Comparative evaluation of human heat stress indices on selected hospital admissions in Sydney, Australia

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Abstract

Objective: To find appropriate regression model specifications for counts of the daily hospital admissions of a Sydney cohort and determine which human heat stress indices best improve the models' fit.

Methods: We built parent models of eight daily counts of admission records using weather station observations, census population estimates and public holiday data. We added heat stress indices; models with lower Akaike Information Criterion scores were judged a better fit.

Results: Five of the eight parent models demonstrated adequate fit. Daily maximum Simplified Wet Bulb Globe Temperature (sWBGT) consistently improved fit more than most other indices; temperature and heatwave indices also modelled some health outcomes well. Humidity and heat-humidity indices better fit counts of patients who died following admission.

Conclusions: Maximum sWBGT is an ideal measure of heat stress for these types of Sydney hospital admissions. Simple temperature indices are a good fallback where a narrower range of conditions is investigated.

Implications for public health: This study confirms the importance of selecting appropriate heat stress indices for modelling. Epidemiologists projecting Sydney hospital admissions should use maximum sWBGT as a common measure of heat stress. Health organisations interested in short-range forecasting may prefer simple temperature indices.

Key words: heatwave, humidity, temperature, morbidity, New South Wales

Extreme heat is a recognised danger to human health,[1,2] and warm days and nights will occur more frequently across Australia due to climate change.[3] A range of indices quantify the impact of heat stress on the human body, but there is little consensus among epidemiologists on the most appropriate heat stress indices to use when modelling public health responses. This is a problem for researchers, who cannot easily compare work on the effects of heat stress in detail, and public health organisations, which cannot predict future changes in public health responses without guidelines on how to specify heat-health relationships.

Hyperthermia – elevated core body temperature – is caused when the heat produced by a person's m etabolism or received from external sources can no longer be dispersed.[4] The effects of heat stress on populations are regularly modelled by epidemiologists: heat extremes are typically linked with increased incidences in respiratory and renal conditions,[5] as well as cardiovascular conditions.[6–8]

Although early papers investigated only temperature as a predictor of health responses,[6,9,10] more recent efforts use a variety of indices of heat stress. But there is little consensus around which heat stress indices best fit observed public health data; indices used by epidemiologists are rarely justified with respect to the selected conditions or location. Work comparing indices is still nascent.[11,12]

This lack of consensus in model specification presents a barrier to understanding the present and future health risks of climate change. Projections on the health impacts of temperature are already occurring in multiple Australian cities, including Brisbane, Sydney and Melbourne,[13] but Tong et al.[14] recognised that predictions of health outcomes in Brisbane were sensitive to the choice of heatwave index. Given this, it is important that the most useful indices are established.

This study builds an epidemiological model framework based around a focused set of medical conditions. As a preliminary study, we evaluate whether model fits can be improved using a range of heat stress indices for Sydney, Australia. Sydney is chosen as it has a population of more than four million people[15] and a warm summer/cold winter climate classification[16] – though continued greenhouse gas emissions are expected to cause more hot summer days and may change the average relative humidity in Australia's East Coast region.[17] This analytical framework could be expanded to other Australian populations that are vulnerable to heat stress.

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Types of heat stress indices

The indices compared in this study are of two types: heat-humidity indices and heatwave indices.

Humidity inhibits heat stress adaptation: in humid conditions, sweat is more likely to drip off the body without cooling it than to be evaporated.[18] Heat-humidity indices quantify this effect by combining temperature, humidity and other weather observations. Two heat-humidity indices—Simplified Wet Bulb Globe Temperature (sWBGT)[19] and Apparent Temperature (AT)[20]—are popular in Australia with both the public and researchers.[11,21–23]

Heatwave indices, in contrast, are rolling functions of temperature alone. Duration of heat stress exposure partly determines the severity of heat stroke,[4] but repeated exposures on longer timescales trigger physiological adaptations.[24] Heatwave indices capture these effects. They range from simple temperature averages, such as the 3-Day Average Temperature (3DAT) and 3-Day Maximum Temperature (3DMT),[12] to more complex indices like Excess Heat Factor (EHF), which models both short-term heat stress accumulation and longer-term adaptation.[25]

