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A system dynamics approach to model heat stress accumulation in dairy cows during a heatwave event

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ABSTRACT

Climate change is expected to increase the number of heat wave events, leading to prolonged exposures to severe heat stress (**HS**) and the corresponding adverse effects on dairy cattle productivity. Modelling dairy cattle productivity under HS conditions is complicated because it requires comprehending the complexity, non-linearity, dynamicity, and delays in animal response. In this paper, we applied the System Dynamics methodology to understand the dynamics of animal response and system delays of observed milk yield (**MY**) in dairy cows under HS. Data on MY and temperature-humidity index were collected from a dairy cattle farm. Model development involved: (i) articulation of the problem, identification of the feedback mechanisms, and development of the dynamic hypothesis through a causal loop diagram; (ii) formulation of the quantitative model through a stock-and-flow structure; (iii) calibration of the model parameters; and (iv) analysis of results for individual cows. The model was successively evaluated with 20 cows in the case study farm, and the relevant parameters of their HS response were quantified with calibration. According to the evaluation of the results, the proposed model structure was able to capture the effect of HS for 11 cows with high accuracy with mean absolute percent error <5%, concordance correlation coefficient >0.6, and R^2 > 0.6, except for two cows (ID #13 and #20) with R^2 less than 0.6, implying that the rest of the nine animals do not exhibit heat-sensitive behaviour for the defined parameter space. The presented HS model considered non-linear feedback mechanisms as an attempt to help farmers and decision makers quantify the animal response to HS, predict MY under HS conditions, and distinguish the heat-sensitive cows from heat-tolerant cows at the farm level.

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Implications

The presented model consists of a fundamental dynamic structure to predict cow response to heat stress. It has a simple heat stress model that considers non-linear feedback mechanisms as an attempt to help farmers and decision makers to quantify the animal response to heat stress, predict milk yield under heat stress conditions, and distinguish the heat-sensitive cows from heat-tolerant cows at the farm level. The model can be further developed to include a complete energy balance and thermodynamics. It represents a minimal structure approach to present an explicit model, not based on black box assumptions, to dynamically describe the cow's heat stress requirements.

Introduction

A global climate change is likely to increase the average temperature and the likelihood of extreme events (IPCC, 2021), such as heat waves (**HWs**), that could impact the livestock sector in terms of production, product quality, and food safety (Rojas-Downing et al., 2017). An animal is considered under heat stress (**HS**) when it cannot dissipate enough heat produced by metabolism and fermentations to maintain homeothermy, and the effective air temperature exceeds the range defining the thermoneutral zone (Bernabucci et al., 2014) within which the animal produces the most with the least energy cost (Johnson, 1987). As homeotherms, cattle exposed to HS tend to maintain constant body temperature by adopting compensatory mechanisms to achieve heat balance (Kibler and Brody, 1953). Animals produce heat from maintenance, digestion, and production (Coppock, 1985). The maintenance requirements of cows increase under HS conditions; hence, they reduce feed intake to reduce energy intake and dissipation, and

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thus, milk production decreases (Sejian et al., 2018). Increasing the respiratory rate, sweating, and peripheral vasodilation are the leading behavioural and physiological mechanisms to increase heat dissipation (Sejian et al., 2018). However, the maximum decrease in DM intake (**DMI**) and losses in milk yield (**MY**) have a delay, occurring a few days after exposure to heat and not on the same day (Spiers et al., 2004), probably due to heat accumulation. The occurrence of HW usually results in or exacerbates HS (Fig. 1) in livestock animals, particularly in high-producing cows. As reported earlier, HWs are expected to occur more frequently; therefore, their effects on the livestock sector have become the subject of investigation in several thermal stress studies (Vitali et al., 2015; Poppe et al., 2021; Maggiolino et al., 2022). There are multiple definitions of HW in the literature regarding their duration, intensity, frequency, and depending on climatic parameters (Founda et al., 2022). However, they are commonly reported as a prolonged period of excessive heat (Perkins and Alexander, 2013), even if no specific models are trying to characterise animals concerning their response to heat stress.

Feeding systems have been predominantly developed through mechanistic and empirical models (Tedeschi et al., 2005; Tedeschi, 2019 and 2022), with some limited information to model HS. In their review, Ji et al. (2020) reported that several mathematical models have been developed to predict the effects of HS in animals. The first and most widely used meteorological quantity to estimate HS is the temperature-humidity index (**THI**), which has been associated to threshold levels of intensity of HS (Kibler, 1964). Gaughan et al. (2008) developed the heat load index incorporating black globe temperatures, relative humidity, and wind speed, using two multiple regression models developed based on the painting score. The panting score was also used to adjust maintenance requirements in the Cornell Net Carbohydrate and Protein System. The effects of weather variables and two different THI indices on cow milk production and composition were analysed with a series of separate linear mixed models (Hill and Wall, 2015). Lees et al. (2018) used a non-linear regression model to develop the dairy heat load index that combines environmental effects and the animal physiological response, i.e., the painting score. Benni et al. (2020) used a generalised additive model to analyse the relationship between environment, milk production, and cow behaviour. Despite these empirical models published in the literature for estimating HS, there seems to be insufficient data for accurate data-driven modelling of maintenance requirements under HS conditions for beef (National Academies of Sciences, Engineering, and Medicine – NASEM, 2016) and dairy (NASEM, 2021), as well as for small ruminants (National Research Council – NRC, 2007). In addition, empirical models are inadequate to describe the phenomenon and account for the complex elements that dynamically contribute to heat stress.

Modelling the animal response under HS conditions is a challenge because it includes several properties of complex systems: it is a typical complex dynamic problem that can be observed on a day-to-day basis, and the interaction of variables results in their change over time; it includes feedback loops due to the endogenous animal ability to regulate heat flows; it is non-linear since the accumulation of HS significantly changes the animal response and the cause-effect relations between variables are not proportional; there are important biological and physiological time delays, which lead to the time lag of reduced animal performance compared with heat exposure. Thus, the impact of HS on animal response can be identified as a complex problem. The HS problem requires complex system approaches, such as System Dynamics methodology (Sterman, 2000; Tedeschi, 2023), for a complete understanding of the intricacies of heat fluxes in an animal under HS and for quantification of the parameters that regulate animal response. It allows the development of explicit models, avoiding black box models in physiological-related phenomena and processes. However, considering the availability of farm outputs under HS conditions instead, the animal response should be considered as starting point, and consequently, an inverse modelling problem approach could be carried out in the problem definition (Vargas-Villamil et al., 2020; Tedeschi, 2019).

This work aimed to apply System Dynamics methodology to (i) develop an explicit model able to capture the dynamic phenomena and system delays that fit observed MY in dairy cows under HS, and (ii) present an initial attempt to estimate the system delays characterising the cow response to HS needed to parameterise the model and discriminate among cow tolerant and not-tolerant to HS.

Material and methods

Description of the case study

Farm description

The data used in the study were collected from a dairy cattle farm located in Arborea, Sardinia, Italy (39°46′26″40N, 08°34′53″04E), in a lowland area near the sea devoted to dairy production in intensively managed farms. The farm was equipped with three automatic milking systems (DeLaval International AB, Model VMS Classic, Tumba, Sweden) and a cooling system consisting of seven fans and sprinklers on the feeding line and five

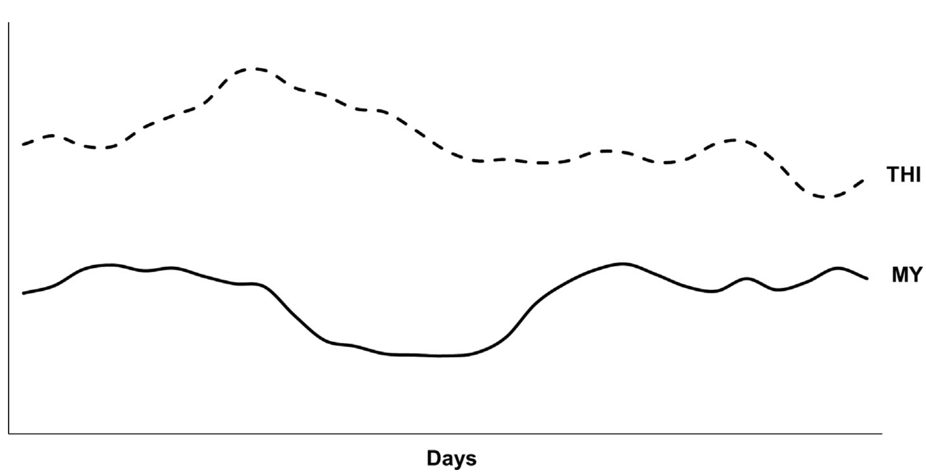

Fig. 1. Example response of highly productive cow to a heat wave. Abbreviations: THI = temperature-humidity index, MY = milk yield.

