School of Earth and Environment
INSTITUTE FOR CLIMATE & ATMOSPHERIC SCIENCE

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Proposal for AEROCOM joint experiments on aerosol perturbations and uncertainty analysis

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Sensitivity and Uncertainty

There are two aspects to this proposal:

1. Quantifying the *response* (sensitivity) of aerosol and radiative effects to realistic perturbations in single emissions
2. Understanding and comparing the *sources of uncertainty* through multi-parameter process perturbations, emulation and uncertainty analysis

Rationale for sensitivity experiments

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Most aerosol model evaluation focuses on the *state* of aerosol

It is the *response of the model to perturbations* that determines the radiative forcing and initiates Earth system feedbacks

The magnitude and causes of diversity in models states and responses may differ

- There are model factors that could cause large differences in states (e.g. wet removal) but which might not so strongly affect response
- Good agreement of model states may hide differences in response

Example of responses: DMS

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Author	Effect	Effects	Model
Rap et al. (2013)	- 0.2 Wm^{-2}	First indirect for +25% ΔDMS	GLOMAP-mode
Six et al. (2013)	- 0.64 Wm^{-2}	All ACI for +25% ΔDMS	ECHAM5-HAM
Thomas et al. (2010)	- 2.0 Wm^{-2}	All sky for +100% ΔDMS	ECHAM5-HAMMOZ
Woodhouse et al. (2010)	<0.1% ΔCCN for 1% ΔDMS	CCN	GLOMAP-bin

Different responses due to differences in baseline aerosol, spatial DMS patterns, nucleation/growth/cloud-processing

Example of responses: Biogenic SOA

Author	Cloud forcing	Effects	Model
Rap et al. (2013)	- 0.02 Wm^{-2}	First indirect	GLOMAP-mode
Goto et al. (2008)	- 0.19 Wm^{-2}	All effects	SPRINTARS
O'Donnel et al. (2011)	+ 0.20 Wm^{-2}	All effects	ECHAM5-HAM
Scott et al. (2013)	- 0.02 to -0.7 Wm^{-2}	First indirect	GLOMAP-mode

Different responses of CCN due to competing effects of nuclei growth, organic-controlled nucleation, and changes in condensation sink.

Different BVOC emission distributions

Example of responses: Arctic sea ice loss

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Effect of complete loss of sea ice

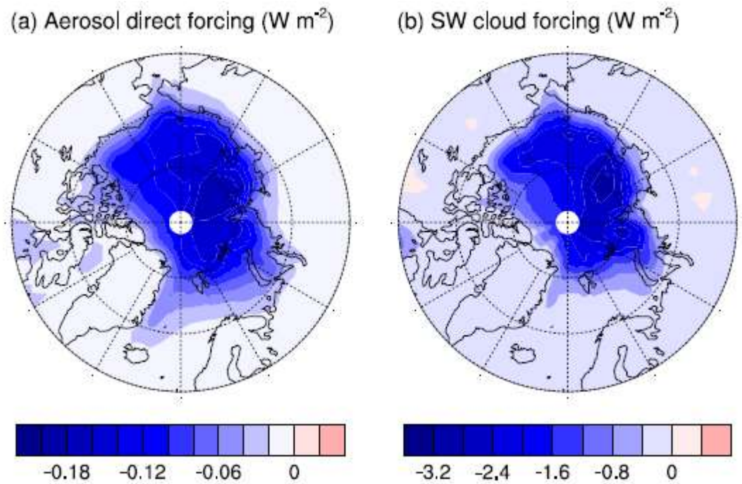
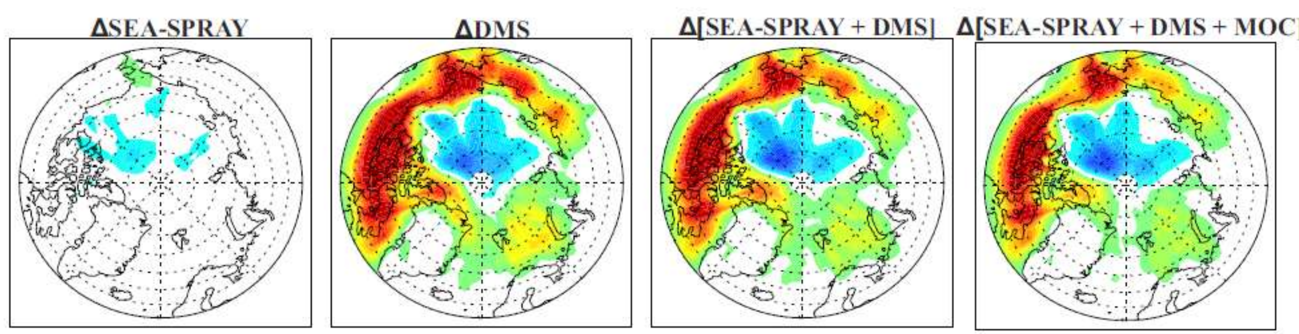


