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Current Project Overview

The Site-Aerial-Basin Emissions Reconciliation (SABER) project aims to reconcile top-down (TD) and bottom-up (BU) methane (CH_4) emission estimates in the Denver-Julesburg (DJ) basin and apply the same approach in the Upper Green basin. Different studies have reported that BU methods underestimate emissions by a factor of about 3 to 6, while TD methods have been reported to overestimate emissions. As BU methods use emission factors (EFs) and activity factors (AFs) to calculate emissions, some of the EFs are considered out-of-date and largely depend on the sample used to generate the EFs which may be unrepresentative nationally or regionally. The most common BU inventories include the Intergovernmental Panel on Climate Change (IPCC) Tier 1 and the Environmental Protection Agency (EPA) Tier 2/3 approaches. In some cases, operator-informed inventories are used. On the other hand, TD estimates have been reported to overestimate emissions by capturing maintenance activities and incorrectly extrapolating these rare events as frequent annual emissions. Currently, the frequency and duration of rare large events commonly called 'super-emitters' is unknown. The relatively short timescale of most TD measurements and incorrect attribution makes it hard to understand the mechanistic causes of super-emitters. Most studies conduct individual measurement campaigns at the site level or basin level, scale to national scale, and then compare the reported emissions to the EPA greenhouse gas inventory. The EPA has worked on updating the inventory using field studies' results. Also, operators are currently required to report their emission factors through the EPA Subpart W.

Through detailed and comprehensive fieldwork and modeling studies, the SABER Project aims to:

1. Demonstrate that high-frequency sampling can be used to create inventory emissions estimates that accurately represent emissions in a basin.
2. Develop a method for estimating emissions that can be replicated in other basins.

The success of a reconciliation attempt heavily relies on understanding the uncertainties of the quantification method in different conditions and emission scenarios, and interference from nearby sources particularly non-oil and gas sources (landfills, consolidated animal feeding operations, wastewater plants and freshwater sources). Due to these uncertainties, my research is divided into two phases: (1) Evaluating the feasibility of using downwind methods to quantify point source oil and gas emissions using continuous monitoring fence-line sensors, and (2) Investigating the temporal and spatial variability in non-oil and gas emissions.

Research Progress

Evaluating the feasibility of using downwind methods to quantify point source oil and gas emissions using continuous monitoring fence-line sensors (in peer review)

Executive Summary

Downwind CH_4 quantification methods using CH_4 measurements on the fence-line of production facilities could be used to generate emission estimates from oil and gas operations at the site level, but it is currently

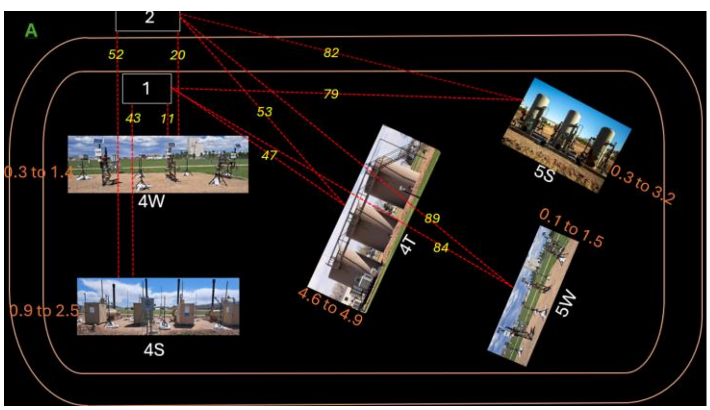
unclear how accurate the quantified emissions are. To investigate model accuracy, this study uses fence-line simulated data collected during controlled release experiments as input for eddy covariance, aerodynamic flux gradient, backward Lagrangian stochastic model and the Gaussian plume inverse methods in a range of atmospheric conditions. Eddy covariance's data failed the quality test based on Mauder and Foken (2004) (0-1-2 system) quality test and could not be used for quantification. The aerodynamic flux gradient method quantified within a relative factor (estimated emission/actual emission) of 1.3 to 1.7 for a single release single emission, and at between 2.4 and 3.4 for multiple releases single emission. The backward Lagrangian stochastic model for point sources using WindTrax performed well for single release single emissions, relative factor of between 0.82 to 1.07, but largely overestimated emissions for multiple releases single emissions, relative factor of 418.8, 2156.7, and 3.91 at 5, 10 and 15-minute averaging. Similar to the backward Lagrangian stochastic model, the Gaussian plume inverse model performed well for single point sources, average 2.57. However, the model largely overestimated emissions when multiple releases were happening, relative factor between 16 and 26. As continuous monitoring of oil and gas sites involves complex emissions where plumes are not defined due to multiple sources, this study shows that the common downwind point source dispersion models could largely overestimate emissions. Aerodynamic flux gradient provided promising results for multiple releases quantification, and this study recommends more testing of flux quantification models for oil and gas continuous monitoring quantification.

1. Background

Downwind methane (CH_4) quantification methods using CH_4 measurements on the fence-line of production facilities are used to generate emission estimates from oil and gas operations at the site level, but it is currently unclear how accurate the quantified emissions are. To investigate model accuracy, this study uses fence-line simulated data collected during controlled release experiments as input for eddy covariance, aerodynamic flux gradient, backward Lagrangian stochastic model and the Gaussian plume inverse methods in a range of atmospheric conditions.

2. Methods

Controlled release experiments were conducted at the Colorado State University's Methane Emissions Technology Evaluation Center (METEC) in Fort Collins, CO, USA, between February 8, and March 20, 2024. Two stationary masts holding the instrumentation were setup on the North-West corner of METEC to take advantage of the predominant wind direction, avoid the largest aerodynamic obstructions and to simulate the likely placement of a fence line instrument (Figure 1A; Day et al., 2024; Riddick et al., 2022a). Fenceline sensors are typically placed within the oil and gas perimeter (~30 m) (Riddick et al., 2022a). This study collected data for both close and far away releases, distances between 9 and 94 m.



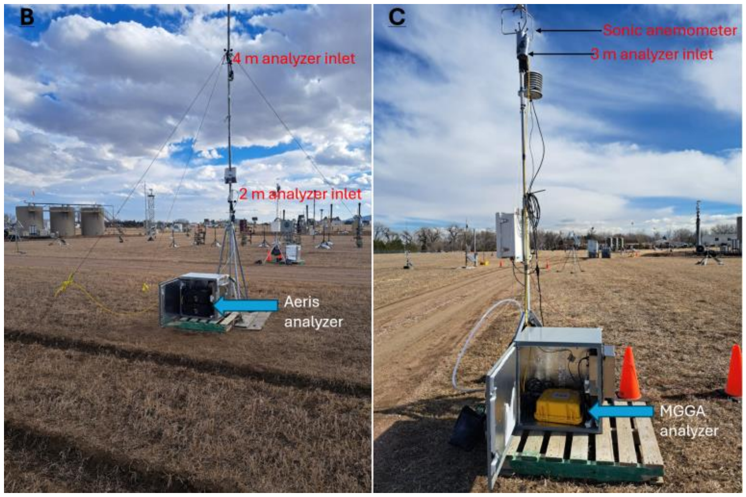


Figure 1: A: Map illustration of major pieces of equipment and the measurements points at Colorado State University's Methane Emissions Technology Evaluation Center (METEC) in Fort Collins, CO, USA. 4S denotes the location of horizontal separators, 4W are well heads, 4T are tanks, 5S are vertical separators and 5W are well heads. 1 is the measurement point for the Microportable Greenhouse Gas Analyzer and 2 is the measurement point for the Aeris analyzers. The red dotted lines with yellow numbers show the average distances (meters) between emission equipment and measurement point. The orange number show the range of emission heights (meters) for each equipment. B: Aeris analyzers sampling at 2 and 4 m heights for aerodynamic flux gradient sampling. C: The eddy covariance, Gaussian plume inverse and backward Lagrangian stochastic model sampling points. The inlet tubing and the sonic anemometer are at 3 m height. The analyzers were hosted in a temperature-controlled box. The two sampling points are 9.4 m apart.

