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# Development and Trial Operation of a Weather Forecasting Service for Excessive Heat Load Events for the Australian Feedlot Industry

FLOT.313

Final Report prepared for MLA by:


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FEEDLOTS

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Abstract

Warning feedlot operators of impending adverse weather conditions that could lead to excessive heat loads (and potential mortality) for feedlot cattle would allow a planned execution of available mitigation measures. Regional public weather forecasts are not sufficiently detailed or site-specific to allow accurate estimation of the necessary animal thermal comfort parameters. An on-site weather station allows better definition of existing and future conditions, especially if used in conjunction with the detailed predictions of routine regional numerical weather prediction models operated by government and private agencies.

Such a system was tested over a four month period in summer at four feedlot sites in Queensland and New South Wales and achieved a considerable degree of skill in predicting various key meteorological variability (including a thermal stress index) out to a time horizon of 5-6 days. Other parameters that may initiate excessive heat load events (e.g. rainfall followed by hot, humid conditions) are less easily forecast in most cases.

The prototype system and associated software can be readily commercialised, either for on-farm implementation or provision by an external service agency. For smaller feedlot operations, there is still considerable utility in accessing results based on the nearest Bureau of Meteorology automatic weather station, rather than installing an on-site facility.

The prototype system is sufficiently flexible to encompass thermal comfort indices defined by other recent Meat & Livestock Association (MLA) projects and to assess production parameters relying on weather conditions.

# Executive Summary

## E1 Introduction

Various Australian and American studies have demonstrated that sustained excessive heat loads can cause severe stress and potentially premature death in feedlot cattle. Prior warning of these events will facilitate various mitigation measures such as change of diet, provision of shade and other heat-relief systems. The forecasting of conditions external to a feedlot can be used to predict internal feedlot conditions, using the results of recent MLA meteorological monitoring projects.

## E2 Key issues

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

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

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

(c) Determination of the utility of on-site micrometeorological measurements for improving forecast accuracy.

(d) Development of a prototype software system for predicting feedlot conditions.

(e) Field testing of prototype, with feedback from feedlot operators.

(f) Review of prototype and alternative delivery mechanisms for feedlot forecasts.

(g) Selection of appropriate business model for commercialisation of final system in Australia and overseas.

(h) Identification of ongoing research and development required for supporting a sustainable commercial system taking advantage of ongoing advances in cattle response evaluation and mitigation measures.

This project has focussed on items (a) – (f) but makes some recommendations on the items (g) – (h) that are outside the project scope.

At the outset, the following constraints and opportunities were identified:

- Whilst Commonwealth agencies such as the Australian Bureau of Meteorology (BoM) and CSIRO provide an ever-expanding variety of services, there is no current system in Australia dedicated to predicting thermal comfort indices on a fine timescale out to the necessary 3-6 day time horizon.

- Numerical weather prediction models, whilst rapidly improving in skill and resolution, are unlikely to be practical for forecasting down to the feedlot scale. Finer spatial resolution usually results in shorter prediction horizons.

- There is considerable research and development occurring in the United States and elsewhere on the prediction of thermal comfort indices and extreme conditions but this is in its infancy.

- Regional climate change models suggest that extreme events such as heatwaves are likely to become more frequent over the next 10-30 years.

- Weather measurement systems and associated communication systems are increasingly sophisticated, inexpensive and easy to use and install.

- Fine resolution weather prediction systems have recently been required in the privatised energy market, both for demand forecasting and risk management.

- In the next 2-5 years numerical weather modelling is likely to produce better forecasts of prediction errors as well as extending the forecast horizon to 6-10 days.

- Whilst temperature, humidity and wind predictions are easily tested, the prediction of site-specific rainfall and cloud cover is fraught with problems, due to the highly localised nature of these parameters.

## E3 Selected methodology

Experience elsewhere and for this project suggested the following preferred approach:

- Utilise fully the information from either a feedlot operator's weather station or the nearest automatic weather station run by the BoM.

- Access the most recent numerical modelling results (via agreement with the BoM or other service provider at least twice per day).

- Value-add to the numerical predictions using the on-site measurements (a "statistical downscaling" approach used by the Katestone Group in energy risk management).

- Calculate the key parameters at a fine time resolution out to 6 days ahead.

- Software system to run either on-site or remotely, including warnings on impending excessive heat load events.

- Software system to include automatic model retraining and reporting facilities (as the skill of the statistical downscaling approach improves with increasing amounts of coincident on-site measurements and numerical predictions).

- Provide fail-safe mechanisms to account for breakdowns in accessing on-site information.

The feasibility of such a system was readily demonstrated from past experience in similar ventures for 6-day ahead predictions for Eastern Australia capital cities. This project included further development of an existing system and customisation of a user interface for feedlot operators.

The preferred statistically downscaling technique utilises statistical and artificial intelligence techniques to find meaningful correlations between on-site measurements (current and historical) with current and historical predictions from the available numerical model. The prototype system accesses (via Internet) the results of the numerical model and recent BoM weather station measurements and (via telephone line) the recent measurements from the feedlot weather station. A normal PC-based system is sufficient to run than the downscaling models, produce forecasts and alert the operator to any required actions.

## E4 Field testing of prototype

Software systems were installed at the Sandalwood, Kerwee, Caroona and Rockdale feedlots in Queensland and New South Wales, in association with measurements for other MLA feedlot projects. The software gave forecasts of several alternative temperature-humidity indices (THI). Until sufficient amounts of concurrent measurements and numerical model predictions were available to train the statistical models, interim advice was based on initially the unimproved numerical model predictions, then the downscaling using regional weather stations and finally models using the feedlot information. Prototype evaluation included accuracy measures for the initial models and a complete re-evaluation at the end of the project, assuming that the system had available a three-month historical database.

Software installation was carried out jointly by Katestone Scientific and EA Systems staff, with ongoing site support by EA Systems. Some problems were experienced at the Caroona site that prevented the full evaluation by feedlot operators. The initial three-month field trial was extended by one month to overcome some of these practical problems.

## E5 Prototype performance

The forecast skill for each site and different forecast horizons was investigated for dry-bulb temperature, relative humidity, dewpoint temperature, windspeed and THI indices for the following types of prediction methods:

(a) Direct predictions of near-surface variables produced directly by the two numerical weather prediction models for the nearest grid point to the feedlot.

(b) No use of the numerical model predictions but direct use of on-site monitoring, with predictions based on assuming persistence of today's on-site conditions over the next 6 days.

(c) Downscaling, using the nearest BoM automatic weather station.

(d) Downscaling, using the on-site MLA weather station.

Table E1 gives an example of the forecast skill (represented by the mean absolute error of all forecasts within a given time horizon) for each of the four different types of prediction methods. For Method (d), the errors become smaller as the amount of concurrent training datasets (of measurements and numerical model predictions) increases. The results are for the Sandalwood, Southern Queensland feedlot. More extensive evaluation has considered the different types of downscaling techniques, other meteorological variables, the confidence limits on the forecasts and model performance at the other three feedlot sites.

Method (a) gave reasonable results, with poorer performance in the early morning and afternoon. Method (b) performed surprisingly well and illustrates the utility of collecting on-site information. Method (c) gave improvements on Method (a) but Method (d), the full on-site downscaling approach, gave the superior skill for key parameters. Method (c) can be used for all existing BoM or feedlot locations that archive historical automatic weather station variables. Method (d) requires the prior collection of 2-3 months of on-site information to provide a robust system.

**Table E1: Example of forecast accuracy (mean absolute errors) at the Sandalwood feedlot for key variables and different methods, for two time horizons.**

| Forecast scheme | Temperature (°C) | | THI (°C) | |
|---|---|---|---|---|
| | To 2 days | 2-6 days | To 2 days | 2-6 days |
| (a) LAPS/GASP raw | 2.04 | 2.57 | 3.39 | 4.03 |
| (b) Persistence | 2.17 | 2.44 | 2.61 | 3.03 |
| (c) Downscaled to nearby AWS | 1.68 | 2.09 | 2.11 | 2.58 |
| (d) Downscaled to on-site AWS* | 1.17-1.77 | 1.57-2.38 | 1.48-2.16 | 2.01-2.92 |

Note: * Range gives performance for models trained after 1 or 3 months

Downscaling approaches lead to significant overall improvements in forecasting the THI, especially if there is sufficient (greater than 2-3 months) of training data. For evaluating the performance in predicting exceedances of chosen excessive head load alert levels, contingency tests showed that, for example, 81% of the observed exceedances of the minimum stress threshold were predicted 1 day ahead, with 70% predicted 6 days ahead.

Longer-term accuracy testing on capital city forecasts has shown that downscaling outperforms weather expert systems run by the BoM and commercial New Zealand equivalents. For example, mean absolute forecast errors in Sydney City temperatures range from 1.26 – 1.44°C over different seasons for the 1-2 day horizon and 1.71 – 2.23°C for the 5-6 day horizon. Brisbane City temperatures are more easily predicted, with corresponding figures of 1.12 – 1.53°C for the 1-2 day horizon and 1.61-1.86°C for the 5-6 day horizon. Downscaling was recently recommended as a preferred approach by an expert panel of the Faraday Society in the United Kingdom.

## E6 Extensions of prototype

The spatial coverage of the prototype system is readily extended, requiring only model training on the available on-site or regional information. Feedlot operators can evaluate the utility of on-site measurements and the associated prediction system. It can be justifiably claimed that statistical downscaling does turn a weather station into an on-site weather prediction system.

The power of statistical downscaling is that the forecast variable can be any observables at the feedlot (e.g. internal feedlot conditions, evaporation measurements, cattle respiration, feed consumption rate) that are measured on a regular basis. Numerical weather models cannot do this without the development of additional mathematical models to describe each process.

## E7 Feedlot operator feedback

The length and nature of the trial made extensive feedback from the chosen feedlots relatively limited. The form and intent of the software were well-received although the degree of use was difficult to determine (especially as the 2001-2 summer conditions were relatively mild). For future projects, either more extensive training and monitoring of operator reactions or an alternative delivery service should be considered.

## E8 Forecast delivery and commercialisation issues

Feedlot operators will vary considerably in terms of available staff and expertise to use on-site software. Two alternative delivery models have been considered to ensure efficient dissemination of key forecast information:

- Redesign of prototype system to minimise the need for operator skill and to provide alert/management information on an exception/request basis.

- Develop the prototype software within a commercial organisation that will access the on-site feedlot information, produce the forecasts and send the results (via email, web or other delivery mechanisms) to the feedlot operator.

There are obvious trade-offs between the initial expense of installing an on-line system that is very flexible and the running of a 24 hour/7 day application service provider (ASP). Data confidentiality, costs and flexibility of software to accommodate changing animal response factors are key issues to consider. Larger feedlot operators or organisations operating many feedlots may find the in-house software option preferable. Smaller feedlots will be more attracted to an ASP mode, dependent on cost-benefits. Both service types are likely to be commercially feasible.

## E9 Recommendations

This project has proved the feasibility of providing 3-6 day forecasts of excessive heat load indicators such as temperature, humidity and windspeed at any feedlot. The skill of the forecasts depends on whether an on-site meteorological station is utilised, the extent of concurrent historical information from on-site monitoring and numerical model predictions and the modelling methods employed. The recent field trial started with no concurrent data; the summer conditions had very few heat-wave events. The correction factors for relating in-feedlot conditions to those predicted at the external feedlot location were not yet determined. Some monitoring/communication problems restricted testing and operator feedback at one of the four feedlots.

In light of the above, the move to a commercial system or service would benefit from a series of further investigations. The next stages of the product development should include:

(a) Assimilation of the results from other MLA projects (e.g. the University of Queensland studies on respiration, the prediction of in-feedlot conditions), and revisions to the current software outputs.

(b) Follow-up trials of the updated software over a full summer period at a major feedlot (possibly with alternative service providers).

(c) More in-depth evaluation of requirements and necessary performance with major feedlot operators.

(d) Investigation of an extension of forecast information for longer timescales using alternative techniques.

(e) Discussions with commercial organisations and any other interested partners, especially for promotion in areas outside Australia.

# 1. INTRODUCTION

## 1.1 Background

Excessive heat loads for feedlot cattle (denoted here EHL events) occur during fairly well understood conditions of high temperatures, moderate humidity, and high radiation input, occurring in conjunction with feeding regimes or cattle storage conditions that are not conducive to the rapid dissipation of heat to the local environment of the cattle.

Various studies over the past 50 years have defined relatively simple combinations of meteorological parameters that are useful in partially quantifying the change in animal behaviour throughout the progression of a heatwave. Intensive studies of feedlot operations in various countries (especially the United States and Australia) have resulted in a categorisation of heatwave events (Hahn, 1999) with effects ranging from mild (some adverse effects on cattle and production) through moderate to strong (where a significant proportion of animals are likely to show many signs of heat stress) to extreme (where a significant proportion of cattle may be at risk of dying) .

Proactive management for reducing the impact of heatwaves on cattle in individual feedlots can obviously benefit by some prior identification of forthcoming weather and heat stress conditions. Actions may then be taken to reduce the exposure of cattle to the effects of solar radiation, temperature and high humidity (for instance through the changing of feeding and watering regimes and the installation of remedial measures to increase the heat loss from affected cattle). For less severe conditions, the forward forecasting of key parameters may also assist in reducing the effects of excessive heat load on animal production and general welfare.

Heatwaves (e.g. for human comfort) are by common definition the occurrence of three (say) or more consecutive days of adverse meteorological conditions (e.g. high temperatures over 35°C). Excessive heat loads for feedlot cattle may be characterised by a different set of conditions that includes thresholds for other meteorological parameters. The information and issues considered in specifying a system for predicting EHL events should include:

- A defined time horizon (e.g. 3-7 days ahead).
- A time resolution for the information (e.g. hourly values, daily maximum).
- Thresholds for forecast or derived parameters that give information on different types of animal responses.
- The confidence levels in a given forecast.
- The sensitivity of key information to small changes in primary forecast variables.
- Some connection with past historical information for the site to set the current forecast in context (e.g. the forecast event is a 1 year occurrence, based on past records).

The meteorological forecasts are likely to be for conditions at a set of standard height levels (e.g. screen (1.2 m), 10 m, surface) and these may have to be adapted to the level appropriate to animal height or the level used for data collection in past thermal comfort experiments on feedlot cattle.

Forecasting of meteorological and associated conditions can be undertaken in many ways, from the prediction of the likely time history of individual meteorological parameters for the next few days through to the identification of the probability of a occurrence of a set of user-defined adverse days within a given time horizon.

Weather forecasting techniques are generally based on various types of numerical meteorological prediction (NWP) schemes. Meteorological models proceed by accumulating recent measurements at a large number of surface stations and for a much smaller number of locations (such as airports) where balloon and electro-magnetic radar measurements can determine the vertical profiles of key meteorological parameters. Such measurements can be readily assimilated and used to initiate computer models that describe the dynamics of the earth's atmosphere at various levels of sophistication and resolution. Over the past 50 years, the revolution in computing power has greatly increased the amount of information that can be accommodated in such data assimilation schemes and hence has improved the level of detail in the prediction for a given region.

Publicly available information is therefore becoming accurate, at least over the 1-2 day time horizon. Publicly available information is likely to be for a location some distance away from the feedlot site and various adjustments may be necessary to obtain relevant site forecasts. This is a key consideration of the current project.

There is a trade-off in NWP techniques between increasing spatial resolution and achieving the required accuracy at given time horizons. For example, recent BoM/CSIRO forecasting advances (e.g. Manins et al, 2002) are producing reasonable accuracy in key variables to a 1-3 km resolution (using significant computing resources), but the forecast horizon is usually restricted to 36-48 hours ahead. The accuracy of forecasts from current numerical models also tends to diminish when extreme conditions such as heatwaves are encountered, mainly because such events in Australia are caused by the interruption of normal westward progression of pressure systems and the greater persistence of features such as heat troughs. Such changes can be very sensitive to even small variations in synoptic wind and humidity conditions and may not be accurately portrayed by most numerical schemes.

In a similar fashion, the forecasting for longer time horizons such as 4-6 days becomes more difficult and inaccurate because of the large number of possible states that the atmospheric system may follow for a given set of initial conditions. The European meteorological agencies are now using ensemble models for providing better realism in short-term forecasts (Palmer 2000). Their model is run not once but 50-100 times to give an ensemble of forecasts for a given location. The mean of the ensemble is likely to give the "most likely" forecast but there will be other members of the ensemble that give possible outcomes consistent with the current information. For example, hurricanes were identified correctly in the ensemble forecasts for a major storm event although the single-run models give no warning of the worst wind storm event in recent European history. A useful forecasting scheme should eventually have an associated level of confidence and expected accuracy over the key time intervals on which to make management decisions.

## 1.2 Forecasting of site-specific meteorological parameters

Alternatives to NWP techniques can be used to produce detailed forecasts at a given point. These utilise historical information (over a much longer time period than NWP models) and are not as computationally intensive. They rely on obtaining reasonable NWP output at a relatively coarse or regional spatial resolution. Historical site information needs to be at a fine time resolution (e.g. hourly) to produce a significant advantage.

Automatic weather stations (AWS) are increasingly used for determining wind, temperature and radiation characteristics for the height range 1-30 m above ground on a 5-60 minute time scale.

Recent studies invariably show the limited applicability of non-continuous historical measurement programmes and the high sensitivity of local flows to station setting. Especially in the sub-tropics and inland Australia where low windspeeds are the rule rather than the exception, the range of applicability of AWS information is often less than 10-20 km (Best and Stumer, 1989).

The degree of influence of terrain/land-use features also becomes important when using numerical models to predict spatial variability of meteorological fields, both for historical events and for future horizons such as the 1-7 day view offered by modern weather forecasting schemes. Prognostic models utilise available surface information as input to the conservation and flow equations for the atmosphere. For example, the BoM offers global and limited area models (GASP, LAPS etc.) that cater for spatial scales of 5-75 km and timescales of 1-6 days. Data assimilation is usually limited to BoM AWS information from key locations and recent radiosonde/balloon profiles at airport sites. By the time of the issue of the weather forecasts, this information is at least 6-10 hours out of date.

Meteorological models such as TAPM and HIRES (Leslie et al, 2002) and air pollution forecasting schemes such as AAQFS (Manins et al 2002) may utilise assimilation schemes that can include any site data but their utility is often limited by computational requirements and the reliability of information at fine spatial scales. The CSIRO "eWeather" scheme (eRisk, 2002) gives 8 day ahead forecasts to a spatial resolution of 1-5 km but its accuracy has yet to be fully demonstrated for routine applications. Manins et al (2002) note that the AAQFS models may not resolve the local flows that are important for air pollution dispersion.

Numerical modelling approaches can forecast standard meteorological parameters and presumably those parameters directly derivable from them. However, it is not obvious how some of the easily observable surface parameters (e.g. black globe temperature, animal skin temperature) can be adequately predicted without major assumptions.

Our approach is to seek an optimal mix of techniques. The BoM can provide a relatively inexpensive web-based delivery of the latest forecasts from routine operational weather forecast models. Site-specific meteorological can be accessed very frequently. Given a suitably large combined information set from these sources, data mining tools can establish robust relationships that can be exploited for producing inexpensive forecasts.

Downscaling is the transfer of model information from large scales to finer scales (such as single locations). Statistical downscaling involves a search for correlations between large scale flows and sub-regional variables, and can be effective if the correlations are strong (Leslie et al, 2002). Numerical downscaling uses a one way information exchange via nesting of higher resolution models within a more global scheme. Roulston (2001) has reported the consensus of opinion from European numerical weather prediction specialists that downscaling techniques are likely to be essential components of practical schemes for forecasting site-specific information.

For meteorological parameters, a statistical "downscaling" procedure essentially transforms an on-site weather station into an adaptive on-site meteorological prediction system capable of predicting the following:

- Standard parameters (e.g. those available via both the AWS and prognostic model) to the time horizon of the prognostic scheme but to the time resolution of the AWS.
- Parameters that are readily derived from standard meteorological variables (but are not available in the prognostic model output).
- Most of necessary boundary layer parameters for detailed evaluation of animal heat budgets.
- Confidence intervals on these parameters, by various means (e.g. using multiple models or estimation of the forecast errors).

For past Katestone projects in energy and air quality forecasting, LAPS/GASP results (e.g. for heights corresponding to 5 pressure levels from 991 hpa to 850 hpa) corresponding approximately to 70-1350 m above local ground-level) for temperature, dewpoint, wind components and other standard variables (e.g. atmospheric stability, surface sensible and latent heat fluxes) together with surface predictions of rainfall and temperature are made available by the BoM to a dedicated client web-site at 8 am and 8 pm each day. The LAPS models give a time resolution of 3 hours, the GASP model 12 hours. These forecasts have as input the interpolated measurements from surface and radiosonde observations up to times of 9 pm and 9 am respectively (10 pm and 10 am as of March 18 2002). The AWS information is accessed electronically and automatically, typically every 30 minutes. The data-correlation "downscaling" schemes are immediately used to give 2 day-ahead (for the LAPS output) and 6 day-ahead (for the GASP output) predictions for the measured parameters. These predictions are displayed as required or made directly available as inputs to any necessary decision-support models (e.g. animal mortality risk estimation production efficiency schemes).

The wind predictions are based on correlations of wind components (U,V) followed by transformation into magnitude and direction.

Model retraining is possible at any time chosen by the operator and is usually recommended at least four times per year (e.g. as the seasons change).

The system performance can be readily reviewed (e.g. mean absolute, rms error and $5^{th}$ and $95^{th}$ confidence intervals from parametric or non-parametric distributions).

The downscaling procedure can be performed either with co-located measurement and numerical grid points or for spatially-separated locations.  The statistical approach and regional nature of the numerical prediction make the choice of numerical grid-point less critical.

This experience has formed the basis for the prediction of EHL events for this project.

# 2. STUDY DEFINITION AND OBJECTIVES

The project consisted of two stages with the following objectives:

## 2.1 Stage 1

(a) Establish the detail of the proposed weather forecast service, using available records and past R&D outcomes to review the following factors:

- Available service providers for numerical modelling results.
- Availability of real-time weather station information.
- Required spatial resolution.
- Additional processing to obtain key feedlot Excessive Heat Load (EHL) parameters.
- Available prediction horizons.
- Current statistics on availability and accuracy.
- Ongoing developments re resolution and update frequency.
- Information available from numerical forecasts.
- Geographical variability.
- Set-up costs and maintenance issues.
- Ability to forecast key set of multi-day conditions necessary for EHL events.
- Evaluation of the mechanisms by which the information could be made available to individual operators within the feedlot industry.

(b) Investigate the datasets from the MLA project FLOT.310, including the possible development of a feedlot microclimate semi-empirical model and inclusion of same into forecast software.

(c) Develop a prototype forecast system using LAPS/GASP NWP results together with available feedlot surface data. Justify the project moving to Stage 2.

## 2.2 Stage 2

(a) Trial the prototype forecast service with four feedlots across the major lotfeeding regions of Australia, during January 2002 to March 2002. Feedlots to be included in the trail include:

1. Sandalwood Feedlot, Dalby
2. Kerwee Feedlot, Jondaryan
3. Caroona Feedlot, Quirindi

4. Rockdale Feedlot, Narrandera

(b) Review prototype forecast service performance on a fortnightly basis and provide progress reports to MLA.

(c) Report project outcomes.

(d) Evaluate the practical and economic feasibility of a potential commercial service, based on the results of the trial process, and including:

1. An outline of the service capability (in terms of potential for advanced warning (days ahead) and regions covered by the service), likely format for the service and likely forecast accuracy;

2. Definition of the parameters that would need to be incorporated into the forecast service, and parameters used in developing a meaningful index;

3. Costs associated with development and ongoing operation of the service, including an evaluation of possible mechanisms for cost recovery;

4. Evaluation of the mechanisms by which the information could be made available to individual operators within the feedlot industry; and

5. Recommendations on the way forward for implementation of a commercial service.

## 2.3 Interactions with other MLA project

Advice on THI indices recommended or currently under investigation was provided by Queensland University researchers investigating cattle thermal stress for MLA project number FLOT 316. Several of these indices were incorporated into the prototype software installed at the four feedlots in the trial.

Installation and maintenance of meteorological equipment and dataloggers was the responsibility of EA Systems, under Project FLOT 317.

The co-operation of these project teams and the MLA Program Co-ordinator, especially in the early stages of the project, is gratefully acknowledged.

# 3. SHORT-TERM FORECASTING OF EXCESSIVE HEAT LOAD

## 3.1 Key parameters

Short-term forecasting is relatively well established for dry bulb temperature, dewpoint temperature or relative humidity, windspeed and wind direction. These are the essential 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 from a numerical model are difficult to use together with site rainfall information as rainfall is much less uniform in space and time than the other variables for which downscaling and other forecasting techniques have been shown to work well.

The forecasting of solar radiation is a relatively new addition to the outputs of many numerical models and any forecasts of solar radiation (or rainfall) should be viewed with caution.

The practical use of such forecasts requires a knowledge of the likely confidence in each variable and how they affect any calculated thermal comfort indices.

## 3.2 Forecasting methodologies for fine spatial resolution

The current project sought to define the potential for more accurate forecasting of excessive heat load conditions than is possible from the publicly available information services. The models on which such services are based are now capable of forecasting some primary meteorological variables at a spatial scale of 5-25 km i.e. the predictions of a location such as Oakey in Southern Queensland are likely to be applicable as an overall spatial average of the conditions likely to occur on a 25 x 25 km grid square centred on Oakey.

Such models do not contain the detailed land use and geographical information that can reflect the often quite significant changes in temperature and other variables that may occur over such relatively short distances. Wind flows, for instance, can be so readily modified by topographic differences that the information from a weather station a distance of 15-20 km away may not give a good representation of winds in a given area.

The project seeks to differentiate between predictions on the various different spatial scales important for feedlot management:

(a) Regional forecasts (useful for knowing the general conditions within a radius of 100 km); a large feedlot organisation or government regulator may be particularly interested in assigning resources between different regions, based on such information.

(b) Conditions in the general locality of a given feedlot (say within 5 km of a chosen location).

(c) Conditions on but not in the feedlot (the macroclimate).

(d) Microclimate scales where the conditions actually experienced by the animals can be evaluated.

Microclimate forecasting involves the smallest treated scale in spatial resolution. The size of a typical feedlot is typically 500 m x 500 m. The likely different soil characteristics, the presence of nearby buildings and the disturbances in local conditions caused by the heat load from the cattle themselves are the main factors likely to affect the micrometeorology of an animal in the feedlot. Whilst it will be useful to provide forecasts of the likely conditions for the region for generalised terrain surrounding the feedlot, it may be important to be able to adapt such forecasts to give an indication of the likely meteorological conditions inside the feedlot so that sensible thermal comfort indices and other indicators of normal behaviour can be predicted.

This project therefore looked at several types of general schemes for forecasting the risk of excessive heat load at a given feedlot to a time horizon of 6-7 days.

## 3.3 Available NWP services

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

(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 gridpoint 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.

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).

## 3.4 Identification of extreme events

Extreme events are almost by definition difficult to predict, either from a statistical climatological basis or from numerical weather prediction models. Ensemble NWP models may in the future give a better idea of the likelihood of either a single or cluster of days with adverse heat stress conditions, but this is very much in the research stage.

Alternative methods include the forecasting of "day types" (using cluster analysis) and the use of historical information stratified by daytype to determine probability of sustained adverse conditions. These methods have not been further investigated for this project.

## 3.5 Key thermal comfort indices

For cattle and human thermal comfort, the simplest and most robust indicator is some form of the temperature-humidity index. Previous and concurrent MLA projects have suggested that simple linear confirmations of temperature, humidity, windspeed or cross-products are sufficient to define a useful index for various cattle responses. Research also shows that an accumulation index (THI-hours) or variants are better measures of the history of exposures, heat imbalance and importance of nighttime recovery.

### *3.5.1 Temperature-Humidity Index*

Several equations for the Temperature-Humidity Index (THI) exist and were supplied for the project. Several are used in the program supplied to the feedlots; however, it was decided that only two would be analysed. The two equations analysed are "equation 4"

$$THI_4 = 0.8T + RH(T - 14.4) + 46.4$$

and a dimensionally-mixed index, "equation 6":

$$THI_6 = THI_4 - 0.5(WS - 5)$$

where
*T* = temperature in °Celsius
*RH* = relative humidity expressed as a value between 0 and 1
*WS* = wind speed magnitude in m/s

The stress thresholds used in the project were determined by the MLA project FLOT.310 and are as follows:

- TH Index of 73 to 78
  ALERT phase - mild heat loads effects especially on vulnerable cattle.
  Time to think about and implement heat load reduction strategies. Death not likely.

- TH Index of 79 to 83
  DANGER phase - strong to severe heat load effects on cattle. Death unlikely but possible.

- TH Index of 84 to 89
  EMERGENCY phase - severe to extreme heat load effects on cattle. Death possible in vulnerable cattle.
- TH index of 90 to 99
  CRISIS phase – extreme heat load (EHL). Death possible EVEN with heat load reduction strategies.

### *3.5.2 THI hours*

The available literature suggests a variety of multi-day conditions determined from past observations produce excessive heat load in various types of cattle. Much of this work has been undertaken by Professor Hahn and associates in North America. Table 1 below gives their latest recommendations as to a classification scheme for extreme events.

**Table 1: Heat wave categories for Bos Taurus feedlot cattle exposed to single heat wave**

**events, based on Grand Island, Nebraska records from 1949-1991.**

| Category | Duration | THI-hours[1] ≥ 79 | THI-hrs ≥ 84 | Nighttime recovery (hrs ≤ 72 THI) |
|---|---|---|---|---|
| 1. Slight | Limited: 3-4 days | 10-25/day | None | Good: 5-10h/night |
| 2. Mild | Limited: 3-4 days | 18-40/day | ≤ 5/day | Some: 3-8h/night |
| 3. Moderate | More persistent (4-6 days usual) | 25-50/day | ≤6/day | Reduced: 1-6h/night |
| 4. Strong | Increased persistence (5-7 days) | 33-65/day | ≤6/day | Limited 0-4h/night |
| 5. Severe | Very persistent (usually 6-8 days) | 40-80/day | 3-15/day on 3 or more successive days | Very limited: 0-2 h/night |
| 6. Extreme | Very persistent (usually 6-10$^+$days) | 50-100/day | 15-30/day on 3 or more successive days | Nil: ≤1 for 3 or more successive days |

Note: [1]THI-hours ≥ 79 is a cumulative sum of the product of (THI-79) and time, e.g. one hour of THI at 83 is equal to 4 THI hours. Similarly for columns 4 and 5.

This work suggests heat wave categories for Bos Taurus feedlot cattle exposed to single heatwave events based on observations in Nebraska over a 42-year period. The descriptive characteristics are based on a THI-hours index together with some consideration of the THI index value at nighttime after a significant daytime THI episode.

The Nebraska studies suggest that the persistence of conditions beyond 3-4 days is necessary for a classification beyond moderate. As this classification scheme only requires a relative straightforward use of temperature and humidity forecast, it is readily implemented in software from the hourly forecast discussed above. The scheme uses no additional information on solar radiation levels and low windspeeds, but notes that extreme category conditions can be lethal for vulnerable cattle when these conditions occur in conjunction with a THI-index of 86 or higher.

Recent MLA projects have suggested alternative schemes whereby extreme events are triggered by a rainfall event followed by a rapid increase in temperatures. The use of this classification scheme therefore relies on obtaining an accurate forecast of feedlot rainfall to initiate an event.

### *3.5.3 Utility of on-site weather 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. Windspeed 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.

Numerical weather prediction 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 AWS is over 15-20 km away or if the feedlot environment is unusual compared to that of the region (say within 25 km).

## 3.6 Downscaling of regional model forecasts

The first approach to 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.

## 3.7 Potential service delivery mechanisms

The BoM provides a variety of on-line services, including general weather forecasts and the results of recent meteorological monitoring from sites run by them. Detailed site predictions are not available. The Bureau could eventually run a suitable service delivery system, if they develop or purchase similar software, train the model and maintain the overall network communications with a feedlot.

This role could also be taken on by some of the agricultural science consultancy groups that now provide on a fees basis on-site meteorological station and data service.

Either government or private agencies will face similar decisions:

- Is it better to provide customised information or on-site tools to facilitate decision making?
- What level of skill should be assumed for the feedlot staff members?
- How robust is the system – is it better to centralise processing systems and rely on good communications or facilitate most information processing on-site?
- Should the system provide ways in which to evaluate the confidence in the forecasts?
- What can a given type of operator afford for capital or ongoing costs?

For this project, the installation of on-site software was chosen as the better way of providing a temporary and relatively flexible system. In the earlier stages of the project, when software was under development, site forecasts were emailed to project participants.

## 3.8 Evaluation methodology for forecast skill

Weather forecasts are now readily available electronically from various sources and at various accuracies. The level of skill can be judged from how better the accuracy is over assuming that tomorrow is a repeat of today (the "persistence forecast"). The American Meteorological Service for example, has issued a policy statement on weather forecasting (AMS, 1979) noting that "skill cannot be said to exist unless forecast accuracy exceeds levels achieved by basic methods such as persistence or climatology". The accuracy of current models generally depends on the spatial scale, weather parameters and forecast horizons, with a general consensus that there is:

(a) To 12 hours, good skill on a scale of several kilometres, except near mountains, coastlines and urban areas.

(b) For 12-48 hours, good skill in general forecasts (10-100 km scale).

(c) For 2-5 days, moderate skill for temperature and precipitation.

(d) For 5-30 days, some skill at least to 10-15 days, dependent on methodology.

Some studies have shown that the skill in temperature forecasts with increasing time horizon decays slower than for precipitation forecasts. Beyond 6-10 days, temperature forecasts often do little better than persistence.

The errors in any forecast of feedlot conditions from the current project approach will be due to:

(a) Errors in the modelling of multivariate processes using past feedlot and weather information.

(b) Errors in upper-level weather predictions.

(c) Errors in extrapolation of upper-level weather to surface variables.

The sources of errors in (a) are the systematic errors involved in the correlation of chosen thermal comfort indices with measurement of cattle stress at other sites and will occur for several reasons (e.g. prior experimental design or transferability of results, incompatible meteorological measurements, implicit assumptions).

The errors in (b) are due to the accuracy and temporal validity of information used in the global and regional forecast models and the representation of local topography within these schemes. These are beyond the control of any user and will be reduced as the BoM and/or other service providers introduce finer-scale regional models and increase the frequency of model updates or if alternative modelling facilities are utilised.

The errors in (c) will be due to inaccuracies in the downscaling modelling procedure and to the limited amount of information available for model training.

The downscaling forecasts contain errors of type (b) and (c) but, being an automatic error-correction technique and as no manual intervention is possible, the overall procedure should become more accurate as more data become available to train the system.

# 4. PROTOTYPE FORECASTING SYSTEM AND TESTING

## 4.1 Overall methodology

The prototype system 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 1.

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

The robustness of this approach was demonstrated by the error statistics Table 2 obtained for a one year period for various parameters and the location of Sydney and Brisbane. For example, there is a pleasing performance for temperature and windspeed, with only minor seasonal variations and the expected slow decrease in accuracy with an increasing prediction horizon.

This MLA project provided some new challenges to the existing methodology:

(a) There was very little, if any, concurrent information available until one month after the project commencement.

(b) On-site information was collected by another organisation working under very tight deadlines.

(c) The data were collected on a 10 minute timescale, not the 30 minute period used in previous studies.

(d) Graphical User Interface (GUI/software) had to be written to access the site information, perform the modelling and provide relevant outputs to a feedlot operator.

Point (a) meant that the accuracy of any initial downscaling models was likely to be relatively poor. It was not known how much concurrent information would be required to obtain stable models.

Point (b) lead to a staged introduction of the full system, with the Sandalwood feedlot being the main initial focus.

Point (c) lead to more complex modelling and a later decision to revert to a 30 minute averaging of either the predictions or the input information.

User-friendly software (point (d)) was facilitated by use of in-house expertise and rapid development/testing techniques.

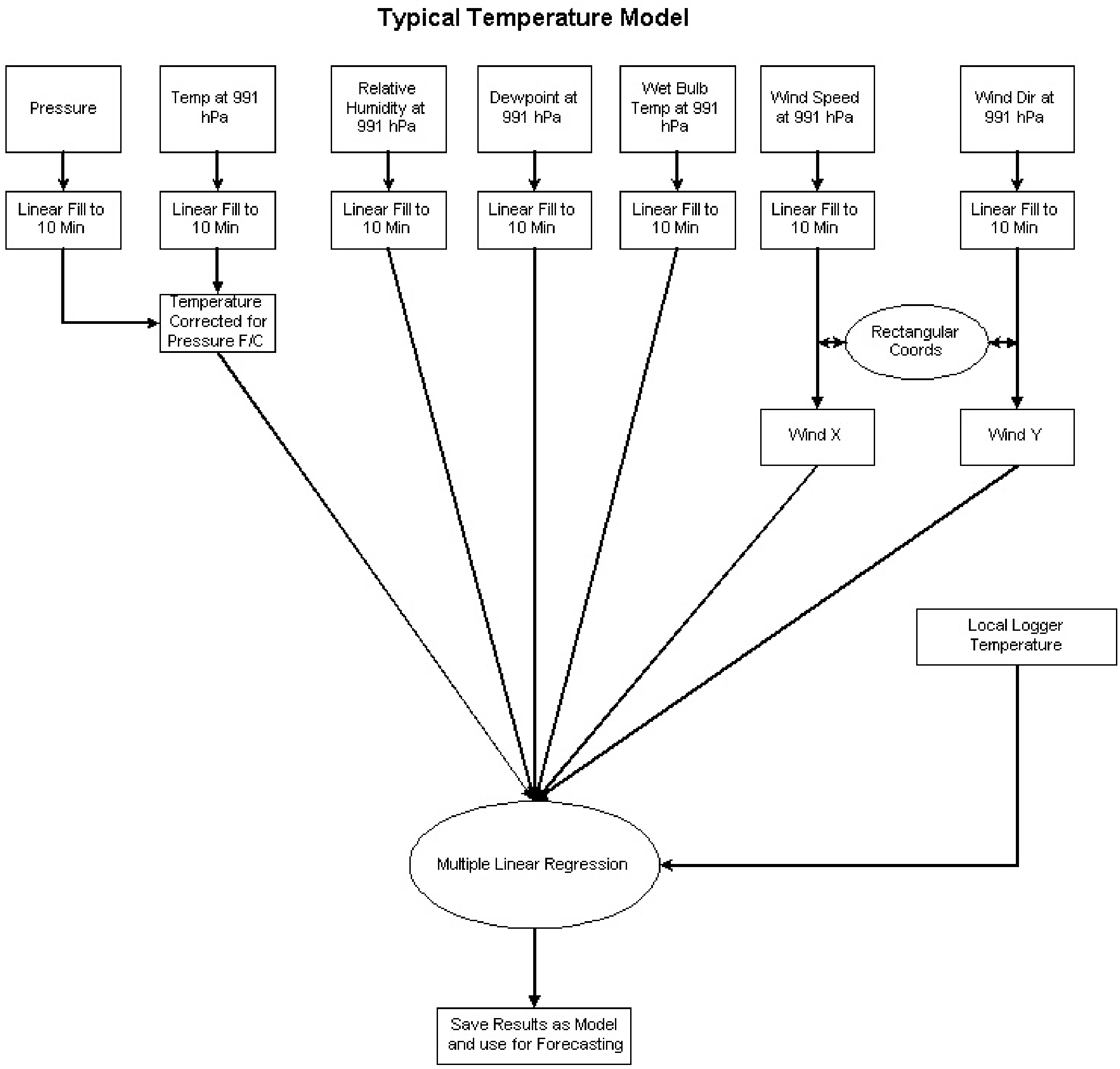



Figure 1: Example of process of using LAPS/GASP data (e.g. 991 hpa parameters) in downscaling to give a surface temperature forecast

At the same time, it was recognised that, with summer well started, there was a need for immediate warnings (of whatever accuracy possible) to the feedlots. The BoM provided almost immediate access to their LAPS/GASP modelling results for the four feedlot locations – their surface level predictions could be utilised immediately. Katestone also had an archive of upper-level forecasts and surface measurements for some regional locations that could give regional downscaled results. Interim measures were therefore possible for the first month or so whilst dedicated site models were being developed.

**Table 2: MAE for Sydney and Brisbane forecasts**

| Variable | Season | Forecast horizon | | |
|---|---|---|---|---|
| | | 1 - 2 days | 3 - 4 days | 5 - 6 days |
| **Sydney Temp (°C)** | Summer | 1.44 | 1.78 | 2.15 |
| | Autumn | 1.26 | 1.72 | 1.88 |
| | Winter | 1.27 | 1.52 | 1.71 |
| | Spring | 1.37 | 1.61 | 2.23 |
| **Sydney Wind Speed (m/s)** | Summer | 1.62 | 1.84 | 1.95 |
| | Autumn | 1.54 | 1.56 | 1.60 |
| | Winter | 1.44 | 1.74 | 1.68 |
| | Spring | 1.86 | 2.03 | 2.09 |

### *4.1.1 Types of site-specific forecasts*

During the course of the trial, several prediction schemes were utilised at each feedlot and forecast accuracy was assessed upon completion. The prediction methods were as follows:

(a) Use persistence only i.e. assume the diurnal profiles for the next six days will be the same as today, as given by the on-site weather station.

