Bunching behavior in housed dairy cows at higher ambient temperatures

Article

Published Version

Chopra, K. ORCID: https://orcid.org/0009-0003-1427-3384, Hodges, H. R., Barker, Z. E. ORCID: https://orcid.org/0000-0002-8512-0831, Vázquez Diosdado, J. A. ORCID: https://orcid.org/0000-0001-6934-9305, Amory, J. R. ORCID: https://orcid.org/0000-0002-0047-8739, Cameron, T. C. ORCID: https://orcid.org/0000-0002-5875-1494, Croft, D. P., Bell, N. J. ORCID: https://orcid.org/0000-0001-6415-0786, Thurman, A., Bartlett, D. and Codling, E. A. ORCID: https://orcid.org/0000-0001-5124-3334 (2024) Bunching behavior in housed dairy cows at higher ambient temperatures. Journal of Dairy Science, 107 (4). pp. 2406-2425. ISSN 1525-3198 doi: https://doi.org/10.3168/jds.2023-23931 Available at https://centaur.reading.ac.uk/116710/

www.reading.ac.uk/centaur

CentAUR

Central Archive at the University of Reading

Reading's research outputs online

Bunching behavior in housed dairy cows at higher ambient temperatures

**Kareemah Chopra,[1]* Holly R. Hodges,[2] Zoe E. Barker,[2]† Jorge A. Vázquez Diosdado,[1]‡
Jonathan R. Amory,[2] Tom C. Cameron,[3] Darren P. Croft,[4] Nick J. Bell,[5]§ Andy Thurman,[6]
David Bartlett,[6] and Edward A. Codling[1]**

[1]Department of Mathematical Sciences, University of Essex, Colchester, Essex, CO4 3SQ, United Kingdom
[2]Writtle University College, Chelmsford, Essex, CM1 3RR, United Kingdom
[3]School of Life Sciences, University of Essex, Colchester, Essex, CO4 3SQ, United Kingdom
[4]Centre for Research in Animal Behaviour, Faculty of Health and Life Sciences, University of Exeter, Exeter, Devon, EX4 4QG, United Kingdom
[5]Royal Veterinary College, Hatfield, Hertfordshire, AL9 7TA, United Kingdom
[6]Omnisense Limited, St. Neots, Cambridgeshire, PE19 6WL, United Kingdom

ABSTRACT

Bunching behavior in cattle may occur for several reasons including enabling social interactions, a response to stress or danger, or due to shared interest in resources such as feeding or watering areas. There is evidence in pasture grazed cattle that bunching may occur more frequently at higher ambient temperatures, possibly due to sharing of fly-load or to seek shade from the direct sun under heat stress conditions. Here we demonstrate how bunching behavior is associated with higher ambient temperatures in a barn-housed UK dairy herd. A real-time local positioning system was used, as part of a precision livestock farming (PLF) approach, to track the spatial position and activity of a commercial dairy herd (~100 cows) in a freestall barn continuously at high temporal resolution for 4 mo between August and November 2014. Bunching was determined using 4 different spatial measures determined on an hourly basis: herd full and core range size, mean herd intercow distance (ICD), and mean herd nearest-neighbor distance (NND). For hourly mean ambient temperatures above 20°C, the herd showed higher bunching behavior with increasing ambient temperature (i.e., reduced full and core range size, ICD, and NND). Aggregated space-use intensity was found to positively correlate with localized variations in temperature across the barn (as measured by animal-mounted sensors), but the level of correlation decreased at higher ambient barn temperatures. Bunching behavior may increase localized temperatures experienced by individuals and hence may be a maladaptive behavioral response in housed dairy cattle, which are known to suffer heat stress at higher temperatures. Our study is the first to use high-resolution positional data to provide evidence of associations between bunching behavior and higher ambient temperatures for a barn-housed dairy herd in a temperate region (UK). Further studies are needed to explore the exact mechanisms for this response to inform both welfare and production management.
Key words: bunching, dairy cow, heat stress, social behavior

INTRODUCTION

Climate change is a pressing global issue which is increasingly concerning to farmers as changes in environmental conditions can directly affect animal physiology, possibly leading to heat stress. Heat stress occurs when excess body heat cannot be dissipated adequately to maintain thermal equilibrium, usually due to a combination of external factors such as elevated ambient temperature, high humidity, and lack of ventilation (Wang et al., 2020). Indoor-housed livestock are at high risk for heat stress given they are typically housed in confined areas. Under heat stress, cows produce less milk (Bohmanova et al., 2007; André et al., 2011; Bernabucci et al., 2014), and have impaired fertility (Ray et al., 1992; De Rensis and Scaramuzzi, 2003; Sammad et al., 2020), leading to both economic and health and welfare concerns.

Physiological changes linked to heat stress are often accompanied by behavioral responses including a reduction in overall activity, to conserve energy and minimize heat production (Cook et al., 2007). In contrast, animals may modify their behavior in cold conditions by increasing activity to generate body heat (Rabaiotti and Woodroffe, 2019; Herbut et al., 2021). Other be-

havioral responses to heat stress include decreased lying time, particularly above 19°C to 21°C, and increased standing time which serves to increase body surface area exposed for heat loss (Cook et al., 2007; King et al., 2016; Tresoldi et al., 2019). Additionally, cattle reduce their feeding behavior at high temperatures, thought to serve to reduce metabolic heat production (Bouraoui et al., 2002), which is likely to lower nutrient intake and may contribute to reduced conception rates under high temperatures (Marai et al., 2002; Morton et al., 2007; Sammad et al., 2020). This is accompanied by an increase in drinking, to cool individuals down, and an increase in competitive events at resources (Pereyra et al., 2010; McDonald et al., 2020; Tsai et al., 2020). Interestingly, subordinate cows appear to avoid drinkers during the hottest and most competitive hours of the day (McDonald et al., 2020). It is therefore important to consider that behavioral responses to increased heat load may be dependent on the individual animal, housing and the time of day.

Bunching behavior (clustering, spatial aggregation) refers to the close grouping of individual animals within a herd. There is evidence that livestock may bunch when their environment is warmer than typical ambient temperatures including indoor (Mader et al., 2002; Erbez et al., 2012; Javorová et al., 2014) and outdoor-housed cattle (Lefcourt and Schmidtmann, 1989). The reason why cattle may bunch in warm conditions is not well understood, but one possibility is that bunching may occur around shaded areas as a strategy to reduce heat load; tree shading can reduce the body temperature of cattle at pasture (Kendall et al., 2006; Giro et al., 2019). This theory fits less well for indoor-housed cattle where they are predominantly blocked from direct sunlight, however shafts of sunlight may still project through panels and gaps in the roofing or walls. It is also possible that cattle group around water at high temperatures because drinking is increased to decrease body temperature. Studies in temperate regions have shown evidence for bunching at high temperatures above a particular threshold (Lefcourt and Schmidtmann, 1989; Erbez et al., 2012; Javorová et al., 2014). In Czech dairy barns, cows were found to bunch more with increasing ambient air temperature above a threshold of 19°C to 20°C (Erbez et al., 2012; Javorová et al., 2014). However, a limitation of these earlier studies is that spatial data collection was not obtained using an automated location system; cow locations were estimated using either video recordings or photographs at 15-min intervals (Erbez et al., 2012; Javorová et al., 2014).

Bunching may also occur at low ambient temperatures, a known response throughout the animal kingdom to help animals thermoregulate (Huynh et al., 2005; Gilbert et al., 2010; Ozella et al., 2020). Similarly, animals may bunch in certain locations due to reasons other than temperature. For example, cows may bunch around areas with good air flow to avoid insects which gather around moist organic material, particularly during warm conditions. Moreover, bunching may help distribute fly burdens; individuals position their tails on the outside of a group for protection through leg kicking and tail swishing (Schmidtmann and Berkebile, 1985; El Ashmawy et al., 2019). Likewise, defensive aggregation is a known response of animals to an external threat (Foster and Treherne, 1981; Mooring and Hart, 1992; Bowen et al., 2013). In cattle, this instinctive response may activate in the presence of heightened fly burdens, or during heat stress when flight responses are impeded, leading to increased vigilance. However, if stocking densities within a barn are high, or if significant bunching occurs, body heat within the herd may contribute to an overall increase in the localized temperature, further increasing the internal body temperature of individuals in a potentially negative feedback cycle (Schütz et al., 2010; Polsky and von Keyserlingk, 2017). Temperature has indeed been found to increase in dense areas such as milking parlors and holdings areas (Papez and Kic, 2015; Celozzi et al., 2020). If bunching is determined to be a maladaptive response of cattle to increasing temperature, this could have significant implications for the health, welfare and profitability of herds (André et al., 2011; Galán et al., 2018; Ekine-Dzivenu et al., 2020). This would be particularly concerning given the growing demand for increased yields and herd sizes across the dairy industry, alongside the projected increase in heat stress caused by climate change (Ji et al., 2020).

Direct behavioral observations by human observers are time-consuming and may be subjective. However, automated spatial positioning sensor systems used as part of precision livestock farming (**PLF**) approaches to provide continuous tracking of animals and their environment, offer a promising solution to help better measure and understand behavior (Gygax et al., 2007; Tullo et al., 2016). Automated sensors have the potential to collect high-resolution spatial data which can be analyzed through time series data (Cagnacci et al., 2010) to determine individual time budgets, space-use patterns, social interactions, and detect behavioral patterns and changes linked to health issues (Barker et al., 2018; Vázquez Diosdado et al., 2018; Chopra et al., 2020). In this study, we use a local positioning sensor system to continuously monitor a housed dairy herd over 4 mo to explore how bunching behavior, defined using 4 different metrics, may be associated with higher ambient temperatures.

MATERIALS AND METHODS

Animals and Housing

The animal study was reviewed and approved by the Royal Veterinary College Ethics and Welfare Committee under the unique reference number 2012 1223. Written informed consent was obtained from the owners for the participation of their animals in this study.

A high-yielding (305-d milk yield of 10,909 L) indoor-housed Holstein-Friesian dairy cow herd was monitored continuously on a commercial farm in southeast England, from August 1 to November 30, 2014. The total number of different individual animals within the herd over this period was 127, and the minimum and maximum numbers of unique cows present per day during the study period were 86 and 111, respectively. The herd was continually housed in a closed freestall barn with open gable ends containing 98 usable cubicles, at a high stocking density (feed space = 0.53 m to 0.68 m per cow, lying space = 0.88 to 1.14 cubicles per cow) with free access to the feeding passage and to water troughs. A layout of the barn is shown in Figure 1. The cows were milked thrice daily (at ~0500, 1300, and 2100 h), with milk yield recorded monthly, and cows were fed a total mixed ration during the first milking (which was subsequently pushed up several times later in the day). Analyses of spatial tracking data for the same herd, in different contexts and over different time periods, were previously reported in (Barker et al., 2018; Vázquez Diosdado et al., 2018; Chopra et al., 2020).

Local Positioning System and Data Preprocessing

Each cow was equipped with a combined real-time local positioning sensor, temperature sensor, and accelerometer, Omnisense 500 (Omnisense Ltd., 2022), mounted on a weighted neck collar to ensure stability (see Supplemental Files S1 and S2; https://doi.org/10.5526/ERDR-00000180, Chopra and Codling, 2023). The Omnisense positioning sensors form a localized radio network which triangulates signals (at 0.1 Hz) between all (fixed and cow-equipped) sensors to determine the spatial position of each individual animal. Fixed sensors were strategically placed around the barn to improve the triangulation network and to fix the absolute spatial position of each sensor. In a separate study in the same barn environment, this sensor system showed a 50% circular error of probability (CEP) measurement of 1.07 m (i.e., 50% of all recorded locations lay within a 1.07-m radius of the mean location of static sensors), which compares favorably to the commercially advertised CEP specification of 1 m, and mean distance error of 2.66 m for a static sensor, and 1.90 m and 2.90 m, respectively, for an animal-mounted sensor (Barker et al., 2018).

All data processing and analysis was conducted in R for Windows with RStudio (RStudio Team, 2020; R Core Team, 2022). Extended interruption occurred on 15 of the study days due to the system malfunctioning and resetting part-way through the day; these days were excluded from the subsequent analysis. The number of cows in the barn on a given day across the study period (not including removed days) varied from n = 86 to 111, and a total of 88,576,716 location data points were collected from these cows.

For the analysis, we excluded hours when most cows were in the milking parlor or collecting yard (0500–0759, 1200–1459, 2000–2259 h), because their behavior was constrained by farm staff during these periods. The sensor system reset at midnight each day for data upload and hence times between 2300 and 0059 were also excluded. A total of 51,630,512 data points remained after removing milking and system reset periods (herein referred to as "original data").

Subsequent data pre-processing consisted of (1) removing location data outside of a 3-m buffer of the functional zones due to minor positional inaccuracies (15.88% of original data; 8,201,449 data points removed), (2) removing nonsensical positional data (e.g., sensors "stuck" in exactly the same or a similar, point location for multiple consecutive time points, often shortly after the system reset at the end of each day; 1.89% of original data; 975,291 data points removed), (3) smoothing using a simple moving average with a 2-sided window size of 15 data points (0.32% of original data removed as 7 data points were removed from the start and end of the location time series for each sensor per day; 166,555 data points), and finally, (4) plots of trajectories were visualized manually and any further nonsensical data were removed (e.g., where the trajectory of a cow was located within an unrealistically small area for an extended period of time); these instances were deemed as biologically implausible given these cows were not subject to any farm management actions during these times (2.17% of original data; 1,119,142 data points removed). In total, 79.74% of the original data remained after these stages, leaving a total of 41,167,975 data points for the main analysis. Further details of all 4 data pre-processing steps are outlined in the supplemental material of Chopra et al. (2020), where a similar approach was used.

