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Green Flash: Designing Energy Efficient Computers for Cloud System Resolving Climate Models and Other Exascale Applications

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http://www.lbl.gov/CS/html/greenflash.html



"...exascale computing will revolutionize our approaches to global challenges in energy, environmental sustainability, and security."

Simulation & Modeling at the Exascale for Energy & the Environment – DOE E3 report

Global Cloud System Resolving Climate Modeling







Individual cloud physics fairly well understood

Parameterization of mesoscale cloud statistics performs poorly.

Direct simulation of cloud systems in global models requires exascale!

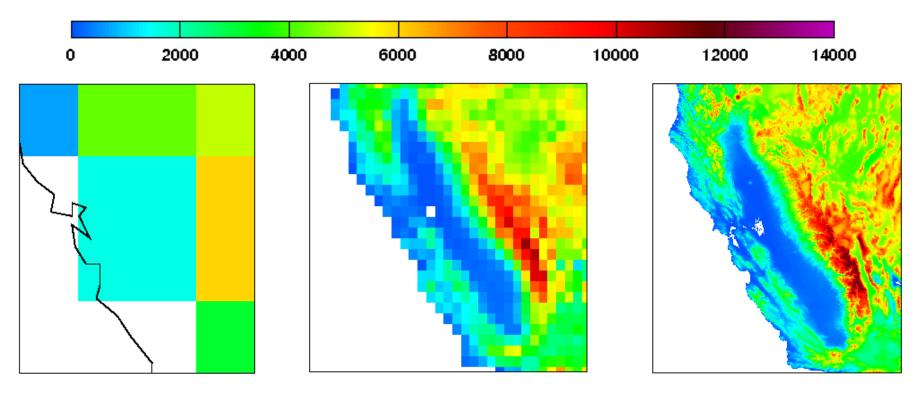
Direct simulation of cloud systems replacing statistical parameterization.
This approach recently was called for by the 1st WMO Modeling Summit.

Championed by Prof. Dave Randall, Colorado State University

Global Cloud System Resolving Models are a Transformational Change



Surface Altitude (feet)



200km Typical resolution of IPCC AR4 models

25km Upper limit of climate models with cloud parameterizations

1km Cloud system resolving models





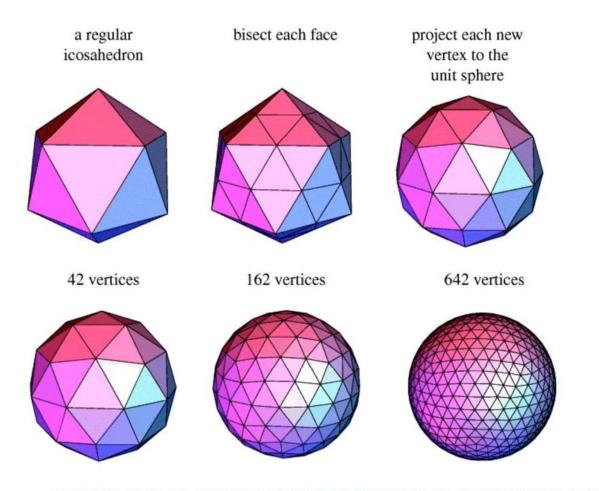
- GCSRM: Global Cloud System Resolving Model
 - -A complete one does not actually exist...
- Build a model to quantify code requirements by measuring and extrapolating the parts
- Four parts for the atmospheric model:
 - -Dynamics
 - -Fast physics (cloud processes and turbulence)
 - -Slow physics (radiation transport)
 - -MultiGrid solver (elliptic equation solution)
- Code requirements model will predict necessary flops, memory, communication, memory i/o to achieve the throughput goals.

-Target is to simulate time 1000 times faster than real time.



Ross Heikes CSU

Target resolution is 167,772,162 vertices, ~128 vertical levels, ~1.75 km



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Code Requirements Model

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- Measure and extrapolate:
 - -Operation count
 - -Main memory footprint
 - -Cache memory footprint (local store, not cache coherent)
 - -Memory bandwidth (bytes/flop)
 - -Instruction mix
 - -Interconnect bandwidth
 - -Interconnect latency
 - -Interconnect topology
- Derived constraints
 - -Power (core + memory+interconnect)
 - -Pins (memory + interconnect)
 - -Mix of instruction in hardware (Flops, integer ops, branch, etc)





- 167,772,162 vertices, ~128 vertical levels, ~1.75 km
 - -A truly transformational change to climate change modeling
 - -12.6+ Pflops <u>sustained (for 1000x speedup)</u>
 - -560TB total memory
- Ensembles of simulations (~10) \rightarrow 100 Pflops sustained
- Climate codes typically run at 5% of peak or less



(or its equivalent)

Traditional Sources of Performance Improvement are Flat-Lining (2004)

