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Intra-urban risk assessment of occupational injuries and illnesses associated with current and projected climate: Evidence from three largest Australian cities

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ABSTRACT

Background: Increased risk of occupational injuries and illnesses (OI) is associated with ambient temperature. However, most studies have reported the average impacts within cities, states, or provinces at broader scales.
Methods: We assessed the intra-urban risk of OI associated with ambient temperature in three Australian cities at statistical area level 3 (SA3). We collected daily workers' compensation claims data and gridded meteorological data from July 1, 2005, to June 30, 2018. Heat index was used as the primary temperature metric. We performed a two-stage time series analysis: we generated location-specific estimates using Distributed Lag Non-Linear Models (DLNM) and estimated the cumulative effects with multivariate meta-analysis. The risk was estimated at moderate heat (90th percentile) and extreme heat (99th percentile). Subgroup analyses were conducted to identify vulnerable groups of workers. Further, the OI risk in the future was estimated for two projected periods: 2016–2045 and 2036–2065.
Results: The cumulative risk of OI was 3.4% in Greater Brisbane, 9.5% in Greater Melbourne, and 8.9% in Greater Sydney at extreme heat. The western inland regions in Greater Brisbane (17.4%) and Greater Sydney (32.3%) had higher risk of OI for younger workers, workers in outdoor and indoor industries, and workers reporting injury claims. The urbanized SA3 regions posed a higher risk (19.3%) for workers in Greater Melbourne. The regions were generally at high risk for young workers and illness-related claims. The projected risk of OI increased with time in climate change scenarios.
Conclusions: This study provides a comprehensive spatial profile of OI risk associated with hot weather conditions across three cities in Australia. Risk assessment at the intra-urban level revealed strong spatial patterns in OI risk distribution due to heat exposure. These findings provide much-needed scientific evidence for work, health, and safety regulators, industries, unions, and workers to design and implement location-specific preventative measures.

1. Introduction

Many epidemiological studies have assessed the association between occupational injuries and illnesses (OI) and ambient temperatures in different regions of the world (Calkins et al., 2019; Dillender, 2021; McInnes et al., 2017a; Marinaccio et al., 2019; Martínez-Solanas et al., 2018; Sheng et al., 2018; Varghese et al., 2019). These studies have suggested that the risk of OI increases at non-optimal ambient temperatures, however, geographical variations have been observed in the risk assessments (Fatima et al., 2021). For example; an increased risk of OI (0.7%) associated with a 1 °C increase in temperature was reported for construction workers in Washington State, US (Calkins et al., 2019) while the risk was 1.9% for all workers in Texas, US (Dillender, 2021), 1.4% in Guangzhou, China (Sheng et al., 2018), and 0.6% in Melbourne, Australia (Varghese et al., 2019). No significant association was detected in Brisbane, Australia (Varghese et al., 2019). Nationwide studies from Italy and Spain respectively noted such associations varied in different provinces of these countries (Marinaccio et al., 2019; Martínez-Solanas et al., 2018). This spatial heterogeneity is potentially attributed to underlying local climate characteristics and workplace-specific characteristics such as type of work, industries, and workers' demographics (Varghese et al., 2019; Fatima et al., 2021).

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In this study, we intend to provide a detailed profile of the exposure-response association between OI and hot weather conditions at an intra-urban scale in three major cities of Australia namely Greater Brisbane, Greater Melbourne, and Greater Sydney. Previous studies have mainly provided evidence from broad-scale risk assessments at the city, state, or province level but were not able to reflect the localized spatial variations within the cities. A recent study carried out in Adelaide, Australia found that the geographical variations in the heat-related risk of OI are profound within the cities at a local scale (Fatima et al., 2022). Location-specific research is needed to quantify the work, health, and safety (WHS) impacts associated with climatic conditions to provide localized information for tailored decision-making, protect workers from the impacts of warming temperatures, and reduce the WHS and economic impacts from extreme heat (McInnes et al., 2017b).

The availability of high-resolution spatio-temporal datasets and recent advancements in statistical methods allow us to estimate temperature-related health associations at a localized scale within rapidly urbanizing cities. Previously, geospatial datasets have been used to develop localized heat stress vulnerability maps and location-specific vulnerability forecasts. Such datasets have been implemented at national levels to help governments and communities prepare for and respond to extreme heat events (The National Integrated Heat Health Information System (NIHHIS), 2018). The evidence from such localized studies will also provide valuable evidence for policy-makers and urban planners in mitigation, planning, and resource allocation (Fatima et al., 2022).

We will also estimate the burden of OI associated with projected climate change scenarios. Projection of occupational burden in future predicted scenarios is increasingly crucial as we are transitioning to hot and more intense climate conditions. The findings will have implications for a better policy framework for heat-related risk prevention and adaptation to warming climatic conditions.

2. Methods

A time-series study design coupled with Distributed Lag Non-Linear Models (DLNM) (Gasparrini et al., 2010) was used to estimate the effects of hot weather on the risk of OI in three cities in Australia. The analyses were carried out at an intra-urban spatial scale at Statistical Area Level 3 (SA3), although the future projected risk was only estimated at the greater city level. SA3s are medium-sized general-purpose geographical regions as determined by the Australian Bureau of Statistics (Australian Bureau of Statistics, 2016a) (Supplementary Figure S1). Generally, they have a population between 30,000 and 130,000 people. These regions are designed to represent a community that interacts together socially and economically.

The daily count of workers' compensation claims data from July 1, 2005, to June 30, 2018, was the response used in the models of the exposure-response associations. The heat index (^{o}C) was used as the exposure temperature metric for the three cities: Greater Brisbane, Greater Melbourne, and Greater Sydney. A major proportion of these regions (particularly Greater Brisbane and Greater Sydney) is characterized by a humid subtropical climate.

Ethics approval for this study was obtained from The University of Adelaide's Office of Research Ethics, Compliance, and Integrity Human Research Ethics Committee (approval number H-2019-219).

2.1. Data sources

2.1.1. Environmental data

For weather metrics, we used daily gridded meteorological data at 5 km spatial resolution (Jeffrey et al., 2001). The set of weather metrics included; maximum temperature (Tmax ^{o}C), minimum temperature (Tmin ^{o}C), solar radiation (MJ/m^2), and relative humidity (%). Additionally, we acquired 16-day Normalized Difference Vegetation Index (NDVI) from Google Earth Engine (Gorelick et al., 2017). The NDVI values represent an entire 16-day time period in the time series (Didan and Munoz, 2019).

For future climatic projections, we used 5 km daily gridded "application-ready" data (Craig and Clarke, 2021; CSIRO and Australian Bureau of, 2015). The data are available for eight selected general circulation models: Access 1.0, CESM1-CAM5, CNRM-CM5, GFDL-ESM2M, HadGEM2-CC, CanESM2, MIROC5, NorESM1-M. We acquired the data for two representative concentration pathways (RCP) (4.5 and 8.5) for a set of two environmental variables, including Tmax and average relative humidity for a projected period from 2016 to 2045 and 2036–2065. Heat index projections were estimated from Tmax and relative humidity following Anderson et al. (2013).

All datasets were extracted for the three cities using centroid points at Statistical Area Level 2 (SA2), and the values were then aggregated to the SA3 level using an area-weighted average of SA2 within SA3 regions. For future climatic projection, all data extracted at the SA2 level were aggregated to the greater city level using an area-weighted average of SA2 within the greater city region. This approach is computationally efficient and weights values based on the geographic area of SA2 within the broader spatial unit (SA3 and greater city) (Fatima et al., 2022).

Additional variables were acquired to define the location-specific characteristics of the regions. We identified hot versus cool SA3 regions based on an average value of 8-day land surface temperature (LST) acquired from Google Earth Engine (Gorelick et al., 2017). LST derived from remote sensing is a reliable and practical variable to classify spatial variability in urban climates (do Nascimento et al., 2022; Geletič et al., 2016). Vegetated versus less vegetated SA3 regions were identified using the average of all 16-day NDVI values in the time series. Similarly, we identified the socioeconomic status, education, and occupation status of the regions based on Indices for relative socio-economic advantage and disadvantage (IRSAD) and education and occupation (IEO) at the SA3 level acquired from the Australian Bureau of Statistics (Australian Bureau of Statistics, 2016b). For each of these additional variables, binary variables were created using the 75th percentile as a cut-point value. Previous studies have also used this cut-off for the separability of features (Cao et al., 2021). The variables were used for stratification purposes only, based on their location-specific characteristics.

2.1.2. Workers' compensation claims data

Daily compensation claims data were acquired from Safe Work Australia, an Australian government statutory agency that compiles the Australian National Dataset for Compensation-Based Statistics (NDS3) from all jurisdictions. The data represents 90% of all Australian workers (Safe Work Australia, 2020a).

Workers' compensation claims data records the location of the claims according to the postal areas (POA) of the workplace where the accidents occurred. For spatial feasibility of the analysis i.e., to cater to the temporal misalignment issue inherent in POA and small sample size across space and time, we aggregated the daily claims' location data to SA3.

Workers' compensation claims between July 1, 2005, and June 30, 2018, were included irrespective of their severity. However, claims were excluded if the POA of the location of the accident was not given, was beyond the greater city area, or when the POA was not an actual address. Claims were also excluded if the claimants were not in the working age group (15–80 years). For subgroup analyses, the workers' compensation claims were stratified based on age, gender, claim type (injury-related claims and illness-related claims), types of occupation (technicians, service workers, laborers, and drivers and machinery operators), physical demands (limited, light, medium, and heavy work), types of exposure (regulated and unregulated indoor, outdoor, and multiple locations), and types of industries (outdoor and indoor). Claim types were identified according to the Type of Occurrence Classification System (TOOCS 3.1) (Safe Work Australia, 2022). The outdoor and indoor industries were classified following Xiang et al. (2014). Industrial sectors including “agriculture, forestry, and fishing”, “construction”, and “electricity, gas, and water” were categorized as outdoor industries, the remaining industries were combined as indoor industries (Xiang et al., 2014). The type of work based on physical demands and types of exposure was categorized based on the Australian and New Zealand Standard Classification of Occupations (ANZSCO) codes assigned to each claimant. The classification system to assign the physical demand and potential workplace exposure to occupations was initially developed by human resources and skills development Canada (HRSDC) (Government of Canada, 2011). This was done by trained occupational analysts in modified Delphi procedure (Government of Canada, 2011). HRSDC was associated with ANZSCO using a common coding structure: The International Standard Classification Occupations (ISCO – 88) (International Labour Organization (ILO), 1988). The systems have been validated in previous studies (Smith and Berecki-Gisolf, 2014; Smith et al., 2014).

