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RobôFrango: Proof of concept of a mobile biosensor robot for environmental monitoring in broiler houses

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ABSTRACT

The use of mobile sensors represents an innovative strategy for monitoring environmental variables in broiler houses, enabling the identification of conditions that directly affect animal welfare. This study developed and validated the proof of concept of RobôFrango, a mobile biosensor robot designed to navigate commercial poultry houses while collecting environmental data in real time. Three customized fixed sensor units, positioned at 30 cm and 2 m above the litter, were used for comparison with the measurements obtained by the mobile robot. RobôFrango achieved 77.5 % accuracy in semi-autonomous navigation and revealed marked discrepancies between fixed and mobile measurements: relative humidity at bird level exceeded 65 % in the robot (vs. <60 % in fixed sensors), CO_2 concentrations were substantially higher near the animals, and litter moisture in partition 1 reached 41.8 % (vs. ≤35 % recommended). Spatial analysis also indicated a progressive increase in litter moisture spatial dependence from the front to the rear of the house, with greater heterogeneity in the initial partition and more uniform, though clustered, conditions in the distal areas. These findings demonstrate that ceiling-mounted sensors may underestimate the environmental stress experienced by broilers and that litter moisture is not evenly distributed throughout the facility. As a proof of concept, RobôFrango confirmed both its technical feasibility and its potential as a precision tool for environmental monitoring, with immediate practical implications for integration into climate control and management systems, enabling dynamic adjustments that enhance animal welfare and production efficiency.

1. Introduction

Robotics in poultry farming includes a range of commercial robots, such as PoultryBot [1], OctopusRobot [2] and ChickenBoy [2]. These robots are designed to perform specific tasks in production systems, including animal behavior analysis, health control, welfare management, and environmental monitoring [3–10]. Several studies highlight the importance of environmental monitoring to ensure ideal conditions for broiler chicken development, as animal performance is strongly influenced by both genetic and environmental factors [11–13]. Within the broader field of precision livestock farming, environmental control in broiler houses is consistently identified as a critical driver of growth, welfare, and biosecurity, linking microclimate dynamics to outcomes such as feed conversion, footpad dermatitis, and mortality [11–13].

Despite technological advances, most monitoring strategies still rely on fixed environmental sensors, which fail to capture microclimate variations at bird level inside poultry houses, particularly along the litter–air interface where birds actually live. This limitation hinders the understanding of localized stressors—such as wet-litter patches, ammonia and CO_2 pockets, or uneven ventilation—that can compromise flock homeostasis and performance. Since broiler chickens are raised in highly controlled systems, maintaining precise and spatially consistent conditions is crucial to optimize growth, ensure welfare, and minimize losses. In this context, mobile and intelligent monitoring systems capable of mapping spatial variability emerge as key tools for more accurate decision-making and efficient farm management.

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Robots such as PoultryBot and ChickenBoy have been tested to monitor internal conditions in response to external climate variations, focusing mainly on temperature and humidity [14,15]. However, prior applications have largely emphasized punctual or route-based measurements and have not established whether robotic platforms can function as validated, bird-level biosensor agents that integrate autonomous navigation, perception (e.g., computer vision/LiDAR), and multi-parameter environmental sensing to generate high-resolution microclimate maps in commercial settings. Consequently, a clear knowledge gap remains: Are mobile robots capable of reliably detecting spatial microclimate heterogeneity (temperature, humidity, gases) at bird height—beyond the detection capacity of conventional fixed sensors—and translating these data into actionable information for flock management?

In this scenario, the present study introduces RobôFrango as a proof of concept of a robotic biosensor that integrates computer vision, LiDAR, and environmental sensors into a mobile platform capable of navigating commercial broiler houses; unlike conventional robots, RobôFrango is conceived as a mobile biosensor agent explicitly designed to sample at bird level and to produce high-granularity, georeferenced maps of the house microclimate, thereby offering a new dimension for environmental data collection in poultry farming. Accordingly, the central research question guiding this study is: can a mobile biosensor robot (RobôFrango) autonomously navigate commercial broiler houses and generate bird-level, validated microclimate maps that reveal spatial heterogeneity not captured by fixed sensors?

The objectives of this study were (i) to implement and test RobôFrango in a commercial broiler environment; (ii) to evaluate and compare its navigation and perception stack (computer vision/LiDAR) for reliable, safe operation among the birds; and (iii) to perform statistical and geospatial analyses to validate the environmental data collected and to quantify spatial variability relative to reference measurements.

The results are relevant because they demonstrate, under real farm conditions, the technical feasibility and measurement validity of a robotic biosensing approach for precision poultry farming. By validating RobôFrango as a bird-level biosensor agent and showing how its georeferenced readings uncover actionable microclimate patterns, this study advances the frontier of intelligent monitoring in livestock production and clarifies a concrete pathway for integrating robotics into decision-support systems aimed at improving welfare, reducing losses, and enhancing production efficiency.

2. Materials and methods

2.1. RobôFrango platform

The development of RobôFrango (Fig. 1A) was based on the conception of a mobile robotic platform capable of navigating within commercial broiler houses while simultaneously performing environmental monitoring. The central processing unit of the robot was a NVIDIA® Jetson Nano™ Developer Kit microcomputer (Nvidia, Santa Clara, USA), which coordinated the integration between perception systems, motorization, and data communication. For spatial perception and navigation, two complementary technologies were used: a 360° LiDAR sensor (RP LiDAR A1; Slamtec, Shanghai, China), responsible for distance detection and mapping of nearby objects, and a Samsung Np350xbe Ba96–07238a camera (Samsung, South Korea), responsible for capturing visual information from the environment. Together, these devices enabled both obstacle detection and the recognition of internal elements of the poultry house, particularly the feeder lines, which served as the main guiding references for robot displacement.

2.2. Environmental sensor unit

In addition to the navigation system, an environmental monitoring unit (hereafter referred to as Environmental Sensor; Fig. 1B) was attached to the robot. This unit was built using a MEGA+WiFi R3 ATmega2560+ESP8266 prototyping board (Robotdyn, Hong Kong), to which a set of sensors was connected for the measurement of multiple environmental variables relevant to poultry production. The following sensors were included: a BME/P 280 sensor (Bosch Sensortec, Germany) for temperature and relative humidity; an MQ-7 sensor (Winsen Electronics, China) for carbon monoxide (CO); an MQ137 sensor (Winsen Electronics, China) for ammonia (NH_3); a DSM501A sensor (Samyoungsnc, South Korea) for particulate matter (PM10 dust); a TEMT6000 sensor (Vishay, USA) for luminosity; an MHZ 19E sensor (Winsen Electronics, China) for carbon dioxide (CO_2); and a GC-58 sensor (Winsen Electronics, China) for litter moisture. All readings obtained by this set of sensors were recorded locally on a microSD card and, in parallel, transmitted in real time to a cloud-based data storage and visualization platform (FarmSciHub; Fig. 2) via Wi-Fi, using the MQTT communication protocol. The information was stored in a PostgreSQL database and made available for later analysis.

