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Percentage change patterns in cloud fraction effectively constrain global cloud feedback

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The radiative effect of cloud changes brings the greatest uncertainty into the projected magnitude of future global warming¹⁻⁶. Key drivers of uncertainty are the pattern effect⁷ of sea surface temperature (SST) change and the beta feedback⁸ that modulates the effect of low-level cloud change. Neither have sufficed to provide a tight constraint on the cloud radiative feedback⁹⁻¹⁴. Using satellite measurements and output from climate models, we identify the percentage change in cloud fraction as key to the SST pattern control over all types of the tropical clouds¹⁵⁻¹⁸. This highlights a clear warmer-get-higher paradigm upon complex cloud fraction change, and inspires a process-oriented emergent constraint on the global cloud feedback. The initial stage of the constraint involves substituting the simulations with the observations via the scaling of the percentage cloud response in addition to correcting model biases in the present-day cloud cover. The eventual stage constrains the SST pattern effect explaining 83% of the remaining intermodel spread in an uncertainty attribution framework. Overall, our two-stage constraint effectively reduces the uncertainty by more than half an order of magnitude, leading to 0.45 ± 0.15 , 0.37 ± 0.11 , 0.14 ± 0.05 , and $-0.06 \pm 0.04 \text{ W m}^{-2} \text{ K}^{-1}$ (90% confidence interval) in total, low, middle, and high cloud feedback, respectively.

As an important component of the global hydrological cycle, clouds, exert a key control over Earth's radiative energy budget¹. This effect consists of reflection of solar radiation by all clouds and infra-red absorption/emission primarily by those in the upper and mid-troposphere². As cloud physics is complex in both convective³ and radiative⁴ contexts, significant spread exists in cloud response to greenhouse effect⁵, leading to great uncertainty in projected climate warming⁶. Using observed statistics emerging in current climate to correct model projections, decades of efforts have been dedicated to emergent constraints on this cloud radiative feedback¹¹. Yet, the latest studies obtain constrained low cloud feedback, for example, as 0.19 ± 0.12 ¹², 0.25 ± 0.18 ¹³, and 0.37 ± 0.37 ¹⁴ $\text{W m}^{-2} \text{ K}^{-1}$.

One major culprit for such a diversity is the poorly understood processes in cloud changes, with at least two distinct drivers: the pattern effect of sea surface temperature (SST) change⁷, and the beta feedback of low-level cloud change⁸. The former emphasizes regional SST warming, an important source of uncertainty in tropical hydrological cycle change¹⁵⁻¹⁸. Such fingerprints impact cloud regions differently between phases 5 and 6 models⁹ from the Coupled Model Intercomparison Project (CMIP)^{19,20}. As a local positive feedback between cloud fraction, radiative cooling, and relative humidity, the latter strongly correlates low-cloud response with the climatological radiative effect. This correlation reverses sign at a tipping cloud cover of 40%¹⁰. It remains a grand challenge to explain these reliances on model generation and cloud regime.

Using Moderate Resolution Imaging Spectroradiometer (MODIS/MCD06COSP) measurements²¹ and 30 CMIP6 simulations²⁰, we identify a simple and clear paradigm that relates percentage change in cloud fraction to cloud feedback calculated with converted radiative kernels². Specifically, the ratio of fraction change over the climatology is shown to be quantitatively controlled by the SST patterns in all types of tropical clouds. This leads to a warmer-get-higher view, consistent in the observations and output of 10 models across 6 scenarios. This paradigm reconciles the drivers of uncertainty described above. Moreover, it redefines cloud feedback to provide a stagewise constraint, reducing the intermodel spread by more than half an order of magnitude. Our findings inspire both an uncertainty attribution framework and a process-oriented emergent constraint on cloud feedback.

Overview of cloud feedback and fraction change

The CMIP6 scenarios adopted here include Tier 1 of the Shared Socioeconomic Pathways (SSPs), 1% per year CO₂ increase (1pctCO₂), and abrupt CO₂ quadrupling (abrupt-4×CO₂). Defined as the global-mean top-of-atmosphere net radiative response to

cloud change driven by unit increase of global-mean surface air temperature, the kernel-derived cloud feedback is 0.14 ± 0.13 , 0.28 ± 0.27 , 0.44 ± 0.6 , and $0.86 \pm 0.85 \text{ W m}^{-2} \text{ K}^{-1}$ (90% confidence) for high, middle, low, and total clouds, respectively (Extended Data Fig. 1). Low clouds dominate the intermodel uncertainty in total feedback²² (57%) via changes in shortwave radiation, and middle clouds contribute 37%. Although the high cloud effects on solar reflection and infra-red absorption are both considerable, they tend to offset each other resulting in a small contribution to net feedback uncertainty (6%).

Such radiative feedback results from changes in cloud coverage (fraction), height (top pressure), and reflectivity (optical depth). Summing throughout optical depths, Figure 1 shows fraction changes much stronger in the tropics ($40^{\circ}\text{S} \sim 40^{\circ}\text{N}$) than in the extratropics²³. This is particularly true for high and low cloud fraction changes, which generally follow the SST warming patterns (T^* , deviations of SST increase from the tropical mean) with spatial correlations (r) of 0.38 and -0.46, respectively. To be brief, moisture in low clouds can be transported to high clouds by convection associated with anomalous SST warming. Here, the SST patterns apparently catch the sign of fraction changes that is opposite between high and low clouds ($r = -0.6$), but fail to match the strength of changes in the tropics. This leaves great diversity among cloud types and complicates the interpretation of fraction changes.

