Geospatial Processing on Hadoop

Hadoop World 2013

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Agenda

- About Monsanto
- Use Case Overview
- Intro to Geospatial Data Types
- Geospatial on Hadoop
- Q&A

Our Vision: Sustainable Agriculture

Providing Choices for Farmers, Meeting Society's Needs

Producing more

 We are committed to increasing yields to meet the growing demand for food, fiber & fuel

Conserving more

 We are committed to reducing the amount of land, water and energy needed to grow our crops

Improving lives

We are committed to improving lives around the world

This is sustainable agriculture and it's what we do



Our Approach to Driving Yield

BREEDING

The art and science

seed

of combining genetic

material to produce a new

A System of Agriculture Working Together to Boost Productivity







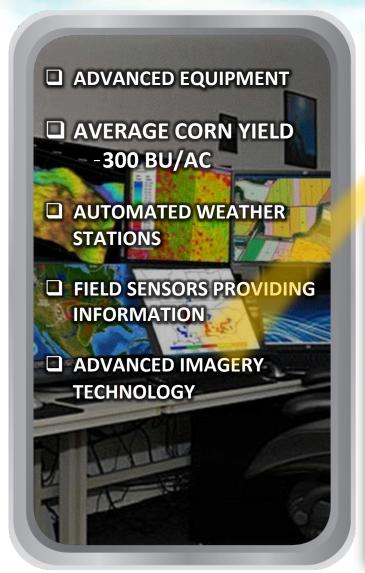


The science of improving plants by inserting genes into their DNA



The farm management practices involved in growing plants

Doubling Yields by 2030 - Farming in the Future Will Be Increasingly Information-Driven







Integrated Farming Systems – FieldScriptsSM for 2014

FieldScripts[™] will deliver, by field, a corn hybrid recommendation utilizing variable rate seeding by FieldScripts management zones to increase yield potential and reduce risk

The science of FieldScripts is based on proprietary algorithms that combine data from the FieldScripts Testing Network and Monsanto generated hybrid response to plant population research

Planting Prescription 2012 (DKC63-84 Brand)

Target Rate (Count) (ksds/ac)

38.00 (24.75 ac)

37.00 (22.63 ac) 35.00 (16.60 ac)

34.00 (8.23 ac)

33.00 (6.00 ac)

32.00 (2.82 ac)







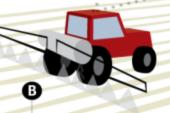
Integrated Farming Systems™ Combine Advanced Seed Genetics, On-farm Agronomic Practices, Software and Hardware Innovations to Drive Yield

DATABASE BACKBONE

Expansive product by environment testing makes on-farm prescriptions possible



BREEDING
Significant
increases in data
points collected
per year to
increase annual
rate genetic gain



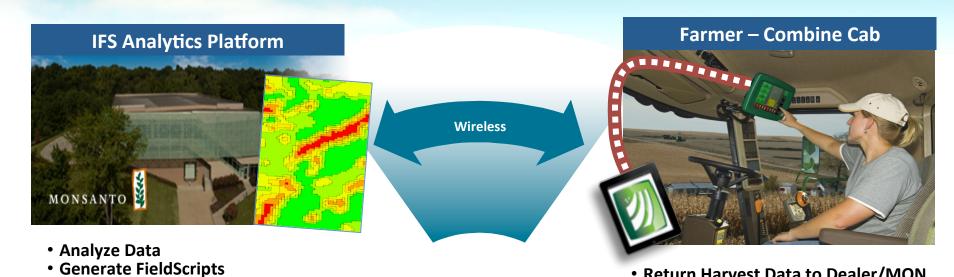
VARIABLE-RATE FERTILITY Variable rate N, P & K "Apps" aligned with yield management zones PRECISION SEEDING
Planter hardware
systems enabling
variable rate seeding &
row spacing of multiple
hybrids in a field by
yield management
zone

FERTILITY & DISEASE
MANAGEMENT
"Apps" for in-season
custom application of
supplemental late
nitrogen and
fungicides

