Development of a Framework for Data Integration, Assimilation, and Learning for Geological Carbon Sequestration (DIAL-GCS)

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National Energy Technology Laboratory
Mastering the Subsurface Through Technology Innovation, Partnerships and Collaboration:
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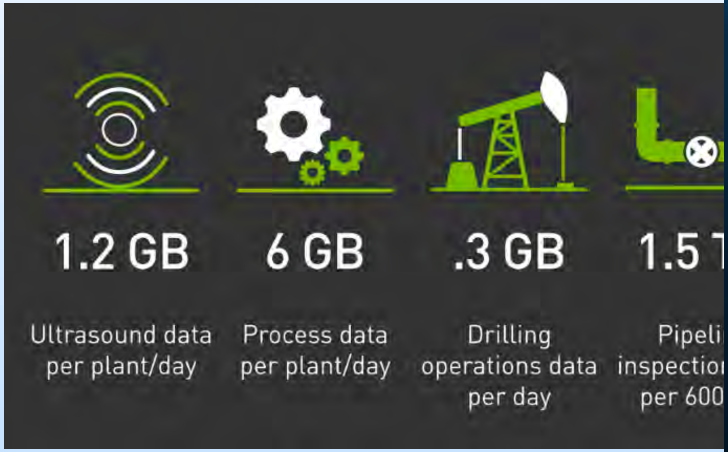
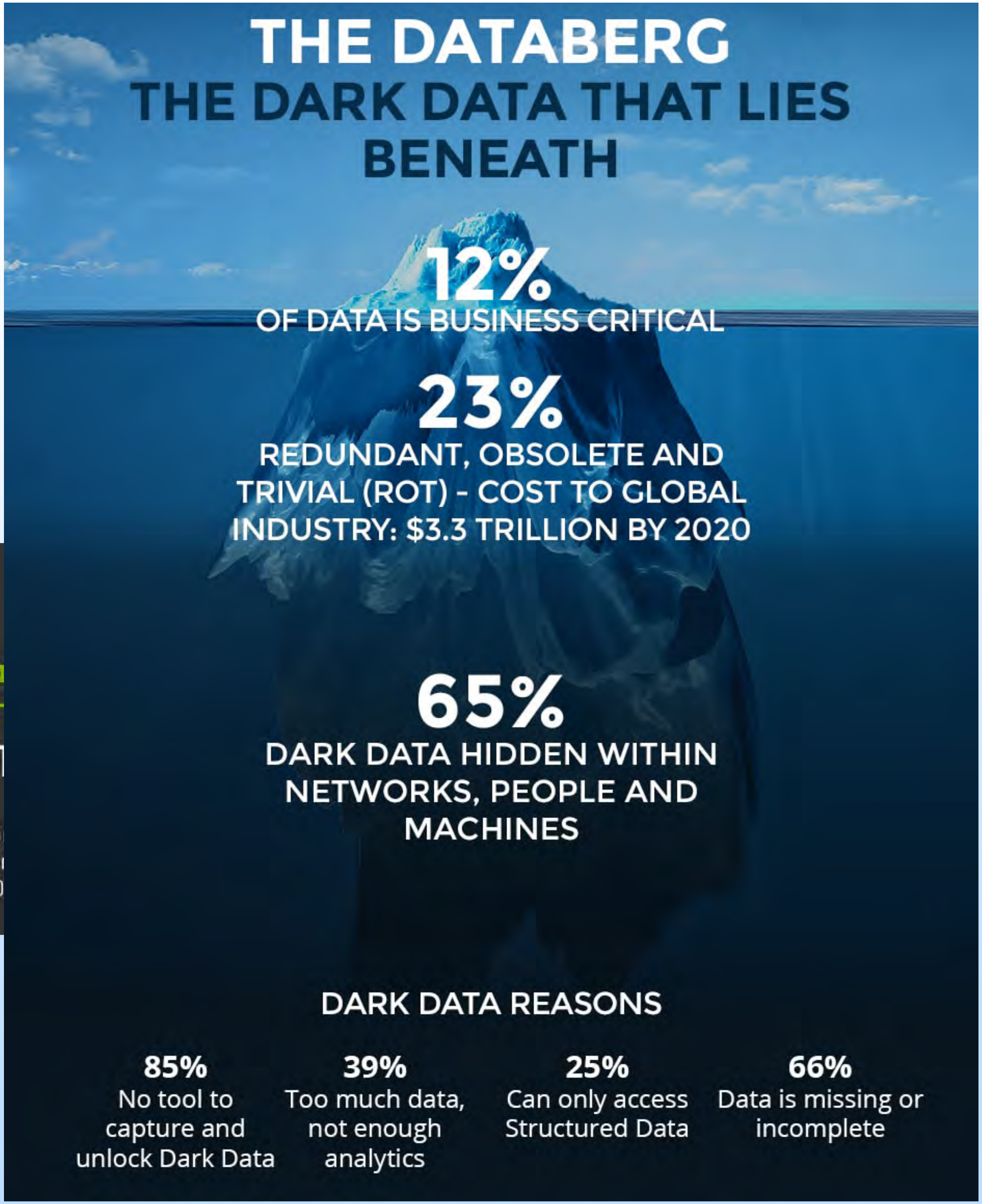
Presentation Outline

- Technical Status
  - Background and system design
  - Online anomaly detection using machine learning
  - Monitoring network optimization
- Accomplishments to Date
- Lessons Learned
- Synergy Opportunities
- Project Summary

Background & Motivation

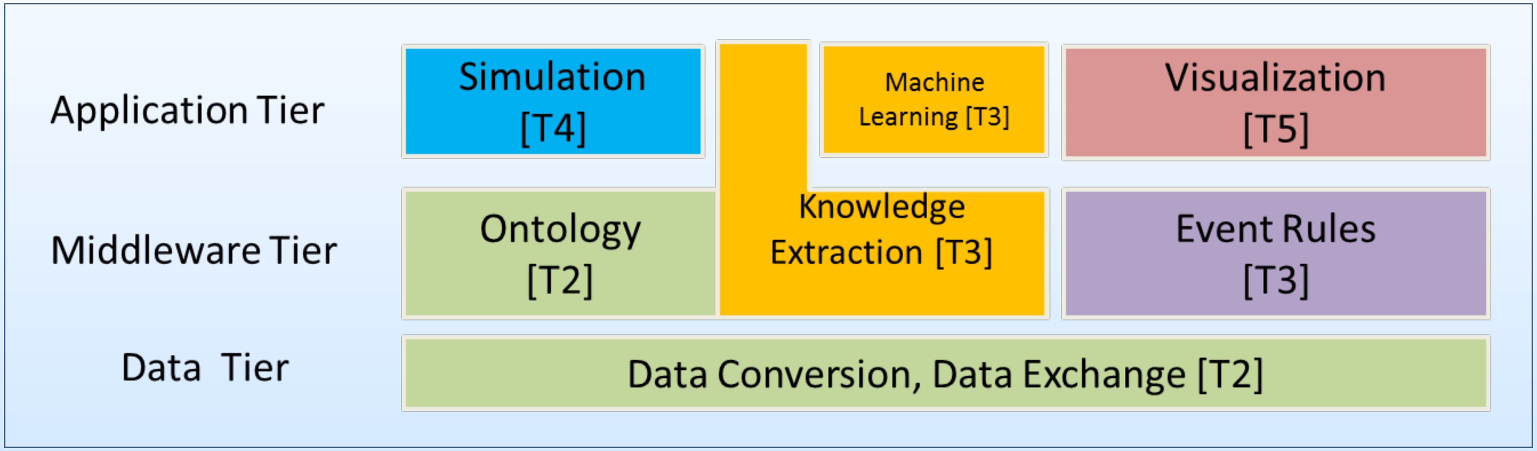
- Internet-of-Things
- Distributed sensing





