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

Project Number DE-FE0026515

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National Energy Technology Laboratory

Carbon Storage Project Review Webinar

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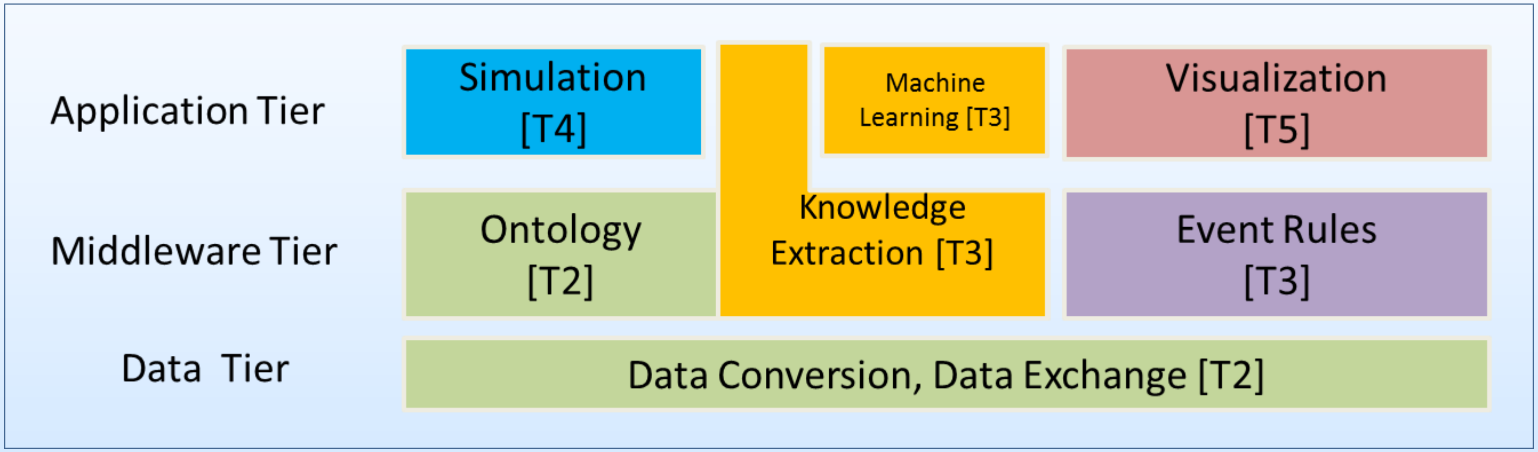
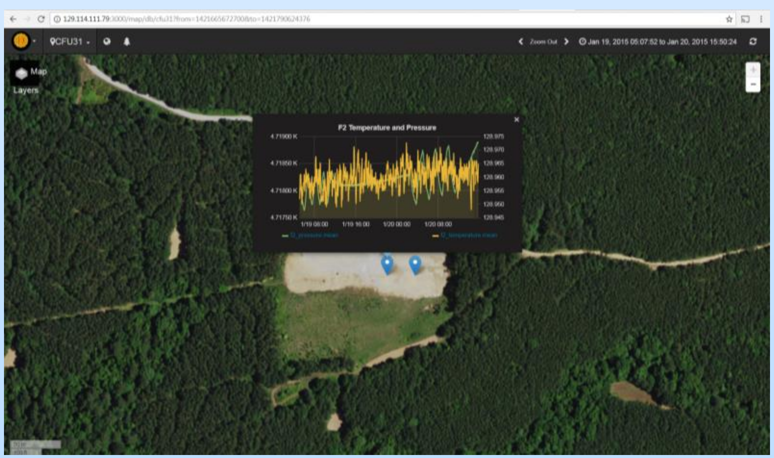
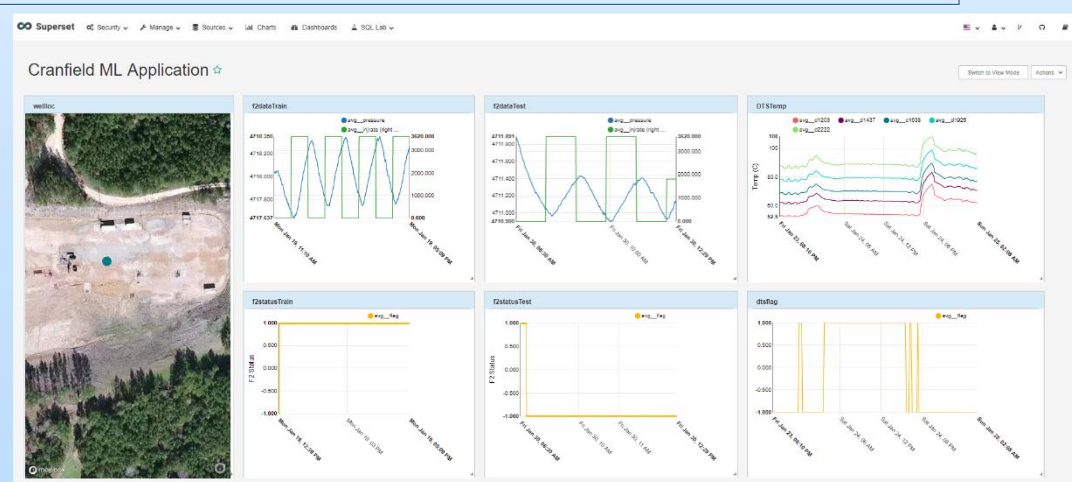
Program Overview

Developing a multi-tiered, intelligent monitoring system (IMS) for automating CCS modeling/monitoring tasks







Program Overview

– Funding
  - Federal \$1.23 M, Cost Share \$346k

– Overall Project Performance Dates
  - Oct 1, 2015–March 31, 2021

– Project Participants
  - Bureau of Economic Geology
  - Texas Advanced Computing Center
  - Graduate students and postdocs

Technical Approach/Project Scope (1-2 Slides)

A. Technical Approach/Project Scope

This project includes a number of meaningful and necessary tasks to transform the human domain knowledge into machine-interpretable rules for automating knowledge extraction and discovery in GCS

a. Major project tasks and schedule

- 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 (Y1-5)
- Task 5: System integration and demonstration (Y1-6)

Technical Approach/Project Scope

b. Project success criteria

- A meaningful set of use cases are identified and the corresponding methods are developed

- A suite of computational tools are developed for expediting optimization, uncertainty quantification, and predictive analytics

