Shade Treatment Effects on Cattle Heat Stress

Rajan Shankar[a]

[a]School of Mathematics and Statistics, University of Sydney, NSW, 2006

This version was compiled on May 29, 2021

Your abstract will be typeset here, and used by default a visually distinctive font. An abstract should explain to the general reader the major contributions of the article.

linear mixed models | time series | outlier detection | drinking patterns | rumen temperature | interactive viz | data processing

1. Introduction

Environmental conditions are known to influence the health, welfare and productivity of feedlot cattle. It has been established that shade structures are beneficial for the health of these cattle. However, such studies have predominantly been conducted in northern, sub-tropical regions. This project considers cattle in un-shaded, shaded (shade cloth) and sheltered (waterproof) pens that are located in the University of New England's research feedlot Tullimba, a southern Australian environment. The general aim of this project was to analyse the effects of different shade structures on the rumen temperature and drinking patterns of cattle.

Experimental design. At Tullimba, there were 90 feedlot cattle divided equally across 9 pens. Each group of 3 pens consisted of one of 3 shade treatments — un-shaded, shade cloth or waterproof. Hence, there were 30 animals under each of the shade treatments. The experiment ran for 105 days from the 23rd of December 2020 to the 7th of April 2021.

Each animal was equipped with a bolus that measured its internal rumen temperature at 10-minute intervals. An instrument that collected weather data and an instrument that collected black globe temperature data at 10-minute intervals were also set up at Tullimba.

The University of New England's animal ethics committee approved the experimental procedures in November 2020 (authority number AEC20-091).

Device details. The weather station at Tullimba was a MCC Hub weather station, supplied by ICT International. It measured variables such as wind speed, solar radiation, air temperature, relative humidity, precipitation, etc. The rumen temperature boluses as well as the custom web interface for visualising the rumen temperature data were developed and supplied by smaXtec.

2. Data Processing and Cleaning

A major component of this project involved the rigorous processing and cleaning of the collected data. Due to the many sources of data — temperature boluses and weather instruments — and the imperfectness of these collection devices, it was a very difficult task to curate a single, tidy data set.

	A	B	C	D	E	F	G	H	I	J
1	Instrument	MCC Hub								
2	Serial Numb	F00001B4								
3	Date	Time	Solar_0 (W	Precipitat	Strikes_0 (	Strike Dist	Wind Spe	Wind Dire	Gust Wind	Air Tempe
4	8/05/2018	13:00:00	261	0	0	0	2.18	144.5	3.089	20.2
5	8/05/2018	14:00:00	276	0	0	0	1.879	123.199	5.809	20.299
6	8/05/2018	15:00:00	200	0	0	0	1.75	144.199	4.989	20.399
7	Instrument	MCC Hub								
8	Serial Numb	F00001B4								
9	Date	Time	Solar_0 (W	Precipitat	Strikes_0 (	Strike Dist	Wind Spe	Wind Dire	Gust Wind	Air Tempe
10	9/05/2018	7:00:00	59	0	0	0	1.389	105.3	1.899	6
11	9/05/2018	8:00:00	173	0	0	0	0.68	125.9	1.529	7.8
12	9/05/2018	9:00:00	343	0.017	0	0	0.61	58.4	1.72	11.199
13	9/05/2018	10:00:00	497	0	0	0	1.039	316.7	2.589	14.699
14	9/05/2018	11:00:00	606	0.017	0	0	1.6	145.5	5.8	17.799
15	9/05/2018	12:00:00	636	0	0	0	2.509	114.9	5.429	19.5
16	9/05/2018	13:00:00	376	0	0	0	3.039	122.5	6.369	20.2
17	9/05/2018	14:00:00	588	0	0	0	3.709	119	9.02	21.2
18	9/05/2018	15:00:00	530	0	0	0	4.67	88.599	9.1	21.2
19	9/05/2018	16:00:00	276	0	0	0	4.409	91.9	8.569	20.6
20	Instrument	MCC Hub								
21	Serial Numb	F00001B4								
22	Date	Time	Solar_0 (W	Precipitat	Strikes_0 (	Strike Dist	Wind Spe	Wind Dire	Gust Wind	Air Tempe
23	10/05/2018	7:00:00	57	0	0	0	1.169	76.599	2.279	1.899
24	10/05/2018	8:00:00	171	0	0	0	0.74	29.799	1.97	4.3

Fig. 1. First 24 rows of the weather data file with troublesome rows outlined in red.

All data cleaning and analysis was performed in the R language (R Core Team, 2020). A multitude of packages from the tidyverse suite (Wickham *et al.*, 2019) were used to read, transform, merge and plot our data. We used janitor (Firke, 2020) for miscellaneous cleaning and tabling, visdat (Tierney, 2017) for visualising missing values, and tsibble (Wang *et al.*, 2020) for working with time series data and record keeping. We also used Python (Python Core Team, 2020) along with the package PyAutoGUI (Sweigart, 2020) to scrape the rumen temperature data from a web interface.

Minimal manual editing was done before processing the data in R; we briefly explain these edits in Appendix X.Y. The code pipelines for all of the processing done in R is available in Appendix X.Y.

Weather data. We first discuss the cleaning process for the weather data.

Initial read. A major problem with the weather data was that the variable names and the details of the data collection instrument were dispersed throughout the .csv file in arbitrary rows. To illustrate this, the first few rows of the file are shown in Figure 1.

Fortunately, this problem was dealt with fairly easily by pre-specifying the variable types when the data file was read in.

