Article

Not peer-reviewed version

Prediction of Heat Wave Risk Based on Thermal Stress Indicators of Lactating Cows in the Amazon Savanna

Henrique Nascimento Paixão , Ana Luiza Santos Oliveira , Jose Teodoro Paiva , Thalles Ribeiro Gomes , Irenilza de Alencar Nääs * , Nilsa Duarte da Silva Lima

Posted Date: 5 September 2024

doi: 10.20944/preprints202409.0339.v1

Keywords: Dairy cows; heat wave predictive models; Northern Amazon; thermal comfort

Article

Prediction of Heat Wave Risk Based on Thermal Stress Indicators of Lactating Cows in the Amazon Savanna

Henrique Nascimento Paixão [1], Ana Luiza Santos Oliveira [1], Jose Teodoro de Paiva [1], Thalles Ribeiro Gomes [2], Irenilza de Alencar Nääs [3,*] and Nilsa Duarte da Silva Lima [1]

[1] Department of Animal Science, Federal University of Roraima, Boa Vista, 69300-000, RR, Brazil
[2] Instituto de Desenvolvimento Rural – IDR, Universidade da Integração Internacional da Lusofonia Afro-Brasileira (UNILAB), Campus das Auroras, José Franco de Oliveira, s/n, Redenção, 62.790-970, CE, Brazil
[3] Graduate Program in Production Engineering, Paulista University. Rus Dr, Bacelar 1212, São Paulo, SP, Brazil
* Correspondence: irenilza.naas@docente.unip.br

Abstract: Thermal comfort indices are risk indicators for environmental conditions in livestock production. Predictive models based on these indices of heat stress, respiratory frequency, and presence of heat waves for lactating cows, comparing the prediction and correlation between these factors, generate responses that can improve animal management regarding physiological responses to heat stress during the incidence of heat waves. Therefore, the objective was to develop predictive models for heat wave risk alerts based on thermal stress indices, physiological responses, and surface temperature of lactating cows. The region's climatic conditions were evaluated based on data on temperature, air humidity, wind speed, black globe temperature, solar radiation, dew point temperature, and precipitation compiled from a meteorological station. In the processing phase, a data set was discretized into classes to apply machine learning techniques to generate a classification model with cross-validation of the data. The performance of the classifiers was evaluated based on the metrics: accuracy, precision, sensitivity (recall), and Kappa statistics. Predicting the risk of heat waves for lactating cows can meet the need to predict the frequency of heat waves for decision-making in environmental, nutritional, and health management to minimize adverse impacts on production. The accuracy of Decision Tree models (J48), Naive Bayes, and Logistic Regression was equal to 96.72%, 96.72%, and 98.36%, respectively. The performance in the evaluation metrics of the Logistic Regression prediction model was better than that of the decision tree and Naive Bayes models.

Keywords: dairy cows; heat wave predictive models; Northern Amazon; thermal comfort

1. Introduction

The Amazon savanna is one of the most biodiverse regions in the world. The region experiences a distinct dry season, contrasting with the rainforest's year-round moisture [1]. This seasonality influences the types of vegetation and animal behaviors in the region. The soils in the Amazon savanna are generally nutrient-poor compared to those of the rainforest, affecting the types of vegetation that can grow and the overall productivity of the ecosystem. A mix of grasslands, shrubs, and scattered trees characterizes the region, and a diverse vegetation structure supports different ecological niches compared to the dense rainforest [2].

Climate change presents substantial global challenges to dairy production systems, affecting milk yield, composition, and dairy cows' overall health and welfare. The convergence of global warming, elevated air temperatures, and a rise in extreme weather events and droughts can induce heat stress conditions, adversely impacting animal health and welfare [3]. The direct effects of climate

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 September 2024 doi:10.20944/preprints202409.0339.v1

change are primarily attributed to the increased temperature and the heightened frequency and intensity of heat waves observed in recent years [4]. Concern about animal welfare in production systems is constantly growing worldwide. Moreover, Brazil is characterized by a predominantly tropical climate, with high average temperatures throughout the year in a large part of its territory.

