Observational Constraint On Low-Cloud Feedbacks Suggests Moderate Climate Sensitivity

Grégory Cesana
Columbia University & NASA-GISS

Anthony Del Genio
NASA-GISS


Can we observationally constrain this?
The surface warming resulting from an hypothetical doubling of CO$_2$ (climate sensitivity) has remained highly uncertain over the past 40 years.
The surface warming resulting from an hypothetical doubling of CO₂ (climate sensitivity) has remained highly uncertain over the past 40 years.

Model projections:
- Strong warming: 5.6°C
- Weak warming: 1.8°C

Mostly contributed by cloud feedbacks (e.g., Zelinka et al. 2020)
The surface warming resulting from an hypothetical doubling of CO$_2$ (climate sensitivity) has remained highly uncertain over the past 40 years

Model projections
- Strong warming 5.6°C
- Weak warming 1.8°C

IPCC likely range

Mostly contributed by cloud feedbacks (e.g., Zelinka et al. 2020)
Low clouds cool the Earth by reflecting SW radiation back to space

Cloud Radiative Effect (CRE)
In response to global warming...

Cloud Radiative Effect (CRE)  Global warming (dT)

Cooling
In response to global warming…
They may dissipate, resulting in less SW radiation reflection, reinforcing the surface warming through a positive feedback.
In response to global warming…
They grow larger, resulting in more SW radiation reflection, weakening the surface warming through a negative feedback
Cloud Feedback (dCRE/dT):
Change of cloud radiative effect at TOA in response to global surface warming.

Cloud Feedback = \frac{dCRE}{dT}

Change of TOA Cloud Radiative Effect (CRE)

Change of global mean surface temperature

=> We focus on the SW tropical low-cloud feedback, referred to as "cloud feedback"
SW tropical low-cloud feedback explains a large part of the spread in climate sensitivity.

\[ r = 0.68 \]

(see also Zelinka et al., 2020, 2013)
Objective:
Reducing the uncertainty in low-cloud feedback would reduce its contribution to the spread in ECS

(see also Zelinka et al., 2020, 2013)
**Objective:**
Reducing the uncertainty in low-cloud feedback would reduce its contribution to the spread in ECS.

**Can we constrain this low-cloud feedback with observations?**

(See also Zelinka et al., 2020, 2013)
\[
\frac{d\text{CRE}}{dT} = ?
\]

Estimating the cloud feedback from observations is challenging because the satellite record is too short.
The cloud feedback is linearly correlated with the change in low cloud cover (in subsidence regime)

\[
\frac{d\text{CRE}}{dT} = a \frac{d\text{LCC}}{dT}
\]

Sensitivity of CRE to low clouds (~ -1 W/m²/%)

Change of low clouds in response to warming

LCC: low cloud cover

T: global mean surface temperature
The change of low clouds results from changes in low-cloud predictors ($x$) multiplied by the sensitivity of low-clouds to their predictors.

\[
\frac{d \text{CRE}}{dT} = a \frac{d \text{LCC}}{dT}
\]

\[
\frac{d \text{LCC}}{dT} = \sum_i \frac{\partial \text{LCC}}{\partial x_i} \frac{dx_i}{dT}
\]

$x_i$: low-cloud predictors (aka controlling factors)

Sensitivity of low clouds to predictors

Change of low-cloud predictors in response to warming

e.g. Qu et al. (2015)
The SST and the inversion strength control the future change of low clouds

\[ \frac{dCRE}{dT} = a \frac{dLCC}{dT} \]

\[ \frac{dLCC}{dT} = \left( \frac{\partial LCC}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC}{\partial EIS} \frac{dEIS}{dT} \right) \]

Sea surface temperature  Inversion strength

x: SST and EIS
High SSTs reduces the low cloud cover while high stability (EIS) increases it.