YIELD MONITOR Advances in Yield Monitoring to deliver higher resolution data



Harvesting & Returning FieldScripts Data





- Harvest Data Collection
- Review Yield Results with Farmer

IFS Analytics Ecosystem Platform

Data Cleansing

Enrichment

Monsanto Data

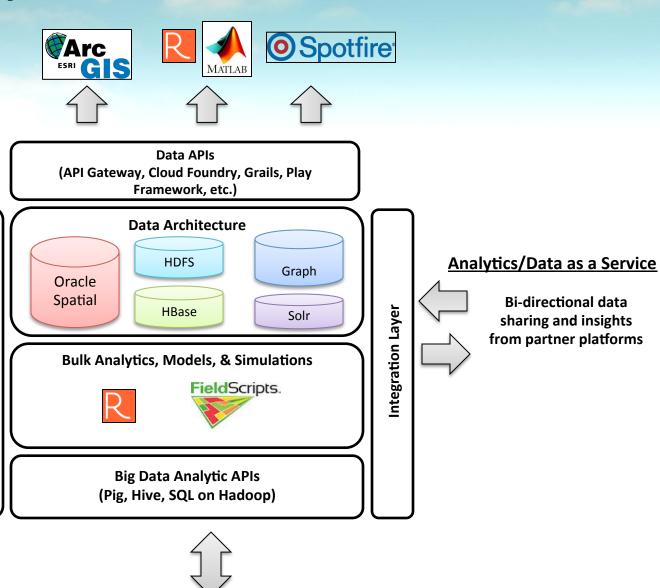
國

R&D Data

Weather

Data Acquisition

Grower



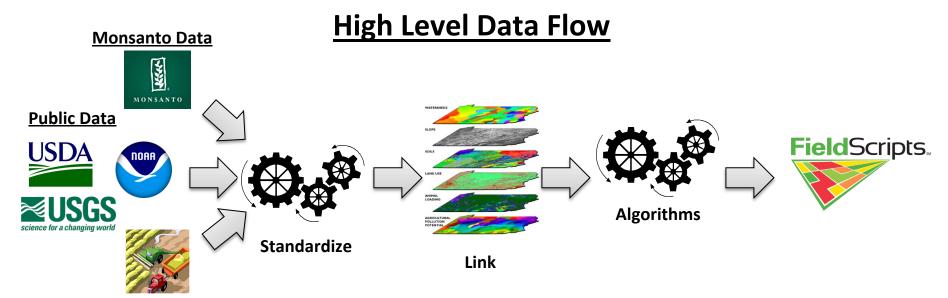
Data Scientist

Platform Needs

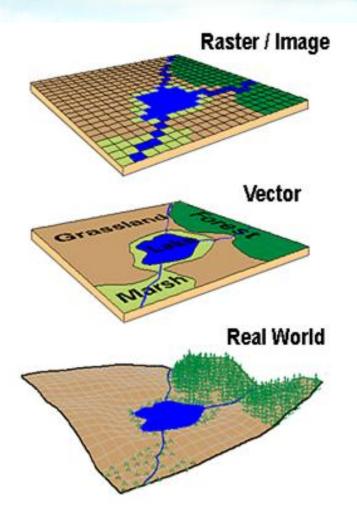
- Load thousands of files containing spatial data
 - 10s TBs of data
- Support diverse range of data types
 - Tabular, xml, vector, raster
- Join & link data spatially

Grower Data

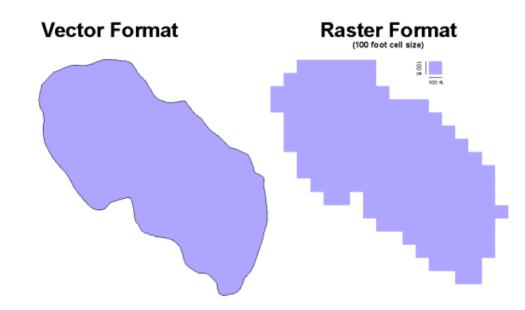
- Make data available for data products such as Field Scripts
- Make data available for data scientists



