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# Anomalous temperatures increase occupational injuries, illnesses and associated cost burden in Australia

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ABSTRACT

Anomalous ambient temperatures elevate the risk of occupational injuries and illnesses (OIIs). However, the associated economic burden is underexplored internationally. This study establishes an Australian profile of heat- and cold-attributable OIIs and their costs. OIIs and costs from seven Australian capital cities in July 2005 to June 2018 were modelled against daily maximum wet bulb globe temperature. 2,321,602 OIIs comprising AU$43 billion in total payouts were included for analysis. 1.66 % (95 % empirical confidence interval [eCI]: 1.38–1.94 %) and 0.66 % (95 % eCI: 0.45–0.89 %) of OIIs were heat-attributable and cold-attributable, respectively, representing 38,540 heat-attributable and 15,409 cold-preventable OIIs. 1.53 % (95 % eCI: 0.77–2.27 %) and 1.33 % (95 % eCI: 0.66–1.97 %) of costs were heat- and cold-attributable, respectively, collectively representing AU$94 million annually and increased costs per OII with colder temperatures. In 2050 (2036–2065) under Representative Concentration Pathway 8.5, 2.10 % (95 % eCI: 1.50–2.70) and 0.21 % (95 % eCI: −0.11 to 0.54 %) of OIIs were heat-attributable and cold-preventable, respectively, and 0.05 % (95 % eCI: −1.84 to 1.83) and 0.76 % (95 % eCI: 0.08–1.43) of costs were heat- and cold-attributable, respectively. Anomalous temperatures pose a substantial occupational morbidity and cost burden. OIIs and their costs do not necessarily share the same temperature-attributable relationship, especially during colder temperatures. Both heat and cold adaptation are important to reduce OII-associated costs.

*Abbreviations:* ABS, Australian Bureau of Statistics; AF, attributable fraction; AN, attributable number; ANZSCO, Australian and New Zealand Standard Classification of Occupations; BLUP, best linear unbiased prediction; DLNM, Distributed lag non-linear model; GAM, Generalized additive model; GCCSA, Greater Capital City Statistical Area; OII, Occupational injury or illness; SWA, Safe Work Australia.

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## 1. Introduction

Heat, and to a lesser extent cold, have been associated with an increased risk of occupational injuries and illnesses (OIIs) (Binazzi et al., 2019; Bonafede et al., 2016; Fatima et al., 2022, 2023; Marinaccio et al., 2019; Martínez-Solanas et al., 2018; Varghese et al., 2019a, 2019b). Causes include workplace exposure to outside heat/cold and radiant heat, weather-inappropriate clothing, metabolic heat production from physical work, and reduced access to thermoregulatory safety interventions such as air conditioning (Binazzi et al., 2019; Bonafede et al., 2016; Ebi et al., 2021). Anomalous temperatures can damage multiple physiological systems and impair physical and mental performance (Ebi et al., 2021; Mäkinen and Hassi, 2009), predisposing to both directly temperature-attributable OIIs such as heat stroke and chilblains, and general OIIs such as falls (Binazzi et al., 2019; Ebi et al., 2021; Mäkinen and Hassi, 2009; Varghese et al., 2018). Extreme temperatures are one of the most threatening health impacts of climate change, and more heat-attributable OIIs are expected from increasing intensity and duration of extreme heat (Ebi et al., 2021).

The temperature-attributable economic burden from OIIs is underexplored (Borg et al., 2021). This includes healthcare costs, compensation costs such as income maintenance, legal expenses, and indirect costs from labor productivity loss (Borg et al., 2021; Martínez-Solanas et al., 2018; Zander et al., 2015). Costs are also incurred by employees, such as personal expenses and potential healthcare costs, and by employers through hiring replacement staff, legal costs and decreased labor productivity (Borg et al., 2021). Although these costs can be substantial, only a few studies have investigated costs secondary to temperature-attributable OIIs (Borg et al., 2021, 2023; Su et al., 2020), and the only study to analyze costs during both hot and cold temperatures assumed costs had an identical relationship to temperature as OIIs instead of modelling costs directly (Martínez-Solanas et al., 2018); this may not reflect cost data's generally highly right-skewed and semi-continuous distribution (Kurz, 2017; Smyth and Jørgensen, 2002). The exposure-cost relationship and its distribution across both hot and cold temperatures have yet to be explored. The effect of temperature on costs is multifactorial, depending not only on the number of OIIs but also on their severity and duration. These affect healthcare costs and policies regarding compensation, legal and other administrative payments, with more severe and longer lasting OIIs generally inducing larger expenses (Borg et al., 2021). Understanding the temperature-attributable variations in costs can help workplaces and public health agencies implement financially viable temperature-attributable OII prevention and management plans. Costs decreased after introducing workplace heat adaptation policies in Guangzhou (Su et al., 2020) and (for directly heat-related illnesses only) implementing a heat stress awareness program in Texas (McCarthy et al., 2019). These costs are avoidable. This is particularly important in the context of climate change.

This study assessed the relationships between temperatures and both OIIs and their associated costs in Australia, using the findings to estimate heat- and cold-attributable health and economic burden nationally. Secondary aims were to evaluate these relationships in association with demographic, work and OII characteristics, and explore the future-projected attributable burden, to enable better tailoring of interventions to the national Australian workforce.

## 2. Material and methods

### 2.1. Data

#### 2.1.1. Workers' compensation claims data

Employers must pay for workers' compensation insurance, which financially covers Australian workers for OIIs. Claims data are collected by Safe Work Australia (SWA). The authors extracted data for all claims submitted from July 2005 to June 2019 from seven compensation schemes, each one representing a different Australian capital city: Adelaide, Brisbane, Darwin, Hobart, Melbourne, Perth and Sydney. These claims represent over 97 % of Australia's workforce in capital cities across the study period and approximately 66 % of the Australian workforce (Australian Bureau of Statistics, 2022). The other capital city, Canberra, was excluded due to its relatively small population size and high proportion of office workers (Australian Bureau of Statistics, 2022), which are generally less exposed to temperature extremes. The study period is OIIs from July 2005 to June 2018, ending one year earlier than the date of claim submission, as claims were commonly submitted in the Australian financial year (July–June) after that of the OII. Compensation payout rates and policies differ between states/territories and change over time but are similar and are comprehensively described online (Safe Work Australia, 2019a). The most notable difference is that the employer excess period, the period when employers pay an excess before the compensation insurer provides financial compensation, varies from 0 to 14 days across states/territories (Collie et al., 2016; Safe Work Australia, 2019a). OIIs occurring from July 2005 to June 2006 in Hobart were excluded from analysis, because workplace postcodes and hence metropolitan status were not available for claims submitted in Tasmania prior to July 2007. (The number of OIIs occurring from July 2006 to June 2007 in Hobart was similar to that of other years; thus these OIIs were retained for analysis). Payouts for a single claim can continue across multiple years.

Claims were limited to non-duplicates, those submitted on the day or after the date of OII, OIIs occurring within the study period, OIIs occurring in metropolitan areas, and pertaining to workers aged 15 to 75 years with occupational data (in the labor force and not completely missing) as per the authors' previous study and similar to previous studies investigating OIIs using SWA data (Borg et al., 2023; Collie et al., 2016; Fatima et al., 2022; Varghese et al., 2019a). Metropolitan status was based on whether the location of OII, based on Australian postcode, was located within a Greater Capital City Statistical Area (GCCSA) (Australian Bureau of Statistics, 2020a). Injuries and illnesses were assessed collectively. The 0.02 % of claims with an overall negative claim cost (i.e. a financial gain, which can be due to workers or a third party reimbursing already-paid compensations) had their payments adjusted to \$0 so that they only impacted number of OII and not cost estimates. Costs were considered to occur on the date that the OII occurred, instead of the date of claim submission or payout, to represent the temporal relationship between heat and OIIs. Costs were adjusted for inflation and standardized to April–June 2019 (Australian Bureau of Statistics, 2021). Consumer price index categories for compensation/administrative costs, health services, and other goods and services were "insurance and financial services", "health services" and "general", respectively. This study focuses on total costs, with additional analyses for costs categorised into: (1) compensation (paid to workers or their families), (2) goods and services (predominantly health services but also out-of-pocket expenses such as medical supplies), and (3) non-compensation (not paid to or on behalf of the worker) (Safe Work Australia, 2019b). Cost per OII (total costs divided by the number of OIIs) on days where at least one OII were reported was also analyzed. A supplementary analysis for costs was performed for claims submitted no later than June 2014 with costs restricted to up to five financial years after the financial year of claim submission. This removed claims that may had artificially decreased costs due to occurring later in the study period.

Indoor/outdoor worker status was determined by cross-matching workers' occupation, as determined by the Australian and New Zealand Standard Classification of Occupations (ANZSCO) with their corresponding occupations from the Canadian National Occupation System (Smith, 2013; Statistics Canada, 2019) as per the authors' previous study (Borg, 2022a; Borg et al., 2023). Indoor/outdoor status for workers with partially but not completely missing occupational data (one to three ANZSCO digits reported, 0.3 % of claims) was estimated based on the more common classification of the possible occupations. Sensitivity analyses were performed with estimated indoor/outdoor status based on workplace industry instead of occupation ("agriculture, forestry and fishing", "construction", "electricity, gas and water" and "mining" industrial sectors were classified as outdoors, all other sectors were indoors) (Borg et al., 2023; Xiang et al., 2016). Indoor/outdoor stratification using industry is more common but less accurate (Borg et al., 2023; Varghese et al., 2019b).

#### 2.1.2. Population count data

Population monthly employed worker counts were derived from the Australian Bureau of Statistics (ABS) labor force detailed survey data, stratified by city (GCCSA) (Australian Bureau of Statistics, 2022). To obtain indoor/outdoor worker counts, the authors (1) extracted worker counts from the ABS Census TableBuilder Basic data (5-yearly data from August 2006, 2011 and 2016) stratified by workplace GCCSA and occupational indoor/outdoor status, (2) logit-transformed the data, (3) interpolated counts using cubic splines and extrapolated linearly per month, and (4) back-transformed to the normal population scale (Australian Bureau of Statistics, 2017). For the 2006 Census, workplace location was reported by Statistical Local Area and then converted to GCCSA (data.gov.au, 2017). Log-transformation and cubic spline interpolation were used to estimate the monthly worker count in Darwin relative to the rest of Northern Territory, as ABS worker 1-monthly counts are available for the entire Northern Territory but not Darwin alone. The sensitivity analysis stratifying indoor/outdoor workers by industry, instead of occupation, used three-monthly industry-stratified worker's population data instead.

Future workforce sizes in 2030 and 2050 were calculated as the ratio between the projected city populations for 2017–2044 and 2036–2065 relative to 2017, respectively (Australian Bureau of Statistics, 2018). Projected populations assumed medium-population growth based on projected fertility, migration and mortality. Low, high and unchanged (from baseline) population growth scenarios were included as sensitivity analyses.

