Ms. Ref. No.: EGUSPHERE-2024-3161

Title: Evaluating the feasibility of using downwind methods to quantify point source oil and gas emissions using continuous monitoring fence-line sensors

The Powerhouse Energy Campus

Colorado State University

430 North College Avenue

Fort Collins, CO 80524

E-mail: Mercy.Mbua@colostate.edu

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Dear Professor Presto,

We appreciate the time and effort you, the reviewers and community dedicated to providing feedback on our manuscript. We have closely followed the suggestions and have revised the manuscript accordingly. We believe the revisions have improved our manuscript and that it is ready for publication. We have listed the original comments and our response in blue below for our reply to comments. All figure numbers, tables, and lines refer to the updated manuscript. Data for reviewers' is available at URL: https://doi.org/10.5061/dryad.hhmgqnkss.

We look forward to hearing from you.

Please find our detailed responses below.

Yours sincerely,

Mercy Mbua (corresponding author)

and co-authors: Stuart N. Riddick, Elijah Kiplimo, Kira B. Shonkwiler, Anna Hodshire and Daniel Zimmerle

Reviewer Comments

Review of revision 2 egusphere-2024-3161 "Evaluating the accuracy of downwind methods for quantifying point source emissions", Mbua et al. (Reviewer Comments by E. Thoma and S. Ludwig)

The authors were responsive to reviewer comments, offering a significantly revised manuscript with improved results visibility and supporting detail. The authors added critical QA/QC information on eddy covariance (EC) and decided to remove the aerodynamic flux gradient analysis. The authors modified the Gaussian plume inverse method (GPIM) approach, and backwards Lagrangian stochastic (bLs) analysis (based on WindTrax). Additional details were added for these emission calculation approaches.

Authors response

Thank you for reviewing our manuscript and for the constructive feedback, which has greatly helped us improve its clarity and rigor.

There remains one major set of concerns with the revised manuscript relating to the EC analysis. As a first point, the EC results changed significantly from manuscript version 2. The reason for this is not clear and the authors are encouraged to double check the analysis and identify the root cause for this difference.

Authors response

Thank you for the comment. Yes, the EC results changed from the previous version because we initially used *absolute flux* rather than *positive flux* to calculate emissions. As a result, large negative fluxes were incorrectly represented as large emissions in our earlier analysis.

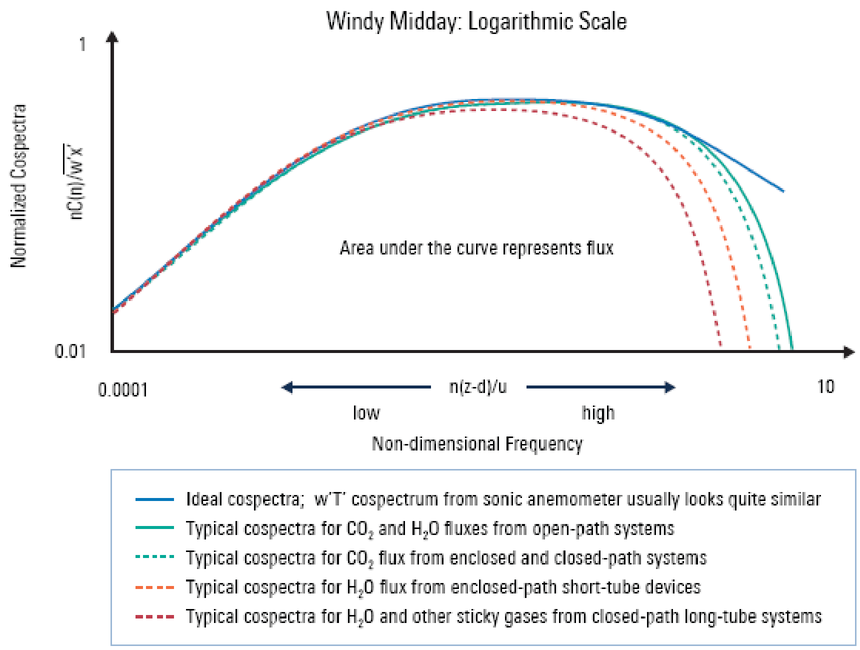
Secondly, version 2 of the manuscript evaluated model performance using the bootstrapped mean, whereas version 3 uses a linear function. The bootstrapped mean in version 2 was disproportionately influenced by large fluxes (and thus large emissions), which gave a misleading impression of strong EC performance. Switching to the linear function in version 3 provided a more accurate and transparent assessment of the results.

