Machine Learning Applications for CCS Project Acceleration

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Outline

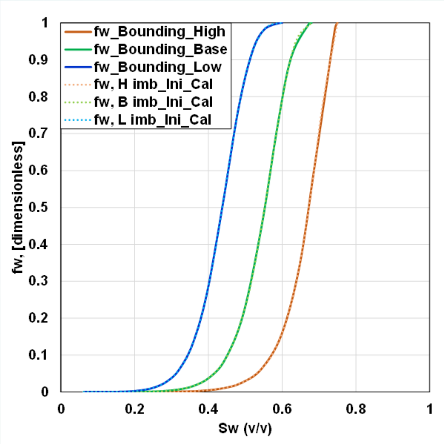
- Introduction
- Methodology
- Results
- Conclusions & Future Work

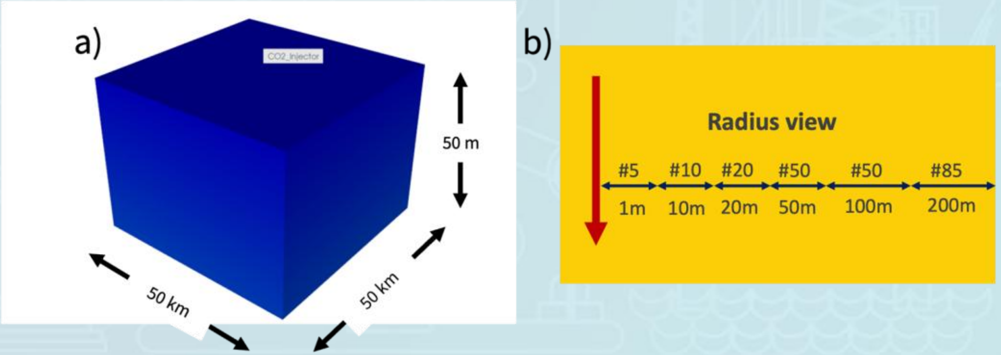
Introduction: Background

- Atlas is a cost-competitive, open-access carbon transport and storage hub in Alberta, Canada operated in a partnership between Shell Canada and ATCO EnPower
- Atlas is critical to ATCO's decarbonization and ESG targets
- The first phase of Atlas will provide permanent underground storage for CO_2 captured by the Polaris project roughly 22 km away at Shell's Scotford refinery
- The objective is to have the site operational by 2028
- Machine learning applications can be applied to accelerate the engineering design process, allowing for faster decision making

Introduction: Background

- A homogeneous sector model was developed to mimic an injection site at the Atlas hub
- CO_2 is injected for 30 years before the well is shut in
- Local grid refinement applied near the wellbore





a) Reservoir model and b) grid discretization

Name	Unit	Values
Permeability	md	10, 20, 50, 100, 200, 1000
Porosity		0.15
RelPerm		low, base, high
KvKh		0.07, 0.2
Thickness	m	30, 50
Dip angle	deg	0
Injection rate	Mtpa	0.1, 0.15, 0.4, 0.6, 1
BHP	Mpa	28

Introduction: Background

- An AI-assisted workflow (pyCCUS) was developed to process ultra-complex subsurface modeling and numerical computations automatically (Li et al., 2024)
- The outputs from pyCCUS can then be applied for other data processing, visualization, and machine learning models

