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Research Paper

Coupling PLF technologies and ML algorithms for predicting the use of shadow as a proxy for heat stress in young dairy cows

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ABSTRACT

Climate change poses significant challenges for livestock productivity and animal welfare due to the increased frequency of high-temperature events leading to heat stress. This is especially relevant in Mediterranean regions, where rising temperatures threaten performance and farm profitability. In addition, calf and heifer rearing, crucial for dairy production, is particularly sensitive to environmental factors, such as heat stress, which can hamper growth and future performance. In this context, young animals are vulnerable to high temperatures, which require adapted management strategies. To provide tailored approaches, the influence of heat stress on shade-seeking behaviour in Holstein heifers was investigated, using precision livestock farming technologies and machine learning (ML) to predict their responses to varying thermal conditions. Three cameras continuously recorded the animals' movements, while environmental data, such as temperature and humidity, were collected to calculate the Temperature-Humidity Index (THI). ML algorithms analysed which variables contributed to predicting the number of animals under shade in relation to different THI variables (nocturnal, diurnal, thresholds, etc.) over broad time intervals (from 1 to 10 days) and approaches. The final model showed that shade-seeking behaviour was influenced not only by momentary THI values but also by their temporal distribution and cumulated values. Furthermore, temporal cut-off points for evaluating THI were identified for the presented conditions, and new behavioural triggers were discussed. These results provide a framework for developing context-specific heat mitigation strategies and improving animal welfare in Mediterranean conditions by predicting animal behaviour in relation to heat stress events.

NOMENCLATURE

Abbreviation	Definition
CNN	Convolutional Neural Network
FOV	Field of view
ML	Machine learning
PLF	Precision Livestock Farming
RF	Random Forest
RH	Relative humidity (%)
RMSE	Root mean square error
THI	Temperature-Humidity Index
TMR	Total mixed ration

1. Introduction

Climate change has become a crucial issue for the three-pillar sustainability and resilience of the global livestock sector. With a temperature increase of 0.2 °C per decade, this phenomenon significantly challenges livestock productivity and animal welfare (Morgado et al., 2022). The consequences of climate change are even more relevant in Mediterranean conditions, where the current and expected temperature increase endangers the current production practices. Furthermore, livestock production is undergoing a process of specialisation, reducing the number and typologies of farms and increasing their size (Schut et al., 2021). This high specialisation, in combination with the specific climate conditions across the Mediterranean, highlights the need to

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establish context-specific frameworks to identify, tackle and mitigate the negative impacts of climate change. This is a much-needed prerequisite for implementing management options to optimise livestock farming while ensuring the farms economic, social and environmental sustainability (Díaz de Otálora et al., 2024).

The calf and heifer-rearing period is crucial for both beef and dairy enterprises, as proper management of young animals influences the lactating stage of the animals, and consequently, it has a direct impact on farm profitability (McCarthy et al., 2021a). In this context, addressing the effects of environmental factors on young cattle is a critical concern affecting adequate growth and future performance (Hulbert & Moisá, 2016). In this aspect, an increasing number of farms are using contract-rearing systems to manage their replacement animals, saving the costs associated with the growing period and maximising the economic benefits of milk production (McCarthy et al., 2021b). Although young cattle are more heat-resistant than adult animals in production, primarily due to their lower metabolic heat production and greater efficiency in dissipating heat, they are still susceptible to heat stress (Wang et al., 2020a). This makes it necessary to implement tailor-made measures and strategies to provide the best possible conditions, ensuring proper development before entering the productive phase.

When evaluating the effect of heat stress on livestock, multiple indicators are available for its determination from a non-invasive perspective (Hoffmann et al., 2020). Among the many indicators evaluated in the literature, the Temperature-Humidity Index (THI) is one of the most common and easy-to-calculate measures of the thermal comfort of animals. By considering ambient temperature and relative humidity together, this bioclimatic index establishes homogeneous thresholds beyond which animals are under thermal stress (Ouellet et al., 2019, 2021). The scientific community has commonly set a THI of 72 as the limit beyond which animals are under high heat stress (M'Hamdi et al., 2021). However, these values do not consider the conditions of each context, the exposure time and the adaptation capacity of the animals to the different climatic conditions on each farm. Likewise, although the cumulative effect of THI values on lactating animals in temperate conditions has been previously addressed (Müschner-Siemens et al., 2024), there is a lack of information regarding warmer Mediterranean contexts. This is still a clear limitation when establishing the limits beyond which animals suffer from stress and assessing the patterns that condition the use of the different interventions (i.e., shadows or shelters) to reduce heat stress on farms.

In contrast to the “one-picture” perspective, a broader assessment that considers the variation of THI as a first step to analysing its effect on animal welfare and behaviour is needed. In this context, Precision Livestock Farming (PLF) technologies and machine learning (ML) algorithms allow big data analysis beyond traditional statistical methods (Morota et al., 2018). The analysis through ML technologies of the large databases collected on farms allows for the design of adapted and context-specific solutions that address the particularities and needs of each farm. This combination (PLF and ML) facilitates the adoption and evaluation of context-specific strategies to predict heat stress by providing knowledge-based solutions for producers (Arshad et al., 2024), thus allowing them to optimise their management practices while ensuring animal welfare. For example, this joint approach can assess how and to what extent heat stress conditions influence the use of shade by animals by considering aspects, such as the THI accumulated during a specific period, and the variability of this indicator throughout the night and day periods.

Evaluating the potential use of animal shading as a proxy to detect different levels of heat stress is presented as a preliminary step towards establishing adapted practices. In this context, it is vital to deploy evaluation frameworks that allow the prediction of animal behaviour patterns in different heat stress conditions. Using PLF technologies and ML, opens the door to better on-farm decision-making based on analysing a large volume of data from multiple aspects of the farm. To this end, this study aims to identify, describe, and discuss the optimal number and type of variables to predict the use of shadows by dairy heifers using PLF technologies and ML algorithms. The results of this trial are intended to shed light on the THI thresholds handled by the animals and how the cumulative values and distribution of these thresholds influence the animals shade-seeking behaviour.

2. Materials and methods

2.1. Farm characteristics

This study was conducted on a Holstein breed rearing farm located in Titaguas (Valencia, Spain) (39°51′40.68"N 1°6′7.07"W) at an altitude of 830 m above sea level. According to the Koppen climate classification, the area has a cool, semi-arid climate (*Bsk*) (Beck et al., 2018).

For this study, an intermediate-aged feedlot with 200 animals (6-7 months of age) was selected, as it is considered a critical growth phase requiring careful management to ensure optimal development and health. To introduce shade within the feedlot, a metal cover with a surface area of 120 m^2 was installed at a height of 3.5 m, centrally located to maximise the shaded area (Fig. 1). This shaded area represented 4% of the total surface of the feedlot (3000 m^2). This installation aimed to provide a protective environment against direct sunlight. The feeding regime for the calves consisted of daily feedings at 10:00 a.m., utilising a collective feeder with a total mixed ration (TMR). The TMR was formulated to meet the nutritional requirements of the growing heifers, ensuring they received a balanced diet essential for their growth and health.

Three cameras positioned on the top of the metal roof were installed to assess the usage and effectiveness of the artificial shading structure. The cameras were strategically placed to capture comprehensive footage of the shaded area, allowing for continuous monitoring of the animals behaviour and interactions with the shaded areas.

