

Looking towards the future – NCAR Computing, Storage and our Models and Workflows

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Software Engineering Assembly

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Challenging Times Ahead – *The end of modeling as we know it?*

- **Atmospheric & rel. science relies on modeling complex systems with multi-scale, multi-physics**
- **Computers have big problems supporting our current approach (next slide)**
- **Is our future ability to advance atmospheric science in jeopardy?**



Computing Challenges

- **Performance:**
 - Individual cores are not getting faster - integration rate is stuck
- **Power:**
 - moving data on/off chip takes lots of energy
- **Complexity:**
 - increasing complexity both software, in human-crafted algorithms and in hardware architecture
- **Data:**
 - the volumes of data generated by climate and weather codes don't play well with current storage technologies, and system software and analysis practices are not keeping up

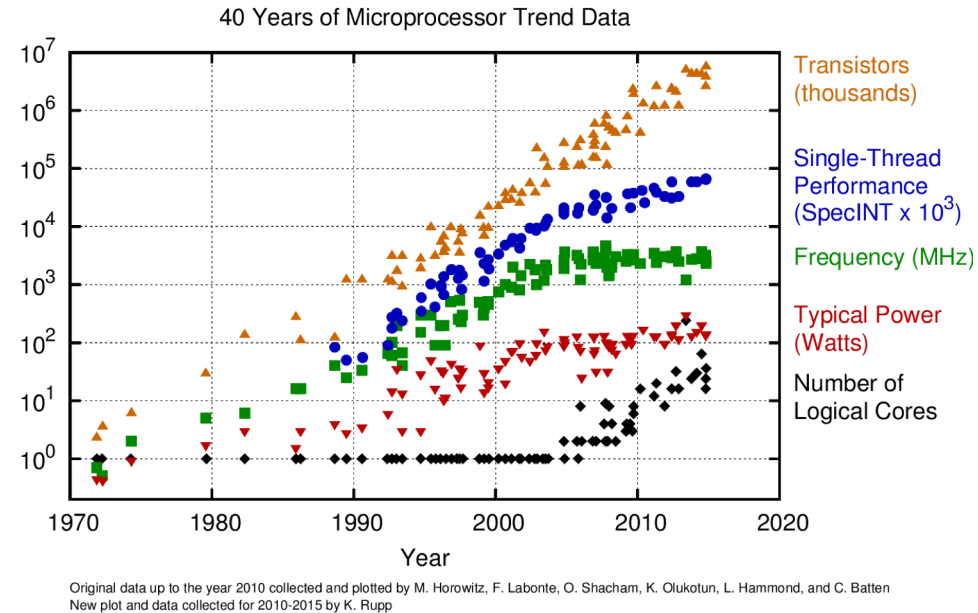
Computing Wall

- **Processor trends**

- More transistors
- More cores (\propto transistors)
- Flat clock speeds and power
- **Slowing thread performance**
- Increasing flops/byte of memory BW
 - SunWei processors ~ 25 flops/byte
 - KNL processors ~ 7 flops/byte

- **Climate modeling not well matched to trends**

- Typically < 1 flop/byte
- Climate applications are state heavy with low computational intensity.
- Physics code is branchy, hard to vectorize, has divides and load imbalances

