On farm

Refined website-based weather forecast service for the Australian feedlot industry

Project number FLOT.324

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Feedlot

Table of Contents

ABSTRACT

A weather forecasting system was developed to assist in warning feedlot operators of impending adverse weather conditions that could lead to excessive heat loads (and potential mortality) for feedlot cattle. This forecasting system covered several locations in the proximity of feedlots where Bureau of Meteorology (BoM) automatic weather stations (AWS) are located.

The forecasts were made over a four month period in summer (2003-04) at 15 sites throughout Queensland, New South Wales, South Australia and Western Australia. Forecasts were made of wind speed, wind direction, temperature, these being the input parameters necessary to calculate a heat load index.

Forecasts for all 15 sites were posted daily onto a website (www.katestone.com.au/mla) for easy access to all feedlot operators.

There was good agreement between the forecast heat load index (HLI) and the observed HLI out to 3 days ahead (60 to 80%), with reduced strength in the relationship out to 6 days ahead (20 to 60%).

EXECUTIVE SUMMARY

Introduction

One of the issues that needs to be addressed in managing feedlots is the possibility of cattle deaths due to heat stress brought on by adverse weather conditions. One facet of managing heat stress is to forecast stress inducing conditions for a prescribed future period. In the summer of 2001-02, Katestone Environmental developed a forecasting system for MLA to predict a cattle heat stress index out to 6 days ahead for four sites in Queensland and New South Wales. Meteorological data were obtained on a daily basis from the on-site meteorological stations and the nearest Bureau of Meteorology (BoM) automatic weather station (AWS). From these data, an indicator of heat stress, the Temperature Humidity Index (THI) was calculated and subsequently made available to feedlot operators.

The forecasting study was expanded over the summer of 2002-03 to incorporate a heat load index (HLI) developed specifically for feedlot cattle and to extend coverage to 14 sites across eastern Australia. The service was further expanded for the 2003-04 summer period with the addition of Katanning to cover more AWS sites across the regions of Australia where feedlots are located. This study now includes the following 15 sites:

- Queensland – Amberley, Emerald, Miles, Oakey, Roma, Warwick;
- New South Wales – Albury, Armidale, Griffith, Hay, Moree, Tamworth, Yanco;
- South Australia – Clare; and
- Western Australia – Katanning.

Key issues

The key issues in implementing a viable feedlot weather forecasting system include:

(a) Identification of primary and derived meteorological parameters that indicate excessive heat load in feedlot cattle and cattle storage mechanisms.

(b) Selection of methodology for predicting primary and derived parameters at AWS locations for a suitable time horizon.

(c) Development of a forecasting software system for predicting feedlot conditions.

(d) Making the forecasting results available to all feedlot operators on a daily basis.

At the outset, the following constraints were identified:

- Forecasting using available BoM AWS sites is limiting for a majority of the areas where feedlots are located. Most AWSs are situated near significant populations or industrial regions and as such only 15 sites were identified to be in close proximity to feedlot operations.

- The BoM's model data from the Limited Area Prediction System (LAPS) and Global Analysis and Prediction Scheme (GASP) models, necessary to conduct a forecast, are only stored by the BoM when requested. Therefore the models created for the recently added sites (viz. Katanning) were based on a small amount of historical LAPS/GASP data which can affect model performance.

- It was found that the most effective technology for making the forecasts available to feedlot operators was through the World Wide Web. The advantages are that the data can be presented in a way which is easily interpreted and is readily accessible by all feedlots.

Selected methodology

The following methodology was adopted following discussions between MLA and Katestone Environmental on the most viable options:

- Utilise fully the information from the nearest AWS maintained by the BoM.
- Calculate the key parameters at a fine time resolution out to 6 days ahead.
- Forecasts transferred daily to a web site, including warnings on impending excessive heat load days.
- Software system to include automatic model retraining as more data become available.

The forecasts were based on the models generated during the previous study conducted by Katestone Environmental for MLA. These models are discussed in Appendix A.

Forecast performance

The forecast skill for each site and different forecast horizons was investigated for the daily maximum HLI, the number of hours per day that the HLI was predicted above 89 and the number of hours over a night time period where HLI was below 79.

The forecast HLI were found to have a high correlation with the HLI calculated from observations for most sites.

Recommendations

If a future forecasting system is to include more sites, we would recommend ample warning of the sites of interest so we can request that the BoM store the LAPS/GASP information for these regions. Having a larger database of information from which to conduct the forecasts would improve forecast performance in the initial months.

As heat stress management in cattle is an ongoing area of research, future projects should include up to date methods for calculating heat stress parameters on cattle and reporting these on a regular basis. Also, since cattle can adapt to heat stress to a limited extent (Leonard et al., 2001), parameters relating to the state of cattle as a result of previous heat stress should also be included.

MAIN RESEARCH REPORT

Introduction

One of the issues facing feedlot managers is the possibility of cattle death in feedlots due to heat stress caused by adverse weather conditions. One facet in the overall management strategy is the ability to forecast stress inducing conditions for a prescribed future period. In the summer of 2001-02, Katestone Environmental undertook a feasibility study for MLA (FLOT.313) for forecasting key meteorological variables that could be used to determine excessive heat load in cattle. This forecasting system utilised four sites where on-site meteorological stations were available at the cattle feedlots and was based on the calculation of the Temperature Humidity Index (THI), previously developed as an indicator of human comfort, derived from available forecast meteorological variables (temperature and dewpoint). Forecasts were conducted for on-site meteorological stations and for the nearest Bureau of Meteorology (BoM) Automatic Weather Station (AWS). These forecasts were then compared with observations and it was confirmed that suitable forecasts could be generated from the AWS stations for the feedlot sites.

Recent studies on cattle heat stress (Gaughan et al., 2002) indicate that the heat load index (HLI) was a better indicator of cattle heat stress than the originally used THI. These studies also found that the number of hours that the HLI was above a threshold (89) was also a good indicator of accumulated heat load in cattle. The studies also found that if the HLI fell below 79 for a number of hours then the cattle would be able to recover somewhat from the heat stress. Each of these variables was therefore supplied in the forecasting system.

This forecasting system was expanded to include several sites around Australia for the 2002-03 summer period and further expanded for the 2003-04 summer period with the addition of Katanning.

The study included the following sites:

- Queensland – Amberley, Emerald, Miles, Oakey, Roma, Warwick;
- New South Wales – Albury, Armidale, Griffith, Hay, Moree, Tamworth, Yanco;
- South Australia – Clare, and
- Western Australia – Katanning.

Forecasts were conducted every day over the summer period.