2.3. Power supply and motorization

The energy supply of RobôFrango was provided by four LiPO 18,650 rechargeable battery cells (Alalito, Hong Kong), arranged in series to

A

B

Fig. 1. Robotic elements for environmental sensing: A) RobôFrango; B) Environmental Sensor.

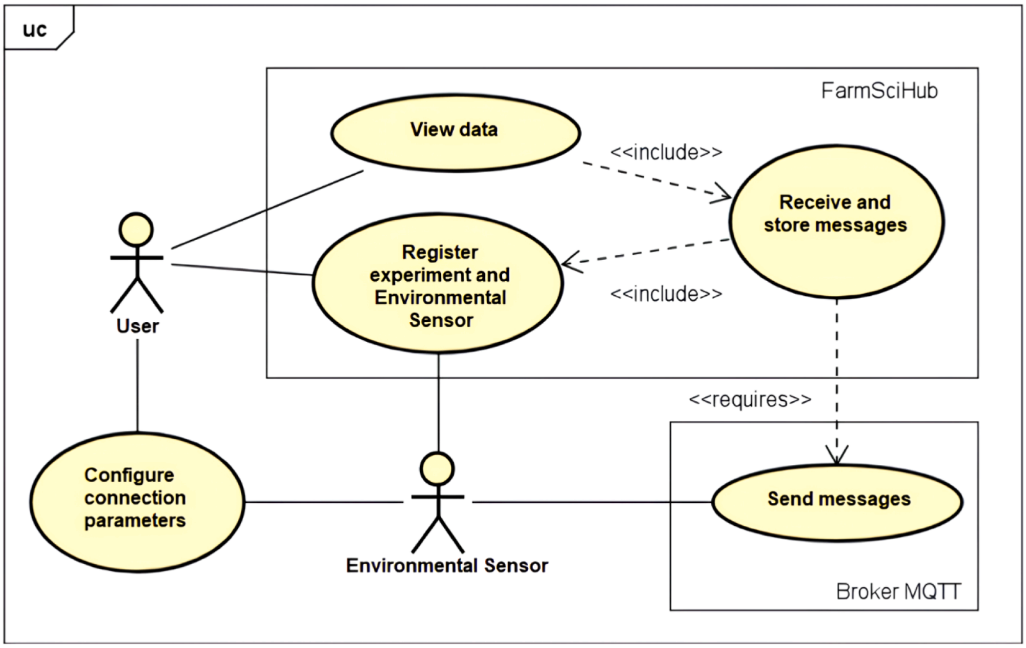


Fig. 2. FarmSciHub System Use Cases. Source: Silva, Siqueira (2024).

maintain a constant voltage of 12 V. This configuration offered a capacity of approximately 200,000 mAh. An LM2596 step-down voltage regulator was employed to convert 12 V to 5 V for the Jetson Nano, while the full 12 V power supply was maintained for the motorization system. Locomotion was ensured by four 25ga 370 high-torque DC motors (XYT Motor Manufacture, Shenzhen, China), each operating at 12 V with a rotation of 26 RPM and capable of generating a stall torque of up to 30 kg·cm. Motor control was performed by two L298N H-bridge drivers (STMicroelectronics, Beijing, China), each responsible for one side of the robot, enabling differential steering and forward motion.

2.4. Navigation system

The navigation of RobôFrango was based on the recognition of feeder lines (Fig. 3), which served as the guiding structure for its displacement within the poultry house. To achieve this, a hybrid navigation strategy was adopted, combining computer vision through the YOLOv8 model with distance sensing by the LiDAR system. The YOLOv8 model was trained specifically for the detection of feeder plates. A dataset of 390 images was captured by the robot's camera while moving within the poultry house, and all feeders present in these images were manually annotated using Labeling software (version 1.8.6). These images were then used to train and validate the model, which reached a detection accuracy of 79.6 %. The LiDAR, in turn, continuously emitted infrared laser signals and calculated the distance and angle of objects from the return signal. Based on these readings, the robot was programmed to maintain a safe trajectory at a distance of 30 to 50 cm (±5 cm) from the feeder line (Fig. 4)

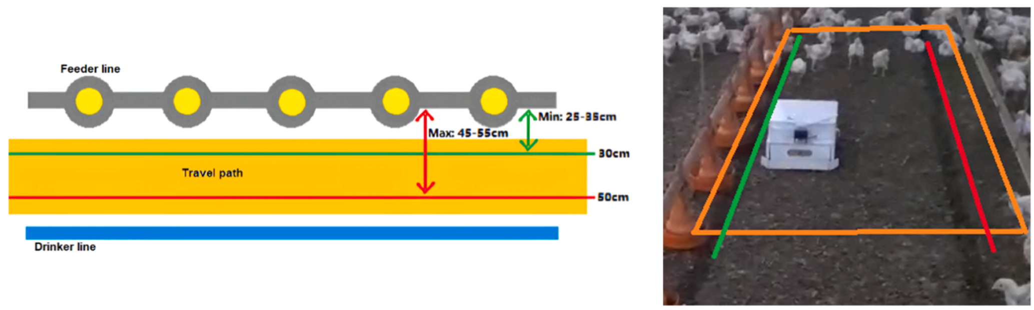
Fig. 3. Detection of feeders by computer vision. Source: Cardoso et al. (2023).

2.5. Field validation

The validation of RobôFrango was conducted in a commercial broiler farm located in the municipality of Itatiba (latitude −23.0068, longitude −46.8387; 23°0′24″ S, 46°50′19″ W; altitude 771 m), São Paulo, Brazil, under Animal Use Ethics Committee protocol number 7364,090,322 of the "Luiz de Queiroz" College of Agriculture, University of São Paulo. The farm raised Ross lineage broilers in a negative-pressure poultry house measuring 135 m in length, 14 m in width, and 3 m in height, equipped with evaporative cooling pads, exhaust fans, and automatic controllers for air temperature and relative humidity (inoBram SMAAI 3 PE system). On the day of the experiment (36th day of production), external temperatures ranged from 25 to 36 °C. The poultry house was divided into three partitions, which were considered independent experimental units.

