

- U.S. Department of Energy, National Energy Technology Laboratory Mastering the Subsurface Through Technology, Innovation and Collaboration:
- Carbon Storage and Oil and Natural Gas Technologies Review Meeting August 16-18, 2016

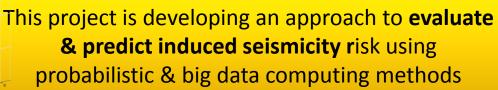
Presented by: Kelly Rose, Geology/Geospatial Researcher





To constrain & understand effects of subsurface engineering:

- At different scales and using different disciplines
- To evaluate a range of potential *environmental, social, and economic* variables
- To evaluate various *scenarios*, for risk reduction, resource evaluation, & improved efficiency
- To highlight *knowledge and/or technology gaps*
- To improve understanding by incorporating *uncertainty information*



National Energy Technology Laboratory Cumulative

Spatial

Impact

Layers

This Project aligns to DOE goals



Outputs &

Results

echnology Gap

BLOSOM

Scenario 1

A Product of NETL

SUBSURFACE

Scenario 2 Scenario 3

> Scenario 4 Scenario n

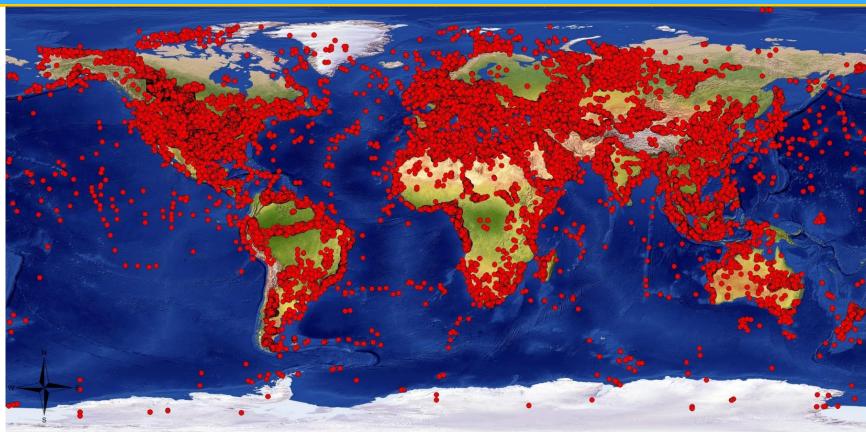
> > VARIABLE GRID METHOD

SUBSURFACE TREND ANALYSIS

Challenge – How do we predict subsurface behaviors?



- Given there is now a global subsurface dataset, how can we use this to better understand the subsurface?
 - Prediction of specific properties and subsurface features
 - Use to predict how our interactions relate to future resource
 - Improve our ability to interact with the subsurface (resource production, CO₂ storage, geohazard prediction, etc)



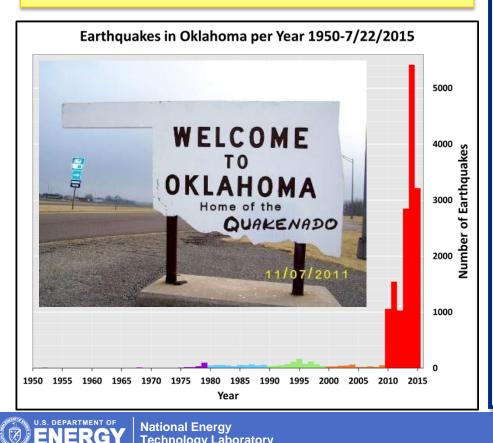
Rose, K., 2016, Signatures in the Subsurface – Big & Small Data Approaches for the Spatio-Temporal Analysis of Geologic Properties & Uncertainty Reduction, 162 pgs, <u>http://hdl.handle.net/1957/59459</u>

- With more than 6 million wells worldwide, to what degree is the subsurface perturbed?
 - What does that mean for the future?

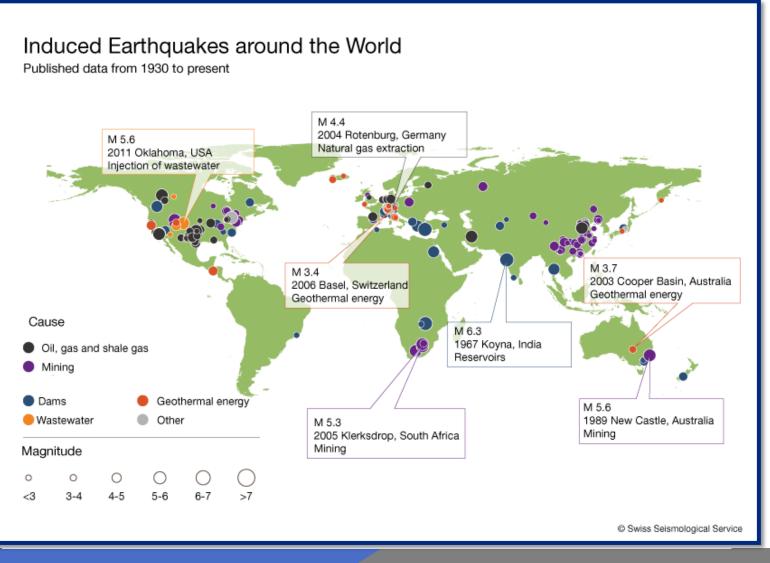
In particular, induced seismicity is shaking things up



Human engineering of the deep subsurface is causing manmade aka induced seismic events in unprecedented #'s and locations



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This project seeks to address the need for rapid, repeat evaluations



This need was spotlighted by a 2016 USGS report



chances are represented as follows: pale yellow, less than 1 percent; dark yellow, 1 to 2 percent; orange, 2 to 5 percent; red, 5 to 10 percent; dark red, 10 to 12 percent. The U.S. Geological Survey (USGS) has produced a 1-year seismic hazard forecast for

2016 for the Central and Eastern United States (CEUS) that includes contributions from both induced and natural earthquakes. The model assumes that earthquake rates calculated from several different time windows will remain relatively stationary and

• <u>Data</u>

- <u>Catalogs</u>
- Source Code

See also Induced Seismicity Research.

