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Assessing Which Climate Model Biases Affect Predictions

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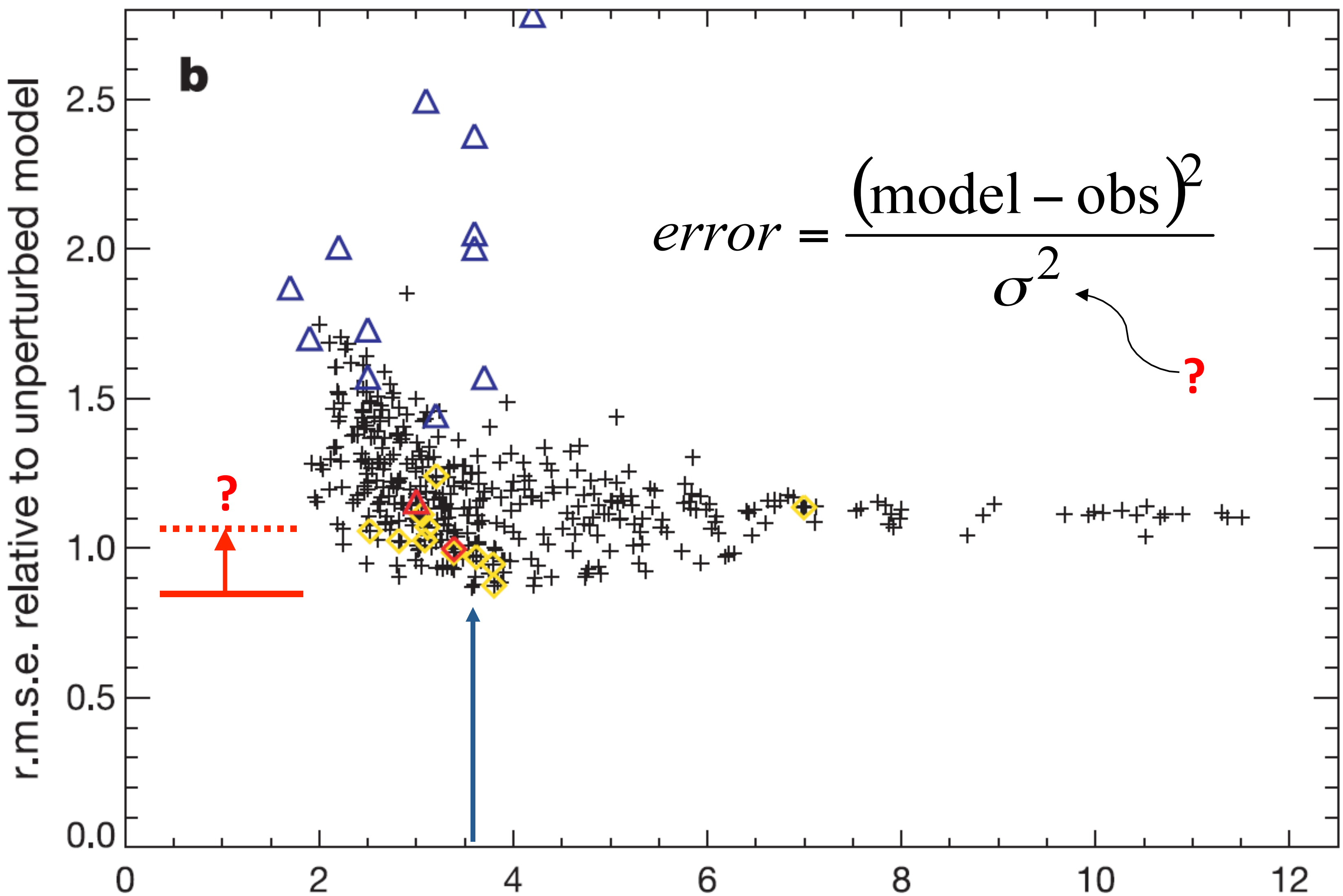
The problem:

- It is not clear what quantifying uncertainties mean when large systematic differences exist between a model and observations (i.e. biases).
- If biases do not affect feedbacks, they would not add to spread in predictions. Biases are removed by looking only at predicted changes.
- If biases do affect predictions, the information about biases should be taken into account when measuring model likelihood.

Outline

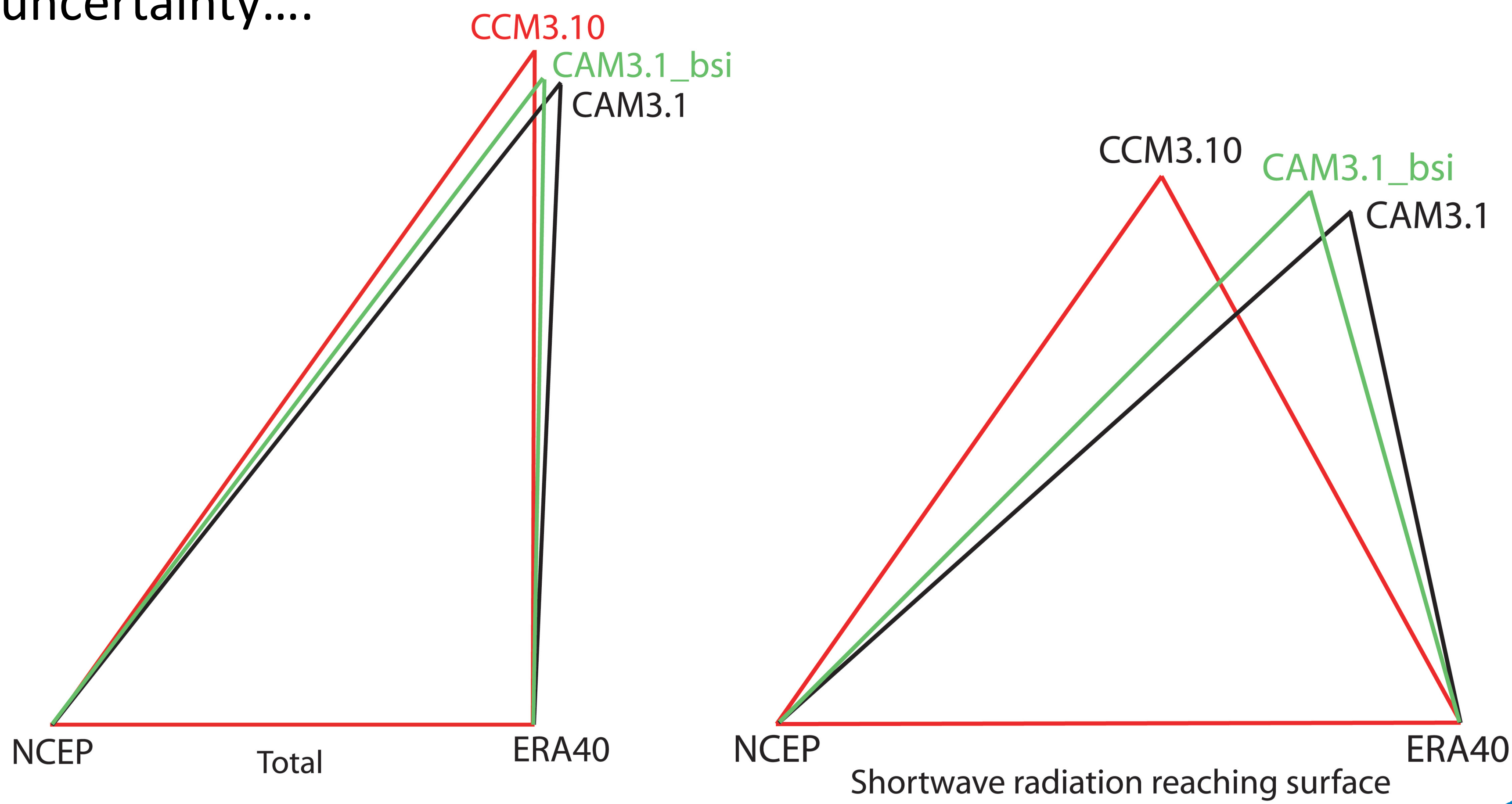
1. What biases look like.
2. A non-scientific, but statistically informative way to account for bias in assessments of climate model uncertainty.
3. A calculation of how model biases affect CAM3 projections of global warming.

What biases look like

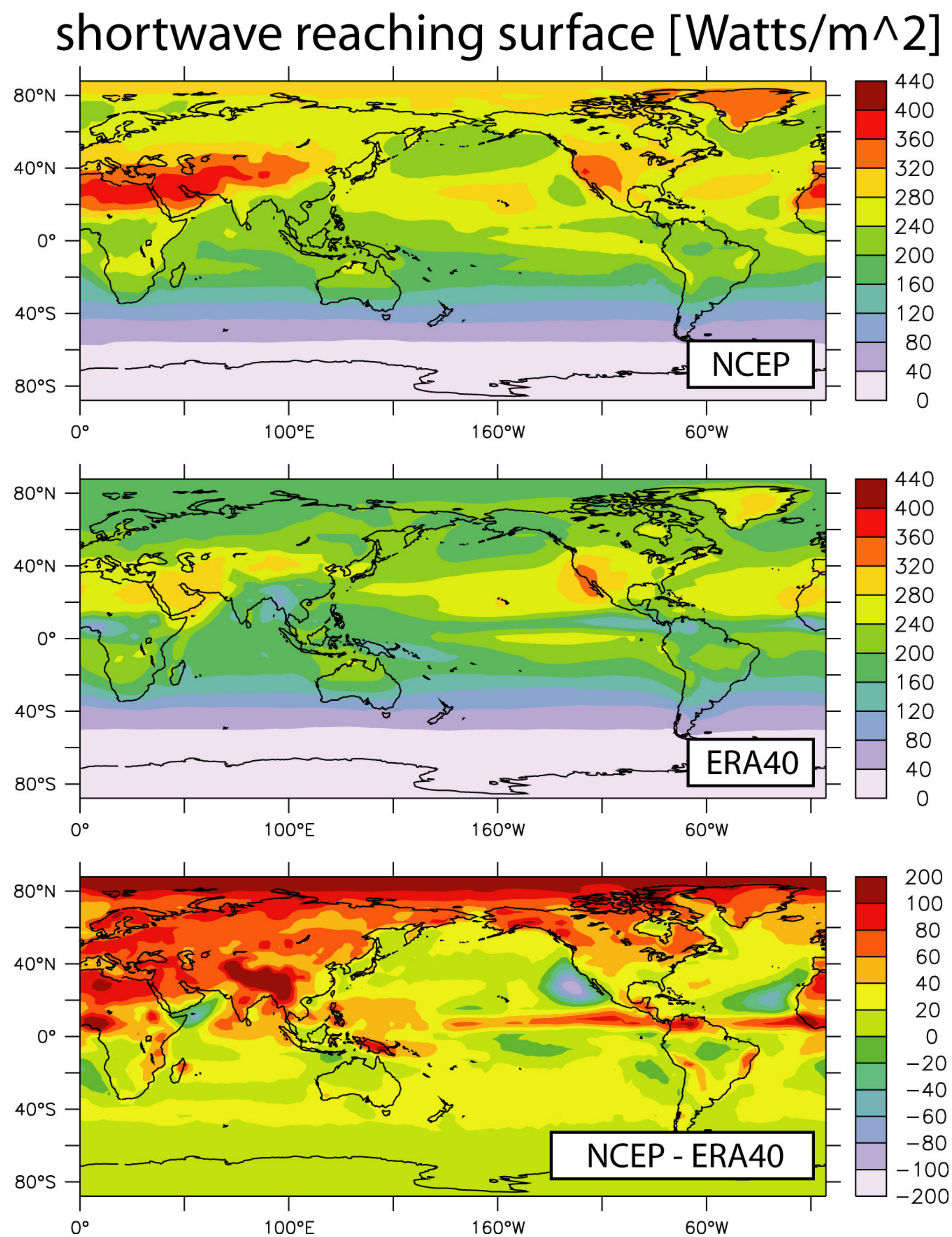


(Stainforth et al., Nature 2005)

Reanalysis projects are used as observational constraints on models. However spread among different products as large as modeling uncertainty….