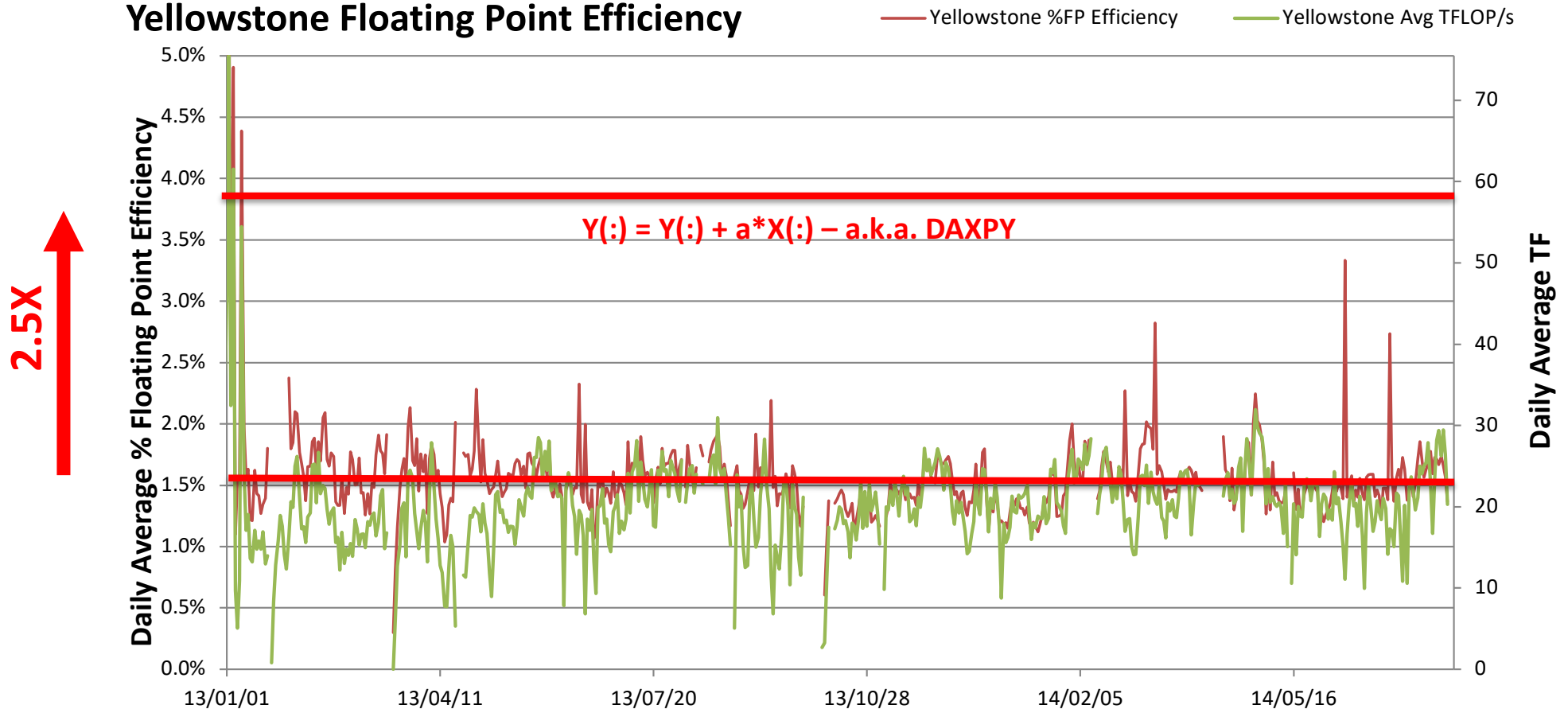


Source: Karl Rupp

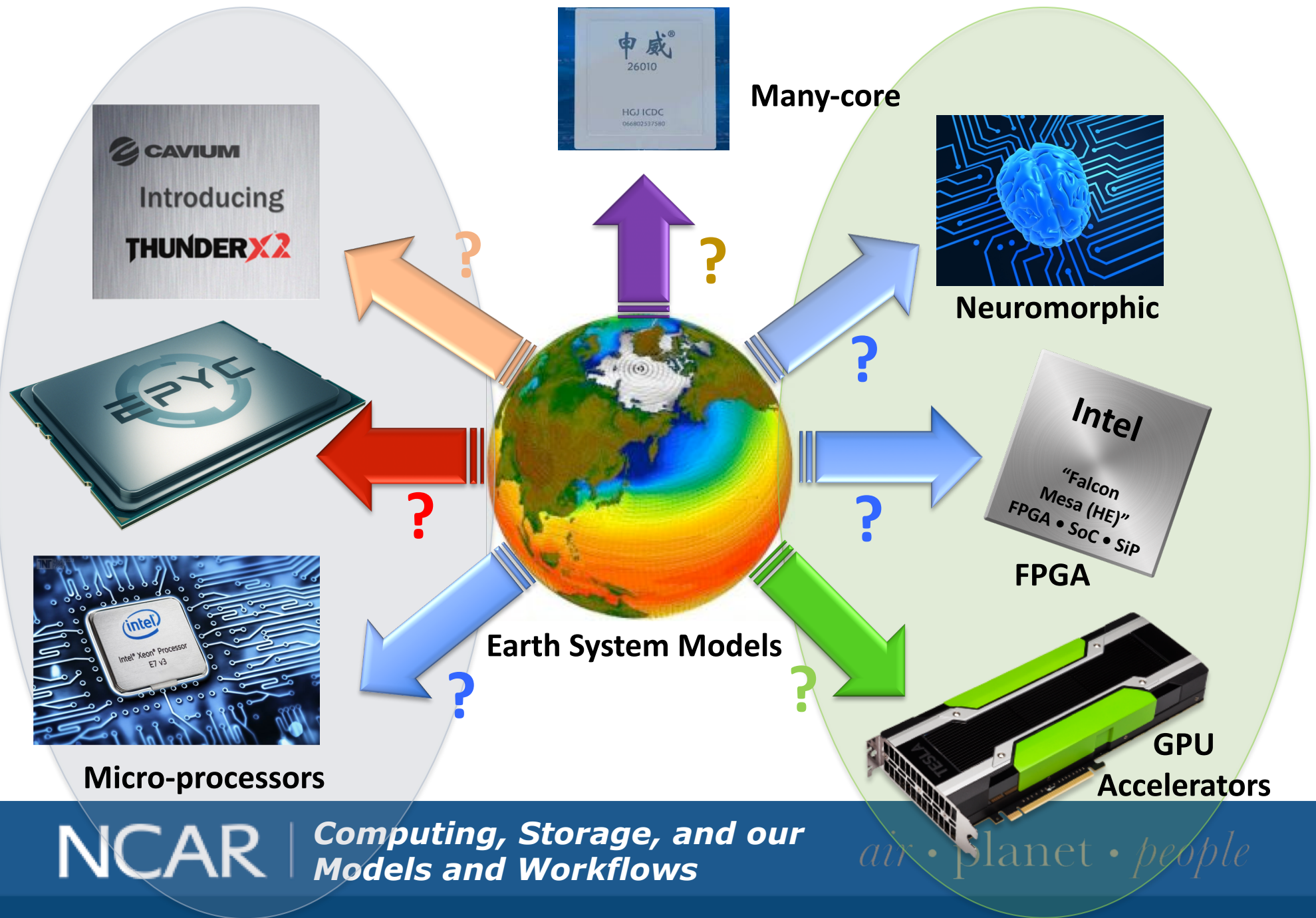
The Vectorization Gap

Yellowstone: Sustained fraction of FP peak is 1.57%

Yellowstone Floating Point Efficiency

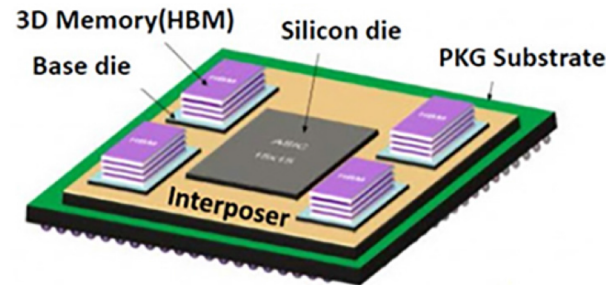
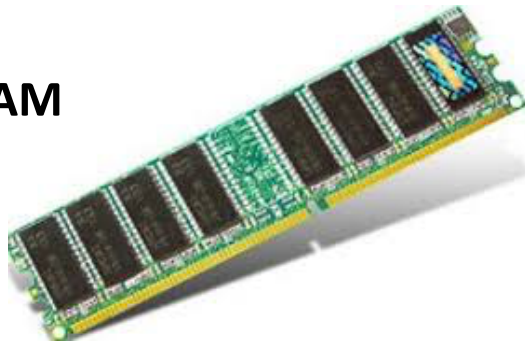


