SMART Initiative

Science-informed Machine Learning to Accelerate Real Time (SMART) Decisions in Subsurface Applications

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U.S. DEPARTMENT OF ENERGY

NATIONAL ENERGY TECHNOLOGY LABORATORY

SMART Initiative Organization

Science-informed Machine Learning to Accelerate Real Time (SMART) Decisions in Subsurface Applications

Transforming decisions through **clear vision** of the present and future subsurface.

Technical Team

Carnegie Mellon University
Los Alamos National Laboratory
National Energy Technology Laboratory
Battelle
EERC University of North Dakota
FACT
Lawrence Livermore National Laboratory
Colorado School of Mines
Oak Ridge National Laboratory
PennState
The University of Utah
Pacific Northwest National Laboratory
Bureau of Economic Geology
Sandia National Laboratories
Berkeley Lab
Illinois

SMART Initiative Goals and Timeline

FY19	FY20	FY21	FY22	FY23	FY24	FY25	FY26	FY27	FY28	FY29

PHASE 1

"Proof of Concept"

PHASE 2

"Development and Validation"

Real-Time Visualization
"CT" for the Subsurface

Virtual Learning
Rapid Prediction

Real-Time Forecasting
"Advanced Control Room"

using science-based Machine Learning to
transform the interactions with the subsurface and
significantly improve efficiency and effectiveness

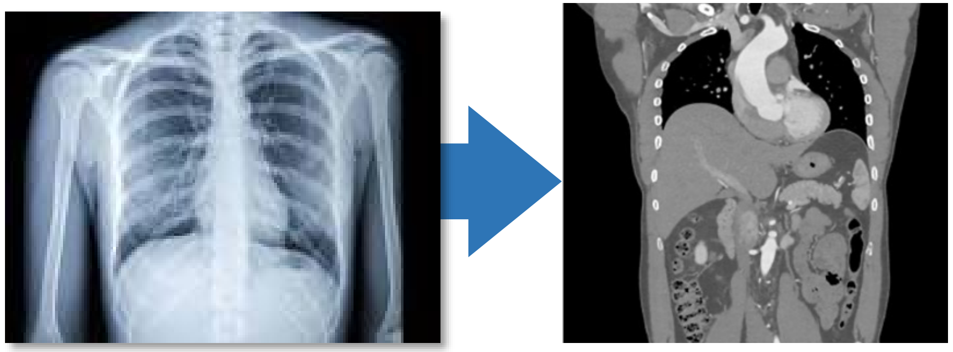
SMART Initiative – Real-Time Visualization

Science-informed **M**achine Learning to **A**ccelerate **R**eal **T**ime (SMART) Decisions in Subsurface Applications

Real-Time Visualization
"CT" for the Subsurface

Rapid Prediction
Virtual Learning

Real-Time Forecasting
"Advanced Control Room"



Phase 1 Outcome – Saturation Imaging

Science-informed **M**achine Learning to **A**ccelerate **R**eal **T**ime (SMART) Decisions in Subsurface Applications

