Int J Biometeorol
DOI 10.1007/s00484-017-1451-9

ORIGINAL PAPER

Changes in relative fit of human heat stress indices to cardiovascular, respiratory, and renal hospitalizations across five Australian urban populations

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Received: 17 July 2017 / Revised: 30 August 2017 / Accepted: 20 September 2017

Abstract Various human heat stress indices have been developed to relate atmospheric measures of extreme heat to human health impacts, but the usefulness of different indices across various health impacts and in different populations is poorly understood. This paper determines which heat stress indices best fit hospital admissions for sets of cardiovascular, respiratory, and renal diseases across five Australian cities. We hypothesized that the best indices would be largely dependent on location. We fit parent models to these counts in the summers (November–March) between 2001 and 2013 using negative binomial regression. We then added 15 heat stress indices to these models, ranking their goodness of fit using the Akaike information criterion. Admissions for each health outcome were nearly always higher in hot or humid conditions. Contrary to our hypothesis that location would determine the best-fitting heat stress index, we found that the best indices were related largely by health outcome of interest, rather than location as hypothesized. In particular, heatwave and temperature indices had the best fit to cardiovascular admissions, humidity indices had the best fit to respiratory admissions, and combined heat-humidity indices had the best fit to renal admissions. With a few exceptions, the results were similar across all five cities. The best-fitting heat stress indices appear to be useful across several Australian cities with differing climates, but they may have varying usefulness depending on the outcome of interest. These findings suggest that future research on heat and health impacts, and in particular hospital demand modeling, could better reflect reality if it avoided "all-cause" health outcomes and used heat stress indices appropriate to specific diseases and disease groups.

Keywords Humidity · Dewpoint · Heatwave · Wind speed · Hospital admissions · Heat stress index · Index comparison · Cardiovascular · Respiratory · Renal · Morbidity · Climate · Climate change

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s00484-017-1451-9) contains supplementary material, which is available to authorized users.

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Introduction

Extreme heat is recognized as a health threat (Gosling et al. 2008; Ye et al. 2012), and as the global climate has changed over the last 50 years, exposure to extremely hot days and nights has increased throughout the world (Donat et al. 2013). For Australians in the eight state and territory capital cities, these changes take place across a range of climates, from temperate conditions in the south through to subtropical and tropical conditions in the north (Bureau of Meteorology 2012).

Heat-health relationships change with location (Curriero et al. 2002; Bambrick et al. 2008). This may be for climatic, socioeconomic, or demographics reasons, but research to characterize heat-health relationships in a unified way across global—or in Australia's case, national—climates is limited.

Australians will be subject to more extreme heat in the future (Alexander and Arblaster 2017), but extreme heat may not have the same effects on health across all locations. These differences complicate our understanding of how heat affects people's health and make it more difficult to predict the impacts of a heat event on population health.

A further hurdle in understanding the relationships between extreme heat and health is that there is little consensus on how to quantify "heat stress." A variety of indices incorporating factors other than maximum temperature reached, such as humidity, wind speed, radiation, and heatwave elements like heat buildup and heat stress acclimation, have been developed (de Freitas and Grigorieva 2015); however, it is not clear for which populations and health outcomes particular indices might be most appropriate.

Understanding whether the most useful heat stress indices change with location or outcome is, therefore, a priority for heat-health research. Scalley et al. (2015) modeled emergency department presentations in Perth, Australia, and found that the Excess Heat Factor index (Nairn and Fawcett 2013) had greater statistical fit than two other heatwave indices. Goldie et al. (2017) found that WetBulb Globe Temperature (Bureau of Meteorology 2010) was a better fit for hospital admissions for three health outcomes in Sydney, Australia, than other temperature, humidity, heat-humidity, and heatwave indices. This set of studies did not compare the same outcomes across cities.

Comparisons of heat stress across multiple cities have typically been restricted to only one heat stress index. As climates can vary substantially between study locations, these studies may overlook critical aspects of the heat-health relationship. This limitation is demonstrated by two studies that have investigated both multiple locations and multiple index types. Rodopoulou et al. (2015) and Barnett et al. (2010) each fitted temperature and heat-humidity indices to mortality data across European and US cities, respectively, and both studies found that no one index best fit all cities' observations. Our study seeks a similar comparative analysis for Australia, where a broad range of climates can be compared within a country with relative ethnic homogeneity (Fearon 2003), few differences in sociodemographic factors, and large population centers.

As ambient temperatures and especially extreme heat events in Australia are projected to increase over at least the next few decades (King et al. 2017), a better understanding of heat-health relationships is essential for reducing population health impacts through targeted and effective prevention and better health service planning. However, the choice of heat stress index may determine the types of outcomes for which a relationship is found and would thus affect projections of future health impacts (Tong et al. 2010; Benmarhnia et al. 2014). In Australia, an inter-city comparison of the associations between several established heat stress indices and a variety of health outcomes is necessary for understanding heat-health relationships and providing insight into future vulnerability. Here, we present a study focused on five Australian cities using the same indices and outcomes that Goldie et al. (2017) used for a single city—an approach that can be applied to regions elsewhere.