In contrast, Figure 1 links tropical cloud changes in strength to the climatology, since prominent responses appear where present-day fraction is large, e.g., more than 20%. In particular, low clouds substantially decrease in the eastern basins of the Pacific and the Atlantic, while high clouds increase much along the equator, except over the Indo-Pacific warm pool where a strong reduction extends toward the subtropics. Moreover, low cloud patterns are closely associated ($r = -0.52$) with the climatology in ensemble mean. These illustrate the importance of the beta feedback but are not limited to low clouds.

Representing the absolute strength, intermodel spread in cloud change is coherent with the ensemble mean and highly correlated with mean climatology for high (0.48), middle (0.56), and low (0.75) clouds. Middle cloud changes are very weak since it is mainly confined to the subtropical southeastern Pacific in the mean state.

SST pattern control over percentage cloud change

The SST patterns usually affect the tropical hydrological cycle in a percentage way. For precipitation^{15,16}, convection¹⁷, and relative humidity¹⁸, changes are proportional to the climatologies. Such convective effect on high clouds can supplement the beta feedback of low clouds, leading to a consistent climatological weighting in all tropical cloud types as shown above. It is therefore possible to develop process-oriented metrics for attributing and constraining cloud feedback based on percentage fraction change (Δ , cloud fraction change divided by the climatology) in the tropics. As in previous works^{18,24}, we use 40°S~40°N to define the tropics, although spatial correlations may increase for a narrower bandwidth.

If overbars indicate ensemble means, Figure 2 clearly reveals a pictorial relationship in the tropics between percentage cloud change ($\overline{\Delta}$) and SST patterns ($\overline{T^*}$) from CMIP6. Similar to CMIP3¹⁶ and CMIP5¹⁸ models, SST patterns feature an El Niño-like warming peak in the eastern equatorial oceans and south-to-north gradients in the subtropics. $\overline{\Delta}$ corresponds to $\overline{T^*}$ in both sign and strength, for high ($r = 0.43$) and low ($r = -0.55$) clouds with consistent patterns but opposite signs ($r = -0.64$). These relationships predict an almost pointwise-proportional raising of clouds (less low and more high) over relatively warmed SST, which we term a warmer-get-higher paradigm. Spatial scatter depicts distinct cloud dynamics, e.g., high clouds have larger slope than low clouds because of nonlinear convective energetics¹⁶. $\overline{\Delta}$ also indicates meridional shifts with high (low) clouds moving away from (towards) the intertropical convergence zone¹⁷, drawing circles in their scatters.

Middle clouds appear insensitive to SST patterns with $r = 0.01$ (Fig. 2b), implying a dynamical transition between cloud types revealed in zonal and equatorial ($5^{\circ}\text{S}\sim 5^{\circ}\text{N}$) meridional means (Fig. 3). The percentage change in cloud fraction following high clouds in the deep tropics is associated with mean ascending air especially over the warm pool, but low cloud features are more evident in the subtropical and eastern equatorial subsidence regions. Composing the V-shape wings in the spatial scatter of middle clouds, such regional distinctions may relate to the depth of convection²⁵.

Consistency among simulations and with observations

In contrast to the disparity in the magnitude of cloud fraction changes (Fig. 1), the percentage cloud change keeps the same magnitude among all cloud types (Fig. 2) with three-dimensional (3-D) accordance (Fig. 3). Warmer-get-higher also seems universal across models and scenarios (Extended Data Fig. 2). A strong relationship is found between all T^* and Δ in high and low clouds with respective ensemble mean correlation coefficients of 0.45 and -0.53, as 3~4 times of their spreads. Without percentage metrics, these values decrease ~ 0.1 . Such control is antisymmetric between high and low clouds (strong/weak in sync) with intermodel $r = -0.75$ and -0.56 for spatial regression and correlation coefficient, respectively. Moderate differences among scenarios exist within the same models, e.g., CESM2 and UKESM1.0-LL, likely due to SST and cloud patterns in natural variability^{7,26}.

Satellite measurements from MODIS during 2003-2020 (Extended Data Fig. 3) show emerging changes in the tropical Pacific and Indian Ocean but not in the Atlantic, probably impacted by spatial variations in internal climate variability²⁷. Our warmer-get-higher paradigm is clearly seen with Δ - T^* correlation (0.43) and anticorrelation (-0.66) in high and low clouds, respectively. And both cloud types have a spatial correlation of -0.56. Zonal and equatorial means (Extended Data Fig. 4) show observed patterns similar to the

CMIP6 models in the equatorial Pacific and northern tropics. Especially for high clouds, regression slopes are larger than in the ensemble-mean simulations, hinting at a scaling substitution with observations. The intercept is ignorable in such short-term observations but significantly negative ($-2.4\% \text{ K}^{-1}$) in long-term low cloud trends (Fig. 2c). Driven by radiative and latent heating²⁸, such proportional dissipation in accordance with beta feedback reduces global radiative cooling and leads to an overall positive tendency of cloud feedback in all model projections. This is considered in the following constraint.

