Overview of SMART Initiative

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

Hema Siriwardane

DOE-NETL

Contributors: Hari Vishvanathan (LANL), Seyyed Housseni (UT BEG), David Alambaugh (LBNL), Christopher Sherman (LLNL), Alex Tartakovsky (UIUC), Jared Schuetter (Bettelle); Hongkyu Yoon (SNL), Joshua White (LLNL), Maruti Mudunuru (PNNL), David Morgan (NETL). Srikanta Mishra (TAMU).

2024 FECM-NETL Carbon Management Research Project Review Meeting

Pittsburgh, PA

06 August 2024

U.S. DEPARTMENT OF ENERGY

NATIONAL ENERGY TECHNOLOGY LABORATORY

Disclaimer

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

This project was funded by the U.S. Department of Energy, National Energy Technology Laboratory, in part, through a site support contract. Neither the United States Government nor any agency thereof, nor any of their employees, nor the support contractor, nor any of their employees, makes any warranty, express 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.

Acknowledgement: This work was performed in support of the U.S. Department of Energy's (DOE) Office of Fossil Energy and Carbon Management.

Our Motivation

Growing momentum for rapid commercial scale deployment of CCS

- Develop relevant experience / understanding among stakeholders
- Facilitate decision-making process during project planning, permitting, operations

Traditional analysis involves physics-based models

- Data interpretation for characterization
- Pre-injection planning and system design
- Observational data integration for operational decision making

Recent focus on Machine Learning based computationally expedient alternatives

SMART- Initiative

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

VISION: Transform our ability to make better, informed decisions related to the subsurface through real-time visualization, forecasting, and virtual learning.

MISSION:

SMART Functionalities

- **Real-Time Visualization** — *"CT" for the Subsurface*
- **ML-based Rapid Prediction** — *Virtual Learning*
- **ML-based Real-Time Forecasting** — *"Advanced Control Room"*

Improve the ability to consolidate technical knowledge, site-specific characterization information, and real-time data in a digestible way.

Enable the optimization of carbon storage reservoirs by creating a capability for "real-time" forecasting of carbon storage reservoir behaviour.

Enable improve the ability to understand and communicate expected subsurface behaviour during carbon storage operations to non-experts.

SMART Initiative

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

- Task 2: Virtual learning to support permitting
- Task 3: Advanced learning and computational methods
- Task 4: Site-specific data management & imaging
- Task 5: Site-specific storage reservoir modeling
- Task 6: Site-specific decision support & visualization
- Task 7: Site-specific data curation
- Task 8: Geomechanical Modeling and Exploration of Longer Term and Emerging Priorities

Technical Team

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

Pacific Northwest National Laboratory

Bureau of Economic Geology

Sandia National Laboratories

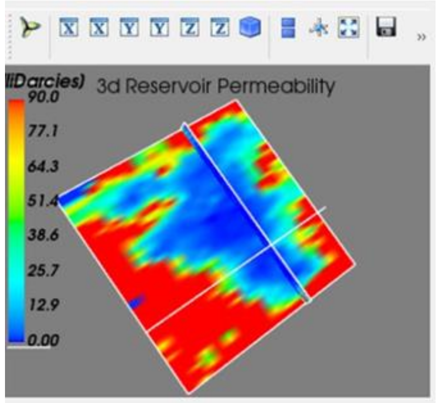
Berkeley Lab

Illinois

Current Progress

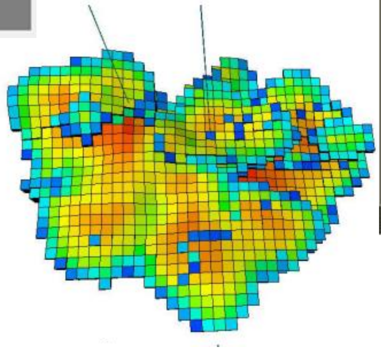
SMART Initiative

- SMART has developed a conceptual design of the SMART Visualization and Decision Support Platform.
- Several modules have been developed (Model Explorer – VLE, USM (Unified Simulation Module), STRIVE (SMART Tools Rapid Visualization Environment Module), ORION (Induced Seismicity Module), RTFO (Real-time Forecasting and Operational Control Module). Developments are continuing.
- Developed a Machine Learning (Transfer Learning) tool to forecast CO_2 plume saturation and pressure under operating conditions different from those used to train an earlier ML model.
- Developed a Machine Learning (ML) based algorithm for fault/fracture identification from FMI logs and passive seismic signatures to further refine the geomodel.
- Developed an ML-based data-assimilation/history matching frameworks for calibrating a site-specific dynamic model to pressure, saturation, temperature data.
- Developed Model Explorer tool to rapidly explore various modeled scenarios and impact of heterogeneity and/or uncertainty using ML-based fast predictive models.
- SMART-NRAP: Developed the Operational Forecasting of Induced Seismicity toolkit “ORION” (ORION), an open-source, observation-based ensemble forecasting toolkit, which is geared towards helping operators understand potential seismic hazards at a site.
- Developed a tool based on integrated computer vision and deep learning workflows for automating image log analysis, helping to rapidly and precisely detect fractures and baffles in subsurface formations.

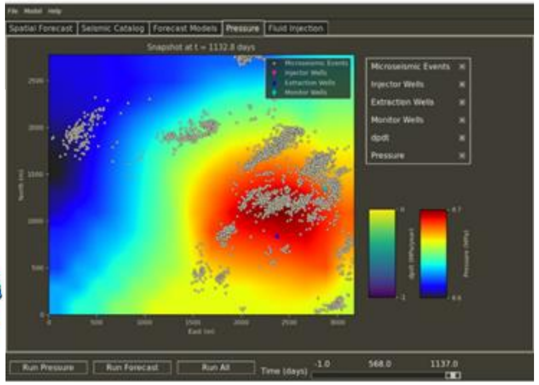


Virtual Learning Environment Module (VLE)

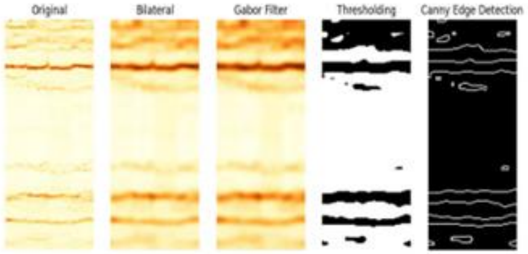
ML History Match



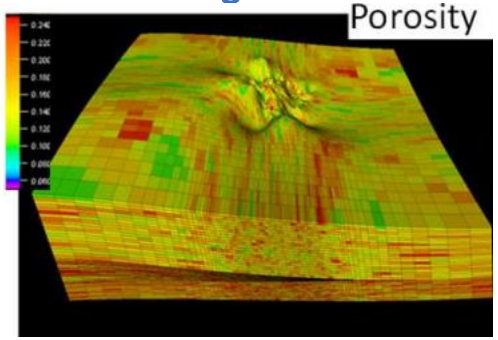
ORION (NRAP/SMART)