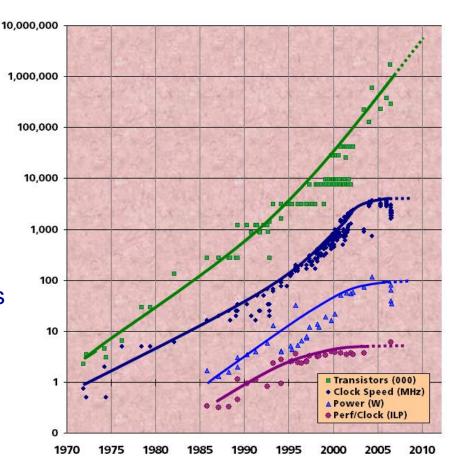
New Constraints

- 15 years of *exponential* clock rate growth has ended
- Moore's Law reinterpreted:
- How to leverage transistors to increase performance at historical rates?
- Power is the new design constraint.
 - Nonlinear: CPU speed & size
- Multicore: # cores double 18-24 months.

Accelerating supercomputing demand:

- End of straightforward serial improvements
- Much higher parallelism will be required to exploit this technology

Figure courtesy of Kunle Olukotun, Lance Hammond, Herb Sutter, and Burton Smith

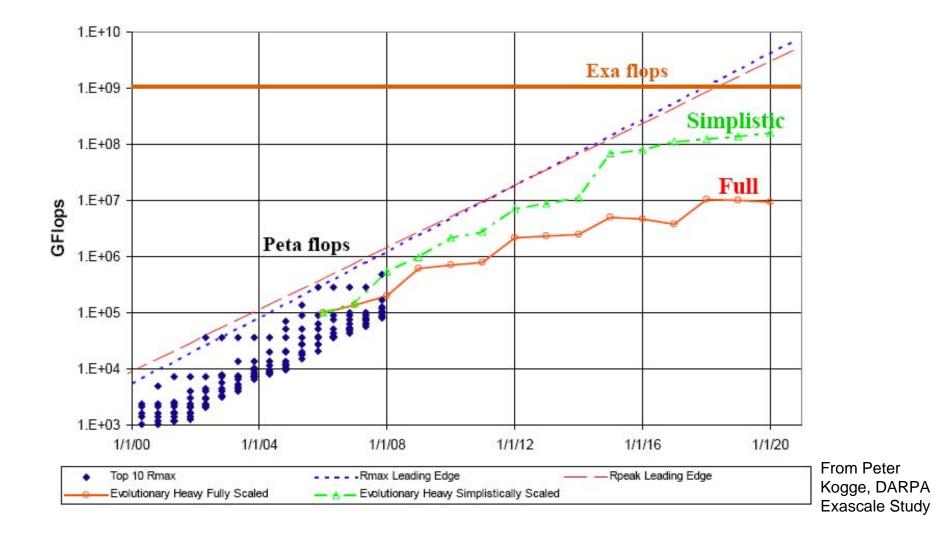




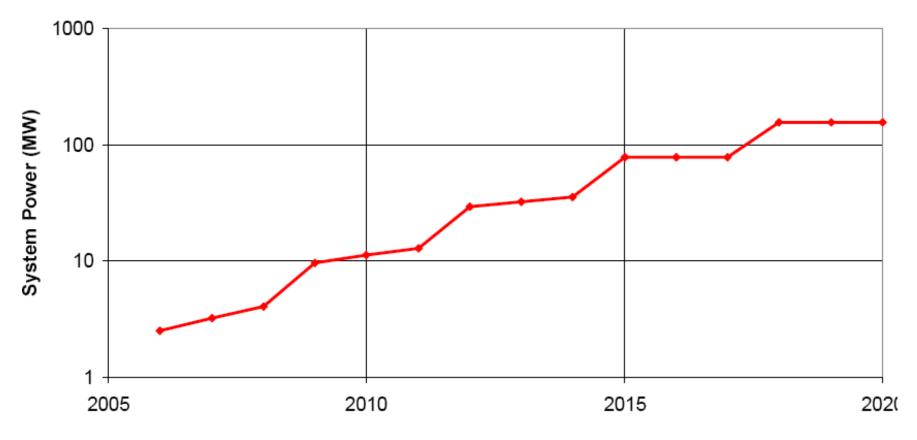
Exaflops will be hard!

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... and the power costs will still be staggering



From Peter Kogge, DARPA Exascale Study

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The Challenge



- How to get to this level of performance without an annual electric bill greater than today's procurement costs?
- How do you achieve this in a decade with a finite development budget?





