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Remotely piloted aircraft for monitoring greenhouse gases in dairy production systems

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Abstract. The monitoring of greenhouse gas (GHG) emissions in dairy cattle facilities is essential for understanding and mitigating the environmental impact of livestock farming. Among the main gases emitted in dairy production systems, methane (CH_4) and carbon dioxide (CO_2) play significant roles in global warming. The objective of this research was to evaluate the spatial variability of CH_4 (ppm) and CO_2 (ppm) concentrations, as well as environmental variables (dry bulb temperature, t_{db}, °C, and relative humidity, RH, %), in a compost barn dairy production system. For gas concentration monitoring, an electrochemical sensor was used for CH_4 and a non–dispersive infrared (NDIR) sensor for CO_2. For the environmental variables, a Hobo® MX2301A datalogger was used, and both pieces of equipment were attached to a remotely piloted aircraft (RPA), the DJI Matrice 350. Measurements were carried out over three days, with flights conducted over the facility's roof. The data obtained were analysed using geostatistics to characterise spatial variability of the GHG. A strong spatial dependence was observed in gas concentrations and environmental variables. The highest concentrations of CH_4 (129–134.4 ppm) and CO_2 (434–479 ppm) were recorded on the first day. T_{db} ranged between 24.2 °C and 32 °C, while RH fluctuated between 38.8% and 68%. The use of RPA proved to be an efficient tool for GHG monitoring, allowing the identification of spatial distribution patterns. This technology provides a novel approach to measuring GHG emissions, addressing the environmental challenges of the agricultural sector.

Key words: carbon dioxide, compost barn, dairy cattle, drone, methane, spatial variability.

INTRODUCTION

The consumption of milk and dairy products benefits more than 6 billion people worldwide (FAO, 2019; Dordevic et al., 2023). According to the Organization for Economic Cooperation and Development (OECD-FAO, 2022), global milk production is projected to grow by 1.8% per year between 2022 and 2031. However, despite its economic significance, dairy cattle production faces increasing environmental challenges, such as greenhouse gas (GHG) emissions and waste generation, which are linked to both environmental and socio-economic factors (Carvalho et al., 2022; Ferraz et al., 2024). With global milk production projected to grow by 1.8% annually from 2022 to 2031 (OECD-FAO, 2022), these challenges are expected to intensify. In response, countries have committed to reducing GHG emissions under the Paris Agreement, with a target of achieving carbon neutrality by 2050 (Horowitz, 2016; Richardson et al., 2024). The dairy industry, particularly in confined animal production systems, is a significant source of GHG emissions, primarily methane (CH_4) and carbon dioxide (CO_2), which result from enteric fermentation and manure management (Dzermeikaite et al., 2024; Oliveira et al., 2024). To address these issues, it is critical to develop accurate methods for measuring and monitoring emissions in real time. The use of Remotely Piloted Aircraft (RPA) in environmental monitoring has shown promise, providing an efficient, non-invasive approach to measure GHG emissions over large areas (Daugela et al., 2019; Shaw et al., 2021). The importance of using RPA lies in their ability to cover extensive areas easily, ensuring a more comprehensive and representative mapping of emissions, unlike traditional methods, which are often limited to small areas or specific points. Additionally, it is a non-invasive method that allows measurements without compromising the behaviour and welfare of animals. RPAs can be equipped with various types of sensors (Giordan et al., 2017), allowing real-time data collection and operation at different altitudes. In precision agriculture, RPAs have stood out by promoting sustainability through remote sensing, image analysis, and spatial variability mapping, contributing to increased agricultural productivity (Ahmad et al., 2020).

In confined animal production facilities, the continuous release of heat, moisture, and gases such as CH_4 (methane), CO_2 (carbon dioxide), H_2S (hydrogen sulphide), and NH_3 (ammonia) is a direct reflection of the intensive activities occurring in this environment (Oliveira et al., 2024). These gases are closely linked to the biological and operational processes characteristic of animals, such as enteric fermentation, manure management, and handling practices (Dzermeikaite et al., 2024), as well as the variability of microclimatic and environmental conditions around the building. For the analysis of gas emissions using RPA to be effective, it is important to understand the processes that generate these emissions within the facility. CH_4 is primarily produced through enteric fermentation and results from biological processes associated with the metabolic activity of methanogenic archaea, a specific group of anaerobic microorganisms (Liu et al., 2024). CO_2 is generated through two processes: anaerobic digestion of manure, which leads to the decomposition of organic matter (Halim et al., 2017), and eructation during enteric fermentation, a digestive process characteristic of ruminants (Astuti et al., 2024). Animal management facilities play a significant role in GHG emissions, particularly the compost barn, a dairy production system where cattle remain on a bed of organic material, allowing them to move freely (Silva et al., 2022). However, the measurement of CH_4 and CO_2 in compost barns remains a challenge due to the reactive behaviour of these gases in the atmosphere and their tendency to disperse easily within the production system, mainly due to environmental factors that may interfere with data collection.

To evaluate the distribution of CH_4, CO_2, and environmental variables around the compost barn facility, geostatistics was used - a tool that enables the analysis of the spatial variability of attributes characterising the production environment (Ferreira et al., 2024). According to El Hamzaoui et al. (2021), geostatistical methods allow the generation of maps from samples collected in a study area, and when subjected to kriging interpolation, these samples provide a detailed visualisation of the dispersion of a variable in the environment.

The objective of this study was to monitor and analyze the spatial distribution of GHG concentrations, specifically methane (CH_4) and carbon dioxide (CO_2), and environmental variables such as dry bulb temperature (t_{db}, °C) and relative humidity (RH, %) in the surrounding area of a compost barn system using a remotely piloted aircraft (RPA).

