Met Office

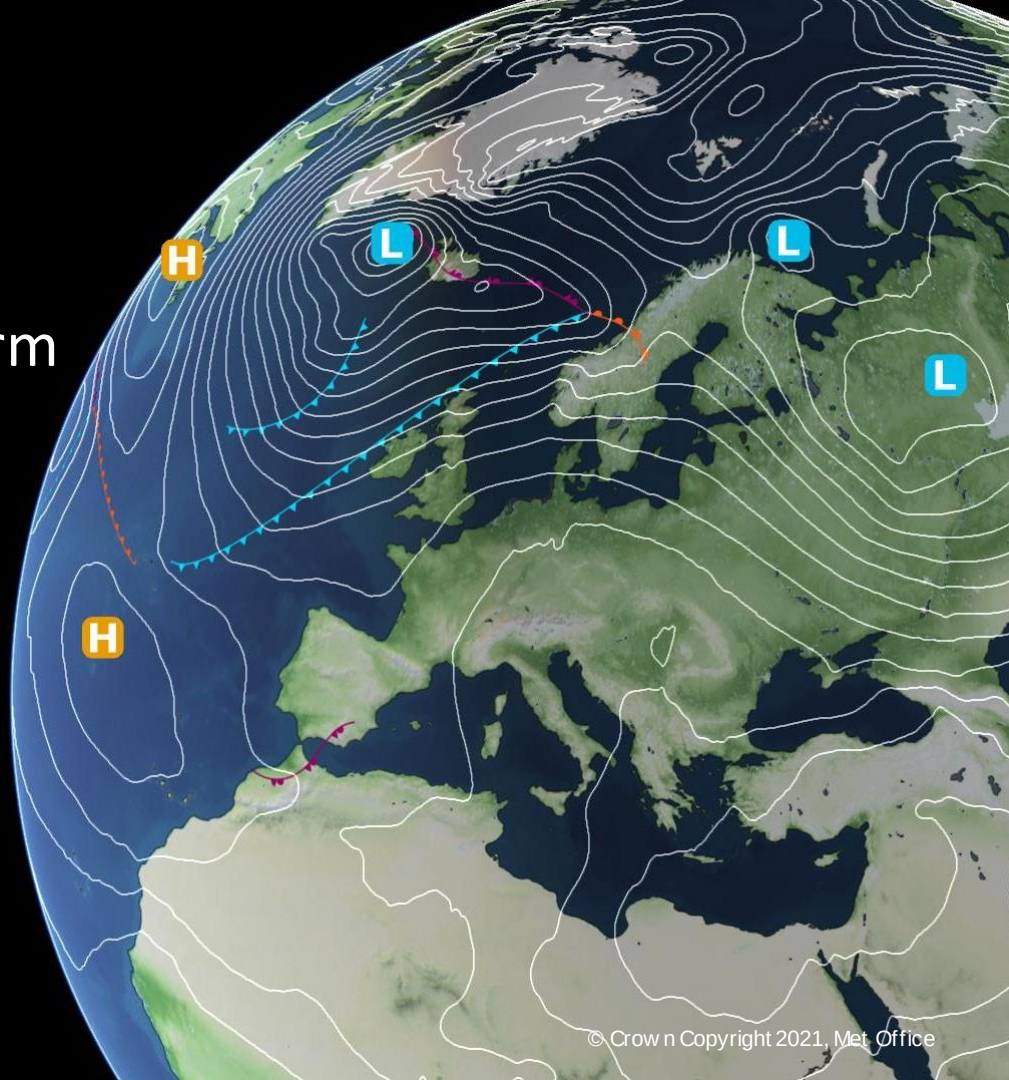
Uncertainty Quantification in Climate Projections Used to Inform Adaptation

David Sexton

The Role of Uncertainty in Mathematical Modelling of Pandemics

Workshop, 9th February 2022

Thanks to Ben Sanderson (CICERO) and Ben Booth (Met Office) for some slides.



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Contents

- UK’s national climate projections
- Climate modelling and evaluation, and constraining climate projections
- How well are model imperfections represented in projections?
- Potential ways forward

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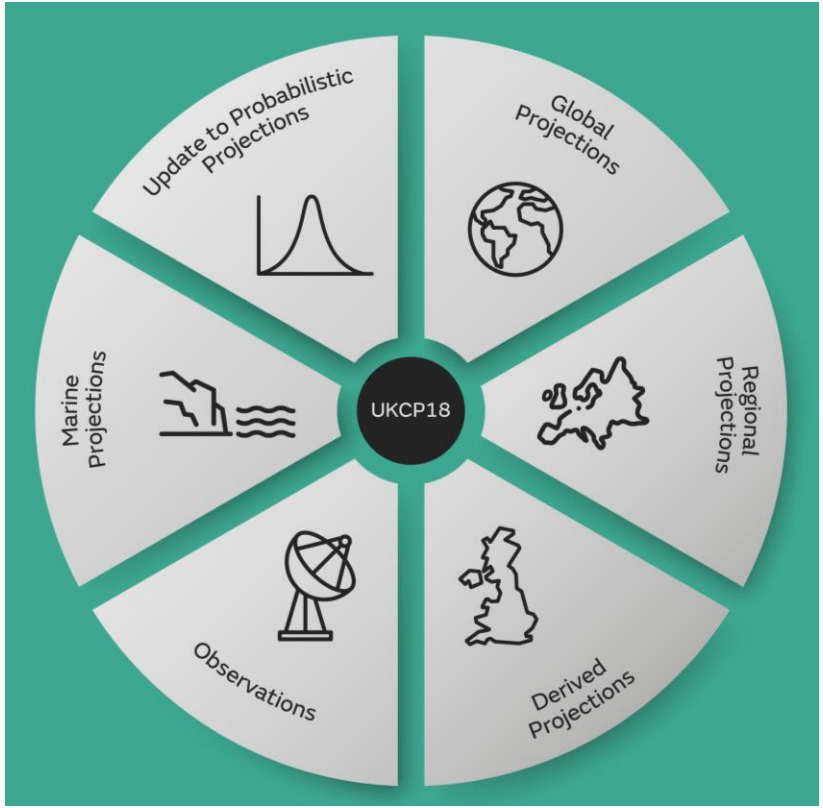
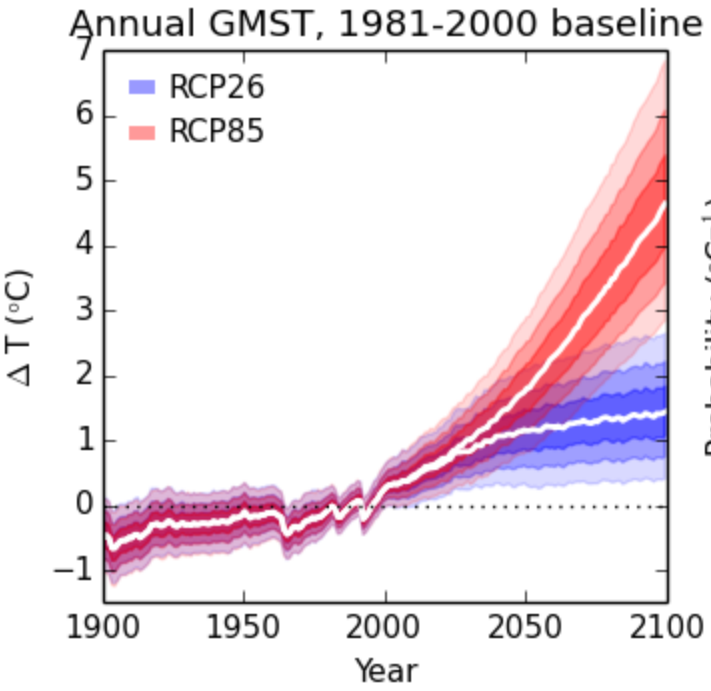
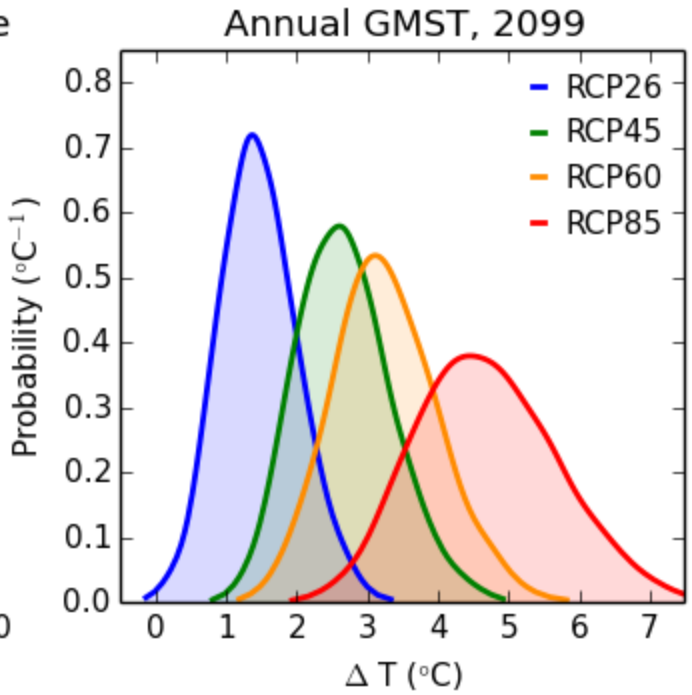
Our latest national climate projections (UKCP18)

- Predecessor was UKCP09.
- New projections has six products, more than UKCP09.
- Driven by new science and developed with users







rojections

- Conditioned on a socioeconomic emission scenarios (e.g. fossil fuel intensive, effective mitigation). These are specified a priori. There is no need for climate simulations to adjust to interventions on a real time basis.

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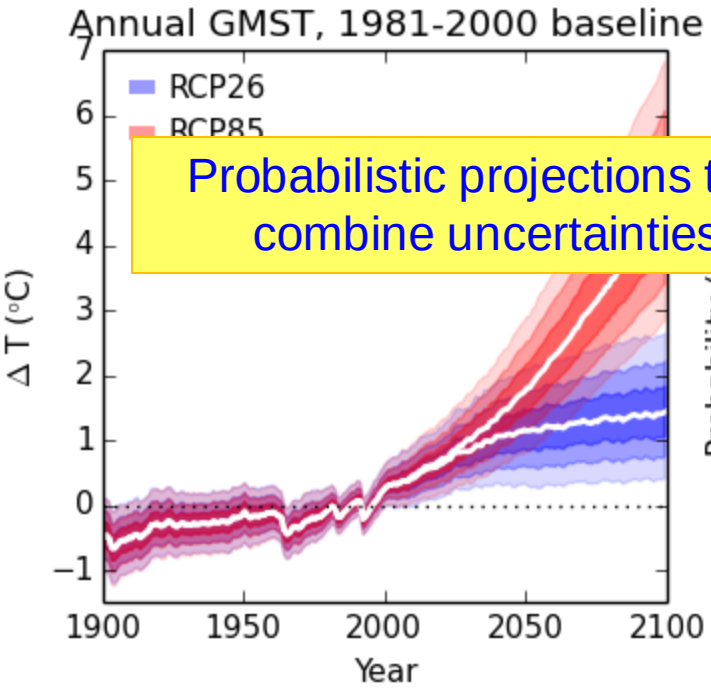
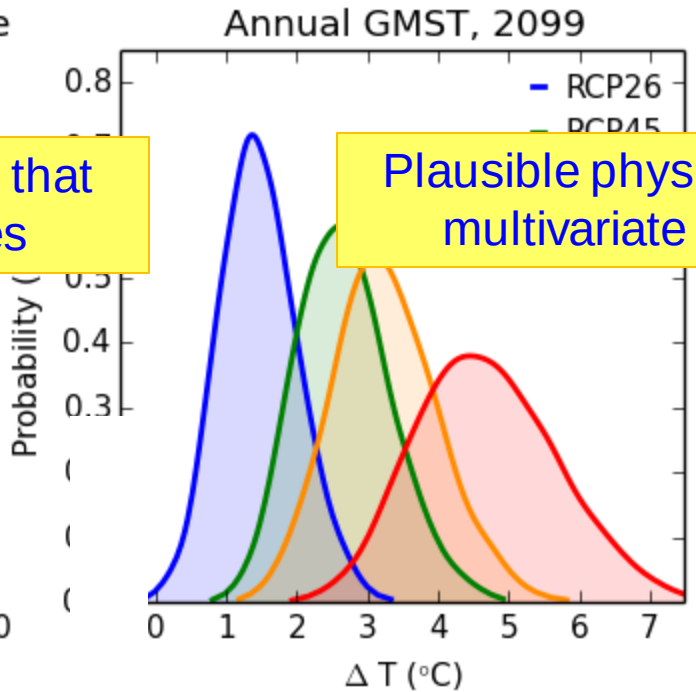
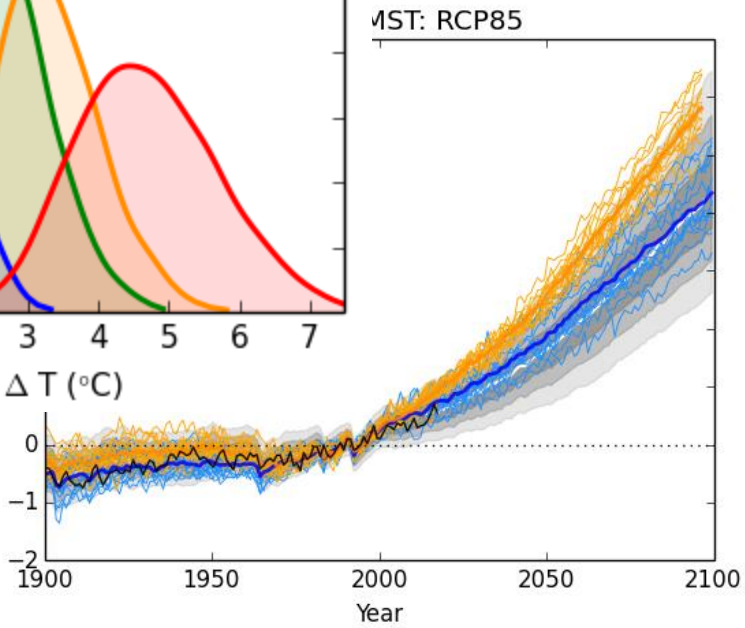


