Predicting the Effects of Heatwaves and Air Quality on Emergency Department Presentations and their Spatial Variations for Children in Perth, Western Australia

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LIST OF ABBREVIATIONS

ABS	Australian Bureau of Statistics
ADT	Average Daily Temperature
AIC	Akaike’s Information Criterion
AR	Attributable Rate
BoM	Australian Bureau of Meteorology
CI	Confidence Interval
CO	Carbon Monoxide
DBCA	Department of Biodiversity, Conservation and Attractions
DER	Department of Environmental Regulation
DOH	Department of Health
DPMD	Disaster Preparedness and Management Directorate
ED	Emergency Department
EHF	Excess Heat Factor
EHI	Excess Heat Index
EHS	Emergency Health Service
ERP	Estimated Resident Population
GAM	Generalised Additive Model
GEE	Generalised Estimating Equations
GRF	Geographical Random Forest
GWR	Geographically Weighted Regression
HW	Heatwave
IDW	Inverse Distance Weighted
IncNodePurity	Increase in the Node Purity
MAE	Mean Absolute Error
MI	Multiple Imputation
NHW	No Heat Wave
NO_2	Nitrogen Dioxide
O_3	Ozone
OLS	Ordinary Least Square
OR	Odds Ratio
PM_{10}	Particulate Matter with Aerodynamic Diameter ≤10 Micro Metres
$PM_{2.5}$	Particulate Matter with Aerodynamic Diameter ≤2.5 Micro Metres
PPM	Parts Per Million
%IncMSE	Percentage Increase in Mean Squared Error
RF	Random Forest
RMSE	Root Mean Square Error
RR	Relative Risk/Risk Ratio/Rate Ratio
R^2	R-squared
SA2	Statistical Area Level 2
SA3	Statistical Area Level 3
SEIFA	Socio-Economic Index for Area
SES	Socio-Economic Status

SHP-HW	State Hazard Plan Heatwave
SO_2	Sulphur Dioxide
WA	Western Australia
3DAT	3-day average daily temperature

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EXECUTIVE SUMMARY

Heatwaves (HWs) are known to be associated with increased mortality and morbidity, including a rise in emergency department (ED) presentations, across the world. It is anticipated that these events will become more frequent, longer in duration, and more severe in the future. Additionally, there has been a changing pattern of air pollution over time. However, there is currently a lack of studies that evaluate the potential joint effect of HWs and air quality on ED presentations as well as the spatial variation of these two environmental factors on ED presentations. In this study, we aimed to assess the potential effects of HWs and air quality on ED presentations and their impact in different geographic areas with a specific focus on children. The study used machine learning approaches to predict ED presentations.

Study aims

- To investigate the effects of HWs and air quality, as well as their potential joint effects on ED presentations for vulnerable populations (specifically children under 15 years old) in various locations within the Perth metropolitan area.
- To explore the time lag for the effect of HWs on ED presentations.
- To identify important risk factors in predicting ED presentations.
- To examine a machine learning approach and spatial models for optimal models to predict the effects of HWs and air quality on ED presentations in different areas within Perth.
- To evaluate the HW measurement used in the State Hazard Plan-Heatwave (SHP-HW) and its related health effects.

Study design

- A spatiotemporal design was used for this study.
- Daily records of ED presentations, HW events (defined as excess heat factor (EHF) > 0), frequencies of landscape fire burns, and concentrations of air pollutants (i.e., CO, SO_2, NO_2, O_3, PM_{10}, and $PM_{2.5}$) were collected for Perth, Western Australia (WA) over a period of 10 years (2006–2015).
- Poisson regression modelling was used to assess associations between HWs, air quality, and ED presentations over time while adjusting for other factors (i.e., weather zone, public holiday and weekend, age, sex, Aboriginal status, and SEIFA).
- Spatial Poisson regression with statistical area level 3 (SA3) was performed to investigate the spatial relationship between HW and ED presentations after adjusting for air quality, age group, and the interaction between SA3s and HW.
- Geographically weighted regression (GWR) was tested to examine its suitability to predict the ED presentations with the whole dataset.
- A novel machine learning approach was used to select the optimal model among the five models for predicting the ED presentations and to analyse the importance

of the risk factors. Validation was performed on the final selected random forest (RF) models and geographical RF (GRF) models.
- The final spatial analysis was conducted by the GRF method to examine spatial variations of the risk factors identified in the RF model for three groups of children.
- A comparison of the two HW definitions [i.e., Excess Heat Factor (EHF) and the three-day average daily temperature (3DAT)] was implemented. Sensitivity analysis was conducted to identify the most suitable trigger for activation of the SHP-HW.

Key findings

1. HW, air quality, and their joint effects on ED presentations

- The significant effect of HWs on ED presentations peaked on the third day of a HW event. Overall, the air quality was poor during HW days compared to non-HW days in Perth.
- The relative risk of all-cause ED presentation (4.2%) and heat-related ED presentation (301%) increased on HW days compared with non-HW days after adjusting for other risk factors, including five air quality indicators, while the relative risks of the two rates excluding air quality measures were only increased by 3.2% and 179%, respectively.
- Dose-response relationships were observed between the relative risk of ED presentations and some air quality pollutants, such as all-cause ED presentations with CO, O_3, and $PM_{2.5}$, and heat-related ED presentations with SO_2, O_3, PM_{10}, and $PM_{2.5}$.
- There is a significant joint effect of HW and air quality (e.g., $PM_{2.5}$) on ED presentations.
- Children younger than 5 years old and adults older than 60 years were among the most vulnerable populations for all-cause ED presentations related to HW exposure. Young children 0–4 years old were also the most vulnerable population to HWs for heat-related ED presentations.
- Aboriginal people, or people living in the most disadvantaged areas or coastal areas had 90.1%, 71.2%, and 12.8% higher risks of all-cause ED presentations than those of non-Aboriginal people, those living in the least social-economic disadvantaged or inland areas, respectively.
- Heat-related ED presentations were more than 3-fold higher during HW days. ED presentations due to renal failure were 1.3 times higher during HW days. However, ED presentations due to stroke, cardiac conditions, respiratory diseases, circulatory diseases, and hypertensive conditions did not show such a relationship.
- When only children were included in the analysis, the relative risk of heat-related ED presentations increased more than 1.5 times. Children younger than 5 years were at the highest risk compared with the other two groups [RR = 1.553 (95%CI: 1.365, 1.768)]. Children living in the most disadvantaged areas and coastal areas

had 40.2% and 4.9% higher risks of heat-related ED presentations than those living in the social-economically advantaged or inland areas, respectively.

2. Machine learning approaches

- The global RF model outperformed the other four models (R^2 =0.953) and demonstrated the suitability of this model for the analysis of hierarchical and non-linear interactions in large datasets.
- The global RF model confirmed that the most important risk factors were age and SEIFA. Overall air quality was more important than HW. Particulate matter (PM) ranked higher than the gaseous air pollutants.

3. Identification of spatial variations

- The GWR models outperformed linear models but had limitations in the types and volume of data to be used.
- GRF models were demonstrated to be much more appropriate to use (R^2 ≥0.90) for data with significant spatial variations than other models.
- Overall, the three GRF models all showed that SEIFA and HW were the two most important risk factors (predictors) for ED presentations for children, and there were spatial joint effects between SEIFA, HWs, and air pollutants for children living in the southern areas.

4. Evaluation of the HW measurements used in the State Hazard Plan – HW, and related health effects

This practical section of the research project was described in a separate report published in 2022 and titled "Evaluation of the Heatwave Measurement Used in the State Hazard Plan – Heatwave and Related Health Effects". This report focused on identifying enhanced HW indicators and triggers for assessing health services related to HW exposure, and can be accessed here:

https://www.health.wa.gov.au/~/media/Files/Corporate/general-documents/Population-health/PDF/Evaluation-of-the-Heatwave-Measurement-used-in-the-State-Hazard-Plan.pdf.

Peer-reviewed journal publications from the project

- Jian L Patel D, Xiao JG, Jansz J., Yun G, Lin T, Robertson A. Can we use a machine learning approach to predict the impact of heatwaves on emergency department attendance? Environmental Research Communications 2023, 5(4) 045005 https://doi.org/10.1088/2515-7620/acca6e (1042 downloads, 3 citations)

- Patel D, Jian L, Xiao JG, Jansz J., Yun G, Lin T, Pereira G, Robertson A. Machine learning approach: identifying the impact of heatwaves and air quality on children's health. International Journal of Epidemiology 2021, 50 (Supplement_1). DOI:10.1093/ije/dyab168.323 (152 views)

- Patel D, Jian L, Xiao JG, Jansz J, Yun G, Lin T, Robertson A. Joint Effects of Heatwaves and Air Quality on Ambulance Services for Vulnerable Populations in Perth, Western Australia. Environmental Pollution 2019, 252:532-542 https://doi.org/10.1016/j.envpol.2019.05.125 (20 citations)

- Patel D, Jian L, Xiao JG, Jansz J, Yun G, Robertson A. Joint Effect of Heatwaves and Air Quality on Emergency Department Attendances for Vulnerable Population in Perth, Western Australia, 2006 to 2015. Environmental Research 2019, 174:80-87 DOI: 10.1016/j.envres.2019.04.013 https://doi.org/10.1016/j.envres.2019.04.013 (35 citations)

1. INTRODUCTION

1.1. Background

Globally, the surface temperature of the earth rose by 1.09°C and ranged from 0.95°C to 1.20°C on average between 1850–1900 and 2011–2020 [1]. October 2023 was ranked as the warmest October in the 174-year global climate record [2].

Climate change is expected to increase the frequency, duration, and severity of heatwaves (HWs) across the world, including Australia [1, 3]. The number of records of extreme heat days has outnumbered the records of extreme cool days in Australia since 2001. Australia has warmed by 1.47°C (±0.24°C) on average since the national record began in 1910, with the highest official temperature on record being 50.7 degrees, which occurred in Onslow, Western Australia (WA), on January 13, 2022 [3, 4]. WA just experienced its third-warmest October days in 2023, with the state-wide mean maximum temperature 3.12 °C above average [5].

Globally, there is a U-shaped association between temperature and mortality [6-8], with a minimum risk of premature mortality between 17 °C and 25 °C and a rising risk of premature mortality as the temperature deviates from this range. Epidemiological studies have reported on the adverse impact of HWs on premature mortality [9-11]. An increase in the number of deaths due to HWs has been observed in Australia over the last 200 years, making it the most important nature hazard for lives lost [12, 13] and a serious and pressing public health issue. HW-related mortality will continue to increase in the future without adequate leadership, preparedness, and prevention [14].

HWs are correlated with excess morbidity in terms of increasing utilisation of health services, such as emergency department (ED) presentations [15, 16], emergency hospitalisations [17, 18], ambulance callouts and transports [16, 19, 20], and hospital admissions [20, 21].

Vulnerable population groups are more susceptible to HW related illnesses than others. Several studies have reported that elderly people, children, and people with chronic diseases are more vulnerable to HWs [16, 22-25]. There are also significant differences in sex and Aboriginal status in regards to HW-related mortality and morbidity [26] [25, 27].

It is well documented that air pollution is one of the greatest environmental risks to health [28-32]. In 2019, 99% of the world population lived in places where the WHO air quality guidelines' levels were not met. Ambient air pollution in both cities and rural areas was estimated to cause 4.2 million premature deaths worldwide [31]. Among many pollutants, particulate matter (PM) can penetrate the respiratory system via inhalation, causing respiratory and cardiovascular diseases, reproductive and central nervous system dysfunctions, and cancer [32].

Some studies explored the potential joint effects of HW and air pollution exposure on mortality [33-39]. An early study in Athens, Greece, showed that there was a synergistic effect of air temperature and air pollution on excess mortality [35]. A recent study of air pollution from wildfires and high temperatures in Moscow proposed that these two factors may have a joint effect on mortality with an excess of 2,000 deaths, which is double the single air pollution effect [40]. However, very few studies have examined the joint effect of HWs and air pollution on ED presentations. A time-series study conducted in Brisbane found a significant difference of RRs with ozone (O_3), nitrogen dioxide (NO_2), and PM_{10} at lag 1 day for ED presentations [41]. Another study in Birmingham, UK, found that all pollutant levels rose during HWs, with the maximum temperature coinciding with the peak levels of O_3 and PM_{10} [42].

Although there is ample literature on how various socioeconomic status (SES), demographic, and geographic factors affect inequities in the risk of mortality, most studies do not use a spatial approach to understanding the environment-mortality relationship. Some spatial studies are concerned with the relationship between geographical patterns or environmental factors (climate, locations, HWs, and air quality) and health outcomes, such as heat-related disorders [43], heat stroke [44], heat-related hospitalisation for acute myocardial infarction [45], and the impact of climate and heatwaves on mortality [46].

Researchers used various methodologies to assess the relationship between HWs and health service utilisation. Most studies used a time-series design. Popular statistical methods included Generalized Estimating Equations (GEE), Generalised Linear Models (GLM), Generalized Additive Models (GAM), Negative Binomial Regression, Poisson Regression, and Logistic Regression. However, there is a lack of studies using a machine learning approach to predict health outcomes and health service utilisation, in particular the joint effects of HWs and air quality on emergency health services (e.g., ED presentations).

Machine learning uses computers to optimise a performance criterion or prediction using training data or experience. In recent decades, there have been various publications in different fields using machine learning approaches, such as population estimation [47-49], developing spatial models of air pollutants [50], defining the HW threshold [51], and mapping the peak daytime temperature [52]. Machine learning uses a training dataset to train the model and identify the general pattern from the data [48]. Therefore, it can generalise or predict the validation dataset and generate less noise. A better prediction model can assist in better health service planning for the protection of the affected populations and reduce HW related adverse health effects. However, there are very few studies assessing health service utilisation using such advanced technology. In this study, apart from temporal analysis, area-adjusted analysis, and the geographically weighted regression (GWR) method, machine learning approaches with a spatial component were used to analyse the effects of HWs and air quality on ED presentations and the spatial variations of these environmental factors across the whole Perth metropolitan area.

The optimal model was assessed and selected based on the goodness of fit analysis. The importance rank of all risk factors and their spatial variations were assessed to improve the prediction of ED presentation services for optimal HW management and prevention of HW-related adverse health effects.