Data cropping. The weather data collection instrument had been recording data at hourly intervals prior to the beginning of the experiment, after which it collected data at 10-minute intervals. These prior observations dated back to 2018 and

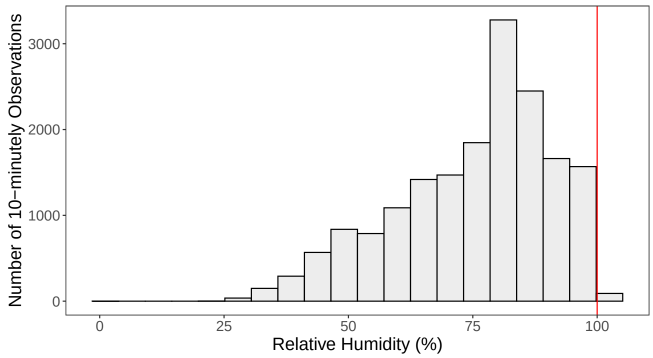


Fig. 2. Histogram of relative humidity highlighting values that are slightly greater than 100 (outside of their expected range).

were not relevant to the experiment, so they were removed from the data. We also removed some irrelevant instrument status variables from the data.

Erroneous values. Upon visualising histograms and box plots for each variable, we noticed that some variables contained values that needed to be corrected.

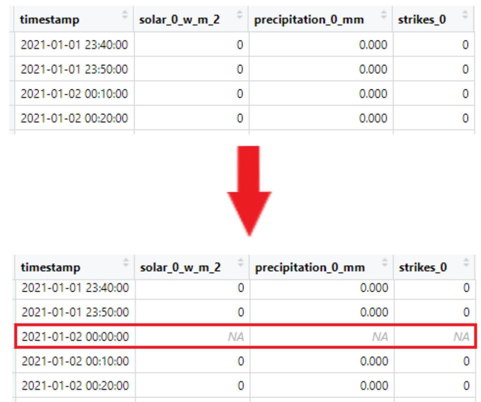
In the wind direction and wind speed variables, there were 486 out of 17541 values recorded as -9990; we deduced that the data collection instrument used -9990 as an error placeholder, so we replaced these with missing values. This only happened in the wind direction and wind speed variables, and these values always occurred in pairs, i.e. the wind speed was recorded as -9990 if and only if the wind direction was recorded as -9990.

Secondly, four of the variables contained values slightly outside of their expected ranges. Figure 2 depicts a histogram of the corrected relative humidity percentage variable.

Since corrected relative humidity percentage is a percentage value, we should not be seeing values above 100. However, since these values were only slightly above 100, we simply rounded them such that they were within the expected range.

Filling gaps. The weather data collection instrument was faulty in the sense that it would not record any observation at midnight, i.e. there was a 20-minute gap between an observation at 23:50:00 and at 00:10:00 the next day. To make sure that such records existed in the data, we used the tsibble package (Wang *et al.*, 2020) to add in blank rows at these missing timestamps. Figure 3 illustrates this procedure.

Missing values. As a final step, we imputed missing values. Figure 4 shows that the missingness was scattered throughout the experiment time series and there were no long, continuous chunks of missing values in any variable. We decided to use a linear interpolation strategy to impute missing values for each variable. This was implemented in R as a custom-written function (Appendix X.Y).



timestamp	solar_0_w_m_2	precipitation_0_mm	strikes_0
2021-01-01 23:40:00	0	0.000	0
2021-01-01 23:50:00	0	0.000	0
2021-01-02 00:10:00	0	0.000	0
2021-01-02 00:20:00	0	0.000	0

timestamp	solar_0_w_m_2	precipitation_0_mm	strikes_0
2021-01-01 23:40:00	0	0.000	0
2021-01-01 23:50:00	0	0.000	0
2021-01-02 00:00:00	NA	NA	NA
2021-01-02 00:10:00	0	0.000	0
2021-01-02 00:20:00	0	0.000	0

Fig. 3. Demonstration of the tsibble's fill_gaps function adding in blank rows at missing timestamps.

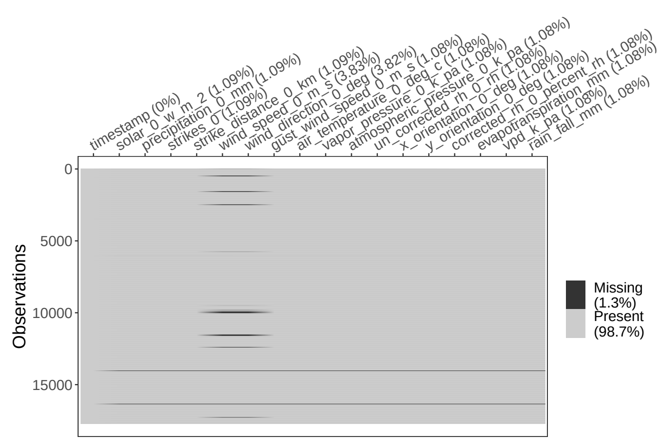


Fig. 4. Locations of missing values in the tidy weather data.

Linear interpolation works by considering the last non-missing value x_n before a chunk of $k-1$ missing values and the next non-missing value x_{n+k}, and imputing $x_{n+i} = x_n + \frac{i}{k}(x_{n+k} - x_n)$ for all $1 \leq i < k$.

Black globe temperature data. The instrument collecting black globe temperature data was different to the one that collected the weather data, so we had a separate file that recorded the black globe temperature data. However, we discovered that these recordings were faulty and thus were not used in the project, so we do not go over the cleaning process of this data. We elaborate on how the recordings were faulty and what was done instead to estimate black globe temperature data in section 3.

Rumen temperature data. We next discuss the cleaning process for the rumen temperature data.

Semi-automatic web scraping. The rumen temperature data collected via an internal bolus within each animal was available to download from smaXtec's web interface. We did not have direct access to the database that stored the data, so we used a Python package called PyAutoGUI (Sweigart, 2020) to automate the downloading of 90 rumen temperature data files from the web interface.

PyAutoGUI allows users to automate mouse and keyboard actions such as clicking, scrolling and typing. We wrote a Python script using PyAutoGUI to perform a series of actions inside of a for-loop, so that we could efficiently download all 90 rumen temperature data files. The process was not completely automatic as someone was needed to supervise the program to stop and restart it if errors occurred. This script will be used again in future work, as there are still 180 animals that will have similar data that needs to be collected. The script code is available in Appendix X.Y.

