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Da un secolo, oltre.

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***Monitoraggio ambientale delle emissioni di gas ad effetto serra,
ammoniacale e materiale particolato, applicazioni di
modellazione di dispersione atmosferica e mappaggio degli
inquinanti negli allevamenti zootecnici***

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Abstract

Il presente lavoro di tesi fornisce una panoramica in termini di sensoristica, tecnologie di misurazione e tecniche di analisi dei dati riguardo il monitoraggio ambientale della qualità dell'aria negli allevamenti zootecnici. I tre articoli scritti durante il percorso di dottorato riguardano la valutazione delle prestazioni di un modello Lagrangiano Stocastico nella stima delle emissioni di CO₂ in atmosfera mediante l'utilizzo di dati ottenuti da piattaforme multi-sensore a basso costo. Il modello è stato valutato in base alla selezione di alcuni parametri come il numero di particelle da implementare. Simulazioni di dispersione atmosferica completate grazie a misurazioni stazionarie e con drone, effettuate in un allevamento di bovini da latte prima, durante e dopo la lavorazione di una lettiera compost in condizioni di stabilità atmosferica hanno permesso il calcolo di flussi di emissione comparabili a quelli riportati in letteratura. Per le concentrazioni calcolate, si riportano sovrastime in termini di errori medi percentuali dall'8 al 39% rispetto alle misurazioni in volo. Si riportano inoltre sovrastime e sottostime in termini di errori medi assoluti percentuali dal 10 al 25% per le misurazioni stazionarie. Le più probabili alternative per ridurre gli errori riportati riguardano una migliore quantificazione della stabilità atmosferica ed un maggiore numero di particelle utilizzato nelle simulazioni. La criticità riscontrata nelle piattaforme multi-sensore riguarda i sensori a basso costo selezionati per rilevare le concentrazioni di NH₃ e CH₄, dotati di campi di misurazione troppo elevati per i monitoraggi in esterna negli allevamenti zootecnici. Risultati preliminari riguardo il monitoraggio di questi due gas vengono riportati esplorando altri sensori, altre tecnologie e altre tecniche di analisi. Un'analisi critica delle piattaforme multi-sensore viene fornita in base alla valutazione delle altre metodologie esplorate, soprattutto per il miglioramento del sistema di monitoraggio della qualità dell'aria con drone.

Abstract

This thesis provides an overview in terms of sensors, measurement technologies, and data analysis techniques for environmental monitoring of air quality in livestock farms. The three articles written during the PhD programme concern the assessment of the performance of a Stochastic Lagrangian model in estimating CO₂ emissions into the atmosphere using data obtained from low-cost multi-sensor platforms. The model was evaluated based on the selection of certain parameters, such as the number of particles to be implemented. Atmospheric dispersion simulations completed using stationary and UAV measurements, carried out on a dairy farm before, during, and after the tilling of compost bedded pack barn under stable atmospheric conditions, allowed calculated emission fluxes comparable to those reported in the literature. For the calculated concentrations, overestimates in terms of average percentage errors ranging from 8 to 39% compared to flight measurements are reported. Overestimates and underestimates in terms of average absolute percentage errors ranging from 10 to 25% are also reported for stationary measurements. The best solutions for reducing the reported errors involve better quantification of atmospheric stability and a greater number of particles used in the simulations. The weakness identified in multi-sensor platforms concerns the low-cost sensors selected to detect NH₃ and CH₄ concentrations, which have measurement ranges that are too high for outdoor monitoring in livestock farms. Preliminary results regarding the monitoring of these two gases are reported by exploring other sensors, other technologies, and other data analysis techniques. A critical analysis of multi-sensor platforms is provided based on the evaluation of other methodologies explored, especially for improving the UAV-based air quality monitoring system.

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1. Introduzione

1.1. Contesto scientifico

Le proiezioni più recenti sulla crescita della popolazione mondiale pubblicate dalle NU (Nazioni Unite) mostrano un aumento fino a 8,5 miliardi di persone per l'anno 2030 e fino a 9,7 miliardi di persone per l'anno 2050 (United Nations, 2024). Quindi, l'industria agroalimentare dovrebbe essere efficiente e sostenibile nelle produzioni di cibo e bevande senza mettere in pericolo l'ambiente, le persone e gli animali. Nell'anno 2015, le NU hanno approvato Agenda 2030, nella quale parte degli obiettivi di sviluppo sostenibile riguardavano il miglioramento della qualità dell'aria (obiettivo 11 di sviluppo sostenibile – Rendere le città e gli insediamenti umani inclusivi, sicuri, duraturi e sostenibili, sotto-obiettivo 11.6 - ridurre l'impatto ambientale negativo pro-capite nelle città, con particolare attenzione alla qualità dell'aria e alla gestione dei rifiuti urbani e di altro tipo) e l'azione contro il cambiamento climatico (obiettivo 13 di sviluppo sostenibile - Azioni per combattere il cambiamento climatico) (United Nations, 2015).

L'OMS (Organizzazione Mondiale della Sanità) ha stimato 6,7 milioni di morti premature all'anno causate dall'inquinamento dell'aria ambiente esterna e interna (World Health Organization, 2024). Queste morti premature vengono causate dagli inquinanti prodotti da sorgenti naturali e antropiche, infatti, esposizioni prolungate a queste sostanze pericolose potrebbero portare cancro degli apparati respiratorio e cardiovascolare (Lelieveld et al., 2015; Fiordelisi, et al., 2017). Un esempio di composto atmosferico pericoloso per la salute è il materiale particolato, originato da differenti sorgenti di emissione, naturali e antropiche, e sostanze, che viene classificato in base al diametro aerodinamico delle particelle (Kelly & Fussell, 2012). Dalla sintomatologia causata da questi composti, la decisione di classificare il materiale particolato come cancerogeno del Gruppo 1 da parte dell'Agenzia Internazionale per la Ricerca sul Cancro (Hamra et al., 2014).

In aggiunta, gli inquinanti in atmosfera possono influenzare il cambiamento climatico, in quanto, alcuni di questi, classificati come gas ad effetto serra, contribuiscono all'effetto serra con un differente impatto radiativo, quantificando il GWP (Global Warming Potential) in termini di CO₂ eq.

(anidride carbonica equivalente), considerando vari orizzonti temporali, cioè 20, 100 e 500 anni. L'IPCC (Intergovernmental Panel on Climate Change) si occupa della quantificazione dei GWP, arrivando alla più recente pubblicazione del Sesto Report di Valutazione (Shukla et al., 2023). Questo tipo di analisi offre un supporto nel monitoraggio degli obiettivi stabiliti a livello internazionale dall'Accordo di Parigi, in vigore dall'anno 2016, al fine di mantenere l'aumento della temperatura media globale al di sotto di 1.5°C rispetto ai livelli preindustriali. A livello Europeo, la direttiva 2008/50/CE mira ad ottenere un'aria più pulita in Europa, essendo recepita a livello nazionale, ad esempio, dall'Italia con il D. Lgs 2010/155. Così, in Italia è stata costituita una rete di monitoraggio degli inquinanti, che viene gestita dalle ARPA (Agenzie Regionali per la Protezione dell'Ambiente). I dati misurati sulle emissioni in atmosfera vengono attualmente utilizzati per costruire report nazionali e inventari annuali, attribuendo le emissioni in atmosfera a specifici settori produttivi.

Tra questi, si trova l'agricoltura e, secondo l'ultimo inventario nazionale sulle emissioni di gas ad effetto serra prodotto dall'ISPRA (Istituto Superiore per la Protezione e la Ricerca Ambientale) emerge che una delle attività agricole più impattanti in termini di emissioni in atmosfera riguarda i processi che fanno parte dell'allevamento del bestiame (Romano et al., 2025). Shukla et al. (2023) hanno stimato per l'anno 2015 che le emissioni antropiche globali nette di gas ad effetto serra hanno raggiunto il valore di 55 Gt (gigatonnelate) $\text{CO}_2 \text{ eq.} \cdot \text{anno}^{-1}$. Per lo stesso anno, il GLEAM (Global Livestock Environmental Assessment Model) ha stimato che il valore delle emissioni in atmosfera di gas ad effetto serra dalle attività di allevamento del bestiame ha raggiunto il valore di 6,2 Gt $\text{CO}_2 \text{ eq.} \cdot \text{anno}^{-1}$, per cui le emissioni attribuite all'allevamento del bestiame rappresentano il 12% delle emissioni antropiche globali nette. All'interno delle attività di allevamento del bestiame, l'allevamento delle specie bovine contribuisce alle emissioni per il 62%, cioè per 3,8 Gt $\text{CO}_2 \text{ eq.} \cdot \text{anno}^{-1}$. All'interno delle attività comprese nell'allevamento di specie bovine, le produzioni di carne e latte raggiungono il 40%, cioè 2,5 Gt $\text{CO}_2 \text{ eq.} \cdot \text{anno}^{-1}$ e il 21%, cioè 1,3 Gt $\text{CO}_2 \text{ eq.} \cdot \text{anno}^{-1}$ rispetto alle emissioni totali dell'allevamento del bestiame (Food and Agriculture Organization, 2022). Dallo stesso database, le emissioni di CO_2

rappresentano il 26%, cioè $1,0 \text{ Gt CO}_2 \text{ eq.} \cdot \text{anno}^{-1}$ rispetto alle emissioni totali derivanti dall'allevamento di specie bovine. In aggiunta, gli altri due grossi contributi al cambiamento climatico dall'allevamento di specie bovine derivano per il 61%, cioè $2,3 \text{ Gt CO}_2 \text{ eq.} \cdot \text{anno}^{-1}$ dalle emissioni di CH_4 (metano) e per il 13%, cioè $0,5 \text{ Gt CO}_2 \text{ eq.} \cdot \text{anno}^{-1}$ dalle emissioni di N_2O (protossido di azoto), rispettivamente. Questi gas ad effetto serra vengono generati principalmente da processi aziendali come la fermentazione enterica degli animali e la gestione dei reflui zootecnici (Romano et al., 2025). Un'altra importante sorgente di emissione da valutare è la lettiera, in quanto la sua gestione è associata alla gestione dei reflui zootecnici, pertanto correlata con l'igiene e il benessere animale.

A livello globale, dal 1987 l'OMS rilascia periodicamente le linee guida sulla qualità dell'aria basate su criteri sanitari per supportare i governi e i civili nella riduzione dell'esposizione umana agli inquinanti presenti in atmosfera e nella circolazione delle informazioni riguardanti i loro effetti rischiosi per la salute. In Europa, la Direttiva 2024/2881 mira ad abbassare i limiti di qualità dell'aria, cercando di allinearsi con quelli indicati nelle linee guida prodotte dall'OMS. È da notare che i limiti di riferimento di qualità dell'aria possono variare di paese in paese, per esempio, gli Stati Uniti adottano i NAAQS (National Ambient Air Quality Standards) prodotti dalla US EPA (United States Environmental Protection Agency, 2025), leggermente differenti dai valori adottati dalle ARPA (Agenzia Regionale per la Protezione dell'Ambiente della Toscana, 2024). I composti presenti nell'aria, pericolosi per umani e animali, contenuti in queste linee guida e standard sono il materiale particolato, l'ozono, il protossido di azoto, il biossido di zolfo e il monossido di carbonio.

L'ISO (International Standard Organization), dal febbraio 2024 ha aggiornato le precedenti norme, aggiungendo un emendamento al fine di includere il cambiamento climatico come una delle sfide che le organizzazioni devono considerare nell'adozione e nel mantenimento dei sistemi di gestione per la qualità. Le norme ISO prodotte successivamente non contengono l'emendamento aggiuntivo sul cambiamento climatico, in quanto già presente nelle norme stesse. Quindi, l'attuale legislazione fornisce un'opportunità per le organizzazioni di considerare l'adozione di sistemi di

supporto alle decisioni basati sulle emissioni al fine di combattere il cambiamento climatico ed ottenere le certificazioni ISO. All'interno di questi sistemi dovrebbero perciò essere previste attività di monitoraggio ambientale locali al fine di comprendere gli impatti generati dai processi produttivi e adottare le corrette strategie di mitigazione.

1.2. Stato dell'arte

1.2.1. I droni per il monitoraggio ambientale

Il monitoraggio della qualità dell'aria può essere effettuato attraverso stazioni fisse e piattaforme in movimento. Un esempio di monitoraggio stazionario della qualità dell'aria è rappresentato dalla rete di stazioni di monitoraggio distribuite sul territorio nazionale, cui le varie ARPA riportano il posizionamento, misurazioni storicizzate, mappe e cruscotti (Agenzia Regionale per la Protezione dell'Ambiente della Toscana, 2025). Per il monitoraggio ambientale in movimento, si possono selezionare varie piattaforme a cui possono essere agganciati i sensori, cioè i palloni aerostatici, gli elicotteri, i satelliti e i droni. I risultati di un'analisi SWOT (Strengths, Weaknesses, Opportunities, and Threats) fatta sulle prime tre piattaforme in movimento considerate vengono mostrati nell'elenco seguente:

- Punti forza: carico utile elevato, raggiungimento di aree specifiche, raccolta dati a quote elevate, monitoraggio globale (per satelliti) e di aree vaste, storicizzazione del dato, stabilità e mantenimento della posizione (per satelliti ed elicotteri), applicazioni di emergenza e sorveglianza in tempo reale.
- Punti debolezza: limitazioni in aree remote e in condizioni meteo avverse, velocità limitate, flessibilità limitata nella modifica della traiettoria e della frequenza di campionamento (per satelliti e palloni aerostatici), limitata risoluzione spaziale, dati non disponibili con densa nuvolosità.
- Opportunità: integrazione di un elevato numero di sensori, monitoraggio su larga scala e a lungo termine, integrazione di tecnologie di comunicazione avanzate.

- **Rischi:** restrizione dello spazio aereo, necessità di piloti esperti e personale altamente qualificato (per gli elicotteri), costi elevati di lancio, disponibilità stazioni terrestri (per satelliti), gestione del volo e individuazione delle piattaforme complesse (per i palloni aerostatici), rischio danneggiamento e perdita della piattaforma (per i palloni aerostatici), costi di manutenzione variabili, impatto ambientale variabile, costi operativi variabili.

Per un confronto diretto tra le varie piattaforme per l'aggancio della sensoristica per il monitoraggio ambientale della qualità dell'aria, in Figura 1 viene riportata l'analisi SWOT relativa ai droni.

DRONI

Punti di forza - Flessibilità operativa - Costi operativi contenuti - Precisione e dettaglio dei dati raccolti (risoluzione spaziale) - Sicurezza per l'operatore (controllo remoto)	Punti debolezza - Autonomia di volo limitata - Carico utile limitato - Sensibilità a condizioni meteo avverse - Restrizioni normative - Costi di investimento elevati
Opportunità - Monitoraggio in tempo reale - Integrazione intelligenza artificiale - Programmazione missioni di volo - Uso antenna RTK a terra	Rischi - Downwash - Surriscaldamento batterie

Figura 1. L'analisi SWOT sui droni utilizzati come piattaforma a cui agganciare la sensoristica per il monitoraggio ambientale della qualità dell'aria.

I droni vengono utilizzati per il monitoraggio ambientale con un ventaglio di soluzioni differente in base alla tipologia di analisi e di sensoristica selezionate. I droni per il monitoraggio ambientale vengono utilizzati in diversi settori produttivi e applicazioni differenti: infrastrutture (Chang et al., 2016; Samad et al., 2022; Baglioli & Godoi, 2023), settore petrolifero (Kemp et al., 2016; Faksness et al., 2022; O'Malley et al., 2024), urbano (Kuuluvainen et al., 2018; Beryozkina & Al-Shakhs, 2020; Lee & Kwak, 2020; Klimczyk et al., 2021; Chang et al., 2022; Järvi et al., 2023; Durgun & Durgun, 2024; Lee et al., 2025), trattamento delle acque reflue (Burgués et al., 2022), ricerca (Angrisani et al., 2019; Morales et al., 2022; Zhao et al., 2022; Afshar-Mohajer & Wu, 2023; Tiwari & Lall, 2023; Bernabeo et al., 2024; Nerini et

al., 2025), discariche (Ranganathan et al., 2023), industria (Tosato et al., 2019), incendi (Aurell et al., 2021), vulcanologia (Rüdiger et al., 2018; Liu et al., 2019) e agricoltura (Habib et al., 2022; Velez et al., 2024).

Il fattore comune in queste pubblicazioni è l'utilizzo di sensori compatti dotati di un peso contenuto, in modo che questi possano essere agganciati ai droni rispettando il massimo carico utile al fine di ottenere appropriati consumi di energia e durate delle batterie, di conseguenza, delle missioni di volo. La sensoristica dovrebbe misurare le concentrazioni degli inquinanti e le condizioni ambientali cercando di raggiungere la massima rappresentatività atmosferica. Principalmente, esistono tre tipologie di droni disponibili sul mercato: ad ala fissa, ad ala rotante e delle soluzioni ibride. Jońca et al. (2022) hanno elencato le principali caratteristiche utili per la selezione del drone corretto per il monitoraggio ambientale. I droni ad ala fissa possono volare a velocità elevate, coprendo grandi aree, ma hanno una capacità di carico utile limitato ed una limitata risoluzione spaziale dovuta alle elevate velocità, richiedendo inoltre lunghe distanze a terra per il decollo e l'atterraggio. I droni ad ala rotante sono anche chiamati multicotteri per la classificazione basata sul numero di rotori orizzontali che possiedono, ad esempio, 4 (quadricotteri), 6 (esacotteri) e 8 (ottocotteri). I droni ad ala rotante possono volare a velocità inferiori con una buona manovrabilità, grazie alla capacità di decollo e atterraggio verticale, anche in aree piccole o limitate, ma le basse velocità e l'autonomia di volo rendono gli studi su grandi superfici costosi e richiedono più tempo, a causa di un maggior numero di missioni di volo necessarie. Esistono anche delle soluzioni ibride che combinano i vantaggi dei droni ad ala fissa e ad ala rotante, soprattutto riguardo la possibilità del decollo e dell'atterraggio verticale tipica dei droni ad ala rotante, ma i costi elevati e le tecnologie complesse implementate rendono queste soluzioni meno frequentemente utilizzate.

Generalmente, la durata di una missione di volo effettuata da un drone ad ala rotante può raggiungere i 30 minuti e la durata del volo tende a diminuire con l'aggiunta di carichi dovuti al peso della sensoristica agganciata allo stesso. Ad ogni modo, i droni ad ala rotante sono usati comunemente per investigare luoghi di difficile accesso o pericolosi per le persone. Chang et al. (2016) hanno usato un drone ad ala rotante per il monitoraggio dei gas di

scarico prodotti dagli autoveicoli in transito in tunnel stradali e convogliati con dei pozzi in un terreno montuoso di difficile accesso. I droni ad ala rotante più recenti sul mercato possiedono inoltre la funzione “ritorno a casa”, che permette al drone di fare ritorno al punto di decollo al suolo in caso di pericolo, danno, condizioni meteo avverse o in caso di batterie scariche. Altre importanti funzioni da annotare risultano l'autopilota, possibile dopo la programmazione di una missione di volo da parte del pilota, utile, ad esempio, per operazioni di aerofotogrammetria e la possibilità di mantenerlo sospeso in un punto fisso. Quindi, per tutti i vantaggi elencati, i droni ad ala rotante risultano un'eccellente piattaforma alla quale agganciare la sensoristica per il monitoraggio ambientale al fine di studiare la distribuzione verticale e orizzontale degli inquinanti nella bassa troposfera. È da notare che l'utilizzo dei droni deve essere conforme con le regolamentazioni internazionali ICAO (International Civil Aviation Organization) e quelle nazionali in termini di patenti per il pilotaggio, limitazioni operative, restrizioni amministrative e dello spazio aereo. Considerando questi aspetti, De Filippis et al. (2011) hanno elencato le condizioni ideali per l'utilizzo di un drone per ottenere le sue migliori prestazioni:

- Il peso del carico utile è il minore possibile;
- Le masse che compongono il carico utile sono distribuite in maniera da causare la minima alterazione al momento di inerzia del drone;
- Il centro di massa del carico utile è allineato al centro di massa del drone lungo la verticale.

Riguardo l'ultimo punto, in alcuni modelli di droni più recenti è disponibile la funzione del calcolo automatico del centro di massa dell'intero sistema composto dal carico utile e dal drone stesso. Se tale funzione viene avviata dal pilota prima di effettuare la missione di volo, le prestazioni energetiche vengono ottimizzate ulteriormente.

La maggior parte degli studi contenuti nella letteratura corrente riportano i risultati di prove sperimentali di monitoraggio ambientale della qualità dell'aria in cui sono stati utilizzati droni ad ala rotante, data la buona manovrabilità, ma il downwash, fenomeno che descrive le turbolenze verso il basso generate dalle eliche dei multicotteri in volo, influenza il

posizionamento della sensoristica sul velivolo per mantenere la rappresentatività atmosferica. Questo problema viene riportato anche nell'analisi SWOT relativa all'utilizzo dei droni come piattaforma per il monitoraggio ambientale in Figura 1. Samad et al. (2022), una volta determinato il posizionamento dei sensori sopra il corpo del drone attraverso un'analisi CFD (Computational Fluid Dynamics), hanno affermato che l'altezza ottimale al di sopra del corpo del drone per il posizionamento della sensoristica è 90 cm. Habib et al. (2022) hanno ritenuto opportuno agganciare un lungo tubo al sensore di concentrazione per eliminare l'influenza del downwash dovuto alle eliche in movimento. Lee et al. (2025) hanno posizionato la sensoristica 60 cm al di sopra dei rotori del drone. Tuttavia, Zhao et al. (2022) hanno preferito posizionare la sensoristica per il monitoraggio ambientale al di sotto del corpo del drone, ma in questo caso la camera di misurazione aveva un apposito ingresso dell'aria progettato in modo da ridurre la velocità del flusso, deviandone la traiettoria verso i sensori di concentrazione. Baglioli & Godoi (2023) hanno posizionato i sensori al centro del corpo del drone per mitigare l'impatto delle turbolenze generate dalle eliche, basandosi su un'analisi CFD (Roldán et al., 2015) fatta su un quadri-rotore. Anche Tiwari & Lall (2023) hanno posizionato i sensori al di sotto del corpo del drone, ma sempre al centro del corpo stesso. Per giustificare le scelte operative sul posizionamento dei sensori, si riportano due analisi CFD, una riferita ad un esacottero (Zheng et al., 2018) e l'altra ad un quadricottero (Flem et al., 2024). Una recente pubblicazione riporta un'analisi CFD condotta su un drone DJI M300 RTK (Kong et al., 2025), modello molto simile a quello utilizzato per le prove sperimentali riportate negli Studi numero 2, 3 e 5 della presente tesi. In aggiunta, in una recente review sui brevetti relativi a sistemi che comprendevano dei droni (Altamira-Colado et al., 2024), nessuno, tra quelli riportati, propone un sistema o un meccanismo in grado di risolvere totalmente o in parte il problema del downwash.

Inoltre, Jońca et al. (2022) hanno dichiarato che il monitoraggio ambientale stazionario con stazioni di misurazione a terra fornisce studi sulla variabilità delle emissioni ad un singolo punto, considerando un basso numero di sorgenti, limitato ad un'area specifica. Il monitoraggio stazionario da solo

non è però in grado di investigare la variabilità verticale delle concentrazioni degli inquinanti e dei parametri ambientali. Invece, il monitoraggio ambientale con drone fornisce studi con una migliore risoluzione spazio-temporale, nonostante l'analisi sia limitata dalla durata delle batterie del drone, in relazione al carico utile utilizzato, e dal problema del downwash. Molti studi tra quelli riportati miravano alla caratterizzazione verticale delle concentrazioni gassose (Chang et al., 2022; Zhao et al., 2022; Baglioli & Godoi, 2023) e di polveri (Kuuluvainen et al., 2018; Samad et al., 2022; Lee et al., 2025) nell'atmosfera per comprenderne i meccanismi di trasporto, misurando anche le condizioni ambientali. Järvi et al. (2023) hanno determinato i profili verticali sia delle concentrazioni gassose sia di quelle del materiale particolato.

Una recente review (Silva-Neto et al., 2024) sul monitoraggio ambientale con drone dichiara che il mercato globale dei droni è stato valutato circa 4.120 milioni di USD nel 2022 ed è prevista una crescita del 13% per l'anno 2030 (Grand View Research, n.d.). Per selezionare un drone sul mercato, tra le principali caratteristiche necessarie si trovano l'autonomia di volo, il tempo di volo senza carico utile, il massimo carico utile e il prezzo. Per un elevato carico utile al decollo, il tempo di volo diminuisce, ad esempio, per un drone DJI M300 RTK, il tempo di volo può essere ridotto da 55 a 30 minuti con un carico utile massimo di 2,7 kg. Questo aspetto limita il periodo del campionamento nelle prove sperimentali che richiedono un drone per il monitoraggio ambientale. Inoltre, considerando anche il problema del downwash, specialmente per le quote più basse da investigare, in quanto il moto turbolento aumenterebbe, un altro fattore che potrebbe influenzare la durata delle batterie è l'altezza della missione di volo, per cui, l'obiettivo dello studio influenza la scelta di questo parametro. Kim et al. (2025) hanno sottolineato che le proprietà dell'aerosol possono variare significativamente con l'altitudine a causa di cambiamenti di temperatura, umidità, stabilità atmosferica, radiazione solare e vento, cioè il valore delle concentrazioni gassose e delle polveri è influenzato dalle condizioni meteo e dai processi di miscelazione turbolenti. Per questa ragione, studiando la distribuzione verticale degli inquinanti, l'accuratezza dei modelli di dispersione

atmosferica, se utilizzati come tecnica di elaborazione del dato misurato, può migliorare.

Studi precedenti si sono serviti del monitoraggio ambientale con drone, programmando missioni di volo ad altitudini differenti per ottenere i profili verticali degli inquinanti. Chang et al. (2022) hanno raccolto campioni di aria, analizzando poi le concentrazioni di alcuni gas (VOC, CO, CO₂, CH₄) con la tecnica della gascromatografia, raggiungendo un'altitudine di 700 m sopra il livello del terreno a Taiwan. Zhao et al. (2022) hanno misurato le concentrazioni gassose di alcuni inquinanti (CO₂, CO, NO₂) in Cina con sensori NDIR (non-dispersive infrared) ed elettrochimici fino a 500 m sopra il livello del terreno. Baglioli & Godoi (2023) hanno rilevato le concentrazioni gassose di alcuni inquinanti (O₃, SO₂, NO₂) liberati in atmosfera da un treno a combustione diesel in Brasile, raggiungendo i 15 m sopra il livello della ferrovia. Kuuluvainen et al. (2018) hanno programmato delle missioni di volo fino a 50 m di altitudine in Finlandia, misurando l'LSDA (Lung Deposited Surface Area) con un rilevatore di nanoparticelle multimetrico. Samad et al. (2018) hanno rilevato particelle ultrafini, materiale particolato con diverso diametro aerodinamico (PM₁, PM_{2.5}, PM₁₀) e carbonio nero con un contatore ottico di particelle, un classificatore delle dimensioni a diffusione e un microetometro portatile fino a 100 m di altitudine in Germania. Lee et al. (2025) hanno raccolto dati relativi alle concentrazioni di particolato (PM_{2.5}) e carbonio nero utilizzando un microetometro portatile e un fotometro per particelle di fuliggine in Corea fino a 150 m di altitudine. Tra queste pubblicazioni, Kim et al. (2025) hanno effettuato un volo con un drone alla massima altitudine, ovvero 2.500 m, misurando le concentrazioni di particolato con un contatore ottico di particelle e un contatore di particelle a condensazione in Corea.

1.2.2. Tecniche di elaborazione del dato

Approfondendo le tecniche di analisi delle concentrazioni degli inquinanti rilevate con sistemi di misurazione basati su drone, la raccolta di campioni di aria in atmosfera è già stata introdotta (Chang et al., 2022). In questo caso, la successiva gascromatografia si è resa necessaria per la caratterizzazione di 109 VOC (Volatile Organic Compounds) ad altitudini differenti. Faksness et al. (2022) hanno misurato le concentrazioni gassose (NO_x, SO₂, CO, CO₂) e

di particolato ($PM_{2.5}$, PM_4 , PM_{10}) con voli verticali e orizzontali, raccogliendo campioni di fuliggine e olio da impianti di combustione di petrolio nel Mare del Nord in Norvegia. Un'altra metodologia di analisi delle concentrazioni rilevate è l'utilizzo di modelli di dispersione atmosferica attraverso l'approccio della modellazione inversa. Kemp et al. (2016) hanno valutato con un modello Gaussiano a pennacchio quattro tecniche di monitoraggio delle perdite di metano negli Stati Uniti. Anche O'Malley et al. (2024) hanno utilizzato un modello Gaussiano a pennacchio per il calcolo delle perdite di metano da pozzi orfani non documentati negli Stati Uniti, ma utilizzando un drone ad ala fissa. Habib et al. (2022) hanno stimato fattori e flussi di emissione di materiale particolato di un allevamento intensivo all'aperto di bovini da carne e di un allevamento di bovini da latte in Texas, Stati Uniti, con un modello chiamato Aermid. Chang et al. (2022) hanno utilizzato il modello Hysplit per ottenere analisi direzionali delle traiettorie. Lee & Kwak (2020) hanno utilizzato modelli WRF (Weather Research and Forecasting) e analisi CFD.

Al posto dei modelli di dispersione atmosferica, alcuni autori si sono serviti invece di tecniche di interpolazione da applicare alle concentrazioni rilevate. Cashikar et al. (2019) non hanno utilizzato un sistema di monitoraggio con drone, ma un robot come piattaforma a cui agganciare un sensore a basso costo per la misurazione del particolato per la valutazione della qualità dell'aria interna in un laboratorio, applicando l'interpolazione di Kriging. Questa tecnica di interpolazione è stata utilizzata anche da Morales et al. (2022) per quantificare le concentrazioni di metano da una sorgente artificiale. Burgués et al. (2022), studiando le emissioni di cattivi odori da un impianto di trattamento delle acque reflue in Spagna con dei nasi elettronici, hanno poi applicato un'interpolazione NNI (Natural Neighbour Interpolator). Mappe di qualità dell'aria sono state ottenute da Ranganathan et al. (2023) per una discarica di rifiuti solidi in India, applicando la tecnica dell>IDW (Inverse Distance Weighting).

Altri studi sono stati indirizzati verso il calcolo dell'AQI (Air Quality Index). L'indice di qualità dell'aria è un indicatore di quanto l'aria sia inquinata. In accordo con i NAAQS, la US EPA ha sviluppato gli AQI negli scorsi anni (Horn & Dasgupta, 2024) per fornire informazioni sulla qualità dell'aria in

esterna, specialmente per l'esposizione di gruppi di persone particolarmente sensibili come anziani, bambini e persone con malattie cardiovascolari e polmonari. Beryozkina & Al-Shakhs (2020) hanno monitorato le concentrazioni gassose (NO_2 , SO_2 , CO_2) interne ed esterne per il calcolo degli AQI. Bernabeo et al. (2023) hanno indicato i livelli di AQI del $\text{PM}_{2.5}$ delle principali città del Vietnam per spiegare l'importanza dello sviluppo di sistemi di monitoraggio della qualità dell'aria con drone. Durgun & Durgun (2024) si sono occupati di monitoraggio ambientale in Turchia, indicando le sei categorie di livelli di AQI riguardo il $\text{PM}_{2.5}$ in tre zone differenti, ovvero agricola, industriale e universitaria. Järvi et al. (2023) e Velez et al. (2024) hanno sviluppato modelli di regressione multivariata, includendo parametri ambientali e indici vegetazionali come predittori. Klimczyk (2021), Afshar-Mohajer & Wu (2023), and Tiwari & Lall (2023) hanno spostato la loro analisi sul protocollo di misurazione, rispettivamente, sull'efficace intercettazione del flusso emissivo, sul percorso della missione di volo e sullo sviluppo di un albero delle decisioni per ottimizzare i parametri di volo.

2. Scopo della ricerca

L'obiettivo principale della presente tesi è la valutazione di varie tecniche di monitoraggio delle emissioni in atmosfera da allevamenti di bestiame, a partire dall'utilizzo di un modello di dispersione atmosferica basato sull'approccio Lagrangiano Stocastico e la modellazione inversa. Le condizioni ambientali e le concentrazioni di vari inquinanti sono state rilevate grazie alla disponibilità di piattaforme multi-sensore sviluppate negli anni precedenti e messe a disposizione dalla sezione di Costruzioni Rurali e Territorio Agroforestale (SSD AGRI-04/C) del DAGRI (Dipartimento di Scienze e Tecnologie Agrarie, Alimentari, Ambientali e Forestali) dell'Università degli Studi di Firenze (Merlini, 2025). La sensoristica in questione può essere posizionata sia a terra per monitoraggi stazionari sia in volo per monitoraggi in movimento, grazie alla possibilità di aggancio su treppiedi e su aeromobili a pilotaggio remoto. Quest'ultima opzione fornisce la possibilità di studiare la dispersione atmosferica di gas e polveri, a patto che si riesca ad intercettare il flusso di emissione. I protocolli di misurazione sviluppati a partire dai rilievi a terra avevano lo scopo di utilizzare i dati ottenuti all'interno del modello. Il monitoraggio stazionario a terra mira a fornire un sistema di misurazione delle emissioni affidabile e autonomo agli allevatori con la possibilità di storicizzare le emissioni in un database per la costruzione di inventari locali al fine di comprendere le emissioni con differenti condizioni meteorologiche durante l'anno. Per migliorare questa tipologia di analisi, possono essere utilizzati anche i droni, che permettono di completare l'analisi svolgendo voli attorno alle stazioni fisse di monitoraggio a terra ed investigando altezze differenti.

Vista l'importanza di un sistema agroalimentare sostenibile in grado di fornire derrate alimentari ad una popolazione mondiale in aumento, il presente lavoro di tesi esplora alcune tecnologie, protocolli di misura, metodologie e tecniche di analisi per la valutazione della qualità dell'aria, quindi per il monitoraggio ambientale negli allevamenti zootecnici. A livello operativo, un sistema di misurazione delle emissioni permetterebbe agli allevatori di adottare le MTD (Migliori Tecniche Disponibili), cioè soluzioni tecniche e gestionali che riducono l'impatto ambientale, ottimizzando l'utilizzo dei fattori della produzione, aumentando la sostenibilità delle

organizzazioni. Le MTD vengono definite dalla Commissione Europea nella Direttiva 2010/75/CE sulle emissioni industriali per la prevenzione e la riduzione integrate dell'inquinamento. La Commissione Europea ha prodotto in anni recenti documenti di riferimento per la raccolta delle MTD in vari settori produttivi e, per l'allevamento zootecnico, ne è stato prodotto uno che riguarda gli allevamenti intensivi di avicoli e suini (Giner Santonja et al., 2025).

Nella presente tesi vengono riportate tre pubblicazioni, che hanno avuto l'obiettivo di testare le prestazioni di un modello di dispersione atmosferica Lagrangiano Stocastico con un approccio di modellazione inversa (Flesch et al., 1995; Flesch & Wilson, 2005). L'applicazione di questo modello è finalizzata al calcolo dei flussi di emissione e delle mappe di concentrazione di inquinanti gassosi. Tali pubblicazioni riportano prove sperimentali effettuate in allevamenti di bovini da latte localizzati in Italia e in Brasile ed hanno riguardato le emissioni di CO₂, in quanto il sensore NDIR integrato nella piattaforma multi-sensore sviluppata negli scorsi anni dal DAGRI risulta tra quelli più affidabili in termini di sensibilità, accuratezza e precisione. Si riportano due studi precedenti, effettuati dal gruppo di ricerca incaricato dello sviluppo delle piattaforme multi-sensore, uno destinato alla descrizione del sistema di misurazione con drone (Becciolini et al., 2022) e l'altro destinato alla calibrazione della sensoristica in camera climatica (Becciolini et al., 2024). Dopo la calibrazione, nello sviluppo della soluzione, la fase successiva ha riguardato le prove di campo, principalmente in allevamenti zootecnici. Durante tali prove, i sensori per la misurazione delle concentrazioni di CO₂, PM₁₀ e PM_{2.5} hanno mostrato buone prestazioni, mentre i sensori per il monitoraggio del CH₄ e dell'NH₃ non hanno mostrato buone prestazioni a causa dell'elevato campo di misurazione, limite soprattutto per i monitoraggi effettuati in esterna. Il gruppo di ricerca ha ritenuto quindi opportuno selezionare altre tipologie di sensori per il monitoraggio del CH₄, come quelli con tecnologia laser, dotati di maggiore sensibilità, ma meno compatti e disponibili sul mercato a prezzi elevati. Il monitoraggio dell'NH₃ con la soluzione attuale si presta maggiormente per i monitoraggi all'interno degli edifici di allevamento per l'elevata volatilità dell'NH₃.

Alcuni risultati preliminari che faranno parte di altre due pubblicazioni in fase di preparazione sono riportati nella presente tesi e riguardano il monitoraggio del CH₄ con un sensore laser agganciato ad un drone nella filiera di produzione del biogas ed il calcolo dei flussi di emissione di alcuni inquinanti (CO₂, CH₄, NH₃, N₂O) all'interno di due edifici adibiti all'allevamento di vitelli da carne aventi due diversi sistemi di ventilazione. Tali prove sperimentali sono state effettuate in Francia con due gruppi di ricerca afferenti all'INRAE (Institut National de Recherche pour l'Agriculture, l'Alimentation et l'Environnement) e all'IDELE (Institut de l'Élevage). Questi due gruppi sono stati selezionati, in quanto hanno adottato metodologie differenti per il calcolo dei flussi di emissione da costruzioni rurali per l'allevamento zootecnico, ma anche sensoristica e protocolli di misurazione diversi. Questi studi vengono riportati per dare una visione più ampia al contesto in cui la presente tesi viene elaborata e per cercare di dare delle soluzioni ai limiti individuati nelle tre pubblicazioni riguardanti il monitoraggio ambientale negli allevamenti zootecnici, riguardo la sensoristica, i protocolli di misurazione e l'elaborazione dei dati misurati.

Riguardo i sensori di concentrazione della CO₂, Chang et al. (2016) si sono serviti della gascromatografia (450-GC e 240-MS, Varian, WalnutCreek, CA, USA) su campioni di aria. Beryozkina & Al-Shakhs (2020) e Ranganathan et al. (2023) hanno utilizzato un sensore a semiconduttore (MQ135, Hanwei Electronics Co., Zhengzhou, Cina). Il sistema di monitoraggio ambientale con drone sviluppato da Burgués et al (2022) non conteneva solo un naso elettronico per il monitoraggio degli odori, ma anche un sensore NDIR per misurare le concentrazioni di CO₂. Anche Zhao et al. (2022) hanno utilizzato un sensore NDIR (Carbon3060S, Nanjing ZTweather Technology Co., Nanchino, Cina). I sensori NDIR sono presi in considerazione nella revisione di Jońca et al. (2022), insieme ad altri tipi di sensori, quali rilevatori amperometrici, chemiresistivi a ossido di metallo e a fotoionizzazione, mostrando elevata selettività, sensibilità e stabilità, tempi di risposta e recupero rapidi e insensibilità a variazioni ambientali. In questa revisione sono stati riportati quattro studi che includevano sistemi di monitoraggio con drone, agganciando sensori NDIR (Rüdiger et al., 2019; Liu et al., 2019; Tosato et al., 2019; Aurell et al., 2021). Liu et al. (2019) hanno dimostrato una

buona correlazione tra le misurazioni effettuate con i droni (NDIR) e quelle effettuate a terra (telecamera PiCam UV).

Come introdotto in precedenza, tra le tecniche di analisi della qualità dell'aria è stato selezionato un modello di dispersione atmosferica chiamato WindTrax. Attraverso un approccio di modellazione inversa, il modello Lagrangiano Stocastico a corto raggio è in grado di generare molte particelle e di seguirle lungo le loro traiettorie dai sensori di concentrazione alle sorgenti di emissione per il calcolo dei flussi di emissione. È stato sviluppato un software con interfaccia user friendly che implementa il modello ed è disponibile online (Crenna, 2020). Questo software è largamente citato in letteratura, specialmente nel settore agricolo. La maggior parte delle pubblicazioni che riportava l'utilizzo del software in agricoltura mirava alla quantificazione delle perdite di inquinanti dai processi di produzione: fertilizzazione dei terreni coltivati (Bai et al., 2014; Lavrsen Kure et al., 2018; Righi et al., 2021; Angelino et al., 2022), digestione anaerobica (Bell et al., 2016; Hrad et al., 2021) e strutture di allevamento, specialmente la gestione dei reflui zootecnici (Leytem et al., 2018; Shonkwiler & Ham, 2018; Genedy & Ogejo, 2022; Tagliaferri et al., 2023). Altri settori nei quali WindTrax è stato utilizzato sono la vulcanologia (Pedone et al., 2017), l'industria (Sauer et al., 2018), il petrolifero (Shaw et al., 2020; Riddick et al., 2022; Tian et al., 2022), i rifiuti (Elpelt-Wessel et al., 2021) e la ricerca (Hu et al., 2016).

Tra gli studi riportati su WindTrax, l' NH_3 è il gas maggiormente monitorato, in quanto uno dei responsabili della formazione del particolato fine in atmosfera, peggiorando la qualità dell'aria, causando l'eutrofizzazione, incidendo negativamente sulla salute pubblica, nella litosfera, nell'idrosfera, sulla biodiversità e sul benessere animale (Bai et al., 2014; Bell et al., 2016; Lavrsen Kure et al., 2018; Leytem et al., 2018; Shonkwiler and Ham, 2018; Ricco et al., 2021; Angelino et al., 2022; Genedy and Ogejo, 2022). Il monitoraggio del CH_4 in atmosfera è stato discusso in altre pubblicazioni (Hu et al., 2016; Sauer et al., 2018; Shaw et al., 2020; Elpelt-Wessel et al., 2021; Hrad et al., 2021; Riddick et al., 2022), in quanto assume il ruolo di uno dei gas ad effetto serra più pericolosi, raggiungendo un valore di GWP pari a 27 CO_2 eq. su un orizzonte temporale di 100 anni (Forster et al., 2023). La CO_2

è stata monitorata in alcune pubblicazioni (Pedone et al., 2017; Sauer et al., 2018), in quanto anch'essa gas ad effetto serra.

La lacuna individuata negli studi riportati nella presente tesi riguarda il fatto che nessun autore ha valutato le prestazioni del modello WindTrax nel calcolo dei flussi di emissione e delle concentrazioni servendosi di un sistema di misurazione prototipale, come quello sviluppato dal DAGRI, agganciato ad un drone. Un confronto diretto tra concentrazioni modellate ed osservate è riportato in due degli studi presenti in questa tesi, cioè gli Studi numero 2 e 3. Questi due studi miravano alla misurazione delle emissioni dal processo di lavorazione di una lettiera compost, utilizzata in un allevamento di bovini da latte in Brasile. Nello specifico, con queste pubblicazioni sono state quantificate le emissioni di CO₂ prima e durante la lavorazione della lettiera con misurazioni a terra e poi dopo la lavorazione della lettiera con misurazioni in volo. Lo Studio numero 1 mirava invece a valutare il modello in termini di quantificazione di alcuni parametri e posizionamento della sensoristica. Il numero di piattaforme multi-sensore utilizzate per questi studi era pari a tre unità.

La gestione della lettiera compost è il processo che è stato valutato in termini di emissioni di CO₂ in due degli articoli riportati nella presente tesi. La lettiera compost negli allevamenti costituisce uno strato soffice con spessore di 0,25-1,00 m composto da materiale lignocellulosico, principalmente paglia, trucioli, cippato, sabbia e reflui zootecnici. Generalmente, una lettiera compost è progettata e gestita in ampie zone di riposo a stabulazione libera con una superficie/capo di 7,4-15,0 m². Le condizioni anaerobiche con le quali la lettiera viene gestita, necessitano di lavorazioni frequenti da 1 a 3 volte al giorno, effettuate da una trattrice con un erpice a dischi o rotante a denti, una fresa o un aratro. La lavorazione frequente consente di incorporare i reflui zootecnici freschi, portando ossigeno al substrato, consentendo l'evaporazione dell'acqua. Per questo ultimo scopo, assicurare elevati tassi di ventilazione è richiesto per ottenere un materiale fresco per il benessere termico degli animali stabulati. La temperatura all'interno della massa tende ad aumentare con la profondità a causa del processo di compostaggio, producendo NH₃, CH₄, N₂O e CO₂, inquinanti rilasciati in atmosfera dalla lavorazione effettuata dalla trattrice (Leso et al., 2020).

