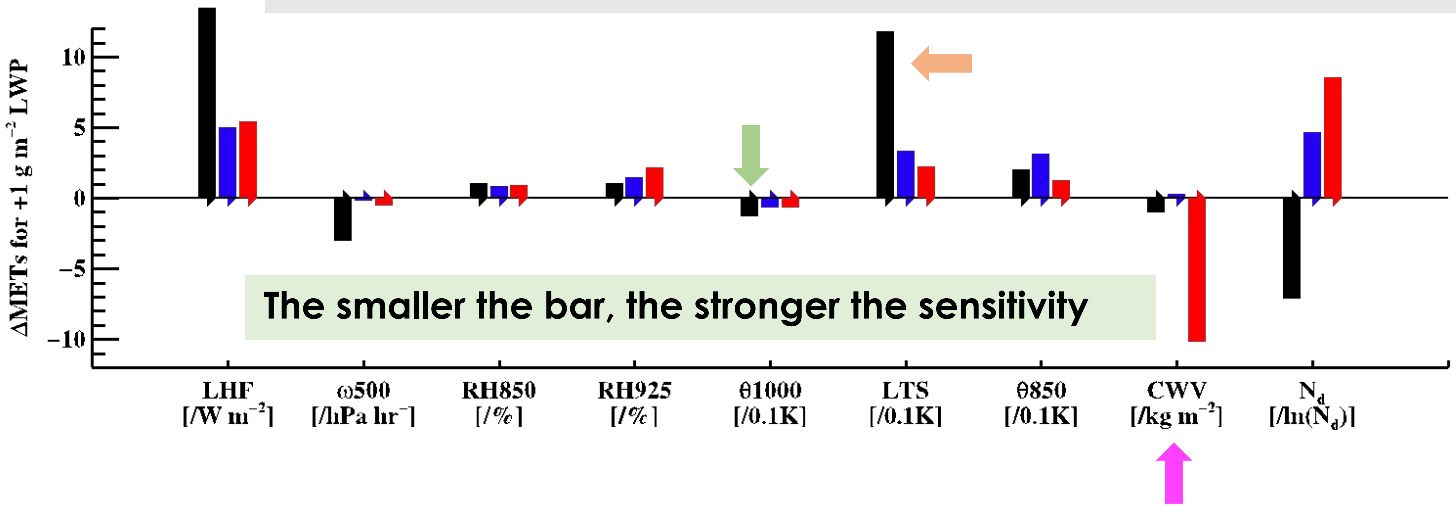
- ❑ ACI in a warmer climate depends on humidity gradient
- ❑ When RH gradient is strong, cloud susceptibility gets more negative with warming
- ❑ When RH gradient is weak, cloud susceptibility remains unchanged with warming
- ❑ Relationships between MET and Sc-cloud in GCMs suggest otherwise

Sensitivities of LCF and LWP **to MET** for Sc regime **differ** between OBS and GCMs

