Challenges in inferring radiative feedbacks from observations of Earth’s energy budget

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CERES Science Team Meeting 2018
Standard Model of global climate response to forcing

- Linearization of global top-of-atmosphere (TOA) energy budget

\[ Q = \lambda T + F \]

- Global TOA radiation flux anomaly [Wm^{-2}]
- Global TOA radiative response to warming [Wm^{-2}K^{-1}][K]
- Global TOA radiative forcing [Wm^{-2}]

Global radiative forcing (\( F \)) changes approximately linearly with time over the CO\(_2\) rampings, by about 3.7 Wm\(^{-2}\) per 70 yr, which is the period of CO\(_2\) doubling or halving [Myhre et al., 1998]. The set in Figure 1 between warming (red) and cooling (blue) trajectories implies a lagged response of hemispheric-mean annual-mean surface temperature anomalies (\( T_{NH} \) and \( T_{SH} \)), as expected from deep ocean heat storage [e.g., Held et al., 2010]. In order to approximately account for this lag, we consider the evolution of ice area as a function of hemispheric temperature rather than time. A justification for this treatment is that annual-mean Arctic sea ice area has been found to decline linearly with increasing global-mean temperature across a range of GCMs, emissions scenarios, and climates [Gregory et al., 2002; Ridley et al., 2008; Winton, 2006, 2008, 2011]. Specifically, we extend the arguments of Winton [2011], relating hemispheric ice cover to global forcing through:

\[ Q = \lambda T + F \]

\[ R_{obs} = 1.7[0.7-0.2] Wm^{-2} \]

\[ H_{obs} = 0.74 \pm 0.08 Wm^{-2} \]

\[ T_{obs} = 0.75 \pm 0.12 C \]
Standard Model of global climate response to forcing

- Linearization of global top-of-atmosphere (TOA) energy budget

\[ Q = \lambda T + F \]

- Equilibrium warming \((Q=0)\) in response to a doubling of atmospheric CO\(_2\) (forcing \(F_{2x} \approx 3.7 \text{ Wm}^{-2}\)):

\[ \text{ECS} = - \frac{F_{2x}}{\lambda} \]

**Equilibrium climate sensitivity (ECS)**
Estimating climate sensitivity should be easy... right?

- All we need to do is estimate the net radiative feedback $\lambda$:

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- **Conclusions up front**: There are a variety of distinct radiative feedbacks governing Earth’s radiative response to warming, and feedback estimated from either method probably doesn’t provide a reliable estimate of the feedback governing long-term warming
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  - Good news! CMIP5 models are generally consistent with radiative feedbacks estimated by either method when treated in a consistent way
1. Introduction

climates

treatment is that annual-mean Arctic sea ice area has been found to decline linearly with
area as a function of hemispheric temperature rather than time. A justification for this

Global radiative forcing (\(F = 0\) \(= 1\) \(= 0\) \(= 0\) \(\pm \)) of warming evolves, resulting in high ECS and large future warming

\[ Q = \lambda T + F \]

- Method #1: Get \(\lambda\) from regression of \(Q - F\) against \(T\) over the CERES record

- Method #2: \(\lambda = \frac{\Delta Q - \Delta F}{\Delta T}\), where \(\Delta\) represents a change relative to pre-industrial

**Conclusions up front:** There are a variety of distinct radiative feedbacks governing Earth’s radiative response to warming, and feedback estimated from either method probably doesn’t provide a reliable estimate of the feedback governing long-term warming

- Good news! CMIP5 models are generally consistent with radiative feedbacks estimated by either method when treated in a consistent way

- Bad news! Poses a major challenge for constraining long-term warming from short climate records; CMIP5 models suggest feedbacks will change over time as the pattern of warming evolves, resulting in high ECS and large future warming
Regression-based feedbacks

CERES-EBAF and NASA GISTEMP
March 2000 to November 2017

Radiative forcing (F) subtracted from global TOA radiation (Q) according to Donohoe et al (2014)

Regression-based feedbacks

Regression of monthly data implies ECS = 3.1 K (2.0-7.6K, 5-95%)

