A Machine Learning Approach to Methane Emissions Mitigation in the Oil and Gas Industry

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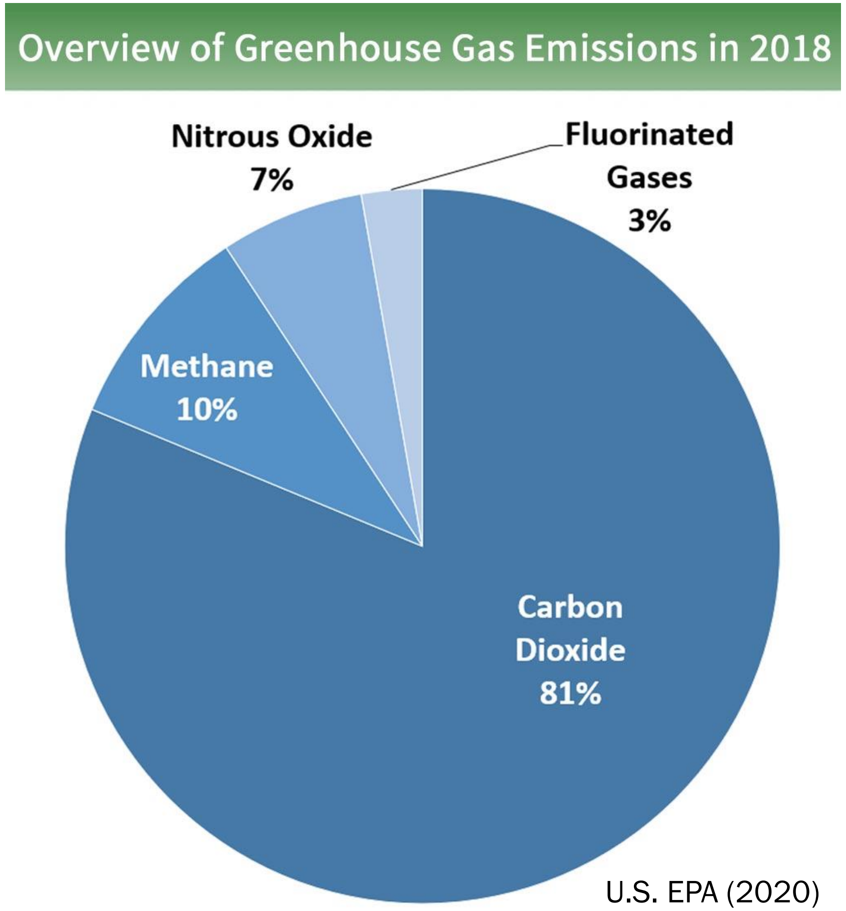
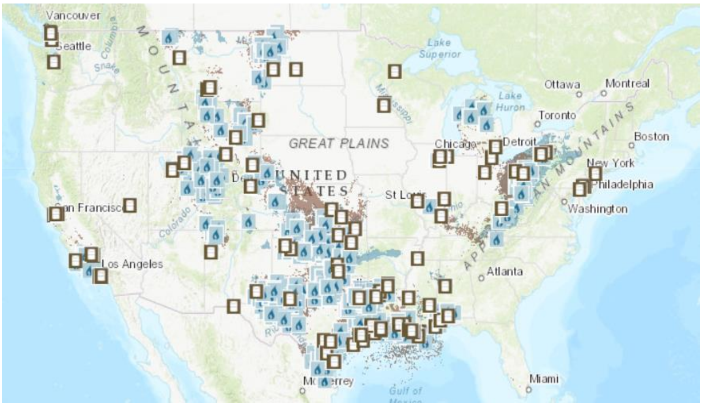
Methane mitigation is an importance part of climate policy.

