TITLE: Development and Validation of a Multi-Source Edge–Cloud IoT-Based Decision Support System for Real-Time Cold Stress Detection and Management in Dairy Buffalo Farming

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Abstract

Climate variability poses new challenges for livestock farming, with cold stress representing an underestimated but critical risk factor for dairy buffalo. This study presents the development and validation of a novel multi-source IoT-based measurement system, structured as an edge–cloud Decision Support System (DSS) for real-time cold stress detection and management. The proposed infrastructure integrates microclimatic data acquired through an IoT weather station with productive information from an Automated Milking System (AMS). A temporal data fusion algorithm and a multilayer decision engine were implemented to derive agroclimatic indices (Cold–Humidity Index, Wind Chill Index, and Daily Thermal Variation) and to define operational thresholds specifically adapted to Mediterranean buffalo. Statistical modeling demonstrated, for the first time, a direct relationship between cold stress conditions and significant reductions in milk yield, with identified breakpoints at $CHI < 58$, $WHI > 14$, and $\Delta T_{\max} \leq -5\,^{\circ}\mathrm{C}$. Field validation confirmed the robustness, reliability, and continuity of the system, with an operational uptime of 98.7% and a LoRaWAN packet transmission reliability of 99.3%. The results highlight how an IoT edge–cloud measurement approach can provide actionable decision support, extend Precision Livestock Farming beyond heat stress, and contribute to improving animal welfare, production sustainability, and resilience to climate variability.

Keywords: IoT-based measurement system, Edge–cloud architecture, Decision Support System (DSS), Agroclimatic indices, Precision Livestock Farming (PLF), Cold stress monitoring

1. Introduction

Climate change is imposing new challenges on livestock farming, not only due to the increase in heat waves but also because of the growing variability and unpredictability of weather events [1]. Because of its tropical origin, the Mediterranean buffalo is more resilient than dairy cattle to hot climate, but shows limited protection against low temperatures [2]. This is mainly due to its thinner coat, the absence of a substantial insulating fat layer, and a marked sensitivity to microclimatic variations. In the case of dairy buffalo, this issue takes on particular importance. Calves are especially vulnerable, facing high risks of hypothermia and consequent impacts on growth and survival [3]. Despite these critical aspects, the tools currently available for monitoring and preventing cold stress remain limited and are often adapted from models developed for cattle, which are not always transferable to the buffalo species. The evolution of digital technologies and Precision Livestock Farming (PLF) has made it possible to design innovative approaches based on environmental sensors, automated data acquisition systems, and edge–cloud architectures [4], [5] capable of collecting, integrating, and analyzing heterogeneous information in real time to support farm management. However, most applications have focused on the effects of heat, leaving a scientific and technological gap in cold stress management.

Several measurement approaches have been proposed to assess animal responses to thermal stress in PLF. Recent reviews confirm that most efforts have concentrated on heat stress, typically quantified through the Temperature-Humidity Index (THI), which remains a rather coarse proxy and often lacks robust validation against physiological or productive responses [6], [7]. Attempts to extend measurement methods to cold stress include multilevel fuzzy evaluation models, but these solutions are still poorly standardized and rarely integrated with real-time production data [8].

At the infrastructural level, IoT-based frameworks and low-cost wireless sensor networks have been introduced to improve spatial coverage and continuity of barn microclimate monitoring [9], [10]. While these systems demonstrate the feasibility of distributed sensing, they often neglect metrological validation of performance parameters such as data reliability, latency, and robustness in real farm conditions. Similarly, more recent IoT platforms for livestock housing monitoring remain focused on environmental data streams, without effective fusion with productivity indicators [11]. As a result, current PLF solutions provide partial insights: they can indicate climatic load, but they do not offer species-specific, validated indices that link microclimate fluctuations to measurable impacts on production.

In this framework, the originality of the present paper lies in its measurement-oriented contributions. First, it introduces the definition and adaptation of new and traditional agroclimatic indices (Cold–Humidity Index, Wind Chill Index, and Daily Thermal Variation), experimentally parameterized for buffalo and derived from synchronized microclimatic measurements. Second, it proposes the design of an integrated measurement pipeline, combining IoT weather station data and Automated Milking System (AMS) performance metrics, harmonized through a temporal data fusion algorithm. Third, it statistically derives validated thresholds linking quantitative variations in these indices to significant reductions in milk yield, ensuring that decision rules are grounded in robust evidence rather than arbitrary cut-offs. Finally, it assesses measurement reliability and continuity, quantifying uptime, packet transmission reliability, latency, and buffering capacity, thus demonstrating the robustness of the infrastructure in real farm conditions.

