

Climbing down Charney's Ladder

UFS Webinar Series

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14 April 2022

Outline

- 1 Climate science and climate models
 - Weather and climate
 - Radiative balance and dynamical response
 - The "infinite forecast"
- 2 Computational climate science
 - Model evolution, from the Charney Report to the IPCC
 - The end of Dennard scaling
 - What computers are good at: Machine Learning
 - Learning from models, learning from observations
 - Learning the physics of fine scales
- 3 Summary: Climbing Down Charney's Ladder

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What is climate?

- Climate is what you expect, weather is what you get
- ... but we are going to have to change our expectations! See [NOAA new normals](#), 4 May 2021.
- What you perceive is the difference between the weather and the climate.
- The climate record is based on careful removal of weather “noise” from observations to see the climate “signal”: the residuals are small compared to the observed quantities.
- Fluctuations, feedbacks and forcings at all scales: minutes to millennia, microbes to megacontinents.
- Solving the climate problem implicates any field of science or engineering you can imagine: fluid mechanics, radiative transfer, chemistry, biology, mathematics, statistics, algorithms, computing hardware, materials science, ... please join the fun!

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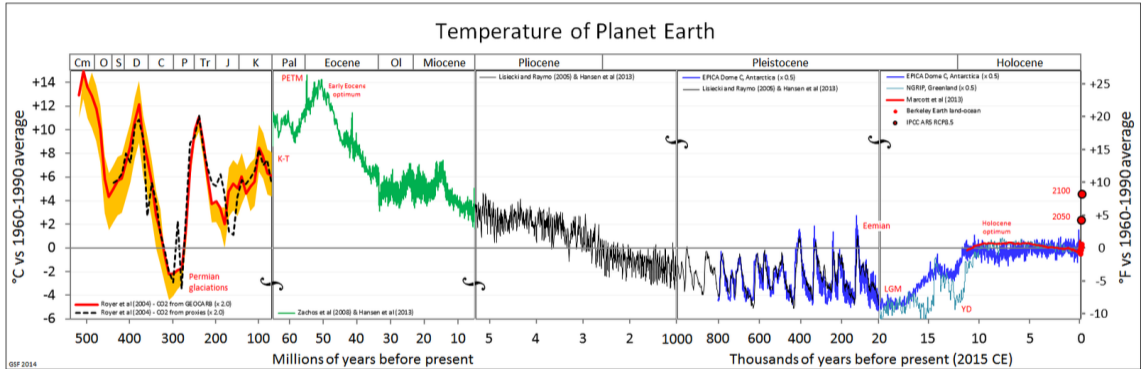
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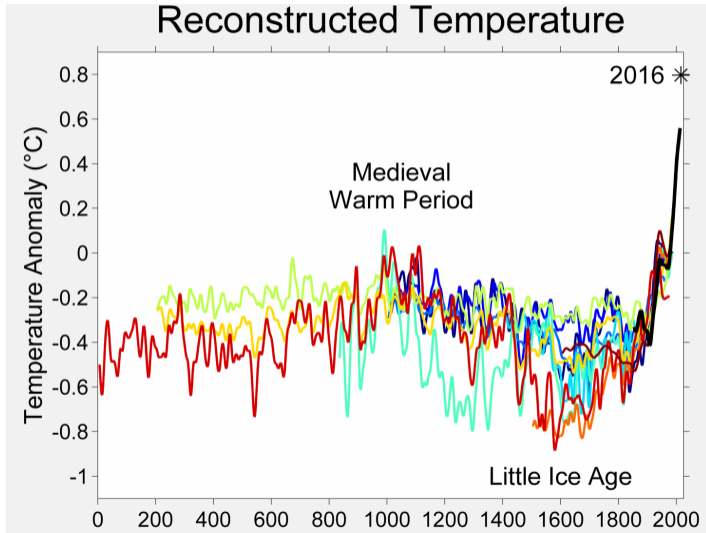
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Earth's Temperature History: observations



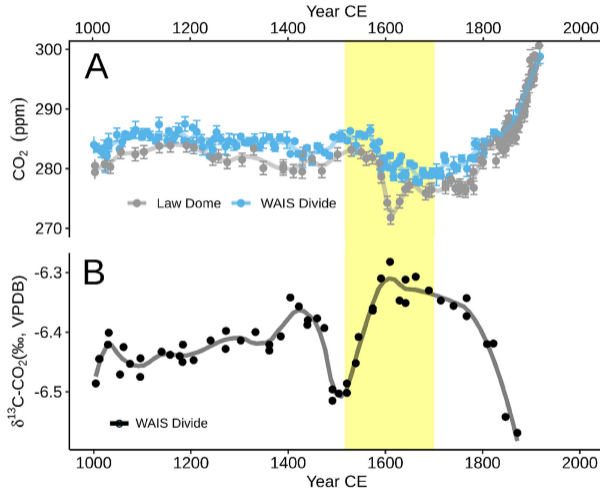
From [Wikipedia](#).

Earth's Temperature History: Common Era



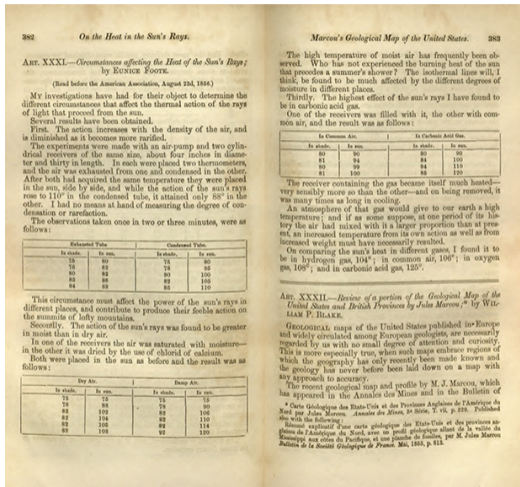
- 1000-year reconstructions from tree rings and ice cores.
- The **Mediæval warm period** and the **Little Ice Age** may be only **regional** signals
- The current warming has a **global signature**
- From **Wikipedia**

The Great Dying in the Americas



From [Koch et al \(2019\)](#). Global impact of depopulation in the Americas, c. 1600 CE.

Eunice Foote discovers the greenhouse effect, 1857



“An atmosphere of that gas would give to our earth a high temperature”. From climate.gov.