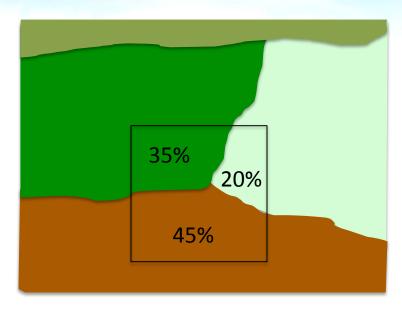
Spatial Data Types

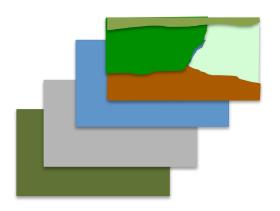


- Vector geometries, with data
 - Point, polygon, line, circle, etc.
 - Compact even for large geographic areas
 - Increases size with level of detail
 - Resolution independent
 - Formats: Shape file, WKT, CAD
- Raster pixels, with data
 - Fixed level of detail
 - Resolution dependent
 - Formats: GeoTiff, BMP



Spatial Data Types





- Querying vector data
 - Load and find geometries near the target area
 - Do the geometries intersect with the target area?
 - How much do they cover the target area?
 - Is there overlap?
 - Spatially weigh values
- Considerations
 - Diverse range of data types
 - Multiple layers
 - Numerous features per layer
 - Overnumerous target areas
 - Spatial index maintenance

Data in Detail

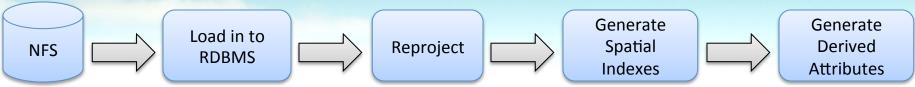
- Environmental Observations
 - Elevation, Soil, Grower Data
- Extremely Dense Structured Data
 - 10 m x 10 m grids
- Even More Dense Raw Data
 - Raw data captured at 5 Hz
- Complex Data Interactions
- Derived Data
 - Slope, Aspect, etc.
- Access Patterns
 - Bulk analytics & random reads

Example Yield Map

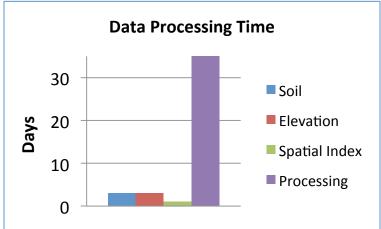


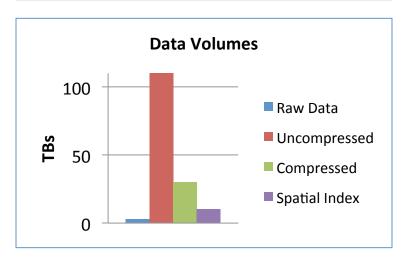
Computed Flow Direction

Take 1: RDBMS - Data Ingestion & Data Processing



- In RDBMS spatial
- PL/SQL
- Just 8% of the data!!
 - 35+ days to load
- TBs in indexes
- Multiple Patches to DB
- Tradeoffs
 - Compressed vs. Uncompressed
 - Performance vs. Storage
 - Read vs. Write performance
- Options/recommendations
 - Limit use of in DB spatial functionality
 - Buy larger RDBMS





A Different Approach

Requirements

- Scalable
- Complex geospatial data types
- Push analytics/data process to the storage
- Commodity/cost effective storage and compute
- Vendor support

Alternative Considered









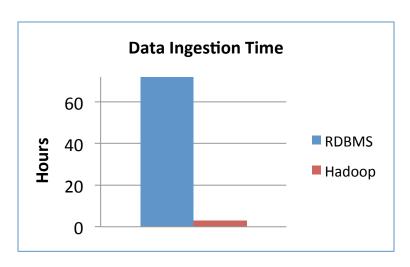


Data Ingestion Revisited



- Bulk load 1,000s of files into HDFS
- Standardize data
 - Common usable format
 - Storage vs. Compute
 - Raster format is easily splitable
- Hadoop Streaming integrated with GDAL
- Streaming API Lessons Learned
 - Lack of documentation
 - Counters to track task progress
 - Jobs run as mapred user
 - HDFS access outside of MR