By addressing cold stress through a dedicated measurement framework, this study extends the scope of PLF beyond the traditional focus on heat stress, introducing a scientifically validated methodology to transform microclimatic sensing and productive data into operational indicators. In doing so, it establishes the basis for a new generation of IoT-based measurement systems for animal welfare and production sustainability. This approach is consistent with the recent evolution of metrology for agriculture and PLF, which highlights the need for robust measurement networks, integrated IoT infrastructures for environmental sensing, and novel measurement systems for animal-related emissions

2. Background and Research Gap

In recent years, Precision Livestock Farming (PLF) has emerged as one of the main tools for improving animal welfare and production efficiency, thanks to the spread of digital technologies and IoT architectures capable of collecting and analyzing data in real time [12], [13]. These solutions have enabled the development of integrated monitoring platforms, based on environmental sensors and automation systems [14], [15], and have laid the foundations for an increasingly data-driven approach to farm management.

Despite this progress, the scientific and practical focus has been almost exclusively on heat stress. The Temperature–Humidity Index (THI) has become the reference standard for assessing the effects of heat in livestock farming, and numerous studies have documented its impact on productivity, milk quality, and animal welfare. Both in cattle and buffalo, THI has been used in experimental trials, field surveys, and even integrated into decision-support systems and farm dashboards, confirming its central role as an operational tool [16], [17], [18], [19]. Recent reviews have further reinforced this perspective, highlighting the variety of mitigation strategies implemented to counteract the effects of heat [20] [21], [22].

In contrast, cold stress remains an almost neglected topic. For dairy cattle, there are some references pointing to the role of wind and the rapidity of temperature drops [23]. However, in the case of the Mediterranean buffalo, no technological tools or specific models are yet available to reliably quantify and manage cold conditions. The literature thus reveals a marked imbalance: on the one hand, indices and thresholds that are well established for heat; on the other, the absence of validated indicators and operational thresholds for cold, which could concretely support farmers in preventing production losses and risks to animal welfare.

This study aims to fill this gap by introducing an original approach that combines three elements: a multi-source edge–cloud IoT architecture capable of integrating microclimatic and production data; an event-driven logic, linking environmental conditions with individual performance recorded by the automatic milking system; and the definition of new climatic indices adapted to the Mediterranean buffalo, transformed into statistically determined operational thresholds. In this way, the scope of PLF is extended beyond heat, addressing for the first time the issue of cold stress with a comprehensive platform that brings together hardware and software components in a system validated under field conditions. .

3. The proposed Multi-Source Edge–Cloud IoT-Based Decision Support System

To enable the early identification of cold stress conditions in dairy buffaloes and to support real-time management decisions, an integrated data collection and analysis system was developed, capable of automatically combining heterogeneous information from two main sources:

- **The Automated Milking System (AMS):** for each animal identified through a radio-frequency identifier (RFID) tag, relevant productive and physiological parameters of milk production are extracted for each visit.
- **The on-site weather station:** used for microclimatic monitoring of the barn, consists of an IoT multi-sensor node capable of measuring temperature, relative humidity, wind speed, and atmospheric pressure.

The overall architecture of the monitoring system is structured as a three-tier integrated edge–cloud pipeline (Figure 1):

- **Level 1 – Field data acquisition:** This stage concerns the collection of data directly from the primary sources, namely the automated milking system and the weather station installed in the barn.
- **Level 2 – Data communication and transfer:** This includes the transmission infrastructure that enables the secure, continuous, and reliable transfer of the acquired data to the cloud IoT platform, through dedicated protocols and technologies (LoRaWAN, 4G, MQTT, FTP).
- **Level 3 – Cloud, data lake, and control logic:** This stage handles the organization and storage of data in a temporal data lake (InfluxDB), the synchronized fusion of information, and processing through a multi-layer decision engine aimed at generating risk indicators and supporting decision-making.