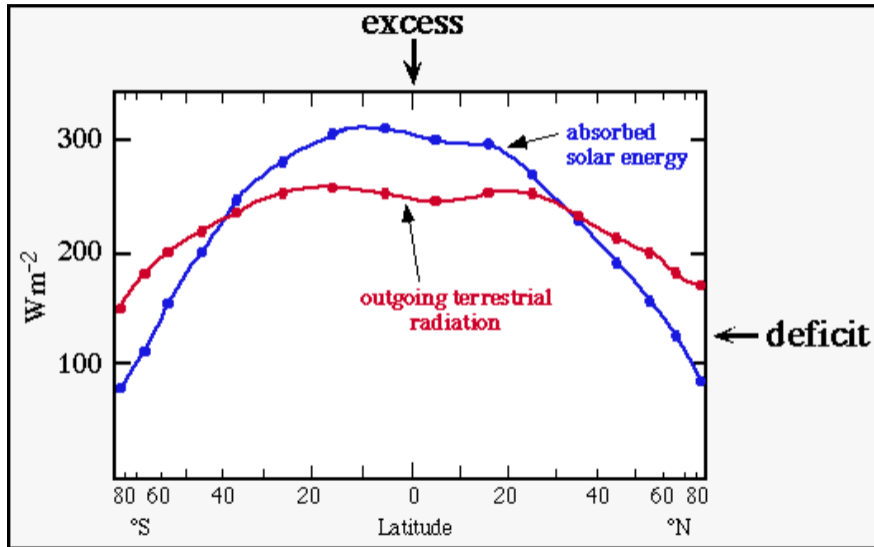
Bjerknes and modern weather forecasting



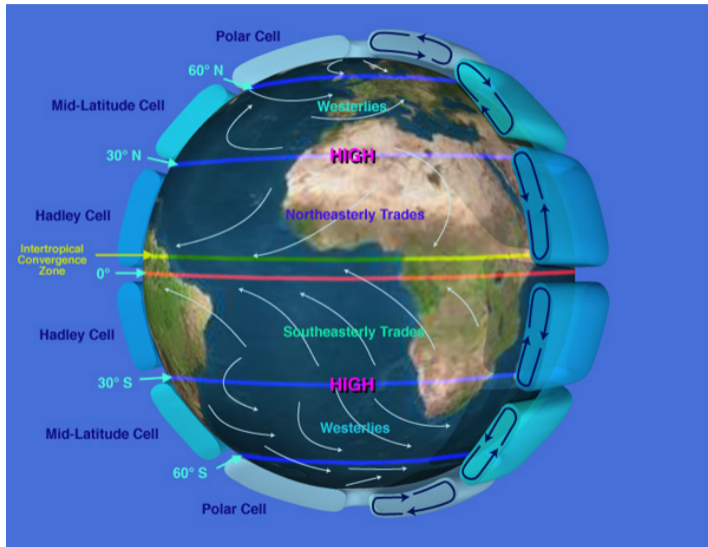
- V. Bjerknes first formulated the **primitive equations** for the general circulation (1904).
- Unable to find a practical way to integrate them forward in time, he attempts a **graphical calculus** on hand-drawn contour maps
- Finally resorts to empirical methods based on libraries of contour maps

Bjerknes develops the foundations of dynamical meteorology but in the end, performs forecasting using methods “**that were neither algorithmic nor based on the laws of physics**”, *Calculating the weather*, Nebeker (1995).

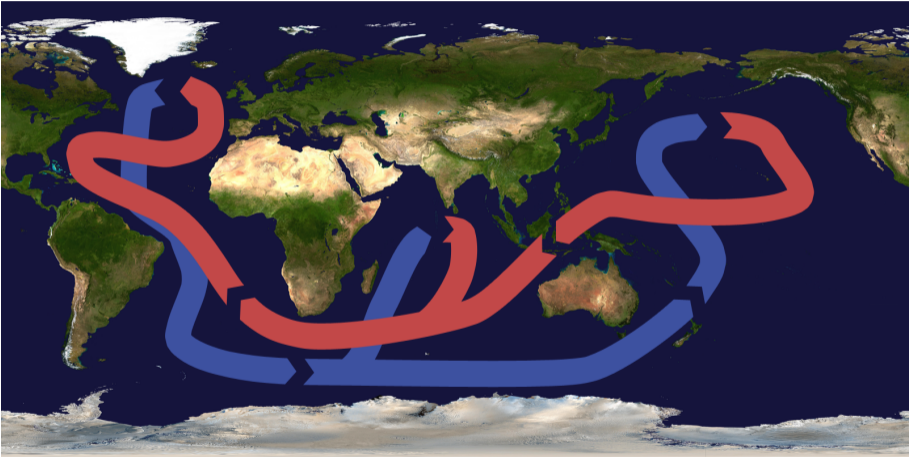
The Earth's radiation budget



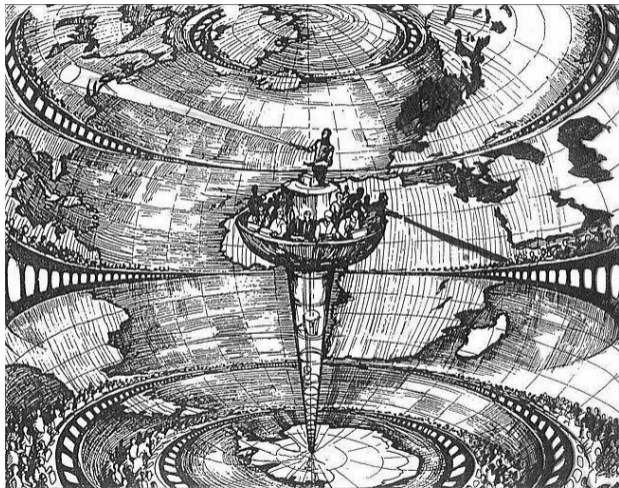
Global atmospheric circulation



Global oceanic circulation



Richardson's failed attempt to compute the general circulation, 1922



From [A Vast Machine](#), Edwards 2010.