2.2. Statistical analyses

A two-stage approach was used for this multi-location time series study (Martínez-Solanas et al., 2018; Gasparrini et al., 2015). First, we implemented generalized linear models with Quasi-Poisson distribution to estimate the associations between hot weather conditions and OI in each SA3 region in three greater cities.

$$\mathrm{Log}[\mathrm{E(y)}] = \beta_0 + \beta_1 \mathrm{cb} + \beta_2 \mathrm{dow} + \beta_3 \mathrm{holidays} + \beta_4 \mathrm{NDVI} + f_1(\mathrm{time}) + f_2(\mathrm{solar\ radiation}) + \log(\mathrm{population})$$

Where [E(y)] is the expected daily count of the OI, cb is the crossbasis for the two dimensions of predictor (heat index) and lags (Gasparrini et al., 2010), with quadratic B-splines with one internal knot placed at the 50th percentile to estimate the crossbasis for the exposure-response association. The statistical models also included a variable corresponding to the day of the week (dow) and an indicator variable denoting public holidays. NDVI was used as an additional covariate in the analysis. B_i represent the regression coefficients for these terms. A lag period of up to seven days was included to estimate the delayed effects of hot weather. Natural cubic splines (f_i (X_i)) were used to flexibly model the effects of time (with 6 df) and solar radiation (with 3 df). Workers' population at SA3 region level was acquired from census data (Australian Bureau of Statistics, 2016c) and log (population) was included as an offset term to account for population exposure. Solar radiation and NDVI were included as covariates because they have been linked previously with the perceived vulnerability to heat effects (Arifwidodo and Chandrasiri, 2020; Otani et al., 2019).

In the second stage of analysis, we pooled the location-specific coefficients estimated from the first stage using multivariate meta-regression models. This approach provided us with the best linear unbiased predictions (BLUPs). The BLUPs were used in the quantification of heat-related impacts of OI (Gasparrini et al., 2015). The overall risk of OI was estimated at moderate heat (90th percentile of heat index metric) and extreme heat (99th percentile) using the heat index percentile of minimum occupational injuries and illness (PMOI) (10th percentile) as the reference value (Martínez-Solanas et al., 2018; Fatima et al., 2022; Gasparrini et al., 2015). Region-wise risk estimates were also presented at moderate heat and extreme heat with respect to location-specific PMOI. The cumulative risk of OI in the three greater cities and the region-wise effect estimates were reported as percent differences. Heat-related attributable fractions (AF) of OI with empirical confidence intervals were estimated following the method outlined by Gasparrini and Leone (2014). Sensitivity analyses were conducted to evaluate model choices, based on: degree of freedom per year for seasonal control, knots for exposure and response and exposure variable (heat index, Tmax, Tmean, and Tmin).

For future projections, the risk of OI was estimated at the greater city level. The baseline data (2005–2018) were used to predict the risk in the future for two 30-year time-series datasets: 2016–2045 and 2036–2065 using log-linear extrapolation with a natural cubic spline function (Vicedo-Cabrera et al., 2019). These predictions are based on the assumptions that the risk of OI observed over the current period remains unchanged in the future and that the extrapolation appropriately represents the risk over the unobserved range (Vicedo-Cabrera et al., 2019). The results are presented at extreme heat (99th percentile of heat index) for the two projected timeframes: 2016–2045 and 2036–2065 for two RCP scenarios RCP 4.5 and RCP 8.5 and eight selected general circulation models. Absolute heat-related AF and empirical confidence intervals were also estimated (Gasparrini and Leone, 2014). All analyses were performed in the R software environment (R 4.1.0) using *dlnm* and *mvmeta* packages (Gasparrini, 2011).

Cumulative subgroup analyses were stratified based on personal factors (age, gender, claim type), workplace characteristics (types of occupation, type of work, and types of exposure), and location-specific characteristics (hot vs cool regions, high vs less vegetated regions, high vs low IRSAD, and high vs low IEO regions). Region-wise subgroup analyses were undertaken for age (younger (<45 years) vs older workers (≥45 years)), gender (males and females), types of industries (outdoor and indoor industries), and claims types (injuries and illnesses).

3. Results

The total number of OI claims was 263,260 in Greater Brisbane, 468,658 in Greater Melbourne, and 924,679 in Greater Sydney. The workers' population based on their place of work was 1.0 million in Greater Brisbane, 2.0 million in Greater Melbourne, and 2.2 million in Greater Sydney as of the 2016 census. Males had a high proportion of claims (>62%) in all three cities. Similarly, a higher proportion of claims were from Indoor industries (>85%) as compared to outdoor industries. Injury-related claims were dominant in Greater Brisbane and Greater Sydney (82 and 85% respectively), whereas illness-related claims were higher (51%) in Greater Melbourne. Particularly, musculoskeletal and connective tissue disorders had a significant proportion of claims in Greater Melbourne (37%). The descriptive statistics for workers' compensation claims are presented in Supplementary Table S1.

3.1. Risk assessment of OI in three major cities of Australia

The estimated OI risk was strongly associated with hot weather conditions in the three cities. In Greater Brisbane, the overall risk of OI was −0.4% (95%CI: 5.6, 5.0) at moderate heat (32.6 °C) and 3.4% (95% CI: 3.8, 11.1) at extreme heat (38.1 °C) (Fig. 1) relative to the 10th percentile (20.3 °C). Although the overall cumulative risk was minimal in Greater Brisbane, many SA3 regions were found to be at high risk of OI for example in Forest Lake - Oxley the risk was estimated to be 13.3% at 33.0 °C and 17.4% at 39.5 °C with reference to 17 °C (Supplementary Table S2).

Similarly, in Greater Sydney, the overall risk of OI associated with heat increased from 4.4% (95%CI: 1.3, 7.6) at 30.9 °C to 8.9% (95%CI: 4.1, 13.9) at 39.4 °C with respect to 10th percentile (15.8 °C) (Fig. 1). Region-wise risk estimates indicated a higher risk of OI in various SA3. For example, the risk increased up to 19.2% at 31.0 °C and up to 32.3% at 40.0 °C with reference to 13 °C in Auburn (Supplementary Table S2).

In Greater Melbourne, the risk of OI associated with heat index was 8.9% (95%CI: 4.6, 13.3) at 29 °C (Fig. 1). At extreme heat, it increased up to 9.5% (95%CI: 4.0, 15.4) at 37.5 °C with respect to 12.1 °C. Location-specific risk estimates were higher for SA3 regions in Greater Melbourne. For example; in Darebin – North the risk of OI associated with heat index increased up to 19.3% at 30.0 °C and 20.5% at 38.0 °C with respect to 9.0 °C (Supplementary Table S2). Summary statistics of the three cities with an estimated location-specific PMOI, 90% percentile, and 99th percentile of heat index are provided in Supplementary Table S3.

