3D numerical modelling of temperature and humidity index distribution in livestock structures: a cattle-barn case study

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Abstract

In dairy cattle farming, heat stress largely impairs production, health, and animal welfare. This study aims to develop a workflow and a numerical analysis procedure to provide a real-time 3D distribution of the temperature and humidity index (THI) in a generic cattle barn based on temperature and humidity monitored in sample points, besides characterising the relationship between indoor THI and outside weather conditions. This research was carried out with reference to the study case of a cattle barn. A model has been developed to define the indoor three-dimensional spatial distribution of the Temperature-Humidity Index of a cattle barn based on environmental measurements at different heights of the building. As a core of the model, the *Discrete Sibson Interpolation* method was used to render a point cloud representing the THI values in the non-sampled areas. The area between 1-2 meters was emphasised as the region of most significant interest to quantify the heat waves perceived by dairy cows. The model represents an effective tool to distinguish different areas of the animal-occupied zone characterised by different values of THI.

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Introduction

The animal welfare of dairy cows has been intensively studied for several decades, and solutions for its achievement represent a topical theme of biosystems engineering due to its importance for the productivity and sustainability of cattle husbandry. The ongoing climate change is strengthening the awareness of the necessity of tools effective in maintaining appropriate microclimate conditions in livestock buildings. For this reason, the developments of smart sensors and monitoring tools exploiting wireless connectivity have allowed to create new agricultural management strategies with the opportunity to monitor animals and take advantage of this individual animal control that is known as precision livestock farming (PLF) (Berckmans and Guarino, 2017). Several scientific investigations have proposed that PLF constitutes a valuable approach for supervising and assessing animal welfare. Their research (Bonora *et al.*, 2018) used the advantage of the amount of data available by implementing the new farming management approaches to provide valuable information to dairy farm decision-makers.

On the other hand, the development of Unsupervised Machine Learning algorithms has generated a widespread application of the continuous monitoring of the behaviours of several cows over extended periods, through the analysis of complex behavioural patterns from such datasets to inform subsequent statistical modelling better (McVey *et al.*, 2020). In the same way, Hofstra *et al.* (2022) performed the identification of individual animals and the registration of their behaviours, which are determined by crucial aspects such as positioning, posture, and locomotion. More recent evidence highlighted the potential of PLF for animal welfare monitoring, for evaluation and management purposes (Halachmi *et al.*, 2019).

In cattle farming, the suitable environment temperature range for milk production is 5-25°C; when the upper limit is exceeded, the cow's body temperature exceeds the animals' heat regulation ability resulting in physiological responses such as decreased forage intake (Wang *et al.*, 2020). However, other parameters require special attention to measure animal welfare, such as wind speed, solar radiation, and precipitation. The adverse impact of all these factors on animal production is known as Heat Stress (Becker *et al.*, 2020).

Reducing the harmful effects caused by heat stress plays a vital role from the point of view of farmers who seek improved production performances. In livestock farming systems located in temperate climate regions, proper management of the thermal environment for the animals is of paramount importance to reduce the influence of climatic conditions on the comfort and the performance of the animals. Behavioural data can be automatically collected through a combination of position and activity sensors, and behaviour analysis proved to be a tool for monitoring the health and welfare of cows (Barker *et al.*, 2018). Accelerometers can provide an indirect measure of flinch, step, and kick, which can be combined with other production and behavioural information available, *e.g.*, the number of visits to milking robots, supplemental feeding, and milk yield. Moreover, the measurement of indoor environmental parameters through the combinations of smart sensors and embedded circuits allows to develop an automated system able to identify animals with early onset distress or discomfort; and, at the same time, to provide a basis for inferential analysis that contribute to increase the farm production. In this way, it is possible to provide a non-invasive assessment of animal welfare, allowing an early intervention by the farmer to improve welfare and production (Stewart *et al.*, 2017). Within the framework of heat stress prediction, a specific thermal comfort indicator, namely the skin temperature index for cows, was developed based on the heat balance equations and an integrative tool to predict and assess heat stress in dairy cows (Yan *et al.*, 2022).

Focusing on the situation in Italy, according to Lovarelli *et al*. (2020), the vast majority of high-income livestock activities are located in northern regions. However, it is also possible to find small traditional farms predominantly in mountains in those areas. The geographical characteristics of northern Italy, with a broad plain area surrounded by the mountain ranges of the Alps and the Apennines, favour the occurrence of significant heat waves and the permanence of warm and humid conditions for several weeks every year.

The temperature and humidity index (THI) developed by Thom (1959) is the most widely used parameter to quantify the magnitude of climatic conditions perceived by living beings based on the combined effects of the dry bulb (T_{db}) and dew point (T_{dp}) temperatures. Besides, a variety of indices were used to estimate the degree of heat stress affecting cattle and other animals (Lees *et al.*, 2019); however, the equation expressing THI referred to by Yousef (1985) continues to be recognised for the reliability of its index of the dairy cow's welfare in livestock buildings.