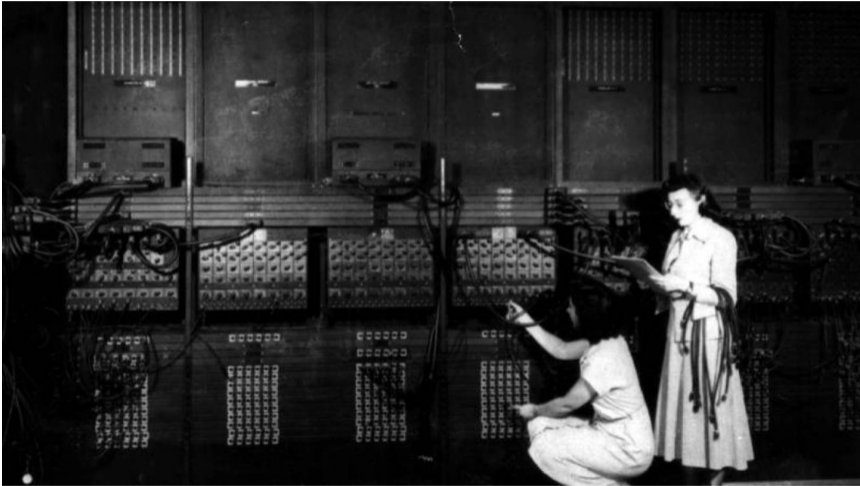
The dawn of digital computing at the IAS



FIG. 2. Some of the members of the IAS Meteorology Group in 1952. Left to right: J. G. Charney, N. A. Phillips, G. Lewis, N. Gilburg, G. W. Platzman (behind the camera: J. Smagorinsky). The IAS Computer is in the background.

From [Climbing down Charney's ladder](#), Balaji (2021). Picture by Joe Smagorinsky.

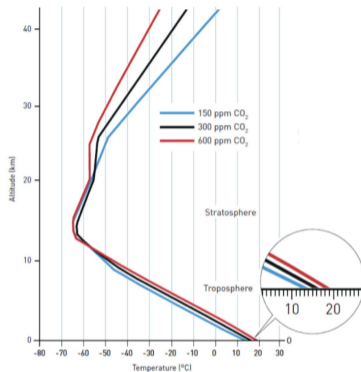
Programming the ENIAC



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Manabe and Wetherald (1967): 1D model response to CO₂ doubling

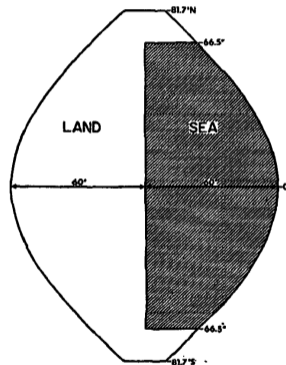


Source: Manabe and Wetherald (1967) Thermal equilibrium of the atmosphere with a given distribution of relative humidity, *Journal of the atmospheric sciences*, Vol. 24, Nr 3, May.

“Radiative convective equilibrium of the atmosphere with a given distribution of relative humidity is computed as **the asymptotic state of an initial value problem**.”. Syukuro Manabe won the Nobel Prize in Physics, 2021.

Manabe and Bryan (1969)

- Recognized as a “milestone in scientific computing”, Nature (2006).
- Sector model of 120°
- 1 atmospheric year coupled to 100 ocean years
- 1200h for 1 simulated year (0.02 SYPD) on Univac 1108



Atmospheric response to doubled CO₂

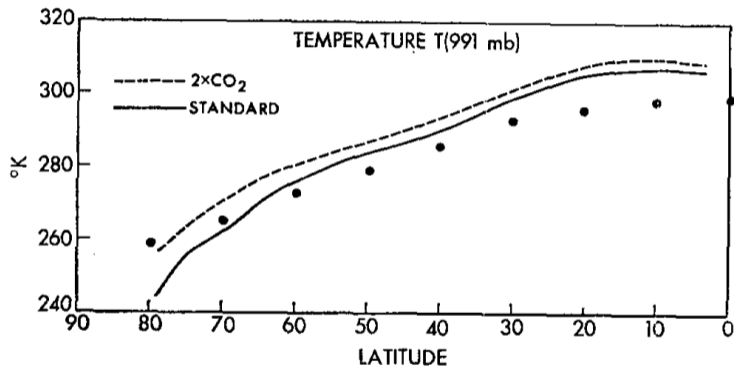


Fig 5 from Manabe and Wetherald (1975), equilibrium response to doubled CO₂.

Atmospheric response to doubled CO₂

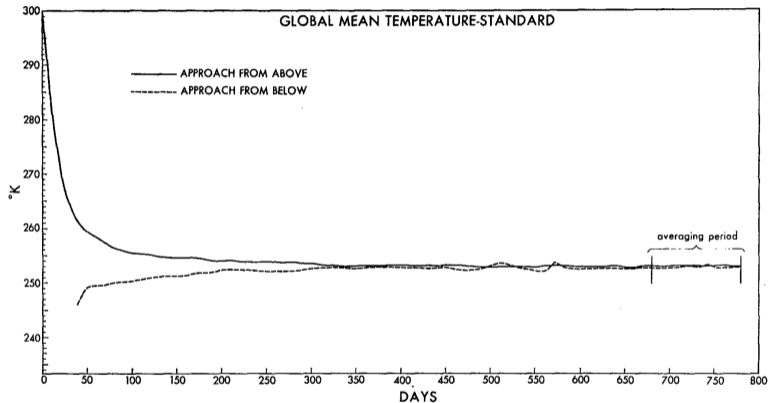
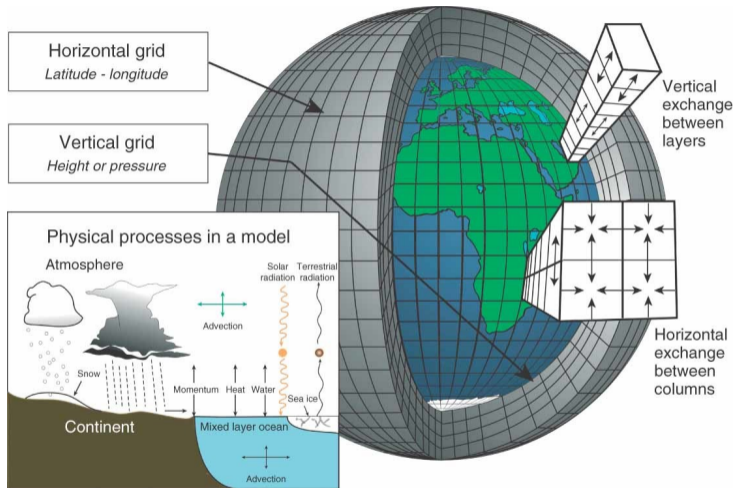


Fig 3 from Manabe and Wetherald (1975), equilibrium response to doubled CO₂. Spinup times in modern GCMs can be $\mathcal{O}(1000)$ years).