- The developed tools are integrated and demonstrated over realistic datasets

c. Significant project risks

- Web implementation and integration

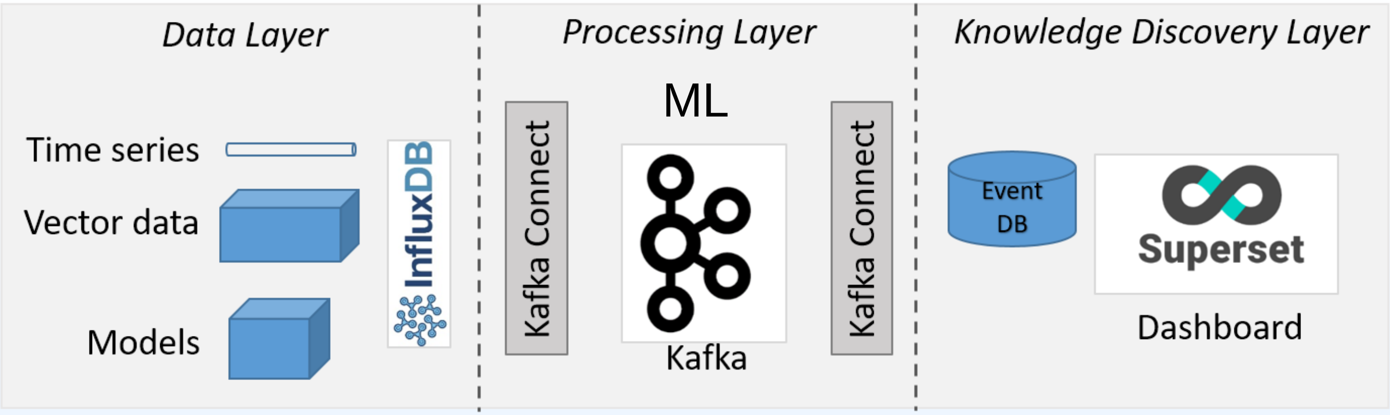
Progress and Current Status of Project

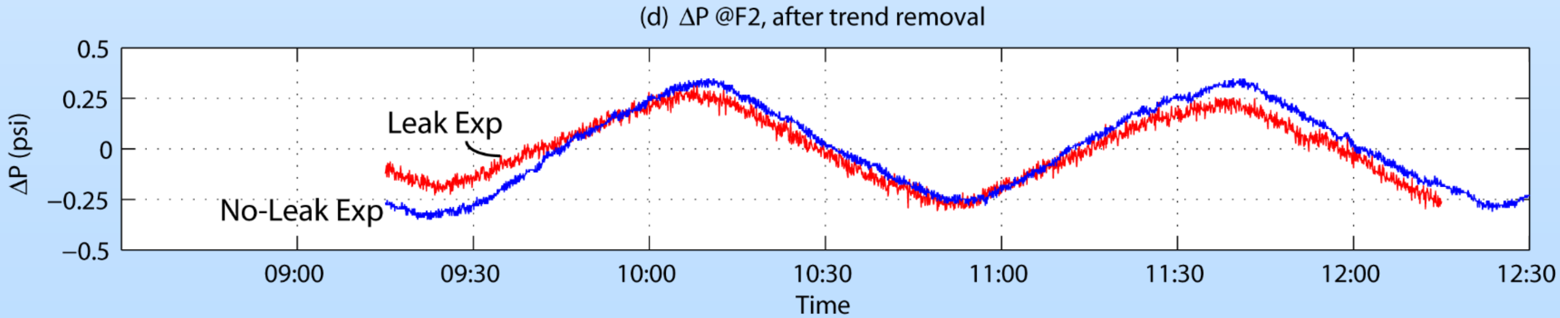
Key Capabilities of DIAL-GCS

- Real-time sensing and anomaly detection
  - Cranfield controlled release data
  - Surface gas controlled leak data
  - Forge distributed acoustic sensing data
- Tools for optimizing GCS monitoring and project planning
  - Multiobjective optimization under uncertainty
  - Reinforcement learning