#### 2.1.3. Climate data

Meteorological data were obtained from the Australian Bureau of Meteorology (BoM) Atmospheric high-resolution Regional Reanalysis (BARRA) (Jakob et al., 2017; Su et al., 2019). The variables extracted were air temperature, specific humidity, air pressure, wind speed, solar radiation (including its diffuse and direct components) and fraction of the sky covered by cloud. An additional analysis utilized future-projected daily meteorological gridded data from Climate Change in Australia (CCiA) as the mean of eight general circulation models (GCMs) detailed online (Commonwealth Scientific and Industrial Research Organisation, 2021). Results were projected to 2030 (2016–2045) and 2050 (2036–2065) under Representative Concentration Pathway [RCP]4.5 and RCP8.5. 3*3 12 km and 7*7 5 km grids were extracted from the BARRA and CCiA datasets, respectively, at grid centroids centered on the cities' central business districts.

Daily maximum wet bulb globe temperature (WBGT) is a measure of the heat stress in direct sunlight and was chosen as the primary exposure variable. It is commonly used for assessing workplace heat stress and heat-related occupational economic costs, has been used previously for assessing both cold and heat impacts on occupational injuries, can be measured on-site, and is used in international workplace guidelines (Borg et al., 2021; Dally et al., 2020; Ma et al., 2019). It can represent both indoor (incorporates air temperature and humidity only) and outdoor (also incorporates wind speed and solar radiation) heat exposure (Lemke and Kjellstrom, 2012). Using the *HeatStress* R package (Casanueva, 2019), these were calculated empirically with Bernard's and Liljegren's equations, respectively, which estimate indoor and outdoor WBGT, respectively, with very high accuracy (Bernard and Pourmoghani, 1999; Lemke and Kjellstrom, 2012; Liljegren et al., 2008). Sensitivity analyses were performed using daily average WBGT, Steadman's apparent temperature, heat index, humidex, air temperature (with and without specific humidity) and relative humidity. The Supplementary Material details the calculations of maximum and average temperatures and all derived meteorological variables.

### 2.2. Statistical analysis

#### 2.2.1. Stage 1

Statistical analysis was conducted in two stages. The first involved assessing the relationships between daily maximum WBGT and OIIs or associated costs over the study period. Each city, stratified into outdoor and indoor workers, was modelled separately (14 models in total) using time series distributed lag non-linear models (DLNMs) (Gasparrini, 2011). Estimates for outdoor workers were modelled using outdoor WBGT, and indoor workers using indoor WBGT. OIIs and costs were fitted using a Poisson and Tweedie distribution, respectively. The Tweedie distribution is a compound Poisson-Gamma distribution reparameterised into a single distribution and is commonly used for analyzing insurance claims (Kurz, 2017; Smyth and Jørgensen, 2002). This choice was justified given the highly right-skewed data, the presence of days with zero costs (which invalidates many continuous distributions including Gamma), and its simplicity compared to two-part models (Kurz, 2017). OIIs were modelled using generalized linear models. Costs were analyzed using generalized additive models (GAMs) fitted with restricted maximum likelihood to (1) potentially better represent more complex and non-linear long-term trends and (2) more precisely estimate (using series expansion) the Tweedie index parameter value with the largest likelihood value from 1.001 to 1.999 to improve model fit (Dunn and Smyth, 2005; Wood et al., 2016, 2017; Wood, 2011).

The statistical model equation was: $log[E(Y_t)] = cb(T_t) + ns(t) + DOW_t + Month_t + PH_t + School_t + D1_t + S_t + Sat : (PH_t + School_t + D1_t) + Sun : (PH_t + School_t + D1_t) + offset(log(n)) + \alpha$where $E(Y_t)$ is the expected number of daily OIIs or costs on day *t*. *cb(T)* is the cross-basis natural cubic spline function for daily maximum WBGT with one internal knot at the 50th percentile. *ns(t)* is a natural cubic spline with four fixed degrees of freedom (df) per year across a 13-year study period (12-year for Hobart), representing long-term trend and seasonality. *DOW* is the day of the week. *Month* is the month of the year. *PH* is a binary marker indicating whether the day was a public holiday or not. *School* designates each of the four school holidays periods, with no school holidays as the reference period (Borg, 2022b). The number of hours worked in Australia is known to vary seasonally with school holidays (Australian Bureau of Statistics, 2020b). *D1* is a binary marker indicating whether it is the first day of the month (excluding New Year's Day). This variable was included because there were more OIIs on the first day of the month relative to the other days; this was likely because OIIs with an unknown day but known month and year of occurrence were reported as occurring on the first day. *S* is a factor variable designating specific days or time periods that were highly influential on model fit with categories being (1) the Christmas break (23rd to 30th Dec), (2) New Year's Eve, (3) New Year's Day, (4) 2nd to 4th January and (5) specific days for Adelaide (the week of 24th to 30th Monday June 2008, which had considerably less OIIs than expected), Brisbane (the city-specific public holidays of the Royal Queensland Show and 2014 G20 Leaders' Summit), Melbourne (the day before Melbourne Cup) and Sydney (Australia Day, which includes a public celebration at the Sydney Opera House). Interaction terms denoted by "*:*" were included with Saturday/Sunday and *PH*, *School* and *D1*. *offset(*log*(n))* is the logarithmic number of workers included as an offset. Finally, $\alpha$ is a modelled intercept. Every Sunday is a public holiday in Adelaide (Borg, 2022c). Thus for Adelaide, *PH* was always zero on a Sunday and $Sun{:}PH_t$ was not included, as this information would instead be conveyed through the *DOW* category for Sunday. The lag dimension was modelled using a natural cubic spline with one central knot and a maximum lag of 20 days to include the delayed effects of cold and represent three weeks including day zero (Gasparrini et al., 2015). Sensitivity analyses were performed for model variations in the exposure-response and lag-response relationships and seasonality trends. Dispersion for OII models was assessed by inspecting the dispersion parameters (the sum of the squared Pearson residuals divided by the residual df).

### 2.2.2. Stage 2

The individual indoor and outdoor city exposure-response relationships were pooled with random-effects multivariate meta-analysis to derive a national (the seven cities combined) overall exposure-response relationship and fit best linear unbiased predictors (BLUPs) to each model to improve precision (Sera et al., 2019). Residual heterogeneity was analyzed using the multivariate extension of the Cochran Q test and $I^2$ statistic (Higgins and Thompson, 2002; Sera et al., 2019). Analyses were centered on the daily maximum WBGT for (1) easier interpretation of results compared to usual working conditions, with an approximately equal time of exposure to temperatures above and below the mean (2) to keep centering consistent across different models for both OIIs and costs. Overall cumulative exposure-response relationships and cumulative lag-response relationships were derived nationally. Exposure-response relationship curves at the city-level (pooled indoor and outdoor) and national indoor/outdoor level (pooled by city) were generated using secondary multivariate meta-analyses to derive BLUPs using a random-effects metapredictor for city and indoor/outdoor status, respectively (Sera et al., 2019).

Attributable fractions (AF) and numbers (AN) of OIIs and costs, alongside empirical 95 % confidence intervals, were calculated for each model fitted with their BLUPs using the methodology from Gasparrini et al. (Gasparrini et al., 2015; Gasparrini and Leone, 2014). For this study, heat and cold represent WBGT values above and below the mean, respectively. WBGT values between the mean value and the 2.5th/97.5th values were defined as moderate cold/heat, and values beyond this range were defined as extreme heat/cold. ANs were pooled across strata to produce national, city- and indoor−/outdoor-level estimates. OIIs and costs per worker were calculated by dividing the AN by the averaged monthly workforce size across the study period.

Additional analyses were performed with data restricted by sex, age, indoor and outdoor industries, occupation and the nature of OII to explore their impact on the national AFs. For these analyses, and all future-projected analyses, seven models were used for each city using indoor WBGT as the exposure metric without stratifying by indoor/outdoor status to improve statistical power. All statistical analysis was performed using R version 4.2.1. DLNMs, GAMs, Tweedie index parameters, Tweedie distributions, multivariate meta-analysis and attributable risk were modelled using the *dlnm*, *mcgv*, *statmod*, *tweedie*, and *mixmeta* packages, respectively (Dunn, 2017; Dunn and Smyth, 2005; Gasparrini, 2011; Lytras, 2019; Sera et al., 2019; Smyth, 2002; Wood et al., 2017). Ethics approval to access and analyze SWA data were obtained from the University of Adelaide Human Research Ethics Committee (Numbers: H-2019-141 and H-2016-085).

## 3. Results

### 3.1. Descriptive statistics

Brisbane and particularly Darwin had higher WBGT values than the other cities, while Hobart had lower values (Table 1). Throughout the study period, on average 14 % of workers were classified as outdoor workers. There were 4,142,872 claims obtained from SWA (Supplementary Table A.1). After restricting claims to workers aged 15 to 75 years in the cities under investigation during the study period, 2,321,602 (56 %) claims were included for analysis. The more populous cities had more claims (Brisbane, Melbourne and Sydney), with fewer claims in Darwin and Hobart. The included claims comprised AU$43 billion total payouts (Supplementary Table A.2). 60 % of financial payouts were compensation payments, 30 % covered goods and services, and 10 % were non-compensation costs. 58 % of compensation payments were for income support, and 95 % of the goods and services costs were for health services (all except the 'Other' category).

Generally, the number of OIIs gradually decreased across successive financial years (July to June). Associated costs gradually increased up to the 2010 financial year and then decreased (Supplementary Table A.3). There were almost three times as many OIIs and associated costs for indoor compared to outdoor workers. Payments predominately occurred in the same or subsequent financial year as the date of claim submission. 64 % of claimants were male, and most claimants (79 %) were 20 to 54 years old. There were approximately 3.5 times more injuries reported than illnesses (diseases/conditions).

### 3.2. Overall cumulative relationships

The relative risk (RR) of OIIs gradually increased with higher WBGT (Fig. 1). Cold had a small "protective effect" against developing OIIs, though statistical significance decreased at extremely cold temperatures. Costs increased during both cold and heat, forming a U-shaped association. At cold temperatures, although there were fewer OIIs, the cost per OII increased. There was no significant association between hot temperatures and the cost of OIIs. Compared to OIIs, heat induced a larger proportional increase in costs albeit with a larger confidence interval. Approximately similar relationships were observed with costs stratified into compensation and non-compensation costs, although goods and services costs had smaller heat estimates and no significant relationship with cold. Exposure-response relationships at the indoor/outdoor and city levels were similar to the national estimates for both OIIs and costs (Figs. 2 and 3), and likewise for the individual models (Supplementary Figs. A.1 and A.2).

Across the 20-day lag period, heat exposure immediately increased the risk of OIIs and the associated costs (Supplementary Figs. A.3 and A.4). The risk for OIIs gradually dissipated after about ten days and slightly increased afterwards, whereas the risk for costs increased throughout the lag period. The risk of OIIs and costs immediately increased after cold exposure for about a week (five days for costs), slightly increased until about 15 days, and was negligible afterwards.

The OII models' dispersion parameters indicated only minor over-dispersion ranging from 1.015 to 1.507 (Supplementary Table A.4). Heterogeneity was not detected in the total cost multivariate meta-regression (Cochran Q-statistic = 22.639, df = 26, *P*-value = 0.653). Although the OII models had statistically significant heterogeneity (Cochran Q-statistic = 42.041, df = 26, P-value = 0.024), it was not substantial ($I^2 = 38.2$ %).

