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Examining Parameter Uncertainty Through Large Cloud-Based Ensembles

Rob von Behren jrvb@google.com
Aaron Sonabend asonabend@google.com

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CESM and Google Climate & Energy

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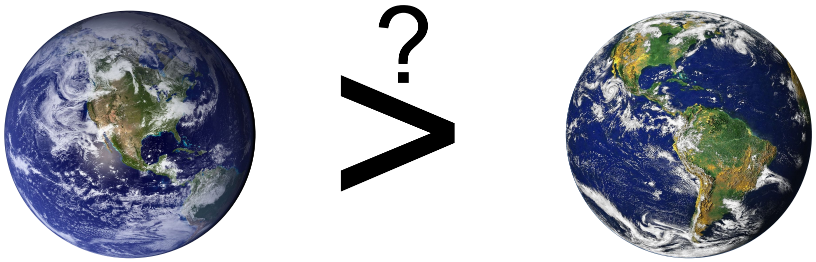
Aspirational goals: answer questions like

- What global heating mitigation work should Google do?
- How much impact will project A have vs project B?
- (Probably both unknowable — but what *can* we learn?)



Challenges

- Compute environment different than typical clusters for CESM
- Lots of uncertainty in CESM outputs

CESM on Google Cloud

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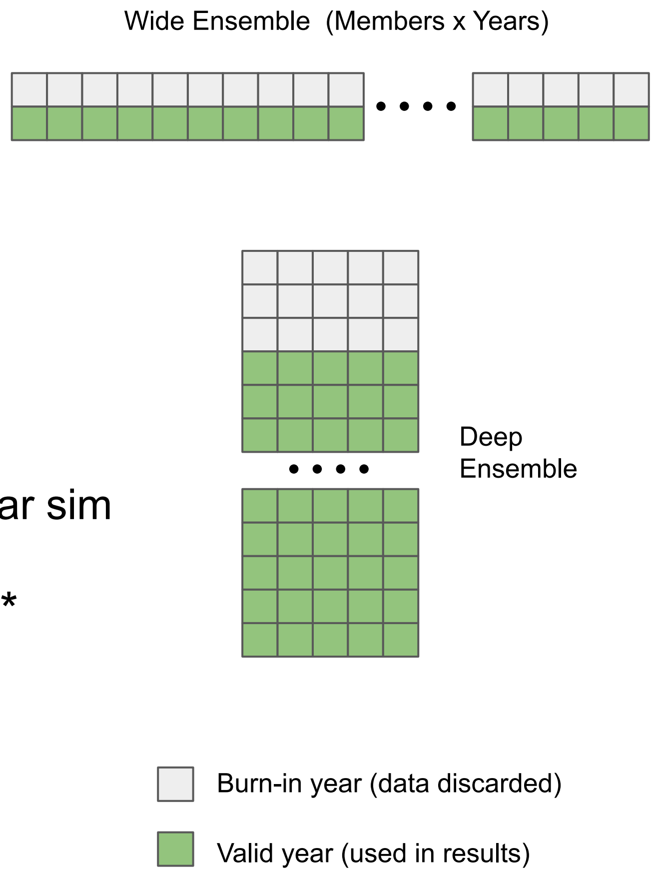
Diffs vs dedicated cluster

- Best price w/ preemptible VMs
  - Fewer network guarantees
  - Failed VMs stall MPI
- ⇒ Focus on single-machine simulations

Ensemble shape: wide vs deep

- Why?
  - On one VM, 1° fixed SST: ~50 days for 100-year sim
  - ….but can easily scale to 1000s of VMs
- Early results: get same stats if we are careful**
- ***Good platform for exploring uncertainties!***



Contrail Impact

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What is the climate impact from contrails?

How big are the error bars on contrail ERF?

Which mitigation strategies are most effective?

