Novel Machine Learning Methods to Detect Small Leaks

(FWP FE-1122-19-FY19)

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U.S. Department of Energy
National Energy Technology Laboratory
2021 Carbon Management and Oil and Gas Research Project Review Meeting
August 2021

R&D Road Map

01 **Previous Work**

Our data-driven leakage detection using Kimberlina synthetic data.

02 **Project R&D: Leak Detection at Cranfield Site**

Demonstration of leakage detection using real-world data from controlled field experiment with downhole pressure data.

03 **Project R&D: In Situ Monitoring at Sleipner Site**

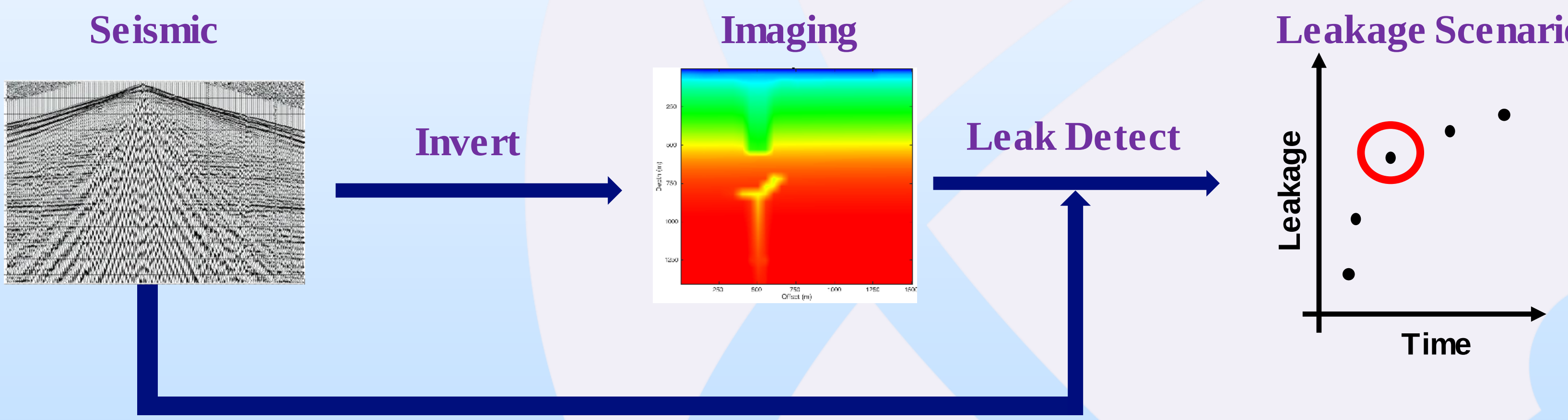
Demonstrated detection of analog leak of super-critical CO2 in a deep reservoir with processed seismic data.

04 **Lessons & Opportunities**

Demonstration of data driven methods to provide economic validation of sequestration at real-world injection project.

Previous Work – Leak Detection using Kimberlina Data

- Spatial signature (induced by leaks) exists in raw seismic data
- **Machine learning can extract spatial signature to detect small leaks**
  - Proof of concept with Kimberlina synthetic seismic data [Zhou et al. (2019)]
- **<u>Limitations:</u>** shallow leaks, synthetic data (gap to real world), large volume of training data needed

