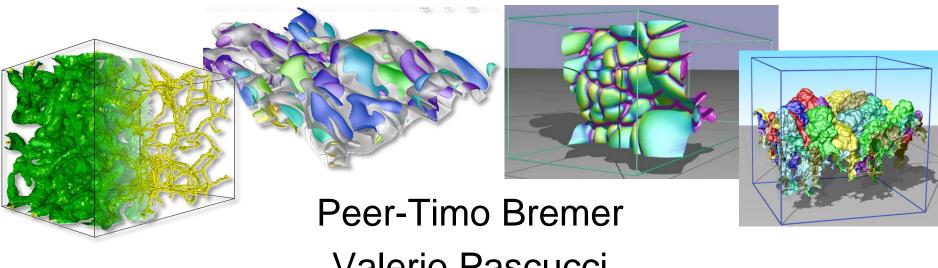


Management, Analysis and Visualization of Massive Scientific Data



Valerio Pascucci

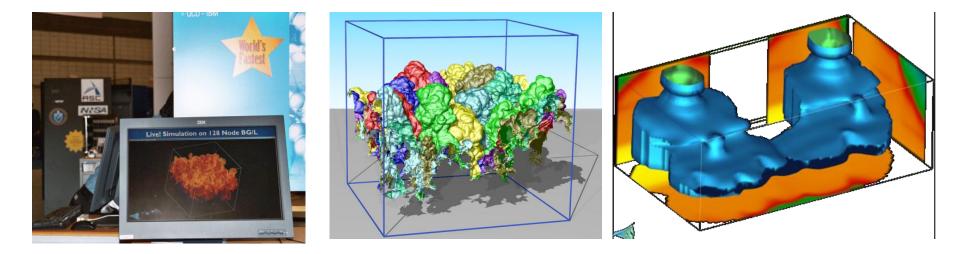
Center for Extreme Data Management Analysis and Visualization







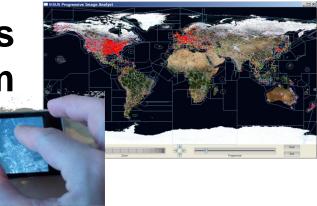
Center for Extreme Data Management, Analysis and Visualization

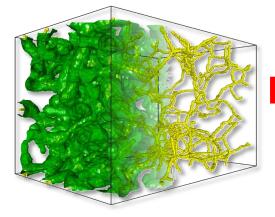




CEDMAV Mission

Research Future Technologies for Knowledge Extraction from Extreme Sized Data





Deployment and Application of State of the Art Tools in Data Intensive Science Discovery

Education of the Next Generation Workforce Supporting Data Intensive Science and Engineering













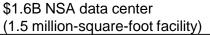
- 10 Faculty + scientists, developers, students, ...
- Other partnerships: NSA, Battelle,
- Involvement in national Initiatives:



