Response to Reviewers

Technical Note: Recommendations for Diagnosing Cloud Feedbacks and Rapid Cloud Adjustments Using Cloud Radiative Kernels
egusphere-2024-2782
by Zelinka et al.

Anonymous Referee #1

Cloud radiative feedbacks and rapid adjustments, both prime sources of climate model uncertainty, are increasingly diagnosed in climate models and observations using the cloud radiative kernel (CRK) technique. A limitations of how CRKs are typically applied is that they rely on either passive satellite data or model output that mimics passive satellite data which, in either case, can provide a misleading representation of the low cloud behavior as the passively sensed high clouds obscure lower level changes. Likewise, nonlow cloud radiative changes can be misinterpreted when the observation/simulator is misrepresenting the low cloud state.This technical note addresses this issue, providing a guide and code for overcoming this issue as best as possible. It then demonstrates the extent to which this obscuration effect can bias the magnitude (and in some cases sign) of the low and nonlow cloud feedbacks (or adjustments). This manuscript is well written, very polished, and timely, as the passive satellite simulators needed to apply this method in models figure to play a large role in the upcoming CMIP7. I have a few comments below I hope the authors can address, but otherwise this manuscript is in good shape for publication.
We appreciate the reviewer for carefully reading the manuscript and providing these helpful comments, which are each addressed in turn below.

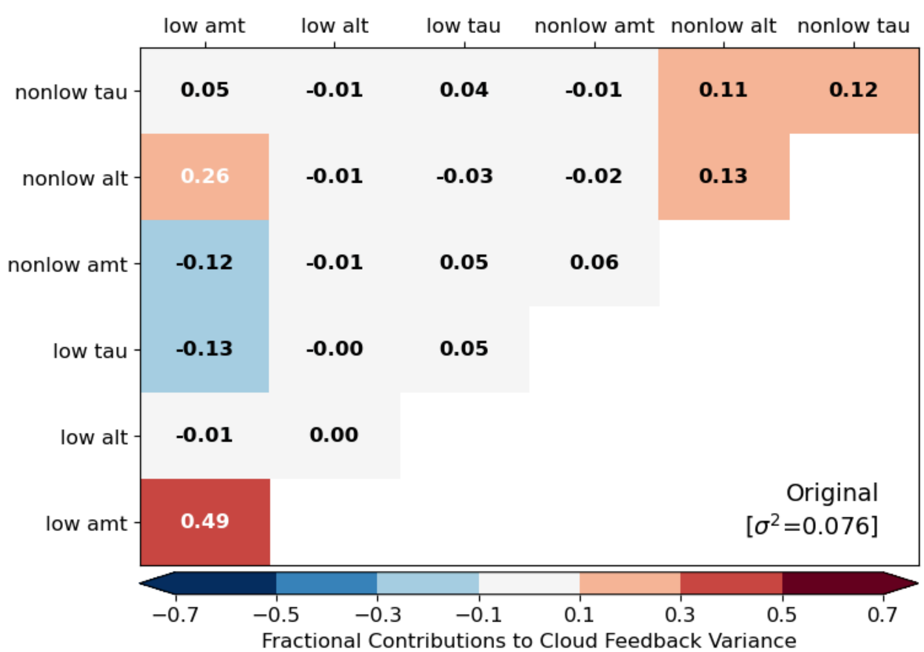
Equation 1 and surrounding text: If I understand correctly, framing of fractionally unobscured, or clear-sky fraction, is really only relevant in the context of grid-scale histograms,. Whereas, at the actual satellite pixel-level, we can't really differentiate between fractions of cloudiness/obscuration. I think it's worth clarifying if so that this is specifically applicable to the use of CRKs /joint histograms and not pixel-level analysis.
That's correct. A given pixel (~4-7 km) is classified as either fully clear or fully cloud-covered as a first step in the ISCCP cloud detection algorithm. Cloud property retrievals (cloud top pressure and optical depth) are then conducted on the cloudy pixels, which are assumed to be fully covered by a single plane-parallel cloud. The aggregation of individual fully clear and fully cloudy pixels over a broader area (280 km in the ISCCP D series) gives rise to the cloud fraction. In the simulator, dozens of sub-columns are first generated within each grid box, with the cloud fraction assigned throughout these subcolumns to be zero or one at every model level consistent with the overlap assumptions used in the model. The ISCCP retrieval is then conducted on these subcolumns, which serve as an analogue to individual pixels observed from space. **We now clarify these points on lines 118-120.**

