Review of "Propagation of Error and the Reliability of Global Air Temperature Projections" submitted to Earth and Space Science

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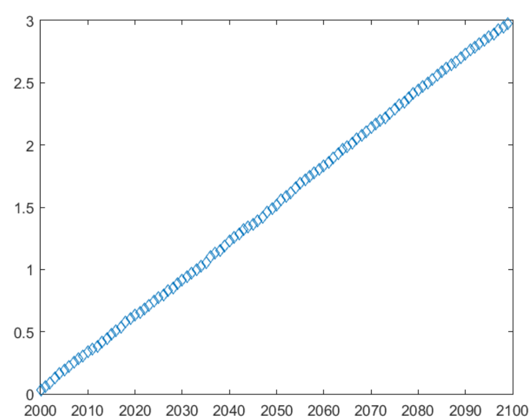
Review:
This manuscript attempts to assess the reliability of global air temperature projections using propagation of error from the long-wave cloud forcing (LWCF). I should point out up front that I am not a climate scientist, but instead someone with expertise in the uncertainties that occur in physics-based modeling and simulation. My primary concerns with this manuscript are listed below. While understanding uncertainties in climate modeling and simulation is an important topic, based on the concerns discussed below, I do not recommend this manuscript for publication.

1. Lines 60-16: The author claims that estimating the uncertainty in climate predictions by examining model variability relative to an ensemble mean is incorrect. However, in the absence of experimental observations (which occurs when making a forecast), then this approach is in fact one method for estimating the uncertainty due to the form of the models. This approach is known as "alternative plausible models" and is discussed in Morgan and Henrion (1990) and Cullen and Frey (1999).
2. Line 66: The author claims that "Propagating physical errors through a model is standard in the physical sciences and yields a measure of predictive reliability." However, the only way you can propagate physical errors through a model is if they are random; if they are bias errors, then one should correct them and evaluate the model w/ the corrected inputs. If they are random, then you are really talking about uncertainty propagation (instead of physical error propagation).
3. Line 87 (equation 1): The author gives the equation for uncertainty analysis used commonly in experimental measurements. However, there are three very important assumptions involved in the use of this equation. First, the equation should be linear over the range of uncertain inputs. Second, all of the uncertainties must be random in nature (i.e., they cannot be bias errors). Third, the uncertainty sources for the inputs must be uncorrelated. The author makes an argument for the first assumption (linearity), but the second and third assumptions are clearly violated. The error in the LWCF represents an unknown bias error. In addition, since the different uncertain inputs used in this manuscript come from a time sequence, they should clearly be correlated in time. That is, if the true error in LWCF in year 2 is +4 W/m^2, it is unlikely that in year 3, the error in LWCF would be -4 W/m^2.
4. Pages 5-6: The use of the LWCF in each year as an independent, random, uncertain input appears to be flawed. For example, what happens if the time sequence is broken down into smaller increments, say months instead of years? Does the uncertainty get much larger? What if it is in increments of 10 years instead of 1 year. Does the uncertainty in the final prediction get drastically smaller? If the answer to either of these questions is yes (which I believe it would be), then this approach is clearly flawed.

5. Regarding Figure 5 and the corresponding discussion around lines 432-435, the author makes the argument that since the TCF versus latitude curves all have similar shapes, that the different models "do not display random-like dispersions around the zero-error line." However, while there may be systematic error in TCF versus latitude, but the actual mean over the earth's area (which I believe would be much more relevant here) would be much less and may display a more random behavior.
6. Lines 511-512: The author states "CMIP5 models were found to produce an annual average LWCF root-mean-squared error (rmse) = ±4 Wm^{-2}." The main point of this manuscript seems to revolve around this uncertainty magnitude. However, I suspect that it is possible that this large uncertainty arises from the fact that each one of the CMIP5 models is highly calibrated based on historical data. In some cases, the LWCF values may have been calibrated to better match the data. However, since it is accepted that the climate models are not perfect (i.e., that they contain significant model form uncertainty), then it is possible that the LWCF values, when examined across a suite of different models, may exhibit variations that are not consistent with the actual uncertainty in LWCF values. Stated differently, the uncertainties in LWCF are likely over-estimated due to the calibration of models with acknowledged model form errors.
7. In order to understand the author's proposed emulation model (equation 6, the Passive Warming Model, or PWM) better, I programmed up the model and applied it to predictions of year 2000 through 2100. Without knowing how the incremental change in greenhouse gas forcing (ΔF) values varied, I simply assumed a constant value. This value was chosen in order to match reasonably well to Figure 7 from the manuscript. The results for mean temperature anomaly are shown below (left) along with Figure 7 reproduced from the manuscript (right). In order to match the final temperature anomaly reasonably well, I had to assume an incremental change in greenhouse gas forcing ΔF of 0.07 W/m^2. However, the quoted uncertainty in this value is 4 W/m^2, which represents one standard deviation. It seems quite implausible to me that the average change in greenhouse gas forcing from year to year is 0.07 W/m^2, while the uncertainty in this number is 4 W/m^2. Something is not right here. Again, I suspect this uncertainty is much too large, as mentioned in item #7 above.