(b) Use the surface predictions of the LAPS/GASP schemes directly.

(c) Utilise downscaling based on correlation of the upper-level data with the nearest BoM AWS.

(d) Utilise downscaling based on correlation of the upper-level data with an on-site AWS.

(a) Scheme (a) gives a simple method that only recognises the value of collecting on-site data. Scheme (b) gives the bare skill of the BoM forecast model, with no additional data assimilation. Scheme (c) may be attractive as a low capital cost option, depending on the distance of the nearest BoM AWS. Scheme (d) is the highest-cost option that may be preferred where the consequences of extreme events are severe

Scheme (d) has been further broken into 5 separate models:

1. Original supplied to the feedlot, trained on 1 month of collected data,

2. A simple re-train of (1) on the first 3 months of collected data,

3. 1 hour data partitioning instead of 3 hourly,

4. (3) including extra post-processing with Katestone's proprietary auto-regressive model component.

(1) 5. (3) with 30 minute averaging of the 10 minute data collected.

### 4.1.2 Numerical model service

The BoM kindly provided the twice daily outputs of the numerical models at the grid points closest to the feedlots to a secure web-site, together with AWS information for the nearest Bureau site and additional information such as synoptic weather charts. The latter were provided to the feedlot operator within the user interface (Appendix F). The Bureau is thanked strongly for their rapid co-operation and for making the information available at no cost for this trial project.

### 4.1.3 Choice of test sites and forecast parameters

The feedlot sites were chosen to cover a range of climates and to facilitate various aspects of the other concurrent MLA research projects. The Sandalwood and Kerwee feedlots were visited by Katestone staff during initial software utilisation but otherwise all feedlot interaction was conducted by telephone by Katestone or during site maintenance visits by EA systems.

Initial testing on regional data showed little utility in the rainfall forecasts for use on a site-specific basis. It was decided to concentrate on the elements of the conventional and University of Queensland thermal comfort indices:

- Temperature, dewpoint and relative humidity.
- Windspeed and direction.

These variables were forecast for the location of the weather station external to the feedlot. An investigation into the project database obtained in project FLOT. 309 during the previous summer at two feedlots (Appendix G) gave site-dependent factors to correct to in-feedlot conditions. A facility to include these external-to-internal feedlot factors was built into the software but not utilised. It is expected that the more detailed monitoring at each site conducted by EA Systems will allow this factor to be more firmly established for future investigations at the various sites.

### 4.1.4 Project timescales

The project timescales were as follows:

| | |
|---|---|
| Project start date | 19/11/01 |
| Inception meeting | 26/11/01 |
| Participating feedlots chosen | 26/11/01 |
| Stage 1 report | 21/12/01 |
| Site data collection start | 27/12/01 |
| BoM forecasts of EHL indices provided for all feedlots | 14/01/02 |
| Sandalwood installation of GUI | 30/01/02 |
| Models and GUI supplied to all feedlots | 11/02/02 |
| Site data collection end | 6/5/02 |
| Data analysis complete (incl. new models) | 23/04/02 |

### 4.1.5 Interface with on-site weather station.

The on-site feedlot weather stations were installed by EA Systems with an external modem access, available to feedlot operators and externally. Katestone staff received on-site data either from EA Systems or by direct, regular downloading from the site itself. Communication problems were experienced at the Caroona site, making downscaled forecasts only available on-site towards the end of the project.

### 4.1.6 On-site software

The 2 programs created and used for the trial, HB and GetMet, are designed to work together to interrogate an on-site weather station datalogger and download weather information. The programs also interrogate the BoM server to download their forecasts. For this project, these interrogations must be initiated manually, due to the necessity of an Internet link.

From the measured and forecast temperature, humidity and wind speed, the temperature humidity index (THI) is calculated and displayed for several time horizons. The capability to view the stored data, as well as BoM generated weather pressure maps, is provided (Appendix F).

It should be pointed out that for the HB program supplied the wind speed data are not all in the same units. The LAPS & GASP data are in knots, the on-site data in km/hr and the AWS data in m/s. All have been converted to m/s for the comparisons in this report and will be converted for future HB programs.

### 4.1.7 Accuracy

Forecast errors are based on the differences between the predictions and the on-site AWS measurements, that is mean forecast errors on the absolute differences (MAE). It should also be noted that the accuracy of the forecasts has a practical, if not theoretical, lower limit due to the nature of the weather. Figures 2 and 3 give examples of forecast accuracy for respectively quasi-stationary and strongly-varying conditions, and are for Model 3, one of the later, more accurate models developed.

Subsequent tables (e.g. Table 3) give mean absolute errors (MAE) for each parameter, model and prediction horizon, together with non-parametric confidence intervals indicated by the two numbers in square brackets. The Confidence Interval Limits column in the table indicate that 95% of the forecast errors will fall within the limits given by the reported values, showing whether the majority are higher, lower or evenly spread about the actual value.

The number of hours ahead indicated in captions for both tables and figures, relates to the length of time past when the forecast was created. Prior to March 18 model creation time was at 9 pm EST and became 10 pm afterwards. Thus 9 hours ahead translates to a forecast for 6 am EST (7 am after March 18), 12 hours to 9 am etc. These points in time coincide with the more important times relating to cattle heat stress as well as the LAPS/GASP data timings.

Note:

1. In the case of the WSpeed variables, forecasts were for the height of 10 m only but have been compared to both the actual 10 m and 2 m winds for testing and interest.

2. Rel Hum and Dew Pt are related by a specific equation. In some cases it was necessary to calculate one parameter from the other. Dew Pt on-site was calculated from the measured humidity.

3. The BoM forecasts are only 3 hourly out to 2 days and 12 hourly out to 6 days and as such have significantly less data points, affecting the overall tables' C.I. Limits.

In the summary produced below, model evaluation considerations are based on the forecasts for the Sandalwood feedlot. Appendices A-E give the relevant statistics for the main models for all sites.

The conventional benchmark for comparing accuracy (persistence i.e. predictions of "Tomorrow will be the Same as Today") has been assessed by using the data recorded by the on-site weather stations effectively duplicated for one to six days ahead.

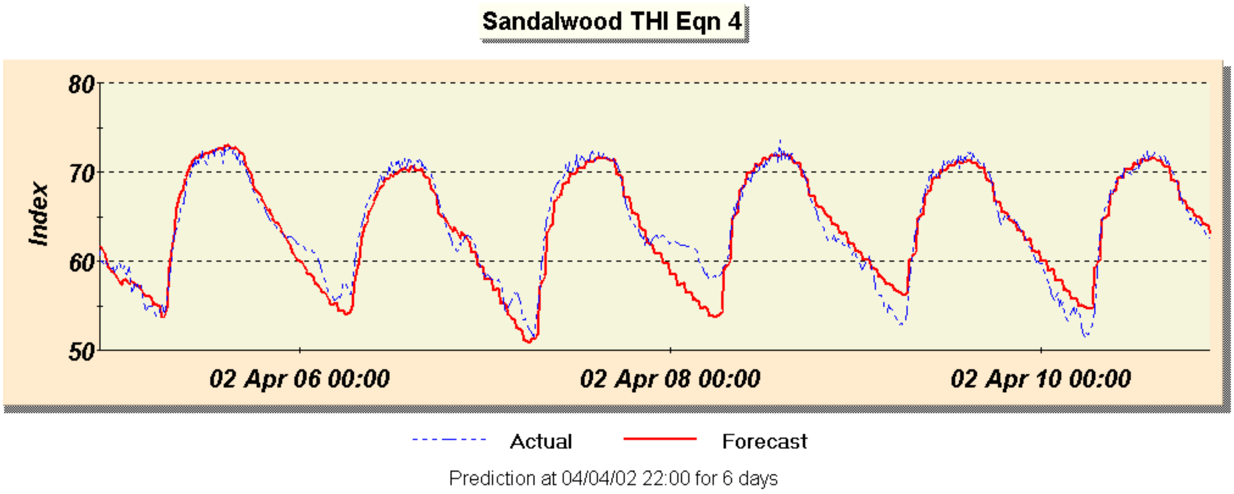



Figure 2: Example of a typical forecast for THI at Sandalwood.

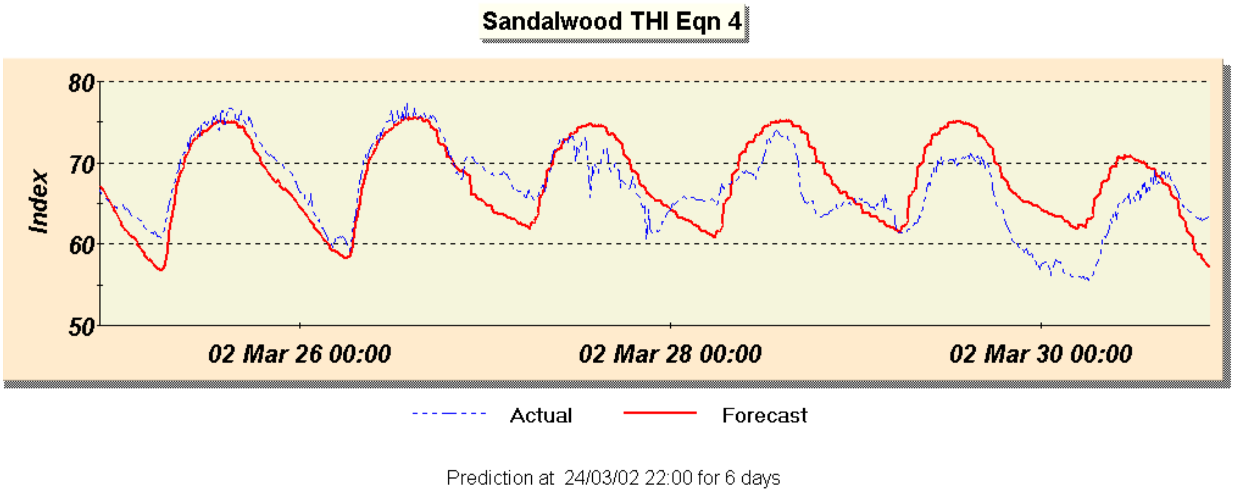



Figure 3: Example of a forecast for THI at Sandalwood when non-typical days occur.

## 4.2 On-site meteorology and persistence forecasting, method (a)

### *4.2.1 Available information, method (a)*

The availability of the data was not under the direct control of Katestone Group and some data are missing. The LAPS and GASP daily files have only a few scattered dates missing whilst the recorded data from a weather station occasionally loses several days in a row for a sensor if it becomes faulty.

Table 3 summarises what feedlot weather station information was unavailable for analysis, noting that this affects analysis for all forecasting methods.

**Table 3: Summary of missing surface data from the four on-site weather stations.**

| Feedlot site and parameters | No. Days | Dates | | | |
|---|---|---|---|---|---|
| Sandalwood | | | | | |
| Air Temp | 5 | Jan 1 - 5 | | | |
| Rel Hum | 5 | Jan 1 - 5 | | | |
| Dew Pt | 5 | Jan 1 - 5 | | | |
| Wspeed 2m | 5 | Jan 1 - 5 | | | |
| Wspeed 10m | 5 | Jan 1 - 5 | | | |
| | | | | | |
| Rockdale | | | | | |
| Wspeed 2m | 9 | Jan 7 - 15 | | | |
| Wspeed 10m | 21 | Jan 7 - 15 | Feb 4 - 6 | Feb 16 - 21 | Feb 27 - 29 |
| | | | | | |
| Caroona | | | | | |
| Air Temp | 13 | Feb 1 - 12 | | | |
| Rel Hum | 13 | Feb 1 - 12 | | | |
| Dew Pt | 13 | Feb 1 - 12 | | | |
| Wspeed 2m | 13 | Feb 1 - 12 | | | |
| Wspeed 10m | 13 | Feb 1 - 12 | | | |
| | | | | | |
| Kerwee | | | | | |
| Air Temp | 27 | Jan 1 - 5 | Jan 18 - 30 | Feb 4 - 9 | Feb 19 - 21 |
| Rel Hum | 45 | Jan 1 - 5 | Jan 18 - 30 | Feb 4 - Mar 2 | |
| Dew Pt | 45 | Jan 1 - 5 | Jan 18 - 30 | Feb 4 - Mar 2 | |
| Wspeed 2m | 27 | Jan 1 - 5 | Jan 18 - 30 | Feb 4 - 9 | Feb 19 - 21 |
| Wspeed 10m | 27 | Jan 1 - 5 | Jan 18 - 30 | Feb 4 - 9 | Feb 19 - 21 |

### *4.2.2 Forecast accuracy, method (a)*

For the persistence benchmark (i.e. no use of NWP information, only the duplication of recent on-site measurements), the means of the difference between predicted and measured values of each variable for various forecast horizon times are shown in Table 4 and are for the entire 4 month duration of the field trial. Temperature MAE are typically 2-5 - 3°C over the first 24 hours, relative humidity errors 10%, windspeed errors 1 – 1.5 m/s and THI errors around 3 (i.e. 3 in 60).

The width of the confidence interval for the difference between predicted and measured values is reasonably consistent for all variables across the four forecast time horizons and the confidence intervals are evenly spread about zero as expected. The interval limits were generally ± (2 to 2.5) times their respective absolute mean.

The 9 hours ahead and 18 hours ahead predictions, which are important as they are nearest to the minimum and maximum temperatures for the day, typically have higher mean errors and tend also to have slightly greater confidence intervals. This seems also to be the case with the other forecast methods detailed later in the report.

**Table 4: Error Comparisons for Method (a), Persistence approach for Sanalwood.**

| Forecast | Overall | | 9hrs Ahead | 12hrs Ahead | 15hrs Ahead | 18hrs Ahead |
|---|---|---|---|---|---|---|
| **Variable** | **MAE** | **C.I. Limits** | **MAE** | **MAE** | **MAE** | **MAE** |
| Temp | 2.44 | [-5.67, 6.13] | 2.57 | 1.75 | 2.35 | 3.21 |
| Rel. Hum. | 10.51 | [-15.93, 23.79] | 8.18 | 9.73 | 9.79 | 11.98 |
| Dew Pt. | 2.50 | [-5.62, 6.21] | 2.79 | 2.27 | 2.40 | 2.30 |
| Wspeed 2 m | 1.04 | [-2.38, 2.40] | 0.69 | 1.38 | 1.49 | 1.38 |
| WSpeed10 m | 2.54 | [-3.89, 3.65] | 1.95 | 3.11 | 2.89 | 2.94 |
| $THI_4$ | 3.03 | [-5.76, 7.57] | 4.18 | 2.33 | 2.57 | 2.83 |
| $THI_6$ | 3.38 | [-6.42, 7.98] | 4.00 | 3.12 | 3.45 | 3.34 |

## 4.3 Direct use of LAPS/GASP forecasts, method (b)

These forecasts refer to the surface level predictions of the LAPS/GASP models as given in the direct output unconditioned by any past comparisons with on-site data. This information is not expected to be accurate as it refers to an average for the region (i.e. dependent on model resolution).

### *4.3.1 Available information, method (b)*

The BoM on request makes LAPS and GASP data available to clients on a password-protected web site. Data are supplied for user-specified sites only, but arrangements can be made for additional sites if required. Data are kept on the site for around 2 weeks and are not archived by the BoM, so a historical database can only be produced by downloading data onto external computers.

**Table 5: Available Sites for Historical LAPS/GASP Data, as held by Katestone Scientific**

| Queensland | NSW / ACT | Victoria | SA | WA |
|---|---|---|---|---|
| Archerfield | Badgerys Creek | Bendigo | Adelaide | Perth |
| Bundaberg | Bankstown | Melbourne | | |
| Cairns | Canberra | | | |
| Coolangatta | Homebush | | | |
| Emerald | Newcastle | | | |
| Gladstone | Penrith | | | |
| Kingaroy | Sydney | | | |
| Mackay | Williamtown | | | |
| Maroochydore | Wollongong | | | |
| Maryborough | | | | |
| Nambour | | | | |
| Rockhampton | | | | |
| Toowoomba | | | | |
| Townsville | | | | |

LAPS/GASP data are updated twice daily, early in the morning and early in the afternoon. The Getmet program provided by Katestone Scientific can automatically check for new data and download it to a local computer for use by other prediction software.

The available information for each site comprises zonal and meridional winds, temperature, mixing ratio, dew point, wet bulb temperature, relative humidity, wind speed and wind direction at various heights defined by pressure levels as well as surface temperature and pressure. Sites for which Katestone Scientific has archived data are summarised in Table 5.

### 4.3.2 Forecast accuracy, method (b)

Errors in parameters predicted using LAPS/GASP method (b) are summarised in Table 6, again for the full period of the trial. Compared with the benchmark persistence method (a), the LAPS/GASP method has a higher mean error by a significant amount for most variables. This means that direct use of LAPS/GASP raw surface predictions is worse than the persistence method for predicting surface level conditions. The differing MAE values can be expected since the LAPS/GASP forecasts are more for upper level, as opposed to ground level.

The forecasts for the first 48 hours are more accurate and have less spread in the C.I. Limits than the forecasts for the next 4 days (Tables 8, 9, 14, 15, 20 and 21, Appendices A - E). Again this is to be expected due to the greater forecast horizon and the difference in LAPS and GASP prediction horizons.

Comparing different times of the day (for the first 48 hours only as GASP forecasts are only available for 2 times per day), the greater errors and larger spreads occur consistently more often in the early morning and in the afternoon (6 am and 3 pm, Table 5, Appendix A). The temperatures at the times expected to correspond to daily minimum and maximum temperatures are therefore more difficult to predict than for the rest of the day. The errors and spreads of the first 2 days, and also of the latter 4 days, for each time, are similar as expected coming form LAPS and GASP respectively.

In a monthly breakdown (Tables 20 and 21 and Figure 11, Appendices A - E), the mean differences for the method (b) remain reasonably consistent as the weather becomes milder, although the confidence interval moves from reasonably evenly spread about zero to having a positive offset.

Windspeed is the only variable for which this method does not at some stage have poorer performance skill than the benchmark. This is probably partly because the method (b) predicts average values relevant to a period of hours while the persistence benchmark contains abruptly changing and directionally influenced 10 minute average values.

There is an obvious difference between the MAE and C.I. Limits of the errors for the 9 hour ahead wind speed forecasts and the other times, probably due to the variability and magnitude of changes between nocturnal and daytime wind conditions as the earth heats up. Nocturnal winds are calmer than daytime winds and this is shown in the lower variability of the forecasts.

Method (b) appears to predict the average wind speed with some accuracy as the C.I. Limits were almost exactly even about zero. On further examination, the wind speed forecasts do not alter in accuracy significantly as the months go by. This last point is true for method (c) and method (d) also.

**Table 6: Error Comparisons for Method (b), the direct LAPS/GASP Method for Sandalwood.**

| Variable | MAE | C.I. Limits |
|---|---|---|
| **Temp** | 2.57 | [-3.72, 6.60] |
| **Rel. Hum.** | 14.94 | [-32.04, 16.61] |
| **Dew Pt.** | 2.18 | [-5.01,3.43 ] |
| **WSpeed 2** | 1.95 | [-1.07, 4.09] |
| **WSpeed 10** | 1.57 | [-2.92, 3.00] |
| **THI 4** | 4.03 | [-6.12, 9.03] |
| **THI 6** | 3.78 | [-5.21, 9.43] |

## 4.4 Downscaling and AWS usage, method (c)

### 4.4.1 Model accuracy with regional AWS, method (c)

Errors for the AWS method (c) are summarised in Table 7, based on a training dataset of 1½ - 3 months and errors evaluated over a 2-4 month period. This method overall resulted in lower MAE for most variables than the benchmark method (a) and by a significant amount (Tables 8, 9, 14 and 15, Appendices A - E). It is worth noting, however, that in those cases where the mean is worse for the AWS method, the spread in C.I. Limits is generally smaller, i.e. where predictions are worse on average, they are not as scattered as the benchmark. The C.I. Limits are also reasonably evenly spread about zero. Wind speed predictions were worse for the downscaled predictions (Tables 20 and 21, Appendices A - E). The generally improved accuracy compared to the LAPS/GASP method (b) is mainly due to the downscaling involved.

The forecasts for the first 48 hours are more accurate and have less spread in the C.I. Limits than the forecasts for the next 4 days (Tables 8, 9, 14, 15, 20, 21, Appendices A - E). Again this is to be expected due to the greater forecast horizon and the difference between LAPS and GASP intervals on which the forecasts are based.

Comparing different forecast horizons, the errors increased as the forecast horizon became larger, as expected. The errors and spreads for the first 2 days, and also the latter 4 days, are similar as expected being based on LAPS and GASP results respectively.

Comparing different times of the day, the greater errors and larger spreads again occurred consistently more often in the early morning and afternoon, for the first 48 hours (Table 6, 12, 18 and 24, Appendices A - E), except for wind speed for which they were generally largest in the evening. The next 4 days are much the same with afternoons being more difficult to predict for the AWS method. This last note is probably due to the GASP 12 hourly timings falling in the late morning and early night.

Finally the monthly statistics showed that the AWS method improved as the weather became milder (Tables 9, 14, 15, 20, 21, 26 and 27, Appendices A - E). The C.I. Limits range moved from generally negative to approximately symmetrical about zero (Figure 14, Appendix A).

**Table 7: Error Comparisons for Method (c), the downscaled regional AWS Method for Sandalwood**

| Variable | MAE | C.I. Limits |
|---|---|---|
| **Temp** | 2.09 | [-5.05, 3.56] |
| **Rel. Hum.** | 8.45 | [-16.65, 19.35] |
| **Dew Pt.** | 2.18 | [-5.20, 3.30] |
| **WSpeed 2** | 2.69 | [-0.94, 5.25] |
| **WSpeed 10** | 2.00 | [-2.03, 4.31] |
| **THI 4** | 2.58 | [-5.79, 4.86] |
| **THI 6** | 2.67 | [-5.40, 5.84] |

## 4.5 Downscaling with on-site AWS, methods (d1) - (d5)

### *4.5.1 Forecast accuracy*

This section reports the error statistics for methods (d1) – (d5) that use on-site meteorological information with different amounts of training data, data partitioning, averaging period and use of short-term memory. Method, model (d1), with only 1 month of training data and the model originally supplied to the feedlots, resulted in lower mean errors for most variables than the benchmark method (a) and by a significant amount. However, for Temperature, Humidity and both THI equations, the AWS method (c) out performed the on-site method, model (d1). Model (d1) outperformed the AWS method (c) for Dew Point and Wind Speed. Again, where the MAE is worse than the benchmark method, the spread in the C.I. Limits is generally smaller, so the predictions are not as scattered, although worse on average .

The C.I. Limits of model (d1), although smaller than the benchmark method (a), are positive for the majority of the time, unlike those for the AWS method that are relatively symmetric about zero. This can be explained by the AWS method being trained on more data than the on-site method. An improvement was seen in the statistics after a simple retraining of the models when more data were available, as demonstrated in the next section of this report.

Once again the forecasts for the first 48 hours are more accurate and have less spread in the C.I. Limits than the forecasts for the next 4 days.

Comparing results for different prediction horizons, the errors increase in general as the horizon gets larger, as expected. The error magnitudes for the first 2 days (from LAPS) are similar for each method at each time. Errors for days 3 – 6 (from GASP) are also similar for each method at each time.

Comparing different times of the day, the greater errors and larger spreads still occur consistently more often in the early morning and afternoon, for the first 48 hours. The performance for the later 4 days are much the same again probably due to the GASP 12 hourly timings falling in the late morning and early night.

Finally, the monthly statistics showed that the MAE for the on-site method became a little worse as the weather became milder and the C.I. Limits range moved from reasonably symmetric about zero to positive.

**Table 8: Error Comparisons for Method (d), downscaling with 1 month of on-site information for Sandalwood**

| Variable | MAE | C.I. Limits |
|---|---|---|
| **Temp** | 2.38 | [-2.81, 6.23] |
| **Rel. Hum.** | 9.57 | [-25.44, 10.46] |
| **Dew Pt.** | 1.73 | [-3.56, 4.13] |
| **WSpeed 2** | 1.48 | [-1.42, 3.11] |
| **WSpeed 10** | 1.27 | [-3.14, 2.28] |
| **THI 4** | 2.92 | [-3.56, 7.81] |
| **THI 6** | 3.44 | [-5.16, 8.80] |

Model (d2) is the same as that supplied to feedlots for evaluation, but re-trained on 6-10 more weeks of data. As expected, forecast performance improved to the extent that it now outperforms the method (c) by a significant amount.

Figure 4 shows the considerable improvement obtained in the THI with the downscaled models between the 1 month (method (1)) and 3 month (method (d2)) training periods, with lower MAE and C.I. intervals. The forecasts from method (d2) are more evenly spread about the observed value whereas method (d1) is based on overprediction the majority of the time. It was also evident that the accuracy varied at differing times of the day, the earlier (cooler) parts being more difficult to forecast than the later (warmer) parts.

**Table 9: THI Error Comparisons for different types on on-site downscaling models for Sandalwood**

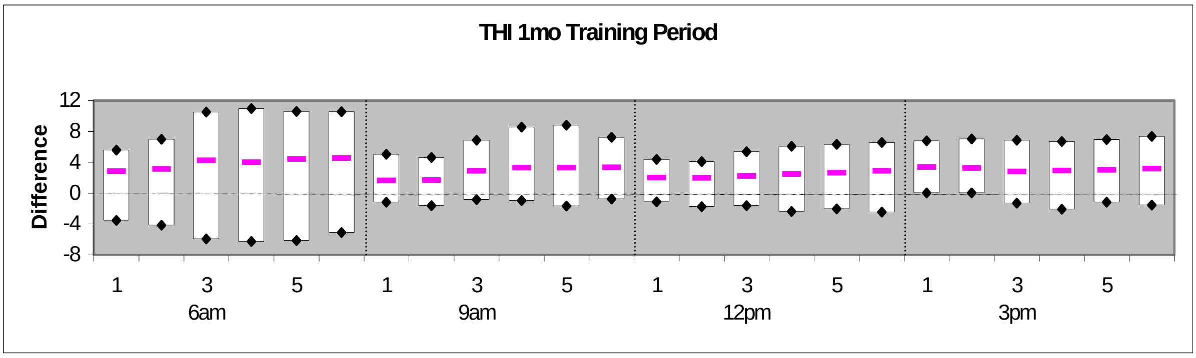
| Forecast horizon | Models for Method (d) | | | | |
|---|---|---|---|---|---|
| | (d1) | (d2) | (d3) | (d4) | (d5) |
| Day 1 | 2.09 | 1.47 | 1.37 | 1.37 | 1.33 |
| Day 2 | 2.24 | 1.71 | 1.66 | 1.66 | 1.63 |
| Day 3 | 3.08 | 2.31 | 2.00 | 2.01 | 1.97 |
| Day 4 | 3.23 | 2.49 | 2.20 | 2.20 | 2.17 |
| Day 5 | 3.39 | 2.69 | 2.43 | 2.42 | 2.41 |
| Day 6 | 3.52 | 2.83 | 2.59 | 2.58 | 2.57 |

Models (d3), (d4) and (d5) are relatively minor improvements to model (d2), the best performing model depends on the variable being considered, indicating a practical, if not theoretical, limit on the accuracy possible. The increase in error with forecast horizon was still apparent.

Breaking the data into the specific forecast horizons, the increase in accuracy for model (d1) forecasts compared to models (a) to (c) is most apparent for 15 and 18 hour ahead forecasts. An increase in accuracy for the temperature of between 0.2° and 2.2°C was obtained. The improvement was more marked for the times and days ahead that the 1 month trained model was worse than the benchmark.

Likewise, the increase in humidity accuracy was between 1.4% and 2.5% for most forecast horizons, with an improvement of up to 7.3% obtained for the times and days ahead that the 1 month trained model was worse than the benchmark.

The result of the improvement in temperature and humidity forecasts leads to an improvement in the THI forecasts. The increase in THI accuracy was between 0.3 and 2.1°C and again was more marked for the times and days ahead that the 1 month trained model was worse than the benchmark.



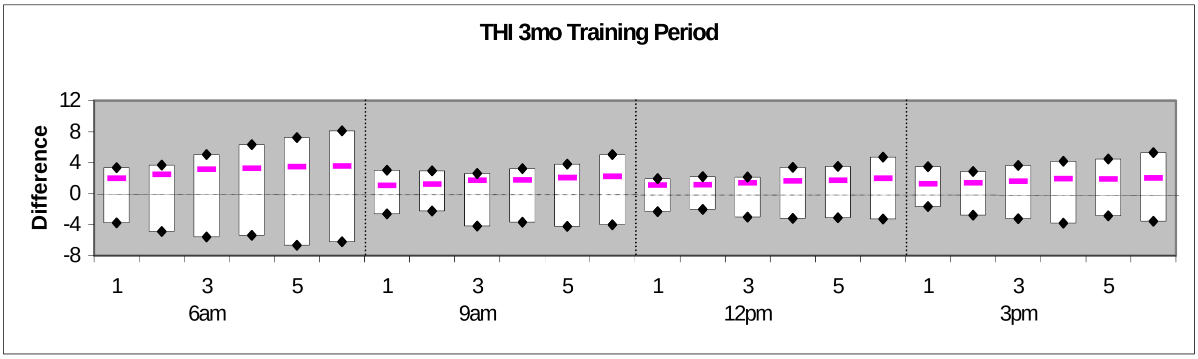




Figure 4: THI Error Comparisons between 1 Month and 3 Month Training Periods, for Sandalwood.

### *4.5.2 Accuracy for predicting exceedances of threshold levels for comfort indice*

Table 10 shows the contingency tables for predicted and observed number of hours[1] over specified THI thresholds for 1, 3 and 6 days ahead as given by model (d4). The second *(italicised)* digit on the diagonals is the observed number of hours for each range. Most predictions fall within their target ranges, although for extreme values and longer forecast horizons, the system underpredicts THI.

Summation of results gives the total hours above the minimum stress threshold (THI 72 and above), showing that over 81% (617 / 759) of observed exceedances are predicted 1 day ahead, and 70% (530 / 759) predicted 6 days ahead. This does not take into consideration the borderline observed values ('69 – 72' column) slightly underpredicted, nor the large number of times when a forecast was not made / missing (up to 80 data points).

[1] An average of the preceding six 10 minute data points was taken to obtain the value of each hour.

**Table 10: Contingency table of Model (d4) THI forecasts**

| | | | | | | |
|---|---|---|---|---|---|---|
| **Day 1 THI Forecast** | | | | | | |
| | | 69 – 72 | 72 – 75 | 75 – 78 | 78 – 81 | 81+ |
| Actual Data | 72 – 75 | 61 | 236 / *361* | 28 | 3 | 0 |
| | 75 – 78 | 1 | 67 | 153 / *267* | 14 | 0 |
| | 78 – 81 | 0 | 6 | 34 | 73 / *131* | 3 |
| | 81+ | 0 | 0 | 0 | 0 | 0 / *0* |
| **Day 3 THI Forecast** | | | | | | |
| Actual Data | 72 – 75 | 100 | 164 / *361* | 64 | 2 | 0 |
| | 75 – 78 | 6 | 75 | 131 / *267* | 18 | 0 |
| | 78 – 81 | 0 | 8 | 33 | 72 / *131* | 4 |
| | 81+ | 0 | 0 | 0 | 0 | 0 / *0* |
| **Day 6 THI Forecast** | | | | | | |
| Actual Data | 72 – 75 | 63 | 139 / *361* | 63 | 12 | 0 |
| | 75 – 78 | 13 | 93 | 73 / *267* | 34 | 4 |
| | 78 – 81 | 1 | 9 | 40 | 54 / *131* | 9 |
| | 81+ | 0 | 0 | 0 | 0 | 0 / *0* |

## *4.5.3 Model performance for all feedlot sites, using method (d)*

Table 11 and 12 show the comparisons between the forecast errors for different variables, at the different feedlots, for the downscaling to on-site A.W.S. method. As shown before the errors for the first 48 hours are significantly less than the errors for forecast horizons of 48-144 hours. The magnitude of these errors is similar for all feedlot sites with the exception of Rockdale, which is probably due to its southerly position and nearby mountainous terrain.

**Table 11: Forecast accuracy for method (d) - comparison between sites for first 48 hours.**

| Variable | **Temperature** | | **Relative Humidity** | | **THI equation 4** | |
|---|---|---|---|---|---|---|
| **Forecast** | **MAE** | **C.I. Limits** | **MAE** | **C.I. Limits** | **MAE** | **C.I. Limits** |
| Sandalwood | 1.77 | [-1.80, 4.70] | 7.54 | [-18.82, 8.43] | 2.16 | [-2.39, 5.87] |
| Rockdale | 2.09 | [-3.74, 5.31] | 9.50 | [-25.13, 16.41] | 2.71 | [-5.00, 7.00] |
| Kerwee | 1.40 | [-2.67, 3.26] | 8.20 | [-18.62, 14.69] | 2.44 | [-3.23, 6.38] |
| Caroona | 1.27 | [-2.24, 3.05] | 6.79 | [-16.00, 13.32] | 1.90 | [-1.76, 5.03] |

**Table 12: Forecast accuracy for method (d) - comparison between sites for 48 hours onwards.**

| Variable | **Temperature** | | **Relative Humidity** | | **THI equation 4** | |
|---|---|---|---|---|---|---|
| **Forecast** | **MAE** | **C.I. Limits** | **MAE** | **C.I. Limits** | **MAE** | **C.I. Limits** |
| Sandalwood | 2.38 | [-2.81, 6.23] | 9.57 | [-25.44, 10.46] | 2.92 | [-3.56, 7.81] |
| Rockdale | 4.06 | [-5.87, 11.01] | 13.42 | [-38.38, 16.23] | 5.05 | [-7.26, 13.79] |
| Kerwee | 2.23 | [-4.55, 5.14] | 10.74 | [-24.74, 20.09] | 3.26 | [-4.52, 8.14] |
| Caroona | 1.75 | [-2.65, 4.69] | 8.36 | [-18.33, 27.33] | 2.69 | [-2.69, 7.36] |

## 4.6 Forecasting of in-feedlot conditions

Normally weather stations inside the feedlot will not be available and some accommodation is required to allow for the differential temperatures, windspeeds etc. between the weather station external to the feedlot and typical internal feedlot conditions (e.g. with and without shade under normal stocking densities).

The MLA intensive studies in the summer of 2001-2 in the summer of 2001-2 have produced a three-month dataset for two feedlot locations, with weather stations external and inside the feedlot. The internal feedlot stations have been for shaded and unshaded locations. This dataset is useful in giving an idea of the variability in feedlot microclimate.

MLA project FLOT 310 investigated conditions external to the feedlot (at 3-4 locations) and internal (1 shaded and 1 unshaded site). The project report considered mainly the monthly average values of key parameters and found the following significant differences:

(a) Relative humidity 8-15% higher in shaded pens compared to external or unshaded sites.

(b) Significantly lower soil temperatures in shaded pens.

(c) Dramatically reduced (by 70-80%) incoming solar radiation in shaded pens.

(d) Significantly different wind speeds in the internal pens compared to external sites.

(e) Higher minimum dry bulb temperatures within the feedlot sites.

For the current project, the full FLOT 310 database has been investigated to determine whether a set of correction factors (where sensible) can be applied to the data for the external site for predicting in-pen microclimate from predictions of values of key parameters external to the feedlot. The correction factors are based on a multiple linear regression of hourly subsets of the database. This methodology has been found previously as a practical approach to the often non-linear relationships between meteorological variables (especially if non-natural factors such as cattle-herding cause microclimate changes). A summary of the findings is given in Appendix G but the results are limited and the analysis should be repeated on the more recent dataset.

The forecasting of microclimate values can be undertaken from any type of forecast for the external site. The overall steps in this process are therefore:

(a) Obtain current measured values for the external site.

(b) Obtain numerical model forecasts for the feedlot region.

(c) Downscale the numerical model results if possible to get primary forecasts of key variables at external feedlot site.

(d) Apply correction factors (or models) to obtain forecasts of in-pen conditions.

(e) Display forecasts for key variables for external, internal shaded and internal unshaded locations.

Future feedlots are unlikely to undertake internal monitoring but the above “correction” scheme can be used if we assume that the correction factors at a given location can be deduced from those found for the past or current four feedlot sites.

# 5. SERVICE DELIVERY AND UTILITY

## 5.1 Service options

### 5.1.1 Alternatives

There are many methods whereby a sub-set of the detailed available information can be provided to various types of feedlot operators. The type of service provided depends upon the individual requirements of the feedlot, the importance of weather information for their ongoing operations as well as the impact of excessive heat load events, the resources that can be devoted to these tasks and the level of skill of feedlot personnel in utilising the information. The following list covers the main types of mechanisms:

(a) Full delivery of information via the use of on-site software to correlate feedlot meteorological measurements with numerical model forecasts.

(b) Provision of a sub-set of information direct to the feedlot user, with all data processing occurring at a central location away from the feedlots. This can be done either electronically, or by normal hard copy facilities and could be sent on a regular basis.

(c) Provision of alert information only to feedlot owners.

### 5.1.2 On-site software installation

The provision of on-site software has the following advantages:

- The operator has access to a full set of displays and visualisation tools.
- Any historical databases that have been collected can be accessed.
- Automatic alarm messages can be provided when critical conditions have been forecast.
- Easy access can be provided to all information on the service provider web site (such as weather maps, general text forecasts and information from other locations) and
- It is possible to integrate the forecast information into a feedlot decision support system.

The use of on-site software requires only moderate computing facilities (a small to medium expenditure in capital), Internet access is essential (preferably with no firewalls to slow down or impede the collection of information from external web sites) and a small amount of user training is required to enable full operation of the system.

The functions of the on-site software are:

- To access the normal forecasts from the service provider web site.
- To determine whether there has been any recent updating of feedlot meteorological information, to collate the forecast of different types into suitable files.
- To process the straight and downscaled forecasts for key parameters into forecasts for the range of heat comfort indices required.
- To determine from these forecasts whether there are any forthcoming conditions that need to be alarmed and,
- As the skill in forecasting and management procedures increases, to recommend remedial actions that should be taken for any predicted forthcoming events.

The software interface has been designed in such a way that key information is continually being updated on a standard front screen but the user can readily navigate through the software to access more detailed information as required (see Appendix F).

The other features of this approach are that there are minimum requirements on the organisations providing the numerical forecasts, the retraining of weather models and setting of alarms can be kept under feedlot control, the service can be enhanced to provide specialised services, the software itself can be customised to suit local requirements and other facilities become possible (e.g. in the event of a feedlot weather station breaking down, it would be possible for the forecast to proceed via access to the nearest BoM AWS site).

It is also possible for major feedlot organisations to undertake forecasts for the range of sites covering other operations from one central location.

### *5.1.3 Application service provider (ASP) mode*

An applications service provider (ASP) mode requires the service hub (e.g. Katestone in the trial program) provide central computing facilities to access all web sites and all feedlot weather stations. This would require the central computer to regularly poll all the participating feedlot sites, download the information, access the numerical modelling for the nearest sites, undertake all downscaling forecasts and calculations of feedlot parameters. Based on an agreed format for the required feedlot information, regular updated reports can be provided via electronic web/fax delivery to the feedlot. All model maintenance and retraining would be undertaken by the ASP organisation.

This mode of operation is one that has a minimum requirement on any feedlot apart from providing access to any on-site information. It does, however, have significant implications for the organisation providing this service.

The ASP organisation needs to provide a 7-day a week, 24-hour per day backup service and in many ways would be responsible for the quality control of feedlot forecasts.

The ASP mode allows for an easy backup by using information from various types of weather station (e.g. both feedlot and BoM) so that, in the event of a feedlot station not being available, a suitable substitute can be found, with any differences between the feedlot stations and the substitute station being handled via correction factors determined from historical records.

The ASP mode offers the facility for extra services such as the better tracking of frontal movements by the service organisation (e.g. via the employment of a meteorologist dedicated to these tasks) to provide a fuller service during heatwave conditions.

The service provider mode also allows feedlots without their own weather station to obtain similar information from the use of the nearest AWS station but with the caveat that this is unlikely to include site microclimate features.

From the feedlot perspective, the arrival of a precis of the relevant information would minimise the time requirements on the feedlot personnel and the information could be included in any decision support system. The ASP mode makes it slightly more difficult for the feedlot operator to have access to the detailed information, although it would be relatively straightforward for the service provider to send precis messages to the feedlots as well as make available other information on a customised web site.

The ASP mode may have some drawbacks if communications between the service provider and feedlot weather stations are temporarily unavailable but this can be handled by the use of back-up stations as described above.