Fig. 15. Comparison of the average JJA modeled TOA natural aerosol direct radiative forcing and first natural aerosol indirect effect derived from the difference be

Struthers et al. (2010): large *<u>increase</u>* in aerosol -> large direct and indirect forcing

Browse et al. (2013): small *<u>decrease</u>* in aerosol because of interaction with scavenging



Change in surface (0-50m) CCN number (R_{CCN}>35nm)

Example of responses: Ageing

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Anecdotal: Addition of more soluble material (sulfate, SOA etc) decreases the lifetime of BC, causing large changes in remote BC concentrations and deposition

Process uncertainty

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Emulation of a complex global aerosol model to quantify sensitivity to uncertain parameters

L. A. Lee, K. S. Carslaw, K. J. Pringle, G. W. Mann, and D. V. Spracklen

Atmos. Chem. Phys., 11, 12253–12273, 2011

Mapping the uncertainty in global CCN using emulation

L. A. Lee, K. S. Carslaw, K. J. Pringle, and G. W. Mann

Atmos. Chem. Phys., 12, 9739–9751, 2012

The magnitude and causes of uncertainty in global model simulations of cloud condensation nuclei

L. A Lee, K. J. Pringle, C. L. Reddington, G.W. Mann, P. Stier, D. V. Spracklen, J. R. Pierce, and K.S. Carslaw

Atmos. Chem. Phys., 13, 8879-8914, 2013

PDFs of CCN concentration due to uncertainty in 28 parameters

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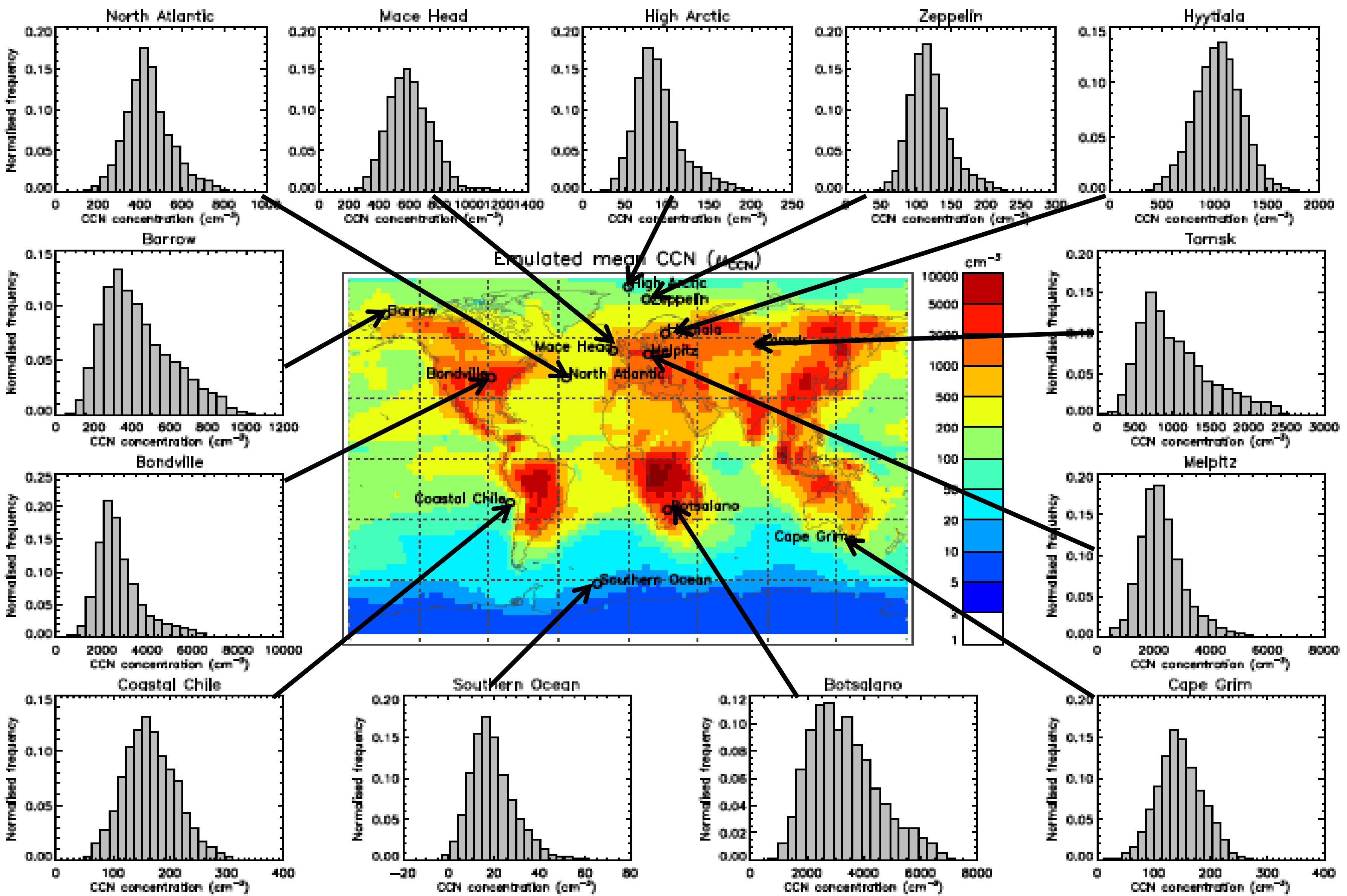
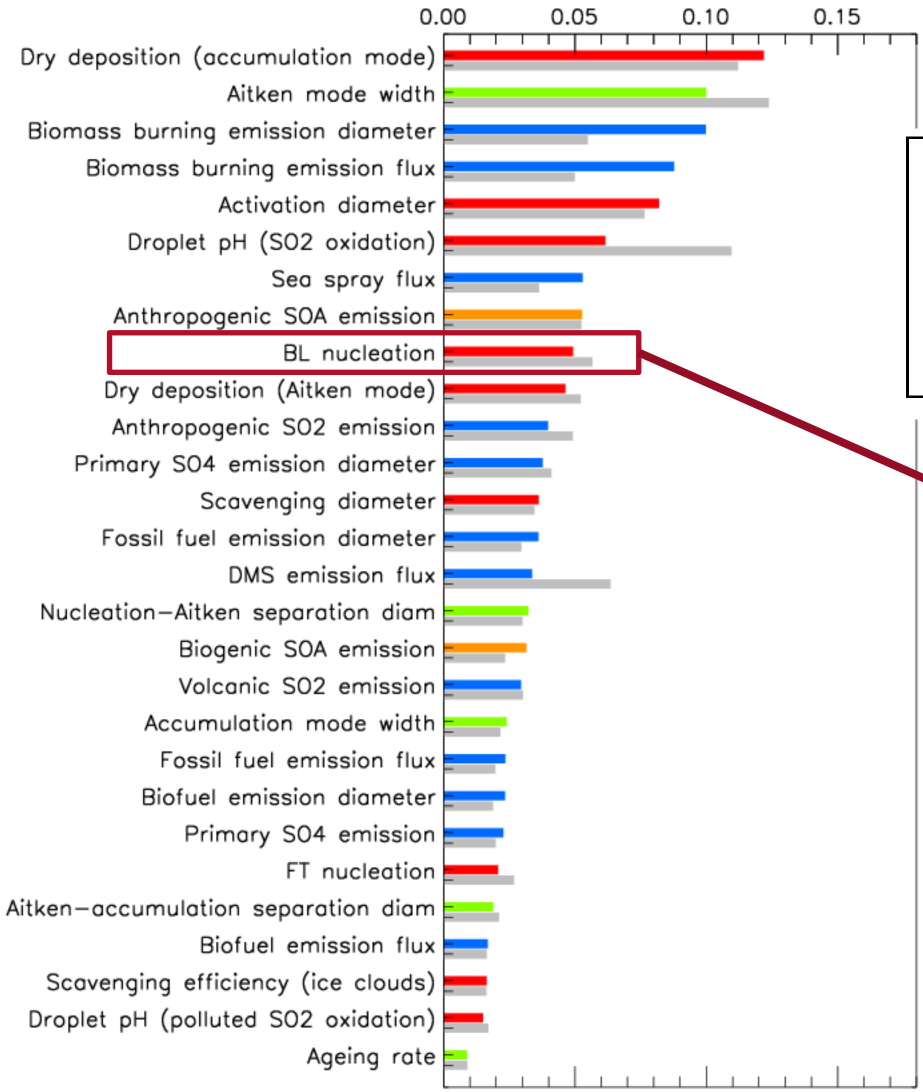
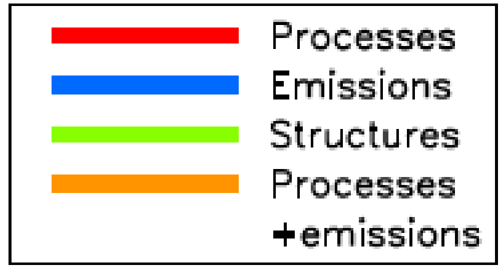


