Stochastic estimation of fugitive methane emissions using drones

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1. Introduction

Methane (CH_4) is a potent greenhouse gas with a **global warming potential 28 times greater** than carbon dioxide (CO_2) over a 100-year period (Fig.1). The global atmospheric CH_4 concentrations have increased from approximately 700 part per billion (ppb) in the 18th century to approximately 1870 ppb in 2020 (IPCC). CH_4 is the **second most important greenhouse gas**, contributing about 25% to the global warming experienced to date (Myhre, G. et al., 2014). Due to its short atmospheric lifetime, near-term warming of the climate could diminish following mitigation actions that reduce CH_4 emissions.

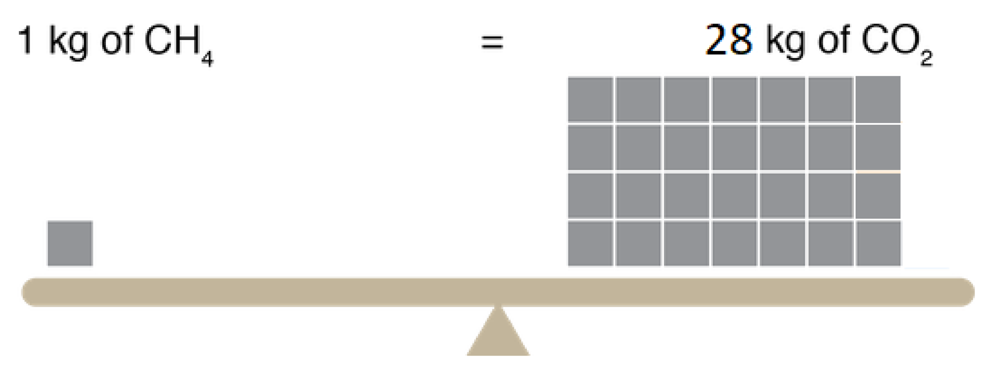

Figure 1: CH_4 100-year global warming potential

2. Fugitive CH_4 emissions

Understanding and quantifying CH_4 emissions is crucial to all climate change action plans. In Australia, **fugitive CH_4 emissions** are estimated to be the second biggest contributor to the overall methane emissions (Fig. 2). However, **the definition of fugitive emissions is rather vague**. In the fossil fuel sector, fugitive emissions are **broadly defined as any emissions unrelated to the end use of fuel** (IPCC). As indicated in Fig. 3, this could include accidental emissions (e.g. pipeline failure), leaks and diffuse escapes (e.g. defective valves, migration of CH_4 to surface, emissions from abandoned wells) and unintentional but non-productive discharges (e.g. mine ventilation, degassing).