3. Results

3.1 Eddy Covariance

Closed-path EC quantification of SRSP emissions quantified emissions correctly within a mean relative factor (MRF) of between 0.67 and 0.97 at ±45° across all averaging periods, with ample sample sizes (Figure 2). For MRSP emissions, closed-path EC quantification was reasonably accurate under a wide wind sector (±45°), with MRFs ranging from 1.02 to 2.43 and ample sample sizes supporting the reliability of the estimates (Figure 3).

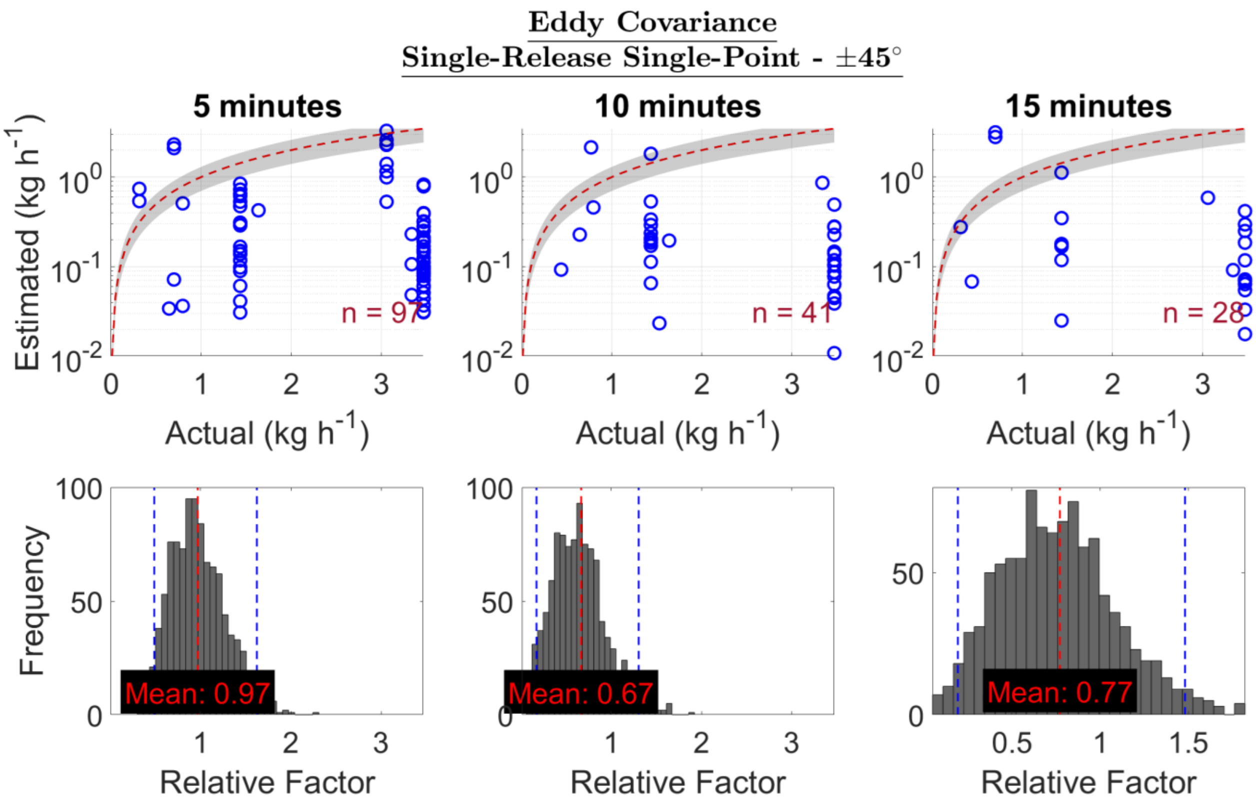


Figure 2. Top plot: Estimated emission vs actual emission (kg h-1) for a single-release single-point at site level, ±45° wind sector range. The red dotted line is a 1:1 line based on actual emissions i.e. points below the line are underestimated and above are overestimated emissions. The gray region represents ±30% of the actual emission. The sample size is n. Bottom plot: A bootstrap of mean relative factor (MRF: estimated emissions divided by actual controlled emission) for a single-release single-point, ±45° wind sector range. An MRF of less than 1 shows an overall underestimation of emissions while an MRF of greater than 1 shows an overall overestimation of emissions. The dotted blue lines are the lower confidence intervals (CI) and upper CI, 95% confidence intervals.

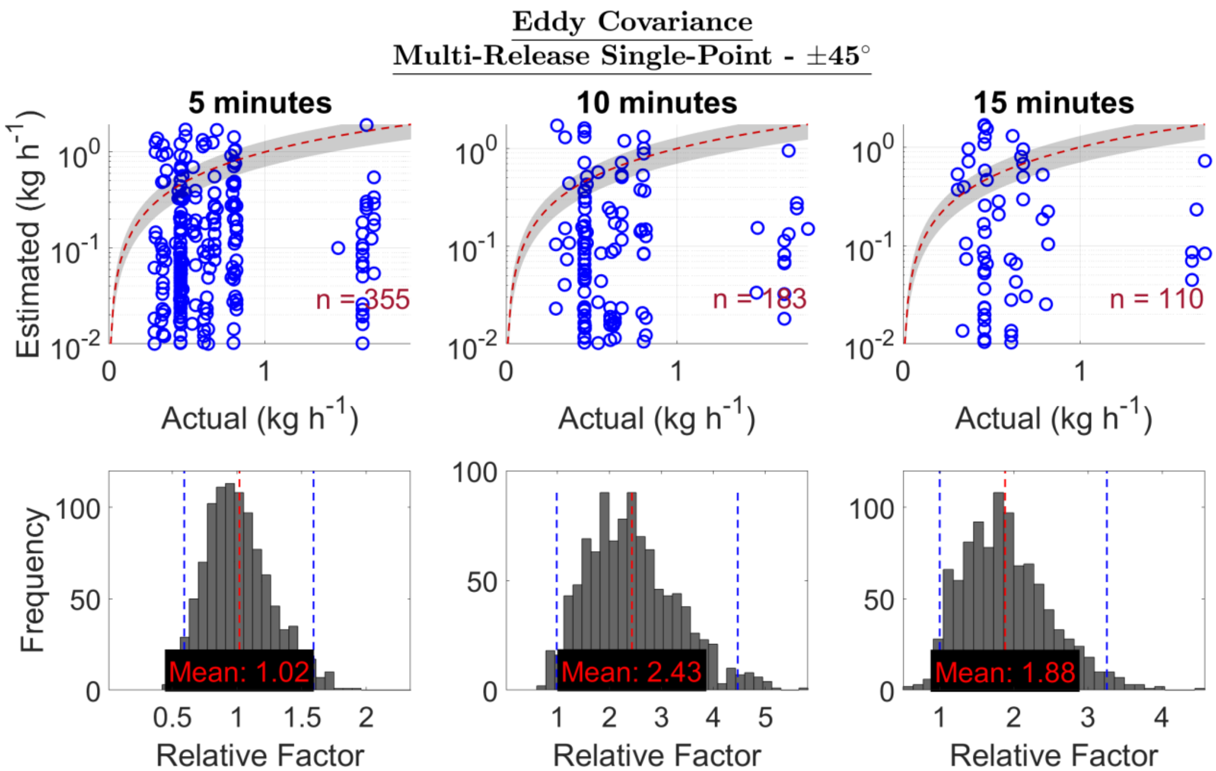


Figure 3. Top plot: Estimated emission vs actual emission (kg h-1) for a multi-release single-point at site level, ±45° wind sector range. The red dotted line is a 1:1 line based on actual emissions i.e. points below the line are underestimated and above are overestimated emissions. The gray region represents ±30% of the actual emission. The sample size is n. Bottom plot: A bootstrap of mean relative factor (MRF: estimated emissions divided by actual controlled emission) for a multi-release single-point, ±45° wind sector range. An MRF of less than 1 shows an overall underestimation of emissions while an MRF of greater than 1 shows an overall overestimation of emissions. The dotted blue lines are the lower confidence intervals (CI) and upper CI, 95% confidence intervals.