Regression-based feedbacks

Regressing **annual** data implies ECS = 0.9 K (0.6-1.6K, 5-95%)
Regression-based feedbacks

Regressing **monthly** data w/ 4 month lag implies ECS = 2.4 K (1.6-4.2K, 5-95%)

Feedback estimate sensitive to choice of:
- lag
- averaging period
- record length

(Forster 2016)

Feedback value depends on source of stochastic forcing (oceanic vs radiative)

(Spencer & Braswell 2010, 2011; Dessler 2011)

Lagged-regression structure between Q and T

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- lag
- averaging period
- record length
(Forster 2016)

Feedback value depends on source of stochastic forcing
(oceanic vs radiative)
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Using models to understand regression structure

- Long pre-industrial unforced control simulation of NCAR's Community Earth System Model (CESM1) reproduces the salient features of observed regression structure with feedback dependence on:
  - lag
  - averaging period
Using models to understand regression structure

- Long pre-industrial unforced control simulation of NCAR's Community Earth System Model (CESM1) reproduces the salient features of observed regression structure with feedback dependence on:
  - lag
  - averaging period

- Suggests that observed regression structure mainly reflects internal variability

- We can use models to understand the regression structure
Intuition from a Hasselmann Model

\[
C \frac{dT}{dt} = \lambda T + F_{\text{rad}} + F_{\text{ocn}}
\]

- \( F_{\text{rad}} \): radiative forcing
- \( F_{\text{ocn}} \): ocean forcing
- \( \lambda T \): white noise
- \( Q \): noise

The equation above represents the balance of temperature change due to changes in radiative forcing, ocean forcing, and white noise.
Intuition from a Hasselmann Model

\[ C \frac{dT}{dt} = \lambda T + F_{\text{rad}} + F_{\text{ocn}} \]

\[ Q = \lambda T \quad \text{(in phase)} \]
Intuition from a Hasselmann Model

\[ C \frac{dT}{dt} = \lambda T + F_{rad} + F_{ocn} \]

\[ Q = C \frac{dT}{dt} \] (in quadrature)
Intuition from a Hasselmann Model

\[ C \frac{dT}{dt} = \lambda T + F_{\text{rad}} + F_{\text{ocn}} \]

\[ Q(t) = \lambda T(t - \theta) \]
Intuition from a Hasselmann Model

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- Will each type of forcing engender the same radiative feedback? For this we need global climate models
Consider a hierarchy of CESM1 pre-industrial unforced control simulations

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Atmosphere</th>
<th>Slab</th>
<th>ENSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>OCN: CAM5 w/dynamic ocean</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>SOM: CAM5 w/thermodynamic slab ocean</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>fSST: CAM5 w/fixed sea-surface temperatures</td>
<td>Y</td>
<td>N</td>
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</tbody>
</table>
1. Introduction

Fixed SST simulation

\[ C \frac{dT}{dt} = \lambda T + F_{rad} + F_{ocn} \]

\[ Q \]

\[ F_{rad} \]

\[ \lambda T \]

\[ F_{ocn} \]

Fixed SST (fSST)

[Graph A: Spectral energy vs. frequency]

[Graph B: Phase vs. frequency]

EBM: T

EBM 95%

CESM1

[Fixed SST simulation diagram]
1. Introduction

\[ C \frac{dT}{dt} = \lambda T + F_{\text{rad}} + F_{\text{ocn}} \]

\[ Q = \lambda T \quad \text{(in phase)} \]

**Fixed SST simulation**

- Note: Stochastic forcing comes from wind variability extracting energy from the ocean through turbulent fluxes (an ocean forcing); air temperature is strongly damped by turbulent heat fluxes.
1. Introduction

\[ C \frac{dT}{dt} = \lambda T + F_{\text{rad}} + F_{\text{ocn}} \]

**Slab ocean model simulation**

\[ Q \]

\[ F_{\text{rad}} \]

\[ \lambda T \]

\[ F_{\text{ocn}} \]
1. Introduction

**Slab ocean model simulation**

\[ \frac{dT}{dt} = \lambda T + F_{\text{rad}} + F_{\text{ocn}} \]

