What have we learned about emergent constraints?*

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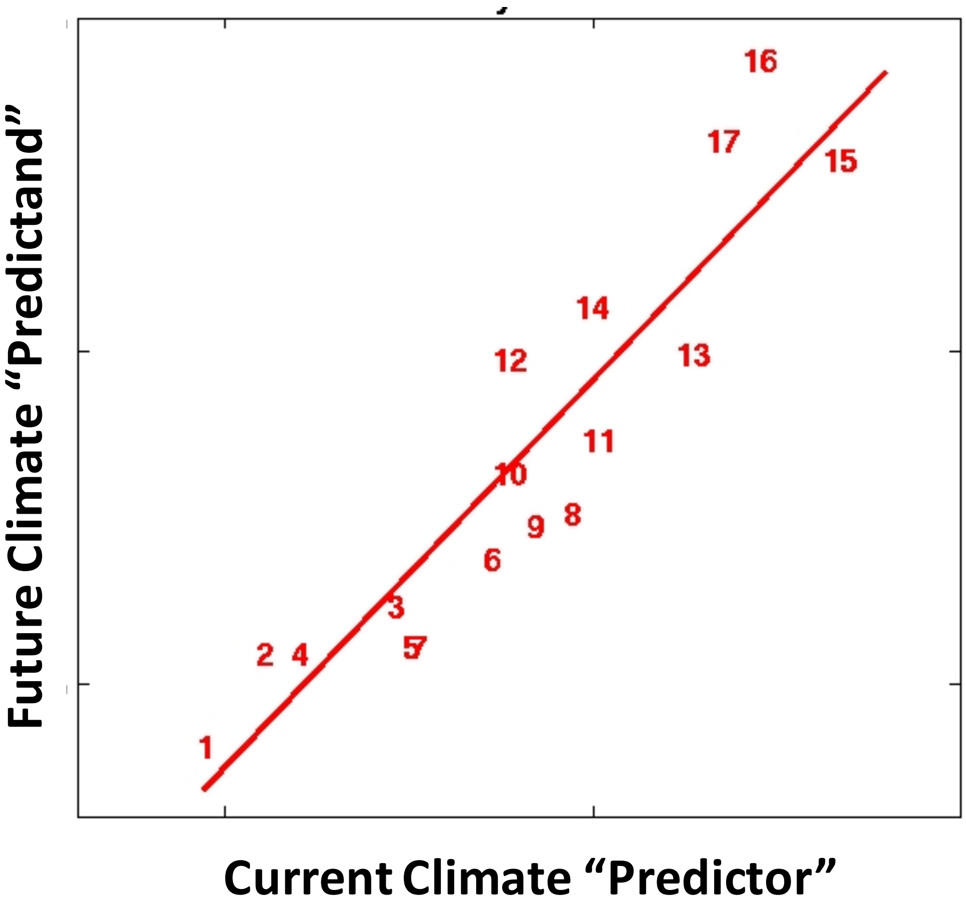
AGCI workshop

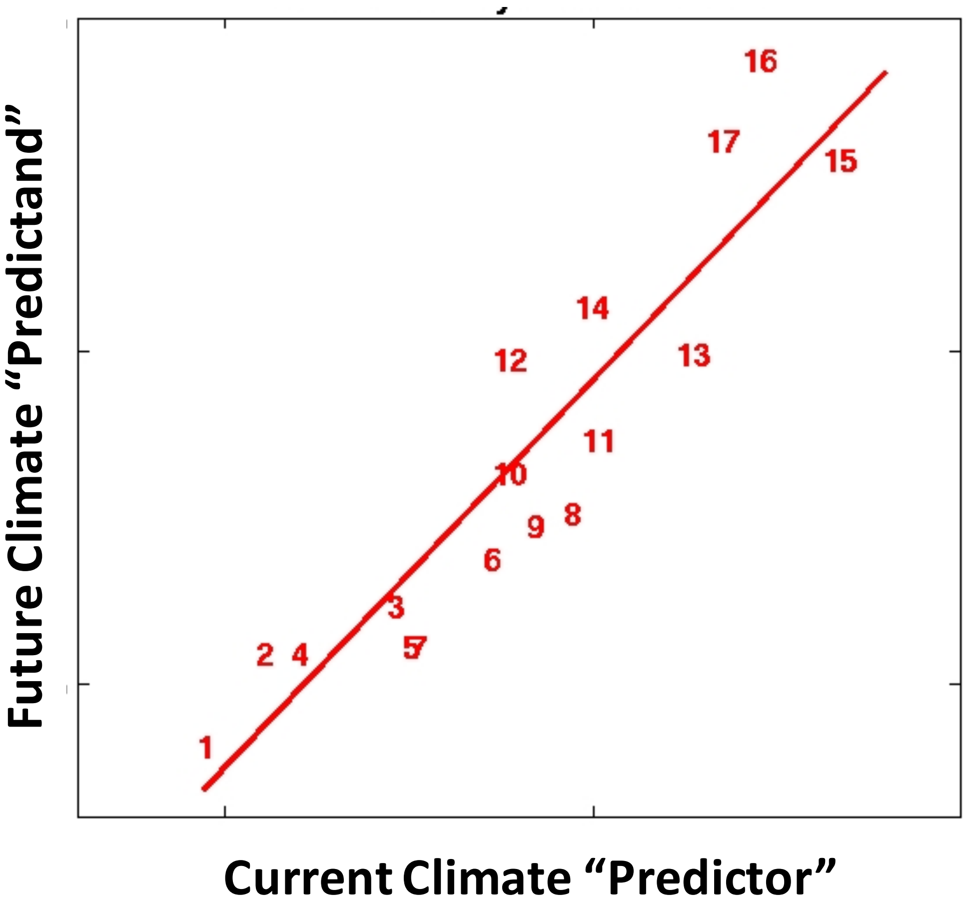
**informed by Klein and Hall (2015), Klein et al. (2017), and conversations with Peter Cox and Chris Huntingford*

What is an emergent constraint?



- We’ve all seen many examples of strong relationships between observable current-climate “predictors”, and future climate “predictands”.
- These examples have been labeled as “emergent constraints” by the authors of the studies finding the relationship.
- Here I will argue that to fully realize the potential of the emergent constraint technique to reduce uncertainty surrounding climate change, it is necessary to categorize these relationships further.

What is an emergent constraint?



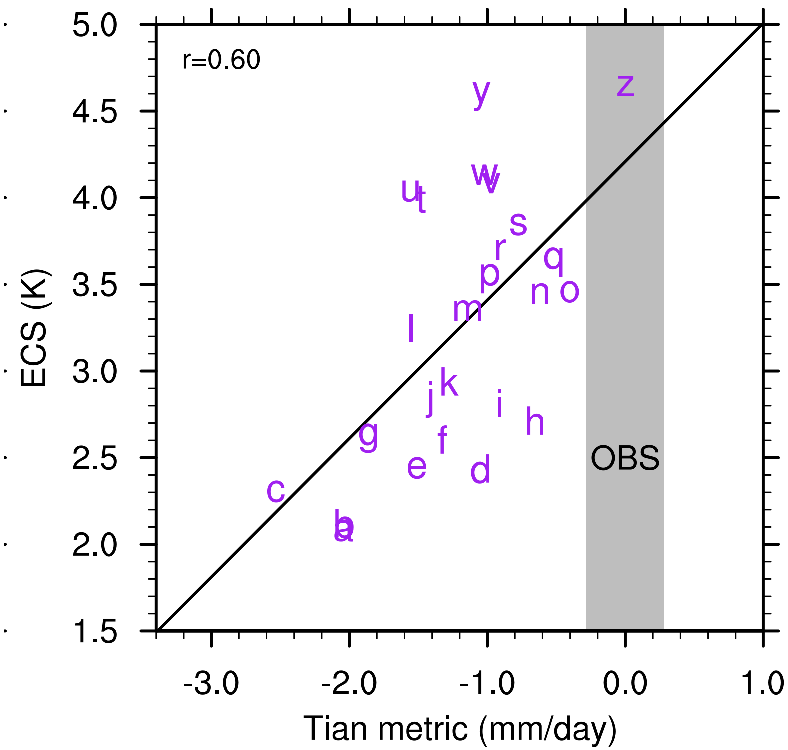
- Relationships between predictors and predictands can be placed in 3 categories, in ascending order of development.
  - Proposed
  - Confirmed
  - Useful

What is an emergent constraint?

- A **proposed** emergent constraint is one where a strong but purely statistical relationship between predictor and predictand has been found.
- A **confirmed** emergent constraint is one where the mechanistic underpinnings of the statistical relationship between predictor and predictand have been demonstrated.
- A **useful** emergent constraint has been confirmed, and is also associated with an understanding of how model structure and parameter choice leads to spread in the current climate predictor.

Emergent constraints discussed in the literature are in reality in very different stages of development. It’s misleading to put them all in the same bin. Let’s look at examples from the literature that illustrate the stages of emergent constraint development.

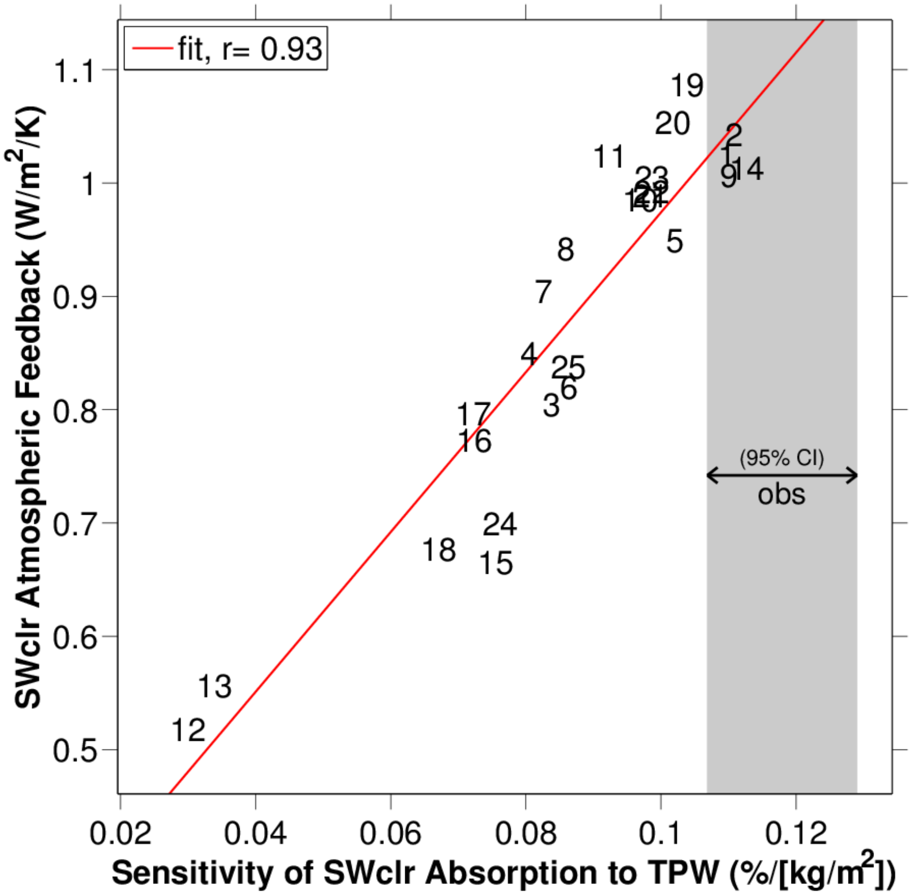
A proposed emergent constraint



Tian (2015), figure adapted from Qu et al. (2017)

- In Tian (2015), equilibrium climate sensitivity is scattered against the GCM bias in climatological precipitation in the southeastern Pacific.
- The predictand (ECS) is fairly well correlated with the predictor (~GCM double ITCZ bias).
- But the physics relating the two are opaque. ECS is shaped by a number of radiative feedbacks, none of which is known to be physcially related to the degree of double ITCZ bias.
- For this reason, we must label this a “proposed” emergent constraint.
- And we cannot take at face value its implication that the true ECS is in the high end of the model range.