The structure of a GCM, from Manabe to present day



From [Edwards \(2011\)](#). $\mathcal{O}(10X)$ increase in resolution from Manabe and Bryan to CMIP6.

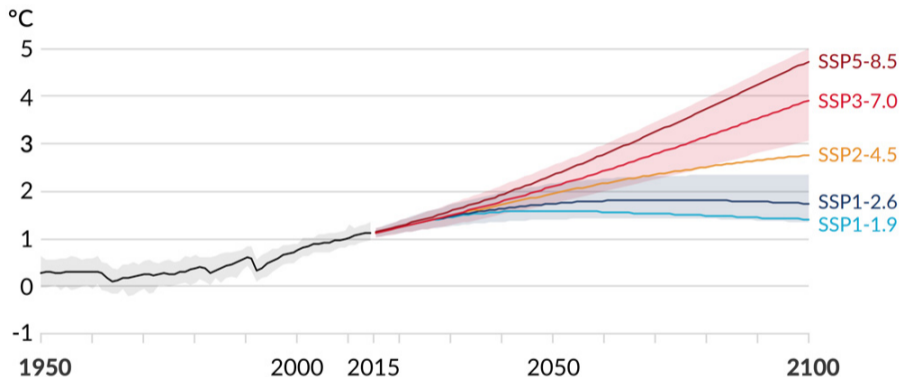
The Charney Report (1979)

“Carbon dioxide and climate: A Scientific Assessment.”

- Precursor to the IPCC Assessment Reports.
- Based on 5 model runs: 3 from Manabe (GFDL), 2 from Hansen (GISS).
- Conclusions:
 - Direct radiative effects due to doubling of CO₂: $\sim 4 \text{ W/m}^2$
 - Feedbacks: water vapour (Clausius-Clapeyron), snow-ice albedo feedback.
 - Cloud effects: “How important the cloud effects are, is, however, an extremely difficult question to answer. **The cloud distribution is a property of the entire climate system**, in which many other feedbacks are involved.”
 - “We believe, therefore, that the equilibrium surface warming will be in the range of **1.5-4.5°C**, with the most probable value near 3°C.”

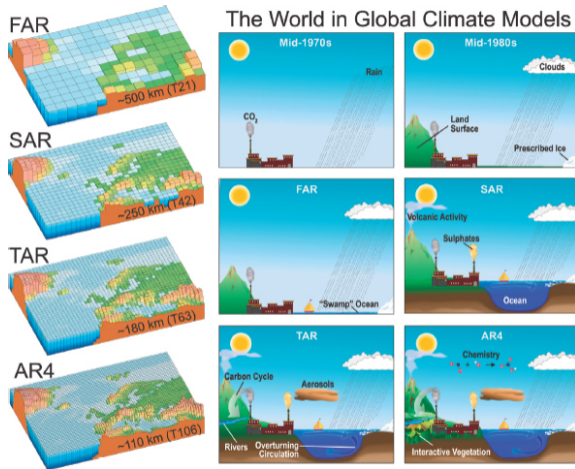
Very nice reassessment of the Charney Report: [Bony et al \(2013\)](#).

... to IPCC AR6



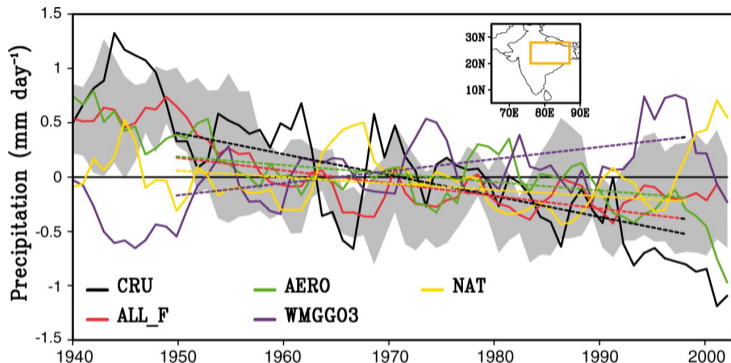
Courtesy IPCC AR6 (2021), Fig 8a from Summary for Policymakers. Based on [114 models from 44 institutions](#).

Models add detail



Models grow in **resolution** and **complexity**. Courtesy IPCC AR4 report. A typical IPCC model today has 25-100 km resolution and $\mathcal{O}(100)$ variables.

Attribution: data from alternate Earths



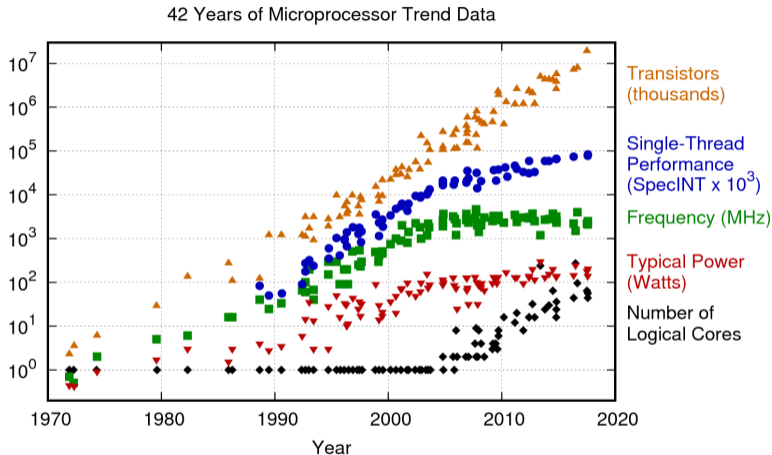
- Cloud-aerosol feedbacks induce a weakening of the Indian monsoon [Bollasina et al., Science 2011](#).
- We can now “attribute” individual events.

