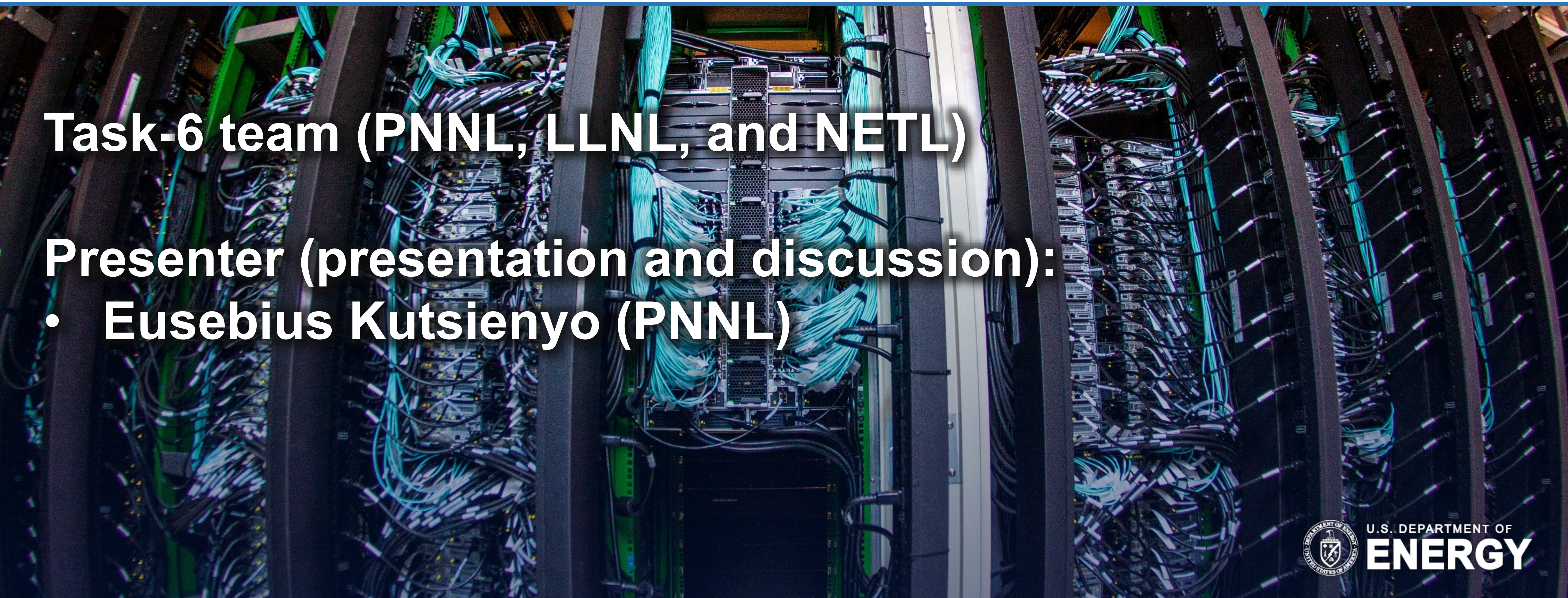
SMART tools for Geologic Carbon Storage Applications

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



Task-6 team (PNNL, LLNL, and NETL)

