Constraints on Future Climate Projections

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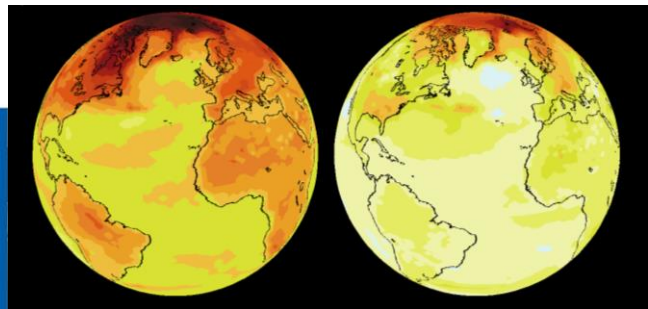
Making Climate Projections

- We use complex climate models/simulators as (i) we think we need to explicitly simulate all the important processes in the climate system and (ii) because we are interested in regional prediction, multiple variables, extremes etc.
- Limitations in computer power and understanding mean that models/simulators have ‘errors’ in the sense of not being able to accurately simulate observed mean climate, climate variability and climate change
- These errors lead to uncertainties in future projections of climate change (conditioned on e.g. future concentrations of greenhouse gases)

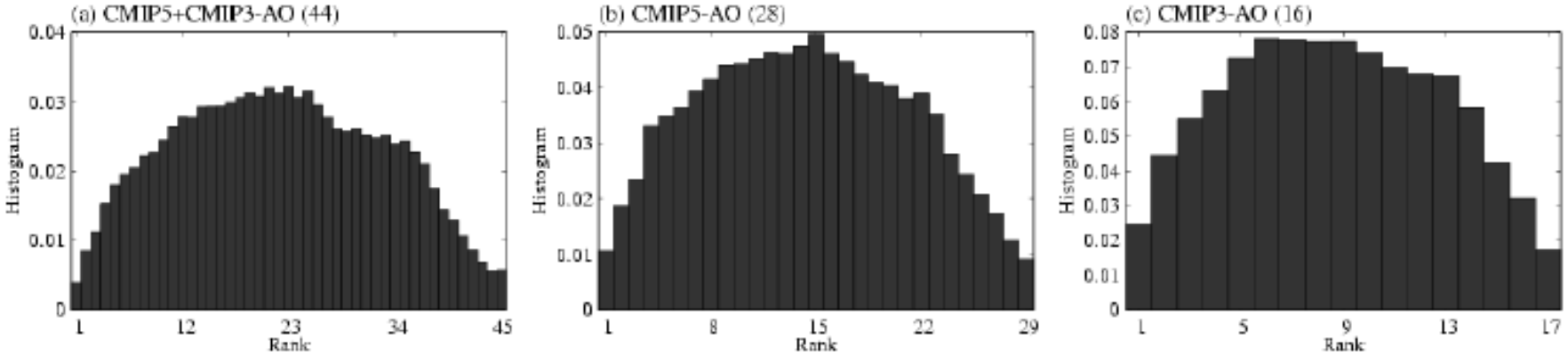


Constraining Models/Simulators with Observations

- Models resolve dynamical processes by solving approximations to the Navier Stokes equations
- Sub-grid-scale ‘paramerisations’ represent either unresolved dynamical processes (e.g. convection) and physical processes such as radiation
- Real-world observations are used in two ways
    - To develop parameterisation schemes – typically observations of the process being parameterised e.g. surface heat flux are used
    - To test emergent properties of models e.g. existence, frequency and amplitude of the El Niño Southern Oscillation
- ‘Tuning’ is never really done systematically and often parameterisation schemes are modified rather than the parameters changes

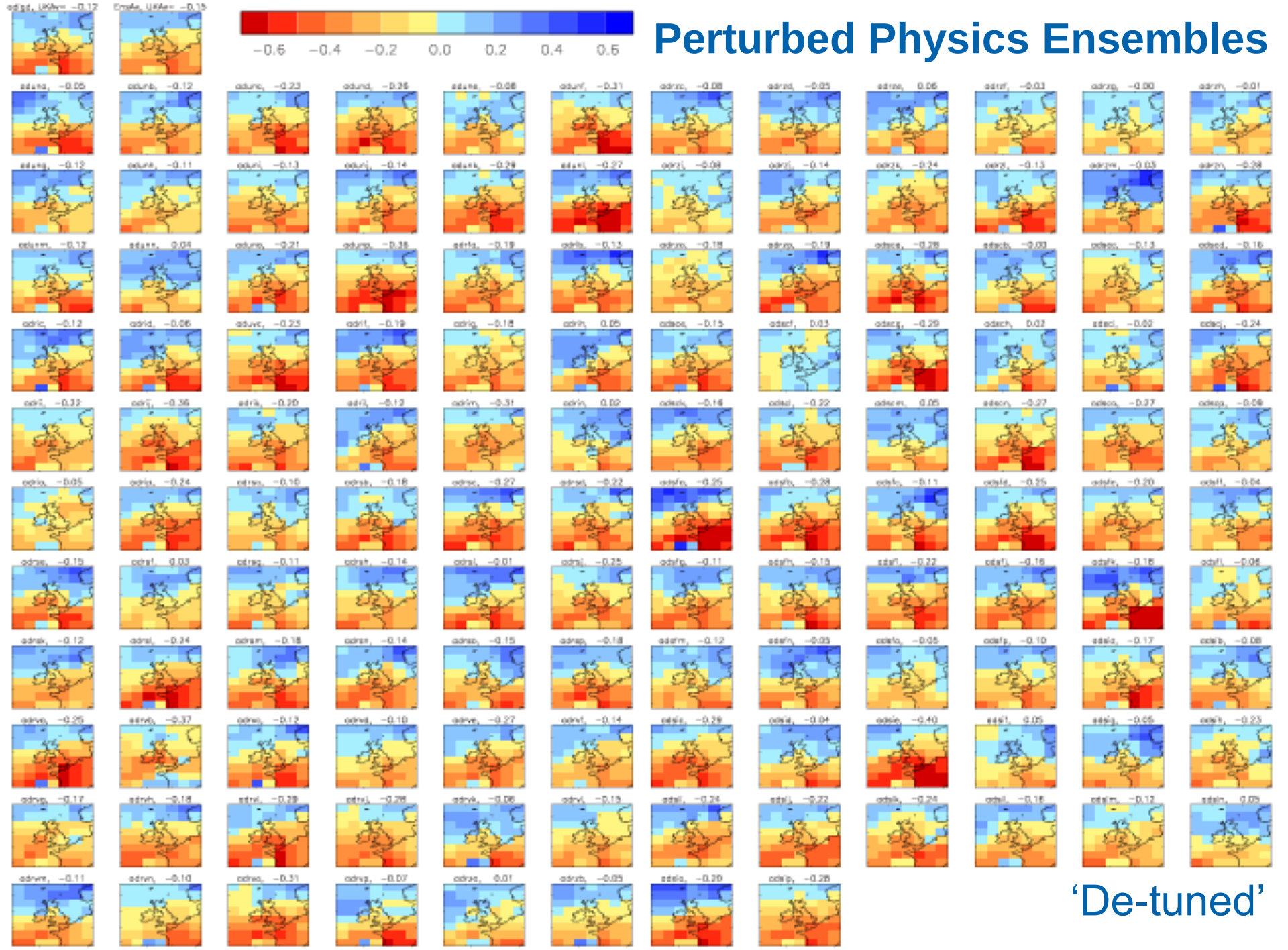
Dealing with Uncertainties in Climate Models

- Multi-model ensembles (MMEs) are essentially collections of 'best-shot' models that are already constrained by observations
- Simplest approach – take the mean and standard deviation of all the best-shot models/simulators you can find
  - Not all models/simulators are independent
  - We don't know how to interpret such a distribution
  - Some models/simulators are better than others
  - 'Everyone knows it is wrong but everyone does it'



Yokohata et al., 2013

Perturbed Physics Ensembles



‘De-tuned’