TABLE I
SCALING RESULTS FOR CIRCUIT PERFORMANCE

Device or Circuit Parameter	Scaling Factor
Device dimension t_{ox}, L, W	$1/\kappa$
Doping concentration N_a	κ
Voltage V	$1/\kappa$
Current I	$1/\kappa$
Capacitance $\epsilon A/t$	$1/\kappa$
Delay time/circuit VC/I	$1/\kappa$
Power dissipation/circuit VI	$1/\kappa^2$
Power density VI/A	1

Table 1 from [Dennard \(1974\)](#). Shows scaling of various quantities when transistor dimension is reduced by factor κ .

End of Dennard scaling



Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten
New plot and data collected for 2010-2017 by K. Rupp

From **42 Years of Microprocessor Trend Data**, courtesy Karl Rupp.

All algorithms are not created equal

- Real codes often gated by memory bandwidth.
- Roofline model:

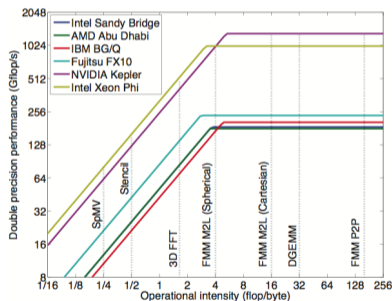
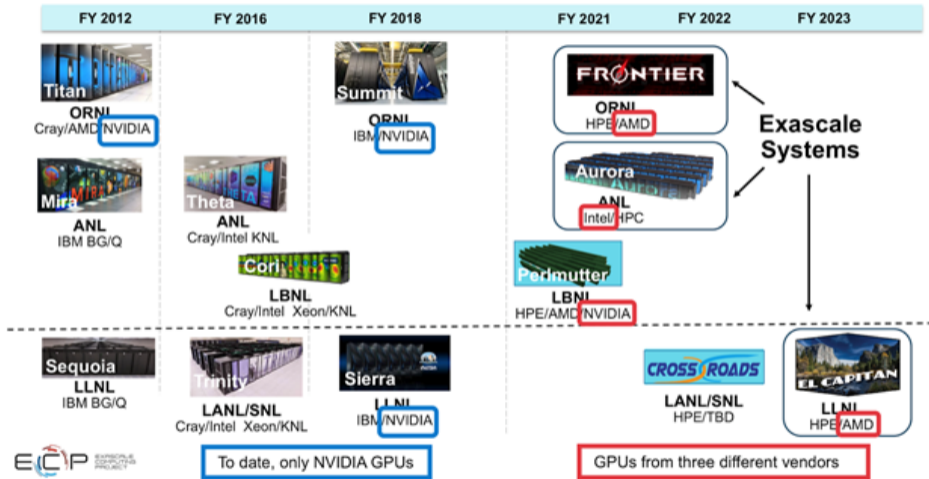


Figure courtesy Barba and Yokota *SIAM News* 2013.

US Exascale Roadmap



From DOE Exascale Computing Project, via [Travis Linderman's blog](#), Oct 2020.

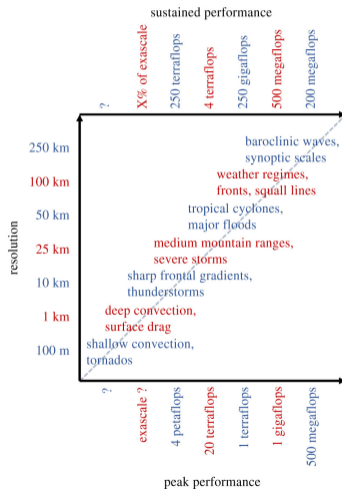
EU and Japan moving forward with ARM



From European Exascale Project, via [EE News](#), April 2020.

What can we expect at an exaflop?

Will exascale be the rescue? Neumann et al (2019).



Hypothesis: vastly reduced uncertainty at 1 km.

- ICON projects that a 1 km global model will run at **0.06 SYPD** on “pre-exascale” technology: **17X** improvement needed for 1 SYPD.
- This will be on 200,000 nodes (roughly **2xGaea**).
- DECK: **1000 SY**.
- A full suite of hindcasts for seasonal forecasting: **10,000 SY**.
- Ocean state needed for monsoon prediction as well!

The carbon cost of climate modeling

CMIP6 Experiments: Institutions/Models	Useful SY	Total SY	Useful Data Produced	Total Data Produced	Useful CH (Mh)	Total CH (h)	Total Energy Cost (Joules)	Carbon Footprint (CO ₂ /KWh)
EC-Earth	17,4				41.8		1.27x10 ¹²	162.6t
CNRM-CERFACS	23,6				306.4	325	3.13E+12	49.5t
IPSL	53,0				100	270	6.16E+12	122t
CMCC	96				1.99	NA	1.61E+12	
UKMO	23,4				473	NA	1.76E+13	572.5t
DKRZ	1,2				5.52	5.90	4.09E+11	24.8t
NCC-NORESM2	6,484	NA	0.297	NA	11.7	NA	4.75E+11	
NERC	640	NA	0.460	NA	55,497	NA	2.17E+12	
MPI	24,175	35,000	1.9	NA	968,116	NA	6.20E+11	37.6t

Please take these numbers as first (and not accurate) approximation

- Total Energy cost is calculated multiplying useful SY and the proportional average of JPSY for the set of CMIP6 experiment per institution.
- CO₂ is calculated using factor conversion and PUE, proposed by carbon footprint group and yet in discussion.

* We have also Useful SY, Useful Data and Useful CH per CMIP6 experiment



The IS-ENES3 project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 824084

From CPMIP Project (Balaji et al, GMD 2017), courtesy Mario Acosta, BSC.