Ossigeno e temperature di circa 65°C promuovono l'attività microbica in aerobiosi, fornendo un materiale asciutto e sicuro dal punto di vista sanitario. È da notare che la lettiera compost non può essere sempre utilizzata, soprattutto in alcuni disciplinari di produzione di prodotti caseari in Italia, a causa della possibile presenza nel substrato di batteri TAS (thermophile aerobic spore formers) e XTAS (extremely thermophile aerobic spore formers). Le spore di questi batteri sono in grado di sopravvivere al processo di sterilizzazione del latte causando problemi alla conservazione dei prodotti caseari ottenuti (Barbari et al., 2019). Zhao et al. (2016) hanno calcolato le emissioni di NH_3 da un impianto di compostaggio chiuso contenente reflui avicoli in Ohio, USA, misurando le concentrazioni di NH_3 con un analizzatore foto-acustico (MSA Chillgard RT, MSA Inc., Pittsburg, PA), temperatura e umidità relativa con sensori Hobo connessi ad un datalogger (U23 Temperature/RH data logger, Onset Computer Corp, Pocasset, MA) e tassi di ventilazione con uno strumento chiamato FANS (Fan Assessment Numeration System), riportando inoltre i risultati di analisi chimiche dei reflui freschi e del compost. Invece, Fournel et al. (2019) hanno calcolato le emissioni di NH_3 , CH_4 , N_2O e CO_2 da quattro diverse tecniche di compostaggio, partendo dallo stesso materiale, cioè il letame separato, per ottenere compost da utilizzare come lettiera negli allevamenti canadesi. Le concentrazioni sono state misurate in camere chiuse con sensori NDIR (Ultramat 6E model, Seimens, Munich, Germany) e analisi gas cromatografiche (model 3600, Varian, Walnut Creek, CA, USA), temperatura, umidità relativa e tassi di ventilazione con una sonda contenente un termometro (modello CS500, Campbell Scientific Canada, Corp., Edmonton, AB, Canada), un sensore di umidità relativa e una serranda a iride (modello 200, Continental Fan Manufacturing Inc., Buffalo, NY) e tutti i sensori erano collegati a un datalogger (modello CR1000, Campbell Scientific, Edmonton, AB, Canada). Secondo El Mashad et al. (2023), una revisione che ha valutato diverse tecnologie di gestione del letame (digestione anaerobica, flushing, raschiatori meccanici e sistema a vuoto), in termini di emissioni di CH_4 , tra queste, il processo di compostaggio presenta picchi di emissione immediatamente dopo la lavorazione del terreno, poiché i gas intrappolati tra le particelle solide nella lettiera vengono

rilasciati nell'atmosfera. Con lo scorrere del tempo dopo la lavorazione, le emissioni tendono a stabilizzarsi (Wolf, 2017), ma il calpestio degli animali tende a compattare la lettiera, riducendone la porosità e di conseguenza lo scambio di ossigeno, favorendo la formazione di siti anaerobici, condizioni favorevoli per la crescita di microrganismi metanogeni.

Ayadi et al. (2015) hanno condotto analisi di laboratorio sul processo di compostaggio con un una camera statica, mostrando emissioni elevate di gas ad effetto serra e NH_3 all'aumentare della temperatura. Fuertes et al. (2023) hanno sottolineato gli aspetti positivi dell'utilizzo della lettiera compost (gestione a basso costo, benessere animale, e alta qualità del latte ottenuto da allevamenti di bovini da latte) ed hanno misurato le più alte emissioni di NH_3 e CH_4 in Spagna con la gascromatografia prima e durante la lavorazione nella stagione estiva. In aggiunta, dichiarano che il rapido rilascio della CO_2 aumenta il pH del substrato, alterando l'equilibrio $\text{NH}_3 \leftrightarrow \text{NH}_4^+$ verso la volatilizzazione dell'azoto. Questo aspetto influenza il valore del compost utilizzato come lettiera a fine vita, che potrebbe essere utilizzato come concime nei terreni coltivati. Nugrahaeningtyas et al. (2023) ha applicato la gascromatografia (iGC7200A, DS Science, Corea) per calcolare le emissioni da lettiere compost di due allevamenti di bovini da latte in Corea, analizzando anche le proprietà chimiche e fisiche. La temperatura della lettiera, il pH e il rapporto C/N influenzano diversamente le emissioni in condizioni aerobiche e anaerobiche.

Nella prima fase del processo di compostaggio, l'ossigeno viene consumato rapidamente dai microrganismi aerobici con la respirazione in condizioni termofile, decomponendo la materia organica nel substrato. Successivamente, le emissioni più elevate di CH_4 e N_2O si verificano con bassi livelli di ossigeno nel substrato, favorendo rispettivamente i processi di metanogenesi e denitrificazione. Quindi, oltre al processo di volatilizzazione dell'azoto, la denitrificazione è un altro processo da considerare quando il letame compostato alla fine del suo ciclo di vita viene utilizzato come concime nei terreni coltivati, in quanto elementi dotati di elevata mobilità nel terreno, a causa della soluzione circolante. Ferreira et al. (2024) hanno misurato le emissioni di CH_4 e CO_2 in 75 punti dell'area di riposo con un letame compostato in un allevamento di bovini da latte brasiliano, creando

mappe di distribuzione spaziale utilizzando l'interpolazione Kriging ordinaria. È stato studiato inoltre il comfort termico degli animali calcolando l'indice THI, considerando che la ventilazione meccanica può influire positivamente sul processo di compostaggio, ma anche portare l'indice THI al di sotto del valore soglia. Inoltre, la CO₂ è un gas denso, che tende a concentrarsi nella parte più bassa dell'area di riposo. Questo fatto dovrebbe essere considerato in termini di benessere degli animali quando le vacche giacciono sulla lettiera, specialmente negli allevamenti chiusi.

Riguardo la letteratura riportata sulla lettiera compost, una lacuna nella ricerca viene identificata, in quanto nessuno degli autori ha utilizzato un sistema di misurazione con drone abbinato ad un modello di dispersione atmosferica. In questo tipo di analisi, la distanza dalla sorgente o eventuali ostacoli e l'altezza della missione di volo potrebbero essere influenzate dal tetto dell'edificio in cui gli animali vengono stabulati, al di sopra del quale possibili turbolenze potrebbero compromettere la rappresentatività atmosferica, considerando anche il problema del downwash da parte del drone. Per questo, altitudini non superiori all'altezza dell'edificio sono state investigate, considerando anche la natura di WindTrax, un modello a corto raggio che calcola dispersioni atmosferiche di inquinanti gassosi nel raggio di 1 km, considerando la distanza tra sorgenti di emissione e il posizionamento della sensoristica.

Interessanti indicazioni per una versione successiva della piattaforma multi-sensore sono state ottenute dalle tre pubblicazioni riportate nella presente tesi, riguardanti principalmente la disposizione dei singoli sensori all'interno della piattaforma multi-sensore e al flusso interno dell'aria, sviluppando altre tre unità (Merlini, 2025). L'ultima versione è stata testata durante le prove di campo effettuate con i gruppi di ricerca francesi ed alcuni dei risultati preliminari vengono riportati nella parte riguardante gli articoli in fase di preparazione (Studi numero 4 e 5).

La progettazione dei cinque studi riportati nella presente tesi aveva lo scopo di soddisfare delle domande di ricerca ben precise, obiettivi cronologicamente impostati per la validazione della soluzione proposta durante i tre anni previsti dal percorso di dottorato (Schema 1). Dopo aver acquisito le competenze necessarie per l'utilizzo del modello, inizialmente

si è provveduto alla creazione di un protocollo di misurazione e alla calibrazione di alcuni parametri del modello. Successivamente, sono state eseguite le prove di campo, integrando misurazioni stazionarie e in movimento con un drone per la valutazione delle prestazioni del modello nella previsione delle concentrazioni degli inquinanti in base ai flussi di emissione calcolati. Contemporaneamente, sono state ottenute delle indicazioni per il miglioramento della piattaforma multi-sensore. Criticità e limitazioni riguardo la soluzione proposta sono state individuate e riportate. Infine, sono stati esplorati altri sensori, altre tecnologie e altre tecniche di analisi per ottenere un confronto diretto con la soluzione proposta.



Schema 1. Programmazione dei risultati da ottenere durante il percorso di dottorato.

3. Materiali e metodi generali

3.1. Le piattaforme multi-sensore

Le tre piattaforme multi-sensore sviluppate dal DAGRI di Firenze negli anni precedenti avevano lo scopo di essere utilizzate in allevamenti di bestiame per il monitoraggio ambientale interno e in esterna. La versatilità di tali piattaforme sta nel fatto che possono essere utilizzate sia per monitoraggi stazionari sia per monitoraggi in movimento, essendo stato sviluppato un dispositivo di aggancio per una delle tre unità che consente il posizionamento su un aeromobile a pilotaggio remoto. L'ultima versione della piattaforma multi-sensore sviluppata contiene sensori di concentrazione per la quantificazione della CO₂ (SCD30, Sensirion, Stäfa, Switzerland), del CH₄ (IRM-AT, Alphasense, Braintree, United Kingdom), dell'NH₃ (NH3-B1, Alphasense, Braintree, United Kingdom), del PM₁₀ e del PM_{2.5} (SDS011, NovaSensor, Shadong, Cina). Vengono rilevate inoltre le condizioni ambientali come la temperatura, l'umidità relativa e la pressione atmosferica. Le misurazioni della temperatura e dell'umidità relativa vengono fornite dal sensore di concentrazione della CO₂ grazie ad un modulo integrato. Questo sensore è stato infatti selezionato per la compattezza del modulo che ha reso facile l'integrazione e l'assemblaggio nella piattaforma multi-sensore, garantendo misurazioni accurate e stabili (Merlini, 2025). Queste caratteristiche sono state prese in considerazione per la selezione di tutti i sensori a basso costo sul mercato. Le piattaforme multi-sensore contengono anche un sensore di pressione barometrica assoluta (BMP280, Bosch Sensortec GmbH, Kusterdingen, Germania) di dimensioni ridotte e basso consumo energetico. In Tabella 1 sono riportati i valori relativi al campo di misura e alla sensibilità di ogni sensore.

Tabella 1. Tipologia di sensore, campo di misura e sensibilità dei parametri misurati dalla sensoristica assemblata nella piattaforma multi-sensore sviluppata dal DAGRI.

Parametro target	Sensore	Campo di misura	Sensibilità
Metano	NDIR	0 ÷ 25.000 ppm	< ±500 ppm
Ammoniaca	Elettrochimico	0 ÷ 100 ppm	< ±3 %
PM ₁₀ e PM _{2.5}	Ottico	(PM _{2.5}) 0 ÷ 1.000 µg · m ⁻³ (PM ₁₀) 0 ÷ 2.000 µg · m ⁻³	±15% & ±10 µg · m ⁻³

Anidride carbonica	NDIR	0 ÷ 5.000 ppm	± 30 ppm
Temperatura	Modulo integrato nel sensore NDIR	- 40 ÷ 70 °C	± (0.4°C + 0.023 × (T[°C] - 25°C))
Umidità relativa	Modulo integrato nel sensore NDIR	0 ÷ 100 % RH	± 3% RH
Pressione	Cella piezoresistiva	300 ÷ 1.200 hPa	± 1 hPa

Rispetto allo studio contenuto in Becciolini et al. (2022), dove viene riportato un peso di 1,20 kg per la piattaforma multi-sensore, in Becciolini et al. (2024) viene indicato un peso inferiore, cioè 0,75 kg, in quanto il prototipo ha subito delle modifiche, rimuovendo alcuni sensori e componenti. Questo ha permesso di allungare il periodo delle missioni di volo per il monitoraggio ambientale di qualche minuto. La distribuzione della sensoristica all'interno della camera di campionamento delle piattaforme multi-sensore è stata inoltre modificata secondo le indicazioni ottenute da un'analisi aerodinamica (Merlini et al., 2025). Viene precisato che la frequenza di campionamento tra le ultime due versioni è stata ridotta, ottenendo un'osservazione da ogni 5 secondi a ogni 20 secondi.

Per le prove sperimentali riportate nel secondo articolo pubblicato, la piattaforma multi-sensore è stata agganciata ad un drone M350 RTK (DJI Sciences and Technologies Ltd., Beijing, China). Come riportato in letteratura, il peso del carico utile al decollo è uno dei parametri più importanti nell'utilizzo di un sistema di misurazione con drone per il monitoraggio ambientale della qualità dell'aria, in quanto questo influenza la durata delle batterie e quindi la durata della missione di volo. In questo caso, è stato raggiunto il valore di 0,84 kg per il carico utile sollevato dal drone, includendo il supporto per l'aggancio della sensoristica al drone e un power bank per fornire energia elettrica alla stessa. Da specificare che nello Studio numero 2 viene riportato un valore di 0,93 kg, in quanto è stato incluso il peso del sensore Temperature/RH Data Logger 297 (Hobo MX2301A, Onset Computer, Bourne, Massachusetts, United States), utilizzato durante tutte le prove sperimentali. Con questa configurazione, ogni prova sperimentale riportata nella pubblicazione ha raggiunto un periodo di campionamento di circa 30 minuti, mantenendo il drone in un

punto fisso, investigando due altitudini. Altra caratteristica importante di un sistema di misurazione con drone per il monitoraggio ambientale della qualità dell'aria è il posizionamento della sensoristica in base al problema del downwash, nello specifico la distanza tra il piano orizzontale delle eliche e l'ingresso dell'aria della sensoristica. In questo caso, la piattaforma multi-sensore è stata posizionata sopra il corpo del drone, raggiungendo una distanza tra le eliche e l'ingresso dell'aria nella piattaforma di circa 30 cm. Questo parametro dovrebbe garantire la rappresentatività atmosferica, anche se Samad et al. (2022) suggeriscono una distanza ottimale di 90 cm. L'ultima versione della piattaforma multi-sensore è stata utilizzata per il progetto PRIN (Programma Nazionale di Ricerca e Progetti di Rilevante Interesse Nazionale) 2022 EMILI (Emission-controlled intensive livestock housing systems for ecological transition: innovative measuring, mitigating and mapping strategies) per rilievi di monitoraggio ambientale in un allevamento di suini nella zona di Bergamo e in un allevamento di bovini da latte nella zona di Ragusa. Le altre prove sperimentali sono state effettuate in Francia con i due gruppi di ricerca afferenti a IDELE ed INRAE.

3.2. Il modello di dispersione atmosferica WindTrax

WindTrax è un modello a corto raggio di dispersione atmosferica valido per periodi di mediazione tra i 15 e i 30 minuti, distanze massime di 1 km tra le sorgenti e i sensori in condizioni di terreno pianeggiante e preferibilmente in assenza di ostacoli. Per periodo di mediazione si intende il periodo sul quale mediare i dati misurati, in modo da fornire al modello dei dati in input validi dal punto di vista meteorologico per meglio rappresentare lo stato dell'atmosfera durante lo svolgimento delle prove sperimentali. Periodi di mediazione più lunghi rispetto ai valori consigliati dall'autore del software sarebbero maggiormente soggetti a variazioni in termini di radiazione incidente in base a come si protrae il ciclo del giorno, soprattutto per periodi di rapida transizione come l'alba e il tramonto. Riguardo l'assunzione sugli ostacoli presenti nel luogo dello studio, risulta particolarmente difficile da rispettare negli allevamenti zootecnici, dove le superfici sono particolarmente dense di ostacoli come alberi o costruzioni rurali. Anche l'assunzione sulle superfici risulta difficile da rispettare, soprattutto in Italia,

in quanto gran parte del territorio nazionale risulta essere in pendenza. Per le pubblicazioni riportate nel presente lavoro di tesi, le prove sperimentali sono state effettuate su terreni pseudo pianeggianti, avendo cura di posizionare la sensoristica vicino alle sorgenti di emissione investigate, riportando risultati a livello locale.

Il modello è in grado di calcolare i flussi di emissione delle sorgenti investigate, avendo a disposizione i valori delle variabili misurate durante le prove sperimentali come la concentrazione di fondo o la concentrazione sopravento e soprattutto le concentrazioni sottovento rispetto alla sorgente. Il modello e il software necessitano, oltre che di misure di concentrazione, anche di informazioni sulle condizioni ambientali come temperatura e pressione, fornite anch'esse dalle piattaforme multi-sensore. Sono richieste per il calcolo anche dati sul vento presente durante le prove sperimentali, nello specifico, almeno direzione e velocità del vento. Durante le prove sperimentali, per fornire i dati per il calcolo dei flussi di emissione con il modello WindTrax, deve essere presente almeno un anemometro che quantifichi direzione e velocità. Per completare i calcoli è richiesta anche la quantificazione della stabilità atmosferica e in questo caso è stata quantificata secondo le classi di Paquill-Gifford. L'autore del software ha reso disponibili due manuali, uno introduttivo e l'altro riferito alla quantificazione delle variabili atmosferiche (Crenna, 2006a, 2006b). Lo stesso autore ha effettuato uno studio sul posizionamento della sensoristica intorno alle sorgenti di emissione (Crenna et al., 2008). I protocolli di misura sia per le misurazioni a terra sia per le misurazioni con drone sono stati sviluppati seguendo le indicazioni dell'autore del software fornendo al modello quello di cui necessita per completare una simulazione.

Il vantaggio principale derivante dall'utilizzo del software WindTrax è la disponibilità di un'interfaccia user friendly che permette agli utenti con competenze limitate in materia di chimica atmosferica di completare simulazioni di dispersione atmosferica gassosa attraverso il calcolo dei flussi di emissione delle sorgenti investigate. L'interfaccia grafica permette di caricare mappe, disegnare le sorgenti di emissione su di esse e di collocare la sensoristica utilizzata nella posizione corretta. Una delle criticità individuate riguarda il fatto che attualmente la versione del software che

implementa dispersioni atmosferiche sul materiale particolato non è stata ancora resa disponibile dall'autore, nonostante una pubblicazione presente in letteratura (Bonifacio et al., 2013). Questa versione permetterebbe una modellazione su superfici più ampie, in quanto la natura del materiale particolato lo rende soggetto al trasporto a lungo raggio.

Sono stati individuati altri modelli di dispersione atmosferica a lungo raggio come AERMOD (United States Environmental Protection Agency, 2025) e HYSPLIT (National Oceanic and Atmospheric Administration, 2025). Per il primo sono stati sviluppati vari software a pagamento che permettono di utilizzare dati meteo aggiornati. Mentre per il secondo, sono stati sviluppati un software scaricabile e un software online dalla National Oceanic and Atmospheric Administration. HYSPLIT, noti i flussi di emissione di una determinata sorgente, permette di modellare, non solo la dispersione atmosferica, ma anche analisi direzionali attraverso il calcolo di traiettorie degli inquinanti a partire dalla sorgente di emissione. Questa analisi permetterebbe di realizzare la fase successiva rispetto al calcolo della dispersione atmosferica di inquinanti da allevamenti zootecnici, ovvero un'analisi dei rischi e dell'impatto ambientale che questi hanno sui centri urbani o aree densamente popolate incrociate dalle traiettorie sopra dette. Esempi di analisi di questo tipo vengono riportate in letteratura in un recente studio (Hwang, 2025). Le simulazioni con questi due modelli di dispersione atmosferica possono essere completate anche con il software Rstudio (Rstudio Team, 2024), utilizzando le apposite librerie aermod (Llana & Pauw, 2016) e splitr (Iannone et al., 2015).

Per le pubblicazioni riportate nel presente lavoro di tesi, l'analisi dei dati è stata effettuata sui dati forniti in input al modello, sui flussi di emissione calcolati e sulle concentrazioni calcolate. WindTrax permette infatti di creare delle mappe di dispersione atmosferica su determinate superfici, specificando l'altitudine. Per l'analisi dei dati è stato utilizzato il software R (R Core Team, 2024) e l'interfaccia Rstudio (Rstudio Team, 2024), selezionando una serie di pacchetti di funzioni come Openair (Carslaw & Ropkins, 2012; Carslaw, 2019), utile per analisi dei dati di qualità dell'aria, Raster (Hijmans, 2024) per mappare e analizzare le concentrazioni calcolate da WindTrax contenute nei file raster che servono a rappresentare le

dispersioni atmosferiche e ggplot2 (Wickham, 2016) per la creazione di grafici.

Fondamentale per la rappresentazione di dati georeferenziati si è rivelato il software QGIS (QGIS Association, 2023), sia in fase preliminare per rappresentare la posizione della sensoristica nel luogo dello studio e il percorso della missione di volo effettuata dal drone sia per rappresentare in mappa i risultati delle dispersioni atmosferiche calcolate da WindTrax. Altri software accessori utilizzati sono stati Microsoft Excel, Google Earth PRO (Google et al., 2021), 3DF Zephyr (3D flow srl, 2023) e Phantom Help (DJI Drone Help, 2025). L'utilità di questi software ha riguardato rispettivamente l'archiviazione dei dati in input e in output, la rappresentazione delle missioni di volo su mappa, il calcolo e la rappresentazione di modelli di superficie digitale dopo operazioni di aerofotogrammetria e la decriptazione dei dati sulle missioni di volo, ottenuti dal radiocomando del drone.

4. Articoli pubblicati

4.1. Studio 1

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Assessment of CO₂ emission rate from extended area sources with WindTrax model in a dairy cattle farm

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Abstract. This paper aimed to evaluate the WindTrax model to quantify CO₂ (carbon dioxide) emissions in a commercial dairy cattle farm in Central Italy with a low-cost measurement system. A field trial of 20 minutes was conducted in February 2023, using two G-eko 2.0 MSPs (multi-sensor platforms), an anemometer, and a GNSS receiver, in unstable atmospheric conditions. Then, 5-minute averaged data were used as input in the WindTrax software for applying the backward Lagrangian Stochastic model. The model was used for calculating four mean CO₂ emission rates ($0.20212 \pm 0.04994 \text{ g m}^{-2} \text{ s}^{-1}$) with 50,000 particles and the horizontal dispersion of CO₂ concentrations around the sources using different numbers of particles (5,000, 10,000, 30,000, and 50,000). Atmospheric dispersion maps, confidence interval concentration maps, and vertical profile plots were obtained by increasing the number of particles. The model shows better performances, in terms of confidence intervals, with a high number of particles with a stabilization of modeled median values between 30,000 and 50,000 particles. Horizontally, the lowest confidence intervals (near to zero) were obtained at 100–150 m from the sources along the wind direction, suggesting that the downwind sensor could be placed at a greater distance. Similarly, a better-defined vertical trend in modeled concentrations is observed as the number of particles increases. Wind gusts could have a great effect on emission rate calculation with limited sampling periods, as in this case, but simultaneously unstable atmospheric conditions affect the increased dispersion and dilution of CO₂.

Key words: greenhouse gases, livestock farming, low-cost sensors, pollutants dispersion.

INTRODUCTION

In recent decades, the exponential increase in human activities has significantly intensified the anthropogenic greenhouse effect, resulting in rising global temperatures and, consequently, climate change. This has increased public awareness of pollution and environmental issues (Tagliaferri et al., 2020). According to the IPCC (2022) report on global emission data from 2015, the livestock sector accounted for 12–17% of total greenhouse gases (GHGs) emissions, with cattle farming contributing 62% of the sector's total emissions (Global Livestock Environmental Assessment Model 3

dashboard, 2022). Within livestock farms, the primary sources of emissions are enteric fermentation in ruminants (67–68%), manure and slurry storage (23–26%), and feed production (Ripple et al., 2014; Grossi et al., 2019).

Environmental chemical monitoring is essential in bottom-up approaches for emissions

inventories and for identifying critical processes that could benefit from targeted mitigation strategies. Various gas sensor technologies are available for this purpose, including amperometric gas sensors (AGS), metal oxide semiconductor sensors (MOX or MOS), nondispersive infrared sensors (NDIR), and photoionization detectors (PIDs) (Cambra-López et al., 2010; Burgués & Marco, 2020). To improve monitoring efficiency, multi-sensor platforms (MSPs) have been developed, enabling the simultaneous operation of multiple sensors. These platforms facilitate the collection of gas concentration data alongside meteorological parameters, providing a comprehensive assessment of emissions (Burgués et al., 2018).

Currently, monitoring GHG emissions is expensive due to the cost of accurate sensors in the market, but the ongoing technological development provides low-cost sensors. The objective of this study was to assess CO₂ emissions obtained with self-engineered multi-sensor platforms on a dairy farm, through the estimation of emission fluxes and the graphical representation of gas concentrations and concentration confidence intervals across the farm area. By employing the WindTrax model to simulate the horizontal and vertical dispersion of the target gas, farmers could adopt an accurate low-cost measurement system that works autonomously, aiming to provide management insights. WindTrax is widely used in agrometeorological studies to estimate emission rates, particularly for GHGs and ammonia (Lin et al., 2015; Yang et al. 2016; Hrad et al., 2021; Genedy & Ogejo, 2022). Existing research primarily evaluates its accuracy in modeling pollutant emissions from area sources, highlighting its relevance as a tool for emission assessment and atmospheric dispersion analysis. Thus, an affordable and accurate emission measurement system that can be easily implemented on commercial farms is needed by farmers to identify critical emission sources, adopting appropriate mitigation strategies.

This study investigated the impact of livestock-related activities on GHG emissions, with a focus on data analysis through specialized simulation methodologies. Specifically, CO₂ (carbon dioxide) emissions were examined using low-cost sensing platforms and atmospheric dispersion modeling as tools for rapid on-farm assessment. This study represented the first application of low-cost sensing platforms combined with dispersion modelling to assess gas emissions and dispersion from livestock buildings in the study area. The study was conducted as part of a research project aiming at assessing greenhouse gases emissions from dairy cattle and swine farming systems across Northern, Central, and Southern Italy using innovative measurement techniques. In Central Italy, the Tuscany region ranks second in terms of dairy cattle population (data provided by the National Zootechnical Registry -BDN- of the Italian Ministry of Health, managed by the 'G. Caporale' Institute in Teramo through the National Services Centre -CSN-). One of the two main dairy production districts in Tuscany is located in the Province of Florence, specifically in the Mugello area, which hosts both larger farms (over 200 lactating cows) and medium-sized farms.

MATERIALS AND METHODS

Study site

The experiment was conducted on a commercial dairy farm in the Mugello area, Province of Florence (Central Italy). The selected farm is representative of the medium-sized dairy farms commonly found in this region. The farm primarily focused on dairy cattle breeding but also operated as an educational farm and agritourism. The cattle housing facility was open on all four sides, and it was situated on relatively flat terrain. At the time of the experiment, the farm housed 123 Holstein Friesian dairy cows in the main building for milk production. Of these, 65 lactating cows were kept in a free-stall pen with cubicles in the resting area and straw bedding, while the remaining 58 cows and heifers were housed in deep-litter pens with permanent straw bedding. All pens had concrete-floored feeding alleys and were equipped with water troughs. A Total Mixed Ration (TMR) was distributed once daily at h 18 00, and a robotic feed pusher regularly repositioned the feed along the self-locking headlocks.

Additionally, 12 calves were kept in individual pens adjacent to the stable, and 12 Belgian Blue White fattening cattle were also present in a pen in the south-east part of the stable. The farm also accommodated a chicken coop and a few donkeys. Contributions to the total emissions were considered negligible.

The slurry from the two rows of pens inside the livestock building, one with permanent litter

and the other in cubicles with straw bedding, was collected by automatic scrapers into two underground concrete tanks. The solid fraction, separated from the liquid, was stockpiled in a rectangular uncovered pit. In contrast, the liquid fraction was transferred to an open-air, circular underground concrete tank located north of the stable (Fig.1).

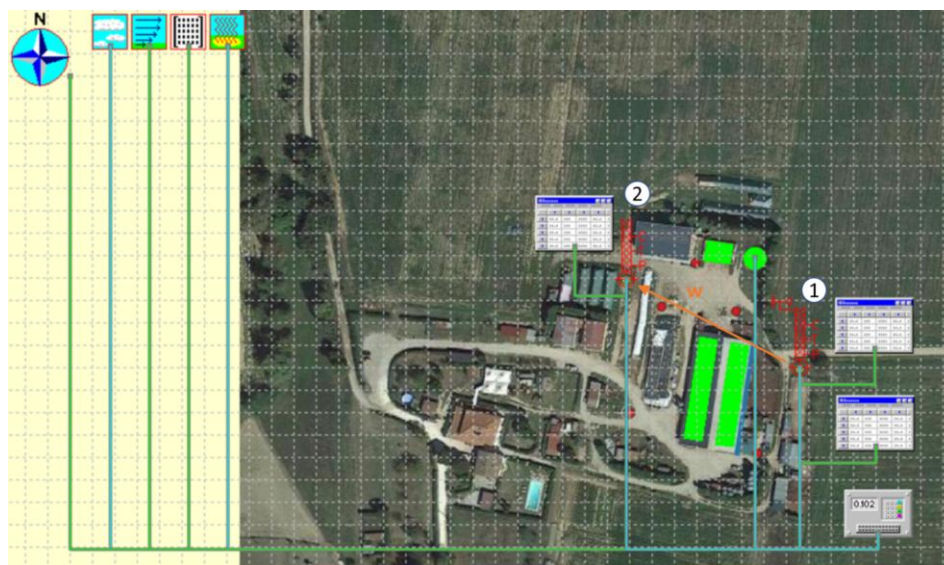


Figure 1. View of the commercial dairy farm (latitude 43.963270°, longitude 11.418885°) and inside the project of the WindTrax software environment. Point 1: upwind G-eko 2.0 multi-sensor unit. Point 2: downwind G-eko 2.0 multi-sensor unit.

Instrumentation

A dual-frequency GNSS receiver (GCX2, Sokkia, Netherlands) with centimetric accuracy was used to georeference the measurement points. Gas concentrations and microclimate parameters were measured using the G-eko 2.0, a self-engineered multi-sensor prototype described in Becciolini et al. (2023). The module, measuring $120 \times 100 \times 67$ mm and weighing 0.75 kg, was designed for environmental monitoring. G-eko 2.0 included sensors for measuring CO_2 , NH_3 , CH_4 , $\text{PM}_{2.5}$ and PM_{10} together with atmospheric pressure, temperature, and humidity.

CO_2 was measured using a Non-Dispersive InfraRed (NDIR) sensor, which also integrated temperature and humidity sensors within the same module. The $\text{CO}_2/\text{T}/\text{RH}$ module had dimensions of $23 \times 35 \times 7$ mm and a weight of 3.4 g. The technical specifications of the sensing module are detailed in Table 1.

Table 1. Specifications of the CMOSens sensing module.

Target parameter	Measurement unit	Measuring range	Accuracy
CO_2	ppm	$0 \div 5,000$	± 30
Temperature	Celsius degree	$-40 \div +70$	$\pm (0.4 + 0.023 \cdot (T - 25))$
Relative humidity	%	$0 \div 100$	± 2

The NDIR sensor was selected due to its documented suitability for CO_2 measurements, attributed to its strong and distinct absorption peak in the mid-infrared region, and the absence of common limitations associated with low-cost electrochemical sensors, such as inter-device variability and susceptibility to poisoning by silicone vapours (Burgués & Marco, 2020). Given the documented influence of temperature on the accuracy of NDIR sensors (Martin et al. 2017), the sensor integrated into the first prototype of the multi-sensor system (G-eko 1.0) was calibrated by an independent laboratory under controlled temperature and humidity conditions (Becciolini et al., 2024a). To improve sensor performance across variable environments, an additional calibration was conducted on the G-eko 2.0 prototype under different temperature and humidity

regimes, enabling the development of correction equations applicable to diverse environmental conditions (Becciolini et al., 2024b).

The anemometer (WT87B, Shenzhen Wintact Electronics Co.,Ltd., China) used in this study is shown in Fig. 2. This device measured wind speed, temperature and humidity.



Figure 2. Anemometer (WT87B, Shenzhen Wintact Electronics Co.,Ltd., China).

Through a dedicated mobile application, the sensor can connect to a smartphone, enabling real-time data recording and storage. The technical specifications of the sensor are provided in Table 2.

Table 2. Specifications of the WT87B anemometer.

Target parameter	Measurement unit	Measuring range	Accuracy	Resolution
Wind speed	$\text{m} \cdot \text{s}^{-1}$	$0 \div 30$	$\pm 5\% \pm 0.1$	0.01
Temperature	Celsius degree	$-10 \div +45$	± 2	0.1
Relative humidity	%	$10 \div 90$	± 5	0.1

Software

Two software packages were used for the analyses: WindTrax (version 2.0.9.7, Thunder Beach Scientific) and QGIS (3.22.5 version, QGIS.org, 2023, QGIS Geographic Information System. QGIS Association. <http://www.qgis.org>).

WindTrax incorporates the WindTrax atmospheric dispersion model (Flesh & Wilson, 2005) and is designed to simulate the dispersion of target gases from both point and extended area emission sources. It includes three modeling approaches: the Atmospheric Surface Layer model, the forward Lagrangian Stochastic (fLS) model, and the backward Lagrangian Stochastic (bLS) model. The bLS model is suited for extended area sources and was used in this study to estimate the CO_2 emission rate (Q , $\text{g m}^{-2} \text{s}^{-1}$) from various sources, including two rows of pens in the main building, the manure storage, and the slurry storage tank located north of the livestock building (Fig. 1). To run the bLS model, WindTrax requires four parameters describing the surface layer wind model: surface roughness length (z_0 , cm), friction velocity (u_* , m/s), atmospheric stability or Monin–Obukhov length (L , m), and mean horizontal wind direction (θ , degrees) (Crenna, 2006a). Additionally, at least one gas concentration measurement per source is needed to estimate the unknown emission rates (Flesch et al., 1995). The model also requires a background concentration (C_{BG}), which can be entered directly if known or derived from an upwind concentration measurement. The software then solves a system of equations to calculate coefficients that relate emission rates to measured concentrations and vice versa (Crenna 2006a, Crenna 2006b).

QGIS, an open-source geographic information system (GIS) software, was used both before and after WindTrax simulations. Initially, it was employed to georeference the two sampling points and generate a scaled map for exporting into WindTrax (Fig. 1), ensuring accurate distance proportions within the software. After the simulations, QGIS was used to create raster images visualizing the atmospheric dispersion of CO_2 as modelled by WindTrax.

Experimental setup

The experiment was conducted during a single day in February 2023. First, the prevailing wind direction was determined. Two G-eko 2.0 units were then positioned at the height of 1 m from the ground, one upwind (sampling point 1) and one downwind (sampling point 2) of the emission sources (Fig. 1), aligned with the wind direction. The units were positioned away from obstacles (Flesch & Wilson, 2005; Crenna et al., 2008). The anemometer was placed upwind, near the G-eko 2.0 unit, at a height of 2 m above the ground. Both G-eko 2.0 units recorded CO₂ concentrations (ppm), atmospheric pressure (Pa), and temperature (°C) at a sampling rate of 5 seconds. Wind speed (m s⁻¹) was measured at a sampling rate of 1 second, while wind direction was estimated. Data collection was conducted continuously for 20 minutes. The choice of the sampling period is due to the fact that the 15-minute averaging period is the most commonly used to include homogeneous weather conditions in the analysis, as suggested by the software author (Crenna, 2006b) for capturing representative atmospheric conditions. Furthermore, this work was part of a larger field trial involving measurements at different heights above the ground, so only this data on a 20-minute sampling period was available. Another reason to choose a 20-minute sampling period is the variability of the wind direction, estimated during the field trial and considered with a constant value during the field trial.

Data processing

After the field trial, data were exported in .csv format. A verification process was conducted to ensure data quality, which included assessing whether the recorded values fell within expected ranges and evaluating the consistency between measurements obtained from the two G-eko 2.0 units.

All collected data were processed using Microsoft Excel to generate input files for WindTrax simulations. The following data processing description has not previously been applied, primarily due to the short duration of the field trial, which imposed specific methodological constraints. Other authors (Lin et al., 2015; Pedone et al., 2017) used data obtained by field trials of longer duration, so the sampling period suggested by the author of the software (Crenna, 2006b) was used. Measurements from the G-eko 2.0 units were averaged at 1-minute intervals, resulting in two datasets of 20 values. The same procedure was applied to wind data yielding, in total, three datasets of 20 measurements each. The scaled map of the farm, created in QGIS, was imported into WindTrax to design the extended area sources and accurately locate the sampling points used during the field trial (Fig. 1). The area sources are represented in lime green and the orange arrow represents wind direction. WindTrax requires the specification of sampling points locations and corresponding datasets; therefore, each point was linked to the corresponding dataset (Fig. 1).

Each set of paired measurements of CO₂ concentration collected upwind (C1, N=20) and downwind (C2, N=20), along with wind data (N=20) was entered into the model to generate 20 simulations, each estimating an emission rate (Q , g m⁻² s⁻¹). Regarding model specifications, the surface roughness length (z_0) was set to 2.3 to represent the short grass surrounding the livestock farm, which is bordered by arable land. The friction velocity u^* was calculated by the model based on wind speed measurements recorded by the anemometer during the field trial. Atmospheric stability was classified as B according to the Pasquill–Gifford stability classes considering wind speeds below 2 m s⁻¹ and weak daytime solar radiation. The mean horizontal wind direction (θ) was determined using topographic methods based on GPS coordinates of the two sampling points aligned with the wind direction during the field trial, yielding a value of approximately 119.3°. The number of particles in the simulation was set to 50,000.

The 20 calculated Q values were converted into a dataset obtained by averaging the collected data over 5-minute intervals. These data were used to run additional 16 simulations to model CO₂ dispersion over a 270 m × 230 m area. The area was defined based on emission sources and wind direction to represent CO₂ concentrations at a height of 2 m above the ground. The simulation parameters remained the same as previously stated, and the number of particles was set to 5,000 (N=4 simulations), 10,000 (N=4), 30,000 (N=4), and 50,000 (N=4). Each simulation generated a raster image consisting of 10,000 pixels, with each pixel representing an estimated CO₂ concentration (ppm). These raster images were georeferenced in QGIS by constructing a rectangle of matching dimensions. This kind of analysis was not used by any of the authors of the analysed

literature, but it helps to make the measuring system reliable. The method of implementation for obtaining atmospheric dispersions was, however, in accordance with the software manual (Crenna 2006a; Crenna 2006b).

A similar approach was applied to the calculation of vertical profile plots at the sampling point 2. Using the calculated Q values, 16 vertical profile plots of estimated CO₂ concentrations were modelled. The simulation parameters were the same as those used for the CO₂ dispersion model. Each vertical profile plot provided estimated CO₂ concentrations at heights ranging from 1 to 10 m above the ground, at an interval of 1 m. Both the CO₂ horizontal dispersion and vertical profile estimates were generated along with their respective confidence intervals. R (R Core Team, 2024, version 4.4.0) and Rstudio (Rstudio Team, 2024, version 2024.4.1.748) were used for data analysis by selecting the library function ggplot2 (Wickham, 2016) for creating the vertical profile plots.

RESULTS AND DISCUSSION

The input data were averaged over five minutes and subsequently used for the WindTrax simulations. This averaging period was selected because of the short sampling period adopted during the field trial, despite WindTrax's potential sensitivity to short-term wind speed and direction variability. Table 3 shows measurements obtained from the G-eko 2.0 units at sampling point 1 (upwind) and 2 (downwind), and the anemometer, which were employed to calculate CO₂ emission rates (Table 4). The highest CO₂ emission rate was obtained for the fourth step, which corresponds to the period with the maximum detected wind speeds.

It should be considered that for all the four steps the atmospheric stability was considered class B (unstable), hence the simulations calculating emission rates are influenced by the wind gusts. For example, observing Tables 3 and 4, step 4 is characterised by maximum wind speed and a consequent calculation of a notable peak in CO₂ emission rate, compared to the other steps. In order to understand the influence of the wind on measured concentrations, i.e. whether the values of detected concentration depends on a real increase of emission rates or on increased particle transport due to increased wind speed, a recent study (Mousavi et al., 2025) assessed the influence of meteorological variables on measured CO₂ concentrations in the Middle East. The correlation between wind speed and CO₂ concentrations is inverse significantly in colder months. The paper explains that higher wind speeds lead to a reduction in detected concentrations through the dispersion and dilution processes. Consistently, in this case, the maximum detected concentrations are not reached upwind and downwind with the maximum wind speed (Table 4), thus it is possible to state a greater dispersion of CO₂ at higher wind speeds. In this study, input data were averaged over 5 minutes and not over an interval of 15-30, as recommended by the author of the software. Shorter averaging periods are more subject to wind gusts and in conditions of atmospheric instability, indeed some studies (Carozzi et al., 2013; Tagliaferri et al., 2023) have highlighted a worse level of accuracy in the calculation of emission rates, underestimating them.

Simulations were conducted for all the four steps, covering the entire sampling period. Different numbers of particles (5,000, 10,000, 30,000, and 50,000) were tested, yielding various outputs including concentration maps, confidence interval maps, and vertical profile plots.

Table 3. Input data averaged over five minutes detected by the two G-eko 2.0 units and the anemometer at the sampling point 1 (upwind) and 2 (downwind).

step (run nr.)	time (CET)	Upwind sampling point					Downwind sampling point			
		temp. (°C)	atm. pressure (Pa)	CO ₂ (ppm)	wind speed (m s ⁻¹)	wind direction (°)	temp. (°C)	atm. pressure (Pa)	CO ₂ (ppm)	
1	10:40	10.47	99,568	450.14	0.73	119.3	9.59	99,636	637.6	
2	10:45	10.55	99,561	453.98	0.72	119.3	9.47	99,630	635.8	8
3	10:50	10.39	99,555	448.51	0.57	119.3	9.43	99,627	629.1	3
									620	0

4	10:55	10.43	99,557	442.26	1.04	119.3	9.58	99,624	621.08
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Table 4. CO₂ emission rates averaged over five minutes calculated using the WindTrax model (50,000 particles).

Step (run nr.)	Time (CET)	Q (g m ⁻² s ⁻¹)
1	10:40	0.19902
2	10:45	0.19054
3	10:50	0.14932
4	10:55	0.26958

The concentration maps in Fig. 3 were generated for step nr. 1 using different numbers of particles, and indicate the simulated CO₂ concentrations at the height of 2 m above the ground. A uniform colour scale was applied to all four concentration maps, using ten value classes ranging from a minimum of 440 ppm to a maximum of 1,250 ppm, with intervals of 90 ppm, to create horizontal contour plots. Additionally, Fig. 4 shows the concentration map generated for step nr. 1 using 50,000 particles at the height of 2 m above the ground, also representing the emission sources.

Table 5 shows the results of the concentration maps corresponding to the four steps in terms of maximum and minimum values of the 10,000 estimated concentrations, while Fig. 5 shows the results of the concentration maps corresponding to the four steps in terms of median values. The median was selected to summarize the distribution due to the high number of minimum concentration values located in the periphery of the raster files for each step. Reporting mean values with standard deviation would have provided a misleading interpretation of the results of the simulations. A general trend was noted across all the steps: the median concentration values tend to stabilise with a high number of particles (30,000 and 50,000).

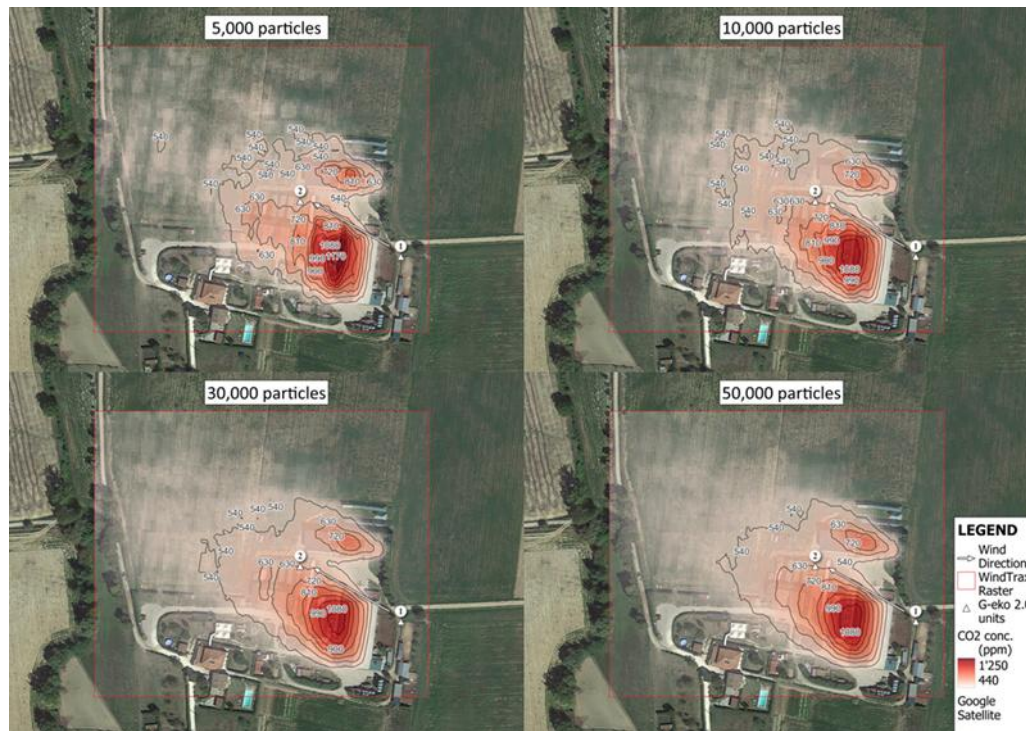


Figure 3. Concentration maps for estimated CO₂ horizontal dispersion at 2 m above ground level modeled with WindTrax simulations using CO₂ measurements averaged at 5-minute intervals. From top left, horizontal contour plots (10 classes separated by 90-ppm intervals) for models computed with 5,000, 10,000, 30,000, and 50,000 particles.

Minimum concentration values remained consistent with the measured mean background concentration at the sampling point 1 up to 30,000 particles, then it decreased by a few decimals for 50,000 particles.

Inside the distribution of calculated CO₂ values, the median value is subject to an upward shift to 30,000 particles and then to a downward shift with 50,000 particles for all the steps.

