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A generalised additive model to characterise dairy cows' responses to heat stress*

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Heat stress is one of the most critical issues jeopardising animal welfare and productivity during the warm season in dairy cattle farms. The global trend of increase in average and peak temperatures is making the problem more and more serious. Many devices have been introduced in livestock farms to monitor and control temperature-humidity index, as well as animal behaviour and production parameters. The consequent availability of collected databases has increasingly enhanced the research aimed to understand the consequences of heat stress in cattle, in relation to genetic, reproductive, productive and behavioural features. Moreover, these investigations laid the foundations for the development, calibration, validation and test of numerical models quantifying the individual responses to heat stress conditions. In this work, a generalised additive model with mixed effects has been developed to analyse the relationship between milk production, animal behaviour and environmental parameters based on data surveyed in 2016 in an Italian dairy farm. Each cow has been characterised in terms of her response to heat conditions, and the results led to define three classes of susceptibility to heat stress within the herd. These attributes have then been related to the various phenotypic parameters collected by the precision livestock farming devices used in the farm. The study provides a model to understand the effects of heat stress conditions on individual animals in relation to the main parameters describing their rearing conditions; moreover, the results contribute to improve the herd management by lending indications to define targeted treatments according to the cow's characteristics.

Keywords: precision livestock farming, temperature-humidity index, susceptibility, data analysis, milk yield

Implications

Heat stress represents a critical issue jeopardising animal welfare and productivity during the warm season in dairy cattle farms, and climate change is likely to sharpen these drawbacks. A numerical model was developed to understand the effects of heat stress conditions on individual animals. The results contribute to improve the herd management by lending indications to define targeted treatments according to cow's characteristics. In fact, the knowledge of the susceptibility to heat stress allows to identify the most problematic animals and thus to implement specific cooling strategies in order to mitigate their critical responses.

Introduction

The rise of the purchase of animal protein, the increase in the number of animals per farm (Barkema *et al.*, 2015), the need of reducing production costs, environmental impacts and use of antibiotics, despite the high number of zoonosis diseases, have fostered the increase of monitoring actions referred to animal welfare and health (Berckmans, 2017). Research institutions and companies of Information and Communication Technologies have developed several models and implemented manifold of devices to control and analyse ever more aspects of the animal life. For example, different precision livestock farming (**PLF**) tools have adopted by dairy cattle farms, where automatic milking and automatic feeding systems are ever more popular. Besides them, the indoor and outdoor climatic conditions, especially in terms of temperature, humidity and wind speed, represent another important issue within dairy livestock barns for PLF, in particular for farm building design and management. Heat stress is one of the hardest enemies for a dairy cattle farmer (Lessire *et al.*, 2015): heat waves have repercussions on cow's behaviour (Hillman *et al.*, 2005), milk production and quality (Bouraoui *et al.*, 2002) and conception rate (Hagiya *et al.*, 2017). The perfect habitat for a dairy cow is defined between −5°C and 22–25°C (Armstrong, 1994; Kadzere *et al.*, 2002),

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*This article has been amended since original publication. Throughout the article 'addictive' has been changed to 'additive'.

50% to 80% of relative humidity (Dragovich, 1979) and an adequate flow of air (CIGR Section II Working Group N 14 – Cattle Housing, 2014). These parameters are mainly summarised by the temperature-humidity index (**THI**), a widespread measure indicating the real authentic climatic impact perceived by the cows (Samal, 2013). Bonora *et al.* (2018) developed a computer procedure using automatic milking system (**AMS**)-generated data and temperature and humidity parameters surveyed from local sensor grids, designed to forecast milk yield trends depending on the expected environmental conditions.

Within these challenging research topics, the goal of this study is to develop a numerical model to describe the response of individual cows to the exposure at high THI conditions. In particular, the research aims to define an analytic relationship between milk production and climatic conditions for individual cows. Such a model appears usefully applicable for livestock building design and management with focus on production efficiency and quality, as well as animal welfare, as it allows to quantify the susceptibility of the animals to heat stress and consequently supports the identification of specific treatments (e.g. shading, ventilation and watering) to be implemented.

