2013JD020840 Patrick Frank

Response to Reviewer #2:

Summary response:

- The uncertainty propagated in the study has been changed to the CMIP5 ±4 Wm^{-2} long wave cloud forcing error derived in [*Lauer and Hamilton*, 2013].
- The reviewer has misapprehended the focus of the study, which is not to relate cloud forcing to energy balance.
- The examples of propagated GCM error provided by the reviewer do not in fact include propagated error.
- The reviewer has misapprehended the author's assumption about cloud forcing.
- The reviewer's view that model tuning removes simulation uncertainty is not correct.

Reviewer comments are indented and in italics, followed by the author response.

> *1. This is an interesting analysis of uncertainty using a simple but remarkably accurate model of climate sensitivity. Unfortunately, the author makes a fatal error in attributing systematic bias in simulated cloud forcing to uncertainty in simulated energy balance.*

1. As noted in items 11 and 13 below, the manuscript analysis does not refer simulated total cloud forcing (TCF) error to simulated energy balance. Rather, TCF error is presented as a lower limit of GCM resolution of the energy state of the climate system, and referred specifically to atmospheric thermal flux. Specifically, climate models are unable to resolve the partitioning of energy within the climate system to better than ±4 Wm^{-2}.

   Within a modeled climate, total energy can be in balance even while the internal energy is incorrectly partitioned. When internal energy is incorrectly partitioned a modeled climate will not evolve correctly. The reviewer's final judgment is thus grounded in a misdiagnosis.

> *2. Lines 114-117. Examples of uncertainty propagation:*
> *Stainforth, D. et al., 2005: Uncertainty in predictions of the climate response to rising levels of greenhouse gases. Nature 433, 403-406.*
> *M. Collins, R. E. Chandler, P. M. Cox, J. M. Huthnance, J. Rougier and D. B. Stephenson, 2012: Quantifying future climate change. Nature Climate Change, 2, 403-409, DOI: 10.1038/NCLIMATE1414.*

2. It is shown in 2.1 and 2.2 below that neither of the reviewer's examples provide propagated error, as it is described in original manuscript pp. 5-6, lines 92-107 and equation 2, and in manuscript Section 2.4.2, pp. 20, 21, lines 424-452 and eq. 8.

The manuscript method of error propagation is referenced to the recommendations of the ISO JCGM, of NIST, and to the literature (Vasquez and Whiting, 1998 & 2005).

2.1 Stainforth, et al., 2005 includes three Figures; all of them present uncertainties relative to a model mean:

- Figure 1: "Frequency distributions of [global temperature] through the three phases of [model] simulation."
- Figure 2a,2b,2c: "The [modeled] response to parameter perturbations." All the uncertainty bars in Figures 2a-2c reflect model variability.
- Finally, from page 405 of Stainforth: "Figure 3 shows the initial-condition ensemble-mean of the temperature and precipitation changes for years 8–15 after doubling CO_2 concentrations, for three model versions..."

These quotes verify the point made in the manuscript, namely that uncertainties stem from variations around model means – precision – rather than derived from observational error – accuracy.

Nowhere in the manuscript did Stainforth, et al., mention or present error propagated through a projection.

2.2 Figure 1 in Collins, et al., 2012, describes the approach to air temperature projections and their evaluation:

> "Figure 1: A schematic of the general framework for producing projections of future climate. ... The model may be run with different parameter values p_1, p_2, ... to produce simulations of historical climate c_h, and projections of future climate, c_f. ... The simulations of historical climate may be compared with observations, o, using a metric, and taking into account observational errors. If one point in the climate model parameter space, p_1, produces a better simulation of historical climate than another point p_2, then the hope is that it will give a better (that is, less error-prone) simulation of future climate."

Collins, et al., 2012, state that mere approach to observational magnitude is enough to "hope" that a model has physical validity. Propagation of observational error is never mentioned. They explain the standard approach in this way:

> "The model is calibrated by determining suitable values for the internal parameters that produce simulations of past climate consistent with the observations and their uncertainties.
>
> "Having calibrated the model, ... [it] acts as a physically-based device to pass from historical or past climate and climate change to future projections."

This approach assumes that the internal dynamics of the model accurately reflect climate, once the parameter set has been tuned to observations. It completely ignores theory bias.