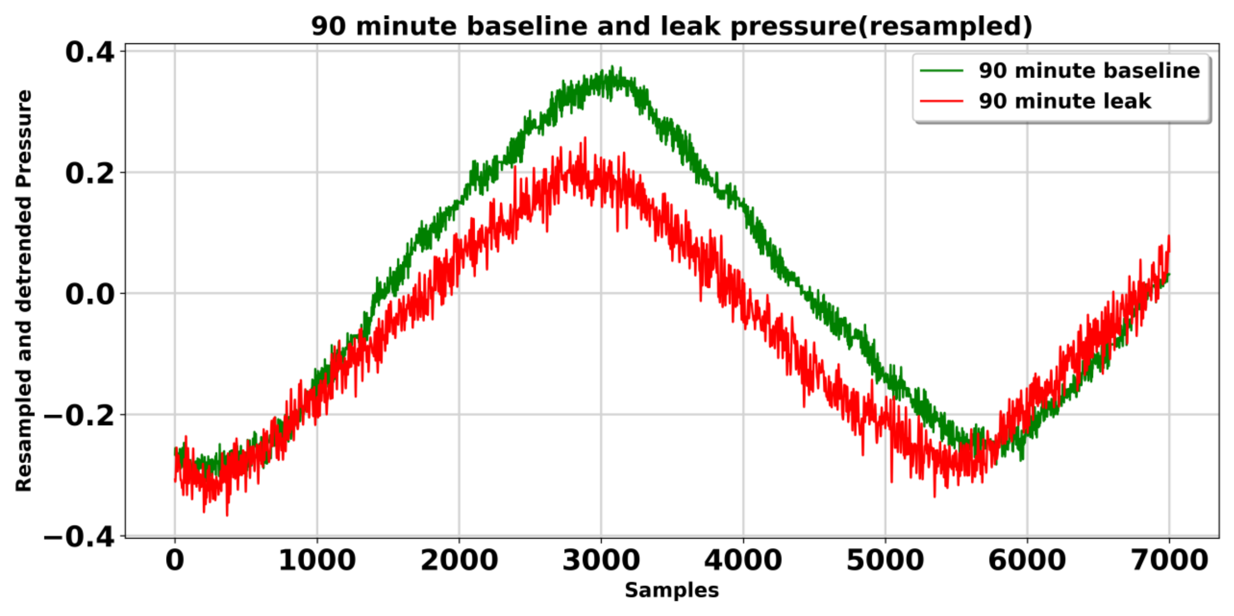


Non-Imaging Seismic Leakage Detection

Zheng Zhou, Youzuo Lin, Zhongping Zhang, Yue Wu, Zan Wang, Robert Dilmore, and George Guthrie, "A Data-Driven CO2 Leakage Detection Using Seismic Data and Spatial-Temporal Densely Connected Convolutional Neural Networks," International Journal of Greenhouse Gas Control, Vol 90, 2019.

Project R&D – Cranfield Site and Data Availability

- *Controlled* experiments were conducted in the Cranfield site
  - Non-leak (baseline) V.S. “artificial leak” case
  - Bottom-hole pressure data were collected
- Leak/Non-leak signatures are in temporal representation

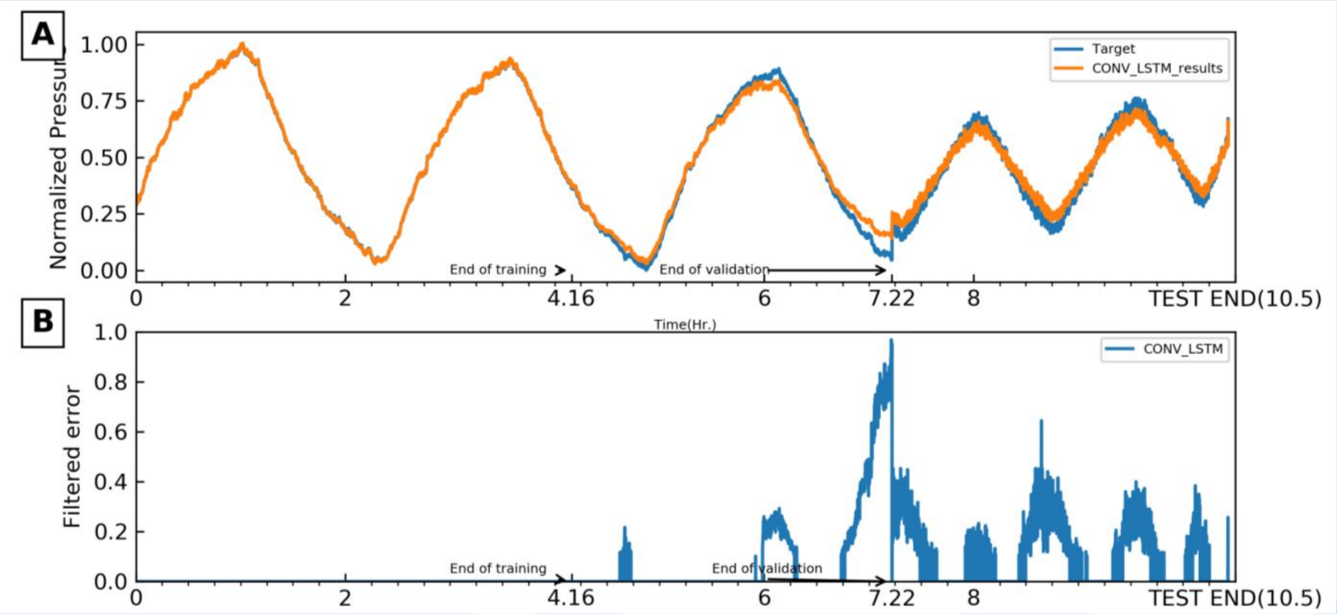


Pressure Temporal Data Acquired

Project R&D – Leak Detection via Temporal Signature

Idea: Reframe the leak problem as the *anomaly detection*

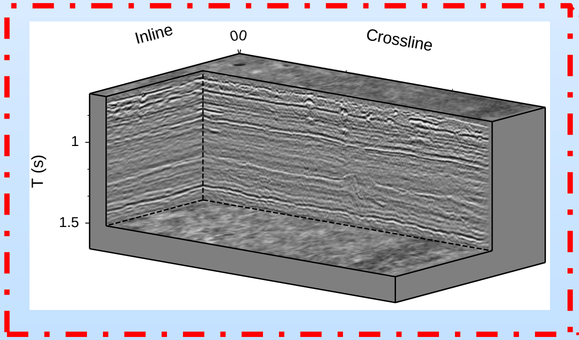
- Normal Phase ("baseline") and Abnormal Phase ("artificial leak")
- Different physical phenomena yield different temporal signatures and dynamics
- ML effectively extracts the temporal signatures