Study definition and objectives

The MLA requested a forecasting system for feedlot sites around Australia to assist in identifying potential cattle heat stress events. The objectives of the study were to:

- Provide forecasts out to 6 days ahead for predicted maximum heat load, the frequency of hours above and below a threshold and forecast of rainfall. These forecasts were necessary for the summer period of 2003-04.
- Allow the forecasts to be accessible on a daily basis by each of the feedlot operators.
- Retrain the models regularly to improve the forecasts.
- Examine the accuracy of the forecasts.

Short-term forecasting of excessive heat load

Key forecasting parameters

Short-term forecasting of dry bulb temperature, dewpoint temperature and wind speed are performed on a routine basis by the BoM. These are the parameters from which many heat comfort indices can be derived. It is also highly desirable to include rainfall and solar radiation parameters in any feedlot forecasting scheme but there is currently less skill in producing such forecasts.

Regional rainfall forecasts are available from the BoM which have been included in the daily forecasts. Solar radiation profiles can be calculated for each day based on site location and typical diurnal radiation profiles. These profiles do not account for cloud cover and therefore will overestimate solar radiation for cloudy days. The dependence of the HLI on radiation used here is relatively minor and as such the resulting overestimation was not considered significant.

The above variables were used to calculate the HLI for each site on a half-hourly basis.

Forecasting methodologies for fine spatial resolution

Most available forecast models give a regional forecast for areas up to usually 25 x 25 km. The forecasting system adopted for this project gives a forecast for the location of interest. This can be more beneficial in incorporating local influences on the meteorology such as terrain.

The forecast models for each site for the meteorological variables were produced using the same methodology as previous forecasting detailed in "FLOT. 313 – Development and trial operation of a weather forecasting service for excessive heat load events for the Australian feedlot industry". A discussion of these models can be found in Appendix A.

In these models, both the wind speed and wind direction are forecast for all sites except Griffith and Hay. For these sites it was necessary to model wind speed alone (as a scalar quantity) due to the large spatial separation between the feedlot and the location of the BoM upper-level forecast (LAPS and GASP data).

Bureau of Meteorology services

LAPS and GASP data were provided by the BoM for each of the forecasting sites along with the AWS data on a daily basis. Details on this information can be found in the previous forecasting report (Katestone Scientific, 2002) and Appendix A. The LAPS and GASP, along with the AWS data, were down loaded, on a daily basis from a web site specially arranged by the BoM.

Key heat load indices

The forecast meteorological variables together with the solar radiation daily profiles were used to calculate the heat load index. The formula used to calculate the HLI, along with the equations necessary to calculate the meteorological variables, are defined below. Further details on these equations and assumptions made are listed in the recent report to the MLA (FLOT.321) titled "Development of statistics and a web site for the display of the risk of excessive heat load events for several Australian sites for the Australian feedlot industry".

Relative Humidity

The relative humidity used in the calculation of HLI was calculated from the half hourly average temperature (Temp in ºC) and dew point temperature (DewPt in ºC) from each AWS using the following equation:

$$\mathrm{Re}\,lHum = 100\left(\frac{1.8DewPt - 0.18Temp + 201.8}{1.62Temp + 201.8}\right)^{8}$$

Equation 1. Relative humidity calculated from temperature and dew point

Solar Radiation

Solar radiation (SolRad in W/m^2) is not recorded at any of the BoM AWS sites. The following equations were used to calculate solar radiation for each hour for each day based on the location of the sun throughout the day and year (Oke, 1987). The equation assumes no reduction in radiation due to cloud cover resulting in a conservative estimate of the HLI.

$$localHr = \frac{15\pi}{180}(12 - t)$$
$$declination = \frac{-23.5\pi}{180}\,Cos\left(\frac{2\pi(day + 10)}{365}\right)$$
$$elevation = Sin^{-1}\left(Sin(lat)Sin(declination) + Cos(lat)Cos(declination)Cos(localHr)\right)$$
$$SolRad = 1050Sin(elevation) - 65$$

Equation 2. Solar radiation equation

where

t is the time of the day in hours
day is the Julian day of the year
lat is the latitude of the site.

Heat Load Index

To calculate the HLI for each hour of recorded data, the following equations were used:

$$BGT = 1.33Temp - 2.65\sqrt{Temp} + 3.21\log(SolRad + 1) + 3.5$$
$$HLI = 1.4BGT + 0.09\,\mathrm{Re}\,lHum - 0.57WSpeed + 32.5$$

Equation 3. Heat Load Index equations

where

WSpeed is measured in km/hr.
Temp is measured in °C.
RelHum is measured in %.
SolRad is measured in W/m^2
BGT is known as the black globe temperature (ºC).

The cattle heat stress thresholds used in the project were provided by the MLA and are as follows:

- Heat Load Index of 74 to 79
  ALERT phase - mild heat load effects especially on vulnerable cattle.
  Time to consider implementing heat load reduction strategies. Death not likely.

- Heat Load Index of 79 to 84
  DANGER phase - strong to severe heat load effects on cattle. Death unlikely but possible.

- Heat Load Index of 84 to 92
  EMERGENCY phase - severe to extreme heat load effects on cattle. Death possible in vulnerable cattle.

- Heat Load index over 92
  CRISIS phase – extreme heat load (EHL). Death possible EVEN with heat load reduction strategies.

Service delivery mechanisms

For this project, forecasts were automatically generated every morning (07:00 hrs), checked by Katestone Environmental staff and transferred to the web site www.katestone.com.au/mla.

Overall methodology

The prototype system was based on the models developed in our previous forecasting system developed for the MLA. It consists of the following steps:

(a) Obtain upper-level forecast data from numerical weather prediction models via a special web site maintained by the BoM.

(b) Collect concurrent information from an automatic weather station close to the site of interest.

(c) Once a sufficient training set of information is collected, use proprietary Katestone software to develop statistical models that relate the surface measurement to a subset of the upper-level variables.

(d) Use these models and the most recent data to provide the necessary forecasts.

The forecasts for daily maximum HLI, number of hours with HLI over 89 and number of hours with HLI less than 79 out to 6 days ahead were compared with the calculated HLI based on measurements. The Pearson Correlation Coefficient, Index Of Agreement (IOA) and the Root Mean Square Error (RMSE) were calculated for each of these forecast variables for each site to give an indication of the accuracy of the forecast.

Accuracy of forecasting system

Statistical measures for forecast accuracy

Three coefficients were used to determine the performance of the forecasting system: the Pearson Correlation Coefficient, Index Of Agreement (IOA) and the Root Mean Square Error (RMSE).