2.2. Data collection

2.2.1. Camera and sensor set-up

For this study, Hikvision dome IP cameras (Hikvision DS-2CD1123G0E-I. Hangzhou Hikvision Digital Technology Co., Ltd., Hangzhou, Zhejiang, China) were used and chosen for their robustness and image clarity under diverse environmental conditions. These cameras have a 2-megapixel progressive scan CMOS sensor, providing a maximum image resolution of 1920 × 1080 pixels. Their fixed focal length lens of 2.8 mm offers a wide 114.8° field of view (FOV), making them ideal for monitoring large areas where animals congregate. Additionally, the cameras are equipped with EXIR 2.0 infrared illumination, allowing them to capture high-quality images at distances of up to 30 m, even in complete darkness.

Environmental data, including temperature and humidity, were measured using a DHT11 sensor (Aosong Electronics Co., Ltd., Guangzhou, Guangdong, China) connected to an Arduino microcontroller (Arduino AG, Monza, Italy), which transmitted the measurements to the embedded unit used for image processing and data logging. This sensor provided real-time information to analyse the environmental factors influencing animal behaviour, complementing the visual data captured by the cameras.

2.2.2. Animal counting procedure

The cameras were installed at fixed, elevated positions to provide comprehensive and uninterrupted coverage of the study area. Images and synchronised environmental data were recorded at 1-min intervals to ensure a sufficient temporal resolution for monitoring changes in animal behaviour and positioning under shaded areas.

Animal detection and classification involved a two-stage computational approach developed by DeepFarm (DeepFarm Technologies S.L., Madrid, Spain). Initially, a convolutional neural network (CNN) was employed to detect the animals visible in the camera's FOV. This CNN

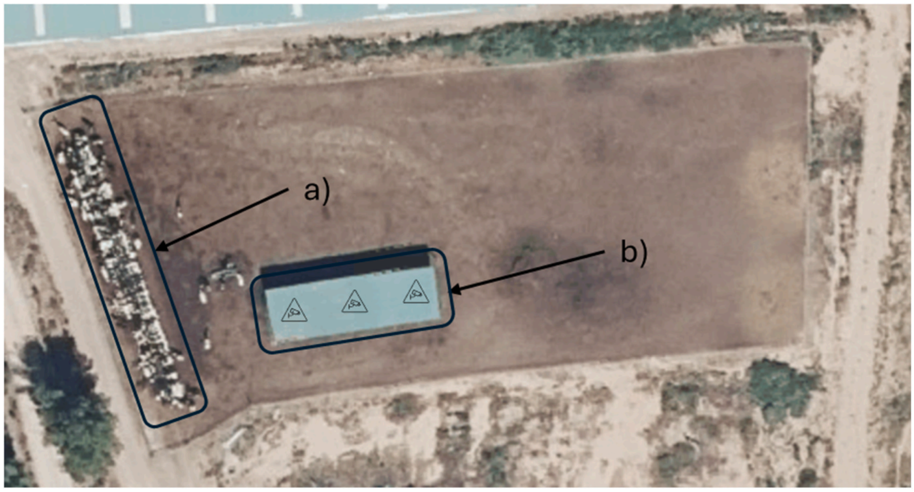

Fig. 1. Aerial view of the feedlot used for this study. Indicating the location of the feeding/drinking area (a) and the roof area (b) with the location of the cameras. Source: Adapted from Google Earth.

was trained on a labelled dataset tailored to the study environment, ensuring high accuracy in recognising animals irrespective of their posture, size, or lighting variations. The network's ability to adapt to dynamic scenes ensured that animals were consistently identified across different times of day and environmental conditions, even in crowded situations.

In the second stage, traditional computer vision methods were applied to determine whether each detected animal was in a shaded or non-shaded area. This process relied on the spectral analysis of images, focusing on variations in pixel intensity and colour properties to segment shaded regions from sunlit ones. Image segmentation algorithms identified the boundaries of shaded areas, and the centroid of each detected animal was calculated. The centroid of each detected animal was used as a robust proxy for its spatial location. Shade exposure was classified binarily ('in shade'/'out of shade') based on whether the centroid lay within the shaded region mask. This criterion is suitable for quantifying shade use over time and is less sensitive to posture variability, partial occlusions, and contour-level segmentation noise than approaches relying on the full body outline. Although ambiguity can occur near the shade boundary, its influence is mitigated by the temporal aggregation strategy: images were acquired at 5 fps and shade-use metrics were summarised over 5-min intervals, which smooths short-lived boundary-related fluctuations.

This combination of deep learning and classical computer vision methods provided a robust and efficient means of analysing animal behaviour in relation to environmental shading. The algorithm's simplicity allowed for real-time processing, even on systems with limited computational power, making it suitable for deployment in resource-constrained environments. The integration of synchronised environmental data added a layer of insight, allowing for a comprehensive understanding of the factors influencing shade-seeking behaviour.

2.3. Database creation

During the data collection period (July 11th, 2023, to October 16th, 2023), animal counts and environmental measurements were recorded every 5 to 10 min. During the daytime period (from 07:00 to 21:00), each observation included the number of cows in the shade, temperature (in °C), relative humidity (in %), and time. Regarding the nighttime period (from 21:00 to 07:00), the same variables were recorded, except for the number of cows in the shade, as this measure is irrelevant for heat protection during nighttime hours. For consistency with our previous analysis (Sanjuan et al., 2025) and to ensure a simple, fully reproducible classification independent of astronomical computations, we used a fixed day–night partition: daytime was defined as 07:00–21:00 and nighttime as 21:00–07:00. This definition is an operational assumption aimed at standardisation and comparability, not an estimate of actual sunrise–sunset photoperiod.

From the temperature and relative humidity dataset, the THI was calculated following the equation proposed by the National Research Council (NRC 1971):

$$THI = (1.8 \times Tdb + 32) - (0.55 - 0.0055 \times RH) \times (1.8 \times Tdb - 26) \quad \text{Eq. 1}$$

where Tdb is the ambient temperature (°C), and RH is the relative humidity (%).

For the database construction, the following variables were defined for each point during the daytime period (from 07:00 to 21:00):

- (1) The "*current THI*" value (the THI value at the given time t).
- (2) The "*night THI*" calculated as the mean of THI values of the previous night (from 21:00 to 07:00).
- (3) The "*accum THI*", which is the mean of the THI from the first hour of the day (07:00) to the current observation time t.

Temporal features incorporating information from preceding days were added to further analyse the relationship between environmental conditions and shade-seeking behaviour. These features were computed by aggregating data from n previous days, where n ranged from one to a maximum of 10. For each previous n days, specific temporal characteristics were calculated to provide a more detailed understanding of the cumulative and progressive effects of environmental conditions on animal behaviour, with the following variables defined for each time during the daytime period:

- (4) The "*mean THI*" as the average THI value over the whole day.
- (5) The "*mean THI daytime*" as the average THI value recorded during the daytime (07:00 to 21:00).
- (6) The "*mean THI nighttime*", as the average THI value recorded exclusively during nighttime periods (21:00 to 07:00).

These variables were calculated as the average of all THI values recorded during the previous n days (excluding the current day) according to the periods mentioned above. By incorporating these features, the analysis accounts for the cumulative thermal stress experienced by animals over multiple days and distinguishes how thermal stress during different parts of the day might differentially impact shade-seeking behaviour.