## 5.2 Feedlot commentary on provided system/software

Generally favourable responses were received on the utility of the graphical user interface and the forecasting system. Detailed feedlot comments on the utility of the system from a decision-support viewpoint were probably hindered by the relatively mild summer conditions and the reduced need for action over the period when the prototype system was fully functional.

## 5.3 Setting up for a new feedlot site

The following actions are required to set up an initial system for any feedlot:

- Negotiations with the BoM to make available LAPS and GASP numerical modelling results for the location of each of the four chosen feedlots. This information was provided direct to a secure Katestone web site and the BoM has not charged for this trial.

- Arrangements were made so that the feedlot computer could access directly the information from the on-site weather stations. This was undertaken by another contractor and service is currently available on an as-required basis by the feedlot operator. It is possible to automate the downloading of the weather station so that updates of both site data and the corresponding downscaled forecasts can be automatically undertaken.

- For downscaling operations, it was necessary to obtain of the order of one month's coincident information from the feedlot station and from the numerical forecasts. This information was then processed by an analyst to provide a suitable set of site weather models. As more information is collated, the weather models should periodically be retrained. This can either be done by the feedlot operator or by the ASP organisation.

- The software has to be installed on site, communications and information retrieval checked and training undertaken of the feedlot operators. For future installations, it is probably worthwhile to use software such as PCAnywhere in an initial period to allow an external person to check the performance of the software on the feedlot computer and, if necessary, to download new weather models or updated software.

Once in operation, the downscaling system works well and there are very few obviously wrong forecasts. The maintenance requirement for a feedlot operator is to ensure that the model retrain facilities are used on a regular basis (e.g. monthly) but this should not be an arduous task if automatic retraining is available.

If information is provided via the ASP mode, all the set-up costs would be borne by the service provider and presumably recharged as part of an annual fee for the full service.

## 5.4 Recommended implementation for a commercial service

### *5.4.1 General considerations*

Staff at feedlots tend to have conflicting priorities and limited experience with computer systems. For these reasons, it is recommended that any system be as automated as possible and preferably regularly checked by an external expert. This would allow, for example, identification of problems such as gradual sensor failure or data errors that might not be obvious to an untrained worker. The system needs to be operating optimally to provide useful warning, but operators are unlikely to pay much attention to it until a potential heatwave conditions are imminent.

Reporting software needs to be readily understandable by an untrained operator and the current Windows-based system should provide a good basis for future development. The main problem that has been encountered to date is the availability of dialup communications links to on-site dataloggers in automatic weather stations and dialup Internet connections which have often not been available. In addition, the lack of permanent connections and the use of computers for other purposes has meant that automatic operations are not easy to implement. Manual update buttons on the main display screen add potential confusion for untrained staff and leaving the update up to an operator means that the data displayed may often be out of date.

For these reasons, it may be desirable for some sites to utilise an application service provider mode (ASP) service in which a central organisation collects all weather station and forecast information, undertakes all processing and delivers various levels of forecasts to different users. This would probably operate as a subscription service, perhaps in conjunction with the data collection and extension services. Operators would be provided with daily bulletins by fax or Internet, without having to worry about issues such as data update frequency, data accuracy and the meaning of various display options.

### *5.4.2 Approximate costings*

The business model for any commercialisation of the prototype can use the following costs:

- Set-up of BoM websites for (say), 100 locations in the feedlot areas, including LAPS/GASP predictions and BoM AWS information, where available - $10,000 initial + $30,000 - $50,000 per annum.
- Purchase of Katestone forecasting engine - $30,000
- Model building (per site) - $1000
- Commercialise prototype GUI - $20,000
- Computing resources for ASP mode - $25,000 + $50,000 per annum.
- Staff resource for ASP mode - $60,000 per annum.

This suggests an ASP operation aiming at 100 feedlot clients would cost $185,000 set-up and $115,000 per annum. This would suggest a commercial price of $3,000 - $5,000 setup and $3,000 per annum for each feedlot location for the basic service (with full flexible service being 3-5 times this cost).

If larger feedlots wish to purchase an on-site software system, the likely costs are $15,000 - $20,000 set-up and $3,000 - $5,000 per annum.

The above costs are indicative only but may be useful in an initial market survey.

# 6. RECOMMENDATIONS FOR FUTURE WORK

Further work is recommended to train models on a longer period of data, improving the accuracy of their predictions. Software could be modified to allow the user to automatically retrain the models from the existing database.

Cluster analysis of synoptic weather conditions would allow more accurate prediction of extended heatwave conditions.

The software could be enhanced for the ready inclusion of modified indices, including specific input parameters such as cattle breed, coat length, age and feeding regime. Indices based on THI hours and recovery periods could readily be included.

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

## 6.1 Further testing of system accuracy

Testing of system accuracy has indicated that the initial prototype system, based on approximately one month of data, gave some indication of the likelihood of heat stress for up to 6 days. The system was subsequently retrained on several months of data and accuracy improved significantly.

Testing for additional summer periods would allow evaluation of performance of the system for extreme events, rather than the limited range of values normally encountered.

## 6.2 Incorporation of other MLA research results

Recommended comfort indices initially under investigation in other MLA contracts have been incorporated into prototype software. The final recommended indices can readily be incorporated into future software versions.

## 6.3 Forecasting extreme events

Work performed for the MLA weather risk assessment has shown that the categorisation of THI events by synoptic daytype is very useful. This may be extended to look at the likelihood of high THI-hours on a succession of days, utilising the available historical databases. For some regions with extensive past information and assuming that past observations are relevant to the current global/regional climate, it may be possible to predict accurately the synoptic daytypes for the next 5-7 days and thus give a risk rating, rather than base the alert system on detailed hourly forecasts. This method could be readily investigated for relevant locations.

## 6.4 Service level options and feedlot risk management

The minimum cost approach that would be useful for feedlot operations management would be to subscribe to a service based on regional BoM upper-level predictions. This could be in the form of daily faxed bulletins, Internet site information or emailed bulletins. This approach has been found to have limited prediction skill at the sites investigated, but may be effective at some geographical locations.

The preferred approach adopted for the trial was to maintain a weather station adjacent to the feedlot measuring those key variables needed to construct a range of thermal comfort indicators (e.g. temperature, humidity, windspeed, rainfall, pressure and incoming solar radiation). A half-hourly or better time resolution is necessary to be of use in a warning system. This information is combined with BoM upper-level data and forecast software provides predictions with interpretation on a local computer.

An alternative is to use application service provider mode (ASP) service in which a central organisation collects all weather station and forecast information, undertakes all processing and delivers various levels of forecasts to different users. This would probably operate as a subscription service, perhaps in conjunction with the data collection and extension services. Operators would be provided with daily bulletins by fax or Internet.

# 7. CONCLUSIONS

Excessive heat load (EHL) events occur in intensive feedlots under persistent hot, moderately humid conditions where high solar radiation, low windspeeds or recent rain prevent heat escaping from the vicinity of the cattle herd. Prediction of feedlot microclimate conditions over a 3-7 day time horizon has been identified as a major aid to proactive management and the selection of remedial measures to reduce the heat load of cattle.

This report summarises the available prediction approaches that were developed and implemented at four feedlots for the first three months of 2002, as part of a major MLA investigation initiative.

There are several potential providers of numerical forecasts of near-surface meteorological conditions over regions of dimension 5-25 km surrounding a given feedlot. The most cost-effective service for the project was available from the BoM and consists of results from both global and regional models, out to time horizons of 6 and 2 days respectively. Other services offer higher spatial and temporal resolution but have not yet demonstrated superior performance for key variables. Rainfall forecasts for any scheme have much poorer accuracy than other key variables.

These models forecast only a first-order estimate of general feedlot conditions for the region and are more skilful at predicting winds, temperature and water content at heights above ground greater than 50 m. Below this height, terrain and surface features not resolved by the numerical model have a considerable influence.

Real-time weather information at or near the feedlot is very useful to improve these forecasts, provide up-to-date values of accumulated thermal comfort indices and provide comparison with past site conditions. The minimum requirement is to access the nearest BoM automatic weather station (AWS), although, in some cases, this may be over 100 km away. Once beyond a range of 10-30 km (dependent on terrain and closeness to the coast), it is unwise to extrapolate some meteorological variables, even for a macroclimate.

Additional methods are required to convert down to the smaller length scales required for the cattle microclimate. The preferred approach adopted for the trial was to maintain a weather station adjacent to the feedlot measuring those key variables needed to construct a range of thermal comfort indicators (e.g. temperature, humidity, windspeed, rainfall, pressure and incoming solar radiation). A half-hourly or better time resolution is necessary to be of use in a warning system.

To be of use in feedlot management, information on predictions of key variables is required at a spatial resolution of 5 km or better (for the general feedlot environment) and preferably corrected to a 250 x 250 m size grid-cell containing the feedlot pens. Only research numerical weather prediction models have this resolution but may be available routinely within 2-5 years. Their ability to forecast conditions for time periods of 2 or more days ahead is expected to be limited. The resolution will never be sufficient to deal with the in-pen environment.

Predictions from numerical weather prediction models with spatial resolution of 25-75 km can be interpolated in time to give hourly values. Good predictions of general feedlot conditions can be obtained if the modelling results are used continuously in conjunction with recent and historical feedlot measurements (e.g. as in a “statistical downscaling” approach).

The predictions from any weather forecasting scheme require further processing to yield a set of thermal comfort parameters for feedlots. The developed software allows for prediction of several indices. Recent recommendations from feedlot researchers on single event heatwave categories can also be readily incorporated.

Model forecast accuracy varies with parameter type. Reliable temperature predictions can be obtained to a 5-6 day time horizon (and often longer for some conditions). Humidity and wind predictions tend to degrade after 3 days. There is currently little information available on the reliability of rainfall and solar radiation (or similar) forecasts. Some numerical models give nominal predictions for a region to 7-10 days but forecast skill (judged against improvement above “same conditions as yesterday” forecasts) is dependent on model and chosen parameter.

Current numerical models operate efficiently at a 25 km resolution and an update frequency of twice per day. This resolution is likely to be improved, the time horizon extended and the update of forecast improved in the next 18 months (for the BoM models). Research models are available with better capabilities but long-term support may not be as readily available.

The additional information available with most numerical models (e.g. contours, windfields, weather maps) are useful in extreme conditions but may not be required by most users on a regular basis. The developed software allows access to such information on the service provider website, including text forecasts and surface pressure charts for the next 3-4 days.

Numerical models are able to provide full coverage of Australian states and the use of global models gives some information for sites external to Australia. Downscaling is in principle available for any site worldwide.

The costs of set-up and maintenance need to be considered in the light of the requirements of individual feedlot organisations. An automated on-site service can be provided at a relatively low cost but without on-call access to a meteorological expert for interpretation of extreme events. The feedlot operator can be trained readily to use the full software at various levels of sophistication.

The alternative to having the full software operating on-site is to operate an application service provider mode (ASP) in which a central organisation collects all weather station and forecast information, undertakes all processing and delivers various levels of forecasts to different users. This would probably operate as a subscription service, perhaps in conjunction with the data collection and extension services.

The delivery of ASP services could cover a variety of mechanisms from weatherfax to emailed spreadsheet files or extending to a customer web site on which summary and detailed files/results are available. An ASP service could also incorporate the provision of expert help in adverse conditions and could more readily deal with rapidly changing conditions by having real-time access to a large number of weather station sites at the different feedlots and BoM sites. The ASP service also allows for ready backup and easier access to updated methodologies.

A series of recommendations has been given to facilitate further development and testing of the prototype system. However, the current base system could be commercialised almost immediately. Alternatively, the BoM could be approached to provide an Australia-wide operational system using the current software applied to existing BoM regional automatic weather stations.

Future research and development could include a further investigation of the different methods for predicting heatwave events (perhaps coupled to a fuller use of long-term on-site or regional surface meteorological information) and a quite different approach to provide information at time horizons of 10 – 180 days, not currently covered by routine numerical weather prediction models.

Finally, the possible integration of short-term predictions of feedlot conditions with a cattle-specific thermal comfort model may be possible in a timeframe of 2 – 5 years, once sufficient experimental information is available for calibration.

Excessive heat load in cattle is likely to be preventable; this project forms one link in the choice of reasonable first steps.

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# TABLES:



# FIGURES:

# APPENDIX A. – SANDALWOOD TABLES AND FIGURES

## Benchmark

Table A1. – Overall Error Comparisons in Persistence Weather Station Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| Variable | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| Temp | 2.57 | [-4.94, 5.74] | 1.75 | [-3.50, 4.45] | 2.35 | [-4.87, 5.69] | 3.21 | [-6.79, 8.36] |
| Rel. Hum. | 8.18 | [-21.78, 18.39] | 9.73 | [-24.44, 22.63] | 9.79 | [-22.17, 22.18] | 11.98 | [-32.59, 30.54] |
| Dew Pt. | 2.79 | [-6.32, 6.48] | 2.27 | [-5.82,5.67] | 2.40 | [-4.72, 5.88] | 2.30 | [-4.85, 5.91] |
| WSpeed 2* | 0.69 | [-1.66, 1.68] | 1.38 | [-2.97, 2.82] | 1.49 | [-3.36, 3.28] | 1.38 | [-2.88, 2.91] |
| WSpeed 10 | 1.95 | [-2.53, 2.31] | 3.11 | [-5.12, 4.35] | 2.89 | [-4.39, 4.43] | 2.94 | [-4.68, 4.27] |
| THI 4 | 4.18 | [-7.93, 9.43] | 2.33 | [-4.76, 5.83] | 2.57 | [-4.97, 6.42] | 2.83 | [-5.51, 6.90] |
| THI 6 | 4.00 | [-7.56, 9.08] | 3.12 | [-6.20, 7.49] | 3.45 | [-6.91, 8.04] | 3.34 | [-6.31, 7.83] |

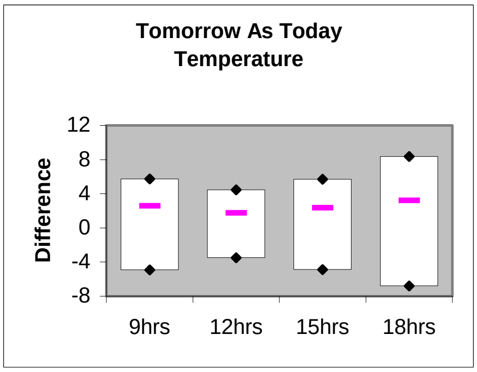



Figure 4(a)

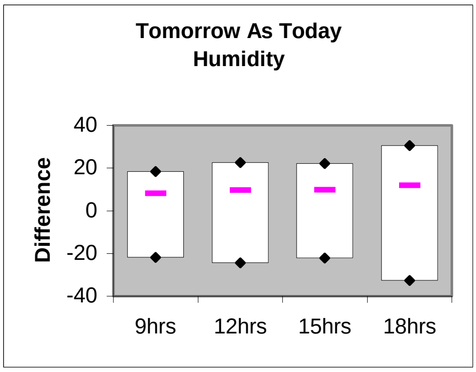



Figure 4(b)

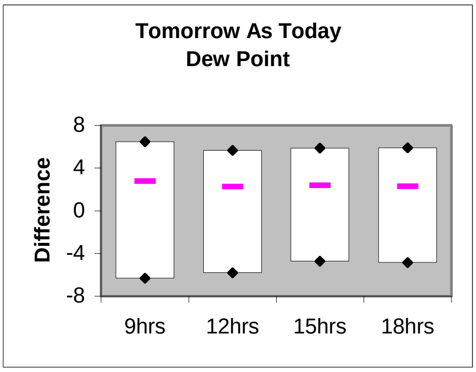



Figure 4(c)

* The exception whereby forecasts are for 2m wind speeds.

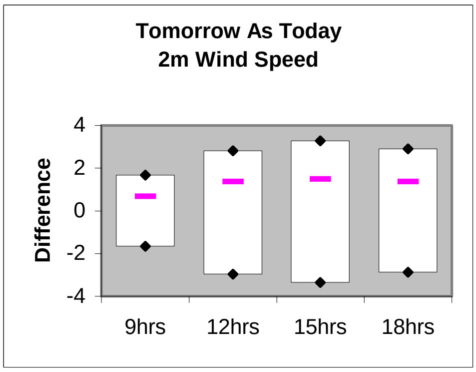



Figure 4(d)

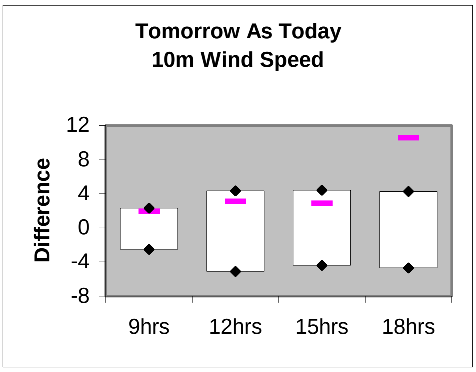



Figure 4(e)

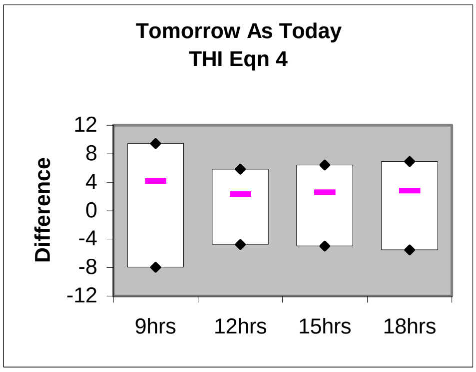



Figure 4(f)

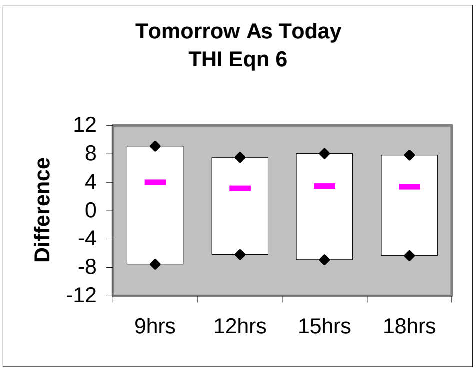



Figure 4(g)

Figure A1. – Persistence forecasts (benchmark) for different variables and time horizons.

# Overall

Table A2. – Overall Error Comparisons by Method and Variable for First 48hrs.

| Forecast | Persistence | | On-Site Downscaled | | BoM Predictions | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Temp** | 2.04 | [-4.07, 5.24] | 1.77 | [-1.80, 4.70] | 2.17 | [-3.91, 4.67] | 1.68 | [-3.92, 2.85] |
| **Rel. Hum.** | 8.17 | [-21.39, 17.63] | 7.54 | [-18.82, 8.43] | 11.61 | [-27.56, 13.48] | 7.11 | [-13.54, 16.45] |
| **Dew Pt.** | 2.03 | [-4.54, 4.74] | 1.36 | [-2.71, 3.00] | 1.93 | [-4.28, 3.28] | 1.88 | [-4.65, 2.54] |
| **WSpeed 2** | 1.01 | [-2.38, 2.29] | 1.43 | [-1.28, 3.24] | 1.46 | [-3.04, 2.22] | 2.53 | [-0.94, 5.14] |
| **WSpeed 10** | 2.68 | [-3.74, 3.61] | 1.22 | [-2.88, 2.34] | 1.52 | [-1.51, 2.99] | 1.81 | [-1.94, 4.02] |
| **THI 4** | 2.61 | [-5.35, 6.73] | 2.16 | [-2.39, 5.87] | 3.39 | [-6.09, 7.05] | 2.11 | [-4.70, 3.94] |
| **THI 6** | 2.94 | [-5.90, 7.09] | 2.86 | [-4.60, 6.83] | 3.14 | [-5.03, 7.47] | 2.24 | [-4.34, 5.15] |

Table A3. – Overall Error Comparisons by Method and Variable for hours 48 onwards.

| Forecast | Persistence | | On-Site Downscaled | | BoM Predictions | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Temp** | 2.44 | [-5.67, 6.13] | 2.38 | [-2.81, 6.23] | 2.57 | [-3.72, 6.60] | 2.09 | [-5.05, 3.56] |
| **Rel. Hum.** | 10.51 | [-15.93, 23.79] | 9.57 | [-25.44, 10.46] | 14.94 | [-32.04, 16.61] | 8.45 | [-16.65, 19.35] |
| **Dew Pt.** | 2.50 | [-5.62, 6.21] | 1.73 | [-3.56, 4.13] | 2.18 | [-5.01,3.43 ] | 2.18 | [-5.20, 3.30] |
| **WSpeed 2** | 1.04 | [-2.38, 2.40] | 1.48 | [-1.42, 3.11] | 1.95 | [-1.07, 4.09] | 2.69 | [-0.94, 5.25] |
| **WSpeed 10** | 2.54 | [-3.89, 3.65] | 1.27 | [-3.14, 2.28] | 1.57 | [-2.92, 3.00] | 2.00 | [-2.03, 4.31] |
| **THI 4** | 3.03 | [-5.76, 7.57] | 2.92 | [-3.56, 7.81] | 4.03 | [-6.12, 9.03] | 2.58 | [-5.79, 4.86] |
| **THI 6** | 3.38 | [-6.42, 7.98] | 3.44 | [-5.16, 8.80] | 3.78 | [-5.21, 9.43] | 2.67 | [-5.40, 5.84] |

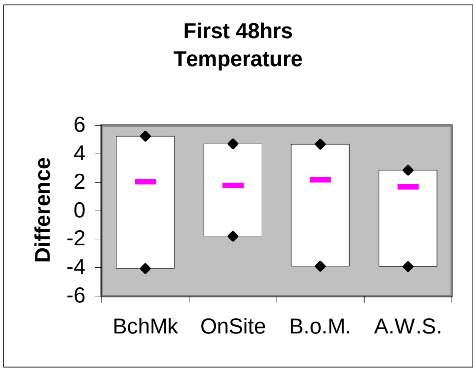



Figure 5a.

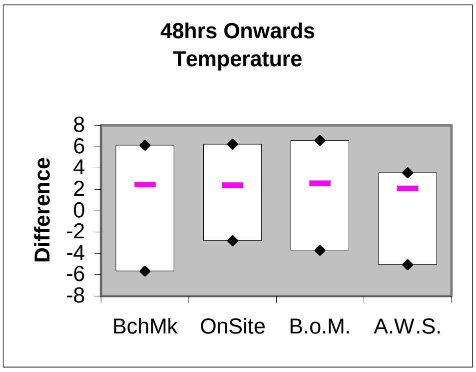



Figure 5b.

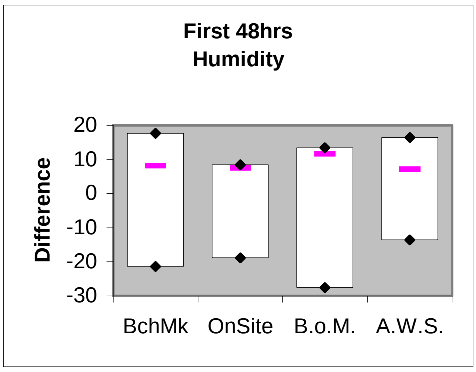



Figure 5c.

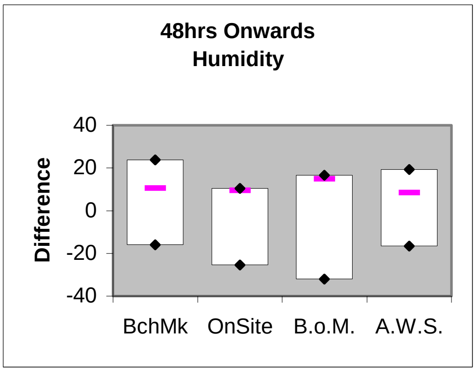



Figure 5d.

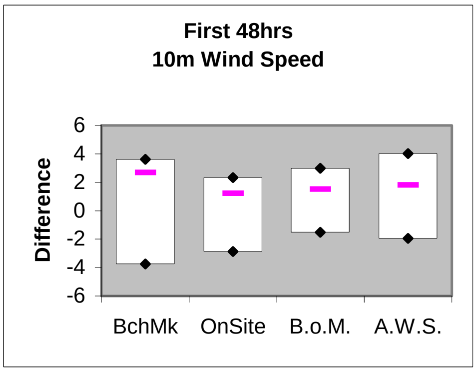



Figure 5e.

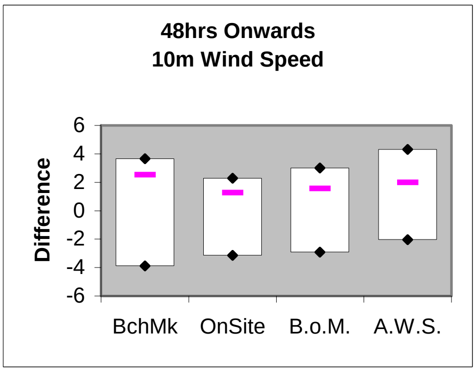



Figure 5f.

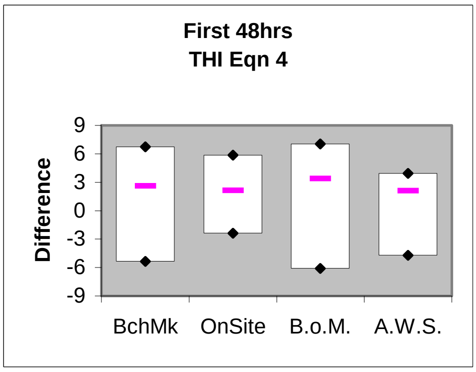



Figure 5g

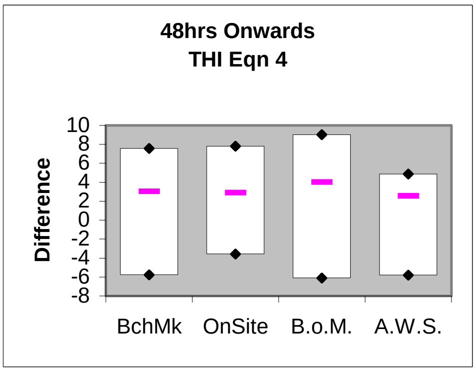



Figure 5h.

Figure A2. – Error statistics for each method and various parameters, both for forecast horizons out to 48 hours and from 48-144 hours

## Various Parameters

Table A4. – Error in On-site Weather Station Temperature Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 1.69 | [-2.22, 3.28] | 1.54 | [-1.26, 4.42] | 2.20 | [-1.88, 4.82] | 3.57 | [-0.33, 7.31] |
| **2** | 1.86 | [-2.22, 4.34] | 1.50 | [-1.21, 4.04] | 2.10 | [-1.56, 4.62] | 3.56 | [-0.52, 7.14] |
| **3** | 2.53 | [-3.60, 6.40] | 2.80 | [-0.61, 5.77] | 2.32 | [-1.97, 4.98] | 3.05 | [-1.92, 6.80] |
| **4** | 2.40 | [-3.65, 6.64] | 3.10 | [-0.51, 7.02] | 2.49 | [-2.34, 5.91] | 3.18 | [-2.71, 7.39] |
| **5** | 2.64 | [-3.74, 6.72] | 3.09 | [-1.07, 8.08] | 2.65 | [-2.36, 5.86] | 3.37 | [-2.01, 7.93] |
| **6** | 2.72 | [-3.03, 6.95] | 3.14 | [-0.40, 6.55] | 2.75 | [-2.36, 6.51] | 3.32 | [-2.56, 7.91] |

Table A5. – Error in B.o.M. Temperature Prediction.

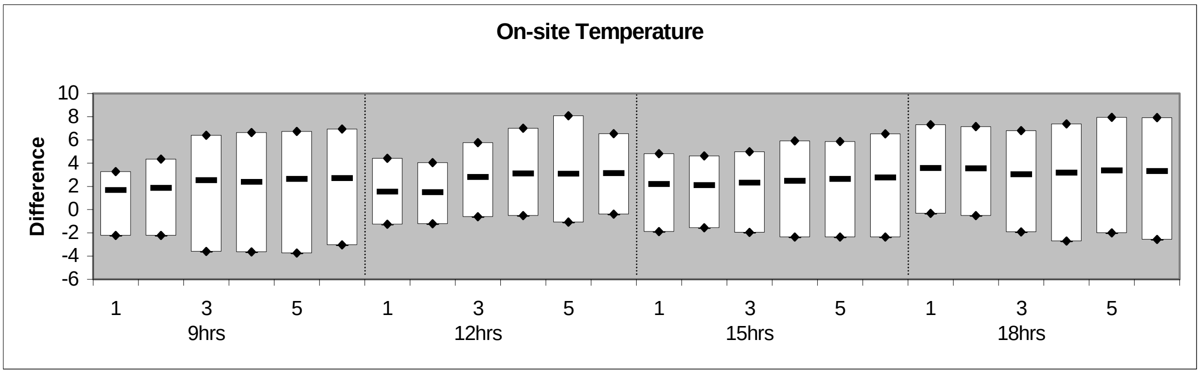
| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 2.10 | [-0.46, 5.73] | 1.94 | [-1.15, 4.39] | 2.28 | [-4.22, 0.34] | 2.62 | [-5.01, 0.57] |
| **2** | 2.09 | [-0.97, 5.58] | 2.03 | [-1.42, 5.58] | 2.37 | [-4.40, 0.04] | 2.62 | [-4.63, 0.21] |
| **3** | N/A | N/A | 2.60 | [-0.44, 6.55] | N/A | N/A | N/A | N/A |
| **4** | N/A | N/A | 2.88 | [-0.90, 7.47] | N/A | N/A | N/A | N/A |
| **5** | N/A | N/A | 3.02 | [-1.37, 8.35] | N/A | N/A | N/A | N/A |
| **6** | N/A | N/A | 3.18 | [-1.16, 8.98] | N/A | N/A | N/A | N/A |

Table A6. – Error in Katestone A.W.S. Downscaled Temperature Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 1.80 | [-3.26, 3.11] | 1.20 | [-2.27, 2.63] | 1.42 | [-3.10, 2.40] | 1.80 | [-3.55, 4.18] |
| **2** | 1.96 | [-4.24, 4.43] | 1.11 | [-1.98, 2.55] | 1.32 | [-2.76, 2.18] | 1.92 | [-3.57, 3.95] |
| **3** | 1.97 | [-2.66, 4.15] | 1.50 | [-1.91, 4.14] | 2.75 | [-5.83, 3.12] | 2.59 | [-5.24, 4.89] |
| **4** | 1.96 | [-2.78, 4.31] | 1.57 | [-1.82, 4.19] | 2.73 | [-5.55, 3.12] | 2.59 | [-5.50, 3.68] |
| **5** | 2.24 | [-3.74, 4.59] | 1.73 | [-2.45, 4.33] | 2.82 | [-6.12, 3.51] | 2.64 | [-5.86, 4.94] |
| **6** | 2.64 | [-3.33, 5.97] | 1.87 | [-1.88, 4.94] | 3.05 | [-6.12, 3.90] | 2.94 | [-6.18, 5.88] |

Table A7. – Error in Persistence Temperature Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 2.13 | [-4.95, 3.83] | 1.46 | [-3.09, 2.80] | 1.69 | [-3.25, 4.48] | 2.33 | [-5.14, 6.91] |
| **2** | 2.53 | [-5.19, 5.39] | 1.75 | [-4.11, 3.67] | 2.21 | [-5.54, 5.39] | 2.91 | [-6.85, 7.29] |
| **3** | 2.76 | [-6.42, 5.74] | 1.73 | [-3.50, 3.90] | 2.35 | [-4.85, 5.64] | 3.11 | [-6.53, 6.81] |
| **4** | 2.74 | [-4.76, 5.81] | 1.74 | [-3.58, 4.39] | 2.45 | [-5.06, 6.00] | 3.44 | [-7.27, 7.15] |
| **5** | 2.65 | [-4.75, 5.50] | 1.78 | [-3.70, 4.05] | 2.61 | [-4.86, 5.36] | 3.72 | [-7.52, 9.23] |
| **6** | 2.61 | [-4.67, 5.51] | 2.06 | [-4.46, 4.40] | 2.80 | [-5.45, 9.14] | 3.74 | [-7.74, 8.34] |



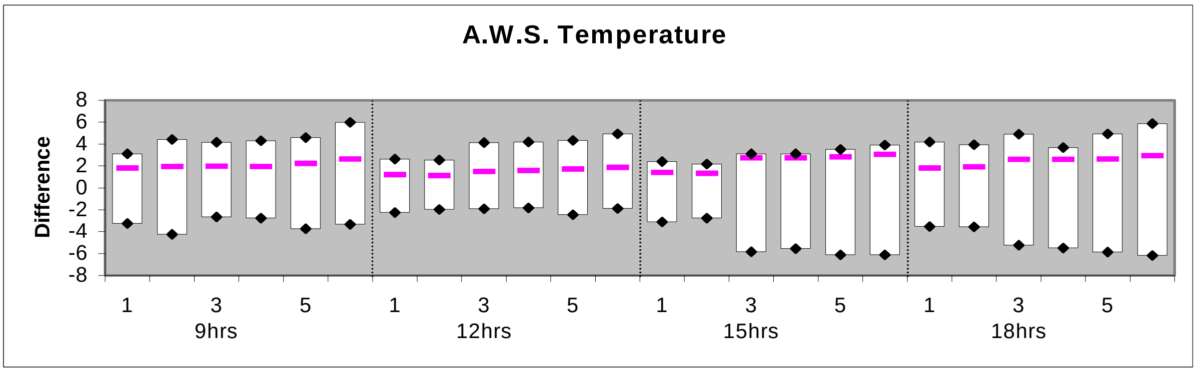
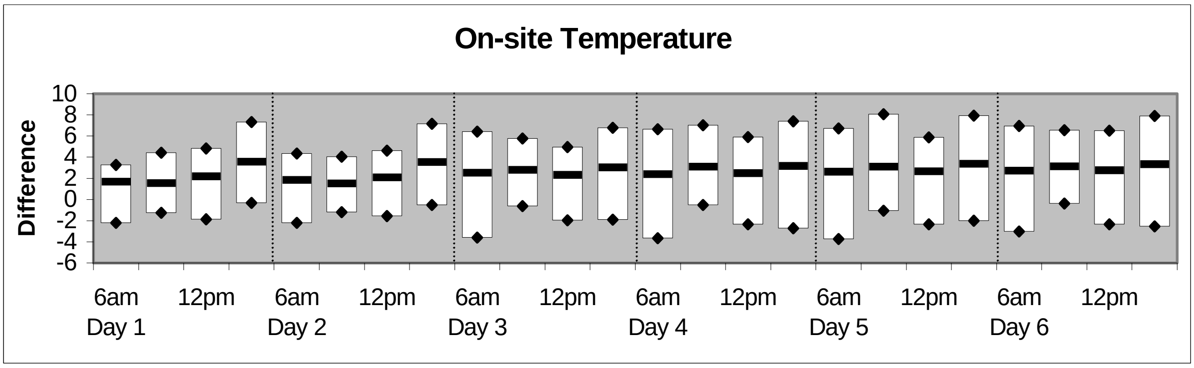




Figure A3. – Temperature errors split by Hour and then by Day, for different models and for different time horizons.



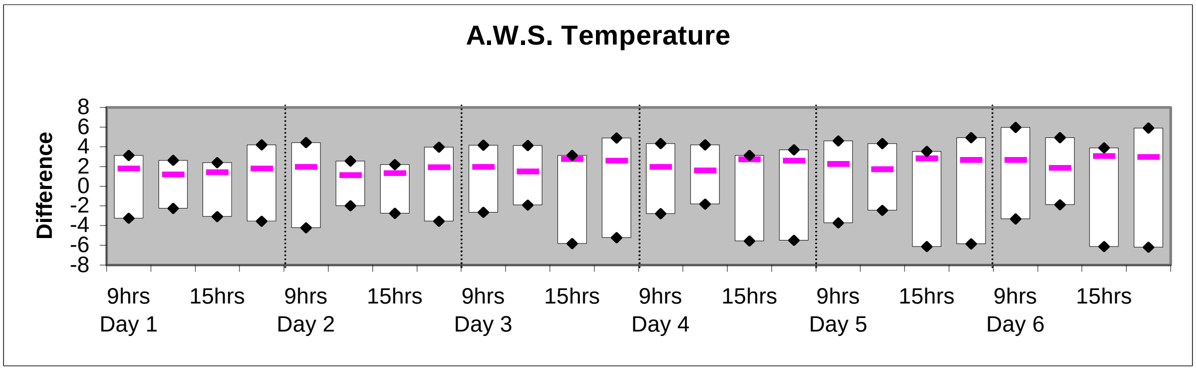



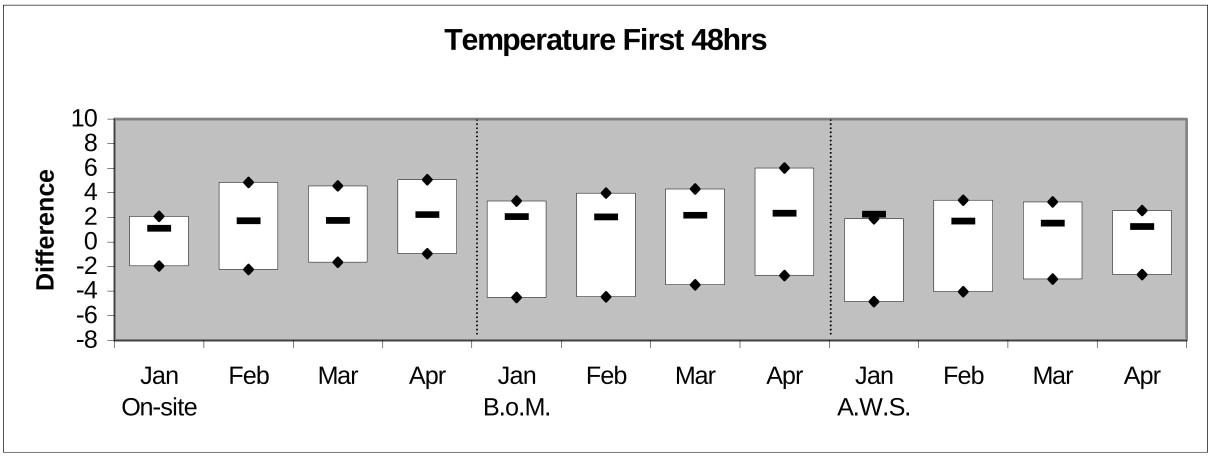

Figure A4. – Temperature errors split by Day and then by Hour, for different models and for different time horizons.

Table A8. – Overall Error in Temperature Comparisons by Month for First 48hrs.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 1.10 | [-1.95, 2.10] | 2.07 | [-4.53, 3.34] | 2.25 | [-4.86, 1.90] |
| **Feb** | 1.73 | [-2.23, 4.84] | 2.03 | [-4.46, 3.99] | 1.69 | [-4.04, 3.40] |
| **Mar** | 1.74 | [-1.66, 4.58] | 2.17 | [-3.48, 4.31] | 1.52 | [-3.01, 3.25] |
| **Apr** | 2.22 | [-0.95, 5.07] | 2.35 | [-2.72, 6.01] | 1.26 | [-2.66, 2.55] |

Table A9. – Overall Error in Temperature Comparisons by Month for hours 48 onwards.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 1.77 | [-3.19, 4.45] | 2.54 | [-4.29, 6.28] | 2.71 | [-6.72, 3.32] |
| **Feb** | 2.36 | [-3.50, 6.44] | 2.61 | [-3.48, 6.43] | 2.07 | [-4.80, 3.60] |
| **Mar** | 2.22 | [-3.01, 5.71] | 2.32 | [-3.74, 5.57] | 2.04 | [-4.73, 3.60] |
| **Apr** | 2.91 | [-1.04, 6.74] | 2.89 | [-3.06, 8.08] | 1.50 | [-2.52, 3.63] |



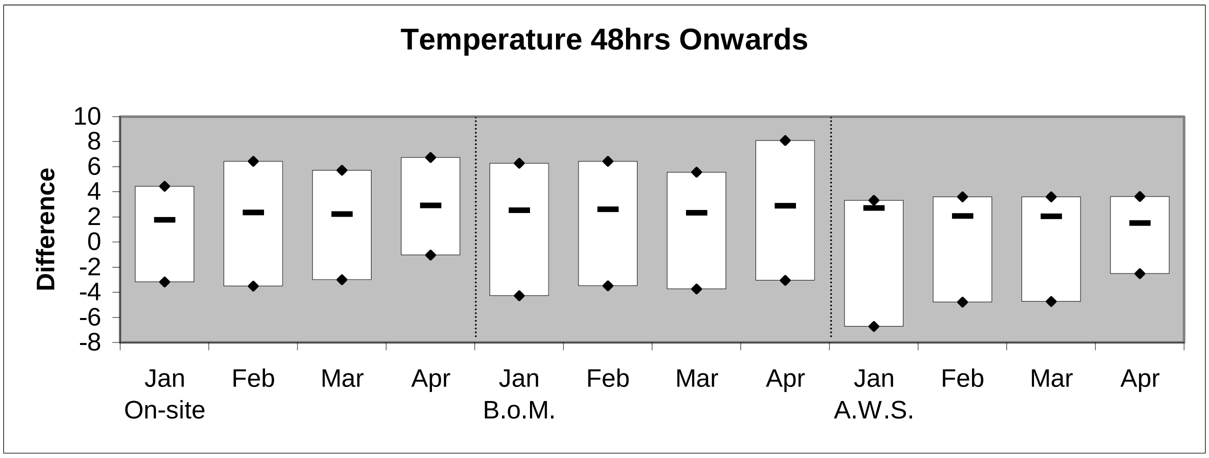




Figure A5. – Temperature errors split by Month for different forecast horizons.