Increasing Computing Complexity



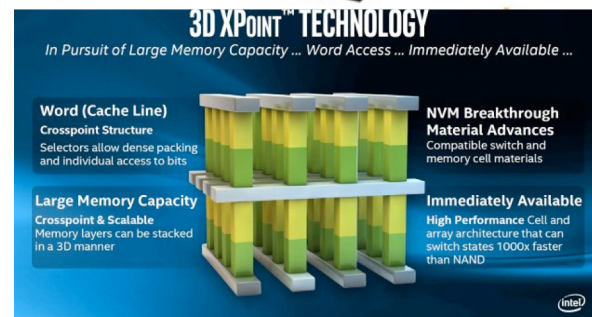
Increasing Storage Complexity

DRAM



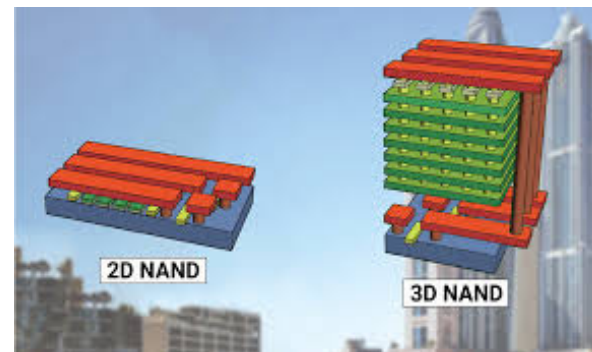
Stacked memory:
Fast, hot & small

DISK



Memory-class storage

TAPE



Storage-class memory

Cloud-base
object store
public or private

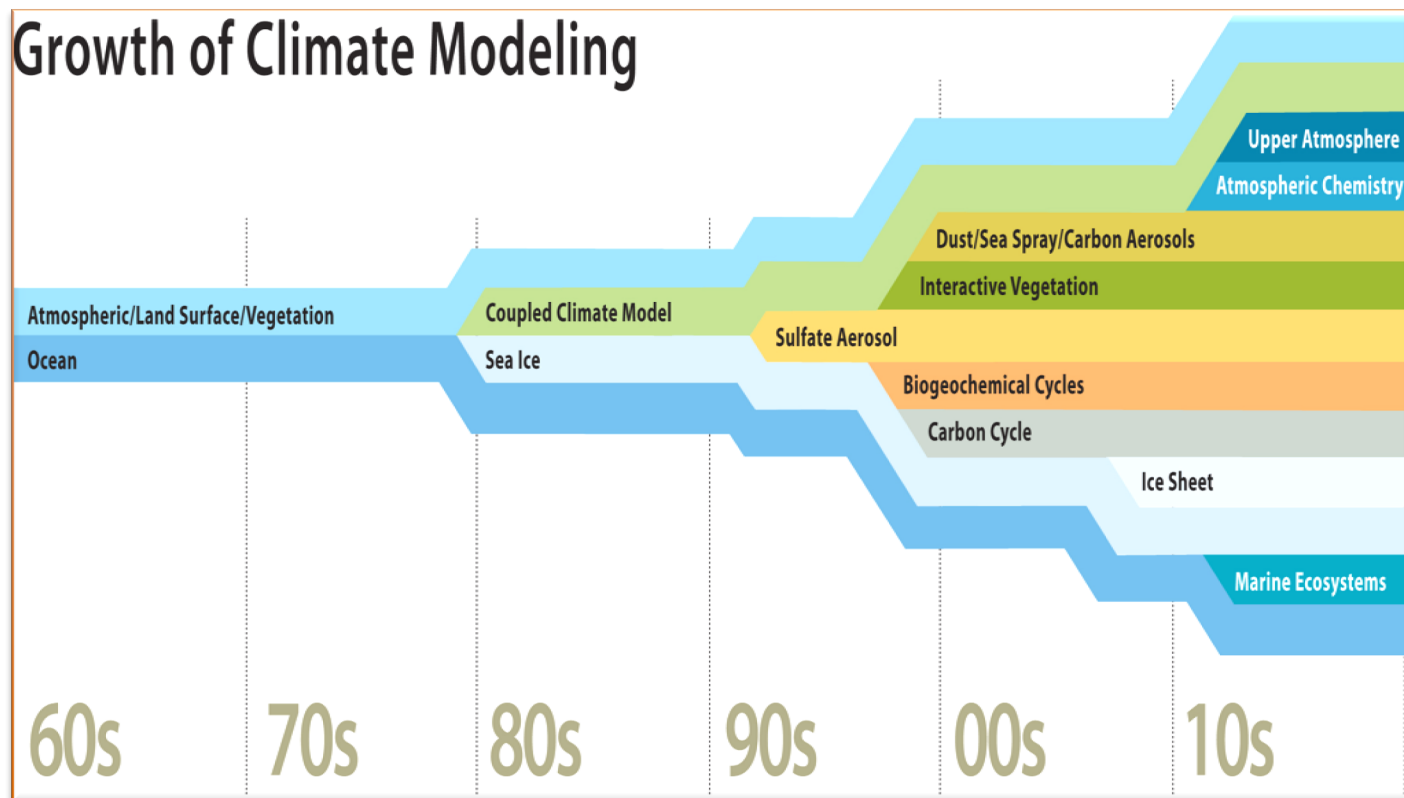


• people

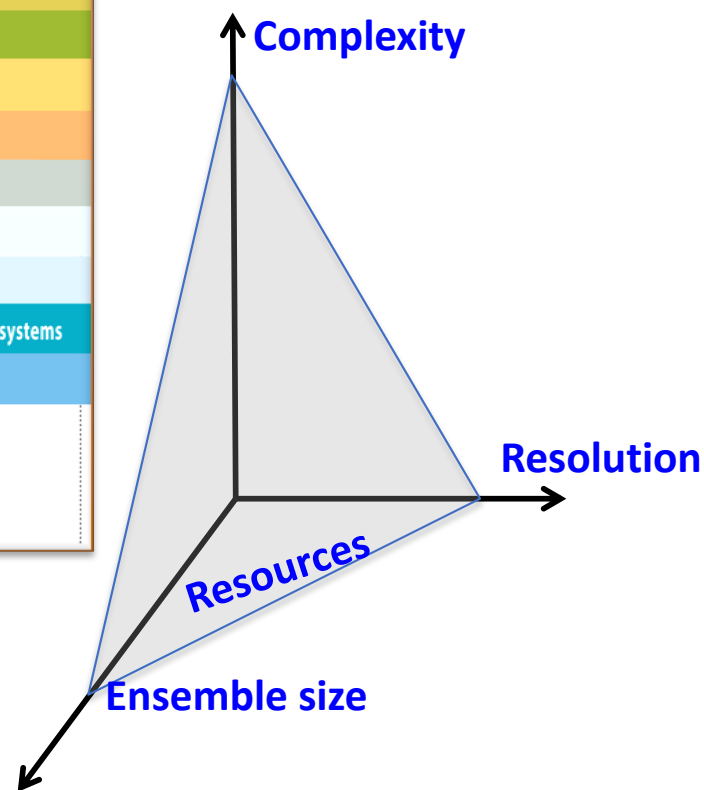
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Computing, Storage
Tools and Work

Increasing Model Complexity



“Lines of Earth System model code increased 10x over the period 1993-2008”, Easterbrook and Johns., 2009



What is the “limit” of model complexity?

- **Modularity, separation of concerns, etc. are strategies developed to manage software complexity. Is it enough?**
- **Possible sources of limits:**
 - Limits in human ability to engineer complex systems
 - Computational cost becomes too high /integration rate becomes too low.
 - Space of tunable parameters grows too large, or the region of stable parameter choices become infinitesimal.
 - Code becomes untestable/unverifiable.
 - Cost (\$) of development/maintenance becomes too high.
- **Which is a real issue, and which an unfounded fear?**

“[software engineering] limits exist but are simply less obvious and more related to limitations in human abilities”, Leveson, N.G.