### 3.3. Attributable fractions

1.66 % (95 % eCI: 1.38–1.94 %) of all OIIs were heat-attributable (Fig. 4, with estimates listed in Supplementary Table A.5). Cold temperatures reduced the attributable proportion of OIIs by 0.66 % (95 % eCI: 0.45–0.89 %). Heat-AFs were higher for indoor workers,

**Table 1**
Mean meteorological metrics and workers' populations per city used for analysis during the study period.

| | Adelaide | Brisbane | Darwin | Hobart | Melbourne | Perth | Sydney |
|---|---|---|---|---|---|---|---|
| Max temperature (°C) | 21·8 (14·4–29·3) | 25·8 (21·5–30·1) | 29·3 (27·6–30·9) | 16.0 (10·4–21·6) | 20·9 (14·1–27·7) | 24·5 (17·9–31·2) | 23·3 (17·8–28·7) |
| Relative humidity (%) | 40·9 (21.0–60·7) | 43·6 (29·4–57·9) | 58·6 (43·1–74·1) | 51·3 (36.0–66·6) | 42·8 (27·3–58·3) | 40.0 (23.0–57.0) | 43·4 (27·7–59·1) |
| Wind speed (m/s) | 4·7 (2·7–6·7) | 4·1 (2·4–5·8) | 4·8 (2·6–7.0) | 4.0 (1·5–6·5) | 5.0 (3.0–7.0) | 4·6 (2·6–6·6) | 5.0 (3·3–6·7) |
| Solar radiation (W/m$^2$) | 645 (384–906) | 710 (474–947) | 391 (29–754) | 561 (296–826) | 541 (270–813) | 700 (431–970) | 609 (330–889) |
| Indoor WBGT (°C) | 16.0 (11·5–20·4) | 20·1 (16·5–23·8) | 24·9 (22·5–27·4) | 12·2 (8·1–16·3) | 15·6 (11·1–20.0) | 18·3 (14·2–22·4) | 17·8 (13·6–22.0) |
| Outdoor WBGT (°C) | 21·1 (15·3–26·9) | 24·6 (20·8–28·4) | 28·6 (25·5–31·6) | 15·5 (11.0–20.0) | 19·7 (14·6–24·9) | 25·8 (20·5–31·2) | 21·7 (17·5–26.0) |
| Indoor workers (000 s) | 543 (526–561) | 974 (914–1034) | 64 (57–70) | 90 (87–93) | 1928 (1767-2088) | 828 (761–895) | 2120 (1982-2258) |
| Outdoor workers (000 s) | 77 (72–81) | 144 (132–156) | 12 (10–14) | 15 (14–15) | 252 (221–283) | 139 (126–153) | 252 (223–280) |

The temperature metrics were recorded at the time of daily maximum temperature and were collectively used to calculate both indoors and outdoors wet bulb globe temperature (WBGT). The ranges represent ±1 standard deviation.

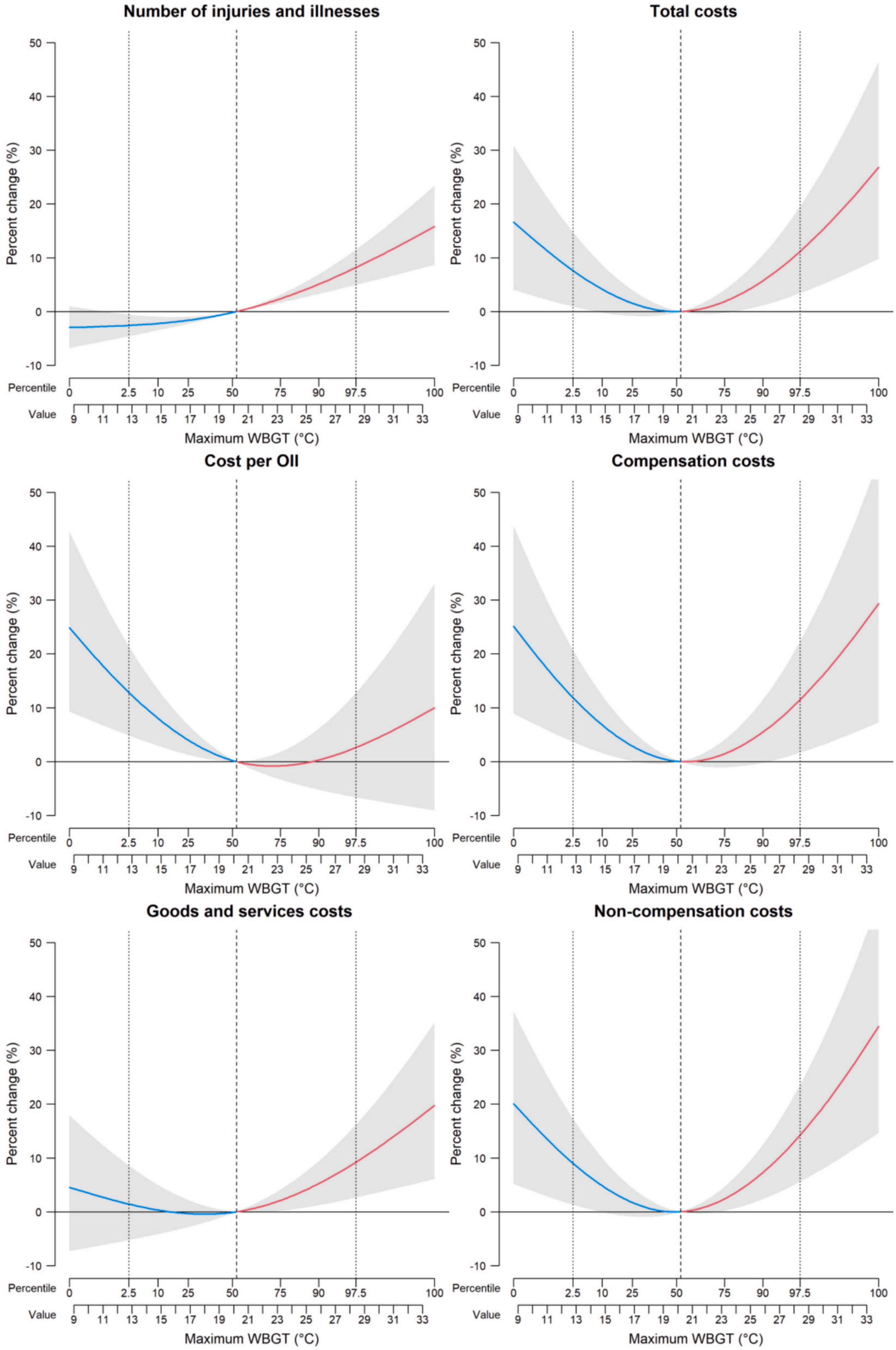


**Fig. 1.** Overall cumulative exposure-response relationships.

Overall cumulative exposure-response curves pooled nationally with 95 % confidence intervals for change in the daily number of occupational injuries and illnesses (OIIs), total costs, cost per OII, and costs for compensation, goods and services, and non-compensation. The three dashed lines represents, from left to right, the 2.5th percentile, mean and 97.5th percentile of daily maximum WBGT. Cold- and heat-attributable effects are compared against the mean and are displayed in blue and red, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

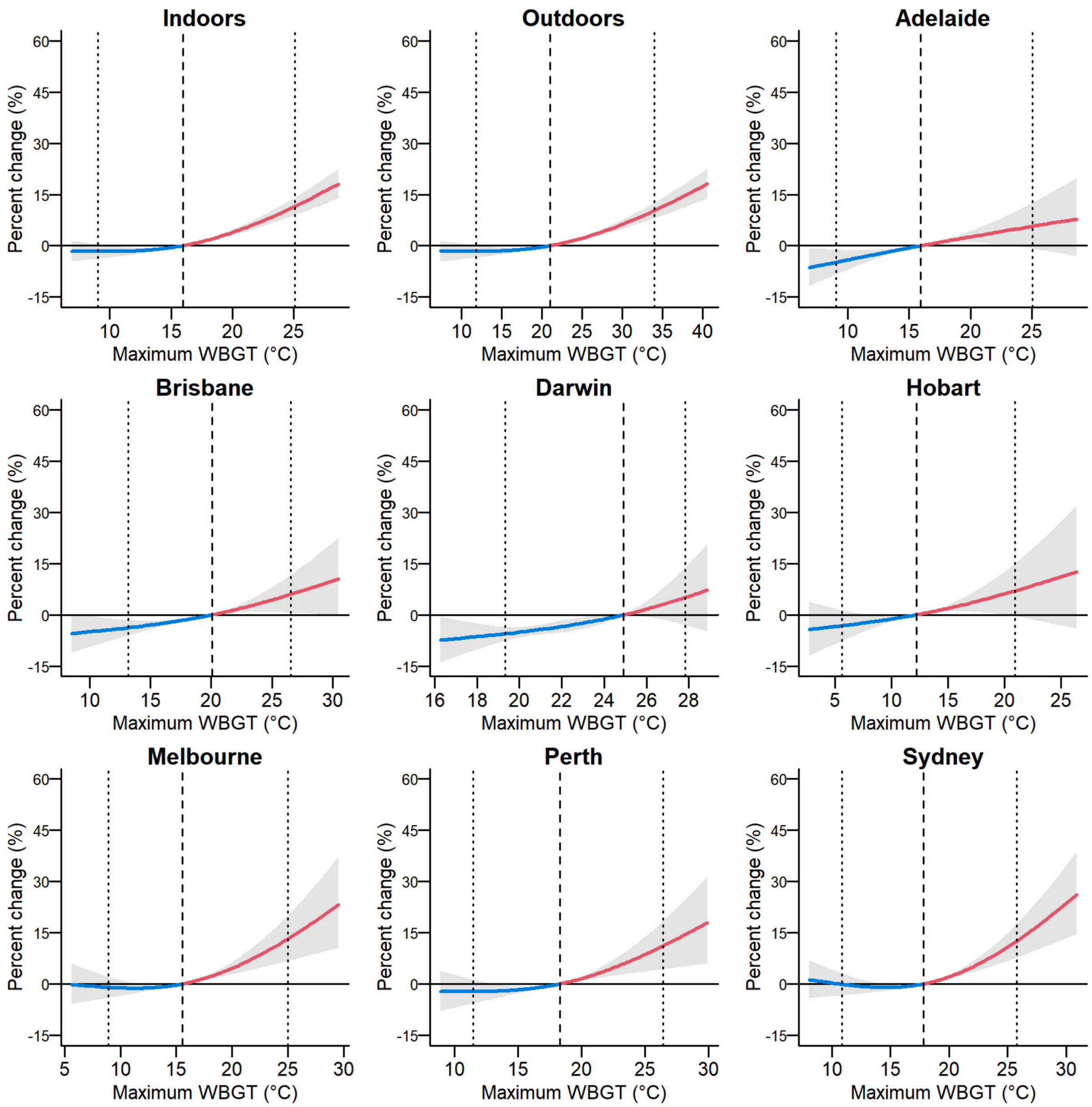


**Fig. 2.** Overall exposure-response curves for each city and national indoor/outdoor status for the daily number of occupational injuries and illnesses.
Overall cumulative exposure-response curves for occupational injuries and illnesses in indoor workers, outdoor workers and workers in Adelaide, Brisbane, Darwin, Hobart, Melbourne, Perth and Sydney. The curves, shown with 95 % confidence intervals, represent percentage change from mean daily maximum wet bulb globe temperature (WBGT). The dashed lines represent the 2.5th percentile, mean and 97.5th percentiles of WBGT.

and workers in Sydney, Melbourne and Perth. Cold-preventable fractions (PFs, equivalent to negative AFs) were higher among workers from Adelaide and Darwin, and similar between indoor and outdoor workers. Across all cities, the extreme heat and cold estimates ranged from 0.14 to 0.31 % and − 0.01 to −0.14 %, respectively.

