Temperature and humidity effects on hospital morbidity in Darwin, Australia

James Goldie¹,²
BSc (Adv) (Hons), MBus (S&T)

Steven C Sherwood¹,²
BSc, MSc, PhD

Donna Green¹,²
BSc (Hons), MA, PhD

Lisa Alexander¹,²
BSc (Hons), MSc, PhD

¹. ARC Centre of Excellence for Climate Systems Science, University of New South Wales, Sydney, New South Wales, Australia
². Climate Change Research Centre, University of New South Wales, Sydney, New South Wales, Australia
* Corresponding author: j.goldie@unsw.edu.au +61 421 747 208

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Running head: TEMPERATURE AND HUMIDITY EFFECTS ON DARWIN ADMISSIONS
Abstract

Many studies have explored the relationship between temperature and health in the context of a changing climate, but few have considered the impact of humidity, particularly in tropical locations, on human health and well-being. To investigate this potential relationship, this paper assesses the main and interacting effects of daily temperature and humidity on hospital admission rates for selected heat-relevant diagnoses in Darwin, Australia. Univariate and bivariate Poisson Generalized Linear Models were used to find statistically significant predictors and the admission rates within bins of predictors were compared to explore non-linear effects. The analysis indicated that nighttime humidity is the most statistically significant predictor ($p < 0.001$), followed by daytime temperature and average daily humidity ($p < 0.05$). There is no evidence of a significant interaction between them or other predictors. The nighttime humidity effect appears to be strongly non-linear: hot days appear to have higher admission rates when they are preceded by high nighttime humidity. From this analysis we suggest that heat-health policies in tropical regions similar to Darwin need to accommodate the effects of temperature and humidity at different times of day.

Introduction

Darwin is the capital city and regional centre of the Northern Territory. It is situated on the Timor Sea, on Australia’s northern coast. The greater city region is home to approximately 120,586 people, and as such is the densest population of the Territory in an otherwise sparsely inhabited region of the country.\textsuperscript{1}

Darwin has a tropical climate characterized by low annual temperature variability but high annual humidity variability. This variability can be seen for the 1945–2015 period with monthly mean morning (9 AM) conditions varying from 23°C to 30°C, and relative humidity varying from 60 per cent to 83 per cent; while afternoon (3 PM) conditions varying from 30°C to 32 °C and 37 per cent to 72 per cent relative humidity. Significantly, these seasonal
trends in temperature and relative humidity are not in phase, resulting in annual temperature maxima that occur three months before annual relative humidity maxima.\(^2\)

Darwin temperatures have increased by 0.5—1.0 °C over the period 1910—2012, and this is projected to increase to up to 4 °C in the 21st century, given a ‘business as usual’ RCP8.5 emissions scenario.\(^3\) However, some observed aspects of temperature change in Australia’s north-west are not replicated in global models,\(^4\) and seasonal temperature changes in the region are still poorly understood.\(^5\)

Warmer air enables the uptake of additional water vapor; the exponential relationship between atmospheric temperature and the water vapor pressure at saturation is known as the Clausius-Clapeyron relationship.\(^6\) Specific humidity—a measure of the water vapor mass of the air\(^7\)—has globally increased ‘mostly at or above the increase expected from the Clausius-Clapeyron relation… with high confidence.’\(^8\)\(^9\)\(^10\) Because of this, relative humidity—the ratio of specific humidity to the saturation water vapor mass expected from the Clausius-Clapeyron relation at a given temperature—has stayed approximately constant globally, and this is expected to continue in the future.\(^9\) However, this global trend masks decreasing relative humidity observations over land surfaces, as relatively slowly warming oceans constrain the water vapor available globally.\(^8\) Annual relative humidity in Darwin may decrease on the order of 1—3% over the 21st century given business as usual, though this may not be distinguishable from internal variability in the region.\(^9\) As constant relative humidity represents a specific humidity increase of approximately 7% per °C of warming,\(^8\) this regional decrease will still represent an increase in specific humidity.

Substantial research, both epidemiological and physiological, links extreme temperatures to poor health globally and in Australian towns and cities.\(^10\)\(^11\)\(^12\) so these climatic changes noted for northern Australia may have consequences for Darwin’s health burden. This research is motivated by recognition of the role environmental heat plays on the human body.\(^10\)

Hyperthermia, in which the body’s core temperature is elevated and organ function is
Degraded, is prevented by heat transfer to the external environment; in warmer conditions, this occurs predominantly through evaporation.

Heat flux from sweating is proportional to the vapor pressure differential between skin and the environment. Increased specific humidity therefore compromises efforts at thermoregulation.