Changes in MET required for unit increase in **LCF**

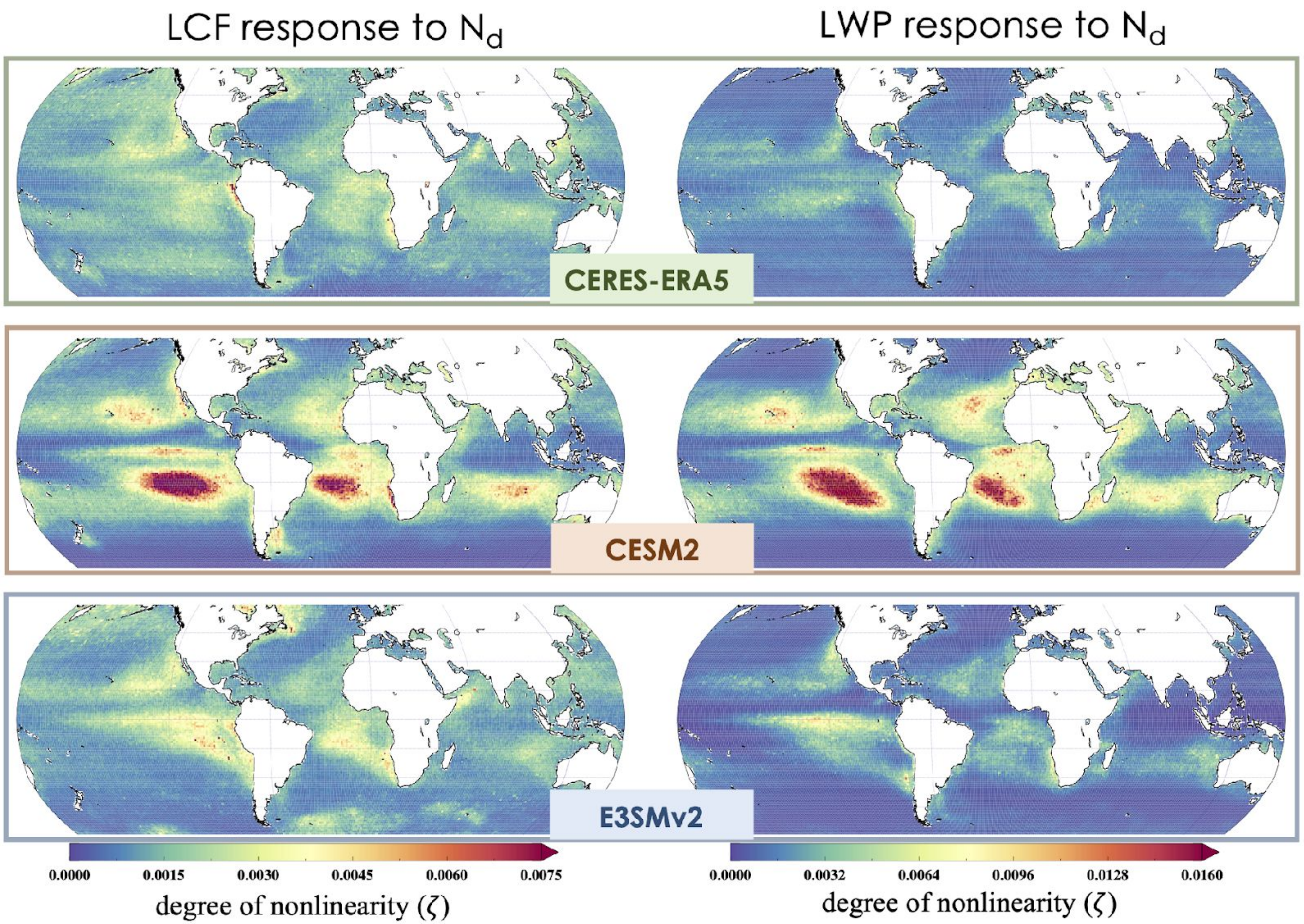


Changes in MET required for unit increase in **LWP**



- ❑ Besides susceptibility to N_d, OBS and GCMs disagree in sign on sensitivities to subsidence and CWV.
- ❑ GCMs' LWP and LCF is more sensitive to LTS than OBS. (A built-in/parameterized relationship?)
- ❑ OBS show stronger LCF sensitivity to SST and LHF, but weaker for LWP, compared to GCMs