Additionally, extreme environmental conditions were considered by means of two variables:

- (7) The "*max THI*" value, representing the highest THI recorded during the previous *n* days, and
- (8) The "*min THI*" value, representing the lowest THI recorded during the same period.

Finally, features capturing the duration of thermal stress were introduced. These included the number of hours in which the THI exceeded specific thresholds (e.g., 72, 76, 80) or fell below others (e.g., 60, 64, 68). For each *n*-day period, the number of hours exceeding or falling below these thresholds was calculated, with the thresholds labelled in the database as follows:

(9) ● "*down* 60".
(10) ● "*down* 64".
(11) ● "*down* 68".
(12) ● "*up* 72".
(13) ● "*up* 76".
(14) ● "*up* 80".

In summary, for each specific time during the daytime period, 3 new variables ((1) to (3)) were defined, and for each *n*-day period, an additional 10 variables ((4) to (14)) were included. A brief scheme is shown in Fig. 2.

The dataset used in this study builds on the work by Sanjuan et al. (2025). The initial dataset consisted of 98 days of recorded data (July 11th, 2023, to October 16th, 2023). Due to missing or incorrectly recorded measurements, the final dataset was reduced to 75% days, comprising a total of 6907 observations. Model performance was evaluated using a 5-fold cross-validation strategy designed to provide a robust and unbiased estimate of predictive accuracy. Given the strong temporal structure of the data, the partitioning was performed at the day level rather than at the individual observation level. In each fold, 20% of the available days (15 days) were randomly selected and reserved exclusively for testing, while the remaining 80% (60 days) were used for model training. This procedure ensures that all observations from a given day belong to a single split, thereby preventing information leakage between training and testing sets and better reflecting real-world deployment conditions. The cross-validation process was repeated across five non-overlapping test sets, and performance metrics were averaged across folds. A comprehensive description of the validation framework and model tuning can be found in Sanjuan et al. (2025).

2.4. Approaches and selection of ML models

To predict the number of animals seeking shade based on environmental variables, two distinct approaches (or models) were proposed. Both approaches share a common foundation: the set formed by the time

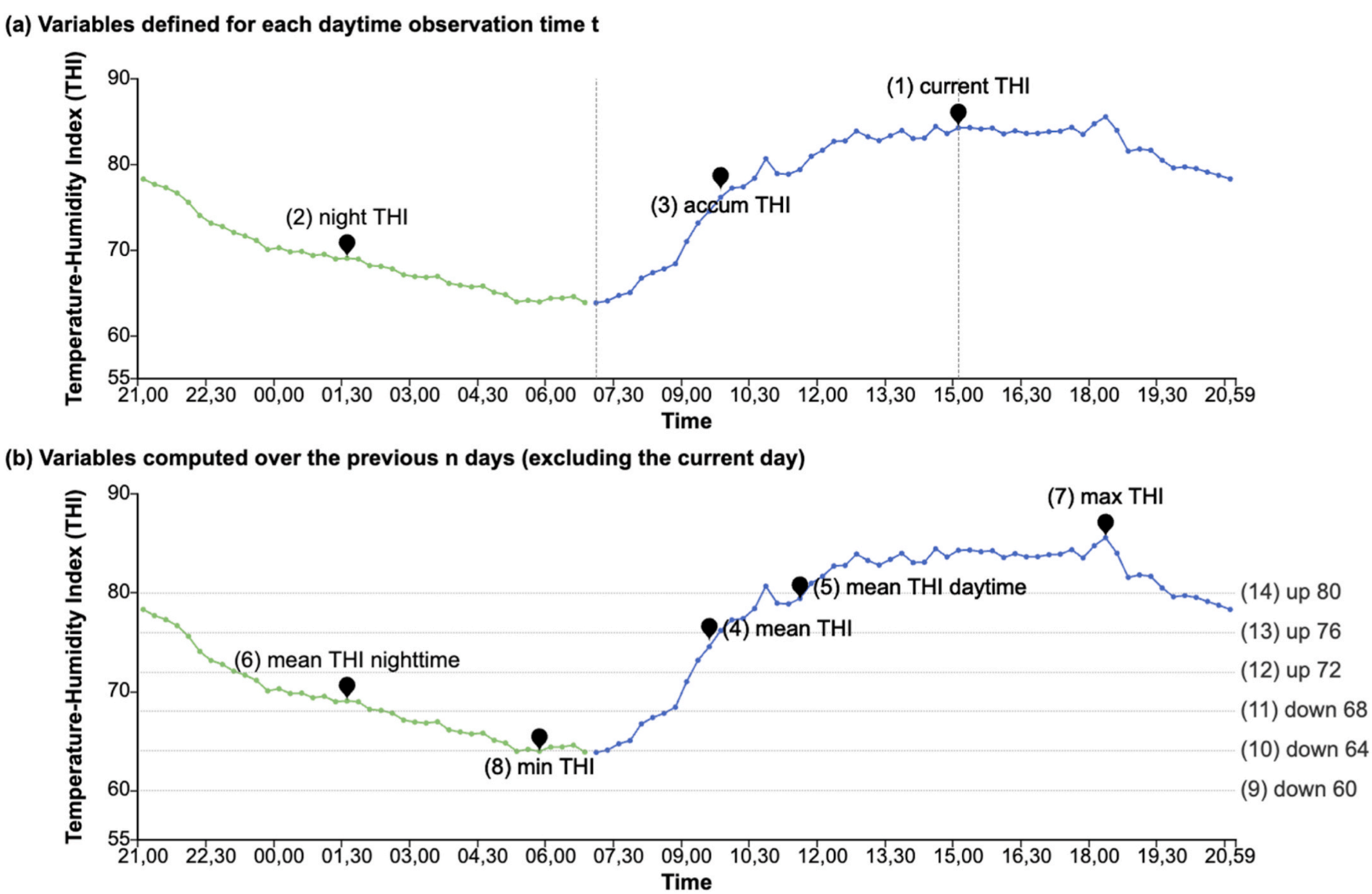

Fig. 2. Schematic representation of the THI-derived variables used for database construction, illustrated with a one-day example. (a) Variables defined for each daytime observation time t: (1) current THI, i.e. the THI value at time t; (2) night THI, i.e. the mean THI during the previous night (21:00–07:00); and (3) accum THI, i.e. the mean THI from 07:00 to time t. The two vertical dashed lines indicate the start of the daytime period (07:00) and the observation time t, respectively. (b) Variables computed over the previous (n) days (excluding the current day): (4) mean THI over the whole day, (5) mean THI daytime, (6) mean THI nighttime, (7) max THI, and (8) min THI. The horizontal reference lines labelled (9) down 60, (10) down 64, (11) down 68, (12) up 72, (13) up 76, and (14) up 80 represent the number of hours during the previous n days in which THI was below 60, 64, and 68, or above 72, 76, and 80, respectively.

and the first set of three variables defined in the previous section (*time*, *current THI*, *night THI* and *accum THI*). However, they differ in how temporal features derived from past n days are incorporated.