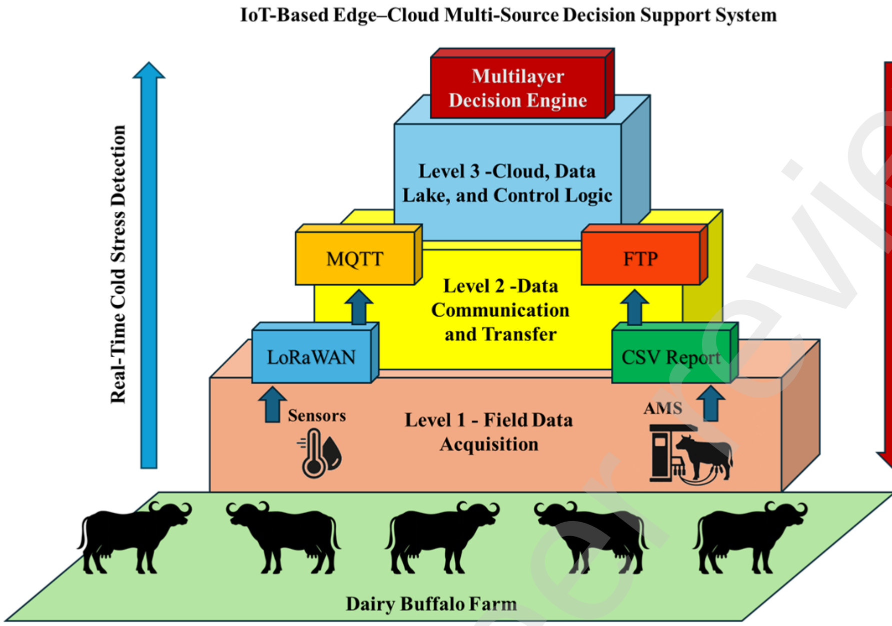

Figure 1: System architecture of the IoT-based edge–cloud pipeline

3.1. Level 1 – Field data acquisition

The first level of the edge–cloud architecture is dedicated to field data acquisition and represents the starting point for the integrated monitoring of cold stress in dairy buffalo farming. This level relies on two heterogeneous yet complementary sources:

- **The Automated Milking System**, designed to enable voluntary milking of the animals without the presence of operators, plays a key role in the continuous and automated collection of productive and physiological data. Each access of an animal to the robot is tracked through a unique identifier (RFID), which allows the personalized recording of the following parameters:
  - Milk yield per visit (kg);
  - Milk conductivity (a possible indicator of mastitis) [24], [25];
  - Milking duration;
  - Milking frequency;
  - Milk flow;

- Any alarms or physiological deviations.

It is worth noting that not all the considered parameters should be available for all the AMS on the market as well as not all of them should be exploited in the analysis. According to the specific model of AMS, these data are aggregated in real time and locally stored (e.g., in CSV format) within a daily report that documents the activities of each animal. The file is automatically updated with every new visit and post-processed for transmission to the cloud. This approach ensures precise historical traceability of each animal's productive profile, useful for individual analysis and for training predictive models.

- **The weather station** must be installed in proximity to the housing area and is equipped with a range of high-precision environmental sensors. The system enables continuous monitoring of the main microclimatic parameters, including:

  - Air temperature;
  - Relative humidity;
  - Wind speed and direction;
  - Atmospheric pressure;
  - Solar radiation and rainfall.

  As for the AMS, It is worth noting that not all the considered parameters should be available for all the weather stations on the market as well as not all of them should be exploited in the analysis. The data collected by the weather station are transmitted to the cloud. To this aim, a LoRaWAN (Long Range Wide Area Network) interface should be exploited to send data to a locally installed edge gateway equipped with 4G cellular connectivity. The use of the LoRaWAN protocol is strategic for several reasons [26]:

  - Low energy consumption, ideal for sensing applications in remote or hard-to-access environments;
  - Long transmission range, up to 15 km in open field, with excellent performance even in the presence of physical obstacles;

- Lower costs compared to other broadband wireless or cellular solutions;
- High scalability, thanks to the ability to serve multiple distributed stations with a single gateway.

These features make the system particularly suitable for the livestock context, where it is often necessary to monitor multiple barns located over a wide area: the LoRa infrastructure allows for the deployment of a distributed network of weather stations, each dedicated to characterizing the specific microclimate of a given barn, thus ensuring localized and differentiated readings of environmental conditions—an essential factor for targeted thermal stress management. Overall, the adoption of this infrastructure significantly reduces operating costs, increases the granularity of microclimatic monitoring, and enables future system expansions towards a multi-barn and multi-sensor logic.

The integration of these two sources enables a synchronized and multimodal view of environmental conditions and individual physiological responses, forming the foundation on which the information pipeline of the entire intelligent monitoring system is built.

3.2. Level 2 – Data communication and transfer

The intermediate level of the edge–cloud architecture implemented in the system is represented by the communication infrastructure, which is responsible for the reliable, secure [27], [28], and timely routing of data acquired from field devices to the centralized cloud IoT platform [29]. This layer serves as the enabling element for transforming raw data into actionable knowledge and has been designed according to the criteria of modularity, scalability, and robustness. The transfer of environmental data is carried out through a LoRaWAN–MQTT chain [30]: data from the weather station are forwarded by the LoRaWAN gateway, which is configured to publish to a local MQTT broker, which acts as a collection hub for asynchronous message exchange according to the publish/subscribe paradigm. MQTT (Message Queuing Telemetry Transport) was chosen as the application protocol because it ensures low overhead, high efficiency in environments with intermittent connectivity, and supports different Quality of Service (QoS) levels, making it ideal for remote agricultural scenarios [31]. Once published to the MQTT broker, the messages are automatically forwarded to the backend of the custom IoT platform, which features native MQTT clients for receiving, analyzing, and visualizing the data. In parallel, for the data component related to the AMS milking system, the daily files generated and locally pre-processed are then securely transferred to the cloud via a protocol capable of ensuring both integrity and confidentiality. This dual communication pathway—asynchronous streaming for environmental data and daily batch transfer for productive data—was developed to match the intrinsic characteristics of the data sources involved, ensuring both the temporal continuity of environmental monitoring and the completeness of the animals' productive profiles. Both data streams are then harmonized and synchronized in the next level (cloud) through timestamp association and the use of a temporal data lake (InfluxDB). The communication architecture, structured in this way, represents an effective example of a hybrid and resilient infrastructure, capable of integrating low-power communication technologies (LoRaWAN) [32], lightweight IoT protocols (MQTT), and traditional file transfer methods (FTP) within an advanced edge–cloud logic.

