Environmental Research 236 (2023) 116852

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Current and projected heatwave-attributable occupational injuries, illnesses, and associated economic burden in Australia☆,☆☆

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ARTICLE INFO

Handling Editor: Jose L Domingo

Keywords:
Attributable risk
Compensation claims
Global warming
Heatwaves
Occupational costs
Worker safety

ABSTRACT

Introduction: The costs of global warming are substantial. These include expenses from occupational illnesses and injuries (OIIs), which have been associated with increases during heatwaves. This study estimated retrospective and projected future heatwave-attributable OIIs and their costs in Australia.

Materials and methods: Climate and workers' compensation claims data were extracted from seven Australian capital cities representing OIIs from July 2005 to June 2018. Heatwaves were defined using the Excess Heat Factor. OIIs and associated costs were estimated separately per city and pooled to derive national estimates. Results were projected to 2030 (2016–2045) and 2050 (2036–2065).

Results: The risk of OIIs and associated costs increased during heatwaves, with the risk increasing during severe and particularly extreme heatwaves. Of all OIIs, 0.13% (95% empirical confidence interval [eCI]: 0.11–0.16%) were heatwave-attributable, equivalent to 120 (95%eCI:70–181) OIIs annually. 0.25% of costs were heatwave-attributable (95%eCI: 0.18–0.34%), equal to $AU4.3 (95%eCI: 1.4–7.4) million annually. Estimates of heatwave-attributable OIIs by 2050, under Representative Concentration Pathway [RCP]4.5 and RCP8.5, were 0.17% (95% eCI: 0.10–0.27%) and 0.23% (95%eCI: 0.13–0.37%), respectively. National costs estimates for 2030 under RCP4.5 and RCP8.5 were 0.13% (95%eCI: 0.27-0.46%) and 0.04% (95%eCI: 0.66-0.60), respectively. These estimates for extreme heatwaves were 0.04% (95%eCI: 0.02–0.06%) and 0.04% (95%eCI: 0.01–0.07), respectively. Cost-AFs in 2050 were, under RCP4.5, 0.127% (95%eCI: 0.27-0.46) for all heatwaves and 0.04% (95%eCI: 0.01-0.09%) for extreme heatwaves. Attributable fractions were approximately similar to baseline when assuming theoretical climate adaptation.

Discussion: Heatwaves represent notable and preventable portions of preventable OIIs and economic burden. OIIs are likely to increase in the future, and costs during extreme heatwaves in 2030. Workplace and public health policies aimed at heat adaptation can reduce heat-attributable morbidity and costs.

1. Introduction

Future global warming will slow economic growth and pressure human socioeconomic systems (Carleton and Hsiang, 2016). Workers are particularly susceptible to increasing temperatures due to additional metabolic heat production from physical work, radiant workplace heat exposure, personal protective equipment, and potentially reduced

☆ This project was supported by the Australian Research Council (ARC Discovery Project Grant: DP190102869). Author Matthew Borg was supported by a University of Adelaide Faculty of Health Sciences Divisional Scholarship.☆☆ This publication uses retrospective workers' compensation claims data supplied by Safe Work Australia and has been compiled in collaboration with state, territory and Commonwealth workers' compensation regulators. Safe Work Australia has provided verified consent for access to this data. Ethics approval to access and analyze the compensation claim data were reviewed and approved by the University of Adelaide Human Research Ethics Committee (H-2019-141 and H-2016-085).

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https://doi.org/10.1016/j.envres.2023.116852
Received 11 June 2023; Received in revised form 21 July 2023; Accepted 6 August 2023
Available online 7 August 2023

Abbreviations

95%eCI	95% empirical confidence interval
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
CMIP	Coupled Model Intercomparison Project
DLNM	Distributed lag non-linear model
DMT	daily mean temperature
EHF	Excess Heat Factor
GAM	Generalized additive model
GCCSA	Greater Capital City Statistical Area
NOC	National Occupational Classification
OII	Occupational injury or illness
RCP	Representative Concentration Pathway
SWA	Safe Work Australia

access to heat safety interventions such as air conditioning (Binazzi et al., 2019; Ebi et al., 2021; Varghese et al., 2018). Heatwaves, when high temperatures occur over consecutive days, have been associated with increased occupational illnesses and injuries (OIIs) globally, including heat-related illnesses and general injuries such as falls (Binazzi et al., 2019; Ebi et al., 2021; Varghese et al., 2018). With global warming, heatwaves are expected to increase in frequency, duration and intensity (Ebi et al., 2021).

Heat-attributable illnesses and injuries induce considerable healthcare financial burden (Adélaïde et al., 2021; Wondmagegn et al., 2019). However, the economic impact of heatwave-attributable OIIs is unknown. Two studies estimated increasing work-related injury costs with higher temperatures in Guangzhou, China (Ma et al., 2019; Su et al., 2020) and one study in Spain (Martínez-Solanas et al., 2018). Decreased costs were observed following the introduction of workplace heat adaptation policies in Guangzhou (Su et al., 2020) and (for heat-related illnesses only) a heat stress awareness program in Texas (McCarthy et al., 2019). More studies have evaluated the economic impact of heat-induced labor productivity loss (Borg et al., 2021; Zhao et al., 2021), including during heatwaves (García-León et al., 2021; Orlov et al., 2019). Incorporating costs from OIIs can result in more comprehensive occupational economic burden estimates.

To the authors' knowledge, currently only two studies have estimated the projected impact of global warming on OIIs (Fatima et al., 2022, 2023). Understanding this risk can aid the development of heat-adaptation measures to reduce morbidity, mortality and associated costs. In Australia, heatwaves are responsible for substantial morbidity (Adnan et al., 2022) and are the most common cause of climate-related mortality (Varghese et al., 2018). To address these concerns and knowledge gaps in the literature, this study created a national retrospective and future cost profile of heatwave-attributable OIIs. This study also assessed the potential benefit of future heat adaptation.

2. Materials and methods

2.1. Data

2.1.1. Workers' compensation claims data

Workers' compensation claims data submitted from July 1, 2005 to June 30, 2019 representing seven Australian capital cities: Adelaide, Brisbane, Darwin, Hobart, Melbourne, Perth, and Sydney were collected from Safe Work Australia (SWA). SWA compiles national workers' compensation data from workers' compensation authorities in each Australian state and territory. Under Australian law, employers must have insurance to cover their workers if they become sick/injured because of work (Safe Work Australia, 2022a). Claims for OIIs are regularly submitted in the Australian financial year (July to June) following that of the OII, and payouts per claim can continue across multiple years. In this study, data were limited to OIIs occurring within a Greater Capital City Statistical Area (GCCSA) of the seven cities (Australian Bureau of Statistics, 2020a)) during the warm season (October to November) from July 1, 2005 to June 30, 2018 claims (not June 2019, because claims were regularly submitted one financial year after OII occurrence). We used on-duplicate OII claims pertaining to workers aged 15–75 years, and those submitted on the day or after the day of OII occurrence as in previous studies (Collie et al., 2016; Fatima et al., 2022; Gray and Collie, 2017; Newnam et al., 2019; Varghese et al., 2019a). OIIs occurring from July 2005 to June 2006 in Hobart were excluded from analysis, because claims submitted in Tasmania prior to July 2007 had missing location status. OII counts in Hobart from July 2006 to June 2007 were similar to those of other years and thus retained for analysis. Compensation policies and payout rates change over time and vary between cities but are generally similar. These differences are comprehensively described in online SWA annual publications (Safe Work Australia, 2019a).

Injuries and illnesses (diseases and conditions) were defined by Type of Occurrence Classification System codes A-G and H–R, respectively (Australian Safety and Compensation Council, 2009), and assessed collectively. For the 0.02% of claims where there was an overall negative claim cost (a financial gain, which can result from reimbursement of already-paid compensations) payments were adjusted to $0 so that they did not impact cost estimates. Payments were adjusted for inflation and standardized to the end of the 2018 financial year (April to June 2019) (Australian Bureau of Statistics, 2021). The 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 (Australian Bureau of Statistics, 2021). Payouts comprise compensation (paid to workers or their families), goods and services (mostly health services), and non-compensation (not paid to workers or their families) payments (Safe Work Australia, 2019b). Costs per OII (total costs divided by the number of OIIs) on days where at least one OII were reported were analyzed. To remove claims that may have had artificially decreased payouts due to occurring later in the study period, a supplementary analysis was performed only using claims submitted no later than June 2014 with payments restricted to up to five financial years after the financial year of claim submission. Ethics approval to access and analyze SWA data were obtained from the University of Adelaide Human Research Ethics Committee (H-2019-141 and H-2016-085).

2.1.2. Meteorological data

Retrospective hourly climate data were obtained from the Australian Bureau of Meteorology (BoM) Atmospheric high-resolution Regional Reanalysis (BARRA) to match the study period (Jakob et al., 2017). Results were projected to 2030 (2016–2045) and 2050 (2036–2065) using daily meteorological gridded data from Climate Change in Australia (Commonwealth Scientific and Industrial Research Organisation, 2021a) under Representative Concentration Pathway [RCP]4.5 and RCP8.5 using eight general circulation models (GCMs) described online (Commonwealth Scientific and Industrial Research Organisation, 2021b). From the retrospective and projected datasets, 3*3 12 km and 7*7 5 km grids, respectively, were extracted at grid centroids correlating to the center of the seven included cities' for study central business districts.