A billbard is seen on the side of the next physical part from the term representing plantifism in a lawauit against the next companies near of comodories, Advancas, August 20, 20, 20, 40 mm, more than a down homenemens in central Advancas were using provide con ol companies in Advance and the disposal of wastemate the molytability in Cartange on the advance and advance and advance and the disposal of 2010 and 2011 that diamaged their property. Photo by Jum Young/REUTERS

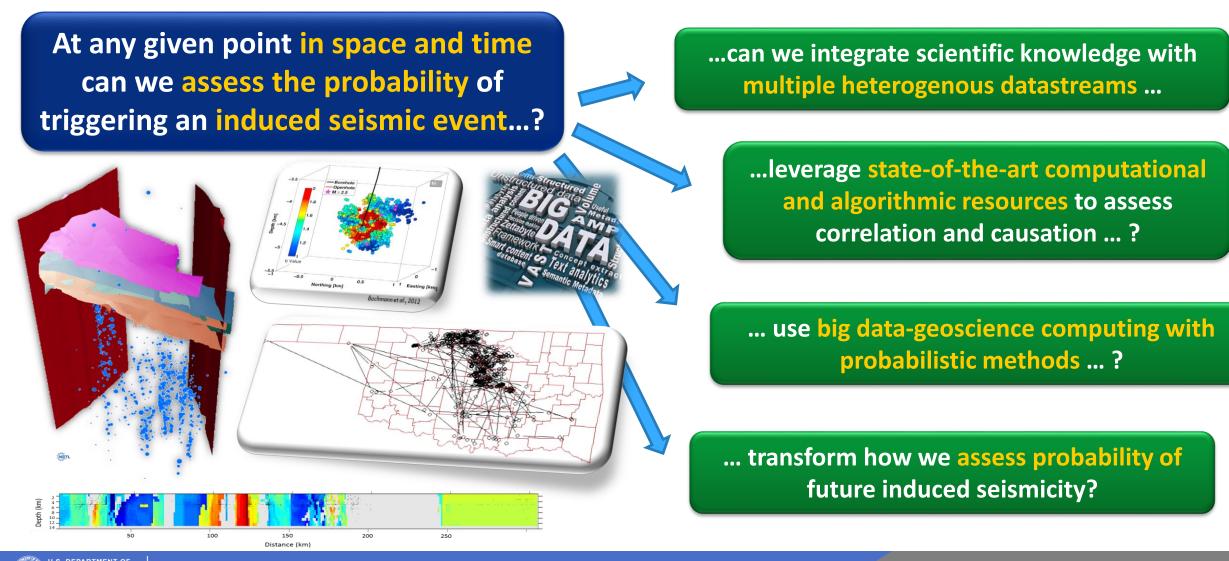
To Cathy Wallace, the earthquakes that have been ratting her tidy suburban home in Dallas feel like underground thunderstorms. First comes a distant roar, then a boom and a jolt. Her house shakes and the windows shudder. Simed prints on the walls clatter and tilt. A heavy glass uses tips over with a crash.

The worst moments are the ones between the numble and the impact. "Every time it happens you know it's going to hit, but you don't know how severe it's going to be," she says. "Is this going to be a bigger one? Is this the part where my house falls down? It's scary. It's very scary."



Project Objectives – 2014 to 2016



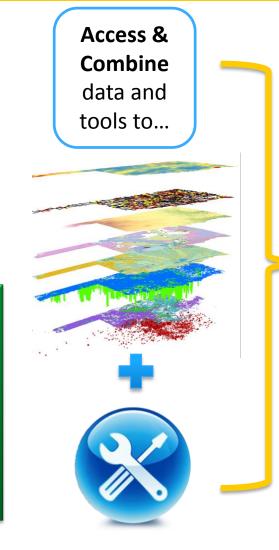


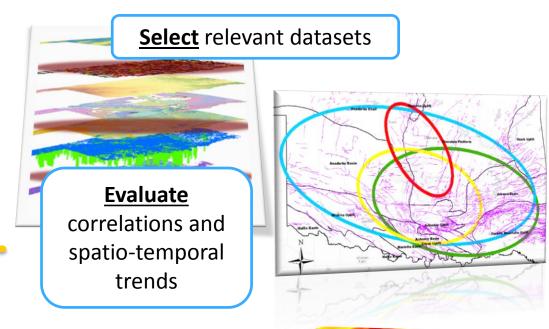
Project Goals



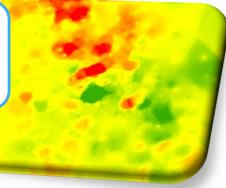
Goal: Address potential for causing induced seismicity events through application of computing techniques for data mining, discovery, integration and analysis

Ultimate product: Produce a platform with data, workflow, and tools that support a spatio-temporal assessments to highlights regions with an increased likelihood of induced seismicity





<u>Highlight</u> regions with an increased likelihood for induced seismic events

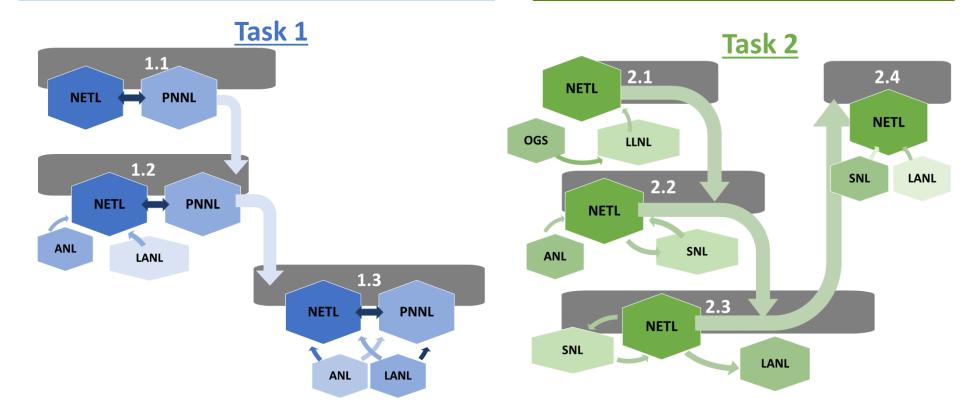


Organization Chart



Task 1 – Geoscience computing advances NETL (EDX team), LANL, & PNNL (Velo team) ANL (in-kind, big data computing)

Task 2, Development of probabilistic approaches for induced seismicity (LANL, LLNL, NETL, OGS, SNL)



What is "big data"



Big datasets tend to be unstructured, distributed and complex

Big data can be defined by:

- The **volume** of information that systems must ingest, process and disseminate
- The **velocity** at which information grows or disappears
- The variety in the diversity of data sources and formats



What is big data computing?