Environmental Data

Wall-mounted temperature sensors automatically recorded the ambient barn temperature (**BT**) con-
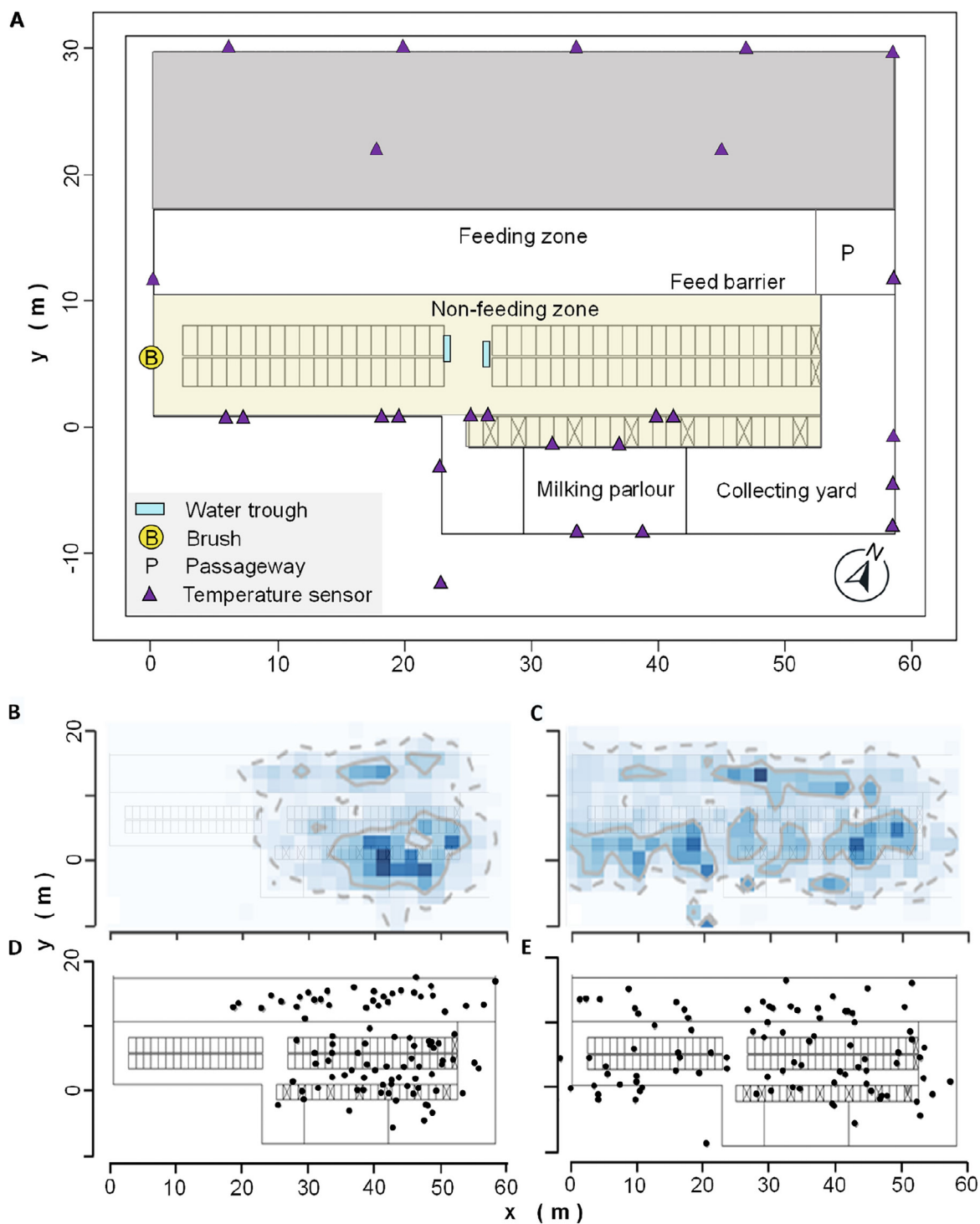
Figure 1. (A) Barn layout of the commercial farm in Essex, UK, showing the positions of sensors recording barn temperature (n = 26; purple triangles). The area shown in gray (upper barn area) was not used by this group of cows during the study period. The barn is divided into the feeding zone and the nonfeeding zone, where cubicles were located, and P marks the passageway. The upper wall of the barn (corresponding to y = 30 m in the plot) is oriented facing north-northwest. (B and C) Space-use distributions showing examples of high bunching (B), where core range (CR, 50%, solid gray boundary) = 46 virtual cells of 2.25 m², full range (FR, 95%, dashed gray boundary) = 166 virtual cells of 2.25 m², and intercow distance (ICD) and nearest-neighbor distance (NND) = 12.78 m and 2.66 m, respectively (for Sep. 18, 2014, at 1100–1200 h; barn temperature [BT] = 20.91°C), and low bunching (C), where CR = 88 virtual cells of 2.25 m², FR = 268 virtual cells of 2.25 m², and ICD and NND = 20.87 m and 3.61 m, respectively (for Oct. 12, 2014, at 1800–1900 h; BT = 13.10°C). (D and E) Examples of "snapshots" of point location data for all individuals in the herd shown for specific time points within each of these hours (D: Sep. 18, 2014, at 11:01:32; and E: Oct. 12, 2014, at 18:00:02).

tinuously throughout the study period; a mean hourly measurement was calculated across all sensors (n = 26 sensors, where n = 22 recorded every 8 s and n = 4 recorded every hour; refer to Supplemental File S1 for further details on temperature sensors and data collected). The sensors were placed at approximately equal distances down the length (x-axis) of the barn at a height of ~2.5 to 3 m (Figure 1).

Further temperature data were also obtained from the cow-equipped positional sensors (**ST**) and from a local weather station (**LT**), Harold Hill, located ~11 km from the study site (Weather Underground, 2014). The ST sensors were housed in an insulated box and were located close to the body of each animal, leading to a buffering effect when comparing the ST ranges to the BT range (Supplemental Figure S1.1B–C in Supplemental File S1; https://doi.org/10.5526/ERDR -00000180, Chopra and Codling, 2023). Meanwhile, LT was used only as a comparator baseline to check temperature trends; LT was weakly correlated with both BT and ST (Supplemental Figure S1.1D–F in Supplemental File S1), which is unsurprising given the short distance from the study site.

Bunching Metrics

There is no formal definition of "bunching" behavior in the context of PLF, although a range of different metrics are available to measure spatial aggregation, spatial clustering, or social proximity from positional data. Previous studies have used direct observations or basic nearest-neighbor aggregation indices to measure bunching, the latter of which would provide a distorted score if cows tend to form dyad pairs (Lefcourt and Schmidtmann, 1989; Mader et al., 2002; Erbez et al., 2012; El Ashmawy et al., 2019). Hence, we consider 4 complementary "bunching metrics," which directly measure the level of spatial separation (i.e., the inverse of bunching), each measured on an hourly basis across the full herd: range size (core and full), mean intercow distance (**ICD**), and mean nearest-neighbor distance (**NND**).

Range Size

Range size was calculated by overlaying a virtual grid (1.5 m × 1.5 m = 2.25-m^2 cells) over the barn map (Figure 1A). At each time-step, location data were used to assign each individual cow within the herd to a given cell (or rejected if it lay outside the main barn region, see Local Positioning System and Data Preprocessing section). The number of individual data points assigned to each cell across the full herd and over a full hour

(360-time steps at 0.1 Hz) were counted giving a final hourly total for each virtual cell within the barn. Following the standard methodology outlined in Vázquez Diosdado et al. (2018), the highest density cells cumulatively adding to 50% or 95% were then used to create an hourly utility distribution (space-use intensity map, Figure 1B, 1C) corresponding to the "core range" and "full range," respectively. The number of unique virtual cells included in each hourly core range and full range distribution are then defined as the range size (**CR** and **FR**, respectively, measured in units of 2.25-m^2 virtual cells).

Intercow Distance

At a given time-step, the herd mean intercow distance is the mean distance (in meters) between each of the $(N^2 - N)/2$ possible dyad pairs across a herd with N individuals. An hourly value (which we define as **ICD**, measured in meters) is then calculated as the arithmetic mean of all (360) values recorded over that hour (assuming 0.1-Hz sampling frequency):

$$ICD$$
$$= \frac{1}{360} \sum_{t=1}^{360} \left(\frac{2}{N^2 - N} \sum_{(i,j) \in N} \sqrt{\left[x_i(t) - x_j(t) \right]^2 + \left[y_i(t) - y_j(t) \right]^2} \right),$$
[1]

where (i, j) is a given dyad pair and $i \neq j$, and t is a given time point.

Nearest-Neighbor Distance

At a given time-step, the NND for a given individual is simply the distance (in meters) to its closest neighbor in the herd (i.e., the smallest intercow distance when considering all dyad pairs involving that individual). A mean value can then be determined across the full herd on an hourly basis (which we define as NND, measured in meters):

$$NND$$
$$= \frac{1}{360} \sum_{t=1}^{360} \left(\frac{1}{N} \sum_{i \in N} min_{j \neq i} \left\{ \sqrt{\left[x_i(t) - x_j(t) \right]^2 + \left[y_i(t) - y_j(t) \right]^2} \right\} \right),$$
[2]

where j indexes all possible dyad pairs for i across the N individuals in the herd.

Although the 4 bunching metrics defined above measure different aspects of space use and social proximity,

they will all decrease as spatial separation decreases and spatial clustering ("bunching") increases. Range size is independent (in a statistical sense) to ICD and NND, but as it is aggregated at an hourly level from the outset, it will not capture short-time variations in proximity between individuals. Nevertheless, a smaller (core or full) range size indicates that the herd as a whole are using less of the barn and are hence sharing a smaller space (Figure 1B, 1C). Both NND and ICD are loosely dependent but capture different aspects of herd bunching. The ICD measures distances across the full herd and hence can be skewed by individuals that are far apart or in separate subgroups (e.g., a herd split into 2 distinct and tightly bunched subgroups could still have a high ICD value, even though the separate groups would be considered to be bunching). Meanwhile, NND only accounts for the distance between animals nearest each other and hence may not capture bunching between multiple individuals (e.g., a herd split into spatially separated dyad pairs could have a very low NND but would have high ICD, and would not usually be considered as herd-level bunching). By measuring the above 4 metrics simultaneously we aim to accurately capture a wide range of herd dynamics that may be indicative of bunching behavior.

Segmentation and Breakpoints

Motivated by findings from previous studies where behavior was observed to change above a certain threshold (Erbez et al., 2012; Javorová et al., 2014), we use segmentation to explore whether bunching behavior is affected by ambient temperature. A segmented relationship describes changes in a trend at specific values, with a point of change referred to as a breakpoint (**BP**; Muggeo, 2003); we consider 2 complementary approaches.

Hypothesis-Driven Approach. motivated by, and consistent with, previous studies on dairy cow behavior (Chen et al., 2016; Tresoldi et al., 2019), we hypothesize that changes in herd behavior may occur above 20°C. To test this hypothesis, we define a BP at 20°C. Linear regression models were then created for data <20°C and ≥20°C, for each bunching metric, using the "lm" function in base R. Chow tests were performed to test the significance of the hypothesized BP of 20°C, for all bunching metrics. For this, the function "sctest" from the R package "strucchange" was used (Muggeo, 2003, 2008).

Data-Driven Approach. The R package "segmented" was used to identify the locations of forced BPs (Muggeo, 2008). For each bunching metric, the original linear model was inputted into the "segmented" func-

tion, specifying one or 2 BP(s) in BT. Linear regression models were then created using the data-driven BP (i.e., 2 models where one BPs identified: BT < BP and BT ≥ BP; or 3 models where 2 BPs identified: BT < BP1, BP1 ≤ BT < BP2 and BT ≥ BP2) and the results analyzed. Chow tests were performed to test the significance of these BPs.

For both approaches, default R settings were used in all linear models, which exclude observations containing not applicable (NA) values and uses QR (Q represents the orthogonal matrix and R represents the upper triangular matrix) factorization, an extensively used method for solving least squares problems. Model assumptions were considered before drawing conclusions: heteroskedasticity through residual versus fitted plots and non-constant error variance (NVC) tests, and residual normality through quantile–quantile plots and the Shapiro-Wilk test (see Supplemental File S3; https://doi.org/10.5526/ERDR-00000180, Chopra and Codling, 2023).

The effect of time of day on the relationship between bunching behavior and temperature was explored to consider the presence of diurnal patterns, differences between the day (morning or afternoon) and night, and to consider that milking was a deterministic event at certain points of the day. To do this, the hourly mean data were divided into 3 intervals between milking times: night (0100–0400 h; no values where BT ≥20°C across the study period), morning (0800–1100 h; n = 33 h where BT ≥20°C) and afternoon/evening (1500–1900 h; n = 142 h where BT ≥20°C). Linear regression models were then created for data where BT ≥20°C, for each bunching metric and each time interval, using the lm() function in base R.