horizontal fans on the resting area. Data were collected in August 2021. During the study period, the mean and SD of cows in lactation and days in milk (**DIM**) were 157.8 ± 1.7 and 202.3 ± 3.2, respectively. On the farm, the total mixed ration used during the study period, expressed as kg of feed as fed per cow, included the following ingredients: 18 kg of ryegrass silage, 4 kg of alfalfa silage, 2 kg of alfalfa hay, 0.8 kg of straw, 3 kg of soybean meal, 8 kg of corn meal, 0.1 kg of calcium carbonate, 0.07 kg of fat. The total mixed ration was prepared and fed along the feeding line once a day at 07:00 a.m. In addition, a daily average of 4.5 kg of concentrate feed was fed directly into the automatic milking system feeding bunk during milking. The Large Ruminant Nutrition System software (version 1.2.2; https://www.nutritionmodels.com) was used to estimate the metabolisable energy (**ME**) and net energy (**NEl**) of the diet used, and thus to calculate the feed efficiency and energy conversion ratios (Fox et al., 2004; Tedeschi and Fox, 2020).

Data collection

The DelPro™ software (DeLaval International AB, v4.5, Tumba, Sweden) was used to create a daily report for each cow, containing information on MY, lactation number, DIM, number of milking and reproductive status (open, inseminated, and pregnant).

A weather station (PCE Italia s.r.l., PCE-FWS 20 N, Lucca, Italy) has been installed inside the barn, two meters above ground level, for hourly measurements of air temperature (°C) and relative humidity (%). The data on air temperature and relative humidity were loaded into management software (Ecostalla, Drop s.r.l., Arborea, Italy) for the automatic calculation of THI in °F (Kibler, 1964).

Fig. 2 shows the distribution of average THI and MY at the farm level for 28 days (3 Aug 2021–31 Aug 2021). The THI began to increase on 7 Aug 2021, reaching the maximum peak on 11 Aug 2021 and then returning to the pre-increase values on 16 Aug 2021. The dates of 9 Aug 2021 and 16 Aug 2021 were used to identify three different periods. The first period, from 3 to 8 Aug 2021, includes the days until the start of the HW, which was supposed that the cows could still dissipate the heat. The second period, from 9 to 16 Aug 2021, includes the days with the highest temperatures and the milk losses. Although the maximum peak of THI was recorded on 11 Aug 2021, the decline in milk is visible (Fig. 2) from 9 Aug 2021, the date chosen for the start of HW. During the same period, the maximum loss of MY was recorded on August 14, 2021. The third period, from 17 to 31 Aug 2021, includes the days with the temperatures close to the ones before the increase. The descriptive statistics of THI and MY per cow in the three periods are listed in Table 1. The minimum, maximum, mean, and SD of THI were 65.0, 82.9, 75.4 ± 4.0 °F for the first period, 67.5, 87.7, 78.6 ± 4.2 °F for the second period, and 62.9, 80.8, 73.0 ± 3.8 °F for the third period. While the minimum, maximum, mean, and SD of MY were 35.3, 36.3, 35.9 ± 0.4 kg/day per cow for the first period, 32.7, 35.6, 33.6 ± 1.1 kg/day per cow for the second period, and 33.2, 36.7, 35.4 ± 0.9 kg/day per cow for the third period.

Model development

Model building paradigm

Among the many different paradigms available for building mathematical models (Tedeschi, 2019 and 2023), System Dynamics is one of the well-established methodologies for understanding the structure that causes the behaviour of complex systems (Barlas, 2007). The System Dynamics approach is based on the developed theory of non-linear dynamics and feedback control (Sterman, 2000).

Among the modelling processes usually adopted with the System Dynamics methodology (Sterman, 2000), we present the first three steps in this paper: (I) problem articulation, which is the dynamic characterisation of the problem through a reference mode consisting of the most relevant data that can describe the behaviour of the problem over time (Sterman, 2000); (II) dynamic hypothesis formulation, that explains the dynamics of the problem with an endogenous theory based on feedback loops, i.e., sequences of variables and causal links that create a closed ring of causal influences (Sterman, 2000; Ford, 2019); (III) simulation

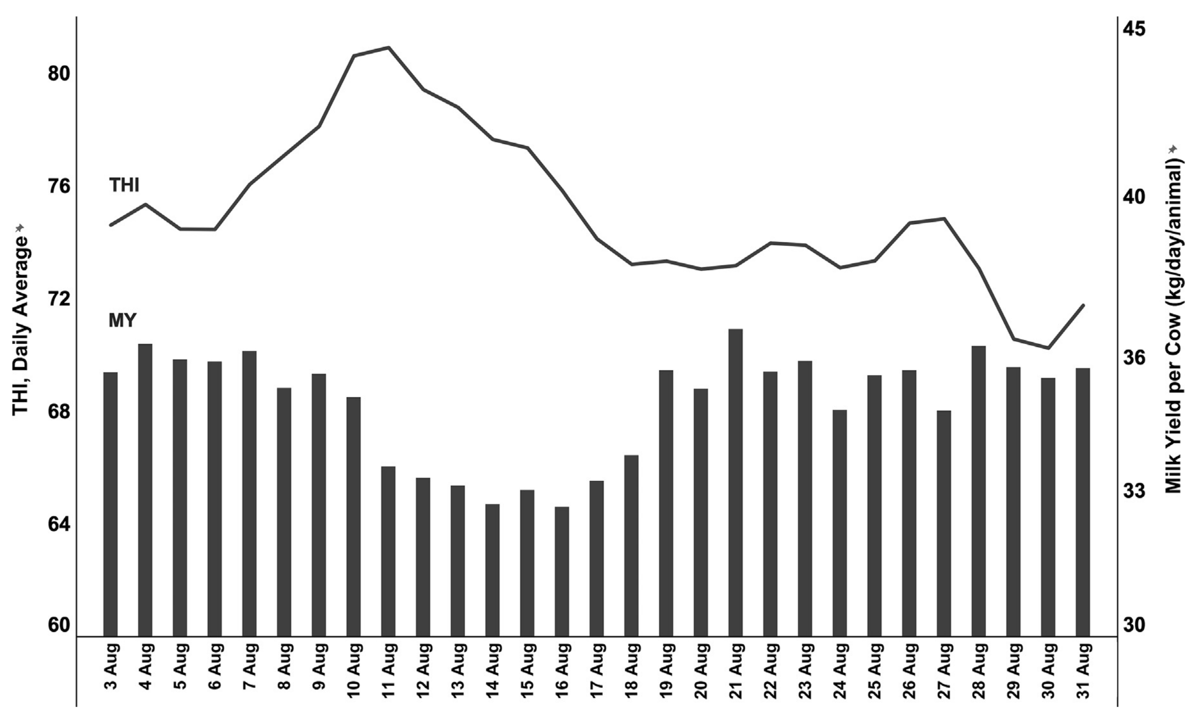

Fig. 2. Average of reported temperature-humidity index (THI) values and milk yield (MY) data from the studied Holstein dairy cattle farm, August 2021.

Table 1
Minimum, maximum, mean and SD of temperature-humidity index (THI) and milk yield (MY), at dairy cattle farm level, in the three periods considered in the study.