The Pearson Correlation Coefficient is a measure of the strength of the linear relationship between the predicted and observed measurements (defined in Equation 4). The closer this value is to unity the stronger the relationship. The Index Of Agreement (IOA) is defined in Equation 6 and gives an index from 0-1 (1 representing strong agreement). The Root Mean Square Error (RMSE) defined in Equation 5 is an indication of the absolute error. The smaller the RMSE (i.e. the closer the value is to zero) the better the forecast. Note that the RMSE does not indicate whether the forecasts are predominantly higher or lower than the observed values – ie whether the method over or under predicts – it only reports on the difference between the observed and predicted values.

The equations for calculating the coefficients are:

$$r = \frac{N\left(\sum_{i=1}^{N} O_i P_i\right) - \left(\sum_{i=1}^{N} O_i\right)\left(\sum_{i=1}^{N} P_i\right)}{\sqrt{\left[N\left(\sum_{i=1}^{N} O_{i\ i}^{2}\right) - \left(\sum_{i=1}^{N} O_i\right)^2\right]\left[N\left(\sum_{i=1}^{N} P_1^2\right) - \left(\sum_{i=1}^{N} P_i\right)^2\right]}}$$

Equation 4. Pearson Correlation Coefficient

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_i - O_i\right)^2}$$

Equation 5. Root Mean Square Error

$$IOA = 1 - \frac{\sum_{i=1}^{N}\left(P_i - O_i\right)^2}{\sum_{i=1}^{N}\left(\left|P_i - O_{mean}\right| + \left|O_i - O_{mean}\right|\right)^2}$$

Equation 6. Index of Agreement

Forecasting results

A summary of the statistics for forecasts (1 day and 3 days ahead) of the number of hours where the heat load index was less than 79 is shown in Table 1. The statistics for 1 day, 3 days and 6 days ahead forecasts for the number of hours the HLI was over 89 and the maximum daily HLI can be seen in Table 2 and Table 3 respectively. Table 4 is the contingency table. Table 5 and Table 6 are the prediction error probability distributions.

As the number of hours per day that the HLI was predicted over 89 may be zero for several days at some sites, the Pearson Correlation Coefficient and Index of Agreement are not a good measure of model performance. In these instances it is reported as “NA”. Instead, the RMSE, the contingency table (Table 4) or the prediction error distributions (Table 5 and Table 6) should be examined.

The results reported for Katanning should be viewed with caution as Katanning is a recent addition to the list of sites and as such, the models have not been trained with a sufficient volume of data to make predictions as accurate as those of the other sites.

Table 1. Statistics for forecast accuracy of the number of hours for the HLI <79 for 1 day and 3 days ahead.

	1 day ahead			3 days ahead		
Site	Pearson	IOA	RMSE	Pearson	IOA	RMSE
Albury	0.64	0.75	4.04	0.68	0.72	4.39
Amberley	0.48	0.67	3.62	0.44	0.57	5.22
Armidale	0.55	0.71	4.71	0.56	0.70	5.23
Clare	0.60	0.78	4.08	0.64	0.79	4.32
Emerald	0.50	0.58	3.40	0.40	0.46	4.19
Griffith	0.77	0.86	3.25	0.77	0.87	3.19
Hay	0.74	0.84	3.64	0.70	0.83	3.66
Katanning	0.24	0.56	4.22	0.34	0.62	3.94
Miles	0.58	0.66	3.18	0.50	0.58	4.06
Moree	0.63	0.78	3.00	0.65	0.72	3.98
Oakey	0.66	0.76	4.00	0.63	0.79	3.38
Roma	0.55	0.69	3.30	0.52	0.63	3.73
Tamworth	0.71	0.82	3.48	0.73	0.82	3.53
Warwick	0.70	0.82	3.21	0.74	0.82	3.34
Yanco	0.72	0.84	3.40	0.67	0.78	3.95

Table 1 shows the statistics for the number of hours where the HLI was predicted to be less than 79. As cattle recover from any previous stress event during these hours, the above table presents the ability of the forecasting method to predict recovery events. The times were taken from midday to midday to give the number of hours overnight that were below 79, therefore, only a 5 day ahead forecast is available. Inspection of the table indicates that the agreement, in general, is good for both the one and three day forecasts. Comparison between the correlation coefficients for the 1 and 3 day ahead forecasts shows that these values are comparable – ie the expected deterioration in forecast accuracy with horizon does not occur. The reason for this behaviour is not clear at this stage.

Table 2: Statistics for forecast accuracy of the number of hours for the HLI >89 for 1 day, 3 days and 6 days ahead.

	1 day ahead			3 days ahead			6 days ahead		
Site	Pearson	IOA	RMSE	Pearson	IOA	RMSE	Pearson	IOA	RMSE
Albury	0.77	0.87	2.20	0.54	0.75	3.09	0.51	0.72	3.50
Amberley	0.69	0.79	2.83	0.69	0.83	2.66	0.55	0.74	3.22
Armidale	NA	0.16	0.78	NA	0.16	0.78	-0.02	0.12	0.94
Clare	0.69	0.83	2.27	0.63	0.80	2.52	0.49	0.70	2.79
Emerald	0.60	0.68	4.18	0.50	0.64	4.43	0.19	0.51	5.34
Griffith	0.70	0.77	3.24	0.56	0.69	3.74	0.50	0.67	3.65
Hay	0.65	0.70	4.57	0.54	0.63	5.07	0.56	0.66	4.91
Katanning	0.05	0.30	1.70	NA	0.28	1.61	-0.05	0.30	1.84
Miles	0.74	0.83	2.95	0.67	0.82	3.12	0.37	0.64	4.22
Moree	0.72	0.83	2.85	0.68	0.81	3.05	0.57	0.76	3.42
Oakey	0.62	0.63	3.00	0.33	0.52	3.32	0.28	0.54	3.47
Roma	0.68	0.77	3.36	0.49	0.70	3.86	0.35	0.63	4.29
Tamworth	0.71	0.77	2.91	0.66	0.78	3.09	0.55	0.74	3.39
Warwick	0.67	0.74	2.51	0.64	0.78	2.48	0.42	0.66	3.11
Yanco	0.79	0.86	2.53	0.56	0.74	3.33	0.50	0.72	3.47

Table 2 presents the forecast results for the number of hours that the HLI is above 89. Since a HLI in excess of 89 indicates extreme heat load effects on cattle, the above table presents the performance of the system in predicting events which are detrimental to cattle. These results indicate that the model performs better in predicting these events than predicting the *hours below 79* events.

Table 2 also illustrates behaviour that is typical of forecasting – predictions far in the future are less reliable than predictions for the immediate future. This manifests itself as decreasing Pearson and IOA coefficients (and increasing RMSE) as the number of days ahead increases.