Probabilistic projections that combine uncertainties



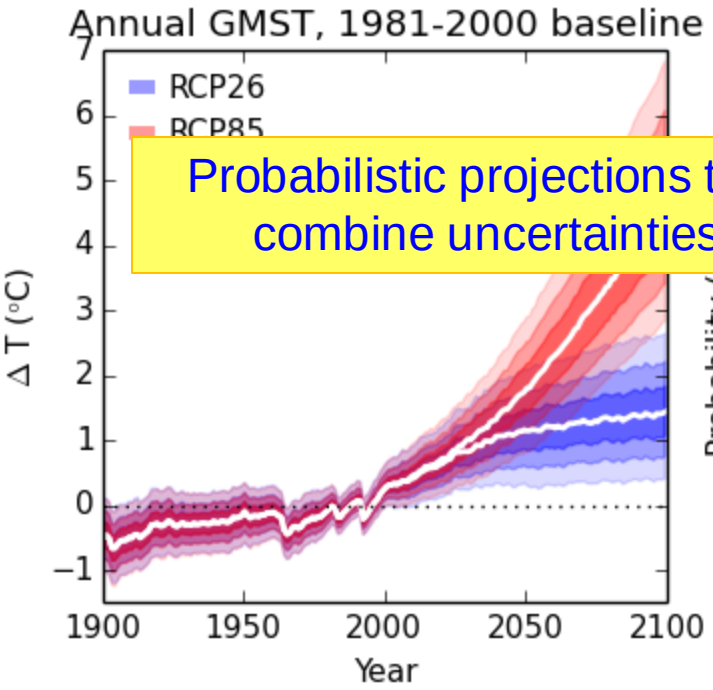
Plausible physically coherent multivariate realisations



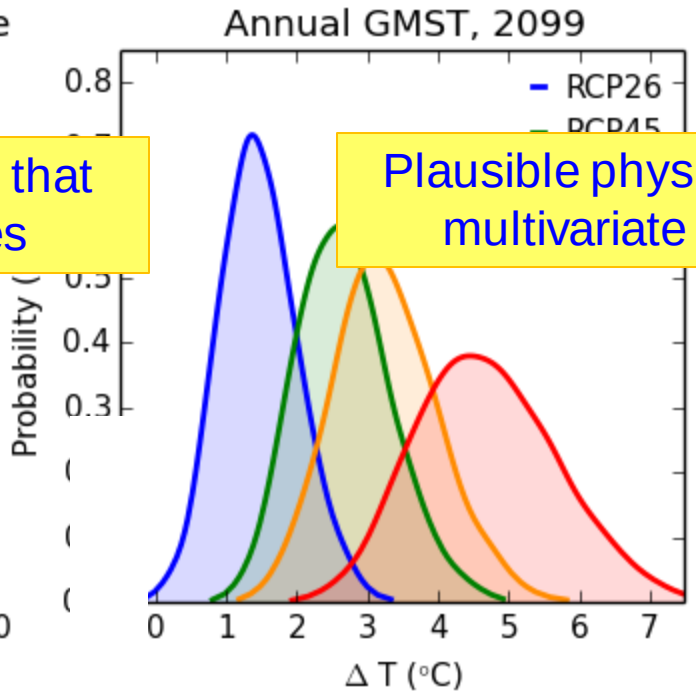
Sexton et al 2012; Harris et al 2013; Murphy et al 2018

Yamazaki et al 2021; Sexton et al 2021

el uncertainty



Probabilistic projections that combine uncertainties



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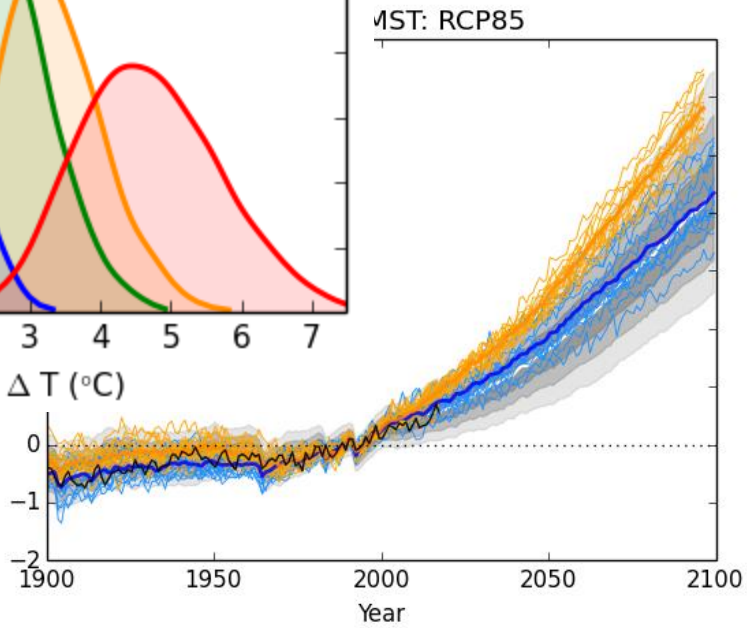
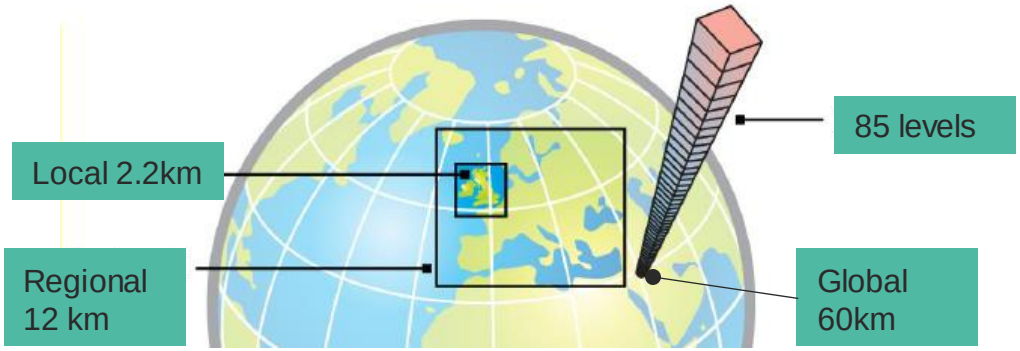


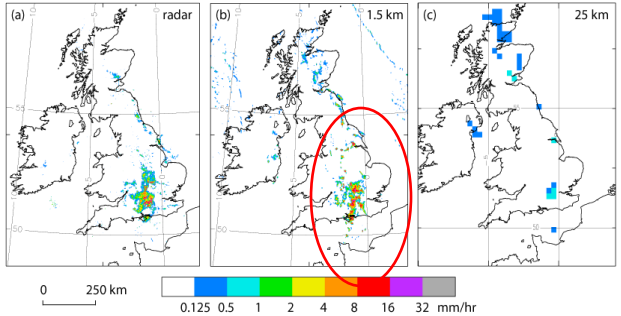
Limited amount of spatial, temporal, physical coherence

Limited exploration of uncertainties

Climate modelling

- Climate models represent a range of processes, some resolved at horizontal/vertical resolution, some un-resolved and so parameterised (e.g. cloud microphysics).
- In our 60km global model, there are hundreds of variables defined at 140,000 grid boxes on each of 85 levels.
- The parameters in the parameterisation schemes control the strength of processes.





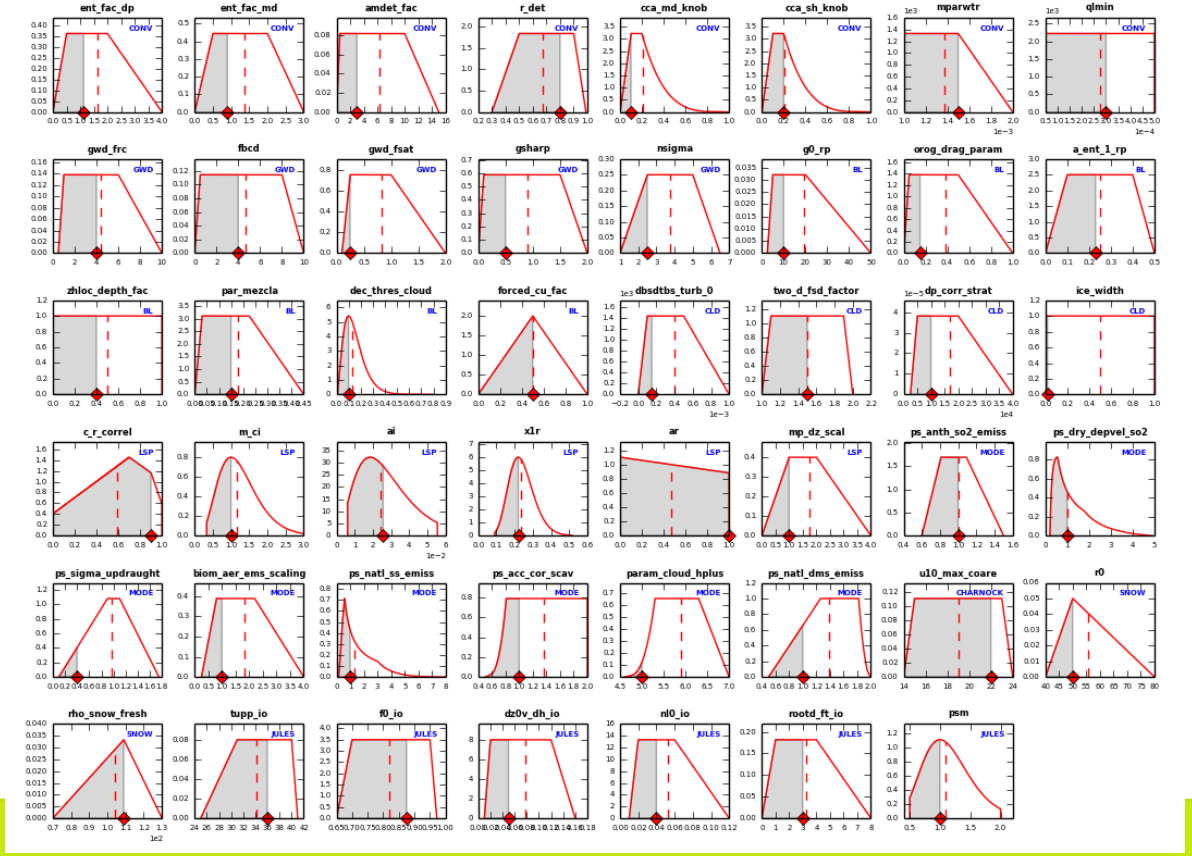
Mesoscale convective system at 0000 UTC 14 June 2014. (Clark et al, 2016, Meteorological Applications)

The set of perturbed parameters for atmosphere and land schemes

7 schemes for GA7.05:

- convection
- microphysics
- GWD
- boundary layer
- land surface
- aerosols
- cloud and cloud radiation

Atmosphere, land, aerosol only. No ocean, carbon cycle in this PPE.