Several non-weather factors may also be included in models. Health responses for heat-related conditions have weekly and seasonal patterns[26–28] and occur at lags of 0–3 days after exposure;[2] cold-related conditions typically occur at longer lags.[29] These features result in J- or U-shaped relationships between temperature and health outcomes.[30,31] Epidemiologists have previously modelled health outcomes with spline functions of temperature. Splines are smoothing functions that allow a response to be separately smoothed along pieces of a predictor's domain. In this context, splines allow hot, mild, and cold conditions to have different effects.[10] However, because of the different lags between hot and cold effects, more recent studies have used distributed lag non-linear (DLNM) models.[32,33] These define a *cross-basis* predictor, which allows effects to be simultaneously described across a range of temperatures and a range of lags.[34]

Methods

We built a set of regression models, each featuring a different heat stress index as a predictor (and parent models that featured no index), with the aim of evaluating which index was the most appropriate for predicting daily hospital admission counts among a Sydney cohort.

This was a two-stage analysis:

- The development of the parent models based on non-weather factors.
- The introduction and comparison of heat stress indices to the parent models and each other.

Data

We combined selected hospital admission records for a cohort of Sydney residents with sub-daily weather observations, Census population data and historical public holiday data.

The cohort comprised residents of the Sydney Statistical Division (SD), as defined by the Australian Standard Geographical Classification 2006,[35] and we requested their admission records from the New South Wales (NSW) Admitted Patient Data Collection (APDC). We used admissions to public and private NSW hospitals for selected cardiovascular, respiratory and renal conditions between 1 August 2001 and 31 May 2013.

The three groups of selected conditions, identified by their codes in the 9th and 10th editions of the International Classification of Diseases (ICD),[36] included:

- **cardiovascular conditions**, including ischaemic heart diseases (ICD-9: 410–414; ICD-10: I20–I25)[8,37,38] and heart failure (ICD-9: 428; ICD-10: I50),[8,38]
- **respiratory** conditions, including pneumonia,[37] lower respiratory infections (ICD-9: 480–486; ICD-10: J12–J18, J20–J22)[38] and chronic lower respiratory conditions (ICD-9: 491, 492, 494, 496; ICD-10: J40–J44), and[38]
- **renal conditions**, including renal failure (ICD-9: 584–585; ICD-10: N17–N19).[39]

The conditions selected were chosen, with assistance, for their previously established epidemiological links to extreme heat (Peter Tait, personal communication). Variables analysed from the admission records included date of admission, primary diagnosis and mode of separation.

Census population estimates for the 2001 and 2006 Sydney SDs were available and had stable boundaries, but no single comparable boundary was available in the 2011 Australian Statistical Geography Standard (ASGS). We therefore selected Statistical Local Areas (SLAs) from the 2011 ASGC[40] that were within the boundary of the 2006 Sydney SD[41] and summed the populations of the selected SLAs in lieu of a singular estimate. Therefore, the populations of 2001[42] and 2006[43] Sydney Statistical Divisions, as well as the sum of the populations of the selected 2011 Statistical Local Areas,[44] were used as the basis for population estimates.

We obtained weather station data for Sydney Airport from HadISD[45]. HadISD was chosen as it contains quality-controlled Bureau of Meteorology sub-daily weather observations. This allows us to accurately calculate high quality daily aggregates of heat-humidity indices from sub-daily temperature, humidity and wind speed data.

Despite the quality-control measures in HadISD, Sydney Airport observations vary in precision across the hours of the day, and data availability during summers after the year 2000 shifts by one hour—possibly a result of changes to daylight savings reporting. These problems could potentially bias calculations of heat-stress index aggregations. To overcome them, we extracted a three-hourly series beginning at 0200 UTC for most periods or 0100 UTC, shifted one hour forward, for summers from the year 2000 onward. The resulting observation series is the largest possible set of observations with uniform precision and coverage across the day.

We calculated three-hourly heat-humidity indices from temperature, humidity and wind speed and then aggregated all series into the daily heat stress index predictors used in the analysis.