Methods

The analysis comprised five groups, made up of the residents of five Australian cities: Cairns, Brisbane, Sydney, Adelaide, and Perth (Fig. 1). These five cities have significant populations—from 57,000 in Cairns to nearly five million in Sydney as of 2011 (Table S1), together comprising nearly 50% of Australia's total population—and sufficient health data available for this study. The airport-based weather stations for the five cities demonstrate varied summer temperature and humidity conditions over the study period (Fig. 2).

For each city, we selected the hospital admission records from between November 2001 and March 2013 of patients whose place of usual residence was within defined city boundaries at the time of admission (Fig. 1). These admissions were made to any public or private hospital within the state. We also used these boundaries to retrieve the populations within each city boundary at the times of the 2001, 2006, and 2011 censuses (Table S1). The spatial units used for each city boundary, and Census population data for each boundary, are provided in Section 1 of the supplementary information.

We sourced deidentified hospital admissions from four databases: Sydney patients from the Admitted Patient Data Collection, Adelaide patients from the South Australian Admitted Patient Activity, Perth patients from the Hospital Morbidity Data System, and Brisbane and Cairns patients from the Queensland Hospital Admitted Patient Data Collection. This research was approved by the UNSW Human Research Ethics Advisory (HREA) (HC15125), the Australian National University Human Research Ethics Committee (HREC) (2015/239), the Royal Brisbane & Women's HREC (HREC/15/QRBW/202), the SA Health HREC (HREC/15/SAH/41), and the Department of Health WA HREC (2015/27).

We focused our analysis on three health outcomes with established epidemiological relationships to extreme heat: *cardiovascular conditions*, including ischemic heart disease (Bull and Morton 1978; Lin et al. 2009; Webb et al. 2014), and heart failure (Lin et al. 2009; Webb et al. 2014); *respiratory conditions*, including pneumonia (Bull and Morton 1978), acute lower respiratory infections (Lin et al. 2009), and chronic lower respiratory diseases (Lin et al. 2009); and *renal conditions*, including renal failure (Hansen et al. 2008a). As well as being linked to extreme heat, admissions for these diseases occur primarily in older people, who represent an

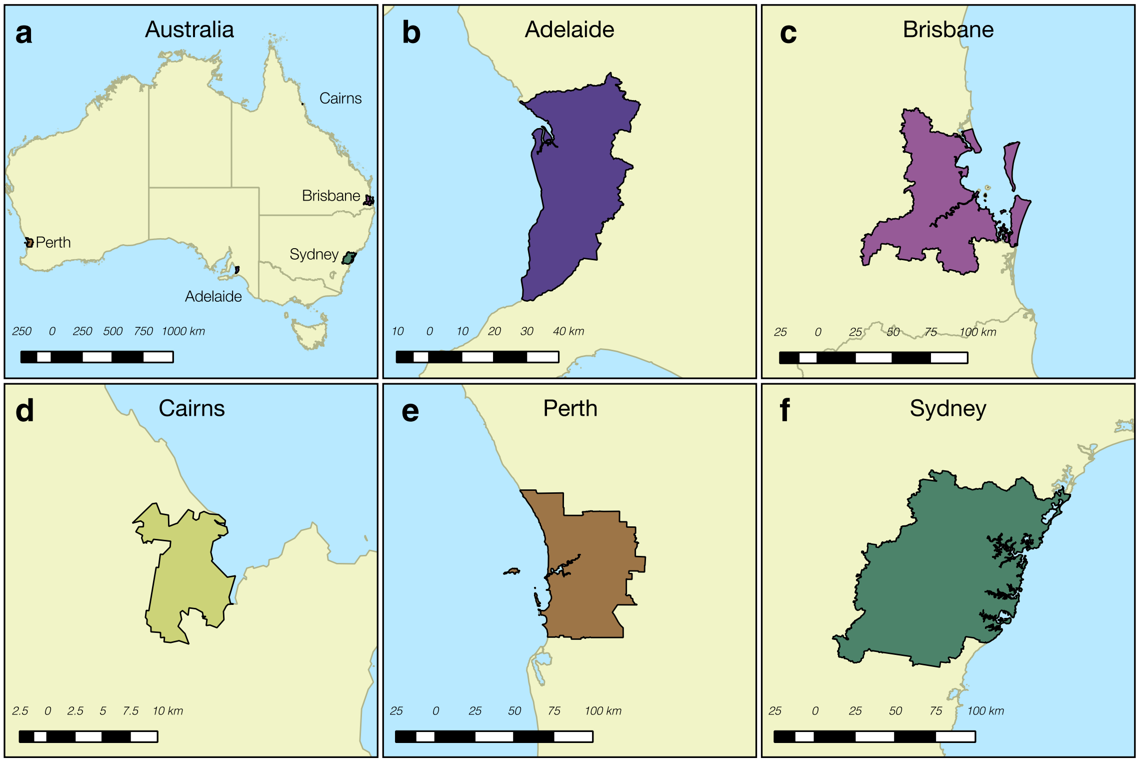

Fig. 1 Maps of the locations (**a**) and residential boundaries (**b**–**f**) of the five Australian cities: **b** Adelaide, **c** Brisbane, **d** Cairns, **e** Perth, and **f** Sydney

increasing proportion of the Australian population (Australian Bureau of Statistics 2014). Codes for these conditions under the 9th and 10th revisions of the International Classification of Disease (ICD) are enumerated in Table S2. We selected only admissions within the analysis period where the principal diagnosis fell within these disease groups, and we extracted four daily counts from each city's returned records:

C1. admissions for cardiovascular conditions;
C2. admissions for respiratory conditions;
C3. admissions for renal conditions; and
C4. admissions for all selected conditions (C4 = C1 + C2 + C3)

We also used negative binomial generalized linear models (GLMs) to build parent regression models for each city using each of the selected counts as an outcome.