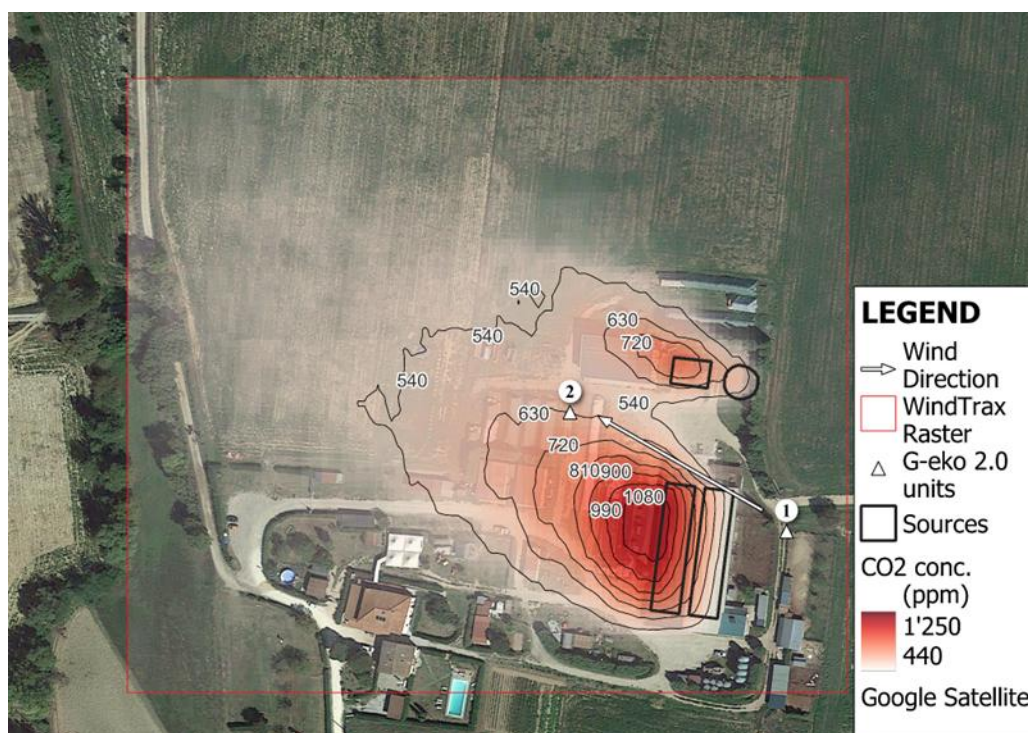


Figure 4. Concentration maps for estimated CO₂ horizontal dispersion at 2 m above ground level modeled with WindTrax simulations using CO₂ measurements averaged at 5-minute intervals. Horizontal contour plots (10 classes separated by 90-ppm intervals) for models computed with 50,000 particles. The sources are shown, as well.

Table 5. Simulated CO₂ concentrations (maximum and minimum values) at 2 m above the ground level using CO₂ and environmental parameter (temperature and pressure) measurements averaged at 5-minutes intervals, using 5,000, 10,000, 30,000, and 50,000 particles for all the four steps.

Step		Particles number			
(run nr.)		5,000	10,000	30,000	50,000
1	Max	1,250.00	1,140.00	1,130.00	1,140.00
	Min	450.14	450.14	450.14	450.05
2	Max	1,230.00	1,121.46	1,110.00	1,130.00
	Min	453.98	453.98	453.98	453.89
3	Max	1,210.00	1,110.00	1,100.00	1,120.00
	Min	448.51	448.51	448.51	448.42
4	Max	1,200.00	1,100.00	1,090.00	1,100.00
	Min	442.26	442.26	442.26	442.17

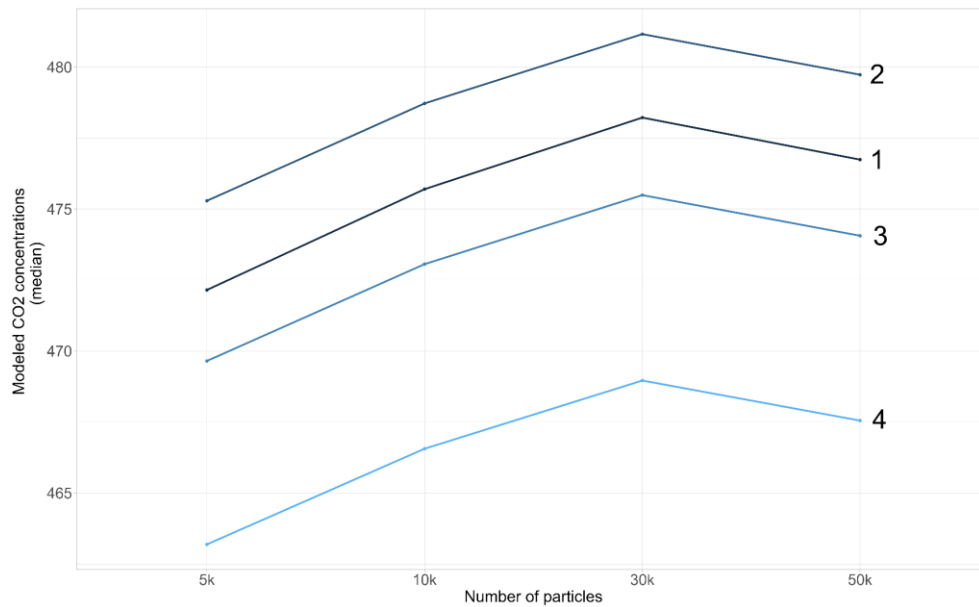


Figure 5. Median modeled CO₂ concentrations of the 16 concentration maps, increasing the number of particles in WindTrax for each step (1-4).

Extending the analysis to the calculated confidence intervals of the estimated CO₂ concentrations, horizontal dispersion maps by WindTrax calculated for the first step are shown in Fig. 6. The same scale of values was used for all the four confidence interval maps, by selecting values from a minimum value of 0 ppm to a maximum value of 290 ppm. It can be observed that by increasing the number of particles included in the simulations, the calculated confidence intervals decreased. Furthermore, as the distance from the source along wind direction increased, the confidence interval decreased.

Pedone et al. (2017) applied the WindTrax model using 2.000, 7.000, and 50.000 particles, obtaining a variability of 20% in CO₂ emission rate. Other authors (Shonkwiler & Ham, 2018; Shaw et al., 2020; Hrad et al., 2021) used the WindTrax model by selecting a number of particles greater than 50,000, mainly for reducing the uncertainty of the model. Studies that selected 50,000 particles adopted smaller distances of sensors from the source i.e. 100-300 m (Hrad et al., 2021), 30 m (Riddick et al., 2022), 0.5 m (Ricco et al., 2021). It should be considered that in studies where sensors are placed close to the source, their number tends to increase. In this study, G-eko units were positioned at 20-40 m from the closer emission source i.e. the bedding inside the livestock building and the manure storage. Hrad et al. (2021) stated that 50,000 particles is the default value to shorten simulation.

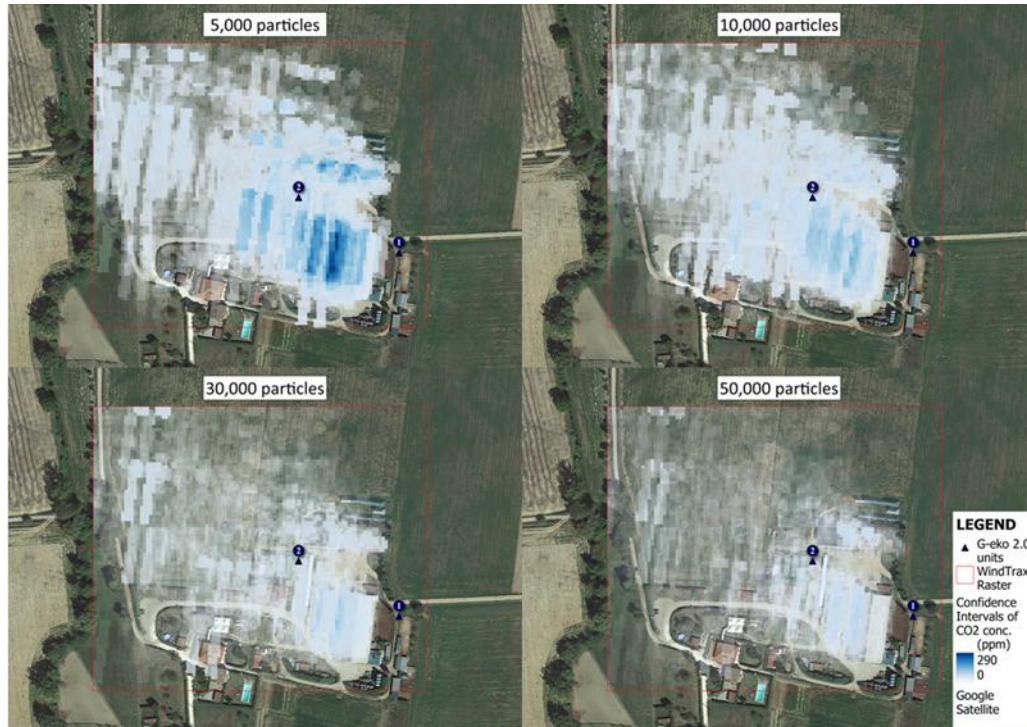


Figure 6. Confidence interval (CI) maps for estimated CO₂ horizontal dispersion at 2 m above ground level modelled with WindTrax simulation using CO₂ measurements averaged at 5-minute intervals. From top left, CI for models computed with 5,000, 10,000, 30,000, and 50,000 particles.

Therefore, simultaneous observation of the concentration maps and the confidence interval maps for the first step (Fig. 3 and 6) showed that the highest values of CO₂ concentration, represented with darker areas, have wider confidence intervals because they are close to the sources. On the other hand, the lowest values represented with lighter areas have smaller confidence intervals because they are further away from the sources. From these considerations, despite the simplicity of applying the bLS approach, the available sensors, type, and positioning have a great impact on atmospheric dispersion simulations.

Table 6 also shows results of the other confidence interval maps, referring to the other steps in terms of maximum and minimum confidence intervals, while Fig. 7 also shows results of the other confidence interval maps, referring to the other steps in terms of median confidence intervals.

For the other steps as well, there is a reduction in the calculated confidence intervals by increasing the number of particles.

Table 6. Simulated CO₂ concentration confidence intervals (maximum and minimum values) at 2 m above the ground level using CO₂ and environmental parameter (temperature and pressure) measurements averaged at 5–minutes intervals, using 5,000, 10,000, 30,000, and 50,000 particles for all the four steps.

Step		Particles number			
(run nr.)		5,000	10,000	30,000	50,000
1	Max	285.77	144.77	117.00	88.81
	Min	0.00	0.00	0.00	0.16
2	Max	276.62	140.13	113.26	85.96
	Min	0.00	0.00	0.00	0.15
3	Max	274.50	139.06	112.39	85.31
	Min	0.00	0.00	0.00	0.15
4	Max	271.71	137.64	111.25	84.44
	Min	0.00	0.00	0.00	0.15

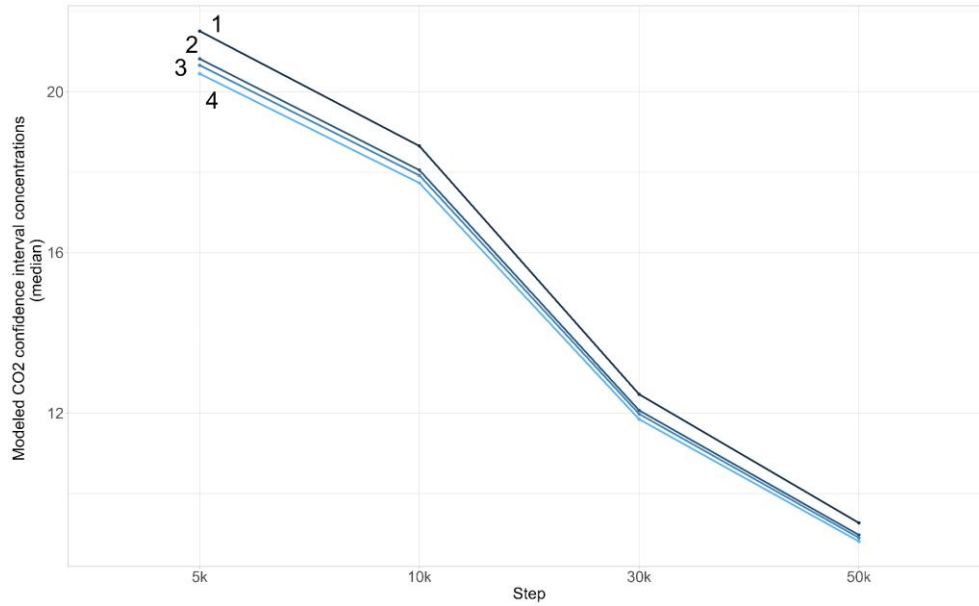


Figure 7. Median modeled CO₂ confidence interval concentrations of the 16 confidence interval concentration maps, increasing the number of particles in WindTrax for each step (1-4).

Additionally, vertical profile plots were calculated with the WindTrax software at the sampling point 2 for observing estimated CO₂ concentrations $\pm$ confidence intervals with several numbers of particles at different heights above the ground, i.e. from 0 to 10 m with 1 m intervals. Fig. 8 shows narrower CO₂ confidence intervals as the number of particles increases. Therefore, what has been observed horizontally with concentration maps and confidence interval maps also occurs vertically with vertical profile plots. Moreover, a better-defined vertical trend in concentrations is observed as the number of particles increases. Again, it is observed that a large number of particles is necessary for a better accuracy in estimating concentrations.

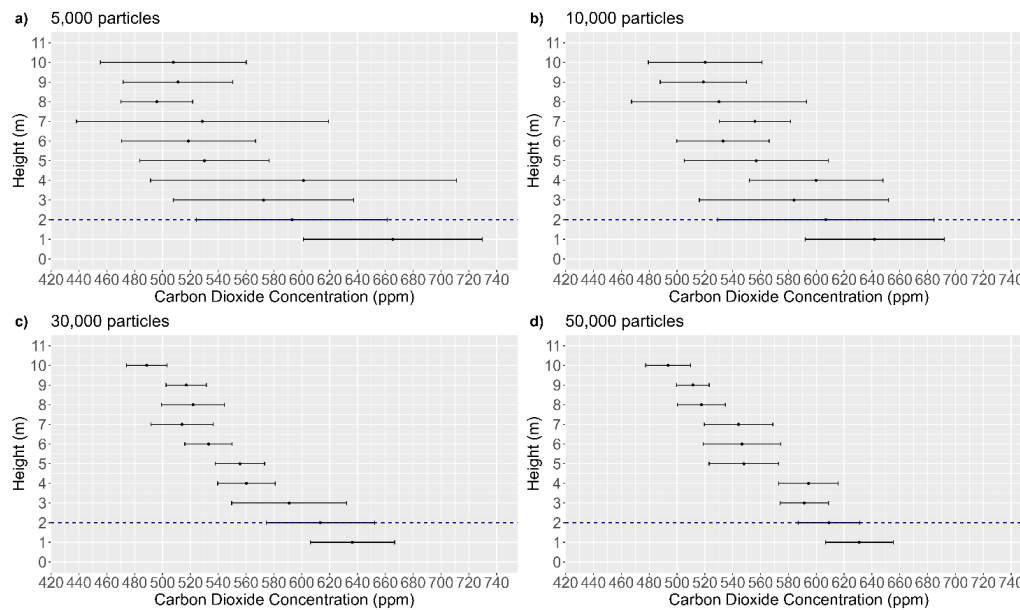


Figure 8. Vertical profile plots of estimated CO₂ concentration $\pm$ confidence intervals in the sampling point 2 of the G-eko 2.0. Simulations were run using 5,000 (a), 10,000 (b), 30,000 (c), and 50,000 (d) particles. Estimations are from heights equal to 1 m a.g.l. to 10 m a.g.l. The dotted blue line indicates the height at which simulations of the horizontal dispersion were carried out.

CONCLUSIONS

This study provided relevant insights into the performance of a Lagrangian atmospheric dispersion model for estimating CO₂ emissions from livestock facilities and mapping their dispersion in the surrounding environment.

The results highlight the importance of adapting the measurement protocol to the specific emission sources under investigation. In this case, overall CO₂ emission rates were estimated for three distinct sources: the livestock building, the manure pit, and the slurry tank. To improve source-specific estimates, it is recommended to deploy at least one sensing unit per emission source, along with one additional unit for background concentration measurements. All sensors should be positioned at appropriate distances within a 1 km radius from the sources, in accordance with model guidelines.

With regard to meteorological data processing, the choice of averaging intervals proved critical. Short averaging periods (e.g., 5 minutes) are more susceptible to wind gusts, potentially reducing the reliability of emission rate estimates, particularly under unstable atmospheric conditions. Simulations revealed that increasing the number of particles improved result stability and reduced the width of confidence intervals. Specifically, median concentration values from simulations of horizontal dispersion increased with higher particle counts up to 30,000. Confidence intervals also decreased with greater downwind distance and with increasing number of particles. A particle number of at least 50,000 is recommended to ensure robust model outputs, despite the increased computational demand.

The study also identified several limitations. The limited number of sensing units prevented the estimation of emission rates for individual sources, restricting the analysis of their relative contributions to overall CO₂ emissions. In addition, the proximity of the downwind sensor to the emission sources may have influenced concentration measurements due to local turbulence effects caused by nearby structures. The short duration of the measurement period (20 minutes) and the selected averaging time (5 minutes) may have amplified the influence of wind fluctuations on emission estimates. Furthermore, the use of an anemometer capable of measuring both wind speed and direction—preferably in 2D or 3D—would have improved the characterization of local atmospheric conditions.

Despite these limitations, the WindTrax protocol proved practical and applicable within a livestock farming context, provided that careful attention is paid to sensor placement. Future studies should incorporate a greater number of sensing units and extended monitoring periods to capture diurnal, seasonal, and annual variability in emission rates. Such efforts are essential to improve the bottom-up assessment of greenhouse gas emissions from livestock farming and to support the development of effective mitigation strategies.

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4.2. Studio 2



Article

A UAV-Based System for Validating a Backward Lagrangian Stochastic Model in a Dairy Cattle Farm

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Abstract

This study characterizes a compost-bedded pack barn of a dairy cattle farm in terms of CO₂ emissions approximately 20 min after tilling under stable atmospheric conditions. Emission fluxes were calculated with the bLS model WindTrax, assessing modeled CO₂ concentrations at two altitudes (5.0 m and 10.0 m ABGL) by comparing them with those measured by a UAV-based system at the same two altitudes. The UAV-based system was equipped with a low-cost self-engineered MSP (multi-sensor platform) containing an NDIR sensor for measuring concentrations and detecting environmental conditions, which were measured both by MSPs and commercial sensors. The input data were provided by the same sensors positioned on the ground (1.5 m ABGL), upwind and downwind with respect to the emission source. A sensitivity analysis of atmospheric stability in the bLS model yielded differences between median calculated emission fluxes for stable and unstable conditions from −0.020 to 0.034 g · m^{−2} · s^{−1}. Mean percentage errors gave overestimates of 8–39% and 13–21% 5.0 m and 10.0 m ABGL. The RMSE also indicated overestimates ranging from 44 to 275 ppm. This is the first study to validate concentrations calculated by a bLS model at two altitudes by using a UAV-based system on a compost-bedded pack barn.

Keywords: drone, CO₂ emissions, GHG, NDIR, compost barn, atmospheric dispersion, WindTrax.

1. Introduction

The most recent published projections by the UN (United Nations) on global population growth show increases to 8.5 billion people for the year 2030 and to 9.7 billion people for the year 2050 [1]. Therefore, the agri-food industry should be efficient and sustainable in food and beverage production without harming the environment, people, or animals. In the year 2015, the UN approved Agenda 2030, where part of the SDGs (Sustainable Development Goals) is focused on improving air quality and taking action against climate change [2]. The WHO has estimated 6.7 million premature deaths per year caused by ambient outdoor and household air pollution [3]. In addition, pollutants affect climate change, since some of these are classified as GHGs (greenhouse gases), contributing to the greenhouse effect with different radiative impacts. At the European level, Directive 2008/50/EC aims to achieve cleaner air in Europe, which has been transposed to the national level, for example, by Italy with Legislative Decree 2010/155. Thus, in Italy, a pollutant-monitoring network managed by regional environmental protection agencies has been set up.

Agriculture is among the most impactful production sectors, and one of the most impactful agricultural activities in terms of atmospheric emissions is livestock farming. Global net anthropogenic GHG emissions for the year 2015 were estimated by [4] (p. 11) and reached a value of about 55 Gt CO₂ eq. year⁻¹. For the same year, the GLEAM (Global Livestock Environmental Assessment Model) estimated emissions from the livestock sector, which reached a value of 6.2 Gt CO₂ eq. year⁻¹, so livestock emissions represent 12% of global emissions. In livestock farming, cattle species contribute to sector emissions of 62%, i.e., 3.8 Gt CO₂ eq. year⁻¹. Within cattle farming, meat and milk production reach 40% (2.5 Gt CO₂ eq. year⁻¹) and 21% (1.3 Gt CO₂ eq. year⁻¹) of total sector emissions [5]. According to the same database, for total cattle farming emissions, CO₂ emissions represent 26% (1.0 Gt CO₂ eq. year⁻¹). Furthermore, the other two major contributions to climate change from cattle farming are CH₄ (methane) and N₂O (nitrous oxide), at 61% (2.3 Gt CO₂ eq. year⁻¹) and 13% (0.5 Gt CO₂ eq. year⁻¹), respectively. Most of these emissions are attributed to enteric fermentation, manure management, and feed management. Another important source to assess is litter, because it is related to manure management and, consequently, hygiene and animal welfare.

UAVs (Unmanned Aerial Vehicles) are used for environmental monitoring, combining different solutions for selected types of analysis and sensor technologies. UAVs for environmental monitoring are used in several sectors with different applications: infrastructure [6–8], gas and oil [9–11], urban environments [12–19], wastewater treatment [20], research [21–26], landfills [27], industry [28], wildfires [29], vulcanology [30,31], and agriculture [32,33]. The common factor in these publications is the use of compact and lightweight sensors mounted on a UAV to comply with the maximum payload for the appropriate consumption and duration of UAV batteries. These sensors should measure gaseous and/or dusty concentrations and environmental conditions with the maximum atmospheric representativeness.

Most of the studies in the current literature use rotary-wing UAVs for environmental monitoring because of their high maneuverability, but the downwash problem has been highlighted, i.e., the downward turbulence generated by the rotors, which affects the sensor positioning on the aircraft used to maintain atmosphere representativeness. When determining where to place sensors above the UAV body through a computational fluid dynamics (CFD) analysis, [7] (p. 21) stated that the optimal height above the drone body for sensor positioning is 90 cm, while [32] (p. 4) connected a long sampling tube to the concentration sensor to avoid air turbulence from the UAV blades, and [19] (p. 4) positioned the sampling inlet 60 cm above the drone rotors. On the other hand, [23] (p. 5) placed sensors under the UAV body, but in this case,

the measuring chamber had a downwash flow spoiler, reducing flow velocity and redirecting flow trajectory through concentration sensors. Sensors were positioned at the center of a UAV by [8] (p. 3) to mitigate the impact of propellers, based on the CFD analysis [34] of a quadrotor. Sensors were also placed under the UAV body by [25] (p. 483), but at the center of the UAV body itself. To justify the operational choices in the positioning of sensors in these studies, two CFD analyses have been reported, one referring to a hexacopter [35] and the other to a quadcopter [36]. Additionally, in a recent patent review [37], there is no explanation of a system or mechanism to deal with the downwash problem.

Moreover, [38] (p. 4) stated that stationary monitoring with a measurement station on the ground provides data on emission variability at a single point, considering a low number of sources, limited to a specific place. Stationary monitoring alone cannot investigate the vertical variability in gaseous and dusty concentrations and environmental parameters. Instead, environmental monitoring with UAVs provides studies with a better spatio-temporal resolution, despite the analysis being limited by battery life, which is related to payload and the downwash problem. Many studies have focused on the characterization of the vertical profiles of atmospheric gaseous [8,16] or dusty [7,12,19,39] concentrations to understand transport mechanisms, complementing measurements of environmental conditions, while another work [17] determined the vertical profiles of both gaseous and dusty concentrations. Aerosol properties can vary significantly with altitude due to changes in temperature, humidity, atmospheric stability, solar radiation, and wind patterns [39] (p. 2); thus, gaseous and dusty concentrations are affected by meteorological conditions and turbulent mixing processes. For this reason, by studying the vertical distribution of pollutants, the accuracy of modeling atmospheric dispersion can be enhanced.

Previous studies flew UAV-based systems at several altitudes for obtaining vertical profiles of pollutants. The range of altitudes reached was from 15 m up to a maximum value of 2500 m ABGL (above ground level) [7,8,12,16,19,23,39]. The most widely detected pollutants included both gaseous species, such as VOCs, CO, CO₂, CH₄, NO₂, O₃, and SO₂ [8,16,23], and particulate matter, including LDSA (lung-deposited surface area), ultrafine particles, PM₁, PM_{2.5}, PM₁₀, and black carbon [7,12,19,39]. The sensors used to detect concentrations of gaseous pollutants included gas chromatographs, NDIR (non-dispersive infrared), and electrochemical methods, while particulate matter was measured using instruments such as multi-metric nanoparticle detectors, optical particle counters, diffusion size classifiers, portable microaethalometers, and condensation particle counters.

Regarding the methodologies used to analyze the detected concentrations, atmospheric dispersion models, particularly inverse dispersion modeling, are widely applied. Four CH₄ leakage monitoring techniques were assessed in the USA by using a Gaussian plume model [9] (p. 4546). A Gaussian plume model was also employed to calculate CH₄ leakage rates of undocumented orphan wells in the USA, using a fixed-wing UAV [11] (p. 19590). Particulate matter emission factors and emission fluxes from a feedlot and a dairy cattle farm in Texas, USA, were estimated with a model called Aermid [32] (p. 5). The Hysplit (Hybrid Single-Particle Lagrangian Integrated Trajectory) model was applied for performing trajectory directional analysis [16] (p. 5). WRF (weather research and forecasting) and CFD models were used in [14] (p. 2).

An NDIR sensor (Carbon3060S, Nanjing ZTweather Technology Co., Nanjing, China) was used in [20] (p. 4) and [23] to detect CO₂. NDIR sensors are considered in a review by [38] (p. 2), along with other sensor types, such as amperometric, metal oxide chemiresistive, and photoionization detectors. These sensors showed high selectivity, sensitivity, and stability; fast response and recovery time; and low susceptibility to environmental variations. In the same review, four studies employing UAV-based systems equipped with NDIR sensors were reported

[28–31]. Moreover, a strong correlation between UAV-based (NDIR) and ground-based (PiCam UV camera) CO₂ measurements was found [31] (p. 743).

Among the techniques for gaseous analysis with UAV-based systems, this study selected an atmospheric dispersion model, i.e., WindTrax. Through an inverse modeling approach, WindTrax [40], a short-range bLS (backward Lagrangian Stochastic) model [41], generates many particles and follows them along their trajectories from sensors measuring gas concentrations back to the emission source for calculating emission fluxes. A graphical interface of the model is available in the associated software [42]. WindTrax is widely cited in the literature, especially in the agricultural sector. Most studies applying WindTrax v2.0 in agriculture focus on gas losses from various agricultural production sources, including fertilized soil management [43–46], anaerobic digestion [47,48], and livestock facilities, especially in relation to manure management [49–52].

CO₂ was monitored in several studies [53,54], as it is classified as GHG. This paper could contribute to the development of a universal emission measurement protocol for updating “top-down” inventories and verifying “bottom-up” inventories [46]. The research gap identified in the current literature is the lack of assessment of the bLS model’s performance in predicting concentrations at the same altitude as UAV missions. Therefore, this study provides a direct comparison between predicted and observed concentrations obtained with a UAV-based system. Additionally, concentrations and environmental parameters measured by a UAV-based system could potentially be used in the WindTrax software tool with the Truck object [55] to enhance the accuracy of simulations that traditionally rely solely on input from stationary monitoring. However, this kind of assessment is beyond the objective of this paper. Overall, this paper focuses on assessing the bLS model in calculating predicted concentrations at the same altitude as a UAV mission.

Generally, a compost-bedded pack barn is designed and managed as a large free walk resting area under aerobic conditions with frequent mixing (1–3 times/day) performed using a tractor equipped with a disk harrow, a rotating tooth harrow, a cutter, or a subsoil plough. Frequent tilling incorporates fresh excrement, brings oxygen into the substrate, and promotes water evaporation. To achieve the latter, high ventilation rates are required to maintain fresh material, ensuring the thermal welfare of cows. The temperature within the litter increases with depth due to the composting process, producing NH₃, CH₄, N₂O, and CO₂, which are released into the atmosphere during tractor tilling [56]. A review assessing different manure management technologies, including anaerobic digestion, flushing, mechanical scrapers, and vacuum systems, reported that composting exhibits emission peaks immediately after tilling, since the gases trapped among solid particles in the litter are released into the atmosphere [57] (pp. 10–11). Over time, emissions tend to stabilize [58]; however, animal walking may compact the litter, reducing its porosity and consequently oxygen exchange. This promotes the formation of anaerobic sites, creating favorable conditions for methanogenic microorganisms.

The composting process has also been studied at laboratory scale with a static chamber, showing high GHG and NH₃ emissions as temperature increases [59] (pp. 791–793). The advantages of using the compost-bedded pack barn include low-cost management, animal welfare, and high quality of milk production in dairy cattle farms. The highest NH₃ and CH₄ emissions were measured in Spain using gas chromatography before and during tilling in the summer season [60] (pp. 2–11). Additionally, it was reported that the rapid release of CO₂ increases the pH of the substrate, tilting the balance of NH₃ ↔ NH₄⁺ toward N volatilization. This aspect affects the value of the compost-bedded pack barn material at the end of its life, which can be used as a fertilizer for cultivated fields.

CH₄ and CO₂ emissions were measured in 75 points of a resting area with a compost-bedded pack barn on a Brazilian dairy cattle farm, and spatial distribution maps were built using ordinary Kriging interpolation [61] (pp. 112–118). Animal thermal comfort was assessed using the THI,

considering that mechanical ventilation can positively influence the composting process while also maintaining the THI below critical threshold values. Furthermore, CO₂ is a dense gas that tends to accumulate in the lowest part of the resting area, which has important implications for animal welfare when cows are lying on litter, especially in closed livestock buildings. Regarding the current literature on compost-bedded pack barns, a research gap is identified: none of the publications have employed both a UAV-based system and an atmospheric dispersion model. In this type of analysis, the distance from the emission source, potential obstacles, and the flight altitude could be affected by the roof of the livestock building, where turbulence may compromise atmospheric representativeness, especially when considering the downwash problem.

The objective of this paper is to validate an atmospheric dispersion model based on a bLS approach using a UAV-based system, detecting CO₂ concentrations with a self-engineered multi-sensor prototype. Two altitudes were investigated by mounting the MSP (multi-sensor platform) on a UAV at a Brazilian dairy cattle farm with a compost-bedded pack barn. Compared with stationary monitoring, this measurement protocol provides an affordable and autonomous emission measurement system to farmers that could potentially constitute a tool to obtain local top-down inventories, understanding emissions under different meteorological conditions throughout the year. UAV-based measurements can also complement stationary ground stations by detecting concentrations in the surrounding air.

In summary, the main research gaps addressed by this study are the assessment of bLS model performance in predicting concentrations at the same altitudes as a UAV mission, using a UAV-based system for environmental monitoring. This is the first study to validate concentrations predicted by a bLS model at two altitudes by using a UAV-based system for the environmental monitoring of CO₂ emissions in the atmosphere from a compost-bedded pack barn in a dairy cattle farm.

2. Materials and Methods

2.1. Animals and Housing

The dairy cattle farm where field trials were conducted is located southeast of Belo Horizonte, approximately 30 km from Lavras in the federal state of Minas Gerais, Brazil. The farm comprises two buildings oriented from east to west (Figure 1). The smaller building contains the milking parlor and the milk room, while the larger one is the livestock building, which contains a compost-bedded pack in the resting area and a solid concrete floor in the feed lane. The building, designed for housing 80 cows, is open on all four sides except for the section occupied by the milking facility. The resting area spans 972.0 m², providing 12.5 m² available per cow. The bedding consists of a sawdust–manure mixture and has a depth of 65.0 cm. The solid grooved concrete floor in the feed lane is cleaned twice a day manually. Litter tillage is performed by a tractor equipped with a tooth harrow (Figure 2a) twice a day, in the morning at 06:00 a.m. and in the evening at 06:00 p.m., while cows are all moved in the feed lane. Twelve fans are installed 4.50 m above the litter to provide forced ventilation and remove moisture from the compost. Each fan has a diameter of 1.1 m, three propellers, a rotation speed of 950 revolutions per minute, and an airflow of 23,000 m³ · h⁻¹. The forced ventilation direction, from northeast to southwest, is illustrated in Figure 2b in relation to the internal distribution of functional areas of the livestock building.

One of the assumptions of the WindTrax model is that the surface surrounding sources and sensors must be flat and free of obstructions [55] (p. 1). In this study, the soil around the livestock building had an average slope of approximately 20%. The slope was calculated from a DSM (Digital Surface Model) of the farm (Figure 3), obtained using the Zephyr v7.5 software tool [62] following UAV aero-photogrammetry operations. Altitude contours obtained with the QGIS

v3.22.5 software tool [63] indicate the ellipsoidal height (WGS 84) in the DSM in Figure 3. Although WindTrax cannot implement the topographic surface of the soil, the present study focuses on assessing model performance through concentration sensors within MSPs placed close to the compost barn source, where the surface is nearly flat. Concentrations predicted by the bLS model at distances beyond the MSP locations are expected to exhibit larger error, as described in [64] (pp. 10–11).

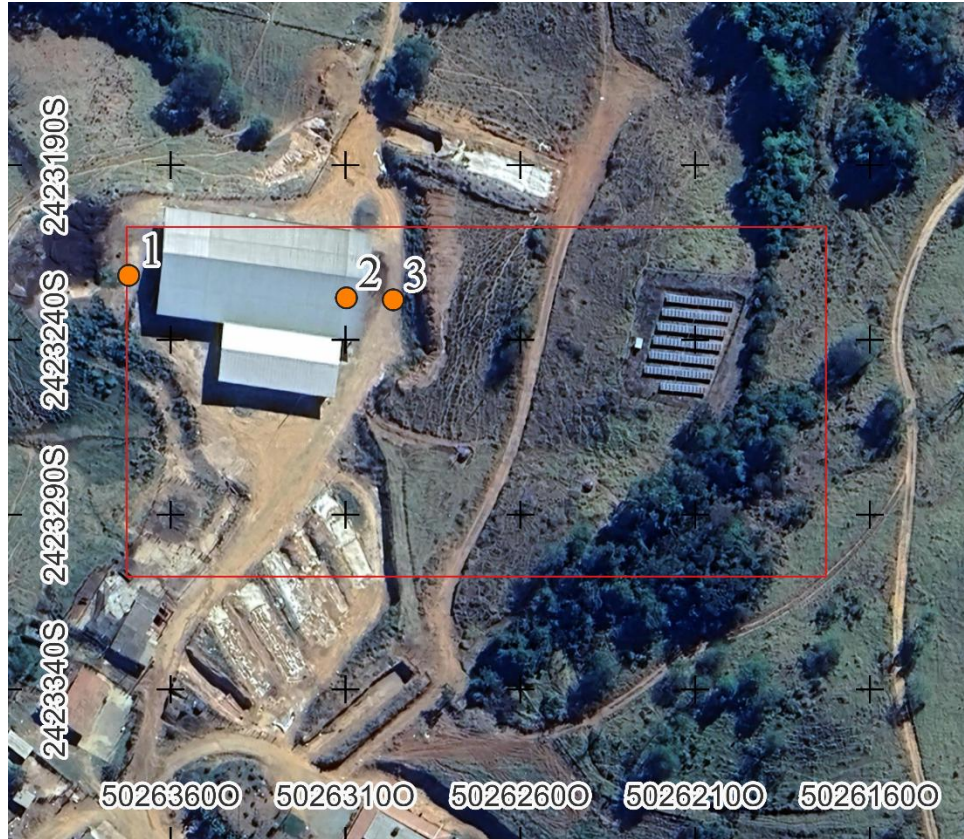


Figure 1. The dairy cattle farm where field trials were carried out, indicating the MSP positions (orange points); MSPs 1 and 2 were positioned on the ground, while MSP 3 was on the drone (WGS 84 reference system for longitude and latitude coordinates). The black marks (+) indicate distances of 50 meters in latitude and longitude.

(a)

(b)

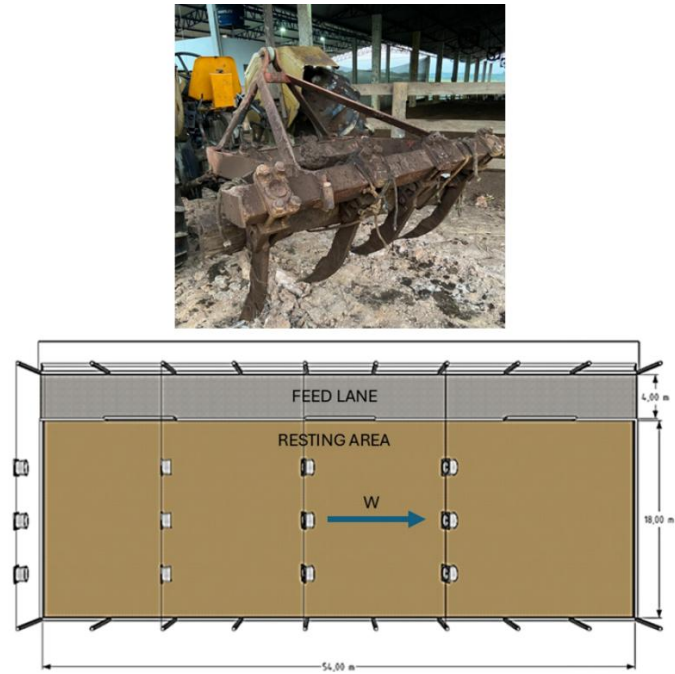


Figure 2. (a) The tooth harrow used for litter tilling; (b) functional area distribution inside the livestock building, where the forced ventilation direction is indicated by the blue arrow (from NW to SE).

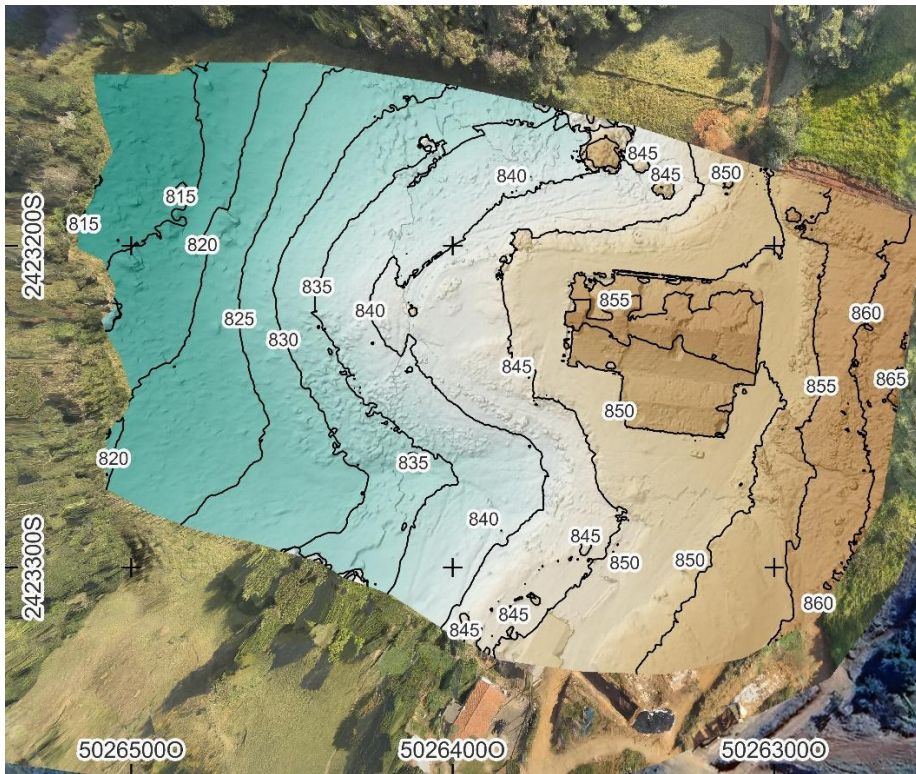


Figure 3. The DSM of the farm, including altitude contour lines above the ellipsoid level (WGS84 reference system for longitude and latitude coordinates). The color scale represents the altitude from 812 to 870 m. The black marks (+) indicate distances of 100 meters in latitude and longitude.

Concerning the experimental conditions, it is stated that all the activities described in this paper were approved by the Ethics Committee on Animal Use of the Dean of research/UFLA on 26 October 2022, Protocol No. 044/22.

2.2. Multi-Sensor Platforms

Three low-cost MSPs, with a sampling frequency of five seconds, were used during an eight-day field trial on the dairy cattle farm. The trial characterized CO₂ emissions from the compost-bedded pack barn by using the bLS model to assess its performance at two different heights above the ground: 5 and 10 m. Each MSP contains a CO₂ concentration sensor (ppm) and sensors for measuring environmental parameters, including temperature (Celsius degree), pressure (Pa), and relative humidity (%). The CO₂ concentration sensor (SCD30, Sensirion, Stäfa, Switzerland) integrated into the MSPs is an NDIR sensor. This type of sensor operates on the principle that certain gases absorb infrared light at specific wavelengths. CO₂ exhibits a strong absorption peak in the mid-infrared region at approximately at 4.26 μm wavelength. Within the sensor, the infrared light passes through a measurement cell, where the amount of light absorbed by CO₂ and the transmitted light are measured to calculate CO₂ concentrations.

Temperature and relative humidity data are also provided by the CO₂ sensor, thanks to an integrated module. The relatively low height of the module allows for easy integration for assembling sensors in an MSP, enabling the accurate and stable monitoring of CO₂ in the air, temperature, and relative humidity. Furthermore, MSPs contain an absolute barometric pressure sensor (BMP280, Bosch Sensortec GmbH, Kusterdingen, Germany), which is compact and has low power consumption. Table 1 reports measuring range and accuracy for each detected parameter. The MSP solution is described in [65] (pp. 1051–1052), and the results of calibration tests in a controlled environment are provided in [66] (p. 931), particularly for the CO₂ sensor ($y = 67.517 + 0.855 \cdot x$, $R^2 = 1$, $p\text{-value} < 0.001$). While MSP weight is indicated as 1.20 kg, an upgraded version was used for field trials, maintaining the same CO₂ sensor, removing some sensors and components, and reaching a weight of 0.70 kg. For the field trials, one MSP was mounted on a UAV (M350 RTK, DJI Sciences and Technologies Ltd., Beijing, China). This drone was selected for its large payload capacity, reaching 2.70 kg, sufficient to carry the sensors and ensure the stability of the UAV-based system. As noted in the literature, take-off weight is a critical parameter in UAV-based system environmental monitoring, as it influences battery life and, consequently, the sampling period duration. For this UAV-based system, a payload weight of 0.93 kg was reached, including a 3D-printed support to attach the MSP, a power bank to supply the MSP, and a Temperature/RH Data Logger (Hobo MX2301A, Onset Computer, Bourne, MA, USA), as shown in Figure 4. With this configuration, a maximum sampling period of 30 min per field trial was possible, keeping the UAV in the same position at two altitudes across several sampling days. As shown in Figure 4, the MSP was installed on top of the UAV body, with the measurement chamber inlet being 30 cm above the horizontal plane of propellers to minimize the effect of turbulence caused by downwash on concentration measurements.

Table 1. Measuring range and accuracy of detected parameters by sensors inside MSPs and by the two types of anemometers (U—ultrasonic; HW—hotwire).

Parameter	Sensors	Measuring Range	Accuracy
Carbon dioxide	MSP	0 ÷ 5.000 ppm	±30 ppm
Temperature	MSP	−40 ÷ 70 °C	± (0.4 °C + 0.023 × (T[°C] − 25 °C))
Relative humidity	MSP	0 ÷ 100% RH	±3% RH
Pressure	MSP	300 ÷ 1.100 hPa	±1 hPa
Wind speed	U	1 ÷ 25 m · s ^{−1}	± 0.3 m · s ^{−1} at 10 m · s ^{−1}
Wind direction	U	0 ÷ 359 °N	±1 °N

Temperature	Temperature/RH Data Logger	$-40 \div 70\text{ }^{\circ}\text{C}$	$\pm 0.2\text{ }^{\circ}\text{C}$ from 0 to $70\text{ }^{\circ}\text{C}$
Relative humidity	Temperature/RH Data Logger	$0 \div 100\%\text{ RH}$	$\pm 3\%\text{ RH}$



Figure 4. The UAV-based system and its parts: 1. the UAV; 2. the 3D-printed support; 3. the MSP; 4. the power bank; 5. the Temperature/RH Data Logger.

Despite efforts for positioning the MSP on the UAV in one of the areas least affected by downwash, following solutions in the literature [7,8,19,23,25,32], it should be noted that UAV-based measurements cannot be considered entirely free from downwash effects. Therefore, caution is advised when interpreting the results reported in this paper, as the UAV-based system can be further improved. Field trials, including those reported here, can provide valuable insights for optimizing such measurements. In this context, data collected using the UAV-based system can serve as input for atmospheric dispersion models.