Finally, we sourced NSW historical public holiday information from the Banks and Bank Holidays Act 1912 (NSW)[46] and the Public Holidays Act 2010 (NSW).[47]

In order to focus on climatic influences, we did not include additional environmental hazards that may also be relevant to disease groups, such as air quality.

Parent model development

We constructed eight admission count time series from the admissions dataset, and these counts served as the response variables for the models. The counts were:

C1. Cardiovascular admissions

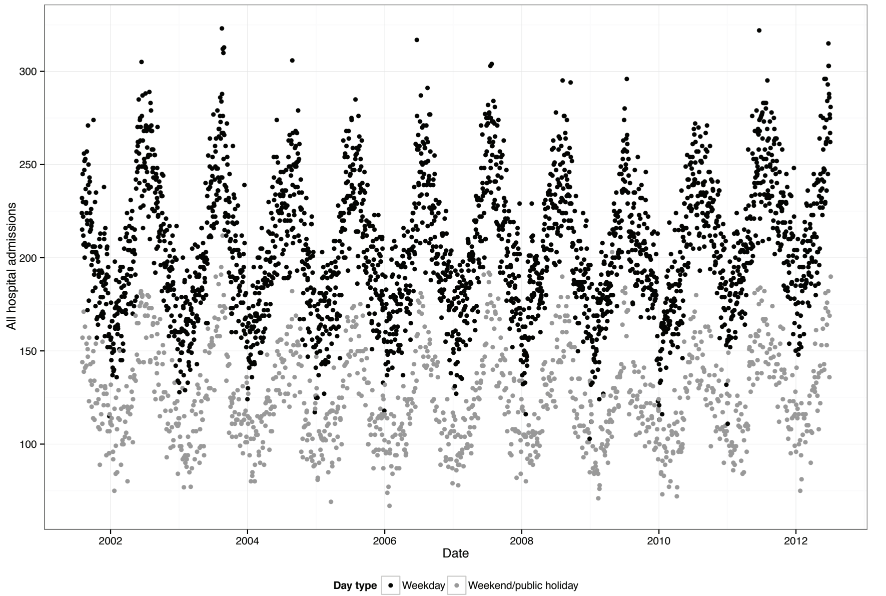
C2. Respiratory admissions

C3. Renal admissions

C4. All selected admissions (C1 + C2 + C3)

C5. Cardiovascular admissions where the mode of separation was death

Figure 1: Time series of all Sydney hospital admissions for all selected diagnoses. Work days are in black; non-work days are in grey. This series shows the seasonal cycle of admissions, which is highest in winter (June–August) and lowest in summer (December–February), as well as the difference in admissions on work days.



C6. Respiratory admissions where the mode of separation was death

C7. Renal admissions where the mode of separation was death

C8 All selected admissions where the mode of separation was death (C5 + C6 + C7).

We built a parent regression model for each of the eight responses using a Generalised Linear Model (GLM) framework. We used a χ^2 deviance goodness-of-fit test as a benchmark for the parent models' goodness-of-fit: the models' deviance from a saturated model—that is, a model with enough parameters for every observation – is compared to a distribution with degrees of freedom equal to the difference between the saturated model's parameter count and that of the tested model. A significant difference between the parent model and the saturated model (using a significance threshold of 0.05) means that the parent model fails this benchmark.

Counts, such as hospital admission counts, are typically modelled as Poisson-distributed variables. However, the Poisson distribution is described by a single parameter, , that influences both mean and variance. We found evidence that the variance was higher than the mean (known as *overdispersion*) when fitting Poisson-distributed GLMs, and deviance goodness-of-fit tests found that the resulting models were significantly different from a saturated model (that is, one with enough parameters for all observations). In order to improve the fit of the parent model against a saturated model, we eliminated overdispersion by switching to a Negative Binomially-distributed model family.

We selected three predictors for the parent models. The first, a daily population estimate, was linearly interpolated from Census figures as described in the previous section. We also modelled weekly and seasonal patterns in the admissions. These series are strongly seasonal, with the lowest admissions in summer and the highest in winter, and admissions fall by about half on weekends and public holidays (Figure 1). We accounted for the seasonal pattern by adding an eight-term Fourier series of time of year.[10,48] We also added a binary indicator predictor of non-work days (weekends and public holidays).