The problem is exemplified in their Figure 3. Figure 3a shows how the range of climate sensitivity affects air temperature projections. Figure 3b shows two histograms; the first is projection variance around the observed global air temperature for the year 2000, and the second extrapolates that variance as an uncertainty in projected air temperature for the year 2050.

From the Figure Legend:

> "**a**, Global mean temperature anomalies produced using an EBM forced by historical changes in well-mixed greenhouse gases and future increases based on [IPCC SRES scenario A1B]. The different curves are generated by varying the feedback parameter (climate sensitivity) in the EBM. **b**, Changes in global mean temperature at 2050 versus global mean temperature at the year 2000, obtained from the figure in **a** showing the relationship between past changes and future temperature changes."

None of the projections in Figure 3a display physically valid uncertainty bars. The range of possible air temperature trends in Figure 3a is presented as though the energy balance model (EBM) they used is a perfect climate model and that climate sensitivity were the only model unknown. But, of course, neither is true.

An EBM does not reproduce the response of the full terrestrial climate system to the changing energy state of the atmosphere. Therefore, the simulated atmospheric energy flux is necessarily incorrect. Every step of every EBM simulation projects the internal energy state of the climate incorrectly. This is ignored in Collins, et al., 2012.

Every projection in Figure 3a should have its own confidence intervals representing the uncertainty in the state of the projected climate; an uncertainty which increases with each calculational step. However, error is not propagated in Collins, et al., 2012.

Properly expressed, the 2050 uncertainty histogram in Figure 3b should be the uncertainty represented by the Figure 3a histogram combined in quadrature with the uncertainty in projection year 2050 as derived from the climate state uncertainty propagated through the simulation.

Figure 3 in Collins, et al., 2012 projects SRES A1B forcing. Revised manuscript Figure 5 shows that for the A1B scenario as projected from 1999, the uncertainty in global air temperature arising from ±4 Wm^{-2} cloud forcing error alone is ±1.6 K in year 2000 and ±11 K in year 2050. A projection from 1850, as done by Collins, et al., would have much wider confidence intervals.

If the implicit 'perfect model, single unknown' assumptions of Figure 3 were correct, then the projection closest to the observed temperature trend would establish the most credible deduced physical magnitude for climate sensitivity. But such a deduction is never claimed, which lacuna illuminates the contradiction that the assumptions are accepted in the context of the Figure but rejected in the wider context of climate physics.

3. Lines 168-169. The CO_2 forcing does not vanish when the condition holds. It becomes progressively smaller.

3. "Zero forcing" has been changed to negligible forcing.

4. Line 256. What is meant by pristine?

4. Pristine was meant to convey, and is now replaced by, 'unperturbed.'

5. Line 261. Where do the numbers 269.3 and 283.7 come from?

5. The origin of the numbers is specified in the immediately preceding paragraph beginning at line 246, section 2.1.3 "*The fractional wve CO_2 forcing.*" They are the intercepts of the fits at 1 ppm CO_2 in Figure 1b.

6. Line 263. We cannot expect this fraction to remain invariant as CO_2 increases.

6. The *wve* GH fraction concerns the behavior of climate models, not of climate. Figures S3-S6 in the Auxiliary Material show that a constant fraction is sufficient to reproduce the projections of all tested CMIP3 GCMs.

   Beyond that, although constant within each scenario, the fraction varies for the same GCM across scenarios, and among GCMs for the identical scenario. Tables S1-S3 show that the *wve* GH fraction varies among GCMs by a factor of 2.6.

7. Line 369. Is lag-1 a one-year lag? Please specify.

7. The lag-1 is in the 2-degree latitudinal steps of the GCM global cloud fraction hindcast. This is now specified in the text and Table. The autocorrelation of error is spatial rather than temporal.

8. Lines 382-383. Such probabilities seem incredible. What is the basis for the estimates?

8. From line 381: "Were the TCF errors normally distributed, the probability..." For a population of random series with normally distributed pair-wise correlations, the most probable pair-wise correlation is zero. A pair-wise correlation of 0.9 is of probability 10^{-17}. The manuscript has been modified to make this point more clearly.