Section 3: One can imagine a scenario where high cloud fraction changes between the perturbed and control state while a low cloud appears in the perturbed state that truly was not present in the control state. How is this scenario differentiated from the scenario in Figure 1 where it is assumed there is no low cloud in the control state even though it is present and just fully obscured? The former scenario is a covariance term case while the latter is an obscuration term case, but can output provided by the simulator actually distinguish between the two?
In the case shown in Figure 1, the simulator would report zero low cloud fraction in the control state and nonzero low cloud fraction in the perturbed climate. This scenario would be indistinguishable from a scenario in which control-state low cloud cover is truly zero but then increases to a nonzero value in the perturbed climate. Note that it is extremely rare for upper level cloud fraction to be 100% or for low-level cloud fraction to be zero at monthly timescales, so these hypothetical situations are mostly for illustrative purposes. In fact, L_R is undefined if upper-level cloud fraction is 100%. In practice, we compute the terms with overbars in Eq 6 as averages over both the control and perturbed state, so in the situation of a zero control-climate low cloud fraction that becomes nonzero in the perturbed climate, the overbar terms would still be nonzero. **We now mention this on lines 178-180.**

Page 8 footnote: The text mentions that the ISCCP retrieval algorithm reports a single cloud type using the optical depth integrated across all cloud types, including a lower-level cloud beneath an upper-level cloud. Does this suggest a disconnect between the model simulator, which would know a low-cloud is present as generated by the model subcolumn, vs. an actual ISCCP passive satellite retrieval which could not see the low level cloud and thus would not be accounting for any low cloud in the optical depth/integrated extinction estimate? Or am I missing something?
The obscuration discussed in this work occurs because the ISCCP algorithm only reports a single cloud for a given scene with a cloud top pressure determined by the infrared brightness temperature, which is typically dominated by the highest cloud layer in the column (if the high cloud is opaque in the LW). In contrast, low clouds impact the visible optical depth of the column even if overlain by high clouds, and this will affect the TOA reflected SW radiation as long as the high clouds are not opaque (i.e., if their visible tau does not exceed several hundred). Hence both the retrieved and simulated optical depths are affected by clouds at all vertical layers, including low clouds below high clouds, and there is no fundamental inconsistency between the simulator and the observational algorithm. That said, there are practical differences in how the optical depth is determined between the simulator and observational algorithms. The ISCCP simulator essentially assumes that optical depth can be retrieved without error by integrating the sum of the extinction due to liquid and ice clouds throughout the depth of the atmosphere. ISCCP observations instead rely on comparing observed reflected visible TOA radiances to those of a pre-computed look-up table that matches reflected visible TOA radiances to a range of single-layer cloud properties (for cloud phase that corresponds to the brightness temperature). **We added parenthetical comments to this footnote to clarify that this is a feature that affects both the observations and the simulator: "The ISCCP retrieval algorithm reports a single cloud type for each pixel (in the case of the observations) or sub-column (in the case of the simulator)..."**

Line 240-248: Total feedback magnitude is conserved with these corrections as they are essentially just moving radiative changes from one category to another, but is total feedback inter-model spread not conserved? If both low and nonlow cloud amount feedback spread are reduced as noted in this paragraph, that must mean either total feedback spread is able to decrease, or it means another type of cloud feedback's spread is increasing after these corrections in order for total cloud feedback inter-model spread to remain the same.

This raises a good point that was probably not clear from the text. Indeed, the total variance of cloud feedback remains unchanged regardless of the decomposition, so if variance in low cloud amount and nonlow cloud amount both decrease, it implies that something else must compensate to preserve the overall variance. To investigate this, we computed across-model covariance matrices of the individual cloud feedback components (Figure R1). These display variance in each component (along the diagonal) and covariances (multiplied by 2) among each component (off-diagonal). The sum of this matrix equals the total cloud feedback variance, which is the same between the original (top) and modified (bottom) decomposition. In the original decomposition, there are two off-diagonal terms that are large and negative, indicating an anti-correlation between low cloud amount feedback and low cloud optical depth and nonlow cloud amount feedbacks. These terms, which act to reduce spread in the total cloud feedback by about 25%, are drastically reduced in the modified decomposition. So while the variance in nonlow and low cloud amount feedback have decreased in the modified decomposition, so too has the large negative covariance between low cloud amount feedback and low cloud optical depth and nonlow cloud amount feedback. This was partly touched on at the end of Section 4.1 when referring to (current) Figure 8. **We now combine the discussion of that figure into this broader discussion at lines 299-308.**