Material and methods

Study case

The methodology was developed and tested on a case study farm located in the municipality of Budrio, about 15 km north-east (**NE**) of Bologna. The barn had a 51-m long and 23-m wide rectangular plan layout, with south-west (**SW**)–NE-oriented longitudinal axis, ridge height of 8.52 m and gutter heights of 4.95 m on the NW side and 6.65 m on the SE side. It consisted of a hay storage area on the SE side, a resting area in the central part of the building and a feeding area with feed delivery lane on the NW side (Figure 1). The resting area, whose floor was partially slatted, hosted 78 cubicles with straw bedding where about 65 Friesian cows were housed; two blocks of head-to-head rows were located in its central part, and another row ran along the entire length of the resting area. Ventilation was controlled by three high volume low speed fans with five horizontal blades which were activated by a temperature-humidity sensor situated in the middle of the barn.

Lactating cows were fed with total mixed ratio kept available along the feeding lane. Cows were milked using an AMS 'Astronaut A3 Next' (Lely, Maassluis, The Netherlands) placed at the SW end of the animal housing area. The robot was programmed to assure a number of daily visits for each cow depending on her productivity and her expected optimal milk yield per visit, with a minimum of two and a maximum of four daily visits as constraints. Animals with less than two visits in a day were signalled by a warning, while the cows that have been milked four times in a day can only pass through the AMS box without being milked and fed. The milk room was located on the SW side of the building, next to the offices and technical plant rooms. The robot also managed the supplement feeding which is calculated based on daily milk yield and day of lactation: it linearly increased with time from 3 to 3.5 kg for each cow during the first 15 days in milk, and then it was proportional to milk yield with coefficient 0.157 kg/l up to the upper limit of 7.50 kg. Finally, during the last 14 days of the milking period, the supplementation decreases linearly with time up to the lower limit of 1.5 kg.

Table 1 *Statistics about the correlation (Bravais–Pearson) ρ between My and THI′ in the three groups of dairy cows*

Group	Cardinality	Avg *My* (l)	SD (*My*)	Avg ρ	SD (ρ)
Significant susceptibility	26	32.6	1.7	−0.38	0.21
Moderate susceptibility	22	31.7	1.9	−0.20	0.14
Poor susceptibility	27	33.1	2.3	0.01	0.20

Avg=average; *My*=daily milk yield.

Data collection and processing

The following data sources were used for the study:

1. AMS robot: after every milking event, it recorded data about milk quality and quantity, cow body mass and supplement feeding.
2. Temperature and humidity sensors: internal temperature, humidity and dew point were measured and recorded every 30 min in the farm by two PCE-HT71 stand-alone dataloggers, which had resolution of 0.2°C (temperature)/0.2% (humidity) and accuracy of 1°C (temperature)/3% (humidity). They were located in the central cubicle rows, at a height of 1 m from the ground;
3. Activity collar: Cows behaviour data were measured in 2 h blocks by means of Lely Qwes-H collar by SCR (Netanya, Israel) mounted for cow identification and activity sensor, which monitored activity levels (α) of each animal by means of an acceleration sensor measuring movement duration and intensity.

Based on the database collected through the AMS management software, a matrix named V (Visit) was created where each row corresponded to a cow passage and the columns contained the parameters listed in Supplementary Table S1.

In particular, *Sf* is the average of the supplementation with additional concentrates per milking event, while *dSf* is the daily amount of the supplementation. *Mr* represents the standard deviations (in hour) of the time interval between two following milking events, and it is calculated with the aim of monitoring the milking regularity of the animals: the greater the *Mr*, the lesser the milking regularity.

Activity data were downloaded also from the collars at each passage through the AMS robot and collected in a matrix named A (Activity), where each row contained the 2-h activity of each cow. Matrices V and A and the internal climate data were jointly processed.

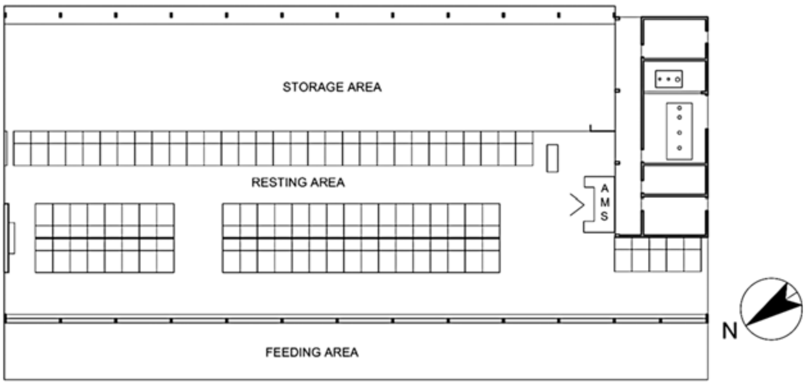

Figure 1 Plan layout of the dairy cattle barn. AMS=automatic milking system.

