EXPLOITING DARK INFORMATION RESOURCES TO CREATE NEW VALUE ADDED SERVICES TO STUDY EARTH SCIENCE PHENOMENA

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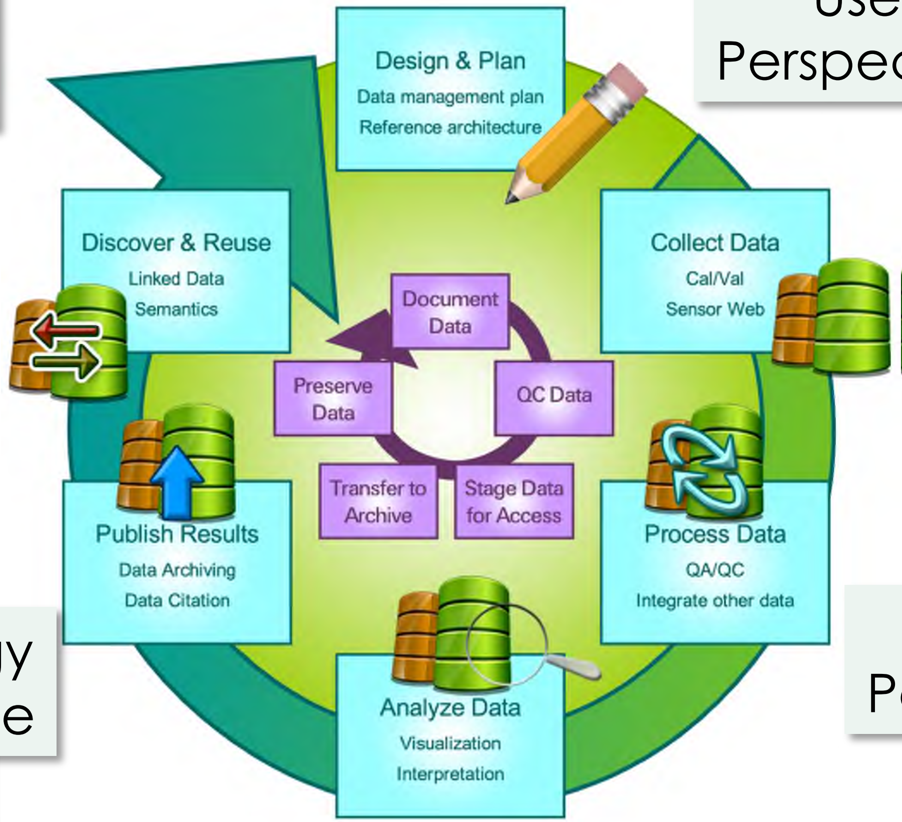
Earth Science Informatics

Data Perspective

User Perspective



Research Knowledge Generation Lifecycle and the foundational Data lifecycle

Technology Perspective

Policy Perspective

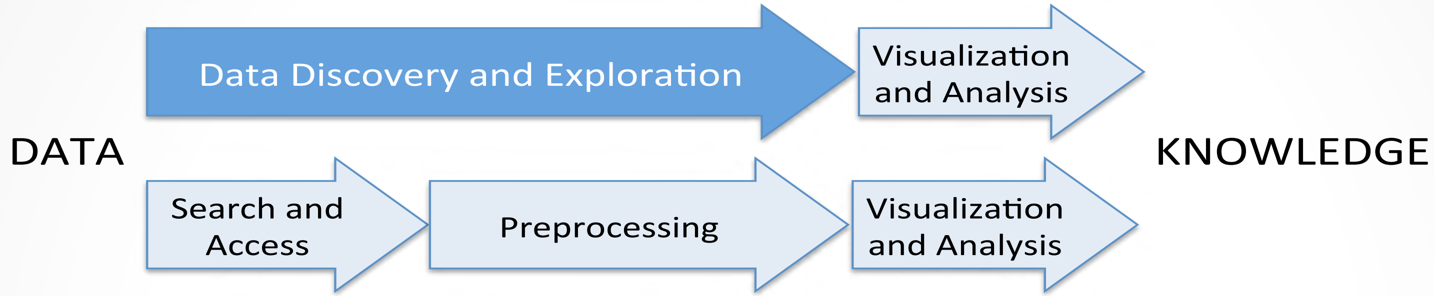
Goals: to make this process efficient, address existing gaps/hurdles, seamlessly integrate new emerging technology, and enable new research capabilities

Outline

1. Project Overview
2. Data Curation Service
3. Rules Engine
4. Application (with Demo)
5. Image Retrieval Service
6. Summary

Part 1: Project Overview

Motivation



- Data preparation steps are **cumbersome** and **time consuming**
  - Covers discovery, access and preprocessing
- Limitations of current Data/Information Systems
  - **Boolean search** on data based on instrument or geophysical or other **keywords**
  - Underlying **assumption** that users have sufficient knowledge of the **domain vocabulary**
  - **Lack support** for those **unfamiliar** with the domain vocabulary or the **breadth of relevant data** available

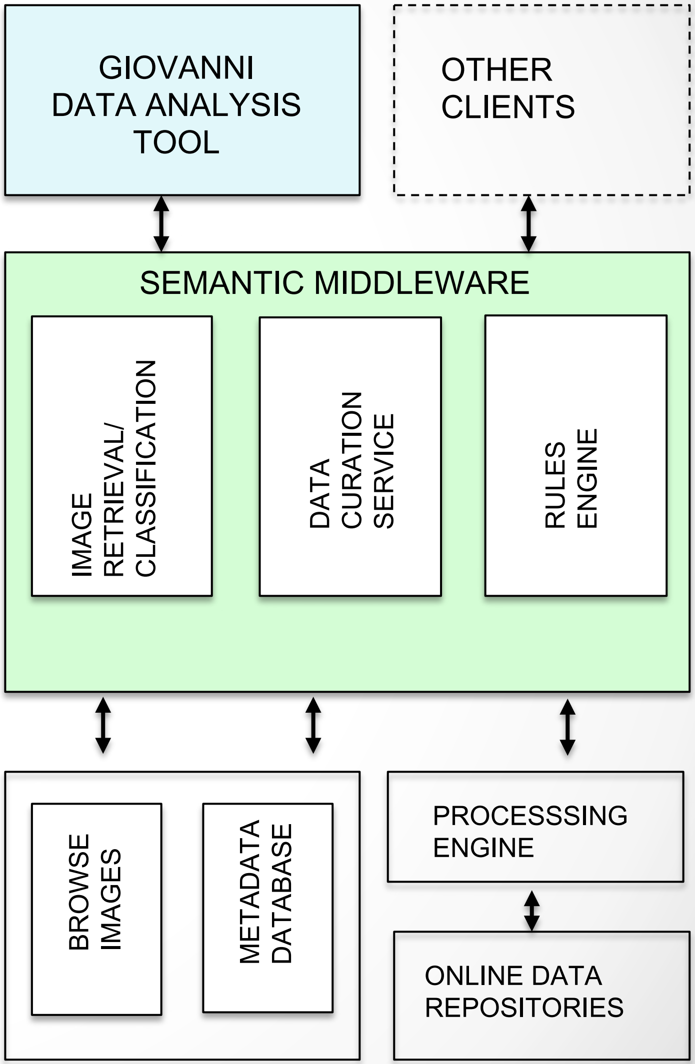
Earth Science Metadata: Dark Resources

- *Dark resources* - information resources that organizations collect, process, and store for regular business or operational activities but fail to utilize for ***other*** purposes
    - Challenge is to recognize, identify and effectively utilize these dark data stores
- Metadata catalogs contain dark resources consisting of structured information, free form descriptions of data and browse images.
    - NASA's Common Metadata Repository (CMR) holds >6000data collections, 270 million records for individual files and 67 million browse images.

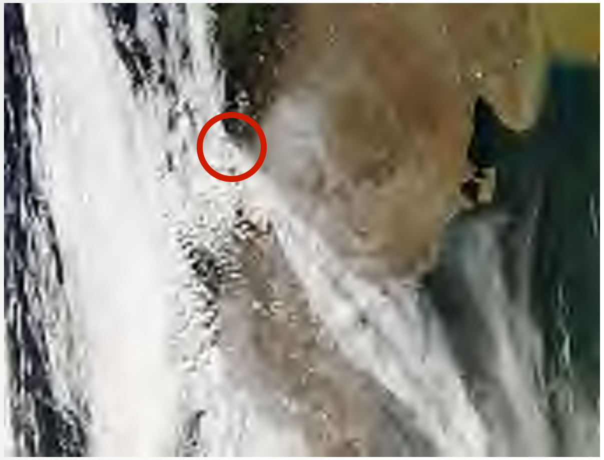
Premise: Metadata catalogs can be utilized *beyond their original design intent* to provide *new data discovery and exploration pathways* to support science and education communities.

Project Goals

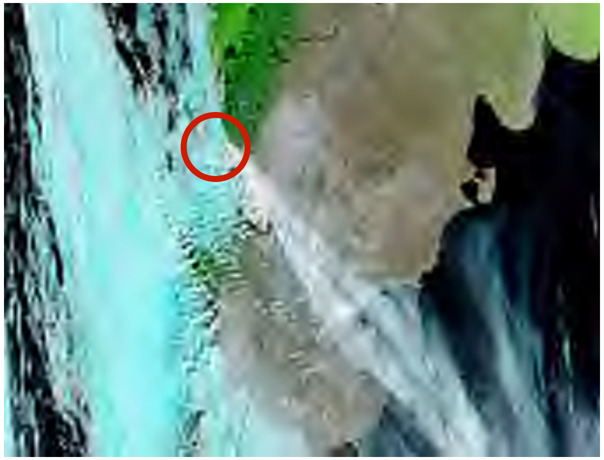
- Design a Semantic Middleware Layer (SML) to exploit these metadata resources
  - provide novel ***data discovery and exploration*** capabilities that significantly reduce data preparation time.
  - utilize a varied set of semantic web, information retrieval and image mining technologies.
- Design SML as a Service Oriented Architecture (SOA) to allow individual components to be used by existing systems



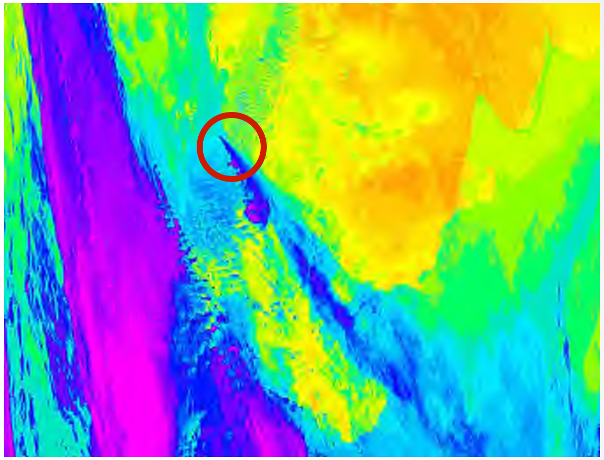
Use Case: *Find Interesting Events from Browse Images*



Band 1-4-3 (true color)



Band 7-2-1



LST

Example: MODIS-Aqua 2008-05-03 18:45 UTC

Chaitén Volcano Eruption
Eruption Time period: May 2 – Nov 2008
Location: Andes region, Chile (-42.832778, -72.645833)

Image Retrieval Service can be used to find volcanic ash events in browse imagery

Suggest Relevant Data

Total SO_2 mass:
e.g. **Chaitén** is 10 (kt) =(kilotons) , (1kt= 1000 metric tons)
ftp://measures.gsfc.nasa.gov/data/s4pa/SO2/MSVOLSO2L4.1/MSVOLSO2L4_v01-00-2014m1002.txt

Daily SO2:
OMI/Aura Sulphur Dioxide (SO2) Total Column Daily L2 Global 0.125 deg
http://disc.sci.gsfc.nasa.gov/datacollection/OMSO2G_V003.html

Calibrated Radiances:
MODIS/Aqua Calibrated Radiances 5-Min L1B Swath 1km
http://dx.doi.org/10.5067/modis/myd021km.006

Aerosol Optical Thickness:
MODIS/Aqua Aerosol 5-Min L2 Swath 10km
http://modis-atmos.gsfc.nasa.gov/MOD0
SeaWiFS Deep Blue Aerosol Optical Dept
Data 13.5km
http://disc.gsfc.nasa.gov/datacollection