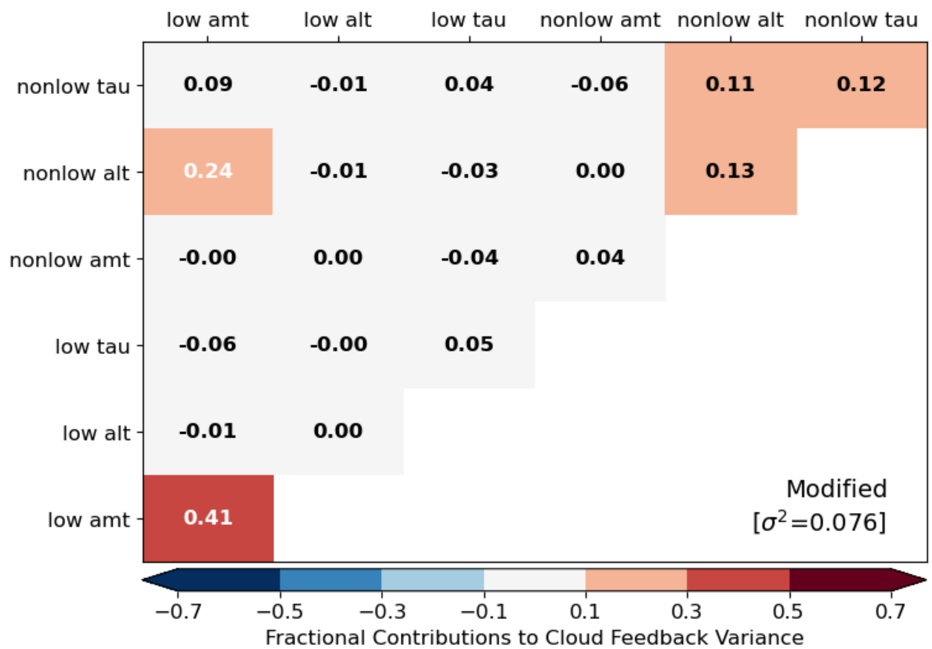


Figure R1. Covariance matrices showing the inter-model variance in each global mean feedback component (along the diagonal) and twice the covariance among each component (off the diagonal), for the original (top) and modified (bottom) decomposition. The values are expressed as fractions of the total such that the sum of each matrix is 1.

Anonymous Referee #2

This paper presents a methodology for diagnosing the impact of changing obscuration on cloud feedbacks and adjustments, and it quantifies these effects across climate models. It documents the effects of obscuration across models, demonstrating that, when obscuration is considered, the multi-model mean radiative effects of both low and non-low clouds are reduced in both cloud feedback and cloud adjustment. Additionally, this paper offers best practice recommendations and provides a codebase.

The paper is well-structured and well-written. I have only minor comments and recommend that it be published once these points are addressed.
We appreciate the reviewer for carefully reading the manuscript and providing these helpful comments, which are each addressed in turn below.

According to Fig. A-2, the inter-model spread in global mean low cloud feedback and non-low cloud feedback appears similar, particularly after modification. However, the spatial maps of the standard deviation of cloud amount feedback reveal additional details. For instance, cloud feedback in stratocumulus deck regions is known to vary significantly among climate models, though the spatial coverage of these regions is limited. It has been suggested that the area-weighted contributions should be considered to identify which regions most influence the