The climate Turing test

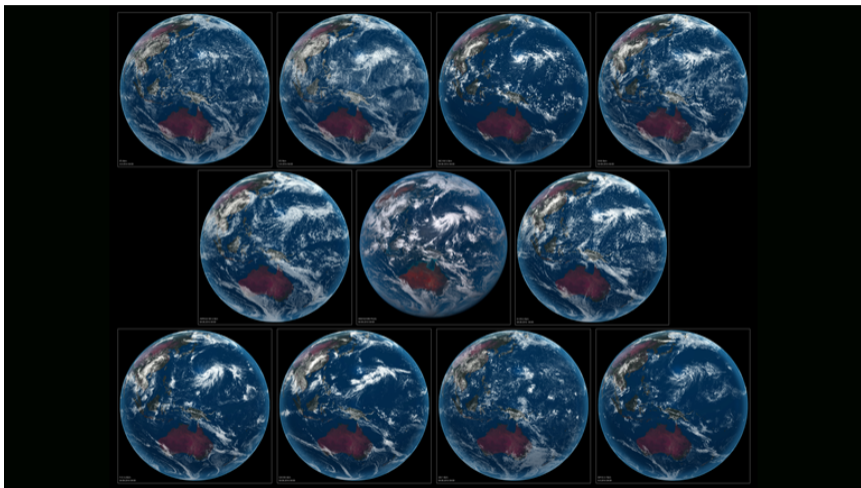
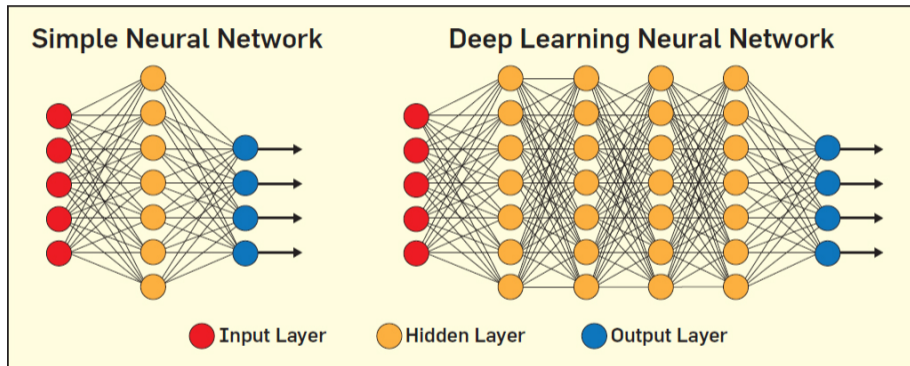


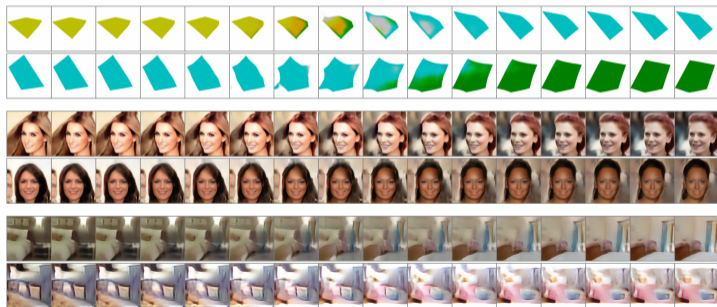
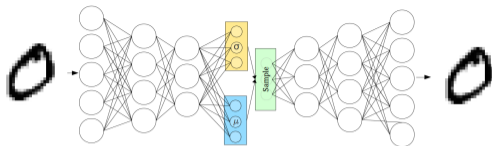
Figure courtesy the [DYAMOND](#) initiative.

Deep Learning



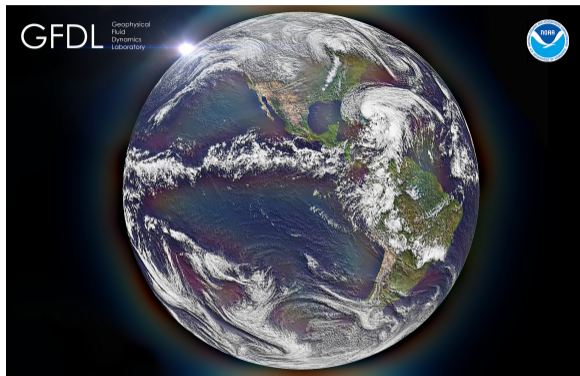
From [Edwards \(2018\)](#), ACM.

The ML approach: finding the essence

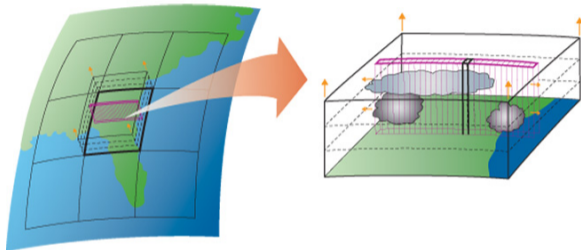


From “features” make new instances that capture the essence. [Angles and Mallat \(2018\)](#)

Coarse-graining using ML



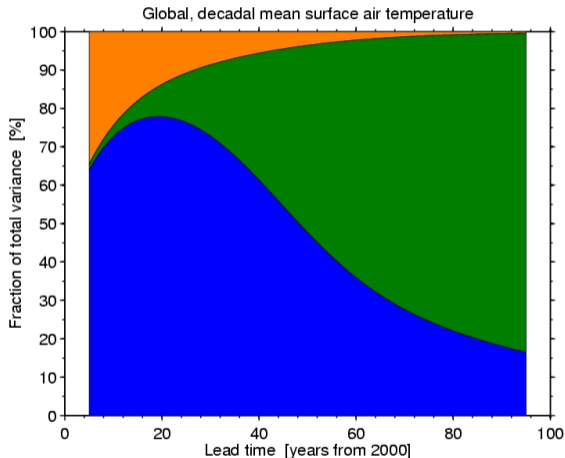
(Courtesy: S-J Lin, NOAA/GFDL).



(Courtesy: D. Randall, CSU; CMMAP).

- From global cloud-resolving models, can we learn the statistical aggregate of small scales? See [Schneider et al 2017](#), [Gentine et al \(2018\)](#), [O’Gorman and Dwyer \(2018\)](#), [Bolton and Zanna \(2019\)](#), ...

Science requires going beyond observations

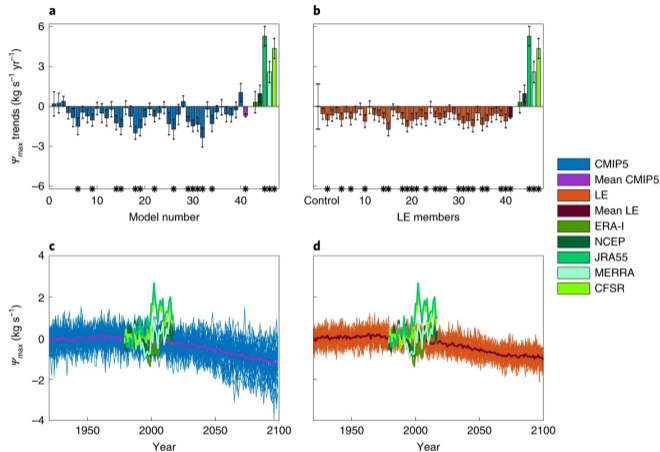


Sources of uncertainty in weather and climate simulation:

- *chaotic uncertainty* or internal variability
- *scenario uncertainty* dependent on policy and human actions.
- *structural/epistemic uncertainty* or imperfect understanding.

