Replay to the review of "The ENSO-driven bias in the assessment of long-term cloud feedback to global warming" by Liu et al.

We thank the editor and the reviewers for their time and constructive comments, which have helped us significantly improve the clarity and quality of our work. We have addressed all comments point by point and revised the manuscript and Supplemental Information (SI) accordingly. Before presenting our detailed responses to the referees' comments and questions, we begin with a brief summary of the major changes implemented in the revised manuscript:

1) Sensitivity tests have been added to assess the assumptions of zero lag, linear trends, and ENSO linearity in our OLS multivariate regression model;
2) Results derived from six additional ENSO indices have been included in the SI to evaluate the sensitivity to the choice of ONI;
3) Further analysis has been added to elucidate the drivers of strong ENSO contributions in specific models; and
4) Text, figures, and captions throughout the manuscript have been refined to provide greater clarity and precision.

Please find below our specific responses to all the comments (marked in blue). Revisions and additions to the manuscript and SI are indicated in *italics*.

Response to Referee #1 of "ENSO contribution to the assessment of long-term cloud feedback to global warming" by Liu et al.

General comments:

I appreciate the authors' efforts in addressing my comments and thoroughly revising the paper. I find the paper to be in much better shape and ready for publication.

My only minor comment is on Fig. 9. The current figure seems a little misleading, as most models actually show a very small ENSO contribution. The outstanding large values of relative ENSO contribution in some models are only because their originally simulated CRE values ("before") are so small that normalization gives rise to a large ratio.

Answer: We sincerely thank the reviewer for the valuable comments and support. Your careful review and insightful suggestions greatly helped refine this manuscript.

Regarding Fig. 9, we fully agree with the reviewer's assessment that the large relative ENSO contributions in some models are primarily driven by their small baseline feedback estimates (the denominator). To prevent misinterpretation, Fig. 9 presents both absolute magnitudes and relative ratios. We have revised the figure caption to explicitly clarify this point:

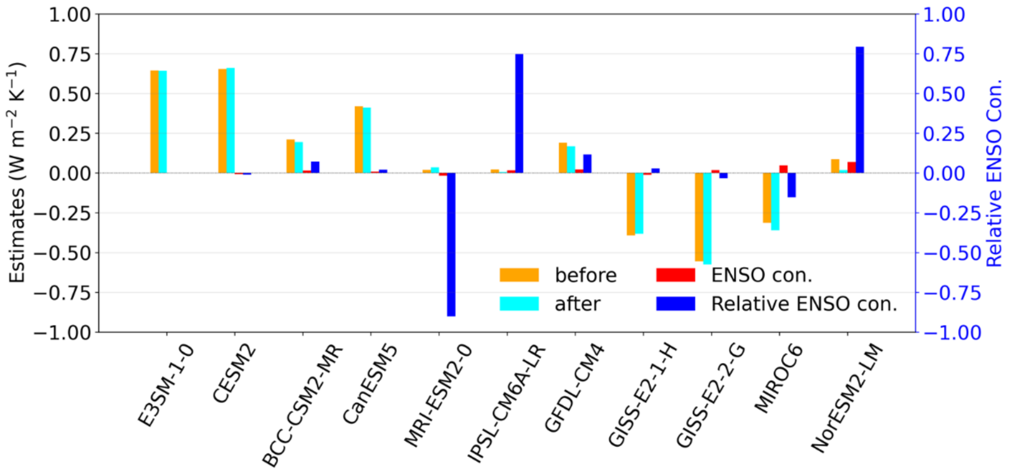


Figure 9: Bar charts of the ENSO contribution to global-mean CRE_{net} derived from GCM simulations of the abrupt-4×CO_2 experiment (first 150 years). The orange and cyan bars indicate global-mean cloud feedback estimates before and after the ENSO correction, respectively. The red bars indicate the ENSO contribution (orange minus cyan). The blue bars indicate relative ENSO contribution (red divided by orange; right y-axis). Note that a large relative value (blue bar) can arise when the original feedback estimate (orange bar) is small.

Response to Referee #2 of "ENSO contribution to the assessment of long-term cloud feedback to global warming" by Liu et al.

General comments:

This manuscript attempts to quantify the ENSO contribution to cloud feedbacks using a multiple linear regression approach. Using reanalysis, satellite data and GCM simulations, the authors identify substantial ENSO contributions to local cloud feedbacks over parts of low- and mid-latitude oceans, and smaller ENSO contributions to the global-long term cloud feedback even after several decades.

The manuscript addresses an interesting problem that would be of interest to the readers of ACP. However, I believe there are some conceptual issues with the multiple regression model and therefore recommend major revisions before this work is suitable for publication. I also have a number of smaller comments on the methods.

Answer: We sincerely thank the reviewer for the detailed review and highly constructive comments, all of which have been thoroughly evaluated and properly incorporated into our revision. In response to the major suggestions, we have conducted additional analyses using lag regression, low-pass filtered GMST, and separate models to verify and enhance the robustness of our results. Furthermore, we have carefully revised the text and figures to address the concerns raised and further refine our manuscript.

Below, we provide the detailed point-by-point response.

Major suggestions:

The authors use a simple multiple regression model to account for the effects of ENSO. For any variable X, they write:

$X(t) = a\, t + b\, ONI(t) + c$,

where t is time, ONI is an ENSO index, c is the residual and a and b are constants. While this is an intuitive model, it has several issues:

1. The relationships between ENSO and the variables of interest here (GMST, CRE) are lag-dependent and tend to peak at lags other than zero (note that this is still an issue even with the band-pass filter). This has been noted in a number of studies, including Xie et al. (2016), Lutsko (2018) and Ceppi and Fueglistaler (2021).