Constructing a comprehensive welfare evaluation system for dairy cows requires the definition of automated detection techniques. The selection process relies on several factors, including the existence and authentication of such methods, the expenses involved, the user-friendliness, and the non-invasive nature of these methods toward the animals under consideration. Additionally, this process facilitates the further refinement of appropriate indicators. Whereas some indicators, such as ambient temperature, are already efficiently monitored using low-cost sensors such as silicon diode-based temperature sensors, others, such as anomalous behaviour, necessitate extensive research to devise a reliable automated detection methodology (Leliveld and Provolo, 2020). This study aims to develop a workflow and a numerical analysis procedure to provide a 3D distribution of the THI in a dairy cattle barn based on temperature and humidity monitored in sample points. This process includes the stages of loading, pre-processing, and interpolating raw data recorded by a monitoring system. The outcome represents an analysis tool able to identify the areas with thermo-hygrometric conditions favourable or, at different levels, unfavourable for animal welfare and thus provide farmers and technicians with indications supporting decisions for better management and design of livestock buildings.

To this end, the work is structured as follows: definition of the experimental farm building adopted as a study case, description of the smart monitoring system deployed on the farm, analysis of the variables measured for the estimation of animal welfare, as well as the statistical tools involved in data analyses. Subsequently, dedicated graphs in 2 and 3 dimensions were generated with the objective of analysing the spatial distributions of the variable under study. Finally, an analysis of the amount of the quantification of the Stress Degree Hours faced by the dairy cows on the period under analysis was performed.

Materials and Methods

Experimental site

The study was carried out with reference to the study case of a dairy cattle farm that collaborated with this research under an agreement with the Department of the authors and therefore plays the role of the experimental farm for what concerns data collection and monitoring of parameters for the environment, production, and animal behaviour. The farm is located in the metropolitan city of Bologna (Emilia-Romagna, Italy), specifically in the municipality of Budrio (coordinates: WGS84 coordinates 44°33'32.7"N 11°31'09.7"E, 25 m above sea level). The dairy cattle barn (Figure 1) is a 50.0 m long and 27.0 m wide rectangular building with a steel frame structure and double-pitched roof of insulated metal panels. The farm building hosted about 70 Holstein-Friesian lactating cows and 15 dried cows, and the internal space is arranged into three main areas for resting, feeding, and milking through one automatic milking system (AMS) station. The resting area, whose floor is partially slatted, has 78 cubicles with sawdust bedding separated into two blocks of head-to-head rows located in its central part, and another row runs along the entire length of the resting area. On the other side, the feeding area is placed on the northeast

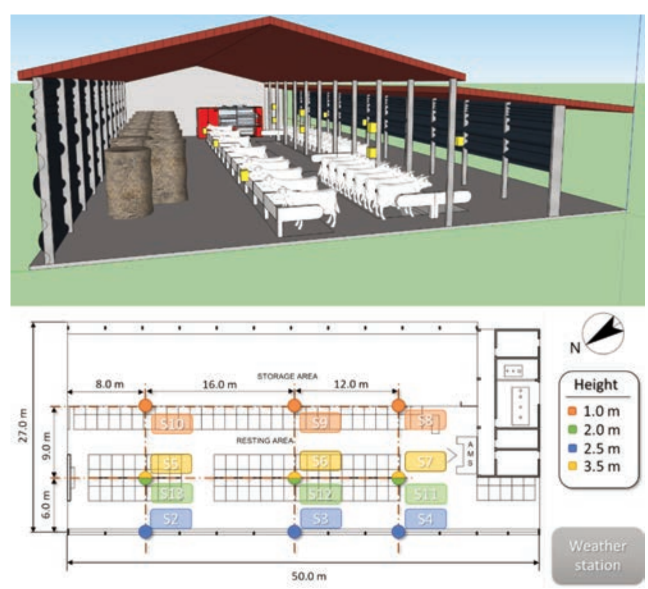

Figure 1. 3D diagram of the farm under study (above) and layout of the temperature humidity sensors positions (below).

side and extends across the entire building width. Lastly, the AMS hosts the robotic milking "Astronaut A3 Next" by Lely that assures several daily visits for each cow depending on the cow's productivity and its expected optimal milk yield per visit, with a minimum and a maximum number of daily visits as constraints, respectively set at 2 and 4.

Smart monitoring system

Temperature and relative humidity measurements were recorded by a smart monitoring system (SMS) deployed in the barn in the frame of the project "Smart dairy farming: innovative solutions to improve herd productivity" (Italian PRIN, Research Projects of relevant National Interest - Call for Proposals 2017) (Bovo *et al.*, 2020). The SMS was composed of 12 sensor nodes and a weather station connected to a gateway through radio LoRaWAN. The positions of the sensor nodes were defined by considering the objective of collecting measurements in several significant points of the volume of the barn at different heights and the feasibility of the location concerning the presence of the cows and the requirement of assuring them proper freedom of movement. The sensors that the animals could reach have been protected through robust cages. The sensor nodes and the weather station were equipped with an electronic board powered either by photovoltaic solar panels or the electric grid (Table 1). Then, a Raspberry Pi was used to collect the information provided by the sensor nodes, package it and send it to the supervisory system through an Internet connection. The study was conducted during the summer of 2021, more precisely from July 4th to September 23rd. Temperature and humidity were logged every 5-minute intervals in the 12 measurement points indoors and one point outdoors of the livestock building, where the weather station was placed.

