### ILLUMINATING THE DARKNESS: EXPLOITING UNTAPPED DATA AND INFORMATION RESOURCES IN EARTH SCIENCE

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#### Project Team:

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Earth Science Technology Forum, 2016



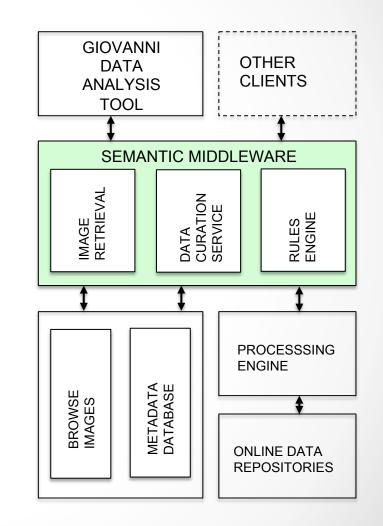
### Earth Science Metadata: Dark Resources

- Dark resources: not used beyond **intended** purpose
  - Challenge: recognize, identify and effectively utilize for other **purposes**
- Metadata catalogs:
  - contain dark resources
  - structured information
  - free form descriptions: data and browse images
- NASA's Common Metadata Repository
  - > 6000 data collections
  - 270 million records for individual files
  - o 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 Earth science and education communities.

# **Project Goals**

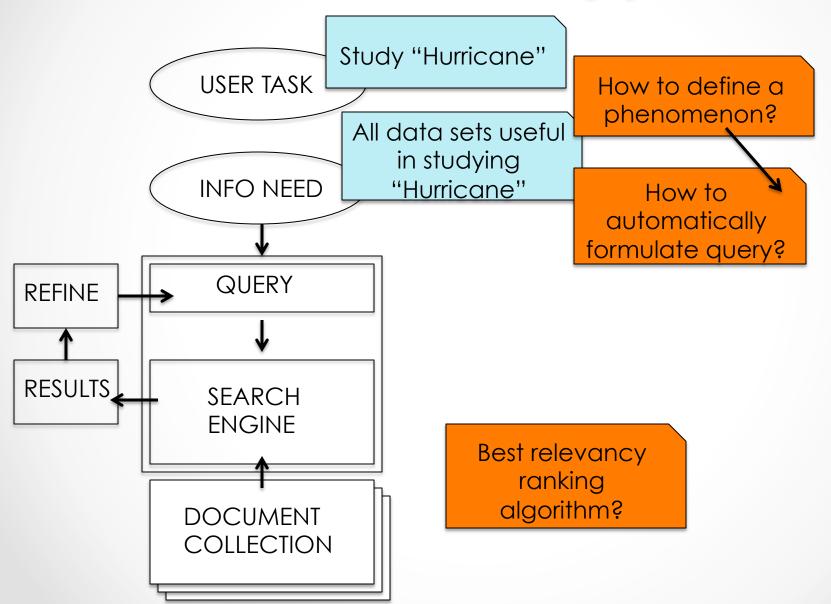
- Design a Semantic Middleware Layer (SML) to exploit metadata resources
  - provide novel data discovery and exploration capabilities that significantly reduce data preparation time.
  - utilize a varied set of semantic web, information retrieval and image mining technologies.
  - o automate
- Design SML as a Service
   Oriented Architecture



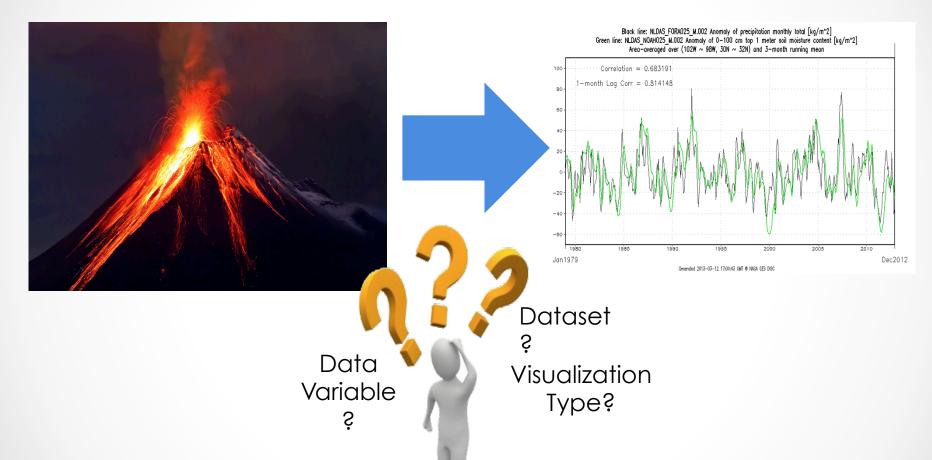
## **Data Curation Service**

- Relevancy ranking algorithm for a set of phenomena
- Stand alone service
- Envisioned Use:
  - Given a phenomenon type (Ex: Hurricane), DCS returns a list of relevant data sets (variables)
    - f 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 Approach**