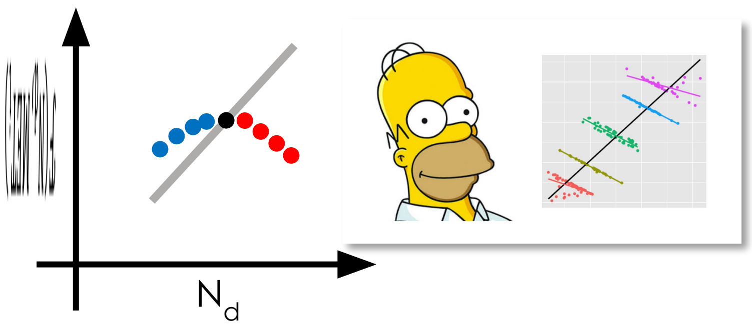
Quantifying the degree of **nonlinearity** in LCF and LWP response to N_d



$$\zeta = \frac{|\Delta\mathcal{F}(-\Delta N_d, MET_i) + \Delta\mathcal{F}(+\Delta N_d, MET_i)|}{\mathcal{F}(N_d, MET_i)}$$

$$\Delta\mathcal{F} = \mathcal{F}(\Delta N_d, MET_i) - \mathcal{F}(N_d, MET_i)$$

$\mathcal{F}()$ is the NN model

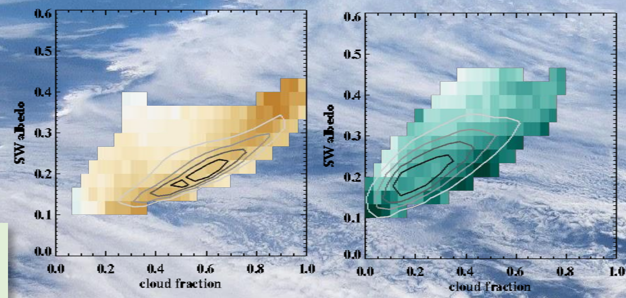


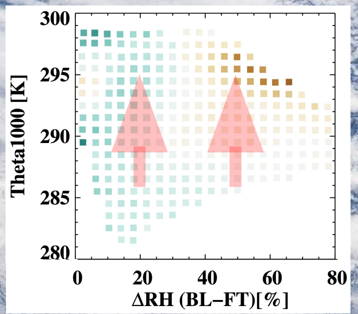
- Degree of nonlinearity in N_d dimension is stronger in low-cloud regions
- Models show higher degree of nonlinearity (especially in CESM2)
- Potentially a higher-order quantity/variable for model evaluation

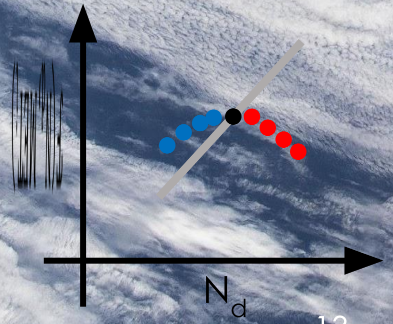
- We developed a **Neural Network framework** to capture the ***non-linear*** relationship among **MET-N_d-Cloud.**
- We use it to assess the **sensitivity** of low-clouds to cloud controlling factors between GCMs and OBS (potentially a framework for model evaluation)

Take-home points

- We find remarkably different cloud susceptibility to N_d (esp. in spatial patterns) between GCMs and OBS, as well as sensitivities to some MET variables.
- E3SMv2 seemingly captures the Sc-regime-mean susceptibility but misses the underlying processes when the association of susceptibility to cloud states and meteorological conditions is unveiled *(likely due to tuning)*
- Monthly MET-N_d-Cld relationship suggests ACI in a warmer climate is base-state dependent – esp. on the gradient between BL and FT RH
- Models have higher degrees of nonlinearity in cloud susceptibility to N_d