Bayes Linear synthesis of multiple lines of evidence

- UKCP PDFs based on a Bayesian methodology of Goldstein and Rougier 2004
- Large multivariate problem
  - Model parameters (X)
  - Historical and future model output (m_h,m_f)
  - True climate (y_h,y_f)
  - Observations (o)
  - Model imperfections = discrepancy (d)
- Best input assumption - Model not perfect so there are processes in real system but not in our model that could alter model response by an uncertain amount. We assume that one choice of these values, x*, is better than all others. Any point in parameter space has a probability of being x* so we need to sample parameter space

$$y = f(x^*) + d$$

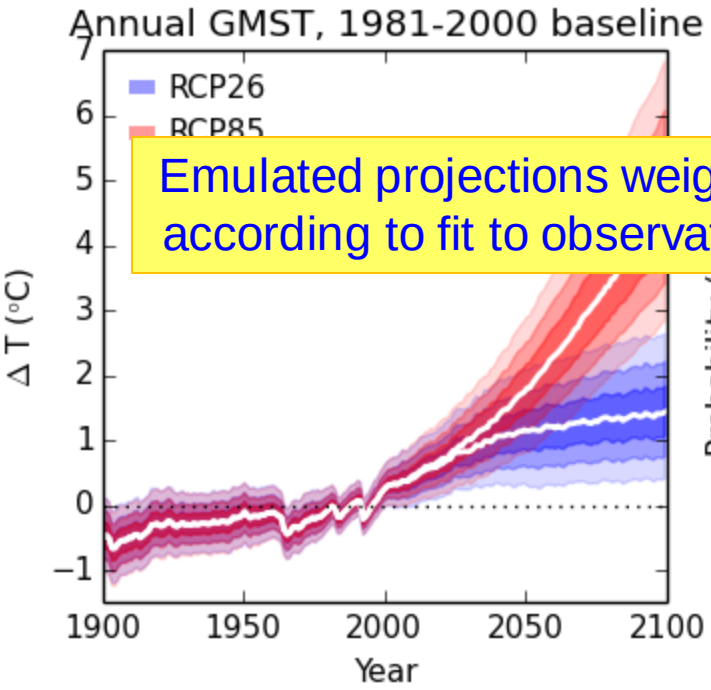
True climate

Model output of best choice of parameter values x*

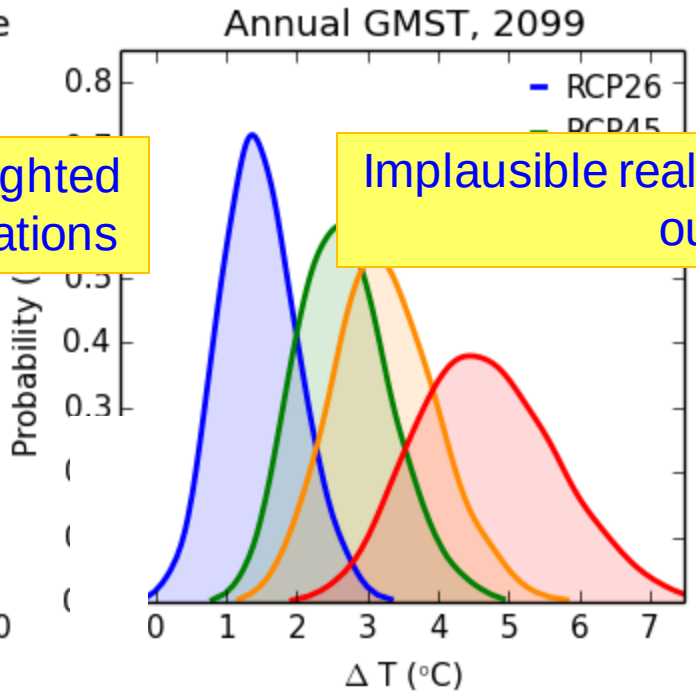
Discrepancy

d=0 for perfect model

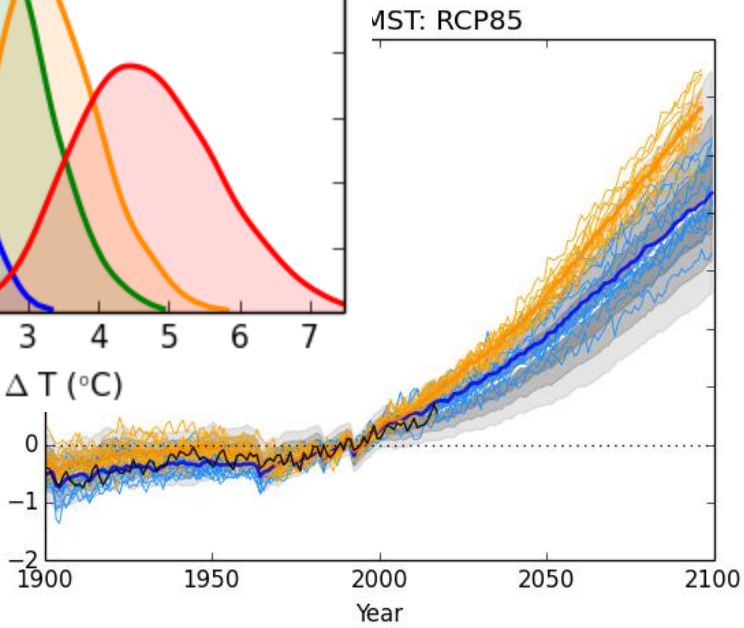
ions



Emulated projections weighted according to fit to observations



Implausible realisations filtered out



The Implausibility Metric, I

Filtering: if I > specified threshold for certain fraction of observables, rule out simulation.

Weighting: weight is proportional to exp(- I^2) in Bayes linear framework

Observ

Implausibility

$$I = \frac{|\mathcal{O} - \mathcal{M}|}{\sqrt{[Var(\epsilon) + Var(\psi) + Var(\phi) + Var(\delta)]}}$$

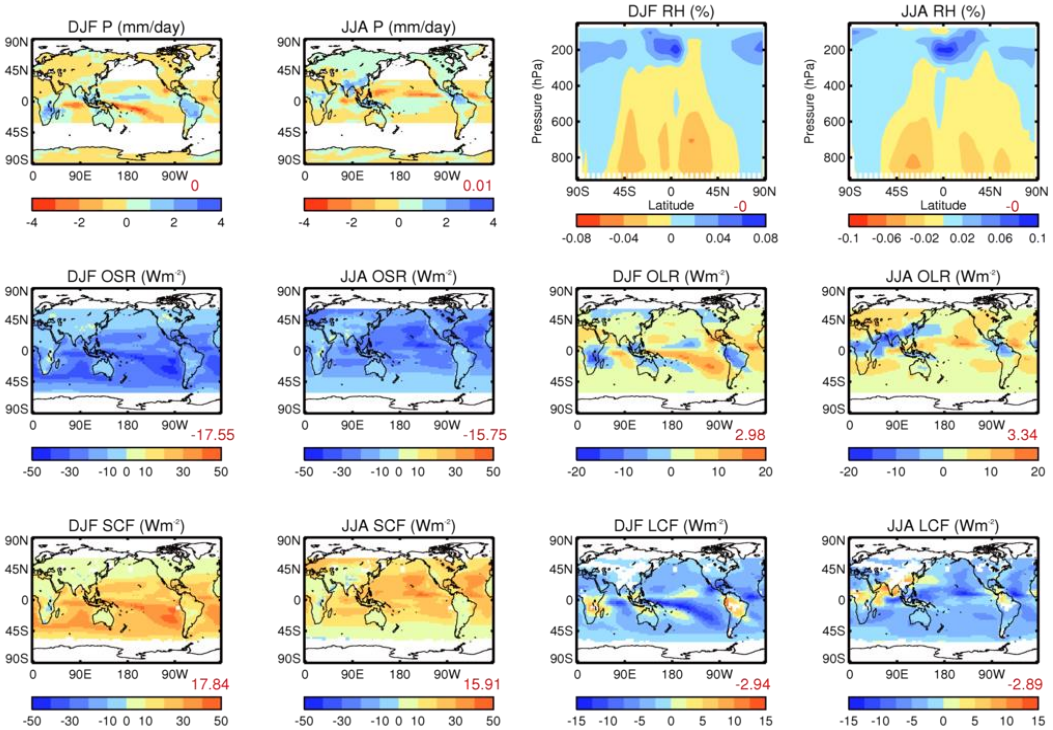
Measurement uncertainty

Representation uncertainty including real-world noise

Model noise

Structural uncertainty (or "discrepancy"

Can use several metrics to constrain climate projections

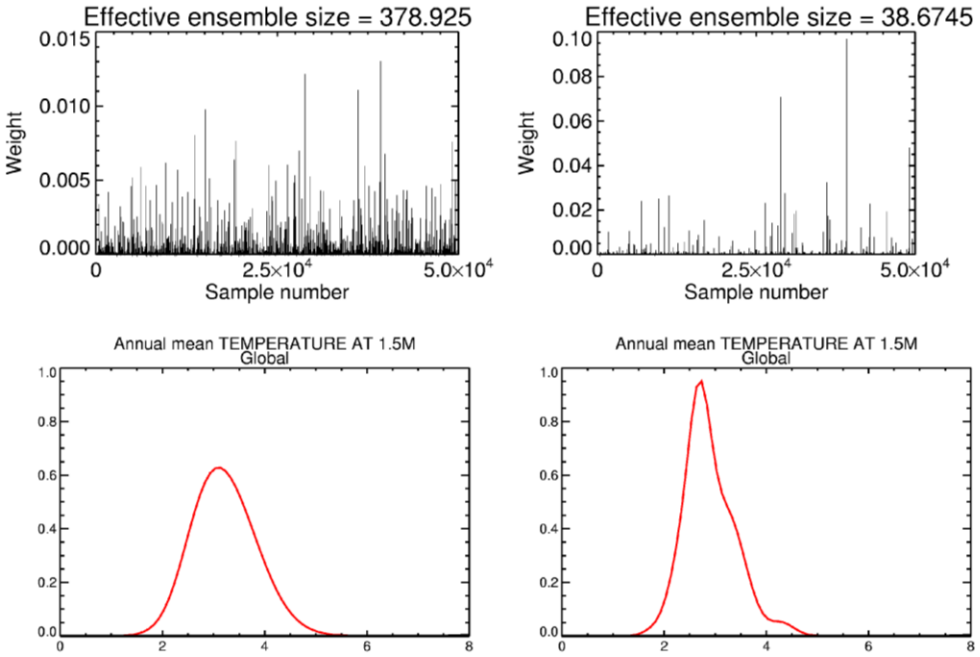


- First of six metrics used in Sexton et al (2012) and UKCP09
- More metrics, less chance for rewarding a poor model
- Where possible use two data sets to represent observational uncertainty from measurements.

Effect of discrepancy on weighting

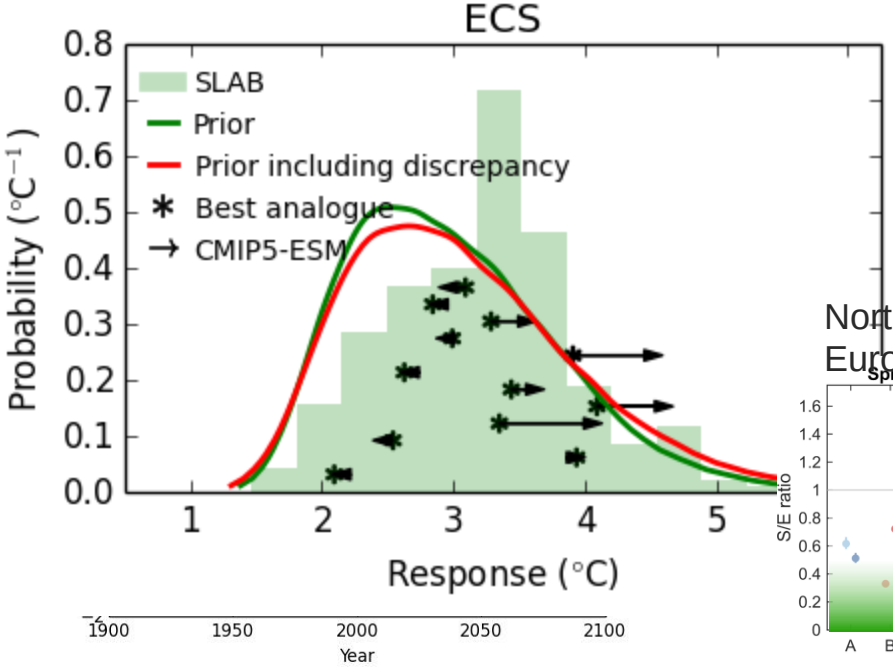
If we do not factor in observational and modelling uncertainties in the implausibility metric, we end up with over-confident projections