Data Assimilation and History Matching with ML

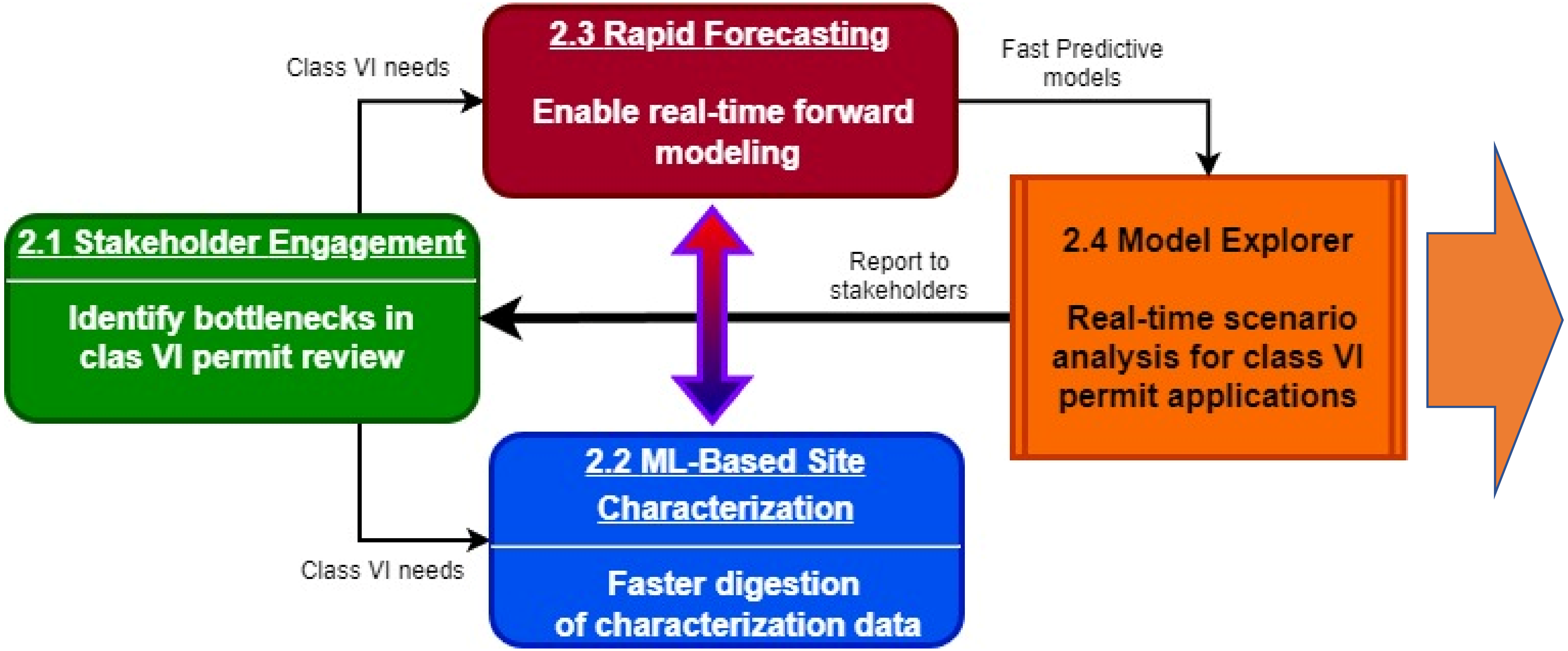


FMI-based Fracture, Bedding, and Baffles Identification using ML (FBBIML)



IBDP SNL Model

TASK 2: Wiring Diagram –Virtual Learning for Permitting

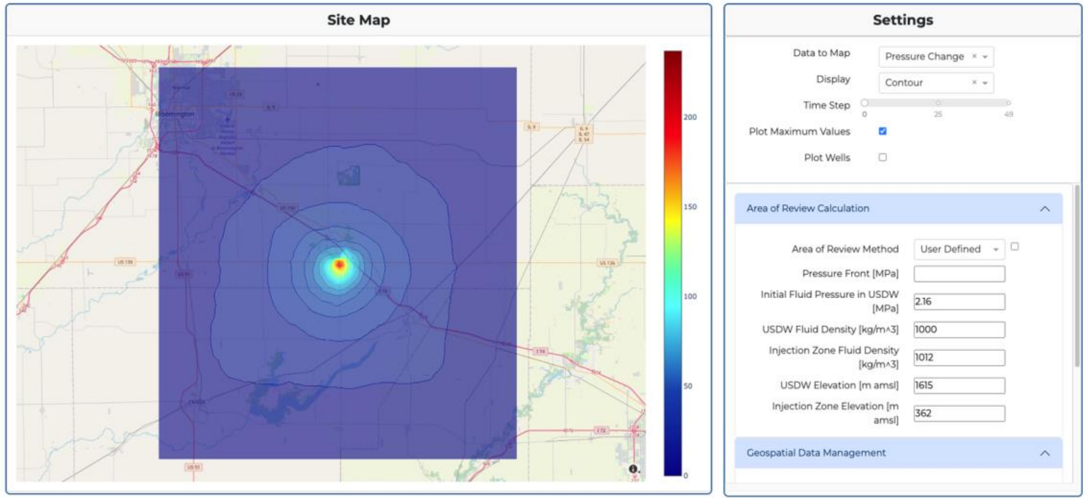


- Regulatory agencies
- Site operators
- Public

TASK 2: Example tools

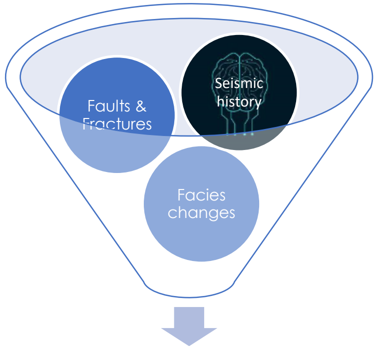
Tool: Model Explorer

Highlight # 1: AoR & Corrective Action - Dynamic Simulation



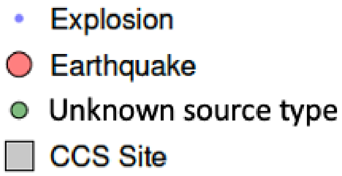
Tool: SmartSeis

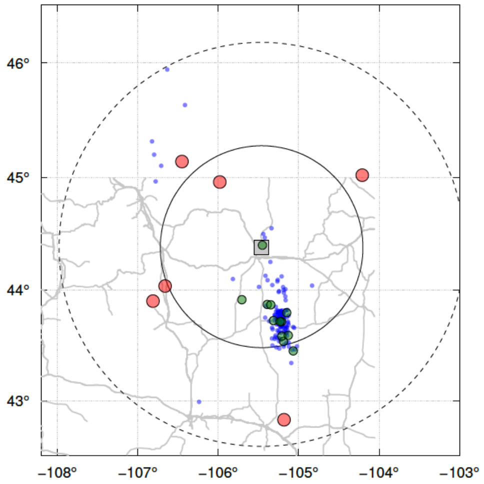
Highlight # 2: Site Characterization – Seismicity Detection →



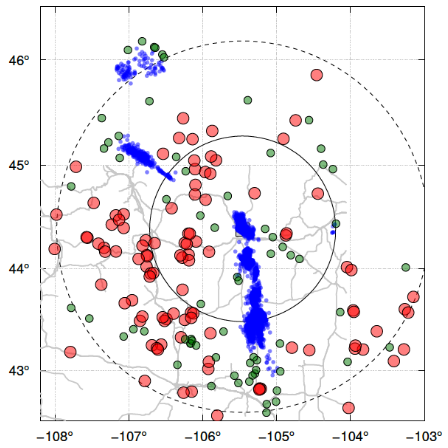
Site Characterization

Conventional detection





ML detection



Conventional methods

- Using catalogs /traffic light
- Biased and hindered by noise
- Slow

ML based method

- Uses trained models (detects ~40 times more events)
- Remove bias and noise
- Fast