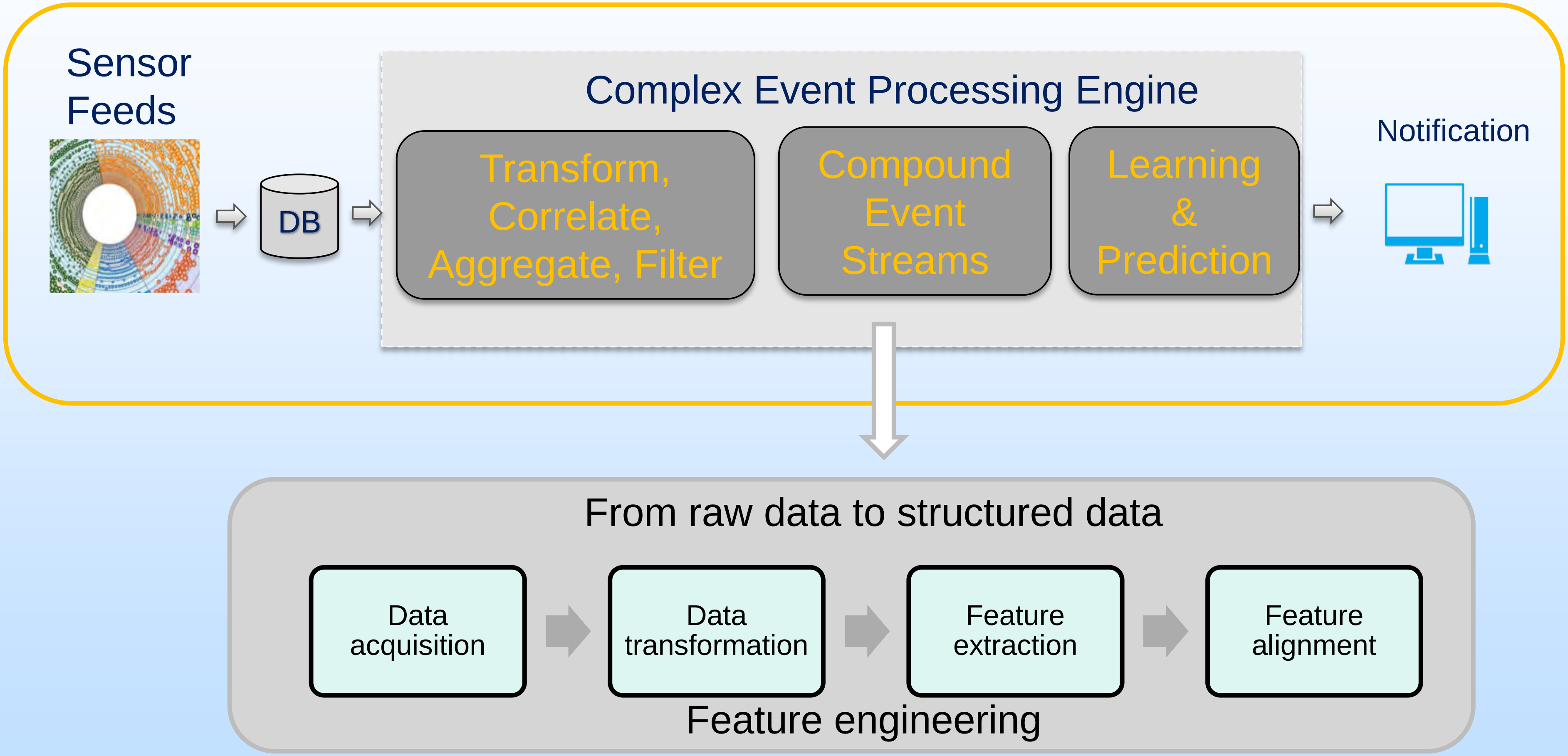
Background & Overview of Project

A multi-tier intelligent monitoring system (IMS)



Task 2: Sensor data schema development and provisioning(Y1)
Task 3: Development of CEP, machine learning (Y1-3)
Task 4: Coupled modeling, UQ, and data assimilation (Y1-4)
Task 5: System integration and demonstration (Y1-4)

Complex Event Processing



Data-Driven Anomaly Detection

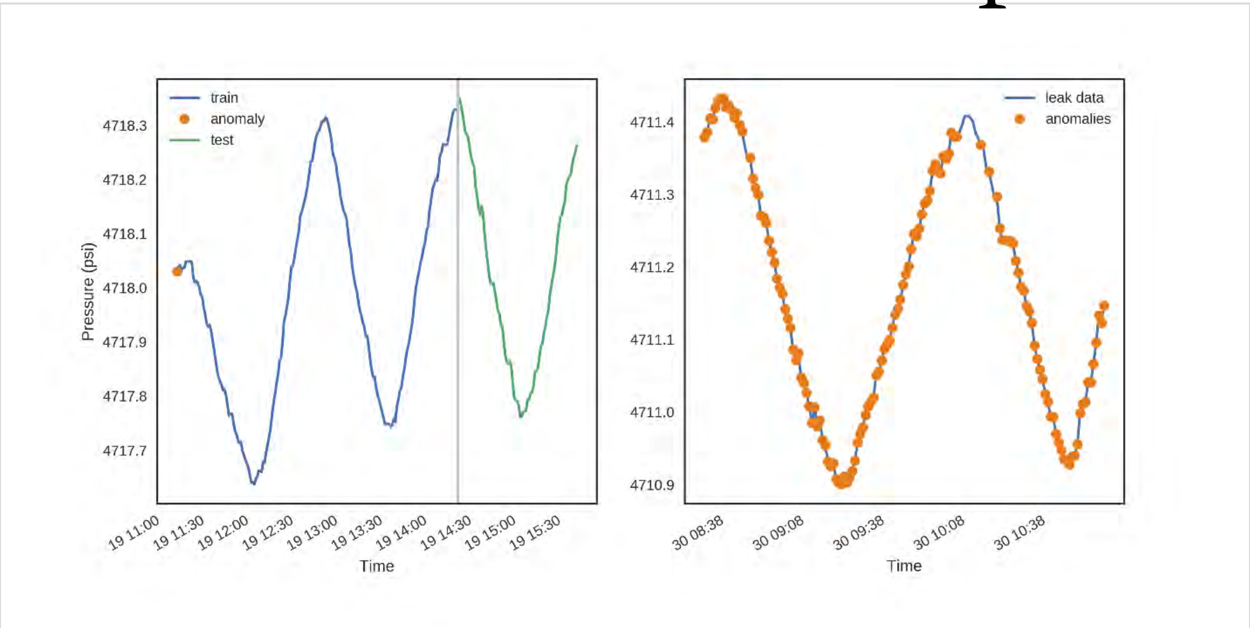
- Adopt machine learning (ML)
- Suitable for
  - Continuous monitoring
  - When physical process is not fully understood
  - Automated anomaly detection
- Requirements
  - Effective <u>online</u> ML algorithms
  - Labeled training data and expert insights!
  - High-performance, integrated computing infrastructure