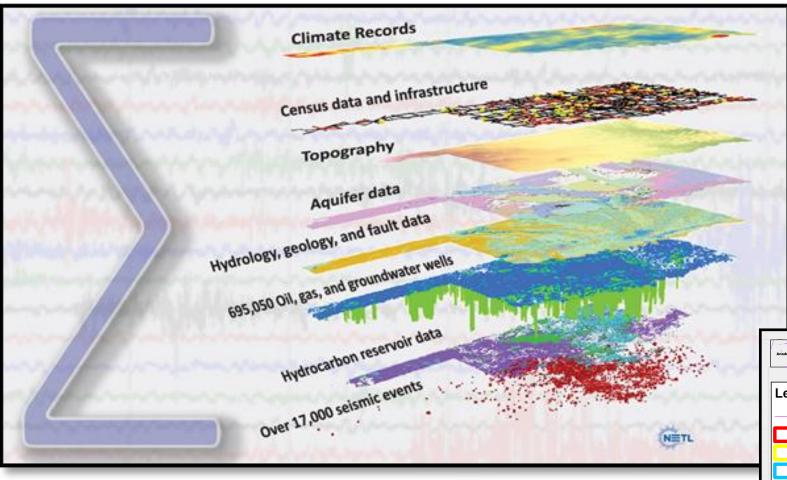
- Combination of hardware & software technologies that make it possible to realize value from "Big Datasets"
- HPC vs BDC
 - Traditional HPC systems are focused on performing calculations at fast speeds
 - BDC is focused on computing to sift through huge amounts of big datasets
 - HPC systems usually cost \$1000's of k
 - BDC can operate on range of hardware, including inexpensive (\$10's of k) clusters optimized for distributed, inmemory, iterative processing for analytics, query, and data mining
- Both HPC and BDC can harness cloud server farms or add additional physical nodes

DistributedSources UserDriven Metadata Process Geosciences Unstructured DataDriven Complex Content Volume Formats DataMining ata Sources DataDiversity MultiScale Ingest ComputingCapabilities Disseminate

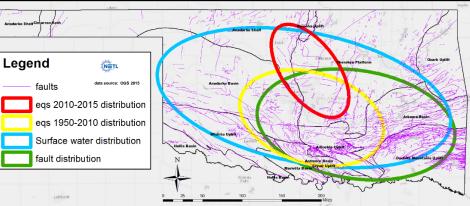
cloudera Spo

How Are We Evaluating Induced Seismicity Probabilistically with Big Data?





- Developing tools and approaches to manage multiple heterogeneous datasets
- Developing a beta probabilistic approach that can be utilized to assess potential for induced seismicity impacts through big data analyses
- Developing approaches to **reduce uncertainty** and constrain subsurface trends
- Improving joint analysis of multiple datasets, using "Big Data" mining and integration techniques



Example analysis: Spatio-Temporal Earthquake Distributions Vs. Fault and Surface Water Distributions

Approach & Results – Need to understand the causes



natial density of active SWD wells is higher

(>5 wells per 5 km²) in the Forth Worth Basin of north-central Texas and the Mississippi Lime Play extending from north-central Oklahoma north

ward into central Kansas. The spatial density of active EOR wells is highest (25 wells per 5 km2) in

the Permian Basin of West Texas, the Fort Worth Basin, south-central Oklahoma, and southeast

We obtained earthquake location and magn tude data from the Advanced National Seismic

System's comprehensive earthquake catalog (ANSS ComCat) (21). During the study period (1973 to 2014), we identified 7175 $M \ge 0.0$ events in the

catalog in the CEUS region (Fig. 2). Although the atalog is not complete down to M 0.0 during the study period, we treated all earthquakes as

potentially induced events to capture the most

nsive data set of associated earthou

ern Kansas (fig. S1).

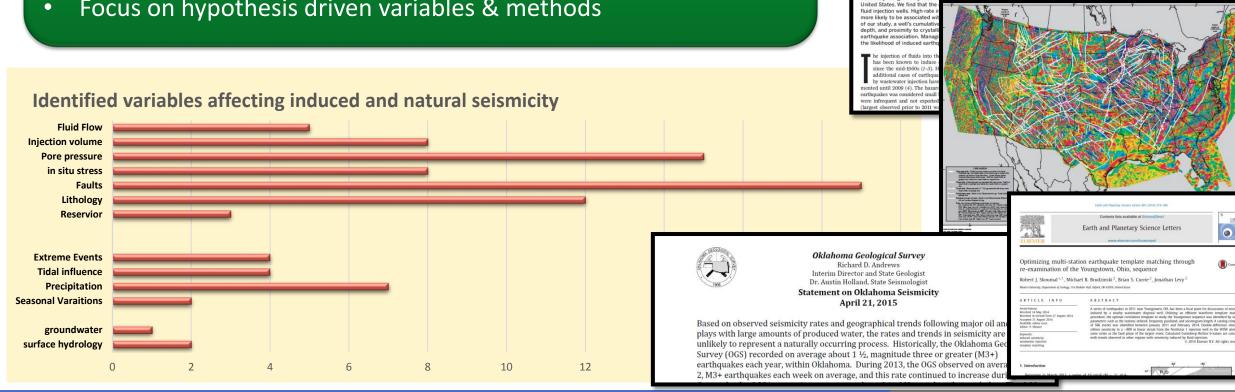
Reviewed 100's of peer-reviewed articles and other references to identify potential causes or correlation factors for both natural and induced seismicity

Focus on hypothesis driven variables & methods

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RESEARCH

REPORTS

INDUCED SEISMICITY

seismicity using a newly as

High-rate injection is associated

M. Weingarten, 18 S. Ge, 1 J. W. Godt, 2 B. A. Bekins, 3 J. L. Rubinstein

An unprecedented increase in earthquakes in the U.S. mid-continent began in 2009 Many of these earthquakes have been documented as induced by wastewater injection

We examine the relationship between wastewater injection and U.S. mid-contine

with the increase in U.S.

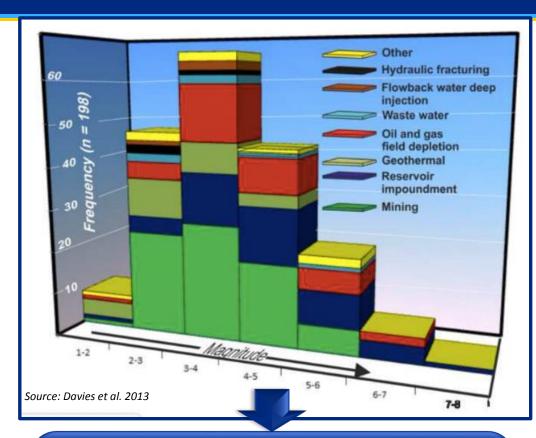
mid-continent seismicity

Approach & Results - Induced Seismicity Causes



Which human activities are thought to trigger earthquakes?