Initial constraint on cloud sensitivity to SST

Based on our warmer-get-higher paradigm, we redefine cloud feedback with percentage change in the tropics to design an uncertainty attribution framework (Methods).

$$\lambda = \langle \delta C \cdot K \rangle = \left\langle \frac{\delta C}{\gamma} \cdot \gamma K \right\rangle = \langle \Delta \cdot \gamma K \rangle, \quad (1)$$

where λ is cloud feedback, C represents cloud fraction with δ marking its normalized change, K indicate cloud radiative kernels, and $\langle \cdot \rangle$ expresses the feedback calculation procedure. γ is the percentage parameter,

$$\gamma = \begin{cases} C, & 40^\circ\text{S} \sim 40^\circ\text{N} \\ 1, & \text{Extratropics} \end{cases} \quad (2)$$

which converts radiative kernels and fraction change to fractional kernels (γK) and percentage change (Δ) directly driven by SST patterns. Uncertainty in cloud feedback is then divided into corresponding two parts as follows.

Initiated by Figure 4 and resulting in Figure 5, our observational constraint (Fig. 4d) starts from investigating low clouds as the dominant contributor to feedback uncertainty. Represented by the slope in spatial regression of Δ against T^* , the cloud sensitivity to SST perturbation¹³ spans a very large intermodel range ($-4 \sim -20\% \text{ K}^{-1}$), with the MODIS value near the centre ($-11.8\% \text{ K}^{-1}$). Besides reasonable coherence with spatial correlation, such a

spread of slopes has a high intermodel correlation with total cloud feedback λ ($r = -0.5$), inducing one quarter uncertainty. The regression intercept is also very diversified but highly correlated ($r = 0.8$) with the slope, indicating that the overall low cloud reduction due to uniform SST warming has a consistent sensitivity with the spatial pattern effect. Thus, simulation diversity can be substituted with observations by scaling Δ with the ratio of MODIS slope over that in each experiment (see Methods).

Compared with radiative kernels K , cloud fraction C drives strong spatial variations in γK (Extended Data Fig. 5). Specifically, fractional shortwave kernel integrates reflective cooling by all clouds and longwave integrates infra-red warming by high cloud cover. With the radiative offset in high clouds, the net effect is dominated by low clouds with a small contribution of middle clouds, assigning heavy weights to the equatorial and eastern subtropical oceans. Comparisons between Extended Data Figures 5 and 6 suggest that CMIP6 develops good skills in simulating present-day clouds, albeit with elevated low clouds and overestimated middle and high clouds. Model biases also anchor considerable spread in cloudy regions to induce moderate feedback uncertainty. This can fortunately be removed by replacing the simulated cloud fraction in γK with the observed (Extended Data Fig. 6), leaving a small diversity from surface albedo in shortwave kernel (see Methods).

The substitution with scaled percentage change and observed fractional kernels reduces feedback uncertainty by $\sim 2/3$ in middle clouds and $\sim 1/2$ in total and low clouds, compared in Figure 5c with the original. This initial emergent constraint has almost halved both ensemble means and spreads to 0.53 ± 0.45 , 0.33 ± 0.33 , 0.16 ± 0.12 , and $0.04 \pm 0.18 \text{ W m}^{-2} \text{ K}^{-1}$ (90% confidence) in total, low, middle, and high cloud feedback, respectively. Next, the intermodel variability in SST patterns is addressed (Fig. 4d).

Attribution of uncertainty to SST modes

SST pattern-forced Δ has a trivial tropical mean by definition, yet γK should apply uneven spatial weights to generate a global-mean radiative imbalance. The T^* uncertainty is hence converted into cloud feedback, with extremes traceable to typical patterns (not shown). CESM2 (SSP1-2.6) has the strongest feedback of $2.51 \text{ W m}^{-2} \text{ K}^{-1}$ with a very El Niño-like warming. As the only La Niña-like response, CNRM-ESM2-1 (SSP3-7.0) has the 3rd to weakest feedback of $0.24 \text{ W m}^{-2} \text{ K}^{-1}$. The weakest feedback ($-0.01, 0.11 \text{ W m}^{-2} \text{ K}^{-1}$) and lowest warming within scenario (1.57, 3.7 K) is seen in MIROC-ES2L under abrupt- $4\times\text{CO}_2$ and 1pctCO2, featuring an equatorial Pacific dipole with west-to-east gradients.

In order to quantify the SST pattern contribution and compare it with other factors, our attribution framework (Methods) further decomposes the cloud feedback in Eq. (1),

$$\lambda = \langle \bar{\Delta} \cdot \overline{\gamma K} \rangle + \langle \bar{\Delta} \cdot (\gamma K)' \rangle + \langle \Delta'^* \cdot \overline{\gamma K} \rangle + \langle \Delta'^* \cdot (\gamma K)' \rangle + \langle \Delta'_R \cdot \gamma K \rangle, \quad (3)$$

where overbars and primes mark ensemble means and intermodel anomalies, Δ'^* is the anomalous percentage cloud change (Δ') driven by T^* , and Δ'_R denotes that by residual factors including inversion strength and relative humidity¹³. Thus, terms on the right-hand-side of Eq. (3) represent, in turn, the ensemble mean of all factors, biases in fractional kernels/cloud simulation, uncertainty induced by T^* and tropical-mean SST increase, nonlinear interaction between these two intermodel variables, and the influence of residual factors. We performed two sets of evaluations with and without the initial constraint.

