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From observational metrics to constraints

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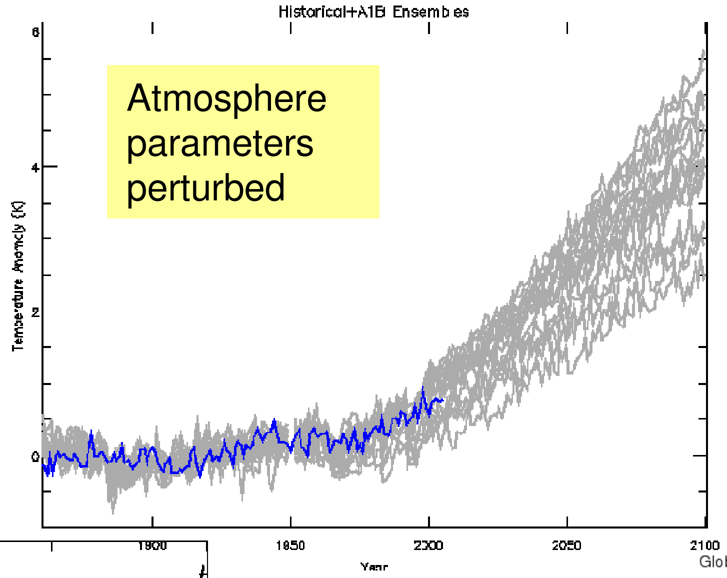
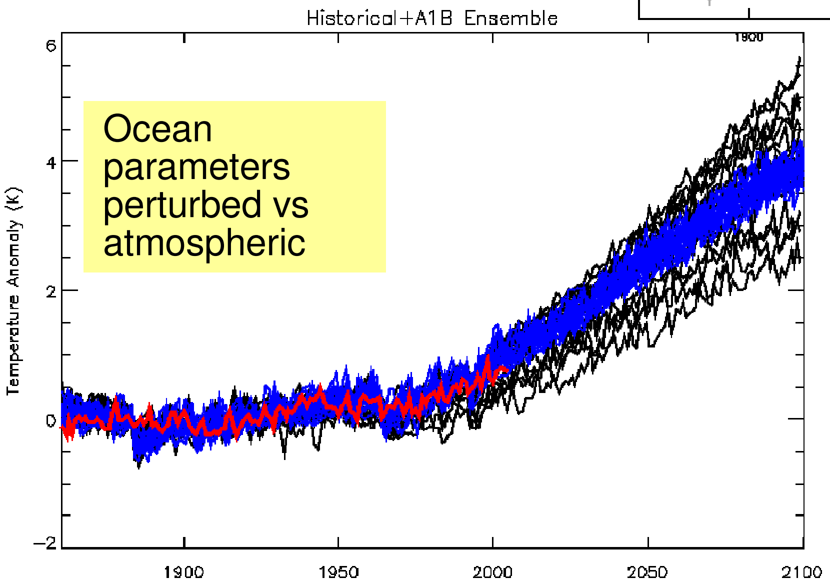
JULES meeting; June 2009

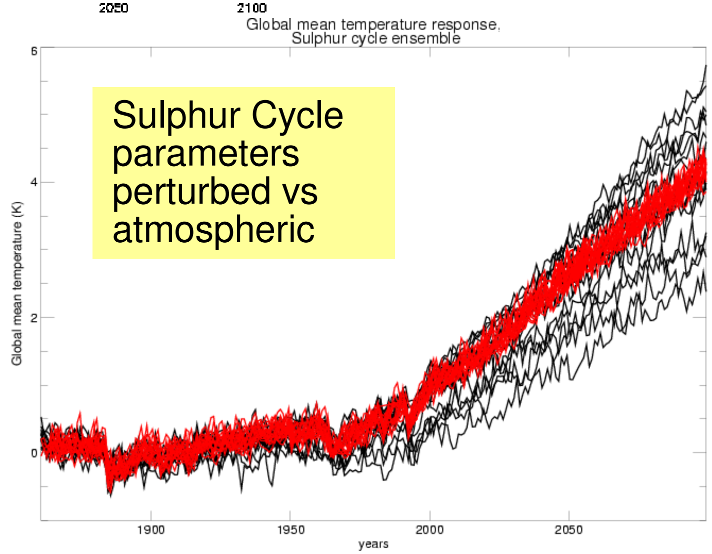
Perturbed parameter approach

- The perturbed parameter approach seeks to explore uncertainties (in various components of the model).
- This is done by:
  - Identifying parameters in the model which are both uncertain and important for the model response
  - Use an ensemble of models to explore the implication of these parameter uncertainties
- In the context of atmospheric physics uncertainty – we have used very large ensembles (350+) to explore the implication of parameter uncertainty on the climate response.

Uncertainties in the transient response of global mean temperature







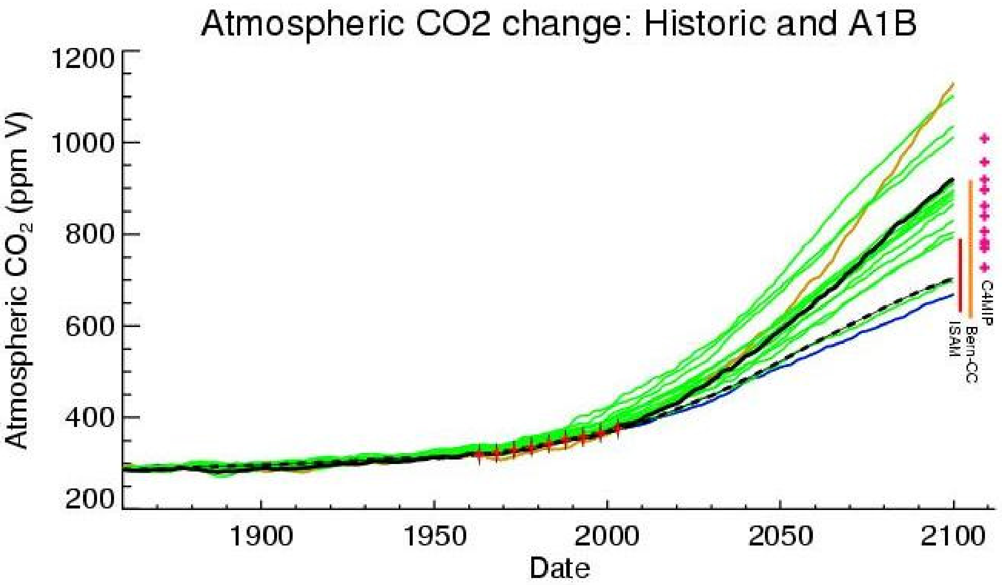
 Year

Carbon Cycle Uncertainties

Exploring land surface carbon cycle uncertainties using ensembles of HadCM3C:

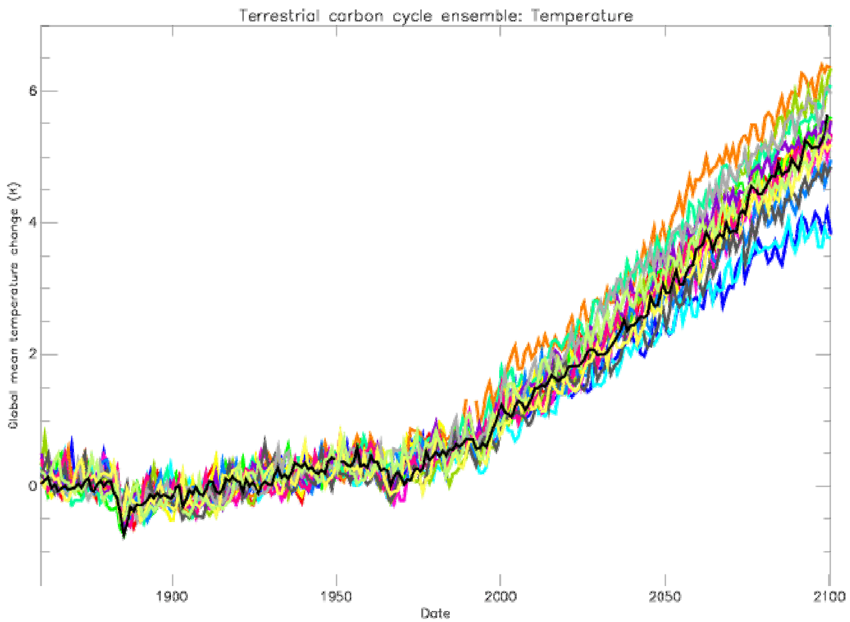
- **Top Leaf nitrogen concentration**
- **Stomatal opening**
  - A factor controlling the CO_2 dependence of stomatal openning.
- **Temperature dependence of soil respiration (Q10)**
- **Critical Soil Moisture concentration**
  - Apart from acting as a direct control on moisture availability to the atmosphere this is also the threshold above which plants are not water stressed
- **Minimum Leaf area index**
  - minimum leaf area coverage which controls plant expansion/competition
- **Temperature dependence of the maximum rate of carboxylation of Rubisco**