It should be pointed out that there are instances in the table for Armidale and Katanning where the coefficients could not be determined. For Armidale, as it is situated in a cool region, the model did in fact predict zero hours for a HLI greater than 89. The poor performance for Katanning, as previously stated, is believed to be due to insufficient data for training the models.

Table 3. Comparison statistics for maximum daily HLI for predicted and observed measurements for 1 day, 3 days and 6 days ahead.

Site	1 day ahead			3 days ahead			6 days ahead		
	Pearson	IOA	RMSE	Pearson	IOA	RMSE	Pearson	IOA	RMSE
Albury	0.82	0.88	5.01	0.72	0.82	5.79	0.47	0.66	8.23
Amberley	0.83	0.86	4.59	0.69	0.81	5.35	0.52	0.69	6.78
Armidale	0.77	0.79	6.4	0.65	0.72	6.93	0.51	0.67	7.83
Clare	0.85	0.9	5.73	0.8	0.88	6.49	0.5	0.7	9.67
Emerald	0.64	0.67	6.86	0.49	0.59	7.66	0.4	0.56	8.03
Griffith	0.88	0.8	8.04	0.74	0.74	8.87	0.53	0.64	10.33
Hay	0.75	0.75	10.69	0.63	0.67	11.54	0.45	0.58	12.86
Katanning	0.54	0.57	11.34	0.61	0.59	11.42	0.29	0.47	13.87
Miles	0.79	0.86	4.47	0.62	0.76	6.16	0.5	0.68	7.07
Moree	0.78	0.86	4.78	0.7	0.81	5.9	0.56	0.73	7.35
Oakey	0.81	0.77	7.25	0.61	0.75	6.14	0.4	0.61	7.94
Roma	0.67	0.76	6.2	0.58	0.72	7.04	0.35	0.57	8.67
Tamworth	0.78	0.85	5.96	0.73	0.81	6.28	0.6	0.73	7.79
Warwick	0.81	0.84	5.3	0.63	0.76	6.54	0.49	0.68	7.61
Yanco	0.85	0.85	6.55	0.72	0.81	6.91	0.47	0.67	9.06

Comparison of Table 3 with the previous two tables reveals that the model performs better overall in predicting the daily maximum HLI with only three sites attaining a correlation coefficient below 0.75 (using Pearson one day ahead coefficient as the indicator) compared with values generally below 0.75 (actually, three instances above 0.75) for the previous tables.

It should be noted that the RMSE should not be used to compare forecast performance as this indicator represents *hours* in Table 1 and Table 2 and *HLI* in Table 3.

As the forecasting accuracy using the correlation coefficients and RMSE is difficult to interpret at times, a contingency table comparing the forecasts was conducted for each classification index as shown in Table 4.

Table 4. Contingency table for number of observations within specified thresholds for predicted and measured for half-hourly average daily maximum HLI.

Site	Observed	Predicted 1 day ahead					Predicted 3 days ahead				
		<74	74-79	79-84	84-92	92+	<74	74-79	79-84	84-92	92+
Albury	**<74**	5	1	1	1	0	3	3	2	1	0
	74-79	6	4	1	0	0	3	6	2	2	0
	79-84	4	7	19	0	0	1	8	15	3	2
	84-92	0	2	18	30	2	0	0	15	31	4
	92+	0	0	0	11	12	0	0	1	11	11
Amberley	**<74**	0	1	0	0	0	0	1	0	2	0
	74-79	0	1	1	0	0	0	1	0	1	0
	79-84	0	13	7	1	1	0	16	4	1	1
	84-92	0	4	23	37	0	0	3	15	38	7
	92+	0	0	0	10	24	0	0	0	11	23
Armidale	**<74**	25	1	1	0	0	23	2	0	0	0
	74-79	15	14	3	0	0	16	20	1	0	0
	79-84	5	17	15	1	0	11	16	6	1	0
	84-92	5	2	14	6	0	6	13	7	2	0
	92+	0	0	0	0	0	0	0	0	0	0
Clare	**<74**	18	0	0	1	0	19	1	1	0	0
	74-79	12	12	1	0	0	13	9	4	0	0
	79-84	1	11	10	1	1	1	12	7	1	1
	84-92	1	3	13	15	0	1	5	9	13	4
	92+	0	0	2	7	15	0	0	1	9	13
Emerald	**<74**	0	0	1	0	0	0	0	0	3	0
	74-79	0	0	0	1	0	0	0	0	0	0
	79-84	0	1	1	1	0	0	0	1	1	0
	84-92	2	11	18	19	3	3	10	16	22	3
	92+	5	0	1	32	28	7	0	3	32	23
Griffith	**<74**	6	1	0	0	0	5	2	1	0	0
	74-79	8	2	1	0	0	8	4	1	0	0
	79-84	12	11	4	0	0	8	13	3	1	0
	84-92	0	14	24	6	0	1	10	24	9	0
	92+	0	0	4	20	11	0	0	8	19	7
Hay	**<74**	6	1	2	1	0	3	2	2	3	0
	74-79	9	2	1	0	0	8	3	3	0	0
	79-84	6	8	3	0	0	3	8	7	0	0
	84-92	5	7	16	13	0	4	5	16	11	2
	92+	0	0	8	19	16	0	1	9	21	12
Katanning	**<74**	11	2	0	1	0	14	1	0	0	0
	74-79	27	6	0	0	0	30	4	1	0	0
	79-84	13	11	1	0	0	16	5	2	1	0
	84-92	15	10	9	1	1	13	13	8	1	0
	92+	0	3	2	3	0	0	1	3	3	0
Miles	**<74**	0	1	0	0	0	0	1	0	1	1
	74-79	0	0	4	1	0	0	1	3	0	1
	79-84	0	3	2	4	0	0	4	1	1	0
	84-92	0	4	20	40	2	0	7	20	27	13
	92+	0	0	0	17	26	0	0	1	16	26