Contrail Impact

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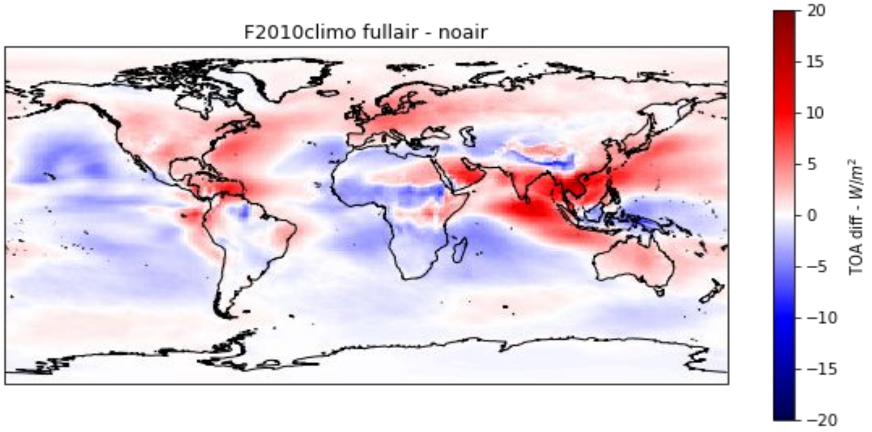
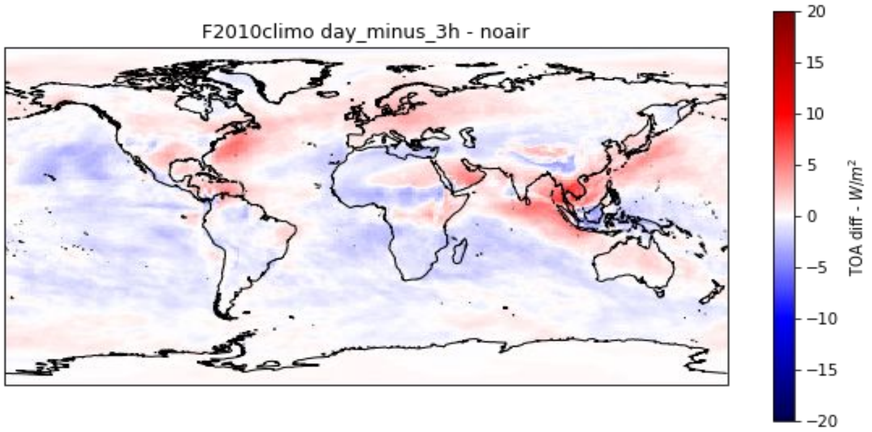
Sim setup
- CAM 6.3; Fixed SST
- Scenarios
  - No aviation
  - Full aviation (FA)
  - Mitigation Strategy (MS)

Measure
- Radiative imbalance at top of atmosphere (TOA)

Explorations last ~4 months
- 83 ensembles
- >10k sim years





Hat tip to Andrew Gettelman and Jack Chen

Contrail ERF Error Bars

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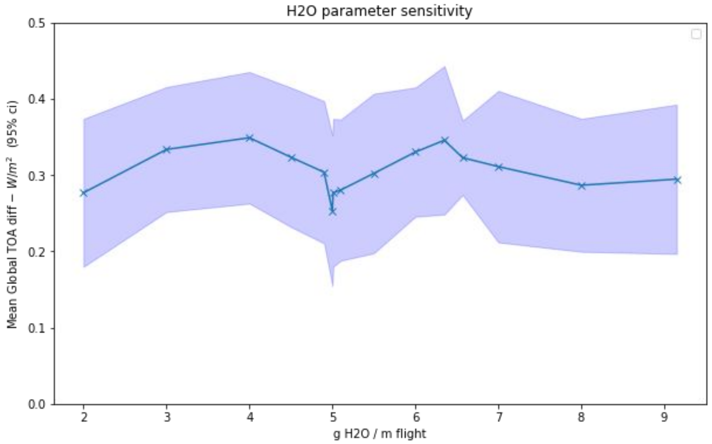
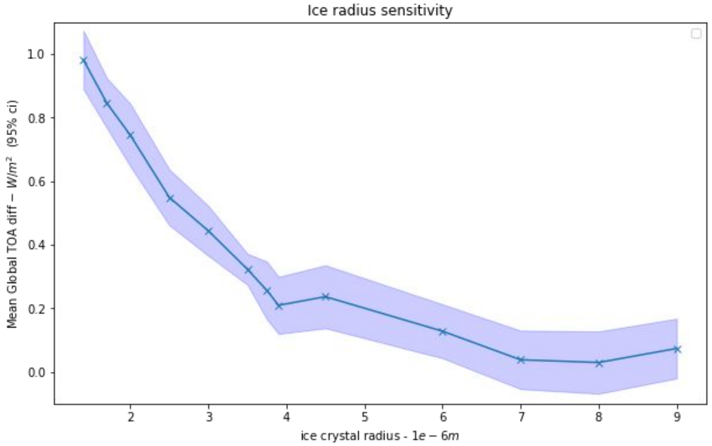
Variation among ensemble members (aleatoric uncertainty)

- Large SEM vanquished via sqrt(N)
- Easy to run large ensembles

Are the contrail module parameters correct? (epistemic uncertainty)

- Some choices have a big impact on computed TOA!