Impact of perturbations on the atmospheric CO_2



Impact of land surface uncertainty on CO_2 concentration

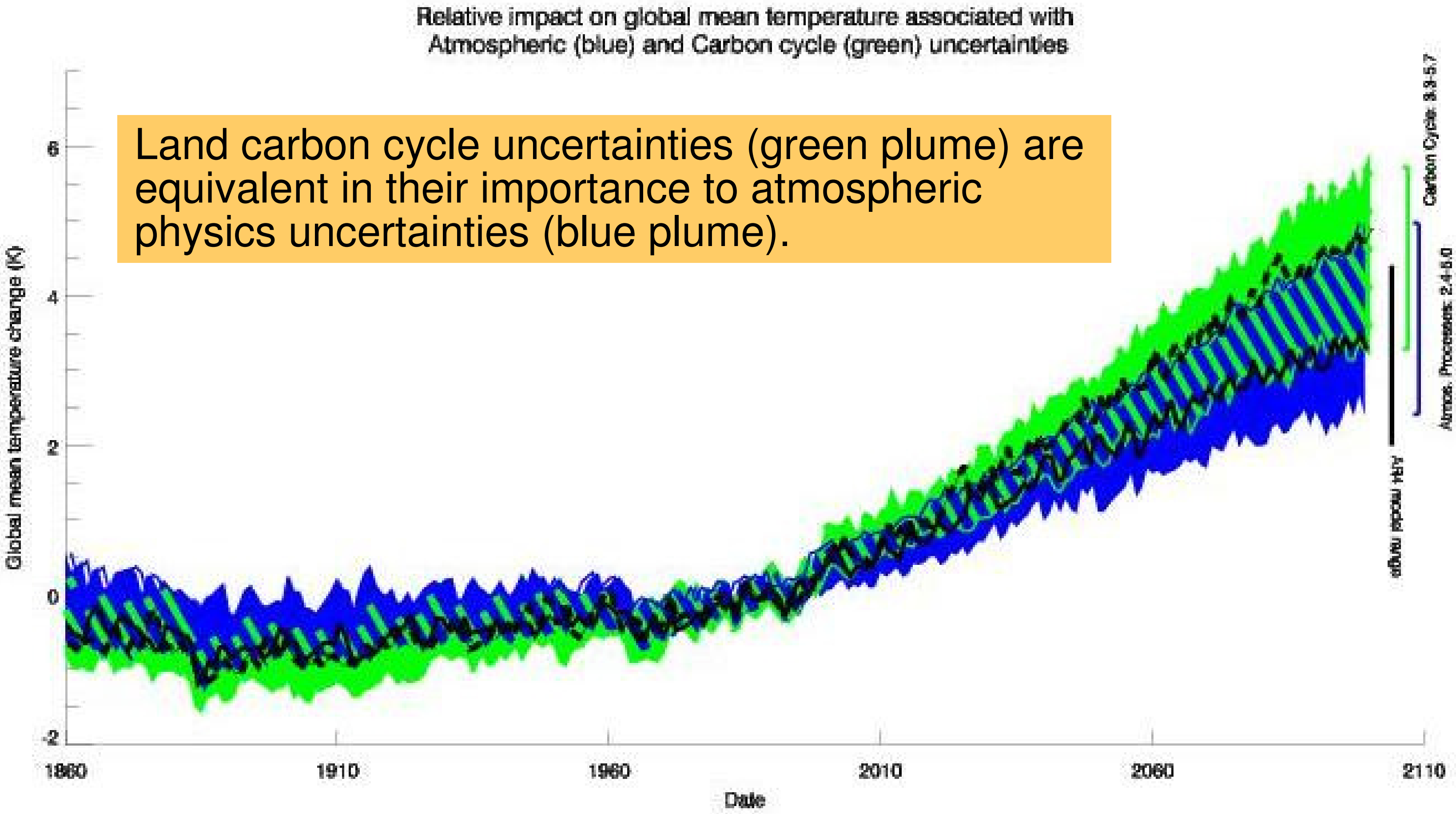
Impact of land surface uncertainty on global mean temperature



17 member ensemble of HadCM3C

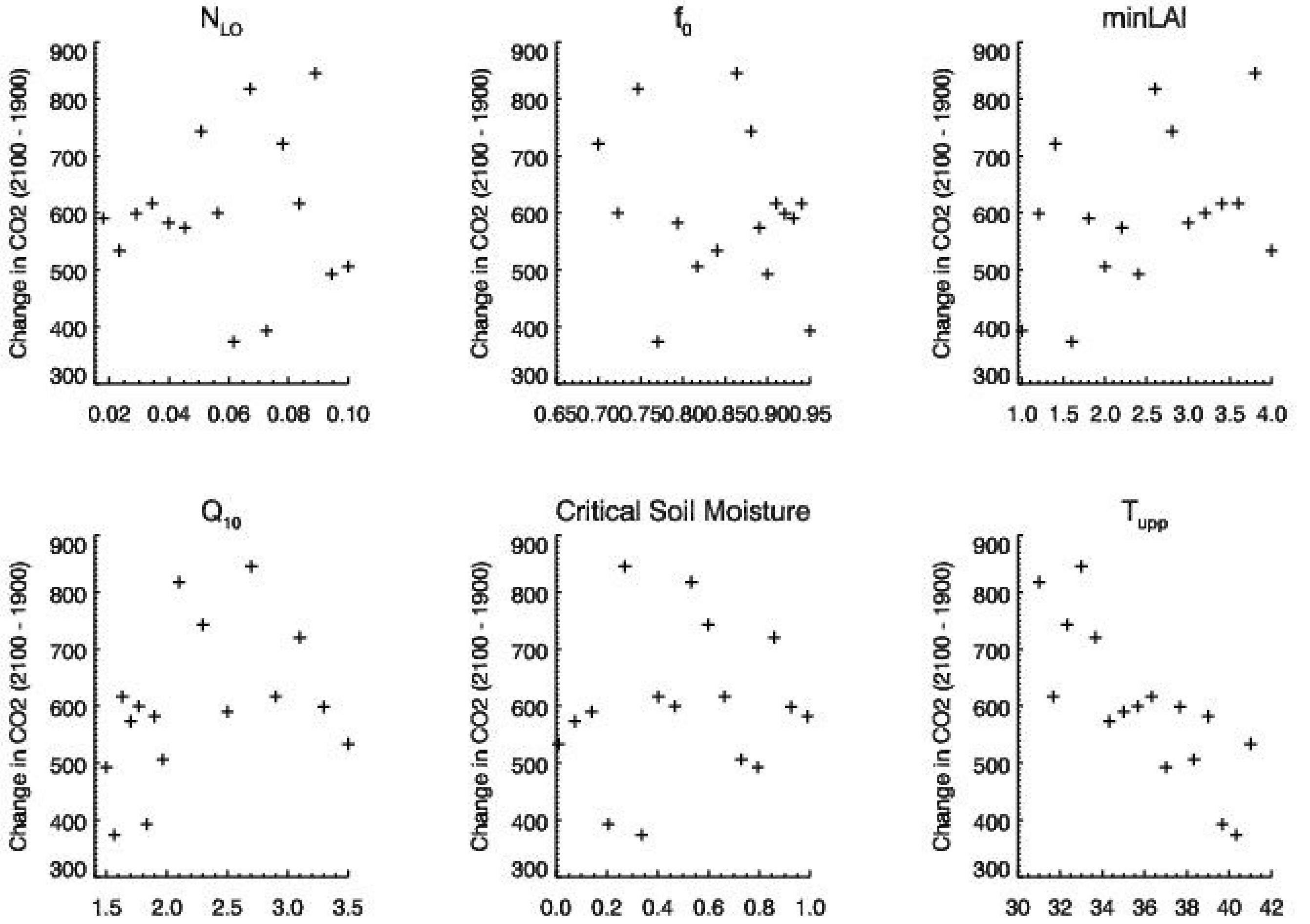
Historical and A1B SRES future scenario

Land surface uncertainty clearly important



Land carbon cycle uncertainties (green plume) are equivalent in their importance to atmospheric physics uncertainties (blue plume).

Relationship between parameters and response



Looking for observational constraints

Does the representation of the observable quantity correlate with the thing we are trying to predict?