As shown in Table 1, an ultrasonic anemometer (Ultrasonic Portable Mini Wind Meter, Calypso Instruments EMEA, S.L, Coral Gables, Miami, FL, USA) was used for obtaining wind speed ($\text{m} \cdot \text{s}^{-1}$) and wind direction (degrees from north) on the ground. The downwind sensors, including the other two MSPs and the anemometer, were positioned as close as possible to the litter source to ensure detectable wind speeds. During the experiment, natural wind speed in the area remained below $1\text{ m} \cdot \text{s}^{-1}$, which corresponds to the sensitivity threshold of the ultrasonic anemometer. To overcome this limitation, the sensors were placed near the building's forced ventilation sources, which generated sufficient airflow for wind speed measurement. For all the sampling days, wind data from the ultrasonic anemometer were used for WindTrax simulations. The precise positions of the sensors were obtained from UAV-based aero-photogrammetry (Mavic 3 Enterprise, DJI Sciences and Technologies Ltd., Beijing, China), providing georeferenced photos in which sensors could be identified. Their geographical coordinates were then calculated using the DSM and imported into QGIS as background maps. For each field trial, the same sensor positions were consistently used.

2.3. Experimental Setup and Data Analysis

In May 2024, the following experimental setup was applied at the dairy cattle farm: Eight field trials were conducted over eight days at approximately the same time each morning, from

05:40 to 06:40 a.m. Each trial included a 15 min sampling period after litter tilling. A 15 min averaging period is commonly recommended in the literature on WindTrax modeling and in the introductory manual [55]. The same three MSP positions were maintained during each field trial, as well as consistent sensor height for the MSPs and anemometers on the ground, i.e., 1.50 m from the ground level. Two MSPs, one upwind (MSP 1) and the other downwind (MSP 2), were used for obtaining input data for the WindTrax simulations. A third MSP (MSP 3) was mounted on a UAV that was flown downwind 5 m ABGL for the first four field trials and 10 m ABGL for the remaining field trials. The UAV-based system was used for comparing observed and modeled CO₂ concentrations. As depicted in Figure 1, the ultrasonic anemometer was positioned on the ground close to the downwind MSP (MSP 2), while a hotwire anemometer was positioned close to the upwind MSP (MSP 1). Figure 5 shows the UAV-based system operating during regular farm activities.

In addition, for each field trial, Temperature/RH Data Loggers (Hobo MX2301A, Onset Computer, Bourne, MA, USA) were positioned near each MSP, including the one mounted on the UAV, comparing temperature and relative humidity data. Technical data of the Temperature/RH Data Logger sensors are shown in Table 1, while the sensors are shown in Figures 4 and 6. Figure 6 depicts the sensors on the ground (1.5 m ABGL), positioned downwind and upwind, respectively. The hotwire anemometer shown in Figure 6b was used only for upwind measurements to assess wind conditions outside the influence of the forced ventilation system. For all the sampling days, the hotwire anemometer detected wind speed close to zero, indicating very weak winds outside the livestock building and strong atmospheric stability. These data were not used in the WindTrax simulations, as they were considered negligible. Furthermore, each MSP was equipped with designated air inlet and outlet directions, aligned with the forced ventilation direction during field trials. The UAV-based system was manually maintained in a hovering position downwind at the two fixed altitudes throughout the trials.



Figure 5. The operations performed by the UAV-based system for investigating the two altitudes in the dairy cattle farm: (a) 5.0 m ABGL; (b) 10.0 m ABGL. The red circle identifies the UAV-based system in flight.

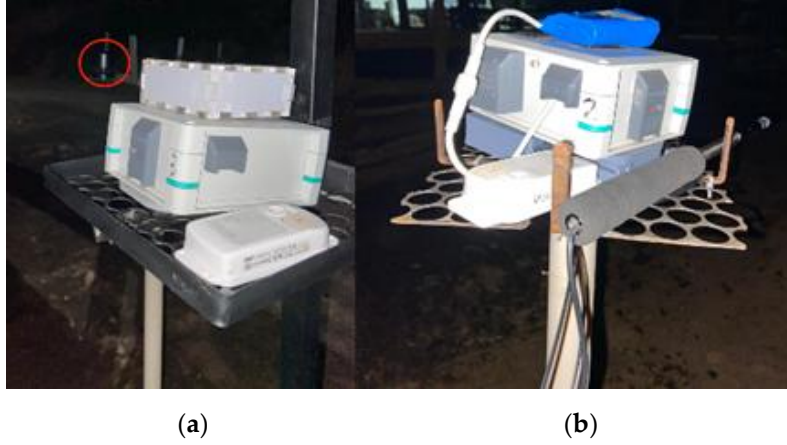


Figure 6. (a) The downwind measurement station on the ground, where the ultrasonic anemometer is indicated by the red circle; (b) the upwind measurement station on the ground, where the hotwire anemometer was positioned. A Temperature/RH Data Logger was positioned at both the stations on the ground.

WindTrax Model Assumptions and Inputs

WindTrax is a short-range atmospheric dispersion model valid for averaging periods between 15 and 30 min, distances within approximately one kilometer, and flat and unobstructed terrain conditions. It solves a linear system of equations (Equations (1) and (2)):

$$a_{11} Q_1 + a_{12} Q_2 + \dots + a_{1n} Q_n + C_{BG} = C_1 \quad (1)$$

$$a_{m1} Q_1 + a_{m2} Q_2 + \dots + a_{mn} Q_n + C_{BG} = C_m \quad (2)$$

C_{BG} is the background concentration, Q_i are the emission fluxes, C_i are the measured concentrations, and the coefficient a_{ij} relates Q_j and C_i . If C_{BG} is unknown, an upwind concentration measurement is required, which was provided in this study via MSP 1. The model requires as inputs at least two concentration measurements; temperature, pressure, wind speed, and direction (via an anemometer); and the spatial coordinates of sources and sensors. It calculates the emission fluxes of the sources and then concentrations as outputs. The WindTrax software tool describes the microclimate thanks to the surface wind model based on Monin–Obukhov theory. For this reason, four parameters are required: the surface roughness length z_0 (related to the height of the elements covering the ground), the friction velocity u^* (the squared root of the covariance between the horizontal and vertical components of the wind), the Monin–Obukhov length L (atmospheric stability), and the mean horizontal wind direction θ [55,67]. The next section explains how these parameters were quantified, but a more extended description of the model is provided in the references [40,41], which also contain a study on sensor positioning according to the emission source [68].

The WindTrax software tool was used for calculating emission fluxes and concentrations from the compost-bedded pack barn. Other parameters required for simulations include the source area, surface roughness length, atmospheric stability, number of particles, and elevation of soil. The surface of the source was obtained by drawing in the software tool over geo-referenced images obtained in QGIS software. The selected surface roughness length z_0 was 2.30 cm, i.e., short grass covering the surface around sources and sensors. Atmospheric stability was determined using Pasquill–Gifford classes. Under nighttime conditions, with wind speed being consistently of $2\text{--}3 \text{ m} \cdot \text{s}^{-1}$ and cloud cover being less than 50%, class F was assigned. The WindTrax software tool calculated the Monin–Obukhov length L from the selected Pasquill–Gifford class. The friction velocity u^* was also calculated by the model using the wind data. As noted in the introductory manual [55] (p. 1), increasing the number of particles reduces

uncertainty; therefore, a high number of particles was selected (50,000) for the simulations. Soil elevation was set to zero, considering the pressure data provided by the MSPs.

Using data from MSPs 1 and 2, the T/RH Data Logger, and the Calypso anemometer, 50 CO₂ emission fluxes per sampling day were calculated with the bLS model by using a fifteen-minute averaging period, resulting in a total of 400 emission fluxes. Descriptive statistics are provided for each field trial, including measured downwind concentrations and calculated emission fluxes. Additionally, a correlation matrix between input data and emission fluxes calculated by the bLS model is presented. Welch's ANOVA test and then Dunn's test with the Bonferroni *p*-value adjustment method were applied to compare the calculated emission fluxes for the same compost-bedded pack barn in three situations, i.e., before, during, and after litter tilling. It should be noted that emission fluxes before and during litter tilling were calculated in a previous study [69]. A sensitivity analysis is provided for modeled emission fluxes under stable (Pasquill–Gifford class F) and unstable (Pasquill–Gifford class B) atmospheric conditions. An additional 400 emission fluxes were calculated under unstable atmospheric conditions for comparison with those calculated under stable conditions. Given the stochastic feature of the bLS model, the several distributions of emission fluxes could assume normality or not, as verified with the Shapiro–Wilk test. Then, for each sampling day, the t-test and the Mann–Whitney U test were selected for comparing the calculated emission fluxes under stable and unstable conditions. Differences between medians are also provided.

Welch's ANOVA test, followed by Dunn's test with Bonferroni *p*-value adjustment, was applied for downwind concentrations detected at three altitudes: on the ground at 1.5 m and at 5.0 m and 10.0 m ABGL. For modeled concentrations, which were obtained using the mean calculated emission flux of each sampling day and the same input data used for calculating emission fluxes, concentration maps were generated over a 20,000 m² surface 5.0 m ABGL for the first four sampling days and 10.0 m ABGL for the remaining days. The modeled concentrations at the two altitudes were compared with the Mann–Whitney U test. Furthermore, to assess model performance, measurements collected by the UAV-based system (MSP 3) at the same two altitudes were used to compute a mean ER (percentage error) between M (modeled) and O (observed) CO₂ concentrations at the same position for each *i*th period:

$$ER (\%) = (M_i - O_i)/O_i \quad (3)$$

Additionally, 95% confidence intervals at the heights from 0.5 to 12.0 m ABGL were calculated using the bLS model, and the mean values of the confidence intervals were used as modeled CO₂ concentrations. For observed concentrations, the 15 min average values were used for the two sampling altitudes. 5.0 m ABGL for the first four days and 10.0 m ABGL for the remaining days. A quantitative validation of model performance is provided through the calculation of the RMSE (Root Mean Square Error):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (M_i - O_i)^2} \quad (4)$$

R [70] and Rstudio [71] were used for data analysis by selecting a set of library functions: packages like Openair [72,73], useful for air quality data analysis; Raster [74], for mapping and analyzing CO₂ concentration data contained in raster files; Corrplot [75], for creating a correlation plot; and ggplot2 [76] for creating the following plots.

3. Results and Discussion

By comparing temperature and relative humidity data obtained from the MSPs and T/RH Data Loggers, on the ground and in flight, the following observations were made: For all field trials, the Data Logger temperatures were lower, and the Data Logger relative humidities were higher than those measured by the MSPs, as can be seen in Figure 7 for the first sampling day.

Graphs for the other sampling days are provided in the Supplementary Material (Figures S1–S8). Two simple regression models were obtained, showing good agreement for temperature ($y = -7.38 + 1.22 \cdot x$, $R^2 = 0.86$, $p\text{-value} < 0.001$) and poorer agreement for relative humidity ($y = -892.19 + 50.11 \cdot x - 0.64 \cdot x^2$, $R^2 = 0.25$, $p\text{-value} < 0.001$). Despite the good performance obtained by the temperature sensor inside the MSPs, to better represent the microclimate around the source, Data Logger temperatures and MSP pressures were selected for the simulations. The temperature detected by the Data Loggers was selected because of the positioning outside the MSP sampling chamber, providing observations that were more representative of atmospheric conditions. The pressure detected by the MSPs was selected because it was measured only by this sensor, despite significant differences in the relative humidity values recorded by the MSPs and the Data Loggers. All sensors and variables selected for each sensor for the bLS model are summarized in Scheme 1, which also shows the model outputs, discussed in detail later.

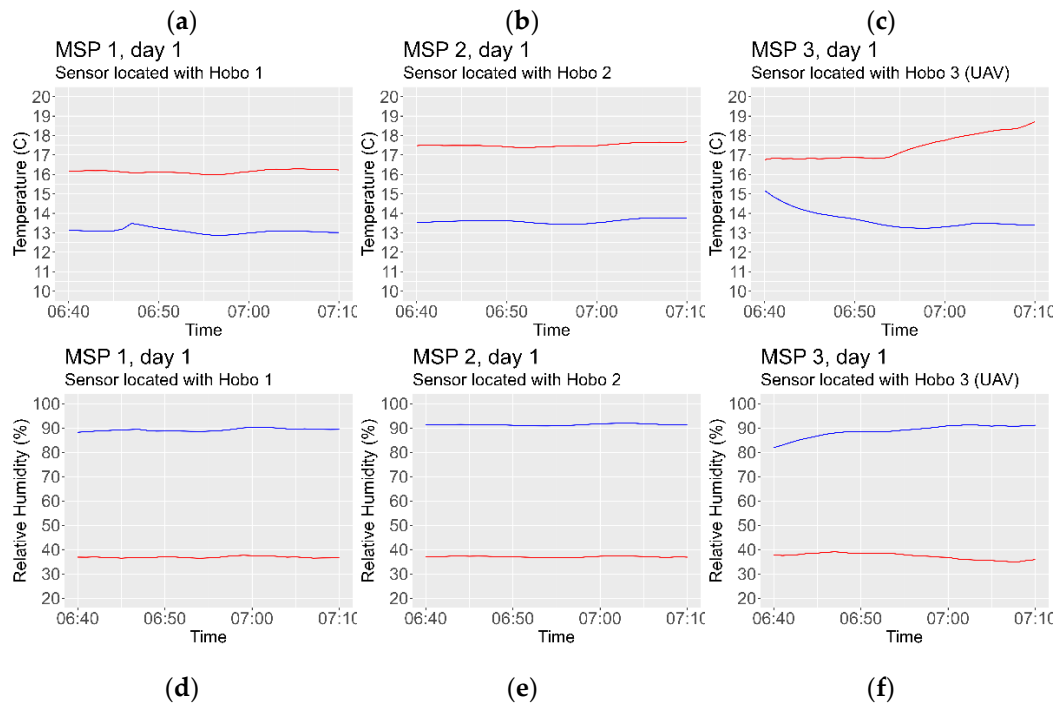
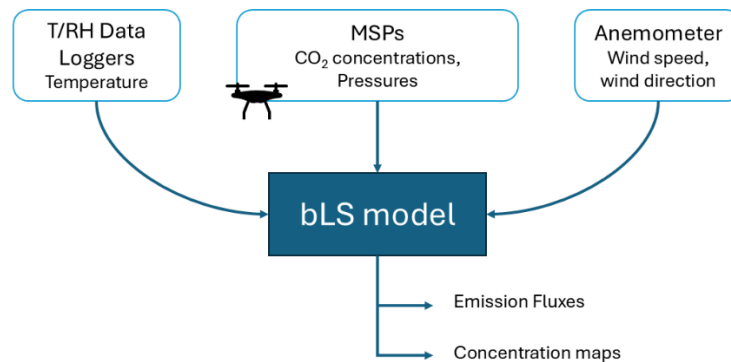


Figure 7. (a–c) Temperatures measured by MSPs (in red) and T/RH Data Loggers (in blue) on the first sampling day from 06:40 to 07:10 a.m.; (d–f) Relative humidity measured by MSPs (in red) and T/RH Data Loggers (in blue) on the first sampling day from 06:40 to 07:10 a.m.



Scheme 1. The variables measured by sensors used for simulations as input data for the bLS model.

Table 2 presents the values of the variables measured by the MSPs and T/RH Dataloggers, averaged over 15 min periods to be used as input data for the bLS model. This table shows the time elapsed since litter tilling during the field trials. It is observed that upwind concentrations of CO₂ were consistently lower than downwind concentrations for each sampling day, suggesting that other nearby emission sources did not contribute to the measurements. Although the ventilation system was always operational, the Calypso anemometer recorded non-uniform winds inside the livestock building during each sampling period, detecting winds with different directions and speeds (Figure 8), which affected pressure and temperature measurements. The maximum average wind speed occurred on the eighth sampling day, reaching a value of 1.83 m · s⁻¹, while the minimum, 1.14 m · s⁻¹, occurred on the second sampling day. Moreover, the wind rose and polar plot in Figure 8 indicate that higher CO₂ concentrations at the MSP 2 position on the ground were measured when winds originated from southwest, with wind speeds exceeding 2.40 m · s⁻¹. However, these winds occurred with the lowest frequency (~20%) during each sampling day. Winds from west and northwest, which occurred most frequently (~ 80%), were associated with lower concentrations. This pattern suggests that the southwest area of the litter may contain a higher density of anaerobic microorganisms or more microbiological growth sites, although further microbiological monitoring of the litter would be required to confirm this.

Table 2. The 15 min average values of temperature (°C), pressure (Pa), CO₂ concentration (ppm), wind speed (m · s⁻¹), and wind direction (degrees from north) measured upwind and downwind of the source by MSPs 1 and 2, the T/RH Data Logger, and the anemometer for each sampling day.

Day	Date (dd/mm/yy)	Time	MSP 1 (Upwind)				MSP 2 (Downwind)				
			Time After Tilling (min.)	Temp. (°C)	Press. (Pa)	CO ₂ (ppm)	Temp. (°C)	Press. (Pa)	CO ₂ (ppm)	WS (m · s ⁻¹)	WD (° from N)
1	10 May 2024	06:56	23	13.14 ^{H1}	92,257.79	586.21	13.57 ^{H2}	92,228.27	727.13	1.49	270.95
2	13 May 2024	07:15	25	12.35 ^{H3}	92,121.86	598.56	13.20 ^{H1}	92,434.90	732.77	1.14	305.35
3	14 May 2024	07:15	21	10.59 ^{H1}	92,150.12	595.48	11.48 ^{H2}	92,131.36	665.19	1.65	309.29
4	15 May 2024	06:39	5	12.92 ^{H3}	92,193.65	556.63	13.71 ^{H2}	92,162.73	672.28	1.50	281.62
5	16 May 2024	07:15	15	14.66 ^{H3}	92,943.47	547.54	15.68 ^{H1}	92,219.53	654.41	1.38	245.89
6	17 May 2024	06:56	27	13.13 ^{H3}	92,770.82	598.13	13.13 ^{H2}	92,446.23	675.35	1.59	272.66
7	21 May 2024	07:15	14	13.12 ^{H2}	92,513.28	555.58	14.13 ^{H1}	92,485.73	650.01	1.36	286.02
8	28 May 2024	07:38	23	15.71 ^{H1}	92,376.23	605.28	15.98 ^{H2}	92,371.84	743.08	1.83	232.44

^{H1}, ^{H2}, ^{H3} are the temperatures measured by the T/RH Data Logger (Hobo MX2301A).

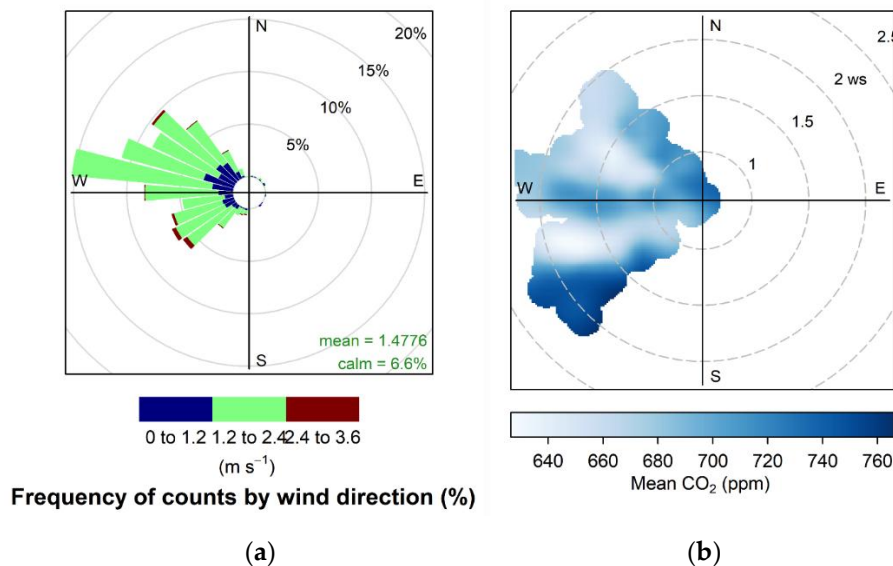


Figure 8. (a) The total wind rose for all sampling periods, using MSP 2 and the Calypso anemometer (wind speed classes ($\text{m} \cdot \text{s}^{-1}$): 0-1.2 in blue, 1.2-2.4 in green, and 2.4-3.6 in dark red). (b) The polar plot (on the right) for all sampling periods, using MSP 2 and the Calypso anemometer (wind speed from 0 to $2.5 \text{ m} \cdot \text{s}^{-1}$).

3.1. CO₂ Emission Fluxes

The WindTrax software tool was used for calculating 50 CO₂ emission fluxes after litter tilling, resulting in a total of 400 CO₂ emission fluxes. A summary of the calculated values for each sampling day is provided in Table S1 of the Supplementary material, including minimum, first-quartile, median, mean, third-quartile, and maximum values. All the calculated CO₂ emission fluxes can be observed in Figure 9 for all sampling days. The minimum CO₂ emission flux occurred on the sixth day of measurements ($0.01153 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$), while the maximum emission flux was calculated for the eighth sampling day ($0.14170 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$), coinciding with the higher observed wind speeds. Across all sampling days, the overall average emission flux was $0.04351 \pm 0.03730 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$, obtained approximately twenty minutes after litter tilling. Consequently, the corresponding standard deviation is relatively high.

CO₂ emission fluxes were calculated by [58] (p. 61) for a compost-bedded pack barn with a moisture content of 49% in Kentucky twenty minutes after tillage; the measurements were performed using a static chamber, yielding a mean emission flux of $100.2 \text{ g} \cdot \text{m}^{-2} \cdot \text{h}^{-1}$ (i.e., $0.02783 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$), a value comparable to those obtained in the present study despite differences in environment and calculation method. It should be noted that the moisture content was not measured in the present study. Mean CO₂ emission fluxes before and during litter tilling were $0.03700 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$ and $0.06511 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$, respectively, based on four sampling days corresponding to the first four sampling days in the present study, so fully comparable due to the same environment and calculation methodology [69]. These data illustrate a trend in CO₂ emission fluxes from compost-bedded pack barns: emissions peak during tilling and subsequently tend to stabilize and decrease twenty minutes after tilling, as animal activity compacts the litter [56–58]. The Shapiro–Wilk test confirmed that the distributions of emission fluxes calculated before, during, and after tilling did not follow normality (p -value < 0.001). Consequently, Welch’s ANOVA test was applied and then Dunn’s test with the Bonferroni p -value adjustment. The results confirmed significant differences between fluxes during and after tilling (p -value < 0.001) and between before and during tilling (p -value < 0.05), while no significant differences were found between after and before tilling.

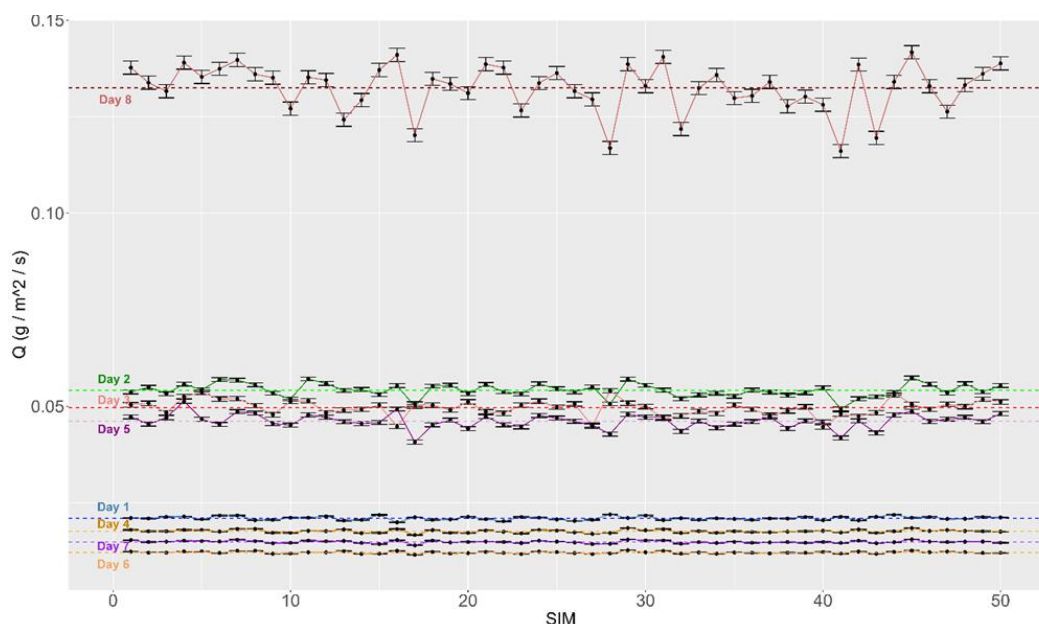


Figure 9. Scatter plot of all calculated CO₂ emission fluxes ($\text{g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$), including the mean values (dashed lines) and 95% confidence intervals (black error bars) for all the simulations performed for each sampling day.

To investigate the relationships among the variables, a correlation matrix and a dendrogram are presented in Figure 10, showing Pearson correlation coefficients for the model input data considered in pairs. Data from stationary monitoring for each sampling day, i.e., those used to obtain input data for the model, were compiled into a dataset as follows: since sensors neither had the same sampling frequency nor started measuring at the same time, input data were averaged over a minute to join data frames from several sensors. As there were two sensors on the ground to obtain input data for the simulations, i.e., upwind and downwind, 15 observations per sensor on the ground were selected, obtaining a dataset of 30 observations per sampling day. In addition, since wind data were obtained only close to the downwind MSP (2), a median imputation was made to replace missing wind direction values, and a low-value ($0.01 \text{ m} \cdot \text{s}^{-1}$) imputation was made to replace missing values of wind speed for the upwind MSP (1). Finally, a random sampling of 30 emission fluxes out of the total 50 per sampling day was performed to create the response variable column, representing the calculated emission fluxes.

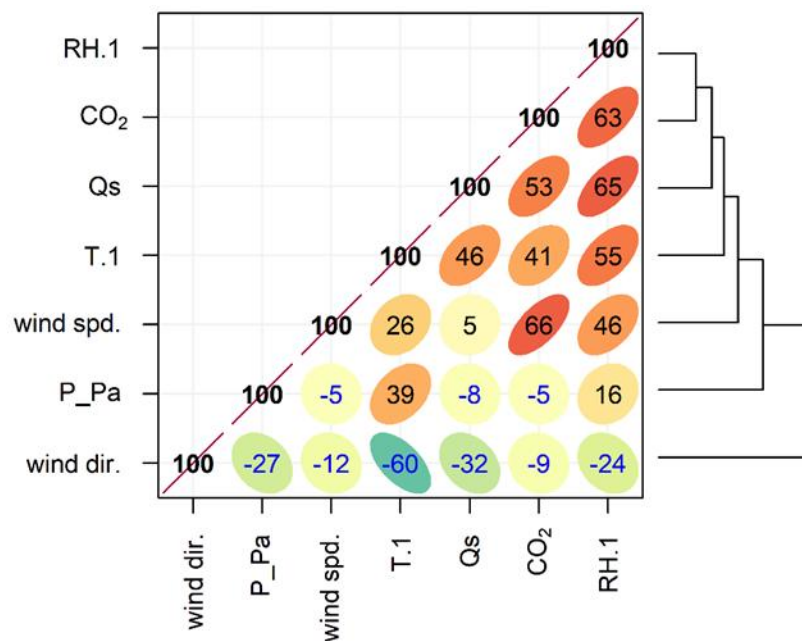


Figure 10. The dendrogram (black lines on the right side) and the correlation plot for the input data. The size of the circle and the intensity of the color in a cell correspond to the strength of the correlation (positives are coded from yellow to red and negatives from yellow to green); the absolute value of the correlation coefficient for two variables in pairs is black for positive correlations and blue for negative correlations. From the top, relative humidity (RH.1) detected by T/RH Data Loggers, CO₂ concentration (CO₂) detected by MSPs 1 and 2, emission fluxes (Qs) calculated by the bLS model, temperature (T.1) detected by T/RH Data Loggers, wind speed (ws) detected by the Calypso anemometer, pressure (P_Pa) detected by MSPs 1 and 2, and wind direction (wd) detected by the Calypso anemometer.

Starting from the environmental parameters used as input data for the emission flux calculation through the bLS model, the following results were obtained: The emission fluxes had a weak positive correlation ($R = 0.46$) with the temperatures detected by the T/RH Data Loggers, while they had a stronger positive correlation ($R = 0.65$) with the relative humidities detected by the same sensors. The temperature and relative humidity detected by the T/RH Data Loggers

were also strongly positively correlated ($R = 0.55$), as in this case, water vapor was transported from the hotter litter toward the sensors by the turbulence generated by the ventilation system. Additionally, the emission fluxes also exhibited a strong positive correlation ($R = 0.53$) with the CO_2 concentrations. The strongest positive correlation ($R = 0.66$) was observed between CO_2 concentrations and wind speed, again reflecting the influence of the ventilation system.

Examining the relationship between emission fluxes and wind speed, a weak positive correlation ($R = 0.05$) was observed. This partially supports the initial hypothesis that the highest average wind speed could be responsible for the highest calculated emission fluxes for the eighth sampling day; however, it is insufficient to account for the calculation of other emission fluxes, as the relationship is not linear. For instance, the lowest mean emission flux ($0.01213 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$) was calculated for sixth sampling day, which coincided with the second highest wind speed, i.e., $1.59 \text{ m} \cdot \text{s}^{-1}$. Another factor to consider is the averaging period used in this study, i.e., fifteen minutes, which is recommended by the software author [67] to reduce the variability due to wind gusts in the atmosphere on short time scales. Other studies used this same averaging period [50], as well as shorter [77] or longer [78] intervals. Wind gusts should be considered in the emission flux calculation because, especially under unstable conditions, they could cause a reduction in the concentrations detected by downwind sensors, impacting calculated emission flux accuracy. Generally, WindTrax underestimates the emission rate under unstable conditions and overestimates it under stable conditions [50,54,79]. Some studies have filtered observations by removing low wind speeds, selecting data based on wind direction and atmospheric conditions characterized by high stability and instability [49,50,79].

Lower calculated emission fluxes have been reported to increase atmospheric stability [80] (pp. 6–7). In the present study, stable atmospheric conditions (Pasquill–Gifford class F) were set in the software tool. However, wind gusts generated by the mechanical ventilation system in the livestock building tend to increase atmospheric instability, promoting CO_2 dispersion and dilution processes. Indeed, as shown in Table 2, the maximum detected downwind concentration was not detected at the highest wind speeds ($>1.50 \text{ m} \cdot \text{s}^{-1}$). For example, on the second and fifth sampling days, the second- and fourth-highest emission fluxes were calculated, respectively.

The sensitivity analysis compared calculated emission fluxes under atmospheric stable and unstable conditions. After applying the Shapiro–Wilk test, the Mann–Whitney U test provided significant differences ($p\text{-value} < 0.05$) for the first, fourth, fifth, and eighth sampling days, while the t-test revealed significant differences ($p\text{-value} < 0.05$) for the second, third, sixth, and seventh sampling days. Table 3 presents the difference between medians of modeled emission fluxes under stable and unstable conditions, ranging from -0.020 to $0.034 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$.

Table 3. Median values of emission fluxes ($\text{g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$) under stable (class F) and unstable (class B) conditions for each sampling day, including the difference between them.

Day	Class F	Class B	Difference
1	0.021	0.041	-0.020
2	0.054	0.045	0.009
3	0.050	0.037	0.013
4	0.018	0.034	-0.016
5	0.046	0.042	0.004
6	0.012	0.024	-0.012
7	0.015	0.026	-0.011
8	0.134	0.100	0.034

3.2. CO₂ Concentrations

Figure 11 shows the real-time environmental parameters (temperature, relative humidity, wind speed, and pressure) and CO₂ concentrations detected at the downwind ground position on the first sampling day. Figure 12 shows the same parameters, except for wind speed detected in flight on the same day 5.0 m ABGL. It should be noted that for these graphs, the *x*-axis does not show the local time but follows the Italian time zone format (CEST). Since the sensors did not share the same sampling frequency or start time, input data were averaged over one-minute intervals to align datasets from several sensors. In both figures, the temperatures and relative humidities were measured by the T/RH Data Loggers, the CO₂ concentrations and pressures by the MSPs, and the wind speeds by the Calypso anemometer, as these data were selected as input for the bLS simulations.

Observing CO₂ concentrations at the two downwind positions (Figures 11 and 12), higher values were measured at the ground level due to greater interception of the emission flux. This effect is attributed to the downward orientation of all 12 fans, which aim to reduce moisture in the compost-bedded pack barn. Furthermore, around 06:55 a.m., the wind speed dropped below 1 m · s⁻¹, increasing atmospheric stability. Consequently, concentration measured by MSP 2 (Figure 11) rose, reaching a peak of 735 ppm until the wind speed increased again, restoring conditions of atmospheric instability and reducing concentrations. This confirms a small short-term accumulation of CO₂ in the building after tilling, due to its high molecular weight [61] and the occurrence of stable stratification. An increase in CO₂ concentrations at the same time was also observed in flight 5.0 m ABGL (Figure 12) but with lower values due to dispersion and dilution at the higher altitude. These trends were consistent across all other sampling days (Supplementary Material, Figures S9–S24).

Greater dispersion was observed 10.0 m ABGL, confirming the presence of a concentration gradient with altitude. Downwind concentrations measured at several altitudes (ground at 1.5 m, and 5.0 m and 10.0 m ABGL) during all the sampling days showed significant differences. The Shapiro–Wilk test confirmed that normality could not be assumed (*p*-value < 0.001) for all calculated concentrations at each altitude. Following the Shapiro–Wilk test, Welch’s ANOVA test was performed, followed by Dunn’s test with Bonferroni *p*-value adjustment. Significant differences were found between 5.0 m (median: 522.55 ppm) and 10.0 m ABGL (median: 490.22 ppm; *p*-value < 0.01). Even larger significant differences were observed (*p*-value < 0.001) between 1.5 m (median: 675.82 ppm) and 10.0 m ABGL, as well as between 1.5 m and 5.0 m ABGL. This analysis covered the period from the moment at which the UAV-based system reached its required position to the end of battery life and subsequent landing. Relative observation frequencies were 50% for ground measurements (211 observations), 25% for 5.0 m ABGL (103 observations), and 25% for 10.0 m ABGL (108 observations). These frequencies reflect that ground measurements were conducted on all sampling days, whereas flight measurements at the two selected altitudes were performed on half of the total sampling days.

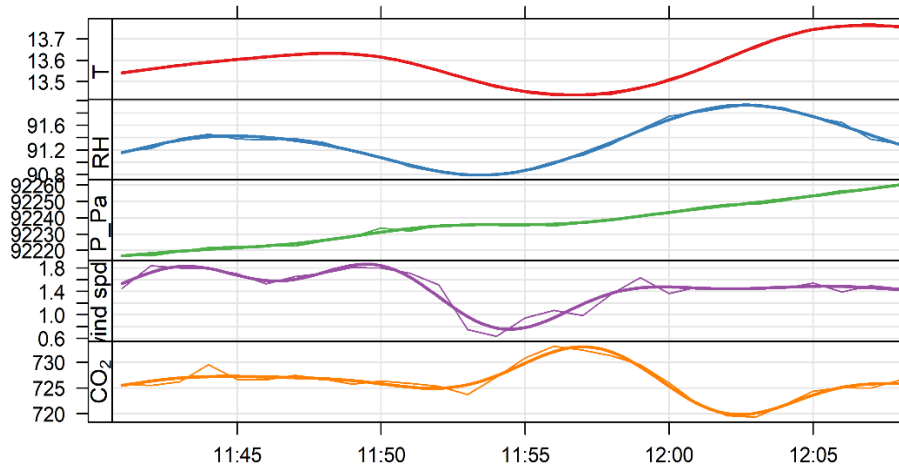


Figure 11. Detected environmental conditions (temperature (T) in Celsius degrees, relative humidity (RH) in %, wind speed (wind spd) in $\text{m} \cdot \text{s}^{-1}$, and pressure (P_Pa) in Pascal) and CO_2 concentrations (CO_2) in ppm at the downwind position on the ground (1.5 m ABGL) on the first sampling day, showing smooth fit lines and a confidence interval of 98% obtained with the local regression method. The time format of the x -axis is CEST.

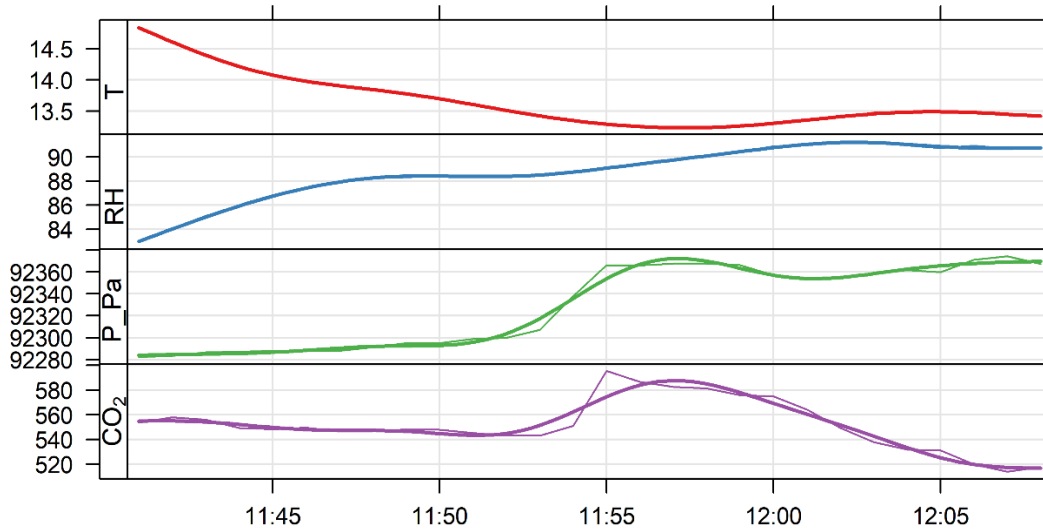


Figure 12. Detected environmental conditions (temperature (T) in Celsius degrees, relative humidity (RH) in %, and pressure (P_Pa) in Pascal) and CO_2 concentrations (CO_2) in ppm at the downwind position in flight (5.0 m ABGL) on the first sampling day, showing smooth fit lines and a confidence interval of 98% obtained with the local regression method. The time format of the x -axis is CEST.

The modeled CO_2 concentrations calculated using the bLS model are shown as concentration maps for 5.0 m ABGL in Figure 13 and for 10.0 m ABGL in Figure 14. The maps in Figure 13 all use the same scale to allow for a comparison of concentrations across the first four sampling days, while the maps in Figure 14 use different scales due to low variability. The CO_2 atmospheric dispersion around the compost-bedded pack barn for each sampling day was represented as follows: Based on the wind direction (Figure 2b) a polygon of 20,000 m^2 around the emission source was selected to capture the plume at both altitudes (Figure 1). Concentration maps were calculated within the polygon and exported by the WindTrax software tool as text files. These maps were then georeferenced using QGIS to generate the raster files shown in Figures 13 and 14. Each raster file contains 7938 cells, with each cell representing a CO_2 concentration calculated by the bLS model. It should be noted that the polygon was shifted northward for the fifth and

eighth sampling days due to a measured wind from the southwest, which displaced the plume northward relative to the emission source.

The criticality of the model is its disregard for the topographic surface around the source and the sensors, meaning that the concentration maps do not represent the real CO₂ atmospheric dispersion. In this study, the focus was on comparing the modeled concentrations with those measured by the UAV-based system (MSP 3), which was kept downwind at approximately the same position during each field trial, with altitude varying from 5.0 m to 10.0 m ABGL from the fifth to the eighth sampling day. Maximum values of modeled CO₂ concentrations 5.0 m and 10.0 m ABGL are reported in Table S2. The analysis of the CO₂ concentration maps shows that higher concentrations generally occurred 5.0 ABGL, reaching peaks of approximately 667 ppm and 635 ppm on the second and third sampling days, respectively. These peaks correspond to the second- and third-highest calculated emission fluxes. This result further confirms the altitude-based concentration gradient, highlighting dilution and dispersion processes at higher altitudes, as well as stable stratification of the target gas at lower altitudes, independently of the ventilation system. Additionally, higher modeled concentrations at 5.0 m ABGL were associated with winds from northwest, which occurred at higher frequency (Figure 8a).

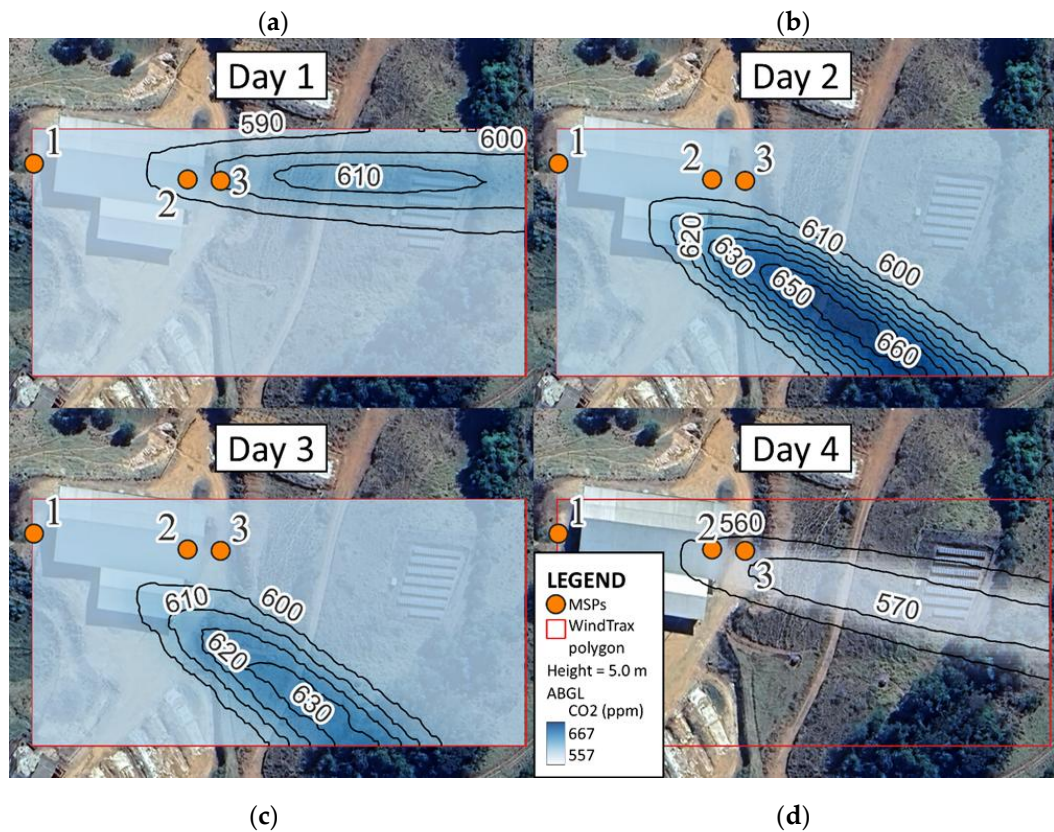


Figure 13. (a) CO₂ atmospheric dispersions in ppm for the first sampling day at the height of 5.0 m ABGL; (b) CO₂ atmospheric dispersions in ppm for the second sampling day at the height of 5.0 m ABGL; (c) CO₂ atmospheric dispersions in ppm for the third sampling day at the height of 5.0 m ABGL; (d) CO₂ atmospheric dispersions in ppm for the fourth sampling day at the height of 5.0 m ABGL. Orange dots represent the positions of the MSPs.

At the height of 10.0 m ABGL, the two highest modeled concentrations, 616 ppm and 601 ppm, were reached on the eighth and sixth sampling days, respectively, corresponding in the simulations to the highest and eighth-highest calculated emission fluxes. This result was obtained under more unstable atmospheric conditions, with the two highest mean wind speeds measured

1.5 m ABGL, i.e., $1.83 \text{ m} \cdot \text{s}^{-1}$ and $1.59 \text{ m} \cdot \text{s}^{-1}$, producing comparable modeled concentrations between the two investigated altitudes. The explanation is that more unstable atmospheric conditions, characterized by more frequent wind gusts, promote upward transport of the target gas. Indeed, the highest modeled concentrations at 10.0 m ABGL were associated with winds from southwest, which occurred less frequently but with greater intensity (Figure 8a). The modeled concentrations at the two altitudes were compared using the Mann–Whitney U test after applying the Shapiro–Wilk test, yielding significant differences ($p\text{-value} < 0.05$).