Δ'^* can be obtained with an intermodel singular value decomposition (SVD), returning the covariant modes (Extended Data Figs. 7 and 8) between global T^* and Δ' (see Methods). The two sets of SVDs contain similar modes in slightly shifted order, e.g., from unscaled Mode 2 (18%) to scaled Mode 4. In the tropics, SST fingerprints are apparent on high/low clouds with large zonal-mean correlations of 0.66/-0.73 in the Pacific (Mode 1: 24%) and 0.66/-0.40 in the Indian Ocean (Mode 4: 11%). The extratropical T^* control is

1 remarkable in the North Atlantic and Ross Sea (Mode 1) and over the Arctic, Greenland-
2 Barents Sea, and Weddell Sea (Mode 4).

3 The cumulative SVD variance¹⁸ in the substituted cloud feedback converges after
4 ~19 leading modes (Extended Data Fig. 9). Accumulation of the first 20 modes contributes
5 83% to total feedback uncertainty with the initial constraint (Extended Data Fig. 10), 78%
6 without. The residual factors account for 9%, while the interaction between T^* and
7 fractional kernels explains 8% with a weak contribution of surface albedo. Biases in the
8 kernels induce 3% of the uncertainty, without observational replacement but is nearly
9 eliminated with. Cloud-type decomposition agrees with total feedback, recognizing residual
10 factors as the secondary contributor and SST patterns as the primary to be constrained.

11 **Eventual constraint on SST pattern effect**

12 SVD Mode 4 presents an outstanding feature that T^* is highly correlated with
13 climatological low clouds (Fig. 1c, $r = 0.42$) and fractional net kernel (Extended Data Fig.
14 5c, $r = -0.45$). Thus, we may regard percentage warmer-get-higher as a trigger of air-sea
15 feedbacks: a spatially uniform SST increase could reduce low clouds in proportion to the
16 present-day fraction, indicating rapid dissipation in the subsiding rather than convective
17 regions; hence, surface solar heating increases more with anomalous warming in the
18 equatorial cold tongue and northeastern subtropic Pacific. Such initial SST anomaly would
19 further perturb clouds, radiation, and surface winds to trigger air-sea interactions (Mode 1)
20 and form equilibrium patterns (Fig. 1d). Here, diversity in cloud sensitivity to SST may
21 play a key role in pattern uncertainty, inspiring the following constraint (Fig. 4d).

22 Along with the MODIS slope of low cloud Δ regressed to T^* , Figure 4 delimits the
23 99% confidence interval confining 6 simulations with relatively reliable percentage cloud
24 sensitivity and associated SST patterns. They are those with CNRM-ESM2-1 (abrupt-

4×CO₂), GFDL/CM4 (SSP2-4.5, 5-8.5, abrupt-4×CO₂), and MRI-ESM2.0 (SSP1-2.6, abrupt-4×CO₂). MRI-ESM2.0 (SSP1-2.6) has a strong cloud feedback (1.78 W m⁻² K⁻¹) probably because of a weak global-mean surface warming (0.44 K) in the denominator²⁶. Other experiments with the same models stay close to the interval in Figure 4. Based on our attribution framework, we finalize the emergent constraint via taking the mean of SST pattern effect among the 6 experiments but retaining the disturbance from residual factors.

Figure 5a shows strong positive feedback in low cloud regions with small spread and negative feedback in the tropical convective regions and Greenland Sea. In comparison with Figure 1d, the SST patterns in Figure 5b are more north-south symmetric in the Pacific with weaker northern subtropical warming, but antisymmetric in the Atlantic with north-to-south gradients. The constrained high, middle, low, and total cloud feedback (Fig. 5c) is -0.06±0.04, 0.14±0.05, 0.37±0.11, and 0.45±0.15 W m⁻² K⁻¹ (90% confidence), respectively. Our constraint on low cloud feedback is similar to that seen in the literature: spread across various models under multiple scenarios is as small as the latest effort¹², but the ensemble mean is as large as the multi-evident work¹⁴. Rather than low clouds only, our two-stage approach based on the warmer-get-higher paradigm applies consistently to radiative feedback associated with all types of clouds, effectively reducing the uncertainty by ~5/6.

Summary and caveats

Beneath the cloud type-dependent fraction change, this study uncovers a consistent warmer-get-higher paradigm highlighting the tropical SST pattern control over percentage cloud change to tightly constrain the global cloud feedback. Major contributors to feedback uncertainty are identified as cloud sensitivity, present-day simulation biases, and regional SST change. After the first two effects are removed by substituting model results with satellite measurements, we obtain an observational constraint on the third factor.

1 The constrained uncertainty of cloud feedback is about 1/6 of the original spread.
2 Nevertheless, a strong intermodel variation still appears in Figure 5b for 6 confined
3 models/experiments, with a maximum in the North Atlantic. In order to resolve uncertainty
4 in T^* and improve reliability of climate projections, global warming pattern formation
5 needs further study. For instance, our warmer-get-higher paradigm of percentage cloud
6 change may open an insightful perspective as a unique trigger of air-sea interactions.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available.

