

Geophysical Research Letters[®]



RESEARCH LETTER

10.1029/2026GL122980

Key Points:

- Neural network applied to observed temperature and extended model simulations predict variations of the global feedback parameter up to 2025
- Radiative feedbacks experienced a minimum around 1983–2012 but have since been trending toward a less stable climate
- The warm subtropical Northeast Pacific weakened the radiative feedback recently

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

S. Van Loon,
senne.van_loon@colostate.edu

Citation:

Van Loon, S., Rugenstein, M., Zelinka, M. D., & Andrews, T. (2026). Recent weakening of the global radiative feedback. *Geophysical Research Letters*, 53, e2026GL122980. <https://doi.org/10.1029/2026GL122980>

Received 12 MAR 2026

Accepted 28 MAY 2026

Author Contributions:

Conceptualization: Senne Van Loon, Maria Rugenstein

Data curation: Senne Van Loon, Mark D. Zelinka, Timothy Andrews

Formal analysis: Senne Van Loon

Funding acquisition: Senne Van Loon, Maria Rugenstein, Mark D. Zelinka, Timothy Andrews

Investigation: Senne Van Loon

Methodology: Senne Van Loon, Maria Rugenstein, Mark D. Zelinka, Timothy Andrews

Project administration: Senne Van Loon, Maria Rugenstein

Resources: Senne Van Loon, Mark D. Zelinka, Timothy Andrews

Software: Senne Van Loon, Mark D. Zelinka, Timothy Andrews

Supervision: Maria Rugenstein

© 2026. The Author(s).

This is an open access article under the terms of the [Creative Commons Attribution License](#), which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

Recent Weakening of the Global Radiative Feedback

Senne Van Loon¹ , Maria Rugenstein¹ , Mark D. Zelinka² , and Timothy Andrews^{3,4} 

¹Department of Atmospheric Science, Colorado State University, Fort Collins, CO, USA, ²Lawrence Livermore National Laboratory, Livermore, CA, USA, ³Met Office Hadley Centre, Exeter, UK, ⁴School of Earth and Environment, University of Leeds, Leeds, UK

Abstract Earth's climate stability, characterized by the global radiative feedback parameter (λ), varies decadal due to changing surface temperature patterns. Recent variations in λ are poorly understood as coordinated model simulations typically end in 2014. We apply a convolutional neural network trained on climate model simulations to observation-based surface temperature reconstructions to estimate variations in λ up to 2025. We find that λ reached a minimum (maximum stability) around the mid 1990s ($\lambda \simeq -3 \text{ Wm}^{-2}/\text{K}$), but has since weakened significantly ($\lambda \simeq -2 \text{ Wm}^{-2}/\text{K}$). We confirm these results with climate model simulations extended to 2022. The recent λ weakening is not significantly affected by El Niño Southern Oscillation or Pacific Decadal Oscillation. Attribution reveals that warming in the subtropical Northeast Pacific is an important driver of the recently weakened feedback, confirmed by targeted experiments in E3SMv2. Our approach enables near real-time monitoring of Earth's climate stability.

Plain Language Summary As Earth warms, it radiates excess heat to space. This cooling mechanism, known as radiative feedback, keeps the climate stable. The strength of the feedback depends on the geographical pattern of surface temperature changes. We use machine learning and climate model simulations with observed surface temperature reconstructions to estimate how the feedback has changed since the beginning of the 20th century to present day. We find that the climate was most stable in the 1990s. Since then, the feedback has weakened, that is, the climate is currently less efficient at losing heat than in the 1980s and 1990s. We attribute this weakening to spatially changing temperature patterns, especially in the subtropical Northeast Pacific Ocean. By using machine learning to process current temperature fields, we can now monitor changes in Earth's climate stability in near real-time, helping us better understand how the planet's warming rate is evolving.

1. Introduction

Variations in the Earth's surface temperature influence the energy flux at the top of the atmosphere. The sensitivity of the global-mean radiative response (R) to changes in global-mean surface temperature (ΔT) is characterized by the global radiative feedback parameter λ : $R = \lambda \Delta T$. The global feedback is negative in the current climate, indicating that the Earth is able to release excess energy by warming. A strong (in magnitude) λ indicates a more stable climate system, while a weak λ indicates a less stable climate system. The Earth's energy imbalance (N) is influenced by both R and effective radiative forcing (F), such that $N = F + R + \epsilon = F + \lambda \Delta T + \epsilon$, with ϵ denoting internal variability.

The feedback λ varies on decadal timescales due to changing spatial surface temperature patterns (e.g., Andrews et al., 2015, 2022; Armour et al., 2013; Gregory & Andrews, 2016; Rugenstein et al., 2023; Senior & Mitchell, 2000). This phenomenon is termed the “pattern effect.” Variations in λ have been linked to lapse rate and low cloud feedbacks, which are sensitive to surface temperature patterns (e.g., Andrews & Webb, 2018; Ceppi & Gregory, 2017; Dong et al., 2019; Zhou et al., 2016), but other cloud types, surface albedo (including sea-ice), and water vapor play a role as well (e.g., Andrews et al., 2018, 2022; Quan et al., 2025; Zhou et al., 2025).

Since R cannot be observed directly, we often use model simulations to estimate λ . Coordinated model efforts, such as the Cloud Feedback Model Intercomparison Project (CFMIP3, Webb et al., 2017), have allowed for quantification of the pattern effect and its expression in different climate models, by running atmosphere-only climate models with observed sea surface temperature (SST) boundary conditions. However, these simulations end in 2014, limiting our understanding of more recent changes in λ . Previous estimates have indicated that λ weakened (i.e., became less stable) after 2014, coinciding with the strong 2015–2016 El Niño event, a sign change

Validation: Senne Van Loon
Visualization: Senne Van Loon
Writing – original draft: Senne Van Loon
Writing – review & editing: Senne Van Loon, Maria Rugenstein, Mark D. Zelinka, Timothy Andrews

of the Pacific Decadal Oscillation (PDO) index, and enhanced Northeast Pacific warming (Andrews et al., 2022; Loeb et al., 2020, 2021).

Here, we use machine learning to estimate λ from historical surface temperature reconstructions, allowing us to extend the analysis to the present day (Rugenstein et al., 2025; Van Loon et al., 2025). We use a convolutional neural network (CNN) trained on climate model simulations to learn the relationship between spatial surface temperature and global-mean R . We then apply this CNN to different surface temperature reconstructions to estimate historical variations in R and λ . We compare this statistical approach to extended climate model runs after 2014 and confirm that λ has weakened more recently (i.e., more positive feedbacks and a less stable climate system; Section 3) and attribute the weaker λ to varying surface temperature patterns (Section 4).

2. Data and Methods

2.1. Climate Model Data

We use a combination of simulations from CMIP5 and CMIP6 atmospheric general circulation models (AGCMs) and coupled Earth system models (ESMs), including *historical* (Eyring et al., 2016), *piClim-histall* (Pincus et al., 2016), and *amip-piForcing* (Webb et al., 2017) experiments (Table S1 in Supporting Information S1). From each simulation, we use the net top-of-atmosphere radiative flux ($N = \text{rsdt} - \text{rsut} - \text{rlut}$ in CMIP notation, defined as positive downwards) and near-surface (2 m) temperature (tas , $\mathbf{T}$). We use bold-faced variables to indicate spatial quantities (i.e., on a latitude-longitude grid), while plain variables indicate global values. The *historical* simulations are fully coupled, *piClim-histall* are atmosphere-only runs with preindustrial climatological SST and sea-ice boundary conditions and historically varying forcing agents, and *amip-piForcing* are atmosphere-only runs with historically varying SST and sea-ice boundary conditions and constant forcing at preindustrial levels.

We use R from *historical* large initial-condition ensemble simulations from one CMIP5 and six CMIP6 ESMs in 1871–2014. All ESMs have at least 20 *historical* ensemble members. We calculate $R_{\text{hist}} = N_{\text{hist}} - F_{\text{piClim-histall}}$, where N_{hist} is the net top-of-atmosphere energy flux (from coupled *historical* simulations) and $F_{\text{piClim-histall}} = N_{\text{piClim-histall}}$ is the effective radiative forcing from the *piClim-histall* experiment (averaged over all ensemble members if multiple are available). The *historical* near-surface temperature $\mathbf{T}_{\text{hist}}$ is taken from the same coupled simulations.

In *amip-piForcing* simulations, $R_{\text{amip-piForcing}} = N_{\text{amip-piForcing}}$ since the effective radiative forcing is zero by design. We use *amip-piForcing* simulations from eight CMIP6-generation AGCMs that contributed to CFMIP3 (CFMIP hereafter) to obtain R_{CFMIP} and $\mathbf{T}_{\text{CFMIP}}$ in 1870–2014. We compare the CFMIP ensemble with two extended AGCM experiments. The first ($\mathbf{T}_{\text{HadGEM3}}$, R_{HadGEM3}) is a single ensemble member from 1871 to 2020 in HadGEM3-GC31-LL (Kuhlbrodt et al., 2018) with PCMDI AMIP SST boundary conditions (Taylor et al., 2000) and preindustrial emissions. The second ($\mathbf{T}_{\text{E3SMv2}}$, R_{E3SMv2}) is a set of AGCM experiments performed with the E3SMv2 atmospheric model (Golaz et al., 2022) and emissions fixed at year-2010 level (*amip-F2010*). The simulations use SST boundary conditions from four reconstructions: HadISST-1.1 (Rayner et al., 2003), NOAA ERSST v5 (Huang et al., 2017), NOAA OISST v2.1 (Huang et al., 2021), and PCMDI AMIP SST (Taylor et al., 2000). We use 10 ensemble members for each SST data set spanning 1979–2022.