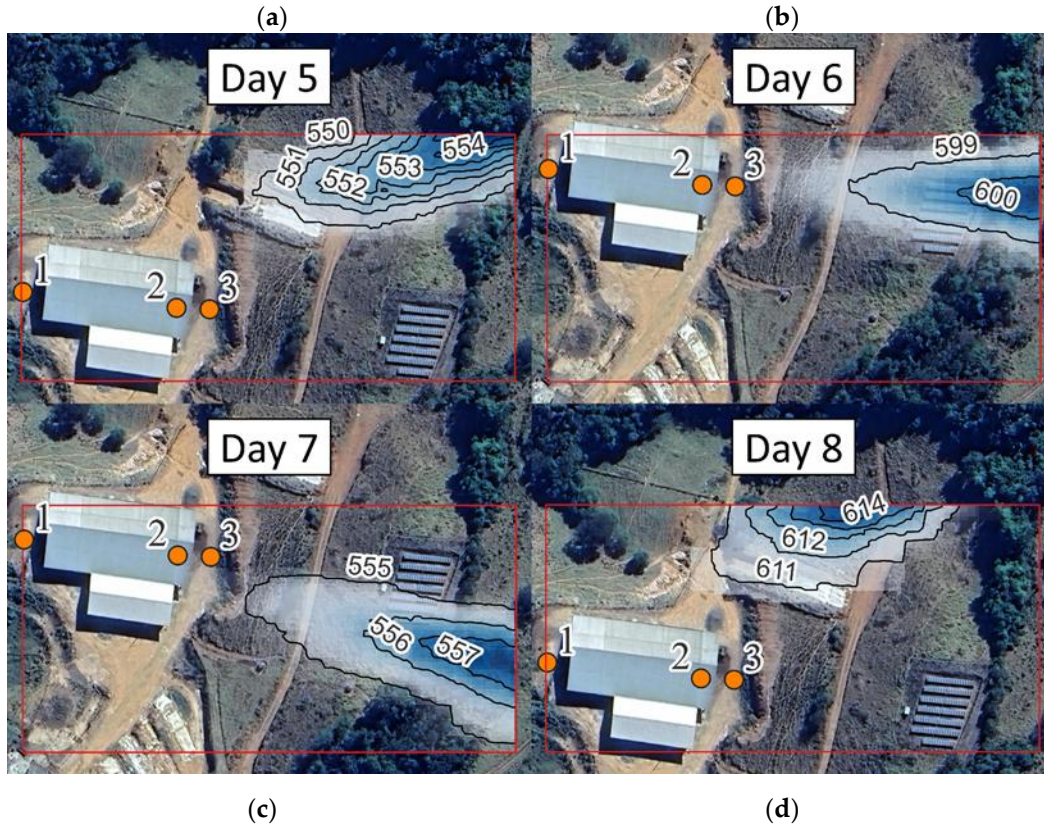


Figure 14. (a) CO₂ atmospheric dispersions in ppm for the first sampling day at the height of 10.0 m ABGL; (b) CO₂ atmospheric dispersions in ppm for the second sampling day at the height of 10.0 m ABGL; (c) CO₂ atmospheric dispersions in ppm for the third sampling day at the height of 10.0 m ABGL; (d) CO₂ atmospheric dispersions in ppm for the fourth sampling day at the height of 10.0 m ABGL. Orange dots represent the positions of the MSPs.

Using Equation 3, the mean ERs between modeled and observed CO₂ concentrations at the same location, i.e., at the MSP 3 position (UAV-based system), were computed for each i th period. The bLS model calculated 95% confidence intervals at altitudes ranging from 0.5 to 12.0 m ABGL, and the mean values of these intervals were used as the modeled CO₂ concentrations. For the observed concentrations, 15 min average values were used for the two sampling altitudes: 5.0 m ABGL for the first four days and 10.0 m ABGL for the remaining days. At the MSP 3 position, Figure 15 shows the predicted vertical profile plots for the first to the fourth sampling days, while Figure 16 shows the plots for the fifth to the eighth sampling days. In both Figures, the calculated 95% confidence intervals are indicated by black error bars for altitudes from 0.5 m ABGL to 12.0 m ABGL, and fifteen mean observed CO₂ concentrations (red points) were obtained by averaging measurements over 1 min intervals. Each vertical profile plot also indicates the mean ER, which ranged from approximately 8% to 39% 5.0 m ABGL and from 13% to 21% 10.0 m ABGL. Lower mean ER values 10.0 m ABGL were obtained due to the greater distance from the influence of the

ventilation system to the UAV-based system, resulting in more stable atmospheric conditions, as set in the software tool.

During each field trial, the wind was measured downwind by a single ground-based sensor (1.5 m ABGL), showing more unstable atmospheric conditions due to wind gusts generated by the ventilation system inside the livestock building, compared with the atmospheric conditions set in the WindTrax software tool (Pasquill–Gifford class F, i.e., high stability). These frequent wind gusts affected all simulations over the limited 15 min averaging period because of rapid short-term changes in atmospheric stability near sunrise [55] (p. 2), overestimating the modeled concentrations at both investigated altitudes. Comparable results were found by other authors [50,54,79], although their studies focused on comparing emission fluxes calculated using different methodologies and sensors.

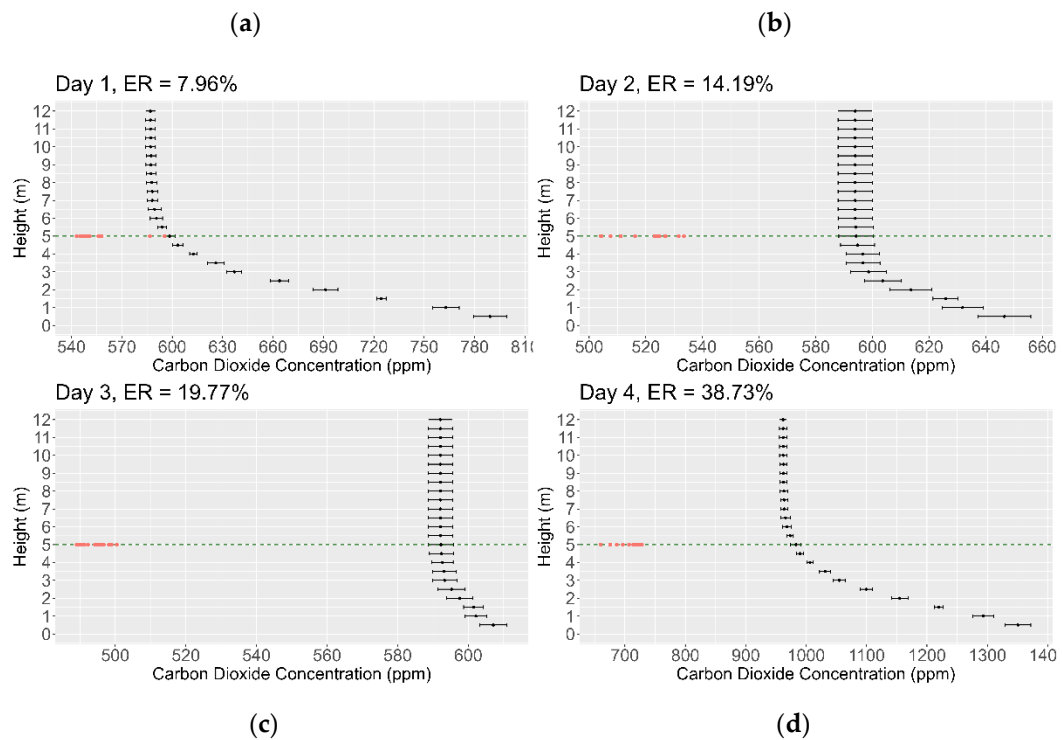


Figure 15. Vertical profile plots of modeled and observed CO₂ concentrations for sampling days (a) 1, (b) 2, (c) 3, and (d) 4. Black intervals are 95% confidence intervals of modeled CO₂ concentration, while red points are 1 min averages of observed CO₂ concentrations at MSP 3. ER is the mean percentage error. The dashed green line represents the investigated altitude (5.0 m ABGL).

By applying Equation (4) and using the same data for the calculation of the mean ERs, RMSE was calculated for each sampling day (Table 4). Overestimated emission fluxes reported in the literature are directly linked to the overestimated concentrations obtained by the bLS model. Considering the environmental conditions during the field trials, RMSE values ranging from approximately 44 ppm to 275 ppm are notably high. These results suggest that more robust statistical validation could be achieved by improving the accuracy and representativeness of the input data used to calculate emission fluxes.

Table 4. RMSE (ppm) calculated for each sampling day at two altitudes.

RMSE (ppm)							
Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8
46.62	74.42	97.83	275.12	61.92	104.74	80.40	77.44

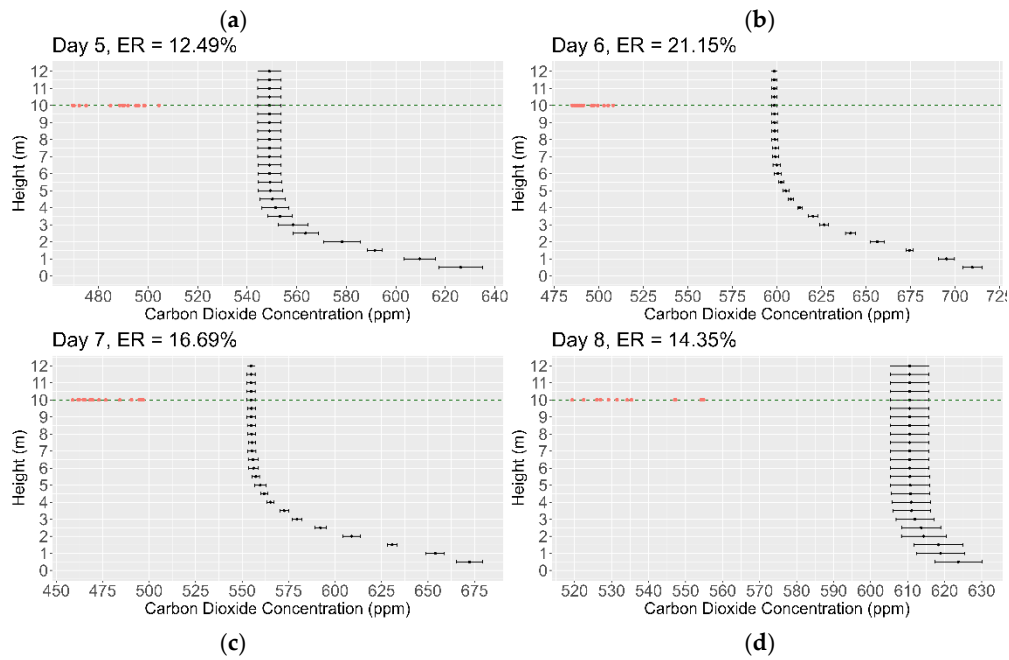


Figure 16. Vertical profile plots of modeled and observed CO₂ concentrations for sampling days (a) 4, (b) 5, (c) 6, and (d) 7. Black intervals are 95% confidence intervals of modeled CO₂ concentration, while red points are 1 min averages of observed CO₂ concentrations at MSP 3. ER is the mean percentage error. The dashed green line represents the investigated altitude (10.0 m ABGL).

3.3. Limitations

A critical analysis of the limitation of applying the bLS model in a dairy cattle farm is provided. The results obtained should be contextualized with respect to the identified issues, including the model assumptions, operational limitations of the measurement system, and the capability to accurately describe the local atmospheric state. In this study, sensors were positioned close to the source, whereas in many previous studies, they were located further away. This choice was made for calculating emission rates in an area characterized by high density of obstacles and complex topographic conditions. Operational limitations related to the downwash issue of the UAV-based system must be considered when validating modeled concentrations. Implementing a new support structure that increases the distance between the rotor plane and the sensors could improve measurement accuracy.

Another key aspect concerns a better characterization of the local atmospheric state. Increasing the number of anemometers, both horizontally and vertically, would enhance the capability to accurately estimate atmospheric stability, currently approximated using Pasquill-Gifford classes. The implementation of ultrasonic anemometers capable of providing all three wind vector components should also be considered in the bLS model. While Eddy Covariance remains the most precise method for defining turbulence, it is expensive and requires multiple sensors [81]. Complementarily, placing anemometers on the UAV-based system could capture vertical wind profiles, further improving the model's input data. To enhance model accuracy, it is also advisable to apply filters to the measured data, as recommended in recent studies [49,50,79], and to increase the number of particles in the simulations [50,79] despite the longer computation time, although 50,000 particles already provide reliable results.

This research study represents a first step toward establishing a methodology for quantifying atmospheric emissions from dairy cattle farms using the bLS model. This methodology could be extended to other processes in livestock farms, employing low-cost sensors and UAVs. By monitoring emissions seasonally and during regular farm activities, farmers could identify the most

effective mitigation strategies or the best available techniques, evaluating their impact on the atmosphere and thus supporting an emission-based decision-making system.

4. Conclusions

This paper analyzed the performance of the bLS model WindTrax by calculating CO₂ concentrations at two altitudes (5.0 m and 10.0 m ABGL), using stationary measurements (1.5 m ABGL) as input data, and comparing modeled concentrations with measurements obtained by a UAV-based system at the same altitudes. The agricultural process investigated was the management of a compost-bedded pack barn approximately 20 min after tilling. From the analysis, in terms of the average percentage error between modeled and measured concentrations, it is evident that a better quantification of on-site turbulence is necessary.

WindTrax is widely applied in agriculture and livestock farming, often combined with various technologies for measuring GHGs and environmental conditions. In this study, NDIR sensors were employed to measure CO₂ concentrations. A critical factor for improving model accuracy is a more precise quantification of in situ atmospheric stability, which could be achieved by equipping the UAV-based system with an anemometer. In the present study, atmospheric stability was approximated using Pasquill–Gifford classes, with high stability (class F) being set in the software tool, because measurements were taken at night but close to sunrise and the average wind speed never exceeded $2.00 \text{ m} \cdot \text{s}^{-1}$. The observed mean percentage errors between modeled and measured concentrations were largely due to increased atmospheric instability caused by wind gusts generated by the ventilation system in the short term. To mitigate the effect of wind gusts, longer averaging periods, 20–30 min, would be beneficial. These findings are consistent with the correlations identified between emission fluxes and environmental conditions. Further studies across different times of the year are recommended to develop predictive models for seasonal emission patterns.

The UAV-based system, designed to place sensors in an area minimally affected by downwash, demonstrates potential for enhancing the accuracy of the atmospheric dispersion models. By enabling downwind measurements at multiple positions, it allows for better interception of the emission plume. However, before this innovative measurement system can be routinely applied, further validation is necessary to address the identified limitations and ensure reliable quantification of emissions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/doi/s1>, Figure S1: The temperatures and relative humidities measured by MSPs (in red) and T/RH Data Loggers (in blue) on the first sampling day, Figure S2: The temperatures and relative humidities measured by MSPs (in red) and T/RH Data Loggers (in blue) on the second sampling day, Figure S3: The temperatures and relative humidities measured by MSPs (in red) and T/RH Data Loggers (in blue) on the third sampling day, Figure S4: The temperatures and relative humidities measured by MSPs (in red) and T/RH Data Loggers (in blue) on the fourth sampling day, Figure S5: The temperatures and relative humidities measured by MSPs (in red) and T/RH Data Loggers (in blue) on the fifth sampling day, Figure S6: The temperatures and relative humidities measured by MSPs (in red) and T/RH Data Loggers (in blue) on the sixth sampling day, Figure S7: The temperatures and relative humidities measured by MSPs (in red) and T/RH Data Loggers (in blue) on the seventh sampling day, Figure S8: The temperatures and relative humidities measured by MSPs (in red) and T/RH Data Loggers (in blue) on the eighth sampling day, Table S1: Five-number summary (minimum, first-quartile, median, third-quartile, and maximum values), including the mean value of the fifty calculated CO₂ emission fluxes ($\text{g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$) for each sampling day, Figure S9: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, wind speed in $\text{m} \cdot \text{s}^{-1}$, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position on the ground on the first sampling day. The time format of the *x*-axis is CEST, Figure S10: Detected environmental conditions (temperature in Celsius

degrees, relative humidity in %, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position in flight (5.0 m ABGL) on the first sampling day. The time format of the x -axis is CEST, Figure S11: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, wind speed in $\text{m} \cdot \text{s}^{-1}$, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position on the ground on the second sampling day. The time format of the x -axis is CEST, Figure S12: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position in flight (5.0 m ABGL) on the second sampling day. The time format of the x -axis is CEST; Figure S13: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, wind speed in $\text{m} \cdot \text{s}^{-1}$, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position on the ground on the third sampling day. The time format of the x -axis is CEST, Figure S14: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position in flight (5.0 m ABGL) on the third day. The time format of the x -axis is CEST, Figure S15: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, wind speed in $\text{m} \cdot \text{s}^{-1}$, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position on the ground on the fourth sampling day. The time format of the x -axis is CEST, Figure S16: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position in flight (5.0 m ABGL) on the fourth day. The time format of the x -axis is CEST, Figure S17: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, wind speed in $\text{m} \cdot \text{s}^{-1}$, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position on the ground on the fifth sampling day. The time format of the x -axis is CEST, Figure S18: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position in flight (10.0 m ABGL) on the fifth day. The time format of the x -axis is CEST, Figure S19: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, wind speed in $\text{m} \cdot \text{s}^{-1}$, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position on the ground on the sixth sampling day. The time format of the x -axis is CEST, Figure S20: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position in flight (10.0 m ABGL) on the sixth day. The time format of the x -axis is CEST, Figure S21: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, wind speed in $\text{m} \cdot \text{s}^{-1}$, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position on the ground on the seventh sampling day. The time format of the x -axis is CEST, Figure S22: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position in flight (10.0 m ABGL) on the seventh sixth day. The time format of the x -axis is CEST, Figure S23: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, wind speed in $\text{m} \cdot \text{s}^{-1}$, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position on the ground on the eighth sampling day. The time format of the x -axis is CEST, Figure S24: Detected environmental conditions (temperature in Celsius degrees, relative humidity in %, and pressure in Pascal) and CO₂ concentrations in ppm at the downwind position in flight (10.0 m ABGL) on the eighth day. The time format of the x -axis is CEST, Table S2: Five-number summary (minimum, first-quartile, median, third-quartile, and maximum values), including the mean value of the fifty calculated CO₂ concentrations (ppm) for each sampling day.

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5. Articolo in revisione

5.1. Studio 3

Proposal of a methodology for quantifying carbon dioxide emissions by customised multi-sensor platforms in a dairy cattle farm: tilling effect of a compost bedded pack barn

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Abstract

This was the first of three studies aiming to characterise a compost bedded pack barn of a dairy cattle farm in terms of CO₂ (carbon dioxide) emissions. The aim was to develop a protocol for monitoring livestock farm GHG (greenhouse gas) emissions. The influence of the litter tillage process on air quality levels was assessed in a rural context using low-cost self-engineered MSPs (multi-sensor platforms) that measured CO₂ concentrations and environmental conditions. Additionally, the detected CO₂ concentrations from the MSPs were evaluated using the inverse dispersion modelling (WindTrax), which has been used to calculate the emission rates and the atmospheric dispersion of CO₂ in terms of concentrations. Measurements were taken for five days in May 2024. Collected data from two MSPs were used as input data for calculating emission rates in two periods: before and during the litter tillage. In terms of CO₂ emission rates, the litter tillage impacted on average with an increase of about 76%. For assessing the model performance, modelled concentrations were compared with those measured by a third MSP positioned at the same height from the ground. The observed discrepancy occurred because the model was applied under some assumptions. The model effectively estimated emissions from compost bedding in the livestock building. Improving MSPs design, including sensor repositioning and increasing their number in field trials, is needed to enhance emission

characterization. Further research should focus on continuous monitoring, optimized sensor placement, and data filtering. These refinements will enhance CO₂ emission assessments across different environmental conditions.

Keywords: CO₂ emissions, GHG, NDIR, compost barn, atmospheric dispersion, WindTrax.

1. Introduction

In recent years, two main reports have been published by the FAO (Food and Agriculture Organization) in which GHGs (greenhouse gases) emissions from the livestock sector were estimated on the global anthropogenic emissions (Steinfeld et al., 2006; Gerber et al., 2013). These reports utilized different data sources to estimate global emissions, i.e. those from the Climate Watch database (Climate Watch Historical GHG Emissions, 2024) and the IPCC (International Panel on Climate Change). The most recent data on emissions from the livestock sector, referred to the year 2015, give a figure of 6.2 Gt (gigatons) CO₂ eq. (carbon dioxide equivalent) corresponding to 12% of total global emissions, which reached about 55 Gt CO₂ eq. in the same year (Shukla et al., 2023). Cattle farming contributes 62% (3.84 Gt CO₂ eq.) to the livestock sector. Within cattle farming, beef and milk production represent 29% (1.8 Gt CO₂ eq.) and 30% (1.9 Gt CO₂ eq.) of total sector emissions (FAO, 2022).

Furthermore, since the above proportions are subject to changes in calculation methodology and GWP (Global Warming Potential) updates by IPCC, they are not comparable with estimates from previous years. As important as the issue of reducing GHG emissions is, a topic that is recognised by the Paris Agreement and United Nations' SDGs (Sustainable Development Goals), a DSS (Decision Support System) that includes not only emissions but also other indicators (Bidoglio et al, 2024) such as water and energy consumptions is needed to identify sustainable management practices that reduce the impact of livestock farms. This paper provides a proposal for quantifying CO₂ (carbon dioxide) emissions in a dairy cattle farm, but it could be potentially used with other kinds of gases. Considering the human population increase in the coming years, the livestock sector should be more efficient in high-biological value product production, applying innovative technologies and best agricultural practices to reduce emissions into the atmosphere (Martin, 2024). In this context, an emission measuring system is necessary for the most suitable mitigation strategy selection. All the stakeholders could benefit from this solution, including not only the farmers but also financing institutions and development agencies for investing in the most environmentally sustainable technology or practice (Mottet et al, 2024). Understanding at which stage of the production process emissions could be decreased is essential.

Developing a shared methodology for calculating GHG emissions helps to know the impact of agricultural activities on the atmosphere. A significant LCA (Life Cycle Assessment) analysis for the global ruminant livestock sector was made by FAO (Opio et al., 2013). This report examines GHG emissions, allocated by species, GHG, product systems (beef and milk), and region. These results could be obtained at the local level for a single livestock farm. This paper proposes a methodology for implementing a GHG monitoring system on livestock farms. Specifically, CO₂ emissions from a dairy cattle farm located in Brazil were measured to assess the compost bedded-pack tilling impact

on the atmosphere around the farm. Low-cost MSPs (multi-sensor platforms) were used in this experiment.

The atmospheric dispersion model selected for this study is WindTrax (Flesch and Wilson, 2005), a short-range backward Lagrangian Stochastic model (Flesch and Wilson, 1995). The model can generate many particles and follow them through their trajectories from sensors measuring gas concentrations to the emission source for calculating emission rates, replicating the turbulent motion of the atmosphere. A graphical interface software of the model is available (Crenna, 2020). The software is widely mentioned in the literature, especially in the agricultural sector, combined with various types of sensors used in several field trials. Most publications on WindTrax for estimating emissions from the agriculture sector concern gas losses from agricultural production factors: fertilized soil management (Bai et al., 2014; Lavrsen Kure et al., 2018; Ricco et al., 2021; Angelino et al., 2022), anaerobic digestion (Bell et al., 2016; Hrad et al., 2021), and livestock facilities, especially manure management (Leytem et al., 2018; Shonkwiler and Ham, 2018; Genedy and Ogejo, 2022; Tagliaferri et al., 2023). Other sectors in which WindTrax has been used are vulcanology (Pedone et al., 2017), industry (Sauer et al., 2018), gas and oil (Shaw et al., 2020; Riddick et al., 2022; Tian et al., 2022), waste (Elpelt-Wessel et al., 2021), and research (Hu et al., 2016).

Figure 1 shows that the authors of the above publications come from research institutions or universities worldwide: Australia, Austria, Canada, Denmark, France, Germany, Italy, United Kingdom, and USA.



Figure 1 - Research institutions or universities where the authors of the reported state-of-art come from.

Among the above state-of-art regarding WindTrax, ammonia is the most monitored gas, because it is responsible for fine particulate matter formation and eutrophication, hurting health, soil, water, biodiversity, and atmosphere (Bai et al., 2014; Bell et al., 2016; Lavrsen Kure et al., 2018; Leytem et al., 2018; Shonkwiler and Ham, 2018; Ricco et al., 2021; Angelino et al., 2022; Genedy and Ogejo, 2022). Other papers discuss non-fossil methane monitoring (Hu et al., 2016; Sauer et al., 2018; Shaw et al., 2020; Elpelt-Wessel

et al., 2021; Hrad et al., 2021; Riddick et al., 2022) because it is one of the most harmful GHG, reaching a GWP (Global Warming Potential) value of 27 in a 100-year time horizon (Forster et al., 2023). The remaining papers argue about CO₂ monitoring (Pedone et al., 2017; Sauer et al., 2018), also classified as a GHG, playing therefore a role in climate change. This paper can contribute to the universal emission measurement protocol for updating “top-down” inventories, i.e. defined from concentration measurements made in the field, to verify “bottom-up” inventories, i.e. defined from statistical data (Angelino et al., 2022). Obtaining emission estimates related to a specific climate context explains the importance of “top-down” inventories, so measuring emissions in a local context helps to validate “bottom-up” inventories. Moreover, many LCA analysis are based on the Ecoinvent database, the most popular LCA database, which contains climate change impact data for the Agriculture, Fishery, and Animal Husbandry sectors mainly from Australia, Brazil, Canada, Switzerland, and United States (Ecoinvent, 2023), leaving a data gap for local applications in other countries.

2. Materials and methods

2.1. *Animals and housing*

The dairy cattle farm where field trials were carried out is located southeast of the city of Belo Horizonte and about 30 km from the city of Lavras in the federal state of Minas Gerais, Brazil (Figure 2). The farm, which includes two buildings oriented from East to West, can be observed in the map in Figure 3. The smaller building contains the milking parlour and the milk room, the bigger is the livestock building. The building, dimensioned for housing 80 cows, is open on all four sides except for the part covered by the milking facility, with compost bedded pack in the resting area and a solid concrete floor in the feed lane. The resting area spans of 972.0 m², providing 12.5 m² available per cow. The bedding is composed of sawdust manure mixture and has a depth of 65.0 cm. In addition, the solid grooved concrete floor in the feed lane is cleaned twice a day by an operator. Litter tillage is made by a tractor twice a day in the morning at 06:00 AM and the evening at 06:00 PM (UTC-3), while cows are all moved in the feed lane. Twelve fans are installed at 4.50 m above the litter to provide forced ventilation and remove moisture from the compost litter. Each fan has a diameter of 1.1 m, three propellers, a rotation speed of 950 revolutions per minute, and an airflow of 23.000 m³ · h⁻¹. The forced ventilation direction (from northeast to southwest) is indicated in Figure 4, observing the internal distribution of functional areas of the livestock building.

One of the assumptions of the WindTrax model states that the surface around sources and sensors must be flat and free of obstructions (Crenna, 2006 a). In this case, the soil around the livestock building had an average slope of about 20%. The slope was calculated from a DSM (Digital Surface Model) of the farm (Figure 5) obtained using the Zephyr software (3D flow srl, 2023) after drone aero-photogrammetry operations. Altitude line contours indicate the ellipsoidal height (WGS 84) in the DSM in Figure 5 were obtained in the QGIS software (QGIS Association, 2023). The WindTrax software cannot implement the topographic surface of the soil, but in this case, the aim is the assessment of concentration sensors inside MSPs placed close to the compost barn source, where the surface is almost flat. Concentrations obtained from the model at distances beyond the positioning of the MSPs will be affected by a larger error.

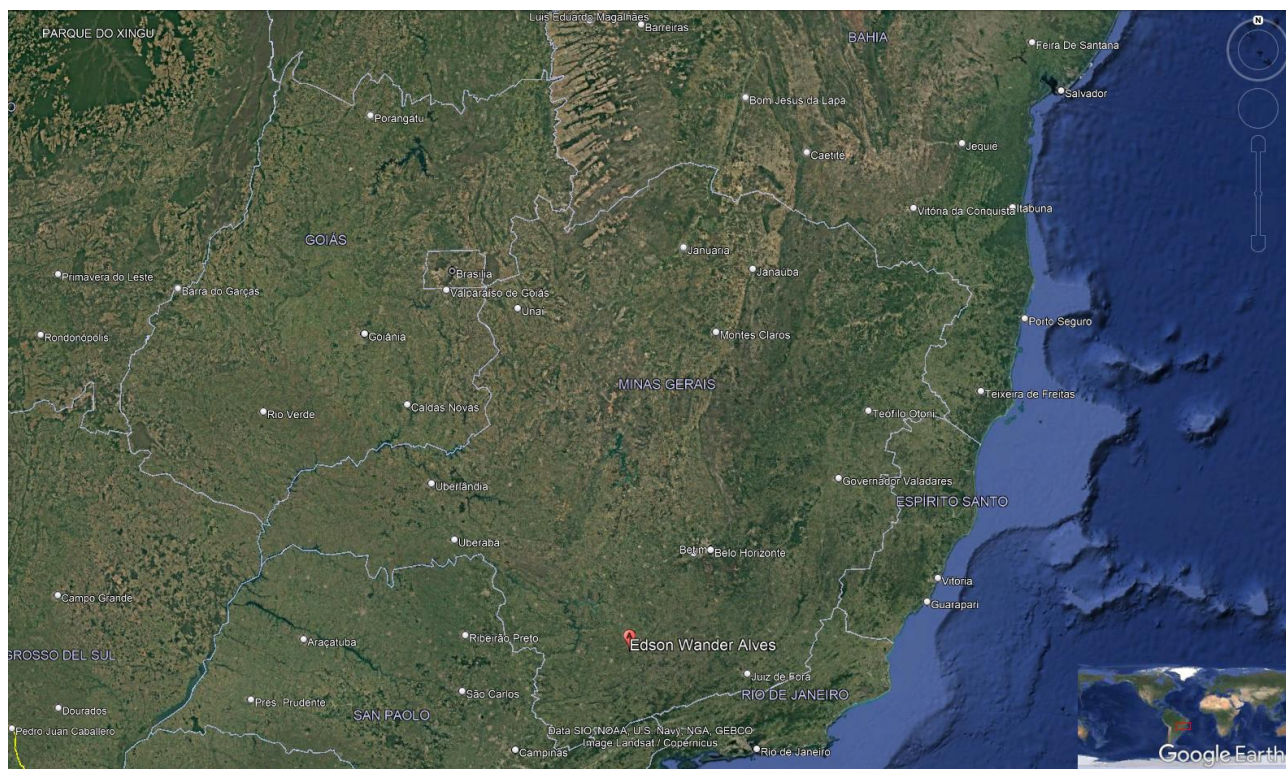


Figure 2 - The dairy cattle farm position in the Minas Gerais federal state, Brazil.

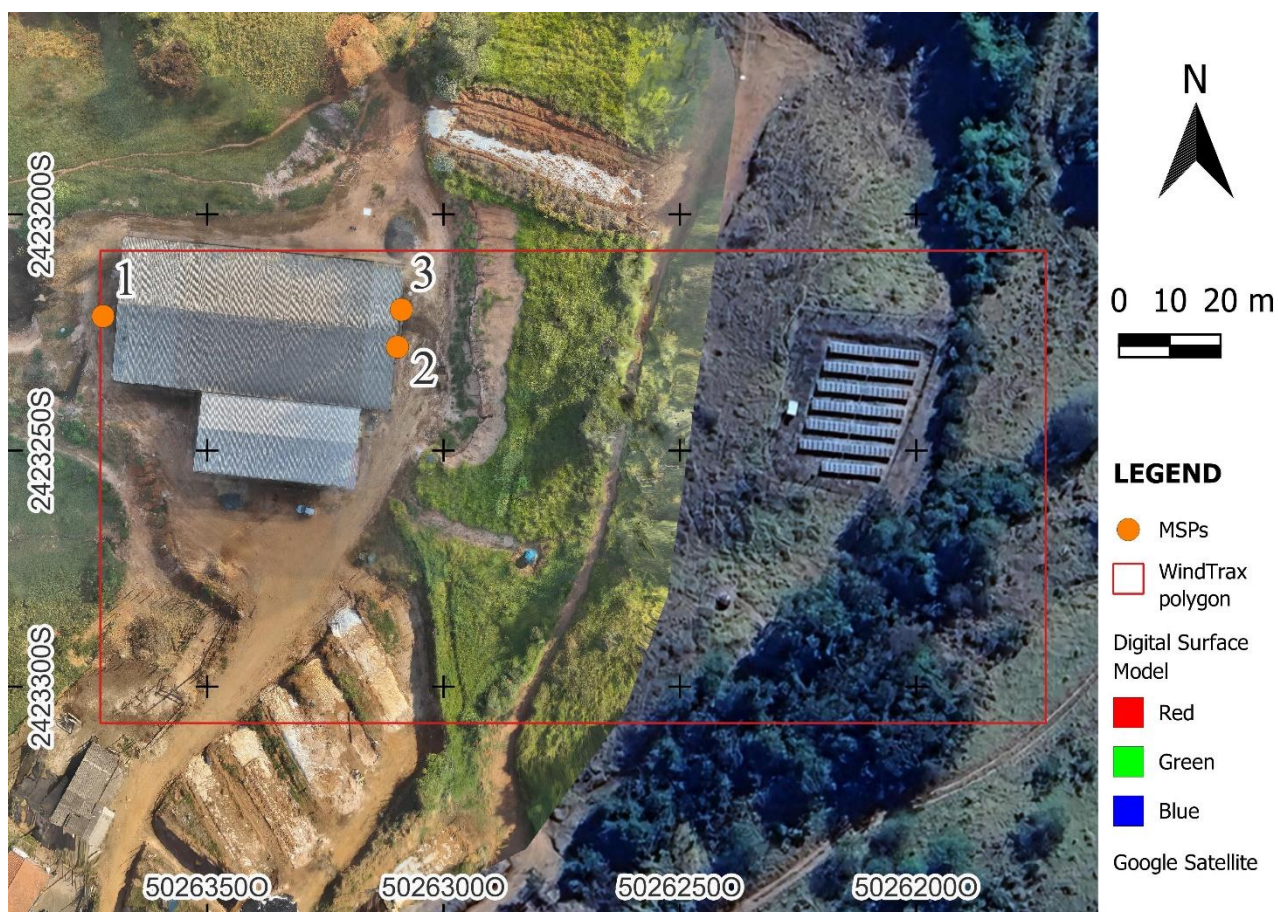


Figure 3 - The dairy cattle farm where field trials were carried out, indicating the MSP positions (WGS 84 reference system for longitude and latitude coordinates, 1:1.600).

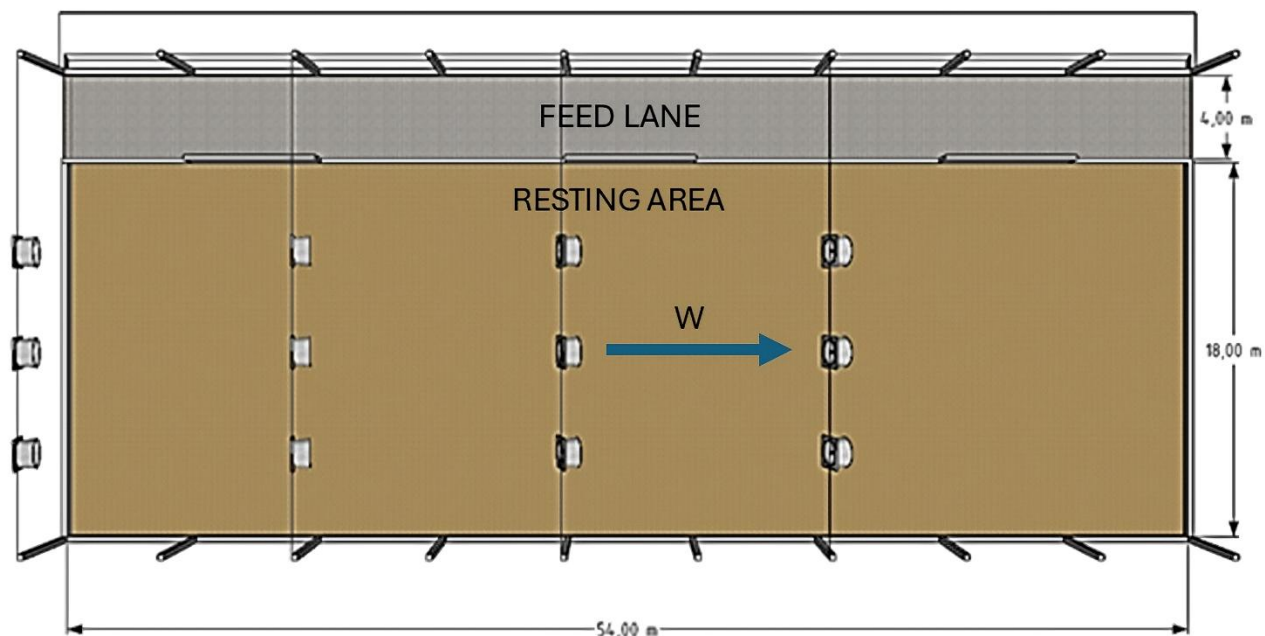


Figure 4 - Internal functional area distribution of the livestock building, indicating the forced ventilation direction (blue arrow).

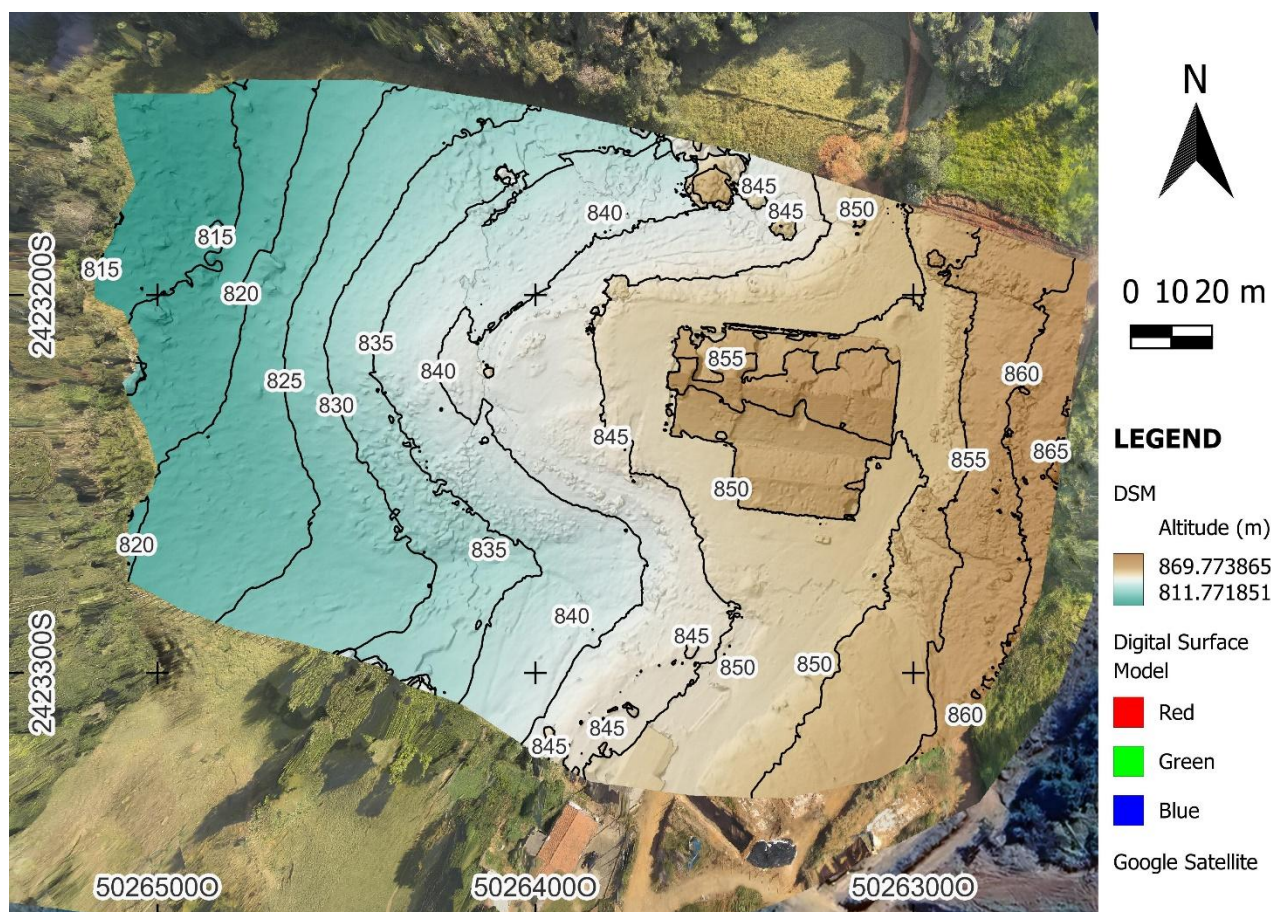


Figure 5 - The Digital Surface Model (DSM) of the farm including altitude contour lines above the ellipsoid level (WGS 84 reference system for longitude and latitude coordinates, 1:2.000).

2.2. Multi-sensor platforms

To characterize CO₂ emission from the compost barn, three low-cost MSPs with a sampling frequency of five seconds were used during field trials in the dairy cattle farm. Each MSP contains a CO₂ concentration sensor, as well as sensors for measuring environmental conditions, i.e. temperature (Celsius degree), pressure (Pa), and relative humidity (%). The CO₂ concentration sensor (SCD30, Sensirion, Stäfa, Switzerland) inside MSPs is a non-dispersive infrared sensor. Several pollutants respond differently when affected by infrared light with different absorption wavelengths, so the implemented sensor technology is based on this concept. CO₂ has an absorption peak in the mid-infrared, approximately at 4.26 µm wavelength. Inside the sensor, infrared light from the source goes through a measurement cell to detect how much light is absorbed by CO₂ and how much light is transmitted for calculating CO₂ concentrations. Temperature and relative humidity data are also provided by this sensor, thanks to an integrated module. In Table 1, measuring range and accuracy values can be observed for each detected parameter. The quite low height of the module allows easy integration for assembling sensors in an MSP. This solution leads to accurate and stable monitoring of CO₂ in the air, as well as temperature and relative humidity. MSPs also contain an absolute barometric pressure sensor (BMP280, Bosch Sensortec GmbH, Kusterdingen, Germany) with small dimensions and low power consumption. Technical data of this sensor are also shown in Table 1, as well as those regarding the two kinds of anemometers used for this study.

An ultrasonic anemometer (Ultrasonic Portable Mini Wind Meter, Calypso Instruments EMEA, S.L, Coral Gables, Miami, Florida) was used for obtaining wind speed ($\text{m} \cdot \text{s}^{-1}$) and wind direction data (degrees from North). On the first sampling day, during the litter tilling, the fans were switched off, and the instrument's sensitivity for wind speed was not reached, so wind speed data from a hot-wire anemometer (HM-385, Highmed) at the same location was used. For this reason, positioning downwind sensors as close as possible to the litter source was decided to match the measurement range of the Ultrasonic anemometer. However, the wind direction was provided by the Ultrasonic anemometer on the first day during the litter tilling. For all the other sampling days, wind speed data from the Ultrasonic anemometer were used for WindTrax simulations, since fans inside the livestock building were always switched-on during field trials. Sensor position data were obtained thanks to aero-photogrammetry operations made with a drone (Mavic 3 Enterprise, DJI Sciences and Technologies Ltd., Beijing, China), providing georeferenced photos in which sensors could be observed, so their geographical coordinates have been calculated through the DSM and imported in the QGIS software as background cartography maps. For each field trial, the same sensor positions were used.

Table 1 - Measuring range and accuracy of detected parameters by sensors inside MSPs and by the two types of anemometers (U - Ultrasonic and HW - Hotwire).

Parameter	Sensors	Measuring range	Accuracy
Carbon dioxide	MSP	0 - 5.000 ppm	± 30 ppm
Temperature	MSP	- 40 - 70 °C	± (0.4°C + 0.023 × (T[°C] - 25°C))

Relative humidity	MSP	0 - 100 % RH	$\pm 3\%$ RH
Pressure	MSP	300 - 1.100 hPa	± 1 hPa
Wind speed	U	1 - 25 m/s	± 0.3 m/s at 10 m/s
Wind speed	HW	0 - 30 m/s	$\pm 3\%$
Wind direction	U	0 - 359° N	$\pm 1^\circ$ N
Temperature	Temperature/RH Data Logger	-40 to 70°C	$\pm 0.2^\circ\text{C}$ from 0 to 70°C
Relative humidity	Temperature/RH Data Logger	0 - 100 % RH	$\pm 3\%$ RH

2.3. Experimental setup and data analysis

The following experimental design was applied in May 2024 in the dairy cattle farm, consisting of five field trials conducted over five days at approximately the same time each morning, from 10:40 to 11:50 AM (CEST, UTC + 2). Each trial included two 15-minute sampling intervals: one before (BEF) and one during (DUR) litter tilling. A 15-minute averaging period is commonly recommended in the literature on WindTrax modelling and in the user guide (Crenna, 2006 a). The same three MSP positions were maintained during each field trial, as well as the same sensor height for MSPs and anemometers (i.e. 1.50 m from the ground level). Two of these MSPs, one upwind (MSP 1) and the other downwind (MSP 2) were used for obtaining input data for WindTrax simulations. The third MSP (MSP 3) was used for comparing observed and modelled CO₂ concentrations. MSP positions can be observed in Figure 2. Both anemometers were positioned close to one of the downwind MSPs (MSP 2) on the first sampling day, while for the other days, the Ultrasonic anemometer was positioned close to one of the downwind MSPs (MSP 2) and the hot wire anemometer was positioned close to the upwind MSP (MSP 1). In addition, for each field trial, Temperature/RH Data Loggers (Hobo MX2301A, Onset Computer, Bourne, Massachusetts, United States) were positioned close to each MSP to compare temperature and relative humidity data. Technical data of Temperature/RH Data Logger sensors are also shown in Table 1, while the sensor can be observed in Figure 6, together with MSPs and the anemometers. Each MSP is equipped with designated air inlet and outlet directions, which were maintained during field trials by aligning with the forced ventilation direction.



Figure 6 - Anemometers and downwind MSPs during the first day of sampling.