- Wastewater injection
- Hydraulic Fracturing
- Oil and gas production
- Mining
- Geothermal energy
- Groundwater extraction
- Dammed lakes
- Large construction projects



How do these activities trigger earthquakes?

- Changes in the state of stress
- Pore pressure changes
- Volume changes
- Applied forces and loads



Activities linked to natural and induced seismicity events Identifying which method(s) are most appropriate for the data and use in the proposed probabilistic tool to 2% 9% assess risks of triggering induced seismicity events Mining Dams Commonly utilized analytical methods for assessing induced and natural seismicity 20 Injection & Disposal 7% 18 16 Geothermal 43% 14 12 15% Infrastructure 10 8 Oil & Gas 6 CO2 2 linear regression cluster analysis MonteCarlo correlation b.value diffusivity Distance uncertainty stress ANOVA **Building off Existing Knowledge**

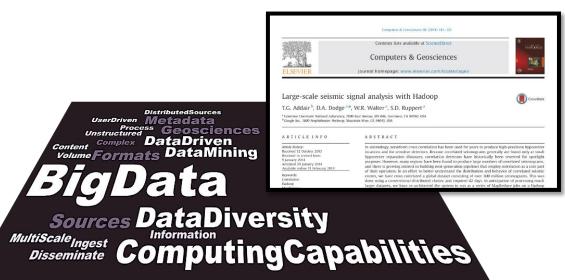


Approach - Adapting big data for geoprocessing



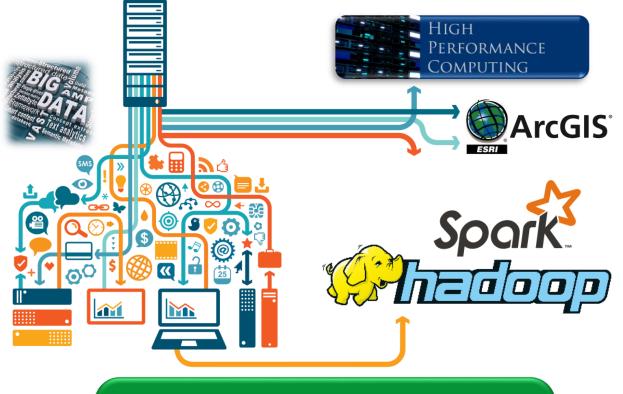
THURSDAY, AUGUST 18, 2016

1:00 PM Advances in Data Discovery, Mining, & Integration for Energy (EDX) – <u>Vic Baker</u>



U.S. DEPARTMENT OF

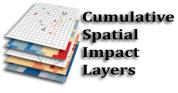
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Big data + Geoprocessing will help:

- Expose geographic & temporal patterns
 - Find spatial relationships
 - Perform predictive modeling



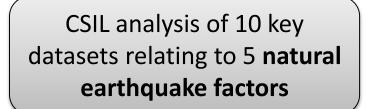


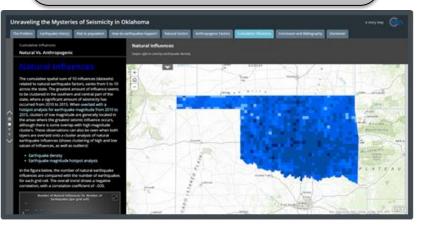
Bauer et al., 2015

Cumulative Spatial Impact Layers (CSILs) is a spatio-temporal approach that identifies potential impacts to various socioeconomic and environmental actives within a region

CSIL's quickly measures the total *number of activities* OR *estimated "cost"* per unit area (cell)

OK CSIL analysis is based on results of meta-analysis (lit review) and "seedling" data mining



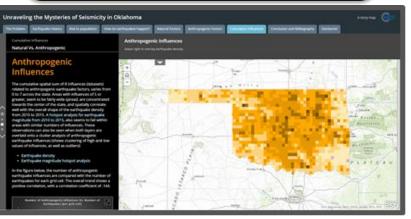


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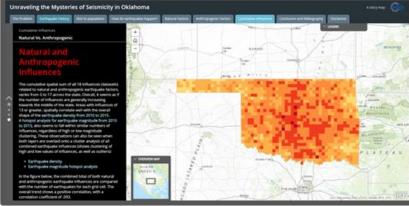
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ENERGY

CSIL analysis 8 key datasets relating to 7 **anthropogenic earthquake factors**

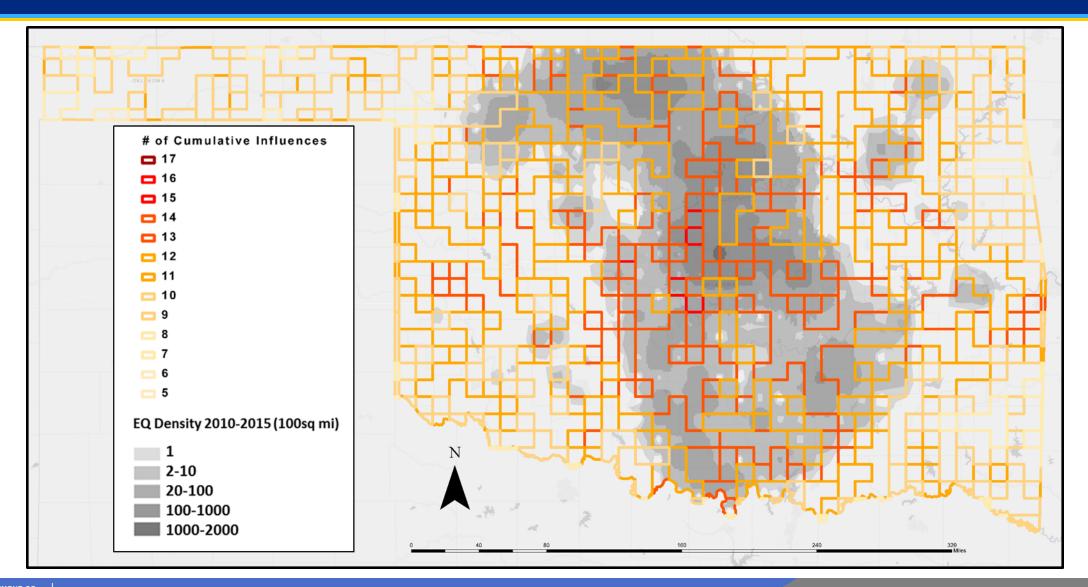


CSIL analysis of 18 key datasets related to **natural and anthropogenic earthquake factors**