The dataset contained the values surveyed in summer 2016 (from 1 June to 12 September): a total of 75 cows were selected for this study, that is, the total number of cows with available data of the previous parameters. Temperature and relative humidity were combined into THI through equation (1) (Asabe, 1986):

$$\text{THI} = T_{db} + 0.36T_{dp} + 41.2 \tag{1}$$

where T_{db} represents the dry bulb temperature (°C) and T_{dp} the dew point temperature (°C).

The total heat produced by each animal through its metabolism was considered in discussing the results, as it could be one of the main factors affecting the susceptibility to heat stress. This variable, expressed in watt, was calculated at time t for each cow i by Landis equation (CIGR, 1984), as follows:

$$Thp(t)_i = 5.52\,Cb\,(t)_i + 23.4\,My(t)_i \tag{2}$$

where *Cb* represents cow's body mass (kg) and *My* is the daily milk yield in kg.

Generalised additive model

A generalised additive model (**GAM**) is a generalised linear model in which the linear predictor is given by a user-specified sum of smooth functions of the covariates plus a conventional parametric component of the linear predictor. The model considered in this study started from the GAM equation described by Yano *et al.* (2014) adding then random effects for intercept and THI guaranteeing a more robust fit. Equation (3) was applied for a dataset composed of all the cows in the barn in the study period in order to analyse the relationship between milk production and THI:

$$\ln(my(t)_i) = (\beta_0 + u_{i,1}) + (\beta_1 + u_{i,2}) \times THI'(t) + ls_1(Ld(t)_i) + fs_2(Sf(t)_i) + \varepsilon_{it} \tag{3}$$

where ln (.) is the mathematical natural logarithm; i represents a generic cow; t is the analysed day of the year; THI′(t) is the average of the THI between 12 and 18 of the day t. This time period was selected because it proved to be characterised by persistent thermos-hygrometric conditions causing heat stress for cows; s_1 and s_2 represent two thin-plate regression smoothing spline functions, in particular $s_1(Ld)$ represents the lactation spline, while $s_2(Sf)$ the feeding one; β_0 and β_1 are the fixed effects; $u_{i,1}$ and $u_{i,2}$ are the random effects; λ and ϕ represent the coefficient respectively of splines $s_1(Ld)$ and $s_2(Sf)$; ε represents the error term (residual).

The two splines and the mixed effects were estimated from the data using the GAM implemented in the package 'mgcv' of the open-source software R (R Core Team, 2017; Wood, 2017). In GAM the relationships between the independent variables and the dependent one are not linear, but they are described by regulated and nonparametric functions (Hastie *et al.*, 2009; James *et al.*, 2013). Therefore, it could be considered as a combination of a linear model and the 'black box' of the machine learning. Moreover, the cows varied in the slope and intercepts, and so the model required incorporating both fixed and random effects. This model allows to estimate the degree of smoothness of the terms as variances of the wiggly components of the smooth terms, which are treated as random effects. It is assumed that the random effects and correlation structures are employed primarily to model residual correlation in the data, and that the prime interest is in inference about the terms in the fixed effects model formula including the smooths (Wood, 2004). For this reason, the routine calculates a posterior covariance matrix for the coefficients of all the terms in the fixed effects formula, including the smooths, with a similar approach to that described in Lin and Zhang (1999).

A general spline for the lactation day and a general spline for the supplement feeding were computed based on the data collected for every considered cow with reference to her last lactation period. Supplementary Figure S1 and Supplementary Figure S2 show them, that is the trends of the milk production depending on the days of lactation and supplementary feeding respectively.

In the lactation spline (Supplementary Figure S1), it is possible to easily recognise the three different sections, already known in the literature (Macciotta *et al.*, 2005; Gasqui and Trommenschlager, 2017):

Table 2 *Average parity of the three groups of dairy cows in the study period*

Group	Mean	SD
Significant susceptibility	2.27	1.00
Moderate susceptibility	1.59	0.80
Poor susceptibility	1.67	0.83