Types of Software Complexity

- **Source lines of code**
 - Can be tricky to measure
 - Definition: executable lines;
- **Number of subprograms**
 - Indication of modularity
 - CESM1 – 9832
 - CESM2 – 10,570
- **Cyclomatic complexity**
 - Number of independent paths through the code
 - 350 routines (CESM1) have >51 paths
 - Impacts application “testability”

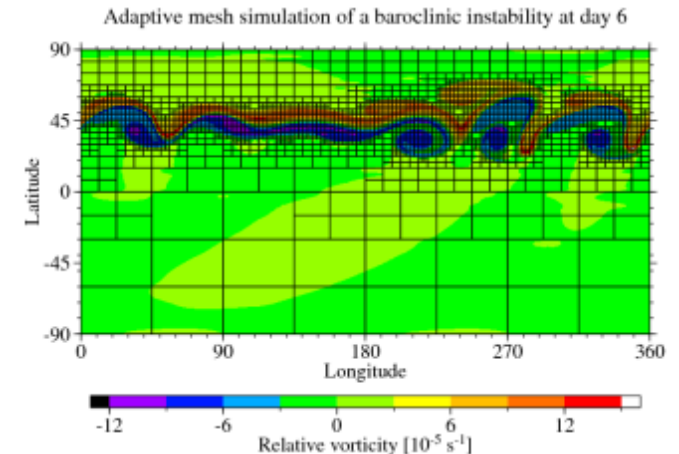
Table V. NUMBER OF SUBPROGRAMS IN EACH CYCLOMATIC COMPLEXITY RANGE

Model	0-10	11-20	21-50	>51
GISS	62	26	34	21
CSIRO-Mk3.6.0	116	63	65	55
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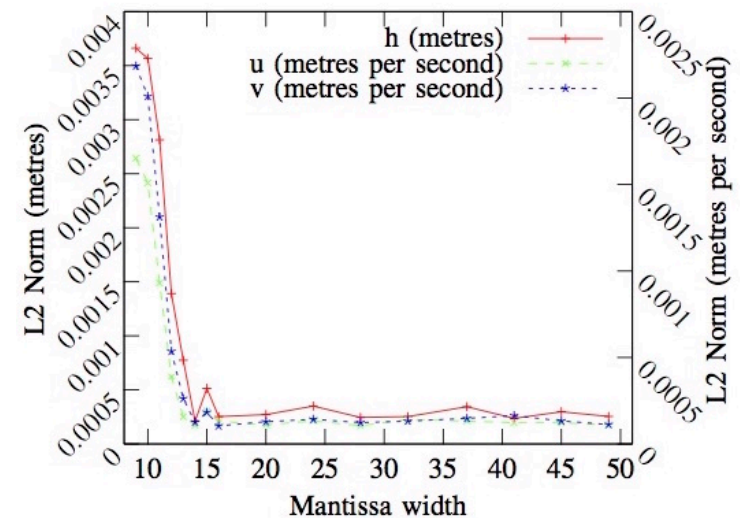
From: Mendez, et al. 2014

Algorithmic ways to deal with numerical complexity

- **Bigger timesteps**
 - Implicit integration
 - Parallel in time (PinT) methods
- **Fewer points**
 - More accurate numerics
 - Adaptive mesh refinement
- **Physics emulators**
 - Neural networks
 - Stochastic forcing
- **Reduced precision**
 - FPGAs



C/o: Paul Ulrich

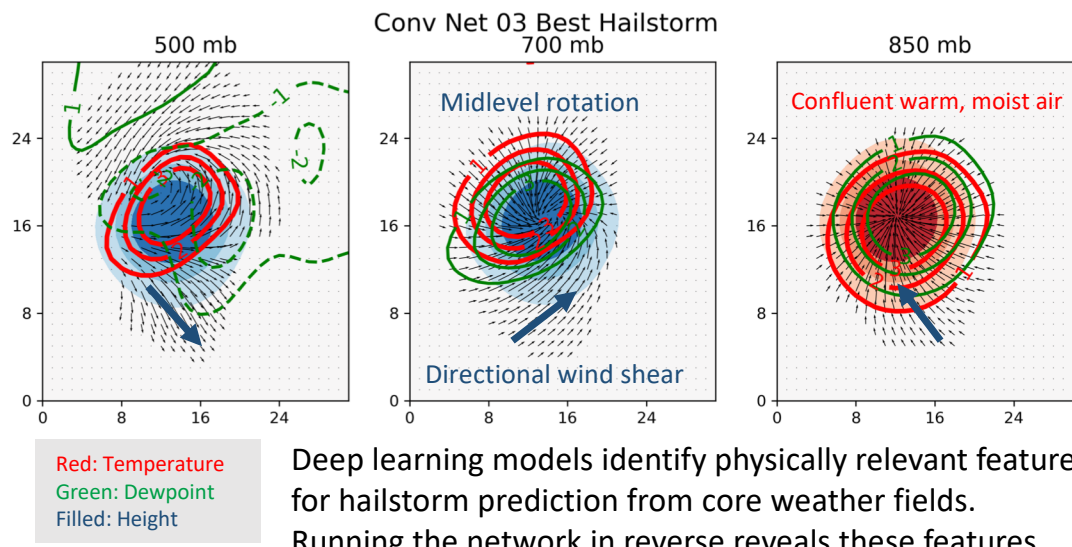


Targett, et al. 2015

Tackling Model Complexity through Machine Learning (ML)



New ML Team - AniMaL (Analytics and Integrative ML) in CISL/NCAR

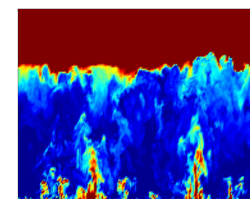
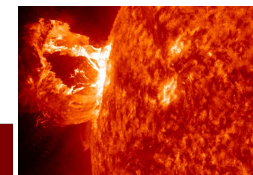


Deep learning models identify physically relevant features for hailstorm prediction from core weather fields. Running the network in reverse reveals these features.

What is a neural net's "dream" hailstorm?

Why machine-learned emulation? Replacing human-crafted parameterizations with machine learning algorithms may simplify, accelerate and improve models.