2. The regression model assumes trends that are linear in time. This is clearly not the case in the 4×CO_2 simulations, where GMST is known to respond on two or more time-scales, and may not even be the case over the historical period. The linear time-dependence may weaken the model performance, and departures from linearity could be aliased into the ENSO term.

3. For CRE in particular, the ENSO effect is likely to be asymmetric/nonlinear between

El Niño and La Niña, and this effect could be retained in the “corrected” variables. These assumptions directly affect the magnitude and persistence of the estimated ENSO contributions and, while the authors seem to be aware of some of these issues, they haven’t attempted to address them. With a little bit of work, the robustness of their model to these assumptions could be tested, which would give the reader more confidence in their results. At minimum I suggest the authors try:

1. Determining the optimal lag between the ONI and each variable, then using this in their regression model.

2. Replacing t in the regression model with low-pass filtered GMST (say, frequencies of (15 years)$^{-1}$ and lower).

3. Developing separate models for strong El Niño and La Niña years, to see how the coefficient b differs.

It would greatly strengthen the paper to either make these changes to their model, or show that they give similar results to the simpler version.

References:

Ceppi, P., & Fueglistaler, S. (2021). The El Niño–Southern Oscillation pattern effect. Geophysical Research Letters, 48, e2021GL095261. https://doi.org/10.1029/2021GL095261

Lutsko, N. J. (2018). The relationship between cloud radiative effect and surface temperature variability at El Niño-Southern Oscillation frequencies in CMIP5 models. Geophysical Research Letters, 45(19), 10599–10608. https://doi.org/10.1029/2018GL079236

Xie, SP., Kosaka, Y. & Okumura, Y. Distinct energy budgets for anthropogenic and natural changes during global warming hiatus. Nature Geosci 9, 29–33 (2016). https://doi.org/10.1038/ngeo2581

Answer: We appreciate the reviewer’s constructive comments regarding the robustness of our regression model. These suggestions are indeed critical for validating our methodology.

In response, we performed comprehensive sensitivity analyses using a representative 40-year subset of ERA5 data (January 1981–December 2020). This period was selected to facilitate the three validation tests, while keeping the climatology. Specifically, we tested the model’s sensitivity to the three key assumptions raised:

1. **Lag dependence:** Following Xie et al. (2016), Lutsko (2018), and Ceppi and Fueglistaler (2021), we determined the optimal lag for each variable within a range of –12 to 12 months (negative lags indicate ONI leads). The optimal lag for GMST is –5 months, while the spatial distribution of optimal lags for CREs is shown in Fig. R1. Notably, the optimal lags for CREs exhibit high spatial heterogeneity, lacking the large-scale coherence expected from physical processes and warranting

further investigation.

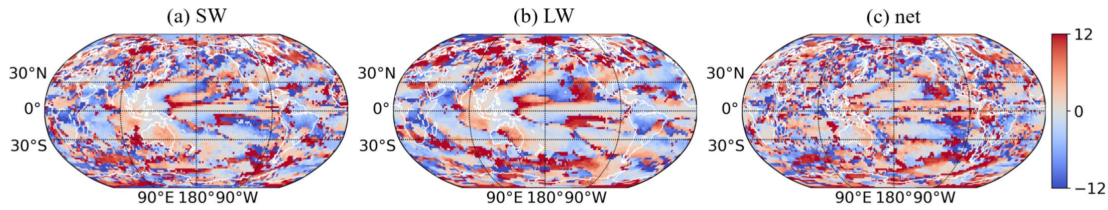


Figure R1: Maps of optimal lags (range: –12 to 12 months; negative lags indicate ONI leads) for (a) CRE_{SW}, (b) CRE_{LW}, and (c) CRE_{net} derived from ERA5 data (January 1981–December 2020).

2. **Non-linear trends:** To account for potential non-linearity in global warming, we replaced the linear time term (t) in Eq. (1) with low-pass filtered GMST (frequencies higher than (15 years)$^{-1}$ removed; Fig. R2). However, the impact of this substitution is expected to be minimal (see fig. S1 below). Since the bandpass-filtered ONI is mathematically uncorrelated with the long-term trend, the estimation of the ENSO coefficient remains independent of the specific form of the trend term.

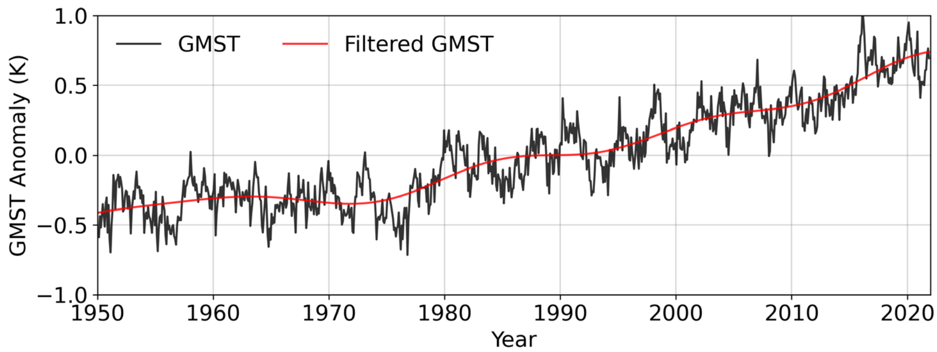


Figure R2: Time series of the original GMST (black curve) and the low-pass filtered GMST (red curve) derived from ERA5 data (January 1981–December 2020). The filtered curve removes frequencies higher than (15 years)$^{-1}$.