We use yearly-mean values as anomalies with respect to 1980–1999. All $\mathbf{T}$ are bilinearly regridded to a common $2.8^\circ \times 2.8^\circ$ grid, R is a global mean, and ΔT is the global-mean 2 m temperature anomaly calculated from the regridded data set.

2.2. Convolutional Neural Network

We follow the methodology of Rugenstein et al. (2025) and Van Loon et al. (2025) to predict the global radiative response R from surface temperature anomalies with a CNN (see SI for details). Whereas Rugenstein et al. (2025) and Van Loon et al. (2025) used only internal variability to train the CNN, here we include the forced signal. The input to the CNN is $\mathbf{T}$ and the output is R in the same year. We first train the CNN on $\mathbf{T}_{\text{hist}}$ to predict R_{hist} from large initial-condition ensemble ESM runs (Table S1 in Supporting Information S1). We use 14 ensemble members from each ESM to train, three for validation, and three for testing. The gradient of the CNN, $\nabla_{\mathbf{T}} R_{\text{CNN}}$, quantifies the sensitivity of R to temperature perturbations in $\mathbf{T}$ and can be interpreted as local feedback (similar

to, e.g., Green's functions; Zhou et al., 2017; Dong et al., 2019; Bloch-Johnson et al., 2024). The gradient (Figure S2 in Supporting Information S1) shows that the pattern of local feedback is consistent with our theoretical understanding of the pattern effect (Rugenstein et al., 2025). Moreover, the CNN performs well on unseen test data (Figure S3 in Supporting Information S1), indicating that the CNN has learned a robust, physical relationship between $\mathbf{T}$ and R .

Then, we finetune the CNN on $\mathbf{T}_{\text{CFMIP}}$ and R_{CFMIP} . We take the CNN trained on *historical* data and continue training on *amip-piForcing* data only. Since CNNs generally require large data sets to train, this two-step process allows the CNN to learn from the limited CFMIP data set. We randomly select 70 years to train, 35 to validate, and 40 to test, and use those years from every AGCM. Validation data is used to stop the training process, to avoid overfitting. Note that, because CFMIP experiments use a historical SST reconstruction (PCMDI AMIP, the same data set for each AGCM; Taylor et al., 2000), the CNN is finetuned on 2 m temperature that is strongly constrained by observations over ocean areas. Temperature over land is freely evolving in AGCM experiments. No extended AGCM runs are used to train the CNN. The gradient of the CNN does not change notably after finetuning (Figure S2 in Supporting Information S1) and hence, historical variability of λ does not change much (Figures S4 and S5 in Supporting Information S1). However, finetuning the CNN improves the magnitude of predicted λ (Section 2.3).

Finally, we apply the trained and finetuned CNN to $\mathbf{T}_{\text{rc}}$ from different spatially complete reconstructions (rc; Table S2 in Supporting Information S1). We use 2 m temperature from three atmospheric reanalyses [ERA5, Hersbach et al. (2020); JRA-3Q, Kosaka et al. (2024); and MERRA-2, Gelaro et al. (2017)] and four data sets that combine SST with land surface air temperature [Berkeley Earth, Rohde and Hausfather (2020); DCENT-I, Chan, Chan, Siddons, Cable, Faulkner, et al. (2026); HadCRUT5, Morice et al. (2021); and NOAA GlobalTempV6, Huang et al. (2024)]. Spatial SST anomalies are similar to 2 m temperature anomalies. We process $\mathbf{T}_{\text{rc}}$ the same as the climate model data: yearly anomalies are defined with respect to 1980–1999 and bilinearly regridded to $2.8^\circ \times 2.8^\circ$. Reconstructions $\mathbf{T}_{\text{rc}}$ are not used to train the CNN, but only for inference.

We use SHapley Additive exPlanations (SHAP) values (Lundberg & Lee, 2017) to decompose R_{CNN} into contributions from each grid box. SHAP is an eXplainable AI attribution technique. SHAP values $\mathbf{S}$ constitute an attribution map that quantifies how much the input $\mathbf{T}$ contributes to the output R_{CNN} . SHAP values are complete, such that $R_{\text{CNN}} = \sum_j S_j$, with j denoting the grid box.

2.3. Differential Global Feedback Parameter

We use the differential feedback parameter to study temporal variations of λ (Andrews et al., 2015, 2022; Rugenstein & Armour, 2021). In a given 30-year period ending in year t , we estimate $\lambda(t) = \partial R / \partial \Delta T|_{[t-29, t]}$ as the linear regression slope of $\{R(t-29), \dots, R(t)\}$ against global-mean near-surface temperature $\{\Delta T(t-29), \dots, \Delta T(t)\}$. The feedback $\lambda(t)$ thus represents how R linearly varies with ΔT over moving 30-year windows and their associated surface temperature patterns. Each $\lambda(t)$ and temperature pattern can be the result of internal variability, external forcing, or a combination of both (e.g., Lin et al., 2025; Rugenstein & Armour, 2021). We calculate λ directly from AGCM output (λ_{CFMIP} , λ_{HadGEM3} , λ_{E3SMv2}) and from the CNN applied to reconstructions (λ_{CNN}).

We compare λ_{CNN} to another observation-based estimate. We use N from a reconstruction (DEEP-C, Allan et al., 2014; Liu et al., 2020) and observations (CERES-EBAF, Loeb et al., 2018) combined with the historical forcing estimate from Forster et al. (2025) to calculate $R_{\text{satellite}} = N_{\text{satellite}} - F_{\text{Forster}}$ and then $\lambda_{\text{satellite}} = \partial R_{\text{satellite}} / \partial \Delta T_{\text{rc}}$, using different reconstructions (Table S2 in Supporting Information S1) for global mean temperature ΔT_{rc} . Because $N_{\text{satellite}}$ uses different satellite products throughout the record (none of which are 30 years long), we cannot exclude that changes in $\lambda_{\text{satellite}}$ are due to inconsistencies between observational products, but we can qualitatively use $\lambda_{\text{satellite}}$ as an independent line of evidence for recent variations in λ .

SHAP values are used to attribute λ to surface temperature patterns. We calculate the local contribution to $\lambda(t)$ by regressing the SHAP values in each grid box j to global mean temperature to obtain $L_j(t) = \partial S_j / \partial \Delta T|_{[t-29, t]}$, with $\lambda(t) = \sum_j L_j(t)$. Similarly, we define the surface temperature pattern $P_j(t) = \partial T_j / \partial \Delta T|_{[t-29, t]}$. In a given 30-year period, $\mathbf{P}(t)$ indicates how surface temperature varies with global mean temperature, while $\mathbf{L}(t)$ indicates the contribution of $\mathbf{P}(t)$ in each grid box to the global feedback $\lambda(t) = \sum_j L_j(t)$.

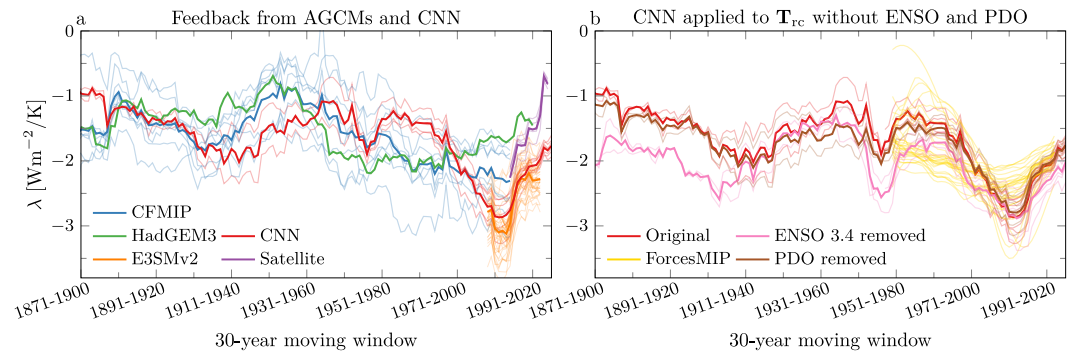


Figure 1. (a) The global feedback parameter λ estimated from AGCMs that contributed *amip-piForcing* experiments to CMIP6 (CFMIP, blue, ending in 2014), an extended *amip-piForcing* experiment in HadGEM3-GC31-LL (green, ending in 2020), *amip-F2010* experiments in E3SMv2 (orange, ending in 2022), the CNN applied to seven historical surface temperature reconstructions (red, ending in 2025), and an estimate based on satellite observations (satellite, purple, ending in 2024). (b) The global radiative feedback parameter λ estimated from the CNN applied to T_{rc} (red, as in a); $T_{rc}^{3.4}$ with the El Niño Southern Oscillation (ENSO) linearly removed (as defined by the Niño 3.4 region; pink); T_{rc}^{PDO} with the Pacific Decadal Oscillation (PDO) linearly removed (brown); and $T_{ForcesMIP}$ (yellow, Wills et al., 2026). Thin lines are individual model simulations (for CFMIP), ensemble members (for E3SMv2), or temperature reconstructions (for CNN and satellite); thick lines are a mean across the thin lines per data set.

