





Beyond Forcing Scenarios: Predicting Climate Change through Response Operators in a Coupled General Circulation Model

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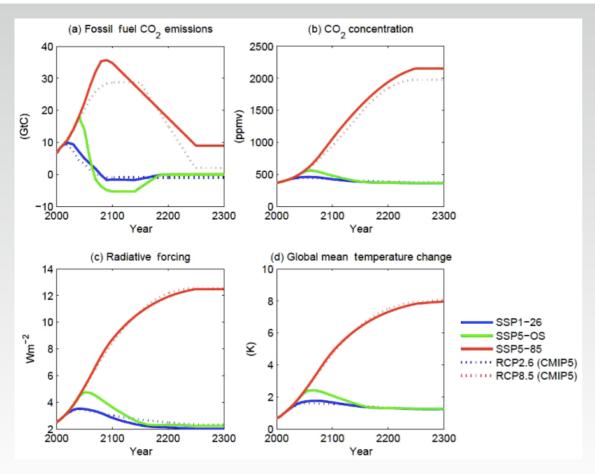




An increasing number of climate model simulations, based on different forcing scenarios...

Experiment	CMIP6 label	Experiment description	Forcing methods	Start	End	Minimum	Major purpose
short name				year	year	no. years per simulation	
DECK experime	nts						
AMIP	amip	Observed SSTs and SICs prescribed	All; CO ₂ concentration prescribed	1979	2014	36	Evaluation, variability
Pre-industrial control	piControl or esm-piControl	Coupled atmosphere- ocean pre-industrial control	CO ₂ concentration prescribed or calculated	n/a	n/a	500	Evaluation, unforced variability
Abrupt quadrupling of CO ₂ concen- tration	abrupt-4×CO2	CO ₂ abruptly quadru- pled and then held constant	CO ₂ concentration prescribed	n/a	n/a	150	Climate sensitivity, feedback, fast responses
1 % yr ⁻¹ CO ₂ concentration increase	1pctCO2	CO ₂ prescribed to increase at 1 % yr ⁻¹	CO ₂ concentration prescribed	n/a	n/a	150	Climate sensitivity, feedback, idealized benchmark
CMIP6 historica	l simulation						
Past ~ 1.5 centuries	historical or esm-hist	Simulation of the recent past	All; CO ₂ concentration prescribed or calculated	1850	2014	165	Evaluation

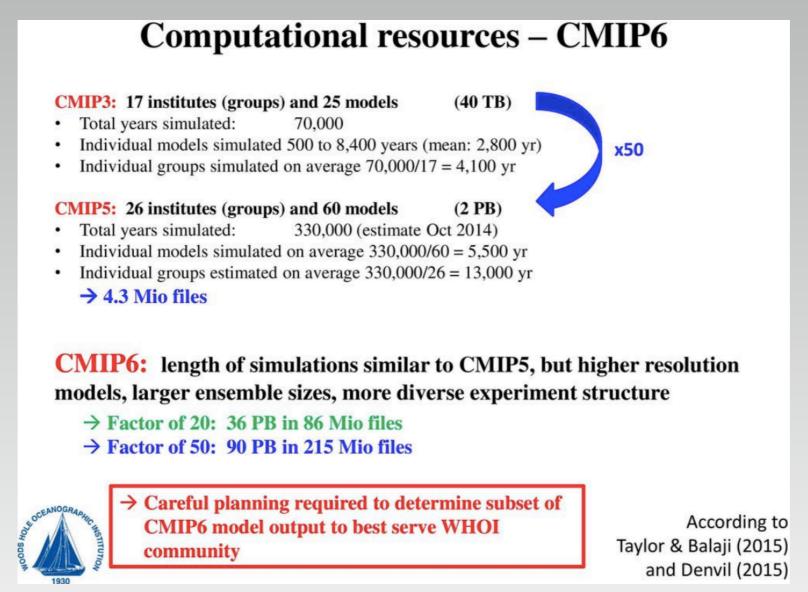
CMIP6 DECK experiments



CMIP6 future climate scenarios

(Eyring et al., 2016)

... require an increasing amount of computational resources (also given the increasing complexity of the models)



(Ummenhofer, 2019)

Can we select what forcing scenarios are actually relevant?