Variables	Minimum	Maximum	Mean	SD
3–8 Aug 2021				
THI (°F)	65.0	82.9	75.4	4.0
MY per cow (kg/day)	35.3	36.3	35.9	0.4
9–16 Aug 2021				
THI (°F)	67.5	87.7	78.6	4.2
MY per cow (kg/day)	32.7	35.6	33.6	1.1
17–31 Aug 2021				
THI (°F)	62.9	80.8	73.0	3.8
MY per cow (kg/day)	33.2	36.7	35.4	0.9

Abbreviations: THI = temperature-humidity index; MY = milk yield.

model formulation, to create a specified formal (quantitative) model describing feedback mechanisms with differential equations, parameters, and initial conditions (Sterman, 2000).

Problem articulation and dynamic hypothesis

The identification of the problem began with the observation of production performance trends during a heat wave. Specifically, it was by observing data trends, to be used as reference mode in MY and THI during August 2021. It was noted that following the exposure to a prolonged period of excessive heat, MY was characterised by two phases: (I) milk reduction and (II) milk recovery. The maximum loss in MY was observed to occur five days after the start of a HW and three days after the maximum peak of THI, as occurs when there are time delays between cause and effect in complex non-linear problems. The delay in the animal response would indicate the heat accumulation in the cow's body with insufficient effectiveness of dissipation mechanisms and prolonged exposure to high temperature.

The dynamic hypothesis was developed to provide explanations regarding the dynamic behaviour of the HS problem (Sterman, 2000). In line with the observations during the problem definition, we developed our dynamic hypothesis about heat flows in a dairy cow using the furnace analogy described in Wright and Meadows (2008). In order to describe the cause-and-effect linkages (Ford, 2019), the furnace example was graphically represented, as shown in Fig. 3a, using causal loop diagrams (**CLDs**), which are system maps connecting variables by arrows, making it easy to identify the feedbacks governing the system (Ford, 2019).

In the example given by Wright and Meadows (2008), the heating of a room is regulated by two feedback loops. Feedback loops are characterised by a positive (+) or negative (−) sign indicating whether a loop is reinforcing (positive) or balancing (negative). The algebraic product of the signs around the loops determines their polarity (Ford, 2019). In the first balancing feedback loop (B1), the room temperature increases with the furnace's heat, which is determined by the discrepancy between the desired and actual room temperature. The latter variable is regulated by both the room temperature and the thermostat setting. The thermostat is set at a specific temperature, and whenever the room temperature falls below that temperature, a gap is created that the heating system tends to cover to return to the ideal temperature. While feedback loop B1 explains the heat input mechanism, the second balancing feedback loop (B2) explains the cooling mechanism as an analogy to heat dissipation. As shown in feedback loop B2, the room temperature also depends on the heat to outside, which is triggered by the discrepancy between inside and outside

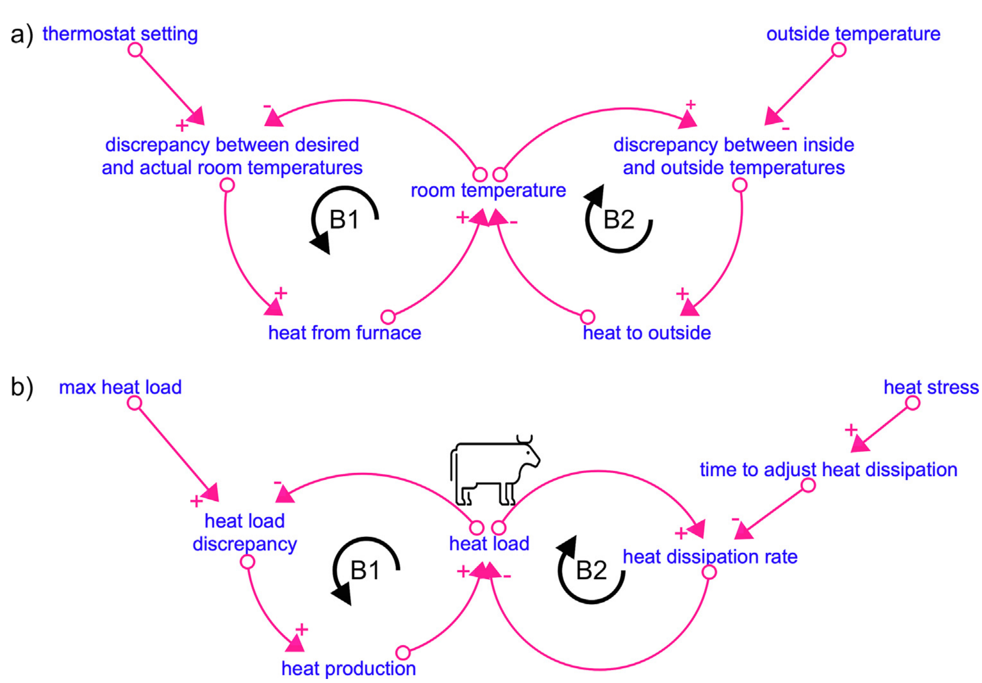

Fig. 3. Causal loop diagrams (CLDs): (a) for a furnace system with first balancing loop (B1) that regulates the inflow (B1) and second balancing loop (B2) the outflow of heat in a room (Source: Wright and Meadows, 2008); (b) of dairy cattle Heat Stress model.

temperatures. In this case, the discrepancy is the gap between the room and outside temperatures. Analogically, Fig. 3b depicts our CLD for the HS model we propose, which is governed by two balancing feedback loops similar to those by Wright and Meadows (2008).

The first balancing feedback loop (B1) generates a goal-seeking behaviour, and it is the one that governs heat production. Heat load increases with heat production depending on the heat load discrepancy. Similar to the furnace example, the discrepancy here is the difference between the max heat load and the heat load. The heat stored in the body stems from the heat for maintenance and milk production, growth, and pregnancy, depending on the physiological stage of the animal. As an example, a 48.5 and 27.3% increase in heat produced, respectively, was reported in high and medium milk-producing cows compared to dry cows (Purwanto et al., 1990). Therefore, it is assumed that the animal produces heat and has the capacity to store it up to a maximum limit (i.e., max heat load), above which it has to find a way to reduce body heat load. Under thermoneutral conditions, the actual heat load never reaches the maximum limit, creating an ideal discrepancy that the animal system tends to cover by continuing to produce internal heat. It is, therefore, a classical feedback (asymptotic regrowth basic pattern) loop in that the heat load determines the magnitude of the discrepancy that influences the production of heat that accumulates in the cow's body as heat load. Similarly, in the furnace example, if the room temperature exceeds the limit set by the thermostat, the heating system would automatically shut down (Wright and Meadows, 2008). Instead, in our case, the cows cannot stop producing heat, and should they exceed their own maximum limit, they would go into hyperthermia to the point of death in the most severe cases.

The second feedback loop shown in the CLD in the HS model, characterised by an exponential decay behaviour, has some differences compared to the one in the furnace model. In this case, the heat load again depends on the heat dissipation rate, governed by the accumulated heat load and the time to adjust heat dissipation. The time required to adjust heat dissipation is affected by heat stress. Just as a low-insulated room tends to dissipate its heat to the outside, the cow, as a homeothermic animal, also tends to dissipate the heat it produces to keep the body temperature constant. Under thermoneutral conditions, the heat load is nearly constant, and the cow can dissipate the heat produced adequately. However, heat dissipation is not immediate. The time required for heat dissipation depends on several factors, such as the cow's body's surface-to-volume ratio and the temperature gradient between the animal and the environment. In addition, the heat loss rate depends on the environment's ability to accept the heat lost by the animal through radiation, conduction, convection, and evaporation (Finch, 1986). In fact, an environment with elevated temperature and humidity hinders the absorption of the heat released by the animal. In this model, the inflow represents the internal heat production, whereas the outflow conceptually aggregates the net dissipation effort and the cow interaction with the environment.

During a HW, prolonged exposure to HS reduces the efficiency of dissipation mechanisms. Under this condition, the maintenance energy requirements for thermoregulation and the time required to dissipate heat increase considerably.