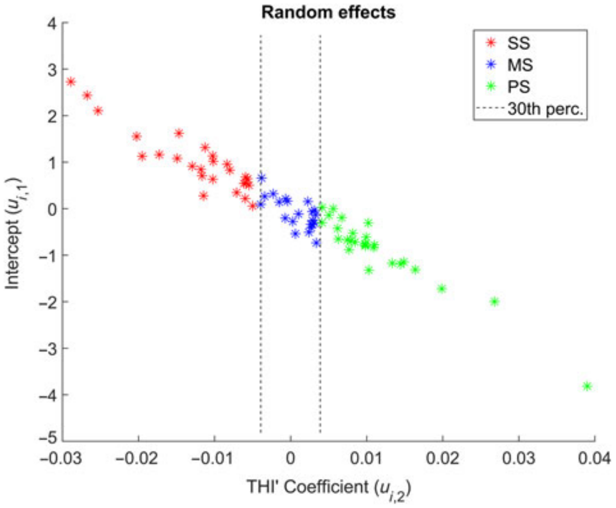

Figure 2 (Colour online) The plot shows the random effects ruling the relationship between milk production and heat stress conditions of dairy cows. Each star is referred to a single cow and it is green for the poorly susceptible (PS) ones, red for the significantly susceptible (SS) animals and blue for the moderately susceptible (MS) cows. Dashed lines represent respectively positive and negative 30th percentiles of $u_{i,2}$ from zero. THI' is the average of the temperature-humidity Index between 12 and 18.

1. First period, corresponding to the first 90 days of lactation. Here, on the one hand, there are the highest values of the milk production, on the other hand, there is a scarce capability of cow for what concerns the ingestion and the digestion, and so the farmer must pay much attention (even more than usual) to the feeding in order to avoid extreme weight losses.
2. Second period, 91 to 210 lactation days. In these days, the milk production is lower than in the previous phase and keeps on decreasing, while the cow rebalances its weight.
3. Third period, after day 210. It is the last phase before the dry period, when it is important to control welfare and feeding to avoid an excessive increase in weight.

The feed spline (Supplementary Figure S2) is clearly connected with the decisions of the farmer and the veterinary about the AMS feeding. In the analysed farm, it depends on the day of lactation and the daily milk production.

On the basis of the values of coefficients $u_{i,1}$ and $u_{i,2}$ calculated for every cow *i* through equation (3), the herd was firstly split into two categories: the cows with u_2 significantly less than zero, which were defined as animals with significant susceptibility (**SS**) to heat stress, and cows with u_2 significantly greater than zero, which were considered as animals apparently not affected by high THI, that is, poorly susceptible (**PS**) to heat stress. Moreover, a third group was defined, made of the cows with u_2 significantly close to 0 – that is, within the 30th percentile – which were identified as the cows with moderate susceptibility (**MS**) to heat stress.

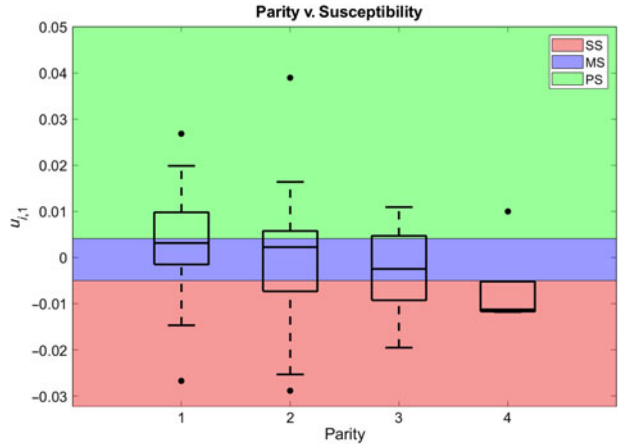

Figure 3 (Colour online) Boxplots of the distributions of susceptibility to heat stress in parity-homogeneous groups of dairy cows and representation of the three levels of susceptibility within such distributions. SS=significant susceptibility; MS=moderate susceptibility; PS=poor susceptibility.

Results

Average THI' over the study period was 80.1, with standard deviation of 3.1. The fixed effects were calculated for the herd through equation (3) and they are shown in Supplementary Table S2, while the values of the coefficients $u_{i,1}$ and $u_{i,2}$ for each cow *i* are plotted in Figure 2. A clear negative correlation index ($\rho = -0.96$) can be noticed between random effect of the intercept ($u_{i,1}$) and that of the slope ($u_{i,2}$), as proved by literature (Yano *et al.*, 2014). This represents a result of quality control test for the critical method proposed.

Moreover, the Bravais–Pearson coefficients between *My* and THI' for the three groups (Table 1) show that a negative correlation was found between milk production and THI' for SS cows, while this correlation is weak for MS cows and negligible for PS ones.