1.2. Aims and Hypotheses

The aims of this study are to:

- Investigate the effects of HWs and air pollutant exposure and their potential joint effects on ED presentations for vulnerable populations (with a particular focus on children less than 15 years old) and locations in the Perth metropolitan area.
- Investigate the time lag for the effects of HWs on ED presentations.
- Explore spatial models and machine learning approaches for the optimal global and local models to predict the effects of HWs and air quality on ED presentations.
- Investigate the importance of risk factors in predicting ED presentations.
- Evaluate the HW measurement used in the State Hazard Plan-Heatwave, and related health effects.

The hypotheses of this study are:

- HWs and air quality have a synergistic effect on ED presentations for vulnerable populations in Perth.
- There is a spatial variation of risk factors across the study area.

1.3. Significance of the Study

This study was conducted in Perth to investigate the effects of HWs and air quality as well as their potential joint effect on ED presentations. It also evaluated the spatial variations of the impact of HW and air quality on ED presentations. Identifying geospatial patterns of high-risk areas has the potential to develop targeted public health interventions to mitigate adverse health effects. Moreover, a machine learning approach was used to select the best model for predicting ED presentations and ranking the importance of risk factors in the model, providing an efficient way to identify the most important risk factors and the most cost-effective preventive measures for future intervention.

The findings from this research can be used as an evidence-based reference to support and improve the HW warning system in WA. In addition, the results can be used as a guide for the improvement of HW-related health services. It is crucial for health service providers, such as hospitals, to enhance their service capacity and meet the needs of vulnerable populations in specific geographic areas affected by HW-related adverse health effects. Furthermore, these research outcomes can assist in targeting high-risk populations in high-risk areas and developing health education programs focused on raising awareness of HW effects and preparedness.

The research findings will be disseminated through publications submitted to peer-reviewed journals, reports, and presentations at national or international conferences in order to widely share the results and benefit more people and communities affected by extreme weather events.

2. MATERIALS AND METHODS

2.1. Study Design

A population-based spatiotemporal design was used for this study. Daily data for the 10-year period from 2006 to 2015 for warm months (i.e., January, February, March, April, November, and December) for the Perth metropolitan area (in short, Perth) were included for analysis. In total, 7,289,969 all-cause ED presentation cases and 5,007 heat-related cases were examined. The ED presentation data were aggregated by statistical area level 2 (SA2), age group, sex, Aboriginal status, and date of ED presentations to obtain daily counts. The data were analysed at an aggregated level.

SA2 is defined as a medium-sized (population range: 3,000 to 25,000 persons) geographical area in the Australian Statistical Geography Standard [53] and is used by the WA health system as the basic geographic unit for the health service coverage area. There are 174 SA2s in Perth. After excluding SA2s with no populations (i.e., industrial areas and national parks), a total of 154 SA2s were included in the final analysis.

Spatial analyses required further aggregation of areas based on statistical area level 3 (SA3). SA3 is a relative larger geographical area built from grouping SA2s based on criteria defined by the ABS, including population, function, and similarities in socio-economic conditions and geographic locations. One SA3 generally has a population between 30,000 and 130,000 people [53]. A total of 21 SA3s were defined for Perth and included for spatial analysis.

2.2. Research Setting and Participants

Perth is the capital city of WA, located at 31°55′S latitude and 115°58′E longitude. Perth has a warm temperate climate where summers are hot and dry because of the dominance of subtropical high-pressure systems, while winters have moderate temperatures with rain because of the polar front [54].

In 2015, the population of WA was 2.59 million. Most people (79%, 1.94 million) lived in Perth, including 497,700 children under 15 years of age, accounting for almost one fifth (19%) of the population of the state. Among them, there were 6.7% (130,118) under 5 years of age [55]. The whole population of Perth was included in this study, with a focus on children. The analysis was conducted for all age groups and for children separately. The study location is shown in Figure 1.

2.3. Data Sources and Data Management

2.3.1. Population Data

The estimated resident populations for each SA2 by age group, sex, and Aboriginal status for Perth were sourced from the ABS for the study period. Populations per month were calculated by using a linear interpolation method, which was based on a mid-year estimated resident population (ERP), and these calculated populations were then applied to all the days in the month. A sum of SA2 level populations, based on a concordance between SA2 and SA3, was used to derive SA3 level populations.

2.3.2. HW Data

Weather data such as temperature and excess heat factor (EHF) were sourced from the Australian Bureau of Meteorology (BoM) as gridded data with 5×5 kilometre pixels in a network common data (NetCDF) format (a format of file for storing multidimensional scientific data such as temperature) [13]. The data was then converted into daily raster layers. A simple model was built to extract the daily EHF value for population weighted centroid of each SA2 using ESRI ArcMap software (Version 10.5). Median SA2 level EHF values were taken to derive SA3 level values for the analysis based on SA3.

a) HW definition by the Australian Bureau of Meteorology

A HW intensity index, the Excess Heat Factor (EHF), has been created in Australia by the Australian Bureau of Meteorology [13]. The EHF compares the daily average temperature (DAT) for 3 days with the historical temperature (95th percentile of DAT for the climate reference period 1971–2000) for that area, known as the significant excess heat index (EHI_{sig}), and the DAT for the preceding 30 days known as heat stress or acclimatisation excess heat index (EHI_{accl}). These measures are joined to produce an EHF that provides a relative measure of the load, intensity, spatial distribution, and duration of a HW day or event. The EHF formula below was used in this study to define a HW day:

$$\mathbf{EHF} = EHI_{sig} \times \max(1, EHI_{accl}).$$

$$\text{where } DAT = (DAT_{max} + DAT_{min})/2$$

$$EHI_{sig} = (DAT_0+DAT_1+DAT_2)/3 – DAT\ 95^{th}$$

$$EHI_{accl} = (DAT_0+DAT_1+DAT_2)/3 – (DAT_{-1}+...+DAT_{-30})/30.$$

In this study, a day was deemed a HW day if the EHF value was greater than 0, and a non-HW day if the EHF was less than or equal to zero. To determine a HW day for the whole of Perth, an 80% cut-off was used. If more than 80% of SA2s in Perth had EHF >0 (i.e., HW day) on a particular day, that day was counted as a HW day for the whole Perth area. Once a day was determined as a HW day, possible lag effects on health utilisation were assessed.

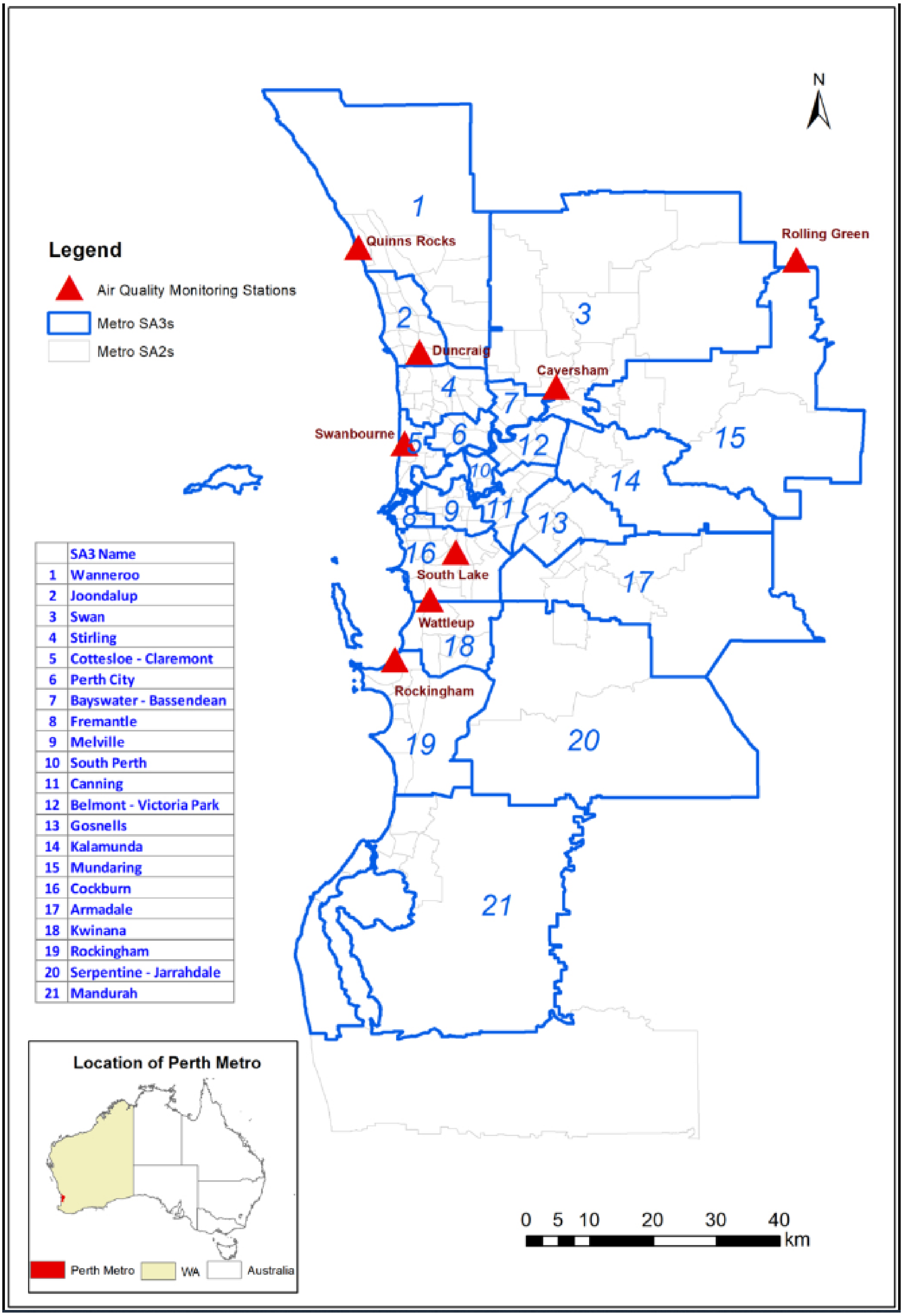

Figure 1 Map of the locations (SA2 and SA3) of the study area with air quality monitoring stations

2.3.3. Air Quality Data

Air quality data such as carbon monoxide (CO), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), ozone (O_3), particulate matter with aerodynamic diameter ≤10 micrometres (PM_{10}), and particulate matter with aerodynamic diameter ≤2.5 micrometres ($PM_{2.5}$) were collected from the Department of Environmental Regulation (DER) (now known as the WA Department of Water and Environmental Regulation) from 8 stations (Figure 1). Data on the date, size, and location of landscape fires (including prescribed burns and wildfires) over the study period were sourced from the WA Department of Biodiversity, Conservation, and Attractions (DBCA). The daily number of landscape fires was used in the machine learning approach to predict the ED presentation rates at SA3 level.

a) Dealing with missing values

Raw air quality data were collected from the DER for the study period, available from eight stations in the study area (Caversham, Duncraig, Quinns Rock, Rolling Green, Rockingham, South Lake, Swanbourne, and Wattleup). The six air quality measures included hourly CO, SO_2, NO_2, O_3, PM_{10}, and $PM_{2.5}$. The daily mean of the maximum eight hourly values of each air pollutant was calculated for the period 2006–2015. As the original six air quality measures had some missing values, these values were estimated using a multiple imputation (MI) procedure in SAS [56]. The MI procedure is based on the concept that the missing values are filled by values that are taken from the distribution estimates of the non-missing dataset (Donders et al., 2006). Five estimated imputation values for five variables (weekday, weekend, month, number of stations, and the air quality measure) were averaged and used to replace the missing values.

b) Inverse distance weighted method and Kriging interpolation method

The concentrations of air pollutants for each SA2 were estimated using the inverse distance weighted (IDW) method, a type of deterministic method for multivariate interpolation with a known scattered set of points in the geospatial analysis [57, 58]. IDW interpolation explicitly assumes that points that are closer to one another are more alike (gives greater weight) than those that are farther apart. The IDW estimation was conducted using ArcMap 10.5. The ArcMap tool (Extract Values to Points) was used to extract the available air pollutant values for each SA2 population centroid. The assigned values to unknown points were calculated with a weighted average of the air pollutant values available at the known eight air quality monitoring stations in the study areas. The values for each air pollutant were then categorised into three levels based on their distribution percentiles, i.e., low (<25th percentile), middle (25th–75th percentile), and high (>75th percentile).

Apart from the IDW method, the Kriging interpolation method was tested, as some studies indicated that the Kriging interpolation method could produce a better unbiased linear estimate for the values of the variable at any non-sampled point with fewer errors [59-62]. Comparisons between the estimated results from the IDW method and the Kriging method were conducted in order to select the best method for further analysis. Overall, the Pearson correlation coefficient values between air quality and EHF were higher in the IDW method than the ones in the Kriging method (Appendix 1). Therefore, the decision was made to use air quality measures derived from the IDW method for further analysis.

2.3.4. ED Presentation Data

Daily ED presentation data was originally aggregated from the WA Emergency Department Data Collection. The data was based on SA2. For the SA3 level analysis, the number of ED presentations for the relevant SA2s was summed to derive the SA3 level values. For the disease cause related analysis, the ED presentation data was extracted based on ICD-10-CM codes (of the International Statistical Classification of Diseases and Related Health Problems, 10th revision, Australian Modification). Stroke, cardiac diseases, respiratory diseases, circulatory diseases, hypertensive cases, renal failure cases, and heat-related ED presentations were analysed. The details of the ICD 10 codes used for the cause related analysis can be found in Appendix 2.

2.4. Statistical and Spatial Analysis

2.4.1. Statistical Analysis

The statistical analysis was conducted using SAS Enterprise Guide 5.1. Descriptive statistics were used to assess the distribution of all-cause and heat-related ED presentation rates with different risk factors such as age, sex, and socio-economic status (SES). The ED presentations among different population groups during HW days were compared with those during non-HW days. Correlation analyses were used to evaluate the correlations between air pollutant concentrations, HW (EHF), and daily ED presentation rates. All Perth residents with an ED presentation during the study period were included in the analysis.

To assess the joint effect of HWs and air quality on ED presentations, the following independent variables were included to identify vulnerable groups : age (0-4, 5-9, 10-14, 15-59, and ≥60 years), sex (male and female), Aboriginal status, and the socio-economic index for area (SEIFA) categories (1= disadvantaged and most disadvantaged, 2= middle, 3= least disadvantaged and less disadvantaged) according to the Index of Relative Socio-economic Disadvantage (IRSD) defined by the ABS [63]. Environmental factors included HWs (HW day and non-HW day) and air quality (low, middle, and high levels). Temporal variables included week periods (weekend vs. weekday), public holidays vs. non-public holidays, and months. The weather zone was also included as the Perth inland (hot, dry summer and cold winter) and Perth coastal (warm summer and cool winter) areas defined by the BoM.