Task 3, Advanced Learning and Computational Approaches

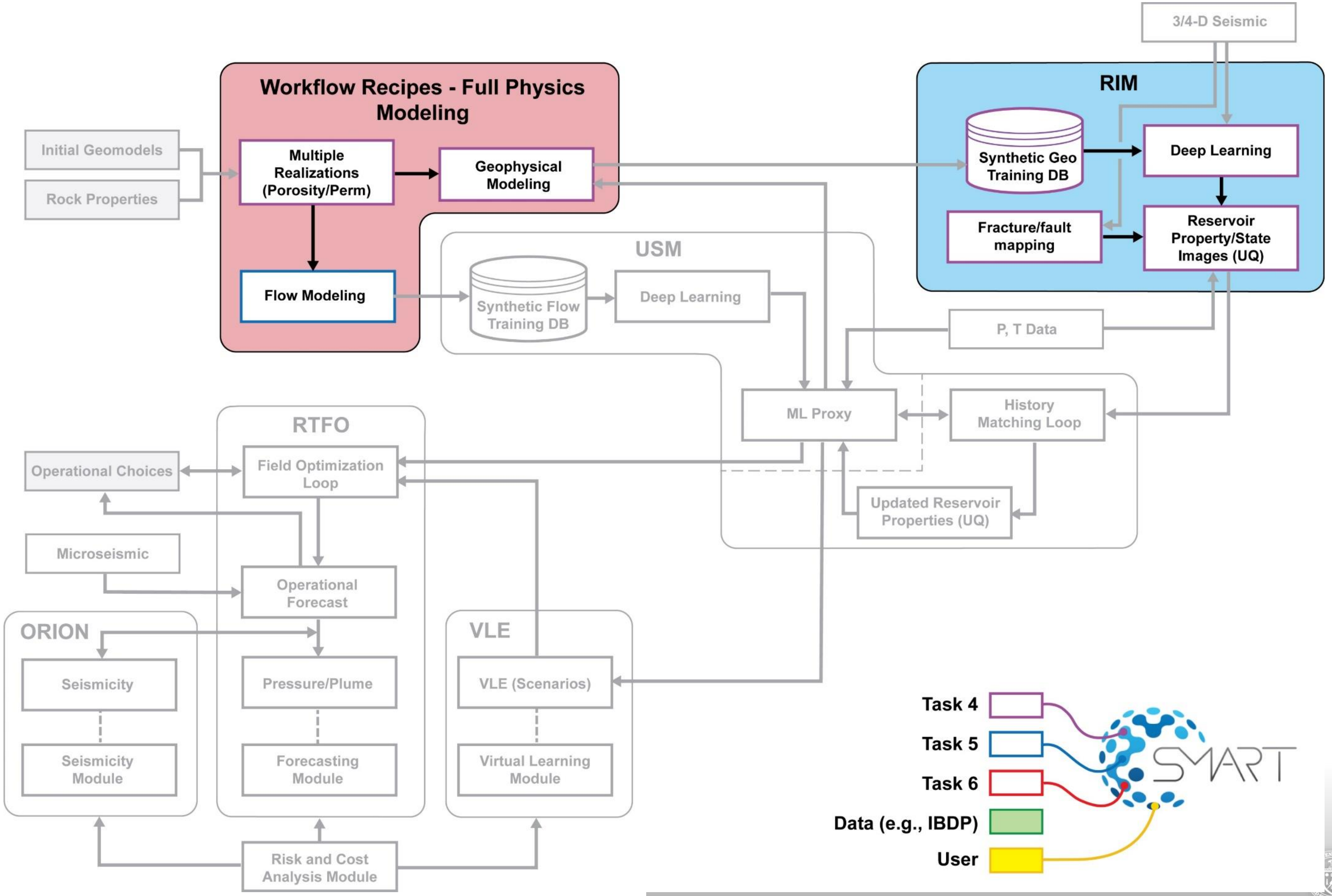
Activities

- **1: Software Quality Assurance (QA)**
  - Ensure that any software in Phase 2 meets a set of agreed upon quality and reliability standards, allowing those tools to satisfy any requirements dictated by the application in which they are being used
- **2: Cross-activity Integration**
  - Identify overlaps in techniques and methodologies developed during Phase 1 and adapting them for ease of applicability by 2A and 2C teams
- **3: Advanced Machine Learning Methods**
  - Focus on AI/ML methods that can make SMART transformational ML models and overcome challenges identified in Phase I
- **4: Advanced Computational Approaches**
  - Focus on advanced methods to enhance performance (accuracy, efficiency, privacy) that could not be achieved by a single ML method

Task 3, Advanced Learning and Computational Approaches

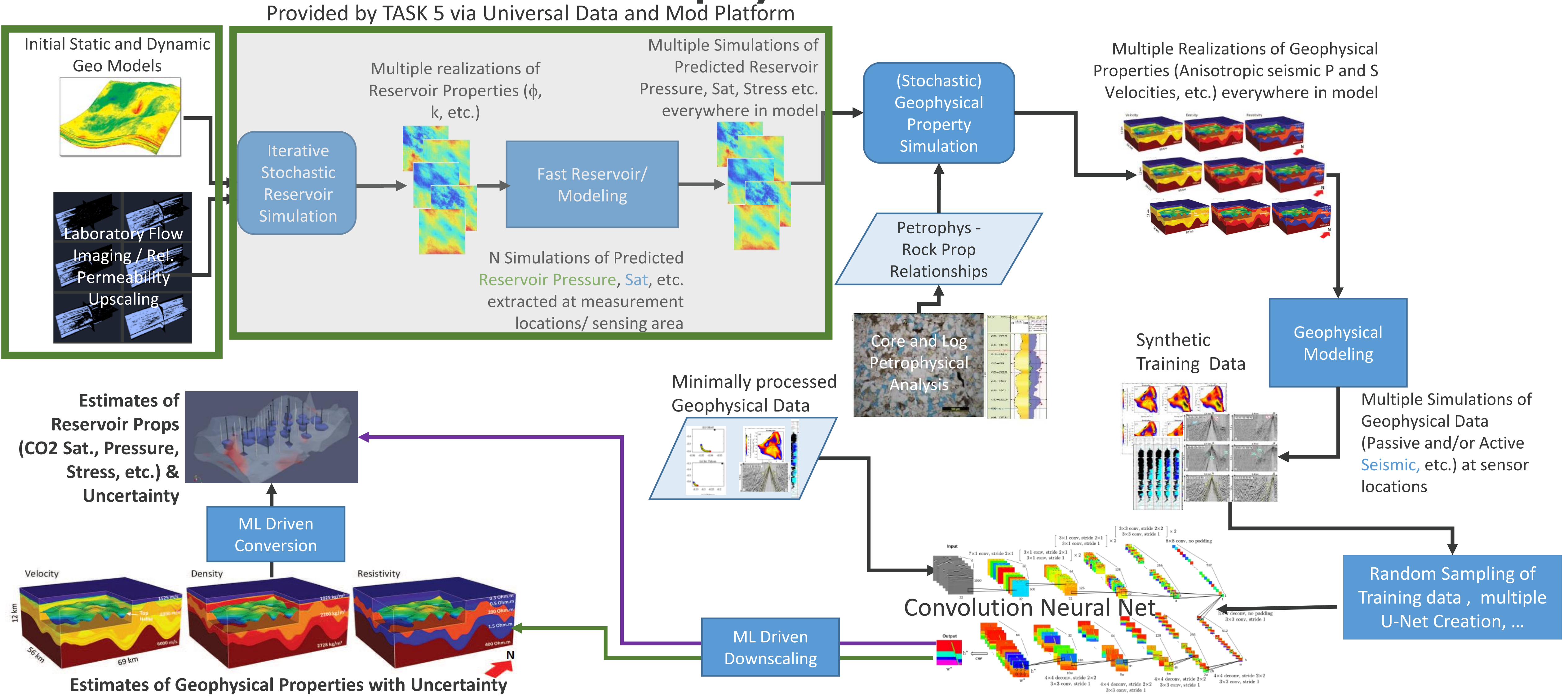
- **Advanced ML Methods & Advanced Computational Approaches**
  - Topic Area: Fast and Flexible Solutions for Fluid Flow Prediction
    - Built flexible models that leverage advanced approaches (e.g., Neural Operators) to handle the dynamic evolution of pressure, saturation, and stress and can serve as the basis to expand to solve other field prediction problems
      - DeepONet
      - Fourier Neural Operator
      - Graph Neural Operator
      - PICKLE
      - HGGNN
      - Wafer Scale Engine Field Equation Application Programming Interface
    - These models also allow for the incorporation of physics and scientific knowledge to increase the user confidence and understanding of the model reasoning processes
    - Models tested on the clastic shelf dataset, with some models also being tested on IBDP

TASK 4: Wiring Diagram –Data Organization and Imaging



U.S. DEPARTMENT OF ENERGY

Task 4 - Reservoir Property Imaging Workflow for Any Type of Geophysical Data

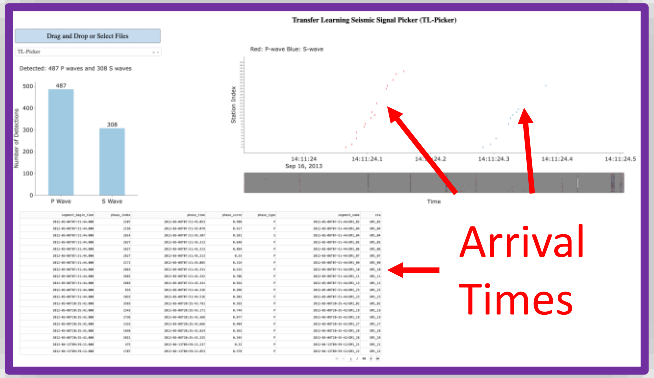


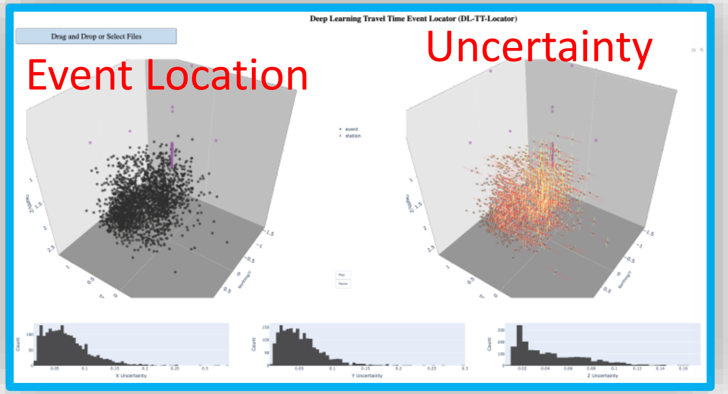
Task 4 – Fault/Fracture Imaging

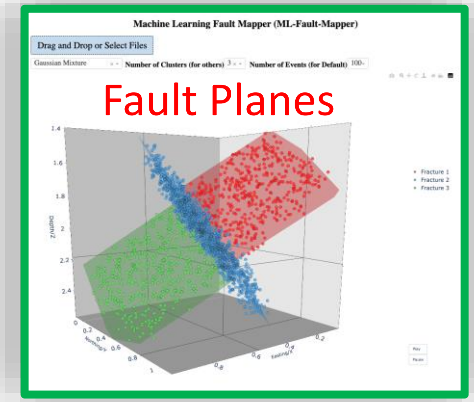
ORNL Workflow

Passive Seismic Waveforms → **TL-Picker** → Signal Arrival Times → **DL-TT-Locator** → Seismic Event Catalog → **ML-Fault-Mapper** → Fault & Fracture

ORNL developed a workflow with three AI applications to improve the speed and reduce the cost of fault and fracture imaging for carbon storage sites.