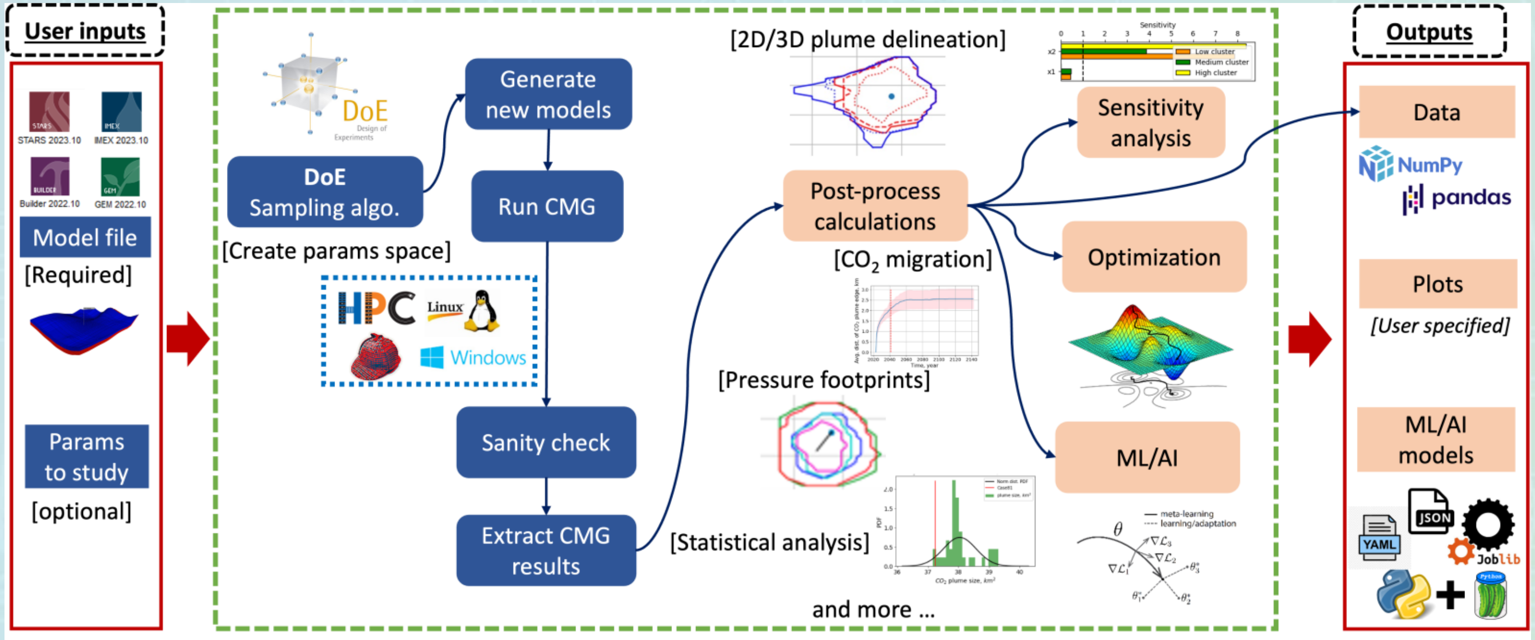


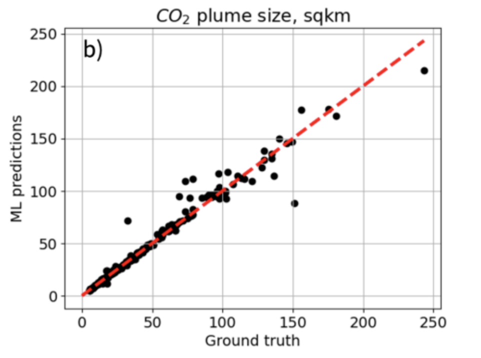
Image obtained from https://github.com/AndyStudio/pyCCUS-public