3.3. Level 3 – Cloud, data lake, and control logic

The third level of the edge–cloud architecture forms the informational and decision-making core of the system. It is here that the data collected in the field are stored, contextualized, and transformed into actionable indicators through an advanced processing chain. This level is composed of three integrated functional elements:

- a temporal data lake for data management and structuring;
- a temporal data fusion algorithm;
- a multilayer decision engine connected to an integrated control logic.

3.3.1. Temporal data lake and automatic labeling

All data acquired from the AMS milking robot system and the weather station are centralized in a temporal data lake implemented in InfluxDB, a high-performance time-series database designed for chronological data analysis. During the ingestion phase, each data point is automatically labeled through a tagging system that assigns:

- a synchronized timestamp;

- a unique animal ID (for AMS data);
- the source (meteorological or physiological);
- and, where applicable, the georeferencing of the barn (the system can manage multiple barns).

This structure allows for modular access, fast querying, and scalable visualization of information over time and space.

3.3.2. Temporal data fusion algorithm

A dedicated data fusion algorithm, implemented in Python, reads the data collected daily and builds a synchronized dataset that consistently links the recorded microclimatic conditions (temperature, humidity, wind, pressure) to the corresponding productive and physiological parameters registered for each animal [33] (milk yield, conductivity, milking duration, flow, frequency). The fusion operates on an event-based approach: for each milking session, marked by a timestamp, the microclimatic state is calculated over a defined time window and associated with that event. This pairing makes it possible to contextualize each animal's performance with respect to the environmental conditions in which it occurred, enabling an integrated reading of the data. The main objective is to build a consistent dataset that allows:

- Highlight the effect of environmental variations on the individual performance of the animals.
- Calculate complex thermal indices such as the CHI (Cold–Humidity Index) and the WHI (Windchill Index), useful for estimating the level of perceived thermal stress;
- Assess critical thermal variations, such as the drop in maximum temperature between consecutive days, for the early identification of risk situations.

The multivariate and synchronized approach enables not only a detailed descriptive analysis, but also the identification of temporal patterns useful for developing predictive models aimed at monitoring animal welfare and optimizing production performance in relation to the environmental context.

3.3.3. Multilayer Decision Engine

The multilayer decision engine represents the core of the decision support system, designed to classify cold stress risk conditions on the basis of climatic and productive information. The engine operates by taking as input three agroclimatic indices specifically adapted to the winter buffalo farming context: the Cold–Humidity Index for cold conditions **CHI**, the Wind Chill Index (**WHI**), and the Daily Thermal Variation ($\boldsymbol{\Delta T}_{\max}$). These indices serve as synthetic descriptors of environmental exposure and constitute the decision variables of the system.

The **CHI** index was defined starting from the literature on animal welfare and experimentally adapted to buffalo physiology, focusing on the most unfavorable daily conditions (nighttime and early morning). It is calculated as:

$$\begin{aligned}\mathbf{CHI} &= (1.80 \times T_{\min} + 32) \\ &\quad - \left[\left(0.55 - 0.0055 \times RH_{\max}\right) \times (1.80 \times T_{\min} - 26)\right]\end{aligned} \tag{1}$$

where:

- $T_{\min}$ is the minimum air temperature recorded during the day (°C);
- $RH_{\max}$ is the maximum relative humidity of the day (%).

The choice of these two daily extremes ($T_{\min}$,$RH_{\max}$) makes it possible to identify the most unfavorable thermal conditions, typically occurring during nighttime and early morning hours, when the risk of hypothermia is highest. This approach addresses the need to assess cold stress risk precisely at the times of day when animals are most exposed to critical temperatures, especially during the winter season.

Alongside **CHI**, the **WHI** quantifies the combined effect of air temperature and wind speed on the perceived temperature [34]:

$$WHI = 33 - (33 - T_{\text{mean}}) \times \left(0.47 + 0.45\sqrt{V} - 0.05V\right) \tag{2}$$

where:

- T_{mean} is the minimum air temperature recorded during the day (°C);
- V is the average daily wind speed (km/h).

Finally, the $\boldsymbol{\Delta T}_{\max}$ index measures abrupt drops in maximum temperature between consecutive days, signaling potentially dangerous deterioration of the thermal environment:

$$\Delta T_{\max}(i) = T_{\max}(i) - T_{\max}(i-1) \tag{3}$$

where $\Delta T_{\max}(i)$ represents the daily thermal variation of the maximum temperature on the i-th day, computed as the difference between the maximum air temperature of the current day $T_{\max}(i)$ and that of the previous day $T_{\max}(i-1)$.