Introduction and evaluation of heat stress indices

With common parameters established, we built a set of regression models nested inside each parent model, each featuring a single heat stress index. The resulting models used the formula:

count ~ offset(log(population)) + nowork + fseries+index

where:

- count is one of the five remaining daily admission counts (C1–C4, C8)
- population is a daily population estimate of the cohort
- nowork is a binary indicator of non-work days (Saturdays, Sundays and public holidays)
- fseries is an eight-term Fourier series of time of year used to adjust for seasonal variation in admissions
- index is a cross-basis of one of the human heat stress indices. This term is not present in the parent models described in the previous section.

We divided the heat stress index predictors (Table 1) into four broad types for the purposes of interpretation:

- daily aggregates of **temperature** (°C) and **humidity** (hPa);
- **heat-humidity indices**, which are linear combinations of temperature and humidity that are calculated at points across the day before being aggregated; and
- **heatwave indices**, which are rolling aggregations of temperature over periods greater than a day.

There were three aggregations of each of the temperature, humidity and heat-humidity indices: daily maximum, minimum and mean, adding up to 18 basic heat stress predictors. We used the *dlnm* package[32] to build a cross-basis of each index, with a maximum lag of 10 days. Thus, 18 different models were compared to each health response's parent model.

To establish the added value of the heat stress indices, we compared the heat stress models to their corresponding parent models using log-likelihood ratio tests. We also compared the heat stress models with each other and their parent models to see which indices provided the best fit for a given response. We used maximum log-likelihood as an absolute measure of fit and Akaike Information Criterion (AIC), a penalised measure of model deviance, as a measure of fit that is corrected for the number of predictors:[50]

AIC=2K-2l

where K is the number of parameters in the model and l=log (L) is the model's maximum log-likelihood. A greater log-likelihood or a *smaller* AIC indicates better fit.

Results

The parent models of counts C1 through C4 and C8 showed adequate goodness-of-fit according to the deviance test. Counts C5 through C7, however, showed inadequate fit. The poor fit in these three models is likely due to the lower counts in these series leading

Table 1: Indices tested. Heat-humidity (HH) indices are a function of temperature (T), vapour pressure (e) and wind speed (u). Heatwave (HW) indices are functions of daily average temperature (T_{an}) or daily maximum temperature (T_{xn}) for day n, which is the average of that day's maximum temperature and the next day's minimum temperature. Excess Heat Factor is also a function of T_{95}, the 95th percentile of daily average temperature; here, because of the limitations of data coverage, we calculated this threshold across the analysis period rather than using Nairn & Fawcett's 1971–2000 reference period. Although this change shifts EHF values, it has a negligible effect on the fit of the models. Temperature (T) and humidity (H) indices are simple daily aggregations of observations.

Index	Type	Source	Formula
Temperature	T	—	Observed
Dewpoint temperature	H	—	Observed
Vapour pressure	H	Murray 1967[49]	$e=6.1078*exp\left(\frac{17.2693882*T}{T+237.3}\right)$
Simplified Wet Bulb Globe Temperature (sWBGT)	HH	BOM 2010[19]	$(0.567*\mathrm{T})+(0.393*e)+3.94$
Apparent Temperature (AT)	HH	BOM 2010[19]	$T+(0.33*e)-(0.7*u)-4.0$
3-Day Average Temperature (3DAT)	HW	Scalley et al. 2015[12]	$\mathrm{mean}(T_{a0},T_{a1},T_{a2})$
3-Day Maximum Temperature (3DMT)	HW	Scalley et al. 2015[12]	$\min(T_{x0},T_{x1},T_{x2})$
Excess Heat Factor (EHF)	HW	Nairn & Fawcett 2013[25]	$EHI_{sig}=\mathrm{mean}(T_{a0,}T_{a1,}T_{a2}) - T_{95}$ $EH_{accl}= \mathrm{mean}(T_{a0,}T_{a1,}T_{a2}) - \mathrm{mean}(T_{(a-1)},\ldots,T_{a-30})$ $EHF=EHI_{sig}*\max(1,EHI_{accl})$

to bad model specifications, and the rest of the analysis proceeded with the five good models.

