Quantifying climate feedbacks using radiative kernels

Soden et al. (Journal of Climate, 2008)

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Climate sensitivity/feedbacks 101

Some definitions

Climate sensitivity is the surface temperature change in response to a unit change in radiative forcing [K/(W/m^2)].

A **feedback mechanism** is a process that changes the sensitivity of the climate.

Positive feedbacks increase the magnitude of the response and **negative feedbacks** reduce it.

Climate feedback strength can be quantified by a **climate feedback parameter** λ [W/m^2/K].

Two methods to compute climate feedback parameters λ

Wetherald & Manabe (1988):

- Substitute one variable at a time from the perturbed climate state into the control climate and compute the change in radiative flux.
- Also called the *partial radiative perturbation* (PRP) method.
- Computationally expensive and implementation details lead to spurious differences.

Cess et al. (1990, 1996):

- Use prescribed sea surface temperature (SST) perturbations to induce a change in the TOA radiative fluxes.
- Only isolates cloud feedback. Doesn't even do it accurately.

Some notation

$$
\begin{aligned}
G &\rightarrow \text{direct radiative forcing} \\
T_s &\rightarrow \text{surface temperature} \\
R(\mu) = Q(\mu) - F(\mu) & \\
R = R(w, T, c, a) &\rightarrow \text{net TOA flux} \\
Q(\mu) &\rightarrow \text{absorbed shortwave radiation} \\
F(\mu) &\rightarrow \text{outgoing longwave radiation (OLR)} \\
\mu &\rightarrow \text{index (position, time of day, day of year)} \\
w &\rightarrow \text{column distribution of water vapor} \\
T &\rightarrow \text{temperature} \\
c &\rightarrow \text{cloud properties} \\
a &\rightarrow \text{surface albedo} \\
A, B &\rightarrow \text{climate states (B is a perturbation of A)} \\
\overline{R}(\mu) &\rightarrow \text{time average}
\end{aligned}
$$

Some notation

The PRP method would investigate the effects of water vapor

$$\delta_w \overline{R} = \overline{R(w_B, T_A, c_A, a_A, \mu)} - \overline{R(w_A, T_A, c_A, a_A, \mu)} \tag{1}$$

The total perturbation can be written as

$$\delta \overline{R} = \delta_w \overline{R} + \delta_T \overline{R} + \delta_c \overline{R} + \delta_a \overline{R} = -G \tag{2}$$

Climate feedback parameters for each variable X can be written as

$$\lambda_X = -\frac{\delta_X \overline{R}}{\delta X} \frac{\delta X}{\delta T_s}\,, \quad X = \{w, T, c, a\} \tag{3}$$

such that $\delta T_s = -G/\lambda$ where $\lambda = \lambda_w + \lambda_T + \lambda_c + \lambda_a$.

Conceptual model of cross-field correlations

Conceptual model of cross-field correlations

Let us use a thought experiment to show the problem with the PRP method, that it assumes all fields are temporally uncorrelated.

We can construct a simple model where water vapor and clouds are correlated.

Assume that when high clouds are present $F = 0$. When high clouds are absent $F = \alpha + \beta w$ where $\alpha, \beta \in \mathbb{R}$ and $\beta < 0$. Letting

$f \rightarrow$ high clouds are present a fraction f of the time

$w_1 \rightarrow$ water vapor in cloud-free regions

$w_2 \rightarrow$ water vapor underneath high clouds

then the average incoming flux is

$$\overline{R} = -(1 - f)(\alpha + \beta w_1) \tag{4}$$

Conceptual model of cross-field correlations

Now consider a change in climate in which f, w_1, and w_2 change by small amounts. Then

$$\delta\overline{R} = \delta_c\overline{R} + \delta_w\overline{R} \tag{5}$$

where

$$\delta_c\overline{R} = \overline{R(f+\delta f, w_1, w_2)} - \overline{R(f, w_1, w_2)} = (\alpha + \beta w_1)\delta f \tag{6}$$

and

$$\boxed{\delta_w\overline{R} = \overline{R(f, w_1 + \delta w_1, w_2)} - \overline{R(f, w_1, w_2)} = -(1-f)\beta\delta w_1} \tag{7}$$

