

# Infrastructure Requirements for Future Earth System Models

Atmosphere, Oceans, and Computational Infrastructure  
Future of Earth System Modeling  
Caltech and JPL Center for Climate Sciences  
Pasadena, CA

V. Balaji

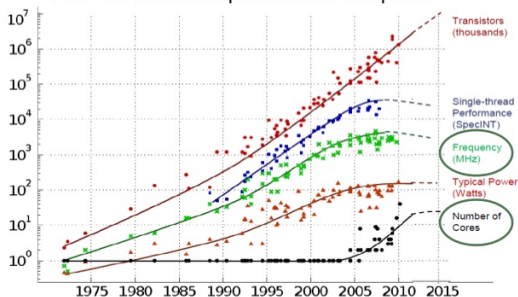
NOAA/GFDL and Princeton University

18 May 2018

# Outline

# Moore's Law and End of Dennard scaling

Power and Heat Problems Led to Multiple Cores and Prevent Further Improvements in Speed



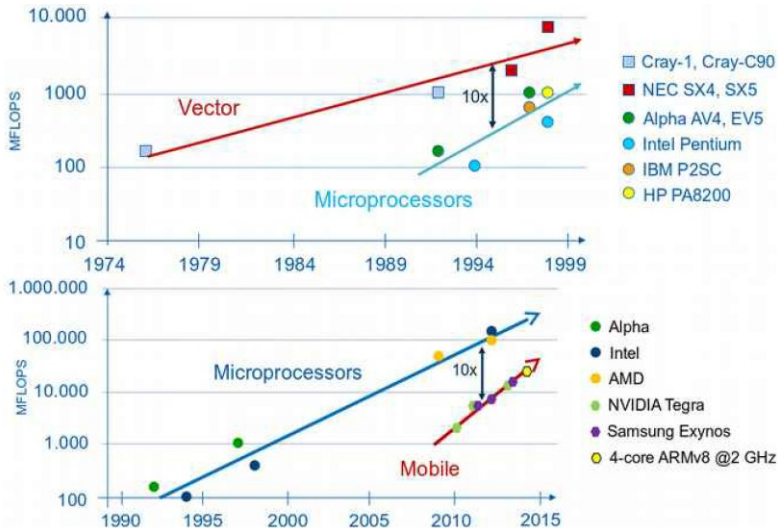
Original data collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond and C. Batten  
Dotted line extrapolations by C. Moore

Source: Chuck Moore, Data Processing in Exascale-Class Systems, April 27, 2011: Salishan Conference on High Speed Computing

Figure courtesy Moore 2011: *Data processing in exascale-class systems.*

- Processor concurrency: Intel Xeon-Phi.
- Fine-grained thread concurrency: Nvidia GPU.

# The inexorable triumph of commodity computing



From *The Platform*, Hemsoth (2015).

# The "Navier-Stokes Computer" of 1986

Navier-Stokes Computer

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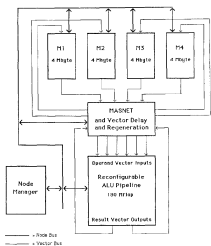


Fig. 5. Block diagram of miniNode

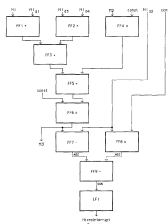
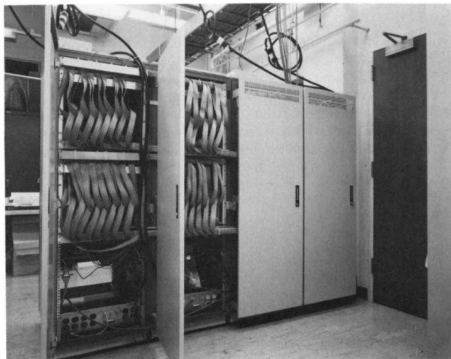


Fig. 6a. Block diagram of pipeline configuration 1.