The relationships between milk production and THI' for SS and PS cows are exemplified by the cases reported in Supplementary Table S3, which represents the three SS cows and the three PS ones with the closest values of the mean ρ in their respective groups. The *z*-scored values of the two variables are plotted in Supplementary Figure S3.

Once the herd had been characterised in terms of susceptibility to heat stress, the distributions of every parameter of Supplementary Table S1 were analysed for the three groups of animals identified in Table 1 and the results are shown in Figure 3 and Supplementary Figure S4.

Table 3 *Comparison between the real and the expected median values of the daily milk production of the dairy cows*

Group	*RMy* (l)	*EMy* (l)	$\frac{RMy}{EMy}$ %
Significant susceptibility	31	41	76
Moderate susceptibility	32	37	86
Poor susceptibility	34	32	106

RMy=median value of real daily milk yield of the group; *EMy*=expected median daily milk yield of the group.

Table 4 *Comparison between the ratio between milk yield and daily supplement feeding (real and expected) of the dairy cows*

Group	*dSf* (kg)	$\eta = \frac{RMy}{dSf}$ (l/kg)	$\eta_E = \frac{EMy}{dSf}$ (l/kg)	$\eta - \eta_E$(l/kg)
Significant susceptibility	4.0	7.8	10.3	−2.5
Moderate susceptibility	4.3	7.4	8.6	−1.2
Poor susceptibility	4.3	7.9	7.4	+0.5

dSf=daily supplement feeding; *RMy*=median value of real daily milk yield of the group; *EMy*=expected median daily milk yield of the group.

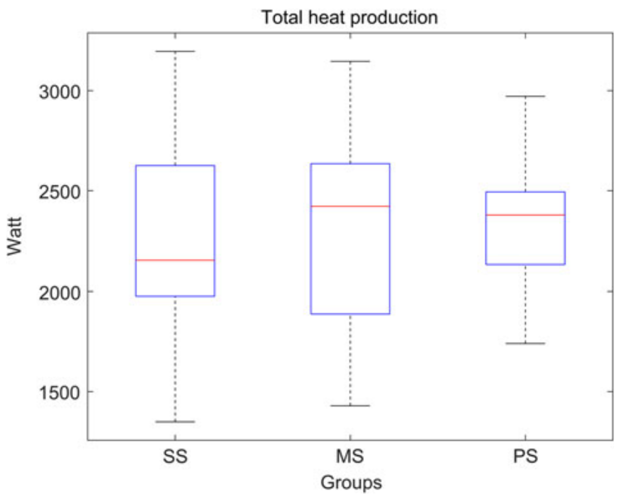

Figure 4 (Color online) Distributions of the total heat production (*Thp*) for the three susceptibility groups of dairy cows. SS=significant susceptibility; MS=moderate susceptibility; PS=poor susceptibility.

Discussion

The analyses highlight that the level of dependence of milk production upon THI in the herd under study is affected by parity (Table 2 and Figure 3). The significance of difference in parity among the groups was verified through the Kruskal–Wallis test with *P*-value equal to 1.93%. In particular, first-calf cows proved to be the less susceptible ones to heat stress: the older the cows get, the more susceptible they become. Therefore, heat stress has stronger effects on the oldest animals, thus confirming the results obtained in a previous study (Bernabucci *et al.*, 2014). Here, data collected from 2001 through 2007 from 484 Holstein cows farms were merged with meteorological ones from 35 weather stations: according to it, the cows with highest parity are more sensitive to heat stress than first-parity cows, for what concerns the production traits.

Supplementary Figure S4 highlights that the number of milking events per day significantly differs for the three levels of susceptibility. In particular, an SS entails fewer milking events than the rest of the herd, specifically about 0.5 events less than the MS group. At the same time, SS cows are clearly less regular in milking, with a standard deviation of inter-milking time that is on average about 1 h greater than the other two groups.

These two parameters are indicative of a worse production performance of SS cows, which is confirmed by the analysis of the milk production quantities and efficiency. First, the reference values of expected daily milk production of each group (*EMy*) were computed based on the median lactation curve of the herd, considering the median days of lactation of the group. In fact, the differences in days in milk among the three groups proved to be significant based on the results of the Kruskal–Wallis test, which provided a *P*-value equal to 3.8%. Then, *EMy* values were compared to the real median values of the three groups (*RMy*), whose distributions are reported in the boxplot of *My* in Supplementary Figure S4. The results of the comparison are reported in Table 3.