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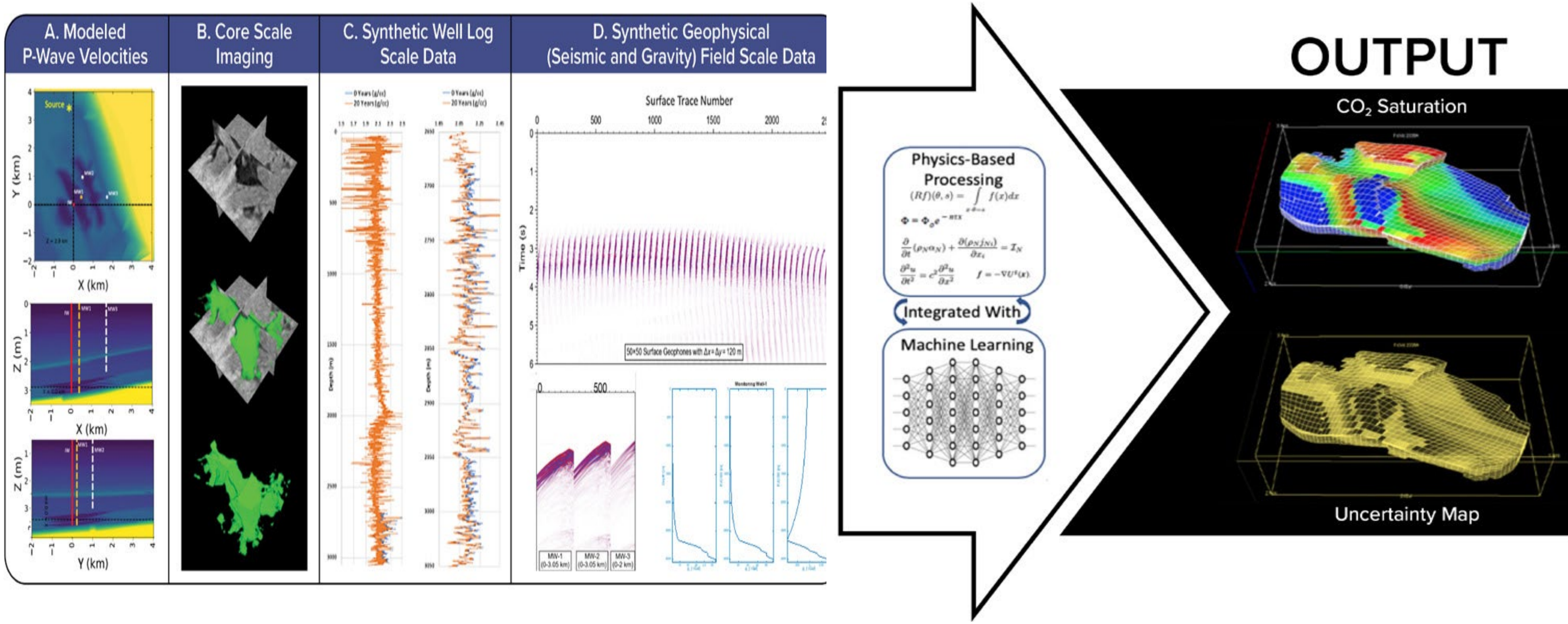
Rapid Multi-Physics Inversion and Uncertainty Quantification



SMART Initiative – Rapid Prediction

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Phase 1 Outcome – Virtual Learning Platform

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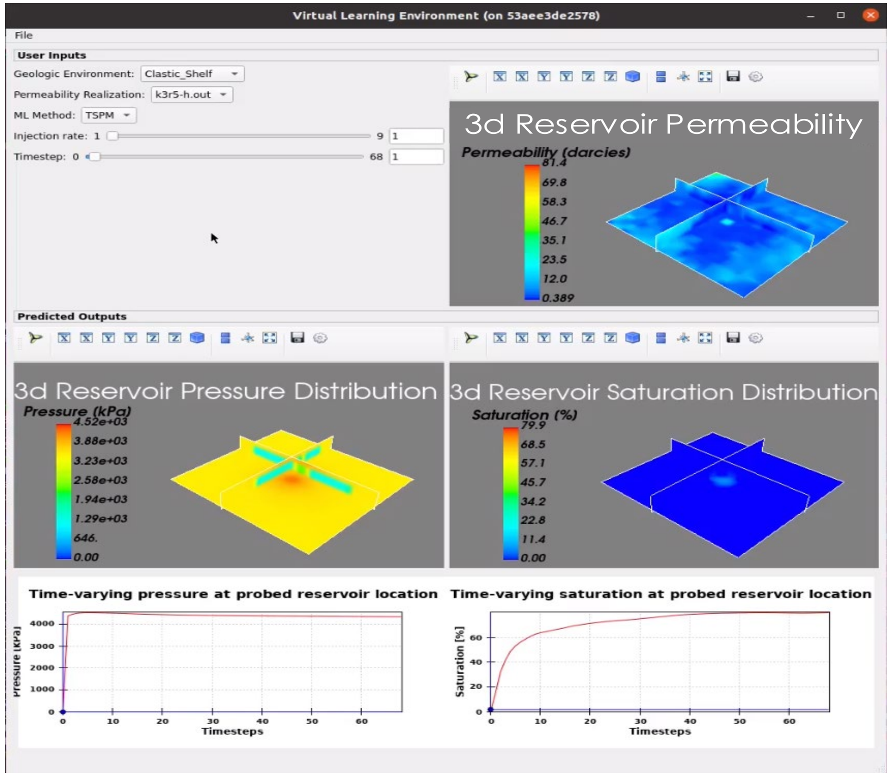
Prototype Virtual Learning Environment for Scenario Exploration



