NSF CluE Project

Performance Evaluation of On-Demand Provisioning Strategies for Data Intensive Applications

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Project Goals

- Investigate whether dynamic allocation of resources (processors/disk) can be more efficient than current static approach for large scientific data archives

- Corollary: Can scientific data portals/archives be effectively backend-ed by cloud platforms?

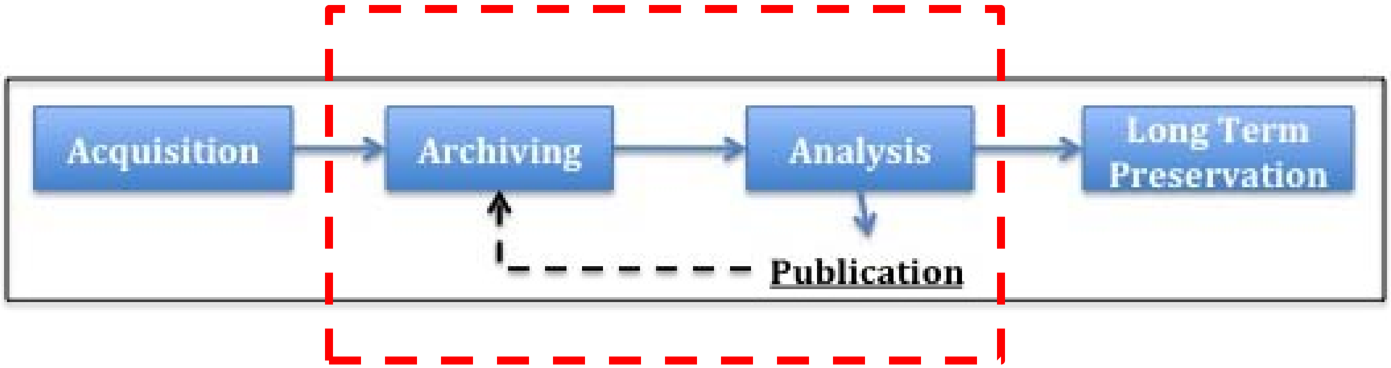
Acknowledgements

- Other team members:
  - Viswanath Nandigam
  - Christopher Crosby
- Funding:
  - NSF CluE / CISE; GEO/Earth Sciences; Office of Cyberinfrastructure
  - Intermural funding among NSF directorates

Outline

- Example application: OpenTopography.org
- Current implementation
- CluE experiments

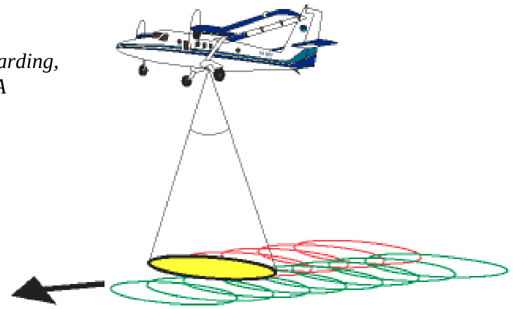
Scientific data lifecycle



The application: OpenTopography.org

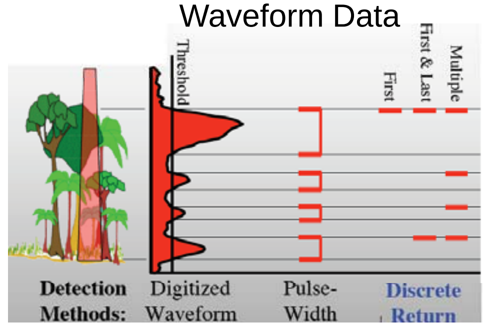
- **Online access to high-resolution topographic data**
  - Airborne
  - Terrestrial