Thermal stress is a significant challenge in dairy production. Previous research has indicated that environmental factors can influence milk production by eliciting physiological responses directly associated with milk yield [5–9]. Comprehending these effects is essential for formulating adaptation and mitigation strategies to maintain dairy production amidst a changing climate. Dairy cows are more impacted by high temperatures than beef animals, given their faster metabolism [10]. This higher metabolic rate adapts dairy breeds to challenging tropical environments, resulting in reduced well-being and productivity and even changes in the milk composition of these animals.

Thermal comfort indices as indicators of risk in the animal environment have been used to evaluate the thermal stress of dairy cows, including the predictive performance of thermal indices typical of dairy cattle, comparing their predictions with thermal stress levels and correlating them with some physiological responses [11]. Another significant element concerns circadian changes in cows, which are associated with disease, stress, or calving/estrus events. Episodes of stress or illness in animals can disrupt their circadian rhythm of activity, which is correlated with the ambiance and well-being of cows [12].

Bioclimatic indices serve as crucial guides for cow welfare, especially in tropical regions with a notable increase in heat load. Technological advances make it possible to monitor external climatic conditions in the internal environment of facilities, including the animals' body temperature. Observation of physiological responses, such as breathing rate and panting score, is valuable for assessing heat stress in ruminants. When applied to complex and scalable models, this approach can be more accurate and informative [13]. Therefore, the objective of the present work was to develop predictive models for heat wave risk alerts based on climate data and heat stress indices of lactating cows raised on pasture and evaluate the best model to predict the heat wave risk for lactating cows under the climate of the Amazon savanna.

2. Materials and Methods

The recording period was between September 1st and October 31st, 2023, in Boa Vista, Roraima (latitude 2° 49′ 12″ N, longitude 60° 40′ 19″ W, and altitude 2.739 m). The recorded data occurred on farm production following the World Organisation for Animal Health (OIE) Terrestrial Animal Health Code, which provides international animal welfare standards, particularly in production systems.

2.1. Environmental Measures and Thermal Stress Indices

The region's climatic conditions were evaluated based on data on temperature (ºC), air humidity (%), wind speed (m s-1), black globe temperature (Tbg), and precipitation (mm/h) compiled in the database NASA climate data [14].

The Black Globe Temperature and Humidity Index (BGHI) was calculated from data on air temperature, air humidity, and radiant thermal energy from the environment, as shown in Eq 1 [15].

$$\mathrm{GHI} = \mathrm{tbg} + 0.36 \times \mathrm{tdp} + 41.5 \quad (1)$$

where tbg black globe temperature (°C); tdp = dew point temperature (°C).

Respiratory Rate Index (RR), based on relative humidity, generates an estimate of the cattle's respiration rate [16,17] when temperatures exceed 25 °C under unshaded conditions and air temperature > 25 °C was calculated from Eq 2 (RR).

$$\mathrm{RRns} = 5.1\mathrm{ta}+0.58\mathrm{rh}-1.7\mathrm{ws}+0.039\mathrm{sr}-105.7 \quad (2)$$

where ta = environmental temperature (°C); rh = relative humidity (%); ws = air speed (m s^{-1}), and sr = solar radiation intensity (W m^{-2}).

The Dairy Cow Heat Load Index (DHLI) is based on the average panting score, black globe temperature (°C), and relative humidity. By utilizing black globe temperature, DHLI can incorporate the combined effects of ambient temperature, relative humidity, solar radiation, and wind speed into a single unit of measurement [18], which was calculated using Eq 3.

$$\text{DHLI}=(1.681813\times(1+e^{-(-8.50749+0.206159\times tbg+0.0488399\times rh)})\text{-}1-0.0002)\times(1.6812-0.0002)\text{-}1\times100 \quad (3)$$

where rh = relative humidity (%); tbg = black globe temperature (°C)

The Equivalent Temperature Index for cattle (ETIC) describes the perceived thermal condition of the cow by air temperature, relative humidity, air speed, and solar radiation [19] and can be calculated from Eq 4.

$$\text{ETIC}=ta-0.0038\times Ta\times(100-rh)-0.1173\times WS0.707\times(39.2-Ta)+1.86\times10-4\times Ta\times sr \quad (4)$$

where ta = environmental temperature (°C); rh = relative air humidity (%); ws = air speed (m s^{-1}); sr = solar radiation (W m^{-2}).