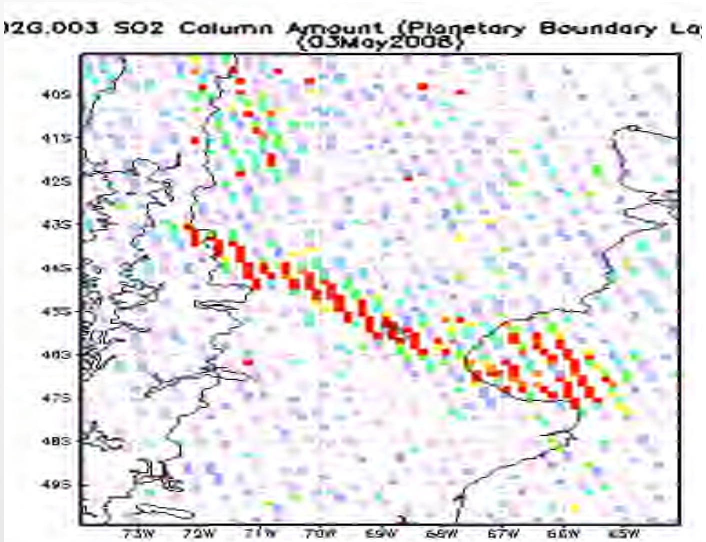
***Data Curation Service** recommends **relevant datasets** to support event analysis*

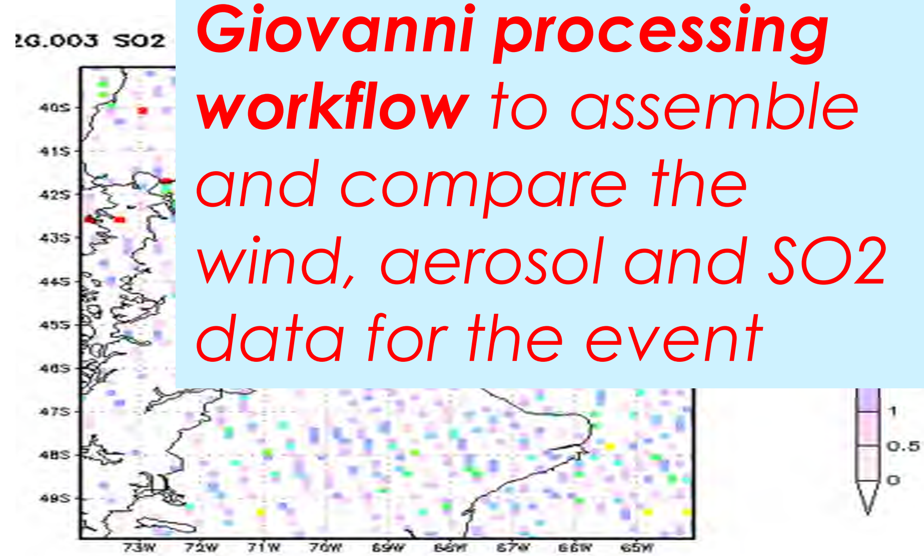
IR Brightness Temperature:
NCEP/CPC 4-km Global (60 deg N - 60 deg S) Merged IR Brightness Temperature Dataset

Generate Giovanni SO2 Plots

MODIS-Aqua 2008-05-03 18:45 UTC

MODIS-Aqua 2008-05-05 18:30 UTC



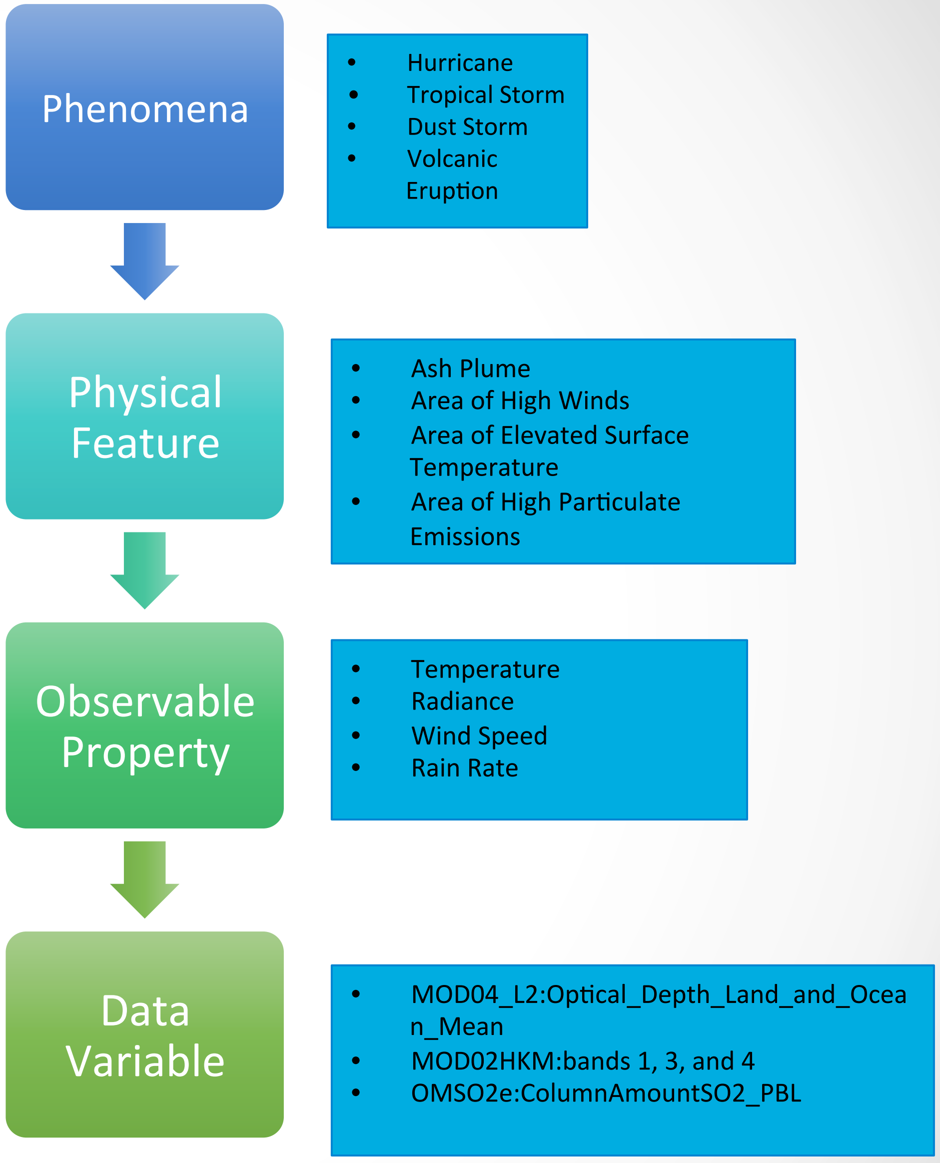


Rules Engine *invokes a* ***Giovanni processing workflow*** *to assemble and compare the wind, aerosol and SO2 data for the event*

http://gdata2.sci.gsfc.nasa.gov/daac-bin/G3/gui.cgi?instance_id=omil2g

Conceptual Model

- Phenomena
  - Event type
- Physical Feature
  - Manifestation / Driver of phenomena
  - Has space/time extent
  - Can precede or linger after what is generally thought of as the phenomena event
- Observable Property
  - Characteristic/property of physical feature
- Data Variable
  - Measurement/estimation of observable feature



Part 2: Data Curation Algorithm for Phenomena

Data Curation

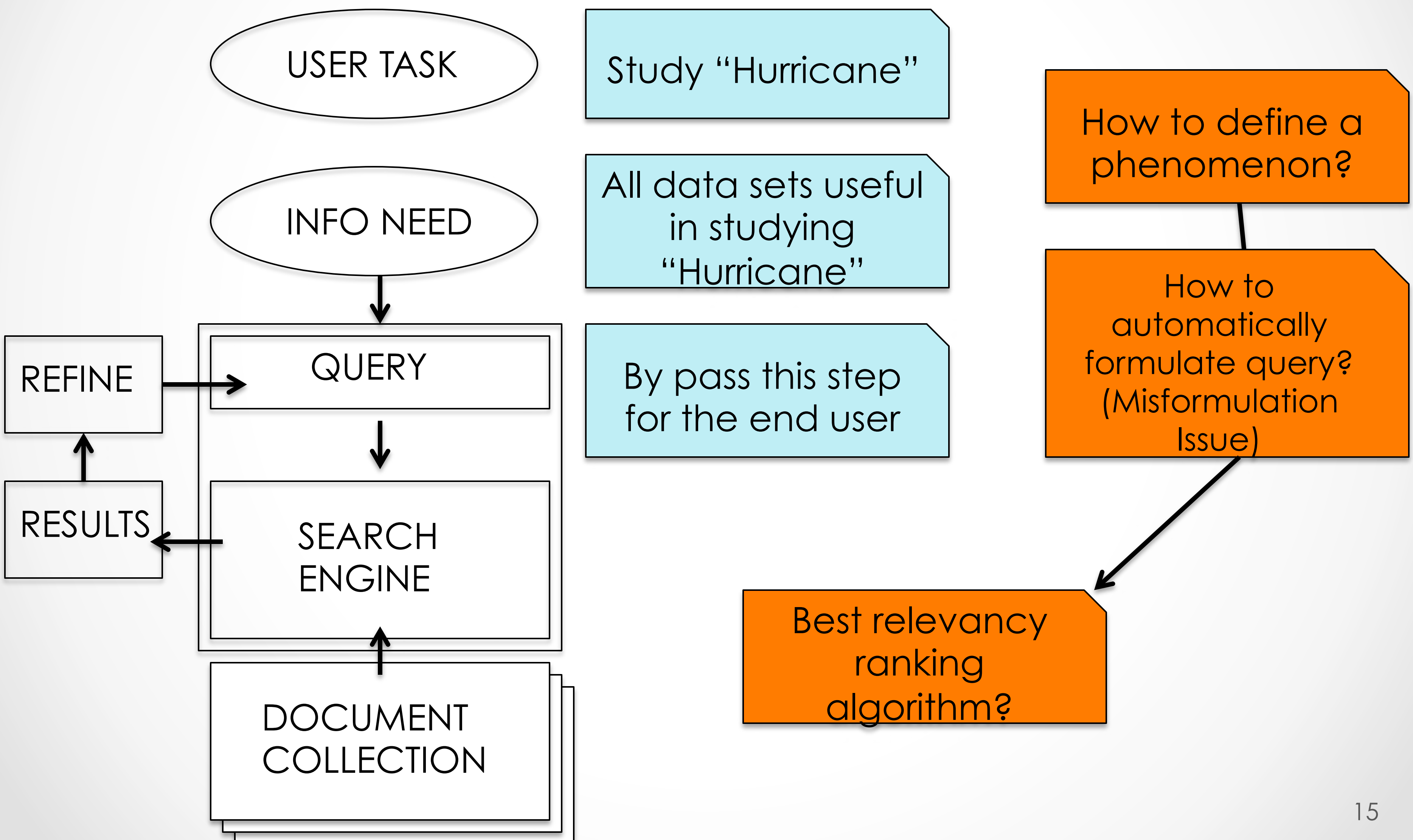
- Curation is traditionally defined as the process of collecting and organizing information around a common subject matter or a topic of interest and typically occurs in museums, art galleries, and libraries.
- Ramachandran et al. [2015] define geocuration as the act of searching, selecting, and synthesizing Earth science data/metadata and information from across disciplines and repositories into a single, cohesive, and useful collection.
  - Manual
  - Automated