Higher SSTs promote mixing with the drier free troposphere ➔ Cloud decrease

High stability reduces mixing with the drier free troposphere ➔ Cloud increase
Cloud feedback can be inferred from (low cloud) observations

\[
\frac{dCRE}{dT} = a \frac{dLCC}{dT}
\]

\[
\frac{dLCC}{dT} = \sum_i \frac{\partial LCC}{\partial x_i} \frac{dx_i}{dT}
\]

\[
\frac{dLCC}{dT} = \left( \frac{\partial LCC}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC}{\partial EIS} \frac{dEIS}{dT} \right)
\]

\[
\frac{dCRE}{dT} = a \left( \frac{\partial LCC}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC}{\partial EIS} \frac{dEIS}{dT} \right)
\]

Inferred Feedback
Cloud feedback can be inferred from (low cloud) observations

\[
\frac{d\text{CRE}}{dT} = a \left( \frac{\partial \text{LCC}}{\partial \text{SST}} \frac{d\text{SST}}{dT} + \frac{\partial \text{LCC}}{\partial \text{EIS}} \frac{d\text{EIS}}{dT} \right)
\]

Cloud sensitivity to predictors

Predictor changes
This method provides some good observational constraint on climate models but the uncertainty is still quite high.

\[
\frac{d\text{CRE}}{dT} = a \left( \frac{\partial \text{LCC}}{\partial \text{SST}} \frac{d\text{SST}}{dT} + \frac{\partial \text{LCC}}{\partial \text{EIS}} \frac{d\text{EIS}}{dT} \right)
\]
This method provides some good observational constraint on climate models but the uncertainty is still quite high.

\[
\frac{d\text{CRE}}{dT} = a \left( \frac{\partial \text{LCC}}{\partial \text{SST}} \frac{d\text{SST}}{dT} + \frac{\partial \text{LCC}}{\partial \text{EIS}} \frac{d\text{EIS}}{dT} \right)
\]

2 shortcomings need to be addressed in this method.
1. The contribution of Sc and Cu must be accounted for separately

\[
\frac{dCRE_{Sc}}{dSST} \neq \frac{dCRE_{Cu}}{dSST}
\]

Bretherton et al. (2015); Cesana et al., (2019)

\[
\frac{dCRE}{dT} = \frac{dCRE_{Sc}}{dLCC_{Sc}} \left( \frac{\partial LCC_{Sc}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Sc}}{\partial EIS} \frac{dEIS}{dT} \right) + \frac{dCRE_{Cu}}{dLCC_{Cu}} \left( \frac{\partial LCC_{Cu}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Cu}}{\partial EIS} \frac{dEIS}{dT} \right)
\]
2. Each cloud-type feedback depends on the relative presence of the cloud type

If no Sc or Cu then \( \frac{dCRE_{Sc \text{ or } Cu}}{dT} \approx 0 \)

\[
\frac{dCRE}{dT} = \frac{dCRE_{Sc}}{dLCC_{Sc}} \left( \frac{\partial LCC_{Sc}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Sc}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Sc}}{LCC} + \frac{dCRE_{Cu}}{dLCC_{Cu}} \left( \frac{\partial LCC_{Cu}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Cu}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Cu}}{LCC}
\]
Can we determine each term of the equation using observations?

\[
\frac{dCRE}{dT} = \frac{dCRE_{Sc}}{dLCC_{Sc}} \left( \frac{\partial LCC_{Sc}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Sc}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Sc}}{LCC} \\
+ \frac{dCRE_{Cu}}{dLCC_{Cu}} \left( \frac{\partial LCC_{Cu}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Cu}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Cu}}{LCC}
\]

\[\rightarrow \text{Need Cu – Sc observations}\]
The Cumulus and Stratocumulus CloudSat-CALIPSO Dataset

- Detects Sc, Cu and transitioning clouds at orbital level
- Method based on morphology
- More than 10 years of data
Shortcoming 1: Different sensitivities of Sc and Cu

We demonstrate that Sc clouds are more sensitive than Cu to predictors.

\[
\frac{\partial LCC}{\partial SST} \quad \frac{\partial LCC}{\partial EIS}
\]

\[
\text{Sensitivity (}/%\text{}/K) \quad \text{Cu} \quad \text{Sc}
\]

\[
\frac{\partial LCC_{Sc}}{\partial x} \neq \frac{\partial LCC_{Cu}}{\partial x}
\]