June – July NCEP discrepancies with ERA40



A non-scientific, but statistically informative way to account for bias in assessments of climate model uncertainty.

Bayesian formulation of climate model parameter uncertainty

$$PPD(\mathbf{m} \mid \mathbf{d}_{obs}, g(\mathbf{m})) \propto \exp\left[-\frac{1}{2}\left(g(\mathbf{m}) - \mathbf{d}_{obs}\right)^T \mathbf{C}_{noise}^{-1}\left(g(\mathbf{m}) - \mathbf{d}_{obs}\right)\right] \cdot prior(\mathbf{m})$$

Likelihood test of model acceptability

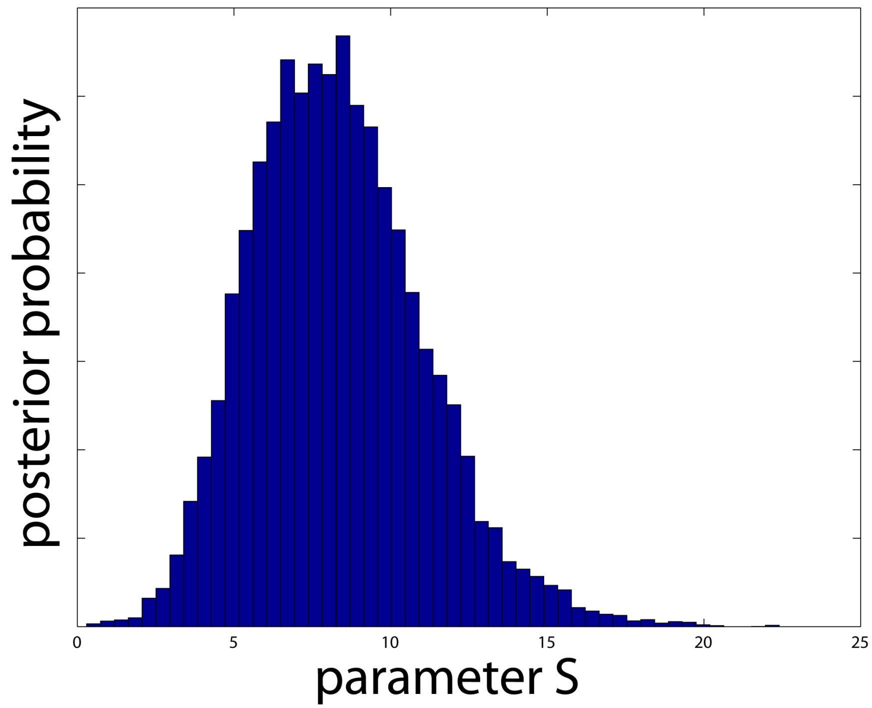
A statistical (not scientific) approach to accounting for effects of model bias:

$$E(m) = \frac{\left(m - 10 + \sqrt{0.1}\eta\right)^2}{2\sigma^2} \qquad \mathrm{var}(\eta) = 1 \qquad \sigma^2 = 1$$

$$prob(m,S) \propto \exp\left(-S \cdot E(m)\right) \cdot prob(S)$$

1. Treat S like an unknown parameter m, but with some idea of what it should be through prob(S).

2. Prob(S) is taken to be a gamma distribution with a mean and variance estimated from the effect of noise on E(m) (note that the maximum likelihood for S is not 0.)



Step 1: Choose m according to the logic of MVFSA.

Step 2: Select S from a Gamma distribution of parameters $k/2+\alpha$ and $E(\mathbf{m}) + \beta$

$$p(S \mid \mathbf{m}, \mathbf{d}_{\mathbf{obs}}) \propto S^{k/2+\alpha-1} \exp(-S \cdot [E(\mathbf{m}) + \beta])$$

where α and β are chosen to reflect information about the effect of natural variability on the cost function $E(\mathbf{m})$.

Step 3: Use MVFSA logic for selecting or rejecting parameters m, except use acceptance probability depends on S:

$$prob = \exp\left(\frac{-S \cdot \Delta E(\mathbf{m})}{T}\right)$$

A calculation of how model biases affect CAM3 projections of global warming.

Correlation between model bias and scatter in level of warming when CO2 is doubled.

$$Corr\left(\phi,\theta\right)=\frac{1}{N_m}\sum_{i=1}^{N_m}\frac{\left(g_i^{1\mathrm{x}}\left(\phi,\theta\right)-obs^{1\mathrm{x}}\left(\phi,\theta\right)\right)\cdot\left(R\left(g_i^{2\mathrm{x}}\right)-R\left(obs^{2\mathrm{x}}\right)\right)}{\sigma^{1\mathrm{x}}\sigma^{2\mathrm{x}}}$$

If biases do not affect feedbacks, correlation should be 0.

Estimate of CAM3.1 uncertainties

- Estimate uncertainty in specifying 15 parameters important to clouds, convection, and radiation in CAM3.1
- Use an objective function based on a common set of model evaluation metrics.
- Uncertainties in metrics estimated from effects of weather on climatologies.
- 3336 4-year long integrations made, using MVFSA to select models from the posterior distribution.

Experiment design

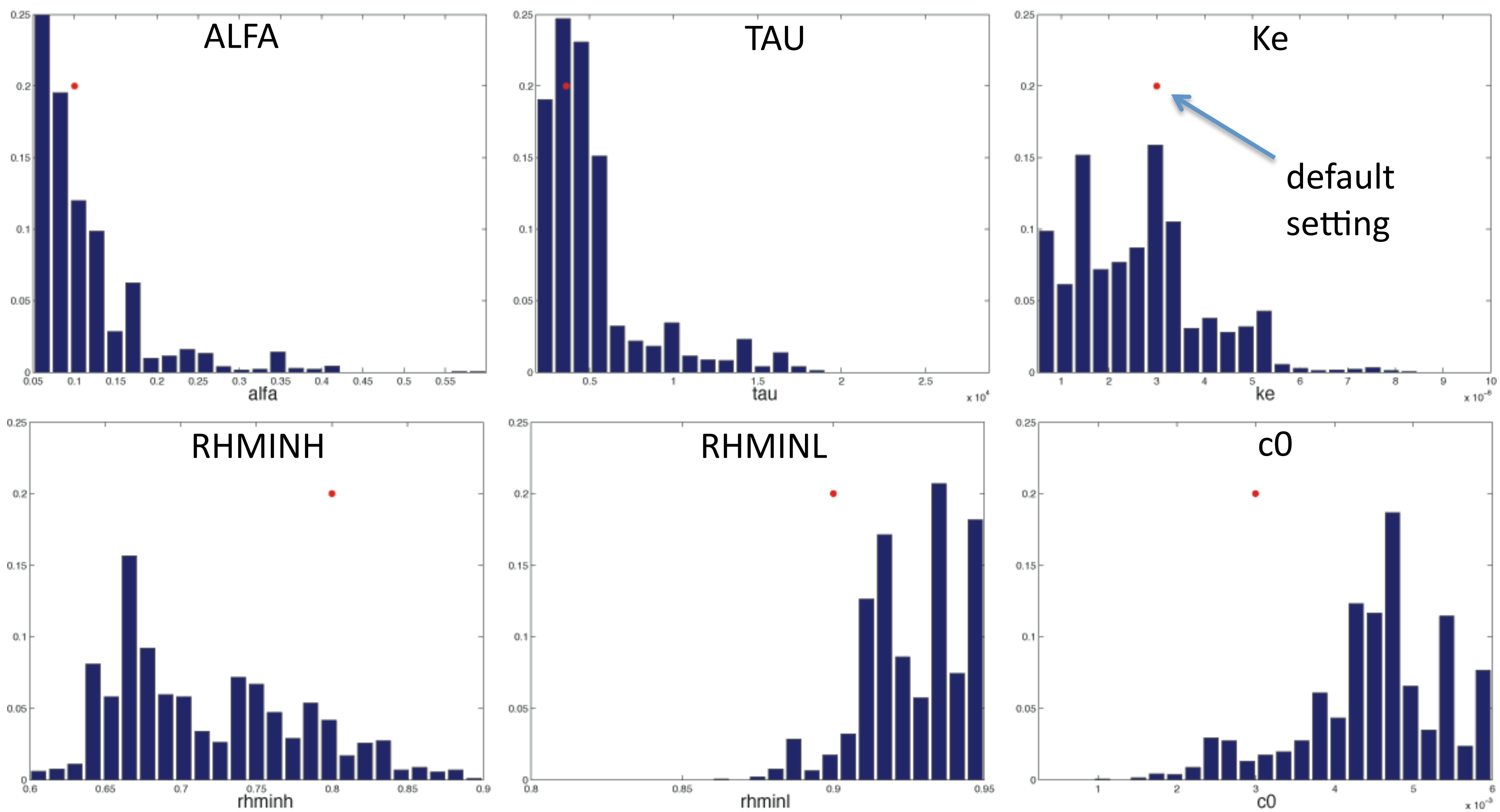
- Fixed sea surface temperatures and sea ice
- Look for parameters that bring model into agreement with observations.
- Climate model developers typically do a 2-year model integration to test model parameters. We do a 4 year integration to beat down noise.

Top “10” metrics + …

(all 30S to 30N, DJF, MAM, JJA, SON, unless otherwise noted)

1. Land 2-m air temperature (Willmott)
2. Vertically averaged (mass weighted) air temperature (ERA40)
3. Latent heat fluxes over ocean (WHOI)
4. Zonal winds at 300 mb (ERA40)
5. Longwave cloud forcing (CERES2)
6. Shortwave cloud forcing (CERES2)
7. Precipitation over land (GPCP)
8. Precipitation over ocean (GPCP)
9. Sea level pressure (ERA40)
10. Vertically averaged (mass weighted) relative humidity (ERA40)
11. Global mean annual mean radiative balance (= 0.5 W/m^2)
12. Pacific ocean wind stress along equator

Shown are marginals of the posterior distribution of 6 of the 15 parameter settings represent uncertainty from natural variability and model biases.