- A potent greenhouse gas (GHG)
- 100-year Global warming potential (GWP) ~25 times CO_2
- 10% of total GHG emissions comes from methane emissions in 2018, as estimated by EPA
  - 28% of methane emissions come from natural gas and petroleum systems

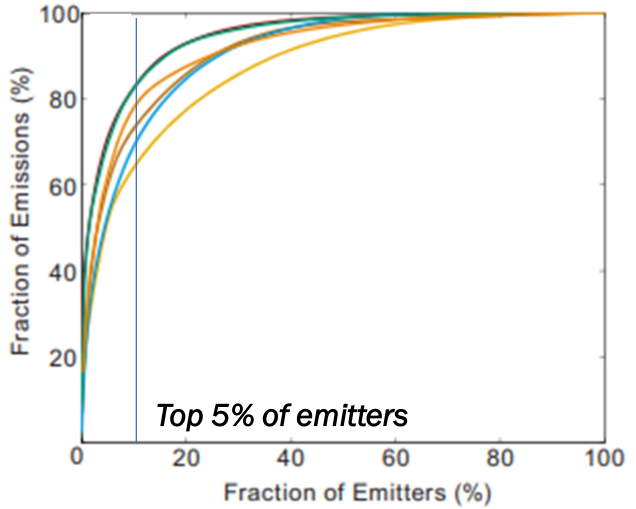


U.S. EPA (2020)

Conventional approach to emissions mitigation is time-consuming and costly.



eia Source: U.S. Energy Information Administration



- Conventional approach - survey all the sites
- Sites located at geographically sparse locations

- ‘Super-emitter’ make up the majority of the emissions

<u>Predicting and prioritizing ‘super-emitting’ sites in a timely manner will reduce methane emissions and improve the cost-effectiveness of methane regulations.</u>

In this work, we explore a machine learning approach to estimate the probability of a site being ‘super-emitting’.

Previous Approaches

From science perspective:

- Understand the relationship between emissions and other factors with regression analysis
- Predict emission amount and occurrence of emissions

Our Approach

From mitigation perspective:

- Optimize mitigation efforts to capture emissions cost-effectively
- Prioritize ‘super-emitting’ sites for repair

Modeling data comes from field measurement and public regulatory website.

- Emission data: collected from field measurement at randomly selected oil and gas production sites that are representative of the production distribution in the region
  - Optical gas imaging (OGI) technology
  - Emitting component, emission rates, etc.