Heatwaves were defined using the BoM Excess Heat Factor (EHF). EHF defines Australian heatwaves nationally (Bettio et al., 2019; Borg et al., 2019) and can measure severity across different climate zones (Nairn et al., 2022, 2018; Nairn and Fawcett, 2014; Oliveira et al., 2022; Blesson M. Varghese et al., 2019). EHF is calculated using daily mean

temperature (DMT) averaged over the current and previous two days (DMT_{3days}) to represent heat that has already occurred (Nairn et al., 2009). DMT was calculated as the average of daily maximum and minimum temperatures within the same 9am-to-9am 24-h period. EHF is determined by two indices calculated separately for each city. The first index (EHI_{sig}) is DMT_{3days} subtract the 95th percentile for DMT (DMT_{95}) across the entire time period covered by the BARRA (January 1990 to February 2019) and (Nairn et al., 2022). EHF assumes long-term adaptation to this near-30 year period, and an approximate 30-year reference period is commonly selected for long-term climate change and climate variability assessments (World Meteorological Organization, 2018). The second index (EHI_{accl}) is DMT_{3days} subtract the averaged DMT over the preceding 30 days. This represents recent climate acclimatization up to 30 days (Nairn and Fawcett, 2014). EHI_{accl} values exceeding 1 °C represent non-acclimatized heat exposure within the last three days that correspond to increased heatwave severity perceived by people. EHF was calculated as the product of EHI_{sig} and the maximum of 1 or EHI_{accl} follows:

$$DMT_{3days} = (DMT_d + \mathrm{DMT}_{d-1} + DMT_{d-2}) \,/\, 3 \ (^{\circ}\mathrm{C})$$

$$EHI_{sig} = DMT_{3days} - DMT_{95} \ (^{\circ}\mathrm{C})$$

$$EHI_{accl} = DMT_{3days} - (DMT_{d-3} + \ldots + \mathrm{DMT}_{d-32}) \,/\, 30 \ (^{\circ}\mathrm{C})$$

$$EHF = EHI_{sig} * max(1, EHI_{accl}) \ \left[(^{\circ}\mathrm{C})^2\right]$$

Using the EHF definition, heatwave days occurred when DMT_{3days} exceeded DMT_{95}. At DMT_{95}, EHF is equal to 0 K ($^{\circ}C^2$), enabling only positive EHF values to represent heatwave days. Severe heatwaves occurred when EHF was at least equal to the 85th percentile of all positive EHF values. Extreme heatwaves were defined as at least twice this 85th percentile value (Blesson M. Varghese et al., 2019). Percentile based thresholds for heatwave conditions enable EHF to be specific for the given area's climate whilst allowing for comparisons between areas accommodating for their different climates (Nairn and Fawcett, 2014).

Sensitivity analyses were performed adding linear variables for relative and specific humidity, using a calculation of EHF using DMT_{3days} representing the current and future two days, and EHF using the heat index (Rothfusz, L, 1990) instead of air temperature. Calculations of humidity and heat index are detailed in Text A1: Humidity calculations.

2.1.3. Workers' population data

Monthly population employed worker counts stratified by city (GCCSA) were derived from the Australian Bureau of Statistics (ABS) labor force detailed survey data (Australian Bureau of Statistics, 2022a). As data for Darwin were unavailable, estimates were obtained by multiplying counts for Northern Territory (NT) by the proportion of NT workers in Darwin obtained with 3-monthly data that were interpolated to monthly data using cubic splines (Australian Bureau of Statistics, 2022a). Projected increases in future workforce sizes relative to 2017 were calculated as the ratio between the projected city populations for 2017–2044 to estimate 2030, and 2036–2065 to estimate 2050 (Australian Bureau of Statistics, 2018a). Projections assumed a medium-population growth scenario based on ABS-projected fertility, migration and mortality rates. High, low and unchanged (from baseline) population scenarios were included as sensitivity analyses (Australian Bureau of Statistics, 2018a).

2.2. Statistical analysis

Daily OIIs and associated costs, on the date of OII occurrence, were modeled against EHF as a continuous metric (Royé et al., 2020; Wondmagegn et al., 2021) per city using time-series distributed lag non-linear models (DLNMs) with a ten-day lag period (Gasparrini, 2011; Gasparrini and Armstrong, 2011). OIIs and costs were fitted using generalized linear and additive models, respectively, with a quasipoisson and Tweedie distribution, respectively (Dunn and Smyth, 2018). The Tweedie distribution is a reparameterisation of a Poisson-Gamma model to fit within a single distributional framework (Kurz, 2017; Smyth and Jørgensen, 2002). This distribution was selected to fit the highly right-skewed data including days with zero costs (which invalidates many continuous distributions such as Gamma) whilst retaining relative simplicity compared to two-part models in terms of clinical interpretation and the number of parameters (Kurz, 2017). Cost models converged using restricted maximum likelihood (Wood, 2011) and included the Tweedie index parameter with the largest likelihood value from 1.001 to 1.999 selected by series expansion (Dunn and Smyth, 2005).

The statistical model equation used was:

$$log[E(Y_t)] = cb(EHF_t) + DOW_t + PH_t + SH_t + D1_t + F_t + Sat$$
$$: (PH_t + SH_t + D1_t) + Sun$$
$$: (PH_t + SH_t + D1_t) + ncs(t) + offset(log(n)) + \alpha$$

$E(Y_t)$ is the expected number of OIIs or costs on day *t*. *Cb(EHF)* is the cross-basis natural cubic spline (ncs) function for EHF with one internal knot at the 50th percentile. Lag effects were modeled using a ncs over ten days with one knot at five days. *DOW* is the day of the week. *PH* is a binary variable indicating whether the day was a public holiday. *SH* designates each of the four school holidays periods, with no school holidays as the reference period (Borg, 2022a). The number of hours worked varies seasonally with school holidays (Australian Bureau of Statistics, 2020b). *D1* is a binary variable indicating whether the day was the first of the month (excluding New Year's Day), which was associated with more claims relative to other days, likely because OIIs with an unknown day of onset were reported as occurring on the first day. *F* is a factor variable designating the following days or periods that were highly influential on model fit: (1) 23rd-30th December, (2) New Year's Eve, (3) New Year's Day, (4) 2nd-4th January and (5) city-specific days for Adelaide (24th-30th June 2008, which had notably less OIIs than expected), Brisbane (the city-specific holidays of the Royal Queensland Show and 2014 G^{20} Leaders' Summit), Melbourne (the day before Melbourne Cup) and Sydney (Australia Day, which includes a public celebration at the Sydney Opera House). Interaction terms (":") were included with Saturday/Sunday and *PH*, *SH* and *D1*. *ncs(t)* is a ncs with 4 degrees of freedom (df) per year across the 13-year study period (12-year for Hobart), representing long-term trend. This was penalized for generalized additive models. *N* is the monthly workforce size, and α is a modeled intercept. Every Sunday is a public holiday in Adelaide (Borg, 2022b). Thus for Adelaide, *PH* was always zero on a Sunday and *Sun:PH* was excluded. Modeling decisions regarding exposure-/lag-response relationships and long-term trends were determined using Akaike information criterion (AIC) considering both the OII and cost models.

Individual city exposure-response relationships were pooled using random-effects multivariate meta-analysis to evaluate national (the seven cities combined) relationships and derive best linear unbiased predictors (BLUPs) from each model (Sera et al., 2019). Residual heterogeneity was assessed using the multivariate-extended Cochran Q test and I^2 statistic (Higgins and Thompson, 2002; Sera et al., 2019).

Attributable fractions (AF) and numbers (AN), as defined by Gasparrini et al. (Gasparrini et al., 2015; Gasparrini and Leone, 2014), were estimated per BLUP for heatwave days including stratification into low-intensity, severe and extreme heatwaves. Empirical 95% confidence intervals (95%eCI) assuming a multivariate normal distribution were created using 5000 Monte Carlo simulations (Australian Bureau of Statistics, 2018a). AFs and ANs were projected to 2030 and 2050 per RCP as GCM-ensemble averages by extrapolating exposure-response relationships using the projected climate dataset (Gasparrini et al., 2017; Vicedo-Cabrera et al., 2019). ANs were adjusted with the projected future workforce sizes per time period. Non-adaptation scenarios assumed an unchanged heatwave threshold (baseline DMT_{95}).

Theoretical 100% long-term climate adaptation (henceforth adaptation) scenarios were created by recalculating EHF using the DMT_{95} in the projected 30-year period as the heatwave threshold. This uses a non-arbitrary statistic inherent to EHF calculation assuming that workers have adapted to the projected climate instead of an arbitrary set value of adaptation, for example 10% (Rai et al., 2022; Vicedo-Cabrera et al., 2019).

Analyses for national, baseline AFs were conducted with data stratified by age, sex, indoor/outdoor status, occupation, and injuries and illnesses separately. Indoor/outdoor status was determined by two separate methods. The first method was based on workplace industry. Industries of agriculture, forestry and fishing", "construction", "electricity, gas and water" and "mining" were denoted as outdoor industries; all other industries were indoors (Australian Bureau of Statistics, 2022b; Varghese et al., 2019a; Xiang et al., 2016). The second method involved matching workers' occupations, as defined by the Australian and New Zealand Standard Classification of Occupations (ANZSCO) (Australian Bureau of Statistics, 2019), with their corresponding occupations from the Canadian National Occupational Classification (NOC) (Smith, 2013; Statistics Canada, 2019) as listed on figshare (Borg, 2022c). Both ANZSCO and NOC are derived from the International Standard Classification of Occupations (International Labour Organization, 2010). NOC occupations classified with an "L3 location" (having main duties with outdoor work for at least part of the working day), including occupations with multiple locations, were classified as outdoor. Occupations without this classification were analyzed as indoor workers (no outdoor work). Cross-matching was done for 6-digit ANZSCO occupations (the lowest level classification) which were then aggregated to 4-digit unit groups to match the SWA data. ANZSCO occupations associated with both indoor and outdoor NOC occupations were classified based on the more common classification, with indoors being selected in the event of a tie. The cross-matching of ANZSCO and NOC occupations used in this study was checked against two previous cross-matches used in previous Australian studies examining the relationship between temperature and OIIs (Fatima et al., 2022; McInnes et al., 2018, 2017; Varghese et al., 2019a, 2019b) derived from older ANZSCO and NOC versions (Smith, 2013; Varghese et al., 2019a). One of these cross-matches, the original cross-match, was validated with a strong correlation between ANZSCO and NOC for outdoor work (Smith, 2013). Stratifying by occupations instead of industry is less likely to misclassify indoor/outdoor status but is less commonly used for assessing outcomes from occupational heat stress (Borg et al., 2021; Varghese et al., 2019a).