The parent models' predictors included a daily interpolation of population based on census records (Table S1), a monthly indicator, and an indicator of non-work days (weekends and public holidays) sourced from the relevant Australian state legislation (1910, 1912, 1972, 1983, 2010). We did not age standardize our population estimates, as all five cities have similar age distributions (Fig. S1).

These parent models served as a basis upon which to compare the effect and change in fit of each heat stress index. The indices fell into four categories: temperature (T) indices, humidity (H) indices, heat-humidity (HH) indices, and heatwave (HW) indices (Table 1). As T, H, and HW indices can be observed or calculated directly from the weather station data, we chose to use daily aggregates—mean, maxima, and minima—as predictor indices. We initially used the *dlnm* (distributed lag nonlinear model) package (Gasparrini et al. 2015) to model distributed lags of the heat stress indices up to 10 days, but because extreme heat effects universally appeared within 0–2 days, we chose to instead model unlagged relationships without *dlnm*. We did, however, lag the HW indices by 2 days: because they are designed for operational use, they typically use forecast data rather than observations. A 2-day lag means that they instead use the day of exposure and the previous 2 days.

We calculated the indices for each summer day (November–March) from November 2001 to March 2013 using subdaily weather station observations in the HadISD (Dunn et al. 2012) dataset, with one airport-based station for each city. Although HadISD data undergoes substantial automated quality control, we did additional quality control testing on the observations, outlined in Supplementary Information Section 1.

We then modeled each count (C1–C4) for each city with one parent model and 15 heat stress index models. We used a likelihood ratio test at a p value threshold of 0.05 to determine which heat stress index models gave a statistically significant improvement in fit over their respective parent model. We also ranked all of the heat stress index models related to a particular parent model by their Akaike information criterion (AIC)

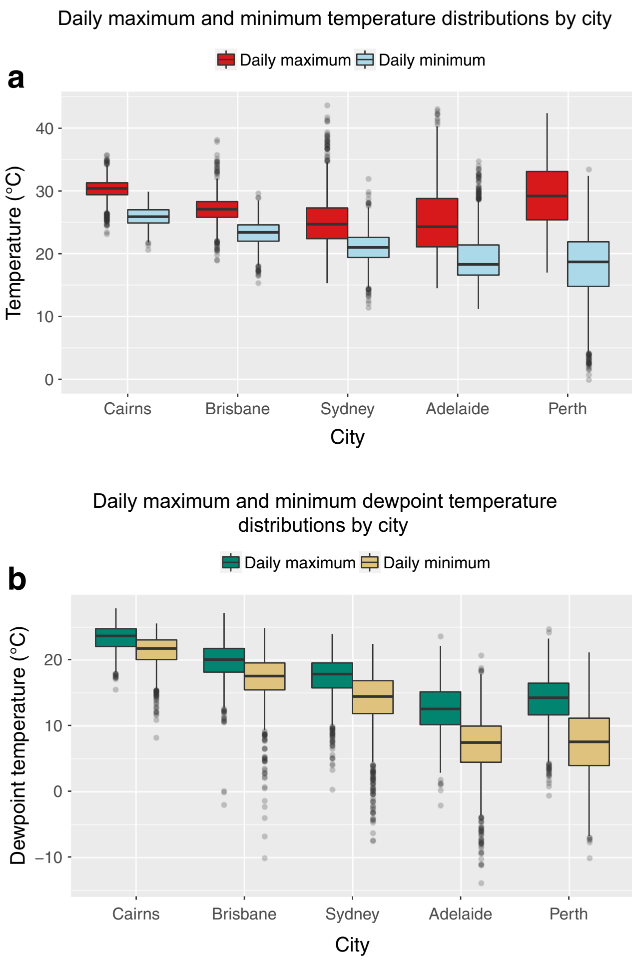

Fig. 2 Box-and-whisker plots of daily maximum and minimum **a** temperature and **b** dewpoint temperature observed by the five stations analyzed. Boxes extend to the 25th and 75th percentiles of each range; whiskers extend 1.5 times the width of the interquartile range beyond the box. Observations beyond this range are displayed as points

(Posada and Buckley 2004): models with a lower AIC demonstrated greater improvement in fit and hence lower rank.

As there were fewer than 1000 renal admissions in Cairns across the time series, we did not perform this analysis for C3, the set of renal admissions, in Cairns. Although some types of air pollution do also influence the selected diseases, we chose to limit this analysis to heat and humidity to reduce the complexity of the models, as there are large population differences between the cities we analyzed.

Results

Stations further north typically experienced warmer, more humid conditions on average, with less temperature variation around the means. Cairns experienced less humidity variation than other locations, and its driest days were still substantially more humid than other cities. Brisbane experienced more humidity variation, ranging from the dry conditions of the more temperate cities like Sydney to nearly as humid as Cairns.