<u>Results</u>

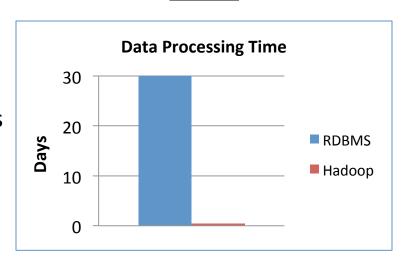


Data Processing Revisited



- Raster Files
- Process raster data
 - Dense matrix
- Generic InputFormat & RecordReader for raster data
- HFiles easily transportable between clusters
- Challenges tuning Jobs
 - I/O Sort Factor
 - Split/Task Size

Results



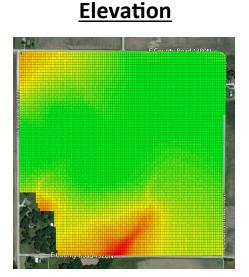
Geospatial in HBase

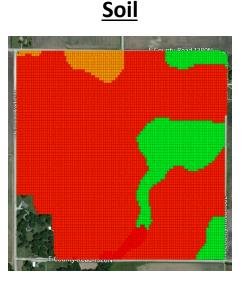
Needs

- Spatially enabled HBase key
- Reduce/eliminate need for index tables
- Scalable & cost efficient
- Support targeted & bulk random reads
- Optimize I/O for reads

Example Data Layers

Yield





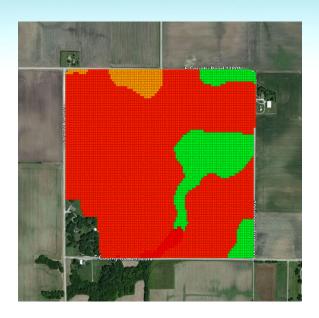
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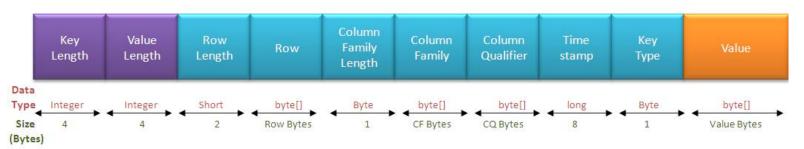
Considerations

- Key overhead
- Scan vs. Get performance
- Reduce reading unnecessary data
- Data within a field only!



Filter data to what overlaps with the Field Boundary

Data Stored with Each Value



Geospatial in HBase

- Needs
 - Spatially enabled HBase key
 - Reduce/eliminate need for index tables
 - Scalable & cost efficient
 - Support targeted & bulk random reads
 - Optimize I/O for reads
- Considerations
 - Key overhead
 - Scan vs. Get performance
 - Reduce reading unnecessary data
- Options
 - GeoHash most notable example
 - Best suited for sparse data
 - MGRS (Military grid reference system)
 - Boundary edge cases
 - Quad tree & R-trees

