SMART-CS Initiative

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

Development of a software platform for machine learning-accelerated model calibration and decision support for geological carbon storage

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U.S. DEPARTMENT OF ENERGY

Project Team

Large, multi-institutional team contributing various insights, datasets, machine-learning models and inversion algorithms

Problem Statement 1

- **Computational run time represents a major limitation in the current inverse modeling process where real-time forecasts are generated and used to constrain forecasts with monitoring data.**
- **Task 4 Solution:**
    - ML-based techniques provide an alternative to inverse modeling that can rapidly generate forecasts, quantify the uncertainty in those forecasts, and learn from measurements to improve forecasts over time.
    - Task 4 incorporated ML-based techniques into both the real-time forecasting and real-time history-matching components of the workflow.

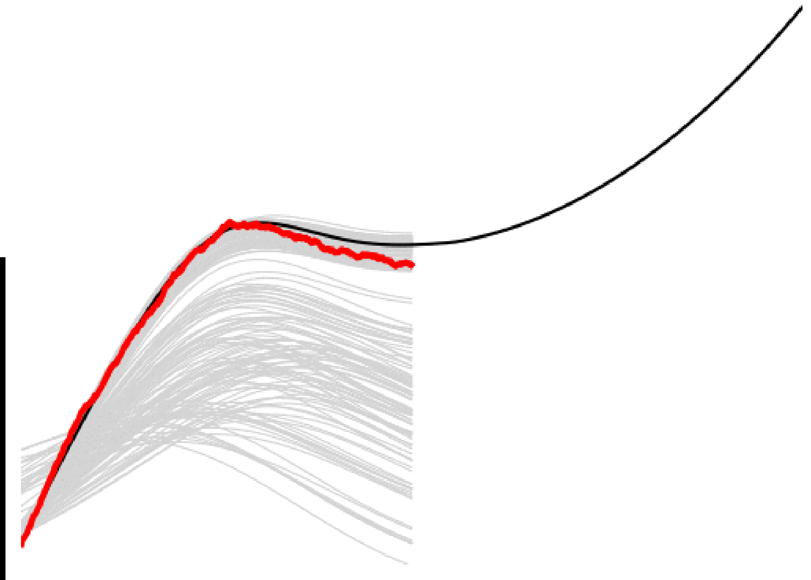
Problem Statement 2

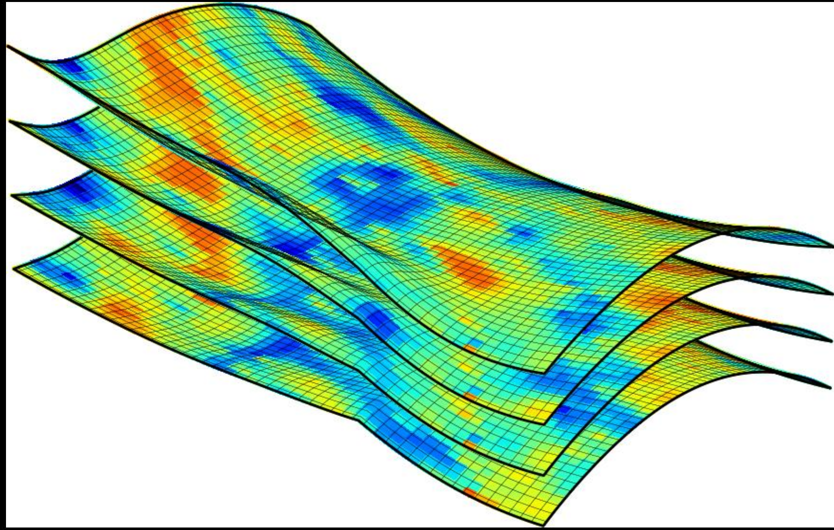
- **Reconciling diverse and disparate monitoring data to update a simulation history match and inform forward forecasts is an exceptionally challenging, complex task. Doing so autonomously and rapidly represents a major challenge but could save significant monitoring costs by decreasing the level of effort of subject matter experts.**
- **Task 4 Solution:**
  - Task 4 incorporated several ML-based methods for accelerating the processing and interpretation of monitoring data into the history-matching/real-time forecasting workflow.
  - Updated forecasts are autonomously evaluated to quantify, communicate, and learn from monitoring data and historical trends to help identify measurements and/or interventions most relevant to improving storage operations that will lead to significant CCUS site-monitoring costs.