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U.S. DEPARTMENT OF ENERGY

Acknowledgments and disclaimers

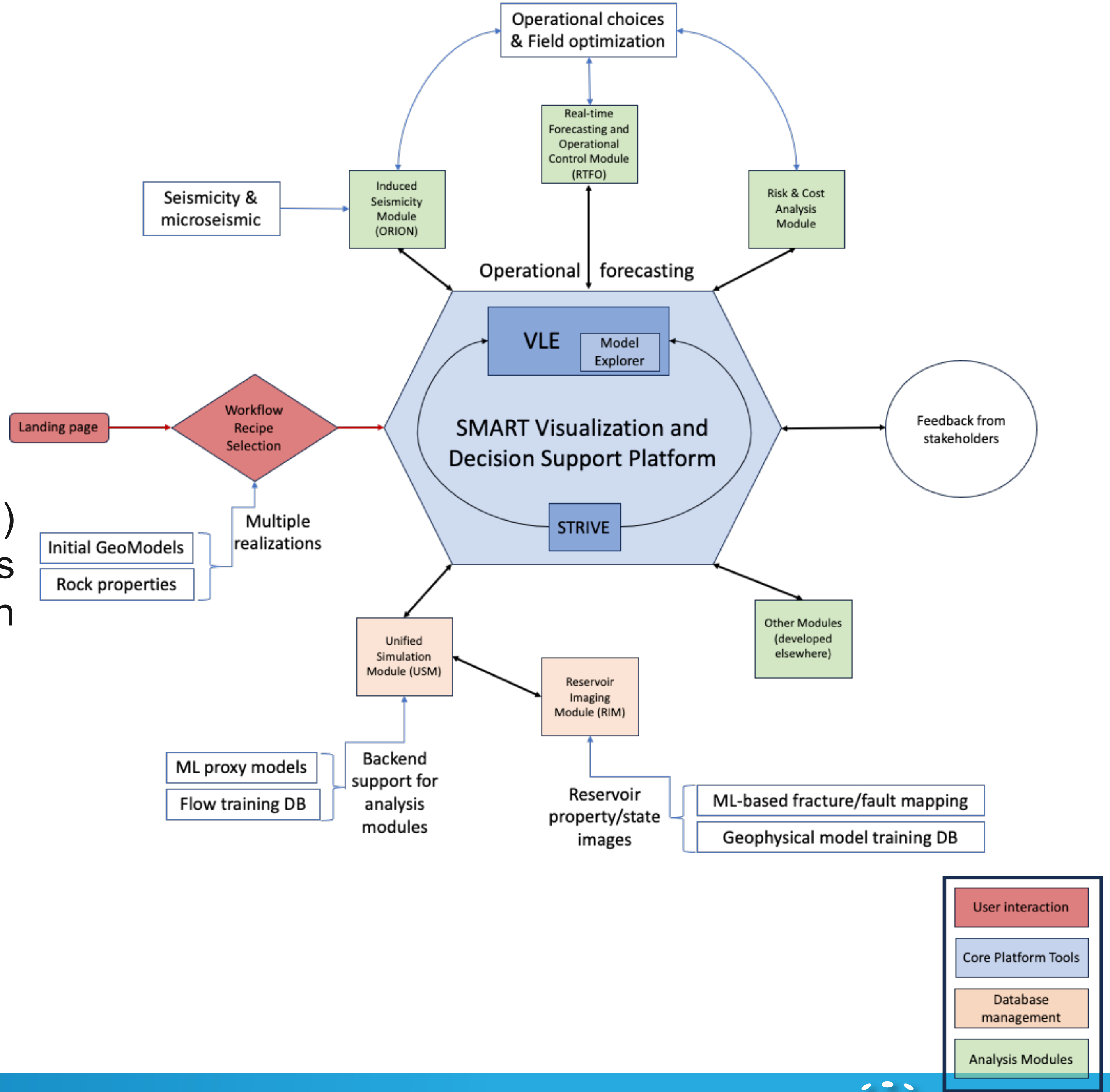
This work is developed with funding support from the United States Department of Energy's Office of Fossil Energy and Carbon Management (DOE-FECM) through the Science-informed Machine Learning to Accelerate Real-Time (SMART) Decisions in Subsurface Applications Initiative. This support is gratefully acknowledged. Portions of this work were produced under the auspices of the U.S. Department of Energy by Pacific Northwest National Laboratory under Contract DE-AC06-76RLO1830.

SMART Initiative

Our objectives:

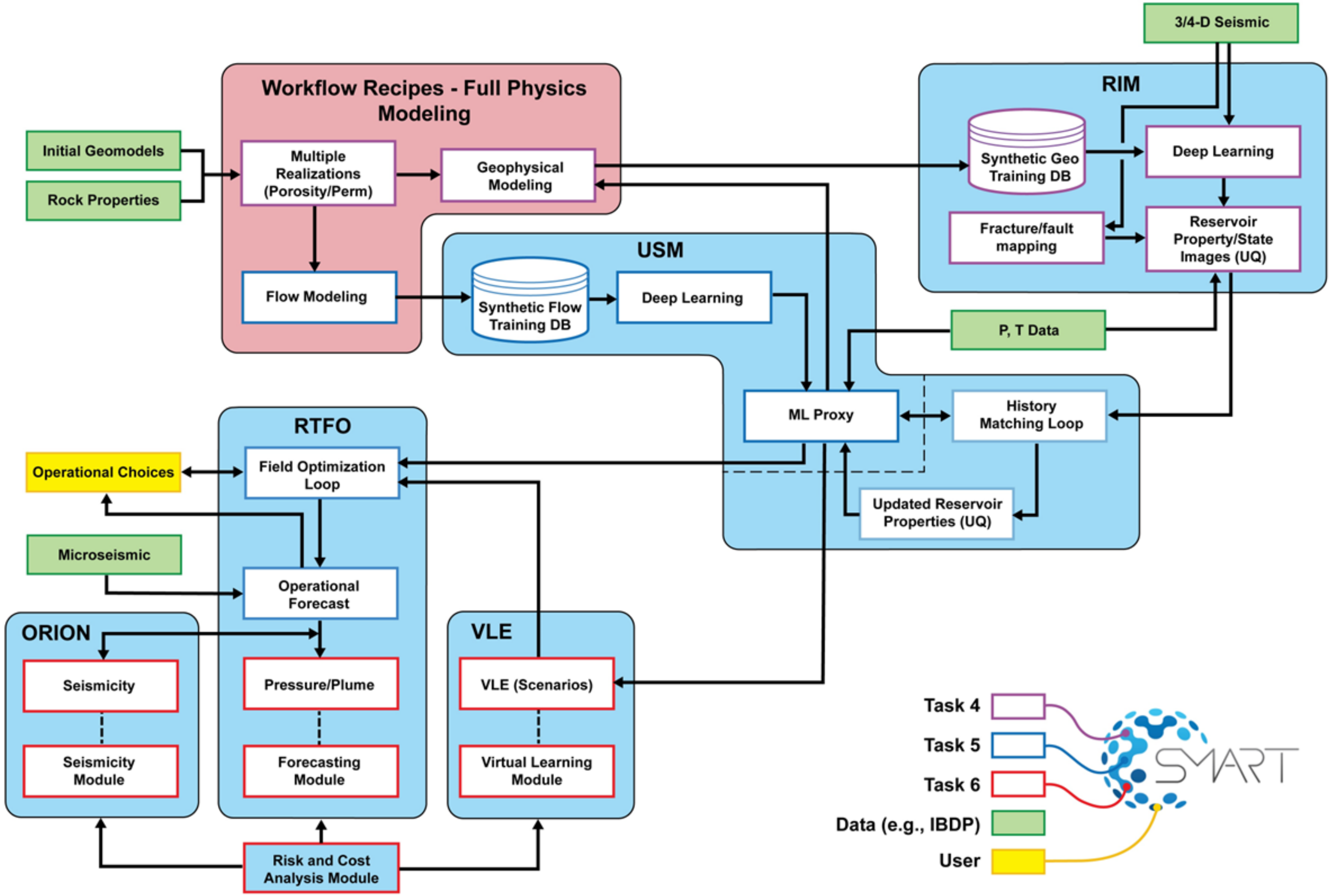
Showcase how the utilization of Machine learning (ML) can significantly improve efficiency and effectiveness of field-scale commercial carbon storage operations in three main areas:

- ❑ Real-time visualization
- ❑ Real-time forecasting
- ❑ Virtual learning



SMART Modules Cross-talk

Summary: The platform is a suite of integrated tools or modules developed within SMART initiative to make better and informed decisions related to the geologic carbon storage through real-time visualization, forecasting, and virtual learning.



Workflow recipes of SMART modules and tools interaction

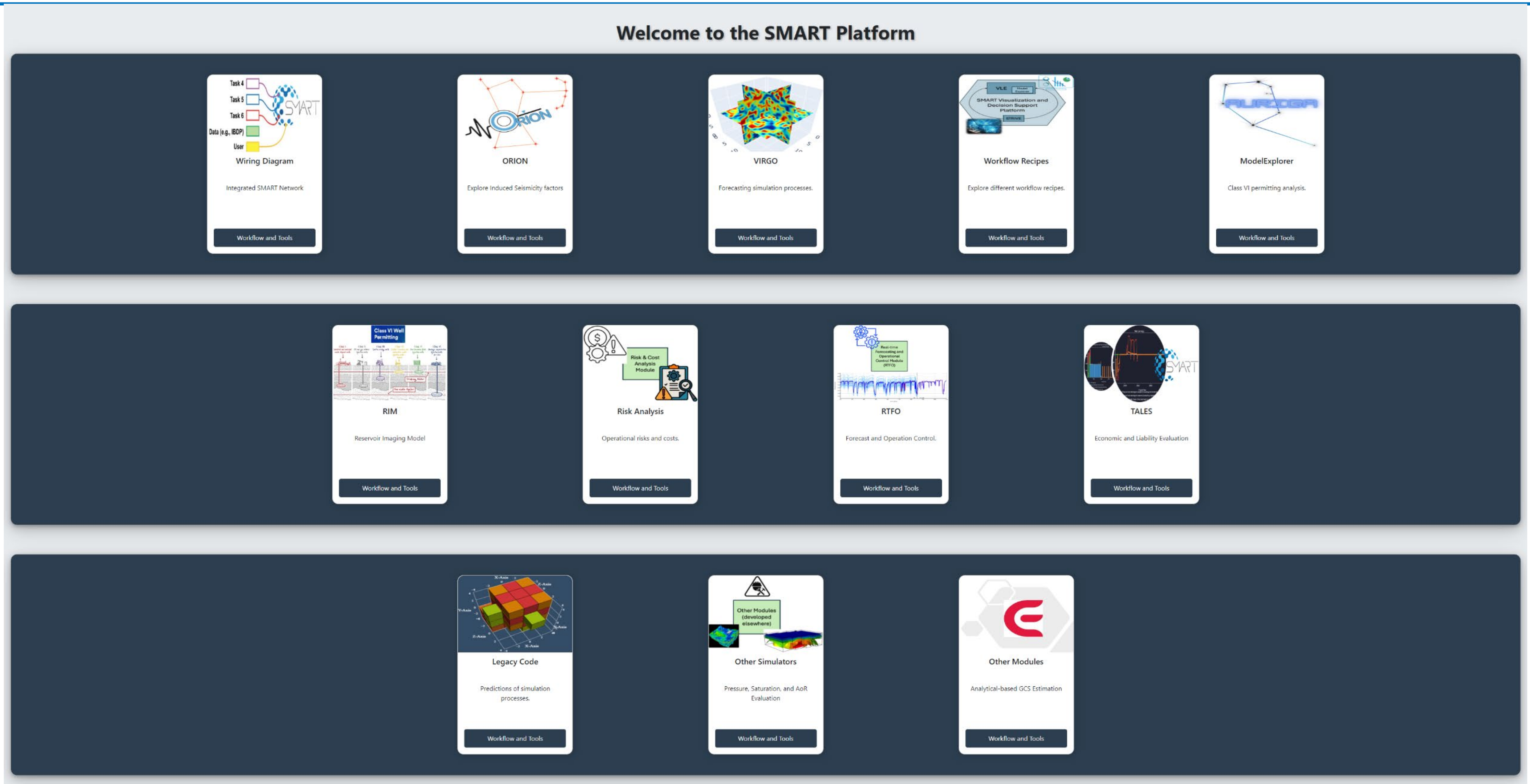
Functionality of the SMART tools

SMART tools deployment in commercial-scale GCS projects

- ➢ Enabling dramatic improvements in the visualization of key subsurface features and flows,
- ➢ Creating a computer-based experiential learning environment to improve field development and monitoring strategies, and
- ➢ Transforming storage reservoir management by rapid analysis of real-time data and rapid forward prediction under uncertainty to inform operational decisions.