Cardiovascular admissions

The number of heat stress indices with statistically significant effects on cardiovascular admissions (C1) varied by city, ranging from none in Sydney to at least half in Perth and Brisbane (Table 2). In all cities with statistically significant heat stress indices, heatwave and temperature indices consistently ranked lower in AIC, indicating better fit to cardiovascular admission counts, than humidity and heat-humidity indices.

The associations between heat stress indices and cardiovascular admissions in most cities varied, with both increased and decreased admissions observed (Table 3). The mix of positive and negative associations may indicate that different categories of disease follow different patterns.

In Cairns, we found a negative association of 2.5% $°C^{-1}$ with 3-day maximum temperature (3DMT) (HW), the only statistically significant index (Tables 2 and 3). In Brisbane, we found statistically significant associations with most indices (Table 2) and that all associations were positive; associations were between 0.3 and 1.6% per unit increase in the index (Table 3). Daily maxima and means were more strongly associated with, and a better fit to, cardiovascular admissions than daily minima.

In Perth, we found statistically significant associations with half of the indices (Table 2). These were both positive and negative: humidity indices had positive associations of about 0.4% per unit, but other types of index had negative associations of about 0.4% per unit (Table 3). Daily maxima of humidity indices tended to be more strongly associated and a better fit than daily minima, but for other index types the opposite was true. In Adelaide, we found statistically significant negative associations of about 0.3% per unit with minimum temperature (T) and the three heatwave indices.

The strong performance of heatwave indices in multiple cities suggests that the accumulation of heat stress over several days is particularly important to cardiovascular health.

Respiratory admissions

We found statistically significant associations between respiratory admissions and most heat stress indices (Table 2). Humidity indices unambiguously ranked lower than other types of index in Adelaide, Brisbane, and Cairns. In Sydney and Perth, a heatwave index had the best fit, but in Sydney, humidity indices also ranked low, while in Perth heat-humidity indices ranked low.

Table 1 Sources of, and formulae for, the human heat stress indices used in this analysis

Heat stress index	Type[a]	Source	Aggregations	Formula
Temperature	T	–	Min, max, mean	Observed
Dewpoint temperature	H	–	Min, max, mean	Observed
Simplified WetBulb Globe Temperature (sWBGT)[bc]	HH	BOM 2010	Min, max, mean	$(0.567^{*}T) + (0.393^{*}e) + 3.94$
Apparent temperature (AT)[bcd]	HH	BOM 2010	Min, max, mean	$T + (0.33^{*}e) - (0.7^{*}u) - 4.0$
3-Day average temperature (3DAT)[e]	HW	Scalley et al. 2015	None	$\mathrm{mean}(T_{a0}, T_{a1}, T_{a2})$
3-Day maximum temperature (3DMT)[f]	HW	Scalley et al. 2015	None	$\min(T_{x0}, T_{x1}, T_{x2})$
Excess heat factor (EHF)[eg]	HW	Nairn and Fawcett 2013	None	$EHI_{sig} = \mathrm{mean}(T_{a0}, T_{a1}, T_{a2}) - T_{95}$ $EHI_{accl} = \mathrm{mean}(T_{a0}, T_{a1}, T_{a2}) - \mathrm{mean}(T_{a-1}, \ldots, T_{a-30})$ $EHF = EHI_{sig}{}^{*}\max(1, EHI_{accl})$

[a] Types include temperature indices (T), humidity indices (H), heat-humidity indices (HH), and heatwave indices (HW). In the results, the parent model (with no heat stress index) is given the type P

[b] Where T is the dry temperature in degrees Celsius

[c] Where e is the vapor pressure in hectopascals

[d] Where u is the wind speed in meters per second

[e] Where T_{an} is the average of the maximum and minimum temperatures, in degrees Celsius, n days later for $n > 0$ and n days prior for $n < 0$

[f] Where T_{xn} is the maximum temperature, in degrees Celsius, n days later for $n > 0$ and n days prior for $n < 0$

[g] Where T_{95} is the 95th percentile of daily mean temperature. In Nairn and Fawcett (2013), this percentile is calculated from a fixed time range; in this analysis, we instead use the period August 2001 to July 2013

Heat stress indices were particularly strongly associated with respiratory admissions in Cairns (Table 3). Maximum AT (HH) and EHF (HW) were the only statistically significantly associated indices with temperature components (Table 2). EHF had a negative association; all other statistically significant heat stress indices had positive associations.

Similarly, in Brisbane, humidity indices had the lowest rankings, followed by heat-humidity indices (Table 2). Humidity and heat-humidity indices had positive associations of about 1.0% °C^{-1}, with no clear bias toward daily maxima or minima (Table 3). We also found that 3DMT (HW) had a negative association of 0.9% °C^{-1} in Brisbane.

In Adelaide, where humidity indices ranked lowest, followed by heat-humidity indices (Table 2), we found positive associations of about 0.5% per unit (Table 3). The type of index determined which daily aggregate performed better: daily maxima of humidity indices had lower ranks and stronger associations, but so did daily minima of heat-humidity and temperature.

The rankings in Perth and Sydney contrasted with the other three groups. 3DMT (HW), followed by heat-humidity indices, ranked lowest in Perth; EHF (HW), followed by humidity indices; and 3DMT (HW), ranked lowest in Sydney (Table 2). All heat stress indices had positive associations in Sydney and Perth (Table 3), but daily minima had mostly weaker associations than daily maxima and means.