MATERIALS AND METHODS

This research followed all experimental procedures approved by the Animal Ethics Committee (CEUA) of the Federal University of Lavras, in accordance with protocol n° 044/22 and n° 010/21.

Characterisation of the Facility

The experiment was conducted in May 2024 in a dairy cattle production system of the compost barn type, located in the municipality of Lavras, MG, Brazil, at an altitude of 920.62 m and geographic coordinates 21°15' South latitude and 45°09' West longitude.

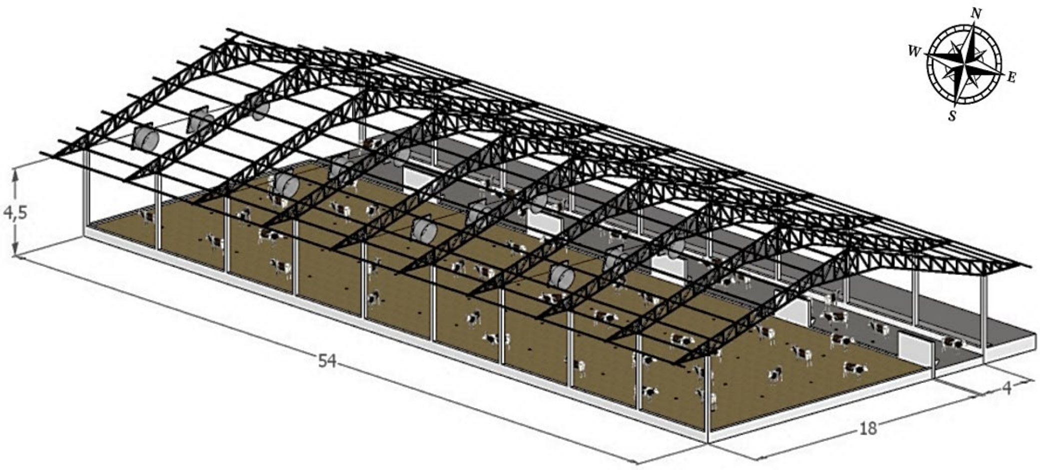

Figure 1. Schematic representation of the compost barn production system and its respective dimensions in metes.

The facility (Fig. 1) was oriented in an east-west direction and has dimensions of 54 m in length, 22 m in width, and a ceiling height of 4.5 m, with four meters of the width allocated to the feed alley, located on the northern side. The facility (Fig. 1) was oriented in an east-west direction and has dimensions of 54 m in length, 22 m in width, and a ceiling height of 4.5 m, with four meters of the width allocated to the feed alley located on the northern side. The facility was covered with Galvalume roofing sheets installed at a 30% slope, featuring eaves extending three meters on the north and south sides, and one meter on the east and west sides. Additionally, it included a shed-type ridge vent with a central opening.

Mechanical ventilation was implemented from the eastern to the western portion of the facility using 12 Ziehl–Abegg® axial fans, installed 2.5 meters above the bedding and arranged in four rows. These fans operate at at high volume and low speed (HVLS), with a diameter of 1.10 m, three blades, a rotation speed of 950 rpm, a power rating of 0.86 kW, and an airflow rate of 23,000 $m^3 \cdot h^{-1}$. The compost bedding consisted of wood shavings with a depth of 65 cm and was turned twice daily during milking sessions.

The production system housed 86 lactating cows, with a stocking rate of 13.81 m^2 per cow. Milking was carried out twice a day: the first at 05:00 and the second at 16:00. Throughout the experimental period, the farm's standard routine was maintained, adhering to the usual milking times, feeding management, and bedding turning schedule.

Acquisition of the Evaluated Variables

To obtain the environmental variables, a Hobo® MX2301A datalogger (Fig. 2) was used, with an accuracy of 0.2 °C for air temperature (t_{db}, °C) and 2.5% for relative air humidity (RH, %).

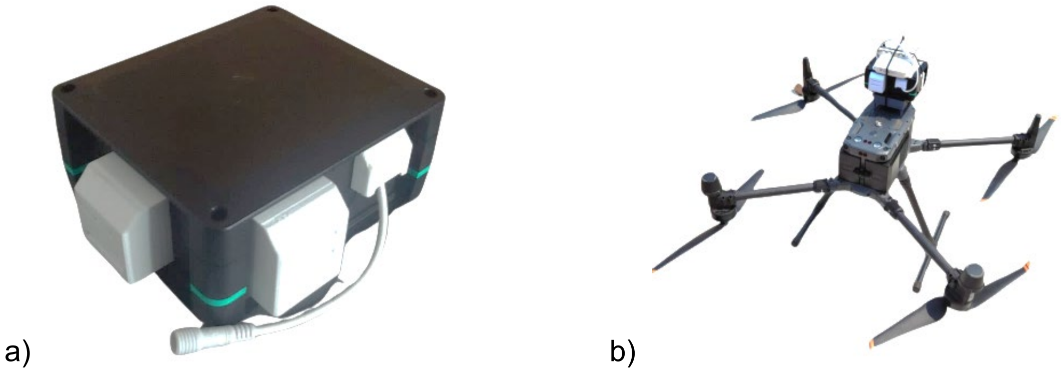

Figure 2. System for CH_4 and CO_2 concentration acquisition (a); Remotely piloted aircraft (RPA) with attached sensor (b).

To measure gas concentrations, a low-cost prototype was used, featuring an electrochemical sensor for CH_4 and a non–dispersive infrared (NDIR) sensor for CO_2, developed in collaboration with the University of Florence. To obtain the environmental variables, a Hobo® MX2301A datalogger (Fig. 2) was used, with an accuracy of 0.2 °C for dry-bulb temperature (t_{db}, °C) and 2.5% for relative air humidity (RH, %). The gas sensor operates within a range of 0 to 5,000 ppm for CO_2, with an accuracy of approximately ± 30 ppm, and 0 to 25,000 ppm for CH_4, with a sensitivity of ± 500 ppm (Becciolini et al., 2022) (Fig. 3, a). This system was integrated into an RPAS, model DJI Matrice 350 (Fig. 3, b).