We present an alternative approach to developing systems to serve the needs of scientific computing

- Choose our science target first to drive design decisions
- Leverage new technologies driven by consumer market
- Auto-tune software for performance, productivity, and portability
- Use hardware-accelerated architectural emulation to rapidly prototype designs (*auto-tune the hardware too!*)
- A holistic approach: innovate algorithm/software/hardware together (Co-tuning)

Achieve 100x energy efficiency improvement over mainstream HPC approach

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Path to Power Efficiency

Reducing Waste in Computing



The portable consumer electronics market:

Optimized for low power, low cost, and high computational efficiency

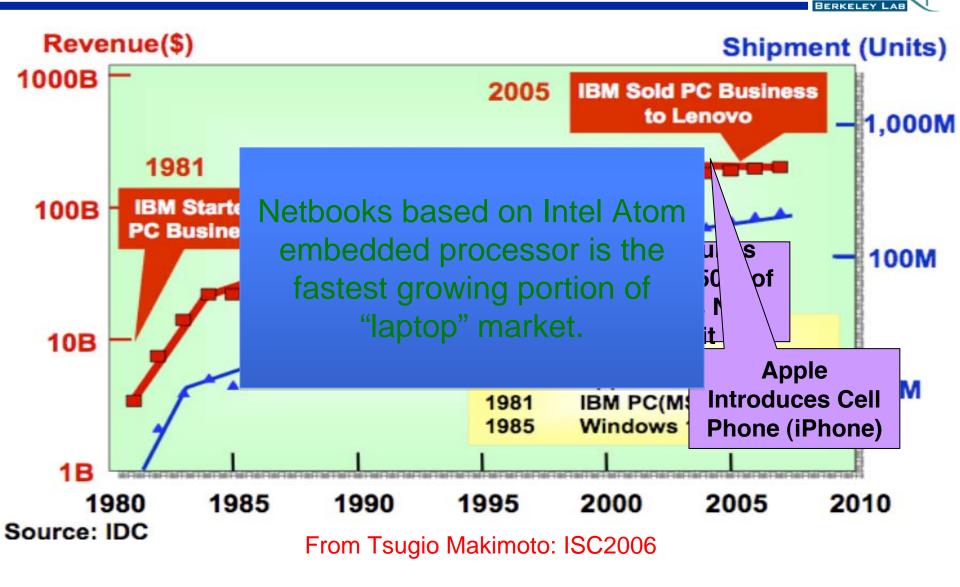
"Years of research in low-power embedded computing have shown only one design technique to reduce power: reduce waste."

-Mark Horowitz, Stanford University & Rambus Inc.

Sources of Waste:

- Wasted transistors (surface area)
- Wasted computation (useless work/speculation/stalls)
- Wasted bandwidth (data movement)

Consumer Electronics has Replaced PCs as the Dominant Market Force in CPU Design

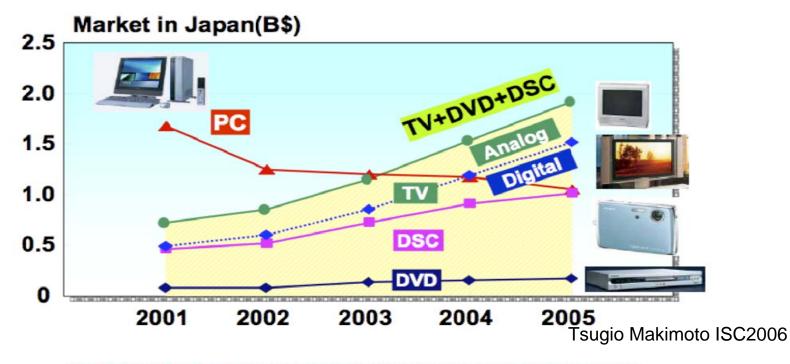




History repeats itself

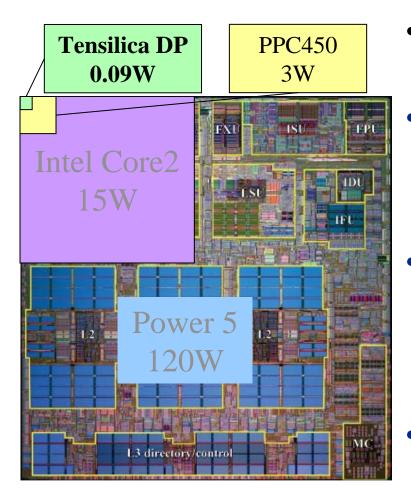


- 1990s HPC made the transition from vector to highly parallel platforms
 - Had to learn how to use desktop COTS technology for scientific computing
- Now- R&D investments moving to consumer electronics/embedded processing
 - Must learn to leverage embedded technology for future HPC systems