Renal admissions

We found statistically significant associations with most heat stress indices among the Adelaide, Brisbane, and Perth groups but with just under half in the Sydney group (Table 2). We did not compute results for renal admissions for Cairns due to a lack of admissions. All of the associations we found were positive, and associations in Adelaide, Brisbane, and Perth were particularly strong (Table 3).

In Adelaide and Perth, the best-performing indices spread across heat-humidity indices, temperature indices, and 3-day average temperature (3DAT) (HW) (Table 2). Daily minima and means fit better and had larger effects than daily maxima (Table 3). Effect sizes ranged from 0.7% per unit to 3.1% per unit in Adelaide and from 1.0% per unit to 4.3% per unit in Perth. Heat-humidity indices also performed well in Brisbane (Table 2), but other aspects of the results were different to Adelaide and Perth. Unlike those two cities, humidity indices performed well here, and daily maxima and means had lower ranks and larger effects than daily minima (Table 3). Effect sizes ranged from 1.0% per unit to 2.4% per unit. In Sydney, only heat-humidity indices, maximum temperature (T), and 3DAT (HW) had statistically significant effects on renal admissions (Table 2). We found no clear bias toward daily maxima or minima. Effect sizes ranged from 0.7% per unit to 1.4% per unit.

Combined admission count

We also built models of all admissions from the three diagnosis groups (C4). The lowest-ranked indices for C4 were daily maxima of humidity and heat-humidity indices (Table S3). Associations with the combined admission count with these index types were all positive (Table S4). Some temperature and heatwave indices also had statistically significant effects,

Table 2 Akaike information criterion (AIC) ranks for heat stress models of daily cardiovascular admissions (C1), respiratory admissions (C2), and renal admissions (C3) in the five cities[a]

Index	Type	C1: cardiovascular admissions					C2: respiratory admissions					C3: renal admissions				
		CAI n = 1 905	BRI n = 43 056	SYD n = 86 772	ADE n = 39 966	PER n = 29 502	CAI n = 1 558	BRI n = 25 321	SYD n = 53 968	ADE n = 26 851	PER n = 16 310	CAI n = 176	BRI n = 3 311	SYD n = 7 170	ADE n = 3 076	PER n = 1 950
Max dewpoint (°C)	H	12	11 *	10	13	5 *	3 *	1 *	3 *	1 *	11 *		4 *	9	14	16
Mean dewpoint (°C)	H	8	13	16	14	15	2 *	2 *	12 *	2 *	13		6 *	10	15	11 *
Min dewpoint (°C)	H	4	16	15	16	13	1 *	3 *	2 *	9 *	15		11 *	11	16	10 *
Max AT (°C)	HH	16	3 *	4	15	12	4 *	10 *	14	8 *	2 *		1 *	2 *	12 *	12 *
Mean AT (°C)	HH	13	9 *	5	12	9	9	6 *	7 *	6 *	5 *		2 *	6 *	8 *	6 *
Min AT (°C)	HH	6	15	11	10	6 *	16	4 *	6 *	7 *	8 *		12	16	6 *	2 *
Max sWBGT (°C)	HH	14	6 *	7	11	11	7	8 *	13 *	5 *	4 *		3 *	1 *	11 *	14 *
Mean sWBGT (°C)	HH	9	8 *	8	9	8 *	8	5 *	8 *	3 *	7 *		5 *	4 *	5 *	5 *
Min sWBGT (°C)	HH	5	12	12	7	4 *	12	7 *	11 *	4 *	10 *		8 *	3 *	1 *	1 *
Max temperature (°C)	T	7	1 *	3	8	14	15	14	9 *	13 *	3 *		7 *	7 *	10 *	13 *
Mean temperature (°C)	T	15	2 *	6	6	3 *	13	16	5 *	11 *	9 *		9 *	8	4 *	7 *
Min temperature (°C)	T	2	10 *	13	4 *	2 *	14	13	15	12 *	12 *		14	13	3 *	3 *
3DAT (-2 days) (°C)	HW	10	4 *	9	3 *	7 *	6	15	10 *	10 *	6 *		10 *	5 *	2 *	4 *
3DMT (-2 days) (°C)	HW	1 *	7 *	14	2 *	16	10	9 *	4 *	16	1 *		16	12	7 *	9 *
EHF (-2 days) (°C^2)	HW	11	5 *	1	1 *	1 *	5 *	11	1 *	14	16		15	15	9 *	8 *
Parent model (no index)	P	3	14	2	5	10	11	12	16	15	14		13	14	13	15

Indices are shaded from green to yellow based on their rank: lower ranks (shaded green) indicate better fit than higher ranks (shaded yellow). The heat stress model shows a statistically significant difference in fit ($p < 0.05$) compared to its parent model using a likelihood ratio test (bolded, italicized)

[a] Cairns (CAI), Brisbane (BRI), Sydney (SYD), Adelaide (ADE), and Perth (PER)

and these associations were mostly, but not entirely, positive. The models of C4 in Cairns include renal admissions, even though we could not model those admissions separately.

City comparison

Although we did not comprehensively compare the sensitivity of heat stress ranking to location against that to outcome, we found generally greater variation between outcomes than between cities. Instead, location tended to be associated with lower-order variations, such as daily maxima outperforming daily minima, or vice versa. These variations were not consistent across different outcomes, and in most cases, there is no clear link between a city's climate and the types of index it favored. For example, humidity indices appeared to be no more or less important in Cairns and Brisbane—cities that experience higher but much less varied humidity than the three temperate cities (Fig. 2).