1.53 % (95 % eCI: 0.77–2.27 %) and 1.33 % (95 % eCI: 0.66–1.97 %) of costs were heat- and cold-attributable, respectively. Indoor workers had larger heat and cold estimates. Heat-AFs were largest in Darwin (2.70 %, 95 % eCI: 0.01–5.23), followed by Brisbane (2.07, 95 % eCI: 0.52–3.57 %) and Perth (2.04 %, 95 % eCI 0.17–3.74 %). Cold-AFs were larger in Adelaide (2.27 %, 95 % eCI:

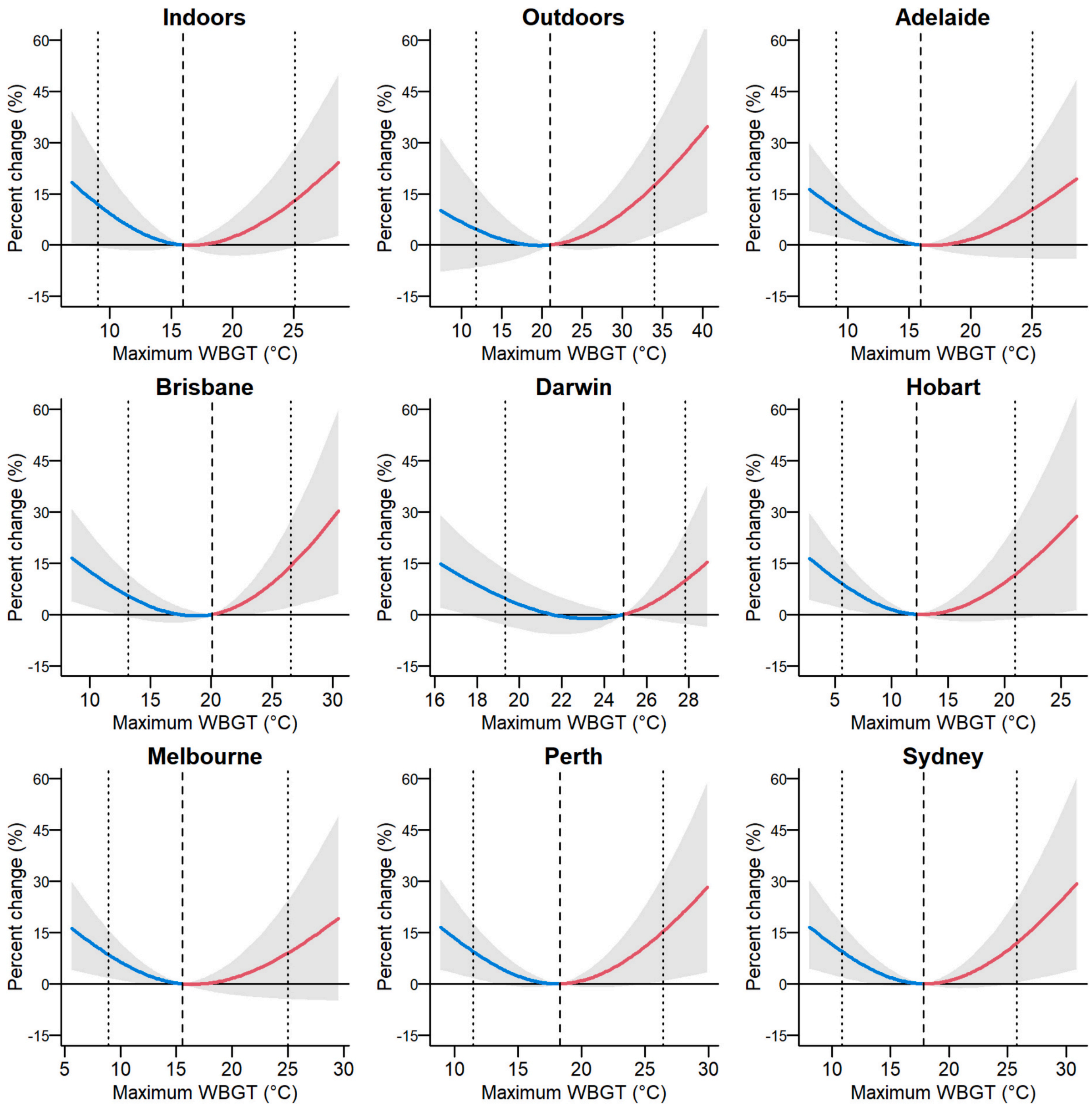


**Fig. 3.** Overall exposure-response curves for each city and national indoor/outdoor status for daily occupational injury- and illness-associated costs. Overall cumulative exposure-response curves for occupational injury- and illness-associated costs in indoor workers, outdoor workers and workers in Adelaide, Brisbane, Darwin, Hobart, Melbourne, Perth and Sydney. The curves, shown with 95 % confidence intervals, represent percentage change from mean daily maximum wet bulb globe temperature (WBGT). The dashed lines represent the 2.5th percentile, mean and 97.5th percentiles of WBGT.

0.55–3.94 %) and smaller in Brisbane (0.35 %, 95 % eCI: −0.80-1.51 %) and Darwin (0.30, 95 % eCI: −1.44-1.90 %). Extreme heat- and cold-AFs were significant in all cities, ranging from 0.23 to 0.40 % and 0.16–0.31 %, respectively.

Similar conclusions were derived with different model choices (Supplementary Table A.6). Although maximum WBGT with indoor/outdoor stratification by occupation showed slightly higher total AFs from heat compared to cold, most of the exposure metrics had slightly higher totals AFs from cold instead of heat, including WBGT without indoor/outdoor stratification (Supplementary Table A.7). Models with air temperature instead of apparent temperature, with and without adjustment for humidity, had lower heat-AFs for both OIIs and costs, with heat-AFs for costs generally being significant only at extreme levels. A similar national AF was obtained when restricting the cost models to only claims submitted before July 2014 and payments occurring up to five financial years after the year of submission.

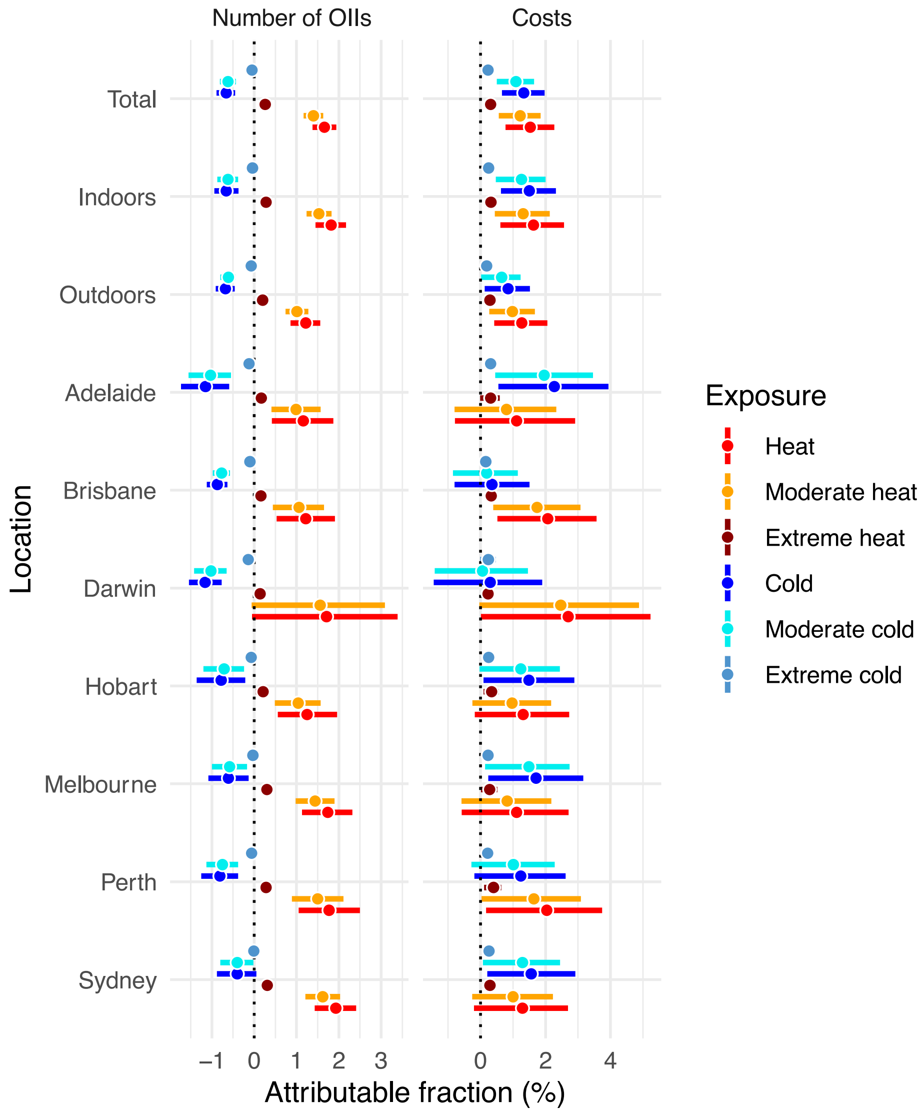


**Fig. 4.** Attributable fractions for heat- and cold-attributable occupational injuries and illnesses (OIIs) and associated costs.
The proportion of the number of OIIs and associated costs attributable to heat and cold, with 95 % empirical confidence intervals. Negative attributable fractions represent preventable fractions.

### 3.4. Attributable numbers

There were 38,540 (95 % eCI: 32,048-44,948) heat-attributable and 15,409 (95 % eCI: 10,438-20,636) cold-preventable OIIs (Table 2). This is equivalent to 5.2 (95 % eCI: 4.3–6.0) and 2.1 (95 % eCI: 1.4–2.8) OIIs per 1000 workers, respectively, and 2965 and 1185 OIIs annually, respectively. The associated heat- and old-attributable costs were AU$655 (95 % eCI: 330–973) million and AU $568 (95 % eCI: 283–846) million, or AU$88.1 (95 % eCI: 44.4–130.8) and AU$76.3 (95 % eCI: 38.1–113.8) per worker, respectively. These represent AU$50 million and AU$44 million annually, respectively. Although many of the OIIs and costs occurred among indoor workers and in Sydney, outdoor workers had more OIIs and costs per worker. Heat-attributable OIIs per worker were highest in Sydney, Perth and Hobart, heat-attributable costs were highest in Brisbane and Darwin (though weakly significant in Darwin), and cold-attributable costs were highest in Adelaide, Sydney, and Hobart.