\( Q \)

\( F_{\text{rad}} \)

\( F_{\text{ocn}} \)

High freq: \( Q = \lambda T \) (in phase)

**Fixed SST (fSST)**

**Slab Ocean (SOM)**

Fast mode with \( \lambda_1 \)
1. Introduction

\[ C \frac{dT}{dt} = \chi T + F_{\text{rad}} + F_{\text{ocn}} \]

- **High freq:** \( Q = \chi T \) (in phase)
- **Low freq:** \( Q = C \frac{dT}{dt} \) (in quadrature)

**Note:** Stochastic forcing for the "slow" mode comes from radiation, leading to different feedback estimate; air temperature is weakly radiatively damped.
1. Introduction

Fully-coupled CESM1 simulation

\[ C \frac{dT}{dt} = \lambda T + F_{\text{rad}} + F_{\text{ocn}} \]

\[ Q \]

\[ F_{\text{rad}} \]

\[ \lambda T \]

\[ F_{\text{ocn}} \]
Modeling the lagged-regression

Stochastic linear energy balance model (EBM):

- Fit to individual simulations (fSST, SOM, ENSO band) sums linearly to capture fully-coupled simulation

- Can be solved analytically to understand lagged-regression structure
Modeling the lagged-regression

Stochastic linear energy balance model (EBM):

- Fit to individual simulations (fSST, SOM, ENSO band) sums linearly to capture fully-coupled simulation

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Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

\[ r(\text{lag}) = \sum \lambda_i \left( \frac{\sigma T_i}{\sigma_{\text{total}}} \right) \text{acf}(\text{lag}) \]
Fixed SST simulation

Regression slope at a given lag is:
- average of distinct feedbacks of different modes
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Fixed SST has single mode:

\[ Q_1 = \lambda_1 T_1 \]
Regression slope at a given lag is:
- average of distinct feedbacks of different modes
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- weighted by autocorrelation of each mode at the given lag

Slab ocean is sum of two modes:

\[
Q_1 = \lambda_1 T_1 \\
Q_2 = \lambda_2 T_2 + F_{\text{rad}} \propto \frac{dT_2}{dt}
\]
Regression dilution

- Temperature variance in one mode biases regression estimates for all (regression dilution)

\[ r(\text{lag}) = \sum \lambda_i \left( \frac{\sigma T_i}{\sigma_{\text{total}}} \right) \text{acf}(\text{lag}) \]

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Fully-coupled model simulation

Regression slope at a given lag is:
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Fully-coupled model is sum of (at least) three modes:

\[ Q_1 = \lambda_1 T_1 \]
\[ Q_2 = \lambda_2 T_2 + F_{\text{rad}} \propto \frac{dT_2}{dt} \]
\[ Q_3(t) = \lambda_3 T_3(t - \theta) \quad \text{(ENSO)} \]
Fully-coupled model simulation

Regression slope at a given lag is:
- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

Annual averaging preferentially eliminates fast, air-sea interaction mode

\[ r(\text{lag}) = \sum \lambda_i \left( \frac{\sigma T_i}{\sigma_{\text{total}}} \right) \text{acf(lag)} \]
Fully-coupled model simulation

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While dynamics are well separated by time-scale, variance and covariance (regression) amalgamate across time scales.

Changing fractional variances & acf explains regression sensitivity to lag and sampling.
Fully-coupled model simulation

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Zero-lag regression

- \( r(0) = 1.2 \)

Peak regression (NOT ENSO!)

- \( r(θ) = 1.0 \)

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### CESM1 feedbacks (Wm\(^{-2}K^{-1}\))

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### Regression Sensitivity

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Thoughts regarding Method #1

- Lagged regression between TOA radiation and surface temperature can be understood as a superposition of linear modes, each with a distinct radiative feedback.
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- Regression slope is sensitive to lag and averaging period, and should not be expected to give an estimate of long-term feedback.