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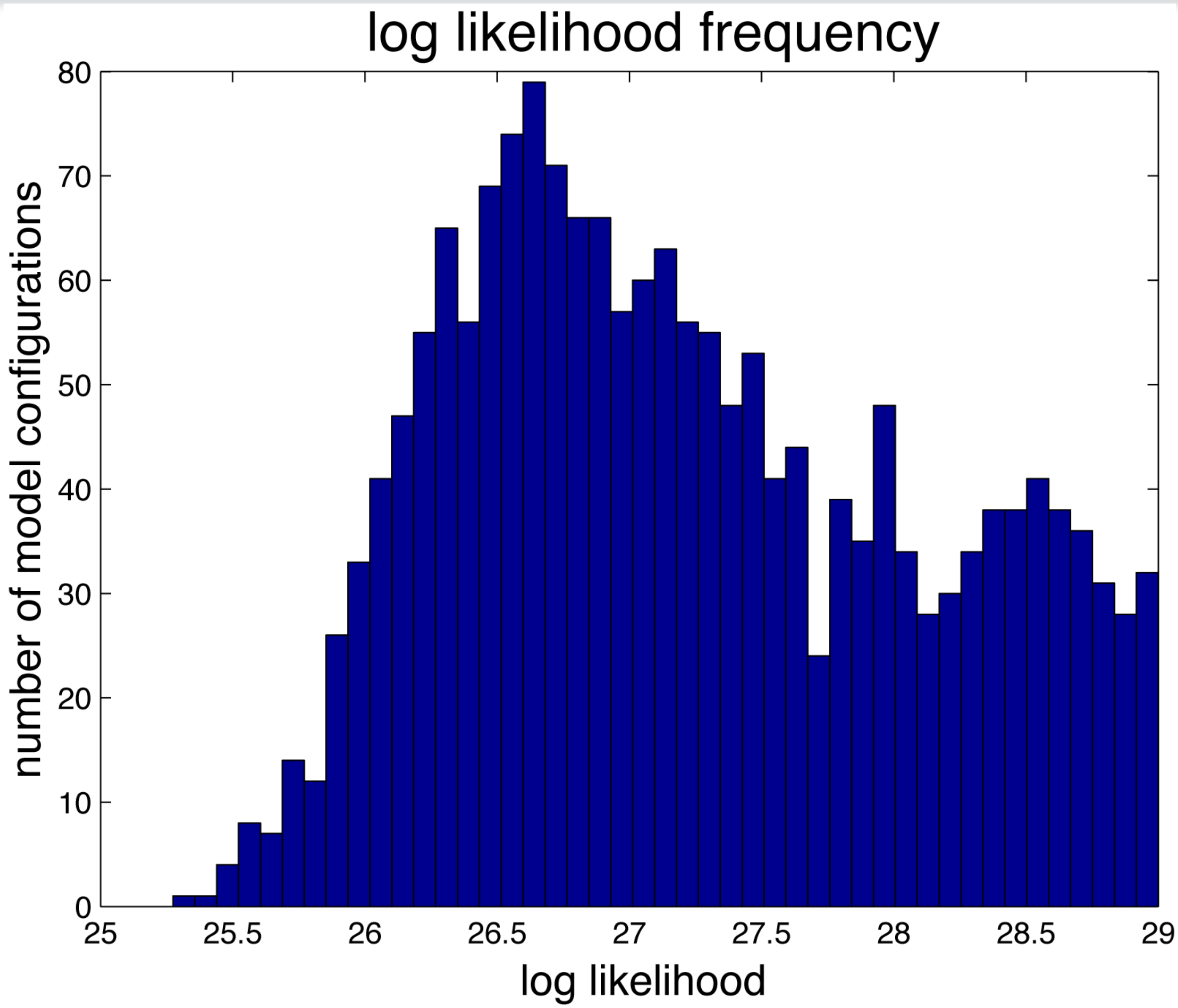
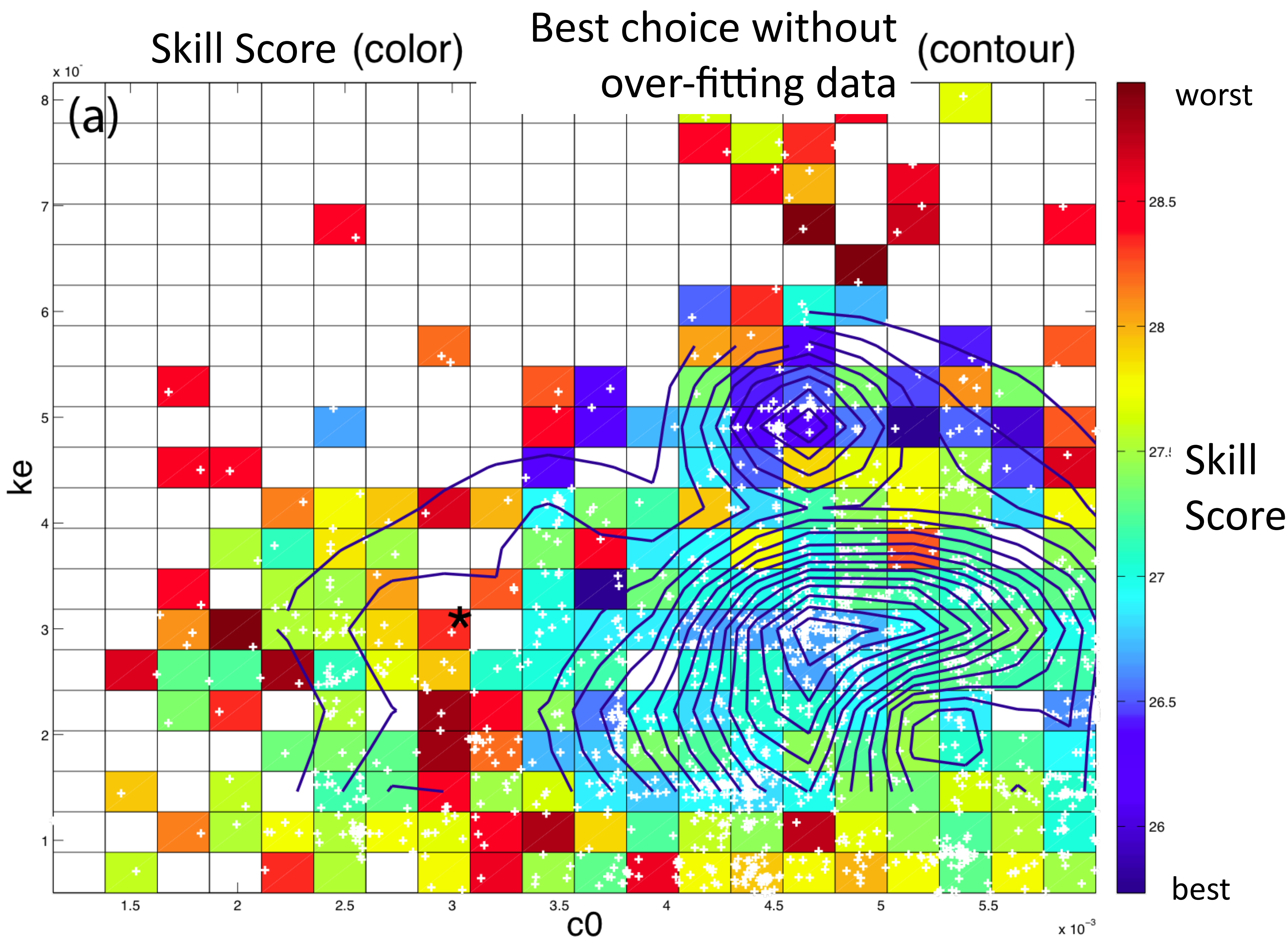
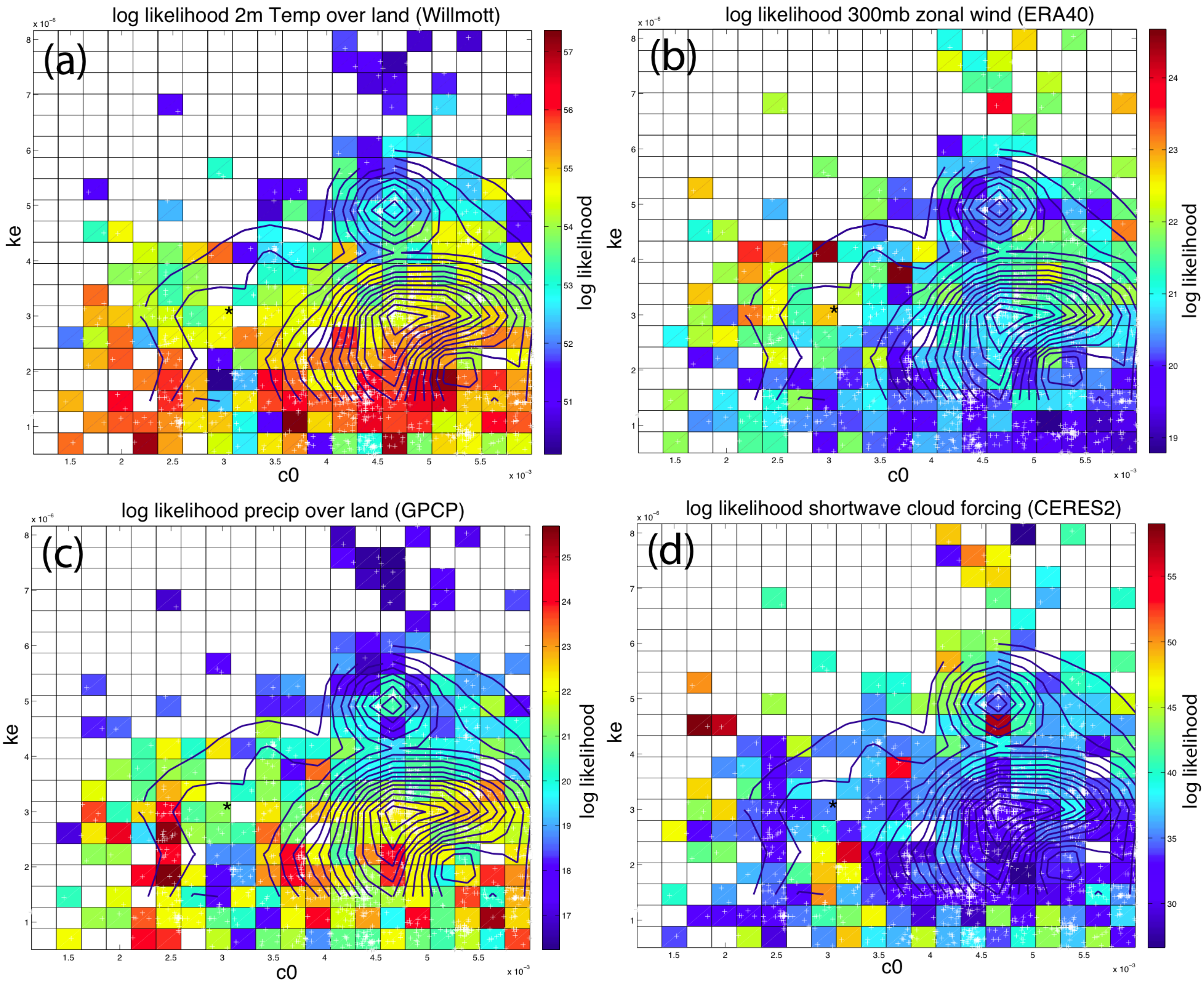


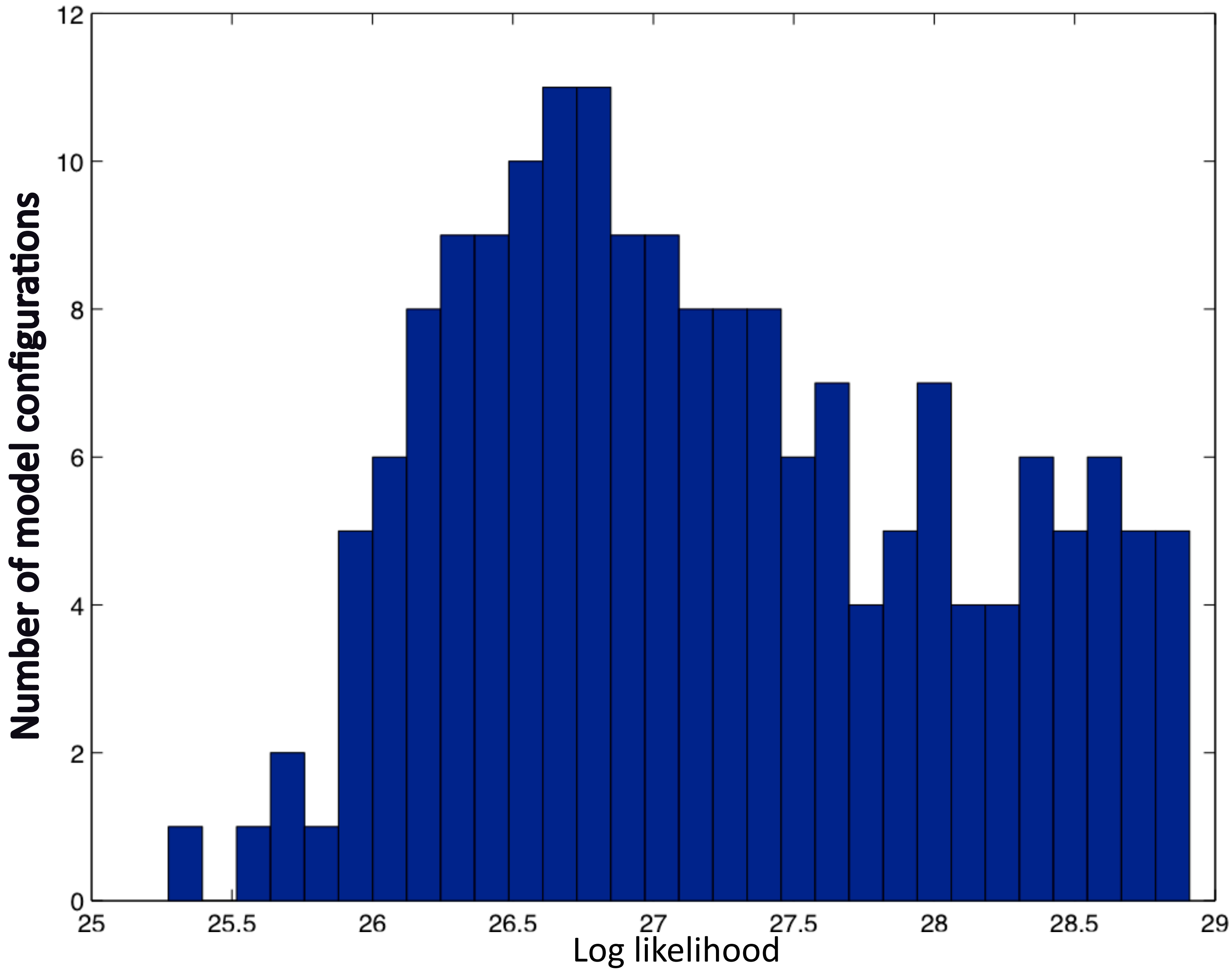
Result summary of how 2 model parameters affect model skill