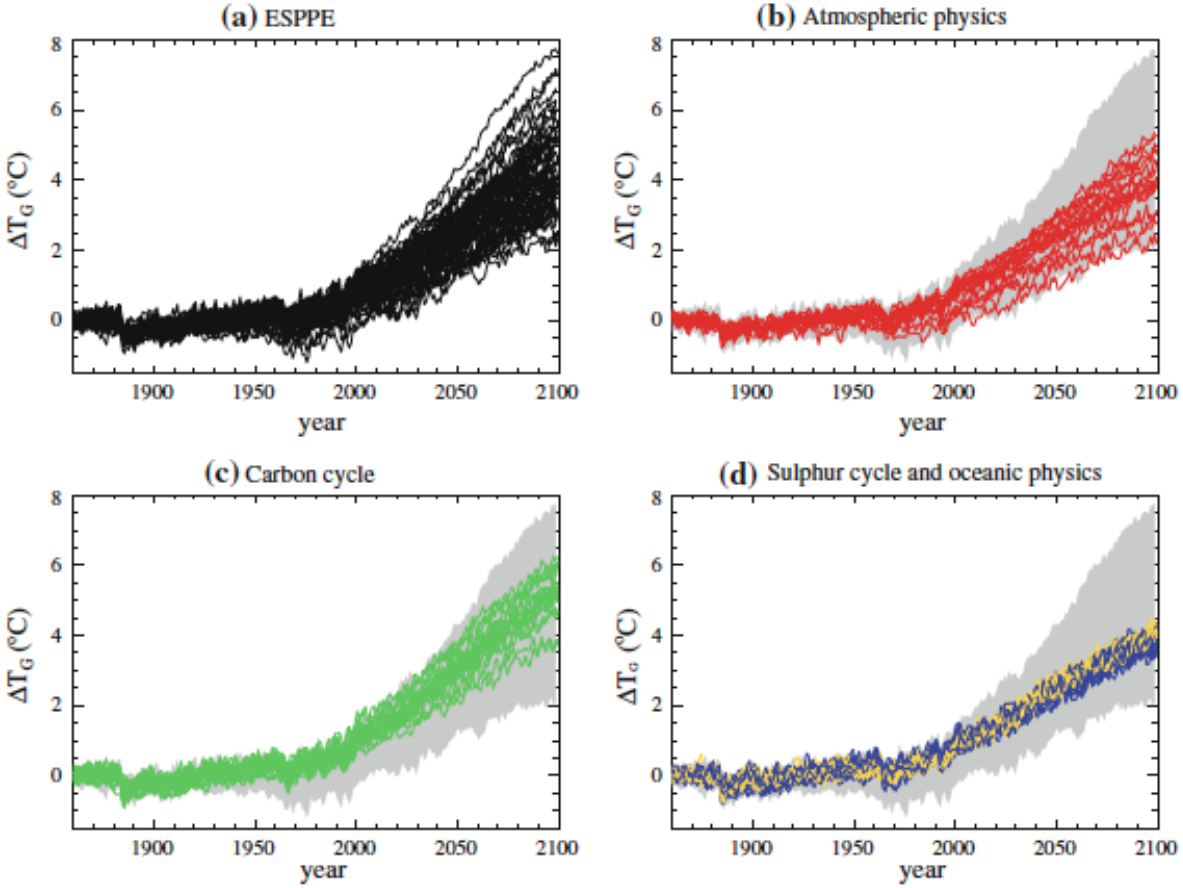
More Perturbed Physics Ensembles

$$y = f(x)$$

y = global mean temp

f = climate model/simulator

x = parameters

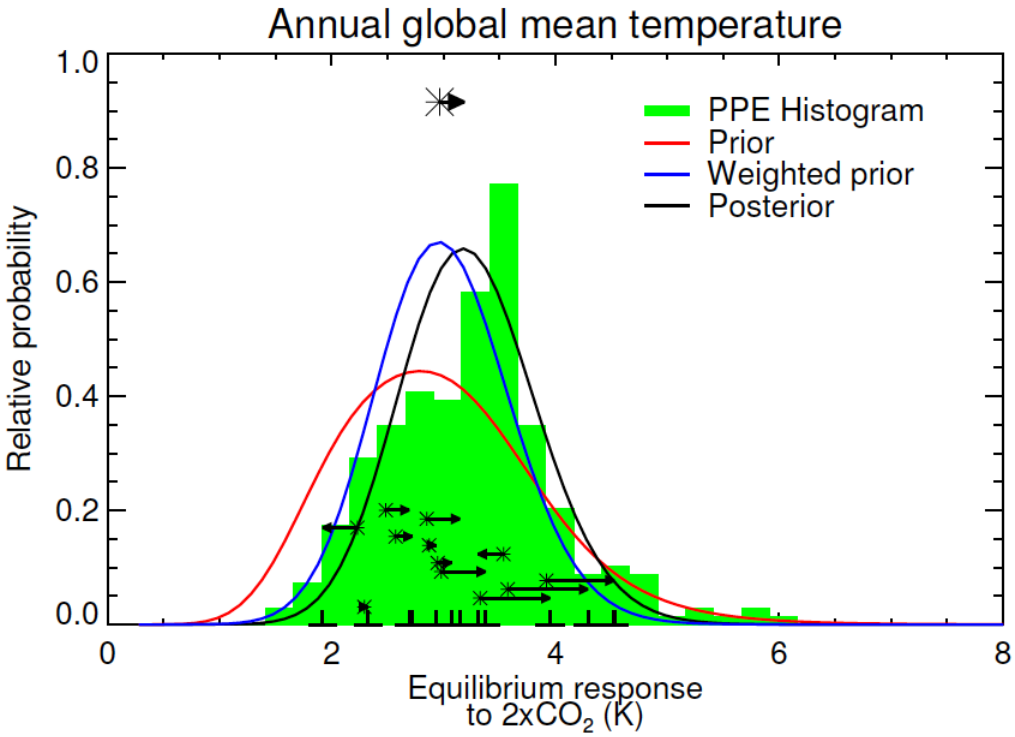


Lambert, F.H., Harris, G.R., Collins, M., Murphy, J., D.M.H. Sexton, B.B.B. Booth,, Interactions between perturbations to different Earth system components simulated by a fully-coupled climate. Climate Dynamics, 2013

Bayesian Approach to Dealing with Uncertainties

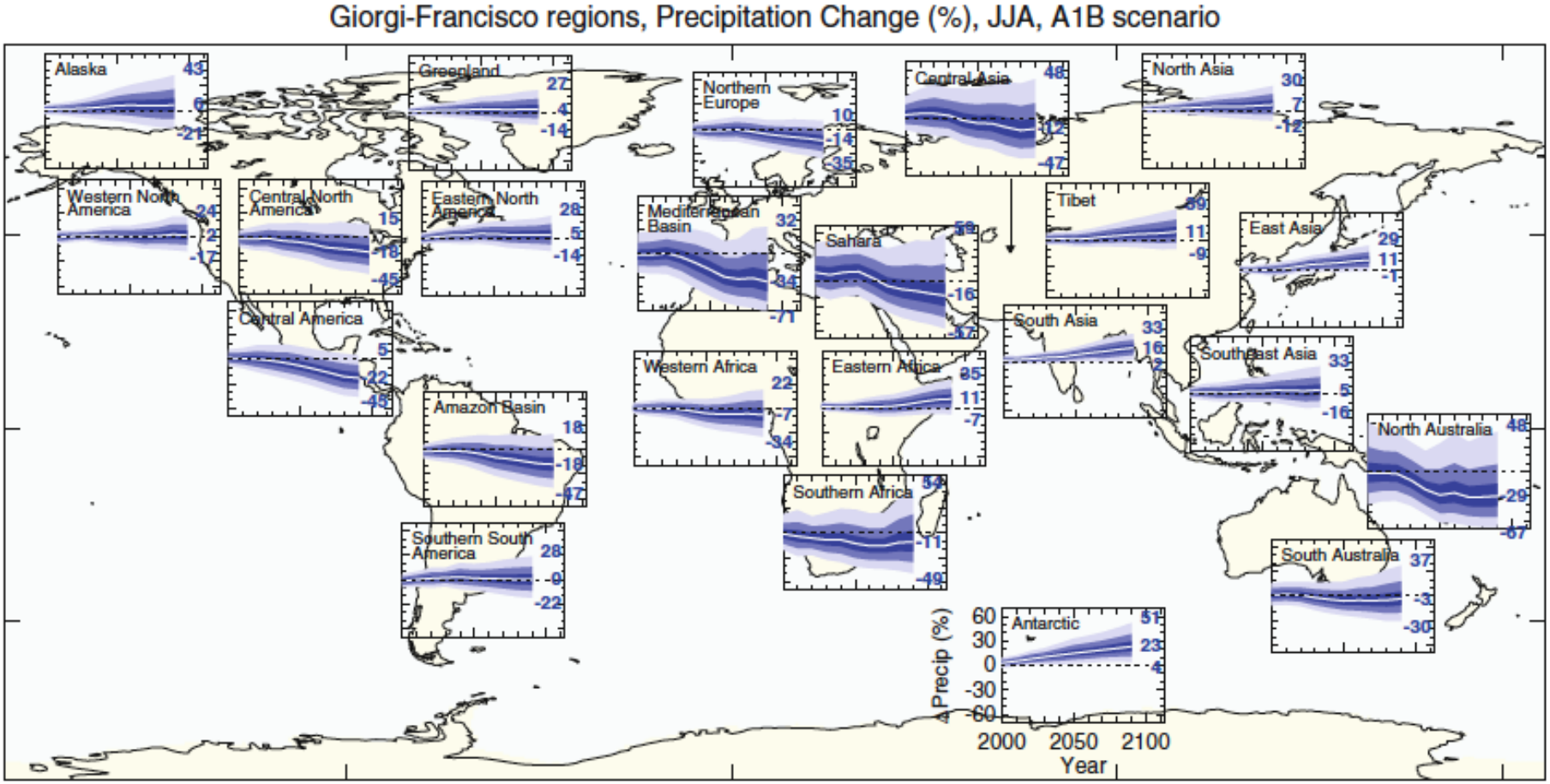
$$p(y \mid o) \propto p(o \mid y)p(y)$$

- Requires a large sample of projections and a way of specifying the prior – develop an emulator
- Likelihood based on comparison with present-day and past climate, climate variability and climate change
- This study based on HadCM3 model constrained by obs of mean T, P, RH, Energy fluxes…
- Projection onto truncated multivariate EOF space
- Discrepancy from CMIP MME to represent 'structural' uncertainty



Sexton DMH, JM Murphy, M Collins, M Webb, Multivariate prediction using imperfect climate models part I: Outline of methodology. Climate Dynamics, 2013

Bayesian Approach to Dealing with Uncertainties



Harris, G.R., D.M.H. Sexton, B.B.B. Booth, Collins, M, J.M. Murphy, Probabilistic prediction of transient regional climate change. Climate Dynamics, 2013

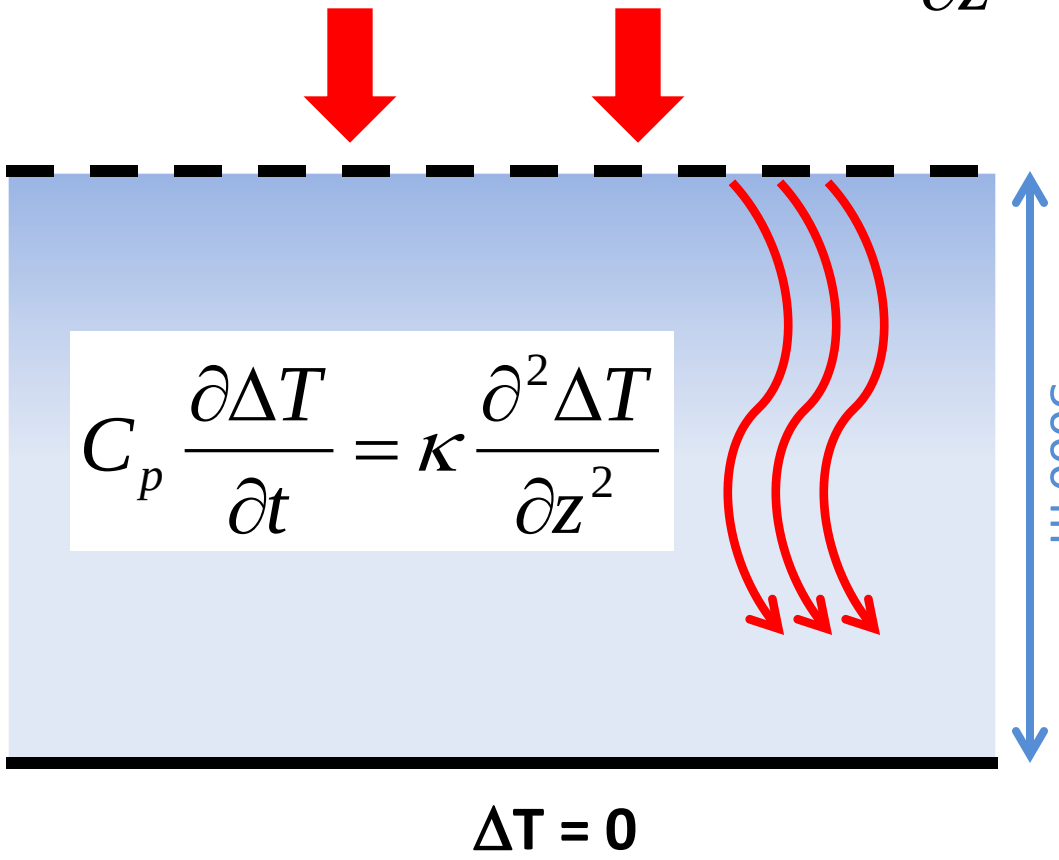
Quantifying Uncertainties using Complex Models

- The main advantage of the complex-model perturbed physics approach is that there exists a statistical framework in which to work
- Using complex models allows for the use of multivariate likelihood functions and the production of multivariate projections
- Approach is severely complicated/limited by the availability of computer resources, both processing power and storage/data transfer
- Complications in the implementation have limited our ability to produce simple explanations of what is going on (for other climate modellers)
- Is there are parallel approach based more on simplified models?

