final report

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Heat load forecasting 2017-18

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Abstract

Heat load forecasting for the Australian feedlot industry is built on over 15 years of research and development. Significant progress has been made over the years and adoption by the feedlots to assist in management of heat stress is now widespread. Ongoing research and development is needed to ensure the service is able to continually add value to the management of heat stress at feedlots. Sensitivity of the forecast model to underlying assumptions has been highlighted and further work is needed to develop a robust validation dataset to allow the system to improve overtime.

Executive summary

Forecasting Service

Heat stress in feedlot cattle can have a deleterious effect on cattle performance and in extreme cases lead to cattle death. The National Feedlot Accreditation Scheme requires that feedlots have a heat stress management plan in place to cope with weather events that can lead to excessive heat loads. The Cattle Heat Load Toolbox, developed by Katestone, alerts feedlot operators of impending adverse weather conditions that could lead to excessive heat load in feedlot cattle.

The toolbox is web based and provides access to weather and heat load forecasts out one week and risk assessment programs. The service is underpinned by over 16 years of research into cattle heat load funded by Meat & Livestock Australia (MLA). The Cattle Heat Load Toolbox brings all this research together and uses a world class weather forecasting system to generate accurate forecasts across Australia. This service provides useful and practical information to help feedlot operators manage heat stress in cattle through advanced warning of adverse conditions. Thus, allowing operators time to undertake appropriate actions to mitigate the risk of heat stress when alerted.

Katestone has been providing this service for over ten years and in that time the service has grown from 16 to 360 forecast locations (including 90 public sites). The forecast for the service is generated using the Weather Research & Forecasting model. The system is monitored by Katestone scientists throughout the summer season and assessed for performance in predicting the location, magnitude and duration of heat load events. The system has proven to accurately predict these key features and alert the relevant operators of the impending situation.

There are currently 541 subscribers, 271 user sites (268 feedlots and 3 abattoirs) registered to use the forecasting service, covering nearly a million head of feedlot cattle across Australia. This season saw 25 new feedlots and 1 abattoir register for the service.

Feedlot operators subscribe to the service free of charge and request a forecast for their feedlot. Subscribers also define risk alert levels suitable to their feedlot management and cattle type and condition through the Risk Assessment Program. Alerts are sent daily by email or SMS to designated recipients (e.g. site managers, veterinarians).

The service provides early warning of potential major heat load events and rapid changes in the HLI through the automated alerts system and regular updates on the web site.

Alternative RAP/ Forecast methodology

During the 2016/17 summer we saw prolonged high heat load across most of Queensland. This resulted in the AHLU reaching levels in the thousands, although the cattle did not respond to the heat load as anticipated by the large AHLU values. In South Australia/Victoria the opposite occurred with relatively cool conditions punctuated by extreme events. The onset of the extreme events was not picked up in the AHLU measures, yet cattle suffered. This anecdotal evidence supports the assumption that the local climate plays an important part in how animals manage heat.

The Bureau of Meteorology (BOM) has been running a heat wave forecasting service for the past few years. This system is based on temperature and uses the concept of excessive heat and the variance

compared to local climate and observed conditions over the past 30 days. A study using the BOM Excess Heat Factor (EHF) concept and substituting Heat Load Index (HLI), Wet Bulb Globe Temperature, (WBGT) and Apparent Temperature has been undertaken as an alternative method to identify a heat load event.

The objective of the study was to assess an alternative method to determine the risk of a heat load event based on long term climatic data for a specific region. This can be used in either the Risk Analysis Program to evaluate the risk of an event in a region or can be used as an alternative method for assessing the short-term risk based on changing weather conditions via a forecast.

It is not clear to what degree the EHF predicted the effect of heat stress on cattle as measured by the pull rates. This is attributable to many confounding factors, including lack of information regarding implementation of mitigating measures and any other animal and environmental conditions that may have had detrimental effects, independent of the heat event itself. The correlation of increased pull rate and the start of a heat event is encouraging and indicates that further investigation of the EHF method is warranted.

The EHF mimics the AHLU with some degree of success in detecting the more significant heat events. However, the EHF provides a significant improvement over the AHLU method for warmer tropical and sub-tropical regions.

A study such as this would benefit greatly if detailed knowledge of the above confounding factors were available, or, a study carried out without any mitigating measures in place and detailed recording made of all aspects of animal behaviour and conditions. The method can also be applied to previously generated datasets with known animal response, if concurrent weather station data are available. Alternatively, a trial forecast could be made available to allow the users to provide direct comment on the accuracy of the method to identify events at their sites.

Alternative Black Globe Temperature (BGT) equation investigations

The BGT values recorded using four different BGT sensors were compared. It was found that at night or when operating in a climate-controlled environment (e.g. an air conditioned workshop) the readings were in close agreement. During the day time, the discrepancy could be as large as 2°C. It was also found that this discrepancy can be affected by the proximity of surfaces in the immediate vicinity that can reflect radiation onto the globe and the glossiness of the black paint. Painting the globe white results, on average, in a reduction of the BGT of about 5°C. A comparable result is obtained by shading the globe.

The performance of four BGT algorithms for calculating the BGT using routinely recorded meteorological parameters was calculated using several statistical measures. It was found that all four models yielded comparable results and that discrepancies were of the order of several degrees. Correlation coefficients in excess of 0.9 were achieved for all algorithms.

The formulation of alternative algorithms was investigated. The algorithms were implemented using simple mathematical expressions that simulated the effect of conduction and radiation. Optimisation of the coefficients in these equations resulted in favourable agreement between observed and calculated BGT values. Optimisation on an individual feedlot basis resulted in better performance than the algorithms found in the literature. It is not clear at this stage how these algorithms would perform when optimised against the combined data from all feedlots. This is an area of investigation that should be pursued.

The implications of these findings, in terms of the impact on feedlot cattle are that any heat stress models that are strongly dependent on the BGT can yield highly variable results for what should nominally be the same input parameters.

Bias Correction Trial

Katestone understands that the forecast provided for the Cattle Heat Load Toolbox is not always representative of feedlot conditions, mainly due to the highly-localised nature of the environment and how a model represents the land surface. Essentially the model is representing a land use (grassland) at a physical scale (12km) that cannot be reconciled with a feedlots physical characteristics. The localised effects of manure depth, feedlot pad design and construction and local structures are not represented in the model. Bias correction is commonly used in weather forecasting to adjust numerical weather model output for site specific features by removing the models bias at a particular location.

Bias correction can improve the forecast under certain conditions and degrade the forecast under others. The key indicator for this project is that the bias correction reduced the error in the HLI prediction over the course of the heat load season, October to March, and over a typical seven-day forecast period.

The results of the trial indicate that bias correction does reduce the overall error in the HLI prediction over a season and a seven-day forecast. The greatest reduction is seen using a combination of model output statistics (MOS) and a decaying average algorithm to update the bias correction in near real time. While bias correction does improve the overall statistics, it cannot account for the random fluctuations in the weather at highly local scales. It is recommended that bias correction be implemented at all forecast locations and that the long-term MOS for the model be updated after every heat load season, as the MOS correction will improve as more data is incorporated into the model.

Key findings

1. BGT sensors are extremely sensitive to their immediate surrounds. The siting of a sensor, proximity and colour of the boom and surface coating can significantly impact the temperature measurements. This means that for the same environmental conditions the BGT can measure 2 degrees difference. This translates to a difference in HLI of 3-5 units (depending on conditions) or 30-50 AHLU units for 10 hours of sunlight.
2. Alternative models to determine the risk of a heat event from climatic conditions are available and can resolve some of the sensitivity issues with the current system. However, validation of any model requires a suitable database against which assumptions can be tested. The use of Pull rate as an indicator of a heat event is not conclusive.
3. The current system is well used by the feedlot industry. An upgrade to the delivery platform of the forecast to keep up with the move to mobile technologies is needed to ensure continued use in the future.
4. The ability of the forecast to predict the increased risk of a heat event is dependent on the ability of the HLI/AHLU model to represent the high risk of an event.

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1 Background

Heat load forecasting for the Australian feedlot industry is built on over 15 years of research and development. Significant progress has been made over the years and adoption by the feedlots to assist in management of heat stress is now wide spread.

In 2016 a project was commissioned by MLA to review the science that underpins the heat stress forecasting and its application to determine areas for future work and gaps in knowledge (B.FLT.0393). This project aims to address some of the gaps in knowledge identified in the review as well as upgrade the current forecasting system to include the following features:

- An alternative source of weather forecast for service to ensure service delivery
- Near real-time calculation and display of AHLU
- Update of weather station data used in the RAP
- Additional help for users via video tutorials and access to download their own site data

These features are now implemented and operational on the Cattle Heat Load Forecast website (chlt.katestone.com.au).

Three major research projects have also been undertaken as part of this project and will be summarised in this report. These include:

1. Investigation of the use of bias correction methods to improve the accuracy of the site-specific forecast.
2. Investigate the measurement of Black Globe Temperature (BGT) and possible methods of estimation via alternative means.
3. Examined alternative approaches to determine the risk of a heat load event, based on long term climatic data for a specific region.

The report will also present a summary of the forecast performance for the 2017/2018 summer season and results from the end of season survey.

2 Project objectives

I. Provided a daily forecast of heat load to the Australian feedlot sector, incorporating:
   a. Continuous monitoring of infrastructure to ensure the security and continued provision of the service.
   b. Timely update of the forecasts, plus review of forecast delivery and performance on a daily basis.
   c. Ongoing integration of new subscribers into the HLDN, plus regular checks with existing users to ensure everything is functioning correctly.

II. Undertaken upgrades to the service and ancillary aspects of the CHLT to:
   a. Incorporate backup data supply for the forecast model, in the event the new US administration restricts access to the Global Forecast System.
   b. Integrate AHLU calculations on a real time basis for those feedlots supplying data to the HLDN.
   c. Incorporate a data downloader to allow feedlots to download their HLDN data for a selected period.

III. Investigated and, where feasible to do so, implemented potential improvements to the forecast service to address a range of recommendations from the B.FLT.0393 review of heat load measurement and management, including:
   a. Use of bias correction to correct for site specific features not captured in the forecast.
   b. Addition of a tutorial that will walk users through the features of the service to improve understanding of its use.
   c. Update the data that underpins the Risk Analysis Tool (RAP) housed within the CHLT.
   d. Examined the use of alternative equations for calculating Black Globe Temperature (BGT) for feedlots that do not possess a BGT sensor.
   e. Evaluated the performance of currently available BGT sensors against that of a BGT sensor that complies with the Australian standard.
   f. Examined alternative approaches to determine the risk of a heat load event, based on long term climatic data for a specific region.

3 Heat Load Forecast 2017/2018

3.1 Method

The following schematic presents an overview of the heat load forecasting system. The blue areas represent the global input from weather stations and models. These data are not gathered or generated directly by Katestone. The purple represents the local weather forecast, generated by Katestone every day. The red box indicates the areas of research that need to go into developing a robust system. The grey box represents the input from feedlot weather stations (HLDN). And finally, the delivery of the information is represented in green and shows the web site and alerts.