Both single- and multiple-risk factor analyses were conducted. The purpose of using the bivariate analysis was to identify significant risk factors for HW-related ED presentations and then include them in the multiple-risk factor and interaction analysis via the Poisson regression models. In the single risk factor analysis, each risk factor was evaluated separately to determine if it was interacted with HW on ED presentations; and its crude ED presentation rate was calculated (without adjusting for other risk factors), as well as attributable rate (AR), and rate ratio/relative risk/risk ratio (RR). The AR was defined as the absolute difference in rates between HW days and non-HW days for a particular risk factor and its subcategory or level (e.g., one category of age group: 0–4 years, and one level of $PM_{2.5}$: low level). In addition, to assess the relative effect of each risk factor on ED presentations, a relative risk (i.e., rate ratio, RR) with a 95% CI was calculated. RR was defined as the ratio of rates on HW days (exposure) and non-HW days (non-exposure). Non-HW days were used as a reference category to evaluate the effects of a risk factor during HW days on ED presentations. The comparison between different levels of a risk factor was deemed statistically significant if the P value was less than 0.05.

In the multiple risk factor analysis, Poisson regression models were used to evaluate the potential association between HWs, air quality, and ED presentations and to identify vulnerable populations and locations, adjusting for all other risk factors. The category of a risk factor with the lowest ED presentation rate was used as a reference category to compare with other categories of the risk factor. The regression model is presented in Equation 1.

$$\text{Logit } p = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p \qquad (1)$$

Where α denotes the baseline ED presentation risk; β_1 is the fraction by which the ED presentation risk is altered by a unit change in X_1; β_2 is the fraction by which the ED presentation risk is altered by a unit change in X_2, and so on.

The delayed effect of HWs on ED presentations was examined for the same day, cumulative 1, 2, 3, ..., up to 21 days after a particular HW event. The day with the strongest association between EHF and cumulative all-cause ED presentation rate in the regression model was selected and used in the final model analysis. For instance, cumulative 3-day data were the sum of the ED presentations for the current day and counts in the subsequent two days. The same principle applied to the calculation of cumulative populations when cumulative ED presentation rates were computed. In regression analysis, RR was calculated to assess the difference in outcome measures by risk factors during HW days and non-HW days. The joint effect of HWs and air pollutants was examined to identify vulnerable populations and locations for HWs by examining their interaction in the model (e.g., HW × $PM_{2.5}$).

As the initial analysis only included children, resulting in uncertain outcomes, a concern about weak statistical power because of the small ED presentation numbers and populations was raised. To increase statistical power and better understand the HW effect on children, the analysis then included two parts: one included all-age groups (which included the three children's groups), and another only included children. Finally, in the evaluation of temporal effects, an all-age model (including three groups of children) was included in the analysis to obtain much more stable outcomes. Those outcomes from child-only analyses were conducted and mainly included in the appendices as references, which enables comparisons between the outcomes from the all-age model and child-only analyses. For spatial effects, both all-age group models and children-only models (with a focus on the 0–4-year age group) were reported for better understanding of the spatial variations of HW impact and the potential joint effect of HW and air quality on ED presentation demand for vulnerable populations. As very limited resources were available, only all-cause ED presentation data were included for spatial analysis and machine learning approaches.

2.4.2. Geographically Weighted Regression

Ordinary least square (OLS) is a widely used global regression method but is unable to identify spatial variation. However, geographically weighted regression (GWR) is a local regression method to model the spatial variation across the study area, considering the relationship between the dependent and independent variables [64]. The GWR model is presented in Equation 2. The modelling was conducted using ArcMap 10.5.

$$Y_i = \alpha_i + \sum_p \beta_{pi} X_p + \varepsilon_i \qquad (2)$$

Where Y denotes the dependent variable, β_{pi} is the value of β_p at point I, and ε is the residuals (differences between the actual and predicted values of the dependent variable Y).

In a GWR model, observed data close to point i has a greater influence on the estimation of the values of β_{pi} than data located far away from point i. Hence, the data from observations near i is weighted more than the data from observations farther away [64].

By selecting different bandwidths, the size of the local neighbourhood in the GWR model was controlled. There are two types of bandwidth selection methods in GWR: fixed and adaptive. A fixed bandwidth is a constant distance that is used to define the neighbourhood around each point. It is suitable for datasets with regular sample configurations. Adaptive bandwidth is a variable distance that is used to define the neighbourhood around each point. It is suitable for datasets with highly irregular sample configurations. Adaptive bandwidths ensure sufficient (and constant) local information for each local calibration. The GWR model with an adaptive kernel can provide more exact results that are closer to reality [65]. Therefore, an adaptive bandwidth was selected for the study.

Akaike's Information Criterion (AIC) and **local R-squared** (R^2) were used to assess the model's goodness of fit for GWR. AIC is a procedure for choosing bandwidth in the GWR models, and a model with lower AIC values indicates a better model fit than the one with higher AIC values. The R^2 value determines the proportion of variance in the dependent variable that can be explained by the independent variables. The closer the R^2 value to 1, the better the model's performance. Spatial autocorrelation was examined by **Moran's I** test. It is performed on the residuals of the model. The range of Moran's I values is from −1 (representing perfect dispersion) to 1 (representing perfect correlation). A value of 0 means perfect spatial randomness [66]. As GWR models cannot model binary or count variables, such variables (e.g., Aboriginal status, sex, weather zone, holiday, and weekend) were excluded.

2.4.3. Machine Learning

Analysis using machine learning was implemented in RStudio (v.1.1.463). The whole dataset was divided into two subsets: training and testing (evaluating) sets. The golden rules of machine learning and modelling in general are that all models are built using a training set, and the final model's performance is evaluated on an independent testing set. The reason for doing this is to minimise the issue of overfitting or underfitting. If the training data is overfitted, the performance of the testing data will be poor. Simple models are often better than complex ones because they are better able to be generalised. In this study, the data were randomly divided into a 70:30 split (70% for training models and 30% for testing). Cross-validation was performed firstly on the training dataset to adjust the hyperparameters of the model during the training process. To ensure reproducibility, the seed number was set to 100. The optimal machine learning models were identified separately for the three different child groups (0–4, 5–9, and 10–14 years). Subsequently, predictions of ED presentations were made using these final models while utilising the nine-year ED dataset from 2006–2014 for model training. Finally, actual ED presentation data from 2015 were compared against predicted values for validation purposes. Several predictive models were developed and assessed based on their accuracy (detailed descriptions of these models can be found below).

a) Models included for testing

i. Baseline model

It is a model that assumes there are no predictors (i.e., no independent variables). In the absence of any predictor, the variable in the model is a dependent variable (e.g., ED presentations). The mean of ED presentations was used in the training data to predict the number of ED presentations on a given day.

ii. Multiple linear regression model

In a multiple linear regression, ED presentations were assumed to be a linear function of several risk factors, where each of them had a weight (regression coefficient) that was expected to be statistically significant in the final model. Linear models do require a linear relationship between the dependent and independent variables.

iii. Decision tree and pruned tree models

A decision tree, also known as a regression tree for continuous outcome variables, is a simple and popular machine learning algorithm. It has an advantage over a linear model in that it makes no assumptions about the relationship between the dependent and independent variables. The process of growing a tree includes root nodes (the starting point of the tree), decision nodes, terminal nodes (the end points of the tree), and the use of different algorithms for splitting [67].

When growing a tree, it internally performs 10-fold cross-validation. Since testing is done at the same time as growing a tree, the result has an error measurement that is used to find the optimal number of splits. The original tree has been pruned, and only the optimal number of splits are kept [67].

iv. Random forest-regression model

A RF model is an ensemble-learning method for which a multitude of decision trees are constructed to explain the relationships between ED presentations and related factors for regression [68]. It works by constructing a multitude of decision trees at the training time and outputting the mean prediction of the individual trees. Random forests correct for the decision tree habit of overfitting to a training set [68]. A RF method is a suitable method for the analysis of hierarchical and non-linear interactions in large datasets [49]. It does not require any assumptions about the relationships between the dependent and independent variables (also called predictor variables or risk factors). Details of these variables are explained in Appendix 3.

The *RandomForest* package was used in RStudio to develop the RF model. The numbers of variables (*mtry*) and decision trees (*ntree*) were chosen corresponding to the maximum model coefficient of determination (i.e., R^2) for better model fitting. Based on parameter sensitivity analysis, the RF model was established with a *mtry* value of four and a *ntree* value of 500. In other words, 500 decision trees were modelled, and four features were randomly chosen on each node of each decision tree. The accuracy of the model was verified by applying the trained model to the testing dataset.

v. Geographical random forest

A geographical random forest (GRF) model is an extension of RF that can address spatial heterogeneity [48]. Local results are obtained instead of global RF using the

GRF model. For each location of the study area, a local RF model is computed and only includes *n* number of nearby observations [48]. In this study, the newly designed package *SpatialML* in RStudio was used to develop the GRF models. An adaptive kernel for the GRF models was selected, and the bandwidth was 20. The weight parameter value was selected for the prediction. To predict the local models, the local weight value was set to 1, while the global weight value was 0 for the GRF models [69].

GRF was applied to three different age groups for children (i.e., 0–4, 5–9, and 10–14 years). The sum of air pollutants and EHF values was computed for each relevant age group to derive a single value for each SA3 area. For example, to derive a single value for CO for each SA3, the sum of CO concentrations for 10 years was computed for the 0–4–year age group. The prediction of ED presentation rates was performed on the validation datasets, which contained a randomly selected 30% of the data. The actual and predicted values were compared, and an R^2 value was obtained to determine the goodness of fit of the model.

b) Variable importance analysis

Variable importance analysis is a technique used in random forests to assess the importance of input variables when dealing with complex interactions, making the machine learning model interpretable and computationally efficient. Through variable importance analysis, the most relevant and important variables for a given model can be identified based on their importance scores, and the ones that are irrelevant will be excluded. Reducing the number of non-meaningful variables in the model may speed it up or even improve its performance. In this study, the positive score for a risk factor in the model is an indication that the risk factor (or independent variable) contributed to the ED presentation prediction.

The RF procedure for importance ranking in RStudio uses two measures: (1) the percentage increase in mean squared error (%IncMSE), and (2) the increase in node purity (IncNodePurity) [68]. Predictors with high importance ranks have significant impacts on dependent variables.

%IncMSE is a measure of the increase in the mean squared error (MSE) when a variable is excluded from the model, and vice versa. It is used to assess the importance of a specific variable in the model. A higher value of %IncMSE indicated greater importance for a model variable. %IncMSE is the most robust and informative measure and determines the importance of a variable based on its contribution to the model's predictive accuracy.

IncNodePurity is a measure of the homogeneity of the samples in a node of a decision tree and measures the total decrease in node impurities by the Gini Index from splitting on the variable, averaged over all trees. The higher the IncNodePurity score, the more important the variable is in the model. It is based on the ability to split the data into pure nodes and is used to determine the optimal split of the data (structure of the data) at each node of the tree.

c) Evaluation metrics for all machine learning models

The Root Mean Square Error (RMSE) is the main error metric used to evaluate the performance of models (Equation 3). It measures the average distance between the predicted and actual values of the response variable. The lower the RMSE, the better a given model can "fit" a dataset. The formula to find the RMSE is as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(yi-xi)^2}{n}} \qquad (3)$$

The Mean Absolute Error (MAE, Equation 4) is a statistical measure of the difference between two continuous variables (e.g., predicted values vs. actual values) and the accuracy of models. It gives equal weight to the residuals, regardless of their direction. It shows, on average, the magnitude of the error obtained by using the model when compared to the actual observed values. The model with the lowest error values was estimated as the best-performed model.

$$\text{MAE} = \frac{\sum_{i=1}^{n} yi-xi}{n} \qquad (4)$$

Where x is the observed value, y is the predicted value, Σ is the summation, i is the sample sequence number running from 1 to n, and n is the sample size.

3. RESULTS

3.1. HWs and Air Quality in Perth

The total number of HW days in Perth from January 2006 to December 2015 using an 80% cut-off, was 163 (Table 1). The highest number of HW days was observed in 2011 and 2012, with a total of 25 HW days in each year. Overall, February was the hottest month in the study period, with a total of 62 HW days during the study period.

Table 1 The number of HW days by month and year in Perth

Year	January	February	March	April	November	December	No. HW days*
2006	1	4	3	0	0	0	8
2007	4	4	4	0	0	3	15
2008	6	10	0	0	0	2	18
2009	4	4	0	0	0	1	9
2010	7	7	3	0	2	2	21
2011	7	13	2	0	0	3	**25**
2012	12	4	2	0	0	**7**	**25**
2013	4	9	0	0	0	2	15
2014	9	5	0	0	0	0	14
2015	6	2	2	0	0	3	13
Total	**60**	**62**	**16**	**0**	**2**	**23**	**163**

HW: heatwave

If 80% of SA2s had an EHF>0 on a day, the whole Perth metropolitan area would be counted as a HW day.

There was a fluctuation in HW intensity in Perth from 2006 to 2015 (Table 2). The year with the highest HW intensity was 2007 with a maximum of 50.39, followed by 2010 (maximum = 44.07) and 2012 (maximum = 37.91).

Table 2 HW intensities in Perth during 2006–2015

Year	EHF Mean	EHF SD	EHF Median	EHF Min	EHF Max	Interquartile Range*
2006	3.582	3.076	2.822	0.002	12.898	12.896
2007	**16.839**	14.858	**13.724**	0.004	**50.394**	50.390
2008	3.724	2.411	3.171	0.003	15.855	15.852
2009	3.769	3.712	2.600	0.002	14.583	14.581
2010	10.141	9.977	6.286	0.007	44.074	44.067
2011	5.048	4.998	4.106	0.001	27.430	27.429
2012	11.009	11.608	4.920	0.001	37.905	37.904
2013	6.95	7.733	2.865	0.001	26.899	26.899
2014	6.553	5.997	6.095	0.001	29.675	29.674
2015	4.245	4.135	2.141	0.001	16.289	16.288
Median	5.8005	5.4975	3.6385	0.0015	27.1645	27.164

EHF: Excess heat factor; Min: Minimum value, Max: Maximum value, SD: standard deviation.

*: difference between 75th and 25th percentile

Table 3 shows the median values and classification of the three threshold levels of air pollutants based on their distribution percentiles, i.e., low level (<25th percentile), middle level (25th–75th percentile), and high level (>75th percentile) for the study period.