- Cloud Microphysics emulation (Dr. Andrew Gettelman, CGD)
 - improved weather and climate modeling
- Interplanetary Coronal Mass Ejection (CME) (Dr. Sarah Gibson, HAO)
 - space weather prediction
- Sub-grid-scale Turbulence (Dr. Sue Haupt, RAL)
 - Application: improved meteorological models



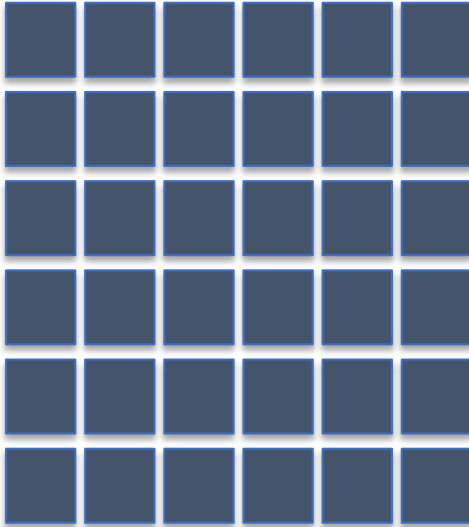
NCAR's Next Super "NWSC-3" (2021)

- **Focus on a design that:**
 - Enhances the end-to-end rate of science throughput
 - Reduces costs and/or enhance reliability
- **Harness emerging technologies:**
 - Accelerators (GPUs)
 - New memory technologies (stacked, NV memory)
 - Machine learning techniques (ML/DL)
- **Prepare application/workflow codes:**
 - scalability and performance
 - Performance-portability



Existing System Architecture

Xeon Super-computer

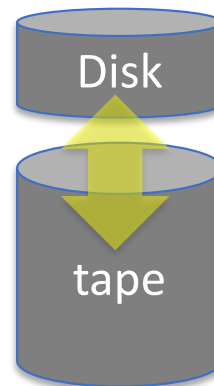


$O(10^5)$ cores
 $O(0.3 \text{ PB DRAM})$

Small Analysis Cluster

$O(10)$
Analysis Nodes

Web servers

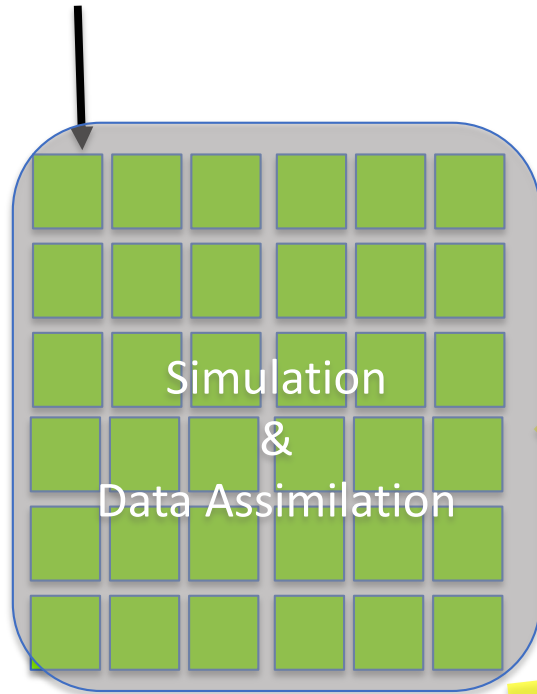


Hot Cache (Disk):
 $\sim O(200) \times \text{DRAM}$

\sim Warm Cache (Tape):
 $\sim O(500) \times \text{DRAM}$

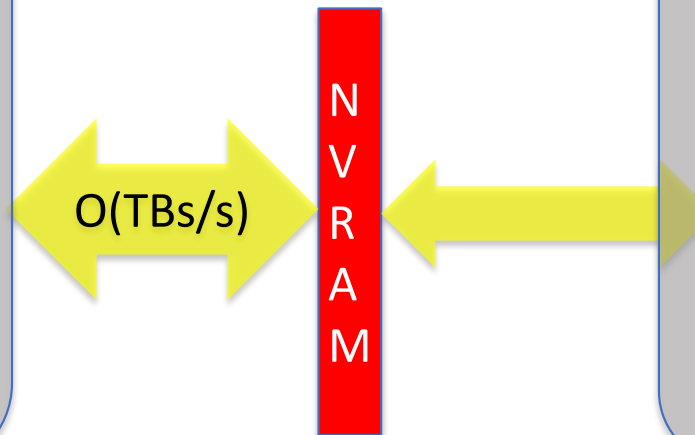
Next-Gen (NWSC-3) Architecture

HBM devices

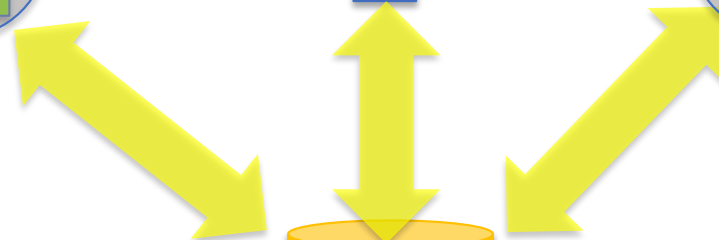
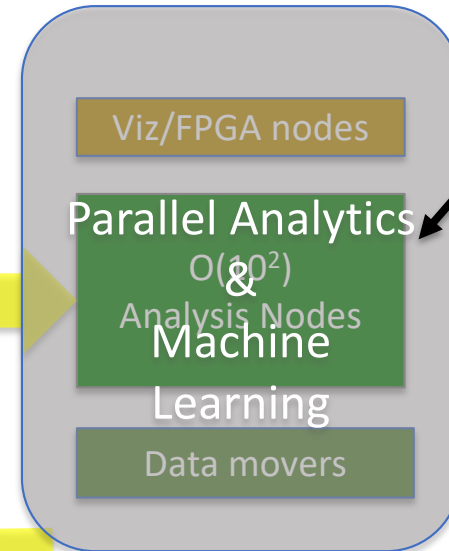


$O(1M \text{ cores})$
 $O(1 \text{ PB DRAM})$

Super-cache
 $O(5x) \text{ DRAM memory}$



More
Analysis
Nodes



Warm Cache (Disk):
 $\sim O(40x) \text{ DRAM}$



$\sim DR/Collections \text{ (Tape):}$
 $\sim O(100) \times \text{DRAM}$

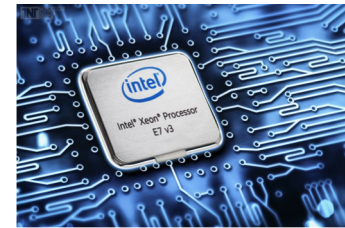
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CPU-GPU Performance Portability

- **Strategy - Single Source Programming Model**
 - CPU: OpenMP directives
 - GPU: OpenACC directives
- **Why?** *GPUs have substantially better energy efficiency and performance per device than CPUs*
- **Growing GPU-enabled Portfolio:**
 - MPAS Dynamics
 - MPAS Physics underway
 - MOM6 about to start
 - MURAM kicking off
- **Annual Multicore workshop** provides forum to better understand application of new HPC technologies for the next generation of weather, climate, and earth-system models
- **Active University partnerships (Wyoming, Delaware) to address workforce challenges**