A confirmed emergent constraint

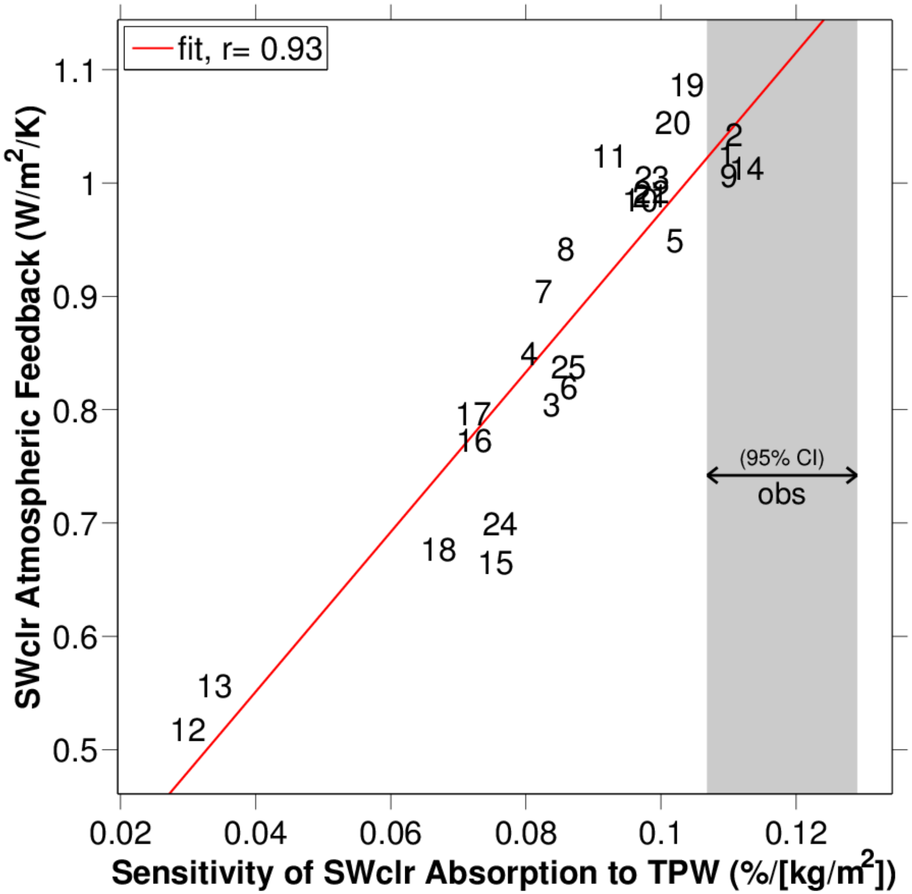


Observations are calculated based on CERES-EBAF solar fluxes and SSM/I water vapor estimates.

- DeAngelis et al. (2015) focused on constraining the global precipitation increase associated with warming.
- The future climate predictand, in this case, is the increase in clear sky shortwave atmospheric absorption per degree global warming.
- (This predictand is a key factor behind the simulated spread in the global precipitation increase, i.e. a “feedback” shaping hydrologic cycle intensification)

DeAngelis et al. (2015)

A confirmed emergent constraint

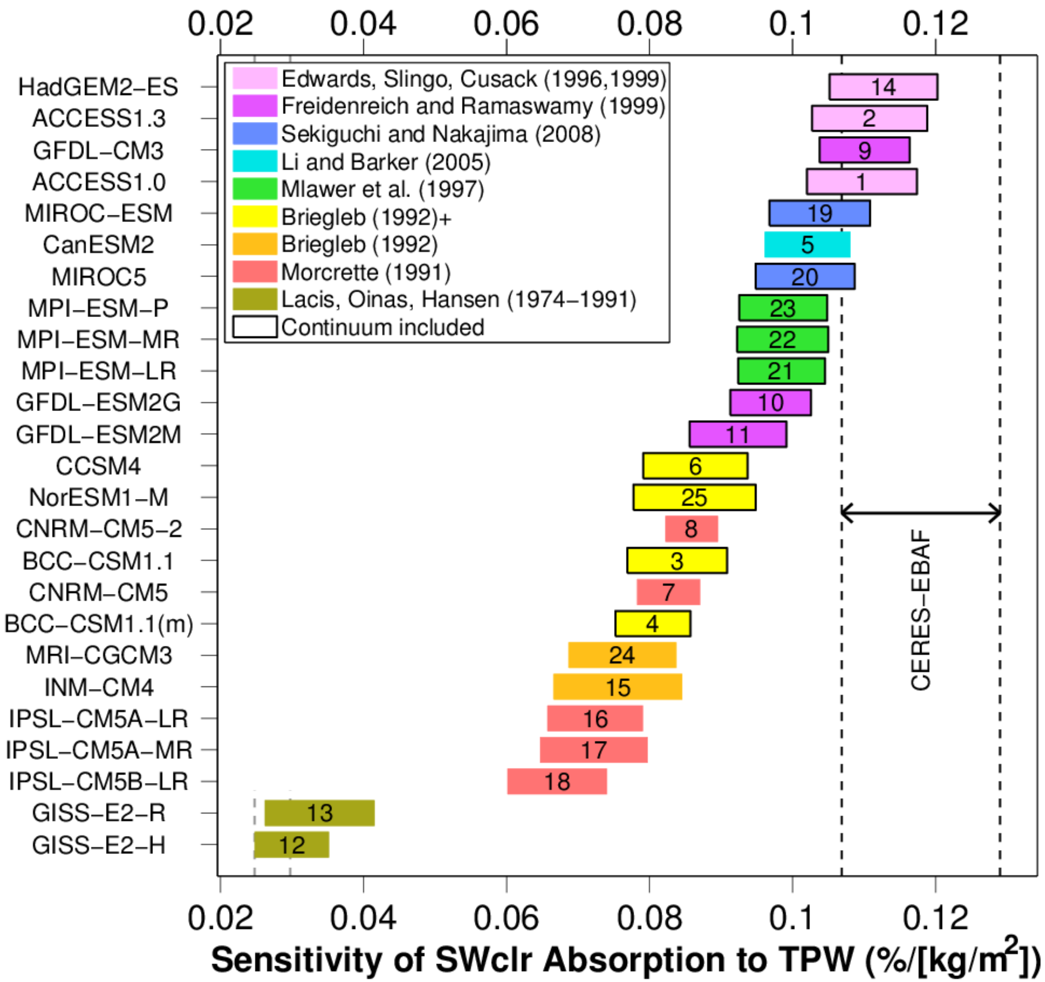


Observations are calculated based on CERES-EBAF solar fluxes and SSM/I water vapor estimates.

- The current climate predictor is the shortwave clear sky absorption anomaly associated with an increase in total precipitable water.
- If a particular model absorbs an unusually large amount of additional shortwave radiation when atmospheric water vapor increases, that model will absorb more shortwave per degree warming.
- In this case, the physical interpretation, via the Clausius-Clapeyron relation, is straightforward. Warming→water vapor increase→more shortwave absorption
- In fact, there really is no other plausible explanation for such a tight relationship.
- Because the mechanistic underpinnings of the statistical relationship are so clear, we can label this a confirmed emergent constraint.

DeAngelis et al. (2015)

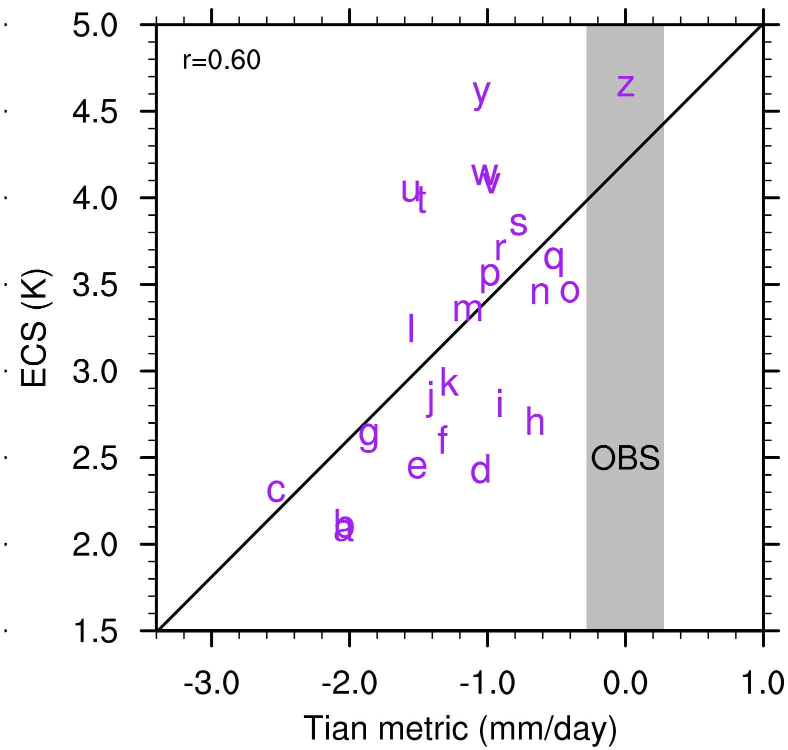
Making it useful too



- DeAngelis et al. (2015) also provided information linking biases in the predictor to modeling groups' parameterization choices.
- When the shortwave radiation schemes are color-coded according to their origin and vintage, a clear pattern emerges.
- The newer schemes tend to resolve more spectral bands, and tend to have much more realistic solar absorptivities due to water vapor.
- This sends a clear signal to the model development community: There are fixable model errors, which if addressed, would reduce climate change uncertainty due to model spread. So this is now a "useful" emergent constraint.