3.2 Aerodynamic Flux Gradient

For single release single emission (single emission at the site level, and the mast was downwind), the aerodynamic flux gradient quantified emissions correctly within a factor of between 1.3 and 1.7 at ±45-degree range (Figure 4). For multi release single emission (multiple releases at the site level, but the mast was downwind of one point), the aerodynamic flux gradient estimated emissions by a factor of 2.4 to 3.4 (Figure 5).

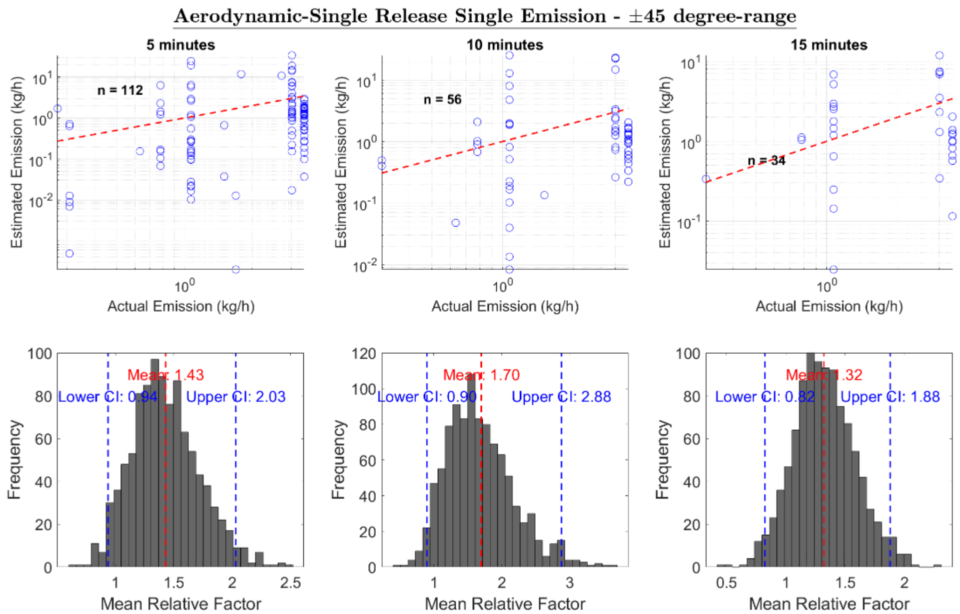


Figure 4. Top plot: A plot of estimated emission vs actual emission (kg/h) for a single release and single emission at site level. The red dotted line is a 1:1 line based on actual emission i.e. points below the line are underestimated and above are overestimated emissions. n is the sample size. Bottom plot: A bootstrap of mean relative factor (estimated emissions divided by actual controlled emission). A mean relative factor of less than 1 shows an overall underestimation of emissions while a mean relative factor of greater than 1 shows an overall overestimation of emissions. The lower CI and upper CI are the 95% confidence intervals.

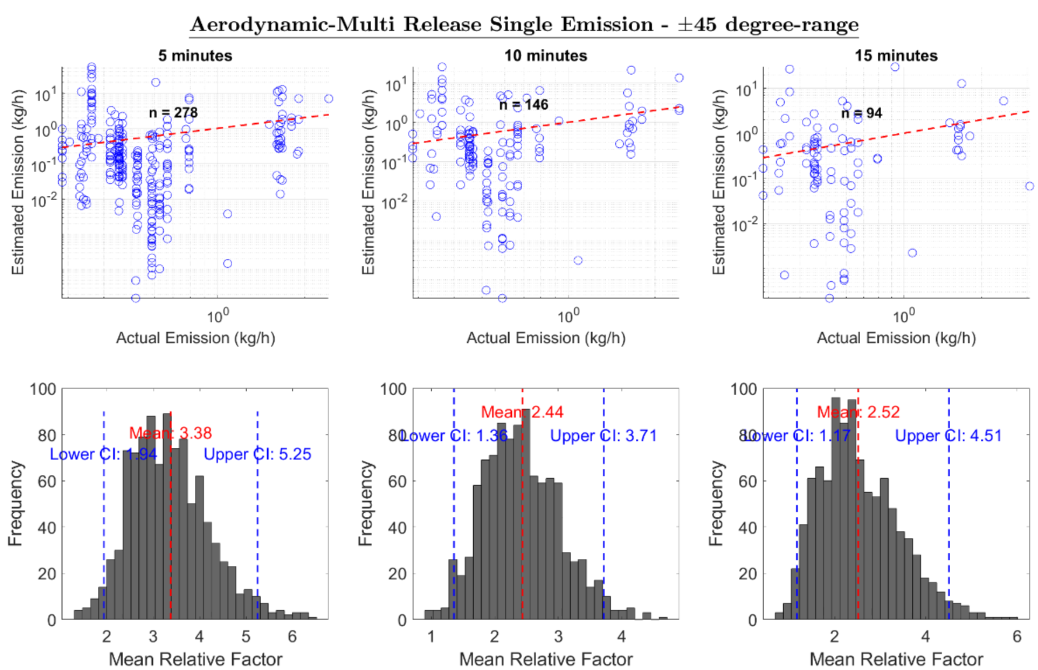


Figure 5. Top plot: A plot of estimated emission vs actual emission (kg/h) for a single release and single emission at site level. The red dotted line is a 1:1 line based on actual emission i.e. points below the line are underestimated and above are overestimated emissions. n is the sample size. Bottom plot: A bootstrap

of mean relative factor (estimated emissions divided by actual controlled emission). A mean relative factor of less than 1 shows an overall underestimation of emissions while a mean relative factor of greater than 1 shows an overall overestimation of emissions. The lower CI and upper CI are the 95% confidence intervals.

3.3 Backward Lagrangian Stochastic Model

For single release single emission, the backward Lagrangian stochastic model quantified emissions correctly within 20% at ± 10 degrees (Figure 6). For multi release single emission, the backward Lagrangian stochastic model largely overestimated emissions at 5- and 10-minute averaging, and the lowest relative factor was 3.91 for 15-minute averaging at ± 10 degrees (Figure75).