Merging rumen temperature data files. We created a custom function to read in a rumen temperature data file given its file name. As an overview, it

1. obtained the timestamp, rumen temperature and smoothed rumen temperature from a specific animal's data file,
2. obtained that animal's ID from the beginning of the file, and
3. combined the time stamp, rumen temperature, smoothed rumen temperature and animal ID into a single data frame.

We used our custom function in conjunction with the purrr package from the tidyverse (Wickham *et al.*, 2019) to produce a single, stacked data frame of all rumen temperature data given a list of the rumen temperature data file names.

To ensure that we had downloaded all of the required rumen temperature data, the animal IDs in the resulting data frame was checked against a file consisting of animal details that was recorded prior to the beginning of the experiment.

Daylight savings and missing records. On the 4th of April 2021, Sydney changed timezone from AEST to AEDT. This resulted in the temperature boluses recording two different entries for each animal between the hours of 2am and 3am. We dealt with this by simply removing the earlier of the two entries for each animal. This issue only occurred with the temperature boluses and not with the weather data collection instrument.

Solving this issue enabled us to convert the data frame into a tsibble object because tsibble requires that the timestamps across all rows are unique (focusing on a single animal). In a similar fashion as with the weather data, we ensured that there were no missing records in the data by adding in blank rows at any missing timestamps.

Pen IDs and shade treatments. The file consisting of animal details mentioned earlier includes the pen ID and shade treatment corresponding to each animal. We joined our data frame of rumen temperature data to the data in this file using animal ID as the key. We retained only the timestamp, animal ID, pen ID, shade treatment, rumen temperature and smoothed rumen temperature variables.

Animal oddities. We noticed that although the boluses were equipped on the 23rd of December 2020, data only started being reliably captured from the 2nd January 2021, so we decided to crop out observations that were recorded before the 2nd of January 2021.

Additionally, animal 244 died prematurely before the experiment ended, so we removed it from the data frame.

Missing values. The numeric variables rumen temperature and smoothed rumen temperature contained various different sizes of continuous chunks of missing values; some that were short (less than 2 hours missing) and some that were very long (a few days missing). We decided to use a linear interpolation strategy for chunks that were less than 2 hours in length, implemented via our custom-written function (Appendix X.Y).

With missing value chunks that were greater than 2 hours in length, we could not simply use linear interpolation because that would have erased temperature drops that occurred during drinking bouts. Instead, we decided to impute them with data sourced from past or future days of the same animal that began at the same hour and minute. For example, to fill in a chunk that began at 2021-01-05 10:00:00 and ended at 2021-01-05 23:30:00, we used that same animal's data beginning at 2021-01-06 10:00:00 and ending at 2021-01-06 23:30:00. Figure 5 illustrates an example of how this procedure works.

This was implemented via a custom function (Appendix X.Y) so that we could repeat it for many animals. One animal (animal 321) however, had 19 days of consecutive missing values. This chunk was far too long, so we decided to leave these values as missing values and deal with them as needed during later analysis.

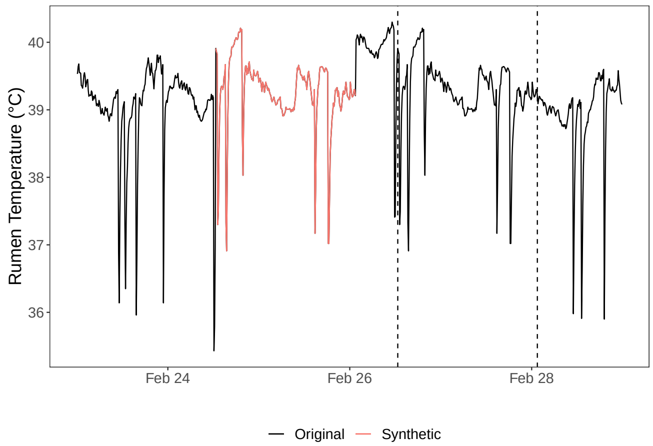


Fig. 5. Synthetic data being used to impute missing values. The portion of the time series between the dotted lines represents where the synthetic data was sourced from.

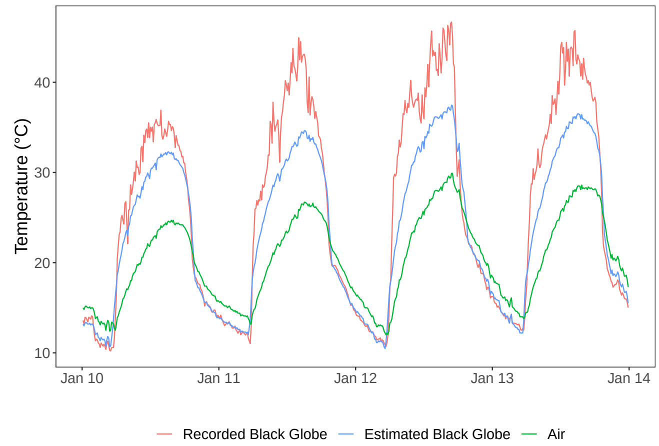


Fig. 6. Comparison of recorded and estimated BGT. The recorded BGT spikes up past the estimated BGT whenever the reading exceeds 20 ℃.

3. Methodology

The temperature boluses were located inside the rumen of each animal in order to provide accurate estimates of each animal's true rumen temperature every 10 minutes. An issue was that, when an animal began a drinking bout, its bolus reported drastically low temperatures due to the rush of cold water into the animal's rumen. We took advantage of this by improving upon an existing algorithm (Vázquez-Diosdado *et al.*, 2019) to detect drinking events based on drops in the rumen temperature data. When it came to modelling the rumen temperature based on weather variables, we used a variation of the rumen temperature variable where the drops in temperature had been smoothed out via a custom algorithm by smaXtec.

Detecting drinking events. Vázquez-Diosdado *et al.* (2019) suggested using an animal-day specific threshold to detect drinking events. The algorithm

1. calculates the mean and standard deviation of the rumen temperature of each animal on each day, and then
2. classifies a point as a drinking event if it is more than one animal-day specific standard deviation s_{i,j_n} below its animal-day specific mean $\bar{x}_{i,j_n}$.