DeAngelis et al. (2015)

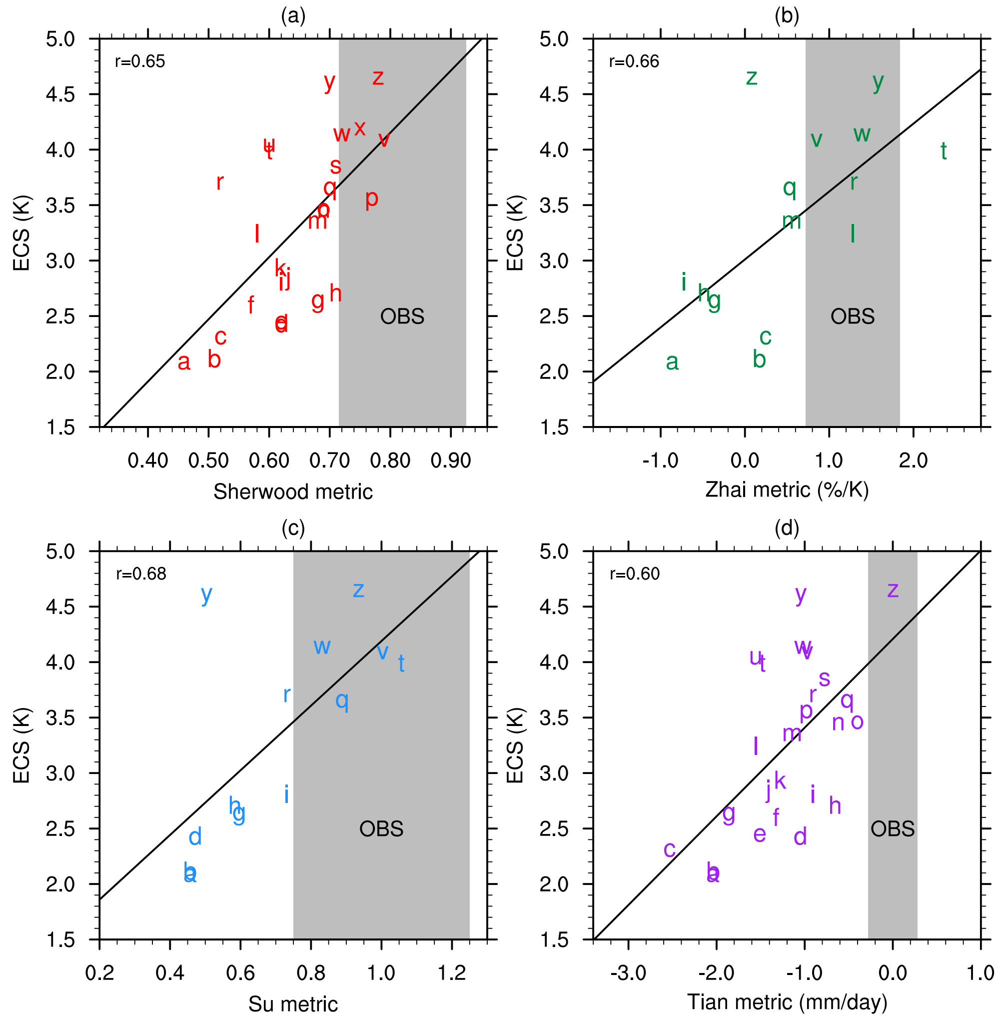
Getting from proposed to confirmed to useful



Tian (2015), figure adapted from Qu et al. (2017)

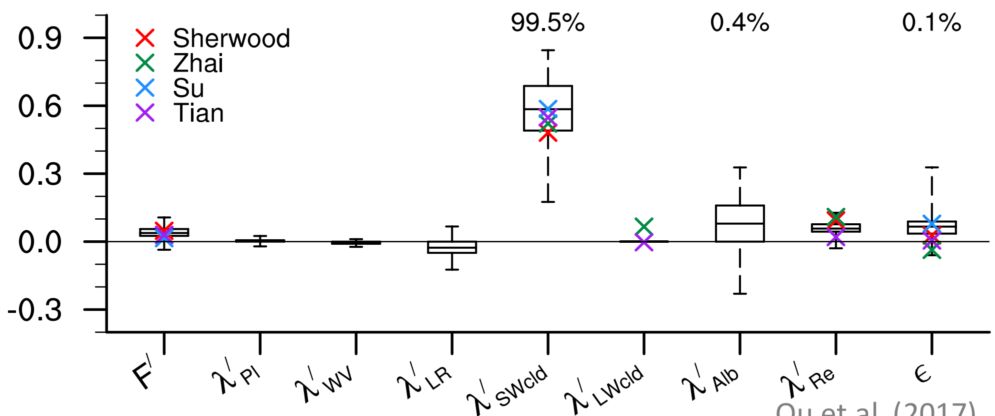
- Let’s return to the proposed emergent constraint on ECS put forward by Tian (2015).
- Can we confirm this emergent constraint and ultimately make it useful?

Getting from proposed to confirmed to useful



- There have in fact been a few emergent constraints proposed on ECS. In addition to Zhai (2015):
  - Sherwood et al. (2014) linked ECS to indices of atmospheric vertical mixing and overturning.
  - Zhai et al. (2015) linked ECS to the sensitivity of marine boundary layer cloud to SST in the seasonal cycle context.
  - Su et al. (2014) linked ECS to a measure of cloud and relative humidity biases in GCMs.
  - Others too, e.g. Fasullo and Trenberth (2012)
- A first step in trying to understand the physical connection between these disparate predictors and ECS might be to understand their connection to the underlying feedbacks shaping ECS.

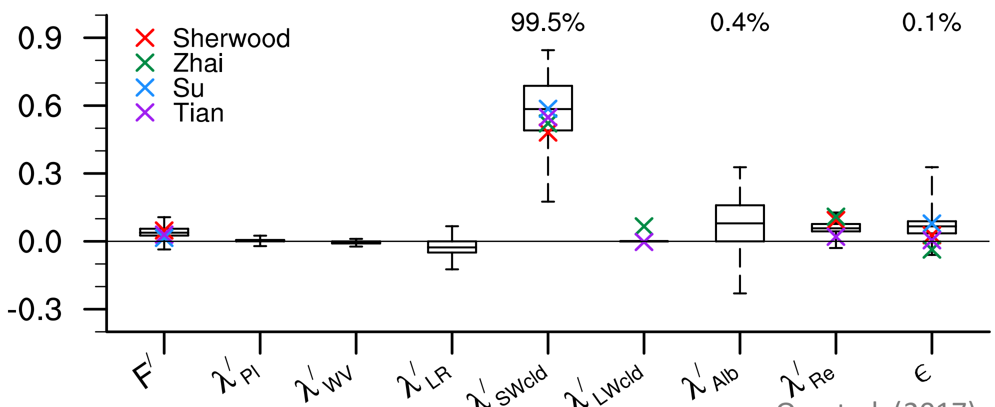
Dominance of shortwave cloud feedback



Qu et al. (2017)

- Qu et al. (2017) decomposed ECS in CMIP5 models into contributions from various factors (forcing, Planck feedback, water vapor feedback, lapse rate feedback, shortwave and longwave cloud feedbacks, surface albedo feedback, and residual terms).
- It is then possible to ask the question, how much do the various factors contribute to the correlation between ECS and the Sherwood, Zhai, Su, and Tian predictors?
- Focusing on the colored X's, we see that shortwave cloud feedback contributes most to the correlation between ECS and all four of the predictors.
- Qu et al. (2017) also generated thousands of artificial predictors that are physically meaningless, but are constructed to be well-correlated (r>0.6) with the ECS's of the CMIP5 models. If somebody found a predictor correlated with ECS, which factors shaping ECS would contribute most to the correlation?
- The bars and whiskers show the distribution of the contributions for the whole population of artificial predictors. Shortwave cloud feedback is almost always the dominant contributor.

Dominance of shortwave cloud feedback



Qu et al. (2017)

- Not only are the four proposed emergent constraints on ECS most likely constraints on shortwave cloud feedback in reality; but any proposed emergent constraint on ECS would most likely be more properly framed as a constraint on shortwave cloud feedback.
- This may not be surprising, given the well-documented strong relationship between shortwave cloud feedback and ECS (e.g. Brient and Schneider 2016).

What about shortwave cloud feedback?

- The dominant component of shortwave cloud feedback is linked to the change in low cloud cover.
- Low clouds are a fast (~hours-days) response to ”cloud-controlling factors” of the environment (Stevens and Brenguier 2009)
- In models, these cloud sensitivities are mostly ”time-scale invariant”. And we know how cloud controlling factors change, so we can predict the low cloud feedback.
- The cloud sensitivities are also observable, making it possible to apply an emergent constraints approach to them.

Cloud Sensitivity to cloud controlling factors (x_i)

Use an emergent constraint approach
(observations usually from inter-annual variability)

$$\frac{dC}{dT_g} = \sum_i \frac{\partial C}{\partial x_i}\frac{dx_i}{dT_g}$$

$x_i \in$ *{ SST, EIS, ω, RH_{tropo}, temperature advection}*

Low Cloud Feedback

Climate Change in cloud controlling factors

from Climate Models

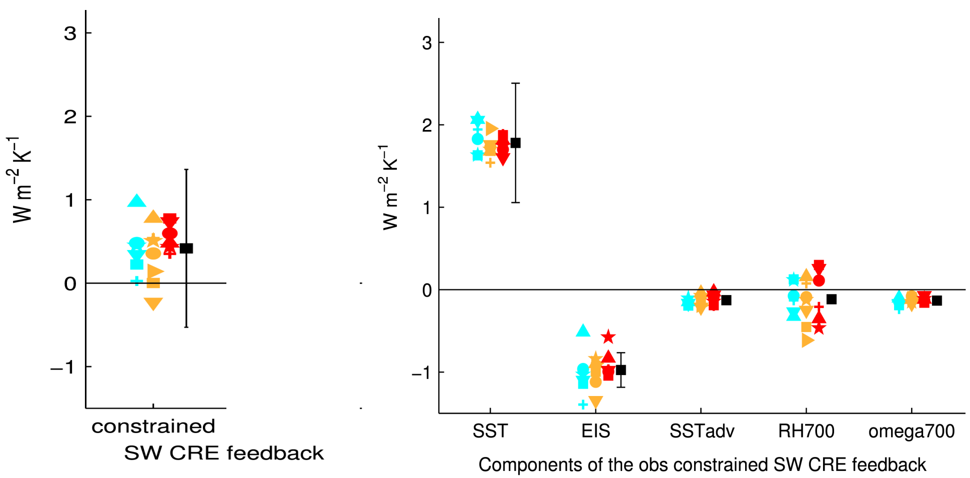
Qu et al. (2014, 2015), Zhai et al. (2015), Zhou et al. (2015), Myers and Norris (2016), Brient and Schneider (2016), and McCoy et al. (2017)

Low Cloud Feedbacks from Cloud-Controlling Factors

- Here are results from one study (Myers and Norris, 2016) that decomposed low cloud feedback into contributions from from various cloud controlling factors, and imposed the observed low cloud sensitivity to cloud controlling factors, together with the simulated changes in cloud controlling factors. (Other studies have similar implications, e.g. Qu et al. 2014, 2015.)