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Figure Legends

Figure 1 | Comparisons of horizontal distributions between (d) T^* (K) and fraction

change (%) in (a) high, (b) middle, and (c) low clouds. Ensemble means are shown in shading with color of T^* flipped from clouds, and intermodel spreads in contours (contour interval: 1.25 corresponding units). Dotted areas in (a-c) denote regions with climatological cloud fraction >20%. Dashed lines mark the tropics (40°S~40°N). Here we used the 30 CMIP6 simulations normalized by the global-mean surface (air) warming. **Strong cloud fraction changes appear in the tropics, with SST pattern effect controlling the sign of changes but cloud climatology determining the strength of changes in all cloud types.**

Figure 2 | Comparisons of horizontal distributions (left) and spatial scatters (right)

between the model ensemble-mean tropical SST patterns $\overline{T^*}$ (contours, K; contour interval: 0.1 K; red positive, blue negative; 0 omitted) and the ensemble-mean percentage cloud fraction change $\overline{\Delta}$ (shading, %) in (a) high, (b) middle, and (c) low clouds. In the left panel, $\overline{\Delta}$ is beyond the intermodel spread of Δ in the dotted areas, while the right panel is marked with the spatial correlations and regression coefficients (% K⁻¹) of $\overline{\Delta}$ against $\overline{T^*}$. Here we use the 30 CMIP6 simulations normalized by the global-mean surface (air) warming. **High and low clouds correlate positively and negatively with the SST patterns, respectively, and the spatial scatters present complex dynamical dependency of the percentage relation on cloud type.**

Figure 3 | Oceanic (a) zonal-mean and (b) equatorial meridional-mean percentage

cloud fraction change $\overline{\Delta}$ (%), and (c, d) corresponding cloud-type changes compared with $\overline{T^*}$ (K). In (a, b), dotted areas denote $\overline{\Delta}$ beyond intermodel spread of Δ and dashed lines split cloud types in altitude (440 and 680 hPa), while (c, d) are marked with correlations between $\overline{\Delta}$ and $\overline{T^*}$. Here we use the 30 CMIP6 simulations normalized by the

global-mean surface (air) warming. On the same order of magnitude as in other cloud types, middle cloud change apparently follows high clouds in the deep tropics especially over the warm pool, but coheres with low clouds in the subtropical and eastern equatorial oceans.

Figure 4 | Intermodel scatterplot between slope ($\% \text{ K}^{-1}$) in the tropical regression of low cloud Δ against T^* and (a) the corresponding correlation coefficients, (b) total cloud radiative feedback ($\text{W m}^{-2} \text{ K}^{-1}$), and (c) intercept ($\% \text{ K}^{-1}$) of the regression, along with (d) a schematic outlining our two-stage constraint for cloud feedback.

Intermodel correlations and regressions of the horizontal against vertical axes are marked.

The horizontal solid bar and dashed lines across (a-c) highlight the regression slope ($\% \text{ K}^{-1}$) in MODIS observations and its 99% confidence interval (confining 6 experiments circled in black), respectively. Here we use the 30 CMIP6 simulations normalized by the global-mean surface (air) warming. In a strong linear relationship with the sensitivity to global-mean surface warming, the percentage cloud sensitivity to SST patterns is apparently an essential contributor of the intermodel spread in cloud feedback to be constrained in the initial stage.

Figure 5 | Patterns of the constrained (a) cloud feedback ($\text{W m}^{-2} \text{ K}^{-1}$) and (b) SST patterns (K), along with (c) comparisons between the original cloud feedback ($\text{W m}^{-2} \text{ K}^{-1}$) and the constrained in two stages. In (a, b), ensemble means (shading) are presented with intermodel spreads (contours; contour interval: 1.6 corresponding units) of residual factors (a) and among the 6 confined experiments (b), and dashed lines mark the tropics ($40^\circ\text{S}\sim 40^\circ\text{N}$). For each feedback in (c), symbols denote the ensemble-mean values, with thin and thick error bars spanning 90% and 66% (1 standard deviation) confidence intervals. Here we use monthly-mean cloud radiative kernels, MODIS observations, and 30 CMIP6 simulations normalized by global-mean surface (air) warming. The constrained intermodel spread is $\sim 1/6$ of that in the original cloud feedback.

1 **Methods**

2 **MODIS observations**

3 Satellite SST data are provided by the Terra product from Moderate Resolution Imaging
4 Spectroradiometer (MODIS). Combining Aqua and Terra cloud observations, MODIS
5 provides a Level-3 Cloud Feedback Model Intercomparison Project (CFMIP) Observation
6 Simulator Package (MCD06COSP). It facilitates the comparison between models and
7 observations by producing synthetic MODIS data from climate model integrations.

8 We use the monthly products with spatial resolution of 1° latitude by 1° longitude
9 covering 2003-2020. Changes in SST (clouds) are calculated as the differences between the
10 last and first 9-year means, normalized by the global-mean surface (air) warming.