Table A10. – Error in On-site Weather Station Humidity Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 6.08 | [-12.95, 8.52] | 8.40 | [-18.87, 4.67] | 8.82 | [-20.09, 6.05] | 10.29 | [-26.42, 5.48] |
| **2** | 7.36 | [-14.95, 9.60] | 8.41 | [-18.43, 4.96] | 8.53 | [-20.73, 4.83] | 10.31 | [-26.21, 5.13] |
| **3** | 6.25 | [-12.70, 6.81] | 11.80 | [-24.29, 1.00] | 8.98 | [-20.53, 10.79] | 9.89 | [-30.72, 8.05] |
| **4** | 6.68 | [-13.02, 12.73] | 13.59 | [-27.63, 5.08] | 9.66 | [-22.42, 9.77] | 10.65 | [-29.77, 8.34] |
| **5** | 7.06 | [-12.99, 9.05] | 13.98 | [-31.23, 5.87] | 10.58 | [-25.30, 11.40] | 11.70 | [-33.02, 9.28] |
| **6** | 7.46 | [-15.06, 12.25] | 14.10 | [-31.65, 7.71] | 10.88 | [-27.73, 13.75] | 11.51 | [-33.68, 11.17] |

Table A11. – Error in B.o.M. Humidity Prediction.

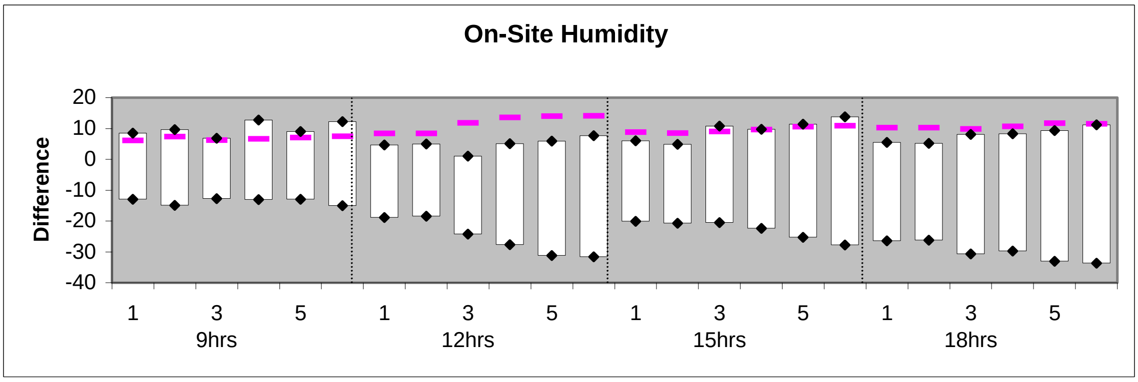
| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 7.85 | [-7.39, 14.29] | 18.21 | [-31.15, 2.11] | 19.10 | [-31.98, -0.10] | 16.55 | [-29.01, 0.69] |
| **2** | 6.74 | [-8.91, 17.13] | 19.36 | [-34.74, 4.57] | 19.25 | [-32.37, 0.14] | 16.46 | [-27.69, 2.75] |
| **3** | N/A | N/A | 8.37 | [-18.73, 18.66] | N/A | N/A | N/A | N/A |
| **4** | N/A | N/A | 9.10 | [-22.67, 22.25] | N/A | N/A | N/A | N/A |
| **5** | N/A | N/A | 9.96 | [-23.44, 21.16] | N/A | N/A | N/A | N/A |
| **6** | N/A | N/A | 11.95 | [31.21, 32.18] | N/A | N/A | N/A | N/A |

Table A12. – Error in Katestone A.W.S. Downscaled Humidity Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 5.73 | [-9.75, 13.90] | 6.91 | [-17.32, 6.03] | 5.50 | [-15.96, 8.02] | 6.03 | [-20.92, 8.53] |
| **2** | 6.40 | [-10.70, 16.50] | 7.20 | [-16.58, 4.97] | 5.40 | [-12.72, 7.85] | 6.18 | [-18.72, 8.45] |
| **3** | 6.47 | [-10.95, 12.63] | 9.24 | [-20.90, 6.43] | 8.66 | [-14.71, 18.37] | 8.29 | [-25.04, 15.38] |
| **4** | 6.70 | [-11.60, 12.34] | 10.07 | [-24.65, 4.79] | 9.11 | [-18.57, 20.20] | 8.63 | [-26.47, 15.92] |
| **5** | 7.54 | [-12.24, 12.79] | 11.07 | [-27.45, 6.59] | 9.65 | [-19.66, 20.99] | 9.60 | [-24.65, 18.23] |
| **6** | 7.44 | [-12.76, 11.74] | 11.52 | [-27.90, 6.67] | 10.50 | [-17.66, 19.24] | 9.88 | [-25.03, 18.28] |

Table A13. – Error in Persistence Humidity Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 6.08 | [-18.54, 13.86] | 6.99 | [-15.87, 15.11] | 6.50 | [-19.09, 13.74] | 8.66 | [-27.44, 19.96] |
| **2** | 7.69 | [-22.16, 17.61] | 8.96 | [-24.44, 20.85] | 8.51 | [-19.77, 15.75] | 10.47 | [-32.11, 27.43] |
| **3** | 8.57 | [-25.54, 19.01] | 9.69 | [-23.43, 23.38] | 10.25 | [-25.29, 21.00] | 11.58 | [-31.15, 24.85] |
| **4** | 8.75 | [-25.47, 19.97] | 10.20 | [-26.86, 23.44] | 10.84 | [-23.48, 22.69] | 13.03 | [-42.07, 32.67] |
| **5** | 9.02 | [-24.56, 18.41] | 10.98 | [-27.97, 20.87] | 10.97 | [-24.97, 23.30] | 13.70 | [-40.01, 31.70] |
| **6** | 8.96 | [-21.77, 18.28] | 11.53 | [-27.75, 23.83] | 11.69 | [-25.39, 23.05] | 14.44 | [-36.05, 34.98] |



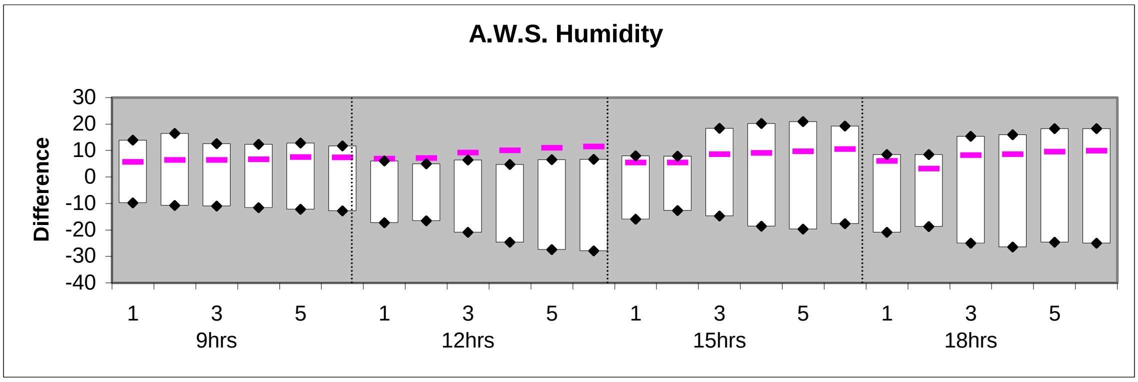
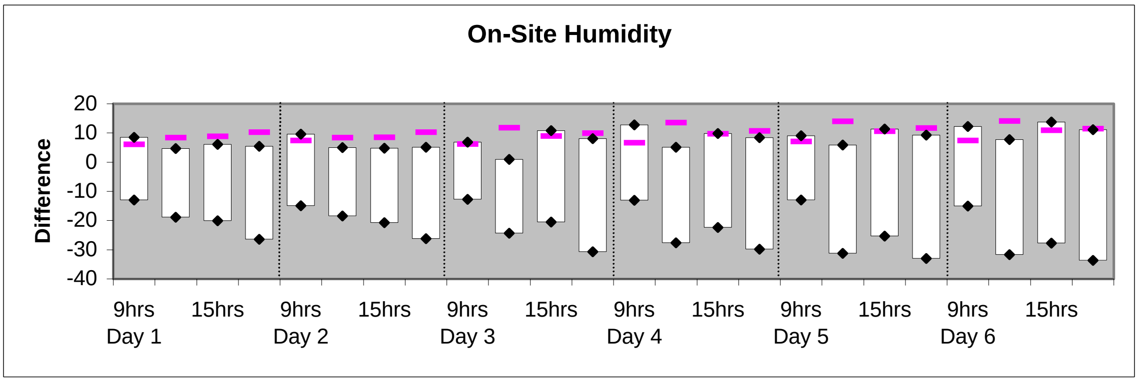




Figure A6. – Humidity errors split by Hour and then by Day, for different models and for different time horizons.



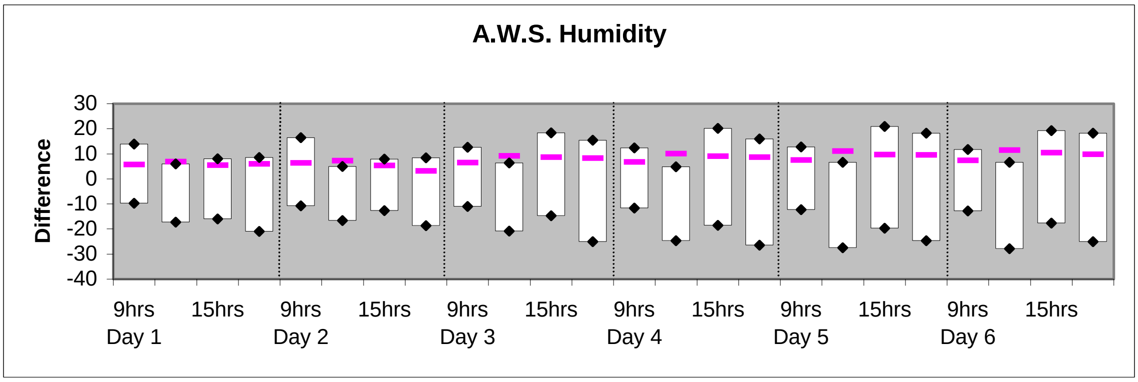



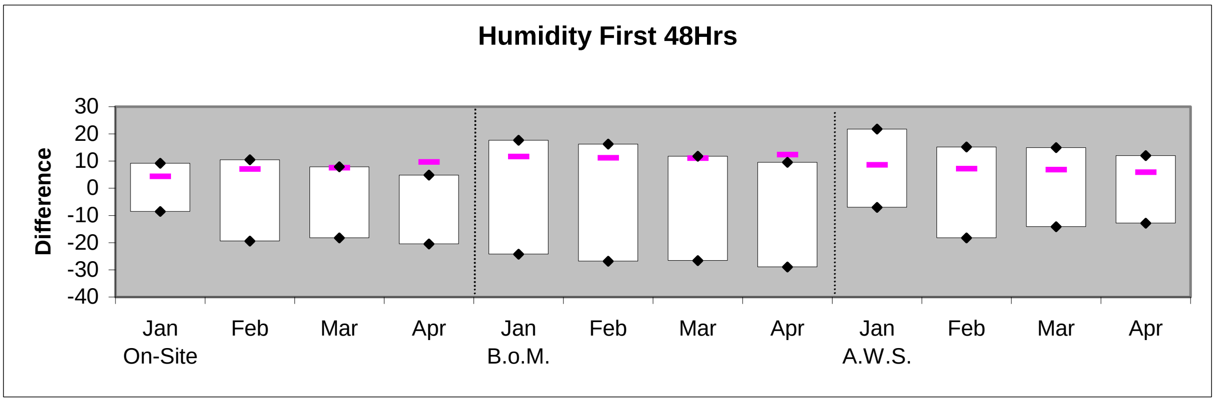

Figure A7. – Humidity errors split by Day and then by Hour, for different models and for different time horizons.

Table A14. – Overall Error in Humidity Comparisons by Month for First 48hrs.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| Month | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| Jan | 4.43 | [-8.48, 9.16] | 11.69 | [-24.25, 17.69] | 8.57 | [-7.03, 21.74] |
| Feb | 7.06 | [-19.47, 10.50] | 11.22 | [-26.80, 16.29] | 7.20 | [-18.22, 15.15] |
| Mar | 7.57 | [-18.22, 7.88] | 11.12 | [-26.58, 11.74] | 6.81 | [-14.12, 14.96] |
| Apr | 9.71 | [-20.47, 4.85] | 12.33 | [-28.96, 9.53] | 5.88 | [-12.83, 12.01] |

Table A15. – Overall Error in Humidity Comparisons by Month for hours 48 onwards.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| Month | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| Jan | 6.59 | [-14.56, 13.47] | 15.26 | [-28.25, 24.90] | 10.25 | [-12.71, 26.28] |
| Feb | 10.88 | [-30.63, 15.45] | 17.83 | [-35.05, 11.25] | 8.77 | [-21.47, 19.07] |
| Mar | 8.88 | [-24.07, 9.73] | 13.23 | [-30.33, 13.95] | 8.30 | [-17.75, 17.62] |
| Apr | 10.97 | [-25.43, 3.51] | 14.26 | [-32.68, 4.37] | 6.39 | [-14.53, 12.22] |



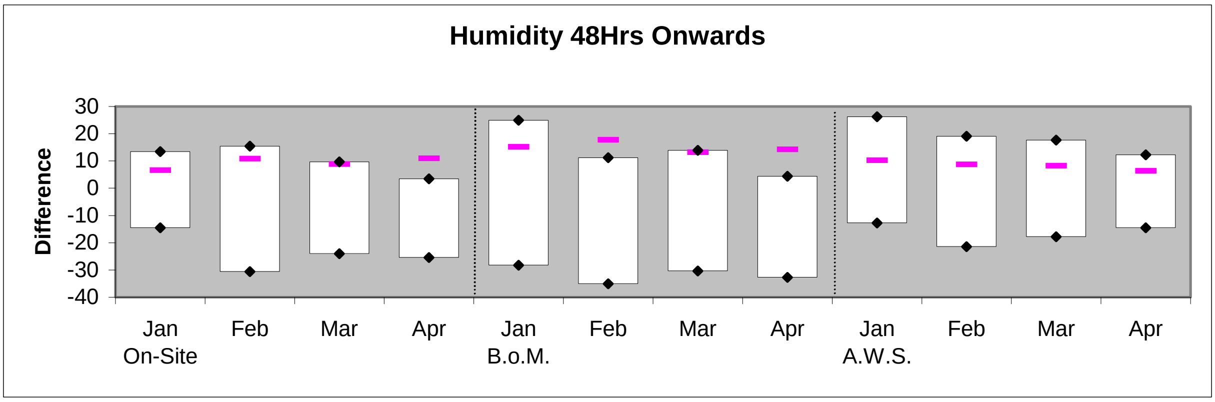




Figure A8. – Humidity errors split by Month for different forecast horizons.

Table A16. – Error in On-site Weather Station Wind Speed Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| Day | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| 1 | 0.71 | [-1.34, 1.86] | 1.41 | [-2.61, 2.31] | 1.45 | [-4.12, 2.04] | 1.52 | [-3.63, 0.91] |
| 2 | 0.69 | [-1.48, 1.68] | 1.45 | [-2.54, 2.54] | 1.64 | [-4.19, 2.24] | 1.71 | [-3.59, 1.79] |
| 3 | 0.80 | [-1.49, 1.44] | 1.36 | [-3.38, 3.10] | 1.69 | [-4.47, 2.71] | 1.59 | [-3.98, 1.35] |
| 4 | 0.84 | [-2.01, 1.51] | 1.47 | [-2.54, 2.78] | 1.68 | [-4.41, 2.44] | 1.74 | [-4.77, 1.57] |
| 5 | 0.77 | [-1.57, 1.39] | 1.49 | [-3.28, 2.74] | 1.60 | [-4.61, 1.84] | 1.75 | [-5.00, 1.76] |
| 6 | 0.77 | [-1.60, 1.43] | 1.51 | [-3.30, 3.38] | 1.44 | [-4.18, 1.85] | 1.85 | [-4.78, 1.43] |

Table A17. – Error in B.o.M. Wind Speed Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| Day | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| 1 | 1.18 | [0.31, 1.95] | 1.10 | [0.06, 2.00] | 1.16 | [-2.07, 1.75] | 1.67 | [-4.03, 2.53] |
| 2 | 1.50 | [0.57, 2.44] | 1.19 | [0.31, 2.29] | 1.22 | [-3.78, 0.71] | 2.14 | [-4.62, 0.37] |
| 3 | N/A | N/A | 1.64 | [-0.85, 3.45] | N/A | N/A | N/A | N/A |
| 4 | N/A | N/A | 1.60 | [-1.03, 3.39] | N/A | N/A | N/A | N/A |
| 5 | N/A | N/A | 1.68 | [-1.28, 3.31] | N/A | N/A | N/A | N/A |
| 6 | N/A | N/A | 1.70 | [-1.97, 3.14] | N/A | N/A | N/A | N/A |

Table A18. – Error in Katestone A.W.S. Downscaled Wind Speed Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| Day | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| 1 | 1.34 | [-1.34, 2.60] | 1.54 | [-2.51, 3.49] | 1.66 | [-1.93, 4.05] | 1.76 | [-2.37, 3.90] |
| 2 | 1.44 | [-1.68, 2.56] | 1.69 | [-3.15, 3.64] | 1.94 | [-2.74, 4.59] | 2.05 | [-3.56, 4.42] |
| 3 | 1.71 | [-1.51, 3.16] | 2.15 | [-3.53, 4.88] | 2.01 | [-2.49, 4.70] | 2.18 | [-2.63, 4.39] |
| 4 | 1.70 | [-1.36, 3.23] | 2.09 | [-2.73, 4.44] | 2.05 | [-2.13, 4.58] | 2.21 | [-3.55, 4.42] |
| 5 | 1.71 | [-1.60, 3.03] | 2.39 | [-3.76, 4.63] | 2.12 | [-2.94, 5.06] | 2.32 | [-3.73, 4.21] |
| 6 | 1.66 | [-1.04, 3.23] | 2.34 | [-3.80, 4.94] | 2.24 | [-2.90, 5.04] | 2.31 | [-3.31, 5.10] |

Table A19. – Error in Persistence Wind Speed Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| Day | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| 1 | 2.11 | [-2.37, 2.24] | 3.24 | [-4.44, 3.98] | 3.19 | [-4.35, 4.48] | 3.38 | [-3.89, 3.84] |
| 2 | 2.42 | [-2.58, 2.08] | 3.64 | [-5.54, 4.35] | 3.39 | [-4.02, 3.98] | 3.40 | [-4.24, 4.38] |
| 3 | 1.74 | [-2.49, 2.46] | 2.95 | [-5.63, 4.38] | 2.71 | [-4.65, 4.21] | 2.70 | [-4.71, 4.46] |
| 4 | 1.83 | [-3.24, 2.24] | 2.88 | [-6.24, 3.61] | 2.57 | [-3.91, 4.38] | 2.79 | [-5.06, 4.80] |
| 5 | 1.81 | [-2.26, 2.16] | 3.01 | [-6.32, 4.40] | 2.64 | [-5.23, 3.95] | 2.60 | [-4.78, 3.75] |
| 6 | 1.81 | [-2.69, 2.62] | 2.93 | [-4.90, 4.33] | 2.84 | [-4.70, 4.73] | 2.76 | [-4.89, 3.86] |

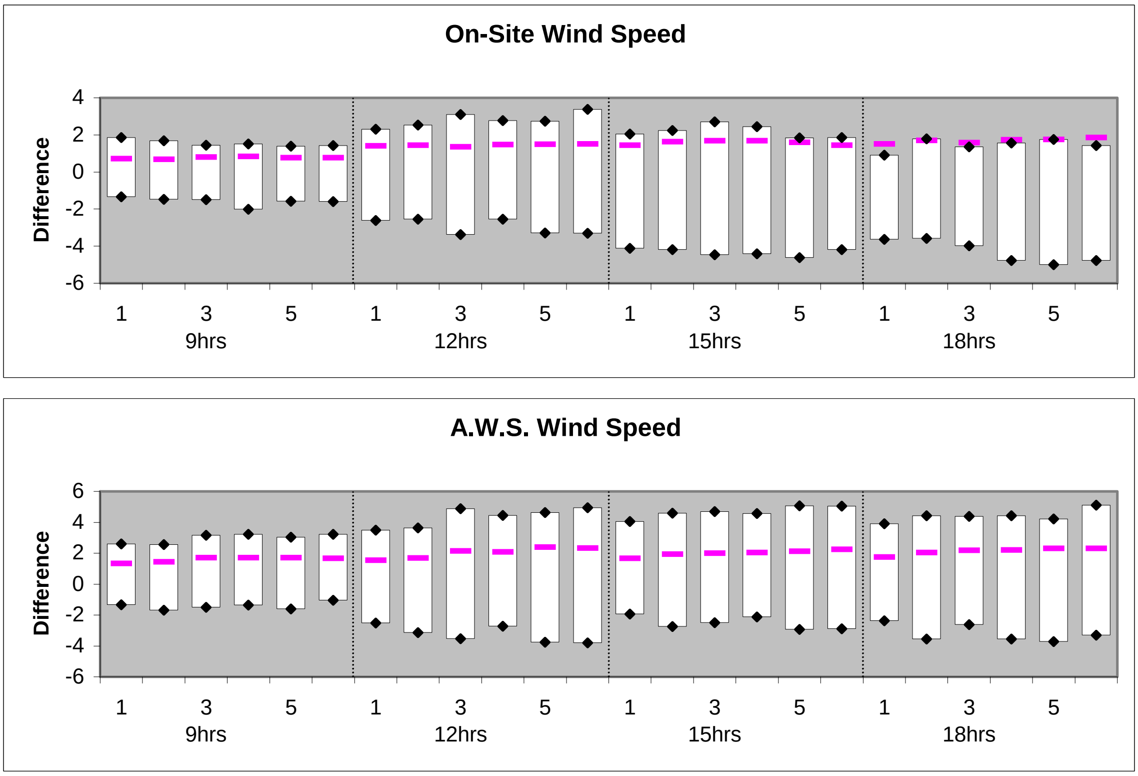



Figure A9. – Wind Speed errors split by Hour and then by Day, for different models and for different time horizons.

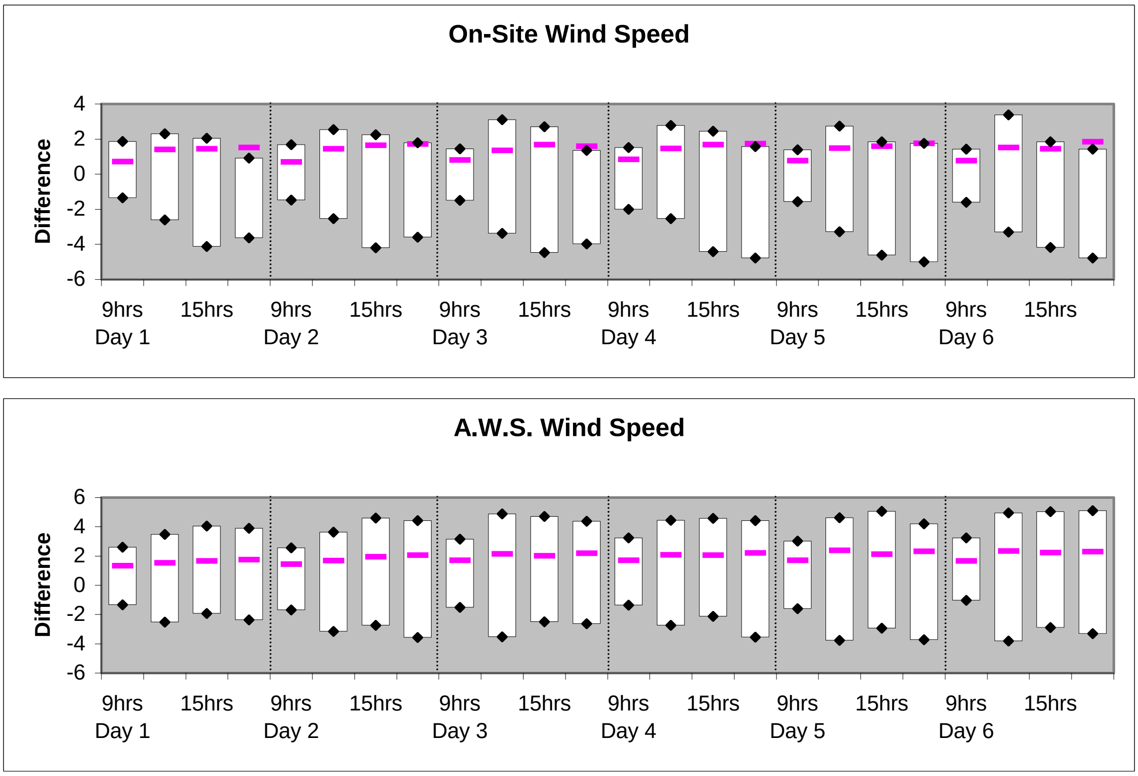


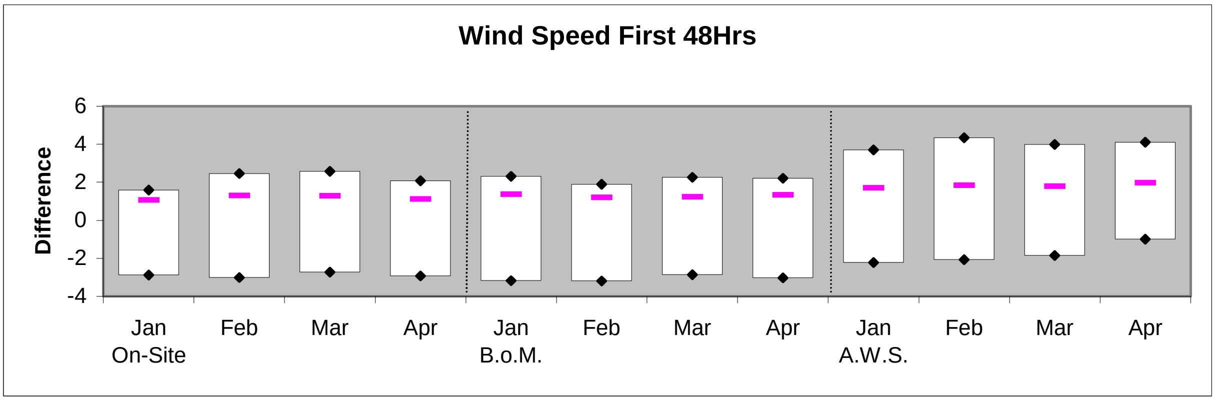

Figure A10. – Wind Speed errors split by Day and then by Hour, for different models and for different time horizons.

Table A20. – Overall Error in Wind Speed Comparisons by Month for First 48hrs.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 1.06 | [-2.88, 1.59] | 1.37 | [-3.17, 2.31] | 1.70 | [-2.22, 3.70] |
| **Feb** | 1.30 | [-3.01, 2.46] | 1.20 | [-3.19, 1.89] | 1.84 | [-2.07, 4.34] |
| **Mar** | 1.28 | [-2.72, 2.58] | 1.24 | [-2.86, 2.26] | 1.79 | [-1.85, 3.98] |
| **Apr** | 1.12 | [-2.93, 2.07] | 1.34 | [-3.02, 2.20] | 1.98 | [-1.00, 4.11] |

Table A21. – Overall Error in Wind Speed Comparisons by Month for hours 48 Onwards.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 1.23 | [-3.27, 1.91] | 1.47 | [-3.13, 2.80] | 1.90 | [-2.53, 4.23] |
| **Feb** | 1.28 | [-3.14, 2.31] | 1.52 | [-3.07, 2.95] | 2.00 | [-1.88, 4.41] |
| **Mar** | 1.28 | [-2.91, 2.46] | 1.34 | [-2.53, 2.75] | 2.01 | [-1.84, 4.38] |
| **Apr** | 1.25 | [-3.33, 2.11] | 1.80 | [-3.34, 3.30] | 2.13 | [-1.51, 4.07] |



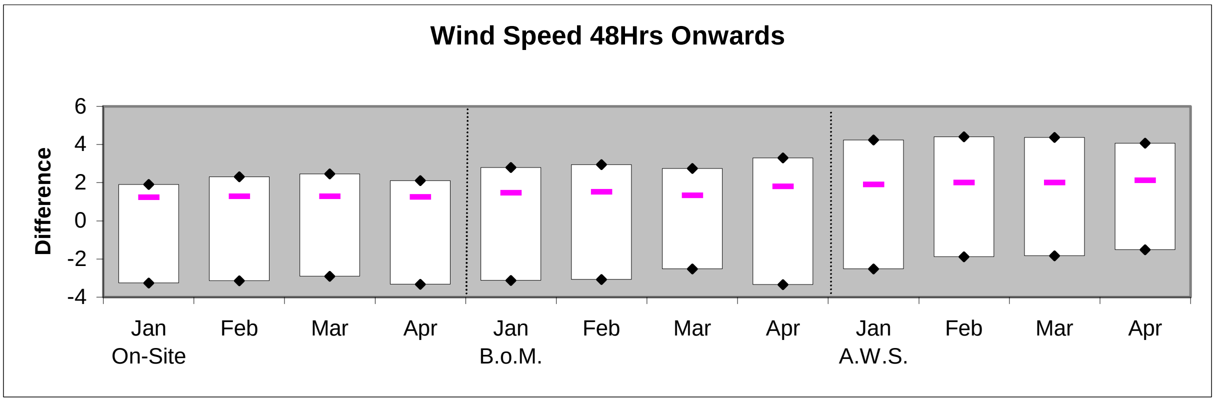




Figure A11. – Wind Speed errors split by Month for different forecast horizons.

Table A22. – Error in On-site Weather Station THI 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 2.84 | [-3.52, 5.58] | 1.65 | [-1.16, 5.06] | 2.02 | [-1.13, 4.39] | 3.39 | [0.05, 6.78] |
| **2** | 3.13 | [-4.15, 7.01] | 1.67 | [-1.63, 4.63] | 1.97 | [-1.76, 4.09] | 3.28 | [0.04, 7.04] |
| **3** | 4.25 | [-5.93, 10.51] | 2.89 | [-0.82, 6.86] | 2.24 | [-1.63, 5.38] | 2.82 | [-1.31, 6.85] |
| **4** | 4.01 | [-6.27, 10.96] | 3.29 | [-0.98, 8.55] | 2.47 | [-2.36, 6.09] | 2.94 | [-2.06, 6.70] |
| **5** | 4.41 | [-6.15, 10.58] | 3.32 | [-1.66, 8.80] | 2.63 | [-2.02, 6.32] | 3.00 | [-1.15, 6.93] |
| **6** | 4.53 | [-5.11, 10.54] | 3.35 | [-0.76, 7.25] | 2.89 | [-2.45, 6.56] | 3.17 | [-1.53, 7.37] |

Table A23. – Error in B.o.M. THI 4 Prediction.

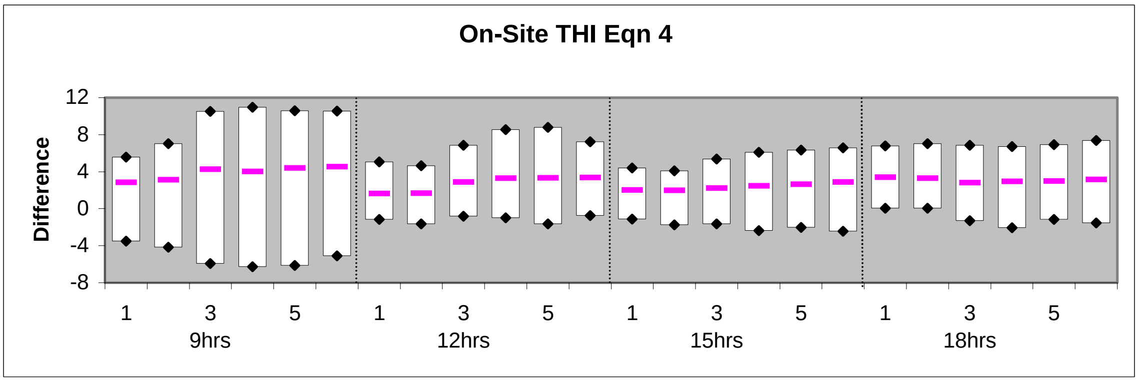
| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 3.56 | [-0.32, 9.29] | 2.28 | [-1.91, 6.95] | 4.44 | [-6.70, -1.63] | 4.73 | [-7.24, -0.92] |
| **2** | 3.45 | [-0.92, 8.84] | 3.04 | [-2.82, 8.17] | 4.57 | [-7.44, -1.48] | 4.86 | [-7.15, -1.23] |
| **3** | N/A | N/A | 3.65 | [-0.44, 9.80] | N/A | N/A | N/A | N/A |
| **4** | N/A | N/A | 3.98 | [-1.07, 10.48] | N/A | N/A | N/A | N/A |
| **5** | N/A | N/A | 4.18 | [-0.96, 10.66] | N/A | N/A | N/A | N/A |
| **6** | N/A | N/A | 4.47 | [-1.18, 12.47] | N/A | N/A | N/A | N/A |

Table A24. – Error in Katestone A.W.S. Downscaled THI 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 2.93 | [-5.21, 5.32] | 1.45 | [-2.77, 2.65] | 1.50 | [-3.13, 2.31] | 1.76 | [-3.67, 3.47] |
| **2** | 3.21 | [-6.26, 7.43] | 1.45 | [-2.73, 2.70] | 1.58 | [-3.12, 2.31] | 1.89 | [-3.29, 3.53] |
| **3** | 3.21 | [-4.38, 6.74] | 1.79 | [-2.69, 4.76] | 2.87 | [-6.23, 2.63] | 2.43 | [-4.59, 3.90] |
| **4** | 3.23 | [-4.52, 7.42] | 1.86 | [-2.69, 4.72] | 2.91 | [-5.56, 2.83] | 2.39 | [-4.47, 4.13] |
| **5** | 3.72 | [-5.71, 7.52] | 2.12 | [-3.65, 4.59] | 2.94 | [-7.00, 3.08] | 2.40 | [-5.22, 3.84] |
| **6** | 4.35 | [-4.82, 9.88] | 2.24 | [-3.35, 5.78] | 3.26 | [-7.12, 4.11] | 2.78 | [-6.07, 5.14] |

Table A25. – Error in Persistence THI 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 3.43 | [-7.79, 6.70] | 1.91 | [-4.15, 3.91] | 1.95 | [-3.93, 5.40] | 2.23 | [-4.69, 6.20] |
| **2** | 4.03 | [-8.10, 8.87] | 2.43 | [-5.90, 5.47] | 2.61 | [-5.58, 6.18] | 2.68 | [-6.23, 6.72] |
| **3** | 4.44 | [-10.01, 9.46] | 2.33 | [-5.16, 5.72] | 2.61 | [-7.36, 6.43] | 2.74 | [-5.45, 6.57] |
| **4** | 4.48 | [-7.76, 9.58] | 2.26 | [-3.98, 5.27] | 2.62 | [-5.04, 6.43] | 2.94 | [-5.49, 6.90] |
| **5** | 4.39 | [-7.70, 9.08] | 2.40 | [-4.59, 6.16] | 2.73 | [-4.80, 6.02] | 3.14 | [-6.55, 7.97] |
| **6** | 4.31 | [-7.64, 10.28] | 2.66 | [-4.83, 6.41] | 2.92 | [-5.68, 6.49] | 3.24 | [-5.51, 6.89] |



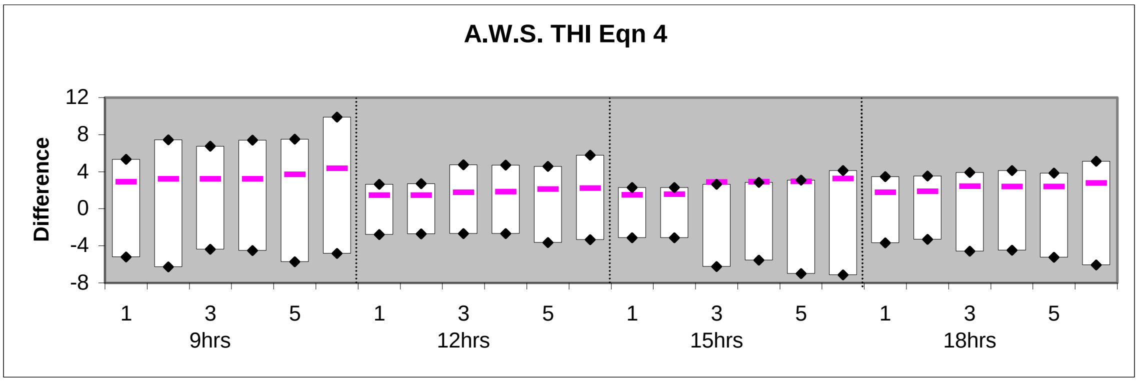
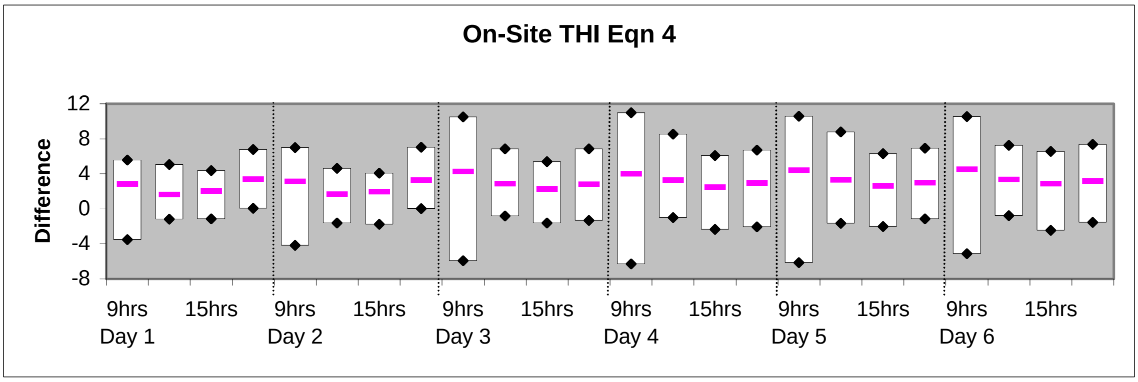




Figure A12. – THI Equation 4 errors split by Hour and then by Day, for different models and for different time horizons.



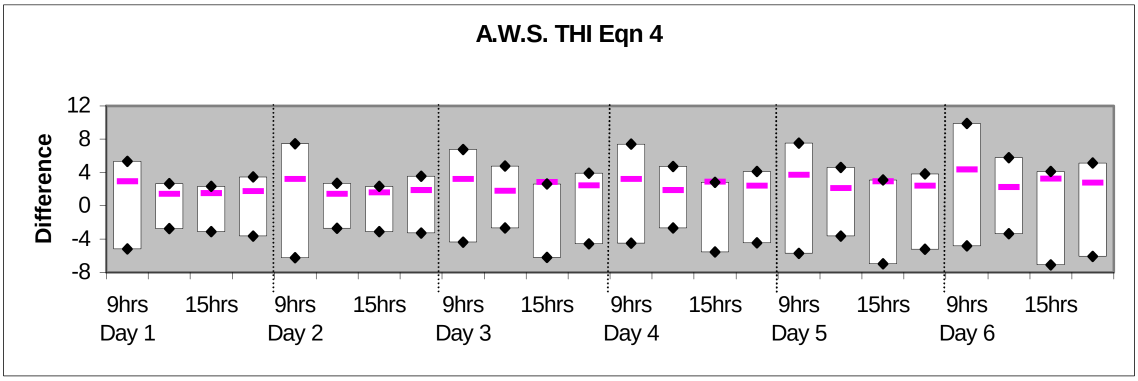



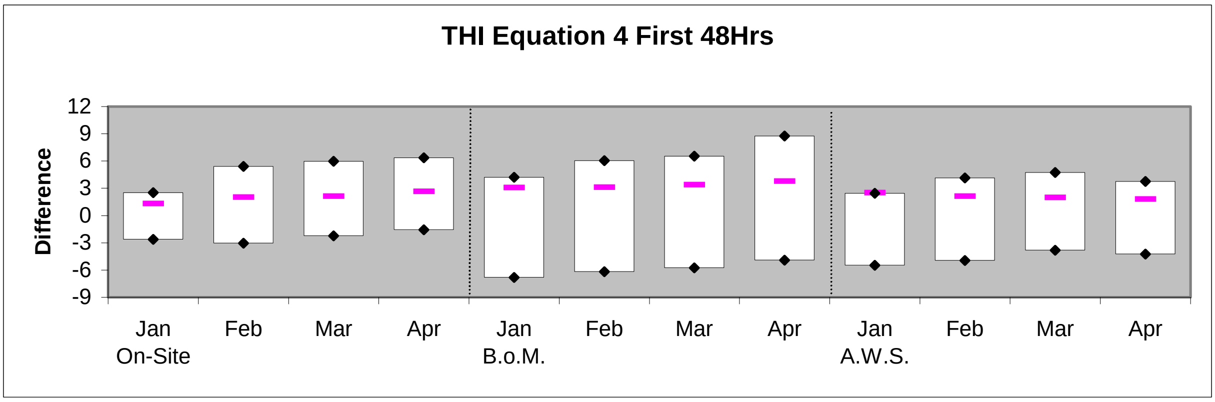

Figure A13. – THI Equation 4 errors split by Day and then by Hour, for different models and for different time horizons.