The impacts of heat on OI aggravate with an increase in heat index in

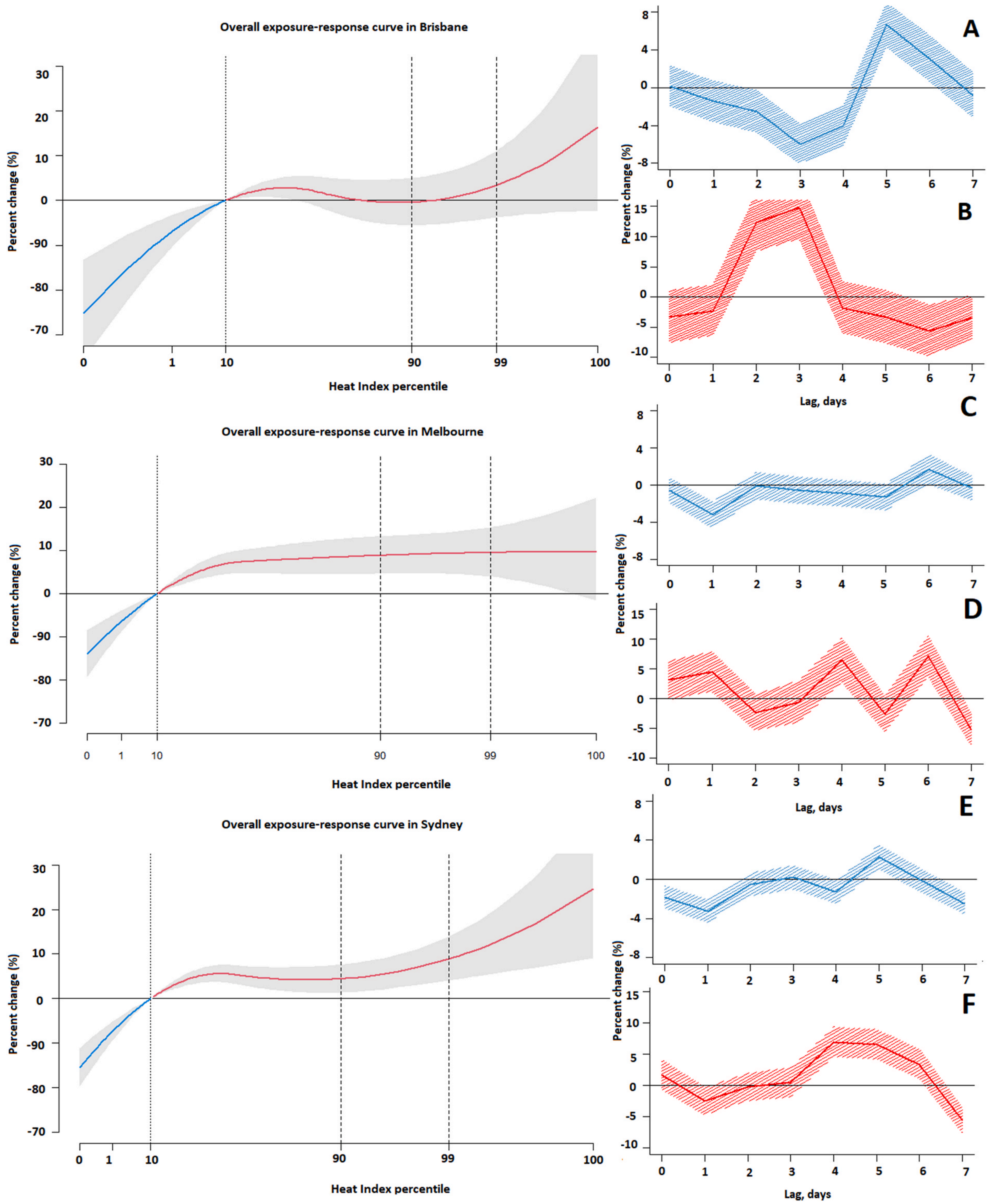

Fig. 1. Overall Cumulative exposure-response curve of OI associated with hot weather conditions given in percent difference [with 95% confidence intervals (CI) – shaded areas] in three major cities of Australia. The dotted line represents the PMOI (10th percentile). The dashed lines represent the moderate heat (90th percentile) and extreme heat (99th percentile) of the heat index. Fig. 1A and B, Lag-response relationship between heat index and OI for cold effects (estimated at 1st percentile) and heat effects (estimated at 99th percentile) respectively for Greater Brisbane. Fig. 1C and D, Lag-response relationship between heat index and OI for cold effects (estimated at 1st percentile) and heat effects (estimated at 99th percentile) respectively for Greater Melbourne. Fig. 1E and F, Lag-response relationship between heat index and OI for cold effects (estimated at 1st percentile) and heat effects (estimated at 99th percentile) respectively for Greater Sydney.

all three cities. Particularly, the exposure-response curve shows an exponential increase in the risk of OI associated with heat in Greater Brisbane and Greater Sydney, while in Melbourne the exposure-response curve remains comparatively stable (Fig. 1). The cold-related effects of the heat index metric (presented at 1st percentile) were delayed in all instances (Fig. 1A, 1C, 1E). The heat-related effects (99th percentile) were slightly delayed in Greater Brisbane and Greater Sydney but were immediate in Greater Melbourne (Fig. 1B, 1D, 1F). Region-wise exposure-response curves for the three greater cities are presented in Supplementary Figures S2, S3, and S4. Spatial maps of various environmental variables for the three cities are presented in Supplementary Figures S5, S6, and S7. Sensitivity analysis for the three cities suggested that the models generally performed well with the selected modelling choices (Supplementary Table S4).

3.1.1. Spatial distribution of the risk of OI associated with heat index

In Greater Brisbane and Greater Sydney, the western inland regions were found to be at higher risk of OI at both moderate and extreme heat (Fig. 2). In Greater Brisbane, Beaudesert, Brown Plains, Centenary, Forest Lake, Ipswich Inner, Ipswich Hinterland, Jimboomba, Kenmore – Brookfield - Moggill, and Springfield-Redbank were regions, particularly at higher risk of OI (up to 25.9%) (Fig. 2A and 2D). Similar, patterns were observed in Greater Sydney. The inland western SA3 regions: Auburn, Bankstown, Blacktown, Blacktown North, Camden, Bringelly – Green Valley, Fairfield, Liverpool, Merryland – Guildford, Mount Druitt, Parramatta, Penrith, Richmond – Windsor, Rouse Hill – McGraths Hill, and St Marys were most vulnerable (up to 32.3%) to the effects of both moderate and extreme heat (Fig. 2C and 2F). While, in Greater Melbourne, Bayside, Darebin – North, Glen Eira, Manningham – East, Monash, Port Phillip, Stonnington – East, Stonnington – West, Whitehorse – East, Whitehorse – West were particularly at high risk of OI (up to 19.3%) at moderate heat (Fig. 2B). Darebin – East, Hobson Bay, Monash, Port Phillip, Whitehorse – East, and Whitehorse – West were particularly at high risk (up to 20.5%) at extreme heat (Fig. 2E).

3.2. Attributable fraction of OI associated with heat index

In Greater Brisbane, the total AF of OI associated with heat (20.3–44.8 °C) was 8.52% (95%CI: 6.84, 10.02). The AF of OI associated with extreme heat was 0.96% (95%CI: 0.72, 1.20), while 7.86% (95%CI: 6.22, 9.30) of the OI burden was attributable to moderate heat. The city's western outskirts had higher AF for OI (>11.5%) (Table 1).

In Greater Melbourne, the total AF of OI 11.15% (95%CI: 9.49, 11.82) was attributable to heat (12.1–45.6 °C). The AF of OI associated with extreme heat was 1.57% (95%CI: 1.36, 1.66), while 9.91% (95%CI: 8.54, 10.51) of OI burden was attributable to moderate heat. In Greater Melbourne, urbanized SA3 regions had a higher burden (>11.0%) of OI associated with heat index (Table 1).

In Greater Sydney, an overall AF of 11.02% (95%CI: 9.95, 11.96) was observed for heat (15.8–50.8 °C). The AF of OI associated with extreme heat was 1.43% (95%CI: 1.29, 1.56), whereas 9.78% (95%CI: 8.77, 10.68) of OI was attributable to moderate heat. The western outskirts of the city had a higher AF of OI burden (>13.0%) (Table 1).

3.3. Risk assessment of OI stratified by various subgroups

The overall subgroup risk estimates suggest that among personal and workplace factors, young workers (15–25 years) and middle-aged workers (35–44 years and 45–54 years), males, workers reporting injury claims, and drivers and machinery operators were more

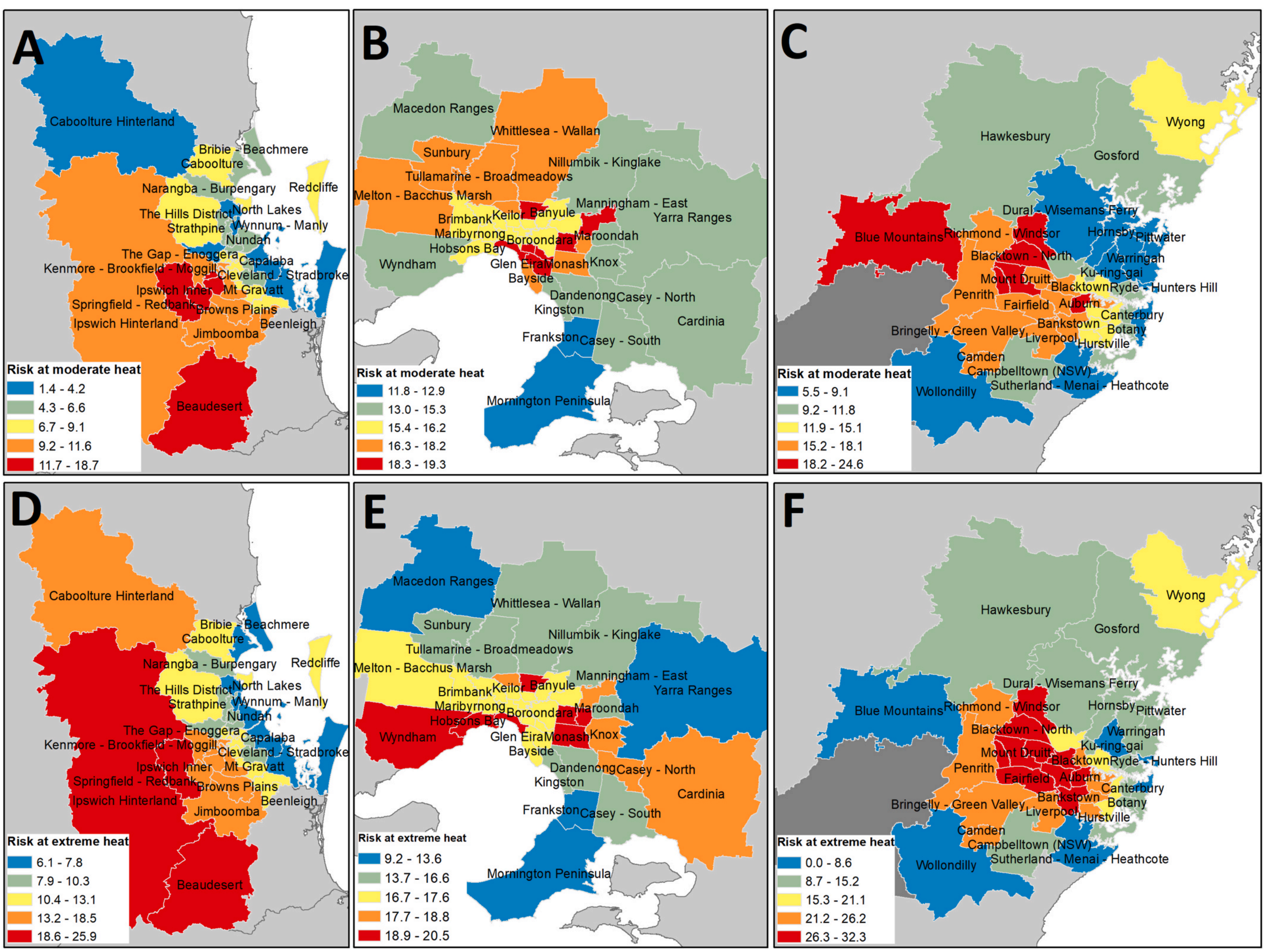

Fig. 2. The spatial distribution of the risk of OI associated with moderate heat for A. Greater Brisbane, B. Greater Melbourne, and C. Greater Sydney and extreme heat for D. Greater Brisbane, E. Greater Melbourne, and F. Greater Sydney.

Table 1
The attributable fraction with 95% confidence intervals of OI for overall heat component for SA3 regions of Greater Brisbane, Greater Melbourne and Greater Sydney from 2005 to 2018.