All analyses were performed using R version 4.2.1 (Team, 2021). DLNMs, GAMs, Tweedie distributions, Tweedie index parameters, multivariate meta-regression models and attributable risk were modeled or calculated with the *dlnm*, *mcgv*, *tweedie*, *statmod*, *mixmeta* and *FluMoDL* packages, respectively (Dunn, 2017; Dunn and Smyth, 2005; Gasparrini, 2011; Lytras, 2019; Sera et al., 2019; Smyth, 2002; Wood et al., 2017). The code for analysis is available upon reasonable request. A reproducible example is available at the first author's GitHub page (https://github.com/mtthwborg/2023_Borg_HW/). Ethics approval to access and analyze SWA data were obtained from the University of Adelaide Human Research Ethics Committee (H-2019-141 and H-2016-085).

3. Results

3.1. Descriptive statistics

The cities' averaged DMT across the study period ranged from 14 to 29 °C (Table 1). Darwin had the highest value and lowest variance, reflective of its tropical climate. Across cities, there was an approximately similar spread of heatwave days, including severe and extreme heatwaves, across cities (Table A.1). Projected climate data generally had more heatwave days annually with lower 50th and 85th positive EHF values compared to baseline in non-adaptation scenarios, and similar or slightly less days in adaptation scenarios (Table A.2). Darwin was an exception, with higher positive EHF values and considerably more heatwave days.

Overall 1,208,004 claims were included for analysis. Details on excluded claims are in Table A.3. Claim payouts totaled to AU$22 billion (Table A.4). Approximately 60%, 30% and 11% of financial payouts covered compensation payments, goods and services (predominantly health services), and non-compensation costs, respectively. Details on national demographics and claim statistics are included in Table A.5. The number of OIIs gradually decreased across successive financial years, whereas associated costs gradually increased up to the 2009 financial year and then decreased. Most payouts occurred in the same or subsequent financial year as the date of claim submission. Injuries were 3.3 times more common than illnesses, but illnesses had on average a 1.6 higher cost per OII ratio.

3.2. Overall cumulative relationships

As EHF increased, OIIs gradually increased across all days with a similar pattern observed with associated costs during heatwaves (Fig. 1). Approximately identical relationships were observed with costs stratified into compensation and goods and services but with larger confidence intervals; a non-significant relationship was observed with non-compensation costs. City-level relationships were similar to the national relationships for OIIs (Fig. 2), and also costs during heatwave but not non-heatwave days (Fig. 3). During heatwaves, the risk of OIIs during heatwaves was elevated throughout the ten-day lag period, although slightly higher in the first few days (Figure A1). For costs, a significant relationship was only observed five to ten days after exposure (Figure A2).

Heterogeneity was not detected in the OII meta-analysis (Cochran Q-statistic = 12.06, df = 12, P-value = 0.44). Substantial heterogeneity was detected with the cost models (Cochran Q-statistic = 39.11, df = 12, P-value = 0.0001, I^2 = 69.32%). Comparing city-level overall exposure-response relationships with and without BLUPs highlighted large statistical shrinkage (estimates pulled towards the national exposure-response relationship) in Adelaide, Darwin, and Hobart (Figure A3).

Table 1
Descriptive meteorological factors per city.

City	Average DMT (SD)	DMT_{95}	EHF_{50p}	EHF_{85p}	$2*EHF_{85p}$	Köppen climate
Adelaide	19.67 (5.10)	26.51	12.29	34.31	68.62	Mediterranean hot summer
Brisbane	24.05 (2.54)	27.28	1.93	7.23	14.45	Humid subtropical
Darwin	29.08 (0.77)	30.02	0.20	0.54	1.08	Tropical savanna climate with dry-winter characteristics
Hobart	14.07 (3.89)	18.79	6.30	17.35	34.70	Marine west coast
Melbourne	19.24 (4.63)	25.23	6.86	25.97	51.93	Marine west coast
Perth	22.08 (4.53)	27.97	5.02	20.72	41.44	Mediterranean hot summer
Sydney	22.08 (3.46)	26.24	4.01	11.01	22.01	Humid subtropical

Daily mean temperature (DMT), standard deviation (SD), 95th percentile of DMT (DMT_{95}), 50th (EHF_{50p}) and 85th percentiles (EHF_{85p}) of all positive EHF values, twice the EHF_{85p} value ($2*EHF_{85p}$), and Köppen climate zones per city. DMT is expressed in °C, and EHF is expressed in °K (°C^2). DMT_{95} is the heatwave threshold (°C), and EHF_{85p} and $2*EHF_{85p}$ are the severe and extreme heatwave thresholds (°K), respectively.

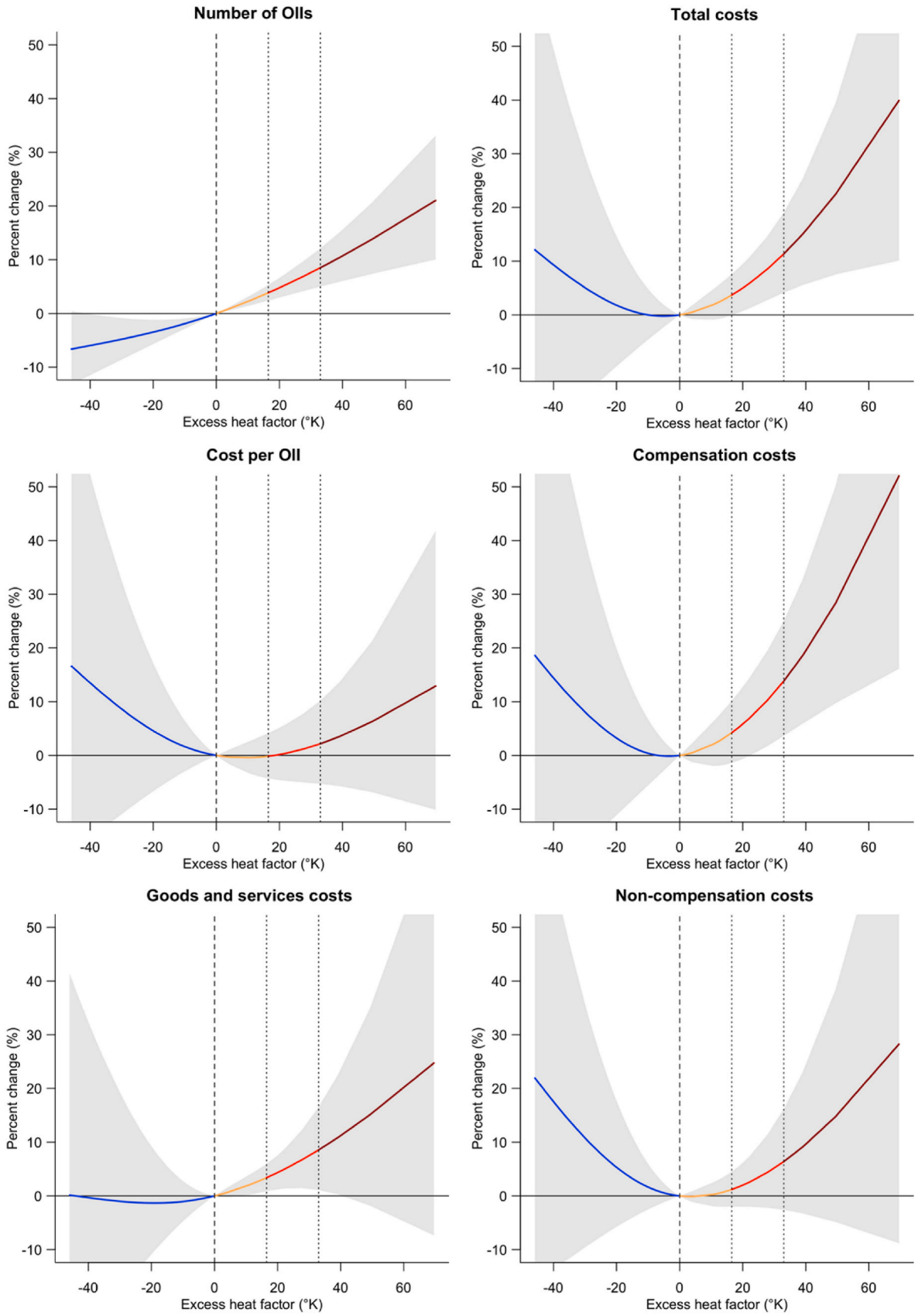

Fig. 1. Overall cumulative exposure-response relationships. Overall cumulative exposure-response curves pooled nationally. The curves with 95% confidence intervals represent percentage change in the number of occupational injuries and illnesses (OIIs), total costs, costs per OII, compensation costs, goods and services costs, and non-compensation costs against excess heat factor. The dashed lines from left to right represent the thresholds for heatwaves, severe heatwaves and extreme heatwaves.