# Rules Engine: What settings should I use to visualize this event?



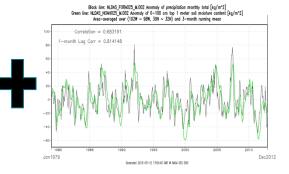
# Goal: Automate data preprocessing and exploratory analysis and visualization tasks

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

### **Compute Compatibility**

Use rules to make assertions about compatibility based on multiple factors





Phenomena: Volcano - Ash Plume Service - Area Averaged Time Series

	Detection of Events	Averaged	Temporal evolution; Detection of events	
Strong	Strong			

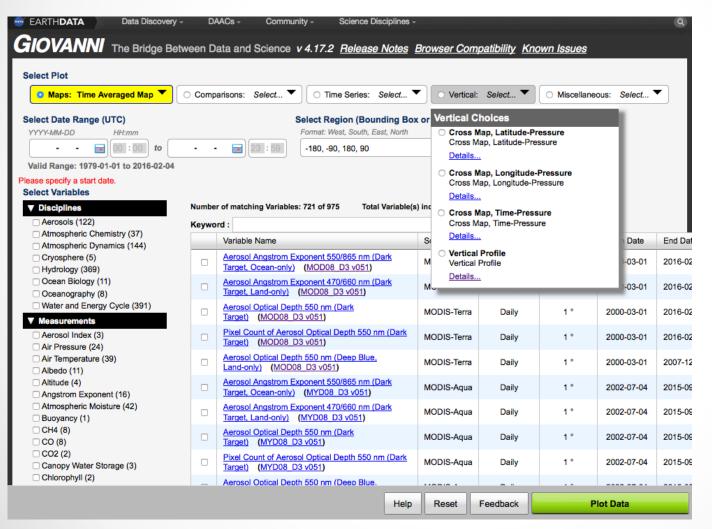
### STRONG COMPATIBILITY x2

#### Service to generate and rank candidate workflow configurations

Images from , http://disc.sci.asfc.nasa.aov/datareleases/imaaes/nldas monthly climatoloav figure 9.aif, 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

### **Giovanni – Standard Edition**



User needs to decide:

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

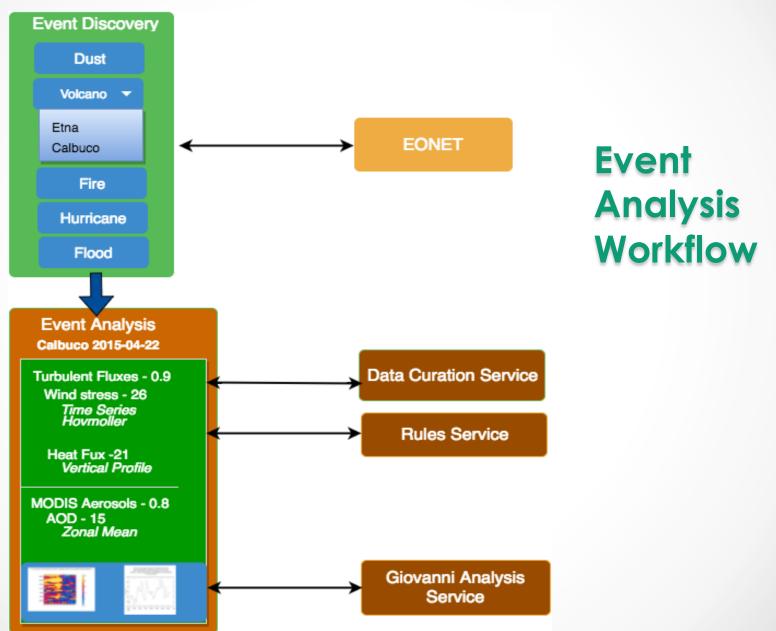
#### http://giovanni.sci.gsfc.nasa.gov/giovanni/