- One key result is that there are two sensitivities that control the low cloud response, the sensitivity to changes in lower atmospheric stability (EIS), and to sea surface temperature. The EIS sensitivity acts to increase low cloud, and the SST sensitivity acts to decrease it.

- The other key result is that the SST component is larger in magnitude than the EIS component, so that the overall constrained feedback is positive. So we have a proposed emergent constraint on shortwave low cloud feedback.



$$\frac{dC}{dT_g} = \sum_i \frac{\partial C}{\partial x_i} \frac{dx_i}{dT_g}$$

Observed cloud sensitivity with CCF change from good, average, or poor models

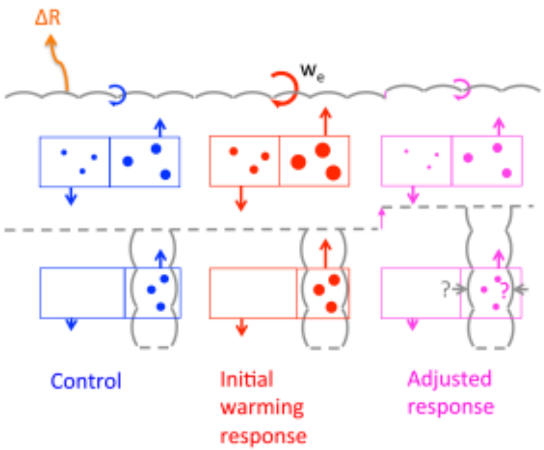
Observed cloud sensitivity and its error bars with average climate model change in cloud-controlling factors

Myers and Norris (2016)

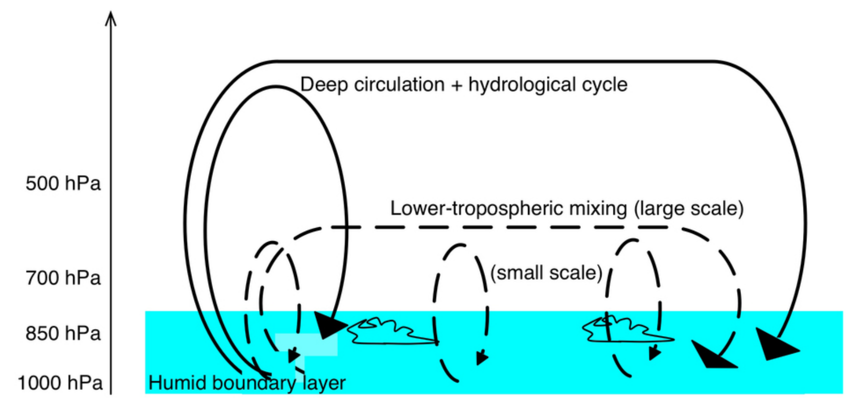
Qu et al. (2014, 2015)

A word about the SST sensitivity

- To get this proposed emergent constraint into the confirmed category, we need to understand the physics underpinning the SST sensitivity. (The EIS sensitivity leading to the smaller negative feedback is relatively well understood, and the emergent constraint associated with it may already be considered "confirmed")
- Explanations based on thermodynamical arguments and large-eddy simulations have been offered.



Bretherton and Blossey (2014)



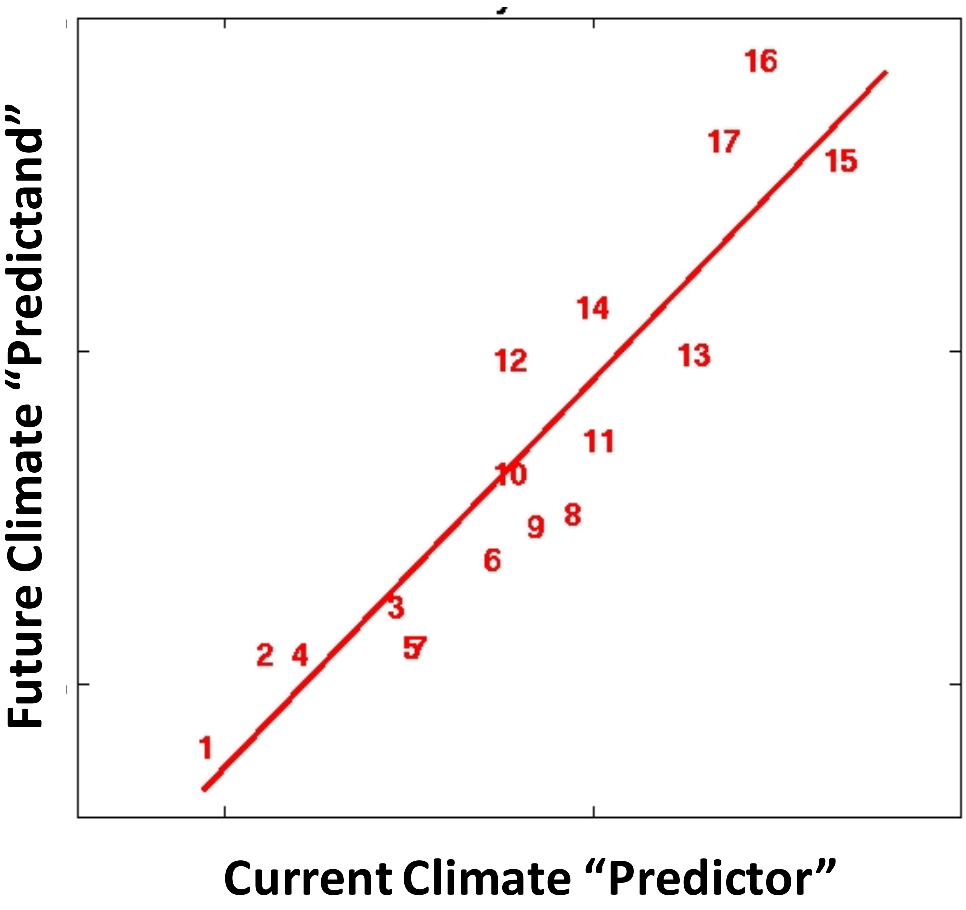
Sherwood et al. (2014)

- Increased vertical moisture flux in a warmer world promotes more efficient entrainment drying of the boundary layer ["entrainment liquid-flux adjustment"] (Bretherton and Blossey 2014, Rieck et al. 2012)
- Increased vertical moisture gradient in a warmer world increases the amount entrainment drying of the boundary layer (Sherwood et al. 2014)

So where are we?

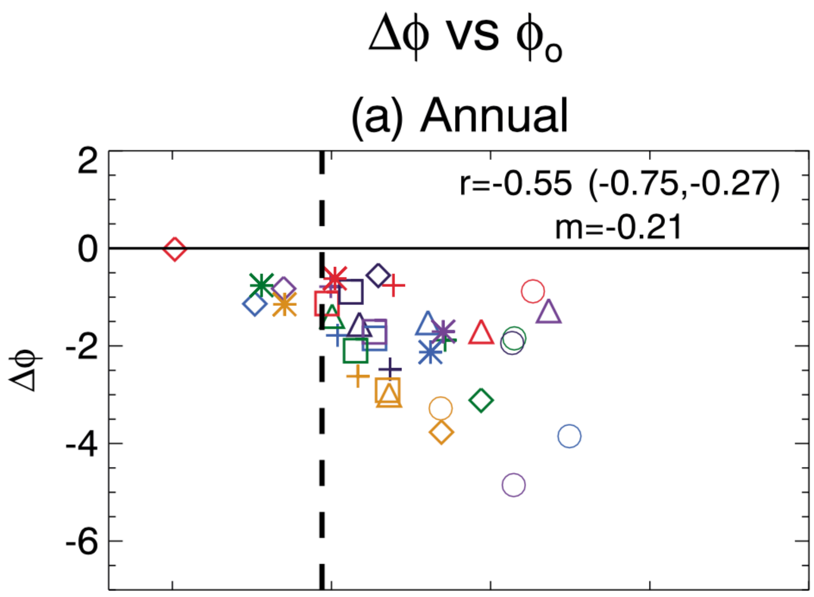
- The strong observed sensitivity of low cloud to SST and the physical explanations supporting such a sensitivity indicate we may be getting close to a confirmed emergent constraint on this component of low cloud feedback.
- The (confirmed) EIS component could provide a countervailing negative feedback, but there are probably physical limits on the subtropical stability increase associated with warming. This coupled with constraints on the observed sensitivity of low cloud to EIS probably imply that the EIS component can't "win".
- So we have an emergent constraint for the feedback behind most of the spread in ECS that is approaching confirmation. And we have multiple proposed emergent constraints on ECS itself that if confirmed, would point to a more positive shortwave cloud feedback than the GCM ensemble mean. Because of the dominance of the shortwave cloud feedback for ECS spread, we now have multiple lines of evidence that the lower end of the canonical climate sensitivity range is unrealistic.
- Next steps could also involve taking the emergent constraint approach to shortwave cloud feedback to the useful stage. This could involve experimentation with physical model parameters. Sherwood et al. (2014) may be some kind of starting point.

Lessons learned



- Correlations between current climate predictors and future climate predictands are only the beginning of the emergent constraint development process, i.e. the "proposed" stage.
- While we're on the topic of correlations, a word about correlation strength.
- It's often assumed that a high correlation means the emergent constraint is more "robust". But robustness or confirmation of an emergent constraint can only come from the credibility of the mechanistic argument supporting the correlation, not the statistics.
- In other words, it's possible to have high correlation that's spurious, and a low correlation that's physically meaningful.
- Of course, the lower the correlation, the less spread in the predictand the predictor accounts for.
- And it's also probably true that higher correlations may be more likely to be associated with credible mechanistic arguments.