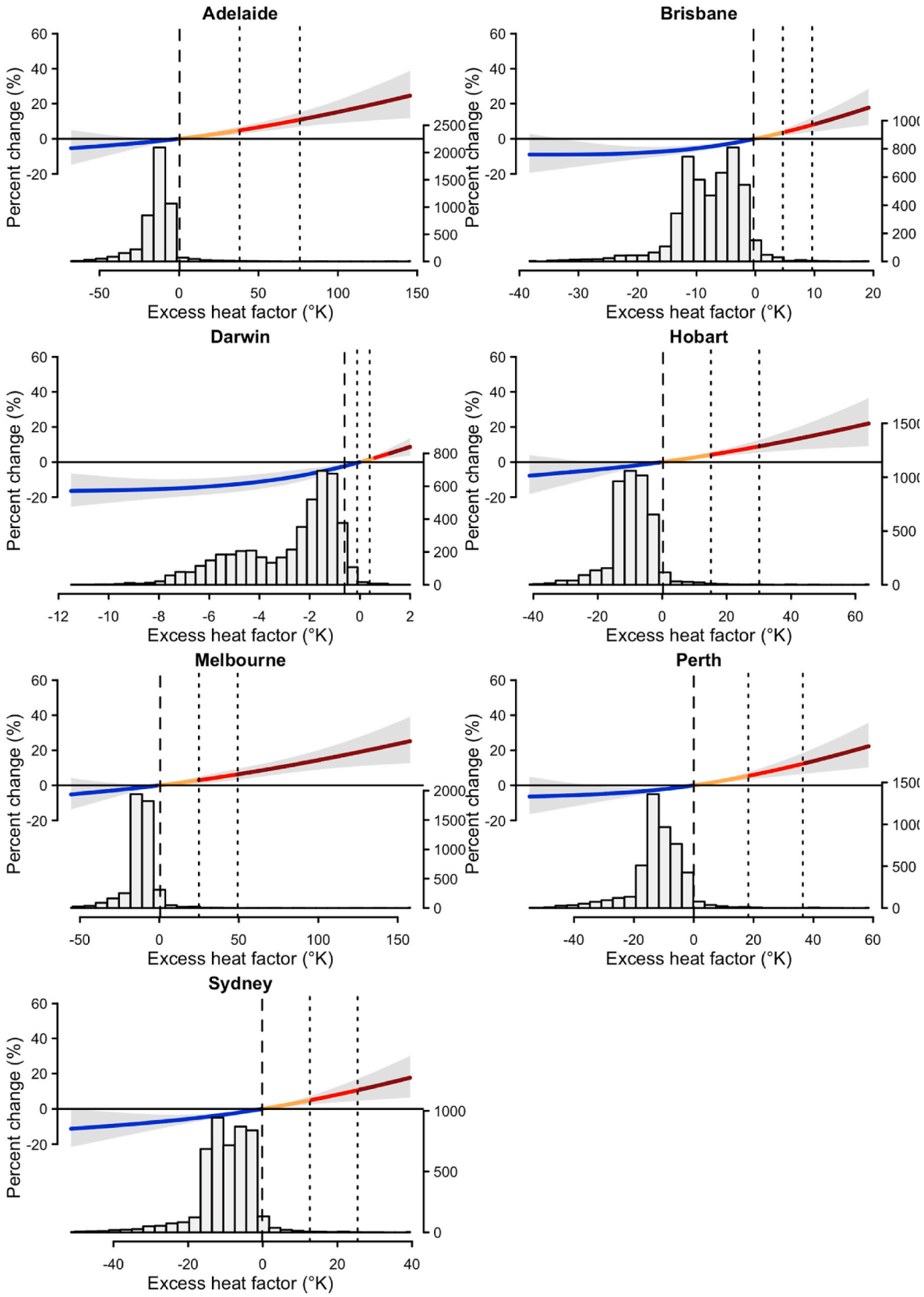

Fig. 2. Overall exposure-response relationships per city for the daily number of occupational injuries and illnesses.
Overall cumulative exposure-response relationships for occupational injuries and illnesses in Adelaide, Brisbane, Darwin, Hobart, Melbourne, Perth and Sydney. The curves with 95% confidence intervals represent percentage change in the number of occupational injuries and illnesses against Excess Heat Factor. The dashed lines from left to right represent the thresholds for heatwaves, severe heatwaves and extreme heatwaves.

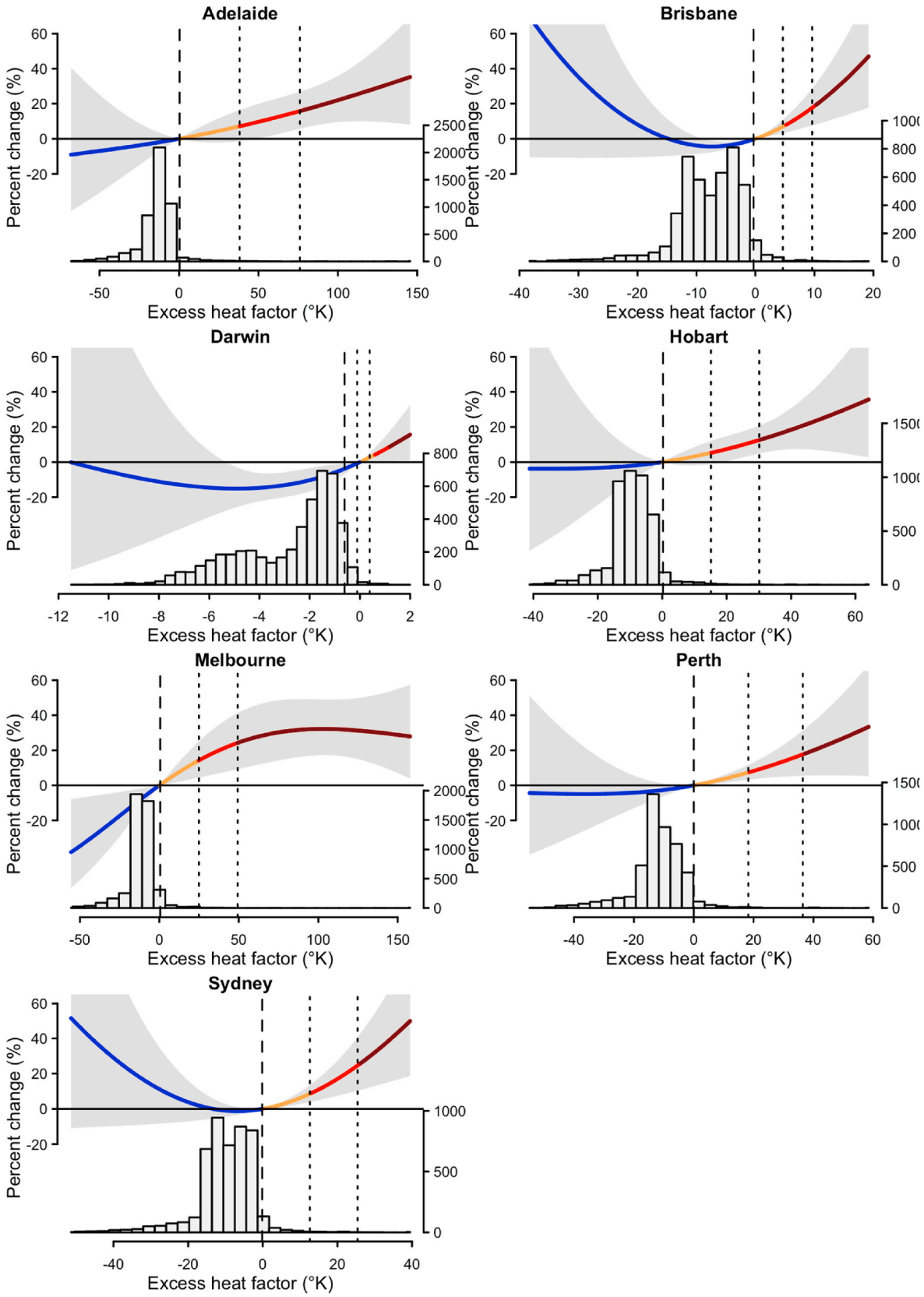

Fig. 3. Overall exposure-response relationships per city for daily occupational injury- and illness-associated costs.
Overall cumulative exposure-response relationships for occupational injury- and illness-associated costs in Adelaide, Brisbane, Darwin, Hobart, Melbourne, Perth and Sydney. The curves with 95% confidence intervals represent percentage change in costs against Excess Heat Factor. The dashed lines from left to right represent the thresholds for heatwaves, severe heatwaves and extreme heatwaves.

3.3. Attributable risk

About 0.129% (95% eCI: 0.106–0.164%) of all OIIs were heatwave-attributable (Fig. 4, estimates listed in Table A.6). Generally similar OII-AFs were observed across all cities although Perth and Darwin had relatively higher and lower AFs, respectively. 0.252% (95% eCI: 0.184–0.342%) of costs were heatwave-attributable. Cost-AFs for heatwaves generally were significant in all cities except Adelaide and Hobart, although these cities had significant AFs for extreme heatwaves (and severe heatwaves in Hobart) (Fig. 4, estimates listed in Table A.7). Cost-AF estimates were lowest in Darwin. The other four cities had similar estimated cost-AFs. Most OIIs and costs were attributable to low-intensity heatwaves. Collectively, 1556 (95% eCI: 1286–1,984, Table 2) OIIs and AU$56 million (95% eCI: 41–76 million, Table 3) were observed, equal to 120 OIIs and AU$4.3 million annually.

Without adaptation, OII-AFs nationally were projected to slightly increase relative to baseline to 0.137% (95% eCI: 0.084–0.195) and 0.151% (95% eCI: 0.091–0.222) by 2030 under RCP4.5 and 8.5, respectively (Fig. 5), representing 162 and 179 additional OIIs annually, respectively. These increased further to 0.176% (95% eCI: 0.104–0.265) and 0.228% (95% eCI: 0.125–0.370) by 2050 under RCP4.5 and 8.5, respectively, representing 270 and 349 OIIs yearly, respectively. Most cities had similar increases in OII-AF, although Brisbane and Sydney had a slight decrease in 2030s under RCP4.5, and tropical city Darwin had projected increases in AF 17 times greater than baseline.

National projected cost-AFs were 0.153% (95%eCI: (−0.062 to 0.345) and 0.150% (95%eCI: 0.118 to 0.392) by 2030 under RCP4.5 and 8.5, respectively, and 0.127% (95%eCI: 0.270 to 0.461) and 0.044% (95%eCI: 0.662 to 0.598) in 2050 under RCP4.5 and RCP8.5, respectively. Significant AFs were projected for extreme heatwaves nationally in 2030 under both RCP4.5 (0.040%, 95%eCI: 0.015–0.057%) and RCP8.5 (0.038%, 95%eCI: 0.011–0.069) but not 2050 (RCP4.5: 0.040%, 95%eCI: 0.012 to 0.087%, and RCP8.5: 0.038%, 95%eCI: 0.094 to 0.143). These projected cost-AF estimates were approximately 66–80% the size those at baseline. In 2030, costs from extreme heatwaves represent AU$768 k and AU$830 k under RCP4.5 and RCP8.5, respectively. Cost-AFs were projected to increase in both 2030 and 2050 in Melbourne and Perth, with slight increases relative to baseline.