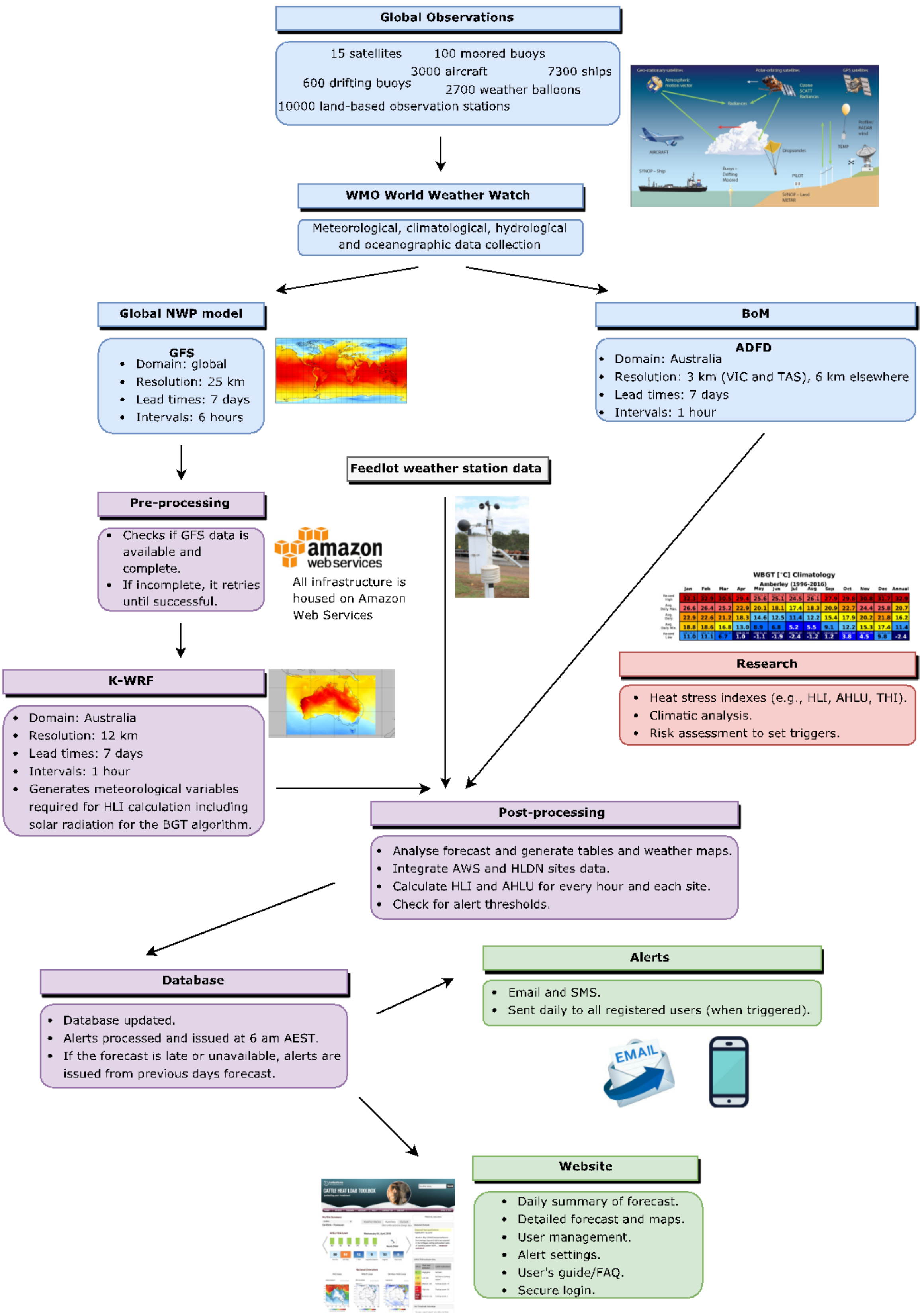

Figure 1 Schematic of the Cattle Heat Load forecasting system (2018)

3.2 Season overview

3.2.1 Temperature and Rainfall

2017 was Australia's third-warmest year on record (the national observational dataset commences in 1910) with the annual national mean temperature 0.95˚C above the 1961-1990 average. Both maximum and minimum temperatures were warmer than average, leading to the 2nd- and 11th-warmest on record, respectively. Regarding rainfall, 2017 was a year of contrasts with a wet start, dry in the middle, then a wet end in much of the west and Northern Territory and dry end in the east. National rainfall for 2017 was 8% above the 1961-1990 average, with an Australian annual total of 504 mm.

Focusing on the 2017-18 season (from October 2017 to March 2018), temperatures were above average for the majority of Australia, particularly for much of central and southern Queensland, New South Wales and adjacent parts of northern Victoria (Figure 2). Nationally, summer 2017-18 was the second-warmest summer on record. Western Australia is the only region to rank outside the top ten for summer temperature, associated with very much above average rainfall (Figure 3 left).

The summer's exceptional warmth was more the result of prolonged, widespread, low-intensity warm weather rather than individual heatwaves. However, a number of periods of very warm weather did occur during the season. December records were set at multiple stations in New South Wales and South Australia. In early January very hot days were observed around the Sydney region, including 47.3˚C at Penrith Lakes AWS on the 7th, which is Greater Sydney's second-warmest day on record for any time of year. At the end of January very warm temperatures were set in northern Tasmania and in Victoria. A prolonged warm spell during February in Queensland resulted in its warmest February day (in area-average terms) with a state-wide mean maximum temperature of 40.5˚C on the 12th.

The 2017-18 season rainfall was near average overall (Figure 3 left). The season was wetter than average for most of the north and southeast Queensland, north of Northern Territory, and northwest of Western Australia. In fact, the summer was the 10th wettest on record for Western Australia, and a number of stations in the north of this state observed their highest total summer rainfall on record. Several tropical lows and cyclones might explain the record-breaking rain. Comparing rainfall of this season to the previous season (2016-17), an increase is observed across most coastal areas for northern Australia, whereas a significant decrease occurred in some areas of interior of Western Australia and Northern Territory, and central coast of Queensland (Figure 3 right).

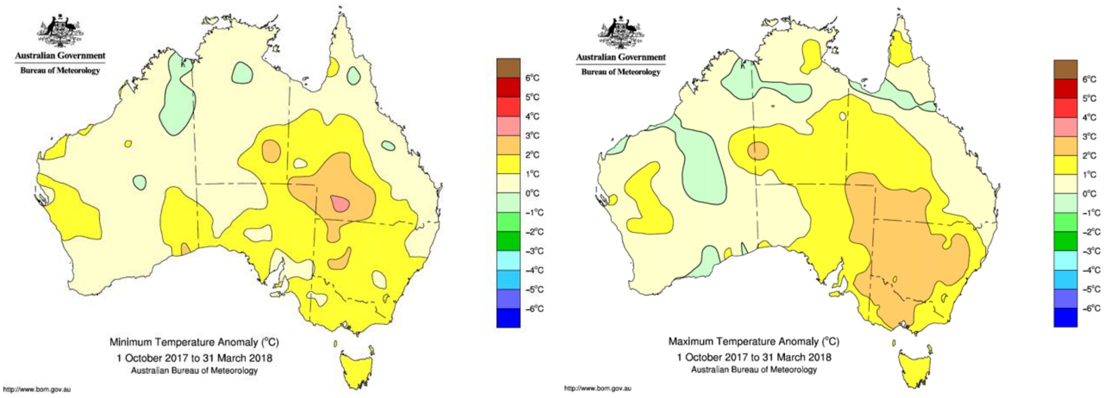

Figure 2 Minimum (left) and maximum (right) temperature anomaly during the 2017-18 season

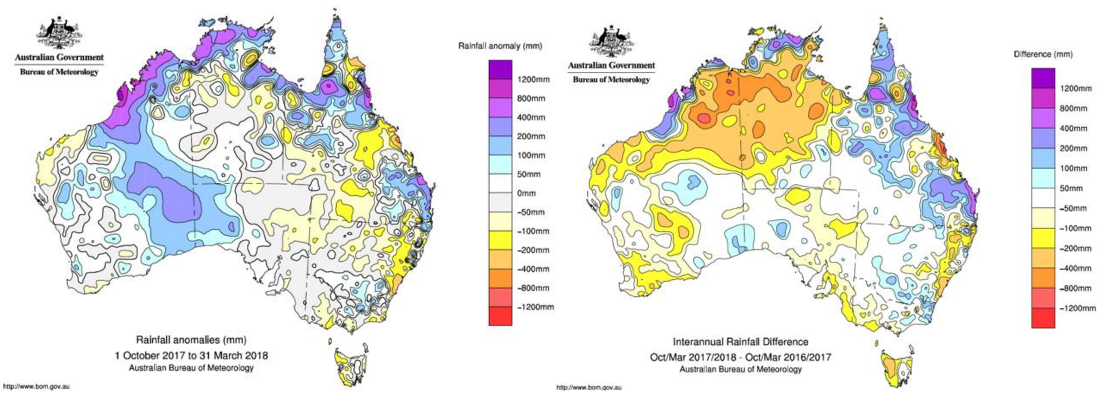

Figure 3 Rainfall anomalies during the 2017-18 season (left) and the difference between this season and last season (right)

3.2.2 Heat Load

The daily average HLI anomaly[1] derived from observations at the 17 benchmark locations for the 2017-18 season is shown in Figure 4. In order to smooth the data, 14-day moving averages are shown. Note that red (blue) bars are used to denote higher (lower) HLIs values than average. The anomalous values are calculated by subtracting the monthly climatology to the actual value.

Most of the sites exhibit some fluctuations of HLI between above and below average throughout the 6-month period with higher HLI than climatology in December-January. Katanning HLI remained close to normal values for this season.

The monthly average daily maximum HLI derived from observations for all sites is presented in Figure 5. For most of the sites, HLI peaks between January and February. Not surprisingly, Yanco,

[1] The HLI anomalous values are calculated by subtracting the monthly climatology to the actual value. In order to smooth the data, 6-day moving averages are shown.

Hay, and Griffith had similar maximum HLIs due to their close proximity. Interestingly, mid-latitude sites show a clear seasonal cycle of HLI with a dramatic decrease after their peak (for instance, Yanco, Hay, Griffith, Albury, Charlton, Clare High School, and Katanning), whereas most QLD sites exhibit slight or non-existent decline of HLI during the second half of the 6-month period.