Greater Brisbane - SA3 Regions	Heat-related AF (95% CI)	Greater Melbourne - SA3 Regions	Heat-related AF (95% CI)	Greater Sydney – SA3 Region	Heat-related AF (95% CI)
Bald Hills - Everton Park	6.3 (-0.4, 12.2)	Banyule	10.9 (5.1, 14.3)	Auburn	14.8 (9.2, 20.3)
Beaudesert	18.7 (-1.4, 33.2)	Bayside	12.4 (4.0, 17.0)	Bankstown	13.8 (9.0, 18.6)
Beenleigh	10.1 (0.5, 19.6)	Boroondara	10.9 (6.1, 13.3)	Baulkham Hills	9.0 (6.3, 11.7)
Bribie - Beachmere	4.9 (-2.2, 11.4)	Brimbank	10.7 (5.9, 13.3)	Blacktown	13.9 (9.6, 18.1)
Greater Brisbane Inner	9.2 (3.5, 14.2)	Brunswick - Coburg	11.0 (5.1, 14.2)	Blacktown - North	15.3 (8.2, 22.5)
Greater Brisbane Inner-East	8.6 (3.5, 13.7)	Cardinia	10.3 (−2.8, 16.9)	Blue Mountains	−0.1 (-0.1, 0.0)
Greater Brisbane Inner-North	7.0 (2.0, 11.9)	Casey - North	10.6 (−1.8, 15.8)	Botany	9.8 (5.8, 13.8)
Greater Brisbane Inner-West	8.8 (3.4, 14.3)	Casey - South	9.9 (5.1, 12.6)	Bringelly - Green Valley	13.9 (6.9, 20.3)
Browns Plains	12.6 (6.0, 18.1)	Dandenong	10.3 (6.0, 12.6)	Camden	13.2 (7.8, 18.0)
Caboolture	9.5 (3.7, 14.4)	Darebin - North	13.2 (7.2, 16.4)	Campbelltown (NSW)	8.4 (5.5, 11.2)
Caboolture Hinterland	1.1 (-2.8, 4.6)	Darebin - South	10.9 (5.1, 13.6)	Canada Bay	12.8 (9.1, 16.2)
Capalaba	4.4 (-1.6, 10.1)	Essendon	11.1 (4.9, 14.5)	Canterbury	11.7 (6.2, 16.4)
Carindale	6.3 (1.0, 11.7)	Frankston	8.1 (2.0, 11.2)	Carlingford	10.5 (7.0, 13.6)
Centenary	13.9 (6.0, 21.3)	Glen Eira	12.4 (3.2, 16.7)	Chatswood - Lane Cove	9.2 (5.3, 13.2)
Chermside	6.1 (-0.9, 12.5)	Hobsons Bay	10.9 (2.0, 15.3)	Cronulla - Miranda - Caringbah	8.6 (4.3, 12.6)
Cleveland - Stradbroke	0.9 (-3.0, 4.7)	Keilor	10.8 (5.8, 13.6)	Dural - Wisemans Ferry	7.8 (3.0, 12.1)
Forest Lake - Oxley	14.1 (6.5, 21.2)	Kingston	10.1 (5.8, 12.2)	Eastern Suburbs – North	7.3 (2.3, 12.4)
Holland Park - Yeronga	9.5 (3.4, 15.1)	Knox	10.4 (−0.7, 15.8)	Eastern Suburbs – South	7.5 (2.8, 12.0)
Ipswich Hinterland	12.6 (-7.1, 27.4)	Macedon Ranges	10.9 (−14.3, 21.3)	Fairfield	14.2 (8.5, 19.2)
Ipswich Inner	16.2 (4.3, 26.7)	Manningham - East	12.8 (3.0, 17.4)	Gosford	8.7 (4.8, 12.3)
Jimboomba	11.4 (3.5, 17.8)	Manningham - West	10.8 (5.1, 13.6)	Hawkesbury	10.4 (-0.5, 19.0)
Kenmore - Brookfield - Moggill	11.8 (6.2, 17.5)	Maribyrnong	11.1 (5.0, 14.1)	Hornsby	7.4 (3.6, 10.6)
Loganlea - Carbrook	8.2 (-2.2, 17.6)	Maroondah	10.6 (6.0, 12.9)	Hurstville	11.6 (6.5, 16.3)
Mt Gravatt	5.9 (0.2, 11.1)	Greater Melbourne City	11.2 (5.1, 14.7)	Kogarah - Rockdale	10.6 (6.2, 14.8)
Narangba - Burpengary	5.6 (-1.2, 12.3)	Melton - Bacchus Marsh	12.4 (4.1, 16.5)	Ku-ring-gai	6.7 (2.4, 10.8)
Nathan	8.2 (2.8, 13.2)	Monash	12.6 (7.0, 15.2)	Leichhardt	10.6 (6.3, 14.6)
North Lakes	3.0 (-6.1, 10.8)	Moreland - North	12.0 (6.4, 14.8)	Liverpool	14.2 (10.3, 17.8)
Nundah	5.2 (-2.5, 12.1)	Mornington Peninsula	9.5 (−4.7, 16.2)	Manly	7.3 (1.5, 11.9)
Redcliffe	2.3 (-3.6, 7.1)	Nillumbik - Kinglake	10.2 (1.2, 15.1)	Marrickville - Sydenham - Petersham	10.8 (6.6, 15.1)
Rocklea - Acacia Ridge	11.6 (3.6, 18.8)	Port Phillip	12.9 (6.2, 16.6)	Merrylands - Guildford	13.4 (8.6, 17.8)
Sandgate	4.1 (-3.4, 10.8)	Stonnington - East	12.5 (3.0, 17.3)	Mount Druitt	14.9 (9.2, 20.3)
Sherwood - Indooroopilly	11.3 (4.2, 18.1)	Stonnington - West	12.9 (1.5, 18.9)	North Greater Sydney - Mosman	8.5 (4.2, 12.7)
Springfield - Redbank	14.2 (5.0, 22.9)	Sunbury	12.3 (3.4, 17.0)	Parramatta	13.2 (8.7, 17.6)
Springwood - Kingston	7.9 (2.3, 13.3)	Tullamarine - Broadmeadows	11.9 (4.5, 15.6)	Pennant Hills – Epping	8.4 (5.5, 11.3)
Strathpine	6.5 (0.1, 12.9)	Whitehorse - East	12.5 (7.1, 15.3)	Penrith	14.7 (5.5, 22.7)
Sunnybank	7.9 (2.4, 13.1)	Whitehorse - West	12.9 (7.6, 15.7)	Pittwater	7.6 (2.9, 12.2)
The Gap - Enoggera	0.5 (-0.8, 1.7)	Whittlesea - Wallan	11.6 (1.4, 16.3)	Richmond - Windsor	14.5 (4.8, 23.4)
The Hills District	8.2 (0.0, 15.5)	Wyndham	10.5 (1.8, 14.8)	Rouse Hill - McGraths Hill	14.7 (9.3, 19.9)
Wynnum - Manly	4.4 (-3.6, 11.0)	Yarra	11.2 (5.3, 14.4)	Ryde - Hunters Hill	12.0 (8.8, 15.2)
–	–	Yarra Ranges	10.1 (−0.3, 15.0)	St Marys	15.3 (7.9, 21.6)
–	–	–	–	Strathfield - Burwood – Ashfield	11.8 (6.6, 17.2)
–	–	–	–	Sutherland - Menai - Heathcote	5.7 (1.1, 9.6)
–	–	–	–	Greater Sydney Inner City	9.4 (5.4, 13.5)
–	–	–	–	Warringah	7.6 (2.9, 11.9)
–	–	–	–	Wollondilly	5.2 (-1.5, 10.9)
–	–	–	–	Wyong	10.8 (6.6, 14.9)

vulnerable to heat impacts. Among location-specific characteristics, workers were at increased risk of OI in regions with both high and low LST, low NDVI, low IRSAD, and low IEO (Supplementary Table S5). Although some variations were observed, for example in Greater Melbourne, workers in regions with high IEO were also vulnerable to theimpacts of heat.

Region-wise subgroup analysis revealed an evident spatial pattern in the distribution of the risk of OI stratified by various subgroups. In Greater Brisbane, a high risk of OI was seen for female workers, younger workers, workers with injury claims only, and outdoor and indoor industries at extreme heat in the inland western regions. In more crowded inner-city SA3 regions, male workers, older workers, and workers reporting illness-related claims only were at higher risk (Figs. 3 and 4). Female workers were at increased risk of OI particularly in the western regions in greater Brisbane, for example, a statistically significant increased risk of up to 60.5% (95%CI: 5.7, 143.6) was observed in The Gap Enogerra at 38.0 °C (Supplementary Table S6).

In Greater Melbourne, workers in urbanized SA3 regions of the city, including Bayside, Glen Eira, and Stonnington - East and Stonnington - West were particularly at high risk of OI at both moderate and extreme heat exposure. Essendon, Melbourne City, Port Phillip, Stonnington – West, and Yarra were generally at higher risk of OI for young workers and workers with illness-related claims. The city's outer fringes, including Macedon ranges, Nillumbik Kinglake, Sunbury, Whittlesea Wallan, and Yarra ranges were at higher risk of OI for older workers and workers reporting injury-related claims (Figs. 5 and 6). The highest risk of OI was recorded for outdoor industries in many SA3 regions including Bayside 50% (95%CI: 8.0, 108.2), Glen Eira 51.4% (95%CI: 7.4, 113.5), Manningham – East 52.3% (95%CI: 9.0, 112.9), Melton – Bacchus Marsh 44.1% (95%CI: 9.3, 90.2), Stonnington – East 52.8% (95%CI: 6.8, 118.7), Stonnington – West 57.6% (95%CI: 4.3, 138.2) at extreme heat (37.0–38.0 °C) (Supplementary Table S7).