Mathematical model formulation

In the third model-building step, a formal, quantitative System Dynamics simulation model was developed based on the mental models (i.e., CLD) elaborated in the dynamic hypothesis formulation step. In mathematical terms, "the basic structure of a formal System Dynamics computer simulation model is a system of coupled, non-linear, first-order differential (or integral) equations" (Richardson, 2020). In System Dynamics modelling, graphical annotation is widely used, especially to visualise the critical feedback loops about the problem in focus. In this graphical annotation, each icon, such as stocks, flows, auxiliaries, clouds, and causal links, represents a specific system element (Richmond, 2001). Stocks, whose icon is a rectangle, represent accumulation at a given time and characterise the system's state (Sterman, 2000; Richmond, 2001). Flows, on the other hand, represent the actions and rates that change the stock (Richmond, 2001). Graphically, they are represented by pipes and arrows that point into the stock in the case of inflow and point out the stock in the case of outflow. Auxiliary variables are generally represented by circles and are intermediate variables to facilitate the expression of functional dependency of flows to stocks (Ford, 2019). Clouds represent the source from which a flow originates and the sink into which the flow drains, and which originate and leave the model outside its boundary (Sterman, 2000). Causal links between the variables describe the relationships between them with the direction of causality (from cause variable to impacted variable) (Ford, 2019).

As discussed in the dynamic hypothesis formulation, a system structure of two interacting balancing feedback loops drives this pattern. Following the annotation principles of System Dynamics, a stock-and-flow diagram with one stock and two flows was developed with two loops (Fig. 4) an exponential decay and an explicit goal-seeking feedback loop, mimicking a furnace structure (Wright and Meadows, 2008). The system studied here resembles a common system archetype known as Eroding Goals (Senge, 1990). A 'system archetype' is a common structure that produces characteristic system behaviour (Wright and Meadows, 2008). Among those, the Eroding Goals archetype consists of two balancing feedback loops and is used to explain the phenomenon of gradually lowering goals to close the gap between desired and actual performance. The HS CLD (Fig. 4) has also two balancing feedback loops as in Eroding Goals, but the structure of the goal is different in the HS case. In the original archetype, both the Desired Goal and the Gap are regulated endogenously, whereas HS CLD has an exogenous goal (max heat load) and an external effect (heat stress) to regulate the endogenous heat discrepancy (i.e., gap) and heat load.

The structure and working principles of the model can be summarised as follows (Fig. 4): (1) depending on the THI value and the corresponding heat stress occurrences, the heat dissipation rate of the animal is adjusted; (2) as the heat dissipation rate of the animal slows down (or speeds up), the accumulation in Heat Load increases (or decreases); and (3) with the increasing (or decreasing) Heat Load level, the heat production rate requirement of the animal decreases (or increases), which directly impacts DMI and consequently the milk yield performance of the animal.

The structure and working principles summarised above were built with Stella Architect (ISEE Systems, v3.1.3, Lebanon, NH, United States). The time unit of the model is set to days with a delta time step (dt) of 1/4 days, allowing a sufficient, limited time step to apply the Euler method for integral calculation and catching the oscillatory patterns of the system. The complete stock-and-flow diagram of the model is provided in the Supplementary Material Fig. S1. The model consists of 24 variables: 1 stock variable, 2 flow variables, and 21 auxiliary variables (8 are equations, 2 are graphical functions, and 11 are parameters). The list of all variables, types and units of the model is presented in Table S1 of the Supplementary Material. A simplified version of the model is depicted in Fig. 4, and the key equations in the model are as follows:

Heat Load (Mcal), the critical stock variable, increases through the inflow of heat production rate (Mcal/day) and decreases through the outflow of heat dissipation rate (Mcal/day) (Eq. (1)). The starting value of Heat Load stock is determined by initial heat load (Mcal) parameter for each cow (Eq. (2)).

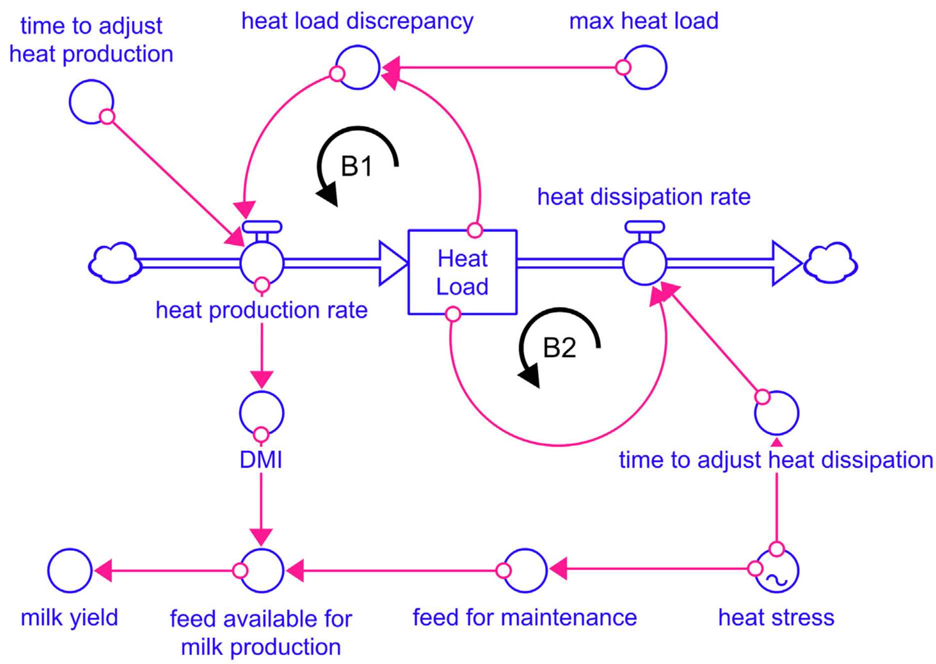

Fig. 4. A simplified stock-and-flow diagram of the heat load model for a Holstein dairy cow. Abbreviations: DMI = DM intake.

$$\text{Heat Load }(t) = \text{Heat Load }(t - dt) + (\text{heat production rate} - \text{heat dissipation rate}) * dt \quad (1)$$

$$\text{Heat Load }(t_0) = \text{initial heat load} \quad (2)$$

The inflow variable heat production rate (Mcal/day) (Eq. (3)) depends on the response time of the animal's metabolism for adjusting its heat production, time to adjust heat production (d) parameter, and heat load discrepancy (Mcal), which represents the gap between the max heat load (Mcal) that the animal's metabolism tends to attain and the current Heat Load level (Eq. (4)). It is assumed that both max heat load and time to adjust heat production parameters may vary depending on the genetic characteristics of the animal, hence may be different from one animal to another.

$$\text{heat production rate} = \text{heat load discrepancy} / \text{time to adjust heat production} \quad (3)$$

$$\text{heat load discrepancy} = \text{max heat load} - \text{Heat Load} \quad (4)$$

The outflow variable, heat dissipation rate (Mcal/day), is determined by the accumulated Heat Load and the response time of the animal's metabolism for adjusting its heat dissipation, time to adjust heat dissipation (d) variable (Eq. (5)). The increasing (decreasing) HS level is expected to increase (decrease) the time required to adjust the heat dissipation, and to decrease (increase) heat dissipation rate. Consequently, this variable is defined based on the animal's expected normal time to adjust heat dissipation without stress (days) plus the additional time to adjust heat dissipation (days) at the corresponding heat stress level (Eq. (6)). Heat stress is quantified as an increasing function of THI (Eq. (7)).

$$\text{heat dissipation rate} = \text{Heat Load} / \text{time to adjust heat dissipation} \quad (5)$$

$$\text{time to adjust heat dissipation} = \text{time to adjust heat dissipation without stress} + \text{heat stress} * \text{additional time to adjust heat dissipation with heat stress} \quad (6)$$

$$\text{heat stress} = f_{+}(\text{THI}) \quad (7)$$

Because the primary source of heat production is the feed intake, DMI (kg/day) is defined as a function of heat production rate (Eq. (8)) following inverse modelling principles and using heat produced per DMI (Mcal/kg) derived from ration analysis. In case of increasing HS conditions, feed requirements for maintenance (kg/day) are expected to increase (Eq. (9)) and hence feed available for milk production (kg/day) decreases, eventually decreasing the milk yield (kg/day) (Eq. (10)).