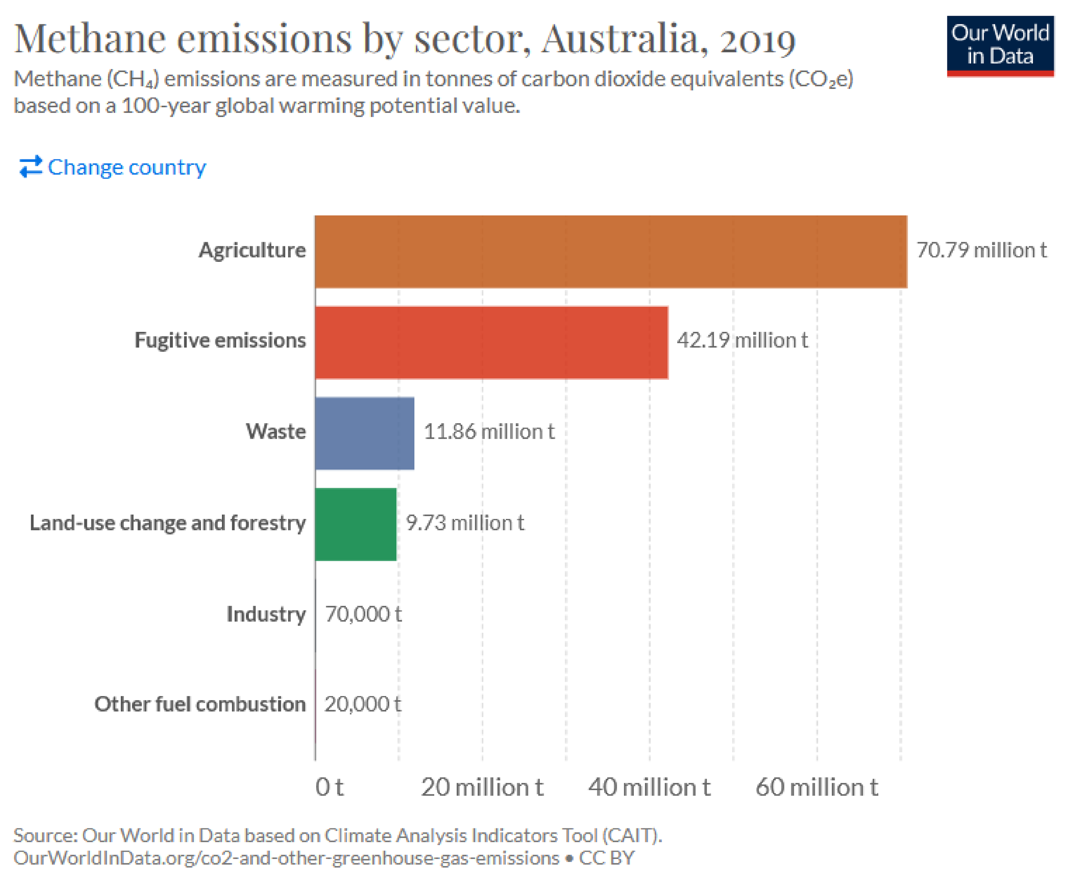

Figure 2: CH_4 emissions by sector, Australia 2019

3. Quantifying fugitive CH_4 emissions

Due to their very nature, **fugitive CH_4 emissions are inherently difficult to quantify** as direct measurement techniques are often not applicable. Therefore, the IPCC has developed an estimation system based on a combination of **emission factors** (Fig. 4) and **activities** (e.g. gas distribution). The problem with that system is, that these emission factors are often based on older US infrastructure and are thus not representative for Australian operations. Further, emissions like gas migration to surface as shown in Fig. 3 are not accounted for.

TIER 1 EMISSION FACTORS FOR DISTRIBUTION SEGMENT, 1.B.2.B.V

Segment	Sub-segment	Emission source	CH_4		Units of measure
			Value	Uncer-tainty (% of value)	
Gas Distribution	Less than 50% plastic pipelines, or limited or no leak detection and repair programsa	All	2.92	-20% to +120%	Tonnes/ million cubic meter gas consumption
			1.17	-20% to +120%	Tonnes/kilometre of pipeline

Figure 4: IPCC emission factors for gas distribution

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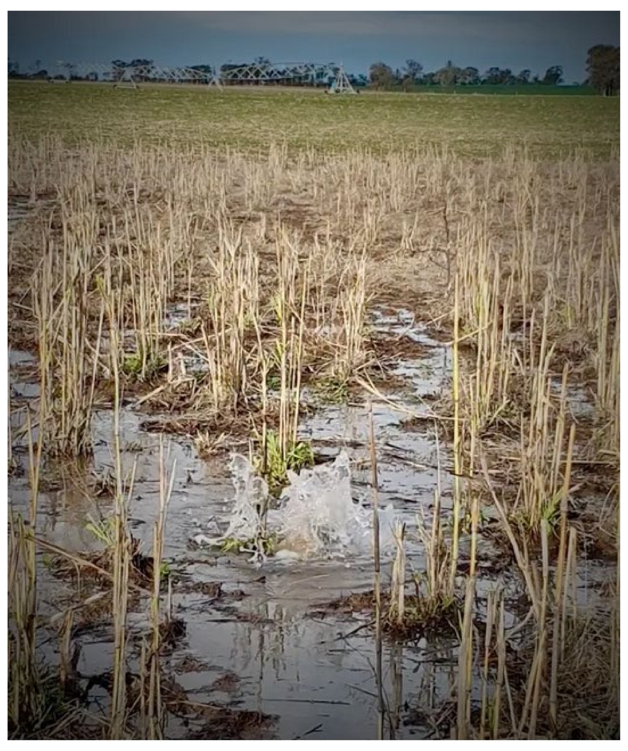