Discrepancy included **excluded**

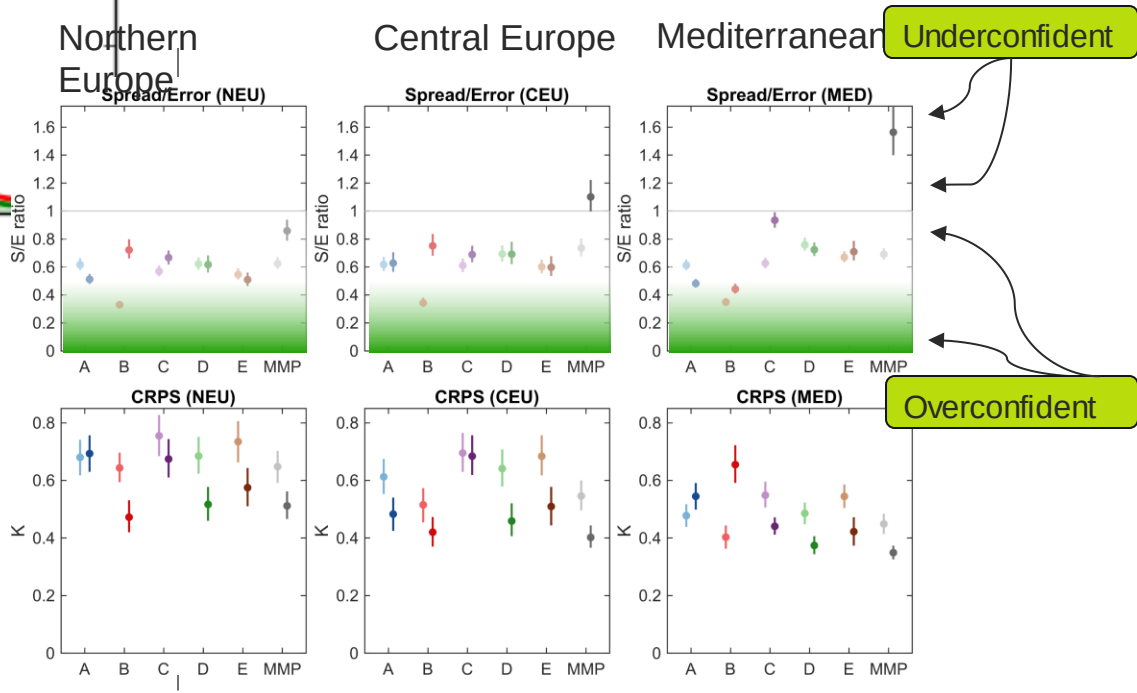


Sexton et al 2012

s from other climate



Out of sample test



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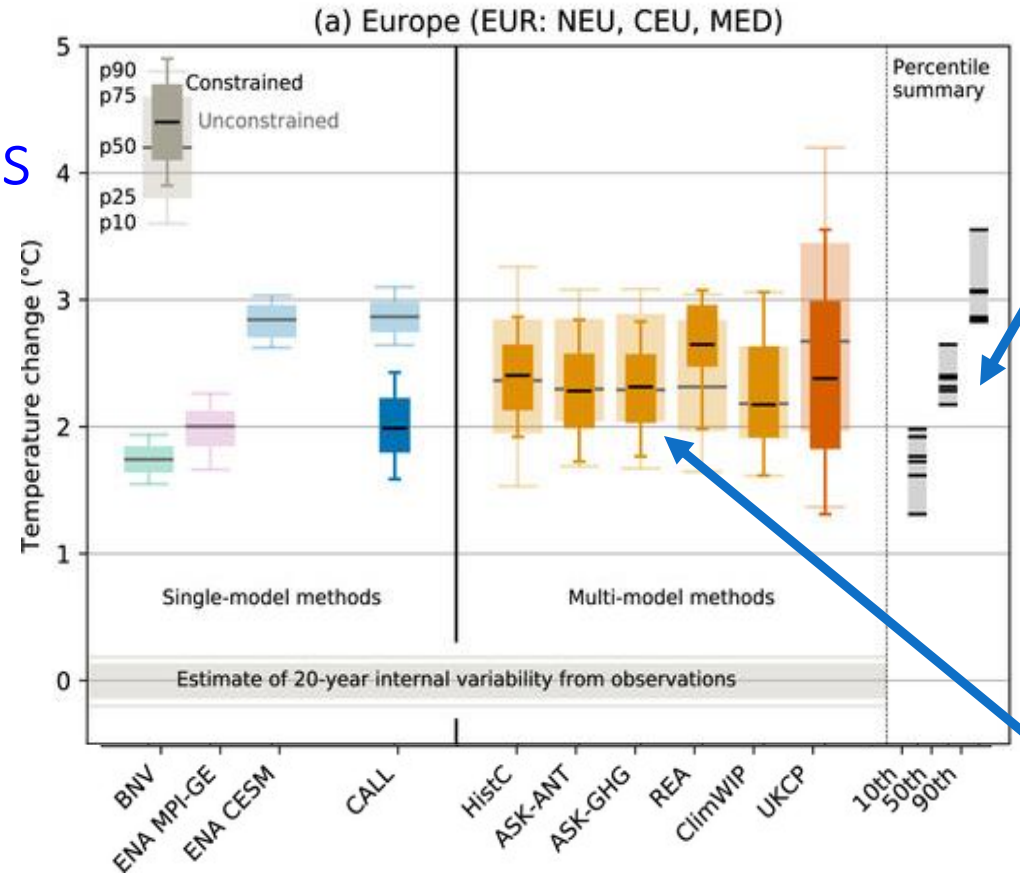
How well are model imperfections represented?

- The inclusion of a discrepancy term is valuable but not a fix.
- If we want the climate projections to be at least usable let alone actionable, we need to understand the limitations.
- Results from higher resolution climate models and the weather expose some limitations…

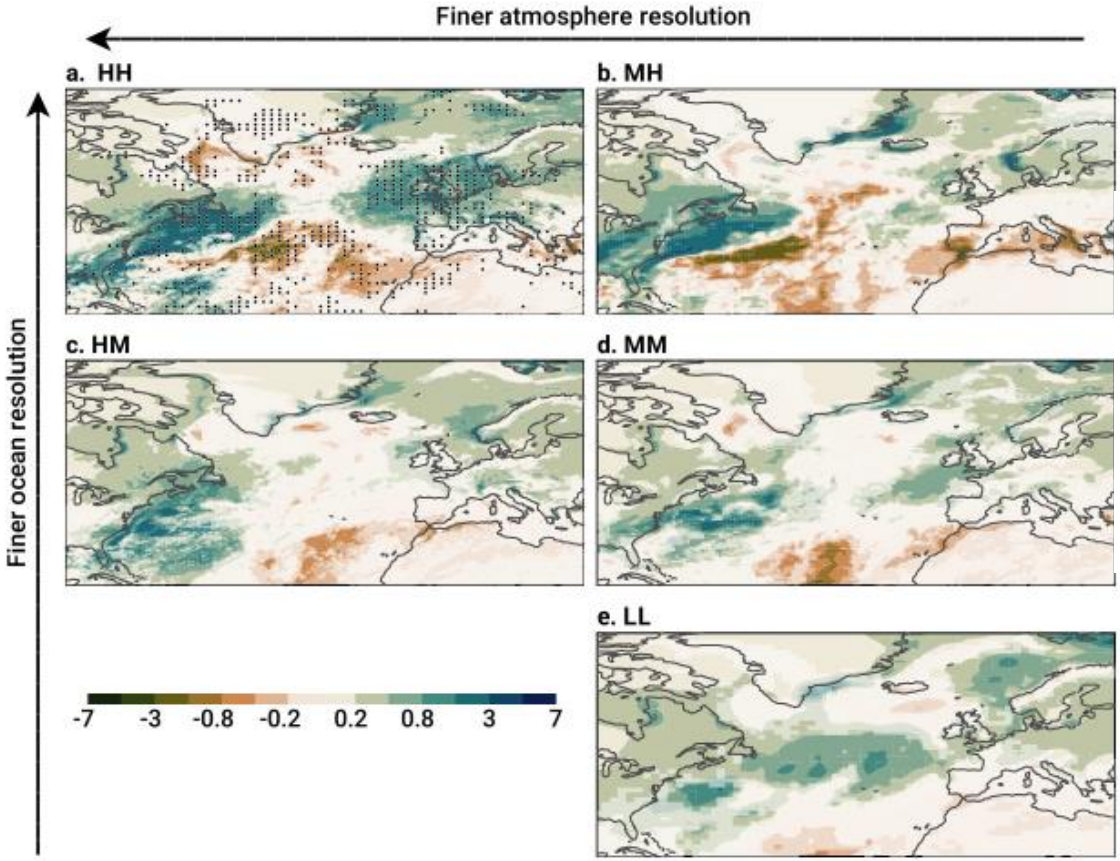
Summer (JJA) temperature change (2041-2060 minus 199

Value of sampling wider uncertainties including discrepancy

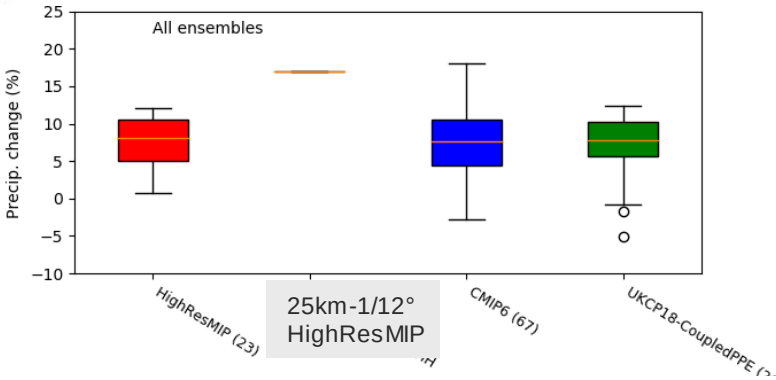


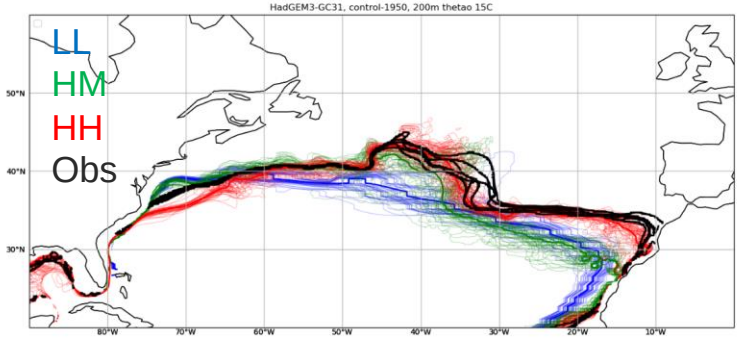
Summary of method uncertainty for 10th, 50th, 90th percentiles

Impact of constraints are diverse! Several shifted down from warmer responses, but also some examples of shift up.
Some much narrower, some little difference!



Rainfall %age change, DJF, 2030-50 - 1960-80
over Europe 20W-30E, 40-65N from different multi-model ensembles

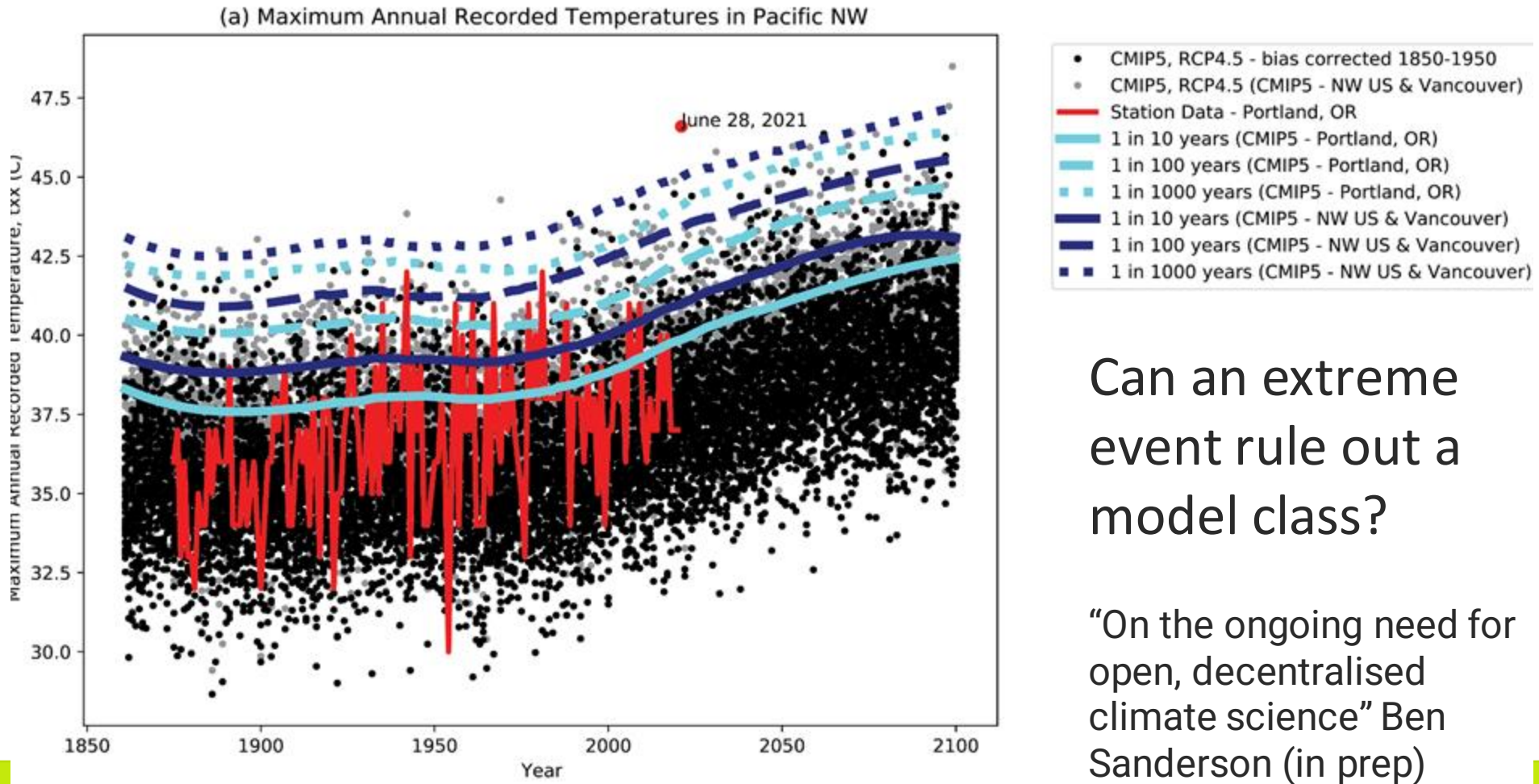




Anomalies in winter precipitation between 2030–2050 and 1960–1980

Stippling in (a) indicates anomalies in HH falling outside a distribution including anomalies from all the other resolutions

Moreno-Chamarro et al., ERL (2021)



Can an extreme event rule out a model class?