log likelihood 2m Temp over land (Willmott)
(a)
log likelihood 300mb zonal wind (ERA40)
(b)
log likelihood precip over land (GPCP)
(c)
log likelihood shortwave cloud forcing (CERES2)
(d)
ke
c0
log likelihood
x 10^-6
x 10^-3

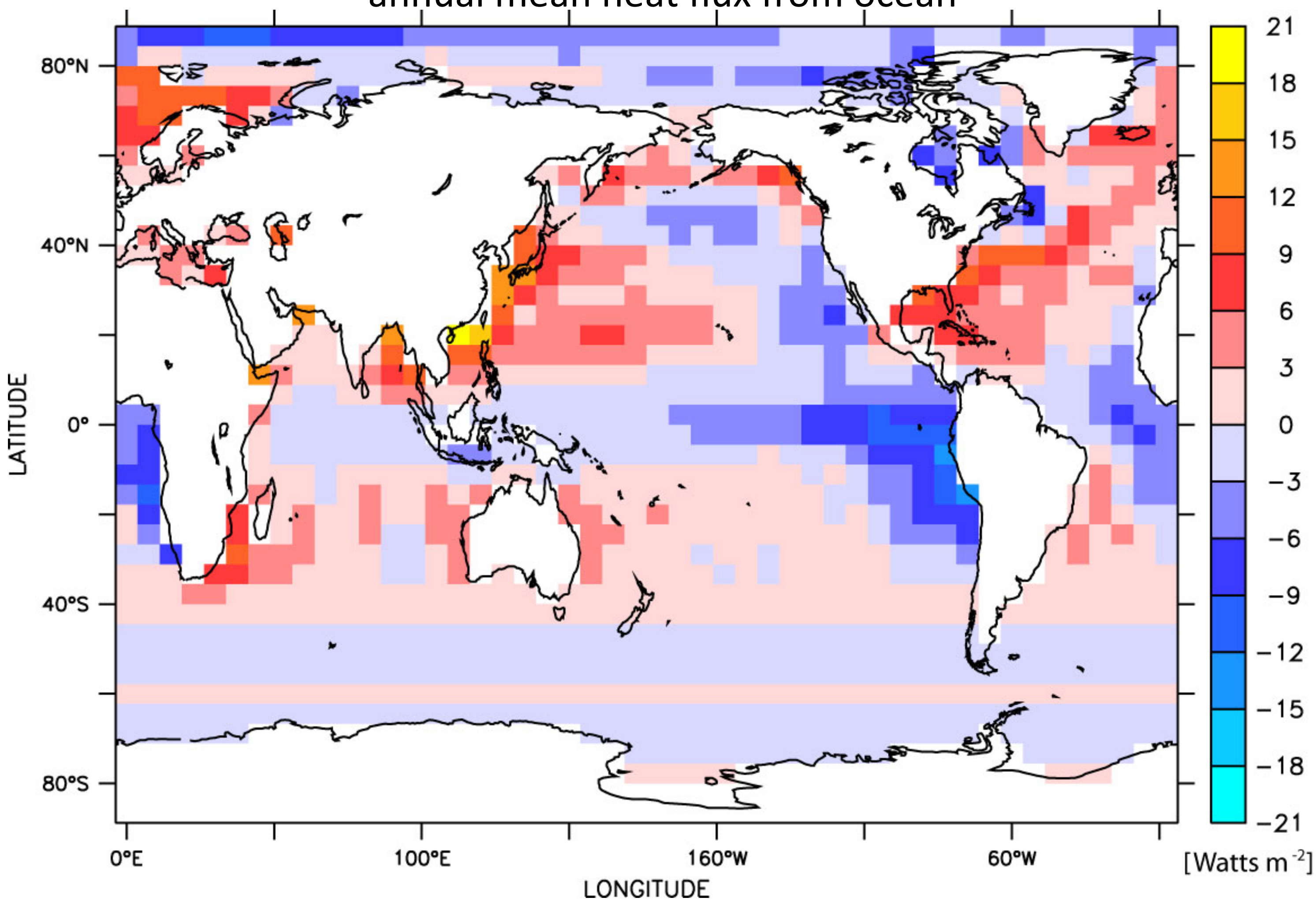
180 member ensemble that represents the posterior distribution



Global warming experiments

- Couple cam3 to a “slab” ocean
- Calculate ocean effects of ocean heat transports, apply as heat flux to base of slab ocean. Allows model to reproduced observed SSTs.
- We chose to keep this heat flux field the same in all global warming experiments.