Design for Low Power: More Concurrency



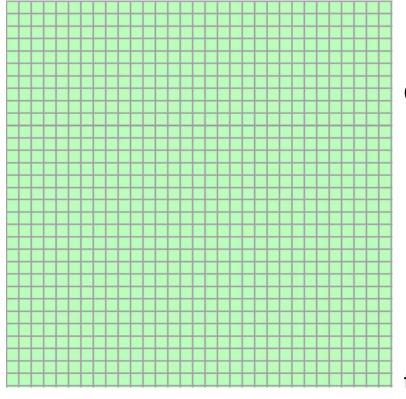
- IBM Power5 (server)•120W@1900MHz
- Cubic power improvement with lower clock rate due to V²F
 Intel Core2 sc (laptop) 15W@1000MHz
- Slower clock rates enable use of simpler cores – shorter pipelines, less area, lower leakage •IBM PPC 450 (BG/P - low power)

3W@800MHz

- Tailor design to application to <u>reduce</u> <u>waste</u>
 - •Tensilica XTensa (Moto Razor) 0.09W@600MHz







Even if each core operates at 1/3 of the frequency of fastest available processors, you can pack 100s of simple cores onto a chip and consume 1/10 the power

One IBM Power5

- •120W
- •1900MHz
- 128 Tensilica Xtensa DP
 - •11.5W
 - equivalent to 76,800MHz

If the application has enough parallelism the many-core chip can be much faster and consume less power.

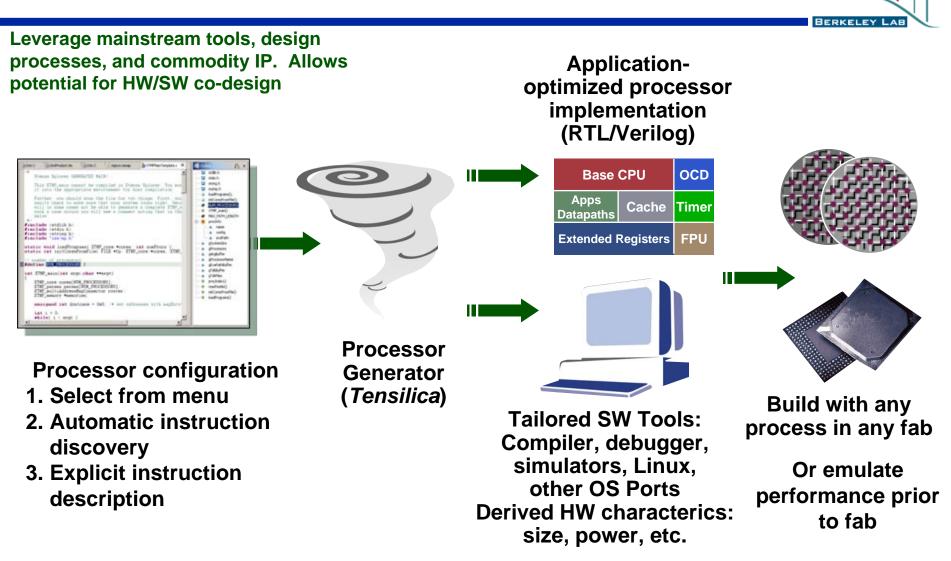


- Spec out the requirements of your code. – Aim for a class of codes, not just one
- Learn how to design processors and interconnects.
 - -We obtained chip design tools from Tensilica, a leading designer of chips for cell phones and other consumer elextronics.
 - Each chip design comes with its own C compiler and debugger
- Emulate your chip design on your code.
 - -RAMP emulates chips with FPGAs
 - Hardware emulation is more accurate and thousands of times faster than software emulation
- Iterate your chip design and your software.
 - -Autotuning takes advantage of the specific C compiler
 - -Profile the code to determine chip parameters.



Embedded Design Automation

(Example from Existing Tensilica Design Flow)



Advanced Hardware Simulation (RAMP)



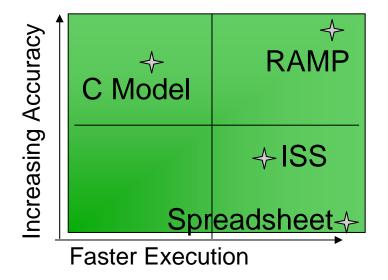
Research Accelerator for Multi-Processors (RAMP)

- Utilize FGPA boards to emulate multicore systems
- 1000x speedup versus software emulation
- Allows fast performance validation
- Emulates entire application (not just kernel)
- Break slow feedback loop for system designs
- Enables tightly coupled hardware/software/science co-design

Technology partners:

- UC Berkeley: John Wawrzynek, Jim Demmel, Krste Asanovic, Kurt Keutzer
- Stanford/ Rambus Inc.: Mark Horowitz
- Tensilica Inc.: Chris Rowen





Demonstration of Green Flash Approach

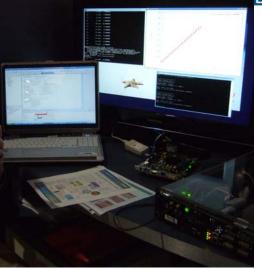
SC '09 Demo of approach feasibility

- CSU limited-area atmospheric model ported to Tensilica architecture
- Dual-core Tensilica processor running atmospheric model
- Eight and Sixteen Core configuration coming online
- MPI Routines ported to custom interconnect

Emulation performance advantage

Processor running at 25MHz vs. Functional model at 100 kHz (250x speedup)

Actual code running - not representative benchmark











Challenge: How to optimize the climate code for the differing chip designs under consideration.