Table A26. – Overall Error in THI 4 Comparisons by Month for First 48hrs.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 1.31 | [-2.63, 2.52] | 3.08 | [-6.80, 4.20] | 2.51 | [-5.47, 2.46] |
| **Feb** | 2.03 | [-3.04, 5.42] | 3.13 | [-6.17, 6.05] | 2.12 | [-4.94, 4.16] |
| **Mar** | 2.13 | [-2.22, 5.96] | 3.40 | [-5.77, 6.53] | 1.99 | [-3.81, 4.73] |
| **Apr** | 2.65 | [-1.55, 6.38] | 3.79 | [-4.91, 8.77] | 1.82 | [-4.25, 3.77] |

Table A27. – Overall Error in THI 4 Comparisons by Month for hours 48 onwards.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 2.45 | [-3.40, 6.73] | 3.89 | [-6.49, 8.35] | 3.01 | [-7.24, 3.93] |
| **Feb** | 2.76 | [-4.85, 7.27] | 3.88 | [-6.44, 7.71] | 2.71 | [-5.86, 4.74] |
| **Mar** | 2.64 | [-3.69, 6.85] | 3.70 | [-6.35, 7.10] | 2.49 | [-5.51, 4.87] |
| **Apr** | 3.53 | [-1.75, 8.68] | 4.44 | [-5.17, 10.52] | 2.11 | [-3.54, 5.51] |



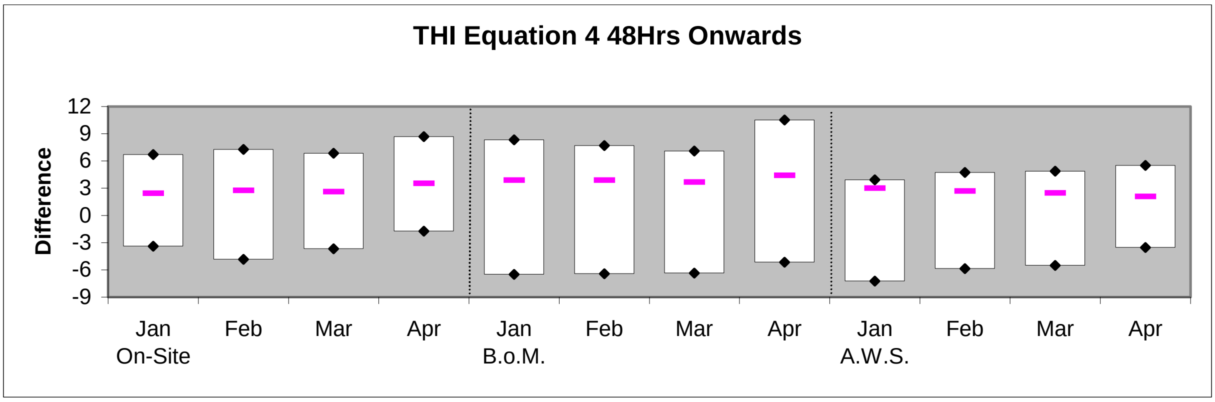




Figure A14. – THI Equation 4 errors split by Month for different forecast horizons.

# TABLES:



# FIGURES:

# APPENDIX B. – SANDALWOOD NEW MODELS TABLES AND FIGURES

## Overall

Table B1. – Overall Error Comparisons by Method and Variable for First 48hrs.

| Variable | Temp | | Rel Hum | | THI 4 | |
|---|---|---|---|---|---|---|
| **Forecast** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Original – 1mo training** | 1.77 | [-1.80, 4.70] | 7.54 | [-18.82, 8.43] | 2.16 | [-2.39, 5.87] |
| **Model 1 – Retrain** | 1.24 | [-2.52, 2.56] | 5.23 | [-10.73, 10.31] | 1.59 | [-3.22, 3.49] |
| **Model 2 – 1hr Partition** | 1.19 | [-2.42, 2.45] | 5.17 | [-10.54, 10.27] | 1.51 | [-3.06, 3.30] |
| **Model 3 – Regression** | 1.2 | [-2.42, 2.47] | 5.07 | [-10.47, 10.55] | 1.52 | [-2.99, 3.36] |
| **Model 4 – 30min Ave** | 1.17 | [-2.39, 2.40] | 5.12 | [-10.44, 10.17] | 1.48 | [-3.02, 3.21] |

Table B2. – Overall Error Comparisons by Method and Variable for hours 48 onwards.

| Variable | Temp | | Rel Hum | | THI 4 | |
|---|---|---|---|---|---|---|
| **Forecast** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Original – 1mo training** | 2.38 | [-2.81, 6.23] | 9.57 | [-25.44, 10.46] | 2.92 | [-3.56, 7.81] |
| **Model 1 – Retrain** | 1.77 | [-3.69, 3.76] | 6.96 | [-14.91, 15.02] | 2.25 | [-4.40, 5.28] |
| **Model 2 – 1hr Partition** | 1.59 | [-3.20, 3.53] | 6.46 | [-13.85, 13.41] | 2.04 | [-3.94, 4.84] |
| **Model 3 – Regression** | 1.59 | [-3.12, 3.57] | 6.37 | [-13.52, 13.41] | 2.04 | [-3.91, 4.82] |
| **Model 4 – 30min Ave** | 1.57 | [-3.12, 3.54] | 6.42 | [-13.76, 13.26] | 2.01 | [-3.91, 4.77] |

Table B3. – Temperature Error Comparisons

| **Forecast** | **Models** | | | | |
|---|---|---|---|---|---|
| | **(i)** | **(ii)** | **(iii)** | **(iv)** | **(v)** |
| Day 1 | 1.72 | 1.18 | 1.11 | 1.12 | 1.09 |
| Day 2 | 1.81 | 1.31 | 1.27 | 1.28 | 1.25 |
| Day 3 | 2.52 | 1.84 | 1.58 | 1.57 | 1.56 |
| Day 4 | 2.63 | 1.97 | 1.72 | 1.71 | 1.70 |
| Day 5 | 2.77 | 2.12 | 1.88 | 1.88 | 1.86 |
| Day 6 | 2.83 | 2.21 | 1.99 | 1.98 | 1.98 |

Table B4. – THI Error Comparisons

| **Forecast** | **Models** | | | | |
|---|---|---|---|---|---|
| | **(i)** | **(ii)** | **(iii)** | **(iv)** | **(v)** |
| Day 1 | 2.09 | 1.47 | 1.37 | 1.37 | 1.33 |
| Day 2 | 2.24 | 1.71 | 1.66 | 1.66 | 1.63 |
| Day 3 | 3.08 | 2.31 | 2.00 | 2.01 | 1.97 |
| Day 4 | 3.23 | 2.49 | 2.20 | 2.20 | 2.17 |
| Day 5 | 3.39 | 2.69 | 2.43 | 2.42 | 2.41 |
| Day 6 | 3.52 | 2.83 | 2.59 | 2.58 | 2.57 |

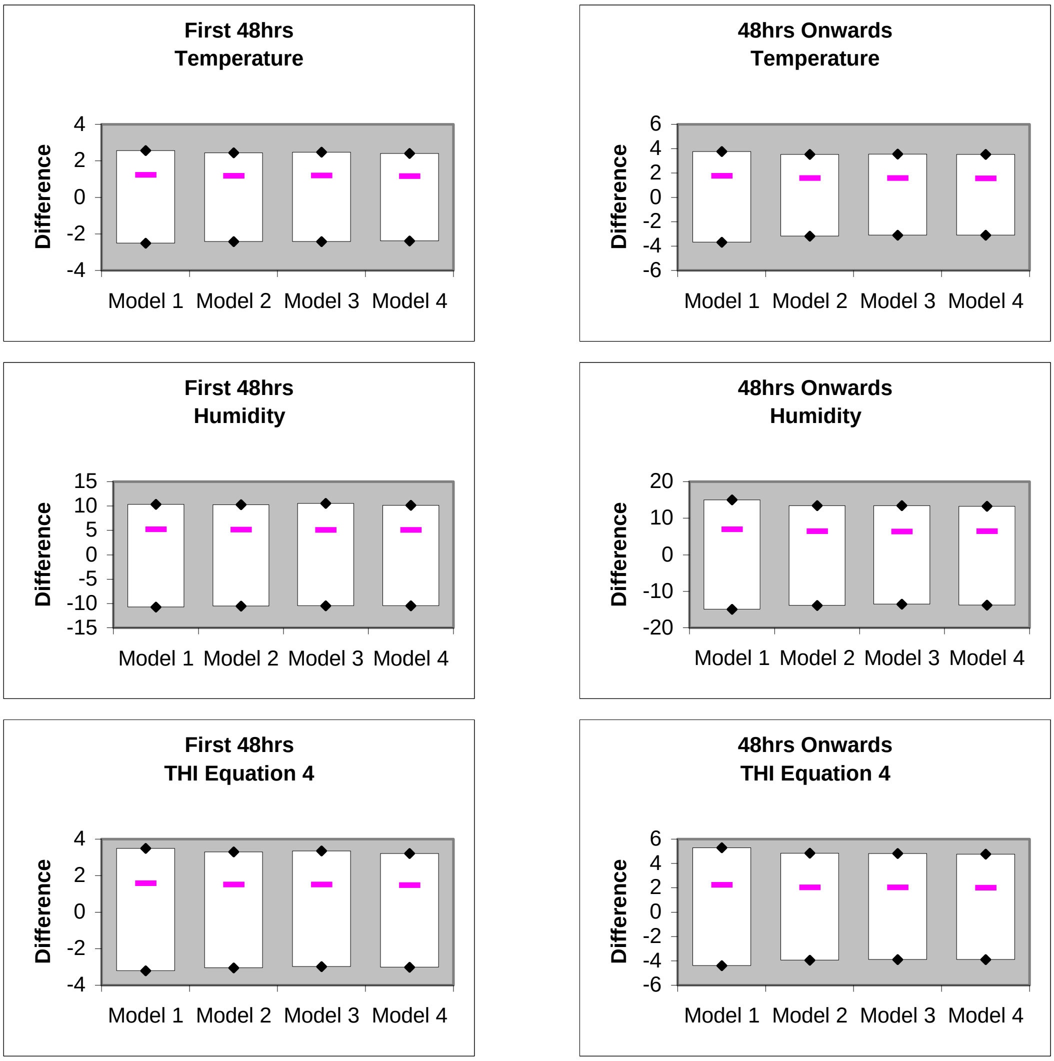
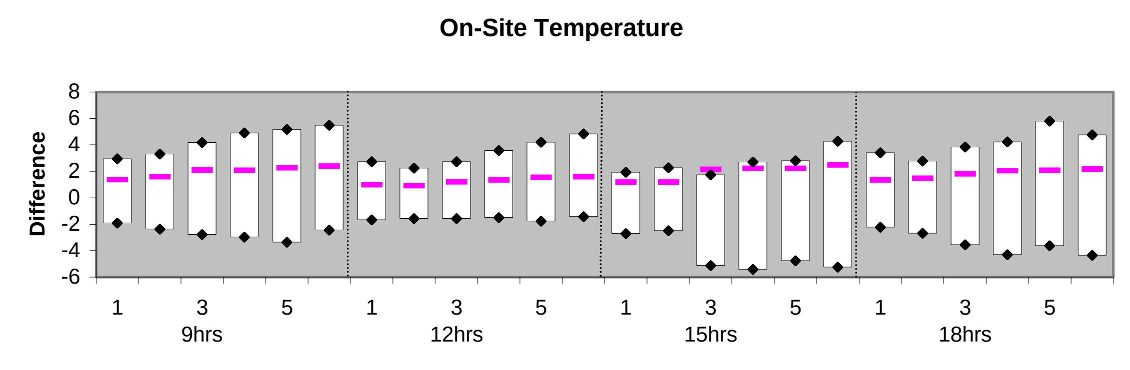



Figure B1. – Error statistics for the new models and various paramters, both for forecast horizons out to 48 hours and from 48-144 hours.

## Model 2

Table B5. – Error in Model 2 Weather Station Temperature Prediction.

| **Forecast Time** | **9hrs Ahead - 6am (+24hrs later days)** | | **12hrs Ahead - 9am (+24hrs later days)** | | **15hrs Ahead - 12pm (+24hrs later days)** | | **18hrs Ahead - 3pm (+24hrs later days)** | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 1.38 | [-1.92, 2.94] | 0.99 | [-1.68, 2.73] | 1.18 | [-2.71, 1.94] | 1.36 | [-2.22, 3.41] |
| **2** | 1.60 | [-2.37, 3.30] | 0.91 | [-1.57, 2.24] | 1.19 | [-2.50, 2.26] | 1.47 | [-2.68, 2.78] |
| **3** | 2.10 | [-2.78, 4.17] | 1.20 | [-1.58, 2.74] | 2.14 | [-5.14, 1.73] | 1.80 | [-3.56, 3.85] |
| **4** | 2.08 | [-2.97, 4.90] | 1.35 | [-1.51, 3.57] | 2.23 | [-5.41, 2.71] | 2.06 | [-4.30, 4.24] |
| **5** | 2.28 | [-3.36, 5.17] | 1.54 | [-1.77, 4.21] | 2.22 | [-4.77, 2.79] | 2.08 | [-3.64, 5.79] |
| **6** | 2.39 | [-2.44, 5.49] | 1.59 | [-1.42, 4.83] | 2.48 | [-5.26, 4.27] | 2.17 | [-4.35, 4.77] |



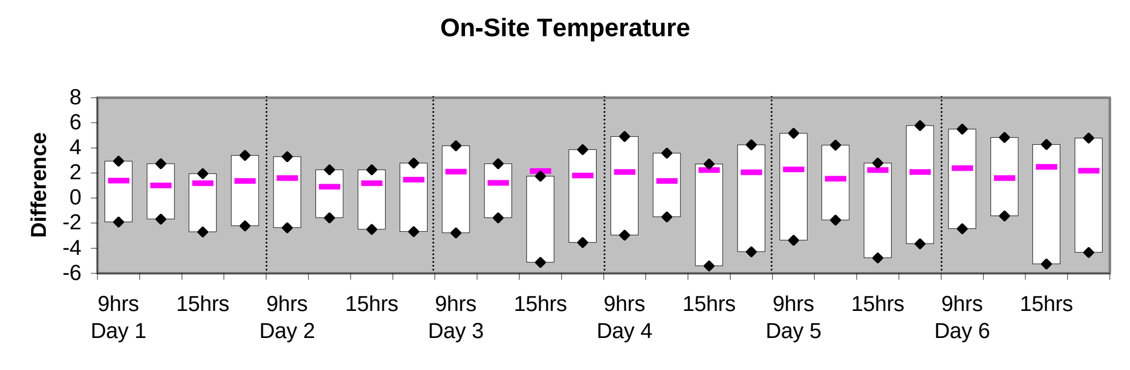



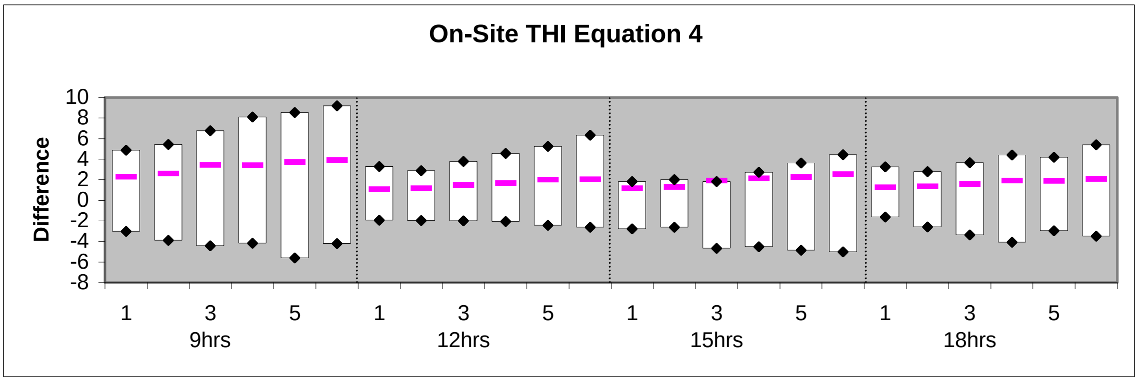

Figure B2. – Model 2 Temperature error statistics.

Table B6. – Error in Model 2 Weather Station Humidity Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| Day | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| 1 | 4.70 | [-8.69, 9.70] | 5.46 | [-11.63, 9.85] | 5.17 | [-13.60, 9.59] | 6.13 | [-17.27, 10.77] |
| 2 | 5.44 | [-10.92, 11.18] | 5.13 | [-11.45, 9.15] | 4.35 | [-9.78, 8.68] | 5.71 | [-15.23, 12.38] |
| 3 | 4.40 | [-9.53, 6.81] | 5.24 | [-12.84, 9.14] | 8.81 | [-8.82, 20.68] | 7.96 | [-16.80, 15.14] |
| 4 | 4.84 | [-8.07, 9.20] | 6.20 | [-16.73, 10.59] | 9.42 | [-12.26, 23.32] | 8.89 | [-16.86, 16.59] |
| 5 | 5.50 | [-11.61, 10.78] | 6.91 | [-18.89, 10.12] | 8.94 | [-12.59, 20.51] | 8.99 | [-25.08, 15.73] |
| 6 | 5.97 | [-13.96, 11.76] | 7.66 | [-19.95, 10.42] | 10.21 | [-14.58, 23.27] | 9.42 | [-23.62, 17.16] |

Table B7. – Error in Model 2 Weather Station THI Equation 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| Day | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| 1 | 2.28 | [-3.04, 4.86] | 1.07 | [-1.95, 3.30] | 1.16 | [-2.78, 1.81] | 1.26 | [-1.64, 3.26] |
| 2 | 2.61 | [-3.89, 5.43] | 1.18 | [-1.98, 2.87] | 1.28 | [-2.63, 2.01] | 1.36 | [-2.58, 2.78] |
| 3 | 3.43 | [-4.42, 6.77] | 1.48 | [-1.99, 3.79] | 1.93 | [-4.66, 1.81] | 1.59 | [-3.38, 3.67] |
| 4 | 3.41 | [-4.17, 8.11] | 1.66 | [-2.05, 4.56] | 2.12 | [-4.51, 2.72] | 1.92 | [-4.08, 4.39] |
| 5 | 3.73 | [-5.60, 8.54] | 2.00 | [-2.43, 5.25] | 2.25 | [-4.87, 3.63] | 1.89 | [-2.95, 4.19] |
| 6 | 3.91 | [-4.22, 9.19] | 2.04 | [-2.61, 6.34] | 2.54 | [-5.03, 4.44] | 2.06 | [-3.50, 5.39] |



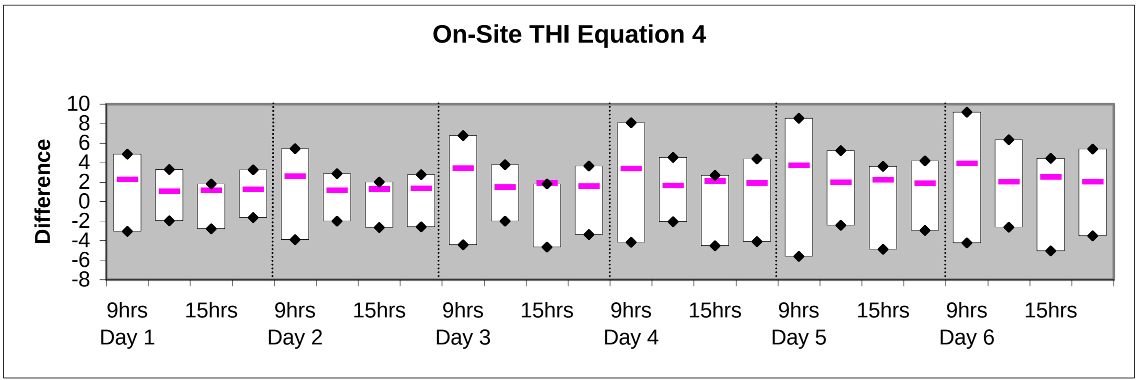
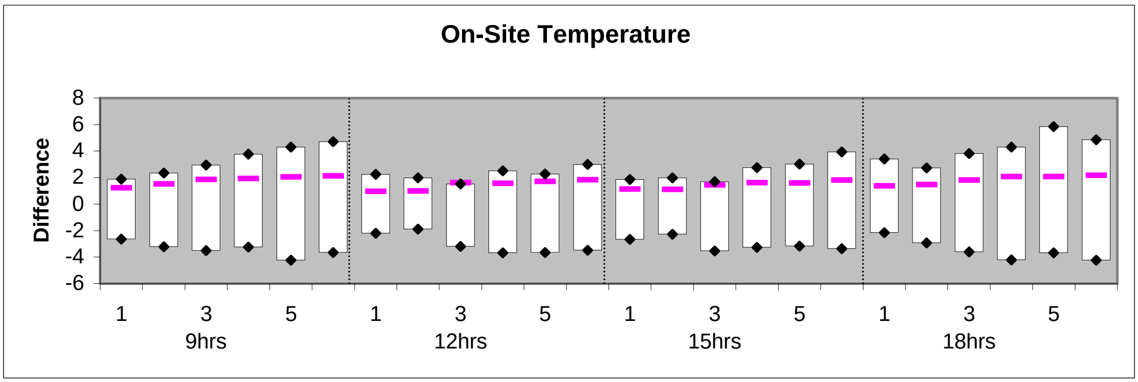




Figure B3. – Model 2 THI Equation 4 error statistics.

## Model 3

Table B8. – Error in Model 3 Weather Station Temperature Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| Day | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| 1 | 1.24 | [-2.65, 1.89] | 0.96 | [-2.20, 2.24] | 1.14 | [-2.66, 1.87] | 1.38 | [-2.16, 3.40] |
| 2 | 1.52 | [-3.22, 2.34] | 0.98 | [-1.89, 1.99] | 1.10 | [-2.28, 1.98] | 1.48 | [-2.93, 2.74] |
| 3 | 1.87 | [-3.51, 2.95] | 1.62 | [-3.20, 1.52] | 1.45 | [-3.54, 1.70] | 1.81 | [-3.61, 3.82] |
| 4 | 1.93 | [-3.24, 3.76] | 1.58 | [-3.69, 2.52] | 1.61 | [-3.27, 2.76] | 2.08 | [-4.22, 4.30] |
| 5 | 2.04 | [-4.24, 4.30] | 1.71 | [-3.65, 2.28] | 1.60 | [-3.17, 3.01] | 2.08 | [-3.67, 5.84] |
| 6 | 2.13 | [-3.66, 4.70] | 1.84 | [-3.49, 3.00] | 1.82 | [-3.36, 3.93] | 2.17 | [-4.23, 4.85] |



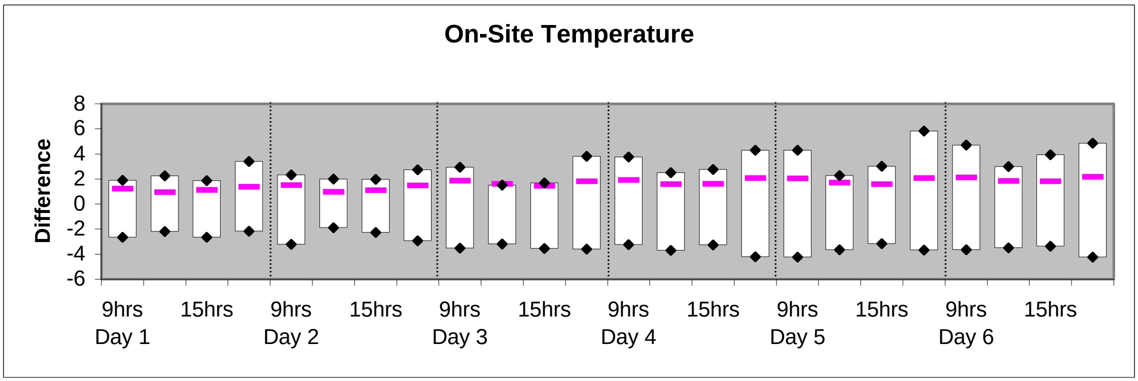



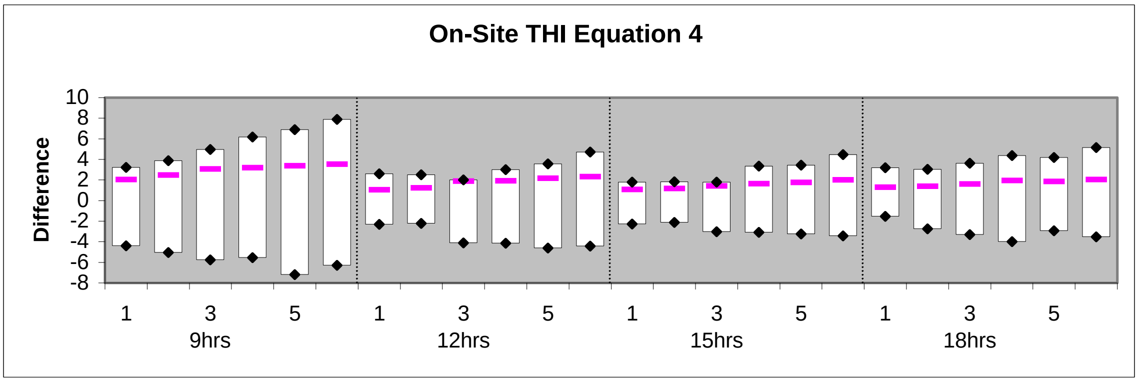

Figure B4. – Model 3 Temperature error statistics.

Table B9. – Error in Model 3 Weather Station Humidity Prediction.

| **Forecast Time** | **9hrs Ahead - 6am (+24hrs later days)** | | **12hrs Ahead - 9am (+24hrs later days)** | | **15hrs Ahead - 12pm (+24hrs later days)** | | **18hrs Ahead - 3pm (+24hrs later days)** | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| 1 | 4.49 | [-7.82, 11.08] | 5.70 | [-10.93, 12.34] | 5.17 | [-10.01, 10.14] | 6.06 | [-15.47, 11.17] |
| 2 | 5.18 | [-9.68,13.18] | 5.27 | [-10.53, 11.03] | 4.32 | [-8.43, 10.09] | 5.76 | [-16.21, 13.34] |
| 3 | 4.22 | [-6.75, 8.33] | 7.56 | [-8.27, 17.69] | 6.36 | [-9.15, 12.93] | 7.72 | [-17.12, 14.45] |
| 4 | 4.71 | [-5.88, 9.83] | 7.93 | [-11.17, 21.52] | 7.04 | [-14.47, 16.39] | 8.72 | [-18.06, 16.27] |
| 5 | 5.01 | [-9.67, 11.96] | 8.18 | [-10.92, 16.92] | 7.29 | [-17.32, 13.31] | 8.75 | [-25.11, 15.68] |
| 6 | 5.67 | [-12.38, 12.46] | 9.06 | [-14.90, 20.73] | 8.06 | [-19.66, 18.33] | 9.20 | [-24.12, 16.71] |

Table B10. – Error in Model 3 Weather Station THI Equation 4 Prediction.

| **Forecast Time** | **9hrs Ahead - 6am (+24hrs later days)** | | **12hrs Ahead - 9am (+24hrs later days)** | | **15hrs Ahead - 12pm (+24hrs later days)** | | **18hrs Ahead - 3pm (+24hrs later days)** | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 2.05 | [-4.40, 3.23] | 1.05 | [-2.30, 2.60] | 1.09 | [-2.28, 1.79] | 1.28 | [-1.52, 3.19] |
| **2** | 2.47 | [-5.05, 3.88] | 1.24 | [-2.21, 2.50] | 1.17 | [-2.13, 1.83] | 1.38 | [-2.74, 3.04] |
| **3** | 3.07 | [-5.76, 4.96] | 1.89 | [-4.12, 2.02] | 1.42 | [-3.04, 1.80] | 1.60 | [-3.31, 3.64] |
| **4** | 3.19 | [-5.54, 6.19] | 1.91 | [-4.13, 3.02] | 1.65 | [-3.10, 3.36] | 1.94 | [-4.00, 4.36] |
| **5** | 3.39 | [-7.18, 6.90] | 2.17 | [-4.60, 3.57] | 1.77 | [-3.25, 3.45] | 1.87 | [-2.94, 4.18] |
| **6** | 3.52 | [-6.30, 7.90] | 2.32 | [-4.42, 4.72] | 2.00 | [-3.42, 4.46] | 2.05 | [-3.53, 5.14] |



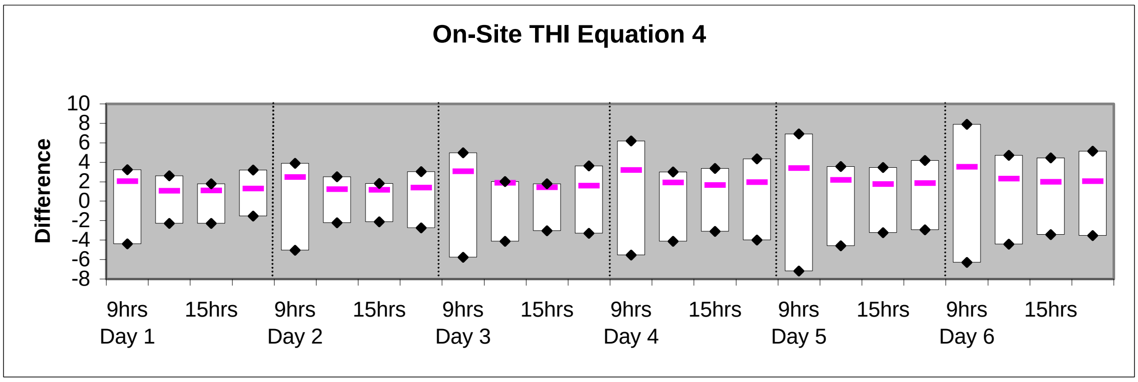
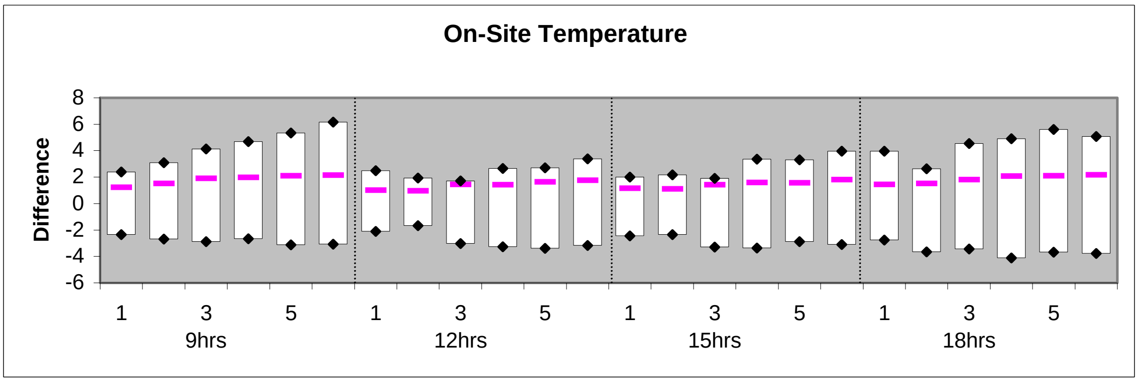




Figure B5. – Model 3 THI Equation 4 error statistics.

# Model 4

Table B11. – Error in Model 4 Weather Station Temperature Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 1.22 | [-2.34, 2.38] | 1.01 | [-2.10, 2.49] | 1.15 | [-2.44, 2.00] | 1.44 | [-2.76, 3.97] |
| **2** | 1.51 | [-2.68, 3.09] | 0.97 | [-1.66, 1.93] | 1.11 | [-2.34, 2.17] | 1.51 | [-3.66, 2.64] |
| **3** | 1.91 | [-2.89, 4.12] | 1.44 | [-3.02, 1.72] | 1.43 | [-3.29, 1.90] | 1.82 | [-3.43, 4.54] |
| **4** | 1.99 | [-2.67, 4.68] | 1.43 | [-3.27, 2.65] | 1.59 | [-3.36, 3.36] | 2.08 | [-4.11, 4.90] |
| **5** | 2.10 | [-3.12, 5.35] | 1.64 | [-3.40, 2.70] | 1.58 | [-2.87, 3.32] | 2.10 | [-3.69, 5.60] |
| **6** | 2.16 | [-3.07, 6.17] | 1.76 | [-3.18, 3.37] | 1.82 | [-3.11, 3.97] | 2.17 | [-3.77, 5.08] |



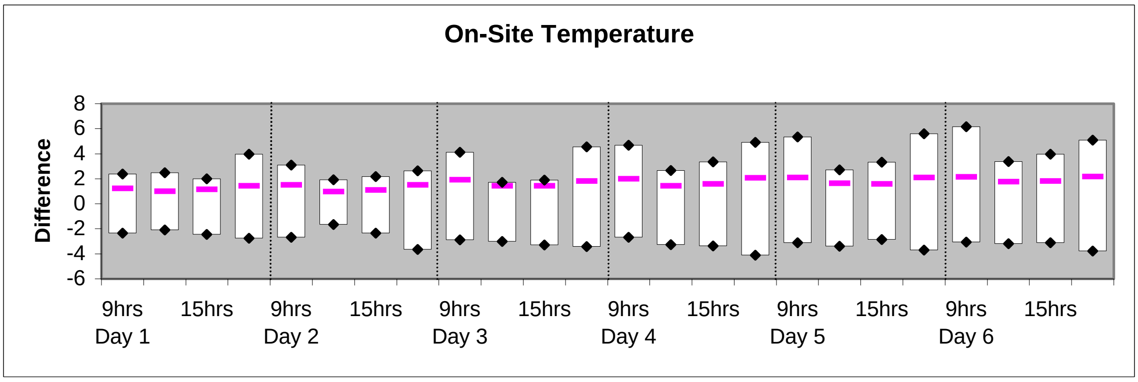



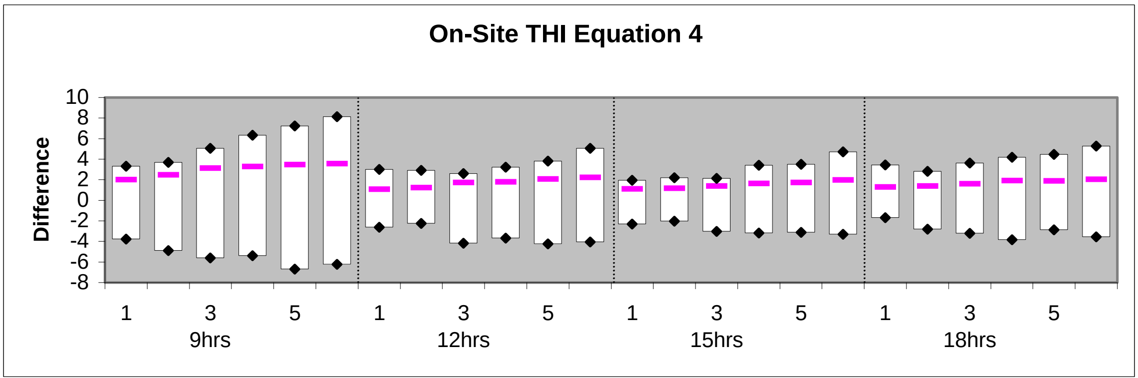

Figure B6. – Model 4 Temperature error statistics.

Table B12. – Error in Model 4 Weather Station Humidity Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 4.02 | [-7.07, 9.78] | 5.92 | [-12.95, 12.21] | 5.28 | [-11.19, 9.39] | 6.20 | [-18.24, 12.43] |
| **2** | 4.87 | [-8.41, 11.52] | 4.97 | [-10.49, 9.99] | 4.38 | [-9.43, 9.08] | 6.09 | [-15.07, 12.45] |
| **3** | 4.27 | [-7.95,9.13] | 6.54 | [-9.22, 14.44] | 6.50 | [-9.72, 13.13] | 7.91 | [-16.83, 15.51] |
| **4** | 4.66 | [-6.66, 10.08] | 7.26 | [-10.87, 19.73] | 7.07 | [-13.94, 16.39] | 8.81 | [-17.39, 17.13] |
| **5** | 4.89 | [-9.91,11.50] | 7.60 | [-12.86, 16.52] | 7.35 | [-18.35, 14.40] | 8.83 | [-25.32, 16.54] |
| **6** | 5.62 | [-12.54, 11.81] | 8.66 | [-16.20, 18.45] | 8.07 | [-20.00, 17.61] | 9.34 | [-24.22, 18.14] |

Table B13. – Error in Model 4 Weather Station THI Equation 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 2.00 | [-3.76, 3.33] | 1.08 | [-2.62, 3.01] | 1.12 | [-2.31, 1.95] | 1.29 | [-1.68, 3.45] |
| **2** | 2.47 | [-4.89, 3.68] | 1.24 | [-2.26, 2.92] | 1.17 | [-2.04, 2.19] | 1.39 | [-2.80, 2.83] |
| **3** | 3.13 | [-5.61, 5.05] | 1.72 | [-4.19, 2.60] | 1.40 | [-3.04, 2.13] | 1.61 | [-3.22, 3.62] |
| **4** | 3.28 | [-5.39, 6.33] | 1.78 | [-3.69, 3.23] | 1.63 | [-3.19, 3.40] | 1.93 | [-3.82, 4.18] |
| **5** | 3.47 | [-6.68, 7.24] | 2.08 | [-4.25, 3.80] | 1.73 | [-3.13, 3.50] | 1.88 | [-2.88, 4.46] |
| **6** | 3.56 | [-6.24, 8.12] | 2.23 | [-4.04, 5.06] | 1.98 | [-3.30, 4.70] | 2.03 | [-3.55, 5.28] |



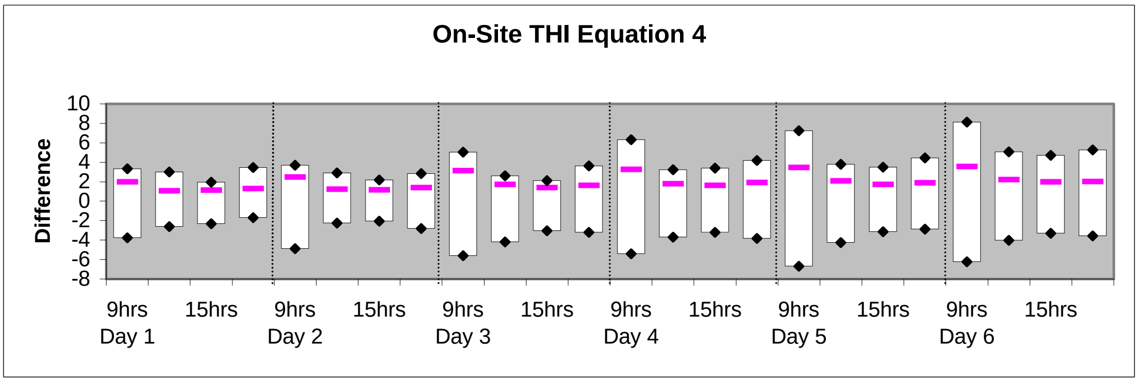
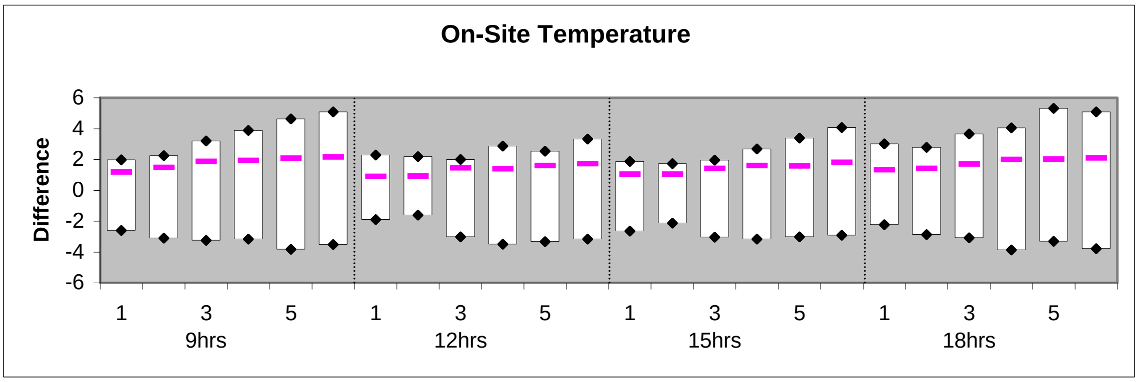




Figure B7. – Model 4 THI Equation 4 error statistics.