Solution Approach

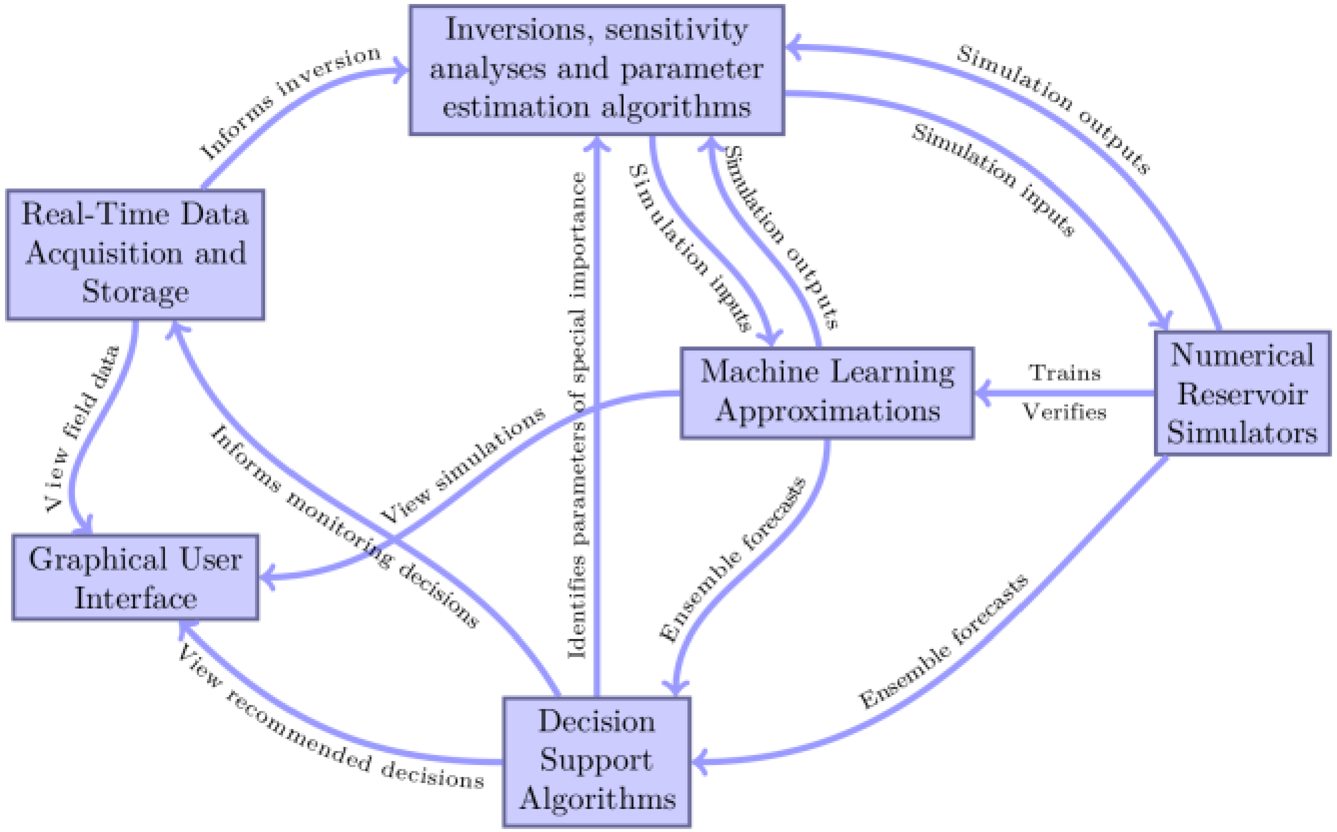
Unified Simulation Platform

- Organizes ML models into a single, centralized software platform
- Allows apples-to-apples comparisons between ML models
- Runs huge numbers of simulations to perform large, hierarchical, multi-objective optimizations
- Runs individual simulations in near real time for efficient end-user interactions