SMART Initiative – Real-time Forecasting

Science-informed **M**achine Learning to **A**ccelerate **R**eal **T**ime (SMART) Decisions in Subsurface Applications

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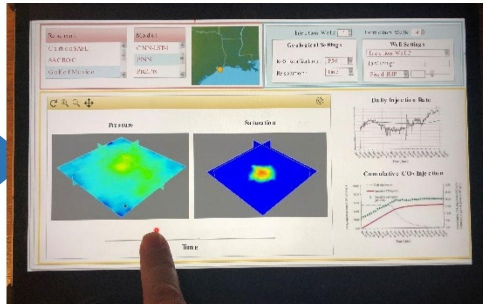

Phase 1 Outcome – Prediction of Leakage Related Anomaly

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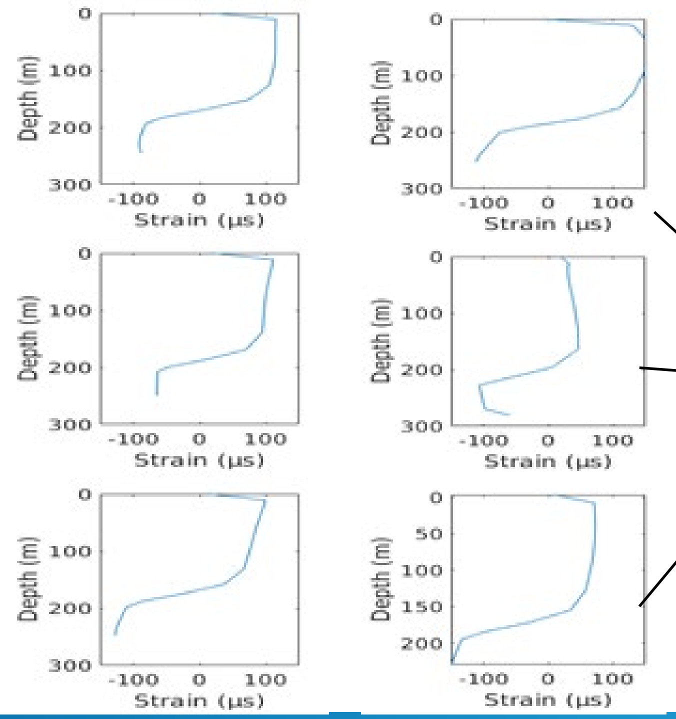
Near-Real Time Prediction, Visualization, and Anomaly Detection

