

## Forecasting CO<sub>2</sub>-driven cold-water geyser eruptions using machine learning

**Maruti Kumar Mudunuru<sup>1,2</sup>**

**Postdoc Mentors and Collaborators: Satish Karra<sup>2</sup>, Hari Viswanathan<sup>2</sup>, Gowri Srinivasan<sup>3</sup>, Paul Allan Johnson<sup>4</sup>, Baichuan Yuan, Yen Joe Tan, Andrew Delorey<sup>4</sup>, Omar Marcillo<sup>4</sup>, Peter Roberts<sup>4</sup>, Jeremy Webster<sup>4</sup>, Christine Gammans<sup>4</sup>, and George Guthrie.**

Thermally driven geysers (such as Yellowstone) are characterized by frequent eruptions of liquid water and steam. Another subsurface system capable of producing periodic eruptions (similar to thermal geysers) is CO<sub>2</sub>-driven cold-water geysers. They erupt for over 24h at a time with relatively high velocity CO<sub>2</sub>-driven discharge from wellbores. Growing interest in geologic carbon storage has brought attention to CO<sub>2</sub>-driven cold-water geysers because of its similarity to high velocity wellbore leakage process. In the CO<sub>2</sub>-driven cold-water geysers, CO<sub>2</sub> (gas) evolves by the pressure reduction (flashing) of CO<sub>2</sub>-rich fluids. Once the internal pressure of CO<sub>2</sub> (aqueous) becomes greater than that of the surrounding fluid, CO<sub>2</sub> separates from the fluid causing bubbles to nucleate, grow, and coalesce. Hydrostatic pressure reduction resulting from increasing CO<sub>2</sub> gas volume fraction enhances expansion of CO<sub>2</sub> bubbles leading to the eruption. In this talk, we present an approach to distinguish eruption and precursory signals of cold-water geysers under noisy environments. In the first step of the framework, we apply a feature extraction and feature filtering algorithm called “Feature Extraction based on Scalable Hypothesis (FRESH)” for a given time-series data to extract comprehensive time-series signal features and then filter the resulting features. In second step, we quantify the significance of each filtered feature for predicting a set of labels/targets. Third, we construct a machine learning classifier, which takes in important filtered features to classify the time-series signals. The framework is then applied to field data from Chimayo geyser, New Mexico and Crystal geyser, Utah. Results show that the classification and forecasting accuracy is greater than 90%.

---

<sup>1</sup>*Speaker and presenter:* Maruti Kumar Mudunuru. *E-mail:* [maruti@lanl.gov](mailto:maruti@lanl.gov)

<sup>2</sup>*Affiliations:* Computational Earth Science Group (EES-16), Earth and Environmental Sciences Division, Los Alamos National Laboratory, Los Alamos, NM, USA.

<sup>3</sup>*Affiliations:* Applied Mathematics and Plasma Physics Group (T-5), Theoretical Division, Los Alamos National Laboratory, Los Alamos, NM, USA.

<sup>4</sup>*Affiliations:* Geophysics (EES-17), Earth and Environmental Sciences Division, Los Alamos National Laboratory, Los Alamos, NM, USA.