1-D Simple Climate Model

$$N(t) = F(t) - \alpha \Delta T_{SFC}(t) = -\kappa \frac{\partial \Delta T}{\partial z}$$

Implicit BTCS time integration
Updated via TOA Imbalance
All TOA imbalance (N) into ocean



ΔT = Temperature
N = TOA Imbalance (OHU)
C_p = Heat Capacity

κ = Thermal Diffusivity
F = Net Radiative Forcing
α = Net Climate Feedback

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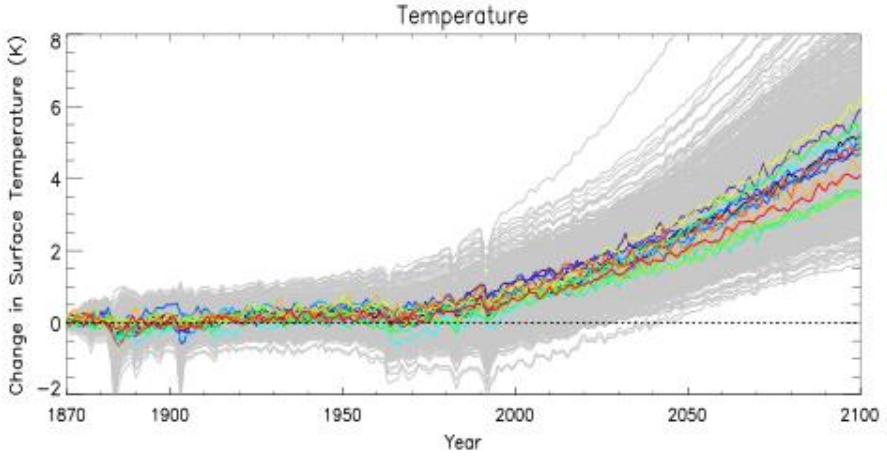
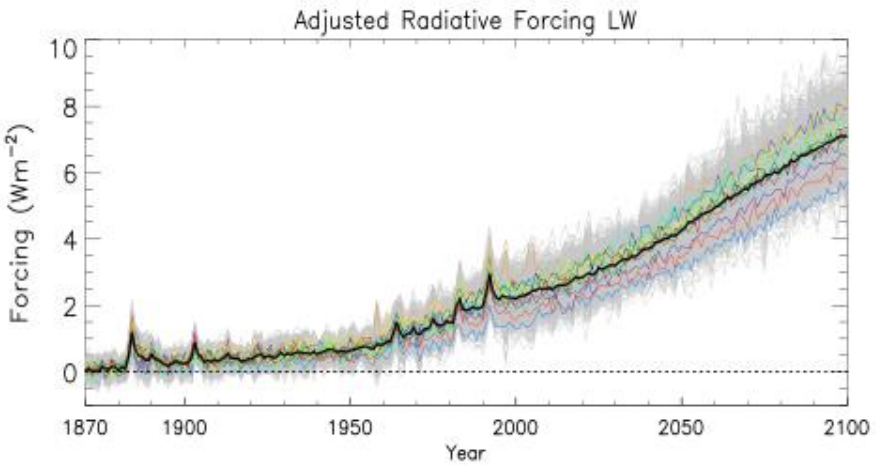
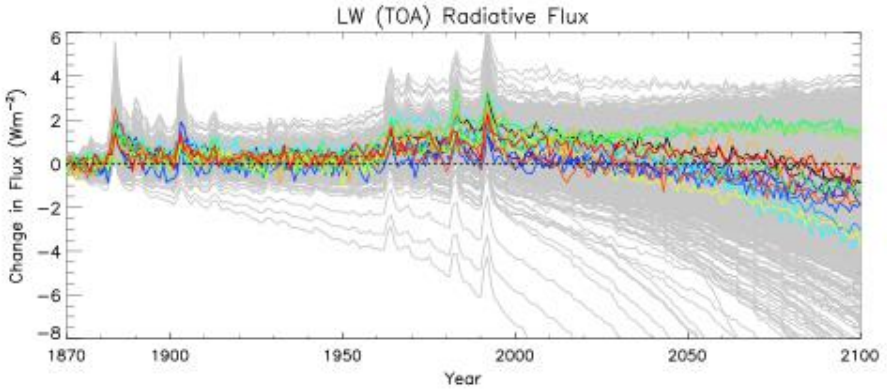
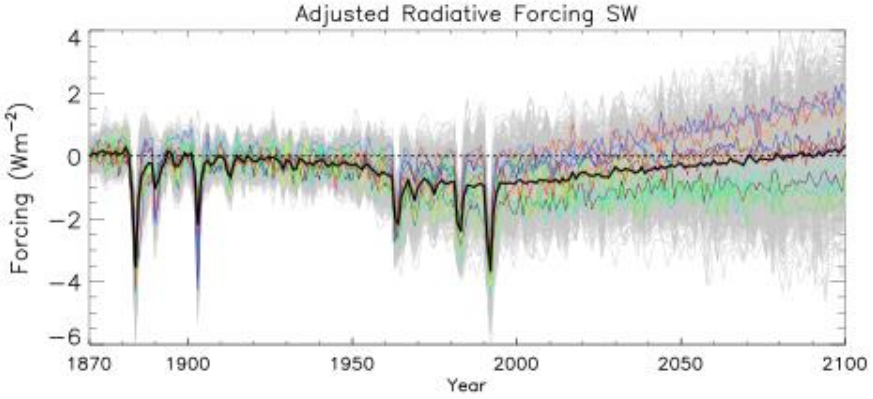
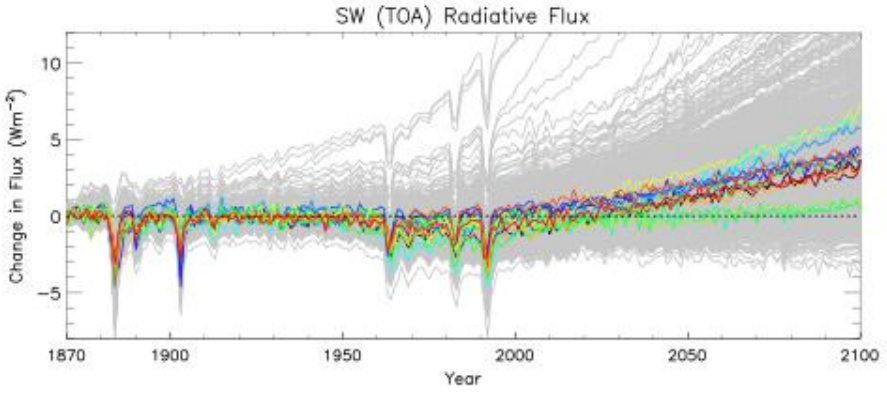