3. **ENSO asymmetry:** We conducted separate regression models for warm (ONI > 0) and cold (ONI < 0) phases to examine ENSO asymmetry. The coefficients show significant differences (Fig. R3a-f), confirming the existence of asymmetry. However, since the removal of ENSO signals targets the entire time series, the effective coefficient corresponds to the mean of the warm and cold coefficients assuming balanced occurrences (Fig. R3g-i). Notably, this mean aligns closely with our original simple model (Fig. R3j-l).

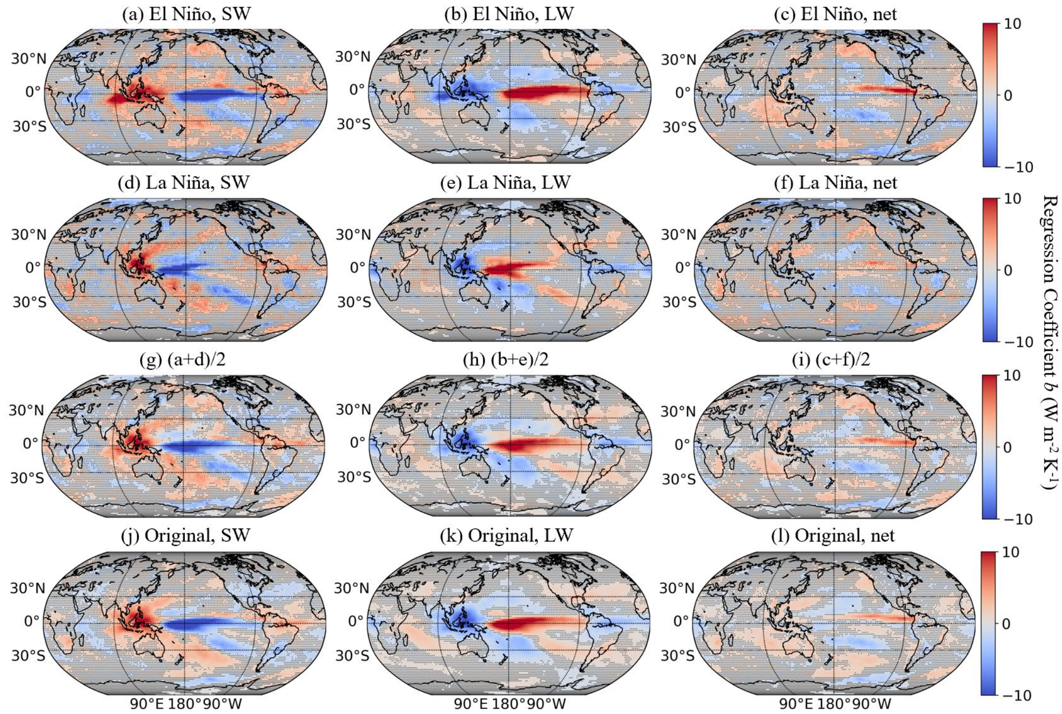


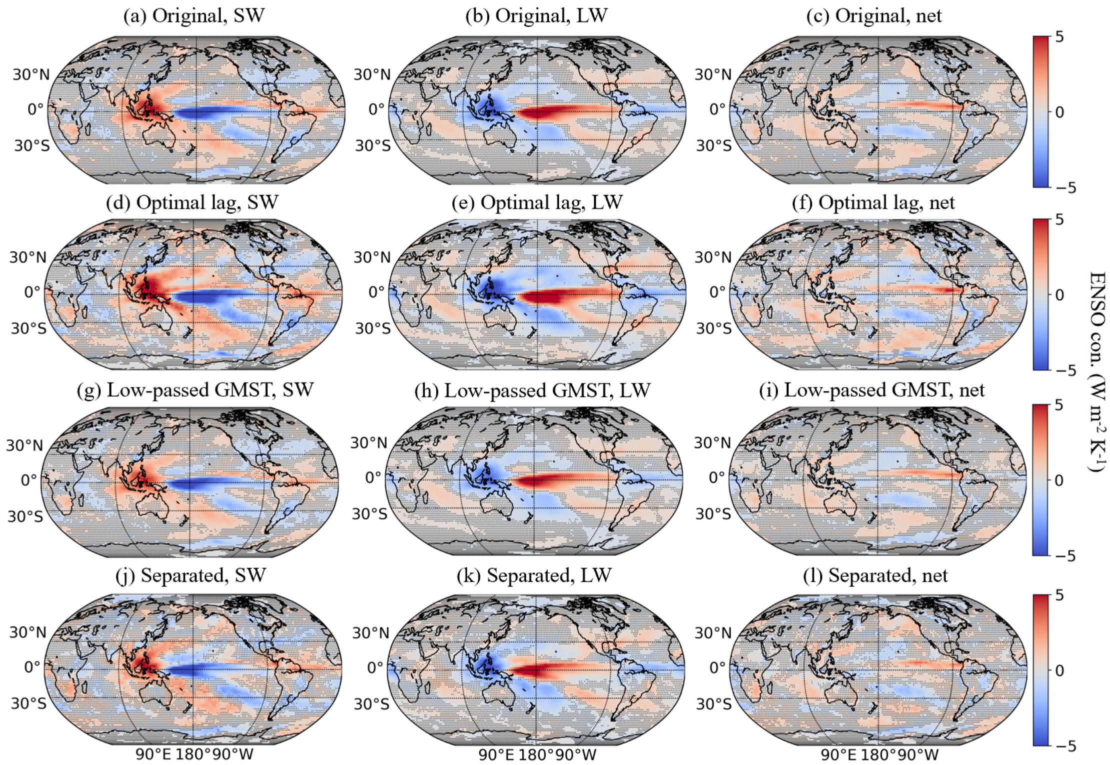
Figure R3: Maps of regression coefficient b in Eq. 1 for CRE_{SW} (left column), CRE_{LW} (middle column), and CRE_{net} (right column) derived from ERA5 data (January 1981–December 2020). (a–c) Coefficient calculated using data with filtered ONI > 0. (d–f) Coefficient calculated using data with filtered ONI < 0. (g–i) The mean of (a–c) and (d–f). (j–l) Coefficient calculated using all data. Black dots denote grids with statistically insignificant results at the 95% confidence level. For (g–i), significance is determined where either the coefficient from the positive or negative phase regression is significant.