Objectives

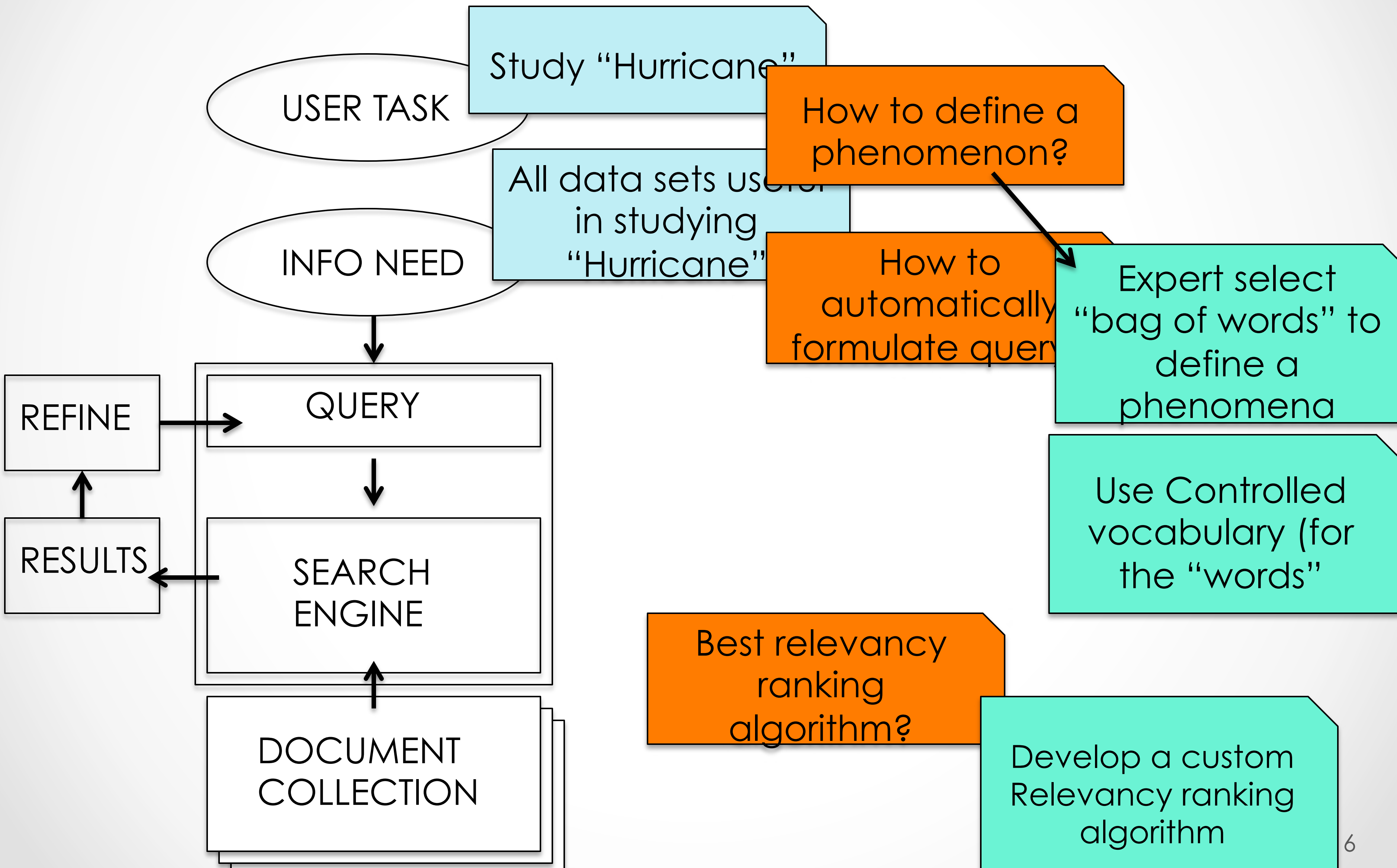
- Design a data curation (relevancy ranking) algorithm for a set of **phenomena**
- Provide the data curation algorithm as a stand alone service

- Envisioned Use:
  - Given a phenomenon type (Ex: Hurricane), DCS returns a list of relevant data sets (variables)
    - <list of data sets (variables)> = DCS(Phenomenon Type)
  - For a specific phenomenon instance (event: Hurricane Katrina), these curated datasets can be filtered based on space/time to get actual granules

Data Curation is a Specialized Search Problem



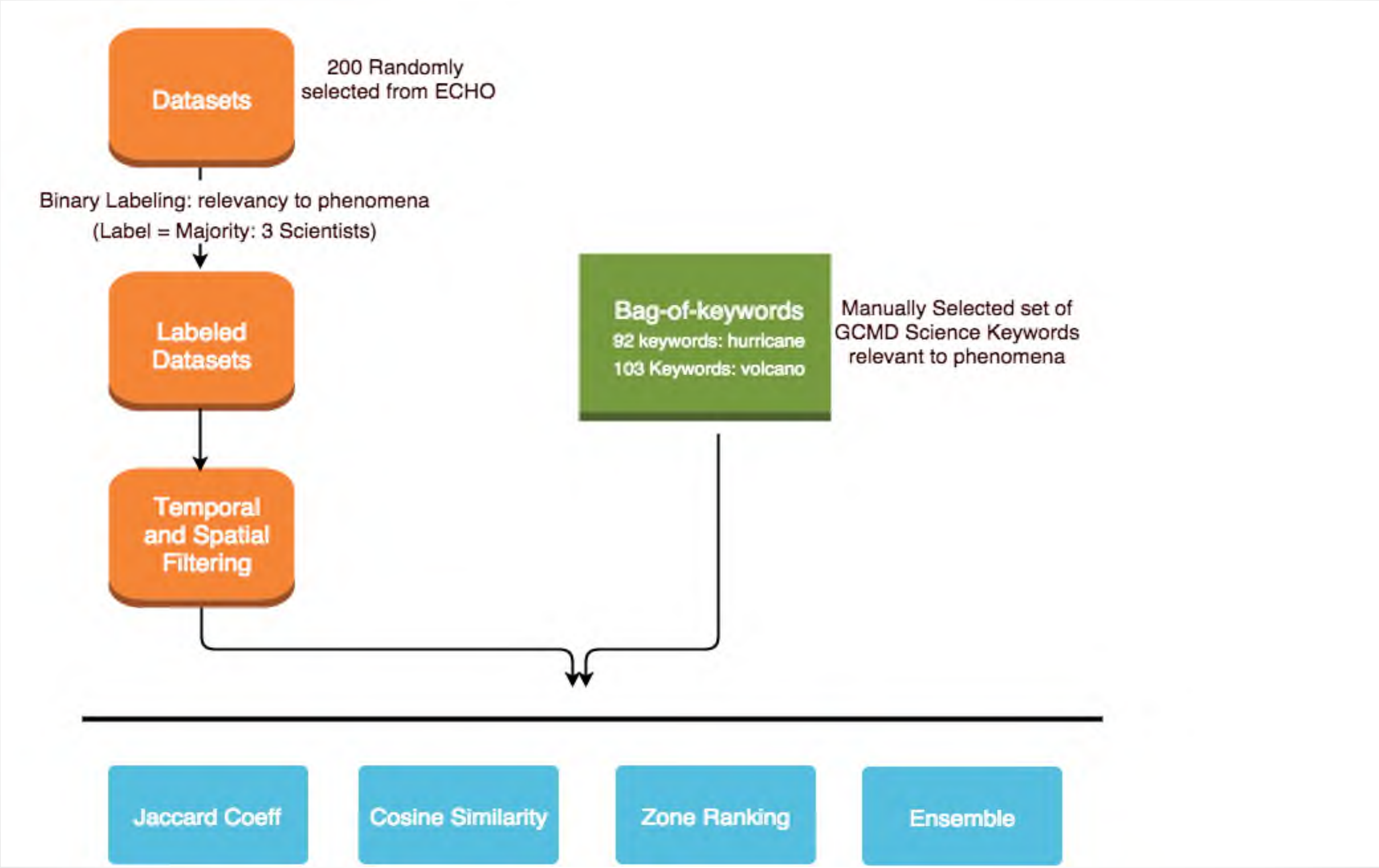
Our Approach



Methodology

- Selected three metadata fields
  - Science Keywords
  - Data set long name (title)
  - Data set description
- Developed customized vector space model for each field
- Compared different similarity measures
  - Cosine vs Jaccard
- Used Weighted Zone Ranking (Ensemble)
  - $S_c(e) = w_s \cdot S_c(s) + w_l \cdot S_c(l) + w_d \cdot S_c(d)$

Experiment Setup



Comparison of Similarity Measures

	Hurricane		Volcanic Eruption	
	Jaccard Coefficient	Cosine Similarity	Jaccard Coefficient	Cosine Similarity
Top 10 retrieval	10	9	6	7
Top 20 retrieval	17	16	15	15
Top 30 retrieval	23	24	22	21

- Both of the measures performed similarly
- Selected Cosine Similarity measure because it is commonly used in space vector model information retrieval

Ranking Results (Top 20) using Ensemble Method

	Optimal Weight		Equal Weight		Random	
	Precision	Recall	Precision	Recall	Precision	Recall
Hurricane	90.0%	47.4%	85.0%	44.7%	54.3%	28.6%
Volcanic Eruption	85.0%	68.0%	80.0%	64.0%	62.5%	50.0%
Fire	75.0%	30.0%	75.0%	30.0%	64.1%	25.6%
Flood	65.0%	48.1%	55.0%	40.7%	35.5%	26.3%

- Different numbers of "relevant" data sets, collection size (recall) exist within each truth set for each phenomenon
- Better to compare the curation results against the random selection rather than compare the performance against each other
- On average, precision improves about 25% when using our method and recall improves about 16%

Optimal ensemble weights for each phenomenon

Phenomenon	Optimal Weight Set ($W_{sciencekeyword}$, $W_{longname}$, $W_{description}$)
Hurricane	(0.6, 0.1, 0.3)
Volcanic Eruption	(0.2, 0.6, 0.2)
Fire	(0.6, 0.2, 0.2)
Flood	(0.5, 0.4, 0.1)

- Weight for science keyword is largest while the weight for description is smallest
  - Science keywords metadata fields use a controlled vocabulary and should be accurate and consistent
  - Description field is free-text and has the most variability in quality

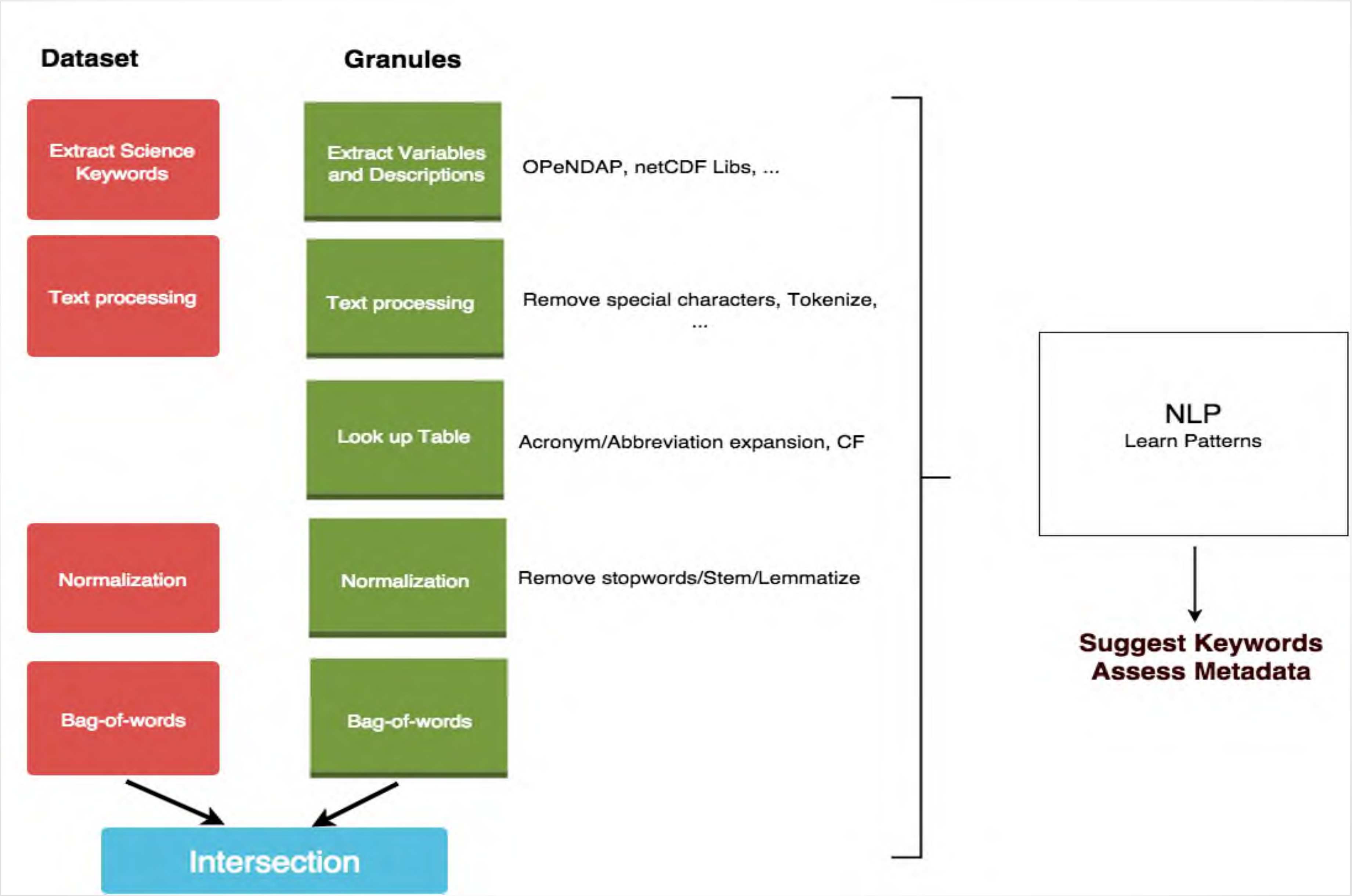
Methodology Limitations

- *Modeling the search intent is difficult*
  - one may be interested in only a specific aspect of a phenomenon whereas another user may only be interested in some other characteristic of a phenomenon
- *Quality of metadata records is variable*
  - Key assumptions is that the metadata records stored in the CMR catalog are consistent, correct, and complete
  - Launched a project to fix this
- Granularity of the Controlled Vocabulary
  - Rich detailed controlled vocabulary provides a better level of annotation granularity to represent different phenomena and help disambiguate data sets
- *Truth set labels may be biased*
  - domain experts on our team have stronger expertise in certain areas such as hurricanes and weaker expertise in others