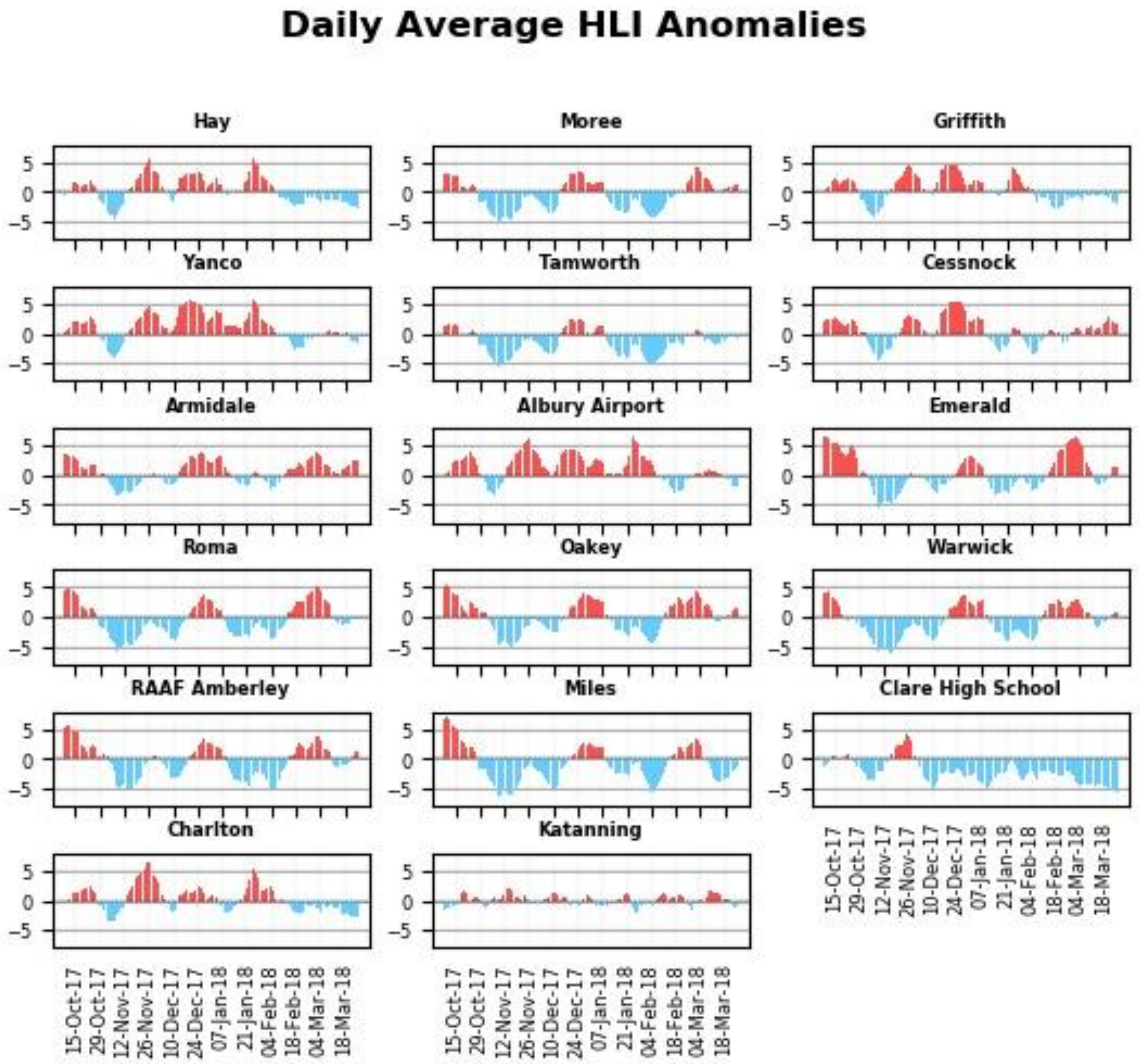

Figure 4 Daily average HLI anomaly for the 17 benchmark locations. Note that red (blue) shades are used to denote higher (lower) HLIs values than usual

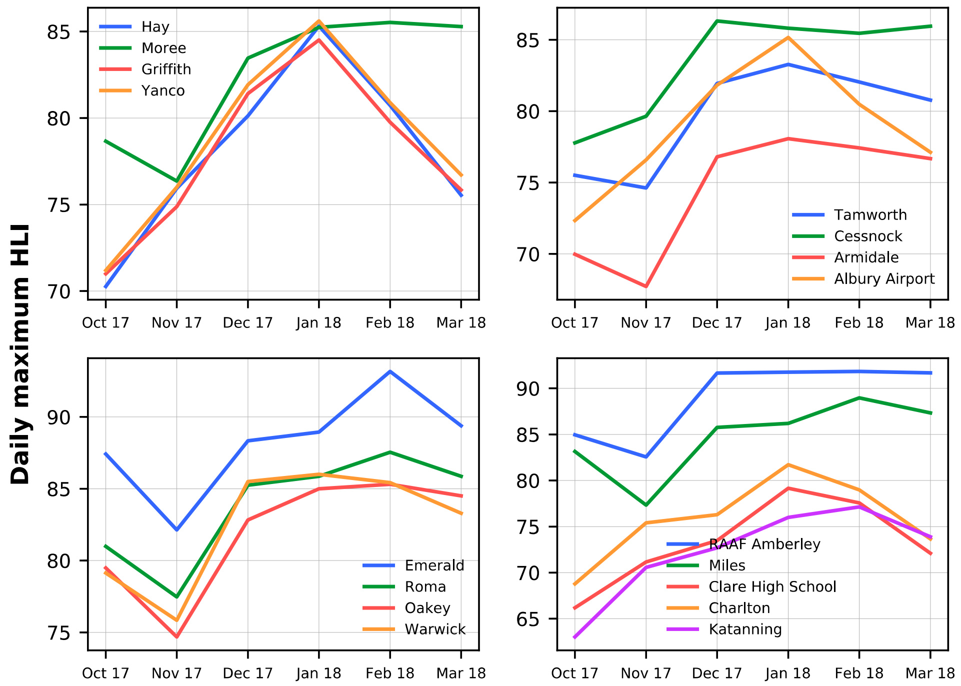

Figure 5 Monthly average of daily maximum HLI for the 17 benchmark locations

3.2.3 Automated alerts

A total of 5,854 emails and 4,958 SMS alert messages were issue during the 2017-18 summer forecast period, with a peak number of email and SMS alerts sent in February (Figure 6). The breakdown of alerts by type for each month is also shown in this figure. Alerts for an extended AHLU event and for today-tomorrow comprise most of the alerts. There were only 88 alerts for Rapid HLI change and none for the incomplete recovery.

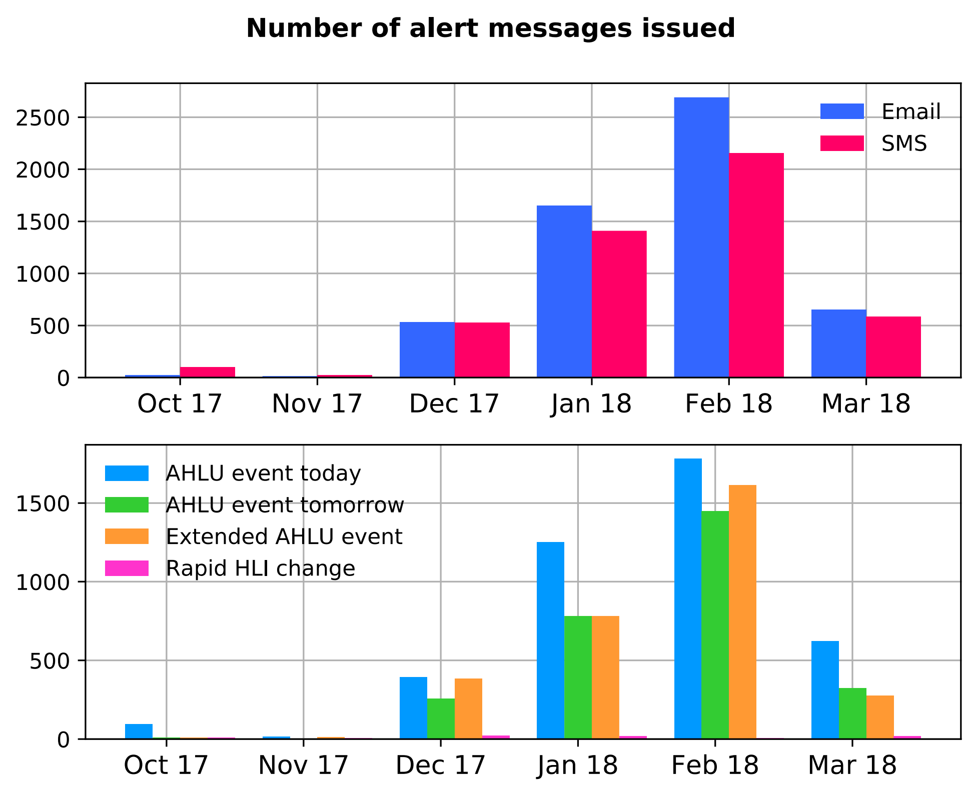

Figure 6 Number of alerts sent by alert and notification types during the 2017-18 season

3.3 Forecast performance of 2017-18 season

3.3.1 Heat Load Index

Figure 7 shows the progression of the forecasts performance since the 2005-06 season for the 17 benchmark locations. It represents the Root Mean Square Error (RMSE), which is the average magnitude of the forecast error zero being the perfect score. Despite some fluctuations, there is a general decline trend (representing an increase in model performance) in the RMSE for both 1- and 3-day forecast. As expected, the 3-day lead time RMSE has been lower than that for the 1-day lead time although their difference was much higher during the first years in contrast to the last years.

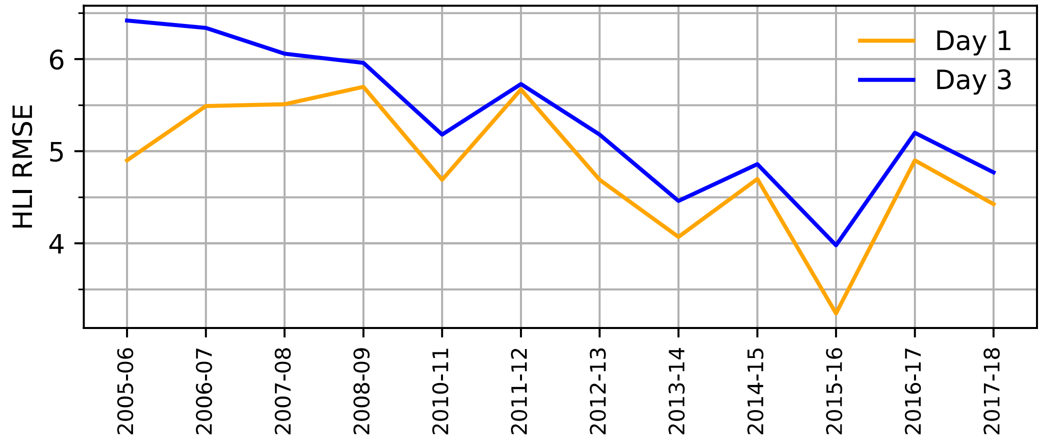

Figure 7 HLI RMSE averaged seasonally (from 1-Oct to 31-Mar) and across the 17 benchmark sites throughout 12 seasons

Focusing on the 2017-18 season, the first 3 days of the forecast exhibit similar values of RMSE followed by a gradual increase for the 4-day, 5-day and 6-day lead time, and finally an abrupt increase for the 7-day out forecast (**Error! Reference source not found.**a). This decrease in model efficiency with increase in lead time can be explained by increase in uncertainty. We point out that RMSE puts greater influence on large errors than smaller errors, but it does not indicate the direction of the deviations.

The model performance in analysed in more detail in the end of season report (available on the CHLT web site).

3.4 Survey results

The main results of the end of season survey are indicated below:

- Most respondents (59%) are very happy with the level of service they received from Katestone team this season, whereas only 4% are unhappy.
- Almost half of the participants perceived moderate risk of heat stress in their feedlot animals during this season, while around 20% rated as low and high risk.
- A large proportion of respondents (up to 61%) find the tools available on the CHLT website and alerts system helpful for a better management of their feedlot whereas only 5% did not find the tools useful.
- In terms of parts of the service rating, the 3 elements that most people (87-92%) consider as essential or useful are: the HLI threshold calculator, being able to see their weather station data, forecast for the next 3 days. On the other hand, the 3 parts of the service with the poorest rate with “somewhat useful” or “not very useful” (20-27%) are: forecast for the next 7 days, the help and supporting documents and the ability to share their site forecast/data with others.
- Regarding the parts of the service that users feel need improving, some comments are summarised below:
    - Design an App.
    - Improve forecast: underpredicted HLI, large differences between forecast and observed AHLU.

    - Calibration of weather stations.
    - Include the effects of mitigation.
    - Website should work on all web browser platforms.
    - Inability to hover over AHLU triangles to see the values with a touch screen.
    - Send alerts all year round.
- The clear majority (up to 80%) would use an App if it was available and only 10% would not.