3. Historical Variations of the Global Radiative Feedback Parameter

We confirm that $\lambda(t)$ varied substantially throughout the twentieth century (Figure 1a). Estimates from the CNN and AGCM experiments show a maximum in the early-to-mid twentieth century ($\lambda \simeq -1 \text{ Wm}^{-2}/\text{K}$) and a minimum in the late twentieth to early twenty-first century, although the exact maximum and minimum periods differ. Some AGCMs show more pronounced decadal variability than others (Figure S6 in Supporting Information S1). HadGEM3-GC31-LL shows a more gradual variation compared to the CNN and E3SMv2 estimates. The latter two indicate a minimum around 1981–2010 to 1985–2014 ($\lambda \simeq -3 \text{ Wm}^{-2}/\text{K}$) and a sharp increase (weakening) afterward ($\lambda \simeq -2 \text{ Wm}^{-2}/\text{K}$). The E3SMv2 ensemble mean predicts $\lambda \lesssim -3 \text{ Wm}^{-2}/\text{K}$ at its minimum, which is more negative than most other estimates, suggesting that E3SMv2 is particularly sensitive to varying SST patterns (Qin et al., 2022, 2024).

The sharp increase in λ after 1985–2014 is confirmed by the satellite-based estimate (purple lines in Figure 1), in line with Loeb et al. (2020) and Andrews et al. (2022). However, $\lambda_{\text{satellite}}$ is weaker than λ_{CNN} and λ_{E3SMv2} , reaching $\lambda_{\text{satellite}} \gtrsim -1 \text{ Wm}^{-2}/\text{K}$ in 1995–2024. This might be due to the estimate of effective radiative forcing from Forster et al. (2025) used to calculate $R_{\text{satellite}}$ and thus $\lambda_{\text{satellite}}$ (Section 2.3). Van Loon et al. (2025) suggest that the Forster et al. (2025) forcing trend estimate is biased low in the last two decades, implying an unphysical underestimation of λ . The CNN estimate λ_{CNN} uses the same method as Van Loon et al. (2025) to determine R and is thus consistent with the strong forcing trend found therein.

The mean CNN estimate deviates from the CFMIP ensemble mean, even though the CNN was finetuned on that data set. When applying the CNN to T_{CFMIP} , the CNN predicts λ similar to the CFMIP multimodel mean (Figure S4 in Supporting Information S1). Therefore, λ_{CNN} has a “model-average” pattern effect, because it has been trained on AGCMs with a wide range of temporal λ variability (Figure S6 in Supporting Information S1). The CNN could be finetuned on separate models to investigate model differences in the pattern effect, which we leave for future work. The difference between λ_{CNN} and λ_{CFMIP} is mainly explained by temperature over land, but differences in near-surface temperature over ocean also play a role, even though SST is the same in each CFMIP simulation. Reconstructions T_{rc} include observed land surface temperature, while T_{CFMIP} has simulated land temperature. Land surface temperature in T_{CFMIP} neglects direct warming due to forcing agents (e.g., CO_2 emissions), that are not included in *amip-piForcing* experiments (e.g., Andrews, 2014; Andrews et al., 2022).

3.1. Spread in Historical Feedback Estimates

The large spread in λ estimates (Figure 1, thin lines) can be due to differences in AGCMs, internal atmospheric variability, or near-surface temperature, both over ocean and land. Averaged over all years, the intermodel

standard deviation is $\sigma_{\text{CFMIP}} \approx 0.43 \text{ Wm}^{-2}/\text{K}$ across CFMIP AGCMs (Figure 1, thin blue lines). Similarly, the standard deviation across E3SMv2 simulations with different SST reconstructions is $\sigma_{\text{E3SMv2}} \approx 0.30 \text{ Wm}^{-2}/\text{K}$ (Figure 1, thin orange lines). Since σ_{E3SMv2} does not include model differences, the variance explained due to model differences is $r_{\text{model}}^2 = 1 - \sigma_{\text{E3SMv2}}^2 / \sigma_{\text{CFMIP}}^2 \approx 50\%$. The standard deviation σ_{CNN} does not change significantly when applying the CNN to **T** output from CFMIP or E3SMv2 instead of reconstructions (Figure S4 in Supporting Information S1). Because σ_{CNN} only includes differences in **T**, the variance explained due to differences in models plus internal atmospheric variability is $r_{\text{model} + \text{IV}}^2 = 1 - \sigma_{\text{CNN}}^2 / \sigma_{\text{CFMIP}}^2 \approx 80\%$. In other words, about $r_{\text{T}}^2 \approx 20\%$ of the λ_{CFMIP} variability in a given year can be explained by differences in near-surface temperature reconstructions alone.

AGCM experiments do not prescribe land temperature, which is freely evolving in response to the prescribed SST. Since CFMIP simulations all use the same SST boundary conditions, we expect most of $r_{\text{T}}^2 \approx 20\%$ to be explained by land temperature variability. To test this, we create an artificial temperature data set **T**_{CFMIP, land}, where we replace near-surface temperature over ocean in **T**_{CFMIP} with the CFMIP multimodel mean, while keeping land temperature unchanged. We then apply the CNN to **T**_{CFMIP, land} and calculate λ . We find that about $r_{\text{land T}}^2 \approx 85\%$ of the variance due to surface temperature differences is explained by land temperature. We find similar results using the E3SMv2 ensemble. When performing the same analysis on **T**_{rc}, we find instead $r_{\text{land T}}^2 \approx 45\%$, because ocean temperature differences across reconstructions are larger than across CFMIP simulations.

In summary, half of the intermodel spread of λ can be explained by AGCM differences ($r_{\text{model}}^2 \approx 50\%$), while differences in near-surface temperature explain $r_{\text{T}}^2 \approx 20\%$ (of which $r_{\text{land T}}^2 \approx 85\%$ is due to temperature over land). The remaining variance is explained by internal atmospheric variability. The sensitivity of λ to observational uncertainties (e.g., Andrews et al., 2022; Fan et al., 2025; Lewis & Mauritsen, 2021; Modak & Mauritsen, 2023) can be investigated by applying the CNN to different reconstructions (Figure S7 in Supporting Information S1). Using the 200-member HadCRUT5 ensemble (Morice et al., 2021), we find that reconstruction uncertainties lead to a spread of about $\pm 0.24 \text{ Wm}^{-2}/\text{K}$ (99% confidence interval) in the satellite era. Using output from the E3SMv2 ensemble, we find a similar spread of about $\pm 0.28 \text{ Wm}^{-2}/\text{K}$. Future work could investigate these uncertainties in more detail, by comparing attribution maps of the CNN applied to different reconstructions or using AGCMs forced with different reconstructions (e.g., the E3SMv2 ensemble).

3.2. Role of the El Niño Southern Oscillation and Pacific Decadal Oscillation

It is an open question to what extent the historical variations in λ are forced or due to internal variability (e.g., Lin et al., 2025; Lutsko & Takahashi, 2018; Proistosescu et al., 2018). El Niño Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) have their own pattern effect (e.g., Ceppi & Fueglistaler, 2021; Guillaume-Castel et al., 2025; Loeb et al., 2020; Meyssignac et al., 2023; Wills et al., 2021). We remove the influence of ENSO and PDO on our λ estimate. First, we regress **T**_{rc} at each grid box onto the Niño 3.4 index $I_{3.4}$ on monthly timescales to obtain the part of **T**_{rc} that is linearly related to $I_{3.4}$, denoted **T**_{rc} ^{$I_{3.4}$} . Then, we subtract the $I_{3.4}$ -related variability and take yearly averages, to create an artificial timeseries **T**_{rc} ^{$I_{3.4}$} = **T**_{rc} - **T**_{rc} ^{$I_{3.4}$} that excludes effects of ENSO. Detrending $I_{3.4}$ does not significantly affect the regression because monthly variability is much larger than decadal trends. Using other methods to remove ENSO (e.g., Gunnarson et al., 2025) or simply leaving out strong ENSO years does not alter our conclusions (Figure S8a in Supporting Information S1). We do the same for the monthly PDO index (NOAA, 2026; Zhang et al., 1997) to create **T**_{rc}^{PDO} = **T**_{rc} - **T**_{rc}^{PDO}. Finally, we apply the CNN to **T**_{rc} ^{$I_{3.4}$} and **T**_{rc}^{PDO} to investigate the influence of ENSO and PDO on λ (Figure 1b). This procedure does not remove long-term El-Niño-like or PDO-like trends or lagged effects, but only the variability that is linearly related to the respective indices on monthly timescales.