In other words, for animal i, a time point $x_{i,n}$ is classified as a drinking event if $x_{i,n} < \bar{x}_{i,j_n} - s_{i,j_n}$, where j_n corresponds to the specific day that timestamp n occurs in.

We developed and deployed an interactive web app (https://rajan-shankar.shinyapps.io/drinking_events) using the shiny R package (Chang *et al.*, 2020) to investigate whether we could improve on this existing approach by adding extra functionality. We incorporated tune-able hyperparameters into the web app based on the following:

- robust measures of centre and spread, i.e. the median and the median absolute deviation
- looking at the first order differences of the rumen temperature time series
- using moving aggregation functions with varying window sizes as opposed to day-specific thresholds.

Users can control these hyperparameters to visualise how different drinking event detection methods fair on different animals' rumen temperature time series. We discuss the optimal combination of hyperparameters as well as the mathematical formulation of the detection method in section 4.

Heat load indices. Certain weather variables are more influential than others when it comes to modelling the rumen temperature of cattle. Gaughan *et al.* (2008) constructed two indices based on weather variables — the Heat Load Index (HLI) and the Accumulated Heat Load (AHL) — that we used in combination with the shade treatment factor to analyse rumen temperature.

One of the weather variables involved in the calculation of these indices is the black globe temperature (BGT). We found that the instrument collecting BGT data was problematic, as it tended to exaggerate the BGT whenever it exceeded 20°C (6). We decided to instead estimate the BGT using air temperature and solar radiation (G. LeRoy Hahn *et al.*, 2009) as

$$\widehat{T}_{\mathrm{BG}} = 1.33\ T_{\mathrm{air}} - 2.65\sqrt{T_{\mathrm{air}}} + 3.21\log_{10}(R_{\mathrm{solar}} + 1) + 3.5.$$

The HLI is then calculated as a function of the estimated BGT, relative humidity H_{rel} and wind speed W (Gaughan *et al.*, 2008) as

$$\mathrm{HLI} = \begin{cases} 10.66 + 0.28\ H_{\mathrm{rel}} + 1.3\ \widehat{T}_{\mathrm{BG}} - W & \text{if } \widehat{T}_{\mathrm{BG}} < 25 \\ 8.62 + 0.38\ H_{\mathrm{rel}} + 1.55\ \widehat{T}_{\mathrm{BG}} - 0.5\ W + e^{2.4 - W} & \text{if } \widehat{T}_{\mathrm{BG}} \geq 25. \end{cases}$$

The AHL calculation involves the hyperparameters L, U and M, and is indexed by time t because it relies on previous HLI values (Gaughan *et al.*, 2008):

$$\mathrm{AHL}_t = \begin{cases} \max\left\{\left(\mathrm{AHL}_{t-1} + \frac{\mathrm{HLI}_{t-1}-L}{M}\right), 0\right\} & \text{if } \mathrm{HLI}_{t-1} < L \\ \mathrm{AHL}_{t-1} & \text{if } L \le \mathrm{HLI}_{t-1} \le U \\ \mathrm{AHL}_{t-1} + \frac{\mathrm{HLI}_{t-1}-U}{M} & \text{if } \mathrm{HLI}_{t-1} > U. \end{cases}$$

L and U are the lower and upper HLI thresholds, and are set depending on the breed of cattle. These were set to 77 and 86 respectively. M represents how often the HLI is collected every hour; our data was collected at 10-minute intervals, so this was set to 6.

Modelling. There were a few things that we needed to consider before we could build models using our data.

Smoothed rumen temperature. The main response variable for modelling purposes was the smoothed rumen temperature. The raw-recorded rumen temperature of an animal was not a good proxy for its true rumen temperature due to the presence of dips from drinking events. The smoothed rumen temperature was produced by the smaXtec web interface by:

1. calculating moving measures of centre and spread on the raw rumen temperature,
2. calculating a minimum threshold based on these measures, and then
3. for each temperature x_t below the minimum threshold, replacing it with $x_{t-1} - 0.05$.

Number of drinking events. Besides the smoothed rumen temperature, we also tried modelling the number of drinking events based on shade treatment. We used our best-performing drinking events detection method to count the number of drinking events per animal per day and used that as the response variable.

Random effects and packages. For both response variables, we used the lme4 package (Bates *et al.*, 2015) to implement linear mixed models. The package allowed us to incorporate animal ID as a random effect to account for animal-specific variation that was not of direct interest. We also used the emmeans package (Lenth, 2020), the car package (Fox and Weisberg, 2019) and the lmerTest package (Kuznetsova *et al.*, 2017) to test hypotheses for statistical significance.

Day/night averaging. We aggregated our 10-minutely data into 6-hourly day summaries (over the hours of 10am – 4pm) and 6-hourly night summaries (over the hours of 12am – 6am). According to our industry expert Dr. Lees, summarising the data in this way allowed us to disentangle cooler night-time patterns and heat-of-day effects. The code that we used to produce this summarised version of our data is located in Appendix X.Y.

4. Results

Drinking events. We first focus on results pertaining to when the response variable is the daily number of drinks.

Detection method. Plot A in Figure 7 showcases the method developed by Vázquez-Diosdado *et al.* (2019) for detecting drinking events. There are two problems with this method; it picks up too many false positives (i.e. highlights time-points that do not represent a drop in rumen temperature), and highlights multiple nearby time-points that represent the same drinking event.

We alleviate the first problem by using robust measures of centre and spread — the median and the median absolute deviation (MAD) — instead of the mean and standard deviation to detect drops. The second problem arises from the fact that drinking events sometimes last longer than 10 minutes, which results in consecutive values that are similar to each other but relatively extreme to the rest of the temperature series. We deal with this problem by considering the differenced temperature series instead of the raw temperature series. Appendix X.Y illustrates how drinking events are detected on a differenced temperature series, using robust measures.

As a final step, if there are still multiple consecutive time-points flagged as drinking events, we only identify the latest one as a drinking event. This sometimes occurs when the drop in rumen temperature is not instant; rather it happens in two or three decrements. Plot B in Figure 7 showcases our final method for detecting drinking events.