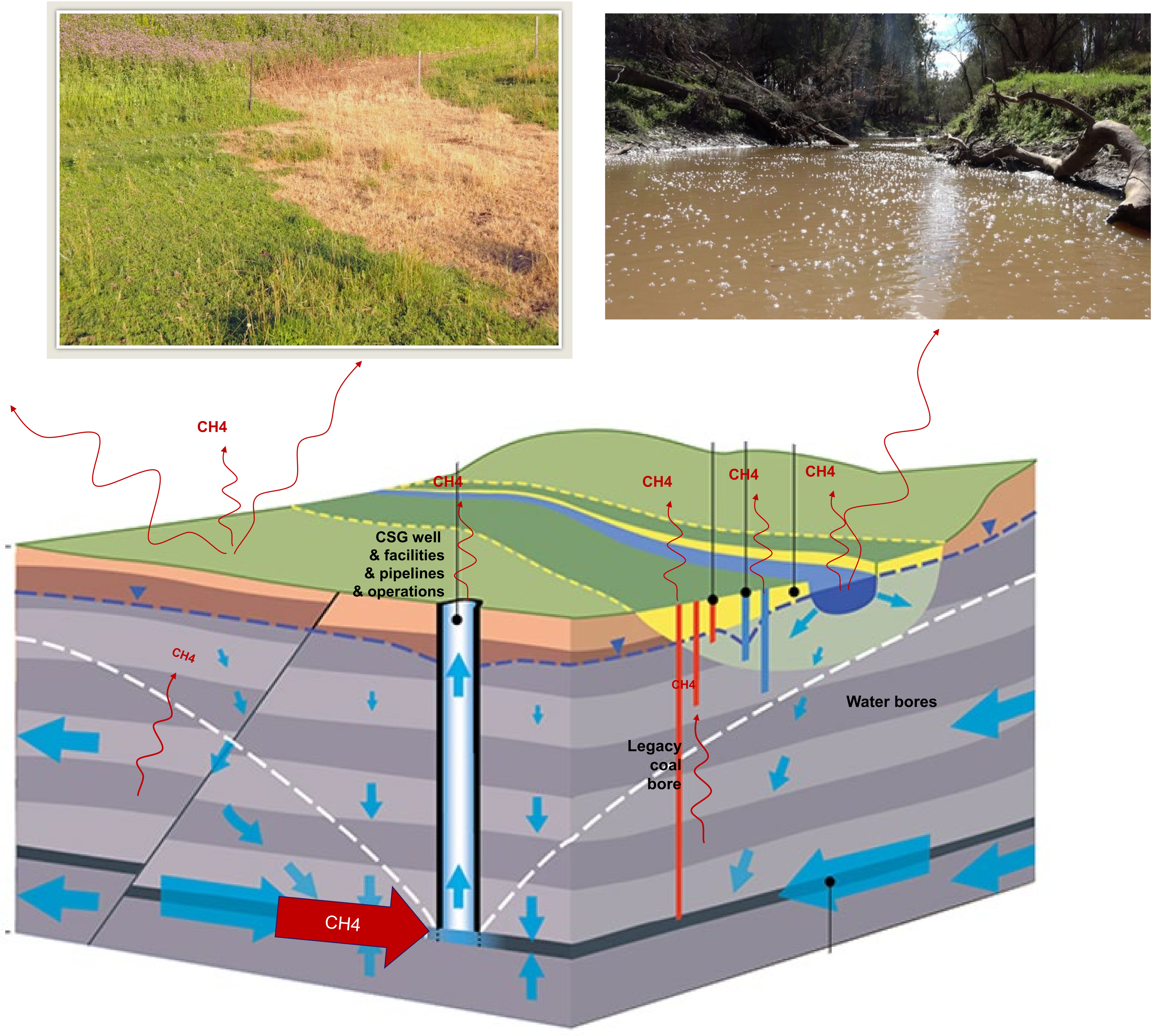

Figure 3: Potential sources of fugitive CH_4 emission (modified from www.industry.nsw.gov.au/water/science/groundwater/) and their **visual consequences**. Left: Gas migration to surface (source: Country Caller Regional News) Middle: Vegetation dieback due to gas migration to surface (source: www.federatedenvironmental.com) Right: Gas bubbles in the Condamine River (source: Country Caller Regional News)