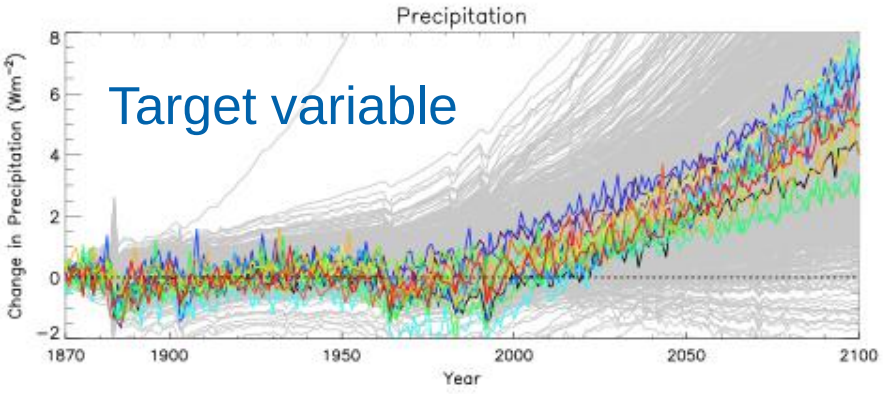






‘Physically-based’ emulator





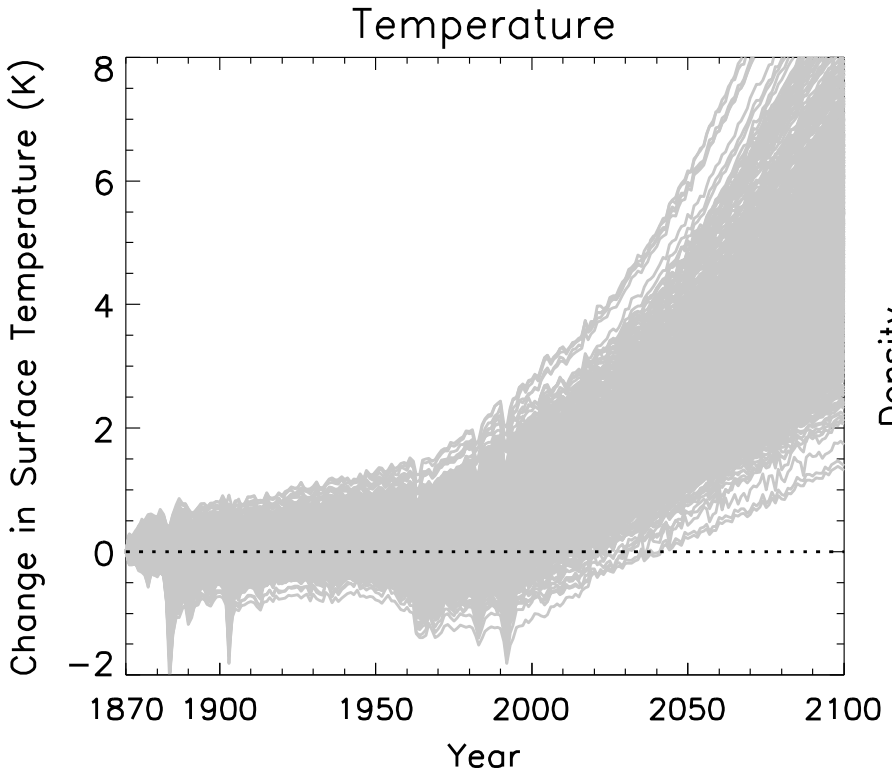
Target variable

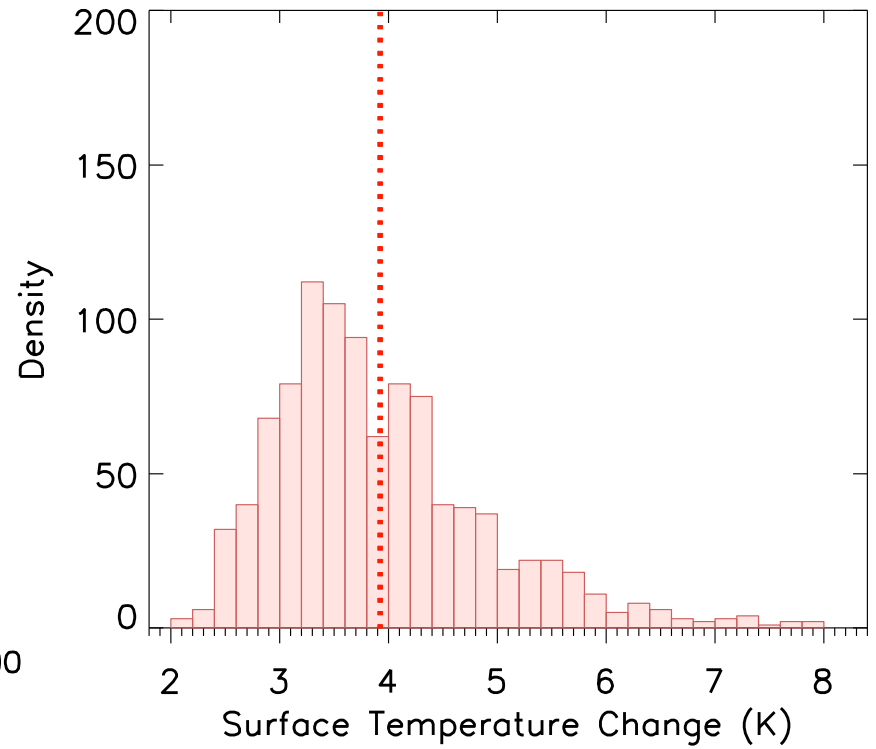
Perfect Ensemble Study

- Sample a wide range of possible projections using our physically based emulator – *prior*
- Take a CMIP5 mode as a representation of a plausible climate system
- ‘Observe’ the behaviour of the CMIP5 model in the recent historical period
- Weight prior distribution to produce a *posterior* distribution of future climate change
- Verify posterior distribution of using the CMIP5 model projection of future change

Weighting Procedure: Linear Trend

Weight: Linear Trend (1993:2012)





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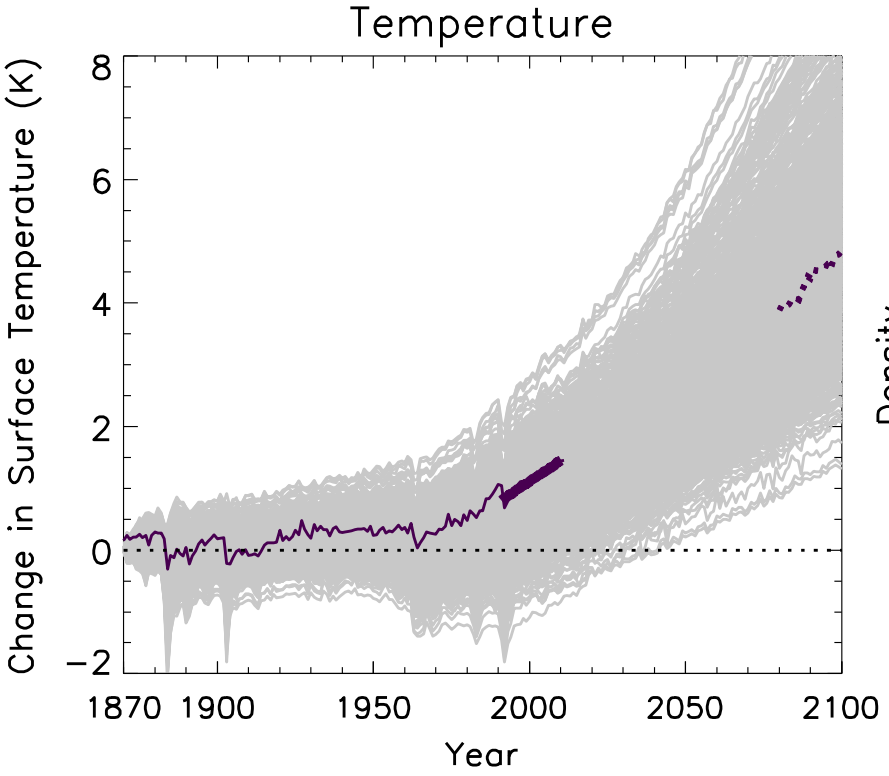

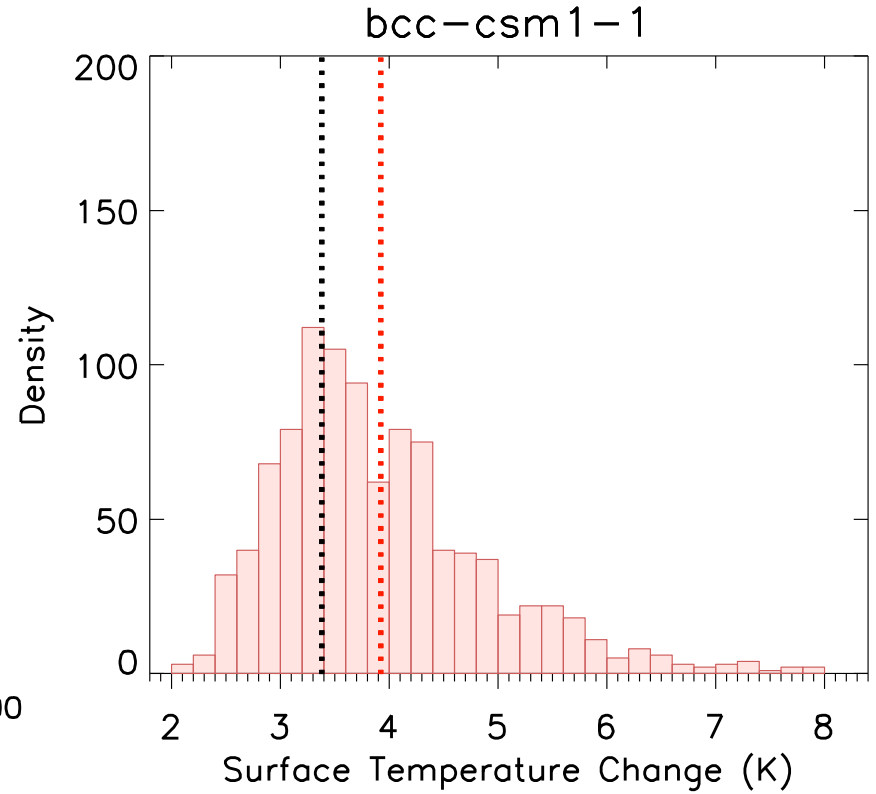

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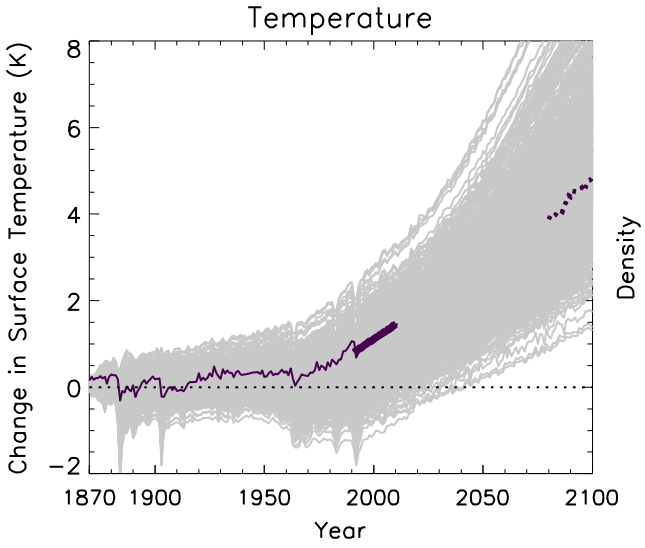

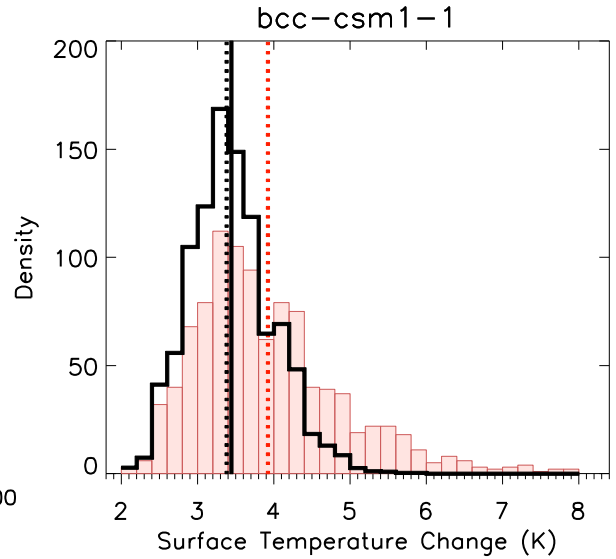

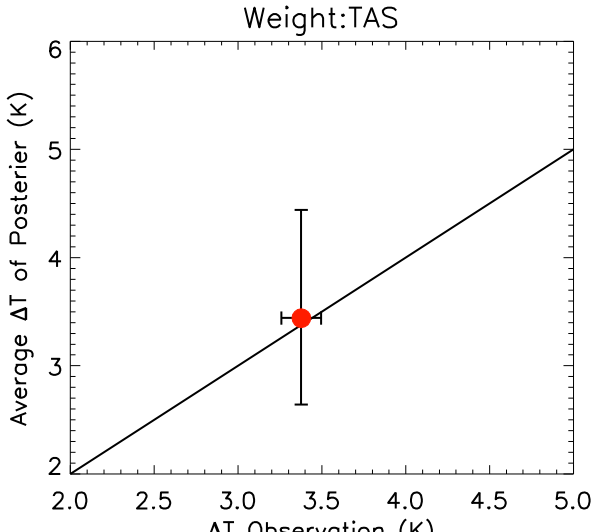

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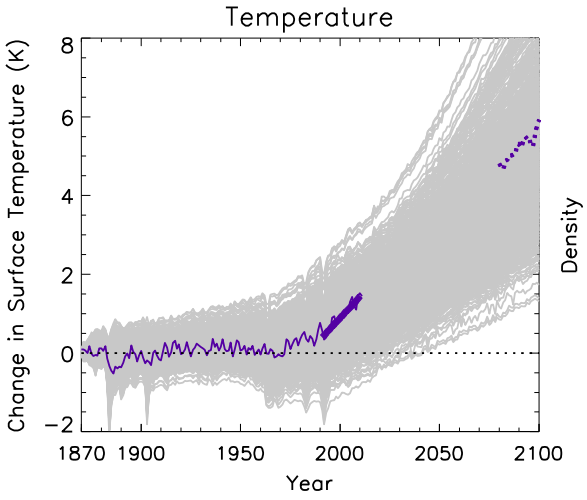