Bunching in Relation to Barn Location and Localized Temperature

Bunching and Barn Location. Space-use intensity distributions were determined (as described in the Range Size section) for those hours corresponding to the lowest 10% of values (n = 127 h) for each individual bunching metric (CR, FR, ICD, and NND; i.e., corresponding to high levels of bunching for each metric separately). A combined space-use distribution was also determined by including the union of all hours identified in the previous step across all bunching metrics (n = 321 h). These aggregated space-use distributions corresponding to periods of high bunching were then compared with the aggregated space-use distribution determined across the entire study period to determine whether animals were distributed differently across the barn during bunching events compared with nonbunching periods.

Space-Use Intensity and Temperature. The animal-mounted sensors were used to determine a mean temperature across the entire barn, which we define as ST (see Supplemental File S1). By matching the spatial location and sensor-measured temperature at each time point for all animals across the herd (i.e., by adapting the method described in the Range Size section), it is also possible to determine a spatially-resolved mean hourly temperature for each 2.25-m^2 (1.5 m × 1.5 m) virtual cell of the barn, which we define as $\mathbf{ST_{XY}}$. Hence, we can create a spatial (heat)map of the variations in temperature across the barn over different time periods (e.g., hourly, monthly). It should be stressed that both ST (the mean sensor-measured temperature across the whole barn; i.e., the mean of all $\mathrm{ST_{XY}}$ values for a given hour) and $\mathrm{ST_{XY}}$ are not true measures of either the ambient or localized temperature(s) within the barn; as the sensor is mounted directly on a neck collar (albeit in an insulated housing) it will be affected by the heat generated by the animal itself. Nevertheless, relative differences in $\mathrm{ST_{XY}}$ across the barn offer a useful measure of how the temperature experienced by each animal, and by the herd as a whole may vary across the barn.

Comparison of Spatial Distributions: The Bhattacharya Coefficient. To compare space-use distributions over different periods or to compare variation in space use against temperature across the barn, we use the Bhattacharya coefficient (**BC**) which provides a quantitative measure to assess the level of similarity between 2-dimensional matrices:

$$BC = \sum \sqrt{(P_x \times Q_x)}, \qquad [3]$$

where P_x and Q_x are the (normalized) distributions being compared. The resulting BC ranges from 0 to 1, where 1 indicates complete overlap between the 2 distributions, and 0 indicates complete dissimilarity.

The BC only gives a single measure of similarity between 2 distributions; to test if this similarity is significant, it is necessary to undertake a randomization test. Our procedure involved calculating the mean BC for each hour of our study (comparing temperature and space-use distributions). The same number of BC values were generated by randomly shuffling the order of hourly space use and temperature distribution matrices, and the mean was determined for these randomized BC values. This randomization process was repeated (n = 10,000 iterations), and the number of times, k, the randomized mean BC was less than the original mean BC from the (nonrandomized) data were used to directly determine a *P*-value (where $P = k/10{,}000$).

To compare the spatial distribution for (union of all) hours of highest bunching (see the Bunching and Barn Location section) with the spatial distribution over the entire study period, we employed a similar randomization approach. First, we computed the BC for each of the highest bunching hours (n = 321 h) when compared with the entire study period. The mean BC was then calculated. Subsequently, we randomly selected the same number of hours (n = 321) across the study duration and computed the BC for each of these hours in relation to the space-use distribution during the entire study period. This process was repeated 10,000 times, recording the instances where the mean BC of the randomized data exceeded the original mean BC. Finally, the count of such occurrences was divided by the total number of iterations to derive the *P*-value. A similar randomization procedure was also undertaken for each bunching metric separately (with n = 127 h in each case; see Supplemental File S4; https://doi.org/10.5526/ERDR-00000180, Chopra and Codling, 2023).

RESULTS

Trends in Temperature and Bunching

Hourly ambient BT peaked during the afternoon, and dropped during the night, as expected (Figure 2A). The coolest median hourly BT was recorded in November (11.77°C; n = 260 h) and the hottest in August (18.330°C; n = 374 h), with mean for September and October as 18.11°C (n = 276 h) and 15.11°C (n = 359 h) respectively. There is a significant difference in mean hourly temperature between months (Friedman chi-squared = 229.48, P < 2.2e-16), with August and September significantly hotter than October (Wilcoxon rank sum (W) = 30,552 and 23,677, P < 2.2e-16, with Bonferroni Correction) and November as significantly cooler than all other months (W = 4,927, 3,696, 77,063 for August, September and October respectively, P < 2.2e-16, with Bonferroni correction; Figure 2A). It should be noted that the mean hourly BT across days reaches above 20°C for some hours during the afternoon in August and September, but not during October and November (Figure 2A). More specifically, Figure 2F shows mean hourly BT over time for the entire study period; most of the values which lie above 20°C occur in August and September (93%, n = 320 of 344 h).

Visualization reveals few clear patterns in the hourly bunching metrics over time, other than a clear decrease in bunching during milking periods; this is expected because cows are located within the restricted space of the milking parlor during these periods (and hence we remove these times from the subsequent segmentation analysis; Figure 2B–2E; Figure 2G–2J).
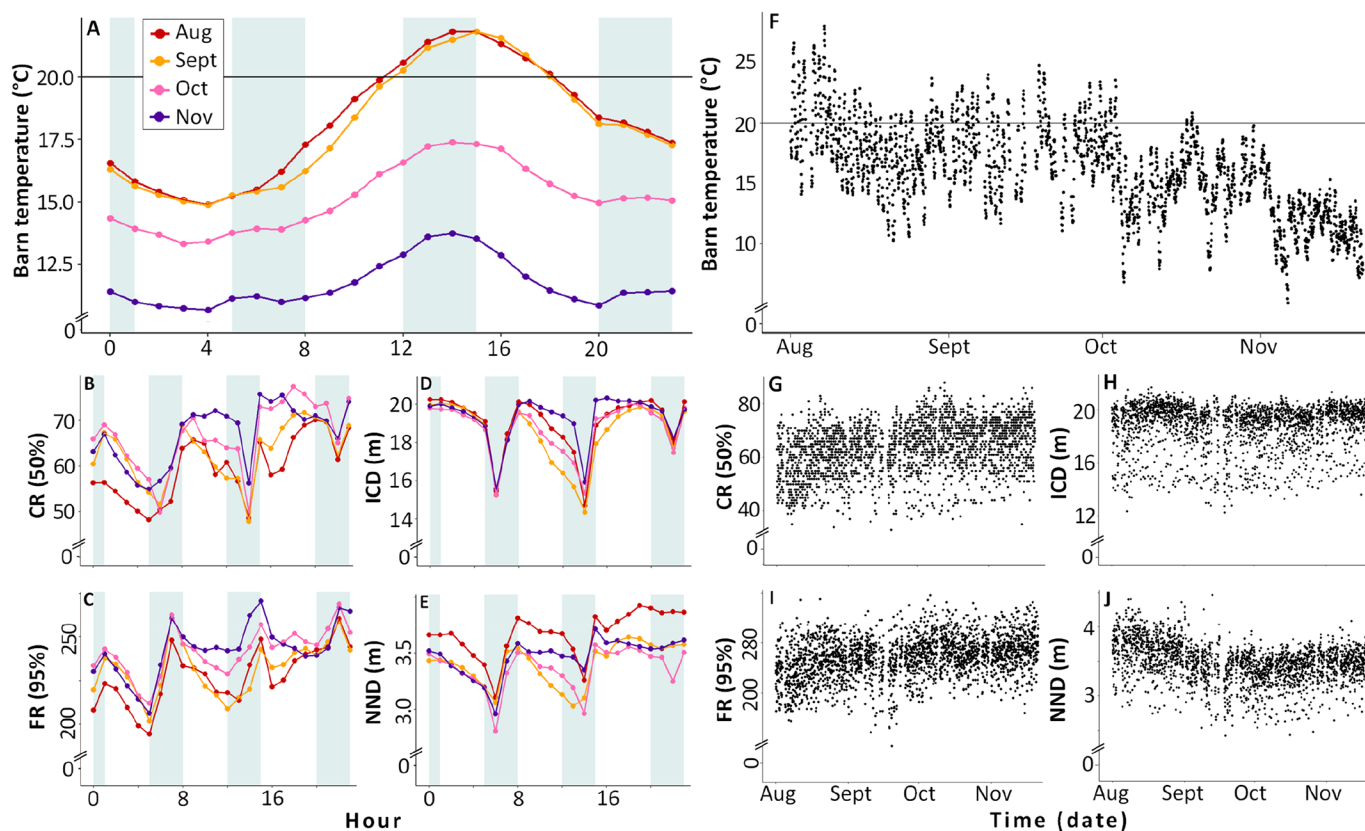
Figure 2. Mean 24-h average of metrics over all days per month. (A) barn temperature (°C), (B) core range (CR; 50%; measured in virtual cells of 2.25 m^2), (C) full range (FR; 95%; measured in virtual cells of 2.25 m^2), (D) intercow distance (ICD, m), and (E) nearest-neighbor distance (NND, m). Months are divided as August (red), September (orange), October (pink), and November (purple) 2014. The vertical bands correspond to milking periods (0500–0759 h, 1200–1459 h, and 2000–2259 h) and periods during which the sensor reset (~2300–0059 h). Also shown (F–J) are mean hourly metrics recorded across the entire study period (August to November 2014) for barn temperature (°C), CR (50%), FR (95%), ICD (m), and NND (m). Of the 2,905 total data points, 358 are above 20°C, with 334 of these occurring in August and September.

Bunching Behavior and Segmented Breakpoints

Bunching Behavior Above and Below 20°C. Above or equal to 20°C, a clear negative trend is shown between all 4 bunching metrics and BT. Although the breakpoint is nonsignificant for 3 of the 4 bunching metrics, these trends are significant for CR, FR, and intercow distance (**ICD**; Table 1; Figure 3E-3G), but nonsignificant for NND (Table 1; Figure 3H). Below 20°C, the relationships between BT and FR, ICD and NND are also negative and significant, but are nonsignificant for CR. For example, for CR < 20°C, correlation coefficient (e) = −0.15, and for ≥20°C e = −2.08 (Table 1; Figure 3A–3C). The direction of the relationship between NND and BT changes from positive to negative either side of the 20°C breakpoint (Table 2; Figure 3D). Qualitatively similar results were obtained when considering relative humidity from a local weather station, through the temperature-humidity index (**THI**; Supplemental File S5; https://doi.org/10.5526/ERDR-00000180, Chopra and Codling, 2023).

For August, at a given BT, the range size values are generally lower in comparison to September (Figure 3I–3L). For example, at 20.1°C (rounded to nearest one decimal point), CR = 60 to 65 (n = 2 h) whereas CR = 65 to 78 for September (n = 4 h). The pattern is the opposite for ICD and NND (Figure 3M–3P). This can be explained by the number of cows present in the barn, consistently lower in August (n = 85 to 86 cows) compared with in September (n = 92 to 96 cows). Moreover, there are negative trends between BT and the bunching metrics ≥20°C when considering August and September separately (Table 1; Figure 3I–3P).

Behavior Above and Below Data-Driven Breakpoints. Forcing a data-driven method to find the location of BT breakpoints gives values close to 20°C for all the bunching metrics, except for FR (Figure 4). The (significant) negative trends using all 4 bunching

Table 1. Outputs from linear regression assessing the relationship between barn temperature and bunching, below and above the breakpoint of 20°C (n = 170 data points), for the full data set (full) and for August and September alone (A and S, respectively), excluding outliers (n = 5 data points)[1]

Bunching metric	Chow test	<20°C	Selected data	≥20°C
CR	$F = 2.23$, $P = 0.11$	e = −0.15, SE = 0.08, t-value = −1.88, $P = 0.06$	Full	e = −2.08, SE = 0.26, t-value = −8.00, P = 1.26e-13*
			A	e = −1.81, SE = 0.30, t-value = −6.03, P = 2.88e-8*
			S	e = −1.35, SE = 0.49, t-value = −2.79, $P = 0.007$*
FR	$F = 1.59$, $P = 0.20$	e = −0.35, SE = 0.16, t-value = −2.19, $P = 0.03$*	Full	e = −2.65, SE = 0.63, t-value = −4.24, P = 3.51e-5*
			A	e = −2.48, SE = 0.81, t-value = −3.05, $P = 0.003$*
			S	e = −0.66, SE = 1.11, t-value = −0.60, $P = 0.55$
ICD	$F = 0.91$, $P = 0.40$	e = −0.03, SE = 0.01, t-value = −3.95, P = 8.46e-5*	Full	e = −0.33, SE = 0.04, t-value = −7.58, P = 1.52e-12*
			A	e = −0.38, SE = 0.05, t-value = −7.44, P = 3.65e-11*
			S	e = −0.31, SE = 0.09, t-value = −3.27, $P = 0.002$*
NND	$F = 3.17$, $P = 0.04$*	e = 0.02, SE = 0.002, t-value = 9.40, $P < 2\text{e-}16$*	Full	e = −0.01, SE = 0.01, t-value = −1.31, $P = 0.19$
			A	e = −0.02, SE = 0.01, t-value = −2.33, $P = 0.02$*
			S	e = −0.06, SE = 0.02, t-value = −4.00, $P = 0.0002$*

[1]Chow test outputs testing the significance of the breakpoint are also shown. Each test is conducted for each bunching metric (CR = core range, FR = full range, ICD = intercow distance, NND = nearest-neighbor distance). Periods during which cows were in the milking parlor or collecting yard (0500–0759 h, 1200–1459 h, and 2000–2259 h), and periods during which the sensor reset (2300–0059 h) were removed.
*Significant P-values (at a threshold of $P < 0.05$).

metrics also hold above these forced breakpoints (Table 2; Figure 4), giving qualitatively similar results to using a hypothesized BP of 20°C (Table 1, Figure 3). Qualitatively similar results were found using forced breakpoints for THI (Table A3 in Supplemental File S5).