Conclusion: Collectively, the estimates of ENSO contributions derived from these advanced models (Fig. S1d–l) are consistent with those from the simpler model employed in our original manuscript (Fig. S1a–c). Therefore, to preserve methodological clarity and conciseness, we have retained the original model in the main text. We added a discussion of these robustness tests in Section 2.3 and provided detailed results in the SI (Text S1 and Fig. S1), as cited below:

Revised text in Section 2.3: "*Additional sensitivity analyses testing the assumptions of zero lag, linear trends, and ENSO linearity, via optimal lags, low-pass filtered GMST, and separate phase regressions, respectively, further confirm the robustness of the simplified model (see further details in Text S1 and Fig. S1).*"

Added text and figure in the SI: "***Text S1: Validation of Regression Model Assumptions***

To assess the sensitivity of our OLS multivariate regression model (Eq. 1, main text) to its underlying assumptions, we conducted three sensitivity tests using ERA5 data (January 1981–December 2020) (Fig. S1). First, we tested the zero-lag assumption by determining the optimal lag for each variable (Figs. S1d–f). Second, we evaluated the *assumption of linear trends by replacing the term t with low-pass filtered GMST (Figs. S1g–i). Third, we examined ENSO asymmetry by performing separate regressions for El Niño and La Niña phases (Figs. S1j–l). The spatial patterns and magnitudes of the ENSO contributions derived from these sensitivity tests are consistent with those from the original model (Figs. S1a–c), validating the robustness of the OLS multivariate regression model used in the main text.*"



"*Figure S1: Maps of the ENSO contribution to CRESW (left column), CRELW (middle column), and CREnet (right column), derived from ERA5 data (January 1981–December 2020). (a–c) Original model (Eq. 1). (d–f) Model with optimal lags (range: –12 to 12 months; negative lags indicate ONI leads). (g–i) Model with the linear time term t replaced by low-pass filtered GMST (periods shorter than 15 years removed). (j–l) Model considering El Niño and La Niña phases separately. Black dots denote grids with statistically insignificant results at the 95% confidence level. For (j–l), significance is determined where either the coefficient from the positive or negative phase regression is significant.*"

Minor Comments, Typos, etc.:

1. L22: The Sherwood et al climate sensitivity review estimates a positive cloud feedback, even if it is still quite uncertain.

Answer: Thank you for this comment. The text has been revised to read: "*While Sherwood et al. (2020) constrained the cloud feedback to be positive (amplifying warming), its magnitude remains highly uncertain across current global climate models*

(GCMs). This uncertainty is the dominant source of the spread in equilibrium climate sensitivity estimates (Forster et al., 2021)."

Added reference: *Sherwood, S. C., Webb, M. J., Annan, J. D., Armour, K. C., Forster, P. M., Hargreaves, J. C. et al.: An assessment of Earth's climate sensitivity using multiple lines of evidence. Rev. Geophys., 58, e2019RG000678, doi.org/10.1029/2019RG000678, 2020.*

2. L50: "data" is plural.

Answer: Thank you for pointing this out. We have corrected the text and thoroughly checked the manuscript to ensure "data" is consistently treated as a plural noun throughout.

3. L78: Please say more about how the ONI is calculated for the different datasets. What is the reference period in the 4xCO_2 simulations? It would also be good to clarify that it has units of K (I usually assume an "index" is non-dimensional).

Answer: We thank the reviewer for raising these important points regarding the ONI calculation. We have revised Section 2.2 to provide a detailed description of the methodology, explicitly stating the units (K) and clarifying the reference period used for both the reanalysis data and the 4xCO_2 simulations. The modified text reads:

"*We first derive the oceanic Niño index (ONI) from these data to quantify ENSO activity. The ONI is calculated as the area-weighted 3-month running mean of sea-surface temperature anomalies (units: K) over the Niño 3.4 region (5° S–5° N, 170° W–120° W). For each dataset, anomalies are defined relative to the climatology over the corresponding study period (see Section 2.1).*"

4. L105: It would be helpful to point out here that using the bandpass filtered ONI mostly eliminates linear trends.

Answer: Thanks. We have revised the relevant text in Section 2.3 as follows:

"*Specifically, because the ONI is calculated without explicitly removing the long-term warming trend, we first use a bandpass filter to retain only the variability within the typical ENSO periodicity band of 2–7 years (Fig. 1). This filtering effectively eliminates linear trends and decouples the core ENSO signal from other climate perturbations, such as the Atlantic Multi-decadal Variability and the Pacific Decadal Oscillation.*"

5. L110/13: There is a circumflex on Y in Eq 1 but not Eq 2.

Answer: We thank the reviewer for pointing out this inconsistency and have added the circumflex on $Y_{ENSO-corrected}$ in Eq. 2 to ensure notational consistency with Eq. 1.