We walk through the mathematical formulation of our drinking event detection method below.

Given a time series of 10-minutely recorded rumen temperatures $x_1, \ldots, x_n$, the first order differences are

$$\begin{aligned} d_t &= x_t - x_{t-1}, \quad 1 < t \le n \\ d_1 &= 0. \end{aligned}$$

The 24-hour rolling medians and median absolute differences (MAD) of the d_t are then

$$\begin{aligned} \mathrm{med}_d(t) &= \mathrm{median}\{d_{t-i} : 0 \le i < \min\{t, 144\}\} \\ \mathrm{MAD}_d(t) &= \mathrm{median}\{|d_{t-i} - \mathrm{med}_d(t)| : 0 \le i < \min\{t, 144\}\} \end{aligned}$$

for $1 \le t \le n$. We say that a time-point t is a *candidate drinking event* if d_t is at least five 24-hour rolling MADs below its 24-hour rolling median. We denote the set of such time-points t as

$$\mathscr{D}_{\text{cand}} = \{t : d_t \le \mathrm{med}_d(t) - 5 \times \mathrm{MAD}_d(t)\}.$$

We now calculate the final set of drinking events $\mathscr{D}$. If there is a *run* of two or more adjacent time-points in $\mathscr{D}_{\text{cand}}$, then we add all time-points except for the latest (highest) one in that run to a discard set denoted $\mathscr{X}$. We do this for every run in $\mathscr{D}_{\text{cand}}$. Thus, our final set of drinking events $\mathscr{D}$ is given by

$$\mathscr{D} = \mathscr{D}_{\text{cand}} \setminus \mathscr{X}.$$

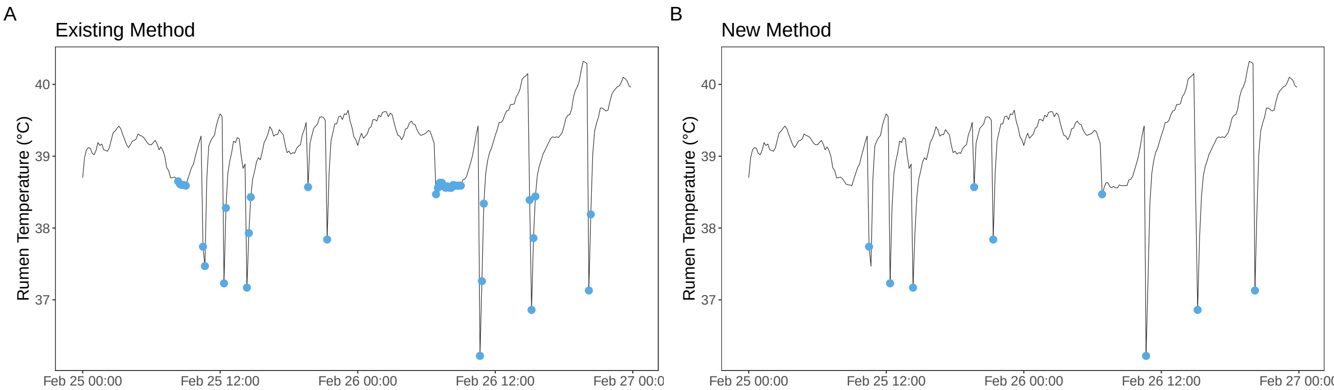


Fig. 7. Comparison of the existing method and our method for detecting drinking events. Each sharp drop is only highlighted once in our method.

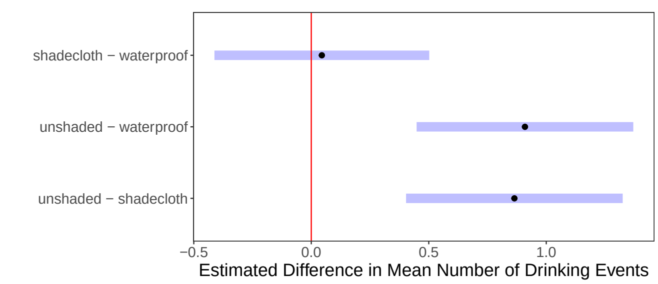


Fig. 8. Pair-wise contrasts of the estimated difference in the mean number of drinking events between the three different shade treatments. The lengths of the 95% confidence bars have been adjusted for multiple comparison issues via Tukey's HSD method.

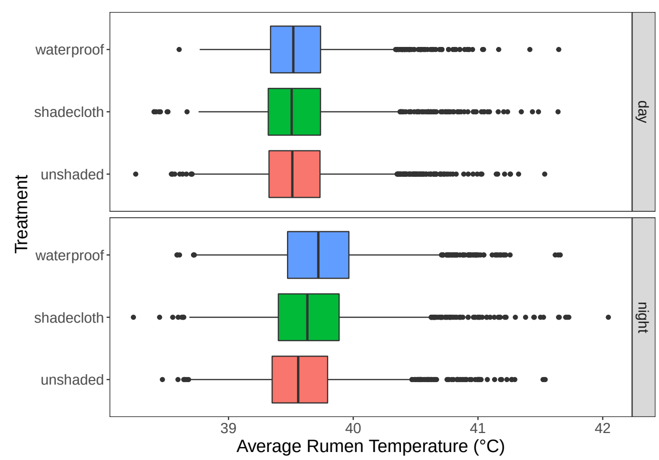


Fig. 9. Box plots of day-average rumen temperature faceted by shade treatment and time-of-day. There is no visible difference in the medians of the boxes in the day-time panel, but there is a pattern of decreasing medians in the night-time panel as such: waterproof > shadecloth > unshaded.

Differences across shade treatments. Using our newly-developed method for detecting drinking events, a one-way ANOVA reveals that there is a significant difference in the mean daily number of drinks across the different shade treatments. We thus conduct a post-hoc test to identify exactly which pairs of shade treatments have different mean numbers of daily drinks. Figure 8 displays the 95% confidence intervals for each treatment pair combination. Interestingly, it is the un-shaded treatment that has a different mean compared to the other two treatments.