CSIL Analysis vs Earthquake Density in OK



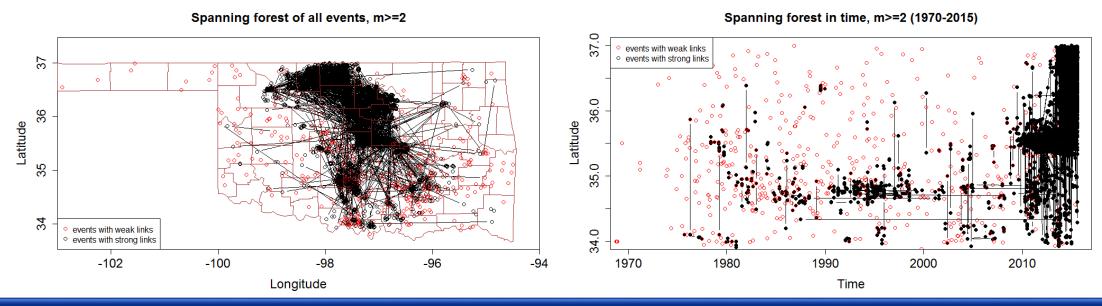


Results to date - Earthquake cluster analysis with modified NN approach



- Each earthquake j in the catalog is **connected to its nearest neighbor** (parent) i according to the NND η .
- All examined events form a single cluster: nearest-neighbor links form a spanning network.
- Spanning network is a **tree** (no loops).

Adapted from: Zaliapin I and Ben-Zion Y (2013), "Earthquake clusters in southern California I: Identification and stability", Journal of Geophysical Research: Solid Earth. Vol. 118(6), pp. 2847-2864. Wiley Online Library.



- Weak links = large distances between neighboring earthquake events, strong links = short distances
- Strong links form spanning forest (collection of distinct trees spanning all events)
- Two types of clusters: singles (single-event trees) and families (multi-event clusters).

Vasylkivska and Huerta, in prep

Evaluating Spatio-temporal Relations in 4D



Vasylkivska and Huerta, in prep

National Energy

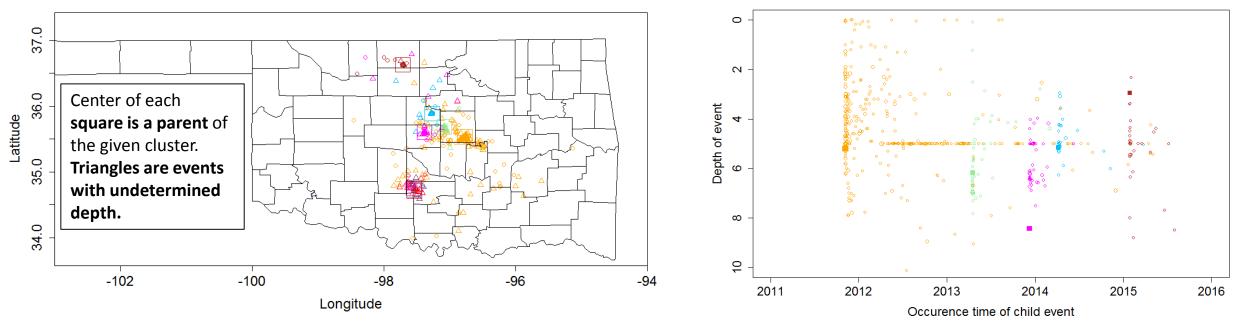
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Preliminary results in time and space (X,Y and Z)

The **largest clusters occurred in 2011-2015**. Many events have undetermined depth of 5 km.

• Color scheme follows map.

- Many of the events in the largest cluster have unknown depths.
- Generally, for each cluster the **depth of the child events (empty** circles) is smaller than the depth of the parent event (filled square).



Selected clusters

Example Results - Big Data Algorithms for Mining & Analysis



- Search/mining algorithm, way to find, acquire and integrate open datasets from across the web
- NN cluster algorithm tested
- VGM uncertainty quant/viz algorithm







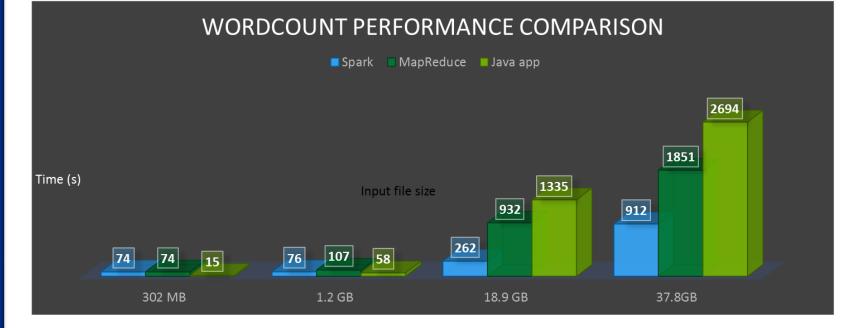
- Hadoop application development
 - Hive, Java-based MapReduce 2.0, Spark, ESRI
- ESRI / Hadoop development:
 - Hive/ESRI development. Good for analysis / data mining)
 - 'Well API correlation' via Hive using spatial binning
 - Focus on Java-based MapReduce dev
- Ongoing:
 - Major upgrades to EDX to improve mining, integration, analysis, and collaboration for DOE R&D community
 - Spark application development
 - Elasticsearch add-on for faster queries

Example Results – big data processing time test



- Compared execution times for varying size data sets using Hadoop cluster-based MapReduce and Spark vs a stand alone, single threaded Java application (running on the Hadoop cluster's main node).
- Spark's in-memory design outperform the single-threaded Java application

Spark vs MapReduce vs Single Threaded Application



- Team succeeded in running the NN algorithm in the geoprocessing, big data cluster.
- Time of execution went from 10 hours on desktop PC to 10 minutes

Example Results – big data geoprocessing



Merging GIS and Big Data computing for advanced 3D/4D geospatial analysis

- Offload intensive geometric operations from desktop to a Hadoop cluster
- Is highly scalable
- Self healing
- The approach is ideal for executing parallel operations on geometric operations involving many features.