Scientific Workflow



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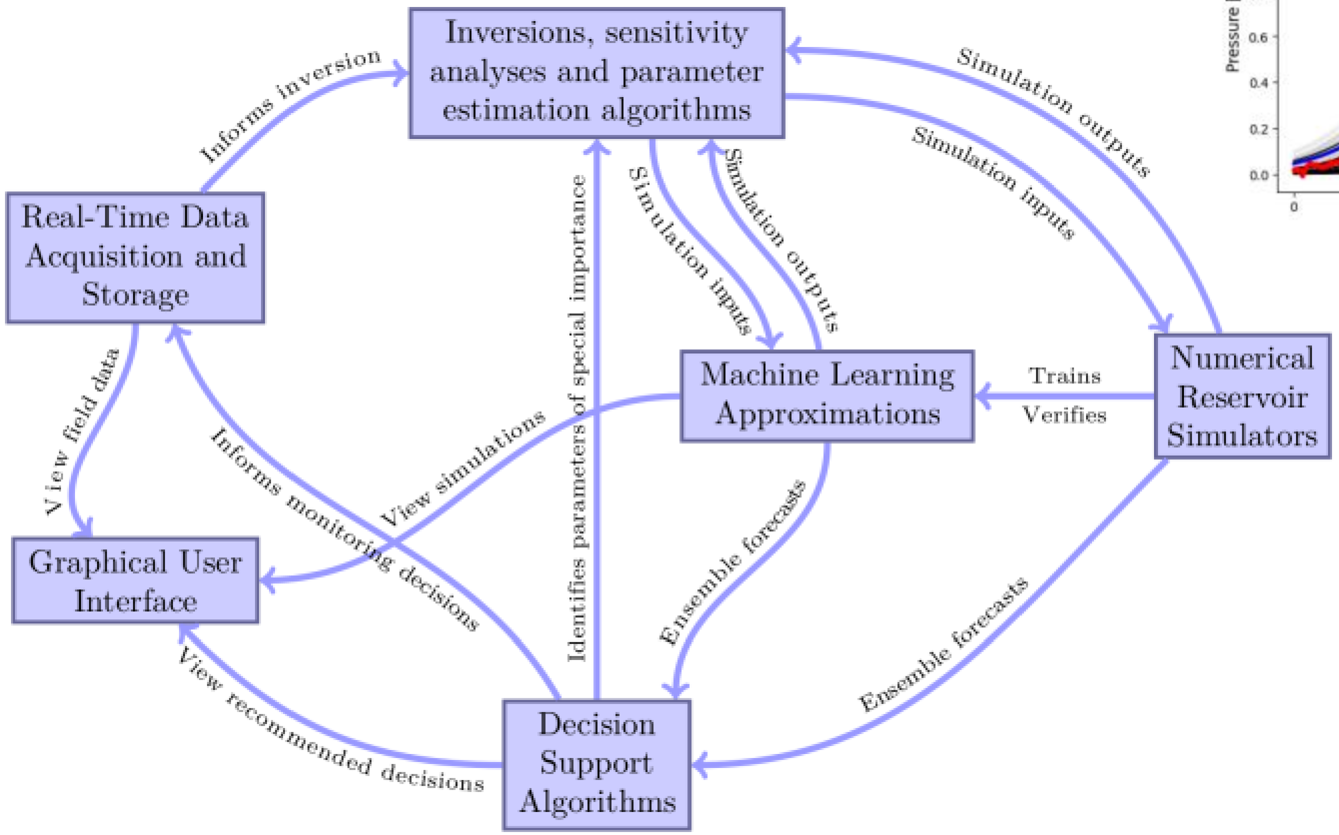
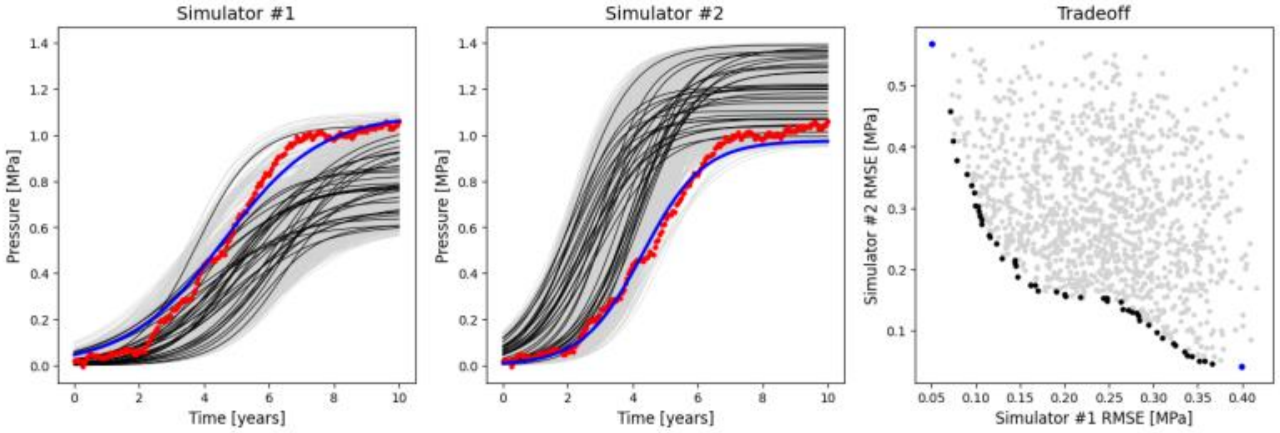