6. L123: Strictly speaking the CRE-GMST regression slope is not the same as the cloud feedback parameter, as it neglects things like cloud masking. Please adjust terminology throughout and add a brief sentence acknowledging the limitations of using the

regression slope (ignores cloud masking, etc.). This doesn't affect the analysis presented here, but it does affect the interpretation.

Answer: We agree that the regression slope is an approximation and does not strictly account for cloud masking effects. To address this, we have revised the terminology to use "cloud feedback estimates" and added a sentence in the methodology section to acknowledge this limitation. The modified text reads:

"*To estimate the cloud feedback on global warming, following previous studies (e.g., Clement et al., 2009; Zhou et al., 2015; Uribe et al., 2022; Ceppi and Nowack, 2021; Dessler, 2010), we derive cloud feedback estimates by calculating the OLS regression slope between CRE and GMST (e.g.,* $\frac{\partial CRE_{net}}{\partial GMST}$*). Although this slope technically differs from the true cloud feedback due to effects such as cloud masking, it serves as a valid proxy for our analysis. However, it is important to note that such a method inherently captures the influence of factors affecting both global temperature and cloud properties, such as ENSO, thereby confounding the true feedback with internal variability.*"

7. Figure 2: Why do you use K for some variables and C for others?

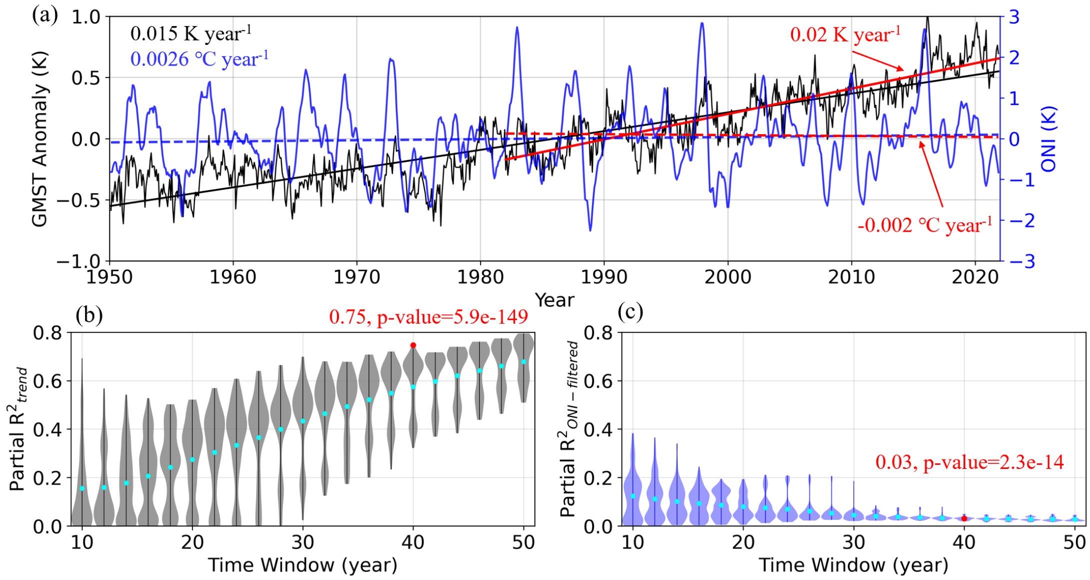
Answer: Thank you for pointing out this inconsistency. We have standardized all temperature units to Kelvin (K) throughout the revised manuscript.

8. L155: Please explain why you aren't using the bandpass filtered ONI here.

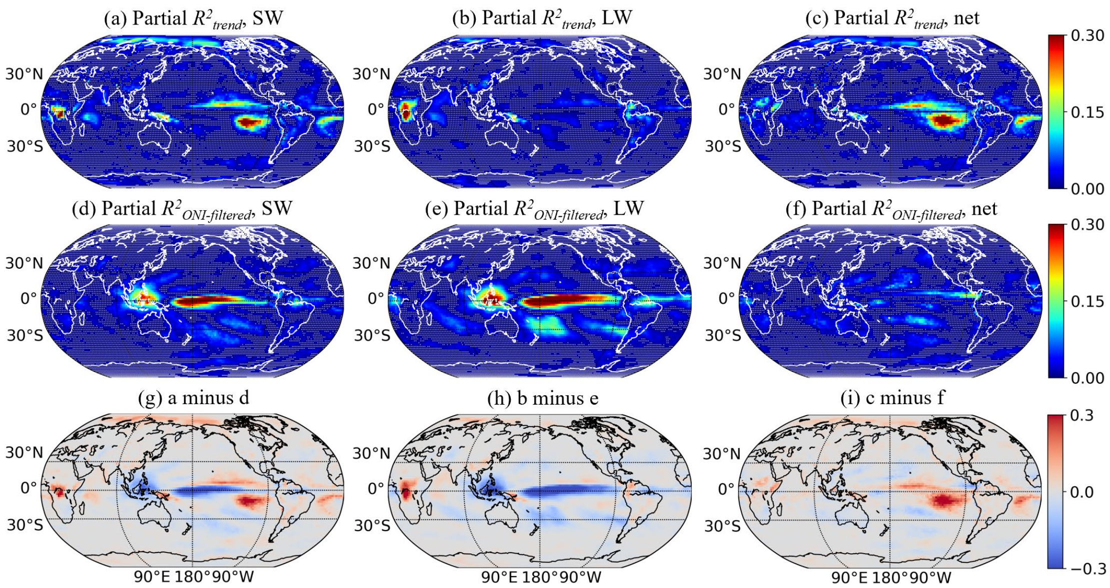
Answer: We initially used the unfiltered ONI to provide a more comprehensive assessment, as the ONI showed no significant long-term trends during the study period, and signals outside the 2–7 year band may represent real ENSO features. However, to ensure consistency throughout the manuscript, we have updated the analysis to use the bandpass-filtered ONI. The revised text and figures (Figs. 2–3, Figs. S2 and S4) are cited below:

"*To quantify this, we calculate the coefficient of partial determination (partial* R^2*) using OLS multivariate regression models (Eq. 1) and present the results as a function of the time window (ranging from 10 to 50 years, the upper limit of 50 years was selected to ensure an adequate sample size for robust analysis). The corresponding test statistics (Fig. S2) suggest that the ONI regression coefficient (b in Eq. 1) is statistically significant at the 95% confidence level across nearly all analyses, even when the explained variance is moderate. This allows us to assess the relative contribution of the warming trend (partial* R^2_{trend}*; Fig. 2b) and ENSO (partial* $R^2_{ONI\text{-}filtered}$*; Fig. 2c) to the total variance of GMST across different timescales with high confidence.*"

"*For instance, in the 40-year subset from January 1982–December 2021 (red dots in Figs. 2b–c), the warming trend explains approximately 75% of GMST variance, whereas ENSO accounts for only about 3%.*"

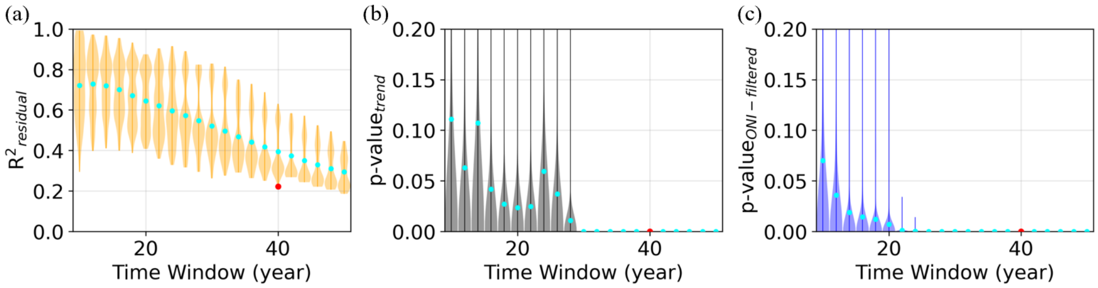


"Figure 2: Analysis of the GMST variations driven by the temporal trend and ENSO, derived from ERA5 data (January 1950–December 2021). (a) Time series of GMST anomaly (black curve; left y-axis) and ONI (blue curve; right y-axis). The black and blue lines represent the corresponding OLS regression fits, with the values indicating their slopes. (b–c) Violin plots of (b) partial R^2_{trend} and (c) partial $R^2_{ONI\text{-}filtered}$ for GMST, shown as a function of the time window (2-year intervals). For each time window, the vertical line indicates the range (minimum to maximum), the shaded area represents the probability density, and the cyan dot denotes the mean value. The red lines, dots and numbers highlight the results for the selected representative 40-year subset (January 1982 – December 2021) that is analyzed in Figs. 3–4. In panel (a), solid and dashed lines represent the statistically significant and insignificant trends at the 95% confidence level, respectively."

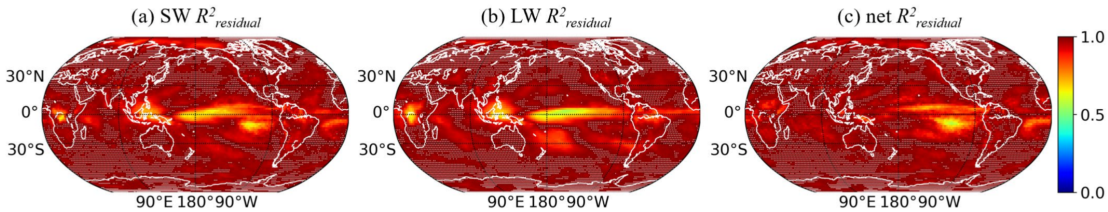


"Figure 3: Analysis of variations in CREs driven by the temporal trend and ENSO, derived from ERA5 data (January 1982–December 2021). (a–c) Partial R^2_{trend} for (a) CRE_{SW}, (b) CRE_{LW}, and (c) CRE_{net}. (d–f) Partial $R^2_{ONI\text{-}filtered}$ for (d) CRE_{SW}, (e) CRE_{LW},

and (f) CRE$_{net}$. (g–i) The difference between (a–c) and (d–f). In panels (a–f), white dots denote grids with statistically insignificant partial regression coefficients for the corresponding variables (time for a–c; ONI for d–f) at the 95% confidence level."