2.3.1. WindTrax Model Assumptions and Inputs

WindTrax is a short-range atmospheric dispersion model valid for averaging periods between 15 and 30 minutes, distances within approximately one kilometer, and under flat and unobstructed terrain conditions. It solves a linear system of equations:

$$a_{11} Q_1 + a_{12} Q_2 + \dots + a_{1n} Q_n + C_{BG} = C_1$$

$$a_{m1} Q_1 + a_{m2} Q_2 + \dots + a_{mn} Q_n + C_{BG} = C_m$$

C_{BG} is the background concentration, Q_j are emission rates, C_i are measured concentrations, and the coefficient a_{ij} relates Q_j and C_i . If C_{BG} is unknown, an upwind concentration measurement is required, which was provided in this study via MSP 1. The model requires as inputs: at least two concentration measurements, temperature, pressure, wind speed and direction (via anemometer), and the spatial coordinates of sources and sensors. It calculates the emission rates of the sources and then concentrations as outputs. The WindTrax software describes the microclimate thanks to the surface wind model through the Monin-Obukhov theory. For this reason, four parameters are required: the surface roughness length z_0 (related to the height of elements covering the ground), the friction velocity u^* (the squared root of the covariance between the horizontal and vertical components of the wind), the Monin-Obukhov length L (atmospheric stability), and the mean horizontal wind direction θ (Crenna, 2006 a, 2006 b). The next section explains how these parameters were quantified, but a more extended description of the model is provided in the indicated bibliography (Flesh and Wilson, 1995, 2005), also containing a study on the sensor positioning according to the emission source (Crenna et al., 2008).

Furthermore, WindTrax is a statistical model that matches each result with an error. Thus, this model can be used for refining a measurement protocol and assessing concentration sensors at the prototype stage. In this case, significant suggestions were obtained to design a new version of the prototype multi-sensor platform used in this study, using also commercial sensors to survey environmental conditions.

The WindTrax software was used for calculating emission rates from the compost barn and concentrations. Other needed parameters for WindTrax simulations are the surface

of the source, the surface roughness length, the atmospheric stability, the number of particles, and the elevation of the soil. The surface of the source is obtained by drawing in the software over geo-referenced images obtained in QGIS. The selected surface roughness length z_0 was 2.30 cm, i.e. short grass covered the surface around sources and sensors. The atmospheric stability was calculated by explicating Pasquill-Gifford classes, during the nighttime relating to the wind speed, always $2-3 \text{ m} \cdot \text{s}^{-1}$, and night cloud cover, always less than 50%, so selecting the F class in this case. The WindTrax software calculates the Monin-Obukhov length L by having the Pasquill-Gifford class. The friction velocity u^* is also calculated by the model, having the wind data. As stated in the user guide (Crenna, 2006 a), as the number of particles increases, the uncertainty decreases, so a high number of particles was selected, i.e. 50.000. The selected elevation of the soil was zero, due to the presence of pressure data provided by MSPs.

Fifty CO_2 emission rates in each BEF fifteen-minutes averaging period and fifty CO_2 emission rates in each DUR fifteen-minutes averaging period were calculated, i.e. one hundred CO_2 emission rates per day. In addition, the analysis of variance (ANOVA) was applied to each BEF and DUR periods using a linear model with a level of significance of 0.05 to test the effect of the period for the second, third, fourth, and fifth sampling days. Normality assumption was validated using the Shapiro-Wilk test. The first day was not considered in the ANOVA because of the difference in wind conditions in the two periods, i.e. the fan switch-off in the DUR period. Least-mean square errors and standard errors are reported for CO_2 emission rates.

PC (percentage change) in terms of maximum predicted concentrations ($\max C$) between the two periods, BEF and DUR litter tilling, were calculated with the following equation:

$$PG (\%) = \frac{\max C_{DUR} - \max C_{BEF}}{\max C_{BEF}} \quad (1)$$

To test the model performances, measurements collected by MSP 3, made at the height of 1.50 meters from the ground, were used to compute a ER (percentage error) between M (modelled) and O (observed) CO_2 concentration data in the same position, for each i^{th} (BEF and DUR 15-min) period:

$$ER (\%) = \frac{M_i - O_i}{O_i} \quad (2)$$

95% confidence intervals at the heights from 0.5 to 4.5 m from the ground surface were calculated using the WindTrax software and mean values of the confidence intervals were used as modelled CO_2 concentrations. For observed concentrations, the 15-minute average values were used. The first day was nevertheless considered for this analysis, despite the difference in experimental conditions.

R (R Core Team, 2024) and Rstudio (Rstudio Team, 2024) were used for data analysis by selecting a set of library functions i.e. packages like Openair (Carslaw and Ropkins, 2012; Carslaw, 2019), useful for air quality data analysis, Raster (Hijmans, 2024) for mapping and analysing CO_2 concentration data contained in raster files, and ggplot2 (Wickham, 2016) for creating following plots.

By comparing temperature and relative humidity data obtained from MSPs and Temperature/RH Data Loggers, the following observations were achieved. For all field

trials, Data Logger temperatures are lower and Data Logger relative humidities are higher than those measured by MSPs. Measured temperatures and relative humidities by MSPs and Data Loggers during the first sampling day can be observed in Figure 7. Graphs for the other sampling days are shown in the Supplementary Material (Figures S1-S5). To better describe the microclimate around the source, commercial sensor temperatures and MSP pressures were selected for WT simulations due to differences in the environmental parameters inside and outside the MSPs.

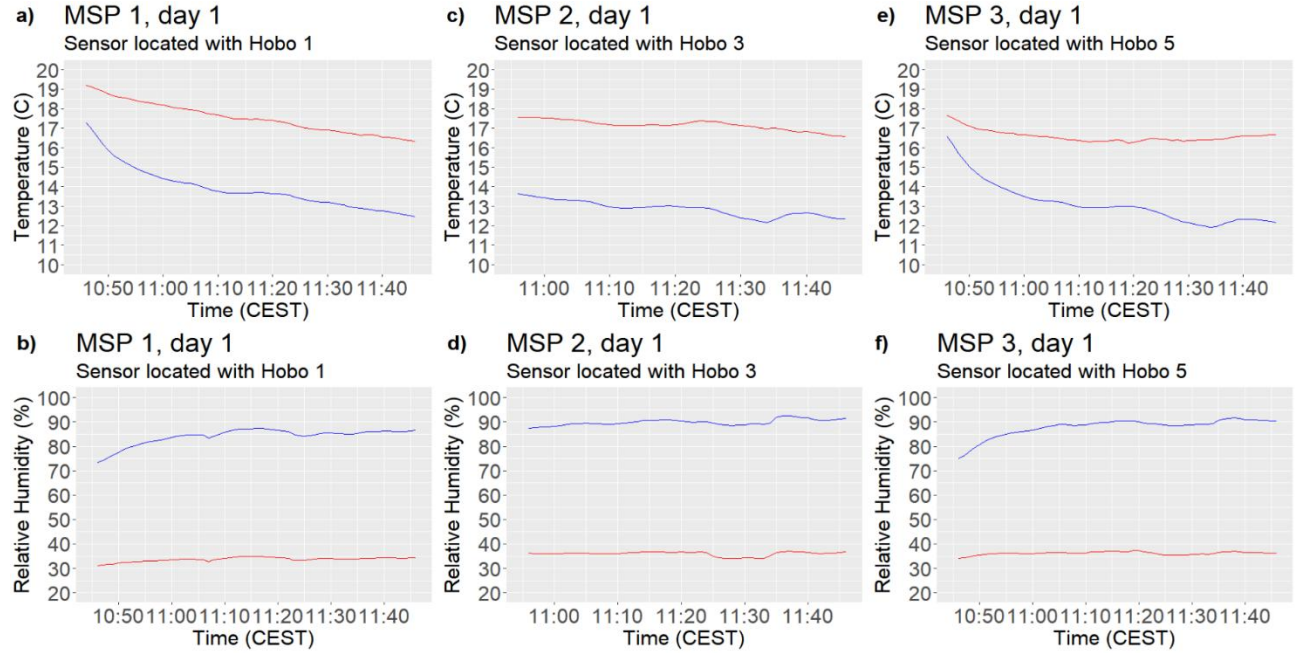


Figure 7 - Measured temperatures (a, c, e) and relative humidities (b, d, f) by MSPs (in red) and T/RH Data Loggers (in blue) during the first sampling day.

3. Results and discussion

3.1. CO₂ Emission rates

The WindTrax software has been used for calculating fifty CO₂ emission rates BEF and fifty CO₂ emission rates DUR the litter tilling, i.e. one hundred CO₂ emission rates per sampling day. Input data can be observed in Table S1 in the Supplementary Material. All the calculated CO₂ emission rates can be observed in Figure 8. All the emission rates calculated from measurements taken DUR the litter tillage were expected to be higher than BEF, due to the handling of litter, which leads to the volatilisation of gases produced by fermentation (Leso et al., 2020; El Mashad et al., 2023; Fuertes et al., 2023). This trend was observed on all sampling days except the first, when the fans were switched off during the tilling phase. For the other days, the emission rates DUR litter tilling are higher than those BEF. Least-square means and standard error of calculated CO₂ emission rates between the two periods are reported in Table 2. Minimum CO₂ emission rates BEF and DUR litter tilling occurred in the second day of measurements (BEF: 0.01818 g · m⁻² · s⁻¹; DUR: 0.03129 g · m⁻² · s⁻¹), despite the high percentage variation between the two periods. Maximum CO₂ emission rates before and during litter tilling occurred on the third day of measurements (BEF: 0.07488 g · m⁻² · s⁻¹; DUR: 0.16400 g · m⁻² · s⁻¹). Putting together all the calculated CO₂ emission rates, excluding those of the first day because of

the fans' switching off DUR the litter tilling, anyway by distinguishing between BEF and DUR litter tilling, respectively the following mean values of $0.03700 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$ and $0.06511 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$ were obtained. Thus, in terms of CO_2 emission rates, the litter tilling in the morning impacts on average with an increase of about 76% in the survey period. Figure 9 shows boxplots concerning modelled CO_2 emission rates for the second, third, fourth, and fifth days in the two periods, including the ANOVA significance level ($p\text{-value} < 0.05$). Wolf (2017) calculated CO_2 emission rates of compost bedded pack barn in Kentucky at twenty minutes after tillage with a static chamber, obtaining $100.2 \text{ g} \cdot \text{m}^{-2} \cdot \text{h}^{-1}$ i.e. $0.02783 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$, a comparable value with those obtained in the present paper, despite the different calculation method.

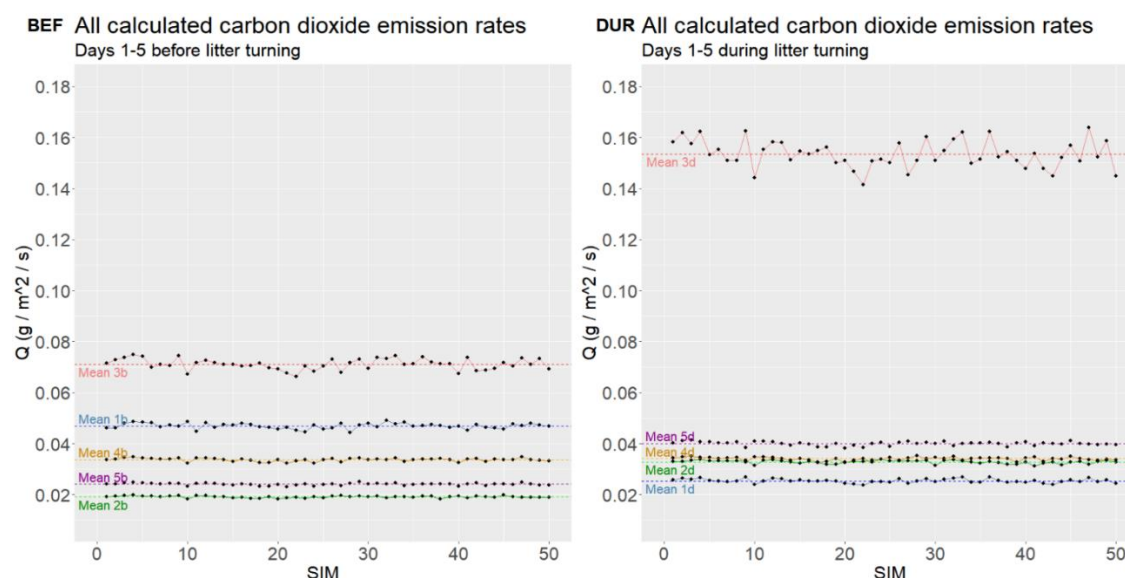


Figure 8 - All calculated CO_2 emission rates ($Q, \text{g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$) for the two periods, before (BEF) and during (DUR) litter turning, including the mean value considering the fifty simulations (SIM) made with the WindTrax[®] software.

Table 2 – Ismeans (Least-square means) and SE (standard error) of calculated CO_2 Qs for the two periods, BEF and DUR litter tilling.

Days	Q_{BEF} ($\text{g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$)		Q_{DUR} ($\text{g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$)	
	Ismean	SE	Ismean	SE
2	0.01910 ^a	$7.55 \cdot 10^{-5}$	0.03283 ^b	$7.55 \cdot 10^{-5}$
3	0.07110 ^a	$5.72 \cdot 10^{-4}$	0.15360 ^b	$5.72 \cdot 10^{-4}$
4	0.03370 ^A	$9.22 \cdot 10^{-5}$	0.03400 ^B	$9.22 \cdot 10^{-5}$
5	0.02405 ^a	$8.89 \cdot 10^{-5}$	0.04000 ^b	$8.89 \cdot 10^{-5}$

^{a,b} Significant differences between columns (treatment) within days of measurement (at $P < 0.001$).

^{A,B} Significant differences between columns (treatment) within days of measurement (at $P < 0.01$).

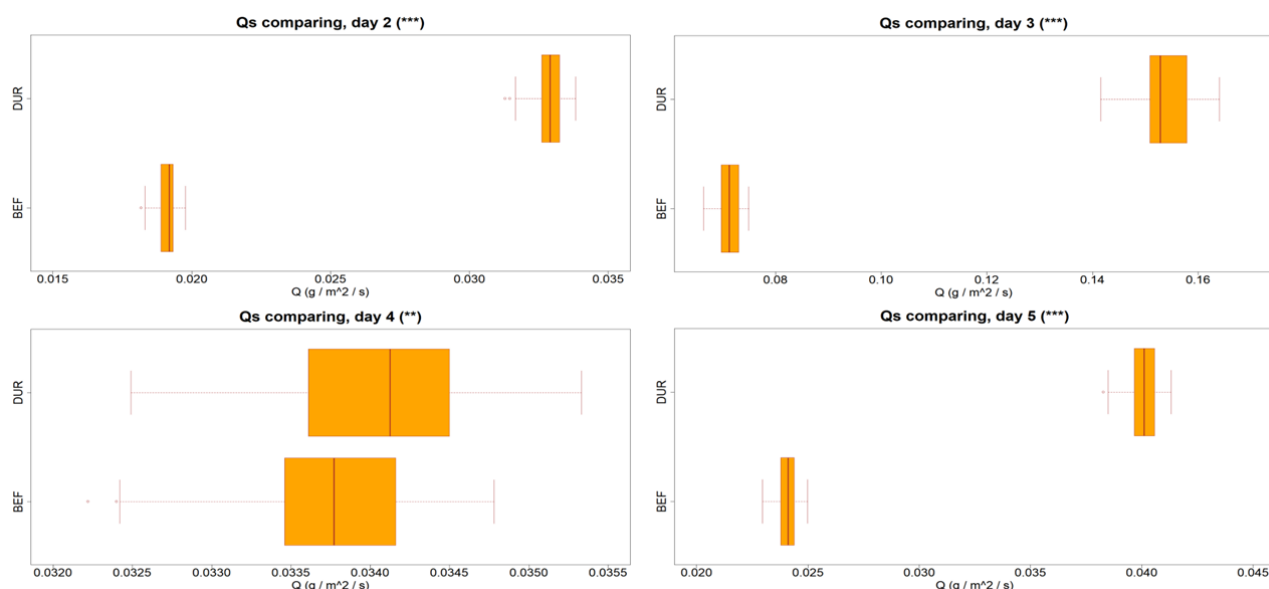


Figure 9 - ANOVA on CO₂ emission rates by distinguishing BEF and DUR litter turning for the sampling day 2, 3, 4, 5.

3.2. CO₂ Concentrations

Figure 10 shows real-time environmental parameters (temperature, relative humidity, and pressure) and CO₂ concentrations detected by downwind MSPs i.e. MSP 2 and 3 during the third day. A clear increase in CO₂ concentration is observed with the tractor tilling in the livestock building from 11:24 to 11:36 AM (CEST, UTC + 2). This trend was consistent across all other sampling days (Supplementary Material, Figures S6-S10).

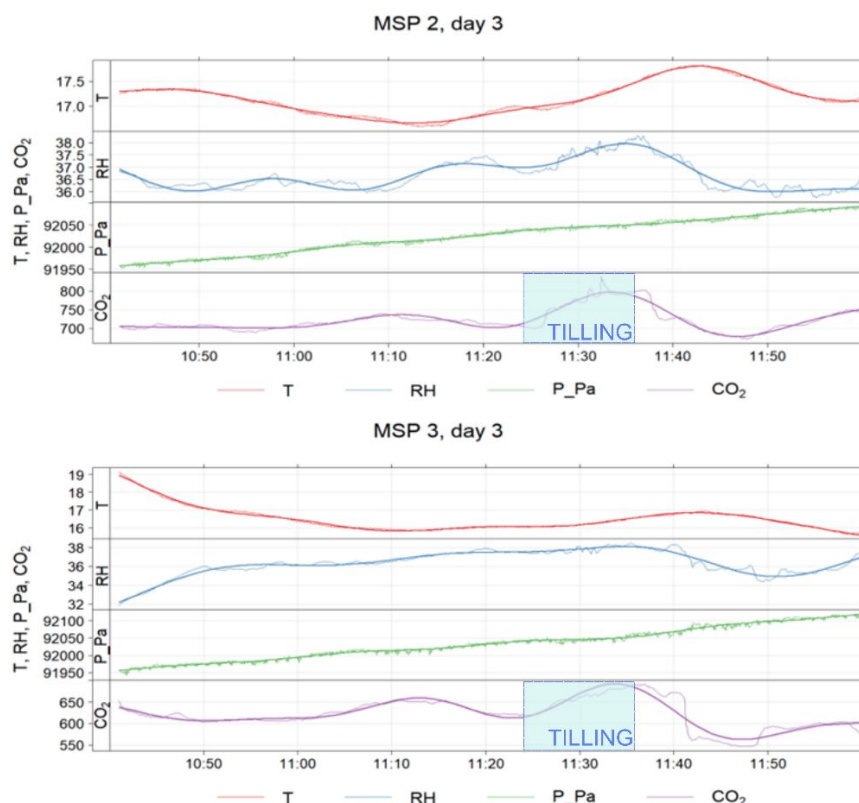


Figure 10 - Detected environmental conditions (temperature in Celsius degrees, relative humidity %, and pressure in Pascal) and CO₂ concentrations in ppm at MSP 2 and MSP 3 positions during the third sampling day, indicating the period of the litter tilling (11:24-11:36 AM) with the dashed blue area.

Calculated emission rates were used for obtaining CO₂ concentrations in a wide area of 20.000 m² at 1.5 m from the ground. The positioning and size of the area were selected to frame the emission flux considering the source and the wind direction (see the red square in Figure 3). Figure 11 shows two raster images obtained from calculated CO₂ emission rates, where predicted CO₂ concentrations are reported. Each raster image was obtained in the QGIS software from text files in which the predicted concentrations from the WindTrax software were saved. Different CO₂ concentrations in the two images are helpful for describing the atmospheric dispersion around the compost barn. In Figure 11, the CO₂ atmospheric dispersions on the third sampling day BEF and DUR the litter tilling are reported, along with the contour lines of the predicted concentrations. Atmospheric dispersions for the other sampling days are contained in the Supplementary Material (Figures S11-S15). The raster images referred to the same sampling day have the same scale of values for CO₂ concentrations between the two periods to be comparable. Although these do not represent the real CO₂ plume due to lack of integration in the analysis of the soil topography, the gas dispersion is accepted for the validation of CO₂ concentrations predicted by WindTrax model against concentrations measured by MSP 3. The Wind Rose for the third-day field trial is shown on the map in Figure 11. Wind data were derived from the ultrasonic anemometer placed close to the MSP 2. The uncertainty of the model may depend on sensor geometry (Crenna et al., 2008) i.e. the position of sensors in the farm since the MSP 3 used for the assessment is not affected by the larger variation of CO₂ concentrations, as shown in Figure 11, even if concentrations were calculated in all the surface of the red square in Figure 3.

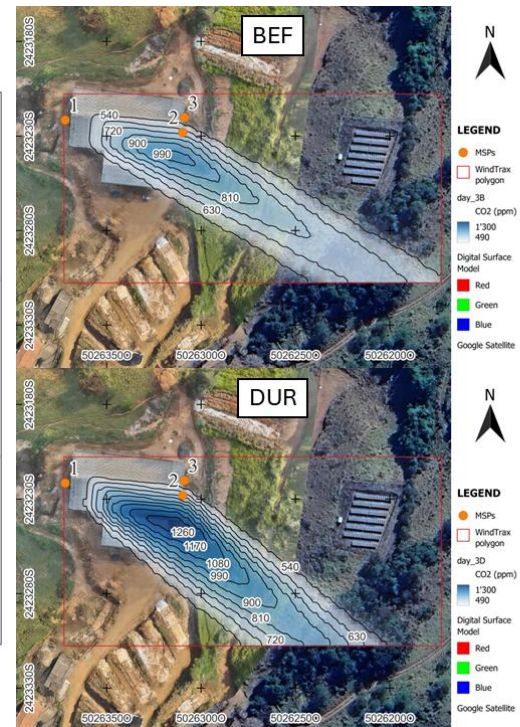
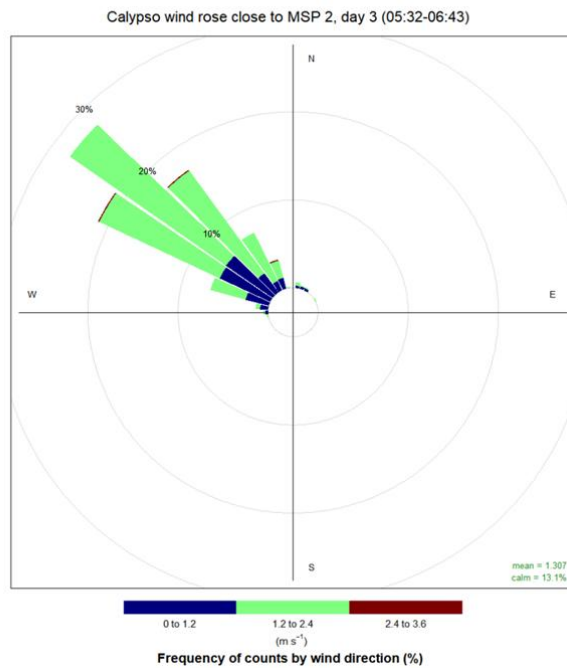


Figure 11 - Third-day CO₂ atmospheric dispersion in ppm and the Wind Rose in degrees from north BEF and DUR the litter turning.

The analysis of concentration data of raster images alone does not lead to a correct description of CO₂ atmospheric dispersion because they contain many minimum values around the plume. For this reason, maximum values BEF and DUR litter tilling are analysed. Despite the lower emission rate obtained on the first day DUR the litter tilling, high concentrations were obtained for this day, which is probably caused by a CO₂ accumulation inside the livestock building. Figure 12 shows a histogram concerning CO₂ concentration frequency and the raster file by WindTrax for the third day DUR the litter tilling, observing modelled CO₂ concentrations from a minimum value of 495 ppm to a maximum value of 1,300 ppm. Most of the results contained here are referred to the third sampling day, because maximum emission rates and concentrations are obtained in this day for the two periods. Atmospheric dispersions and their histograms for the other sampling days are contained in the Supplementary Material (Figures S16-S20). Results in terms of maximum predicted CO₂ concentrations are shown in Table 3 by using equation 1, emphasising the second-highest maximum PC on the first day, confirming the hypothesis of CO₂ build-up in the livestock building due to the fans being switched off on the first sampling day DUR the litter tilling. The maximum PC in terms of CO₂ concentrations was obtained for the third day, while the minimum PC occurs for the fourth sampling day, the only day when the ANOVA shows the lowest significance (p -value < 0.01) between the two periods. This is probably caused by the minimum temperatures that occurred during the fourth day, using a range of input data of 10.44-11.68°C against a range of input data of 12.54-14.4°C for the other days. So, with the detected low values of temperatures during the fourth day, small atmospheric dispersions were obtained with a little difference between the two periods. Moreover, the fourth is the day when the tilling duration reached the minimum value of 10 minutes as can be observed in Table S1 in the Supplementary Material.

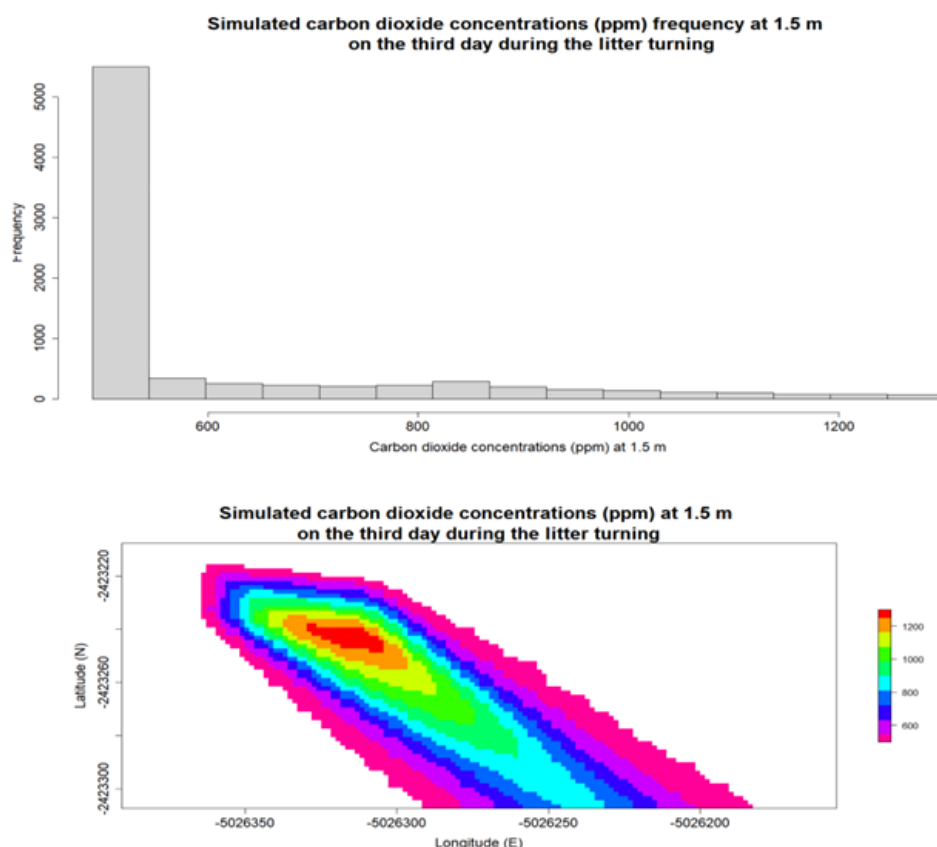


Figure 12 - Modelled CO₂ concentration frequency histogram and CO₂ atmospheric dispersion by WindTrax® for the third day during the litter turning.

Table 3 - Max Cs, including the PC for the two periods, BEF and DUR litter tilling.

Days	Max C _{BEF} (ppm)	Max C _{DUR} (ppm)	PC
1	839.04	935.60	+ 11.51%
2	706.49	758.41	+ 7.35%
3	1,020.00	1,300.00	+ 27.45%
4	694.10	708.77	+ 2.11%
5	681.85	718.95	+ 5.44%

Percentage errors between modelled and observed CO₂ concentrations measured by MSP 3 for BEF and DUR periods are noted in Table 4 by using equation 2, showing over- and underestimates of modelled CO₂ concentrations. Despite the statistical result not obtained, results show a good agreement, except for the third day, i.e. the day in which the percentage error reached the maximum value of 24.69%. These results are referred to the following detected environmental conditions for each field trial in the Minas Gerais Federal State, Brazil in May 2024: 10-14°C temperatures, 92,022-92,416 Pa pressures, 0.61-1.76 wind speeds, and 271-309° wind directions. As an example, Figure 13 shows a vertical profile plot for the third sampling day DUR the litter tilling, indicating 95% confidence intervals with black intervals for heights from the ground between 0.5 and 4.5 m. At 1.5 m above ground level, the fifteen mean observed CO₂ concentrations (red points), obtained by averaging measurements with 1-minute intervals at MSP 3 position are reported. Vertical profile plots of each sampling day for the two periods are shown in the Supplementary Material (Figures S21-S25). These results are explained focusing on

the WindTrax model assumptions (Crenna 2006 a). In all the sampling days, the assumption of a homogeneous and flat surface around the source and sensors is not respected, due to the average slope of the soil of about 20%. Furthermore, the advice of a distance of at least fifteen times the obstacle heights is not respected, i.e. sensors were positioned too close to the livestock building, which generated turbulence that affected the measurements. All the bibliography here on the WindTrax model reports experiments in which the sensors were placed at the recommended distance from the sources. Recent publications (Lemes et al., 2023; Bühler et al. 2024), which did not use the WindTrax software, but a backward Stochastic Lagrangian model (Häni, 2021) consistent with the results of the WindTrax software, draw attention to this advice given by the model's authors. Another source of uncertainty could be traced back to the input data, especially pressure. In this case, given the difference between MSPs and commercial sensors in temperature and relative humidity detecting (Figures 7, S1-S5), the input pressure should also correctly represent the environment outside the MSPs, but for this study, the pressure detected by MSPs was used.

Table 4 - ERs (percentage errors) between modelled and observed CO₂ concentrations BEF and DUR the litter tilling for all sampling days.

Days	ER _{BEF}	ER _{DUR}
1	- 9.81%	+ 11.84%
2	+ 17.26%	+ 10.85%
3	- 21.12%	- 24.69%
4	- 15.13%	- 18.33%
5	- 12.69%	- 16.74%

Day 3 DUR

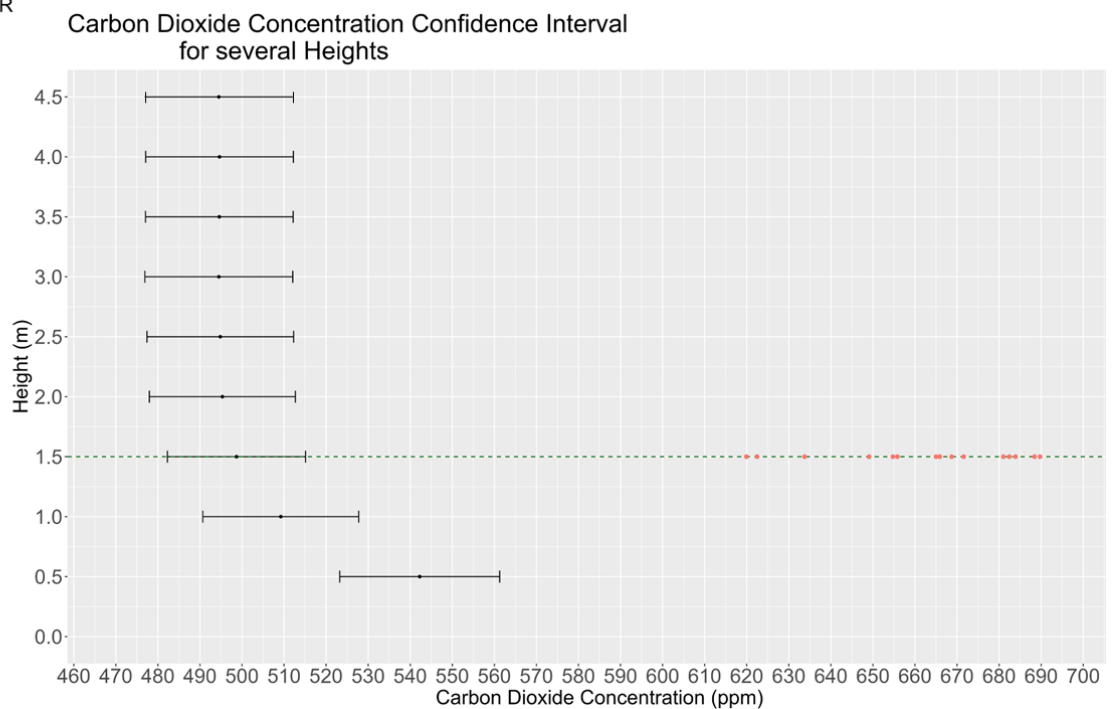


Figure 13 - Overestimate of detected CO₂ concentrations by MSP 3 for the third sampling day during the litter turning. Black intervals are modelled CO₂ concentration 95% confidence intervals, while red points are mean observed CO₂ concentrations.

4. Conclusions

In conclusion, the WindTrax model provided a good methodology for calculating emission rates and concentrations of the compost material used as bedding material in a livestock building in moderately stable atmospheric conditions (F Pasquill-Gifford class) as described in this study. The use of MSPs (multi-sensor platforms) was valuable for evaluating modelled concentrations, and several key considerations emerged from the results. By referring to the second section, it is necessary to improve the design of the MSP, developing a new internal layout to optimize airflow and sensor placement. This requires, besides, the outwards positioning of the sensitive part of the temperature, relative humidity, and pressure sensors, because of the differences in internal and external environment. Another corrective action is increasing the number of sensors and field trials to better describe compost barn emissions in different seasons or environmental conditions. One of the sensors to be implemented in air quality monitoring is certainly a sonic anemometer capable of measuring wind statistics that can be directly entered into the WindTrax software for the calculation of three of the four required parameters: the Monin-Obukhov Length L , surface roughness length z_0 , and the friction velocity u^* (Crenna et al., 2006 b). For this study, the Monin-Obukhov length L was calculated by estimating atmospheric stability through Pasquill-Gifford classes, however, for all studies in the current state-of-art that achieved a low level of uncertainty, a sonic anemometer was used. Finally, other CO₂ sources that could have contributed to the modelled concentrations are animals (respiration and enteric fermentations), the tractor (fuel combustion), and manure fermentations over the feed lane. Further studies are needed to better describe daily and seasonal variations in CO₂ emission rates and CO₂ concentrations, improving the analysis with continuous monitoring, a better sensor placement in the farm, and data filtering related to meteorological conditions (Flesh et al., 2005).

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CRedit authorship contribution statement

Alessio Mattia: Writing - original draft, Conceptualization, Methodology, Investigation, Data Curation, Visualization, Formal analysis. **Valentina Becciolini:** Writing – review & editing, Formal analysis, Supervision, Validation. **Giuseppe Rossi:** Writing - Review & Editing, Supervision. **Leonardo Conti:** Project administration, Funding acquisition. **Marco Merlini:** Software, Resources. **Patricia Ferreira Ponciano Ferraz:** Supervision, Resources. **Gabriel Araújo Silva Ferraz:** Supervision. **Jacqueline Cardoso Ferreira:** Investigation, Data Curation. **Franck Morais de Oliveira:** Investigation, Data Curation.

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6. Articoli in preparazione

Al fine di completare il presente lavoro di tesi con altri protocolli di misura, metodologie e tecniche di analisi delle emissioni in atmosfera dagli allevamenti zootecnici, soprattutto in base alle criticità riscontrate nel sistema di misurazione sviluppato dal DAGRI, sono state effettuate a giugno e luglio 2025 delle prove sperimentali in Francia con due gruppi di ricerca di Rennes, Francia, appartenenti all'IDELE e all'INRAE, di cui vengono riportati alcuni risultati preliminari.

6.1. Studio 4

La collaborazione con l'IDELE aveva l'obiettivo di calcolare i fattori di emissione di vari gas con il metodo semplificato (Vergé et al., 2023) da due edifici per la stabulazione di vitelli da carne aventi un diverso sistema di ventilazione e ubicati presso il CIRVEAU (Centre d'Innovation et de Recherche sur le Veau) a Maunon, poco distante da Rennes. Il metodo semplificato consente di calcolare i fattori di emissione attraverso misurazioni di concentrazione e l'applicazione del bilancio di massa alla scala dell'edificio considerato come sorgente. Le misurazioni di concentrazione avvengono con un apposito apparato per la raccolta di campioni di aria a 0,5 m e a 2,0 m dal suolo, all'interno e all'esterno dei locali di allevamento. È possibile completare il bilancio di massa che fa parte del metodo semplificato grazie alla compilazione di un questionario da sottoporre agli allevatori, relativo alla gestione della mandria, della loro alimentazione, delle superfici e dei reflui zootecnici. Nell'ambito del progetto europeo CCC (Climate Care Cattle) Farming (CCC Farming, 2020), sono stati sviluppati protocolli di misura e metodologie per valutare le emissioni gassose dagli allevamenti zootecnici, così IDELE e la sezione di Costruzioni Rurali e Territorio Agroforestale (SSD AGRI-04/C) del DAGRI dell'Università degli Studi di Firenze hanno collaborato attivamente allo sviluppo di varie tecniche di misura e analisi.

L' NH_3 , non rilevata durante i rilievi in esterna inclusi nelle pubblicazioni precedenti riportate nel presente lavoro di tesi, è stata invece rilevata all'interno dei due edifici del CIRVEAU, entrambi delimitati da pareti, perciò chiusi sui quattro lati, dalla sensoristica sviluppata dal DAGRI, ma anche da

tubi passivi (Gas Detector Tube System n. 3DL NH₃, Gastec Corporation, Ayase, Kanagawa, Giappone) e da pipette apposite (Dräger tube: ammoniaca 0,25/a, Drägerwerk AG & Co. KGaA, Lubecca, Germania). Il prelievo di campioni di aria a due altitudini, analizzati successivamente in laboratorio con la tecnica della gascromatografia ha permesso di rilevare le concentrazioni di CH₄, CO₂ e N₂O. L'ultima versione delle piattaforme multi-sensore non integra il sensore del CH₄, a causa dell'elevato campo di misurazione del sensore selezionato per la versione precedente e testato nei monitoraggi in esterna in allevamenti di bovini da latte, ma questo gas è stato rilevato con la gascromatografia. In questo modo è stato possibile confrontare la sensoristica a disposizione e il calcolo dei fattori di emissione di CO₂, CH₄, NH₃ e N₂O. I fattori di emissione sono stati calcolati grazie ad un foglio di calcolo Excel elaborato durante il progetto CCC Farming. La sensoristica sviluppata dal DAGRI è stata inoltre predisposta per un monitoraggio continuo di dieci giorni nei due edifici in numero pari ad un'unità per edificio. I tubi passivi per il monitoraggio dell'NH₃ e della CO₂ (Gas Detector Tube System n. 2D CO₂, Gastec Corporation, Ayase, Kanagawa, Giappone) sono stati distribuiti nei due edifici a due diverse altezze e i dati ottenuti sono stati poi utilizzati per l'applicazione dell'interpolazione spaziale di Kriging ordinaria, utile per verificare se i due diversi sistemi di ventilazione creassero delle zone di accumulo, soprattutto ad altezza spalla degli animali stabulati, nell'ottica del benessere animale e degli operatori.

La distribuzione interna dei due edifici, la collocazione dei tubi passivi e delle piattaforme multi-sensore e la posizione dei punti di prelievo dell'aria vengono mostrate in Figura 2. Le superfici interne non coperte dai box e dalle mangiatoie rappresentano i corridoi percorsi per la raccolta dei campioni di aria all'interno dei due edifici.

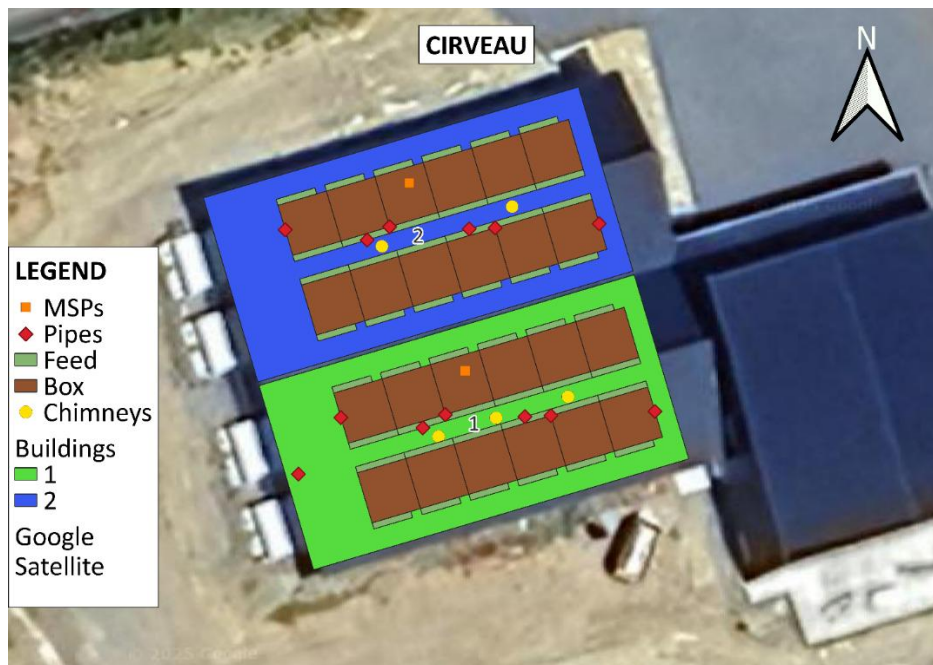


Figura 2. I due edifici aventi differente sistema di ventilazione presso il CIRVEAU, Mauron, Francia: distribuzione interna (box in marrone e mangiatoie in verde), collocazione della sensoristica (piattaforme multi-sensore in arancione, tubi passivi in rosso) e posizione dei punti di prelievo dell'aria (in giallo).

I due edifici sono identici, costituiti principalmente da due file di box corredati da mangiatoie ed aventi pavimentazione grigliata in legno al di sopra delle fosse per convogliare i reflui zootecnici da rimuovere successivamente verso una concimaia coperta. La distribuzione dell'alimento e la pulizia delle fosse sono automatiche ed avvengono entrambe due volte al giorno. I due edifici hanno un diverso sistema di ventilazione:

- Edificio 1: l'aria viene pompata verso l'esterno grazie a tre ventilatori posizionati nel tetto, rappresentando il sistema tradizionale principalmente adottato in Francia negli allevamenti al chiuso.
- Edificio 2: l'aria viene pompata all'interno da due ventilatori posizionati nel tetto e prosegue il suo percorso attraverso la pavimentazione e le fosse, per poi essere aspirata da un'altra ventola posta al di sotto del piano della pavimentazione verso l'esterno.

Per come sono stati concepiti i due sistemi di ventilazione, le finestre vengono tenute aperte soltanto nell'Edificio 1. Una descrizione schematica dei flussi dell'aria nei due edifici viene fornita in Figura 3.

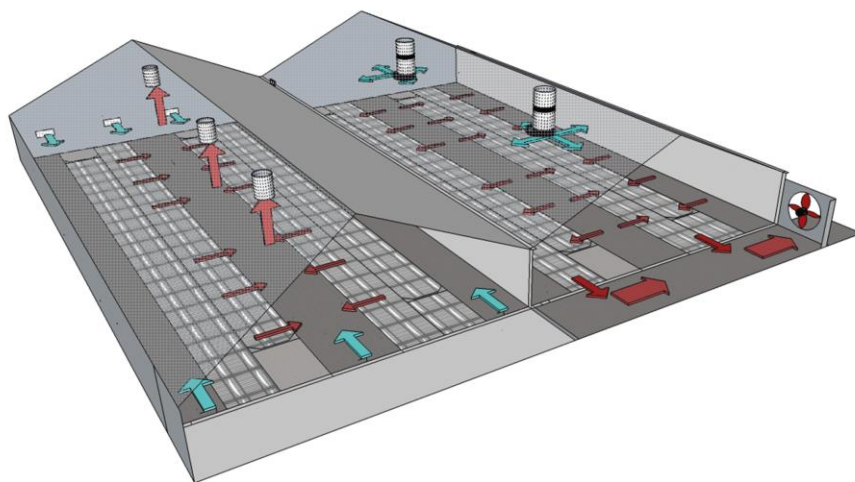


Figura 3. Rappresentazione schematica del flusso dell'aria nell'edificio 1 (a sinistra) e nell'edificio 2 (a destra). Le frecce celesti rappresentano i flussi di aria in entrata, mentre le frecce rosse rappresentano i flussi di aria in uscita.