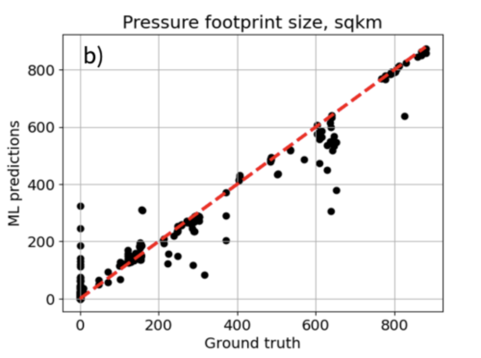
Introduction: Background

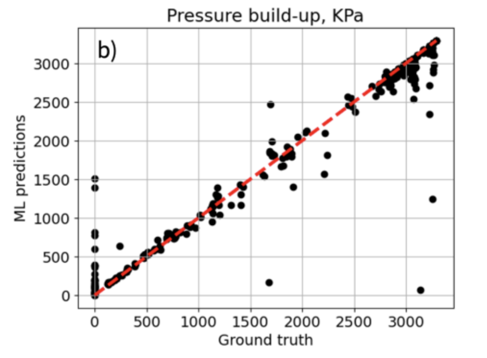
- pyCCUS generated hundreds of cases for the Atlas sector model
- In addition to analyzing gas saturation and pressure changes, **<u>the injection rate is also a quantity of interest</u>**

k
Φ
k_r
k_v/k_h
Thickness
Dip angle
q
BHP

→ pyCCUS →



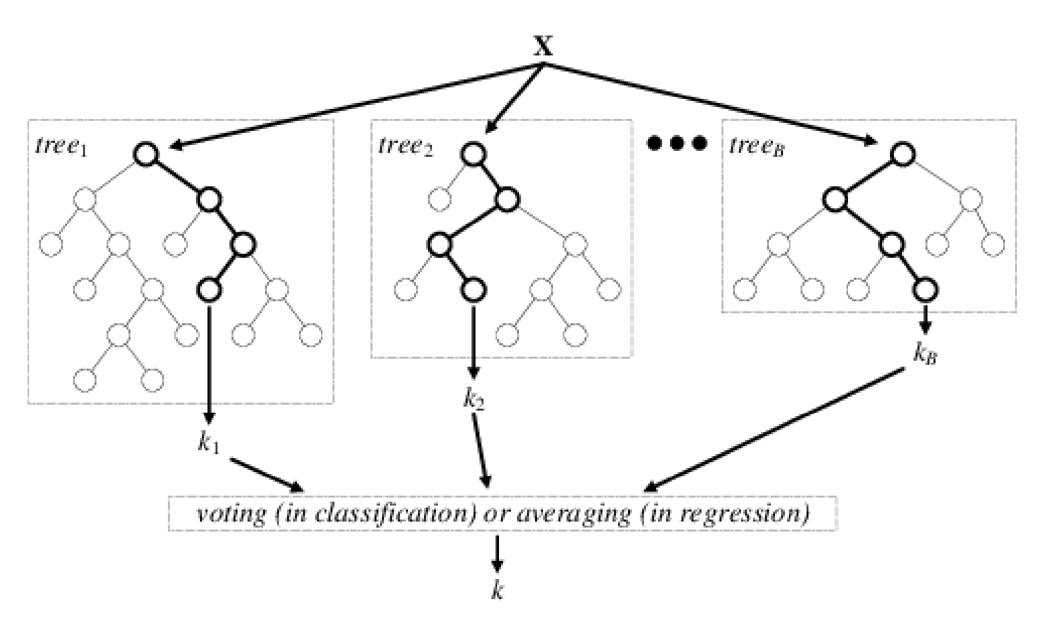




Next: Given a set of model input parameters, can we predict the CO_2 injection rate at a given time in the modeling process?

Methodology: Random Forest (RF) Models

- Supervised learning algorithm that can solve both regression and classification problems
- Random forest models can be advantageous due to:
  - ✓ No pre-assumptions on data distribution
  - ✓ Fast training process
  - ✓ Ability to handle non-linear relationships
  - ✓ Ensemble learning
- Disadvantages:
  - ✗ long prediction times for complicated models
  - ✗ Cannot extrapolate outside the range of the training set



$$\hat{f}^B_{\mathrm{rf}}(x) = \frac{1}{B}\sum_{b=1}^{B} T(x;\Theta_b).$$

Methodology: RF Models for Subsurface Engineering

Prediction of original oil in place (OOIP) using RF models (Shafiei et al., 2022)