Removing ENSO generally strengthens the feedback, indicating that ENSO tends to weaken λ in the 30-year regression definition used here. The same is true for PDO, although the effect is small. The effect of ENSO is largest in early periods, when internal variability is much larger than decadal trends. Different ENSO indices can alter λ to various degrees, with the Niño 1 + 2 region weakening the feedback the most, possibly because of its proximity to low cloud decks (Figure S8b in Supporting Information S1). ENSO can have an effect on R and ΔT in a given year (e.g., Ceppi & Fueglistaler, 2021; Guillaume-Castel et al., 2025), but only weakly influences how R varies with ΔT in a 30-year period (Figures S8c–S8e in Supporting Information S1). The weak influence of

ENSO and PDO on the λ -minimum around 1981–2010 indicates that there is likely a forced component to the pattern effect on decadal timescales. This is confirmed by applying the CNN to estimates of the forced component of observed T (ForceSMIP, Wills et al., 2026, who compared 30 different statistical methods to separate the forced signal from interval variability). Although there is no consensus on the forced signal in observed T , most estimates indicate a λ -minimum around 1981–2010 (Figure 1b, yellow). Since the CNN can make fast predictions for any temperature pattern, it can be used to test such hypotheses by applying it to artificial surface temperature anomalies.

4. Attributing Changes in the Global Radiative Feedback Parameter to Surface Temperature Patterns

Which spatial patterns and physical processes led to the historical variations of λ , in particular the minimum around 1983–2012? We attribute the change in λ to changes in surface temperature patterns using SHAP values (explained in Section 2). Figure 2 shows surface temperature patterns and feedback attribution maps for three different periods: 1951–1980, 1981–2010, and 1996–2025 (note an overlap between the latter two periods). The temperature patterns indicate how local surface temperature varies with global mean temperature in each period and are not necessarily indicative of regional cooling or warming in that period. The feedback attribution maps show how much temperature in each grid box contributes to the global feedback parameter, through both local and remote processes. The attribution maps are noisy, but the large-scale patterns are robust across different CNN architectures or training data.

The year 1980 is considered a turning point for the pattern effect (Andrews et al., 2022; Fueglistaler & Silvers, 2021; Wu et al., 2025), with λ strengthening (stabilizing) for 30-year windows ending after 1980 (Figure 1). After 1980, surface temperature patterns changed notably in the Pacific Ocean, with slower warming or even cooling in the eastern Pacific (Figures 2a, 2b, and 2g). This pattern change is associated with a weakened positive feedback contribution from the equatorial and subtropical eastern Pacific (Figures 2d, 2e, and 2i). This is consistent with a switch from positive to negative low cloud feedbacks over the same period, driven mostly by marine cloud decks in the subtropical eastern Pacific (Myers et al., 2023). Other regions contributed positively to the feedback, such as the central Pacific and the West coast of South America, but the global net effect was a stronger, more stabilizing feedback ($\Delta\lambda \simeq -1.6 \text{ Wm}^{-2}/\text{K}$ between 1951–1980 and 1981–2010). The strong feedbacks in the early 2000s might be connected to stabilized global mean temperatures during the global warming hiatus (e.g., Hedemann et al., 2017; Medhaug et al., 2017; Modak & Mauritsen, 2021), but shorter timescales than 30 years need to be considered since the hiatus lasted only around 2000–2012.

For 30-year windows ending after 2010, λ rapidly weakened (Figure 1). This weakening is associated with a sign-change of the temperature pattern in the Northeast Pacific (Figures 2b, 2c, and 2h), which contributed to a strong positive feedback (Figures 2f and 2j). Also the equatorial East Pacific contributed positively to the feedback. These positive contributions appear once 2015–2016 is included in the 30-year window, consistent with prior studies (Andrews et al., 2022; Loeb et al., 2020), and intensify over subsequent years. Removing 2015–2016 from the regression does not significantly affect the increased λ , indicating that the weakening trend is not due to a single ENSO event. The subtropical North Atlantic contributed less positively to the feedback after 1981–2010, but globally the feedback weakened ($\Delta\lambda \simeq 1.1 \text{ Wm}^{-2}/\text{K}$ between 1981–2010 and 1996–2025). In 1996–2025, λ is still stronger than predicted by abrupt CO_2 forcing experiments (e.g., Andrews et al., 2022), possibly due to residual effects of other climate forcings (e.g., Gregory et al., 2020). Delayed warming in the Southeast Pacific kept λ stronger relative to uniform warming (Figure S9 in Supporting Information S1). With more uniform warming, λ would weaken further, getting closer to λ predicted from CO_2 -only forcing experiments.

Over the full historical period, different regions contributed to temporal variability of λ . Ocean temperature dominates the variability of λ , but land temperature has a considerable contribution. The CNN attributes the overall magnitude of the feedback mostly to land temperature changes (Figure S10 in Supporting Information S1), possibly because of the stronger global warming signal over land. Therefore, we do not use the CNN to attribute the overall magnitude of λ , but only its predicted variations in time. Figures 2k–2p show the regional attribution of changes in λ , by summing attribution maps over regions indicated in Figure 2d.

Among different ocean regions, the Southeast Pacific (Figure 2k) and Niño 3 (Figure 2n) regions correlate most closely with the global feedback and contributed to the strengthening after 1951–1980. The contribution from the Niño 4 region anticorrelates with λ (Figure 2p), in line with results of Guillaume-Castel et al. (2025), who found

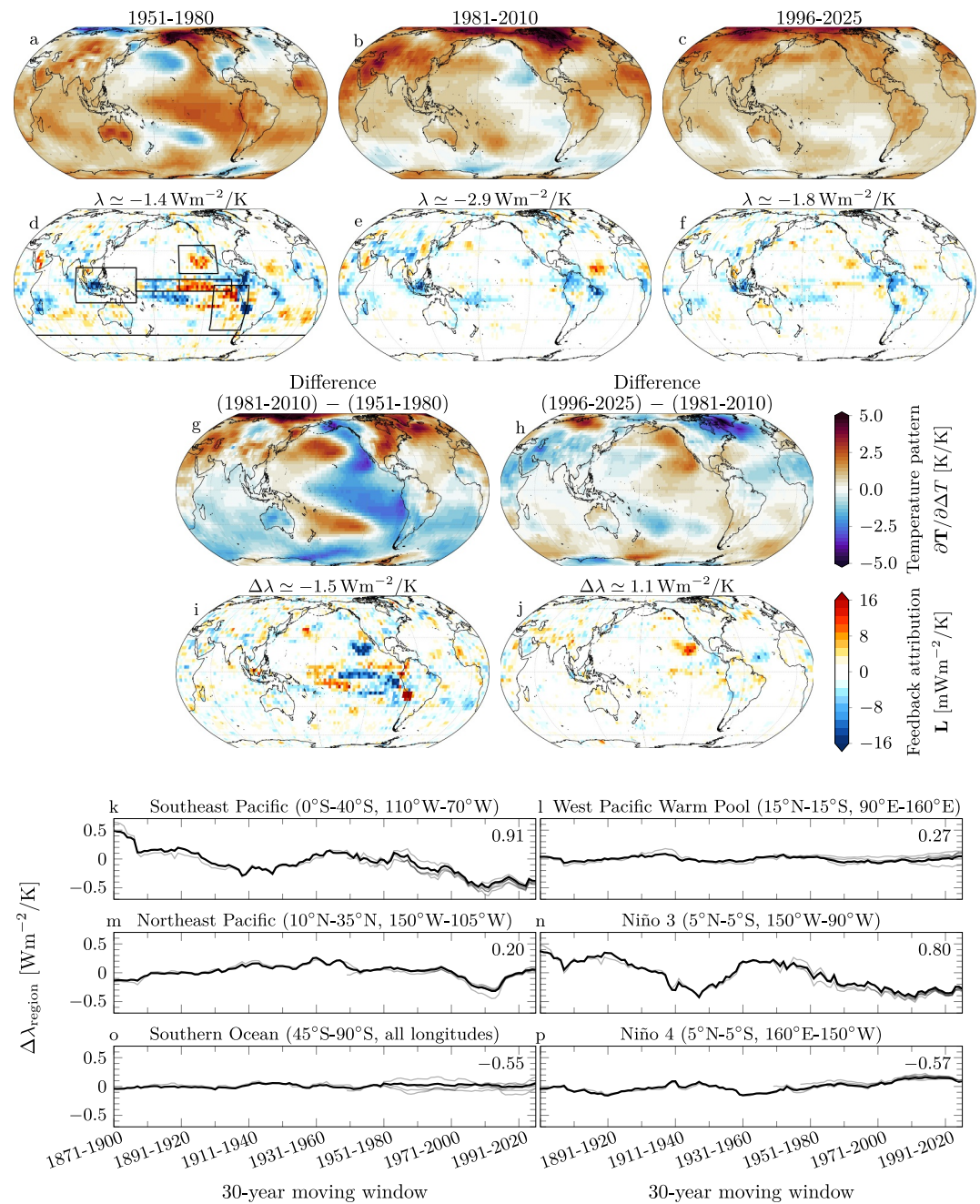


Figure 2. Attribution of changes in the global radiative feedback parameter. Panels (a–c) show the surface temperature patterns (linear regression slope of local temperature against global mean temperature). Panels (d–f) show the local temperature contribution to the feedback parameter. The sum over all grid boxes equals λ in the same period (indicated above the maps). Bottom panels show the difference between two periods for the surface temperature pattern (g–h) and feedback attribution maps (i–j). Maps are averaged over seven reconstructions T_{re} , except for 1951–1980, with only 3 available data sets. All temperature patterns and attribution maps share their respective colorbars. Panels (k–p) show the contribution of six different regions (see panel a) to the global feedback parameter, considering only ocean area in each box. All values are anomalies with respect to the 1871–2025 mean. Thin lines are individual T_{re} , thick lines are an ensemble mean. Values on the top right indicate the Pearson correlation coefficient with the global feedback (Figure 1).