Table 3 Concentrations of air pollutants in Perth and the three threshold levels

Air pollutants	Median	Min	Max	Low level*	Middle level	High level
CO (PPM)	0.195	0	1.971	<0.138	0.138-0.272	>0.272
SO_2 (PPM)	0.002	0	0.027	<0.001	0.001-0.004	>0.004
NO_2 (PPM)	0.008	0	0.036	<0.005	0.005-0.011	>0.011
O_3 (PPM)	0.028	0.009	0.084	<0.024	0.024-0.034	>0.034
PM_{10} (μg/m^3)	26.947	0.129	**204.324**	<20.791	20.791-34.619	>34.619
$PM_{2.5}$ (μg/m^3)	11.036	3.531	**131.972**	<8.891	8.891-13.882	>13.882

* Reference category; Min: Minimum; Max: Maximum; PPM: parts per million; μg/m^3: micrograms per cubic metre. CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micrometres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micrometres.

Table 4 shows the ambient air quality standard in Australia and the median level of air pollutants during the study period. Overall, the air quality was good in Perth during the study period.

Table 4 Australian ambient air quality standard and the air quality in the study period

Air pollutants	Median (this study)	Australian standard
CO (PPM)	0.195	9.0 ppm 8 hours average
SO_2 (PPM)	0.002	0.20 ppm 1 hour average
NO_2 (PPM)	0.008	0.12 ppm 1 hour average
O_3 (PPM)	0.028	0.10 ppm 1 hour average
PM_{10} (μg/m^3)	26.947	50 μg/m^3 daily average
$PM_{2.5}$ (μg/m^3)	11.036	25 μg/m^3 daily average

PPM: parts per million; μg/m^3: micrograms per cubic meter.CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micrometres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micrometres.

Table 5 shows the comparison of air quality on HW days and non-HW days between 2006 and 2015. Overall, the air quality was worse during HW days compared to non-HW days in Perth ($p<0.0001$).

Table 5 Air quality during HW and non-HW days in Perth, 2006-2015

	HW days			Non-HW days		
Air pollutants	**Median**	**Min**	**Max**	**Median**	**Min**	**Max**
CO (PPM)	0.191	0	1.445	0.196	0	1.971
SO_2 (PPM)	0.003	0	0.027	0.002	0	0.026
NO_2 (PPM)	0.008	0.001	0.036	0.008	0	0.034
O_3 (PPM)	0.034	0.018	0.067	0.027	0.009	0.084
PM_{10} (μg/m^3)	31.577	12.689	144.885	26.402	0.129	204.324
$PM_{2.5}$ (μg/m^3)	12.376	4.714	60.482	10.855	3.531	131.972

Min: Minimum value; Max: Maximum value; PPM: parts per million; μg/m^3: micrograms per cubic metre. CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micrometres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micrometres.

3.2. ED Presentations in Perth

The total number of all-cause ED presentations in Perth from January 2006 to December 2015 was 7,289,969 (Table 6). The number of ED presentations increased each year, with the highest number of ED presentations in 2015. Overall, the highest number of ED presentations was observed in December, with a total of 1,312,818 ED presentations in December during the study period. The ED presentation numbers in December 2012 were higher than those in 2013, along with the highest number of HW days (7 days) in December 2012.

Table 6 The ED presentation counts by month and year in Perth

Year	Jan	Feb	March	April	Nov	Dec	Total
2006	86,247	74,463	85,239	83,793	87,902	95,017	512,661
2007	88,255	79,656	90,336	87,461	92,619	108,276	546,603
2008	105,903	98,733	108,795	101,473	105,403	113,814	634,121
2009	112,448	99,309	110,080	108,904	111,980	121,831	664,552
2010	115,474	105,024	118,970	116,898	120,508	127,460	704,334
2011	127,383	115,894	131,332	127,533	134,499	145,912	782,553
2012	142,489	131,945	145,211	138,704	138,292	**149,618**	846,259
2013	146,875	127,497	147,285	142,612	143,328	148,972	856,569
2014	145,621	131,675	145,422	143,151	144,554	150,244	860,667
2015	146,559	137,136	151,514	143,793	150,974	151,674	881,650
Total	1,217,254	1,101,332	1,234,184	1,194,322	1,230,059	**1,312,818**	7,289,969

ED presentations: emergency department attendances.

Figure 2 displays the association between ED presentation rates and the number of HW days over the study period. There was a steady increment in the ED presentation rate with an increase in the number of HW days over time up to 2012, except for the year 2009. The ED presentation rate reached a peak in 2012 with a rate of 81.62 per 100,000 populations and 25 HW days.

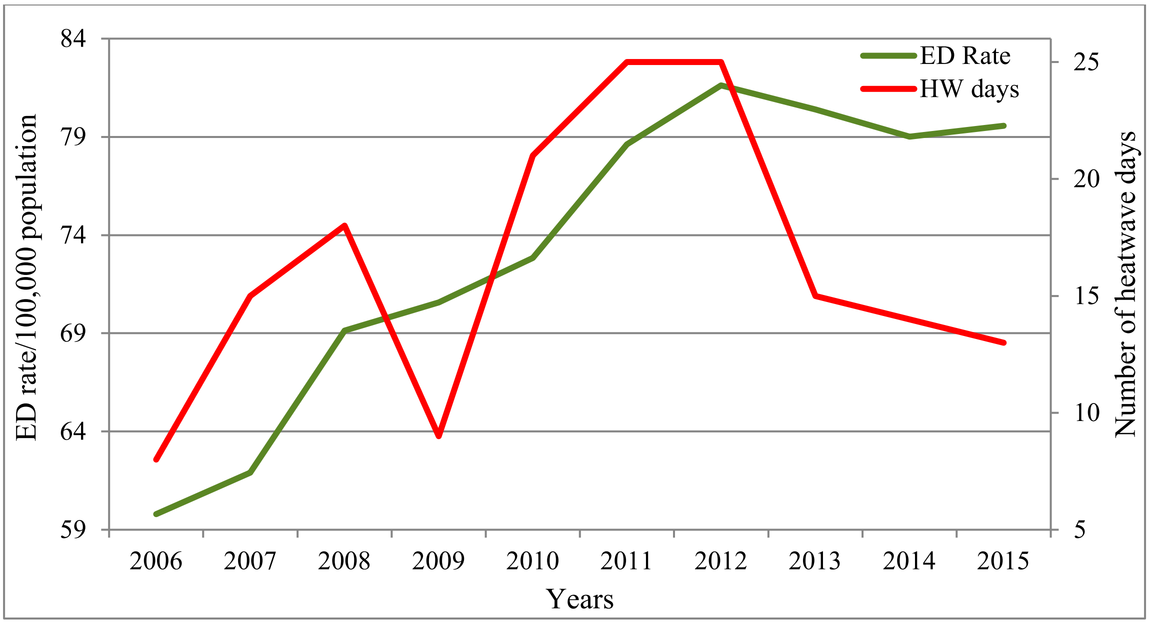

Figure 2 The relationship between the rate of ED presentations (/100,000/day) and the number of HW (HW) days in Perth from 2006 to 2015

3.3. Correlations between HWs, Air Quality and ED Presentations

Table 7 displays the Pearson correlation coefficients for the relationship between HWs (EHF) and air quality and between air quality and ED presentation rate (/100.000/day). There was a significant positive association between HWs and all air quality measures, except for CO. The strongest association was observed between HWs and O_3 (r=0.243, P<0.0001). Only three air quality measures, O_3, PM_{10}, and $PM_{2.5}$, were significantly and positively correlated with the ED presentation rate.

Table 7 Pearson correlations between HWs (EHF), all-cause ED presentation rate (/100,000/day) and air quality measures

		CO	SO_2	NO_2	O_3	PM_{10}	$PM_{2.5}$
EHF	r value	-0.0204	0.1023	0.0190	0.2426	0.1743	0.0514
	P value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Rate	r value	-0.0032	-0.0022	-0.002	0.0009	0.0019	0.0009
	P value	<.0001	<.0001	<.0001	0.0443	<.0001	0.0330

EHF: excess heat factor; r value: Pearson correlation coefficient value; CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micrometres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micrometres.

3.4. Summary of the Impact of HWs on ED Presentations by Conditions

Table 8 summarises Poisson regression results for various conditions alongside different maximin delayed effects. All-cause and heat-related ED presentations showed the earliest peak effects on cumulative day 3. ED presentations due to renal failure reached a peak on the 4th day. Because the most significant lag effect of HWs on ED presentations was on lag day 3, lag 3 was used in all subsequent analyses of the association between ED presentations and HWs.

The impact of HWs on all-cause and some cause specific ED presentation rates, HW affected age groups, sex, weather zone, specific times (holidays and weekends), social economic status (SES), and the maximum lag effect day are summarised in Table 8. Overall, HWs had significant effects on all-cause ED presentations, heat-related ED presentations, and ED presentations due to renal failure. However, ED presentations due to stroke, cardiac conditions, respiratory diseases, circulatory diseases, and hypertension did not show such significant relationships with HWs. Detailed all-cause and heat-related ED presentation results are presented in Tables 11 and 12.

Table 8 Summary of the impact of HWs on ED presentations by conditions

	ED counts	HW effect*	HW on age groups	HW on sex	HW on weather zone	HW on period	HW on SES	Lag day
All-cause	7,289,969	Yes	0–4, 5–9, 15–59 60+	Male> Female	Coastal >Inland	HOL>Non -HOL WKND > WKD	Most-Disadv> Least-Disadv	3
Heat-related	5,007	Yes	0–4, 5–9, 10–14, 15–59	Male> Female	Coastal >Inland	HOL>Non -HOL WKND > WKD	Most-Disadv> Least-Disadv	3
Renal failure	13,350	Yes	0–4, 15–59, 60+	Male> Female	Coastal <Inland	HOL>Non-HOL WKND > WKD	Most-Disadv> Least-Disadv	4
Stroke	8,385	No	-	-	-	-	-	-
Cardiac	539,796	No	-	-	-	-	-	-
Circulatory	277,344	No	-	-	-	-	-	-
Respiratory	396,282	No	-	-	-	-	-	-
Hypertension	9,972	No	-	-	-	-	-	-

* Significant increased ED presentation rate.
HOL: holiday; WKND: weekend; WKD: weekday; SES: social economic status; Disadv: disadvantaged.

3.5. Temporal Effects of HWs and Air Quality on ED Presentation Rates

3.5.1. Effect of Risk Factors on Crude ED Presentation Rates by HWs

Table 9 presents the effects of air pollutants (three levels), sociodemographic factors, weather zone, holidays, and weekends on the crude rates of all-cause ED presentations, ARs, and RRs on HW days and non-HW days.

The crude all-cause ED presentation rate was significantly higher on HW days (76.43/100,000 populations/day) than that on non-HW days (73.66/100,000 populations/day), with a RR of 1.038 (95% CI: 1.035, 1.040).

The crude all-cause ED presentation rates were significantly higher for all air quality measures at all three levels on HW days than those on non-heatwave days, as also reflected in the positive ARs and RRs with 95% CIs >1. There was a dose-response relationship between ED presentation rates and air pollutant PM_{10} on HW days. For example, when PM_{10} levels increased from low, middle, to high during HW days, the RR of ED presentations increased from 2.1, 3.2, to 3.8%, respectively. $PM_{2.5}$ levels also increased from middle to high, with significantly increased ED presentation rates.

Adults, males, Aboriginal people, and those who lived in the most disadvantaged areas had higher crude all-cause ED presentation rates than other population groups. There was a significant dose-response relationship between the SES level and the crude all-cause ED presentation rate. People living in the most disadvantaged area had the highest risk (106.19/100,000/day) compared with those living in the middle (77.90/100,000/day) and the least disadvantaged area (60.65/100,000/day). HW ARs (4.93, 2.54, and 1.91) and RRs (1.048, 1.033, and 1.032) also showed significant dose-response relationships between different SES levels (from the most disadvantaged to the least disadvantaged area).

Although all subcategories of weather zone, holiday, and week period had significantly increased crude all-cause ED presentation rates on HW days compared with those on non-HW days, people who lived in the coastal area, and during holidays or weekends had higher rates on HW days than those who lived in the inland area during non-holidays and weekdays. People who lived in the coastal area also had higher ARs and RRs on HW days than those who lived in the inland area.

Table 10 displays crude heat-related ED presentations by the risk factors and their subcategories on HW days and non-HW days. Compared with the results in Table 9, crude heat-related ED presentation rates significantly increased on HW days for all risk factors and their subcategories, including the three child groups. Although the total counts, rates, and AR values in heat-related ED presentations were lower than those in all-cause ED presentations, the relative risk of ED presentations on HW days was significantly increased from 3.8% in all-cause to nearly 2-fold (184%) in the heat-related ED presentations, indicating a significant contribution of the rate from HWs.