Solution: Auto-tuning

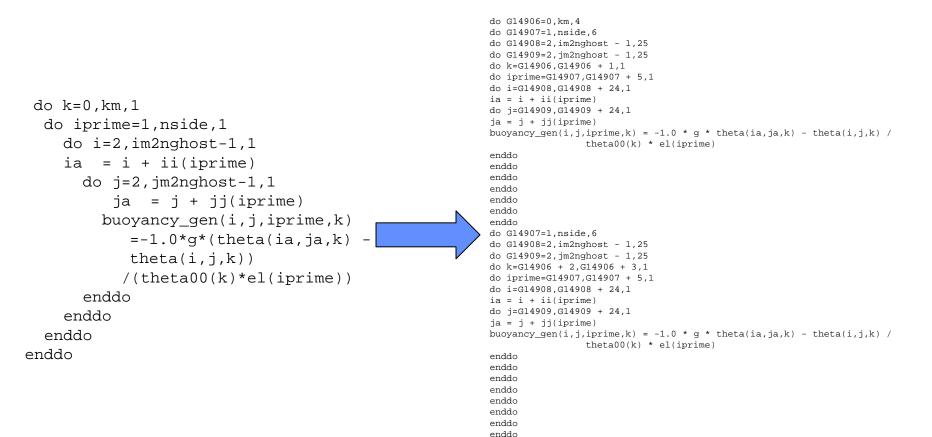
- Different chip designs may require vastly different optimizations
- Labor-intensive
- Automate search across a complex optimization space

"Never send a human to do a machine's job." – Agent Smith, *The Matrix*





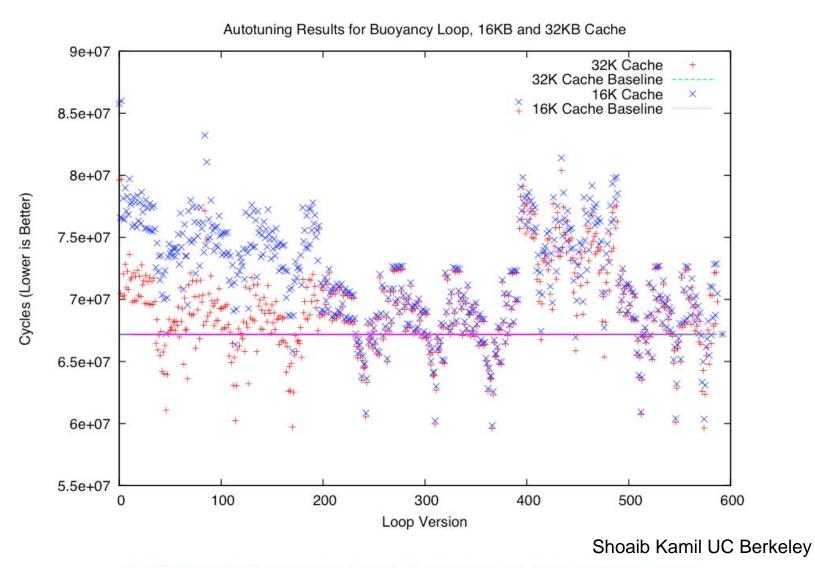
Operators extracted from climate code before and after auto-tuning





Auto-tuning Results

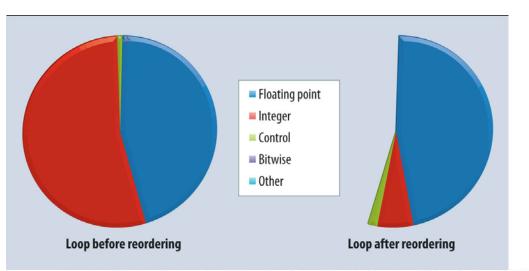




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Co-tuning: feedback on chip design

- We are fully profiling each loop in the code ->
- Auto-tuning can reduce the number of instructions but changes the mix of instructions.
 Iterate this information in the chip design
- Example: the loop with the largest footprint
 - decreased the cache footprint from 160kb to 1kb
 - halved the instruction count