2.4.1. Approach 1

In the first approach (*Appr. 1*), a single variable for each previous n-day period was aggregated to capture the overall environmental conditions across n days. Let "$variable_n$" denote this aggregated variable. In this case, the variables were:

$$(time, current\ THI, accum\ THI, night\ THI, variable_n)$$

Here, "$variable_n$" could be any of the features (4) to (14) defined earlier (e.g. "*mean THI*", "*min THI*", or "*down* 64"). For example, if "*max THI*" was considered as the variable for $n = 3$, then this approach included a single variable representing the maximum THI value across all three previous days combined ("$variable_3$").

2.4.2. Approach 2

In contrast, the second approach (*Appr. 2*) represents temporal variables in greater detail. Instead of aggregating data across n days, consecutive temporal features for each interval from one to n days prior were included. Thus, the variables added were:

$$(time, current\ THI, accum\ THI, night\ THI, variable_1, \ldots, variable_n)$$

For example, if for $n = 3$ we consider "*max THI*" as our variable, then this approach includes separate variables for the maximum THI on the previous day ("$variable_1$"), the previous two days ("$variable_2$"), and all three days ("$variable_3$") combined. This approach retains a higher temporal resolution, allowing the model to capture the progressive effect of environmental conditions over time.

This difference between the two approaches has a direct impact on the requirements and performance of the ML algorithms. While *Appr. 1* simplifies the temporal representation and reduces the dimensionality of the dataset, *Appr. 2* provides a more granular view at the cost of increased complexity. Consequently, the choice of the predictive model must account for these differences to ensure optimal performance and an appropriate balance between accuracy and computational efficiency.

Once the temporal approach offering the best results had been identified, the individual contribution of each variable to the reduction in the root mean square error (RMSE) was assessed. To do this, the inclusion of each variable in the model was analysed to determine the effect on the prediction error, identifying those variables that generated a notable larger decrease in the error. In addition, the specific time at which the inclusion of each variable ceased to provide significant improvements in the model's accuracy was determined. This time point represented the instant at which the error began to stabilise, thus making it possible to determine the optimal time limit beyond which the accumulation of more data did not generate additional benefits in terms of accuracy. The selected variables were retained to identify the final model to predict the number of animals under shade.

Based on previous approaches and variables, the final model was created in the third and final stage. The selection was based on an optimisation process based on identifying combinations of variables that generated the lowest possible RMSE and evaluating all potential combinations regarding the number of cumulative days. In this process, the minimum error achieved, and the time required to achieve this error were considered. Consequently, priority was given to selecting combinations that minimised the RMSE and achieved this minimum error in as few days as possible.

This approach allowed the model to be optimised from the perspective of absolute accuracy and time efficiency, ensuring that the selected model could provide accurate results in a reduced time frame.

2.4.3. Selection of the ML model

The selection of the ML algorithm used to predict the number of animals seeking shade was based on previous work by Sanjuan et al. (2025). This prior research evaluated three supervised machine learning algorithms (decision trees, random forests, and neural networks) for their ability to predict the number of cows seeking shade. The models were evaluated considering the time, the current THI for each observation, the average THI from the previous night, and the cumulative THI derived from the same database used in the present manuscript, which also forms the common foundation of the two approaches proposed in this study. The optimal ML approach for this dataset was based on the principles of interpretability and explainability in combination with the RMSE of the prediction, ultimately selecting the model that best balanced these three.

Regarding the decision tree, the optimal depth was 5, achieving a RMSE of 16.03 animals. Despite its interpretability, its predictive accuracy is limited. In contrast, the random forest technique combined multiple decision trees, introducing randomness in the training data and the variables used, which improved accuracy and reduced overfitting. With a tree depth of 5 and 10 trees, the random forest achieved an RMSE of 14.97, effectively balancing accuracy and interpretability. Finally, for neural networks, the most efficient neural network achieved an RMSE of 14.78, with 3 hidden layers of 16 neurons each and a learning rate of 10^{-3}.

While neural networks demonstrated the highest precision, their complexity hinders understanding of their decision-making process. Conversely, although the decision tree is highly interpretable, its predictive accuracy was lower. By combining multiple decision trees, the random forest achieves an accuracy comparable to that of neural networks while maintaining an acceptable degree of interpretability.

Thus, based on these findings, the random forest algorithm was selected as the best approach for this manuscript. In this work, the final random forest model consisted of 150 trees with a maximum depth of 20. These parameters were selected after optimising the model for the largest set of input variables used in this study, which included approximately 50 variables. This higher number of variables justified the need for a more complex random forest model with a larger number of trees, allowing the algorithm to effectively explore the numerous possible interactions among variables. It was observed that increasing the number of trees beyond 150 or the depth beyond 20 did not yield significant improvements in prediction performance (data not shown).

For models with fewer variables, Sanjuan et al. (2025) demonstrated that even simpler random forest configurations achieved comparable predictive accuracy and increasing the complexity of the random forest in these cases did not improve predictions, as the model reached a performance plateau. Nevertheless, given the higher number of variables considered in this study, a more complex random forest model was selected to ensure robust predictions while accommodating the complex relationships among the input features.

2.4.4. Software and implementation

Feature engineering and model training were implemented in Python (version 3.8) using NumPy/Pandas for data handling and scikit-learn for machine learning. The Random Forest model was fitted as a regression problem to predict the number of animals under shade from the defined THI-derived predictors. The final model was a RandomForestRegressor with n_estimators = 150 and max_depth = 20; other parameters were left at library defaults (criterion, minimum samples per split/leaf, and feature subsampling strategy) unless stated otherwise. Model performance was assessed via 5-fold cross-validation performed at the day level (splitting by whole days to avoid leakage), following the same partition rationale described previously. A fixed random seed was used to ensure reproducibility. Further information and scripts are available at https://github.com/serjj99/CowShadeSeeking.

3. Results

The following section presents the results for (i) the time-step approach, (ii) the choice of variables and time interval, and (iii) the performance of the final prediction model. All prediction RMSE details are found in the Supplementary Material 1.

3.1. Selection of the temporal approach

The individual analysis of the results reveals differences in the performance of the two approaches for calculating prediction errors. Specifically, when the prediction errors were based as a function of the *Appr. 1* (upper part of Fig. 3, a mean RMSE of 13.08 was obtained. In contrast, the model's performance as a function of the daily cumulative effect of *Appr. 2* (lower part of Fig. 3) yielded a lower RMSE of 12.86.

Further examination shows a more homogeneous distribution of prediction errors in *Appr. 2*. In this case, errors were relatively consistent and homogeneous across variables and time, providing a more predictable pattern. Moreover, *Appr. 2* shows a trend toward error stabilisation as time of past days considered increased. This suggests that, as time progressed, the effect of time on the prediction was less determinant. In contrast, the *Appr. 1* showed a more heterogeneous distribution of errors without a clear trend over time, indicating greater variability and less consistency in the prediction errors.

Given the obtained results, *Appr. 2* is presented as particularly useful for identifying critical inflection points where errors began to stabilise. The variables that contributed most to the prediction could be identified and retained by identifying these elbow points. This led to the selection of *Appr. 2* as the preferred method for further data assessment.

3.2. Selection of model variables

While *Appr. 2* was more suitable for identifying critical turning points and defining optimal periods of analysis, it was still necessary to determine which variables and time intervals contributed the most to reduce the prediction error. The final variables were selected based on two fundamental criteria: minimising the prediction error (RMSE) and prioritising the earliest day the error stabilised. In cases where similar minimal errors occurred on an earlier and a later day, priority was given to the earlier day (even if it did not have the absolute minimum error) to ensure early detection of the heat stress event.