4. Quantifying fugitive CH_4 emissions using top-down approaches

To overcome the shortcomings of the emission factors based estimation and to obtain more representative estimates of fugitive CH_4 emissions, **top-down approaches** can be applied. Top-down approaches involve **measuring of changes in concentration** over space and time from which emissions (i.e. fluxes) can be estimated. The concentration measurements can be done using a variety of technologies, ranging from satellites (with nearly global coverage) to drones (for high-resolution spatial mapping up to 1km^2) or even handheld devices. Most of these technologies use some kind of absorption spectrometer that detects and quantifies CH_4 by measuring its associated optical absorption when irradiated with a light beam. Using the observed concentrations to **estimate the underlying emissions** is however **non-trivial** as it involves solving a **high-dimensional inverse problem** (Fig. 5).

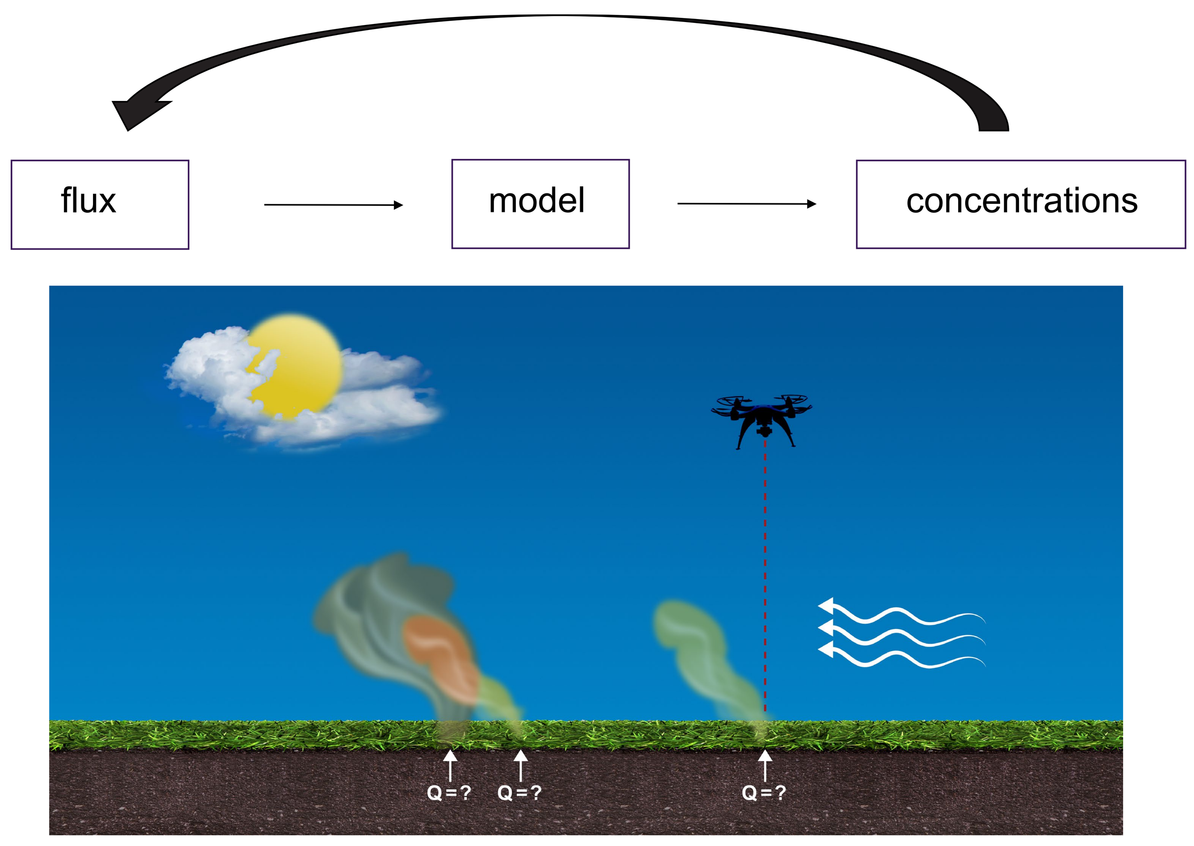

Figure 5: Schematic representation of the inverse problem

5. Bayesian atmospheric tomography

'The inverse problem consists of using the actual result of some measurement to infer the value of the parameter that characterize the system' (Tarantola, 2005). **Bayesian atmospheric tomography** (Eq. 1) is a stochastic approach to address such an inverse problem using **conditional probabilities** (Bayes' theorem) and **Markov Chain Monte Carlo** sampling. This allows the estimation of the underlying emissions and their locations based on observed concentrations and other variables (e.g. air temperature, air pressure, wind speed, wind direction)