that different ENSO flavors can influence top-of-atmosphere radiation in opposite ways on inter-annual time-scales. The high correlation of λ with its contribution from ENSO regions indicate that long-term variability in the Tropical Pacific has a strong influence on the pattern effect, even though the influence of single ENSO events on λ

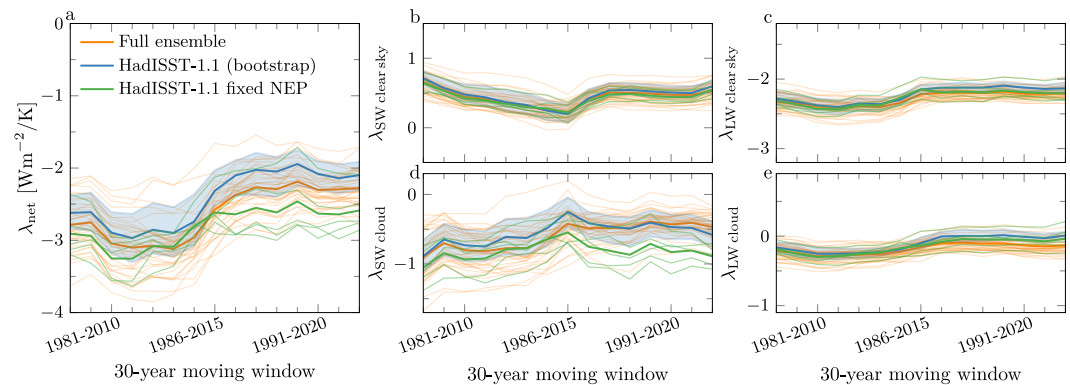


Figure 3. Decomposition of the net global feedback (a) into its shortwave (SW) clear-sky (b), longwave (LW) clear-sky (c), SW cloud (d), and LW cloud (e) components in the E3SMv2 ensemble (orange). Five members of E3SMv2 are run with HadISST-1.1 boundary conditions and fixed Northeast Pacific (NEP) SSTs (green). Thin lines are individual ensemble members, thick lines are an ensemble mean. We compare with bootstrapped 5-member averages from the 10-member E3SMv2 ensemble with HadISST-1.1 boundary conditions. Thick blue line shows the median, shading the two-sided 95% confidence bounds.

variations is relatively weak (Figure 1b and Figure S8 in Supporting Information S1), highlighting the distinction between decadal trends and interannual variability. After 1981–2010, the Northeast Pacific (NEP, Figure 2m) stands out as a contributor to the weakening of λ (see also Figure 2j). Between 1981–2010 and 1996–2025, the NEP contributed $\Delta\lambda_{\text{NEP}} \approx 0.33 \text{ Wm}^{-2}/\text{K}$ to the feedback weakening ($\sim 30\%$ of the total change). The West Pacific Warm Pool (WPWP, Figure 2l) and Southern Ocean (Figure 2o) have the weakest contribution to the global feedback variations. The WPWP contributes to the overall negative sign of the feedback (Figures 2d–2f), but the temperature has little interannual to decadal variability (Figures 2a–2c, 2g–2h). Since the relative warm pool temperature with respect to the tropical-mean temperature is more important for the pattern effect than the absolute temperature (e.g., Dong et al., 2019; Fueglistaler & Silvers, 2021), the CNN might attribute some changes in the feedback to where the temperature and top-of-atmosphere radiation change are occurring, not where they are caused (e.g., low clouds in the East Pacific might respond to warming in the WPWP). The CNN in its current setup cannot distinguish between these local versus remote processes.

The net radiative feedback is influenced by many different processes, including lapse rate, cloud, and sea-ice feedbacks. Decomposing the net radiation into shortwave (SW)/longwave (LW) and clear-sky/cloud components can give additional insights into these different components (Andrews et al., 2018). Cloud fluxes are calculated as all-sky minus clear-sky fluxes. Training CNNs on the different components is beyond the scope of this paper, but we investigate the decomposition in the E3SMv2 ensemble and find that all components of λ weaken after 1985–2014 (Figure 3). Aside from variations in the SW cloud feedback (predominantly driven by low clouds) and LW clear-sky feedback (predominantly lapse rate feedback), also the SW clear-sky feedback shows a significant increase after 1986–2015. The latter might be due to a decline in Antarctic sea-ice after 2015 (e.g., Duspayev et al., 2024; Riihelä et al., 2021; Zhou et al., 2025). The local feedback in the Southern Ocean shows a positive change of the same order as the feedback change in the NEP (Figure S11 in Supporting Information S1), mainly driven by the SW clear-sky feedback, highlighting the role of Antarctic sea-ice in the weakening of λ .

We confirm the relevance of the NEP in E3SMv2. We perform five additional AGCM simulations in E3SMv2 with HadISST-1.1 boundary conditions and year-2010 emissions, but keep SST in the NEP fixed to 1979 values. Keeping the NEP SST fixed reduces the overall feedback, mostly due to the SW cloud component (Figure 3), since the NEP is dominated by low cloud feedbacks. We compare the fixed-NEP to the original 10-member ensemble of E3SMv2 with HadISST-1.1 boundary conditions (Section 2.1). We sample five members from all 10 members with replacement, take the 5-member average, and repeat this process 1000 times to obtain the median 5-member mean (Figure 3, blue) and the two-sided 95% confidence bounds (Figure 3, shading). From 1986–2015 onward, the SW cloud feedback in the fixed-NEP experiment is lower than in the original ensemble (Figure 3d), which results in a lower net feedback in 1993–2022 (Figure 3a). No other feedback components are significantly affected by fixing NEP SST.

5. Discussion and Conclusions

The CNN is a surrogate model that relates any surface temperature pattern to R and λ . Therefore, the CNN can be used for fast experimentation on the effect of temperature variations on λ , exemplified here by linearly removing ENSO and PDO from T_{re} (Figure 1b) or local attribution (Figure 2). Such experiments can inform climate model runs, as done here to study the influence of the Northeast Pacific on the recent λ weakening in E3SMv2, to gain robust understanding of the pattern effect.

We update λ with various surface temperature reconstructions up to present day. This means that we can now monitor changes in λ in near real-time, without relying on new climate model simulations, currently lagging more than a decade. Our estimate generally follows the CFMIP3 multi-model mean before 2014, but additional uncertainty could be introduced by applying the CNN to much warmer (out-of-distribution) surface temperature maps. Because the CNN uses global surface temperature maps, not just ocean temperature, we capture the effect of land temperature on λ . In future work, it is important to compare the CNN results with climate model simulations with fixed land surface temperature (e.g., Andrews et al., 2021) to confirm the importance of land temperature variability for λ variations in a causal framework instead of a statistical one.

Regional attribution of changes in λ confirms the importance of the East Pacific for the pattern effect (e.g., Andrews et al., 2022; Loeb et al., 2020; Myers et al., 2023). The CNN attributes the strengthening of λ after 1980 to cooling in the tropical and subtropical eastern Pacific, while the weakening after 2010 is mainly attributed to warming in the subtropical Northeast Pacific (Figure 2). AGCM experiments with SSTs fixed in this region confirms the regional attribution suggested by the CNN.

We only use near-surface temperature to predict top-of-atmosphere radiation with the CNN. In reality, other factors, such as sea-ice or direct aerosol effects, also play a role (e.g., Andrews et al., 2022; Duspayev et al., 2024; Riihelä et al., 2021; Zhou et al., 2025). Still, the CNN performs well on unseen test data, indicating that near-surface temperature contains most of the information needed to predict R , with r^2 values above 80 % (Figure S3 in Supporting Information S1). Future work could include sea-ice as a predictor to the CNN, which can give additional insight into the SW clear-sky feedback (Figure 3b). AGCM experiments with varying SST but fixed sea-ice could confirm the role of sea-ice on the recent weakening of the feedback.