Anomaly Detection Case Study

Cranfield, MS, experiments

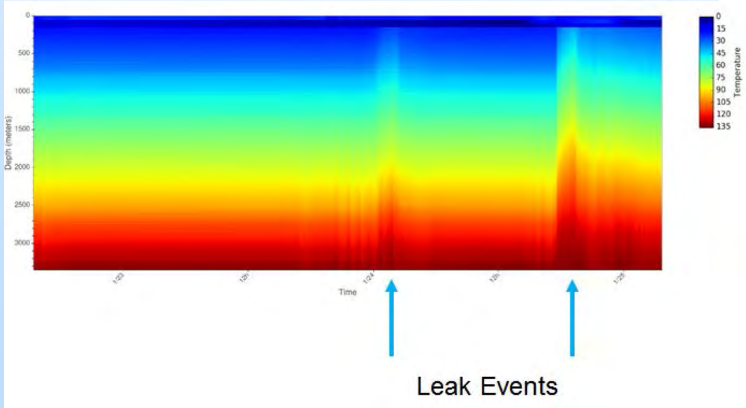
Dataset include Pressure and Temperature measurements from
- Base experiments (no leak)
- Controlled release experiments (artificial leak)

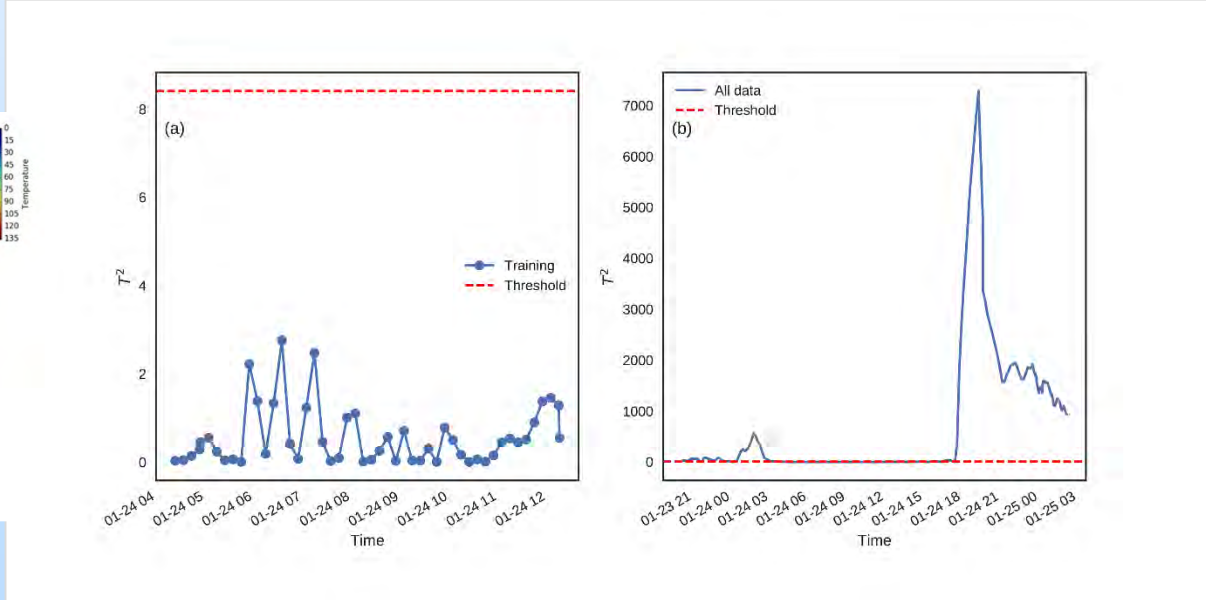
Problem-Dependent ML



Pressure anomaly
IsolationForest algorithm

DTS anomaly, PCA algorithm

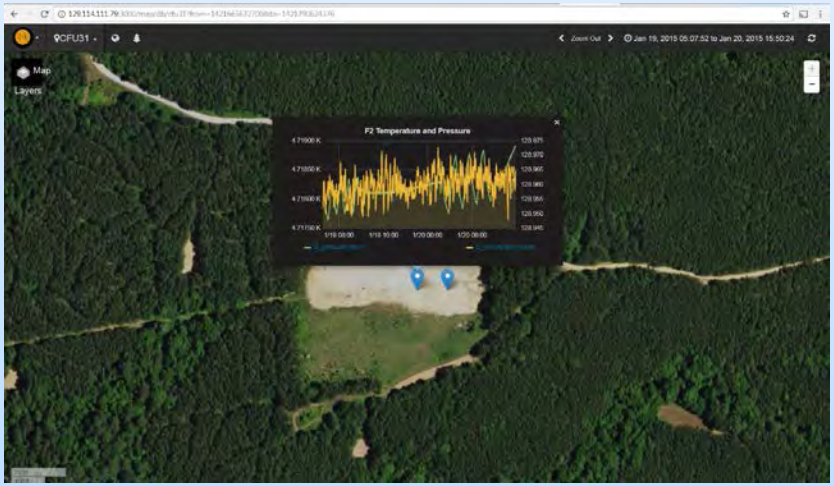


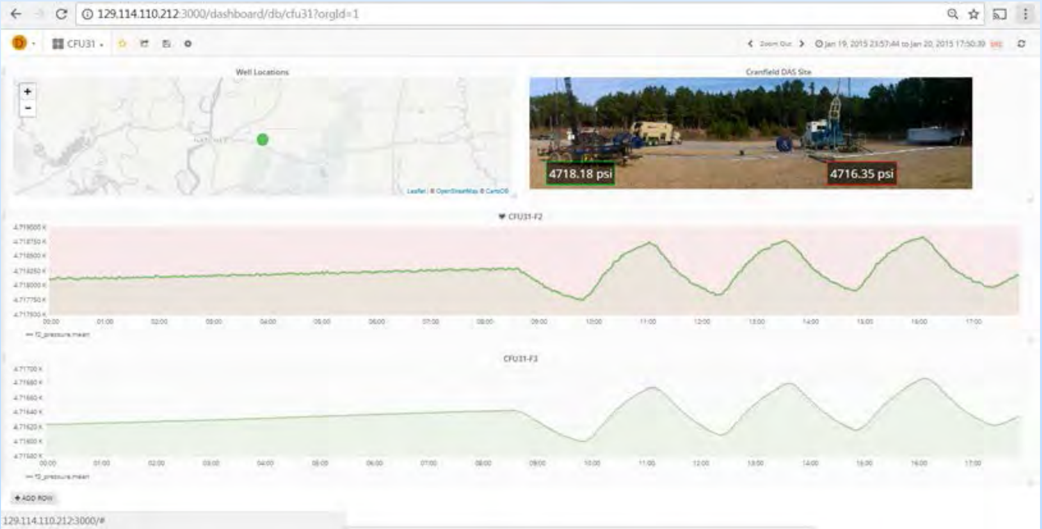


DIAL-GCS 1.0

Design 1.0:

- Web GIS
- Time series management
- A lot custom coding

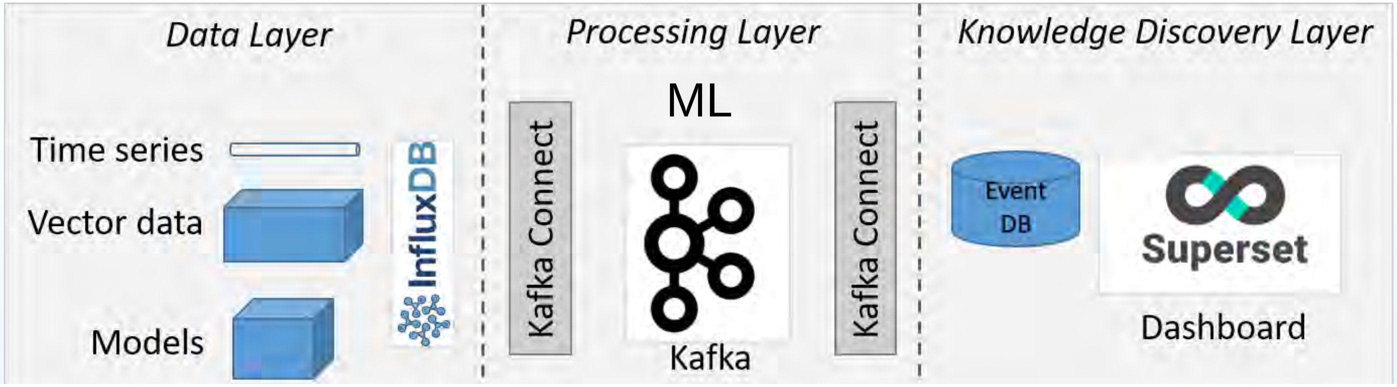


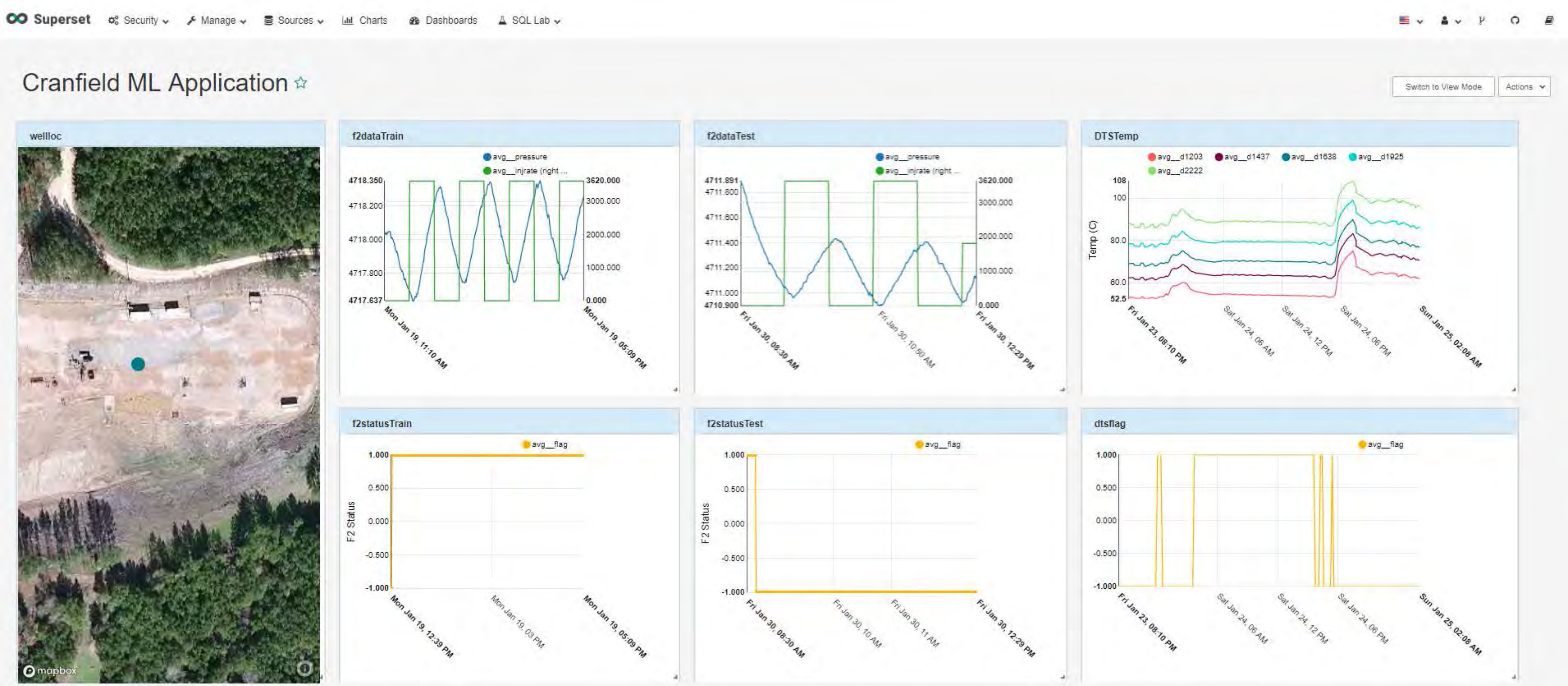


DIAL-GCS 2.0

Design 2.0:

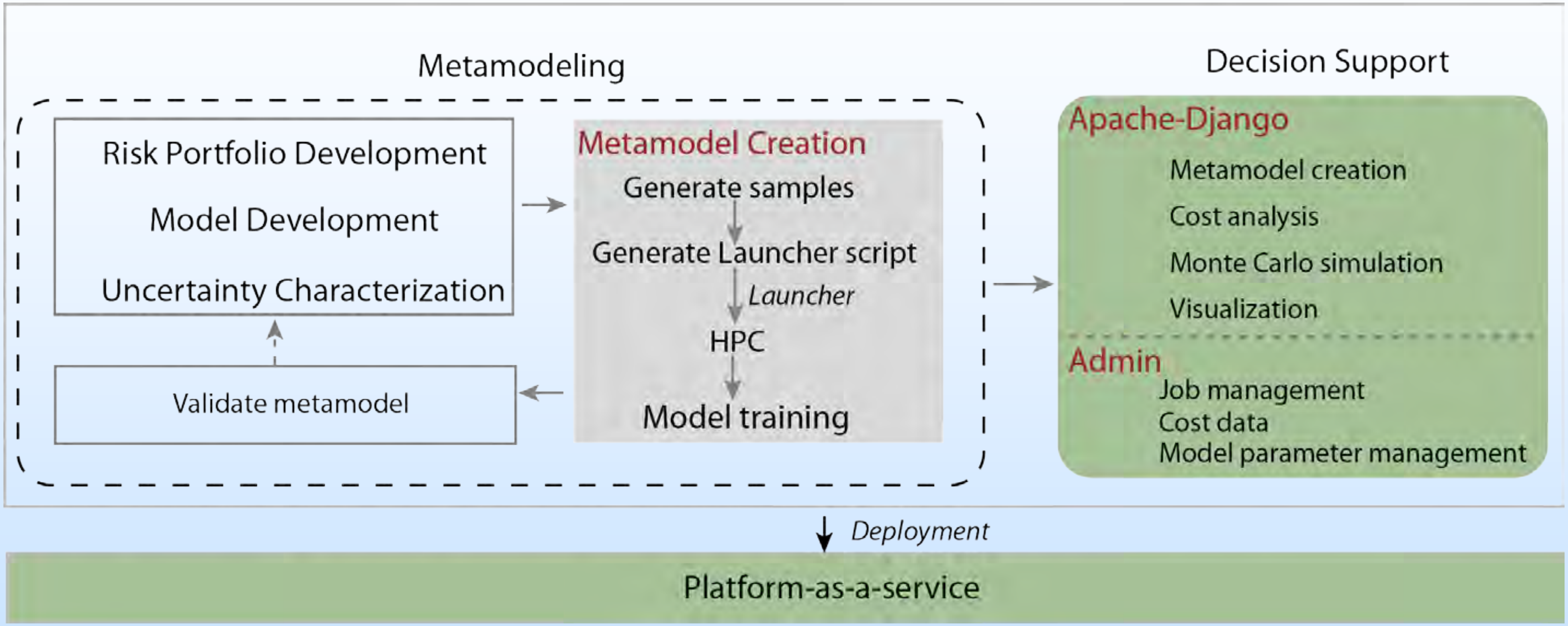
- Loosely coupled web-based stack
- Expandable