Table 9 Crude all-cause ED presentation counts, rates, ARs, and RRs (/100,000/day) by risk factors on HW and non-HW days

Risk factor	Subcategory	HW indicator	ED count	ED rate	AR	RR (95% CI)
HW		HW day	721,441	**76.43**	**2.77**	**1.038 (1.035,1.040)**
		Non HW day*	6,568,528	73.66		
CO	High	HW day	113,133	**74.17**	**1.15**	**1.015 (1.009,1.021)**
		Non HW day*	1,698,598	73.02		
	Middle	HW day	454,822	**76.90**	**2.56**	**1.034 (1.031,1.037)**
		Non HW day*	3,264,861	74.33		
	Low	HW day	153,486	**76.80**	**3.81**	**1.052 (1.046,1.057)**
		Non HW day*	1,605,069	72.99		
SO_2	High	HW day	211,657	**73.18**	**1.89**	**1.026 (1.021,1.031)**
		Non HW day*	1,558,272	71.29		
	Middle	HW day	331,173	**78.03**	**2.81**	**1.037 (1.033,1.041)**
		Non HW day*	3,415,215	75.22		
	Low	HW day	178,611	**77.59**	**4.79**	**1.065 (1.060,1.071)**
		Non HW day*	1,595,041	72.80		
NO_2	High	HW day	167,260	**69.37**	**0.30**	1.004 (0.999,1.009)
		Non HW day*	1,513,480	69.07		
	Middle	HW day	401,978	**77.49**	**4.16**	**1.056 (1.053,1.060)**
		Non HW day*	3,258,143	73.33		
	Low	HW day	152,203	**82.71**	**3.99**	**1.050 (1.045,1.056)**
		Non HW day*	1,796,905	78.72		
O_3	High	HW day	400,435	**76.47**	**1.81**	**1.024 (1.020,1.027)**
		Non HW day*	1,478,353	74.66		
	Middle	HW day	277,554	**76.07**	**2.08**	**1.028 (1.024,1.032)**
		Non HW day*	3,400,204	73.99		
	Low	HW day	43,452	**78.50**	**6.33**	**1.087 (1.077,1.098)**
		Non HW day*	1,689,971	72.17		
PM_{10}	High	HW day	250516	**76.91**	**2.83**	**1.038 (1.033,1.042)**
		Non HW day*	1526356	74.07		
	Middle	HW day	409,509	**76.51**	**2.43**	**1.032 (1.029,1.036)**
		Non HW day*	3,295,742	74.08		
	Low	HW day	61,416	**74.06**	**1.54**	**1.021 (1.013,1.029)**
		Non HW day*	1,746,430	72.52		
$PM_{2.5}$	High	HW day	243,166	**77.34**	**3.44**	**1.046 (1.042,1.051)**
		Non HW day*	1,580,409	73.9		
	Middle	HW day	398,567	**76.12**	**2.09**	**1.028 (1.024,1.031)**
		Non HW day*	3,279,932	74.03		
	Low	HW day	79,708	**75.28**	**2.54**	**1.034 (1.027,1.042)**
		Non HW day*	1,708,187	72.74		
Age group (years)	15-59	HW day	408,347	**67.98**	**4.08**	**1.063 (1.060,1.067)**
		Non HW day*	3,623,419	63.90		
	60+	HW day	152,466	**92.34**	**2.12**	**1.023 (1.018,1.028)**
		Non HW day*	1,406,718	90.22		

	5-9	HW day	38,410	66.08	-0.04	0.999 (0.989,1.010)
		Non HW day*	364,527	66.12		
	0-4	HW day	87,363	142.66	-0.99	0.993 (0.986,1.000)
		Non HW day*	830,238	143.65		
	10-14	HW day	34,855	59.37	-2.16	0.964 (0.954,0.975)
		Non HW day*	343,626	61.53		
Sex	Male	HW day	367,736	**77.98**	**2.90**	**1.038 (1.035,1.042)**
		Non HW day*	3,344,928	75.08		
	Female	HW day	353,705	**74.88**	**2.64**	**1.036 (1.032,1.040)**
		Non HW day*	3,223,600	72.24		
Aboriginal status	Aboriginal	HW day	30,367	**170.39**	**15.20**	**1.098 (1.085,1.111)**
		Non HW day*	262,810	155.19		
	Non-Aboriginal	HW day	691,074	**74.62**	**2.54**	**1.035 (1.032,1.037)**
		Non HW day*	6,305,718	72.08		
SEIFA	Most Disadvantaged	HW day	268,890	**106.19**	**4.93**	**1.048 (1.044,1.052)**
		Non HW day*	2,440,804	101.26		
	Middle	HW day	152,083	**77.90**	**2.54**	**1.033 (1.028,1.039)**
		Non HW day*	1,385,473	75.36		
	Least Disadvantaged	HW day	300,468	**60.65**	**1.91**	**1.032 (1.028,1.036)**
		Non HW day*	2,742,251	58.74		
Weather zone	Coastal	HW day	372,165	**78.14**	**3.02**	**1.040 (1.036,1.043)**
		Non HW day*	3,350,768	75.12		
	Inlands	HW day	349,276	**74.69**	**2.49**	**1.034 (1.030,1.038)**
		Non HW day*	3,217,760	72.20		
Holiday	Holiday	HW day	60,162	**83.52**	**2.33**	**1.028 (1.019,1.037)**
		Non HW day*	322,519	81.19		
	Non-holiday	HW day	661,279	**75.85**	**2.54**	**1.034 (1.032,1.037)**
		Non HW day*	6,246,009	73.31		
Week period	Weekend	HW day	226,556	**79.26**	**2.46**	**1.032 (1.027,1.036)**
		Non HW day*	1,945,449	76.80		
	Weekday	HW day	494,885	**75.20**	**2.79**	**1.038 (1.035,1.041)**
		Non HW day*	4,623,079	72.41		

* Reference category; CI: confidence interval; HW: heatwave; CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micrometres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micro metres; RR: relative risk; SEIFA: socio-economic index for areas.

Table 10 Crude heat-related ED presentation counts, rates, ARs, and RRs (/100,000/day) by risk factors on HW days and non-HW days

Risk factor	Subcategory	HW indicator	ED count	ED rate	AR	RR (95% CI)
HW		HW day	1,155	0.122	**0.079**	**2.837 (2.652,3.025)**
		Non HW day*	3,852	0.043		
CO	High	HW day	164	0.108	**0.074**	**3.176 (2.689,3.765)**
		Non HW day*	786	0.034		
	Middle	HW day	742	0.125	**0.079**	**2.717 (2.517,2.979)**
		Non HW day*	2,012	0.046		
	Low	HW day	249	0.125	**0.077**	**2.604 (2.264,2.984)**
		Non HW day*	1,054	0.048		
SO2	High	HW day	345	0.119	**0.065**	**2.203 (1.942,2.468)**
		Non HW day*	1,191	0.054		
	Middle	HW day	522	0.123	**0.081**	**2.928 (2.673,3.245)**
		Non HW day*	1,896	0.042		
	Low	HW day	288	0.125	**0.090**	**3.571 (3.129,4.103)**
		Non HW day*	765	0.035		
NO2	High	HW day	249	0.103	**0.070**	**3.121 (2.692,3.599)**
		Non HW day*	728	0.033		
	Middle	HW day	622	0.12	**0.077**	**2.790 (2.526,3.026)**
		Non HW day*	1,927	0.043		
	Low	HW day	284	0.154	**0.102**	**2.961 (2.586,3.349)**
		Non HW day*	1,197	0.052		
O3	High	HW day	666	0.127	**0.067**	**2.961 (2.586,3.349)**
		Non HW day*	1,193	0.06		
	Middle	HW day	411	0.113	**0.076**	**3.054 (2.755,3.418)**
		Non HW day*	1,687	0.037		
	Low	HW day	78	0.141	**0.099**	**3.357 (2.695,4.276)**
		Non HW day*	972	0.042		
PM10	High	HW day	441	0.135	**0.077**	**2.327 (2.095,2.606)**
		Non HW day*	1,194	0.058		
	Middle	HW day	607	0.113	**0.068**	**2.511 (2.316,2.778)**
		Non HW day*	1,989	0.045		
	Low	HW day	107	0.129	**0.101**	**4.607 (3.788,5.696)**
		Non HW day*	669	0.028		
PM2.5	High	HW day	448	0.142	**0.087**	**2.581 (2.324,2.899)**
		Non HW day*	1,176	0.055		
	Middle	HW day	595	0.114	**0.070**	**2.590 (2.361,2.837)**
		Non HW day*	1,945	0.044		
	Low	HW day	112	0.106	**0.075**	**3.419 (2.785,4.146)**
		Non HW day*	731	0.031		
Age group (years)	60+	HW day	203	0.123	**0.103**	**6.150 (5.197,7.405)**
		Non HW day*	309	0.020		
	15-59	HW day	712	0.119	**0.078**	**2.902 (2.669,3.158)**

		Non HW day*	2,315	0.041		
	0-4	HW day	120	0.196	**0.111**	**2.305 (1.882,2.805)**
		Non HW day*	493	0.085		
	10-14y	HW day	69	0.118	**0.043**	**1.573 (1.22,2.031)**
		Non HW day*	417	0.075		
	5-9	HW day	51	0.088	**0.030**	**1.517 (1.132,2.045)**
		Non HW day*	318	0.058		
Sex	Female	HW day	508	0.108	**0.070**	**2.842 (2.587,3.155)**
		Non HW day*	1,680	0.038		
	Male	HW day	647	0.137	**0.088**	**2.795 (2.578,3.073)**
		Non HW day*	2,172	0.049		
Aboriginal status	Non-Aboriginal	HW day	1,134	0.122	**0.079**	**2.837 (2.652,3.028)**
		Non HW day*	3,780	0.043		
	Aboriginal	HW day	21	0.118	**0.075**	**2.744 (1.705,4.506)**
		Non HW day*	72	0.043		
SEIFA	Most Disadvantaged	HW day	469	0.185	**0.124**	**3.032 (2.723,3.351)**
		Non HW day*	1,478	0.061		
	Middle	HW day	209	0.107	**0.064**	**2.488 (2.115,2.868)**
		Non HW day*	799	0.043		
	Least Disadvantaged	HW day	477	0.096	**0.062**	**2.823 (2.576,3.162)**
		Non HW day*	1,575	0.034		
Weather zone	Coastal	HW day	569	0.119	**0.080**	**3.051 (2.789,3.371)**
		Non HW day*	1,738	0.039		
	Inlands	HW day	586	0.125	**0.078**	**2.659 (2.411,2.895)**
		Non HW day*	2,114	0.047		
Holiday	Non-holiday	HW day	1,051	0.121	**0.079**	**2.880 (2.661,3.053)**
		Non HW day*	3,603	0.042		
	Holiday	HW day	104	0.144	**0.081**	**2.285 (1.832,2.896)**
		Non HW day*	249	0.063		
Week period	Weekend	HW day	435	0.152	**0.104**	**3.166 (2.865,3.567)**
		Non HW day*	1,206	0.048		
	Weekday	HW day	720	0.109	**0.068**	**2.658 (2.431,2.867)**
		Non HW day*	2,646	0.041		

* Reference category; CI: confidence interval; HW: heatwave; CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micrometres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micro metres; RR: relative risk; SEIFA: socio-economic index for areas.

3.5.2. Effects of Risk Factors and the Joint Effect of HWs & Air Quality on Adjusted ED Presentation Rates

Table 11 presents the results of the final Poisson regression model for the impact of adjusted relative risk of HWs, air quality, and other risk factors and the joint effect (interaction) of HWs and air quality on all-cause ED presentation rates.

Table 11 Effects of risk factors and the joint effect of HWs & air quality on adjusted relative risk of all-cause ED presentations

Risk factor[#]	Category	Joint effect	RR (95% CI)	P value
HW	HW day		**1.042 (1.029,1.056)**	<.0001
	Non HW day*		1.000	
CO	High		**1.082 (1.079,1.085)**	<.0001
	Middle		**1.052 (1.050,1.054)**	<.0001
	Low*		1.000	
O_3	High		**1.078 (1.075,1.081)**	<.0001
	Middle		**1.050 (1.048,1.052)**	<.0001
	Low*		1.000	
$PM_{2.5}$	High		**1.019 (1.016,1.022)**	<.0001
	Middle		**1.016 (1.013,1.018)**	<.0001
	Low*		1.000	
$PM_{2.5}$ × HW	High	HW day	**1.038 (1.027,1.050)**	<.0001
	Middle	HW day	1.007 (0.998,1.016)	0.1139
	Low*	HW day*	1.000	
	High*	Non HW day*	1.000	
	Middle*	Non HW day*	1.000	
	Low*	Non HW day*	1.000	
Age group	0–4y		**2.306 (2.297,2.315)**	<.0001
	60+y		**1.488 (1.483,1.494)**	<.0001
	5–9y		**1.072 (1.067,1.076)**	<.0001
	15–59y		**1.068 (1.065,1.072)**	<.0001
	10–14y*		1.000	
Sex	Male		**1.043 (1.042,1.045)**	<.0001
	Female*		1.000	
Aboriginal status	Aboriginal		**1.901 (1.894,1.908)**	<.0001
	Non-Aboriginal *		1.000	
SEIFA	Disadvantaged		**1.712 (1.709,1.715)**	<.0001
	Middle		**1.295 (1.292,1.297)**	<.0001
	Advantaged*		1.000	
Weather zone	Coastal		**1.128 (1.126,1.130)**	<.0001
	Inlands*		1.000	
Holiday	Holiday		**1.109 (1.105,1.112)**	<.0001
	Non-Holiday*		1.000	
Weekend	Weekend		**1.054 (1.053,1.056)**	<.0001
	Weekday*		1.000	

*Reference category. RR: relative risk; CI: confidence interval; [#]Only risk factors having significant effect on ED presentations were included in the table. HW: heatwave; HW: heatwave; CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micro metres; SEIFA: socio-economic index for areas.

Compared with non-HW days, the relative risk of all-cause ED presentations increased by 4.2% (2.9%–5.6%) on HW days after adjusting for all other risk factors, including air quality measures. While the model without air quality measures

(Appendix 4) only increased 3.2% (3.0%–3.5%). The relative risk of all-cause ED presentations significantly increased along with the increased concentrations of air quality indicators CO, O_3, and $PM_{2.5}$ and showed dose-response relationships and a significant joint effect between HWs and $PM_{2.5}$. Using 10–14-year-old children as the reference group, all other age groups, including 0–4-year and 5–9-year-old child's groups, had a significantly increased relative risk of all-cause ED presentations, and the RR in the 0–4-year group was among the highest. SES (SEIFA) continued to show the dose-response relationship with adjusted all-cause ED presentation rates. Furthermore, males, Aboriginal residents, individuals living in coastal areas, as well as those attending ED departments during public holiday days and weekends exhibited higher adjusted all-cause ED presentation rates compared to their respective reference groups (Table 11).

Table 12 below presents the final Poisson regression model for the effects of all risk factors and the joint effect of HWs and air quality on the adjusted relative risk of heat-related ED presentations. Compared with the results in Table 11 on adjusted all-cause ED presentation rates (4.2%), the heat-related ED presentation rates (Table 12) increased more than 3-fold on HW days (301%) after adjusting other risk factors. Which was also higher than the model without including air quality measures (179%, in Appendix 5). There were more air quality indicators (e.g., SO_2, PM_{10}, and $PM_{2.5}$) that showed dose-response relationships with adjusted heat-related ED presentation rates and joint effects (CO, NO_2, and $PM_{2.5}$) with HWs on adjusted heat-related ED presentation rates (Table 12).

Heat-related adjusted ED presentation rates were significantly higher in all three child's groups than the rates in adults, and the RR of ED presentations in the 0–4-year group was also among the highest. SES (SEIFA) continued to show the dose-response relationship with adjusted heat-related ED presentation rates. Male, non-Aboriginal population, those who lived in the coastal area, on public holidays and weekends also had higher adjusted heat-related ED presentation rates compared with female, Aboriginal population, those who lived in the inland area, on non-holidays and weekdays, respectively (Table 12). The children-only model for heat-related ED presentations obtained similar results compared with the model that included all age groups (Appendix 7), except for SES, which had a stronger association and dose-response relationship between heat-related ED presentations (2.402 (2.133, 2.704) of the children-only model and 1.817 (1.705, 1.937) of the all-age model in the most disadvantaged area.