"On the ongoing need for open, decentralised climate science" Ben Sanderson (in prep)

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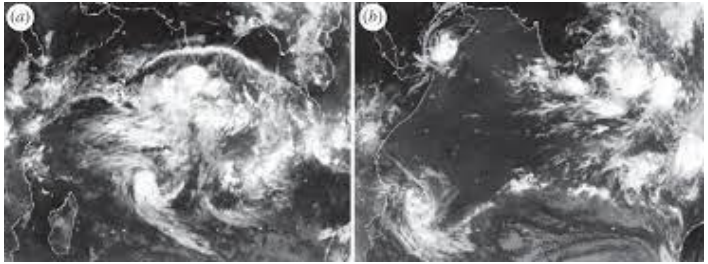
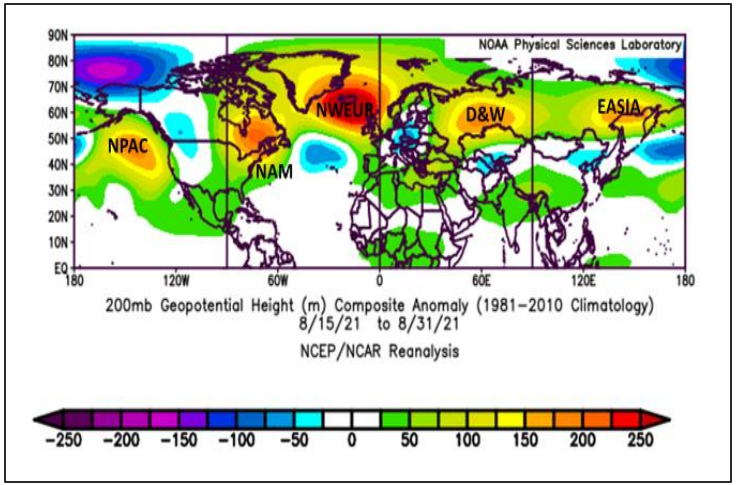
Need for higher resolution simulations…





- And if small scale tropical convection events are having large impact on extratropical circulation patterns causing those extremes…

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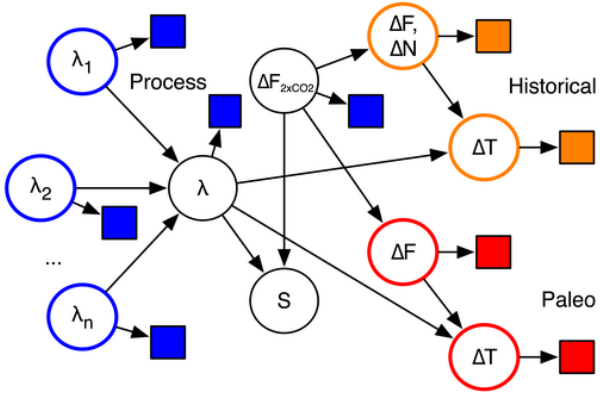
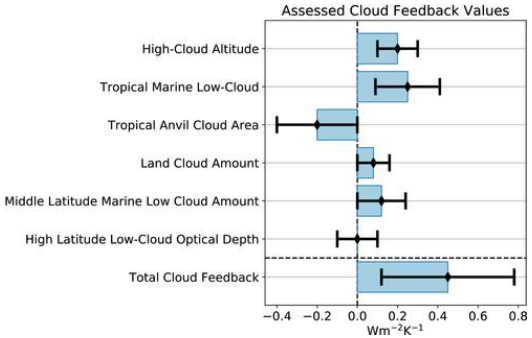
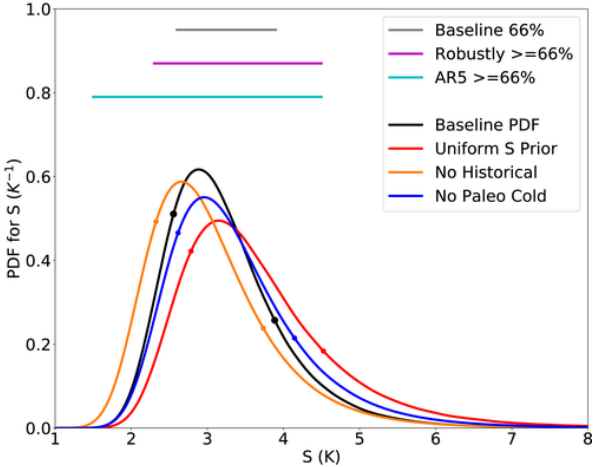
Potential ways forward

- Key is to understand the processes and recognise when key processes in the real weather are not captured by the climate model being used for the projections.
  - better expose it by evaluating the processes
  - do something about it – higher resolution, better scale-aware parameterisations, experimental designs, bias correction

Causal process-based evaluation



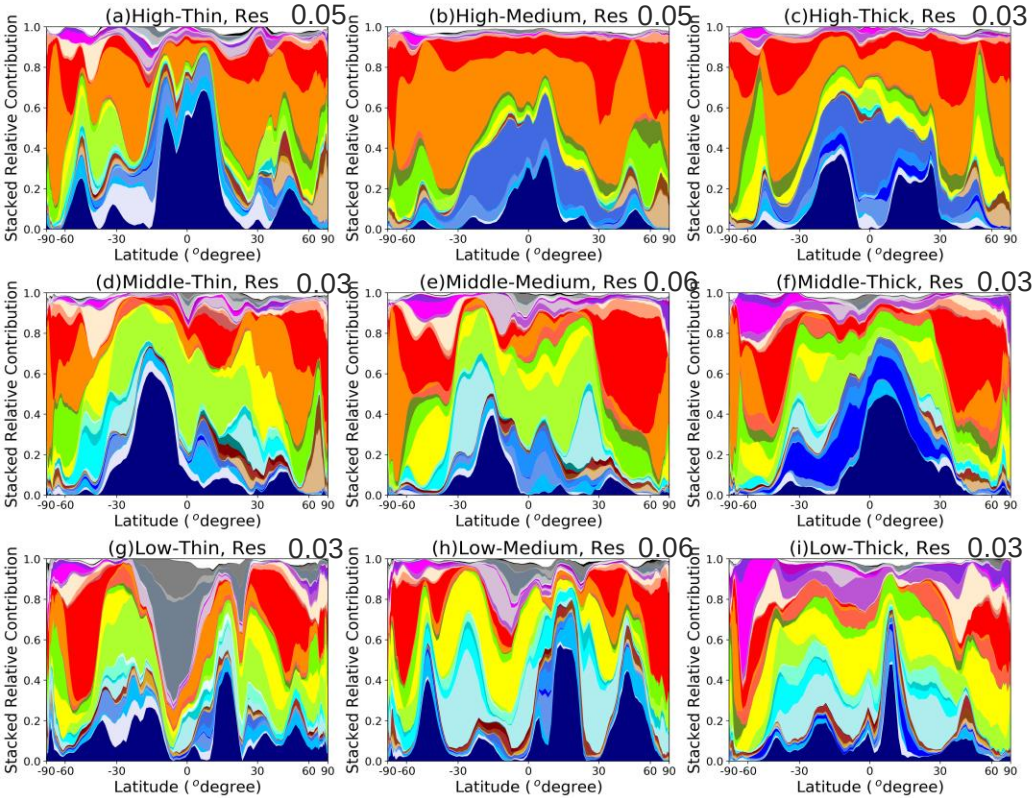




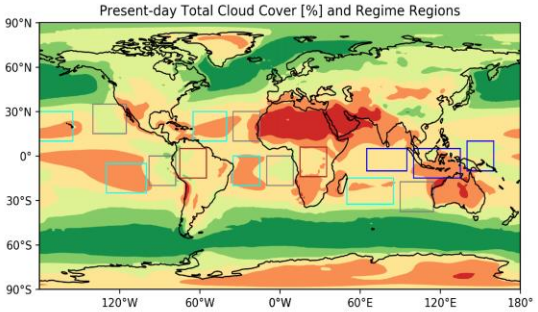
Sherwood et al 2020

Non-targeted constraints

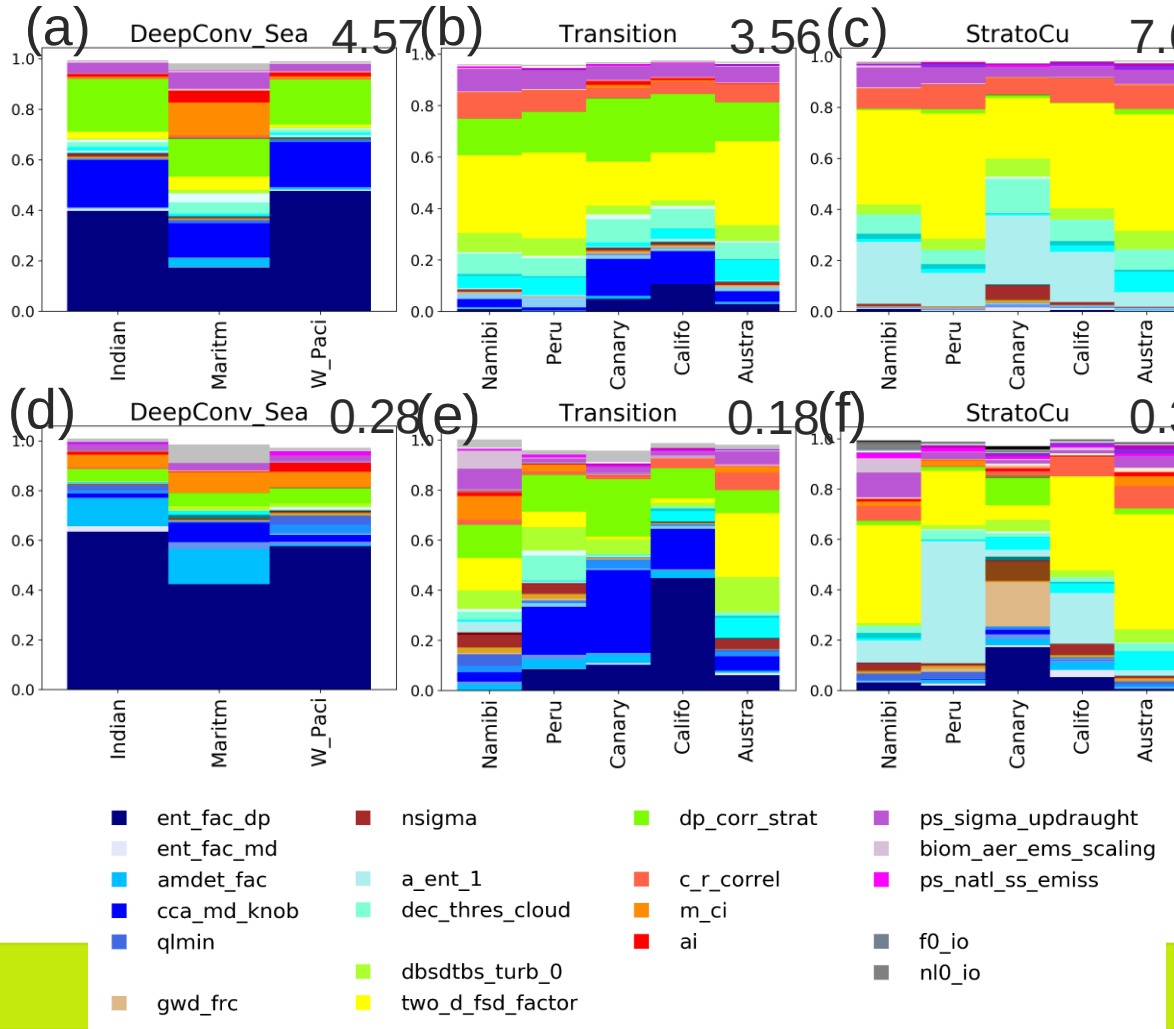
- Tsushima et al 2021 shows fraction of variance explained by different parameters for cloud averaged across longitude shows multiple parameter effects.
- Hard to use this variable to constrain relevant parameters.