Sun et al., under review

Web-Based Monitoring Planning



Sun et al., 2018, Metamodeling-based approach for risk assessment and cost estimation: Application to geological carbon sequestration. Computers & Geosciences.

Types of metamodeling supported:

- Gaussian process regression
- Sparse grid

Leakage Assessment and Cost Estimation Tool

Admin | Metamodeling | Cost Estimate |

Browse... No file selected. Upload

File uploaded at: media/metamodel.json

Variable	Distribution	Parameters
Log Reservoir Permeability:	normal	[-29.93360621, 0.5]
Log AZMI Permeability:	normal	[-30.62675339, 0.5]
Reservoir Porosity:	uniform	[0.1, 0.2]
AZMI Porosity:	uniform	[0.05, 0.3]
Aquitard thickness:	uniform	[10.0, 30.0]
Injection Rate:	uniform	[0.5, 5]

Algorithm: gpr

Create Metamodel

Reservoir porosity[-]: 0.2

Aquifer porosity[-]: 0.1

Permeability (m^2): 0.00000000000005

Porosity (-): 0.2

Injection Rate [Mt/yr]: 3

Above Zone Parameters

CO2 density (kg/m^3): 479

Brine density (kg/m^3): 1045

CO2 viscosity (Pa*s): 0.0000395

istration

WELCOME, ADMIN. VIEW SITE / CHANGE PASSWORD / LOG OUT

Home › Reducedmodel › Expert elicitations

Select expert elicitation to change

ADD EXPERT ELICITATION +

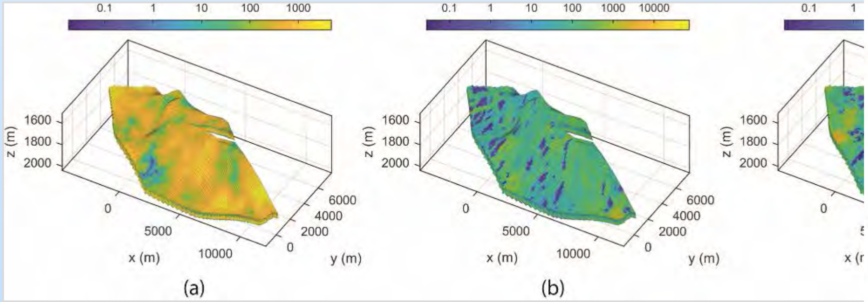
Action: ---------- Go 0 of 32 selected

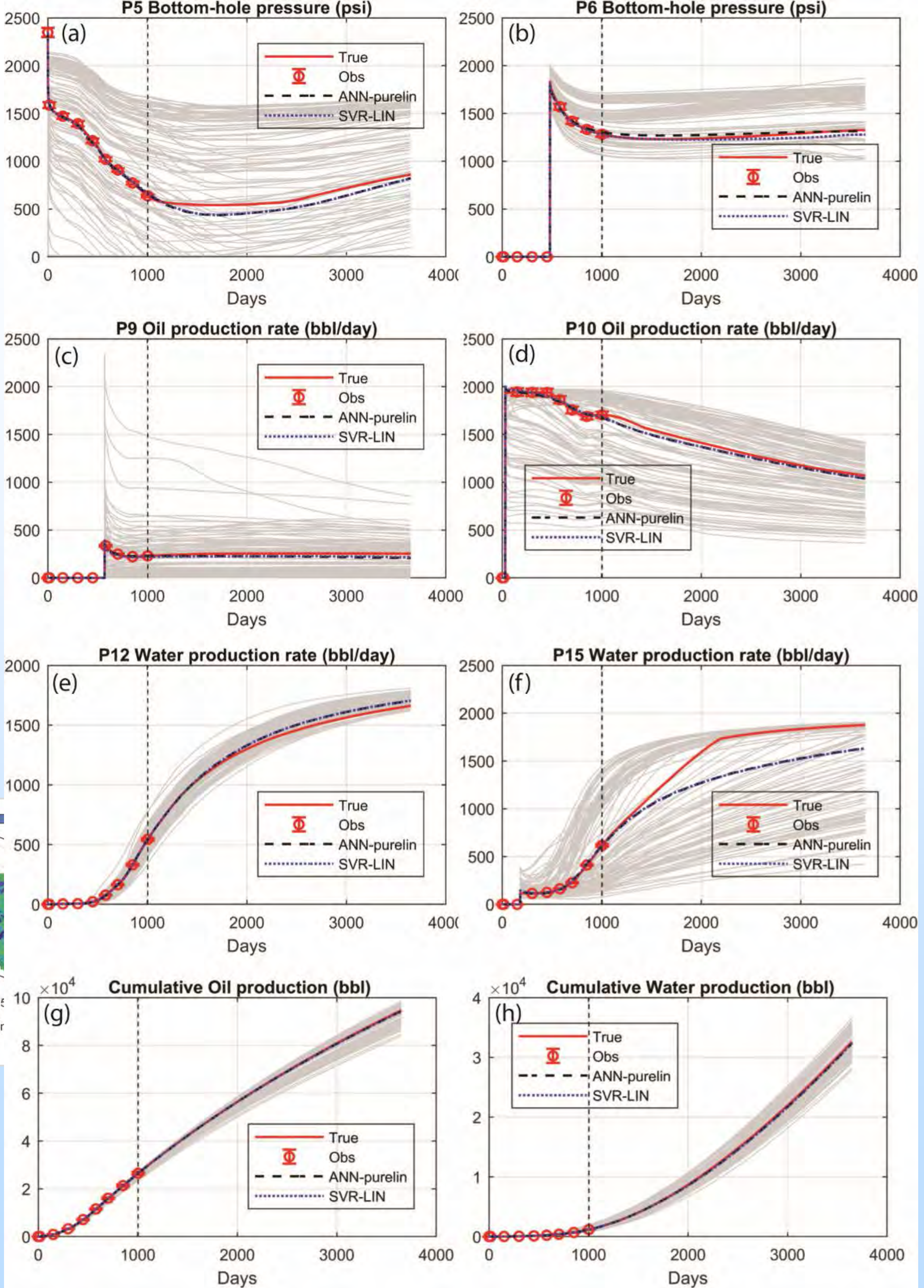
EXPERT	LEAK COST CATEGORY	SCALE
Teresa C.	B: Injection interruption	1
Teresa C.	B: Legal costs	3
Teresa C.	B: Well remediation	6
Teresa C.	C: Other property interference	1
Teresa C.	C: Injection interruption	3
Teresa C.	C: Environmental remediation	2
Teresa C.	C: Legal costs	1
Teresa C.	C: Well remediation	3

Data-Space Inversion (DSI)

What is DSI?