The data were collected over three consecutive days (May 13th, 23rd, and 28th), always starting at 12:00 PM, with an average of 27 points per flight. The RPA was programmed to stabilise for one minute at each point, allowing the sensor and datalogger to record the values of the evaluated variables. The flight altitude was maintained at 13.0 m relative to the starting point, while the speed between points was approximately 4 m s^{-1}. After completing the data collection, the RPA returned to the starting point, concluding the flight plan, as shown in Fig. 3.

Figure 3. Data collection points recorded during flights over the three evaluated days.

Evaluation of CH_4 and CO_2 Concentrations and the Thermal Environment

The collected data were subjected to geostatistical analysis, aiming to characterise the spatial variability of CH_4, CO_2, t_{db}, and RH using the R® software.

The data were initially analysed by semivariance to assess spatial dependence, followed by interpolation using kriging. The semivariance was calculated using Eq. 1, proposed by Bachmaier & Backes (2008):

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(Xi) - Z(Xi + h)]^2 \tag{1}$$

where N (h) is the number of experimental pairs of observations $Z(x_i)$; and $Z\ (x_i + h)$ separated by a distance h.

The semivariance was adjusted using the restricted maximum likelihood (REML) method, which results in less biased estimates (Ferraz et al., 2019). The mathematical model used for the semivariance adjustment was the spherical model, widely used in geostatistical studies. The nugget effect (C_0), contribution ($C_0 + C_1$), and range (a) parameters were obtained from the semivariance equation adjusted according to the behaviour of the graphs. To assess the quality of the fit, the spatial dependence degree (SDD) was used, following the classification by Cambardella et al. (1994).

After the adjustments, the data were interpolated using kriging to visualise the spatial distribution patterns of the variables across the facility. The maps were generated with Surfer® 13 software, which, through kriging, allows for predicting the value of a variable at unsampled points based on the information collected from other locations.

RESULTS AND DISCUSSION

The results of the geostatistical analysis for assessing the spatial variability of the variables: CH_4, CO_2 t_{db}, and RH, based on the data collected during the three days of flights, are detailed in Table 1.

Table 1. Geostatistical Analysis of the Spatial Variability of CH_4, CO_2, t_{db}, and RH

D/V	Variables	C0	(C0+C1)	A	SDD	Clas	ME	S_{ME}	RME	S_{RME}
D1	CH_4	0.0	3.02	4.0	0	Forte	9.47	1.86	-5.25	1,035
F1	CO_2	0.0	204.7	2.0	0	Forte	2.65	15.33	-1.78	1,035
	t_{db}	0.0	0.22	2.5	0	Forte	7.34	0.50	-1.48	1,035
	RH	0.0	1.31	0.93	0	Forte	8.52	1.22	7.17	1,035
D2	CH_4	0.0	29.45	1.32	0	Forte	7.49	5.74	1.34	1,028
F1	CO_2	0.0	52.47	1.23	0	Forte	3.78	7.66	5.07	1,028
	t_{db}	0.0	0.52	1.15	0	Forte	5.33	0.76	7.16	1,028
	RH	0.0	1.96	1.25	0	Forte	1.18	1.48	7.99	1,028
D2	CH_4	0.0	82.53	5.38	0	Forte	-1.42	9.56	-0.15	1,028
F2	CO_2	0.0	194.63	1.65	0	Forte	2.55	14.69	1.77	1,028
	t_{db}	0.0	0.23	1.02	0	Forte	5.32	0.51	1.10	1,028
	RH	0.0	1.04	1.56	0	Forte	3.19	1.07	-3.06	1,028
D3	CH_4	18.9	29.45	10.6	0	Forte	0.07	4.34	0.01	1,031
F1	CO_2	0.0	34.74	5.0	0	Forte	2.10	6.12	3.56	1.019
	t_{db}	0.0	1.25	2.0	0	Forte	9.21	1.16	8.07	1,019
	RH	0.0	4.87	31.6	0	Forte	0.02	1.11	0.01	0.913
D3	CH_4	0.0	57.46	6.0	0	Forte	0.00	7.87	9.32	1,019
F2	CO_2	2,594	11,091	10.9	0	Forte	-1.85	120.14	-0.01	1,038
	t_{db}	0.0	0.69	1.30	0	Forte	1.05	0.87	1.24	1,019
	RH	0.0	4.6	4.30	0	Forte	1.58	2.23	7.21	1,019

D – Day; F – Flight; C_0 – Nugget effect; C_1 – Contribution; $C_0 + C_1$ – Sill variance; A – Range; SDD – Spatial dependence degree; Clas – Classification; ME – Mean error; S_{ME} – Standard deviation of the mean error; RME – Reduced mean error; S_{RME} – Standard deviation of the reduced mean error.

The results obtained indicated a strong spatial dependence for all the analysed variables, suggesting that the evaluated environment exhibits significant spatial variability, which influences the concentrations of GHGs (CH_4 and CO_2) and environmental variables such as t_{db} and RH. To assess the spatial dependence degree (SDD) of the variables under study, the classification proposed by Cambardella et al. (1994) was adopted. According to this methodology, the SDD is determined by the ratio $C_0/(C_0+C_1) \times 100$, where values below 25% indicate strong spatial dependence, values between 25% and 75% indicate moderate dependence, and values above 75% characterise weak spatial dependence. The analysis revealed that most of the variables showed SDD values indicating strong spatial dependence, reinforcing the idea that gas concentrations and environmental variables are closely linked to the local conditions of the production environment.