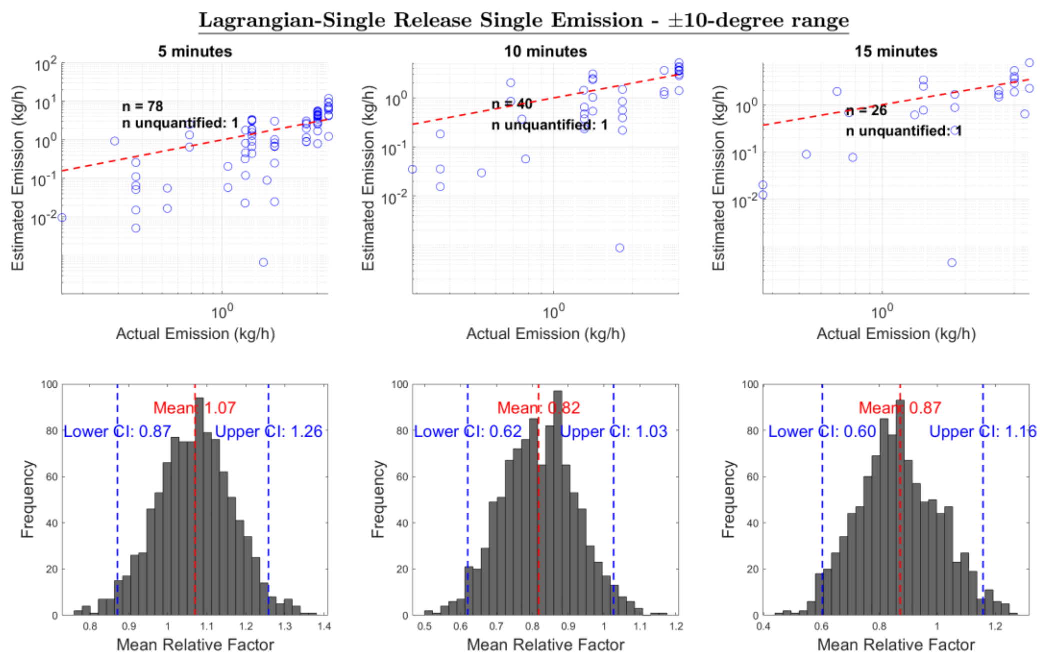


Figure 6. Top plot: A plot of estimated emission vs actual emission (kg/h) for a single release and single emission at site level. The red dotted line is a 1:1 line based on actual emission i.e. points below the line are underestimated and above are overestimated emissions. n is the sample size and n unquantified is the number of points WindTrax reported -9999 (i.e. could not quantify). Bottom plot: A bootstrap of mean relative factor (estimated emissions divided by actual controlled emission). A mean relative factor of less than 1 shows an overall underestimation of emissions while a mean relative factor of greater than 1 shows an overall overestimation of emissions. The lower CI and upper CI are the 95% confidence intervals.

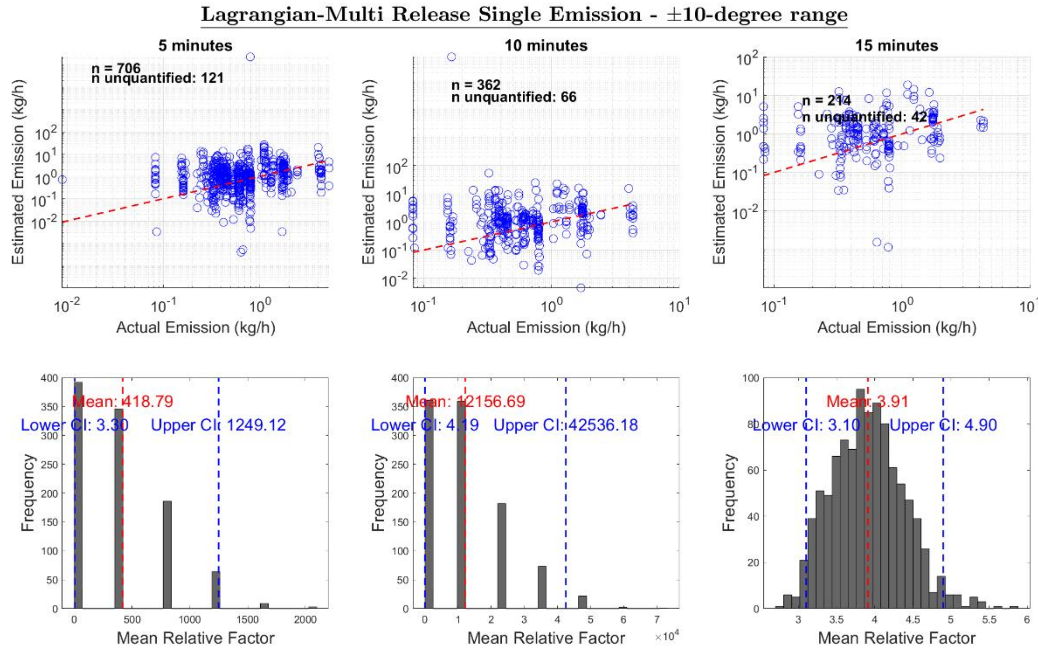


Figure 7. Top plot: A plot of estimated emission vs actual emission (kg/h) for a single release and single emission at site level. The red dotted line is a 1:1 line based on actual emission i.e. points below the line are underestimated and above are overestimated emissions. n is the sample size and n unquantified is the number of points WindTrax reported -9999 (i.e. could not quantify). Bottom plot: A bootstrap of mean relative factor (estimated emissions divided by actual controlled emission). A mean relative factor of less than 1 shows an overall underestimation of emissions while a mean relative factor of greater than 1 shows an overall overestimation of emissions. The lower CI and upper CI are the 95% confidence intervals.

3.4 Gaussian Plume Inverse Method

For single release single emission, the Gaussian plume inverse model quantified emissions within a factor of 2.6 average at ± 10 degrees (Figure 8). For multi-point single emissions, the Gaussian plume inverse model largely overestimated emissions when there were multiple releases at the site level, but the mast was downwind of one release point in that degree range (Figure 9).