To ensure flock uniformity, the poultry house was divided into three physical partitions (Cobb, 2019), where the robot validation was conducted independently. According to Eurachem [16] and Freitas et al., [17], which recommend a minimum of 10 sampling points, 35 sampling points were established per partition (seven points per line, considering five feeder lines).

The sampling points were identified by Quick Response Code (QR Code) markers, which the robot was trained to detect and classify using the OpenCV library in Python through computer vision. Each marker represented an environmental data collection point and its specific location within the partition. The collected data were stored locally on a memory card and simultaneously transmitted to the FarmSciHub cloud platform. FarmSciHub stored the sensor data in a database and made them available in real time via a web interface, enabling continuous



a) b)

Fig. 4. Robot movement: a) boundary measurements; b) execution.

monitoring of the poultry house environmental conditions.

Three Environmental Sensor units with identical hardware and software architecture were used simultaneously. The first was fixed at the geometric center of each partition at a height of 2 m above the litter, called the High Fixed Sensor (HFS), simulating industrial sensors normally installed in poultry houses. The second was also fixed in the geometric center of each partition but placed at 30 cm above the litter, simulating the perception of animals; this unit was called the Low Fixed Sensor (LFS). The third was attached to RobôFrango itself, at approximately 30 cm above the litter, called the Mobile Robot Sensor (MRS), simulating the perception of environmental variables at the animal level while moving along the 35 predetermined points of each partition.

2.6. Data analysis

To predict displacement decisions (move forward, turn right, or turn left), different supervised machine learning algorithms were evaluated using datasets generated during training runs of the robot inside the poultry house. The tested models included Logistic Regression, Support Vector Classifier (SVC), Random Forest Classifier, k-Nearest Neighbors (KNN), Decision Tree Classifier, Gradient Boosting Classifier, and Multi-Layer Perceptron (MLP) Classifier. Model performance was compared to identify the algorithm with the highest predictive accuracy, which was subsequently implemented in the navigation system.

The environmental variables analyzed were air temperature, relative humidity, carbon monoxide, ammonia, dust (PM10), carbon dioxide, luminosity, and litter moisture. Data were analyzed in four complementary steps. First, descriptive statistics and data normality were verified using the Shapiro–Wilk test. For normally distributed data, homoscedasticity was tested by Levene's test, followed by analysis of variance (ANOVA) and Tukey's test for pairwise mean comparisons. For non-normally distributed data, homoscedasticity was tested using the Fligner–Killeen test, followed by the Conover test for cases of variance homogeneity or Dunnett's test when variance heterogeneity was detected. All tests adopted a significance level of 95 %.

Geostatistical analyses were performed to explore spatial variability in environmental conditions. Kriging was used to generate interpolated maps of each variable, and K-means clustering was applied to identify zones with similar environmental characteristics. The number of clusters was determined using the silhouette coefficient, with a maximum of three clusters considered. Spatial autocorrelation was quantified using Moran's I, with values near +1 indicating spatial grouping of similar values, values near –1 indicating spatial dispersion, and values close to zero indicating randomness. The variogram range was calculated to determine the distance up to which data points were spatially correlated.

Thermal comfort was evaluated by calculating the specific enthalpy of air (h, $kJ \cdot kg^{-1}$ dry air), combining air temperature, relative humidity, and atmospheric pressure according to the model proposed by Rodrigues et al., [18]. Litter moisture was estimated in real time by the GC-58 sensor, and calibration was performed using the oven-drying technique (NBR 6457), with results adjusted by linear regression and validated through curve fitting

3. Results

3.1. Robot navigation performance

The navigation of RobôFrango was evaluated during the validation trial on the 36th day of broiler production (March 28, 2024). The robot moved along the five feeder lines of each partition, covering the entire poultry house at an average displacement speed of 0.031 $m \cdot s^{-1}$. The best-performing model was the RandomForestClassifier, achieving an accuracy of 93.89 % (Table 1). When tested with random data, it reached 89.32 % correct predictions. In the field validation inside the poultry house, the robot completed one lap in the central partition with 81 predictions, of which 62 were correct (77.5 %) and 18 incorrect (22.5 %). Errors were manually corrected via remote control, and predictions during these corrections were disregarded

No training for intelligent decision-making was implemented when the robot reached the end of the feeder lines and encountered the partition division grids. In these situations, the robot received movement commands via remote control in order to make the turn, pass under the feeder line, and position itself in the next line. Once correctly positioned, it resumed autonomous movement. Therefore, it was concluded that the robot operated in a semi-autonomous manner: independently when identifying the feeder line and its feeding dishes through computer vision and machine learning, and manually when facing the dividing grids. Fig. 5 presents the flowchart of the RobôFrango movement algorithm.

3.2. Environmental data acquisition

RobôFrango successfully identified and recorded data at 35 predefined sampling points per partition, guided by QR codes, transmitting the collected values in real time to the FarmSciHub platform. All environmental variables of interest (air temperature, relative humidity, ammonia, carbon dioxide, carbon monoxide, PM10, luminosity, and litter moisture) were obtained by the Mobile Robot Sensor (MRS) and

Table 1
Comparisons between groups.

Models	Accuracy
LogisticRegression	70.9923
SVC	72.5190
RandomForestClassifier	93.8931
KNeighborsClassifier	88.5496
DecisionTreeClassifier	92.3664
GradientBoostingClassifier	92.3664
MLPClassifier	90.8396