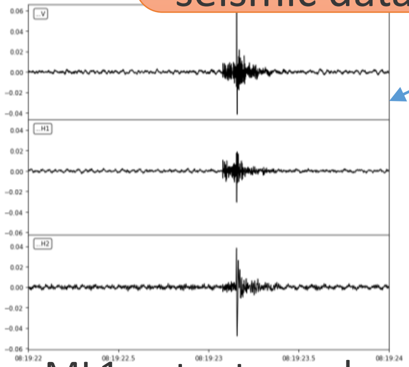




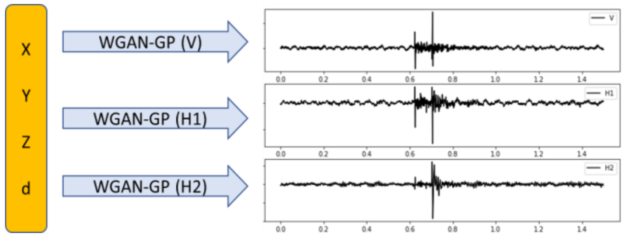


SNL Workflow

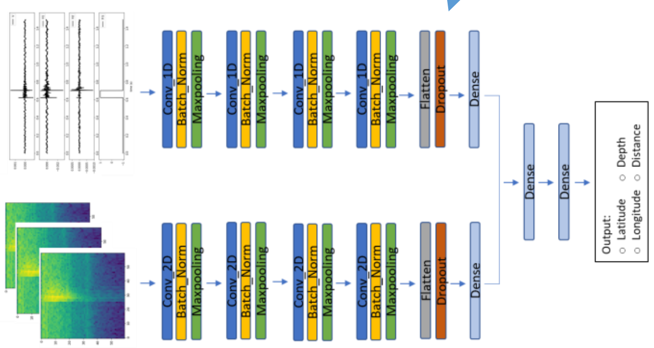
Continuous passive seismic data → **ML1** → MS event detection → **ML2** → Synthetic data augmentation → **ML3** → Quality control → **ML4** → Event catalog → **ML5** → Faults & Fractures



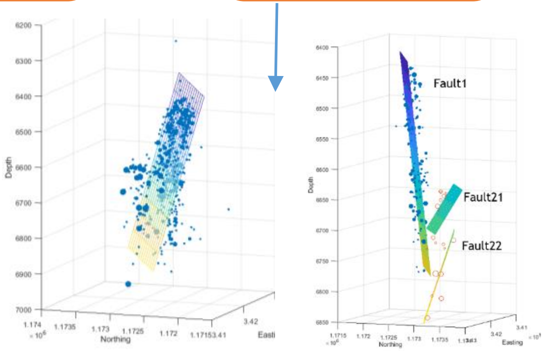
ML1 output: newly detected event



ML2: Waveform generative model for catalog augmentation

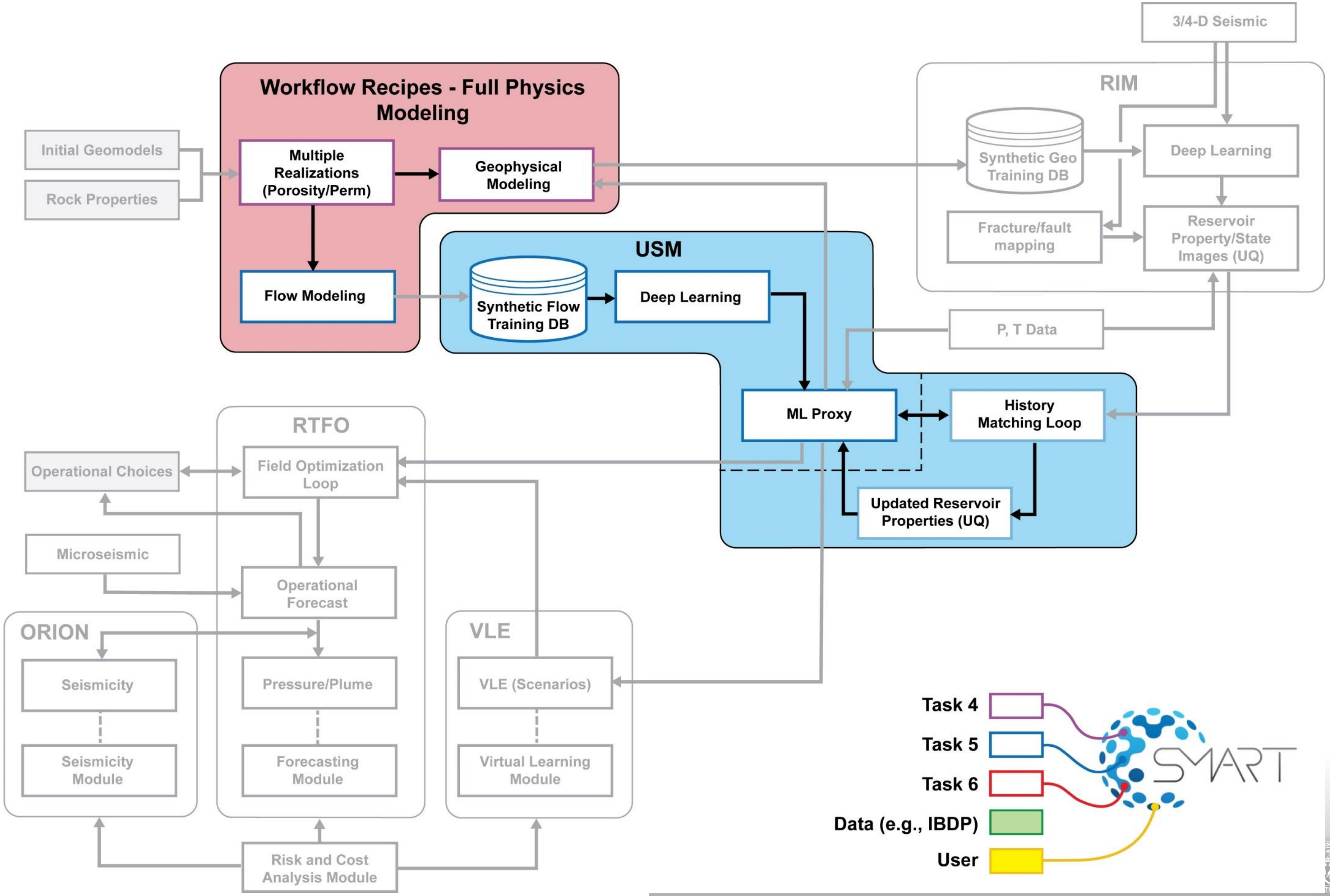


ML4: Source location model



ML5 output: Event clustering and fault plane fitting

TASK 5: Wiring Diagram –Storage Reservoir Modeling



Task 5 –Dynamic Storage Reservoir Modeling

Vision: Provide <u>real-time</u> modeling, data assimilation and forecasting to support:

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

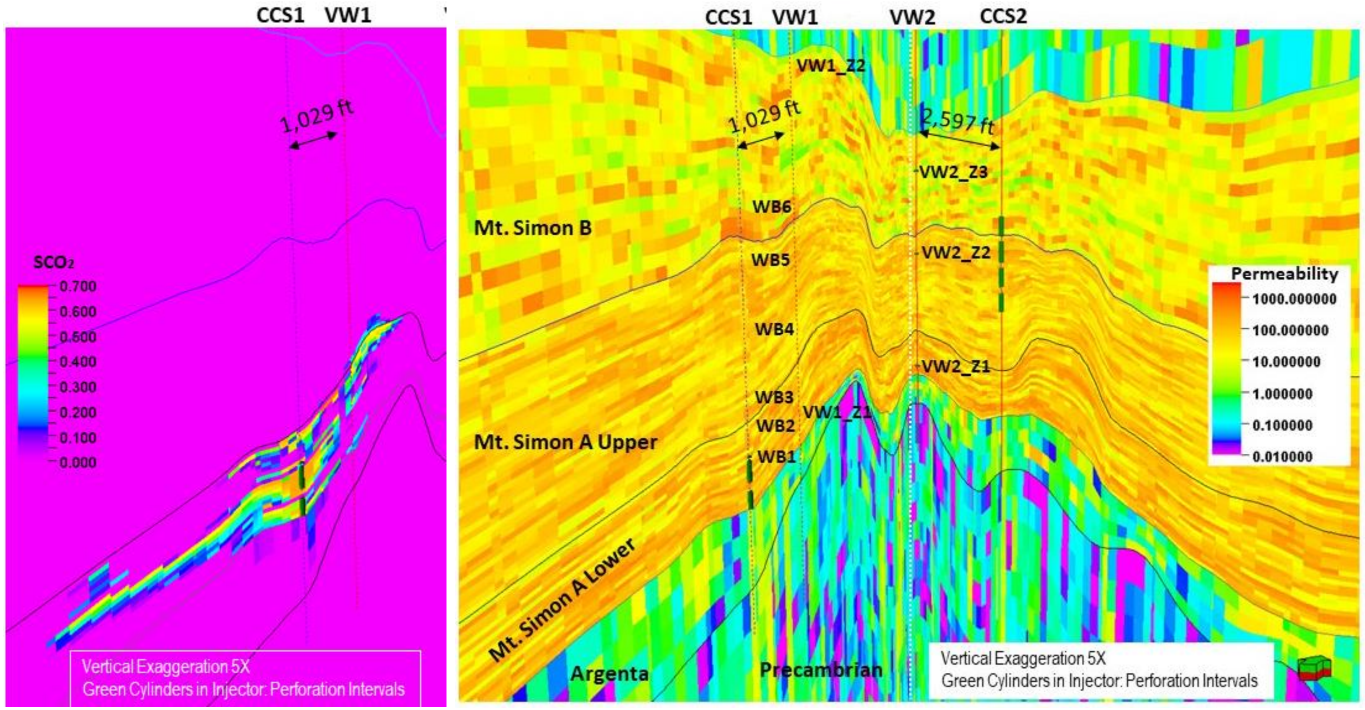


Figure: Physics-based simulation of CO_2 saturation plume at the end of 3 years injection (left) at the Illinois Basin-Decatur Project (IBDP) site with a geologic model (right)