In Greater Sydney, a higher risk of OI was calculated for male workers, younger workers, outdoor industries, and injury-related claims in the inland western regions including Auburn, Blacktown, Blacktown North, Blue Mountains, Bringelly - Green Valley, Camden, Fairfield,

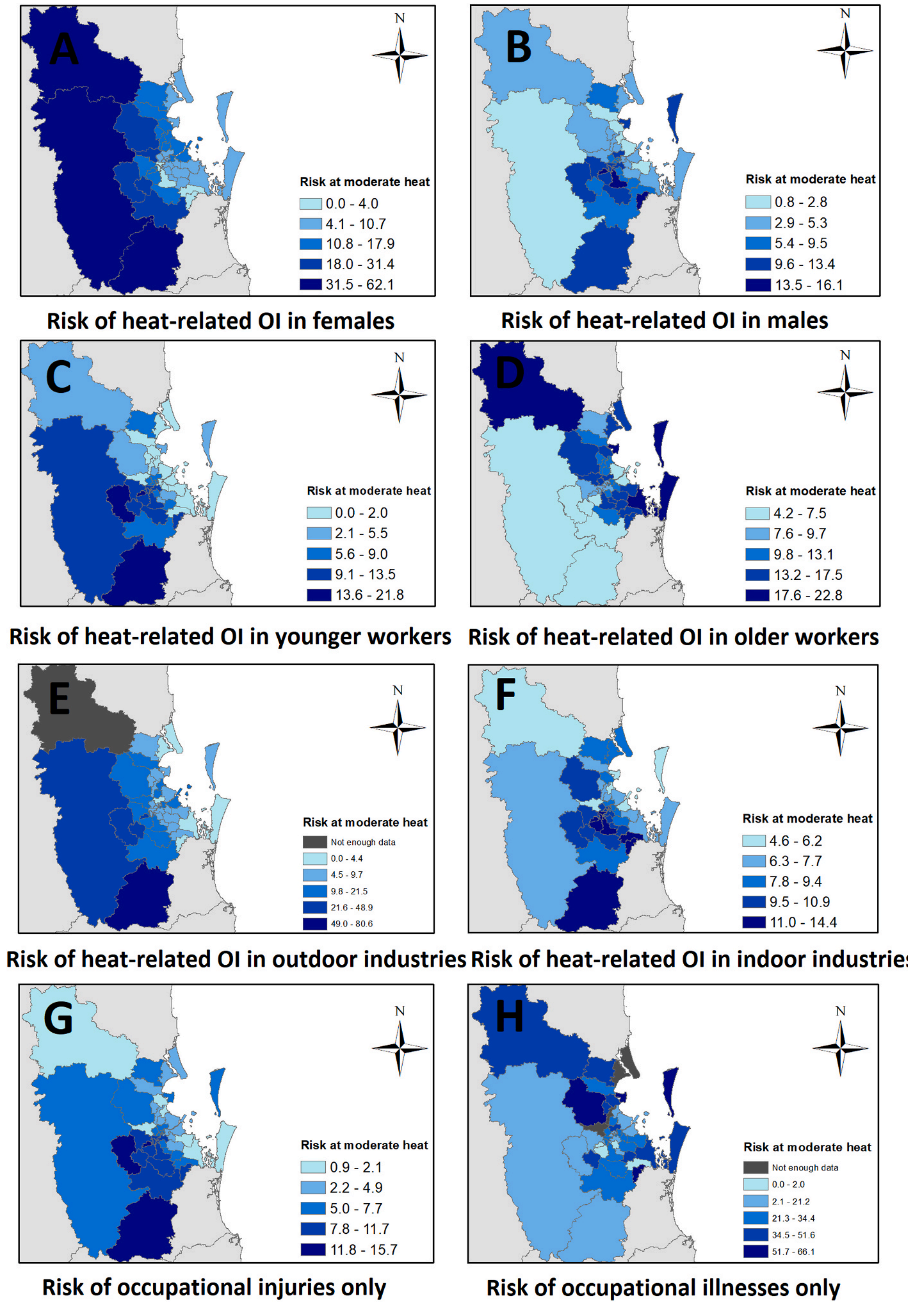

Fig. 3. Risk assessment of OI associated with moderate heat stratified by gender: A. females, B. males, by age C. younger (age <45) and D. older (age ≥45), types of industries E. outdoor industries and F. indoor industries and types of claims G. injury-related claims only and H. illness-related claims only in Greater Brisbane.

Merrylands - Guildford, Mount Druitt, Parramatta, Penrith, Richmond - Windsor, Rouse Hill - McGarths Hill, and St Marys (Figs. 7 and 8). More urbanized regions including Canada Bay, Canterbury, Hurstville, Kogarah-Rockdale, Strathfield-Burwood-Ashfield, and Greater Sydney Inner City were predominantly associated with higher risk for female workers, older workers, and workers with illness-related claims. Statistically high risk of OI associated with extreme heat was found for various subgroups, for example, in St Marys, an increased risk of OI 42.8% (95% CI: 22.5, 66.5) was estimated for male workers and 49.0% (95%CI: 26.7, 75.3) for younger workers at 43.0 °C. Workers in outdoor industries were particularly at high risk for most regions. In Richmond - Windsor, the risk increased up to 54.3% (95%CI: 1.7, 134.2) at 43.0 °C for workers in outdoor industries (Supplementary Table S8).

3.4. *Risk assessment of OI associated with the projected heat index*

The risk estimates of OI at extreme heat for two 30-year projected periods (2016-2045 and 2036-2065) for Greater Brisbane, Greater Melbourne, and Greater Sydney are presented in Table 2. The estimates are based on the NorESM1-M general circulation models, as the model is known to perform well in representing the range of projected changes in the climate from all models (CSIRO and Australian Bureau of, 2015). The risk of OI increased in future projected scenarios (2016–2045 and 2036–2065) as compared to the baseline period particularly for Greater Sydney (6.5%) and Greater Brisbane (4.5%) at extreme heat in the projected period 2036–2065 (RCP 8.5), while for Melbourne we observed a slight reduction in the risk of OI (0.1%).

Projected risk estimates for other general circulation models are presented in Supplementary Table S9. Similar estimates were observed

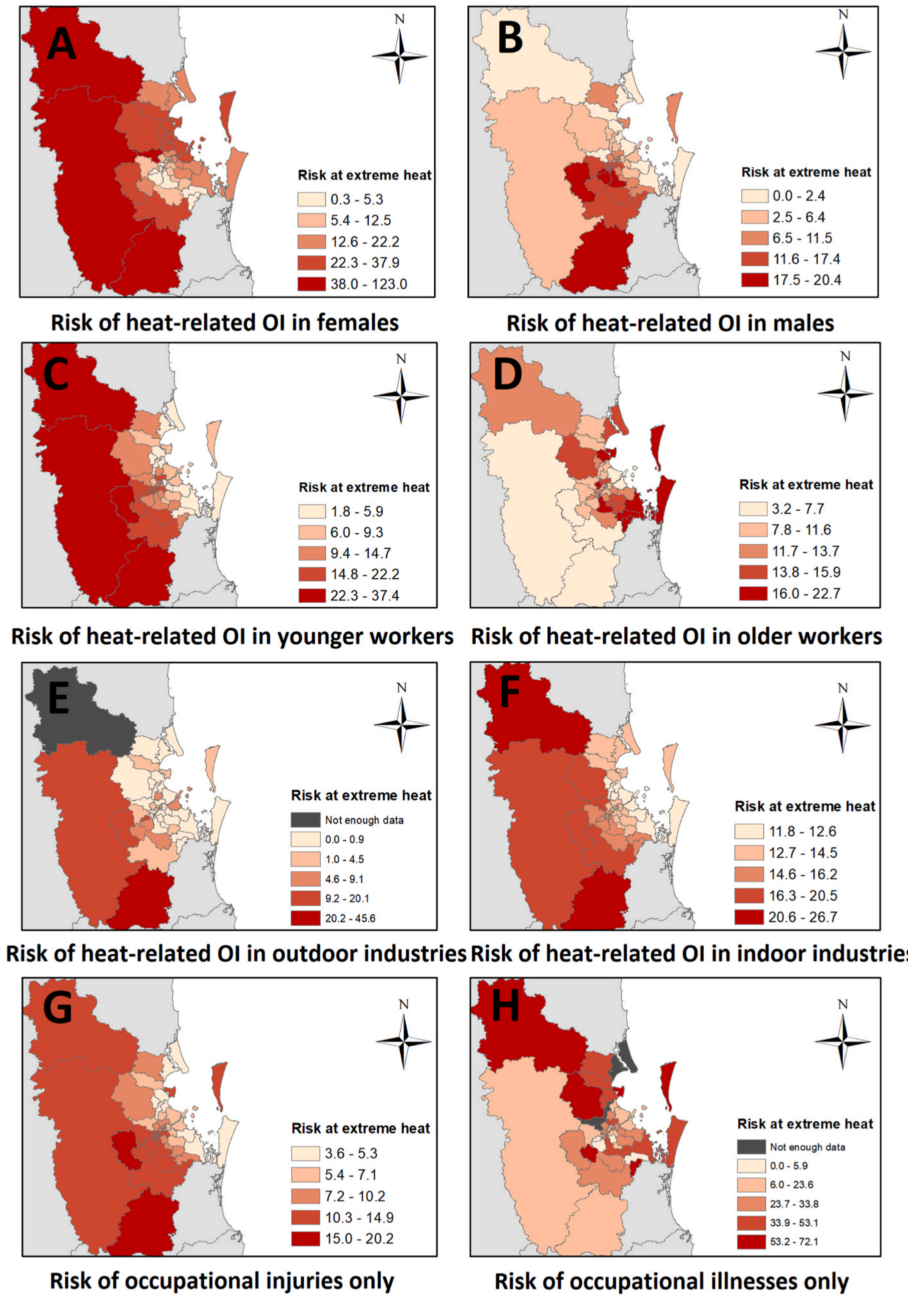

Fig. 4. Risk assessment of OI associated with extreme heat stratified by gender: A. females, B. males, by age C. younger (age <45) and D. older (age ≥45), types of industries E. outdoor industries and F. indoor industries and types of claims G. injury-related claims only and H. illness-related claims only in Greater Brisbane.

for all general circulation models and RCP scenarios. The absolute AF of OI for baseline and projected periods associated with heat is given in Supplementary Table S10. We observed that AF increased for all three cities.

