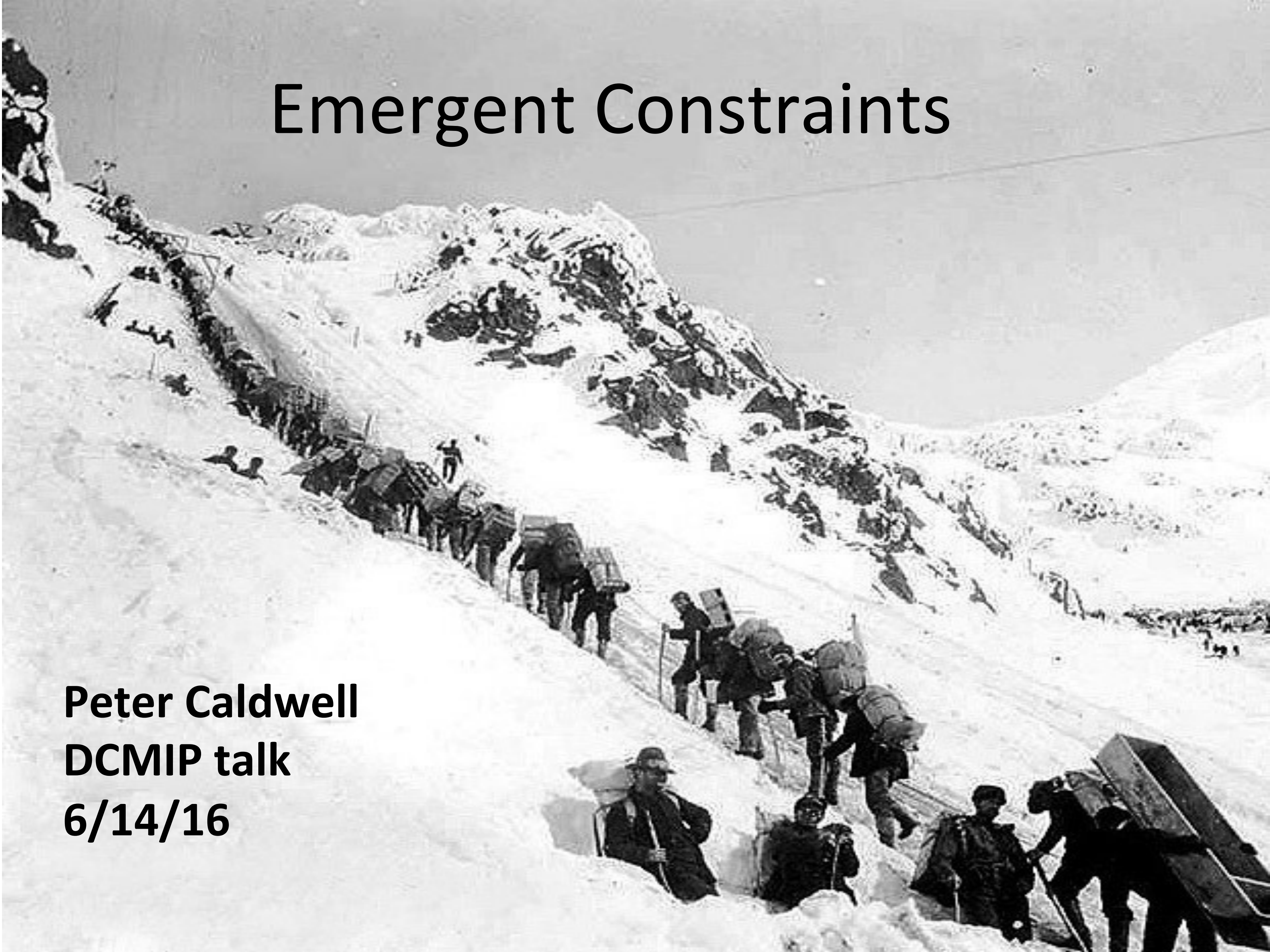
Emergent Constraints



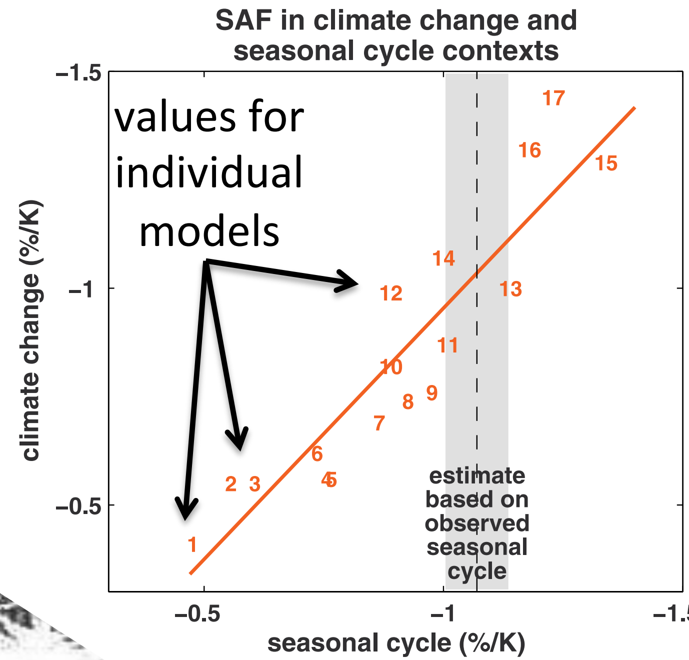
Peter Caldwell
DCMIP talk
6/14/16

Emergent Constraints

Science

Nature

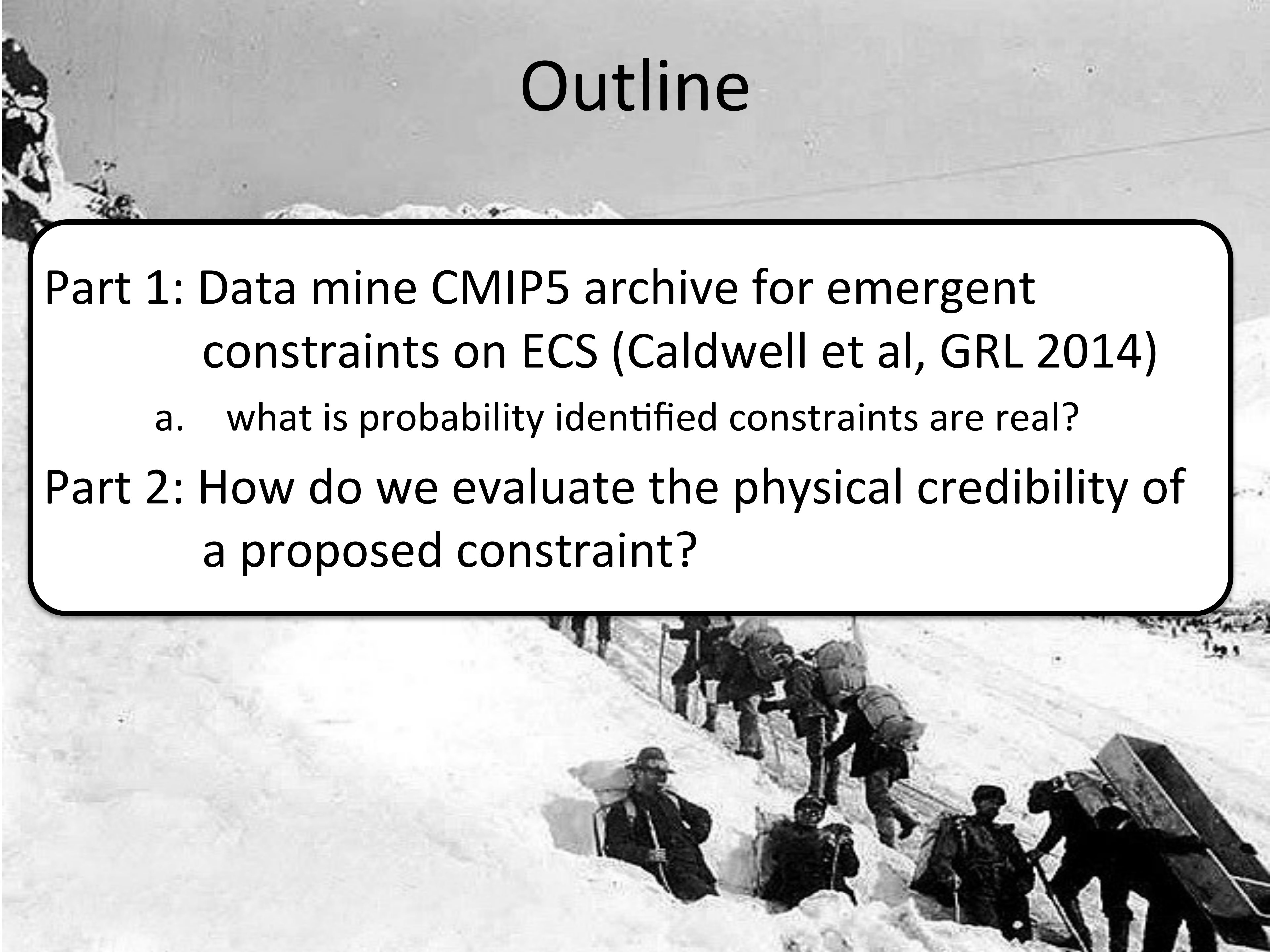
Hall + Qu (2006) showed that the seasonal cycle of snow albedo in the current-climate is a good proxy for snow-albedo feedback (SAF).



Equilibrium climate sensitivity (ECS) is our primary measure of the severity of global warming but has proven hard to constrain... which has led to a clamor to identify emergent constraints for climate sensitivity

Def: Emergent constraint: a currently-observable quantity with skill at predicting future climate

Def: Equilibrium climate sensitivity (ECS) = global-averaged equilibrium surface warming due to CO2 doubling



Outline

Part 1: Data mine CMIP5 archive for emergent constraints on ECS (Caldwell et al, GRL 2014)

a. what is probability identified constraints are real?

Part 2: How do we evaluate the physical credibility of a proposed constraint?

Data Considered

- Compute ECS for 28 CMIP5 models
  - using "Gregory method"
- Use all times from "historical" runs to get:
  - Climatological average
  - Interannual standard deviation
  - Seasonal (JJA-DJF) amplitude
- Break data by season into 20^{O} ½ overlapped latitude bands; consider pressure levels independently
  - Regrid "native" grid 3D variables to standard pressure levels
- Also compute daily T range and # of horizontal and vertical grid cells in model

Def: A particular variable, latitude band, level, season, and type (ave, standard deviation, or seasonal amplitude) will be called a *field*.

~42,000 fields are used for the following analysis

Do CMIP5 Fields Have Skill at Predicting ECS?