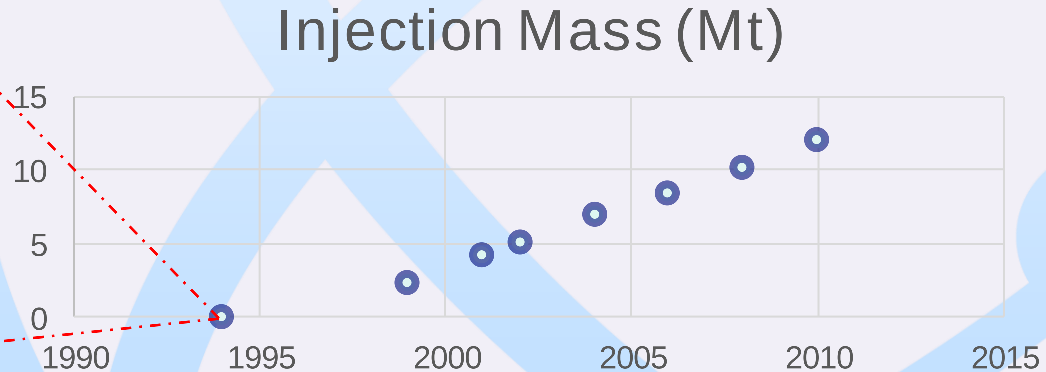


Saurabh Sinha, Rafael Pires de Lima, Youzuo Lin, Alexander Y. Sun, Neill Symons, Rajesh Pawar, and George Guthrie, "Normal or Abnormal? Machine Learning for the Leakage Detection in Carbon Sequestration Projects Using Pressure Field Data," International Journal of Greenhouse Gas Control, Vol. 103, 2020.

Project R&D – Sleipner Site and Data Availability

- Super-critical CO_2 was injected into deep porous utsira formation
  - **No leakage** was reported
- Repeated seismic data (3D post-stack section) were acquired in 8 years
  - Spatial dimension: $480 \times 480 \times 144$
  - Temporal period: 1994 – 2010
- Can we come up with an "**analog leak detection**" problem with existing data?
  - Yes, from Leak Detection to In-Situ Monitoring
  - **<u>Challenges</u>:** data scarcity, spatio-temporal dynamics in deep formation, underline physics





Availability of Repeated 3D Seismic Survey

Project R&D – Motivation behind

"*What I* ***cannot create,***

I do not understand"

Richard P. Feynman

Project R&D – Idea to "*Connect the Dots*"

Challenge and Idea [Feng et al. (2021)]

Data Scarcity

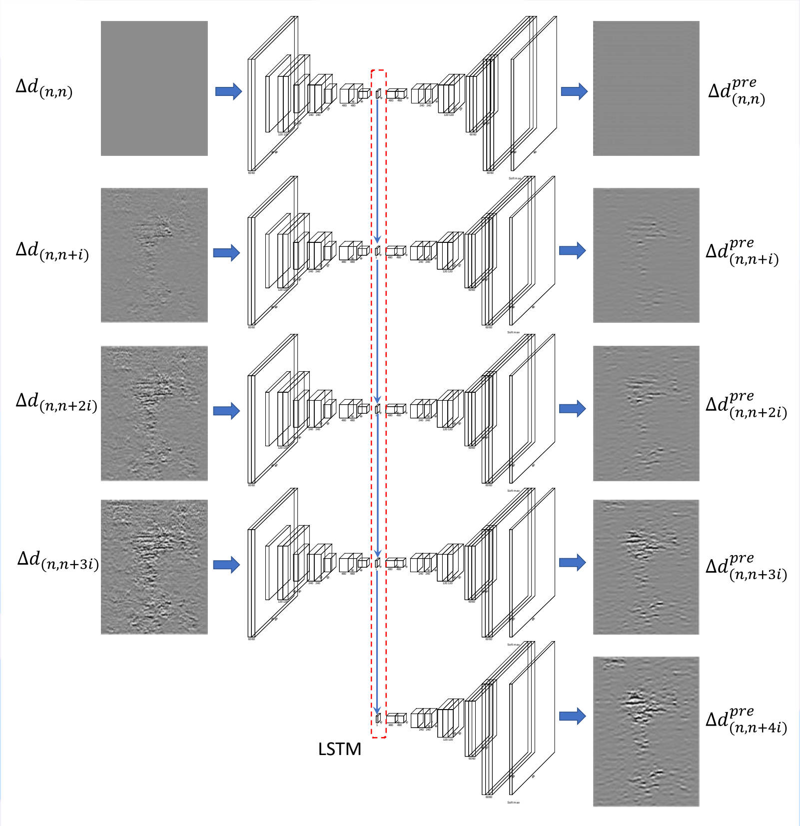
- Develop deep generative models to synthesize more data and fill in the knowledge gap

Spatio-temporal Signatures

- Encoder-decoder network architecture – learn spatial dynamics
- Long short-term memory – capture temporal dynamics