9. Lines 405-412. This analysis assumes all clouds produce the same cloud forcing, which is absolutely false. Low clouds produce a very strong cooling of up to 100 W/m2, while high thin clouds produce a strong warming. High thick clouds produce a *small forcing due to balancing between solar cooling and longwave warming. Given the variety of radiative forcing by clouds, one cannot translate a global cloud fraction error into an error in cloud radiative forcing.*

9. The reviewer has misapprehended the author's assumption, which is that cloud forcing error can be estimated as a linear fraction, when it stems from a relatively modest (±12%) error in a multi-year multi-model average hindcast of global total cloud fraction (TCF), relative to the same multi-year average of observed TCF.

In comparing multi-year multi-model averages of total global cloud fraction vs. multi-year averages of observed global total cloud fraction, only multi-year means are compared. Model-distinctive variations can average away. Year-by-year observational variations average away.

That is, it is assumed that the change in global average cloud forcing following from small changes in the total multi-year average global cloud fraction can be approximated linearly.

This is a very different assumption than that all sorts of cloud produce the same forcing.

10. In addition, the term "cloud feedback" is reserved for the response of cloud radiative forcing to changes in surface temperature, the diversity of which drives much of the diversity in sensitivity of simulated warming to increasing CO_2.

9. The term has been changed to cloud forcing throughout.

11. Lines 414-418. Your estimate of radiative flux uncertainty cannot be compared with the greenhouse gas forcing. All climate models are adjusted to ensure the Earth is in radiative energy balance (to within less than 1 W/m^2) before CO_2 is changed. Otherwise the simulated climates will drift even without increasing CO_2.

11.1 Cloud forcing contributes to the total atmospheric thermal radiative flux. GHG forcing contributes to the identical total atmospheric thermal flux. The total thermal flux of the atmosphere determines air temperature. Uncertainty in the magnitude of cloud forcing injects uncertainty into the total energy flux, which in turn makes uncertain the impact of GHGs. This coupling is a direct consequence of the physics of the system.

The coupling of cloud forcing and GHG fluxes was discussed under section 2.4.2, line 424 (p. 20) and under section 3, line 614ff (p. 29).

11.2 The reviewer has ignored manuscript lines 634-666, where it is shown that model tuning does not dismiss projection error. The TOA flux mentioned by the reviewer is used to illustrate the problem (line 664).

TOA flux has an observational uncertain of ±3.9 Wm^{-2}. [*Stephens et al.*, 2012] Therefore, it is unclear how models can be tuned to within less than ±1 Wm^{-2} of true TOA radiative balance.

Rather, models are likely tuned to within ±1 Wm^{-2} of the observational **mean** of TOA flux, which is a very different standard and which does not remove the observational uncertainty.

12. The above considerations render the rest of the analysis meaningless.

12. Items 1-11 show that the reviewer has not made this case.

13. If the simulated Earth energy balance were as off as the author suggests, none of the climate simulations would be realistic.

13. The analysis does not concern energy balance. The analysis concerns resolution of the energy state. TCF error provides a lower limit of model resolution of the climate energy state. This error shows that the internal energy state of the climate is incorrectly modeled. The model climate can be in over-all energy balance while the internal state is incorrect. The internal state of the climate – the way the total energy is partitioned among the climate subsystems -- determines the air temperature.

The author is compelled to add that physically predictive, not "realistic," is the measure of science.

14. The author should consult the IPCC AR5 for extensive evaluation of historical simulations of climate change for the last century.

14. The author has examined the IPCC AR4 in detail. All GCM evaluations involved tuned models. Hindcasts hid their projection uncertainty within anti-correlated errors. No IPCC evaluation of any climate simulation considered, included, or displayed propagated errors. There is no reason to think the AR5 will be different.

References

Lauer, A., and K. Hamilton (2013), Simulating Clouds with Global Climate Models: A Comparison of CMIP5 Results with CMIP3 and Satellite Data, *Journal of Climate*, *26*(11), 3823-3845, doi:10.1175/jcli-d-12-00451.1.

Stephens, G. L., J. Li, M. Wild, C. A. Clayson, N. Loeb, S. Kato, T. L'Ecuyer, P. W. Stackhouse, M. Lebsock, and T. Andrews (2012), An update on Earth's energy balance in light of the latest global observations, *Nature Geosci*, *5*(10), 691-696.