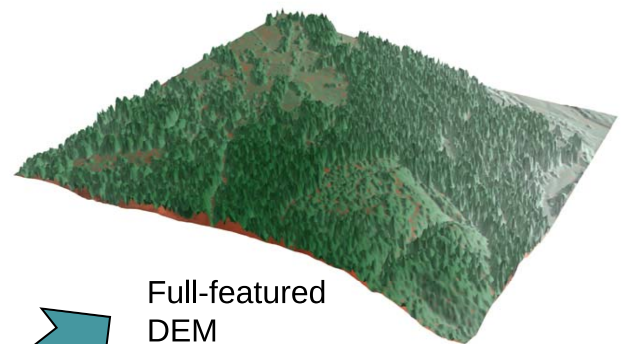
LiDAR Data



D. Harding, NASA

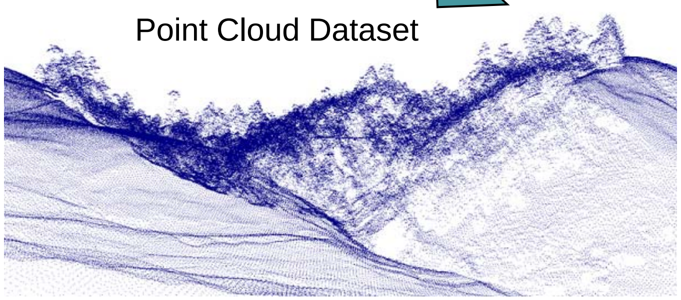
Waveform Data





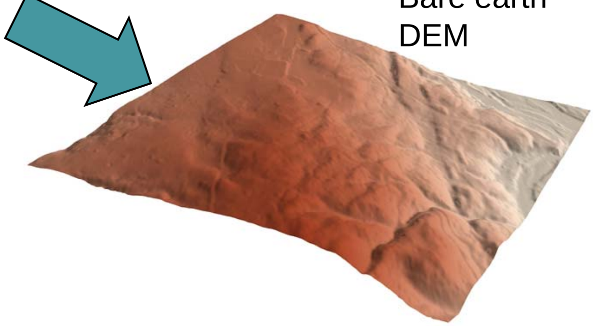
Full-featured DEM

Point Cloud Dataset



Portal

Bare earth DEM



Current system characteristics

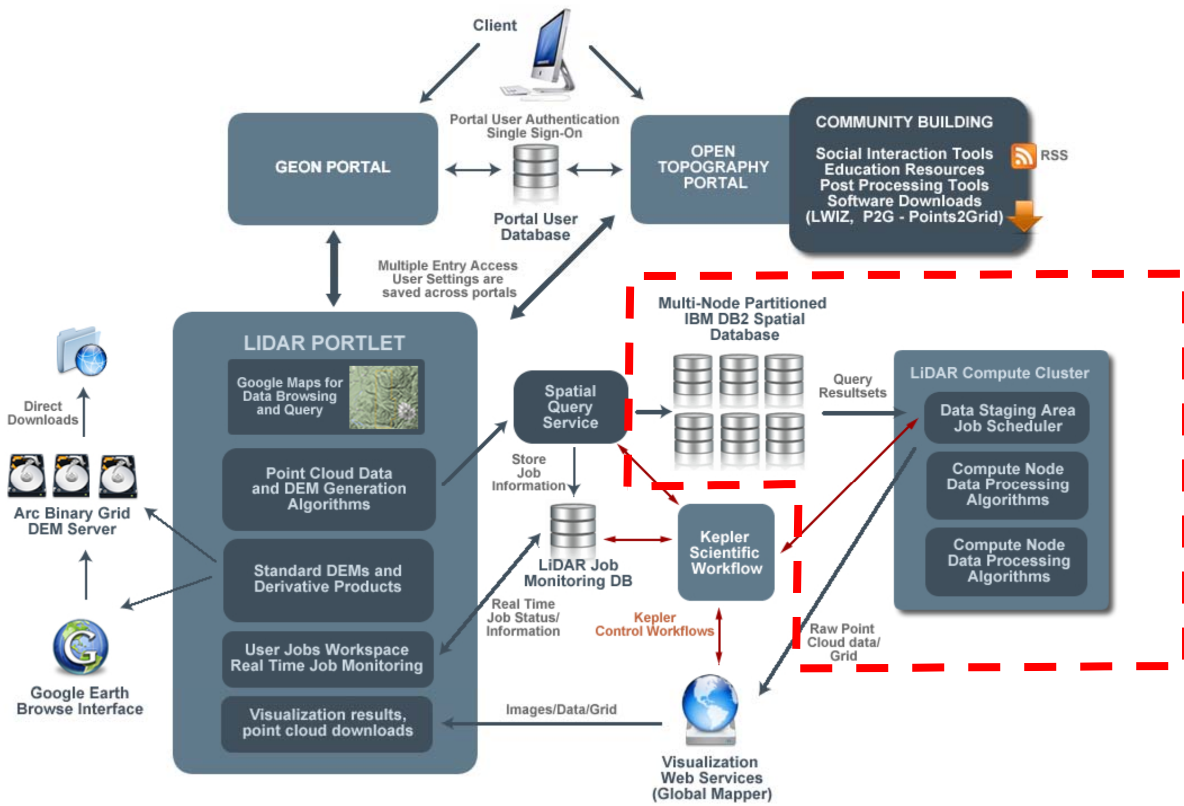
- Data
  - Currently, 7 datasets (3 from EarthScope)
    - Each is independent
  - ~3TB (50% indexes); ~30 billion entries
- Users
  - 80-20 split
    - 80% want “standard” products, e.g. pre-computed DEMs, KML
    - 20% want to derive their own data products
- Access
  - “Online”, service-oriented access to data is highlight