[https://edx.netl.doe.gov/dataset/illinois-state-geological-survey-isgs-illinois-basin-decatur-project-ibdp-geological-models]

Carbon Storage Simulation Workflows Today:

- Strong physical basis
- Decision-driven
- Ensemble-based

- Human-labor intensive
- Slow and non-interactive
- Heuristic optimization

SMART Vision:

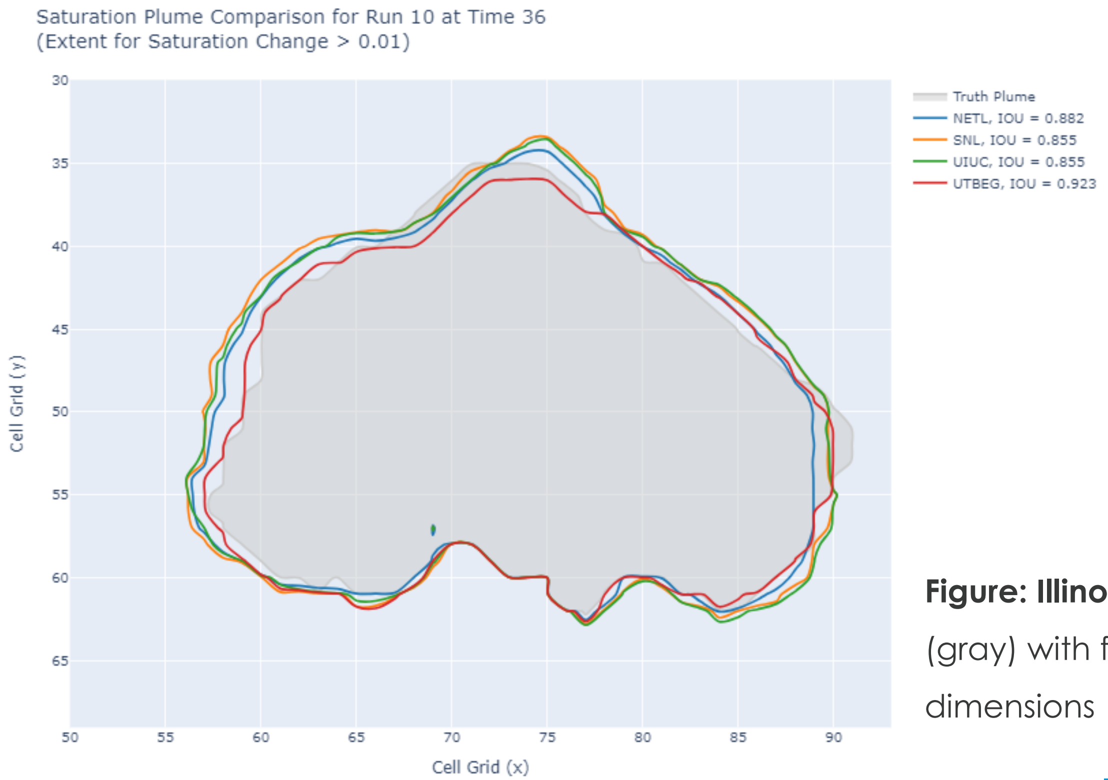
- Strong physical basis
- Decision-driven
- Ensemble-based

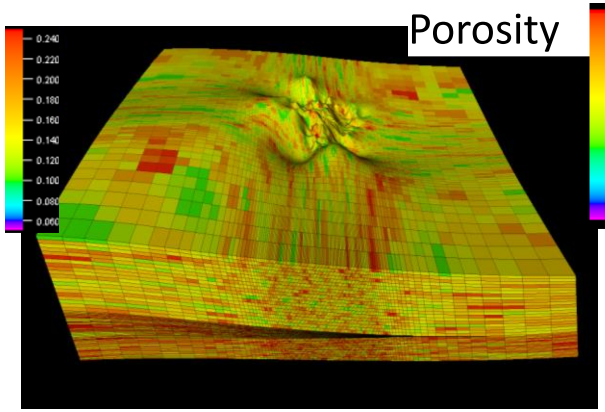
- Human-labor efficient
- Highly interactive
- Automated workflows
- Rapid data assimilation

Task 5 –Dynamic Storage Reservoir Modeling

Key Idea: Use ML models, trained on physical simulations, to create a rapid surrogate

- Learns physical-basis embedded in full-physics models
- Is exposed to a broad array of possible surface configurations (porosity, permeability, baffles)
- Achieve prediction accuracy, training efficiency (with 1.73 M cells of IBDP model), and portability of trained models in an interactive user interface (i.e., unified simulation module)