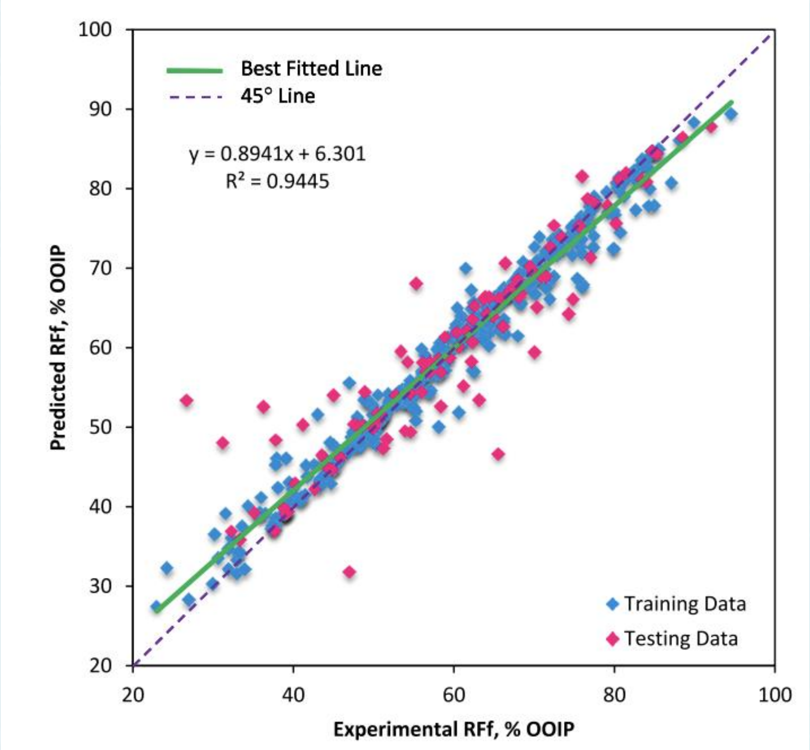


Image obtained from Shafiei et al (2022)

Predicted proppant filling index using RF and gated recurrent unit models (Hou et al., 2023)