In a few instances, one or two cities had heat stress indices that ranked very differently from the others. Most notably, humidity indices performed very strongly in most cities–but in Perth, they performed quite poorly, outperformed by heat-humidity indices (Table 2). This could be because, in most cases, greater temperature is associated with less temperature variation—and the same with humidity. Perth, however, is as warm as Cairns on average but sees hotter conditions far more regularly (Fig. 2). This could create an opportunity for extremely hot-humid conditions, even though Cairns is generally more humid.

Some heatwave and temperature indices predicted cardiovascular admissions poorly in Cairns and especially Perth. In Cairns, this is mostly because only one index was statistically significant—possibly a result of its lower counts—but in Perth, maximum temperature and 3DMT fitted more poorly than nearly every other index. This is very likely because Perth has far colder temperature minima than the other four cities.

Heat-humidity indices consistently fitted renal admissions well in all cities, but there were some important geographical differences as well. In Adelaide, Perth, and Sydney, temperature indices also performed well—but in Adelaide and Perth, daily minima outperformed daily maxima for these index types, while in Sydney daily maxima performed better. In Brisbane, daily maxima also performed well, but humidity indices were more strongly associated than temperature-only ones.

There are no consistent inter-city patterns across the three health outcomes, and time of day is not consistently associated with cities or types of heat stress index.

Table 3 Effect sizes, expressed in the change in admissions per unit increase in the index, of heat stress indices in models of daily cardiovascular admissions (C1), respiratory admissions (C2), and renal admissions (C3) in the five cities[a]

Index	Type	C1: cardiovascular admissions					C2: respiratory admissions					C3: renal admissions				
		CAI n = 1 905	BRI n = 43 056	SYD n = 86 772	ADE n = 39 966	PER n = 29 502	CAI n = 1 558	BRI n = 25 321	SYD n = 53 968	ADE n = 26 851	PER n = 16 310	CAI n = 176	BRI n = 3 311	SYD n = 7 170	ADE n = 3 076	PER n = 1 950
Max dewpoint (°C)	H	+0.8%	+0.4% *	+0.1%	+0.1%	+0.4% *	+4.0% *	+1.0% *	+0.7% *	+0.6% *	+0.5% *	—	+1.8% *	+0.8%	+0.5%	+0.6%
Mean dewpoint (°C)	H	+1.2%	+0.3%	+0.0%	+0.1%	+0.1%	+4.1% *	+0.9% *	+0.4% *	+0.6% *	+0.3%	—	+1.3% *	+0.7%	+0.2%	+1.2% *
Min dewpoint (°C)	H	+1.3%	+0.1%	-0.0%	+0.0%	-0.1%	+3.7% *	+0.7% *	+0.2% *	+0.3% *	+0.1%	—	+1.0% *	+0.5%	-0.1%	+1.3% *
Max AT (°C)	HH	-0.1%	+0.8% *	+0.1%	-0.0%	+0.1%	+2.1% *	+0.6% *	+0.6%	+0.3% *	+0.5% *	—	+2.3% *	+0.7% *	+1.2% *	+0.9% *
Mean AT (°C)	HH	+0.5%	+0.7% *	+0.1%	-0.1%	-0.2%	+1.5%	+0.8% *	+0.7% *	+0.3% *	+0.5% *	—	+2.3% *	+0.7% *	+1.5% *	+2.5% *
Min AT (°C)	HH	+0.9%	+0.3%	-0.0%	-0.1%	-0.2% *	+0.4%	+0.8% *	+0.6% *	+0.3% *	+0.3% *	—	+1.1%	+0.4%	+1.6% *	+2.6% *
Max sWBGT (°C)	HH	+0.5%	+0.9% *	+0.1%	-0.1%	+0.3%	+2.7%	+0.9% *	+1.0% *	+0.6% *	+0.9% *	—	+2.3% *	+1.2% *	+2.3% *	+1.5% *
Mean sWBGT (°C)	HH	+1.4%	+0.8% *	+0.1%	-0.2%	-0.4% *	+2.6%	+1.0% *	+1.1% *	+0.7% *	+0.7% *	—	+2.3% *	+1.2% *	+2.8% *	+4.3% *
Min sWBGT (°C)	HH	+1.5%	+0.4%	+0.1%	-0.3%	-0.4% *	+1.9%	+0.9% *	+0.9% *	+0.7% *	+0.4% *	—	+1.7% *	+1.2% *	+3.1% *	+4.0% *
Max temperature (°C)	T	-1.3%	+1.2% *	+0.1%	-0.1%	+0.1%	-0.8%	-0.2%	+0.7% *	+0.2% *	+0.6% *	—	+1.9% *	+0.7% *	+1.4% *	+1.0% *
Mean temperature (°C)	T	+0.5%	+1.3% *	+0.1%	-0.2%	-0.3% *	-1.6%	-0.0%	+0.9% *	+0.3% *	+0.4% *	—	+2.0% *	+0.8%	+1.8% *	+2.7% *
Min temperature (°C)	T	+2.4%	+0.8% *	-0.0%	-0.3% *	-0.4% *	-1.7%	+0.4%	+1.0%	+0.3% *	+0.2% *	—	+1.2%	+0.8%	+2.1% *	+2.7% *
3DAT (-2 days) (°C)	HW	-1.4%	+1.6% *	-0.1%	-0.4% *	-0.4% *	-3.6% *	-0.1%	+1.3% *	+0.4% *	+0.6% *	—	+2.4% *	+1.4% *	+2.3% *	+3.8% *
3DMT (-2 days) (°C)	HW	-2.5% *	+1.1% *	+0.0%	-0.4% *	+0.0%	-1.8%	-0.9% *	+0.9% *	+0.1%	+0.8% *	—	+0.6%	+0.8%	+2.0% *	+2.0% *
EHF (-2 days) (°C^2)	HW	-1.1%	+1.2% *	-0.3%	-0.2% *	-0.3% *	-3.8% *	-0.6%	+0.1% *	-0.1%	-0.0%	—	+0.7%	+0.6%	+0.7% *	+1.5% *