Table 12 Effects of risk factors and the joint effect of HWs & air quality on adjusted relative risk of heat-related ED presentations

Risk factor#	Category	Joint effect	RR (95% CI)	P value
HW	HW day		**4.006 (2.904,5.525)**	<.0001
	Non HW day*		1.000	
SO_2	High		**1.367 (1.234,1.515)**	<.0001

	Middle		**1.152 (1.054,1.258)**	0.002
	Low*		1.000	
O_3	High		**1.490 (1.351,1.643)**	<.0001
	Middle		0.914 (0.842,0.992)	0.032
	Low*		1.000	
PM_{10}	High		**1.578 (1.389,1.793)**	<.0001
	Middle		**1.359 (1.225,1.507)**	<.0001
	Low*		1.000	
$PM_{2.5}$	High		**1.385 (1.212,1.582)**	<.0001
	Middle		**1.209 (1.090,1.340)**	0.000
	Low*		1.000	
CO × HW	High	HW day	**1.386 (1.083,1.775)**	0.01
	Middle	HW day	**1.174** (0.986,1.397)	0.071
	Low*	HW day*	1.000	
	High	Non HW day*	1.000	
	Middle	Non HW day*	1.000	
	Low*	Non HW day*	1.000	
NO_2 × HW	High	HW day	**1.202** (0.954,1.515)	0.118
	Middle	HW day	**1.064** (0.893,1.268)	0.483
	Low*	HW day*	1.000	
	High	Non HW day*	1.000	
	Middle	Non HW day*	1.000	
	Low*	Non HW day*	1.000	
$PM_{2.5}$ × HW	High	HW day	**1.200** (0.892,1.616)	0.227
	Middle	HW day	**1.034** (0.800,1.335)	0.796
	Low*	HW day*	1.000	
	High	Non HW day*	1.000	
	Middle	Non HW day*	1.000	
	Low*	Non HW day*	1.000	
Age group	0-4y		**1.561 (1.372,1.777)**	<.0001
	10-14y		**1.310 (1.144,1.500)**	<.0001
	5-9y*		**1.000**	
	15-59y		0.795 (0.714,0.886)	<.0001
	60+y		0.482 (0.422,0.552)	<.0001
Sex	Male		**1.268 (1.200,1.341)**	<.0001
	Female*		1.000	
Aboriginal status	Aboriginal		0.716 (0.583,0.880)	0.002
	Non-Aboriginal *		1.000	
SEIFA	Disadvantaged		**1.817 (1.705,1.937)**	<.0001
	Middle		**1.206 (1.117,1.302)**	<.0001
	Advantaged*		1.000	
Weather zone	Coastal		**1.099 (1.037,1.165)**	0.001
	Inlands*		1.000	
Holiday	Holiday		**1.453 (1.301,1.623)**	<.0001
	Non-Holiday*		1.000	
Weekend	Weekend		**1.179 (1.109,1.252)**	<.0001
	Weekday*		1.000	

*Reference category. RR: relative risk; CI: confidence interval; #Only variables having significant effect on ED presentations were included. HW: heatwave; CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micrometres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micro metres; SEIFA: socio-economic index for areas.

3.6. Spatial Variations of HWs and Air Quality on ED Presentation Rates

3.6.1. Poisson Regression Models

The spatial variations of HWs on crude and adjusted all-cause ED presentation rates were explored for all-age and child-only groups in all 21 SA3s in Perth. The results showed that, compared with the ARs on non-HW days, HW atributable rates were positive and significant in all 21 SA3s in the all-age model and in 8/21 SA3s in the child-only model (Appendices 8-9). Using Melville as the reference area, Poisson regression analyses were conducted for the two age group models and adjusted for air quality measures and an interaction between HWs and SA3s. The results showed that compared with the Melville area, all 20 other SA3 areas had significantly increased RRs of ED presentations on HW days in both the all-age and child-only models, with the highest risk in southern areas (Appendices 10–11). Overall, the variations observed in the crude rate analysis between the two age group models were significantly reduced after adjusting for risk factors. The degrees of HW impact on the adjusted relative risk of all-cause ED presentations (Figure 3, red>yellow>blue) between SA3 geographical areas were similar and significant in both age models, especially in the southern (e.g., Mandurah, Armadale, Kwinana, Rockingham, and Serpentine–Jarrahdale), northern (e.g., Swan and Wanneroo), and inland (e.g., Mundaring) areas. Air quality influenced ED presentations with CO, SO_2, O_3, and $PM_{2.5}$ displayed significant dose-response relationships in the all-age model, and CO, SO_2, and O_3 in the child-only model.

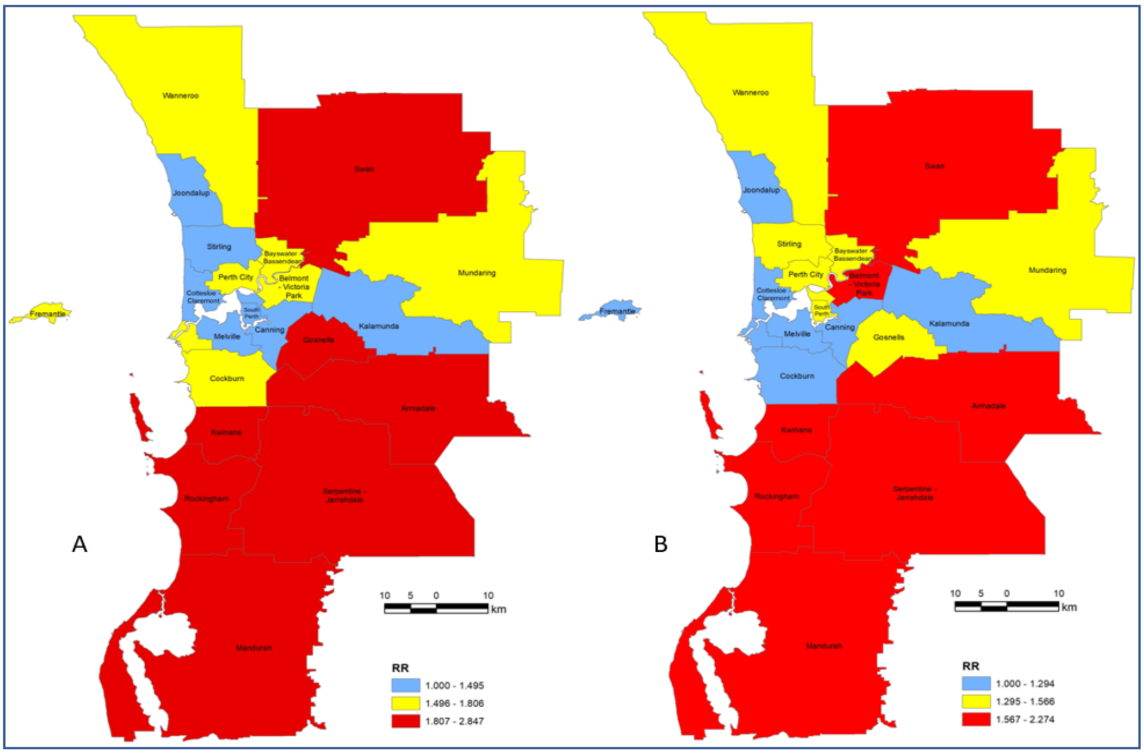

Figure 3 Adjusted relative risk of HW-related all-cause ED presentations for all-age (A) and child-only (B) group models

The significant joint effect of HWs and SA3s on the relative risk of all-cause ED presentations (Figure 4) was observed in 15/21 SA3 areas for the all-age model and in 11/21 SA3 areas for the child-only model. The maximum joint effect of HWs and SA3 on ED presentations was observed to be almost double in the child-only group (8.1%) in South Perth compared to that in the all-age group (4.5%) in Joondalup. The significant joint effects of SA3 areas with HWs were observed in both age group models in the southern (e.g., Kwinana, Mandurah, and Serpentine-Jarrahdale), northern (e.g., Wanneroo), inland (e.g., Mundaring), and middle (Belmont-Victoria Park, Gosnells, and Stirling) areas.

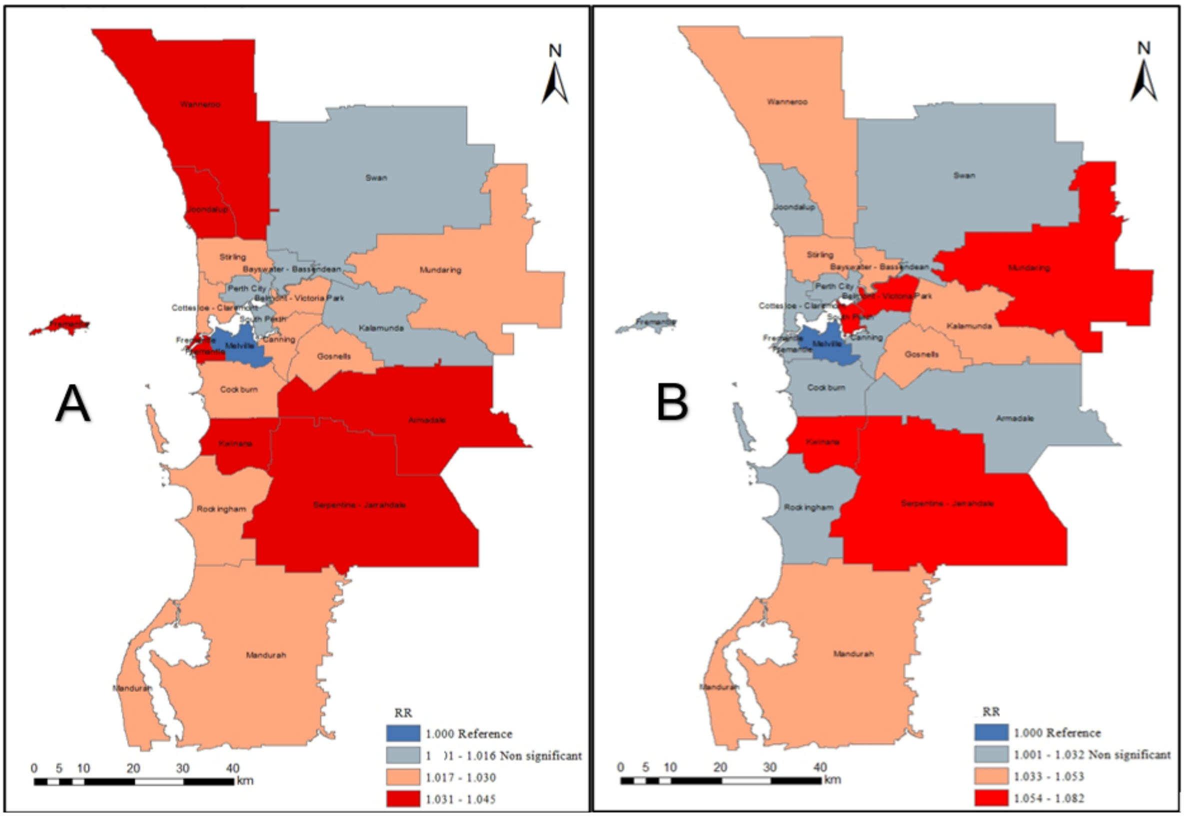

Figure 4 The joint effect between HWs and SA3 on adjusted relative risk of ED presentations for all-age (A) and child-only group (B) model

3.6.2. Geographically Weighted Regression Models

GWR models were tested in ArcGIS Pro using 10-year data and included all important predictors identified in the final Poisson regression model as independent (explanatory) variables and ED presentation rates as dependent variables. At the beginning, as the time series dataset had high autocorrelation and there were limitations of the GWR model (e.g., it could not handle categorical variables and large record numbers), both OLS and GWR models could not produce results in ArcGIS Pro. After removing categorical variables (e.g., sex and Aboriginal status) and reducing record numbers to 0.34% of the original records (from 5,580,960 to

19,005, about one year data), the results could be produced by ArcGIS Pro. The results from the limited GWR models were compared with OLS models for the five selected years (2007, 2009, 2011, 2013, and 2015).

Table 13 presents a comparison between the OLS and GWR models for the selected five years. Compared with OLS models, all five GWR models had lower AIC values, higher adjusted R-squared values, and improved Morans' I index values. Thus, the GWR models outperformed the OLS models. No models showed significant clusters in the study area for these five years.

Table 13 Comparison between OLS and GWR models for different years

Year	AIC value		Adjusted R-Squared		Moran's I	
	OLS	GWR	OLS	GWR	OLS	GWR
2007	169,978	142,100	0.635	0.917	0.324	-0.001
2009	164,710	140,195	0.815	0.949	0.314	-0.001
2011	167,556	143,163	0.841	0.956	0.317	-0.001
2013	170,572	145,773	0.841	0.957	0.320	-0.001
2015	167,409	145,488	0.864	0.957	0.294	-0.001

AIC: Akaike's Information Criterion; GWR: geographically weighted regression; OLS: ordinary least square

Figure 5 presents the spatial variations of the effect of HWs (EHF) on all-cause ED presentation rates for each of the five years by GWR models. Each year, the impact of the HWs differed significantly in different areas. The years 2007 and 2009 showed a significant effect of HW in the northern areas, but in 2011 and 2013, the southern areas were at high risk of ED presentations. Then in 2015, the pattern shifted back and was like that in 2009. Spatial variations of the effect of each air quality indicator on all-cause ED presentation rates for each of the five different years by GWR models can be found in Appendices 12–16.