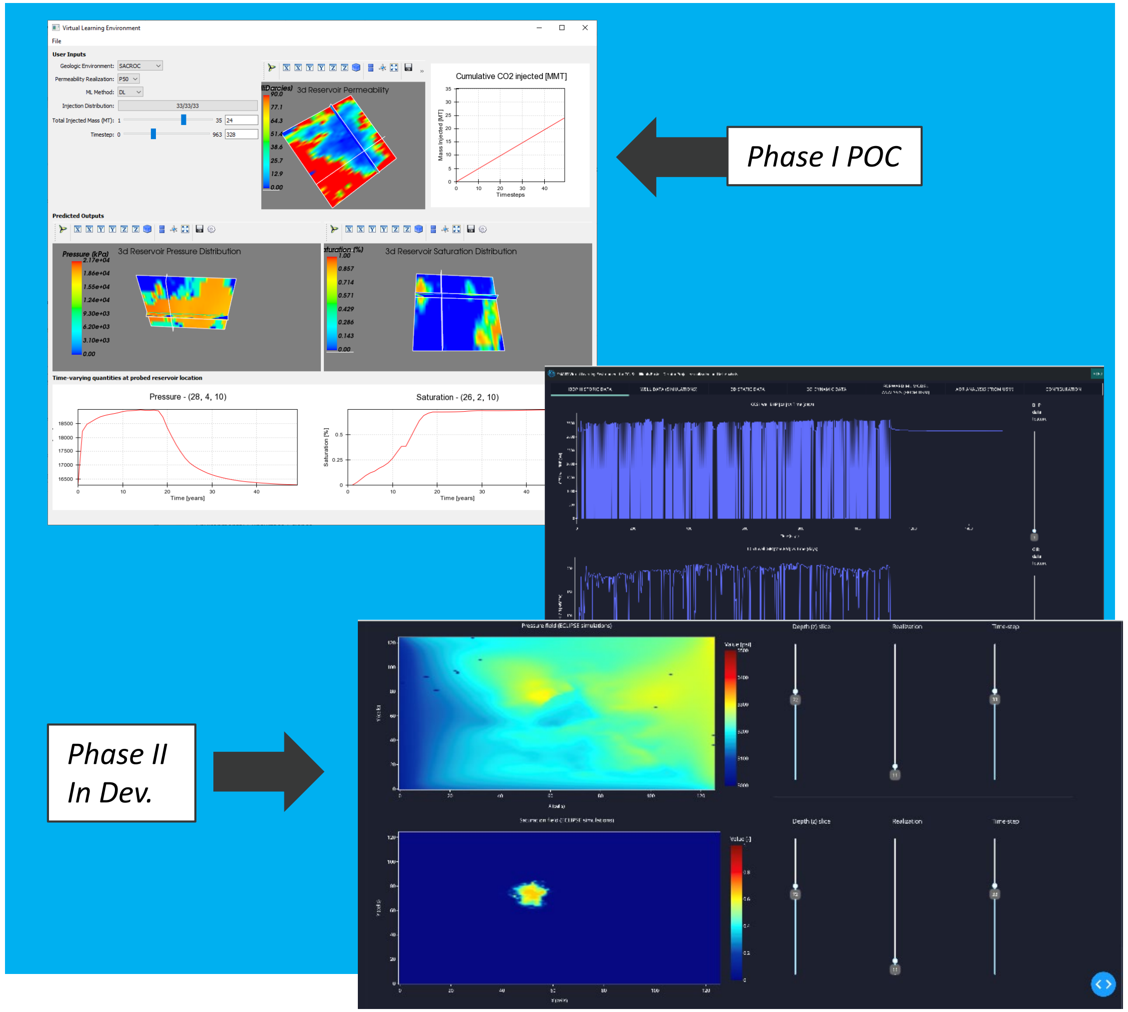
- **Outcome**
  - ➢ Successfully deployed tools: Awaiting feedback from CCS stakeholders - incorporating feedbacks into SMART module development

SMART platform and its graphical user interface (EY24 early version)



STRIVE-based Virtual Learning Environment (VLE) Module

*The **Virtual Learning Environment (VLE)** is an exploratory module which uses ML predictions to rapidly inform an end user of how a given reservoir simulation would likely change in response to altered inputs (i.e., “What-if” scenarios)*



Phase II development utilizing STRIVE progress includes:

- Encompass Phase I behavior
  - Explore *predicted* changes in pressure and saturation over time given injection rate and rock property profile
  - Additional framing data (AoR) is integrated
  - ML model analysis and visualizations
- Be migrated to an online environment
- Import ML data from Unified Simulation Module (USM)
- Exploring the during and post-injection scenarios

Benefit to CCS industry:

- **Virtual learning:** Computer-based experiential learning environment to improve field development and monitoring strategies
- **Real-time visualization:** Visuals of key subsurface features and flows by exploiting ML to substantially increase speed and enhance detail

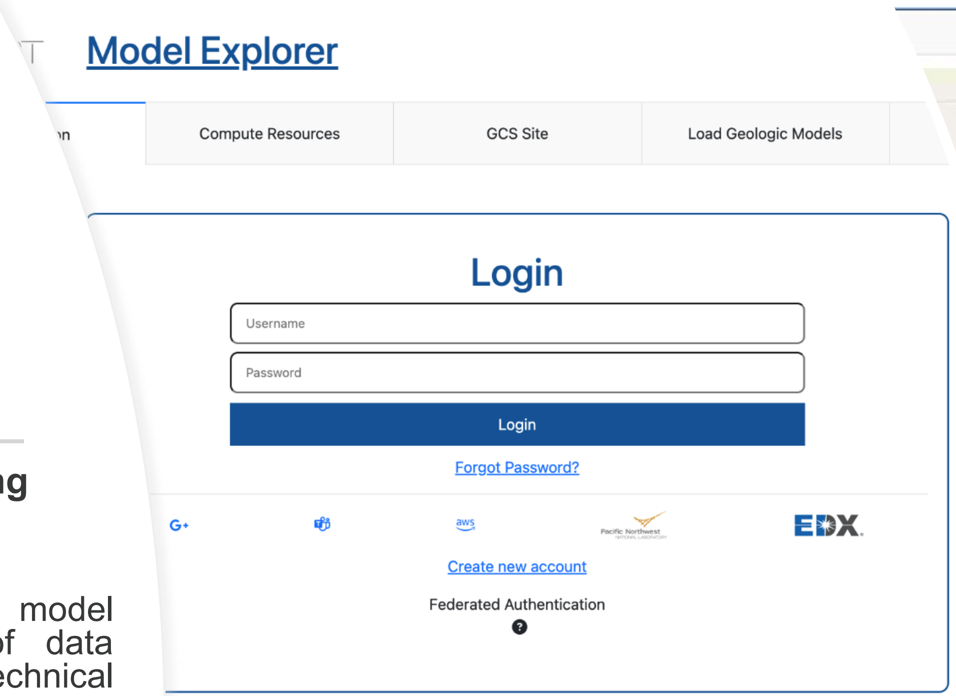
Model Explorer

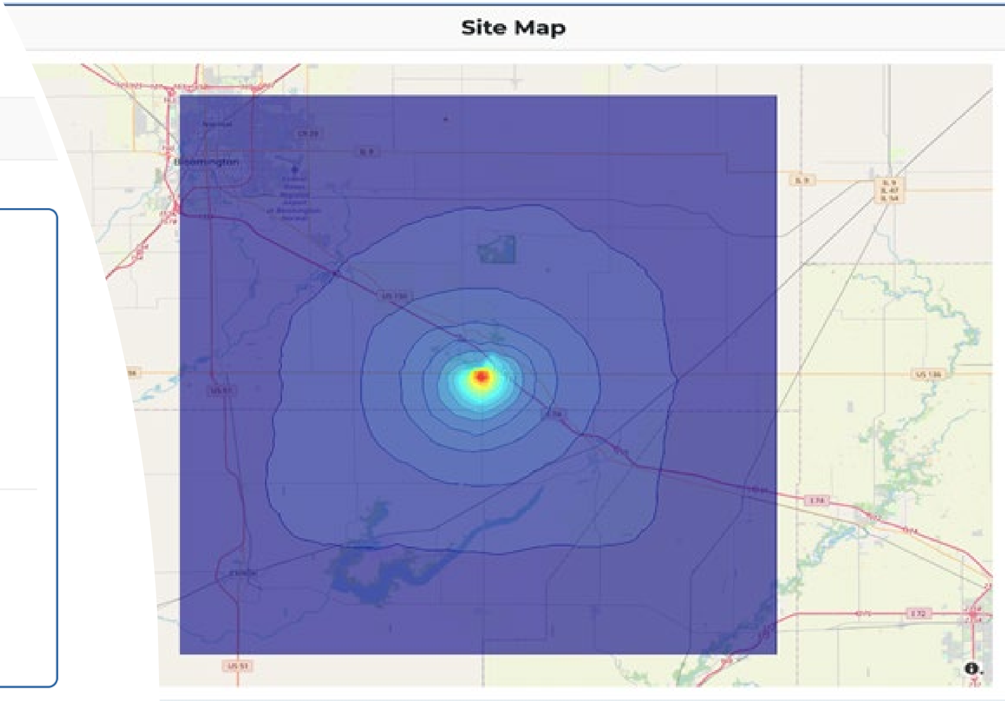
Accelerate the Class-VI permitting process:

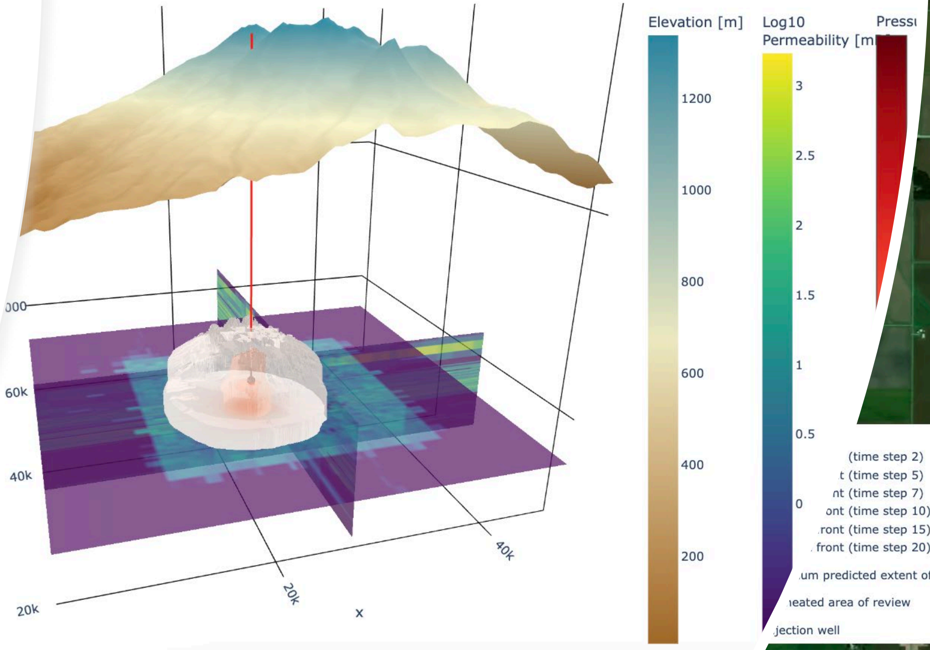
- Allows for quick visualization of the model inputs, output, and other types of data integration, where multiple sets of technical information (e.g., site characterization data and modeling input) can be visualized and evaluated in an integrated fashion.

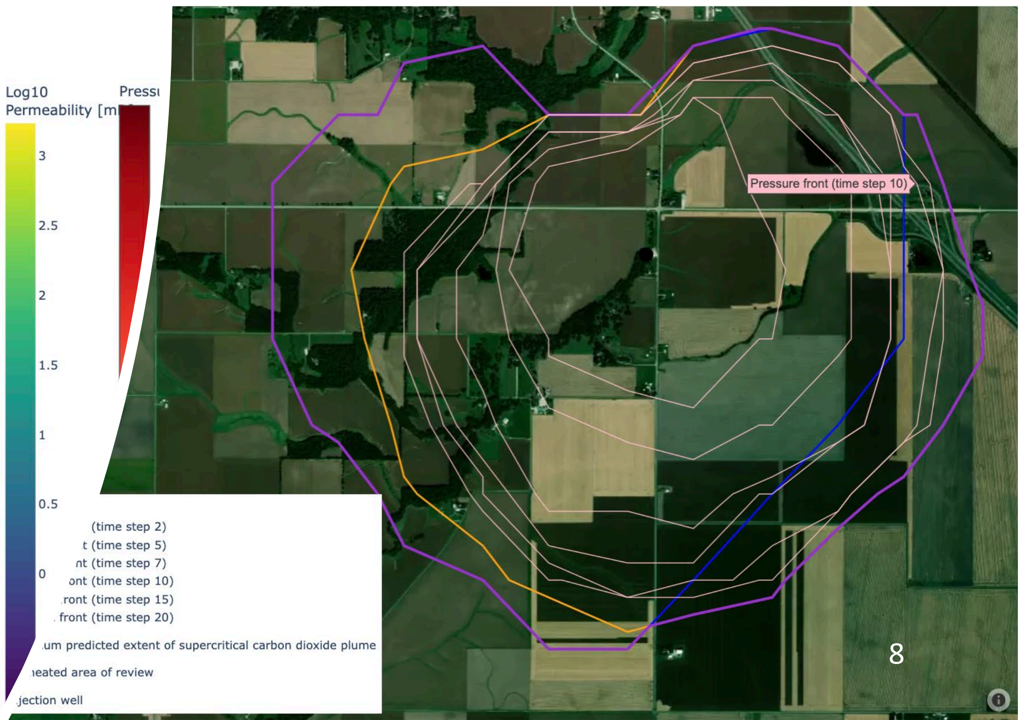
- Calculates and maps Area of Review (AoR) in real-time in response to model inputs.
  - ➢ Displays the evolution and maximum predicted extent of the supercritical CO_2 plume, pressure front, and the combined AoR.

- AoR calculation is based on a pressure-front that can be user defined or determined using the suggested EPA methods.









SMART-Model Explorer

Status - Module Workflow – Area of Review Calculation

1. Pressure Front

- User defined threshold.
- EPA Method 1. Under-pressurized injection zone. Pressure front based on bringing injection zone and USDW to equivalent hydraulic heads.

$$P_{i,f} = P_u + \rho_i g \cdot (z_u - z_i)$$

- EPA Method 2. Hydrostatic injection zone. Pressure front based on displacing fluid initially present in the borehole.