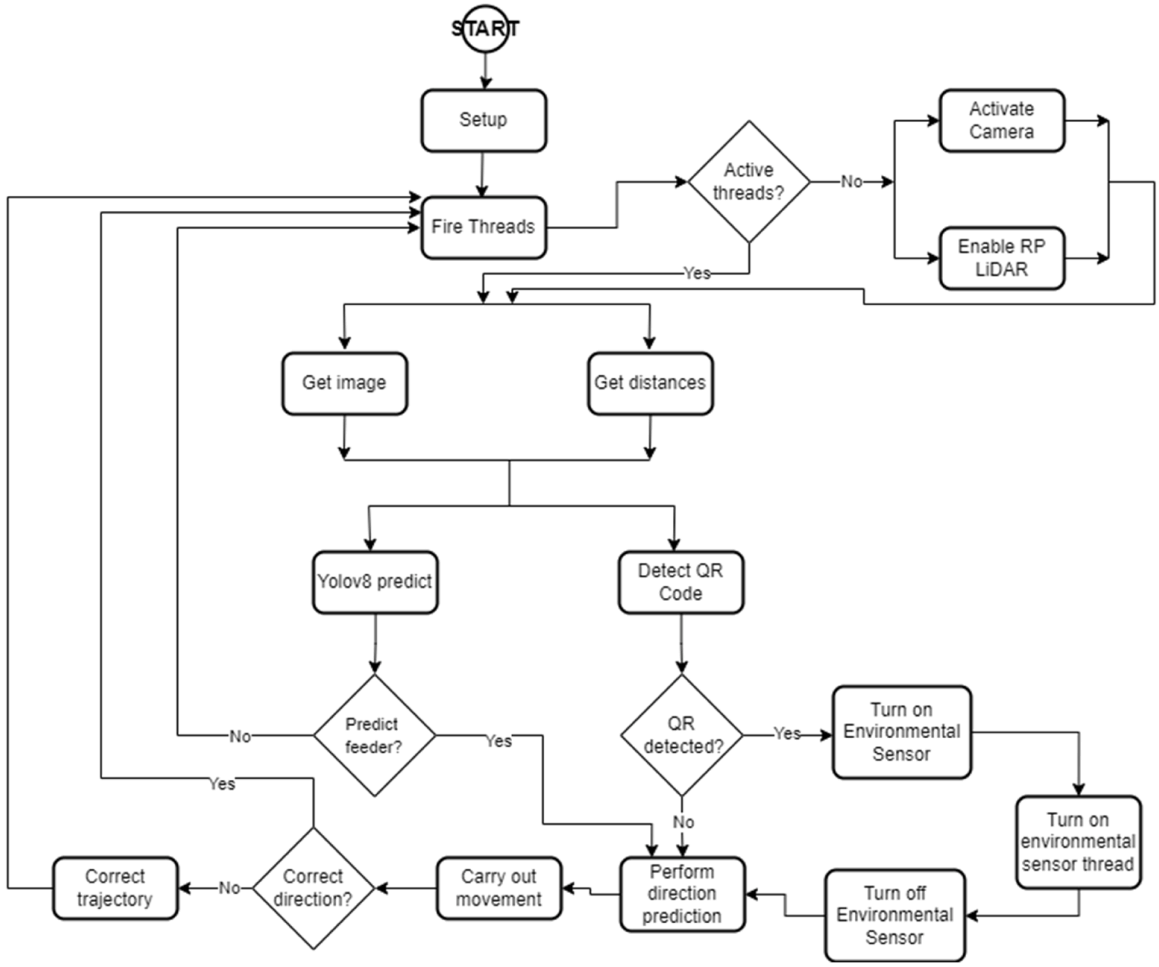


Fig. 5. FarmSciHub system.

compared against the High Fixed Sensor (HFS) and Low Fixed Sensor (LFS).

3.3. Environment variables

Environmental variables showed significant differences among sensors positioned at different heights (Table 2). The same pattern associated with sensor height or the use of the mobile sensor was consistently observed across the three partitions of the poultry house. Air temperature values recorded by the high fixed sensor (HFS) were consistently higher compared with those obtained from the low fixed sensor (LFS) and the mobile robot sensor (MRS). Light intensity measured by the HFS and MRS remained higher than that recorded by the LFS in all partitions. For ammonia, the lowest concentrations were observed at 30 cm above the litter (LFS) and by the MRS.

Carbon dioxide (CO_2) and relative humidity values varied significantly among sensors ($p < 0.001$): the HFS recorded the lowest concentrations, the LFS showed intermediate values, and the MRS indicated the highest levels. In contrast, carbon monoxide followed the opposite pattern ($p < 0.001$), with higher concentrations detected by the sensor positioned at 2 m above the litter. Regarding particulate matter (PM_{10}), the fixed sensors reported the highest concentrations ($p < 0.001$).

3.4. Litter moisture

The distribution of litter moisture varied among the poultry house partitions. Partition 1 showed higher concentrations of moisture, mainly near the feeder lines. Partition 2 presented intermediate values with moderate heterogeneity, whereas Partition 3 remained drier and more uniform, indicating better environmental conditions (Fig. 6). These findings highlight the influence of ventilation management and water supply on the spatial distribution of litter moisture.

The litter moisture analysis performed by the mobile robot sensor (MRS) revealed significant spatial dependence in all partitions (Table 3), with Moran's I values ranging from 0.124 in partition 1 to 0.286 in partition 3 ($p = 0.001$), indicating a progressive increase in spatial autocorrelation along the poultry house. The range of moisture variation was wider in partition 1 (0 to 976.40) and gradually decreased in partitions 2 (0 to 942.65) and 3 (0 to 898.29), suggesting greater heterogeneity at the beginning and increased uniformity in the distal areas. Significant differences among partitions ($p = 0.001$), demonstrating that litter moisture distribution was not uniform throughout the poultry house

3.5. Enthalpy and thermal comfort

The specific enthalpy of air, calculated from temperature, humidity, and pressure, provided an integrated view of thermal comfort (Table 4). Partitions 1 and 2 presented values close to the upper threshold of comfort due to excessive humidity, whereas partition 3 remained within the optimal comfort zone. These findings indicate that despite stable average temperatures, the combined effect of high humidity can place animals under suboptimal conditions in certain areas of the poultry house.

Table 2
Mean values of environmental variables (air temperature, luminosity, ammonia, carbon dioxide, relative humidity, PM10, and carbon monoxide) recorded by fixed sensors at different heights (High Fixed Sensor – HFS; Low Fixed Sensor – LFS) and by the mobile sensor attached to RobôFrango (Mobile Robot Sensor – MRS) across the three partitions of the poultry house (P1, P2, and P3).