Effect of Time of Day for Breakpoint of 20°C. Barn temperature did not reach ≥20°C during the night, and most data points ≥20°C were recorded during the afternoon/evening (n = 142 and 33 data points, during the afternoon/evening and the morning respectively). Above (or at) 20°C, the negative relationship between BT and the range sizes and ICD, change from nonsignificant during the morning to significant during the afternoon and evening (Figure 5A–5C; morning: CR: e = −1.49, SE = 0.87, t-value = −1.71, $P = 0.10$, FR: e = −3.41, SE = 2.20, t-value = −1.55, $P = 0.13$, ICD: e = −0.42, SE = 0.19, t-value = −2.16, $P = 0.04$; afternoon/evening: CR: e = −2.30, SE = 0.27, t-value = −8.61, P = 7.93e-15; FR: e = −3.28, SE = 0.66, t-value = −4.93, P = 2.08e-6; ICD: e = −0.35, SE = 0.04, t-value = −8.20, P = 8.85e-14). The relationship between BT and NND remains nonsignificant and negative across the 2 time periods (Figure 5D; morning: e = −0.05, SE = 0.03, t-value = −1.53, $P = 0.14$; afternoon/evening: NND: e = −0.01, SE = 0.01, t-value = −0.66, $P = 0.51$).

Bunching in Relation to Barn Location and Temperature

Bunching and Barn Location. Visualization of space use over the entire study duration suggests that the cows preferred to position in the right-hand cubicles which are nearer to the exit of the milking parlor (26.90 m ≤ x ≥52.85 m and 0.80 m ≤ y ≥10.50 m and 25.10 m ≤ x ≥52.85 m and −1.62 m ≤ y ≥0.80 m) over the left-hand cubicles (2.55 m ≤ x ≥23.10 m and 0.80 m ≤ y ≥10.50 m) in the nonfeeding zone (Figure 6A; refer to Figure 1 for barn layout).

The highest instances of bunching are mostly during September and August (n = 8 of 9 h), which is consistent with results from the segmentation analysis as these are also the hottest months of the study period (refer to Figure 2). The median location of the herd is x = 31.77 m and y = 4.52 m across the entire study period (white cross in Figure 6A) and x = 32.01 m and y = 4.63 m during instances of high bunching (white cross in Figure 6B), indicating very little difference in median location between bunching and nonbunching
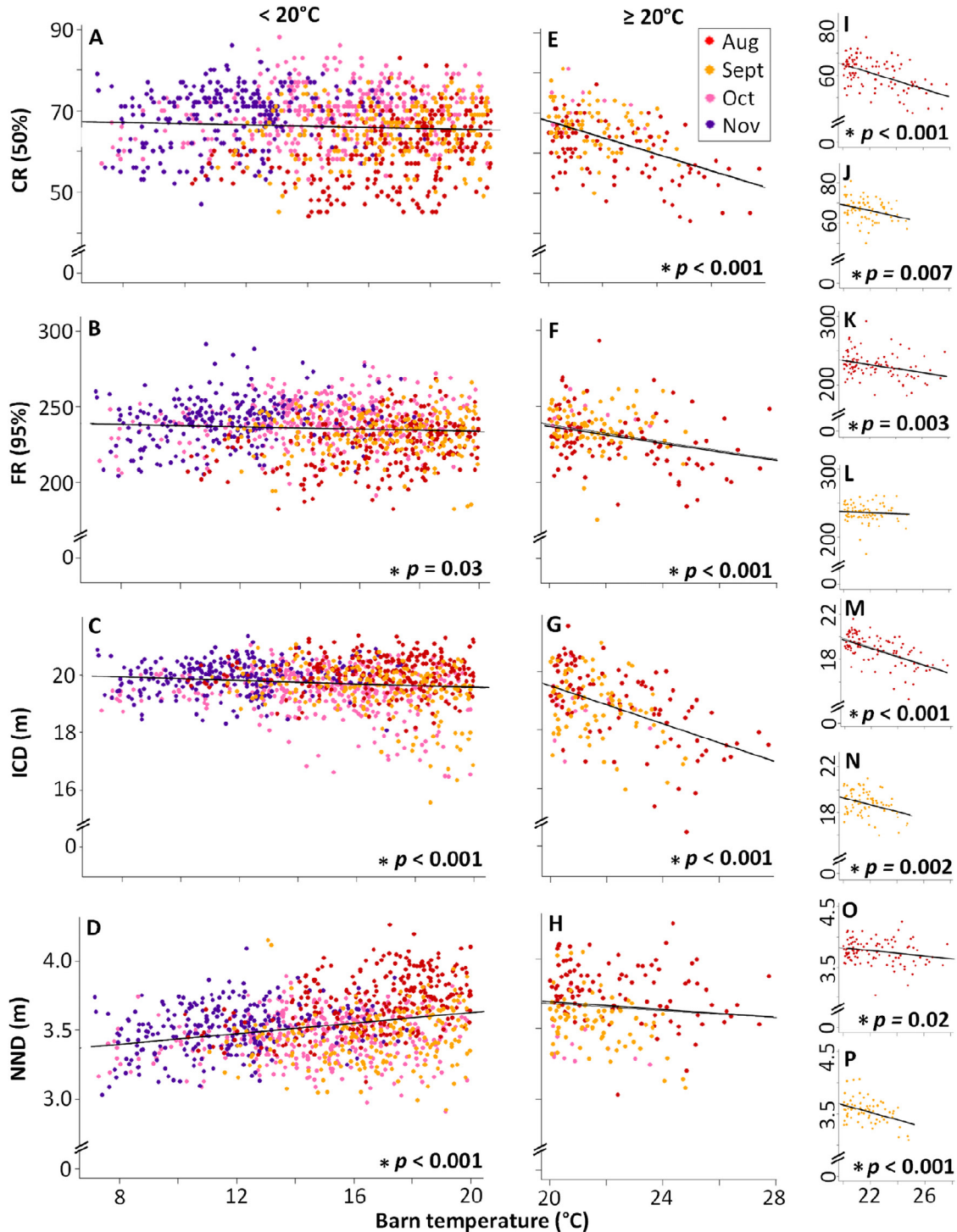
Figure 3. Linear regression plots showing the relationship between bunching and barn temperature, below and above (or equal to) the breakpoint of 20°C ($\geq$20°C; n = 170 data points). Plots are shown for each bunching metric: core range (CR; 50%; measured in virtual cells of 2.25 m²), full range (FR; 95%; measured in virtual cells of 2.25 m²), intercow distance (ICD; m), and nearest-neighbor distance (NND; m), below the breakpoint of 20°C (A–D respectively) and above or equal to the breakpoint (E–H). A single point represents a mean average per hour, and points are colored by month: August = red, September = orange, October = pink, and November = purple. Insets showing the patterns for August and September alone where $\geq$20°C are also shown (I and J for CR, K and L for FR, M and N for ICD, and O and P for NND). Significant relationships are marked with asterisks (* at a threshold of $P < 0.05$), and the corresponding P-values are given. Outliers (n = 5 data points) were excluded based on model assumption testing as shown in Supplemental File S3 (https://doi.org/10.5526/ERDR-00000180, Chopra and Codling, 2023). Periods during which cows were in the milking parlor or collecting yard (0500–0759 h, 1200–1459 h, and 2000–2259 h) or periods when the sensor reset (2300–0059 h) were removed.

Table 2. Data-driven barn temperature breakpoints (BP) and corresponding results assessing the linear relationship between barn temperature and each bunching metric, on the commercial farm in Essex, UK[1]

Bunching metric	BP (°C)	Chow test	<BP	≥BP
CR	22.03	$F = 2.05$, $P = 0.13$	e = −0.12, SE = 0.07, t-value = −1.83, $P = 0.07$	e = −2.85, SE = 0.54, t-value = −5.29, $P = 1.15$e-6*
FR	12.18	$F = 0.63$, $P = 0.54$	e = 1.60, SE = 0.78, t-value = 2.06, $P = 0.04$*	e = −0.82, SE = 0.16, t-value = −5.19, $P = 2.58$e-7*
ICD	19.69	$F = 1.38$, $P = 0.25$	e = −0.03, SE = 0.01, t-value = −3.56, $P = 0.0004$*	e = −0.35, SE = 0.04, t-value = −7.86, $P = 1.87$e-13*
NND	20.77	$F = 4.14$, $P = 0.02$*	e = 0.02, SE = 0.002, t-value = 11.00, $P < 2$e-16*	e = −0.01, SE = 0.01, t-value = −0.50, $P = 0.62$

[1]Bunching metrics: CR = core range, FR = full range, ICD = intercow distance, NND = nearest-neighbor distance. Outliers have been excluded, based on linear model assumption testing (n = 5). Periods during which cows were in the milking parlor or collecting yard (0500–0759 h, 1200–1459 h, and 2000–2259 h) or times when the sensor reset (2300–0059 h) were removed.
*Significant P-values (at a threshold of $P < 0.05$).

periods. Both coordinates are close to the milking parlor (29.40 m ≤ x ≥42.25 m and (−8.42 m ≤ y ≥ −1.62 m) between the high-density cells in the feeding zone and the right-hand cubicles (refer to Figure 1). The case is similar when considering the highest instances of bunching for each bunching metric separately (Supplemental File S4).

A mean BC of 0.903 was calculated when comparing space-use distribution during the union of specific hours of high bunching (n = 321) to aggregated space use over the entire study period (Figure 6A, 6B). The randomization procedure (comparing space use across n = 321 randomly selected hours to the entire study period) shows that, although it is still relatively high, the BC during bunching periods is significantly lower than expected by chance (range of mean BC = 0.914 to 0.921 over 10,000 iterations, $P < 0.0001$), indicating more variation in the spatial distribution during bunching periods when compared with the rest of the study period. Similar results are obtained when considering each bunching metric separately (Supplemental File S4).

Bunching and Temperature Variation Across the Barn. On a monthly average basis, ST_{XY} can be seen to vary across the barn with the central areas closest to the feeding passage and exit from the milking parlor consistently hotter across all months than the gable ends (left and right sides) of the barn (Figure 6C–6F). Visual comparisons of Figure 6A and Figure 6C–6F suggest that, on average and across the study period, those areas of the barn with highest space-use intensity are similar to those areas where ST_{XY} is higher.

This finding is further highlighted when comparing spatial variation in ST_{XY} with space-use intensity across the barn across the entire study, the hourly BC varied from 0.775 to 0.927, with medians of 0.877 for August, 0.900 for September, 0.898 for October, and 0.897 for November (all values exclude milking periods). Illustrative examples of the spatial distribution

highlight that the coefficient of variation (**CV**) is very low for temperature (ST_{XY}), with a median hourly CV of 3.65% (range = 1.41% to 9.41%), indicating low variation across the barn (Figure 6G, 6H). In contrast, space-use intensity is highly variable across the barn with a median hourly CV of 98.88% (range = 78.13% to 218.38%); this suggests that variation in space-use intensity across the barn, rather than temperature variation, drives differences in BC.

Over the full study period, the mean BC between the hourly space-use intensity and temperature distributions across the barn was 0.888; randomization suggests this is highly significant (range of mean BC = 0.857 to 0.863 for randomly paired space use and temperature distributions; $P < 0.0001$), suggesting significant high correlation between space-use intensity and the localized temperature within the barn as measured by animal-mounted sensors.

There is a significant negative relationship between the hourly (temperature and space-use distribution) BC and hourly BT, and this negative relationship is stronger ≥20C compared with <20C (Figure 7E; overall: e = −0.001, SE = 0.0001, t-value = −7.20, $P = 1.02$e-12 where BT <20: e = −0.0004, SE = 0.0002, t-value = −2.21, $P = 0.03$; where BT ≥20C: e = −0.007, SE = 0.001, t-value = −7.21, $P = 1.23$e-11). The fact that BC decreases at higher temperatures is most likely due to bunching (which we previously observed is more likely at higher temperatures); bunching will cause higher variation in space-use intensity across the barn, which in turn will lead to a lower BC because temperature is consistently more uniform across the barn.