Site	Observed	Predicted 1 day ahead					Predicted 3 days ahead				
		<74	74-79	79-84	84-92	92+	<74	74-79	79-84	84-92	92+
Moree	**<74**	0	0	1	1	0	1	0	1	2	0
	74-79	2	2	2	0	0	3	2	1	1	0
	79-84	1	5	3	2	0	1	2	4	1	0
	84-92	0	1	10	43	4	0	3	10	42	4
	92+	0	0	1	14	32	0	0	1	17	28
Oakey	**<74**	1	0	0	0	0	0	1	1	1	0
	74-79	7	5	2	0	0	4	3	3	3	0
	79-84	14	11	4	2	0	5	7	11	5	1
	84-92	4	13	13	25	2	0	6	10	39	3
	92+	0	0	0	12	9	0	0	0	16	5
Roma	**<74**	0	1	0	0	0	0	1	1	1	0
	74-79	0	1	1	3	0	1	1	2	1	0
	79-84	1	5	3	1	2	0	4	2	3	0
	84-92	0	8	21	24	1	2	7	17	26	3
	92+	0	0	1	26	24	0	0	8	24	19
Tamworth	**<74**	5	3	0	2	0	5	2	2	3	0
	74-79	5	2	1	0	0	3	1	3	0	0
	79-84	1	6	16	1	0	0	7	8	8	0
	84-92	1	2	18	28	0	0	2	17	29	0
	92+	0	0	0	15	15	0	0	1	15	15
Warwick	**<74**	2	1	0	0	0	1	1	1	2	0
	74-79	7	2	3	0	0	6	3	1	1	0
	79-84	5	18	10	2	0	8	12	5	7	0
	84-92	0	5	17	27	3	0	6	15	31	2
	92+	0	0	1	12	9	0	1	0	8	13
Yanco	**<74**	4	1	1	0	0	3	3	1	1	0
	74-79	9	2	2	0	0	5	5	2	1	0
	79-84	8	12	5	1	0	2	10	10	2	1
	84-92	0	5	22	16	1	0	6	14	21	3
	92+	0	0	4	13	18	0	0	4	18	12

Table 4 is a contingency table showing the number of successfully predicted events for each threshold class. Two subsections or matrices are presented for each site – a one day forecast horizon and a three day forecast horizon. Ideally, all off-diagonal elements of these matrices should be zero. In reality, any non zero elements which are not on the main diagonal represent an over or under prediction.

Inspection shows that there is an overall tendency for the forecast system to under predict the maximum daily HLI. The poorest performing site is Katanning for reasons previously mentioned.

Table 5. Probability distributions of prediction error for number of hours HLI is below 79 for 1 and 3 day forecasts.

		Percentage probability of occurrence of prediction error														
Site		**-7**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Albury	**1 day**	5.9	3.4	7.6	8.5	5.9	14.4	17.8	18.6	2.5	2.5	2.5	3.4	4.2	2.5	0.0
	3 day	12.4	5.3	5.3	3.5	18.6	13.3	19.5	13.3	3.5	1.8	1.8	0.9	0.9	0.0	0.0
Amberley	**1 day**	5.7	0.0	0.0	2.8	2.8	6.6	17.9	41.5	3.8	9.4	1.9	1.9	2.8	0.0	2.8
	3 day	15.5	0.0	2.9	2.9	5.8	12.6	16.5	29.1	5.8	4.9	0.0	1.0	1.0	1.0	1.0
Armidale	**1 day**	7.7	1.7	4.3	8.5	2.6	6.0	5.1	35.0	6.8	2.6	3.4	6.0	6	1.7	2.6
	3 day	11.6	5.4	2.7	5.4	3.6	4.5	8.9	26.8	8.0	5.4	5.4	3.6	4.5	2.7	1.8
Clare	**1 day**	9.3	2.5	5.9	3.4	6.8	8.5	13.6	20.3	6.8	5.1	6.8	5.1	0.8	2.5	2.5
	3 day	10.6	3.5	5.3	4.4	4.4	12.4	13.3	23.0	5.3	4.4	2.7	4.4	0.9	3.5	1.8
Emerald	**1 day**	5.2	0.0	0.9	1.7	2.6	7.0	17.4	32.2	11.3	5.2	7.8	7.0	0	0.9	0.9
	3 day	9.0	0.0	0.9	0.0	8.1	3.6	12.6	39.6	9.0	2.7	3.6	3.6	0.9	2.7	3.6
Griffith	**1 day**	2.5	0.0	0.8	0.8	8.5	5.1	11.0	23.7	11.0	8.5	10.2	5.9	3.4	6.8	1.7
	3 day	1.8	1.8	2.7	3.5	3.5	9.7	9.7	23.0	15.0	6.2	10.6	4.4	3.5	3.5	0.9
Hay	**1 day**	1.9	1.9	0.0	4.7	2.8	5.7	10.4	20.8	13.2	10.4	6.6	4.7	7.5	2.8	6.6
	3 day	5.9	3.0	4.0	2.0	2.0	7.9	8.9	23.8	11.9	11.9	3.0	3.0	5.0	4.0	4.0
Katanning	**1 day**	0.9	1.8	2.7	1.8	3.6	4.5	3.6	34.5	6.4	7.3	1.8	4.5	8.2	5.5	12.7
	3 day	1.0	2.9	2.9	1.0	1.9	4.8	6.7	35.6	4.8	3.8	4.8	8.7	3.8	6.7	10.6
Miles	**1 day**	6.0	4.3	2.6	2.6	7.7	24.8	23.9	19.7	4.3	1.7	0.9	1.7	0.0	0.0	0.0
	3 day	9.7	3.5	0.0	11.5	7.1	18.6	23	19.5	3.5	1.8	0.0	0.0	0.9	0.9	0.0
Moree	**1 day**	5.1	0.0	0.0	5.1	8.5	16.2	16.2	21.4	7.7	7.7	6.0	2.6	1.7	0.9	0.9
	3 day	8.9	1.8	6.2	6.2	10.7	16.1	12.5	16.1	5.4	2.7	7.1	2.7	1.8	0.9	0.9
Oakey	**1 day**	0.9	0.9	0.0	0.9	3.4	3.4	11.1	20.5	9.4	7.7	9.4	6.8	6.8	7.7	11.1
	3 day	3.5	3.5	1.8	5.3	5.3	9.7	21.2	17.7	9.7	7.1	4.4	3.5	3.5	1.8	1.8
Roma	**1 day**	3.5	1.8	1.8	2.7	6.2	11.5	22.1	24.8	8.8	4.4	3.5	3.5	1.8	0.9	2.7
	3 day	8.3	1.8	2.8	7.3	5.5	6.4	19.3	28.4	8.3	4.6	4.6	0.0	0.9	0.0	1.8
Tamworth	**1 day**	6.4	0.9	1.8	5.5	4.6	17.4	14.7	24.8	5.5	5.5	5.5	0.9	1.8	2.8	1.8
	3 day	3.8	3.8	2.9	10.6	10.6	23.1	12.5	16.3	2.9	4.8	2.9	2.9	1.0	1.9	0.0
Warwick	**1 day**	2.6	0.9	4.4	3.5	5.3	12.3	21.1	21.9	7.9	1.8	5.3	5.3	4.4	1.8	1.8
	3 day	5.5	0.9	2.7	5.5	12.7	14.5	25.5	14.5	6.4	1.8	4.5	3.6	0.9	0.0	0.9
Yanco	**1 day**	3.4	0.8	3.4	5.1	4.2	12.7	16.1	19.5	7.6	7.6	5.1	3.4	2.5	6.8	1.7
	3 day	9.7	3.5	3.5	6.2	13.3	13.3	10.6	15.9	5.3	5.3	2.7	5.3	0.9	3.5	0.9

Table 6. Probability distributions of prediction error for numbers of hours HLI is above 89 for 1 and 3 day forecasts.