Lessons learned



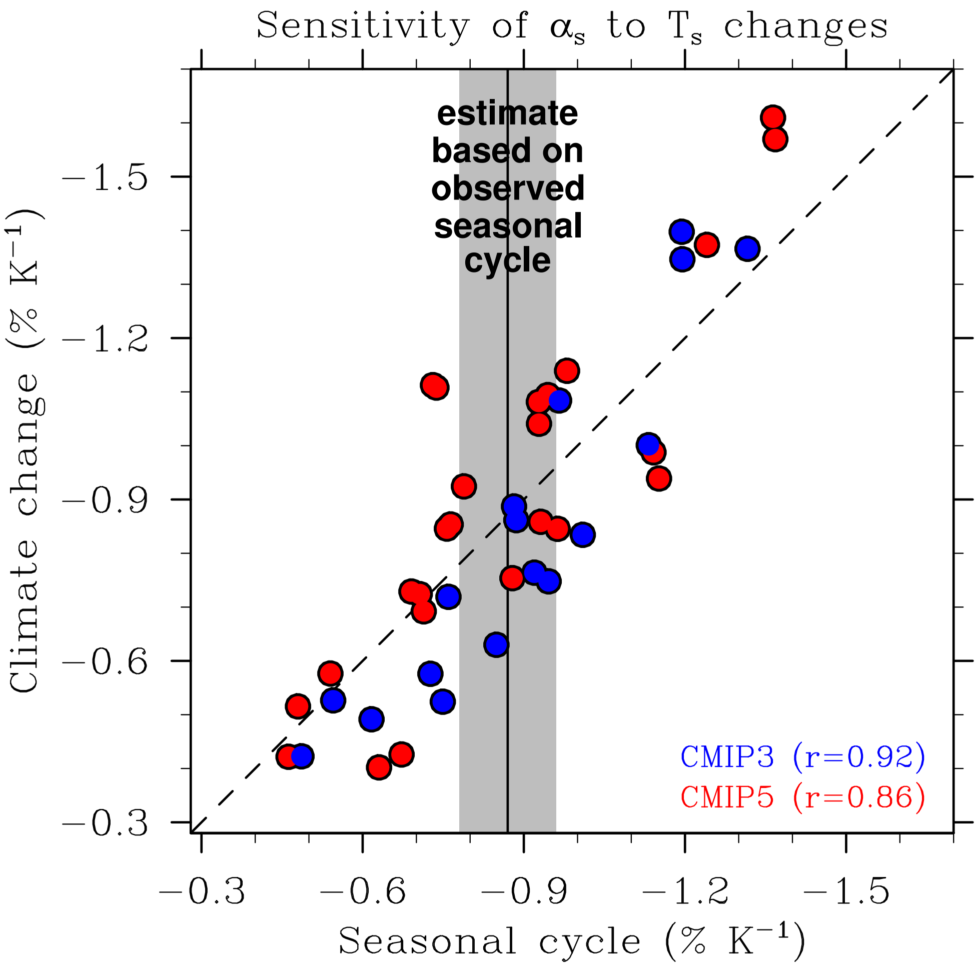
Simpson and Polvani (2016)

- For an emergent constraint to be confirmed, correlations must be accompanied by convincing evidence of an underlying mechanism.
- The quest for mechanistic understanding may not be quick or easy (e.g. Simpson and Polvani, 2016).
- Just as we should not automatically declare all proposed emergent constraints to be confirmed, neither should we judge proposed emergent constraints as failures just because the mechanistic evidence is embryonic.
- In fact, most proposed emergent constraints at least have hints of mechanisms associated with them, and seem to occupy a "limbo" between proposed and confirmed. We should work to either demonstrate that they are spurious, or that they belong in the confirmed category.
- A final thought on mechanisms: The fewer mechanistic influences on the predictand, the easier it is to confirm the emergent constraint. A corollary is that the correlation is not readily interpretable if the predictand is influenced by multiple mechanisms.

Lessons learned

- Because of the need for a clean mechanistic interpretation to have a confirmed emergent constraint, we will need many emergent constraints on individual processes to maximize convergence in climate models. This is a significant effort, and it will take time.

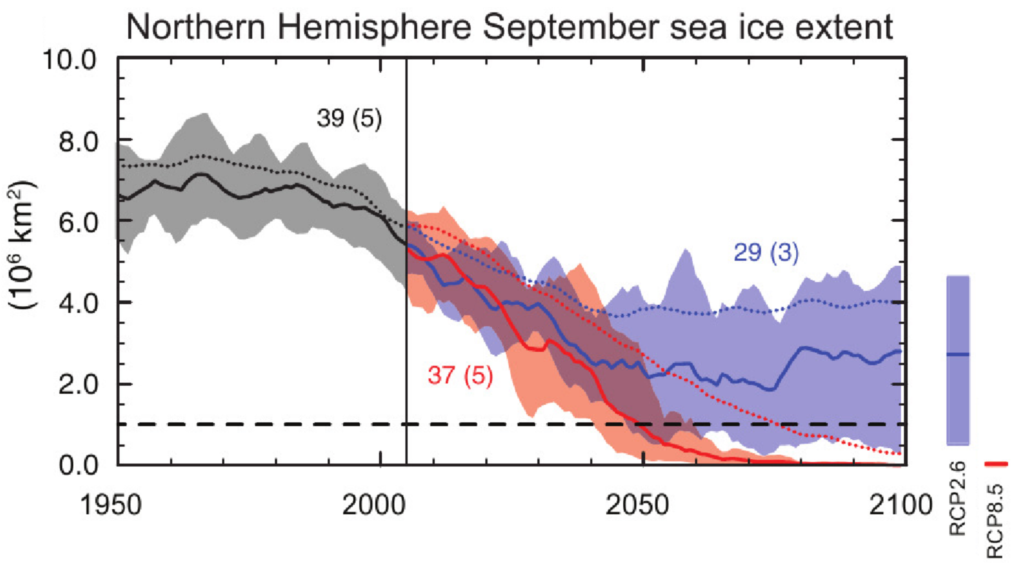
Lessons learned



Qu and Hall (2014)

- We also must commit to the final step of relating model structure and parameterization choices to model biases in current climate predictors (i.e. get them from confirmed to useful). This is the only way we will fully realize the full potential of the emergent constraint technique.

Other issues – weighting models



- I've been emphasizing the use of emergent constraints to improve the next generation of models. But another use is to weight models to refine projections based on the current generation of models.

- This is what was done in AR5 to produce weighted sea ice projections. The climatological sea ice extent is anti-correlated with simulated 21st century sea ice loss, and the models with more realistic sea ice produce a much earlier ice-free Arctic. This is essentially an emergent constraints approach.

- I would argue that similar principles to ones I've already articulated apply: The relationship has to be confirmed with physical argumentation; when a single process is involved the relationship is much easier to interpret and more credible, etc.

Other issues

- Practitioners of emergent constraint techniques should take advantage of more robust observational estimates (ensemble-based observational estimates, accounting for internal variability in observational estimates through large ensembles, etc.)
- What is the significance of observational estimates that are outside the model range of the current climate predictor?
- Should we assign different value to emergent constraints developed through analysis of perturbed physics ensembles vs multi-model archives like CMIP6?
- If models converge due to application of an emergent constraint, do we declare the future climate predictand to be realistic?

Emergent constraints fall into one of 3 categories

- A **proposed** emergent constraint is one where a strong but purely statistical relationship between predictor and predictand has been found.
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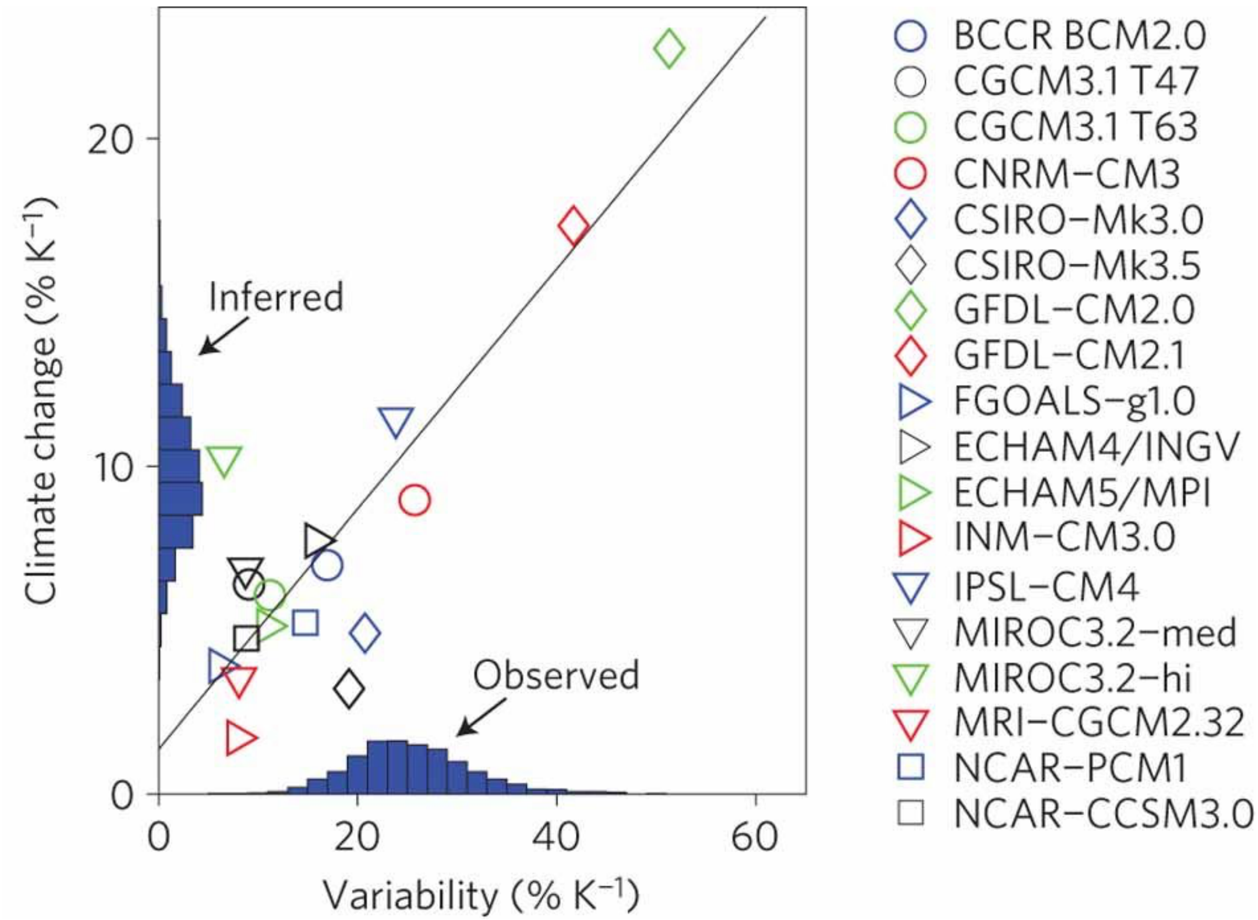
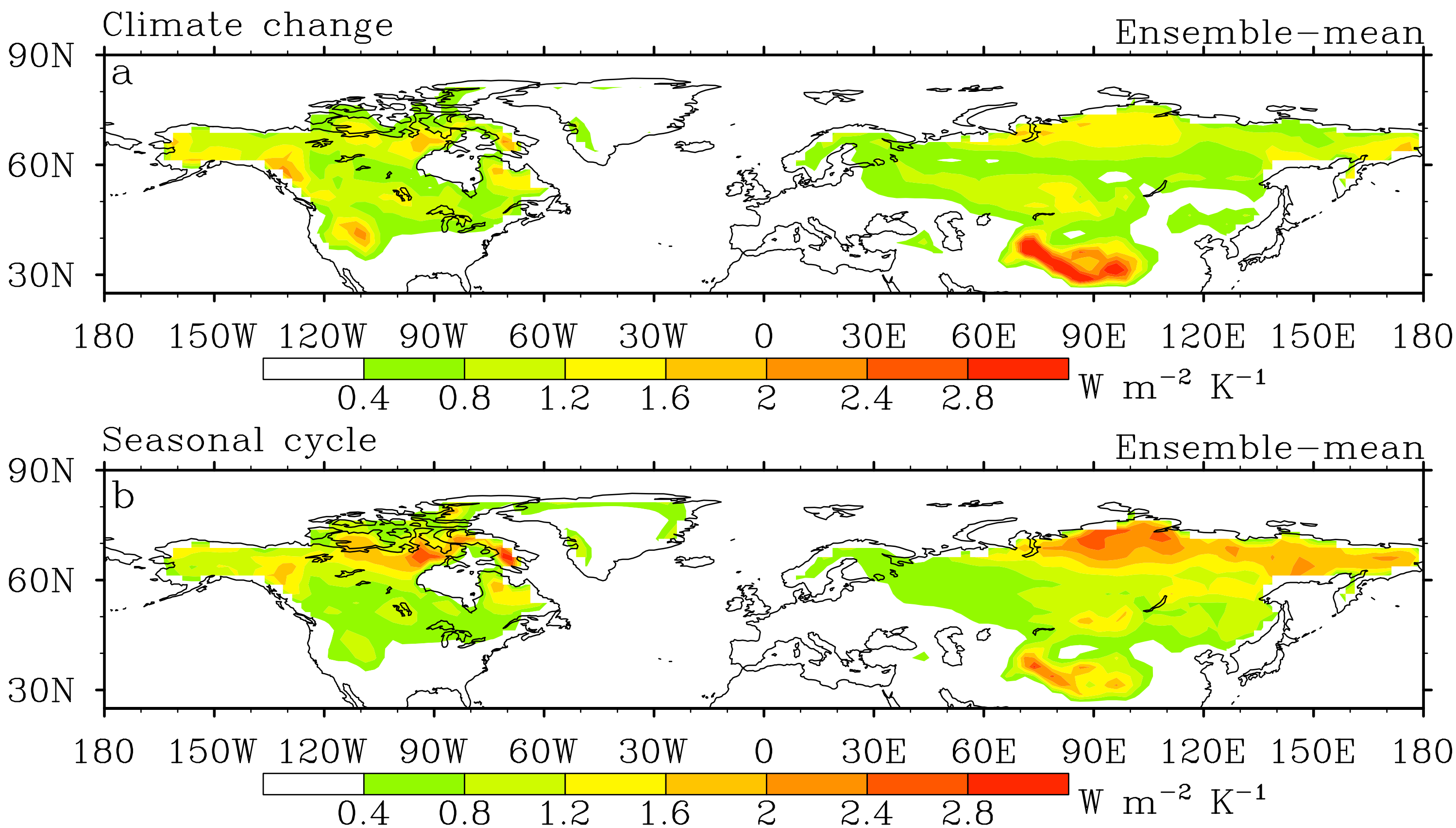