The nugget effect (C_0), which indicates the variability present at shorter distances between samples, was null for many of the variables analysed, indicating a discontinuity in the semivariogram for distances smaller than the minimum distance between the samples (Ferraz et al., 2017). This result suggests that samples very close to each other did not exhibit significant variations, possibly due to the homogeneity of the variables at shorter scales. This is important for optimising the sampling design in future measurements, considering the minimum distance required between points to capture significant variations.

The range (a) was used to quantify the maximum distance at which sampled points maintain a significant correlation between each other, as per McBratney & Webster (1983) and Curi et al. (2014). The range values are highly relevant for defining the spatial dependence boundary, i.e., the extent to which a variable maintains its influence in space. It was observed that the ranges varied significantly across different days and flights, suggesting that the distribution of the analysed variables is not homogeneous over time and space. Specifically, the variables of t_{db} and CO_2 exhibited shorter ranges, while RH showed a more extensive spatial range. These results indicate that the influence of environmental conditions (such as t_{db} and RH) tends to extend over greater distances than greenhouse gas concentrations, which may be related to air circulation dynamics and the dispersion of gases in the production environment.

The mean error (ME) of the variables was close to zero, indicating that the applied model provided good fitting results (Ferraz et al., 2020). The standard deviation of the mean error (S_{DME}) varied significantly between the variables, with lower values for t_{db} and higher values for CO_2. This suggests that, although the model fitted most of the variables well, there was greater variability in the CO_2 estimates, possibly due to the higher dispersion and spatial variability of CO_2 concentrations in the environment.

Furthermore, the reduced mean errors (RME) and their respective standard deviations (S_{RME}) showed low values, reinforcing the reliability of the adjusted model for all variables. These results demonstrate that the applied geostatistical technique was efficient for the modelling and spatial analysis of the variables, contributing to a detailed understanding of the distribution of gas concentrations and environmental variables within the internal environment of the facility.

Using the kriging technique in Surfer® software, contour maps were generated to illustrate the spatial distribution of the variables CH_4, CO_2, t_{db}, and RH around the facility. These maps provide a detailed view of the observed spatial patterns, allowing for the identification of areas with higher or lower concentrations of these variables. This approach aids in visualising patterns and facilitates the implementation of management strategies to mitigate GHG emissions, as well as optimising the control of environmental conditions in compost barn facilities.

Through Fig. 4, it is possible to observe the behaviour of CH_4 on the three collection days (D1, D2, D3) and flights (F1, F2), as demonstrated below.

The CH_4 maps indicate that on Day 1, the highest accumulation of CH_4 over the facility was recorded, reaching 134.4 ppm, marked by the dark green colour (Fig. 4, a). CH_4 emissions are associated with animal burping, as enteric CH_4 emissions are strongly influenced by the ruminal digestibility of the food (Knapp et al., 2014). Additionally, according to González–Quintero et al. (2024), the management of animal waste is also a determining factor in GHG emissions. The production of CH_4 from manure is influenced by factors such as its composition, nutrient availability, oxygen and water content, pH levels, management practices adopted, and environmental conditions (Singaravadivelan et al., 2023). In compost barn systems, where manure is mixed with bedding material, the type of management adopted for this bedding directly impacts CH_4 emissions in the environment and, subsequently, into the atmosphere. According to the EPA (2022), enteric CH_4 and manure-derived CH_4 can account for 26.9% and 9.2%, respectively, of the total atmospheric CH_4 emissions in the United States, demonstrating the impact of CH_4 produced in animal production systems on the atmosphere.