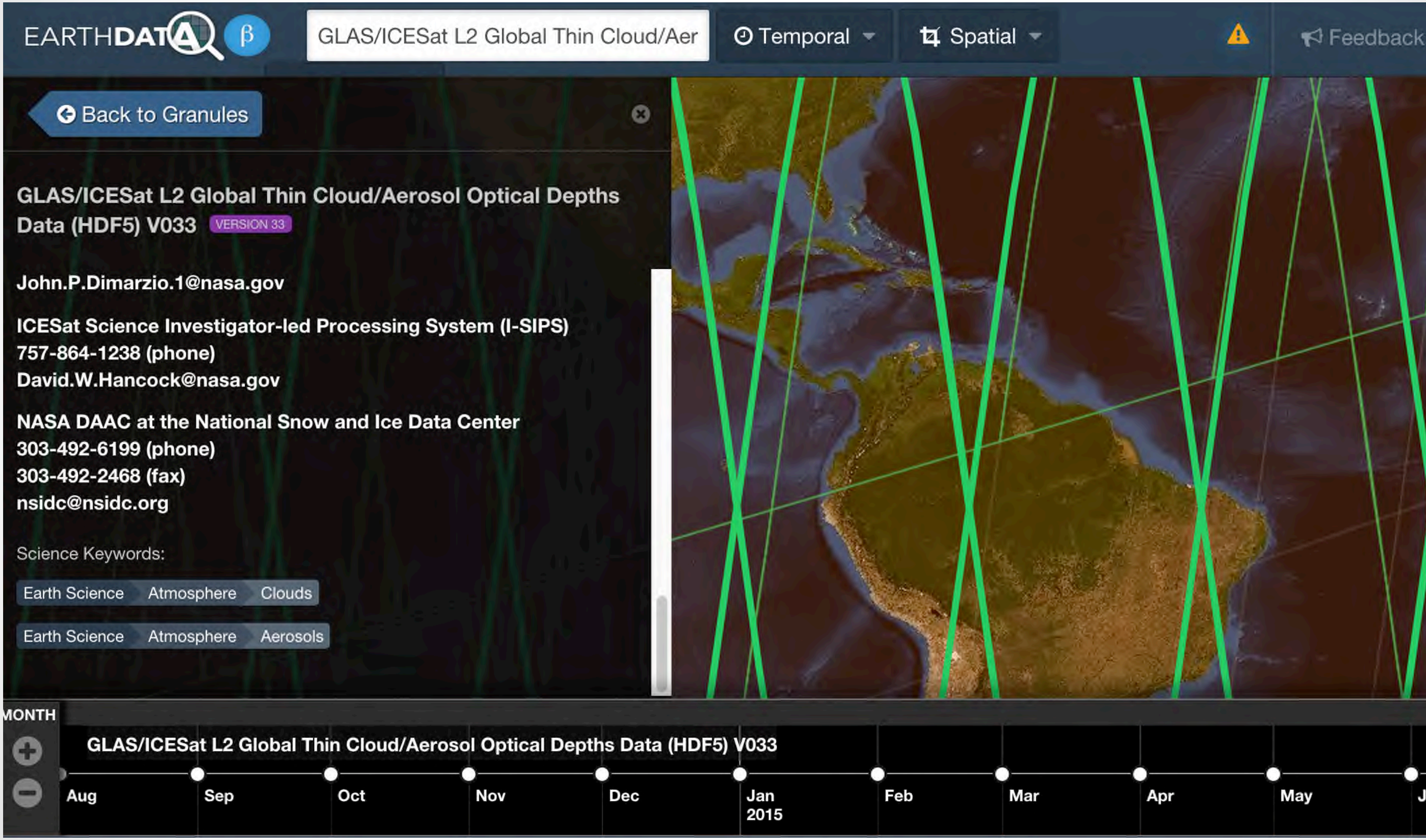
Next: Find relevant data fields

- Need actual data variables
  - o Example: Giovanni uses these fields for visualization
- What we know
  - o Data set (Collection) level science keywords (GCMD) – Experts
  - o Granule data fields and metadata – Auto extract*
- How do we map?
  - o Start with GCMD to CF Standard name
  - o Most don't follow CF Standard names

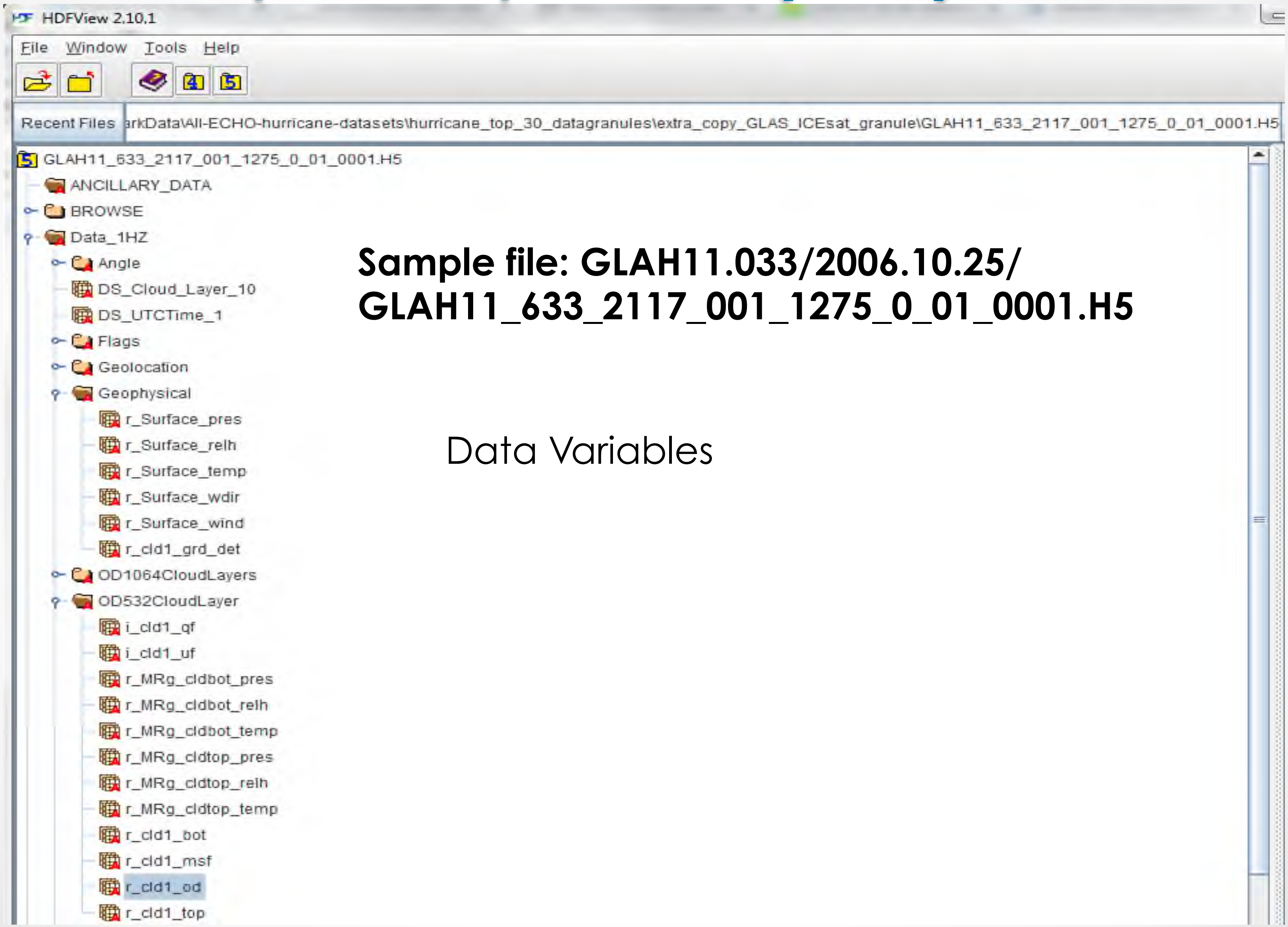
Approach


Dataset
Granules
Extract Science Keywords
Extract Variables and Descriptions
OPeNDAP, netCDF Libs, ...
Text processing
Text processing
Remove special characters, Tokenize, ...
Look up Table
Acronym/Abbreviation expansion, CF
Normalization
Normalization
Remove stopwords/Stem/Lemmatize
Bag-of-words
Bag-of-words
Intersection
NLP
Learn Patterns
Suggest Keywords
Assess Metadata

Example: GLAS/ICESat L2 Global Thin Cloud/Aerosol Optical Depths Data (HDF5) V033 – Dataset Metadata



Example: GLAS/ICESat L2 Global Thin Cloud/Aerosol Optical Depths Data (HDF5) V033



Sample file: GLAH11.033/2006.10.25/ GLAH11_633_2117_001_1275_0_01_0001.H5

Data Variables

Example: GLASICESat L2 Global Thin Cloud Aerosol Optical Depths Data (HDF5) V033

Science keyword to variable mapping

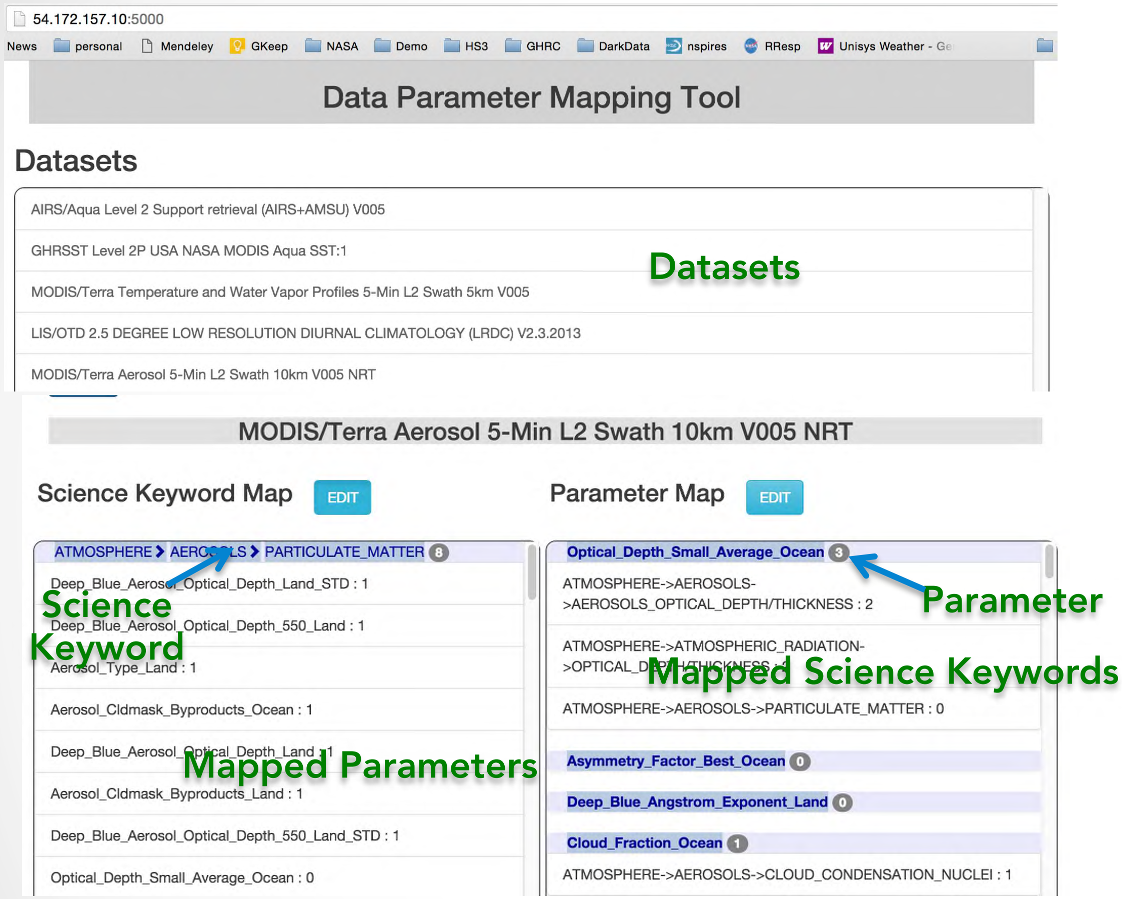
- r_Surface_relh | Surface Relative Humidity
  - No match
- r_Surface_temp | Surface Temperature
  - No match
- r_Surface_wind | Surface Wind Speed
  - No match
- r_cld1_od | Cloud Optical Depth at 532 nm
  - Score=3 keyword: ATMOSPHERE->CLOUDS->CLOUD OPTICAL DEPTH/THICKNESS
  - Score=2 keyword: ATMOSPHERE->AEROSOLS->AEROSOL OPTICAL DEPTH/THICKNESS