$$\text{DMI} = \text{heat production rate} / \text{heat produced per DMI} \quad (8)$$

$$\text{feed for maintenance} = f_{+}\ (\text{heat stress}) \quad (9)$$

$$\text{milk yield} = f_{+}(\text{feed available for milk production}) = f_{+}(\text{DMI} - \text{feed for maintenance}) \quad (10)$$

Model parameters and calibration

The key exogenous variables of the model are max heat load, THI, time to adjust heat production, time to adjust heat dissipation without heat stress, and the key endogenous variables are heat dissipation and heat production rates, and milk yield. Among the exogenous model parameters provided in the model, three parameters are assumed to be constant and similar for each cow and calculated based on the available literature. The parameter thermoneutral feed for maintenance was obtained from the following equation for calculating DMI in lactating cows reported by NRC (2001): DMI (kg/day) = (0.372 × FCM + 0.0968 × $BW^{0.75}$). Where FCM = 4% fat-corrected milk (kg/day), and BW (kg). The DMI value of 12.46 kg/day for maintenance was derived assuming an FCM equal to zero and an average BW of 650 kg. For the calculation of the parameter, Milk production per DMI (available for milk), the following equation, based on the one reported before (NRC, 2001), was used: Milk production per DMI (available for milk) = 1/(0.372 x FCM). The constant value used in the model was obtained by assuming 1 kg/day of FCM. The third parameter corresponds to the NEl for maintenance, obtained from analysis of the ration used on the farm during the study period, which in our model is reported as heat produced per DMI, equal to 1.67 Mcal/kg DM. The same analysis estimated that the ME for maintenance was 2.59 Mcal/kg DM. From the ratio of NEl to ME, the conversion coefficient of ME to NEl is 0.64, confirming that reported by the NRC (2001).

Formulation of the calibration problem

For the application and calibration, 20 cows were selected based on the following criteria. The selection criteria were DIM and reproductive status. Specifically, only cows with a DIM between 70 and 220 days and were pregnant during the study period were selected. Therefore, fresh cows or cows close to the dry period were not considered for calibration to avoid production performance being mainly influenced by the stage of lactation. The MY characteristics of the 20 selected cows are provided in Table 2.

The other eight parameters, which are listed below with upper and lower bounds, are assumed to vary for each individual cow depending on their genetics and other individual characteristics. Hence, for the rest of the parameters, a parameter calibration problem was solved for each cow. The objective function of the parameter calibration problem is set as "minimising the sum of squared errors" between the model generated and the observed (yet smoothed) value of milk yield over the time horizon of the model, T, where t below represents the timestamp of both the historical data point and the model-generated value.

$$\text{Sum of squared errors} = \sum_{t=0}^{t=T} (\text{milk yield}_{\text{model-generated},t} - \text{milk yield}_{\text{data,smoothed},t})2$$

subject to:

0.1 < time to adjust heat dissipation without heat stress (Days) < 2.
0.1 < additional time to adjust heat dissipation with heat stress (Days) < 2.
0.1 < time to adjust heat production (Days) < 2.
0 < additional feed for maintenance (kg/day) < 3.
13.5 < max heat load (Mcal) < 63.3.
13.5 < initial heat load (Mcal) < 22.5.
1 < THI smoothing coefficient (Days) < 8.
1 < milk yield smoothing coefficient (Days) < 8.
all equations of the model.

The parameter limits were intentionally kept wider than those found in the literature to allow the model to move with a large degree of freedom. A range of 0.1 to 2 days was chosen (Table 3) for the parameters "time to adjust heat dissipation without heat stress", "time to adjust heat dissipation with heat stress" and "time to adjust heat production" based on the results obtained by Kennedy and Kuhla (2022). In their study, Kennedy and Kuhla (2022) observed that at different stages of lactation during the 24 h fasting period with ad libitum feeding, the trend of heat production followed the same pattern of progressive decrease. Instead, the bounds for the parameter "additional feed for maintenance" were calculated from the equations for estimating the DMI (Fox et al., 2004) and the farm data. The DMI was calculated for a no-HW situation (July 2021) and for the HW condition (August 2021) considered in this paper. The difference in DMI between the two periods was 2.04 kg/day. This value was taken as a reference for the upper limit, which was set at 3 kg/day (Table 3) for the abovementioned reasons. The reference values for the parameters "max heat load" and "initial heat load" were taken from the study by Zimbelman et al. (2010). The work reported stored heat values of 18 073 and 18 223 Mcal for a thermoneutral and a heat stress condition, respectively. Specifically, the reference value of 18.073 Mcal was used to calculate the lower limit of both parameters and the upper limit of the "initial heat load" parameter by subtracting and adding 25%, respectively (Table 3). At the same time, the reference value of 18,223 Mcal was used to derive the upper limit of the "max heat load" parameter by adding 250% in order to allow the model to consider a broad range of variation in heat load that could originate from genetic, physiological, or environmental factors (Table 3). The limits of the "THI smoothing coefficient" and "milk yield smoothing coefficient" were chosen based on the different time delays reported in the literature. Several studies have reported a time lag of 2, 4, and 5 days between exposure to HS and its negative effects on dairy cattle production performance (West et al., 2003; Spiers et al., 2004; Atzori and Cannas, 2011). Thus, parameters were set wider than the values found in the literature again to allow the model to move between them.

The observed data points for MY depict high variability and show sharp ups and downs between consecutive data points; hence, individual data points cannot reflect the MY performance of the individual cow. In order to capture the overall MY performance behaviour over time, third-order exponential smoothing (Sterman, 2000) was applied on the MY data observed using an exponential averaging time (i.e., milk yield smoothing coefficient), and the smoothened values are used for parameter calibration. The smoothened MY behaviour of all cows in this study is provided in the results (Figs. 5 and 6) and Supplementary Material (Figs. S2 and S3). As another smoothing coefficient, THI smoothing coefficient is defined as the third-order delay duration, which represents the biological delay for the cow's body to anticipate HS due to changing THI values.

Table 2
Minimum, maximum, mean and SD of milk yield (MY) and days in milk (DIM) of the 20 selected Holstein dairy cows, in the three periods considered in the study.

Variables	Minimum	Maximum	Mean	SD
3–8 Aug 2021				
MY per cow (kg/day)	25.9	48.5	40.4	5.7
DIM (Days)	66.5	208.5	159.2	37.1
9–16 Aug 2021				
MY per cow (kg/day)	26.7	46.7	37.7	5.8
DIM (Days)	73.5	215.5	166.2	37.1
17–31 Aug 2021				
MY per cow (kg/day)	23.4	49.4	38.9	6.3
DIM (Days)	85.0	227.0	177.7	37.1

Abbreviations: MY = milk yield; DIM = days in milk.

Table 3
Description of dairy cattle Heat Stress model's parameters.

Parameters	Description	Lower bound	Upper bound	Unit	Reference
Time to adjust heat dissipation without heat stress	Days needed to dissipate heat produced in thermoneutrality	0.1	2	Days	Kennedy and Kuhla, 2022
Additional time to adjust heat dissipation with heat stress	Days needed to dissipate excess heat during HS	0.1	2	Days	None
Time to adjust heat production	Days needed to produce heat in thermoneutrality	0.1	2	Days	Kennedy and Kuhla, 2022
Additional feed for maintenance	kg of DM required to meet increased maintenance requirements	0	3	kg/day	Fox et al., 2004; farm data
Max heat load	Maximum heat storage capacity	13.5	63.3	Mcal	Zimbelman et al., 2010
Initial heat load	Heat stored in thermoneutral condition	13.5	22.5	Mcal	Zimbelman et al., 2010
THI smoothing coefficient	Biological delay in cow response to HS due to variation in THI	1	8	Days	West et al., 2003 Spiers et al., 2004 Atzori and Cannas, 2011
Milk yield smoothing coefficient	Overall MY performance behaviour over time	1	8	Days	West et al., 2003 Spiers et al., 2004 Atzori and Cannas, 2011

Abbreviations: HS = heat stress; THI = temperature-humidity index; MY = milk yield.