“The Navier-Stokes computer (NSC) has been developed for solving problems in fluid mechanics involving complex flow simulations that require more speed and capacity than provided by current and proposed Class VI supercomputers. The machine is a parallel processing supercomputer with several new architectural elements which can be programmed to address a wide range of problems meeting the following criteria: (1) the problem is numerically intensive, and (2) the code makes use of long vectors.”  
**Nosenchuck and Littman (1986)**

# The Caltech "Cosmic Cube" (1986)



(b)

Figure 2. The 128-node Mark II system at Caltech (a) showing, in the back view (b), the cabling that implements the hypercube interconnect.

“Caltech is at its best blazing new trails; we are not the best place for programmatic research that dots i’s and crosses t’s”. Geoffrey Fox, pioneer of the Caltech Concurrent Computation Program, in 1986.

# Beowulf clusters



[Read about the Stone SouperComputer In the News!](#)

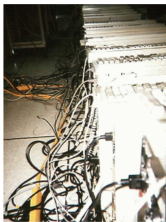
## Introduction

While our first Beowulf-style parallel computer isn't built out of the most impressive hardware, we got tired of fighting for funding and went ahead with what we could find. Much like the classic [Tale of Stone Soup](#), many individuals contributed to the existing machine\*. Because of a complete lack of funding, we used *surplus* personal computers donated by individuals from [ORNL](#), the Procurement Dept., Y-12, and K-25, to build a parallel computer system which uses public domain compilers and message passing libraries. This system was built at *literally no cost*.



~~No~~  
Low Cost Parallel Computing

We are adding more nodes every week. Click [here](#) to donate your personal computer equipment to the Stone SouperComputer. And be sure to tell your friends.



People are often interested in the price-to-performance ratio of their computer systems. Since our cost was approximately nothing, any performance results in a zero price-to-performance ratio:

$$\frac{\text{Price}}{\text{Performance}} = \frac{\sim 0}{\text{anything}} \rightarrow 0$$

Performance-to-price is more interesting. If we get any performance at all, the performance-to-price ratio goes quickly to infinity.

$$\frac{\text{Performance}}{\text{Price}} = \frac{\text{anything}}{\sim 0} \rightarrow \infty$$

As soon as you login, we all win!!

# Google TPU (Tensor Processing Unit)

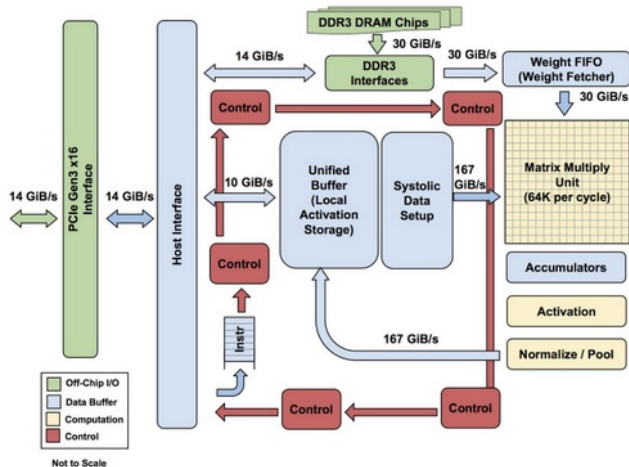
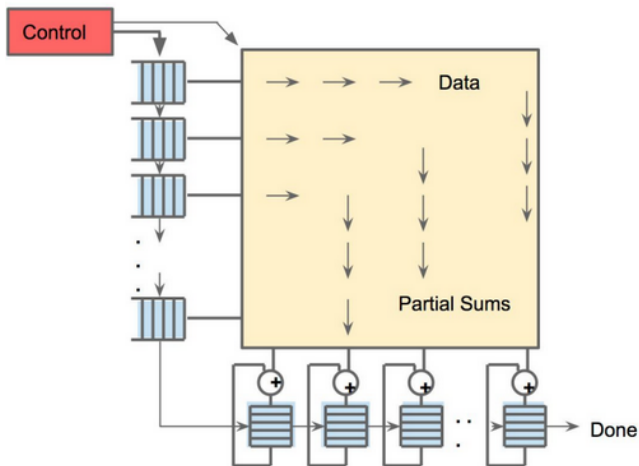


Figure courtesy Google.