# Model 5

Table B14. – Error in Model 5 Weather Station Temperature Prediction.

| **Forecast Time** | **9hrs Ahead - 6am (+24hrs later days)** | | **12hrs Ahead - 9am (+24hrs later days)** | | **15hrs Ahead - 12pm (+24hrs later days)** | | **18hrs Ahead - 3pm (+24hrs later days)** | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 1.20 | [-2.61, 1.98] | 0.91 | [-1.89, 2.30] | 1.05 | [-2.64, 1.88] | 1.34 | [-2.23, 3.01] |
| **2** | 1.49 | [-3.09, 2.25] | 0.92 | [-1.60, 2.18] | 1.05 | [-2.12, 1.74] | 1.41 | [-2.87, 2.78] |
| **3** | 1.88 | [-3.24, 3.21] | 1.47 | [-3.01, 1.99] | 1.43 | [-3.04, 1.95] | 1.71 | [-3.07, 3.65] |
| **4** | 1.93 | [-3.16, 3.88] | 1.39 | [-3.49, 2.88] | 1.60 | [-3.17, 2.68] | 2.00 | [-3.86, 4.06] |
| **5** | 2.09 | [-3.82, 4.64] | 1.60 | [-3.33, 2.54] | 1.59 | [-3.02, 3.39] | 2.03 | [-3.31, 5.31] |
| **6** | 2.17 | [-3.51, 5.08] | 1.73 | [-3.16, 3.33] | 1.81 | [-2.91, 4.08] | 2.11 | [-3.78, 5.08] |



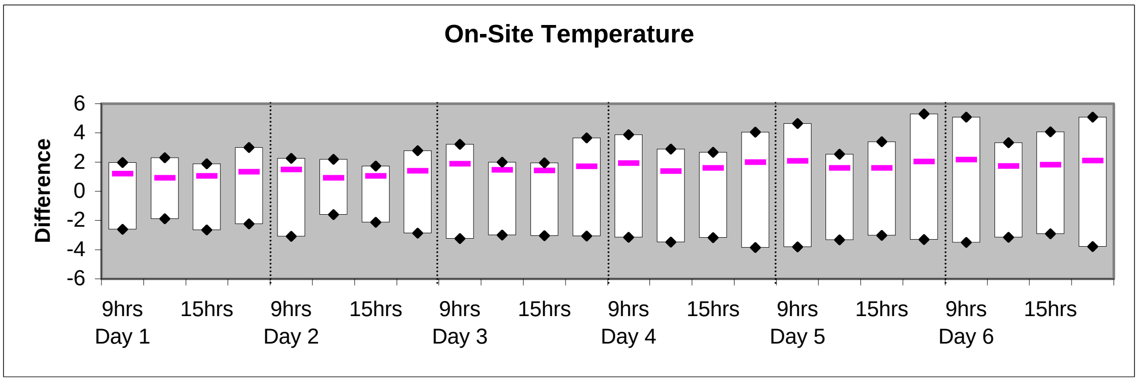



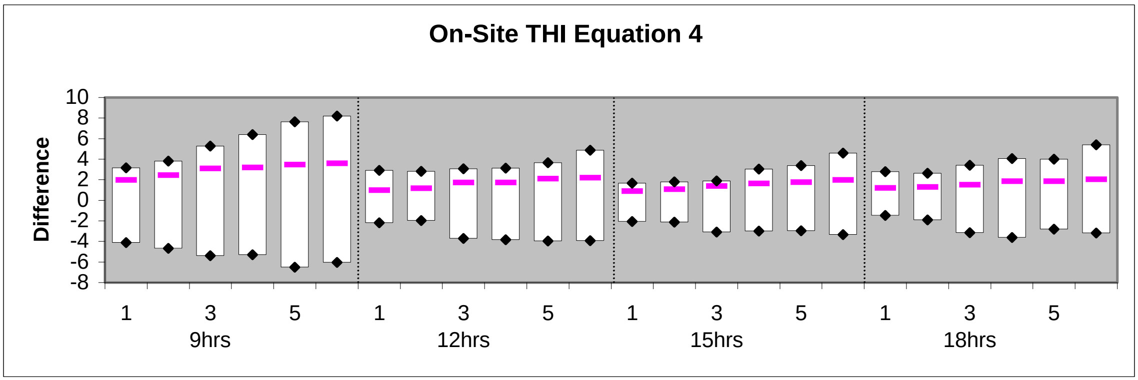

Figure B8. – Model 5 Temperature error statistics.

Table B15. – Error in Model 5 Weather Station Humidity Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 4.29 | [-7.29, 10.39] | 5.47 | [-12.36, 11.53] | 5.09 | [-10.30, 9.49] | 6.05 | [-16.34, 11.36] |
| **2** | 5.01 | [-8.24, 12.52] | 5.22 | [-10.39, 9.84] | 4.21 | [-8.45, 9.23] | 5.71 | [-16.10, 13.22] |
| **3** | 4.26 | [-6.56, 8.88] | 6.78 | [-10.60, 15.85] | 6.10 | [-10.81, 12.39] | 7.60 | [-17.24, 14.78] |
| **4** | 4.71 | [-6.44, 11.15] | 7.20 | [-11.45, 19.63] | 6.86 | [-14.59, 15.72] | 8.53 | [-17.50, 16.13] |
| **5** | 4.99 | [-9.37, 11.87] | 7.61 | [-12.38, 16.24] | 7.09 | [-18.71, 12.55] | 8.61 | [-22.56, 15.47] |
| **6** | 5.60 | [-11.90, 12.90] | 8.52 | [-15.33, 18.85] | 7.89 | [-16.21, 17.67] | 9.05 | [-22.87, 16.53] |

Table B16. – Error in Model 5 Weather Station THI Equation 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 1.98 | [-4.11, 3.17] | 0.97 | [-2.20, 2.91] | 0.90 | [-2.06, 1.66] | 1.20 | [-1.48, 2.79] |
| **2** | 2.45 | [-4.68, 3.82] | 1.16 | [-1.98, 2.82] | 1.07 | [-2.11, 1.79] | 1.31 | [-1.92, 2.62] |
| **3** | 3.10 | [-5.38, 5.28] | 1.74 | [-3.72, 3.07] | 1.40 | [-3.10, 1.90] | 1.50 | [-3.15, 3.42] |
| **4** | 3.18 | [-5.31, 6.38] | 1.74 | [-3.84, 3.13] | 1.63 | [-3.01, 3.03] | 1.85 | [-3.63, 4.07] |
| **5** | 3.46 | [-6.51, 7.63] | 2.09 | [-3.95, 3.65] | 1.76 | [-2.97, 3.37] | 1.85 | [-2.82, 4.00] |
| **6** | 3.60 | [-6.05, 8.19] | 2.21 | [-3.92, 4.86] | 1.98 | [-3.33, 4.59] | 2.04 | [-3.17, 5.41] |



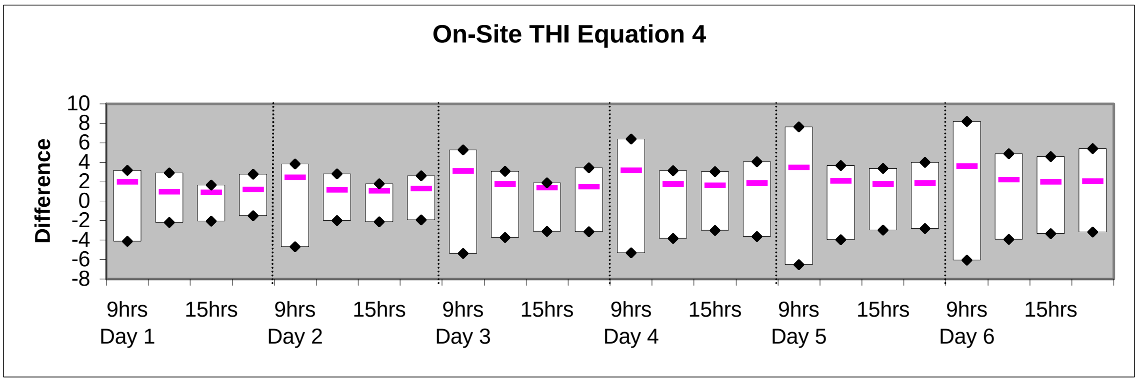




Figure B9. – Model 5 THI Equation 4 error statistics.

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# APPENDIX C. – ROCKDALE TABLES AND FIGURES

Table C1. – Overall Error in Comparisons by Method and Variable for First 48hrs.

| **Forecast** | **Persistence** | | **On-Site Downscaled** | | **B.o.M. Predictions** | | **A.W.S. Downscaled** | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Temp** | 3.73 | [-7.00, 9.32] | 2.09 | [-3.74, 5.31] | 2.84 | [-2.91, 7.38] | 1.90 | [-1.56, 4.98] |
| **Rel. Hum.** | 10.66 | [-28.12, 21.95] | 9.50 | [-25.13, 16.41] | 13.71 | [-30.84, 10.89] | 7.57 | [-19.03, 12.33] |
| **Dew Pt.** | 2.64 | [-5.27, 6.34] | 2.26 | [-4.55, 5.12] | 2.66 | [-6.67, 2.92] | 2.51 | [-6.30, 4.16] |
| **WSpeed 2** | 1.44 | [-3.29, 3.33] | 1.34 | [-2.40, 2.88] | 1.29 | [-3.13, 11.88] | 1.79 | [-1.82, 3.82] |
| **WSpeed 10** | 1.88 | [-4.25, 4.26] | 1.45 | [-3.47, 2.50] | 1.54 | [-4.96, 9.46] | 1.63 | [-2.87, 3.37] |
| **THI 4** | 4.66 | [-9.08, 11.50] | 2.71 | [-5.00, 7.00] | 4.06 | [-2.83, 2.26] | 2.42 | [-2.03, 6.87] |
| **THI 6** | 5.11 | [-9.90, 12.11] | 3.59 | [-6.35, 8.72] | 4.92 | [-3.97, 2.01] | 4.09 | [-1.07, 10.06] |

Table C2. – Overall Error in Comparisons by Method and Variable for hours 48 onwards.

| **Forecast** | **Persistence** | | **On-Site Downscaled** | | **B.o.M. Predictions** | | **A.W.S. Downscaled** | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Temp** | 4.28 | [-8.80, 9.09] | 4.06 | [-5.87, 11.01] | 4.45 | [-2.18, 10.87] | 2.86 | [-2.90, 7.88] |
| **Rel. Hum.** | 12.51 | [-32.40, 25.63] | 13.42 | [-38.38, 16.23] | 19.67 | [-44.76, 6.21] | 10.47 | [-30.76, 13.14] |
| **Dew Pt.** | 3.08 | [-6.57, 6.57] | 3.54 | [-8.20, 7.43] | 3.20 | [-8.29, 2.48] | 2.82 | [-6.85, 4.70] |
| **WSpeed 2** | 1.58 | [-3.53, 3.54] | 1.54 | [-2.60, 4.40] | 5.78 | [-3.42, 3.36] | 1.83 | [-2.15, 3.99] |
| **WSpeed 10** | 2.11 | [-4.59, 4.61] | 1.56 | [-3.60, 3.01] | 1.74 | [-16.73, 2.60] | 1.72 | [-3.23, 3.55] |
| **THI 4** | 5.35 | [-10.98, 11.70] | 5.05 | [-7.26, 13.79] | 5.28 | [-3.90, 12.99] | 3.52 | [-3.41, 9.74] |
| **THI 6** | 5.89 | [-12.22, 12.56] | 5.75 | [-8.76, 14.94] | 6.53 | [-1.45, 14.93] | 4.95 | [-2.11, 12.01] |

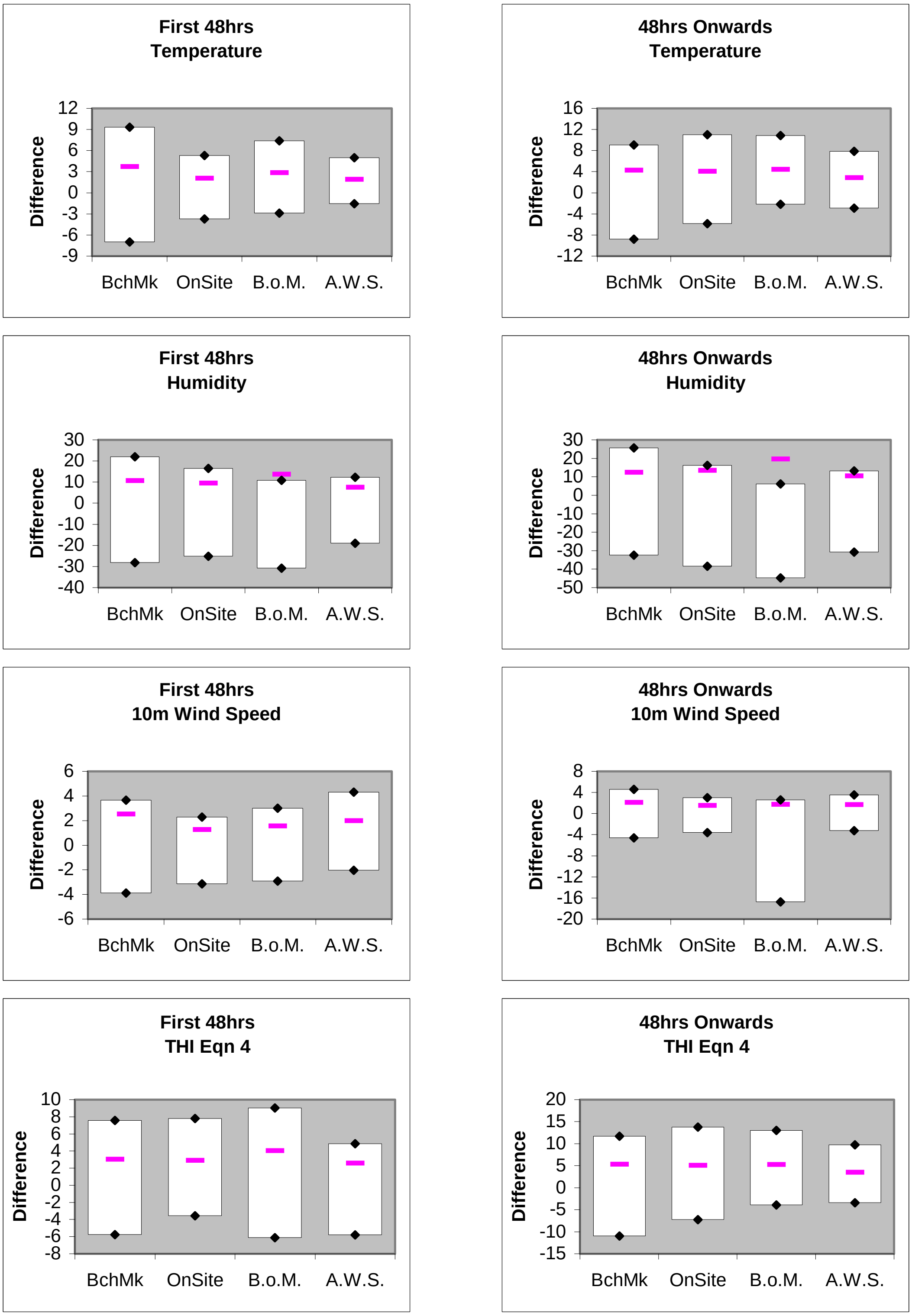


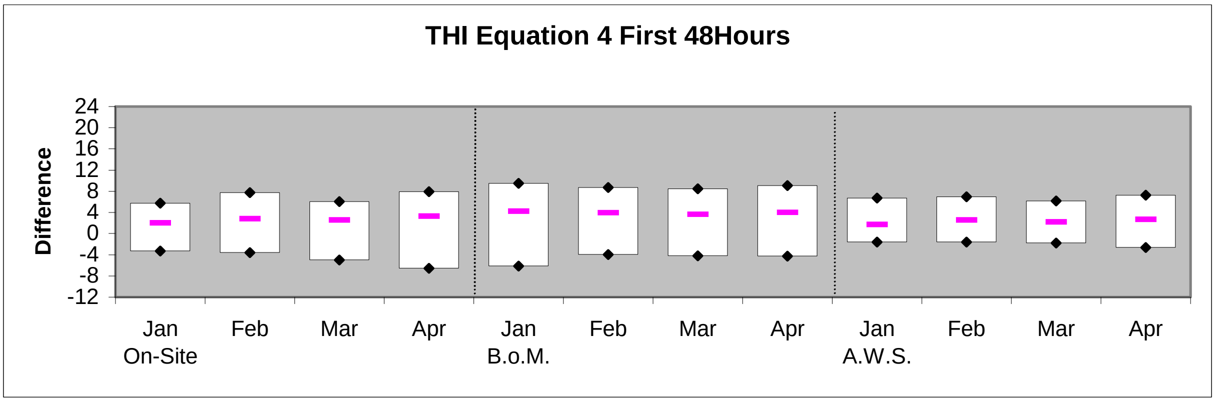

Figure C1. – Error statistics for each method and various parameters, both for forecast horizons out to 48 hours and from 48-144 hours

Table C3. – Overall Error in THI 4 Comparisons by Month for First 48hrs.

| **Forecast** | **On-site Downscaled** | | **B.o.M.** | | **A.W.S. Downscaled** | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 1.99 | [-3.31, 5.75] | 4.24 | [-6.16, 9.51] | 1.74 | [-1.62, 6.74] |
| **Feb** | 2.82 | [-3.60, 7.73] | 3.96 | [-3.97, 8.70] | 2.57 | [-1.62, 6.94] |
| **Mar** | 2.56 | [-4.99, 6.07] | 3.66 | [-4.19, 8.50] | 2.19 | [-1.80, 6.19] |
| **Apr** | 3.30 | [-6.59, 7.95] | 4.03 | [-4.28, 9.10] | 2.70 | [-2.62, 7.25] |

Table C4. – Overall Error in THI 4 Comparisons by Month for hours 48 onwards.

| **Forecast** | **On-site Downscaled** | | **B.o.M.** | | **A.W.S. Downscaled** | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 4.08 | [-4.83, 12.09] | 5.13 | [-5.08, 12.44] | 3.21 | [-2.97, 10.43] |
| **Feb** | 6.03 | [-6.35, 21.78] | 5.26 | [-3.50, 11.22] | 3.39 | [-3.10, 9.26] |
| **Mar** | 4.23 | [-7.48, 10.72] | 5.10 | [-3.36, 12.30] | 3.39 | [-3.78, 9.32] |
| **Apr** | 5.81 | [-9.95, 13.45] | 5.43 | [-3.12, 14.65] | 3.84 | [-3.45, 10.52] |



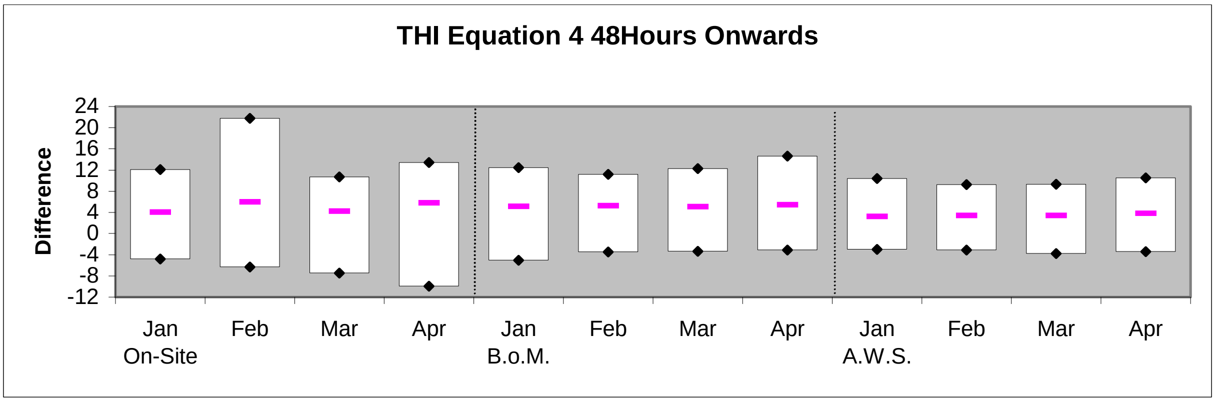




Figure C2. –Temperature Humidity Index Equation 4 errors statistics for different horizons.

Table C5. – Error in Katestone A.W.S. Downscaled THI 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 3.12 | [-8.44, 3.88] | 2.64 | [-1.71, 8.67] | 2.33 | [-2.59, 8.23] | 3.07 | [-3.97, 8.12] |
| **2** | 3.18 | [-8.70, 5.34] | 3.05 | [-1.37, 9.52] | 2.61 | [-3.52, 8.62] | 3.23 | [-3.90, 8.28] |
| **3** | 5.04 | [-12.58, 7.44] | 6.81 | [-1.18, 17.02] | 5.55 | [-4.38, 18.32] | 6.23 | [-3.30, 17.58] |
| **4** | 5.58 | [-15.54, 9.33] | 7.19 | [-1.94, 18.63] | 5.89 | [-4.62, 19.88] | 6.69 | [-3.05, 18.64] |
| **5** | 5.86 | [-14.50, 8.59] | 7.46 | [0.02, 16.56] | 5.98 | [-4.45, 16.63] | 6.79 | [-3.45, 17.34] |
| **6** | 6.05 | [-15.34, 6.63] | 7.73 | [-1.68, 17.58] | 6.39 | [-4.58, 16.05] | 7.02 | [-4.00, 17.09] |

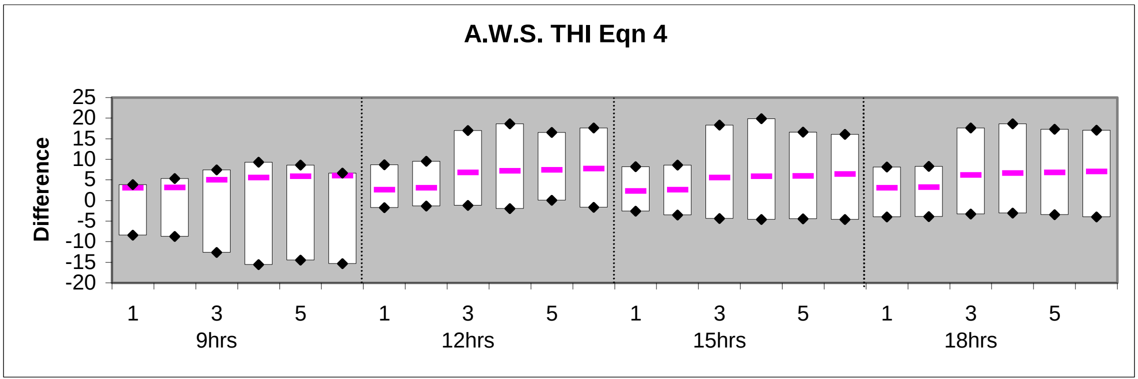



Figure C3. –THI Equation 4 errors split by Hour and then by Day, for different models and for different time horizons.

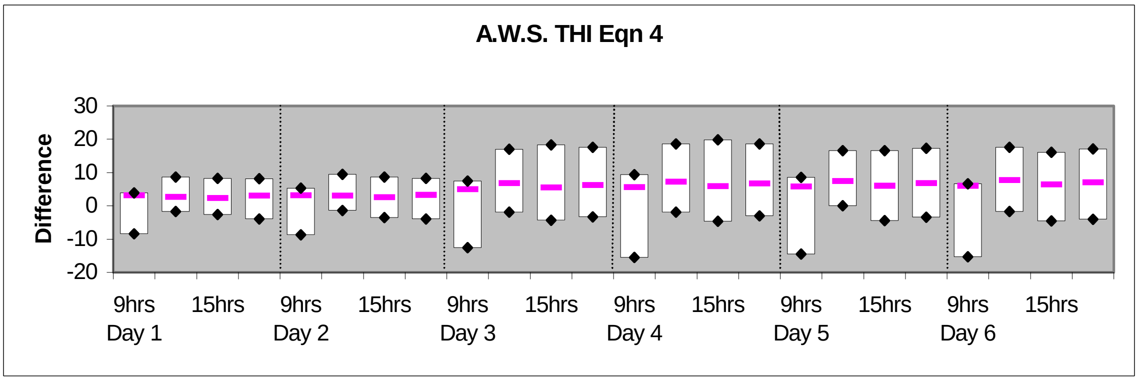



Figure C4. –THI Equation 4 errors split by Day and then by Hour, for different models and for different time horizons.

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# APPENDIX D. – KERWEE TABLES AND FIGURES

Table D1. – Overall Error in Comparisons by Method and Variable for First 48hrs.

| **Forecast** | **Persistence** | | **On-Site Downscaled** | | **B.o.M. Predictions** | | **A.W.S. Downscaled** | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Temp** | 2.05 | [-5.48, 4.04] | 1.40 | [-2.67, 3.26] | 2.24 | [-3.46, 4.96] | 1.57 | [-3.11, 3.65] |
| **Rel. Hum.** | 8.01 | [-19.73, 17.90] | 8.20 | [-18.62, 14.69] | 11.11 | [-26.11, 15.56] | 6.67 | [-13.31, 14.97] |
| **Dew Pt.** | 2.05 | [-4.56, 4.65] | 2.00 | [-4.33, 4.39] | 1.96 | [-3.45, 4.14] | 1.74 | [-4.00, 3.37] |
| **WSpeed 2** | 1.41 | [-3.19, 3.33] | 1.22 | [-1.92, 2.74] | 1.26 | [-2.37, 2.39] | 2.01 | [-1.24, 4.43] |
| **WSpeed 10** | 1.58 | [-3.70, 3.53] | 1.21 | [-2.95, 2.25] | 1.36 | [-3.55, 2.00] | 1.64 | [-2.11, 3.71] |
| **THI 4** | 2.40 | [-4.70, 6.39] | 2.44 | [-3.23, 6.38] | 3.84 | [-4.87, 7.99] | 2.69 | [-2.95, 7.72] |

Table D2. – Overall Error in Comparisons by Method and Variable for hours 48 onwards.

| **Forecast** | **Persistence** | | **On-Site Downscaled** | | **B.o.M. Predictions** | | **A.W.S. Downscaled** | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Temp** | 2.48 | [-4.81, 6.30] | 2.23 | [-4.55, 5.14] | 2.38 | [-2.94, 6.25] | 1.99 | [-4.26, 4.39] |
| **Rel. Hum.** | 9.90 | [-22.38, 12.95] | 10.74 | [-24.74, 20.09] | 13.67 | [-29.24, 18.24] | 8.14 | [-17.53, 18.03] |
| **Dew Pt.** | 2.46 | [-4.93, 5.95] | 2.36 | [-4.44, 5.66] | 1.97 | [-3.97, 3.87] | 2.01 | [-4.77, 3.93] |
| **WSpeed 2** | 1.49 | [-3.20, 3.50] | 1.39 | [-1.96, 3.12] | 5.89 | [-14.59, 1.53] | 2.18 | [-1.25, 4.58] |
| **WSpeed 10** | 1.65 | [-3.76, 3.60] | 1.38 | [-3.10, 2.71] | 1.61 | [-3.46, 2.94] | 1.82 | [-2.21, 3.97] |
| **THI 4** | 2.89 | [-5.37, 7.44] | 3.26 | [-4.52, 8.14] | 4.20 | [-4.65, 9.93] | 2.95 | [-4.11, 7.57] |

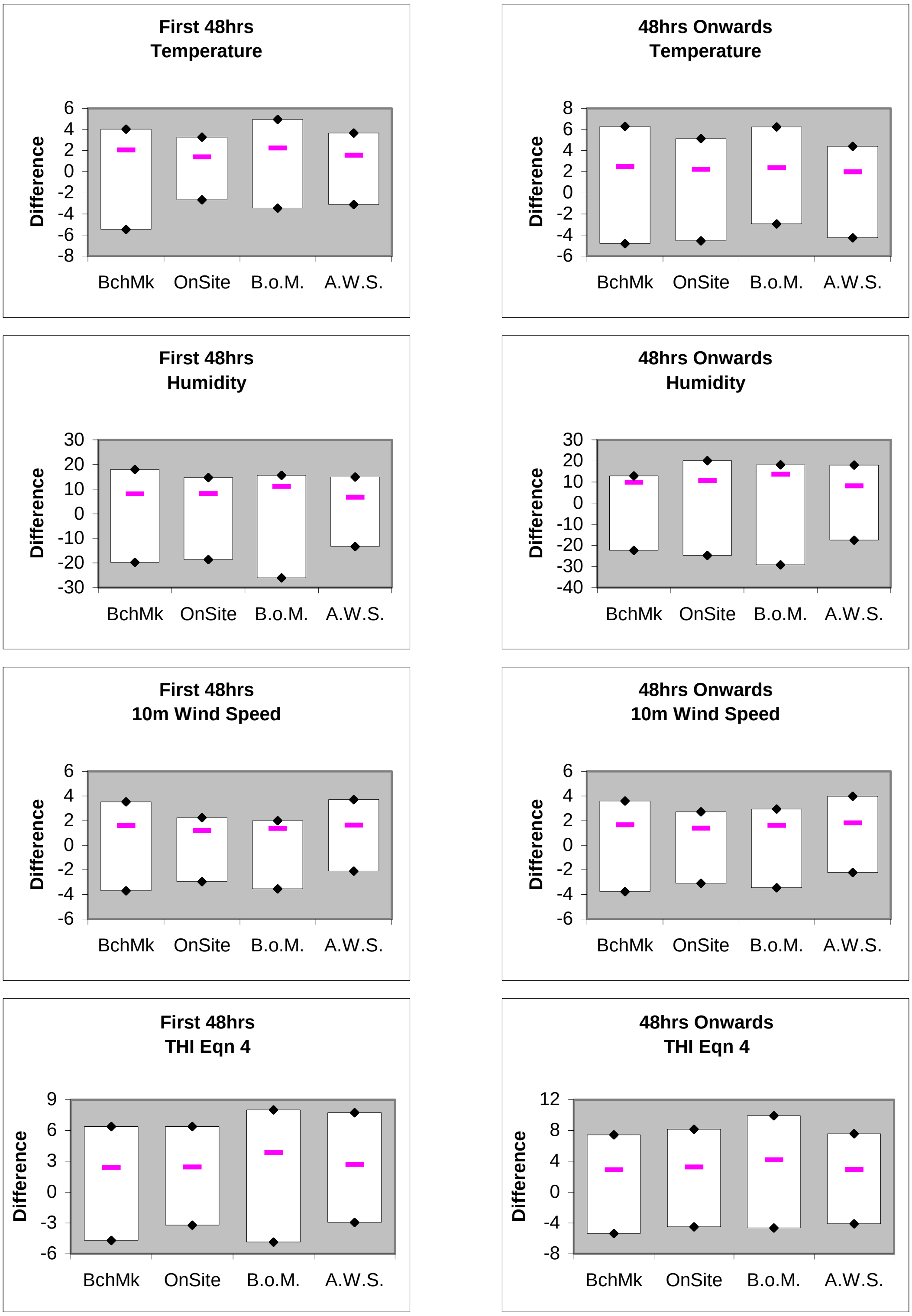


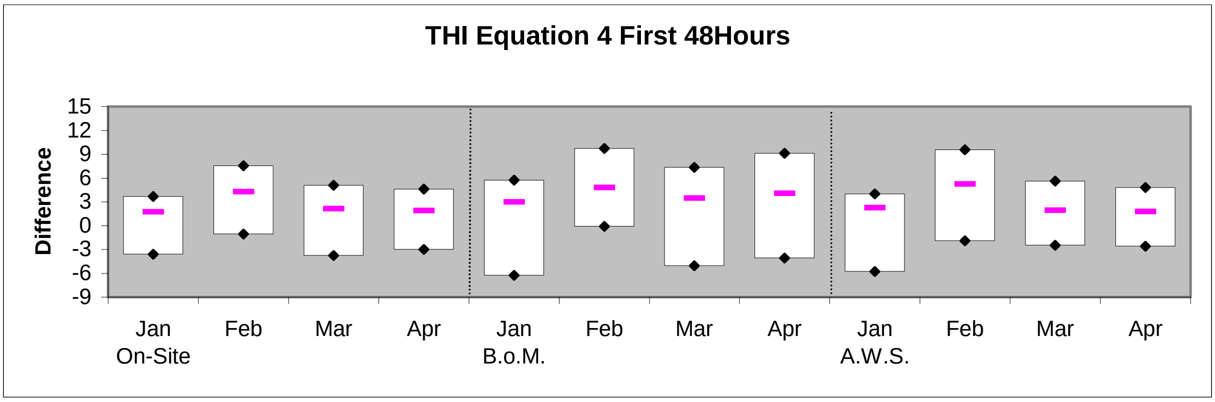

Figure D1. – Error statistics for each method and various parameters, both for forecast horizons out to 48 hours and from 48-144 hours

Table D3. – Overall Error in THI 4 Comparisons by Month for First 48hrs.

| **Forecast** | **On-site Downscaled** | | **B.o.M.** | | **A.W.S. Downscaled** | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 1.76 | [-3.60, 3.70] | 3.01 | [-6.26, 5.75] | 2.29 | [-5.77, 4.01] |
| **Feb** | 4.30 | [-1.05, 7.54] | 4.81 | [-0.10, 9.71] | 5.25 | [-1.91, 9.55] |
| **Mar** | 2.15 | [-3.76, 5.08] | 3.48 | [-5.07, 7.33] | 1.96 | [-2.47, 5.61] |
| **Apr** | 1.90 | [-3.00, 4.62] | 4.09 | [-4.09, 9.13] | 1.81 | [-2.60, 4.81] |

Table D4. – Overall Error in THI 4 Comparisons by Month for hours 48 onwards.

| **Forecast** | **On-site Downscaled** | | **B.o.M.** | | **A.W.S. Downscaled** | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 2.39 | [-4.99, 5.26] | 3.80 | [-5.40, 8.30] | 2.86 | [-7.15, 5.16] |
| **Feb** | 4.41 | [-1.96, 8.88] | 5.58 | [-0.39, 13.26] | 4.61 | [-2.02, 9.71] |
| **Mar** | 2.93 | [-5.35, 7.24] | 3.37 | [-5.37,8.12] | 2.44 | [-4.37, 5.72] |
| **Apr** | 3.22 | [-4.20, 9.16] | 4.47 | [-4.03, 10.27] | 2.26 | [-2.11, 6.32] |



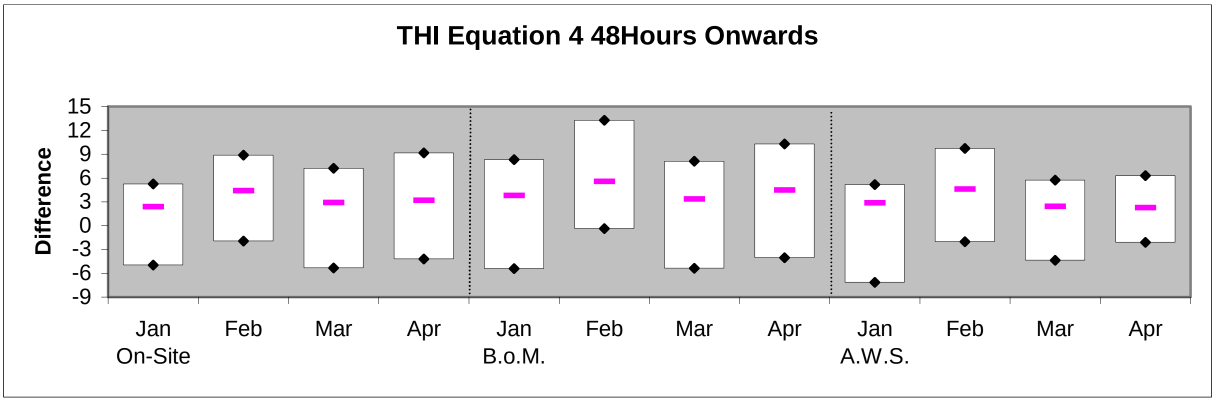




Figure D2. –Temperature Humidity Index Equation 4 error statistics for different horizons.

Table D5. – Error in Katestone A.W.S. Downscaled THI 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 1.82 | [-1.74, 5.28] | 1.82 | [-1.78, 5.41] | 2.49 | [-1.61, 5.28] | 2.01 | [-1.79, 4.42] |
| **2** | 1.96 | [-2.54, 5.10] | 2.38 | [-3.47, 6.66] | 2.50 | [-3.26, 6.71] | 2.41 | [-3.05, 6.76] |
| **3** | 2.77 | [-3.48, 7.19] | 2.81 | [-3.15, 6.13] | 2.72 | [-2.52, 6.39] | 2.70 | [-2.78, 6.70] |
| **4** | 2.14 | [-2.32, 5.58] | 2.30 | [-2.06, 5.35] | 2.76 | [-2.67, 5.00] | 2.59 | [-2.17, 5.48] |
| **5** | 2.03 | [-3.18, 5.38] | 2.34 | [-3.47, 3.59] | 2.83 | [-3.29, 6.37] | 2.55 | [-3.49, 6.44] |
| **6** | 2.78 | [-4.22, 6.98] | 2.83 | [-4.18, 6.03] | 3.22 | [-3.99, 6.41] | 2.78 | [-4.14, 6.67] |

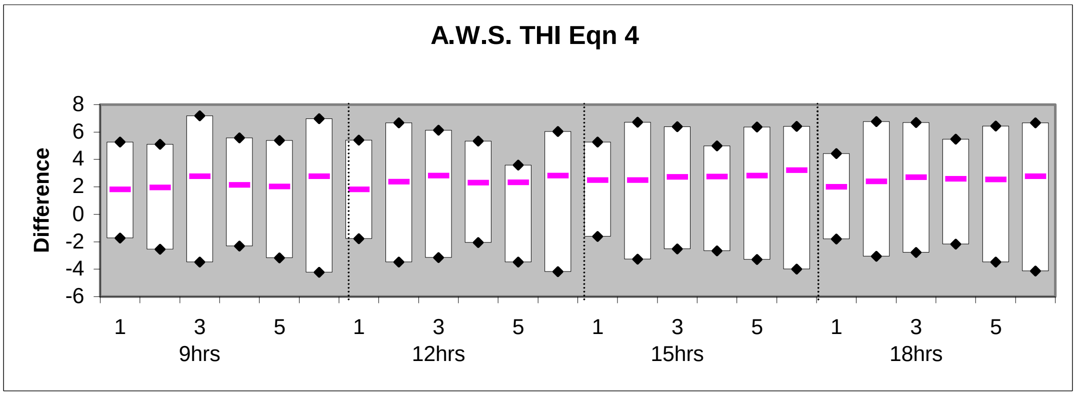



Figure D3. –THI Equation 4 errors split by Hour and then by Day, for different models and for different time horizons.

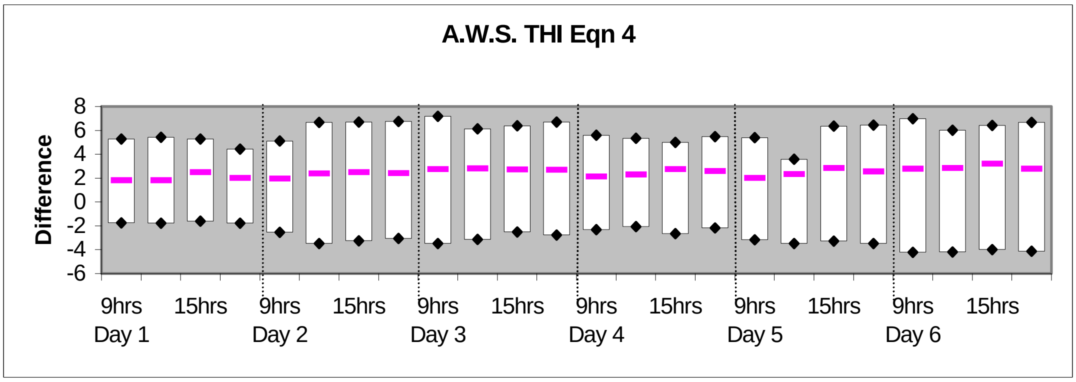



Figure D4. –THI Equation 4 errors split by Day and then by Hour, for different models and for different time horizons.