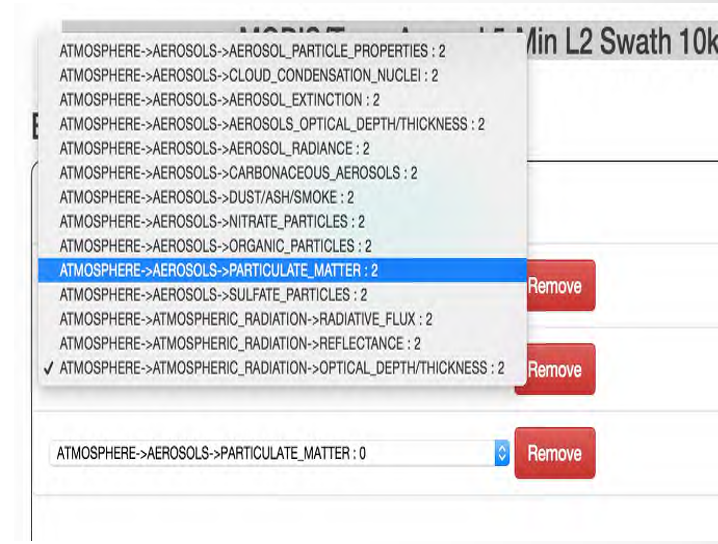
Variable to keyword mapping

- ATMOSPHERE->CLOUDS->CLOUD OPTICAL DEPTH/THICKNESS
  - Score=3 name: r_cld_ir_OD | Cloud Optical Depth at 1064 nm
  - score=3 name:i_cld1_qf | Cloud optical depth flag for 532 nm
  - Score=3 name:i_cld1_uf | Cloud optical depth flag for 532 nm
  - Score=3 name:r_cld1_od | Cloud Optical Depth at 532 nm
  - more with low scores

- ***Serendipitous Discovery*** - Data Curation Parameter Mapping Algorithm can be used to assess
  - Metadata quality for both dataset and granules
  - Find incorrect/incomplete keyword annotations
  - Automatically suggest science keywords

Parameter Mapping Tool



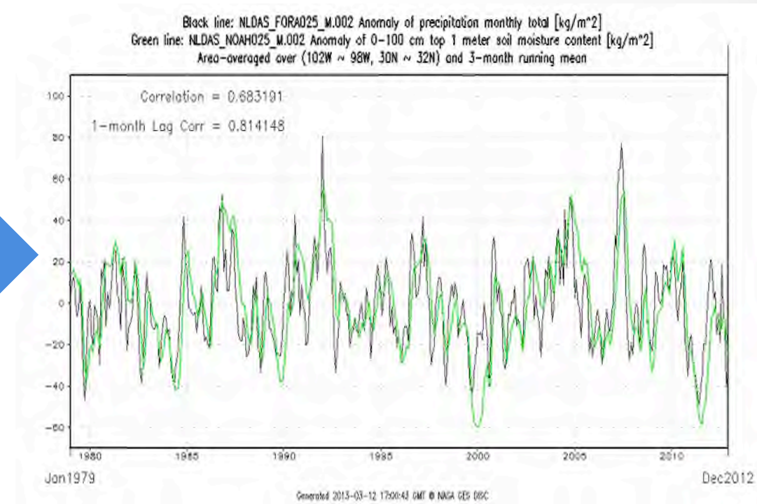


Edit/Save Mapping

Mapping Scores Generated by Algorithm

Part 3: Rules Engine

What settings should I use to visualize this event?



Data Variable ?

Dataset ?

Visualization Type?

Goal: Automate data preprocessing and exploratory analysis and visualization tasks

Images from : http://globe-views.com/dcim/dreams/volcano/volcano-03.jpg , http://grecaira.users37.interdns.co.uk/essay/images/confused.png , http://disc.sci.gsfc.nasa.gov/datareleases/images/nldas_monthly_climatology_figure_9.gif

Strategy

- Service to generate and rank candidate workflow configurations
- Use rules to make **assertions** about **compatibility based on multiple factors**
  - does this data variable make sense for this feature?
  - does this visualization type make sense for this feature?
  - does the temporal / spatial resolution of this dataset make sense for this feature?
- Each compatibility assertion type is assigned weights.
  - ex: Strong = 5, Some = 3, Slight = 1, Indifferent = 0, Negative = -1.
- Based on the aggregated compatibility assertions, we calculate the score for each visualization candidate.

Ruleset Development

Survey asked users to rate characteristics of phenomena features

Feature characteristics for analysis *

What characteristics are of interest when analyzing the feature?

	negative value	indifferent	slight value	some value	strong value
east-west movement	○	○	○	○	○
north-south movement	○	○	○	○	○
temporal evolution	○	○	○	○	○
spatial extent of event	○	○	○	○	○
year-to-year variability	○	○	○	○	○
may impact seasonal variation	○	○	○	○	○
variation with atmospheric height	○	○	○	○	○
global phenomena	○	○	○	○	○
detection of events	○	○	○	○	○

Survey results used to formulate rules

```
[rule1:
   (?feature rdf:type
dd:AshPlume)
   ->
   (?feature
dd:strongCompatibilityFor
dd:temporal_evolution),
   (?feature
dd:indifferentCompatibilityFor
dd:east-west-movement),
   …
]
```

Phenomena Feature Characteristic Mappings

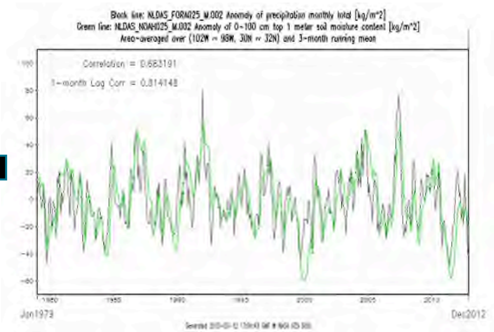
Phenomena	East-West Movement	North-South Movement	Temporal Evolution	Spatial Extent of Event	Year-to-Year Variability	May Impact Seasonal Variation	Variation with Atmospheric Height	Global Phenomena	Detection of Events
Volcano - Ash Plume	Indifferent	Indifferent	Strong	Slight	Strong	Strong	Strong	Strong	Strong
Flood	Some	Some	Strong	Some	Some	Strong	Some	Slight	Some
Dust Storm	Strong	Strong	Strong	Strong	Indifferent	Indifferent	Strong	Indifferent	Some

Service to Characteristic Mappings

Service	Visualization	East-West Movement	North-South Movement	Temporal Evolution	Spatial Extent of Event	Year-to-Year Variability	Seasonal Variation	Variation with Atmospheric Height	Global Phenomena	Detection of Events
Time-averaged Map	Color-Slice Map				✓					
Area-averaged Time Series	Time Series			✓						✓
User-defined Climatology	Color-Slice Map						✓			
Vertical Profile	Line Plot							✓		
Seasonal Time Series	Time Series					✓				
Zonal Means	Line Plot								✓	
Hovmoller (Longitude)	Color-Slice Grid	✓								
Hovmoller (Latitude)	Color-Slice Grid		✓							

Compute Compatibility

+



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Phenomena: Volcano - Ash Plume

Temporal Evolution	Detection of Events
Strong	**Strong**

Service - Area Averaged Time Series

Area Averaged Time Series : bestFor →	Temporal evolution; Detection of events

STRONG COMPATIBILITY x2

Images from , http://disc.sci.gsfc.nasa.gov/datareleases/images/nldas_monthly_climatology_figure_9.gif, http://www.clipartbest.com/cliparts/biy/bAX/biybAXGiL.png

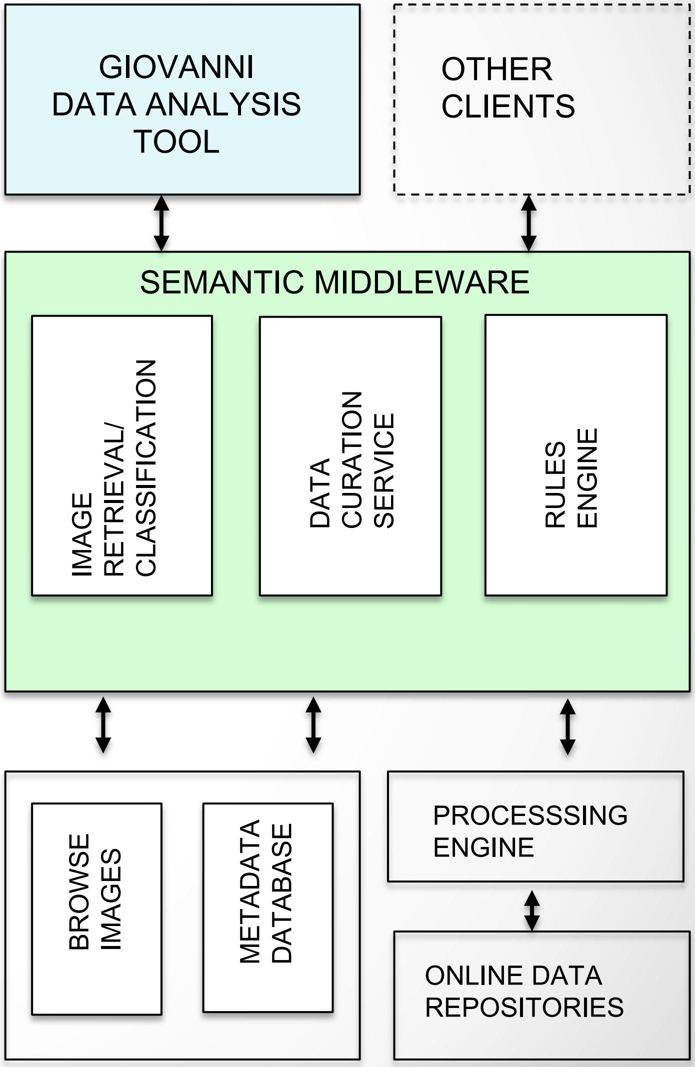
volcanic ash image - By Boaworm (Own work) [CC BY 3.0 (http://creativecommons.org/licenses/by/3.0)], via Wikimedia Commons

Part 4: Application (Demo)