Weather and Climate Alliance (WACA): Refactoring MPAS for CPU-GPU portability



*High resolution global atmospheric
models: too slow for long-range
simulations*

- **Goal:**
 - Single source performance portability across CPUs and GPUs using the OpenACC & OpenMP directive-based system.
- **Participants:**
 - NCAR (CISL and MMM)
 - NVIDIA Corporation and IBM Corporation/The Weather Company
 - University of Wyoming, CE&EE Department
 - Korean Institute of Science and Technology Information (KISTI)
- **MPAS 64-bit dynamical core results (40,962 grid-points)**
 - Comparison Intel Broadwell node (CPU) vs NVIDIA GP100 (GPU)
 - 8-15% better performance on CPU after porting to GPUs
 - **1 GPU = 2.8x CPU nodes**

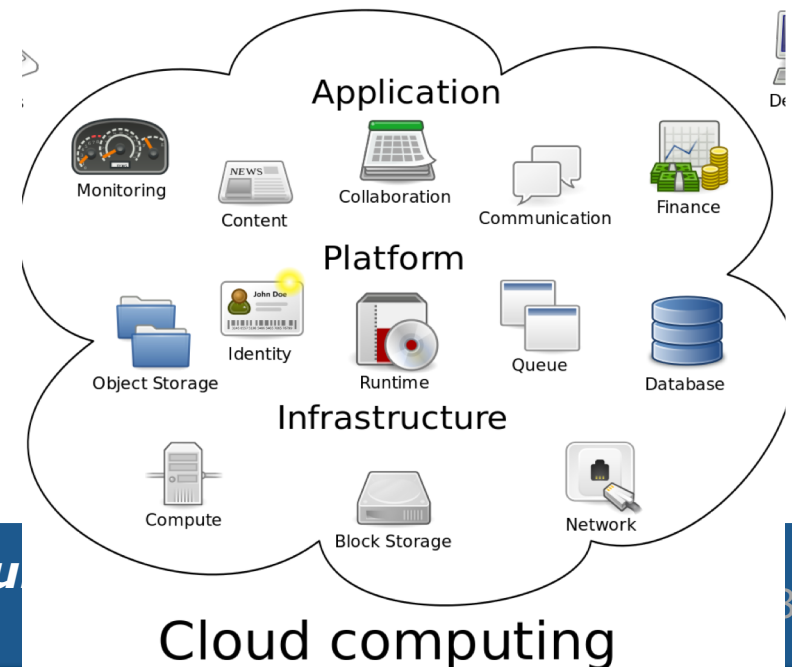
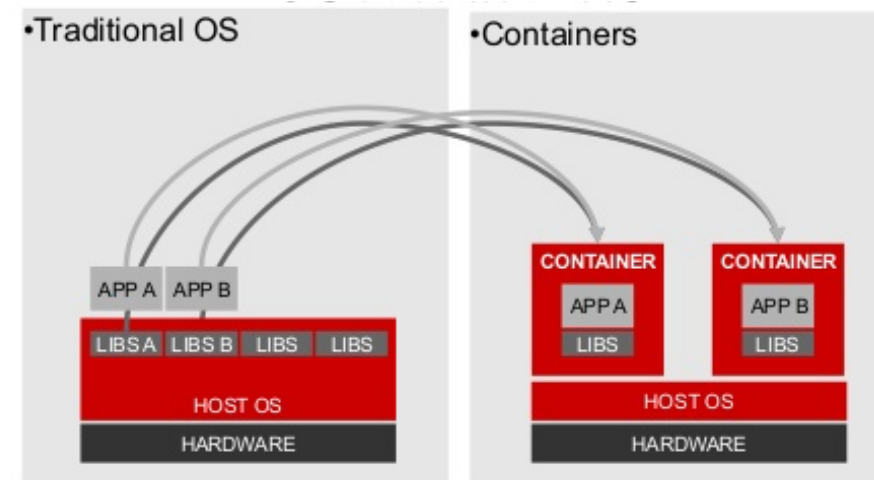
GPU accelerated code

```
!$ACC KERNEL
!$ACC LOOP
do i=1,imax
    a(i)-a(i)+z
enddo
!$ACC END KERNELS
```

***OpenACC directives
avoid a total rewrite in
CUDA.***

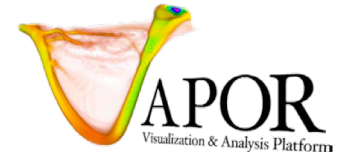
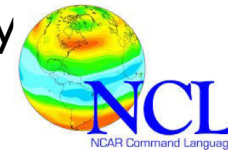
Enabling and Supporting Cloud-based Solutions

- **HPC Cloud-based solutions emerging across NCAR**
 - AMPs Forecast on Penguin Cloud for High Availability Needs
 - CESM2 1^o running on AWS EC2 at 10 SYPD with I/O
- **Environment “around apps” most valuable (i.e., Containerization)**
 - Working with SW Development teams for containerization (capturing complex environment needs)
- **Data Analysis and Storage**