	sM": †alse,
"sp	atialReference": {"wkid":4326},
"fe	atures": [
{	
"at	tributes": {
	"UWIAPINu": 3708520259.0,
	"OR_Base_m_": 0.0,
	"Surf_Lat": 41.484683,
	"Salinity": 0.0,
	"WSN": 1.0,
	"Surf_Lon": -80.103193,
	"Brine_Dens": 0.0,
	"OR_Gross_T": 0.0,
	"Porosity": 0.0,
	"NET_THICKN": 0.0,
	"Oriskany_T": 1190.549
},	
"ge	ometry": {
	"y": 5084098.520442805,
	"x": -8917047.03754837,
	"spatialReference": {
	"wkid": 4326,
	"latestWkid": 4326
	}
}	
},	
{	
"at	tributes": {
	"UWIAPINu": 3703920665.0,
	"OR_Base_m_": 1077.9,
	"Surf_Lat": 41.730652,
	Example JSON from
	ArcMap

Hadoop-Based VGM Detailed Workflow



VGM-Step-0	VGM-Step-1	VGM-Step-2
Description: Convert 'enclosed-Json' ESRI feature class into 'feature-per-row' unenclosed- Json.	Description: Generate multi-resolution bounding quads for input point data set (i.e., ORWells-wgs84)	Description: Generate non-overlapping topology of vgm-step-1 quads and calculate well point data per new geometries.
Input: 'Enclosed-Json' formatted data (i.e., ORWells-wgs84.json) uploaded from ArcMap using ESRI/Hadoop toolbox tools 'Features to	Input: vgm-step-0 output 'Unenclosed-Json' of row-per-feature representation of orwells-wgs84 data	Input: Multi-resolution quads generated in vgm- step-1 AND the point data generated from vgm- step-0
Json' & 'Copy to HDFS'. Output: Processed 'Unenclosed-Json' with	Output: Quads of varying extents with attribution (i.e., point count, max/min/avg	Output: Non-overlapping polygons as 'unenclosed-Json' features with attribution (point count, min/max/avg porosity, etc.)
'feature per row' layout suitable for Mapper. Mapper (Setup): Create EsriFeatureClass from input file and write each feature as a row	salinity, porosity, brine density) Mapper (Setup): Load point features from vgm- step-0 and use to generate quadtree node	Mapper (Setup): Load vgm-step-1 output files representing attributed quads of varying resolutions to generate non-overlapping topology.
represented as unenclosed-Json. Reducer: Aggregate Mapper output into one or more files	extents. Mapper: Feed mapper each row of 'unenclosed-Json' from vgm-step-0 point data and query the quadtree for all quads that contain	Mapper: Feed the Mapper with rows from the vgm-step-0 'unenclosed-Json' point feature data, query topology for 'point in polygon' to generate polygon's attributes, and perform geometry subtraction using ESRI Hadoop libs
	Reducer: Aggregate Mapper output into one or more files and store in vgm/working/output-0/.	Reducer: Tally the attributes for each polygon and write attributed polygon as unenclosed- Json.
$ \begin{array}{c} \label{eq:2} $$ $ $ $ $ $ $ $ $ $ $ $ $ $ $ $ $ $ $$		

Overlapping attributed quads

(shown via ArcMap)

'Feature per row' formatted data for MapReduce

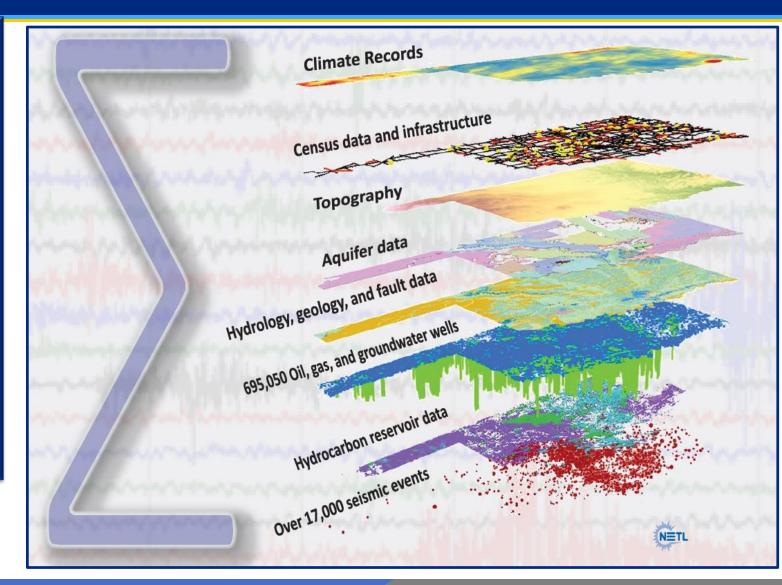


Tech Transfer & Accomplishments to Date



- >15 presentations & publications, more publications in prep
- Acquired & utilized millions of data records in 3D & 4D preliminary analyses
- Some analytical methods tested show promising results
- Completed review of advanced probabilistic methods, assessed strengths & weaknesses of each
- Developed novel big data mining, integration & analytical algorithms
- Integrating existing DOE computing capabilities with new BDC capabilities resulting in geoprocessing advances





Synergy Opportunities - Alignment to SubTER

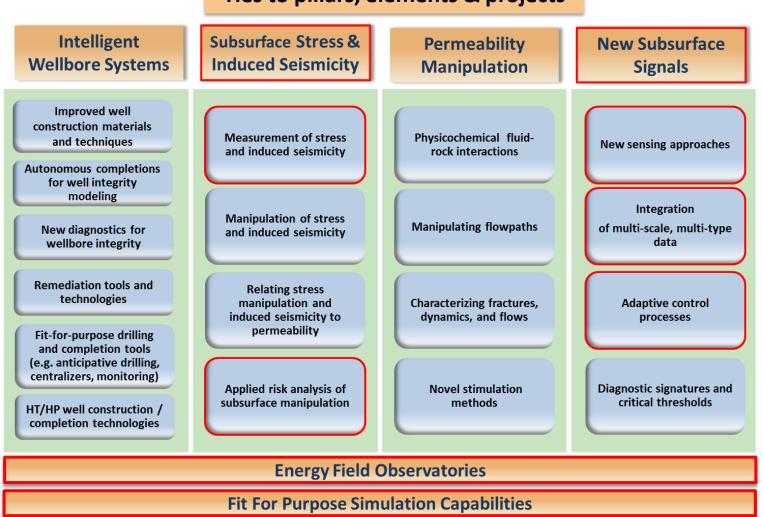




- New multi-scale, multi-type analyses for uncertainty reduction & spatial analysis
- Geoprocessing and computing advances