Overall, the survey results indicate that most users are well satisfied with the service provided by Katestone this season. However, we received some comments that help us to determine the weaknesses of CHLT so that we can improve the product for the next seasons. One of the most common comment is about the need for an App. Regarding CHLT availability, we will emphasize that the website is active throughout the year, although alerts are only sent via txt from October to March.

3.5 Conclusions and Recommendations

The CHLT service has become an integral part of heat load management at Australian Feedlots. The number of subscribers and feedlots that are registering for the service continues to grow every year. Overall the user base is satisfied with the delivery and performance of the service.

The 2017-18 season was particularly hot for extended periods of time, from January through to February as evidenced by the significant number of alerts issued during this period. Several feedlots reported multiple extended heat load events at their site, however only a handful resulted in cattle loses. It is our understanding that the service provided adequate warning of these events. The specific timing and magnitude of events is very much site dependent and cannot be accounted for accurately without real-time updates of cattle, pen and environmental conditions.

The rapid change in the HLI alert threshold has not been adequately investigated and events may be missed or misinterpreted. This alert threshold needs further developed to allow a more accurate warning of these type of events.

Several subscribers have requested that a mobile phone friendly version of the CHLT service be provided. Given the increase in users accessing the service through mobile devices it would be prudent to implement this change soon.

The forecast performance for prediction of HLI was comparable to the last 5 years and slightly better than the previous season. The volatility of the HLI algorithm has been shown in previous studies (B.FLT.0392), indicating that a near perfect forecast can still produce an error of 5 to 7 HLI units, which is similar to the RMSE for a 3-day forecast.

Overall the variability in the predicted HLI is within the known error bounds of the HLI algorithm. Nonetheless, subscribers are questioning the accuracy of the forecast and how to further improve the information received onsite.

4 Alternative RAP investigation

4.1 Description and Method

During the 2016/17 summer we saw prolonged high heat load across most of Queensland. This resulted in the AHLU reaching levels in the thousands, although the cattle did not respond to the heat load as anticipated by the large AHLU values. In South Australia/Victoria the opposite occurred with relatively cool conditions punctuated by extreme events. The onset of the extreme events was not picked up in the AHLU yet cattle suffered. This anecdotal evidence supports the assumption that the local climate plays an important part in how animals manage heat.

The BOM has been running a heat wave forecasting service for the past few years. This system is based on temperature only and uses the concept of excessive heat and the variance compared to local climate and observed conditions over the past 30 days. We propose to review the BOM Excess Heat Factor (EHF) concept and substitute Heat Load Index (HLI), Wet Bulb Globe Temperature, (WBGT) and Apparent Temperature to determine heat load events.

In the publication titled "The Excess Heat Factor: A Metric for Heatwave Intensity and Its Use in Classifying Heatwave Severity", by Nairn and Fawcett (2013), the authors present an algorithm for calculating the Excess Heat Factor (EHF) which is a method for identifying heat waves.

In this study, the EHF based on four parameters was used as a precursor to feedlot cattle heat stress. These included ambient temperature (AMBT, as originally used by Nairn and Fawcett), the Apparent Temperature (APPT), the Wet Bulb Globe Temperature (WBGT) and the Heat Load Index (HLI). It is well understood that the physical parameters that determine heat stress are wind speed, an atmospheric moisture term which includes parameters such as relative humidity, water vapour pressure and dew point, and finally, a factor that represents a direct thermal energy input. Various parameters have been used to represent this including combinations of ambient temperature, black globe and solar radiation. It is worth mentioning that the black globe temperature includes the effects of solar radiation, ambient temperature and wind speed although the exact relationship has not been established.

The EHF method was used to review about 20 feedlot locations with suitable long term climate data. These were a mixture of BOM data and feedlot weather station data (obtained via the HLDN) where these were available.

There are various indicators of feedlot cattle heat stress. These include panting score, body temperature (timpanic, rectal), death rate and pull rate. The pull rate is the number of animals that were identified as unhealthy (possibly suffering early signs of heat stress) and pulled from the pen for the purpose of additional care or treatment in the hospital pen. Of these indicators, those that are available over a sufficiently long time interval are death and pull rates. It was suggested that pull rates are a more robust measure of heat stress as it involves feedlot personnel identifying stressed animals (D.Bowler, Management for Technology, 2017, private communication)[2].

[2] Following completion of the project, communication with a feedlot manager indicated that it was common practice to cease pulling cattle from the pens once a heat event is underway. Therefore, increased pull rate may be an indicator of the start of an event but not a good indicator of event duration or severity.

4.2 Results

4.2.1 EHF Factors used

The Wet Bulb Globe Temperature, the Heat Load Index, the Apparent Temperature and Ambient Temperature were each used to generate the corresponding EHF indices. Figure. 8 shows the behaviour of these indices over a period of five years. Figure. 9 is an expanded section of Figure. 8 showing only the events that occurred during the 2016 – 2017 summer period.

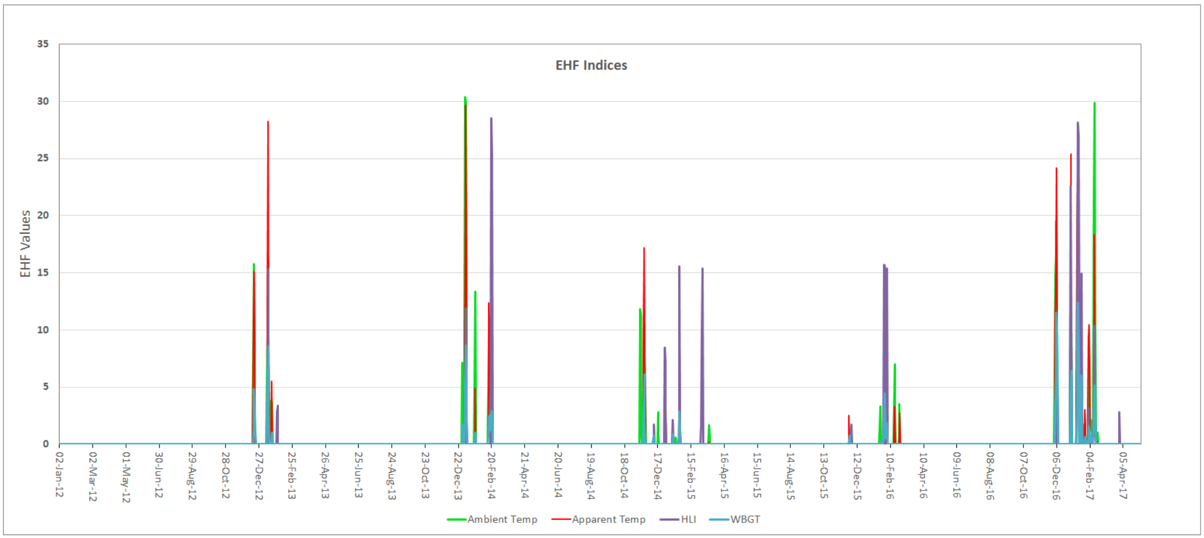

Figure. 8 EHF indices for a 5 year period

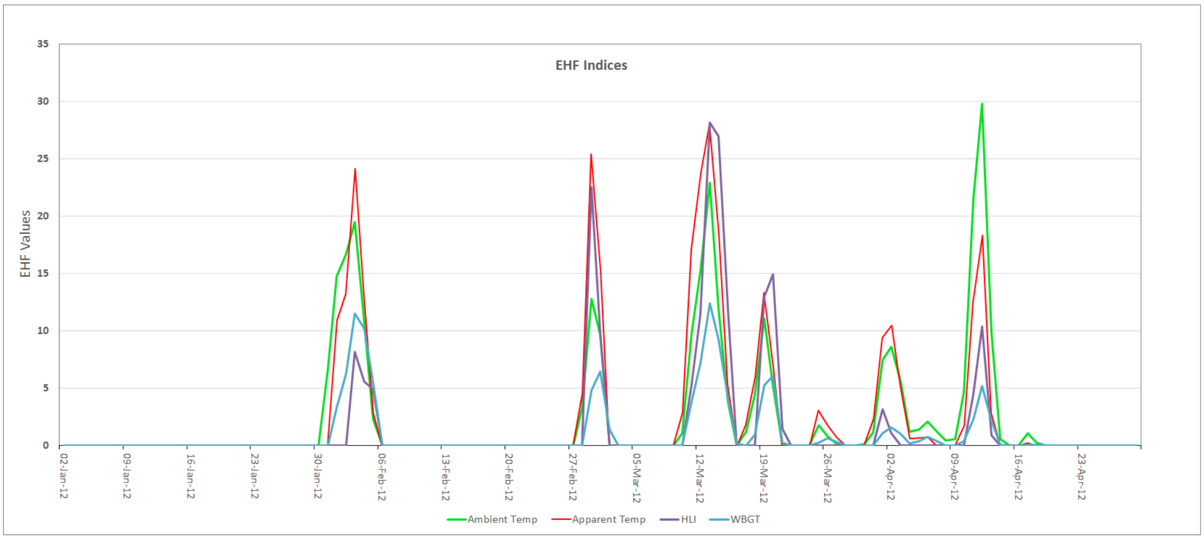

Figure. 9 EHF indices for the 2012 summer period

These figures reveal that the severity attributed to events by all four indices is variable and can be attributed to the different weighting that each index assigns to each of the input variables (temperature, humidity, wind speed) used to calculate the respective index.

4.2.2 Comparison to existing AHLU index

Currently, the heat stress indicator is the Accumulated Heat Load Unit (AHLU). The AHLU is approximately linearly related to the panting score. The basis of the HLI/AHLU formulation is the extensive analyses of a large number of cattle (J.Gaughan et. al., 2008). For tropical locations (e.g. Darwin), the relatively high humidity and temperature that shows little diurnal variation prevents overnight recovery. As a result, the AHLU for all but the highest thresholds increase as shown in **Error! Reference source not found.**. Two noteworthy features in this figure are that an AHLU value of 100 corresponds to an extreme risk – the AHLU in Darwin attains values in the hundreds of thousands - and that an "event" may have a duration of several months. Although this behaviour is predominant at sites with similar climate to Darwin, it has also been observed at feedlots that are located significantly further south. Figure 11 shows the EHF indices for the same period.

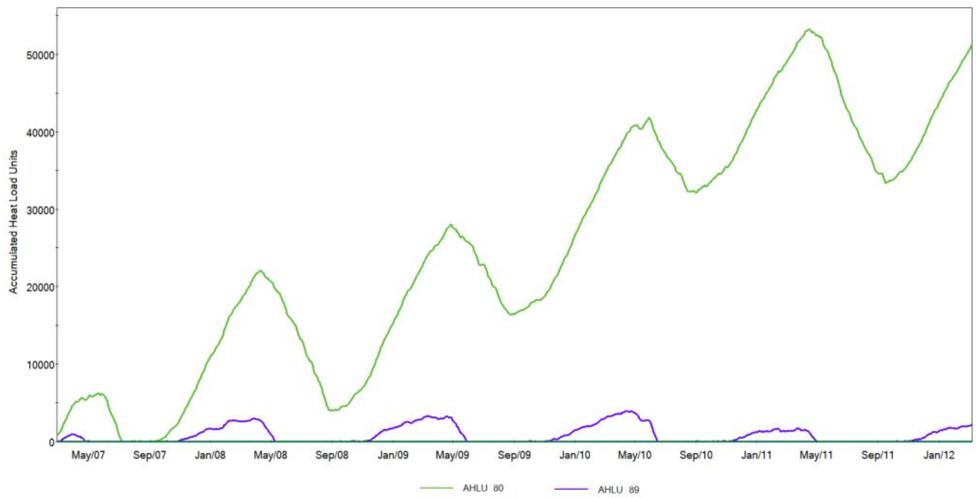

Figure 10 AHLU behaviour at Darwin

Error! Reference source not found. Further comparisons between AHLU and EHF were carried out between two sites with contrasting climates – Armidale a high altitude temperate location in New South Wales and Emerald, a subtropical site in Queensland. These are shown in Figure. 11 and Figure. 12 The following observations can be made:

- The EHF and AHLU both indicate a heat event at about the same time, although the EHF tends to respond to the more severe AHLU events

- The HLI thresholds for Armidale are lower (80 and 83) compared to Emerald (92, 95) for about the same AHLU values. This is to be expected as Armidale is a colder site.
- The EHF response is not as extreme as the AHLU response. This is exemplified in the case for Darwin where the AHLU exhibits thermal runaway.