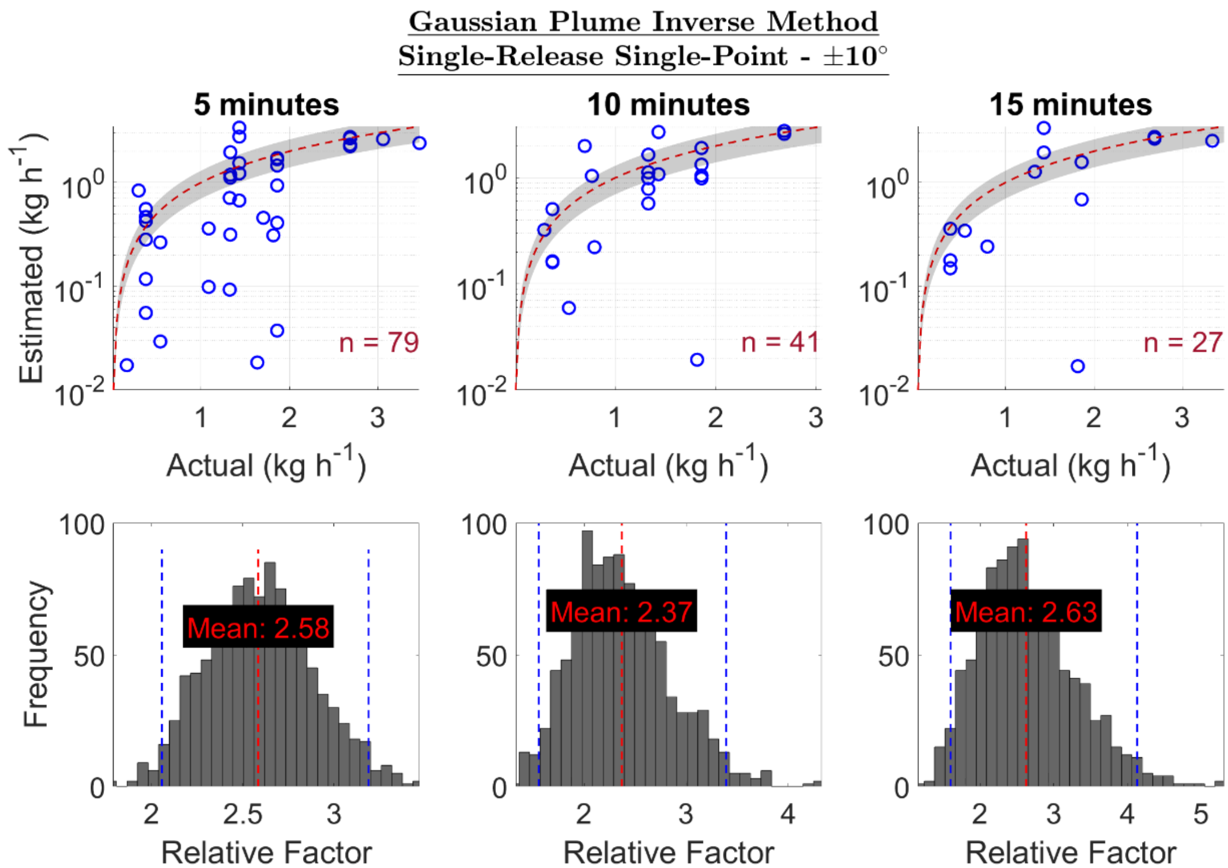


Figure 8. Top plot: Estimated emission vs actual emission (kg h-1) for a multi-release single-point at site level, ±45° wind sector range. The red dotted line is a 1:1 line based on actual emissions i.e. points below the line are underestimated and above are overestimated emissions. The gray region represents ±30% of the actual emission. The sample size is n. Bottom plot: A bootstrap of mean relative factor (MRF: estimated emissions divided by actual controlled emission) for a multi-release single-point, ±45° wind sector range. An MRF of less than 1 shows an overall underestimation of emissions while an MRF of greater than 1 shows an overall overestimation of emissions. The dotted blue lines are the lower confidence intervals (CI) and upper CI, 95% confidence intervals.

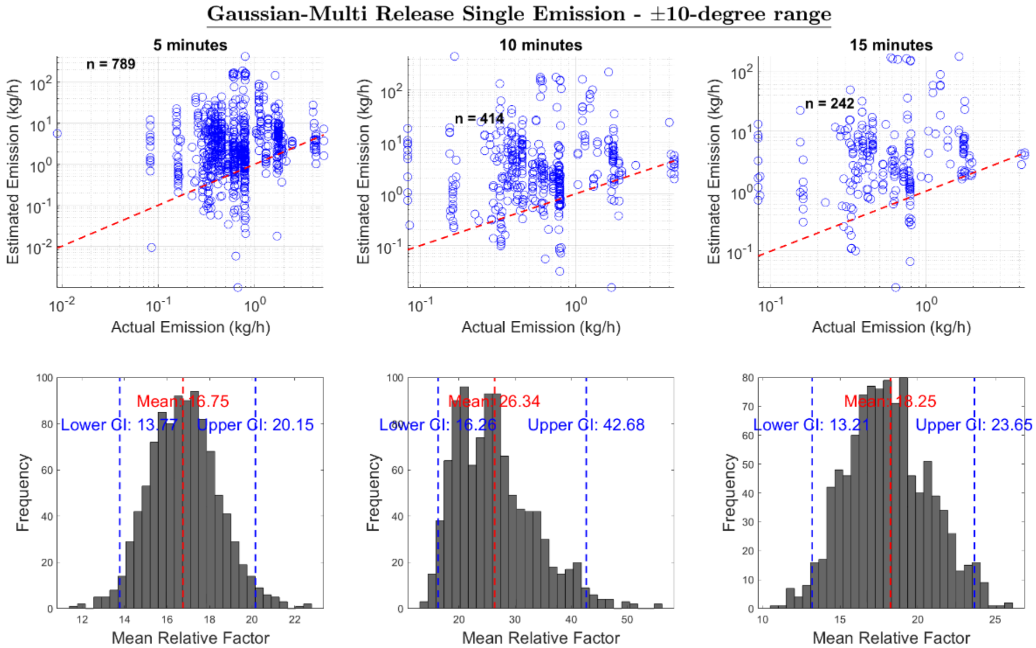


Figure 9. Top plot: A plot of estimated emission vs actual emission (kg/h) for a single release and single emission at site level. The red dotted line is a 1:1 line based on actual emission i.e. points below the line are underestimated and above are overestimated emissions. n is the sample size. Bottom plot: A bootstrap of mean relative factor (estimated emissions divided by actual controlled emission). A mean relative factor of less than 1 shows an overall underestimation of emissions while a mean relative factor of greater than 1 shows an overall overestimation of emissions. The lower CI and upper CI are the 95% confidence intervals.

4.0 Implications

Oil and gas point sources could either be single emissions or multiple emissions occurring concurrently. In cases of multiple emissions with more than one release point being downwind, the Gaussian model and the backward Lagrangian stochastic models are limited, as they can only quantify one source at a time, and interference from neighboring emissions affects the underlying principles of dispersion on which these models were developed. As a result, flux quantification models used in other applications such as eddy covariance and aerodynamic flux gradient have been proposed as the solution. Even though this study could not generate emissions using eddy covariance due to instrumentation, steady tests and turbulence tests, aerodynamic flux gradient showed promise with multi release single emission quantification. Even though the study worked with a single sonic anemometer that was 9.4 m away limiting our study to one footprint model and stability classification at a single height, this study shows that aerodynamic flux gradient could have better quantification than the common Gaussian and Lagrangian quantification models for multi releases. For point sources, this study acknowledges that inclusion of the horizontal advection could be needful for better accuracy of the flux gradient, however, as the method technically requires two sampling heights each with a 1 Hz frequency analyzer and a sonic anemometer, instrument deployment limitations might necessitate use of the vertical flux and the footprint for continuous monitoring calculations. This study recommends more testing of flux quantification models for oil and gas quantification as they could improve emissions quantification for leak repair prioritization and methane reporting.

(2) Investigating the variability in non-oil and gas methane emissions in the Denver-Julesburg basin

1. Background

Methane measurements of 6 landfills, 5 cattle farms, 12 dairy, 2 sheep farms, 4 wastewater treatment plants and 4 freshwater sources are taken during monthly surveys of non-oil and gas sources in the DJ basin (Figure 7). Understanding the temporal and spatial variability of non-oil and gas sources is crucial as these sources' emission factors are used in understanding their attribution in non-oil and gas sources.

2. Measurements and Quantification

Methane measurements are taken using an Aeris Strato analyzer at 1 Hz frequency, while meteorological measurements are taken using the Airmar (150WX) also at 1 Hz frequency, at 2 m height. Methane measurements are aggregated to meteorological measurements. The aggregated measurements are filtered to when the surveying truck was downwind of the source for at least 30 seconds as these sites are surveyed each for about 2 to 15 minutes depending on accessibility, wind direction and traffic. Using the mean truck location, methane and meteorological measurements, methane integrated emission rate is generated using WindTrax (areas source backward Lagrangian stochastic model).


3. Results

Preliminary Results

The data collection and analysis process to answer Research Question (2) is still ongoing.

Concentrated Animal Feeding Operations (CAFOs)

Facility-level CH_4 emissions varied substantially across livestock categories (Figure 10). Cattle operations exhibited the highest emissions and variability, with extreme outliers and an interquartile range wider than that of other categories. In contrast, dairy facilities showed more moderate emissions and variability, while sheep facilities had the lowest emissions and narrowest distribution. On a per-animal basis, dairy animals had the highest emission factors, averaging ~15.9 g CH_4 h^{-1} $animal^{-1}$, compared to 10.7 for cattle and 1.4 for sheep (Figure 10). These trends suggest that cattle and dairy operations not only contribute more CH_4 emissions per facility but also demonstrate the greatest heterogeneity in emission profiles, underscoring their importance in targeted mitigation efforts.