2.2. Predictive Analysis and Model Performance

The database was composed of 19 attributes and 61 instances, including weather data (minimum and maximum air temperature range,ºC; minimum and maximum air humidity range, %; minimum and maximum wind speed amplitude, m s-1; black globe temperature (Tbg); rain precipitation (mm h-1), solar radiation, W m-2; and thermal stress indices Black Globe Temperature and Humidity Index, BGHI; Respiratory Rate, RR; Heat load index for dairy cows, DHLI; and Equivalent Temperature Index for cattle, ETIC). The database was pre-processed to compose an integrated dataset for processing and validation through cross-validation.

In pre-processing, the data set was organized, cleaned (noise reduction/cleaning), and discretized into classes to apply supervised machine learning techniques to build predictive classification models with cross-validation of the data. The target attribute was created based on the criteria for detecting heat waves considering the temperature interval between the minimum and maximum temperature of the day; therefore, heat wave risk was considered at an amplitude above 10°C.

The following algorithms were applied in the data processing phase: J48 decision tree, Naive Bayes, and Logistic Regression. The classifiers' performance was evaluated based on the metrics of accuracy, precision, sensitivity (recall or true positive rate), Kappa statistics, Matthews correlation coefficient (MCC), and confusion matrix [20] by applying the following equations (Eq. 5 to 9).

$$\text{Accuracy}=(VP+VN)/(VP+VN+FP+FN) \quad (5)$$

$$\text{Precision}=VP/(VP+FP) \quad (6)$$

$$\text{Sensitivity}=VP/(VP+FN) \quad (7)$$

$$\text{Kappa} = \frac{\Pr(o) - \Pr(e)}{1 - \Pr(e)} \quad (8)$$

$$\text{MCC} = \frac{(VP * VN) - (FP * FN)}{\sqrt{(VP + FP) * (VP + FN) * (VN + FP) * (VN + FN)}} \quad (9)$$

where VP = true positive; VN = true negative; FP = falsepositive; FN = false negative; Pr(o) = observed values; Pr(e) = aimed values.

A confusion matrix is a simple cross-tabulation of what is predicted by the actual classes. It is the basis for calculating several accuracy measures, including accuracy and error or misclassification rate. For each class, the number of correct answers is located on the matrix's main diagonal, and the other elements represent errors in the classification (Table 1).

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 September 2024 doi:10.20944/preprints202409.0339.v1

Table 1. Confusion matrix.

Actual class (reference)	Predicted Class (model)		
	Positive	Negative	Total
Positive	VP	FN	P
Negative	FP	VN	N
Total	P′	N′	P + N = P′ + N′

VP = true positive; VN = true negative; FP = false positive; FN = false negative; P′ = total predicted positive values; N′ = total predicted negative values; P = total positive values; N = total negative values. Source: [21].

2.3. Spearman Correlation Coefficient

Spearman's correlation coefficient (ϱ or rho) was calculated to assess whether the presence of a heat wave is related to milk production. Correlations were calculated between milk production pairs and temperature amplitude and wind speed amplitude that characterize heat waves and between milk production pairs and Black Globe Humidity Index (BGHI), Respiratory Rate Index (RR), Dairy Cow Heat Load Index (DHLI), Equivalent Temperature Index for cattle (ETIC), Air Temperature Range (ATR), and Wind Speed Range (WSR).