4. Discussions

In this study, we have undertaken a risk assessment of OI associated with hot weather conditions at an intra-urban scale to identify high-risk areas in three large Australian cities. In Greater Brisbane and Greater Sydney, we found that the inland western regions were at higher risk of OI at both moderate and extreme heat. In Greater Melbourne, the urbanized coastal areas were particularly at higher risk of OI during moderate heat and extreme heat. In terms of the types of industries and claims, the risk of OI was typically high for workers in outdoor industries and workers with injury-related claims, in the outer fringes of the three cities. In contrast, workers in the more crowded inner-city regions were at high risk for illness-related claims. Future projection analysis indicates that the risk of OI is predicted to increase.

Fine-scale risk assessment offers valuable information in the development of targeted interventions in high-risk areas. Risk assessment at the intra-urban level quantifies the risk more accurately, by considering local exposure differences (Gasparrini, 2022). These variations are often overlooked in broad-scale risk assessments, i.e., risk assessments at the city level. For example, workers in some SA3 regions in Greater Brisbane were particularly vulnerable (risk of OI > 15%) to the effects of extreme heat, which was not reflected in the cumulative risk of OI 3.4 (95%CI: 3.8-11.1). Therefore, such assessments at a finer level can help to develop location-specific tailored interventions.

Many location-specific factors could play an important role in the

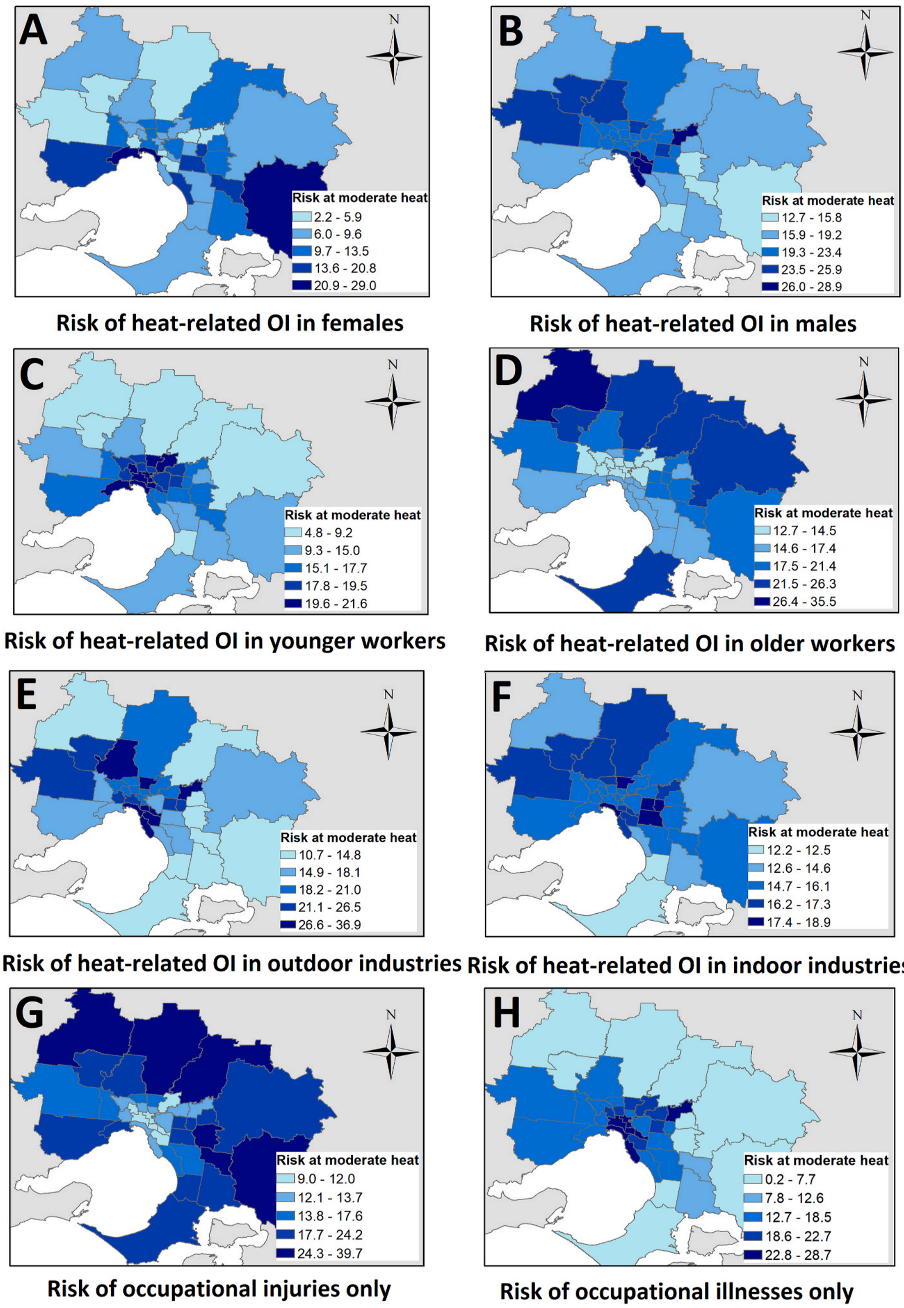

Fig. 5. Risk assessment of OI associated with moderate heat stratified by gender: A. females, B. males, by age C. younger (age <45) and D. older (age ≥45), types of industries E. outdoor industries and F. indoor industries and types of claims G. injury-related claims only and H. illness-related claims only in Greater Melbourne.

spatial distribution of the heat-related risk of OI. We found that regions with low NDVI, low IRSAD, and IEO had a higher risk of OI. For example, Blacktown North, Fairfield, Mount Druitt, Penrith, Richmond – Windsor are some of the western inland regions in Greater Sydney characterized by lower NDVI, IRSAD, and IEO (Supplementary Figure S7). These regions were particularly vulnerable to the impacts of heat on WHS. Similarly, Centenary, Forest Lake – Oxley, Ipswich Inner, Kenmore – Brookfield – Moggil are some of the low socio-economic indexed regions highly vulnerable to the impacts of heat in Greater Brisbane (Supplementary Figure S5). The high risk of OI in regions with low socioeconomic status and low index of education and occupation suggests that workers are generally less adaptive and more sensitive to heat exposure because of limited resources to stay cool and usually have low awareness and education, as suggested in previous studies (Gronlund, 2014). The results suggest that urban policymakers and employers should consider targeted mitigation responses, implement heat-related injury and illness reduction strategies in socio-economically vulnerable regions and promote green spaces in lower-income neighbourhoods. Previous studies have also identified, that these factors are associated with the impacts of hot temperatures on both workers and the general population (Gasparrini et al., 2022; Guerri et al., 2022).

In Greater Sydney and Greater Brisbane, workers in the hotter western inland regions were at higher risk of OI and had higher heat-related AF, as compared to more crowded inner-city areas where workers were also vulnerable to heat exposure. The western inland regions of these two cities were generally 4–6 °C hotter than other regions (Supplementary Figures S5 and S7), potentially because coastal winds keep the coastal areas cool but could not penetrate inland (Santamouris et al., 2017). In Greater Sydney, the impacts are further compounded by rapid urbanization, the destruction of bushland, and their replacement

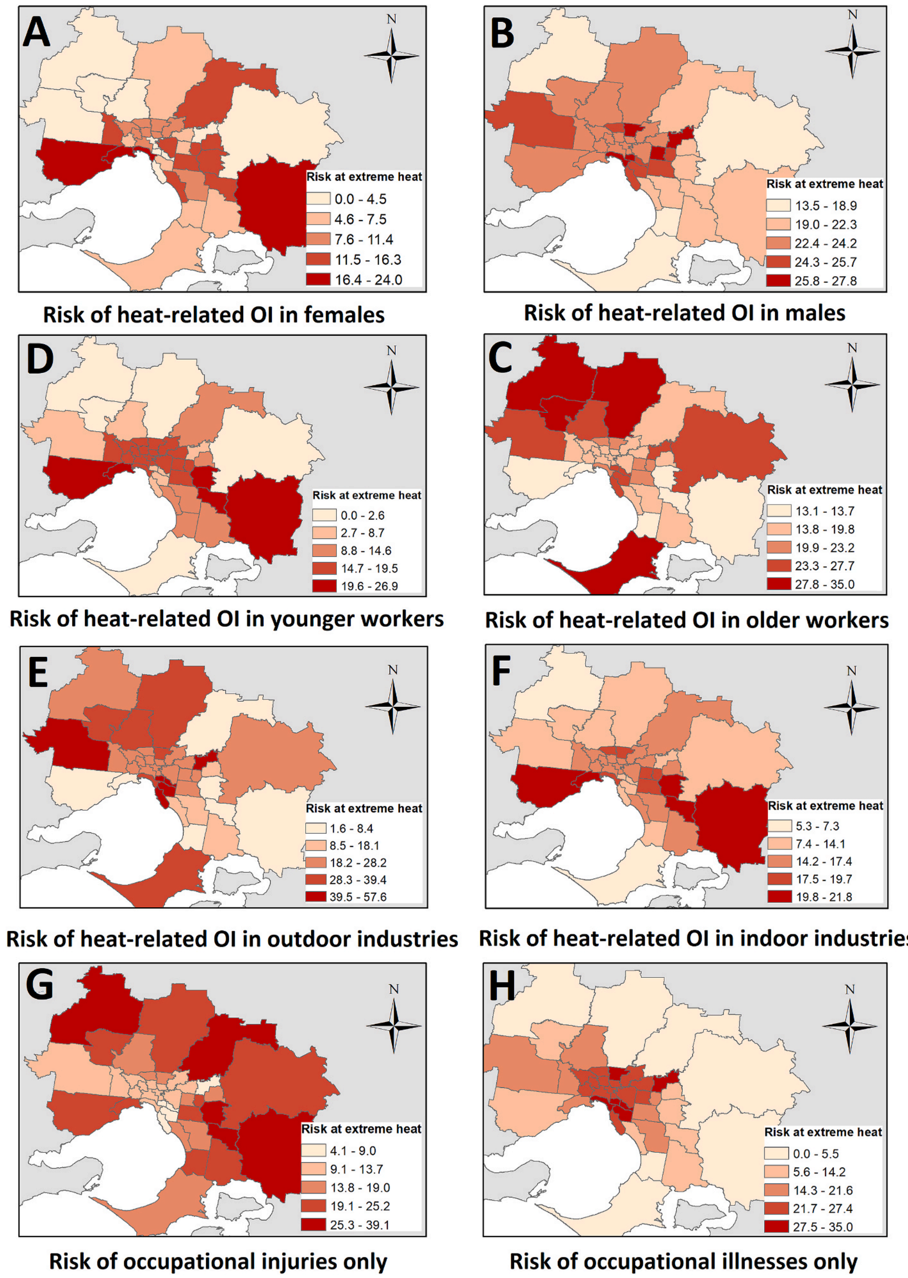

Fig. 6. Risk assessment of OI associated with extreme heat stratified by gender: A. females, B. males, by age C. younger (age <45) and D. older (age ≥45), types of industries E. outdoor industries and F. indoor industries and types of claims G. injury-related claims only and H. illness-related claims only in Greater Melbourne.

by buildings and roads. These activities contribute to urban heat island effects in many suburbs and consequently higher temperatures in the western foothills of the Blue Mountains (Santamouris et al., 2017; Pfautsch et al., 2020).