Conceptual model of cross-field correlations

But if we use the PRP method then

$$\overline{R(w_B, c_A)} = -(1 - f_A)\{\alpha + \beta\left[f_B w_{2B} + (1 - f_B) w_{1B}\right]\} \tag{8}$$

and so

$$\begin{aligned} \delta_w \overline{R} &= \overline{R(f, w_{1B}, w_{2B})} - \overline{R(f, w_{1A}, w_{2A})} \\ &= -\beta(1 - f_A)\left[(w_{1B} - w_{1A}) + f_B(w_{2B} - w_{1B})\right] \\ &= \underbrace{-\beta(1 - f)\delta w_1}_{\text{expected result}} - \underbrace{\beta(1 - f) f (w_2 - w_1)}_{\text{unwanted } \mathcal{O}(1) \text{ term!}} \end{aligned} \tag{9}$$

if we assume $A = B$ when multiplying by a perturbation quantity.

Conceptual model of cross-field correlations

Two ways to correct this problem!

Computing the effects of decorrelating w and c by using another realization of the base climate A'

$$\overline{R(w_B, c_A)} - \overline{R(w_A, c'_A)} \tag{10}$$

or use a two-sided PRP

$$\frac{1}{2}\left[\overline{R(w_B, c_A)} - \overline{R(w_A, c_A)} + \overline{R(w_B, c_B)} - \overline{R(w_A, c_B)}\right] \tag{11}$$

both of which replace the unwanted $\mathcal{O}(1)$ term with an $\mathcal{O}(\epsilon)$ term.

Radiative kernel method

Radiative kernel method

Instead of replacing variables like X_A with X_B as in the PRP method, instead replace X_A with $X_A + \delta\overline{X}$.

We will show that this separates the feedback into two factors!

Radiative kernel $K^X \rightarrow$ depends on the radiative algorithm and base climate.

Climate response pattern $\delta\overline{X} \rightarrow$ change in the mean climatology of the feedback variable between the two climate states.

Then

$$\lambda_X = K^X \delta\overline{X} \tag{12}$$

so that intermodel differences are only due to different climate responses $\delta\overline{X}$.

Applying radiative kernels to the conceptual model

We will replace w_A with $w_A + \delta\overline{w}$. The mean water vapor is

$$\overline{w} = (1-f)w_1 + fw_2 \tag{13}$$

so the change in water vapor with a change in climate is

$$\delta\overline{w} = \overline{w}_B - \overline{w}_A = \delta w_1 + \delta\left[f(w_2 - w_1)\right] \tag{14}$$

so that

$$\delta_w\overline{R} = \overline{R(w_A + \delta\overline{w}, c_A)} - \overline{R(w_A, c_A)} = -\beta(1-f)\delta w_1 - \beta(1-f)\delta\left[f(w_2 - w_1)\right] \tag{15}$$

so the error is still $\mathcal{O}(\epsilon)$ but you get the other benefits of radiative kernels!

Where is the radiative kernel K^X?

Since $\delta\overline{w}$ is small we can compute the response to water vapor perturbations using a first-order Taylor expansion

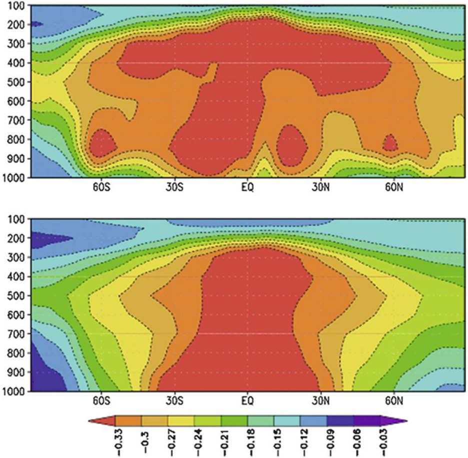
$$\overline{R(w_A + \delta\overline{w}, T_A, c_A, a_A)} - \overline{R(w_A, T_A, c_A, a_A)} \approx \overline{\frac{\partial R}{\partial w}(w_A, T_A, c_A, a_A)}\delta\overline{w} \equiv K^w \delta\overline{w} \quad (16)$$