Initially, variables that showed a lower potential to reduce the prediction error were excluded (i.e., "*mean THI nightime*" and "*mean THI*"). For the group of variables describing different THI thresholds, only those with the best performance in reducing the prediction error were retained. The variables selected were those that had a lower RMSE: "*down* 60", which represents the number of hours during which the THI fell below 60, and "*up* 76", which reflects the number of hours during which the THI exceeded 76. The other retained variables that had a relevant impact on the predictions were: "*max THI*", which represents the maximum THI value reached during the day, "*min THI*", which indicates the minimum daily temperature, and "*mean THI daytime*", which reflects the average THI during the daytime period.

Further analysis of the RMSE evolution across the assessed period, as shown in Fig. 4, showed how the variables "*down* 60" and "*max THI*" yielded their optimal performance considering seven consecutive days. Likewise, both "*mean THI daytime*" and "*min THI*" had better results

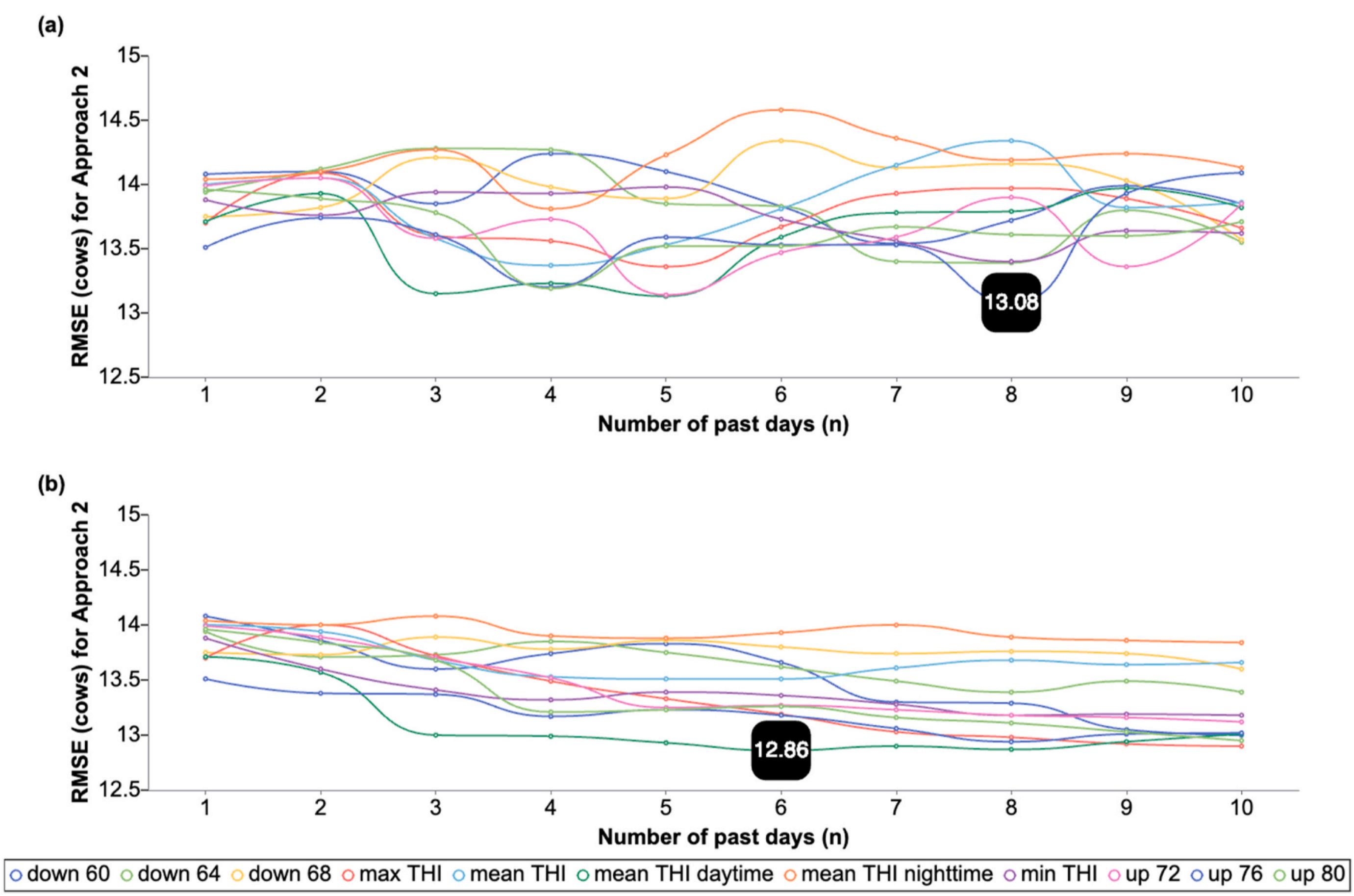

Fig. 3. Root mean square error (RMSE) obtained for the prediction model as a function of the number of past days (n) and the THI-derived variable included in the model. (a) Results for Approach 1, in which each temporal feature is represented by a single aggregated variable over the previous ndays. (b) Results for Approach 2, in which the same temporal feature is represented by consecutive variables from 1 to n days prior, thus preserving greater temporal resolution. Each coloured line corresponds to one THI-derived variable. Approach 2 yielded a lower mean RMSE (12.86) than Approach 1 (13.08) and showed a more homogeneous error pattern across the evaluated variables and time windows.

