# **CAAP Quarterly Report**

# March 25, 2025

*Project Name:* Determination of Potential Impact Radius for CO<sub>2</sub> Pipelines using Machine Learning Approach

Contract Number: 693JK32250011CAAP

Prime University: Texas A&M University

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*Reporting Period:* 12/27/2024 – 3/26/2025

# **Project Activities for Reporting Period:**

The following relevant tasks in the proposal have been completed:

- Studied the evacuation time of five terrain for required distance from the release point. More details are provided in the appendix.
- Established web-based tool for PIR and response time for distance of concern (draft tool).
- Presented the project in REX 2025 by PRCI in Houston.
- Submitted a copyright application document.

# **Project Financial Activities Incurred during the Reporting Period:**

Based on the proposed budget, the cost is broken down into two parts:

- Efforts from the PI Dr. Wang for about one month.
- Efforts and work by graduate students, Chi-Yang Li and Jazmine Aiya D. Marquez, totally for about 3 months for each of them.

# **Project Activities with Cost Share Partners:**

Dr. Wang's time and efforts (0.25 month) in this quarterly period are used as cost share. He devoted his time to supervising the graduate students, reviewing all paperwork, traveling to Houston to present the project in REX 2025 by PRCI, filing the copyright application (meeting with TEES commercialization division and lawyer), and preparing the progress report.

# **Project Activities with External Partners:**

During the REX 2025 in Houston, PRCI Executive Director is interested in supporting the related project. A few ideas were discussed including using the software for pipeline siting and possible validation of the developed CO2-PIR software.

# **Potential Project Risks:**

None.

# **Potential Impacts to Pipeline Safety:**

• The variables for pipeline characteristics and weather conditions cover the upper limits and lower limits of the current industrial practices; therefore, the machine-learning model is believed to have accurate predictions for other CO<sub>2</sub> pipelines in the range.

### **Appendix**

## 1. Evacuation time

As discussed in the previous report, to assess the time to reach steady state, the case with the farthest dispersion was used and the corresponding parameters are enumerated in Table 2 for each terrain.

Pressure (MPa)	Diameter (inch)	Flow rate (MMcfd)	Wind speed (mph)	Temperature (°F)
10	30	1300	25	60

Table 1. Parameters applied for study.

Based on the information from the studies, the equation was built to calculate the time to reach 1%, 4%, and 9% CO<sub>2</sub> concentrations as below:

$$t = \left(\frac{D}{w}\right)^a - b * \left(\frac{D_{ss} - D}{w}\right)$$

Where, D represents the distance of concern (m), w represents wind speed (m/s), and  $D_{ss}$  represents the distance for steady state.

The fitted parameters for each terrain are shown in Table 2 and the comparison between prediction and actual values are shown in Figures 1-5.

Terrain	a	b	R <sup>2</sup>
Flat	1.04453744	-0.10944903	0.99
SH	1.08151136	-0.03337882	0.97
BH	1.20004264	0.05452555	0.95
VM	1.14365025	-0.21011946	0.99
VB	1.06696115	-0.07087655	0.99

Table 2. Parameters and performance for response time.



Figure 1. Flat: Actual values versus predicted values (a) 9 % CO<sub>2</sub>, (b) 4 % CO<sub>2</sub>, and (c) 1 % CO<sub>2</sub>.



Figure 2. SH: Actual values versus predicted values (a) 9 % CO<sub>2</sub>, (b) 4 % CO<sub>2</sub>, and (c) 1 % CO<sub>2</sub>.



Figure 3. BH: Actual values versus predicted values (a) 9 % CO<sub>2</sub>, (b) 4 % CO<sub>2</sub>, and (c) 1 % CO<sub>2</sub>.



Figure 4. VM: Actual values versus predicted values (a) 9 % CO<sub>2</sub>, (b) 4 % CO<sub>2</sub>, and (c) 1 %



Figure 5. VB: Actual values versus predicted values (a) 9 % CO<sub>2</sub>, (b) 4 % CO<sub>2</sub>, and (c) 1 % CO<sub>2</sub>. With the predictions from the machine learning (ML) models, the equation can be used to predict the according response time at the distance of concern.

### 2. Web-based tool

Since machine learning models are established in the python environment, the web-based tool uses Flask, which also utilizes Python (version 3.11.9) libraries such as NumPy, Joblib, XGBoost, and Scikit-learn. With the inputs of terrain type, CO<sub>2</sub> pipeline characteristics (including operating pressure, diameter, flow rate, wind speed, and ambient temperature), and distance of concern from users, the web-based tool can predict the potential impact radiuses (PIR) and response time at the distance of concern. The interface demonstrations are shown in Figures 6 and 7.

# CO2-PIR

Terrain (Enter '1' for plain, '2' for medium hills, '3' for big hills, '4' for medium valley, or '5' for big valley):

Operating pressure of CO2 pipeline (MPa):

Diameter of CO2 pipeline (inch):

Flow rate of CO2 pipeline (mmcfd):

Wind speed (mph):

Ambient temperature (°F):

Distance of location of concern from the release point (meter):

Generate

Figure 6. Input for the web-based tool.

# Scenario

Terrain: {{ terrain }} Operating pressure of CO2 pipeline (MPa): {{ pressure }} Diameter of CO2 pipeline (inch): {{ diameter }} Flow rate of CO2 pipeline (mmcfd): {{ flow\_rate }} Wind speed (mph): {{ wind\_speed }} Mbient temperature (°F): {{ ambient\_temperature }} Distance of location of concern from the release point (meter): {{ location\_of\_concern }}

# Predictions

Distance for 9% CO2:

{{ CO2\_009 }} meters

Distance for 4% CO2:

{{ CO2\_004 }} meters

#### Distance for 1% CO2:

{{ CO2\_001 }} meters

#### Response time for 9% CO2:

{{ T\_009 }}

#### Response time for 4% CO2:

{{ T\_004 }}

Response time for 1% CO2:

{{ T\_001 }}

Back to Home

Figure 7. Output for the web-based tool.