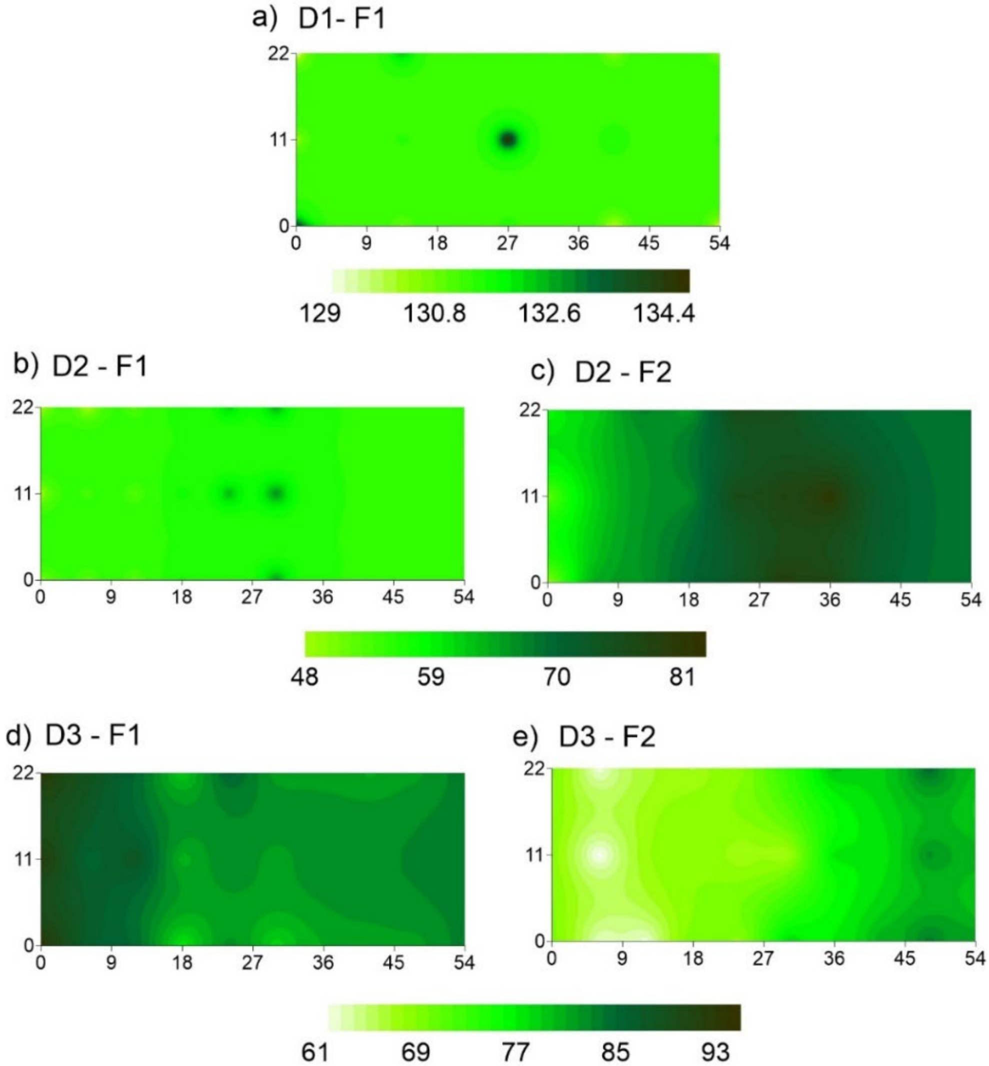

Figure 4. Spatial distribution of methane (CH_4) above the roof in the dairy cattle facility on the evaluated days (D1F1 = Day 1 – Flight 1 (a); D2F1 = Day 2 – Flight 1 (b); D2F2 = Day 2 – Flight 2 (c); D3F1 = Day 3 – Flight 1 (d); D3F2 = Day 3 – Flight 2 (e).

Aguirre-Villegas & Rebecca (2017) complement that CH_4 emissions derived from manure primarily depend on the amount of undigested food excreted by the animals, as well as the practices adopted for the management, processing, and storage of this waste.

Therefore, the combination of these factors should be considered in strategies to mitigate GHG emissions in animal production systems and may fully influence the differences in the concentrations of these gases across the three analysed days.

On Day 2, in F1, the lowest CH_4 concentrations were recorded (Fig. 4, b), indicated by the light green colour. In the second flight (Fig. 4c), there was a greater distribution of the gas around the facility, evidenced by the higher gas concentration in the central region over the ridge. On Day 3 (Figs 4, d; 4, e), it was observed that the CH_4 concentrations exhibited opposite behaviours, with the highest gas concentrations in F1 being distributed in the western part of the facility, while in F2, the highest concentrations were recorded in the eastern portion of the facility. According to Damasceno (2020), CH_4 tends to concentrate in the higher parts of the compost barn. This information is crucial for understanding the dispersion patterns of this gas.

CH_4 has a global warming potential 25 times greater than CO_2 over a 100-year horizon (IPCC, 2021). Inside the compost barn facility, this gas is predominantly generated by the anaerobic fermentation of organic matter present in the manure accumulated in the bedding, as well as by enteric emissions from cattle. The natural and mechanical ventilation of the facility promotes the release of this methane into the surrounding area, where it can disperse and reach higher layers of the atmosphere. As indicated by the maps generated in this study (Fig. 4), the external concentrations of CH_4 reflect the interaction between enteric sources and manure management practices, which are characteristic of animal production systems. Once in the atmosphere, CH_4 acts as a highly reactive greenhouse gas, significantly contributing to global warming. Its ability to dissipate and rise into the troposphere favours the formation of ozone, making it a harmful pollutant for human health and ecosystems (Rodrigues et al., 2024). Despite its shorter persistence in the atmosphere compared to CO_2, the high emission rate of CH_4 demands efficient mitigation strategies to reduce its climatic impact. Among the mitigation alternatives, modifications in animal diets, genetic improvement for selecting individuals with lower methane production, and proper bedding and organic waste management to reduce anaerobic fermentation and subsequent emissions stand out (Levrault et al., 2025). The combined adoption of these strategies can contribute to the mitigation of this gas in the atmosphere and the sustainability of livestock production.

From Fig. 5, it is possible to observe the dispersion behaviour of CO_2 around the facility on the three different collection days (D1, D2, D3) and flights (F1, F2), as demonstrated below.

The analysis of the maps on the dispersion of CO_2 around the facility reveals that on Day 1, there was the highest recorded accumulation of CO_2 over the facility, with concentrations reaching 479 ppm, the highest value among the three days analyzed, as indicated by the dark brown color (Fig. 5, a). This increase in CO_2 can be explained, as noted by Acaravci & Erdogan (2016) and Zou et al. (2020), by the release of the gas during processes such as enteric fermentation and animal respiration. Hamilton et al. (2010) emphasize that cattle respiration significantly contributes to CO_2 emissions. Furthermore, Giannone et al. (2023) highlight that under stress conditions, animals show changes in respiratory frequency, which can increase CO_2 release within the facility.

Although CO_2 has a lower global warming potential compared to CH_4 per unit, its contribution to the greenhouse effect is substantial due to the large amounts released into the atmosphere. The dispersion of CO_2, as captured in the maps of this study, highlights its rapid diffusion in the external environment, which reduces the local concentration of the gas but facilitates its incorporation into the atmosphere.

On Day 2, the recorded CO_2 concentrations were the lowest, reaching a minimum of 320 ppm, as indicated by the light brown color in the generated maps (Figs 5, b; 5, c). On Day 3 (Figs 5, d; 5, e), a significant variation was observed between Flights F1 and F2. In Flight F1 (Fig. 5, d), there was a higher concentration of CO_2 in the central region of the facility, while in Flight F2 (Fig. 5, e), the levels were lower, particularly in the western portion of the assessed area.