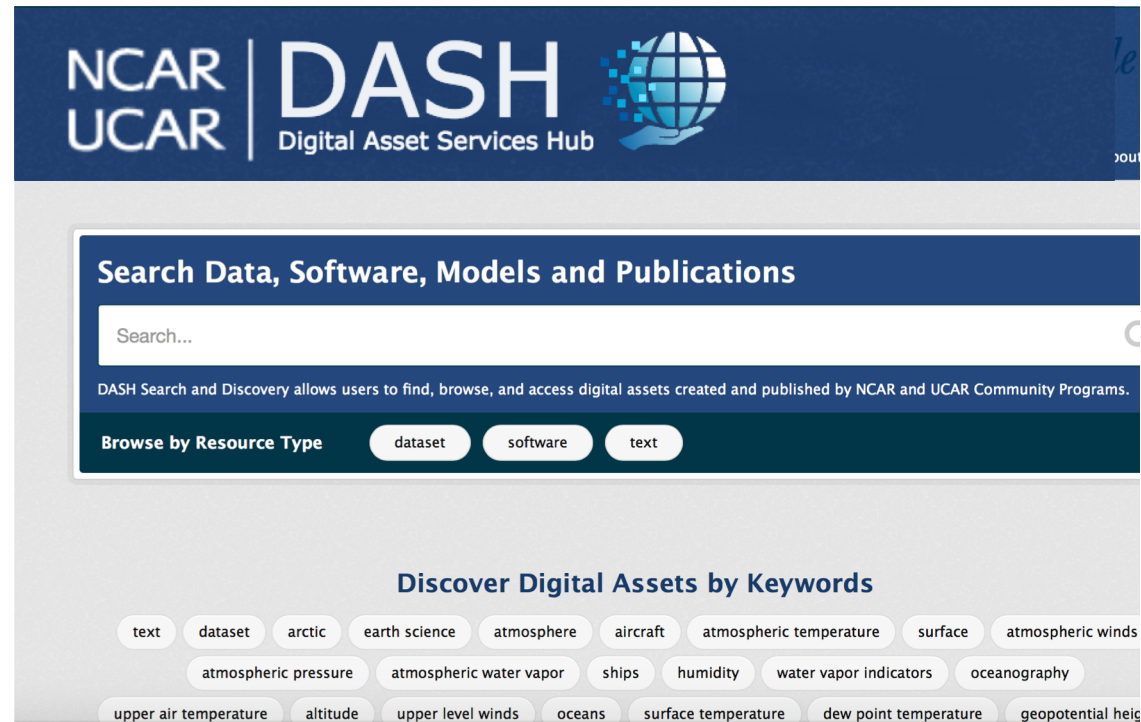
Confronting the Data Challenges

- **Positioning NCAR for increasing Data Focus**
 - **DSET (Data Stewardship Engineering Team)** – Cross NCAR team to tackle NCAR-wide data challenges
 - **DASH** - Digital Asset Services Hub deployed
 - **CISL** - creating an “Information Systems Division” (Leader is being actively recruited)
- **Prioritization and Collaboration around Data Portfolio**
 - Creation of “DASH” – for better data discovery
 - CMIP Analysis Platform
 - Capstone
 - Pangeo: Open Source Big Data Climate Science Platform
 - NCAR’s Research Data Archive (RDA)
 - Globus and Globus+
- **Architecting and integrating our data discovery, serving and analysis portfolio**



DSET and DASH

- Integrated front door to data discovery digital scientific assets (datasets and supporting metadata, publications, software applications, and model code) across NCAR
- Improve coordination, shared expertise, and data management standards across organization
- DSET identified 102 distinct NCAR digital assets
<http://data.ucar.edu>
- Expanding DASH to support Public Access Mandate and NCAR PI Data Plans
- Hosting: “*Geoscience Digital Data Resource and Repository Service (GeoDaRRS) workshop*” (Aug 7-9, 2018)



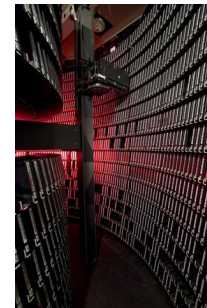
CMIP Analysis Platform

- **New Service - Lending Library for CMIP with DAV access**
 - Still early days for CMIP6. Good test experience with CMIP5 data
 - Up to 10 PB will be allocated
- **Working to meet community needs**
 - Reaching out to NSF Funded CMIP researchers
 - Providing a platform for developing analytics tools
 - Future - look to provide all the data on “the Cloud”?
- **More than 70 allocation requests for CMIP AP received to date**
 - More than 40 show some amount of DAV cluster use
 - And 45 user requests for data to be added to the lending library

Pangeo: Open Source Big Data Climate Science Platform

Scalable analytics solutions are required to work with large datasets

- **Goal:** create an open-source toolkit for the analysis of climate datasets, built on the **Python** language ecosystem, **Xarray** multi-dimensional array tools, and **Dask** parallel analytics system
- **Funding: \$1.2M NSF-funded EarthCube project**
- **Pangeo Participants:**
 - Lamont-Doherty Earth Observatory
 - Columbia University's Data Science Institute
 - NCAR (Kevin Paul)
 - Anaconda



Parallelism is key: single device performance is falling behind!

NCAR

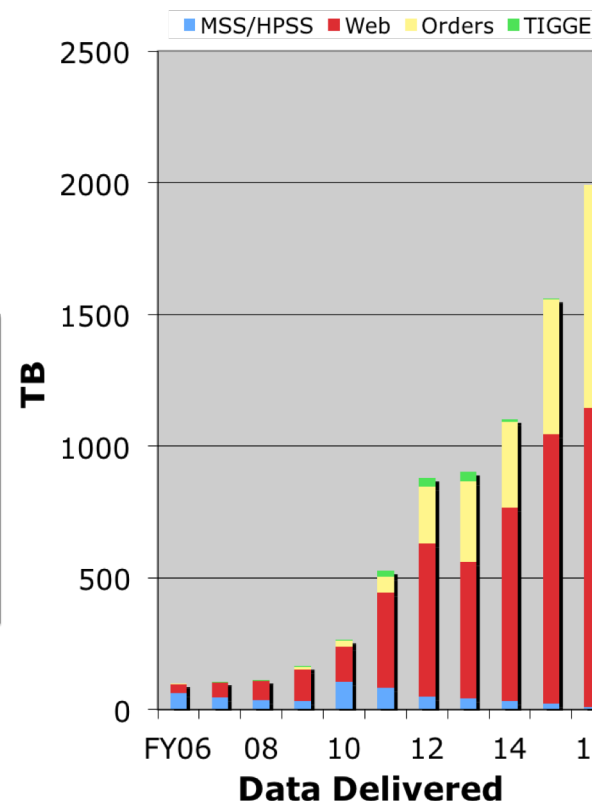
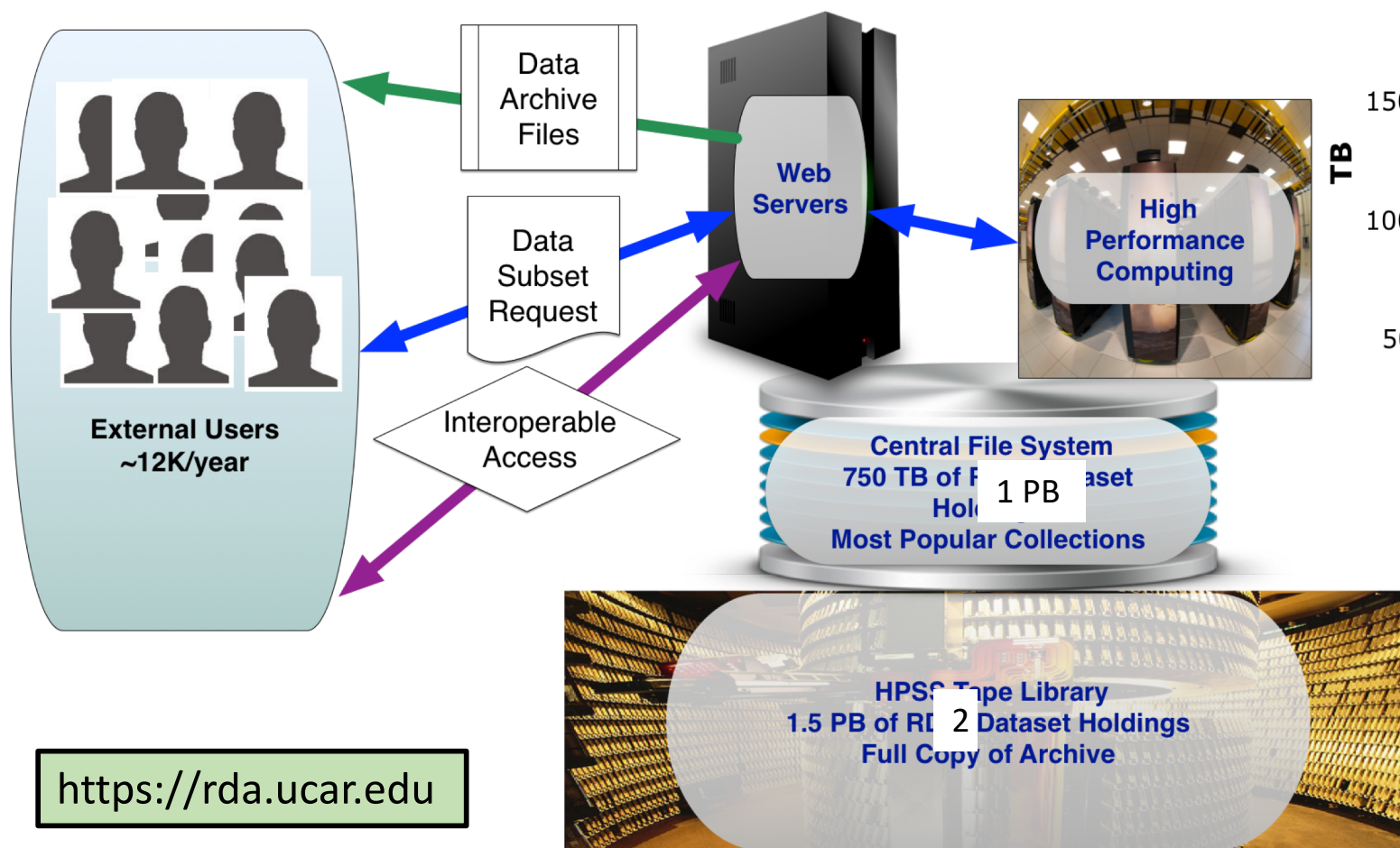
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RDA Data Processing