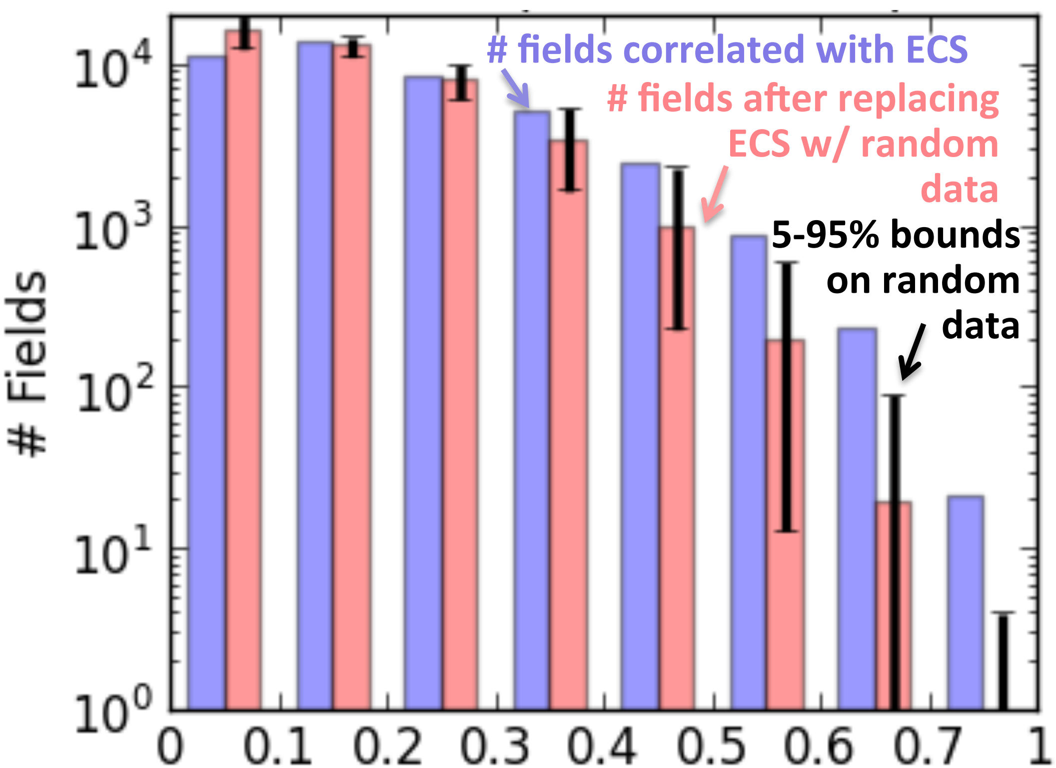


Fig: Histogram of |correlations| with ECS

- High correlations seem ***more frequent than expected by chance***

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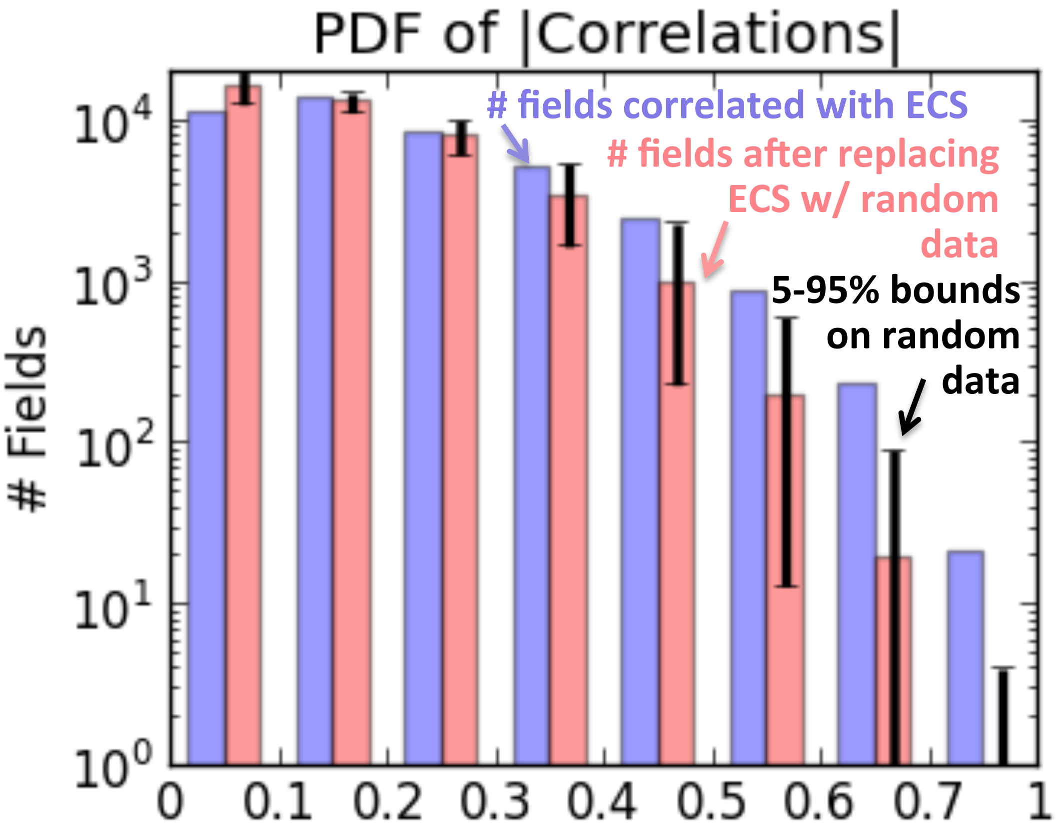

Fig: Histogram of |correlations| with ECS

- High correlations seem ***more frequent than expected by chance***

But does this pass the sniff test?

Models and Fields are Not Independent!