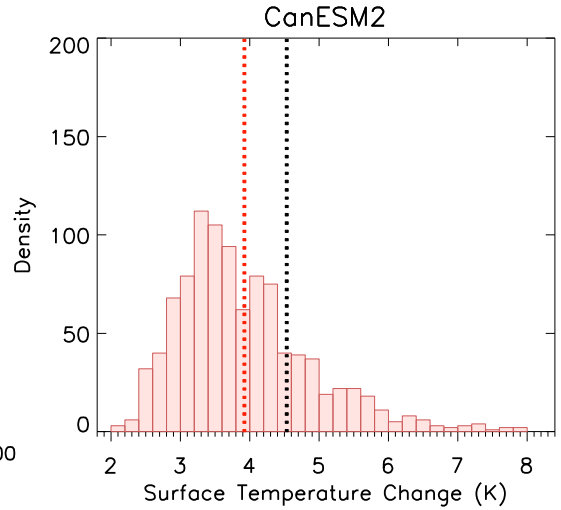

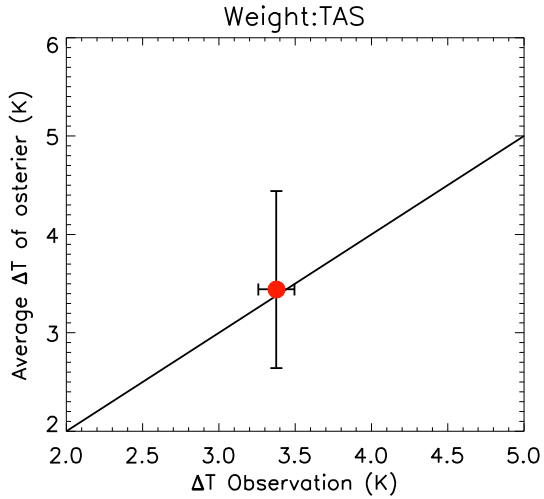

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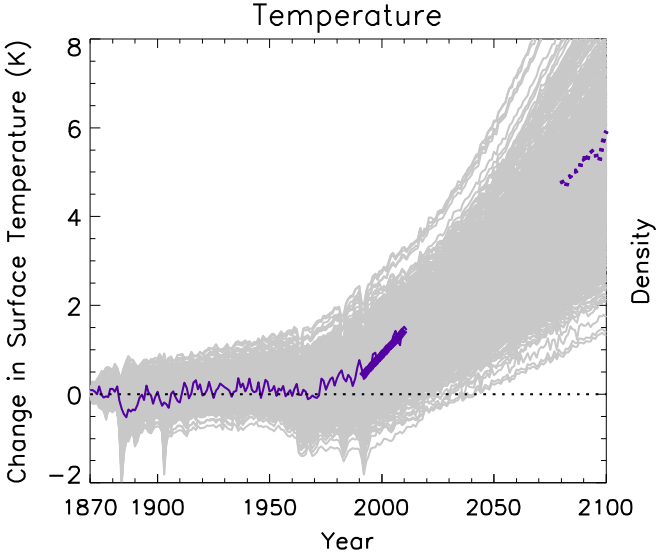

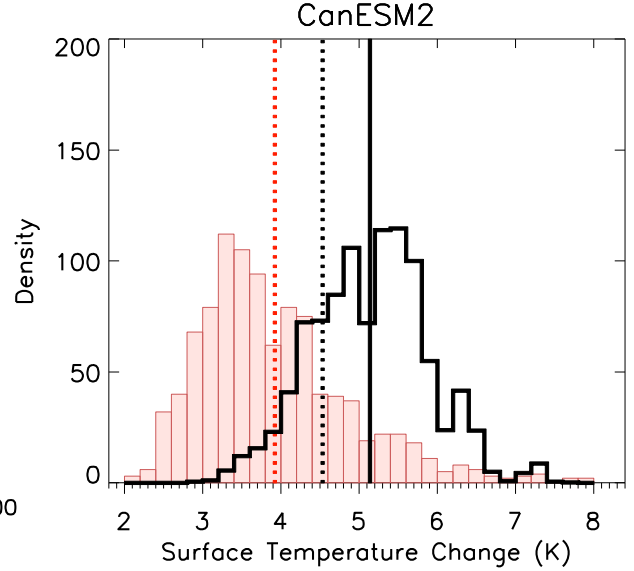

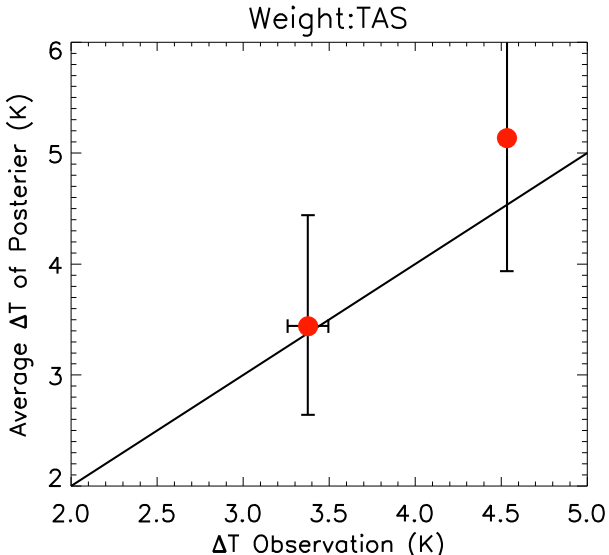

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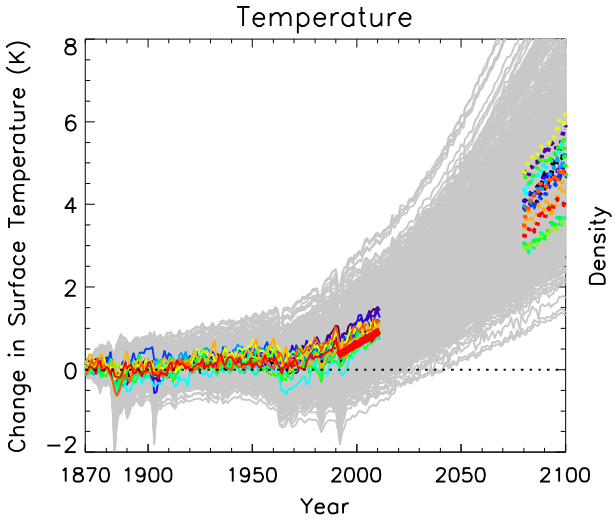