		Percentage probability of occurrence of prediction error														
Site		**-7**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Albury	**1 day**	2.5	1.7	5.0	1.7	1.7	1.7	6.6	73.6	1.7	1.7	0.0	0.8	1.7	0.0	0.0
	3 day	5.0	1.7	4.2	2.5	1.7	1.7	2.5	65.8	4.2	0.8	0.0	3.3	2.5	1.7	2.5
Amberley	**1 day**	2.8	2.8	4.6	9.2	6.4	6.4	7.3	54.1	0.9	2.8	0.9	0.9	0.9	0.0	0.0
	3 day	2.7	0.9	1.8	7.2	3.6	5.4	5.4	54.1	7.2	2.7	2.7	3.6	1.8	0.9	0.0
Armidale	**1 day**	0.0	0.0	0.8	0.8	1.7	1.7	0.8	94.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	3 day	0.0	0.0	0.8	0.8	1.7	1.7	0.8	94.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Clare	**1 day**	3.3	1.7	1.7	2.5	1.7	4.1	6.6	71.9	1.7	0.8	2.5	0.0	0.8	0.0	0.8
	3 day	3.3	0.8	1.7	0.8	2.5	4.2	4.2	73.3	0.8	0.8	0.8	0.8	2.5	1.7	1.7
Emerald	**1 day**	13.6	7.6	11.0	2.5	14.4	7.6	9.3	28.8	3.4	0.8	0.8	0.0	0.0	0.0	0.0
	3 day	19.3	6.7	7.6	4.2	9.2	9.2	9.2	28.6	1.7	0.8	0.0	0.8	1.7	0.8	0.0
Griffith	**1 day**	9.9	5.0	3.3	2.5	5.0	5.0	5.8	62.8	0.0	0.8	0.0	0.0	0.0	0.0	0.0
	3 day	15.0	3.3	5.0	0.8	5.8	2.5	3.3	61.7	0.8	0.0	0.8	0.0	0.8	0.0	0.0
Hay	**1 day**	12.8	2.8	6.4	3.7	5.5	6.4	3.7	58.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	3 day	15.7	3.7	7.4	3.7	5.6	3.7	4.6	52.8	0.0	0.9	0.0	0.9	0.0	0.0	0.9
Katanning	**1 day**	0.9	1.8	3.5	0.9	3.5	0.9	3.5	84.2	0.0	0.0	0.0	0.9	0.0	0.0	0.0
	3 day	1.8	0.0	3.6	0.9	3.6	0.9	3.6	85.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Miles	**1 day**	5.0	2.5	2.5	6.7	6.7	9.2	12.6	47.9	3.4	0.0	0.8	1.7	0.8	0.0	0.0
	3 day	3.3	4.2	3.3	5.0	5.0	4.2	15	40.8	7.5	4.2	2.5	0.8	0.8	0.8	2.5
Moree	**1 day**	2.5	5.0	4.2	5.8	5.0	8.3	8.3	46.7	3.3	5.8	3.3	1.7	0.0	0.0	0.0
	3 day	5.0	4.2	3.4	5.0	7.6	8.4	6.7	44.5	6.7	2.5	2.5	1.7	0.8	0.8	0.0
Oakey	**1 day**	5.0	5.0	5.9	3.4	6.7	4.2	5.0	64.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	3 day	6.7	5.8	4.2	5.0	7.5	0.8	5.0	55.0	5.0	2.5	0.8	0.8	0.8	0.0	0.0
Roma	**1 day**	8.5	4.3	5.1	6.0	6.8	9.4	9.4	46.2	1.7	0.9	1.7	0.0	0.0	0.0	0.0
	3 day	11.0	5.9	5.9	3.4	5.9	9.3	3.4	37.3	6.8	4.2	1.7	2.5	1.7	0.0	0.8
Tamworth	**1 day**	5.4	2.7	3.6	8.1	9.0	4.5	7.2	55.0	0.9	1.8	1.8	0.0	0.0	0.0	0.0
	3 day	8.2	3.6	2.7	6.4	4.5	2.7	7.3	61.8	0.9	0.0	0.9	0.9	0.0	0.0	0.0
Warwick	**1 day**	2.6	3.4	0.9	7.7	7.7	5.1	6.0	62.4	1.7	1.7	0.0	0.0	0.0	0.9	0.0
	3 day	0.8	5.9	1.7	7.6	1.7	5.1	3.4	65.3	1.7	2.5	2.5	0.8	0.0	0.0	0.8
Yanco	**1 day**	5.0	3.3	3.3	2.5	3.3	5.0	8.3	66.9	0.8	0.8	0.8	0.0	0.0	0.0	0.0
	3 day	9.2	3.3	2.5	3.3	3.3	5.0	6.7	57.5	2.5	0.0	2.5	2.5	0.0	0.0	1.7

Table 5 and Table 6 summarise the number of hours that the predicted number of hours differs from the observed number of hours that the HLI is below 79 and above 89 respectively. Forecast performance for 1 and 3 days ahead are tabulated as probability distributions. The first row of each table represents the difference (in hours) that the predicted differs from the observed. The differences range from –7 hours (under predicting by 7 hours) to +7 hours (over predicting by 7 hours). The main body of the table is the probability that the error occurred, expressed as a percentage.

For example, in the very last entry in Table 6 (Yanco, 3 day ahead), there was a 57.5% probability that the predicted and observed number of hours were equal (zero difference), 6.7% probability that the number of hours was under predicted by 1 hour (difference is –1), and 2.5% probability of over predicting by 4 hours (difference is +4). All errors equal to or greater than 7 hours are binned into the 7 hour difference bin. Thus for this example, under prediction of 7 hours or greater occurred 9.2% of the time.

Visual inspection of Tables 5 and 6 reveal that there is a tendency to underpredict both the *hours under 79* and *hours over 89* parameters.

The *hours under 79* distributions tend to be broader than the *hours over 89*. Also, the hours over 89 tend to have a higher proportion of predictions in the "zero prediction error" column.

