Referee #1

This manuscript presents direct methane flux measurements from an aerobic wastewater treatment lagoon and compares the observed fluxes with inventory-based estimates. The topic is important because wastewater lagoons remain poorly constrained sources of methane, and field measurements are still limited in the literature. The dataset has potential value, and the paper addresses a relevant gap for greenhouse gas accounting. However, in its current form, I think the manuscript requires major revision before publication. The main conclusions are potentially important, but several aspects of the analysis and interpretation need stronger justification. In particular, the representativeness of the measurements, uncertainty treatment, site characterization, and extrapolation to broader inventory implications require more detailed discussion.

We thank the Reviewer for the thorough and constructive review of our manuscript. Below, we address each of the reviewer's comments.

My Specific comments are as follows:

1. What motivated the authors to study an aerobic pond instead of an anaerobic pond, given that the latter could be a larger concern for methane production? Is it possible to provide any comparison between these two types of ponds?

Pond 1 is largely an anaerobic pond and to some degree there are aerobic processes as well due to the *surface* aerators. However, the surface aerators only cover a small percentage of the entire pond area and do not deliver a satisfactory dissolved oxygen level that enables the categorising the Pond 1 as an aerobic pond. Other research using hoods and a mobile CH_4 sensor have shown that the Pond 1s have by far the highest CH_4 emissions at the WTP and therefore are the largest concern with respect to CH_4 emissions. This is because they are the first ponds after the covered anaerobic pots where anaerobic digestion of raw sewage takes place. Effluent from the anaerobic pots is saturated with dissolved methane, once agitated and/or under different atmospheric pressure (in Pond 1), releases CH_4 emissions to the environment. Wastewater in the downstream facultative ponds such as Pond 2 has a much lower COD than in Pond 1, and Pond 2 typically emits less than 1/10 of the CH_4 emissions compared to Pond 1.

2. The atmospheric transport model is 3-dimensional. However, the authors' measurements only happened at ground level. How could this fact be addressed in uncertainty analysis? Could drone-based vertical measurement of methane concentrations improve the credibility of the emission rate estimation?

The IDM is an inverse-dispersion, surface-layer model. In our study the pond-to-sensor distance was within 300 m, which is appropriate for a surface-layer model: emission plume emitted from the pond can be sampled by the ground-level sensor before it rises above the surface layer and escapes detection from the sensor.

In the previous section we described flux footprint. For each 15-minute period we used WindTrax to generate 150,000 Monte Carlo replicates to simulate the origin points of discrete particles (i.e., touchdowns) that might have contributed to the flux (in practice these particles are generated from the measurement to the source, hence WindTrax is said to be an inverse dispersion model). To determine the source area for each 15-minute measurement, we first filter the touchdowns that fall outside the pond (as they correspond to background concentrations). We aggregate the touchdowns into 10 by 10 m raster cells. We count the number of touchdowns per cell. As is customary in footprint analysis, we then estimate the footprint area as the area contributing to 80% of the touchdowns that fall within the pond (Kljun et al., 2015).

The anaerobic pond was treated as an area source, and the inverse-dispersion model was used to measure gas emissions from the pond. IDM has been well reported in the literature, it requires the horizontal concentration difference between the upwind and downwind of the pond, coupled with three-dimensional wind variables to characterize the atmospheric turbulence. Each measurement technique has advantages and limitations, and emission estimates could be substantial differences using different measurement approaches, due to their spatial footprint and capability of long-term measurement. Using drone technique is a top-down measurement approach. It may be well suitable for targeting emission hotspots within a complex source configuration, but footprint is usually limited by the flying height due to nationwide regulations of flying zone. It is usually used for mobile survey and data quality assessment but spatial interpretability of concentration changes relies on wind regime and atmospheric stability (Dash et al., 2026). Therefore, interfering emission sources, shorter period on site, and requirement of consistent weather conditions limit the use of this method (Gong et al., 2023; De Jong et al., 2026). Recently Flesch et al. (2023) used IDM technique coupled with concentrations measured by uncrewed aerial vehicle (UAV) to quantify CH_4 flux from waste pond.

3. The measurement only happened in Summer and Winter, which was not representative enough for the annual case. Also, the manuscript would benefit from a clearer justification of whether the monitoring period is representative of longer-term methane emissions.

I agree with the reviewer's comment. A longer-term measurement would be ideal; however, the funding was short and resources are limited, importantly the snapshot measurement can indicate seasonal emissions variability. Our measurements in each season obtained over 25% valid data over the measurement period, which is sufficient to represent the emissions status.

4. In L151-L154, could you elaborate more on how the WindTrax model works, instead of treating it like a black box? What assumptions does the model use? What uncertainties does it bring? And does it work equally well on point source and areal source?

Sure, WindTrax is a software (www.thunderbeachscientific.com) based on the backward Lagrangian stochastic dispersion (bLs) model for calculating gas emission rate from a source area (Flesch et al., 1995). It is described in a few scientific publications (e.g., (Usepa); Wilson et al. (2012); Bai et al. (2025)), and has a substantial record of use with IDM (Bai et al., 2023). It includes a graphical interface that creates a map showing the target source and sensor locations, including sensor heights. By default, WindTrax releases 50,000 trajectories from 30 points- particles distributed along the measurement path. Trajectories travel in the dispersion plume upwind, starting at the senor position backwards towards the source surface; some trajectories intersect with the source surface, while others avoid the source surface. When trajectories touch the ground, surface information including the particle's touchdown position and vertical velocity (x,y,w) is recorded.