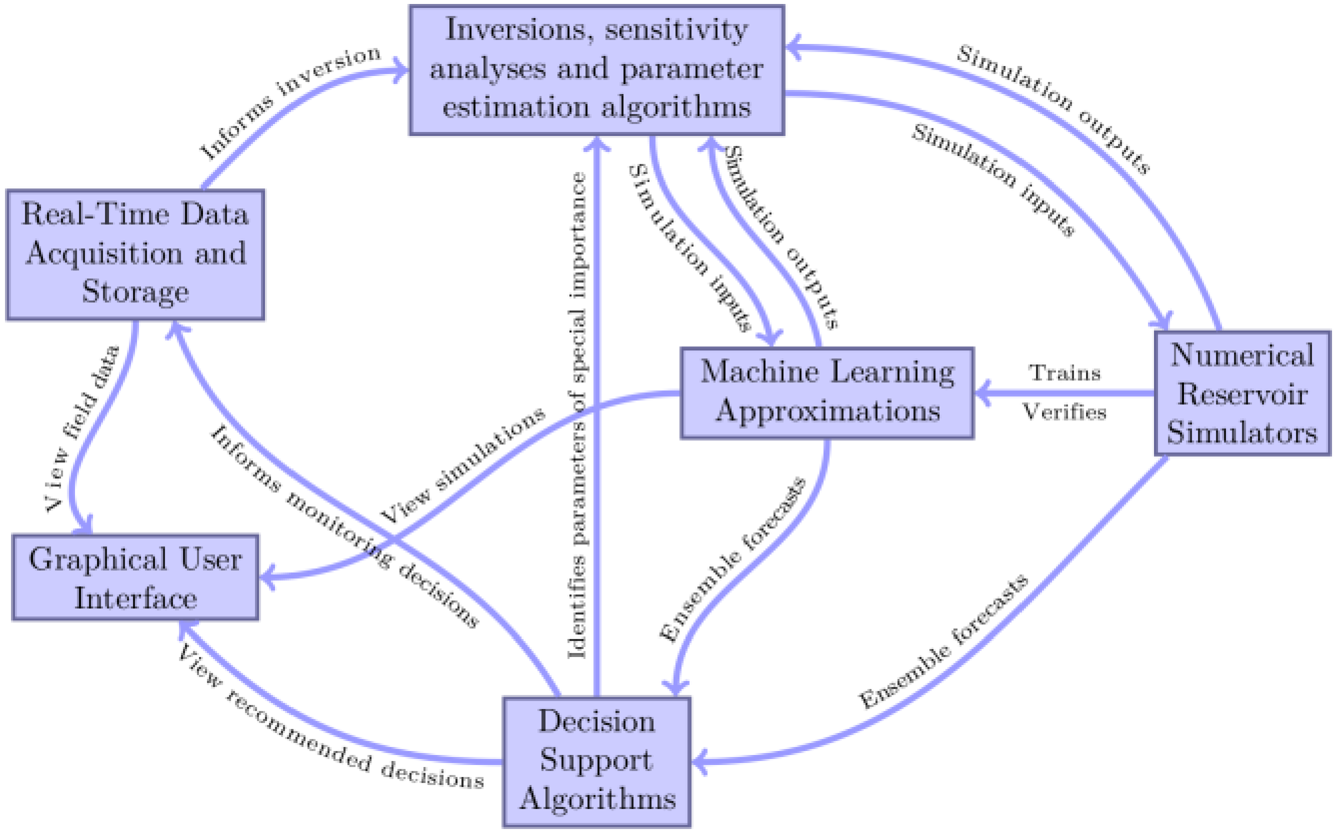
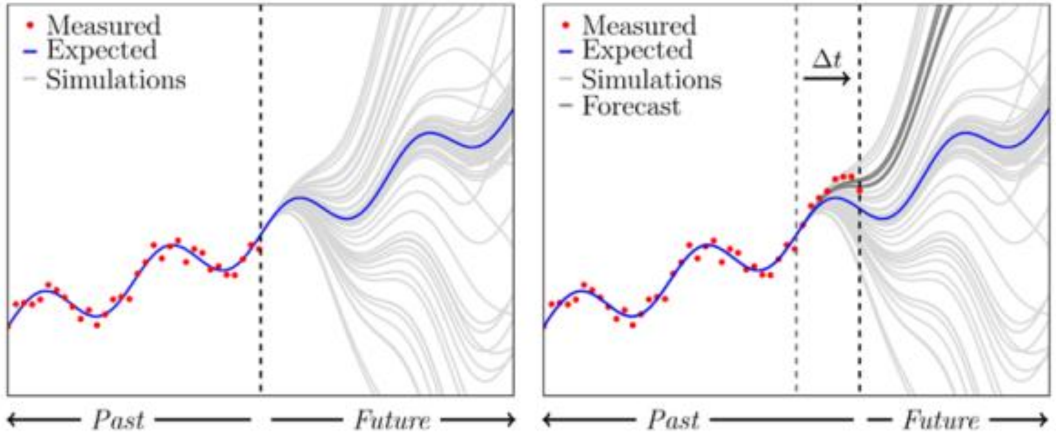