Rumen temperature. We next focus on results pertaining to when the response variable is the daily day-average rumen temperature.

Differences across shade treatments and time of day. Similar to the drinking events, we want to see if there is a significant difference in the mean daily day-average rumen temperature across the different shade treatments. This time however, the response is split into a day-average and a night-average, as plotted in Figure 9. A one-way ANOVA reveals that the means across the different shade treatments are only significantly different for the night-average rumen temperature. We thus conduct a post-hoc test to identify exactly which pairs of shade treatments have different means. As shown in Figure 10, there is a significant difference between the un-shaded and waterproof treatments.

Investigating interaction effects. In this section, we explore how the shade treatment factor can be combined with the AHL index to explain the day-day-average rumen temperature. We do not use the night-average because the AHL is always 0 during the night time. We further use the daily day-maximum AHL instead of the daily average due to the nature of the AHL — it is an *accumulated* measure, so it makes more sense to focus on its peaks.

Plot A in Figure 11 reveals that the slope relating day-average rumen temperature with day-maximum AHL actually differs depending on the shade treatment. This suggests that there is a potential interaction effect between the shade treatment and the day-maximum AHL. An ANOVA confirms that this is the case, as depicted in Table 1.

Plot A in Figure 11 also reveals that there are only a

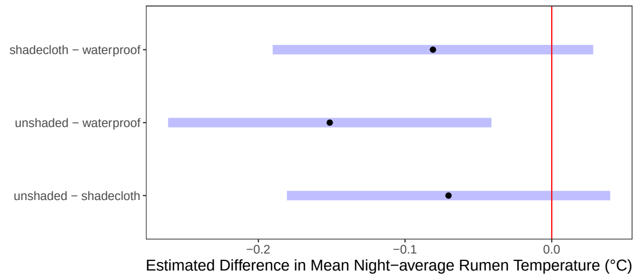


Fig. 10. Pair-wise contrasts of the estimated difference in the mean night-average rumen temperature between the three different shade treatments. The lengths of the 95% confidence bars have been adjusted for multiple comparison issues via Tukey's HSD method.

Table 1. Two-way interaction model ANOVA

term	p.value
treatment	0.944
max_ahl	< 0.001
treatment:max_ahl	< 0.001

handful of dates where the day-maximum AHL is visibly higher than 0. Out of these dates, only two of them (2021-01-27 and 2021-03-01) appear to follow the increasing trend in day-average rumen temperature. There are in fact, three weather variables — air temperature, relative humidity and vapour-pressure deficit — that have histograms of day-time 10-minutely observations that are distinctly different for those two aforementioned dates. Figure 12 depicts this difference using the vapour-pressure deficit (VPD) variable.

Taking note that air temperature and relative humidity are already indirectly involved in the calculation of the AHL, we would like to further investigate VPD. We want to produce a variable that separates days into those with low VPD and those with high VPD so that we can better explain the trends in day-average rumen temperature. Figure 13 reveals that the distribution of day-time third-quartile VPD is bimodal, so it makes sense to use the inflexion point (day-time third-quartile VPD $= 2$) as a separation threshold.

Upon separating days using a day-time third-quartile VPD threshold of 2, we would like to see how the slopes differ between both treatment and VPD level. Plot B in Figure 11 reveals that the slopes are indeed quite different between the two VPD levels; however, we need to be careful to note that there are very few days with high AHL values in both VPD levels. We construct a three-way interaction model that incorporates interactions between the day-maximum AHL, shade treatment and VPD level, and its ANOVA results are shown in Table 2. All interaction terms are statistically significant.

Tuning the HLI upper threshold in the AHL calculation via cross–validation. According to our industry expert Dr. Lees, decreasing the HLI upper threshold from its current value of 86 in the calculation of the AHL for our animals may increase

Table 2. Three-way interaction model ANOVA

term	p.value
treatment	0.944
max_ahl	< 0.001
vpd_threshold	< 0.001
treatment:max_ahl	< 0.001
treatment:vpd_threshold	0.003
max_ahl:vpd_threshold	< 0.001
treatment:max_ahl:vpd_threshold	0.004

the accuracy of a model based on AHL in predicting rumen temperature. We test this theory using a cross-validation strategy with the two models that we constructed before — the three-way interaction model involving day-maximum AHL, shade treatment and VPD level, and the simpler two-way interaction model involving day-maximum AHL and shade treatment — trained on the following values of the HLI upper threshold: 86, 85, 84, 83, 82 and 81.

To assess the performance of competing models on unseen data, we perform a 10-times repeated 5-fold stratified cross-validation for each model, where we construct our folds by sampling across our 89 animals instead of sampling from 8000+ individual observations. Figure 14 shows the results of this procedure, along with 95% confidence error bars (constructed using the 10 repeats). There is plenty of overlap across the error bars in both plots.

5. Discussion

Drinking events. Our drinking event detection method was a nice, self-contained outcome for the project, as it managed to solve the problems that existed with the method developed by Vázquez-Diosdado *et al.* (2019). Looking at different time periods across different animals showed that our method was able to detect drops almost perfectly. However, it is important to note that we did not test our method in a supervised context; we did not have a variable in our data that contained information about when the animals were truly drinking.

A one-way ANOVA then revealed that the mean daily number of drinks was different across the different shade treatments; specifically, that it was higher for un-shaded animals than for those under shade cloth or waterproof shelter. This increased frequency of drinks suggests that un-shaded animals experience heat stress more readily. However, we do not know if these animals drank more water in total; they may have just taken smaller, more frequent drinks.