# Google TPU (Tensor Processing Unit)



Hardware pipelining of steps in matrix-multiply. Figure courtesy Google.

# Low precision arithmetic for Deep Learning

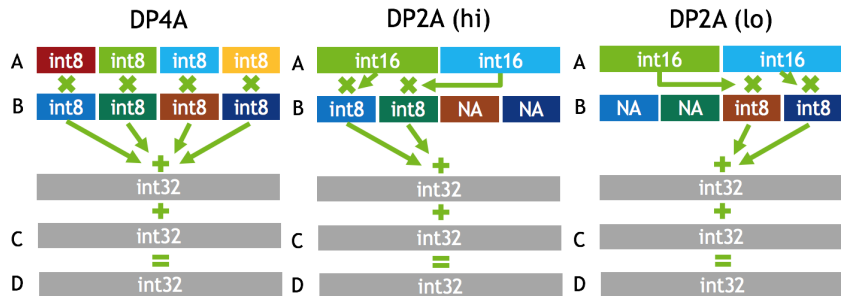
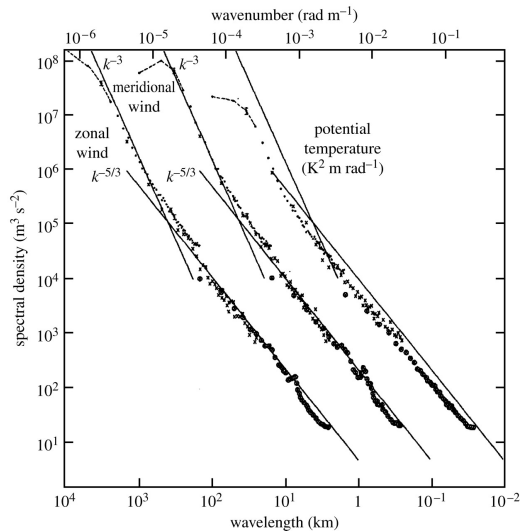


Figure courtesy NVidia. Low-precision arithmetic.

# No separation of "large" and "small" scales



Nastrom and Gage (1985).





# Sources of diversity: model tuning

Model tuning or “calibration” consists of reducing overall model bias (usually relative to 20th century climatology) by modifying parameters. In principle, minimizing some cost function:

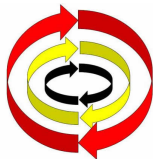
$$C(p_1, p_2, \dots) = \sum_1^N \omega_i \|\phi_i - \phi_i^{obs}\|$$

- Usually the  $p$  must be chosen within some observed or theoretical range  $p_{min} \leq p \leq p_{max}$ .
- “Fudge factors” (applying known wrong values) generally frowned upon (see Shackley et al 1999 discussion on history of “flux adjustments”)
- The choice of  $\omega_i$  is part of the lab’s “culture”!
- The choice of  $\phi_i^{obs}$  is also troublesome:
  - overlap between “tuning” metrics and “evaluation” metrics.
  - “Over-tuning”: remember “reality” is but one ensemble member!

# Ideas and Challenges

- No scale separation implies a catastrophic cascade of dimensionality: we're off by  $10^{10}$  from required flops, Schneider et al (2017), Baylor Fox-Kemper's talk here..
- Multiple “fit-for-purpose” cost functions depending on the question asked.
- Learning algorithms may play multiple roles:
  - Building emulators, fast surrogate models of low dimensionality.
  - Replace empirical closures with data-driven approaches.
  - Recognize viable models quickly.
- Other fields exploring same terrain face substantial difficulties: see Frégnac (2017): “Big data and the industrialization of neuroscience: A safe roadmap for understanding the brain?” See also Jonas and Kording (2017): “Could a Neuroscientist Understand a Microprocessor?”
- In the face of the above, we must regard it a success that we hold the line on Charney (1979) despite a vast increase in dimensionality!