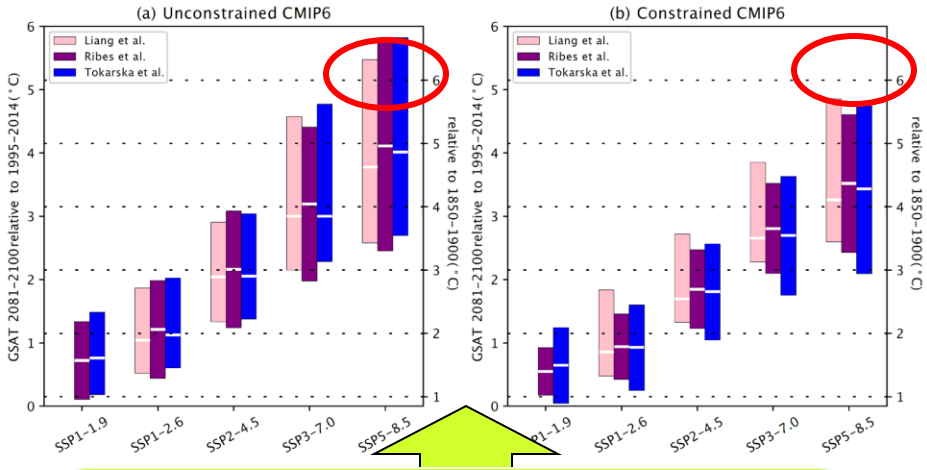
Targeted constraints



- Better to use process-based constraints which more directly measure the impact of the parameter.
- Tsushima et al 2021 shows that considering separate cloud regimes helps to isolate individual parameter effects.



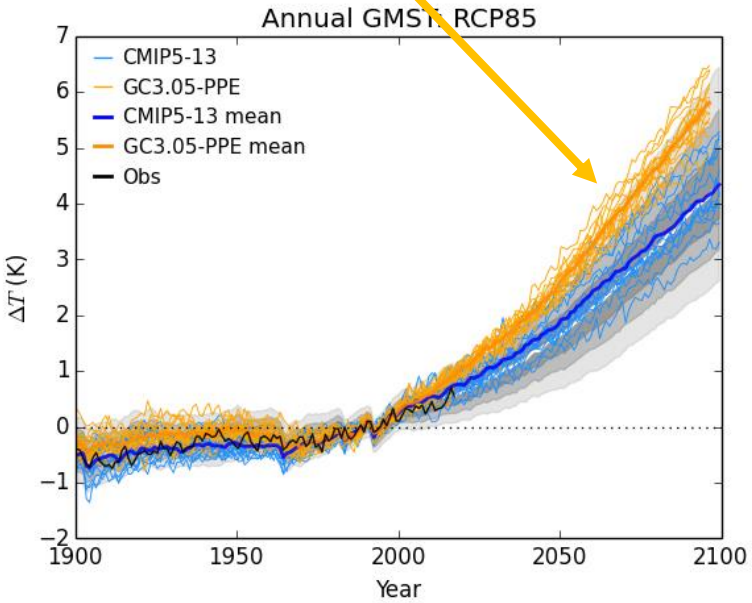
AR6 WG1 – constrained or unconstrained



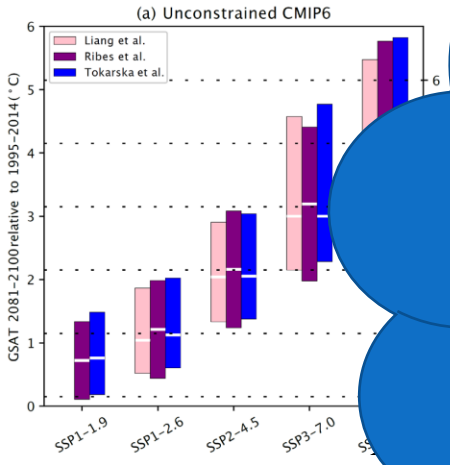
IPCC used constraints to reconcile synthesis global assessment with new CMIP6 simulations

"For the first time in an IPCC report, assessed future changes in global surface temperature, ocean warming and sea level are constructed by combining multi-model projections with observational constraints based on past simulated warming, as well as the AR6 assessment of climate sensitivity." *Summary for Policy Makers, AR6, IPCC*

IPCC WG1 Atlas, however, presents raw, unconstrained CMIP6 ranges. Like UKCP18 projections…



AR6 WG1 – con



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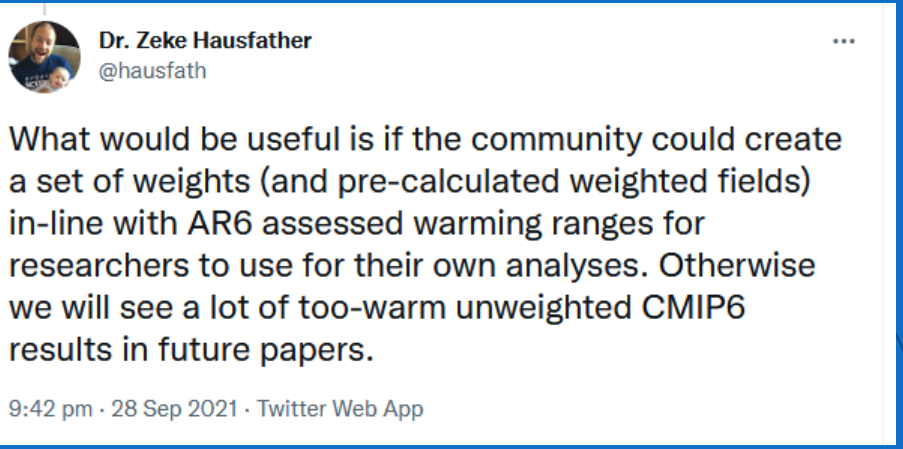
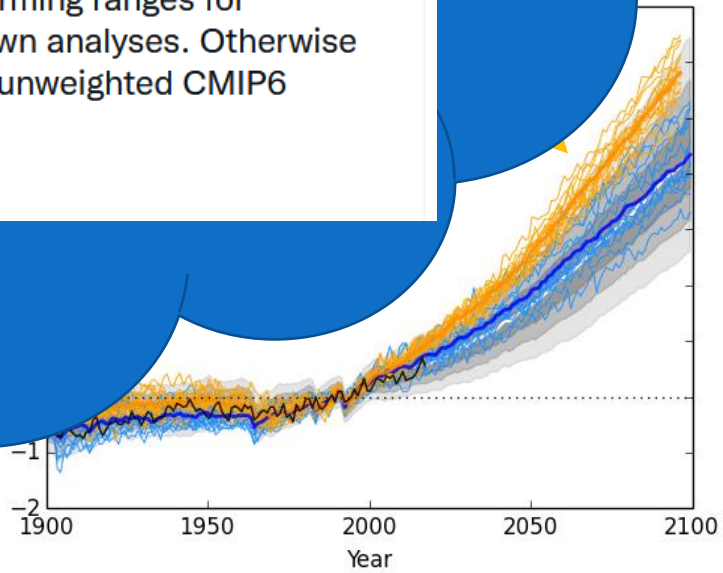


Dr. Zeke Hausfather
@hausfath

What would be useful is if the community could create a set of weights (and pre-calculated weighted fields) in-line with AR6 assessed warming ranges for researchers to use for their own analyses. Otherwise we will see a lot of too-warm unweighted CMIP6 results in future papers.

9:42 pm · 28 Sep 2021 · Twitter Web App

IPCC used constrai
synthesis global assess
new CMIP6 simulations



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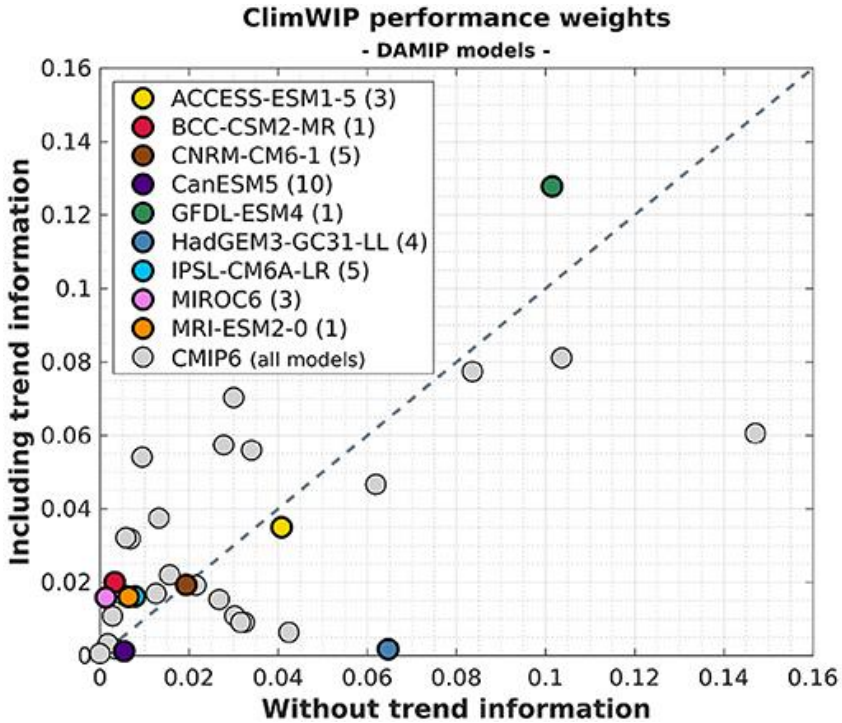
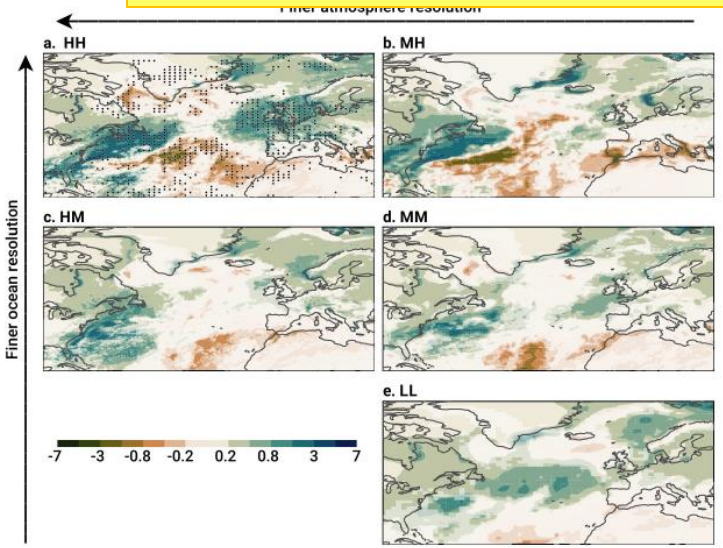
Just weight or bias correct as v

Do we really want to give zero weight to the 'HH' pattern of UK winter rainfall because it warms too fast?