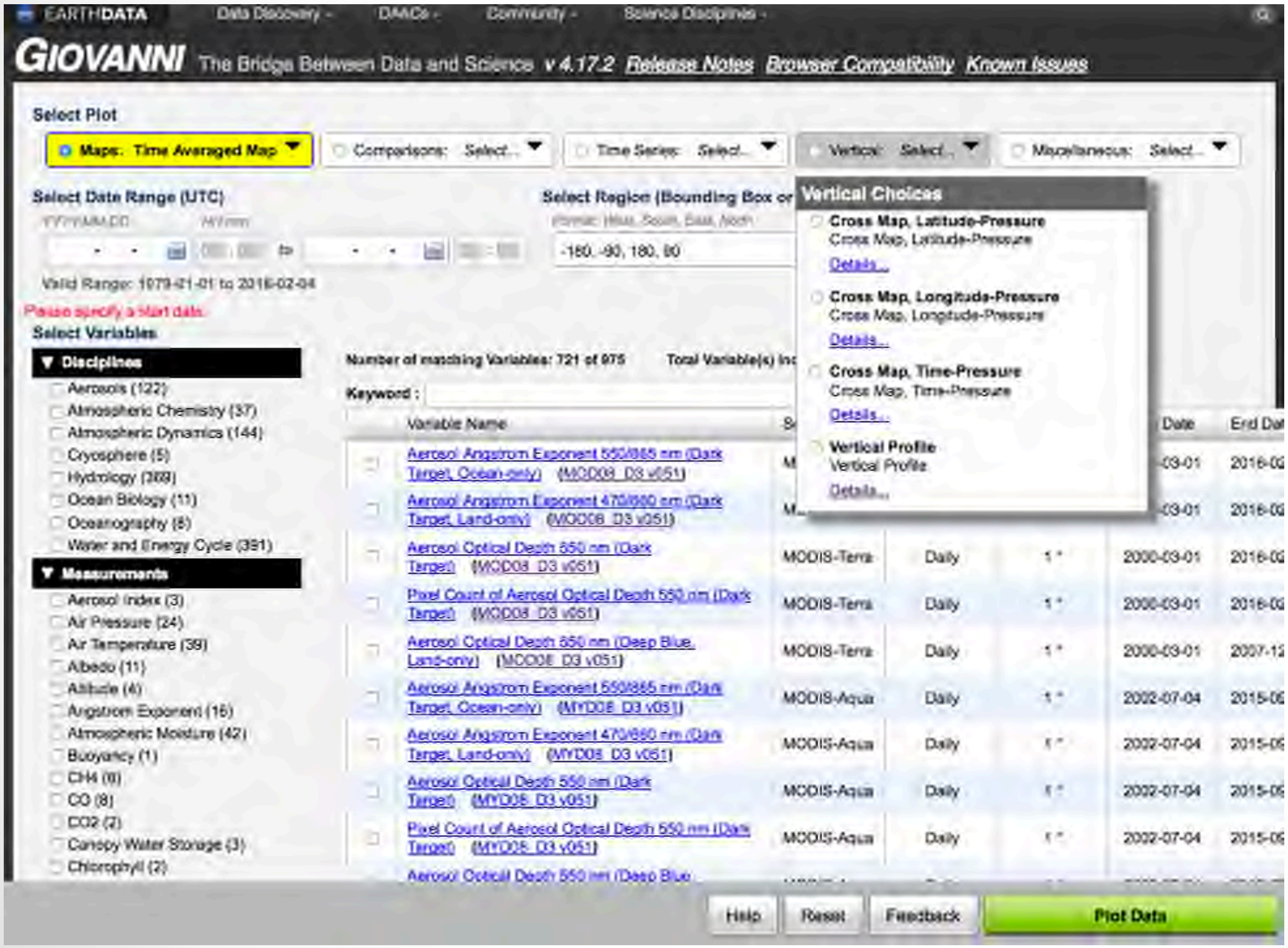
Integrating Services in Giovanni

- **Tool**: Giovanni is a popular on-line environment that lets users discover, plot, and download a number of geophysical parameters (data variables)
- **Goal**: Leverage Dark Data services and technologies to assist Giovanni users in discovering and exploring data

'Success will be realized when Giovanni requests can be automatically invoked with the appropriate spatial and temporal extents, variables and workflow / visualization type for a particular event'



Giovanni – Standard Edition



User needs to decide:

- Variable(s)
- Time
- Space
- Plot type

http://giovanni.sci.gsfc.nasa.gov/giovanni/

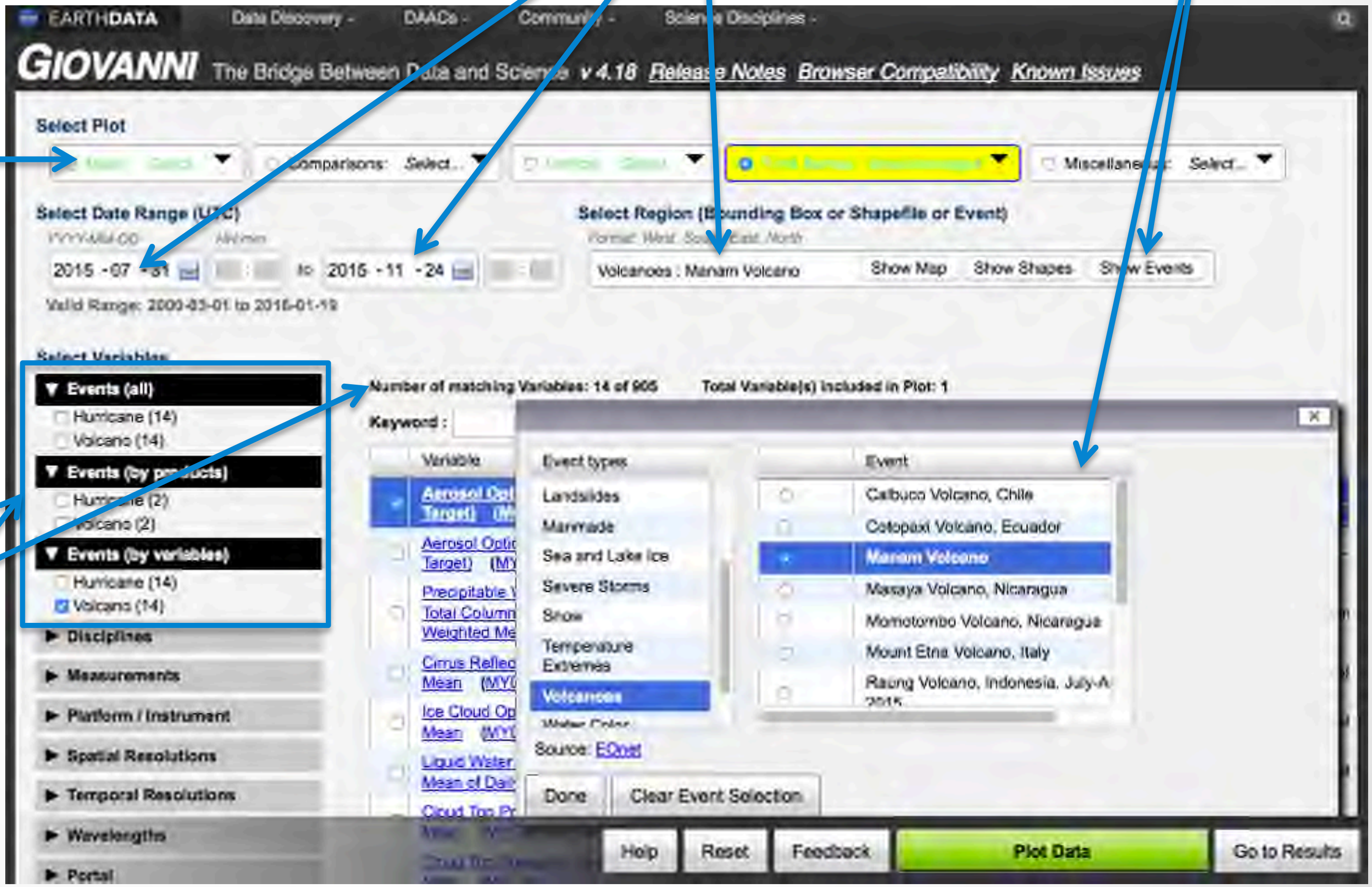
Giovanni – Dark Data Edition

Selected event & its time

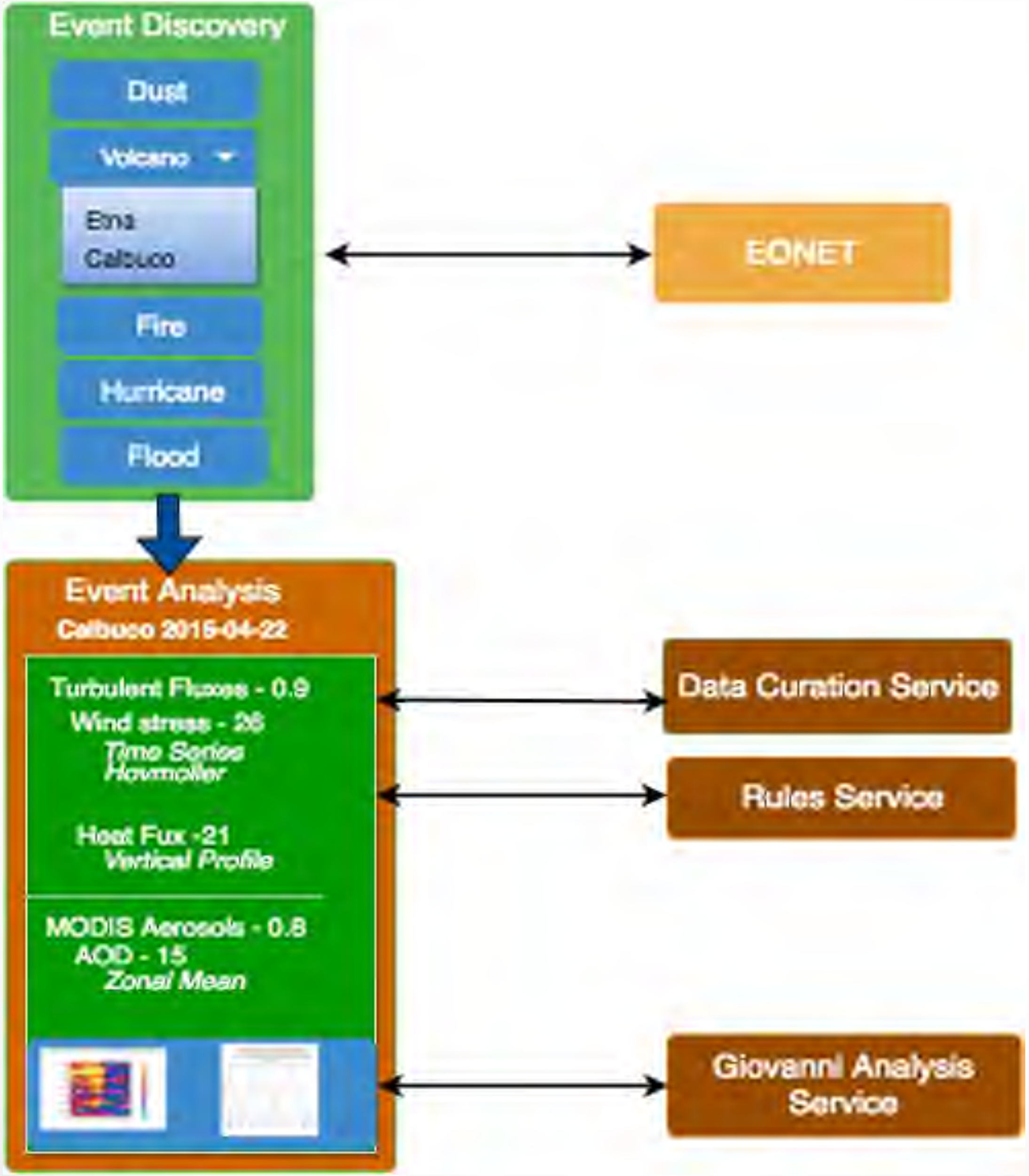
Event Client

Rules Service: highlights suitable plots based on selected event & variables

Curation Service: event type filters relevant variables



Giovanni - Dark Data Edition



Event Analysis Workflow

DEMO

Part 5: Image Retrieval

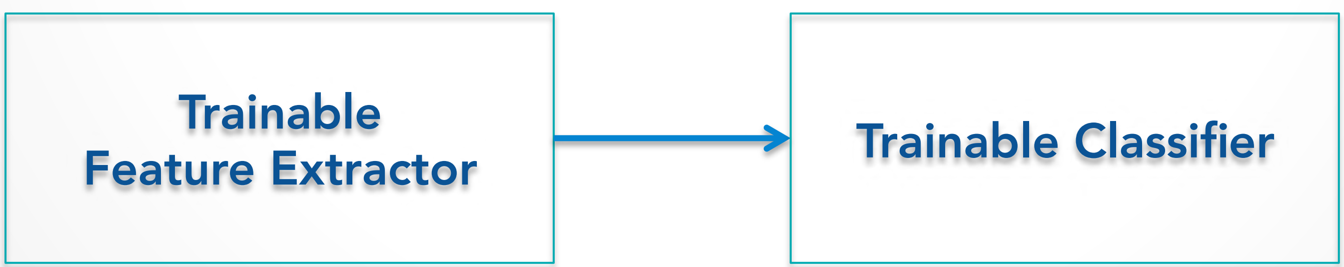
Image Retrieval

- Goal: given an image of Earth science phenomenon retrieve similar images

- Challenge: “semantic gap”
  - low-level image pixels and high-level semantic concepts perceived by humans