- A new paradigm for long-term prediction and UQ without using history matching
- Prior knowledge is used to generate possible scenarios, but not to calibrate model
- DSI combines physically-based model with ML



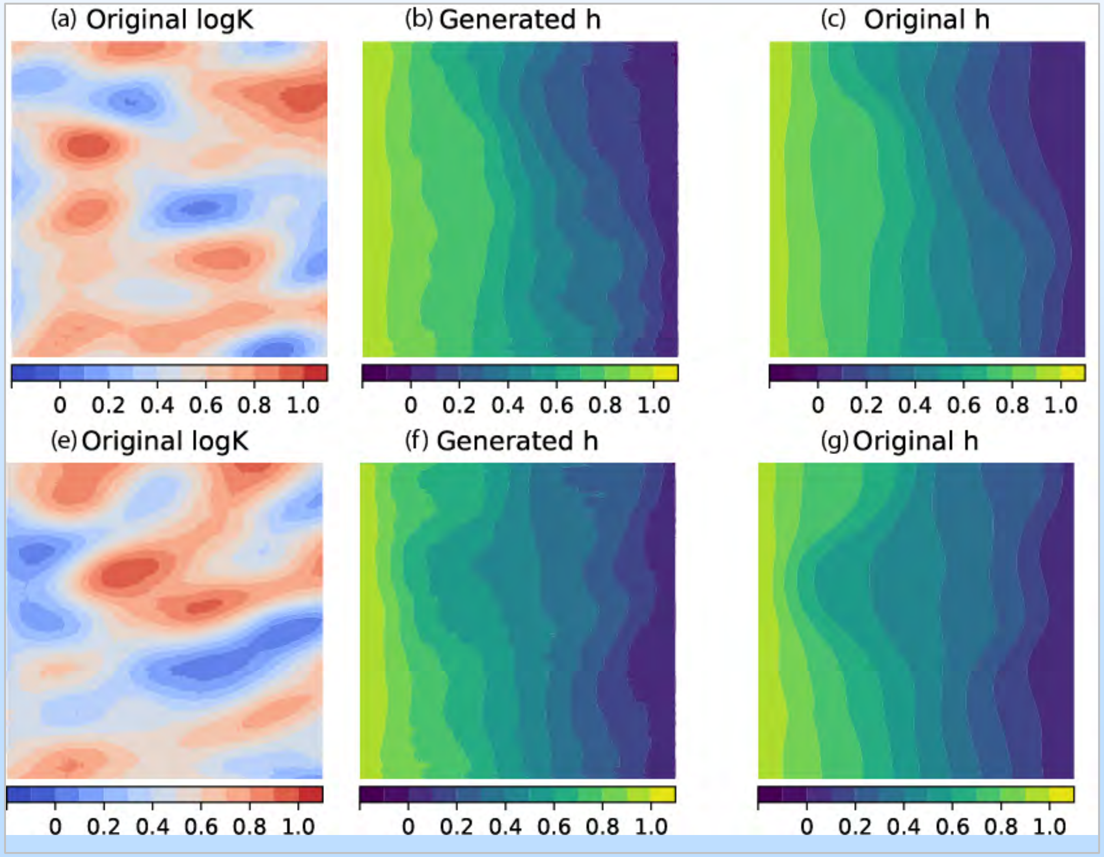


Jeong et al., 2018a, A learning-based data-driven forecast approach for predicting future reservoir performance. AWR.

Deep Learning for Surrogate Modeling

- Deep learning (DL) is a very powerful tool for pattern recognition. However it requires a large amount of labeled data for training
- In geosciences, there's a lot of hype on DL but also many questions
- We developed an innovative DL pipeline for combining DL with physics-based models

Single phase flow example



Dimensions 128x128

Sun, under review

Optimal Monitoring Network Design

Objective Function

Well cost =
CAPEX($/well)+
OPEX($/well/day)+
Intervention($/well)

Leakage cost =
Brine($/ton)+
CO_2($/ton)

Optimization toolbox

Binary Integer Programming

- Linear problem
- Convex

Optimize monitoring network

Constraints

\# of monitoring wells ≤ N_{max}

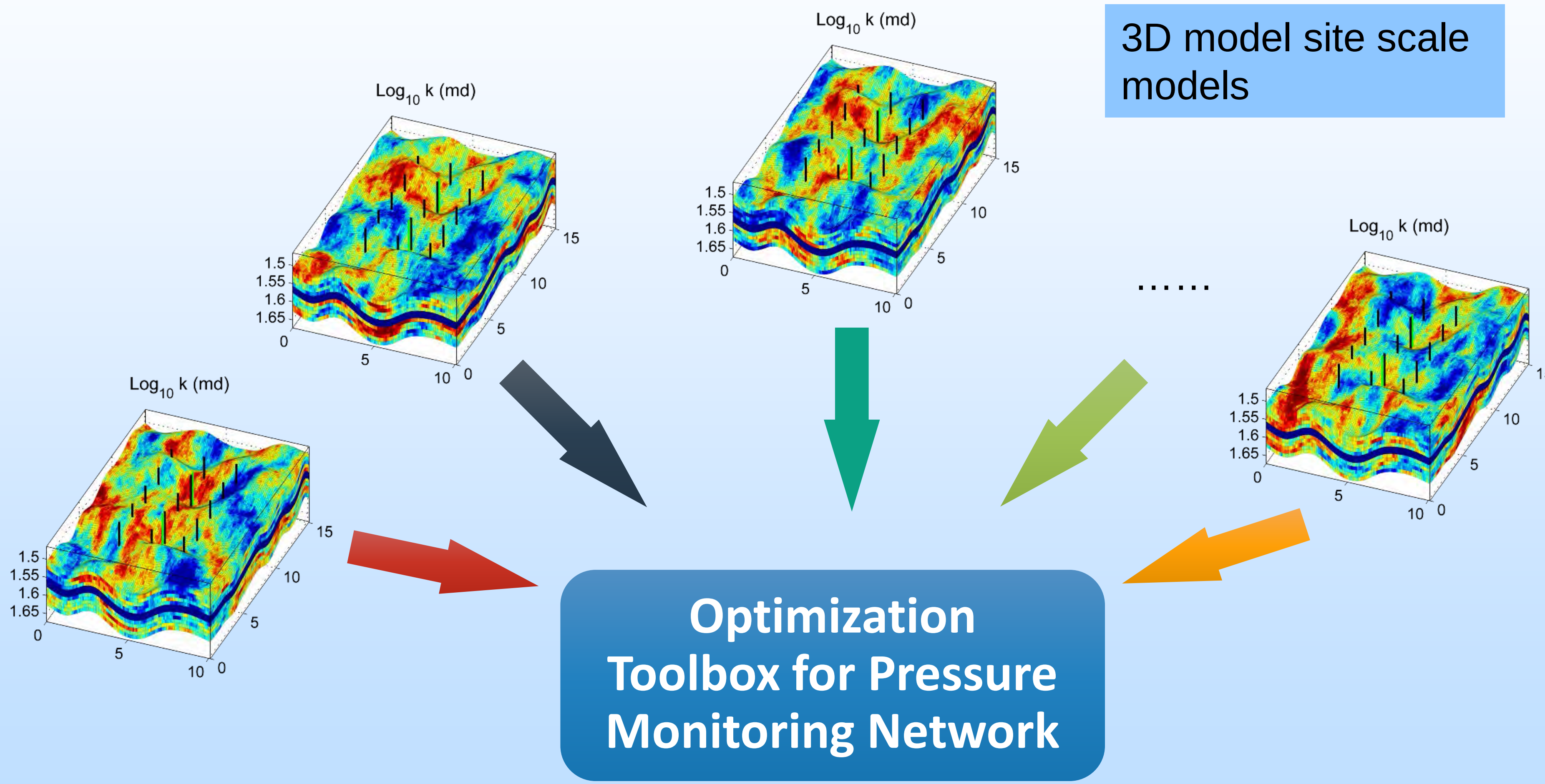
CO_2 leakage ≤ M% of total injected CO_2