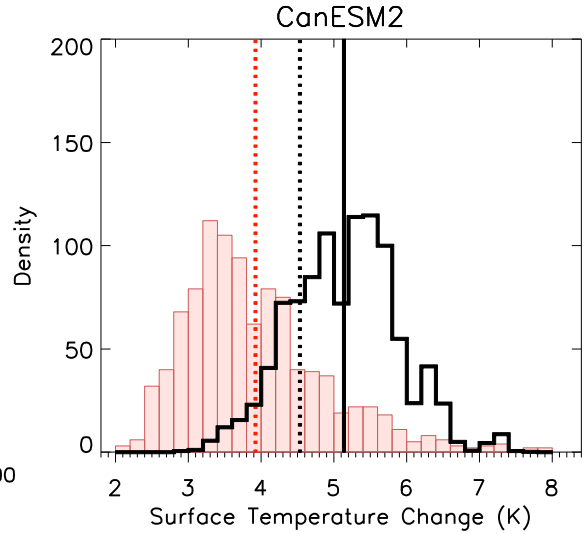

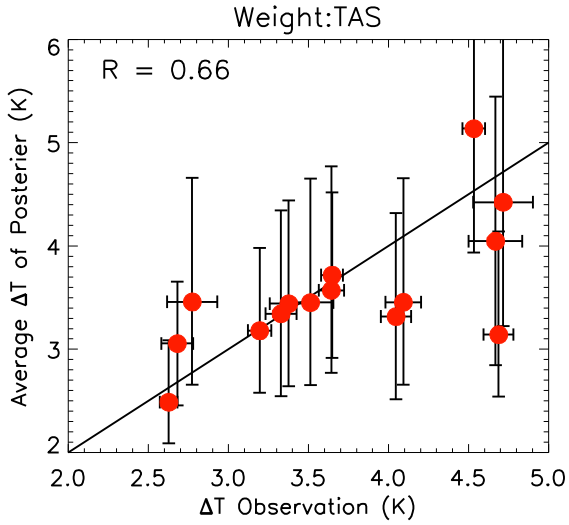

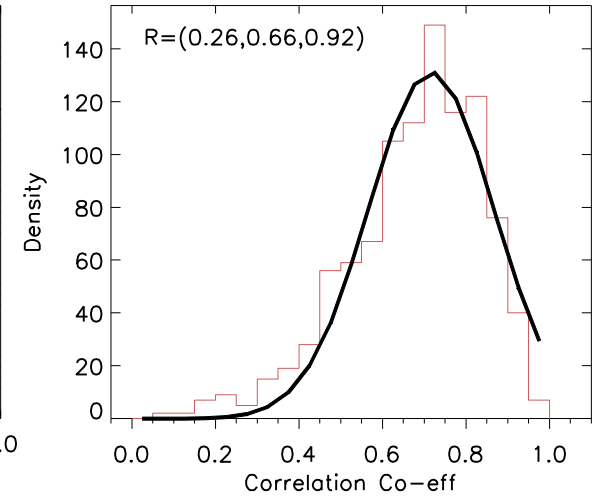

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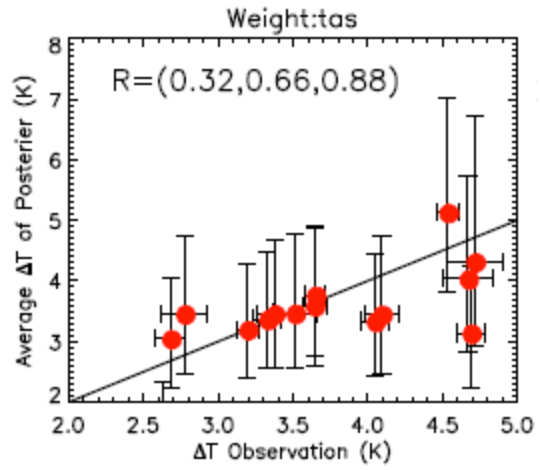
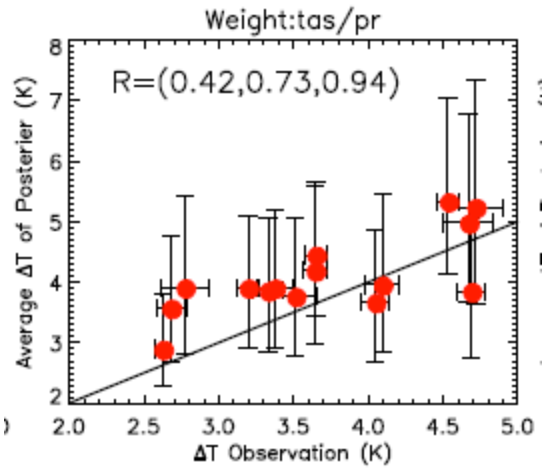
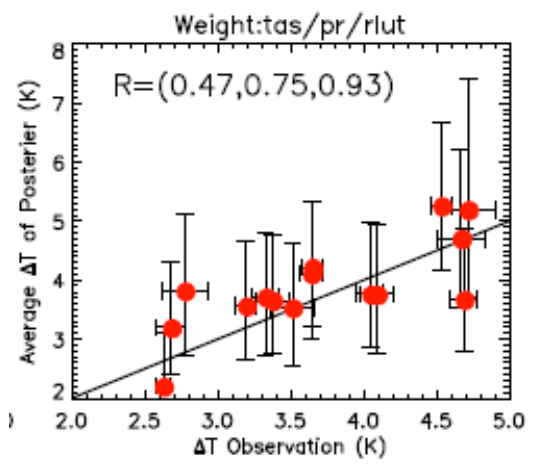
Multivariate: Linear Trend (1993:2012)

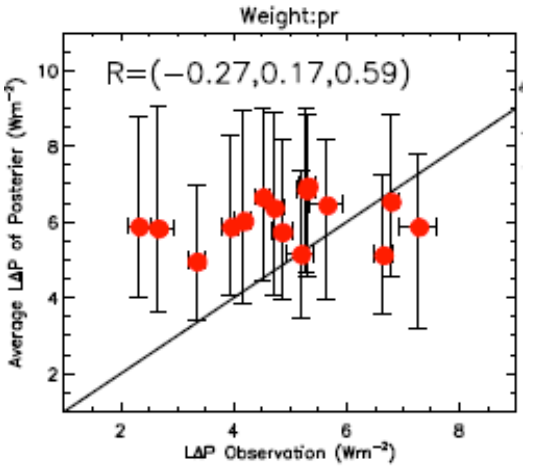
Temperature

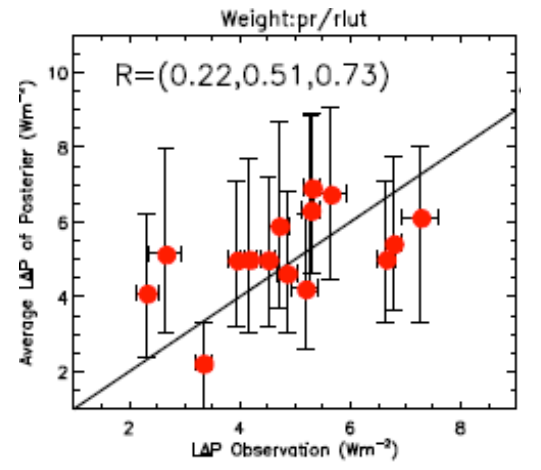


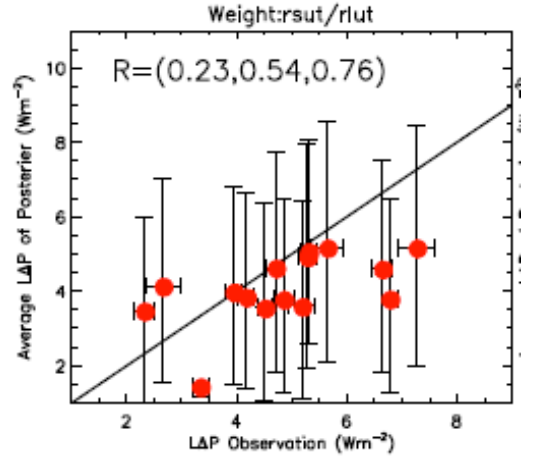




Precipitation







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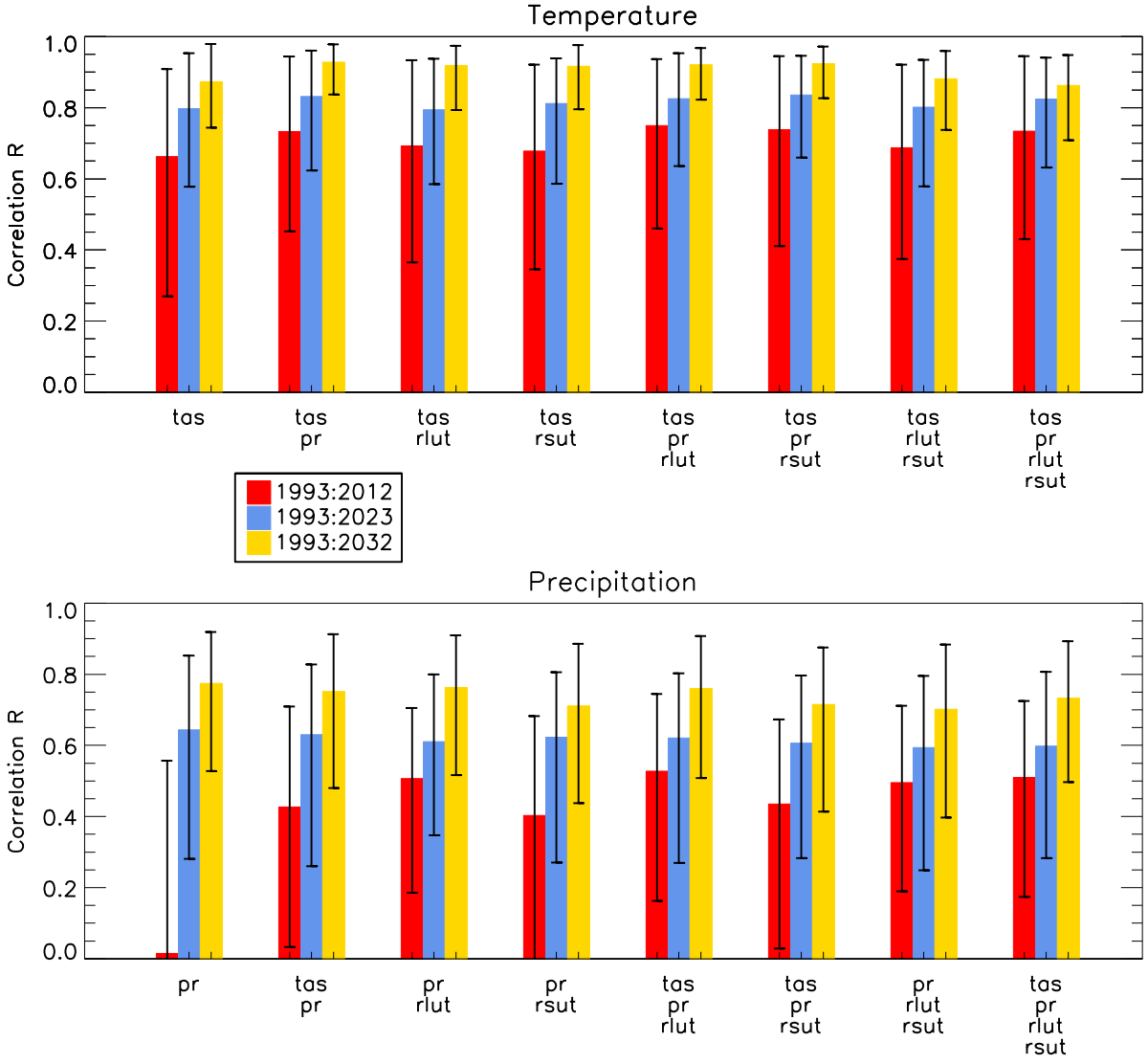
Comparison Using Future Observations



