A calibrated single-model ensemble (SME) derived from the NCAR Community Atmosphere Model, version 3.1, is used to test two hypothesized emergent constraints on cloud feedback and equilibrium climate sensitivity (ECS). The Fasullo and Trenberth relative humidity (RH) metric and the Sherwood et al. lower-tropospheric mixing (LTMI) metric are computed for the present-day climate of the SME, and the relationships between the metrics, ECS, and cloud and other climate feedbacks are examined. The tropical convergence zone relative humidity (RH_{M}) and the parameterized lower-tropospheric mixing (LTMI_{S}) are positively correlated to ECS, and each is associated with a different spatial pattern of tropical shortwave cloud feedback in the SME. However, neither of those metrics is linked to the type of cloud response hypothesized by its authors. The resolved lower-tropospheric mixing (LTMI_{D}) is positively correlated to ECS for a subset of the SME having LTMI_{D} over a threshold value. LTMI and the RH for the dry, descending branch of the Hadley cell (RH_{D}) narrow and shift upward the posterior estimates of ECS in the SME, but the SME bias in RH_{D} and concerns over poorly understood physical mechanisms suggest the narrowing could be spurious for both constraints. While calibrated SME results may not generalize to multimodel ensembles, they can enhance the process understanding of emergent constraints and serve as out-of-sample tests of robustness.

1. Introduction

The sensitivity of Earth’s globally averaged surface temperature to perturbations in atmospheric CO_{2} concentration varies between climate models, causing their projections of future climate change for identical emissions scenarios to diverge. Equilibrium climate sensitivity (ECS)—the change in Earth’s surface temperature for a doubling of atmospheric CO_{2}—is a model prediction that is used as a proxy of that sensitivity. As a model construct and a prediction of a distant future state, ECS cannot be validated by observational data (Knutti and Rugenstein 2015). To constrain predictions of ECS, “emergent constraints” have been hypothesized to relate the present-day or recent state of climate models—which can be tested against observations—to their predictions of ECS. In theory, climate models with superior observed fidelity for emergent constraint metrics would be more likely to make accurate predictions of ECS, which could help quantify and constrain uncertainty in ECS. Dozens of emergent constraints have been hypothesized, but little consensus exists on how to determine whether hypothesized emergent constraints are credible.

Demonstrating an empirical correlation between a metric and ECS in the Coupled Model Intercomparison Project (CMIP) ensembles is the de facto prerequisite to consideration as an emergent constraint (Klein and Hall 2015). But while the CMIP ensembles are the largest collection of diverse models available, CMIP samples are interdependent and selected arbitrarily, that is, they are neither randomly nor systematically drawn from a larger population of climate models (Knutti 2010) that would, theoretically, represent the uncertainty in modeling and predicting climate. These sampling concerns complicate quantitative analysis of emergent constraints’ credibility.
Single-model perturbed-physics ensembles (SMEs) are collections of model configurations that differ for well-understood reasons within the structure of a single climate model. These ensembles are commonly used to estimate parametric sensitivity and uncertainty in climate models, (e.g., Murphy et al. 2004; Sanderson et al. 2008; Klocke et al. 2011; Shiogama et al. 2012; Gettelman et al. 2012), or to optimize parameters according to objective functions (e.g., Yang et al. 2013; Tett et al. 2017). The model configurations within any of these ensembles exist according to decisions made about which uncertain model parameters to perturb, the selection of perturbation values, and whether to weight models according to performance. SMEs have been shown to be insufficient for developing emergent constraints that are robust across multimodel ensembles (MMEs; Klocke et al. 2011), but carefully constructed SMEs can be used to examine emergent constraints from MMEs (Masson and Knutti 2013; Klein and Hall 2015). Such tests are not definitive—despite their capacity for generating large sample sizes, SME samples could all be similarly flawed and unable to simulate the empirical evidence for or against the emergent constraints regardless of whether the constraint is grounded in a real physical process. However, the same disclaimer must be made of some or all members of multimodel ensembles. The usefulness and interpretability of any SME should be determined on a case-by-case basis dependent on the scientific question and details of the SME design.

To test an emergent constraint, we argue that a SME should be calibrated such that its distribution of model parameters is neither uniformly sampled across a range, which could admit model configurations that fail to uphold a true emergent constraint because of inadequacy, nor should it consist of only optimized model configurations, which could contain correlations to ECS because of a lack of parametric diversity (Masson and Knutti 2013). Optimized models could also fail to generate correlations between any metric and ECS because of a lack of diversity in the metric, known as underdispersion (Yokohata et al. 2012), and they could overfit the observations. In this context, we describe a SME as “calibrated” if its samples of model configurations approximate the posterior probability density (ppd) of model configurations according to the likelihood that they could have simulated the observed climate. To the extent that a calibrated SME is “weighted,” it is so by having more model configurations (samples) from parts of the parameter space that are more likely according to observations and fewer in parts of the parameter space that are less likely but cannot be ruled out. Consider two subspaces A and B of the parameter space. If the climate observations d are 10 times more likely to have been simulated by models from subspace A than subspace B, the calibrated ensemble will contain 10 times more models with parameters from subspace A than subspace B (without any duplicate model configurations). For hypothesis testing, calibration allows the ensemble to be interpreted through the “one model one vote” (Knutti 2010) paradigm.

In this paper, hypothesized emergent constraints from Fasullo and Trenberth (2012) and Sherwood et al. (2014) are tested using a SME derived from the National Center for Atmospheric Research (NCAR) Community Atmosphere Model, version 3.1 (CAM3.1), global climate model calibrated according to Bayesian inference (herein the CAM3 SME; Jackson et al. 2004, 2008; Jackson and Huerta 2016). CAM3 SME feedbacks are analyzed in relation to the hypothesized emergent constraints, as is the evidence for their hypothesized physical mechanisms of influence on ECS and their ability to constrain probabilistic estimates of ECS. These hypothesized emergent constraints were chosen as examples because they are simple to calculate and pertain to cloud feedback, but the process for selecting them is admittedly somewhat arbitrary, and they are not representative of the full spectrum of the growing field of hypothesized emergent constraints—for a more exhaustive review of emergent constraints, see Klein and Hall (2015), Knutti et al. (2017), and Caldwell et al. (2018).