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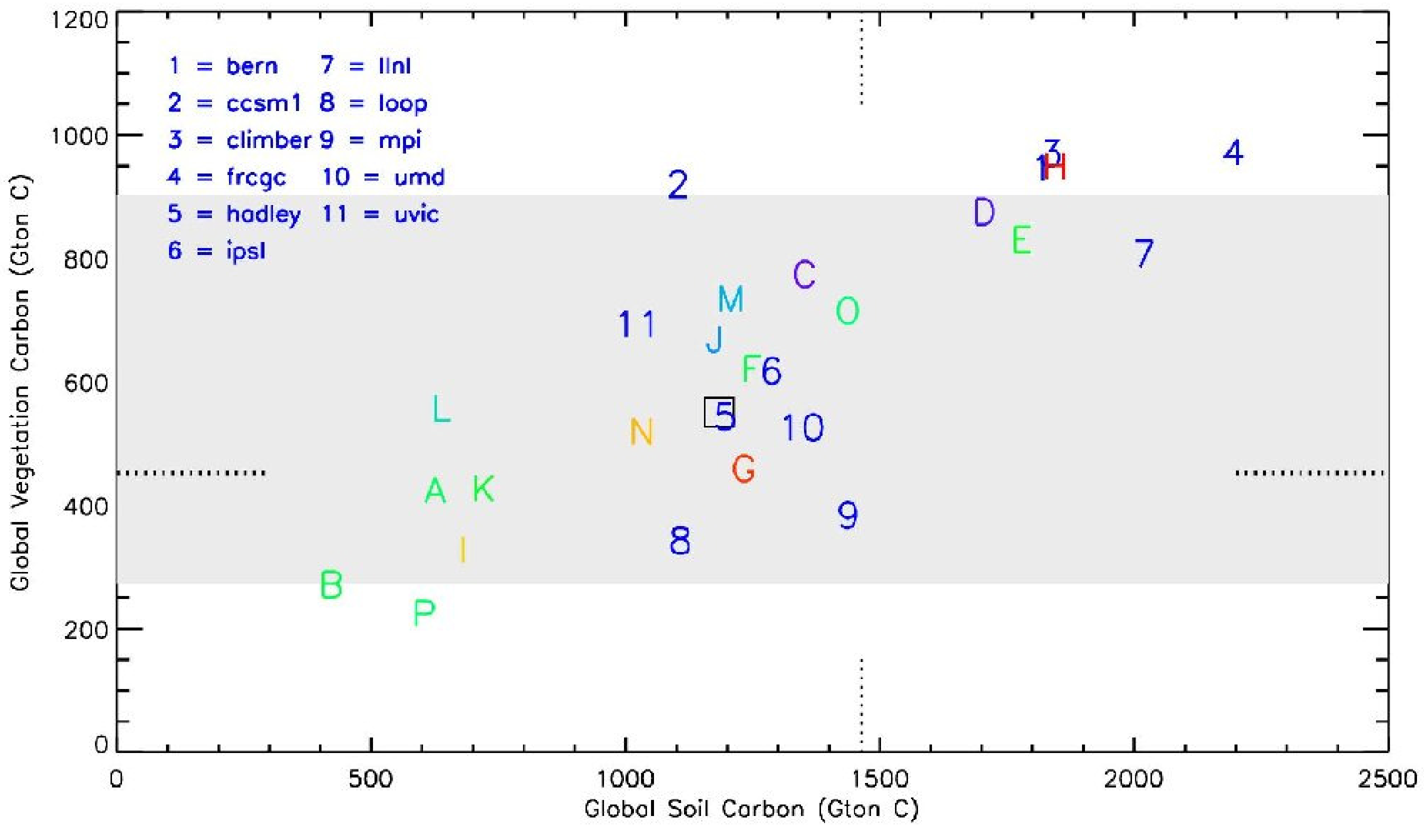
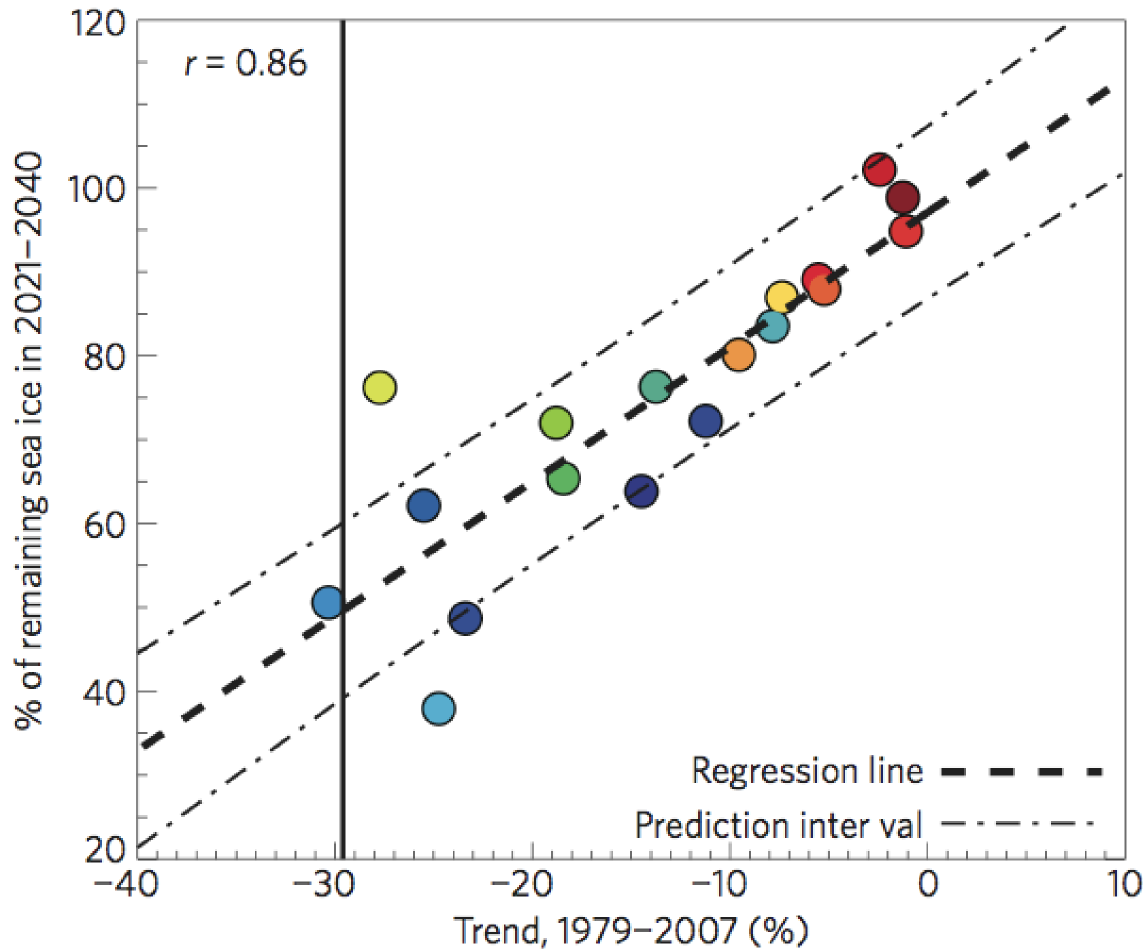


There are many properties of the models which we can observe but weighting models by how well they reproduce these observables doesn't provide information on the likely future response of these models, unless there is a correlation between the observable and the future response..

The elegant approach

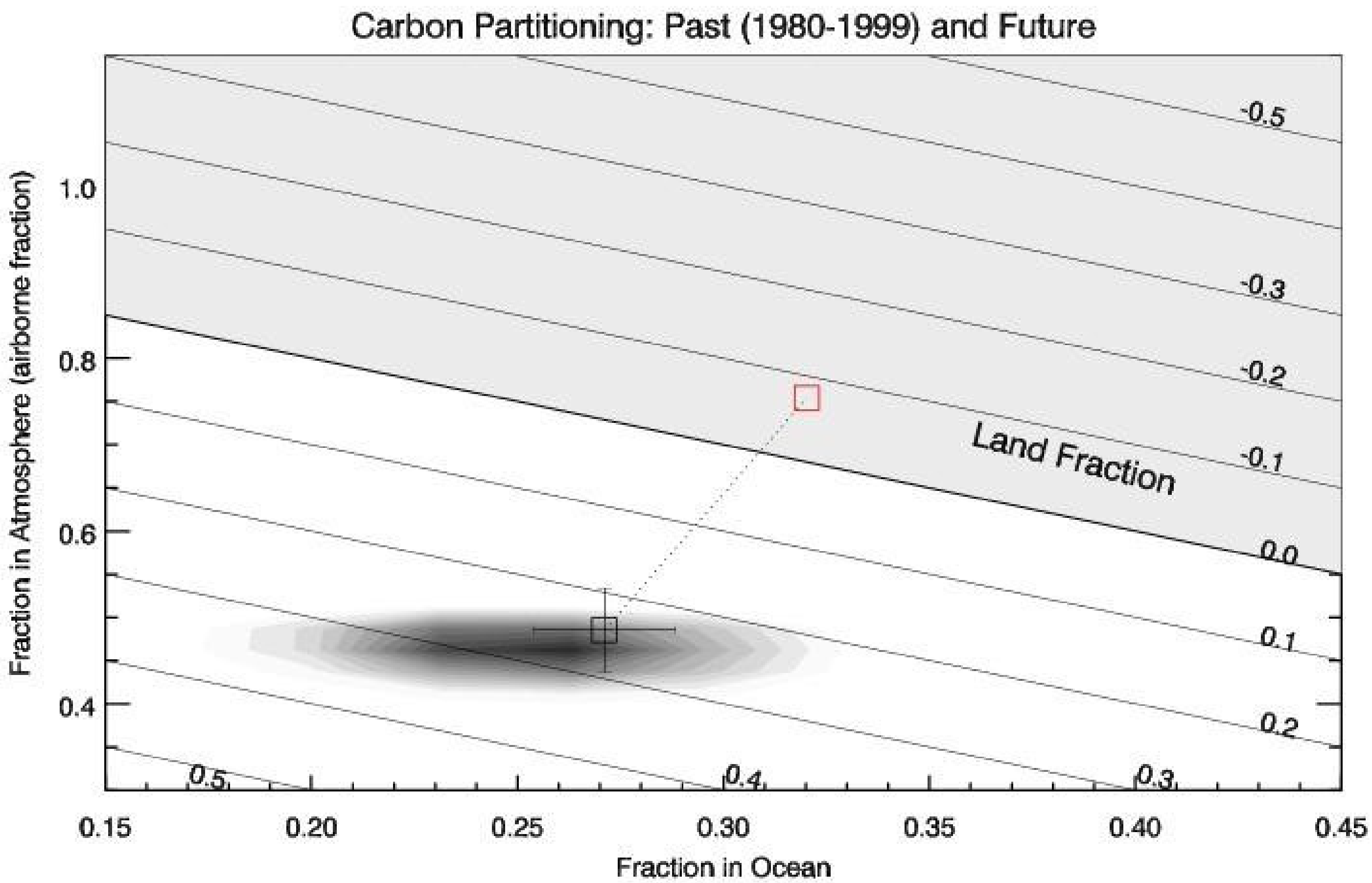
Boe et al, found that there was a fantastic relationship between the trend during the observational period and what they wanted to predict (fraction of arctic ice free).

However this example is extremely rare - normally we don't find these relationships