We have carefully reviewed the analysis and confirm that the EC results presented in the current manuscript are final.

Assuming the current version of the EC analysis is final, the major concern centers on the strength of conclusions on the performance of the EC approach that can be drawn from this study. The authors have progressed their EC footprint and QA/QC analysis significantly from the original manuscript. However, new supporting information on ogive and cospectra departs significantly from expected form. These results indicate that EC analysis is likely not possible with these data and in fact illustrate "textbook examples" of issues illuminated by these QA/QC checks. This general issue with the EC analysis is further evidenced by the presence of large negative fluxes (which indicate issues in the EC data collection).

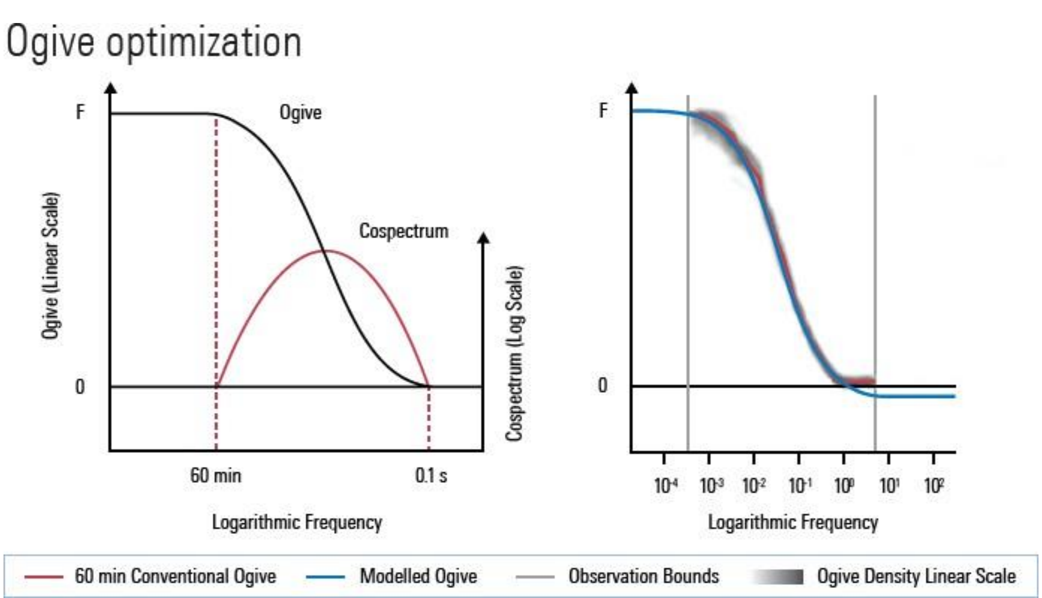
When examining both ogives and cospectra as a part of the QA/QC process, there is both a qualitative shape expected and quantitative metrics of slopes (for portions of the cospectra) and sigmoidal parameters (for the ogives) when good EC data are collected. Some deviations from the ideal form are expected. For example, especially in closed-path eddy covariance, there is often tube attenuation or increased lag that results in poorer performance with data at the highest frequencies. This is seen as a slightly steeper slope than ideal in the cospectra shape at high frequencies and is compensated for during the transfer function calculations when processing data into fluxes. However, even in closed-path EC or EC sampled at 5 Hz rather than 10 Hz, the cospectra still closely follow the ideal shape (especially when examining the cospectra of sonic temperature, which should not suffer any of the issues of the closed path gas sampling system), and slope changes at high frequencies are well modeled by the transfer functions. When the shape of cospectra deviate significantly from the ideal curve (as is the case here), it is an indication the data were not collected properly in a way that can be used for eddy covariance, with causes that include obstructions, mis-aligned time series, too slow system response time, among other issues with the instrumentation as seen here.