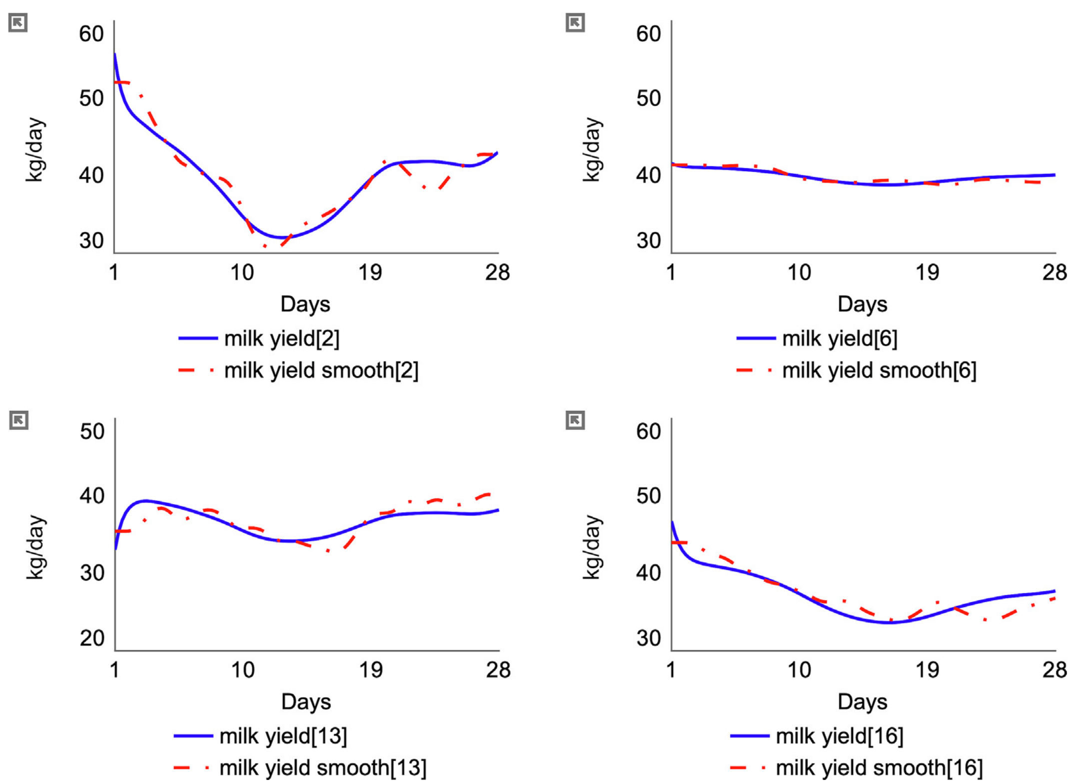

Fig. 5. Examples of results that conform with the observed behaviour: model-generated milk yield results and smoothened milk yield data (with cow ID's in brackets).

Results

Model application

As an initial attempt to quantify the impact of HS on MY at an individual cow level, the model was evaluated with 20 cows in the selected farm. The time horizon of the model is set to between 4 Aug 2021 and 31 Aug 2021, during which period, HW was observed.

Parameter calibration and model results

The optimal parameter calibration problem defined in the methods section is solved for each cow to determine the best parameter estimations, and the feasibility and consistency of the parameters are investigated in each step of the calibration process. During the parameter calibration, MY behaviour of particular cows was observed to withstand the HS conditions and follow different patterns than expected. In line with this observation, a visual

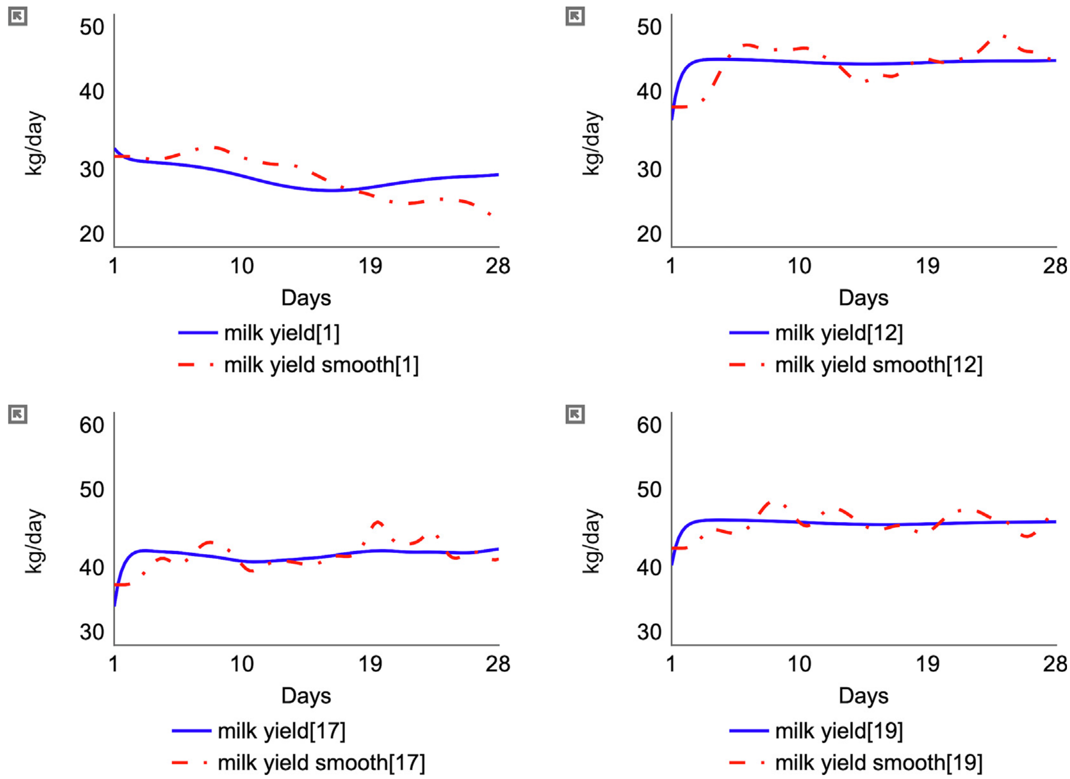

Fig. 6. Examples of results that do not conform with the observed behaviour: model-generated milk yield results and smoothened milk yield data (with cow ID's in brackets).

inspection was conducted for each cow's model-generated MY behaviour. As a result of visual inspection, 11 of 20 cows were following the model-generated behaviour, while the behaviour of the other nine could not be explained with the current model structure and the parameter space. Fig. 5 shows examples of MY results that are well-captured by the model, whereas Fig. 6 has examples that do not conform with the model-generated results. The comprehensive presentation of MY results is delineated in the Supplementary Material, with Fig. S2 illustrating results that were effectively captured by the model and Fig. S3 depicting instances where compliance was not achieved. Note that the numbers in brackets in Figs. 5 and 6 represent different animal ID's.

In addition to visual inspection, R^2, mean absolute per cent error (**MAPE**) and concordance correlation coefficient (**CCC**) (Tedeschi, 2006) measures are calculated for each data set pair. The resulting statistical performance of the model is listed in Table 4 for each cow. The cows that were visually inspected to follow the model-generated behaviour are shown in Figs. 5 and 6. Almost all these conforming cows had R^2 and CCC values greater than 0.6, except two cows (ID #13 and #20), having weaker performance in R^2 and a cow (ID #20) with also a low MAPE of 1.25%. On the other hand, the majority of non-conforming cows exhibit R^2 and CCC values smaller than 0.4 and 0.6, respectively, whereas two of the non-conforming cows (ID #8 and #18) show limited performance in MAPE despite high R^2 and CCC results. Overall, MAPE values are generally below 5% for all cows, and the largest MAPE belongs to cow #1, with 7.50% (Table 4).

The resulting parameter values as the outputs of parameter calibration problems for all 20 cows are given in Fig. 7. Due to the dynamic nature of the problem and dependency of the MY data points in time, the performance of the pattern reproduction of the model is used as the primary basis for model evaluation, whereas the statistical measures are used as supporting criteria. These results indicate that the available model structure and the parameter space can explain the effect of HS on MY for 11 cows among the selected 20 and not for the other 9. The summary of parameter values for conforming 11 cows is summarised in Table 5. In line with these results, the evaluation of the parameter values needs to be conducted only for the conforming cows because the original modelling purpose was to understand the impact of HS.