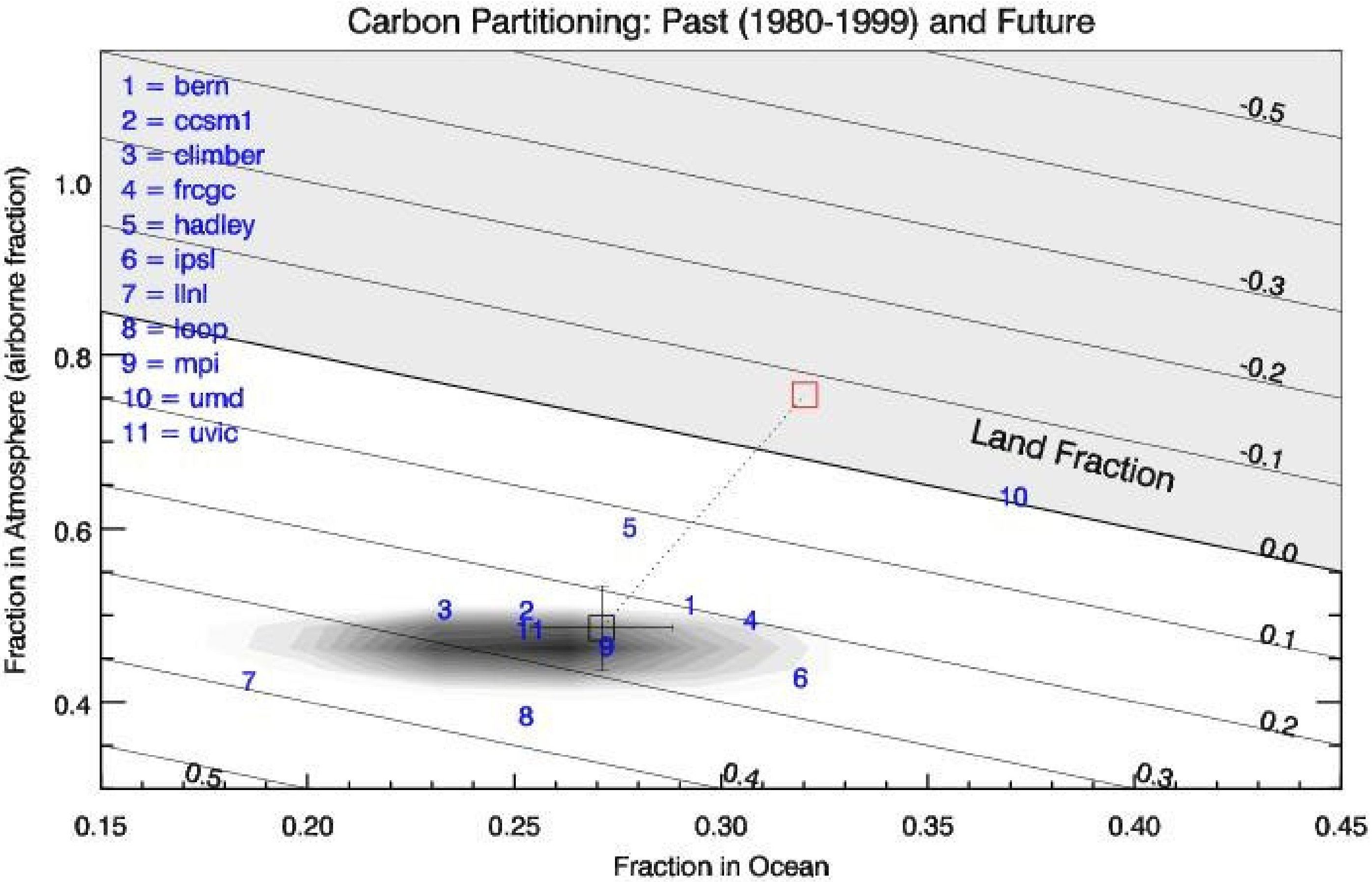


Boe, Nature GS, 2009

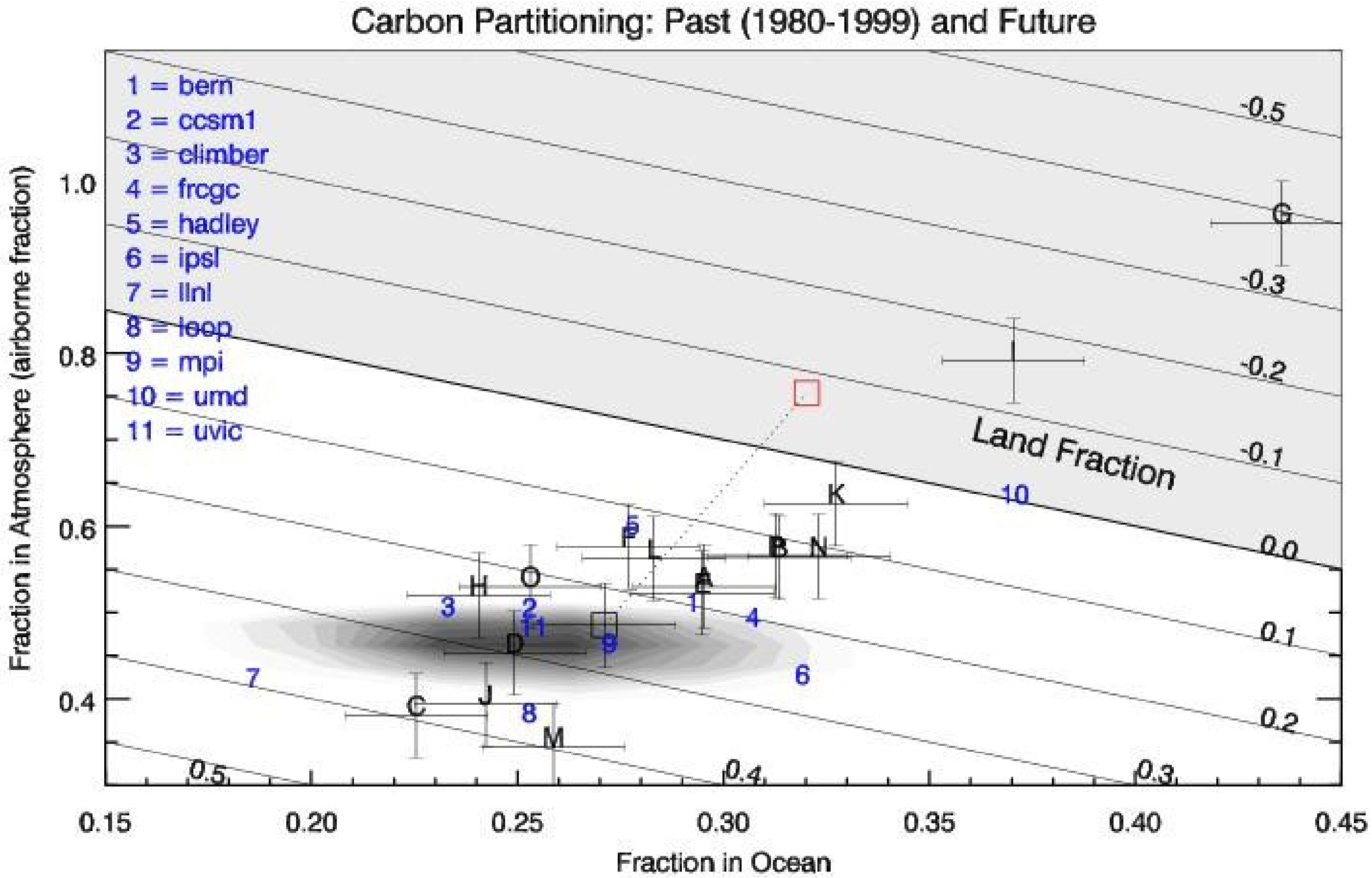
Carbon cycle constraints?



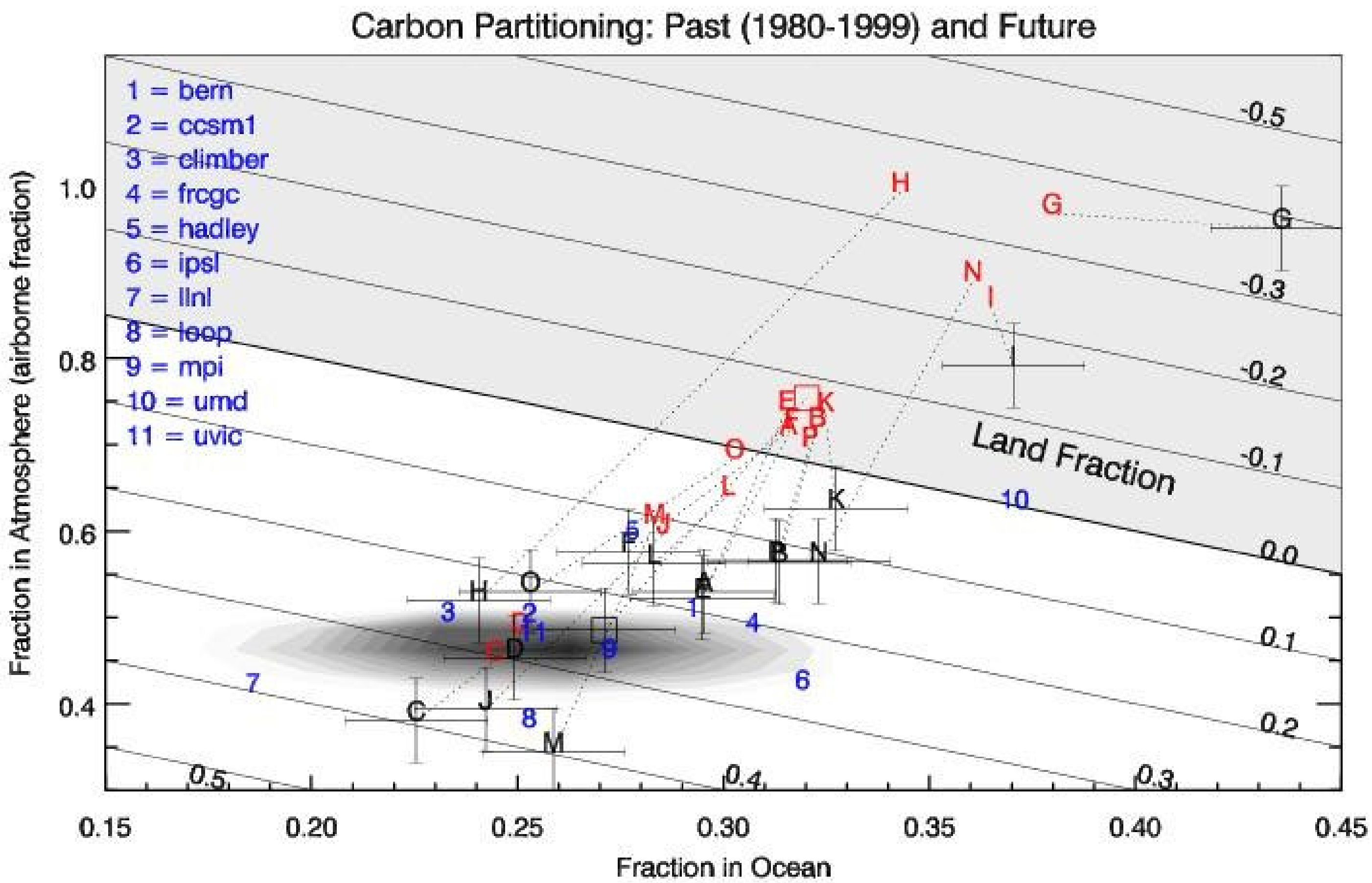
Carbon cycle constraints?



Carbon cycle constraints?



Carbon cycle constraints?



Looking for observational constraints

The ‘all models are bad models’ paradigm

Are all models bad models?