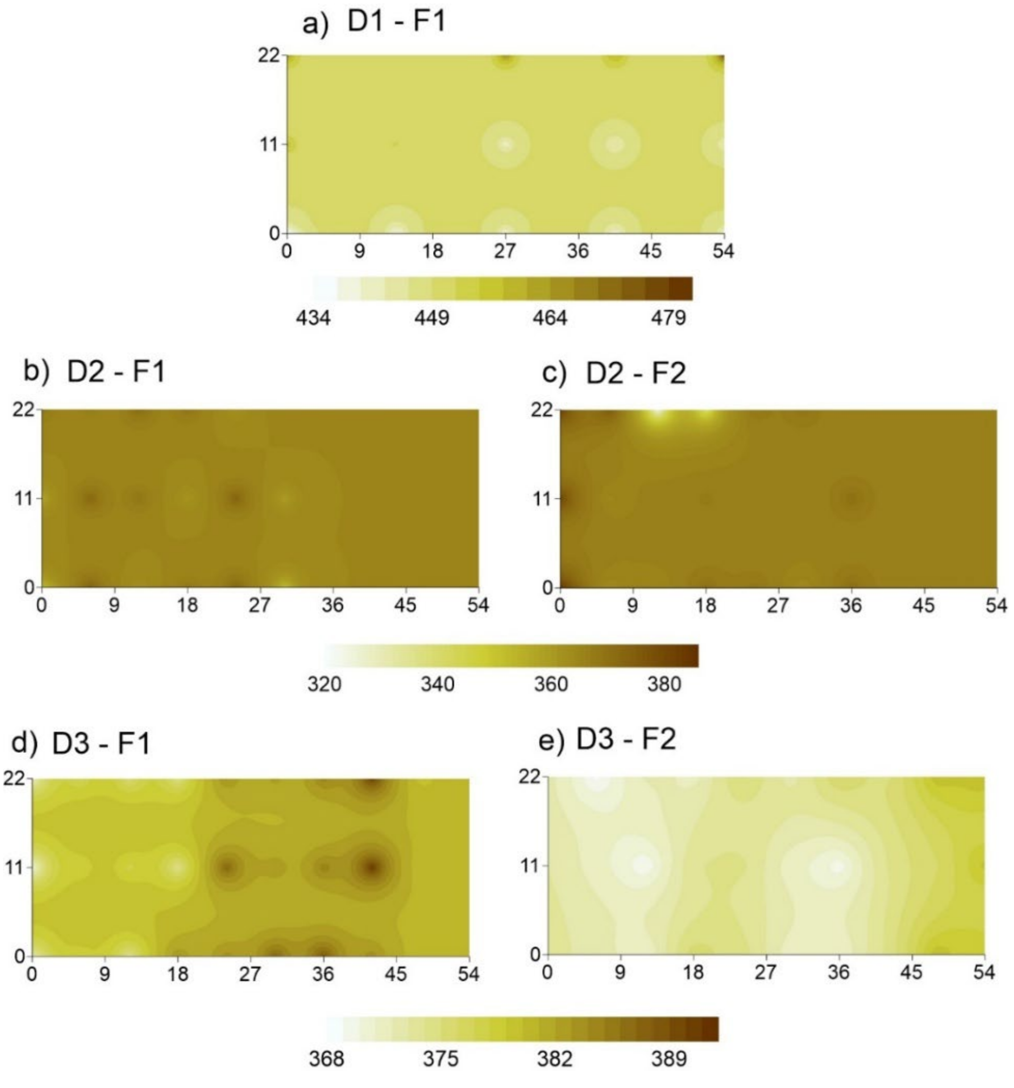

Figure 5. Spatial distribution of carbon dioxide (CO_2) above the roof in the dairy cattle facility on the evaluated days (D1F1 = Day 1 – Flight 1 (a); D2F1 = Day 2 – Flight 1 (b); D2F2 = Day 2 – Flight 2 (c); D3F1 = Day 3 – Flight 1 (d); D3F2 = Day 3 – Flight 2 (e).

In a study conducted by Jungbluth et al. (2001) inside dairy cattle facilities, CO_2 concentrations ranged between 970 ppm and 1,480 ppm, values significantly higher than those observed in this study. This discrepancy may be attributed to the methodological difference, as the present study measured in the external environment, where CO_2 has a greater ability to disperse.

Measuring CO_2 concentrations in animal production systems is essential to understand the dispersion patterns of this gas and its dynamics at the interface between the facility and the external environment. CO_2, in addition to being an indicator of indoor air quality, is also directly related to ventilation rates and the efficiency of greenhouse gas mitigation processes. Quantifying CO_2 in the surrounding area allows for the assessment of spatial and temporal variability in emissions, contributing to the development of more effective strategies for reducing the environmental impact of production systems.

