

Physics Coupled Machine Learning Applications for Geological Carbon Storage



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

Motivation and Objectives

- CO₂ storage (CO₂ injection, brine extraction, pressure management) is a strategic design to meet the regulations based on the limited site characterization and dynamic reservoir responses for sequestration target.
- Coupled Capacitance & Resistance Model (CRM) and machine learning based upon machine learning techniques provide a bridge for operations and reservoir management for CO₂ storage.
- Demonstrating the synergy of physics coupled machine learning concept for CO₂ storage decision support.
- Potential to transfer the efforts learned from one datasets to another for the application purpose.

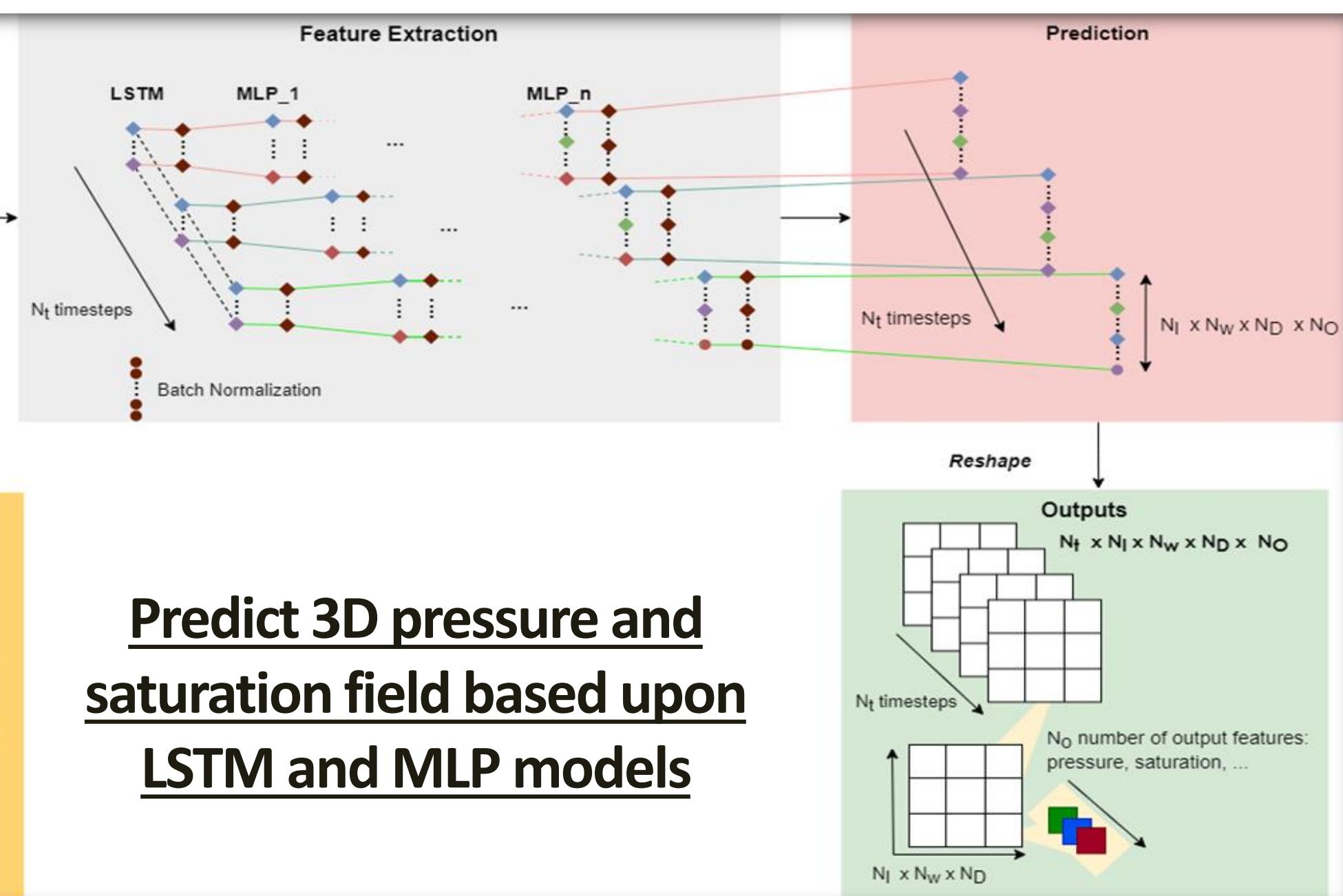
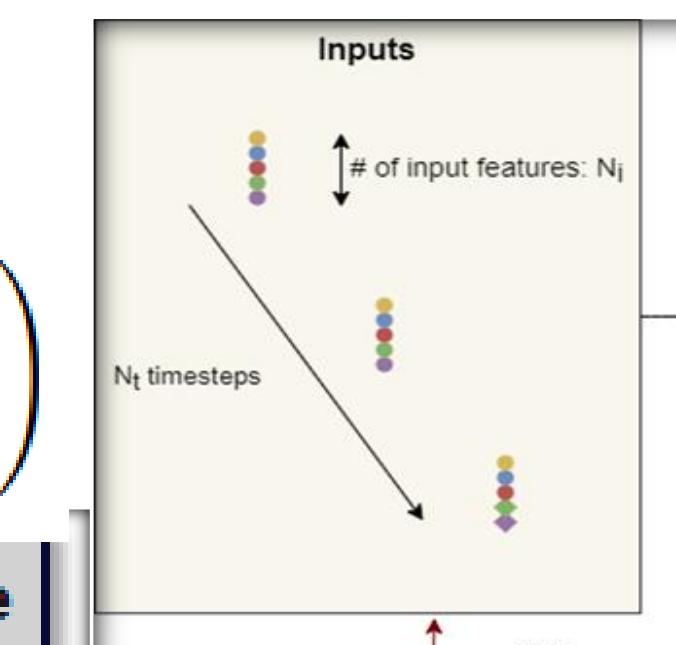
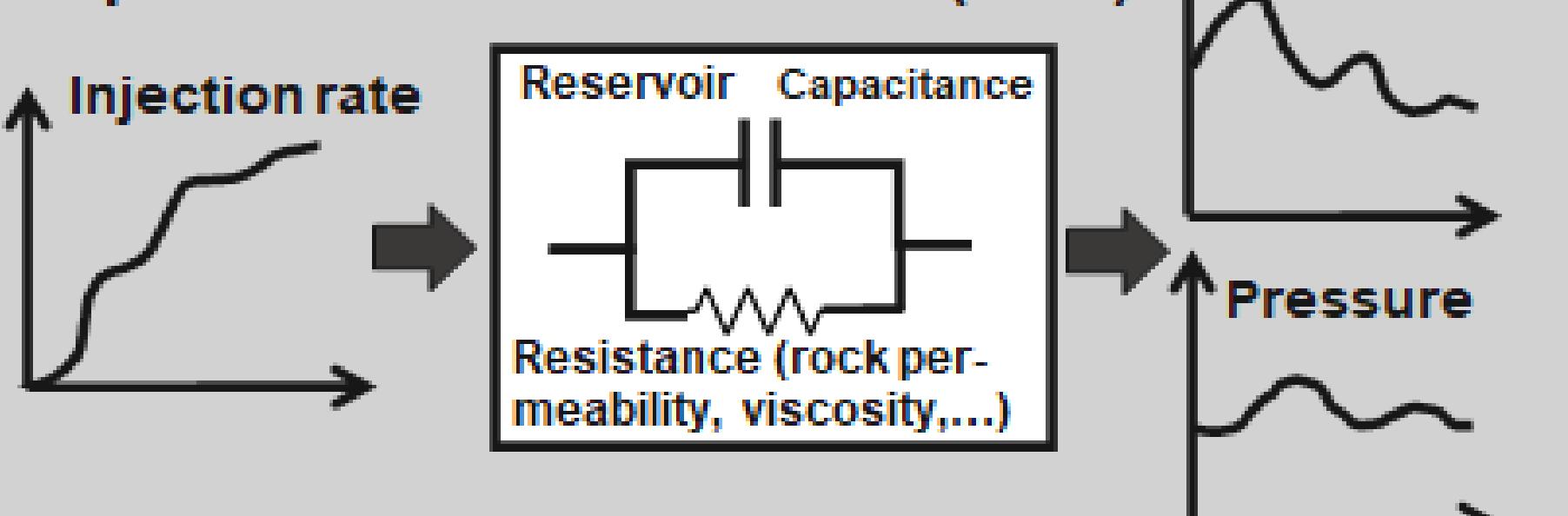
The Model Overview

Electric Circuit Borrowed Material Balance Principle

Capacitance & Resistance Model

$$q_k = q_{(k-1)} e^{-\frac{\Delta t}{\tau}} + \left(1 - e^{-\frac{\Delta t}{\tau}}\right) \left(f_{i_k} - J\tau \frac{p_{wf}^{(k)} - p_{wf}^{(k-1)}}{\Delta t} \right)$$