11 **CMIP6 multi-scenario outputs**

12 Considering the limited availability of cloud property histogram² variable (clisccp), we
13 analysed 30 CMIP6 simulations from 10 models across 6 scenarios²⁰ (Extended Data Fig.
14 2). Shared Socioeconomic Pathways (SSPs) in ScenarioMIP represent an integrated
15 scenario of future climate and societal change. We adopt 15 runs from 4 Tier 1 experiments
16 dubbed the SSP1-2.6, 2-4.5, 3-7.0, and 5-8.5. The other 15 runs come from the 1% per year
17 CO₂ increase (1pctCO₂) and abrupt CO₂ quadrupling (abrupt-4×CO₂) setups.

18 Details of the model names and scenarios, counted 4, 3, 3, 5, 6, and 9 are in order:
19 SSP1-2.6: CESM2, IPSL-CM6A-LR, MRI-ESM2.0, UKESM1.0-LL;
20 SSP2-4.5: CESM2, GFDL/CM4, UKESM1.0-LL;
21 SSP3-7.0: CESM2, CNRM-ESM2-1, UKESM1.0-LL;
22 SSP5-8.5: CESM2, GFDL/CM4, HadGEM3-GC3.1-LL, MRI-ESM2.0, UKESM1.0-LL;

1 1pctCO₂: CNRM-CM6-1, CNRM-ESM2-1, E3SM-1.0, HadGEM3-GC3.1-LL, MIROC-
2 ES2L, UKESM1.0-LL;
3 abrupt-4×CO₂: CNRM-CM6-1, CNRM-ESM2-1, E3SM-1.0, GFDL/CM4, HadGEM3-
4 GC3.1-LL, IPSL-CM6A-LR, MIROC-ES2L, MRI-ESM2.0, UKESM1.0-LL.

5 We analyse the monthly output of one realization from each simulation. Most SSP
6 simulations cover the period 2015-2100 for clisccp, except CNRM-ESM2-1 (2015-2055)
7 and MRI-ESM2.0 (2015-2020, 2080-2100), and all DECK experiments are at least 150
8 years long. Changes are defined as the difference between the last and first 10-year means,
9 except for MRI-ESM2.0 under SSPs calculated between 5-year-long means. Because cloud
10 feedback is expressed as responses of the top-of-atmosphere radiative flux to changes per
11 unit global-mean surface air warming, all atmospheric changes are accordingly normalized.
12 The SST patterns are an exception and are normalized by global-mean surface warming,
13 before computing ensemble means, spreads, kernels, correlations, regressions, and SVDs.

14 **Cloud feedback calculated with radiative kernels**

15 The CFMIP3 variable clisccp represents a 7 by 7 cloud property histogram along cloud top
16 pressure (p) and optical depth (τ). It can be used to calculate the fraction covered by total
17 and each type of clouds with summations in p and τ , for both climatology and change.

18 Here, cloud types are categorized as follows:

19 High clouds: 0-440 hPa (pressure levels 5-7), all optical depths;

20 Middle clouds: 440-680 hPa (pressure levels 3-4), all optical depths;

21 Low clouds: 680-1000 hPa (pressure levels 1-2), all optical depths;

22 Total clouds: 0-1000 hPa (all pressure levels), all optical depths.

23 Cloud radiative kernels² provide a simple and reliable methodology to convert the
24 clisccp change per unit global-mean surface air warming to its corresponding radiative

effect, quantifying cloud feedback across various models and scenarios in a consistent way. The kernels use incremental monthly cloud change to describe the differential response of top-of-atmosphere shortwave and longwave radiative fluxes. Such conversions act as spatial weights for changes in cloud property to calculate global feedback: (a) Normalize change of cloud property histogram with global-mean surface air warming; (b) Interpolate shortwave kernel with surface albedo (upward/downward shortwave flux) along longitude in each model; (c) Multiply the histogram by the longwave and interpolated shortwave kernels; (d) Perform vertical summation for total and each cloud type; (e) Average annually among 12 months and horizontally across the globe. The whole procedure is noted as $\langle * \rangle$.

Percentage attribution framework of cloud feedback

Based on the warmer-get-higher paradigm, we redefine cloud feedback with percentage change in the tropics and design an uncertainty attribution framework in Eqs. (1-3), to quantify contributions from factors including SST patterns and biases in mean-state clouds.

$$\lambda = \langle \delta C \cdot K \rangle = \left\langle \frac{\delta C}{\gamma} \cdot \gamma K \right\rangle,$$

where λ is cloud feedback, C represents cloud fraction with δ marking its normalized change, K are the cloud radiative kernels, and $\langle \cdot \rangle$ expresses the feedback calculation procedure. γ is the percentage parameter,

$$\gamma = \begin{cases} C, & 40^\circ\text{S} \sim 40^\circ\text{N} \\ 1, & \text{Extratropics} \end{cases}$$