annual mean heat flux from ocean

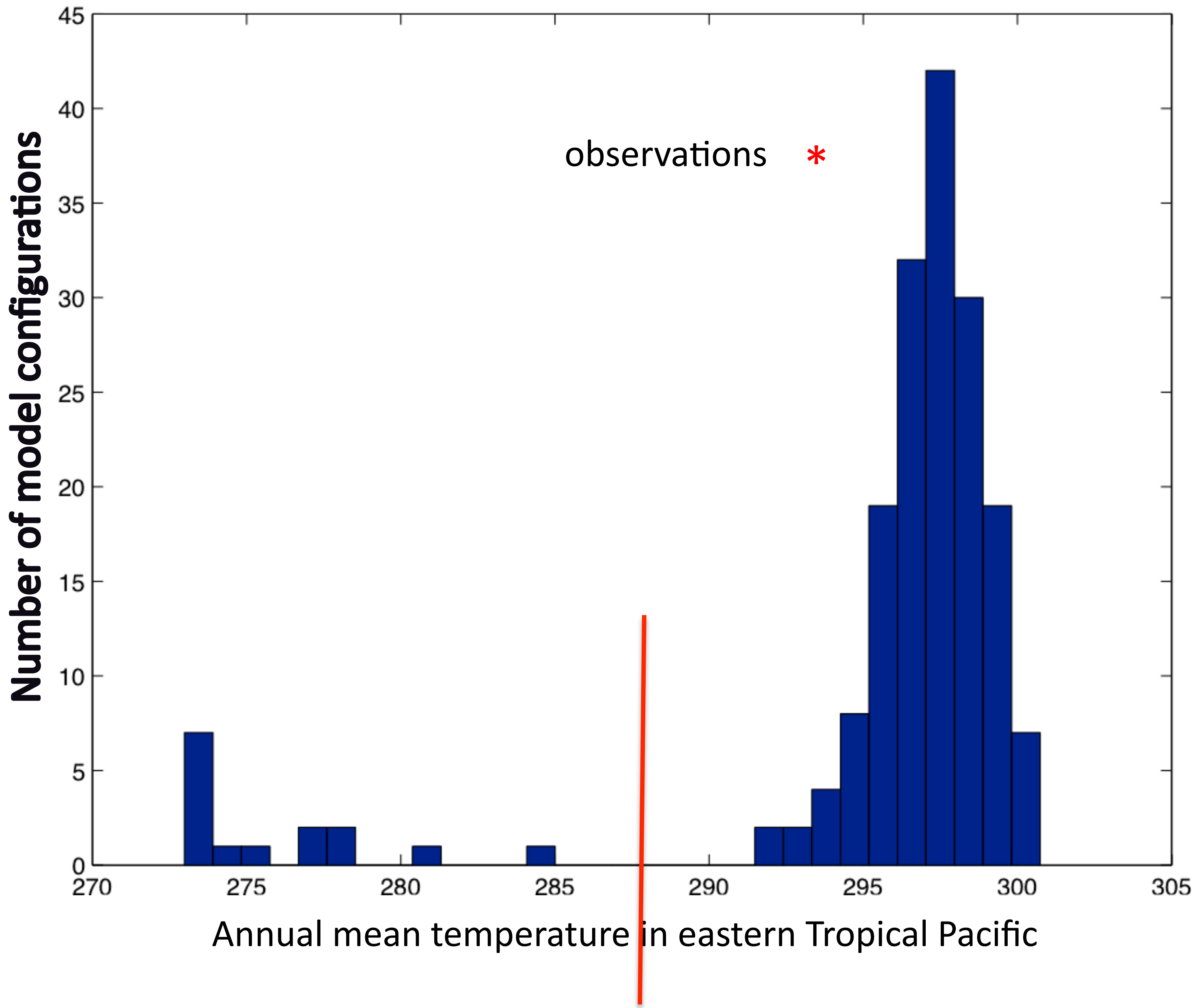


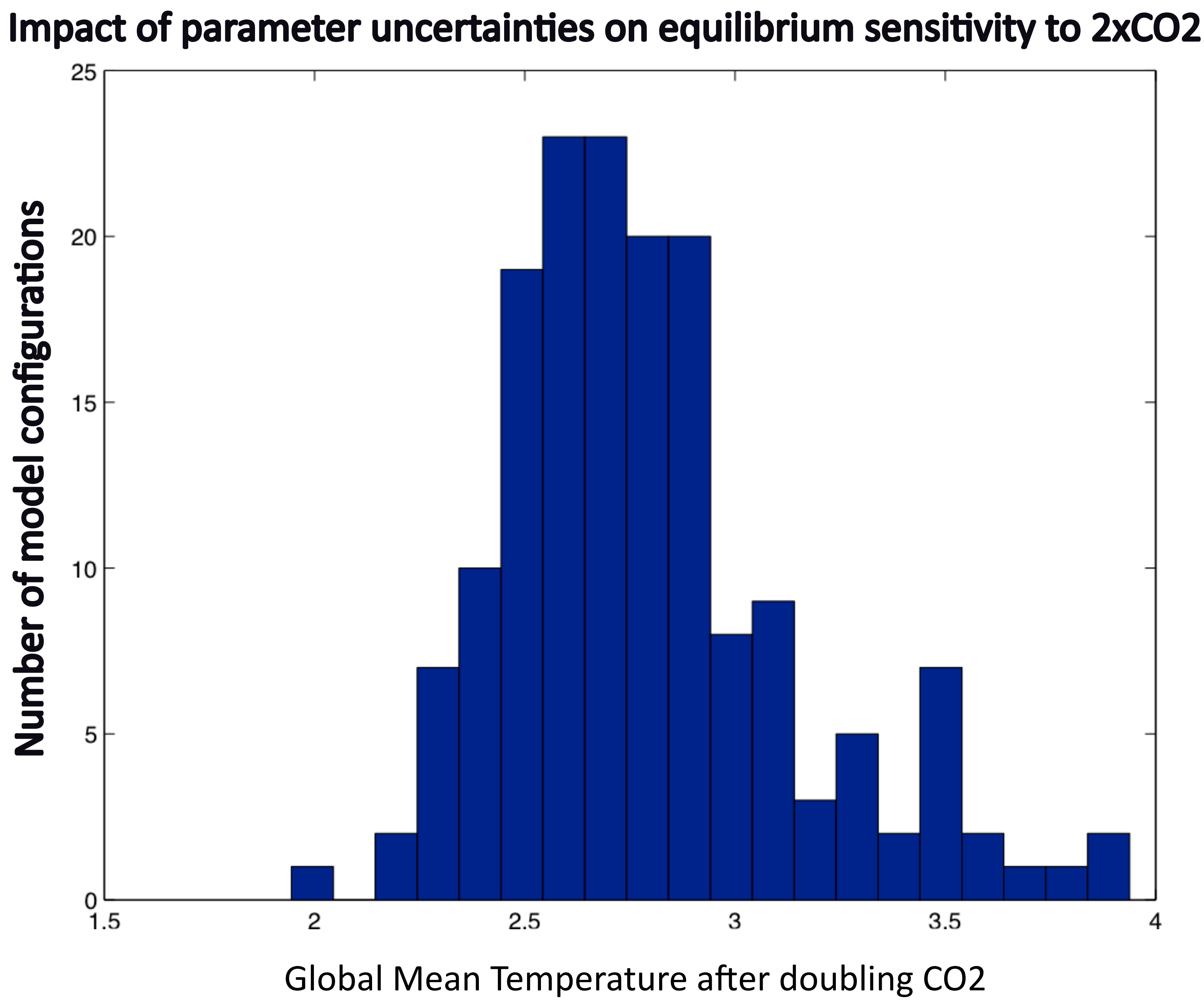
Jackson 2006

Why keep ocean fluxes fixed?

- Normally recalculated when atmosphere model changes.
- Our models are in radiative balance (with fixed SSTs)
- Sensitivity tests show that sensitivities are nearly equivalent (but not a guarantee).
- How can you test for the effects of bias if you alter the boundary conditions to minimize their effects?

“Control” version simulation of point in eastern Tropical Pacific

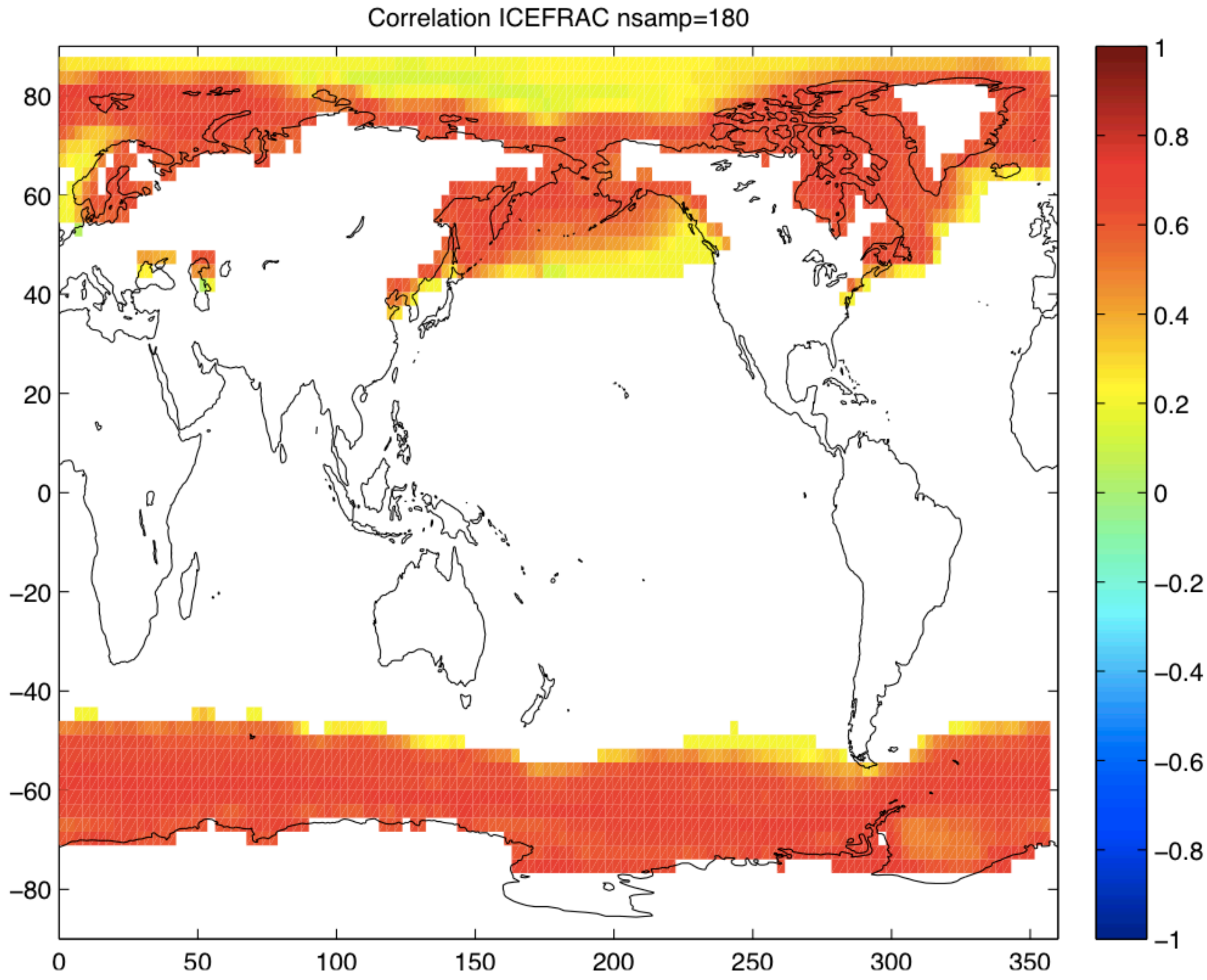



Impact of parameter uncertainties on equilibrium sensitivity to 2xCO2
Number of model configurations
Global Mean Temperature after doubling CO2
0
5
10
15
20
25
1.5
2
2.5
3
3.5
4

Correlation between model bias and scatter in level of warming when CO2 is doubled.

$$Corr\left(\phi,\theta\right) = \frac{1}{N_m}\sum_{i=1}^{N_m}\frac{\left(g_i^{1\mathrm{x}}\left(\phi,\theta\right) - obs^{1\mathrm{x}}\left(\phi,\theta\right)\right)\cdot\left(R\left(g_i^{2\mathrm{x}}\right) - R\left(obs^{2\mathrm{x}}\right)\right)}{\sigma^{1\mathrm{x}}\sigma^{2\mathrm{x}}}$$

If biases do not affect feedbacks, correlation should be 0.


Correlation ICEFRAC nsamp=180
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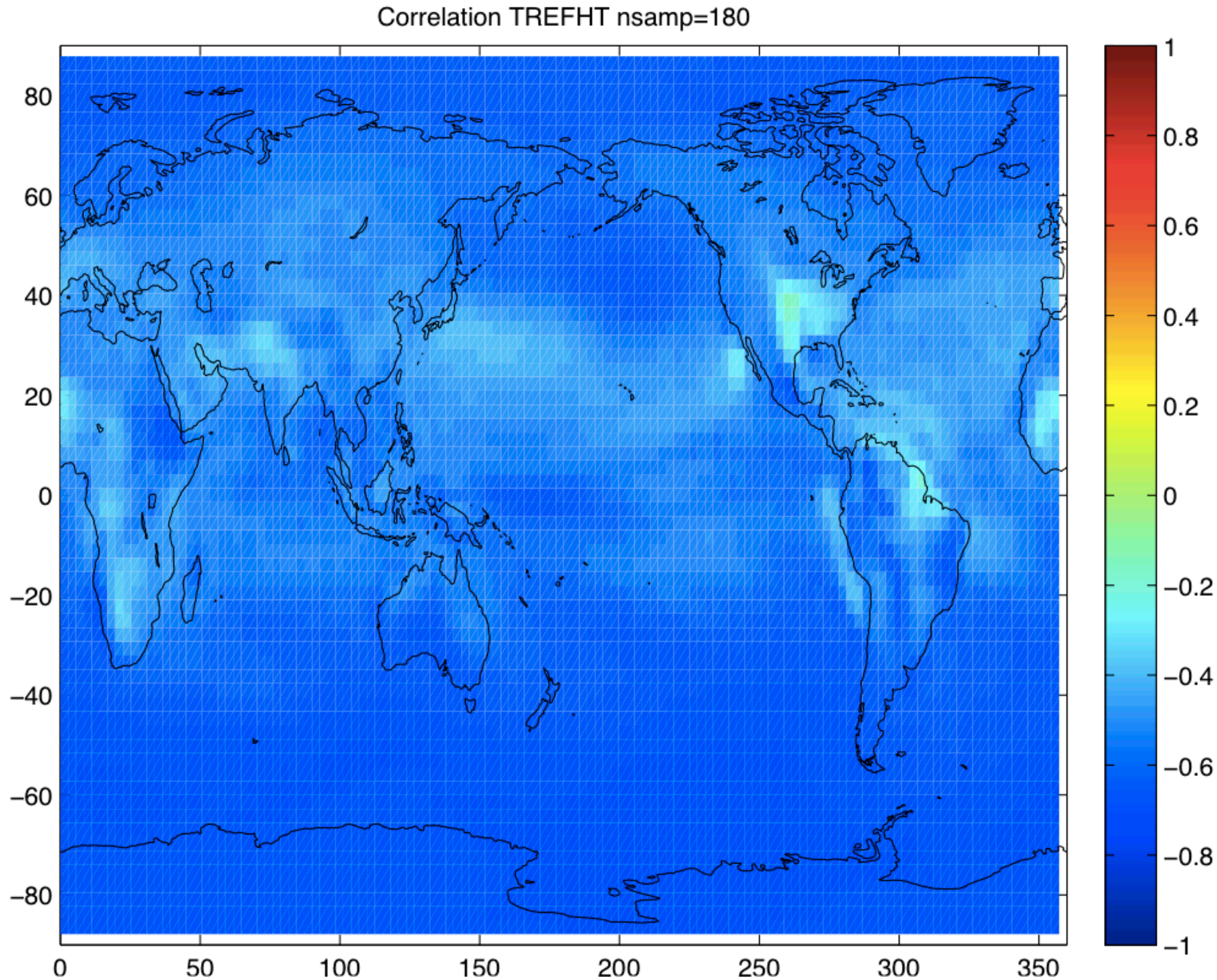
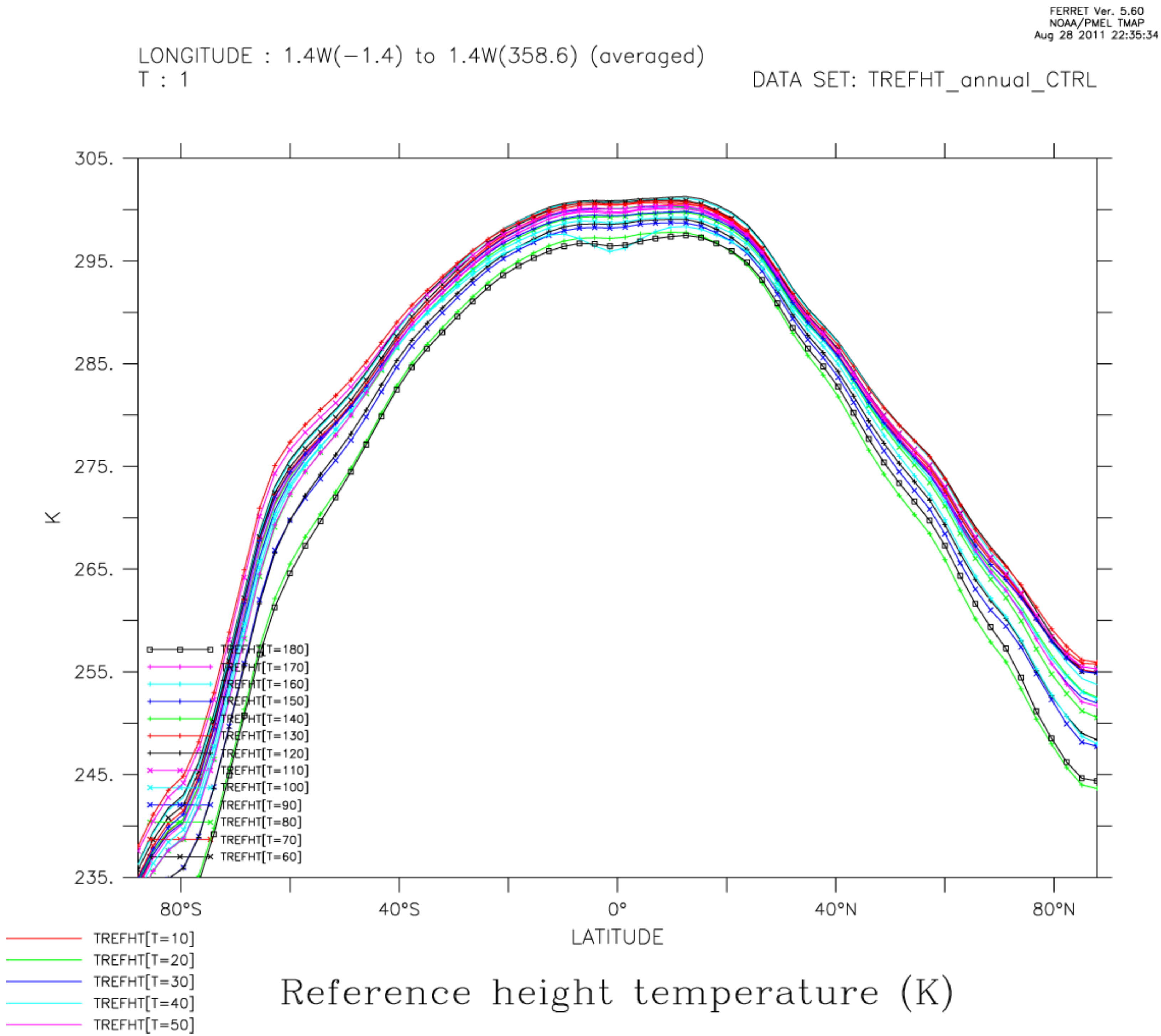
Correlation between scatter in control 2m air temperature and climate sensitivity