Relatively few epidemiological studies have directly investigated the effects of humid heat. One study in Barcelona found that the threshold for increased heart disease mortalities increased approximately 2 °C on very humid days. Another study of hospital admissions in 12 US cities found no humidity effects in any of them. A third in Brisbane, Australia used a suite of biometeorological indices comprising temperature, humidity and other factors, but found that they did not produce significantly different results to average daily temperature. Some epidemiological studies have instead treated humidity as a confounding variable in heat-health relationships. Finally, epidemiological models featuring temperature and humidity have also been comparatively evaluated in European cities. However, none of these studies were situated in tropical locations featuring higher specific humidity.

Humidity effects are better documented in physiological studies: in one study, exercising study participants sweated more when exposed to a controlled increase in humidity, but their sweat evaporation rate plateaued or fell. Heat exposure also causes changes to sleep architecture, and humid heat in particular has been documented to compromise the important Slow Wave Sleep and Rapid Eye Movement phases of sleep. The lack of epidemiological support for humidity worsening heat stress is surprising, given the strong physiological evidence.

This study aims to test temperature and humidity relationships to rates of hospital admission among Darwin residents for a selection of diagnoses using daily aggregates of subdaily
weather observations, allowing the exploration of diurnally-independent contributions from
temperature and humidity.

**Methods**

For this study, statistical regression models were built using daily temperature and humidity
series as predictors and a daily hospital admission count as the health response.

The predictors were daily time series of temperature and humidity. Because Bureau of
Meteorology station data does not contain daily aggregates of humidity, subdaily
temperature and humidity data from the HadISD station dataset was used instead. Daily
maximum, minimum and mean temperature ($T_{\text{max}}, T_{\text{min}}, T_{\text{mean}}$) and relative humidity ($RH_{\text{max}}, RH_{\text{min}}, RH_{\text{mean}}$) were calculated from the subdaily observations. HadISD variables interrogated
were temperature and dewpoint temperature (in degrees Celsius). These were converted to
saturated vapour pressure ($e_s$) (Eqn. 1) and vapour pressure ($e$) (Eqn. 2), which were in turn
converted to relative humidity (RH) for this analysis (Eqn. 3):

\[
e_s = 6.1078 \cdot \exp \left( \frac{17.269T}{T + 237.3} \right) \quad \text{Eqn. 1}
\]

\[
e = 6.1078 \cdot \exp \left( \frac{17.269T_d}{T_d + 237.3} \right) \quad \text{Eqn. 2}
\]

\[
RH = 100 \times \frac{e}{e_s} \quad \text{Eqn. 3}
\]

The health response was a daily admission count running over the period 1993–2011, drawn
from the admission records of Darwin residents to five Northern Territory hospitals in the
Northern Territory Inpatient Activity dataset. Although some of the hospitals were located
outside the admissions cohort, it is assumed that all Darwin residents were exposed to
Darwin weather at the time of their admission.
Figure 1: map of Statistical Local Areas (SLAs), shown in green, associated with the Darwin HadISD station. Other Northern Territory SLAs falling outside the Darwin station catchment are shown in white.

The residential addresses of patients from the five hospitals were geocoded by admission dataset’s custodian to Statistical Local Areas (SLAs) from the 2006 Australian Statistical Geographical Classification (ASGC); only residents living in SLAs closer to the Darwin Airport HadISD station than other stations were included as part of the Darwin cohort. Figure 1 shows the boundaries of the SLAs making up this cohort, as well as the Darwin Airport station. SLAs defined in the 1991, 1996, 2001 and 2011 ASGC were also used to build population estimates of the cohort’s residence area from Australian censuses, and a stable daily population series was generated by linearly interpolating these estimates, from 80 234 residents at the 1991 census to 122 365 residents at the 2011 census.
Patients' diagnoses were coded using the 9\textsuperscript{th} and 10\textsuperscript{th} editions of the International Classification of Diseases (ICD).\textsuperscript{28} Admissions were filtered by the principal diagnosis (PDX) or any secondary diagnoses (DXn) using criteria developed on personal communications with Peter Tait based on Webb et al. (2014)\textsuperscript{29}: diagnoses with an existing epidemiological link to temperature and a physiological basis that were also prevalent in the Northern Territory. A limited number of cases with diagnoses that directly stated heat or sunlight exposure were selected, though these cases represented a negligible fraction of the total, as illustrated by Table 1.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Count</th>
<th>ICD-9 Code</th>
<th>ICD-10 Code</th>
<th>Diagnoses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ischaemic heart diseases</td>
<td>5,487</td>
<td>410—414</td>
<td>I20—125</td>
<td>PDX</td>
</tr>
<tr>
<td>Heart failure</td>
<td>1,497</td>
<td>428</td>
<td>I50</td>
<td>PDX</td>
</tr>
<tr>
<td>Pneumonia, lower respiratory infections</td>
<td>6,689</td>
<td>480—486</td>
<td>J12—J18, J20—J22</td>
<td>PDX</td>
</tr>
<tr>
<td>Chronic lower respiratory conditions</td>
<td>3,532</td>
<td>491, 492, 494, 496</td>
<td>J40—J44</td>
<td>PDX</td>
</tr>
<tr>
<td>Renal failure</td>
<td>693</td>
<td>584—586</td>
<td>N17—N19</td>
<td>PDX</td>
</tr>
<tr>
<td>Direct heat</td>
<td>35 (35)</td>
<td>992</td>
<td>T67</td>
<td>PDX, DX2—5</td>
</tr>
<tr>
<td>Exposure to sunlight</td>
<td>18 (18)</td>
<td>-</td>
<td>X30</td>
<td>PDX, DX2—5</td>
</tr>
<tr>
<td>Total admissions</td>
<td>17,951</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Admission counts, grouped by ICD-9 and ICD-10 diagnosis codes selected for aggregation. Diagnoses for direct heat and exposure to sunlight are shown before-and, parenthesized, after-ruling those admitted for other included conditions.