To consider the effects of water vapor at all levels

$$\overline{R(\boldsymbol{w}_A + \delta\overline{\boldsymbol{w}}, T_A, c_A, a_A)} - \overline{R(\boldsymbol{w}_A, T_A, c_A, a_A)} \approx \sum_i \overline{\frac{\partial R}{\partial w_i}(\boldsymbol{w}_A, T_A, c_A, a_A)}\delta\overline{w_i} \equiv \sum_i K_i^w \delta\overline{w_i} \quad (17)$$

Results

Zonal-mean, annual-mean temperature kernel K^T



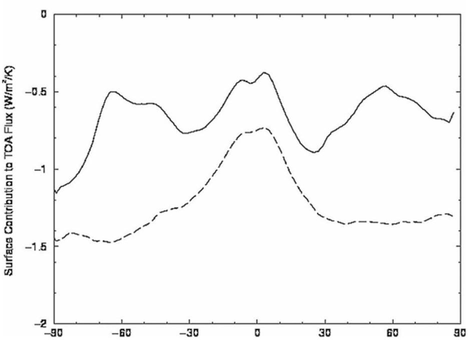


FIG. 1. The zonal-mean, annual-mean temperature kernel K^T under (top) total-sky and (middle) clear-sky conditions in units of W m^{-2} K^{-1}/100 hPa. (bottom) The surface component of the kernel is shown separately for both total sky (solid) and clear sky (dashed).

Zonal-mean, annual-mean water vapor kernel K^w (longwave)

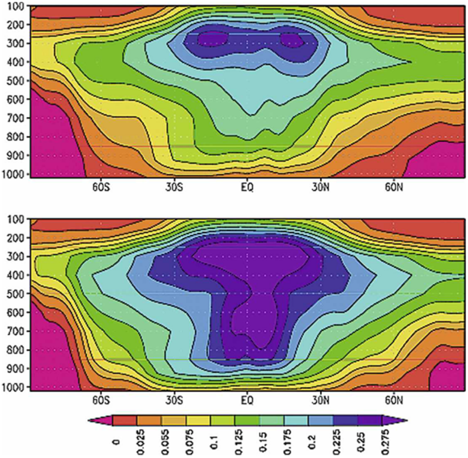


FIG. 2. The zonal-mean, annual-mean water vapor kernel K^ω under (top) total-sky and (middle) clear-sky conditions in units of W m^{-2} K^{-1}/100 hPa. When multiplied by the vapor response (1 unit of vapor is required to maintain constant relative humidity for a 1-K temperature increase), a pressure average of K^ω yields the total effect of the column temperature perturbation on the TOA longwave flux.

Zonal-mean, annual-mean water vapor kernel K^w (shortwave)

TABLE 1. The global-mean vertically integrated values of the temperature and water vapor kernels for total-sky and clear-sky conditions. The kernels are integrated from surface to the tropopause and the results are expressed in units of W m^{-2} K^{-1}.

	Temperature	Water vapor [longwave (LW)]	Water vapor [shortwave (SW)]
Total sky	−3.25	1.13	0.27
Clear sky	−3.56	1.62	0.16