Converted from cloud fraction change and radiative kernels, percentage change (Δ) and fractional kernels (γK) are defined and further decomposed as

$$\begin{cases} \frac{\delta C}{\gamma} = \Delta = \bar{\Delta} + \Delta' = \bar{\Delta} + \Delta'^* + \Delta'_R, \\ \gamma K = \overline{\gamma K} + (\gamma K)' \end{cases}, \quad (4)$$

where overbars and primes mark ensemble means and intermodel anomalies, Δ'^* and Δ'_R are the components of Δ' induced by T^* and residual factors, respectively. Thus, the cloud radiative feedback can be decomposed into

$$\lambda = \langle (\bar{\Delta} + \Delta'^* + \Delta'_R) \cdot [\overline{\gamma K} + (\gamma K)'] \rangle, \quad (5)$$

$$\Rightarrow \lambda = \langle \bar{\Delta} \cdot \overline{\gamma K} \rangle + \langle \bar{\Delta} \cdot (\gamma K)' \rangle + \langle \Delta'^* \cdot \overline{\gamma K} \rangle + \langle \Delta'^* \cdot (\gamma K)' \rangle + \langle \Delta'_R \cdot \gamma K \rangle.$$

Here, terms on the right-hand-side represent, in turn, the ensemble mean of all factors, biases in fractional kernels/cloud climatology, uncertainty induced by T^* and tropical-mean SST increase to be estimated by the intermodel SVD, nonlinear interaction between these two intermodel variabilities, and the influence of residual factors.

We perform two sets of evaluations with and without the initial constraint, and illustrate the substituted factor contributions in Extended Data Figures 9 and 10. The former only examines cloud feedback anomalies associated with the ensemble-mean fractional kernels ($\langle \Delta' \cdot \overline{\gamma K} \rangle$). Influences of the SST patterns ($\langle \Delta'^* \cdot \overline{\gamma K} \rangle$) converge after ~ 19 leading SVD modes, with ~ 15 modes in the original feedback. In contrast, the latter quantifies all intermodel terms of Eq. (3) as 0%, 83%, 8%, 9% in turn and 3%, 78%, 1%, 18% unsubstituted. Thus, the T^* dominations are slightly different between the two figures.

Intermodel statistical analysis

This analysis probes dynamical interpretations to locate the source of uncertainty, specifically via replacing time series with the model series. Intermodel correlations and regressions are performed for cloud feedback, and variances explained by different factors are estimated as exclusive R^2 (to be introduced) with the total effect.

The SST pattern effect can be extracted with a singular value decomposition (SVD) that returns the covariant modes of two variables. Using monthly intermodel anomalies,

two sets of intermodel SVD analyses (scaled/unscaled) are performed between SST patterns (4-D: $x, y, \text{month}, \text{model}$) and cloud change (6-D: $x, y, p, \tau, \text{month}, \text{model}$) in percentage for the tropics (40°S - 40°N) and in fraction outside. Then, we calculate the partial feedback parameter with the fractional kernels and cloud patterns in each SVD mode, and multiplied these parameters by the corresponding principal components to reconstruct the T^* -related intermodel variability for each mode. After reordering the modes according to their individually explained variances (direct R^2) of cloud feedback, the cumulative variance¹⁸ of the reconstruction is quantified as the exclusive R^2 between the cumulative combinations of leading modes and the total feedback.

Process-oriented emergent constraint in two stages

Figure 4 illustrates how to substitute the simulated sensitivity of Δ to T^* with the observed values for each cloud type. After summing annual-mean clisccp changes across all optical depths, we perform a percentage calculation, Pearson correlation with, and linear regression against T^* spatially in the tropics. Hence, slopes at 7 pressure levels are obtained for all 30 experiments (S_m) and the MODIS observations (S_o). Then, percentage changes of clisccp in each climate model are multiplied by the corresponding $\frac{S_o}{S_m}$, except those with spatial correlation < 0.15 (mostly for middle clouds). In this procedure, cloud sensitivity to spatially uniform warming (Fig. 4c) is automatically scaled by the same factor. Meanwhile, the observed cloud fraction is used to replace the simulated climatology (tropical γ) in the fractional kernel of each model. These compose the initial stage of our constraint.

The eventual stage confines 6 experiments with the 99% confidence interval of the percentage cloud sensitivity to T^* in the MODIS observations (Fig. 4), and constrains the cloud feedback based on the attribution framework. On the right-hand-side of Eq. (3), we keep the first and last terms unchanged, but use the mean of the 6 experiments in other

terms. Thus, the uncertainty induced by SST patterns is removed but that due to residual factors is retained. Applied to the cloud sensitivity, present-day simulation biases, and regional SST change, this stagewise emergent constraint reduces the uncertainty in cloud feedback by greater than half an order of magnitude.

Variances explained by linearly dependent factors

An exclusive R^2 method developed here can avoid the overfitting problem among linearly dependent factors for cloud type decomposition and uncertainty attribution. For example (Extended Data Fig. 1a), the summation of variances (direct R^2) explained by cloud types exceeds 1 for shortwave feedback, probably due to the marked anticorrelation between high and low cloud changes. To correct this, we have to remove its portion counted repeatedly in other factors due to linear dependency. This study involves situations with 2-4 factors.