CEDMAV

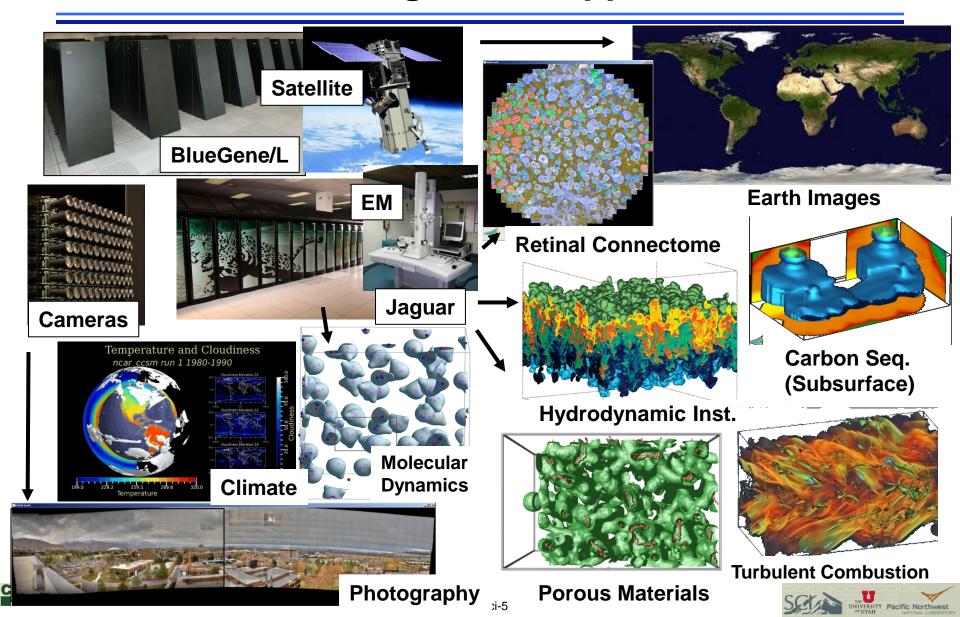








Massive Simulation and Sensing Devices Generate Great Challenges and Opportunities

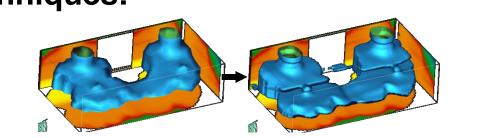


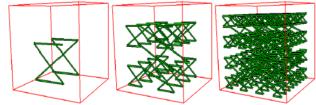
A Science Cyberinfrastructure Requires Efficient Big Data Management and Processing

- Advanced data storage techniques:
 - Data re-organization.
 - Compression.
- Advanced algorithmic techniques:
 - Streaming.
 - Progressive multi-resolution.
 - Out of core computations.
- Scalability across a wide range of running conditions:
 - From laptop, to office desktop, to cluster of PC, to BG/L.
 - Memory, to disk, to remote data access.









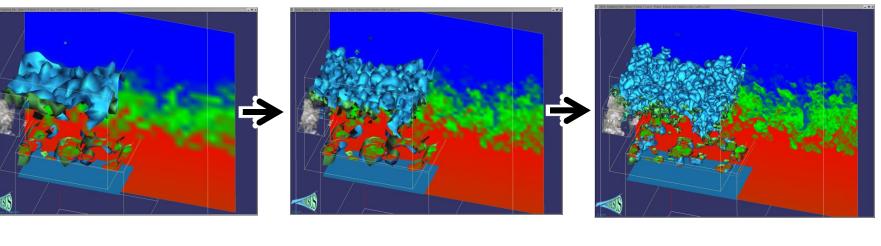


OF UTAH NATIONAL LABORA

We Redesigned the Data Management and Visualization Pipeline with New Principles

- Basic core techniques:
 - Slicing, Volume rendering, Iso-surfaces
 - Topology
 - Statistics
- Cache-oblivious out-of-core processing optimizing access locality for any size of data blocks
- Pipelines of progressive algorithms

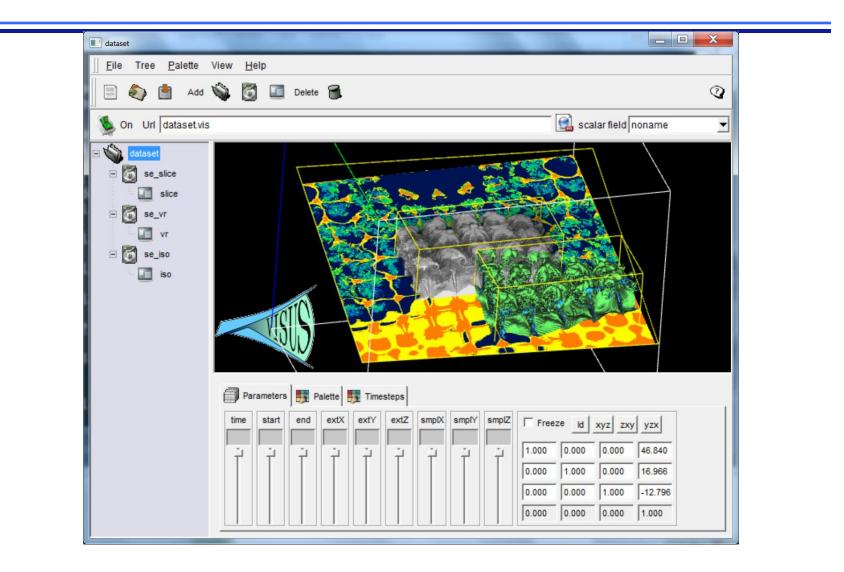
- Coarse-to-fine construction of multi-resolution models
- Remote data streaming