## Giovanni – Dark Data Edition

Selected event & its time Event Client

**Rules Service:** highlights EARTHDATA Data Discovery -DAACs -Communit / -Scien e Disciplines suitable plots GIOVANNI The Bridge Between Data and Science v 4.18 Release Notes Browser Compatibility Known Issues based on Select Plot selected event Select... 🔽 O Vertical: Select... 💿 Time Series: Area-Averaged 🍸 O Miscellane us: omparisons: Select... Select... Select Region (Bounding Box or Shapefile or Event) Select Date Range (UTC) & variables Format: West, Sour East, North YYYY-MM-DD HH:mm Show Events 2015 - 07 -31 🖃 to 2015 - 11 - 24 🖃 Show Map Show Shapes Volcanoes : Manam Volcano Valid Range: 2000-03-01 to 2016-01-19 Select Variables Number of matching Variables: 14 of 905 Events (all) Total Variable(s) included in Plot: 1 Hurricane (14) X Keyword : Volcano (14) Variable Event types Event ▼ Events (by preducts) Aerosol Opt Landslides Calbuco Volcano, Chile Hurricane (2) Target) (N volcano (2) Manmade Cotopaxi Volcano, Ecuador Aerosol Opti Events (by variables) Sea and Lake Ice Manam Volcano Target) (M' Hurricane (14) Severe Storms Curation Masaya Volcano, Nicaragua Precipitable Volcano (14) Total Column Snow 0 Momotombo Volcano, Nicaragua Weighted Me Disciplines Temperature Service: event Mount Etna Volcano, Italy Cirrus Reflect Extremes Measurements Raung Volcano, Indonesia, July-A Mean (MY Volcanoes 2015 type filters Ice Cloud Op Platform / Instrument Water Color Mean (MYI Source: EOnet Spatial Resolutions Liquid Water relevant Mean of Dai Temporal Resolutions Done Clear Event Selection Cloud Top Pr variables Wavelengths Feedback Plot Data Go to Results Help Reset Portal

### **Giovanni - Dark Data Edition**



### **Serendipitous Discovery**

**Data Curation Goal:** map dataset keywords to granule variables

# Application of Data Curation for Operational Use:

Data Curation Algorithm can be used to assess

- Metadata quality for both dataset and granules
  - Find incorrect/incomplete keyword annotations
- Automatically suggest science keywords