12,000+ Unique Web users in FY 2016

~2 PB Data Delivered in FY 2016

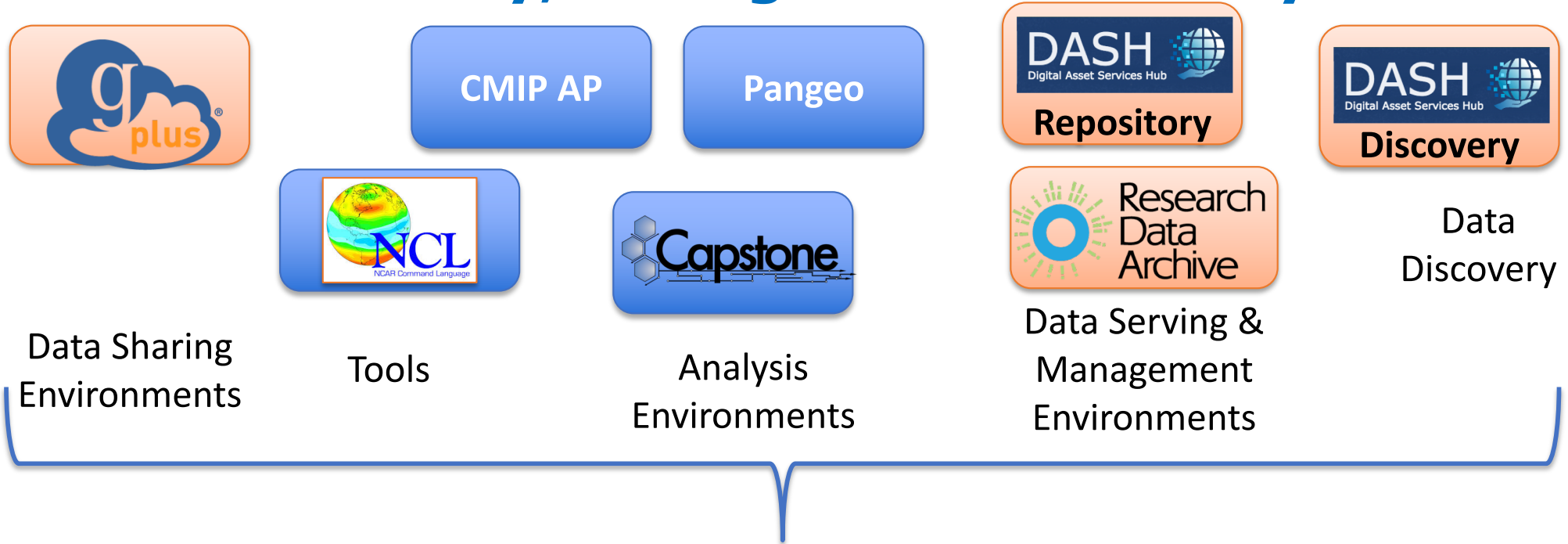


Data Movers, Sharing and Globus+

- **Data Transfer Protocols**
 - Globus
 - GridFTP
 - SCP/SFTP
- **Science Gateway Support**
 - RDA/ESG/CDP
- **Globus Features**
 - Reliable, Secure, High-performance file transfer
 - “Fire and Forget”
 - Automatic fault recovery
 - Powerful GUI, APIs and CLI
 - Integrated with RDA file lists
 - Integration with authentication systems



Developing an integrated Data Architecture for Discovery, Management and Analysis



- **Goals:**
 - Data portfolio needs more coordination/prioritization (do fewer things better ... headroom to tackle new initiatives)
 - Managing Legacy Needs
 - Move to Open Development
 - Cloud-enabled
 - Reusable components - Reduce/remove duplication

Thank you

Questions?



Complexity Metrics

Table V. NUMBER OF SUBPROGRAMS IN EACH CYCLOMATIC COMPLEXITY RANGE

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Table III. NUMBER OF SUBPROGRAMS

Model	Subpr.	Func.	In Mod.	Subpr.	In Mod.
GISS	143	18	0	125	0
CSIRO-Mk3.6.0	299	3	0	296	0
INM-CM4	739	42	0	697	45
GFDL-CM2.1	2012	331	329	1681	1670
HadGEM2	2032	89	14	1943	319
HadGEM3	2566	222	184	2344	1219
CCSM3	2740	327	320	2414	1950
CMCC-CESM	2822	524	451	2298	1360
GEOS-5	3171	721	487	2450	1645
IPSL	3361	441	413	2920	2222
MPI-ESM-LR	3410	453	393	2957	2198
CFSv2-2011	3774	1113	818	2661	1248
BCC-CSM1.1	3784	802	781	2982	2090
ModelE	3944	619	474	3325	1697
CCSM4	6424	1150	1117	5274	4649
CESM1	9832	1852	1809	7980	7516
total	51053	8707	7590	42534	29828

From: Mendez, et al. 2014