In summary, the climate was the most stable in recent history between the mid-1980s and early 2010s ($\lambda \simeq -3 \text{ Wm}^{-2}/\text{K}$). Over the last three decades, λ has been less stable ($\lambda \simeq -2 \text{ Wm}^{-2}/\text{K}$). This result is found both with a statistical (CNN) approach and in two AGCMs (HadGEM3-GC31-LL and E3SMv2). Temperature pattern differences between 1981–2010 and 1996–2025 are opposite in sign to those between 1951–1980 and 1981–2010 (Figures 2g and 2h), suggesting that the climate is returning to a state with a less stabilizing feedback, possibly explaining the recent accelerated warming (Alessi & Rugenstein, 2023; Foster & Rahmstorf, 2026). If the current surface temperature pattern persists, future global mean warming rates might be large (possibly larger than anticipated by freely running climate models). Weakening of λ might be counteracted or enhanced by ocean heat uptake and T , calling for research on their local drivers and interactions.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

We acknowledge the World Climate Research Programme, which, through its Working Group on Coupled Modeling, coordinated and promoted CMIP6. We thank the climate modeling groups for producing and making available their model output, the Earth System Grid Federation (ESGF) for archiving the data and providing access, and the multiple funding agencies who support CMIP6 and ESGF. All training data used in this manuscript can be accessed freely from <https://esgf-node.ornl.gov/> for CMIP model output. Near-surface temperature reconstructions are available through Copernicus Climate Change Service (2023), Global Modeling and Assimilation Office (2015), Japan Meteorological Agency (2024), Huang et al. (2024), Chan, Chan, Siddons, Cable, Cornes, et al. (2026), Morice et al. (2021), and Rohde and Hausfather (2020) and top-of-atmosphere fluxes from Liu and Allan (2022) and NASA/LARC/SD/ASDC (2024). Software and global mean values of T , R , and λ from AGCM and CNN output can be found at Van Loon et al. (2026).

Acknowledgments

TA was supported by the Met Office Hadley Centre Climate Programme funded by DSIT. The work of MDZ was supported by the U.S. Department of Energy (DOE) Regional and Global Model Analysis Program and was performed under the auspices of the US DOE by Lawrence Livermore National Laboratory under contract DEAC52-07NA27344. This research used resources of the National Energy Research Scientific Computing Center (NERSC), a Department of Energy User Facility, using NERSC award BER-ERCAP0033047. SVL and MR were supported, in part, by the National Science Foundation (NSF) under Grants 2233673 and 2530919. SVL and MR thank Elizabeth A. Barnes for discussions. Generative AI was used to assist with software development and text clarity, but all research conceptualization, design, analysis, interpretation, and conclusions are original to the authors, who take full responsibility for the content's accuracy and academic integrity.

References

- Alessi, M. J., & Rugenstein, M. (2023). Surface temperature pattern scenarios suggest higher warming rates than current projections. *Geophysical Research Letters*, 50(23), e2023GL105795. <https://doi.org/10.1029/2023GL105795>
- Allan, R. P., Liu, C., Loeb, N. G., Palmer, M. D., Roberts, M., Smith, D., & Vidale, P.-L. (2014). Changes in global net radiative imbalance 1985–2012. *Geophysical Research Letters*, 41(15), 5588–5597. <https://doi.org/10.1002/2014GL060962>
- Andrews, T. (2014). Using an AGCM to diagnose historical effective radiative forcing and mechanisms of recent decadal climate change. *Journal of Climate*, 27(3), 1193–1209. <https://doi.org/10.1175/JCLI-D-13-00336.1>
- Andrews, T., Bodas-Salcedo, A., Gregory, J. M., Dong, Y., Armour, K. C., Paynter, D., et al. (2022). On the effect of historical SST patterns on radiative feedback. *Journal of Geophysical Research: Atmospheres*, 127(18), e2022JD036675. <https://doi.org/10.1029/2022JD036675>
- Andrews, T., Gregory, J. M., Paynter, D., Silvers, L. G., Zhou, C., Mauritsen, T., et al. (2018). Accounting for changing temperature patterns increases historical estimates of climate sensitivity. *Geophysical Research Letters*, 45(16), 8490–8499. <https://doi.org/10.1029/2018GL078887>
- Andrews, T., Gregory, J. M., & Webb, M. J. (2015). The dependence of radiative forcing and feedback on evolving patterns of surface temperature change in climate models. *Journal of Climate*, 28(4), 1630–1648. <https://doi.org/10.1175/JCLI-D-14-00545.1>
- Andrews, T., Smith, C. J., Myhre, G., Forster, P. M., Chadwick, R., & Ackerley, D. (2021). Effective radiative forcing in a GCM with fixed surface temperatures. *Journal of Geophysical Research: Atmospheres*, 126(4), e2020JD033880. <https://doi.org/10.1029/2020JD033880>
- Andrews, T., & Webb, M. J. (2018). The dependence of global cloud and lapse rate feedbacks on the spatial structure of tropical Pacific warming. *Journal of Climate*, 31(2), 641–654. <https://doi.org/10.1175/JCLI-D-17-0087.1>
- Armour, K. C., Bitz, C. M., & Roe, G. H. (2013). Time-varying climate sensitivity from regional feedbacks. *Journal of Climate*, 26(13), 4518–4534. <https://doi.org/10.1175/JCLI-D-12-00544.1>
- Bloch-Johnson, J., Rugenstein, M., Alessi, M. J., Proistosescu, C., Zhao, M., Zhang, B., et al. (2024). The green's function model intercomparison project (GFIMP) protocol. *Journal of Advances in Modeling Earth Systems*, 16(2), e2023MS003700. <https://doi.org/10.1029/2023MS003700>
- Ceppi, P., & Fueglistaler, S. (2021). The El Niño–Southern Oscillation pattern effect. *Geophysical Research Letters*, 48(21), e2021GL095261. <https://doi.org/10.1029/2021GL095261>
- Ceppi, P., & Gregory, J. M. (2017). Relationship of tropospheric stability to climate sensitivity and Earth's observed radiation budget. *Proceedings of the National Academy of Sciences*, 114(50), 13126–13131. <https://doi.org/10.1073/pnas.1714308114>
- Chan, D., Chan, S., Siddons, J., Cable, A., Cornes, R., Kent, E., & Huybers, P. (2026). DCENT-I: A Globally Infilled Extension of the Dynamically Consistent ENsemble of Temperature Dataset [Dataset]. *Harvard Dataverse*. <https://doi.org/10.7910/DVN/ROG38Q>
- Chan, D., Chan, S. C., Siddons, J. T., Cable, A., Faulkner, A., Cornes, R. C., et al. (2026). DCENT-I: A globally infilled extension of the Dynamically Consistent ENsemble of Temperature Dataset. *Geoscience Data Journal*, 13(2), e70054. <https://doi.org/10.1002/gdj.70054>
- Copernicus Climate Change Service. (2023). ERA5 monthly averaged data on single levels from 1940 to present [Dataset]. *Copernicus Climate Change Service (C3S) Climate Data Store (CDS)*. <https://doi.org/10.24381/cds.f17050d7>
- Dong, Y., Proistosescu, C., Armour, K. C., & Battisti, D. S. (2019). Attributing historical and future evolution of radiative feedbacks to regional warming patterns using a green's function approach: The preeminence of the Western Pacific. *Journal of Climate*, 32(17), 5471–5491. <https://doi.org/10.1175/JCLI-D-18-0843.1>
- Duspayev, A., Flanner, M. G., & Riihelä, A. (2024). Earth's sea ice radiative effect from 1980 to 2023. *Geophysical Research Letters*, 51(14), e2024GL109608. <https://doi.org/10.1029/2024GL109608>
- Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the coupled model intercomparison project phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, 9(5), 1937–1958. <https://doi.org/10.5194/gmd-9-1937-2016>
- Fan, C., Paynter, D., Kramer, R. J., & Lin, P. (2025). Sensitivity of Earth's radiation budget to lower boundary condition data sets in historical climate simulations. *Geophysical Research Letters*, 52(17), e2025GL115914. <https://doi.org/10.1029/2025GL115914>
- Forster, P. M., Smith, C., Walsh, T., Lamb, W. F., Lamboll, R., Cassou, C., et al. (2025). Indicators of Global Climate Change 2024: Annual update of key indicators of the state of the climate system and human influence. *Earth System Science Data*, 17(6), 2641–2680. <https://doi.org/10.5194/essd-17-2641-2025>
- Foster, G., & Rahmstorf, S. (2026). Global warming has accelerated significantly. *Geophysical Research Letters*, 53(5), e2025GL118804. <https://doi.org/10.1029/2025GL118804>
- Fueglistaler, S., & Silvers, L. (2021). The peculiar trajectory of global warming. *Journal of Geophysical Research: Atmospheres*, 126(4), e2020JD033629. <https://doi.org/10.1029/2020JD033629>
- Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., et al. (2017). The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). *Journal of Climate*, 30(14), 5419–5454. <https://doi.org/10.1175/JCLI-D-16-0758.1>
- Global Modeling and Assimilation Office. (2015). MERRA-2 instM_2d_asm_Nx: 2d,Monthly mean,Single-Level,Assimilation,Single-Level Diagnostics V5.12.4 [Dataset]. *Greenbelt, MD, USA: Goddard Earth Sciences Data and Information Services Center (GES DISC)*. <https://doi.org/10.5067/5ESKGQTZG7FO>
- Golaz, J.-C., Van Roekel, L. P., Zheng, X., Roberts, A. F., Wolfe, J. D., Lin, W., et al. (2022). The DOE E3SM Model Version 2: Overview of the physical model and initial model evaluation. *Journal of Advances in Modeling Earth Systems*, 14(12), e2022MS003156. <https://doi.org/10.1029/2022MS003156>
- Gregory, J. M., & Andrews, T. (2016). Variation in climate sensitivity and feedback parameters during the historical period. *Geophysical Research Letters*, 43(8), 3911–3920. <https://doi.org/10.1002/2016GL068406>
- Gregory, J. M., Andrews, T., Ceppi, P., Mauritsen, T., & Webb, M. J. (2020). How accurately can the climate sensitivity to CO₂ be estimated from historical climate change? *Climate Dynamics*, 54(1), 129–157. <https://doi.org/10.1007/s00382-019-04991-y>
- Guillaume-Castel, R., Ceppi, P., Dorrington, J., & Meyssignac, B. (2025). ENSO diversity explains interannual variability of the pattern effect. *Geophysical Research Letters*, 52(20), e2025GL116952. <https://doi.org/10.1029/2025GL116952>
- Gunnarson, J. L., Wang, Y., Gagliardi, A., Hiung, D. L. C. Y. L. S., Takahashi, N., Wong, J., et al. (2025). Removing ENSO's influence from global SST variability, with insights into the record-setting marine heat waves of 2023–24. *Bulletin of the American Meteorological Society*, 106(8), E1498–E1516. <https://doi.org/10.1175/BAMS-D-24-0023.1>
- Hedemann, C., Mauritsen, T., Jungclaus, J., & Marotzke, J. (2017). The subtle origins of surface-warming hiatuses. *Nature Climate Change*, 7(5), 336–339. <https://doi.org/10.1038/nclimate3274>
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., et al. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049. <https://doi.org/10.1002/qj.3803>
- Huang, B., Liu, C., Banzon, V., Freeman, E., Graham, G., Hankins, B., et al. (2021). Improvements of the daily optimum interpolation sea surface temperature (DOISST) Version 2.1. *Journal of Climate*, 34(8), 2923–2939. <https://doi.org/10.1175/JCLI-D-20-0166.1>