FERRET Ver. 5.60
NOAA/PMEL TMAP
Aug 28 2011 22:35:34
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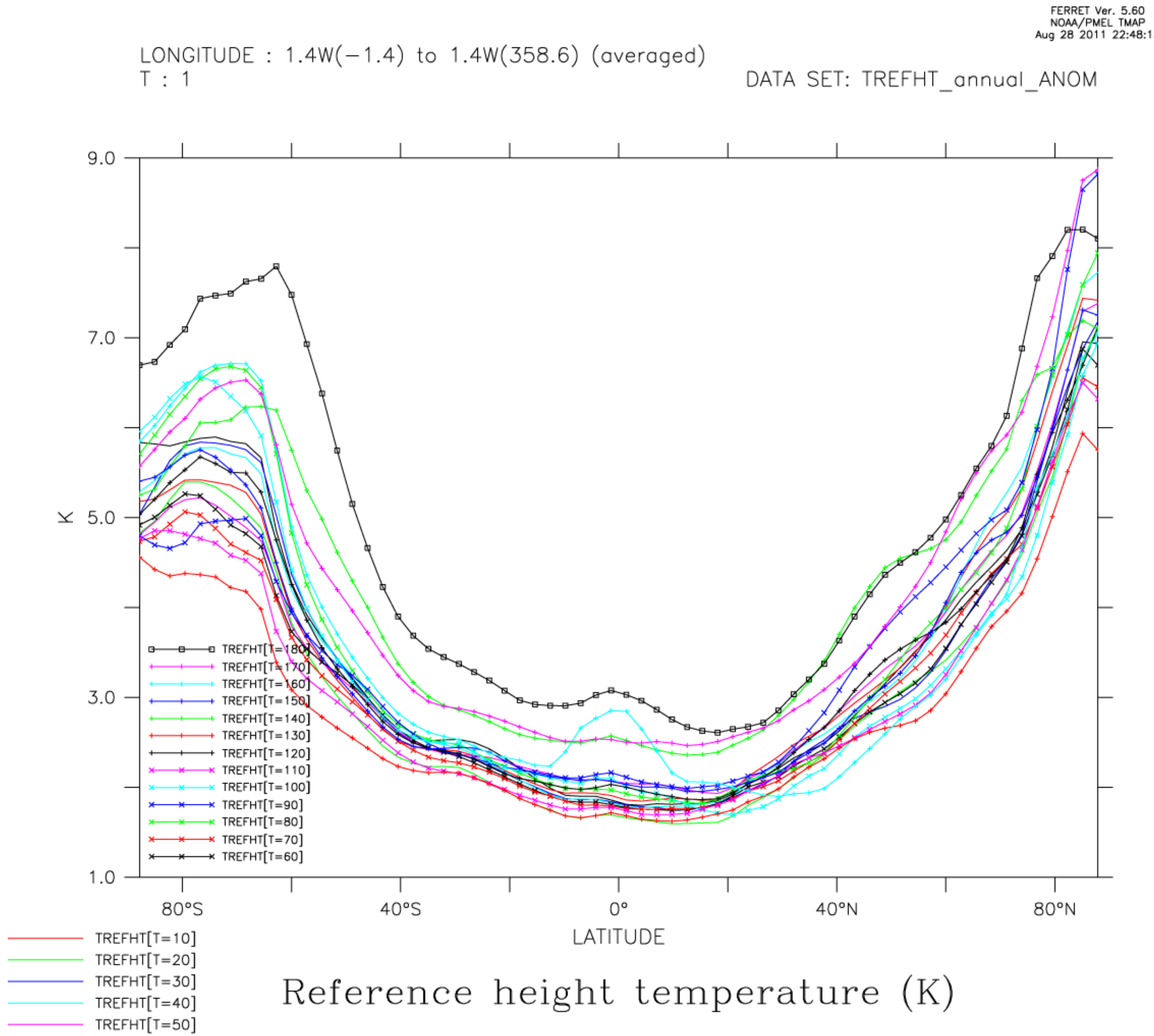
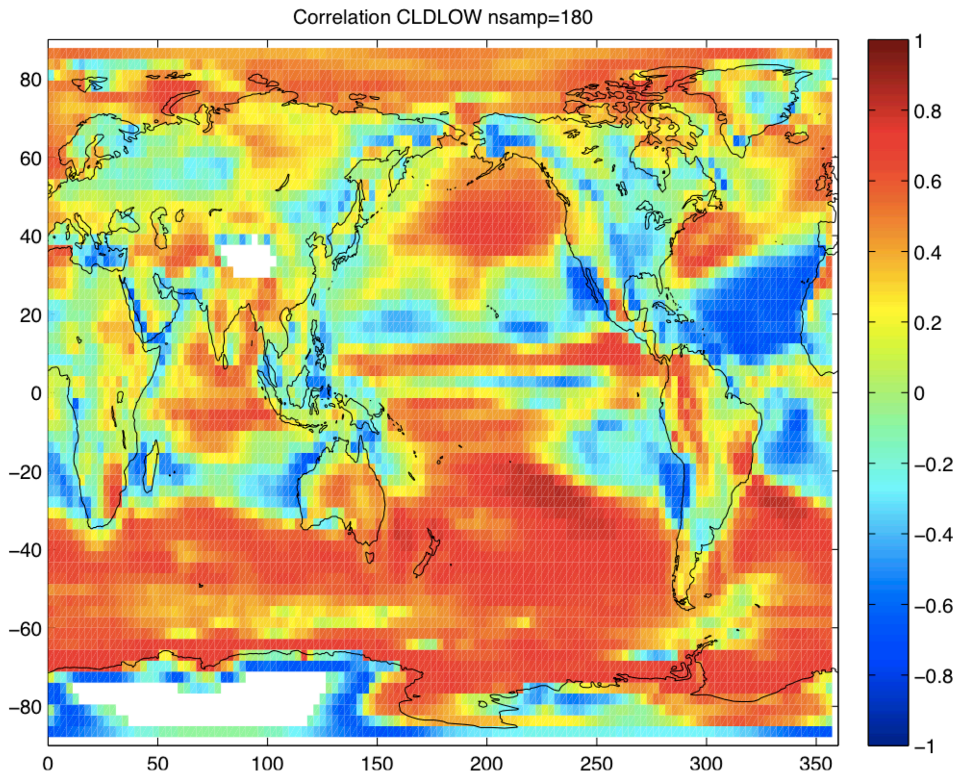
Reference height temperature (K)

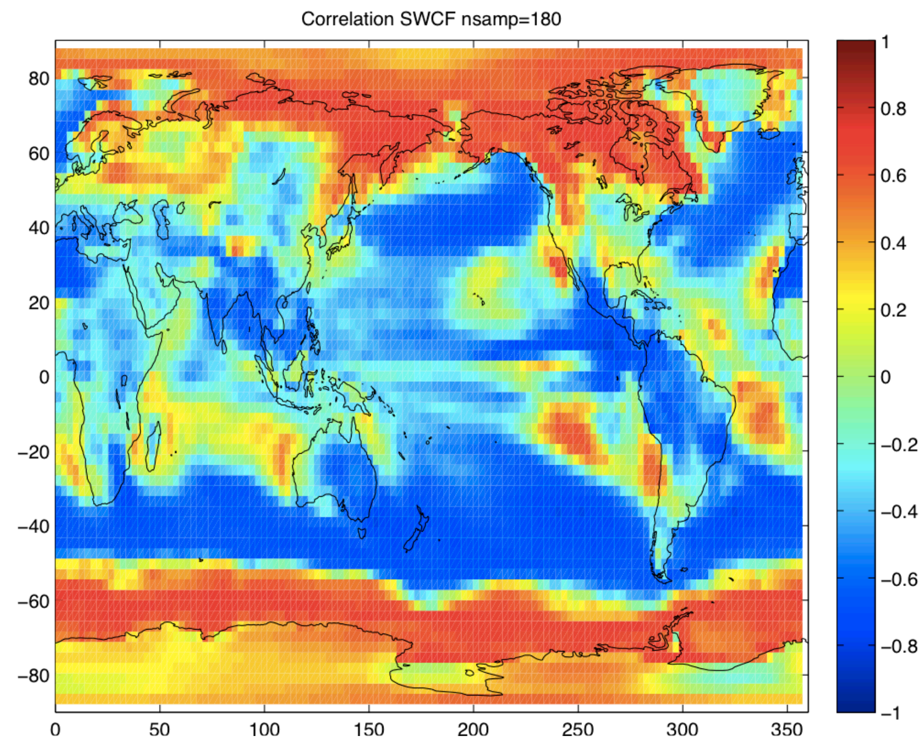


Reference height temperature (K)