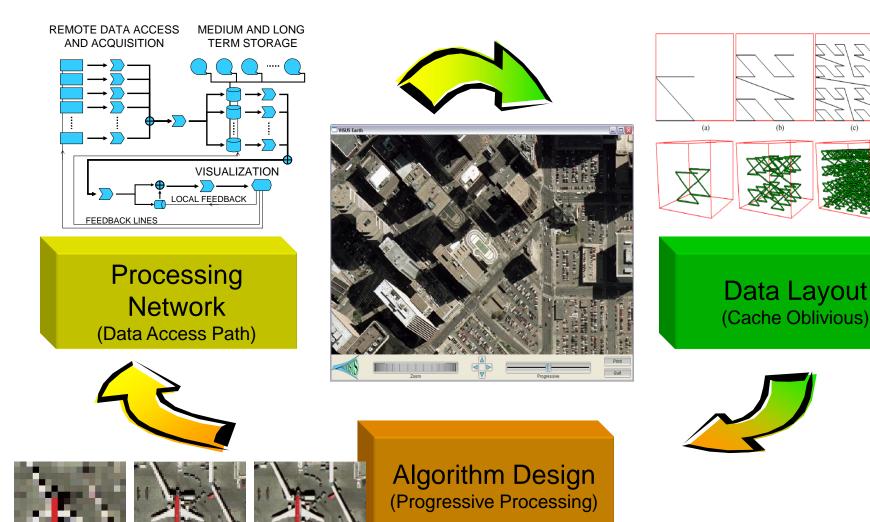
Basic Demo





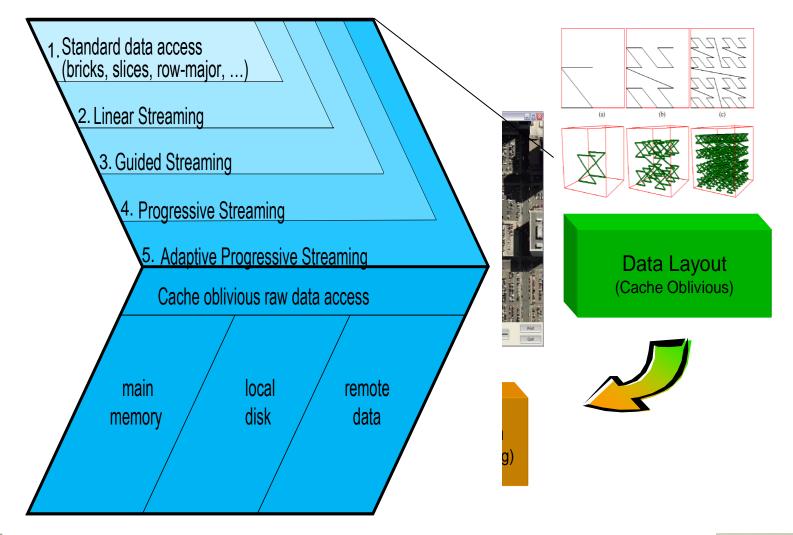


We Consider the Three Main Components Defining a Computing Infrastructure





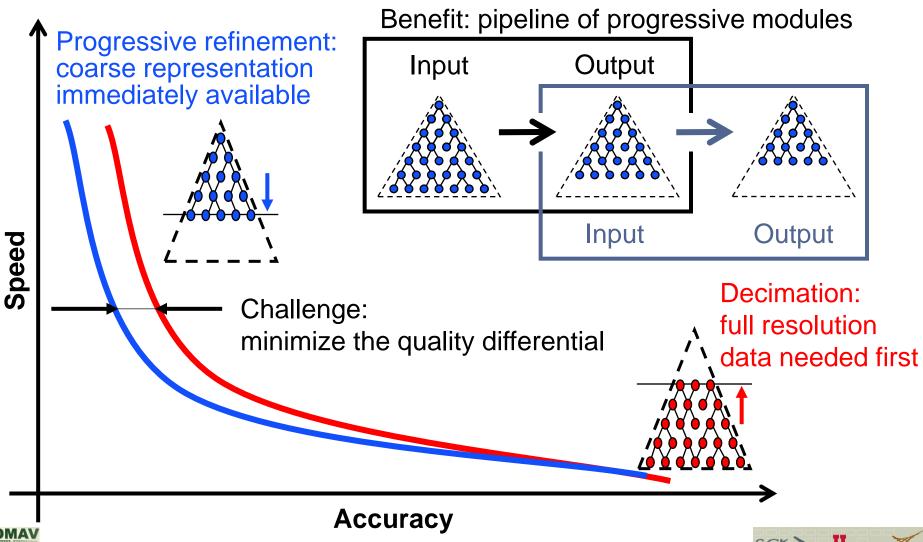
We Characterize Algorithmic Classes Based on Effect in a Processing Network