6.2. Studio 5

La collaborazione con INRAE, nello specifico con OPAALE (Optimisation des Procédés en Agriculture, agro-Alimentaire et Environnement), ha avuto l'obiettivo di misurare le emissioni di CH_4 nella filiera della produzione del biogas. Il CH_4 non è mai stato rilevato in esterna dalle piattaforme multi-sensore sviluppate dal DAGRI, a causa di un campo di misurazione del sensore selezionato che risulta troppo elevato per i monitoraggi in esterna. OPAALE ha quindi adottato un'altra soluzione, selezionando sul mercato un sensore con tecnologia laser (LGD Compact-A CH_4 , Axetris AG, Kägiswil, Svizzera), che possiede un limite di rilevamento al di sotto di 1 ppm. Il loro sistema di misurazione è quindi composto dal sensore laser, agganciato ad un drone DJI M350 RTK (DJI Sciences and Technologies Ltd., Beijing, China), a cui viene agganciato anche un anemometro a ultrasuoni. L'aggancio del sensore laser avviene al di sotto del corpo del drone, per cui, per ridurre l'influenza del downwash sul sensore di concentrazione, è stato collegato un tubo di prelievo con filtro all'estremità che impedisce alla polvere di entrare nella camera di campionamento. Tutti i sensori vengono alimentati direttamente dalle batterie del drone con l'utilizzo di una E-Port (DJI Sciences and Technologies Ltd., Beijing, China). Questa soluzione permette di non sovraccaricare il drone con un ulteriore carico utile rappresentato dal power bank per l'alimentazione dei sensori, come avviene invece per la soluzione sviluppata dal DAGRI. OPAALE ha anche sviluppato

un'interfaccia di visualizzazione dei dati misurati in tempo reale con grafici e cruscotti. Il protocollo di misura riguarda principalmente il percorso effettuato dal drone e quindi la missione di volo. Questa viene programmata attraverso un codice Python che permette di ottenere un file in formato *.kml* da caricare direttamente nel radiocomando del drone. La missione prevede che il drone, ma soprattutto il tubo per il prelievo dell'aria, sia rivolto verso la sorgente di emissione, quindi sottovento, muovendosi ad una velocità di $0,5 \text{ m} \cdot \text{s}^{-1}$ lateralmente, per sollevarsi di circa mezzo metro al termine di ogni strisciata. La distanza percorsa lateralmente a comporre ogni strisciata deve essere tale da coprire l'intera lunghezza della sorgente di emissione. La frequenza di campionamento è pari a 1 secondo. Questa tipologia di missione mira ad intercettare la maggiore superficie possibile della sezione trasversale del flusso di emissione. Procedendo con il calcolo dei flussi di emissione in $\text{g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$, viene applicata l'equazione 1, utilizzata da Gålfalk et al. (2021) a partire dalla legge dei gas ideali:

$$F_{CH_4} = 1,928 \times 10^{-6} \times \frac{P_{air}}{T_{air}} \times C_{CH_4} \times v \quad (1)$$

dove 1,928 è dato dal rapporto tra la massa molare del CH_4 ($16,031 \text{ g} \cdot \text{mol}^{-1}$) e la costante universale dei gas ($8,314 \text{ J} \cdot \text{K}^{-1} \cdot \text{mol}^{-1}$), 10^{-6} è il fattore di conversione della massa del CH_4 da ppm a grammi, P è la pressione (Pa), T è la temperatura (K), C è la concentrazione del CH_4 in ppm e v è la velocità del vento ($\text{m} \cdot \text{s}^{-1}$).

Il giorno 19 giugno 2025, una missione di volo è stata effettuata a Retiers, non molto distante da Rennes, in un allevamento di bovini da latte. L'obiettivo era quello di confrontare i flussi di emissione calcolati con il software WindTrax e quelli calcolati secondo Gålfalk et al. (2021). La sorgente di emissione considerata in questo caso di studio era una vasca di stoccaggio scoperta e circolare di raggio pari a 15 m che conteneva digestato per la distribuzione nei vicini campi coltivati. Per permettere il calcolo dei flussi di emissione con il software WindTrax, la missione di volo è stata eseguita in modalità manuale, percorrendo 2 strisce a 5,0 m e a 7,0 m dal suolo, nelle quali il drone si è fermato per 5 secondi in 15 punti per la striscia a 5,0 m e in 13 punti per la striscia a 7,0 m. In entrambe le strisce, ogni fermata era distante circa 1,0 m l'una dall'altra. Le due strisce erano parallele

sul piano verticale e circa perpendicolari alla direzione del vento, quantificata al suolo con una banderuola agganciata all'estremità di un palo. La missione di volo così pianificata, inclusi i punti in cui si è fermato il drone è visibile in Figura 4, dal punto 1 al punto 15 per la striscia a 5,0 m e dal punto 16 al punto 28 per la striscia a 7,0 m dal suolo. La missione di volo è stata avviata alle ore 17:54 ed è terminata alle ore 18:11 per una durata totale di 18 minuti.



Figura 4. La vasca di stoccaggio del digestato nell'allevamento di bovini da latte a Retiers, presso il quale è stato effettuato il monitoraggio delle emissioni di CH_4 il giorno 19 giugno 2025.

7. Risultati e discussione

Mattia et al. (2025), ovvero lo Studio numero 1, riportato nel paragrafo 4.1 della presente tesi, mostra i risultati di simulazioni effettuate con il software WindTrax con un periodo di mediazione dei dati di 5 minuti in condizioni di instabilità atmosferica (classe B di Pasquill-Gifford). Il calcolo dei flussi di emissione di CO₂ per lo Studio numero 1 è stato eseguito con un diverso numero di particelle implementate nel modello, cioè 5.000, 10.000, 30.000 e 50.000. Questa pubblicazione aveva l'obiettivo di valutare il modello nel calcolo dei flussi di emissione e delle concentrazioni, soprattutto sulla superficie in cui le misurazioni non erano state eseguite, all'aumentare del numero di particelle. Il primo fondamentale risultato, discusso in sede di revisione, riguarda la relazione tra le concentrazioni misurate sottovento e le velocità del vento misurate dall'anemometro. È stato consolidato, anche osservando i dati in input riportati nello Studio 1, che elevate velocità del vento non sono responsabili di concentrazioni più elevate rilevate dalle piattaforme multi-sensore. Questa relazione inversa si verifica proprio in condizioni di instabilità atmosferica, in quanto folate di vento di maggiori velocità risultano responsabili dei processi di diluizione e dispersione (Mousavi et al., 2025). Questa precisazione permette di comprendere che le variazioni dei flussi di emissione calcolati erano veritieri e non dovute ad un maggiore trasporto delle molecole del gas target causato da venti di maggiore intensità. Inoltre, per il processamento dei dati in input, il periodo di mediazione selezionato era di 5 minuti, invece che di 15-30 minuti, come consigliato dall'autore del software (Crenna, 2006a). Questa scelta era dovuta alla quantità limitata dei dati misurati a disposizione per le simulazioni. Un periodo di mediazione inferiore rispetto a quello consigliato rende il modello più sensibile alle variazioni di velocità e direzione del vento. Ad ogni modo, il massimo flusso di emissione è stato calcolato con la massima velocità del vento ed alcuni autori hanno sottolineato un peggiore livello di accuratezza nel calcolo dei flussi di emissione, sottostimandoli (Carozzi et al., 2013; Tagliaferri et al., 2023) nel momento in cui WindTrax veniva confrontato direttamente con altri modelli di dispersione atmosferica di diversa natura matematica.

Ottenendo le mappe di concentrazione dal modello, osservando le mappe degli intervalli di confidenza e i profili verticali delle concentrazioni calcolate sottovento, WindTrax ha restituito intervalli di confidenza verticalmente e orizzontalmente via via più ristretti all'aumentare del numero di particelle, migliorando quindi l'accuratezza delle simulazioni. Per questo motivo, è stato stabilito di effettuare le successive simulazioni per prove sperimentali successive con un numero di particelle almeno pari a 50.000 e con un periodo di mediazione almeno pari a 15 minuti. Un numero maggiore di particelle influenza il tempo necessario a completare una simulazione per ottenere le mappe di dispersione atmosferica e degli intervalli di confidenza, mentre la rapidità di calcolo dei flussi di emissione rimane inalterata.

Gli Studi numero 2 e 3, riportati nei paragrafi 4.2 e 4.3 della presente tesi, complessivamente miravano a valutare le prestazioni del modello WindTrax in condizioni moderate di stabilità atmosferica (classe F di Pasquill-Gifford), utilizzando le piattaforme multi-sensore e il sistema di monitoraggio della qualità dell'aria con drone sviluppati dal DAGRI nella caratterizzazione delle emissioni della CO₂ da una lettiera compost a base di segatura inserita nella zona di riposo di una stalla per la stabulazione di bovini da latte in Brasile. In questo caso, per osservare l'impatto della lavorazione della lettiera sulle emissioni di CO₂ in atmosfera, sono stati calcolati flussi di emissione e mappe di concentrazione nelle situazioni ante, durante e post lavorazione. Le situazioni ante e durante la lavorazione sono state considerate nello Studio numero 3, utilizzando misurazioni stazionarie a terra. Dal calcolo dei flussi di emissione di CO₂ risulta che la lavorazione della lettiera impatta mediamente sull'atmosfera con un aumento del 76%. La situazione post è stata considerata nello Studio 2 utilizzando misurazioni stazionarie e in volo. Le prove sperimentali sono state eseguite avendo a disposizione tre unità di piattaforme multi-sensore, per cui due di queste sono state utilizzate a terra per il monitoraggio stazionario della sorgente considerata, sopravento e sottovento, in modo da fornire i dati in input al modello. Le prestazioni del modello sono state valutate confrontando le concentrazioni misurate dalla terza unità, posizionata a terra in un altro punto nello Studio 2 e in volo, investigando due altitudini, nello Studio 3.

Complessivamente, si riportano i flussi di emissione medi di CO₂ calcolati per la lettiera compost nelle seguenti situazioni:

- Ante lavorazione: $0,03700 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$;
- Durante la lavorazione: $0,06511 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$;
- Post lavorazione: $0,04351 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$.

Differenze significative sono state individuate tra le situazioni ante e durante (p-value < 0,05) e tra le situazioni durante e post (p-value < 0,001) attraverso i test statistici ANOVA di Welch e Dunn con il metodo di Bonferroni dell'aggiustamento del p-value. Non sono state individuate differenze significative tra le situazioni ante e post. Un valore comparabile per la situazione post lavorazione pari a $100,2 \text{ g} \cdot \text{m}^{-2} \cdot \text{h}^{-1}$, cioè $0,02783 \text{ g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$ è stato trovato in letteratura (Wolf, 2017), calcolato con il metodo della camera statica.

Passando alla valutazione del modello nel calcolare le concentrazioni nella posizione in cui era posizionata la terza unità delle piattaforme multi-sensore, si riportano sovrastime in termini di errori medi percentuali dall'8 al 39% per lo Studio 2 e sovrastime e sottostime in termini di errori medi assoluti percentuali dal 10 al 25% per lo Studio 3. Ad ogni modo, questi risultati mostrano un andamento nelle emissioni di gas ad effetto serra che raggiunge dei picchi durante la lavorazione della lettiera per poi stabilizzarsi, confermato anche in altre pubblicazioni (Leso et al., 2020; El Mashad et al., 2023). Altri risultati di questi due studi hanno riguardato l'utilizzo contemporaneo di registratori di temperatura e umidità relativa (Hobo 184 MX2301A, Onset Computer, Bourne, Massachusetts, United States). È stato osservato che per i registratori la temperatura risultava più bassa di circa 5-6°C, mentre l'umidità relativa risultava più alta di 50 punti percentuali rispetto alle misurazioni effettuate dalle piattaforme multi-sensore per le stesse grandezze durante tutti i giorni di campionamento. Per cui è stato stabilito di utilizzare la temperatura rilevata dai registratori per le simulazioni in entrambi gli Studi 2 e 3. La differenza nelle misurazioni delle condizioni ambientali tra i registratori e le piattaforme ha permesso di ottenere importanti indicazioni, in quanto l'ambiente nella camera di campionamento era molto differente da quello esterno. Al fine di mantenere la rappresentatività dell'atmosfera, la forma della camera di campionamento

e la distribuzione della sensoristica all'interno delle piattaforme multi-sensore è stata modificata in base ad un'analisi aerodinamica (Merlini et al., 2025), che ha messo in evidenza aree interessate da flussi laminari, turbolenze ed aree di ristagno.

Per entrambi gli Studi 2 e 3 è stata selezionata un'elevata stabilità atmosferica secondo la classe F di Pasquill-Gifford, quantificata grazie all'utilizzo di un anemometro (Ultrasonic Portable Mini Wind 298 Meter, Calypso Instruments EMEA, S.L, Coral Gables, Miami, Florida) per ottenere misurazioni di velocità e direzione del vento. La criticità riscontrata nella quantificazione della stabilità atmosferica riguarda la sensibilità del sensore, non in grado di rilevare velocità inferiori ad $1 \text{ m} \cdot \text{s}^{-1}$. Per questo motivo l'anemometro è stato posizionato sottovento e molto vicino alla lettiera, in modo che le misurazioni potessero essere influenzate dall'impianto di ventilazione in funzione, che produceva delle folate di vento. Per migliorare la quantificazione della stabilità atmosferica dovrebbero essere presenti vari anemometri sulle superfici aziendali, posizionati a varie altezze. Attualmente, la tecnica più accurata e precisa per la definizione delle turbolenze è la covarianza di Eddy, che risulta però costosa e richiede un numero elevato di sensori (Billesbach et al., 2024). Alcuni studi hanno applicato un filtro ai dati misurati, scartando le osservazioni che includevano velocità del vento troppo basse e troppo alte, utilizzando un numero di particelle maggiore di 50.000 (Shonkwiler et al., 2018; Shaw, 2020).

Riguardo lo Studio 4, mostrando i risultati ottenuti dalle misurazioni di NH_3 con le pipette Dräger nelle Tabelle 2 e 3, si precisa che i campioni di aria sono stati raccolti all'interno dei due edifici e all'esterno trasportando l'apposito apparato per circa 15 minuti. Si precisa che la raccolta di campioni di aria all'esterno dell'edificio 1 è stata eseguita nel corridoio che permette l'accesso ai due edifici, mentre all'esterno dell'edificio 2 è stata eseguita nell'area esterna adiacente all'edificio stesso.

Tabella 2. NH_3 in ppm rilevata all'interno dell'edificio 1 a due altitudini e all'esterno.

Edificio 1		
IN (2,0 m)	IN (0,5 m)	OUT
1,3	1,2	0,85

Tabella 3. NH_3 in ppm rilevata all'interno dell'edificio 2 a due altitudini e all'esterno.

Edificio 2		
IN (2,0 m)	IN (0,5 m)	OUT
1,1	1,5	0,2

Mostrando i risultati ottenuti dal monitoraggio continuo effettuato per dieci giorni, dal 23 giugno al 4 luglio 2025, da due piattaforme multi-sensore posizionate all'altezza di 2,0 m dalla pavimentazione nei due edifici, vengono riportate dalla Tabella 4 alla Tabella 10 le statistiche descrittive (minimo, mediana, massimo) per ogni variabile rilevata e dalla Figura 5 alla Figura 11 il grafico del modello di regressione e il relativo R^2 . Poiché la registrazione dei dati nei due edifici non è avvenuta nello stesso momento, per ottenere un data frame che contenesse le osservazioni di ogni edificio, queste sono state mediate su un periodo di un minuto.

Tabella 4. Statistiche descrittive per la temperatura rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

Temperatura (°C)		
Edifici	1	2
Min.	17,93	18,64
Med.	24,21	23,98
Max.	32,98	32,96

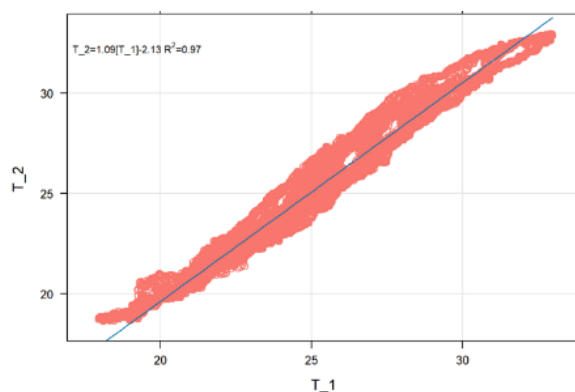


Figura 5. Regressione lineare e R^2 (0,97) per la temperatura rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

Tabella 5. Statistiche descrittive per l'umidità relativa rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

Umidità relativa (%)		
Edifici	1	2
Min.	45,28	47,90
Med.	72,03	74,68
Max.	84,97	85,72

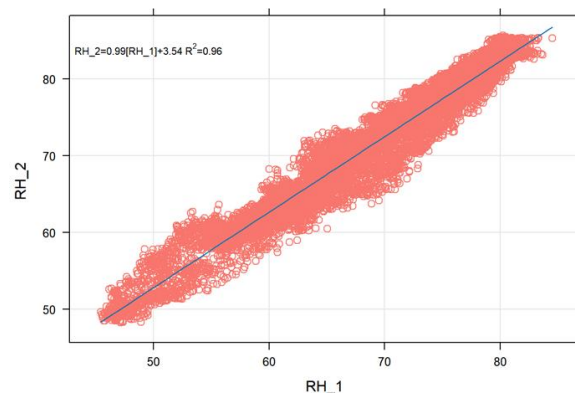


Figura 6. Regressione lineare e R^2 (0,96) per l'umidità relativa rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

Tabella 6. Statistiche descrittive per la pressione rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

Pressione (Pa)		
Edifici	1	2
Min.	100.184	100.251
Med.	101.161	101.235
Max.	102.125	102.196

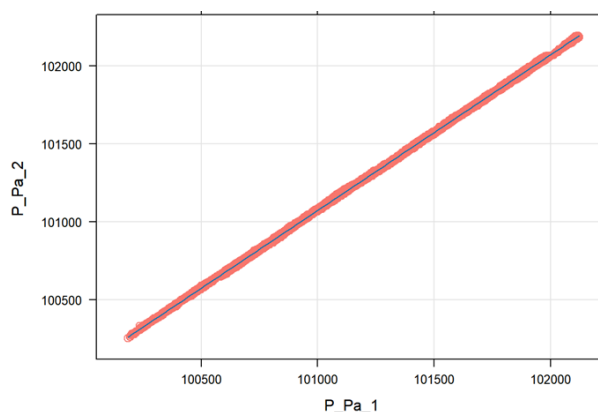


Figura 7. Regressione lineare e R^2 (0,99) per la pressione rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

Tabella 7. Statistiche descrittive per il PM₁₀ rilevato durante la sperimentazione di dieci giorni nei due edifici a Mauron.

PM ₁₀ (µg m ⁻³)		
Edifici	1	2
Min.	0,3	1,7
Med.	4,8	10,5
Max.	1.247,8	1.466,8

Tabella 8. Statistiche descrittive per il PM_{2.5} rilevato durante la sperimentazione di dieci giorni nei due edifici a Mauron.

PM _{2.5} (µg m ⁻³)		
Edifici	1	2
Min.	0,2	1,3
Med.	2,0	8,9
Max.	165,3	112,8

Tabella 9. Statistiche descrittive per la NH₃ rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

NH ₃ (ppm)		
Edifici	1	2
Min.	0,65	0,57
Med.	1,48	1,40
Max.	8,08	7,19

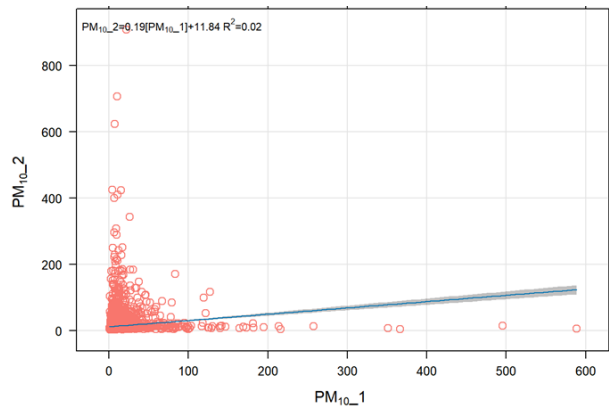


Figura 8. Regressione lineare e R² (0,02) per il PM₁₀ rilevato durante la sperimentazione di dieci giorni nei due edifici a Mauron.

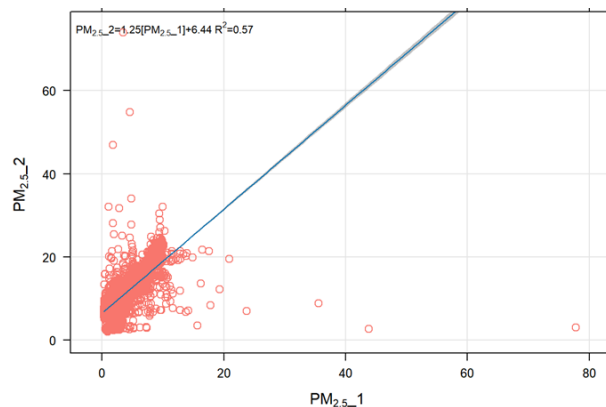


Figura 9. Regressione lineare e R² (0,57) per il PM_{2.5} rilevato durante la sperimentazione di dieci giorni nei due edifici a Mauron.

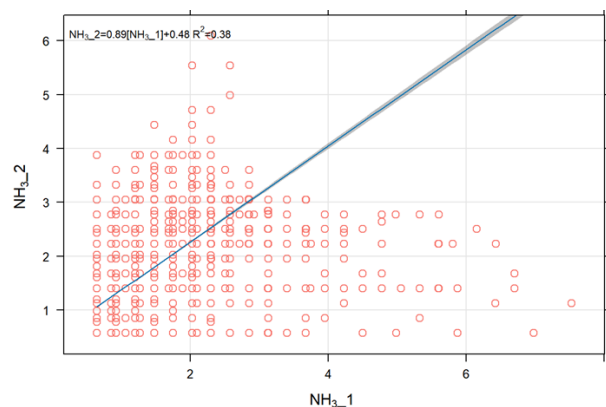


Figura 10. Regressione lineare e R² (0,38) per la NH₃ rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

Tabella 10. Statistiche descrittive per la CO₂ rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

CO ₂ (ppm)		
Edifici	1	2
Min.	379,0	0,0
Med.	650,0	878,0
Max.	1.368,0	1.351,0

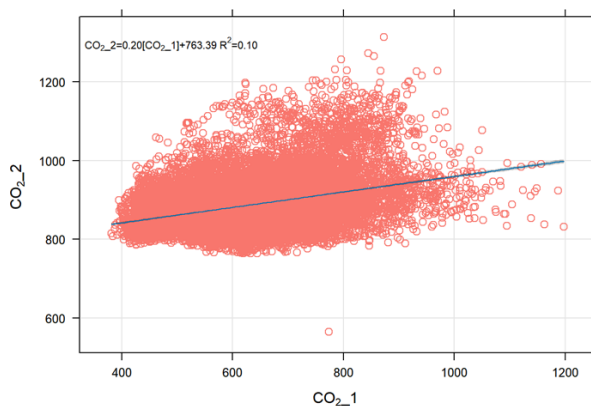


Figura 11. Regressione lineare e R² (0,10) per la CO₂ rilevata durante la sperimentazione di dieci giorni nei due edifici a Mauron.

I risultati riportati nelle precedenti Tabelle (4-10) mostrano valori maggiori di umidità relativa, pressione, PM₁₀, PM_{2.5} e CO₂ per l'edificio 2, mentre valori maggiori di temperatura e NH₃ per l'edificio 1. Anche in Tabella 2 e 3 vengono riportate concentrazioni di NH₃ maggiori per l'edificio 1, rilevate con pipette Dräger grazie al prelievo di campioni di aria. Forti correlazioni sono state riscontrate per le condizioni ambientali, mentre correlazioni più deboli sono state riscontrate per le concentrazioni degli inquinanti rilevati. Da notare che questi risultati vengono esposti in una fase preliminare, in quanto il data frame utilizzato andrebbe ripulito dagli outlier ed un filtro dati andrebbe applicato per selezionare le osservazioni registrate durante l'esecuzione di pratiche di gestione come la distribuzione dell'alimento e la pulizia delle fosse di contenimento dei reflui zootecnici per comprendere se esistono differenze in termini di emissioni in atmosfera tra i due edifici. Da approfondire risultano anche le relazioni tra le variabili misurate all'interno del singolo edificio, che dalle matrici di correlazione e dai dendrogrammi associati in Figura 12 sembrano essere differenti.

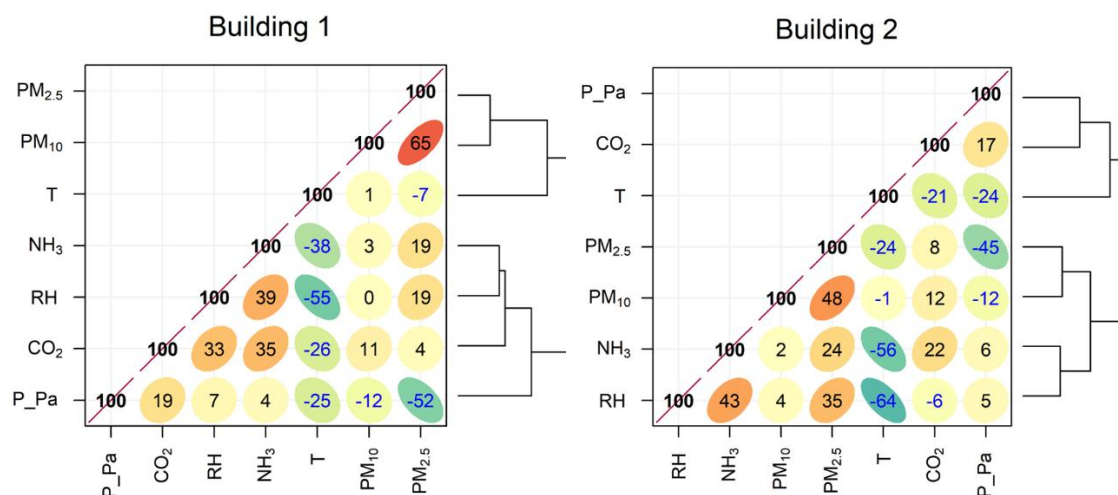


Figura 12. Matrici di correlazione e dendrogrammi per l'edificio 1 (a sinistra) e per l'edificio 2 (a destra).

Gli altri risultati preliminari riguardano la distribuzione dei tubi passivi nei due edifici a due diverse altezze, cioè a 30-60 cm e a 180 cm dalla pavimentazione, il giorno 23 giugno 2025. I risultati ottenuti vengono riportati nelle Tabelle 11 e 12. Da notare che per l'edificio 1 era presente anche una coppia di tubi passivi sulla finestra aperta.

Tabella 11. Concentrazioni di NH_3 e CO_2 rilevate con i tubi passivi nell'edificio 1 in alto, in basso e sulla finestra.

Posizione	NH_3 (ppm)	CO_2 (ppm)
Alto	> 10	3.000
Basso	> 10	2.500
Alto	6,80	2.500
Basso	7,50	3.000
Alto	3,90	2.500
Basso	2,10	2.500
Alto	2,70	2.000
Basso	2,00	2.000
Finestra	1,80	2.000

Tabella 12. Concentrazioni di NH_3 e CO_2 rilevate con i tubi passivi nell'edificio 2 in alto e in basso.

Posizione	NH_3 (ppm)	CO_2 (ppm)
Alto	5,50	3.500
Basso	6,00	3.500
Alto	NA	NA
Basso	NA	NA
Alto	6,00	3.500
Basso	6,00	4.000
Alto	7,20	4.000
Basso	7,20	4.000

I valori non disponibili in Tabella 12 sono dovuti al fatto che i tubi passivi sono caduti dal supporto in un momento rimasto incognito, per cui tali osservazioni sono state scartate. Da precisare che i valori riportati nelle Tabelle 11 e 12 fanno riferimento a misurazioni fatte con tubi passivi mantenuti nelle posizioni indicate in Figura 2 per circa 90 minuti, soggette quindi ad accumulare i gas target nella camera di campionamento. Non sono

quindi direttamente confrontabili con le osservazioni rilevate dalle piattaforme multi-sensore e dalle pipette Dräger per la differente natura dei sensori stessi e per il differente posizionamento. Riguardo l' NH_3 , differenze più marcate tra le due altitudini investigate sono state riscontrate nell'edificio 1, mentre nell'edificio 2 sembra esserci una distribuzione del gas senza particolari differenze tra le due altitudini. Ad ogni modo, anche con l'utilizzo di tubi passivi, come verificato con il monitoraggio continuo con le piattaforme multi-sensore sviluppate dal DAGRI e con le pipette Dräger, maggiori concentrazioni di NH_3 sono state rilevate per l'edificio 1. Riguardo la CO_2 , concentrazioni maggiori sono state rilevate per l'edificio 2, confermando il risultato ottenuto con il monitoraggio continuo per 10 giorni. Da notare che i massimi di concentrazione di CO_2 rilevati con il monitoraggio continuo raggiungono valori di circa 1.400 ppm, mentre i massimi rilevati con i tubi passivi raggiungono valori di 4.000 ppm. Questa differenza marcata è dovuta probabilmente al differente posizionamento della sensoristica, cioè i tubi passivi intercettavano direttamente il flusso creato dai sistemi di ventilazione dei due edifici, in quanto posti proprio al di sotto dei ventilatori. Le piattaforme multi-sensore erano invece posizionate verso una zona meno interessata dai flussi, spostate verso le pareti a nord-ovest nei rispettivi edifici.

Dopo aver calcolato le coordinate geografiche dei tubi passivi nei due edifici, cioè la latitudine e la longitudine con il sistema di riferimento RGF93 attraverso l'utilizzo del software QGIS, è stato possibile abbinarle alle osservazioni ottenute, per poi performare l'interpolazione di Kriging ordinaria con il software Rstudio, utilizzando apposite librerie di funzioni chiamate *sp* (Pebesma & Bivand, 2005) e *gstat* (Pebesma, 2004). I risultati grafici dell'interpolazione di Kriging ordinaria, ottenuti dopo il calcolo dei semivariogrammi, per ogni edificio alle due altezze investigate, vengono riportate nelle Figure 13 e 14. Le stime effettuate con questa metodologia ipotizzano un accumulo dei gas rilevati con i tubi passivi come segue:

- Edificio 1: accumulo di NH_3 in basso a nord-est e in alto a sud-est; accumulo di CO_2 in basso al centro e in alto a nord-est.
- Edificio 2: accumulo di NH_3 in basso e in alto ad ovest; accumulo di CO_2 in basso a sud-est e in alto a sud-ovest.

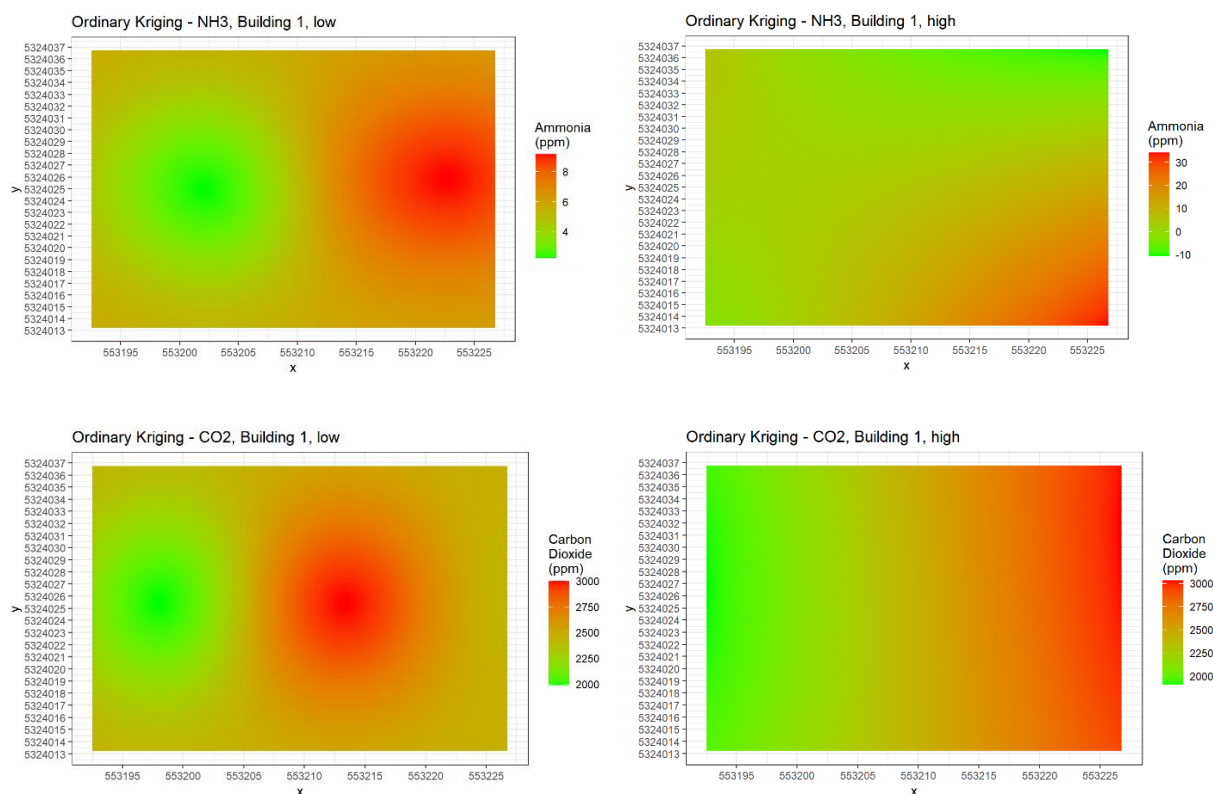


Figura 13. Concentrazioni di NH₃ e CO₂ calcolate in basso e in alto nell'edificio 1 con la tecnica dell'interpolazione di Kriging ordinaria a partire dalle concentrazioni misurate dai tubi passivi posizionati il 23 giugno 2025.

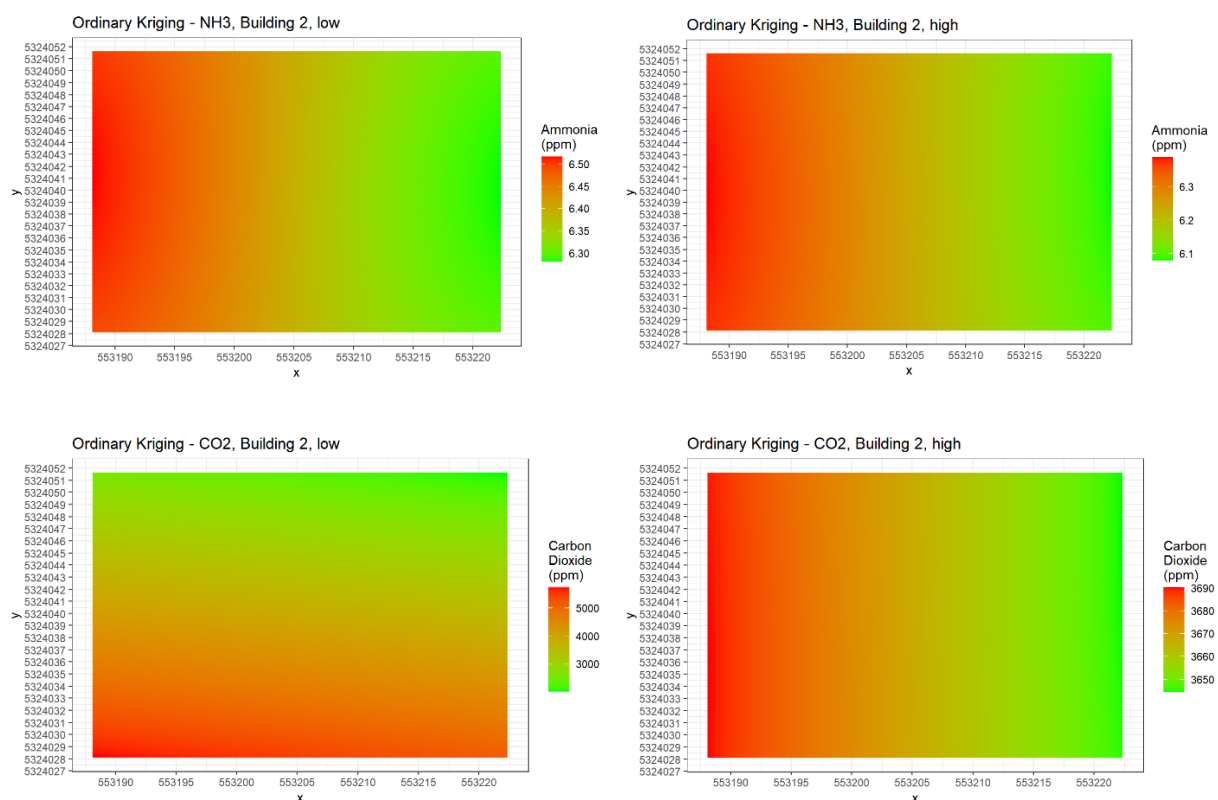


Figura 14. Concentrazioni di NH_3 e CO_2 calcolate in basso e in alto nell'edificio 2 con la tecnica dell'interpolazione di Kriging ordinaria a partire dalle concentrazioni misurate dai tubi passivi posizionati il 23 giugno 2025.

Si precisa che i risultati così ottenuti non sono da considerarsi reali, in quanto i semivariogrammi sono stati calcolati avendo a disposizione un numero limitato di punti in cui le misurazioni sono state effettuate, vista anche la complessa dinamica del fenomeno studiato. Delle perdite di carico da parte dei sistemi di ventilazione possono essere ipotizzate nel momento in cui le porte dei due edifici venivano aperte per permettere l'accesso agli operatori. Ad ogni modo, concentrazioni più elevate sono state rilevate sia in basso che in alto nell'edificio 1, ma, come è possibile osservare nelle Tabelle 11 e 12, osservando contemporaneamente anche il posizionamento dei tubi passivi in Figura 2, la maggior parte di essi è stata posizionata in modo da intercettare gran parte del flusso dell'aria, senza descrivere adeguatamente le zone di accumulo e le zone di dispersione.

Per la raccolta dei campioni di aria all'interno dei due edifici sono state investigate le due altitudini, mentre all'esterno una sola, cioè 1,5 m. Ad ogni altitudine investigata all'interno corrisponde una sacca per la raccolta dell'aria, ottenendo due sacche di aria per i monitoraggi all'interno ed una sacca per i monitoraggi in esterna. Da ogni sacca sono stati prelevati due campioni da inviare in laboratorio per l'analisi con la gascromatografia e le concentrazioni rilevate di CH_4 , CO_2 e N_2O vengono riportate nelle Tabelle 13 e 14.

Tabella 13. Concentrazioni di CH_4 , CO_2 e N_2O ottenute dalla gascromatografia in laboratorio sui campioni di aria prelevati all'interno e all'esterno dell'edificio 1 il 23 giugno 2025.

Posizione	CH_4 (ppm)	CO_2 (ppm)	N_2O (ppb)
Basso 1	5,32	608,46	342,49
Basso 2	4,82	703,95	392,07
Esterno 1	2,20	498,92	363,73
Esterno 2	2,15	533,38	363,73
Alto 1	5,89	646,45	352,28
Alto 2	6,01	639,59	348,68

Tabella 14. Concentrazioni di CH_4 , CO_2 e N_2O ottenute dalla gascromatografia in laboratorio sui campioni di aria prelevati all'interno e all'esterno dell'edificio 2 il 23 giugno 2025.

Posizione	CH_4 (ppm)	CO_2 (ppm)	N_2O (ppb)
Basso 1	12,41	877,67	353,62
Basso 2	13,05	960,69	350,64

Esterno 1	2,23	521,33	347,85
Esterno 2	2,28	494,14	349,81
Alto 1	13,08	920,98	351,15
Alto 2	12,73	896,14	350,84

Dalla gascromatografia risulta che le concentrazioni maggiori di CH₄ sono state rilevate nell'edificio 2 per entrambe le altitudini investigate e lo stesso risultato è stato ottenuto per la CO₂. Riguardo il N₂O non è possibile affermare che uno dei due edifici sia responsabile di maggiori concentrazioni, perciò risultano necessarie ulteriori analisi, anche mediante l'utilizzo di altre tipologie di sensoristica, viste le concentrazioni molto basse rilevate.

Utilizzando le concentrazioni di NH₃, ottenute mediante l'analisi con le pipette Dräger e riportate nelle Tabelle 2 e 3, le concentrazioni di CO₂, CH₄ e N₂O, ottenute mediante la gascromatografia in laboratorio e riportate nelle Tabelle 13 e 14, sono stati calcolati i fattori di emissione di CO₂, CH₄, NH₃ e N₂O, riportati in Tabella 15.

Tabella 15. Fattori di emissione di CO₂ (in kg capo⁻¹ giorno⁻¹), CH₄ (in kg capo⁻¹ giorno⁻¹), NH₃ (in g capo⁻¹ giorno⁻¹) e N₂O (in g capo⁻¹ giorno⁻¹) calcolati con il metodo semplificato per i due edifici.

Edificio	Posizione	CO ₂	CH ₄	NH ₃	N ₂ O
1	IN-Alto	1,933	0,021	2,666	-
	IN-Basso	1,950	0,015	1,934	-
	Esterno	1,942	0,018	2,284	-
2	IN-Alto	1,939	0,019	1,685	-
	IN-Basso	1,941	0,018	2,555	-
	Esterno	1,940	0,018	2,126	-

Nonostante le maggiori concentrazioni di CO₂ e CH₄ rilevate nell'edificio 2, fattori di emissione molto simili sono stati calcolati con il metodo semplificato. Sono stati calcolati invece fattori di emissione di NH₃ maggiori per l'edificio 1. Non è stato possibile calcolare invece i fattori di emissione di N₂O dai due edifici a causa delle concentrazioni troppo basse rilevate. È quindi possibile affermare che il diverso sistema di ventilazione selezionato per i due edifici agisce diversamente in base all'inquinante considerato.

Riguardo lo Studio 5, il sistema di misurazione sviluppato da OPAALE restituisce un file in formato .csv nel quale vengono riportate tutte le osservazioni delle variabili misurate dalla sensoristica agganciata al drone,

includendo anche le tempistiche e le coordinate geografiche nel sistema di riferimento WGS84 del drone durante la missione di volo. Essendo la frequenza di campionamento impostata ad 1 secondo, sono state registrate durante la missione 1.013 osservazioni, anche nei punti in cui il drone non era fermo. Anche durante le fermate sono state registrate varie osservazioni, in quanto il drone era sottoposto a velocità medie del vento di $4,17 \text{ m} \cdot \text{s}^{-1}$, che tendevano a spostarlo dal punto prescelto. La missione di volo rappresentata secondo le concentrazioni di metano rilevate viene mostrata in Figura 15, in cui è possibile osservare il percorso del drone dal punto di decollo al primo punto della prima strisciata a 5,0 m e la seconda strisciata a 7,0 m dal suolo.

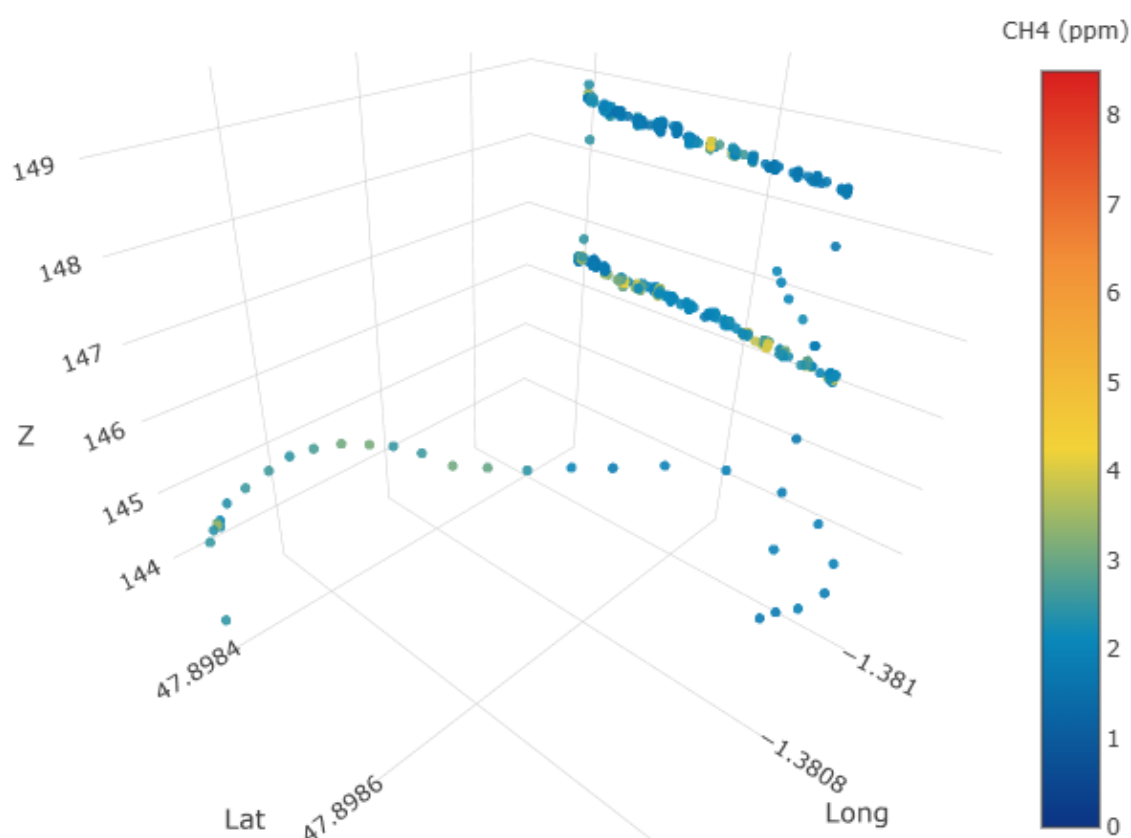


Figura 15. La missione di volo eseguita a Retiers il giorno 19 giugno 2025, utilizzando una scala di colore per rappresentare la concentrazione di CH_4 rilevata in ogni punto che va da 0 ppm (blu) a 8 ppm (rosso).