Capacitance Resistance Model (CRM)



Adapted CRM Model

$$q_k = q_{(k-1)} e^{-\frac{\Delta t}{\tau}} + \left(1 - e^{-\frac{\Delta t}{\tau}}\right) \left(f_{i_k} - J\tau \frac{p_{wf}^{(k)} - p_{wf}^{(k-1)}}{\Delta t} \right)$$

$$0 = (1 - e^{-\frac{\Delta t}{\tau}}) (i - J\tau \frac{\Delta p}{\Delta t})$$

$$J\tau \frac{\Delta p}{\Delta t} (1 - e^{-\frac{\Delta t}{\tau}}) = i (1 - e^{-\frac{\Delta t}{\tau}})$$

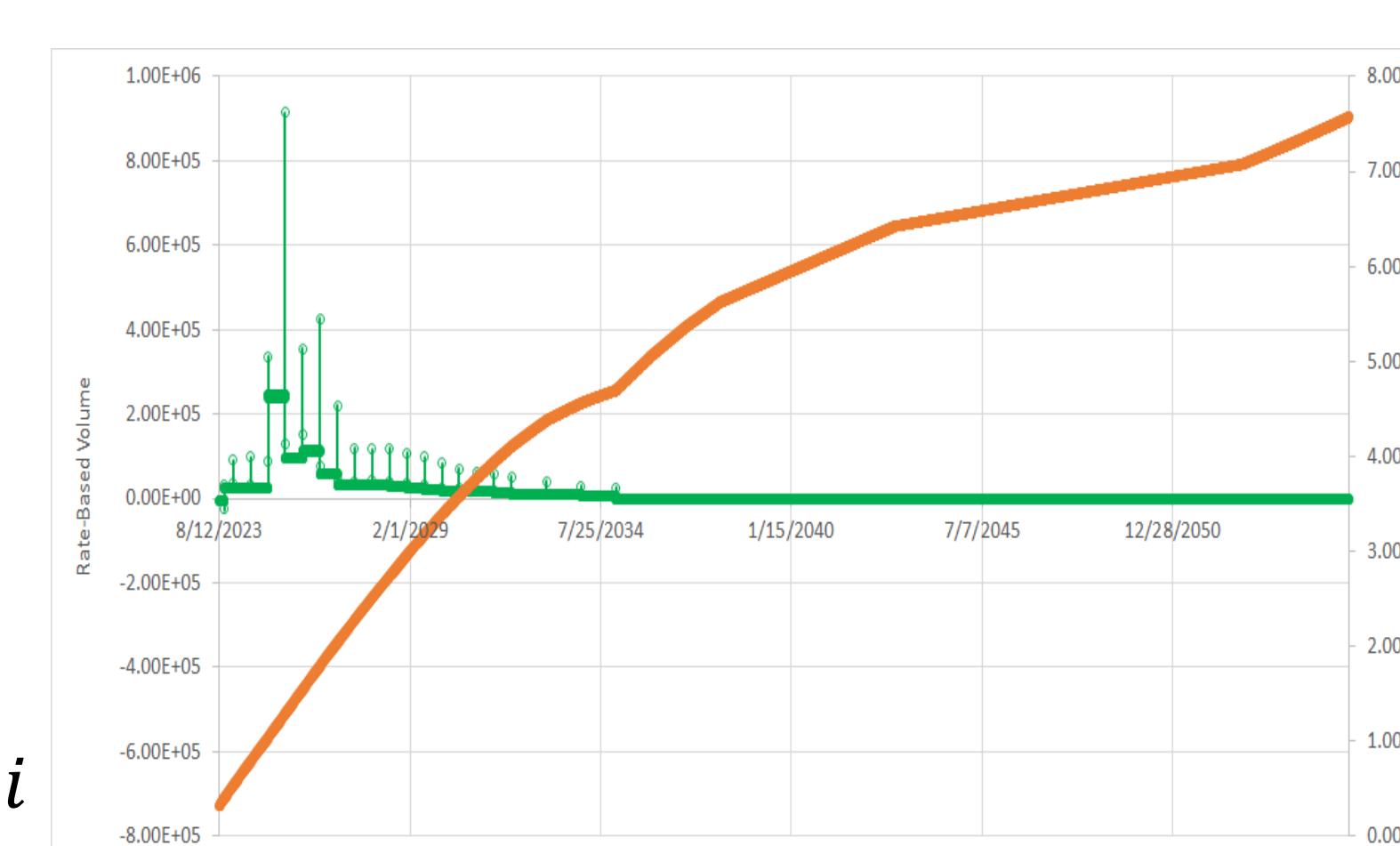
$$c_t v_p \frac{\Delta p}{\Delta t} = i \quad J\tau \frac{\Delta p}{\Delta t} = i \quad \rightarrow i = J\tau(\bar{p} - p_{wf})$$

