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Microclimate modeling in naturally ventilated dairy barns during the hot season: Checking the accuracy of forecasts

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A R T I C L E I N F O

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A B S T R A C T

Monitoring and predicting the microclimate in naturally ventilated barns (NVB) is important given the adverse effects of high summer temperatures on dairy cows in the context of global climate change. The aim of the work was to verify the accuracy of the microclimate forecast in a NVB using linear regression (LR). Our working hypothesis suggested that multiple periodic measurements of air temperature and relative humidity outside and inside the barns at the same time will allow us to build LR models for predicting the temperature-humidity index (THI). This was done not only for a specific dairy barn based on this indicator outside, but also in other dairy barns with a similar design, located in similar weather conditions. The results of the research indicate that the use of LR had a high accuracy of forecasting (93–96%) the THI in NVB of various designs during the summer heat. At the same time, differences were found between traits (air temperature, relative humidity as well as resulting THI) provided by meteorological weather stations and these data measured simultaneously next to the dairy barns. The proposed LR models can be used to predict THI in NVBs of different designs.

1. Introduction

Animal husbandry must be animal- and environment-friendly (Hempel et al., 2018). More extreme conditions and greater variability are predicted in the regional climate, under various scenarios of climate change, which is mainly associated with an increase in the number of heat waves and their duration in the eastern and southeastern regions of Europe (Tomczyk et al., 2019). It is known that heat load leads to a decrease in milk production (Tao et al., 2018), impaires reproductive functions in cows (Dahl et al., 2016; Schüller et al., 2016) and affects animal welfare, which also may have long-term effects (Whay and Shearer, 2017).

In Europe, dairy cattle breeding is mainly characterized by intensive milk production due to highly productive cows, kept predominantly in naturally ventilated barns (NVB) (Algers et al., 2009; Milostiviy et al., 2017; Hempel et al., 2019). On the one hand, the main advantage of these buildings lies in their energy-saving properties, since in general natural ventilation does not require electricity to operate the fans. On the other hand, this housing system is particularly vulnerable to climate change as the microclimate in the barn directly depends on the ambient climatic conditions (Hempel et al., 2018). Therefore, NVB are commonly equipped with mechanical systems in summer, typically through the use of circulation fans, to mix the air within the barn. This serves to support the natural ventilation through recirculation. Whereby, ventilation is when fresh air enters the barn whereas recirculation is when the same air in the barn is speed up (Mondaca, 2019). Whenever in the following text reference is made to NVB, this refers to naturally ventilated barns with a temporary support (in summer) through recirculation.

Classically, the level of heat stress is estimated by the temperature-humidity index (THI), which is based on measurements of air temperature (AT) and relative humidity (RH), whereby the combined effect of them can be extremely fatal for the entire livestock and its productivity in hot periods (Bohmanova et al., 2007; Chaidanya and Sejian, 2015). Additional variables that can increase or decrease the heat load, such as radiation and air velocity are sometimes considered as well (Mader et al., 2006; Herbut et al., 2018; Yao et al., 2019).

It is important to prevent the occurrence of heat stress by predicting it, adhering to microclimate conditions and using meteorological forecasts. Thanks to these measures, the farmer can prepare and implement appropriate animal welfare solutions (Herbut et al., 2018). To evaluate

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the THI in a NVB, either the external temperature and humidity values (from the nearest weather stations) are mainly used, or the average daily values or maxima of these parameters measured in the center of the barn are taken into account. A study already demonstrated that climate conditions differ significantly between the barn and data obtained from the closest official meteorological station as well as between 4 different locations inside one dairy barn (Schüller et al., 2013). These microclimatic parameters are not evenly distributed in the barn, since neither sources of heat and moisture, nor air velocity are uniform throughout the barn (Herbut, 2013)). Furthermore, there are no available recommendations on the number and location of measuring devices or the frequency of measurements to achieve the accuracy of measurements of microclimatic conditions (Hempel et al., 2018).

Beside the use of animal-related methods (e.g., sensors and behavioral observations) for determining heat stress in dairy cows (Hoffmann et al., 2020), mathematical modeling is widely used to predict the reaction of animals to heat stress (Heinicke et al., 2019; Ji et al., 2019; Pinto et al., 2019; Müschner-Siemens et al., 2020). It can be a useful tool for predicting the microclimate (Maniatis et al., 2017), optimizing indoor ventilation and thermal comfort (Wang et al., 2018a; Mukhtar et al., 2018; Yao et al., 2019).

Statistical regression is a common method for developing a mathematical model, and the accuracy of prediction is highly dependent on the number of tests (Bezerra et al., 2008). Performing a large number of tests using laboratory or field experiments is expensive and time-consuming (Wang et al., 2018a), making such studies especially valuable. Despite the fact that the use of mathematical models for predicting the indoor climate is quite common, there are only a limited number of sources in literature for checking their accuracy, especially under real production conditions.

Therefore, the aim of the present work was building models and to verify the accuracy of the microclimate forecast in a NVB using linear regression (LR). The studies included: (1) multiple pairwise (outside and inside) measurements on farm of AT and RH in a NVB in the cold, transitional (spring) and hot (summer) periods of the year, in order to obtain a sufficient number of measurements for constructing regression models; as well as carrying out verification of the accuracy of these models in the field during the hot season; (2) examination of the convergence of external temperature and humidity conditions around uninsulated dairy barns to data from the nearest remote weather stations.

2. Material and methods

2.1. Research methodology

The study involved two series of experiments. The preliminary study onsisted of numerous registrations of AT and RH in two different NVBs (indoors and outdoors simultaneously) at one dairy farm. These data were used to construct LR models for predicting the THI in dairy barns based on measurements of air parameters outside the barn. Latter served as inputs for the LR equations and the outputs were the parameters inside NVBs.

The verification study involved checking the accuracy of previously obtained statistical models in a production environment, both on the dairy farm of the preliminary study and on a farm with a similar content of dairy cows in a NVB in the hot season.