Based on the 2024 CDPHE dataset, this study estimates approximately 429,000 cattle, 288,000 dairy animals, and 32,500 sheep in the DJ Basin. Using these population estimates, preliminary annual CH_4 emissions were highest from cattle (40.3 Gg y^{-1}), followed by dairy (40.0 Gg y^{-1}), and lowest from sheep (0.41 Gg y^{-1}) (Table 1). Preliminary cattle emission estimates are higher than prior measurement-informed and inventory-based studies (Table 2; Riddick et al., 2024a, 2022). Sheep emissions also showed agreement with the two studies within 95% CI (Table 2), while dairy emissions were lower than the measurement informed and SIT values reported in Riddick et al. (2022) and Riddick et al. (2024a), suggesting potential differences caused by temporal variability.

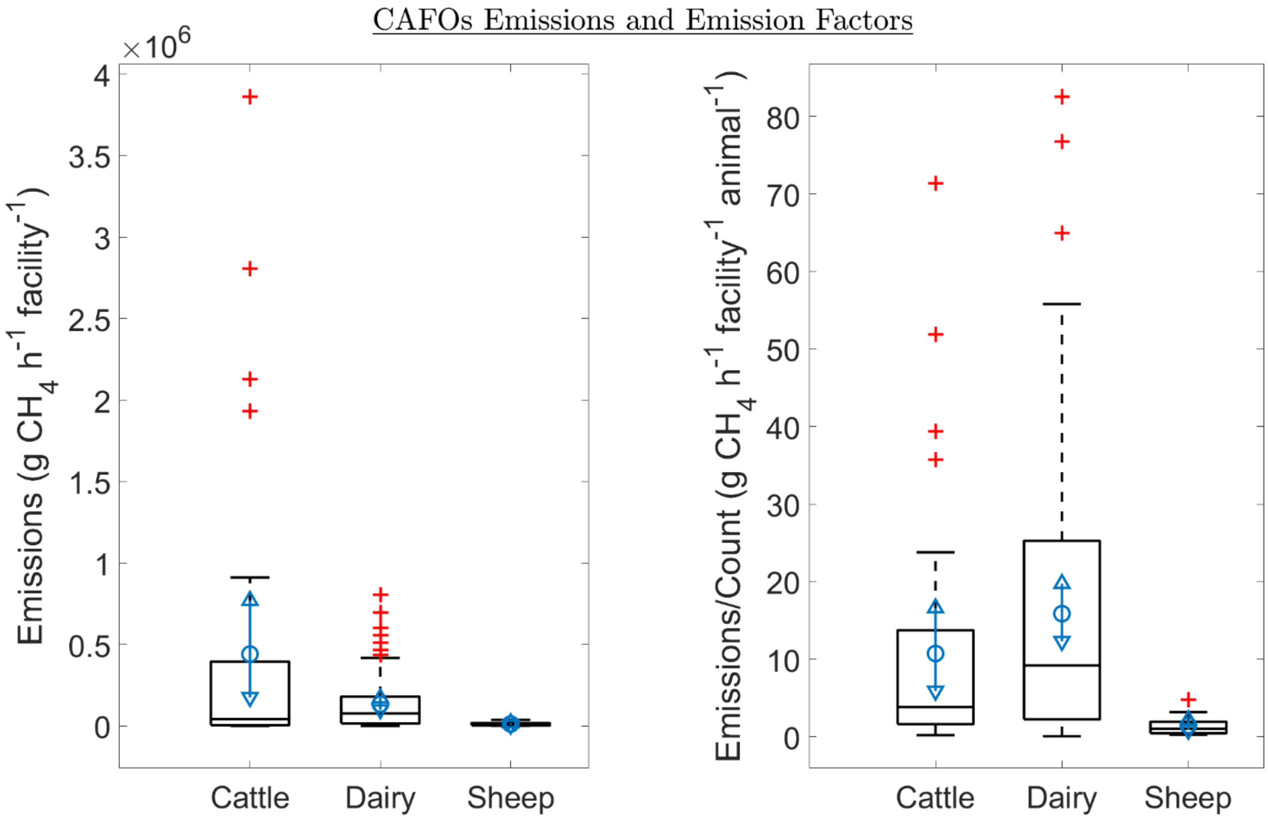


Figure 10. Left figure: A box plot distribution of emissions for CAFOs. Right figure: A box plot distribution of emission factors (emissions/animal count) for CAFOs. The black box plot shows the median and interquartile range. Red points are the outliers. The blue point with the error bars is the bootstrapped mean and 95% confidence interval.

Table 1: A comparison of this study, Riddick et al. (2022), Riddick et al. (2024a) measurement-informed, and Riddick et al. (2024a) state inventory tool (SIT) CAFOs estimates

	Animal count			*Mean Annual Emission (Gg y^{-1})*				*Lower CI*	*Upper CI*
	This study	*Riddick et al. (2022)*	*Riddick et al. (2024a)*	*This study*	*Riddick et al. (2022)*	*Riddick et al. (2024a)-measurement informed*	*Riddick et al. (2024a)-SIT estimate*		
Cattle	428,636	409,550	426,636	40.3	19	19.8	43.8	22.1	62.3
Dairy	287,630	184,463	285,401	40.0	50	77.5	74.0	31.0	49.8
Sheep	32,500	27,000	32,500	0.41	0.2	0.26	0.27	0.24	0.62

Landfills

Methane emissions from landfills varied widely across sites, ranging from negligible levels to over 4500 kg CH_4 h^{-1} (Figure 11). Sites D and F exhibited the highest absolute emissions. However, when emissions were normalized by waste mass, Site D emerged with the highest emission factor (~1.2×10^{-4} kg CH_4 h^{-1} ton^{-1}), suggesting disproportionately high emissions relative to its reported waste volume. In contrast, although Site F had the highest mean emission overall, its normalized emission factor was lower, indicating that its higher emissions likely stem from a greater volume of waste. These findings underscore the importance of contextualizing landfill emissions with waste volume to accurately identify high-emitting facilities.