WindTrax uses the bLs method, which is based on Monin-Obukhov Similarity Theory (MOST), and simulates the relationship between concentration and emission rate, $(C/Q)_{\mathrm{sim}}$, based on the vertical velocity of the trajectories (w_0) that infers the pond surface ("touchdown").

$(C/Q)_{\mathrm{sim}} = 1/N\ \Sigma|2/w_0|$

Where $(C/Q)_{\mathrm{sim}}$ is the simulated relationship ratio, N is the total number of particles released, w_0 is the vertical 'touchdown' velocity, which is the function of u^* (friction velocity, m s^{-1}), L (Obukhov stability length, m), z_0 (surface roughness length, m) and β (average wind direction). These parameters can be derived from a 3-D sonic anemometer. The summation includes all 'touchdown' trajectories within the source area from each release point.

Assuming a horizontally homogenous surface layer (Flesch et al., 2004), and given the downwind concentration increase above the background level ($C_{downwind}$-C_{upwind}), the unknown source emission rate (e.g., the effluent pond) Q_{IDM} is determined using:

$Q_{IDM} = \Delta C/\ (C/Q)_{\mathrm{sim}}$

Where Q_{IDM} is the pond emission rate, ΔC is the concentration enhancement between upwind (background) C_{upwind} and downwind $C_{downwind}$, $\Delta C = C_{downwind}$-C_{upwind}, $(C/Q)_{\mathrm{sim}}$ is the simulated concentration and emission rate relationship ratio, it is associated with source geometry, wind variables, surface layer meteorology, and the sensor coordinates.

Wind variables, including ambient temperature and pressure, and the standard deviations of the velocity fluctuations in the three directional components ($\sigma_{u,v,w}$), can be derived from a 3-D sonic anemometer.

As the IDM is based on the Monin–Obukhov similarity theory (MOST), which assumes a horizontally homogenous terrain with no tree lines, tall buildings, or other nearby sources, it also requires a well-defined, spatially uniform source area. As a result, the accuracy of the IDM can be sensitive to the conditions that are not ideal (for example, wind complexity or a non-uniform source area) (Gao et al., 2010). Bai (2010) discussed several factors that contribute to the Windtrax uncertainty, such as the number of trajectories releases, the number of particles distributed along the measurement path, the averaging interval for flux estimates, the distance of the sensors to the source, and boundary layer stability. Flesch et al. (2007) noted that in many situations MOST may not be well adapted, accurate IDM calculation can be obtained with assumptions of winds under ideal conditions. Harper et al. (2010) and Laubach and Kelliher (2005) reported uncertainties of approximately 10% and 20% in IDM flux estimates, respectively. Wilson et al. (2001) tested IDM accuracy by introducing disturbed winds around a lagoon to create wind complexity and found good agreement between IDM and a mass-balance method, and the IDM measurements were within 15% of the true emission rate. Bühler et al. (2021) reported an uncertainty range of 14-21% when using IDM coupled with line-average concentrations in a dairy cow study but rising to as much as 36% when external sources were included. However, in this study we applied filtering criteria so that external sources are not included in the flux calculation. An average of 20% uncertainty from IDM simulation is applied in our uncertainty estimation.

The IDM technique has been shown to offer the efficiency (over survey approach), simplicity (single gas concentration sensor and basic wind information) and flexibility (any location at any arbitrary shape). IDM techniques are suitable for well-defined surface source; however, for some point sources, such as flares, leaky pipes, biodigesters, or a barn, small animal pen, it can be challenging because they create wind complexity. Flesch et al. (2011) approved to overcome these complications by adjusting the distance between sensor and point source until concentration is measured far enough so that the IMD is insensitive to the complications.

As a rule of thumb for a single source, the distance from the point source should be ten times the height of the largest wind obstacle, and roughly two times the maximum distance between potential sources. The IDM method has also been widely used in intensive feedlots and grazing dairy cows where individual cattle is treated as a point source, but a group of cattle can be treated as a source area.

5. In L151-L154, did the authors treat the entire pond as a homogeneous areal source? If so, what uncertainty can that bring?

No. We did not treat the entire pond as one homogeneous source. The two OPL paths sampled two different footprint areas, one associated with the west laser and one with the east laser. At each time step, each footprint gives one aggregated estimate for the area it samples. This does not mean that emissions within the footprint are homogeneous, only that the method measures an average response over that footprint.

To scale these estimates to the full lagoon, we used a weighted average of the west and east estimates, where the weights represent the relative lagoon areas associated with each laser footprint. The uncertainty from this scaling was assessed using a sensitivity analysis with different weights. We report the resulting range in the manuscript.

6. In L182, what does "stratified sampling" mean?

Stratified sampling means that the lagoon was divided into different sampling groups, or strata, before calculating the overall estimate. In our case, the strata correspond to the west and east footprint areas sampled by the two laser paths. Each stratum was represented by its own OPL-IDM estimate, and the full-lagoon estimate was then calculated by weighting these estimates according to the relative area represented by each footprint. This is a common approach in survey sampling when different parts of a study area are sampled separately and then combined using weights.

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