The effects of the six predictors on rates of hospital admission for the pre-selected heat-relevant diagnoses (herein simply ‘admission rates’) were studied to look for univariate and bivariate effects, as well as linear and non-linear effects. First, Poisson Generalized Linear Models (GLMs) were run using a univariate formula to find simple linear relationships:

\[
\text{admission count} \sim \text{offset(log(population))} + \text{predictor}
\]
Bivariate GLMs were then run to find the linear effects of two predictors, with and without an interaction term respectively:

admission count $\sim$ offset(log(population)) + predictor A * predictor B
admission count $\sim$ offset(log(population)) + predictor A + predictor B

To find non-linear effects, days in the series were binned into fifths – $P_{0–20}$ for the lowest fifth through to $P_{80–100}$ for the highest fifth – according to each predictor's quintiles (Table 2). Reference source not found., and 95% Poisson confidence intervals were generated for the mean admission rate in each fifth. By testing admission rates between the bins of one predictor within a single bin of a second predictor, non-linear interactions were considered (for example, whether $T_{\text{mean}}$ affected admission rates specifically on days of high $RH_{\text{max}}$).

<table>
<thead>
<tr>
<th>Bin</th>
<th>Temperature Predictors (°C)</th>
<th>Relative Humidity Predictors (p.p.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$T_{\text{max}}$</td>
<td>$T_{\text{min}}$</td>
</tr>
<tr>
<td>$P_{0–20}$</td>
<td>[23.0, 30.1]</td>
<td>[12.8, 21.0]</td>
</tr>
<tr>
<td>$P_{20–40}$</td>
<td>(30.1, 31.1]</td>
<td>(21.0, 23.5]</td>
</tr>
<tr>
<td>$P_{40–60}$</td>
<td>(31.1, 32.0]</td>
<td>(23.5, 24.7]</td>
</tr>
<tr>
<td>$P_{60–80}$</td>
<td>(32.0, 33.0]</td>
<td>(24.7, 25.8]</td>
</tr>
<tr>
<td>$P_{80–100}$</td>
<td>(33.0, 37.4]</td>
<td>(25.8, 31.7]</td>
</tr>
</tbody>
</table>

Table 2: closed and half-open intervals specifying the range of each predictor fifth used to bin the time series. Parentheses specify an open half; brackets specify a closed half. Temperature predictors are in units of °C; relative humidity predictors are in units of percentage points.

Spatial analysis work was done in ArcMap 10.2, while statistical analysis was done in R 3.0.2.

Results
Tables 3, 4 and 5 list the effects sizes and p-values of predictors in the univariate and bivariate GLMs; effect sizes are scaled to show contributions with approximately equal changes in specific humidity. The univariate GLMs showed T\textsubscript{max} and RH\textsubscript{max} and RH\textsubscript{mean} to be statistically significant predictors of hospital admissions (Table 1). Admissions increased 1.74% for every 2 °C of T\textsubscript{max} and 3.73% for every 10 percentage point increase in RH\textsubscript{max}.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Effect Size</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>T\textsubscript{max}</td>
<td>1.74%</td>
<td>0.049</td>
</tr>
<tr>
<td>T\textsubscript{min}</td>
<td>-0.19%</td>
<td>0.800</td>
</tr>
<tr>
<td>T\textsubscript{mean}</td>
<td>0.13%</td>
<td>0.863</td>
</tr>
<tr>
<td>RH\textsubscript{max}</td>
<td>3.73%</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>RH\textsubscript{min}</td>
<td>0.02%</td>
<td>0.968</td>
</tr>
<tr>
<td>RH\textsubscript{mean}</td>
<td>1.21%</td>
<td>0.049</td>
</tr>
</tbody>
</table>