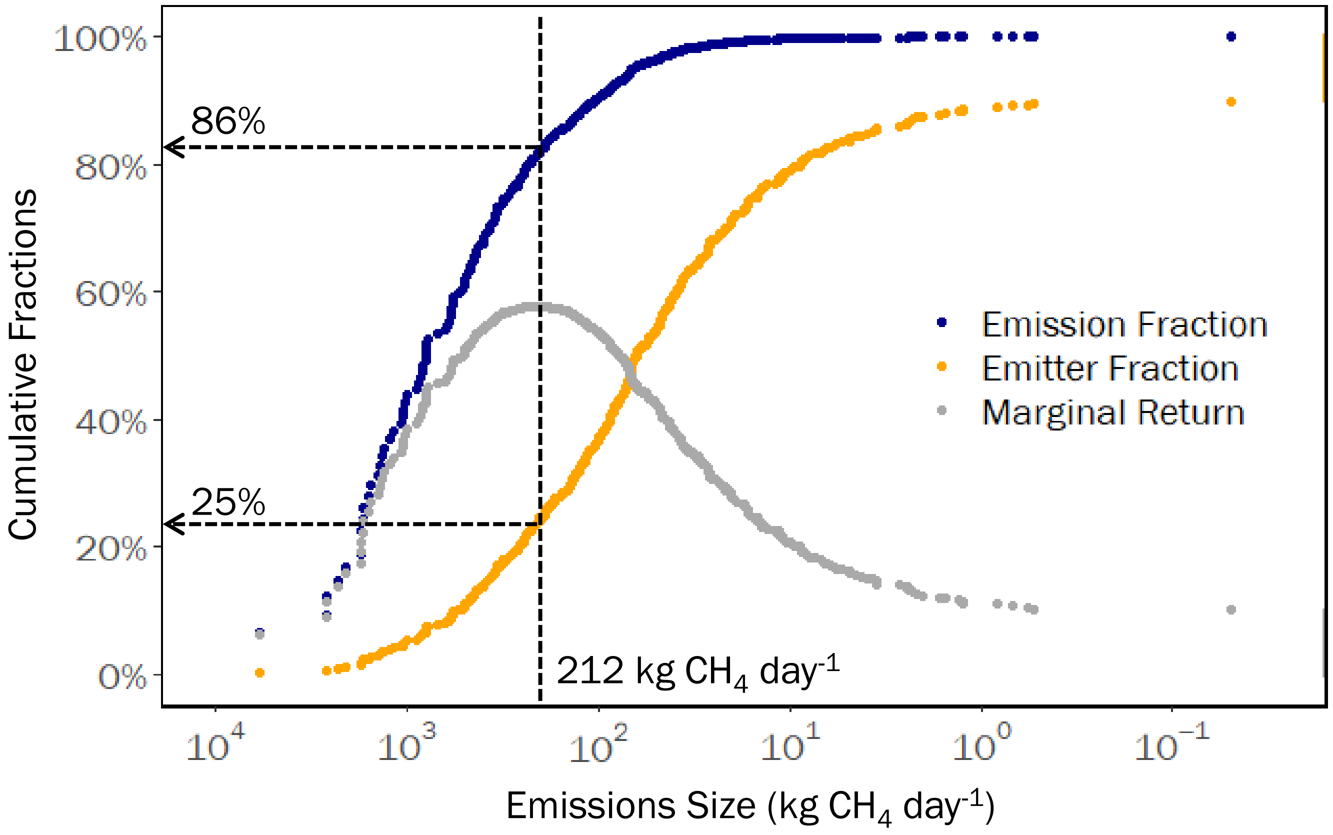
- Site production and characteristic data: collected from public regulatory website
  - Oil/gas production/displacement amount
  - Site type, age, number of active/inactive wells on site

Key Question: Can we predict which sites are prone to be 'super-emitting'?

We define 'super-emitting' sites with marginal return of emission coverage.

- Defining 'super-emitting' sites by % creates a large range of emission cutoff sizes from various studies

- We use marginal return of emission coverage to find emission cutoff size



Sites with emission >200 kg CH_4 day^{-1} are 'super-emitting'.

Predictive models and performances

Model Setup

- 75% training vs. 25% testing
- Use oversampling techniques to address imbalanced dataset issue
- Evaluation metric: accuracy, recall/sensitivity, and balanced accuracy

Model	Accuracy	Recall/Sensitivity	Balanced Accuracy
Logistic Regression	70%	57%	66%
Decision Trees	72%	46%	64%
Random Forests	73%	20%	56%
AdaBoost	72%	32%	59%

We compare emissions mitigation and cost-effectiveness of three scenarios.

Scenario 1
Baseline

- Survey all sites in random order, simulating current regulatory approaches
- Monte-Carlo simulations are used to derive confidence intervals