- Huang, B., Thorne, P. W., Banzon, V. F., Boyer, T., Chepurin, G., Lawrimore, J. H., et al. (2017). NOAA Extended Reconstructed Sea Surface Temperature (ERSST), Version 5 [Dataset]. *NOAA National Centers for Environmental Information*. <https://doi.org/10.7289/V5T72FNM>
- Huang, B., Yin, X., Menne, M. J., Vose, R., & Zhang, H. (2024). NOAA Global Surface Temperature Dataset (NOAAGlobalTemp), Version 6.0.0 [Dataset]. *NOAA National Centers for Environmental Information*. <https://doi.org/10.25921/rzxxg-p717>
- Japan Meteorological Agency. (2024). Japanese Reanalysis for Three Quarters of a Century (JRA-3Q) Monthly Statistics [Dataset]. *Boulder, CO: NSF National Center for Atmospheric Research*. <https://doi.org/10.5065/PH0D-MH18>
- Kosaka, Y., Kobayashi, S., Harada, Y., Kobayashi, C., Naoe, H., Yoshimoto, K., et al. (2024). The JRA-3Q reanalysis. *Journal of the Meteorological Society of Japan. Series II*, 102(1), 49–109. <https://doi.org/10.2151/jmsj.2024-004>
- Kuhlbrodt, T., Jones, C. G., Sellar, A., Storkey, D., Blockley, E., Stringer, M., et al. (2018). The low-resolution version of HadGEM3 GC3.1: Development and evaluation for global climate. *Journal of Advances in Modeling Earth Systems*, 10(11), 2865–2888. <https://doi.org/10.1029/2018MS001370>
- Lewis, N., & Mauritsen, T. (2021). Negligible unforced historical pattern effect on climate feedback strength found in HadISST-Based AMIP simulations. *Journal of Climate*, 34(1), 39–55. <https://doi.org/10.1175/JCLI-D-19-0941.1>
- Lin, Y.-J., Cesana, G. V., Proistosescu, C., Zelinka, M. D., & Armour, K. C. (2025). The relative importance of forced and unforced temperature patterns in driving the time variation of low-cloud feedback. *Journal of Climate*, 38(2), 513–529. <https://doi.org/10.1175/JCLI-D-24-0014.1>
- Liu, C., & Allan, R. (2022). Reconstructions of the radiation fluxes at the top of atmosphere and net surface energy flux: DEEP-C Version 5.0 [Dataset]. *University of Reading*. <https://doi.org/10.1175/JCLI-D-17-0137.1>
- Liu, C., Allan, R. P., Mayer, M., Hyder, P., Desbryères, D., Cheng, L., et al. (2020). Variability in the global energy budget and transports 1985–2017. *Climate Dynamics*, 55(11–12), 3381–3396. <https://doi.org/10.1007/s00382-020-05451-8>
- Loeb, N. G., Doelling, D. R., Wang, H., Su, W., Nguyen, C., Corbett, J. G., et al. (2018). Clouds and the Earth's radiant energy system (CERES) energy balanced and filled (EBAF) top-of-atmosphere (TOA) edition-4.0 data product. *Journal of Climate*, 31(2), 895–918. <https://doi.org/10.1175/JCLI-D-17-0208.1>
- Loeb, N. G., Johnson, G. C., Thorsen, T. J., Lyman, J. M., Rose, F. G., & Kato, S. (2021). Satellite and ocean data reveal marked increase in Earth's heating rate. *Geophysical Research Letters*, 48(13), e2021GL093047. <https://doi.org/10.1029/2021GL093047>
- Loeb, N. G., Wang, H., Allan, R. P., Andrews, T., Armour, K., Cole, J. N. S., et al. (2020). New generation of climate models track recent unprecedented changes in Earth's radiation budget observed by CERES. *Geophysical Research Letters*, 47(5), e2019GL086705. <https://doi.org/10.1029/2019GL086705>
- Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In I. Guyon, et al. (Eds.), *Advances in neural information processing systems* (Vol. 30). Curran Associates, Inc. Retrieved from https://proceedings.neurips.cc/paper_files/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf
- Lutsko, N. J., & Takahashi, K. (2018). What can the internal variability of CMIP5 models tell us about their climate sensitivity? *Journal of Climate*, 31(13), 5051–5069. <https://doi.org/10.1175/JCLI-D-17-0736.1>
- Medhaug, I., Stolpe, M. B., Fischer, E. M., & Knutti, R. (2017). Reconciling controversies about the 'global warming hiatus'. *Nature*, 545(7652), 41–47. <https://doi.org/10.1038/nature22315>
- Meyssignac, B., Chenal, J., Loeb, N., Guillaume-Castel, R., & Ribes, A. (2023). Time-variations of the climate feedback parameter λ are associated with the Pacific Decadal Oscillation. *Communications Earth & Environment*, 4(1), 241. <https://doi.org/10.1038/s43247-023-00887-2>
- Modak, A., & Mauritsen, T. (2021). The 2000–2012 global warming hiatus more likely with a low climate sensitivity. *Geophysical Research Letters*, 48(9), e2020GL091779. <https://doi.org/10.1029/2020GL091779>
- Modak, A., & Mauritsen, T. (2023). Better-constrained climate sensitivity when accounting for dataset dependency on pattern effect estimates. *Atmospheric Chemistry and Physics*, 23(13), 7535–7549. <https://doi.org/10.5194/acp-23-7535-2023>
- Morice, C. P., Kennedy, J. J., Rayner, N. A., Winn, J. P., Hogan, E., Killick, R. E., et al. (2021). An updated assessment of near-surface temperature change from 1850: The HadCRUT5 data set. *Journal of Geophysical Research: Atmospheres*, 126(3), e2019JD032361. <https://doi.org/10.1029/2019JD032361>
- Myers, T. A., Zelinka, M. D., & Klein, S. A. (2023). Observational constraints on the cloud feedback pattern effect. *Journal of Climate*, 36(18), 6533–6545. <https://doi.org/10.1175/JCLI-D-22-0862.1>
- NASA/LARC/SD/ASDC. (2024). CERES Energy Balanced and Filled (EBAF) TOA and Surface Monthly means data in netCDF Edition 4.2.1 [Dataset]. *NASA Langley Atmospheric Science Data Center DAAC*. Retrieved from <https://ceres-tool.larc.nasa.gov/ord-tool/jsp/EBAFTOA421Selection.jsp>
- NOAA, N. C. F. E. I. (2026). Pacific Decadal Oscillation (PDO) [Dataset]. Retrieved from <https://www.ncei.noaa.gov/access/monitoring/pdo/>
- Pincus, R., Forster, P. M., & Stevens, B. (2016). The radiative forcing model intercomparison project (RFMIP): Experimental protocol for CMIP6. *Geoscientific Model Development*, 9(9), 3447–3460. <https://doi.org/10.5194/gmd-9-3447-2016>
- Proistosescu, C., Donohoe, A., Armour, K. C., Roe, G. H., Stuecker, M. F., & Bitz, C. M. (2018). Radiative feedbacks from stochastic variability in surface temperature and radiative imbalance. *Geophysical Research Letters*, 45(10), 5082–5094. <https://doi.org/10.1029/2018GL077678>
- Qin, Y., Zelinka, M. D., & Klein, S. A. (2022). On the correspondence between atmosphere-only and coupled simulations for radiative feedbacks and forcing from CO₂. *Journal of Geophysical Research: Atmospheres*, 127(3), e2021JD035460. <https://doi.org/10.1029/2021JD035460>
- Qin, Y., Zheng, X., Klein, S. A., Zelinka, M. D., Ma, P.-L., Golaz, J.-C., & Xie, S. (2024). Causes of reduced climate sensitivity in E3SM from Version 1 to Version 2. *Journal of Advances in Modeling Earth Systems*, 16(1), e2023MS003875. <https://doi.org/10.1029/2023MS003875>
- Quan, H., Zhang, B., Wang, C., & Fueglistaler, S. (2025). The sea surface temperature pattern effect on outgoing longwave radiation: The role of large-scale convective aggregation. *Geophysical Research Letters*, 52(11), e2024GL112756. <https://doi.org/10.1029/2024GL112756>
- Rayner, N. A., Parker, D. E., Horton, E. B., Folland, C. K., Alexander, L. V., Rowell, D. P., et al. (2003). Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *Journal of Geophysical Research*, 108(D14). <https://doi.org/10.1029/2002JD002670>
- Riihela, A., Bright, R. M., & Anttila, K. (2021). Recent strengthening of snow and ice albedo feedback driven by Antarctic sea-ice loss. *Nature Geoscience*, 14(11), 832–836. <https://doi.org/10.1038/s41561-021-00841-x>
- Rohde, R. A., & Hausfather, Z. (2020). The Berkeley Earth land/ocean temperature record. *Earth System Science Data*, 12(4), 3469–3479. <https://doi.org/10.5194/essd-12-3469-2020>
- Rugenstein, M., & Armour, K. C. (2021). Three flavors of radiative feedbacks and their implications for estimating equilibrium climate sensitivity. *Geophysical Research Letters*, 48(15), e2021GL092983. <https://doi.org/10.1029/2021GL092983>
- Rugenstein, M., Van Loon, S., & Barnes, E. A. (2025). Convolutional neural networks trained on internal variability predict forced response of TOA radiation by learning the pattern effect. *Geophysical Research Letters*, 52(4), e2024GL109581. <https://doi.org/10.1029/2024GL109581>