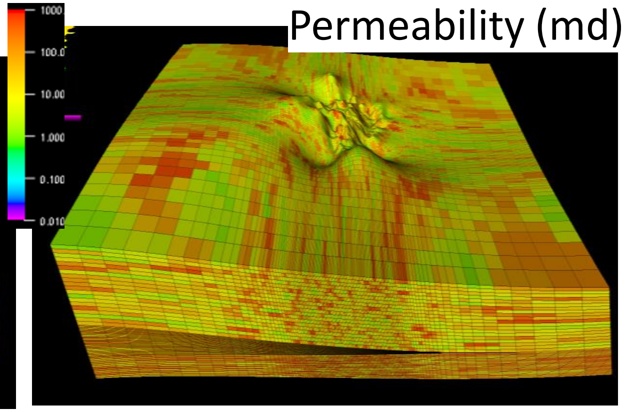
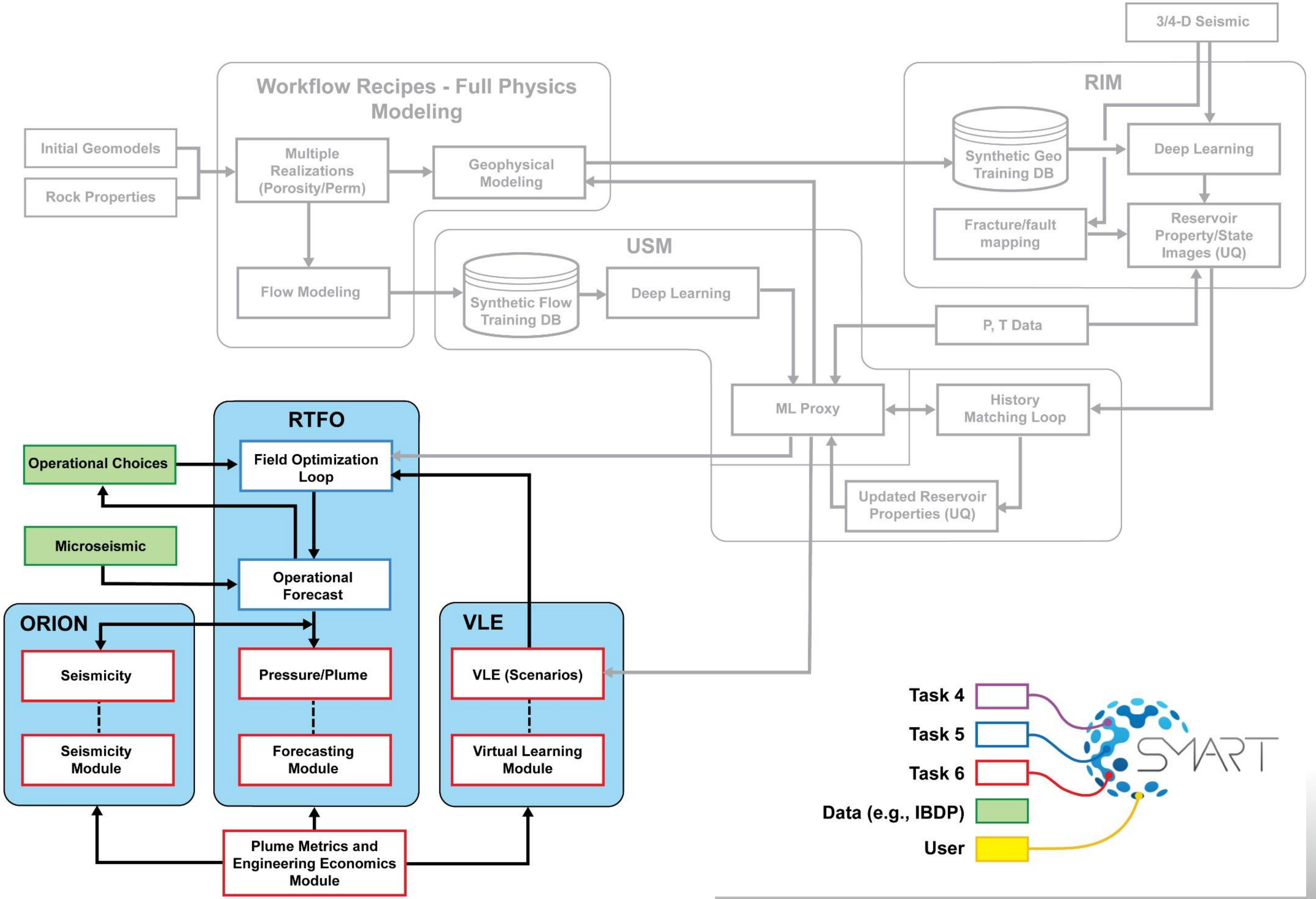
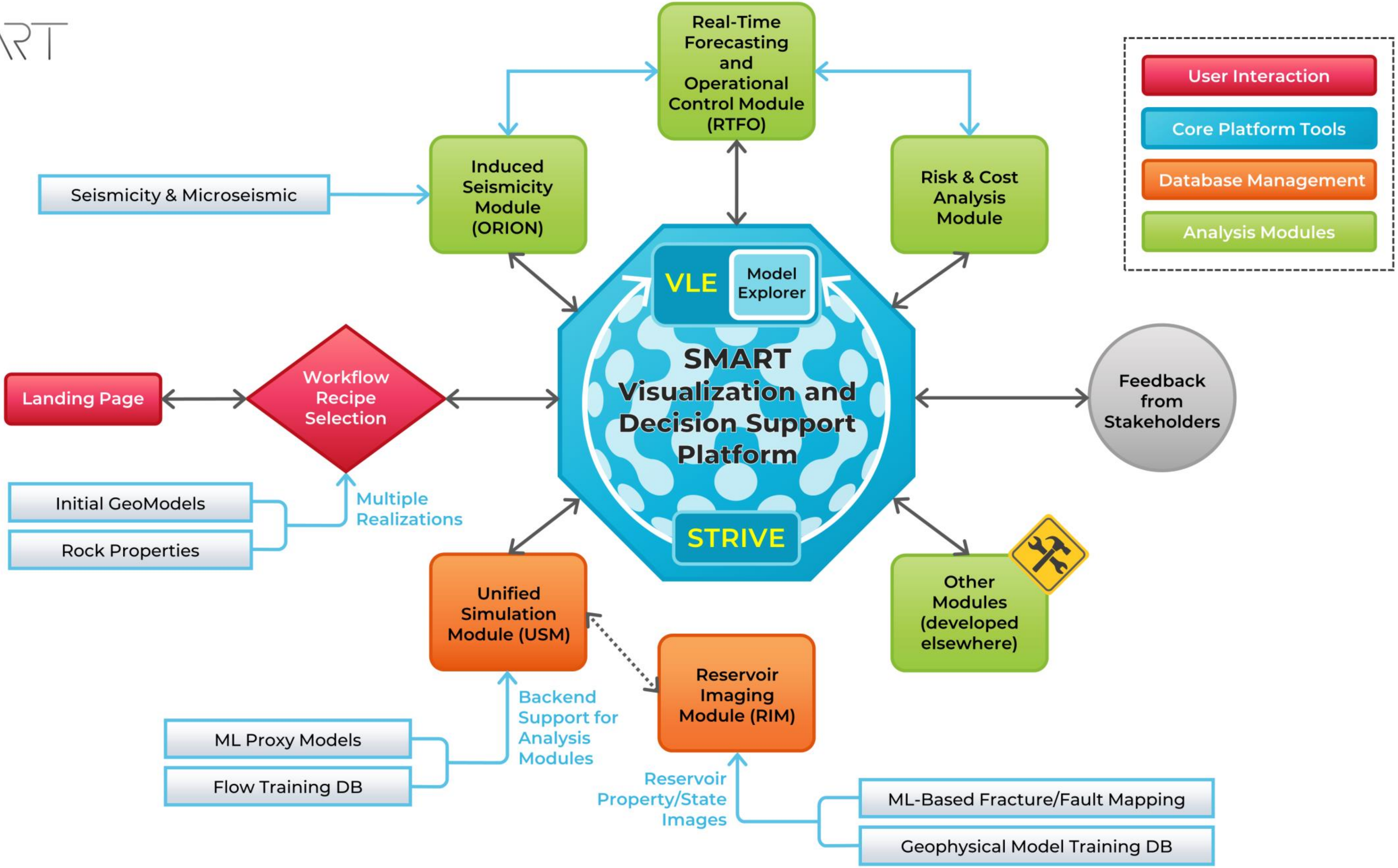


Figure: Illinois-Basin Decatur Test. Comparison of physic-based model (gray) with four ML models (lines), showing predicted saturation plume dimensions (plan view) on test case for IBDP.

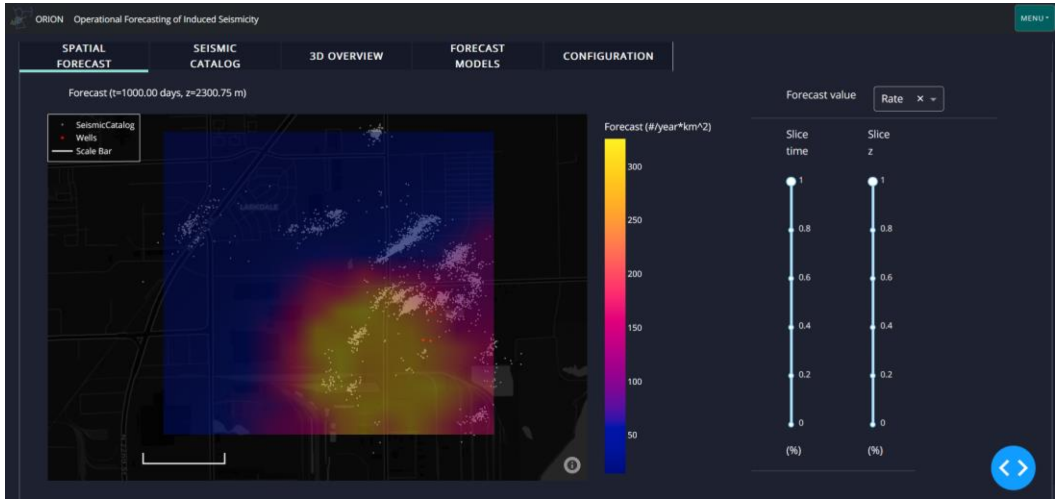
TASK 6: Wiring Diagram – Decision Support & Visualization

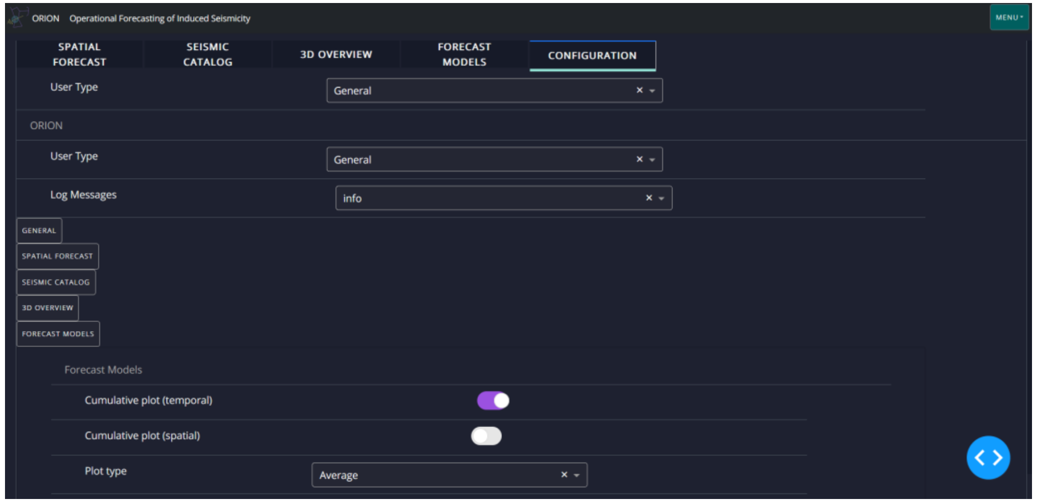



Real-Time Forecasting and Operational Control Module (RTFO)
Induced Seismicity Module (ORION)
Risk & Cost Analysis Module
Seismicity & Microseismic
User Interaction
Core Platform Tools
Database Management
Analysis Modules
VLE
Model Explorer
SMART Visualization and Decision Support Platform
STRIVE
Landing Page
Workflow Recipe Selection
Feedback from Stakeholders
Initial GeoModels
Rock Properties
Multiple Realizations
Unified Simulation Module (USM)
Other Modules (developed elsewhere)
Reservoir Imaging Module (RIM)
Backend Support for Analysis Modules
ML Proxy Models
Flow Training DB
Reservoir Property/State Images
ML-Based Fracture/Fault Mapping
Geophysical Model Training DB