NOTE: These graphs are from a set of debugging runs, so the specific TOA values are not relevant.

Contrail Mitigation Effectiveness

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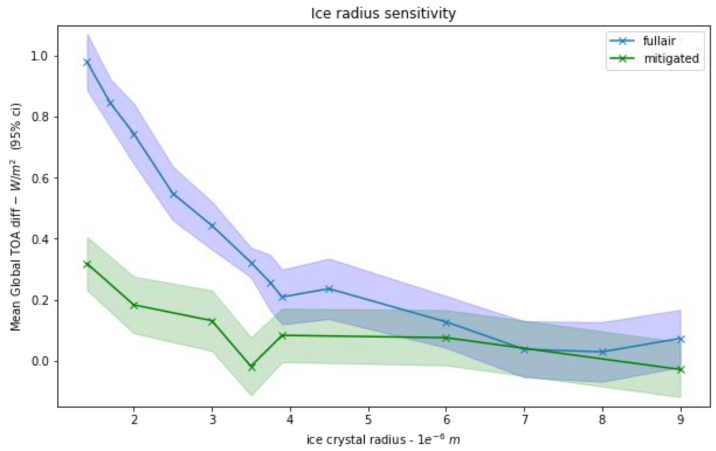
Problem: Baseline warming depends on params

Heavyweight Solution: Many ensembles

- Pick several sets of params
- Run FA and MS ensembles for each
- Compare %mitigated across param vals



More Problems

- Compute costs
- How to compare?

Better Solution: MC Sampling + ANOVA

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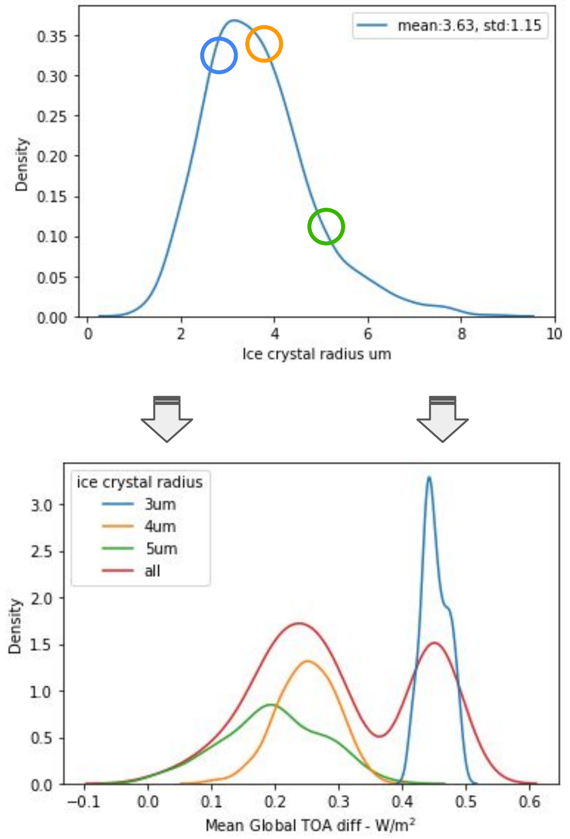
Intuition

- Pick a reasonable distribution for each param
- Sample params & run sims to get TOA
- Use analysis of variance
  - Extract the experimental effect
  - …in spite of param diffs



Evaluating mitigation

- Use effect ratio to compare across TOA baselines
- Bootstrap sampling to analyze variance
- 95% CI of ratio < 1.0 ⇒ mitigation works!