Sensors location

The wireless sensor network was placed in three lines at different heights to cover the indoor spatial distribution of the environmental parameters of the livestock building as much as possible. This arrangement was studied to obtain measurements of the environmental parameters that could take into account the effect of the presence of the animals. The scientific literature provided detailed analyses of the influence of the heat produced by the cows on the thermo-hygrometric conditions of the animal occupied zone (AOZ) (Chung *et al.*, 2022), and these considerations guided the definition of the sensors' positions. On the northeast side of the barn, sensors S2, S3, and S4 were placed at a distance of 8, 16, and 12 meters, respectively, and at a fixed height of 2.5 metres. On the opposite side, sensors S8, S9, and S10 cover the lowest part of the southwest end of the building, located at a height of 1 meter above the ground. Finally, in the centre line, two rows of sensors were deployed at equal distances but at different heights; this measurement setup is depicted in Figure 1.

Environmental indicators

Measuring the impact of animal heat stress is the key to implementing mitigation strategies. That is why the proper selection of a mathematical model to compute thermal comfort is relevant. The current literature provides various heat-stress assessment methods for different on-farm conditions (*e.g.*, different ventilation systems) and different breeds (Frigeri *et al.*, 2023). Table 2 summarises the three widely applied THI equations; however, the generality of models requires carrying out statistical tests to quantify the model's capability of correctly reflecting the actual farm conditions. The index referred to by Equation (1) proposed by (National Research Council (U.S.), 1971), represents the Oklahoma Mesonet Cattle Heat Stress Index, designed to indicate the level of heat stress of outdoor cattle. This index has been used in several researches focused on the incidence of body temperature on the genetic performance of dairy cows (Ravagnolo and Misztal, 2002; West, 2003). On the other hand, Equation (2), developed by Yousef (1985), was initially intended to measure human welfare. Subsequently, its use was extended empirically to measure the effects of heat stress on cattle from a physiologic and productive standpoint. Furthermore, with Equation (3), Hahn (1997) developed a THI model as a support for decision-making by producers in the event of heat waves, considering environmental parameters like relative humidity and dry bulb temperature, which refers to the ambient air temperature. Table 3 summarises the descriptive statistics of the thermal index for the entire period under study. It is possible to notice the similar performance of the minimum, maximum,

Table 1. Specifications of the environmental sensor.

Sensor model name	Data output	Resolution	Accuracy	Range
AM2315C	Relative humidity	0.024	±2	0~100% RH
	Air temperature	0.01	±0.3	-40~80°C

RH, relative humidity.

Table 2. List of temperature humidity indices compared in this study.

Equations	Year	Index
$THI = (1.8*T_{db} + 32)-[(0.55 - 0.0055*RH)*(1.8*T_{db} - 26.8)]$	1971	(1)
$THI = T_{db} + 0.36*T_{dp} + 41.2$	1985	(2)
$THI = 0.8*T_{db} + (RH/100)*(T_{db} -14.4) + 46.4$	1997	(3)

THI, temperature-humidity index, RH, relative humidity.

Table 3. Descriptive statistics for the thermal indices during this study.

Item	Number	Minimum	Maximum	Mean	Standard deviation
Equation (1)	1944	58.51	85.12	73.58	5.2400
Equation (2)	1944	60.53	85.39	73.10	4.8157
Equation (3)	1944	58.51	84.76	73.40	5.1611

and average values, while Equation (2) achieved the lowest standard deviation compared to that exhibited by the other two equations. In order to quantify the sensitivity of the equations under study, the correlation between the THI values computed and the inputs of the equation (temperature and relative humidity) was analysed. Despite the similarity of the THI values obtained from the different equations in Table 4, it should be noticed that the thermal index calculated through Equation (2) shows the highest absolute value of the correlation coefficient for both input variables. Although the three equations proved to be scientifically sound, Equation (2) was selected for the calculation of THI in the present study because it showed the highest correlation with both variables affecting the thermo-hygrometric welfare of cattle. The relationship between environmental and production parameters might be characterised by abrupt changes that a standard linear regression cannot correctly detect. However, several studies established the use of threshold values of heat stress to group the neglected effect (on animal behaviour or production). Due to the variability in terms of parity, days in milk and age of the animal population under study, the general scale of thresholds proposed by Eigenberg *et al*. (2005) was selected with the aim of labelling the adverse factors of THI value incidence on a broader scale (Table 5). The reference values of this scale were also indicated in the scientific literature as thresholds referred to the equation by Yusef (1985) for assessing heat stress in dairy cattle (Ji *et al*., 2020).

Comfort assessment

As shown in Figure 2, the raised THI values reached during the daytime can be recovered during the night due to the decrease in temperatures and the consequent increase in relative humidity of the air. In this context, quantifying the time at which the herd has been exposed to THI exceeding the different thresholds (Table 5) previously defined and to what extent is a crucial way to determine the possibility of recovery of adverse effects, as well as their incidence in the subsequent days. The stress degree hours (SDH) introduced by Hahn (1997) provide a measure of the magnitude of daytime heat load (intensity and duration) on dairy cows.

$$SDH = \sum_{i=1}^{24}(THI_i - base) \tag{4}$$

where THI is the hourly temperature-humidity index, and the base represents the threshold's lower boundary corresponding to the onset of heat stress.