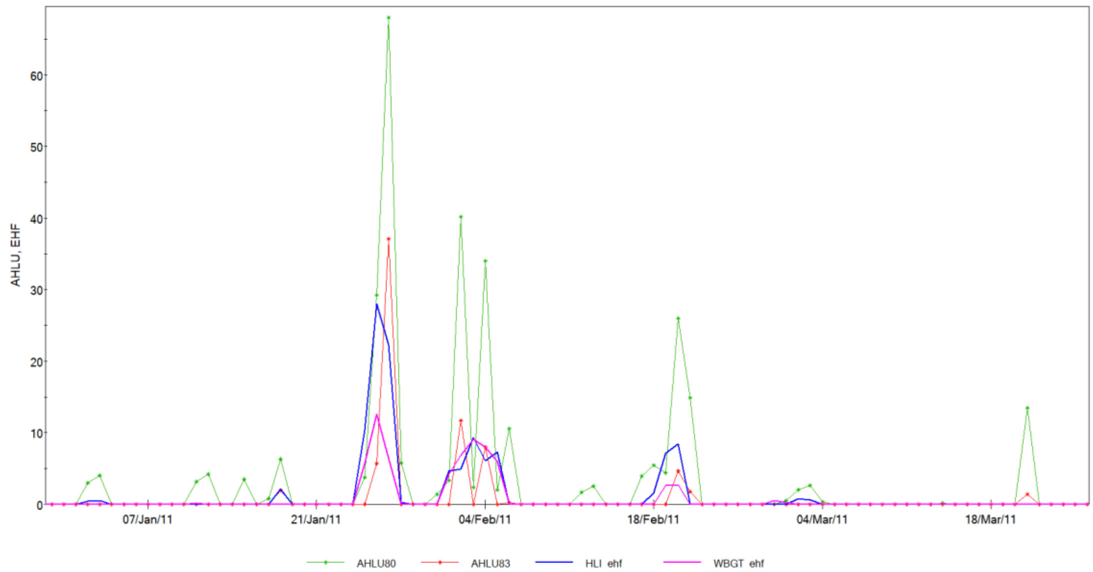

Figure. 11 AHLU and EHF for Armidale

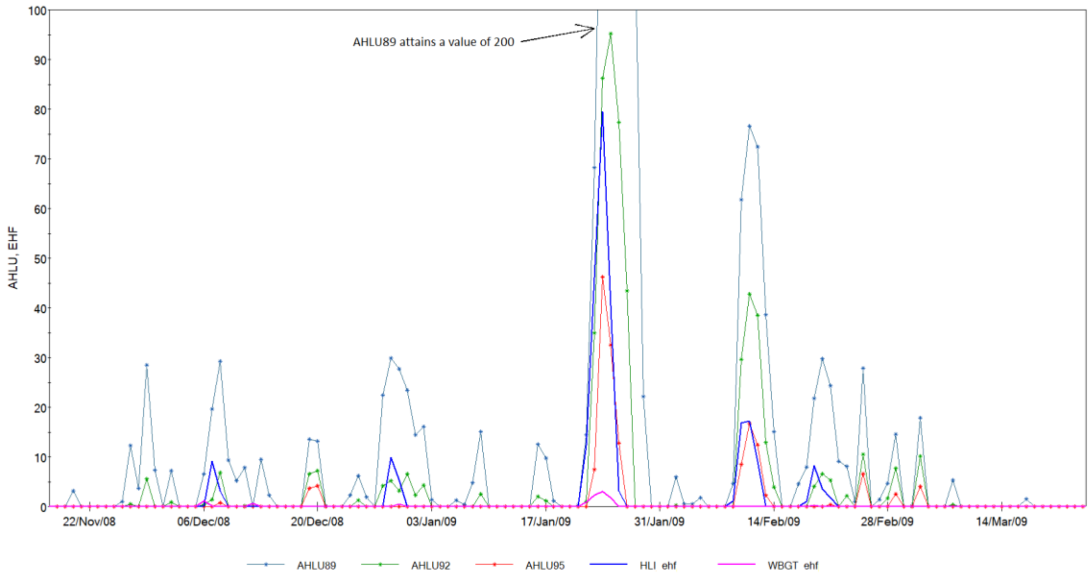

Figure. 12 AHLU and EHF for Emerald

4.2.3 Comparison of on-site to BoM

Excess Heat Factors calculated using data recorded at a feedlot are compared to EHFs calculated using data recorded at a nearby Bureau of Meteorology weather station on the Darling Downs within 20km of the feedlot are shown in Figure. 13. The HLI and WBGT are shown as both of these indices include ambient temperature, wind speed and a moisture component. Overall, the indices show similar behaviour; events are detected although the relative magnitudes are different. This is not surprising as the various indices place different weights on each of the constituent meteorological variables.

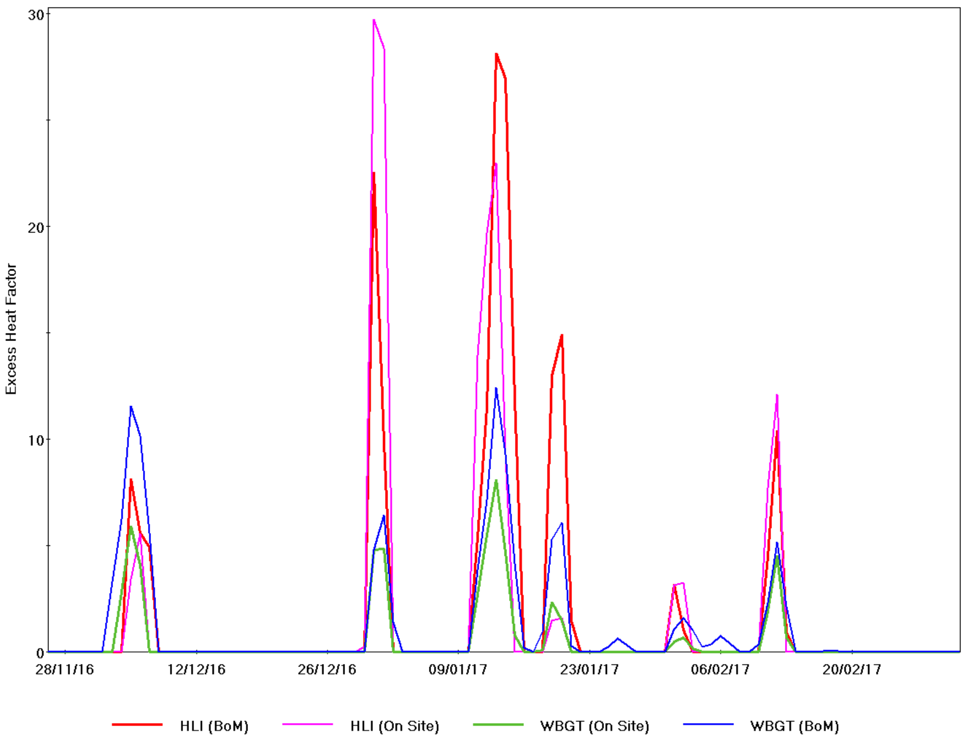

Figure. 13 Comparison of On-Site and BoM calculated EHF values

4.2.4 Ability to predict pull rates

The pull percentage and the EHF indices are shown plotted in Figure. 14. Note that the graduations on the horizontal scale are in two monthly increments.

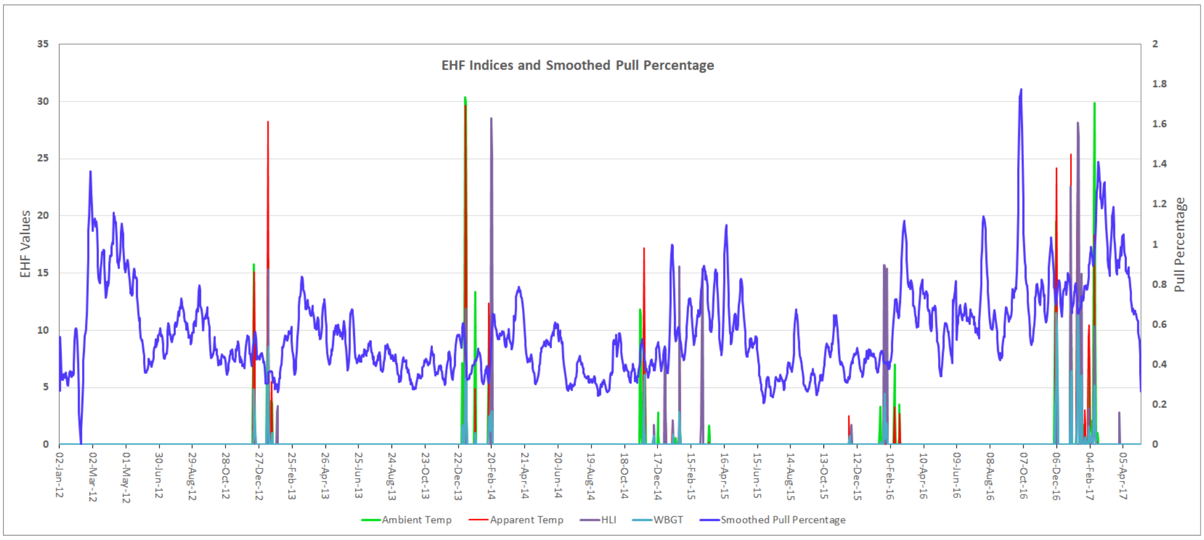

Figure. 14 EHFs superimposed on the percentage pull rate

The following can be gleaned from Figure. 14:

- The heat events manifest themselves as short duration events clustered around the summer months. The duration can range from one day to about one week.
- There does not appear to be any pattern in the pull rates
- There does not appear to be any spike in pull rates consistently following a heat event
- Spikes in the pull rate can occur independently of the presence of a heat event (which is not unexpected due to other illness that may result in an animal being pulled).

4.2.5 Effects immediately following events

To ascertain whether there is an increase in stress during and immediately after an event, the daily pull rates were analysed for 14 days after the start of an event. The results shown in **Error! Reference source not found.** are for one feedlot for the four indices considered in this study. Here, zero on the horizontal axis signifies the start of the event; the surge in pulls occurred during the first day of the event. There is a relative increase in pull rates starting on the first day of the event and continuing for about another two days, but with diminishing magnitude. The large relative decrease in pull rate from day 0 to day 1 (particularly for ambient temperature and apparent temperature) could be due to the feedlot management practise of not pulling animals from pens once a heat event is underway.