Underline Physics

- Impose optical flow regularization, i.e., a physics-informed constraint

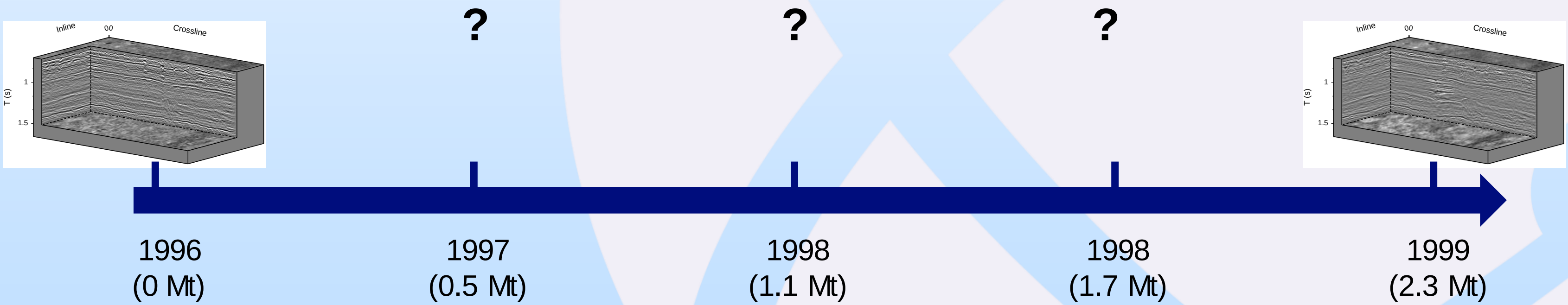


Network Architecture

Shihang Feng, Xitong Zhang, Brendt Wohlberg, Neill Symons, and Youzuo Lin "*Connect the Dots: In Situ 4D Seismic Monitoring of CO_2 Storage with Spatio-temporal CNNs*," Under review in IEEE Transactions on Geoscience and Remote Sensing, 2021.

Project R&D – High-level Idea of Interpolation

- The seismic image changes nonlinearly with the CO_2 injection over time
- Assume the representations of the seismic images lie on the same line in the latent space
- Generate seismic images over time through the interpolation in the latent space



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Project R&D – Details of Interpolation

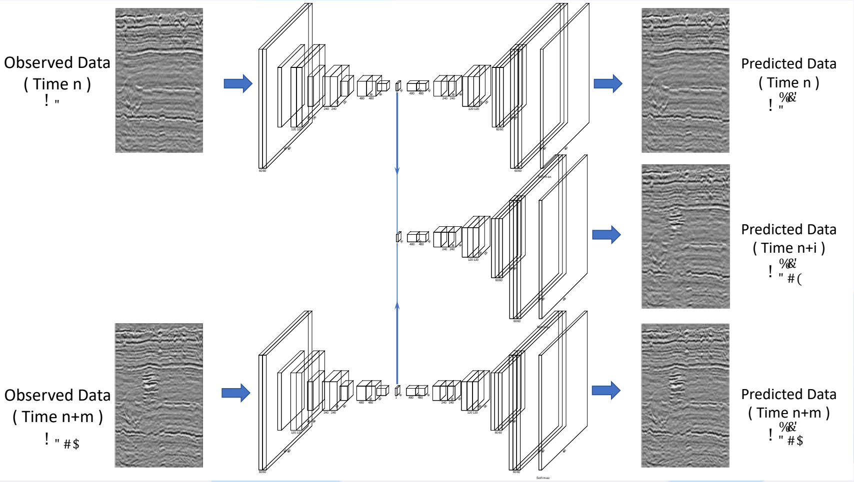
Interpolation

- Use an encoder-decoder network to generate a compressed representation of the seismic data in the latent space
- Impose linear regularization on the latent space of the seismic image
- Interpolate the latent space based on the CO_2 injection volume
- Use the decoder to reconstruct the interpolated seismic data from the interpolated latent space

$$L_{n+i} = L_n + \frac{m-i}{m-n}(L_{n+m} - L_n),$$

m, n, i — CO_2 Injection volume

L_n, L_{n+i}, L_{n+m} — Latent space of the seismic image with CO_2 Injection volume at n, $n+i$, $n+m$



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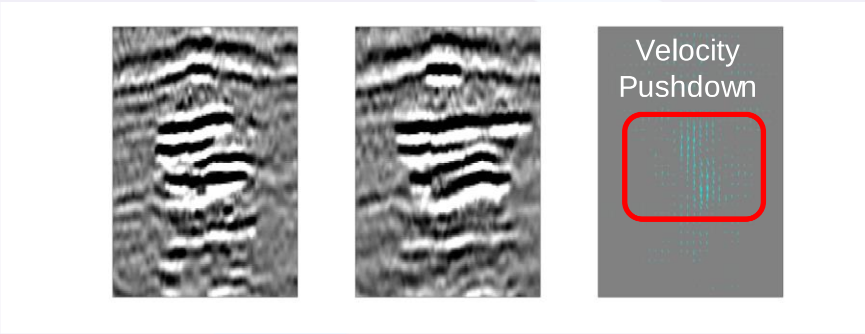
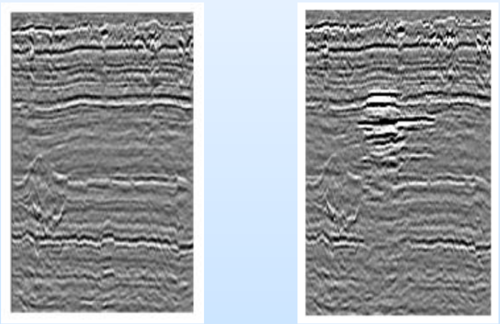
Project R&D – High-level Idea of Extrapolation