### **Operational Use: Prototype Variable Mapping**

Demo

HS3

🥺 GKeep

🔚 🔚 GHRC 📄 DarkData 🚽 nspires 🚭 RResp 🛛 Unisys Weather - Ge

**Data Parameter Mapping Tool** 

#### Datasets

personal 🗋 Mendeley

AIRS/Aqua Level 2 Support retrieval (AIRS+AMSU) V005	
GHRSST Level 2P USA NASA MODIS Aqua SST:1	Datasets
MODIS/Terra Temperature and Water Vapor Profiles 5-Min L2 Swath 5k	
LIS/OTD 2.5 DEGREE LOW RESOLUTION DIURNAL CLIMATOLOGY (L	.RDC) V2.3.2013
MODIS/Terra Aerosol 5-Min L2 Swath 10km V005 NRT	
MODIS/Terra Aerosol	I 5-Min L2 Swath 10km V005 NRT
Science Keyword Map	Parameter Map
	Optical_Depth_Small_Average_Ocean
ATMOSPHERE > AERCCOLS > PARTICULATE_MATTER ③ Deep_Blue_Aeroso_Optical_Depth_Land_STD : 1	ATMOSPHERE->AEROSOLS-
Deep_Blue_Aeroser_Optical_Depth_Land_STD : 1 Science Deep_Blue_Aerosol_Optical_Depth_550_Land : 1	ATMOSPHERE->AEROSOLS- >AEROSOLS_OPTICAL_DEPTH/THICKNESS:2
Deep_Blue_Aerosc_Optical_Depth_Land_STD : 1	ATMOSPHERE->AEROSOLS-
Deep_Blue_Aerosc_Optical_Depth_Land_STD : 1 Science Deep_Blue_Aerosol_Optical_Depth_550_Land : 1	ATMOSPHERE->AEROSOLS- >AEROSOLS_OPTICAL_DEPTH/THICKNESS : 2 Parame ATMOSPHERE->ATMOSPHERIC_RADIATION-
Deep_Blue_Aeroso_Optical_Depth_Land_STD : 1 Science Deep_Blue_Aerosol Optical_Depth_550_Land : 1 Aerosol_Type_Land : 1 Aerosol_Cidmask_Byproducts_Ocean : 1	ATMOSPHERE->AEROSOLS- >AEROSOLS_OPTICAL_DEPTH/THICKNESS : 2 Parame ATMOSPHERE->ATMOSPHERIC_RADIATION- >OPTICAL_DIVISION SCIENCE Keywoo ATMOSPHERE->AEROSOLS->PARTICULATE_MATTER : 0
Deep_Blue_Aerosc_Optical_Depth_Land_STD : 1 Science Deep_Blue_Aerosol_Optical_Depth_550_Land : 1 Keyword Aeroso_Type_Land : 1	ATMOSPHERE->AEROSOLS- >AEROSOLS_OPTICAL_DEPTH/THICKNESS : 2 Parame ATMOSPHERE->ATMOSPHERIC_RADIATION- >OPTICAL_DIVISION SCIENCE Keywoo ATMOSPHERE->AEROSOLS->PARTICULATE_MATTER : 0
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ATMOSPHERE->AEROSOLS->AEROSOL_PARTICLE_PROPERTIES : 2	/lin L2 Swath 10k
ATMOSPHERE->AEROSOLS->CLOUD_CONDENSATION_NUCLEI : 2	
ATMOSPHERE->AEROSOLS->AEROSOL_EXTINCTION : 2	
ATMOSPHERE->AEROSOLS->AEROSOLS_OPTICAL_DEPTH/THICKNESS : 2	
ATMOSPHERE->AEROSOLS->AEROSOL_RADIANCE : 2	
ATMOSPHERE->AEROSOLS->CARBONACEOUS_AEROSOLS : 2	
ATMOSPHERE->AEROSOLS->DUST/ASH/SMOKE : 2	
ATMOSPHERE->AEROSOLS->NITRATE_PARTICLES : 2	
ATMOSPHERE->AEROSOLS->ORGANIC_PARTICLES : 2	
ATMOSPHERE->AEROSOLS->PARTICULATE_MATTER : 2	<b>B</b>
ATMOSPHERE->AEROSOLS->SULFATE_PARTICLES : 2	Remove
ATMOSPHERE->ATMOSPHERIC_RADIATION->RADIATIVE_FLUX : 2	
ATMOSPHERE->ATMOSPHERIC_RADIATION->REFLECTANCE : 2	
ATMOSPHERE->ATMOSPHERIC_RADIATION->OPTICAL_DEPTH/THICKNESS: 2	Remove
ATMOSPHERE->AEROSOLS->PARTICULATE_MATTER : 0	Remove
	Tiomovo

#### Edit/Save Mapping

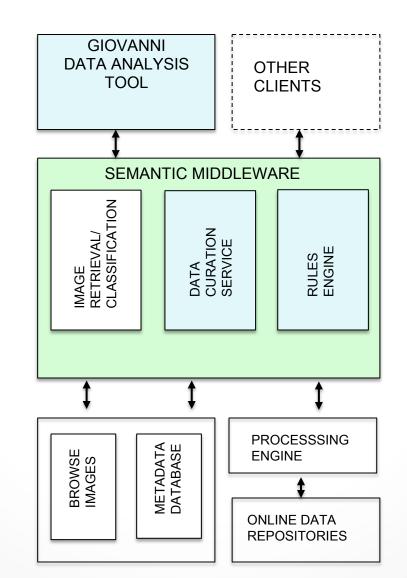
Mapping Scores Generated by Algorithm

Opportunity to develop this prototype and infuse into operational use at DAACs to improve metadata quality

### DEMO



### **SML Components**



## **Image Classification**

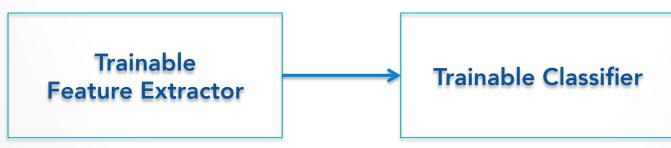
 Goal: label images in archives with a known Earth science phenomenon

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
  - Uultiple stages of representation



Convolutional Neural Network (CNN)

- Applicable to Images
- Supervised

### **Transfer Learning**

- CNN requires large number of parameters
- Transfer learning
  - Use internal representation learned from one classification task to another
- Faster learning
- Better accuracy

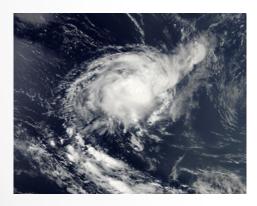
### **Applications: Searching for Events**

Detection of phenomena in Browse Imagery

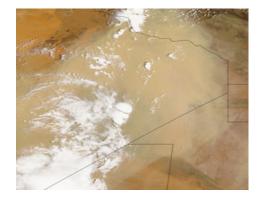
True/Pred	Dust	Hurricane	Smoke	Other
Dust	287	8	32	33
Hurricane	0	379	1	10
Smoke	12	12	443	9
Other	33	9	23	211