We determine each of the terms using observations

\[
\frac{dC RE}{dT} = \frac{dC RE_{Sc}}{dLCC_{Sc}} \left( \frac{\partial LCC_{Sc}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Sc}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Sc}}{LCC}
\]

\[
+ \frac{dC RE_{Cu}}{dLCC_{Cu}} \left( \frac{\partial LCC_{Cu}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Cu}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Cu}}{LCC}
\]

Sensitivity of Sc and Cu to SST and EIS
Shortcoming 2: Different relative presence of Sc and Cu

We demonstrate that Sc and Cu clouds are spatially well separated.
We determine each of the terms using observations

\[
\frac{dCRE}{dT} = \frac{dCRE_{Sc}}{dLCC_{Sc}} \left( \frac{\partial LCC_{Sc}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Sc}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Sc}}{LCC} \\
+ \frac{dCRE_{Cu}}{dLCC_{Cu}} \left( \frac{\partial LCC_{Cu}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Cu}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Cu}}{LCC}
\]

Presence ratio for each cloud type
We determine each of the terms using observations and reanalysis

\[
\frac{dC_{RE}}{dT} = \frac{dC_{RE}}{dL_{CC}} \left( \frac{\partial L_{CC}}{\partial S_{ST}} \frac{dS_{ST}}{dT} + \frac{\partial L_{CC}}{\partial E_{IS}} \frac{dE_{IS}}{dT} \right) \frac{L_{CC}}{L_{CC}} \\
+ \frac{dC_{RE}}{dL_{CC}} \left( \frac{\partial L_{CC}}{\partial S_{ST}} \frac{dS_{ST}}{dT} + \frac{\partial L_{CC}}{\partial E_{IS}} \frac{dE_{IS}}{dT} \right) \frac{L_{CC}}{L_{CC}}
\]

Change of SST and EIS in response to warming

\[\rightarrow\] Can be determined from:
- historical trends using the past few decades
- simulated future warming from CMIP6 models
Observed historical trends are different from simulated future changes (*yet all positive*).

Consider two scenarios:

- **Observed historical trend (1979-2018)**
  - dSST/dT: 0.62 K K⁻¹

- **Simulated future change (4xCO2 - piC)**
  - dSST/dT: 0.73 K K⁻¹
  - dEIS/dT: 0.21 K K⁻¹
  - dEIS/dT: 0.25 K K⁻¹

→ Consider two scenarios
We have determined each of the terms using observations and reanalysis

\[
\frac{dC_{RE}}{dT} = \frac{dC_{RE_{Sc}}}{dLCC_{Sc}} \left( \frac{\partial LCC_{Sc}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Sc}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Sc}}{LCC} \\
+ \frac{dC_{RE_{Cu}}}{dLCC_{Cu}} \left( \frac{\partial LCC_{Cu}}{\partial SST} \frac{dSST}{dT} + \frac{\partial LCC_{Cu}}{\partial EIS} \frac{dEIS}{dT} \right) \frac{LCC_{Cu}}{LCC}
\]
We have determined each of the terms using observations and reanalysis.

\[
\frac{d\text{CRE}}{dT} = \frac{d\text{CRE}_{\text{Sc}}}{dLCC_{\text{Sc}}} \left( \frac{\partial LCC_{\text{Sc}}}{\partial \text{SST}} \frac{d\text{SST}}{dT} + \frac{\partial LCC_{\text{Sc}}}{\partial \text{EIS}} \frac{d\text{EIS}}{dT} \right) \frac{LCC_{\text{Sc}}}{LCC} \\
+ \frac{d\text{CRE}_{\text{Cu}}}{dLCC_{\text{Cu}}} \left( \frac{\partial LCC_{\text{Cu}}}{\partial \text{SST}} \frac{d\text{SST}}{dT} + \frac{\partial LCC_{\text{Cu}}}{\partial \text{EIS}} \frac{d\text{EIS}}{dT} \right) \frac{LCC_{\text{Cu}}}{LCC}
\]

We can now infer an estimate of the low cloud feedback using observations.