Once the indices have been defined, the multilayer decision engine generates alerts by applying threshold-based rules [35]. In practice, each climatic index (**CHI**, **WHI**, $\boldsymbol{\Delta T}_{\max}$) is compared against specific cut-off values that delimit the transition from normal to risk conditions. These thresholds represent the critical points beyond which cold stress is statistically associated with significant reductions in animal performance and welfare and are specifically related to the operating conditions of the considered barn.

The adoption of such rule-based thresholds allows the system to translate complex climatic and productive data into a clear and actionable daily alert. When one or more thresholds are exceeded, the decision engine automatically activates a "Warning" level, classifies the risk, and notifies the farmer in real time. This real-time capability is crucial: it enables farm managers to promptly recognize emerging cold stress conditions and to adopt preventive or corrective measures (e.g., adjusting barn microclimate or nutritional strategies such as supplemental fat during mild cold stress; see [36]) before production losses or welfare impairments become irreversible. In this way, the decision support system transforms continuous data monitoring into timely, science-based decision-making, ensuring both operational simplicity and robust scientific grounding [37].

3.3.4. Dashboard and Control Logic

The results are made available in real time through an interactive dashboard integrated into the cloud IoT platform. The dashboard allows the visualization of:

- The historical and real-time trends of climatic parameters;
- The individual status of the animals and their associated risk indices;

- An automatic ranking of the animals most at risk, to prioritize management attention.

The backend is already equipped with an integrated control logic, designed to be extended to the manual or automatic operation of environmental actuators that can be installed in the barn, such as:

- windproof movable curtains;
- localized heating systems;
- intelligent ventilation systems.

When activated, this functionality will enable the closure of the monitoring–control loop, evolving the system towards an adaptive, automated microclimatic digital twin.

4. Results on Case study: Statistical Derivation of Thresholds for Real-Time Cold Stress Decision Support

The function of the multilayer decision engine introduced in subsection 3.3.3 is to transform the fused climatic and productive data into actionable alerts for farm management. To this end, the engine relies on threshold-based rules applied to three agroclimatic indices (**CHI**, **WHI**, $\boldsymbol{\Delta T}$max). The present section details the statistical methodology adopted to derive these thresholds and to validate their association with significant changes in buffalo performance under cold stress conditions. This clarification ensures that the decision logic is not based on arbitrary cut-off values, but on robust experimental evidence.

4.1. Animal population and data curation

The trial was carried out in a commercial buffalo farm located in Caserta province (South Italy) at 40°27'N, 15°01'E, 31 m above sea level for a total period of 9 months, between September 2023 and May 2024. 60 Italian Mediterranean buffaloes were involved in the study. Animals were maintained in free stall housing conditions, allowing 15 $m^2/head$ and a front manger of 80 cm and were fed twice daily through a total mixed ration (TMR). The composition of the diet and the nutritional characteristics are reported in Table 1.

Table 1: Composition (kg), chemical characterization (% of dry matter, DM) and energy density (Milk Forage Unit, MFU) of the diet utilized during the trial.

Feed	
Maize silage	18.0
Brewers grains	10.0
Ryegrass hay	1.6
Alfa alfa hay	2.5
Straw	0.9
Corn flakes	3.2
Soybean meal	1.9
Hydrogenated fat	0.4
Calcium carbonate	0.07
Sodium bicarbonate	0.05
Chemical composition	
DM (kg)	16.71
CP (%/DM)	14.92
EE (%/DM)	5.96
CF (%/DM)	18.85
NDF (%/DM)	40.57
ADF (%/DM)	23.07
Ashes (%/DM)	5.72
NSC (%/DM)	34.11
Starch (%/DM)	20.22
Calcium (%/DM)	0.81
Phosphorus (%/DM)	0.42
MFU (%/DM)	0.94

Abbreviations: CP = crude protein; EE = ether extract; CF = crude fiber; NDF = neutral detergent fiber; ADF = acid detergent fiber; ADL = acid detergent lignin; NSC = non-structural carbohydrates.

A selection gate was present between the pen and milking robot and a minimum time interval of 7 hours was set between one milking and the subsequent. Buffaloes were milked on average twice a day with an automated robotic system (DeLaval VMS 300, Tumba, Sweden), which automatically recorded daily milk yield (kg/day) for each animal [38]. Additional information included date of birth, parity order, and days in milk (DIM). Parity was categorized into the two available classes, namely first and second. To ensure physiological consistency, only records between the 5th and 305th DIM were retained. DIM was aggregated into ten 30-day classes, with the last class including all records ≥ 270 DIM, capturing the main lactation phases.