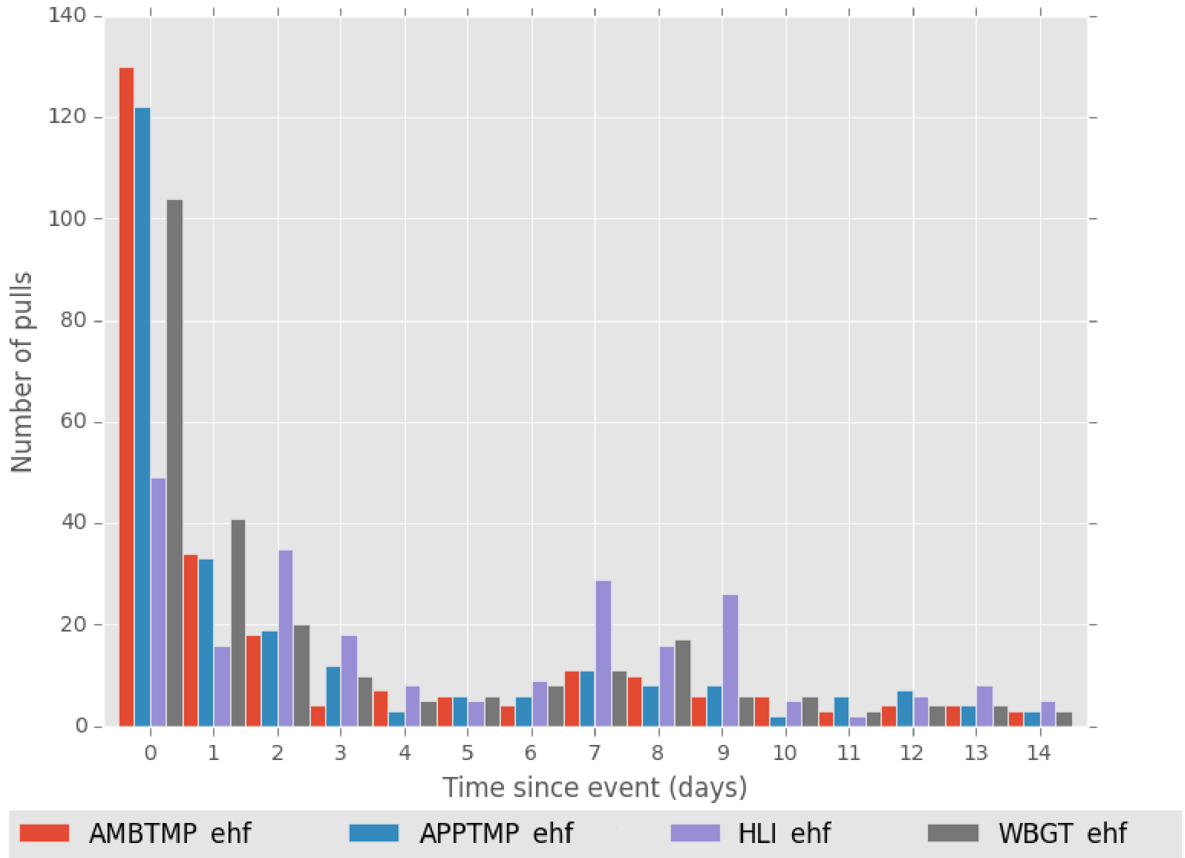

Figure. 15 Pull rate during and immediately following events

The trend shown in **Error! Reference source not found.**

5 References

There are no sources in the current document.

is present in the majority of feedlots analysed in this study. Taking into consideration comments made earlier and given that mitigating measures were probably in place, we believe that this effect is not necessarily representative of the response for all events. It is not clear firstly, to what extent this is a chance effect - an event occurring when there were many other random (detrimental) factors present, and secondly whether this effect is representative of a small or large fraction of events. The confounding impact of management practices to stop pulling sick animals from pens during a heat event make drawing any conclusion from these data even more problematic.

5.1 Conclusions/recommendations

The aim of this project was to determine whether the EHF could be used to predict effects on feedlot cattle resulting from a heat event. EHFs were calculated using Ambient Temperature, Apparent Temperature Wet Bulb Globe Temperature and the Heat Load Index and the smoothed percentage pull rates were used as an indicator of heat stress.

It is not clear to what degree the EHF predicted the effect of heat stress on cattle as measured by the pull rates. This is attributable to many confounding factors, including lack of information regarding implementation of mitigating measures and any other animal and environmental conditions that may have had detrimental effects, independent of the heat event itself

The EHF mimics the AHLU with some degree of success in detecting the more significant heat events. However, the EHF provides a significant improvement over the AHLU method for warmer tropical and sub-tropical regions.

A study such as this would benefit greatly if detailed knowledge of the above confounding factors were available, or, a study carried out without any mitigating measures in place and detailed recording made of all aspects of animal behaviour and conditions. The method can also be applied to previously generate datasets with known animal response, if concurrent weather station data are available. Alternatively, a trial forecast could be made available to allow the users to provide direct comment on the accuracy of the method to identify events at their sites.

6 Alternative BGT equation investigations

6.1 Background

The BGT is used in the calculation of the Heat Load Index (HLI), a measure of the accumulation rate of heat stress in feedlot cattle. The HLI equations are moderately sensitive to the BGT, consequently, any errors in BGT could result in either an over or underestimate of HLI. Currently, little is known about the consistency of the BGT measurement obtained from different manufacturers or between BGT sensors in different environments.

Three areas were investigated in this study. The performance of BGT sensors from four different manufacturers. The performance of four algorithms for calculating the BGT from meteorological parameters. And finally, investigate alternative algorithms for calculating the BGT.

In addition, Katestone has hosted the Heat Load Data Network for a number of years, resulting in the accumulation of a substantial amount of data. These data include all the parameters required to investigate the BGT behaviour for a sensor that is exposed to typical feedlot operating conditions. These results should provide insight into the factors that affect the BGT reliability and accuracy inherent in the points enumerated above.

6.2 Methodology

6.2.1 BGT Sensor Inter-comparison

BGT sensors from four different manufacturers were used in this study, the technical specifications for these sensors can be found in the Appendix. Two data recording systems were used to record BGT and key meteorological data. The first system, which was acquired in the past for a different study, consisted of a Campbell Scientific (CSC) weather station that also included a BGT sensor. The second system was used solely for recording the BGT data from the remaining three BGT sensors. This second system was assembled by a commercial firm. Data recorded during the assembly allowed the response of the three BGT sensors to be evaluated whilst the system was located on the bench in an air-conditioned electronics workshop.

The sensors and accompanying support items (data loggers, solar panels) were mounted on booms attached to a mast situated in the grounds of an abattoir away from holding pens and other areas of activity.

Several experiments were carried out and BGT comparisons were made. The CSC BGT sensor was used as a control, no modifications were made to this sensor. Comparisons were carried out for the following experiments:

- The BGT sensors located on the bench in an air-conditioned workshop. This provided readings for a temperature controlled environment away from any solar radiation and winds.
- The BGT sensors mounted in place at the abattoir. This provided readings for BGT sensors in conditions typical of those experienced at a feedlot.
- The positions of two sensors were swapped to ascertain whether the position on the mast affected the readings. This would reveal the extent that factors such as radiation reflected off shiny aluminium booms may have on the response.

- The PDS sensor, as supplied, was painted with semi-gloss black paint. It was repainted using matt black paint.
- The aluminium booms were painted matt black to see if reflections off shiny aluminium booms affected the response – the CSC sensor boom was not painted.
- The PDS sensor was painted a light (very pale lime green) colour using some ceiling paint that was on hand at the time to ascertain the effect that colours other than matt black would have on the response.
- The MEA sensor was shielded by attaching an umbrella to the boom to ascertain the effects of shade on the response.

6.2.2 BGT equation performance

The BGT values calculated using four algorithms published in the literature were compared to the observed BGT values using data recorded at a number of feedlots. These algorithms are described below.

(1) Gaughan Algorithm

The derivation of this equation is described in E.A. Systems Pty Limited and the University of Southern Queensland (2003). It will be referred to as the Gaughan method since a significant body of work that incorporates this equation has been carried out by Gaughan.

$$BGT = 1.33 * AT - 2.65 * sqrt(AT) + 3.21 * log10(SR + 1) + 3.5$$

(2) Liljegren Algorithm

This algorithm is based on the thermodynamic energy exchange between the globe and the environment including exchange by conduction and black-body radiation. There are several equations that need to be solved simultaneously to arrive at the BGT estimate. The model is described in Liljegren et al. (2008).

(3) Turco et al. Algorithm

This algorithm is implemented with two equations, one calculating for day time BGT values and the other for night time. The algorithm is described in Turco et al. (2008).

$$BGT_{DAY} = (1.36 * AT - 2.358) * (0.075 * log(SR) + 0.562)$$

$$BGT_{NIGHT} = 0.942 * AT$$

(4) Hajizadeh et al. Algorithm

This model requires ambient temperature, solar radiation and relative humidity as inputs to the following equation. The description of this model can be found in Hajizadeh et al. (2017).

$$BGT = 0.01498 * SR + 1.184 * AT – 0.0789 * RH – 2.739$$

In the above equations, the variables have the following meanings:

BGT is the black globe temperature

AT is the air or ambient temperature

SR is the solar radiation

RH is the relative humidity

The algorithms presented by Turco, Gaughan and Hajizadeh do not appear to be based on any physical processes but consist of carefully formulated equations that accurately describe the data. In contrast, the algorithm developed by Liljegren is based on the physics of heat exchange by conduction and radiation.

BGT values were calculated using each of the above algorithms and data from a number of feedlots. The feedlots were restricted to those that recorded temperature, wind speed, solar radiation, relative humidity and BGT. The statistics used to rate the performance of each algorithm included the Pearson Correlation Coefficient, R^2, the BGT difference ($BGT_{calculated} - BGT_{observed}$) and the Root Mean Square Error (RMSE). Performance ratings were carried out by hour of the day and month to ascertain diurnal and seasonal dependencies. The algorithms were also rated in terms of the magnitude of the BGT value to ascertain whether the performance was BGT dependent.

6.2.3 Alternative BGT algorithm

Alternative BGT algorithms were formulated. The equations describing the algorithms are based on the physical principles of energy exchange by radiation and conduction. The coefficients in the algorithm equations were optimised using the least squares method with observed BGT values recorded at the feedlots.

6.3 Results

6.3.1 BGT Sensor Inter-comparison

Preliminary results were obtained when the system was in the process of being assembled and tested. Although it was not intended to carry out any analyses at this stage, the availability of these data provided an opportunity to compare performance of the sensors in a controlled environment. The three BGT sensors were placed on a bench in an air-conditioned (temperature range: 21 to 24 degrees) electronics workshop. BGT measurements thus obtained showed that readings from all three sensors were within 0.25 degrees.

After deployment, several experiments were carried out. One of the sensors was supplied painted with semi-gloss black paint. It was subsequently painted matt black. This resulted in a reduction in variability of up to about 50% during the daylight hours (the reader is referred to Appendix 1 of the Milestone report for detailed results). Changing position of the sensor (relocating to a different boom) also affected the hourly variability of the BGT readings although the variability was not as marked as for the case when the globe was repainted matt black. Similar results were obtained when the supporting boom was painted matt black.