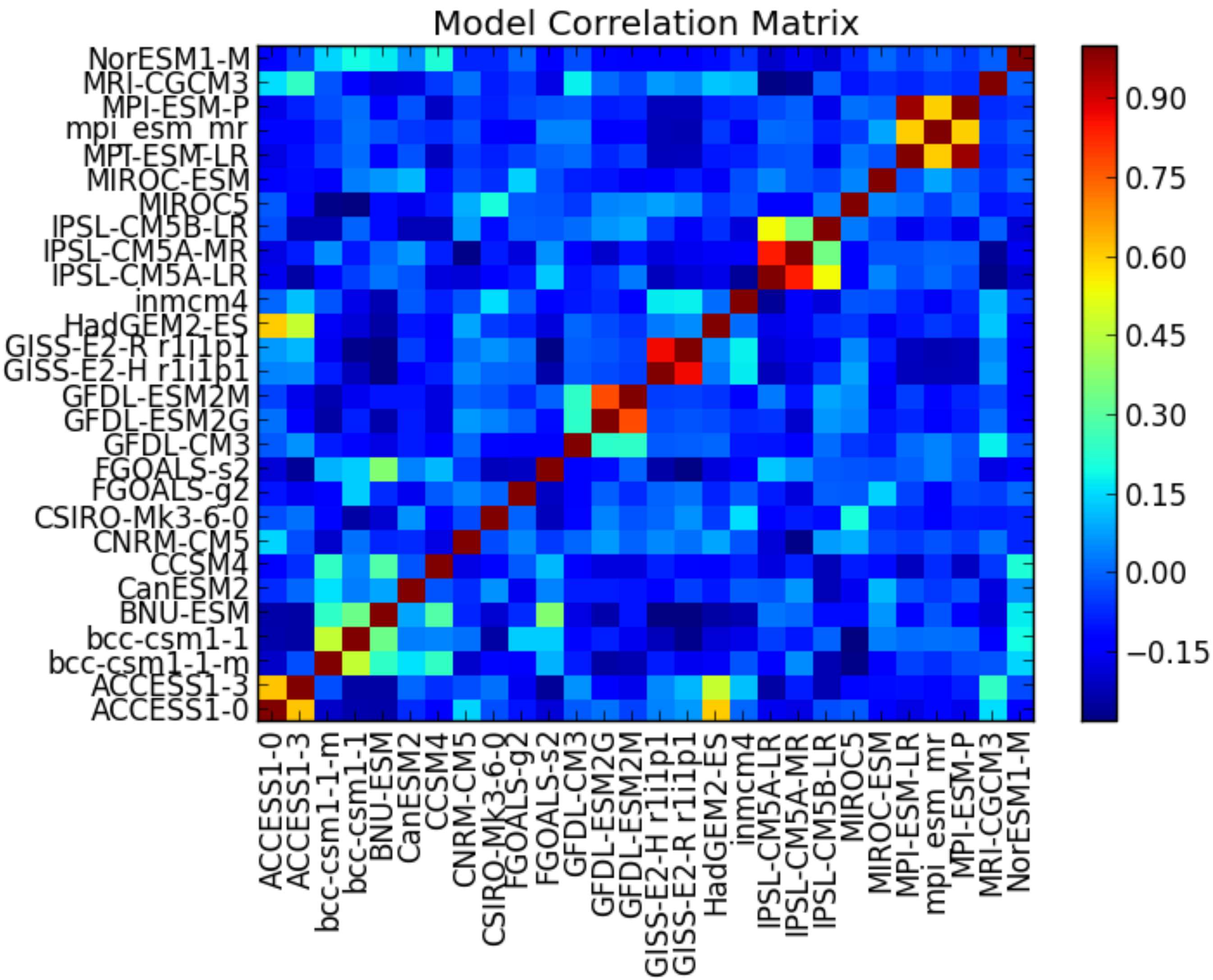

Fig 3: Correlations (in colors) between models computed using the set of all 42,000 CMIP5 fields.

- Some CMIP5 models are very similar to others
- Fields aren't independent either

A Better Approach for Determining Significance of Data-Mined Correlations

1. Apply EOF analysis to the cross-model correlation matrix to replace the original inter-related models with linearly independent “meta-models” (EOFs) formed as linear combinations of the original models.
2. Use eigenvalues of the inter-model correlation matrix to identify and discard meta-models related to near-singular dimensions in the original field data
3. Compute “meta-field” vectors for the remaining meta-models by projecting each field onto the basis of retained EOFs.

PDF of Correlations between A^* and ECS^*

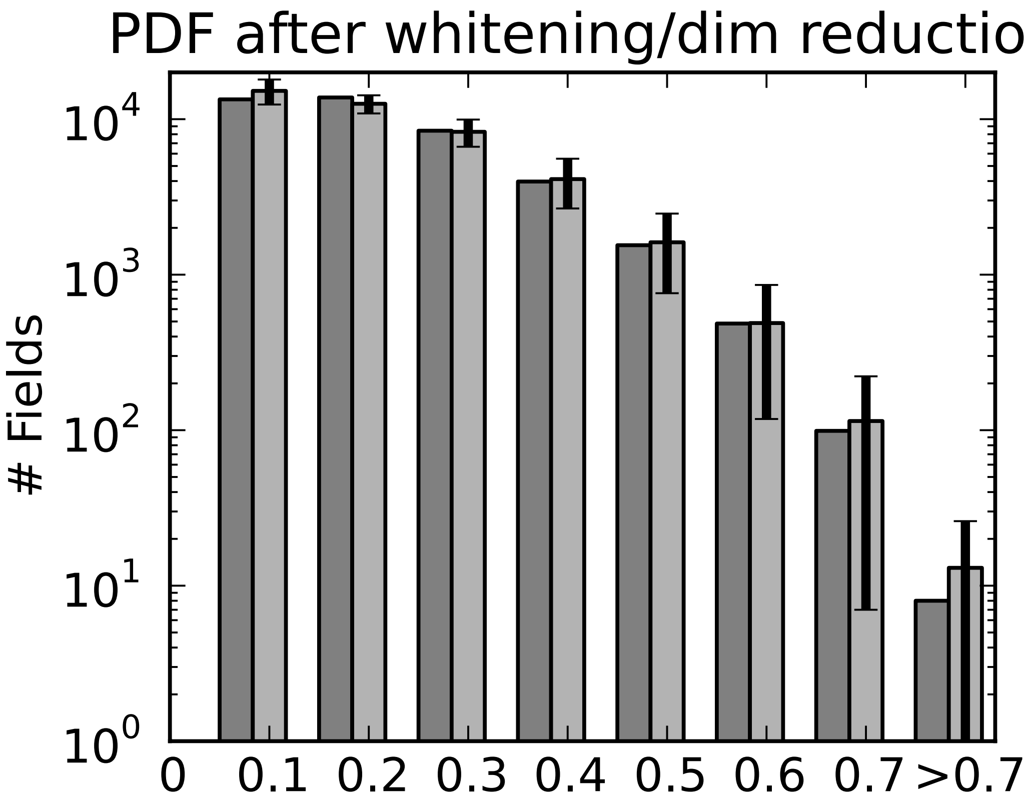

Fig: As in previous histogram, but using A^* and ECS^*. Dimensions truncation was chosen to retain 90% of the total variance in A.