Variables	Partitions (P)			
	Sensor	P1	P2	P3
Air temperature (°C)	High Fixed Sensor	22.81a	23.65a	23.99a
	Low Fixed Sensor	22.27b	22.85b	23.80b
	Mobile Robot Sensor	22.23b	22.84b	23.36b
Luminosity	High Fixed Sensor	11.58a	11.55a	11.35a
	Low Fixed Sensor	8.37b	8.42b	8.34b
	Mobile Robot Sensor	10.95a	10.57a	10.44a
Ammonia	High Fixed Sensor	6.87a	8.26a	8.95a
	Low Fixed Sensor	6.04b	7.48b	8.42b
	Mobile Robot Sensor	5.38b	4.42b	3.96b
Carbon dioxide	High Fixed Sensor	594.71c	553.91c	573.91c
	Low Fixed Sensor	790.17b	754.01b	779.76b
	Mobile Robot Sensor	920.82a	1058.39a	995.14a
Relative humidity (%)	High Fixed Sensor	54.38c	54.47c	54.24c
	Low Fixed Sensor	57.71b	56.04b	59.21a
	Mobile Robot Sensor	73.55a	67.98a	58.08b
PM10	High Fixed Sensor	1534.65a	1502.18a	1661.14a
	Low Fixed Sensor	1347.16a	1728.25a	1750.89a
	Mobile Robot Sensor	1158.67b	1331.22b	1337.98b
Carbon monoxide	High Fixed Sensor	9.35a	9.21a	9.59a
	Low Fixed Sensor	8.59b	8.82b	8.72b
	Mobile Robot Sensor	7.20c	7.52c	7.78c

Different letters within the same column indicate statistically significant differences among means, according to the applied test ($p < 0.05$).

4. Discussion

The validation of RobôFrango demonstrated that the use of mobile robotics in poultry farming is a feasible approach for both environmental monitoring and precision management. The robot's semi-autonomous navigation, combined with the acquisition of multiple environmental variables, confirms its potential to function as a biosensor agent within commercial broiler houses. By comparing results from the Mobile Robot Sensor (MRS) with fixed ceiling- and animal-level sensors, it became clear that mobile monitoring provides a more accurate representation of the conditions experienced by the animals. Beyond feasibility, these findings support a theoretical proposition for precision livestock farming: a *bird-level sensing principle*, whereby inference about welfare-relevant microclimates is valid only when measurements are taken at, or mapped to, the animals' stratum; ceiling-level signals are necessary but insufficient. This principle reframes environmental supervision from point estimates to spatially explicit fields, enabling control laws that act on localized exceedances rather than house-wide averages.

4.1. Navigation and autonomy

The navigation system, based on the hybrid use of computer vision (YOLOv8) and LiDAR distance sensing, allowed RobôFrango to achieve a correct prediction rate of 77.5 % in real conditions. Although this rate indicates the need for further improvement, it represents a significant step compared to systems relying solely on vision or distance sensors [19]. The use of machine learning, specifically the Random Forest Classifier, improved decision-making and suggests that adaptive algorithms can enhance robotic autonomy in dynamic environments. However, the need for manual corrections when encountering partition grids indicates that environmental complexity in poultry houses remains a challenge for robotics, as also reported in studies on agricultural robots operating in confined or obstacle-rich environments [2,11].

4.2. Environmental monitoring at bird level

One of the main findings of this study is the discrepancy between values recorded at bird level (MRS and LFS) and those obtained by ceiling-mounted sensors (HFS). Relative humidity and CO_2 concentrations were consistently higher at the animal level, while ammonia levels were more pronounced at ceiling height. This pattern confirms that fixed monitoring systems may underestimate or overestimate the exposure of animals to environmental stressors. Similar results were reported by Abreu & Abreu [20], who highlighted the vertical stratification of gases in poultry houses.

The detection of elevated relative humidity values (above 65 %) in partitions 1 despite ceiling sensors remaining within recommended limits, demonstrates the critical role of localized monitoring. High humidity has been associated with impaired thermoregulation in broilers and increased susceptibility to respiratory disorders [21,22]. By moving through the partitions, RobôFrango captured this variability more effectively than fixed sensors, reinforcing its role as a biosensor agent.

The higher temperature recorded by the 2-m sensor (HFS) is consistent with the typical thermal stratification observed in poultry houses: heated air rises and accumulates in the upper layers, where additional heat sources are also present. Furthermore, periods of minimum ventilation and low turbulent mixing favor the persistence of this vertical gradient, whereas at bird level, litter evaporation and latent heat losses from the animals tend to cool the surrounding air, explaining the relatively lower readings of the LFS/MRS. These mechanisms are in agreement with previous reports of vertical temperature variation inside poultry houses [23,24].

Taken together, we advance a *stratified exposure model* in which the sign and magnitude of bias from fixed sensors depend on gas buoyancy, turbulence regime, and latent heat flux at the litter interface. This model predicts systematic underestimation of CO_2/RH and overestimation of temperature by high-mounted sensors—precisely the pattern observed—thereby offering testable hypotheses for sensor placement and data fusion in future studies.

4.3. Air quality and litter conditions

The analysis of ammonia and CO_2 confirmed expected physical properties of these gases: ammonia accumulated near ceiling height, while CO_2 was concentrated at animal level. Although all values were below harmful thresholds, these differences highlight the importance of positioning monitoring devices at levels that reflect animal exposure. Previous studies also emphasized that inadequate positioning of sensors can lead to misleading conclusions about environmental quality [25,26].

Litter moisture emerged as another critical variable, with partition 1 showing values above 40 %, surpassing the recommended maximum of 35 %. This condition coincided with higher ammonia concentrations, confirming the relationship between excessive litter moisture, microbial activity, and gas production [27,28]. Excessive moisture in litter has also been linked to increased incidence of footpad dermatitis and reduced animal welfare [29]. The ability of RobôFrango to detect these micro-environmental hotspots indicates its utility as a management tool for preventive interventions, such as targeted ventilation or litter conditioning.