Operational ForecastIng Of INduced Seismicity (ORION) SMART AND NRAP

- **ORION serves as the Induced Seismicity Module for Platform**
- **Key inputs:**
  - Observed seismic activity
  - Pressure model
  - Geologic model
- **Outputs:**
  - Independent seismic forecast models that are based off different physical assumptions, statistics, and ML (in development)
  - An ensemble seismic forecast
  - Visualizations to assist end-users understanding of seismic activity / risks





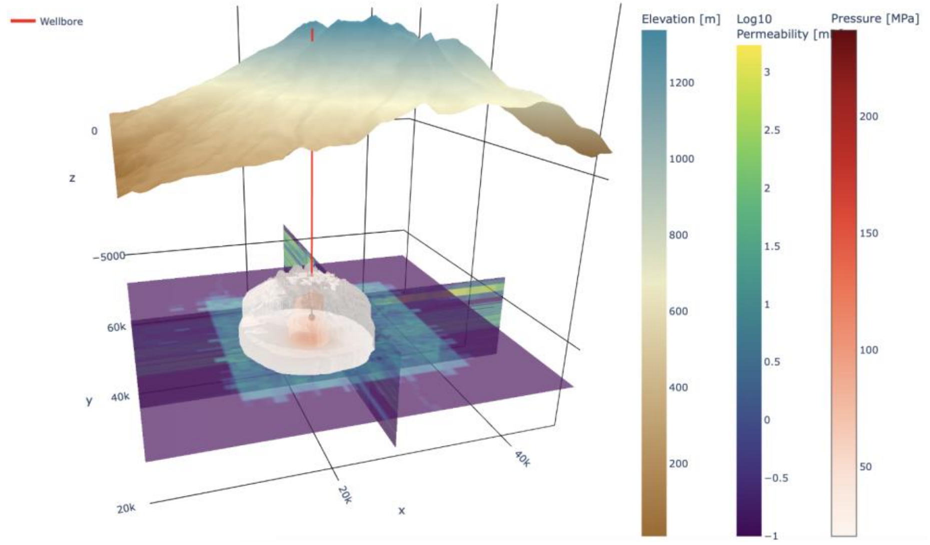
Model Explorer Module

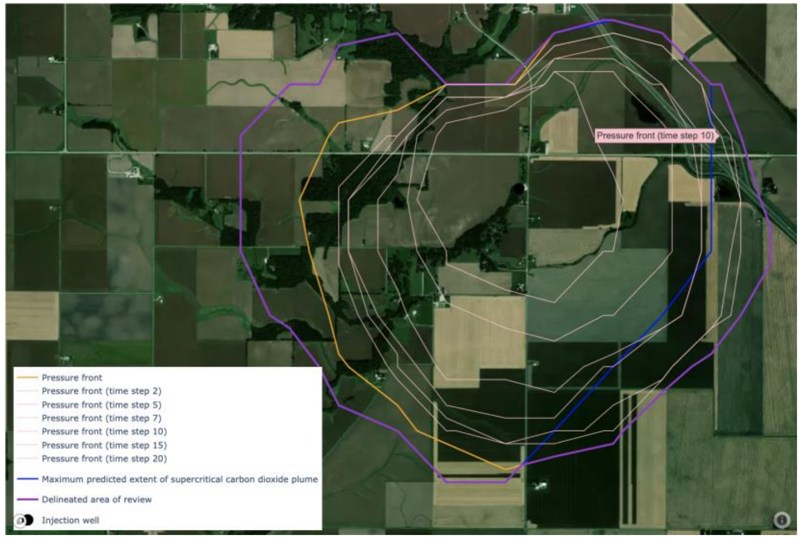
Why is Model Explorer important, and how can it accelerate the Class-VI permitting process?

•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. Able to display 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.

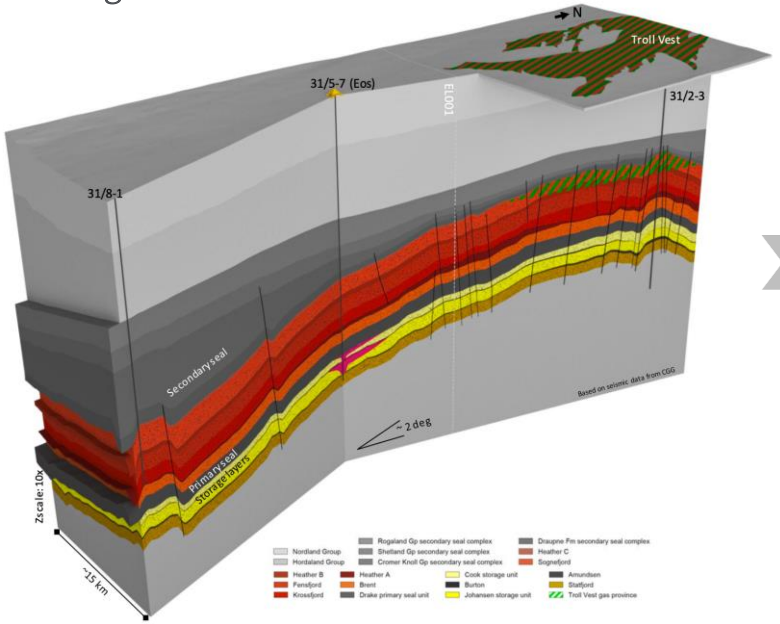




TASK 8 – Geomechanical Modeling

- **Full-physics poromechanical and fault reactivation modeling capabilities are increasingly mature, but they remain computationally expensive and see limited application in industry.**
- **Ensembles of physics-based poromechanical simulations to train a rapid ML surrogate and efficient transfer learning**

Geological Model



GEOS simulation model

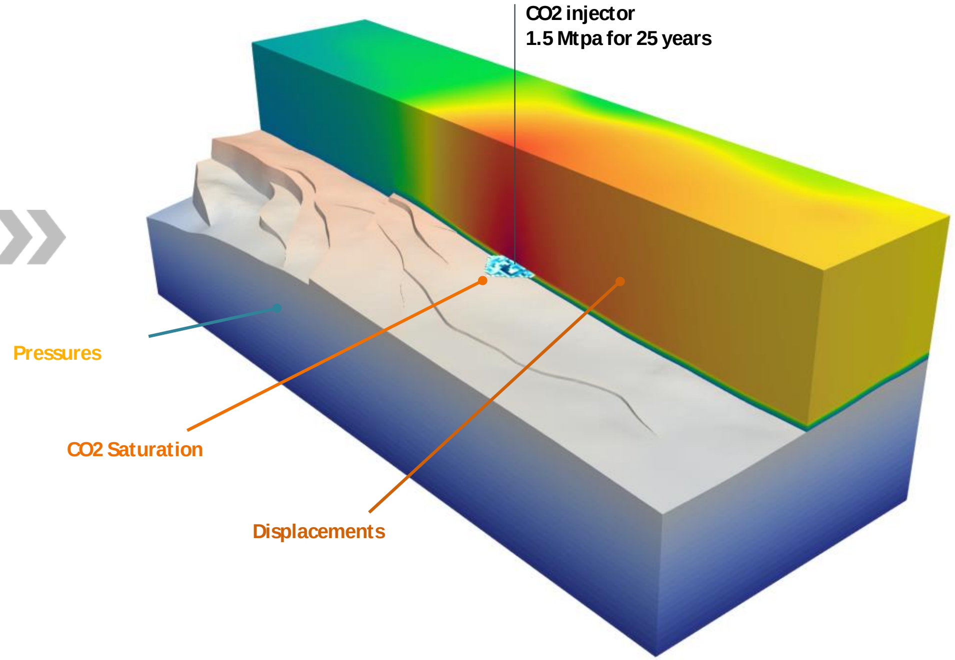


Figure: GEOS poromechanical simulation of the Northern Lights injection project [courtesy TotalEnergies].