3. Results and Discussion

The results of the general performance metrics and accuracy by model classes are presented in Table 2. The accuracy of the decision tree models (J48), Naïve Bayes, and Logistic Regression was equal to 96.72%, 96.72%, and 98.36%, respectively. Incorrectly classified instances were equal to 3.28% for decision tree (J48), 3.28% for Naïve Bayes, and 1.64% for Logistic Regression. The Kappa statistic was equal to 0.89 for decision tree (J48), 0.89 for Naïve Bayes, and 0.94 for Logistic Regression. Considering the detailed accuracy per class for the decision tree (J48), the precision was 98% (yes) and 91.7% (no), the sensitivity was 98% (yes) and 91.7% (no), and the Matthews correlation coefficient was equal to 89.6% (yes) and 89.6% (no).

In the Naïve Bayes model, the accuracy was 96.1% (yes) and 100% (no), the sensitivity was 100% (yes) and 83.3% (no), and the Matthews correlation coefficient was equal to 89.5% for both classes. In the Logistic Regression model, the precision was 100% (yes) and 92.3% (no), the sensitivity was 98% (yes) and 100% (no), and the Matthews Correlation Coefficient was equal to 100% (yes) and 100% (no). These results indicate that all models predicted heat wave risk for lactating cows well. However, the Logistic Regression model presented better overall results in performance metrics considering precision, sensitivity, and MCC.

Table 2. Performance of prediction models for heat wave risk.

Overall performance metrics	**Decision tree**		**Naïve Bayes**		**Logistic regression**	
Accuracy (%)	96.72		96.72		98.36	
Incorrectly classified instances (%)	3.28		3.28		1.64	
Kappa	0.89		0.89		0.94	
	Presence of risk of heat waves					
Accuracy details by class	Yes	No	Yes	No	Yes	No
Precision (%)	98.0	91.7	96.1	100.0	100.0	92.3
Sensitivity (%)	98.0	91.7	100.0	83.3	98.0	100.0
MCC (%)	89.6	89.6	89.5	89.5	100.0	100.0

MCC: Matthews correlation coefficient.

The results of the confusion matrix are presented in Table 3. The decision tree model correctly classified 48 instances into the "yes" class and 11 instances into the "no" class for the risk of heat waves. The Naïve Bayes model correctly classified 49 instances into the "yes" class and 10 instances into the "no" class for the risk of hot flashes. The Logistic Regression model correctly classified 48 instances into the "yes" class and 12 instances into the "no" class for the risk of heat waves. These results indicate that all models predicted heat wave risk for lactating cows well. However, the model that responded best in the confusion matrix metric was Logistic Regression, as it presented greater sensitivity (yes = 98% and no = 100%) and better results in the metric that assesses model quality (MCC: 100% for yes and not).

Table 3. Confusion matrix of predictive models.

Decision tree (J48) model (ni)			**Presence of risk of heat waves**
Yes	No	Total	Classified as
48	1	49	Yes
1	11	12	No
49	12	61	
Naïve Bayes model (ni)			
Yes	No	Total	Classified as
49	0	49	Yes
2	10	12	No
51	10	61	
Logistic regression model (ni)			
Yes	No	Total	Classified as
48	1	49	Yes
0	12	12	No
48	13	61	

ni: number of instances.

Heat waves are increasingly frequent, persistent, and intense in almost all inhabited regions [22]. With increased environmental temperature, heat waves can threaten animal production, affecting behavior and productivity [23]. Regions with humidity and temperatures cause adverse effects of heat stress on animals due to low heat tolerance or low adaptation, which can be minimized with heatwave forecasts. This generates indications for management adjustments for better behavioral and physiological adaptation, such as facility improvements.

It takes animals three to four days to reach thermal balance through thermoregulation, considering the reduction in body temperature for acclimatization. The interaction of climatic factors, including preceding or consecutive climatic events, contributes to the effects of heat waves in an extreme event [24].

The application of predictive models can help in the environmental management of the effects of heat waves in terms of predictability. The thermal stress indices of the animals in the data set used to build the model are risk indicators in managing the animal breeding environment [25].