Regression-based Variance Analysis

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Generate Monte-Carlo dataset[1]: $\{(TOA_i, FA_i, r_i)\}_{i=1}^{n}$

1) Sample ice radius $r_i \sim f_r$
2) Run CESM under baseline (FA_i=0) or full air traffic (FA_i=1, r_i) scenarios *to get* TOA_i

Estimate full aviation effect β_1, with any $g()$ where $E[g(r)] = 0$

$$E[TOA|FA, r] = \beta_0 + FA\{\beta_1 + \beta_2 g(r)\}$$

Note:

- Baseline TOA is β_0 since $E[TOA|FA = 0] = \beta_0$
- Fullair effect is β_1 since $E_r\{E[TOA|FA = 1, r]\} = \beta_0 + \beta_1$

1. For simplicity, this example uses a single ice radius parameter, but the method applies for vector-valued *r*

Regression-based Variance Analysis

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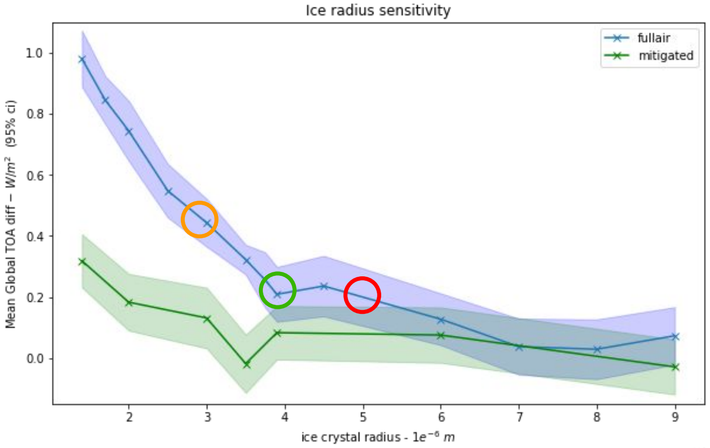
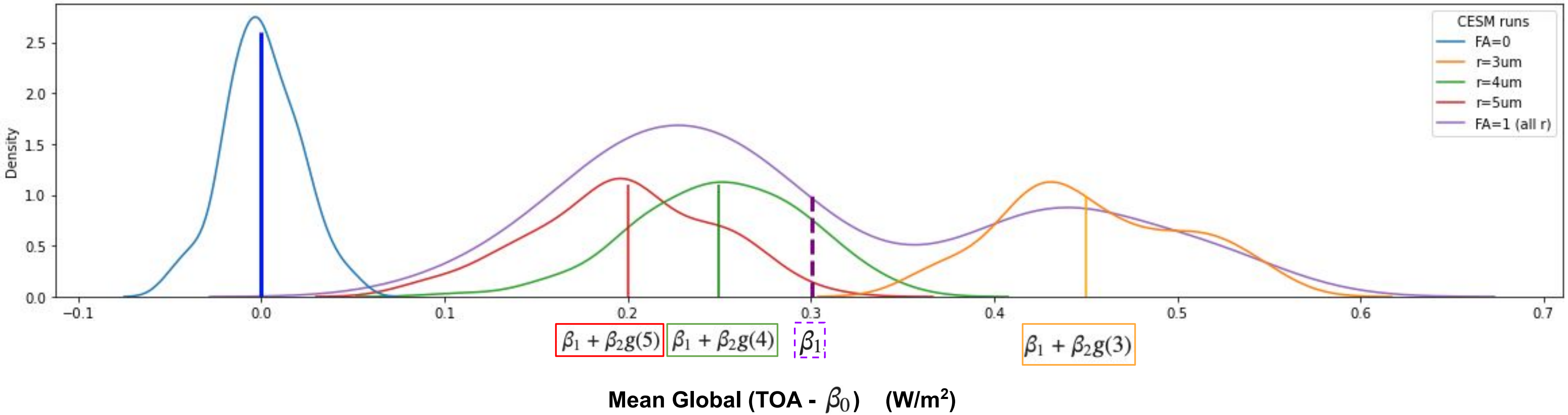
$$E[TOA|FA, r] = \beta_0 + FA\{\beta_1 + \beta_2 g(r)\}$$

Combine simulations with different r_i to estimate β_1.