Ties also to geothermal, waste disposal, unconventional, offshore, and carbon storage projects, tools, and data

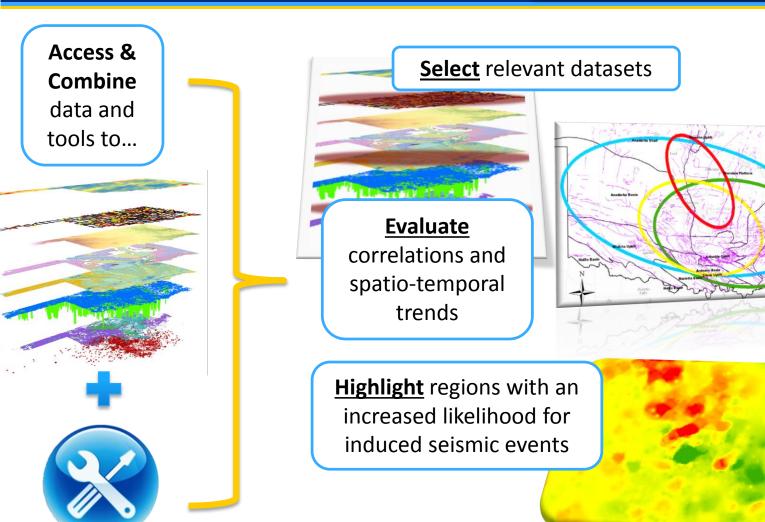


Ties to pillars, elements & projects

Anticipated next steps ...

Ultimate product: Produce a platform with data, workflow, and tools to support efficient & repeatable probabilistic assessments to highlight regions with increased likelihood of induced seismicity





- Further develop, test & then refine **probabilistic approach**
- **Test** at different scales, other areas, e.g. Geysers
- Validation, address and test "why" we are seeing results we are seeing in test cases etc.
- Considerations on scale or evaluation & advanced uncertainty analyses
- **Computing**, continue growing and enhancing capabilities from big data computing world, HPC arena, and GIS domain
- Continue leveraging capabilities and tools from DOE efforts

Phase 1 Project Team:

1st Name	Last Name	Role	Organization	
Kelly	Rose	Project PI & NETL POC	NETL	
Jennifer	Bauer	Task 2 alt POC NETL	NETL	
Vic	Baker	Task 1 alt POC NETL	NETL/Matric	
Devin	Justman	GIS/Geologist	NETL	
Veronika	Vasylkivska	Applied Math/Stats	NETL	
Dennis	Donaldson	Structural Geology	NETL	
Roy	Miller III	GIS/Geologist	NETL	
Brian	Tost	Wellbore geophysics	NETL	
Gary	Black	PNNL POC/Lead	PNNL	
Chandrika	Sivaramakrishn an	Velo developer	PNNL	
Zoe	Guillen	Velo developer	PNNL	
Xingyuan	Chen	Velo, data assimilation etc	PNNL	
Carina	Lansing	Velo developer	PNNL	
Pavan	Balaji	Computer Scientist	ANL	
Randy	Gentry	ANL POC/Lead	ANL	
Joanne	Wendelberger	Group Leader Statistical Sciences	LANL	
James	Ahrens	Data science at scale	LANL	
Lawrence	Ticknor	Statistician	LANL	
Divya	Banesh	Post-Doc	LANL	



1st Name	Last Name	Role	Organization	
Diane	Woodbridge	SNL POC/Lead computer scientist, data mining projects	SNL	
Danny	Dunlavy	Tensor analysis	SNL	
Dave	Cuyler	software eng. NGDS, CKAN, uncertainty	SNL	
Randy	Brost	Data mining/Stats	SNL	
David	Stracuzzi	Data mining/Stats	SNL	
Kristina	Czuchlweski	data mining, stats, artificial intelligence	SNL	
Stephen	Myers	Geophysics / Bayesloc	LLNL	
Stanley	Ruppert	Geoscience HPC & Big Data	LLNL	
Joe	Morris	Geophysics	LLNL	
Rob	Mellors	Geophysics	LLNL	
Steven	Magana-Zook	LLNL POC / Data scientist Developer	LLNL	
Amberlee	Darold	OGS POC / Seismologist	OGS	







For more information on the SubTER crosscut: <u>http://esd.lbl.gov/subter</u>

For more information on data and tools visit: <u>https://edx.netl.doe.gov</u>





Acknowledgment: This technical effort was performed in support of the National Energy Technology Laboratory's ongoing research under the RES contract DE-FE0004000.

Disclaimer: This project was funded by the Department of Energy, National Energy Technology Laboratory, an agency of the United States Government, through a support contract with AECOM. Neither the United States Government nor any agency thereof, nor any of their employees, nor AECOM, nor any of their employees, makes any warranty, expressed or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

TUESDAY, AUGUST 16, 2016

- 12:40 PM Monitoring Groundwater Impacts <u>Christina Lopano</u>
- 1:55 PM Multi Variate Examination of the Cause of Increasing Induced Seismicity <u>Kelly Rose</u>
- 4:40 PM Exploring the Behavior of Shales as Seals and Storage Reservoirs for CO₂ Ernest Lindner
- 5:05 PM Risk Assessment for Offshore Systems Kelly Rose
- 5:30 PM Metal-based systems in Extreme Environments <u>Jeff Hawk</u>
- 6:15 p.m. Poster Session
 - Kelly Rose Developing a carbon storage resource assessment methodology for offshore systems
 - Doug Kauffman Catalytic Conversion of CO2 to Ind. Chem. And eval. Of CO2 Use and Re-Use
 - Liwel Zhang Numerical simulation of pressure and CO2 saturation above an imperfect seal as a result of CO2 injection: implications for CO2 migration detection

WEDNESDAY, AUGUST 17, 2016

- 12:30 PM MVA Field Activities Hank Edenborn
- 1:20 PM Microseismicity Erik Zorn
- 2:35 PM Resource Assessment Angela Goodman
- 2:35 PM Understanding Impacts to Air Quality from Unconventional Natural Gas <u>Natalie Pekney</u>
- 4:05 PM Improving Science-Base for Wellbore Integrity, Barrier Interface Performance <u>Nik Huerta</u>
- 5:20 PM Wellbore Integrity and Mitigation <u>Barbara Kutchko</u>