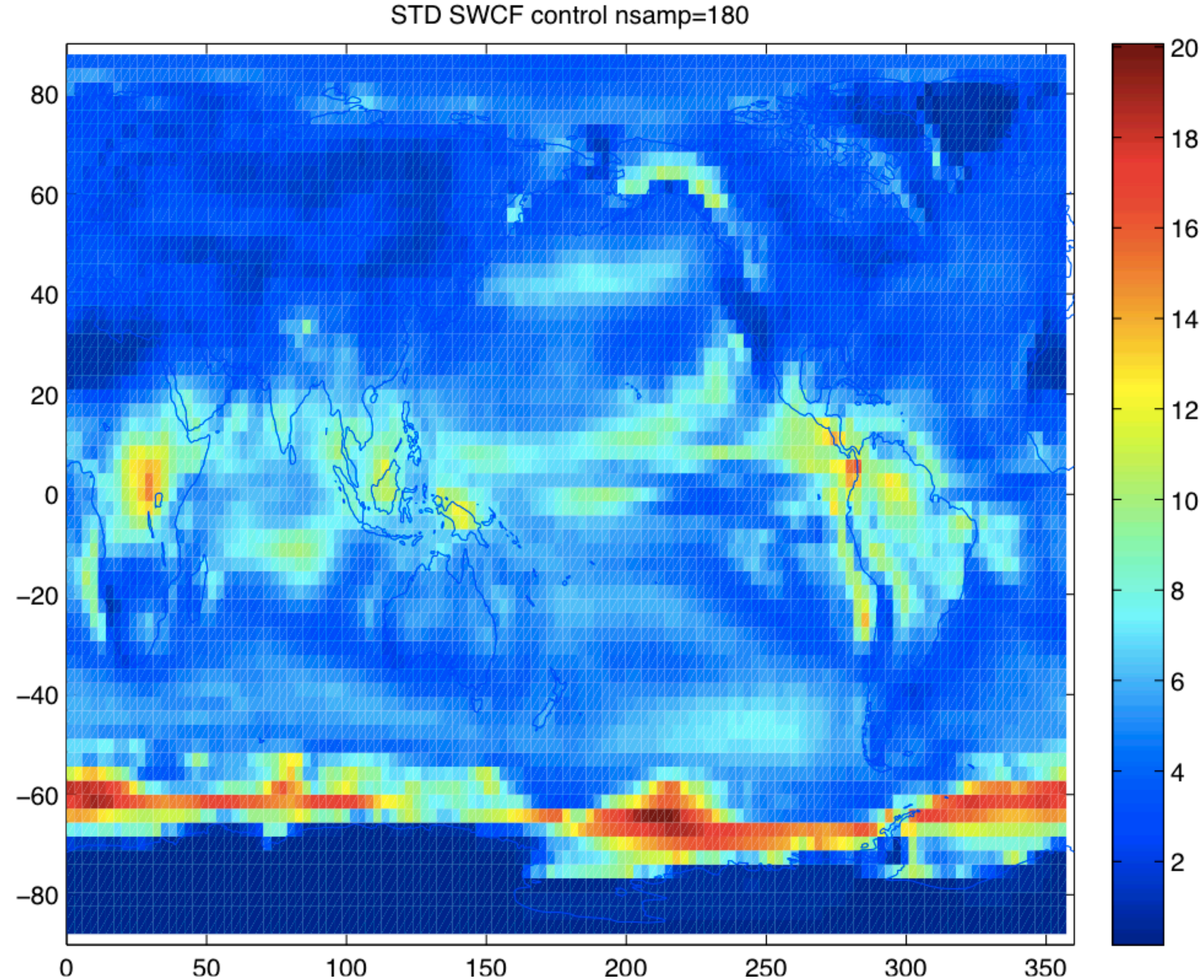
low cloud



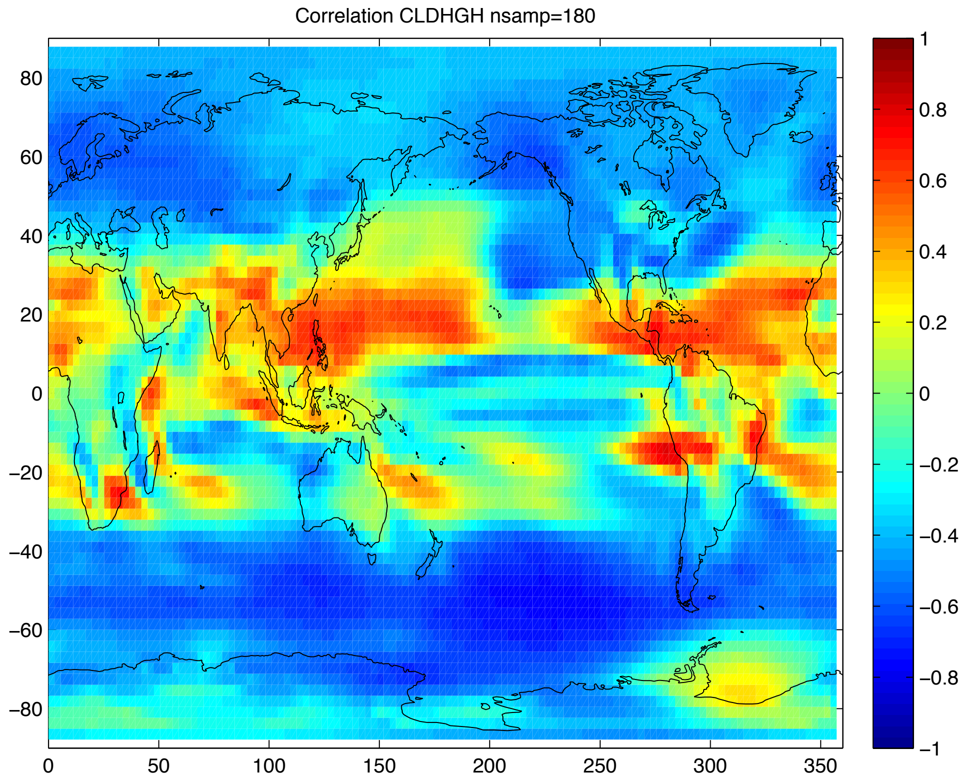
short wave cloud forcing



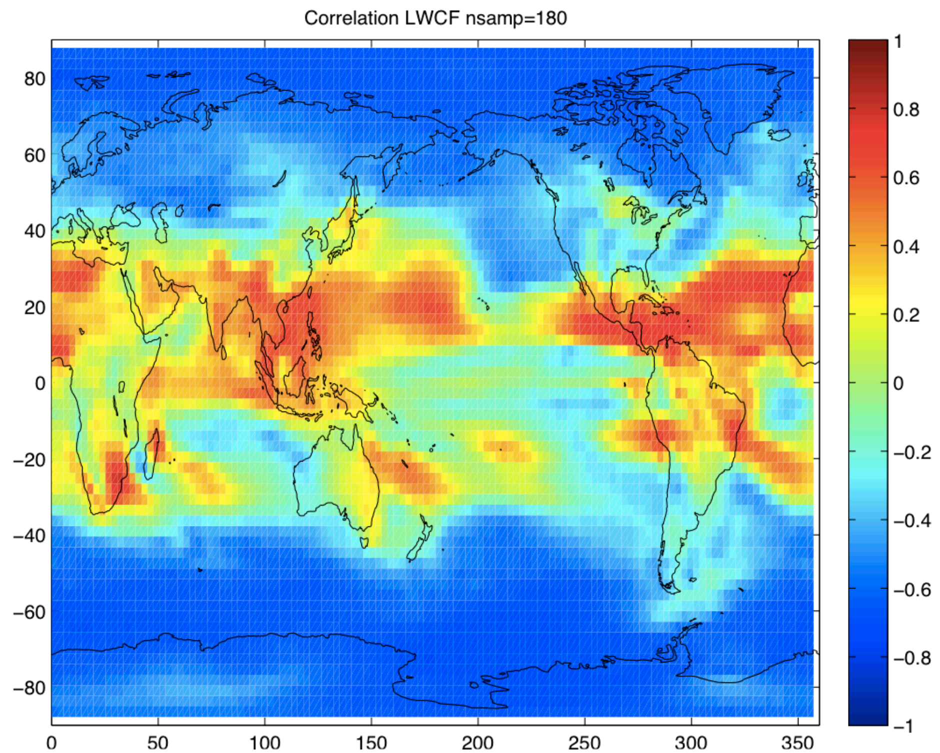
Standard deviation of shortwave cloud forcing in control ensemble



high cloud



long wave cloud forcing

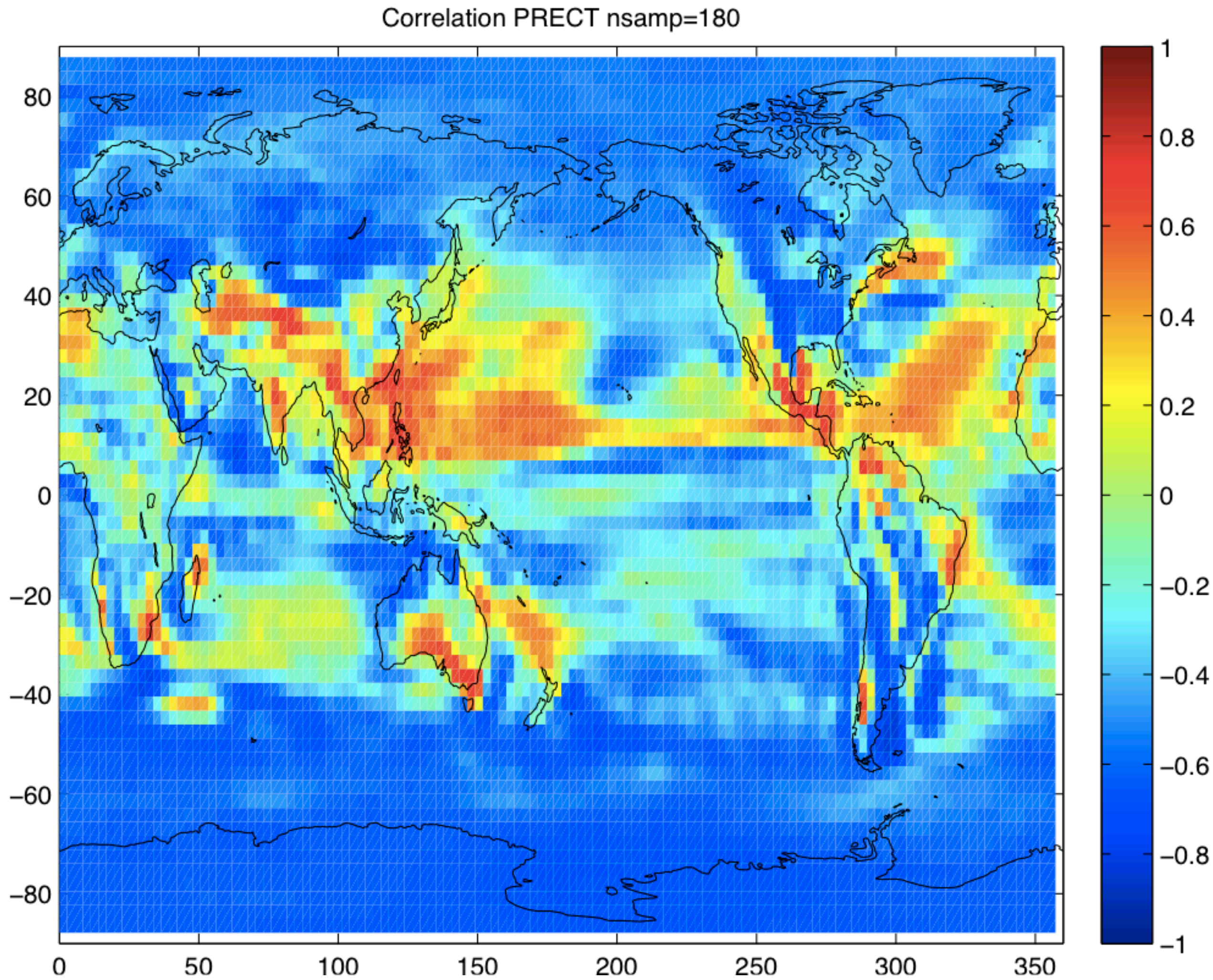


Maximum bias — Compensating errors

Ocean heat flux fixed ⟷ Sea surface temperatures fixed (different heat fluxes)