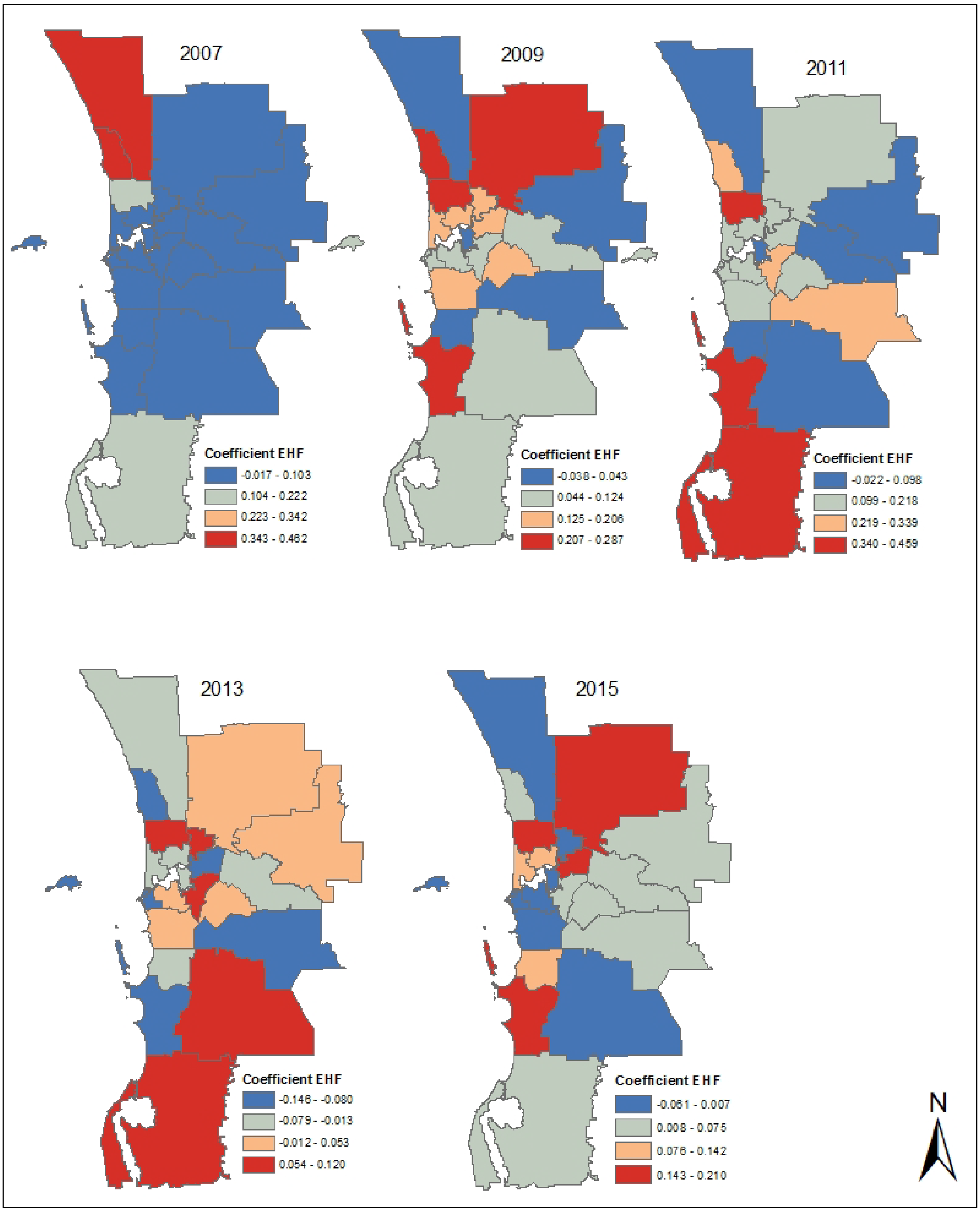

Figure 5 The impacts of HWs (EHF) on all-cause ED presentation rates for each of the five years in GWR models

3.7. Machine Learning Approaches

3.7.1. Selection of the Optimal Models for Prediction of ED Presentations

Five models were tested using machine learning approaches to estimate optimal models with the testing dataset. Table 13 presents the goodness of fit results for all models in all-age and young children (0–4 years) groups using RMSE and MAE as the measures. The baseline model was based on the mean of the predicted variable (ED presentations). Both the full decision tree and the pruned decision tree showed the same results. Among the five models tested, the RF models outperformed other models with the lowest errors in both age groups.

Table 14 Models tested using machine learning approaches for all-age and young children's groups

Model	All-age group		0-4-year age group	
	RMSE	MAE	RMSE	MAE
Baseline	0.00047	0.00036	0.00052	0.00041
Linear Regression	0.00031	0.00023	0.00046	0.00036
Full tree	0.00031	0.00023	0.00047	0.00037
Pruned tree	0.00031	0.00023	0.00047	0.00037
Random forest	0.00030	0.00022	0.00045	0.00035

RMSE: root mean square error; MAE: mean absolute error.

All models were then applied to the validation dataset for validation purposes (Figure 6). The horizontal axis gives the predicted rate of all-cause ED presentations, and the vertical axis gives the actual observed rate of ED presentations in the testing data set. Among all five models, the RF model again outperformed other models and predicted the rate of all-cause ED presentations closest to the observed values.

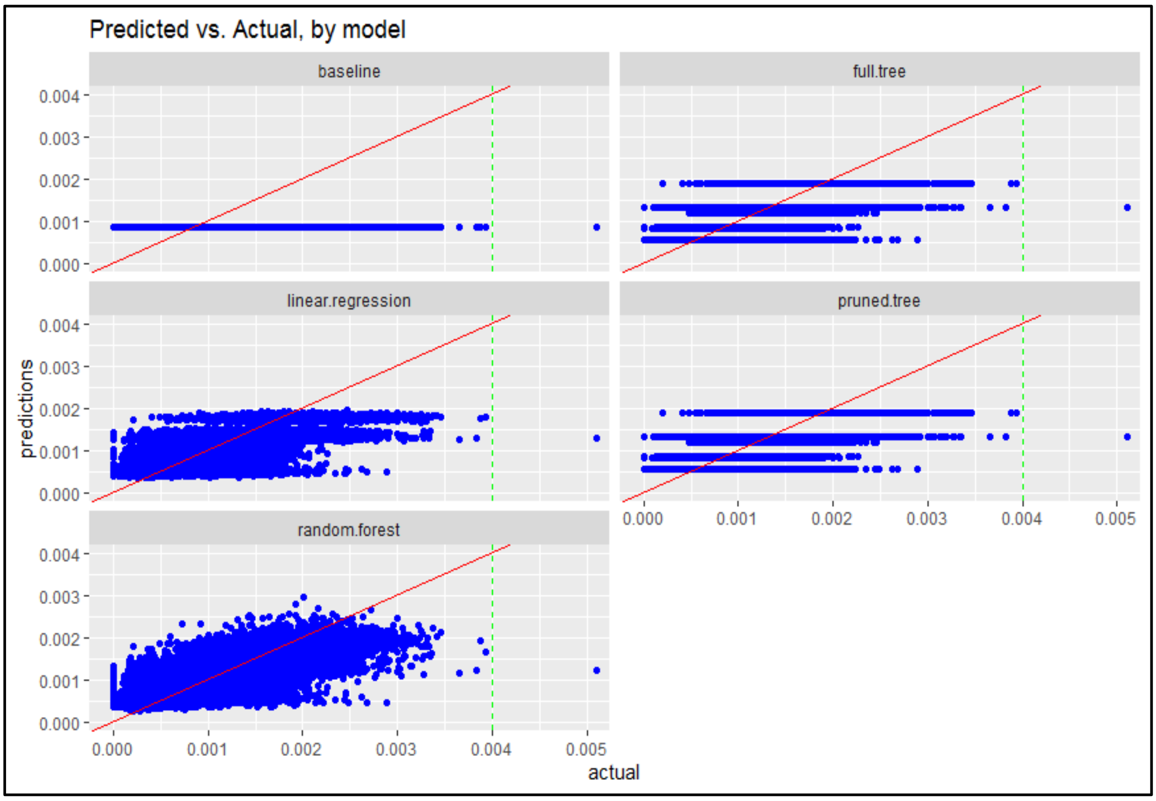

Figure 6 Comparisons between the predicted (y-axis) and actual (x-axis) rates of all-cause ED presentations

Based on parameter sensitivity analysis, the RF model in this study was developed using four randomly selected variables (mtry) on each node of each decision tree, and a total of 500 decision trees (ntree) were tested with the training dataset. The mean squared error decreased as the number of trees in the model increased (Figure 7). Even after separating the models by age group, RF still outperformed all other models for all age groups. Therefore, the RF model was chosen for further analysis.

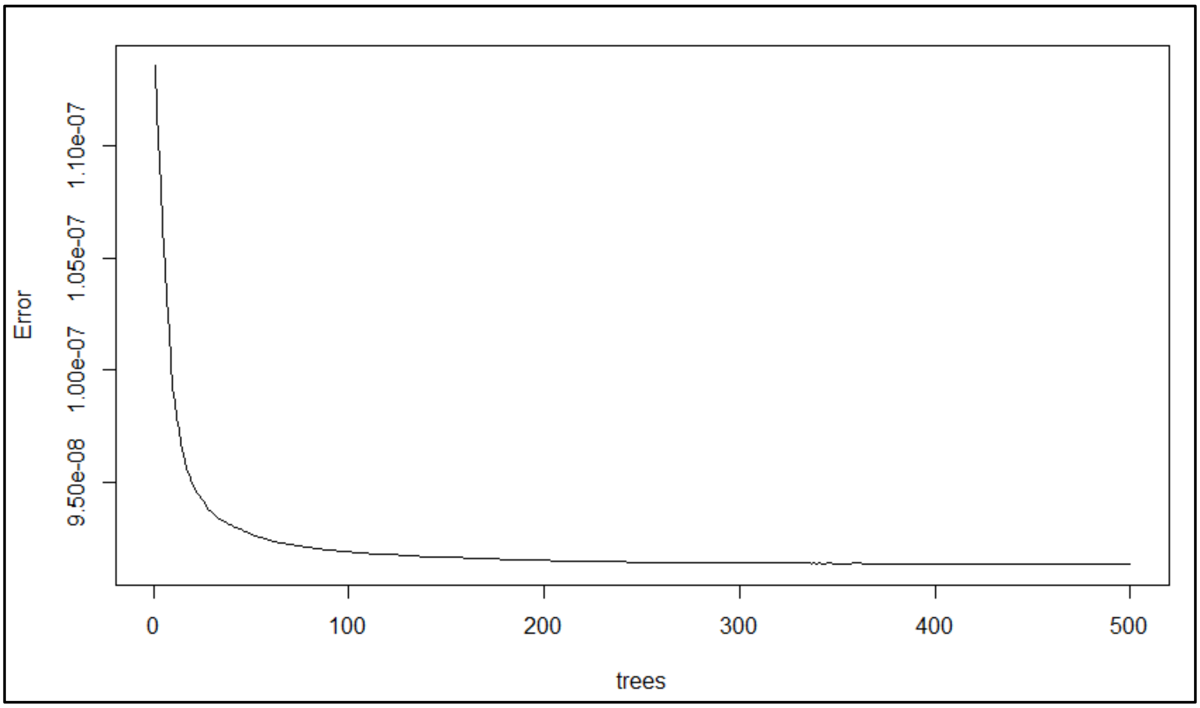

Figure 7 Mapping the error values versus the number of trees in the RF model

3.7.2. Importance Rank of Predictors

As the RF model was constructed from multiple decision tree models, the important predictors and their split nodes in the model were shown as a tree structure; see Figure 8 as an example. It was evident that the two most important predictors in the model were age and SES (SEIFA). In this tree, for example, when the age group was within 0–4 years (20% of the data), the predicted risk of ED presentation rate was 0.0014/100,000/day. When those young children lived in the most disadvantaged area (SEIFA, 4% of the data), there was a predicted risk of ED presentation rate of 0.0019/100,000/day, which was the highest among all groups, followed by young children living in an advantaged or middle area, and then the 5–14-year age group living in the most disadvantaged area.

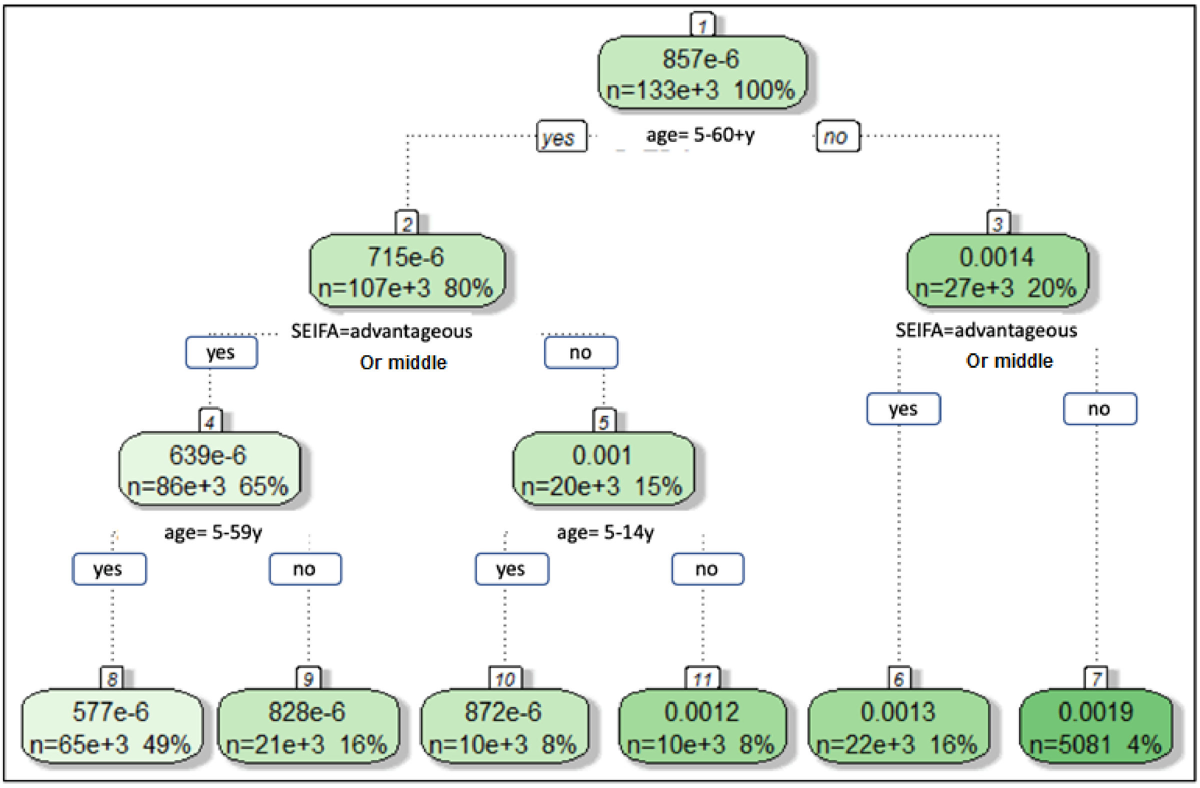

Figure 8 The tree structure of the important predictors

1st row: predicted ED presentation rate
2nd row: n=number of records and percentage of records used from the total training set

Figures 9 and 10 display the rank of important predictors in RF models for all-age and 0–4-year age groups in descending order. Among all predictors included in the all-age RF model (Figure 9), the age groups had the highest %IncMSE value of 188.0 $\times 10^{-9}$, followed by the SEIFA (69.6×10^{-9}) then the particulate air pollutants. The IncNodePurity values also indicated that age groups and SEIFA were the most important contributors in the tree structure for predicting ED presentations. When only young children were included in the model, SEIFA still ranked as the most important predictor, followed by air pollutants and HWs in slightly different order (Figure 10).