Rumen Temperature. We saw that the animals under the waterproof shelter were significantly warmer during the night than un-shaded animals. This suggests that the waterproof shelter provides some form of thermal insulation during the cooler hours. Alternatively, it may be that the waterproof shelter simply protected the animals against precipitation, as

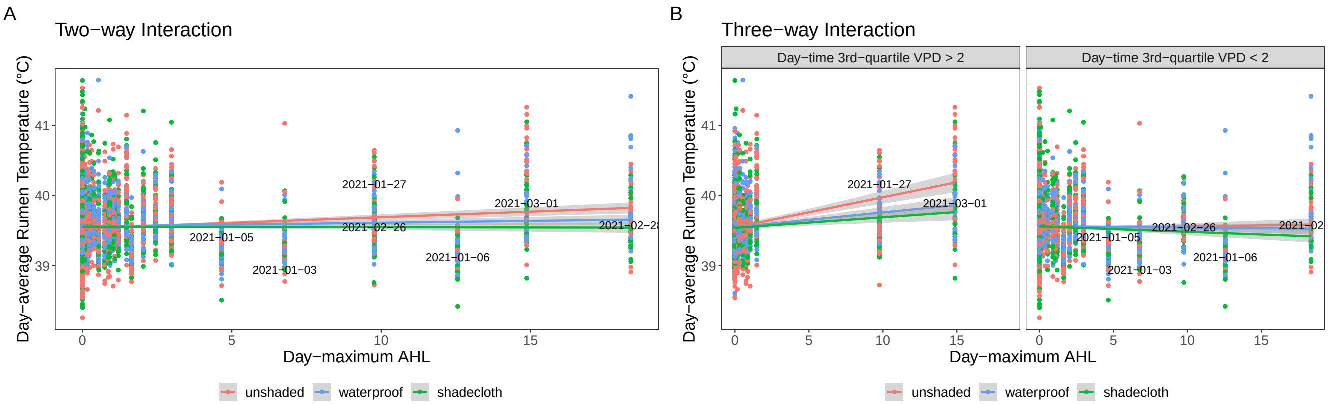


Fig. 11. Plots depicting interactions between shade treatment and AHL, and shade treatment, VPD level and AHL. Each column of data points represents a date, and these dates have been labelled for columns with high AHL. Although our models account for animal-specific random effects, the fitted lines in these plots do not. This does not noticeably change the shapes of the lines, however.

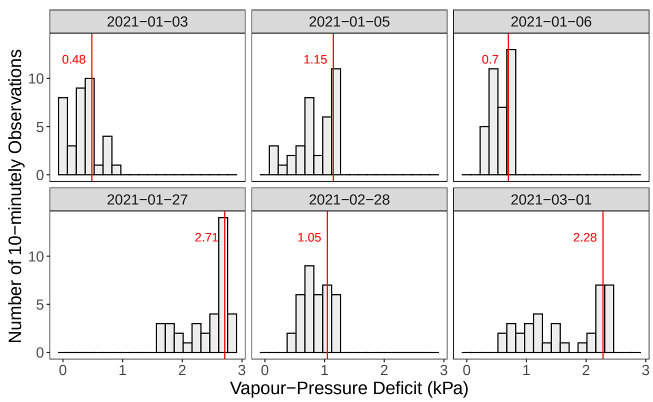


Fig. 12. Day-time 10-minutely VPD histograms of six high-AHL dates. The histograms for 2021-01-27 and 2021-03-01 are located much more to the right than the histograms of the other four dates. The red markers represent the third-quartile, and are relevant when considering Figure 13.

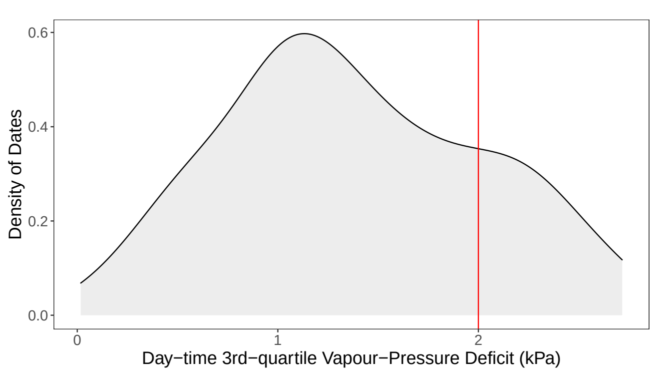


Fig. 13. Density plot of the day-time third-quartile VPD of all dates of the experiment. The inflexion point at 2 is an ideal threshold for separating dates into cloudy days and clear days. We discuss the connection between VPD and cloud coverage in section 5. Using the third-quartile instead of the mean or median exaggerates the inflexion point and thus allows for better separation.

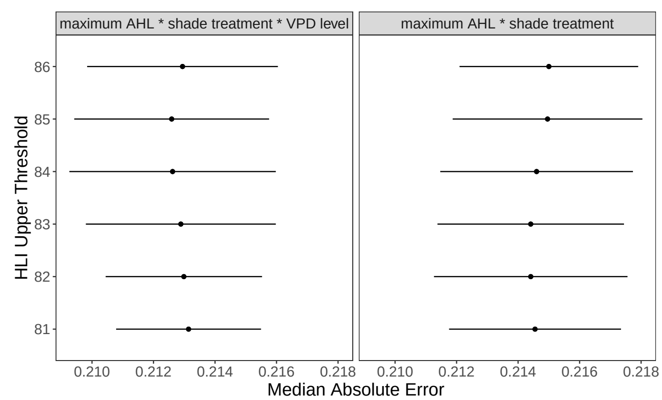


Fig. 14. 10-times repeated 5-fold stratified cross-validation results of our two models using different values of the HLI upper threshold hyperparameter. The predictive performance — measured by the median absolute error (MAE) between fitted values and true values — for the three-way interaction model improves slightly when the HLI threshold is 85, but degrades as the threshold decreases. The performance for the two-way interaction model improves as the HLI upper threshold decreases to 82, and then degrades again.

animals under the regular shade cloth were not significantly warmer than un-shaded animals.

While the shade treatment alone did not have a significant effect on the mean day-average rumen temperature, there was a significant interaction effect when it was combined with the day-maximum AHL. This meant that when the day-maximum AHL was high (say, > 10), then the shade treatment *did* have a significant effect on the mean day-average rumen temperature. Not surprisingly, it was the un-shaded animals that had a higher mean day-average rumen temperature. In other words, un-shaded animals are more prone to heat stress on high AHL days.