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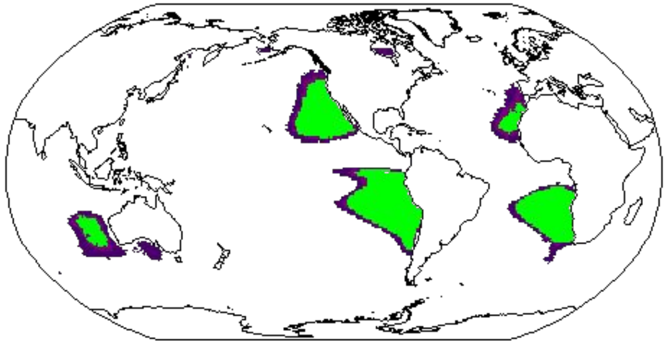
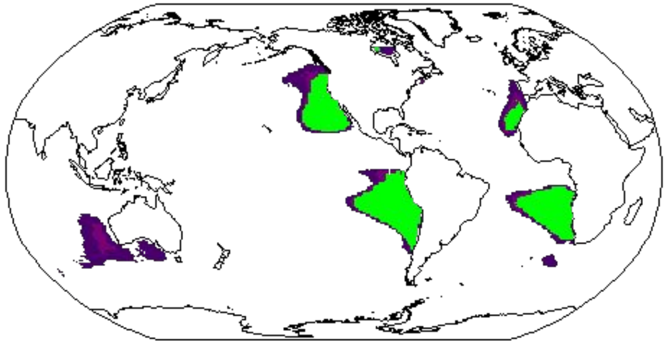
Extra slides

Focusing on low-cloud regions for process understanding

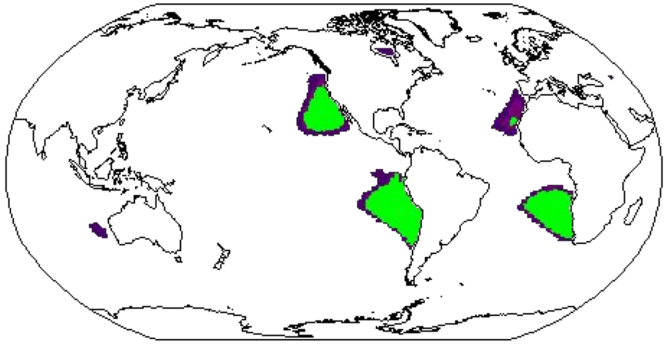
ERA5



CESM2



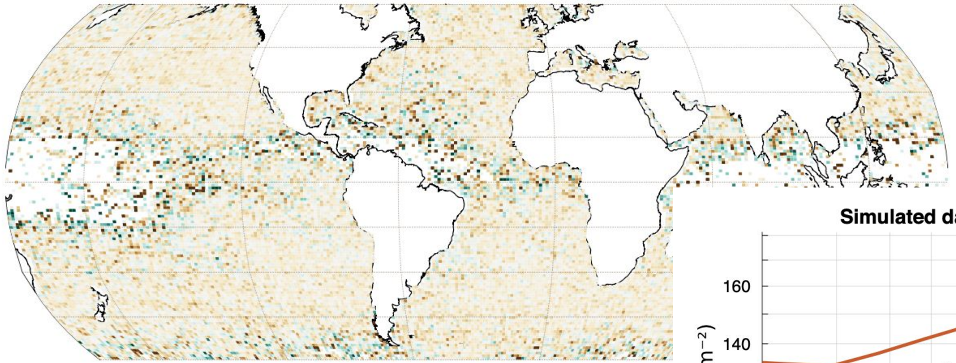
E3SMv2

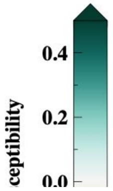


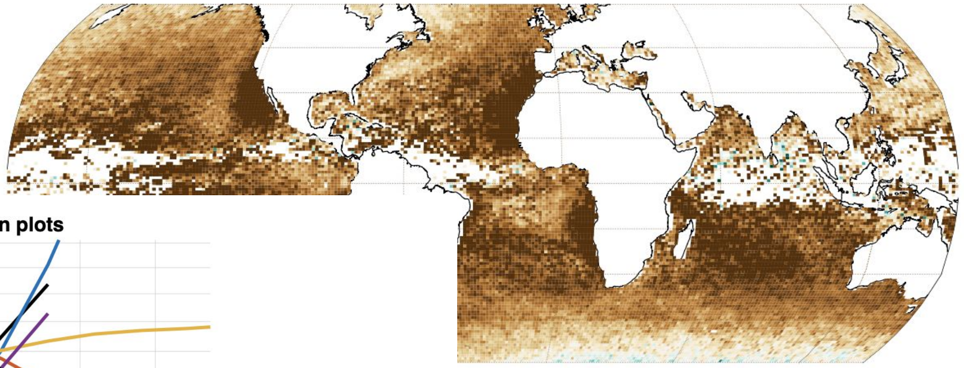
Impact of MODIS retrieval errors and adiabatic-Nd calculations (trained on instantaneous outputs)