Predicting the risk of heat waves for lactating cows can meet the need to predict the frequency of heat waves for decision-making in environmental, nutritional, and health management to minimize adverse impacts [22,25].

3.1. Heat Waves and Milk Yield

The results of the present study (Table 4) show that milk production had a very weak correlation with WSR (0.01), BGHI (0.01), RRI (0.14), and ETIC (0.16) and a weak correlation for DHLI (0.30, p-value = 0.02). However, only DHLI was significant (Table 4). ATR was negatively correlated with milk production (-0.16, p-value = 0.21) but was also insignificant. The correlations between the RR and the DHLI (0.76, p-value = < 0.0001), between the DHLI and the RRI (0.76, p-value = < 0.0001), and

ETIC (0.77, p-value = < 0.0001) were strong and significant. The correlations were strong between BGHI and RR (0.85, p-value = < 0.0001) and ETIC (0.81, p-value = < 0.0001) and very strong between RR and ETIC (0.99, p-value = < 0.0001) and significant.

Table 4. Spearman's correlations between bioclimatic indices and milk production.

Spearman's Test	ATR	WSR	BGHI	RRI	DHLI	ETIC	Milk production
ATR (rs)	1.00	0.52	0.68	0.32	0.11	0.29	-0.16
t-stats	-	4.70	7.08	2.58	0.82	2.30	-1.28
p-value	< 0.0001	< 0.0001	< 0.0001	0.01	0.41	0.02	0.21
WSR (rs)	0.52	1.00	0.42	0.05	-0.10	-0.02	0.01
t-stats	4.70	-	3.56	0.41	-0.79	-0.16	0.07
p-value	< 0.0001	< 0.0001	0.001	0.68	0.43	0.88	0.94
BGHI (rs)	0.68	0.42	1	0.85	0.50	0.81	0.01
t-stats	7.08	3.56	-	12.37	4.47	10.67	0.06
p-value	< 0.0001	0.0007	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.96
RRI (rs)	0.32	0.05	0.85	1	0.76	0.99	0.14
t-stats	2.58	0.41	12.37	-	8.93	56.47	1.08
p-value	0.0124	0.6815	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.29
DHLI (rs)	0.11	-0.10	0.50	0.76	1	0.77	0.30
t-stats	0.82	-0.79	4.47	8.93	-	9.15	2.40
p-value	0.4137	0.4348	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.02
ETIC (rs)	0.29	-0.02	0.81	0.99	0.77	1	0.16
t-stats	2.30	-0.16	10.67	56.47	9.15	-	1.24
p-value	0.0248	0.8751	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.22
Milk production (rs)	-0.16	0.01	0.01	0.14	0.30	0.16	1
t-stats	-1.28	0.07	0.06	1.08	2.40	1.24	-
p-value	0.21	0.94	0.96	0.29	0.02	0.22	< 0.0001

ART: Air Temperature Range; WSR: Wind Speed Range; BGHI: Black Globe Humidity Index; RR: Respiratory Rate Index; DHLI: Dairy Cow Heat Load Index; ETIC: Equivalent Temperature Index for cattle.

The correlations between bioclimatic indices are strong and very strong as they significantly impact the thermal conditions perceived by cows and include climatic factors, such as temperature, humidity, wind speed, and solar radiation, to evaluate these indices to verify thermal stress. The ATR and WSR correspond to the amplitude of variation in temperature and wind speed, which always present high values during heat waves [22], strongly influencing the results of the indices and consequently negatively affecting animal's well-being [19].

However, the indices may not have significantly affected milk production due to the animals' greater tolerance to heat and radiation in this region of the extreme north of Brazil, which does not mean that it does not affect well-being and the sensation of thermal comfort proven by the increase in the positive correlation between RRI and BGHI and ETIC. Tolerance to heat or extreme climates and a greater frequency of heat waves will require constant genetic adjustments in reproduction and production traits to have economic relevance in production systems due to the climate impact of global warming [26,27].