Data processing

The general workflow followed in this study can be divided into three main steps, starting with a preprocessing of temperature and humidity datasets recorded by the SMS; then the computation

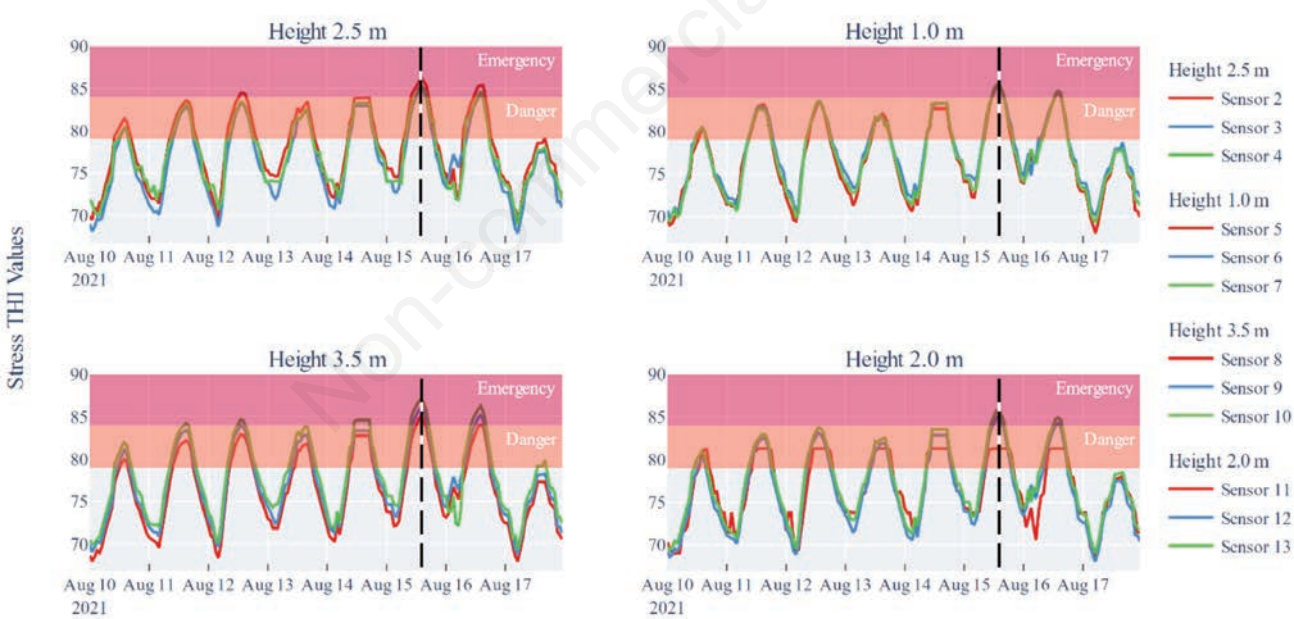

Figure 2. Time series representation of temperature-humidity index values inside the barn.

Table 4. Pearson correlation coefficient temperature and relative humidity index *vs* temperature and relative humidity.

Variable/Equation		Equation (1)	Equation (2)	Equation (3)
Temperature	Correlation coefficient	0.960824	0.976873	0.955738
	p	<0.001	<0.001	<0.001
Humidity	Correlation coefficient	-0.590304	-0.620091	-0.575161
	p	<0.001	<0.001	<0.001

of the welfare index selected, and finally, a strategy to handle missing values was applied in order to obtain a clean dataset that allows to performance statistical analysis that supports the operational and strategical decision systems. As a first step, simple comparison rules were applied to identify the inliers values from the sensors' measurement range, as reported in Table 1. Furthermore, the interquartile range method was applied to detect and remove the outliers found in the dataset. Afterwards, a THI index was computed following Equation (2), as previously stated. Finally, a strategy to handle missing data was implemented directly to the THI values computed.

Handling missing data

To guarantee an accurate analysis during the time interval analysed in this work, a machine learning model was trained to predict the missing measurements of the sensors based on THI measurements computed by external temperature and humidity measurements provided by the weather station. The process includes fitting Random Forest Regressor algorithm that uses the external THI as an independent variable and as a target for the THI at the different measurement points. As a result, a regression was obtained that allows reproducing with high precision the behaviour of the different sensors without missing values. However, to work with as many raw values as possible, only the missing values calculated by the regression were imputed in the initial dataset.

It should be noted that the environmental measurements recorded by SMS deployed on the farm under study, as well as the structural characteristics of the livestock building, limit the use of interpolation strategies based on the thermal characteristics of the facility. That is why the application of the Discrete Interpolation algorithm constitutes a feasible solution to infer the indoor spatial distribution of the THI through the measuring points.

The relationship between indoor *vs*. outdoor THI values was carried out to complete the preliminary analyses of the data available. It is, in fact, an analysis that provides a starting point for future research on the estimation of welfare indexes from external measurements. In this respect, the Pearson's Correlation was calculated between the set of internal variables and the data from the weather station. Table 6 shows the high correlation between the different data sets and the presence of a probability value (p-value) lower than the significant threshold (0.05).