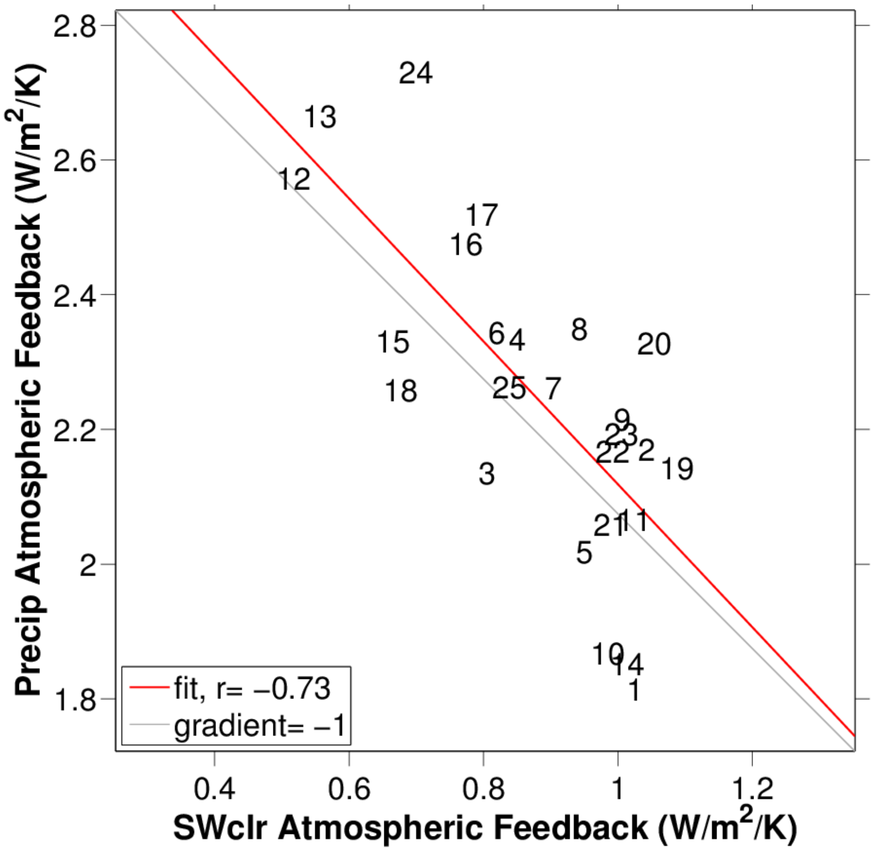
O’Gorman 2012

Geographic distribution of SAF



The ensemble-mean of the local SAF contribution in the contexts of (a) climate change and (b) seasonal cycle.

A proposed emergent constraint



The target in this case is the global increase in precipitation associated with anthropogenic warming.

If we plot this increase, normalized by the global warming,

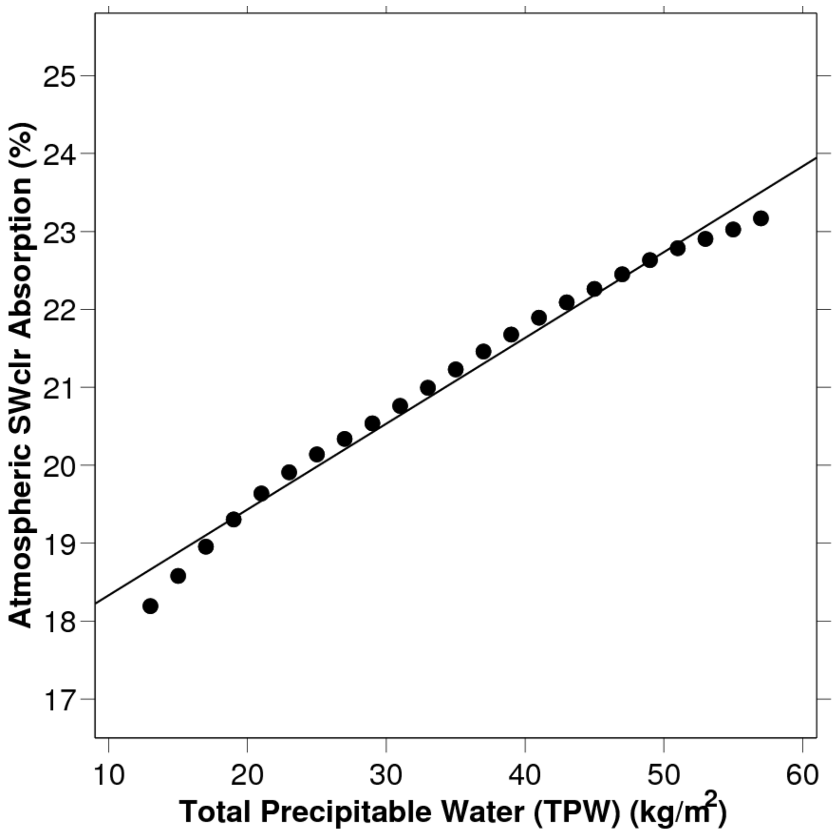
The best correlated component is the dominant one in driving the intermodel variation in the precipitation slope.

It turns out that the shortwave component is dominant.

The key component can be isolated further as that related to clear-sky shortwave radiation.

DeAngelis et al. (2015)

Water vapor absorption



Water vapor is the main atmospheric absorber of clear-sky solar radiation.

We can quantify how absorptive a particular GCM is by scattering the current climate's average fraction of clear-sky shortwave radiation absorbed at any particular location against average total column water at that same location.

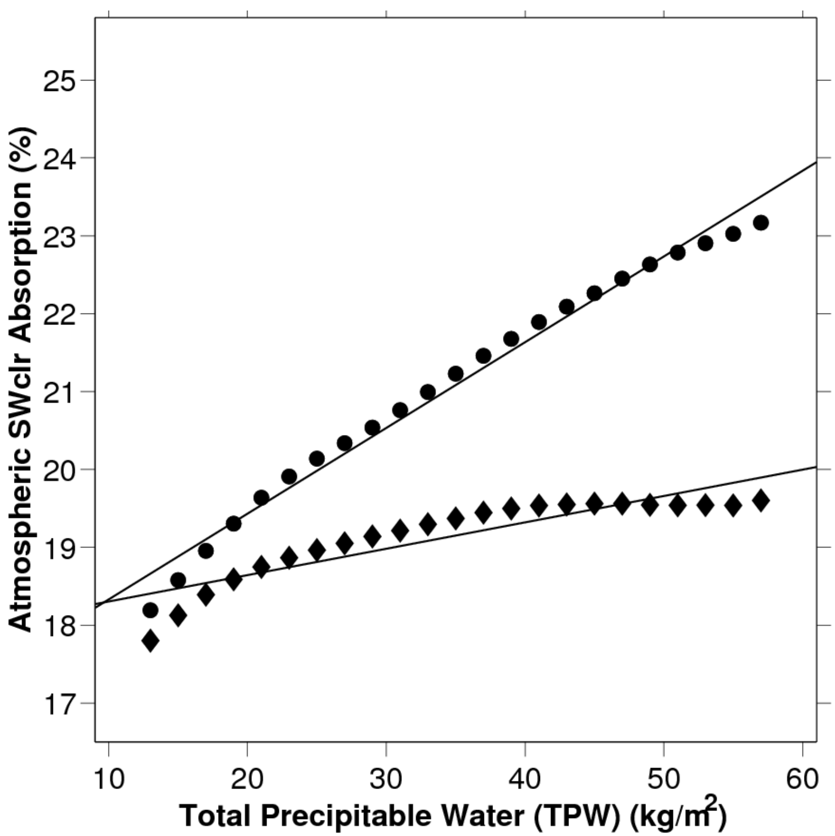
This analysis does not depend on future climate data.