2.2. Characteristics of barns and methods to register microclimate parameters when obtaining initial data for statistical modeling (preliminary study)

Multiple periodic measurements of AT and RH were conducted in a barn of frame type (Fig. A1) from steel structures (n = 334) and a barn of hangar type (Fig. A2) with an awning covering (n = 493) to get the material for conducting regression analysis. These studies were carried out in Ukraine in the dairy farm of the private Joint-Stock Company Argo-Soiuz (48°28′44″N, 35°36′46″E) from January to June 2018.

The dimensions of the barn of frame type were 252 m × 34.5 m in the axes, and 9.25 m was the internal height. The volume of the barn was 35294 m^3 in total, or rather about 35.3 m^3 per animal. The barn area was 8.7 m^2 per cow. The internal layout provided 1144 lying cubicles with a respective area of 2.5 m^2 (1.1 m × 2.25 m) in six rows. The dairy barn had 4 drinking throughs, and delta scrapers collected and removed regularly manure from the concrete floor.

The barn of hangar type had an awning covering from textile, the dimensions in the axes were 230 × 32 m, and the internal height was 9.2 m at the gable peak and 3.6 m at the eaves. The lying cubicles (n = 768) were placed in four rows. Their size was 2.24 m^2 (1.0 m × 2.24 m) per cow (herd size: 600 cows). The sections also had water troughs designed for a group of animals.

Both barns had feeding alleys, no rooflight, side regulated curtains made of canvas on the two long sides, and in the cubicles they used sand as bedding The longitudinal axes of the barns were in north-south orientation.

AT and RH were measured by thermohygrometers (Benetech GM 1360, Shenzhen Jumaoyuan Science and Technology Co., Ltd, Shenzhen, China) simultaneously outside and inside the barn according to

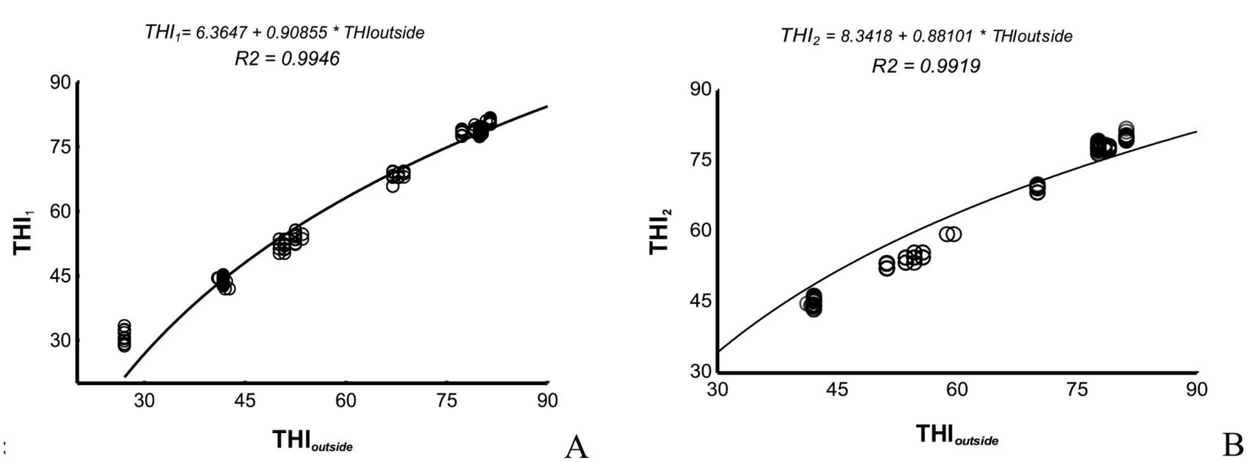

Fig. 1. Dependence of the temperature-humidity index (THI) in the barn of hangar type (A, THI_1) and in the barn of frame type (B, THI_2) on the THI value outside the buildings ($THI_{outside}$).