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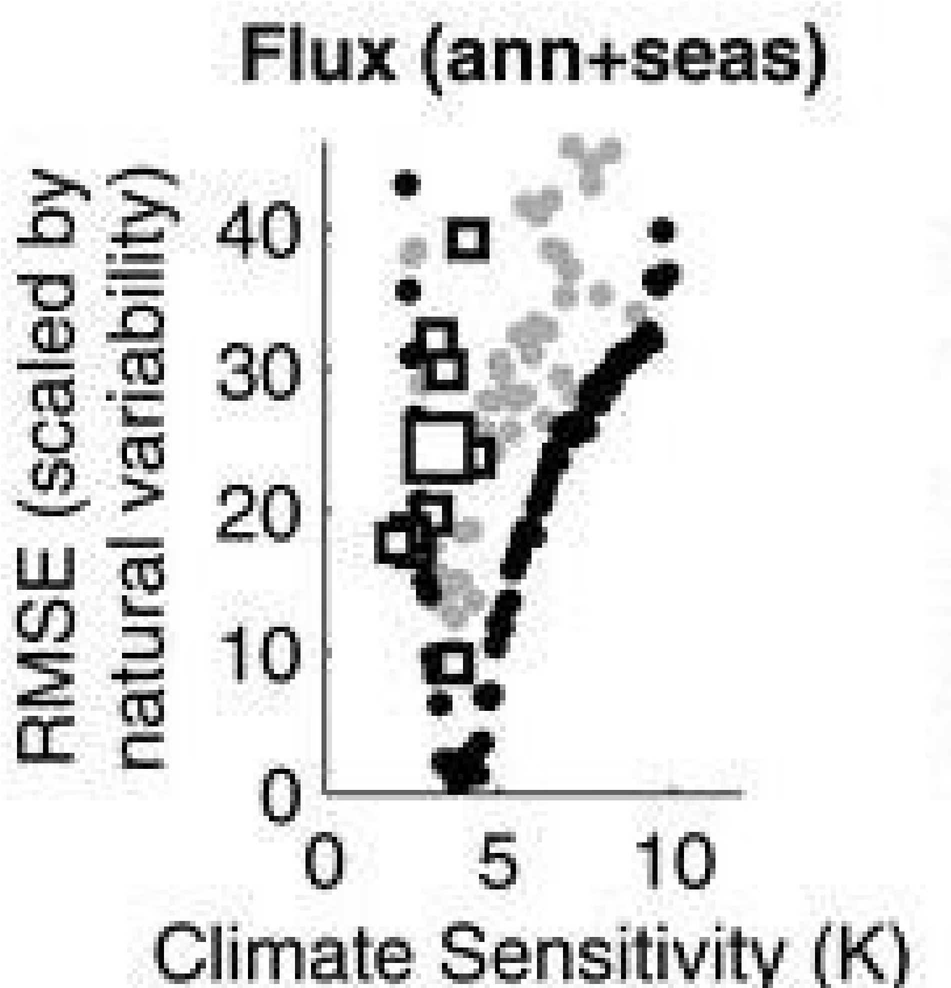
Looking across a very wide range of models we find that models which reproduce seasonal and annual top of atmosphere fluxes correspond with models which predict changes in climate sensitivity of roughly 4K



Sanderson, 2008

Are all models bad models?

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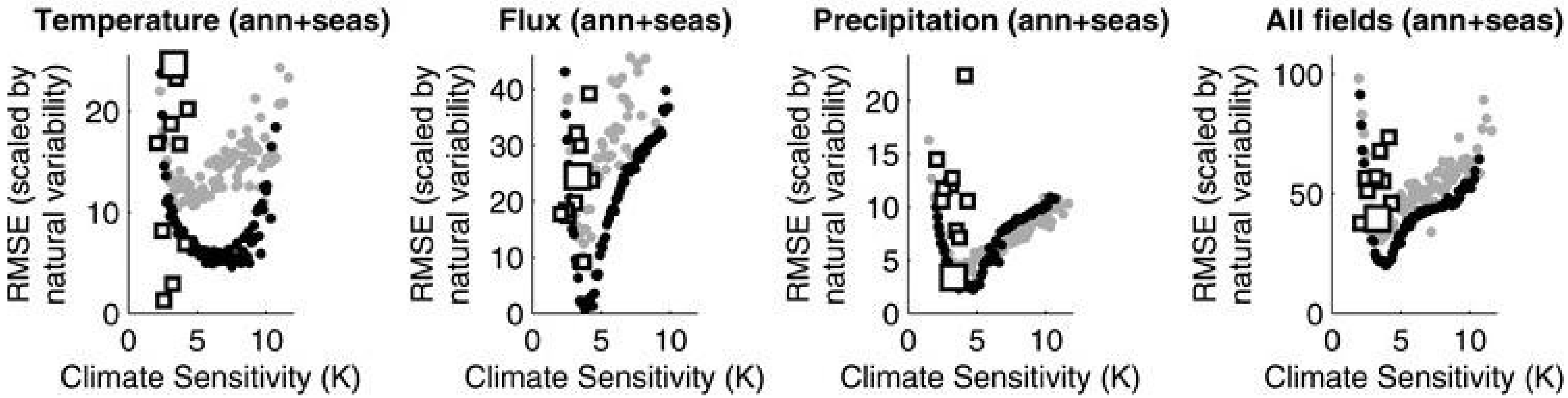
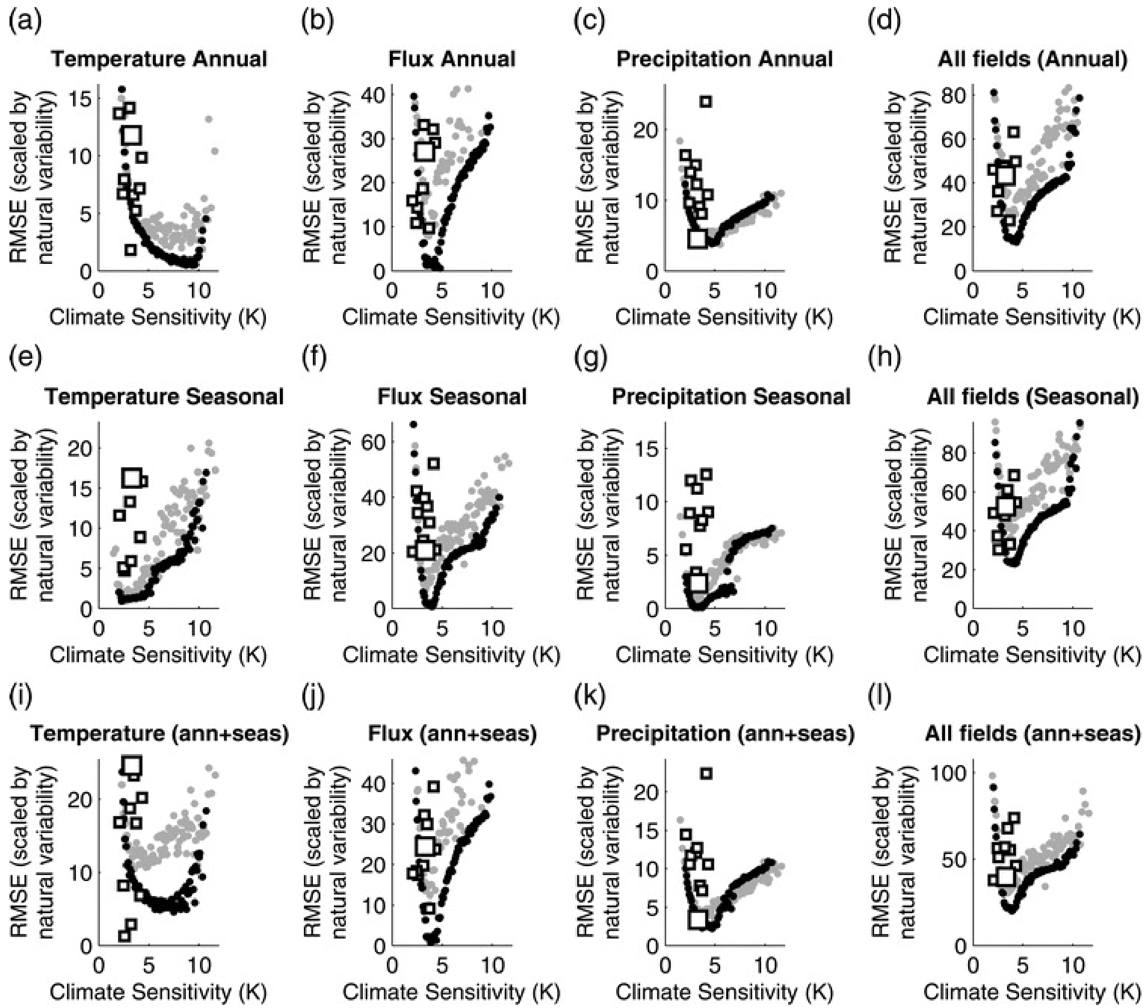


However when look at how the same models reproduce other observable properties we find that the other observable suggest other relationships; and taken all together even the best model is very far from reproducing the observed world.

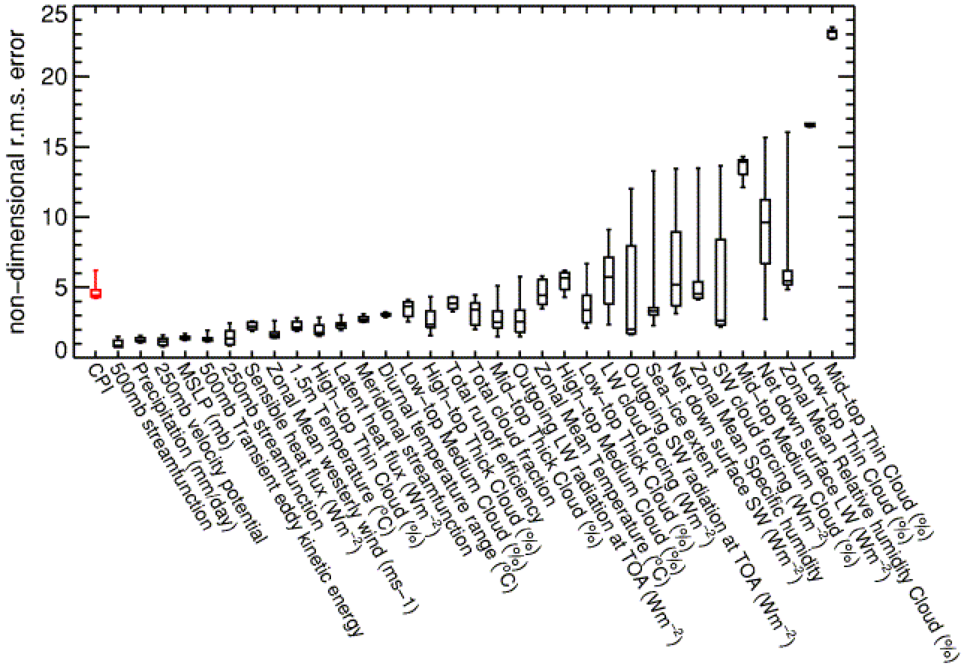
Are all models bad models?