The results revealed a clear pattern of spatial dependence in litter moisture among the partitions of the poultry house. A progressive increase in spatial autocorrelation was observed, indicating that moisture distribution became more structured in the distal areas of the barn. This behavior suggests that environmental and management factors, such as ventilation dynamics, bird density, and water supply, may have

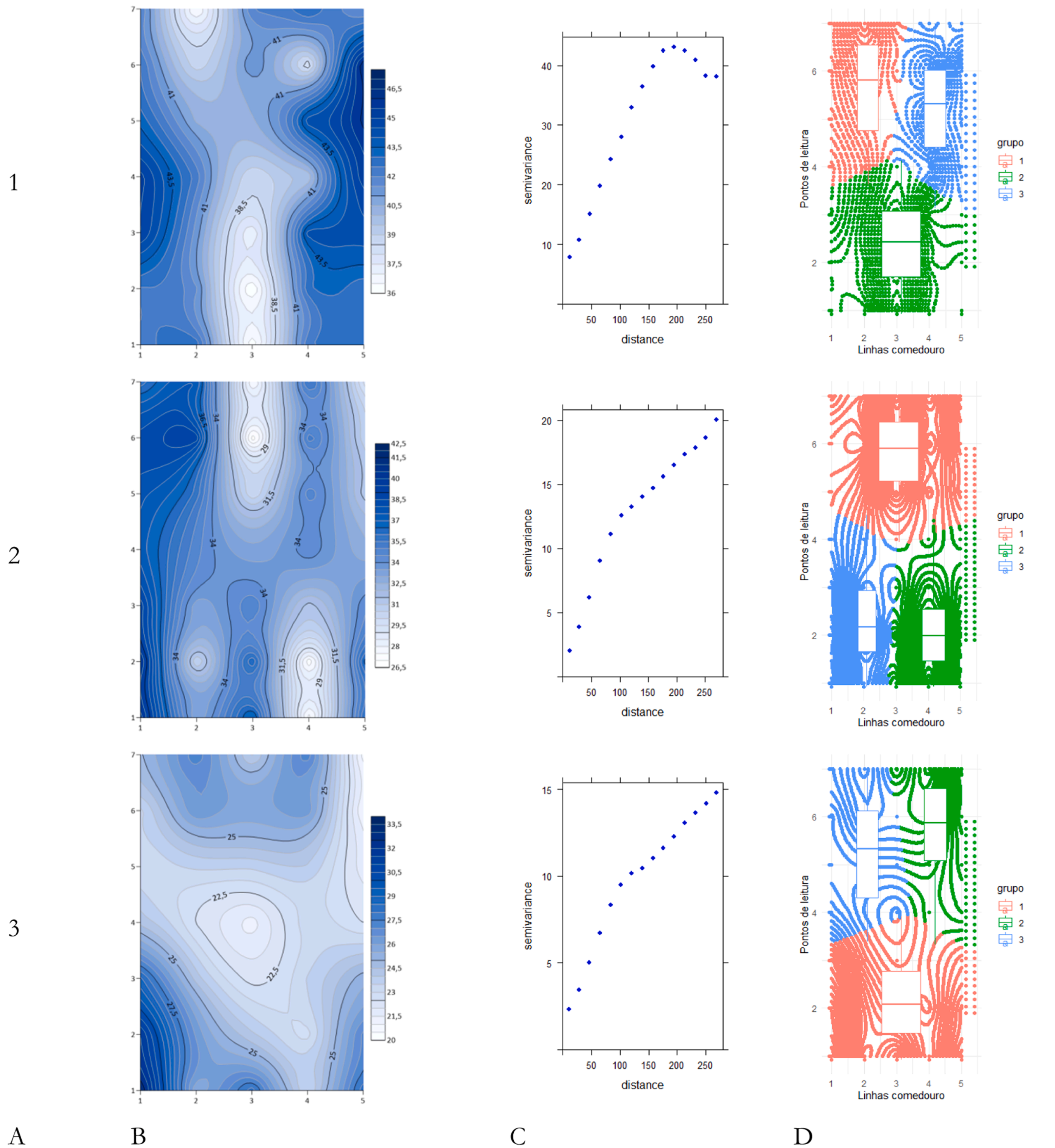


Fig. 6. Distribution of humidity in the bed in the three partitions. A: Partition; B: kriged map; C: Variogram; D: K-means algorithm.

contributed to the formation of more concentrated wet zones in the later partitions [30]. In addition, the wider variation found in the initial partition reflects greater heterogeneity, possibly associated with localized water spillage or irregularities in the litter, whereas in the distal partitions a more uniform condition prevailed, although still showing a tendency toward spatial clustering.

From a practical standpoint, these findings emphasize that litter moisture is not evenly distributed throughout the poultry house. Localized accumulations and unevenness can compromise indoor air quality by promoting ammonia release and microbial proliferation, whereas drier and more balanced conditions contribute to better welfare and performance of broiler chickens. In this context, the use of spatial analysis tools proves to be essential for understanding litter moisture distribution patterns and guiding more precise management strategies, thereby improving indoor environmental quality and overall system productivity [31].

Table 3
Bed moisture analysis metrics collected by the robot (Robot Mobile Sensor).

Partition	Moran		Range	p- value
	MIS	P *value*		
1	0.124	0.001	0 to 976.40	0.001
2	0.219	0.001	0 to 942.65	0.001
3	0.286	0.001	0 to 898.29	0.001

MIS: Moran I statistic.

Table 4
Metrics of thermal comfort analysis in the three partitions.

Partition	Min.	Max.	MEAN	SD	Situation
P1	41.88	48.54	45.85	1.49	In comfort
P2	39.28	48.84	43.19	1.84	In comfort
P3	39.20	48.67	42.87	1.75	In comfort

4.4. Thermal comfort and enthalpy

Thermal comfort assessment using enthalpy provided a more integrated view than temperature alone. Despite average air temperatures being within recommended limits, the combination of high humidity in partitions 1 and 2 resulted in enthalpy values approaching the upper comfort threshold. This finding supports the argument of Rodrigues et al., [18] that enthalpy is a more reliable indicator of animal thermal comfort in intensive production systems. The data reinforce that broilers may experience suboptimal comfort even when conventional controllers indicate acceptable conditions, highlighting the added value of mobile sensing.

4.5. Implications for precision poultry farming

By combining mobility, perception, and environmental sensing, RobôFrango transcends the role of a simple monitoring tool and moves toward the concept of a biosensor robot. Unlike fixed sensors, which provide punctual and limited readings, mobile robots can capture environmental gradients, identify risk zones, and transmit data in real time to cloud-based platforms such as FarmSciHub. This functionality aligns with the principles of Precision Livestock Farming (PLF), where data-driven decision-making enhances productivity, animal welfare, and sustainability.

Moreover, the system provides practical insights for farm management. For example, identifying areas with excessive humidity or gas accumulation can help guide targeted interventions, reducing the need for blanket corrective measures and lowering energy costs. From a broader perspective, integrating robotics into poultry production systems can contribute to reducing environmental impacts by optimizing resource use and minimizing animal stress.