The Ruelle's response theory allows to consider the response as a property of the system, independently from the forcing

A dynamical system is perturbed with a vector field perturbation of the form $\Psi(x,t) = X(x)f(t)$.

The expectation value of any observable in the system is:

$$\langle \Phi_f(t) \rangle = \langle \Phi \rangle_0 + \sum_{n=1}^{\infty} \langle \Phi \rangle_f^{(n)}(t)$$
 (1)

The 1st order perturbation is given by:

$$\langle \Phi \rangle_f^{(1)}(t) = \int d\sigma G_{\Phi}^{(1)}(\sigma_1) f(t - \sigma_1)$$
 (2)

 If the time modulation of the perturbation is a Heaviside function, the observable-dependent Green function is:

$$f(t) = \kappa H(t) \tag{3}$$

where H(t)=0 for t=0 and 1 for t>0, k is a constant value of the forcing

 The evolution of any observable is related to its 1st order (linear) Green function as:

$$\frac{d\Phi_{f2CO2}^{(1)}}{dt}(t) = \kappa G_{\Phi}^{(1)}(t)$$
 (4)

- f(t) in (3) is equivalent to the typical forcing scenario with instantaneous
 CO2 doubling (or quadrupling);
- The Green function obtained by inverting (4) is independent of the forcing
 The problem reduces to a simple impulse-response experiment!

Experimental setting

We use a step forcing scenario to construct a linear Green function for an observable and predict its evolution in another forcing scenario

PREDICTOR

A step increase in CO2
 concentrations at time t=0 until
 2x the preindustrial value (0-2000
 yrs);

PREDICTAND

- A ramp function experiment:
 - 1.CO2 linear increase by 1% until doubling (0-70 yrs);
 - 2.Stationary CO2 with 2x the preindustrial value (70-1000 yrs);
- Model version: MPI-ESM-CR v1.2 ECHAM6 (T31L31) + MPIOM (GR30L40);
- 2 ensembles, 20 members for each ensemble with same initial conditions;
- Focus on: 2-metre temperature, ocean heat uptake, AMOC at 26N and ACC;

Prediction of 2-metres temperature

2xCO2 step forcing at t=0 (predictor)

Near-surface temperatures 291.0 290.5 290.0 ∑ ^{289.5} 0.5 289.0 288.5 288.0 287.5 2000 2250 2500 2750 3000 3250 3750 1750 3500 291.0 290.5 290.0 289.5 ∑ ⊢ _{289.0} 288.5 288.0 287.5 1750 2000 2250 2500 2750 3000 3250 3500 3750

The Green function is shown in the inset for the first 1000 years

Red: ensemble mean evolution

Blue: predicted evolution with linear response

1% CO2 increase (predictand)



Prediction of AMOC at 26N

2xCO2 step forcing at t=0 (predictor)