- Impose LSTM in the latent space to predict the future states of the seismic images
- Impose Optical flow to detect the spatial movement of the seismic images and constrain the seismic images in the future

Year 1999 (2.3 Mt) | Year 2001 (4.2 Mt) | Optical Flow from Year 1999 to Year 2001





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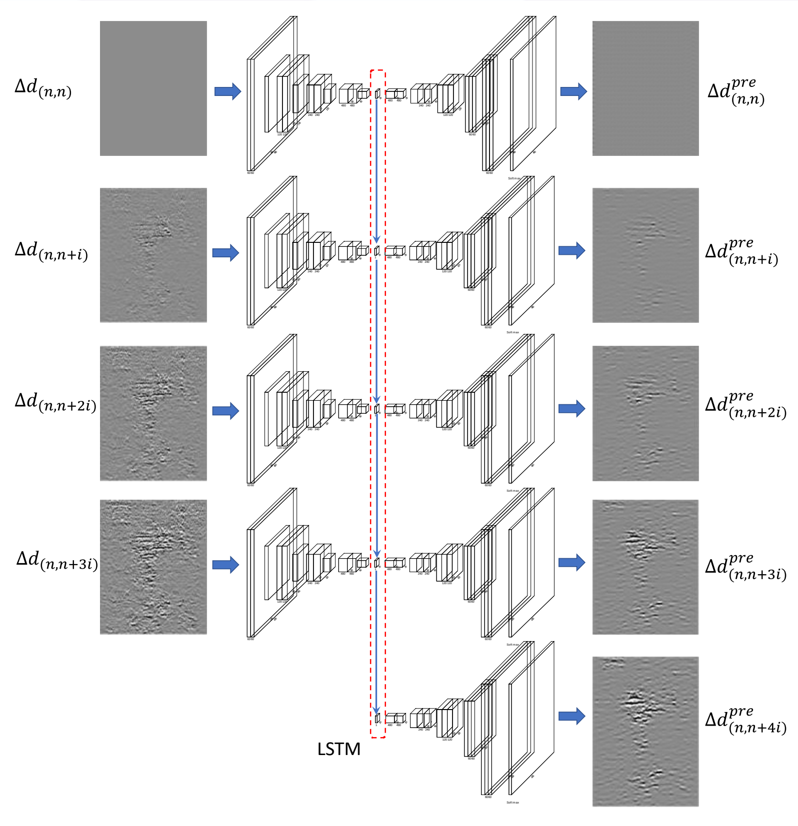
Generated Future Seismic Imaging Data

Shihang Feng, Xitong Zhang, Brendt Wohlberg, Neill Symons, and Youzuo Lin "*Connect the Dots: In Situ 4D Seismic Monitoring of CO_2 Storage with Spatio-temporal CNNs*," Under review in IEEE Transactions on Geoscience and Remote Sensing, 2021.

Project R&D – Details of Extrapolation

Extrapolation

- Use an encoder-decoder network to generate a compressed representation of the seismic data in the latent space
- Impose Long short-term memory in the latent space to capture temporal dynamics
- Impose the optical flow regularization to constrain the seismic image change overtime
- Extrapolation the latent space based on the CO_2 injection volume
- Use the decoder to reconstruct the extrapolated seismic data from the extrapolated latent space



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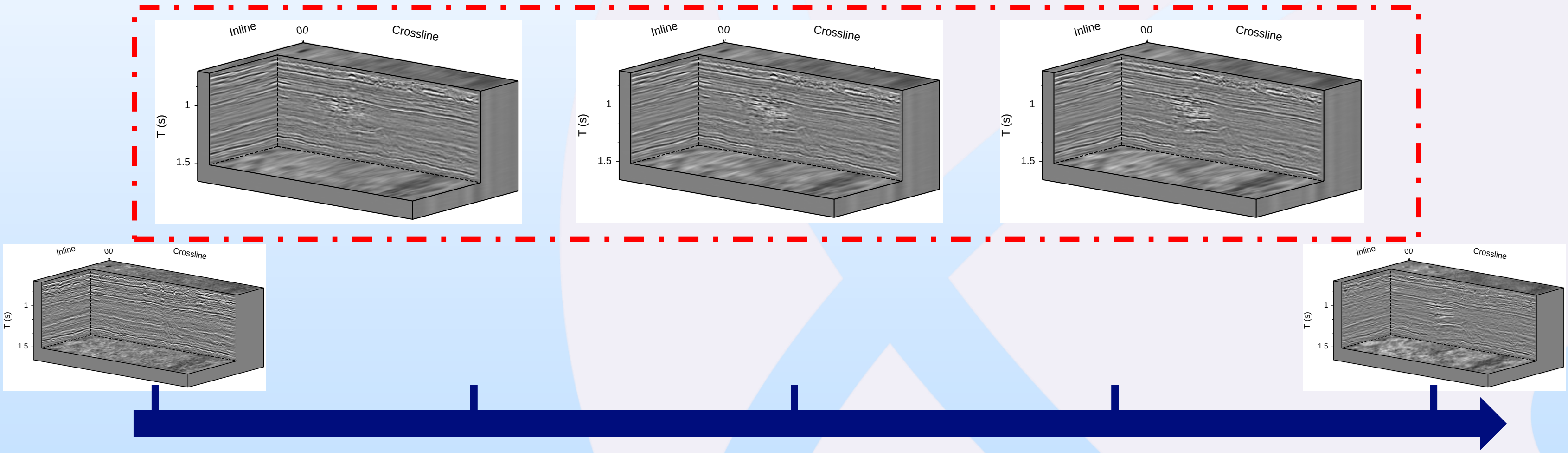
Project R&D – Generated Seismic Images (Interpolation)

