

D8.2: Emergent constraints on climate sensitivities

Mark Williamson¹

Chad Thackeray², Peter Cox¹, Alex Hall², Chris Huntingford³ and Femke Nijse⁴

¹CEMPS & GSI, University of Exeter

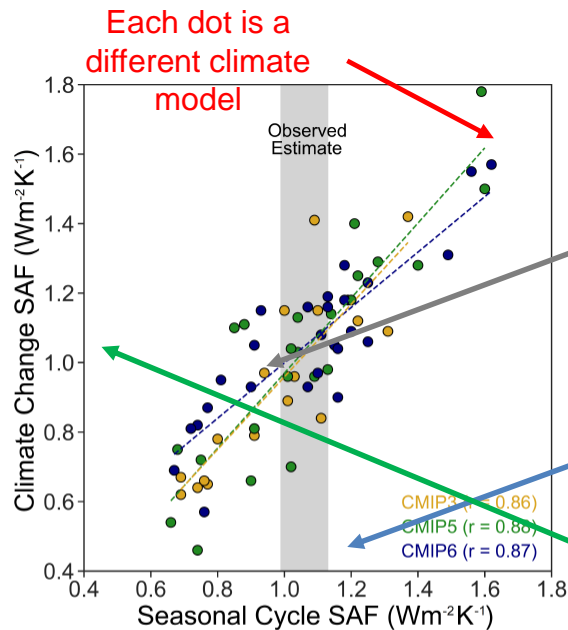
²Atmos & Ocean Sci, UCLA

³CEH Wallingford

⁴CLES & GSI, University of Exeter

What are emergent constraints?

A method to constrain a real world unknown using model ensembles and observations



Emergent relationship: Low dimensional relationships in model ensembles between something that one can measure in the real world (trend or variation, x axis) and something you want to know for the real world (Earth system sensitivity, y axis)

Observable measured in real world

Emergent constraint: Emergent relationship combined with value of observable in real world implies a constraint on real world value of Earth system sensitivity

Snow albedo feedback (SAF) - Hall, A. & Qu, X. Using the current seasonal cycle to constrain snow albedo feedback in future climate change. *Geophysical Research Letters* **33** (2006).

Emergent constraints found

Since the snow albedo feedback emergent constraint many more have been found.

Emergent constraints on:

- Climate sensitivity
- Carbon cycle
- Cloud feedbacks
- Cryosphere
- Hydrological cycle

Comprehensive table in **Rev. Mod. Phys.**
(in press)/arXiv:2012.09468.

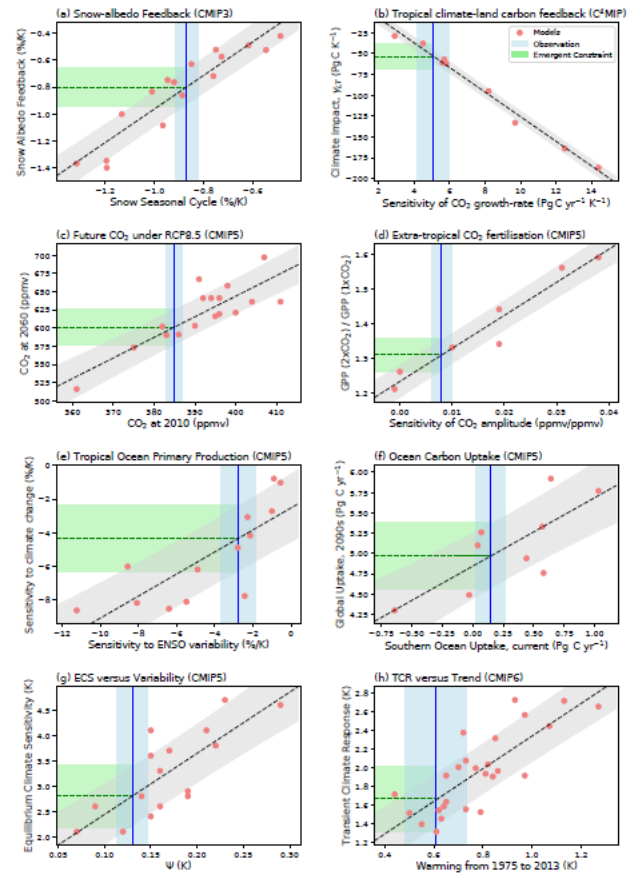


FIG. 3 Emergent constraints on Earth System sensitivities based on some key examples published in the literature: (a) snow-albedo feedback, from snow seasonal cycle (Hall and Qu, 2006); (b) sensitivity of tropical land carbon to global warming, from interannual variability in CO₂ (Cox et al., 2013); (c) atmospheric CO₂ concentration at 2060, from atmospheric CO₂ concentration at 2010 (Hoffman et al., 2014); (d) CO₂ fertilization of plant photosynthesis, from changes in the seasonal cycle of CO₂ (Wenzel et al., 2016); (e) sensitivity of tropical ocean primary production to warming, from interannual variability (Kwiatkowski et al., 2017); (f) global ocean carbon sink in the 2090s, from the current day carbon sink in the Southern Ocean (Kessler and Tjiputra, 2016); (g) Equilibrium climate sensitivity, from interannual variability of temperature (Cox et al., 2018a); (h) Transient climate response, from increase in global mean temperature (Nijse et al., 2020). In each case the emergent constraint was reconstructed from data available in the literature or provided directly by the authors. The model ensemble used in each original study is shown in the brackets after the panel title.