Introduction to emergent constraints tested

Both the relative humidity (RH; Fasullo and Trenberth 2012) and lower-tropospheric mixing (LTMI; Sherwood et al. 2014) emergent constraints attempt to reduce the intermodel spread in ECS by connecting the cloud response to a warming climate to present-day climate model biases. The RH emergent constraint targets the intermodel spread in the reduction of the upward shortwave radiative flux at the top of the atmosphere (TOA) from the subtropical dry zones poleward to 50°. The differential reductions in albedo are linked to differential reductions in relative humidity and cloud amount. Model responses are hypothesized to relate to the present-day relative humidity biases in the dry, descending branch of the Hadley cell (RH_D) and moist, ascending branch of the Hadley cell (RH_A). Models that best resolve the stark differences in relative humidity between these branches are hypothesized to best predict the future drying attributable to the poleward expansion of the descending Hadley cell branch (Fasullo and Trenberth 2012).

The LTMI constraint relates the projected decrease in tropical low-cloud amount to the tendency for models to...
dry the boundary layer through turbulent mixing with the free troposphere in the present-day climate. Models that mix the most at present are hypothesized to dry the boundary layer more in a warming climate because the vertical gradient of specific humidity will steepen because of the Clausius–Clapeyron effect. The tendency to mix across the boundary layer in the present-day climate is decomposed into indices of small-scale parameterized-mixing (LTMI$_s$) and large-scale, resolved-mixing (LTMI$_D$). The indices are uncorrelated in CMIP and additive into a single LTMI index. Models with high LTMI indices at present are hypothesized to lose more low clouds and have more positive low-cloud shortwave cloud feedbacks in the tropics, subtropics, and potentially midlatitudes (Sherwood et al. 2014). For the details of calculating these emergent constraints from the present day climate, see appendix A.

2. Methods

a. Calibrating the CAM3 SME using Bayesian inference

Uncertain model parameters in CAM3.1 are treated as continuous random variables forming a continuous random vector $\mathbf{M}$. According to Bayes’ theorem, the posterior probability density for the model parameters after observing climate data $\mathbf{d}$ is

$$p_{pd}(\mathbf{M} \mid \mathbf{d}) \propto L(\mathbf{d} \mid g(\mathbf{M}))p(\mathbf{M}), \tag{1}$$

where $L$ is a probability density function that specifies the likelihood of observing $\mathbf{d}$ given GCM climate $g(\mathbf{M})$. The common choice for a likelihood function is the multivariate normal density. Because of the nonlinear relationship between model parameters $\mathbf{m}$ and model climate $g(\mathbf{m})$, Eq. (1) cannot be solved analytically.

Markov chain Monte Carlo (MCMC) sampling approaches can solve Eq. (1) by iteratively stepping through parameter space and accepting or rejecting model configurations based on their relative likelihood (e.g., Metropolis et al. 1953; Hastings 1970). There are significant challenges to using MCMC to solve inverse problems for computationally expensive models like GCMs (Qian et al. 2016). The standard approach is to develop a computationally cheap surrogate model and use MCMC sampling on the surrogate until the sampler converges to the $p_{pd}(\mathbf{M} \mid \mathbf{d})$. Our approach is to abandon exact (convergent) solutions to the $p_{pd}(\mathbf{M} \mid \mathbf{d})$ and instead sample the GCM directly using a more efficient but less exact “greedy” sampling technique, multiple very fast simulated annealing (MVFSAs). MVFSA is adapted from an optimization algorithm for identifying maximum a posteriori estimates for uncertain model parameters called very fast simulated annealing (VFSA; Ingber 1989). Sen and Stoffa (1996) demonstrate that the combination of multiple Markov chains each following the VFSA algorithm but launched from different points in parameter space (MVFSA) effectively approximates the $p_{pd}(\mathbf{M} \mid \mathbf{d})$ even for multimodal distributions, and Jackson et al. (2004) and Villagran et al. (2008) show that MVFSA performs sufficiently well on GCMs relative to the Metropolis–Hastings algorithm at a fraction of the computational cost. This technique suits our needs as climate scientists because we are interested in obtaining the actual model climate for each model configuration, rather than an estimation of the climate from a surrogate model.

The calibrated CAM3 SME consists of 1800 CAM3.1 model configurations, which are realizations of $\mathbf{M}$ drawn from the approximate $p_{pd}(\mathbf{M} \mid \mathbf{d})$ [Eq. (1)] using MVFSA. Each model configuration is defined by a vector $\mathbf{m}$ that specifies values of 15 uncertain cloud and convection parameters. The prior distribution for each random variable within $\mathbf{M}$ is uniform within the ranges for each parameter (supplied in Table B1 in appendix B). The CAM3 SME is an update on the calibration described in Jackson et al. (2008).

Each model configuration from $p_{pd}(\mathbf{M} \mid \mathbf{d})$ is run for four model years at T42 resolution, with prescribed present-day monthly varying climatological (1950–2001) sea surface temperatures and sea ice. After each simulation, the likelihood $L$ is calculated from the biases of the present-day climate $g(\mathbf{m})$ relative to a broad set of observations and reanalysis $\mathbf{d}$ used by NCAR in the development of CAM3.1, a complete description of which can be found in Jackson and Huerta (2016). The likelihood function assumes a multivariate Gaussian distribution for climate anomalies with a covariance matrix $\mathbf{C}$ incorporating observations of natural variability and covariance for observed fields

$$L[\mathbf{d} \mid g(\mathbf{m})] \propto \exp \left\{ -S \times \frac{1}{2} [g(\mathbf{m}) - \mathbf{d}]^T \mathbf{C}^{-1} [g(\mathbf{m}) - \mathbf{d}] \right\} , \tag{2}$$