# TABLES:



# FIGURES:



# APPENDIX E. – CAROONA TABLES AND FIGURES

Table E1. – Overall Error in Comparisons by Method and Variable for First 48hrs.

| Forecast | Persistence | | On-Site Downscaled | | BoM Predictions | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Temp** | 2.35 | [-4.45, 5.87] | 1.27 | [-2.24, 3.05] | 2.07 | [-4.84, 2.14] | 1.53 | [-3.33, 3.13] |
| **Rel. Hum.** | 10.33 | [-25.52, 22.46] | 6.79 | [-16.00, 13.32] | 13.41 | [-23.90, 27.18] | 8.61 | [-15.90, 19.63] |
| **Dew Pt.** | 2.45 | [-5.14, 5.11] | 3.08 | [-2.22, 7.13] | 3.05 | [-4.16, 7.04] | 2.65 | [-4.81, 5.61] |
| **WSpeed 2** | 1.05 | [-2.38, 2.44] | 3.24 | [-1.63, 2.05] | 1.05 | [-2.10, 1.97] | 1.89 | [-1.38, 4.05] |
| **WSpeed 10** | 1.32 | [-2.98, 2.96] | 0.94 | [-2.46, 1.64] | 1.06 | [-2.86, 1.51] | 1.67 | [-2.25, 3.50] |
| **THI 4** | 2.90 | [-5.52, 7.10] | 1.90 | [-1.76, 5.03] | 3.04 | [-6.87, 3.19] | 1.94 | [-4.48, 3.96] |

Table E2. – Overall Error in Comparisons by Method and Variable for hours 48 onwards.

| Forecast | Persistence | | On-Site Downscaled | | BoM Predictions | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Temp** | 2.78 | [-5.44, 6.56] | 1.75 | [-2.65, 4.69] | 2.53 | [-5.11, 3.56] | 1.89 | [-3.41, 4.48] |
| **Rel. Hum.** | 12.05 | [-30.76, 25.21] | 8.36 | [-18.33, 27.33] | 17.15 | [-31.29, 29.22] | 9.55 | [-21.86, 18.16] |
| **Dew Pt.** | 2.85 | [-6.22, 6.04] | 3.59 | [-2.11, 8.82] | 2.57 | [-7.14, 3.14] | 3.01 | [-5.61, 6.49] |
| **WSpeed 2** | 1.06 | [-2.32, 2.53] | 0.98 | [-1.79, 2.31] | 3.14 | [-9.66, 2.33] | 1.88 | [-1.40, 4.08] |
| **WSpeed 10** | 1.33 | [-2.92, 3.06] | 1.04 | [-2.69, 1.90] | 1.64 | [-1.36, 3.33] | 1.68 | [-2.27, 3.60] |
| **THI 4** | 3.43 | [-6.60, 7.87] | 2.69 | [-2.69, 7.36] | 3.75 | [-7.29, 4.88] | 2.35 | [-4.89, 5.39] |

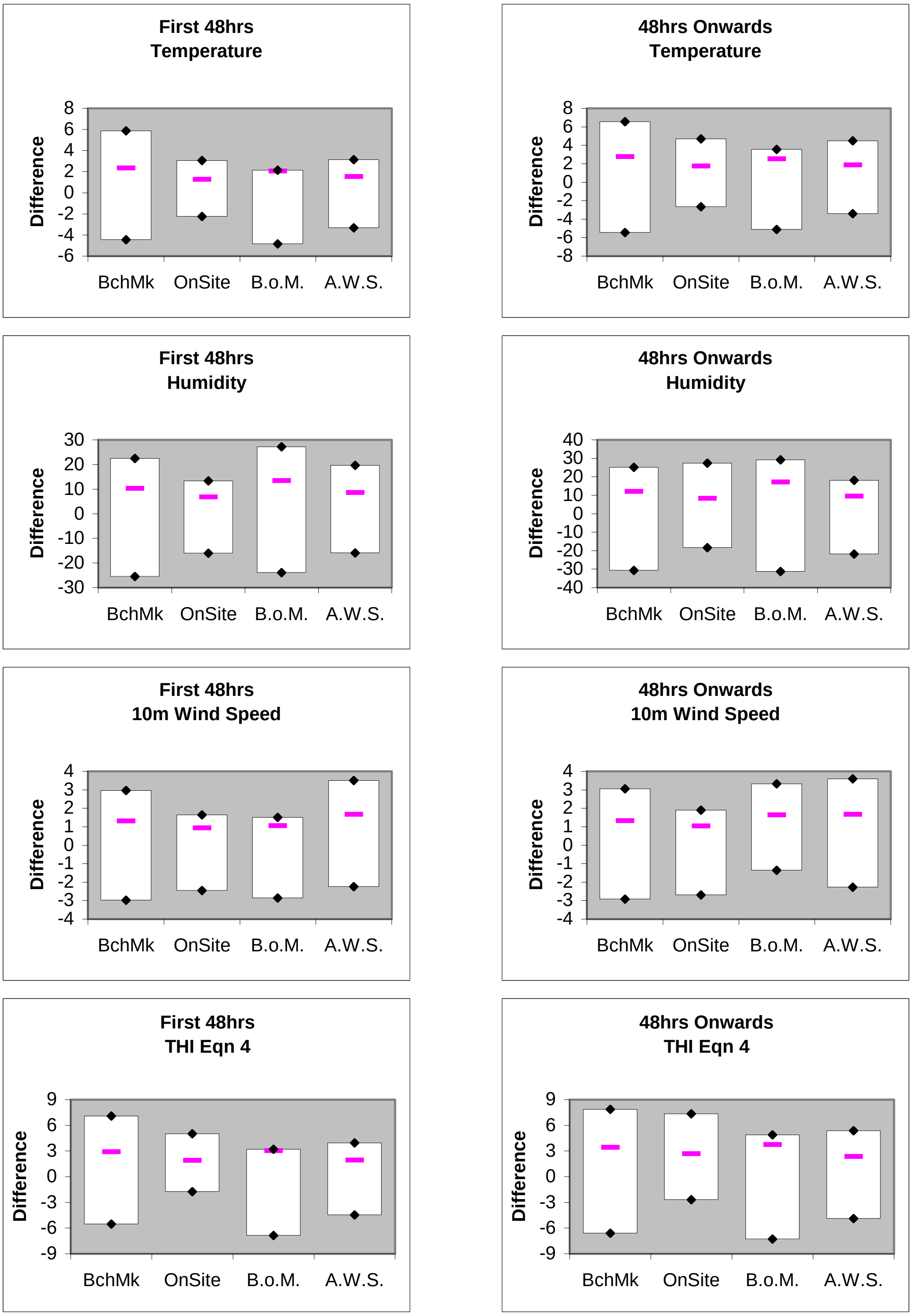


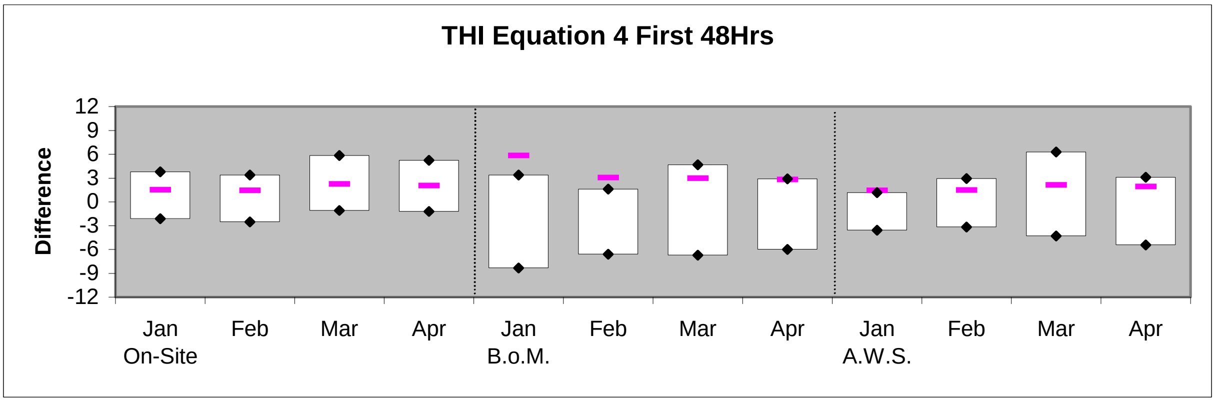

Figure E1. – Error statistics for each method and various parameters, both for forecast horizons out to 48 hours and from 48-144 hours

Table E3. – Overall Error in THI 4 Comparisons by Month for First 48hrs.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 1.53 | [-2.14, 3.77] | 5.84 | [-8.33, 3.37] | 1.43 | [-3.59, 1.15] |
| **Feb** | 1.44 | [-2.54, 3.38] | 3.06 | [-6.62, 1.60] | 1.49 | [-3.17, 2.92] |
| **Mar** | 2.25 | [-1.09, 5.84] | 2.96 | [-6.73, 4.67] | 2.14 | [-4.32, 6.27] |
| **Apr** | 2.05 | [-1.22, 5.24] | 2.80 | [-5.99, 2.91] | 1.95 | [-5.43, 3.11] |

Table E4. – Overall Error in THI 4 Comparisons by Month for hours 48 onwards.

| Forecast | On-site Downscaled | | BoM | | A.W.S. Downscaled | |
|---|---|---|---|---|---|---|
| **Month** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **Jan** | 2.59 | [-2.81, 6.62] | 3.57 | [-7.07, 4.71] | 1.79 | [-4.09, 1.15] |
| **Feb** | 1.99 | [-4.95, 3.96] | 4.09 | [-9.09, 2.41] | 2.15 | [-5.55, 2.92] |
| **Mar** | 3.18 | [-1.41, 8.94] | 3.58 | [-6.86, 6.42] | 2.78 | [-4.70, 6.27] |
| **Apr** | 2.66 | [-2.05, 7.45] | 3.88 | [-6.96, 3.98] | 2.05 | [-4.85, 3.11] |



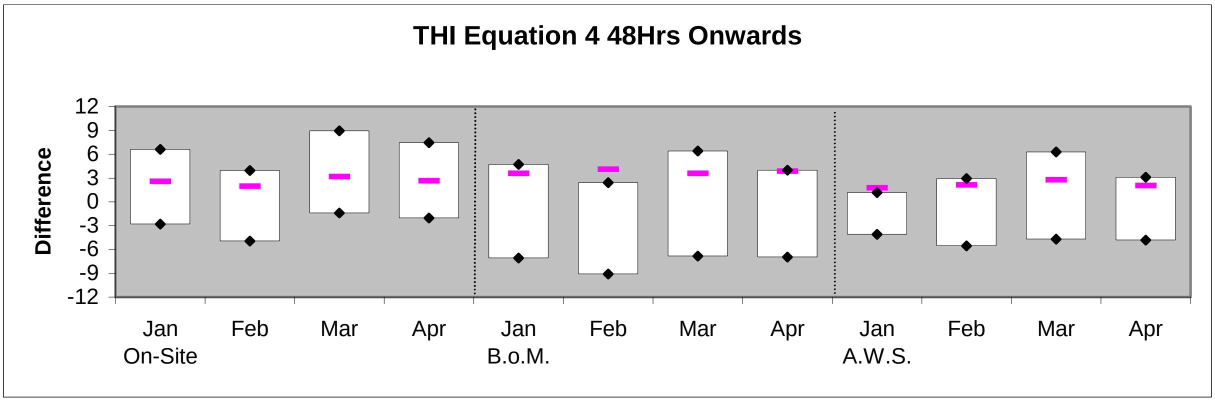




Figure E2. –Temperature Humidity Index Equation 4 error statistics for different horizons

Table E5. – Error in Katestone A.W.S. Downscaled THI 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 2.12 | [-5.37, 3.84] | 1.44 | [-1.25, 4.23] | 1.23 | [-1.91, 2.24] | 1.26 | [-2.18, 2.62] |
| **2** | 2.92 | [-6.52, 5.03] | 1.59 | [-1.73, 4.21] | 1.56 | [-2.81, 4.07] | 1.70 | [-2.61, 3.92] |
| **3** | 2.76 | [-5.09, 5.55] | 2.31 | [-1.66, 6.17] | 1.81 | [-3.85, 3.05] | 1.87 | [-3.31, 3.20] |
| **4** | 2.72 | [-4.53, 5.67] | 2.39 | [-1.73, 6.27] | 1.97 | [-3.72, 4.05] | 2.11 | [-4.44, 3.65] |
| **5** | 3.43 | [-5.23, 6.99] | 2.40 | [-2.56, 6.04] | 2.17 | [-4.99, 4.17] | 2.11 | [-4.52, 5.05] |
| **6** | 3.49 | [-5.58, 8.11] | 2.55 | [-1.95, 5.88] | 2.35 | [-4.75, 3.35] | 2.42 | [-5.83, 4.18] |

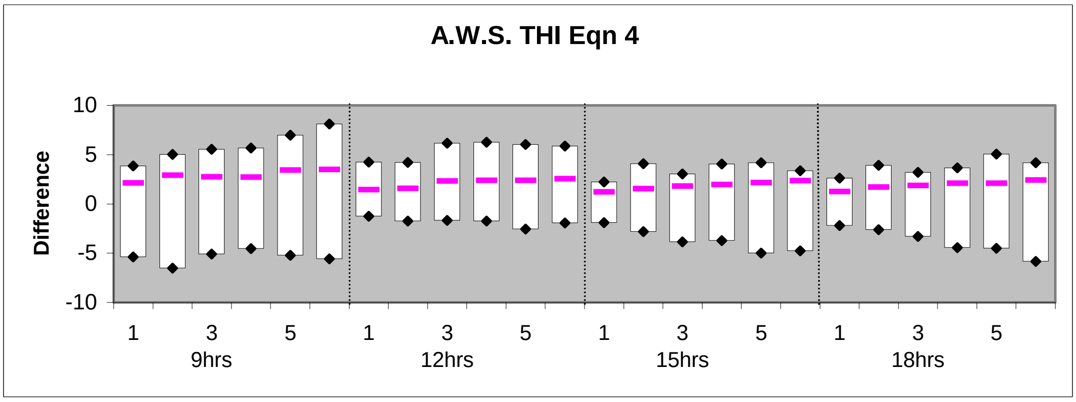



Figure E3. –THI Equation 4 errors split by Hour and then by Day, for different models and for different time horizons.

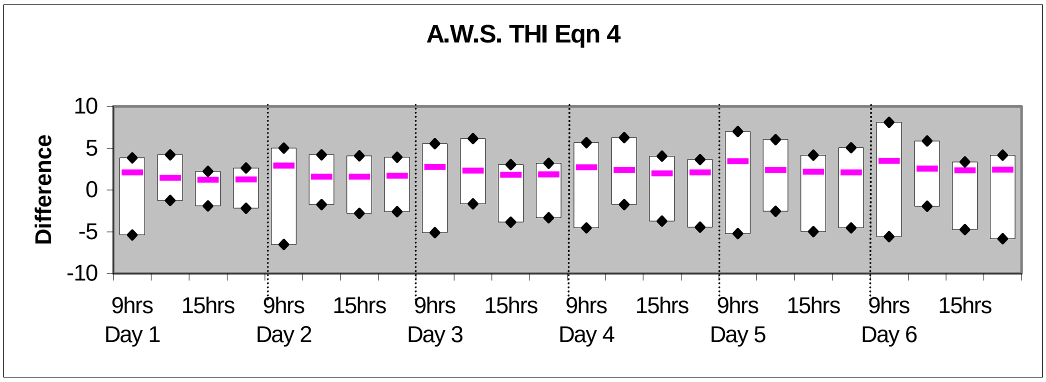



Figure E4. –THI Equation 4 errors split by Day and then by Hour, for different models and for different time horizons.

Table E6. – Overall Error in BoM Comparisons by Variable LAPS.

| Forecast Variable | Local BoM MAE | Local BoM C.I. Limits | Non-Local BoM MAE | Non-Local BoM C.I. Limits |
|---|---|---|---|---|
| **Temp** | 2.07 | [-4.84, 2.14] | 2.81 | [-6.43, 4.99] |
| **Rel. Hum.** | 13.41 | [-23.90, 27.18] | 13.88 | [-21.56, 32.52] |
| **WSpeed 10** | 1.06 | [-2.86, 1.51] | 1.23 | [-2.55, 2.48] |
| **THI 4** | 3.04 | [-6.87, 3.19] | 3.82 | [-6.97, 7.59] |

Table E7. – Overall Error in BoM Comparisons by Variable for GASP.

| Forecast Variable | Local BoM MAE | Local BoM C.I. Limits | Non-Local BoM MAE | Non-Local BoM C.I. Limits |
|---|---|---|---|---|
| **Temp** | 2.53 | [-5.11, 3.56] | 2.29 | [-4.03, 5.60] |
| **Rel. Hum.** | 17.15 | [-31.29, 29.22] | 17.20 | [-29.38, 33.15] |
| **WSpeed 10** | 1.64 | [-1.36, 3.33] | 4.67 | [-12.35, 1.21] |
| **THI 4** | 3.75 | [-7.29, 4.88] | 3.31 | [-5.40, 8.03] |

Table E8. – Coarse Error in BoM. Temperature Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 2.93 | [-0.07, 5.59] | 2.89 | [0.32, 5.50] | 1.68 | [-4.01, 2.39] | 3.63 | [-7.13, 0.94] |
| **2** | 2.73 | [-0.56, 5.71] | 2.59 | [-0.44, 5.40] | 1.77 | [-3.96, 1.98] | 3.59 | [-7.14, 0.48] |
| **3** | N/A | N/A | 2.53 | [-3.81, 5.52] | N/A | N/A | N/A | N/A |
| **4** | N/A | N/A | 2.60 | [-4.05, 5.13] | N/A | N/A | N/A | N/A |
| **5** | N/A | N/A | 2.74 | [-5.13, 5.38] | N/A | N/A | N/A | N/A |
| **6** | N/A | N/A | 2.75 | [-4.20, 6.29] | N/A | N/A | N/A | N/A |

Table E9. – Error in Coarse BoM Humidity Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 13.11 | [-13.04, 37.90] | 16.54 | [-28.30, 14.60] | 12.04 | [-23.38, 6.66] | 8.57 | [-16.47, 18.69] |
| **2** | 12.28 | [-11.72, 35.95] | 15.88 | [-28.59, 13.81] | 13.12 | [-23.72, 8.48] | 8.75 | [-17.91, 14.41] |
| **3** | N/A | N/A | 17.73 | [-12.52, 34.95] | N/A | N/A | N/A | N/A |
| **4** | N/A | N/A | 17.85 | [-17.06, 35.31] | N/A | N/A | N/A | N/A |
| **5** | N/A | N/A | 18.71 | [-13.52, 34.34] | N/A | N/A | N/A | N/A |
| **6** | N/A | N/A | 18.38 | [-15.90, 38.97] | N/A | N/A | N/A | N/A |

Table E10. – Error in Coarse BoM THI Equation 4 Prediction.

| Forecast Time | 9hrs Ahead - 6am (+24hrs later days) | | 12hrs Ahead - 9am (+24hrs later days) | | 15hrs Ahead - 12pm (+24hrs later days) | | 18hrs Ahead - 3pm (+24hrs later days) | |
|---|---|---|---|---|---|---|---|---|
| **Day** | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits | MAE | C.I. Limits |
| **1** | 4.90 | [0.74, 9.42] | 4.17 | [-0.14, 8.74] | 2.56 | [-5.48, 2.22] | 4.50 | [-8.36, -0.07] |
| **2** | 4.46 | [0.17, 8.69] | 3.71 | [-1.06, 8.13] | 2.73 | [-5.70, 1.76] | 4.66 | [-8.34, 0.55] |
| **3** | N/A | N/A | 3.62 | [-3.63, 7.41] | N/A | N/A | N/A | N/A |
| **4** | N/A | N/A | 3.83 | [-4.10, 8.05] | N/A | N/A | N/A | N/A |
| **5** | N/A | N/A | 4.01 | [-4.74, 8.89] | N/A | N/A | N/A | N/A |
| **6** | N/A | N/A | 4.06 | [-5.13, 9.75] | N/A | N/A | N/A | N/A |

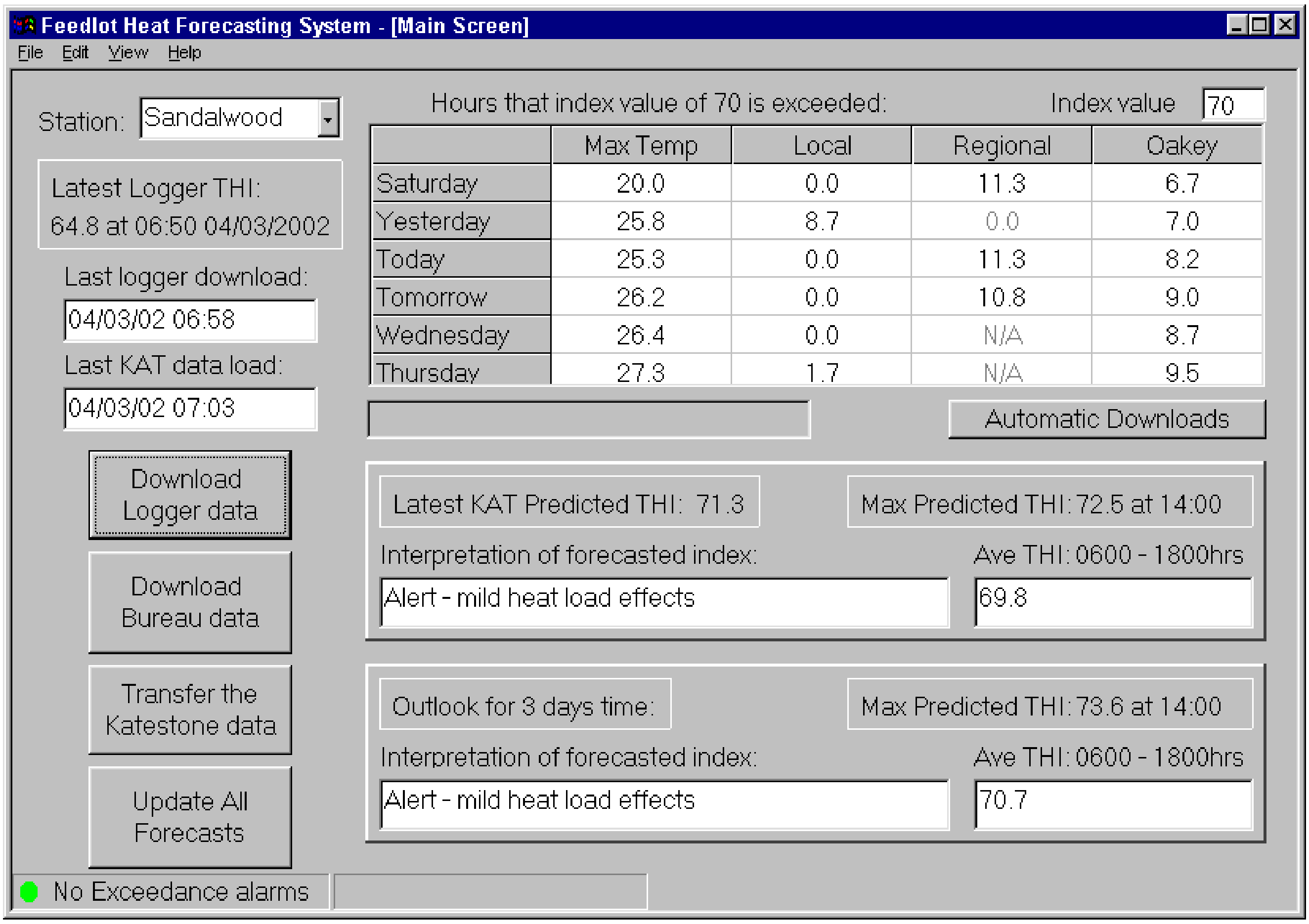
# APPENDIX F. – SOFTWARE

When the software is run, the user is shown Figure 1. This screen gives a summary of the download times, short term forecasts and warnings of impending high THI alerts.

The section in the upper left corner informs the user of what feedlot station the data displayed is applicable for as well as the latest download dates and time or how current the information is. The station should not need to be changed, for individual operators, after initial installation.

The table to the right gives the number of hours that the index value is exceeded for the different forecast mechanisms. The index value can be altered in the upper right box with the display changing to reflect the alteration within seconds. Note that the first two rows of the 'Max Temp' and 'Local' columns are recorded observed on-site AWS values whereas the final four are all predictions. The Max Temp column is currently linked to the Katestone nearby AWS prediction scheme for its forecast values. Any greyed out boxes do not have a full day of data.

**Figure 1. The Software Main Screen**




The Automatic downloads button will set the program to automatically download all the necessary data at specific preset times. This is not recommended for feedlots that have modem connections to the internet. There is also a menu option available to individually set the automation.

The status bar indicates warnings of alarm exceedances that can be set via a menu option.

The buttons on the left of the screen are for collecting the forecast data:

- Download Logger data
  Interrogates the on-site weather station automatically and downloads all of the data from midnight of the previous day. (done on a secondary screen). Calls the GetMet program to run, to create the Katestone nearby and on-site AWS forecasts.

- Download Bureau data
  Uses the Internet to access the Bureau of Meteorology web site and downloads the latest available LAPS forecasts, formatting them as it goes. (done on a secondary screen)

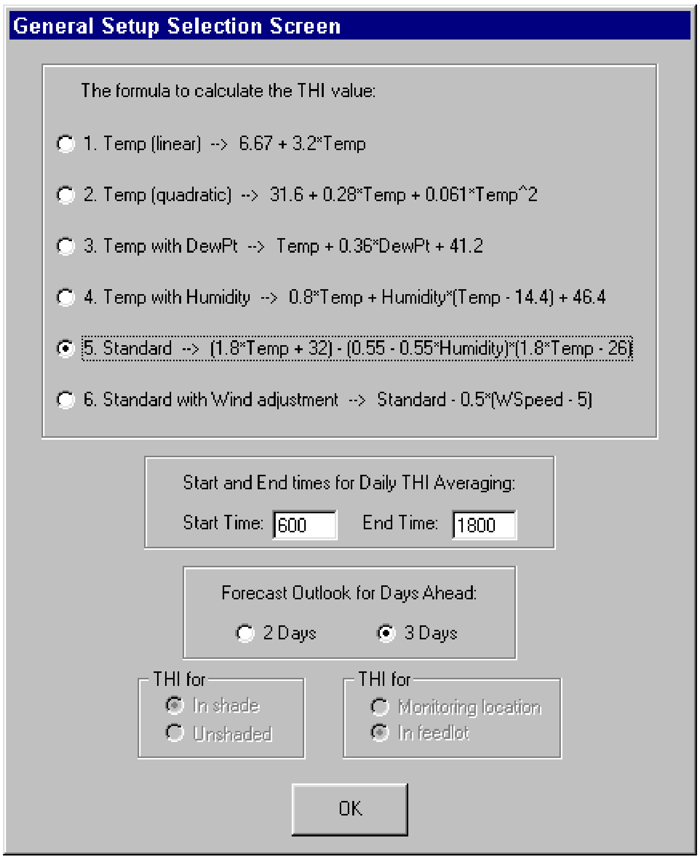
- Transfer the Katestone data
  Transfers the relevant data from the GetMet forecasts calculating the THI values.

- Update all forecasts
  This performs all of the above functions sequentially.

The lower right section of the main screen is a brief summary of the data for today and either two or three days time, also currently linked to the Katestone nearby AWS prediction scheme. The value next to the 'Latest KAT Predicted THI' does change as the day progresses, to give an indication of the current cattle stress levels. Under the Edit Menu, the set up screen, Figure 2, allows customisation of this section with the selection of the averaging and outlook options.

The upper half of the setup screen shows the different THI equations that can be used to generate the display values in the main screen. All values are pre-calculated and stored in the file to speed up the access and display times, for example, when the index is altered. Through experience, equations 4 and 5 tie in best with the alert levels supplied.

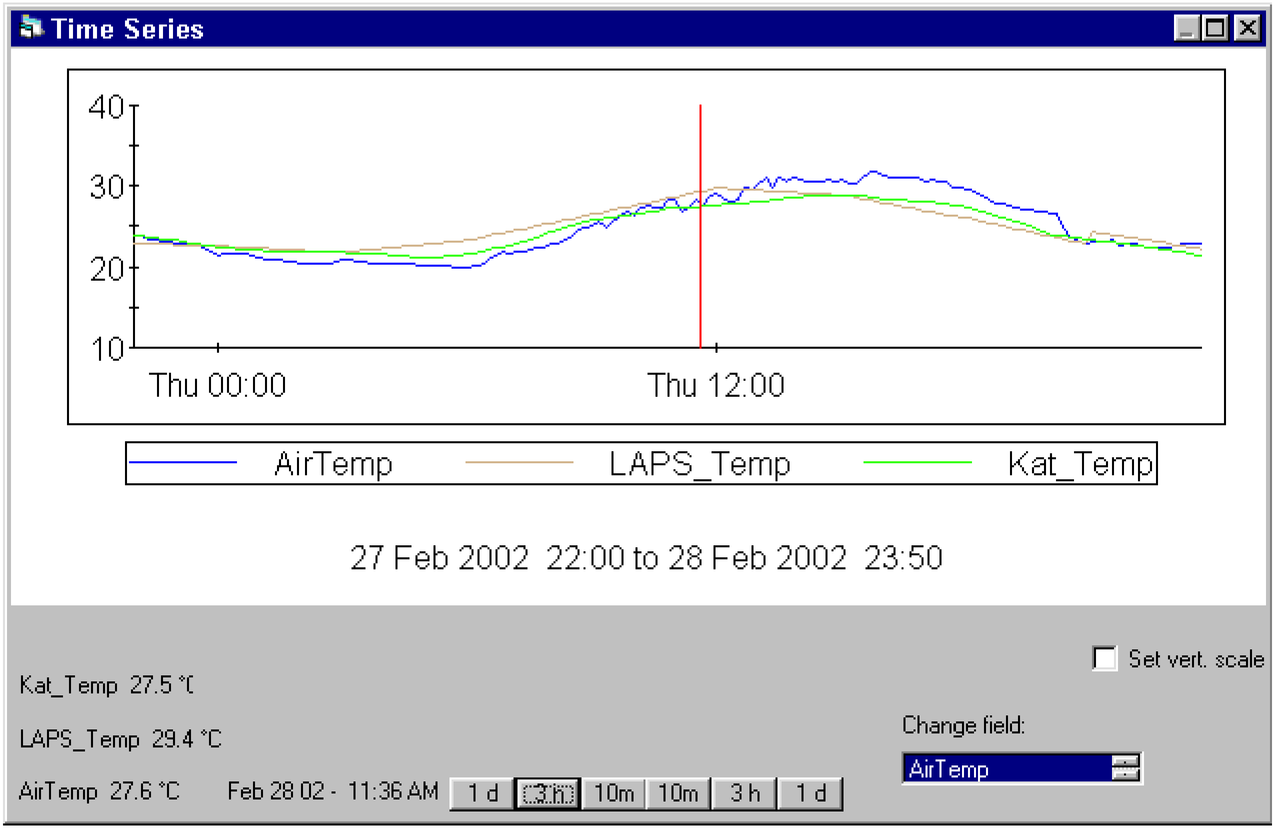
**Figure 2. The Setup Selection Screen**



From the View Menu, several options exist to view the stored data or the Bureau of Meteorology forecasts. The 'View Data' option presents a screen showing the data in a spreadsheet style display. The 'Plot Data' option gives the timeseries graph, as shown in Figure 3, of up to 6 variables. Moving the mouse over the display produces the red line and alters the numbers shown in the bottom left corner of the screen. Scrolling through the data is possible via the buttons at the bottom, which alter the times shown on the x-axis by 1 day, 3 hours or 10 minutes in the desired direction.

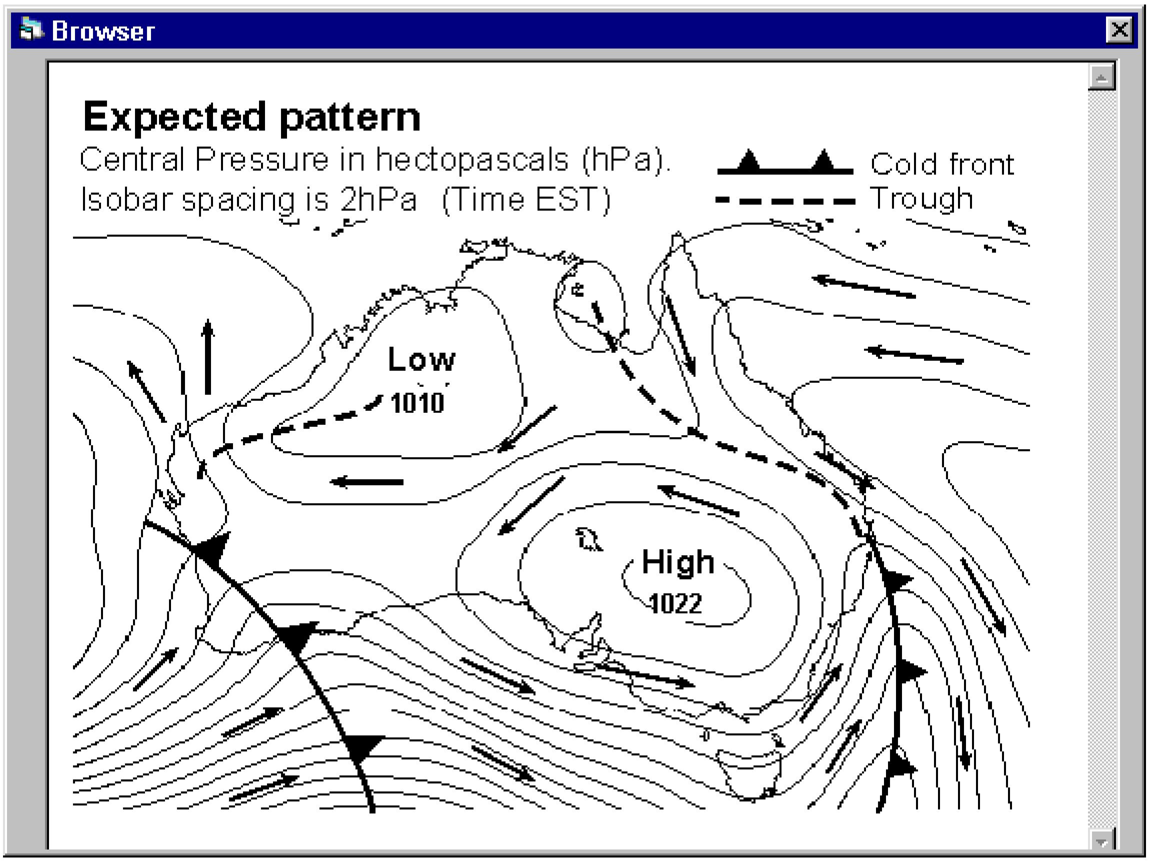
The last selected variable graphed can also be altered if desired, as well as the vertical scale.

**Figure 3. The Plot Data Screen showing the 3 Temp variables set to a date in the past.**




The Bureau of Meteorology forecasts of the Central Pressure pattern for the entire country, for up to seven days in advance, is also available and produces an image similar to the one shown in Figure 4. This is an on-line service and as such requires and internet connection to be established.

**Figure 4. Bureau of Meteorology Central Pressure Forecast**



# Appendix G - Analysis of Differences Between In Feedlot and Out of Feedlot Climatic Variables

## Abstract

Climatic data for two Australian cattle feedlots was analysed. Variables investigated include the difference between out of feedlot and in feedlot air temperature, relative humidity and wind speed and direction for both shaded and unshaded pens. The aim of the analysis was to investigate if models could be formed of these differences that would be applicable to other feedlots. Differentials were analysed to determine the effected hour of the day, and cluster analysis was used to determine the effects of external air temperature, humidity and wind speed and direction. It is shown that hour of the day has a minor relationship to shaded air temperature differentials that holds for both feedlots. Other relationships include hour of the day to relative humidity differentials, the effect of humidity and temperature on shaded humidity differentials and the effect of temperature and humidity on shaded temperature differentials. These relationships did not hold for both feedlots and as such may not be applicable to developing generalised models.

## 1. Introduction

This report details the analysis of differentials between climatic variables in and out of feedlots to enable the prediction of extreme weather conditions that can result in catastrophic loss of cattle. The aim of the analysis was to investigate weather models of the differentials may be produced that can be applied to other feedlots.

The data used in this report was detailed in a report issued by Meat and Livestock Australia [1]. The data collected represents two separate feedlots. One feedlot was located in Qld near Dalby (Feedlot A) and the other in NSW near Narrandera (Feedlot B). At each of these feedlots six weather stations were used to collect weather data. Two of these stations were located inside the feedlot, one in a shaded cattle pen and another in an open pen. The other four of these stations were located at the cardinal points north, south, east and west externally to the feedlots.

The data that was measured at the four external stations included, but was not limited to, air temperature at 1.2m, relative humidity at 1.2m, wind speed at 2m and 10m and wind direction at 10m. The two stations at the shaded and the unshaded pens also measured these variables. At the shaded pen wind speed and direction was measured at 2m. At the unshaded pen wind speed was measured at both 2m and 10m and wind direction was only measured at 10m for feedlot A and 2m for feedlot B. The data collection started on the 1$^{st}$ of January 2001 for feedlot A and on the 9$^{th}$ January 2001 for feedlot B and concluded on the 22$^{nd}$ April for feedlot A and on the 7$^{th}$ May for feedlot B.

The variables modeled include the difference between externally and internally measured air temperature, relative humidity and wind speed and wind direction for each of the two feedlots with both shaded and open differentials. Wind speed and direction were converted from polar coordinates in the original data to rectangular wind speeds for the purpose of analysis. Rectangular wind speed is measured by two variables, one representing the wind speed component from the east with negative values representing a westerly component and the other representing the wind speed component from the north with southerly components represented by negative values. The rectangular wind speed differentials were computed for a 10m altitude from the external stations differenced with a 2m altitude for the shaded differentials and feedlot B open differentials. Open feedlot A differentials were based on a 10m altitude for both the external and internal stations.

# 2. Analysis of Externally Measured Climate Data

Climate data were measured at four external sites to each of the feedlots, to the north, south, east and west. These data were analysed to test for major differences between the four sites. The data for certain variables and sites contained a significant number of missing values. The primary condition for selecting external variables as the basis of the modelling is that a reasonable amount of data has been collected. Additionally wind direction should be looked at with a preference given to the external station that is upwind from the feedlot to prevent the potential influence on the external station from the feedlot being upwind to the station.

Additionally the corresponding variables for each external feedlot were graphed in a time series to observe any major difference that a station may have due to sensor degradation, wind or landscape features.

## 2.1 Feedlot A

The time series graph of the four external temperature readings showed closely comparable readings for the north, east and west stations with the south station sometimes indicating daily peaks approximately one degree above those of the other stations.

The relative humidity graphs displayed a close correspondence with each site having occasional peaks and bottoms that were different to the other sites. The north site was most different to the other sites and the west showed the closest correspondence to other sites.

Ten-meter wind speed displayed greater variations between sites than temperature or humidity with the greatest difference being the east site with considerably lower wind speeds than the other three sites. Ten-meter wind direction had time frames where each of the four stations displayed significantly different readings. Over a large portion of the graph, there was a reasonably close correspondence between north, east and west readings with south displaying greater differences.

Wind direction for feedlot A was primarily from the east. Both the west and the south stations contained minimal missing data for the required variables with the north and east stations containing large segments of missing data. Of the west and the south stations the west was chosen due to its greater correspondence of data to the other stations for temperature, and wind direction.

## 2.2 Feedlot B

A time series graph of the temperatures of the 4 stations was created. It became evident that the northern station was up to a degree higher in temperatures, at all times of the day, than the other sites (see Figure G1). Although the western and eastern sites had comparable temperatures the southern site had a general tendency to have lower minimum temperatures.

Relative humidity appeared to be comparable between the north, east and west stations. The southern station having a generally higher maximum humidity than the other stations.

A time series of the 10m-wind speed revealed great variations over the four stations. With the northern station having a generally higher wind speed than the other stations. Wind roses of the shaded and unshaded internal stations were produced. These showed that the main directions of wind were south westerly and easterly winds. Data was inspected to determine the station with the least amount of data missing. This station was the eastern station. Easterly weather patterns prevailed in the area so the eastern station was chosen as the external station to determine the differences. These differences were to be calculated on the four main variables: air temperature, relative humidity and the easterly and northerly components of wind speed. All differences mentioned will be pertaining to the eastern station compared to the unshaded or shaded internal pens.

