In search of the best match:
probing a 6-D cloud microphysical parameter space to better understand what controls cloud thermodynamic phase

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Introduction

Mixed-phase clouds, ubiquitous at temperatures between $\sim -35^\circ$C and 0°C, contain both supercooled liquid droplets and ice crystals that possess markedly different optical properties and lifetimes in the atmosphere. Thus, the Earth's energy budget and equilibrium climate sensitivity (ECS) will delicately depend on their relative proportions. An outstanding weakness of microphysical schemes is global climate models (GCMs) lies in the arbitrariness of their tuning parameters, which are notoriously fraught with uncertainties.

Objectives

1. Probe a 6-D space of cloud microphysical parameters in NCAR's CAM5.1 model to determine how various microphysical processes impact the proportion of liquid to the total amount of liquid and ice in mixed-phase clouds (***supercooled cloud fraction (SCF)***)
2. Obtain three sets of parameters that are able to "best" reproduce observations of SCF from NASA's CALIOP instrument to implement into fully-coupled CESM1.0.5 simulations that will yield ECS estimates (Part II of this project).

Quasi-Monte Carlo Sampling of a 6-D Parameter Space

256 parameter combinations were selected within their specified ranges (Table 1) via Quasi-Monte Carlo (QMC) sampling. The six parameters were assumed to have uniform probability distributions to further guarantee good dispersion. 256 CAM5.1 simulations (at $4^\circ \times 5^\circ$ horizontal and 30 level vertical resolution) were run with these parameter combinations.

Process Investigated	Relevant Parameter	Default Value	Investigated Range
Ice nucleation	fin	1	[0,1]
WBF timescale exponent for ice	epsi	0	[-6, 0]
WBF timescale exponent for snow	epss	0	[-6, 0]
Ice crystal fall speed	ai	700 s^{-1}	[350,1400] s^{-1}
Wet scavenging (stratiform clouds)	sol_facti	1	[0.5,1]
Wet scavenging (convective clouds)	sol_factic	0.4	[0.2,0.8]

Table 1: Description of the six selected CAM 5.1 cloud microphysical parameters modified in the 256 simulations selected via QMC sampling, along with their investigated ranges.

Sensitivity Analysis

Application of a Generalized Linear Model (GLM) can used as a variance-based sensitivity analysis (SA) to quantify the individual and two-way interaction effects of each of the parameters on the variance in SCF [1]. The GLM used in this study can be written as

$$Y^i = \beta_0 + \sum_{j=1}^{n} \beta_j \cdot p_i^j + \sum_{j=1}^{n}\sum_{k=1}^{n} \beta_{j,k} \cdot p_j^i \cdot p_k^i + \varepsilon_i, \varepsilon_i \overset{iid}{\sim} N(0, \sigma^2),$$

where p_j^i represents the i-th realization of the j-th parameter, Y^i represents the i-th response variable, SCF, and β_i and $\beta_{j,k}$ represent the coefficients of linear and two-way interaction terms, respectively. Statistical significance (P<0.05) is evaluated via null hypothesis testing, which assumes that the regression coefficients are zero.
Results for the GLM SA can be visualized in the form of heat maps (Figure 1). *epsi* and its interaction with *epss* are the two most important contributors to SCF variance. *fin* has less of an impact on SCF variance than expected. All other effects are essentially negligible.