### 3.5. Associated factors

Male workers had a slightly larger heat-AF and cold-PF for OIIs compared to females (Table 3). For costs, males had a higher cold-AF (1.76: 95 % eCI: 0.84–2.65 %) but females had a slightly higher heat-AF (1.32, 95 % eCI: 0.43–2.16 %). Older workers (50–75 years) had fewer heat-attributable but more cold-attributable OIIs compared to younger (15–29 years) and middle-aged (30–49 years)

**Table 2**
Heat- and cold-attributable occupational injuries and illnesses and associated costs across the study period.

| Location | Exposure | Number of OIIs | OIIs per 1000 workers | Total costs (000 s) | Cost per worker |
|---|---|---|---|---|---|
| Total | Heat | 38,540 (32,048 to 44,948) | 5·2 (4·3 to 6.0) | 655,143 (330,168 to 972,603) | 88·1 (44·4 to 130·8) |
| | Cold | −15,409 (−20,636 to −10,438) | −2·1 (−2·8 to −1·4) | 567,784 (283,148 to 846,096) | 76·3 (38·1 to 113·8) |
| Indoors | Heat | 31,197 (24,949 to 37,243) | 4·8 (3·8 to 5·7) | 506,539 (191,307 to 801,863) | 77·4 (29·2 to 122·5) |
| | Cold | −11,308 (−16,239 to −6384) | −1·7 (−2·5 to −1.0) | 468,727 (195,987 to 722,918) | 71·6 (29·9 to 110·4) |
| Outdoors | Heat | 7343 (5193 to 9385) | 8·2 (5·8 to 10·5) | 148,605 (49,678 to 241,322) | 166·9 (55·8 to 271.0) |
| | Cold | −4101 (−5476 to −2783) | −4·6 (−6·1 to −3·1) | 99,057 (15,218 to 177,922) | 111·2 (17·1 to 199·8) |
| Adelaide | Heat | 2833 (1018 to 4551) | 4·6 (1·6 to 7·3) | 37,759 (−27,046 to 99,016) | 60·9 (−43·6 to 159·6) |
| | Cold | −2800 (−4211 to −1430) | −4·5 (−6·8 to −2·3) | 77,308 (18,683 to 134,128) | 124·6 (30·1 to 216·2) |
| Brisbane | Heat | 4878 (2111 to 7628) | 4·4 (1·9 to 6·8) | 188,253 (47,260 to 324,704) | 168·3 (42·3 to 290·4) |
| | Cold | −3449 (−4476 to −2514) | −3·1 (−4.0 to −2·2) | 31,854 (−72,558 to 137,725) | 28·5 (−64·9 to 123·2) |
| Darwin | Heat | 275 (−8 to 546) | 3·6 (−0·1 to 7·2) | 11,037 (49 to 21,395) | 146.0 (0·6 to 283·1) |
| | Cold | −186 (−248 to −124) | −2·5 (−3·3 to −1·6) | 1223 (−5886 to 7775) | 16·2 (−77·9 to 102·9) |
| Hobart | Heat | 566 (252 to 884) | 5·4 (2·4 to 8·4) | 9299 (−1262 to 19,439) | 88·6 (−12.0 to 185·3) |
| | Cold | −354 (−615 to −97) | −3·4 (−5·9 to −0·9) | 10,585 (640 to 20,579) | 100·9 (6·1 to 196·2) |
| Melbourne | Heat | 6876 (4461 to 9143) | 3·2 (2.0 to 4·2) | 79,420 (−41,925 to 194,329) | 36·4 (−19·2 to 89·2) |
| | Cold | −2390 (−4246 to −526) | −1·1 (−1·9 to −0·2) | 123,040 (17,583 to 226,756) | 56·5 (8·1 to 104.0) |
| Perth | Heat | 5660 (3346 to 7970) | 5·9 (3·5 to 8·2) | 124,272 (10,177 to 227,861) | 128·5 (10·5 to 235·6) |
| | Cold | −2569 (−4002 to −1223) | −2·7 (−4·1 to −1·3) | 75,268 (−11,628 to 159,697) | 77·8 (−12.0 to 165·1) |
| Sydney | Heat | 17,452 (12,924 to 21,819) | 7·4 (5·4 to 9·2) | 205,103 (−31,286 to 428,368) | 86·5 (−13·2 to 180·6) |
| | Cold | −3661 (−7925 to 459) | −1·5 (−3·3 to 0·2) | 248,506 (32,961 to 465,343) | 104·8 (13·9 to 196·2) |

The number of occupational injuries and illnesses (OIIs) and associated costs attributable to heat and cold stress across the study period, with 95 % empirical confidence intervals. OIIs and costs per worker were calculated using the mean number of workers as listed in Table 1. Negative values represent temperature-preventable estimates.

workers. For costs, middle-aged workers had larger heat-AFs and older workers had higher cold-AFs.

Outdoor industries had a slightly higher heat-AF and no significant cold-PF for OIIs compared to indoor industries. For costs, outdoor industries had a higher but insignificant cold-AF (3.08 %, 95 % eCI: −0.34-5.90 %) and an unremarkable heat-AF (−0.14 %, 95 % eCI: −1.89-1.32 %). Occupations with higher heat-AFs for OIIs included machinery operators and drivers (MODs), technicians and trades workers, and managers. Significant heat-AFs for costs were only identified for MODs at extreme heat. Cold-AFs for costs were high for MODs (4.69 %, 95 % eCI: 2.53–6.59 %) and sales workers (4.89 %, 95 % eCI: 2.56–7.06 %), and strongly negative (preventative) for managers (−7.73 %, 95 % eCI: −19.79 to −0.52 %).

The number of occupational illnesses had larger heat-AFs compared to injuries. For costs, illnesses had larger heat- and cold-AFs compared to injuries generally. However, the only significant heat-AFs were for musculoskeletal and connective tissue diseases and injuries other than fractures, musculoskeletal, wounds, lacerations, amputations and internal organ damage, and extreme heat-AFs for illnesses (0.35 %, 95 % eCI: 0.02–0.60 %).

### 3.6. *Projected risk*

Mean future indoor WBGT values across projections in the seven cities are included in Supplementary Table A.8. Similarly to the retrospective analysis, Darwin had the highest WBGT values followed by Brisbane. The projected findings were generally similar in both 2030 and 2050, and both RCP4.5 and RCP8.5 apart from some minor differences under RCP8.5 in 2050. Moderate heat and cold were the main contributors to projected attributable burden instead of extreme heat and cold. OIIs were projected to significantly increase during heat in all cities except for Hobart, where decreases were observed (Fig. 5, AF estimates in Supplementary Table A.9). Larger heat-attributable increases were projected for Darwin (Supplementary Fig. A.5) and Brisbane. Across the seven cities in 2030, these represent 4294 (95 % eCI: 2958-5596, AF = 1.89 %) and 4367 (95 % eCI: 3002-5699, AF = 1.93 %) heat-attributable OIIs annually under RCP4.5 and RCP8.5, respectively (Table 4). In 2050, these represent 5880 (95 % eCI: 4117-7596, AF = 2.00 %) and 6117 (95 % eCI: 4411-7953, AF = 2.10 %) heat-attributable OIIs annually under RCP4.5 and RCP8.5, respectively. Cold-PFs for OIIs were observed in all cities, but they were only statistically significant in Adelaide, Melbourne and Hobart (Fig. 6). For projected costs, no significant changes were observed during heat except for increases in Melbourne. However, costs were projected to increase during the cold across all cities except for Darwin, Hobart and Melbourne (although Melbourne was significant under RCP8.5 in 2050). Nationally, the projected annual cold-attributable costs were AU$37 (95 % eCI: 2–72, AF = 0.90 %) million and AU$36 (95 % eCI: 2–70, AF = 0.87 %) million in 2030 under RCP4.5 and RCP8.5, respectively, and AU$45 (95 % eCI: 3–85, AF = 0.82 %) million and AU $41 (95 % eCI: 5–78, AF = 0.76 %) million in 2050 under RCP4.5 and RCP8.5, respectively.

## 4. Discussion

This study is the first, to the author's best knowledge, to report a national cost profile of both heat- and cold-attributable OIIs together by modelling costs directly, and also to estimate OIIs and their costs whilst incorporating indoor/outdoor weather exposure based on occupation to represent heat and cold impacts more accurately. Across the seven Australian cities, the health and financial burden from OIIs under anomalous temperatures is substantial. The financial burden is considerably greater when also considering