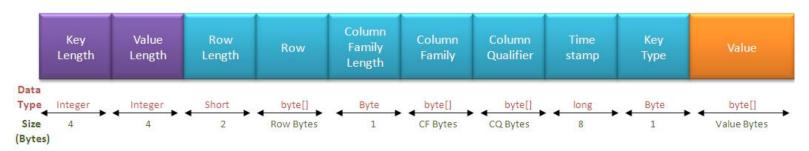
Geohash Z-order-curve



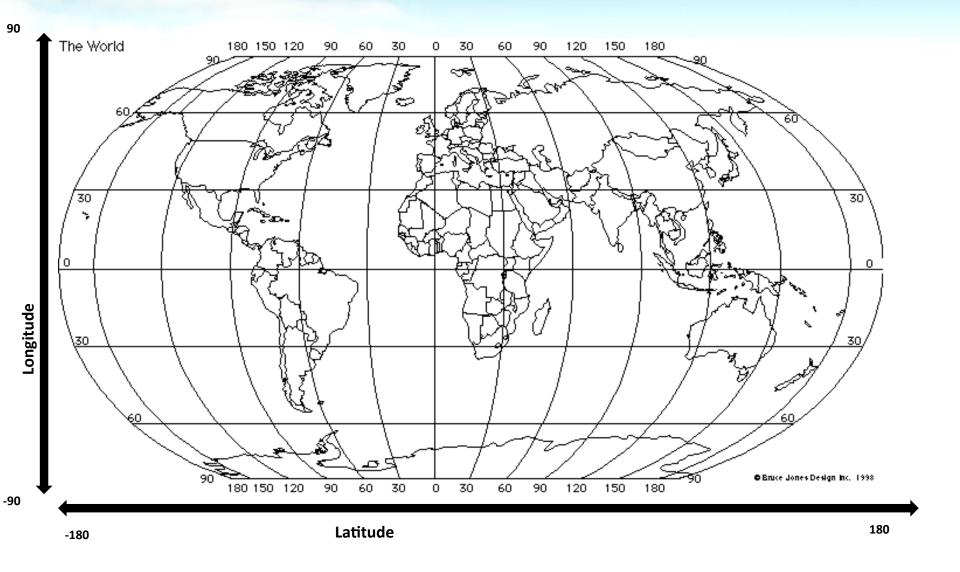
Alphanumeric Keys

4QFJ123678precision level 100 m 4QFJ12346789precision level 10 m 4QFJ1234567890precision level 1 m