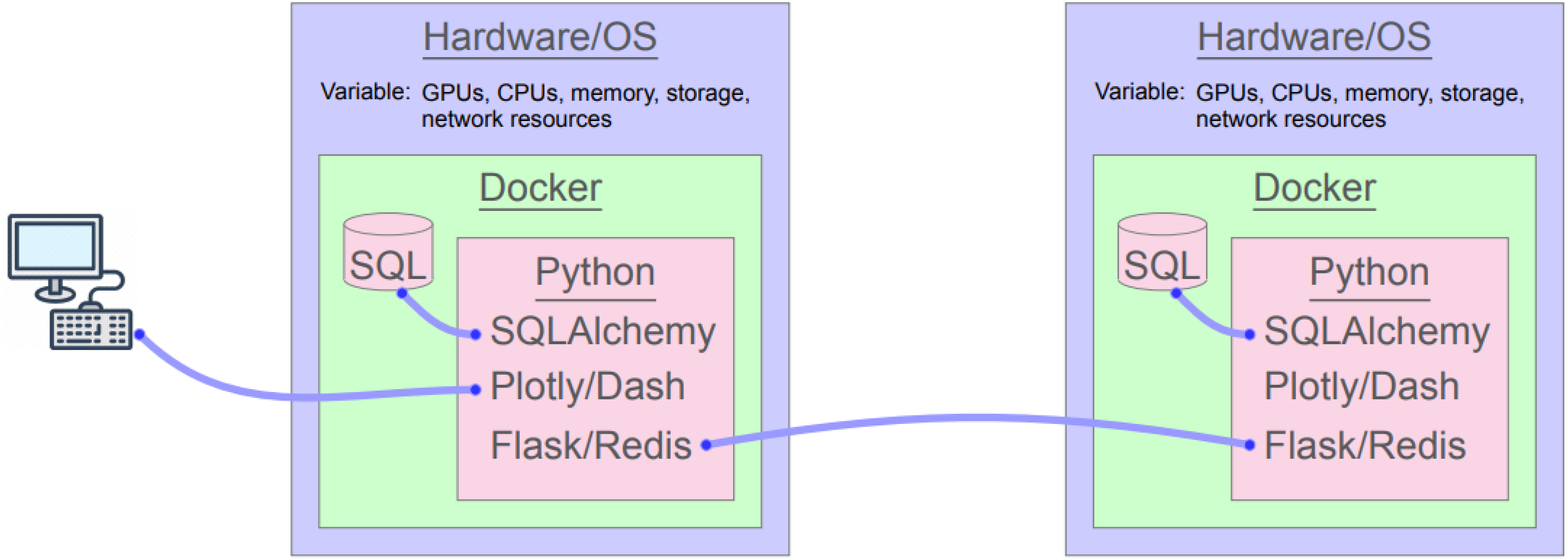


Scientific Workflow

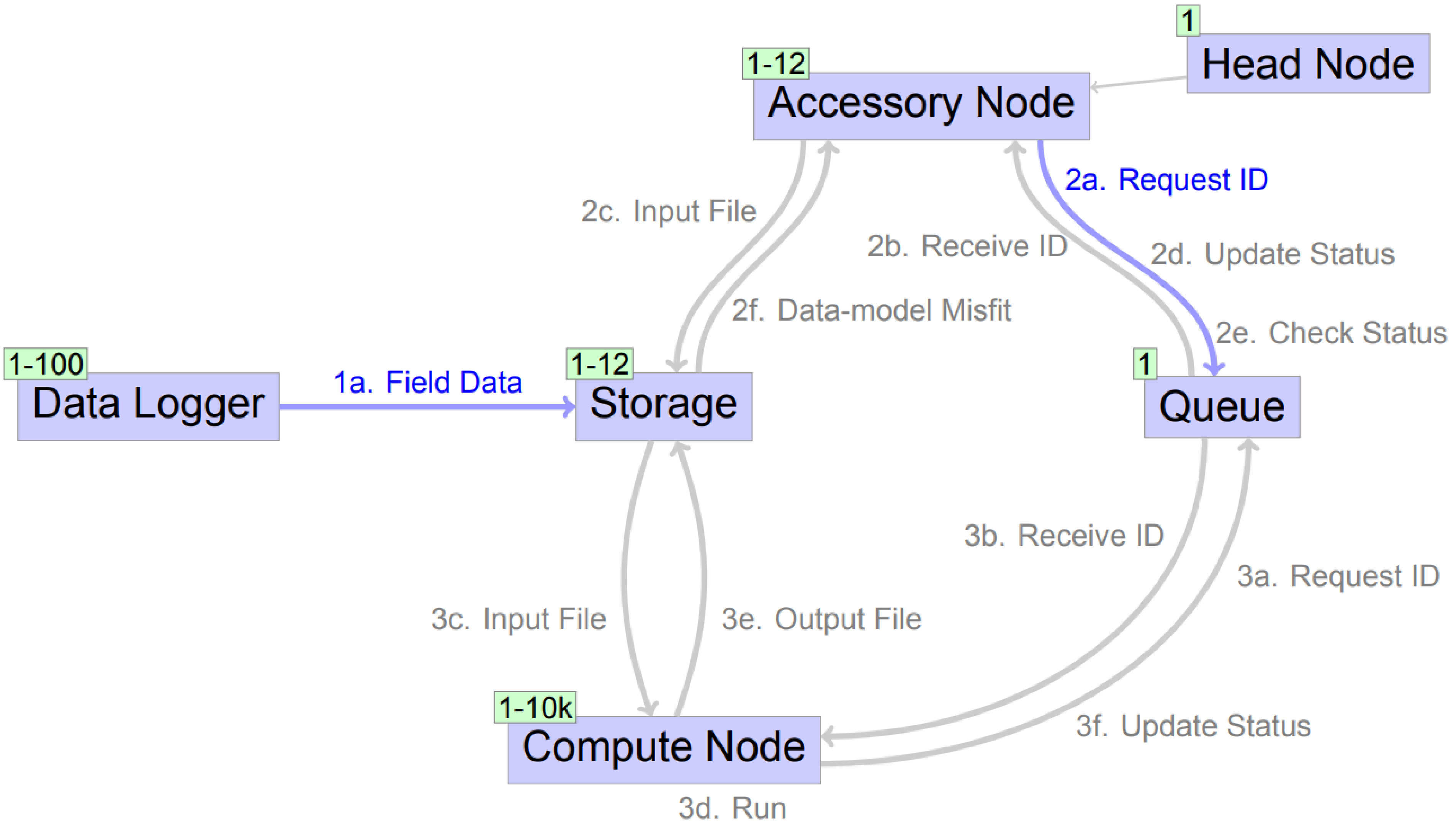




Node Architecture



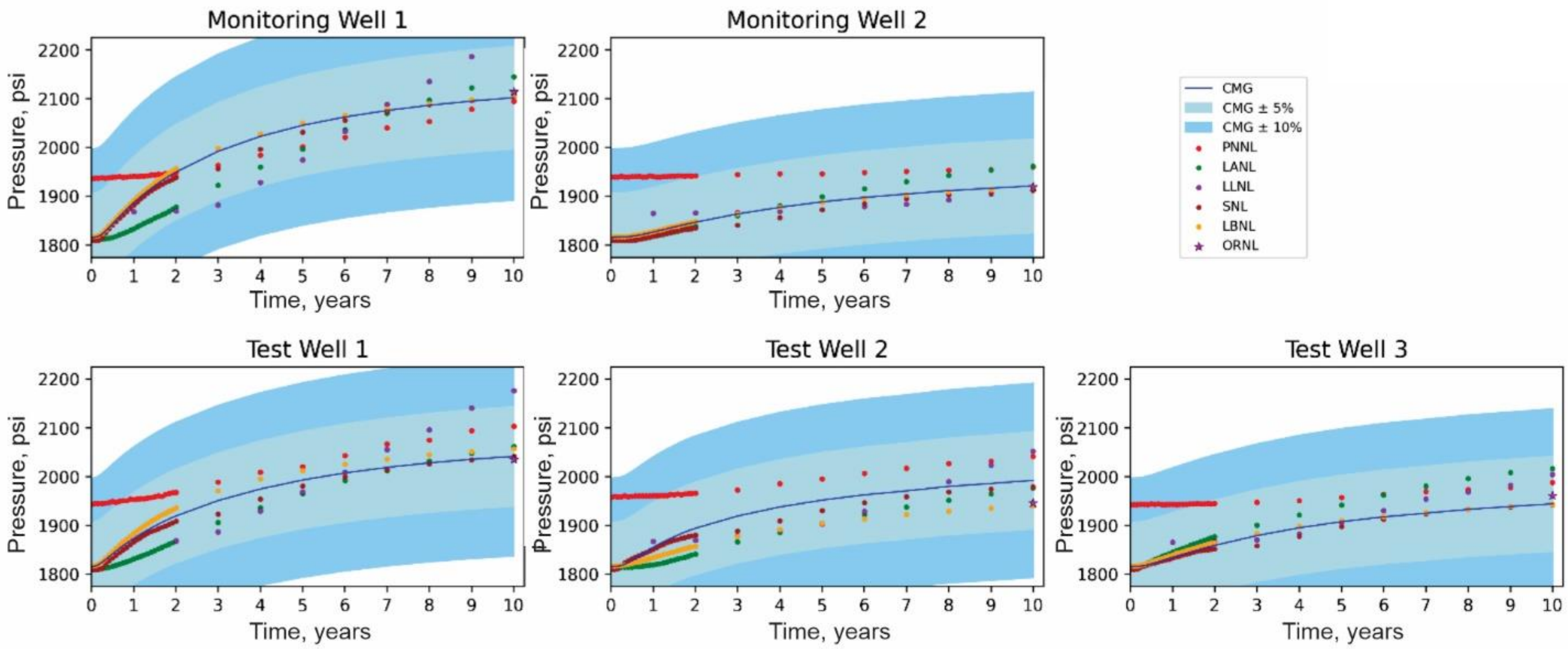
Platform Architecture



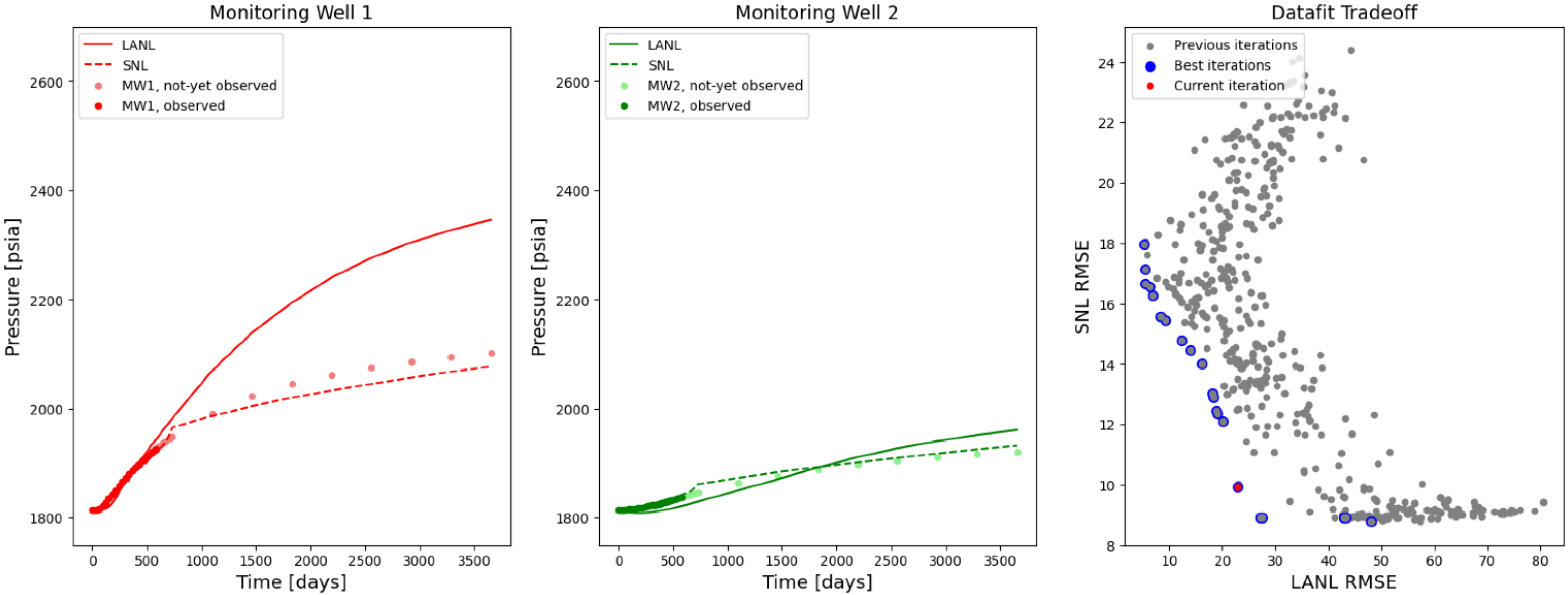
Forward Model Types

- Deep learning and convolutional neural networks
- Convolutional neural network-based autoencoders
- Wide residual networks
- Long short-term memory
- Convolutional long short-term memory methods
- Generative adversarial networks
- Capacitance-resistance models
- Inversionless forecasting
- Top-down modeling approach w/ spatio-temporal learning and deconvolutional neural networks

Forward Model Types



Hierarchical Optimization



Key Findings

- Many of the different approaches have different strengths—that is, better accuracy with comparable speed for different predictions.
- Some of the approaches were unable to be fully integrated into the Task 4 platform, making comparison of the speed on the same platform impossible.
- Saline aquifer models were able to compare with one another in an apples-to-apples fashion and, in many cases, agreed quite closely.
- A larger and more dynamic training data set would allow these models to agree more consistently.

Next Steps

- **In the future, developing a more user-friendly, low-code interface for the SMART platform would allow ML developers to share code and data sets more easily.**
- **During Phase II, this platform will**
  - incorporate new models from several new carbon storage sites
  - Interface with enhanced visualization capabilities

Thank you!

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Questions?