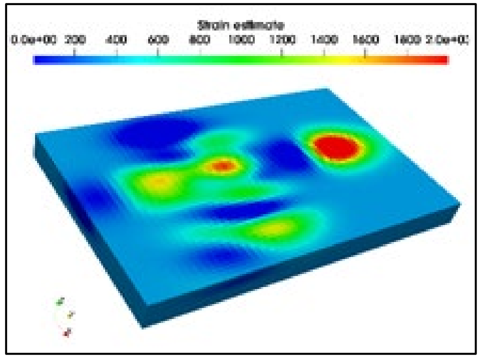
Input: Field data in near real-time



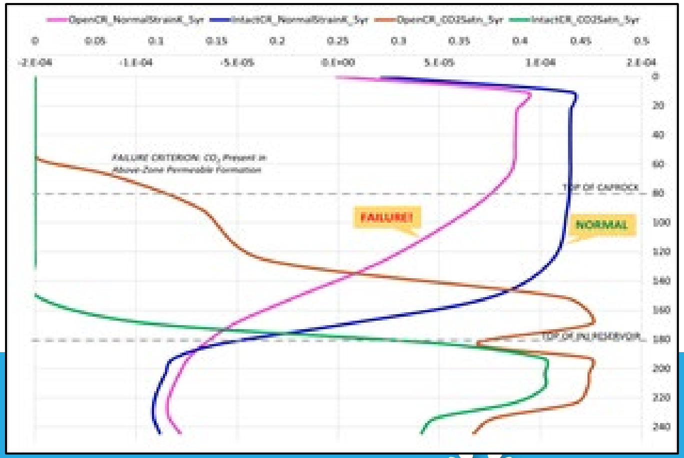
Trained ML models

Implementation

Strain distribution X days after start of injection



Normal vs. abnormal behaviour detection



SMART ⇨ Making Better Decisions

***Transforming** decisions through **clear vision** of the present and future subsurface.*

Decision-makers

Project Engineers

Regulators

High-level Executives

Landowners/Public

Phases

Site/Field Selection

Permitting

Development

Operations

Closure

Questions

❶ Where is the CO_2 now?

❷ How do I move the CO_2 where I want it to be?

❸ Is the project safe?

- Will it leak, and if so, where?
- Will it cause induced seismicity?

Phase 2 Important Technical Goals

***Transforming** decisions through **clear vision** of the present and future subsurface.*

Near-term Targets
(6-12 months)

- Exploration of reservoir behavior during injection relative to P, saturation, geologic uncertainties (evolution of AOR)
- Integration of early stage (pre-injection) risk-based workflows

Mid-term Targets
(2-5 years)

- Exploration of changes to state-of-stress during injection or extraction
- Exploration of subsurface characteristics (core to basin)
- Optimization of reservoir operations (injection–extraction) to maximize sweep and minimize delta-pressure

Overall Phase 2 Framework (FY22 – FY26)

- **Phase 2a ⇨**
  Demonstrate virtual learning in action to support regulators & stakeholders during permitting

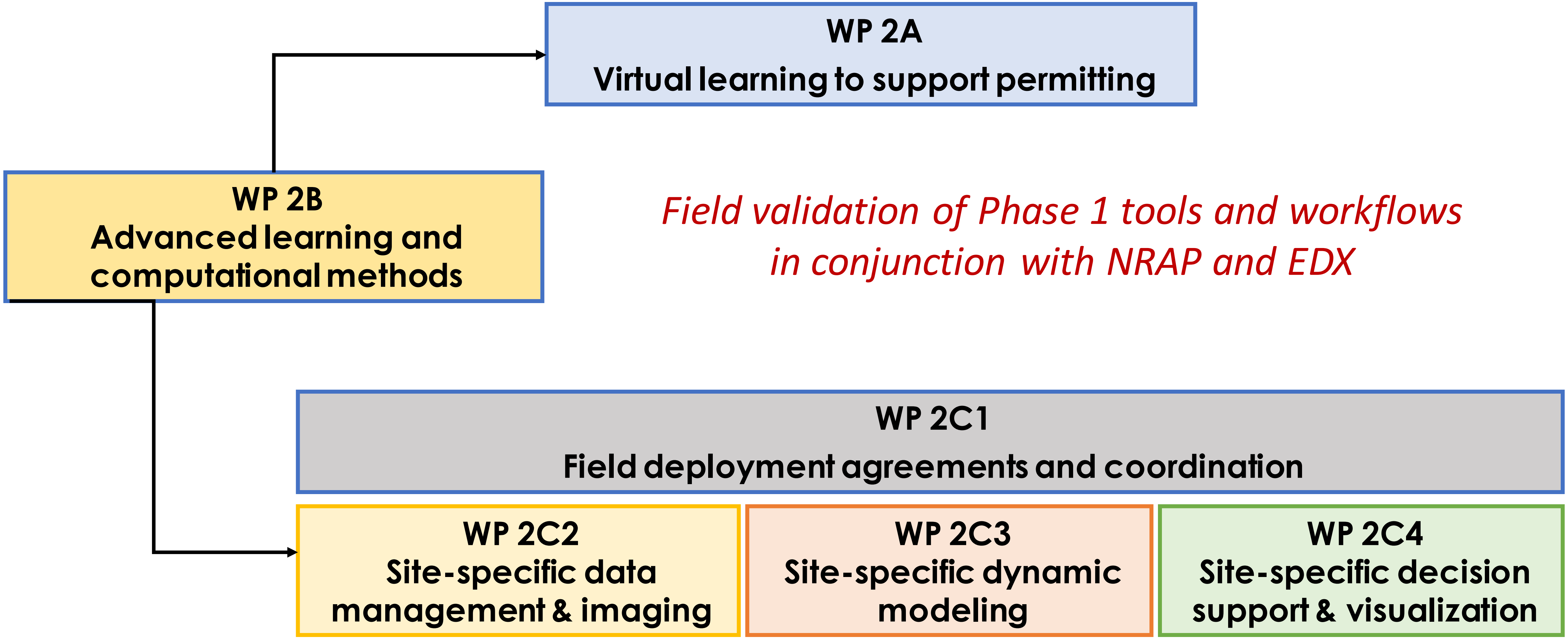
- **Phase 2b ⇨**
  Develop advanced learning and computational methods