The MVFSA algorithm steps through parameter space, either accepting proposed model configurations or rejecting them based on their relative likelihoods as computed using Eq. (2) (Jackson et al. 2004). A precision parameter $S$ (Jackson et al. 2008) makes the MVFSA more accepting of alternative model configurations to compensate for model structural bias and prevent overconfident posterior densities (Jackson and Huerta 2016), but the structural bias is not explicitly modeled.
Climate sensitivity for the calibrated CAM3 SME is a continuous random variable

\[ \text{ECS} = g_{2X}(M), \]

where \( g_{2X} \) represents equilibrium temperature change for a doubling of CO2. To approximate the distribution of ECS for the calibrated CAM3 SME, we subsampled the \( \text{ppd}(M | d) \) 165 times: \( m = \{m_1, m_2, \ldots, m_{165}\} \). Each subsample was run with a slab ocean and preindustrial (PI) CO2 for 40 years and again for 40 years after a doubling of CO2. The last 20 years were used for climatologies. The 165 samples from \( g_{2X}(M) \), \( \text{ecs} = \{\text{ecs}_1, \text{ecs}_2, \ldots, \text{ecs}_{165}\} \) range from 1.95 °C to 3.94 °C with a mean of 2.7 °C, slightly narrower than the combined ECS range of the CMIP3 and CMIP5 archive combined (2.1°–4.6°C; Fig. 1b). When normalized to integrate to 1, the histogram would be a coarse approximation of the probability mass function \( \text{pmf}(\text{ECS}) \) (Fig. 1). We make the leap to a probabilistic interpretation of the CAM3 SME because of our calibration technique, but resist the same interpretation for CMIP. Note that the probability mass function of ECS is a property of the CAM3 SME and the method of model–data comparison—an uncertainty in prediction that arises from the randomness of choosing one model configuration to predict ECS among many possible model configurations, given the observed climate; it is not straightforward to connect this distribution to the uncertainty of ECS for the actual climate system.

b. Testing emergent constraints

The efficacy of an emergent constraint is judged by its correlation to ECS in the CAM3 SME models, on the apparent relevance of its hypothesized physical mechanism in the CAM3 SME, and by the constraint it provides on the posterior density of ECS in the CAM3 SME. Computing the correlation between the indices and ECS is straightforward and is the status quo for demonstrating the efficacy of an emergent constraint hypothesis on CMIP models. This study explicitly computes cloud and other climate feedbacks in the CAM3 SME using the Shell et al. (2008) radiative kernel and examines correlations between each feedback and emergent constraints for insight into the physical mechanisms that may connect the emergent constraints to ECS. Additionally, CAM3 SME models are composited by their emergent constraint indices, and the spatial pattern of the cloud feedbacks for each composite are compared to each other to reveal where emergent constraints relate to the intraensemble spread in cloud feedback. Finally, the impact of updating estimates of ECS using evidence from each emergent constraint is tested as described below. For brevity we refer to hypothesized emergent constraints as emergent constraints despite the fact that they are not “confirmed” (Klein and Hall 2015).
Constraining Estimates of ECS

An emergent constraint narrows or shifts the posterior probability density of ECS by changing our confidence in a model configuration based on the comparison of its model climate to a set of observable criteria or metrics. Consider the hypothesis that \( c(x) \) is an emergent constraint, which operates on high-dimensional climate data and can be applied to observations \( c(\text{obs}) \) and model climate \( c[\text{g}(M)] \). Ideally, we would apply MCMC sampling using the emergent constraint \( c(x) \) in the likelihood [Eq. (2)] and a prior distribution for model parameters from the posterior of the calibrated CAM3 SME. However, MCMC is too expensive to perform each time we test an emergent constraint, so instead of generating new samples, we reweight the existing model configurations according to the emergent constraint likelihood. The posterior probability density for \( M \) is

\[
\text{ppd}(M | c(\text{obs}), d) \propto L[c(\text{obs}) | c[\text{g}(M)]] \text{ppd}(M | d). \tag{4}
\]

Because \( \text{ppd}(M | d) \) is approximated by the 165 sample model configurations, Eq. (4) is solved by calculating \( L \) for each realization \( m \), based on the distance between \( c(\text{obs}) \) and \( c[\text{g}(m)] \). We assume that \( c(\text{obs}) \) is distributed normally with \( \pm 2\sigma_{\text{obs}} \) of the density falling within the authors’ reported uncertainty of observations so that

\[
L[c(\text{obs}) | c[\text{g}(m)]] \propto \exp \left[ - \frac{(c[\text{g}(m)] - c(\text{obs}))^2}{2\sigma_{\text{obs}}^2} \right]. \tag{5}
\]

By propagating the weights from each sample configuration to its associated ECS, we generate a weighted histogram for ECS (abandoning one model one vote) and then normalize it to integrate to 1 to approximate pmf[ECS | c(\text{obs}), d]. The weighted histogram can be compared to pmf(ECS | d) to evaluate the impact of the constraint on the estimate of ECS.

3. Results

a. Characterizing the feedbacks and ECS in the CAM3 SME

Global-mean shortwave (SW) and longwave (LW) cloud feedback \( \lambda_{\text{cld,SW}} \) and \( \lambda_{\text{cld,LW}} \), respectively, contain roughly the same variance in the CAM3 SME, but \( \lambda_{\text{cld,SW}} \) is positively correlated to ECS \( (r = 0.83) \) and \( \lambda_{\text{cld,LW}} \) is not \( (r = -0.029) \) (Fig. 2; Table 1). The global-mean surface albedo feedback \( \lambda_{\text{iav,SW}} \) is correlated to ECS \( (r = 0.70) \). The primary source of intraensemble variance in SW\( _a \) is the sea ice response to warming. The water vapor \( \lambda_{\text{Q,LW}} \) and Planck \( \lambda_{\text{Pl,LW}} \) feedbacks are strongly positive and negative, respectively, but have little variance (Fig. 2). An exceptional model run with the lowest ECS and unique feedbacks (Fig. 2), is included in the analysis because we found no reason to exclude it based on its skill scores or climate fields.

In the CAM3 SME ensemble mean, \( \lambda_{\text{cld,SW}} \) is strongly negative along the Pacific Ocean intertropical convergence zone (ITCZ) and tropical Indian Ocean, and positive over the Southern Ocean and Northern Hemisphere storm tracks (Fig. 3). Ensemble-mean \( \lambda_{\text{cld,SW}} \) is also negative over the stratocumulus regions where annual-mean midtropospheric pressure velocity \( v_{500} \) is maximally downward and is also generally negative over areas of transition between sinking and rising air in the tropics; \( \lambda_{\text{cld,LW}} \) is positive along the ITCZ and South

Table 1. Correlation coefficients between climate feedback parameters and ECS in the CAM3 SME (including the “outlier model configuration”).

<table>
<thead>
<tr>
<th>Feedback</th>
<th>( r(\text{ECS}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \lambda_{\text{cld,SW}} )</td>
<td>0.83</td>
</tr>
<tr>
<td>( \lambda_{\text{cld,LW}} )</td>
<td>-0.029</td>
</tr>
<tr>
<td>( \lambda_{\text{Q,LW}} )</td>
<td>-0.31</td>
</tr>
<tr>
<td>( \lambda_{\text{iav,SW}} )</td>
<td>0.70</td>
</tr>
<tr>
<td>( \lambda_{\text{Pl,LW}} )</td>
<td>-0.035</td>
</tr>
</tbody>
</table>
Pacific convergence zone and over the Indian Ocean (Fig. 3). The spatial pattern of positive $\lambda_{\text{cd, LW}}$ overlaps with areas of upward $\omega_{500}$.