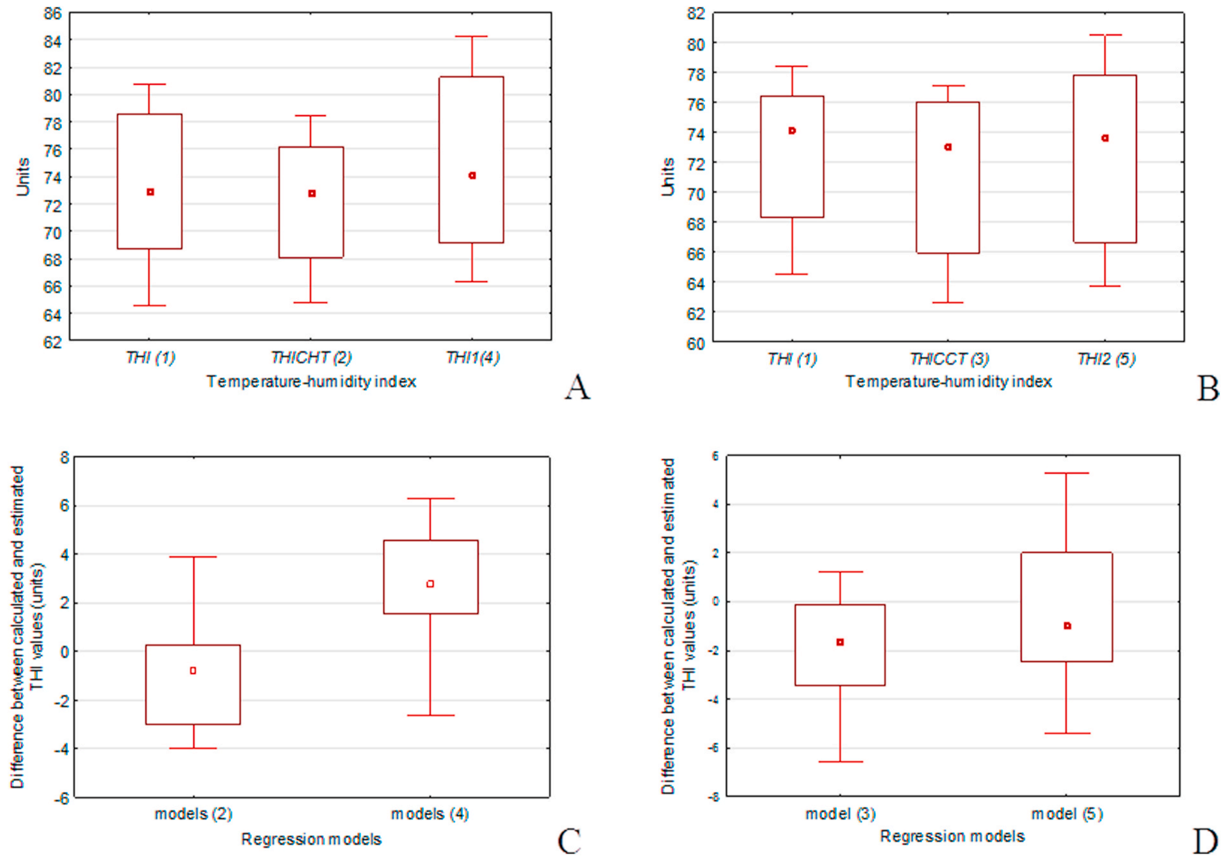

Fig. 2. Temperature-humidity index (THI) calculated with formula (1) according to Kibler (1964) and estimated with models (2) and (4) for the barn of hangar type (A) and with models (3) and (5) for the barn of frame type (B) with insulated roof. Differences between calculated and estimated THI values of models (2) and (4) for the barn of hangar type (C) and models (3) and (5) for the barn of frame type with insulated roof (D).

generally accepted rules (Antonenko et al., 2018): periodically during studies from 8:00 a.m. until 2:00 p.m. at 3 points along the diagonal of the barn (central and lateral parts of the sections), as well as vertically at the level of 0.5, 1.2 and 1.6 m from the floor.

2.3. *Characteristics of barns and methods for recording microclimate parameters when checking the accuracy of regression models (verification study)*

The accuracy of the regression models during the hot period was verified in the barn of hangar type at the dairy farm of Agro-Soyuz (described above) and in a NVB of frame type (Fig. A3) of the dairy farm of Yekaterynoslavskyi (48°34′03.1″N, 34°54′47.0″E) which was located nearby. Holstein cows (n = 548) of middle lactation (days in

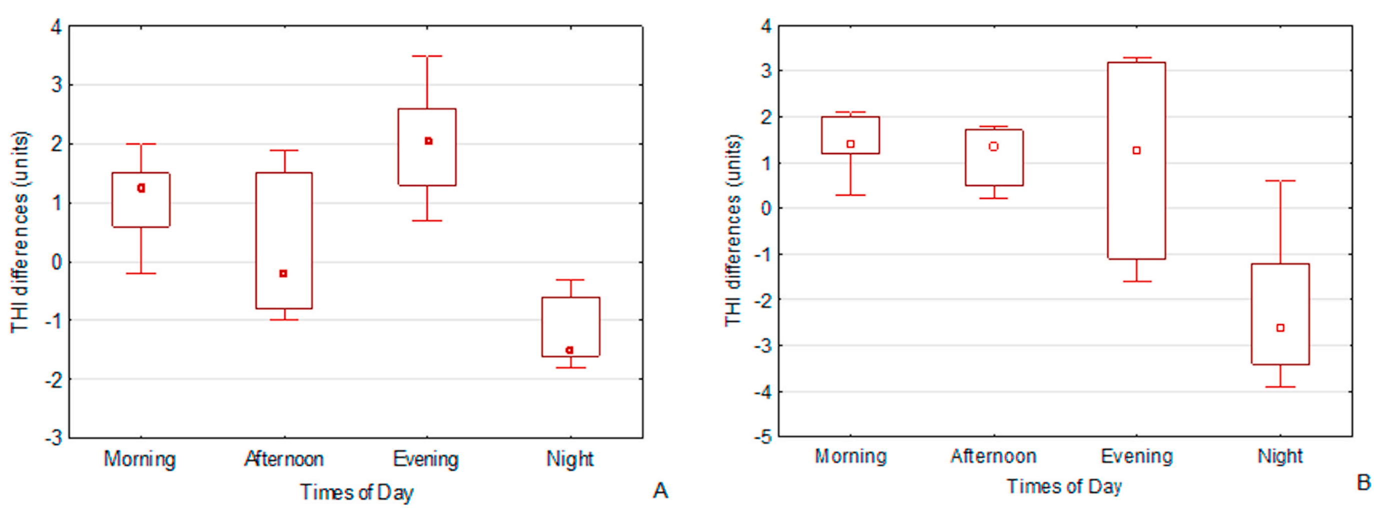

Fig. 3. Differences between the temperature-humidity index (THI) data provided by weather stations and the measured data outside the barn of hangar type (A) and of frame type with insulated roof (B) on one summer day in August and June during the verification study, respectively.

milk: 91 to 210) were in the barn of hangar type during the study. Their number in sections, designed for 150 cows, was between 127 and 143. The average daily milk yield for this technological group was 24–26 kg.

The barn of frame type (Yekaterinoslavsky) had an insulated roof, room for 600 dairy cows, and was placed along the longitudinal axis from the north-east to the south-west relative to the cardinal points. Its dimensions in the axes were 240.0 m × 32.4 m. This barn had four separat sections for 150 cows each and 150 lying cubicles (1.2 × 2.5 m) per section located in two rows. The side walls with a height of 3.0 m had a reinforced concrete base with fastening for canvas curtains. The opening and closing of the curtains was automatically controlled, depending on the inside barn temperature. Latter was recorded by a NORSOL WH-T-42 recorder (Norsol Electronics, St. Hubert, QC, Canada); its temperature sensors were placed indoors at a height of 3.5 m from the floor (above the suspended vertical axial fans). The gable roof was made of sandwich panels. The height of the barn in the ridge was 9 m. At the time of the study, 142 to 148 cows of the Schwyz breed of middle lactation (days in milk: 91 to 210) were in each sections; their average daily milk yield was between 25 and 27 kg.