Positive associations (increased admissions) are shaded in purple, deepening with effect size; negative associations (decreased admissions) are similarly shaded in green. The heat stress model shows a statistically significant difference in fit ($p < 0.05$) compared to its parent model using a likelihood ratio test (bolded, italicized)

[a] Cairns (CAI), Brisbane (BRI), Sydney (SYD), Adelaide (ADE), and Perth (PER)

Discussion

We compared the effects and the variation in goodness-of-fit criteria for a number of human heat stress indices to models of hospital admission-based health outcomes for five urban Australian populations. The biggest, most consistent differences—by health outcome—suggest that different physiological mechanisms are at work for each set of diseases, in contrast to the typical understanding of heat stroke as increased core temperature resulting in reduced cardiac output, hypovolemia, and finally multiple organ failure (Kosaka et al. 2004). This accords with Vaneckova and Bambrick (2013), who found different effect sizes and statistical significance for different hospitalization-based health outcomes in Sydney. They also found that outcomes based on broad disease categories like "cardiovascular" or "respiratory," rather than specific diagnoses, sometimes masked antithetical signals between diseases within the group. This may explain why few heat stress indices had a significant effect on cardiovascular admissions in Sydney, the largest population within our study. It also further emphasizes the sensitivity of the heat-health relationship to the outcome studied.

The relative importance of heat-humidity indices to renal admissions over other types also suggests a separate physiological mechanism. García-Trabanino et al. (2015) observed that sugarcane workers in Central America working in hot-humid conditions had both low kidney function before their shifts and further deleterious changes in kidney function after their shifts. They noted that the workers consumed enough water "for maintaining body weight, but not for protecting the kidneys from a heavy load on tubular reabsorption and from reduced glomerular filtration" (García-Trabanino et al. 2015). In turn, when a kidney injury reduces the number of tubules available, the increased reabsorption load on the remaining ones induced additional failures: a positive feedback progresses chronic kidney disease (Schnaper 2014). However, this population studied suffered from the long-term progression of chronic kidney disease.

This feedback is not always observable. In the 1995 heatwave in Chicago, USA, for example, incidence of acute renal failure increased while incidence of chronic kidney disease did not (Semenza et al. 1999). On the other hand, Hansen et al. (2008b) found that summer heatwave days over a 12-year period in Adelaide, Australia, increased both acute renal failure and chronic kidney disease.

Nevertheless, these studies suggest that inadequate fluid replacement may injure the kidneys even if classical hyperthermia does not occur or does not lead to hospitalization. This may explain why hot-humid weather, which requires greater fluid replacement because of reduced evaporative efficiency than merely hot weather, appears to be a stronger factor in renal admissions than cardiovascular ones (Kenefick and Cheuvront 2016). The difference between renal and other diseases in other studies could also be influenced by medical conditions or medications that inhibit perspiration; these people would exhibit less sensitivity to environmental humidity. More study is required to investigate this hypothesis in other populations and to understand the relationships between chronic and acute renal conditions in extreme humid heat.

This hypothesis is unlikely to explain the superior fit of humidity indices over temperature, heatwave, *and* heat-humidity indices in respiratory admissions, especially in temperate Adelaide. Adelaide is not particularly humid; nor does it exhibit greater humidity variation than Perth. A condition unrelated to heat stress, such as an interaction with air pollution, may cause these admissions, although this study does not explore these complexities. Emerging evidence suggests that low specific humidity, especially in winter, exacerbates the health effects of several common types of air pollution, rather than mitigating them (Davis et al. 2016). Summer effects, which were the focus of this study, have not yet been explored, but they may be important. The role of pollen is of particular interest in Australia following large-scale "thunderstorm asthma" events (Woodhead 2016). We chose to exclude asthma from our admissions criteria partly in order to rule out the role of thunderstorm asthma, but the combination of heat and humidity may contribute to that phenomenon too. Investigating this relationship may be an important direction for future research given the potentially substantial morbidity impacts.

When modeling all three condition groups together, daily humidity and heat-humidity maxima provide the best fit (Table S3). This conclusion is consistent with Goldie et al. (2017), who used a similar method but in only one city and across the entire year. However, the disparity of the results between health outcomes means that modeling them together is a poor solution if there is enough data in a location to model them separately.