Data collected by the AMS are saved into a CSV file and, at the end of the day, processed through a custom Python script that structures, cleans, and prepares the data for secure transmission to the cloud via FTP protocol. Implausible records were excluded according to biologically motivated thresholds ($< 0.50\,\mathrm{kg/day}$; $> 14\,\mathrm{kg/day}$ for primiparous; $> 24\,\mathrm{kg/day}$ for second-parity). Animals with fewer than 25 valid daily observations were excluded, and days with fewer than 30 lactating buffaloes monitored were discarded. After filtering, the dataset comprised 21,042 daily records from 60 buffaloes, with 64% from multiparous and 36% from primiparous animals. Descriptive statistics of milk yield across parity classes are reported in Table 2.

As weather station, a Davis Vantage Pro 2 [39] has been selected; its main accuracies for temperature and relative humidity measurements are equal respectively to $0.5°C$ and 2%. the weather station is equipped with a LoRaWAN communication module and connects with a gateway that is installed near the AMS management room and connected via Ethernet to the farm router, ensuring reliable internet connectivity and simplifying maintenance.

Table 2: Descriptive statistics of daily milk yield according to parity order

Parity order	Mean	STD	Minimum	Maximum
1	6.96	3.47	0.10	14.0
2	9.87	4.93	0.10	24.0

4.2. Statistical modelling

Climatic indices were tested as fixed categorical effects to identify thresholds associated with significant reductions in milk yield. Analyses were carried out with SAS (SAS Institute Inc., Cary, NC, USA). A repeated-measures linear mixed model was fitted as follows:

$$\begin{aligned} y_{ijklm} = \mu &+ \mathrm{Parity}_i + \mathrm{DIM}_j + \mathrm{Month}_k + \mathrm{Climatic\ Index}_l \\ &+ (\mathrm{DIM} \times \mathrm{Climatic\ Index})_{jl} + (\mathrm{Parity} \times \mathrm{Climatic\ Index})_{il} \\ &+ \mathrm{Animal}_m + \varepsilon_{ijklm}. \end{aligned} \tag{4}$$

where, y_{ijklm} is the daily milk yield of animal m; μ is the population mean for daily milk production; Parity_i is the fixed effect of the i-th category of parity Parity (Primiparous and multiparous); DIM_j is the fixed effect of the j-th class of DIM (j = from 1 to 10); Month_k is the fixed effect of the k-th month of sampling (k = from Septemebr 2023 to May 2024); Index_l is the fixed effect of the l-th class of index, i.e. CHI, WHI $\Delta T_{\max}$ (l = from 1 to 10); $(\text{DIM} \times \text{Index})_{jl}$ is the fixed interaction effect between DIM classes and Index classes; $(\text{Parity} \times \text{Index})_{il}$ is the interaction effect between parity order and Index classes; Animal_m is the random effect of the m-th Animal; and $\varepsilon_{ijklm}$is the random residual error variance.

The significance level was set at $P < 0.05$, and Bonferroni's post-hoc test was used for multiple comparisons. This framework allowed testing of different candidate thresholds for each index and identification of the breakpoints where milk yield significantly declined [40].

The significance values of the minimum selected models are reported in Table 3.

Table 3: Significance values (P-value) of minimum selected models applied to daily milk yield (kg/day).

Index	Parity	Month	DIM	Index	DIM× Index	Parity× Index
CHI	<0.001	<0.001	<0.001	0.02	<0.001	<0.001
WHI	<0.001	<0.001	<0.001	0.01	<0.001	0.09
$\Delta T_{\max}$	<0.001	<0.001	<0.001	0.001	0.45	0.32

All climatic indices CHI, WHI, and $\Delta T_{\max}$) significantly affected daily milk yield, although interaction terms varied in magnitude and significance.

Following the significance results reported in Table 3, Figure 2 shows the least-square means (LSMeans) of daily milk yield across classes of the three climatic indices (CHI, WHI, and $\Delta T_{\max}$), used to identify the operational thresholds adopted in the decision engine.