Indoor and outdoor temperature and humidity in these barns were evaluated using thermohygrometers (Ambient Weather WS-10, Ambient LLC, Chandler, AZ, USA) for more than 30 h continuously, with sensor readings every 10 min. The remote sensors (F007TH) included in the Ambient Weather WS-10 were placed at the resting level of the animals (at a height of 50 cm from the floor) directly between the first and second lying cubicles on the side of the end sections (from the south-east and northwest) and in the central part (between the first and second lying cubicles). The external WS-10 thermohygrometer was placed outside the barn in shade at a height of 2 m from the floor.

The design of the vertical axial fans was similar in all types of barns. They were suspended at a height of 3.0 m from the floor in a vertical position with a slope at an angle of 10°. All fans were 90 cm diameter circulation fans, and were rated for airflow of 318 m^3/min. Their power was 0.7 kW. The distance between the fans was 10–15 m. In the barn of hangar type (Agro-Soyuz), they were located both above the lying cubicles and over the manure passage from the side of the feeding alley (alternating in a checkerboard pattern); in the barn of frame type with insulated roof (Yekaterinoslavsky), they were located above the lying cubicles.

2.4. Weather data

Weather data was provided by the Ukrainian Hydrometeorological Center (as a summary of data from local weather stations), they were publicly available on the Internet at Meteo.ua (https://meteo.ua/) in the weather archive section. The data were obtained from a weather station in the city of Pavlograd and weather station of the international airport "Dnepropetrovsk" (Dnipro) which are located in the Dnipropetrovsk region in central Ukraine. The distance from them to the nearby dairy complexes (Agro-Soyuz and Yekaterinoslavsky) was 27 and 19 km in a straight line, respectively. We recorded outside data on AT and RH directly around the barns using a thermohygrometer (Ambient Weather WS-10, Ambient LLC, Chandler, AZ, USA). We compared these data in order to understand how large the differences between them were, and whether the use of meteorological data would be justified to assess the impact of weather on the microclimate in a NVB in further studies.

2.5. Calculation of temperature and humidity indices

The temperature-humidity index (THI) indoors and outdoors was calculated according to the formula of Kibler (1964):

$$THI = 1.8 \times T - (1 - RH/100) \times (T - 14.3) + 32 \quad (1)$$

where THI is the temperature-humidity index, T is the air temperature in °C, and RH is the relative humidity in %.

The previously proposed principle of constructing LR models for the prediction of the THI in uninsulated barns only considered the magnitude of the external temperatures using equations (2) and (3), for the convenience of field calculations (Mylostyvyi et al., 2019b; Mylostyvyi and Chernenko, 2019):

$$THI_{CHT} = 46.00549 + 1.04460 \times T \quad (2)$$

$$THI_{CCT} = 47.05419 + 0.99649 \times T \quad (3)$$

where THI_{CHT} is the temperature-humidity index in the hangar type barn, THI_{CCT} is the temperature-index in the frame type barn, and T is ambient air temperature in °C.

Despite the fact that the above equations were calculated to determine the THI in uninsulated barns for both low and high outside temperatures, we carried out their verification at high summer temperatures, because this can have a negative impact on the performance of dairy cows and therefore, is most important in the context of global climate change.

2.6. Statistical analysis

The mathematical processing of the obtained data and the construction of LR models was performed using the software package for statistical analysis STATISTICA 10 (StatSoft, Inc., Tulsa, OK, USA). The obtained indicators were presented as a median. The differences between the samples, determined by the *U* test of Mann-Whitney (*U* test), were considered significant at $P < 0.05$.

3. Results

3.1. Building regression models for predicting climate in dairy barns and checking their accuracy

The THI was used to characterize the impact of heat stress on the dairy cows in NVBs. It was calculated according to the data of simultaneous registration of AT and RH of air outside and inside barns of two types (Table 1). We used the THI values that are summarized in this table to construct LR models; they should have predicted THI inside barns based on AT and RH outside the buildings.

The data presented (Table 1) indicate a significant difference between the parameters of the air environment inside and outside the barns in a wide range of external temperatures, despite slight differences in the median of their values. This shows the feasibility of taking into account weather conditions when assessing and predicting the microclimate in NVBs. The LR equation obtained for predicting the THI for a barn of hangar type (4) and a barn of frame type (5) will look like this:

$$THI_1 = 6.3763 + 0.90851 \times THI_{outside} \quad (4)$$

$$THI_2 = 8.3418 + 0.88101 \times THI_{outside} \quad (5)$$

where THI_1 is the temperature-humidity index for a barn of hangar type; THI_2 is the temperature-humidity index for a barn of frame type; and $THI_{outside}$ is the temperature-humidity index in the environment, calculated by formula (1) according to Kibler (1964).

Fig. 1 shows the corresponding scatter plots of these models.

The experimental data obtained in the form of median THI values outside and inside the dairy barns during the hot period (Table 2) served as material for checking the accuracy of the proposed regression models. These data were from measurements on one of the hot days of summer (in June and August, during heat waves).

Significant differences were recorded (Fig. 2) when comparing data obtained in the NVBs (experiment) with forecasts of the four regression models (named model (2), (3), (4), (5)) using equations (2)–(5), respectively.

With regard to the barn of hangar type, the median values of the THI fluctuated during the day from 66.3 at night (0:00–6:00 h) to 79.1

Table 1
Air temperature, relative humidity and temperature-humidity index outside and inside (before and behind the oblique stroke (/), respectively) of naturally ventilated dairy barns from January to June.

