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Title: Accounting for spatiotemporally correlated errors in wind speed for remote surveys of methane emissions
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Point-by-point Responses to Reviewer Comments

Reviewer 1

In their work Conrad and Johnson handle the importance of error correlation in wind speed data when deriving Methane emissions from measured concentrations. An algorithm to quantify spatiotemporal auto-correlation is described, giving guidelines on how to best perform measurement campaigns in certain regions of interest. While this study mainly focuses on the methane emission example, the core method is applicable for any method that relies on model wind data, further underscoring the scientific significance of this work. Overall, the presentation quality of this study is excellent. In the following some minor revisions and technical corrections are suggested that mainly focus on improving the understand-ability of the study.

We thank the reviewer for their helpful feedback and technical comments, for noting the significance and applicability of the methodology to researchers in other fields, and for commending the presentation quality of our manuscript.

Minor revisions:

As a reader who is not proficient on measurement statistic algorithms, section 2 would largely benefit from a more tangible explanation approach using less mathematical detail and more graphics that explain the used methods. It would be very helpful to have a clear recipe of what is needed to apply the described algorithm (e.g. NWP data on a fine grid with high temporal resolution and statistically independent station data).

The methods section leverages the mathematical detail necessary to clearly describe and explain the methodology. To aid the reader we have organized the text to begin by describing our case study (Section 2.1.1), detailing the ground-truth (Section 2.1.2) and NWP (Section 2.1.3) data being analyzed, and how such data are "pre-processed" (Section 2.1.4). We continue by outlining the high-level approach to considering spatial autocorrelation (Section 2.2.1) and provide detailed descriptions of the modelling steps (Sections 2.2.2 and 2.2.3) before finally noting how the model can be used in practice (included step-by-step pseudocode in Section 2.3).

In addition to noting the requirement for NWP and weather station data as a limitation of our method (see our response to the reviewer's last minor comment), we have revised the introduction to also explicitly note this data requirement (additions in bold):

> *In this manuscript, we detail a methodology to probabilistically model the true wind speed ~~at~~* ***in*** *an arbitrary ~~location~~* ***region*** *and* ***during an arbitrary*** *time* ***period*** *from gridded, discrete-time NWP model estimates* ***and statistically independent weather station data****.*

Finally, as now specifically noted in the revised text, code used in our analysis can be shared upon request.

While the authors give a clear explanation on the importance of error calculation for the resulting Methane emission estimate, an estimate on how the described method compares to other sources of uncertainty could provide more insight in said importance. Examples for other sources of uncertainty in emission calculation: Injection height and resulting usage of the wind field (speed and direction), missing "measured" wind data in the atmosphere above ground level, uncertainty of the measured concentrations.

The reviewer is right to assert that wind speed uncertainty is only one contributor to the overall "uncertainty budget" of methane emissions quantification. However, other sources of uncertainty are dependent on the measurement technique being employed and the (potentially proprietary) quantification algorithms; a generalized comparison of wind speed uncertainty against other sources of uncertainty would be challenging to fairly create and is out-of-scope for this work. This present method is intended to provide robust uncertainties for the wind speed uncertainty contribution alone.

Section 3.5 nicely shows the effect of model resolution on the wind speed error model. However, the aforementioned comparison to other sources of uncertainties could provide information on how the importance of the described model changes for different spatial or temporal resolutions of the NWP data set. This would also help the reader to understand the importance of the wind speed error model.

Please see our previous response regard the challenge of generalized uncertainty comparison across different measurement techniques and quantification algorithms.

A methane emission calculation comparison between the following three approaches would further the understanding of the importance of using a wind error model: detailed handling of error calculation (main topic of this study), a simple approach to error handling (probably similar to RER approach described in the study) and the approach of neglecting wind error.

Section 3.3 of the submitted manuscript provides a detailed comparison of the simple error handling approach (the RER approach referred to by the reviewer) and the new methodology without and with consideration of error correlation. We specifically chose not to compare against the reviewer's third recommendation (neglecting wind error) as uncertainties in this case are not generalizable; they are highly dependent on the measurement technique, survey size, and emissions profile in the region of interest. Moreover, when excluding (correlated) wind speed errors, aggregated random errors in an inventory application quickly and unrealistically average toward zero, especially for high-precision active sensors like Bridger Photonics' Gas-Mapping LiDAR, which was used in our case study.

The work motivates why a model of the wind speed error is important and how to best apply the gained knowledge, e.g. in planning of measurement campaigns. However, I'd like to see at least a small focus on how to handle imperfect conditions: What do I do if I don't have an independent measurement data set in addition to a NWP using data assimilation? Is it possible to generalize some of the found features? Maybe using parameters like surface roughness, main wind direction and topography?