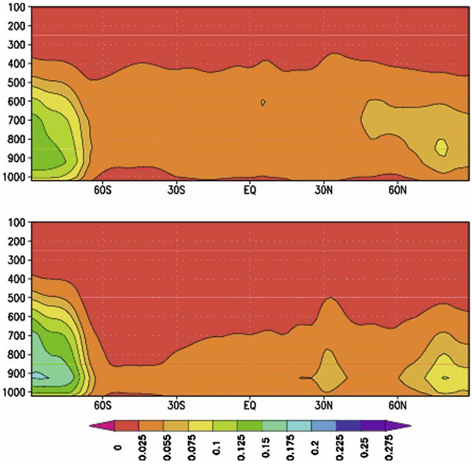
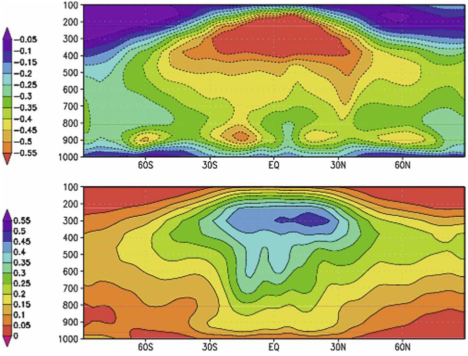


FIG. 3. As in Fig. 2 but for the net downward shortwave radiation at the TOA.

Total-sky TOA flux response $\sum K_i^T \delta \overline{T}_i$ and $\sum K_i^w \delta \overline{w}_i$



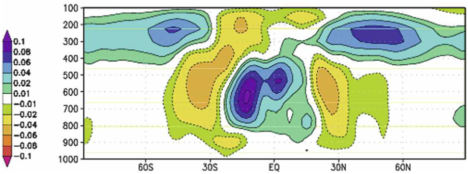


FIG. 4. The total-sky TOA flux response due to the (top) temperature perturbations and (middle) water vapor displayed in Fig. 5. (bottom) The portion of the water vapor effect that is due to departures from constant relative humidity. Positive values indicate an increase in net outgoing radiation (i.e., a cooling effect). The results are normalized by the change in global-mean surface temperature and are expressed in units of W m^{-2} K^{-1}/100 hPa.

TABLE 2. Comparison feedback calculations using the PRP method and kernel method for the GFDL AM2 under a ±2 K SST perturbation. All values are in units of W m^{-2} K^{-1}.

Feedback	Kernel	Forward PRP	Reverse PRP	Average PRP
Temperature	−4.06	−4.42	−3.64	−4.03
Water vapor	2.01	2.12	1.78	1.95
Surface albedo	0.15	0.17	0.13	0.15
Clouds	0.37	0.28	0.39	0.34

Intermodel comparison of zonal-mean, annual-mean K^T and K^w

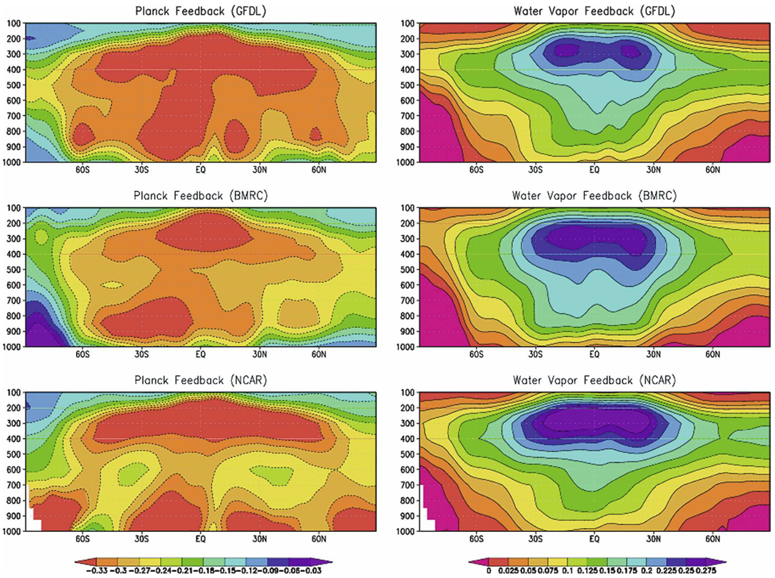


FIG. 5. The annual-mean, zonal-mean temperature K^T and water vapor K^ω kernels under total-sky conditions for the (top) GFDL, (middle) CAWCR, and (bottom) NCAR models in units of W m^{-2} K^{-1} /100 hPa.