(1) (2)

Injection cumulative-based drainage volume:

$$c_t v_p \frac{\Delta p}{\Delta t} = i \quad \rightarrow c_t v_p \Delta p = i \Delta t$$

$$c_t v_p \sum_{t=0}^{t=n} \Delta p = \sum_{t=0}^{t=n} i \quad \rightarrow v_p = \sum_{t=0}^{t=n} i / (c_t \sum_{t=0}^{t=n} \Delta p)$$



Rate-based and cumulative-based drainage volume

Injection cumulative-based pressure:

$$c_t v_p \frac{\Delta p}{\Delta t} = i \quad \rightarrow c_t v_p \Delta p = i \Delta t \quad \rightarrow c_t v_p \int \frac{\Delta p}{\Delta t} = \int i$$

$$\rightarrow c_t v_p \sum_{t=0}^{t=n} \Delta p = \sum_{t=0}^{t=n} i \quad \rightarrow \sum_{t=0}^{t=n} \Delta p = \sum_{t=0}^{t=n} i / (c_t v_p)$$

Disclaimer

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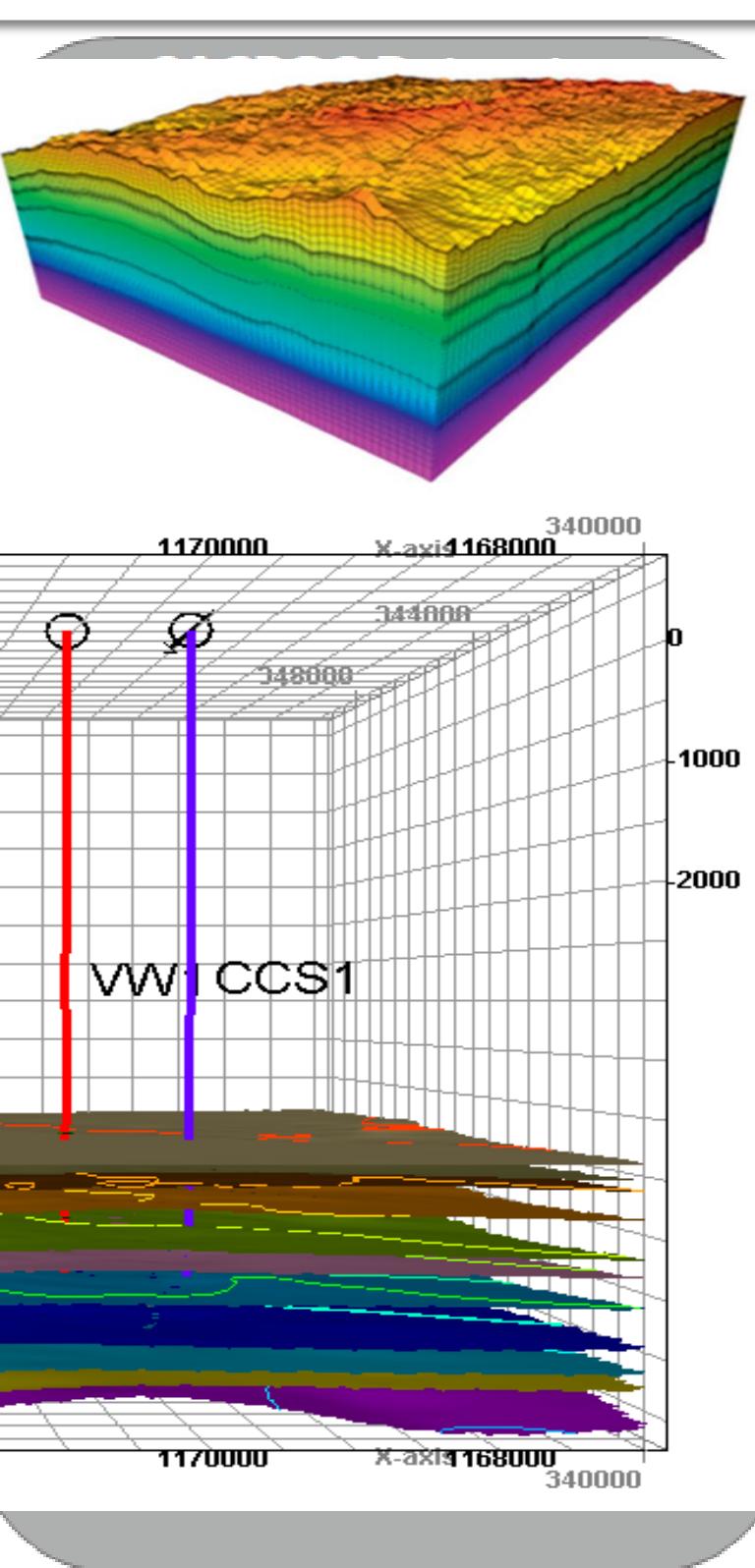