Similarly, the ogive analysis should follow a characteristic shape, a sigmoid curve plateauing at the y-axis at 1 and also at 0. The ogive analysis is used to indicate if an appropriate averaging interval was used, as those that are too short will not sufficiently plateau at 1. Furthermore, those ogives which do not follow a sigmoid shape at all indicate issues in data collection. Even accounting for the log-scale y-axis in the authors' ogive figures, they do not follow an acceptable shape, and all ogives here would indicate issues leading to removing the data during QA/QC. I am including examples of the appropriate expected shapes of cospectra and ogives as described in the textbook "Eddy Covariance Method" by George Burba, section 5.1 "Quality Control of Eddy Covariance Flux Data". This chapter provides several examples of how the shapes of cospectra can be used to diagnose issues with the instrumentation and data collection (such as is the case here) that invalidate the EC method.



From the book "Eddy Covariance Method" by George Burba, section 5.1 Quality Control of EC data; Cospectra Analysis. This figure depicts both the ideal cospectra and expected slope deviations at high frequencies for certain gases and systems.

From the book "Eddy Covariance Method" by George Burba, section 5.1 Quality Control of EC data; Ogive Optimization. This figure depicts the expected ogive shape for observations at a site with an optimized averaging interval of 60-minutes.



Authors' response

Thank you for your comment. We acknowledge there were issues with the data collection system that invalidates EC analysis and conclusions. To clarify this to our readers, we have added the section below to the manuscript.

Changes to the Manuscript

Section 3.6

3.6 Eddy Covariance Quality Assurance and Control

Evaluation of the EC data revealed quality assurance and control issues that compromised both the analysis and the conclusions drawn from the EC results. The flux data were flagged as "2" (low quality) according to the 0–1–2 quality classification system of Mauder and Foken (2004), indicating that the data were not suitable for EC analysis. In EC quality assessment, both the qualitative shape of the cospectra and the quantitative slopes of selected portions are examined to determine if the data meet accepted standards. In this study, the cospectra deviated significantly from the ideal shape, indicating problems in data collection and pre-processing. Possible causes include obstructions in the testing area, misalignment between CH_4 and sonic anemometer time series (due to the absence of a reliable method for alignment), slow response time of the gas analyzer, increased lag from the 3 m inlet tubing, and inconsistent sampling frequency. Similarly, ogive analysis—used to evaluate whether the averaging time is sufficient—showed that the ogive curves did not follow the characteristic sigmoidal shape (plateauing at the y-axis and at zero). Although the ogive shapes were similar across all averaging intervals, none plateaued sufficiently, further indicating data collection issues that invalidate the EC method for this study. For clarity and to guide future studies, Burba (2013) provides examples of ideal cospectra and ogive shapes illustrating how these tools can be used to diagnose instrumentation and data collection problems.

The authors now acknowledge the limitations in design of the EC data acquisition system for this study and attempt caveat in numerous places. They also point to non-stationarity in the data as part of the issue with the EC measurement.

However, if the EC results are deemed invalid, then these caveats are insufficient and conclusions around EC performance are not supported. The authors should either remove the EC analysis or suitably modify description to further clarify the severity of the issues for the reader. With little further work, the authors may choose to take this opportunity to illustrate some basic aspects of QA/QC assessment of EC data for this application. The information would be beneficial to the oil and gas/leak detection community (that largely consists of non-EC experts) and would assist future efforts to assess EC for this application.