Naturally ventilated dairy barns (NVB)						
	barn of hangar type (n = 493)			barn of frame type (n = 334)		
Month	median	min	max	median	min	Max
Air temperature (°C)						
Jan I	−7.8/−4.8[a]	−7.8/−6.2	−7.8/−3.5	−7.2/−3.0[a]	−7.5/−4.9	−6.5/−1.7
Jan II	3.5/4.8[a]	3.3/3.7	4.0/5.9	3.8/5.5[a]	3.5/4.8	3.8/6.8
Feb	9.5/10.8[a]	9.5/9.5	9.9/11.5	10.1/11.5[a]	10.1/10.8	10.1/11.5
Mar	10.8/12.2[a]	10.8/10.8	11.5/12.9	12.2/12.2	11.5/11.5	15.6/15.6
Apr	21.1/21.8[a]	21.1/21.8	22.5/22,5	23.9/23.2[a]	23.9/22.5	23.9/23.9
May	30.7/29.4[a]	30.7/28.7	31,2/30.1	28.7/28.7	28.7/28.0	28.7/29.4
Jun	32.1/31.4	30.1/30.1	34.2/34.2	34.2/31.4[a]	32.1/30.7	34.2/32.8
Relative humidity (%)						
Jan I	58.8/62.3[a]	58.8/56.8	58.8/63.1	75.5/68.3[a]	61.3/43.3	75.5/75.3
Jan II	68.2/69.2[a]	66.5/68.8	72.7/69.5	69.5/69.5	69.5/69.3	72.7/72.5
Feb	78.7/74.9[a]	75.9/72.9	78.7/85.2	75.5/74.0[a]	75.5/73.0	76.4/83.2
Mar	69.7/72.2[a]	69.0/68.5	71.5/74.4	68.1/70.5[a]	59.3/58.8	69.5/72.9
Apr	55.9/57.0[a]	52.9/54.2	55.9/60.2	48.0/51.5[a]	48.0/48.0	48.0/55.4
May	55.1/56.7[a]	53.3/52.8	55.1/61.4	58.2/58.7	58.2/56.7	58.2/63.6
Jun	40.5/44.4[a]	36.3/36.8	43.6/50.2	37.6/45.1[a]	36.3/38.3	39.2/51.0
Temperature-humidity index (units)						
Jan I	27.1/30.5[a]	27.1/28.7	27.1/33.4	24.3/32.0[a]	23.8/29.7	28.8/37.3
Jan II	41.7/43.6[a]	40.9/41.9	42.7/45.2	42.0/44.4[a]	41.2/43.5	42.0/46.5
Feb	50.1/52.3[a]	50.1/50.2	50.9/53.4	51.2/53.4[a]	51.2/52.2	51.2/53.5
Mar	52.2/54.5[a]	52.4/52.3	53.6/55.6	54.6/54.6[a]	53.6/53.5	59.6/59.6
Apr	67.0/68.1[a]	67.0/67.9	68.6/69.2	70.0/69.4[a]	70.0/68.4	70.0/70.2
May	79.9/78.4[a]	79.9/77.4	80.3/79.6	77.6/77.7[a]	77.6/76.6	77.6/79.4
Jun	79.2/79.0	77.3/77.4	81.5/81.6	81.1/79.6[a]	78.4/77.4	81.1/82.0

Jan I and Jan II: measurement in the beginning and end of January, respectively.
[a] - significant difference between data outside/inside the barn ($P < 0.05$).

Table 2
Daily dynamics of the temperature-humidity index in dairy barns recorded during summer (June and August) over 30 consecutive hours and measurements every 10 min, presented as median (min-max).

Day time	Naturally ventilated dairy barns			
	Barn of hangar type (n = 402), month: August		Barn of frame type with insulated roof (n = 414), month: June	
	outside	inside	outside	inside
1:00	68.0 (67.6-68.6)	68.0 (67.0-69.1)	63.7 (63.3-64.0)	67.2 (64.4-70.6)[a]
2:00	66.5 (66.4-66.8)	66.7 (66.2-68.0)	62.5 (62.1-63.3)	65.5 (63.7-70.6)[a]
3:00	66.4 (64.7-66.8)	66.7 (64.0-68.2)	61.5 (61.4-61.8)	64.5 (64.2-67.6)[a]
4:00	64.3 (64.0-67.2)	64.6 (62.5-68.3)	61.6 (61.4-61.7)	67.0 (64.8-67.9)[a]
5:00	64.6 (64.4-66.2)	64.6 (62.7-68.3)	63.1 (62.2-64.4)	68.3 (66.3-69.3)[a]
6:00	65.5 (65.2-66.4)	65.3 (63.5-67.1)	66.7 (64.6-67.6)	68.0 (67.1-68.8)[a]
7:00	67.9 (67.1-68.7)	69.7 (66.5-74.0)[a]	70.2 (68.4-71.9)	70.4 (68.5-72.3)
8:00	70.2 (69.1-71.6)	72.6 (70.2-73.9)[a]	73.0 (71.8-74.1)	73.1 (71.2-74.5)
9:00	73.4 (72.1-74.6)	75.8 (74.1-77.4)[a]	73.7 (73.6-75.2)	74.8 (72.8-75.9)
10:00	76.1 (75.0-77.1)	78.7 (77.0-83.5)[a]	75.9 (73.7-76.7)	76.3 (73.2-77.3)
11:00	77.9 (76.5-78.7)	80.1 (78.6-81.5)[a]	75.3 (75.0-77.7)	75.2 (73.8-78.0)
12:00	79.4 (78.6-81.1)	80.8 (78.9-81.6)[a]	75.5 (75.5-75.6)	75.7 (75.0-76.9)
13:00	78.9 (78.4-79.7)	79.8 (78.8-81.1)[a]	77.0 (75.4-77.1)	76.1 (75.5-76.9)
14:00	78.5 (78.3-79.1)	78.7 (78.1-79.8)	77.6 (77.3-78.6)	76.5 (75.6-76.9)[a]
15:00	78.1 (76.9-79.2)	79.7 (78.5-80.0)	78.0 (77.7-78.0)	76.5 (76.1-77.3)[a]
16:00	76.8 (76.5-77.1)	78.5 (77.8-79.0)[a]	77.4 (76.4-77.7)	77.2 (76.2-78.2)
17:00	76.7 (76.6-76.9)	78.5 (77.6-79.4)[a]	77.0 (76.9-77.5)	77.1(76.6-78.3)
18:00	76.6 (75.8-78.3)	78.2 (76.0-81.2)[a]	77.0 (77.0-77.1)	77.2 (76.3-78.5)
19:00	76.1 (74.5-78.0)	75.7 (73.7-77.8)	76.5 (76.0-76.9)	78.4 (75.9-80.0)
20:00	73.4 (73.1-74.3)	73.1 (69.9-74.2)[a]	74.6 (73.0-75.6)	75.6 (73.4-79.3)[a]
21:00	72.2 (72.4-73.7)	71.5 (69.3-72.7)[a]	70.8 (69.2-73.2)	73.2 (71.9-79.3)[a]
22:00	71.5 (70.4-72.7)	70.6 (68.1-70.9)[a]	68.1 (67.4-69.1)	71.4 (69.9-72.9)[a]
23:00	72.6 (70.5-72.9)	69.6 (68.2-70.2)[a]	66.0 (65.1-67.4)	68.9 (65.4-72.1)[a]
24:00	69.1 (68.4-69.5)	69.4 (68.7-71.0)	64.8 (64.4-65.0)	68.3 (65.4-70.6)[a]