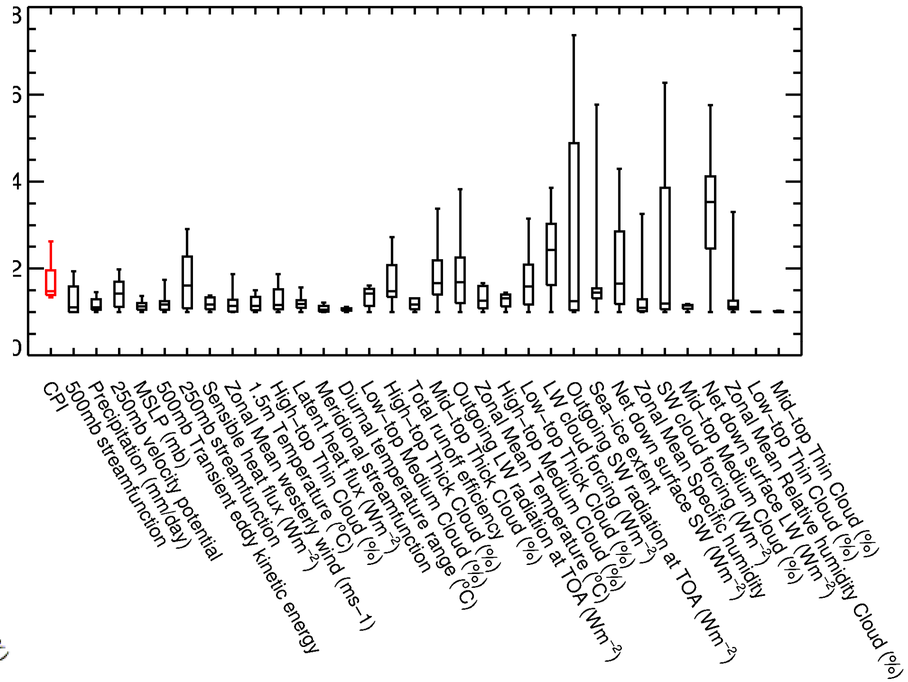


Looking for observational constraints

Accounting for the discrepancy between our models and the real world

Discrepancy – a schematic of what it does



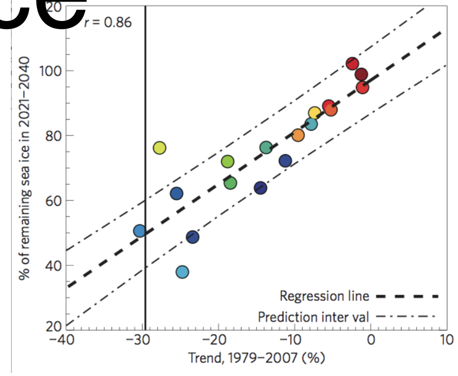


- If we don’t account for the fact that there is discrepancy in how models represent the real world then we are likely to give more weight to properties which models badly capture compared to properties that they do well.

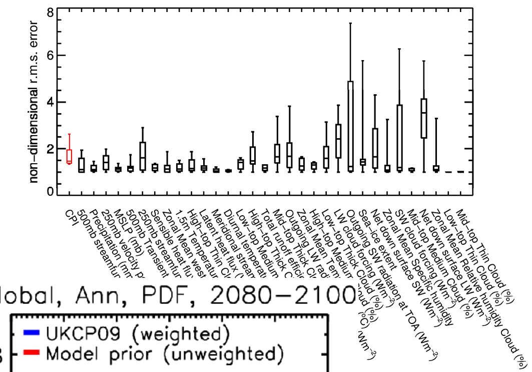
Relating back to moving land surface uncertainties

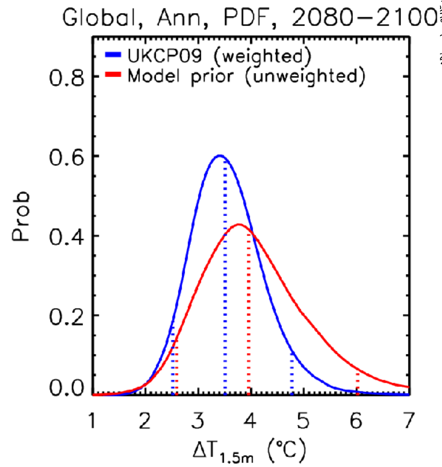
observational constrains Elegant vs Brute Force

- Identifying elegant constraints requires sufficient ensemble members to establish a relationship between what we observe and the thing we are trying to predict



- Brute force approaches to constraining predictions are required when we haven't been able to identify a simple relationship or perhaps when we are trying to predict multiple things with the same system => We throw many datasets of observations at very large ensembles





Relating back to land surface uncertainties

- Efforts to bring quality controlled observations are really starting to come together.
  - JULES benchmarking, WATCH, C-LAMP (in USA)
- We are starting to get to the situation where we have ensembles of simulations to interrogate
  - Many of the models in the (next) CMIP5 (AR5) are come to the archive in the near future (accessible to all soon) - and many will contain much more sophisticated land surface representations (e.g. carbon cycle, nitrogen)
  - We have our perturbed parameter simulations
  - Ensembles of offline JULES simulations, or IMOGEN runs.

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Evaluation of atmospheric CO_2

Global metrics results

	Long term trend			Seasonal Cycle			Inter annual variability			γ_{SC} and γ_{IAV}		
	H	I	L	H	I	L	H	I	L	H	I	L
ALT	0.30	0.40	0.50	0.50	0.67	0.70	0.50	0.05	0.00	0.75	0.50	0.50
BRW	0.30	0.40	0.50	0.57	0.80	0.53	0.50	0.20	0.00	0.55	0.55	0.50
MHD	0.30	0.40	0.60	0.30	0.47	0.60	1.00	0.00	0.40	0.65	0.05	0.90
SCH	0.50	0.45	0.80	0.20	0.40	0.67	0.80	0.00	0.30	0.55	0.50	0.50
NWR	0.40	0.80	0.90	0.07	0.30	0.53	0.50	0.00	0.00	0.50	0.50	0.50
AZR	0.50	0.80	0.90	0.27	0.40	0.67	0.30	0.20	0.00	0.30	0.05	0.50
KUM	0.60	0.80	0.90	0.30	0.40	0.60	0.50	0.10	0.05	0.90	0.50	0.50
MLO	0.80	0.90	0.80	0.47	0.37	0.67	0.50	0.05	0.05	0.95	0.05	0.50
SMO	0.40	0.60	0.60	0.17	0.30	0.30	0.20	0.05	0.40	0.30	0.25	0.60
AMS	0.30	0.40	0.40	0.03	0.57	0.23	0.25	0.00	0.30	0.10	0.40	0.55
CGO	0.60	0.60	0.70	0.03	0.07	0.53	0.35	0.05	0.20	0.05	0.35	0.55
SPO	0.60	0.80	0.80	0.37	0.27	0.23	0.05	0.20	0.30	0.10	0.50	0.55
Scores avg	0.46	0.60	0.70	0.27	0.42	0.52	0.45	0.08	0.17	0.48	0.35	0.55

score: 1. 0.9 0.8 0.7 0.6 0.5 0.4 0.3 0.2 0.1 0.