With adaptation, both OII- and cost-AFs were similar across RCPs and time periods, and were slightly smaller than baseline in most cities, although they approximately doubled in Darwin (Fig. 6, estimates listed in Tables A.8 and A.9). Cost-AFs assuming adaptation for heatwaves

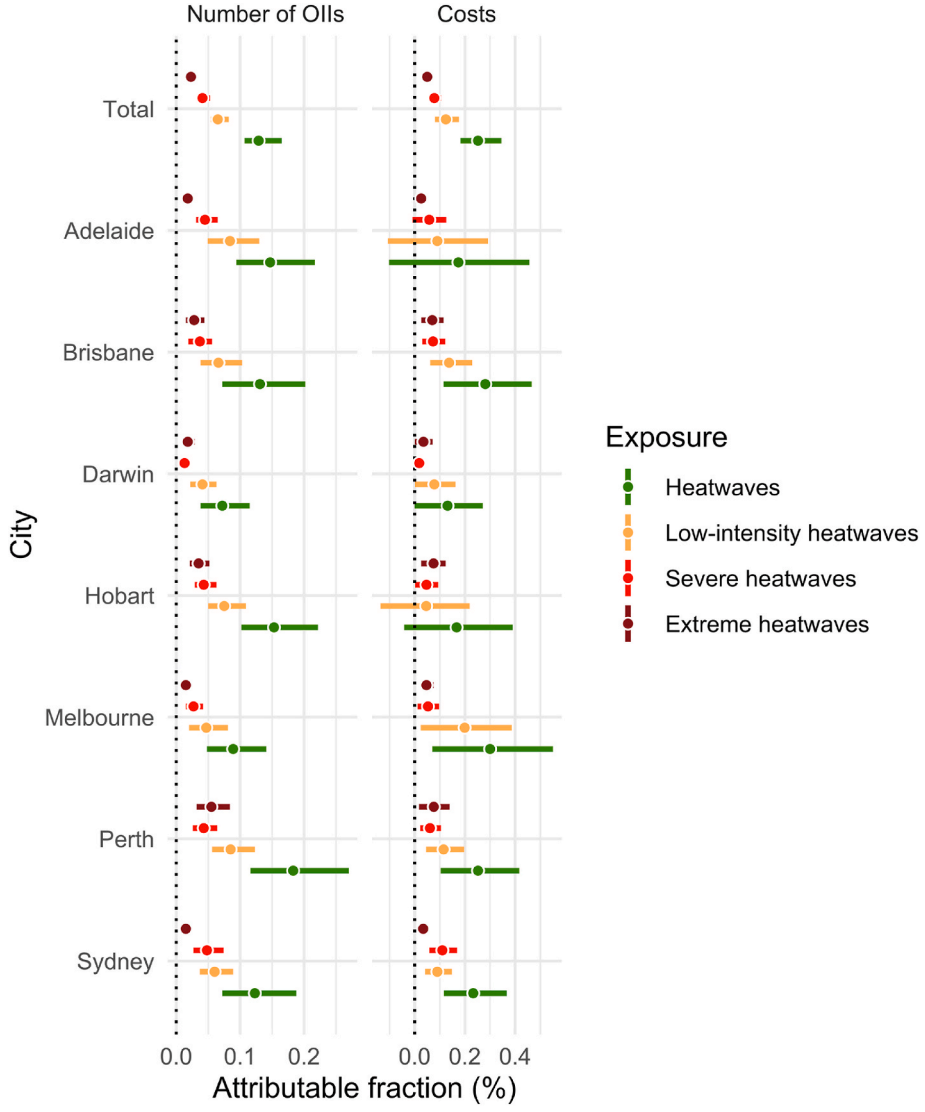

Fig. 4. Heatwave-attributable fractions for occupational injuries/illnesses and associated costs.
The proportion of the number of occupational injuries/illnesses (OIIs) and associated costs attributable to heatwaves, with 95% empirical confidence intervals. Results are included for all heatwaves as well as its constituents: low-intensity, severe and extreme heatwaves.

Table 2
Number of occupational injuries and illnesses attributable to heatwaves per year.

Location	Period	RCP	Heatwaves	Low-intensity heatwaves	Severe heatwaves	Extreme heatwaves
Total	Baseline	NA	119.90 (70.92–182.38)	60.16 (35.04–92.04)	37.97 (22.10–57.85)	21.76 (12.38–33.14)
	2030	4.5	162.10 (98.73–229.68)	84.56 (48.90–121.63)	51.88 (31.37–74.66)	25.66 (14.31–40.69)
		8.5	178.27 (107.33–261.97)	91.30 (52.72–134.99)	56.96 (34.05–84.22)	30.01 (16.30–49.16)
	2050	4.5	269.82 (159.33–406.02)	134.88 (73.56–205.77)	86.40 (51.72–127.66)	48.55 (27.22–84.40)
		8.5	349.40 (190.87–566.42)	167.55 (80.97–276.02)	108.92 (63.55–167.80)	72.93 (37.62–132.51)
Adelaide	Baseline	NA	15.11 (9.64–22.22)	8.64 (4.98–13.29)	4.64 (3.16–6.70)	1.84 (1.19–2.64)
	2030	4.5	19.73 (10.85–28.93)	12.16 (5.70–18.54)	6.16 (3.71–8.78)	1.41 (0.68–3.25)
		8.5	20.66 (11.12–31.27)	12.44 (5.61–19.46)	6.52 (3.66–10.27)	1.69 (0.77–2.86)
	2050	4.5	25.54 (13.30–39.86)	15.18 (6.63–24.20)	8.42 (4.65–13.67)	1.95 (0.97–3.35)
		8.5	29.44 (14.25–47.37)	16.56 (6.36–27.49)	10.11 (5.27–16.97)	2.78 (1.52–4.50)
Brisbane	Baseline	NA	20.34 (11.28–31.48)	10.31 (5.90–16.00)	5.70 (3.01–8.80)	4.33 (2.26–6.80)
	2030	4.5	25.56 (14.69–41.55)	10.84 (6.12–17.40)	7.94 (4.35–14.10)	6.78 (3.63–10.75)
		8.5	30.30 (17.61–45.74)	12.42 (7.02–19.09)	9.96 (5.56–15.26)	7.92 (4.22–12.28)
	2050	4.5	46.26 (27.04–74.22)	18.54 (9.72–30.39)	14.94 (8.74–22.57)	12.78 (7.10–22.62)
		8.5	66.39 (33.21–121.46)	26.46 (10.73–50.15)	19.13 (10.02–34.01)	20.80 (10.37–38.65)
Darwin	Baseline	NA	0.45 (0.24–0.72)	0.25 (0.14–0.39)	0.08 (0.04–0.13)	0.11 (0.06–0.18)
	2030	4.5	9.84 (5.75–14.42)	1.05 (0.57–1.56)	2.59 (1.56–3.70)	6.20 (3.27–10.07)
		8.5	11.06 (6.50–17.21)	1.03 (0.53–1.53)	2.68 (1.58–3.85)	7.36 (3.98–12.59)
	2050	4.5	18.20 (10.56–27.62)	1.20 (0.47–1.92)	3.46 (1.68–5.17)	13.54 (7.61–21.84)
		8.5	22.68 (11.64–37.67)	0.94 (0.15–1.74)	3.24 (0.90–5.36)	18.50 (9.47–31.88)
Hobart	Baseline	NA	2.83 (1.88–4.11)	1.39 (0.92–2.02)	0.80 (0.53–1.16)	0.64 (0.39–0.96)
	2030	4.5	3.43 (1.58–5.36)	1.54 (0.47–2.64)	1.14 (0.53–1.81)	0.76 (0.47–1.05)
		8.5	3.79 (1.69–6.39)	1.70 (0.49–3.12)	1.24 (0.56–2.14)	0.85 (0.50–1.29)
	2050	4.5	5.04 (2.00–9.84)	2.23 (0.51–4.79)	1.67 (0.71–2.93)	1.15 (0.61–2.26)
		8.5	5.65 (2.05–10.08)	2.50 (0.44–4.94)	1.83 (0.71–3.15)	1.32 (0.69–2.12)
Melbourne	Baseline	NA	15.60 (8.36–24.82)	8.24 (3.44–14.16)	4.68 (2.64–7.34)	2.67 (1.80–3.80)
	2030	4.5	21.46 (10.41–34.09)	11.84 (4.59–19.44)	6.55 (3.19–12.41)	3.07 (1.81–4.67)
		8.5	22.99 (10.92–37.34)	12.32 (4.61–20.53)	7.37 (3.61–13.35)	3.30 (2.00–4.85)
	2050	4.5	35.11 (15.89–59.11)	18.77 (6.42–32.94)	11.34 (5.48–20.43)	5.00 (2.88–7.27)
		8.5	42.31 (17.36–72.83)	21.94 (6.49–38.37)	14.20 (6.28–26.14)	6.17 (3.49–10.70)
Perth	Baseline	NA	22.71 (14.45–33.48)	10.54 (6.97–15.33)	5.30 (3.25–7.93)	6.86 (3.92–10.44)
	2030	4.5	32.41 (19.67–46.07)	15.49 (9.34–22.12)	12.14 (7.14–17.43)	4.79 (2.50–7.81)
		8.5	32.92 (18.65–49.14)	15.90 (9.21–24.19)	12.36 (6.54–18.26)	4.66 (2.33–7.68)
	2050	4.5	50.77 (29.26–72.65)	24.37 (13.82–36.00)	18.42 (10.10–26.19)	7.98 (4.10–12.02)
		8.5	58.94 (34.13–87.71)	27.78 (14.85–42.57)	20.53 (12.36–29.68)	10.63 (4.97–18.34)
Sydney	Baseline	NA	42.86 (25.08–65.54)	20.78 (12.71–30.84)	16.77 (9.45–25.80)	5.31 (2.75–8.33)
	2030	4.5	47.08 (27.70–69.40)	30.08 (17.82–44.57)	14.50 (7.82–22.61)	2.50 (0.90–6.22)
		8.5	53.90 (31.80–82.45)	33.89 (20.61–50.81)	15.95 (8.61–25.61)	4.06 (1.01–10.03)
	2050	4.5	84.09 (48.81–129.27)	50.80 (29.87–76.30)	26.38 (14.92–39.28)	6.91 (2.22–19.87)
		8.5	118.78 (66.30–201.93)	67.28 (36.52–113.33)	37.71 (21.89–57.84)	13.80 (4.67–35.88)

The number of annual occupational injuries and illnesses attributable to heatwaves across to 2016–45 and 2036–65 centered at 2030 and 2050 with 95% empirical confidence intervals. Projected results do not assume climate adaptation. NA: not applicable, RCP: Representative Concentration Pathway.

were generally non-significant in all cities except for Melbourne (similar to baseline) and Perth (slightly smaller than baseline).