3D interpolation

In agricultural engineering, interpolation plays an essential role in applying standard visualisation techniques such as contouring, slicing, and volume rendering to scattered data. In our case, interpolating THI measurements of the different indoor sampling points allowed us to detect areas with critical THI values not directly measured. Among the most peculiar characteristics of the variable under analysis, there is the stability in surrounding areas within indoor environments; hence discrete interpolation is a feasible way to infer the THI values in non-measured areas. Natural-neighbour interpolation method, and more precisely, Discrete Sibson, is an algorithm that has shown good performance in the applications of the interpolation of environmental variables (Etherington *et al.*, 2021); hence it is suitable for the present context of the application. Developed by Park *et al*. (2006), Discrete Sibson Interpolation uses a Discrete Voronoi diagram, which can be computed from three-dimensional graphics exploiting geometrical properties of the Sibson's method, which reduce the interpolation algorithm to rendering and blending spheres whose radii are determined by the distance between an evaluation location and its nearest neighbour in the dataset. The Python Natural Neighbor library is the implementation of the Discrete Sibson Interpolation method that uses as input the measured values of each sensor at a fixed position (*x,y,z*), and a mesh grid occupying the volume of the building object of study. As a result, a multidimensional array was obtained, corresponding to the spatial distribution of the THI values inside the livestock building. Subsequently, using one of the most widely used Python libraries for graphs (Plotly), we proceeded to represent the gridded points, corresponding to a sampling time.

Validation of spatial interpolation

Despite the reliable performance of Discrete Sibson Interpolation highlighted by Park *et al*. (2006), a validation of the accuracy of the spatial interpolation was performed. The Leave One Out (LOO) algorithm in the Python scikit-learn library was employed at each sampling instant. James *et al.* (2013) refer to LOO as a simple cross-validation. Each learning set is created by taking all but one sample, with the test set being the left out sample. As a result, the mean and standard deviation of the mean absolute error (MAE) and root mean square error (RMSE) were calculated from the mean residuals obtained from each process iteration.

Results and Discussion

Time series analysis

The time series shown in Figure 2 represents the outcome of the different steps of the selected data processing methods, grouped according to the height values at which they were placed.

Table 5. Dairy cow's thermal environmental classification based on the values of the temperature-humidity index, derived from the classes presented in the papers cited.

Thermal environmental classification	THI values range
Normal	THI≤74
Alert	74<*THI*≤79
Danger	79<*THI*≤84
Emergency	84<*THI*

THI, temperature-humidity index.

Table 6. Pearson's correlation coefficient between the weather station and indoor sensor nodes.

Weather station	Correlation coefficient	p
Sensor 2	0.971413181	<0.05
Sensor 3	0.974734771	<0.05
Sensor 4	0.963707038	<0.05
Sensor 5	0.9747492	<0.05
Sensor 6	0.971683325	<0.05
Sensor 7	0.971636456	<0.05
Sensor 8	0.966068954	<0.05
Sensor 9	0.972278099	<0.05
Sensor 10	0.97839969	<0.05
Sensor 11	0.979708887	<0.05
Sensor 12	0.971827708	<0.05
Sensor 13	0.971380867	<0.05

Table 7 summarises the main metrics reached by the Random Forest Regressor algorithm, where it is possible to note, first, the proximity to the best possible value (1.0) of the coefficient of determination (R^2), indicating goodness of fit and therefore a measure of how well-unseen samples are likely to be predicted by the model. Furthermore, the MAE and mean square error show satisfactory results guaranteeing the correspondence to the expected value of the absolute error loss and the squared error, respectively.

The two shaded areas in Figure 2 show the threshold corresponding to danger and emergency situation according to the THI values recorded by the different measurement points. In addition, the dashed black line placed on August 15th refers to the peak THI value recorded by almost all sensors during the study period. The diagrams also show that the level of the AOZ (1-2 m height) is overall characterised by THI trends which are not significantly lower than those registered at higher levels of the building volume, and this can be ascribed to the effect of heat and moisture produced by the cows themselves.

Spatial distribution of temperature and humidity index

The spatial distribution of THI values within the livestock building is shown in Figure 3 as a result of the 3D spatial interpolation of discrete values of THI corresponding to the distribution of indoor THI at 14:00 on August 15th. It is possible to observe that the significant part of the indoor spaces of the building has high THI values that place it in the emergency range, except for the southwest corner, which is in the danger range, which may be related to the wind direction or other parameters of the building structure itself.

As a validation of the interpolation, the LOO algorithm executed on the whole dataset permitted the elaboration of Figure 4, where it is possible to analyse the stability of the mean and standard deviation values of MAE and RMSE, which are between and respectively, denoting robustness for the current application context since the THI would not be noticeably affected by an oscillation in this range. To get into details about the indoor distribution of THI values, four horizontal sections were created considering the time intervals in which THI's highest and lowest values were appreciated. Several researches have demonstrated the adverse effects of high THI values on livestock production in general (Samal, 2005) and specifically on milk production (Carvajal *et al.*, 2021; Habeeb *et al.*, 2018). In this vein, monitoring of the zones of greatest discomfort is an essential parameter to support farmers in making decisions about the management of the herd. Through Figure 5, it is possible to analyse in detail the spatial distribution of the THI by using the predefined layers according to the height values of the sampling points.