Further experimentation was carried out as follows. One of the globes was painted a very light colour. When viewed from a distance, the globe appeared white. For the daytime hours, the discrepancy between the light-coloured sensor and the reference sensor ranged from about 2°C on an overcast day (with occasional rain) up to about 9°C on a clear sunny day. The effects of shading on the sensors was investigated by lashing an umbrella to the boom, shielding the sensor from the sun. It was found that shading the sensor lowered the BGT value by 4°C compared to the reference sensor. Interestingly, the white coloured sensor reading for that time was also about 4°C cooler than the reference sensor.

In all the above experiments, it was found that at night time, all sensors recorded very similar BGT values – to within 0.5°C. Similar behaviour was found to some extent in the data recorded in the electronics workshop.

6.3.2 BGT Algorithm Performance

The BGT difference ranged between -10°C to +10°C. The Gaughan and Turco models were the better performers (BGT difference between +5°C and -5°C) whereas the Hajizadeh and Liljegren algorithms showed errors in the range of -10°C to +10°C.

The correlation coefficient for night time data was generally above about 0.90. This is attributed to the absence of solar radiation. The performance improved during the winter months, a consequence of the longer night time hours. During the daylight hours, R^2 ranged from about 0.50 to 0.90. Of these, the best performing model was that developed by Turco et al. with the remaining three showing similar performance. Detailed results are presented in Appendix 1 of the Milestone report.

Performance with temperature was carried out by binning the BGT values in 10°C bins starting at 0°C, 10°C, … 50°C. R^2 was calculated for each bin for each of the models. All algorithms showed similar behaviour. The R^2 decreased from about 0.90 at the lower temperature to 0.50 at the 50°C bin. The overall performance as measured by R^2 for all algorithms was greater than 0.90.

The RMSE showed an increasing trend with temperature for the Gaughan, Liljegren and Turco algorithms. No trend was discernible for the Hajizadeh algorithm, here the RMSE was approximately constant with BGT.

It was found that the performance of all four algorithms varied by hour of the day and season. Performance was poorer during daylight hours than night time and improved during winter due to the lengthier night time. Performance deteriorates at higher BGT values since higher BGT values tend to occur during daytime hours. This behaviour mirrors the behaviour observed when readings from four different sensors are presented and compared, that is poorer agreement during the day than at night.

The underlying factor appears to be the presence of solar radiation.

6.3.3 Alternative BGT algorithm

Algorithms for calculating the BGT using meteorological parameters are presented. These are based on the physical principles of heat exchange by conduction and radiation. The radiation component includes solar radiation impinging directly on the globe and all other sources of radiation such as reflection from surfaces and radiation from objects in the immediate neighbourhood. The conduction component exists because the globe is in contact with the air, thus warm air will impart thermal energy to a globe that is at a lower temperature. In addition, the rate that the energy is transferred also depends on the air speed past the globe. This is in effect a wind chill factor, however, if the air temperature is above the globe temperature, the effect would be to heat the globe rather than chill it.

To investigate the flexibility of this approach, two similar sets of equations were used. The equations that describe these algorithms are:

$$BGT\_A = A + B*at + C*f(ws)*sr^{0.25} \quad – eq(1)$$

$$BGT\_B = A + B*(at + C*f(ws)*sr^{0.25}) \quad – eq(2)$$

$$f(ws) = 1 - (1 / (1 + exp(D – E*ws))) – eq(3)$$

where

BGT is the Black Globe Temperature
at is the air (ambient) temperature
sr is solar radiation
ws is the wind speed
exp(…) is the exponentiation function
A, B, …E are coefficients

Briefly, from eqs. 1 and 2, the BGT value is a weighted sum of the contributions from conduction and radiation. The radiation contribution is the solar radiation raised to the power of 0.25 consistent with the Stefan-Boltzman equation and weighted by a wind speed dependent factor, *f(ws)* (eq. 3). The purpose of *f(ws)* is to reduce the contribution of solar radiation with increasing wind speed, in effect, implementing a wind-chill factor. The conduction component is implemented simply as the ambient air temperature multiplied by a constant coefficient.

The coefficients *A … E* are optimised on an individual feedlot basis using a least squares method. The difference between the equations for BGT_A (eq. 1) and BGT_B (eq. 2) is that in eq. 2, the relationship is forced to pass through the origin whereas in eq. 1 this restriction is removed.

Observational data from nine feedlots were used to optimise the coefficients. The amount of data ranged from 10,000 to 20,000 hours.

Establishing the performance of these algorithms is necessarily a lengthy procedure as it involves optimisations embedded in an iterative process.

The performance for these algorithms is shown in Figure 16 to Figure 18. Figure 16 shows the performance for one of the better test cases, together with the BGT values calculated using Gaughan's formula. Overall, the BGT algorithm described above generally performed better than the Gaughan algorithm although the improvement as measured with the Pearson Correlation Coefficient is marginal – about 1 percentage point. Also noteworthy is the general appearance of the plots. The current algorithm can produce "thinner" scatter plots when compared to the Gaughan method, particularly at the higher BGT values where the quality of the relationship is more critical in terms of feedlot cattle heat stress. It is also interesting to note that removing the restriction that the graph must pass through the origin yields a slightly higher correlation (0.9910 to 0.9925) and the relationship is better at the higher and more critical BGT values.

Table 1 lists the values of the coefficients for the BGT_A algorithm, the gradient, intercept and correlation coefficient for the line of best fit for nine of the data sets. The variability in some of the coefficients indicate that there may be too many degrees of freedom (in terms of the number of coefficients) associated with a particular parameter. For example, coefficients D and E exhibit high variability compared to their mean values. As these are both associated with the wind speed, it is likely that the wind effect expression can be simplified with the removal of one of the coefficients.

Table 1 Values of coefficients for a selection of data sets

Coefficients	Feedlot									Average	StDev
	1	2	3	4	5	6	7	8	9		
A	0.369	0.504	0.504	0.441	0.325	0.231	0.365	0.231	0.371	0.371	0.101
B	0.923	0.949	0.949	0.949	0.808	0.943	0.923	0.957	0.944	0.927	0.046
C	5.974	3.270	3.270	2.297	2.297	3.353	2.297	2.297	3.257	3.146	1.171
D	-0.162	0.574	0.574	1.039	1.757	0.782	1.620	1.789	0.793	0.974	0.650
E	0.257	0.262	0.262	0.002	-0.315	0.262	-1.415	0.403	0.257	-0.003	0.570
Gradient	0.881	0.913	0.913	0.915	0.783	0.939	0.914	0.896	0.896	0.894	0.045
Intercept	2.451	2.133	2.133	2.528	5.622	1.846	2.493	2.447	3.398	2.783	1.147
R^2	0.980	0.987	0.987	0.989	0.988	0.991	0.985	0.991	0.986	0.987	0.003

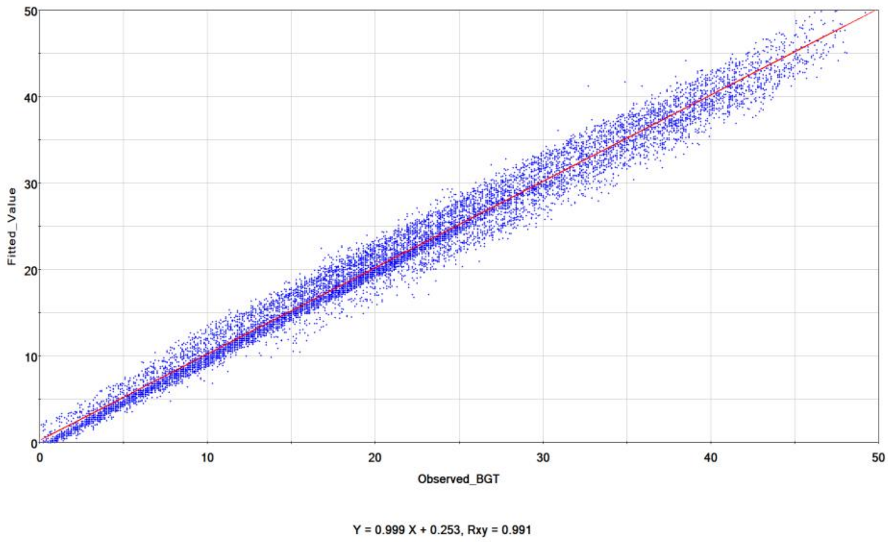

Figure 16 *Scatter plot of Observed BGT against BGT_A*

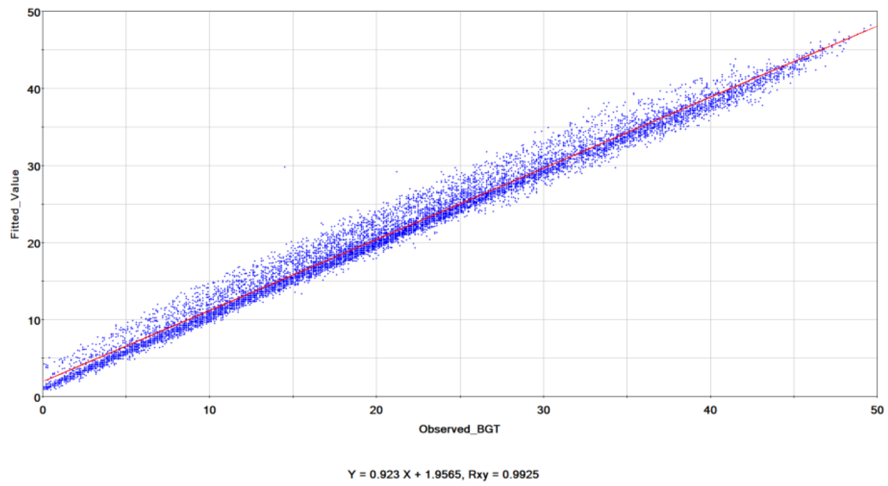

Figure 17 *Scatter plot of Observed BGT against BGT_B*

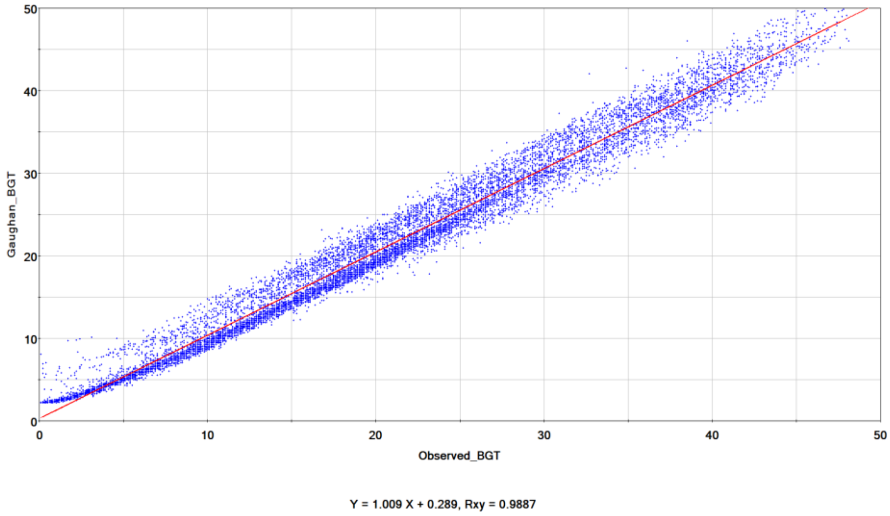

Figure 18 *Scatter plot of Observed BGT against BGT calculated using the Gaughan formula*

6.4 Discussion

The equations that comprise the algorithms were optimised to the extent that R^2 values exceeding 0.98 were readily achieved. The equations were implemented as simple mathematical expressions. The high R^2 indicate that the equations were of the appropriate general form. Further increase in performance could be obtained through fine-tuning without altering the general form of the equations. It should be noted that these optimisations were carried out on a feedlot by feedlot basis and the performance is necessarily better than if the optimisations were carried out using the combined data from all feedlots. It is not clear at this stage what the magnitude of any improvement or otherwise would be without further extensive analyses.