Sample LIDAR Dataset

Northern San Andreas Fault Data 1205 148544.74364 6135780.64 2074881.21 1557.35 1 5 5.48 14 V 1205 148544.76241 6135770.33 2074880.95 1526.20 2 6 5.45 0 G 1205 148544.76246 6135775.01 2074884.30 1529.68 1 5 5.47 15 G 1205 148544.78122 6135765.79 2074881.62 1524.31 1 5 5.44 80 B

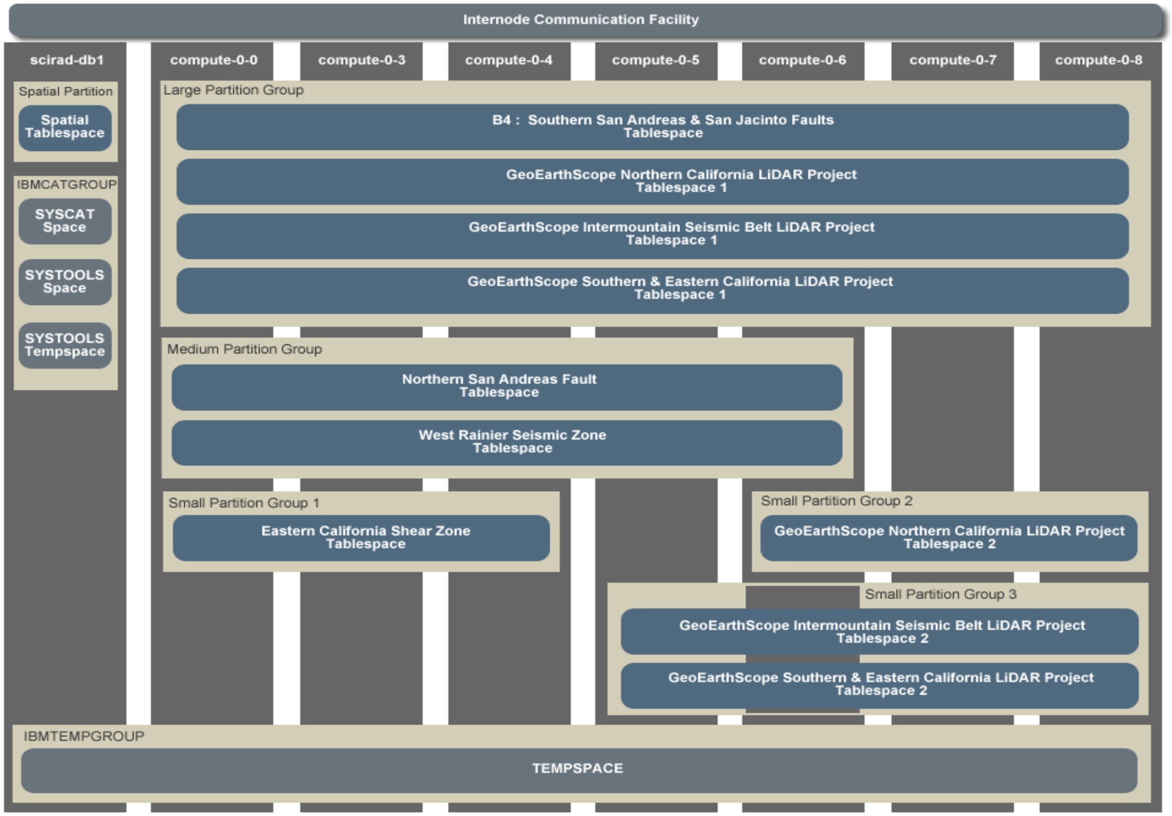
Column 1 : Date - Day or week of acquisition Column 2 : Time - GPS time stamp uniquely identifying laser pulse time Column 3 and 4 : X and Y (Lat, Long) Column 5 : Elevation. Column 6 : Return number - Return number of this return. Column 7 : Number of Returns - Number of returns for this pulse. Column 8 : Off Nadir Angle - Angle between nadir and transmitted pulse Column 9 : Return Intensity - Intensity of return pulse Column 10: Classification Code - Classification of return B-Blunder; G-Ground or water; V-Vegetation; S-Building/Structure; N-Not ground or water - Could be V or S