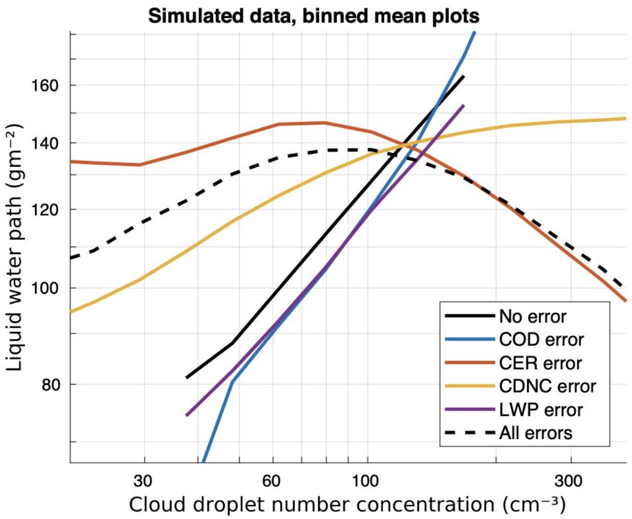
Model native LWP & Nd

Model MODIS-simulated LWP & Nd



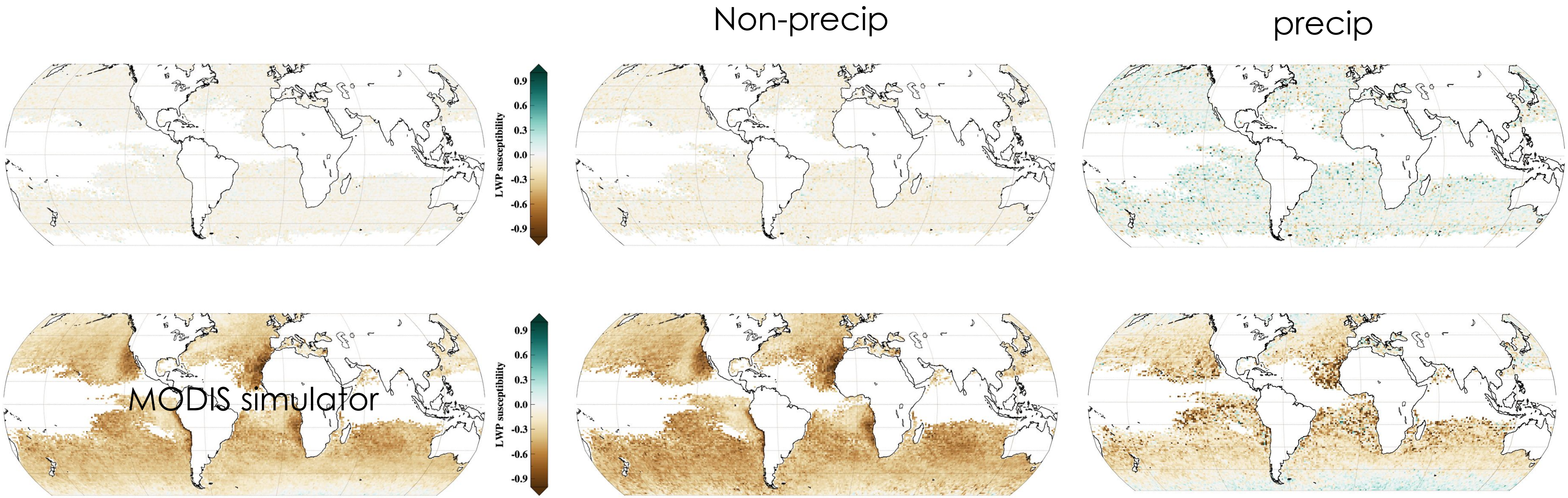






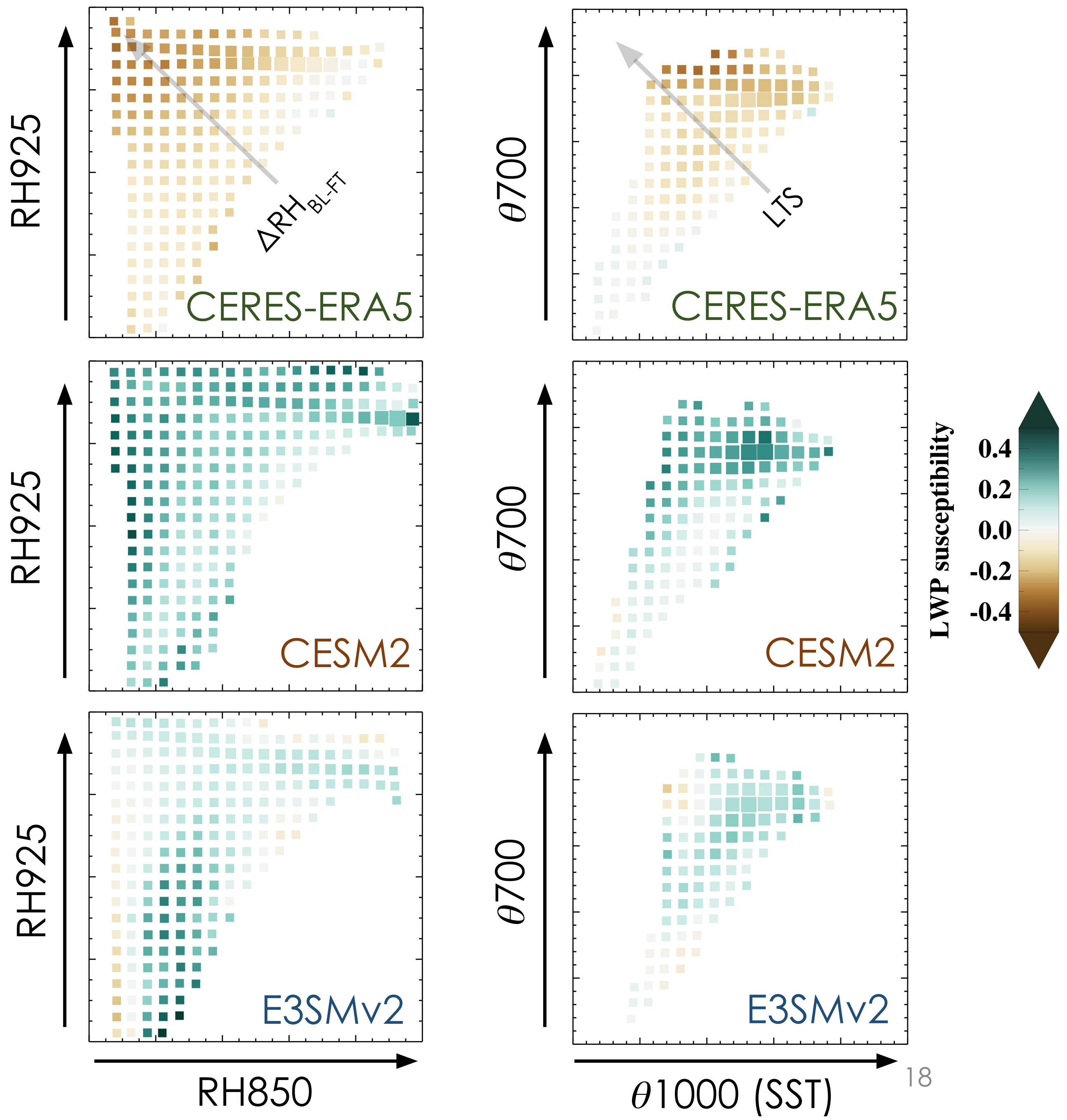
propagated to LWP, only to CDNC. **f** Combined plot of the binned mean values from cases **a**–**e**, and the initial values without any variability (No errors, solid black line). Both COD and CER were without variability (black line); CER was accurate but COD included variability/error (blue line); COD was accurate but CER included variability (red line); CER and COD errors influenced only LWP calculation (purple line); CER and COD errors influenced only CDNC calculation (yellow line); CER and COD errors influenced both LWP and CDNC calculation (dashed black line).