- After accounting for dependence between models and between fields, the number of strong correlations with ECS in CMIP5 ***is not remarkable***

Punchline:

When you data mine, very large correlations are expected by chance...

– by publishing positive results and ignoring negative results, our community engages in unintentional, distributed data mining

Identifying real emergent constraints requires a undeniable physical explanation.

Part 2: Assessing the Credibility of Emergent Constraints

Studies Examined

Name	Description
Covey	Amplitude of seasonal cycle of surface temperature
Volodin	Difference between tropical and southern-hemisphere midlatitude total cloud fraction
Trenberth	Net TOA radiation averaged over the southern hemisphere
Fasullo D	Southern hemisphere zonal-average mid-tropospheric RH in dry-zone between 8.5°-20°S
Fasullo M	Tropical zonal-average lower-tropospheric RH in moist-convective region
Qu	BL cloud amount response to SST variations in subtropical stratocumulus regions (after removing LTS contribution)
Klein ctp-tau	Error in the distribution of cloud-top pressure and optical thickness for regions between 60°N and S
Klein TCA	Error in total cloud amount for regions between 60°N and S
Su	Error in vertically-resolved tropospheric zonal-average RH between 40°N and 45°S
Gordon	Mid- and high-latitude low cloud optical depth response to changes in surface temperature
Sherwood D	Strength of resolved-scale mixing between BL and lower troposphere in tropical E Pacific and Atlantic
Sherwood S	Strength of mixing between BL and lower troposphere in tropical convective regions
Sherwood LTMI	Sum of Sherwood S and D constraints
Zhai	Seasonal response of BL cloud amount to SST variations in oceanic subsidence regions between 20-40° latitude
Brient	Fraction of tropical clouds with tops below 850 mb whose tops are also below 950 mb
Tian	Strength of double-ITCZ bias

Notes:

1. The first ~5 constraints haven't been tested against CMIP5 data. I will do so.
2. Blue circles indicate constraints not originally meant to apply to ECS

Constraint Skill

	# CMIP3 Models	CMIP3 Values	# CMIP5 Models (models passing test)	CMIP5 Values (models passing test)	# CMIP5 Models (all models)	CMIP5 Values (all models)
Covey	11	-0.42	19	0.24	27	**0.35**
Volodin	11	**-0.91**	19	**-0.58**	27	**-0.60**
Trenberth	11	**-0.87**	19	-0.19	27	-0.22
Fasullo D	8	**-0.80**	16	-0.12	23	-0.16
Fasullo M	8	**0.88**	16	-0.12	23	-0.15
Qu	11	**-0.58**	11	**-0.63**	16	-0.29
Klein ctp-tau	*	*	8	**-0.74**	9	**-0.74**
Klein TCA	*	*	8	**-0.73**	9	**-0.71**
Su	*	*	10	0.52	13	**0.58**
Gordon	*	*	7	-0.36	8	-0.30
Sherwood D	11	0.27	18	0.36	26	**0.40**
Sherwood S	11	**0.76**	18	0.28	26	**0.37**
Sherwood LTMI	11	**0.62**	18	**0.49**	26	**0.65**
Brient	*	*	17	0.05	21	**0.38**
Zhai	9	-0.53	11	**-0.75**	15	**-0.73**
Tian	11	**-0.73**	18	**-0.49**	25	**-0.60**

Table: Correlation of each emergent constraint with ECS as reported in the original paper, using CMIP3 data, using CMIP5 models passing clear-sky linearity at 15%, and using all CMIP5 models. # of models is also given. Bold = Correlation is significant at 90% using a t-test. Missing data is indicated by ''.*

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Most constraints confronted with new data for the first time don't hold up

– This is an important cautionary tale for constraints based on CMIP data!

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Omitting models which fail to close the clear-sky kernel budget to within 15% can significantly impact our results

– Again suggests caution in embracing CMIP-based constraints

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Decomposing ECS

An imposed radiative forcing F causes a top-of-atmosphere energy imbalance ΔN which is partially balanced by surface temperature change ΔT modulated by the climate feedback parameter λ:

$$\Delta N = F + \lambda \Delta T$$

In equilibrium, ΔN=0 and ΔT = ECS so:

$$\mathrm{ECS} = \frac{-F}{\lambda}$$

A number of feedback processes combine to form the net feedback:

$$\lambda = \lambda_{Pl} + \lambda_{WV} + \lambda_{LR} + \lambda_{Alb} + \lambda_{Cld}$$

Planck: emission increases as the 4^{th} power of T

Water Vapor: vapor traps outgoing radiation

Lapse Rate: warming is stronger higher in the atmosphere

Albedo: less snow/ice means more absorbed radiation

Cloud: clouds both trap and reflect radiation

Decomposing Constraints

To figure out why an emergent constraint is correlated with ECS, break ECS into its constituent forcing and feedback terms:

$$
\begin{aligned}
\text{ECS} = \frac{-F}{\lambda} & \\
&= \frac{-F}{\overline{\lambda}} \frac{1}{1+\frac{\lambda'}{\overline{\lambda}}} \\
&\approx \frac{-F}{\overline{\lambda}} \left[1 - \frac{\lambda'}{\overline{\lambda}}\right] \\
&\approx -\frac{\overline{F}}{\overline{\lambda}} - \frac{F'}{\overline{\lambda}} + \frac{\overline{F}}{\overline{\lambda}^2} \sum_{i \in P} \lambda_i' \\
&= \sum_{i \in A} T_i
\end{aligned}
$$

where:

$$T_{\text{const}} = -\overline{F}/\overline{\lambda},\; T_F = -F'/\overline{\lambda} \text{ and } T_i = \overline{F}/\overline{\lambda}^2 \lambda_i'$$

and P={Pl, WV, LR, Alb, Cld} and A=P ∪ {const,F}

Now use covariance properties to write correlation with ECS as a sum of correlations:

$$
\begin{aligned}
r(X, \text{ECS}) &= \frac{\text{cov}(X, \sum_{i \in A} T_i)}{\sigma(X)\sigma(\text{ECS})} \\
&= \sum_{i \in A} \frac{\text{cov}(X, T_i)}{\sigma(X)\sigma(\text{ECS})} \frac{\sigma(T_i)}{\sigma(T_i)} \\
&= \sum_{i \in A} \frac{\sigma(T_i)}{\sigma(\text{ECS})} r(X, T_i)
\end{aligned}
$$