Generalized Linear Model Results

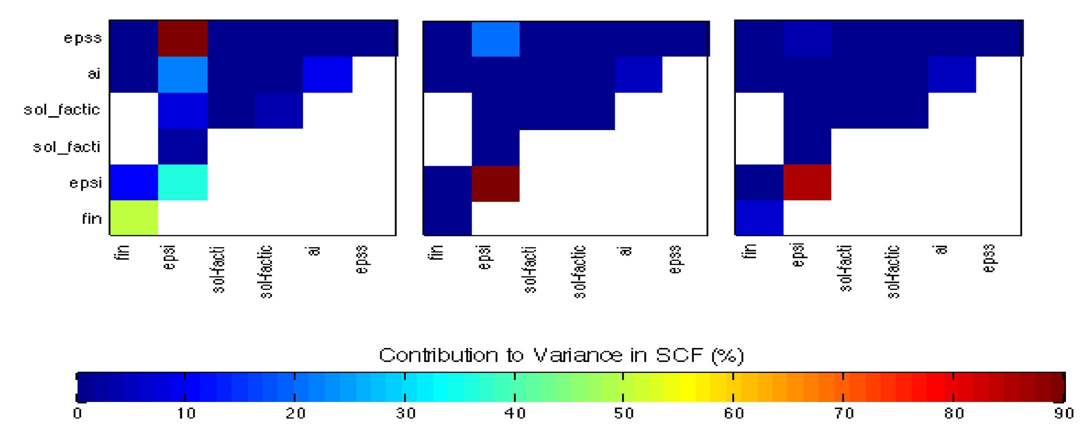

Figure 1: Heat maps displaying the individual and two-way interaction effects of the six parameters using global averages of SCF, time-average over the last year of simulation at the (left) -10°C, (centre) -20°C and (right) -30°C isotherms. Only statistically significant interactions are shown.

GLM results are separately displayed for the Southern Ocean (Figure 2). *epsi* accounts for most of the contribution to SCF variance. *epss* also plays a significant role. *fin* does not play an important role at the colder isotherms; however, is quite important at the -10°C isotherm, where the interaction between *epsi* and *ai* is also important. This implies that active ice nuclei (IN) in the Southern Ocean at warm mixed-phase clouds temperature and the sedimentation speed of the ice crystals they nucleate plays a significant role in SCF variance.

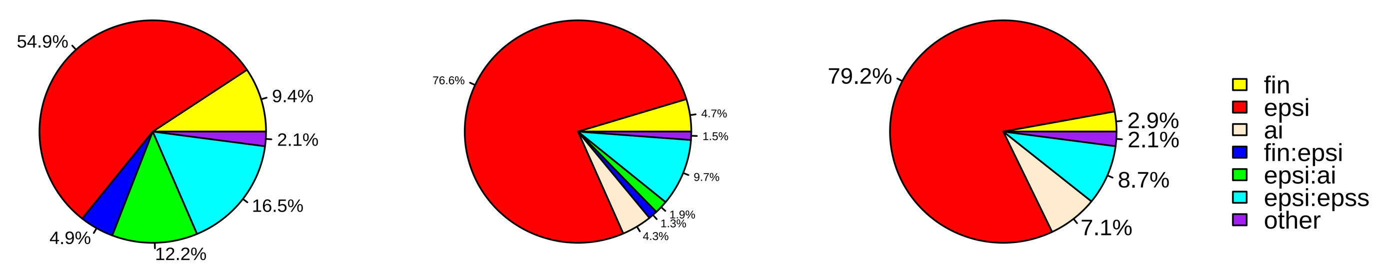

Figure 2: Pie graphs of the contributions of the most important parameter effects between 58° and 90° according to the GLM SA at the -10°C (left), -20°C (centre) and -30°C (right) isotherms.

Best Matches

Out of the 256 simulations, we define the "best" match to be that with the lowest *SCF score*,