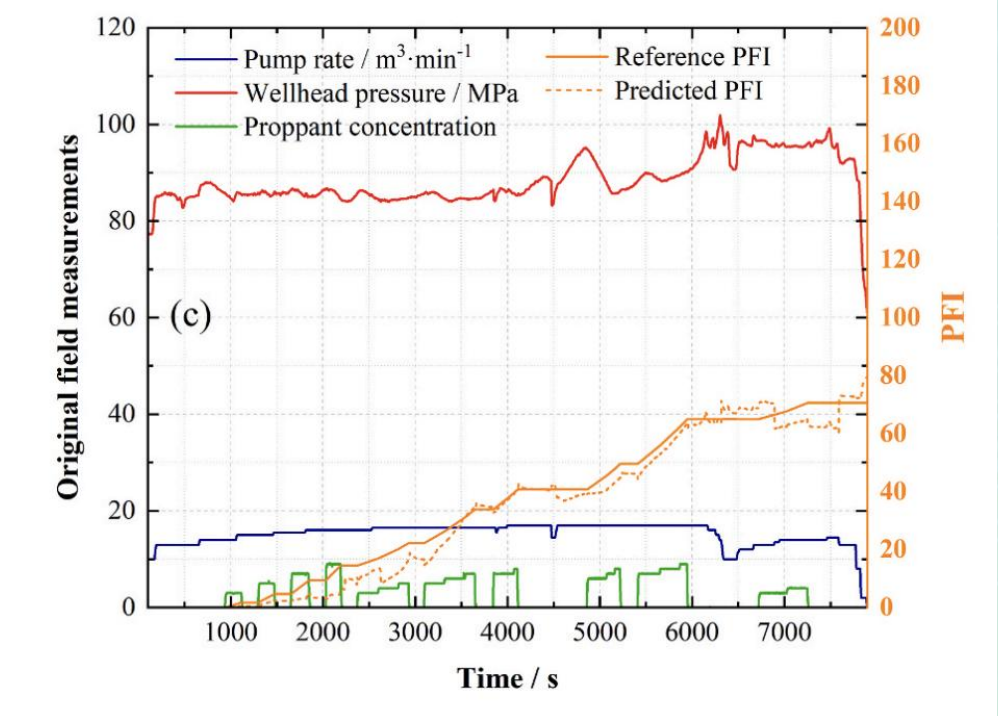


Image obtained from Hou et al. (2023)

Methodology: Comparison of Methods

Variable Features	Value
Permeability, mD	10, 20, 50, 100, 200
k_v/k_h	0.07, 0.2
Relative Permeability	Low, Base, High
Formation Thickness, m	30, 50
Targeted Injection Rate, MTPA	0.1, 0.15, 0.4, 0.6, 1.0

Builder 2022.10

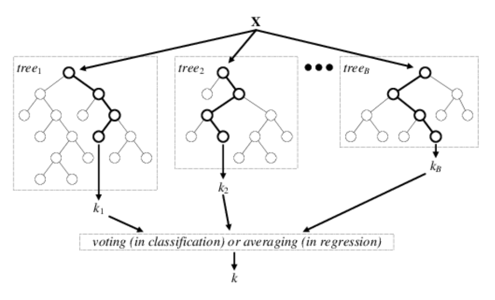
GEM 2022.10

COMPUTER MODELLING GROUP LTD.