This is a terrific point. While there would always be some available NWP model (there are models with global coverage), there are certainly regions where wind speed measurement data are not publicly available. Characterizing specific NWP models as a function of the confluence of prevailing winds, topography, surface roughness, etc. is beyond the scope of this work; however, in these situations we would suggest seeking representative ground-truth wind speed measurements from a *similar and nearby* region, if possible. In this scenario, we would of course expect potential bias in the model of error and its correlation, which would unfortunately be challenging to robustly quantify. We have added the following paragraph to the limitations section to address this.

> *The methodology we have outlined requires ground-truth wind speed measurement data in the specific region of interest. We expect that such data do not exist or are not publicly available in some regions. In such a case, we would recommend that representative wind data be sought from a nearby region with similar topography and prevailing winds, if possible, while recognizing that there would be some unquantifiable bias in the model of wind speed error and its autocorrelation.*

Technical corrections/suggestions:

Page 1 Lines 20—24: Instead of providing the finding of how to best perform measurements w.r.t. correlation, the estimate on how large the emission uncertainty increases if neglecting wind speed error correlation would in my opinion be beneficial for this study.

We agree that this is a key result of this manuscript. But, estimating the change in emissions inventory uncertainty when considering wind speed error correlation is challenging to generalize as it theoretically depends on the region of interest, the time of year, the measurement technique (i.e., how wind affects quantification), and the size of the survey. We have added the following text to the abstract to refer to this key result for our case study, without providing an explicit magnitude:

> *We observe in our case study region that correlation in wind speed errors can starkly increase overall uncertainties in emissions inventories, especially for large surveys.*

Page 2 Lines 3—24: I'm missing a step in between describing the common challenge and why/how much the correlation of "wind speeds (and hence their uncertainties)" affects the emission. Maybe the authors could give an example emission calculation from given methane enhancements. This could help to better explain where in that calculation, correlation of measurements and underestimation of the wind speed error affect the derived emission.

At lines 3−16 of the original text, we present the importance of wind speed in the calculation of emissions and how NWP models can be a key contributor to uncertainties in emissions. At lines 17−24 of the original text, we then discuss how *correlation* in wind speed (and, therefore, emission rate) errors cannot be ignored when "aggregating sources to produce an inventory". We believe that the potential source of confusion surrounds what happens if correlation is ignored in large surveys. We have revised the text to now explicitly note the effect of central limit theorem when aggregating with uncorrelated errors (additions in bold):

> *Neglecting this autocorrelation when aggregating sources to produce an inventory will**, through central limit theorem,** artifically reduce the contribution of wind speed precision error ~~to that of~~ **and hence** the overall uncertainty of the inventory.*

Page 2 Line 11: I had difficulties finding the work from Branson et al., 2021. The other example for an aerial measurement approach (Thorpe et al., 2021) describes methane emission estimates using a LiDAR *technique, while LiDAR is separately mentioned in the second half of the sentence. The currently sentence suggests that these two methods are different, but the references point to the same measurement technique.*

Thank you for identifying this. We intended to reference a different work by (Thorpe et al., 2023) and have updated the text accordingly. We have also removed the reference to Branson et al., which is a white paper by Kairos Aerospace (now Insight M) that we can also no longer source, in favour of a reference by (Duren et al., 2019) that explicitly describes methane plume quantification with airborne imagers.

Page 17 Line 11: […] of their semivariogram (left axis) and the their correlogram […] - remove the "the" after "and"

Revised, thank you.

Page 18 Line 2: […] the spatial correlogram is trivially calculated by […] - remove the "trivially" after "is"

Revised as recommended.

Page 19 Lines 7/8: […] At large lags, temporal correlations, representing bias over the diurnal cycle, oscillate with an amplitude of approximately 0.13. […] – is there a physical reason for this diurnal bias? Is it connected to sub-model-scale meteorology?

We suspect that this there are some physical process(es) that are simply not captured by the NWP models. We have revised the text to note this (additions in bold):

> *… representing bias over the diurnal cycle**, presumably due to temporally dependent physical process(es) not captured by the NWP Model**, …*

References

Duren, R. M., Thorpe, A. K., Foster, K. T., Rafiq, T., Hopkins, F. M., Yadav, V., Bue, B. D., Thompson, D. R., Conley, S., Colombi, N. K., Frankenberg, C., McCubbin, I. B., Eastwood, M. L., Falk, M., Herner, J. D., Croes, B. E., Green, R. O. and Miller, C. E.: California's methane super-emitters, Nature, 575(7781), 180–184, doi:10.1038/s41586-019-1720-3, 2019.

Thorpe, A. K., Kort, E. A., Cusworth, D. H., Ayasse, A. K., Bue, B. D., Yadav, V., Thompson, D. R., Frankenberg, C., Herner, J., Falk, M., Green, R. O., Miller, C. E. and Duren, R. M.: Methane emissions decline from reduced oil, natural gas, and refinery production during COVID-19, Environ. Res. Commun., 5, 021006, doi:10.1088/2515-7620/acb5e5, 2023.