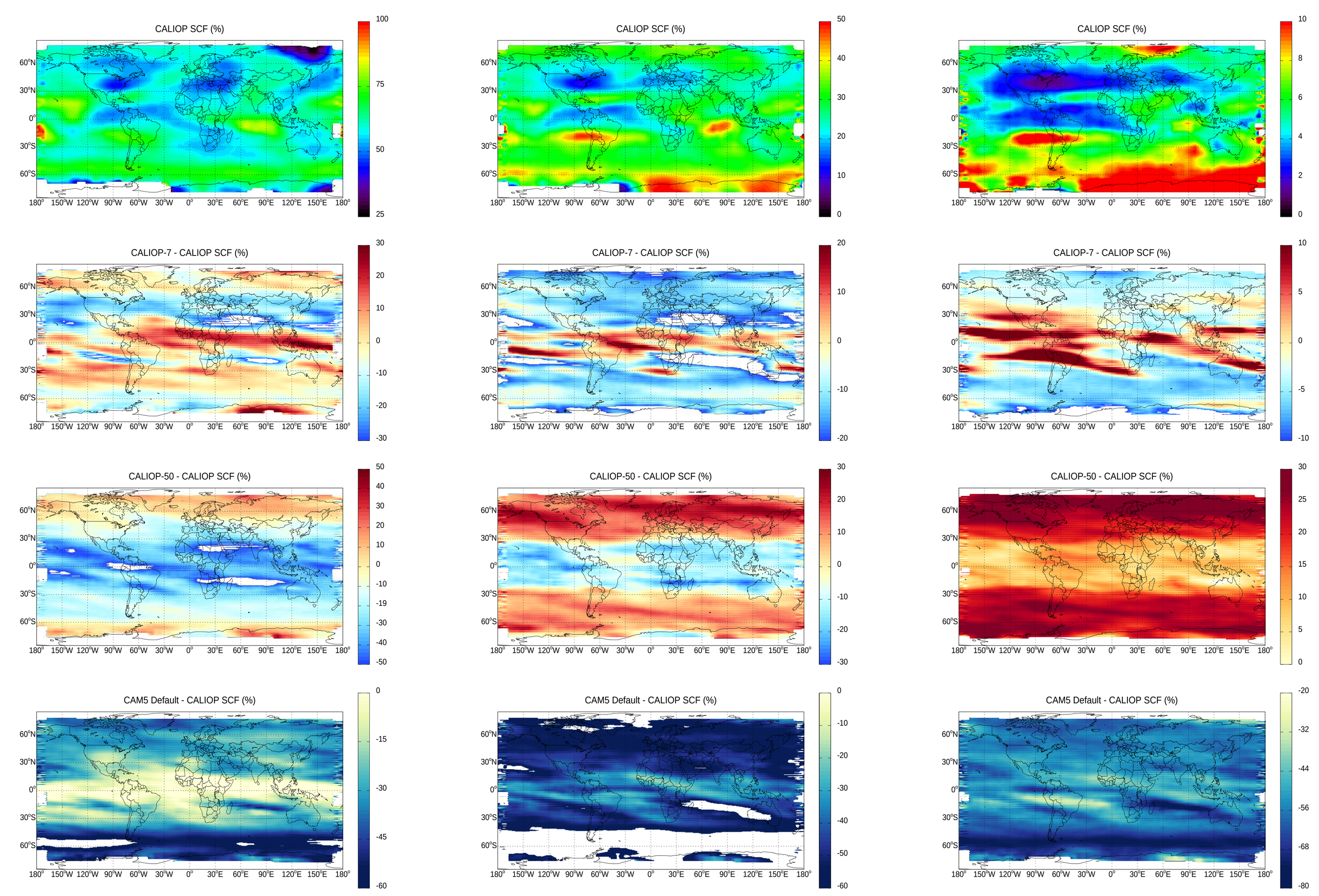

Figure 3: CALIOP product-observed SCF (79 months) [2] (top) and their differences with CAM5.1-modelled SCF.

defined as the difference between the modelled SCF and that of CALIOP observations, normalized by the maximum average value across all nine 20° latitude bands at a given isotherm.

The "best" (CESM-7) and "worst" (CESM-50) matches are shown in Figure 3 as their difference with CALIOP-observed SCF. The QMC simulations all have a new ice nucleation scheme [3] and modified detrainment scheme to increase SCFs, that reproduce CALIOP observations much better than the default CAM5.1. The three "best" matches, with wide-spanning parameter ranges were selected to implement in fully-coupled CESM1.0.5 simulations.
To get a sense of the parameter values that yield lower scores, the values were arranged into 16 bins, with their global cumulative scores arranged into box and whisker plots for *epsi* (Figure 4).