The use of top-down and bottom-up processes have a strong impact on the data stream

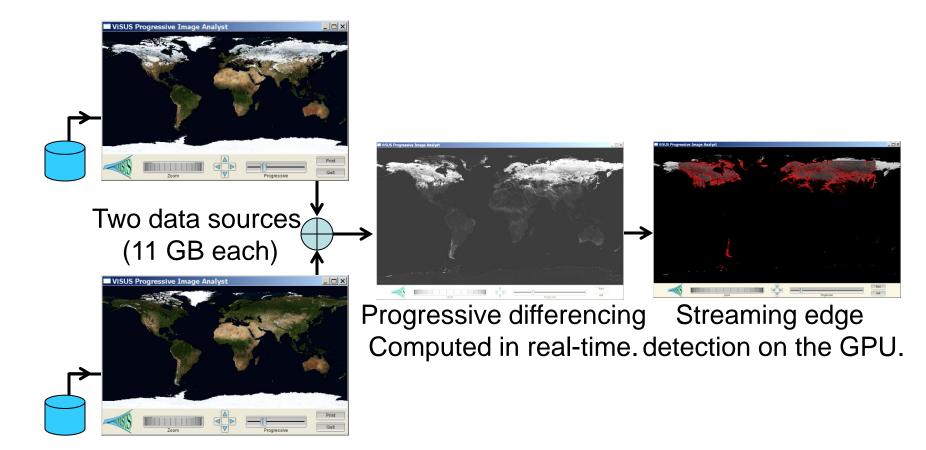


Pascucci-11

VERSITY Pacific Northwest

We Allow Distributed Computations at Different Stages of the Data Stream

• Progressive Image Differencing + Editable GPU filter.

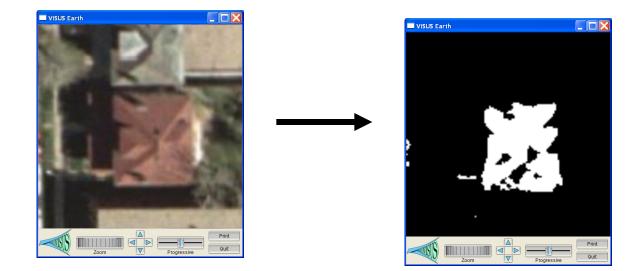






We are Developing Progressive Scheme for Content Based Image Processing

• Hypothesis:



Progressive Analysis:









Poisson Solver for Image Cloning in Massive Image Collections

• Color correction of 600+ images in real time



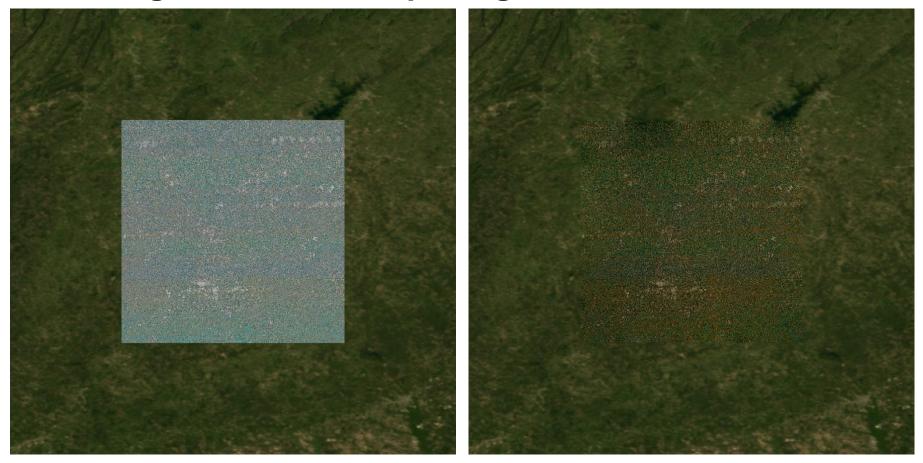






Poisson Solver for Image Cloning in Massive Image Collections

 Pasting a 300GB satellite image of a city in background world map merged in real time