- Ongoing work:
  - can feedbacks of individual modes be derived from observations?
  - do any of the individual feedbacks correlate with long-term feedbacks across models? (potentially for an observational constraint on ECS)
  - for how long will we have to observe before forced feedbacks emerge above internal variability? (estimate from Cristi: minimum ~25 years)
Radiative feedbacks from stochastic variability in surface temperature and radiative imbalance

Cristian Proistosescu\textsuperscript{1}, Aaron Donohoe\textsuperscript{2}, Kyle C. Armour\textsuperscript{3,4}, Gerard H. Roe\textsuperscript{5}, Malte F. Stuecker\textsuperscript{4,6}, Cecilia M. Bitz\textsuperscript{4}

Online at Geophysical Research Letters as of yesterday
Estimating climate sensitivity should be easy... right?

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\[ Q = \lambda T + F \]

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Estimates of climate sensitivity

Energy budget constraints on climate response

Alexander Otto\textsuperscript{1*}, Friederike E. L. Otto\textsuperscript{1}, Olivier Boucher\textsuperscript{2}, John Church\textsuperscript{3}, Gabi Hegerl\textsuperscript{4}, Piers M. Forster\textsuperscript{5}, Nathan P. Gillett\textsuperscript{6}, Jonathan Gregory\textsuperscript{7}, Gregory C. Johnson\textsuperscript{8}, Reto Knutti\textsuperscript{9}, Nicholas Lewis\textsuperscript{10}, Ulrike Lohmann\textsuperscript{9}, Jochem Marotzke\textsuperscript{11}, Gunnar Myhre\textsuperscript{12}, Drew Shindell\textsuperscript{13}, Bjorn Stevens\textsuperscript{11} and Myles R. Allen\textsuperscript{14}

\[ Q = \lambda T + F \]

\[ T_{\text{obs}} = 0.75 \pm 0.2 \degree \text{C} \]

\[ Q_{\text{obs}} = 0.65 \pm 0.27 \text{ Wm}^{-2} \]

\[ F_{\text{obs}} = 2.3 \pm 1 \text{ Wm}^{-2} \]

(years 2000-2009 relative to 1860-1879)

\[ \text{ECS} = - \frac{F_{2\times}}{\lambda} \]

\[ = \frac{F_{2\times}T_{\text{obs}}}{F_{\text{obs}} - Q_{\text{obs}}} \]
Estimates of climate sensitivity

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\[ \text{ECS} = -\frac{F_{2\times}}{\lambda} = \frac{F_{2\times}T_{\text{obs}}}{F_{\text{obs}} - Q_{\text{obs}}} \]

Median ECS: 2.0 °C
5-95% range: 1.2-3.9 °C

[Graph showing probability density of equilibrium climate sensitivity]
Energy budget constraints on climate response

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\[
ECS = -\frac{F_{2x}}{\lambda} \\
= \frac{F_{2x}T_{obs}}{F_{obs} - Q_{obs}}
\]

(Armour 2017; see also Proistosescu & Huybers 2017)
Global energy budget constraints produce estimates of ECS that are quite a bit lower than ECS simulated by CMIP5 models.

- Are the models overly sensitive?
- Or is something else going on…?

\[
ECS = -\frac{F_2 \times \lambda}{\lambda} = \frac{F_2 \times T_{\text{obs}}}{F_{\text{obs}} - Q_{\text{obs}}}
\]

(Armour 2017; see also Proistosescu & Huybers 2017)
Emerging consensus: model-observational comparisons must be made in a *like-with-like* way

(Armour 2017; see also Proistosescu & Huybers 2017)
Like-with-like comparisons of climate sensitivity

- Emerging consensus: model-observational comparisons must be made in a *like-with-like* way, accounting for possibility that:

  1) Feedbacks ($\lambda$) vary over time as the spatial pattern of warming evolves (Armour 2017; Proistosescu & Huybers 2017)
Like-with-like comparisons of climate sensitivity

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1) Feedbacks ($\lambda$) vary over time as the spatial pattern of warming evolves (Armour 2017; Proistosescu & Huybers 2017)

2) Feedbacks affected by the “efficacy” of non-$CO_2$ forcings (Shindell 2014; Kummer & Dessler 2014; Marvel et al. 2015)