**Table 3**
Attributable fractions by worker and OII characteristics.

| | Number of OIIs | | Total costs | | |
|---|---|---|---|---|---|
| | Heat | Cold | Heat | Extreme heat | Cold |
| All workers | 1·77 (1·43 to 2·11) | −0·62 (−0·91 to −0·34) | 1.08 (0.51 to 1·65) | 0·23 (0·15 to 0·31) | 1·41 (0·66 to 2·10) |
| Male | 2.00 (1·48 to 2·52) | −0·81 (−1·11 to −0·53) | 0·97 (0·21 to 1·67) | 0·23 (0·12 to 0·33) | 1·76 (0·84 to 2·65) |
| Female | 1·34 (1.07 to 1·61) | −0·32 (−1·13 to 0·42) | 1·32 (0·43 to 2·16) | 0·26 (0·11 to 0·38) | 0·95 (−0·29 to 2·18) |
| Aged 15 to 29 years | 2·24 (1·85 to 2·65) | −1·69 (−2·48 to −0·93) | 0·32 (−3·55 to 3·25) | 0·11 (−0·70 to 0·56) | 2·41 (−0·47 to 4·68) |
| Aged 30 to 49 years | 1·91 (1·34 to 2·44) | −1·10 (−1·55 to −0·66) | 1·96 (1·13 to 2·74) | 0·34 (0·22 to 0·45) | 0·55 (−0·50 to 1·57) |
| Aged 50 to 75 years | 1·14 (0·72 to 1·54) | 1.03 (0·52 to 1·54) | 0·10 (−0·86 to 1.02) | 0·12 (−0.04 to 0·25) | 2·51 (1·41 to 3·57) |
| Industrial sector | | | | | |
| Indoor industries | 1·72 (1·41 to 2.02) | −0·65 (−1.06 to −0·26) | 1·27 (0·66 to 1·89) | 0·26 (0·16 to 0·34) | 1·18 (0·41 to 1·93) |
| Outdoor industries | 2·11 (1·25 to 2·91) | −0·28 (−0·96 to 0·35) | −0·14 (−1·89 to 1·32) | 0·08 (−0·26 to 0·34) | 3.08 (−0·34 to 5·90) |
| Occupation | | | | | |
| Clerical & administrative workers | 1·48 (0·54 to 2·39) | −0·56 (−1·64 to 0·45) | 1·92 (−0·17 to 3·72) | 0·33 (−0·10 to 0·64) | −0·10 (−7·80 to 5·16) |
| Community & personal service workers | 1.05 (0·43 to 1·69) | −1.03 (−1·63 to −0·47) | −0·52 (−2·15 to 0·93) | −0.09 (−0·34 to 0·12) | −0·14 (−3·97 to 3.03) |
| Laborers | 1·75 (1·26 to 2·25) | −0·82 (−1·28 to −0·40) | 0·64 (−0·54 to 1·70) | 0·15 (−0.02 to 0·30) | 1·22 (−0·22 to 2·50) |
| Machinery operators & drivers | 2·73 (2.01 to 3·41) | −0·98 (−1·56 to −0·40) | 2·10 (−1·13 to 4·58) | 0·49 (−0·11 to 0·85) | 4·69 (2·53 to 6·59) |
| Managers | 1·97 (0·14 to 3·52) | 0·22 (−1·51 to 1·79) | −1·14 (−13.03 to 5·63) | −0·48 (−3·60 to 0·53) | −7·73 (−19·79 to −0·52) |
| Professionals | 0·65 (−0·35 to 1·58) | 0·46 (−0·23 to 1·11) | 0·59 (−2·21 to 2·91) | 0·26 (−0·15 to 0·56) | 4·22 (−1·74 to 8·48) |
| Sales workers | 1·47 (0·36 to 2·49) | 0·84 (0.05 to 1·61) | −1·32 (−5·45 to 1·91) | −0.03 (−0·71 to 0·42) | 4·89 (2·56 to 7.06) |
| Technicians & trade workers | 2·27 (1·67 to 2·82) | −1·29 (−1·96 to −0·64) | 0·60 (−1.09 to 2·11) | 0.08 (−0·29 to 0·37) | 0·36 (−3.06 to 3·25) |
| OII nature | | | | | |
| All injuries | 1·64 (1·27 to 2.00) | −0·70 (−1·23 to −0·20) | 0·69 (−1·94 to 2·94) | 0·16 (−0·22 to 0·43) | 1·22 (−0·79 to 3.04) |
| Fractures | 1·31 (0·68 to 1·94) | 1·96 (1·19 to 2·71) | −1·79 (−3·78 to −0.06) | −0·19 (−0·65 to 0·14) | 3·35 (−2·82 to 7·74) |
| Traumatic joint, ligament, muscle & tendon injuries | 1.01 (0·48 to 1·53) | −0·73 (−1·34 to −0·16) | 1.01 (−1·48 to 3.04) | 0·20 (−0·15 to 0·46) | 1.08 (−1·28 to 3·15) |
| Wounds, lacerations, amputations & internal organ damage | 2·16 (1·82 to 2·50) | −1·11 (−1·57 to −0·66) | 1·13 (−1·11 to 3.07) | 0.09 (−0·17 to 0·31) | −3.00 (−9·52 to 1·79) |
| All other injuries | 3·68 (2·50 to 4·77) | −1·90 (−3·80 to −0·22) | 1·25 (−8.05 to 7.06) | 0·14 (−2·10 to 0·90) | −0·58 (−13.05 to 6·69) |
| All illnesses (diseases/conditions) | 2·19 (1·74 to 2·64) | −0·34 (−1·15 to 0·48) | 1·61 (−1.08 to 3·96) | 0·35 (0.02 to 0·60) | 1·97 (−1·65 to 4·99) |
| Mental disorders | 2·76 (1·26 to 4·11) | −0·31 (−1·50 to 0·78) | 2·24 (−1·66 to 5·42) | 0·51 (0.05 to 0·83) | 2·79 (−3·88 to 7·57) |
| Musculoskeletal & connective tissue diseases | 2·14 (0·87 to 3·37) | −1·11 (−2·72 to 0·34) | 1·68 (0·18 to 3.00) | 0·30 (0.03 to 0·51) | 0·25 (−1·95 to 2·26) |
| All other illnesses | 0·96 (−0·90 to 2·53) | 0·82 (−1·64 to 2·92) | 0·44 (−6·74 to 5·24) | 0·15 (−0·97 to 0·71) | 1·70 (−6·57 to 7·14) |

Attributable fractions (%) of the number of occupational injuries and illnesses (OIIs) and associated costs attributable to heat and cold stress from daily indoor wet bulb globe temperature stratified by demographic, occupational and OII characteristics, with 95 % empirical confidence intervals.

labor productivity loss beyond compensation payouts (Borg et al., 2021); an Australian study estimated annual costs of US$655 per person to employers from subjective productivity loss (Zander et al., 2015). Future research investigating heat-attributable occupational costs should consider both productivity loss and those from OIIs, as well as the impact of cold, for a more holistic economic estimate.

As compensation schemes are funded by employers' premium, and premium rates increase if projected and previous compensation

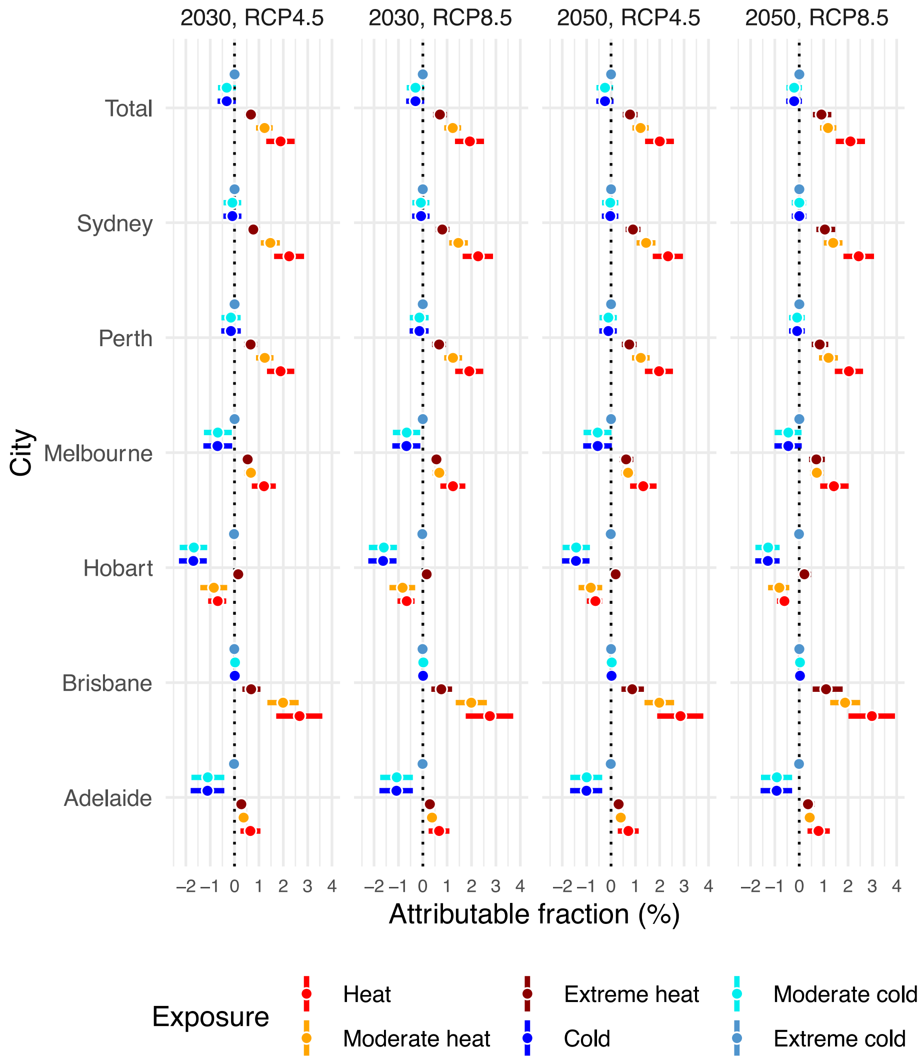


**Fig. 5.** Attributable fractions for heat- and cold-attributable occupational injuries and illnesses projected to 2030 and 2050.
The proportion of the number of OIIs and associated costs attributable to heat and cold, with 95 % empirical confidence intervals. Negative attributable fractions represent preventable fractions.

payouts are greater, OII-associated costs reduce employer's funds (Safe Work Australia, 2019a). Reduced funds can lead to less business production, leading to reduced consumer spending and business growth that could benefit the wider economy. Less funding can also lead to less investment into worker wages, worker quality of life features, and hiring new staff, potentially increasing unemployment. Hence reducing OII-associated costs can benefit workers, employers and the wide economy.

The results align with a similar study using the same population observing increased OIIs and associated costs during heatwaves (Borg et al., 2023), and a previous study in Guangzhou, China observing the RR for occupational injuries increases with WBGT and increased claim payouts beyond WBGT thresholds (Ma et al., 2019). Similarly, previous Australian studies using air temperature instead of WBGT observed increased RRs for OIIs during heat in Adelaide, Melbourne, Sydney and Brisbane, and decreased RRs during cold in Brisbane, although this study found a protective instead of an adverse cold effect in Adelaide and a significant relationship with heat in Perth (Fatima et al., 2022, 2023; Varghese et al., 2019a, 2019b). Two studies in Spain and Italy observed increased OIIs during both high and low air temperatures (Marinaccio et al., 2019; Martínez-Solanas et al., 2018). These countries have colder climates than Australia, which may predispose workers to OIIs during their cold seasons.

Exposure-response relationships differed between costs and OIIs in particular during cold temperatures, despite using similar models, and resulted in an increased cost per OII during cold temperatures. Even if cold decreases the risk of OIIs, OIIs more likely to occur during cold may be more severe or longer-lasting, incurring increased healthcare, compensation and associated legal and administrative fees. These fees are all likely involved given the significant exposure-response relationships with compensation, goods and services, and non-compensation costs. The findings from this study suggested that neither hot nor cold temperatures are optimal for minimizing overall burden from OIIs. Although the number of OIIs did decrease with cold, this decrease was small in comparison to

**Table 4**
Projected annual number of heat- and cold-attributable occupational injuries and illnesses and associated costs.