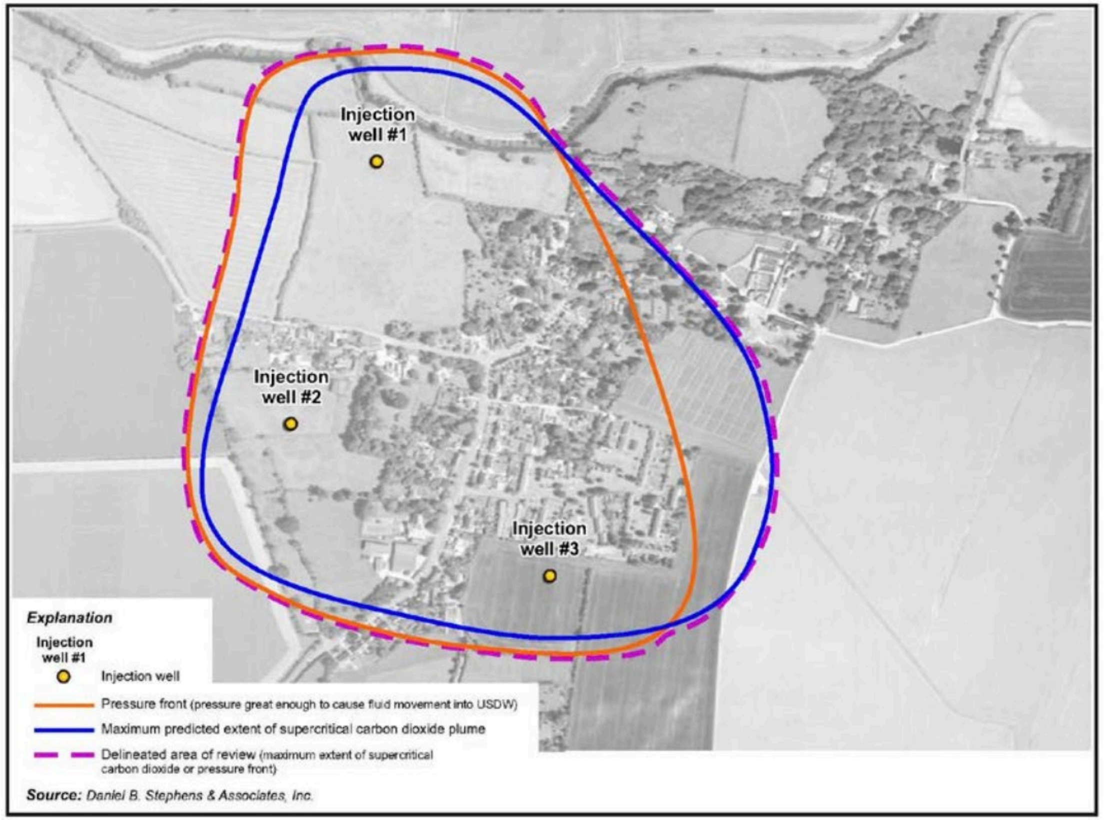
$$\Delta P_c = \frac{1}{2} \cdot g \cdot \xi \cdot (z_u - z_i)^2$$

2. Supercritical CO_2 Plume

- Maximum predicted extent of the separate-phase plume.

3. Area of Review

- Combined maximum extent of pressure front and supercritical CO_2 plume.



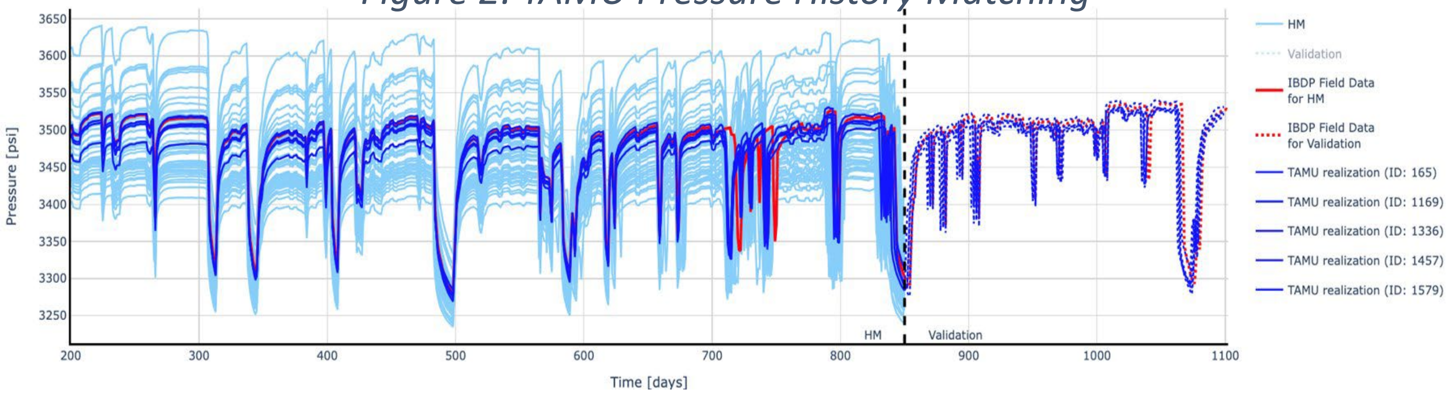
Example area of review contour epa.gov

RTFO module

- RTFO is integrated with advanced machine learning models, optimization algorithms, and interactive data visualization tools.

- RTFO provides a robust platform for managing and analyzing reservoir data.