Sensitivity analysis showed different modeling choices regarding parameters and inclusion of humidity led to similar baseline, national AFs (Table A.10). Cost-AFs lowered when only assessing claims submitted no later than June 2014 with payments restricted to up to five financial years post-claim submission but remained significant. ANs under high, low and unchanged population scenarios without adaptation are listed in Table A.11.

3.4. Claim characteristics

Baseline OII-AFs were similar across different sexes, age groups and industries (indoor vs outdoor) with a slightly higher AF in the 15–29 age group (Table 4). Across occupations, indoor occupations, “clerical and administrative workers,” “laborers” and “machinery operators and drivers” had higher OII-AFs, with heatwave-preventable fractions (negative AFs) observed in “professionals.” Illnesses had higher OII-AFs compared to injuries.

Differences across demographic and OII characteristics were generally more pronounced in cost-AFs than OII-AFs. Cost-AFs were highest with females, the 30–49 years age group, indoor workers, and illnesses. Apart from indoor/outdoor classification, there was insufficient power to compare cost-AFs across occupations.

4. Discussion

To the authors’ knowledge, this is the first study internationally to evaluate the impact of heatwaves on OIIs alongside associated economic costs and project their future impact from climate change. Increased OIIs and costs were observed during heatwaves at baseline, and projected future increases were predicted for OIIs, with some evidence for increases in costs at least during extreme heatwaves. The EHF inherently incorporates heatwave presence, heatwave severity, and climate acclimatization, and long-term adaptation was explored through updating the heatwave threshold.

Workplace and broader public health heat adaptation measures can reduce morbidity from OIIs and associated costs to employees, employers and governments. This impact is likely to increase with global warming, as evidenced by increased projected AFs for OIIs in 2030 and particularly 2050. Workplace interventions for heatwaves include easy access to hydration, shade, air conditioning and (if required) medical services, reduced or no work hours, and minimizing radiant workplace-generated heat (Borg et al., 2021; Jay et al., 2021). Public health measures include guidelines and legislation to implementing workplace interventions and educational messages highlighting awareness and prevention of occupational heat stress. As AFs for OIIs were generally similar across different cities and worker characteristics, adaptation measures should be aimed at the national, general working population. Although relative risks for both OIIs and costs were higher during heatwave days with greater severity compared to days with lower

Table 3
Heatwave-attributable costs secondary to occupational injuries and illness per year.

Location	Period	RCP	Heatwaves	Low-intensity heatwaves	Severe heatwaves	Extreme heatwaves
Total	Baseline	NA	4292.8 (1430.7–7434.5)	2107.1 (477.3–3932.1)	1336.4 (534.7–2224.0)	849.3 (342.6–1386.5)
	2030	4.5	3313.2 (−1332.4–7445.1)	1312.4 (−1937.4–4214.3)	1232.8 (50.3–2344.0)	768.0 (317.0–1239.9)
		8.5	3239.4 (−2549.0–8463.4)	1178.5 (−2687.3–4606.9)	1230.5 (−291.9–2629.1)	830.4 (245.1–1485.4)
	2050	4.5	3552.5 (−7583.5–12,922.5)	929.8 (−6090.5–6849.4)	1509.2 (−1385.8–3971.5)	1113.6 (−347.9–2437.8)
		8.5	1226.6 (−18559.7–16,771.6)	−870.2 (−12381.0–8144.2)	1042.4 (−3852.6–4964.6)	1054.4 (−2650.0–4003.9)
Adelaide	Baseline	NA	236.8 (−139.5–621.2)	122.5 (−146.1–398.0)	78.4 (−12.8–171.0)	35.8 (15.5–59.0)
	2030	4.5	303.4 (−319.8–879.4)	175.1 (−319.5–626.8)	102.6 (−33.6–226.5)	25.7 (8.2–61.7)
		8.5	315.0 (−359.2–967.5)	177.1 (−343.8–672.0)	107.0 (−43.8–265.4)	30.9 (10.0–57.8)
	2050	4.5	386.4 (−477.4–1217.1)	214.0 (−452.0–839.0)	137.3 (−62.4–348.1)	35.1 (12.4–66.0)
		8.5	436.0 (−662.8–1478.6)	226.5 (−579.0–974.0)	160.5 (−118.3–451.5)	49.0 (17.1–89.6)
Brisbane	Baseline	NA	983.0 (401.9–1631.4)	480.9 (217.4–802.0)	255.9 (104.2–427.3)	246.2 (96.0–401.4)
	2030	4.5	183.3 (−837.5–972.6)	−116.2 (−786.5–384.4)	61.1 (−260.7–327.4)	238.3 (100.7–400.3)
		8.5	−9.6 (−1529.9–1070.7)	−248.9 (−1187.5–438.3)	1.6 (−498.5–353.7)	237.8 (77.1–379.9)
	2050	4.5	−478.7 (−3520.9–1584.4)	−614.8 (−2357.4–665.9)	−147.9 (−1107.3–515.8)	284.0 (−109.5–518.1)
		8.5	−1947.6 (−8597.8–2284.1)	−1505.6 (−5220.5–950.0)	−576.6 (−2545.2–657.1)	134.7 (−897.0–756.9)
Darwin	Baseline	NA	20.4 (−0.1–42.1)	12.2 (0.1–25.2)	2.7 (−0.1–5.6)	5.5 (0.0–11.0)
	2030	4.5	219.6 (−288.9–646.1)	10.3 (−82.4–92.2)	41.3 (−149.7–194.4)	168.0 (−66.8–391.6)
		8.5	204.0 (−550.1–831.8)	4.2 (−107.0–104.5)	28.3 (−221.7–233.4)	171.5 (−231.8–525.2)
	2050	4.5	190.6 (−1583.9–1604.5)	−11.1 (−192.8–156.2)	−4.1 (−457.9–377.9)	205.8 (−971.8–1119.5)
		8.5	−72.7 (−3794.9–2681.3)	−25.9 (−225.3–156.9)	−65.4 (−729.8–478.6)	18.6 (−2889.3–2096.9)
Hobart	Baseline	NA	47.1 (−11.9–109.7)	12.9 (−38.2–61.5)	13.2 (0.6–26.5)	21.1 (7.2–34.7)
	2030	4.5	−24.1 (−289.0–199.9)	−25.9 (−179.7–109.7)	−6.2 (−93.7–64.0)	8.0 (−16.9–27.7)
		8.5	−30.0 (−341.9–235.5)	−30.7 (−212.0–129.5)	−7.5 (−107.4–73.5)	8.2 (−23.5–33.8)
	2050	4.5	−55.5 (−556.5–333.8)	−48.5 (−335.1–182.1)	−15.0 (−169.0–101.4)	7.9 (−53.8–54.8)
		8.5	−76.1 (−654.9–381.2)	−61.1 (−383.2–207.1)	−21.4 (−203.9–115.3)	6.3 (−69.0–61.1)
Melbourne	Baseline	NA	997.2 (231.7–1830.7)	662.9 (80.0–1282.7)	176.7 (39.4–323.7)	157.6 (74.9–249.7)
	2030	4.5	1406.5 (295.5–2603.6)	917.0 (132.1–1705.0)	388.8 (93.5–862.5)	100.7 (45.9–176.6)
		8.5	1542.5 (317.1–2919.4)	981.9 (143.1–1850.1)	448.5 (108.2–946.0)	112.0 (52.0–195.0)
	2050	4.5	2447.1 (449.3–4821.6)	1548.7 (193.7–3067.5)	716.6 (156.7–1524.4)	181.9 (77.1–309.4)
		8.5	3106.2 (504.2–6136.1)	1906.8 (203.7–3671.7)	952.1 (184.7–2041.4)	247.3 (97.4–553.3)
Perth	Baseline	NA	591.4 (241.0–975.5)	270.1 (107.7–461.6)	142.2 (50.5–243.8)	179.1 (39.4–326.1)
	2030	4.5	759.4 (174.6–1347.5)	338.6 (−63.2–732.7)	291.3 (105.2–480.0)	129.5 (40.2–229.1)
		8.5	762.3 (153.1–1472.0)	342.1 (−94.0–823.4)	294.6 (102.8–509.5)	125.7 (37.7–222.1)
	2050	4.5	1144.4 (37.3–2300.0)	504.3 (−297.4–1318.0)	429.3 (114.0–754.2)	210.8 (73.0–347.7)
		8.5	1276.5 (−260.4–2870.6)	543.3 (−549.6–1632.7)	463.2 (43.5–891.0)	270.0 (93.0–499.6)
Sydney	Baseline	NA	1416.9 (707.6–2223.7)	545.7 (256.4–901.0)	667.3 (352.8–1026.0)	203.9 (109.5–304.7)
	2030	4.5	470.8 (−586.0–1336.8)	22.1 (−871.8–703.6)	350.8 (77.8–643.7)	97.9 (41.2–210.3)
		8.5	463.2 (−1284.3–1577.9)	−37.2 (−1433.4–781.9)	356.1 (−86.4–728.8)	144.3 (45.7–280.9)
	2050	4.5	−8.4 (−3563.5–1986.0)	−614.4 (−3443.2–963.9)	397.1 (−430.8–929.5)	208.9 (81.6–451.4)
		8.5	−1423.2 (−8076.1–1980.8)	−1887.3 (−7031.2–819.7)	133.3 (−1432.8–892.5)	330.9 (120.9–667.4)

Annual costs secondary to occupational injuries and illnesses attributable to heatwaves across to 2016–45 and 2036–65 centered at 2030 and 2050 with 95% empirical confidence intervals. Costs are presented per AU$1000 dollars. Projected results do not assume climate adaptation. NA: not applicable, RCP: Representative Concentration Pathway.

severity, severe and extreme heatwave days were associated with lower AFs. This was because there were fewer severe and extreme heatwave days compared to lower-intensity heatwave days. It is recommended that interventions be applied during all heatwave days in order to minimize the heatwave-attributable burden.