Opentopography.org infrastructure

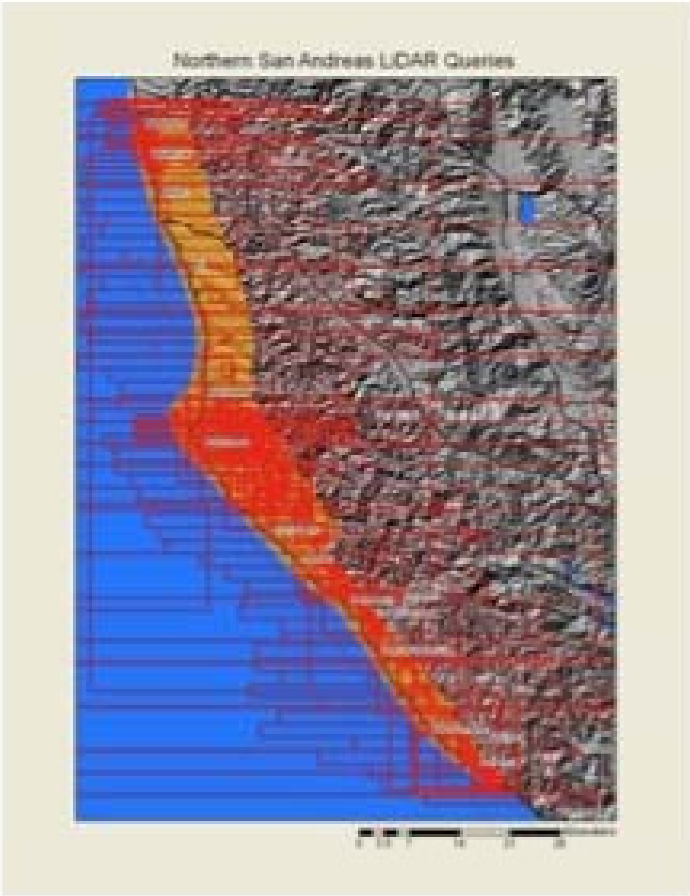


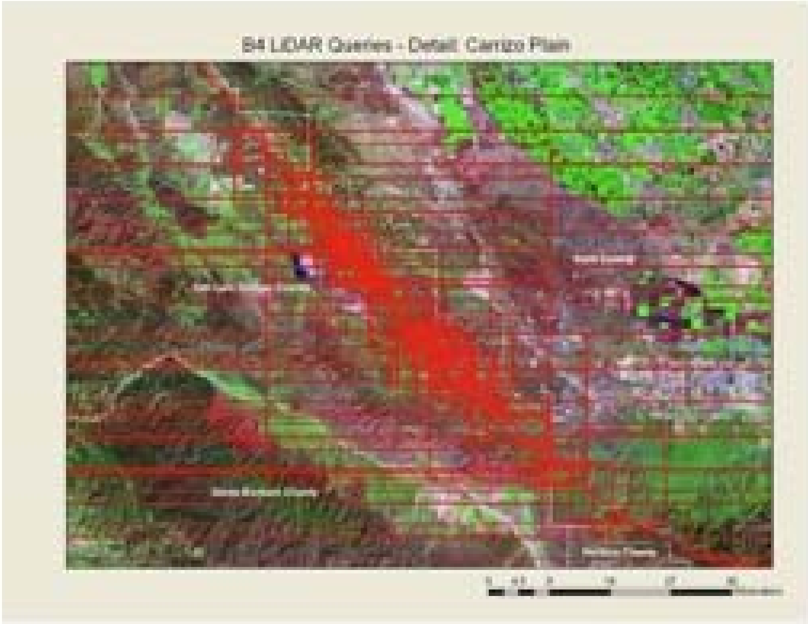
- DB2 Parallel (Enterprise Edition) with spatial extender
- Database cluster
  - 8 x dual-core Intel Xeon 3.0 GHz, 8GB, 750GB disk
  - 4 x 3TB disk arrays; 1.5TB/node