Figure 2: TAMU Pressure History Matching



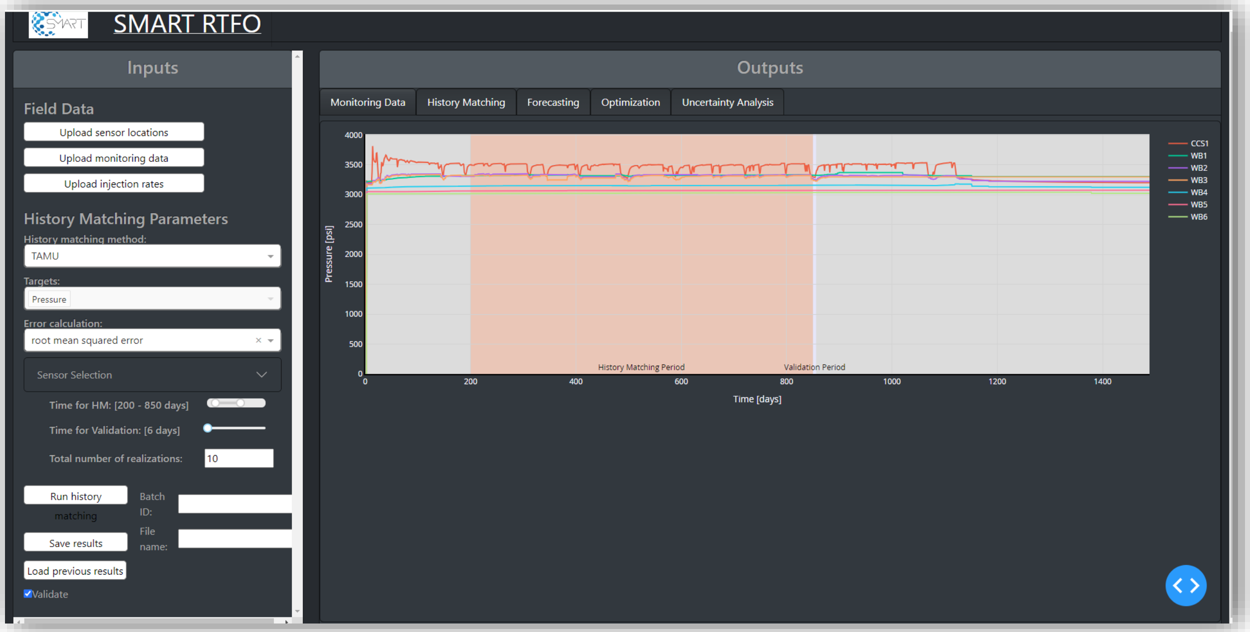


Figure 1: Interface of RFTO SMART Tool

IBDP CO_2 plume (3D view) *IBDP CO_2 plume (2D view)*

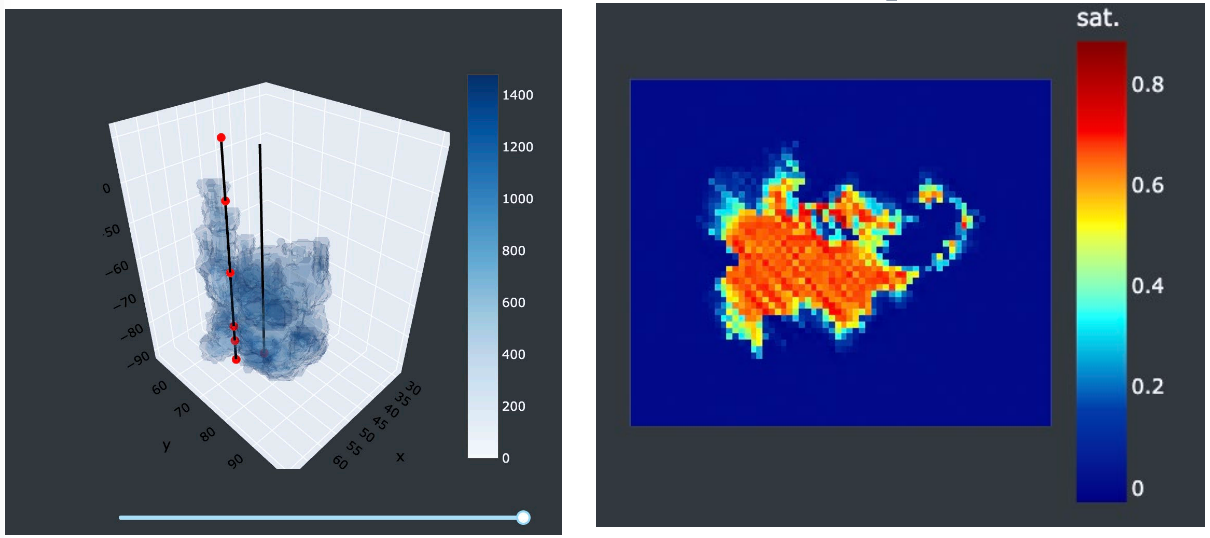


Figure 3: CO_2 plume in 3D and 2D

SMART Visualization and Decision Support Platform

Task-6 (EY23 and on-going EY24): Key Developers, Contributors, and Participants – PNNL, LLNL, NETL

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Questions?

Thank you!

PNNL-SA-

SMART modules integration into overall platform (video)