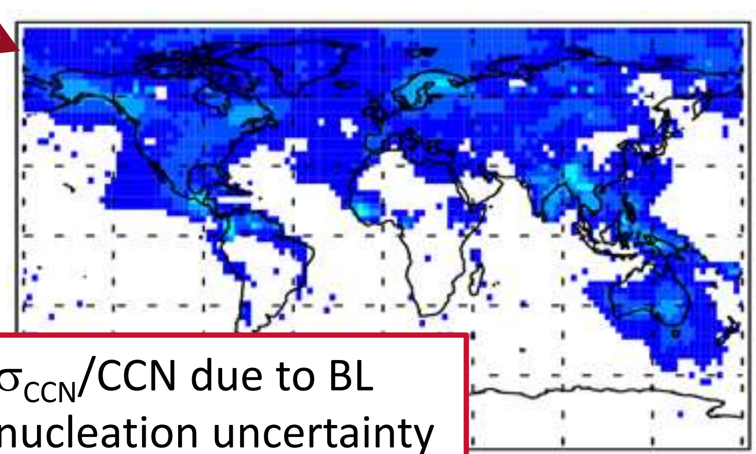
Sources of CCN uncertainty in GLOMAP

σ_{CCN}/CCN (global mean)



From variance decomposition





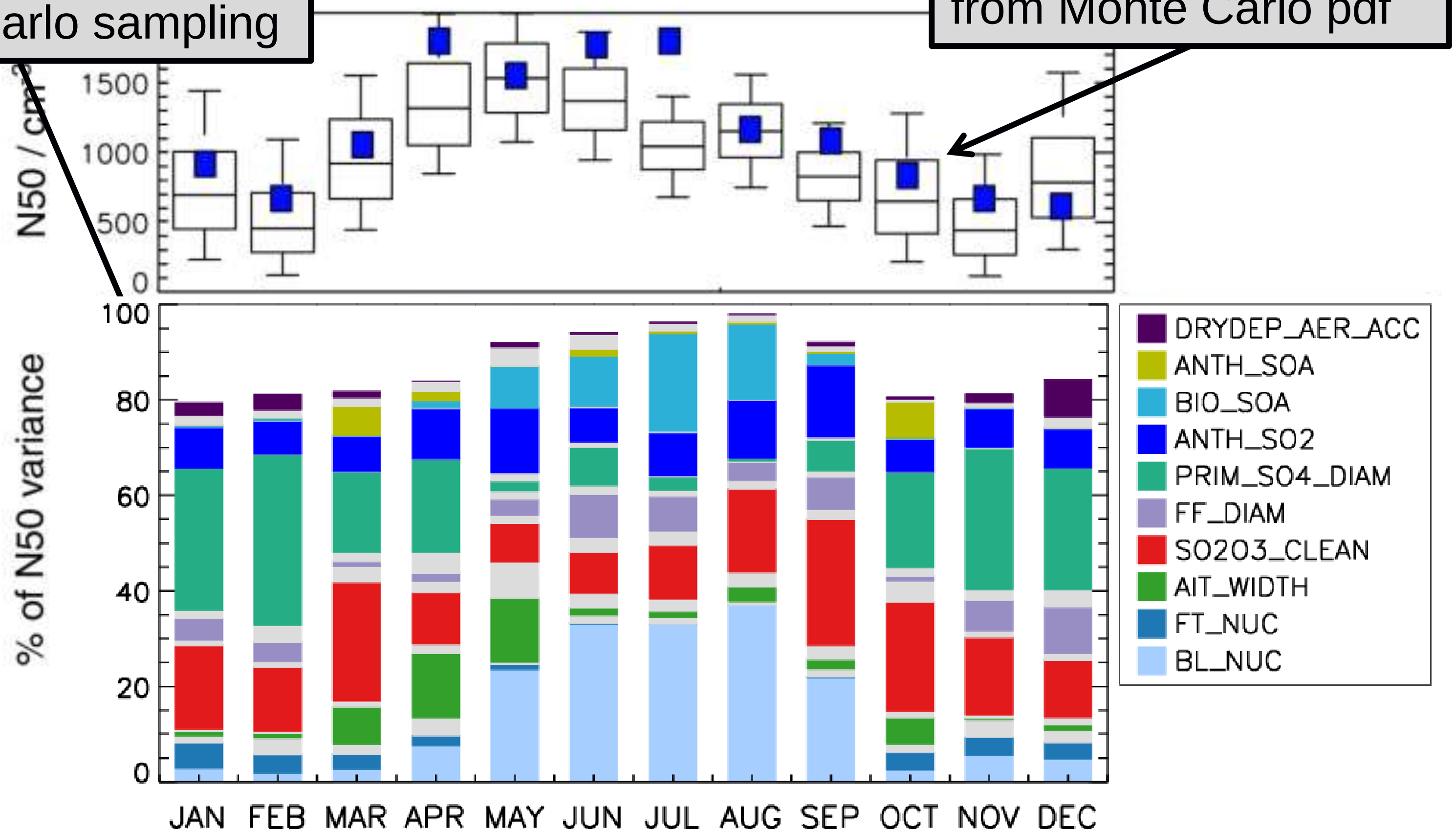
σ_{CCN}/CCN due to BL nucleation uncertainty

Lee L.A. et al., The magnitude and causes of uncertainty in global models of CCN, **ACP**, 2013.

Sources of model uncertainty at one site

Fraction of variance due to each process from variance decomposition of the Monte Carlo sampling

Model interquartile range and 9th /91st confidence intervals from Monte Carlo pdf



Lee L.A. et al., The magnitude and causes of uncertainty in global models of CCN, **ACP**, 2013.