The Green function is shown in the inset for the first 1000 years

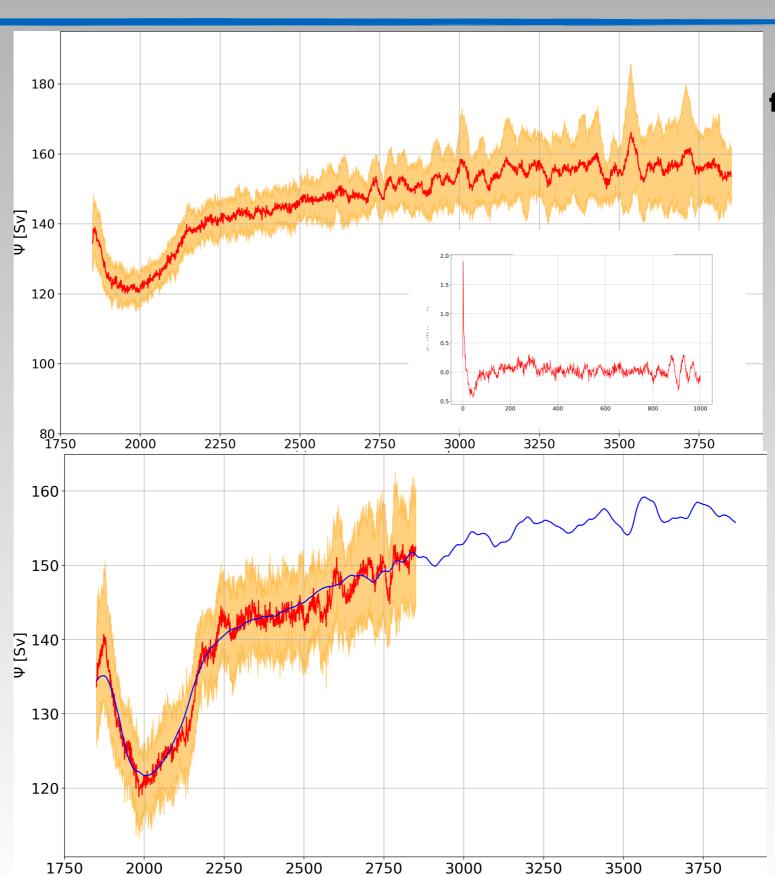
Red: ensemble mean evolution

Blue: predicted evolution with linear response

1% CO2 increase (predictand)

Prediction of ACC at Drake passage

2xCO2 step forcing at t=0 (predictor)



The Green function is shown in the inset for the first 1000 years

Red: ensemble mean evolution

Blue: predicted evolution with linear response

1% CO2 increase (predictand)

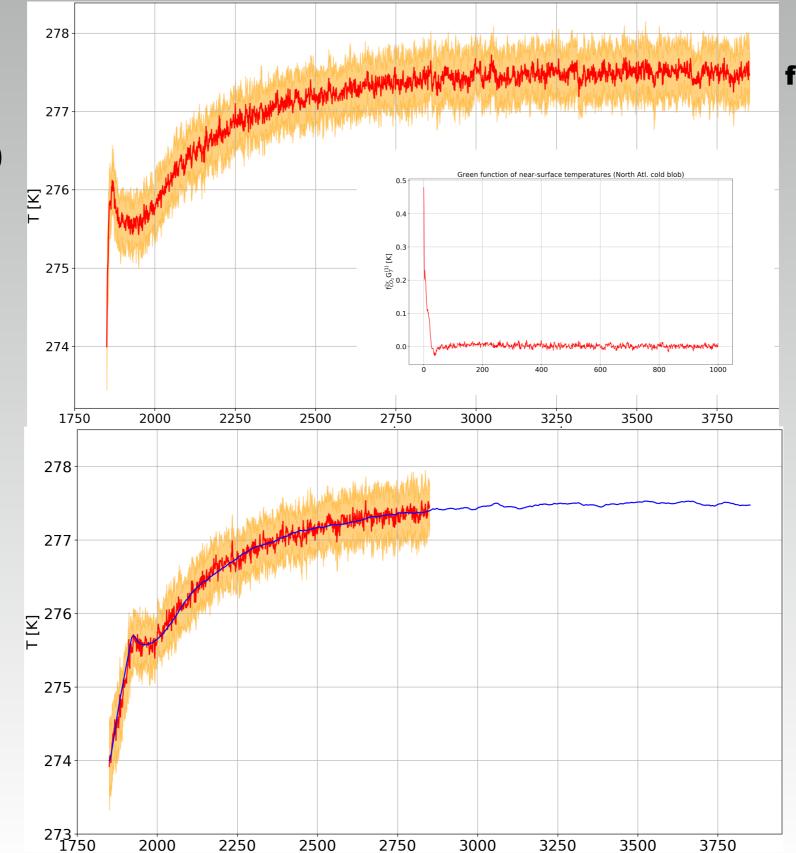
Prediction of SSTs in the extratropical Northern Atlantic



1% CO2

increase

(predictand)