More importantly however, these results indicate that although the general form of the equations is appropriate, the variations in the coefficients indicate that these may be sensor and/or site dependent, possibly due to the responses of the air temperature, wind speed solar radiation, BGT sensors and any factors in the immediate environment such as surfaces reflecting or radiating energy onto the globe. Regarding the accuracy of the BGT sensor, we note that the variability in the calculated BGT values is the same order of magnitude as the discrepancy between the readings recorded by different BGT sensors located in close proximity.

6.5 Conclusions/recommendations

The BGT values recorded using four different BGT sensors were compared. It was found that at night or when operating in a climate-controlled environment (e.g. an air conditioned workshop) the agreement between the readings were in close agreement. During the day time, the discrepancy could be as large as 2°C. It was also found that this discrepancy can be affected by the proximity of surfaces in the immediate vicinity that can reflect radiation onto the globe and the glossiness of the black paint. Painting the globe white results, on average, in a reduction of the BGT of about 5°C. A comparable result is obtained by shading the globe.

The performance of four BGT algorithms for calculating the BGT using routinely recorded meteorological parameters was calculated using several statistical measures. It was found that all four models yielded comparable results and that discrepancies were of the order of several degrees. Correlation coefficients in excess of 0.9 were achieved for all algorithms.

The formulation of alternative algorithms was investigated. The algorithms were implemented using simple mathematical expressions that simulated the effect of conduction and radiation. Optimisation of the coefficients in these equations resulted in favourable agreement between observed and calculated BGT values. Optimisation on an individual feedlot basis resulted in better performance than the algorithms found in the literature. It is not clear at this stage how these algorithms would perform when optimised against the combined data from all feedlots. This is an area of investigation that should be pursued.

The implications of these findings, in terms of the impact on feedlot cattle are that any heat stress models that are strongly dependent on the BGT can yield highly variable results for what should nominally be the same input parameters.

7 Bias Correction investigation

7.1 Description and Method

Katestone understands that the forecast provided for the Cattle Heat Load Toolbox is not always representative of feedlot conditions, mainly due to the highly-localised nature of the environment and how a model represents the land surface. Essentially the model is representing a land use (grassland) at a physical scale (12km) that cannot be reconciled with a feedlots physical characteristics. The localised effects of manure depth, feedlot pad design and construction and local structures are not represented in the model. Bias correction is commonly used in weather forecasting to adjust numerical weather model output for site specific features by removing the models bias at a particular location.

Bias correction can improve the forecast under certain conditions and degrade the forecast under others. The key indicator for this project is that the bias correction reduced the error in the HLI prediction over the course of the heat load season, October to March, and over a typical seven-day forecast period.

Two types of bias correction algorithms were tested using observations and model output for two trial periods covering the 2015/2016 operational forecast season and the 2016/2017 operational forecast season.

Five Bureau of Meteorology (BoM) and five Heat Load Data Network (HLDN) automatic weather station (AWS) sites were chosen based on climate classification, geographic distribution and co-location (Table 1).

Table 1 Co-located BoM and HLDN sites selected for bias correction trial

Site Name	Lat	Lon	State	Region Name	Climate
Emerald	-23.56	148.17	QLD	Central Highlands and Coalfields	Subtropical
Goonoo Feedlot	-23.76	148.53	QLD	Central Highlands and Coalfields	Subtropical
Miles	-26.65	150.18	QLD	Darling Downs and Granite Belt	Subtropical
Stanbroke Feedlot	-26.8	150.41	QLD	Darling Downs and Granite Belt	Subtropical
Glen Innes Airport	-29.67	151.69	NSW	Northern Tablelands	Temperate
Rangers Valley Feedlot	-29.5	151.73	NSW	Northern Tablelands	Temperate
Yanco	-34.62	146.43	NSW	Riverina	Grassland
Riverina Beef Feedlot	-34.64	146.47	NSW	Riverina	Grassland
UQ Gatton	-27.54	152.33	QLD	Southeast Coast	Subtropical
QASP Feedlot	-27.55	152.34	QLD	Southeast Coast	Subtropical

7.1.1 Bias correction algorithms

The bias correction algorithms selected for the trial were Model Output Statistics (MOS) and Decaying Average (DC).

The MOS bias correction algorithm require a training period to determine the models bias in predicting the variable, thus allowing for its correction in the trial period. The training period select was October 2015 to March 2016, the previous seasons operational forecasting period for the CHLT service. The trial period was October 2016 to March 2017, the most recent operational forecasting period.

MOS removes bias by linking observed weather variables to modelled weather variables through best linear fits. MOS is particularly good at removing representative biases (i.e. where the land use surrounding a station is not well represented in the model). MOS typically performs better than raw model outputs when local factors have a small or large influence on the weather situation, when the weather regime is climatologically typical and well represented. However, the method is limited when events or conditions are poorly represented in the observational dataset or are regime-dependent. The method also requires recalculation on a regular basis to update the underlying climatological biases for the most recent events and any changes or updates to the model itself.

The MOS statistics were generated using the R statistics multiple linear regression library (lm) and the relimp package for deriving the relative importance of each regressor in the model in predicting the HLI.

The Decaying Average (DC) method addresses the limitations in MOS by placing greater weight on the most recent bias statistic relative to the preceding period, typically 14 to 30 days. This method responds to the day to day changes in the forecast bias, hence it can provide a more accurate prediction when the weather regime abruptly changes or is atypical for that time of year. However, it does not perform as well as MOS in removing persistent biases in the model. Operational weather forecast systems will generally employ both algorithms to remove the persistent bias and account for situational changes.

The DC method was applied to the forecast period January 11 to January 17 2017 for each of the BoM and HLDN sites. The case period was selected to represent a typical seven-day forecast issued by the CHLT service during a high HLI period. The DC algorithm is defined as:

$$Forecast = (1-\alpha) * 20day + \ \alpha * 24hour$$

where α is the weight applied the 20-day running mean bias and the 24-hour mean running bias. α was tested at 2% and in 10% increments up to 90% finishing at 98% to determine the sensitivity of the weighting. No significant difference was found between the weights for the test period. An α of 2% (0.02) was chosen for the remainder of the trail.

7.1.2 Analysis

The MOS method is based on the long-term (seasonal) variability in the predicted HLI while the DC method is based on short-term (daily) variations. The results of the MOS and DC methods were analysed in isolation for each location and as combined bias correction system.

The statistical measures for the algorithms are the BIAS, root mean square error (RMSE) and the mean absolute error (MAE). Key indicators for performance is a reduction in all statistics for the bias corrected forecast compared to the un-corrected (RAWu) forecast. Regression analysis of the predictions (RAWu and Bias Corrected: RAWc, MOS1x and MOS6x) against the observations is presented with the r2 coefficient, representing the percentage of the variability in the observed HLI that is predicted by the regression model. Quantile-Quantile (QQ) plots are provided for assessment of the change in the distribution of the predicted HLI.

7.2 Discussion

The application of bias correction has been shown to reduce the overall BIAS, RMSE and MAE in the predicted HLI at most of the trial locations. The combination of the long-term multi-variable MOS model (MOS6x) with a 20 day and 24 hour weighted decaying average provided the best results for most sites. Some locations saw little to no improvement indicating that other factors may be influencing the variability in the forecast not the model itself. Some locations also saw the best improvement with only applying the DC to MOS1x.

The BoM trial locations all responded very well to the application of bias correction while the HLDN sites can only be described as having moderate success, with little improvement at some locations. The locations for the trial were chosen to facilitate comparison between AWS in similar locations and climatic regions. The variability seen between the BoM and HLDN locations indicates that some HLDN AWS require further investigation to determine the cause of any discrepancies.

The HLDN sites record an actual black globe temperature (BGT) while the BoM sites and the model calculate the BGT using the same equation, albeit with different inputs. Nonetheless this can be skewing the results in favour of the BoM sites. The results of the BGT investigation work also support this conclusion indicating that there are very site or instrument specific factors that are impacting on the BGT measurements.

7.3 Conclusions/recommendations

The bias correction trial has shown that a significant improvement to the predicted HLI can be obtained through the use of long-term MOS and a near-real time weighted decaying average. The model cannot account for random fluctuations in the weather or discrepancies due to AWS maintenance or siting issues. The bias correction algorithms can reduce the systematic (linear) error in the model not the unsystematic (non-linear) error in the environment. It is recommended that the MOS model be updated to include the 2016-2017 operational forecast period and that this continues following each operational forecast season. This MOS model should them be applied to the uncorrected prediction in near-real time along with the weighted decaying average. The selection of MOS variables, singular or variable, also needs to be applied for each location where the combination of variables and weights is chosen that provides the best outcome.

Application of the bias correction to HLDN sites is not recommended at this stage due to sensitivity of BGT measurements to site specific factors.

8 Key messages

Key Message 1

BGT sensors are extremely sensitive to their immediate surrounds. The siting of a sensor, proximity and colour of the boom and surface coating can significantly impact the temperature measurements. This means that for the same environmental conditions the BGT can measure 2 degrees difference. This translates to a difference in HLI of 3-5 units (depending on conditions) or 30-50 AHLU units for 10 hours of sunlight.

This is a significant finding and has major implications to the following:

- Deriving a global equation to estimate BGT from other meteorological variables is problematic and contains errors that are too sensitive for the current HLI/AHLU model
- If derivation of a global BGT equation, accurate enough for the current HLI/AHLU model, is not possible the ability to accurately forecast the risk of an event or to assess the long term climatic risk of a site based on BOM AWS data is questionable.
- The validity of the original heat load model and its ability to be applied to different sites that may have slightly different weather station configurations
- Coming up with an accurate method for estimating BGT from solar ration, temperature and wind speed is only possible if the equation coefficients were fitted to each feedlot weather station data

Key Message 2

Alternative models to determine the risk of a heat event from climatic conditions are available and can resolve some of the sensitivity issues with the current system. However, validation of any model requires a suitable database against which assumptions can be tested. The use of Pull rate as an indicator of a heat event is not conclusive.

We recommend designing a system for collecting the occurrence of cattle experiencing heat stress along with concurrent weather station data (possibly from a centrally managed unit with a standard configuration), animal information (breed, coat colour, days of feed, health status), pen information (shade, days since pen cleaned, pen surface) and feed (feed type, consumption rate, heat ration). Development of a system that will collect data every year to help build up a massive dataset will ensure that the ability to forecast high risk event improves every year.

Key Message 3

The current system is well used by the feedlot industry. An upgrade to the delivery platform of the forecast to keep up with the move to mobile technologies is needed to ensure continued use in the future.

Key Message 4

The ability of the forecast to predict the increased risk of a heat event is dependent on the ability of the HLI/AHLU model to represent the high risk of an event.

For feedlots with their own weather stations improvements in the forecast can be achieved by incorporating the site derived BGT equations. However, it would not be possible to apply a globally derived indicator of heat load as each site would be different (i.e. 50 AHLU measured at feedlot X does not necessarily = 50 AHLU measured at feedlot Y)

Small improvements can be made to the underlying meteorological forecast via the use of bias correction methods. However, this has limited success for the feedlots sites. Possibly due to the issues identified with the BGT sensors. Using site derived BGT equations may change this conclusion.

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