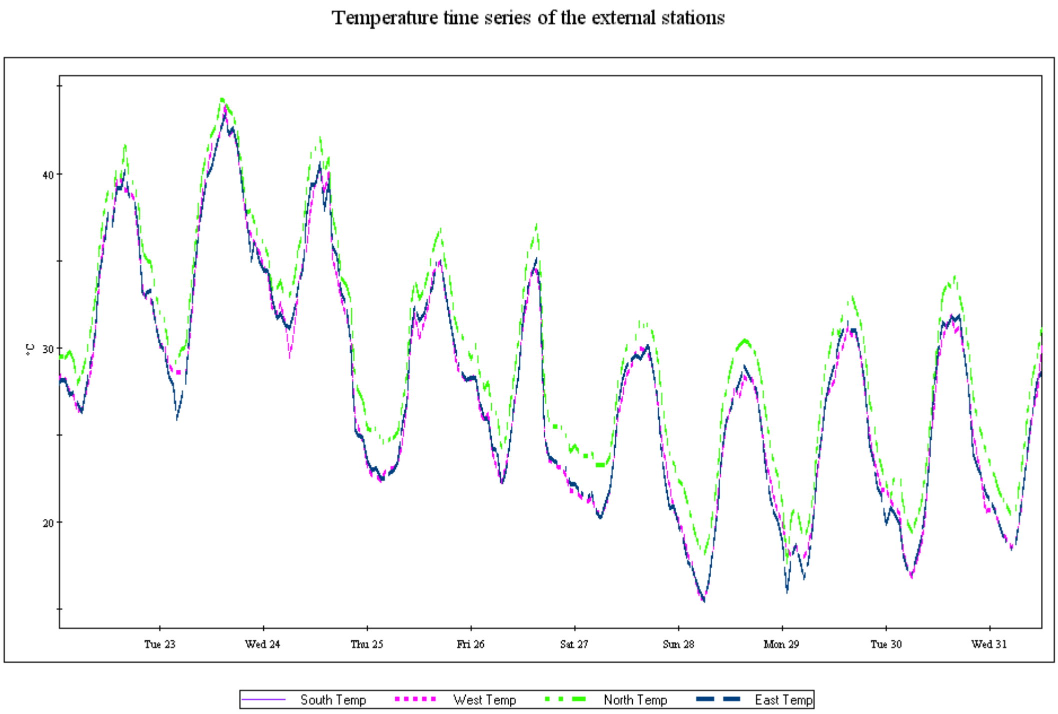



Figure G1 Feedlot B temperature time series for the four external stations.

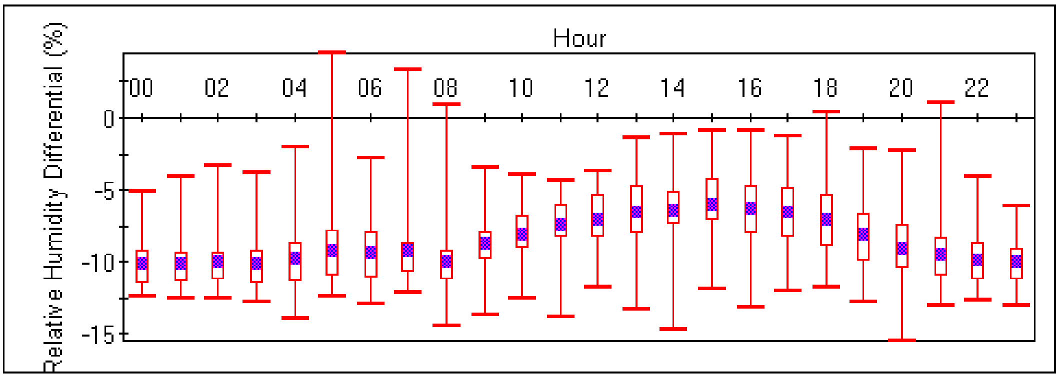
# 3. Analysis of Differentials Based on Hour of the Day

To measure the effect that hour of the day has on each of the modeled differentials, graphs were produced that displayed the mean differential, maximum, minimum and 25th and 75th percentiles for each of the modeled differentials at each different hour of the day. This can be used to determine if the various hours provide a strong separation of the differentials for each modeled variable.

## 3.1 Feedlot A

The majority of the differentials analysed showed weak or no relationships to hour of the day. The primary exception to this was the shaded relative humidity differential. A box whiskers plot showing this relationship is illustrated below in G3.1.

Plot of Shaded Relative Humidity Differential Based on Hour

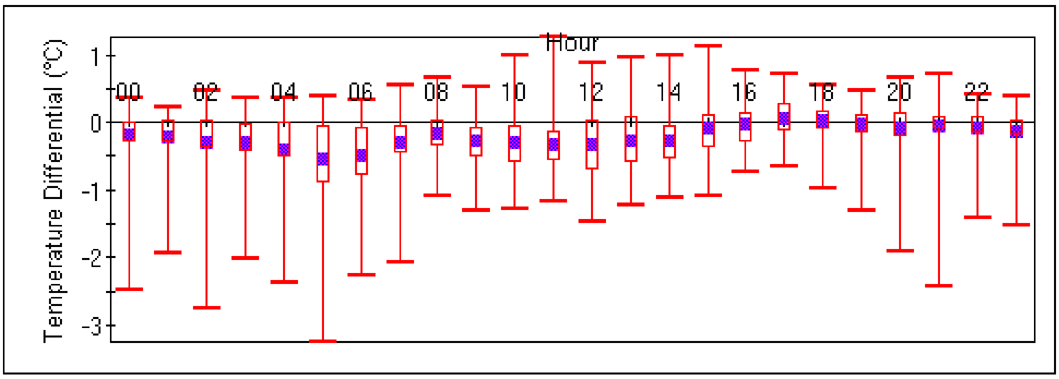



Whisker: Low=Min, High=Max; Box: Low=25.0%, High=75.0%
Middle: Mean

Figure G2 Feedlot A shaded relative humidity differentials based on hour of the day.

As can be seen by the graph, the mean differentials rise to a peak at around 3pm and find a low at around midnight. The 25th to 75th percentile range for the mid afternoon does not overlap with that of the early hours of the morning indicating the humidity differential is substantially different for different times of the day.

Plot of Shaded Temperature Differential Based on Hour




Whisker: Low=Min, High=Max; Box: Low=25.0%, High=75.0%
Middle: Mean

Figure G3. Feedlot A shaded temperature differentials based on hour of the day.

A weaker relationship can be observed for the shaded temperature differential (Figure G2). The mean temperature differentials peak at around 5pm and reach a low at around 5am. The 25th to 75th percentile range between 6pm and 1am is also substantially smaller than other times of the day. This is during the time of higher differentials.

## 3.2 Feedlot B

Box Whisker diagrams were made of all the main differentials for feedlot B. For many of the differentials the diagrams did not reveal any separations based on hour of the day. One interesting diagram was relative humidity difference to the unshaded pen.

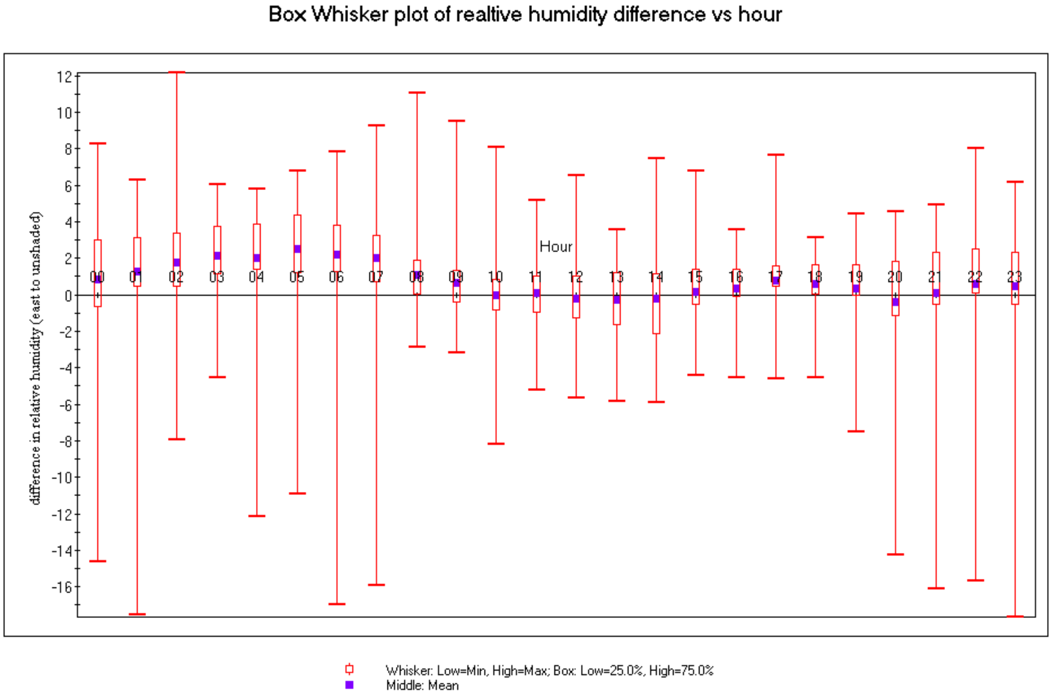



Figure G4. Feedlot B unshaded relative humidity differentials based on hour of the day.

Figure G4 shows that the 25th to 75th percentile differences are high in the mornings around 3am to 7am, which are separated from the low differences around 11am to 2pm. The 25th to 75th percentile range of the early morning does not overlap with the afternoon percentile range indicating different differentials for these times of the day.

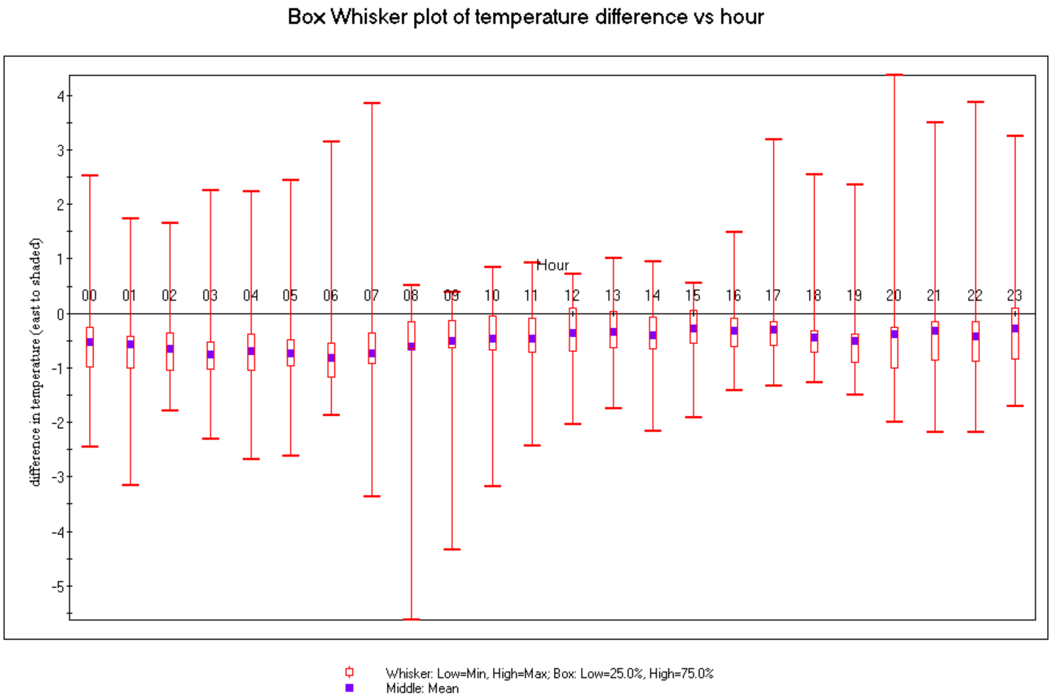



Figure G5. Feedlot B shaded temperature differentials based on hour of the day.

Figure G5 shows the temperature differentials for the shaded pen. This figure shows a slight separation in temperature differentials between the early hours of the morning and the afternoon.

# 4. The Use of Cluster Analysis to Measure the Effect of Climatic Variables on Differentials

In order to determine the effect of air temperature, relative humidity and ten-meter wind speed and direction, cluster analysis was used. A separate cluster analysis was performed for a number of different numbers of clusters extracted.

Plots were then generated indicating the differentials assigned to each cluster for each differential modeled and clustering formed. These plots were used to indicate if the clustering found groupings of climatic conditions that result in different differentials being formed. A clustering that contains a majority of lower or higher differentials that are preferably contained within a relatively small differential range is considered stronger.

After selecting a strong clustering for modeled differentials, the underlying climatic conditions represented by the cluster are analysed to determine what climatic effects are resulting in different ranges of differentials being observed.

## 4.1 Feedlot A

A lot of the clusters analysed for feedlot A were not defining distinguishing differentials. There were however some interesting results that arose for some variables. Figure G6 displays the shaded temperature differentials for each cluster in a 10 cluster partitioning.

Shaded Air Temperature Differentials for a 10 Cluster Partitioning

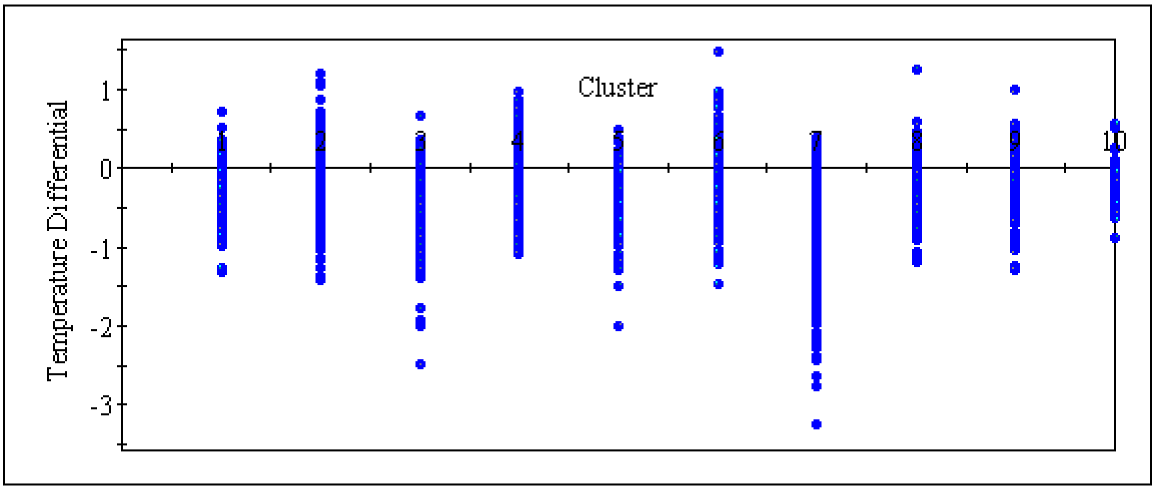



Figure G6. Feedlot A shaded air temperature differentials for a 10 cluster partitioning.

While the majority of the clusters are not really distinguishing, cluster 7 captures most of the lower differentials without covering the higher differentials. This cluster represents low temperatures (mean 17.4 degrees) with high relative humidity (mean 84.8%) and comparatively low wind speeds. This cluster occurs between the times 7pm and 9 am.

Figure G7 and G8 display the shaded wind speed differentials for 10 a cluster partitioning.

Shaded Wind Speed from the East Differentials for a 10 Cluster Partitioning

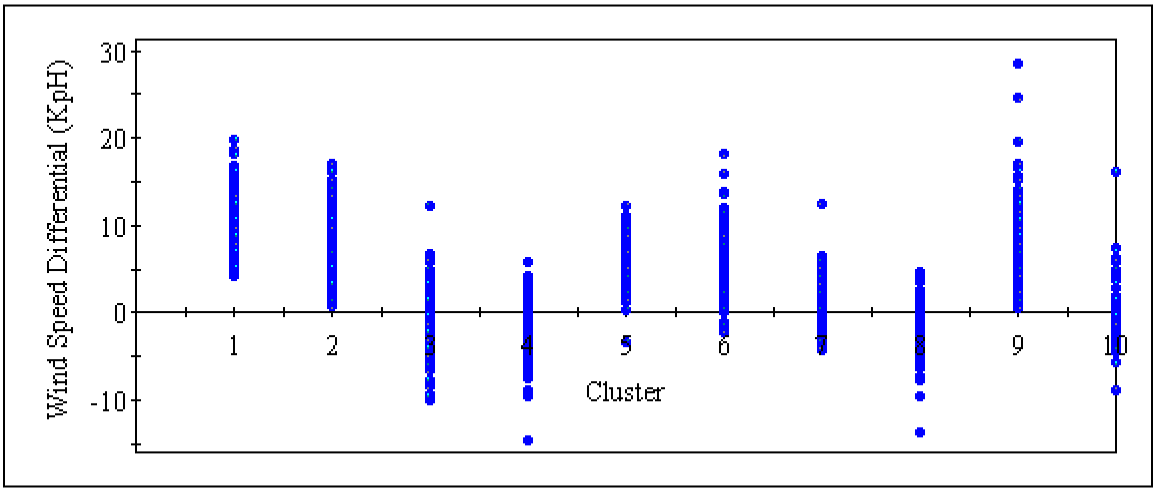



Figure G7. Feedlot A shaded wind speed from the east differentials for a 10 cluster partitioning.

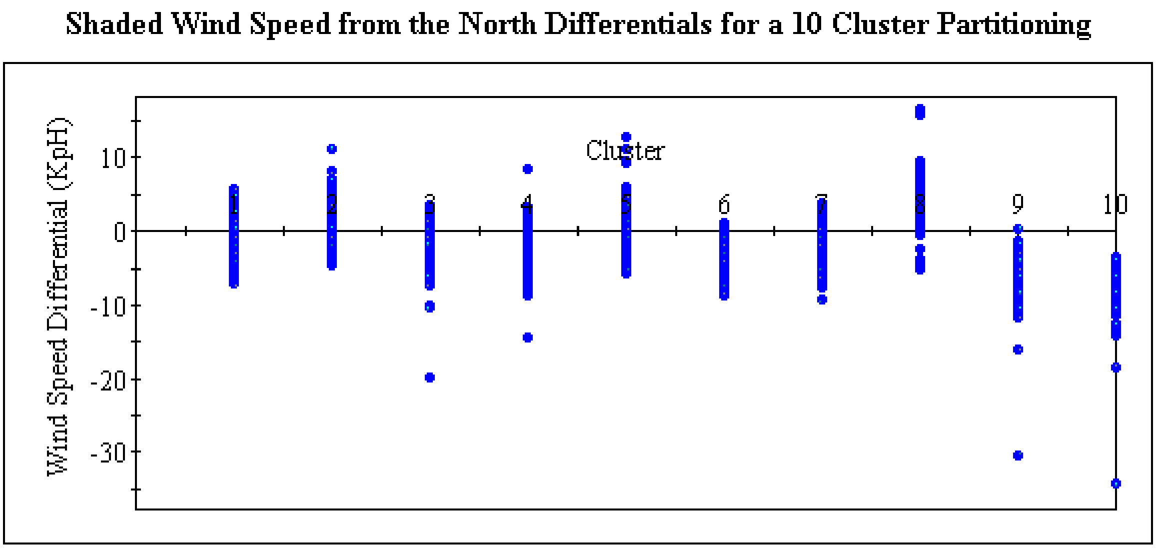



Figure G8. Feedlot A shaded wind speed from the north differentials for a 10 cluster partitioning.

The differentials for wind speed from the east are well separated by the cluster analysis. Cluster 9 captures the majority of the extreme high differentials. This cluster is primarily distinguished by high wind speeds and can occur throughout the day. Clusters 1, 2, 5 and 6 represent typically higher differentials. Clusters 1 and 2 are distinguished by higher wind speeds typically from the east north east while clusters 5 represents high humidity with moderately high easterly wind speeds. Cluster 6 is defined by low humidity, relatively high temperatures and relatively high east southeast wind speed. All of these clusters represent comparatively high easterly wind speeds and represent differentials in which the out of feedlot ten-meter easterly wind speed is higher than the in feed lot two-meter easterly wind speed. Clusters 3, 4 and 8 are representative of lower differentials and typically have a low westerly component to their wind speeds. Due to their lower easterly or greater westerly component to wind speed, the differentials observed are also lower.

The differentials for wind speed from the north have some interesting clusters. Cluster 9 and 10 define partitions with lower differentials. These clusters contained the highest southerly component to wind speed. The negative differentials indicate that the in feedlot southerly component to the two-meter wind speed is less than the out of feed lot southerly component of the ten-meter wind speed. Cluster 8 defines a partitioning with higher differentials. This cluster represents the highest northerly component to wind speed. The positive differentials are indicating a reduction in the northerly wind speed for in lot compared to out of lot.

All of these results for shaded wind speed differentials are consistent with a reduction in two-meter in feedlot wind speed compared to ten-meter out of feedlot. This would be due to lower wind speeds at lower heights above ground-level.

Figure G9 displays shaded relative humidity differentials for a 30 cluster partitioning.

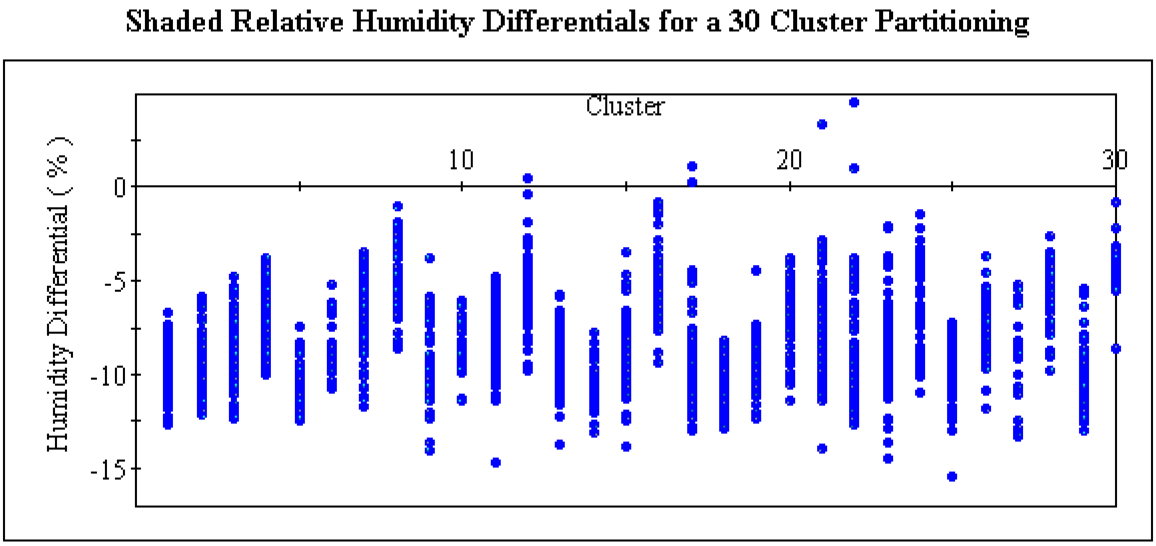



Figure G9. Feedlot A shaded relative humidity differentials for a 30 cluster partitioning.

The differentials here are primarily negative. This indicates that shaded in feedlot humidity is higher than out of feedlot humidity.

Within this clustering, a number of clusters indicate typically higher or lower differentials. Clusters 5, 9, 13, 14, 18, 19, 25 and 29 indicate lower negative differentials. These clusters are distinguished by higher than average relative humidity. These clusters represent times when the increase in shaded relative humidity of in feed lot over out of feed lot humidity is high. This relationship does not always hold as clusters 17, 21 and 22 were also characterised by high humidity but did not show the same range of differentials.

Clusters 8, 12, 16 and 30 indicate higher negative differentials. These clusters are characterised by low humidity and relatively high temperatures. This would indicate that increase in shaded relative humidity above out of feedlot humidity is lower on days with lower humidity and higher temperatures.

## 4.2 Feedlot B

The clusters analysed for feedlot B showed little to no distinguishing of the differential variables that we are interested in. Temperature and relative humidity showed no results for 10, 20, or 30 clusters. The only variables showing an interesting relationship are easterly and northerly wind speeds. Wind speeds with similar directions and magnitudes will have similar components in the easterly and northerly directions.

Figures G10 to G13 are included to show the lack of distinguishing clusters for unshaded temperature and relative humidity differentials.

Temperature difference east to unshaded vs Cluster

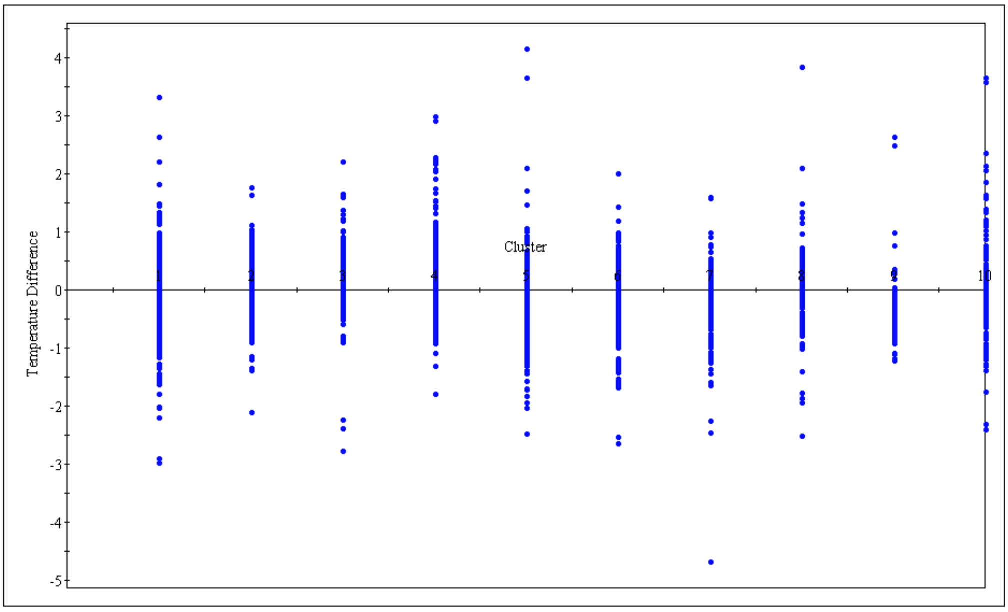



Figure G10. Feedlot B unshaded temperature differentials for a 10 cluster partitioning.

There seems to be no separation of temperature differences occurring with 10 clusters.

Temperature difference east to unshaded vs Cluster

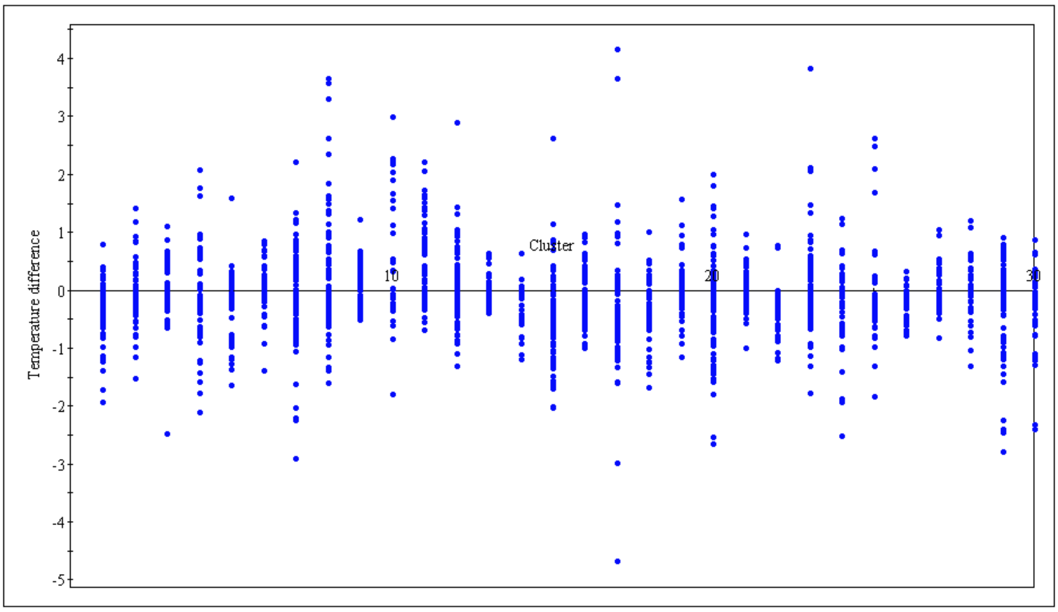



Figure G11. Feedlot B unshaded temperature differentials for a 30 cluster partitioning.

Unshaded temperature for 30 clusters displayed no obvious separation.

Relatvie humidity difference east to unshaded vs Cluster

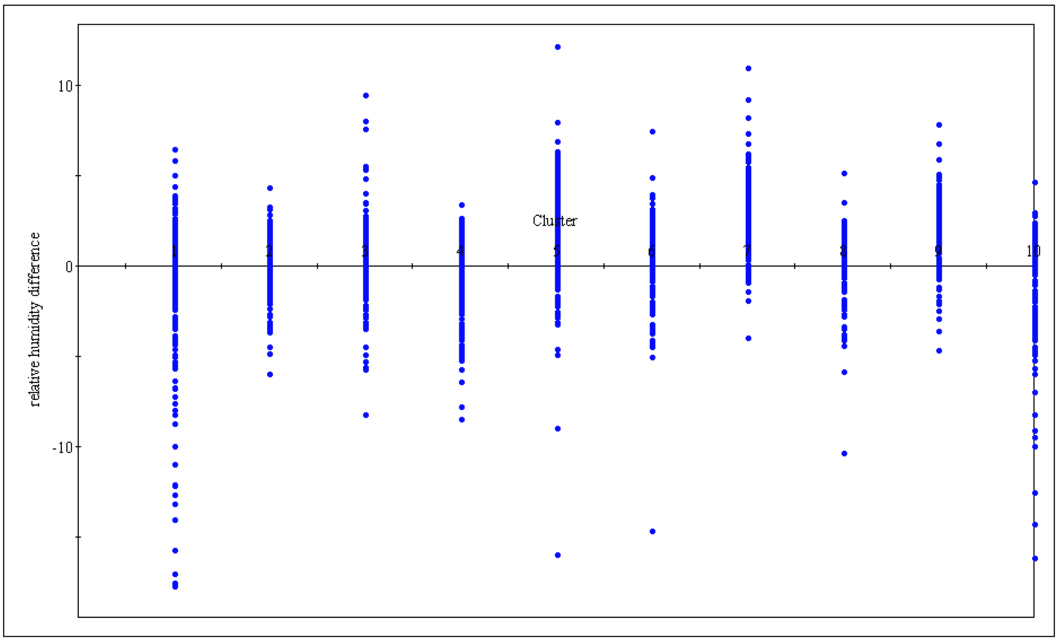



Figure G12. Feedlot B unshaded relative humidity differentials for a 10 cluster partitioning.

Unshaded relative humidity also showed no separation over 10 clusters.

Relatvie humidity difference east to unshaded vs Cluster

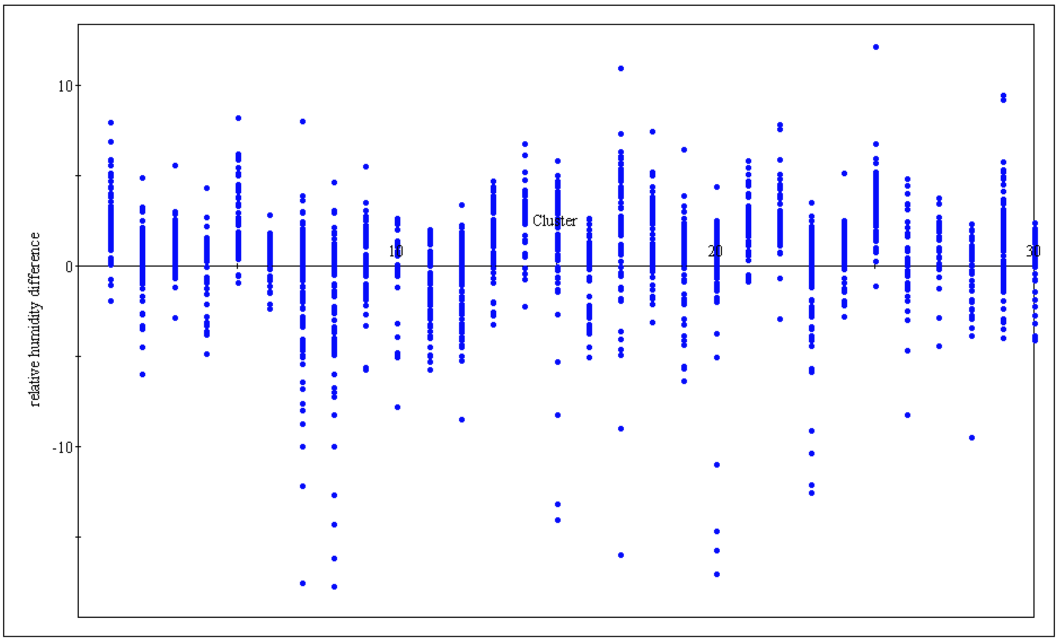



Figure G13. Feedlot B unshaded relative humidity differentials for a 30 cluster partitioning.

No separation of unshaded relative humidity over 30 clusters.

The unshaded northerly wind speed differential had 2 interesting clusters as displayed in Figure G14. Cluster 4 captured all of the highly negative differences while cluster 2 captures all of the high positive differences. Cluster 2 consists of mainly low relative humidity and low temperatures, with northerly to easterly winds. Cluster 4 consists of mainly low relative humidity and high temperatures, with mainly southern to western winds.

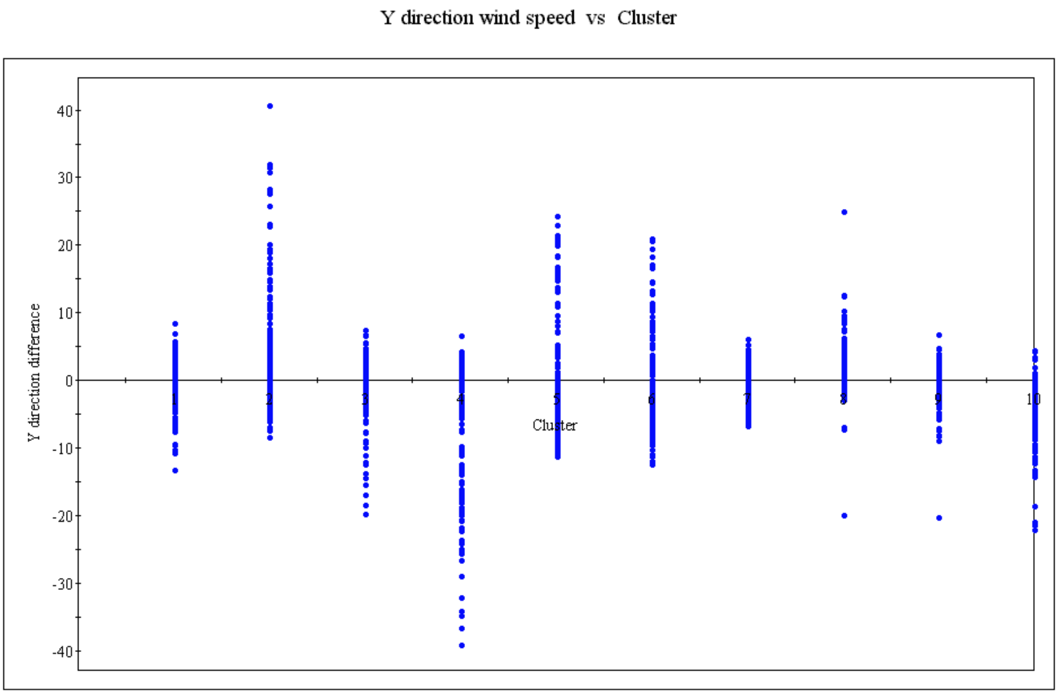



Figure G14. Feedlot B differentials in wind speed for the northerly direction relative to the unshaded station for a 10 cluster partitioning.

The unshaded easterly wind speed differentials are displayed in Figure G15. Clusters 3 and 4 are separated from the rest representing negative differentials while clusters 5 and 6 are also separated, containing mainly positive values.

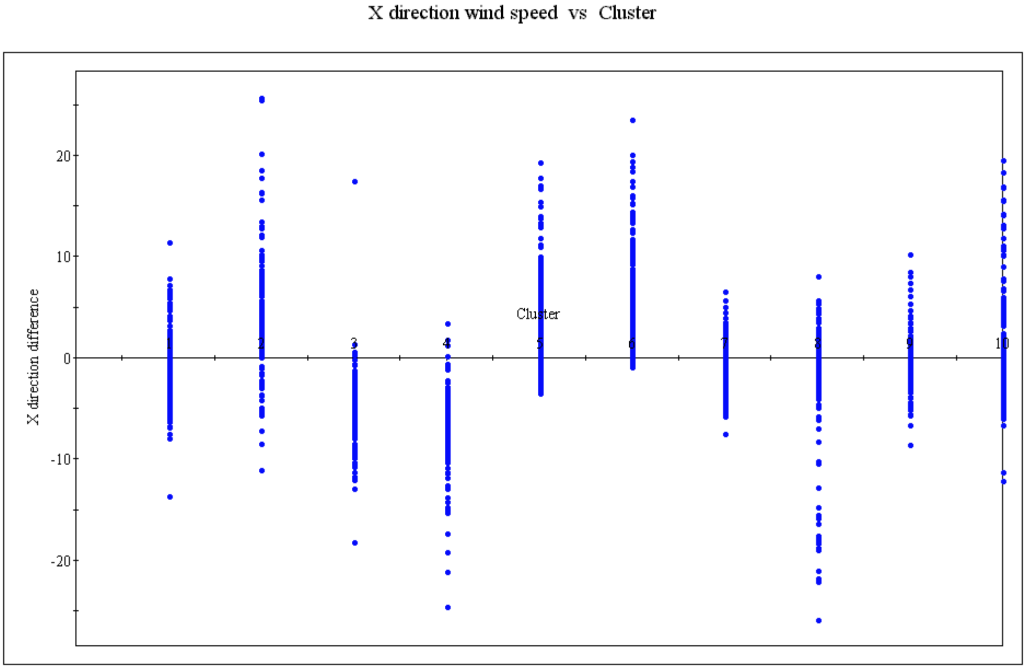



Figure G15: Feedlot B difference in easterly direction wind speeds relative to the unshaded station for a 10 cluster partitioning.

The shaded northerly difference had only one interesting cluster. This was cluster 2 which contained many of the highly positive differences and little of the negative values.

Shaded easterly difference had two interesting clusters. Clusters 3 and 4 had a lot of the negative differences and none of the positive values. Cluster 3 consists of mainly high relative humidity, low temperatures and mainly southerly to westerly winds.

As for feedlot A, the wind speed cluster results can be explained by the difference in height of within feedlot to outside feedlot measurements. For example, an easterly wind will result in a positive differential for the easterly component of wind speed resulting from a decrease at the two-meter altitude. A westerly wind will result in a negative differential for the easterly component of wind speed also representing a decrease in westerly wind speed at the two-meter altitude.

All other variables showed no real relationships between the clusters and the differential variables and hence were not reported on here.

# 5. Summary

The differences between out of feedlot and in feedlot climatic conditions have been analysed for both shaded and unshaded cattle pens for two Australian feedlots. Differentials modeled included air temperature, relative humidity, the easterly component of wind speed and the northerly component of wind speed. The analysis investigated the potential effect of hour of the day on the differentials analysed as well as applying cluster analysis to determine the effects of temperature, relative humidity and wind speed and direction. The aim of the analysis was to investigate the possibility of constructing models of these differentials that would be applicable to other feedlots.

Both feedlots displayed a relationship between the differentials of relative humidity and temperature to the hour of the day. Relative humidity differentials showed a different relationship for feedlot A compared to feedlot B with feedlot A reaching a peak in the afternoon and a low in the early morning and feedlot B reaching a low in the afternoon and a high early in the morning. The difference between these relationships would indicate that the results may not be applicable to other feedlots.

Shaded temperature differentials for different hours of the day showed a minor relationship that did correspond for feedlots A and B. Both feedlots observed higher differentials in the afternoon and lower differentials in the early morning. This would imply that this might be a relationship that could be exploited for other feedlots that have not had data recorded.

For both feedlots the cluster analysis displayed a strong separation of wind speed differentials. In both cases this is simply due to a lower wind speed at the two-meter altitude than the ten-meter altitude. Feedlot A showed a relationship with lower negative shaded temperature differentials during periods of low temperature and high humidity between the hours of 7pm to 9am. This relationship was not found for feedlot B and as such may not be applicable to other feedlots. Feedlot A also resulted in a partitioning that had some relationship to shaded relative humidity differentials. The differentials here were primarily negative indicating a higher shaded in feedlot humidity than out of feedlot humidity. This increase of in feedlot to out of feedlot humidity was in some cases greater when a higher than average humidity was experienced and lower in cases of low humidity and high temperature. Once again this relationship was not observed for feedlot B.

# 6. References

Measuring Microclimate Variations in Two Australian Feedlots. Project No. FLOT.310, Meat and Livestock Australia Ltd.