The intraensemble variance in $\lambda_{\text{cd, SW}}$ and $\lambda_{\text{cd, LW}}$, and the difference between high- and low-ECS models, is at a maximum in the tropics and Southern Ocean (Fig. 4). High-ECS models ($\text{ECS}^H$) and low-ECS models ($\text{ECS}^L$) are composites of the approximately 30 models each that are greater than 1σ over and under the ensemble-mean ECS, respectively. There is a “seesaw” in zonal-mean $\lambda_{\text{cd, SW}}$, $\lambda_{\text{cd, LW}}$, and $\lambda_{\text{cd, NET}}$, with $\text{ECS}^H$ models actually exhibiting anomalously negative cloud

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**Fig. 3.** CAM3 SME ensemble- and annual-mean spatial pattern of (a) SW, (b) LW, and (c) net cloud feedback parameter $\lambda$ (shaded), and $\omega_{500}$ where rising air is contoured in cyan, and sinking air is contoured in gray at intervals of 2 Pa s$^{-1}$. 
feedback over the Southern Ocean, relative to the ECS\(^L\) models (Fig. 4).

The spatial pattern of the difference in \(\lambda_{\text{cl},\text{SW}}\) between ECS\(^H\) models and ECS\(^L\) models is maximized in the sub-tropics where annual-mean \(\omega_{500} = 0 \pm 1\) Pa s\(^{-1}\), which are neither areas of strong convection nor areas of strong descent, such as the subtropical stratocumulus decks (Fig. 4a) in the annual mean. Regressing the cloud feedback at each grid point on ECS in the CAM3 SME, the slope for \(\lambda_{\text{cl},\text{SW}}\) over the stratocumulus areas is near zero or negative,
meaning anomalously positive feedbacks in the stratus-
cumulus are more often found in ECS<sup>4</sup> models than ECS<sup>5</sup> models. The same type of analysis on CMIP3 models found the regression slopes in stratuscumulus areas were strongly positive in CMIP3 (Soden and Vecchi 2011) and positive in CMIP5 (Chung and Soden 2015). Clearly the relative lack of importance of stratuscumulus in determining CAM3 SME ECS is a stark difference between the SME and the MME ensembles. These and other broad conclusions drawn from spatial patterns of cloud feedback are insensitive to the inclusion of the apparent outlier model configuration with the lowest ECS in the ensemble.

b. Testing emergent constraints: Correlation to ECS

Both the RH and LTMI constraints are correlated to ECS in the CAM3 SME, but with weaker correlations than in CMIP (Table 2). Each hypothesis is composed of two indices, and for both hypotheses, only one index is found to be significantly correlated to CAM3 SME ECS. We also recompute the emergent constraints over a subset of CMIP3 and CMIP5 models and generally replicate the published findings (Tables 2 and A1).

1) CORRELATION: RH CONSTRAINT

The correlations between RH and ECS in the dry zone ($r = -0.13$) and moist zone ($r = 0.53$) (Table 2; Fig. 5) are of the same sign but are both weaker than reported for CMIP3 in Fasullo and Trenberth (2012) ($-0.81$ and $0.65$, respectively). The relationship between RH and ECS is unconstrained by the published observations (AIRS retrievals and MERRA and ERA reanalyses) when accounting for uncertainty in observing the mean state and for temporal variability (Fasullo and Trenberth 2012).

Both RH<sub>D</sub> and RH<sub>M</sub> correlations could have been improved in the SME if the domains of their calculations were shifted northward about 7° (Fig. 6a); however, this would displace each domain north of the peak dry and humid zones. All CAM3 SME members have a wet bias in RH<sub>D</sub>, the descending branch of the circulation. This is likely due to underdispersion of the CAM3 SME (Yokohata et al. 2012), but may also relate to the dry zone being defined higher in the atmosphere than the peak dryness in the CAM3 SME—in the CAM3 SME’s peak dry zone, 103 of the 165 model configurations are within the observed dry zone relative humidity, albeit over a smaller spatial domain. The RH constraint failed conclusively across a subset of CMIP5 piControl models ($n = 18$), with weak correlations opposite the hypothesized sign (Fig. 6c). This result is consistent with the findings from the supplementary materials in Fasullo and Trenberth (2012), which showed the RH constraint’s inability to predict twenty-first century warming under the RCP8.5 scenario.

2) CORRELATION: LTMI CONSTRAINT

The small-scale, parameterized index of LTMI (LTMI<sub>S</sub>) is correlated to ECS in the CAM3 SME ($r = 0.49$) (Fig. 7a), almost exactly matching its correlation in CMIP ($r = 0.50$); the large-scale, resolved index of LTMI (LTMI<sub>D</sub>) is poorly correlated to ECS ($r = -0.10$) (Fig. 7b; Table 2). Their linear combination is correlated with ECS in the CAM3 SME ($r = 0.25$)(Fig. 7c), but the correlation is degraded by the inclusion of LTMI<sub>D</sub>. The CAM3 SME spans similar ranges in LTMI<sub>S</sub>, LTMI<sub>D</sub>, and LTMI as the CMIP ensembles. LTMI<sub>S</sub> and LTMI<sub>D</sub>

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**Table 2. Correlation coefficients between hypothesized emergent constraints and ECS.** Bold font indicates statistical significance at the 95% level. Subscript $p$ indicates a published value, and subscript $c$ indicates a calculation from this paper in an effort to replicate published results.