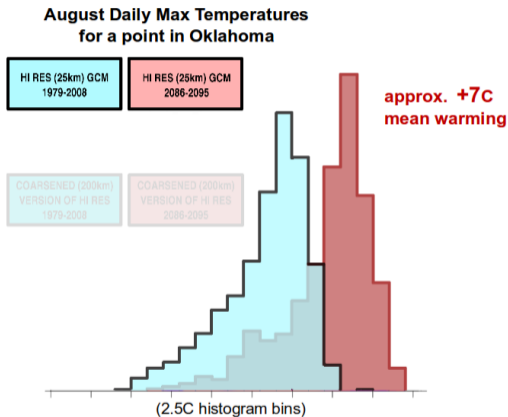
Models must also generate **counterfactual** values! From [Hawkins and Sutton \(2009\)](#).

Models or observations?



Hadley cell strength is likely correct in models and not in “observations”!
From [Chemke and Polvani \(2019\)](#).

Error patterns associated with stationarity assumption



Errors can be traced with warming outside the temperature distribution of the training period. Caution needed at distribution tails (“extreme events”). [Dixon et al \(2016\)](#).

Where models and data are both weak...

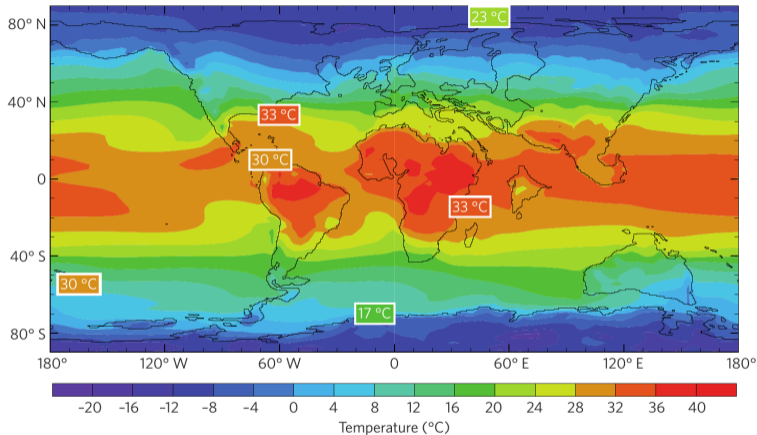
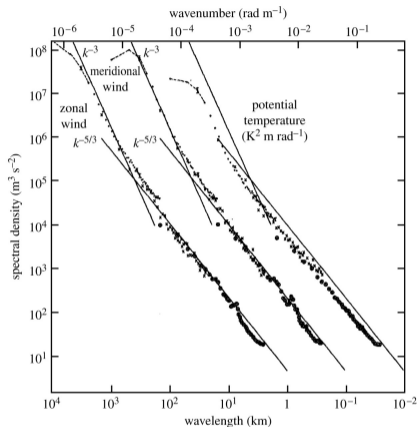


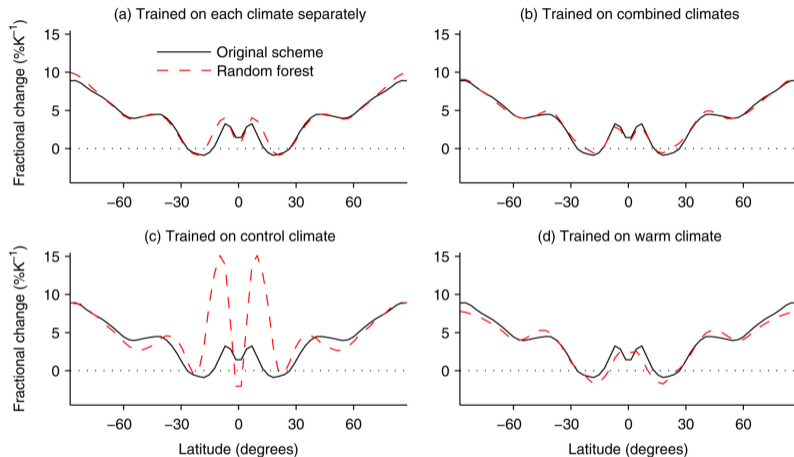
Fig 1 from [Valdes \(2011\)](#). GCMs are unable to simulate the Paleocene-Eocene climate of 55 My ago.

No separation of "large" and "small" scales



Nastrom and Gage (1985). More model fidelity, more complexity over time in small scales (“physics”). The **backscatter** idea (Jansen and Held 2014) provides an energetically consistent framework for SGS.

Replacing a parameterization with DL



From [O’Gorman and Dwyer \(2018\)](#). Limitations of training on short non-stationary time series. See also [Dixon et al \(2016\)](#).

Learning sub-gridscale turbulence

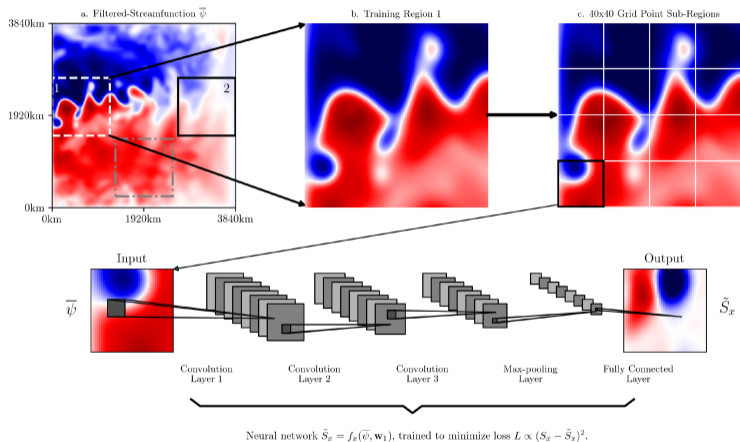
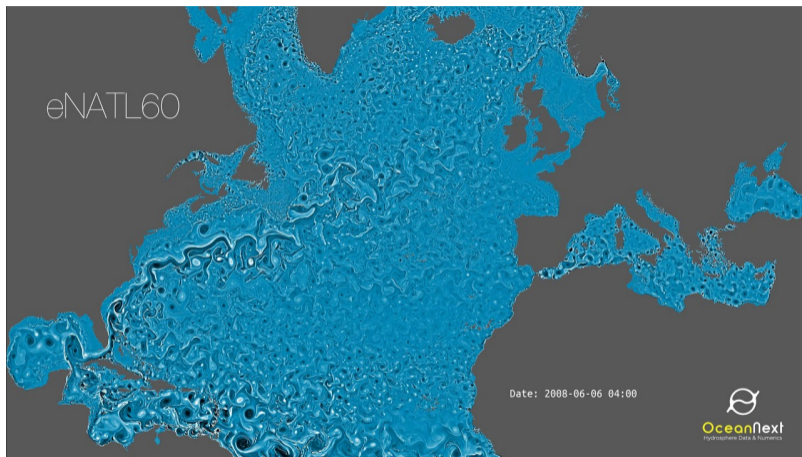