The heat stress models of counts C1–C4 and C8, like their respective parent models, showed adequate goodness-of-fit using the deviance test. The heat stress models all also showed a statistically significant difference to their parent model, with p-values below 0.0002. All the heat stress models had correspondingly lower AICs than their respective parent models, confirming the statistically significant difference between them.

Heat stress indices are ranked in a similar order across counts C1–C4 (Figure 2, Figure S1 a–c). Maximum sWBGT (HH) performs consistently well across all three diagnosis groups and the combined count, while 3DMT (HW), daily minimum temperature (T) and daily mean temperature (T) each perform well in two of the three diagnosis groups. The rankings of all admissions (Figure 2) is most like those of respiratory admissions (Figure 2b), owing to their overrepresentation in the admission set.

The best aggregation type depended on the type of heat stress index: for temperature (T) indices, daily means and minima produced the lowest AIC values, while for indices that included humidity (H and HH), daily maxima produced the lowest values in most cases.

Many of these results are inverted for count C8, those patients who died following their admission (Figure 2d). Humidity (H) indices, which modelled the other counts consistently poorly, performed consistently well here, outranked only by minimum and mean sWBGT. Daily means and minima outranked daily maxima for all index types. The heatwave indices all modelled this count comparatively poorly.

The Excess Heat Factor (EHF) heatwave index improved predictions relative to all the parent models, but not as much as most other indices. Because the number of model terms did not vary between indices, ranking by log-likelihood produced the same results as ranking by AIC.

The effects of heat stress indices varied by health outcome. There were few robust effects on cardiovascular admissions in cold or cold/dry conditions, and in hot or hot/wet conditions, cardiovascular admissions either showed no effect or decreased (Figure S1). All indices that used temperature showed increasing respiratory and renal admissions (counts C2 and C3 respectively) in increasingly cold or cold/dry conditions (Figure S2–S3). However, robust increases in admissions only appeared for renal admissions in hot or hot/wet conditions (Figure S3). The combined counts, C4 and C8, also showed either monotonic decreases with increasing heat stress indices, or insignificant effects (Figure S4–S5).

Discussion and conclusions

Daily maximum sWBGT consistently modelled admission counts of Sydney residents well, though it was not the single best index in all diagnosis groups. All other factors being equal, this would make it a good candidate for use in short-term forecasting by hospitals and long-term projection by epidemiologists.