<table>
<thead>
<tr>
<th>Ensemble</th>
<th>RH constraint</th>
<th>LTMI constraint</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r$ (ECS)</td>
<td>$r$ (ECS)</td>
</tr>
<tr>
<td>CMIP3</td>
<td>$-0.81$</td>
<td>$0.65$</td>
</tr>
<tr>
<td>CMIP3</td>
<td>$-0.71$</td>
<td>$0.28$</td>
</tr>
<tr>
<td>CMIP5</td>
<td>$-0.25$</td>
<td>$0.49$</td>
</tr>
<tr>
<td>CMIP5</td>
<td>$0.03$</td>
<td>$-0.16$</td>
</tr>
<tr>
<td>CMIP3 and 5</td>
<td>$-0.50$</td>
<td>$0.46$</td>
</tr>
<tr>
<td>CAM3 SME</td>
<td>$-0.13$</td>
<td>$0.25$</td>
</tr>
</tbody>
</table>

**Fig. 5.** ECS vs zonally averaged relative humidity over ocean for RH<sub>D</sub> and RH<sub>M</sub> zones of the May–August Hadley cell as in Fasullo and Trenberth (2012) computed for CAM3 SME (gray), CMIP3 slab control simulations (blue), and CMIP5 preindustrial control simulations (orange). Domains defining each zone are shown in Fig. 6. Observed RH% values (red and black outlines) are reported in Fasullo and Trenberth (2012) and are derived from AIRS retrievals and ERA and MERRA reanalyses. CMIP3 ECS values are as reported in Randall et al. (2007), and CMIP5 ECS values are from Sherwood et al. (2014). RH% values for CMIP models are computed by these authors (see Table A1).
are not significantly correlated to each other in CMIP, which is why their linear combination, LTMI, is more strongly correlated to ECS than either of its components. In the CAM3 SME, LTMI$_S$ and LTMI$_D$ are significantly anticorrelated ($r = -0.38$). However, above a threshold (LTMI$_D > 0.4$), LTMI$_S$ and LTMI$_D$ are uncorrelated. LTMI$_D$’s relationship to ECS is nonlinear, with low-LTMI$_D$ models having a negative correlation to ECS, and gradually transitioning to a positive correlation to ECS for high-LTMI$_D$ models. This phenomenon is attributable to $\lambda_{cld,SW}$ and discussed in the following evaluation of physical mechanisms.

c. Testing emergent constraints: Physical mechanisms

1) PHYSICAL MECHANISMS: RH CONSTRAINT

While the hypothesized physical mechanism for the RH constraint is not fully described, Fasullo and Trenberth (2012) speculate that RH$_M$ and RH$_D$ relate to future cloud loss in the midlatitudes because of the poleward expansion of the Hadley cell. Hadley cell expansion is a likely explanation for the positive CAM3 SME ensemble mean $\lambda_{cld,SW}$ over midlatitude oceans (Fig. 3), and the decrease in upward TOA SW flux at 40°N and 40°S is correlated to ECS across ensemble members, so it also relates to the intraensemble spread in ECS.

Cloud feedback is defined by the change in radiative flux due to changes in clouds normalized by the change in global-mean temperature. The CAM3 SME midlatitude
change in adjusted shortwave cloud forcing (change in cloud forcing adjusted for changes in clear sky radiative forcing) is correlated to ECS. But the midlatitude cloud feedback is relatively similar for all CAM3 SME ensemble members (the zonal mean midlatitude $\lambda_{\text{cl},SW}$ and $\lambda_{\text{cl},\text{NET}}$ have about 50% less intraensemble variance as in the tropics). Additionally, the relatively small variance in the midlatitude cloud feedback is not associated with ECS (Fig. 4). Therefore, the midlatitude cloud feedback in areas of poleward Hadley cell expansion is not a predictor of ECS in the CAM3 SME. Instead, the change in adjusted shortwave cloud forcing in the midlatitudes tends to act as an amplifier of a tropical cloud feedback–related warming signal.

Is the RH constraint related to that signal? To test that hypothesis, we test whether the RH constraint is associated with the change in midlatitude-adjusted shortwave cloud forcing, without normalizing by global-mean temperature change. Because of bias and under-dispersion in the CAM3 SME for the RH mean temperature change. Because of bias and under-dispersion, without normalizing by global-associated with the change in midlatitude-adjusted warming signal.

2) PHYSICAL MECHANISMS: LTMI CONSTRAINT

For LTMI$_D$, the relationship with $\lambda_{\text{cl},SW}$ is linear and in the hypothesized direction. The LTMI$_D^H$ composite tends to have anomalously positive $\lambda_{\text{cl},SW}$ where the annual-mean $\omega_{500}$ is upward (Fig. 9a), overlapping the domain for computing the LTMI$_D$ index and extending beyond that domain into the subtropics. Although LTMI$_S$ is correlated as hypothesized to tropical $\lambda_{\text{cl},SW}$ in the CAM3 SME, the correlation comes only from the midlevel (400–700 hPa) cloud fraction response, rather than the low-cloud response (1000–700 hPa) as hypothesized by Sherwood et al. (2014). We decompose the atmosphere over tropical ocean into annual-mean sinking (upper-third $\omega_{500}$), neutral (middle-third $\omega_{500}$), and rising (lower-third $\omega_{500}$) regimes and find correlation coefficients of 0.64 and 0.47 between LTMI$_S$ and midlevel cloud loss for the rising and neutral regimes, respectively. In all regimes, LTMI$_S$ is actually positively correlated to the low-cloud fraction change, opposite the expectation, although the correlation coefficients are relatively weak ($r < 0.19$).

For LTMI$_D$ the relationship to ECS is complex, as there are two groups of models that have high ECS and $\lambda_{\text{cl},SW}$ in the CAM3 SME: one within LTMI$_D^H$ and another within LTMI$_D^L$. We composite the 10 models with lowest LTMI$_D$, the 10 with the highest LTMI$_D$, and a third group of 10 models nearest where the LTMI$_D$–ECS correlation switches sign from negative to positive (Fig. 10). Both groups with high ECS and $\lambda_{\text{cl},SW}$ have broadly distributed anomalously positive tropical $\lambda_{\text{cl},SW}$ because of anomalous low-level and midlevel cloud loss where $\omega_{500}$ is relatively near zero. But the lowest LTMI$_D$ models have intensely positive $\lambda_{\text{cl},SW}$ in the deep tropics on the flanks of the Pacific ITCZ because of anomalous low-cloud loss, which is partially compensated by negative $\lambda_{\text{cl},SW}$ due to anomalous low-cloud gain in the stratuscumulus (Fig. 10). LTMI$_D$ separates models according to these groups and is a predictor of ECS for each group, but the correlation is negative, the opposite as in CMIP, for LTMI$_D^L$ models.

High- (low) LTMI$_D$ models tend to have high (low) parameter values for tau, alfa, and icritic (see Table B1), fewer (more) low clouds along the flanks of the ITCZ, and more (less) shallow convective precipitation. Neither group is more credible than the other as indicated by the model skill scores for the present-day climates. But one line of evidence suggesting the LTMI$_D^H$ models may be more credible than the LTMI$_D^L$ models is the observation of LTMI$_D$ itself. LTMI$_D$ is computed as an average over a spatial domain, with large contributions coming from the ITCZ in the central and eastern Pacific where cooler ocean temperatures favor shallow ascent (Sherwood et al. 2014). Because the lowest LTMI$_D$ models are likely biased low for the LTMI$_D^L$ metric in that region, their intensely strong positive $\lambda_{\text{cl},SW}$ in the same region may be suspicious (Fig. 10).