Discussion

In this work, we developed a model following the System Dynamics rules to predict cows' milk production trend under HS during a HW. The results illustrate that a simple but dynamic model considering a feedback relationship can be used to identify a dairy cow's heat production and dissipation and to quantify its animal response to environmental changes in weather conditions in terms of milk production. Throughout the literature, most approaches used to predict HS have been presented with empirical or statistical quantifications. Hill and Wall (2015) quantified with a mixed model the effects of HS with the classification of the managerial factors that influence the effect of weather. Many studies focus on the threshold of HS observation but few on the pattern of the animal response related to temperature variation in consideration of the animal's energy balance. Differently, we proposed a dynamic mechanistic approach to develop an explicit model.

The current model replicates, by using an explicit modelling approach, the classical shape of the response to HS as reported by Benni et al. (2020) and in Fig. 4 of André et al. (2011). Benni et al. (2020) reported a max milk drop after four days after the heat peak. André et al. (2011) proposed an adaptive dynamics model based on Bayesian Statistics to estimate the effects of HS on the cows in a group of farms in the Netherlands, but it can also be applied at the individual level. They observed a max milk loss with a delay of 7 days (range 3–9) after the onset of the heat period, very similar to the average delay of 7.3 days observed in our study for conforming cows. Souza et al. (2022) showed that milk losses could

Table 4
Statistical evaluation metrics for milk yield (MY) and the results of the dairy cattle Heat Stress model evaluation.

Cow ID	R^2	MAPE	CCC	Result
1	0.247	7.50%	0.385	Non-conforming
2	0.909	3.10%	0.952	Conforming
3	0.679	3.32%	0.812	Conforming
4	0.265	5.76%	0.413	Non-conforming
5	0.221	2.33%	0.337	Non-conforming
6	0.784	0.93%	0.871	Conforming
7	0.844	0.63%	0.911	Conforming
8	0.726	3.93%	0.840	Non-conforming
9	0.819	2.03%	0.899	Conforming
10	0.742	0.97%	0.857	Conforming
11	0.365	4.96%	0.468	Non-conforming
12	0.240	3.76%	0.330	Non-conforming
13	0.578	3.11%	0.734	Conforming
14	0.843	1.72%	0.914	Conforming
15	0.752	1.06%	0.859	Conforming
16	0.815	2.97%	0.899	Conforming
17	0.248	2.80%	0.405	Non-conforming
18	0.827	4.56%	0.905	Non-conforming
19	0.136	2.49%	0.280	Non-conforming
20	0.490	1.25%	0.628	Conforming

Abbreviations: MAPE = mean absolute per cent error; CCC = concordance correlation coefficient.

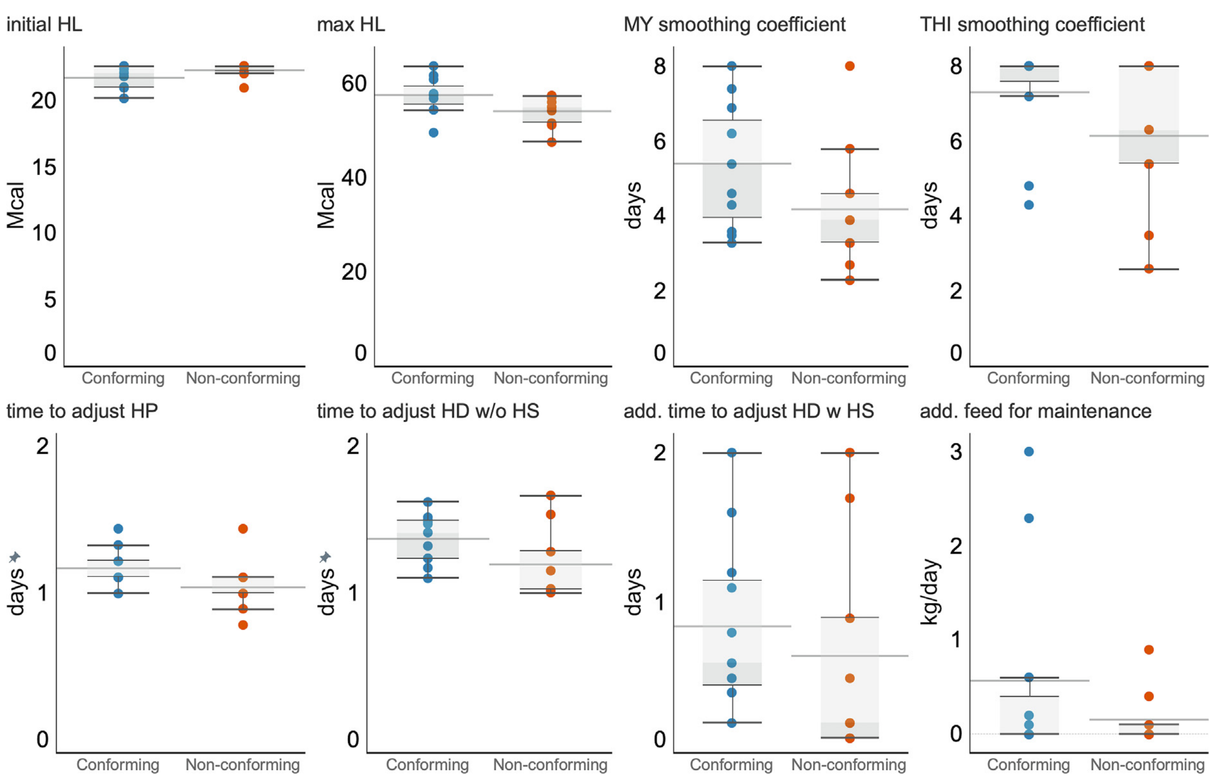

Fig. 7. Parameter calibration results of the 20 selected Holstein dairy cows for initial and maximum heat load, milk yield (MY) and temperature-humidity index (THI) smoothing coefficient, time to adjust heat production, time to adjust heat dissipation without heat stress, additional time to adjust heat dissipation with heat stress, and additional (add.) feed for maintenance. Abbreviations: HL = heat load; HP = heat production; HD = heat dissipation; HS = heat stress.

be affected even after 20 days from the HS event. They presented a mathematical description of the pattern of animal response for DMI and MY that showed a slightly different shape with delayed milk loss, a recovery attempt, and a further decline without considering climate variables such as temperature or THI.

The model can be helpful to model animal energy requirements further and not only to quantify, on average, the milk production losses as a consequence of HW. In fact, our model is built explicitly on energy-based flows that might be integrated and decomposed to fit the main thermoregulation flows related to the maintenance requirements of the animal, including the dissipation rates (Baldwin, 1995) and the total heat produced also pointed out by Benni et al. (2020).

Our study could also contribute to specific applications in animal nutrition modelling and, in particular, to implement submodels in mechanistic and dynamic nutrition systems. Tedeschi and Fox (2020) estimate for the Ruminant Nutrition System model, additional nutritional requirements of maintenance due to heat stress based on the only weather variables combined in the CETI index, whereas basal and feed supply energy flows are already computed by the model but without the whole estimation of the energy balance for thermoregulation purpose.

Table 5
Summary of parameter values for conforming cows.

Parameter	Minimum	Maximum	Mean	Median	SD
additional feed for maintenance (kg/day)	0	3	0.6	0	1.06
additional time to adjust heat dissipation with heat stress (Days)	0	2	0.8	0.6	0.59
time to adjust heat dissipation without heat stress (Days)	1	1.4	1.2	1.1	0.12
time to adjust heat production (Days)	1.8	2	1.9	2	0.08
initial heat load (Mcal)	20.2	22.6	21.7	22.1	0.96
max heat load (Mcal)	49.4	63.6	57.4	57.6	3.88
milk yield smoothing coefficient (kg/days)	3.3	8	5.4	5.4	1.66
THI smoothing coefficient (Days)	4.3	8	7.3	8	1.38

Abbreviations: THI = temperature-humidity index.