Using emulators to enable Monte Carlo simulations

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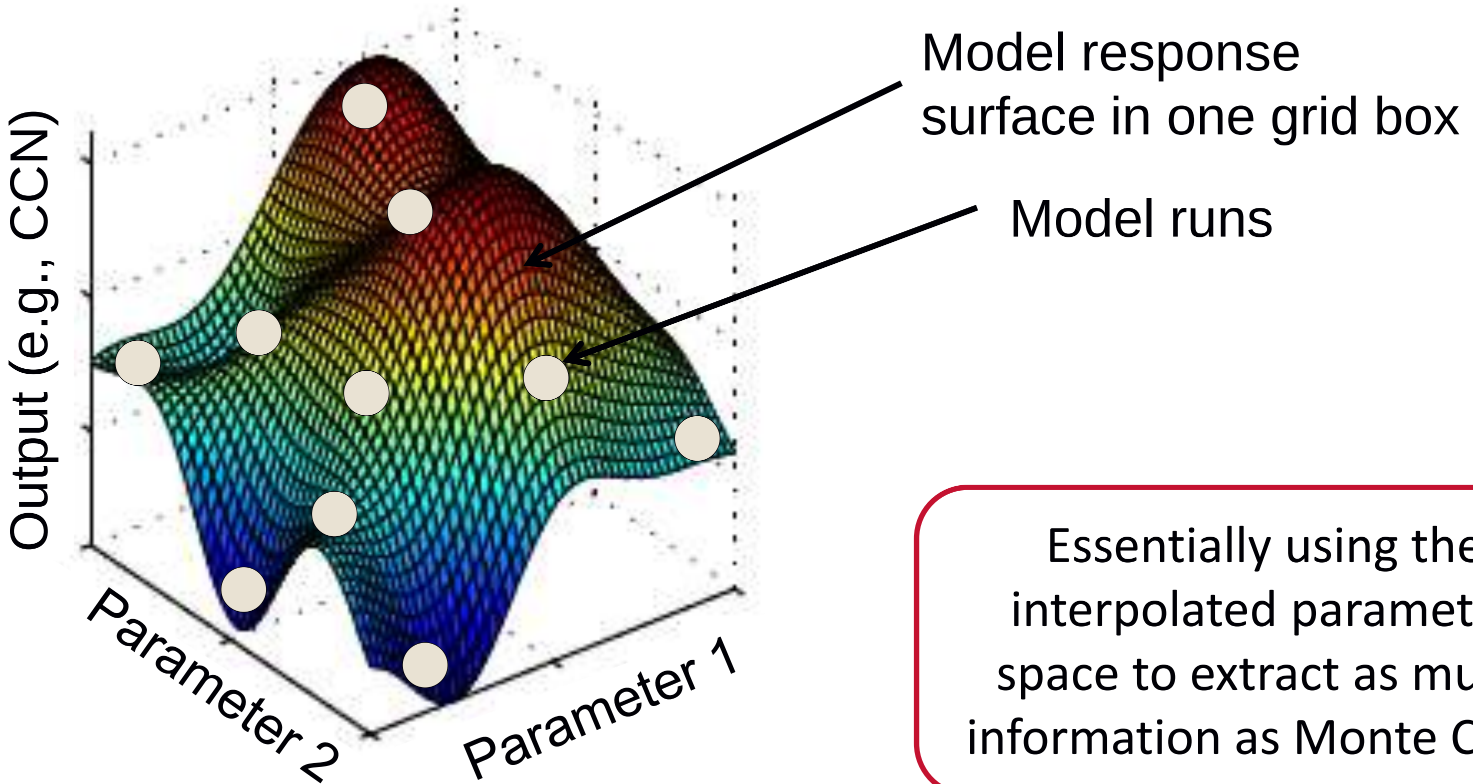

Essentially using the interpolated parameter space to extract as much information as Monte Carlo

Oakley, J. and O'Hagan, A.: Probabilistic sensitivity analysis of complex models: a Bayesian approach, J. Roy. Stat. Soc. B, 66, 751–769, 2004.

Lee, L.A. et al., Emulation of a complex global aerosol model to quantify sensitivity to uncertain parameters, ACP 2011.