You can similarly decompose correlation geographically:

$$
\begin{aligned}
\frac{\sigma(T_i)}{\sigma(\text{ECS})} r(X, T_i) &= \frac{\sigma(T_i)}{\sigma(\text{ECS})} \frac{\text{cov}(X, \sum_{k=1}^{N} w_k T_{ik})}{\sigma(X)\sigma(T_i)} \\
&= \sum_{k=1}^{N} \frac{w_k \sigma(T_{ik})}{\sigma(\text{ECS})} r(X, T_{ik})
\end{aligned}
$$

where w_k is the area of cell k divided by global area

Correlation Decomposition

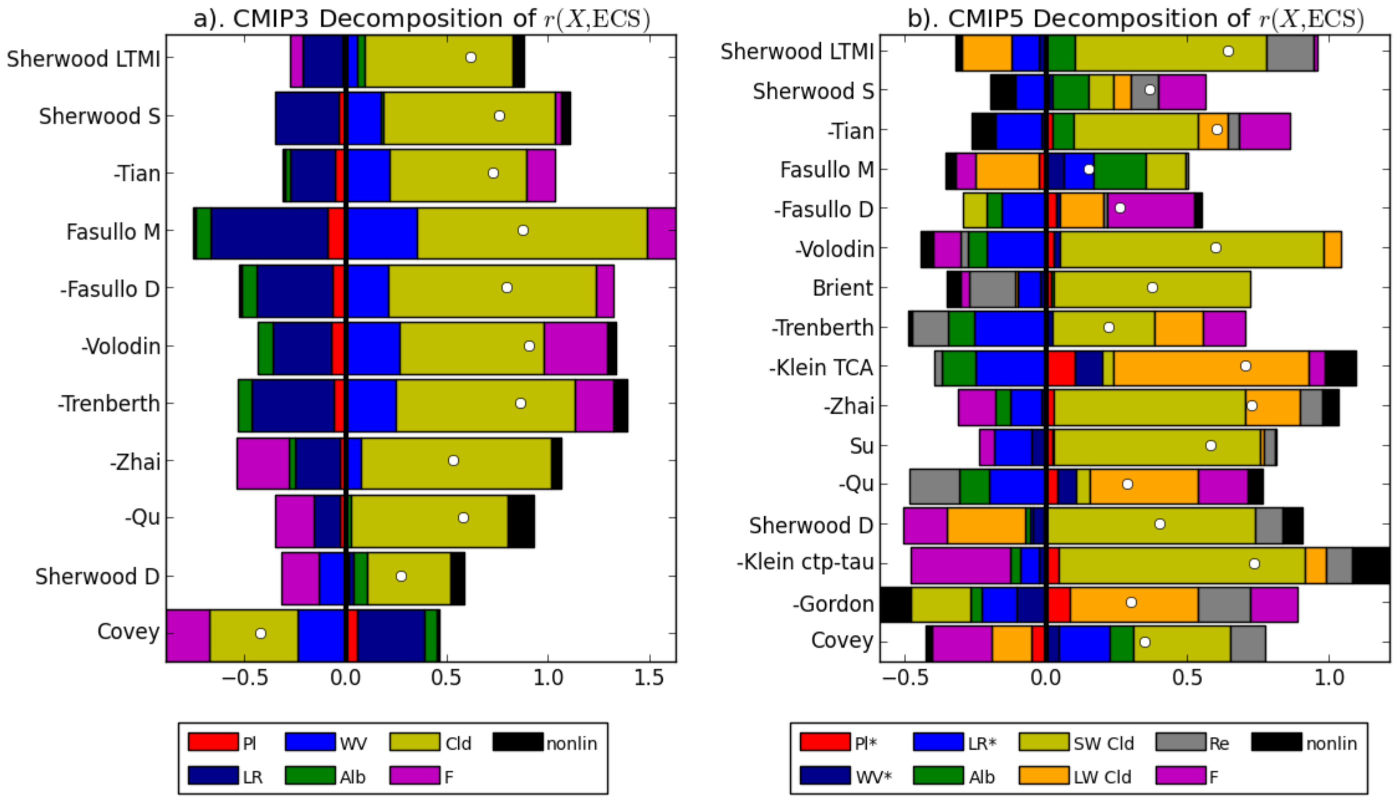


Fig: Decomposition of correlation with ECS for each emergent constraint.

- λ_{Cld} is the main source of correlation with ECS (because it dominates ECS variance)
- It's hard to imagine a physical mechanism involving lots of processes
  - Covey and Fasullo M, Qu, Trenberth, Fasullo D, and Sherwood S stand out as being due to an unlikely patchwork of processes
  - but processes covary, so no constraint is correlated with ECS due to one process alone