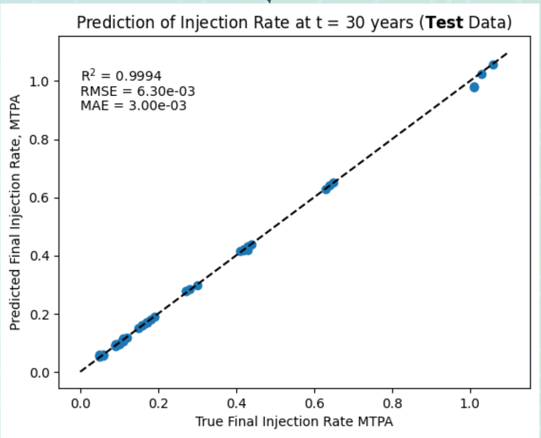
Days – weeks to run

Minutes to run

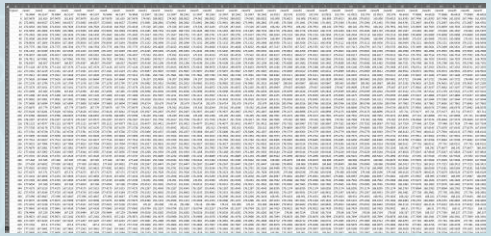
scikit learn



Output: Injection Rate



Methodology: Modeling Workflow



Training data
239 cases

Model
training & fit

Hyperparameters

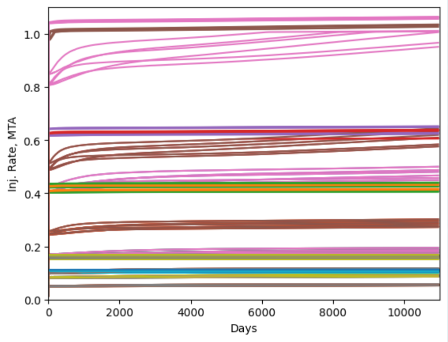
Injection
rate data
299 cases

Split data

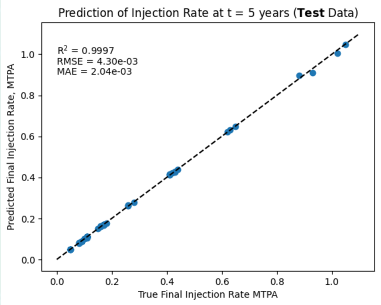
Model testing

Test data
60 cases

Prediction

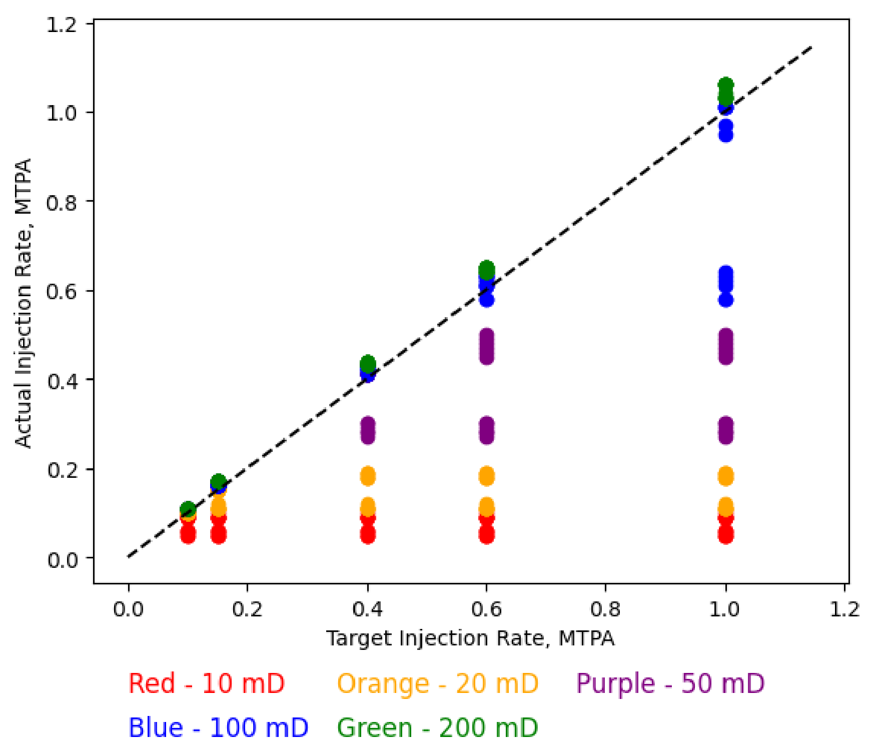


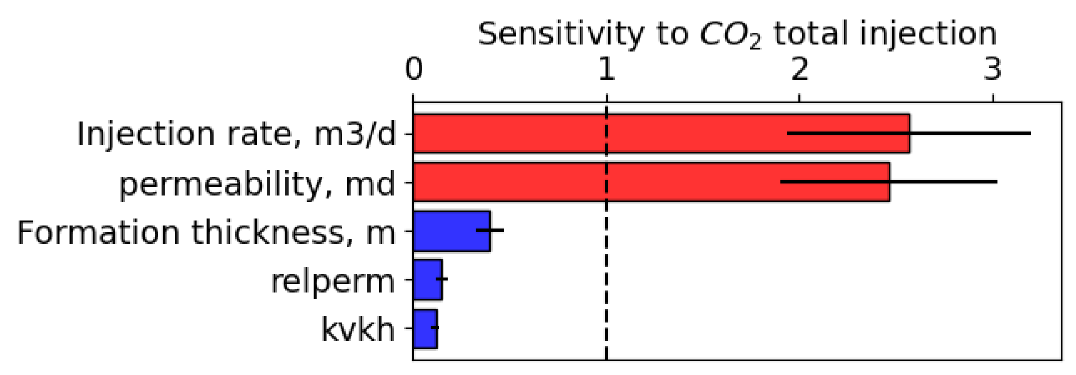
Plot of all injection rates as a function of time.