Here is that plot for the GFDL-CM3 model.

Other models have very different rates of increase of atmospheric absorption as water vapor increases.

DeAngelis et al. (2015)

Water vapor absorption



Here's the same scatterplot for the GISS-ER2 model.

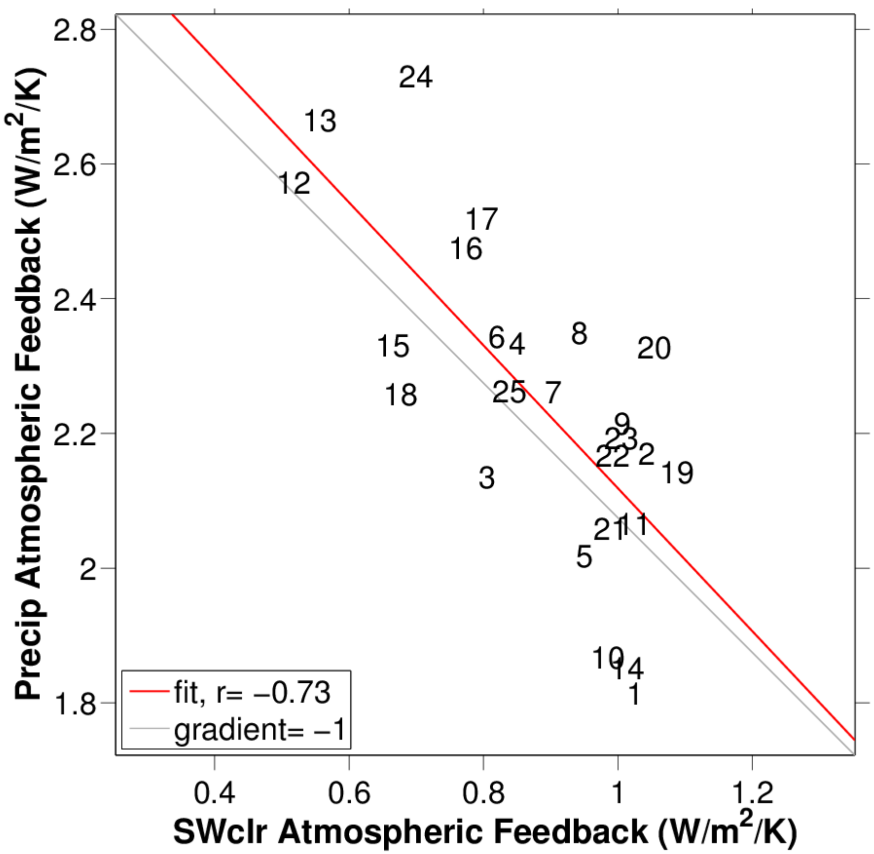
When there is a lot of water vapor in the atmosphere, it absorbs significantly less than in GFDL-CM3.

We can measure these differences by calculating the slope of this relationship.

These two GCMs differ significantly in how they parameterize absorption of solar radiation by water vapor!

DeAngelis et al. (2015)

Shortwave component is key

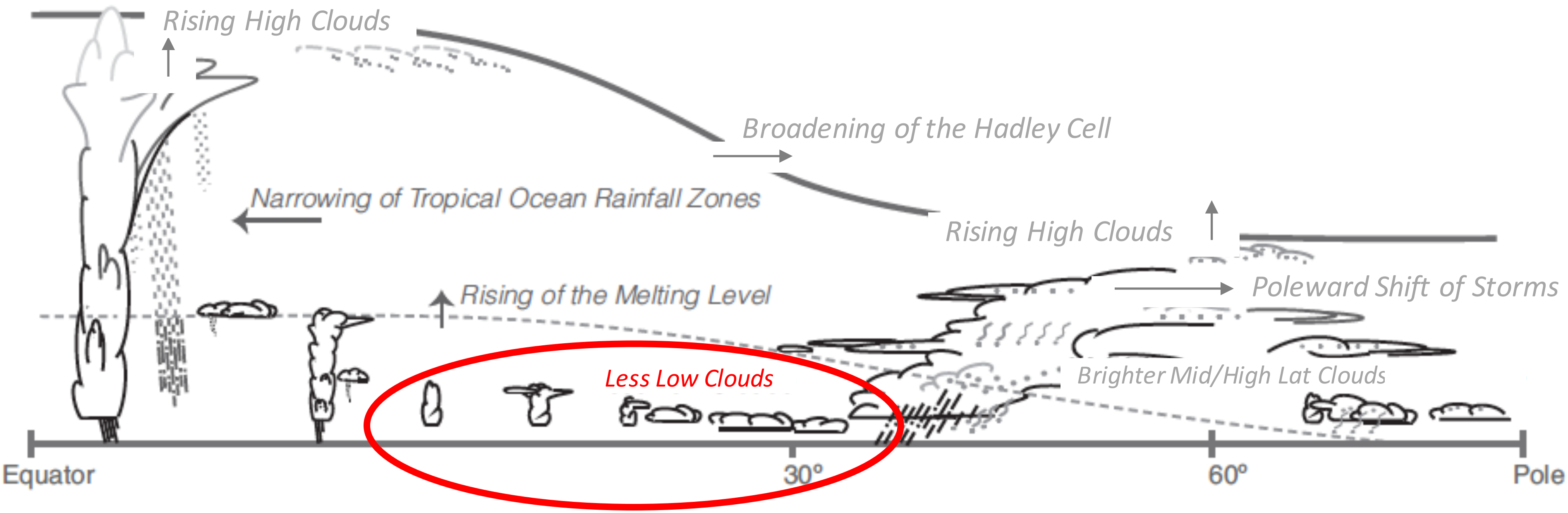


The GCMs predict different amounts of additional clear-sky shortwave heating for a warming of one degree. (We'll call this the clear-sky shortwave feedback.)

If a GCM predicts a lot of additional clear-sky shortwave heating as warming proceeds (strong feedback), less latent heat increase is required to bring the atmospheric energy budget into balance, and the associated precipitation increase is smaller.

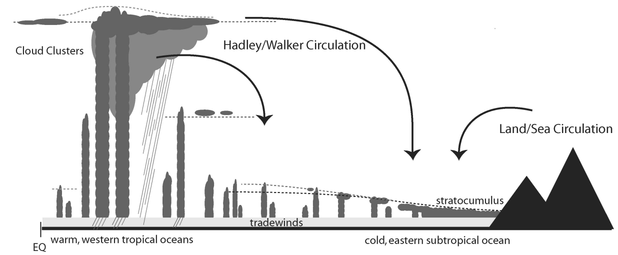
DeAngelis et al. (2015)

- **Introduction**
- **Cloud Feedbacks for**
  - **Tropical Low Clouds**
  - Extra-tropical Low Clouds
- **Summary**



Modified from IPCC AR5, Figure 7.11

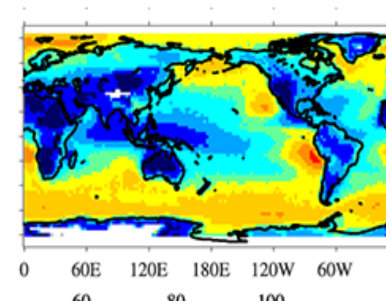
Tropical Low Clouds in Observations & Models



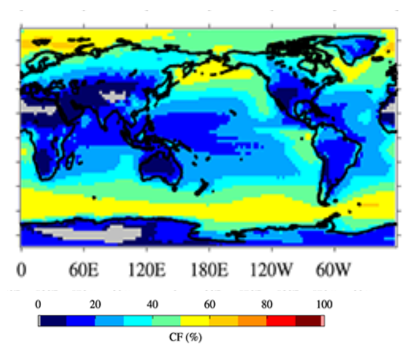
Stevens (2005)

- Climate models typically underestimate low clouds
- Usually "too few - too bright"
- Problematic to represent a thin (~100-300 m) stratiform cloud under trade inversion
- Clouds have improved a lot in some models

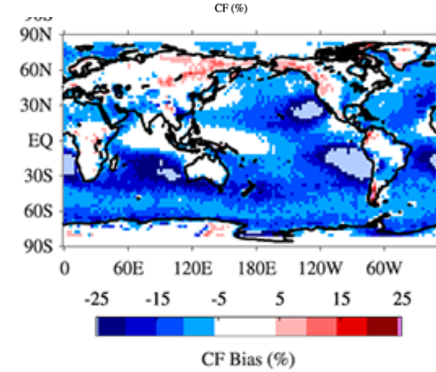
Calipso Satellite Observations



Climate Models (w/Calipso simulator)



Models Minus Observations

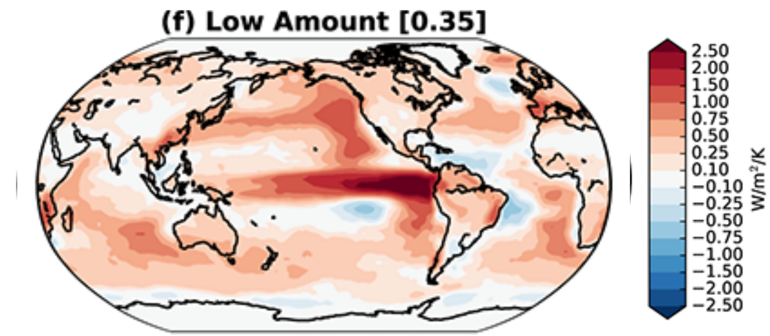


Cesana and Waliser (2016)

Tropical Low Cloud Feedbacks

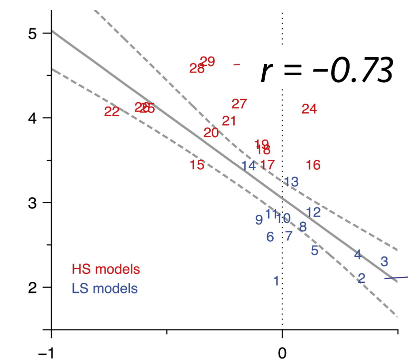
- Climate models predict low-cloud amount to decrease on average
  - Largest single feedback on average
- The response of tropical low clouds to warming is the single cloud type with the strongest correlation to equilibrium climate sensitivity
  - Due to albedo changes not compensated by longwave radiation trapping changes
- Observations and high-resolution modeling agree that tropical low cloud feedbacks should be positive

Average Low Cloud Amount Feedback in Climate Models



Zelinka et al. (2016)

Equilibrium Climate Sensitivity



Albedo temperature sensitivity (% K^{-1})

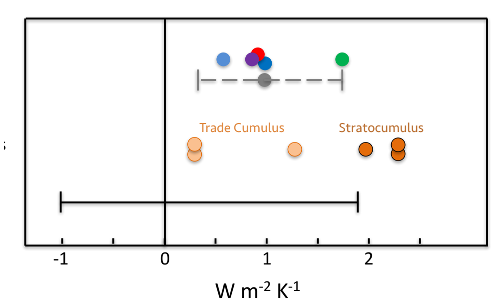
Brient and Schneider (2016)