Correlation Decomposition

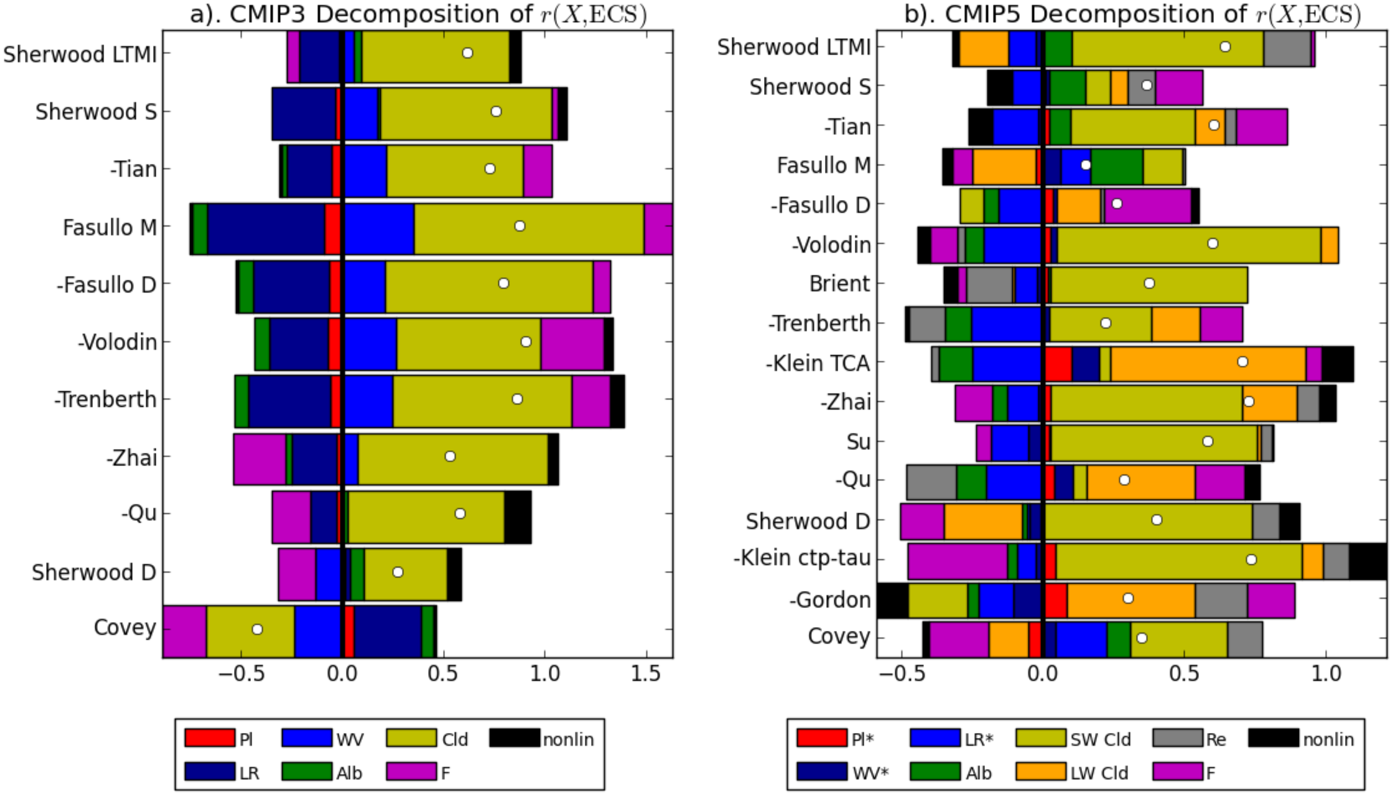


Fig: Decomposition of correlation with ECS for each emergent constraint.

Is correlation with ECS due to the expected mechanisms?

- Sherwood, Zhai, Qu, Brient, Trenberth, Fasullo D, and Gordon were proposed to be due to BL clds and/or λ_{SW}.
  - Qu, Gordon, Trenberth, Fasullo D, and Sherwood S fail this test for CMIP5.