Here is one example of unsupported conclusions from the abstract.

Ln 17 "*Generally, the closed-path EC system used in this study proved generally unreliable and largely underestimated emissions, primarily due to non-stationarity and study limitations associated with using a non-standard setup. In comparison, the Gaussian Plume Inverse Method (GPIM) consistently outperformed the EC system for both single-release and multi-release single-point emissions.*"

This is an inappropriate indictment of the EC methodology. If your primary QA/QC data indicate that the attempt at the application of the EC method was not successful (for whatever reason), then it is not possible to draw this conclusion. If the EC analysis is to remain in this manuscript, the description needs to be recast as an attempt at EC that failed. This would render the presented comparisons to other methods invalid. The issues with the method application were detected and reasons for these issues are presented here as lessons learned. Future attempts at exploring EC for this application will benefit from the information in this paper.

Authors' response

Thank you for your comment. We acknowledge that issues with the EC data collection system invalidate the results and the conclusions previously drawn. However, we have chosen to retain the EC analysis in the manuscript, reframing it as a "lessons learned" case study. We believe this provides valuable guidance for future studies by documenting the challenges encountered, the diagnostic tools applied, and the indicators of compromised data quality.

Changes to the Manuscript

Abstract

Lines 17-20

This study's EC attempt was unsuccessful due to data collection and instrumentation issues, resulting in invalid outputs characterized by underestimated emissions, large negative fluxes, and cospectra/ogives that deviated from their ideal shapes. Consequently, the EC results could not be compared with the GPIM or the bLS models.

Section 4.1

Lines 507-518

As a result, the conclusions drawn from the EC data are invalid and not comparable to the other tested models are constrained.

This study identified data collection and instrumentation issues that future work can address to enable successful EC application. Based on flagged low-quality data, non-ideal cospectra and ogive shapes, and the presence of large negative fluxes, the dataset was deemed unsuitable for EC analysis. The primary causes of the unsuccessful application were: (1) the CH_4 analyzer was not designed for EC measurements, exhibiting slow response time, low pump flow rate, and inconsistent sampling frequency; (2) the 3 m inlet tubing length for the closed-path analyzer caused signal attenuation and increased lag; (3) the sonic anemometer and CH_4 analyzer data were not synchronously logged, preventing accurate time-series alignment; (4) the EC system was installed near obstacles that disrupted smooth eddy formation; and (5) ogive plots suggested that the maximum 30-minute averaging interval used in this study may have been insufficient. We recommend further EC testing with these issues corrected to properly evaluate its application in continuous oil and gas monitoring.

Lines 569-582

Oil and gas point sources could either be single emissions or multiple emissions occurring concurrently. In this study's design, cases involving multiple emissions with more than one release point located upwind posed challenges for the specific Gaussian and backward Lagrangian stochastic (bLs) model implementations, which were applied assuming a single active source at a time. While these models can be extended to handle multi-source scenarios, the assumptions used here limited their ability to distinguish individual contributions when plumes overlapped. As a result, interference from neighboring emissions introduced ambiguity in model-observation alignment, particularly under complex wind conditions. Closed-path eddy covariance was generally unreliable in this study due to data-collection and instrumentation issues non-stationarity and limitations associated with using a non-standard EC system. This resulted in invalid EC results that could not be compared with the GPIM and the bLs models. In contrast, the Gaussian Plume Inverse Method (GPIM) outperformed the non-standard EC system for both single-release and multi-release single-point emissions. The backward Lagrangian stochastic (bLs) method was the most accurate for single-release single-point emissions but was less accurate than the GPIM under multi-release conditions. For both GPIM and bLs, 15-minute averaging with a narrow wind-sector (5°) yielded the best performance. While EC results in this study were limited by system constraints, future work is recommended using standard EC instruments and further optimizing GPIM and bLs models—particularly for complex multi-release scenarios—to improve accuracy and reduce uncertainties.