High temperatures and elevated relative humidity also impact gas emissions, accelerating enteric fermentation processes and intensifying the release of methane from manure accumulated in the bedding of composting barns (Ding et al., 2016). From the following Figs (6 and 7), it is possible to observe the spatial distribuition of temperature (t_{db}, °C) and UR (%) on the three different days of evaluation (D1, D2, D3) and flights (F1, F2):

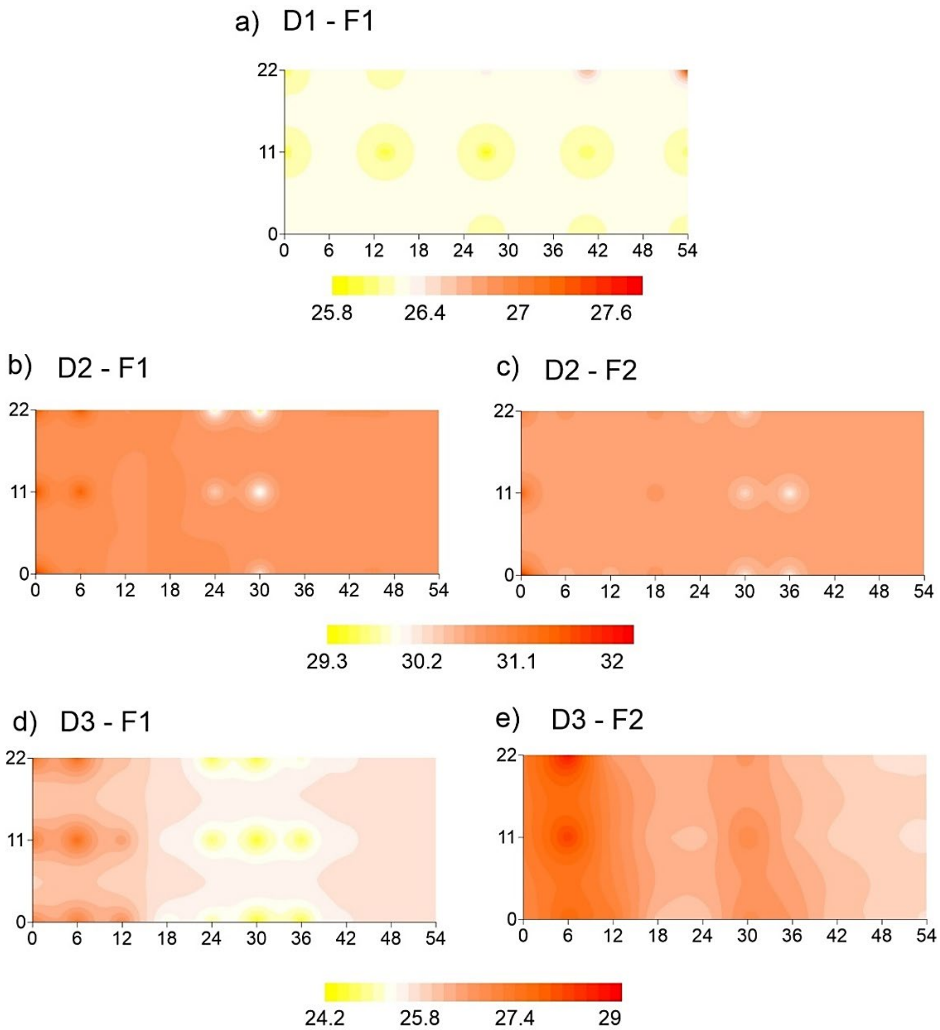

Figure 6. Spatial distribution of dry bulb temperature (t_{db}, ºC) above the roof of in the dairy cattle facility on the evaluated days (D1F1 = Day 1 – Flight 1 (a); D2F1 = Day 2 – Flight 1 (b); D2F2 = Day 2 – Flight 2 (c); D3F1 = Day 3 – Flight 1 (d); D3F2 = Day 3 – Flight 2 (e).

In Fig. 7, the spatial distribution of the thermal variables observed (t_{db} and RH) during the analysed days is shown.