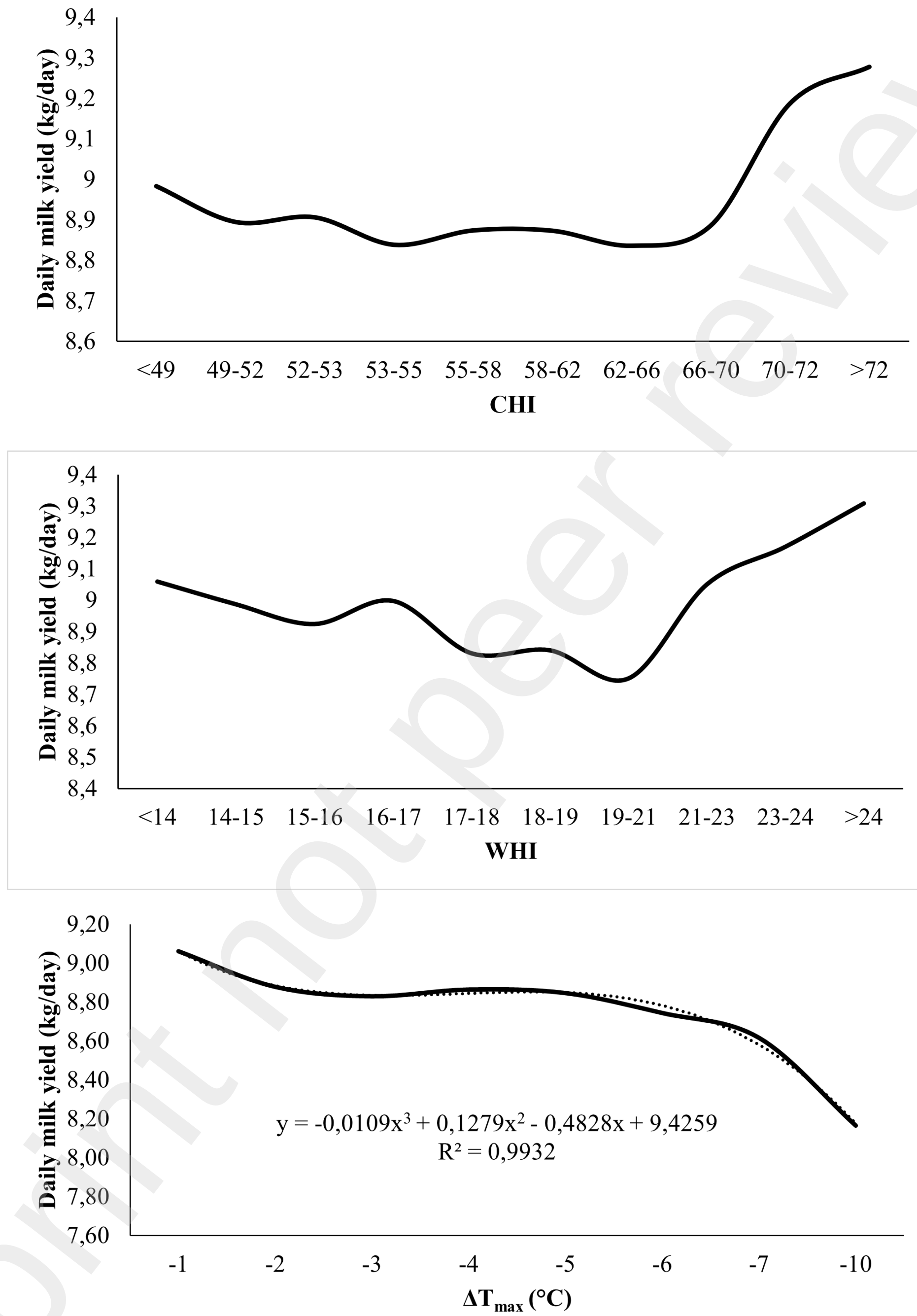

Figure 2: Least-square means (LSMeans ± SE) of daily milk yield according to classes of (top) CHI, (middle) WHI, and (bottom) $\Delta T_{\max}$. Operational thresholds: CHI<58, WHI>14, $\Delta T_{\max} \leq -5\,^{\circ}$C.

Thanks to the considered statistical analysis, the following thresholds have been determined:

- **CHI** < 58 identifies environmental conditions where the combination of low temperature and high humidity generates severe cold stress;
- **WHI** > 14 denotes a situation where wind amplifies the perception of cold, particularly if persisting across consecutive days;
- $\boldsymbol{\Delta T}_{\text{max}} \leq -5\,^{\circ}\text{C}$ signals a sudden and dangerous drop in maximum daily temperature, indicative of climatic instability.

The definition of the thresholds stems from identifying the exact breakpoints at which milk yield begins to show significant deterioration under cold conditions. In particular, daily milk production significantly decreased as CHI drop below 70 and reached the minimum values with CHI values of 58. Similar results have been reported by Matera et al. (2022) [41], where in their study on Italian Mediterranean buffaloes it has been found that milk production and composition significantly decreased under THI values of 62-58. However, the study calculated the standard THI with average temperature and relative humidity. Moreover, a linear reduction in daily milk production has been observed as negative ΔT increased, with a drop in milk production after a deltaT of -5°C. On the contrary, WHI index proved to be not significant for the daily milk production for the considered case study; a threshold equal to the lowest available level means that WHI do not affect the considered performance factor. However, in order to highlight the generality of the proposed approach, its value has been nonetheless considered, since it will be useful for other case studies.