DISCUSSION

This study is the first to use automated sensors, continuously over 4 mo as part of a PLF approach, to highlight associations between bunching behavior and higher ambient BT in an indoor dairy herd
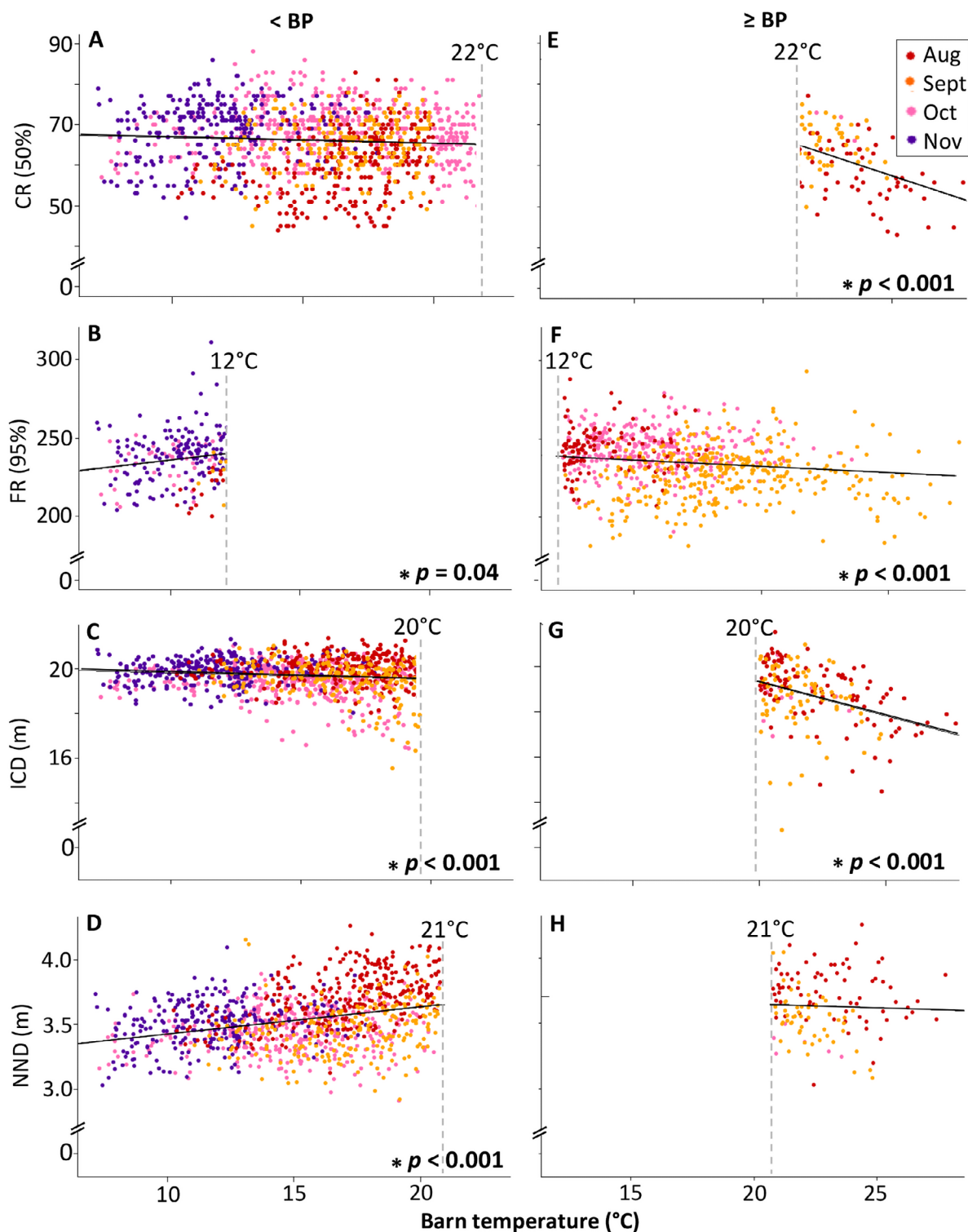
Figure 4. Linear regression plots showing the relationship between bunching and barn temperature, below and above (or equal to) the forced breakpoints. The plots are shown for each bunching metric where the breakpoints are 22°C, 12°C, 20°C, and 22°C (nearest decimal place; marked with dashed vertical lines), for core range (CR; 50%; measured in virtual cells of 2.25 m²), full range (FR; 95%; measured in virtual cells of 2.25 m²), intercow distance (ICD; m), and nearest-neighbor distance (NND; m), respectively. Outliers (n = 5 data points) were excluded, based on model assumption testing (refer to Table 2). A single point represents an average per hour, and points are colored by month: August = red, September = orange, October = pink, and November = purple. Periods during which cows were in the milking parlor or collecting yard (0500–0759 h, 1200–1459 h, and 2000–2259 h) or periods when the sensor reset (2300–0059 h) were removed. Where a subplot is marked with an asterisk, the relationship is significant (threshold of 0.05).
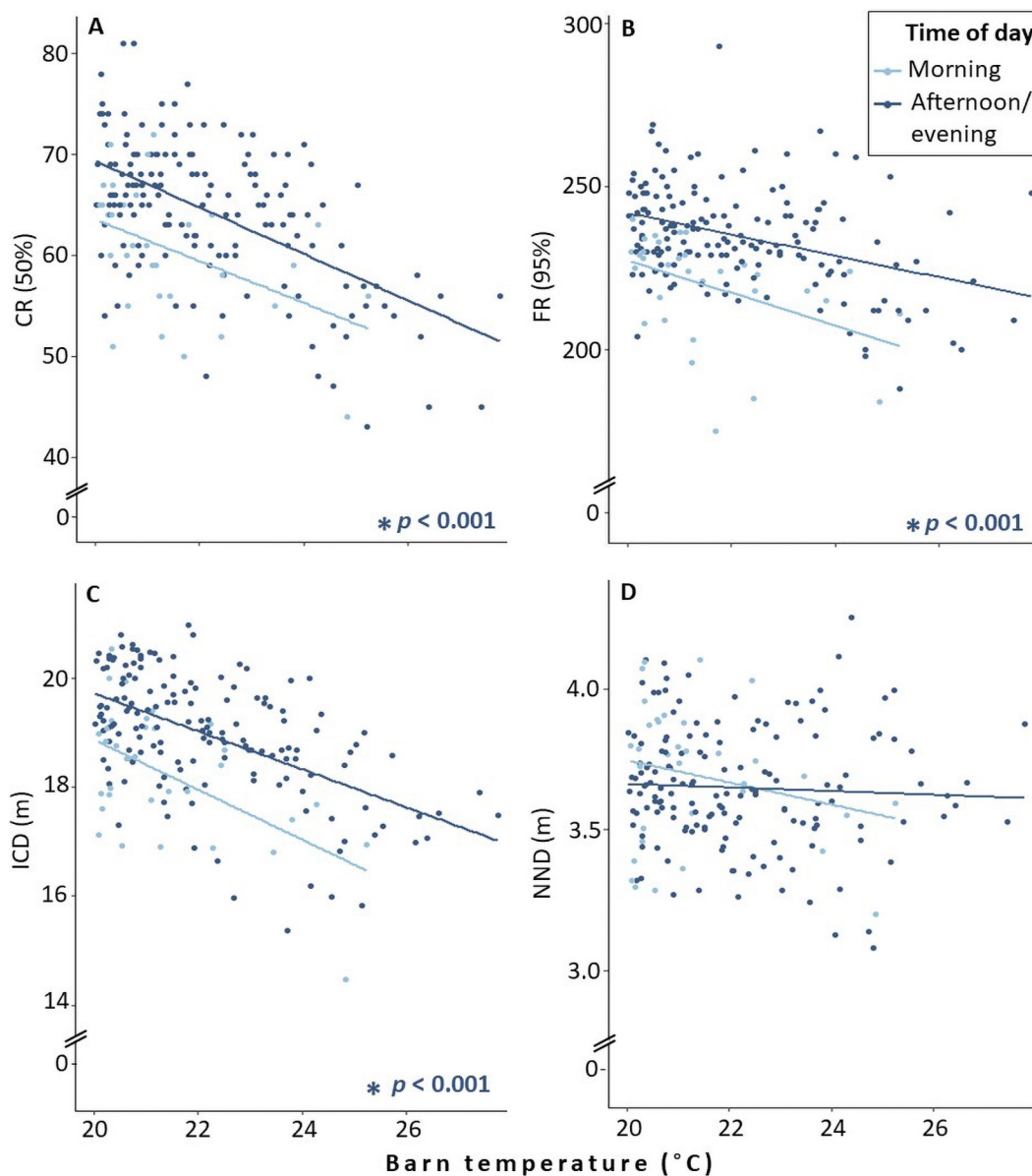
Figure 5. Barn temperature against bunching metrics where barn temperature $\geq 20°C$, data split according to time of day: core range (CR; 50%; measured in virtual cells of 2.25 m^2 [A]), full range (FR; 95%; measured in virtual cells of 2.2 m^2 [B]), intercow distance (ICD [C]), and nearest-neighbor distance (NND [D]). Time of day is inputted as a categorical variable, divided into 3 intervals between milking times: night (0100–0459 h, no data), morning (800–1159 h, light blue), and afternoon/evening (1500–1959, dark blue). A single point represents an average per hour. Significant relationships are marked with asterisks in colors corresponding to the fitted lines. The threshold of significance is 0.05. Note that no values $\geq 20°C$ were recorded during the night. Periods during which cows were in the milking parlor or collecting yard were removed (0500–0759 h, 1200–1459 h, and 2000–2259 h), as well as periods during which the sensor reset (2359–0059 h).

in a temperate region (UK). Four different measures of bunching behavior were considered, accounting for various aspects of space use and social proximity: CR and FR, ICD, and NND. In addition, our novel methodology, which uses combined animal-mounted sensors that measure both location and localized temperature at high spatiotemporal resolution, enables us for the first time to map and compare space use and localized temperature variations across the barn over time.

Our results highlight the importance of understanding animal space-use behavior within the context of farm management under the increased threat of rising temperatures due to climate change.

Bunching Behavior Increases at Higher Ambient BT

Herd bunching behavior increased with increasing BT, and this relationship is significant above or equal
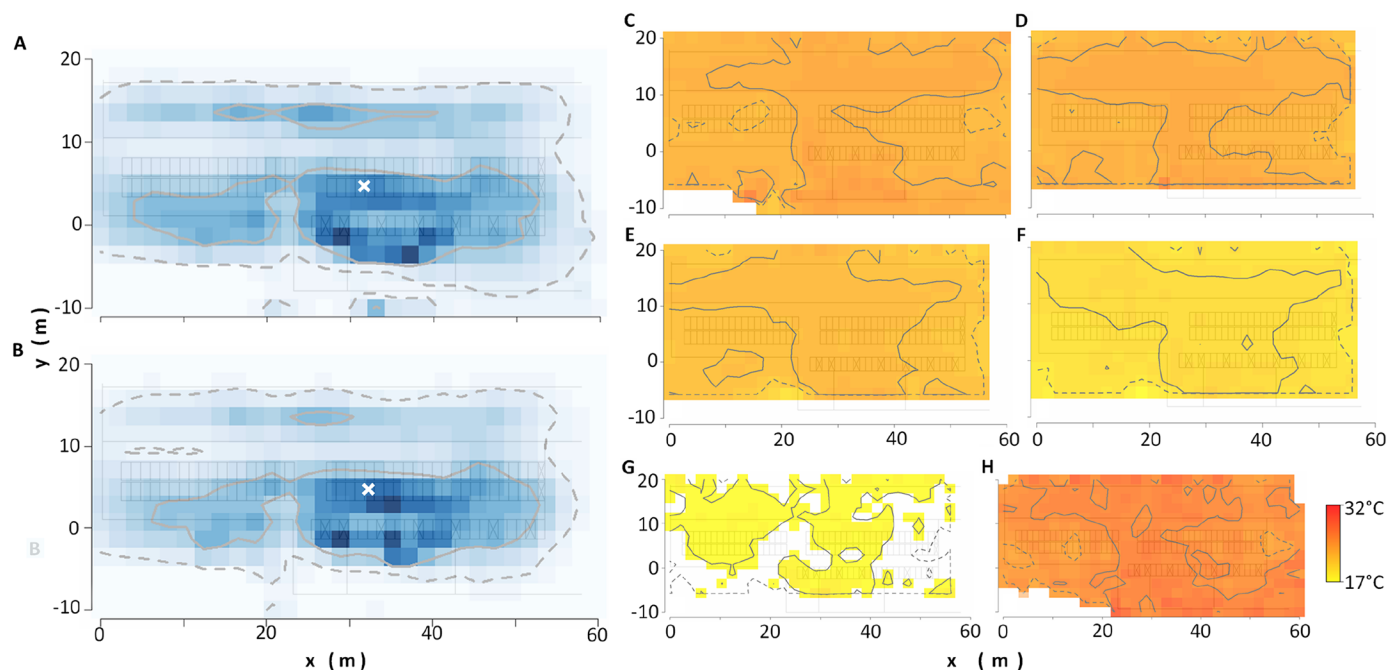
Figure 6. (A) Aggregated space-use distribution for the full herd over the entire study duration and (B) during the highest hours of bunching, defined as the union of the lowest 10% of any bunching metric (n = 321). (C–H) Aggregated sensor temperature distribution (per 2.25-m^2 virtual cell) for the full herd over the entire study duration for each month: (C) August (mean hourly sensor temperature for each 2.25-m^2 virtual cell of the barn [ST_{XY}] = 23.56°C, range ST_{XY} = 21.63°C to 26.77°C), (D) September (mean ST_{XY} = 23.52°C, range ST_{XY} = 20.71°C to 26.42°C), (E) October (mean ST_{XY} = 22.15°C, range ST_{XY} = 19.23°C to 23.53°C) and (F) November 2014 (mean ST_{XY} = 19.75°C, range ST_{XY} = 17.38°C to 20.73°C); and for hours with the (G) lowest barn temperature (Nov. 20, 2014; mean hourly barn temperature = 8.29°C, mean ST_{XY} = 17.06°C, range ST_{XY} = 15.39°C to 19.40°C) and (H) highest barn temperature (Aug. 7, 2014; mean hourly barn temperature = 22.58°C, mean ST_{XY} = 26.24°C, range ST_{XY} = 24.03°C to 29.61°C). In panels A and B, the median position is marked with a white cross. In panels C to H, sensor temperatures were calculated using recordings from cow-equipped sensors (n = 127 different cows, with a minimum of n = 86 cows and maximum of n = 111 cows present per day across the study period). Color gradients represent averages per 2.25-m^2 cell, with (A, B) lighter shades of blue indicating areas of low density or space use and darker shades of blue indicating areas of high density, and (C–H) yellow cells representing low ST_{XY} from 17°C and red cells representing high ST_{XY} of 32°C. In all subplots, the highest-density 2.25-m^2 cells cumulatively adding to 50% and 95% are shown within solid gray and dashed gray boundaries, respectively. Milking times are not included in any of the calculations. The nonfeeding zone is 1.62 m ≤ y ≤ 10.5 m, −1.6 m ≤ x ≤ 58.6 m, and the feeding zone is 10.5 m ≤ y ≤ 17.2 m.

to 20°C (Table 1; Figure 3) for CR, FR, and ICD (noting that a decrease in these metrics corresponds to increased bunching). For NND, a negative relationship was similarly found above or equal to 20°C, although this is nonsignificant, and this relationship did not hold below the 20°C threshold (Table 1; Figure 3). The increase in bunching with temperature ≥20°C held across the morning to the evening, but this trend was stronger during the afternoon/evening (1500–1900 h, n = 33) compared with the morning (0800–1100 h, n = 142) for the CR, FR, and ICD, potentially partly attributed to the smaller sample size available for the morning analysis (Figure 5).