Hegerl et al (2021)

The Implausibility Metric, I

Implausibility

Observations

Model output

Structural bias correction to M

$$I = \frac{|O - M|}{\sqrt{[Var(\epsilon) + Var(\psi) + Var(\phi) + Var(\delta)]}}$$

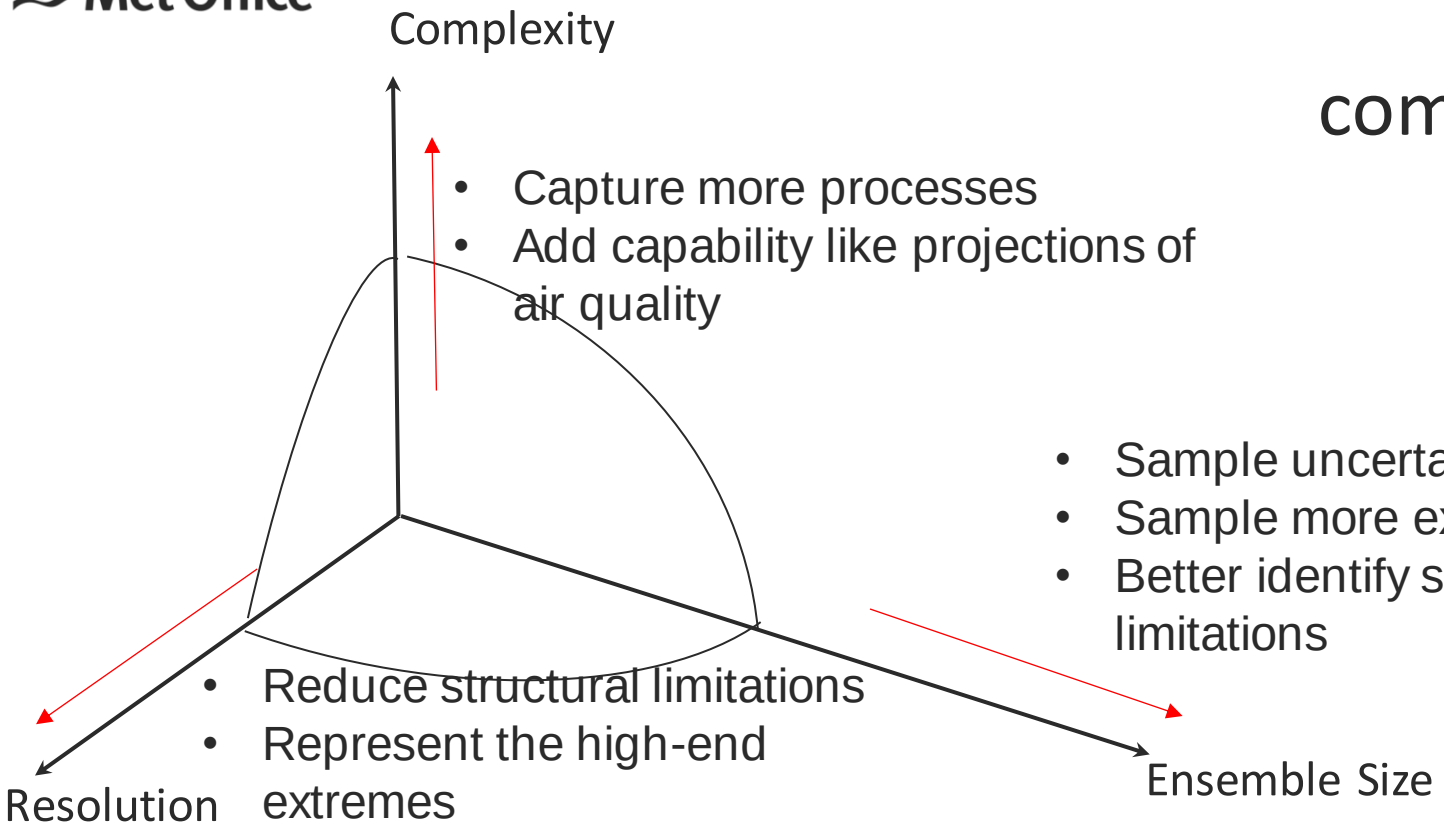
Measurement uncertainty

Representation uncertainty including real-world noise

Model noise

Structural uncertainty (or "discrepancy"

Balancing computational resources



- Capture more processes
- Add capability like projections of air quality

- Sample uncertainty
- Sample more extremes
- Better identify structural limitations

- Reduce structural limitations
- Represent the high-end extremes

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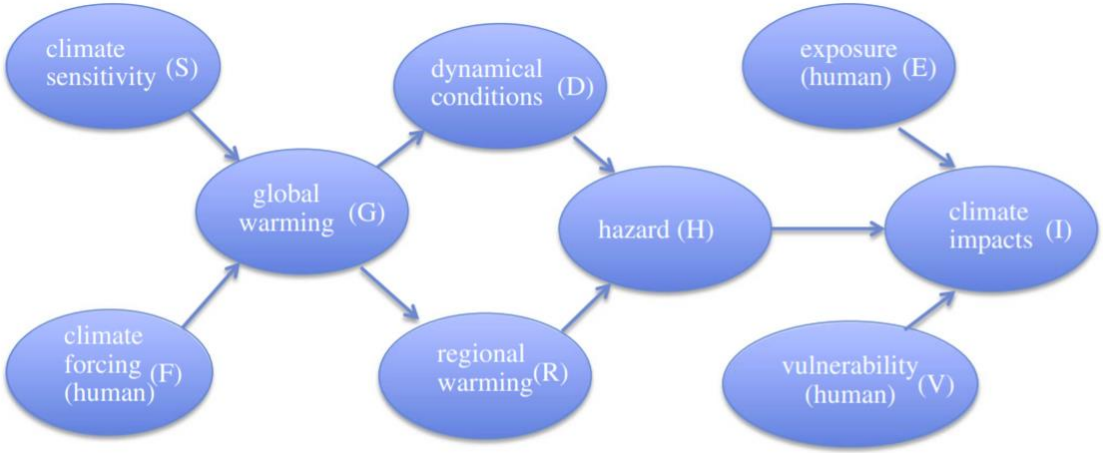
Summary

- Despite the use of a rigorous mathematical framework to capture effects of model imperfection, there are times when the projections do not cover the possible outcomes.
- We need to include process-based observables to constrain and/or bias-correct projections.
- Use process-based evaluation in large ensembles to identify these structural limitations and explain when they might affect the usability of the projection.
- But we also need simulations at very high resolution to cover the limitations.

Backup slides

How do we provide information for climate adaptation before climate models catch up?

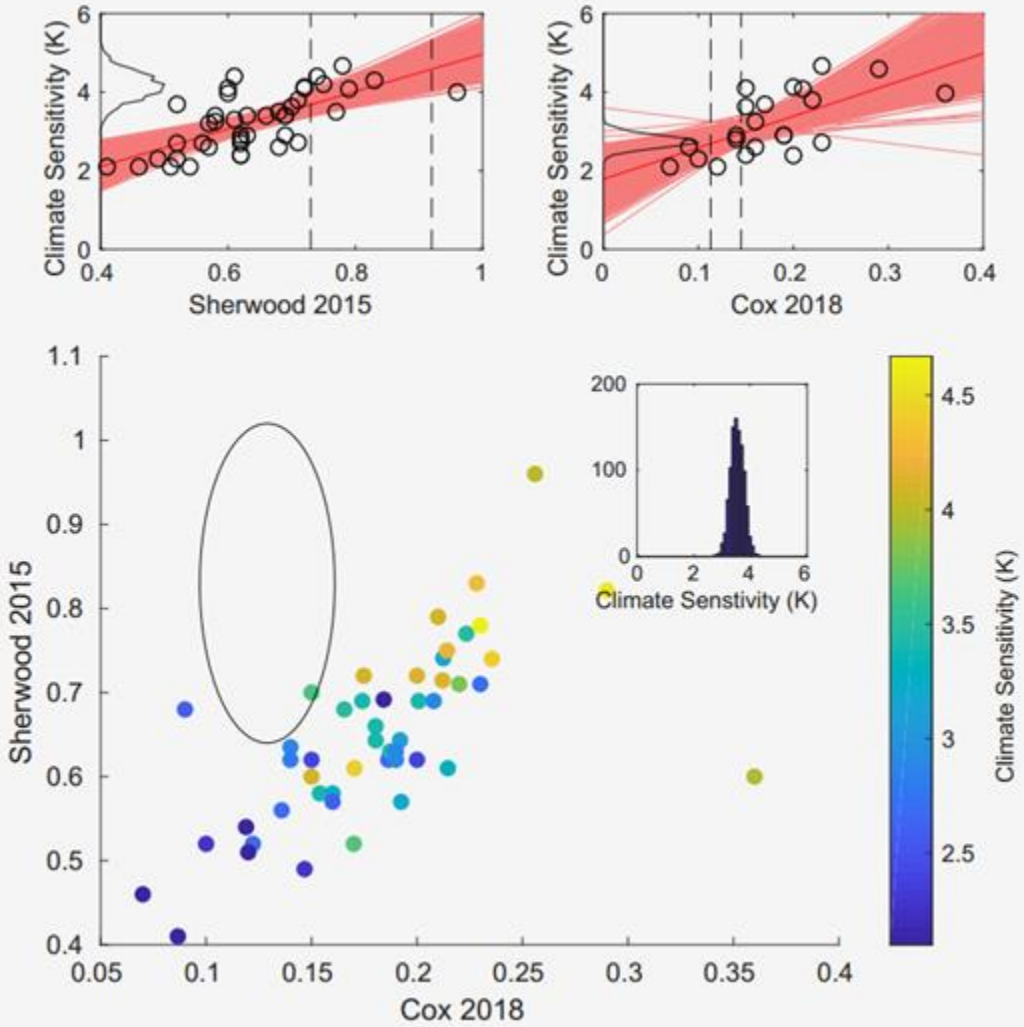


"Causal networks can provide the diagnostic framework within which to extract the relevant climate information from simulations, and combine it with other sources of information in a format that is suitable for decision-making." Shepherd (2019)

Causal Network describing regional climate risk from Shepherd (2019): causal networks allow us to combine expert knowledge with probability

More Diversity

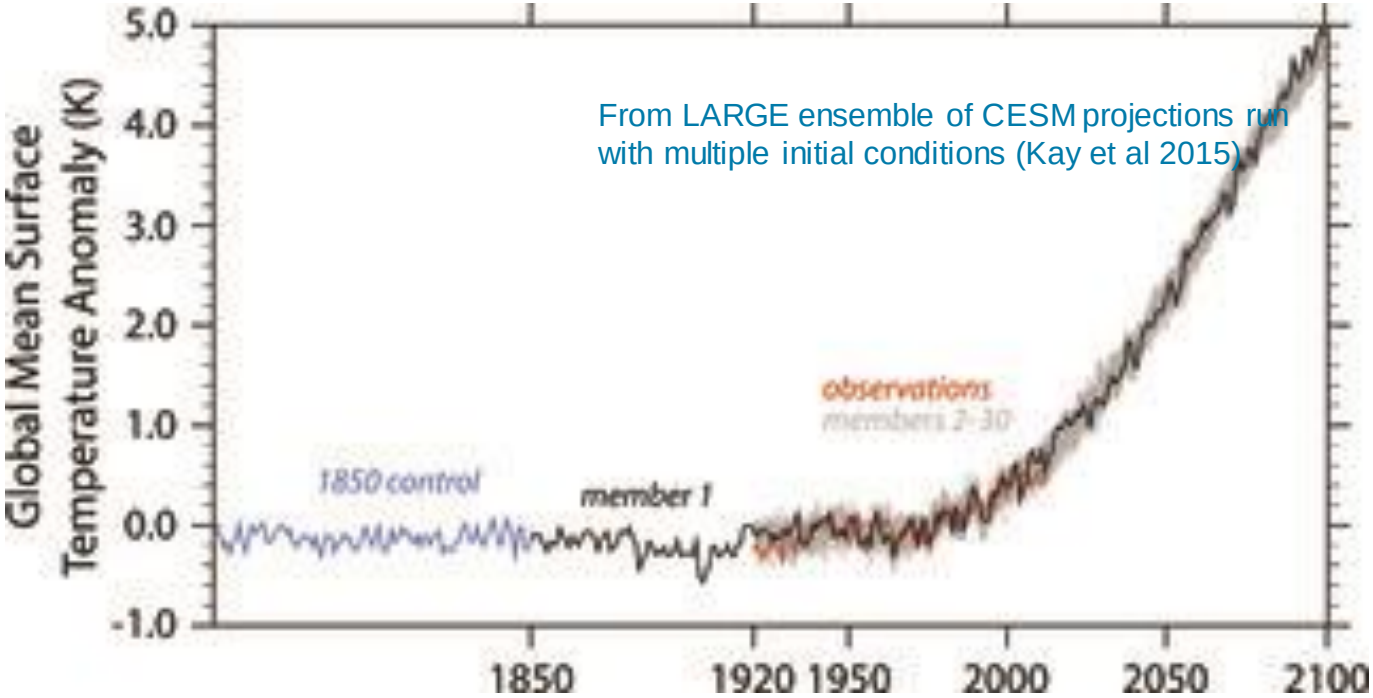
But we should be wary of weighting models on a single line of evidence



Sanderson, B. M., Pendergrass, A. G., Koven, C. D., Brient, F., Booth, B. B., Fisher, R. A., & Knutti, R. (2021). The potential for structural errors in emergent constraints. *Earth System Dynamics*, *12*(3), 899-918.