[a] - significant difference ($P < 0.05$) between indicators outside and inside.

during the afternoon (13:00–18:00 h). Moreover, the largest differences were recorded between experimental data and forecasts for model (2) in the morning (7:00–12:00 h) - 3.1 units and in the afternoon (13:00–18:00 h) - 1.6 units. The predicted THI values of model (2) were lower than the experimental ones in all cases ($P < 0.05$). Model (4) had the largest error during the afternoon (13:00–18:00 h) - 4.4 units and also in the evening (19:00–24:00 h) - 2.6 units. In all cases, the predicted values of model (4) were higher than observed ($P < 0.05$). The difference was the smallest between the observed and estimated values for the models (2) and (4) at night, making −0.2 units and +1.6 units, respectively. This difference was not significant.

With regard to the barn of frame type with an insulated roof, the median values of THI ranged from 64.1 units (at night) to 76.5 units (during the day). The differences were significant between the observational data and the forecast for model (3) at night - 3.4 units and also in the evening - 2.9 units. Forecasted values of model (3) were lower than experimental values in all cases ($P < 0.05$). The largest differences were recorded between observations and forecasts for the model (5). The differences were minus 3.9 units at night and also plus 3.3 units during the day; while the differences were minimal (0–1.0 units) between the observed and estimated values for models (3) and (5) in the morning.

The accuracy for predicting the THI in NVBs, based on the external state of the air outside the barn, is shown in Table 3.

The forecast accuracy turned out to be high enough for the proposed regression models (93–96%). However, the difference in THI values was quite large (from 0 to 4.4 units) between forecasted and observed data in experiments.

3.2. Possibility to use meteorological data for climate forecasting in naturally ventilated dairy barns

We assumed that there were differences between the data of weather

Table 3
The accuracy of the regression forecast models of the temperature-humidity index (THI) in naturally ventilated dairy barns, with models (2) and (4) for the barn of hangar type and models (3) and (5) for the barn of frame type with insulated roof.

Indicator	Linear regression models (based on climate data outside)			
	(2)	(4)	(3)	(5)
PM (R2)	0.8535*	0.9209*	0.8602*	0.8807*
MeD (%):				
night (0:00–6:00 h)	0.3	1.6	5.0*	3.9*
morning (7:00–12:00 h)	3.9*	2.5	1.3*	0.0
afternoon (13:00–18:00 h)	1.6*	5.6*	0.4	3.3*
evening (19:00–24:00 h)	0.4	3.6*	4.0*	2.9*
MD (%)	4.0*	6.3*	6.6*	5.4*
Prediction Accuracy (%)	96.0	93.7	93.4	94.6

The performance of models (PM) was evaluated by the coefficient of determination (R2). MeD: median deviations of observed and estimated THI values, MD: maximum deviations of observed versus estimated THI values; * – significant difference ($P < 0.05$) between observed and estimated THI values.

stations located near dairy farms and data of AT and RH close to dairy barns. In support of this hypothesis, we compared the values of AT and RH used to calculate the THI (Table 4).

Significant differences were identified between the parameters provided by weather stations and the climate data outside the dairy barns. With regard to the barn of hangar type, the RH near this barn was on the contrary lower (by 8%) at night than indicated by the weather station data. The observed AT was 2.8–2.9 °C higher ($P < 0.05$) outside the barn; however, there was no significant difference in the values of THI between the measured parameters and data from weather stations during the day.

With regard to the barn of frame type with an insulated roof, the median RH was 18% higher outside this barn than recorded by the weather station at night. In the morning and until late evening it was 1.3-2.7 °C warmer near this barn, and the values of the THI were higher, exceeding meteorological data by 0.9-3.0 units (Fig. 3). The difference was statistically significant in THI values during daytime.

4. Discussion

Microclimatic conditions in dairy barns affect animal welfare and gaseous emissions, in particular ammonia and methane (Hempel et al., 2018). Literature sources indicate that current research is not limited to indoor climate monitoring, but increasingly to its prediction using mathematical modeling Mondaca and Choi, 2016; Wang et al., 2018a). However, even measuring microclimate parameters is difficult when it comes to NVBs. This housing system is particularly vulnerable to climate change, since the microclimate in the NVB is directly dependent on environmental climatic conditions (Hempel et al., 2018).