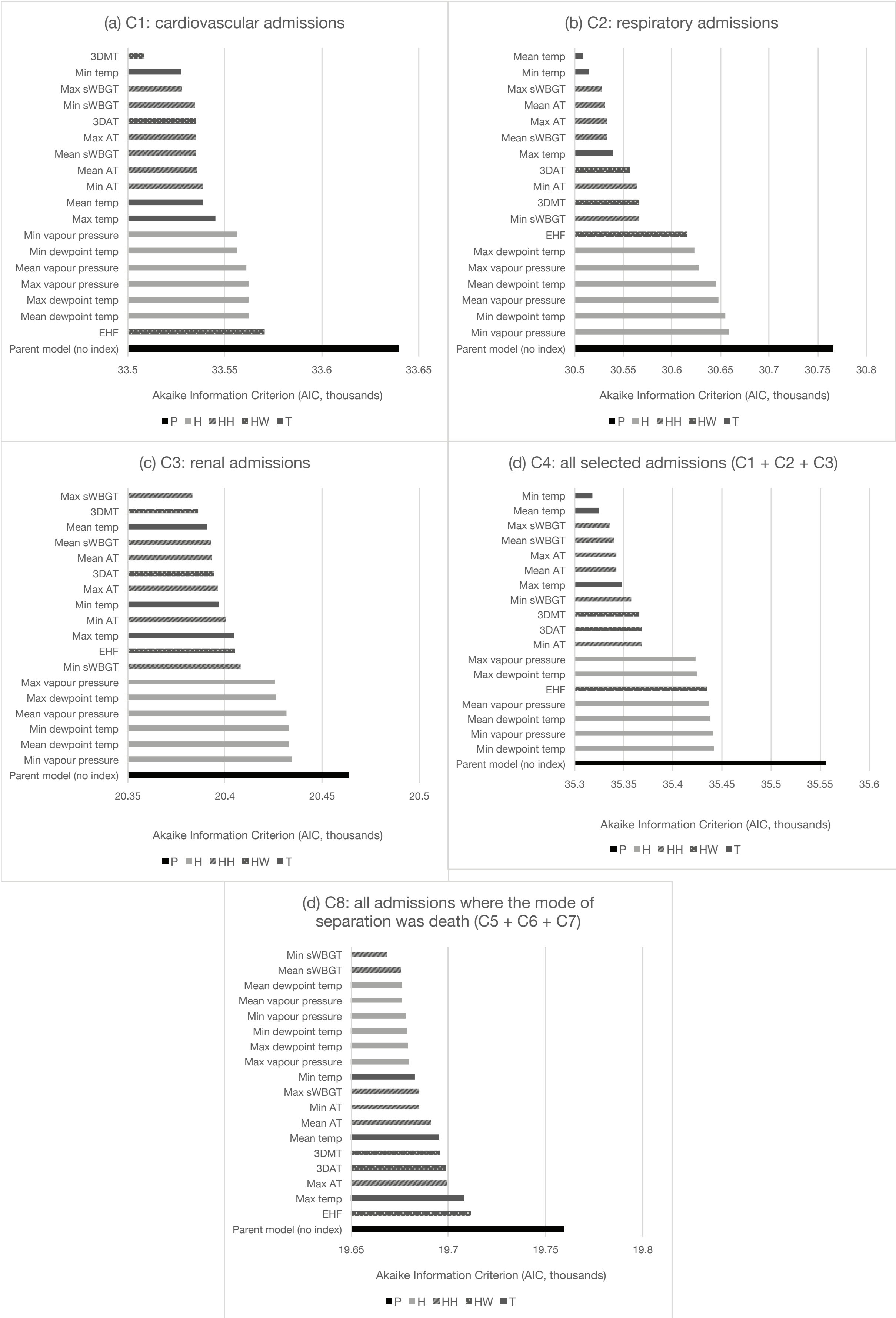
However, index fit is not the only factor when considering the use of these indices: the availability and uncertainty of prerequisite observations or climate model output also play a large role in our knowledge of future public health changes. Simple temperature statistics modelled different counts well, and they are an attractive choice for observational purposes: heat-humidity indices require two variables to be near-simultaneously recorded, and they and heatwave indices require additional calculation. The 3DMT heatwave index, which modelled cardiovascular and renal admission counts well, also relies solely on temperature data.

Heat-humidity indices generally display similar uncertainty to temperature indices when projecting into the future despite the additional input, because global temperature and humidity are not independent.[51] Projection of heat-health impacts has mostly focussed on daily maximum temperature[10,52,53] or mean temperature,[33,54,55] while heat-humidity and heatwave indices have occasionally been used.[23,56] This analysis suggests that maximum sWBGT may be a good point of comparison for future projection work. Simple temperature statistics may be a better fit in some cases, especially since mean temperature is already in wide use, but this depends on the health response projected.

These results may not be the case in other locations, and a sensitivity study of projections to the selected heat stress index is required to determine whether the differences in model fit presented here translate into differences in projections, particularly if heat stress indices diverge as the Earth's climate changes.

Although heat-humidity indices best modelled those patients who died following their admission (C8), humidity admissions with no measure of temperature also performed well. This stark difference from the other counts demonstrates the importance of heat stress index selection when making statements about present or future changes in heat stress, as noted by Tong, Wang and Barnett.[14] Humidity appears to improve model fit to this count more than temperature.

Figure 2: Akaike Information Criterion (AIC) scores for models of counts C1–C4 and C8. A lower AIC indicates a better fit to the data. Models are shaded by the type of human heat stress predictor used: humidity (H), heat-humidity (HH), heatwave (HW) and temperature (T). Each count also has one parent model (P) featuring no heat stress index.