Adaptation was estimated to result in relatively lower future OII- and cost-AFs in most cities that were relatively consistent across time periods and RCPs compared to non-adaptation scenarios. This study assumed a theoretical 100% adaptation rate irrespective of cause (e.g. workplace or lifestyle changes, physiological long-term adaptation). A partial adaptation scenario in between that of the non-adaptation and adaptation scenarios is more likely to occur. Although most projected AFs assuming adaptation were lower than baseline, this likely represents the baseline EHF heatwave threshold which incorporates 15 years (1990–2005) of climate observations occurring before the study period (2005–2018). These AFs would likely be more similar if claims data during those 15 years were available and assessed. Climate mitigation (RCP4.5 compared to RCP8.5) was projected to reduce OII-AFs in no-adaptation scenarios. Given that 100% adaptation is an unlikely scenario, limiting greenhouse gas emissions would likely help prevent future OIIs.

The groups with higher cost-AFs include females, middle-aged workers, and indoor employees. This may reflect increased risks of more severe heat-attributable OIIs. Females have been linked with lower sweat rates (Notley et al., 2017), reduced heat loss during exercise (Notley et al., 2019) and reduced water intake during work (to avoid using a toilet for hygienic reasons) (Venugopal et al., 2016). Middle-aged workers may have longer working hours, because younger workers are more likely to prioritize secondary or tertiary education over work, and older workers may reduce worktime as they approach retirement. Longer working hours require larger compensation payments from worktime loss (Safe Work Australia, 2022b). Indoor workers are often overlooked as being at risk of heat-associated OII. Australian outdoor workers are more often targeted by heat-minimization strategies (Safe Work Australia, 2021.) that may reduce the incidence of severe heatwave-attributable OIIs associated with larger costs.

Although there was substantial heterogeneity across the cost models, the BLUPs still reflect study-specific estimates improved by utilizing information from the other cities (Aert et al., 2021). The seven cities for analysis include 97% of the metropolitan workforce (Australian Bureau of Statistics, 2022a) and hence clinically represent the Australian national metropolitan workforce. Due to the heterogeneity, results are more likely to differ when pooling results with different datasets (or without pooling) than those used in this study, particularly for Adelaide, Darwin and Hobart, the three smallest capital cities.

Larger AF estimates were observed for Darwin, both with and (especially) without adaptation. Although EHF can accurately capture the climate in most Australian cities and partially incorporates humidity through minimum daily temperature (Nairn and Fawcett, 2014), it cannot fully capture Darwin's high tropical humidity and very humid heatwaves (Nairn et al., 2022). This was evidenced at baseline by

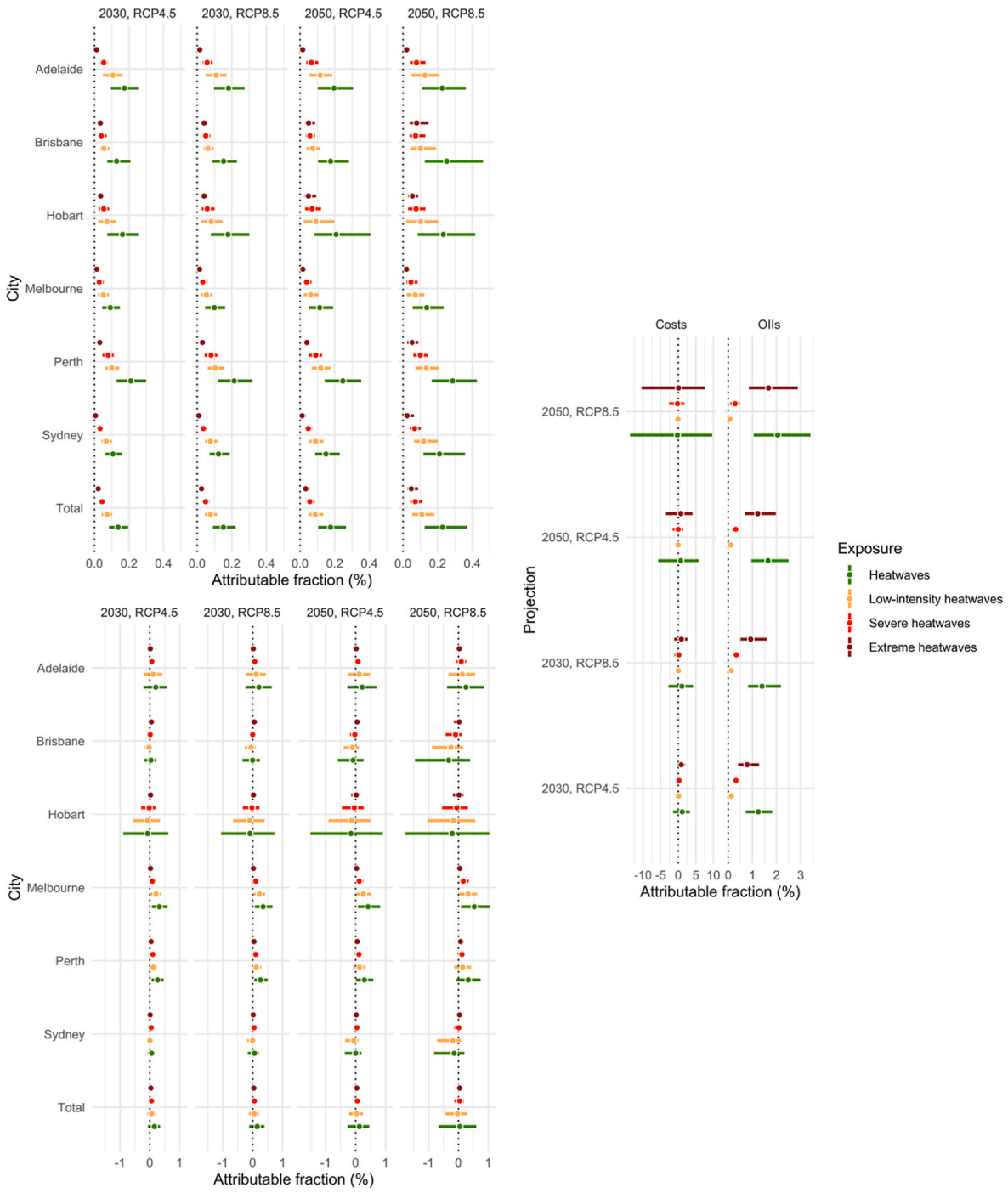

Fig. 5. Projected attributable fractions for heatwave-attributable OIIs and associated costs without climate adaptation.
The proportion of the number of occupational injuries and illnesses (OIIs) and associated costs attributable to heatwaves, with 95% empirical confidence intervals. Results are included for all heatwaves as well as its constituents: low-intensity, severe and extreme heatwaves.

Darwin's little air temperature variation, lower positive EHF values, and smaller AF estimates. Consequently, there was a large increase in the projected number of heatwave days due to global warming. Caution is therefore required when interpreting projected attributable risk in Darwin and other highly tropical areas; alternative heatwave metrics should be researched for more accurate evaluations in these areas.

The primary study limitation is that the claims data only include reported OIIs. Mild OIIs are less likely to be reported (Australian Bureau of Statistics, 2018b); thus the true quantity of OIIs and associated costs is likely underrepresented. Data for workers not covered by state compensation schemes, in particular self-employed workers and those with separate private schemes that partially or completely cover payments, are not collected (Safe Work Australia, 2022b). Compensation payments due beyond the study period would not be captured in collected data for said claims, particularly affecting claims submitted later in the study period. This was partially addressed with a supplementary analysis. However, most payments occurred in the same or subsequent financial year as claim lodgment. Because only claims for OIIs occurring within capital cities were included, these results are not representative of, and cannot be generalized to, rural and remote workers and workers from other metropolitan but non-capital cities such as the Gold Coast. As some claims were removed from the dataset due to