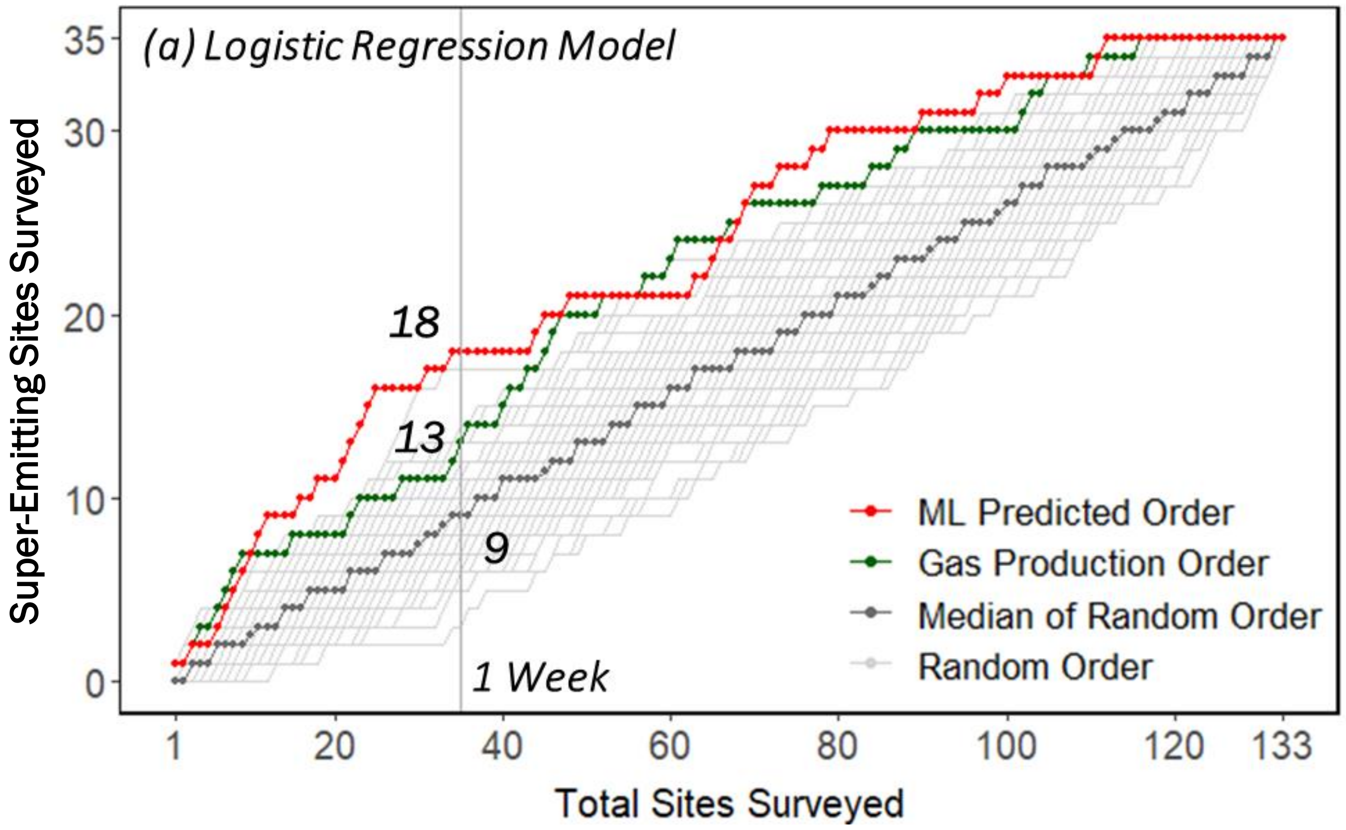
Scenario 2
Machine Learning

- Machine-learning generated survey order based on descending probabilities of being a super-emitting site
- Conduct survey from sites with highest probability to lowest