The Green function is shown in the inset for the first 1000 years

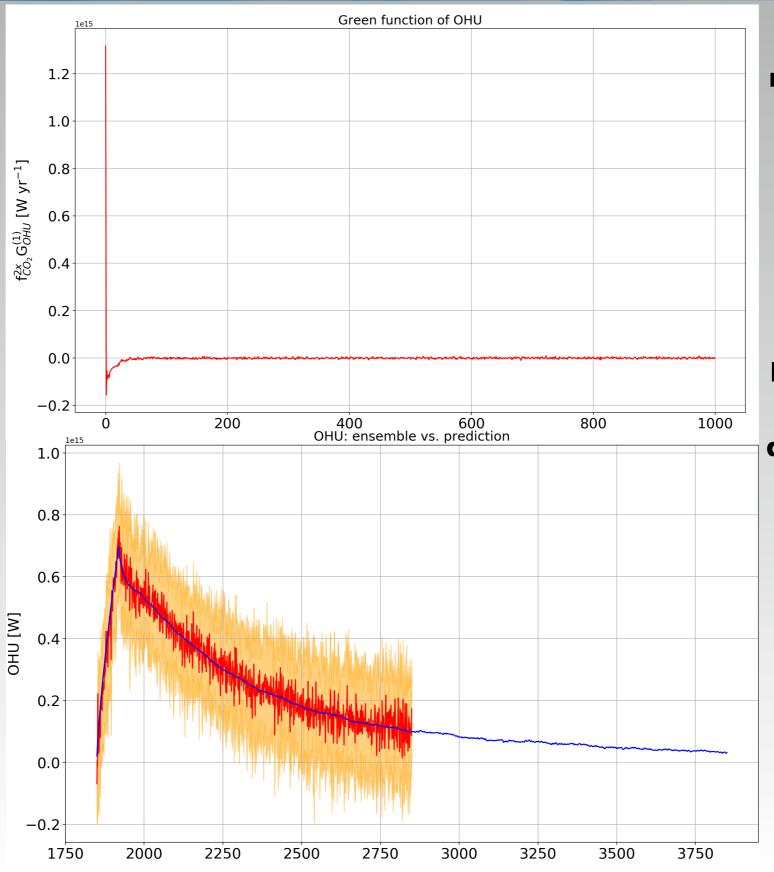
Red: ensemble mean evolution

Blue: predicted evolution with linear response

Ocean Heat Uptake (OHU): A Green function with a Dirac's

Green function

1% CO2 increase (predictand)



The OHU is representative of the TOA energy imbalance at these scales

The OHU
anomaly is
largest at t=0, as
the step forcing
drives the system
out of balance

OHU tends to vanishing values as the system approaches statistically steady state

Conclusions

- We have applied an algorithm to retrieve the first order Green function for the response of a generic observable in the climate system;
- For suitable choices of the forcing, the retrieval of the Green function is straightforward;
- We demonstrated the power of the algorithm predicting the evolution of key observables in a typical forcing scenarios;
- The response of the overturning circulation is to a large extent predicted via the linear response;
- A key feature of the regional climate response, the North Atlantic cold blob, is also well predicted;
- The response theory is a valid alternative to running fully coupled climate models for various applications related to climate prediction;

References

- ➤ Lembo, V., Ragone F., and V. Lucarini, 2020, Predicting Climate Change through Response Operators: A Coupled GCM Study, Sci. Rep. accepted
- ➤ Lucarini, V., Ragone, F. and Lunkeit, F., 2017, Predicting climate change using response theory: Global averages and spatial patterns. J. Stat. Phys. 166, 1036–1064, DOI: 10.1007/s10955-016-1506-z
- ➤ Ragone, F., Lucarini, V. and Lunkeit, F., 2016, A new framework for climate sensitivity and prediction: a modelling perspective, Clim. Dyn. 46, 1459–1471, DOI: 10.1007/s00382-015-2657-3
- ➤ Ruelle, D., 1998, General linear response formula in statistical mechanics, and the fluctuation-dissipation theorem far from equilibrium. Phys. Lett. A 245, 220–224, DOI: 10.1016S0375-9601(98)00419-8
- ➤ Ruelle, D. 1998, Nonequilibrium statistical mechanics near equilibrium: computing higher-order terms. Nonlinearity 11, 5–18, DOI: 10.1088/0951-7715/11/1/002
- ➤ Ruelle, D., 2009, A review of linear response theory for general differentiable dynamical systems. Nonlinearity 22, 855–870, DOI: 10.1088/0951-7715/22/4/009