DIAL-GCS Cranfield Use Case

- Demonstrated real-time sensing
- Complex event processing
- Flexible framework

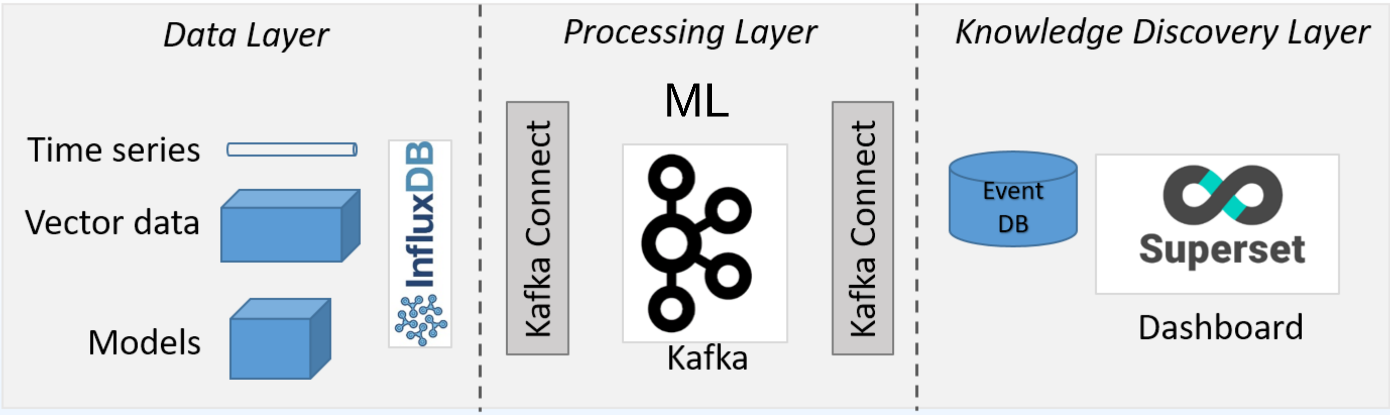


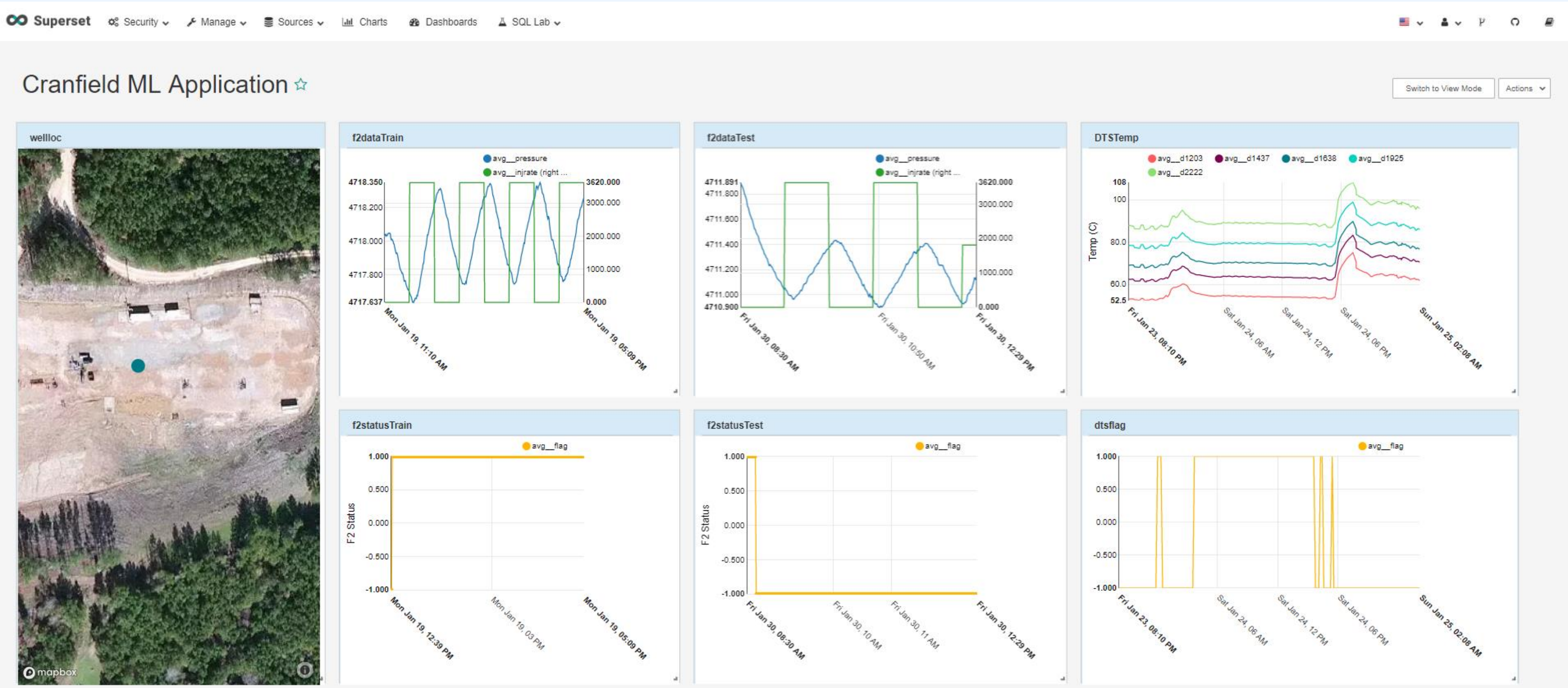


Sun et al., 2019

DIAL-GCS Cranfield Use Case

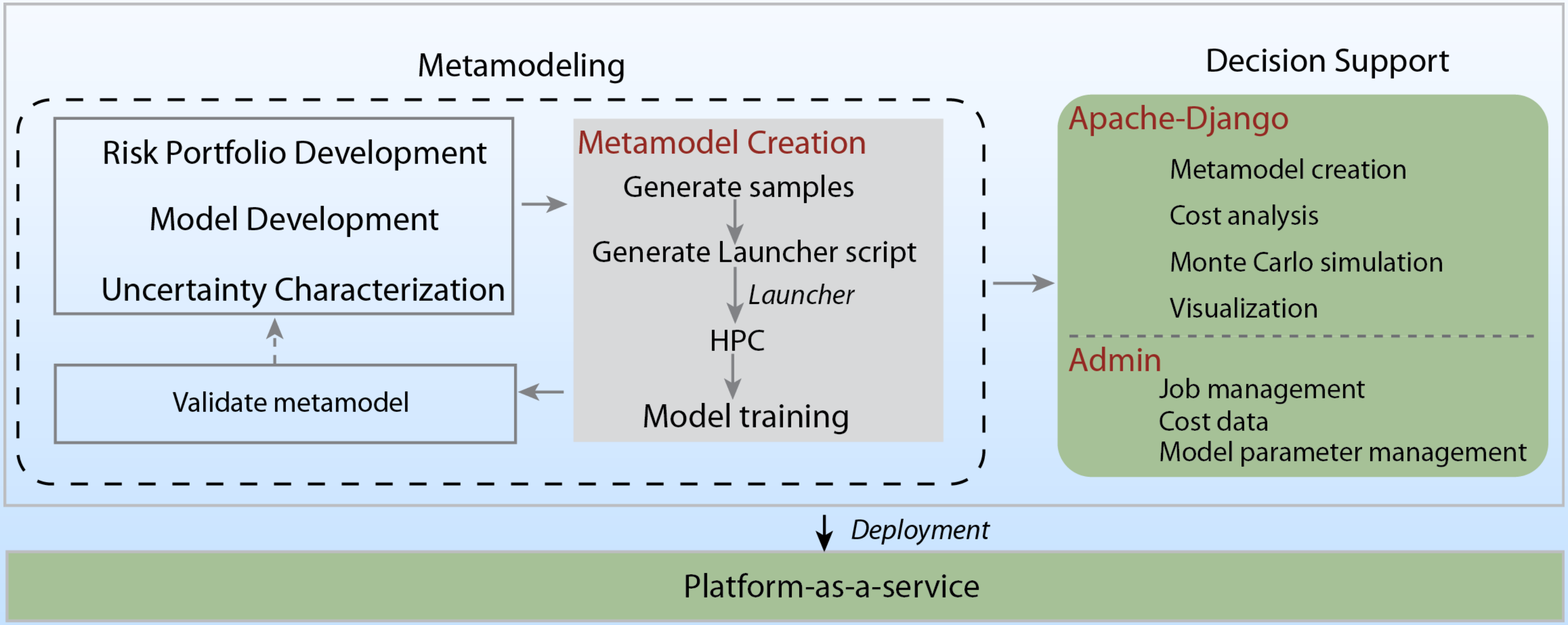
Design 2.0:
- Kafka-based
- Flexible





DIAL-GCS Leakage Cost Estimation Use Case

- A web-based tool for project planning & risk assessment
- Illustrated reduced-order modeling and uncertainty quantification on the web



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

DIAL-GCS Leakage Cost Estimation Use Case

Leakage Assessment and Cost Estimation Tool

Admin | Metamodeling | Cost Estimate |

Injection Zone Parameters

CO_2 density (kg/m3):	479
Brine density (kg/m^3):	1045
CO_2 viscosity (Pa*s):	0.0000395

Uncertain Variable Values:

Reservoir perm [m^2]:

Aquifer perm[m^2:

Aquitard thick [m]:

Injection rate [Mt]:

Leaked CO_2 Mass

Types of metamodels currently supported:

- Gaussian process regression
- Sparse grid

Leakage Assessment and Cost Estimation Tool

Admin | Metamodeling | Cost Estimate |

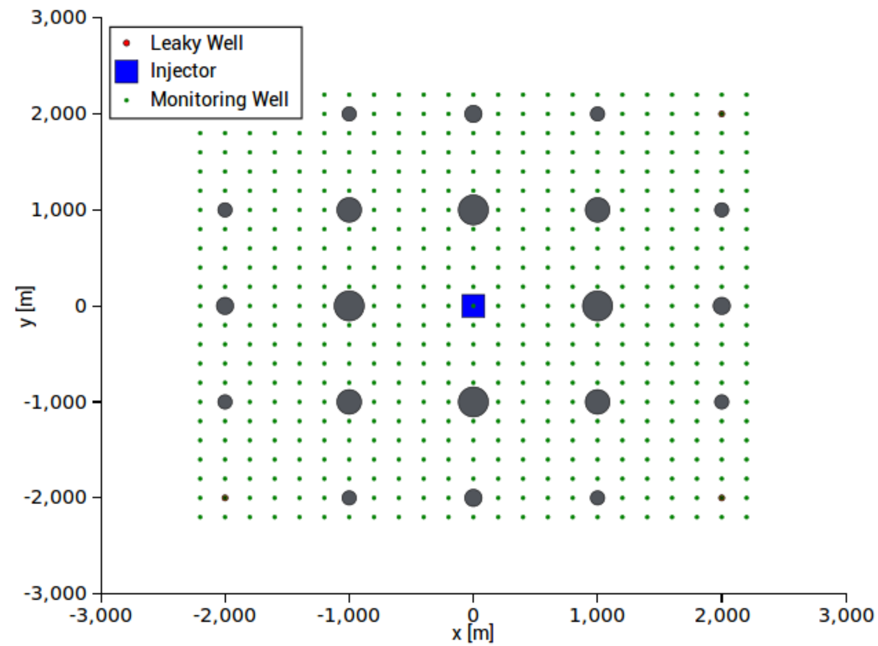
Browse... No file selected. Upload

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



Total leaked CO_2 = 1.52 Mt; Total leaked Brine = 0.13 Mt

Estimated damage = $ 1.71MM

Cost-Effective GCS Monitoring Network Design Use Case

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}

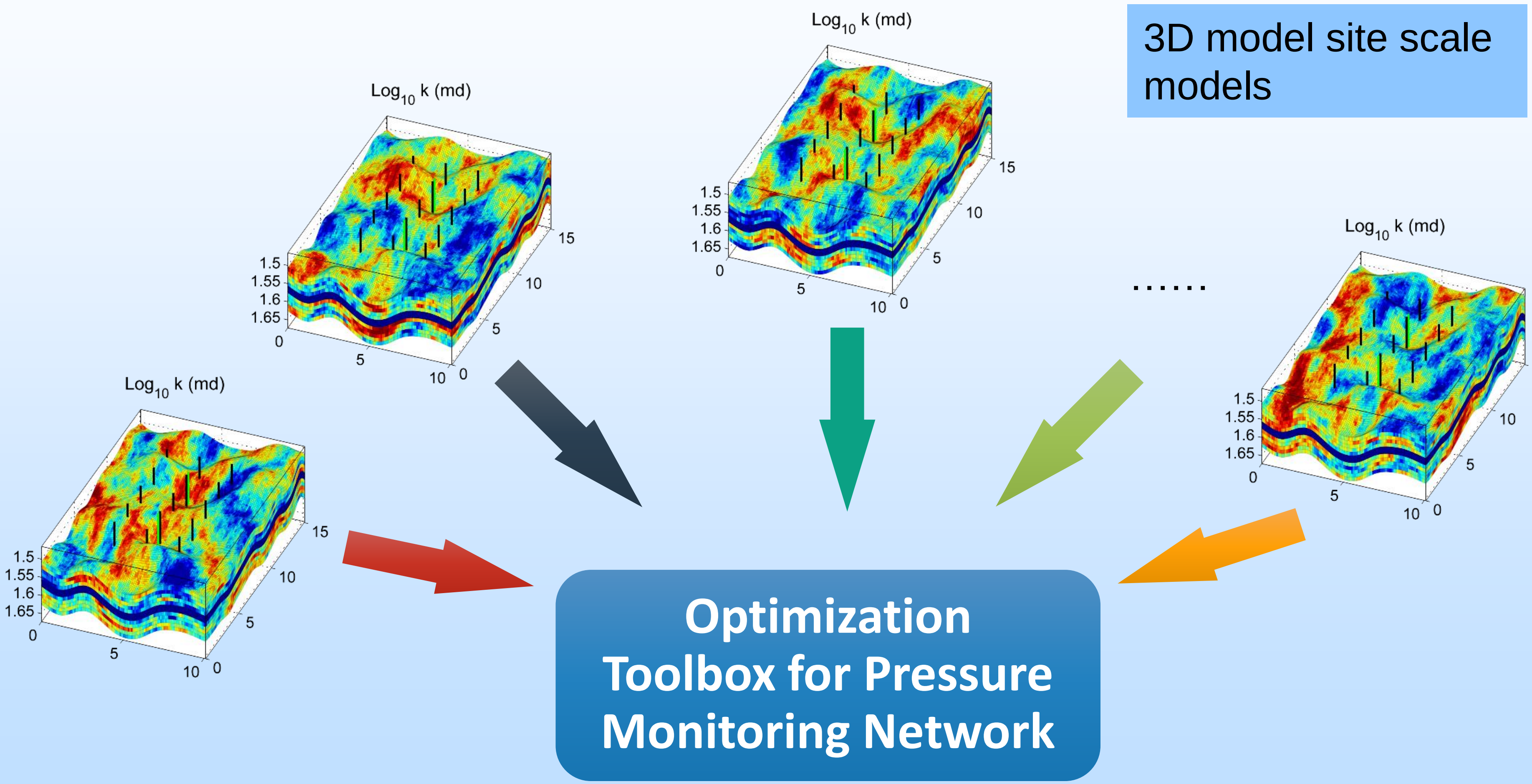
CO_2 leakage ≤ M% of total injected CO_2

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

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

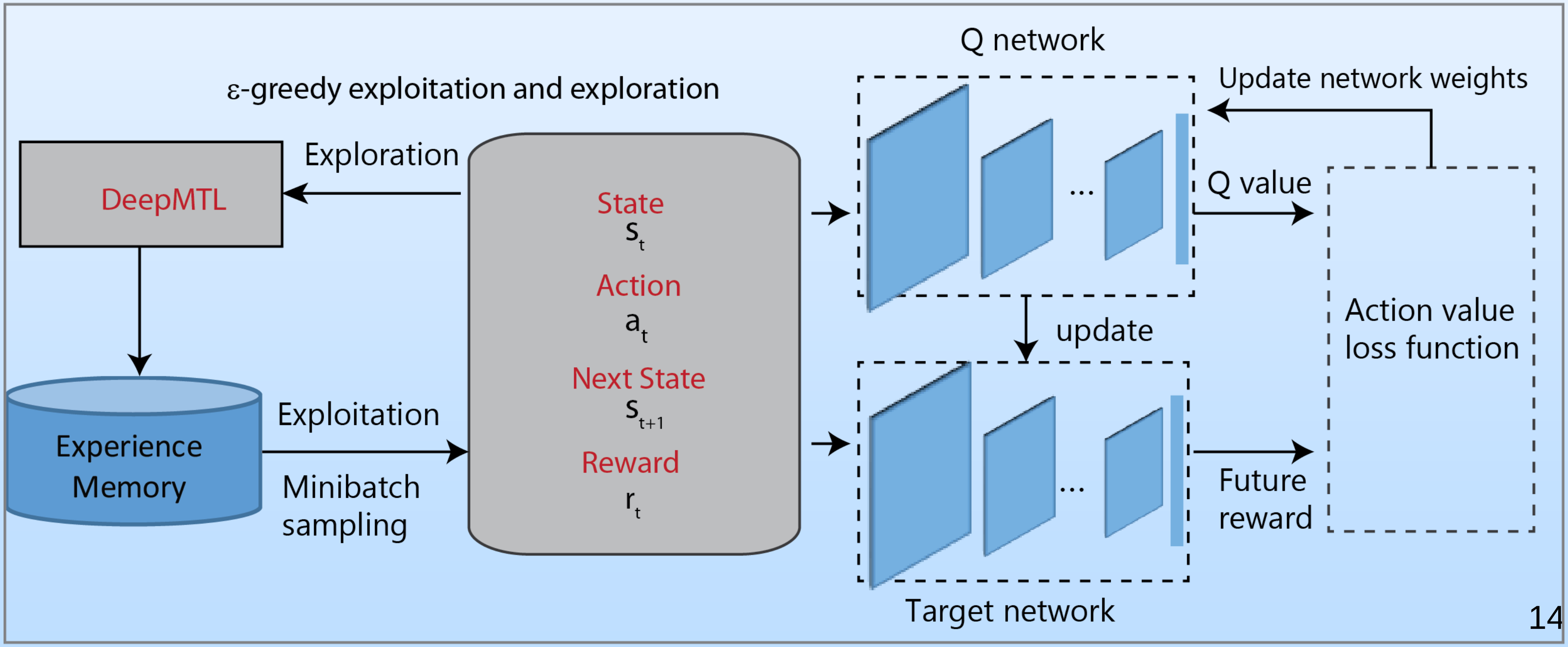
- High uncertainty in geologic models
- Monitoring budget
- Leakage damage cost
- 45Q carbon tax credit