Scenario 3
Gas Production

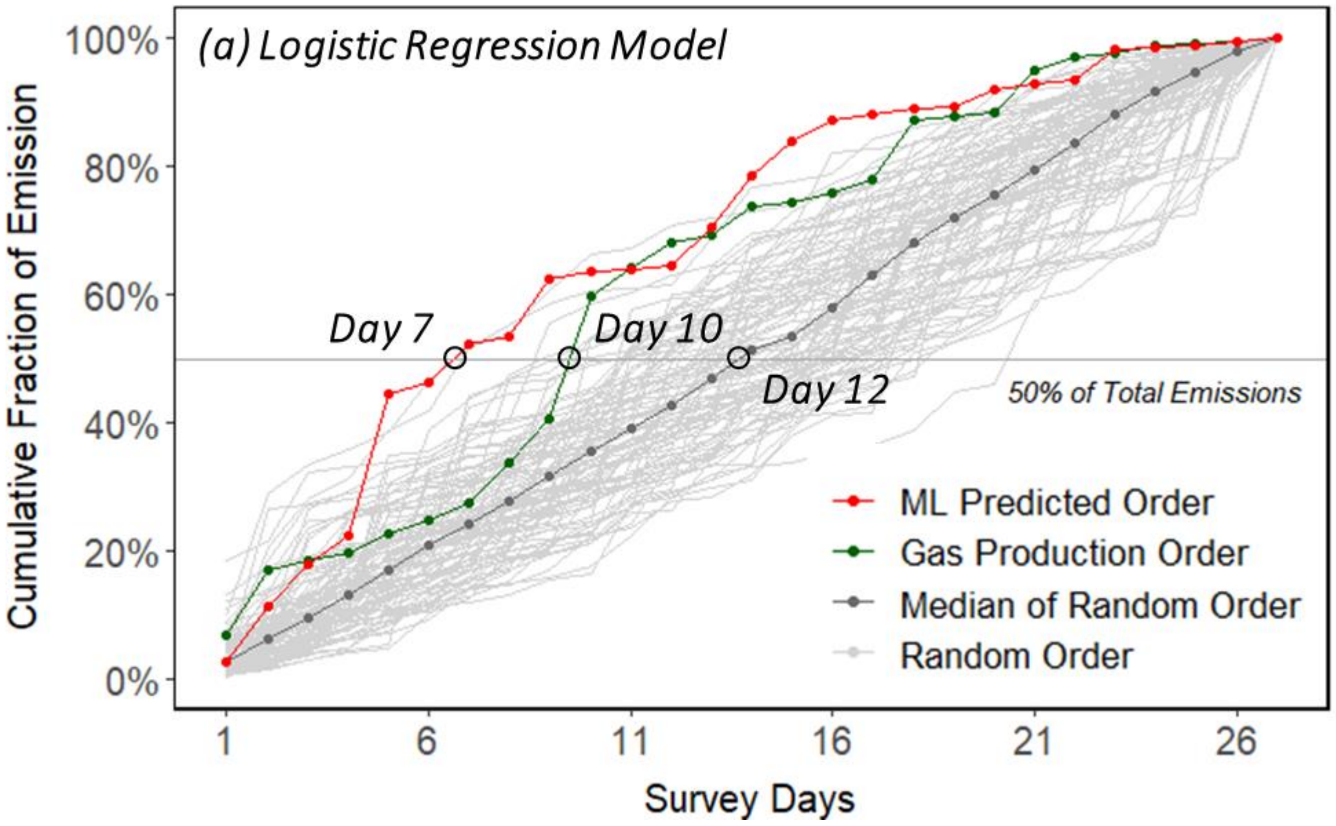
- Survey order based on descending order of production volumes

Survey order from machine learning model covers up to twice the amount of 'super-emitting' sites in the first week.



- Machine learning model cover 51% of 'super-emitting' sites by end of week 1
- Up to twice faster than the baseline and gas production scenarios

Machine learning order reduces cost per site in reaching 50% mitigation target by 74%, compared to EPA estimates.



- Time reduced by up to 42%
- Average cost per site is \$158, ~26% of EPA's estimate of \$600
- Mitigation cost decreased from \$85/t CO2e to \$49/t CO2e

Future work

Results

- Reduced survey costs by 76%, from $600/site to $158/site
- Decrease mitigation cost of CO_2e by 42%, from $82/t CO_2e to $49/t CO_2e

Future Work

- Expand dataset to include more basins in North America
- Incorporate more variables, such as site equipment count, geologic features, time since last survey, etc.
- Explore the use of ranking models

THANK YOU

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