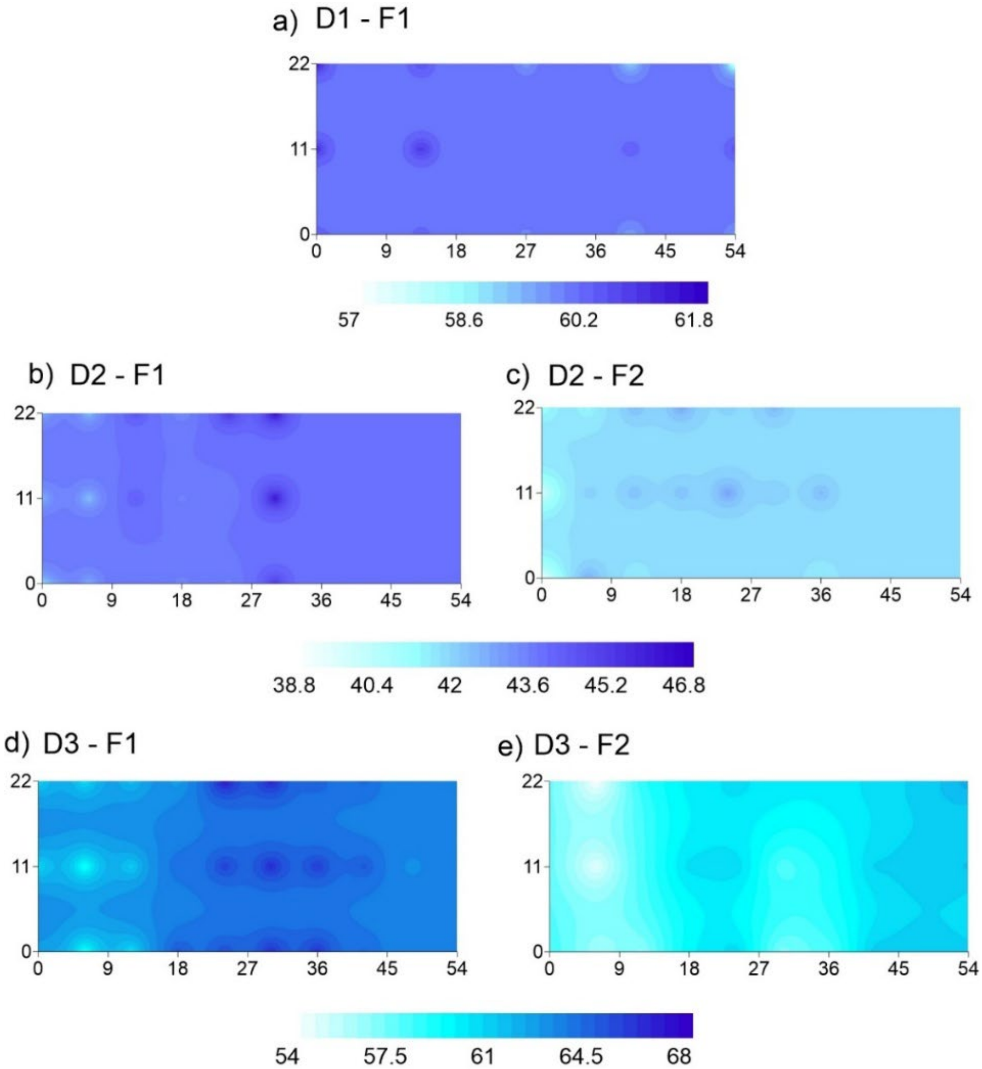

Figure 7. Spatial distribution of relative humidity (RH, %) above the roof of in the dairy cattle facility on the evaluated days (D1F1 = Day 1 – Flight 1 (a); D2F1 = Day 2 – Flight 1 (b); D2F2 = Day 2 – Flight 2 (c); D3F1 = Day 3 – Flight 1 (d); D3F2 = Day 3 – Flight 2 (e).

During the evaluated period, the t_{db} ranged from 24.2 °C to 32 °C. On Day 1, regions with lower temperatures were identified across the analysed area, with values concentrated in the lower range (24.2 °C), as indicated by the light blue colour in the generated maps.

The use of RPA to measure t_{db} above the facility allowed for the observation of thermal variability in the external environment. While no interior measurements or detailed distribution of parameters within the facility were conducted in this study, the data collected above the installation provide valuable information into how external factors, such as t_{db}, RH, and V might influence the environmental conditions inside the production system.

On Day 2 (D2F1 and D2F2), as shown in Figs 7, b; 7, c, an increase in the t_{db} was observed, with values ranging from 29.3 °C to 32 °C, indicated by the red colour on the maps. This increase in t_{db} was recorded outside the installation, and although it does not directly cause thermal stress in the animals, it may influence the internal environmental conditions. Thermal stress in cattle occurs when the accumulation of metabolic heat, combined with environmental heat (temperature and relative humidity), exceeds the animal's ability to dissipate the excess heat (Kadzere et al., 2002; Bertens et al., 2024).

Regarding the RH, a variation ranging form 38.8% to 68% was observed above the roof of the facility over the three days analysed (Fig. 7). On Day 1, the RH values were predominantly around 60% across the entire installation (Fig. 7, a). On Days 2 and 3, Flight F1 recorded higher values of RH compared to Flight F2 (Figs 7b, 7c). However, on Day 3, a greater variation in RH levels was observed throughout the installation, with more pronounced differences, indicated by the dark blue colour (Figs 7, d; 7, e).

The external t_{db} and RH conditions can directly influence the internal microclimate of the installation and impact the dispersion and concentration of GHGs, in addition to potentially affecting the comfort and well-being of the animals. External t_{db} and GHG emissions must be carefully considered, as the increase in t_{db} may be associated with the observed increase in CH_4 and CO_2 emissions. According to Ding et al. (2016), higher temperatures accelerate the enteric fermentation processes and intensify the release of methane from manure accumulated in the compost barn bedding. This suggests that more severe external thermal conditions can exacerbate GHG emissions, both through the intensification of biological activities, such as enteric fermentation and decomposition of manure, and by compromising the thermal comfort of the animals, which may reduce their ability to dissipate heat and thus increase metabolic heat production.

Monitoring gas concentrations and climatic variables in livestock production units, particularly in bovine confinement systems, is essential for the development of effective environmental control strategies. The use of advanced technologies, such as RPAs and geostatistical analyses, shows promise in generating detailed spatial data, contributing to a more accurate understanding of environmental dynamics. However, the application of these approaches across different construction typologies can significantly expand knowledge regarding GHG emission levels in diverse production contexts.

Additionally, the market for sensors designed for the instantaneous measurement of gases in open environments offers a wide range of devices based on various operating principles. Careful selection of these sensors is crucial, with preference given to those featuring high sensitivity and the ability to detect minimal gas fractions. Despite technological advances, the high acquisition costs of these sensors, as well as RPAs, remain a barrier to widespread adoption by producers.

In this context, there is a clear need to promote research focused on developing environmental monitoring systems that are simultaneously accurate, economically viable, and non-invasive to animal welfare. Such advancements are vital for formulating sustainable strategies that enhance production efficiency while mitigating the environmental impacts of livestock farming.

CONCLUSIONS

The use of remotely piloted aircraft has proven to be a valuable tool for obtaining gas concentrations in the exterior of cattle facilities. With the application of geostatistics, it was possible to identify the spatial variability of these concentrations throughout the facility. The combination of these two techniques is associated with the adoption of non-invasive monitoring strategies, enabling environmental diagnosis without causing negative impacts on animal welfare.

The variability maps of CH_4 and CO_2 gases allowed for the identification of dispersion and momentary concentrations, highlighting that these gases do not distribute homogeneously, even in areas distant from the emission sources. When measuring gas concentrations, it is important that environmental variables are monitored in an integrated manner to help identify possible aggravating or attenuating factors of the emissions.

The monitoring of greenhouse gas concentrations, originating from the facilities and production environment, is still underexplored, despite being valuable information for understanding the contribution of the dairy sector to climate change. However, the technologies and equipment available can still be costly for the rural producer.

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