"Deep" Architecture

- Features are key to recognition
- What about learning the features?
- Deep Learning
  - Hierarchical Learning
  - Mimics the human brain that is organized in a deep architecture
  - Processes information through multiple stages of transformation and representation



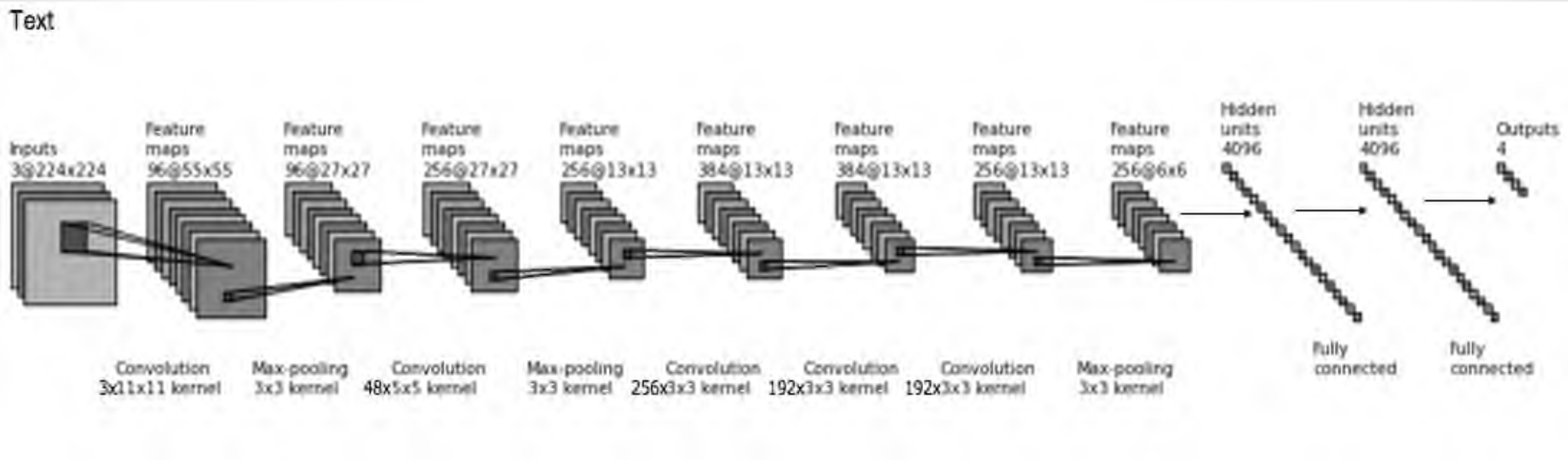
Convolutional Neural Network (CNN) - Applicable to Images

Transfer Learning

- CNN requires large number of parameters
- Learning parameters from *a few thousand training samples* is unrealistic
- Transfer learning
    - Use internal representation learned from one classification task to another
  - o AlexNet architecture - Krizhevsky et. al.
  - o Weights learned from ImageNet 1.3 million high-resolution images
  - o State-of-the-art classification accuracy

A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Advances in Neural Information Processing Systems 25, Curran Associates, Inc., pp: 1097-1105, 2012.

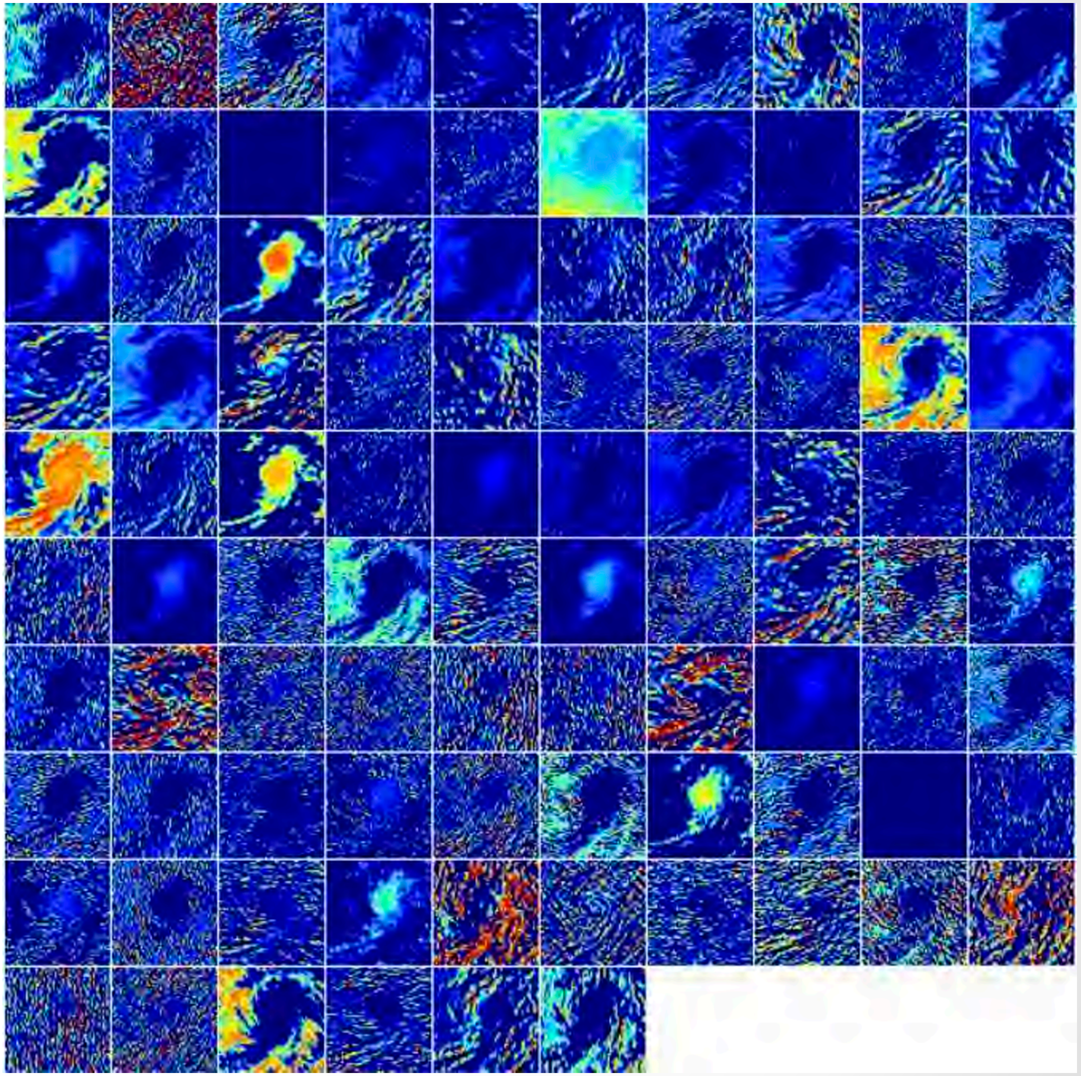
Experiment: CNN Configuration



- AlexNet architecture
    - Initialized weights with ImageNet trained model
    - Adaptive learning rate
    - GPU implementation

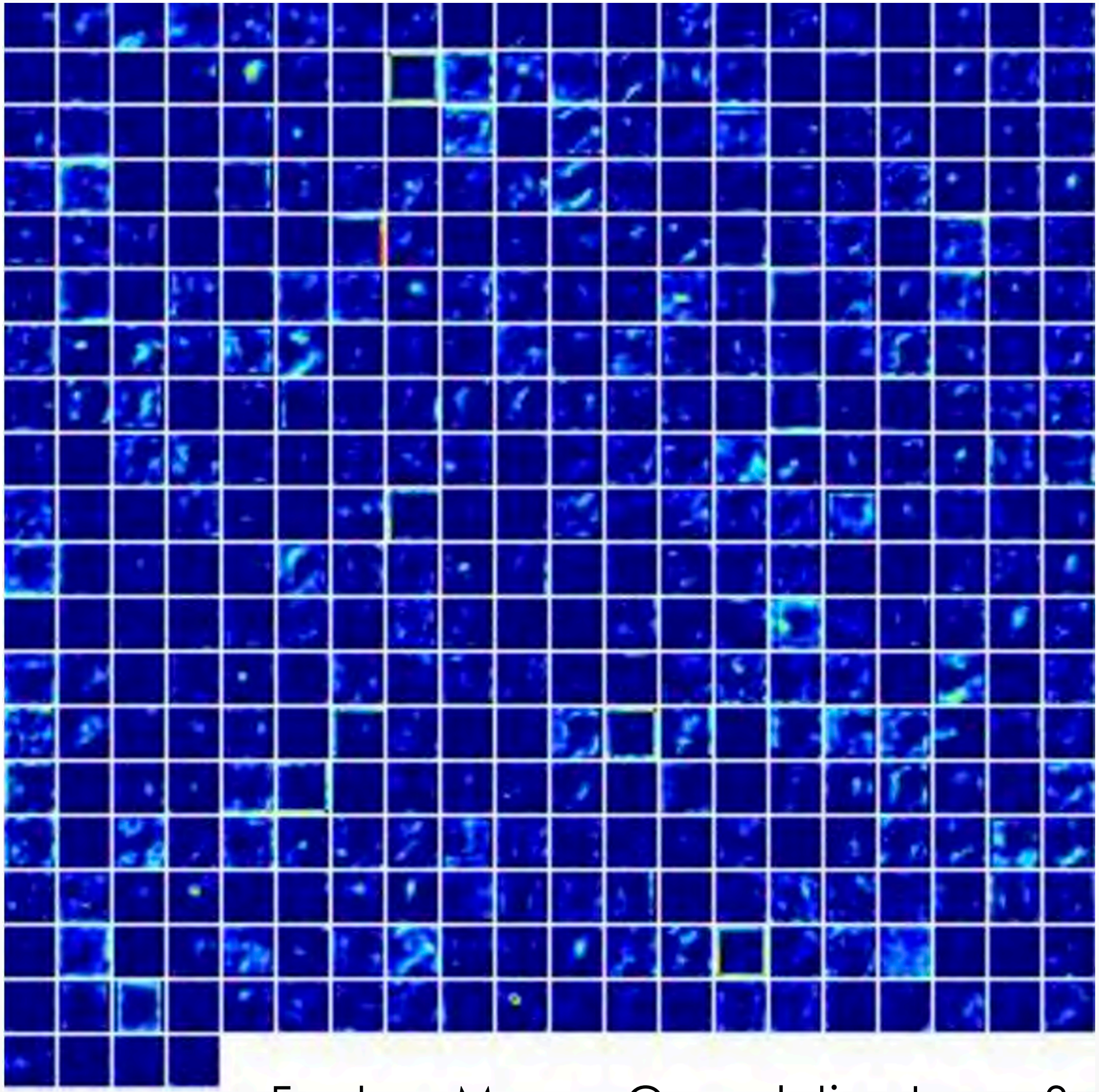
Experiment CNN – Visualization

Input Image



Feature Maps – Convolution Layer 1

Experiment CNN – Visualization



Feature Maps – Convolution Layer 3

Results: Confusion Matrix

MODIS Rapid Response Test Images (Images are New to Trained CNN)

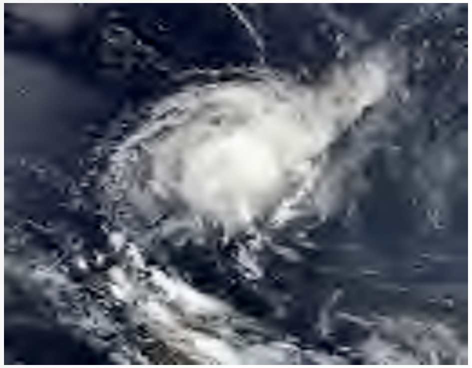
True/Pred	Dust	Hurricane	Smoke	Other
Dust	**287**	8	32	33
Hurricane	0	**379**	1	10
Smoke	12	12	**443**	9
Other	33	9	23	**211**

Overall Accuracy = **87.88%**

Producer's Accuracy
Dust 86.45%
Hurricane 92.89%
Smoke 88.78%
Other 80.23

User's Accuracy
Dust 79.72%
Hurricane 97.18%
Smoke 93.07%
Other 76.45%

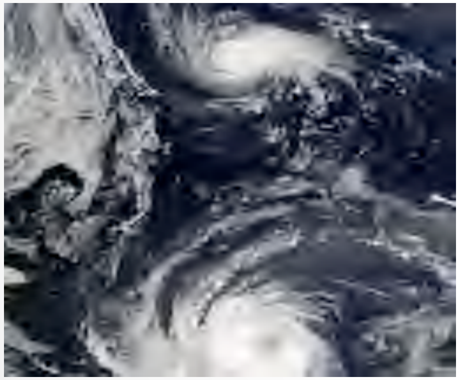
Results (MODIS Rapid Response)