A final comment on the physical mechanism for LTMI relates to the suggestion of Sherwood et al. (2014) and Klein and Hall (2015) that the hypothesized physical mechanism for LTMI may be incomplete, given that the correlation between LTMI and ECS is stronger than the correlation between LTMI and a subset of CMIP models providing shortwave cloud radiative effect (Sherwood et al. 2014). This finding is replicated in the CAM3 SME: LTMI is more correlated to ECS ($r = 0.25$) than it is to net cloud feedback ($r = 0.17$) (Table 3). LTMI benefits from its correlation to the surface albedo feedback $\lambda_{a,SW}$ ($r = 0.28$) (Table 3), which is positively correlated to ECS ($r = 0.70$) in the CAM3 SME (Table 1). The correlation between LTMI and $\lambda_{a,SW}$ comes from LTMI$_S$ ($r = 0.62$) (Table 3).
The $\lambda_{\text{a,SW}}$ feedback enhances the LTMI–ECS correlation for reasons unrelated to clouds. The $\lambda_{\text{a,SW}}$ in the CAM3 SME is controlled by sea ice extent, raising the question as to why it should be so strongly correlated to LTMI$_{S}$.

Speculatively, LTMI$_{S}$ and base-state sea ice extent could be related via teleconnection as in Chiang and Friedman (2012), where high-latitude cooling induces a response in the tropical circulation. Whatever the source of the
connection between LTMI$^S$ and λ$_{\text{cld,SW}}$, such a connection is not part of its hypothesized physical mechanism (Sherwood et al. 2014).

d. Testing emergent constraints: Posterior estimates of ECS

The posterior probability mass function for ECS, computed using Eqs. (4) and (5) and generating weighted histograms for each emergent constraint, is narrowed and shifted upward for RH$_D$ and LTMI (Fig. 11). Any metric with a relationship to ECS and sufficient observational certainty will change the posterior probability, but the credibility of the shift should be considered a function of the credibility of the constraint itself. The posterior estimate for RH$_D$ is dubious because the CAM3 SME fails to span the observed range (Fig. 5)—each model configuration’s likelihood is exceedingly low, and the posterior ECS peaks at just above 3 K because a handful of models with an ECS of approximately 3 K are incrementally closer to the observed range than the other model configurations. Given such a large RH$_D$ bias, it is doubtful that those incrementally improved models are actually better estimators of ECS. The shift and narrowing of the posterior mass for LTMI may be credible. Its credibility hinges on our acceptance that the LTMI$^D$ metric, nonlinear as it is, is a reliable predictor of ECS. We must also accept the given bounds of observational uncertainty in LTMI$^D$ from Sherwood et al. (2014). However, interannual and interdataset variability across reanalysis products for LTMI$^D$ indicates a larger observational uncertainty may be more accurate (C. Schumacher 2018, personal communication).

Fig. 9. Difference in CAM3 SME cloud feedback parameter between composites of high and low (a)–(c) LTMI$^S$ and (d)–(f) LTMI$^D$. Annual-mean ensemble-mean rising air at 500 hPa is contoured in cyan, and sinking air is contoured in gray at intervals of 2 Pa s$^{-1}$. 
4. Discussion and conclusions

We find RH\textsubscript{M} and LTMI\textsubscript{S} to be correlated to ECS through tropical \(\lambda_{\text{cld,SW}}\), but observational uncertainty prevents these potential constraints from having a strong effect on the estimates of ECS. The RH\textsubscript{D} metric is considered too biased and underdispersed to test or use for adjusting our confidence in ECS. The LTMI\textsubscript{D} relationship with ECS and \(\lambda_{\text{cld,SW}}\) is nonlinear, appearing to confirm the hypothesized relationship between LTMI\textsubscript{D}, \(\lambda_{\text{cld,SW}}\), and ECS except for in a subset of models in which the correlation is negative instead of positive. As a whole, incorporating LTMI into our estimates of ECS suggests a shift in probability toward slightly higher ECS.

For both the RH and LTMI constraints, we find reasons to suspect the hypothesized physical mechanisms, even when the index is correlated to ECS. For RH\textsubscript{M}, there is no evident relationship to the poleward expansion of the Hadley cell in the midlatitudes. Perhaps the lack of a well-understood connection to the midlatitudes helps explain why this constraint failed in the CMIP5 models (Figs. 5 and 6c). LTMI\textsubscript{S} is correlated to reductions in midlevel cloud fraction (700–400 hPa) and

![Fig. 10](image)

**Fig. 10.** Scatterplot of \(\lambda_{\text{cld,SW}}\) vs LTMI\textsubscript{D} where dot color indicates groups of 10 models that are composited together, and map plots of \(\lambda_{\text{cld,SW}}\) anomalies (relative to ensemble mean) composited by group. Annual-mean bin-mean rising air at 500 hPa is contoured in cyan, and sinking air is contoured in gray at intervals of 2 Pa s\(^{-1}\).

<table>
<thead>
<tr>
<th>Ensemble</th>
<th>RH constraint</th>
<th>LTMI constraint</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(r(\text{ECS}))</td>
<td>(r(\lambda_{\text{cld,SW}}))</td>
</tr>
<tr>
<td>CAM3 SME</td>
<td>-0.13</td>
<td>-0.11</td>
</tr>
<tr>
<td>CAM3 SME</td>
<td>-0.49</td>
<td>-0.07</td>
</tr>
<tr>
<td>CAM3 SME</td>
<td>0.53</td>
<td>0.47</td>
</tr>
<tr>
<td>CAM3 SME</td>
<td>0.25</td>
<td>0.42</td>
</tr>
</tbody>
</table>

**Table 3.** Correlation coefficients between hypothesized emergent constraints and ECS or selected global-average climate feedback parameters \(\lambda\). Variables \(Q\) and \(\alpha\) are water vapor and surface albedo, respectively, and SW and LW are the shortwave and longwave components of climate feedbacks. Bold font indicates statistical significance at the 95% level.
weakly correlated to gains in low-cloud fraction, which is not what one would expect from the hypothesized physical mechanism of mixing-induced boundary layer drying. LTMI₅ is more strongly correlated to $\lambda_{o,SW}$ ($r = 0.62$) than any of the tested indices are correlated to any feedback (Table 3).