An AEROCOM multi-model parametric uncertainty analysis

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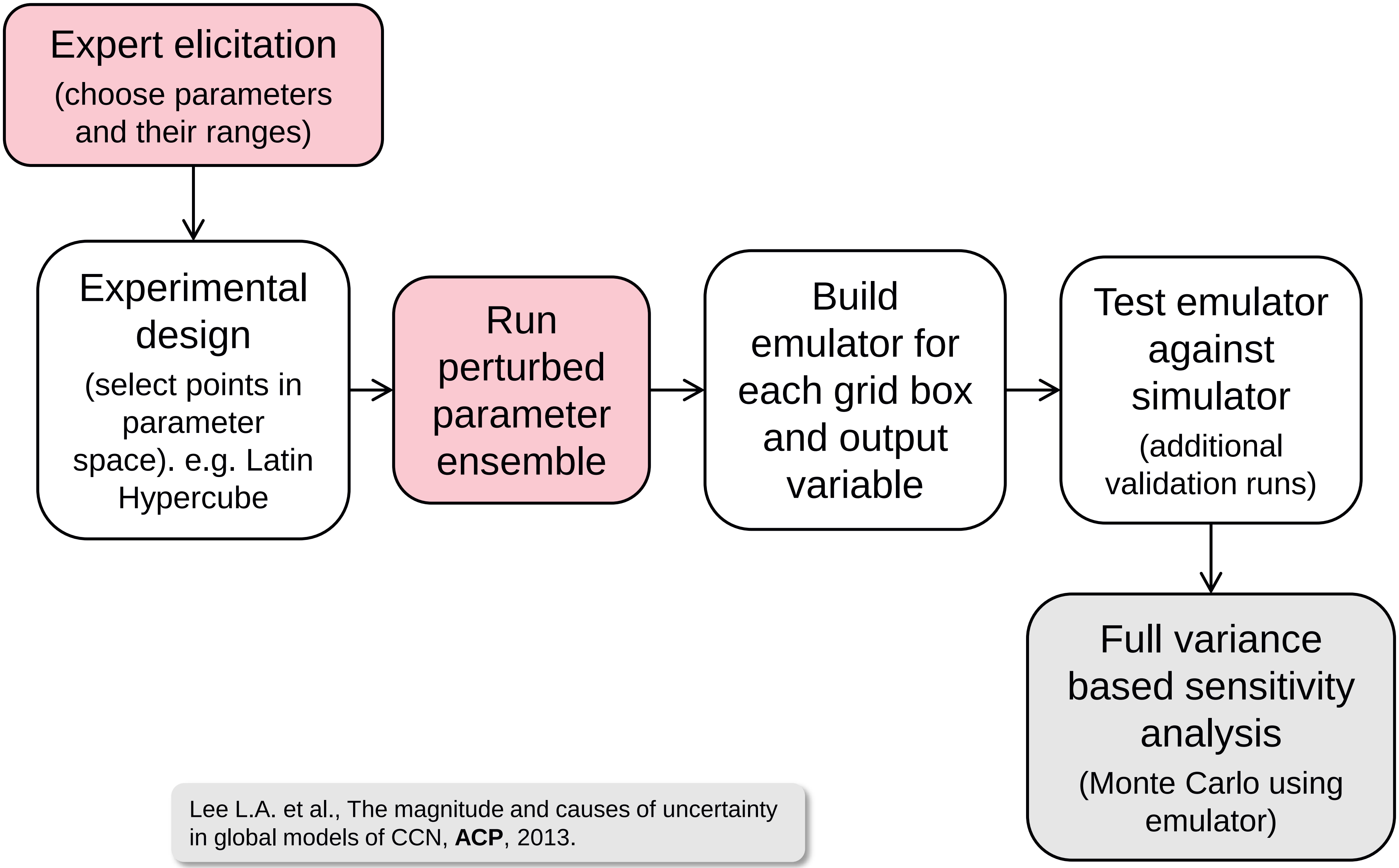

Lee L.A. et al., The magnitude and causes of uncertainty in global models of CCN, **ACP**, 2013.