Figure 6 represents the behaviour of THI on the day following the occurrence of the peak values of the index. It is possible to notice the similarity of the behaviour in the interior zones of the building (southwest corner within the range of danger values). It is also possible to notice that the area covered by the danger threshold values was extended compared to the previous day (Figure 5).

Temperature and humidity index metrics

Several studies have shown that the duration of heat loads can lead to significant reductions in milk production (Benni *et al.*, 2020; Bonora *et al.*, 2018), so it is a piece of important information to be considered by farmers. Based on the categories defined above (Table 5) for the THI values calculated in the period under study, Table 8 summarises the duration in hours of the different thresholds reached. It must be said that the quantification of the hours shown in the following table represents the total duration of thermo-hygrometric conditions corresponding to the various levels of heat stress during the week analysed, in the position of each sensor

Table 7. Regression metrics of filling missing values algorithm.

Sensor ID	R^2	MAE	MSE
Sensor 2	0.943658	0.817126	1.346449
Sensor 3	0.954011	0.791696	1.127177
Sensor 4	0.957707	0.423279	0.67454
Sensor 5	0.95129	0.801082	1.1122
Sensor 6	0.945866	0.847782	1.247269
Sensor 7	0.940255	0.879513	1.473713
Sensor 8	0.93924	0.91315	1.484271
Sensor 9	0.944059	0.752761	1.037722
Sensor 10	0.964642	0.538003	0.710516
Sensor 11	0.993429	0.138599	0.126711
Sensor 12	0.946604	0.847539	1.253052
Sensor 13	0.944183	0.851527	1.265363

R^2, coefficient of determination; MAE, mean absolute error; MSE, mean square error.

Table 8. Average daily duration (h) of the threshold reached.

Category/Sensor	2	3	4	5	6	7	8	9	10	11	12	13
Normal	9714	11440	12784	12011	11046	9545	11299	11133	11619	12284	11937	10768
Alert	1476	1058	1118	1072	1190	1458	1140	1324	1238	1232	1070	1249
Danger	597	342	450	307	446	602	333	411	369	360	318	475
Emergency	14	3	4	3	11	35	5	5	5	0	3	9

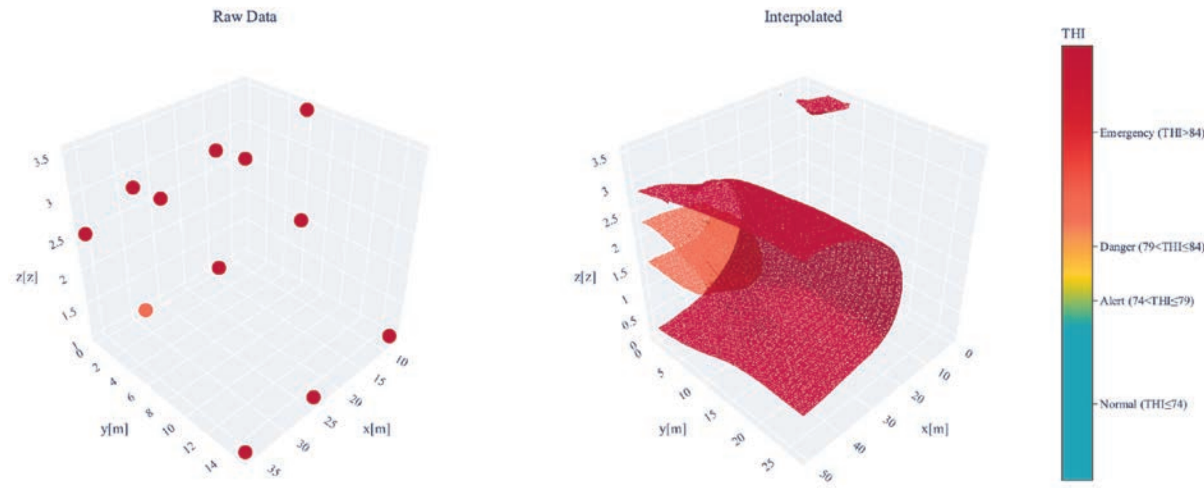

Figure 3. 3D spatial representation of the indoor temperature-humidity index values measured by the sensor nodes (left); 3D spatial representation of the continuous values of temperature-humidity index obtained through interpolation (right). The coloured surfaces represent the boundaries of the danger heat stress range.

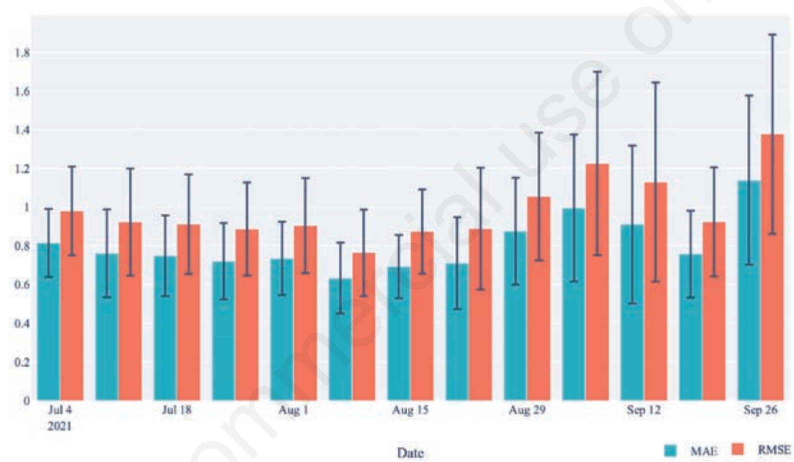

Figure 4. Mean and standard deviation of mean absolute error and root mean square error of Discrete Sibson Interpolation of temperature-humidity index weekly grouped.