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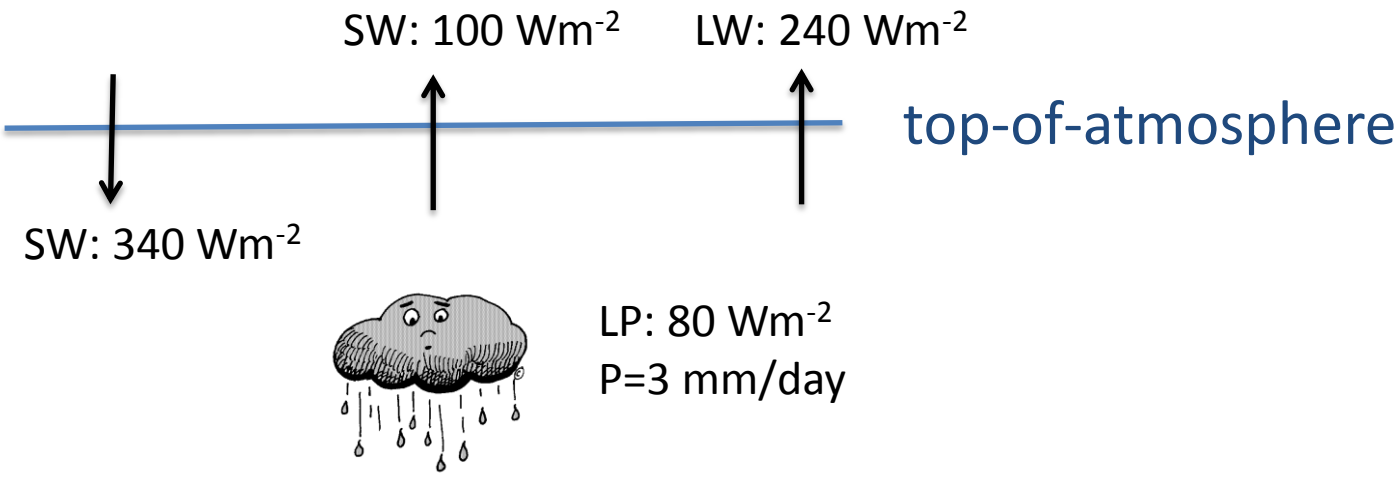
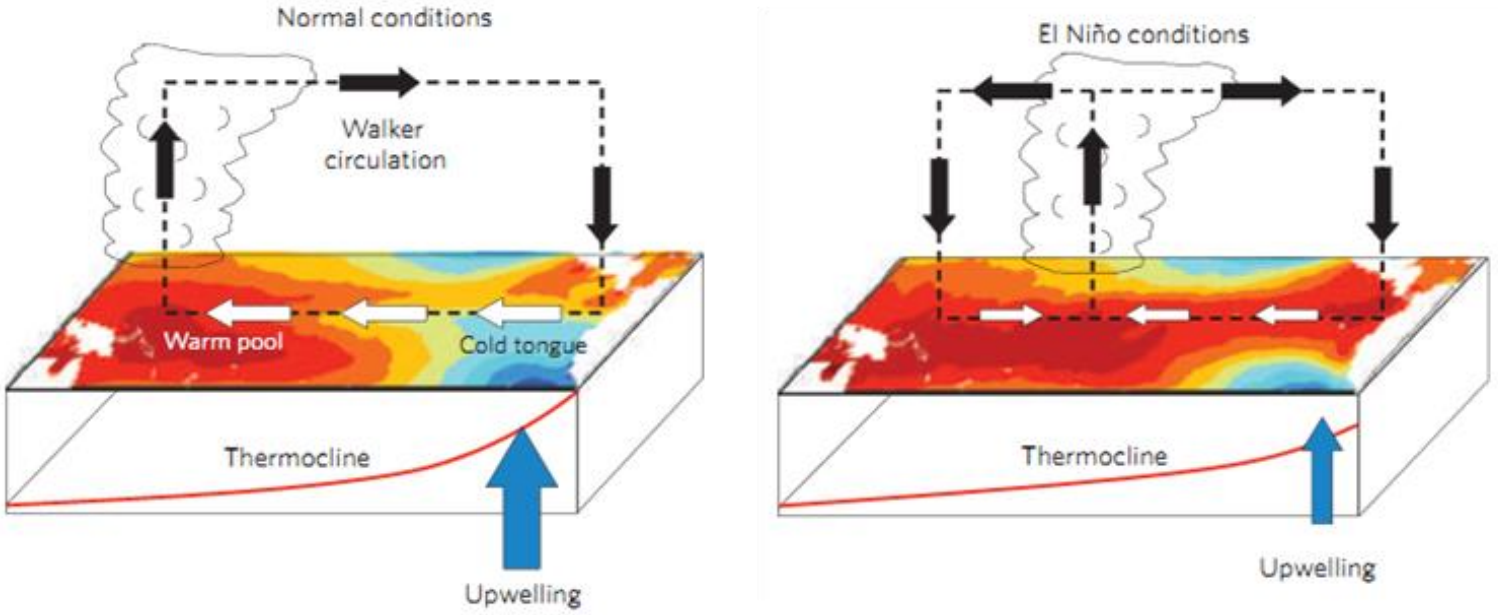
Global Hydrological Cycle Energy Balance



El Niño Southern Oscillation (ENSO)



- Naturally occurring variation in climate in tropical Pacific region between abnormally cold (La Niña) and abnormally warm (El Niño) conditions.
- Has a large effect on weather in other parts of the world so important to understand ENSO

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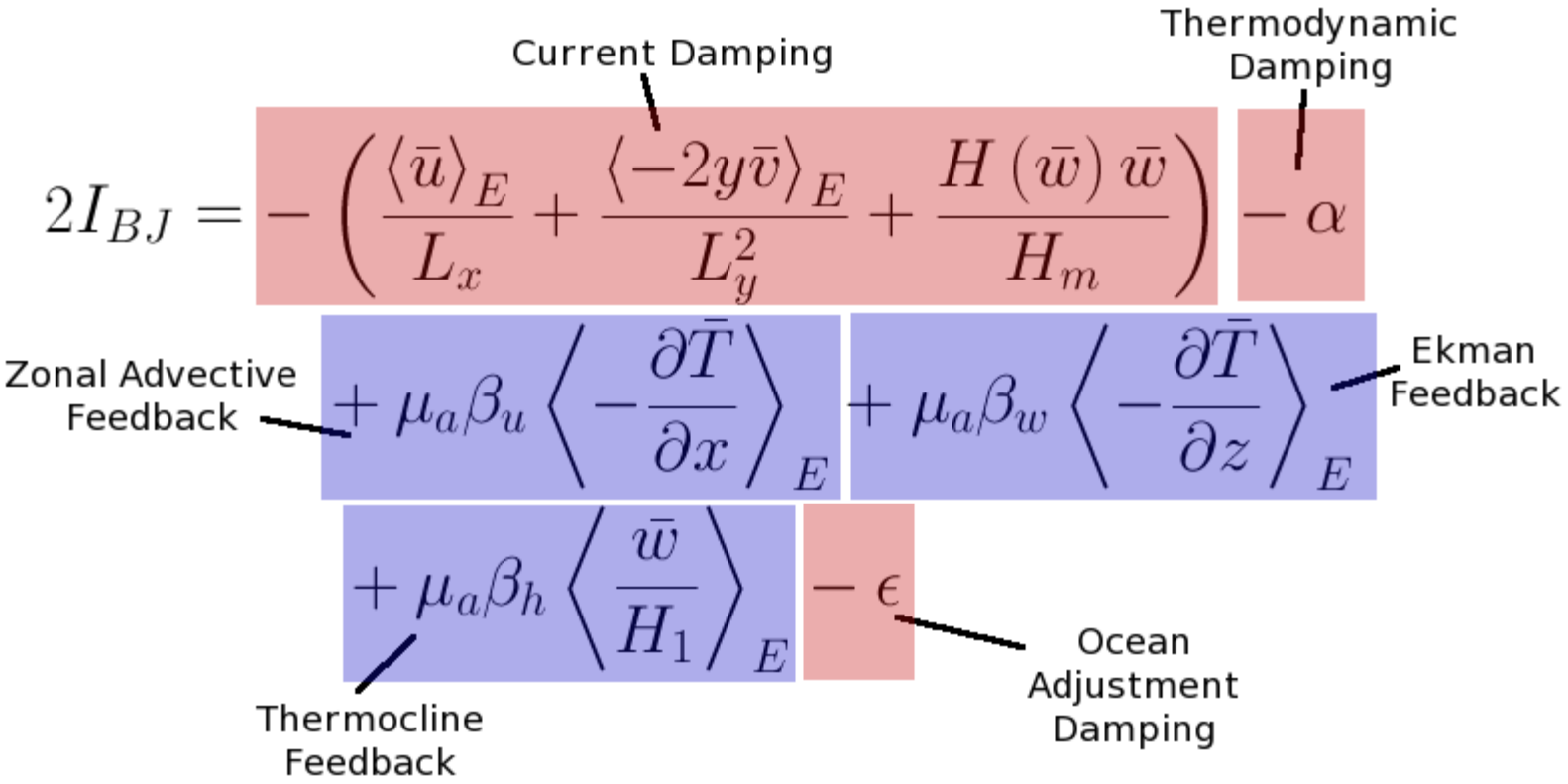
ENSO Stability Index (Jin, F-F)



$$[\tau_x] = \mu_a \langle T \rangle_E$$

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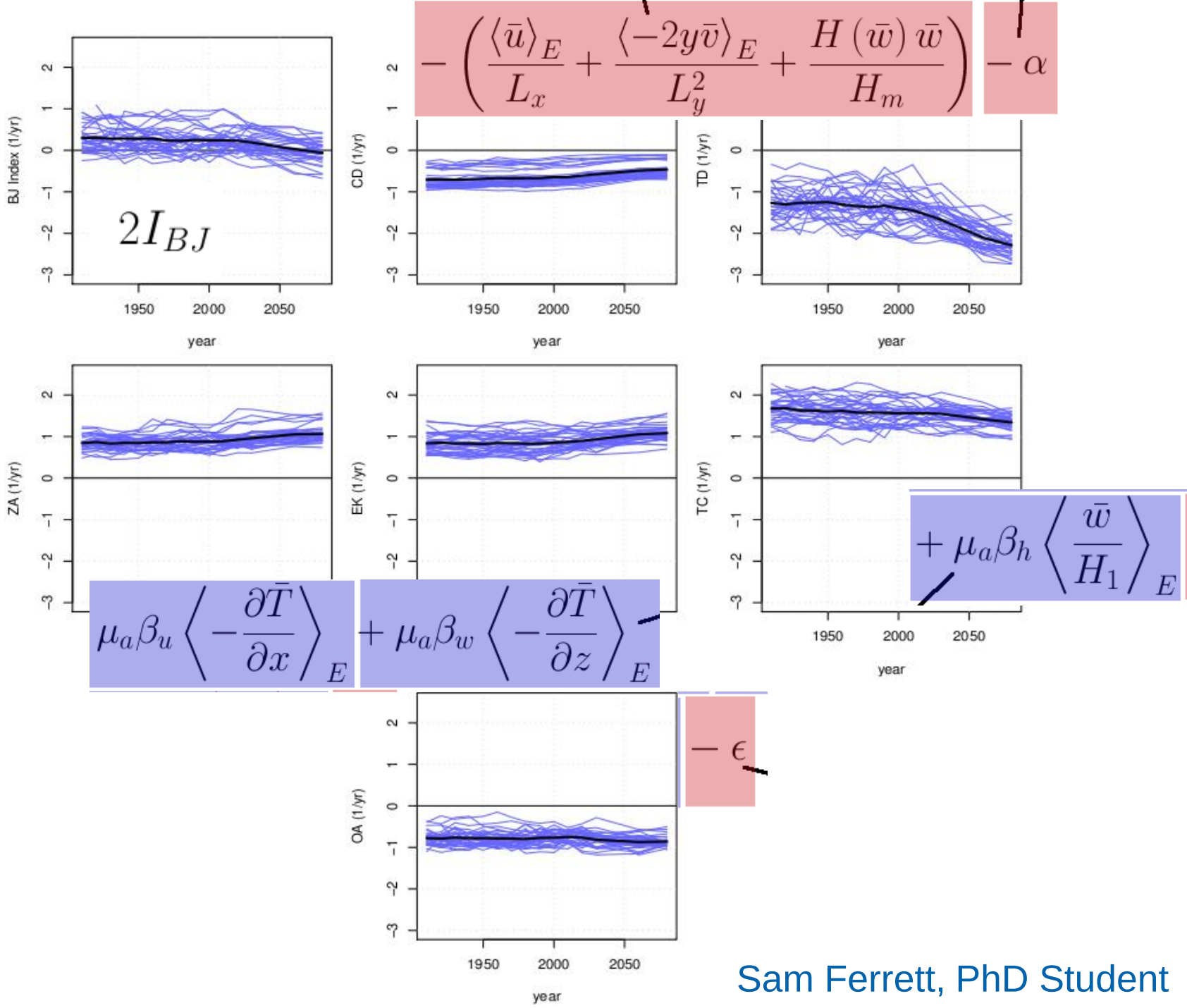