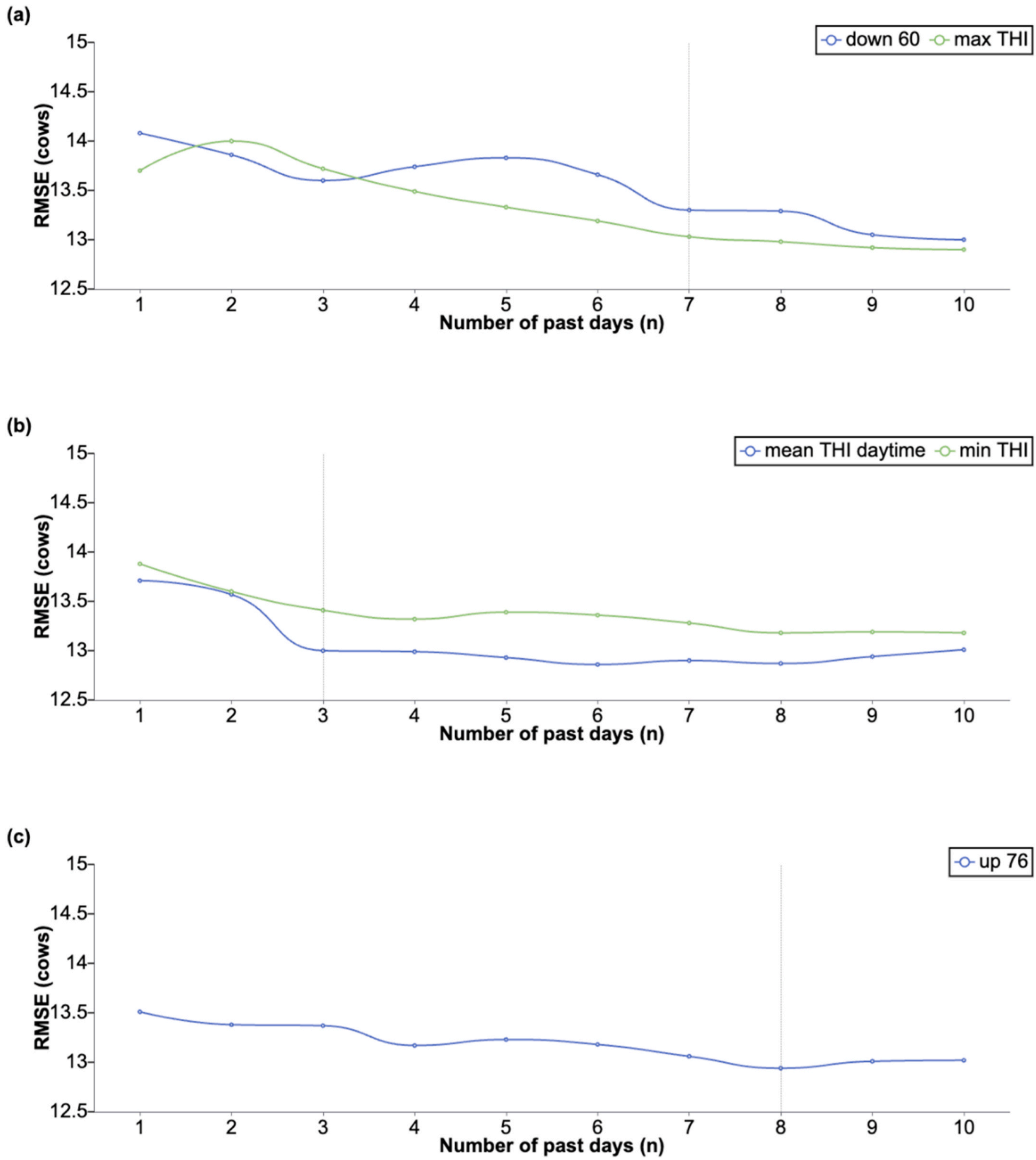

Fig. 4. RMSE as a function of the number of past days (*n*) for the THI-derived variables with the best predictive behaviour. Panels show the variables down 60 and max THI in (a), mean THI daytime and min THI in (b), and up 76 in (c). The vertical dashed lines indicate the selected number of past days for each case, corresponding to the most favourable RMSE values.

when considering three consecutive days, while "*up* 76" showed better stability when evaluated over eight days, thus showing greater robustness

This methodology allowed the selection of the most relevant variables and identified the period for which their influence in reducing the prediction error was the best.

3.3. Model performance

The RMSE of all the combinations of variables identified and selected in previous section were evaluated to obtain the final model (Supplementary Material 1). The final variables and analysis period were chosen according to the following criteria: minimise the prediction error and prioritise the first day when the error stabilised, as detailed in previous sections. An optimal combination of variables including "*mean THI daytime*", "*min THI*" and "*up* 76", was identified as the most efficient, as it had the lowest RMSE over four days, with a value of 12.93, as illustrated in the lower left part of Fig. 4c.

This combination of variables outperformed other configurations, showing lower error, even when the configurations tested covered longer periods. In Fig. 5 the behaviour of all possible combinations of the selected variables is shown. If a single variable is to be selected, the best variable was "*mean THI daytime*" that stabilised from the third day with an error of 13.00 (upper left of Fig. 5a). In the case of a two-variable model from among all the combinations, the best option was "*mean THI daytime* + *min THI*" that was stable from the fourth day with an error of 12.94 (Fig. 5b). For a three variable model, "*mean THI daytime* + *min THI* + *up* 76" was the best option taking four previous days with error of 12.93 (lower left of Fig. 5c). Finally, for more than four variables the best option was "*mean THI daytime* + *min THI* + *up* 76 + *down* 60" with four days and an error 13.16 (Fig. 5d).

In short, the presented model configuration achieved an adequate balance between the number of variables used and the model's predictive accuracy, thus aligning with the objectives of this study.

In addition, the final model improved the original prediction, reducing the error from 14.97 to 12.93, an improvement of 13.6%. As shown in Fig. 6, the model performed well in following the trends in the number of animals in the shade. However, it presented more significant uncertainty during heat peaks, reflected in the average error range. The THI correlated with animals under the shade, being higher in the central hours of the day. Furthermore, the highest error between the real animal numbers under the shade and the obtained prediction occurred between 10:00 and 13:00, probably due to the coincidence with feeding times.

4. Discussion

4.1. Enhanced heat stress event assessment through a PLF-ML approach

The approach proposed by this study, based on the use of precision livestock farming (PLF) technologies combined with machine learning (ML), is presented as a practical and accurate tool to assess the impact of heat stress phenomena on animal behaviour. Unlike previous studies in which animals were equipped with sensors to measure their behaviour (Benaissa et al., 2023; Hut et al., 2022), the completely non-invasive approach presented in this manuscript allows for establishing a direct relationship between cumulative and distributed values of temperature and humidity index (THI) and shade-seeking behaviour. In line with what has been described by previous authors, this is one of the most evident behavioural changes observed in animals subjected to heat stress (Sejian et al., 2018).

Compared to the THI value of 72, commonly mentioned as the reference value at which an animal is considered to be under heat stress (Ravagnolo et al., 2000), the identification of THI above 76 as a variable that reduces the error in predicting the number of animals under shade suggested that this value might serve, in this particular context, as reference behavioural trigger within the context of the present study. In this context, and in comparison with studies relating THI and behaviour in northern European contexts (Heinicke et al., 2018; Hoffmann et al., 2020), the animals analysed in this study might present a higher tolerance to heat, which would mean that the onset of heat stress occurs at higher THI values. In this sense, the results confirmed this specificity, demonstrating the need to make decisions adapted to each context rather than resorting to universal solutions.

One of the main contributions of this study is to highlight the relevance of analysing both instantaneous and cumulative THI values to estimate the number of animals seeking shade in response to heat stress. By observing the obtained prediction errors and considering shade-