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Emerging consensus: model-observational comparisons must be made in a like-with-like way, accounting for possibility that:

1) Feedbacks ($\lambda$) vary over time as the spatial pattern of warming evolves
   (Armour 2017; Proistosescu & Huybers 2017)

2) Feedbacks affected by the “efficacy” of non-CO$_2$ forcings
   (Shindell 2014; Kummer & Dessler 2014; Marvel et al. 2015)

3) Feedbacks depend on natural variability in the pattern of warming

(Armour 2017; see also Proistosescu & Huybers 2017)
1) Feedbacks vary as the pattern of warming evolves

CMIP5 response to $4\times\text{CO}_2$ (Andrews et al. 2015)
1) Feedbacks vary as the pattern of warming evolves

What is the radiative response to this change in warming pattern?

CMIP5 response to 4×CO$_2$ (Andrews et al. 2015)
1) Feedbacks vary as the pattern of warming evolves

CMIP5 response to 4×CO₂ (Andrews et al. 2015)

Localized patches of warming

Radiative response to localized patches of warming in NCAR’s CAM4 (Dong et al., in preparation)

see also Andrews and Webb 2017; Zhou et al. 2016; Zhou et al. 2017
1) Feedbacks vary as the pattern of warming evolves

SST increase in W Pacific

SST increase in E Pacific
1) Feedbacks vary as the pattern of warming evolves
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- SST increase in W Pacific
- Near-surface air temp
- Zonal-mean warming
- TOA radiative response

- SST increase in E Pacific
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- Zonal-mean warming
- TOA radiative response
1) Feedbacks vary as the pattern of warming evolves

CMIP5 response to 4×CO₂ (Andrews et al. 2015)

Global radiative feedback

Global feedback response to localized patches of warming in NCAR’s CAM4 (Dong et al., in preparation)

see also Andrews and Webb 2017; Zhou et al. 2016; Zhou et al. 2017
1) Feedbacks vary as the pattern of warming evolves

CMIP5 response to $4\times CO_2$ (Andrews et al. 2015)
1) Feedbacks vary as the pattern of warming evolves

- Feedbacks under transient warming ($\lambda$) are more negative than those at equilibrium ($\lambda_{2\times}$).
- Inferred (or instantaneous) climate sensitivity (ICS) is generally smaller than equilibrium climate sensitivity (ECS).

\[
\text{ICS} = -\frac{F_{2\times}}{\lambda} \quad \text{ECS} = -\frac{F_{2\times}}{\lambda_{2\times}}
\]

CMIP5 models

CMIP5 response to CO$_2$ forcing (Armour 2017)

see also Proistosescu & Huybers 2017
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- Feedbacks under transient warming ($\lambda$) are more negative than those at equilibrium ($\lambda_{2x}$)
- Inferred (or instantaneous) climate sensitivity (ICS) is generally smaller than equilibrium climate sensitivity (ECS)

$$ICS = -\frac{F_{2x}}{\lambda}$$

$$ECS = -\frac{F_{2x}}{\lambda_{2x}}$$

$$ICS = \frac{F_{2x}T_{obs}}{F_{obs} - Q_{obs}}$$

- Global energy budget constraints provide estimates of ICS only, so should be compared with model values of ICS (not ECS!)

CMIP5 models

CMIP5 response to CO$_2$ forcing (Armour 2017)

see also Proistosescu & Huybers 2017
1) Feedbacks vary as the pattern of warming evolves

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2) Feedbacks depend on the type of radiative forcing

- Feedbacks under historical forcing may differ from those under CO$_2$ forcing alone (Shindell 2014; Marvel et al. 2015)

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![Probability density](https://example.com/probability-density.png)

Historical simulations with GISS-E2-R (Marvel et al. 2015)
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![Graph showing probability density of ICS or ECS temperatures]

Historical simulations of NCAR’s CESM1-CAM5 Large Ensemble
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![Graph showing probability density of ICS or ECS temperatures with different model simulations.](image-url)
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1979-2012 DJF surface air temperature trends (K/34 years)