These results are broadly consistent with the few other comparisons of heat stress indices published. The best indices in our study varied less with location than in the analysis of Rodopoulou et al. (2015), who compared temperature and heat-humidity indices in Rome, Athens, and London. However, there are some indications in our results that humidity was more important in the subtropical and especially tropical cities, which is consistent with that study and with Goldie et al. (2015), who found that overnight humidity had the strongest effects on the same health outcomes among temperature and humidity indices in Darwin, Australia. A comparison of the same three heatwave indices in Perth, Scalley et al. (2015), found EHF to be a superior predictor of all-cause emergency admissions. EHF was the best predictor of cardiovascular admissions in Perth in our study, as well as the second-best predictor of mortalities from all selected groups, behind daily minimum temperature, which Scalley et al. (2015) did not compare.

These results have important implications for projecting future heat-health relationships, which is still in its infancy. Daily mean and maximum temperature are the most widely used indices for projecting mortality (Knowlton et al. 2007; Li et al. 2013, 2016; Gasparrini et al. 2015), though heatwave indices are increasingly used (Peng et al. 2011). One of the few studies to project other health outcomes, Kingsley et al. (2016), also uses daily maximum temperature to predict emergency admissions for similar diseases to this study.

Future studies to estimate heat-health impacts should consider disaggregating health outcomes based on the disease group and matching each disease group to an appropriate heat stress index. Where sufficient data are not available for this kind of disaggregation, heat-humidity maxima may be a better de facto standard for health impacts projection than the temperature indices used today.

The results of this study show robust effects for renal and respiratory admissions, as well as for cardiovascular admissions where a low-ranked, statistically significant heat stress index is used. The exception is for cardiovascular in Cairns, where 3DMT, the top-ranked index, displays the opposite sign to all other statistically significant indices. However, the associations in these models still display some variety in magnitude, if not sign. This underscores the importance of heat stress index selection. For example, Benmarhnia et al. (2014) analyzed the sensitivity of projections of health outcomes to temperature in Montreal, Canada, and found that "uncertainty related to the temperature–mortality relationship had much more impact on heat-related mortality projections than did uncertainty due to climate models," although their 32 simulations were drawn from only three Global Climate Models. Understanding the full sensitivity of future health impacts to heat stress index selection will require continuing this work with more diverse climate model output.

Comparing the magnitude of effects across indices with different contributions from temperature and humidity or even different units is difficult. However, these results suggest that neither daily maxima-, minima-, nor mean-based indices can a priori be taken as preferable for projection work in a previously uninvestigated location. Health outcomes like cardiovascular admissions may also need to be further disaggregated in the manner of Vaneckova and Bambrick (2013) to be effectively modeled.

This study also does not evaluate nonlinear heat stress effects. This reduces the complexity of the models, maximizing statistical power. But previous work has found that health outcomes deteriorate nonlinearly in extreme heat (Curriero et al. 2002). This limitation is particularly important with respect to the prediction of future health outcomes, as global populations are exposed to new degrees of extreme heat for the first time. Correctly extrapolating the current impacts of extreme heat may not be possible with a linear response. The most dire example of this limitation is shown by Sherwood and Huber (2010), who describe a wet bulb temperature of 35 °C as the upper thermodynamic limit for human survival.

As our models used only 12 years of data, rebuilding them with a longer data series may help to minimize uncertainty in projections. Further splitting the selected disease groups may also improve the results, though this may require switching to a model that prioritizes statistical power over inferential specificity. Demographic differences appeared to be minimal in this study, but it is possible that accounting for air pollution or expanding the time series using future observations as they become available may change the results.

Conclusions

The most appropriate heat stress indices for modeling counts of hospital admissions remain remarkably stable across Cairns, Brisbane, Sydney, Adelaide, and Perth—five climatically diverse Australian cities. However, the health outcome modeled plays a large role in determining the best-fitting heat stress indices.

Hospital admissions in Australian cities for cardiovascular, respiratory, and renal conditions are best modeled separately, using different types of index for each disease group. Humidity has a greater effect on respiratory and renal admissions than on cardiovascular admissions.

These differences suggest that population-scale extreme heat events affect several distinct physiological processes, and that separately modeling outcomes more closely related to these processes may yield better predictions than modeling "all-cause" outcomes.

Where statistical power allows it, future public health work on heat stress may benefit from further disaggregating counts of heat-related morbidity and mortality by disease, as well as testing the sensitivity of models to a variety of disparate heat stress indices.

Acknowledgements The authors would like to thank Marissa Parry of the Climate Change Research Centre for her assistance defining public holidays across Australia, Peter Tait of the Australian National University Medical School for his assistance identifying relevant diseases, and Donna Mary Salopek of the UNSW Statistical Consulting service for her guidance in optimizing the fit of the regression models.

Funding information S.C.L. is funded through the Australian Research Council (DE160100092). J.G., L.A., S.C.L., and S.C.S. are funded by an Australian Research Council grant (CE110001028).

Compliance with ethical standards This research was approved by the UNSW Human Research Ethics Advisory (HREA) (HC15125), the Australian National University Human Research Ethics Committee (HREC) (2015/239), the Royal Brisbane & Women's HREC (HREC/15/QRBW/202), the SA Health HREC (HREC/15/SAH/41), and the Department of Health WA HREC (2015/27).

Conflict of interest The authors declare that they have no competing interests.

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