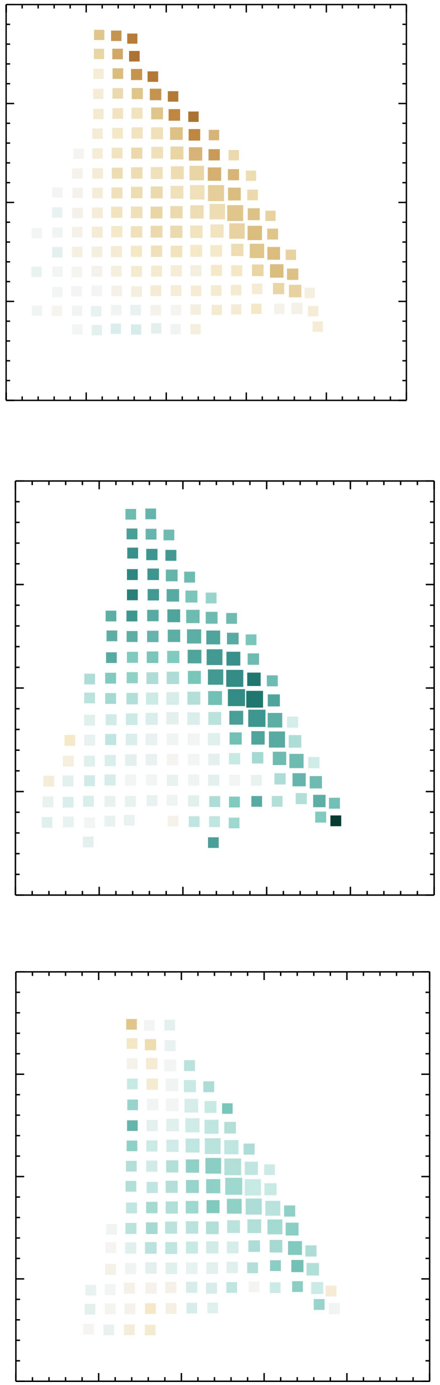
Impact of precip



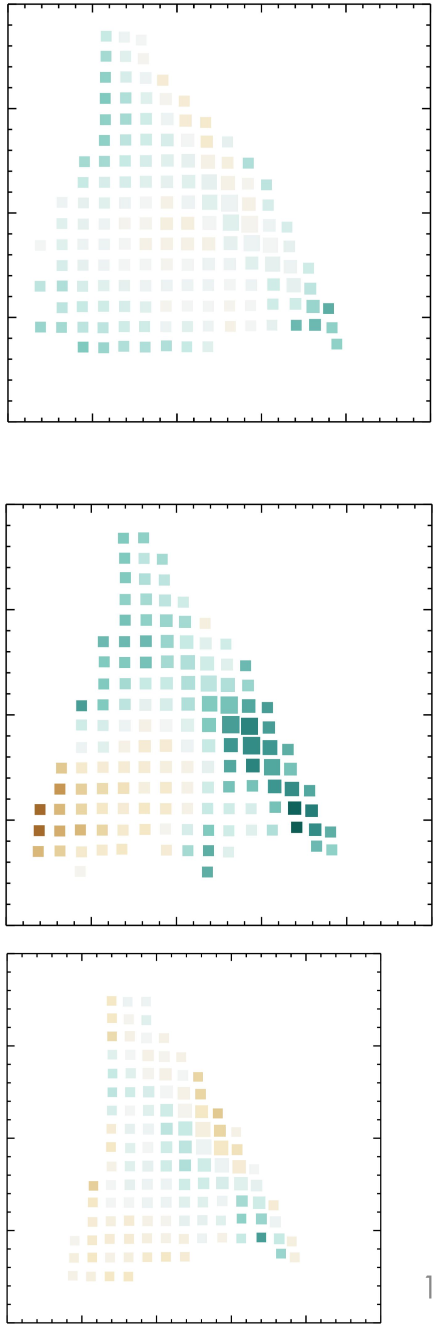
LWP susceptibility in **MET** spaces show contrasting features between Obs and GCMs, again

- Obs suggests stronger –ve LWP adjustments under high LTS (strong subsidence condition).