- Once fully trained, the spatio-temporal neural network can
  - Capture the spatio-temporal features and dynamics from field data
  - Generate **high-quality** 3D seismic imaging at any given time very efficiently



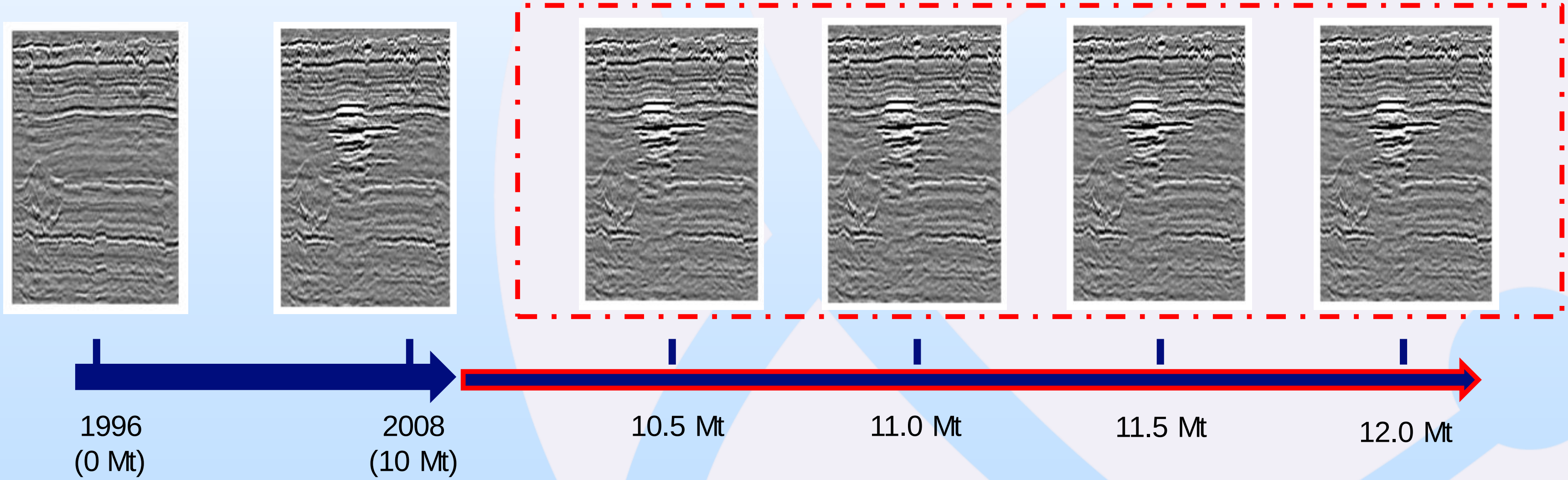
1996 (0 Mt) | 1997 (0.5 Mt) | 1998 (1.1 Mt) | 1998 (1.7 Mt) | 1999 (2.3 Mt)

Generated 3D Seismic Imaging Data over Time

Shihang Feng, Xitong Zhang, Brendt Wohlberg, Neill Symons, and Youzuo Lin "*Connect the Dots: In Situ 4D Seismic Monitoring of CO_2 Storage with Spatio-temporal CNNs*," Under review in IEEE Transactions on Geoscience and Remote Sensing, 2021.

Project R&D – Generated Seismic Images (Extrapolation)

- Once fully trained, the spatio-temporal neural network can
  - Capture the spatio-temporal features and dynamics from field data
  - Predict **high-quality** seismic image in the future with given CO_2 injection volume