Kamae et al. (2016) found that the LTMI emergent constraint is effective in SMEs derived from the MIROC3 and MIROC5 GCMs but only when using the older of two choices for convection schemes. Although that result applies to different sets of SMEs, we find it comparable to our finding that LTMI₅ only has a positive correlation to ECS and $\lambda_{o,SW}$ in a subset of the CAM3 SME (Figs. 7b and 10a). A second similarity is that when LTMI₅ is effective at predicting ECS in their SMEs, it does so by predicting both low-level and midlevel shortwave cloud feedback. We find this result interesting because LTMI₅ also predicts midlevel (but only midlevel) cloud reduction in the CAM3 SME. Caldwell et al. (2018) traced the effectiveness of the LTMI₅ emergent constraint to $\lambda_{o,NET}$ in CMIP3 but to a variety of forcing and feedback terms with only a small contribution from $\lambda_{o,SW}$ in CMIP5. The largest positive feedback contribution for LTMI₅ in CMIP5 is actually the surface albedo feedback. This reinforces our finding that the LTMI₅–ECS correlation in the CAM3 SME is enhanced by a correlation to $\lambda_{o,SW}$ ($r = 0.62$), which is inconsistent with its hypothesized physical mechanism.

An ensemble for testing emergent constraints is only as useful as its models are both credible and diverse. A lack of diversity is a significant limitation in the interpretation of emergent constraints with SMEs. For example, it may be possible that RH₅ is correlated to intraensemble scatter in midlatitude cloud feedback given an ensemble with more diversity in that quantity. Gettelman et al. (2012) found that, in a SME representing a one-step-at-a-time evolution from CAM4 to CAM5, the storm-track feedbacks contribute the most warming (Gettelman et al. 2012) and have very high regression slopes against ECS (Gettelman et al. 2013). The difference in which cloud feedbacks are important to ECS can be explained by the Gettelman et al. (2012) ensemble using two different shallow cumulus schemes: Hack (1994) and Bretherton and Park (2009). Storm-track feedbacks are sensitive to the choice of scheme, so, as the CAM3 SME contains only ensemble members with the Hack shallow cumulus convection scheme, it under-samples diversity in storm-track cloud feedback relative to Gettelman et al. (2012). Similarly, the CAM3.1 low-cloud fraction is diagnosed using, among other factors, an empirical term that increases the low-cloud fraction for increased lower-tropospheric stability (Medeiros et al. 2008). This empirical relationship was not perturbed in generating the CAM3 SME, which may limit the low-cloud fraction variability relative to CMIP models in which low-cloud fraction is prognostic or is not

FIG. 11. Histogram approximation of pmf(ECS) and weighted histogram approximations pmf[ECS | c(obs)].
constrained by the empirical relationship between lower-tropospheric stability and low-cloud fraction.

Part of the motivation for using a calibrated SME to test emergent constraints is that the diversity within the ensemble is mathematically defensible. But, that diversity still arises because of choices in ensemble design, some of them arbitrary. Among the factors that can affect the diversity exhibited by a single-model ensemble are the sampling technique, the parameters perturbed, and the structure of the base model being perturbed. The calibrated CAM3 SME does not represent the final word for uncertainty quantification or the merits of these constraints.

Despite the limitations of SMEs, the interpretability of a calibrated SME is a major advantage over non-calibrated MMEs and SMEs. For example, although a scientist must set bounds on parameter ranges and select an appropriate likelihood function [a challenging problem (Nosedal-Sanchez et al. 2016)], the calibration process determines how broad or narrow a region of parameter space is included in the ensemble, and the density of samples from each part of parameter space is proportional to its likelihood. The CAM3 SME’s structural uniformity may be advantageous for emergent constraint hypothesis testing, as models differ for a limited number of understandable reasons that are tied to known processes (e.g., clouds and convection as in the CAM3 SME) and traceable to a few lines of code. An analogy can be made to testing hypotheses against intermediate complexity models in that one can rule out certain hypotheses or processes that are not included in the model/ensemble. For example, because the RH constrains is correlated to ECS in the CAM3 SME even though the ensemble lacks variability in cloud feedback because of Hadley cell expansion, we conclude that Hadley cell expansion is not a necessary component of the physical mechanism of RH. A similar argument can be made for using CAM3.1 to generate a SME despite the fact that there are more recent versions of the CAM model. Older releases of climate models tend to be cheaper to run, which is crucial to generating a calibrated ensemble using a sampling technique like VFSA. There is no clear reason to exclude older models from multimodel ensembles (Rauser et al. 2015), and, similarly, there is no reason not to use them for SMEs, so long as one is aware of their limitations.

Neither MMEs nor SMEs represent all of the uncertainties in climate model base state and prediction, but combining the two types of ensembles maximizes both the sample size and the amount of diversity. In lieu of a technique of ensemble construction that contains structural and parametric uncertainty, combining separate MMEs and SMEs to challenge emergent constraints is a pragmatic solution.

As computing power and developments in ensemble calibration develop, the posterior density of SMEs, or collections of SMEs and MMEs, could potentially gain more acceptance as actual measures of uncertainty in climate prediction. Within that framework, the potential use for emergent constraints grows—should they be found robust for reasons we understand, they could help guide the interpretation of scatter in model projections from qualitative to quantitative. Our results suggest that the tested emergent constraints are not yet reliable and well understood enough to be used for that purpose.

Acknowledgments. We thank Dr. Steven Sherwood for making his lower-tropospheric mixing code public and for his guidance in computing the LTMI constraint. We acknowledge the World Climate Research Programme’s Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups for producing and making available their model output. For CMIP, the U.S. Department of Energy’s Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. We thank Dr. Pedro DeNeizio for his assistance in processing CMIP data and Dr. Karen Shell for publishing her radiative kernels. This work was supported by the U.S. Department of Energy Office of Science, Biological and Environmental Research Regional and Global Climate Modeling Program under Award Number DE-SC0006985. The calibration of the CAM3.1 SME was supported by allocation award ATM100049 from the Extreme Science and Engineering Discovery Environment (XSEDE) program, which is supported by the National Science Foundation. We thank three anonymous reviewers for their thoughtful and helpful advice on how to improve this paper.