inter-model spread of cloud feedback. After accounting for obscuration effects, the standard deviation of low cloud feedback over stratocumulus deck regions remains the largest, but the spread is considerably reduced. Could you comment on the cloud types and/or regions that most contribute to the inter-model spread of global mean cloud feedback after modification?
This is a good point that was not addressed in the paper. To answer this, we compute the across-model correlation (squared to express as variance explained) between the global mean total net cloud feedback and the nonlow and low net cloud amount feedbacks, for both the original and modified methodologies. This follows the analysis approach taken in Soden and Vecchi (2011). As expected from the literature, the spread in global mean net cloud feedback is strongly related to the low cloud amount feedback in regions of prevalent low cloud, including the subtropical and midlatitude oceans (Fig. R2d). The modified methodology highlights the same regions, but the variance explained is larger nearly everywhere, especially over the Atlantic and Indian Oceans, subtropical S. Pacific, equatorial Pacific cold tongue, and N. Pacific (Fig. R2e,f). The modification also results in a reduction in the variance explained by nonlow clouds over the subtropical Atlantic Ocean (Fig. R2c). That the variance in global mean cloud feedback explained by modified low cloud amount component has increased at most locations is interesting because the inter-model spread in the modified low cloud amount feedback is actually reduced at most locations (Fig. 4f). This may provide further evidence of the importance of properly accounting for obscuration effects, as it leads to a clearer attribution of inter-model spread to its true source (low clouds). **We now add a paragraph discussing these results on lines 255-265, and have added Figure R2 as a new Figure 5.**

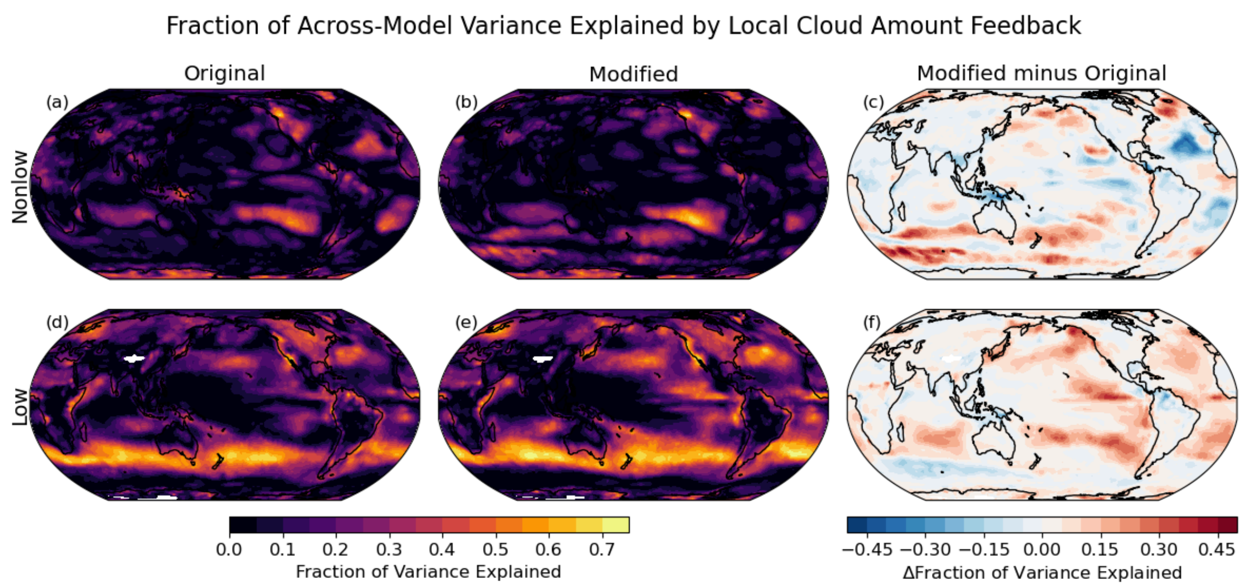


Figure R2. Fraction of across-model variance in global mean net cloud feedback explained by local net (top) nonlow cloud amount feedback and (bottom) low cloud amount feedback using the (left) original and (middle) modified methodology. In the right column, we show the difference between modified and original methodologies.

I noticed that the authors added equations for obscuration effects at three vertical levels: high, middle, and low. If the threshold for 'low clouds' is defined at 680 hPa, then high and middle clouds combined would correspond to 'non-low clouds' in a two-level categorization. I am interested in (1) which of the middle or high clouds are primarily responsible for the obscuration effects on low clouds, and (2) how significant the obscuration effects of high clouds are on middle clouds.

We show the multi-model mean maps of the obscuration terms in Figure R3 and the global means of these terms for each model in Figure R4. In the multi-model mean, it is clear that changes in high clouds are primarily responsible for the obscuration effects on low clouds (note similarity between Figure R3a and c). This statement also holds for most models' global mean obscuration, for which 13 of 21 models have a larger obscuration by high clouds than by mid-level clouds (Figure R4). Finally, inter-model differences in the magnitude of obscuration of low clouds by non-low clouds is primary driven by the high cloud component (Figure R5).