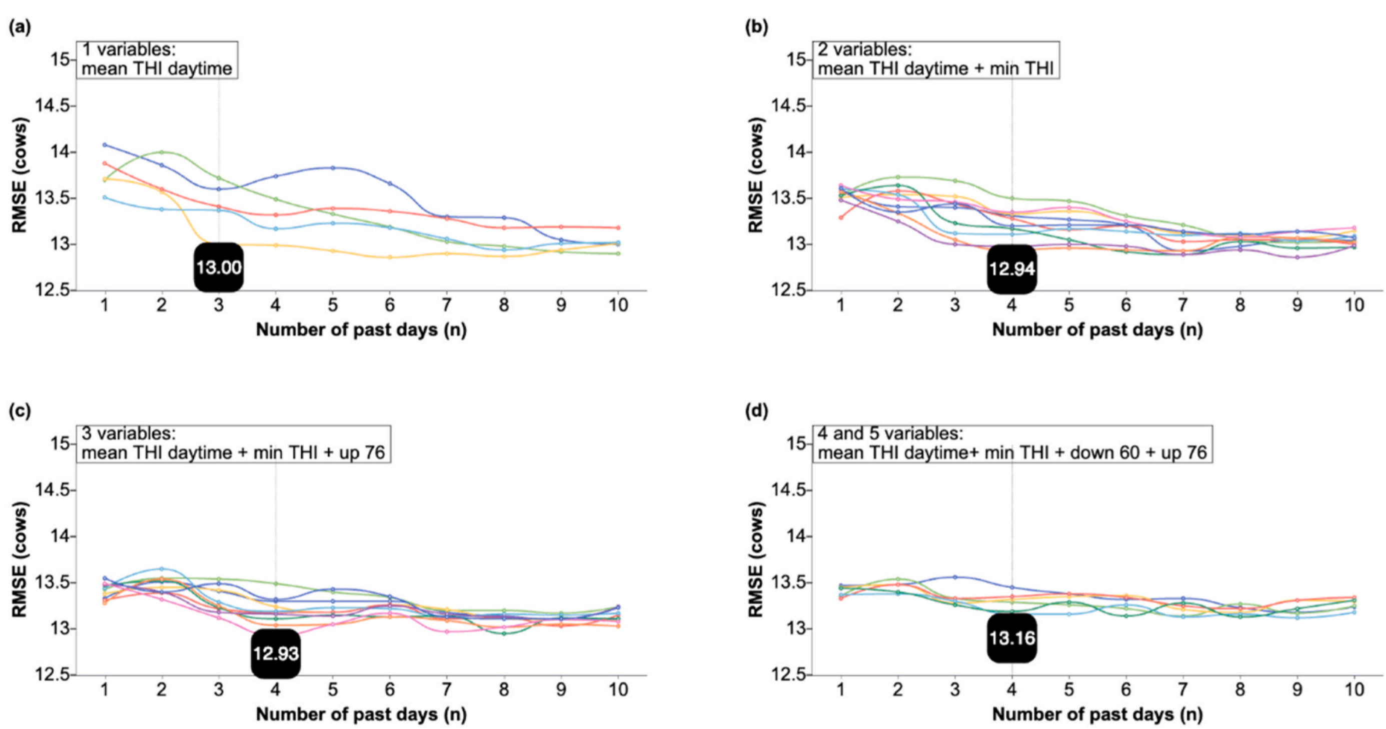

Fig. 5. RMSE distribution for different combinations of selected variables and numbers of past days analysed using Appr. 2. The figure shows the error reduction as the number of past days increases and highlights the combinations achieving the lowest RMSE. (a) One-variable models (mean THI daytime). (b) Two-variable models (mean THI daytime + min THI). (c) Three-variable models (mean THI daytime + min THI + up 76). (d) Four- and five-variable models, with the best-performing combination given by mean THI daytime + min THI + up 76 + down 60. In each panel, the dotted vertical line indicates the selected value of *n*, corresponding to the lowest RMSE or to the earliest day at which the error stabilised.

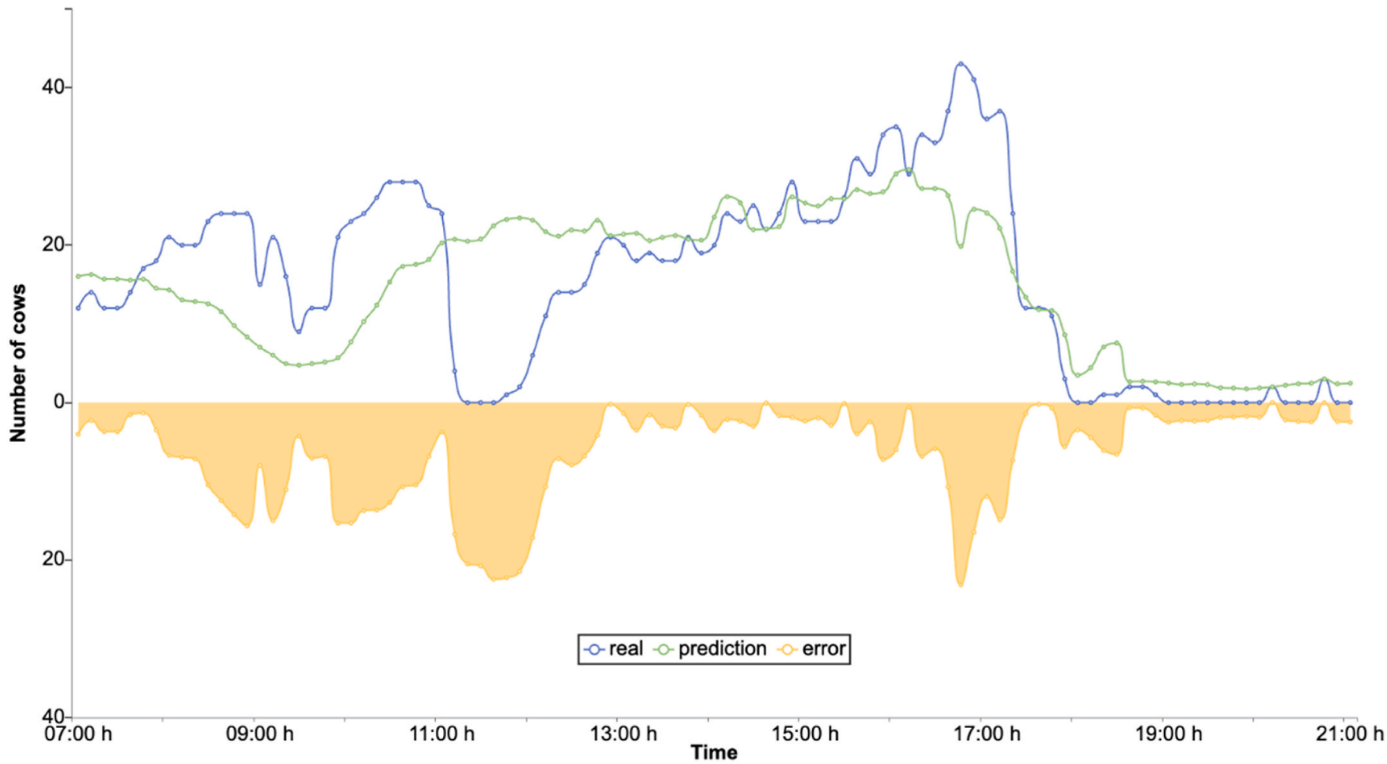

Fig. 6. Predicted number of animals seeking shade on August 18th, 2023. This figure replicates the analysis for the same date shown in Figure 9 of Sanjuan et al. (2025). The blue line represents the observed number of animals seeking shade (real), the green line the predicted values (prediction), and the shaded orange area the absolute prediction error (error). For visual clarity, the absolute error is plotted below the horizontal axis, but it should not be interpreted as taking negative values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

seeking behaviour as an indicator of heat stress, this approach underscores the importance of context-specific THI thresholds in assessing animal welfare. Until now, the point value of THI has been used as the primary indicator to determine whether an animal is suffering from heat stress. However, few studies have considered the cumulative effect of THI (Mbuthia et al., 2022), and even fewer studies have tried to identify the day from which this accumulation is relevant to animal behaviour. In this sense, the results obtained in this study contribute to the evidence that cumulative time above certain THI levels directly influences shade-seeking behaviour. Furthermore, these findings agree with previous studies highlighting the importance of considering nocturnal and diurnal THI as key factors in conditioning animal behaviour (Leliveld et al., 2022).