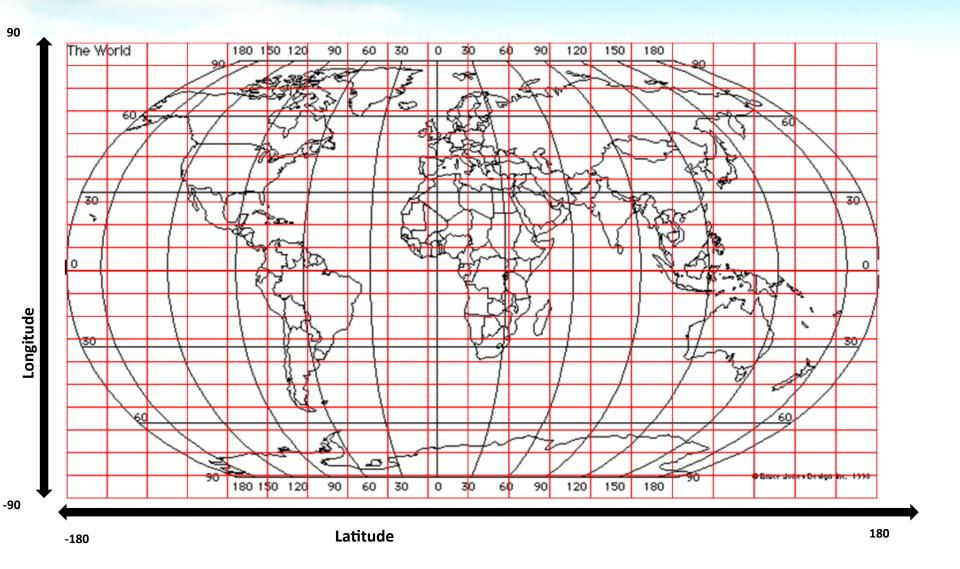
Data Stored with Each Value



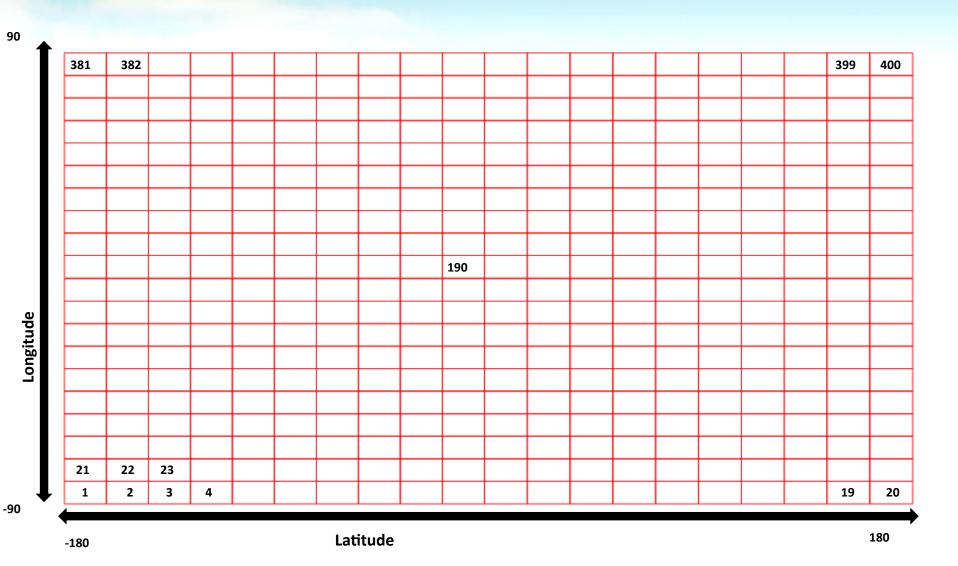
Global Coordinate System



Reference System



Reference System Continued



HBase Schema Take 1

Spatial Table

Key: cell_id long

Column Family: A

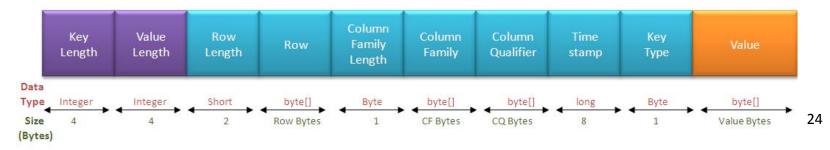
Column: Data Holder

elevation: float

slope: float

- Each spatial dataset is a separate table
- All attributes for a layer that are read together are stored together
 - Attributes packed into a single column as an Avro object
- 1 row per record
- 120 billion rows total!
- 1,000s of Get requests per field
- TBs of key overhead roughly 56% of the data

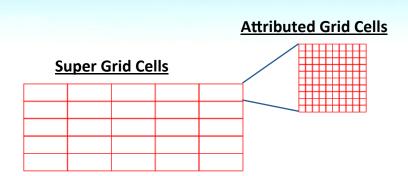
Data Stored with Each Value



HBase Schema Take 2

Spatial Table

- Key: super_cell_id long
- Column Family: A
 - Column: Data Holder
 - elevation : array float [values]
 - slope: array float [values]
 - aspect: array float [values]



- Data grouped into 100 x 100 super cells
- A super cell of 100 x 100 cells is a single row in HBase
- At most 4 disk reads are required to read all data for one layer for a 150 acre field
- Given a bounding box the super cells and attributed grid cells containing the desired data can easily be computed
- A generic geospatial data service when given a set of layers will read each layer in parallel
- Overhead of key data reduced from 56% to below 0.1%

Results

- Significant cost savings in required hardware
- 120 billion unique polygons in total
- 1.5 trillion data points
- Dense grid of the entire U.S.
- Foundational architecture for other spatial data sets
- Fully unit tested implementation

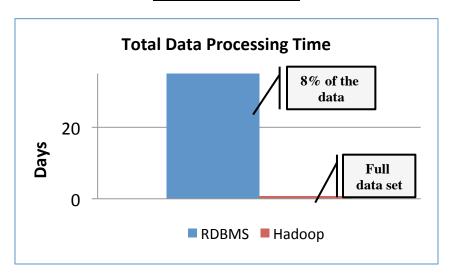
Hadoop

- Entire U.S.
- 18 hour load time
- 3 months of development
- 100% scalable

RDBMS

- 4 states only
- 30+ days to load
- 8 months of development

Total Run Time



Future Considerations

- HBase Filters
 - Push spatial functionality into RegionServer
- Pre-computed aggregates at different resolutions
- Distributed Vector Data Store
 - Solr/Lucene via Cloudera Search
- Spatial UDFs
 - Pig, Hive/Impala
- Metadata repository & data lineage

Thank You

Yes, we are hiring.

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eric.d.turcotte@monsanto.com
Big Data Engineer - http://bit.ly/16luojt
Geospatial Analytics Scientist - http://bit.ly/16iZgtM
Discovery Engineer - http://bit.ly/1byFLNQ
Technical Architect - http://bit.ly/1gXQp7T
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