Intermodel comparison of zonal, annual-mean K^T and K^w

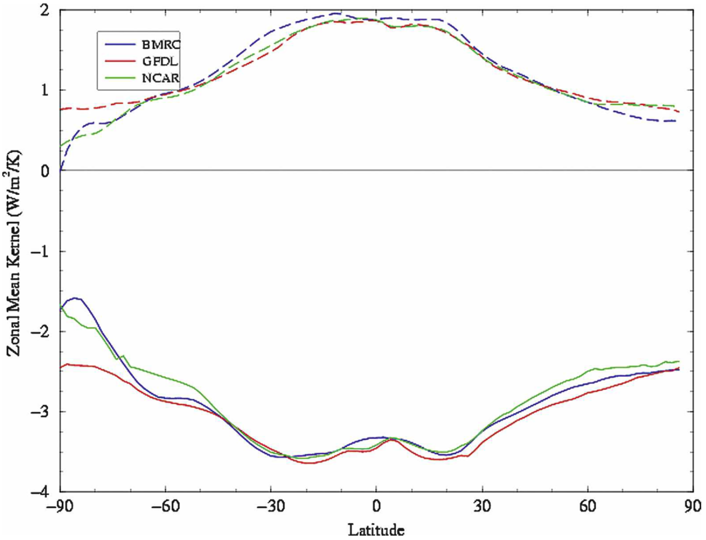


FIG. 6. Zonal, annual mean of the vertically integrated temperature K^T (solid) and water vapor K^{ω} (dashed) kernels under total-sky conditions for the GFDL (red), the CAWCR (blue), and the NCAR (green) models in units of W m^{-2} K^{-1}.

Intermodel comparison of global-mean vertically integrated K^T and K^w

TABLE 3. Global-mean vertical integrals from surface to the tropopause of the temperature and water vapor feedback kernels in units of $W\ m^{-2}\ K^{-1}$. For surface albedo, the units are $W\ m^{-2}$ per 1% decrease in surface albedo. The corresponding integrals for the clear-sky kernels are listed in parentheses.

Model	Temperature	Water vapor (LW)	Water vapor (SW)	Surface albedo
GFDL	−3.25 (−3.56)	1.13 (1.62)	0.27 (0.16)	1.39 (2.11)
NCAR	−3.13 (−3.52)	1.19 (1.68)	0.23 (0.15)	1.35 (2.13)
CAWCR (FS/LH)	−3.17 (−3.58)	1.25 (1.76)	0.23 (0.17)	1.56 (2.22)
CAWCR (SES)	−3.14	1.35	0.26	1.61

Global-mean feedback parameters

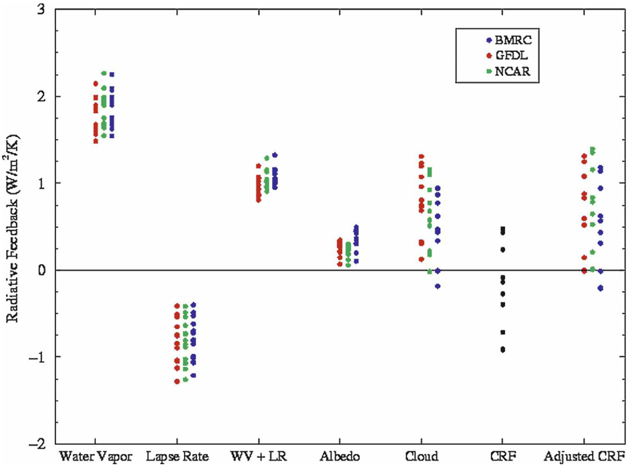


FIG. 7. The global-mean water vapor, lapse rate, water vapor + lapse rate, surface albedo, and cloud feedbacks computed for 14 coupled ocean–atmosphere models (listed in Table 1 of Soden and Held 2006) using the GFDL (red), NCAR (green), CAWCR (blue) kernels. The global-mean change in cloud radiative forcing (CRF) per degree global warming (black dots) and the adjusted change in CRF based on each of the three kernels are also shown. Only 12 of the 14 models archived the necessary data for computing cloud feedbacks, and only 11 of the 14 archived the necessary data for computing the change in CRF.