Overall, model performance in predicting detrimental events is better than the prediction of recovery events.

In comparing the results in Table 5 and Table 6 with the other results presented here, the reader should bear in mind that these data cannot be compared directly. The parameters in Table 3 and Table 4 are the maximum HLI values (not hours that HLI is greater than a specified value) and it does not necessarily follow that if a high maximum HLI value is observed on a given day, then that day should also exhibit a high *Hours Over 89* value. For instance, the day may have been generally overcast and cool with a brief period when the clouds cleared and the HLI momentarily increased in value.

A more direct comparison can be made with Table 1 and Table 2. Here the RMSE is a measure of the difference between the predicted and observed values. This parameter is related to the width of the distributions presented in Table 5 and Table 6. Visual inspection of these tables indicates that there is self-consistency in the behaviour of the data presented in these tables. Considering the one day ahead data, the RMSE values in Table 1 are generally in the range 3 to 5 whereas in Table 2 these are in the range 2 to 4 (with one entry above 4). The lower RMSE in Table 2 implies that the model has higher probability of correctly predicting that event (zero error), than the recovery events. This is reflected in the high probability values found under the zero difference column in Table 6. Similar comparisons can be made between Table 1 and Table 5.

Service delivery and utility

Forecasts of the following parameters were checked by the Katestone Environmental staff and posted to the web site www.katestone.com.au/mla on a daily basis:

- Daily half-hourly average maximum predicted heat load index;
- Daily half-hourly average minimum heat load index;
- Total number of hours per day with HLI predicted to be over 89;
- Total number of hours with HLI predicted to be less than 79; and
- Total amount of rainfall from the BoM regional forecast out to 6 days ahead.

These forecasts were transferred to the web site on a daily basis for access by all feedlot operators. The previous week's forecasts were also made available should the feedlot operators need to check an earlier forecast.

The implementation of the forecast model is very flexible. Any future need for forecasting at these same locations will require only a basic retraining of the models with more recent data. The addition of new sites would require correspondence with the BoM in order to make the additional data available. Katestone Environmental would then need to extend the existing models to incorporate the new sites. If the excess heat load formulas change then the models would only require a minor adjustment to the output equations.

Recommendations for future work

It is recommended that earlier advice is necessary on the need for any new forecasting sites to ensure an ample amount of concurrent upper-level and AWS data are available to train the models. This will improve the initial forecast accuracy of the models.

No allowance has currently been made for the difference between feedlot conditions and conditions at the AWS site, or for factors such as shading. These factors could readily be included when results of other studies are available.

As heat stress management in cattle is an ongoing area of research, future projects should include up to date methods for calculating heat stress parameters on cattle and reporting these on a regular basis. Also, since cattle can adapt to heat stress to a limited extent, (Leonard et al., 2001), calculation of parameters relating to the state of cattle as a result of previous heat stress should also be investigated and incorporated into the modelling.

Conclusions

A forecasting system operating over the summer 2003/2004 period for MLA has proved to provide relatively accurate forecasts for 1 and 3 days ahead for cattle heat stress at a majority of the locations. The forecasts out to 6 days ahead are less accurate but are still very useful in determining whether the excessive heat load conditions are expected to continue.

The models should be more accurate in the future as more data becomes available for the models to be retrained.

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APPENDIX A

Description of Models

The first step in producing site-specific weather forecasts takes advantage of detailed information made readily available from well-proven numerical models in association with determined correlations of local weather variables with such numerical forecasts. The direct predictions from the traditional numerical modelling may be very useful for some variables under normal conditions but are unlikely to properly predict the detailed diurnal variations of key parameters required for constructing heat comfort indices.

Some type of expert system is needed to improve such forecasts. This could involve, for example, the use of more detailed or a wide variety of numerical models to give greater confidence in predictions or alternatively the use of a trained meteorologist to be able to estimate the likely differences between feedlot conditions and those forecast by the numerical model.

An automated approach would utilise the available database of concurrent site measurements and upper-level forecasts to determine statistically significant correlations. These correlations are then assumed to hold over forthcoming events and are used with numerical forecasts to predict feedlot conditions over the next 48-144 hours. The predicted time history of individual meteorological variables can then be combined in various ways to give a time history of a selected thermal comfort index. These index values can be screened against critical thresholds determined from field studies in order to give suitable alarms for various types of likely animal reactions.

This “downscaling” methodology (i.e. relying on a correlation procedure to produce site-specific values from a regional model prediction of atmospheric profiles) has been shown by experience elsewhere to require at least a period of 1-3 months of training data before adequate results are obtained and thereafter a regular retraining over a one year period to produce optimal results. The correlations themselves are only as good as the database upon which they are based.

For general predictions, a short database may suffice as relatively simple relationships are likely to be useful for normal conditions. Extreme conditions are less frequently encountered and may not be present in a short-term database. Given that there is considerable variability between years in general weather conditions (and even more so for extreme events), there is no guarantee that the recent past is a good guide to the forecasting of a series of adverse days, as required in heatwave analysis. The accuracy of the downscaling methodology in heatwave conditions is reliant on the ability of numerical models to accurately predict fluctuations in parameters outside the ranges for which they have been optimised and hence is expected to be limited.

A1 Available data

Over the past 30 years, many field and theoretical studies have demonstrated the sensitivity of near-surface meteorological conditions to changes in local and regional terrain characteristics. Temperatures are very sensitive to terrain elevation, distance from the nearest coastline and vegetation cover. Relative humidity is sensitive to the presence of vegetation cover, local water bodies or the coastline. Wind speed is strongly influenced by the presence of trees, hills or valleys, inland location and the aerodynamic roughness of land within 1 km of the weather station.

In contrast, numerical weather prediction models (regional forecast models) use relatively coarse terrain and land-use information and are very unlikely to capture the influences of the surface characteristics within 1-3 km of the site. On the other hand, on-site measurements will show directly the influences of the local environment by the presence of strong diurnal patterns in wind and, to a lesser extent, temperature variables. On-site weather information is often very important, especially if the nearest BoM automatic weather station is over 15-20 km away or if the feedlot environment is unusual compared to that of the region (say within 25 km).

There are several Australian agencies (hereafter referred to as “service providers”) that routinely run numerical models that could be suitable for either direct forecasts or in conjunction with an expert system using local meteorological information (that is, the prediction of parameter values at a given point from values predicted over a broader scale). These include:

(a) The BoM operates the Global Analysis and Prediction Scheme (GASP) and Limited Area Prediction System (LAPS) models on a regular basis for their Australia-wide weather prediction service. The LAPS model covers an area of Australasia, South East Asia and much of the Indian and Pacific Oceans at various resolutions. The finest resolution (5 km) is only currently used in research work or for the use of the internal BoM consulting arm. The 25 km resolution forms the basis of most publicly-available forecasts.