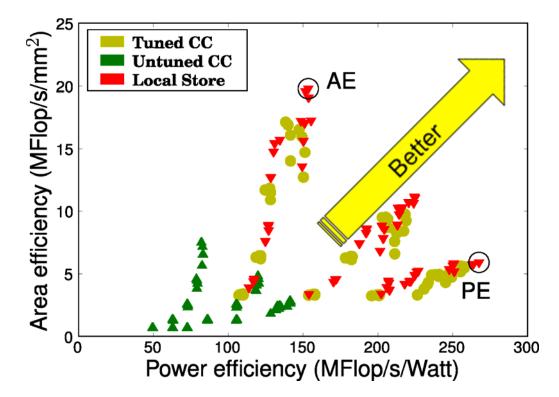
unique addrs unique clines footprint footprintcache tot ins Bvtes/Inst Bandwidth (MB/s) fpload fpstore FP Arith fpmov fprf FP L/S intload intstore intmov Int Arith Int L/S i/call branch control loop entry Control bitwise shift Logic

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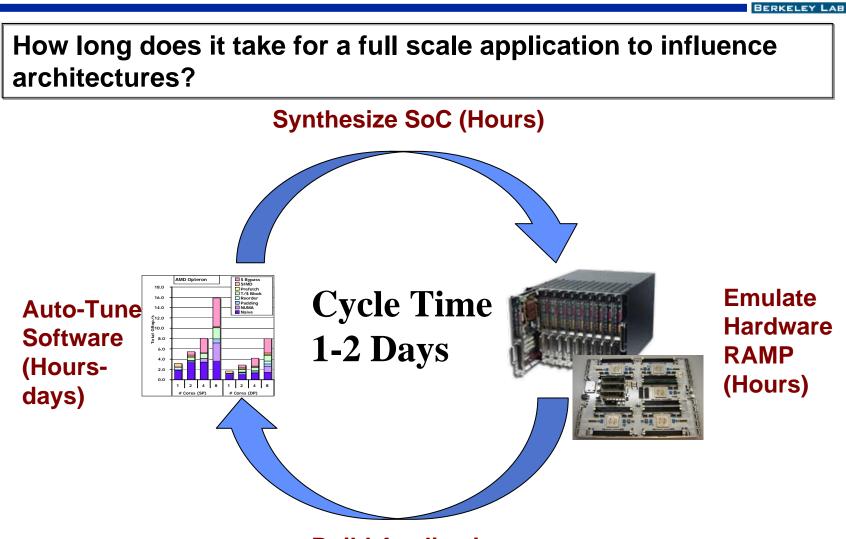
- The information from auto-tuning is relevant to the optimal chip design
- Iterate on the design process and autotuning



Marghoob Mohiyuddin, UC Berkeley



Holistic Hardware/Software Co-Design



Build Application



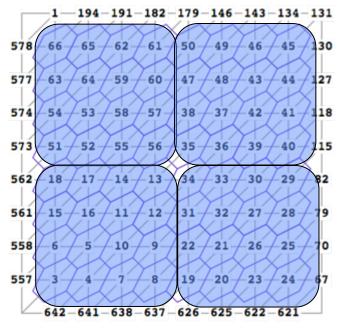


- CSU icosahedral code -167,772,162 vertices, ~128 vertical levels
- A strawman design concept
 - -2,621,440 horizontal subdomains (logically rectangular, 8x8 cells each)
 - -8 vertical subdomains of 16 levels each.
 - 20,971,520 processing cores.
 - 163,840 chips with 128 cores each.
 - Specific processor and network properties to be determined from the code requirement model.





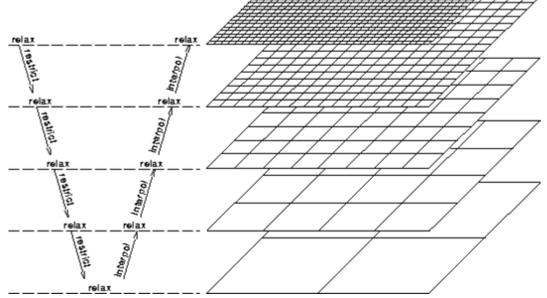
- Preliminary results for CSU code -167,772,162 vertices, ~128 vertical levels
- Anelastic Dynamics only (w/o multigrid solve)
 - -Sustained speed of 12 Pflops (600 Mflop per processor)
 - -Total memory 560TB (27MB per processor)
 - -7623 messages per second per processor
 - -Bandwidth 78MB/sec per processor
- Strong scaling w/ smaller domains
 - -10x lower latency & higher BW on chip
 - Many-core actually enables 20 million way parallelism!







- The MG solve is communication bound if the subdomains are too small.
- But multi-core chips helps this dramatically by reducing the communication costs of first few levels of the solve.
- 165K chips is better than 21M!!