References

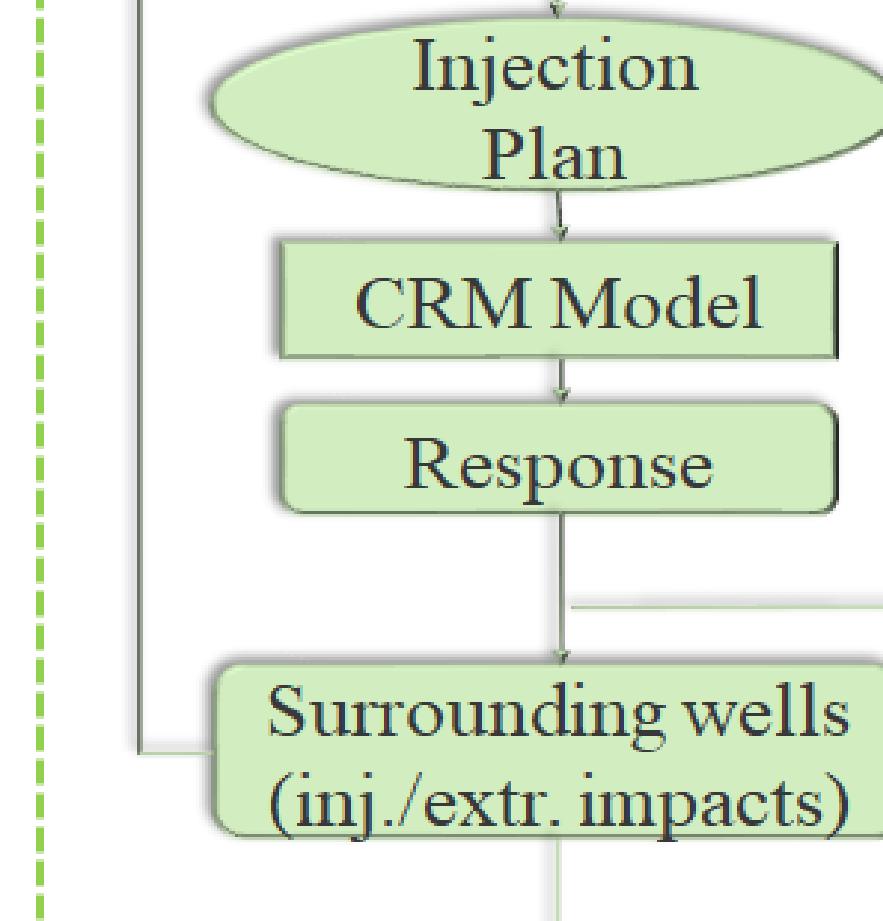
¹Tao, Q., Bryant, S., Optimizing CO₂ Storage in a Deep Saline Aquifer with the Capacitance-resistance Model, Energy Procedia, Volume 37, 2013, Pages 3919-3926, ISSN 1876-6102, <https://doi.org/10.1016/j.egypro.2013.06.290>.