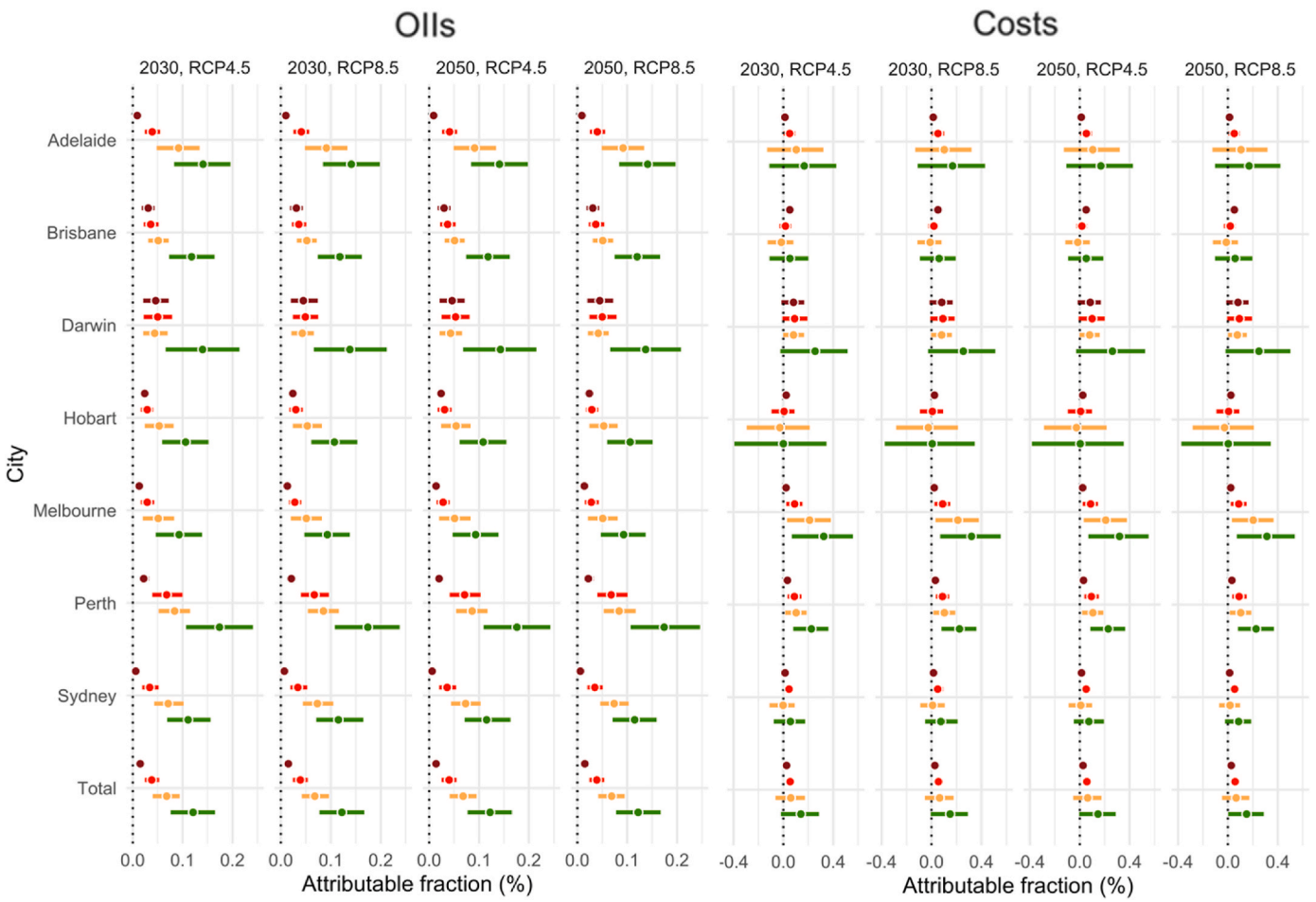

Fig. 6. Projected attributable fractions for heatwave-attributable OIIs and associated costs with climate adaptation.
The proportion of the number of occupational injuries and illnesses (OIIs) and associated costs attributable to heatwaves, with 95% empirical confidence intervals. Results are included for all heatwaves (green) as well as its constituents: low-intensity (orange), severe (red) and extreme heatwaves (dark red).

missing data, selection bias may exist. Non-meteorological temperature variation including workplace-generated heat and air conditioning could not be analyzed due to data unavailability. However, the impact of air conditioning may have been partially and indirectly assessed (theoretically) through evaluating the impact of future climate adaptation. The projected climate dataset utilized Coupled Model Intercomparison Project [CMIP]5 instead of the newer CMIP6 scenarios that include Shared Socioeconomic Pathways. To the authors' knowledge, no CMIP6 datasets with sufficient resolution to accurately represent Australian cities currently exist. However, different socioeconomic projections were considered through different projected population growths (Australian Bureau of Statistics, 2018a). Furthermore, eight GCMs were used, which is relatively more than other studies projecting temperature-attributable outcomes. Finally, there is huge uncertainty in projections, attenuated further by real-life phenomena not captured in the projections such as the SARS-CoV-2 outbreak. As part of this uncertainty, the allocation of work duties and the costings of expenses associated with OIIs amongst workers may change in the future. This may change the predicted future risk of workers' heatwave-attributable OIIs and costs.

5. Conclusions

Heatwaves are responsible for a considerable preventable portion of OIIs and associated economic burden. Heatwave-attributable OIIs are likely to increase in the future with some evidence for an increase in costs. Adaptation can potentially prevent these future increases. Workplace and public health action is imperative to reduce heatwave-attributable occupational morbidity and costs.

Restrictions apply to the availability of the compensation claims 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 the Australian Bureau of Meteorology Atmospheric high-resolution Regional Reanalysis: http://www.bom.gov.au/research/projects/reanalysis/. The license under which the data were used is available online: http://www.bom.gov.au/metadata/catalogue/view/ANZCW0503900566.shtml?template=full.

The projected climate data have been deposited in figshare (https://doi.org/10.25909/23709657). They are derived from Climate Change in Australia gridded datasets available online: https://data-cbr.csiro.au/thredds/catalog/catch_all/oa-aus5km/Climate_Change_in_Australia_User_Data/Application_Ready_Data_Gridded_Daily/catalog.html. The license under which the data were used is available online: https://www.climatechangeinaustralia.gov.au/en/overview/about-site/licences-and-acknowledgements/.

The retrospective workers' population data were derived from the

Table 4
Attributable fractions by worker and OII characteristics.

Factor	Category	OIIs	Costs
Overall	All workers	0.129 (0.107–0.165)	0.252 (0.182–0.345)
Sex	Male	0.135 (0.109–0.176)	0.161 (0.069–0.266)
	Female	0.122 (0.053–0.202)	0.323 (0.172–0.486)
Age (years)	15 to 29	0.165 (0.124–0.222)	0.013 (−0.140 to 0.150)
	30 to 49	0.120 (0.075–0.177)	0.295 (0.180–0.430)
	50 to 75	0.113 (0.071–0.166)	0.145 (0.048–0.251)
Industries	Indoor	0.126 (0.102–0.165)	0.275 (0.201–0.371)
	Outdoor	0.144 (0.079–0.220)	0.130 (−0.112 to 0.345)
Occupation	Indoor occupations	0.150 (0.127–0.191)	0.231 (0.146–0.338)
	Outdoor occupations	0.037 (−0.037 to 0.110)	0.182 (−0.229 to 0.496)
	Clerical & administrative workers	0.202 (0.071–0.346)	0.160 (−0.415 to 0.553)
	Community & personal service workers	0.130 (−0.020 to 0.276)	0.176 (0.048–0.309)
	Laborers	0.194 (0.120–0.283)	0.107 (−0.193 to 0.365)
	Machinery operators & drivers	0.195 (0.120–0.286)	0.148 (−0.234 to 0.453)
	Managers	0.069 (−0.071 to 0.200)	0.006 (−0.947 to 0.515)
	Professionals	−0.144 (−0.283 to −0.034)	0.197 (−0.053 to 0.415)
	Sales workers	0.141 (−0.080 to 0.336)	−0.084 (−0.709 to 0.288)
	Technicians & trade workers	0.106 (0.054–0.168)	0.090 (−0.248 to 0.350)
Injuries	All injuries	0.110 (0.080–0.153)	0.146 (0.050–0.250)
	Fractures and traumatic joint, ligament, muscle & tendon injuries	0.071 (−0.026 to 0.161)	0.203 (0.079–0.335)
	Wounds, lacerations, amputations & internal organ damage	0.104 (0.038–0.174)	0.057 (−0.233 to 0.299)
	All other injuries	0.337 (0.216–0.485)	−0.598 (−1.917 to 0.029)
Illnesses	Illnesses (diseases/ conditions)	0.186 (0.140–0.253)	0.429 (0.281–0.613)

National heatwave-attributable fractions (%) for the number of occupational injuries and illnesses (OIIs) and associated costs stratified by demographic, occupational and OII characteristics with 95% empirical confidence intervals.

Australian Bureau of Statistics (ABS) Labour Force, Australia, Detailed dataset (LM1) and have been deposited in figshare (https://doi.org/10.25909/63a2d38c1b295, which also contains the indoor/outdoor occupation classifications. The LM1 dataset (https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia-detailed/latest-release) and projected population dataset (https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3222.02017%20(base)%20-%202,066?OpenDocumenthttps://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3222.02017%20(base)%20-%202,066?OpenDocument) are publicly available online.

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

Credit author statement

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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

Some data are available, and some are unavailable. This is explained in the Data Availaibility section.

Acknowledgements

The authors thank Dr John Nairn, Professor Lisa Alexander, Syeda Hira Fatima, and A/Prof Peter Smith for their advice with utilizing EHF, advice for usage of projected climate data, assistance with spatial analysis, and for providing their ANZSCO-NOC cross-walk version for cross-checking, respectively.

This publication uses workers' compensation claims data supplied by Safe Work Australia and has been compiled in collaboration with state, territory and Commonwealth workers' compensation regulators. The views expressed are the responsibility of the authors and are not necessarily the views of Safe Work Australia or the state, territory and Commonwealth workers' compensation regulators.

The authors acknowledge the World Climate Research Programme's Working Group on Coupled Modeling, which is responsible for CMIP, and we thank the climate modeling groups (listed at https://www.climatechangeinaustralia.gov.au/en/obtain-data/application-ready-data/eight-climate-models-data/) for producing and making available their model output for projected climate data. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

This project was supported by the Australian Research Council (ARC Discovery Project Grant: DP190102869). Author Matthew Borg was supported by a University of Adelaide Faculty of Health Sciences Divisional Scholarship.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2023.116852.

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