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Green Flash 100PF (peak) Strawman System Design 🚠

We examined three different approaches (in 2009 technology)

- AMD Opteron: Commodity approach, lower efficiency for scientific codes offset by advantages of mass market. Constrained by legacy/binary compatibility.
- BlueGene: Generic embedded processor core and customize system-onchip (SoC) to improve power efficiency for scientific applications
- Tensilica XTensa: Customized embedded CPU w/SoC provides further power efficiency benefits but maintains programmability. Mainstream design process, tool chain, commodity IP

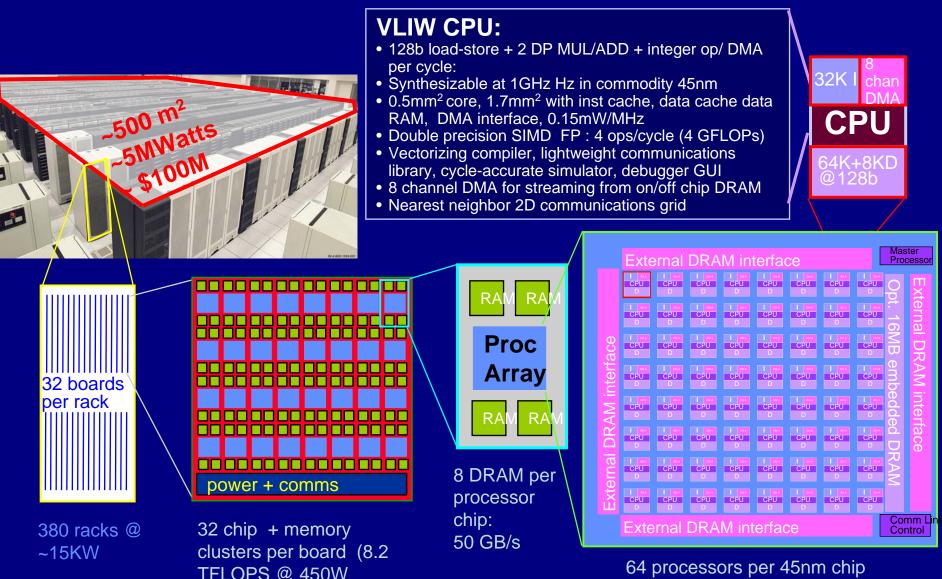
Processor	Clock	Peak/ Core (Gflops)	Cores/ Socket	Sockets	Cores	Power
AMD Opteron	2.2GHz	8.8	6	1.8M	11M	,142MW
IBM BG/P	0.8GHz	3.4	4	7M	29M	,198MW
Green Flash / Tensilica XTensa	1GHz	4	64	0.4M	25M	5 MW

1

Climate Modeling System

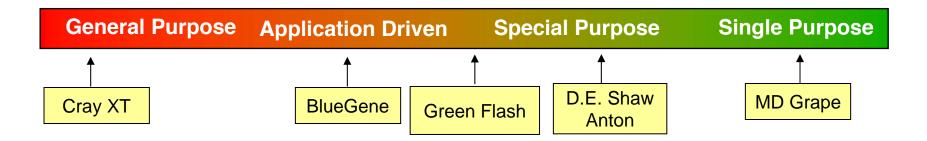
Strawman 100PF Design





512 GFLOPS @ 10W

Green Flash Customization Continuum



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Application-driven does NOT necessitate a special purpose machine (or exotic tech)

Riken MD-Grape: Full custom ASIC design

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• 1 Petaflop performance for one application using 260 kW for \$9M

D.E. Shaw Anton System: Full and Semi-custom design (bio-molecular)

• Simulate 100x–1000x timescales vs any existing HPC system (~200kW)

Application-Driven Architecture (Green Flash): Semicustom design

- Highly programmable core architecture using C/C++/Fortran
- Goal of 100x power efficiency improvement vs general HPC approach

Summary



We propose a new approach to high-end computing with potentially transformational impact on science

- Choose the science target first (climate in this case)
- Design systems for applications (rather than the reverse)
- Leverage power efficient embedded technology
- Design hardware, software, scientific algorithms together using auto-tuning, co-tuning, hardware emulation
- Achieve exascale computing sooner and more cost/power efficiently

Applicable to broad range of exascale-class applications

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At the exascale, numerical experimentalists must take a lesson from actual experimentalists.

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At the exascale, numerical experimentalists must take a lesson from actual experimentalists.

Design machines to answer specific scientific questions rather than limit our questions by available machines.



Questions?



http://www.lbl.gov/cs/html/greenflash.html

LBNL Contributors: John Shalf, Lenny Oliker, David Donofrio, Tony Drummond, Shoaib Kamil, Norman Miller, Marghoob Mohiyuddin, Woo-Sun Yang, Kathy Yelick

External Collaborators: UC Berkeley, Stanford, Colorado State University, Tensilica

This work was funded in part the DOE Office of Science under contract number DE-C02-05CH11231.