Mitigation Strategies

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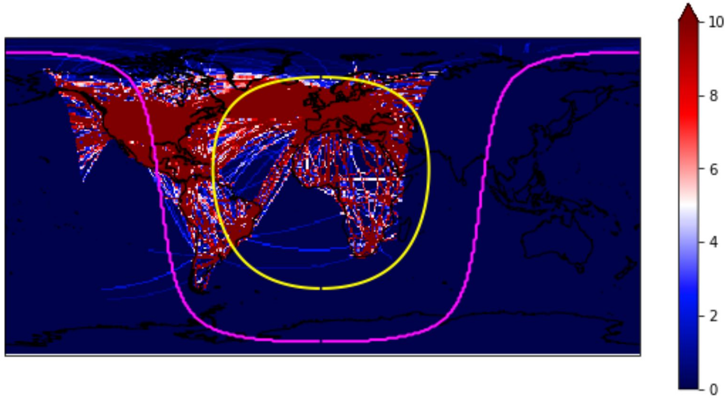
What about turning off air traffic only at night?



Similar MC approach can be used to generate dataset: $\{(TOA_i, MS_i, r_i)\}_{i=1}^{m}$

Estimate effect of mitigation strategy with:

$$E[TOA|MS, r] = \alpha_0 + MS\{\alpha_1 + \alpha_2 h(r)\},\ E[h(r)] = 0$$

Air Traffic Effect Ratio

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How do different mitigation strategies compare?

Mitigation strategy
vs.
full air traffic

$$\frac{E_r\{E[TOA|MS=1,r]-E[TOA|MS=0]\}}{E_r\{E[TOA|FA=1,r]-E[TOA|FA=0]\}}=\frac{\alpha_1}{\beta_1}$$

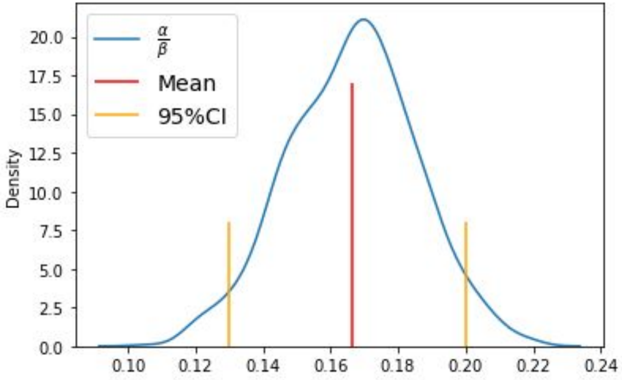
How do we account for parameter uncertainties?

Bootstrap for handling epistemic uncertainty:

1. Sample CESM runs from $\begin{cases}\{(TOA_i,FA_i,r_i)\}_{i=1}^{n}\\ \{(TOA_j,MS_j,r_j)\}_{j=1}^{m}\end{cases}$

2. Estimate $\widehat{\alpha}_1^{(b)},\ \widehat{\beta}_1^{(b)}, b=1,\ldots,B$

3. Compute ratio $\left\{\frac{\widehat{\alpha}_1^{(b)}}{\widehat{\beta}_1^{(b)}}\right\}_{b=1}^{B}$, and quantiles for uncertainty



$\frac{\widehat{\alpha}_1^{(b)}}{\widehat{\beta}_1^{(b)}}$

Certainty from Uncertainty?

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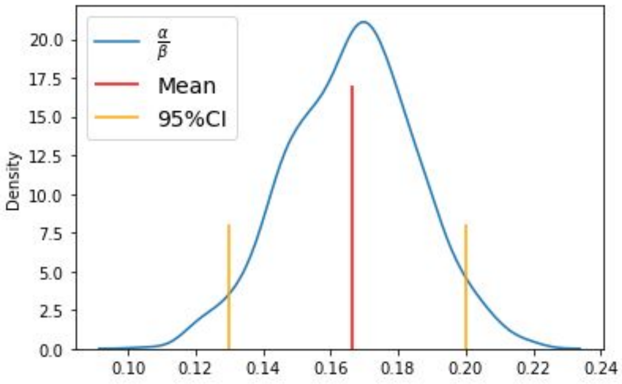
Compute infrastructure

- Wide parallelization allows rapid exploration
- Short sims good enough (for some cases)

Variance analysis

- Allows conclusions about mitigation effectiveness
  - In spite of aleatoric and epistemic uncertainty
- Reduces compute requirements
  - eg O(500) ensembles instead of O(5000)



$$\frac{\hat{\alpha}_1^{(b)}}{\hat{\beta}_1^{(b)}}$$