# Model development: Nested cycles



- **Component development:** detailed understanding of climate process (e.g radiative transfer) **representations** through theory, observation.
- **Coupled model development:** assembly of components, ensuring global physical constraints are met (e.g conservation of mass, Earth radiation budget).
- **Model evaluation:** by comparison against each other and against observations.
- Little feedback from outer cycles to inner.
- Entire cycle takes 6-7 years (**CMIP** is pacemaker).

# CM4 evaluation: “standard” metrics

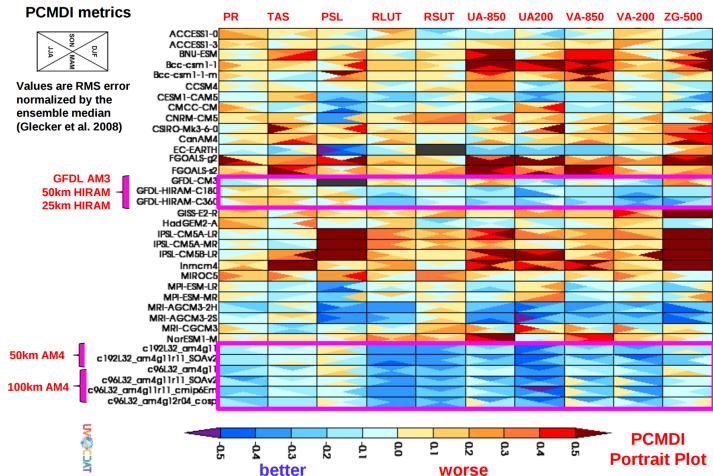


Figure courtesy Ming Zhao, NOAA/GFDL.

# CM4: new evaluation metrics: TC climatology

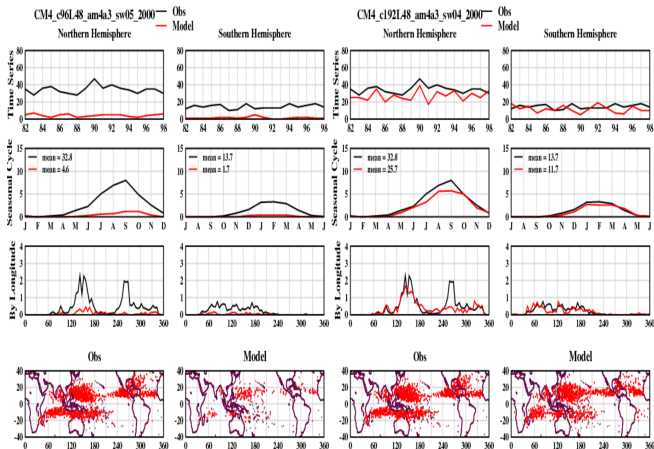


Figure courtesy John Dunne.