Partial declustering of LiDAR data sets



Data access patterns





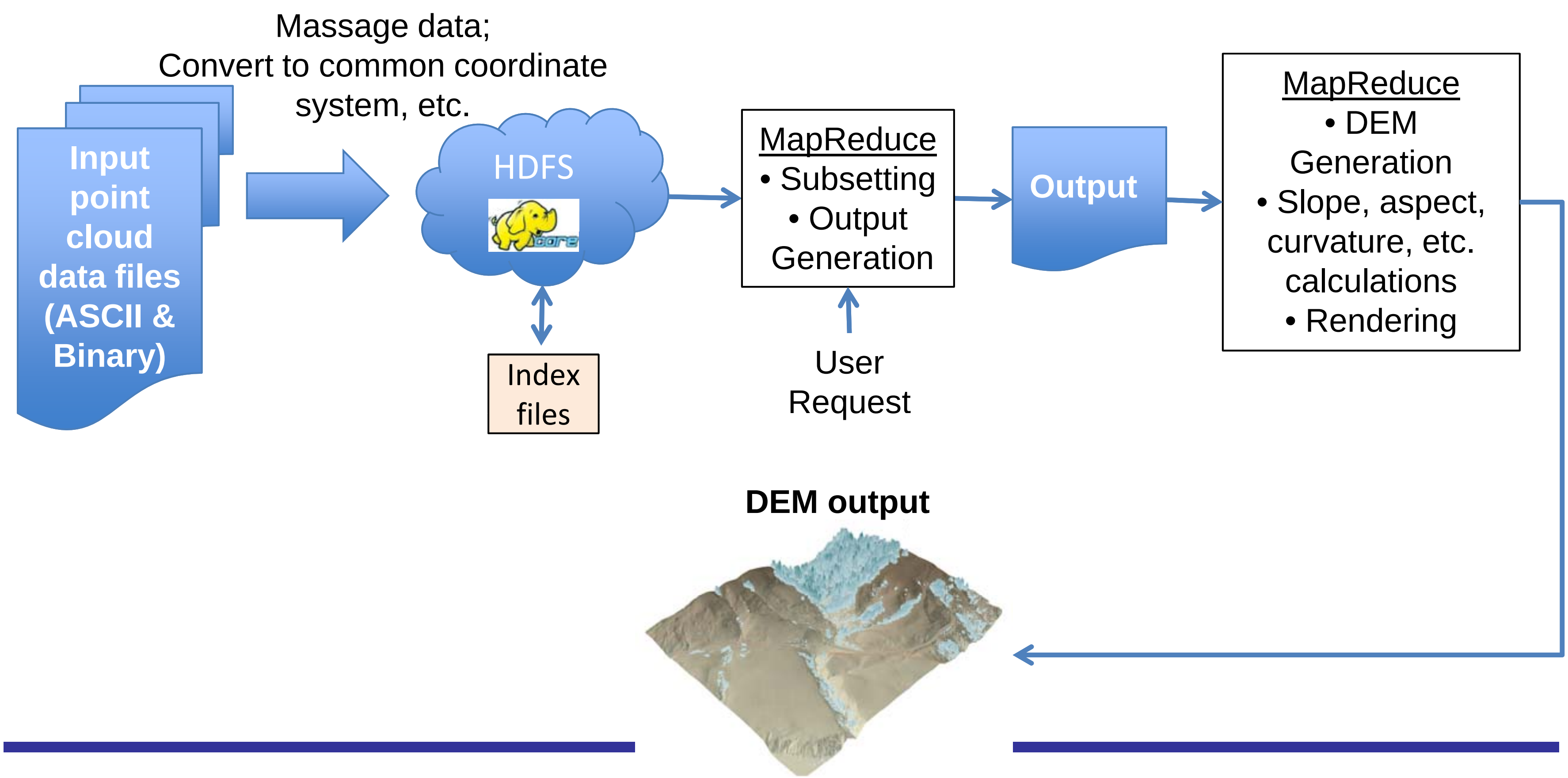
Application Requirements

- Scale to:
  - More data sets
  - Larger data sets
  - Increased processing, e.g. “parameter sweeps” for DEM generation; hydrologic modeling; waveform LiDAR; ecological applications; …
  - More users

Experiences with DBMS

- Database Pros
  - Simple SQL-based querying of data
  - Robust production-quality software/hardware stack
  - High performance access to data (shared nothing platform)
- But
  - Loading, indexing and storage overhead
  - Scaling to very large configurations (price / performance)
  - ASCII data

MapReduce Implementation



DEM Generation

- Pushdown into DBMS
  - Generate grid file based on user's request
  - Do "band join" between dataset and grid file and compute DEM
- MapReduce
  - Implement using HQL / HIVE
  - Programmed in MR
    - Use grid file, create overlapped data regions and computer DEM
    - Merge DEMs

The need for dynamic provisioning

- Provision data based on access patterns
  - DBMS provides much better response for smaller datasets
  - MapReduce may be better for much larger datasets
- Access patterns change:
  - Over time (after initial release of data)
  - When events occur
  - When results are published, etc.
- Personalized database for intensive analysis (myDB)
- Performance vs cost differential
  - DBMS on small configs vs Hadoop on large configs

Experiences with MapReduce

- SQL vs MapReduce
  - Programmer is the optimizer
- Investigating HIVE, but may not yet be suitable for complex SQL
  - We require spatial functions, “band joins”, outer joins
  - Need extensions to HIVE

Experiments

- "On-demand" database vs Hadoop
- Implement binary data formats
- Provision different data sets, or different parts of a data set, differently
- Platforms to be used
  - Google-IBM cluster
  - 8-node lab cluster at SDSC
  - UIUC CCT (Cluster Computing Testbed)
  - SDSC Triton resource
  - AWS for Education