#### **Confusion Matrix**

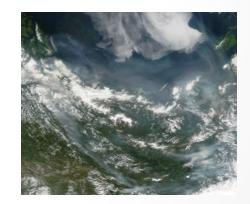
Overall Accuracy = 87.88%



Hurricane – True Positive



Dust – True Positive



Smoke-True Positive

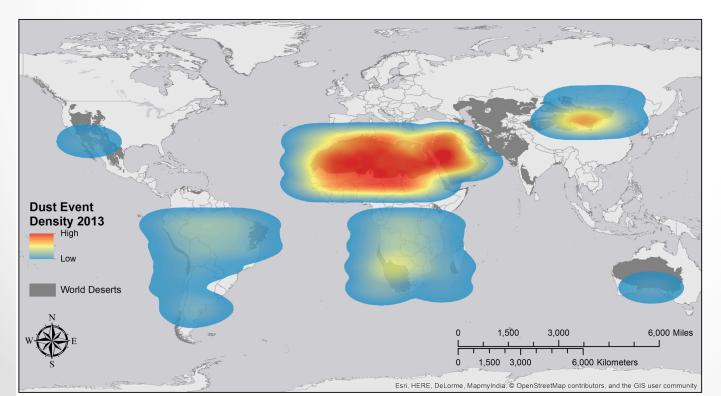
### **Applications: Enabling new science**

 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 Martin					

Validation Accuracy = **91**%





**Based on GIBS** 

# Applications: Improving forecast operations

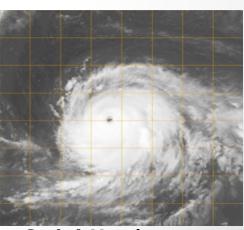
 Hurricane intensity estimation - Collaboration with Dan Cecil, NASA/MSFC Atmospheric Scientist

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

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

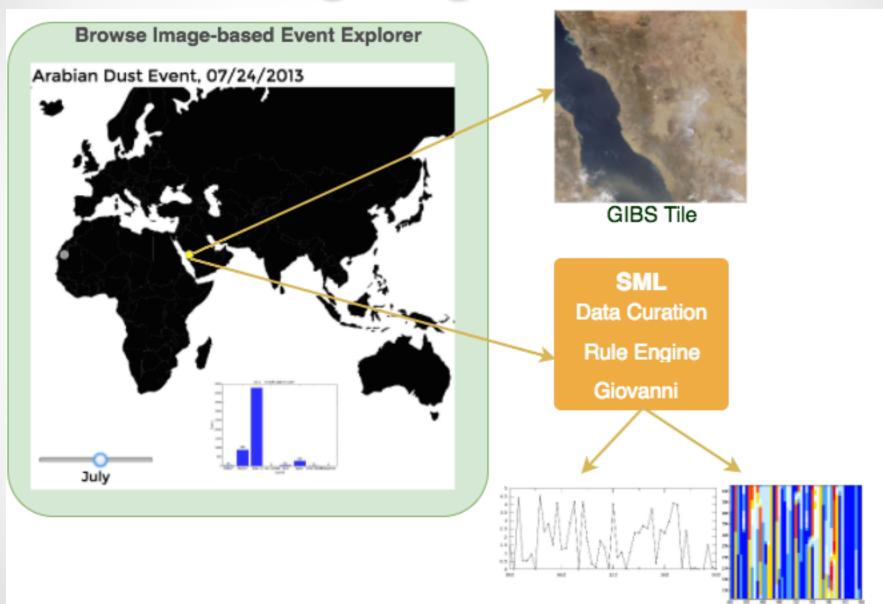
#### Data: NRL Images, HURDAT





Cat 4 Hurricane

### **Ongoing Work**



### **Journal Publications**

- Submitted:
  - Deep Learning for Phenomena-based Classification of Earth Science Images - IEEE Geoscience and Remote Sensing Letters
- In Progress:
  - Relevancy Algorithm to Curate Earth Science Data for Different Phenomena – to be submitted to Computers and Geoscience
  - Detecting Transverse Cirrus Bands using Deep Learning IEEE Geoscience and Remote Sensing Letters (collaboration with U.S. Nair)
- Planned:
  - Dust climatology (collaboration with Sundar Christopher)
  - Hurricane intensity estimation (collaboration Dan Cecil)

# Thanks to NASA ESTO for their support



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