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- Key question: what global feedback (and ICS) has the observed warming pattern engendered?
  - absent this knowledge, this internal variability uncertainty is swamped by the forcing uncertainty
  - can be thought of as uncertainty that would remain given perfect observations of forcing, heat uptake, etc

Historical simulations of NCAR’s CESM1-CAM5 Large Ensemble
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**Observed warming pattern**

AMIP II boundary conditions (Hurrell et al. 2008)

**Global radiative feedback**

Global feedback response to localized patches of warming in NCAR’s CAM4 (Dong et al., in preparation)
3) Feedbacks vary due to internal climate variability

- Prescribed sea-surface temperature (SST) simulations produce the same feedbacks as are induced by climate forcings (Haugstad et al. 2017)
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Prescribed observed SST simulation with CAM5
3) Feedbacks vary due to internal climate variability

Global near-surface air temperature, TOA radiation and global radiative feedback well-reconstructed by Green’s function.
3) Feedbacks vary due to internal climate variability

Global near-surface air temperature, TOA radiation and global radiative feedback well-reconstructed by Green’s function

What regions contribute most to the increasingly negative radiative feedback in recent decades?
3) Feedbacks vary due to internal climate variability
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Green’s functions tell you which regions contributed most to global TOA radiation (Q) or surface warming (T_s):

\[
\frac{\partial Q}{\partial SST} \bigg|_{\Delta SST_i}
\]

\[
\frac{\partial T_s}{\partial SST} \bigg|_{\Delta SST_i}
\]
3) Feedbacks vary due to internal climate variability

\[
\frac{\partial \bar{Q}}{\partial \text{SST}} |_{i} \Delta \text{SST}_{i} - \lambda_{\text{global}} \frac{\partial T_{s}}{\partial \text{SST}} |_{i} \Delta \text{SST}_{i}
\]

This quantity equals zero in the global mean (by definition) but tells you what regions most contribute to global feedback changes due to regional radiative response to warming being different from the global feedback.

West Pacific warming (negative feedback) wins out over all other regions (generally positive feedbacks), small contribution from Southern Ocean cooling.
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Parting thoughts

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- How much of the intermodel spread in ECS might be due cloud response to different SST patterns, rather than different cloud physics/parameterizations?
An aside: does ECS or ICS matter more for transient warming?

- Transient warming is weekly correlated with ECS

TCR = warming at year 70, the time of $\text{CO}_2$ doubling under 1%/yr $\text{CO}_2$ ramping

$r = 0.67$
An aside: does ECS or ICS matter more for transient warming?

- Transient warming is weekly correlated with ECS
- Transient warming is highly correlated with ICS

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Like-with-like comparisons of climate sensitivity

- Emerging consensus: model-observational comparisons must be made in a *like-with-like* way, accounting for possibility that:

1) Feedbacks ($\lambda$) vary over time as the spatial pattern of warming evolves (Armour 2017; Proistosescu & Huybers 2017)

2) Feedbacks affected by the “efficacy” of non-$\text{CO}_2$ forcings (Shindell 2014; Kummer & Dessler 2014; Marvel et al. 2015)

3) Feedbacks depend on natural variability in the pattern of warming

4) Different definitions of global-mean temperature used in models vs observations (Cowtan et al. 2015; Richardson et al. 2016)
4) Sensitivity estimates depend on global temperature definition

- Global temperature record is a blend of SST over ocean, near-surface air temperature over land; lacks full global coverage
- Global temperature in models is calculated as a full global average of near-surface air temperature

Prescribed observed SST simulations with CAM4, CAM5, HadGEM2, HadAM3, ECHAM6, AM2.1, AM3, AM4 (Yue Dong, Malte Stuecker, Cristi Proistosescu, Tim Andrews, Jonathan Gregory, Thorsten Mauritsen, Levi Silvers & David Paynter)
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- Global temperature in models is calculated as a full global average of near-surface air temperature
- Blending/masking models consistently with observations suggests an increase to Otto et al. ICS estimate (Richardson et al. 2016)

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- Accounting for the observed pattern of warming being pretty odd gives model values of ICS that are in good agreement.

- Accounting for consistent global temperature definitions brings model ICS values to low end of observation-based ICS values.