With the current climate, rising temperatures, and more frequent heat waves, the thermal comfort conditions of cows raised on pasture are more affected than animals in facilities with controlled environments. Climate change could significantly affect milk-producing livestock, especially regarding the increasing severity of heat waves [6,8,27,28].

4. Conclusions

The performance in the evaluation metrics of the Logistic Regression prediction model was better than that of the decision tree and Naive Bayes models. All algorithms have similar performance metrics regarding the classification task; however, the Logistic Regression model predicts quality when using data sets with the complexity of environmental attributes and thermal stress indices.

The bioclimatic indices had weak, non-significant correlations with milk production. However, we found strong correlations between BGHI, RRI, and DHLI, indicating that cows' heat tolerance, even with large thermal and wind amplitudes, does not favor the thermal balance, leading to a high correlation between RRI and ETIC.

Author Contributions: All authors contributed equally to this study. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data will be available from the corresponding author.

Acknowledgments: To CNPQ for the PQ 303712/2020-1 research scholarship.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Devecchi, M. F., Lovo, J., Moro, M. F. et al. (2020). Beyond forests in the Amazon: biogeography and floristic relationships of the Amazonian savannas. *Botanical Journal of the Linnean Society* **2020**, *193*(4), 478-503.
2. Costa-Coutinho, J. M., Jardim, M. A. G., Miranda, L. S., & Castro, A. A. J. F. (2022). Climate change effects on marginal savannas from central-north Brazil. *Anais da Academia Brasileira de Ciências* **2022**, *94*, e20210191.
3. Lacetera, N. Impact of climate change on animal health and welfare. *Animal Frontiers* **2019**, *9*(1), 26–31. https://doi.org/10.1093/af/vfy030
4. Sejian, V., Gaughan, J., Baumgard, L., Prasad, C. *Introduction to concepts of climate change impact on livestock and its adaptation and mitigation*. Springer India. 2015, 1–532. https://doi.org/10.1007/978-81-322-2265-1
5. Jordan, E. R. Effects of heat stress on reproduction. *Journal of Dairy Science* **2003**, *86*, E104-E114.
6. Abbott, C. R et al. An in vivo model to assess the thermoregulatory response of lactating Holsteins to an acute heat stress event occurring after a pharmacologically-induced LH surge. *Journal of Thermal Biology* **2018**, *78*, 247–256. https://doi.org/10.1016/j.jtherbio.2018.10.003
7. Hall, L. W., Villar, F., Chapman, J. D. et al. An evaluation of an immunomodulatory feed ingredient in heat-stressed lactating Holstein cows: Effects on hormonal, physiological, and production responses. *Journal of Dairy Science* **2018**, *101*(8), 7095–7105. https://doi.org/10.3168/jds.2017-14210
8. Tao, S., Orellana Rivas, R. M., Marins, T. N. et al. Impact of heat stress on lactational performance of dairy cows. *Theriogenology* **2020**, *150*, 437–444. https://doi.org/10.1016/j.theriogenology.2020.02.048
9. Leondro, H., Widyobroto, B. P., Agus, A. Physiological responses of the Holstein Friesian dairy cows raised under tropical conditions in Indonesia. *Journal of Physics* **2021**, *1869* https://doi.org/10.1088/1742-6596/1869/1/012161
10. Ferreira, F et al. Physiological parameters of crossbred cattle subjected to heat stress. *Arquivo Brasileiro de Medicina Veterinária e Zootecnia* **2006**, *58*, 732- 738.
11. Yan, G., Li, H., Zhao, W., Shi, Z. Evaluation of thermal indices based on their relationships with some physiological responses of housed lactating cows under heat stress. *International Journal of Biometeorology* **2020**, *64*, 2077-2091.
12. Wagner, N., Mialon, M. M., Sloth, K. H. et al. Detection of changes in the circadian rhythm of cattle in relation to disease, stress, and reproductive events. *Methods* **2021**, *186*, 14-21.
13. Wijffels, G., Sullivan, M., Gaughan, J. Methods to quantify heat stress in ruminants: Current status and future prospects. *Methods* **2021**, *186*, 3-13.
14. NASA. Power Data Access Viewer. 2023. Available online:https://power.larc.nasa.gov/data-access-viewer/ (accessed on 10 October 2023)
15. Buffington, D.E.; Collasso-Arocho, A.; Canton, G.H. Black globe-humidity index (BGHI) as comfort equation for dairy cows. *Transaction of the American Society of Agricultural Engineering* **1981**, *24*, 711-714.
16. Hahn, G. L., Gaughan, J. B., Mader, T. L., & Eigenberg, R. A. Thermal indices and their applications for livestock environments. In Livestock energetics and thermal environment management (pp. 113-130). American Society of Agricultural and Biological Engineers. 2009.
17. Eigenberg, R. A., Brown-Brandl, T. M., Nienaber, J. A., Hahn, G. L. Dynamic response indicators of heat stress in shaded and non-shaded feedlot cattle, Part 2: Predictive relationships. Biosystems Engineering 2005, 91(1), 111-118. https://doi.org/10.1016/j.biosystemseng.2005.02.001
18. Lees J. C., Lees A. M., Gaughan J. B. Developing a heat load index for lactating dairy cows. *Anim Prod Sci* **2018**, *58*, 1387. https://doi.org/10.1071/AN17776