The main finding that cows significantly increase their bunching behavior above warmer than average ambient temperatures (20°C; Table 1, Figure 3), supports previous observational studies, where cows were found to crowd above but not below an ambient temperature of 19°C to 20°C (Erbez et al., 2012; Javorová et al., 2014). In these earlier studies, bunching was measured

by counting the number of individuals in barn segments every 15 min (Erbez et al., 2012; Javorová et al., 2014). Our findings are consistent with this earlier work but provide more detailed understanding of bunching behavior in indoor dairy herds; our data were derived from higher-frequency recordings and by using 4 different metrics of bunching (FR, CR, ICD, NND) we can consider various aspects of space use and social proximity. Specifically, our results indicate that the herd used less space as a whole at high barn temperatures (FR, CR), and not only may dyads (NND) position closer together at higher temperatures, but multiple individuals may, too (ICD; Table 1, Figure 3). Conversely, bunching has been found to decrease with ambient temperature ≤30°C in temperate and arid climates (El Ashmawy et al., 2019), but this earlier study only categorized bunching using a binary method (bunching or not bunching) weekly, twice per day. Another previous study used a more detailed method to measure bunching in a dairy herd in a temperate climate, observing and categorizing
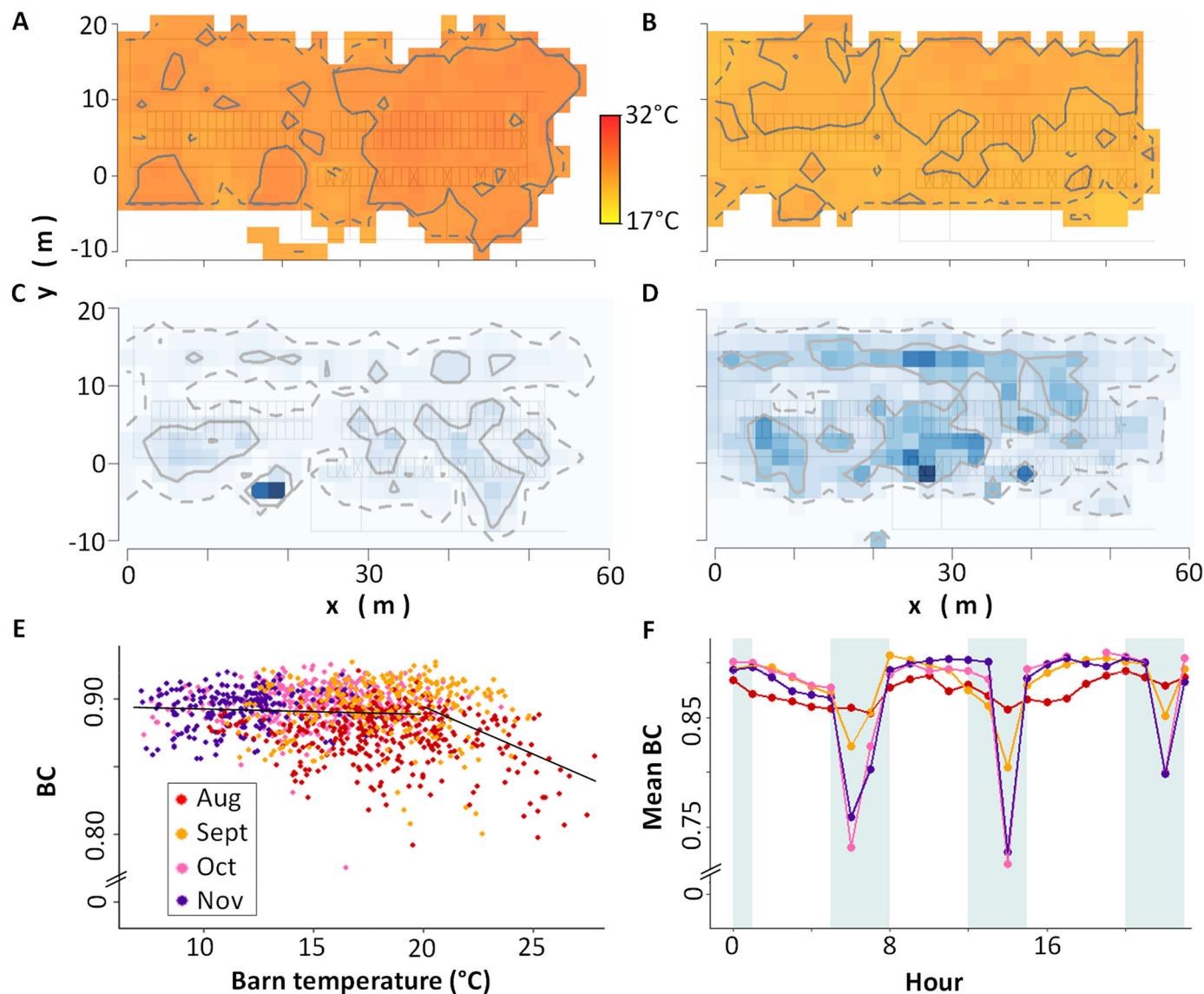
Figure 7. (A, C) Lowest Bhattacharyya coefficients (BC) observed between temperature and space-use intensity across the barn (Aug. 12, 2014, at 1700 h; BC = 0.76; barn temperature [BT] = 19.52°C). Coefficients of variation for panels A and C = 2.22% and 98.08% respectively. Range of sensor temperature per 2.25-m^2 virtual cell (ST_{XY}) = 25.50°C to 28.95°C (A); range of density = 3.5e-5 to 4.0e-5 (C). (B, D) Highest BC between temperature and space-use intensity across the barn observed during the study period (Aug. 10, 2014, at 1800 h; BC = 0.92; BT = 15.77°C). Coefficients of variation for panels B and D = 3.27% and 88.49%. Range of ST_{XY} = 21.54°C to 25.23°C (B); range of density = 2.90e-5 to 1.30e-2 (D). (E) Relationship between BT and BC over the full study period, and (F) hourly BC across the study period, both divided by month. The highest-density 2.25-m^2 cells cumulatively adding to 50% and 95% in A–D (core and full range in both C and D) are shown within solid gray and dashed gray boundaries, respectively. The ST_{XY} in A and B was calculated using recordings from cow-equipped sensors (n = 127 different cows, with a minimum of n = 86 cows and maximum of n = 111 cows present per day across the study period). E excludes milking periods and sensor reset, whereas F includes these times.

individuals into one of 4 nearest-neighbor groups, with recordings taken every 20 min for 10 d, then 1 d/wk for 6 wk (Lefcourt and Schmidtmann, 1989). Although bunching appeared to increase with THI (using an ambient temperature measure), a specific temperature threshold where behavior qualitatively changed was not reported, which was potentially attributed to the study's consistently high daily ambient temperatures

recorded i.e., weekly least mean squares of daily ambient temperature between 21°C and 28°C (Lefcourt and Schmidtmann, 1989).

The increase in bunching ≥20°C, in terms of 3 of our 4 metrics (FR, CR, ICD), is found to be clearer during the afternoon/evening (1500–1900 h; maximum = 27.77°C and median = 18.25°C) than during the morning (0800–1100 h; maximum = 25.25°C and

median = 16.42°C; Figure 5). This is consistent with previous studies whereby cows were found to crowd during the afternoon, where temperatures were consistently recorded above 22°C, but not during the night/early morning, where temperatures did not exceed 11°C (Erbez et al., 2012; Javorová et al., 2014). Alterations to the spatial positioning of the herd during specific periods of the day are likely to disrupt normal behaviors, such as feeding if stocking rates at the feed face are increased (Hill et al., 2009). Such changes have the potential to disproportionately affect cows with health issues; for example, lame cows have been reported to moderate their feeding times to avoid competition at the feed face (Blackie et al., 2011; Barker et al., 2018). The lack of bunching we found overnight (0100–0400 h), as temperatures remained below 20°C, suggests these periods are important for cows to undertake activities which may have been avoided during the day (Figure 5). The rise of tropical nights in the UK (Hanlon et al., 2021) may further diminish the ability of cows to adapt to changing climatic conditions and to catch up on important behaviors, such as lying (Schütz et al., 2008).

Our hypothesized temperature breakpoint of 20°C was motivated by previous studies on dairy cows that reported physiological or behavioral changes at or around this threshold (Berman et al., 1985; Nonaka et al., 2008; Dikmen and Hansen, 2009; Hut et al., 2022). Results from using an alternative approach with purely data-driven forced breakpoints support our main conclusions (Table 1, Figure 3). These forced breakpoints were found to be close to 20°C for 3 of the 4 bunching metrics (CR, ICD, NND; Table 2, Figure 4), and the negative trend above these data-driven thresholds is consistent with results from the 20°C breakpoint (Table 1 and Table 2, Figure 3 and Figure 4).

Other Factors That May Affect Bunching Behavior

Many studies have considered the THI, which considers both the effects of relative humidity and temperature, in the context of behavioral responses of cattle to heat stress e.g., (Tresoldi et al., 2019; Tsai et al., 2020). Relative humidity was not recorded within the barn so data were obtained from a local weather station, and results show that the relationships between the bunching metrics and THI were largely qualitatively similar to those for barn temperature alone (Supplemental File S5). Local or regional measures of relative humidity from local weather stations are unlikely to reflect the fine scale microclimate changes experienced by cows in different areas of the barn at different times. Hence, further investigation should consider finer-scale humidity readings recorded within the barn, as well as other environmental factors (e.g., airflow, methane, or carbon

dioxide levels, and so on) to better understand other possible factors contributing to bunching behavior.

Cows may alter their spatial positioning during the day due to a preference for specific areas of the barn at high ambient temperatures. Possible factors which might have resulted in the presence of microclimates in the study barn (i.e., temperature, humidity and air flow) were 1) mechanical ventilation provided by fans in the middle and right of the barn, 2) water troughs located in the center cross passage, and 3) sunlight radiating through the wooden cladding on the left gable end side (west-southwest) of the shed (due to the position of the parlor, no sunlight would come through the right side of the shed). Cows may have detected microclimatic variations in the barn due to these factors, as found in previous studies i.e., at high temperatures, cattle are known to seek shade and avoid sunlight (Bennett et al., 1985; Kendall et al., 2006; Schütz et al., 2010), but may be drawn to areas with water to cool down and good air flow to avoid flies. These factors may also contribute to increased activity at higher temperatures (see Supplemental File S2); for instance, cows may be more active as a group at higher ambient temperatures to seek preferable microclimates or to deter fly burdens through behavior such as tail swishing (El Ashmawy et al., 2019). However, activity and ambient temperature are not entirely independent; an increase in cow activity may increase the ambient temperature in the barn, given activity generates body heat, although the extent to which is unclear. It is not clear to what extent each of these microclimatic factors affect their bunching behavior, but it can be hypothesized that cows are either drawn to preferable microclimates or driven away from adverse microclimates when temperatures increase above 20°C.

We found no evidence that the average location and spatial distribution of cows was different during bunching periods when compared with the aggregated spatial distribution across the entire study (Figure 6A, 6B). However, there was more variation within the observed spatial distribution when cows were bunching (median hourly CV of 98.88%; range = 78.13% to 218.38%; Figure 7C, 7D). In general, cows appeared to prefer positioning in the right-hand cubicles over the left and lower cubicles in the nonfeeding zone, across the entire study duration and during hours of high bunching (Figure 6A, 6B). The right-hand cubicles were closer to the collecting yard/milking parlor which would have allowed cows to relieve their high milk yield sooner compared with if they were positioned elsewhere in the barn (the study group consisted of high-yielding cows). It has previously been observed that higher-parity cows and cows with more days in milk spent greater time in cubicle areas closer to a collecting yard (Vázquez Di-

osdado et al., 2018). Similarly, (Churakov et al., 2021) found that higher-parity cows occupied cubicles closer to a milking area. As discussed above, this apparent preference for the right-hand cubicles could also be due to other possible factors such as better ventilation in these areas. (Churakov et al., 2021) also reported higher occupancy near feeding areas, which is consistent with the high-space use in the feeding zone observed in our study, although this is likely driven by the requirement for feed intake rather than any other factors.