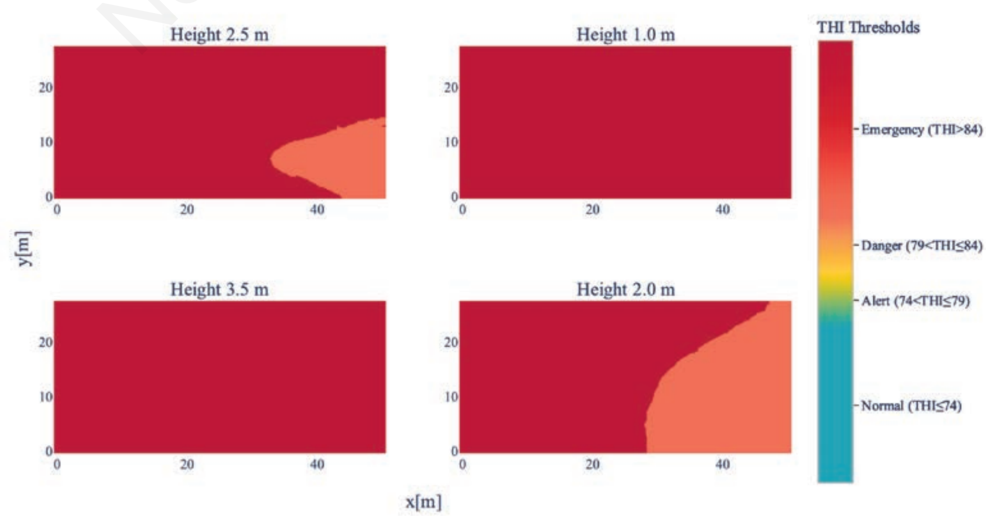

Figure 5. Heat map of temperature-humidity index indoor values at 2021-08-15 14:00 (same orientation as Figure 1).

node. Table 8 shows that sensor number 7, located in the central row of the building at the height of 3.5 meters, experienced the most significant number of hours in the emergency threshold, which is explained by the fact that it is one of the highest SMS sampling points, which is close to the milking robot and the drinking trough, both places prone to a significant accumulation of animals. A similar behaviour can be seen in the danger and alert thresholds. To assess in detail the probability of occurrence of heat waves within the farm, the stress degree hours quantity, expressed by Equation (1), was used to elaborate Figure 7, which reflects the behaviour of the parameter above at the different sampling points.

Figure 7 represents the SDH cluster captured by each measurement point; specifically, the graph was focused on the week in which the highest THI values were experienced. In line with the

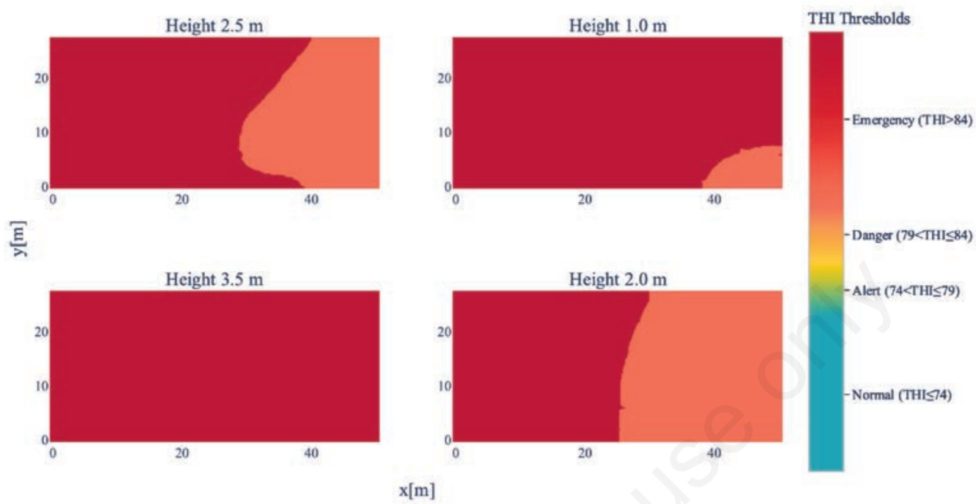

Figure 6. Heat map of temperature-humidity index indoor values at 2021-08-16 14:00 (same orientation as Figure 1).