 doi:10.20944/preprints202409.0339.v1

19. Wang, X., Gao, H., Gebremedhin, K. G., Bjerg, B. S. et al. A predictive model of equivalent temperature index for dairy cattle (ETIC). *Journal of Thermal Biology* **2018**, *76*, 165-170. https://doi.org/10.1016/j.jtherbio.2018.07.013
20. Han, J., Pei, J., Tong, H. *Data mining: concepts and techniques.* Morgan Kaufmann Publishers is an imprint of Elsevier. 225 Wyman Street, Waltham, MA 02451, USA. 2012.
21. Bowes, D., Hall, T., Gray, D. Comparing the performance of fault prediction models which report multiple performance measures: recomputing the confusion matrix. In: Proceedings of the 8th international conference on predictive models in software engineering. 2012. p. 109-118.
22. Domeisen, D. I., Eltahir, E. A., Fischer, E. M., et al. Prediction and projection of heatwaves. *Nature Reviews Earth & Environment* **2023**, *4*(1), 36-50.
23. Jige, S. B. *Impact of Development on Climate Change. In Multidisciplinary Approaches to Sustainable Human Development* (pp. 206-219). IGI Global, Hershey, Pennsylvania, USA. 2023.
24. Hahn, G. L. Bioclimatology and zootechnical installations: theoretical and applied aspects. In: Proceedings of Brazilian Workshop on Animal Bioclimatology, Jaboticabal: Funep, 1993. p. 132-146
25. Mader T. L., Johnson L. J., Gaughan. A comprehensive index for assessing environmental stress in animals. *J. Anim. Sci* **2010**, *88*, 2153-2165. https://doi.org/10.2527/jas.2009-2586.
26. Cheruiyot, E. K., Haile-Mariam, M., Cocks, B. G., Pryce, J. E. Improving genomic selection for heat tolerance in dairy cattle: current opportunities and future directions. *Frontiers in Genetics* **2022**, *13*, 894067.
27. Astuti, P. K., Ayoob, A., Strausz, P., Vakayil, B., Kumar, S. H., Kusza, S. Climate change and dairy farming sustainability; a causal loop paradox and its mitigation scenario. *Heliyon* **2024**, *10*(3). https://doi.org/10.1016/j.heliyon.2024.e25200
28. Yan, G, Liu, K., Hao, Z., Shi, Z., Li, H. (2021). The effects of cow-related factors on rectal temperature, respiration rate, and temperature-humidity index thresholds for lactating cows exposed to heat stress. *Journal of Thermal Biology* **2021**, *100*. https://doi.org/10.1016/j.jtherbio.2021.103041