Microclimate measurement accuracy in buildings varies greatly due to the heterogeneous distribution of heat and humidity sources associated with equipment operation, air flow turbulence, and different comfort zones of the animals (Hempel et al., 2018). Errors in temperature data (up to ± 2 °C) and air humidity (up to ± 20%) were related to instruments accuracy and spatial placement of sensors. It is quite reasonable that one temperature sensor inside the barn is not enough to estimate the risk of heat stress based on microclimatic parameters. In particular, differences in AT and RH in different parts of the uninsulated barn were 1.1–3.6 °C and 6.8–11.8%, respectively, and this refers only to the animal occupied zone (Mylostyvyi et al., 2019a). In this sense, the inside THI is a very doubtful measure of the risk of heat stress (Hempel et al., 2018).

Hempel et al. (2018) recommend measuring the air parameters that constitute the microclimate at a height of about 3–3.5 m from the floor in a NVB, where monitoring in the direct vicinity of the animals is not possible. In our case (after the cows got used to the sensors for several days), the measurements of AT and RH were done in the cow's occupied zone at cow height to get most reliable results. This is significant because this is where the animals experience the greatest heat stress and therefore, the effects on milk productivity can be better assessed (Collier et al., 2006; Schüller et al., 2016).

Despite the long history of the use of modeling in environmental studies (Maclean et al., 2018), and the relatively high accuracy of forecasts (about 90%), nevertheless, some aspects of the models remain poorly developed, partly due to the limitations of the conditions in which they were tested, and therefore, without taking into account the influence of the entire range of factors. When modeling, it is important to take into account that the microclimate of the area can significantly differ from large-scale average weather forecasts (Bramer et al., 2018) due to the influence of the shape of the landscape, height above sea level, proximity to the sea or inland waters, whether the site is in a valley or on a hilltop, and the structure of the vegetation on the ground. Detailed spatial and temporal data on microclimate obtained from remote sensing (Zellweger et al., 2019) or, as in the present study, directly outside buildings, can lead to more realistic forecasts of the microclimate and related biotic reactions to changes in weather conditions.

Similar studies on climate modeling in NVB were conducted earlier (Segnalini et al., 2012), however, only THI values of the external environment were used as inputs to the modeling. Comparable to our study THI inside NVB was also taken into account by Hempel et al. (2019), what, in their opinion, can improve the assessment of future heat stress events and thereby contribute to the adaptation of the livestock system.

Limited information in the literature on long-term microclimate measurements in a large number of NVBs, and direct measurement data in the animal occupied zone (using appropriate devices), complicates the development of universal microclimate monitoring and forecasting approaches (Hempel et al., 2018). Difficulties are also associated with approaches to statistical modeling processes that require a large number of tests (Wang et al., 2018c). It has been reported (Wisnieski et al., 2019a) that model results tended to overestimate the result in small-sample cases and lower the result in a large number of observations. Another limitation of modeling is that most researchers use explanatory modeling instead of predictive modeling (Wisnieski et al., 2019a). A limitation of such studies (their disadvantage) is that these models are not validated (Wisnieski et al., 2019b). The determination coefficient is considered a good criterion for evaluating the performance of statistical models (Matsoukis and Chronopoulos, 2017; Maniatis et al., 2017), however, reports on the validation of such models under experimental conditions are difficult to find.

Table 4
Median of air temperature (AT), relative humidity (RH) and temperature-humidity index (THI) recorded during 24 h of the verification study (weather station/outside the barn)

Time of day	Naturally ventilated dairy barns, n = 76					
	Barn of hangar type (August 16-17, 2018)			Barn of frame type with insulated roof (June 21-22, 2018)		
	AT, °C	RH, %	THI, units	AT, °C	RH, %	THI, units
Night	20.5/ 20.9	58.5/ 50.5[a]	66.5/ 65.3	20.3/ 19.2	55.3/ 73.0[a]	65.9/ 65.2
Morning	28.5/ 30.3	43.3/ 40.8	75.2/ 76.5	26.5/ 29.2	41.7/ 42.0	73.0/ 76.0
Afternoon	33.0/ 35.5[a]	25.8/ 15.0[a]	77.7/ 77.6	33.5/ 35.1	27.0/ 23.5	78.2/ 79.1[a]
Evening	24.3/ 26.8	41.8/ 38.3	69.8/ 72.7	28.7/ 30.0	33.5/ 32.5	74.4/ 75.3

Night: 0:00–6:00 h; morning 7:00–12:00 h; afternoon 13:00–18:00 h; evening 19:00–24:00 h.

[a] Significant difference ($P < 0.05$) between weather station and outside the barn.

The forecast accuracy of the present study to predict the THI in NVBs based on the external state of the air outside the barn was between 93 and 96%. However, the difference in THI values was quite large (0–4.4 units) between forecasted and observed data in experiments. Therefore, further scientific research should provide the identification of causes that determine the quality of statistical modeling.

The task of statistics and machine learning is to extract useful information and knowledge from a large amount of data. Errors in the construction and evaluation of models can have negative consequences. Therefore, special attention should be given to validating models, preferably using an external dataset. The latter is possible only for the so-called white box models, which allow to interpret the model parameters. Black box models, such as reference vector machines or artificial neural networks, do not allow this interpretation and can only be verified externally. However, their ability to distinguish is often significantly better than white-box models, which may explain their popularity (Dreiseitl and Ohno-Machado, 2002).

The preference for choosing artificial neural networks may be due to the fact that these models can be considered as nonlinear generalizations of logistic regression, and they were more accurate in forecasts (Bilgili and Sahin, 2010; Matsoukis and Chronopoulos, 2017; Hempel et al., 2019). However, linear models differ in the interpretability of model parameters and ease of use (Dreiseitl and Ohno-Machado, 2002), which leads to our choice in this study.