Generated Future Seismic Imaging Data

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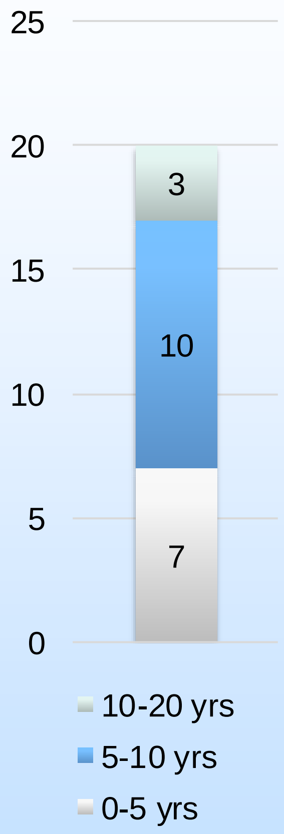
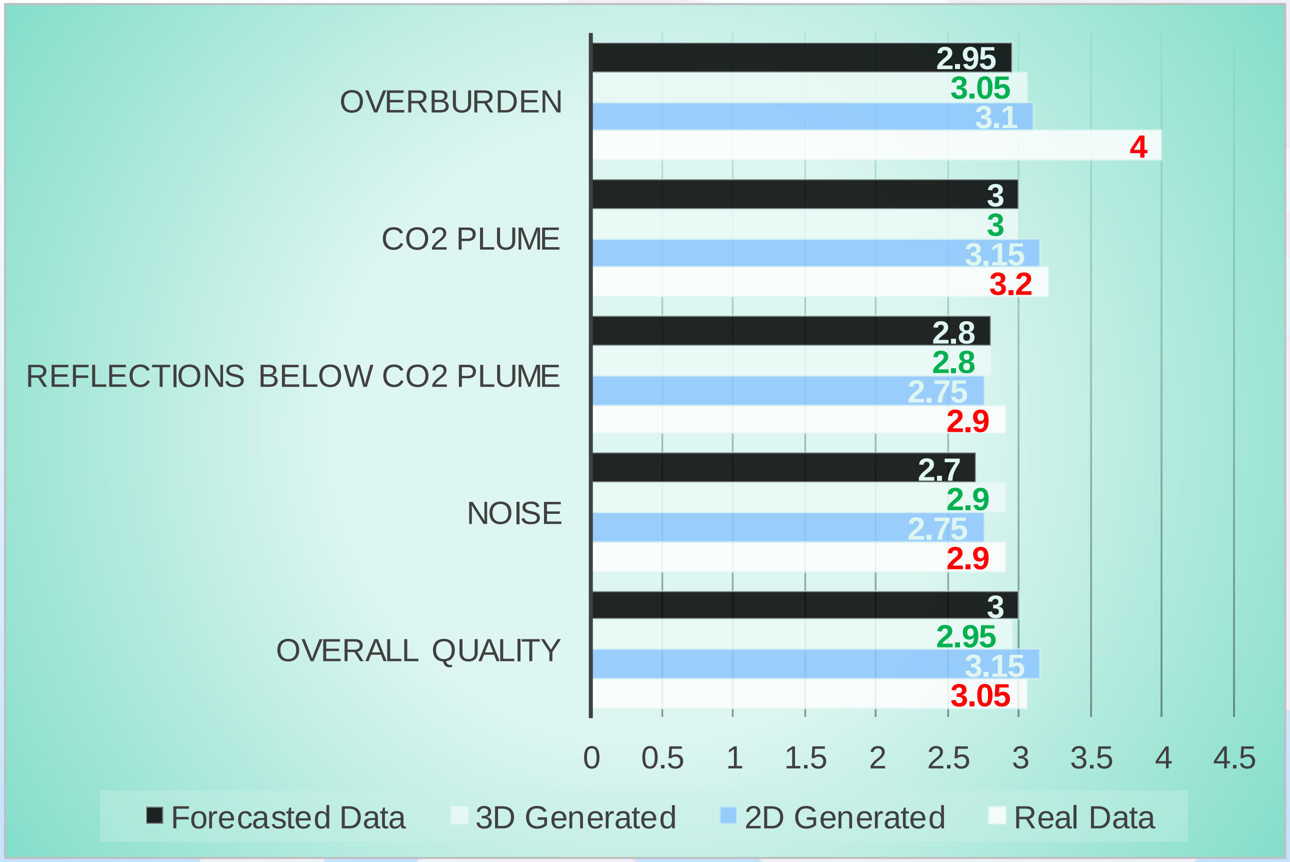
Project R&D – Expert Blind QA Evaluation



Expertise in Yrs
(20 Experts)