Ad ogni modo, il data frame iniziale è stato filtrato, selezionando, tra le osservazioni registrate per ogni fermata, quella contenente la maggiore concentrazione di CH_4 . Nel software WindTrax sono stati così caricati i dati

in input contenuti in Tabella 15, ricalcolando le coordinate geografiche in un sistema di riferimento proprio.

Tabella 15. Dati in input per il calcolo dei flussi di emissione in WindTrax: osservazioni, altitudine (metri dal suolo), temperatura (°C), pressione (Pa), concentrazione di CH₄ (ppm), velocità del vento (m · s⁻¹) e direzione del vento (° nord).

Oss.	Alt.	T	P	CH ₄	ws	wd
1	5,0	35,80	101.129	3,92	2,37	370
2	5,0	36,80	101.126	4,01	4,58	360
3	5,0	37,53	101.123	2,95	5,42	361
4	5,0	37,85	101.127	4,37	2,40	366
5	5,0	38,42	101.128	4,84	1,62	371
6	5,0	36,28	101.117	2,29	5,16	293
7	5,0	36,21	101.118	2,2	5,12	302
8	5,0	36,25	101.114	2,19	5,39	312
9	5,0	35,85	101.117	2,15	3,48	290
10	5,0	36,09	101.120	5,10	5,40	364
11	5,0	37,10	101.124	4,22	2,50	390
12	5,0	37,12	101.121	4,39	4,11	367
13	5,0	36,89	101.120	3,70	3,99	328
14	5,0	35,00	101.110	1,93	5,82	326
15	5,0	35,55	101.123	3,23	2,48	360
16	7,0	37,3	101.105	2,18	3,51	369
17	7,0	37,57	101.108	2,26	3,22	351
18	7,0	37,01	101.102	3,88	3,54	357
19	7,0	37,09	101.102	2,43	3,27	362
20	7,0	36,49	101.096	2,34	3,39	364
21	7,0	36,89	101.100	2,25	2,36	370
22	7,0	36,52	101.098	2,44	2,99	379
23	7,0	37,51	101.102	5,27	2,17	364
24	7,0	37,81	101.100	3,05	2,99	327
25	7,0	37,61	101.098	2,89	4,8	361
26	7,0	37,84	101.100	2,04	2,83	357
27	7,0	36,57	101.101	1,99	3,77	357
28	7,0	35,88	101.097	1,89	5,26	328

Per le simulazioni completate in WindTrax, è stato inserito un valore pari a 2,03 ppm per la contrazione di fondo, valore corrispondente al 40% della distribuzione delle concentrazioni di CH₄ rilevate. Questa soglia per impostare la concentrazione di fondo è stata selezionata in accordo a quanto stabilito con il gruppo di OPAALE, in quanto altre sorgenti di emissione vicine a quella studiata, come la stalla ed una pre-vasca di stoccaggio dei reflui zootecnici, avrebbero potuto avere un'influenza nel calcolo dei flussi

di emissione. Per le osservazioni numero 14, 27 e 28 in Tabella 15 sono stati calcolati dei flussi di emissione negativi, a causa di concentrazioni sottovento inferiori rispetto alla concentrazione di fondo impostata, per cui tali flussi di emissione sono stati scartati. Nel software sono stati impostati un numero di particelle pari a 50.000, una stabilità atmosferica secondo la classe B di Pasquill-Gifford ed una lunghezza della rugosità superficiale pari a 10 cm, cioè quella dell'erba alta, in quanto nei terreni coltivati attorno alla sorgente studiata era presente grano duro pronto per la raccolta. In Tabella 16 vengono riportati i flussi di emissione calcolati secondo la metodologia riportata in Gálfalk et al. (2021), utilizzata dal gruppo di OPAALE, e con il software WindTrax, calcolando rispettivamente 1.013 e 100 flussi di emissione.

Tabella 16. Flussi di emissione ($\text{g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$) calcolati secondo Gálfalk et al. (2021) e con WindTrax utilizzando come dati in input i valori ottenuti durante il monitoraggio con drone effettuato a Retiers il giorno 19 giugno 2025.

	OPAALE	WindTrax
Minimo	0,001841	0,000040
1° quantile	0,004529	0,000535
Mediana	0,005672	0,002150
Media	0,006020	0,003423
3° quantile	0,007164	0,004745
Massimo	0,019265	0,018350

Dai valori in Tabella 16 è possibile notare che WindTrax ha calcolato flussi di emissione di CH_4 più bassi rispetto a quelli calcolati con la metodologia applicata da OPAALE per la stessa vasca di stoccaggio del digestato. Da considerare se i valori di concentrazione rilevati dalla sensoristica durante le prove sperimentali siano influenzati da reali aumenti dei flussi di emissione oppure da un maggiore trasporto delle molecole dell'inquinante causato dall'aumento della velocità del vento. Come indicato in Mattia et al. (2025) per la CO_2 , anche per il CH_4 le concentrazioni diminuiscono all'aumentare della velocità del vento a causa dei processi di diluizione e dispersione (Delkash et al., 2016; Riddick, 2025). Infatti, osservando la Tabella 15, la massima concentrazione di CH_4 (osservazione numero 23) non viene rilevata con la massima velocità del vento (osservazione numero 14). Per questo, anche nel contesto pedo-climatico in cui la missione di volo è stata

eseguita, è possibile affermare la presenza di una maggiore dispersione e diluizione del CH₄ con le velocità del vento più elevate. In questo studio, i dati non sono stati mediati su un periodo di 15-30 minuti, come consigliato dall'autore del software, ma sono stati selezionati i punti in cui il drone si è fermato, rilevando le maggiori concentrazioni. La selezione dei punti di misura così eseguita rende l'analisi maggiormente soggetta all'influenza delle folate di vento in condizioni di instabilità atmosferica (classe B di Pasquill-Gifford), sottostimando i flussi di emissione anche in questo caso, come indicato anche da altre pubblicazioni (Carozzi et al., 2013; Tagliaferri et al., 2023).

8. Conclusioni

Lo Studio numero 1, riportato nel paragrafo 4.1 della presente tesi ha permesso di ottenere indicazioni rilevanti sulle prestazioni del modello Lagrangiano Stocastico WindTrax per la stima di flussi di emissione da un allevamento di bovini da latte, mappandone inoltre la dispersione nell'ambiente circostante. L'utilizzo del software ha permesso di ottenere un protocollo di misura, costruito in base a ciò di cui il modello ha bisogno per completare una simulazione. In questo caso, il modello ha stimato flussi di emissione per tre sorgenti differenti. L'aumento delle piattaforme multi-sensore a disposizione permetterebbe di ottenere flussi di emissione specifici per ogni sorgente, a patto che il modello sia alimentato da almeno una misurazione di concentrazione sottovento per sorgente considerata, oltre a fornirgli la concentrazione di fondo. Come accennato nel Capitolo 7, periodi di mediazione corti sono maggiormente influenzati dalle folate di vento, riducendo l'affidabilità delle stime dei flussi di emissione in condizioni di instabilità atmosferica. Le simulazioni hanno inoltre mostrato che aumentando il numero di particelle si ottiene una migliore stabilità dei risultati, riducendo gli intervalli di confidenza restituiti dal modello. Un numero di particelle di almeno 50.000 è consigliato per dare robustezza ai risultati del modello, anche se numeri di particelle maggiori potrebbero richiedere più tempo per completare una simulazione di dispersione atmosferica. Un'altra criticità individuata riguarda la quantificazione della stabilità atmosferica, stimata attraverso le classi di Pasquill-Gifford. Un anemometro che sia in grado di quantificare almeno direzione e velocità del vento è richiesto per la caratterizzazione delle condizioni atmosferiche locali. Nonostante le limitazioni individuate, WindTrax ha permesso di sviluppare un protocollo pratico e applicabile negli allevamenti zootecnici, anche se particolare attenzione deve essere posta sul posizionamento della sensoristica, viste anche le assunzioni del modello.

Gli studi numero 2 e 3, riportati nei paragrafi 4.2 e 4.3 della presente tesi, hanno fornito risultati comparabili con quelli trovati in letteratura in termini di flussi di emissione di CO₂ di una lettiera compost. Attraverso l'utilizzo della vecchia versione delle piattaforme multi-sensore sviluppate dal DAGRI, è stato possibile verificare l'affidabilità del sensore NDIR per la

quantificazione della CO₂. Non è stato possibile dire lo stesso per le misurazioni della temperatura e dell'umidità relativa, ottenute grazie al modulo integrato nello stesso sensore. Al fine di mantenere la rappresentatività dell'atmosfera, la forma della camera di campionamento e la distribuzione della sensoristica all'interno delle piattaforme multi-sensore sono state migliorate in base ad un'analisi aerodinamica. Per entrambi gli studi è stata selezionata un'elevata stabilità atmosferica secondo la classe F di Pasquill-Gifford, quantificata grazie all'utilizzo di un solo anemometro per ottenere misurazioni di velocità e direzione del vento. La criticità riscontrata nella quantificazione della stabilità atmosferica riguarda la sensibilità del sensore, non in grado di rilevare velocità inferiori ad $1 \text{ m} \cdot \text{s}^{-1}$. Per questo motivo l'anemometro è stato posizionato sottovento e molto vicino alla lettiera, in modo che le misurazioni potessero essere influenzate dall'impianto di ventilazione in funzione, che produceva delle folate di vento, aumentando l'instabilità atmosferica. Per una migliore quantificazione della stabilità atmosferica dovrebbero essere presenti vari anemometri con un campo di misurazione più ampio sulle superfici aziendali, posizionati a varie altezze. Nonostante la tecnica più accurata e precisa per la definizione delle turbolenze sia la covarianza di Eddy, un compromesso potrebbe essere rappresentato dall'utilizzo di un anemometro sonico in grado di rilevare le tre componenti vettoriali del vento, strumento utilizzato nei test di campo riportati in letteratura, ottenendo un livello basso di incertezza. Vista l'elevata stabilità atmosferica impostata nel software, l'entità degli errori medi percentuali tra le concentrazioni osservate e modellate viene spiegata dagli aumenti di instabilità atmosferica dovuti alle folate di vento generate dall'impianto di ventilazione. Mirando ad una migliore accuratezza dei risultati delle simulazioni, oltre a migliorare la quantificazione della stabilità atmosferica, dovrebbe essere aumentato il periodo di mediazione dei dati input da 15 minuti a 20-30 minuti, in modo da ridurre l'effetto delle folate di vento, soprattutto in periodi di rapide variazioni di stabilità, come all'alba, periodo in cui sono state effettuate le prove sperimentali. Altra fonte di incertezza è dovuta alla presenza di altre sorgenti di emissione di CO₂ durante le prove

sperimentali, cioè gli animali, la trattrice e le fermentazioni dei reflui zootecnici sulla corsia di alimentazione.

Nonostante le criticità riscontrate nella sensoristica a disposizione, il sistema di monitoraggio della qualità dell'aria con drone, considerando il posizionamento della sensoristica in un'area limitatamente influenzata dal downwash, ha il potenziale per migliorare le simulazioni di dispersione atmosferica, in quanto fornisce misurazioni in più posizioni, investigando altezze diverse, cercando di intercettare il più possibile il flusso di emissione. Per ridurre ulteriormente l'incertezza dei risultati del modello andrebbero sottoposti dei filtri ai dati misurati e le simulazioni andrebbero eseguite con un numero di particelle maggiore di 50.000.

Lo Studio numero 4, riportato al paragrafo 6.1 della presente tesi, contiene varie tipologie di risultati, in quanto, rispetto all'utilizzo delle piattaforme multi-sensore utilizzate in esterna, sono state utilizzate altre tecnologie, altri protocolli di misura, altre metodologie e tecniche di analisi dei dati. Le piattaforme multi-sensore, tra gli inquinanti misurabili, è stata in grado di rilevare l' NH_3 grazie ad un monitoraggio continuo per 10 giorni all'interno di un allevamento di vitelli da carne. Questo gas è stato rilevato anche da tubi passivi, ma anche da pipette Dräger, utilizzate su campioni di aria prelevati il giorno 23 giugno 2025. Nonostante valori differenti di concentrazione di NH_3 rilevati dalle tre diverse tecnologie di misurazione, è stato ottenuto lo stesso risultato, cioè nell'edificio 1 sono state misurate concentrazioni maggiori rispetto all'edificio 2. La CO_2 è stata rilevata sia dalle piattaforme multi-sensore sia dai tubi passivi, riscontrando valori differenti di concentrazioni, ottenendo lo stesso risultato, cioè nell'edificio 2 sono state misurate concentrazioni maggiori rispetto all'edificio 1. L'utilizzo dei tubi passivi per la misurazione delle concentrazioni di NH_3 e CO_2 a due diverse altezze ha permesso di ottenere delle mappe di accumulo dei gas target attraverso l'interpolazione di Kriging ordinaria, nonostante il limitato numero di misurazioni a disposizione. Il prelievo di campioni di aria e la successiva analisi di questi in laboratorio con la tecnica della gascromatografia ha permesso di applicare il metodo semplificato per il calcolo dei fattori di emissione di NH_3 , N_2O , CH_4 e CO_2 dai due edifici, sottoponendo un questionario all'allevatore per il completare il bilancio di

massa. Rispetto all'utilizzo delle piattaforme multi-sensore, queste tecnologie di misurazione risultano dispendiose in termini di tempo, a partire dalla collocazione dei tubi passivi nelle posizioni desiderate, passando dal periodo richiesto per completare la rilevazione, fino al momento in cui i risultati devono essere letti e annotati. Risulta quindi necessario un numero maggiore di prove sperimentali e di tubi passivi per ottenere interpolazioni più precise ed accurate. Gli stessi fattori vengono considerati per l'utilizzo delle pipette Dräger, dispendiose in termini di tempo in quanto necessitano della raccolta dei campioni di aria e il successivo prelievo dalle sacche per la misurazione. È da notare che le misurazioni con i tubi passivi e le pipette Dräger fanno riferimento a concentrazioni rilevate nel periodo di tempo prefissato, ovvero 90 minuti per i tubi passivi e 15 minuti per la raccolta dei campioni di aria, e non sono in grado di studiare le variazioni intermedie delle concentrazioni dovute ai processi avvenuti all'interno dei periodi prefissati. Ad ogni modo, delle indicazioni sommarie possono essere ottenute dalla distribuzione di questa tipologia di sensoristica nell'edificio, studiando le variazioni in termini di emissioni in base all'utilizzo delle superfici aziendali. Questa metodologia potrebbe essere migliorata ulteriormente mediante l'utilizzo di un sistema di riferimento per il calcolo istantaneo delle coordinate di ogni tubo passivo utilizzato. Stessa considerazione viene fatta per la sensoristica in movimento, in quanto non è possibile studiare i campioni di aria prelevati nei due edifici e in esterna secondo un percorso casuale in base alle diverse superfici attraversate.

Per lo Studio numero 5 valgono le considerazioni fatte per gli Studi 1 e 2, rispettivamente riguardo la sottostima dei flussi di emissione in condizioni di instabilità atmosferica da parte di WindTrax e l'utilizzo del sistema di monitoraggio della qualità dell'aria con drone sviluppato dal DAGRI.

In conclusione, da un'analisi delle tecnologie di misurazione, emerge che la sensoristica a basso costo integrata nelle piattaforme multi-sensore consente la misurazione istantanea e contemporanea di vari inquinanti e delle condizioni ambientali, permettendo anche l'aggancio ad un drone per le misurazioni in volo, come indicato nello Studio numero 2. Le altre tecniche di misurazione consentono invece la misurazione di un solo inquinante, per

cui devono essere implementati nelle prove sperimentali altri sensori per la misurazione delle condizioni ambientali. Altro aspetto da considerare riguarda le tempistiche per portare a termine una misurazione. I tubi passivi richiedono un periodo di 90 minuti per ottenere un'osservazione, mentre la raccolta dei campioni di aria per l'applicazione del metodo semplificato richiede 15 minuti. L'aria all'interno delle sacche deve essere poi prelevata per essere analizzata con le pipette Dräger e/o inviata in laboratorio, che in questo caso ha impiegato circa 20 giorni per inviare i risultati. Da considerare sono anche le tempistiche per annotare i risultati ottenuti dai tubi passivi e dalle pipette Dräger su file Excel.

Per quanto le piattaforme multi-sensore sviluppate dal DAGRI possano risultare utili nel fornire contemporaneamente misurazioni di qualità dell'aria e delle condizioni ambientali contemporaneamente, sono state individuate delle criticità. I cruscotti e i grafici per la visualizzazione del dato in tempo reale possono essere osservate su PC o smartphone soltanto in vicinanza delle piattaforme, in quanto le stesse devono essere connesse alla stessa rete internet del dispositivo che si utilizza. La questione non rappresenta una difficoltà invalicabile nel caso dei monitoraggi stazionari, in cui basta avvicinarsi alle piattaforme, ma nel caso dei monitoraggi in volo non si è in grado di visualizzare il dato in tempo reale. Il problema sorge nel momento in cui si decide di utilizzare il sistema di monitoraggio della qualità dell'aria con drone per verificare se siano presenti delle perdite di CH₄, ad esempio, rimanendo nel settore agricolo, in degli impianti di digestione anaerobica.

Altre indicazioni per il miglioramento del sistema di monitoraggio della qualità dell'aria con drone sviluppato dal DAGRI provengono dal gruppo OPAALE. Il sensore laser per la rilevazione del CH₄, se acquisito, andrebbe posto al di sotto del corpo del drone per poi inserire un tubo da collegare alla camera di campionamento per far fronte al problema del downwash. Nonostante i droni riescano a calcolare la velocità e la direzione del vento incidenti in base ai consumi di corrente elettrica di ogni rotore necessari alla stabilizzazione dell'intero sistema, queste non sono utilizzabili, ad esempio, in modelli di dispersione atmosferica in quanto stime di vento apparente. Per questo, un anemometro andrebbe aggiunto all'insieme di sensori che

compongono il carico utile da agganciare al drone, in modo da ottenere informazioni anche sul gradiente verticale del vento. Sarebbero da considerare anemometri che, oltre a misurare direzione e velocità del vento, forniscano anche una misurazione esterna di temperatura, umidità relativa e pressione, in modo da correggere le misurazioni delle condizioni ambientali delle piattaforme multi-sensore, fatte all'interno della camera di campionamento, ambiente sicuramente differente rispetto all'esterno, come indicato anche negli Studi 2 e 3. Altro aspetto da considerare è quello di alleggerire il carico utile per il drone, a partire dall'eliminazione del power bank per poi alimentare la sensoristica con le batterie del drone, grazie alla E-Port. Prima di effettuare la missione di volo, viene poi sempre consigliato di avviare il calcolo del centro di massa dell'intero sistema per ottimizzare le prestazioni da parte del drone. Nell'ottica di utilizzare il bilancio di massa nel calcolo dei flussi di emissione con misurazioni effettuate con drone, sarebbe da ridurre la frequenza di campionamento delle attuali piattaforme multi-sensore, portandola da 20 s, adeguata al monitoraggio stazionario, a 1 s. Sarebbe inoltre utile riuscire ad ottenere un file in output che riporti per ogni osservazione tempistiche, dati da drone e dati di ogni sensore agganciato. In questo modo, sarebbero disponibili dati già elaborati, utilizzabili con la tecnica di analisi delle emissioni in atmosfera che si ritiene più idonea.

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Mapping atmospheric concentration of gas and particulate matter in livestock farms using drone-based measurements

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1. Introduction

The use of UAVs to assess and locate sources of gaseous and particulate emissions is rapidly increasing in several fields. Different approaches have been employed so far, e.g. 2D mapping using spatial interpolation (Burgués et al. 2021) or 3D mapping strategies (Bing et al. 2015).

Our study aimed to explore the possibilities of spatial interpolation methods in GIS environment for mapping air pollutants concentrations, as tool to detect emission hotspots in livestock farms.



Fig. 2 – Drone DJI® Matrice 300 RTK and multi-sensor system.

3. Results and Discussion

In this work, concentration maps of PM_{10} and CO_2 are reported.

Air concentrations of PM_{10} ranged from 5.90 to 9.80 $\mu g m^{-3}$. The interpolation map (Figure 3) allowed to locate sites characterized by higher concentrations (dark blue), that corresponded to the areas alongside the barn and manure storages. The result appears significant given that, during the flight, the unifeed wagon was operating around the barn for feed preparation.

Air concentration of CO_2 ranged from 389 to 469 ppm. The interpolation map (Figure 4) highlighted higher concentrations (dark orange) over the barn and over the manure storage areas.

4. Conclusions

Although 2D mapping solutions, as interpolation methods available in GIS environment, are not able to account for the effects of air speed and direction on gas and particulate dispersion in the bottom atmospheric layer, they represent a tool to rapidly identify and locate emission sources in a farming context.

This opportunity is dependent on the ability to record multi-species gas and particulate data rapidly with small multirotor drones, which represent an innovative approach resulting from this research.

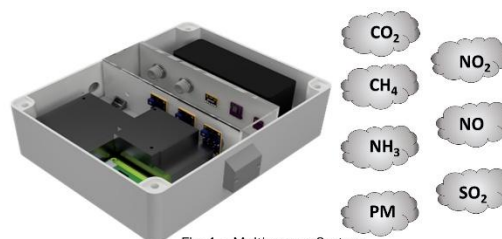


Fig. 1 – Multi-sensor System.

2. Materials and Methods

A prototype multi-sensor system (MS) to monitor air quality was developed (Figure 1). The MS weight was 0.75 kg, with total size of 120x100x67 mm.

It embedded a set of commercial sensors for gas (CH_4 , CO_2 , NH_3 , NO , NO_2 , SO_2) and particulate matter ($PM_{2.5}$, PM_{10}) measurement, plus additional sensor for temperature, relative humidity and atmospheric pressure.

A ESP32® microcontroller and a Raspberry Pi® microprocessor were embedded for data collection, processing and storage. The MS was deployed on top of a quadrotor drone (DJI® Matrice 300 RTK; Figure 2) and a measurement campaign was carried out in a commercial dairy farm located in Tuscany, Central Italy in September 2022.

Data were collected during a 10-minutes flight over the farm facilities at a sampling rate of 5 seconds.

Georeferenced gas and PM concentrations were processed in GIS environment (QGIS® 3.22.5). Data points were interpolated using the Inverse Distance Weighted (IDW) method.



Fig. 3 – Concentration maps of PM_{10} obtained by IDW interpolation method in QGIS® 3.22.5.



Fig. 4 – Concentration maps of CO_2 obtained by IDW interpolation method in QGIS® 3.22.5.



The research was carried out within the CCCfarming project (Climate Care Cattle Farming Systems – ID 39274).





IV Convegno AISSA#under40

Campus di Fisciano, 12-13 luglio 2023

Corso di Agraria-DIFARMA - Università degli Studi di Salerno



Deducing emission rates from gas concentrations in a dairy cattle farm through a backward Lagrangian stochastic method-based model

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Introduction

Cattle farming is the most impactful sector in agriculture worldwide in terms of atmospheric emissions with 4.6 Gt CO₂e year⁻¹, corresponding to 9.4% of all anthropogenic greenhouse gas (GHG) emissions (Ripple et al., 2014). Processes like ruminal fermentation, grazing, housing, feces management, and cultivated fields fertilization by manure spreading generate GHG emissions such as carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O), other dangerous substances like ammonia (NH₃) and particulate matter (fine PM_{2.5} and coarse PM₁₀), impacting climate, animal, and human health. Monitoring these processes is essential for obtaining low ecological footprint product systems. Backward Lagrangian stochastic (bLS) dispersion models (Flesh & Wilson, 1995) quantify emission rates (g m⁻² s⁻¹) from a few gas concentrations, GPS, and environmental data. The calculated emission rates are used for estimating gas target concentrations (ppm or µg m⁻³) on a wide area around extended sources at several heights from the ground. Designing a valid protocol for measuring emissions at the farm level is the aim of this project.

Materials and Methods

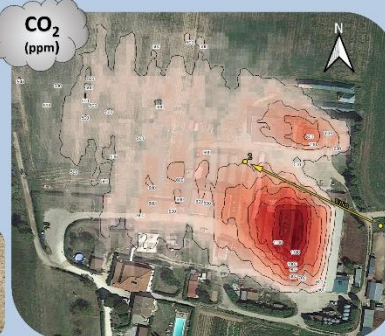
G-eko multi-sensor platforms, an anemometer, and a GPS were used in dairy cattle farm field trials. The bLS model needs at least two concentrations measurement along the wind direction: one up- (background concentration) and one downwind. Multi-sensor platforms (MSPs) measure CO₂ concentration, temperature, and pressure. In addition, each MSP is positioned far from obstacles like buildings or trees. The atmospheric stability is specified through the surface layer model, in this case with Pasquill-Gifford classes to apply the Monin-Obukhov similarity theory. The anemometer is necessary to know wind speed and direction. Furthermore, a GPS is needed for georeferencing sources, obstacles, and ground control points (Crenna, 2006-a). Firstly, measurements obtained from field trials are imported in WindTrax® (<http://www.thunderbeachscientific.com/>), a free software tool for simulating short-range gas atmospheric dispersion (1.0 km), as 15-30 minutes averaged gas concentrations, temperature, and pressure data, integrating the bLS and the surface layer models. Secondly, the unique average emission rate obtained for each extended area source in the farm is used for monitoring the gas concentrations on a wide area still with WindTrax®. Finally, gas atmospheric dispersion maps are built in a GIS environment.

Results

A CO₂ horizontal contour plot at 2.0 m from the ground was obtained from extended area sources in a dairy cattle farm at Borgo San Lorenzo (FI). The farm contains three main CO₂ sources: the straw bedding in the livestock building, the manure storage, and the slurry tank. The average emission rate for these three sources was calculated in WindTrax® thanks to a 20-minute field trial, in which two MSPs (1 and 2 in the figure below) able to detect CO₂ concentrations, pressure, and temperature were located at 1.5 m from the ground along the wind direction (119° from the north). Moreover, the anemometer was located near the upwind station (1) at 2.0 m from the ground. Then, using the average emission rate and the downwind measurements (2), CO₂ concentrations around the sources were calculated in WindTrax®. Concentrations were represented in a geo-referenced raster file with editable symbology, adding for example contour lines to join the same concentration values.



[Screenshot the poster here](#)



Conclusions

WindTrax® is a good software for assembling valid measure protocols. If a new gaseous emission-based decision support system is built, the bLS model validates downwind gas concentration values that occurred during experimental tests. A G-eko MSP fixed on an unmanned aerial vehicle would provide the system with additional downwind measurements to assign an emission rate to each extended area source. Thus, the development of an in-flight measure protocol will increase the precision of the emission rate estimation. WindTrax® simulations are also used for planning field trials: if not enough concentration and environmental sensors are present, the simulation does not start (Crenna, 2006-b).

References: Crenna, B. (2006-a). An introduction to WindTrax; Crenna, B. (2006-b). Atmospheric data in WindTrax; Flesch, T. K., Wilson, J. D., & Yee, E. (1995). Backward-time Lagrangian stochastic dispersion models and their application to estimate gaseous emissions. *Journal of Applied Meteorology and Climatology*, 34(6), 1320-1332; Ripple, W. J., Smith, P., Haberl, H., Montzka, S. A., McAlpine, C., & Boucher, D. H. (2014). Ruminants, climate change, and climate policy. *Nature Climate Change*, 4(1), 2–5. <https://doi.org/10.1038/nclimate2081>

Emission-controlled intensive livestock housing systems for ecological transition: innovative measuring, mitigating and mapping strategies (EMILI)

Finzi A.¹, Mautone A.¹, Becciolini V.², Mattia A.², Rossi G.², Conti L.², Vitaliano S.³, D'Urso P.³ & Arcidiacono C.³

¹ Department of Agricultural and Environmental Sciences, University of Milan, via Celoria 2 - 20133, Milan, Italy;

² Department of Agriculture, Food, Environment and Forestry, University of Florence, Via San Bonaventura, 13 - 50145, Florence, Italy;

³ Department of Agriculture, Food and Environment (Di3A), Building and Land Engineering Section, University of Catania, Via Santa Sofia, 100 - 95123, Catania, Italy

EMILI project aims to improve knowledge about innovative strategies to reduce the impacts of emissions from livestock housing systems, specifically piggeries and dairy cattle barns, and their effects on the environment at the landscape level in the Mediterranean area.



UNIMI activities:

Air quality monitoring in piggeries and emission factors calculation of different housing systems

Mitigation strategy:
slatted floor with a vacuum system

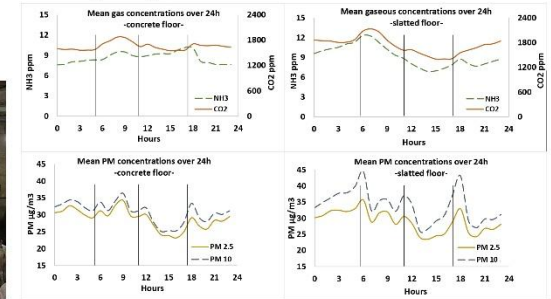


Reference method:
full concrete floor



A long-term monitoring to evaluate the most appropriate monitor protocol and sampling strategies

Preliminary findings:



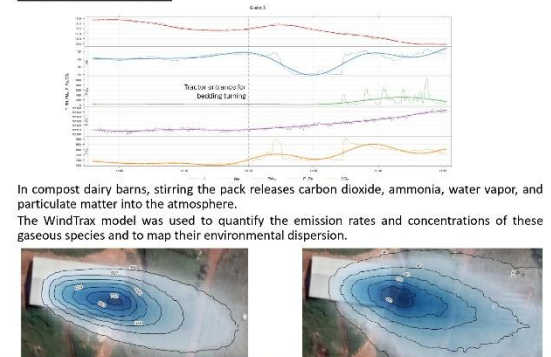
Feeding distribution (vertical bars) increased PM concentration. Windows, closing between 8 p.m. at 11 p.m. reduced air exchange and increased gas accumulation. These events can be responsible for a detrimental effect of air quality in the barns.

UNIFI activities:

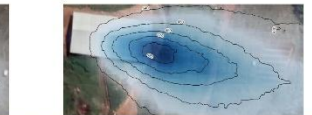
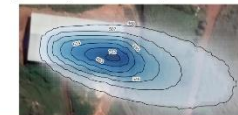
Development of a protocol for air quality monitoring in dairy cattle farms using ground and drone-based measurements, featuring prototype multi-sensor platforms specifically developed for this project.



Preliminary findings:



In compost dairy barns, stirring the pack releases carbon dioxide, ammonia, water vapor, and particulate matter into the atmosphere. The WindTrax model was used to quantify the emission rates and concentrations of these gaseous species and to map their environmental dispersion.



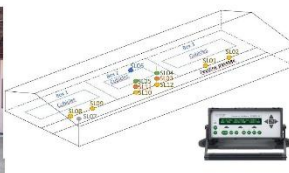
UNICT activities:

Air quality monitoring in dairy barns

- to measure gas concentrations in the indoor environment and validate innovative mitigation strategies for emission reduction.



Barn typology: Open free stall dairy barn with cubicles and concrete floor



Measuring system: commercial photo-acoustic spectroscopy system that monitor gases at different locations in the barn.

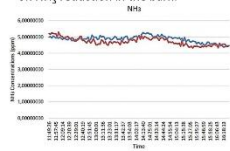
- to assess the impacts of housing at landscape level by identifying vulnerable areas

Preliminary findings:



Preliminary laboratory study to test the efficacy of the tegument in reducing pH. Experimental field investigations, including collection and subsequent analyses both in situ and in the laboratory, of samples taken from point "C" (where the mitigation strategy was applied) and point "T" (control).

Monitoring of NH₃ concentrations to assess mitigation techniques. The use of byproduct of the coffee processing industry and a weak acid characterized by low pH values were used to evaluate the impact on gas concentrations in the barn. Preliminary results showed a reduction in the pH of animal effluents in both laboratory and in-field application, with effect on NH₃ reduction in the barn.



The graph shows the trend of NH₃ concentrations detected in the barn during the experiment, where (SL-A) represents the measurements in the control area "T" and (SL-B) represents the experimental area "C".



XIII Allia International Conference - Padova 17-19 June 2024
Biosystems engineering promoting resilience to climate change

Project funded by the European Union - Next generation EU for Research Projects of Relevant National Interest (PRIN PNRR 2022) of the Italian Ministry of University and Research (MUR). Project code (CUP): C33C23000800007. "Emission-controlled intensive livestock housing systems for ecological transition: Innovative measuring, mitigating and mapping strategies (EMILI)".



PhD Day

Florence, 3rd July 2024

PhD in Sustainable Management of Agricultural, Forestry, and Food resources
University of Florence



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FOOD, ENVIRONMENT AND FORESTRY

CO₂ emission monitoring from a compost barn in a dairy cattle farm

Alessio Mattia ¹, Giuseppe Rossi ¹, Matteo Barbari ¹, Valentina Becciolini ¹, Ugo Rossi ², Marco Merlini ².

¹ Department of Agriculture, Food, Environment, and Forestry (DAGRI), University of Florence, Florence, 50144, Piazzale delle Cascine, 18

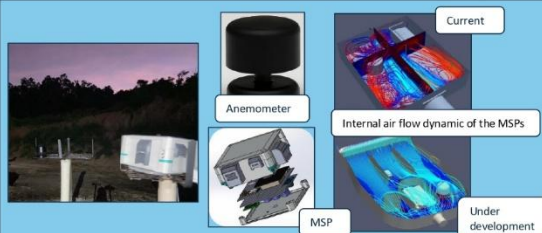
² Project & Design s.r.l.s., Florence, 50142

Introduction

Cattle farming is the most impactful sector in agriculture worldwide in terms of atmospheric emissions with 4.6 Gt CO₂e year⁻¹, corresponding to 9.4% of all anthropogenic greenhouse gas (GHG) emissions (Ripple et al., 2014). Processes like ruminal fermentation, grazing, housing, feces management, and cultivated fields fertilization by manure spreading generate GHG emissions such as carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O), other dangerous substances like ammonia (NH₃) and particulate matter (fine PM_{2.5} and coarse PM₁₀), impacting climate, animal, and human health. Monitoring these processes is essential for obtaining low ecological footprint production systems. Backward Lagrangian stochastic (bLS) dispersion models (Flesch & Wilson, 1995) quantify emission rates ($\text{g} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$) from a few gas concentrations, GPS, and environmental data. The calculated emission rates are used for estimating gas target concentrations (ppm or $\mu\text{g} \cdot \text{m}^{-3}$) on a wide area around extended sources at several heights from the ground. Designing a valid protocol for measuring emissions at the farm level is the aim of this project.

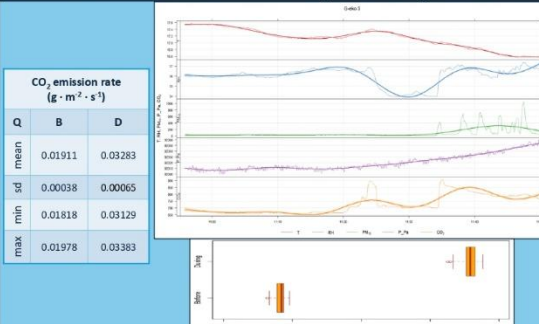
Materials and Methods

G-eko multi-sensor platforms, an anemometer, and a GPS were used in dairy cattle farm trials for studying CO₂ emissions of a compost barn. The bLS model needs at least two concentrations measurement along the wind direction: one up- (background concentration) and one downwind. Multi-sensor platforms (MSPs) measure CO₂ concentration, temperature, and pressure. The atmospheric stability is specified through the surface layer model, in this case with Pasquill-Gifford classes to apply the Monin-Obukhov similarity theory. The anemometer is necessary to know wind speed and direction. Furthermore, a GPS is needed for georeferencing sensors, sources, and ground control points (Crenna, 2006-a). Firstly, measurements obtained from field trials are imported in WindTrax®, a free software tool for simulating short-range gas atmospheric dispersion (1.0 km), as 15 minutes averaged gas concentrations, temperature, and pressure data, integrating the bLS and the surface layer models. Secondly, the average emission rate obtained for the compost barn is used for monitoring the gas concentrations on a wide area. Finally, gas atmospheric dispersion maps are built in a GIS environment. R® software was used for data analysis.



Results

CO₂ horizontal contour plots at 1.5 m from the ground were obtained. The farm, located in Lavras (MG), Brasil, contains a main CO₂ source: the compost barn inside the livestock building. The average emission rate for this source was calculated in WindTrax® thanks to a 15-minute field trial, in which two MSPs (2 and 3 in the figure below) able to detect CO₂ concentrations, pressure, and temperature were located at 1.5 m from the ground along the wind direction. Moreover, the anemometer was located near the downwind station (3) at 1.5 m from the ground. Then, using the average emission rate and the two measurements (2 and 3), CO₂ concentrations around the sources were calculated in WindTrax®. Concentrations were represented in a geo-referenced raster file with editable symbology, adding contour lines to join the same concentration values. The other downwind station (4) was used for validating CO₂ measured concentrations before and during litter turning at 1.5 m.



Conclusions

WindTrax® is a good software for assembling valid measure protocols. If a new gaseous emission-based decision support system is built, the bLS model validates downwind gas concentration values that occurred during experimental tests. WindTrax® simulations are also used for planning field trials: if not enough concentration and environmental sensors are present, the simulation does not start (Crenna, 2006-b).



References: Crenna, B. (2006-a). An introduction to WindTrax; Crenna, B. (2006-b). Atmospheric data in WindTrax; Flesch, T. K., Wilson, J. D., & Yee, E. (1995). Backward-time Lagrangian stochastic dispersion models and their application to estimate gaseous emissions. *Journal of Applied Meteorology and Climatology*, 34(6), 1320-1332; Ripple, W. J., Smith, P., Haberl, H., Montzka, S. A., McAlpine, C., & Boucher, D. H. (2014). Ruminants, climate change, and climate policy. *Nature Climate Change*, 4(1), 2-5. <https://doi.org/10.1038/nclimate2081>; WindTrax website: <http://www.thunderbeachscientific.com/>

Insights on UAV-based methods for dust and gas emissions measurement: sensing technologies and protocols in the perspective of rapid on-farm assessments

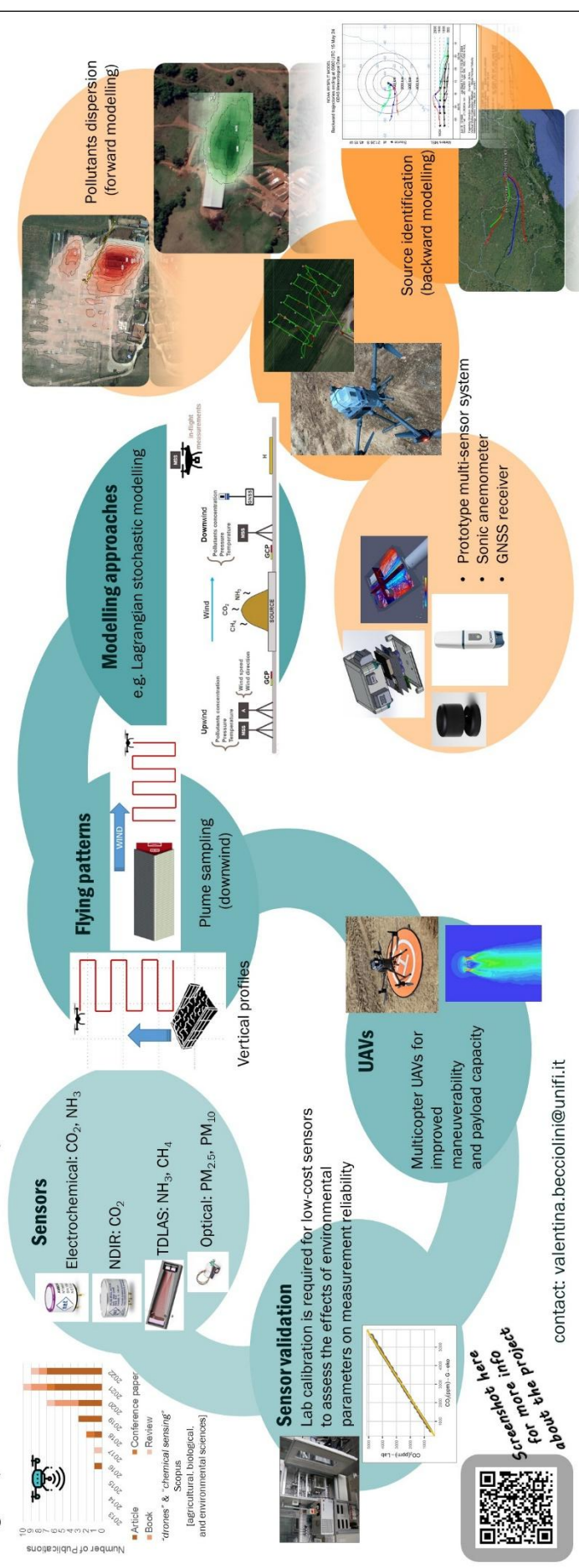
Becciolini V., Mattia A., Merlini M., Rossi G., Barbari M., Conti L.
University of Firenze, Dept. of Agriculture, Food, Environment and Forestry – Florence, Italy

BACKGROUND

In livestock farming, the rapid identification of critical emitting processes and their quantification is crucial to adopt precision mitigation practices and to assess farm environmental performances.

AIM

- Investigate and test approaches based on UAV sensing for the assessment of dust and gaseous emissions at the farm level.
- Provide a comprehensive view on the perspective of their applications in the livestock sector.





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Deducing CO₂ emission rate from extended area sources with WindTrax model in a dairy cattle farm

A. Mattia, M. Merlini, F. Squillace, G. Rossi, L. Conti and V. Becciolini*

University of Florence, Department of Agriculture, Food, Environment and Forestry (DAGRI)

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*correspondence: valentina.becciolini@unifi.it

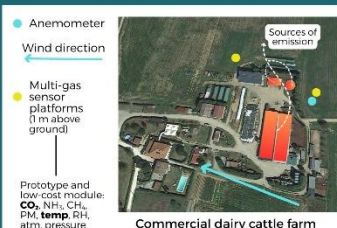
BACKGROUND

Environmental chemical monitoring plays a key role in **bottom-up emission inventories** and in identifying critical processes



Inverse-dispersion technique based on a backward Lagrangian Stochastic (bLS) model

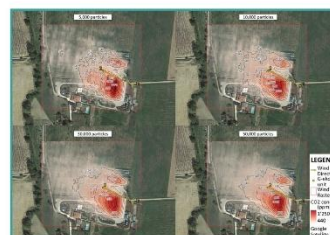
Widely used in agrometeorology to estimate **emission rates** and simulate **gas dispersion**



bLS model parameters (WindTrax)

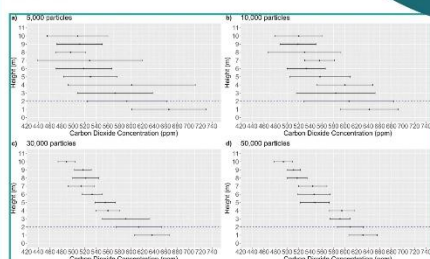
Z ₀	2.3
Atmospheric stability	B
θ	119.3°
Nr. particles	50,000

Simulation	Estimated Q g m ⁻² s ⁻¹ CO ₂
1	0.19902
2	0.19054
3	0.14932
4	0.26958



MATERIALS & METHODS

Vertical profile plots of estimated CO₂ concentration ± confidence intervals in the downwind sampling point. Simulations were run using 5,000 (a), 10,000 (b), 30,000 (c), and 50,000 (d) particles. Estimations are at **heights from 1 m a.g.l. to 10 m a.g.l.** The dotted blue line indicates the height at which simulations of the horizontal dispersion were carried out.



RESULTS

1. Estimated emission rates from the sources (cow housing and manure stores) ranged from 0.149 to 0.270 g m⁻² s⁻¹. As the average wind speed increase, the estimated Q also increase.
2. Both for horizontal and vertical simulations of CO₂ dispersion, the increase of number of particles in the simulations leads to a decrease of the confidence intervals of the estimates.
3. Furthermore, as the distance from the source along wind direction increased, the confidence interval of the estimates decreased.
4. For vertical profile plots, as the number of particles used for the simulation increased, confidence intervals for CO₂ concentration estimates became smaller. Moreover, a better defined vertical trend in concentrations is observed as the number of particles increases.

Concentration maps for estimated CO₂ horizontal dispersion at 2 m above ground level. Maps were obtained using WindTrax simulations from CO₂ measurements averaged at 5-minutes intervals. From top left, horizontal **contour plots** (10 classes separated by 90-ppm intervals) for models computed with **5,000 10,000 30,000, and 50,000** particles.

Sensor positioning is critical. Accurate placement of sensors within a 1 km radius of emission sources is essential for protocol effectiveness. Increasing the number of sensing modules enables more detailed emission estimates for each source type (litter, manure, slurry).

Optimization of model parameters:

Using a high number of particles improves the accuracy of concentration estimates; however, it also increases computational time.

Long-term data collection: Continuous monitoring over daily, seasonal, and annual cycles is necessary to better understand emission variability

CONCLUSIONS



15th International Conference
Biosystem Engineering 2025
7th-9th May 2025, Tartu, Estonia



Project funded by the European Union - Next generation EU for Research Projects of Relevant National Interest (PRIN PNRR 2022) of the Italian Ministry of University and Research (MUR).
Project code (CUP): C52C23003900001, "Emission-controlled intensive livestock housing systems for ecological transition: innovative measuring, mitigating and mapping strategies (EMILI)".