- **Phase 2c ⇨**
  Apply ML-assisted workflows from Phase I for field-scale deployment

[Q] What new insights/information can be obtained by applying ML-assisted workflows to the same data? Can we improve ease of use/communication during Class VI permitting?
(case study - WY CarbonSAFE)

[Q] Can (near) real-time feedback be provided for operational control and optimization? How can ML-assisted workflows improve system understanding?
(case study – IBDP/ICCS)

SMART Phase 2 Overview



2A – Virtual Learning in Action to Support Permitting

Goal ⇨ Demonstrate how ML and virtual learning can be used in permitting process:

- Regulators and site developers are key customers
- Work with the existing permit application (FutureGen/IBDP) to show added value

Activity 1:
Outreach to Regulators

Identify how Machine Learning based approaches can help during Class VI permitting process

Activity 2:
Improved Site Characterization

Demonstrate application of ML-based approaches to improve site-characterization efforts performed during the pre-injection phase

Activity 3:
Rapid Forecasting

Demonstrate how ML-based rapid forecasting can help with pre-injection reservoir management decisions under data uncertainties

Activity 4:
Model Explorer

Show how a visualization platform with ML models can help stakeholders explore key prediction uncertainties that affect injection/storage operations.

Activity 5:
Value of Information and Economic Decisions

Demonstrate how Machine Learning based approaches can be used to help with the value of information using FutureGen and/or IBDP data/models.

2B – Advanced Learning & Computational Methods

Goal ⇨ Develop advanced machine learning and computational methods:

- Standardization and integration of software development
- Keep up with technology beyond Phase 1 tools and workflows

Activity 1:
Software QA

Develop quality, reliability, and version control standards for SMART software

Activity 2:
Cross-task Integration

Combine, select, and adapt the tools to be better suited to WP 2A and 2C needs, and as well will continually work to identify gaps and weak points in the evolving workflow system

Activity 3:
Advanced Machine Learning Methods

Focus on new AI/ML methods (beyond those used in Phase 1) that could be quickly transitioned to the applications being addressed by WP 2A and 2C activities

Activity 4:
Advanced Computational Approaches

Continue development of new computational approaches to enhance performance (accuracy, efficiency, privacy) of predictive models

2C.1 – Field Deployment - Site-Specific Implementation

Goal ⇨ Coordinate project management and stakeholder interaction:

- Goal is to work with data from 1-3 sites undergoing CO_2 injection
- ADM project likely candidate + CarbonSAFE projects + external projects

Activities:

[1] Data sharing agreements + privacy + confidentiality

[2] Project management and stakeholder interaction

2C.2 – Field Deployment - Data Management and Imaging

Goal ⇨ Acquire, organize, and image various static and dynamic data:

- Provide "images" of the subsurface (saturation, pressure/stress, fracture/faults)
- Develop and maintain shared geomodel for modeling and visualization

Teams:

Team 1 - **Geostatistics, ensemble** generation, data compression

Team 2 - **Seismic and microseismic** methods

Team 3 - **Non-seismic** methods (e.g.: Gravity, EM, InSAR/geodetic)

Team 4 - **Dynamic** methods (e.g.: Pressure, temperature, strain, injection/production, chemistry, tracers)

Team 5 **- Fracture/fault mapping** utilizing a range of data streams (E.g.: microseismic, wellbore, DAS, DTS, tracer).