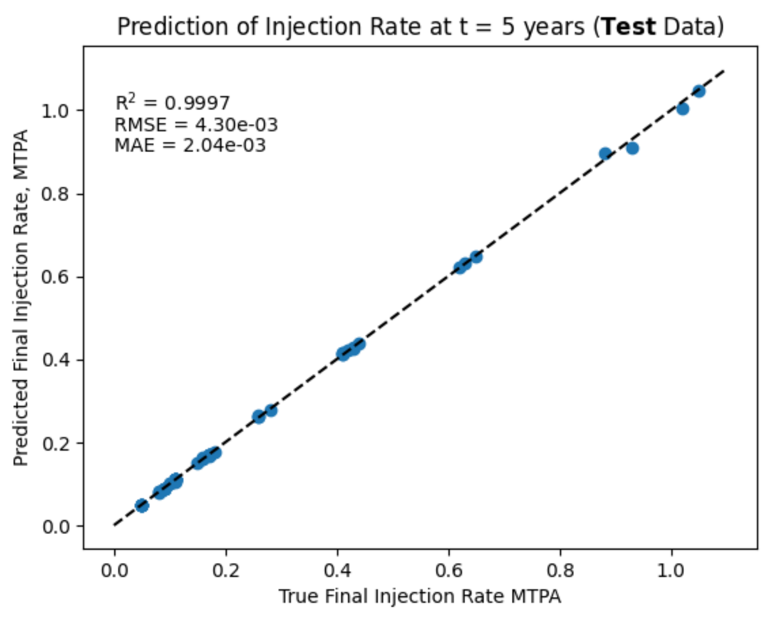
Results: Variable Sensitivity to Injection Rate

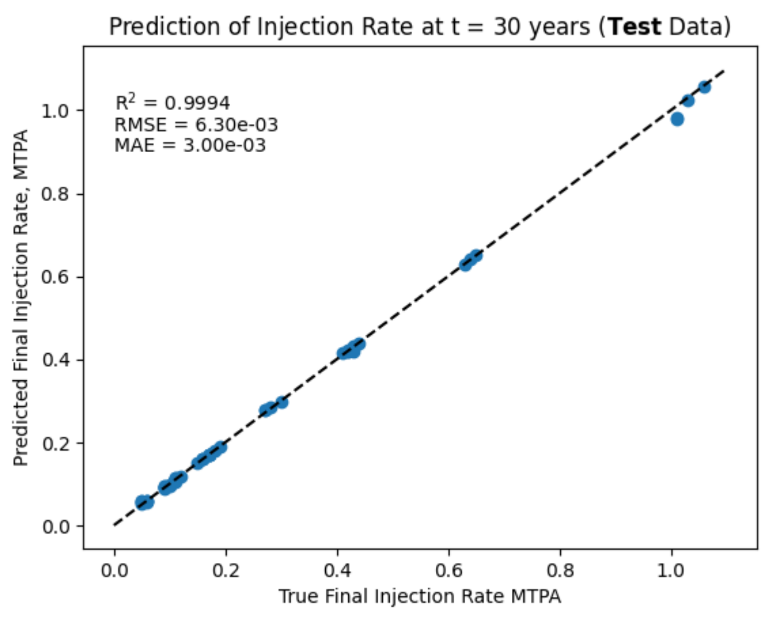
- Formation permeability plays a crucial role in achieving target injection rate
- Actual injection rate is calculated based on average reservoir CO_2 density
- The results agree with the distance-based sensitivity analysis performed by Li and Perez Claro (2023)