Optimal GCS Reservoir Management Use Case

- Multi-period planning horizon
- The operator wants to maximize total CO2 storage while minimizing risks
- Very expensive optimization problem
- We combined deep reinforcement learning and surrogate modeling to expedite the process

Deep Q Learning

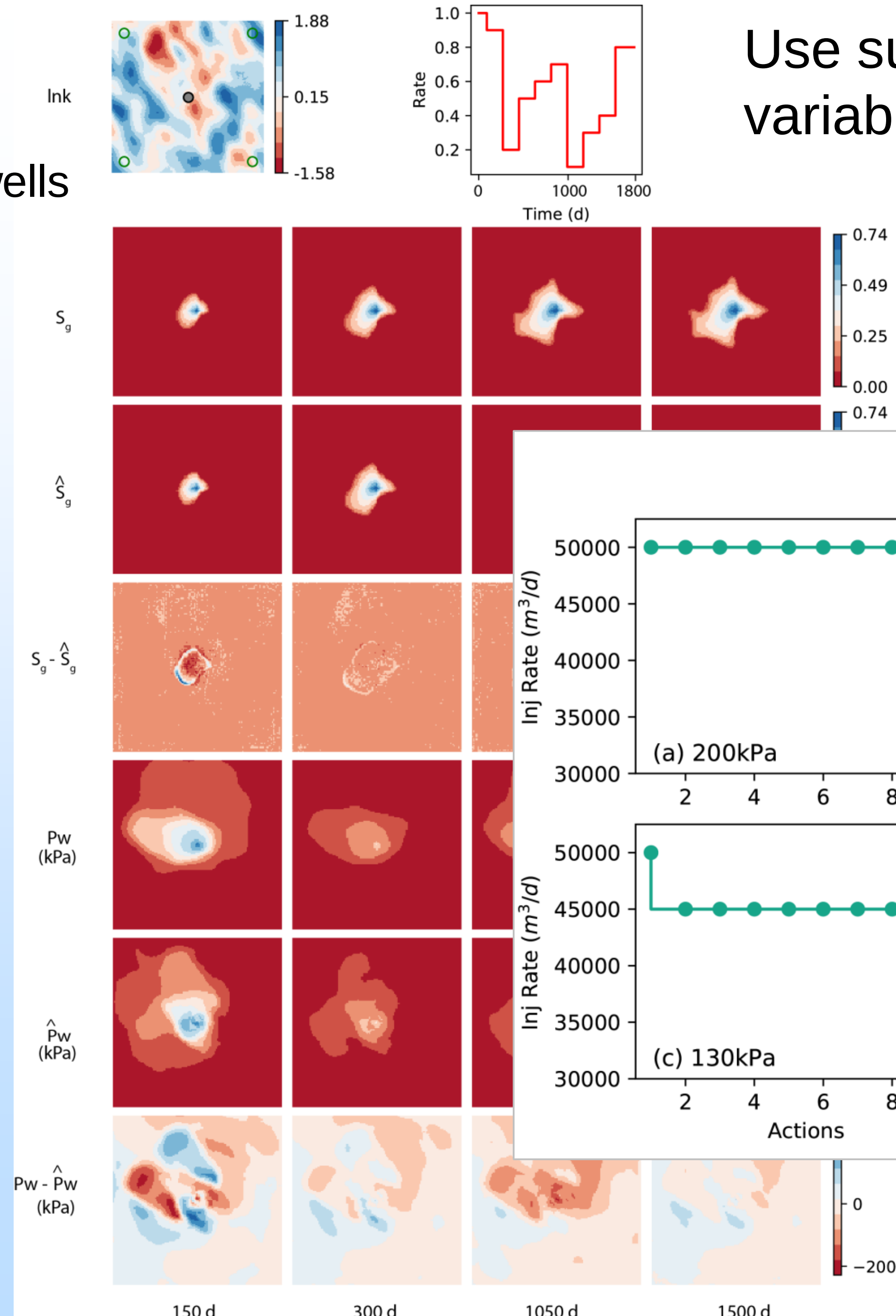


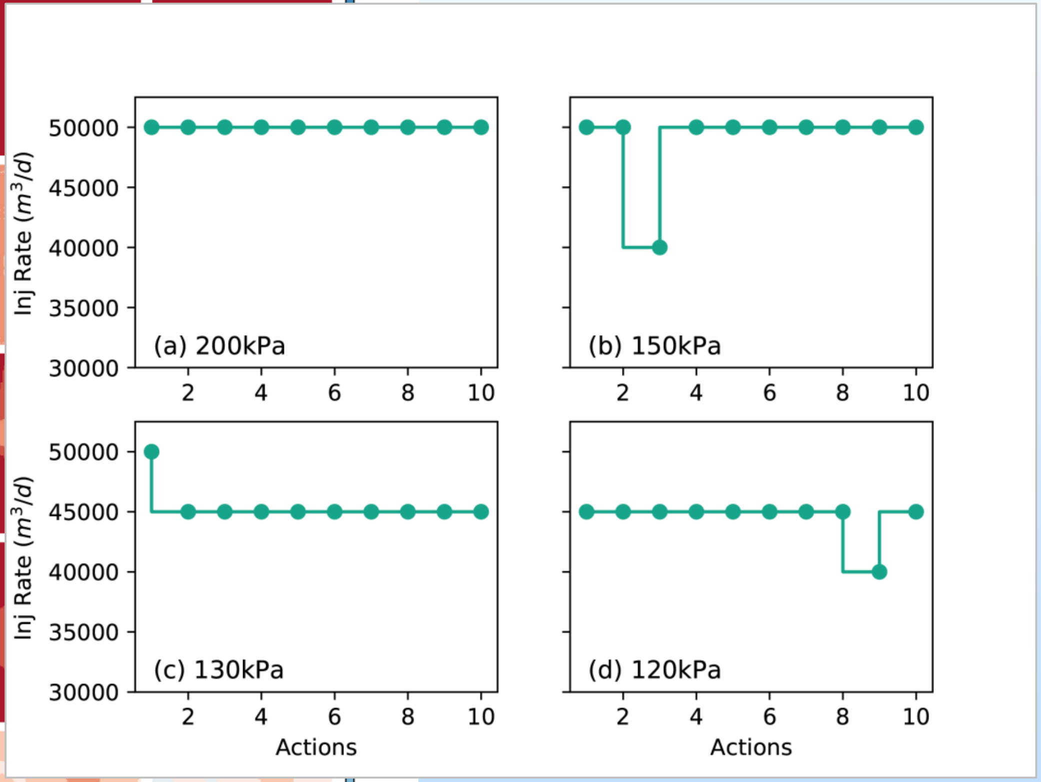
Sun, 2020

Use surrogate model to handle variable injection rate

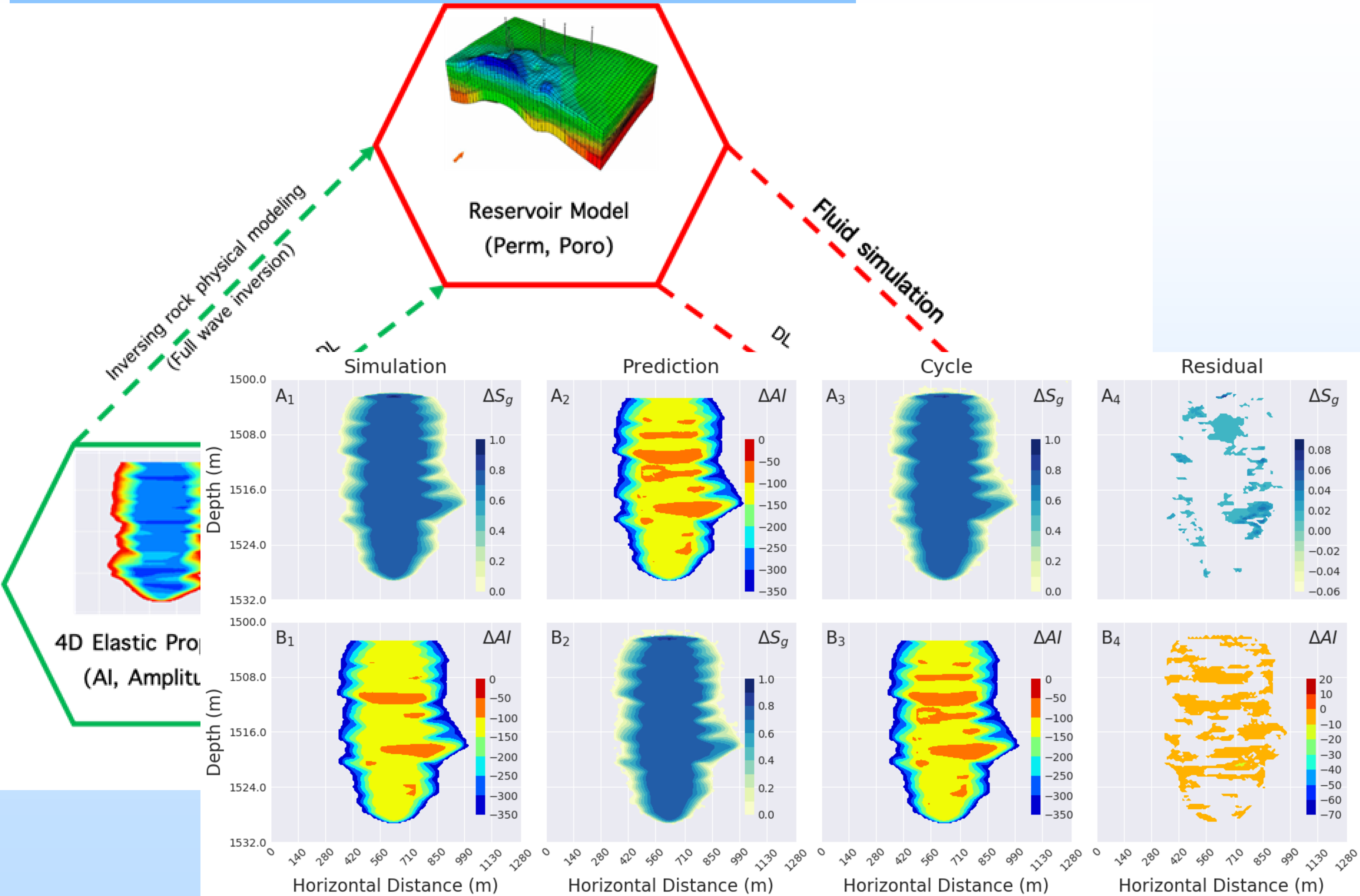
Injector

Monitoring wells