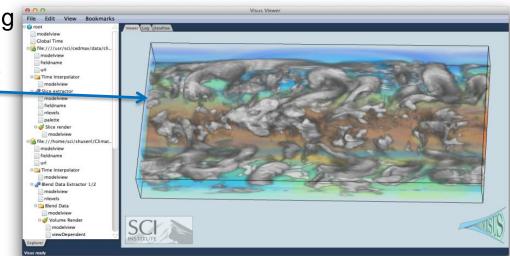




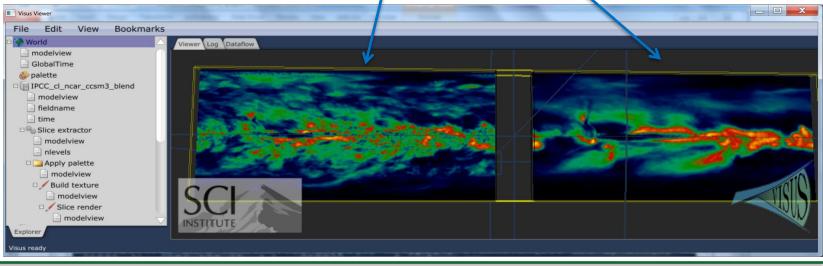


ViSUS Remote climate Data Analysis and Visualization

- ViSUS data streams allow to merging multiple datasets in real time
- Time interpolation of and concurrent visualization of climate data ensembles defined on different time scales
- Server side and client side computation of statistical functions such as median, average, standard deviation,
 Standard



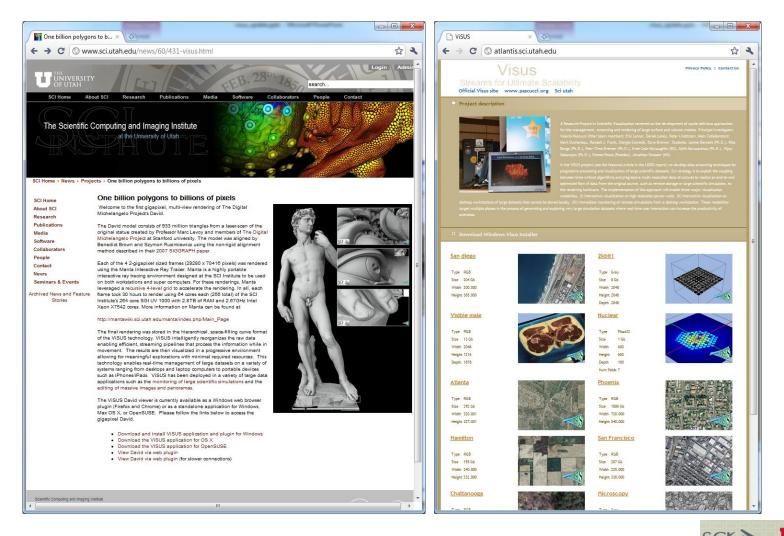
Standard Deviation and Average of ten climate models