conclusions

- Biases important to take into account when calculating model likelihood.
- Need to know which biases affect predictions.
- Surprising level of interaction with ocean heat fluxes to maintain atmospheric model skill.
- We need a new strategy to test how models can be tested against data. Current strategy allows significant errors to emerge after testing.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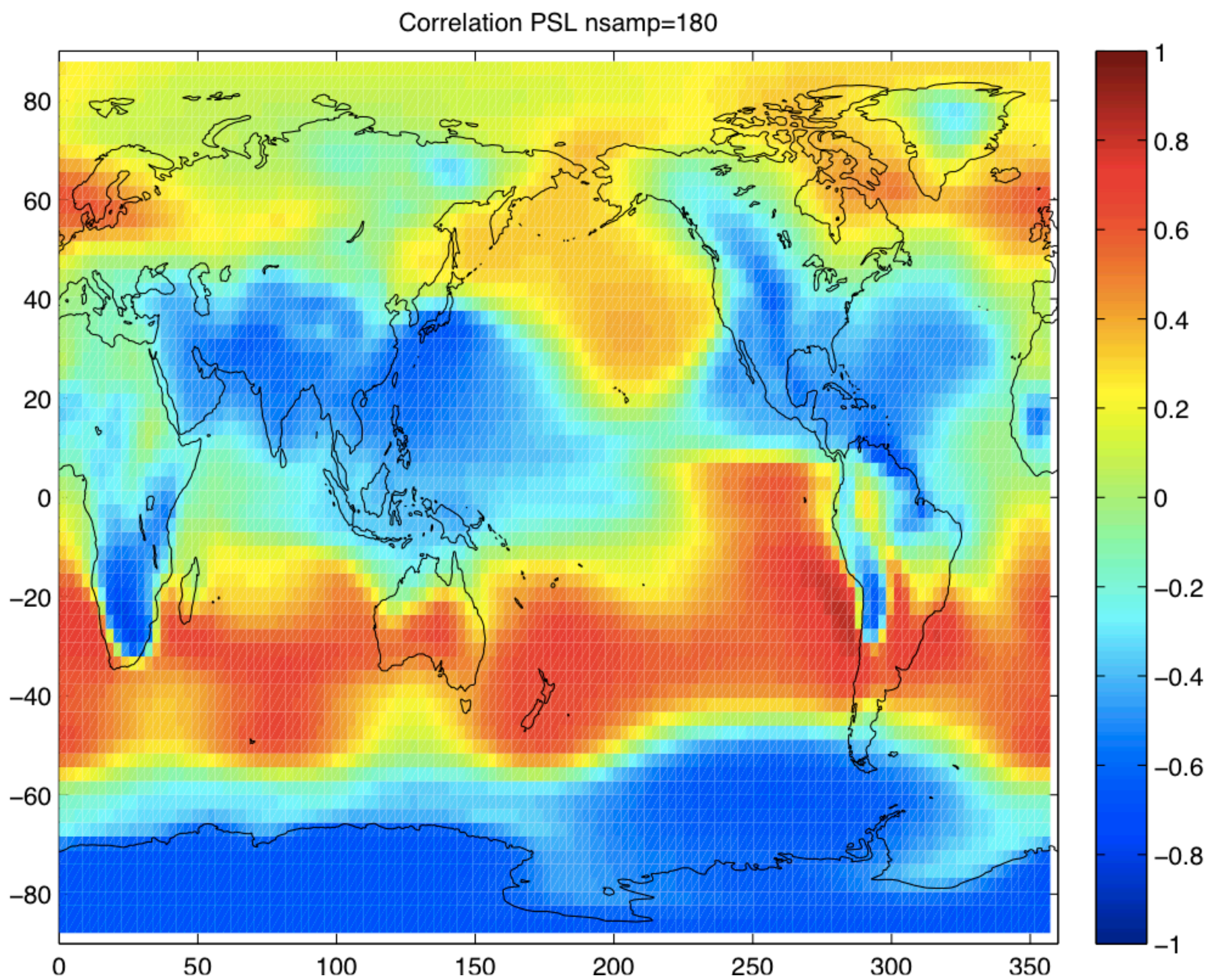

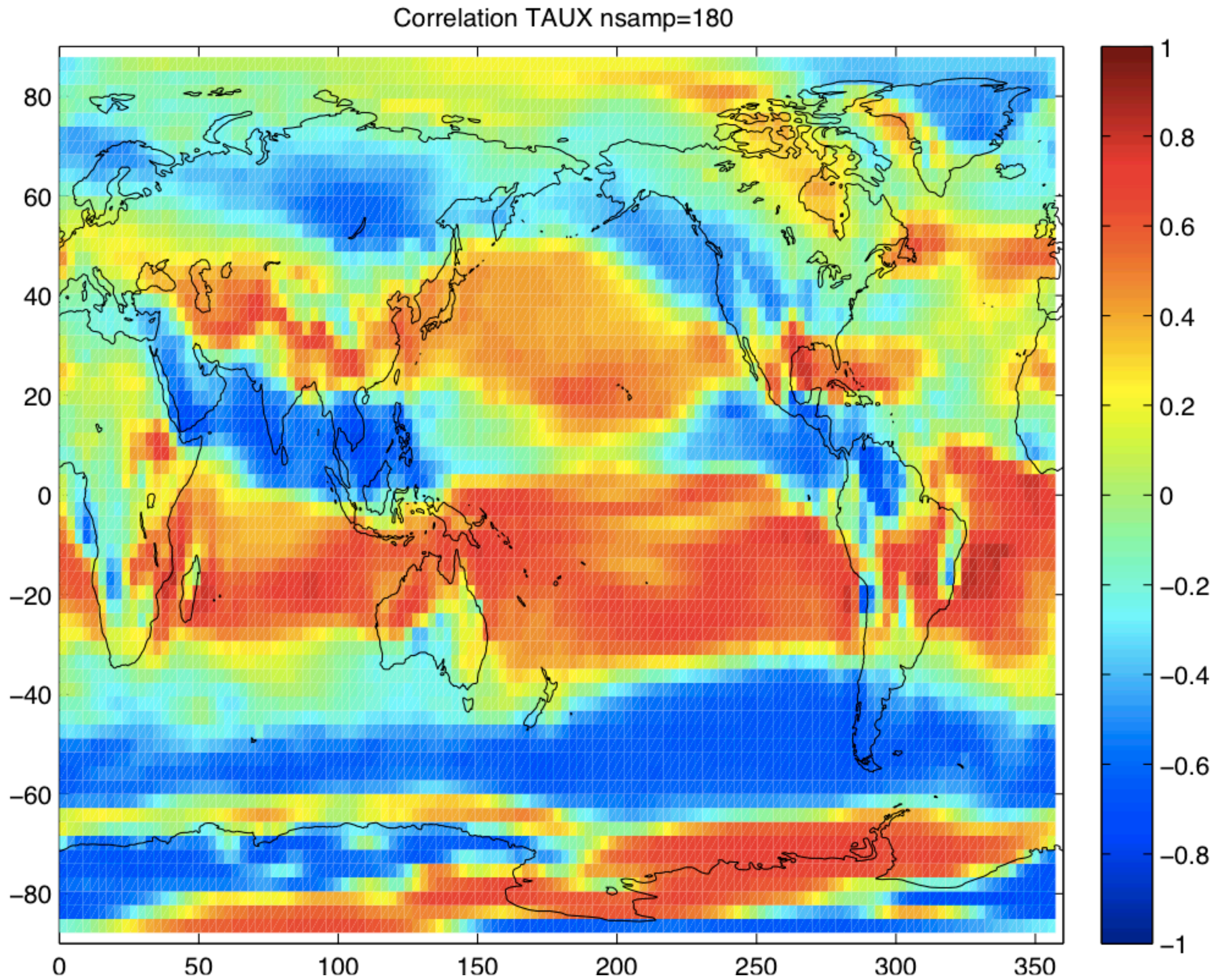
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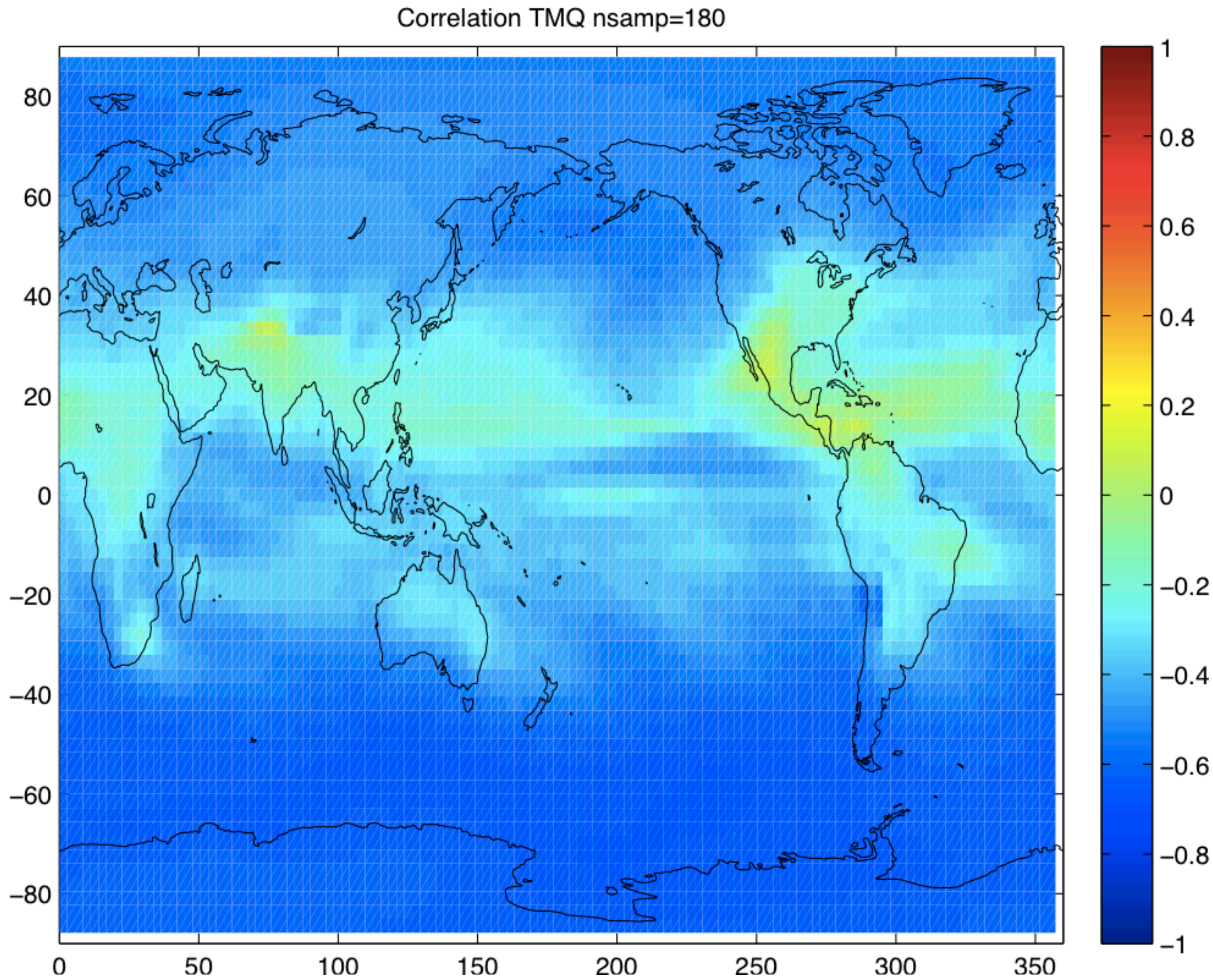
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