Eq. 1: $$p(Q \mid \mathbf{Y}, \boldsymbol{\theta}_{k_i}) \propto p(Q) \int_0^{\infty} \prod_{i=1}^{N} p(Y_i \mid \tau, Q, \boldsymbol{\theta}_{k_i}) p(\tau)\, \mathrm{d}\tau.$$

6. Results and Outlook

First results of the Bayesian atmospheric tomography approach using synthetic test data (assumptions: single source, unknown rate, unknown location, drone-based concentration observations, known wind speeds and directions, known temperature and pressure) are promising. The model is able to identify the location as well as the rate (Fig. 6) of the synthetic emissions.

However, various blind-test experiments show that the estimation of real-world emissions is more difficult. For example, Fig. 7 shows the parity chart of Picarro's performance at Stanford's Mobile Monitoring Challenge (Ravikumar et al., 2019).

To address these additional difficulties, UQ CNG is going to perform a validation experiment. A controlled rate of CH_4 will be released and a drone survey (through Terra Sana Consultants) will be conducted to obtain CH_4 concentration measurements. Additional variables will be measured using a weather station. This controlled release experiment will allow:

- Validation and calibration of the inversion approach
- Optimization of the data acquisition strategy

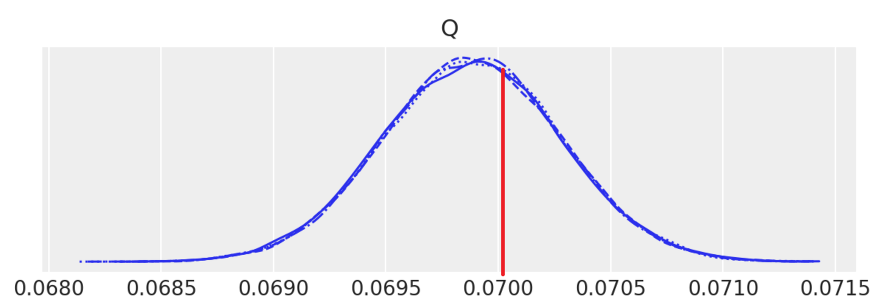

Figure 6: Estimated flux distributions (blue lines), true flux (red line) for a synthetic test case

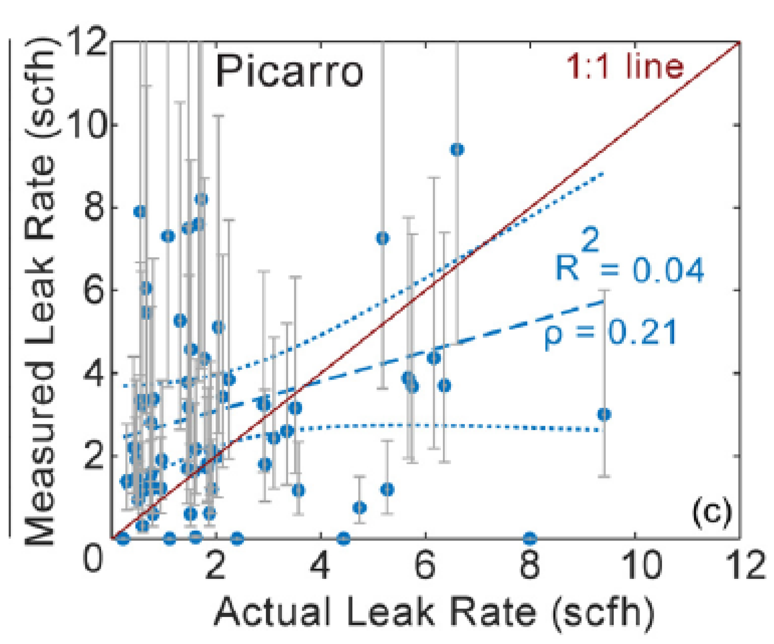

Figure 7: Estimated against actual leak rate from Picarro's MMC results.

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