Activities:

[1] Initial background data collection and data platform

[2] Advanced data processing and data preparation

[3] Data inversion for generating reservoir "images"

2C.3 – Field Deployment - Dynamic Storage Reservoir Modeling

Goal ⇨ Provide real-time modeling, data assimilation, and forecasting to provide:

- Induced seismicity risk assessment
- Field management to maximize storage while minimizing pressure buildup

Activity 1:
Fast ROMs for Flow & Geomechanics

Provide very rapid forward models that can either be used directly in data assimilation workflows or for training ML surrogates

Activity 2:
Machine Learning Surrogates

Provide ML-based forward-model surrogates that can replace full physics or reduced-order models within data-assimilation workflows

Activity 3:
Rapid Data Assimilation

Perform history matching and related data-assimilation activities to update site geomodel using the observation database to improve the model (or ensemble model) predictivity.

Activity 4:
Optimization of Field Parameters

Determine optimal well management strategy (rates, locations, perforation depths) to maximize storage volume while minimizing pressure buildup or other operational constraints.

2C.4 – Field Deployment - Decision Support & Visualization

Goal ⇨ Translating imaging and modeling results to decision-making metrics

- Clear, actionable decision support platform
- Regulators and stakeholders will be key customers

Activity 1: Induced Seismicity Module	Activity 2: Virtual Learning Module	Activity 3: Real-time Forecasting & Operational Control Module	Activity 4: Risk and Economic Analysis Module
Build decision-making intuition for end-users using fast simulation approaches relating to: • Seismic hazards • Detected anomalies • Induced seismicity risk	Offer functionality to leverage ML-based rapid forecasting models to evaluate the effects of reservoir management decisions at partnering sites at pre-, during, and post-injection instances.	Rapidly integrate monitoring data to generate real-time updates and visualizations of CO_2 storage performance. Provide actionable decision support to improve or modify operations or monitoring strategies.	Translate ML-based modeling forecasts generated from geologic, operational, and observational data into meaningful metrics related to risk and economic insights.

Stakeholder Advisory Group

- Providing an independent check on the technical innovativeness and practical relevance of ideas and approaches
- Representing an operator and/or end-user perspective (as appropriate)
- Advising SMART on how to inform external audiences most effectively about the initiative and its outcomes

- Dr. Ganesh Thakur, University of Houston (Chair)
- Dr. Detlef Hohl, Shell
- Ms. Molly McEvoy, U.S. EPA
- Dr. Neeraj Gupta, Battelle Memorial Institute
- Dr. Robert Zeller, Oxy Low Carbon Ventures
- Dr. Iraj Ershaghi, U. of Southern California
- Ms. Kimberly Sams Gray, SSEB
- Mr. Wesley Peck, EERC

General Remarks

- **Phases 2A and 2C will be for specific sites**
  - Working with actual data
  - Structured as a typical O&G field project (with teams)
  - Working to apply the latest advances from within SMART and beyond
  - Limited scope for answering fundamental research questions
- **Focus on providing added value for decision making**
  - Show utility of ML-assisted tools (beyond physics-based methods)
- **Linkage with visualization prize winners and tools/platforms**

SMART and NRAP – Distinct But Complementary

- Focus on ML-assisted tools and workflows for GCS performance
  - Improved imaging of subsurface
  - Rapid performance prediction and "what-if" scenario evaluation
  - Real-time feedback for optimal operational control
- Virtual Learning tools for improved community and regulatory understanding (AoR, site description)

National Risk Assessment Partnership

- Physics-based forecasting tools for GCS risk management
  - Leakage risk assessment
  - Induced seismicity risk management
- Strategic monitoring for risk reduction
- Addressing stakeholder needs for permitting and project startup (risk assessment & management)

Thank You!

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