Signal and noise

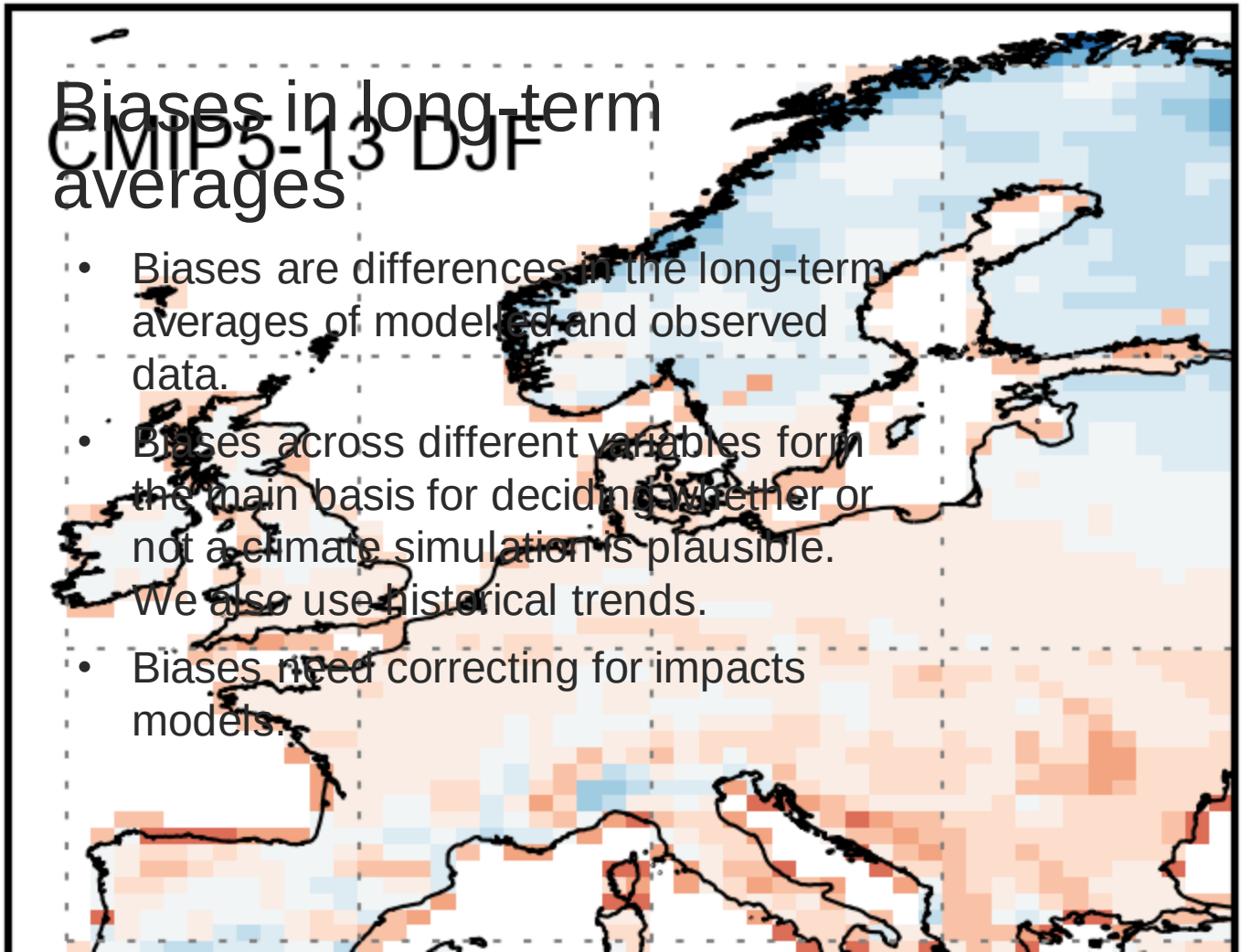
- Both real world and climate models have inherent variability due to chaotic nature of climate system.
- Simulations not designed to reproduce real-world noise, just the real-world signal.
- Models are imperfect and have structural differences caused by approximations and missing processes common to all our models

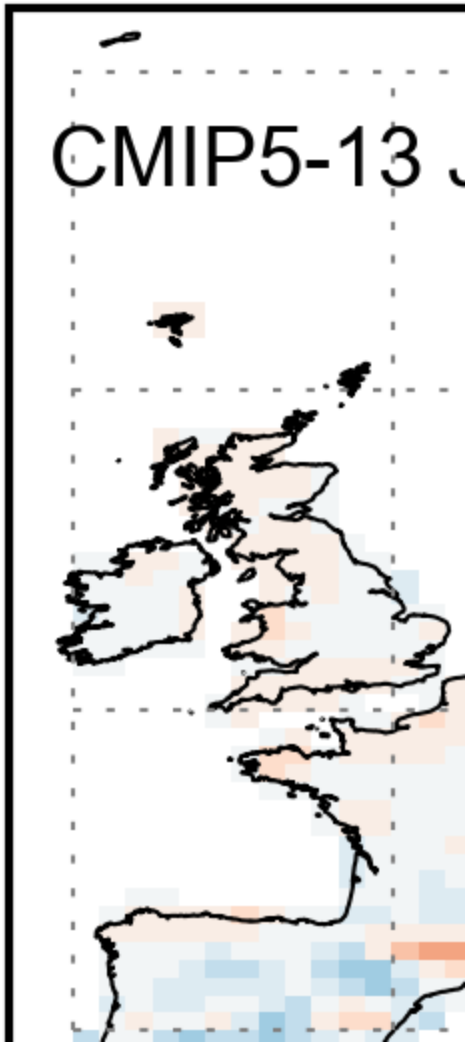


From LARGE ensemble of CESM projections run with multiple initial conditions (Kay et al 2015)

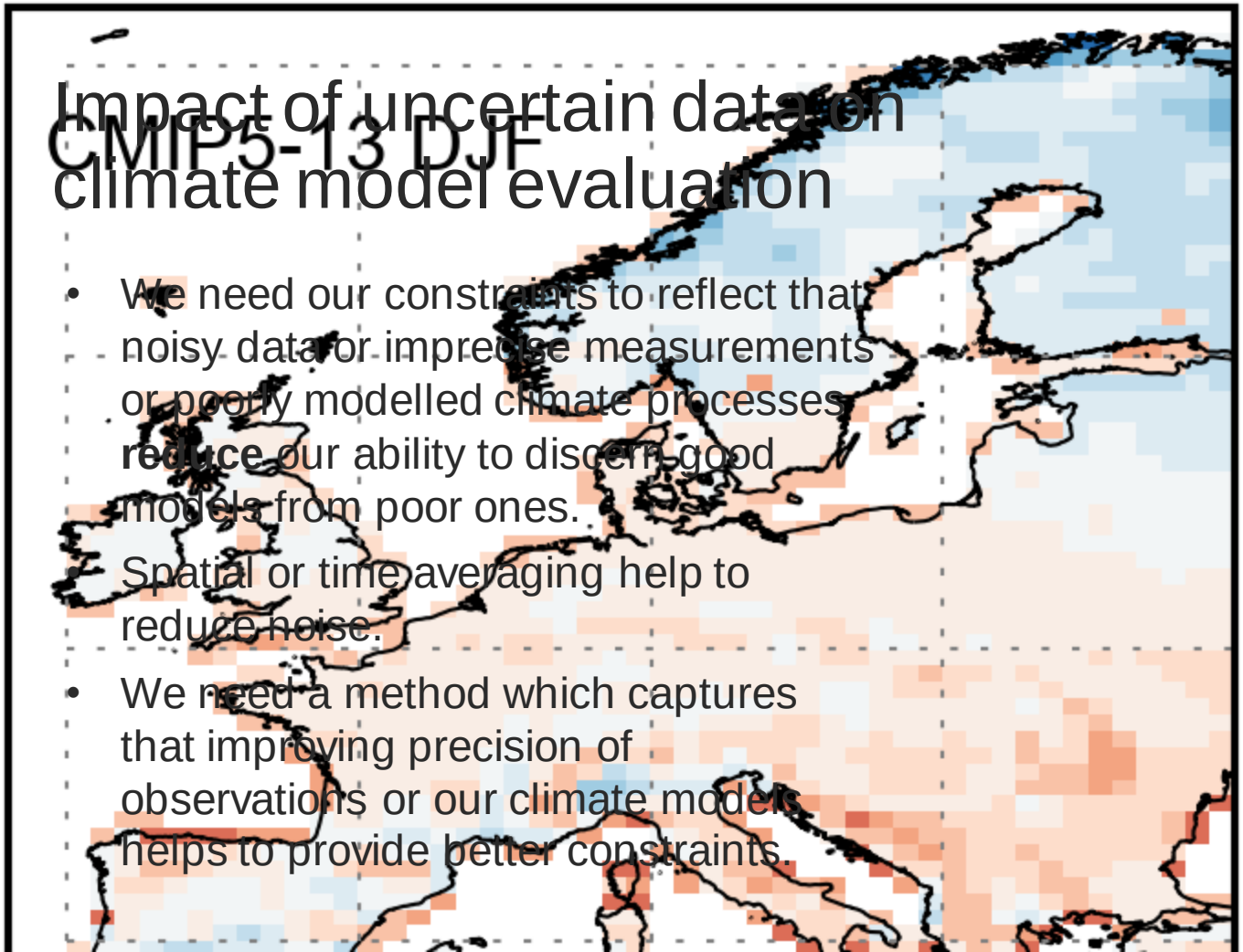
Biases in long-term averages

- Biases are differences in the long-term averages of modelled and observed data.
- Biases across different variables form the main basis for deciding whether or not a climate simulation is plausible. We also use historical trends.
- Biases need correcting for impacts models.

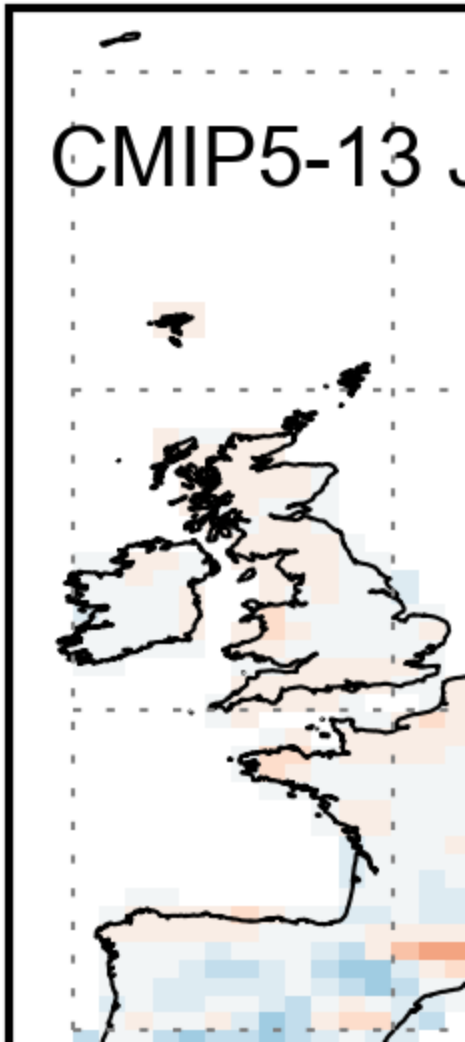




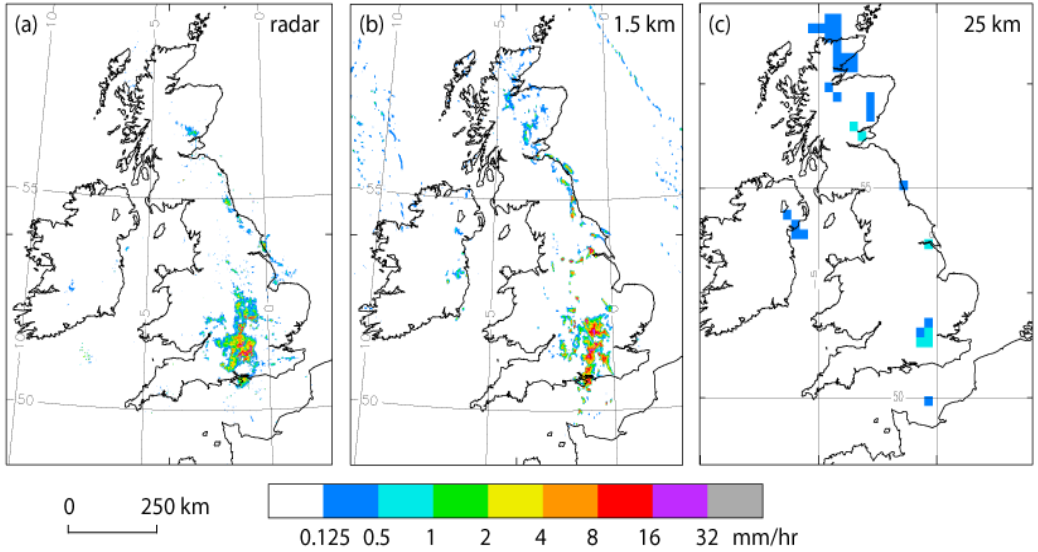
Impact of uncertain data on climate model evaluation



- We need our constraints to reflect that noisy data or imprecise measurements or poorly modelled climate processes **reduce** our ability to discern good models from poor ones.
- Spatial or time averaging help to reduce noise.
- We need a method which captures that improving precision of observations or our climate models helps to provide better constraints.



Qualitative comparisons with observations to build confidence in climate simulations



Mesoscale convective system at 0000 UTC 14 June 2014. (Clark et al, 2016, Meteorological Applications)

- In general, the radar data provide reliable information on the spatial patterns and temporal characteristics of rainfall.
- We have lower confidence in the absolute rainfall amounts especially for intense events and for hail events. Rain gauges are trusted more for rainfall intensity.

Harrison et al, 2000