"*Figure S2: Violin plots of residual R^2 and P-value corresponding to Figs. 2b–c in the main text. (a) Residual R^2, (b) p-value of the partial regression coefficient of time (i.e., a in Eq. 1), and (c) p-value of the partial regression coefficient of ONI (i.e., b in Eq. 1).*"



"*Figure S4: Maps of residual R^2 for results in Fig. 3 in the main text. (a) CRE$_{SW}$, (b) CRE$_{LW}$, and (c) CRE$_{net}$. White dots denote grids with statistically insignificant partial regression coefficients of both time and ONI (i.e., a and b in Eq. 1) at the 95% confidence level.*"

9. L171: Please list the indices and show the results in the supplement.

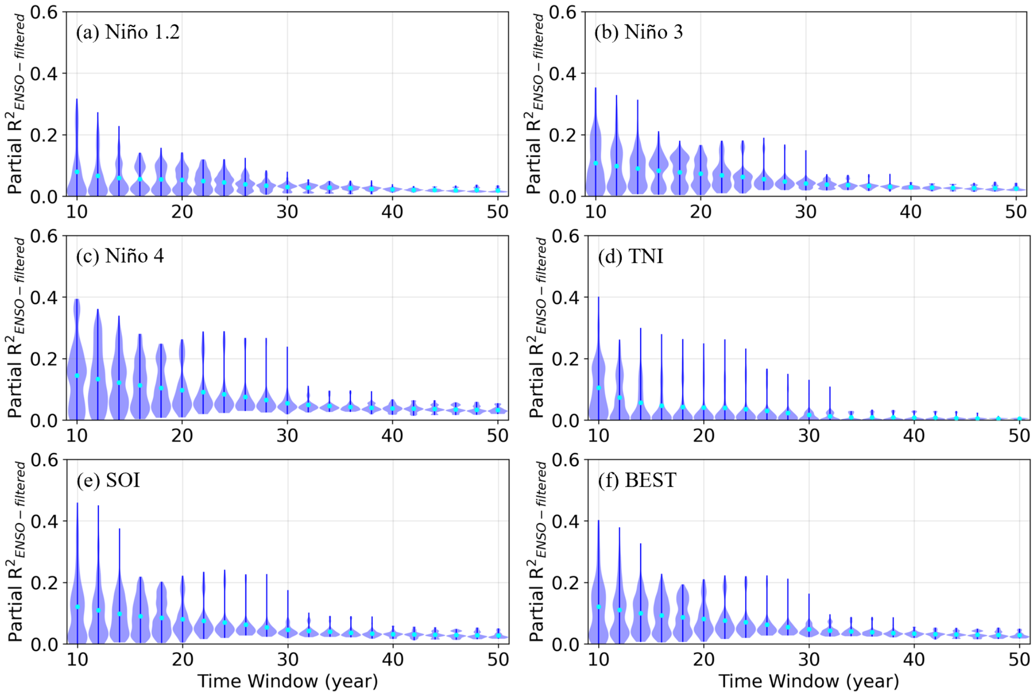
Answer: We thank the reviewer for this suggestion. We have added a detailed description of the additional indices and the corresponding analysis to the SI (Text S2 and Fig. S3). The relevant content is presented below:

Revised text in Section 3.1: "*In addition, to account for the potential limitations of ONI in fully representing ENSO (Johnson, 2013), we conducted a similar analysis using six other ENSO indices and obtained similar results (see further details in Text S2 and Fig. S3).*"

Added text in the SI: "***Text S2: Sensitivity to ENSO Index Selection***

In the main text, we use the ONI as the primary measure of ENSO intensity, as it is NOAA's standard indicator for monitoring the ENSO oceanic signal. However, the ONI focuses specifically on the Niño 3.4 region and may not fully capture ENSO dynamics. To assess the sensitivity of our results to this choice, we analyzed six additional ENSO indices for 1950–2021, including the Niño 1+2, Niño 3, and Niño 4 indices, as well as the Trans-Niño Index (TNI), Southern Oscillation Index (SOI), and Bivariate ENSO Timeseries (BEST).

Specifically, the Niño 1+2, 3, and 4 indices were derived from ERA5 sea-surface *temperature anomalies over the far eastern (10°S–0°, 90°W–80°W), central (5°S–5°N, 150°W–90°W), and western (5°S–5°N, 160°E–150°W) equatorial Pacific. The TNI (standardized difference between Niño 1+2 and Niño 4), SOI (standardized difference between surface pressure at Darwin and Tahiti), and BEST (combination of normalized Niño 3.4 and SOI) were obtained from NOAA (https://psl.noaa.gov/enso/dashboard.html). The partial R^2 values for these indices (Fig. S3) exhibit similar temporal variations and are consistent with the ONI-based results (Fig. 1c), confirming that the conclusions of this study are robust and not strongly dependent on the specific ENSO index used.*"



"*Figure S3: Same as Fig. 1c in the main text, but for different ENSO indices (January 1950–December 2021). (a) Niño 1+2, (b) Niño 3, (c) Niño 4, (d) TNI, (e) SOI, and (f) BEST.*"

10. Figure 3 and associated discussion: I think it would be worth explicitly pointing out that these maps show where there's a forced CRE signal and where the CRE is still dominated by ENSO-induced variability. It's interesting that outside the Pacific the CRE is generally not related to either of these.