Geographic Decomposition

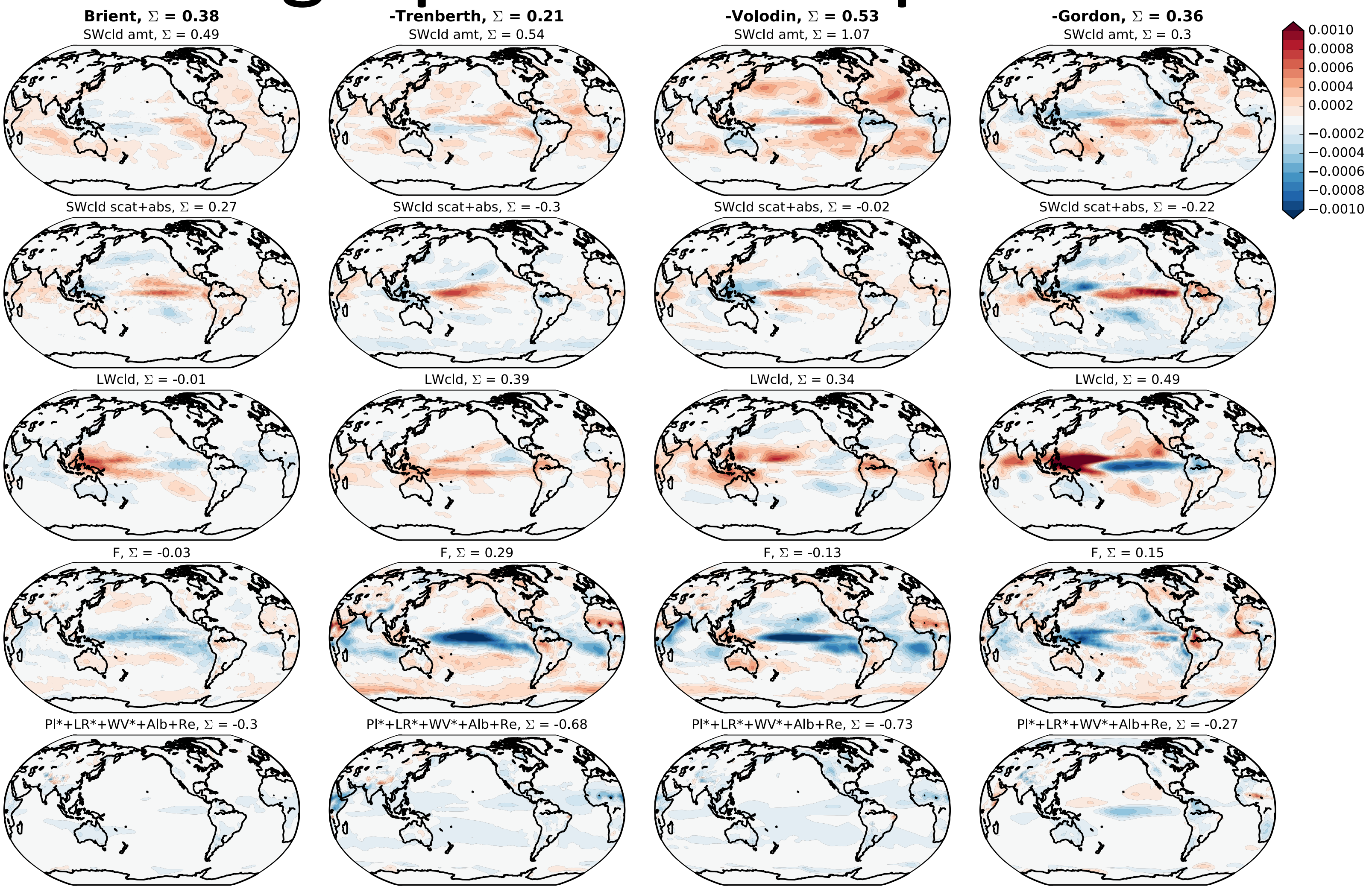
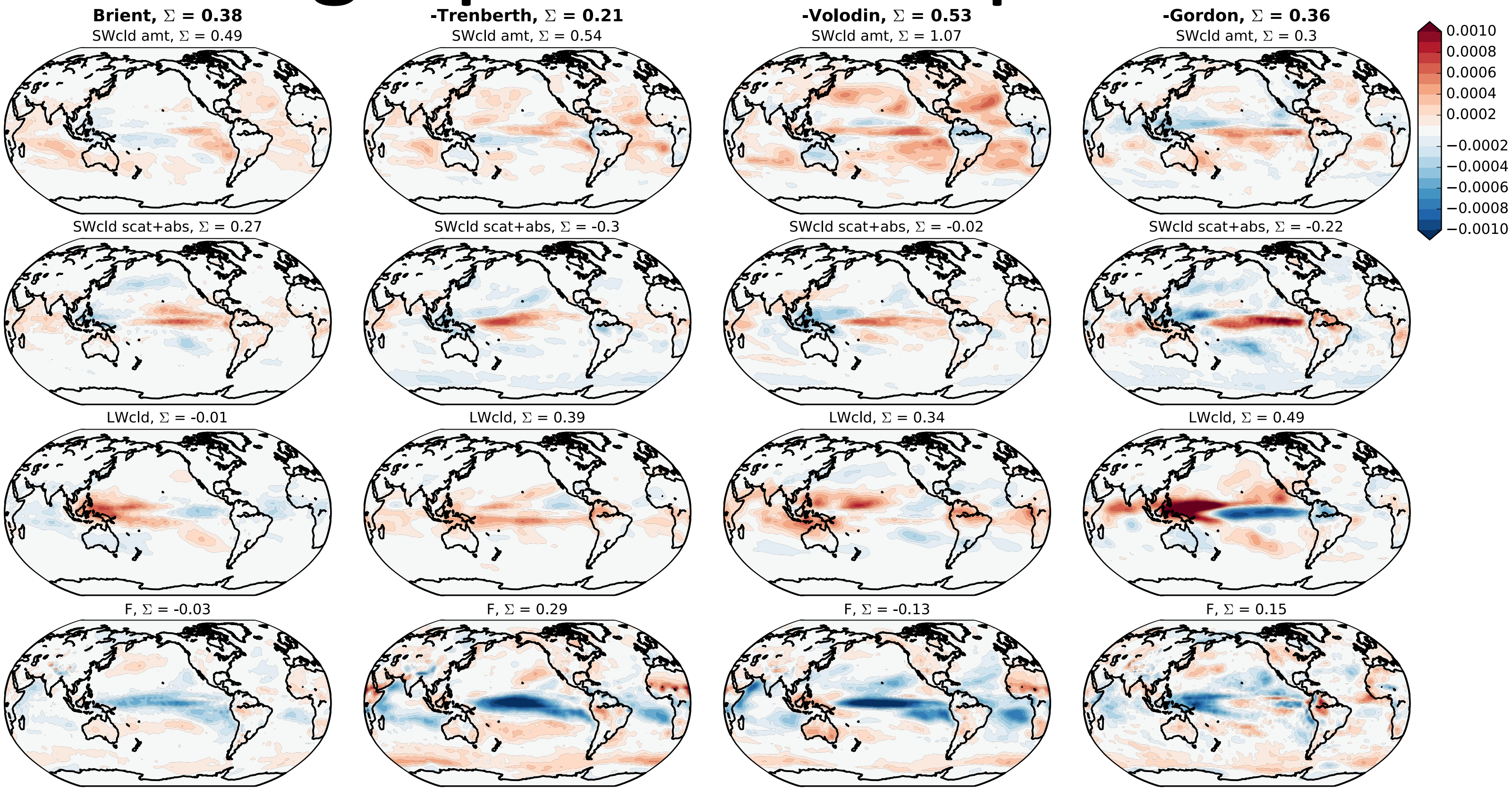


Fig: Geographic decomposition of r(constraint,ECS) for selected constraints.

Geographic Decomposition



- Brient is dominated by $\lambda_{SW\ amt}$ in low cloud regions - as expected
- Trenberth is not affected by Southern Ocean but is influenced by tropical SW as noted by Grise et al (2015)
- Volodin is strongly correlated with cloudiness everywhere
- Gordon is not affected by SW cld at high latitudes

Part 2 Punchline:

- r(ECS,constraint) varies greatly depending on models used
  - draws into question the use of CMIP archives for identifying emergent constraints
- Correlation decomposition is useful for determining which constraints are credible
  - Brient, Zhai, and Sherwood D stand out as operating for the a priori-proposed reasons
  - Covey, Fasullo, Trenberth, Qu, Sherwood S, and Gordon are not operating as proposed and/or have low correlation with ECS
  - Other constraints lack a physical explanation at all. These constraints should not be taken seriously until they have one.


That's all Folks!