Hackathon: EY24 Early win – SMART platform development and outcomes

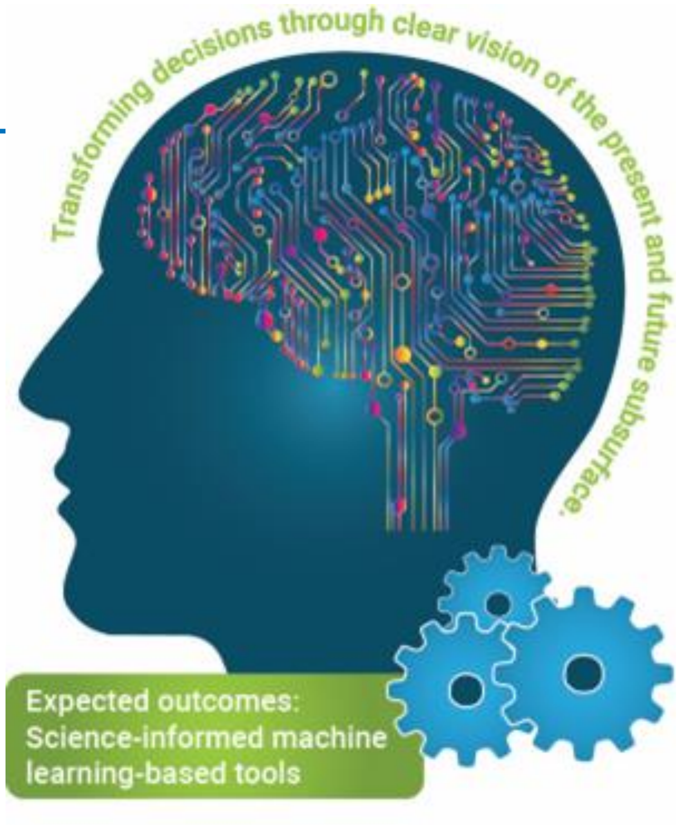
- SMART platform development hackathon was held at PNNL Seattle Campus (July 9-10, 2024)
- Platform developers from PNNL, LLNL, and NETL
- **Objectives:**
  - Using STRIVE, integrating key SMART modules into the platform.
  - Develop workflow recipes and establish coupling between modules within the SMART platform.
- **Outcomes:**
  - Functional SMART platform landing page with integrated SMART modules.
  - Established preliminary workflows and module coupling within the platform.
  - A demo at DOE-FECM meeting on early prototype of SMART platform and key functionalities.

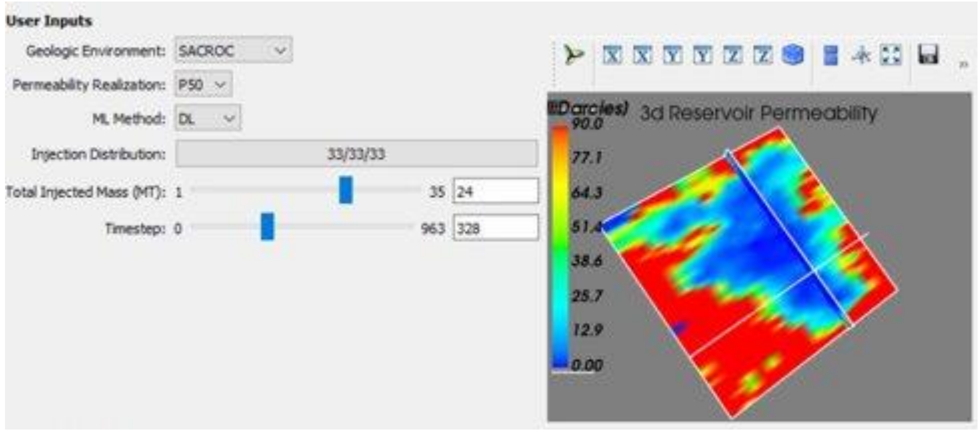
How Can SMART Assist CCS Projects?

- SMART tools can be applied for (a) virtual learning during the pre-injection permitting phase, and (b) ML-assisted operational decision making & visualization.

- **Virtual Learning** - During pre-injection permitting phase, rapid exploration and communication of the impact of data and model uncertainties and "what-if" scenarios on system evolution after CO_2 injection.

- **Operational Decision Making and Visualization**
  - Rapid interpretation of geophysical images for improved visualization of subsurface rock and fluid properties and dynamic model updates.
  - Near (real) time optimization of CO2 injection operations using fast predictive models that are regularly calibrated to observations of pressure, temperature, saturation etc.





AI/ML at Work for CCS: Example

The **Virtual Learning Environment (VLE)** is an exploratory tool which uses ML predictions to rapidly inform an end user of how a given reservoir simulation would likely change in response to altered inputs.

Making Better Decisions with ML-Based Tools

Phase 2

***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?

Rapid predictive analysis and stakeholder outreach

Better imaging and subsurface visualization

Faster model calibration and operational forecasting

SMART Presentations at FECM Meeting, Pittsburgh, PA

Program Details (Tuesday, August 6, 2024)

10:30 a.m. - 12:10 a.m.	**SMART Session 1 – Computational and Visualization Advances** **7 Presentations**
1:25 p.m. – 3:25 p.m.	**SMART Session 2 – Field Applications** **6 Presentations**
4:00 p.m. - 5:20 p.m.	**SMART Session 3 – Applications** **4 Presentations**
5:45 p.m. - 7:45 p.m.	**SMART – Poster Session** **18 Poster Presentations**
5:45 p.m. - 7:45 p.m.	**SMART – Tool Demonstration Session** **11 Tool Demonstrations**

SMART Presentations at FECM Meeting, Pittsburgh, PA

2024 Program Details (Tuesday, August 6, 2024)

10:30 a.m. - 10:40 a.m.	**SMART Initiative Overview** Hema Siriwardane, National Energy Technology Laboratory
10:40 a.m. - 10:55 a.m.	**ML-based Dimension Reduction Strategies** Seyyed Hosseini and Hongsheng Wang, University of Texas Bureau of Economic Geology
10:55 a.m. - 11:10 a.m.	**Physics-Informed Machine Learning** Alexandre Tartakovsky, University of Illinois Urbana-Champaign
11:10 a.m. - 11:25 a.m.	**Transfer Learning for Multi-Physics Problems** Hongkyu Yoon, Sandia National Laboratory
11:25 a.m. - 11:40 a.m.	**Model Explorer for Virtual Learning** Maruti Mudunuru and Ashton Kirol, Pacific Northwest National Laboratory
11:40 a.m. - 11:55 a.m.	**Induced Seismicity Forecasting with ORION** Kayla Kroll and Chris Sherman, Lawrence Livermore National Laboratory
11:50 a.m. - 12:10 p.m.	**SMART Visualization and Decision Support Platform (FWP-1025011)** Maruti Mudunuru, Pacific Northwest National Laboratory, Chris Sherman, Lawrence Livermore National Laboratory and Patrick Wingo, National Energy Technology Laboratory

SMART Presentations at FECM Meeting, Pittsburgh, PA

2024 Program Details (Tuesday, August 6, 2024)

1:25 p.m. - 1:45 p.m.	**Comparison of ML-Based Proxy Modeling Strategies** Jared Schuetter, Battelle Memorial Institute
1:45 a.m. - 2:05 a.m.	**ML-Based Data Assimilation and History Matching** Masahiro Nagao, Texas A&M University and Akhil Data-Gupta, Texas A&M University
2:05 a.m. - 2:25 a.m.	**ML-Based Optimization for CO2 Injection** Bailian Chen, Los Alamos National Laboratory
2:25 a.m. - 2:45 a.m.	**ML-Based Rock Properties and Seismic Volume Enhancement** Athanasios (Athos) Nathanail and Manika Prasad, Colorado School of Mines
2:45 a.m. - 3:05 a.m.	**ML-Based Fracture and Fault Identification** Youzuo Lin, University of North Carolina
3:05 a.m. - 3:25 a.m.	**ML-Based Rock Physics Modeling and Reservoir Imaging (FWP-FP00014427)** David Alumbaugh, Lawrence Berkeley National Laboratory

SMART Presentations at FECM Meeting, Pittsburgh, PA

2024 Program Details (Tuesday, August 6, 2024)

4:00 p.m. - 4:20 p.m.	**Comparison of ML-Based Proxy Modeling Strategies** Jared Schuetter, Battelle Memorial Institute
4:20 p.m. – 4:40 p.m.	**ML-Based Data Assimilation and History Matching** Masahiro Nagao, Texas A&M University and Akhil Data-Gupta, Texas A&M University
4:40 P.m. – 5:00 p.m.	**Overview of the NRAP/SMART Technoeconomic and Liability Evaluation for Storage (TALES) Model** David Morgan and Chung-Yan Shih, National Energy Technology Laboratory
5:00 P.m. - 5:20 p.m.	**USM - Unified Simulation Module in SMART** Jeff Burghardt and Wenjing Wang, Pacific Northwest National Laboratory

Concluding Remarks

- SMART motivation, structure, organization, wiring diagrams
- Goal ⇨ Empower various stakeholders with advanced ML and related tools that can accelerate decision-making
- Outcomes of SMART expected to be publicly available
- Each Task will present its key accomplishments from EY23

Thank you for your attention