Answer: Thank you for this comment. The updated discussion associated with Fig. 3 reads:

"*Figures 3a–c show the spatial distribution of variations in CRE_{SW}, CRE_{LW}, and CRE_{net} attributed to the temporal trend (partial R^2_{trend}). High values indicate regions with a significant forced CRE signal. Given the significant warming trend in GMST during this period (0.02 K year^{-1}), the resulting patterns reveal strong co-variations between CREs and recent warming in regions such as the Arctic, central Africa, and the tropical eastern oceans. Figures 3d–f illustrate the variations in CREs attributed to ENSO (partial $R^2_{ONI\text{-}filtered}$). High values indicate regions where the CRE is dominated by*

ENSO-induced variability. These dominant spatial patterns align well with previous findings revealing the influence of ENSO on cloud properties (Yang et al., 2016; Li et al., 2021; Liu et al., 2023). Figures 3g–i display the difference between the two components (partial R^2_{trend} minus partial $R^2_{ONI\text{-}filtered}$). Compared to ENSO, the temporal trend has a much weaker impact on CREs over a large portion of the low- to mid-latitude oceans (blue shading in Figs. 3g–i). This is particularly evident for CRE_{SW} and CRE_{LW} across the Pacific, implying a region-dependent ENSO contribution to long-term cloud feedback estimates. Notably, outside the Pacific, CRE variations are generally weakly influenced by either of these factors, suggesting a potential role of other drivers or background noise."

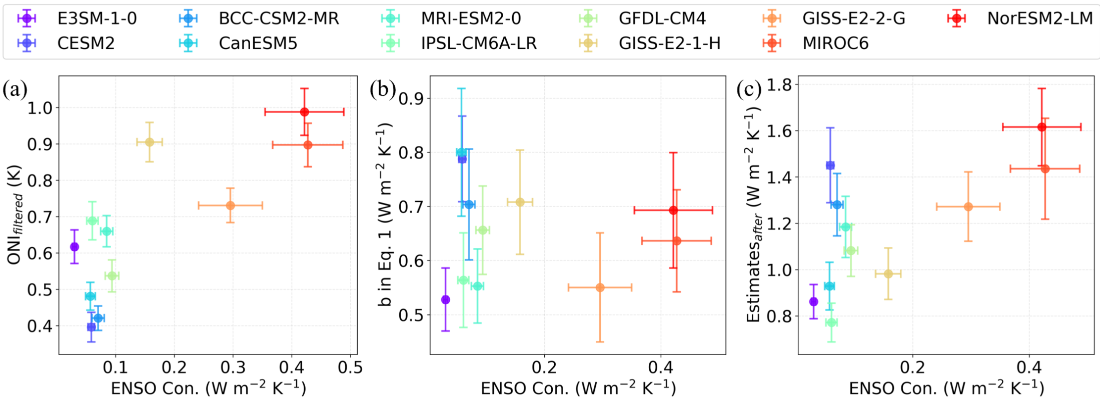
11. Figure 5: I agree with the previous reviewer that the "ENSO effect minimal time" is kind of odd. Maybe a better definition would be to repeat the ENSO relative contribution calculation (panels j-l of Fig 4) for all times >=10 years and find when the relative contribution first goes above 50%.

Answer: We sincerely thank the reviewer for this alternative perspective. While the choice of metric can vary depending on the research focus, we believe prioritizing physical objectivity is advantageous for our analysis. As noted by the previous reviewer, metrics based on relative contribution are highly sensitive to the magnitude of the trend term, which introduces uncertainty regarding robustness. Therefore, we have adopted the definition based on an absolute threshold (1 W m^{-2} K^{-1}). This approach provides a clearer benchmark by directly quantifying when the ENSO influence becomes negligible, which we believe aligns well with the objectives of the current study.

12. L272: Can you say more about why these models feature strong ENSO contributions? There are several possibilities: (1) weak forced CRE trends (e.g., MRI), (2) large ENSO amplitudes, (3) large responses to ENSO (large b in equation 1). In fact, it would be interesting to dig into these a little more. E.g., you could add a scatter plot across of ENSO contribution vs (1) ONI standard deviation, (2) regression coefficient b, and (3) forced CRE trend magnitude.

Answer: We thank the reviewer for this insightful suggestion. Following your recommendation, we have added a new figure (Fig. S8) to the SI to systematically examine the three potential drivers. Our analysis clarifies that: (1) weak forced trends are not the cause, as models with larger ENSO contributions actually exhibit stronger forced trends (Fig. S8c); (2) large ENSO responses (coefficient *b*) play a secondary role (Fig. S8b); and (3) strong ENSO amplitude is the primary driver (Fig. S8a). We have revised Section 3.4 to incorporate these findings:

"*Further analysis (Fig. S8) reveals that the substantial ENSO contributions found in these models are primarily driven by their strong ENSO variability (Fig. S8a), while the ENSO sensitivity (b in Eq. 1) plays a secondary role (Fig. S8b). Notably, these models also tend to exhibit stronger forced cloud feedback estimates (Fig. S8c).*"



"*Figure S8: Scatter plots derived from GCM simulations of the abrupt-4×CO_2 experiment (first 150 years), showing the relationship between ENSO contribution and (a) bandpass-filtered ONI, (b) regression coefficient b in Eq. 1, and (c) cloud feedback estimates after the ENSO correction. Dots represent the mean absolute magnitude (temporal mean for ONI, spatial mean for others); error bars indicate the corresponding standard deviations (scaled by 1/10 for visual clarity)*."