Server can be wrapped in Apache plug-in Client can be run in a web browser







UNIVERSITY Pacific Northwest

Geospatial Data Rendering on iPad

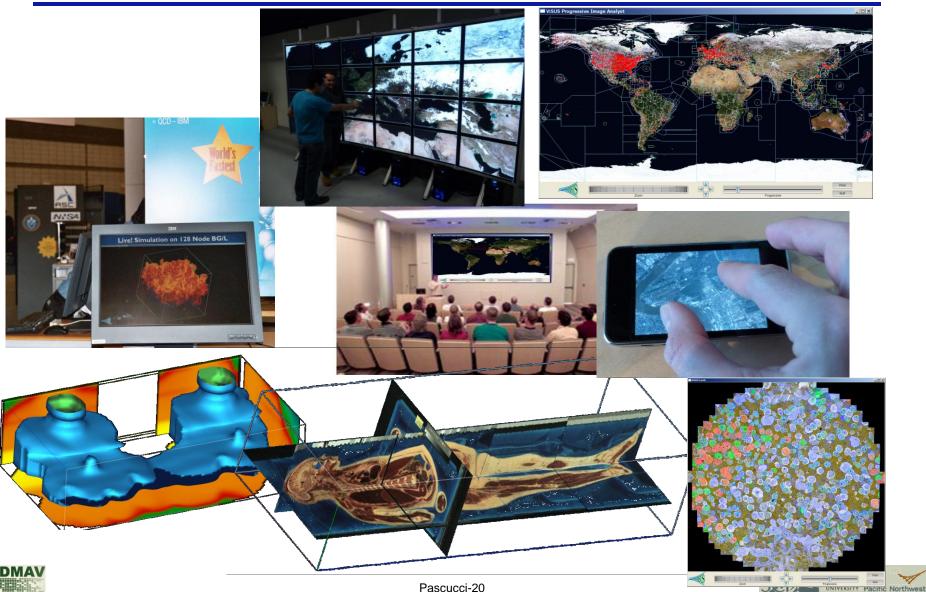
Both client and SERVER run of handheld devices, e.g. multiple iPhones can be clients and servers for each other to share information on the field



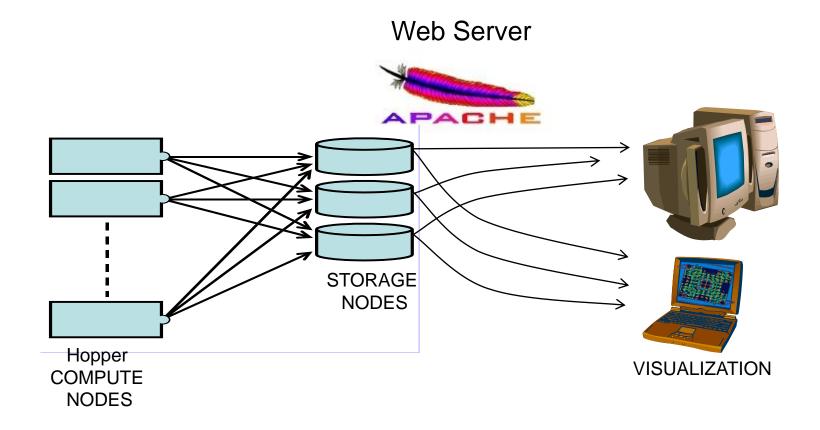




We Demonstrated Performance and **Scalability in a Variety of Applications**



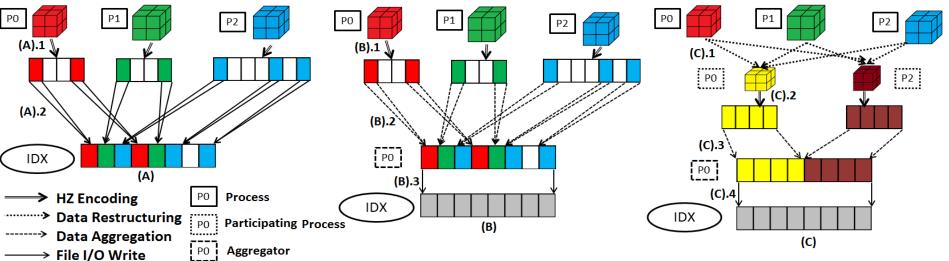
Streaming IDX directly from large scale (S3D) simulations







The ViSUS Parallel I/O Infrastructure (PIDX) Adopts a 3–Phase Data Transfer Model



One-Phase I/O:

(A).1 HZ encoding of irregular data set leads to sparse data buffers interleaved across processes.

(A).2 I/O writes to underlying IDX file by each process, leading to a large number of small accesses to each file.

Two-Phase I/O:

(B).1 HZ encoding of irregular data set leads to sparse data buffers interleaved across processes.