4.6. Limitations and future perspectives

This study advances the use of mobile robotics as a biosensor agent in poultry farming, but certain aspects require careful consideration. The experimental validation was restricted to a single day and one production cycle (36th day), which limits the representativeness of the findings. Broader replication across multiple flocks, ages, and environmental contexts will be necessary to improve robustness and generalizability.

The navigation approach, although functional, is still semi-autonomous and relies on feeder lines as guiding references. While this strategy is well suited to the linear structure of commercial broiler houses, it may restrict applicability in facilities with more complex or irregular layouts. Incorporating more advanced solutions such as SLAM-based mapping, stereo vision, or reinforcement learning could expand the system's adaptability and autonomy.

In terms of artificial intelligence, the machine learning model reached 89 % accuracy during training but dropped to 77.5 % under real conditions. This decline highlights the importance of larger, more diverse datasets and suggests the need for additional models capable of coping with the variability of commercial farms while avoiding overfitting.

Environmental monitoring successfully captured significant microclimatic differences, but the implications for animal welfare deserve stronger integration. Higher relative humidity (>65 %), elevated CO_2 concentrations at bird level (35–48 % higher than at 2 m), and litter moisture exceeding 40 % are not only engineering measurements but also risk factors for respiratory disorders, microbial proliferation, and thermal stress in broilers. Future research should combine robotic data with direct welfare and health indicators to enhance practical significance.

Although this work demonstrates feasibility, the system is not yet ready for immediate large-scale deployment. Future directions should focus on replication under different production systems, integration with automated climate control to enable real-time corrective actions, and analysis of cost-effectiveness and usability to ensure adoption by poultry producers.

In summary, RobôFrango represents an innovative proof of concept that expands the role of robotics in precision livestock farming. At the same time, the findings highlight opportunities for further refinement, broader validation, and practical implementation aimed at improving environmental management, animal welfare, and production sustainability.

5. Conclusions

RobôFrango demonstrated the feasibility of using mobile robotics as a biosensor agent in poultry farming, capable of semi-autonomous navigation and capturing environmental variability at bird level with greater accuracy than fixed sensors — and showed that management based solely on fixed, ceiling-mounted sensors tends to underestimate bird-level hotspots. By integrating mobility, multi-sensor monitoring, and real-time data transmission, the system offers theoretical contributions—expanding the concept of precision livestock production with robotics—and practical applications, enabling zone-targeted interventions (ventilation rebalancing, litter drying, drinker maintenance) and the definition of bird-level set-points that reduce welfare risks and losses. Although tested under limited conditions, the results indicate potential for broader adoption, with priority now to couple the robot's maps to automated actuation and to quantify causal gains in KPIs (FCR, footpad dermatitis, mortality) across houses and seasons, supporting scale-up.

Ethical committee approval

This work is part of a research on robotics with broiler chickens that was submitted, analyzed and approved by the Ethics Committee on the Use of Animals of the Luiz de Queiroz College of Agriculture of the University of São Paulo, under protocol number 7364,090,322.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT (GPT-5, OpenAI) in order to improve the readability of the text and enhance the language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Consent to participate

Informed consent was obtained from all individual participants included in the study.

CRediT authorship contribution statement

Glauber da Rocha Balthazar: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Robson Mateus Freitas Silveira:** Writing – review & editing, Visualization, Validation, Investigation, Conceptualization. **Thauane Cordeiro Soares:** Writing – review & editing, Visualization, Validation, Investigation, Conceptualization. **Iran José Oliveira da Silva:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

All persons gave their informed consent prior to their inclusion in the study and the authors declare have no relevant financial or non-financial interests to disclose.

Data availability

The datasets generated during and/or analyzed during the current study are available in the GitHub repository: https://github.com/glauberbalthazar83/AnaliseSensoresAtuadoresAgenteBiosensor, https://github.com/glauberbalthazar83/RoboFrango and https://youtube.com/shorts/IspkORjGo58?feature=share.

References

[1] B.A. Vroegindeweij, S.K. Blaauw, J.M.M. IJsselmuiden, E.J. van Henten, Evaluation of the performance of PoultryBot, an autonomous mobile robotic platform for poultry houses, Biosyst. Eng. 174 (2018) 295–315, https://doi.org/10.1016/j.biosystemseng.2018.07.015.

[2] G. Ren, T. Lin, Y. Ying, G. Chowdhary, K.C. Ting, Agricultural robotics research applicable to poultry production: a review, Comput. Electron. Agric. 169 (2020) 105216, https://doi.org/10.1016/j.compag.2020.105216.

[3] C. Chen, X. Yu, L. Yu, S. Xue, Design of the mechanical part of the autonomous inspection robot for broiler cage raising mode, SSRN. 1 (1) (2023) 12–24, https://doi.org/10.2139/ssrn.4457376.

[4] J.D. Fei, W. Hao, J. Wang, X. Wei, Real-time recognition study of egg-collecting robot in free-range duck sheds, SSRN. 1 (1) (2023) 37–49, https://doi.org/10.2139/ssrn.4396479.

[5] R. Lin, J. Fan, Z. Sun, Y. Yan, X. Zhan, Design of integrated robot for risk waste transfer and disinfection, Journal of Physics: Conference Series 2587 (1) (2023) 012054, https://doi.org/10.1088/1742-6596/2587/1/012054.

[6] N.Y. Kim, S.J. Kim, M. Oh, S.Y. Jang, S.H. Moon, Changes in facial surface temperature of laying hens under different thermal conditions, Anim. Biosci. 34 (7) (2021) 1235–1242, https://doi.org/10.5713/ab.20.0647.

[7] G. Li, R.S. Gates, M.M. Meyer, E.A. Bobeck, Tracking and characterizing spatiotemporal and three-dimensional locomotive behaviors of individual broilers in the three-point gait-scoring system, Animals 13 (4) (2023) 717, https://doi.org/10.3390/ani13040717.

[8] X. Yang, Y. Zhao, G.M. Street, Y. Huang, S.D.F. To, J.L. Purswell, Classification of broiler behaviours using triaxial accelerometer and machine learning, Animal. 15 (7) (2021) 100269, https://doi.org/10.1016/j.animal.2021.100269.

[9] Q.C. Feng, X. Wang, Design of disinfection robot for livestock breeding, Procedia Comput. Sci. 166 (2020) 310–314, https://doi.org/10.1016/j.procs.2020.02.093.

[10] Poultry Patrol, Revolutionizing poultry production with autonomous robots, Disponível em, https://poultrypatrol.com/?page_id=472, 2019 (acessado em 20/01/2023).