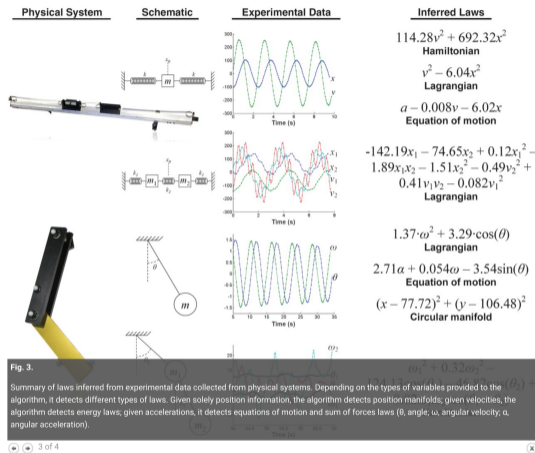
Fig 1 from [Bolton and Zanna \(2019\)](#).

Coarse-graining without scale separation



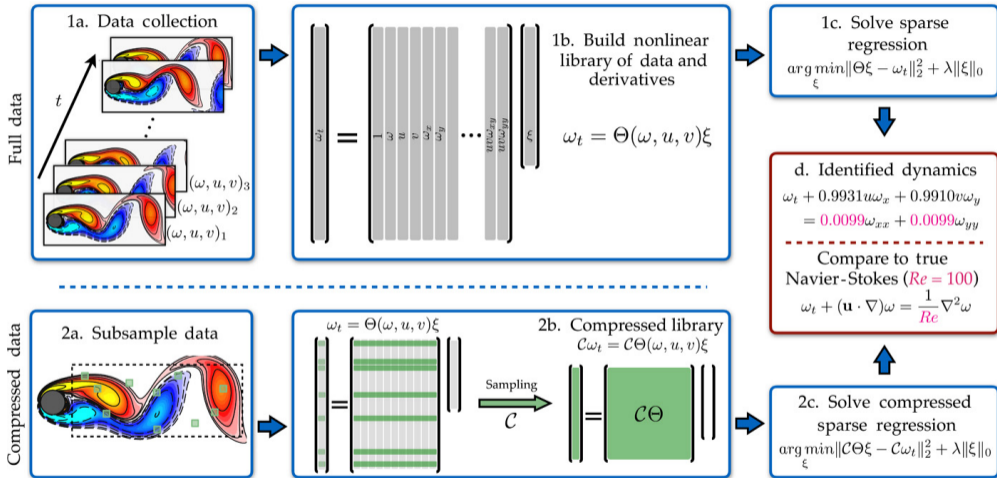
eNATL60 dataset courtesy Julien le Sommer and collaborators. Can we assume a structure for learning. e.g “GM+E” [Bachman 2019](#). See Sommer et al AGU 2019.

Distilling Free-Form Natural Laws from Experimental Data



From [Schmidt and Lipson, Science, 2009](#). My little *hommage*, [Gaitán et al \(2016\)](#), *Can we obtain viable alternatives to Manning's equation using genetic programming?*

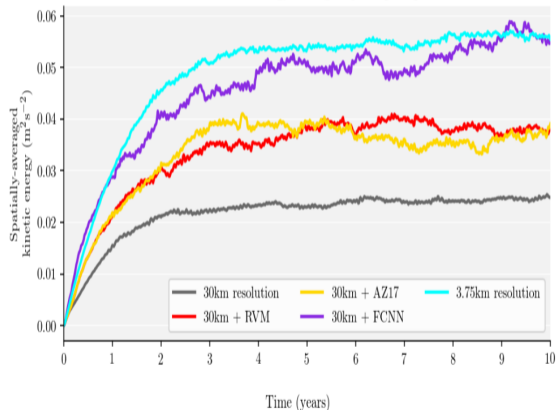
Navier-Stokes from data



From Rudy et al (2017).

Discovering subgrid momentum closures

A Kinetic energy during 10 year spin-up



Zanna and Bolton 2020 builds on work previously shown, and returns a closed-form expression for subgrid momentum closures:

$$\mathbf{S}_u = (\bar{\mathbf{u}} \cdot \nabla) \bar{\mathbf{u}} - \overline{\mathbf{u} \cdot \nabla \mathbf{u}}$$

where *relevance vector machine* techniques yield a representation similar in form to Anstey and Zanna (2017).

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Summary: where is climate modeling headed?

- Models today embody a dizzyingly detailed Earth system. **Trust** comes from fidelity to individual processes and feedbacks, fidelity relative to other lines of evidence. But there is the **Borges conundrum** (see “On exactitude in science”, and Lewis Carroll’s “Sylvie and Bruno”).
- Would you trust “**model-free**” simulations from an AI?
- Machine learning and “AI” still is in the positive phase of a **hype cycle** (**publication bias, reproducibility crisis**) but it isn’t *all* hype. Dominating the hardware market.
- ML-derived models must be capable of **going outside observational bounds**
- Imperative to derive **hierarchies** of simple models from expensive ones.
- **Energy and carbon cost of computing** must be factored into model development and experiment design: carbon-intensive data must be maximally utilized by the community.
- Survey paper: *Climbing down Charney’s ladder*, Balaji *Phil Trans* Feb 2021.
- **Disclaimer: views expressed here are my own!**