In Greater Melbourne, workers in coastal areas were at higher risk of OI associated with moderate heat. Regions including Bayside, Darebin – North, Glen Eira, Manningham – East, Monash, Port Phillip, Stonnington - East, Stonnington - West, Whitehorse – East and Whitehorse – West were characterized by high IRSAD and IEO, but were vulnerable to the impacts of heat (Supplementary Figure S6). Although the coastal areas are generally characterized by relatively cool weather conditions and lower LST, many of these SA3 regions have a major proportion of workforce from occupations such as technicians and trade workers, machinery operators, and drivers and laborers. These occupations are generally more vulnerable to heat effects as workers are required to do heavy work outside (Li et al., 2016). In addition, construction and manufacturing are among the major industries in many of these SA3 (Australian Bureau of Statistics, 2016c). Further, the risk of OI was consistently higher for workers at moderate heat in these regions, similar results were also found in a previous study from Melbourne (McInnes et al., 2018). In oceanic climates, characterized by cool and temperate weather conditions, people are generally less acclimatized to hot weather and a sudden increase in temperature can put workers at acute risk of OI. These findings suggest that heat preventive measures should be implemented at moderate heat well before extreme weather conditions are approaching (McInnes et al., 2018). This is an important finding in terms of implementing heat-related policies at the onset of hot weather conditions. Some previous studies suggested a higher risk at extreme heat when city-level risk assessments were undertaken (McInnes et al., 2017a; Varghese et al., 2019). The discrepancies with our findings could be due to different geographical levels of assessment or the use of different statistical models.

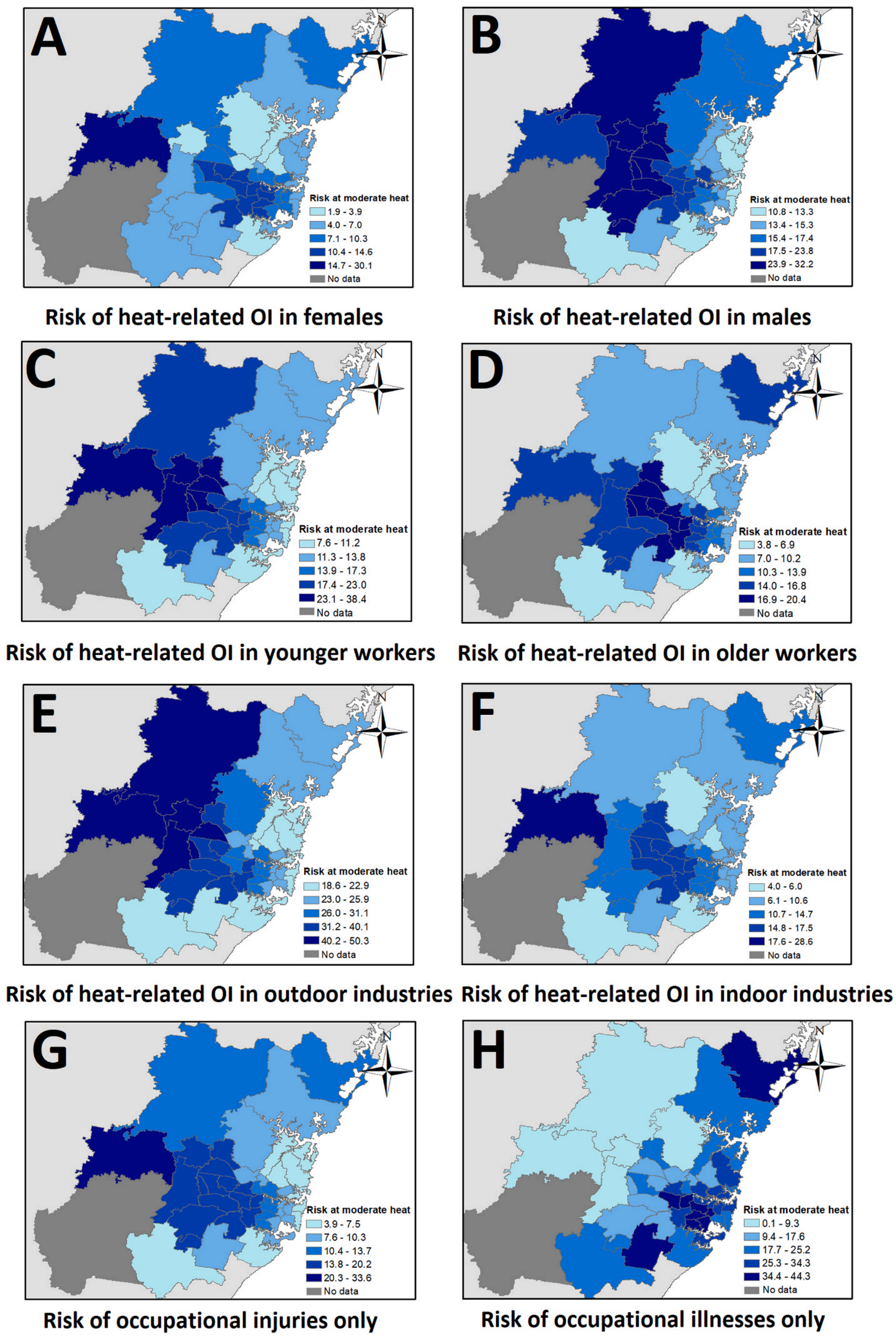

Fig. 7. Risk assessment of OI associated with moderate heat stratified by gender: A. females, B. males, by age C. younger (age <45) and D. older (age ≥45), types of industries E. outdoor industries and F. indoor industries and types of claims G. injury-related claims only and H. illness-related claims only in Greater Sydney.

Based on regional climatic conditions we can infer that workers in humid subtropical climates were generally at high risk of OI during extreme heat and the curve showed an exponential increase, as compared to workers in oceanic climates. A higher risk of OI was predicted in many SA3 regions of Greater Sydney (up to 32.3% increase) and Greater Brisbane (up to 25.9%) as compared to Greater Melbourne (20.5%). These findings support the existing evidence from the literature that revealed spatial heterogeneity in heat-related risk of OI across different climate zones (Fatima et al., 2021). In addition, hot and humid regions in Greater Brisbane and Greater Sydney had lagged effects (2–6 days) of hot weather conditions on OI, whereas in Greater Melbourne the effects were immediate (0–1 days) (Fig. 1). In humid subtropical climates, people are generally acclimatized to hot weather conditions but at extreme heat, humidity plays a significant role in the thermoregulatory response of the human body (Oppermann et al., 2017).

The risk of OI associated with heat index was ubiquitously high for outdoor industries particularly in outer SA3 regions in all three greater cities. Many SA3 regions vulnerable to the impacts of hot weather conditions for workers in outdoor industries, had a workforce predominantly employed in the construction sector (Australian Bureau of Statistics, 2016c). This finding suggests that relevant adaptive policies, guidelines, and codes of practice should be developed and adequate resourcing should be provided in the outdoor industrial sector where workers are required to do heavy work outside in unsafe thermal conditions at both moderate and extreme heat. Workers in indoor industries in hotter SA3 regions were also at high risk. In western regions of