Reviewer's Simulation for Mean Global Temperature Anomaly

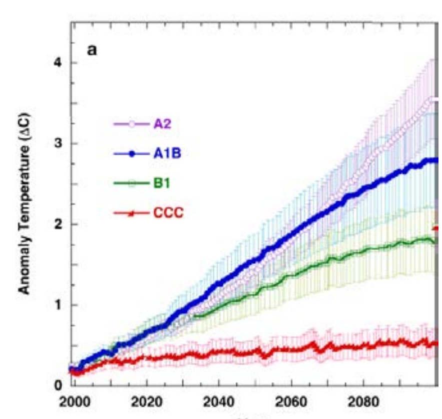
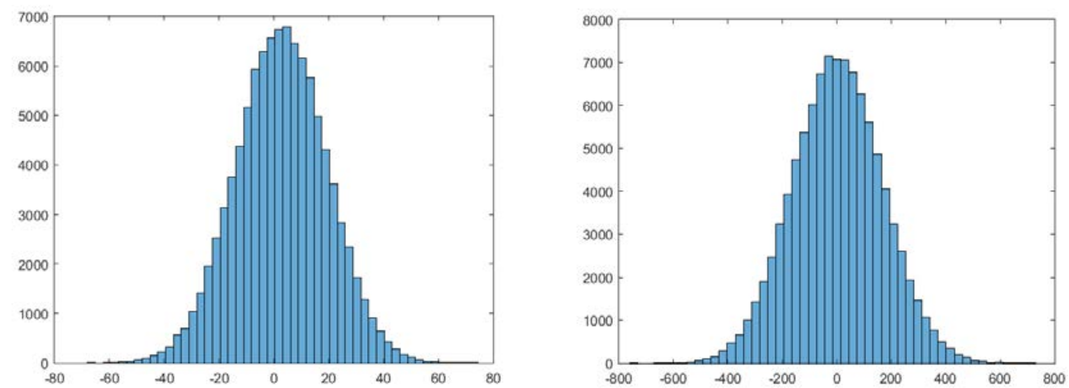


Fig. 7 (from manuscript)

8. As mentioned before, the author assumed that uncertainties in thermal flux (due to LWCF error) from year to year are independent, random variables. In order to test the effects of this assumption, I ran Monte-Carlo simulations (using 100,000 samples) using my rough approximation of the author's PWM. When assuming that the input uncertainties were independent, I found that the final temperature anomaly at year 2100 had a mean of 2.76 K and a standard deviation of 16.7 K, which is consistent with the result given in the manuscript. I then re-ran the simulations assuming that the uncertainties were perfectly correlated from year to year (i.e., using the same uncertainty sample each year). The result was that the year 2100 temperature anomaly had a mean of 2.78 K and a much larger standard deviation of 166 K. Histograms of these two simulations are shown below: uncorrelated (left) and perfectly correlated (right). While the true result is likely somewhere in between, it strains credibility to believe that the actual one standard deviation uncertainty in global temperature anomaly could be on the order of ±100 K and that the two standard deviation uncertainty (~95% probability) could be in the range ±200 K.



Independent, Random Uncertainties — Perfectly Correlated Random Uncertainties

Year 2100 Temperature Anomaly Histograms

References:

Cullen, A. C. and H. C. Frey (1999). Probabilistic Techniques in Exposure Assessment: a Handbook for Dealing with Variability and Uncertainty in Models and Inputs, New York, Plenum Press.

Morgan, M. G. and M. Henrion (1990). Uncertainty: a Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. 1st ed., Cambridge, UK, Cambridge University Press.