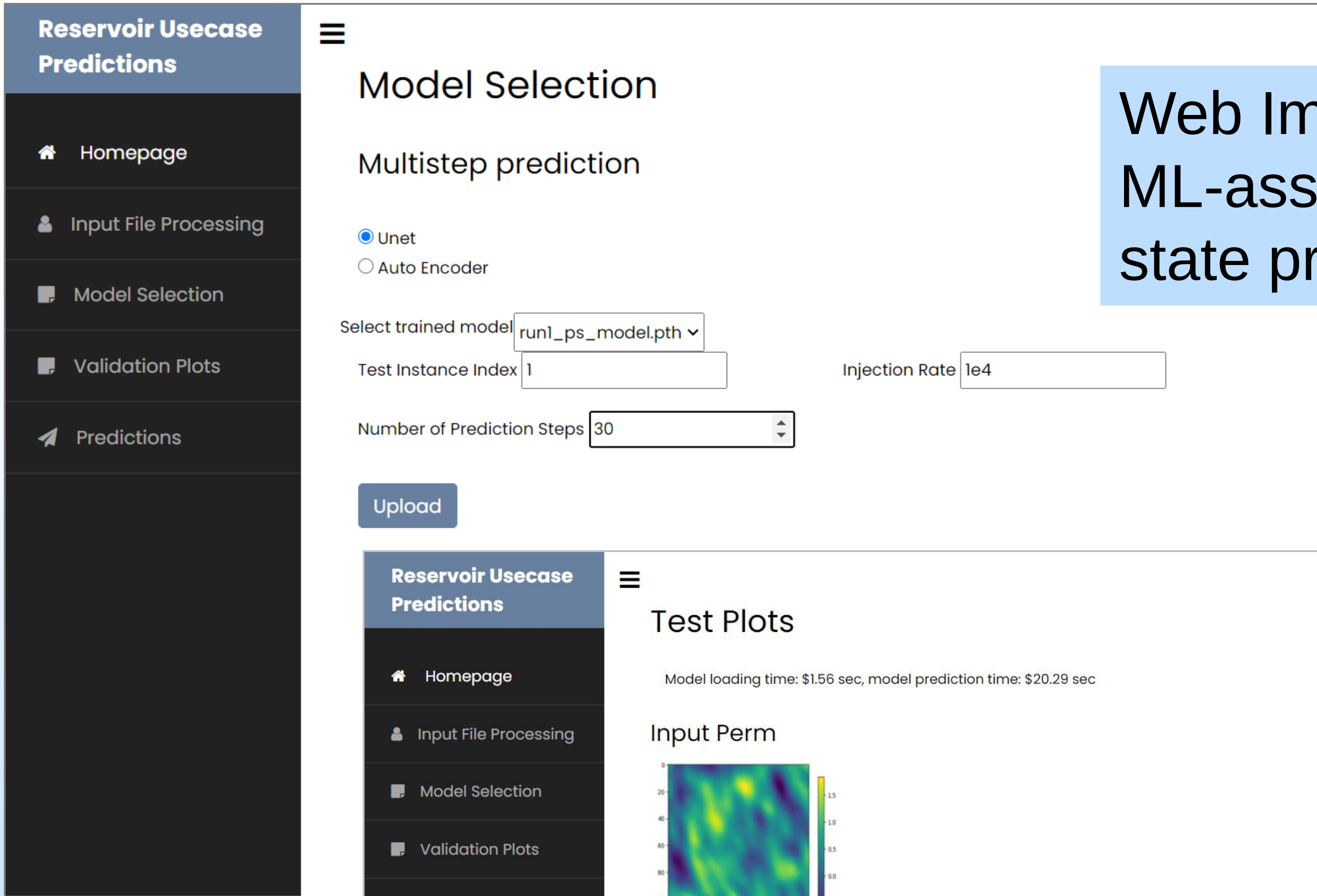


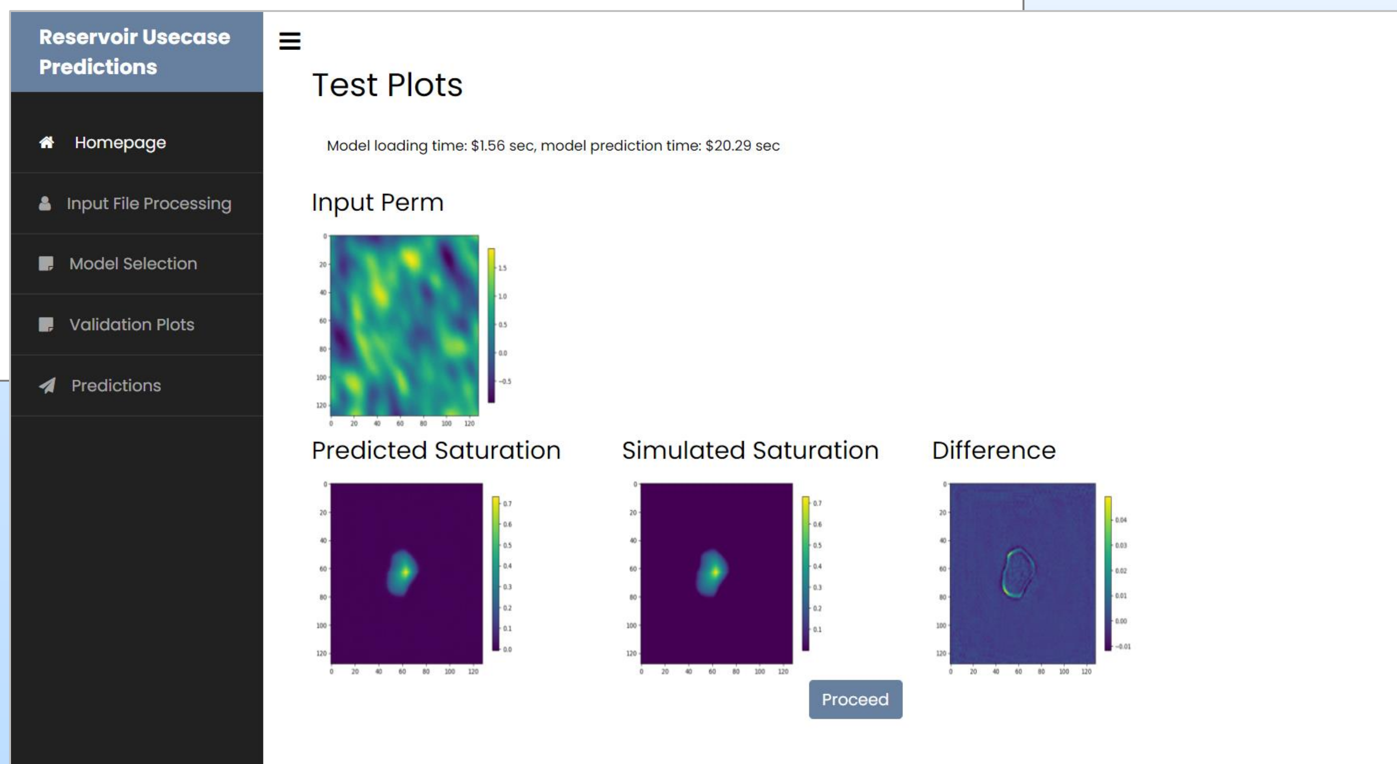
Joint Fluid-Seismic Inversion Use Case



Zhong et al., JGR, 2020

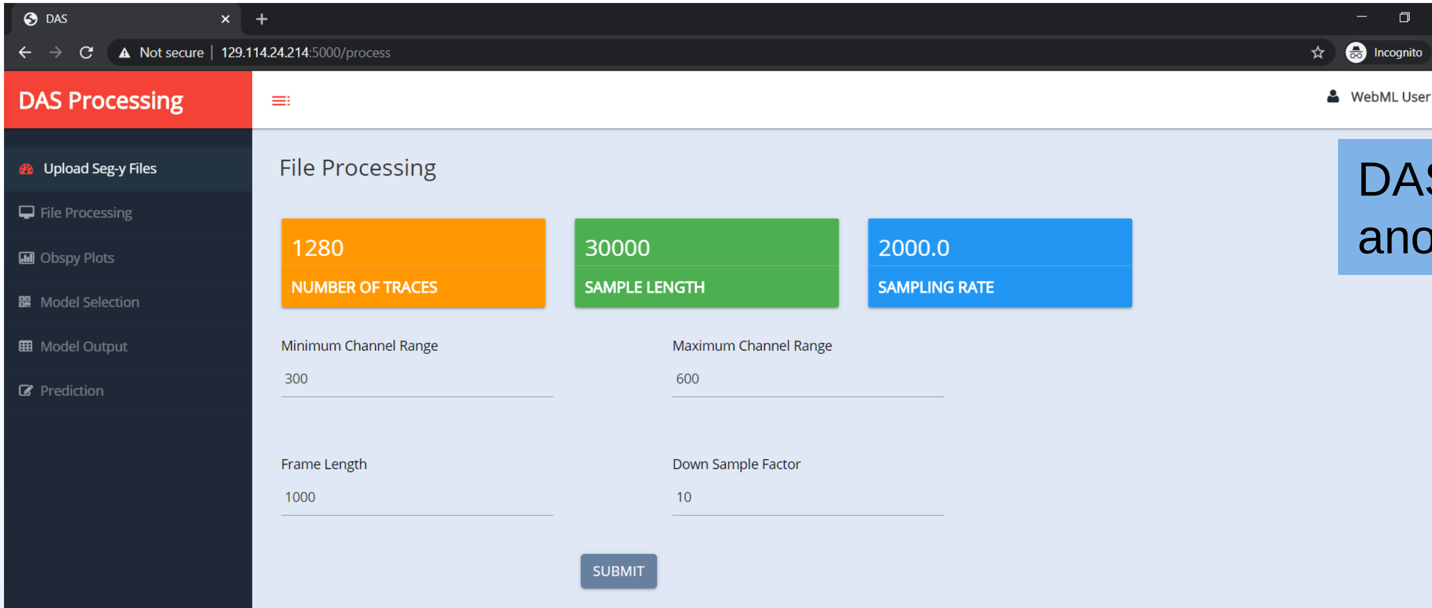
Web Implementation of ML-assisted reservoir state prediction