[11] F. Spiess, B. Reckels, A.A. Wahab, M.F.E. Ahmed, C. Sürie, M. Auerbach, S. Rautenschlein, O. Distl, J. Hartung, C. Visscher, The influence of different types of environmental enrichment on the performance and welfare of broiler chickens and the possibilities of real-time monitoring via a farmer-assistant system, Sustainability. 14 (9) (2022) 5727, https://doi.org/10.3390/su14095727.

[12] W.F. Pereira, L.S. Fonseca, F.F. Putti, B.C. Góes, L.P. Naves, Environmental monitoring in a poultry farm using an instrument developed with the internet of things concept, Comput. Electron. Agric. 170 (2020) 105257, https://doi.org/10.1016/j.compag.2020.105257.

[13] M.H. Bach, F.M. Tahamtani, I.J. Pedersen, A.B. Riber, Effects of environmental complexity on behaviour in fast-growing broiler chickens, Appl. Anim. Behav. Sci. 219 (2019) 104840, https://doi.org/10.1016/j.applanim.2019.104840.

[14] Cobb-Vantress, Manual De Manejo De Frangos De Corte, Cobb, 2019. Disponível em: https://wp.ufpel.edu.br/avicultura/files/2012/04/Cobb-Manual-Frango-Corte-BR.pdf (acessado em 10/04/2024).

[15] Ross Aviagen, Manual De Manejo De Frangos De Corte, Ross, 2018. Disponível em: https://pt.aviagen.com/assets/Tech_Center/BB_Foreign_Language_Docs/Portuguese/Ross-BroilerHandbook2018-PT.pdf (acessado em 10/04/2024).

[16] Eurachem, CITAC, Quantifying Uncertainty in Analytical measurement, Guide CG4, 3rd ed., Eurachem, 2012. Disponível em: https://www.eurachem.org/images/stories/Guides/pdf/QUAM2012_P1.pdf (acessado em 03/06/2022).

[17] S.M. Freitas, Metodologia Estatística Para Validação De Métodos Analíticos Aplicável à Metrologia Em Química, Dissertação (Mestrado), PUC-Rio, Rio de Janeiro, 2003, p. 68. Disponível em, https://www2.dbd.puc-rio.br/pergamum/tesesabertas/0116460_03_cap_03.pdf (acessado em 03/06/2022).

[18] V.C. Rodrigues, I.J.O. Silva, F.M.C. Vieira, S.T.A. Nascimento, Correct enthalpy relationship as thermal comfort index for livestock, Int. J. Biometeorol. 55 (2011) 455–459.

[19] J. Johnson, D.J. Godwin, Indoor navigation of mobile robot using fuzzy logic controller, in: 2015 3rd International Conference on Signal Processing, Communication and Networking (ICSCN), IEEE, 2015, pp. 1–6, https://doi.org/10.1109/icscn.2015.7219873.

[20] V.M.N. Abreu, P.G. Abreu, Os desafios da ambiência sobre os sistemas de aves no Brasil, Revista Brasileira de Zootecnia 40 (2011) 1–14.

[21] C.S. Utama, M. Christiyanto, Chemical and microbiological properties of broiler litter kept at different altitudes, Online J. Animal Feed Res. 11 (3) (2021) 88–94, https://doi.org/10.51227/ojafr.2021.15.

[22] D. Sohsuebngarm, S. Kongpechr, P. Sukon, Microclimate, body weight uniformity, body temperature, and footpad dermatitis in broiler chickens reared in commercial poultry houses in hot and humid tropical climates, J. World's Poultry Res. 9 (4) (2019) 241–248, https://doi.org/10.36380/scil.2019.wvj30.

[23] L.G.V. Sarmento, R.T. Dantas, D.A. Furtado, J.W.B. Nascimento, J.H.V. Silva, Efeito da pintura externa do telhado sobre o ambiente climático e o desempenho de frangos de corte, Revista Agropecuária Técnica 26 (2005) 117–122.

[24] N.M.H. Mascarenhas, A.N.L. Costa, M.L.L. Pereira, A.C.A. Caldas, L.F. Batista, E. L. Gonçalves, Thermal conditioning in the broiler production: challenges and possibilities, J. Animal Behav. Biometeorol. 6 (2) (2018) 52–55, https://doi.org/10.31893/2318-1265jabb.v6n2p52-55.

[25] H.H. Kristensen, C.M. Wathes, Ammonia and poultry welfare: a review, World's Poultry Sci. J. 56 (3) (2000) 235–245, https://doi.org/10.1079/wps20000018.

[26] W. Zheng, Y. Xiong, R.S. Gates, M.M. Wang, K.W. Koelkebeck, Air temperature, carbon dioxide, and ammonia assessment inside a commercial cage layer barn with manure-drying tunnels, Poult. Sci. 99 (8) (2020) 3885–3896, https://doi.org/10.1016/j.psj.2020.05.009.

[27] P.B. DeLaune, P.A. Moore Jr., T.C. Daniel, J.L Lemunyon, Effect of chemical and microbial amendments on ammonia volatilization from composting poultry litter, J. Environ. Qual. 33 (2004) 728–734.

[28] C.S.L. Vaz, Manejo da cama de frango, in: *Conferência FACTA WPSA-Brasil*, 1. Campinas, 2022, pp. 3–14. Disponível em: https://www.alice.cnptia.embrapa.br/alice/bitstream/doc/1143623/1/final9917.pdf (acessado em 22/04/2024).

[29] M.F.A. Vieira, Caracterização e Análise Da Qualidade Sanitária De Camas De Frango De Diferentes Materiais Reutilizados Sequencialmente, Dissertação (Mestrado), Universidade Federal de Viçosa, Viçosa, 2011, p. 93. Disponível em: https://www.locus.ufv.br/bitstream/123456789/3600/1/texto%20completo.pdf (acessado em 22/04/2024).

[30] G.D. Guesine, R.M.F. Silveira, I.J.O. da Silva, Spatial modeling via geostatistics of the bed in a compost barn system: thermal performance assessments, Int. J. Biometeorol. 67 (2023) 1775–1788, https://doi.org/10.1007/s00484-023-02538-9.

[31] G. Balthazar, R.M.F. Silveira, M.V.A. Cruz, I.J.O. da Silva, Development of an electromechanical device for real-time detection of litter moisture in commercial broiler, Smart Agric. Technol. (2025) 101103, https://doi.org/10.1016/j.atech.2025.101103.