THURSDAY, AUGUST 18, 2016

- 1:00 PM Advances in Big Data Discovery, Mining, & Analysis for Energy (EDX) Vic Baker
- 1:25 PM Methods for Locating Legacy Wells Garrett Veloski
- 2:40 PM Reservoir Performance Johnathan Moore
- 3:05 PM Geochemical Evolution of Hydraulically-Fractured Shales <u>Ale Hakala</u>













- These slides will not be discussed during the presentation, but are mandatory



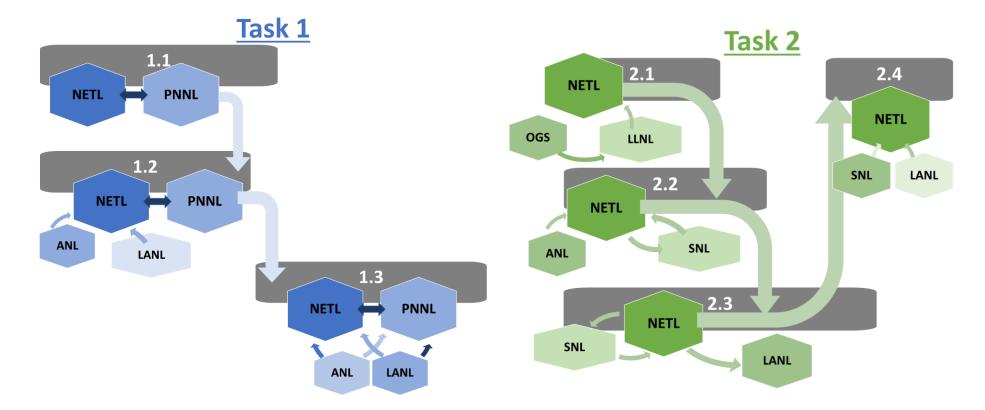
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Organization Chart



Task 1 – Geoscience computing advances

NETL (EDX team), LANL, & PNNL (Velo team) ANL (in-kind, big data computing) Task 2, Development of probabilistic approaches for induced seismicity (LANL, LLNL, NETL, OGS, SNL)



Organization Chart



Phase 1 Project Team:

Task	Task	1st Name	Last Name	Role	Phone	Email	Organization
1	2	Kelly	Rose	Project PI & NETL POC	5419675883	kelly.rose@netl.doe.gov	NETL
1	2	Jennifer	Bauer	Task 2 alt POC NETL	5419184507	jennifer.bauer@netl.doe.gov	NETL
1		Vic	Baker	Task 1 alt POC NETL		vic.baker@matricinnovates.com	NETL/Matric
	2	Devin	Justman	GIS/Geologist	5419184561	devin.justman@netl.doe.gov	NETL
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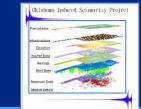
Gantt Chart

Kischames Line Kalanes





Phase 1, Task 1 – Goals, Milestones, Schedule





Task 1 – Geoscience computing advances

NETL (EDX team), LANL, & PNNL (Velo team)

ANL (in-kind, big data computing)

1.1 - Develop an EDX / Velo / Hadoop integration to support data gathering, mining, and analytical needs (NETL, PNNL)

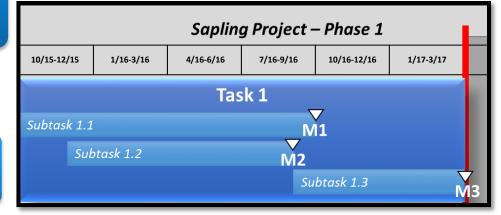
1.2 - Evaluate tools for irregular data management (ANL, LANL, NETL, PNNL) 1.3 - Integrate irregular data management capabilities (NETL, LANL, ANL, PNNL)

Argonne

Los Alamos

NETL





Sandia National Laboratorie

	Phase 1, Task 1 - Milestone Summary Table					
Task No.	Task Title	MS Type	MS #	Milestone Description	Milestone Verification Process (Who, What, When, Where)	Anticipated Date of Completion
1.1	Develop an EDX / Velo / Hadoop integration to support data gathering, mining, and analytical needs for the induced seismicity use case	MS	1	Deploy baseline mining-fusion functionality via EDX	Quarterly report	Month 12
1.2	Evaluate ANL tools for irregular data management and fusion capabilities for integration within EDX	MS	2	Complete assessment of irregular data management options	Quarterly report	Month 11
1.3	Integrate preliminary irregular data management capabilities based on 1.2 recommendations/priorities	MS	3	Complete use case based testing of new EDX / Velo functionality	Quarterly report & EDX capabilities	Month 18





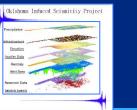
Task 2 – Goals, Milestones, Schedule

U.S. DEPARTMENT OF

2.4

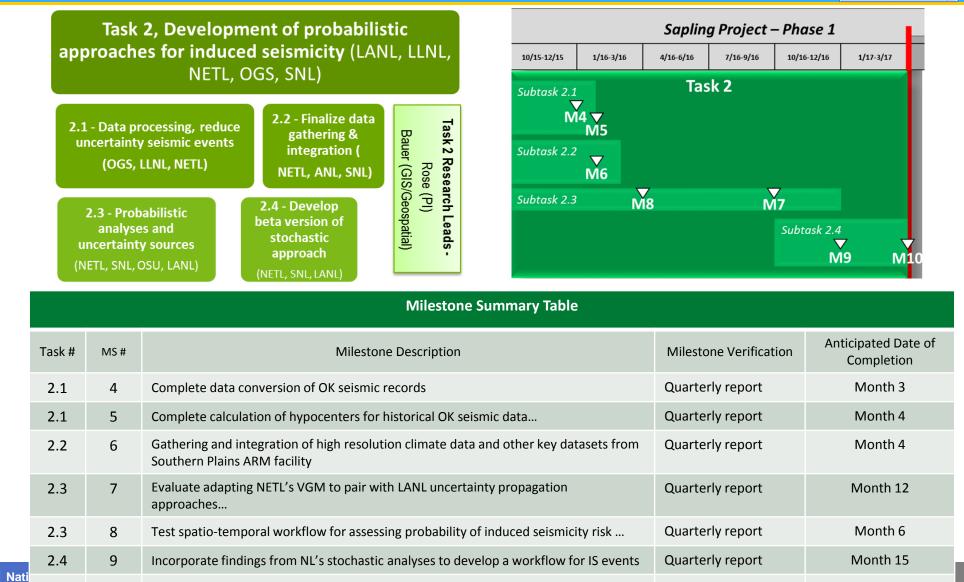
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Develop beta version of a stochastic tool for IS



Month 18





Quarterly report

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