²Liu, G., Wu, X., Shih, C., Vasylkivska, V., Bromhal, G., Physics-Coupled Machine Learning Toolset for Geological Carbon Storage Evaluation and Performance Analysis (November 10, 2022). Proceedings of the 16th Greenhouse Gas Control Technologies Conference (GHGT-16) 23-24 Oct 2022, Available at SSRN: <https://ssrn.com/abstract=4273411> or <http://dx.doi.org/10.2139/ssrn.4273411>

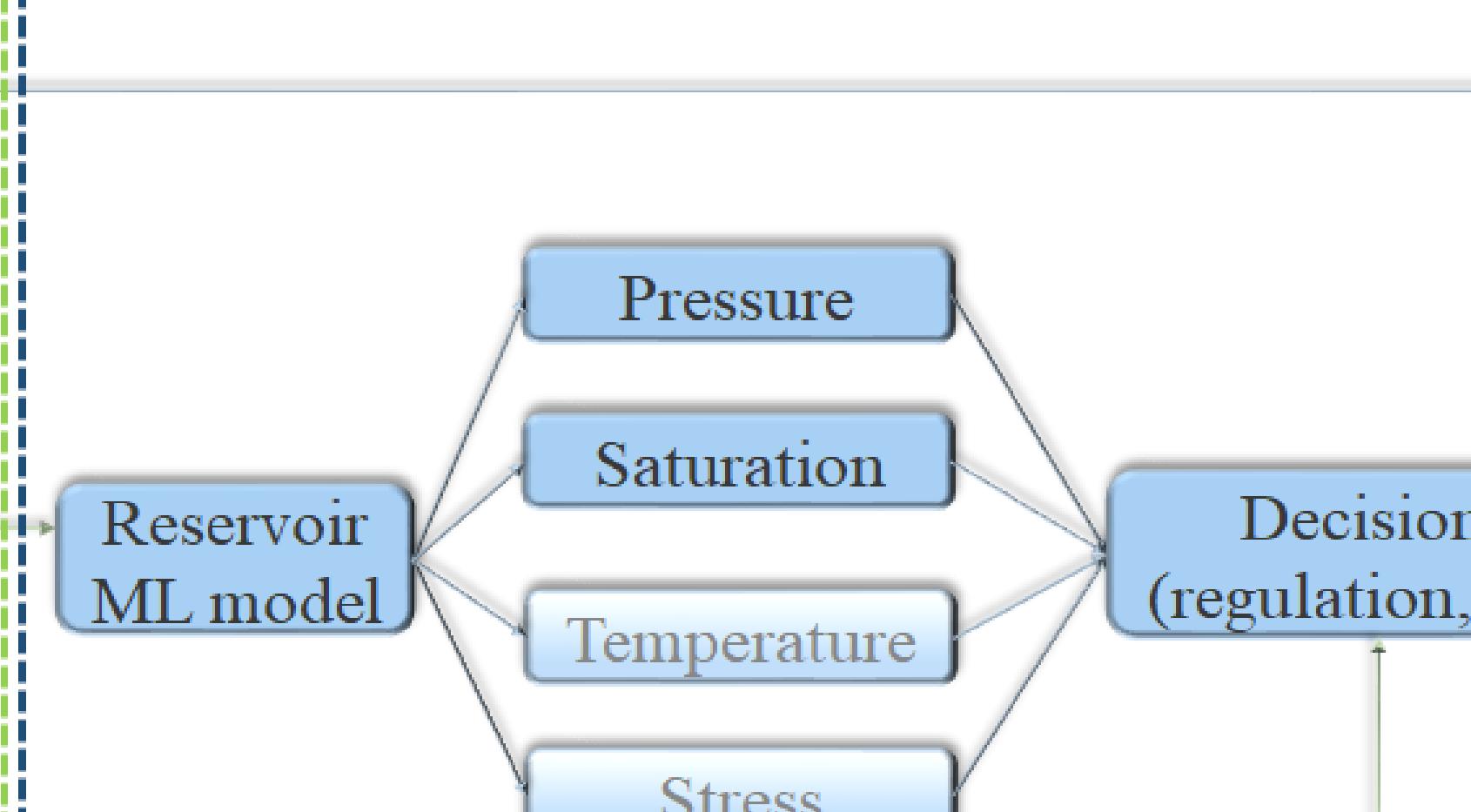
Coupled Workflow



Rapid Operations Forecasting



Virtual Learning for Reservoir Management



- Rapid HM & forecasting
- Monitoring design

- Injection/extract exploration
- What-if scenarios/studies
- Reservoir management
- Operation optimizations

Remarks

- This study illustrates a physics coupled machine learning method for CO₂ storage application, particularly, providing insights of reservoir pressure build-up and drainage volume understanding over CO₂ injection.
- The adapted CRM model for CO₂ injection is driven from the classic form of the model to find out the relationships between injection and the reservoir pressure build-up and drainage volume.
- Such insights also can be used as constraint/s for machine learning to guide the training and testing.
- More cross validation and benchmark testing is still on-going.