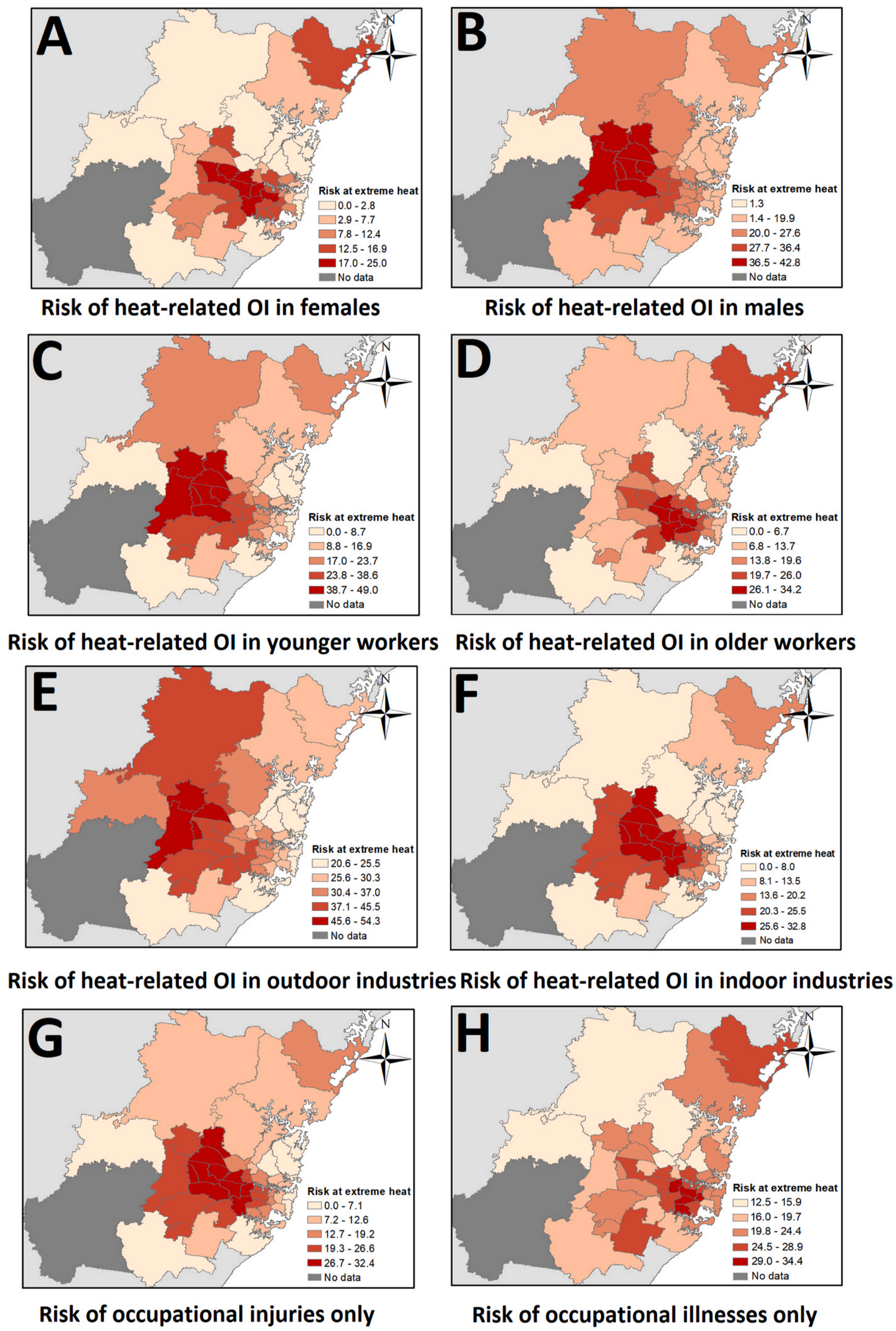

Fig. 8. Risk assessment of OI associated with extreme heat stratified by gender: A. females, B. males, by age C. younger (age <45) and D. older (age ≥45), types of industries E. outdoor industries and F. indoor industries and types of claims G. injury-related claims only and H. illness-related claims only in Greater Sydney.

Greater Brisbane, females were particularly at higher risk of OI. Some of the major indoor industries such as retail trade, education and training, and health care and social assistance are female-dominated sectors (Australian Bureau of Statistics, 2016c). These findings suggest that workers are also vulnerable to heat effects in regulated indoor workplaces. Industries and various levels of government need to deploy standards for heat management, in all industrial sectors, to help workers cope better with hot climate (Zander et al., 2018). Resource allocation should be prioritized in high-risk areas.

We also found a significant association between illness-related claims and hot weather conditions. The risk of occupational illnesses in workers was consistently high in the crowded city areas in all three cities. Recent literature provides evidence of the increased risk of illness and conditions associated with hot weather conditions in the general population (Liu et al., 2021, 2022). These findings have important implications for current and future healthcare prevention strategies which should be focused on both injuries and illnesses in occupational health and safety.

The risk of OI and AF associated with heat is predicted to increase in the projected periods: 2016–2045 and 2036–2065 in the three cities. Previous studies from multiple locations suggested an increase in heat-related health burden associated with warming climates (Gasparrini et al., 2017; Martínez-Solanas et al., 2021). Although, there are geographical variations in the impacts based on local climatic conditions and socio-economic factors (Gasparrini et al., 2017). Consistent with previous findings we observed that regions characterized by warm

Table 2
The risk estimates of OI associated with projected heat index (extreme heat - 99th percentile) for two timeframes (2016–2045, 2036–2065) and two RCP scenarios (4.5 and 8.5) for the NorESM1-M general circulation model in the three cities of Australia.

City	Prediction Period	RCP Scenario	Heat Effects (95% CI)
Greater Brisbane	Baseline	NA	2.7 (−10.0, 17.2)
	2016–2045	RCP 4.5	7.1 (−19.7, 42.9)
		RCP 8.5	6.8 (−19.1, 41.2)
	2036–2065	RCP 4.5	7.8 (−21.6, 48.1)
		RCP 8.5	7.2 (−20.5, 44.5)
Greater Melbourne	Baseline	NA	7.6 (−7.4, 24.9)
	2016–2045	RCP 4.5	7.5 (−17.4, 39.7)
		RCP 8.5	7.5 (−16.1, 37.8)
	2036–2065	RCP 4.5	7.5 (17.4, 39.7)
		RCP 8.5	7.5 (−17.4, 39.7)
Greater Sydney	Baseline	NA	11.3 (−5.5, 31.2)
	2016–2045	RCP 4.5	16.9 (−10.2, 52.1)
		RCP 8.5	16.9 (−10.2, 52.1)
	2036–2065	RCP 4.5	18.7 (−11.6, 59.2)
		RCP 8.5	17.8 (−10.8, 55.5)

baseline climates i.e. Greater Brisbane and Greater Sydney are particularly at higher risk of OI associated with the projected hot weather. Further investigations are warranted to assess the magnitude of the impacts of projected climate change on OI by considering factors like adaptations and changes in workforce size and composition (Arbuthnott et al., 2016; Petkova et al., 2014).

Exposure to extreme heat can result in a greater risk of OI and the impacts are disproportionate on a local scale. Therefore, it is of prime importance to issue localized warnings of hot weather conditions for timely preparedness and response. The national and state regulatory authorities should develop a holistic response to minimize the impacts of persistent hot weather conditions. These may include 1. Identifying vulnerable areas and implementing location-specific targeted interventions and resource allocation; 2. Promoting green spaces in urban planning will curb heat impacts, provide cool spaces, and help prevent the long-run impacts of climate change; and 3. Providing cooling assistance in socio-economically vulnerable regions.

4.1. Strength and limitations

Fine-scale assessment of the risk of OI associated with hot weather provides much-needed scientific evidence for WHS regulators, industries, unions, and workers. It will help them identify high-risk areas within a city and implement location-specific preventative measures to reduce the occupational health impacts associated with hot climate. The findings from this study will provide a valuable resource for policymakers in WHS and planning in integrating effective occupational health and climate policies at both local and national scales. Safe Work Australia has extensive information on working in heat (Safe Work Australia, 2020b). The findings from this study could add significantly to the existing information. The results are based on modelling choices that performed consistently well in the three cities as shown in the sensitivity analysis. The use of heat index improved the models' performance as compared to maximum temperature. As the heat index considers the combined effect of air temperature and relative humidity, it is a more reliable exposure metric, particularly in regions characterized by high humidity (Edirisinghe and Andamon, 2019).

This study has some limitations. First of all, to estimate the risk of OI at a finer geographical scale within cities, we have used SA3 as our spatial unit of analysis instead of POA, the geographical unit at which workers' compensation claims data is collected. The selection of SA3 was necessary to avoid methodological challenges such as the temporal boundary misalignment issue, which is inherent in POA, and the small sample size issue across space and time. SA3 regions are known to have similar labour market characteristics. Second, the results from this study were based only on workers' compensation claims data from Safe Work Australia. These data capture information on compensation claims only and do not reflect the additional burden associated with workplace incidents that do not progress to formal claims (McInnes et al., 2014). As such, our results are likely to be an underestimate of the total burden associated with injuries and illnesses of this nature. Third, in this study, we only considered workplace and location-specific characteristics. Many other factors related to workers' adaptability, personal risk factors, heat perceptions, and interventions in workplaces may significantly contribute to the geographic disparities in the risk, but these variables were not assessed due to the lack of availability of the datasets. Fourth, we have not adjusted for air pollutants in the models to estimate the association between OI and heat. While this could be considered as a limitation, previous studies have argued the need for such adjustments in heat-related studies (Buckley et al., 2014), as air pollutants act as a mediator rather than a confounder (Xu et al., 2019; Varghese, 2019). Furthermore, previous studies suggest that adjustments for air pollutants are likely to have a minimal effect on the heat-health associations (Zhao et al., 2019; Schifano et al., 2019). Fifth, we did not consider the potential for demographic changes over the projected periods. Although this could potentially lead to an underestimate of the overall impact of heat, it offers a straightforward interpretation of the results as it separates the impacts of global warming from other changes that may occur anyway even in a stable climate scenario (Vicedo-Cabrera et al., 2019). Finally, the indirect impacts on workers' health such as those arising due to more frequent extreme weather events such as excessive bushfires, floods, or droughts were also not considered in the future predictions.

5. Conclusions

This study provides a comprehensive spatial profile of the risk of occupational injuries and illnesses (OI) associated with hot weather conditions across three major cities in Australia. Risk assessment at the intra-urban city level revealed strong spatial patterns in the distribution of risk in all greater cities. The inland western regions in Greater Sydney and Greater Brisbane were at higher risk of OI. In Greater Melbourne, urbanized coastal areas were more vulnerable to heat effects. Regions characterized by lower vegetation, and lower socio-economic status were generally at higher heat-related risk of OI. Further, analysis stratified by various subgroups identified vulnerable groups of workers at a local level within the cities. These findings provide a strong base for policymakers and urban planners to implement location-specific risk prevention and mitigation strategies that should consider both climatic and workplace characteristics to mitigate the impacts of heat. Future projections suggest that Greater Sydney is the most vulnerable of the three cities in climate change scenarios.

Credit author statement

Syeda Hira Fatima: Conceptualization, Formal Analysis, Methodology, Writing-original draft preparation, **Paul Rothmore:** Conceptualization, Writing-reviewing and editing, Supervision, **Lynne C Giles:** Conceptualization, Writing-reviewing and editing, Supervision, **Peng Bi:** Conceptualization, Writing-reviewing and editing, Supervision.

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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

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2023.115855.

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