From this table, it is clear that SS group is effectively the most suffering of the herd as its production is only 76% of its potential. From the other side, MS cows' production is moderately affected by the heat stress, the real value being 86% of the expected one. Finally, PS cows proved to be the least susceptible animals, with milk yield greater than the rest of the herd, while it should be the smallest, according to the median lactation curve.

Then, a measure of the effectiveness of conversion of the concentrates was assessed: the ratios respectively of *RMy* and *EMy* to the median values of the daily supplement feeding *dSf* of each group were computed and the results are reported in Table 4, where also the differences between the real and the expected performances are provided.

The results show that, in the study case considered, one of the effects of heat stress on the most susceptible cows is a dramatic drop in production efficiency, which is 2.5 l/kg less than the potential. A moderate reduction of the performance affects MS cows, while the difference has a small positive value for the PS group. These results thus suggest that supplemental feeding strategies could be rethought in the studied farm, taking also into account THI and considering that a high THI leads to a drop of profitability of this investment for SS cows.

The analysis indicated also that one of the main factors affecting the susceptibility to heat stress could be the total heat produced by each animal through its metabolism (*Thp*). The distributions of *Thp*, computed according to equation (2), are shown in Figure 4, from which no particular difference appears among the three susceptibility groups.

Differently from the previous studies (Herbut and Angrecka, 2018) where the general herd behaviour in three summer months was analysed in terms of average parameters aggregating the features of every animal, this procedure allows to group the animals according to their different susceptibility to the heat stress and then to lead specific analysis on the subgroups through an user-friendly approach, completely using the information available from all the devices installed in the farm. It is a process that permits to take a 'picture' of the conditions of the herd in the summertime, and to pay particular attention to the different susceptibility levels within it, thus activating measures to help the most suffering animals.

This analysis represents the basis to develop a software tool that can contribute to improve the management of the herd, identifying the cows likely to be the most suffering in order to implement some specific actions for these animals in terms of cooling treatments, enhancement of the feeding strategies and in attention to their specific welfare conditions. Moreover, the procedure could be implemented and tested in any farm, as it is totally independent from the selected case study, although the results are expected to be dependent on the specific features of each farm, which can be significantly different in terms of genotypes, climate, feeding strategies, structures and equipment.

Conclusions

A GAM analysis method was defined for the application to datasets collected by AMSs and related devices, containing the time series of the main parameters recorded for each cow, as well as data collected about dairy barn microclimatic conditions. This numerical approach was developed in order to study the consequences of the heat stress in dairy farm. The model was tested in summertime in an Italian farm. The generalised additive model with mixed effects proved suitable to characterise each cow in terms of the repercussions of critical THI conditions on milk production. The results of the application carried out in this study are dependent on the herd characteristics, while the model can be considered as generally applicable and thus useful for farmers, once it has been implemented in commercial software. Further tests of the model on a wide pool of farms are planned in the development of the research, and they are expected to provide results with a more general validity about the performances of groups of cows with different susceptibility to heat stress.

The results can lend support to cow monitoring specially in periods when heat waves affect cow behaviour and production, and to herd management. In fact, a proper herd partitioning based on the susceptibility to heat stress allows to identify the most problematic animals and so to implement specific cooling strategies in order to mitigate their critical responses.

Further developments of the research – currently ongoing – firstly consist in applying the model to a number of farms in different geographic contexts and under different climatic and farming conditions to refine the calibration. Moreover, the introduction of new devices and variables connected to the milk production and cow welfare in future study cases could enrich the characterisation of critical cows.

Further insights also include the monitoring of the trends and the values of the animals in the SS group and the 'pre' and 'post' analysis of new management actions. As mentioned before, the testing of different strategies on a small subgroup of these animals could be useful to identify a new approach to improve the prospects for wellness of the significantly susceptible cows. Finally, the developments of the research focus also on the implications of the climatic conditions for innovations in the definition of spatial layout, thermo-hygrometric control strategies and cooling systems, with expected benefits for the design of dairy barns.

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Declaration of interest

None of the authors has a conflict of interest.

Ethics statement

This manuscript conforms to the Ethical Policy of the Journal.

Software and data repository resources

None of the data were deposited in an official repository. The model was not deposited in an official repository.

Supplementary material

To view supplementary material for this article, please visit https://doi.org/10.1017/S1751731119001721

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