$Z = A + B$ is the simplest case with 2 factors. The results of exclusive R^2 are noted as R_A^2 and R_B^2 , and the direct R^2 equaling to squared correlations as $R^2(Z, A)$ and $R^2(Z, B)$ for A and B , respectively. The repeating portion between A and B is excessively counted by twice in $R^2(Z, A) + R^2(Z, B)$, so that it is expressed as $R_{AB}^2 = \frac{R^2(Z, A) + R^2(Z, B) - 1}{2}$. With the summation guaranteed equaling to 1, the exclusive R^2 can be obtained as

$$\begin{cases} R_A^2 = R^2(Z, A) - R_{AB}^2 = \frac{1 + R^2(Z, A) - R^2(Z, B)}{2} \\ R_B^2 = R^2(Z, B) - R_{AB}^2 = \frac{1 - R^2(Z, A) + R^2(Z, B)}{2} \end{cases}$$

The 3-factor case excessively counts the common portion among A , B , and C by 6 times in $R^2(Z, A) + R^2(Z, B) + R^2(Z, C)$, and that between either 2 factors by twice. In the 4-factor case, the excessive count for the common portion among all factors increases to 12, and those for less factors remain the same as in simpler cases. Both situations can be processed with more complicated mathematical procedures following the 2-factor case.

Data availability

The MODIS data are freely available for download at <https://oceandata.sci.gsfc.nasa.gov/directaccess/MODIS-Terra> for SST, and <https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/science-domain/cloud#modis> for clouds. Cloud radiative kernels can be accessed at <https://github.com/mzelinka/cloud-radiative-kernels>. CMIP6 output is archived at <https://esgf-node.llnl.gov/search/cmip6/> and <https://data.ceda.ac.uk/badc/cmip6/data/CMIP6>.

Code availability

The MATLAB code used to process and analyse data can be obtained by contacting the corresponding author.

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Author contributions J.M. designed the analyses and wrote the manuscript. J.F. performed all computations with technical support from Y.Z. on SVD. I.S.K., M.C., M.W. and J.L. revised the original draft manuscript.

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Figure 2 | Comparisons of horizontal distributions (left) and spatial scatters (right) between the model ensemble-mean tropical SST patterns $\overline{T^*}$ (contours, K; contour interval: 0.1 K; red positive, blue negative; 0 omitted) and the ensemble-mean percentage cloud fraction change $\overline{\Delta}$ (shading, %) in (a) high, (b) middle, and (c) low clouds. In the left panel, $\overline{\Delta}$ is beyond the intermodel spread of Δ in the dotted areas, while the right panel is marked with the spatial correlations and regression coefficients (% K⁻¹) of $\overline{\Delta}$ against $\overline{T^*}$. Here we use the 30 CMIP6 simulations normalized by the global-mean surface (air) warming. High and low clouds correlate positively and negatively with the SST patterns, respectively, and the spatial scatters present complex dynamical dependency of the percentage relation on cloud type.

Figure 3 | Oceanic (a) zonal-mean and (b) equatorial meridional-mean percentage cloud fraction change $\bar{\Delta}$ (%), and (c, d) corresponding cloud-type changes compared with $\bar{T}^*$ (K). In (a, b), dotted areas denote $\bar{\Delta}$ beyond intermodel spread of Δ and dashed lines split cloud types in altitude (440 and 680 hPa), while (c, d) are marked with correlations between $\bar{\Delta}$ and $\bar{T}^*$. Here we use the 30 CMIP6 simulations normalized by the global-mean surface (air) warming. On the same order of magnitude as in other cloud types, middle cloud change apparently follows high clouds in the deep tropics especially over the warm pool, but coheres with low clouds in the subtropical and eastern equatorial oceans.

Figure 4 | Intermodel scatterplot between slope (% K^{-1}) in the tropical regression of low cloud Δ against T^* and (a) the corresponding correlation coefficients, (b) total cloud radiative feedback ($W m^{-2} K^{-1}$), and (c) intercept (% K^{-1}) of the regression, along with (d) a schematic outlining our two-stage constraint for cloud feedback.

Intermodel correlations and regressions of the horizontal against vertical axes are marked. The horizontal solid bar and dashed lines across (a-c) highlight the regression slope (% K^{-1}) in MODIS observations and its 99% confidence interval (confining 6 experiments circled in black), respectively. Here we use the 30 CMIP6 simulations normalized by the global-mean surface (air) warming. In a strong linear relationship with the sensitivity to global-mean surface warming, the percentage cloud sensitivity to SST patterns is apparently an essential contributor of the intermodel spread in cloud feedback to be constrained in the initial stage.

Figure 5 | Patterns of the constrained (a) cloud feedback ($\text{W m}^{-2} \text{K}^{-1}$) and (b) SST patterns (K), along with (c) comparisons between the original cloud feedback ($\text{W m}^{-2} \text{K}^{-1}$) and the constrained in two stages. In (a, b), ensemble means (shading) are presented with intermodel spreads (contours; contour interval: 1.6 corresponding units) of residual factors (a) and among the 6 confined experiments (b), and dashed lines mark the tropics ($40^\circ\text{S}\sim 40^\circ\text{N}$). For each feedback in (c), symbols denote the ensemble-mean values, with thin and thick error bars spanning 90% and 66% (1 standard deviation) confidence intervals. Here we use monthly-mean cloud radiative kernels, MODIS observations, and 30 CMIP6 simulations normalized by global-mean surface (air) warming. **The constrained intermodel spread is $\sim 1/6$ of that in the original cloud feedback.**

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [ExtendedData.pdf](#)