Hurricane – True Positive

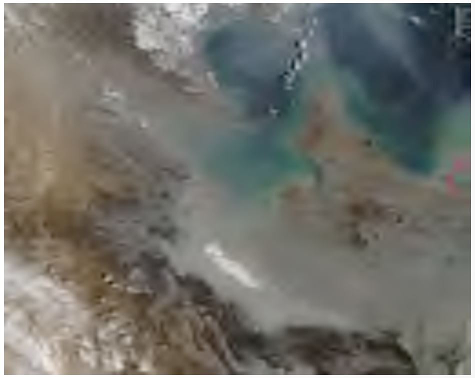
Dust – True Positive

Smoke– True Positive



Hurricane – False Negative

Dust – False Positive



Smoke– False Positive

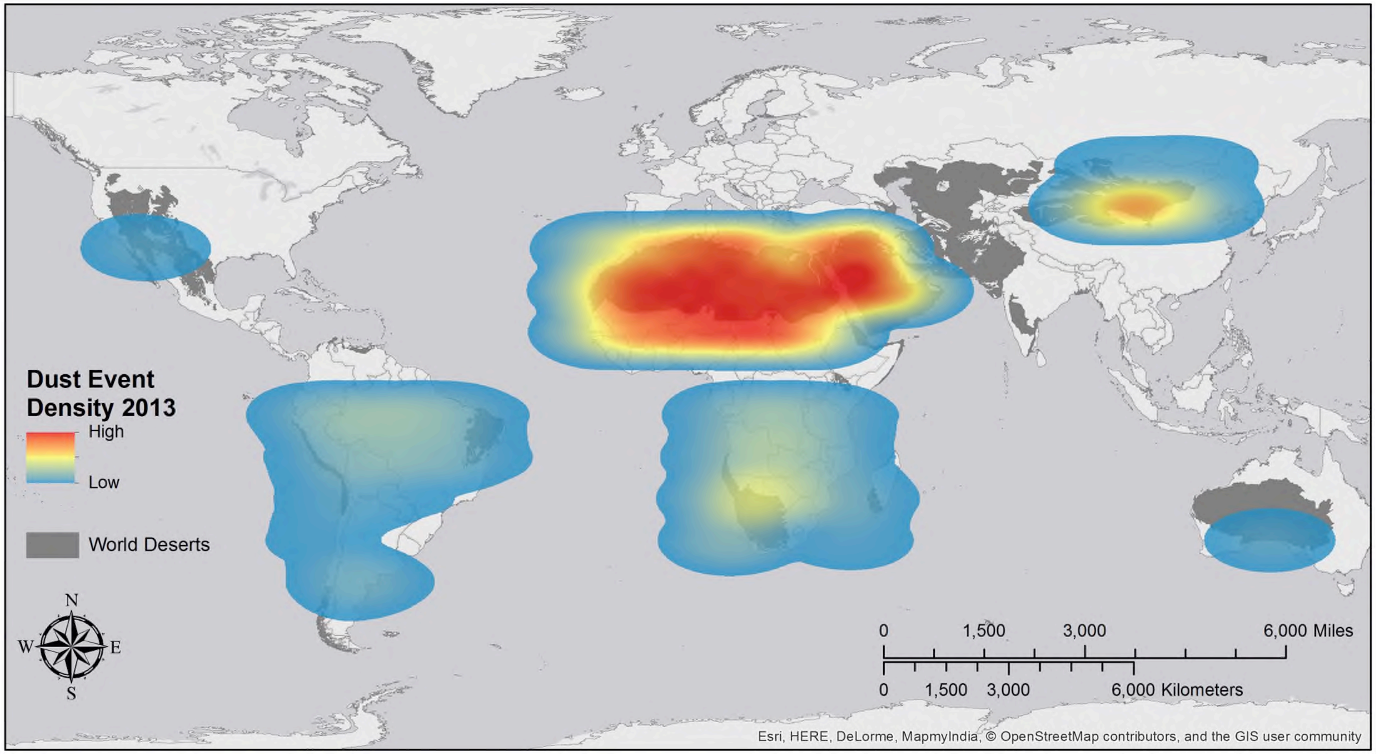
Applications: Enabling new science

- Dust climatology – Collaboration with Sundar Christopher, UAH Atmospheric Science Professor

True\Predicted	**Dust**	**Other**	Total
Dust	**1379**	379	1758
Other	260	**4932**	5192
	1639	5311	6950

Confusion Matrix

Validation Accuracy = **91%**

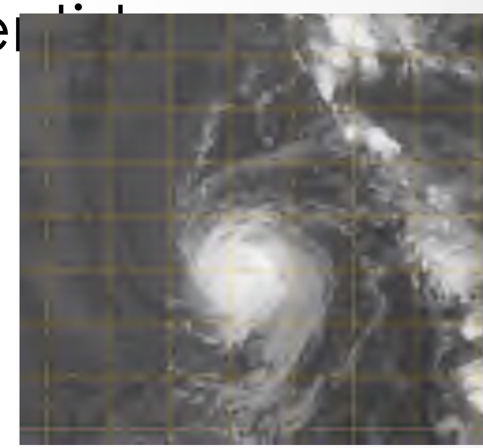


Based on GIBS

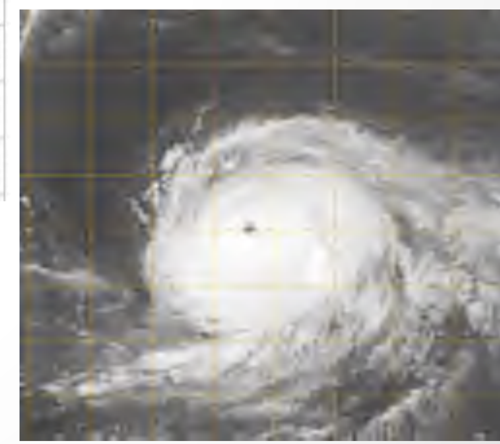
Applications: Improving forecast operations

- Hurricane intensity estimation - Collaboration with Dan Cecil, NASA/MSFC Atmospheric Scie

True\Predicted	td	ts	h1	h2	h3	h4	h5	no_cat	total
td	3168	335	0	1	0	0	0	6	3510
ts	489	4823	159	5	11	3	6	0	5496
h1	9	484	1158	92	20	6	1	0	1770
h2	3	76	214	513	145	4	0	5	960
h3	6	40	33	155	689	55	0	0	978
h4	1	18	17	12	142	810	32	0	1032
h5	2	2	0	0	27	59	216	0	306
no_cat	22	0	0	0	0	0	0	32	54
	3700	5778	1581	778	1034	937	255	43	14106



Cat 2 Hurricane

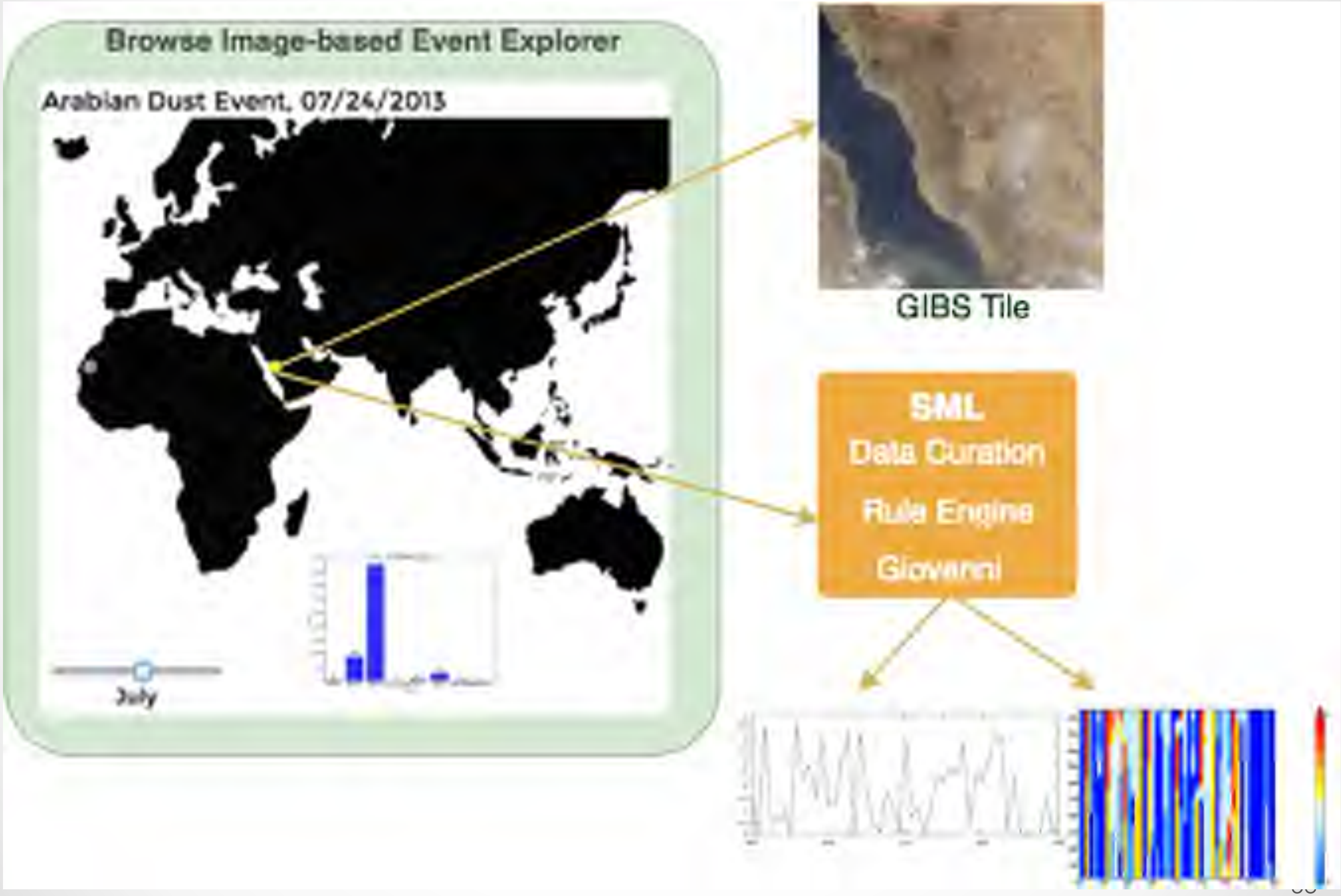


Cat 4 Hurricane

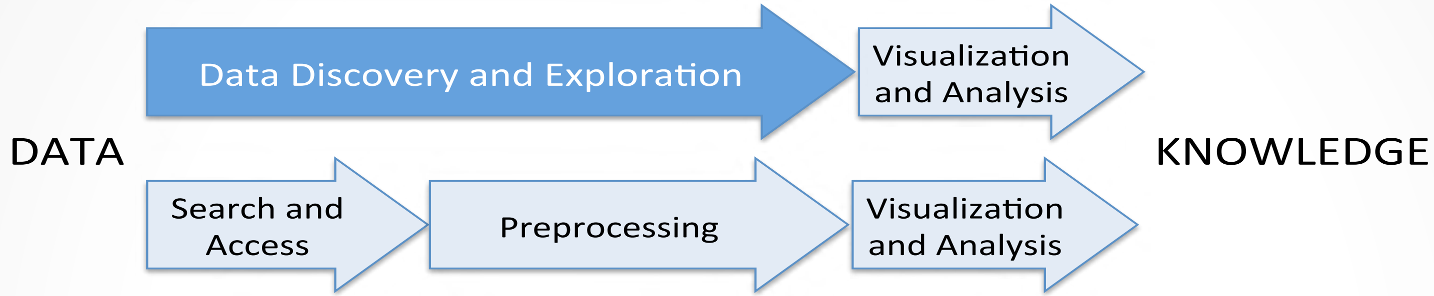
Overall Accuracy : 81 %(Top 2 Probabilities 95.73%)

Data: NRL Images, HURDAT

Ongoing Work



Summary



- Science data and information systems need to evolve to enable better data *search, access and usability*!
- Need operational services like – Data Curation Service, Rules Engine and Image Retrieval

Questions

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