We also saw in Figure 14 that some dates did not support the increasing trend in day-average rumen temperature as the day-maximum AHL increased, and suspected that the vapour-pressure deficit (VPD) variable was causing this phenomenon. The VPD is connected to the relative humidity in that it measures the difference between the amount of moisture in the air and maximum moisture the air can hold when it is saturated. The VPD can be thought of as a measure of inverse cloud coverage; a high VPD means that there is not much moisture in the air, which leads to less cloud formation. Then, categorising dates into those with low VPD and those with high VPD can be interpreted as separating dates into cloudy days and clear days. The significant interaction terms in the model incorporating this binary separation variable in Table 2 support the utility of the VPD in explaining which dates follow the increasing trend in day-average rumen temperature and which dates do not. We must be careful to note that there are only two clear days with high day-maximum AHL values (2021-01-27 and 2021-03-01) in our data — primarily due to the cloudy summer experienced in 2021 — and that it would be interesting to see if our three-way interaction model remains significant with more days of data.

Finally, we saw that decreasing the HLI upper threshold in the calculation of the AHL did not greatly affect the cross-validated performance of neither the two-way nor the three-way interaction model. The current industry-standard upper threshold of 86 was constructed based on studies conducted in northern, sub-tropical regions, so it was worth checking to see if the same threshold was viable for cattle in a southern Australian climate.

6. Conclusion

Lean and Moate (2021) discuss the impact of climate change on the sustainability of the Australian cattle herd. They note that if we continue to see more extreme weather events as a result of climate change more Australian cattle will need some form of shelter.

Let's try referencing from here and it's A.1

7. Appendix A — Data Processing and Cleaning

A.1 . *Explain manual editing in excel*

A.2. *Cleaning code pipelines*

A.3. *Semi-automatic web scraping script*

A.4. *Custom functions*

8. Appendix B — Methodology

B.1. *Day/night averaging code*

9. Appendix C — Results

C.1. *Detecting drinking events using the differenced temperature series*

Acknowledgments. This template package builds upon, and extends, the work of the excellent gratefully acknowledged as this work would not have been possible without them. Our extensions are under the same respective licensing term rticles package, and both packages rely on the PNAS LaTeX macros. Both these sources are (GPL-3 and LPPL (>= 1.3)).

References

Bates D, Mächler M, Bolker B, Walker S (2015). "Fitting Linear Mixed-Effects Models Usinglme4." *Journal of Statistical Software*, **67**(1). doi:10.18637/jss.v067.i01. URL http://dx.doi.org/10.18637/jss.v067.i01.

Chang W, Cheng J, Allaire J, Xie Y, McPherson J (2020). *shiny: Web Application Framework for R*. R package version 1.5.0, URL https://CRAN.R-project.org/package=shiny.

Firke S (2020). *janitor: Simple Tools for Examining and Cleaning Dirty Data*. R package version 2.0.1, URL https://CRAN.R-project.org/package=janitor.

Fox J, Weisberg S (2019). *An R Companion to Applied Regression*. Third edition. Sage, Thousand Oaks CA. URL https://socialsciences.mcmaster.ca/jfox/Books/Companion/.

G LeRoy Hahn, John B Gaughan, Terry L Mader, Roger A Eigenberg (2009). *Chapter 5: Thermal Indices and Their Applications for Livestock Environments*, pp. 113–130. American Society of Agricultural and Biological Engineers. doi:10.13031/2013.28298. URL http://dx.doi.org/10.13031/2013.28298.

Gaughan J, Mader T, Holt S, Lisle A (2008). "A new heat load index for feedlot cattle1." *Journal of Animal Science*, **86**(1), 226–234. doi:10.2527/jas.2007-0305. URL http://dx.doi.org/10.2527/jas.2007-0305.

Kuznetsova A, Brockhoff P, Christensen R (2017). "lmerTest Package: Tests in Linear Mixed Effects Models." *Journal of Statistical Software*, **82**(13). doi:10.18637/jss.v082.i13. URL http://dx.doi.org/10.18637/jss.v082.i13.

Lenth R (2020). *emmeans: Estimated Marginal Means, aka Least-Squares Means*. R package version 1.5.2-1, URL https://CRAN.R-project.org/package=emmeans.

Python Core Team (2020). *Python: A dynamic, open source programming language*. Python Software Foundation. URL https://www.python.org/.

R Core Team (2020). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Sweigart A (2020). *PyAutoGUI: A cross-platform GUI automation Python module for human beings*. URL https://readthedocs.org/projects/pyautogui/downloads/pdf/latest/.

Tierney N (2017). "visdat: Visualising Whole Data Frames." *The Journal of Open Source Software*, **2**(16), 355. doi:10.21105/joss.00355. URL http://dx.doi.org/10.21105/joss.00355.

Vázquez-Diosdado J, Miguel-Pacheco G, Plant B, Dottorini T, Green M, Kaler J (2019). "Developing and evaluating threshold-based algorithms to detect drinking behavior in dairy cows using reticulorumen temperature." *Journal of Dairy Science*, **102**(11), 10471–10482. doi:10.3168/jds.2019-16442. URL http://dx.doi.org/10.3168/jds.2019-16442.

Wang E, Cook D, Hyndman R (2020). "A New Tidy Data Structure to Support Exploration and Modeling of Temporal Data." *Journal of Computational and Graphical Statistics*, **29**(3), 466–478. doi:10.1080/10618600.2019.1695624. URL http://dx.doi.org/10.1080/10618600.2019.1695624.

Wickham H, Averick M, Bryan J, Chang W, McGowan L, François R, Grolemund G, Hayes A, Henry L, Hester J, Kuhn M, Pedersen T, Miller E, Bache S, Müller K, Ooms J, Robinson D, Seidel D, Spinu V, Takahashi K, Vaughan D, Wilke C, Woo K, Yutani H (2019). "Welcome to the Tidyverse." *Journal of Open Source Software*, **4**(43), 1686. doi:10.21105/joss.01686. URL http://dx.doi.org/10.21105/joss.01686.