- Rugenstein, M., Zelinka, M., Karnauskas, K. B., Ceppi, P., & Andrews, T. (2023). Patterns of surface warming matter for climate sensitivity. *Eos*, 104. <https://doi.org/10.1029/2023EO230411>
- Senior, C. A., & Mitchell, J. F. B. (2000). The time-dependence of climate sensitivity. *Geophysical Research Letters*, 27(17), 2685–2688. <https://doi.org/10.1029/2000GL011373>
- Taylor, K. E., Williamson, D., & Zwiers, F. (2000). The sea surface temperature and sea-ice concentration boundary conditions for AMIP II simulations. *PCMDI Report No.*, 60, 1–25.
- Van Loon, S., Rugenstein, M., Zelinka, M. D., & Andrews, T. (2026). CNN_RadiativeResponse: Recent Weakening of the Global Radiative Feedback [Software and Dataset]. *Zenodo*. <https://doi.org/10.5281/zenodo.19958908>
- Van Loon, S., Rugenstein, & Barnes, E. A. (2025). Observation-based estimate of, Maria Earth's effective radiative forcing. *Proceedings of the National Academy of Sciences*, 122(24), e2425445122. <https://doi.org/10.1073/pnas.2425445122>
- Webb, M. J., Andrews, T., Bodas-Salcedo, A., Bony, S., Bretherton, C. S., Chadwick, R., et al. (2017). The cloud feedback model intercomparison project (CFMIP) contribution to CMIP6. *Geoscientific Model Development*, 10(1), 359–384. <https://doi.org/10.5194/gmd-10-359-2017>
- Wills, R. C. J., Armour, K. C., Battisti, D. S., Proistosescu, C., & Parsons, L. A. (2021). Slow modes of global temperature variability and their impact on climate sensitivity estimates. *Journal of Climate*, 34(21), 8717–8738. <https://doi.org/10.1175/JCLI-D-20-1013.1>
- Wills, R. C. J., Deser, C., McKinnon, K. A., Phillips, A., Po-Chedley, S., Sippel, S., et al. (2026). Forced component estimation statistical method intercomparison project (ForceSMIP). *Journal of Climate*, 39(8), 1927–1953. <https://doi.org/10.1175/JCLI-D-25-0326.1>
- Wu, Q., Gregory, J. M., Zanna, L., & Khaliwala, S. (2025). Time-varying global energy budget since 1880 from a reconstruction of ocean warming. *Proceedings of the National Academy of Sciences*, 122(20), e2408839122. <https://doi.org/10.1073/pnas.2408839122>
- Zhang, Y., Wallace, J. M., & Battisti, D. S. (1997). ENSO-like interdecadal variability: 1900–93. *Journal of Climate*, 10(5), 1004–1020. [https://doi.org/10.1175/1520-0442\(1997\)010<1004:ELIV>2.0.CO;2](https://doi.org/10.1175/1520-0442(1997)010<1004:ELIV>2.0.CO;2)
- Zhou, C., Wang, Q., Tan, I., Zhang, L., Zelinka, M. D., Wang, M., & Bloch-Johnson, J. (2025). Sea ice pattern effect on Earth's energy budget is characterized by hemispheric asymmetry. *Science Advances*, 11(9), eadr4248. <https://doi.org/10.1126/sciadv.adr4248>
- Zhou, C., Zelinka, M. D., & Klein, S. A. (2016). Impact of decadal cloud variations on the Earth's energy budget. *Nature Geoscience*, 9(12), 871–874. <https://doi.org/10.1038/ngeo2828>
- Zhou, C., Zelinka, M. D., & Klein, S. A. (2017). Analyzing the dependence of global cloud feedback on the spatial pattern of sea surface temperature change with a Green's function approach. *Journal of Advances in Modeling Earth Systems*, 9(5), 2174–2189. <https://doi.org/10.1002/2017MS001096>

References From the Supporting Information

- Boucher, O., Servonnat, J., Albright, A. L., Aumont, O., Balkanski, Y., Bastrikov, V., et al. (2020). Presentation and evaluation of the IPSL-CM6A-LR climate model. *Journal of Advances in Modeling Earth Systems*, 12(7), e2019MS002010. <https://doi.org/10.1029/2019MS002010>
- Danabasoglu, G., Lamarque, J.-F., Bacmeister, J., Bailey, D. A., DuVivier, A. K., Edwards, J., et al. (2020). The community Earth system model version 2 (CESM2). *Journal of Advances in Modeling Earth Systems*, 12(2), e2019MS001916. <https://doi.org/10.1029/2019MS001916>
- Lee, W.-L., Wang, Y.-C., Shiu, C.-J., Tsai, I., Tu, C.-Y., Lan, Y.-Y., et al. (2020). Taiwan Earth System Model Version 1: Description and evaluation of mean state. *Geoscientific Model Development*, 13(9), 3887–3904. <https://doi.org/10.5194/gmd-13-3887-2020>
- Maher, N., Milinski, S., Suarez-Gutierrez, L., Botzet, M., Dobrynin, M., Kornblueh, L., et al. (2019). The Max Planck Institute Grand Ensemble: Enabling the exploration of climate system variability. *Journal of Advances in Modeling Earth Systems*, 11(7), 2050–2069. <https://doi.org/10.1029/2019MS001639>
- Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., et al. (2019). PyTorch: An imperative style, high-performance deep learning library. In *Proceedings of the 33rd International Conference on Neural Information Processing Systems*. Curran Associates Inc.
- Swart, N. C., Cole, J. N. S., Kharin, V. V., Lazare, M., Scinocca, J. F., Gillett, N. P., et al. (2019). The Canadian Earth System Model version 5 (CanESM5.0.3). *Geoscientific Model Development*, 12(11), 4823–4873. <https://doi.org/10.5194/gmd-12-4823-2019>
- Tatebe, H., Ogura, T., Nitta, T., Komuro, Y., Ogochi, K., Takemura, T., et al. (2019). Description and basic evaluation of simulated mean state, internal variability, and climate sensitivity in MIROC6. *Geoscientific Model Development*, 12(7), 2727–2765. <https://doi.org/10.5194/gmd-12-2727-2019>
- Voldoire, A., Saint-Martin, D., Sénési, S., Decharme, B., Alias, A., Chevallier, M., et al. (2019). Evaluation of CMIP6 deck experiments with CNRM-CM6-1. *Journal of Advances in Modeling Earth Systems*, 11(7), 2177–2213. <https://doi.org/10.1029/2019MS001683>
- Yukimoto, S., Kawai, H., Koshiro, T., Oshima, N., Yoshida, K., Urakawa, S., et al. (2019). The Meteorological Research Institute Earth System Model Version 2.0, MRI-ESM2.0: Description and basic evaluation of the physical component. *Journal of the Meteorological Society of Japan. Series II*, 97(5), 931–965. <https://doi.org/10.2151/jmsj.2019-051>