(B).2 Data transfer from inmemory HZ ordered data to an aggregation buffer involving large number of small sized data packets.

(B).3 Large sized aligned I/O writes from aggregation buffer to the IDX file.

Three-Phase I/O:

(C).1 Data restructuring among processes transforms irregular data blocks at processes P0, P1 and P2 to regular data blocks at processes P0 and P2.

(C).2 HZ encoding of regular blocks leading to dense and non-overlapping data buffer.

(C).3 Data transfer from in-memory HZ ordered data to an aggregation buffer involving fewer large sized data packets.

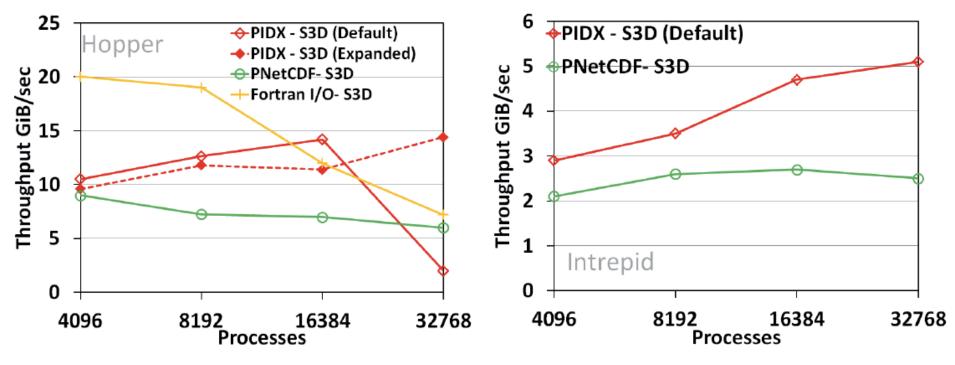
(C).4 I/O writes from aggregation buffer to a IDX file.





Strong Scaling Results Comparing PIDX Performance with PNetCDF and Fortrain I/O on Two Major Platforms

 The PIDX Infrastructures Achieves Better Scalability than Competing Frameworks While Maintaining Advantageous Hierarchical Data Representation



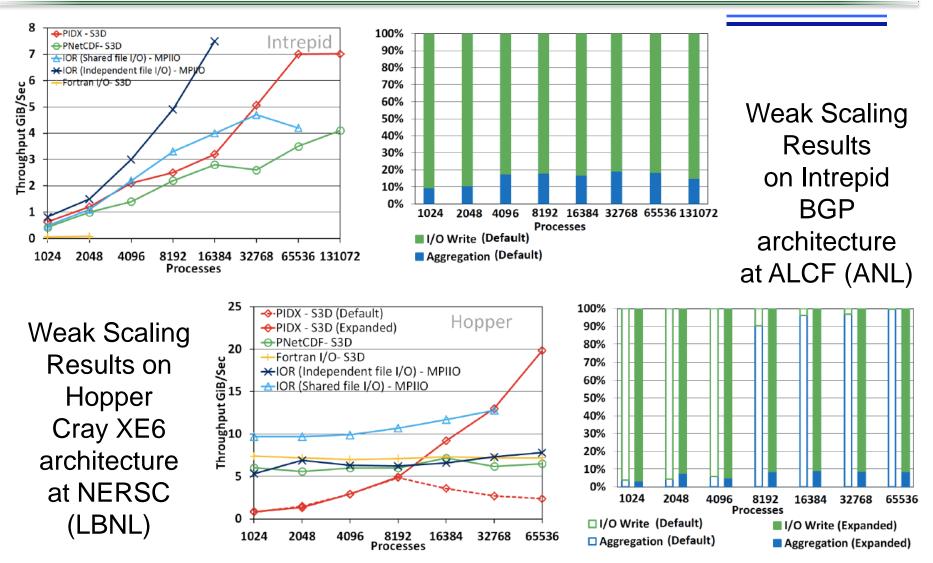
Scaling Results on Hopper Cray XE6 architecture at NERSC (LBNL)

CEDMAV

Scaling Results on Intrepid BGP architecture at ALCF (ANL)



Weak Scaling Results Comparing PIDX Performance with Major Competing Techniques





Topological Methods Have Been Successful for Analysis and Visualization of Massive Scientific Data