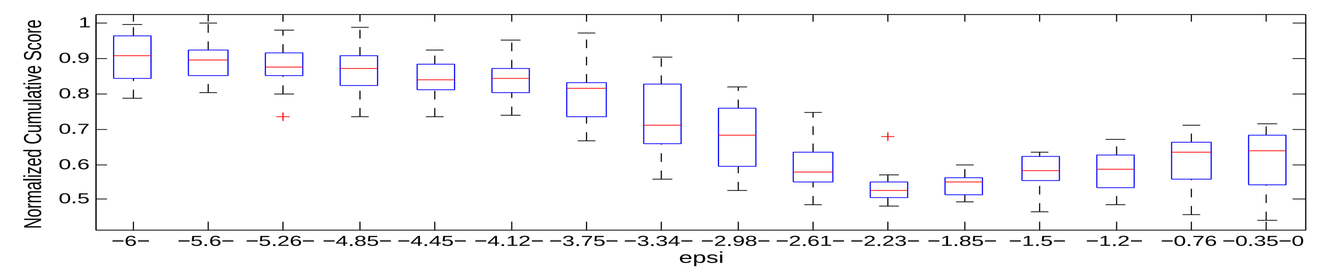

Figure 4: Global cumulative SCF scores for *epsi*. The shape results from the fact that faster WBF timescales act in the extratropics and high latitudes due to the modification in detrainment, while the opposite is true for the tropics.

Gregory Method Equilibrium Climate Sensitivity Estimates

Before the simulations equilibrate, preliminary ECS values can be calculated using the method of *Greogry et al. [2004]* [4], which shows a wide range in ECS values for the three "best" matches along with high and low limiting cases on IN (Figure 5).

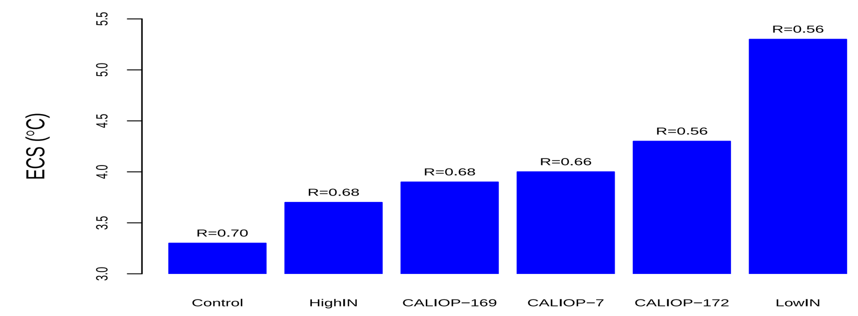

Figure 5: ECS estimates for all CESM1.0.5 simulations based on the Gregory Method. The relatively low R values result from large internal variability in the simulations.

Conclusions

- *epsi* along with its interaction with *epss*, are by far, the two most important parameters that influence variance in SCF. *fin*, the parameter that determines the fraction of dust particles that are active as IN, has less of an impact than originally hypothesized. All other parameters and their two-way interaction effects contribute negligibly to SCF variance.
- The three sets of six CAM5.1 parameter values that "best" match CALIOP observations of SCF all have highly contrasting spatial distributions and a noticeable spread in ECS values.

Forthcoming Research

Actual ECS values will be calculated for all simulations. Global and regional radiative kernel for various climate feedback mechanisms will be calculated for to shed light on the important processes controlling ECS when cloud thermodynamic phase is more accurately modelled.

References

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Acknowledgments

This work was supported by NASA Headquarters under the NASA Earth and Space Science Fellowship Program - Grant NNX14AL07H. We would also like to acknowledge high-performance computing support from Yellowstone provided by NCAR's Computational and Information Systems Laboratory, sponsored by the National Science Foundation.