Table 3: Effect sizes (expressed as percentage change in the admission count given a 2 °C change in temperature or a 10 percentage point change in RH) and p-values (statistical significance) of univariate Poisson GLMs. Predictors, top to bottom, are maximum, minimum and mean temperature (T\textsubscript{max}, T\textsubscript{min}, T\textsubscript{mean}) and relative humidity (RH\textsubscript{max}, RH\textsubscript{min}, RH\textsubscript{mean}). Statistically significant predictors are shaded in dark grey (p < 0.001) and light grey (p < 0.05).

There was no evidence of a statistically significant interaction between temperature and relative humidity (Table 4).

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>AB Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predictor</td>
<td>Effect Size</td>
<td>p-value</td>
</tr>
<tr>
<td>T\textsubscript{max}</td>
<td>-7.18%</td>
<td>0.332</td>
</tr>
<tr>
<td>T\textsubscript{max}</td>
<td>2.11%</td>
<td>0.376</td>
</tr>
<tr>
<td>T\textsubscript{max}</td>
<td>-2.65%</td>
<td>0.572</td>
</tr>
<tr>
<td>T\textsubscript{min}</td>
<td>0.39%</td>
<td>0.930</td>
</tr>
<tr>
<td>T\textsubscript{min}</td>
<td>-0.40%</td>
<td>0.791</td>
</tr>
<tr>
<td>T\textsubscript{min}</td>
<td>0.53%</td>
<td>0.857</td>
</tr>
<tr>
<td>T\textsubscript{mean}</td>
<td>-3.04%</td>
<td>0.613</td>
</tr>
<tr>
<td>T\textsubscript{mean}</td>
<td>0.59%</td>
<td>0.782</td>
</tr>
<tr>
<td>T\textsubscript{mean}</td>
<td>-0.99%</td>
<td>0.813</td>
</tr>
<tr>
<td>RH\textsubscript{max}</td>
<td>10.97%</td>
<td>0.368</td>
</tr>
</tbody>
</table>
Table 4: Effect sizes (expressed as percentage change in the admission count given a 2
°C change in temperature or a 10 percentage point change in RH) and p-values
(statistical significance) of bivariate Poisson GLM predictors. Effect sizes of the
interaction terms are given for a 1°C change in the temperature predictor and a 1
percentage point change in the relative humidity predictor.

The bivariate GLMs without interactions (Table 5) confirmed the results of the univariate
analysis. RH_{max} was very significant, even after accounting for the effects of any temperature
predictor, and showed increases in admissions rates of between 3.68% and 4.12% for 10
percentage point increases in RH_{max}. RH_{mean} also continued to be significant after accounting
for temperature; admissions rates increased between 1.24% and 2.01% per 10 percentage
point increase in RH_{mean}. T_{max} remained significant after the effects of RH_{mean} and RH_{min},
increasing admission rates 1.78% for a 2°C increase, but the effect size dropped to 1.54%
and became insignificant after accounting for RH_{max}. This suggests that RH_{max} may be a
superior predictor to T_{max} in Darwin.
Table 5: Effect sizes (expressed as percentage change in the admission count given a 2 °C change in temperature or a 10 percentage point change in RH) and p-values (statistical significance) of bivariate Poisson GLM predictors with no interaction terms. Statistically significant predictors are shaded in dark grey (p < 0.001), medium grey (p < 0.01) and light grey (p < 0.05).

Binning the series by one predictor at a time (Figure 2) confirmed the importance of $T_{\text{max}}, RH_{\text{max}}$ and $RH_{\text{mean}}$.

Figure 2: mean admission rates (points) and 95% confidence intervals (lines) for the fifths of maximum, minimum and mean temperature ($T_{\text{max}}, T_{\text{min}}, T_{\text{mean}}$), from coldest to warmest, and relative humidity ($RH_{\text{max}}, RH_{\text{min}}, RH_{\text{mean}}$), from driest to wettest.

Low $RH_{\text{max}}$ ($P_{0-20}$) showed significantly lower admission rates on high $T_{\text{max}}$ days (Figure 3a) and high $T_{\text{mean}}$ days (Figure 3b). There was limited evidence of $RH_{\text{max}}$ effects also occurring...
on cooler days. Given the results of the bivariate analysis, it seems likely that this coincidence is due to both predictors having non-linear effects, rather than the presence of an interaction between them.