Multimodel ensemble-mean maps of feedbacks

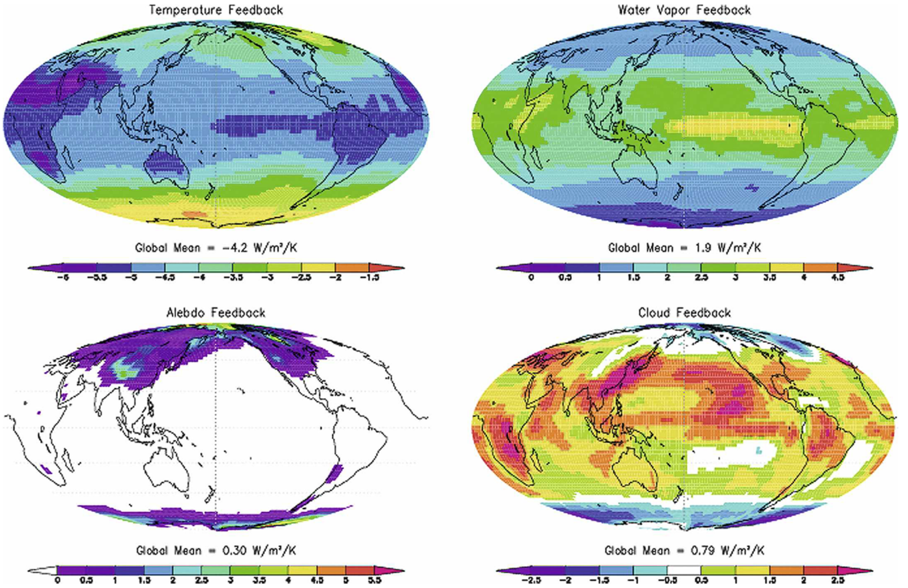


FIG. 8. Multimodel ensemble-mean maps of the temperature, water vapor, albedo, and cloud feedback computed using climate response patterns from the IPCC AR4 models and the GFDL radiative kernels.

Multimodel ensemble-mean maps of feedbacks (clear-sky)

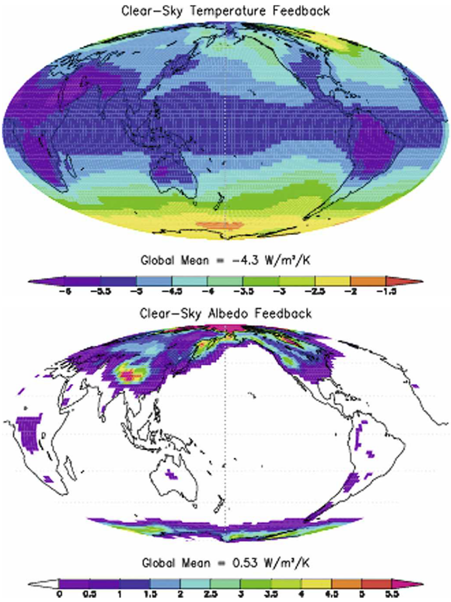


FIG. 9. As in Fig. 11 but for the clear-sky feedbacks.