- E3SMv2 captures –ve LWP adj, mostly under the driest free-troposphere (condition where entrainment at cloud-top is favored).
- CESM2 again suggests weak –ve LWP adj under cold conditions.





<LWP LCF>
LTS-TH1000



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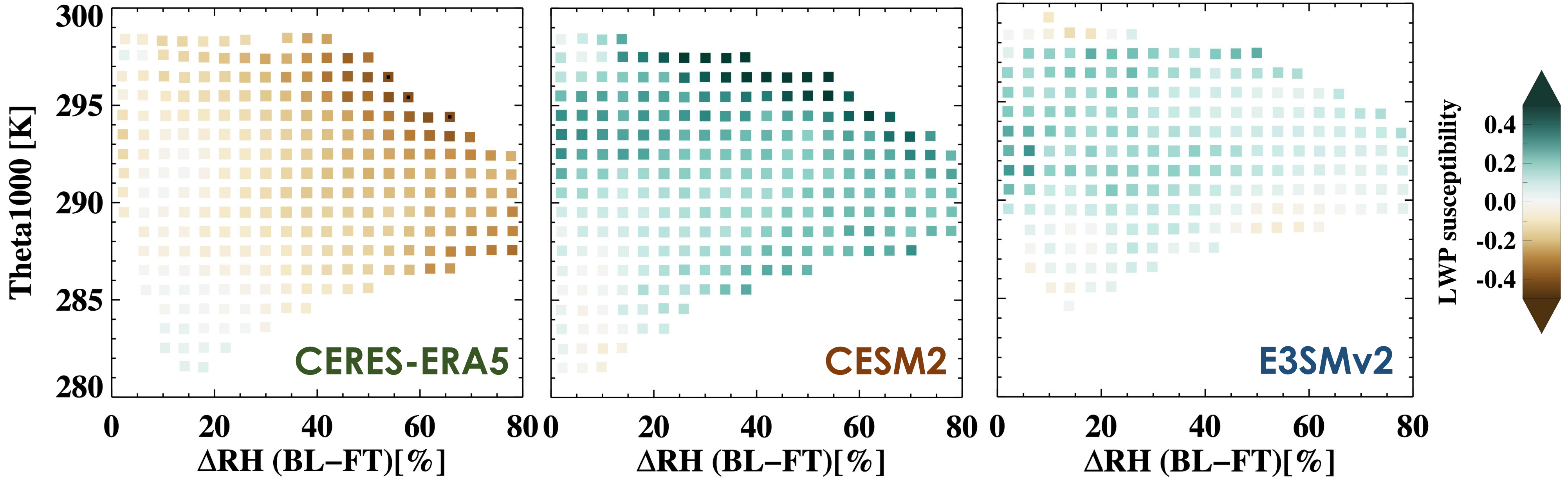

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