![Figure 3: Mean admission rates (points) and 95% confidence intervals (lines) for the fifths of RH\textsubscript{max} within fifths of (a) T\textsubscript{max} and (b) T\textsubscript{mean}.](image)

RH\textsubscript{mean} also appeared to have a strong non-linear effect on high T\textsubscript{max} days (Figure 4).
Figure 4: Mean admission rates (points) and 95% confidence intervals (lines) for the fifths of RH$_{\text{mean}}$ within fifths of $T_{\text{max}}$.

Discussion

The analyses indicate that maximum temperature, maximum relative humidity and mean relative humidity are significant predictors of hospital admission rates in Darwin. This is an unexpected result for two reasons. The first is the presence of any sort of humidity effect, as studies addressed in this paper have previously to find no humidity effect in other locations.

The second reason is that maximum temperature and maximum relative humidity occur at opposing times of day: maximum temperature occurs in mid-afternoon, while maximum relative humidity occurs overnight, in the early morning. This may not necessarily mean that temperature and humidity act on human health at different times of day; it may simply be characteristic of Darwin’s climate, and mean relative humidity was also statistically significant. On the other hand, mean relative humidity’s statistical significance may merely be maximum relative humidity, which it partially captures.

A large body of literature links heat stress to sleep disruption: high overnight temperatures are associated with reduced sleep quality in people of all ages but especially the elderly.\textsuperscript{22,23}
In particular, ‘Humid heat exposure further increases wakefulness, decreases [rapid eye movement] and [slow wave sleep], and excessively suppresses the decrease in [core body temperature].’ Sleep disruption is, in turn, associated with immediate respiratory and cardiovascular problems. Because maximum relative humidity occurs early in the morning, hospital admission counts in the models investigated here would likely represent admissions following this peak; this is somewhat less likely for maximum temperature, which occurs later in the day. A comparison of health outcomes across tropical, subtropical and extratropical locations, where temperature and humidity variances change, would help to make the underlying mechanisms of heat stress clear: epidemiological studies situated in the tropics are virtually non-existent, although a collection of studies used survey data from approximately 40 000 Thai workers to make inferences about occupational heat stress effects.

Nighttime humidity effects in Darwin appear to be strongly non-linear. Days with less than 84.5% nighttime humidity were associated with significantly lower admission rates (Figures 2, 3); this could be because nighttime humidity has a strongly non-linear relationship, a threshold relationship or simply due to the width of that particular bin. Daytime temperature and mean relative humidity exhibited more evenly distribution bins (Table 2), and Figure 4 shows a monotonic increase in admission rates on hot days with mean relative humidity, suggesting that the bin width could be the cause of this ostensible non-linearity.

Extrapolations of these results for future warming require caution for at least two reasons. First, confidence in northern Australian temperature and humidity projections is still limited, especially with regard to seasonal changes. Finer model resolutions have enhanced modeling outcomes in southeast Australia, but the same improvements may not necessarily be possible in northwest Australia; better theoretical understanding of the mechanisms in the northwest may be required. Second, heat-health models based on different indices or statistical models may diverge as the climate changes; some, such as Wet Bulb Globe Temperature and Physiological Equivalent Temperature, are developed
on the basis on entirely different methodologies. Heat-health models with robust physiological explanations of these phenomena are required to reliably extrapolate results.

Conclusions

This analysis looked at the effects of six daily temperature and humidity predictors on hospital admission rates in five hospitals in the Northern Territory. Using univariate and bivariate Poisson GLM, significant increases in hospital admission rates were found with daytime temperature, nighttime humidity and average daily humidity. There is no evidence of a significant interaction between them. The effect of nighttime humidity appears to be strongly non-linear; high nighttime humidity is associated with increased admission rates on hot days.

These results have implications for heat related health policies in northern Australia. The results presented here show that at different times of day temperature and humidity act differently on the health of people living in the Northern Territory. Health providers in climatically similar locations may benefit from considering temperature and humidity separately.

These results are preliminary in some ways, and there is room for further research in this area to expand its scope. More complex models of heat stress, such as those employing heat stress indices, were not investigated, and methods of correcting predictors for cyclical effects, such as seasonal or weekly cycles, were avoided in favor of a simpler analysis of temperature and humidity relationships. Further, the study did not account for many socioeconomic or behavioral factors that may influence heat-health, including age, sex, Indigenous status, country of birth or employment status. The results are limited to Darwin, Australia; comparison with a variety of climatic regions, including tropical and extratropical population centers, is an ideal topic for further research.
References


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