The changing obscuration of mid-level clouds by high clouds is a relatively small effect at all locations (Figure R3d) and in the global mean for each model, with a mutli-model mean of 0.01 W/m^2/K and and standard deviation of 0.04 W/m^2/K.

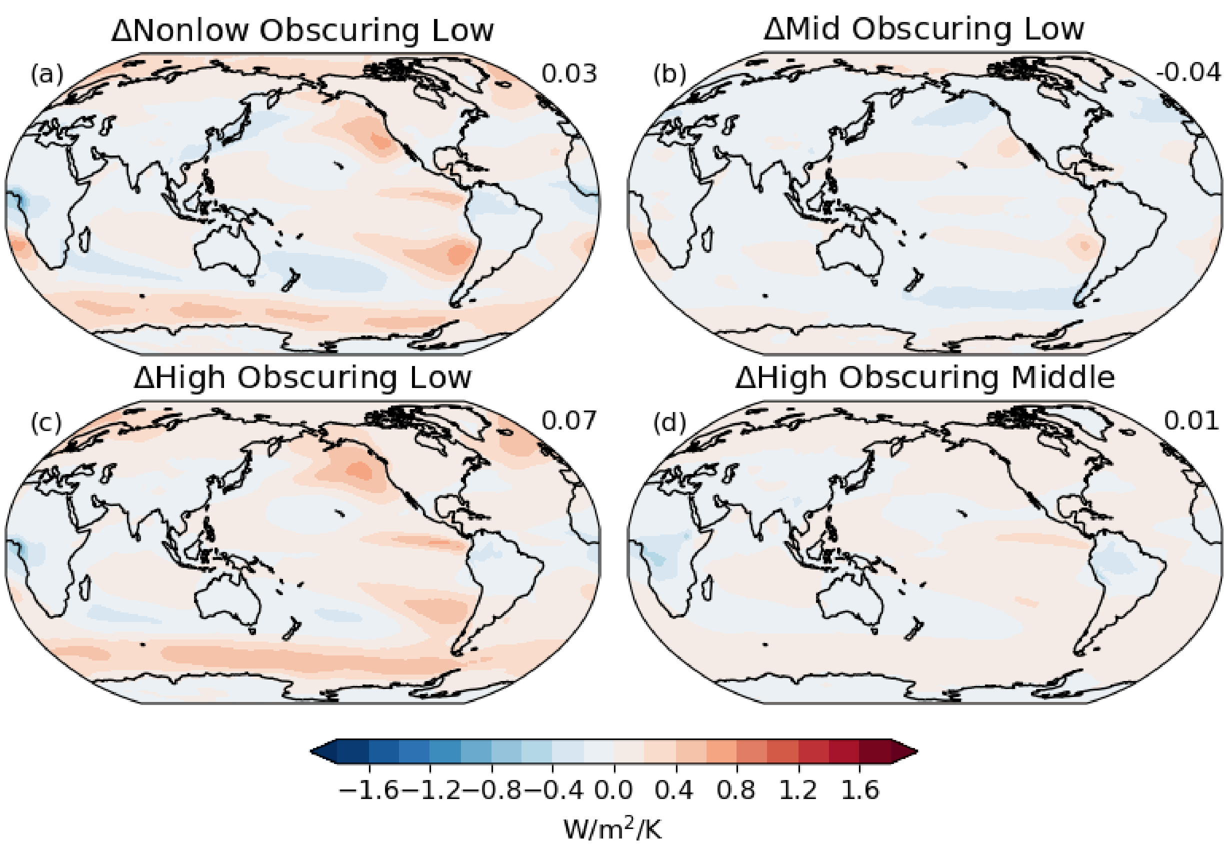


Figure R3. Multi-model mean impact of changes in obscuration by (a) nonlow clouds on low cloud feedback, which is equivalent to the sum of the impact of changes in obscuration by (b) mid-level clouds and (c) high clouds on low cloud feedback. Also shown is the impact of changes in obscuration by (d) high clouds on mid-level cloud feedback. Positive values indicate that increases in upper-level clouds obscure lower-level clouds, making a positive contribution to the original low-level cloud feedback. Panel (a) is identical to Figure 3c in the main text.