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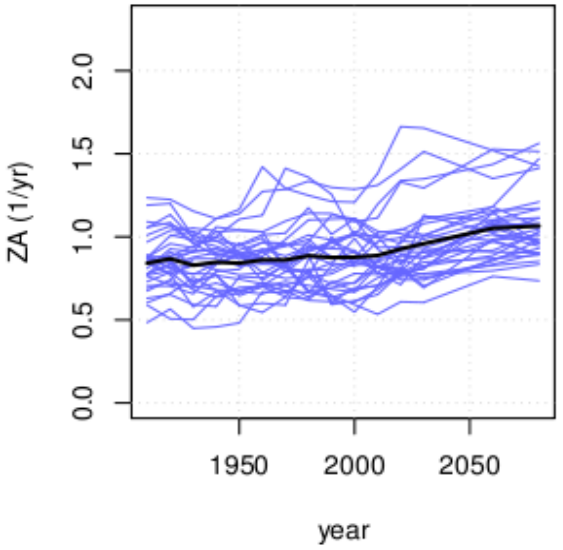
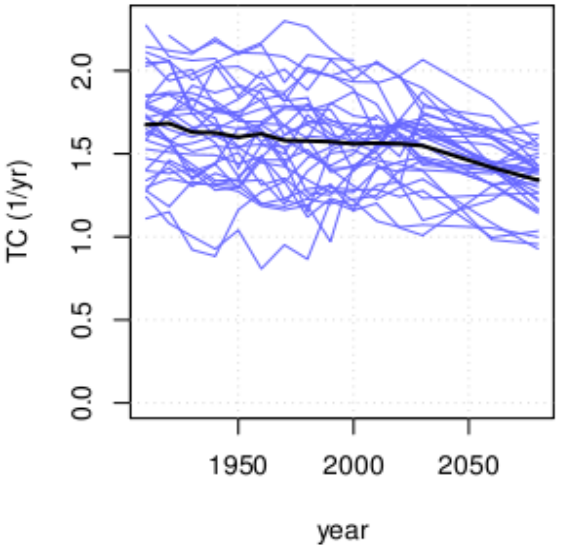
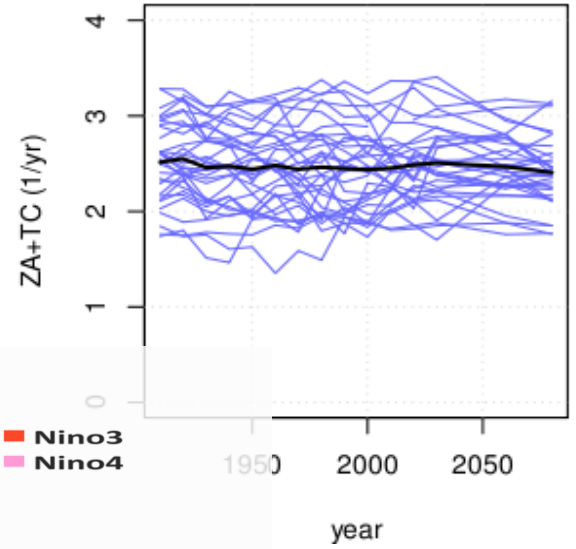
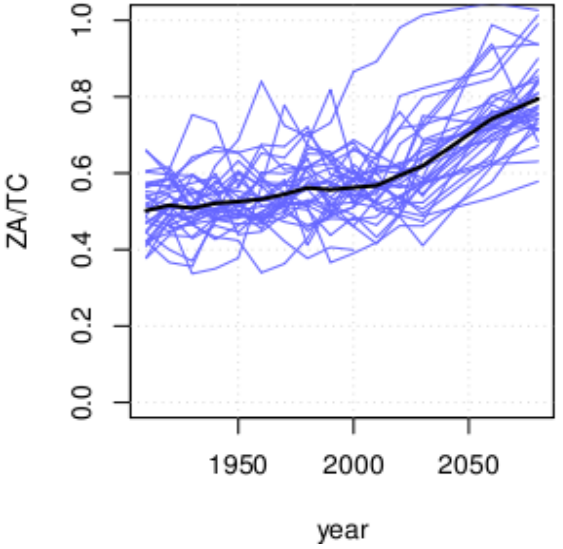
- Zonal Adv (ZA) feedback, thermocline (TC) feedback, ZA+TC and ZA/TC as a function of time

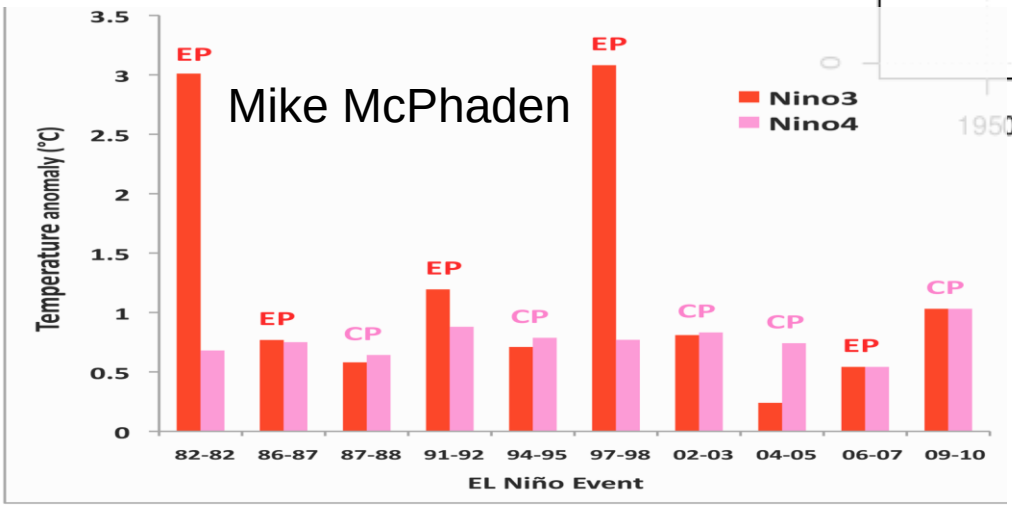
- Increase in ZA/TC, but no difference in ZA+TC suggests a possible change in contributing ENSO feedbacks that does not impact stability





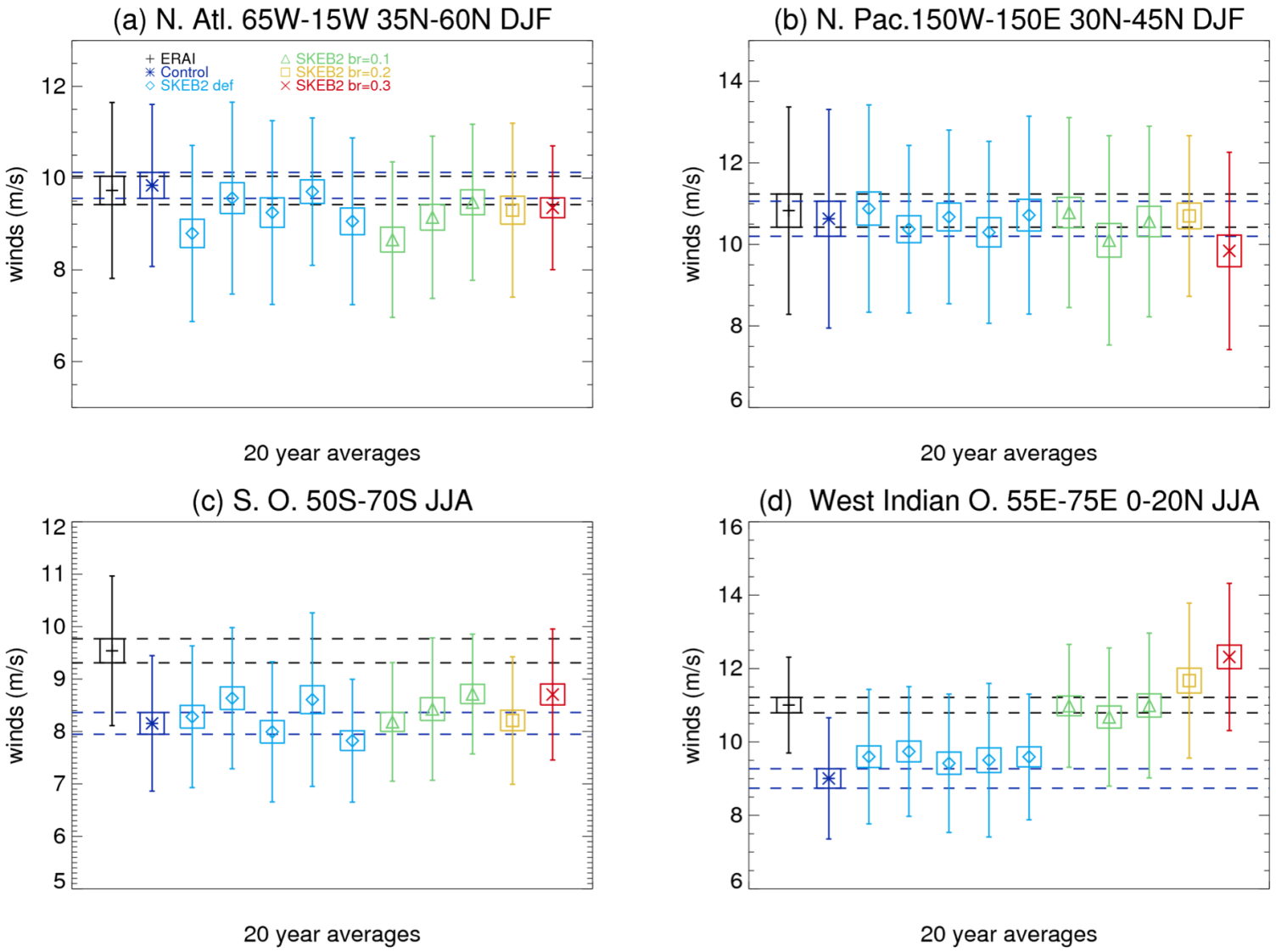






Sam Ferrett, PhD Student

Use of Stochastic Parameterisation?



Sanchez, C *et al*., Impact of stochastic energy backscatter scheme across timescales and resolutions. QJRMS, submitted.

Summary and Conclusions

- Difficult to interpret multi-model ensembles (MMEs) as robust estimates of uncertainty in projections
- Perturbed physics ensembles allow you to use a formal statistical framework to synthesis models and observations to produce observationally-constrained projections…
- …but, implementation can be hard work and make projections difficult to interpret
- Parallel approach of using physically-based simplified models of climate to understand how to interpret and constrain projections
- (Stochastic parametrisation may help but can't do everything)