Multimodel ensemble-mean maps of correction to dC_{RF}

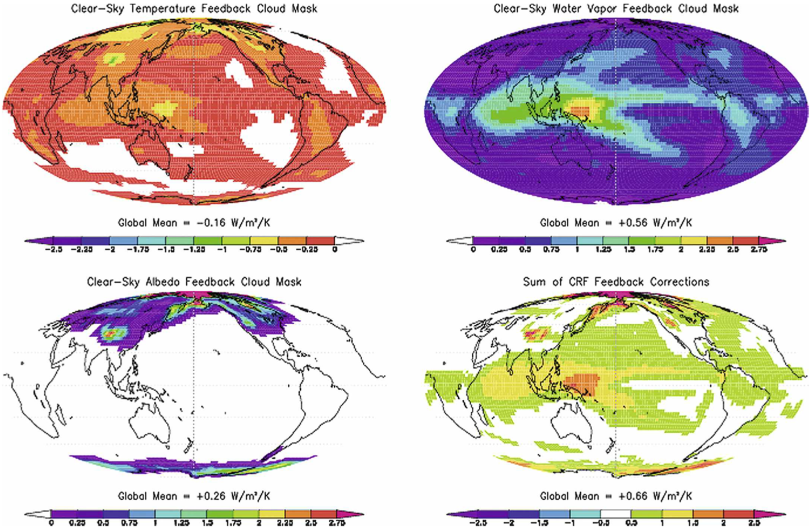
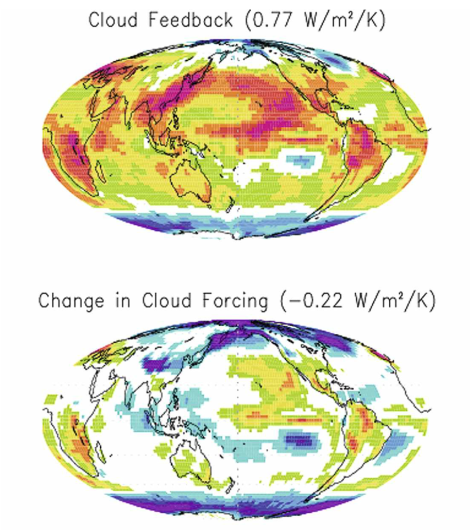


FIG. 10. Multimodel ensemble-mean maps of the corrections to dC_{RF} for (top left) temperature, (top right) water vapor, (lower left) surface albedo, and (lower right) their sum computed using climate response patterns from the IPCC AR4 models and the GFDL radiative kernels.

Multimodel ensemble-mean maps of cloud feedback parameter



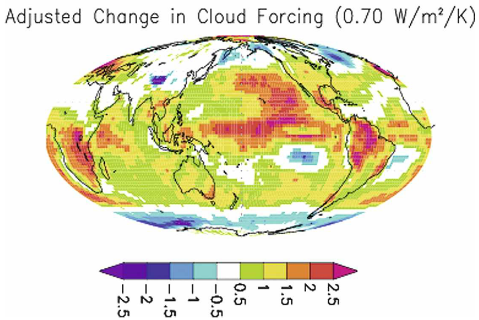


FIG. 11. Multimodel ensemble-mean maps of the cloud feedback estimated as (top) the residual of the kernel calculations, (middle) the change in cloud forcing, and (bottom) the change in cloud forcing after adjusting for the effects of cloud masking on noncloud feedbacks and external radiative forcing. Only those models for which both the cloud feedback and CRF were available are included in the ensemble mean. Both the cloud feedback and cloud-masking adjustments to the change in cloud forcing are estimated using the GFDL kernel.

Conclusion

Conclusion

Radiative kernels describe the differential response of the TOA radiative fluxes to incremental changes in the feedback variables.

They allow us to decompose a climate feedback into two factors:

- **Radiative kernel** $K^X \rightarrow$ intrinsic to the radiative physics.
- **Climate response pattern** $\delta\overline{X} \rightarrow$ arises from a particular pattern of climate response.

Conclusion

Main benefits

- Separation of radiative and climate response components of the feedback allows for better understanding of feedback physics.
- Avoids the extra computation and biases of the PRP method.
- Kernel can be reused for comparing feedbacks across models or between different climate change scenarios.

Key limitations

- Kernels for cloud feedbacks cannot be computed directly.
- The feedback processes are assumed to be linear. Cloud feedbacks can be pretty nonlinear.

Would you recommend radiative kernels to a friend?