| City | Period | RCP | Number of OIIs | | Total costs (000 s) | |
|---|---|---|---|---|---|---|
| | | | Heat | Cold | Heat | Cold |
| Total | 2030 | 4·5 | 4294·29 (2958·44 to 5596·36) | −732·66 (−1579·45 to 124·64) | 15,150·7 (−51,298·4 to 76,594·5) | 37,588·2 (1895·1 to 72,441·4) |
| | | 8·5 | 4367.06 (3002·30 to 5699·11) | −689·99 (−1536.02 to 126·85) | 13,409·9 (−53,844·3 to 77,271·3) | 36,470.0 (1506·8 to 70,182·8) |
| | 2050 | 4·5 | 5880·35 (4116·76 to 7596·31) | −741·98 (−1793·90 to 283·35) | 10,212·4 (−84,233·4 to 98,751.0) | 44,804·1 (3186·1 to 85,331·1) |
| | | 8·5 | 6177·14 (4411·43 to 7952·75) | −611.03 (−1588·46 to 324·66) | 2730·7 (−99,920·6 to 99,178·5) | 41,043·5 (4616·4 to 77,942·9) |
| Adelaide | 2030 | 4·5 | 136.06 (49·33 to 221·21) | −232·81 (−376·90 to −88·32) | 1491·6 (−707·2 to 3546.0) | 4896·4 (260·4 to 9413·6) |
| | | 8·5 | 140·21 (50·79 to 228·30) | −226·50 (−371·67 to −86·33) | 1447·6 (−749·7 to 3593·9) | 4863·4 (210·8 to 9292·8) |
| | 2050 | 4·5 | 169·65 (66·91 to 271·92) | −241·41 (−401·87 to −85·22) | 1615.0 (−1029·5 to 4125·3) | 5325·8 (345·5 to 10,128·1) |
| | | 8·5 | 187·99 (81·90 to 297·39) | −221·11 (−378·88 to −69·57) | 1455·4 (−1445·5 to 4256·9) | 5167·6 (591·4 to 9777·1) |
| Brisbane | 2030 | 4·5 | 1051·17 (674.07 to 1415·72) | 2·90 (−22·18 to 25·49) | 1886·9 (−22,280·3 to 24,166.0) | 1083·8 (385.0 to 2005·8) |
| | | 8·5 | 1080·94 (694·17 to 1457·67) | 4·76 (−21.05 to 24·15) | 1208·3 (−23,332·7 to 24,556·9) | 914·4 (245·3 to 1886·2) |
| | 2050 | 4·5 | 1476.09 (977·84 to 1964·23) | 12·16 (−10·18 to 28·79) | −1729·8 (−36,455·7 to 30,843·2) | 658·4 (31·1 to 1617·2) |
| | | 8·5 | 1541·73 (1047·73 to 2034·11) | 14·34 (−1.04 to 24·75) | −4867·8 (−42,780·8 to 30,370.0) | 233·5 (−547·2 to 1048·7) |
| Darwin | 2030 | 4·5 | 101.02 (47·77 to 150·98) | 4·55 (−6·75 to 15.06) | −3058·3 (−7263·6 to 590·5) | −515·4 (−939·6 to −130·8) |
| | | 8·5 | 102.08 (48·81 to 153·50) | 4·27 (−6·49 to 14·58) | −3131·2 (−7328·7 to 639·3) | −496.0 (−909·8 to −122·6) |
| | 2050 | 4·5 | 144·86 (62·84 to 222·10) | 5·35 (−8·98 to 19.00) | −4753·3 (−10,893·4 to 762.0) | −653·1 (−1197·8 to −169·1) |
| | | 8·5 | 147·91 (60.08 to 233·20) | 4·47 (−8·30 to 16·69) | −5103·9 (−11,666·8 to 575·1) | −579·2 (−1076.0 to −158·2) |
| Hobart | 2030 | 4·5 | −29·80 (−46·59 to −14·55) | −73·12 (−98·30 to −49·16) | −73·9 (−522·6 to 363·3) | 362·2 (−787·1 to 1482.0) |
| | | 8·5 | −28·71 (−45.07 to −14·87) | −70·16 (−96·66 to −46·54) | −33·8 (−495.0 to 398·2) | 395·4 (−753·7 to 1476·6) |
| | 2050 | 4·5 | −31·46 (−48·70 to −17·90) | −70·78 (−99.06 to −43·20) | 57·8 (−487·1 to 586·5) | 501·1 (−704·4 to 1629·4) |
| | | 8·5 | −29·94 (−45·17 to −18.01) | −63·62 (−89·11 to −40.01) | 149·2 (−392·8 to 673.0) | 549·2 (−553·3 to 1599·3) |
| Melbourne | 2030 | 4·5 | 484·11 (284·99 to 680·66) | −280·52 (−514·48 to −40·82) | 5618.0 (355·1 to 10,586·6) | 10,400·6 (−1037·3 to 21,586·5) |
| | | 8·5 | 496·45 (287·28 to 704·29) | −267·91 (−500·77 to −38·57) | 5706·2 (436·8 to 10,836.0) | 10,223·6 (−1093·7 to 21,038·9) |
| | 2050 | 4·5 | 704·54 (415·37 to 1004·21) | −294·84 (−610·33 to 15·19) | 7675·6 (135·4 to 14,918·7) | 13,568·3 (−631·5 to 27,342·4) |
| | | 8·5 | 761·70 (459·30 to 1084·60) | −240·53 (−545.02 to 51·27) | 7814·4 (−442·3 to 15,889·2) | 13,005·8 (80·5 to 25,855·3) |
| Perth | 2030 | 4·5 | 577·78 (404·63 to 748·62) | −44·77 (−168·66 to 80.01) | 310·9 (−9468·2 to 9423·7) | 5733.0 (1016·1 to 10,420·8) |
| | | 8·5 | 582·63 (407.02 to 755·39) | −42·32 (−163·22 to 73·84) | 117·9 (−9672·9 to 9490·2) | 5470·2 (888·4 to 10,002.0) |
| | 2050 | 4·5 | 800·30 (566.02 to 1030·60) | −45·28 (−195·13 to 98·29) | −987·1 (−15,380·4 to 12,421·6) | 6671·1 (1188·1 to 12,232·9) |
| | | 8·5 | 829.08 (593.01 to 1064·18) | −35·47 (−172·16 to 94·92) | −2217·1 (−17,869·3 to 12,222·2) | 6057·8 (1232·8 to 11,235·3) |
| Sydney | 2030 | 4·5 | 1974·77 (1426·87 to 2511·83) | −80·21 (−405·41 to 247·75) | 8998.0 (−14,523·4 to 30,845·9) | 15,215·3 (1786·5 to 28,494·8) |
| | | 8·5 | 1994·31 (1442·61 to 2535·77) | −64·16 (−387·51 to 246·25) | 8120·8 (−15,810·5 to 30,955·7) | 14,684·9 (1582·4 to 27,429·2) |
| | 2050 | 4·5 | 2636·64 (1927·59 to 3332·35) | −36·84 (−427·29 to 343.03) | 7832·5 (−25,898.0 to 39,337·1) | 17,700.0 (2375·9 to 32,919·6) |
| | | 8·5 | 2757·29 (2049·19 to 3471·17) | −3·40 (−349.08 to 326·74) | 4959·9 (−31,930·9 to 39,712·5) | 15,594·2 (2653·1 to 28,985·2) |

The number of annual occupational injuries and illnesses attributable to heat and cold stress across to in 2016–45 and 2036–65 centered at 2030 and 2050 with 95 % empirical confidence intervals. Negative values represent temperature-preventable estimates. OII: Occupational injury and illness, RCP: Representative Concentration Pathway.

the increase in costs with cold. Future research on temperature-attributable occupational outcomes should consider both adverse heat and adverse cold. Because AFs for both OIIs and costs were significant across different ages, sex, industries and occupations, interventions should be aimed at the general working population.

Workplace and public health measures can prevent, detect and/or manage OIIs. Although only prevention lowers the number of

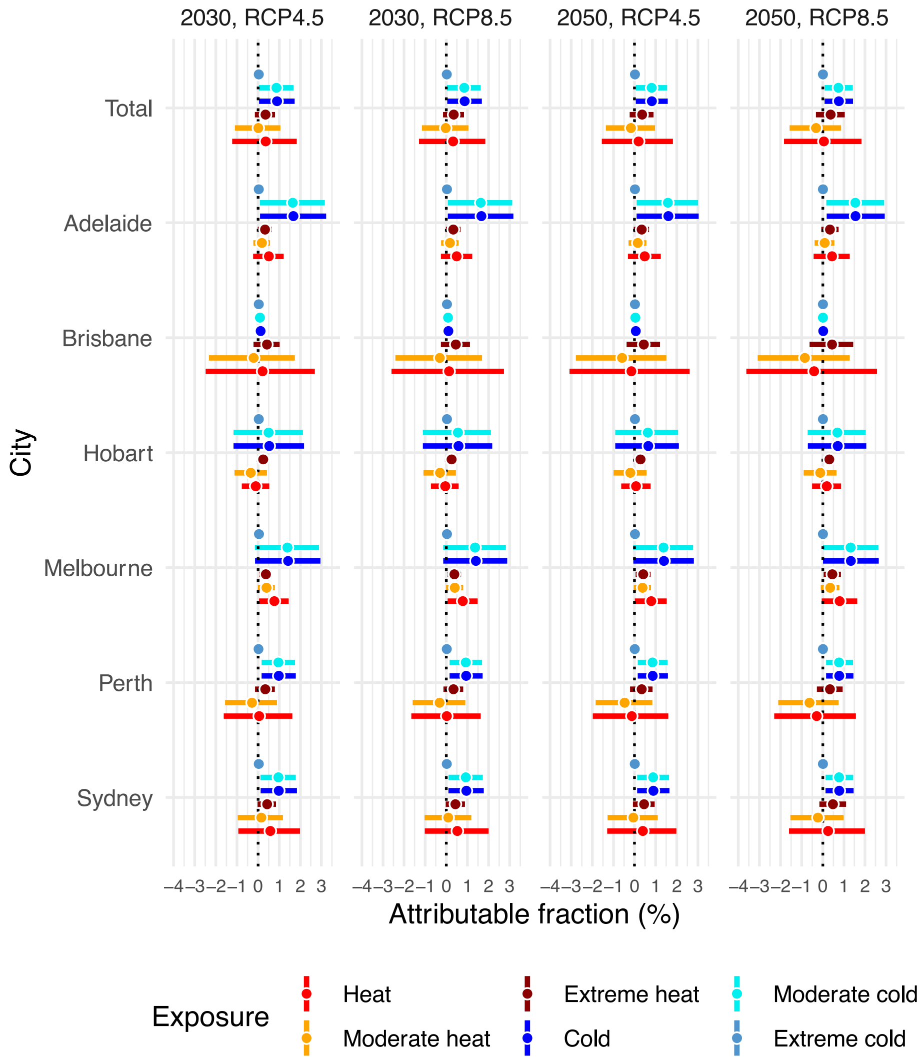


**Fig. 6.** Attributable fractions for costs secondary to heat- and cold-attributable occupational injury and illness-associated costs projected to 2030 and 2050.
The proportion of the number of OIIs and associated costs attributable to heat and cold, with 95 % empirical confidence intervals. Negative attributable fractions represent preventable fractions. Projections for Darwin are presented in appendix p21.