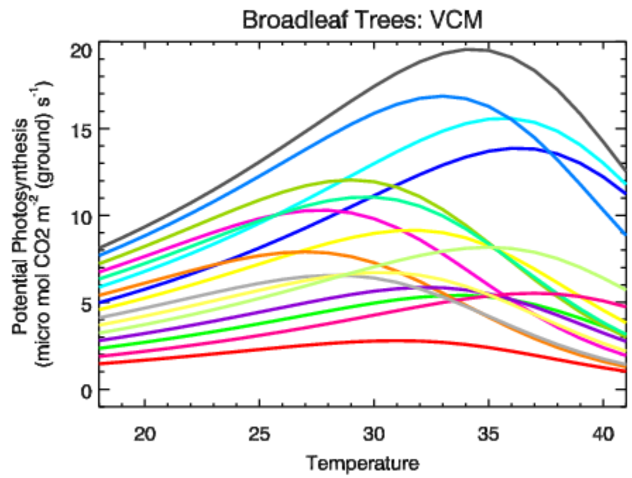
H: HadCM3LC

I: IPSL-CM2C

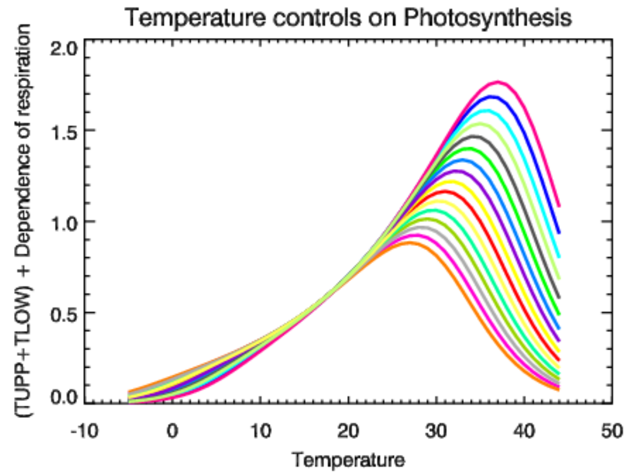
L: IPSL-CM4-LOOP

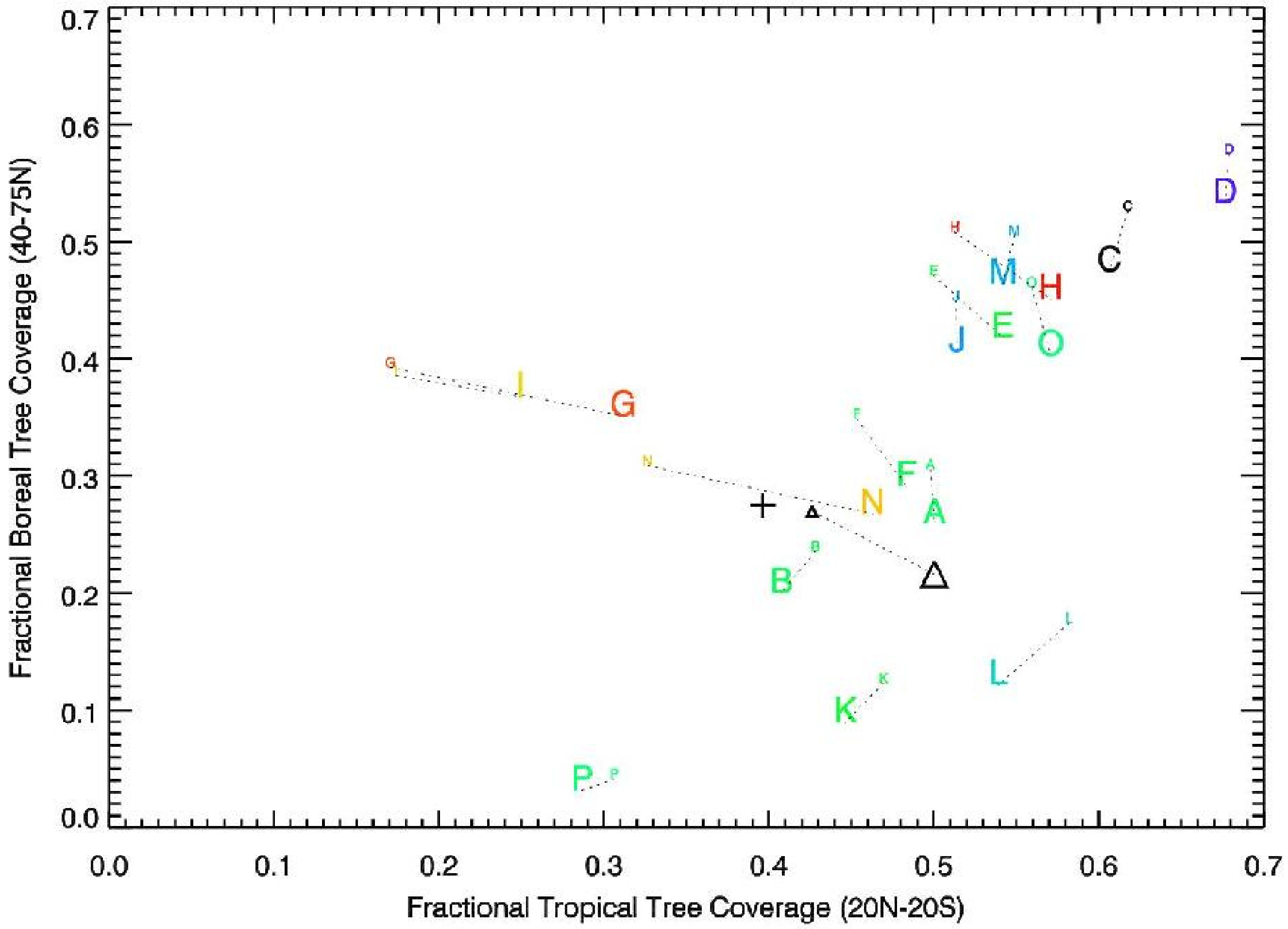
Role of temperature controls on plant photosynthesis.

It is the turn over temperature (the point where increasing temperature ceases to increase photosynthesis|) which appears to determine the magnitude of future carbon cycle response:



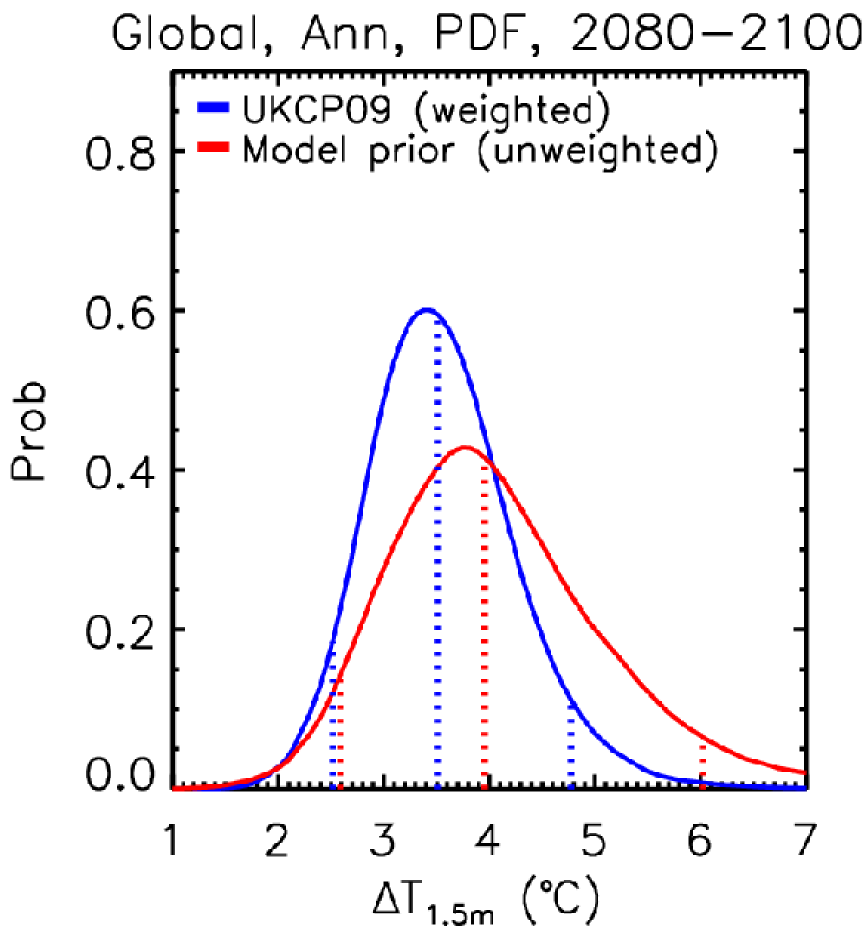
• We can feed back insights to the land surface modeling community. Do the plant physiologist believe these ranges? Can we devise further experimental work to narrow this range? In this case this has highlighted the role of 'acclimatisation' - and the need to represent this process in the models.



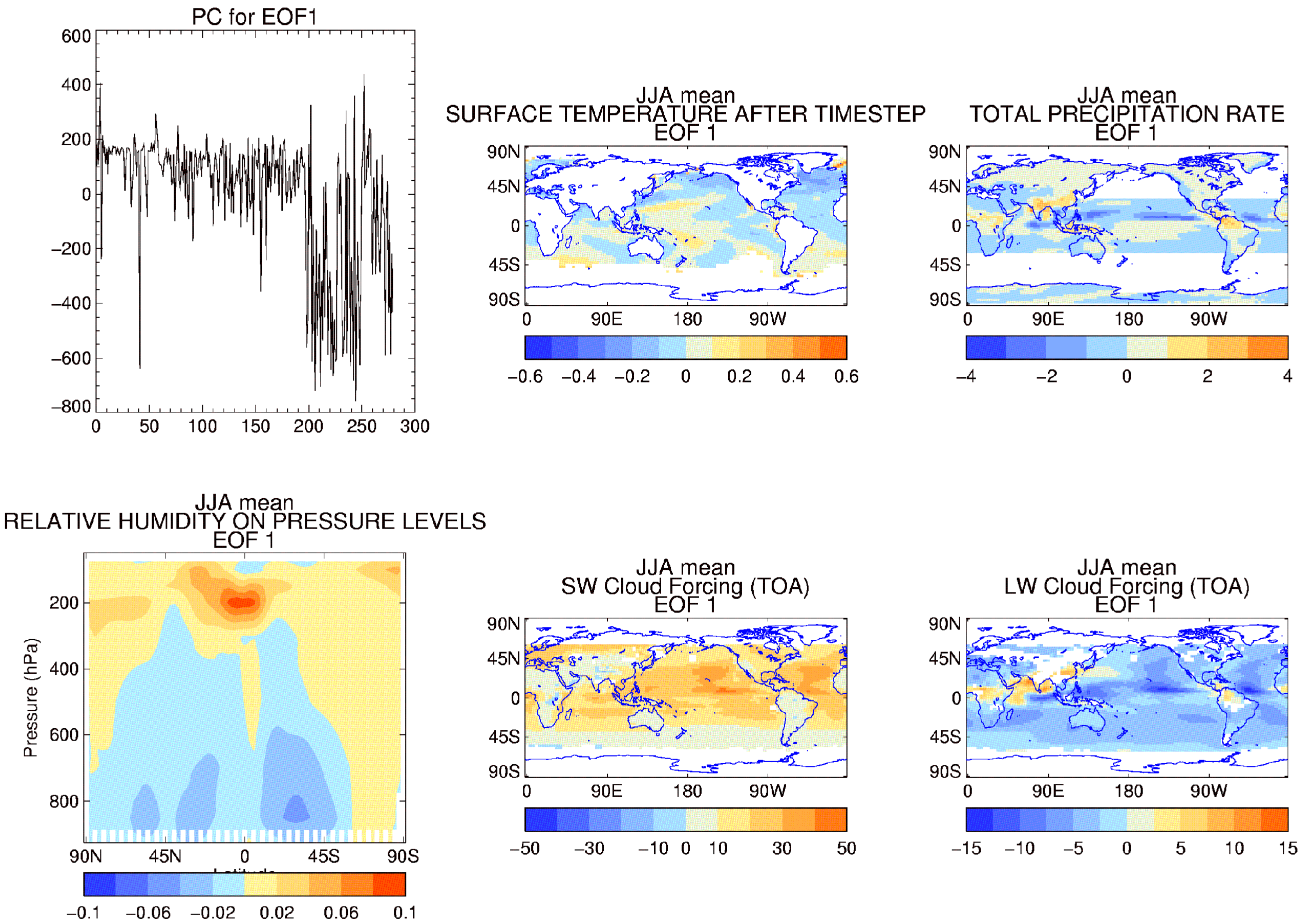


Fractional Boreal Tree Coverage (40-75N)
Fractional Tropical Tree Coverage (20N-20S)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