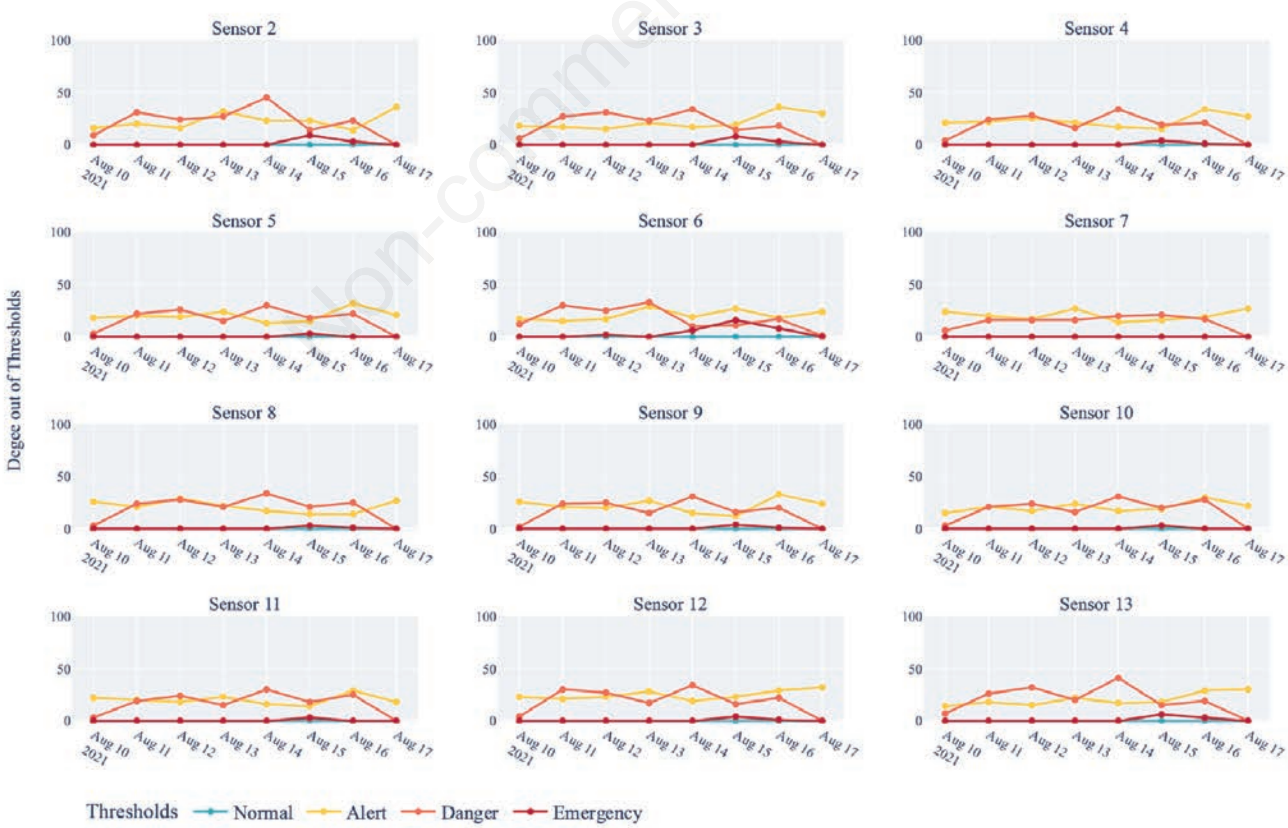

Figure 7. Trends of stress degree hours in the points of the barn monitored through sensor node.

above, the highest part of the centre row of the building recorded the highest amount of SDH, specifically in the range of danger. Further, special attention should be paid to the measurements by sensors 8-9-10 and 11-12-13 (located at 1 and 2 meters above the ground) since they recorded measurements of environmental variables at approximately the same height as the cattle under study. The similarity of the measurements between the pairs of sensors 8-11, 9-12, and 10-13 indicates the correspondence in the spatial distribution of the environmental measurements according to the location of the pairs of sampling points located in the same position with respect to the x-axis of reference (Figure 1).

Conclusions

In this research, a model was developed to define the three-dimensional spatial distribution of the THI within the volume of a cattle barn based on data measured in a certain number of points. Specifically, the model was applied to a study case of a cattle barn where a SMS had been deployed. The spatial interpolation of the THI values through the Discrete Sibson Interpolation method allowed the detection of critical areas inside the livestock building that require special attention to ensure animal welfare. By dividing the resulting point cloud into the different layers corresponding to the heights of the SMS sampling points, it was possible to analyse in detail the distribution of the thermo-hygrometric conditions of the barn. The area between 1-2 meters was emphasised as the region of most significant interest to quantify the heat waves perceived by dairy cows. The model represents an effective tool to distinguish different areas of the AOZ, characterised by different values of THI, which can also lead to identifying areas classified with different ranges of the index according to the threshold acknowledged in scientific literature.

Moreover, to quantify the amount of heat stress perceived by the animals under study, the SDH experienced in the different sampled areas of the building were computed and analysed in detail, with a procedure that can be applied to build the trends of such parameter in several positions of the barn volume. This analysis was made possible by applying the model developedfor the spatial distribution of THI. The results highlighted that, within the animal-occupied zone, there can be a significant variability in the time of exposure of cows to various levels of heat stress. Therefore, this analysis tool proved helpful in address effective measures to reduce temperature or humidity in the most critical areas and periods. Farmers require such measures to ensure animal welfare and thereby promote the quantity of milk yield and the quality of the production.

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