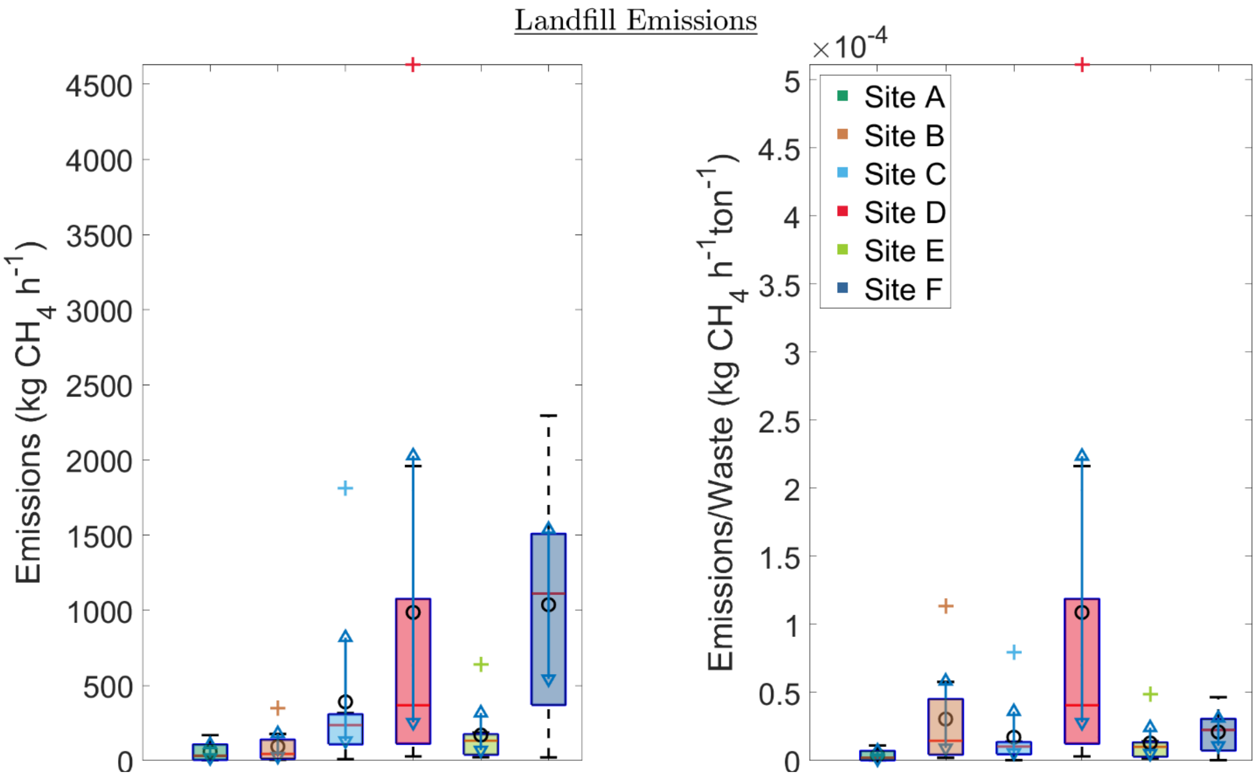


Figure 11. Left figure: A box plot distribution of emissions for 6 landfills in the DJ region. Right figure: A box plot of the distribution of emission factors, landfill emissions normalized by the amount of waste in the facility. The red and black lines are the median and the mean, respectively. The scatter points are the outliers. The black point with the error bars is the bootstrapped mean and 95% confidence interval.

Riddick et al. (2024a) estimated landfill methane emissions in the DJ Basin at 31–40 Gg y^{-1} based on different EF approaches (IPCC Tier 1/2, EPA-specific, and Nebraska-derived measurement-based EFs). In this study, we refined the inventory using satellite imagery to identify six landfills within the DJ boundary. Two previously measured sites were outside this boundary, and one additional landfill was inaccessible and lacked waste data, leaving five landfills for inclusion in our regional estimate. Site A comprises both North and South sections; only the South site was measured due to access constraints, and its emission factor was applied to the North site. Based on this approach, we estimate total DJ Basin landfill emissions at 14.3 Gg y^{-1} [7.3 to 24.5], substantially lower than Riddick et al.'s prior estimates. Annual emissions by landfill are provided in Table 2.

Table 2. Landfill emissions in the DJ basin. Landfill specific data is obtained from the EPA Landfill Methane Outreach Program (LMOP) data publicly available.

Landfill	*Current Status*	*Amount of Waste (tons)*	*Waste in Place Year*	*Landfill Gas Collection System in Place?*	*Annualized Emission (Gg y^{-1})*		
					Mean	*Lower CI*	*Upper CI*
Site A North	Closed	6,319,775	1992	Yes	0.22	0.08	0.39
Site A South	Closed	15,157,900	2020	Yes	0.53	0.18	0.94
Site C	Open	22,704,246	2022	Yes	3.43	1.16	7.18
Site D	Open	13,102,853	2022	Yes	8.65	2.23	17.8
Site E	Open	9,057,425	2022	Yes	1.49	0.61	2.78

Wastewater Treatment Facilities

Methane emissions from wastewater treatment plants (WWTPs) varied across the three sampled sites, with highest emissions observed at Sites A and B (~10–11 kg CH_4 h^{-1}) and lower emissions at Site C (~3 kg CH_4 h^{-1}). When normalized by facility flow rate, Site B had the highest emission factor (~0.6 kg CH_4 h^{-1} mgd^{-1}), followed by Sites A and C (Figure 12). While the state database listed 55 WWTPs in the DJ Basin, field verification revealed that many were inactive or not actual treatment facilities, indicating potential overcounts in inventory-based approaches. Riddick et al. (2024a) reported higher total emissions (up to 3.1 Gg y^{-1}), but those estimates likely reflect the inflated facility count. Using 2025 Google Maps satellite imagery, we identified 26 wastewater treatment facilities with infrastructure similar to the three measured sites. Applying the overall bootstrapped mean emission factor of 0.52 kg CH_4 h^{-1} mgd^{-1}, total basin-wide emissions from wastewater treatment were estimated at 0.75 [0.52, 1.01] Gg y^{-1}—falling between the lower IPCC/EPA-based estimates and the higher measurement-informed inventory reported by Riddick et al. (2024a).

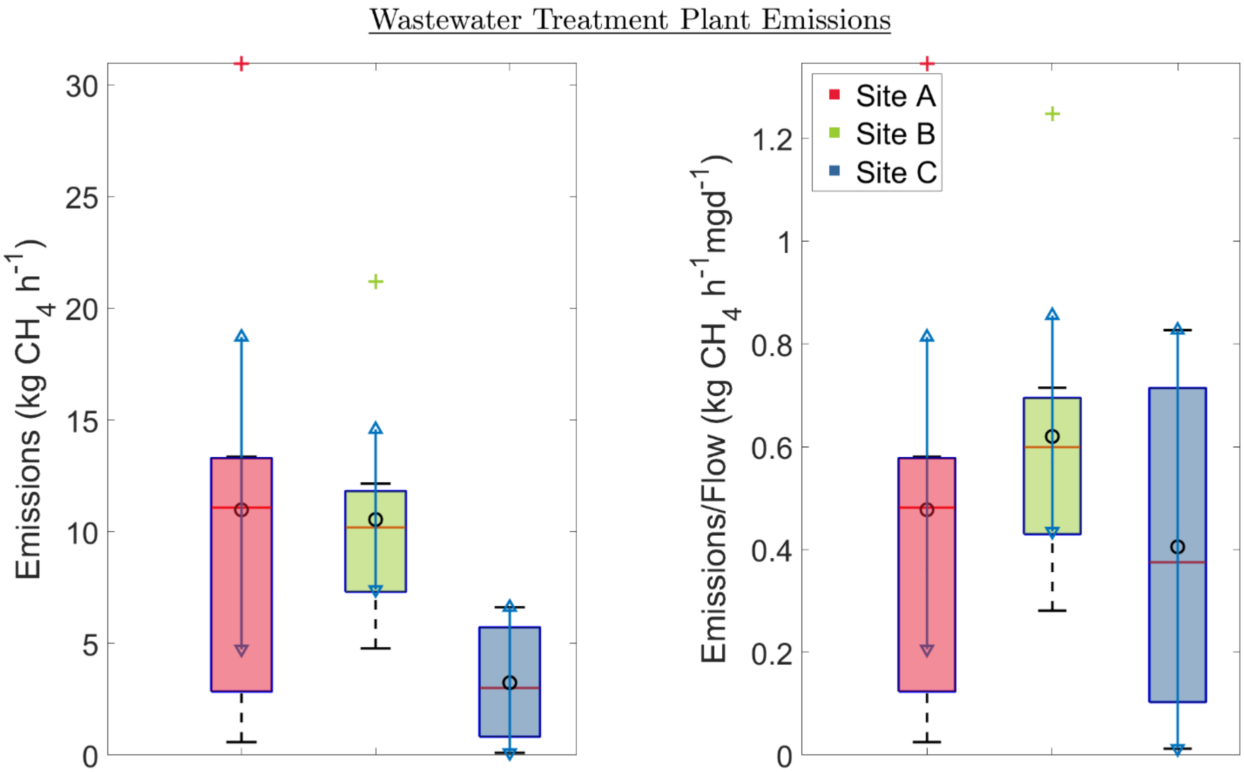


Figure 12. Left figure: A box plot distribution of emissions for 3 wastewater treatment plants in the DJ region. Right figure: A box plot of the distribution of emission factors, emissions normalized by the amount of waste in the facility. The red and black lines are the median and the mean, respectively. The scatter points are the outliers. The black point with the error bars is the bootstrapped mean and 95% confidence interval.