Further model expansion should be considered, including animal characteristics such as production level and genetic merits. With respect to milk production, in this model, only data from multiparous cows were used, as they were considered less heat resistant and showed a more pronounced reduction in milk production than primiparous cows, which brings the need to include parity effects. Indeed, the 11 conforming cows had mean and SD of parity equal to 2.72 ± 0.78, while the nine non-conforming cows had 2.66 ± 1. Although the two groups were parity-homogeneous, it is possible to speculate that the higher number of conforming cows can be attributed to parity order. In fact, heat tolerance is also a function parity order (Benni et al., 2020). Furthermore, primiparous cows are more heat tolerant than multiparous cows. This assumption was recently confirmed by Benni et al. (2020), who report an average parity equal to 2.27, 1.59, and 1.67 for cows with significant, moderate, and poor heat susceptibility, respectively. Otherwise, genetic components also have effects on heat tolerance. For example, from a study by Maggiolino et al (2020), the Brow Swiss breed showed no clear THI threshold in milk production when using a 2-phase regression approach. Unlike Holsteins, there was no change in MY trend as THI values increased (Maggiolino et al., 2020). Additionally, individual variability in heat tolerance can also explain part of the differences among animals (Nguyen et al., 2016). Parity and genomic values also have their interaction. The genomic estimated breeding value, developed using a BLUP model, had an accuracy for heat tolerance concerning changes in milk production equal to 0.48 when only genotyped sires and first parity data were used. It held down when second and third parity data were included because of their low numbers (Nguyen et al., 2016).

The model can also be applied to raw individual data, especially with the purpose of discriminating among cows that respond to HW with typical milk production losses and recovery or differently for phenotyping cows in genetic studies. In fact, meta-modelling approaches could be attempted using the animal parameters estimated by the model (e.g., maximum heat load, time to adjust heat dissipation) as phenotypic traits to be associated with the genomic information and markers of the individual animals (Tedeschi, 2015).

Benni et al. (2020) also reported total heat produced by the cow as a potential limiting factor for heat tolerance. However, no differences in the distribution of heat produced among the three heat susceptibility classes were reported. In our study, cows considered to be compliant and potentially less tolerant to HS had initial and maximum heat loads varying between 20.2 and 22.6 Mcal and between 49.4 and 63.6 Mcal (Table 5), respectively. The wide variability in heat load, even among heat-susceptible cows, can be related to the different quantitative and temporal efficiency of dissipation mechanisms. The model evaluation results showed that our simple model structure can explain the animal response to HS more accurately in some animals than others. In System Dynamics models, the evaluation of the model's performance in behaviour reproduction is based on "pattern prediction (periods, frequencies, trends, phase lags, amplitudes, etc.), rather than point (event) prediction" (Barlas, 1996). Hence, the essential part of the model evaluation was done through visual comparisons for "the most typical behaviour pattern characteristics", such as the amplitude of a peak time between two peaks, minimum value, slope, and the number of influential points (Barlas, 1996).

In this study, among the selected 20 cows, the MY responses of 11 cows were successfully captured. When the MY responses of these two cow groups are investigated (Figs. 5, 6, S2, and S3), most of the conforming cows can be labelled as more "sensitive" to changing THI levels and HS. On the other hand, the behaviour of the other nine cows could not be fully captured with the available structure and feasible parameter space. One explanation for this result is that some of these cows can be resistant to HW, and their production is not affected (e.g., milk yield [ID #12] and milk yield [ID #17] in Fig. 6). For example, Amamou et al. (2019) clustered dairy cows into heat-sensitive and heat-tolerant based on the slopes of individual responses. The lower heat tolerance and higher loss of milk production were attributed to inefficient heat dissipation through respiration. In contrast, the tolerant group of cows showed positive slopes for milk production and respiration rate, indicating a more timely response to HS and better maintenance of homeostasis.

Recall that our simple model is built to capture the HS effect and generates a constant Heat Load level if HS is equal to 0. Hence, if a cow is resistant to this effect, its milk production performance may not be explained by the model structure. In the subsequent phase of the study, the model structure can be improved by incorporating additional impacts (e.g., body temperature, body mass, days in milk), especially to capture the variations in milk yield responses of non-conforming cows. In fact, the animal's temperature is a variable closely related to the efficiency of thermoregulatory mechanisms (McArthur, 1987). Under an HS condition, cows that spend most of the day standing tend to have a higher body temperature than those that spend more time lying down, and this is because, despite the greater surface area exposed for heat dissipation, the increased maintenance requirements also result in heat accumulation (Allen et al., 2015).

Based on the delay of as much as 20 days that a heat peak can have on milk production (Souza et al., 2022), an alternative explanation may be that some of these cows can still be sensitive to HS but may be experiencing much longer biological delays until the changes in THI values impact their metabolism (e.g., milk yield [ID #1] in Fig. 6 and milk yield[ID #18] in Fig. S3). For alternative values of THI smoothing coefficient and milk yield smoothing coefficient parameters with longer delay times, the model might also capture their MY behaviour. To draw generalisable conclusions from these findings, it is necessary to apply the model to a larger sample of cows in the near future and perhaps automatise the cow screening with the model run.

Among the conforming cows whose behaviour was captured by the model, the average time to adjust heat production was found to be 1.9 days, closely approximating the reference value of 2 days established by Kennedy and Kuhla (2022). Additionally, in situations devoid of HS, the average time to adjust heat production exceeded the average time to adjust heat dissipation by 0.7 days, with the former taking 1.9 days and the latter 1.2 days, as detailed in Table 5. It was crucial to bear in mind that the HS variable in the model was scaled between 0 and 1. Under conditions of HS, the model suggested that the additional time to adjust heat dissipation with heat stress could extend to nearly an additional day (0.8 days on average) when HS reached 1 (Table 5). One plausible explanation for this phenomenon could be that the range of values considered for the parameter additional time to adjust heat dissipation with heat stress was adequate in accommodating the rise in heat accumulation resulting from the diminished efficiency of thermoregulation mechanisms. Interestingly, no animal variables concurrent with heat accumulation, such as body temperature, were incorporated into the model. For these cows, the average THI smoothing coefficient stood at 7.3 days (Table 5). This implied the biological lag that changing THI conditions were anticipated as HS by the animal's body and took effect on milk performance. Notably, this value exceeded that reported in the literature used to identify the parameter's reference range (i.e., 2, 4 and 5 days; West et al., 2003; Spiers et al., 2004; Atzori and Cannas, 2011). This discrepancy underscored that the effects of HS in dairy cows might have extended over relatively prolonged periods, as reported by Souza et al. (2022), who found the adverse effects of heat exposure on the production performance of dairy cows even up to 20 days later. It has to be noticed that many factors other than THI might affect the animal response delay.

Although the current phase of the study is based on a relatively small sample of 20 cows, the findings suggest that this simple model can help decision makers obtain MY predictions under HS conditions and identify the animals that show HS sensitivity. In the following phase of the study, the model will be calibrated for more animals, and the animal response to HS will be analysed with extensive multivariate analysis. One study limitation is the model relationship between DMI and MY. It is anticipated that DMI may not be the only mechanism that explains the decline in MY, and the model structure will be expanded accordingly with relevant variables (such as parity order, days in milk, body temperature). Another limitation of the study is the potential multicollinearity among the calibrated parameters due to the large number of parameters calibrated simultaneously. In the following stages of the study, this issue will be addressed by decreasing the number of parameters calibrated simultaneously and tightening the feasible space used in the parameter calibration, which will improve the identifiability of the results.

This study mainly contributes to the dynamics of the HS in dairy cows for applications in nutritional modelling and estimation of energy requirements with proper model expansion in the endogenous energy production from feed and energy dissipation rates. Furthermore, it can contribute to cow characterisation, in terms of the pattern of the MY, for the individual response to HS and tolerance to HW, for trait phenotyping and selection applications at the population level, or for culling and managerial purposes within farms.

Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.animal.2023.101042.

Ethics approval

Not applicable.

Data and model availability statement

The data/models were not deposited in an official repository. The data/models that support the study findings are available from the authors upon request.

Declaration of Generative AI and AI-assisted technologies in the writing process.

The authors did not use any artificial intelligence-assisted technologies in the writing process.

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Declaration of interest

None.

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Transparency declaration

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