How might (low) dimensional emergent relationships appear in ensembles of complex models?...

...given climate models (and the real world) have very high dimensional parameter spaces and their responses are generally functions of all these parameters?

Null hypothesis: They occur by chance and are not indicative of a deeper, predictive mechanistic relationship – This is a real danger in small ensembles of models with large numbers of outputs (Caldwell et al, 2014)

- Dangers of data mining and p -hacking
- Statistical errors/assumptions

Non-null hypothesis (!): They are indicative of an approximate, deeper mechanistic relationship

- Certain responses may be dominated by a few degrees of freedom – effective dimension reduction.
- Can happen when a particular response becomes sensitive (close to an instability for example) or when the range of values of one process in the model ensemble is large relative to the other processes controlling that response.
- Other parameters are relatively weakly coupled to that response.

How might ECs go wrong and how to guard against it?

- **Chance relationships:** Guard against using predictive theoretical basis for emergent relationships that can be independently falsified
- **Overconfidence in constraints:** Guard against by taking into account all sources of uncertainty
- **Missing processes/feedbacks in latest models**
- **Compensating errors in models**
- **Errors in observations/observations not directly comparable to model outputs**

Emergent constraints can be a powerful tool to reduce uncertainty and promote understanding of the important processes in a variety of climate projections provided one is aware of the possible pitfalls

Awareness and understanding of these pitfalls should lead to EC research becoming more rigorous and more useful

Emergent constraints on climate sensitivities

Mark S. Williamson,^{1,2} Chad W. Thackeray,³ Peter M. Cox,¹ Alex Hall,³ Chris Huntingford,⁴ and Femke J. M. M. Nijssen¹

¹College of Engineering,
Mathematics and Physical Sciences,
University of Exeter,
UK

²Global Systems Institute,
University of Exeter,
UK

³Department of Atmospheric and Oceanic Sciences,
University of California,
Los Angeles, CA,
USA

⁴Centre for Ecology and Hydrology, Wallingford,
UK

(Dated: December 29, 2020)

Despite major advances in climate science over the last 30 years, persistent uncertainties in projections of future climate change remain. Climate projections are produced with increasingly complex models which attempt to represent key processes in the Earth system, including atmospheric and oceanic circulations, convection, clouds, snow, sea-ice, vegetation and interactions with the carbon cycle. Uncertainties in the representation of these processes feed through into a range of projections from the many state-of-the-art climate models now being developed and used worldwide. For example, despite major improvements in climate models, the range of equilibrium global warming due to doubling carbon dioxide still spans a range of more than three. Here we review a promising way to make use of the ensemble of climate models to reduce the uncertainties in the sensitivities of the real climate system. The emergent constraint approach uses the model ensemble to identify a relationship between an uncertain aspect of the future climate and an observable variation or trend in the contemporary climate. This review summarises previous published work on emergent constraints, and discusses the huge promise and potential dangers of the approach. Most importantly, it argues that emergent constraints should be based on well-founded physical principles such as the fluctuation-dissipation theorem. It is hoped that this review will stimulate physicists to contribute to the rapidly-developing field of emergent constraints on climate projections, bringing to it much needed rigour and physical insights.

CONTENTS

I. Introduction	2	2. Linearly-increasing forcing	12
II. How relationships in model ensembles might ‘emerge’	4	3. White-noise forcing	12
A. Commonly used ESM ensembles: Multi-model (MME) and perturbed physics (PPE) ensembles	6	IV. How might emergent constraints go wrong and how to guard against it?	12
B. Null hypothesis: Emergent relationships occur by chance	6	A. Risks of purely using data mining	12
C. Low dimensional relationships ‘emerge’ from high dimensional ESMs	7	B. The risk of p-hacking and overconfidence	13
D. Range in response due to the same physical process having a wide range across ESMs	9	C. Missing process in all current models, measurement errors and model compensating errors	13
E. What is needed for an EC?	9	D. System passes through a tipping point	14
1. Observable (X) range and uncertainty	9	E. Problems with common code across many models and implications for ‘out-of-sample’ testing	15
2. Response (Y) range and uncertainty	9	F. What to do when different ECs are found for the same quantity, but differ in value, or differ between ensembles?	15
3. Relationship between X and Y	9	G. ECs may cause future CMIP-type climate model ensembles to have much less spread in projections	16
4. Large ensemble size n	10	H. Inability to verify an EC	16
III. Underlying theory for emergent constraints based-on temporal variability	10	I. Lack of perturbed physics experiments with ESMs	17
A. Relationships between variability of fluxes and the sensitivity of stores	11	V. Emergent constraints found in the Earth system	17
B. Theoretical emergent relationships for idealised time-varying forcing	11	A. Equilibrium Climate Sensitivity	18
1. Sinusoidal forcing	11	B. Cloud Feedbacks	20
		C. Carbon Cycle	20
		D. High-latitude Processes	22
		E. Hydrologic Cycle	22