ΔP at $t_{leakage\ detection} \geq \Delta P_{threshold}$

Jeong et al., 2018b, Cost-optimal design of pressure-based monitoring networks for carbon sequestration projects, with consideration of geological uncertainty, International Journal of Greenhouse Gas Control.

Our tool maximizes NPV by considering

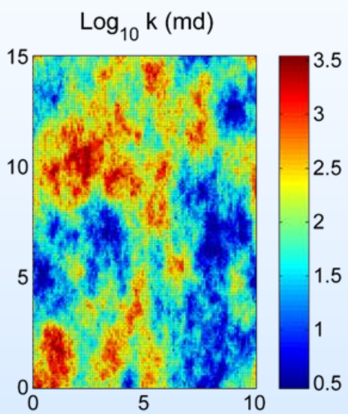
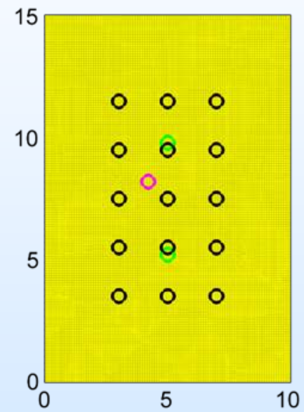
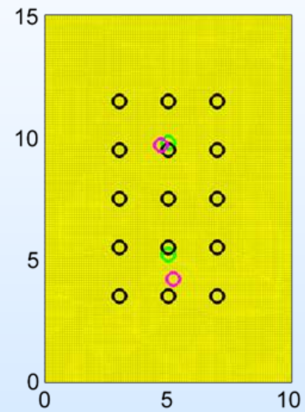
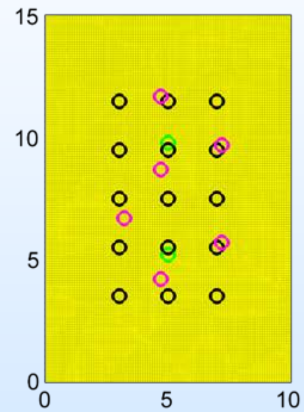
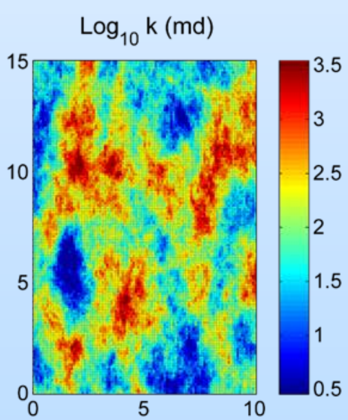
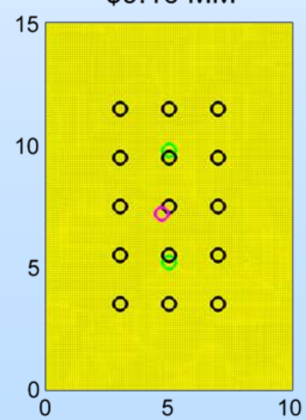
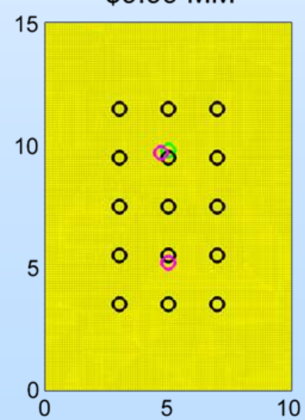
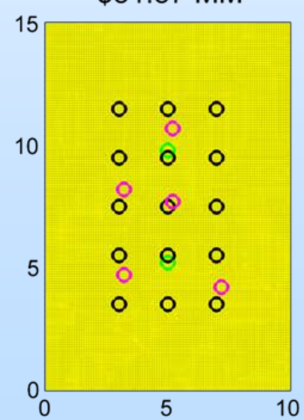
- High uncertainty in geologic models
- Monitoring budget
- Leakage damage cost
- Carbon credit <= *45Q Tax Incentives for CCUS*



The optimal monitoring well locations are different because heterogeneous permeability affects

- Spatial pressure distribution
- Leakage detection time

Black: leaky well
Green: injector
Magenta: monitoring well

		C_{brine}	C_{CO2}	C_{brine}	C_{CO2}	C_{brine}	C_{CO2}
Geologic model		**$10/t**	**$10/t**	**$10/t**	**$1,000/t**	**$100/t**	**$10/t**
	**Total cost**	$8.76 MM		$9.63 MM		$29.75 MM	
	Optimal monitoring well location						
	**Total cost**	$9.16 MM		$9.99 MM		$31.37 MM	
	Optimal monitoring well location						

Lessons Learned

– We have developed an intelligent monitoring system to help generate “intelligent information” and reduce “dark data” Applications include
  - Web-based monitoring planning
  - Pressure-based monitoring network design
  - Data space inversion
  - Deep learning tools
– Data-driven machine-learning models are suitable for continuous monitoring and anomaly detection and can be used together with physics-based models for surrogate modeling
– A viable approach is to combine prior information, expert knowledge, and state-of-the-art machine learning tools for knowledge discovery and representation

Accomplishments to Date

- Task 2: Data management
  - Year 1: Developed schema and data adaptors for storing, exchanging information, and visualizing information
- Task 3: Complex event processing using machine learning
  - Year 2: Implemented predictive models on different test datasets
  - Year 3: Updated the existing platform for usability
- Task 4: Coupled modeling / data assimilation
  - Year 2: Implemented workflow for automating data assimilation. Demonstrated Web-based modeling approaches
  - Year 3: Focused on ML and DL tool development
- Task 5: Integration and demonstration
  - Year 1-3: Experimented with a large number of web-based technologies for making the system more user friendly