5. Performance assessment of the IoT-based infrastructure

During the field-testing phase, the system demonstrated high service continuity, with an availability rate (uptime) of 98.7 % calculated over a 90 d winter observation period. The only significant downtime (approximately 27 h in total) was due to two episodes of 4G cellular connectivity interruption, which the system automatically resolved upon signal restoration. The Mean Time Between Failures (MTBF) was estimated at 1350 h of continuous operation, while the Mean Time to Repair (MTTR) for routine maintenance interventions or remote resets averaged 35 min. The average end-to-end latency (from sensor detection to data availability on the dashboard) was 6.8 s for microclimatic data transmitted via LoRaWAN–MQTT and 2.5 min for batch updates of AMS data.

To manage communication errors, the system implements a local buffer with a capacity of up to 72 h for microclimatic data and up to 7 d for productive data, preventing information loss in the event of prolonged network outages or unavailability of the central server. Tests conducted under extreme cold conditions (minimum temperature 0 °C) and relative humidity close to 90 % confirmed the operational robustness of both the weather station and the LoRaWAN gateway, with no measurable degradation in sensor performance or transmission quality.

During the validation period, the occurrence rates of specific failures were also estimated:

- Weather station battery depletion: estimated probability 0.6 %/month in the absence of preventive maintenance;
- Milking robot downtime due to technical or maintenance causes: average occurrence 1.1 event/month, average downtime 2 h 40 min;
- Centralized FTP server unavailability: average occurrence 0.8 event/month, average duration 1 h 15 min, causing delays in daily AMS data synchronization but no information loss thanks to local buffering;
- LoRaWAN packet transmission reliability: 99.3 % of packets received without retransmission; average packet loss 0.7 %, mainly due to temporary interference or signal issues.

Table 4: Reliability and Operational Performance Metrics of the Cold Stress Monitoring System

Parameter	Measured Value	Notes
Operational uptime	98.7 %	Observation period: 90 d
MTBF	1350 h	Continuous operation
MTTR	35 min	Remote reset or routine maintenance
Microclimatic data latency	6.8 s	LoRaWAN + MQTT
AMS data latency	2.5 min	Daily batch update
Local buffer for microclimatic data	72 h	Data loss prevention
Local buffer for productive data (AMS)	7 d	Data loss prevention
Extreme cold test	0 °C / RH 90 %	No performance loss
Probability of weather station battery depletion	0.6 %/month	Without preventive maintenance
Milking robot downtime	1.1 event/month	Average duration: 2 h 40 min
Centralized FTP server unavailability	0.8 event/month	Average duration: 1 h 15 min
LoRaWAN packet transmission reliability	99.3 %	Average packet loss 0.7 %

6. Concluding Remarks

The edge–cloud system developed for monitoring cold stress in dairy buffaloes represents a strategic innovation in the field of Precision Livestock Farming. By integrating environmental and physiological sensors, a distributed data acquisition architecture, a temporal fusion algorithm, and a multilayer decision engine, the platform is able to assess microclimatic risk conditions in real time at both collective and individual levels. The implementation of CHI and derived indicators has extended the paradigm of animal welfare monitoring beyond the traditional focus on heat stress, addressing the specific challenges of the winter context.

Field validation demonstrated that the system is effective in detecting critical situations and in supporting timely and targeted management decisions. In practical terms, this means providing farmers with an operational tool capable of improving resilience to climatic variability, reducing the physiological and health consequences of cold stress, and ensuring continuity of production. The interactive dashboard, automatic alarm notifications, and the possibility of interfacing the decision logic with environmental actuators make the system readily integrable into the daily routines of modern farms.

From a sustainability perspective, the system contributes in multiple dimensions:

- **Animal sustainability**, by improving welfare and reducing health risks associated with cold stress;
- **Economic sustainability**, through the prevention of production losses and the reduction of costs related to morbidity and treatments;
- **Environmental sustainability**, as the use of low-power LoRaWAN networks and automated climate management reduces energy waste and enhances overall farm efficiency.

Future developments will focus not only on broadening the technical scope of the system—by integrating new sensors (e.g., bedding, accelerometers, thermographic imaging,3D camera–based feed volume/weight measurement [42],and biomarker-based sensing such as milk whey cortisol via radioimmunoassay [43]), extending coverage to multiple barns and animal categories (buffalo heifers, dry cows), and enhancing the decision engine with machine learning for customized predictive models—but also on scaling up validation. A wider deployment across heterogeneous farms and production systems will allow the assessment of robustness, generalizability, and adaptability of the proposed tool in different management and climatic contexts. Ultimately, the evolution towards a fully closed monitoring–control loop and the implementation of an adaptive digital twin [44] will provide farmers with an intelligent, proactive ally to ensure thermal comfort, production efficiency, and resilience in increasingly variable climatic scenarios.

Funding

This study was carried out within the research project Agritech National Research Center and received funding from the European Union Next-Generation EU (Piano Nazionale di Ripresa e Resilienza (PNRR)–Missione 4, Componente 2, Investimento 1.4–D.D. 1032 17/06/2022, CN00000022). This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

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