The use of machine learning methods in predicting environmental parameters (temperature, humidity, emission of greenhouse gases) could show better results than linear models, due to account nonlinearities (Sousa et al., 2007). Further studies are necessary to show if the use of artificial neural networks, as an alternative to LR, would be more effective due to the elimination of collinearity problems.

Gardner et al. (2019) reported that many models neglect physiological variables. We agree with the authors that the inclusion of climate variables should be justified from a physiological point of view. Further work will take this into account by considering physiological indicators and milk production in the models as variables. However, numerous studies (Bohmanova et al., 2007; Allen et al., 2015; Herbut et al., 2019) show a relationship between THI and the welfare, behavior and milk yield of dairy cows.

Ongoing studies should also include air speed inside and outside the barns as LR inputs. A modeling that contained these variables (included in the ETIC calculation) had more accurate prediction results (Hempel et al., 2019). Furthermore, Yi et al. (2018) showed that there is a high degree of turbulence leading to significant spatial heterogeneities in the velocity field inside the barn, which can be significantly due to the surface wind speed, which is very diverse regionally (Kjellström et al., 2018).

In addition, the accuracy of linear models depends on the completeness of the inputs presented. However, the number of them should not overload the model. This contradiction may be resolvable (Bilgili and Sahin, 2010) by determining reliable correlations between independent variables that need to be included in the model. In one of our previous studies (Mylostyvyi and Chernenko, 2019) a stronger reliable correlation between environmental factors (AT, RH, THI) and milk components than between them and wind strength was revealed. To some extent, this justifies our approach to modeling, in which we used only AT and RH in composite THI, as inputs for LR.

The data provided by the nearest weather stations are considered to be appropriate in assessing the impact of weather on the behavior, welfare and performance of cows (Bohmanova et al., 2007). However, weather conditions near livestock premises can depend significantly on thermal insulation materials, which significantly affect the energy efficiency and environmental performance of barns (Schüller et al., 2013; Valančius et al., 2018). It is known that the building can "smooth" the amplitude of daily temperatures in the evening, at night and in the morning, so that the sensor near the barn registers the air temperature above the real by 5–10 °C (depending on cloudiness); that is, a temperature that is only 60% dependent on the weather and 40% on the barn's thermal radiation. Terrain, insolation, wind speed and farm location above sea level can also significantly affect the microclimate of barns and the milk production (Angrecka et al., 2017; Yi et al., 2018; Broucek et al., 2019). The present study showed significant differences in the values of AT and RH between the measured parameters and data from weather stations during the day. Thus, the differences in AT and RH found between weather station data and values near the barn should be taken into account when assessing the influence of weather conditions on the microclimate in dairy barns.

In addition, various data in different monitoring points may not only be due to the design of the barn (Sahu et al., 2018), but also to the numerous factors affecting the microclimate in the animal occupied zone; e.g., animal crowding, bedding material and residual manure indoors (Fregonesi et al., 2007; Morabito et al., 2017; Poteko et al., 2019), as well as barn equipment and animal body postures that significantly affect airflow distribution (Herbut et al., 2012; Bustos-Vanegas et al., 2019). This proves that studies of the most representative sensor positions should be conducted for each barn individually to reduce the error in the animal welfare assessment from the THI perspective (Hempel et al., 2018). Such monitoring points (Banhazi, 2013) will have to provide an accurate and representative assessment of the whole building or specific problem areas (e.g., the emission or the animal occupied zone).

The concepts of adaptation to heat stress should also take into account the peculiarities associated with individual physiological and behavioral responses of cows to actual microclimatic conditions (Hempel et al., 2018). Taking into account the position of the body in dairy cows during periods of heat stress will help to develop more effective strategies to mitigate the heat load on dairy cattle (Cook et al., 2007; Wang et al., 2018c; Nordlund et al., 2019). Dairy farmers could improve the health of their cows by introducing measures to increase the residence time of animals in stalls in lying posture when the THI rises beyond the threshold of thermal stress to a THI >68 (Zimbelman et al., 2009) by directing the horizontal airflow of the ventilation systems into the animal's area (Wang et al., 2018b). In this sense, the recently proposed ventilation systems based on the concept of directing fresh air directly into the animal's area (Mondaca and Choi, 2016; Wang et al., 2018c) may be particularly in demand.

5. Conclusions

The construction of statistical models was effective for predicting the microclimate in dairy barns on the basis of multiple recordings of air temperature and relative humidity outside and inside the barn over a wide temperature range. The use of linear regression had a high accuracy of prediction (93–96%) of the THI in naturally ventilated dairy barns of various designs based on the state of the external environment. The coefficient of determination between observed and estimated data was in the range of $R2 = 0.854–0.921$. Prediction of microclimate parameters in naturally ventilated dairy barns based on data from weather stations should be careful; since significant differences were revealed between meteorological data and measurements of air temperature and relative humidity (differences of 1–3 °C and 8–18%, respectively) outside the barn in the warm period.

CRediT authorship contribution statement

Roman Mylostyvyi: Conceptualization, Methodology, Writing - original draft. **Olena Izhboldina:** Funding acquisition, Supervision. **Oleksandr Chernenko:** Resources, Validation. **Olga Khramkova:** Formal analysis. **Natalya Kapshuk:** Data curation. **Gundula Hoffmann:** Validation, Writing - review & editing.

Declaration of competing interest

None.

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Appendices

Fig. A.1. Barn of frame type at the dairy farm in Argo-Soiuz.

Fig. A.2. Barn of hangar type at the dairy farm in Argo-Soiuz.

Fig. A.3. Barn of frame type of the dairy farm of Yekaterynoslavskyi.

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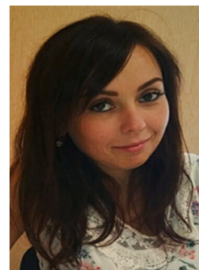

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