Synergy Opportunities

- DIAL-GCS is an intelligent monitoring system designed for anomaly detection, monitoring network design, leakage cost estimation
- Most tools are web-based, or can be readily converted to web-based, for CCS decision support needs

Project Summary

- Developed and improved DIAL system
- All tasks are on revised schedule
- Next steps
  - Formalize data transformation and work flow
  - Improve web-based monitoring network design
  - Experiment with different data-driven models and data types
  - Provide useful web services
  - Provide deep learning based web service

Acknowledgements

- DOE/NETL PM: Bruce Brown

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  - Texas Advanced Computing Center: Weijia Xu, David Walling

- LBNL: Barry Freifeld (provided DTS data)

Appendix

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

Benefit to the Program

- Carbon storage program goals being addressed

Develop and validate technologies to ensure 99 percent storage permanence

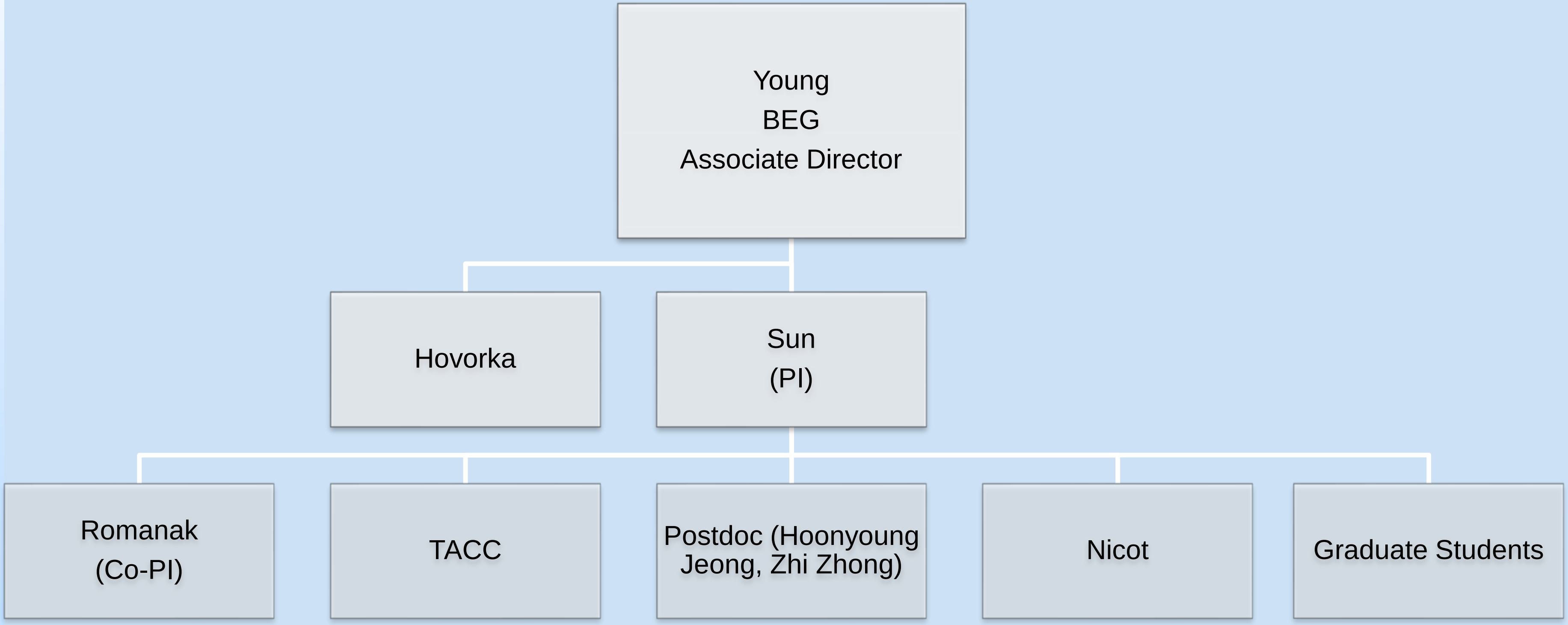
- Expected benefits of this IMS Project
  - Transform scientific knowledge to decision power and public knowledge
  - Promote data sharing and visual analytics
  - Better collaboration among team members
  - Public outreach
  - Streamline CCS data management and decisionmaking
  - Facilitate the optimal allocation of monitoring resources

Project Overview

Goals and Objectives

- Develop GCS data management module for storing, querying, exchanging, and visualizing GCS data from multiple sources and in heterogeneous formats
  - Success Criterion: Whether a flexible, user-friendly Web portal is set up for enabling data exchange and visual analytics
- Incorporate a complex event processing (CEP) engine for detecting abnormal situations by seamlessly combining expert knowledge, rule-based reasoning, and machine learning
  - Success Criterion: Whether a set of decision rules are developed for identifying abnormal signals in monitoring data
- Enable uncertainty quantification and predictive analytics using a combination of coupled-process modeling, data assimilation, and reduced-order modeling
  - Success Criterion: Whether a suite of computational tools are developed for UQ and predictive analytics
- Integrate and demonstrate the system's capabilities with both real and simulated data
  - Success Criterion: Whether the IMS tools developed under Goals A to C are integrated, streamlined, and demonstrated for a realistic GCS site

Organization Chart



Gantt Chart

Table 2. Project Gantt chart
(Numbers in table rows indicate milestones).
(Phase I ; Phase II)

Task	**Description**	**Year 1**				**Year 2**				**Year 3**			
		1	2	3	4	1	2	3	4	1	2	3	4
1	Update project management plan	1											
2	Sensor data management												
2.1	Ontology/schema development												
2.2	Sensor data adaptor development		2										
3	CEP Development												
3.1	Rule definition												
3.2	Reasoning and machine learning												
3.3	Testing					3							
4	Coupled modeling/Assimilation												
4.1	Coupled modeling												
4.2	Data assimilation						4						
5	Integration and demonstration												
5.1	Integration											5	
5.2	Demonstration												
6	Synthesis of results												
6.1	Dissemination of results												
6.2	Technology transfer												6

Bibliography

– Peer-Review Manuscripts

- Sun, A. Y., Jeong, H., Gonzalez, A., and Templeton, T., 2018, Metamodeling-based approach for risk assessment and cost estimation: application to geological carbon sequestration, Computers and Geosciences, v. 113, p. 70-80.
- Jeong, H., Sun, A. Y., Lee, J., and Min, B., 2018a, A learning-based data-driven forecast approach for predicting future reservoir performance. Advances in Water Resources, v. 118, p. 95-109.
- Jeong, H., Sun, A. Y., and Zhang, X., 2018b, Cost-optimal design of pressure-based monitoring networks for carbon sequestration projects, with consideration of geological uncertainty, International Journal of Greenhouse Gas Control, v. 71, p. 278-292.

– Presentations

- Development of anomaly detection models for deep subsurface monitoring, presented at the fall meeting of American Geophysical Union, New Orleans, LA, December, 2017