OIIs, detection and management also reduce OII-associated costs. Earlier detection and effective management can potentially prevent (acute) injuries and (often insidious) illnesses from becoming more severe and reducing the OII duration, minimizing costs. As OIIs only increased in frequency during hot temperatures, preventative measures and code of practice should include heat stress reduction. Employer-driven preventative measures include work-to-rest ratios guided by heat thresholds and work characteristics, adequate access to hydration, shade and cooling such as air conditioning, hydration monitoring, appropriate clothing, heat acclimatization plans for new workers, and minimizing workplace-generated heat (Borg et al., 2021; Morrissey et al., 2021). These can be mandated in workplaces by policy makers. Urban planning approaches to reduce heat include constructing new buildings that minimize heat (and cold) retention, increasing greenspace, landscapes that promote cycling and walking, and increased public electric vehicle chargers (to promote electric vehicles over petrol vehicles) (Jay et al., 2021). Interventions for detecting and managing OIIs should have increased focus during times of both heat and cold stress. This is especially important for cold stress given the significant increase in cost per OII observed during colder temperatures, suggesting that cold-attributable OIIs are associated with greater costs irrespective of the number of cold-attributable (or cold-preventable) OIIs. Detection strategies include increased employee supervision, and for high-risk workers, regular medical examinations and/or physiological monitoring (Morrissey et al., 2021). Management strategies include workplace emergency action plans, simple access to first aid and medical services, and adaptation of work to suit unwell employees such as reducing physical workloads and enabling work from home (Morrissey et al., 2021). Both can be enforced by employers, regulators and policy makers. Workplace and public health education on these topics can support implementation of these interventions. Preventative and detection strategies can be guided by daily on-site measurements for WBGT or another heat metric, with this study providing risk estimates for both indoor and outdoor workers based on WBGT for both heat and cold. Although assessing the impact of the aforementioned measures was not a study aim, this should be addressed in future research.

Heat-AFs were higher for workers in Sydney, Melbourne and Perth for OII numbers, and Darwin, Brisbane and Perth for OII-related costs. This may be because Darwin, Brisbane and Perth had higher maximum air temperatures and WBGTs (Table 1), and a smaller proportion of Sydney and Melbourne households have air conditioning than in other capital cities (Australian Bureau of Statistics, 2014) (assuming this correlates with smaller proportions in workplaces). Brisbane and Darwin have warmer and more tropical climates than the other cities, which may explain their smaller cold-AFs for costs. Conversely, Adelaide had higher cold-AFs for costs. Adelaide has a dry climate with cold winters which may predispose to more severe OIIs during cold, although Adelaide also has a high household proportion of heating (Australian Bureau of Statistics, 2014). This study observed slighter larger heat-AFs for indoor compared to outdoor workers for the main analysis, aligning with the findings from a previous meta-analysis (Binazzi et al., 2019). Thermoregulatory workplace regulations are likely to benefit both indoor and outdoor workers.

Males had higher heat-AFs for OIIs compared to females, but females had higher heat-AFs for costs – heat-attributable OIIs among females, although less in proportion, incurred more costs. The converse was true for cold-AFs. This likely reflects their different occupational distributions, with males more likely to undertake physically demanding jobs associated with more heat-attributable OIIs (Bonafede et al., 2016), but the OIIs have shorter recovery periods and hence less costs. The occupations with the highest heat-AFs for OIIs in this study, machinery operators and drivers, technicians and trade workers, and managers, are more frequently undertaken by males (Australian Bureau of Statistics, 2022). Cold-attributable OIIs, however, may be longer-lasting. Females are more likely to suffer from chronic illnesses (Australian Institute of Health and Welfare, 2021), which are likely associated with payments over longer durations. Supporting this, heat- and cold-AFs were higher for the number of illnesses than injuries. Although there was only sufficient power to determine that illnesses generally were associated with increased costs in extreme and not moderate heat, they are associated with higher financial expenditure than injuries (Australian Institute of Health and Welfare, 2021). Musculoskeletal and connective tissue diseases, which had a significant heat-AF for costs, are also more common in Australian females (Australian Institute of Health and Welfare, 2021). These different occupational and illness patterns may explain the AF differences observed in workers by age and indoor/outdoor (the construction industry had more claims than all other outdoor industries combined). Sales workers and managers had considerably higher and lower cold-AFs with costs, respectively. Sales work involves high person-to-person contact, which may predispose workers to common infectious winter illnesses such as influenza. Managers likely have easier access to heating and additional clothing to prevent more severe diseases during cold, although they did not have significant cold-AFs for OIIs.

Attributable fractions for heat-attributable OIIs were projected to increase in the future. This aligns with a previous study that observed increased future projected OIIs attributable to heatwaves (Borg et al., 2023). Future projections for costs predicted an increase in cold-attributable costs but generally could not predict significant findings for heat-attributable costs. This may be explained by the future projections using indoor WBGT only, as sensitivity analyses using WBGT without stratification by occupation estimated higher national cost burden attributable to cold than heat. Even with global warming, interventions for detecting and managing OIIs during the cold are likely to be beneficial. Future research on future projected costs from OII should be undertaken with larger sample sizes to evaluate whether costs from OII change with heat.

The main research limitation is that the claims data only include reported OIIs; hence the results only represent minimum OII and cost burdens that are likely underestimated. OIIs of mild severity are less likely to be reported, potentially biasing the data to over-represent more severe OIIs. Claims data for workers with separate private schemes or those not covered by compensation schemes were not collected, in particular self-employed workers. Claims can have future payments due beyond the study period. These payments would not be included in the data, underestimating costs. However, a supplementary analysis only including claims submitted before July 2014 and payments occurring up to five financial years after the year of submission had a similar national AF to the main cost analysis. Furthermore, most payments occurred in the same or subsequent financial year as the claim lodgment. There were fewer claims in Hobart and Darwin due to their smaller populations, resulting in less precise estimates for these cities. This was partially mitigated by refitting models with multivariate meta-analysis derived BLUPs. Selection bias may exist because some claims were removed due to missing data, with higher proportions of claims removed to represent Darwin, Melbourne, and Hobart. Similar to most ecological studies, non-meteorological temperature variation such as air conditioning and workplace-generated heat was not analyzed. However, stratification of indoor and outdoor workers would partially mitigate potential confounding from air conditioning, as indoor workers likely have more access to air conditioning. Minor biases existing in the climate dataset for low and high wind speed values, an issue shared with other global reanalysis datasets (Su et al., 2019). This only affects outdoor apparent temperature in this study, and the impact is likely very low, especially compared to the bias from using the frequently-used "simplified" WBGT (Kong and Huber, 2022; Lemke and Kjellstrom, 2012). The meteorological projections used Coupled Model Intercomparison Project Phase 5 instead of the newer Phase 6 scenarios. This enabled projections representing cities in Australia with higher resolution at the expense of not incorporating Shared Socioeconomic Pathways. However, different socioeconomic scenarios were considered by using different projected population scenarios (Australian Bureau of Statistics, 2018). Finally, the results may be less applicable to countries with different (non-temperate) climates, with studies in colder countries observing cold-attributable instead of cold-preventable OIIs (Marinaccio et al., 2019; Martínez-Solanas et al., 2018), or rural areas, as these were excluded from the study.

## 5. Conclusions

Environmental heat and cold temperatures in workers, both moderate and extreme, poses a substantial morbidity and cost burden in Australia. The relationship between suboptimal temperatures and costs does not necessarily follow that of OII occurrence, which is likely more influenced by heat compared to cold relative to their associated costs. Reducing anomalous heat can prevent OIIs, whereas minimizing both excessive heat and cold can be effective in reducing OII-associated costs. Strategies to reduce the number of OIIs should be given increased consideration during high temperatures, whereas strategies to detect and manage OIIs are important during both higher and colder temperatures. The risk of developing heat-related OIIs is likely to increase with global warming, although the change in risk for associated costs is unclear. Future research investigating occupational economic burden should consider OIIs and productivity loss together, in particular consider future projected changes in costs from OIIs.

## Code availability

The R code for analysis is available upon reasonable request. A reproducible example is available online at the first author's GitHub page (https://github.com/mtthwborg/2025_Borg_UC) using simulated compensation claims data and publicly available climate data sourced from Brambilla et al. 2022 (doi: https://doi.org/10.1016/j.dib.2022.108291).

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## Author contributions

M.A.B., J.X., O.A., B.V., K.D., D.P., A.H., K.Z., M.R.S. and P.B. were involved in conceptualization. M.A.B., J.X., O.A., B.O., K.D., D. P., A.H., K.Z., M.R.S. and P.B. designed the methodology. M.A.B. and B.O. were involved in programming. M.A.B. conducted the formal analysis, validation, visualization and writing of the draft manuscript. M.A.B., O.A., B.O., B.V. and A.H. were involved in data curation. All authors were involved in revising the manuscript. O.A. and P.B. were involved in project administration. J.X., O.A., K.D., D.P., A.H., K.Z., M.R.S. and P.B. were involved in funding acquisition. J.X., O.A. and P.B. supervised the project.

## CRediT authorship contribution statement

**Matthew A. Borg:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Jianjun Xiang:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Olga Anikeeva:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Bertram Ostendorf:** Writing – review & editing, Software, Methodology, Data curation. **Blesson Varghese:** Writing – review & editing, Data curation, Conceptualization. **Keith Dear:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Dino Pisaniello:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Alana Hansen:** Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization. **Kerstin Zander:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Malcolm R. Sim:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Peng Bi:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Restrictions apply to the availability of the SWA data which were used under license for the current study. The data used can be requested from SWA at https://www.safeworkaustralia.gov.au/data-and-research/request-data and may be made available with the permission of SWA. SWA has made some of this data publicly available in the Australian workers' compensation statistics report, which provides detailed statistics about workers' compensation claims lodged in Australia from July 2000 to June 2020. This report can be accessed at https://www.safeworkaustralia.gov.au/doc/australian-workers-compensation-statistics-2019-20.

The retrospective climate data were sourced from BARRA: http://www.bom.gov.au/research/projects/reanalysis/ and were used in accordance with their licensing and usage policy: http://www.bom.gov.au/metadata/catalogue/view/ANZCW0503900566.shtml?template=full.

The projected climate data have been deposited in figshare doi: 10.25909/23709657. They were used in accordance with their license listed online (https://www.climatechangeinaustralia.gov.au/en/overview/about-site/licences-and-acknowledgements/) and were derived from publicly available CCiA gridded datasets: https://data-cbr.csiro.au/thredds/catalog/catch_all/oa-aus5km/Climate_Change_in_Australia_User_Data/Application_Ready_Data_Gridded_Daily/catalog.htm.

The workers' population data, derived from the ABS, and their indoor/outdoor stratifications has been deposited in figshare (doi: 10.25909/63a2d38c1b295)[doi: 10.25909/63a2d38c1b295]. The ABS labor force data (LM1) are publicly available at https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia-detailed/latest-release, and the ABS Census TableBuilder Basic data are available online at https://tablebuilder.abs.gov.au/webapi/jsf/login.xhtml under specified conditions of use: https://www.abs.gov.au/statistics/microdata-tablebuilder/responsible-use-abs-microdata/conditions-use. The projected population data is publicly available online at https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3222.02017%20(base)%20-%202,066?OpenDocument. A list of GCCSAs and conversion of 2006 Statistical Local Areas to GCCSA are publicly available online: https://data.gov.au/data/dataset/asgs-geographic-correspondences-2016/resource/951e18c7-f187-4c86-a73f-fcabcd19af16?inner_span=True. Australian consumer price index data is publicly available online at https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/consumer-price-index-australia/latest-release.

The public and school holidays data have been deposited in figshare (doi: 10.25909/6311e7a0dcb3f and doi: 10.25909/6311e7b3bc760, respectively).

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### Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.uclim.2025.102307.

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