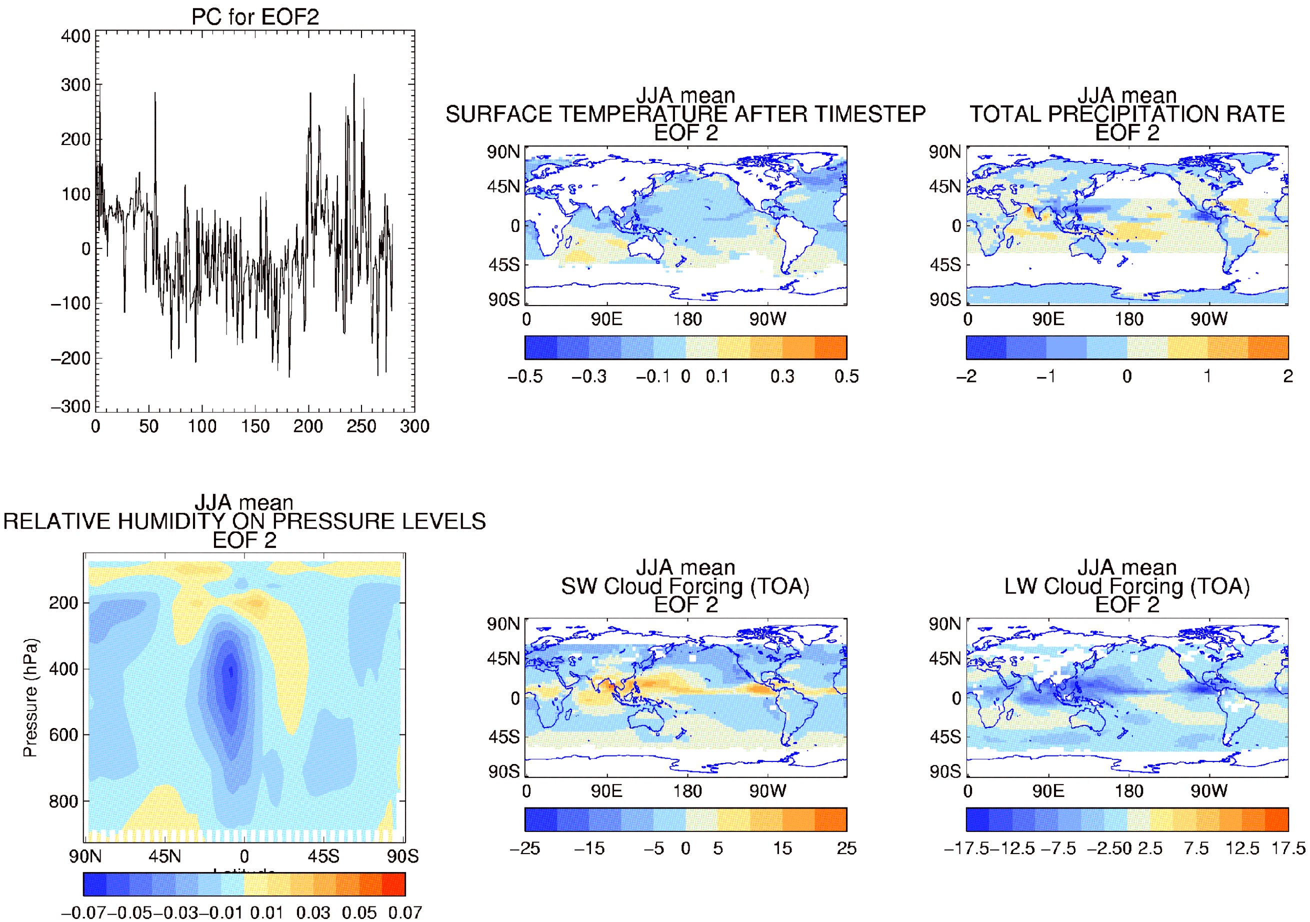
So can we say something?



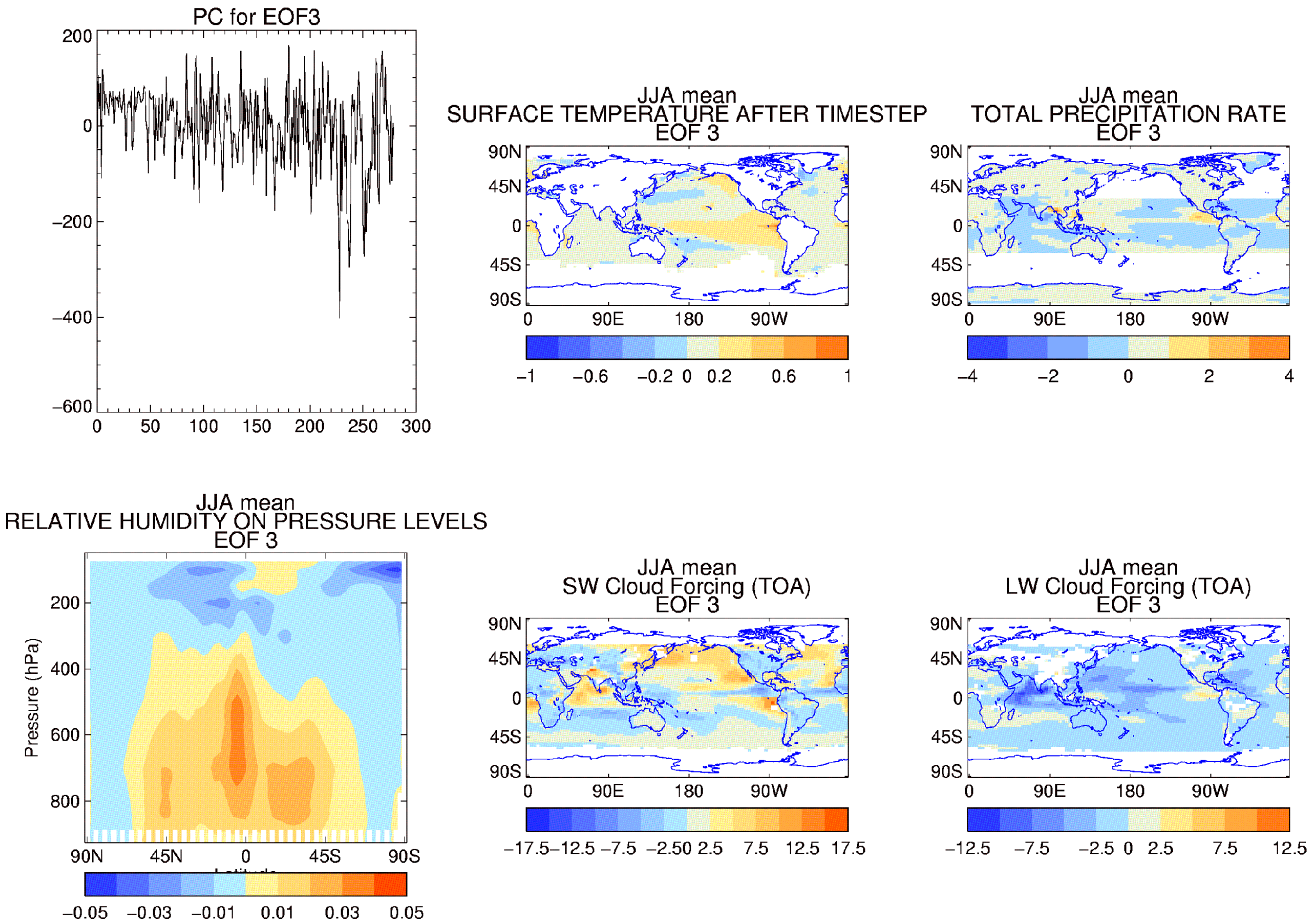
First eigenvector of observed climate



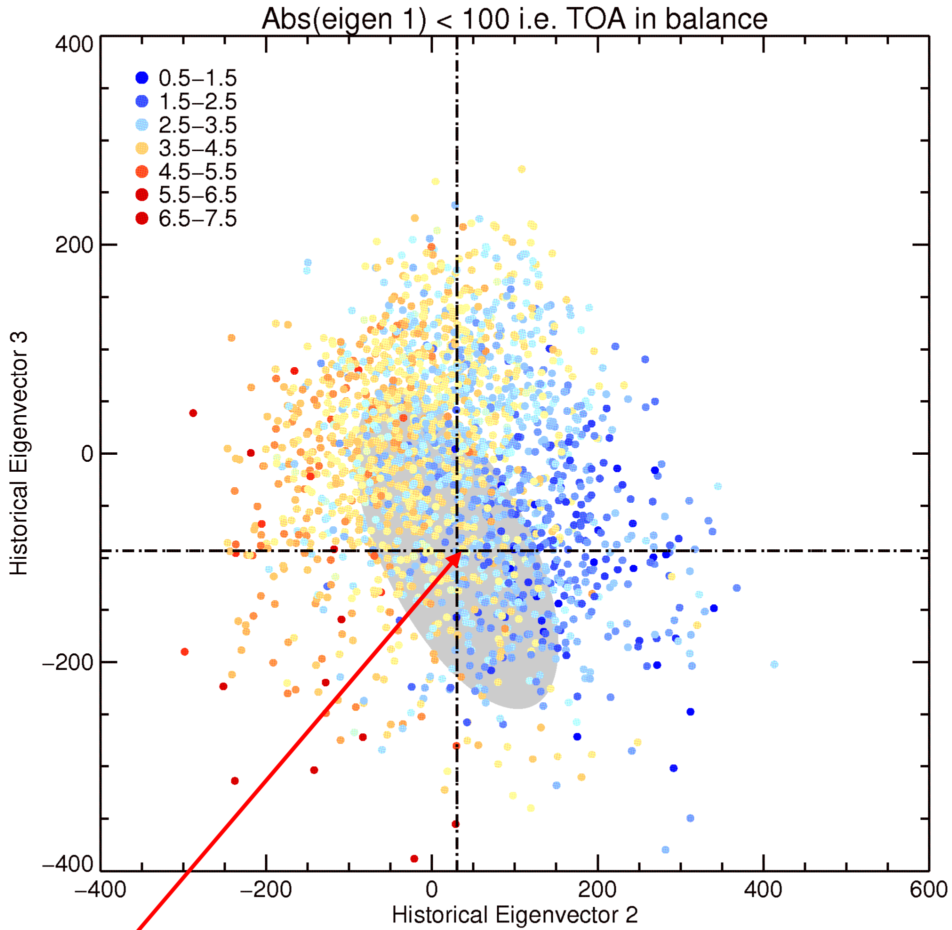
Second eigenvector of observed climate



Third eigenvector of observed climate



Constraining predictions



Observed value

- Weighting particularly effective if there exists a strong relationship between a historical climate variable and a parameter AND that parameter and a future climate variable. So weighting can still have a different effect on different prediction variables.