VI. Statistical underpinnings	25
A. Uncertainty in observations	26
B. Uncertainty from internal variability	26
C. Uncertainty in the functional form of the relationship	26
D. Uncertainty from imperfect models	27
E. Combining sources of uncertainty in an EC	27
F. Combining multiple constraints	28
VII. Outlook	28
A. Key gaps in ECs to date	28
B. Targeted model development	29
C. Use of conceptual models as the basis of emergent relationships and understanding of more complex ESMs	29
D. Multidimensional ECs and nonlinear emergent relationships	30
E. Continued improvement of climate projections and impacts-led requirements	30
F. Better understanding of the effects of parametric and structural uncertainty on ECs	30
G. Machine Learning	30
H. Building connections to other fields	31
VIII. Conclusion	32
Acknowledgments	32
References	32

I. INTRODUCTION

Numerical methods have become a standard technique to simulate complex systems. The equations governing components of such systems may be well-known. But their solutions cannot be solved analytically, creating a need for numerical approaches. Because of the discretization of time and space inherent in numerical techniques, modelling complex systems must involve ways to include effects of unresolved processes. Often there is no ‘first principles’ approach to do this. Typically, the effects of unresolved processes are included by resorting to quasi-empirical relationships between them and explicitly-resolved variables, otherwise known as ‘parameterization’. There are usually multiple defensible ways to parameterize unresolved processes. Thus, independently developed models of the same complex system might incorporate different parameterization choices. The more models that are independently developed, the greater the diversity of approaches for modelling the same natural system.

A classic example of this model diversity is the use of numerical models of the atmosphere to predict hurricane development. Initial conditions are imposed on a model at some time, and it is integrated forward in time to produce simulations of critical hurricane features such as intensity and track. This approach might be replicated for multiple models incorporating different parameterization choices, producing an ‘ensemble’ of hurricane forecasts. The spread in the forecasts is a measure of the uncertainty in the future hurricane behaviour, given the range

of plausible approaches to atmospheric time, with enough hurricanes and associated variables that the various models can be evaluated for skill. Certain parameterization choices producing systematically better predictions can then be rebuilt or re-calibrated choices. Over time the ensemble will be full, with less spread. In fact, this is a process that has resulted in dramatic improvement only in hurricane prediction, but in weather generally over the past seven decades.

Earth’s climate is another example of a system whose governing equations can only be solved by numerical methods. (In fact, the dynamics for the atmospheric component of a climate system are typically almost identical to those in the models referred to above.) As expected, there are a number of plausible approaches to parameterizing components of Earth system models (ESMs) that have been used by modelling groups throughout the world have used ESMs with different approaches to parameterization. Because of these differences, these models produce different future climate states, even when the same radiative forcing is imposed (associated, for example, with an increase in greenhouse gases).

A classic climate change experiment is to simulate future concentrations in the atmospheric component of a model and measure the surface warming that results. A simulation has equilibrated (Manabe *et al.*, 1975), an important number in climate science is the equilibrium climate sensitivity (ECS), the change in equilibrium with a full complexity ESM in response to a computationally expensive simulation of a doubling of CO₂ so ECS is usually estimated from CO₂ doubling experiments. When these experiments are done with contemporary ESMs, the spread in ECS across the ensemble of ESMs is large, typically 1 to 6 degrees Celsius (Forster *et al.*, 2019). The median ECS across the ensemble is higher (median ECS is 3.3 degrees Celsius (Riahi *et al.* (2020))). The international climate community has organised itself to generate a common greenhouse gas (GHG) emissions that would result in a realistic future radiative forcing than the current scenario. These correspond to scenarios (RCPs) that lack thereof) on future GHG emissions (Riahi *et al.*, 2017). The scenarios are

¹ State-of-the-art climate models are also called general circulation models (GCMs). This was the case in the past when they consisted of just an atmosphere and a mixed layer ocean. As time has progressed and more components have been included the term ESM has become more common. An ESM may have referred to models of only the atmosphere (featuring a carbon cycle). In this review we use the term ESM to mean a full complexity dynamical state-of-the-art climate model although this could be used interchangeably.

Summary

- Emergent constraints can be a powerful tool to reduce uncertainty and promote understanding of the important processes in a variety of climate projections provided one is aware of the possible pitfalls
- Awareness and understanding of these pitfalls should lead to EC research becoming more rigorous and more useful
- One way to make ECs more rigorous is to base them on testable, simplified models
- This should also allow a better understanding of the important processes in complex climate models and ultimately the real world
- These models imply a fundamental link between climate sensitivity, climate variability and climate trends

Williamson, M.S., Thackeray, C. W., Cox, P. M., Hall, A. Huntingford, C., & Nijse, F. M. M. Emergent constraints on climate sensitivities, Rev. Mod. Phys. (in press) and arXiv:2012.09468.