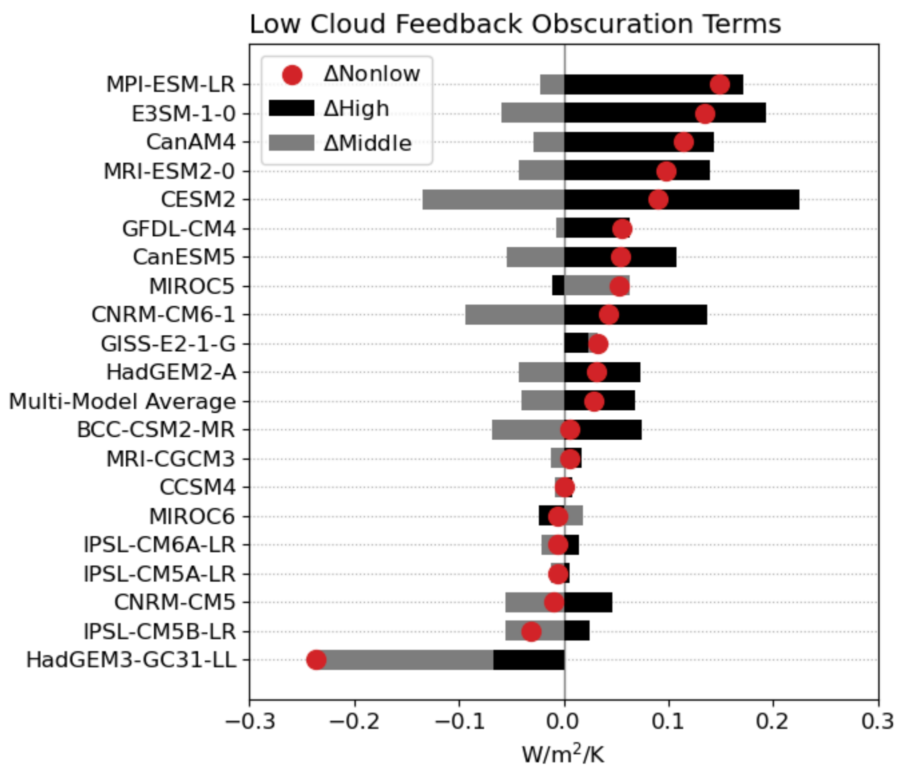


Figure R4. Global mean obscuration of low cloud feedback by nonlow clouds (red marker), and its breakdown into contributions from changes in obscuration by high (black) and mid-level (gray) clouds. Positive values indicate that increases in upper-level clouds obscure lower-level clouds, making a positive contribution to the original low-level cloud feedback. The red symbols are equivalent to the gray bars in Figure 6c, but with the sign reversed.

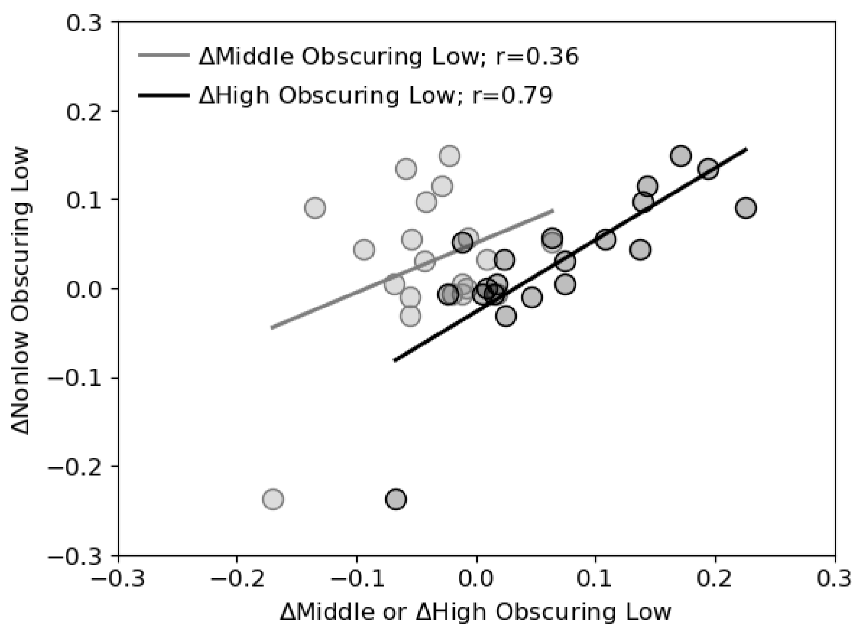


Figure R5. Global mean obscuration of low cloud feedback by nonlow clouds (y-axis) scattered against the obscuration of low cloud feedback by middle and high clouds (x-axis).