The information available from these forecasts that is most applicable to the current project includes surface level (screen height) temperature, dew point, sensible and latent heat fluxes, total heat flux and a set of upper-level temperature, dew point and wind components.

By special arrangements, these forecasts can be provided for any given grid point on a three-hourly basis out to a prediction horizon of 48 hours. They do not generally take account of local weather station data from the nearest BoM AWS site. The numerical forecasts from the model are not edited or screened for reliability and are from one model run.

The GASP model provides a similar set of temperature and wind variables at a coarser resolution of 75 km on a twelve-hourly basis to a time horizon of 6 days. No local data assimilation is included at this scale.

The numerical model results can be made available relatively cheaply on a dedicated web site. Various energy companies have used such information over the past 4 years (using the Katestone downscaling software) as a basis for demand prediction and trading activities. The service has proved to be very reliable with only very infrequent excursions in some parameters. The BoM model accuracy is reported in various BoM publications.

(b) The CSIRO runs a different type of numerical model on a regular basis for a current trial service for agricultural and energy users. The model is run at a resolution of 5 km or better to a time horizon of 8 days. The predicted variables include rainfall and cloud cover, as well as the standard temperature, wind and moisture variables.

(c) The University of New South Wales provides a commercial prediction system to a time horizon of 7-10 days at spatial resolution to 1 km. Their approach is claimed to be a more refined model than the operational models used by the BoM and can include site-specific data assimilation. The support services and reliability are less clear as they depend on staff availability but several publications have been produced showing the very satisfactory performance in extreme events (e.g. bushfires, air quality and sailing forecasts).

A2 Description of model

The system that was implemented was strongly based on a pre-existing and proven scheme developed by Katestone Scientific for use in energy forecasting. It consists of the following steps:

(a) Obtain upper-level forecast data from numerical weather prediction models via a special web-site provided by the BoM.

(b) Collect concurrent information from an automatic weather station close to the site of interest.

(c) Once a sufficient training set of information is collected, use proprietary Katestone software to develop statistical models that relate the surface measurement to a subset of the upper-level variables.

(d) Use these models and the most recent data to provide the necessary forecasts.

The process is illustrated in Figure A1.

Past experience has shown that an accounting of natural diurnal and seasonal cycles together with a partitioning of the data into half-hourly time steps allows relatively simple linear regression techniques to be used, rather than more complex hybrid statistical/neural network schemes often used.

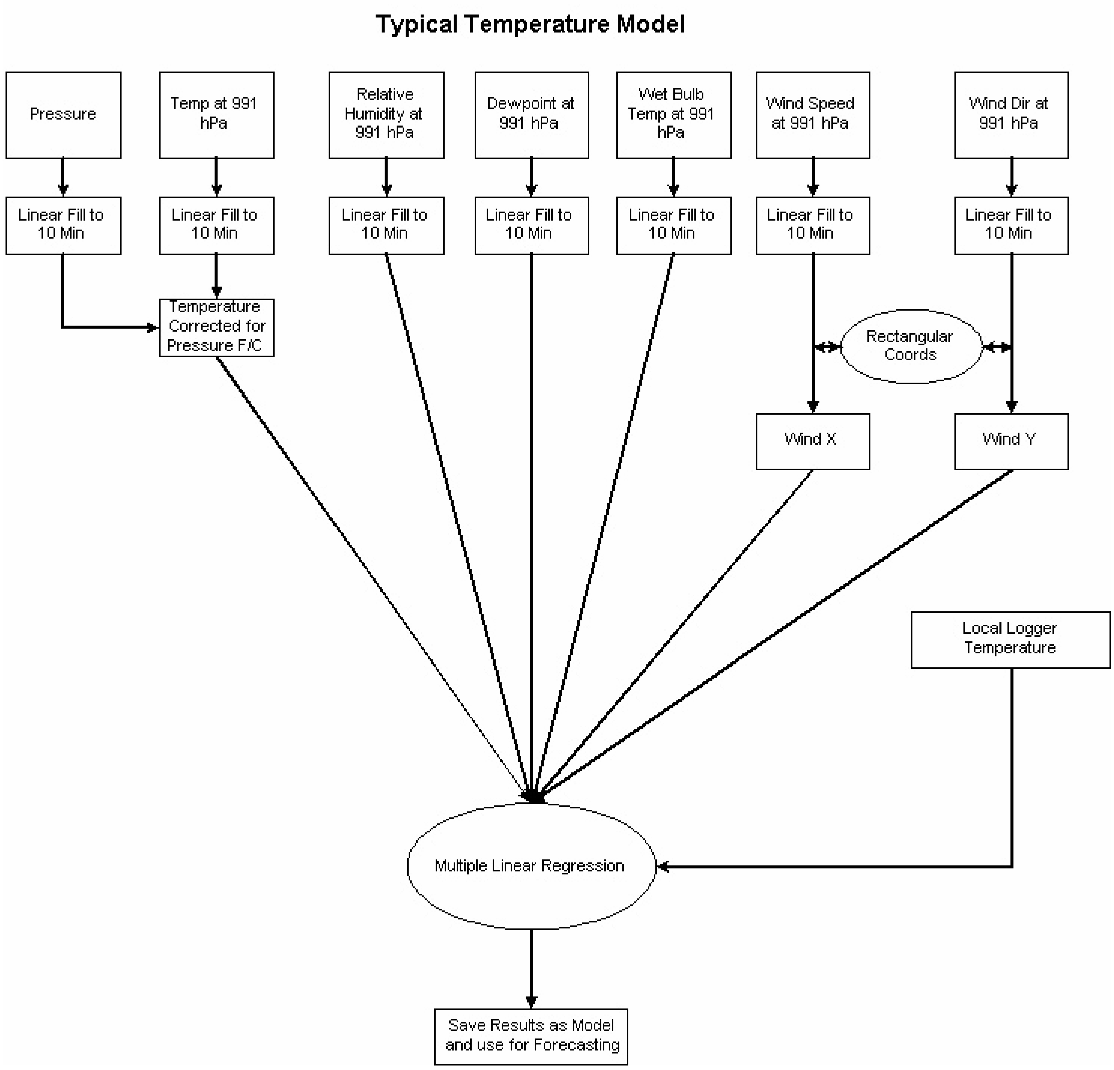

Figure A1: Example of process of using LAPS/GASP data (e.g. 991 hpa parameters) in downscaling to give a surface temperature forecast