The predictions made with the final model presented in this work underline the need to optimise the number and analysis period of the variables considered to predict heifer behaviour. This is in line with previous research that highlighted the importance of having an adequate and adapted amount of climatic data in different contexts and production systems to improve animal heat stress predictions (Chapman et al., 2023). Optimising the number and period of analysis of variables to predict heifers' behaviour would improve the accuracy of predictions, identify more specific patterns and adapt more effective management strategies. This would optimise resources and reduce costs by focusing on relevant data contributing to animal welfare and developing more dynamic management models applicable in different productive and climatic contexts.

4.2. Practical implications for animal production

The findings presented in this work allow for the optimisation of management strategies to reduce the impact of heat stress under various climatic conditions. The ability to predict shade-seeking behaviour not only facilitates the implementation of more effective mitigation measures, such as the design of shade structures tailored to the specific needs of each species and region, but also allows the identification of critical points in daily management, reducing adverse physiological responses of animals to heat events (Edwards-Callaway et al., 2021).

As indicated in previous work, the results of this study may contribute to the development of early warning systems based on environmental data and animal behavioural patterns, enabling proactive responses to heat waves or other heat-stress situations (Woodward et al., 2024). In a broader context, the integration of PLF and ML technologies could facilitate continuous, real-time monitoring of farms, strengthening the ability of producers to make informed decisions that promote greater sustainability of production systems by optimising resources while improving animal welfare (García et al., 2020).

From a productive standpoint, heat stress during young cattle growth can have significant long-term impacts on their productive and reproductive performance (Dash et al., 2016; Wang et al., 2020a). During this stage, adverse environmental conditions can alter physiological processes, affecting weight gain, immune system development and reproductive maturity. In this sense, proper management by producers can mitigate the immediate effects of heat stress. It establishes a solid foundation for cows to cope more effectively with future heat stress events, avoiding adverse effects on their reproductive efficiency (Jordan, 2003).

From an economic perspective, developing and implementing reliable prediction tools adapted to each context is key. In this way, producers can make informed and proactive decisions, optimising available resources and improving animal welfare. For example, strategies based on predictive models could include environmental adjustments and preventive measures against heat waves, resulting in more efficient animal growth and, consequently, higher economic profitability for livestock farms derived from automated animal monitoring (Lovarelli et al., 2020). Additionally, the proposed combined framework of ML and PLF could optimise the use of key resources (i.e., water and energy). This not only contributes to the optimisation of their unnecessary use but also strengthens the overall sustainability of the system (Lovarelli et al., 2024). In the case of water, more efficient management, facilitated by PLF and smart systems, could minimise waste in cases where this resource is used to mitigate heat stress (e.g., water sprinklers), which is especially relevant in regions where the water resource is limited (Marchewka et al., 2018). Also, an accurate prediction of decreased animal welfare due to heat stress could encourage more rational use of energy resources, such as fans, thus reducing overall farm energy consumption (Costantino et al., 2023). Addressing heat stress from a holistic perspective by combining PLF and ML favours productive efficiency and economic sustainability, generating tangible benefits for farms.

4.3. Limitations and future prospects

The predictive model presented in this study provides valuable results to support producers' decision-making when ensuring animal welfare and anticipating the effects of heat stress on contract-rearing farms in Mediterranean regions. Although this manuscript presents novel findings derived from the joint application of PLF and ML technologies, there are opportunities to improve the developed framework by including more data and additional indicators related to animal behaviour. We acknowledge that the fixed daytime definition (07:00–21:00) is a simplification that may deviate from the true photoperiod, especially in early autumn. Consequently, during September–October some low-irradiance or post-sunset intervals may be included within ‘daytime’, potentially capturing instances of ‘nighttime shade’ under the daytime label. While this introduces a seasonal misclassification risk, we expect its influence on our main findings to be limited because shade-seeking is chiefly associated with thermal stress (THI) rather than light, and because the modelling relies on cumulative multi-day THI indicators that reduce the weight of short transitional periods.

The results obtained are limited to a single production system under specific Mediterranean conditions, which restricts the generalisability of the findings to other climatic contexts, breeds or production systems. Furthermore, the study was carried out over a specific period of one year. Although the very construction of the model allowed its testing with data representative of an entire summer, it would be essential to incorporate data from additional years and periods to ensure the replicability of the results. In this line, future work should focus on extending the duration of the experiment, which would allow us to analyse how animals adapt to heat stress throughout the year with more significant climatic variability.

Although the category and number of animals included in the study allow relevant conclusions to be drawn, their number is limited due to the study design and the farm's daily operations. Furthermore, the study did not consider social interactions between animals among the variables assessed, which could significantly influence the behaviour of the animals. Consequently, future model developments should incorporate individual animal monitoring and indicators related to individual interactions. In this way, a better understanding of the causes of animals presence in the shade could be facilitated, reducing the uncertainty of predictions associated with ethological factors.

Moreover, while THI serves as a well-established proxy of the potential effect of heat stress on animal welfare, the absence of direct physiological indicators (e.g., body temperature or respiratory rate) hampers a more detailed understanding of the results. In this regard, future studies should integrate physiological variables. However, it should be mentioned that this could compromise the non-invasive approach adopted in this study. Also, to further characterise the effect of climate on the animals, it would be beneficial to incorporate additional variables such as wind speed or solar radiation. In this way, the accuracy of the model and its applicability in different climatic conditions could be increased.

5. Conclusions

This study presents a novel approach that shows how the coupling of ML algorithms and PLF technologies can predict shade-seeking behaviour in heifers in response to heat stress. The final model presented in this manuscript, based on a random forest approach, was optimised with the most appropriate variables and time range to reduce error in the shortest possible time. As an alternative to analyses that considered only the instantaneous value of the THI as a determinant proxy to assess heat stress levels in animals, the results of this study confirmed that both instantaneous and cumulative THI values were determinant. In this way, specific thresholds and key time periods have been identified that optimise the accuracy of the predictions. The results obtained reduced by 13.6% the RMSE of the initial prediction. This underlines the importance of adapted variables and specific period selection to maximise the effectiveness of the model predictions. Furthermore, in contrast to one-size-fits-all solutions, this manuscript provided tailored THI thresholds for heat stress adjusted to the conditions of this study. These findings were necessary for more effective and targeted farm management strategies. Moreover, the presented results highlight the usefulness of coupling PLF and ML to address key challenges in livestock farming, contributing to improved animal welfare, resilience, and sustainability.

CRediT authorship contribution statement

X. Díaz de Otálora: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **D.A. Méndez:** Writing – review & editing, Methodology, Investigation, Data curation. **S. Sanjuan:** Writing – review & editing, Visualization, Methodology, Investigation, Formal analysis, Data curation. **R. Arnau:** Writing – review & editing, Visualization, Methodology, Investigation, Formal analysis, Data curation. **J.M. Calabuig:** Writing – review & editing, Visualization, Methodology, Investigation, Formal analysis, Data curation. **A. Villagrá:** Writing – review & editing, Resources, Investigation, Conceptualization. **S. Calvet:** Writing – review & editing, Resources, Funding acquisition. **F. Estellés:** Writing – review & editing, Resources, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of generative AI use

During the preparation of this work the authors used Grammarly to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biosystemseng.2026.104448.

Data availability

Data available upon reasonable request due to privacy/contractual constraints.

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