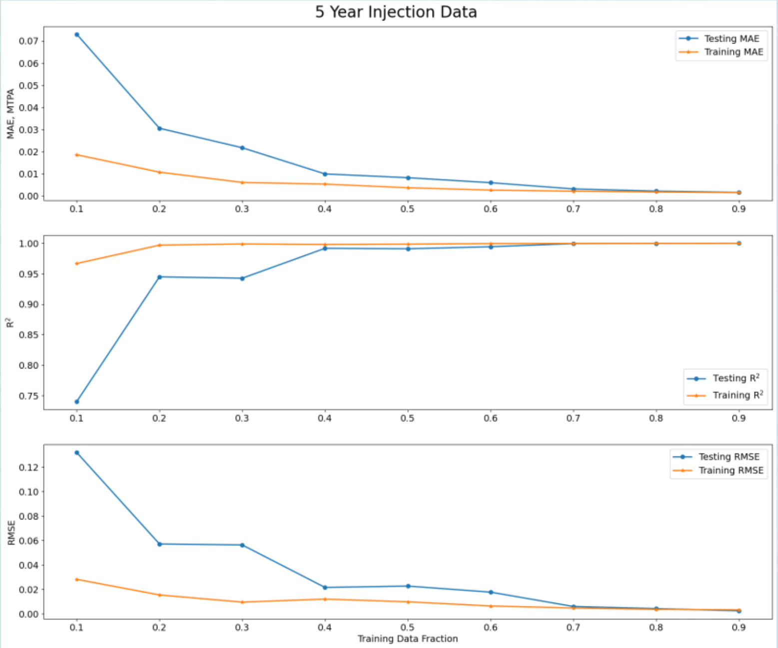
Results: Injection Rate Prediction at 5 years and 30 years

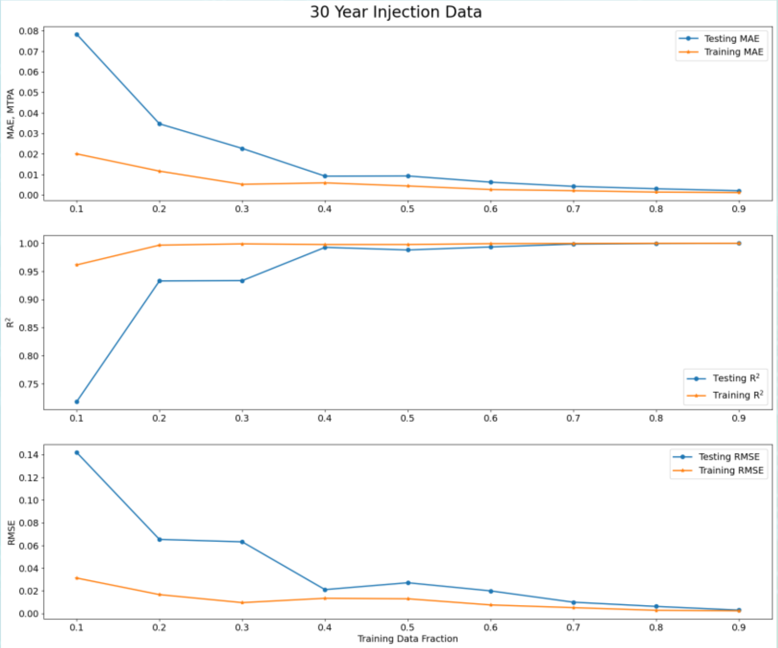




- Trained with 80% of the available data and tested on the remaining 20% (60 cases)
- Fast training and prediction times:
  - Training: 0.25 seconds
  - Testing: 0.42 seconds

Results: Scarcity of Training Data vs. Accuracy





- Increasing the amount of training data will improve model accuracy
- It is recommended that a **<u>minimum of 20% of the total data</u>** should be set aside for training data to yield accurate predictions

Results: Conclusions

- CO_2 injection rate is primarily driven by formation permeability and thickness
- A random forest model was created to predict early and late-stage injection rates for the Atlas sector model with great accuracy
- The model trains and predicts at faster rates compared to the CMG model (~2 minutes vs. several days)
- Future work will work on developing a preprocessing pipeline to help train the model with more samples and features (i.e. variable porosity, permeability, etc.)

Acknowledgments

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Thank You!

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