Observations/Reanalyses or CMIP models
The inferred feedback is 2.3 times smaller using the historical scenario...

\[
\begin{align*}
    \frac{dSST}{dT} & \quad \text{from observed historical trend} \\
    \frac{dEIS}{dT} & \quad \text{from simulated future change}
\end{align*}
\]

Total

\[
\begin{align*}
    \text{a.} & \quad 0.24 \text{ W/m}^2/\text{K} \\
    \text{d.} & \quad 0.56 \text{ W/m}^2/\text{K}
\end{align*}
\]
The inferred feedback is 2.3 times smaller using the historical scenario... and comes from Sc clouds

d_{SST}/dT  _____ from observed historical trend

d_{EIS}/dT  from simulated future change

Total

Cu

Sc

a. 0.24 W/m²/K
b. 0.11 W/m²/K
c. 0.13 W/m²/K
d. 0.56 W/m²/K
e. 0.12 W/m²/K
f. 0.44 W/m²/K

d_{CRE}/dT (W/m²/K)
How does the future-scenario inferred feedback compare with the low- and high-ECS CMIP6 feedbacks?

Observationally
Inferred feedback
(using dSST/dT & dEIS/dT from simulated future change)

\[
\frac{d\text{CRE}}{dT} = \frac{d\text{CRE}_\text{Sc}}{dLCC_\text{Sc}} \left( \frac{\partial LCC_\text{Sc}}{\partial \text{SST}} \frac{d\text{SST}}{dT} + \frac{\partial LCC_\text{Sc}}{\partial \text{EIS}} \frac{d\text{EIS}}{dT} \right) \frac{LCC_\text{Sc}}{LCC} \\
+ \frac{d\text{CRE}_\text{Cu}}{dLCC_\text{Cu}} \left( \frac{\partial LCC_\text{Cu}}{\partial \text{SST}} \frac{d\text{SST}}{dT} + \frac{\partial LCC_\text{Cu}}{\partial \text{EIS}} \frac{d\text{EIS}}{dT} \right) \frac{LCC_\text{Cu}}{LCC}
\]
Both high and low-ECS models simulate unrealistic cloud feedbacks

Observationally Inferred feedback
(using $dSST/dT$ & $dEIS/dT$
from simulated future change)

Actual simulated CMIP6 feedback

High-ECS
- $0.56 \text{ Wm}^{-2}\text{K}^{-1}$
- $1.02 \text{ Wm}^{-2}\text{K}^{-1}$

Low-ECS
- $0.19 \text{ Wm}^{-2}\text{K}^{-1}$
- $0.60 \text{ Wm}^{-2}\text{K}^{-1}$

All models
- $0.60 \text{ Wm}^{-2}\text{K}^{-1}$
Compared to previous literature
By separating Sc and Cu contributions, we can:
- Infer a direct constraint on Sc and Cu feedbacks
- Reduce overall uncertainty in low-cloud feedbacks

\[ \text{Tot} = \text{Sc} + \text{Cu} \]

Compared to previous literature
By separating Sc and Cu contributions, we can:
- Infer a direct constraint on Sc and Cu feedbacks
- Reduce overall uncertainty in low-cloud feedbacks

*Multiplied by CASCCAD Sc Cu cloud fractions
What are the implications for the climate sensitivity

Feedback (Wm⁻²K⁻¹)

Climate Sensitivity (K)
Our observational constraint
- Substantially reduces the uncertainty on low-cloud feedback

Previous range

Climate Sensitivity (K)

Feedback (Wm⁻²K⁻¹)

Low ECS

High ECS

CMIP6

Future

Our constraint suggests that both low- and high-ECS models seem unlikely
Our observational constraint

- Substantially reduces the uncertainty on low-cloud feedback
- Suggests a moderate ECS if historical trends persist

- Historical SST-EIS trends suggest more moderate ECS (3.47 ± 0.33 K) than most CMIP6 models (22/40)
Take-away messages

1. Most of the low-cloud sensitivity to cloud predictors is driven by Sc

2. Unrealistic simulated feedbacks particularly in Cu regions
Take-away messages

3. Our method provides:
   - Constraint on Sc and Cu feedbacks
   - Smaller uncertainty on feedback

4. Historical SST-EIS trends suggest more moderate ECS (3.47 ± 0.33 K) than most CMIP6 models (22/40)


Acknowledgments
NASA CALIPSO-CloudSat ROSES 2015 and 2018: NNH15ZDA001N and NNH18ZDA001N