Tropical Low Cloud Feedbacks

Observations

Large-Eddy Simulations

Global Climate Models



Klein et al. (submitted)

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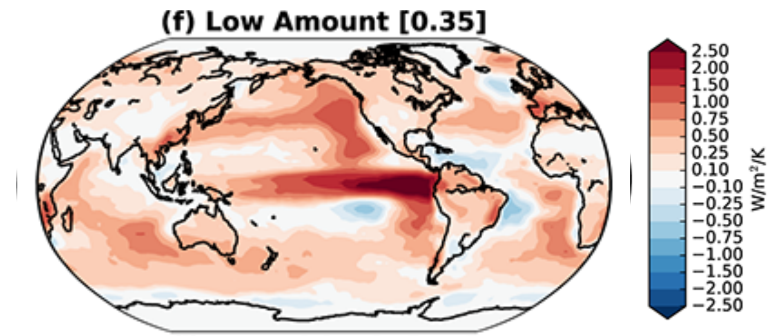
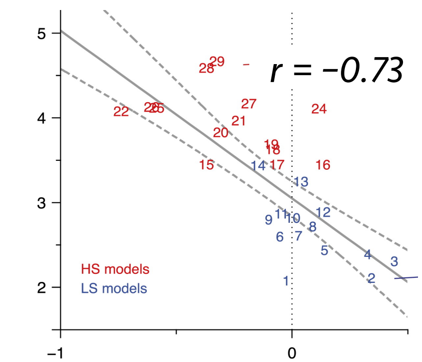


Zelinka et al. (2016)

Equilibrium Climate Sensitivity



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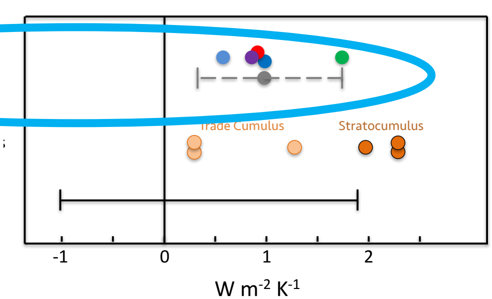

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Low Cloud Feedbacks from Cloud-Controlling Factors

- Low clouds are a fast (~hours-days) response to ”cloud-controlling factors” (CCF) of the environment *(Stevens and Brenguier 2009)*
- If we assume that these cloud sensitivities are ”time-scale invariant”, and we know how CCF change, then we can predict the cloud feedback:

Cloud Sensitivity to CCF (x_i) ← **from Observations (Usually inter-annual variability)**

$$\frac{dC}{dT_g} = \sum_i \frac{\partial C}{\partial x_i} \frac{dx_i}{dT_g}$$

$x_i \in$ *{ SST, EIS, ω, RH*$_{tropo}$*, temperature advection}*

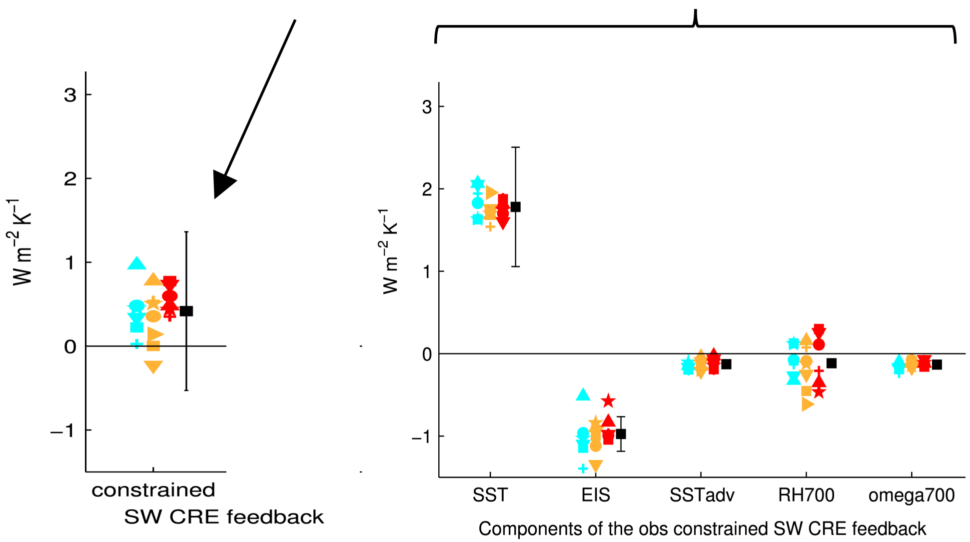
Low Cloud Feedback

Climate Change in CCF ← **from Climate Models**

Qu et al. (2014, 2015), Zhai et al. (2015), Zhou et al. (2015), Myers and Norris (2016), Brient and Schneider (2016), and McCoy et al. (2017)

Low Cloud Feedbacks from Cloud-Controlling Factors

$$\frac{dC}{dT_g} = \sum_i \frac{\partial C}{\partial x_i}\frac{dx_i}{dT_g}$$



Observed cloud sensitivity with CCF change from good, average, or poor models

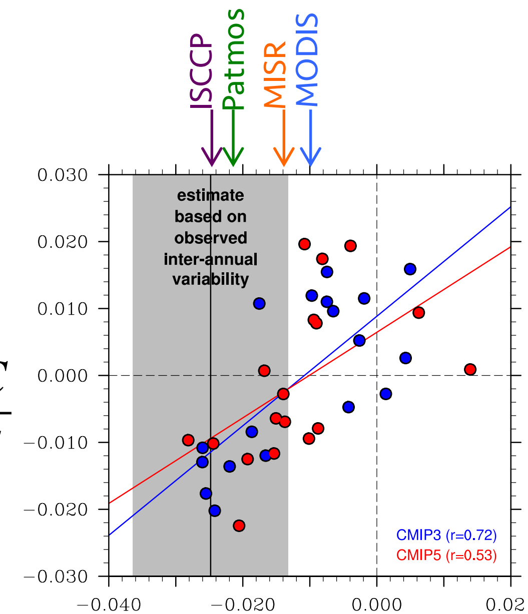
Observed cloud sensitivity and its error bars with average climate model CCF change

Myers and Norris (2016)

Climate Change

$$\frac{\Delta LCC}{\Delta SST}$$

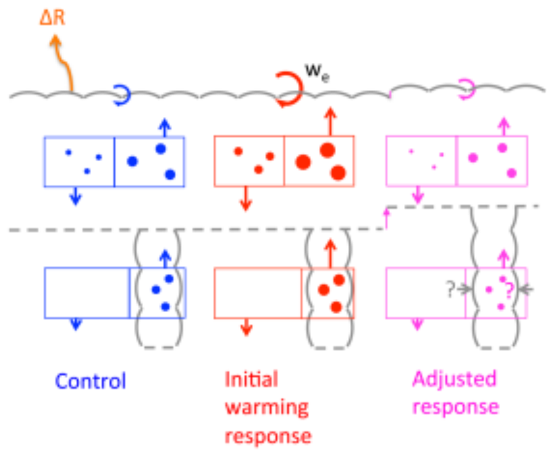
(K^{-1})



Sensitivity from Natural Variability $\left.\frac{\partial LCC}{\partial SST}\right|_{EIS}$ (K^{-1})

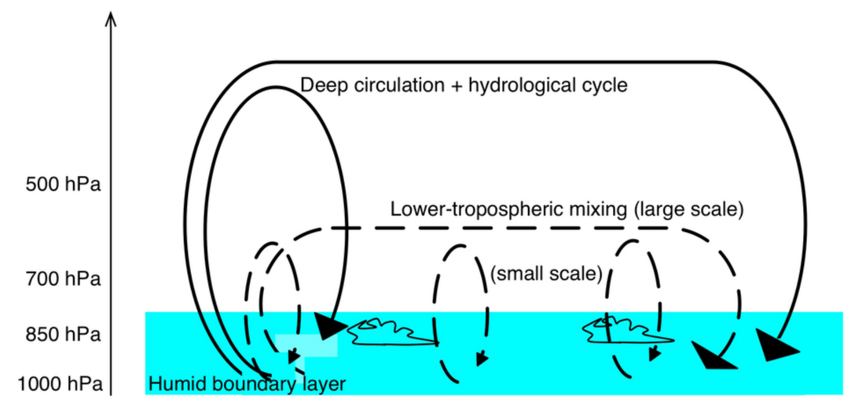
Qu et al. (2014, 2015)

Physical Basis for Cloud Sensitivities



Bretherton and Blossey (2014)

- Increased vertical moisture flux in a warmer world promotes more efficient entrainment drying of the boundary layer ["entrainment liquid-flux adjustment"] *(Bretherton and Blossey 2014, Rieck et al. 2012)*



Sherwood et al. (2014)

- Increased vertical moisture gradient in a warmer world increases the amount entrainment drying of the boundary layer *(Sherwood et al. 2014)*

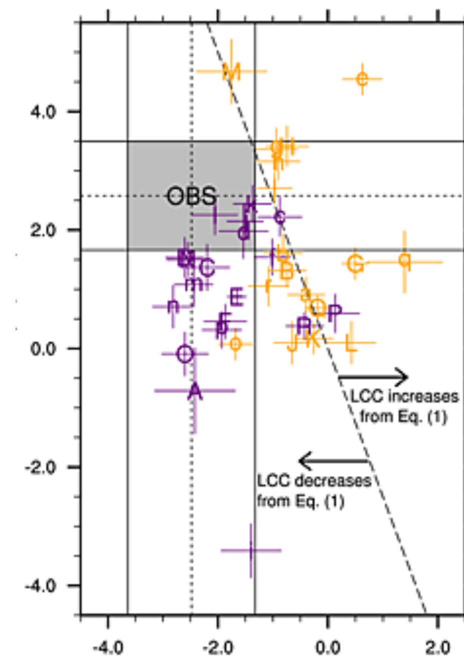
- Physical bases for cloud sensitivities to *EIS*, ω, RH_{tropo}, and *temperature advection* are well established

Climate Modeling Challenge #1

- Models should better simulate
  - Low-cloud sensitivities in stratocumulus regions are highly variable and rarely correct *(Qu et al. 2015)*
  - Trade cumulus cloud sensitivities are just as problematic *(Nuijens et al. 2015)*

- How to improve models?
  - Obviously, mixing parameterizations matter a lot *(Brient et al. 2015)*
  - Vertical resolution still important
  - Cloud fraction parameterizations tied to EIS explained some of the negative low cloud feedbacks found in (older) models *(Qu et al. 2014, Geoffroy et al. 2017)*

$\frac{\partial C}{\partial EIS}$ (% K^{-1})



$\frac{\partial C}{\partial SST}$ (% K^{-1})

Qu et al. (2015)