Freshwater Sources

Freshwater emissions ranged from ~0 to 1100 kg CH_4 h^{-1} $facility^{-1}$ and emission factors from ~0 to 7 E-4 kg CH_4 m^{-2} h^{-1} (Figure 13). The bootstrapped mean emission factors were 11.7 mg CH_4 m^{-2} h^{-1} for Site A ; 44.8 mg CH_4 m^{-2} h^{-1} for Site B; 13.6 mg CH_4 m^{-2} h^{-1} for Site C and; 18.4 mg CH_4 m^{-2} h^{-1} for Site D (Figure 13). We estimate the overall EF for freshwater sources to be 51.5 mg CH_4 m^{-2} h^{-1}, which is higher than Riddick et al. (2024a)'s 15 mg CH_4 m^{-2} h^{-1}. Using the same water coverage area of 26,329 acres in the DJ region as Riddick et al. (2024a), we estimate total emissions from fresh water sources at 49.09 [11.3, 113.4] Gg y^{-1}.

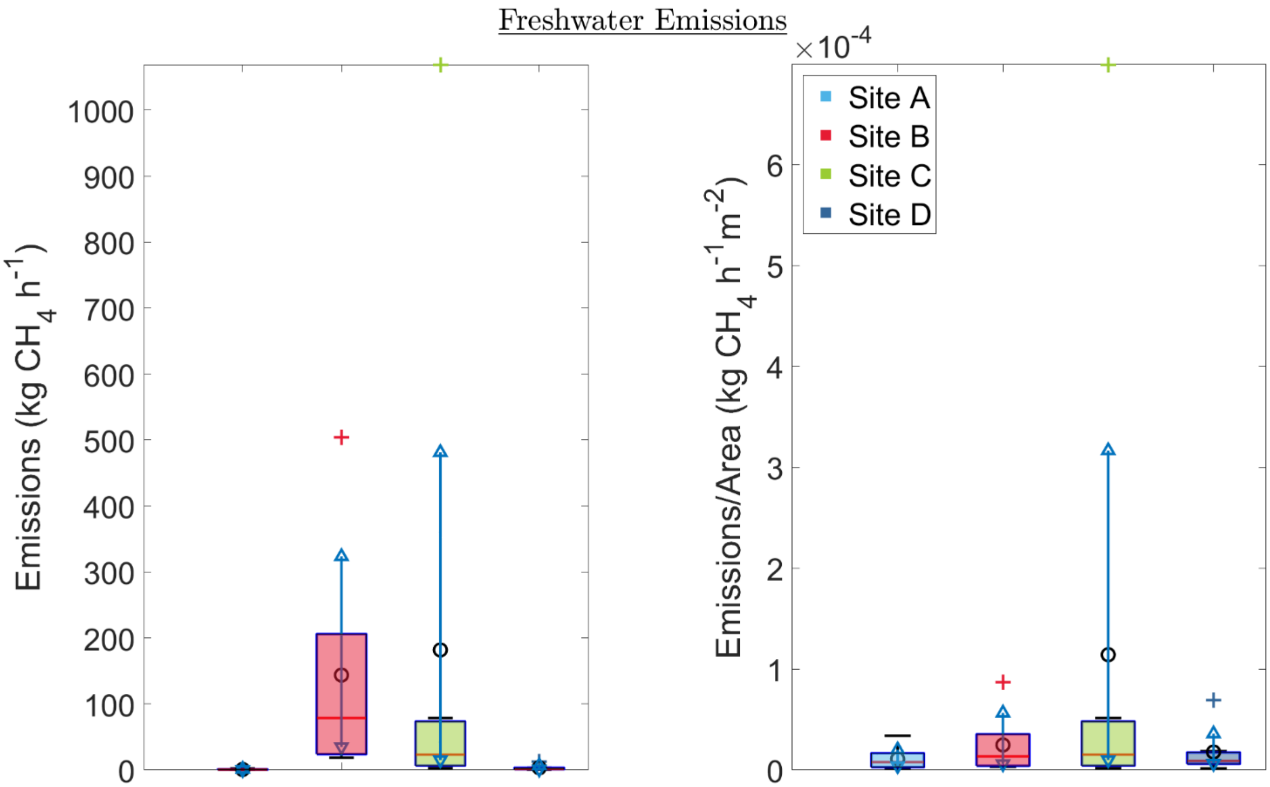


Figure 13. A box plot of the distribution of freshwater emission factors, emissions normalized by area. The red and black lines are the median and the mean, respectively. The scatter points are the outliers. The black point with the error bars is the bootstrapped mean and 95% confidence interval.

Discussion

This study provides an inventory of CH_4 emissions estimates for CAFOs, landfills, wastewater treatment plants and freshwater sources calculated using facility level downwind measurements. Using 7 months of survey measurements conducted between June to March 2025, the study estimates preliminary total emissions in the DJ boundary at 144.8 [72.5, 251.6] Gg y^{-1}. Our study agrees with Riddick et al. (2024b)'s estimates of 155.4 Gg y^{-1} measurement-based inventory within 95% confidence interval although there were siginificant disagreements in landfill and freshwater emissions. By generating facility-level measurements that vary temporally and spatially, this study reduces the 'snapshot bias' inherent in short-term campaigns that could cause large variability when emissions are scaled regionally and annually. For CAFOs, factors such animal age and weight, diet composition, manure management practices, weather at the time of measurement and variation in feeding times and times of measurement could result in different emission factors. For landfills, factors such organic content and age of waste, landfill operations at the time of measurement, efficiency of gas collection systems, efficiency of covers for closed landflls, microbial processes depending on the decomposition phase, and environmental conditions such as pressure, temperature and precipitation could all result in varying emissions. Wastewater treatment facility emissions could vary with organic load of the wastewater, plant design and operations such as gas collection efficiency, and treatment process type such as aerobic digestion versus aerobic treatment. For freshwater sources, emissions can vary depending on climate and elevation effects (warmer lowland reservoirs could have higher emissions than those in cold temperatures) or organic matter sources (if the source connects to wastewater or fertilizer from agricultural lands runoff). In this study, by measuring these sources at different times of the year, and different geographic locations, we were able to capture the temporal and spatially variability of emission factors which gave us a robust understanding of emissions that can be used regionally. Ongoing work will integrate 12 months of data to resolve seasonal extremes (e.g., winter manure storage at CAFOs, summer reservoir stratification.

Research Plans

- Continue the data collection, and analysis of the non-oil and gas emissions. I'm targeting annual measurement (September 2024 to September 2025).
- I'm also part of the marginal wells project. Measurements will start on Spring 2025.

Publications

- Investigating the variation in non-oil and gas methane emissions in the Denver-Julesburg basin (2025). *In writing*.
- Evaluating the feasibility of using downwind methods to quantify point source oil and gas emissions using continuous monitoring fence-line sensors (2024). *EGUsphere*, 1-22. (2024). *In peer review*. https://doi.org/10.5194/egusphere-2024-3161
- Mbua, M., Riddick, S.N., Tian, S., Cheptonui, F., Houlihan, C., Smits, K.M., Zimmerle, D.J., 2023. Using controlled subsurface releases to investigate the effect of leak variation on above-ground natural gas detection. Gas Sci. Eng. 120, 205153. https://doi.org/10.1016/j.jgsce.2023.205153
- Potential Underestimate in Reported Bottom-up Methane Emissions from Oil and Gas Operations in the Delaware Basin (2024). *Atmosphere*, *15*(2), 202. https://doi.org/10.3390/atmos15020202
- Estimating Total Methane Emissions from the Denver-Julesburg Basin Using Bottom-Up Approaches (2024). *Gases*, *4*(3), 236-252. https://doi.org/10.3390/gases4030014
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