As expected, there was a gradual decrease in both ambient temperature and localized temperatures within the barn over the duration of the study period (August to November; Figure 2F, Figure 6C–6F). Localized temperature throughout the barn (ST_{XY}, measured by animal-mounted sensors) showed relatively low spatial variation (median hourly CV of 3.65%; range = 1.41% to 9.41%; Figure 6C–6F), although visual inspection shows that in general the hottest temperatures were recorded in the passageways and the feeding zone, which is perhaps not surprising as this is where the highest density of cows is typically observed (Figure 6A, 6B; Papez and Kic, 2015; Celozzi et al., 2020). There was a significant correlation (Bhattacharyya coefficient, BC = 0.888; $P < 0.0001$ in randomization test) between localized temperature and space-use intensity across the barn over the study duration. However, the observed BC was negatively correlated with ambient barn temperature (Figure 7E), and this was significant $\geq 20°C$. This result can be explained by the fact that bunching leads to higher spatial variation (higher CV) and hence a lower BC (in comparison to nonbunching periods), and as previously discussed, bunching is more likely to be observed at higher ambient temperatures. Nevertheless, further investigation is required to fully understand the detailed spatiotemporal dynamics of the barn environment and to identify the specific factors driving space use and bunching behavior, to help improve housing designs.

Implications for Herd Management

Due to the high metabolic demands of dairy cows their bodies radiate significant heat into their local environment to maintain a stable core body temperature (Spiers, 2003). Bunching of dairy cattle, whether due to management practices such as collection for milking or behavioral choices, has the potential to exacerbate hot and humid conditions capable of increasing heat load i.e., given temperatures are known to increase in areas of high stocking densities (Papez and Kic, 2015; Celozzi et al., 2020), which is consistent with our results in Figure 6. This has implications for welfare, as cows under heat stress undergo physiological changes such as an in-

crease in respiration rate and panting (Osei-Amponsah et al., 2020; Yan et al., 2021) and production losses such as reduced milk yield (Gantner et al., 2011; Gorniak et al., 2014; Wildridge et al., 2018). Moving forward, heat stress is becoming an increasing concern as demand in the dairy sector increases (Bayvel et al., 2012; Cembalo et al., 2016; Miglior et al., 2017) alongside heightened effects of climate change. In regions such as the UK cattle have historically had limited experience of such high temperatures and hence little time to adapt (Fodor et al., 2018; Hanlon et al., 2021). Further study is required to better understand the relationship between bunching and temperature, alongside effects on production, considering appropriate heat stress thresholds at which to alert farmers.

Precision livestock farming approaches provide opportunities to study and understand animal behavior, allowing us to collect and analyze vast amounts of data in real-time, and to identify patterns and associations that would be difficult to detect using traditional methods such as manual observations (Berckmans, 2014). The findings of this study demonstrate the potential of PLF approaches to uncover previously unknown links between environmental factors and animal behavior (e.g., the overlap between space-use intensity and localized temperature, Figure 6), with implications for health, welfare, and productivity. In this study, dairy cows were found to increase their bunching behavior above average ambient temperatures, and possible mitigation strategies could focus on addressing heat loads, such as through increasing access to shade (Mitlöhner et al., 2001), providing sprinklers and improving ventilation (Fournel et al., 2017), and reducing stocking densities (Celozzi et al., 2020).

Our results have highlighted the association between bunching behavior and ambient temperatures in a large housed dairy herd. Using automated sensors and continuous monitoring at high spatiotemporal resolution that provides an unprecedented level of detail, we provide evidence of how bunching behavior of a dairy cow herd increases above 20°C, as measured by a range of different metrics of spatial clustering and social proximity (Table 1). Given that temperatures are predicted to increase under climate change, there is a need for further exploration and understanding of the drivers of bunching behavior to explore potential mitigation strategies for heat stress (Hanlon et al., 2021), particularly if bunching behavior is itself contributing to the formation of localized higher temperatures. Our study underscores the importance of considering behavioral responses in relation to changing environmental conditions, so that we can implement effective strategies to protect animal health, welfare, and productivity within agricultural settings.

ACKNOWLEDGMENTS

REFERENCES

André, G., B. Engel, P. B. M. Berentsen, Th. V. Vellinga, and A. G. J. M. Oude Lansink. 2011. Quantifying the effect of heat stress on daily milk yield and monitoring dynamic changes using an adaptive dynamic model. J. Dairy Sci. 94:4502–4513. https://doi.org/10.3168/jds.2010-4139.

Barker, Z. E., J. A. Vázquez Diosdado, E. A. Codling, N. J. Bell, H. R. Hodges, D. P. Croft, and J. R. Amory. 2018. Use of novel sensors combining local positioning and acceleration to measure feeding behavior differences associated with lameness in dairy cattle. J. Dairy Sci. 101:6310–6321. https://doi.org/10.3168/jds.2016-12172.

Bayvel, A., T. Diesch, and N. Cross. 2012. Animal welfare: A complex international public policy issue: Economic, policy, societal, cultural and other drivers and constraints. A 20-year international perspective. Anim. Welf. 21(Suppl. 1):11–18. https://doi.org/10.7120/096272812X13345905673485.

Bennett, I. L., V. A. Finch, and C. R. Holmes. 1985. Time spent in shade and its relationship with physiological factors of thermoregulation in three breeds of cattle. Appl. Anim. Behav. Sci. 13:227–236. https://doi.org/10.1016/0168-1591(85)90046-2.

Berckmans, D. 2014. Precision livestock farming technologies for welfare management in intensive livestock systems. Rev. Sci. Tech. 33:189–196. https://doi.org/10.20506/rst.33.1.2273.

Berman, A., Y. Folman, M. Kaim, M. Mamen, Z. Herz, D. Wolfenson, A. Arieli, and Y. Graber. 1985. Upper critical temperatures and forced ventilation effects for high-yielding dairy cows in a subtropical climate. J. Dairy Sci. 68:1488–1495. https://doi.org/10.3168/jds.S0022-0302(85)80987-5.

Bernabucci, U., S. Biffani, L. Buggiotti, A. Vitali, N. Lacetera, and A. Nardone. 2014. The effects of heat stress in Italian Holstein dairy cattle. J. Dairy Sci. 97:471–486. https://doi.org/10.3168/jds.2013-6611.

Blackie, N., J. Amory, E. Bleach, and J. Scaife. 2011. The effect of lameness on lying behaviour of zero grazed Holstein dairy cattle. Appl. Anim. Behav. Sci. 134:85–91. https://doi.org/10.1016/j.applanim.2011.08.004.

Bohmanova, J., I. Misztal, and J. B. Cole. 2007. Temperature-humidity indices as indicators of milk production losses due to heat stress. J. Dairy Sci. 90:1947–1956. https://doi.org/10.3168/jds.2006-513.

Bouraoui, R., M. Lahmar, A. Majdoub, M. Djemali, and R. Belyea. 2002. The relationship of temperature-humidity index with milk production of dairy cows in a Mediterranean climate. Anim. Res. 51:479–491. https://doi.org/10.1051/animres:2002036.

Bowen, M. T., R. C. Kevin, M. May, L. G. Staples, G. E. Hunt, and I. S. McGregor. 2013. Defensive aggregation (huddling) in *Rattus norvegicus* toward predator odor: Individual differences, social buffering effects and neural correlates. PLoS One 8:e68483. https://doi.org/10.1371/journal.pone.0068483.

Cagnacci, F., L. Boitani, R. A. Powell, and M. S. Boyce. 2010. Animal ecology meets GPS-based radiotelemetry: A perfect storm of opportunities and challenges. Philos. Trans. R. Soc. Lond. B Biol. Sci. 365:2157–2162. https://doi.org/10.1098/rstb.2010.0107.

Celozzi, S., M. Zucali, L. Bava, F. M. Tangorra, L. Zanini, A. Tamburini, and A. Sandrucci. 2020. The use of integrated data collection system to evaluate milking performance, microclimatic condition and cows' behaviour. Ital. J. Anim. Sci. 19:856–864. https://doi.org/10.1080/1828051X.2020.1805034.

Cembalo, L., F. Caracciolo, A. Lombardi, T. Del Giudice, K. G. Grunert, and G. Cicia. 2016. Determinants of individual attitudes toward animal welfare-friendly food products. J. Agric. Environ. Ethics 29:237–254. https://doi.org/10.1007/s10806-015-9598-z.

Chen, J. M., K. E. Schütz, and C. B. Tucker. 2016. Cooling cows efficiently with water spray: Behavioral, physiological, and production responses to sprinklers at the feed bunk. J. Dairy Sci. 99:4607–4618. https://doi.org/10.3168/jds.2015-10714.

Chopra, K., and E. A. Codling. 2024. Dairy herd bunching metrics and ambient temperatures. Dataset. Colchester, University of Essex. https://doi.org/10.5526/ERDR-00000180.

Chopra, K., H. R. Hodges, Z. E. Barker, J. A. Vázquez Diosdado, J. R. Amory, T. C. Cameron, D. P. Croft, N. J. Bell, and E. A. Codling. 2020. Proximity interactions in a permanently housed dairy herd: Network structure, consistency, and individual differences. Front. Vet. Sci. 7:583715. https://doi.org/10.3389/fvets.2020.583715.

Churakov, M., A. M. Silvera, M. Gussmann, and P. P. Nielsen. 2021. Parity and days in milk affect cubicle occupancy in dairy cows. Appl. Anim. Behav. Sci. 244:105494. https://doi.org/10.1016/j.applanim.2021.105494.

Cook, N. B., R. L. Mentink, T. B. Bennett, and K. Burgi. 2007. The effect of heat stress and lameness on time budgets of lactating dairy cows. J. Dairy Sci. 90:1674–1682. https://doi.org/10.3168/jds.2006-634.

Dikmen, S., and P. J. Hansen. 2009. Is the temperature-humidity index the best indicator of heat stress in lactating dairy cows in a subtropical environment? J. Dairy Sci. 92:109–116. https://doi.org/10.3168/jds.2008-1370.

El Ashmawy, W. R., D. R. Williams, A. C. Gerry, J. D. Champagne, T. W. Lehenbauer, and S. S. Aly. 2019. Risk factors affecting dairy cattle protective grouping behavior, commonly known as bunching, against *Stomoxys calcitrans* (L.) on California dairies. PLoS One 14:e0224987. https://doi.org/10.1371/journal.pone.0224987.

Ekine-Dzivenu, C. C., R. Mrode, E. Oyieng, D. Komwihangilo, E. Lyatuu, G. Msuta, J. M. K. Ojango, and A. M. Okeyo. 2020. Evaluating the impact of heat stress as measured by temperature-humidity index (THI) on test-day milk yield of small holder dairy cattle in a sub-Sahara African climate. Livest. Sci. 242:104314. https://doi.org/10.1016/j.livsci.2020.104314.

Erbez, M., K. E. Bøe, D. Falta, and G. Chládek. 2012. Crowding of dairy cows in a cubicle barn during the hot summer months. Arch. Tierzucht 55:325–331. https://doi.org/10.5194/aab-55-325-2012.

Fodor, N., A. Foskolos, C. F. E. Topp, J. M. Moorby, L. Pásztor, and C. H. Foyer. 2018. Spatially explicit estimation of heat stress-related impacts of climate change on the milk production of dairy

cows in the United Kingdom. PLoS One 13:e0197076. https://doi.org/10.1371/journal.pone.0197076.

Foster, W. A., and J. E. Treherne. 1981. Evidence for the dilution effect in the selfish herd from fish predation on a marine insect. Nature 293:466–467. https://doi.org/10.1038/293466a0.

Fournel, S., V. Ouellet, and É. Charbonneau. 2017. Practices for alleviating heat stress of dairy cows in humid continental climates: A literature review. Animals (Basel) 7:37. https://doi.org/10.3390/ani7050037.

Galán, E., P. Llonch, A. Villagrá, H. Levit, S. Pinto, and A. del Prado. 2018. A systematic review of non-productivity-related animal-based indicators of heat stress resilience in dairy cattle. PLoS One 13:e0206520. https://doi.org/10.1371/journal.pone.0206520.

Gantner, V., P. Mijić, K. Kuterovac, D. Solić, and R. Gantner. 2011. Temperature-humidity index values and their significance on the daily production of dairy cattle. Mljekarstvo 61:56–63.

Gilbert, C., D. McCafferty, Y. Le Maho, J.-M. Martrette, S. Giroud, S. Blanc, and A. Ancel. 2010. One for all and all for one: The energetic benefits of huddling in endotherms. Biol. Rev. Camb. Philos. Soc. 85:545–569. https://doi.org/10.1111/j.1469-185X.2009.00115.x.

Giro, A., J. R. M. Pezzopane, W. Barioni Junior, A. F. Pedroso, A. P. Lemes, D. Botta, N. Romanello, A. N. Barreto, and A. R. Garcia. 2019. Behavior and body surface temperature of beef cattle in integrated crop-livestock systems with or without tree shading. Sci. Total Environ. 684:587–596. https://doi.org/10.1016/j.scitotenv.2019.05.377.