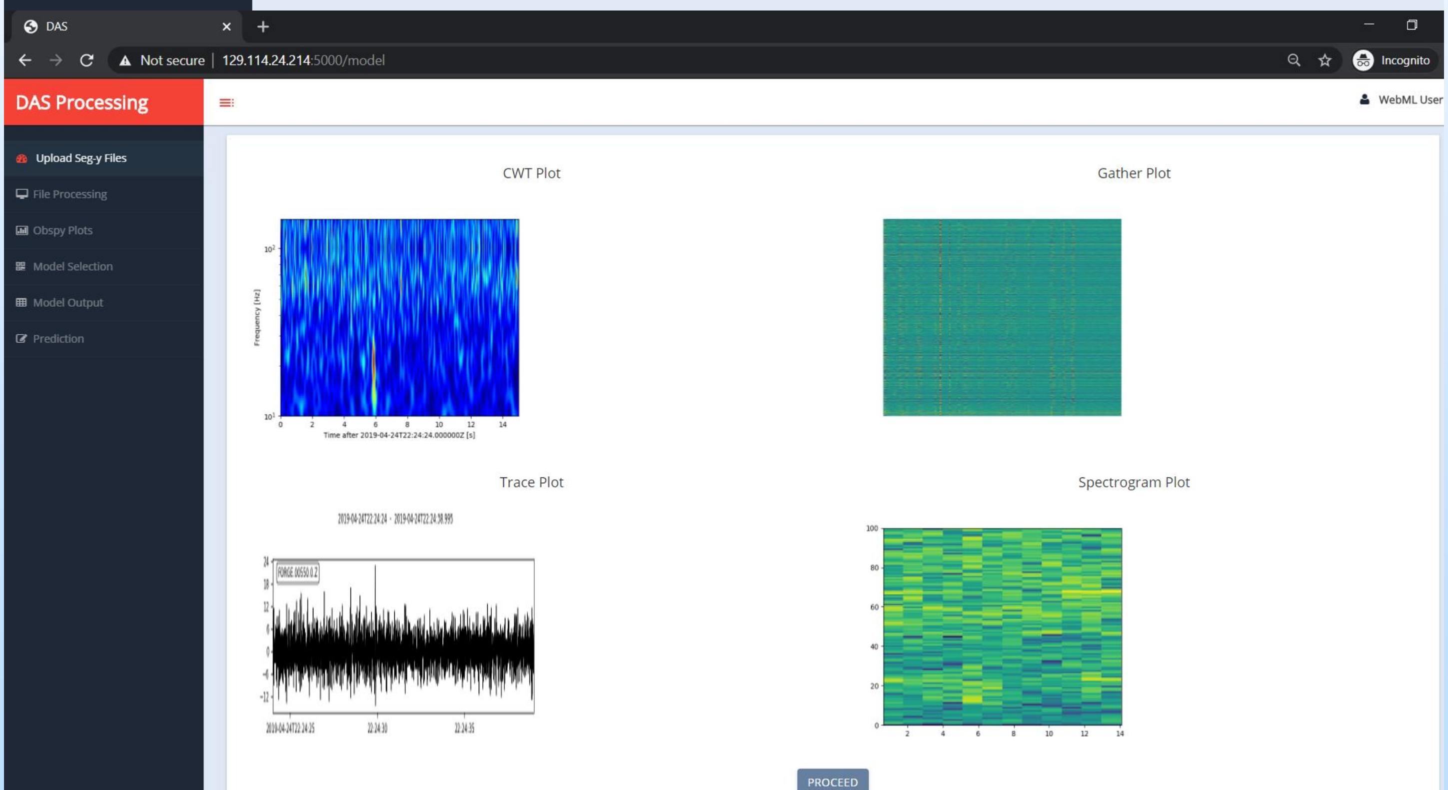




Web implementation of gas leakage detection system

DAS data stream anomaly detection





Accomplishments to Date

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

Lessons Learned

- Combining machine learning with domain knowledge may significantly improve efficacy of GCS management and risk mitigation
  - Time series anomaly detection can be automated effectively with current technologies
  - High-dimensional cases (e.g., distributed acoustic sensing) present more challenges

- All anomalies are different and no single method works for all cases

- The community needs a functional spec for intelligent monitoring system for GCS

Summary Slide

Project Summary

a. We developed a suite of tools for automating monitoring and anomaly detection in geological carbon sequestration projects
b. Combined machine learning with domain knowledge, implemented a web-based platform, and demonstrated over real and synthetic data
c. Results suggest that combining modern instrumentation with integrated, off-the-shelf platforms can significantly improve monitoring effectiveness.

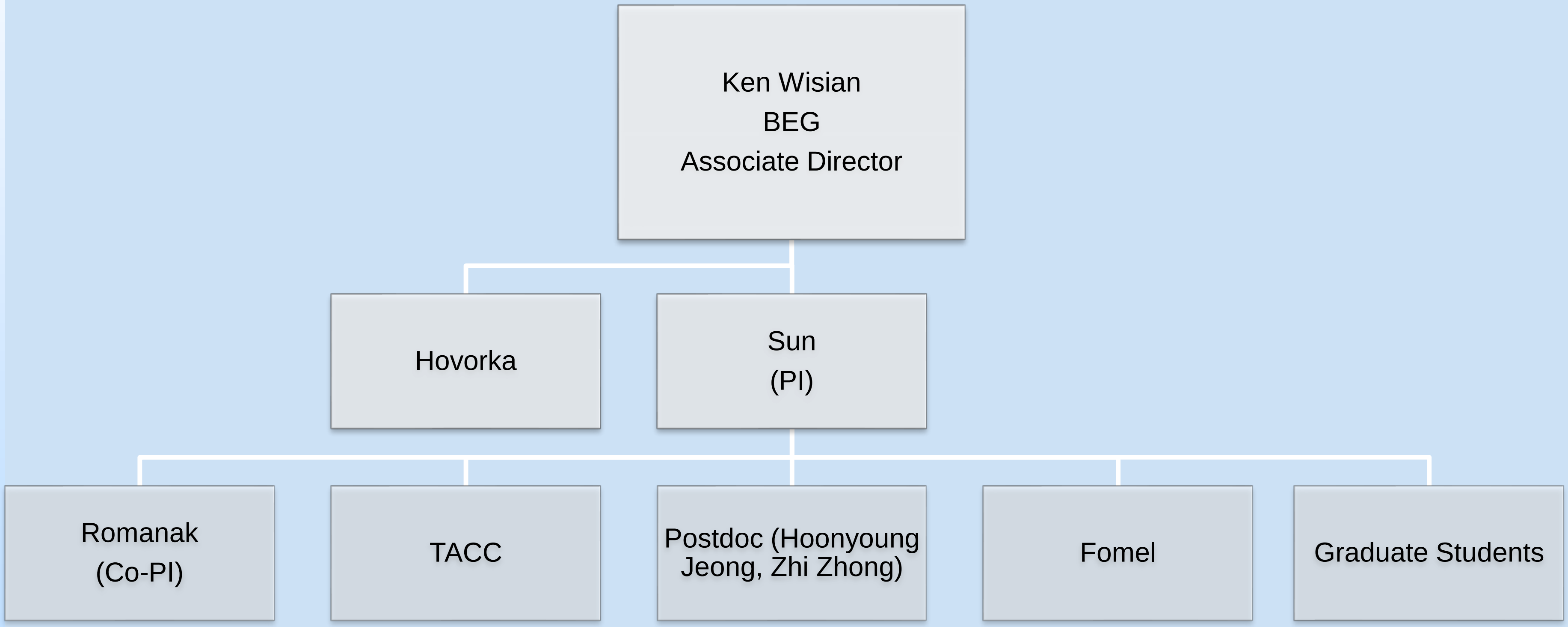
Future plans

a. Finish implementing and integrated Web-based tools
b. Complete the final project report

Appendix

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

Organization Chart



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Gantt Chart

Table 1. Revised Project Gantt chart
(Numbers in table rows indicate milestones).
(BP1-2 ; NCTE)

Task	Description	Year 1				Year 2				Year 3				Year 4				Year 5				Y6	
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2
1	Update project management plan																						
2	Sensor data management																						
2.1	Ontology/schema development																						
2.2	Sensor data development																						
3	CEP Development																						
3.1	Rule definition																						
3.2	Reasoning and learning																						
3.3	Testing																						
4	Coupled modeling/Assimilation																						
4.1	Coupled modeling																						
4.2	Reduced order modeling																						
5	Integration and demonstration																						
5.1	Integration																						
5.2	Demonstration																						
6	Synthesis of results																						
6.1	Dissemination of results																						
6.2	Technology transfer																						