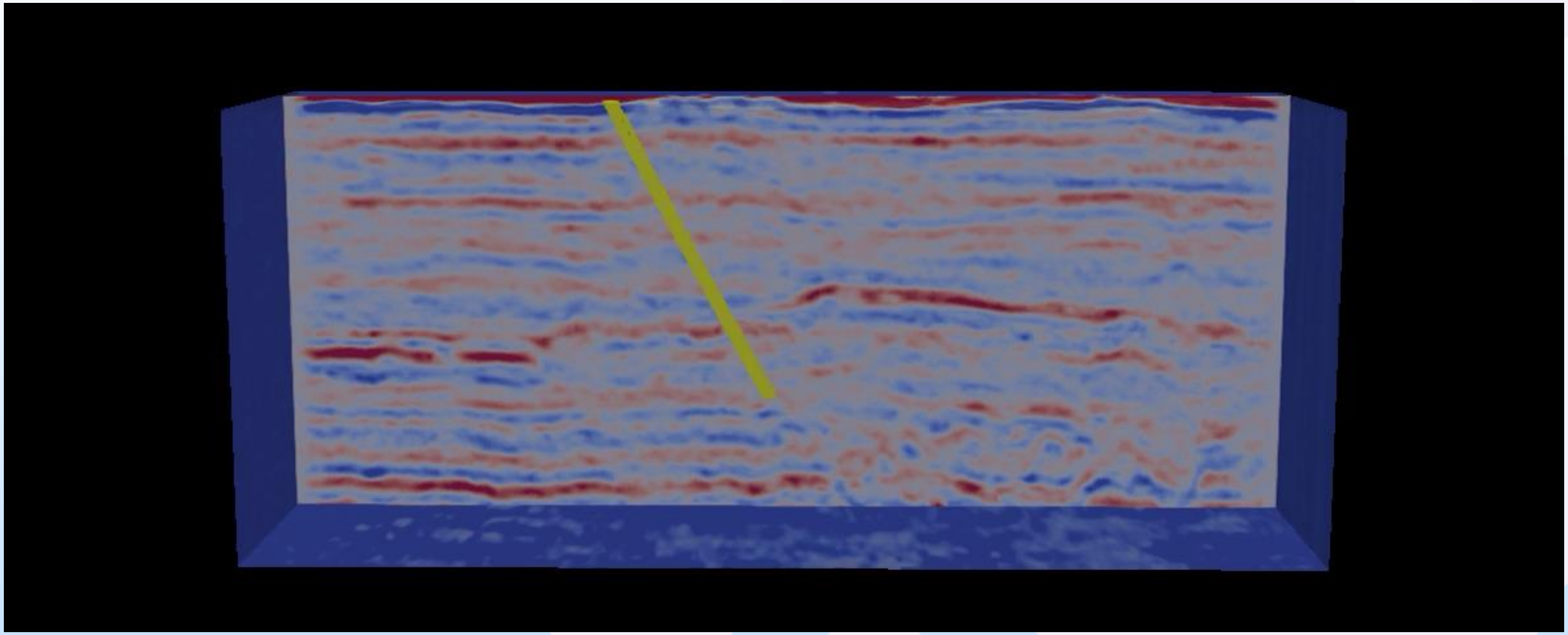


Expert Evaluation Scores

Shihang Feng, Xitong Zhang, Brendt Wohlberg, Neill Symons, and Youzuo Lin "*Connect the Dots: In Situ 4D Seismic Monitoring of CO_2 Storage with Spatio-temporal CNNs*," Under review in IEEE Transactions on Geoscience and Remote Sensing, 2021.

Project R&D – In Situ 4D Monitoring

In Situ Visualization of the CO_2 Plume Migration over Time



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Accomplishments to Date

- We developed two machine learning methods to extract leakage signatures directly from measurements
  - Extract temporal leakage signature using convolution neural nets
  - Extract spatio-temporal signature using physics-constrained neural nets
- Our methods have been proved effective using both real pressure data and field seismic data
  - Pressure data collected at Cranfield oil field
  - Seismic data collected at Sleipner CO_2 sequestration field

Lessons Learned

- Small signatures exist in rough geophysical data
- Machine learning can be an effective tool to extract the small signatures
  - Data challenge
- Importance of underlying physics
- Robustness and generalization ability of machine learning models

Synergy Opportunities

– Our work can be leveraged by the SMART and NRAP programs

Project Summary

- Key Findings
  - Machine learning can be an effective tool to detect very small leak
  - Physics knowledge plays an critical role
    - Known knowns versus unknown unknowns

- Next Steps
  - Machine learning model for small-data regimes
    - Data challenge
  - Space and time trade-off with a more efficient 3D implementation.
    - Group convolution and invertible network

Bibliography

Journal

[Cranfield]: Saurabh Sinha, Rafael Pires de Lima, Youzuo Lin, Alexander Y. Sun, Neill Symons, Rajesh Pawar, and George Guthrie, "***Normal or Abnormal? Machine Learning for the Leakage Detection in Carbon Sequestration Projects Using Pressure Field Data,***" International Journal of Greenhouse Gas Control, Vol. 103, 2020.

[Cranfield]: Saurabh Sinha, Rafael Pires de Lima, Youzuo Lin, Alexander Y. Sun, Neill Symons, Rajesh Pawar, and George Guthrie, "***Machine Learning Provides Effective Leak Detection in Carbon Sequestration Projects***," in Journal of Petroleum Technology, July 1, 2021.

[Sleipner]: Shihang Feng, Xitong Zhang, Brendt Wohlberg, Neill Symons, and Youzuo Lin "***Connect the Dots: In Situ 4D Seismic Monitoring of CO_2 Storage with Spatio-temporal CNNs***," Under review in IEEE Transactions on Geoscience and Remote Sensing, 2021.

Conference

[Cranfield]: Saurabh Sinha, Rafael Pires de Lima, Youzuo Lin, Alexander Y. Sun, Neill Symons, Rajesh Pawar, and George Guthrie, "***Automated Leakage Identification in Carbon Sequestration Projects***", in Proceeding of SPE Annual Technical Conference and Exhibition, 2020.

[Sleipner]: Shihang Feng, Xitong Zhang, Brendt Wohlberg, Neill Symons, and Youzuo Lin "***Monitoring and Forecasting CO_2 Storage in the Sleipner area with Spatio-temporal CNNs***," Society of Exploration Geophysics Annual Meeting, 2021 (Accepted).

Benefit to the Program

- Our work addresses the critical problem of detecting small leakage accurately and effectively.
- The techniques developed can be potentially applied to many other subsurface applications within the portfolio.

Project Overview

Goals and Objectives

Through our previous work, we have developed different ML tools/methods to extract useful but small geophysical signatures that could be induced by CO_2 leakage using synthetic Kimberlina dataset. Our results were focused on scenarios where CO_2 exists in gaseous phase resulting in detection at shallow depths. Here, we want to explore applicability of our ML approaches to detect leaks at depth where CO_2 will be in dense phase (such as liquid or super-critical) using lab/field dataset.