Gorniak, T., U. Meyer, K.-H. Südekum, and S. Dänicke. 2014. Impact of mild heat stress on dry matter intake, milk yield and milk composition in mid-lactation Holstein dairy cows in a temperate climate. Arch. Anim. Nutr. 68:358–369. https://doi.org/10.1080/1745039X.2014.950451.

Gygax, L., G. Neisen, and H. Bollhalder. 2007. Accuracy and validation of a radar-based automatic local position measurement system for tracking dairy cows in free-stall barns. Comput. Electron. Agric. 56:23–33. https://doi.org/10.1016/j.compag.2006.12.004.

Hanlon, H. M., D. Bernie, G. Carigi, and J. A. Lowe. 2021. Future changes to high impact weather in the UK. Clim. Change 166:50. https://doi.org/10.1007/s10584-021-03100-5.

Herbut, P., G. Hoffmann, S. Angrecka, D. Godyń, F. M. C. Vieira, K. Adamczyk, and R. Kupczyński. 2021. The effects of heat stress on the behaviour of dairy cows—A review. Ann. Anim. Sci. 21:385–402. https://doi.org/10.2478/aoas-2020-0116.

Hill, C. T., P. D. Krawczel, H. M. Dann, C. S. Ballard, R. C. Hovey, W. A. Falls, and R. J. Grant. 2009. Effect of stocking density on the short-term behavioural responses of dairy cows. Appl. Anim. Behav. Sci. 117:144–149. https://doi.org/10.1016/j.applanim.2008.12.012.

Hut, P. R., J. Scheurwater, M. Nielen, J. van den Broek, and M. M. Hostens. 2022. Heat stress in a temperate climate leads to adapted sensor-based behavioral patterns of dairy cows. J. Dairy Sci. 105:6909–6922. https://doi.org/10.3168/jds.2021-21756.

Huynh, T. T. T., A. J. A. Aarnink, W. J. J. Gerrits, M. J. H. Heetkamp, T. T. Canh, H. A. M. Spoolder, B. Kemp, and M. W. A. Verstegen. 2005. Thermal behaviour of growing pigs in response to high temperature and humidity. Appl. Anim. Behav. Sci. 91:1–16. https://doi.org/10.1016/j.applanim.2004.10.020.

Javorová, J., M. Velecká, D. Falta, M. Večeřa, J. Andrýsek, S. Studený, and G. Chládek. 2014. The effect of air temperature and time of day on distribution of Czech Fleckvieh cows within the barn. Acta Univ. Agric. Silvic. Mendel. Brun. 62:117–124. https://doi.org/10.11118/actaun201462010117.

Ji, B., T. Banhazi, K. Perano, A. Ghahramani, L. Bowtell, C. Wang, and B. Li. 2020. A review of measuring, assessing and mitigating heat stress in dairy cattle. Biosyst. Eng. 199:4–26. https://doi.org/10.1016/j.biosystemseng.2020.07.009.

Kendall, P. E., P. P. Nielsen, J. R. Webster, G. A. Verkerk, R. P. Littlejohn, and L. R. Matthews. 2006. The effects of providing shade to lactating dairy cows in a temperate climate. Livest. Sci. 103:148–157. https://doi.org/10.1016/j.livsci.2006.02.004.

Kibler, H. H. 1964. Environmental physiology and shelter engineering with special reference to domestic animals. LXVII, Thermal effects

of various temperature-humidity combinations on Holstein cattle as measured by eight physiological responses. Mizzou 1–40.

King, M. T. M., E. A. Pajor, S. J. LeBlanc, and T. J. DeVries. 2016. Associations of herd-level housing, management, and lameness prevalence with productivity and cow behavior in herds with automated milking systems. J. Dairy Sci. 99:9069–9079. https://doi.org/10.3168/jds.2016-11329.

Lefcourt, A. M., and E. T. Schmidtmann. 1989. Body temperature of dry cows on pasture: Environmental and behavioral effects. J. Dairy Sci. 72:3040–3049. https://doi.org/10.3168/jds.S0022-0302(89)79457-1.

Mader, T. L., S. M. Holt, G. L. Hahn, M. S. Davis, and D. E. Spiers. 2002. Feeding strategies for managing heat load in feedlot cattle. J. Anim. Sci. 80:2373–2382. https://doi.org/10.2527/2002.8092373x.

Marai, I. F. M., A. A. M. Habeeb, and A. E. Gad. 2002. Rabbits' productive, reproductive and physiological performance traits as affected by heat stress: A review. Livest. Prod. Sci. 78:71–90. https://doi.org/10.1016/S0301-6226(02)00091-X.

McDonald, P. V., M. A. G. von Keyserlingk, and D. M. Weary. 2020. Hot weather increases competition between dairy cows at the drinker. J. Dairy Sci. 103:3447–3458. https://doi.org/10.3168/jds.2019-17456.

Miglior, F., A. Fleming, F. Malchiodi, L. F. Brito, P. Martin, and C. F. Baes. 2017. A 100-year review: Identification and genetic selection of economically important traits in dairy cattle. J. Dairy Sci. 100:10251–10271. https://doi.org/10.3168/jds.2017-12968.

Mitlöhner, F. M., J. L. Morrow, J. W. Dailey, S. C. Wilson, M. L. Galyean, M. F. Miller, and J. J. McGlone. 2001. Shade and water misting effects on behavior, physiology, performance, and carcass traits of heat-stressed feedlot cattle. J. Anim. Sci. 79:2327–2335. https://doi.org/10.2527/2001.7992327x.

Mooring, M. S., and B. L. Hart. 1992. Animal grouping for protection from parasites: Selfish herd and encounter-dilution effects. Behaviour 123:173–193. https://doi.org/10.1163/156853992X00011.

Morton, J. M., W. P. Tranter, D. G. Mayer, and N. N. Jonsson. 2007. Effects of environmental heat on conception rates in lactating dairy cows: Critical periods of exposure. J. Dairy Sci. 90:2271–2278. https://doi.org/10.3168/jds.2006-574.

Muggeo, V. M. R. 2003. Estimating regression models with unknown break-points. Stat. Med. 22:3055–3071. https://doi.org/10.1002/sim.1545.

Muggeo, V. M. R. 2008. Segmented: An R package to fit regression models with broken-line relationships. R News 8:20–25.

Nonaka, I., N. Takusari, K. Tajima, T. Suzuki, K. Higuchi, and M. Kurihara. 2008. Effects of high environmental temperatures on physiological and nutritional status of prepubertal Holstein heifers. Livest. Sci. 113:14–23. https://doi.org/10.1016/j.livsci.2007.02.010.

Omnisense Ltd. 2022. Omnisense real-time geolocation home page. Accessed Jul. 26, 2022. http://www.omnisense.co.uk/.

Osei-Amponsah, R., F. R. Dunshea, B. J. Leury, L. Cheng, B. Cullen, A. Joy, A. Abhijith, M. H. Zhang, and S. S. Chauhan. 2020. Heat stress impacts on lactating cows grazing Australian summer pastures on an automatic robotic dairy. Animals (Basel) 10:869. https://doi.org/10.3390/ani10050869.

Ozella, L., J. Langford, L. Gauvin, E. Price, C. Cattuto, and D. P. Croft. 2020. The effect of age, environment and management on social contact patterns in sheep. Appl. Anim. Behav. Sci. 225:104964. https://doi.org/10.1016/j.applanim.2020.104964.

Papez, J., and P. Kic. 2015. Indoor environment in milking parlor and cowshed during the milking process. Pages 112–118 in 14th Int. Sci. Conf. Eng. Rural Dev. Jelgava, Latvia, May 20–22, 2015.

Pereyra, A. V. G., V. M. May, C. G. Catracchia, and M. A. Herrero. 2010. Influence of water temperature and heat stress on drinking water intake in dairy cows. Chil. J. Agric. Res. 70:328–336. https://doi.org/10.4067/S0718-58392010000200017.

Polsky, L., and M. A. G. von Keyserlingk. 2017. Invited review: Effects of heat stress on dairy cattle welfare. J. Dairy Sci. 100:8645–8657. https://doi.org/10.3168/jds.2017-12651.

R Core Team. 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing.

Rabaiotti, D., and R. Woodroffe. 2019. Coping with climate change: Limited behavioral responses to hot weather in a tropical carnivore. Oecologia 189:587–599. https://doi.org/10.1007/s00442-018-04329-1.

Ray, D. E., T. J. Halbach, and D. V. Armstrong. 1992. Season and lactation number effects on milk production and reproduction of dairy cattle in Arizona. J. Dairy Sci. 75:2976–2983. https://doi.org/10.3168/jds.S0022-0302(92)78061-8.

De Rensis, F., and R. J. Scaramuzzi. 2003. Heat stress and seasonal effects on reproduction in the dairy cow—A review. Theriogenology 60:1139–1151. https://doi.org/10.1016/S0093-691X(03)00126-2.

RStudio Team. 2020. RStudio: Integrated development for R. RStudio, PBC, Boston, MA.

Sammad, A., S. Umer, R. Shi, H. Zhu, X. Zhao, and Y. Wang. 2020. Dairy cow reproduction under the influence of heat stress. J. Anim. Physiol. Anim. Nutr. (Berl.) 104:978–986. https://doi.org/10.1111/jpn.13257.

Schmidtmann, E. T., and D. R. Berkebile. 1985. Relationship between numbers of face flies (*Diptera: Muscidae*) and nearest-neighbor distance among Holstein cows. J. Econ. Entomol. 78:102–105. https://doi.org/10.1093/jee/78.1.102.

Schütz, K. E., N. R. Cox, and L. R. Matthews. 2008. How important is shade to dairy cattle? Choice between shade or lying following different levels of lying deprivation. Appl. Anim. Behav. Sci. 114:307–318. https://doi.org/10.1016/j.applanim.2008.04.001.

Schütz, K. E., A. R. Rogers, Y. A. Poulouin, N. R. Cox, and C. B. Tucker. 2010. The amount of shade influences the behavior and physiology of dairy cattle. J. Dairy Sci. 93:125–133. https://doi.org/10.3168/jds.2009-2416.

Spiers, D. E. 2003. How cows dissipate heat. Page 77 in Dairy Management Conference.

Tresoldi, G., K. E. Schütz, and C. B. Tucker. 2019. Cooling cows with sprinklers: Effects of soaker flow rate and timing on behavioral and physiological responses to heat load and production. J. Dairy Sci. 102:528–538. https://doi.org/10.3168/jds.2018-14962.

Tsai, Y.-C., J.-T. Hsu, S.-T. Ding, D. J. Rustia, and T.-T. Lin. 2020. Assessment of dairy cow heat stress by monitoring drinking behaviour using an embedded imaging system. Biosyst. Eng. 199:97–108. https://doi.org/10.1016/j.biosystemseng.2020.03.013.

Tullo, E., I. Fontana, D. Gottardo, K. H. Sloth, and M. Guarino. 2016. Technical note: Validation of a commercial system for the continuous and automated monitoring of dairy cow activity. J. Dairy Sci. 99:7489–7494. https://doi.org/10.3168/jds.2016-11014.

Vázquez Diosdado, J. A., Z. E. Barker, H. R. Hodges, J. R. Amory, D. P. Croft, N. J. Bell, and E. A. Codling. 2018. Space-use patterns highlight behavioural differences linked to lameness, parity, and days in milk in barn-housed dairy cows. PLoS One 13:e0208424. https://doi.org/10.1371/journal.pone.0208424.

Wang, J., J. Li, F. Wang, J. Xiao, Y. Wang, H. Yang, S. Li, and Z. Cao. 2020. Heat stress on calves and heifers: A review. J. Anim. Sci. Biotechnol. 11:79. https://doi.org/10.1186/s40104-020-00485-8.

Weather Underground. 2014. Harold Hill, Forecast for Romford, GB. Accessed Sep. 22, 2022. https://www.wunderground.com/history/daily/gb/romford.

Wildridge, A. M., P. C. Thomson, S. C. Garcia, A. J. John, E. C. Jongman, C. E. F. Clark, and K. L. Kerrisk. 2018. Short communication: The effect of temperature-humidity index on milk yield and milking frequency of dairy cows in pasture-based automatic milking systems. J. Dairy Sci. 101:4479–4482. https://doi.org/10.3168/jds.2017-13867.

Yan, G., K. Liu, Z. Hao, Z. Shi, and H. Li. 2021. The effects of cow-related factors on rectal temperature, respiration rate, and temperature-humidity index thresholds for lactating cows exposed to heat stress. J. Therm. Biol. 100:103041. https://doi.org/10.1016/j.jtherbio.2021.103041.

ORCIDS

Kareemah Chopra ⓘ https://orcid.org/0009-0003-1427-3384

Zoe E. Barker ⓘ https://orcid.org/0000-0002-8512-0831

Jorge A. Vázquez Diosdado ⓘ https://orcid.org/0000-0001-6934-9305

Jonathan R. Amory ⓘ https://orcid.org/0000-0002-0047-8739

Tom C. Cameron ⓘ https://orcid.org/0000-0002-5875-1494

Nick J. Bell ⓘ https://orcid.org/0000-0001-6415-0786

Edward A. Codling ⓘ https://orcid.org/0000-0001-5124-3334