# CM4: new evaluation metrics: MJO

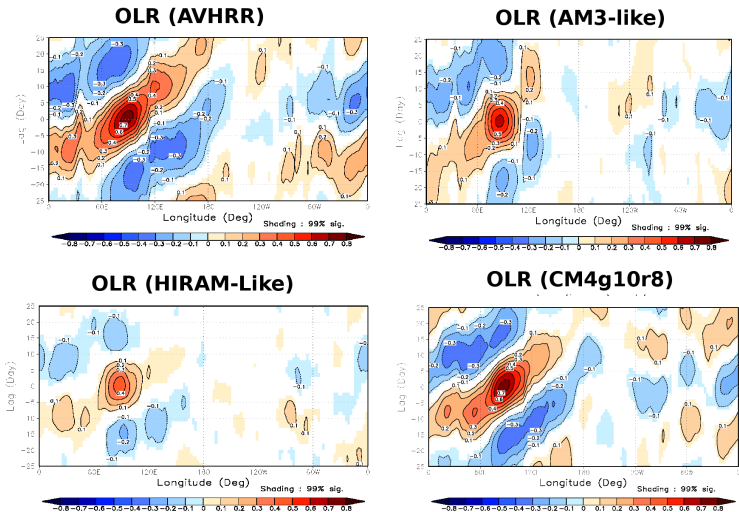
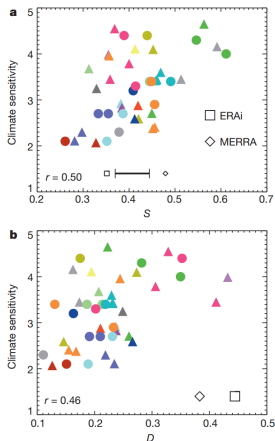


Figure courtesy Ming Zhao and Isaac Held, NOAA/GFDL.

# Emergent constraints



Sherwood et al (*Nature*, 2014): “Spread in model climate sensitivity traced to atmospheric convective mixing”. Observational constraints on model uncertainty.

# Built for stability?

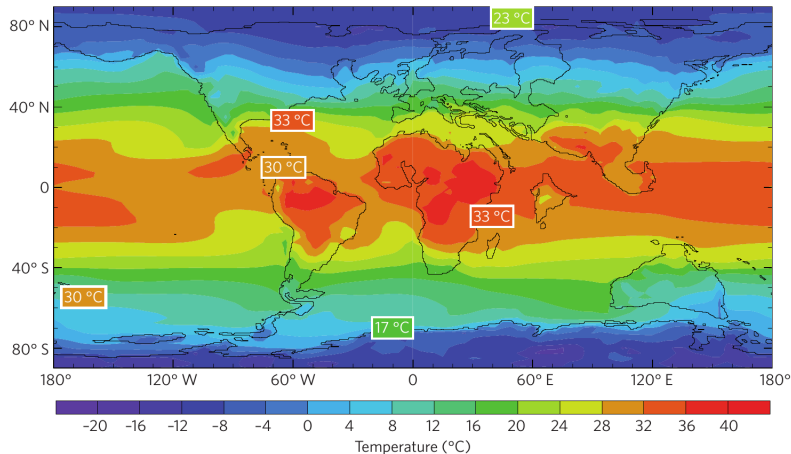


Fig 1 from Valdes (2011). GCMs are unable to simulate the Paleocene-Eocene climate of 55 My ago.

# Select quotes, questions from this meeting

- Do we want better simulations or increased understanding?
- Wouldn't it be great if we could do this with no people involved?
  - No students?
  - No senior scientists?
- Learnt methods must obey convergence, conservation laws, etc: how much physics is imposed on learning? (And what if you impose the wrong physics?)
- What is the coupled system response to process level learning? Can we learn everything all at once?
- Would learning from present-day (late Holocene) observations help with paleoclimate studies? counterfactual worlds?

# What would future infrastructure look like?

- A unified modeling infrastructure with:
  - $\leq \sim 1$  SYPD models, “LES”, “DNS” for generating training data
  - $\sim 10$  SYPD comprehensive models for “doing science” – e.g climate sensitivity, detection-attribution, predictability, prediction, projection, ...
  - $\geq \sim 100-1000$  SYPD fast approximate models for uncertainty exploration
- Massive re-engineering to speed up the 10 SYPD model by a few X will not be transformational (scientists will add to it to bring it back to  $\sim 10$  SYPD)
- A flexible open evaluation and testing framework where metrics can be added with little effort (see e.g Pangeo)
- A system of composing cost functions at will and generating the learnt models within a period attuned to human attention span