APPENDIX A

Calculating Emergent Constraints and Cloud Feedbacks

a. Calculating emergent constraints

1) RH CONSTRAINT

The domains used by these authors to calculate the RH constraint are:

- Latitude: \(\text{RH}_D\) (from \(-21^\circ\) to \(-9.5^\circ\)), \(\text{RH}_M\) (from \(-1^\circ\) to \(10^\circ\))
- Pressure: \(\text{RH}_D\) (from 480 to 310 hPa), \(\text{RH}_M\) (from 800 to 600 hPa)
2) LTMI CONSTRAINT

(i) LTMI_S (S) is a calculation of the difference between the annual average of monthly mean area-weighted RH and T vertical gradients over tropical oceans where the mean annual ascent at 500 hPa is in the top quartile. The RH and T gradients are normalized by the difference between their dry and saturated values

$$S = \frac{\Delta RH_{700-850}}{100\%} - \frac{\Delta T_{700-850}}{9 \text{ K}}.$$  \hspace{1cm} (A1)

Annual-mean climate data are used to calculate S because it is sufficient to replicate the results of Sherwood et al. (2014) for the CMIP models and observations tested (Fig. A1). However, Sherwood et al. (2014) calculate an S value for each month using monthly means and then calculate its annual average.

(ii) LTMI_D (D) is an area-weighted calculation of the annual mean of monthly means of the ratio between shallow and deep ascent. Divergence in the lower troposphere D is defined as $\omega_2 - \omega_1$, where low-level ascent is

$$\omega_1 = \text{avg}(\omega_{850, \omega_{700}}),$$  \hspace{1cm} (A2)

and midlevel ascent is

$$\omega_2 = \text{avg}(\omega_{600, \omega_{500, \omega_{400}}}),$$  \hspace{1cm} (A3)

and the calculation is made at each grid cell over oceans from $-30^\circ$ to $30^\circ$ latitude and $-160^\circ$ to $45^\circ$ longitude.

LTMI_D is

$$D = \frac{(\Delta H(\Delta)H(-\omega_2))}{(-\omega_2 H(-\omega_2))},$$  \hspace{1cm} (A4)

where the Heaviside function $H$ requires both divergence and rising air at midlevels. We also require rising air at low levels, which is likely if not guaranteed by having rising and diverging air at midlevels.

Eq. (A4) appears consistent with the code made publicly available by S. Sherwood (https://github.com/scs46/LTMI-mixing), which requires ascent at low and midlevels. The code differs slightly from the equation for D in Sherwood et al. (2014), which would admit into the domain those grid cells in which air is sinking and diverging at midlevels:

$$D = \frac{(\Delta H(\Delta)H(-\omega_2))}{(-\omega_2 H(-\omega_2))}.$$  \hspace{1cm} (A5)

See Fig. A1 for LTMI_D results using Eqs. (A4) and (A5).

<table>
<thead>
<tr>
<th>Table A1. Model details for published and replicated calculations of emergent constraint metrics on the CMIP ensemble.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RH constraint</strong></td>
</tr>
<tr>
<td><strong>Fasullo and Trenberth (2012)</strong></td>
</tr>
<tr>
<td>CMIP3 config</td>
</tr>
<tr>
<td>CMIP3 years</td>
</tr>
<tr>
<td>CMIP3 n</td>
</tr>
<tr>
<td>CMIP5 config</td>
</tr>
<tr>
<td>CMIP5 years</td>
</tr>
<tr>
<td>CMIP5 n</td>
</tr>
</tbody>
</table>
3) Replicating the Published Emergent Constraint Results in CMIP

Each constraint was computed across a subset of models from CMIP3 and CMIP5 and correlations with ECS were compared to their authors’ published results (Table 2). A complete validation of the metric calculation, and of the authors’ published results, was not possible because of differences between CMIP model configurations used in published results and the configurations tested in this study (Table A1). However, for both the RH and LTMI constraints, the metric calculations are, to the best of our knowledge, calculated similarly or exactly the same way as by Fasullo and Trenberth (2012) and Sherwood et al. (2014).

b. Cloud feedback calculation

Cloud feedbacks in the SME are calculated using the Shell et al. (2008) radiative kernel. The Planck longwave feedback (Pl) in Fig. 2 is the sum of the surface temperature, atmospheric temperature, and lapse rate feedbacks. The feedback analysis does not separate rapid tropospheric adjustments to CO2 from globally averaged surface temperature–modulated changes.

APPENDIX B

Single-Model Ensemble Perturbed Parameters

The CAM3 SME was constructed by perturbing parameters in Table B1 using MVSFA to select parameter values within the specified ranges.

<table>
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<tr>
<th>Name</th>
<th>Description</th>
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<th>Default</th>
<th>Low</th>
<th>High</th>
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<td>alfa</td>
<td>Initial cloud downdraft mass flux</td>
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<td>$5 \times 10^{-2}$</td>
<td>$6 \times 10^{-1}$</td>
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<tr>
<td>c0</td>
<td>Precipitation efficiency</td>
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<td>Cold, oceanic cloud particles</td>
<td>Particles per cm$^3$</td>
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<td>50</td>
<td>300</td>
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<td>Sea ice cloud particles</td>
<td>Particles per cm$^3$</td>
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<td>50</td>
<td>300</td>
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<td>capnw</td>
<td>Warm continental cloud particles</td>
<td>Particles per cm$^3$</td>
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<td>icritw</td>
<td>Threshold for autoconversion of warm ice</td>
<td>—</td>
<td>$8 \times 10^{-4}$</td>
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<td>$10 \times 10^{-4}$</td>
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<td>ke</td>
<td>Environmental air entrainment rate</td>
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<td>$1 \times 10^{-5}$</td>
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<td>Critical relative humidity high clouds</td>
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<td>rhminl</td>
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<td>rligice</td>
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<td>18</td>
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<td>Cloud droplet size, liquid and continental</td>
<td>µm</td>
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<td>10</td>
<td></td>
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<tr>
<td>rligoce</td>
<td>Cloud droplet size, liquid and oceanic</td>
<td>µm</td>
<td>7</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>tau</td>
<td>Consumption rate of CAPE</td>
<td>s</td>
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<td>$1.8 \times 10^{3}$</td>
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<td>vice_small</td>
<td>Ice fall velocity</td>
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<td>0.5</td>
<td>100</td>
</tr>
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</table>

REFERENCES

——, M. K. Sen, and P. Stoffa, 2004: An efficient stochastic Bayesian approach to optimal parameter and uncertainty


Knutti, R., 2010: The end of model democracy?