The difference in indices between C8 and other counts could be due to an unaccounted confounder relationship, including smoke from bushfires,[57] smoking,[58] lead exposure[59] and other forms of air pollution.[60] Some of these hazards may interact with temperature and particularly humidity, and a confounder relationship may explain the less robust hot or hot/wet effects we found for some counts. Further study of the interactions between temperature, humidity and particulate hazards is warranted. However, thunderstorm asthma,[61] is likely less relevant: we excluded asthma from this study despite mixed evidence of its association with temperature because it is also linked to several non-weather-related environmental hazards, including indoor mould and pests.[62]

Differences between the counts for different disease groups may also occur because humidity inhibits the physiological response to extreme heat. In humid-hot conditions, humans sweat more to compensate for a loss of evaporative efficiency.[63] In extreme conditions, sweat may drip off the body without evaporating, lowering evaporative efficiency even further.[63] This means that dehydration, and the associated health consequences, may be more likely.

Although 3DMT performs well in some cases, these results suggest that heatwave indices are generally less effective than simpler indices. This could be because they act as distributed lag functions of temperature, and techniques such as DLNM modelling allow distributed lag relationships to be represented in a more comprehensive way. They may be better suited to operational 'heat alert' systems, such as those undertaken by the Bureau of Meteorology,[64] where more complex modelling is not undertaken.

All the heat stress indices compared here provide additional value when added to an otherwise correctly specified model. This suggests that projection work modelling future heat stress is useful, as hospital admission loads in Sydney can be expected to change in the long-term if temperature and humidity do.

This work could be important in other locations, particularly those with common socioeconomic and climatic features. The recent projection work of Gasparrini et al. across 384 locations[33] demonstrates that the epidemiology community can compare heat stress indices in a large range of locations. Further multi-city studies of effects may be able to establish the way these factors modify heat stress effects, or this analysis may be repeated across cities to determine whether the most useful indices change with location. Additional analyses should also consider the way other modelled environmental hazard exposures modify the improvements in fit from heat stress indices—though this introduces many dimensions for analysis.

Another model specification, a larger group of conditions or a more populous location may be required to correctly model those who died following admission in individual diagnosis groups.

Implications for public health

Heat stress indices are commonly used by researchers, health organisations and the public to understand the impacts of extreme heat on human health, but with a variety in active use, there has been little agreement on the relative merits of each one. This lack of consensus inhibits meta-analysis of the projection work beginning to occur in the epidemiological community, which in turn clouds public health policy decisions around climate change adaptation.

This analysis evaluated the ability of a variety of heat stress indices to predict a Sydney residential cohort's hospital admissions for a group of heat-related cardiovascular, respiratory and renal conditions. We found that daily maximum sWBGT, a heat-humidity index, consistently models hospital admission counts for a variety of conditions well. Simple temperature statistics are also useful in some situations where health organisations do not have access to humidity data or projections.

We suggest that continuing work projecting the future health impact of climate change in Sydney use daily maximum sWBGT as a primary measure of heat stress, especially when several types of disease are considered in aggregate. Further work is required to see whether this should also be done in other population centres.

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Supporting Information

Additional supporting information may be found in the online version of this article:

Supplementary Figure 1: Overall effect sizes (across the entire lag period) of heat stress predictors on C1, the count of admissions for cardiovascular conditions (shaded region is the 95% confidence interval). Effect sizes are expressed as rate ratios.

Supplementary Figure 2: Overall effect sizes (across the entire lag period) of heat stress predictors on C2, the count of admissions for respiratory conditions (shaded region is the 95% confidence interval). Effect sizes are expressed as rate ratios.

Supplementary Figure 3: Overall effect sizes (across the entire lag period) of heat stress predictors on C3, the count of admissions for renal conditions (shaded region is the 95% confidence interval). Effect sizes are expressed as rate ratios.

Supplementary Figure 4: Overall effect sizes (across the entire lag period) of heat stress predictors on C4 (C1 + C2 + C3), the count of admissions for all selected conditions (shaded region is the 95% confidence interval). Effect sizes are expressed as rate ratios.

Supplementary Figure 5: Overall effect sizes (across the entire lag period) of heat stress predictors on C8 (C5 + C6 + C7), the count of those admissions for all selected conditions who died following admission (shaded region is the 95% confidence interval). Effect sizes are expressed as rate ratios.