Note also that we corrected a typo in Equation A2.

I understand that the authors have developed cloud radiative kernels for radiative feedbacks and adjustments and documented the obscuration effects of clouds on these radiative processes. However, the modified cloud distributions themselves would also be valuable information. Is the provided code capable of outputting these modified cloud distributions for low and non-low, as well as high, middle, and low cloud levels?
The code is indeed easily modified to output the three components of Eq 6 (the change in unobscured low cloud fraction, the change in low cloud fraction due to changing obscuration, and the covariance term). To do so, one would simply modify the do_obscuration_calcs() function to include the three components computed on L308-L310 as output at Line 315, and propagate them through as output from the main CloudRadKernel() function (Lines 528-530). In the interest of keeping the demo code clean and targeted to feedback calculations, we have opted to not make this the default behavior.

L113-114: Can you describe a (few) example(s) of the context or needs of having different definitions of upper- and lower-level clouds?
Two papers that have used different definitions of “low” are Myers et al (2021) and Ceppi et al (2024). This was done because it was found that in some datasets, true low-level clouds were mis-assigned to mid-levels and so using the bottom 3 CTP bins of the ISCCP histogram was deemed a better representation of “low” clouds than the bottom 2 CTP bins. In the interest of not interrupting the flow of this section, we have chosen to simply cite these two papers rather than describing these examples (**line 114**).

L126: (I cannot type in upper score here, so use [], instead.) [LRF] must be [LR][F]
Thanks, this has been fixed (**line 128**). We have also replaced the subscript “R” with “U”. We did this to more clearly signify “unobscured” and to avoid confusion with “retrieved” low cloud fraction which has no subscript.

L131 & L145: The authors explain their approach by using the areal fraction of low cloud and clear sky. They then describe breaking this fraction down into 'amount,' altitude, optical depth, and residual components. However, I find the use of 'fraction' and 'amount' confusing. It is unclear how a 'fraction' can be divided into 'amount,' altitude, optical depth, and residual components. Could you please clarify this?
We now clarify in the text (**lines 133-135**): “Recall that this term represents the low cloud fraction as a joint function of cloud top pressure and optical depth. Therefore, we can further break this down into amount, altitude, optical depth, and residual components following Zelinka et al. (2012b, 2013).”

L283: halved ‘in the opposite sign of feedback’
We are not sure what this suggestion means, and so are leaving the text as written, which we believe is clear: “... HadGEM3-GC31-LL’s large positive nonlow cloud feedback is roughly halved.”

L304-307: Cannot follow. Please clarify. Positive rapid cloud adjustment: 1) ' … being dominated by nonlow clouds': yes, but it is because adjustment by low clouds in the original is negative. 2) 'switches to being dominated by a large positive low cloud contribution…. is opposed slightly by a small nonlow cloud contributions': are you talking about negative values in low cloud adjustment in Fig 8(e) and small values in nonlow cloud adjustment in Fig8(b)?
Regarding (1), we note this in the previous paragraph when discussing the low cloud adjustments (Figure 9d-f) and therefore do not feel that it is necessary to repeat this here. Regarding (2), we are referring to the large positive global mean low cloud amount adjustment shown in Figure 9e that is only slightly opposed by the small negative global mean nonlow cloud amount adjustment shown in Figure 9b. To make this clearer, we now refer to the respective Figure panels in this discussion and also explicitly state "averaged globally and across models" **(lines 327-328)**.

References

Ceppi, P., T. A. Myers, P. Nowack, C. J. Wall, and M. D. Zelinka, 2024: Implications of a Pervasive Climate Model Bias for Low-Cloud Feedback. *Geophys. Res. Lett.*, **51**, e2024GL110525, https://doi.org/10.1029/2024GL110525.

Myers, T. A., R. C. Scott, M. D. Zelinka, S. A. Klein, J. R. Norris, and P. M. Caldwell, 2021: Observational constraints on low cloud feedback reduce uncertainty of climate sensitivity. *Nat. Clim. Change*, **11**, 501–507, https://doi.org/10.1038/s41558-021-01039-0.

Soden, B. J., and G. A. Vecchi, 2011: The vertical distribution of cloud feedback in coupled ocean-atmosphere models. *Geophys Res Lett*, **38**, https://doi.org/10.1029/2011GL047632.