- Our Design does not expose unique risks
 - Faults proportional to # sockets (not # cores) and silicon surface area
 - -We expose less surface area and fewer sockets with our approach

Hard Errors

- -Spare cores in design (Cisco Metro)
- -SoC design (fewer components and fewer sockets)
- -Use solder (not sockets)

Soft Errors

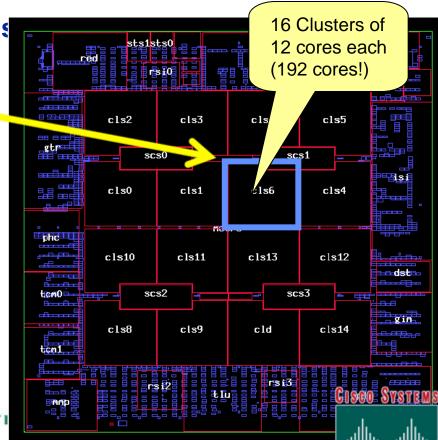
- -ECC for memory and caches
- -On-board NVRAM controller for localized checkpoint
- -Checkpoint to neighbor for rollback

Green Flash: Fault Tolerance/Resilience

- Large scale applications must tolerate node failures
- Our design does not expose unique risks
 - Faults proportional to sockets (not cores) & silicon surface area
 - Low-power manycore uses less sockets
- Hard Errors
 - Spare cores in design (Cisco Metro: 188 cores + 8 spares)
 - SystemOnChip design (fewer components→fewer sockets)

Soft Errors

- ECC for memory and caches
- On-board NVRAM controller for localized checkpoint



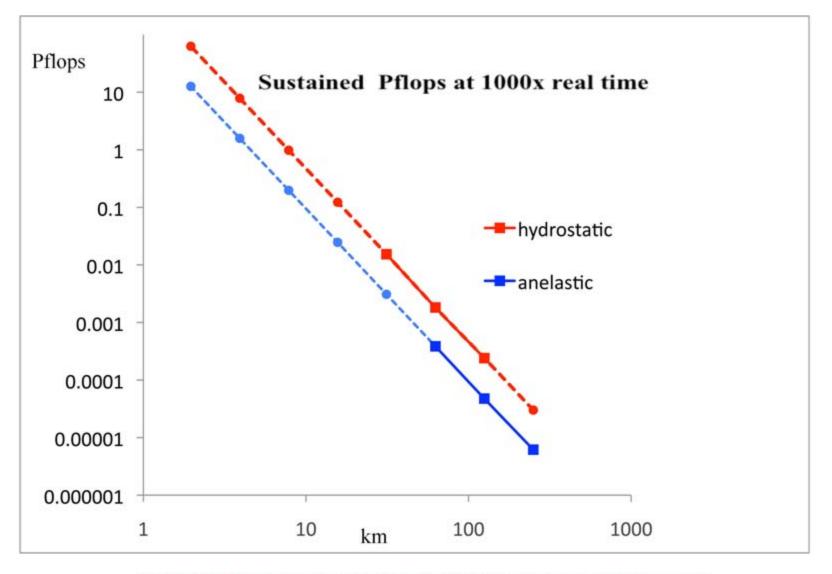




Sustained speed

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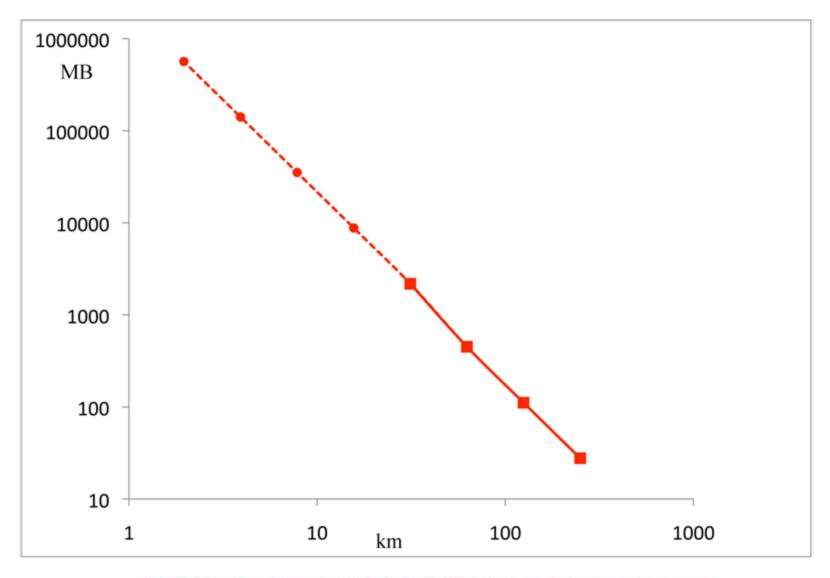
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Total Memory requirement

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