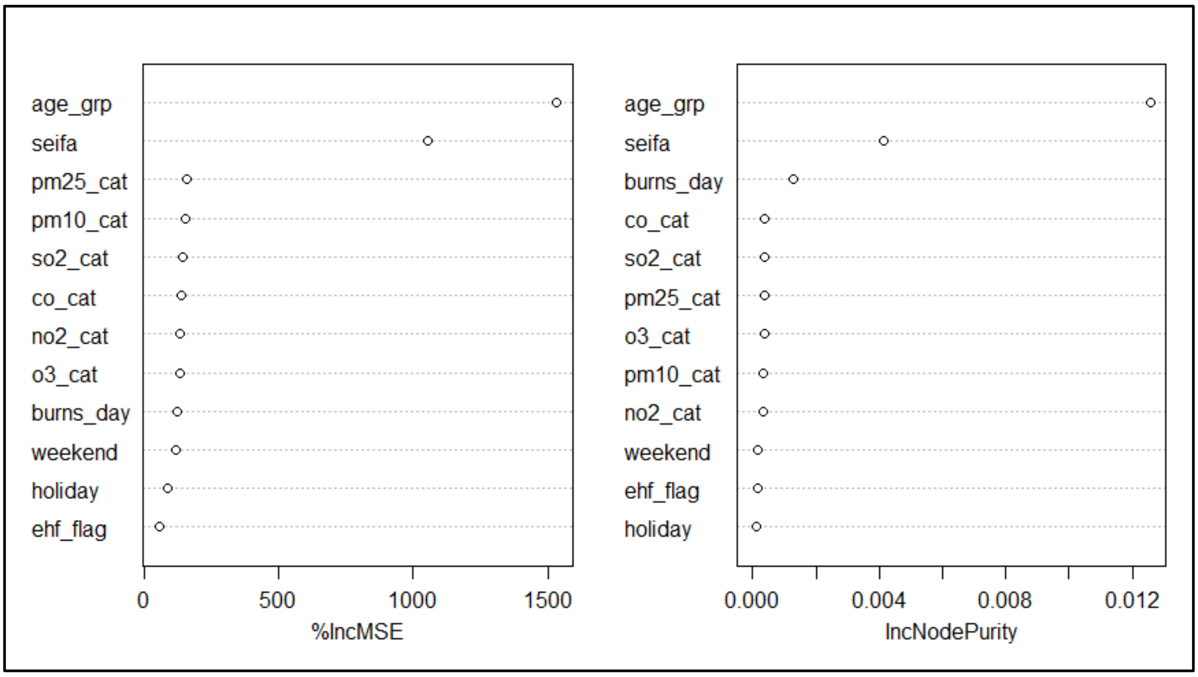

Figure 9 Importance rank of predictors in the RF model for all-age model

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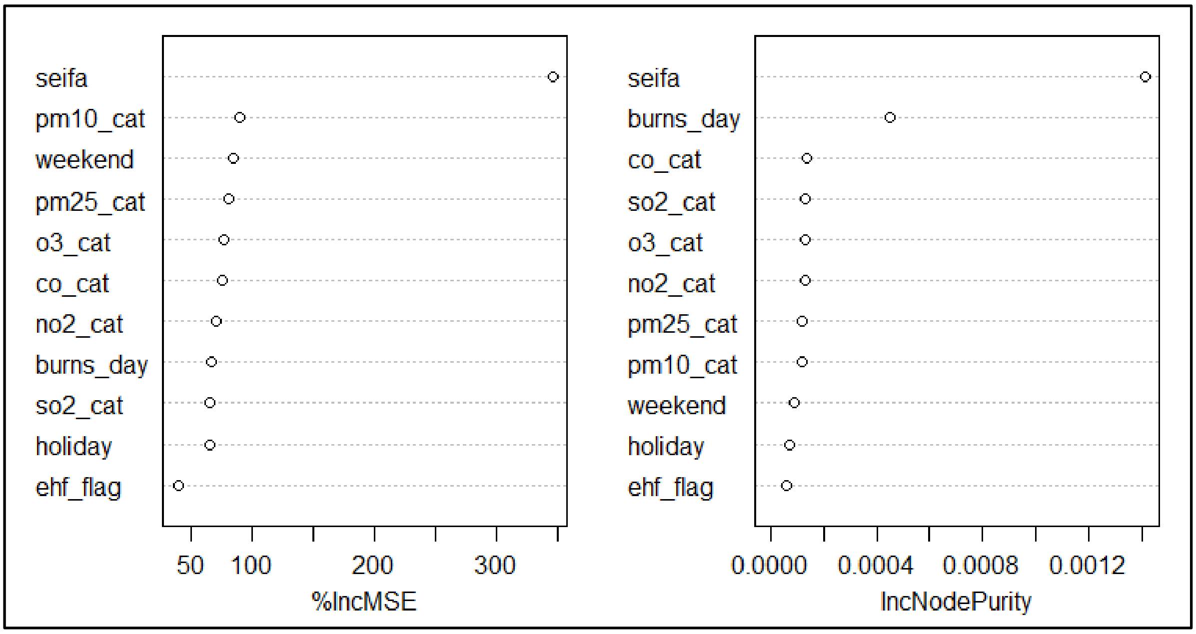

Figure 10 Importance rank of predictors in the RF model for children 0-4 years

Table 15 below summarises the importance rank of predictors in the RF models for various age groups based on %IncMSE. SES (SEIFA) has always ranked as the most important predictor for ED presentation rates in all models. Particulate matter was the most important predictor of all air pollutants in the all-age and 0–4-year models. HW (EHF) was included after the air quality indicators as a significant predictor. The summary of important predictors based on IncNodePurity is included in Appendix 17.

Table 15 Summary of the important predictors based on %IncMSE from the RF models

Order#	0–4 years model	5–9 years model	10–14 years model	All-age model
1	-	-	-	5 age groups
2	SEIFA	SEIFA	SEIFA	SEIFA
3	PM_{10}	NO_2	CO	$PM_{2.5}$
4	weekend	PM_{10}	NO_2	PM_{10}
5	$PM_{2.5}$	SO_2	PM_{10}	SO_2
6	O_3	Burns	$PM_{2.5}$	CO
7	CO	$PM_{2.5}$	O_3	NO_2
8	NO_2	CO	Burns	O_3
9	Burns	weekend	SO_2	Burns
10	SO_2	O_3	EHF	weekend
11	holiday	holiday	weekend	holiday
12	EHF	EHF	holiday	EHF

%IncMSE: percentage increase in mean squared error; #: order 1 means the most important variable and 12 means the least important variable; EHF: excess heat factor (yes vs. no); CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micro metres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micro metres; all air quality measures used the 3 levels (low, middle, and high); Burns: daily fire burn numbers; SEIFA: socio-economic index for areas

3.7.3. Validation of RF Model for Prediction of ED Presentations

a) ED presentation counts

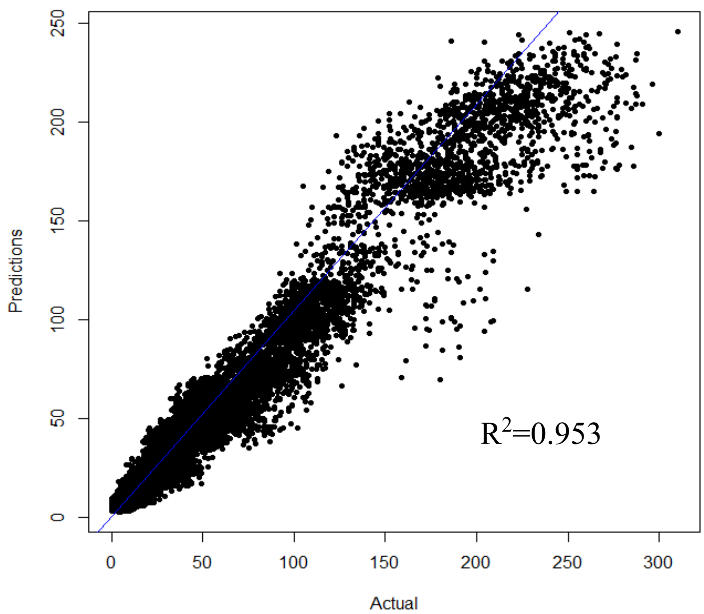

Figure 11 Comparison between predicted and actual counts of ED presentations for year 2015

Predicted ED presentation counts in 2015 were obtained using the RF model with the actual 2006–2014 ED presentation data. Construct validation was then conducted by comparing results between the predicted and actual 2015 ED presentation data adjusted for population (Figure 11). The horizontal axis coordinate is the actual ED presentation count in 2015. The vertical axis coordinate is the ED presentation count in 2015 predicted by the RF model. The goodness of fit for the model measure R^2 for ED presentation counts was 0.953, indicating the model simulated reality extremely well.

b) ED presentation rate

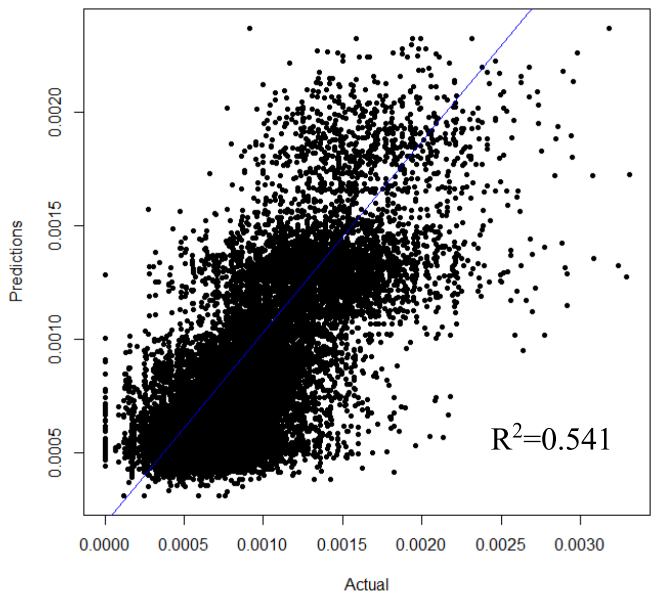

Figure 12 Comparison between predicted and actual rates of ED presentations for year 2015

The prediction of the ED presentation rate was also carried out for the year 2015. The RF model was trained using the 2006-2014 dataset. Figure 12 presents the goodness of fit results for the actual and predicted ED presentation rates for 2015. The goodness of fit measure R^2 was 0.541, indicating that the model simulated reality relatively well.

3.7.4. Geographical Variation of RF Models

GRF is an extension of the global RF method and can be used for creating a local RF model of the study area. GRF models are more suitable and reliable for datasets with strong degrees of spatial heterogeneity, thus increasing the prediction power compared to the traditional global model. In this study, the GRF models were performed to explore the spatial variations of the important predictors for the three children's groups, i.e., 0-4, 5-9, and 10-14-year-old children.

a) Validation of GRF models for children

The prediction of the ED presentation rate was performed on the validation dataset using the GRF model. The model was trained using the 10-year dataset described in the methodology section. The validation of ED presentations was performed for the three children's groups (0–4, 5–9, and 10–14 years) and compared predicted ED presentation rates with actual rates. Table 16 presents the validation matrices for these GRF models. The goodness of fit measures R^2 for the three age groups were 0.975, 0.934, and 0.899, respectively, indicating the models fit the data extremely well.

Table 16 Validation of GRF models for different children's groups

Age group	RMSE	MAE	R^2 value
0–4 year	0.000129	0.000107	0.975
5–9 year	0.000065	0.000048	0.934
10–14 year	0.000067	0.000048	0.899

GRF: geographical random forest; RMSE: root mean square error; MAE: mean absolute error

b) Important predictors for children in different locations

The importance rank of all predictors (predictors) identified in global RF models was included in GRF models for prediction of ED presentation rates for the three age groups in children. Detailed values of %IncMSE and IncNodePurity from GRFs for each age group in each SA3 were presented in Appendices 18–23. The importance of these predictors did vary throughout the study area in different age groups.

Table 17 summarises the average ranking results (%IncMSE) for all predictors for the three child groups from GRF models. In summary, SEIFA and EHF were the two most important predictors (predictors) among the eight for ED presentations, with the highest values of %IncMSE in all three GRF models. Gaseous and particulate air pollutants were also important contributors to predicting ED presentations.

Table 17 Summary of the important predictors based on %IncMSE from the GRF models

Order#	0–4-year model	5–9-year model	10–14-year model
1	SEIFA	SEIFA	SEIFA
2	EHF	EHF	EHF
3	NO_2	NO_2	SO_2
4	CO	SO_2	NO_2
5	O_3	O_3	O_3
6	SO_2	PM_{10}	CO
7	$PM_{2.5}$	$PM_{2.5}$	PM_{10}
8	PM_{10}	CO	$PM_{2.5}$

%IncMSE: percentage increase in mean squared error; #: order 1 means the most important variable, and 12 means the least important variable; EHF: excess heat factor (yes vs. no); CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micrometres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micrometres; all air quality measures used the 3 levels (low, middle, and high); Burns: daily fire burn numbers; SEIFA: socio-economic index for areas

c) Spatial joint effect of HWs and air quality on ED presentation rates

Using the young children group aged 0–4-years as an example, a geographic variation of importance rank (three levels evenly distributed, red (high), yellow(middle), and blue (low)) for each of the eight predictors is presented separately in a map format (Figure 13). Detailed rank values for each predictor across these three levels can be find in Appendix 24. In the GRF model for young children, the top-ranking predictors were SEIFA and EHF. With the exception of ozone, all other seven predictors demonstrated spatially joint effects, with the greatest influence on ED presentations in the southern areas, including Kwinana, Mandurah, and Serpentine-Jarrahdale, suggesting that these predictors interact spatially.

Appendices 25–27 contain the original maps created for each child group based on eight predictors.

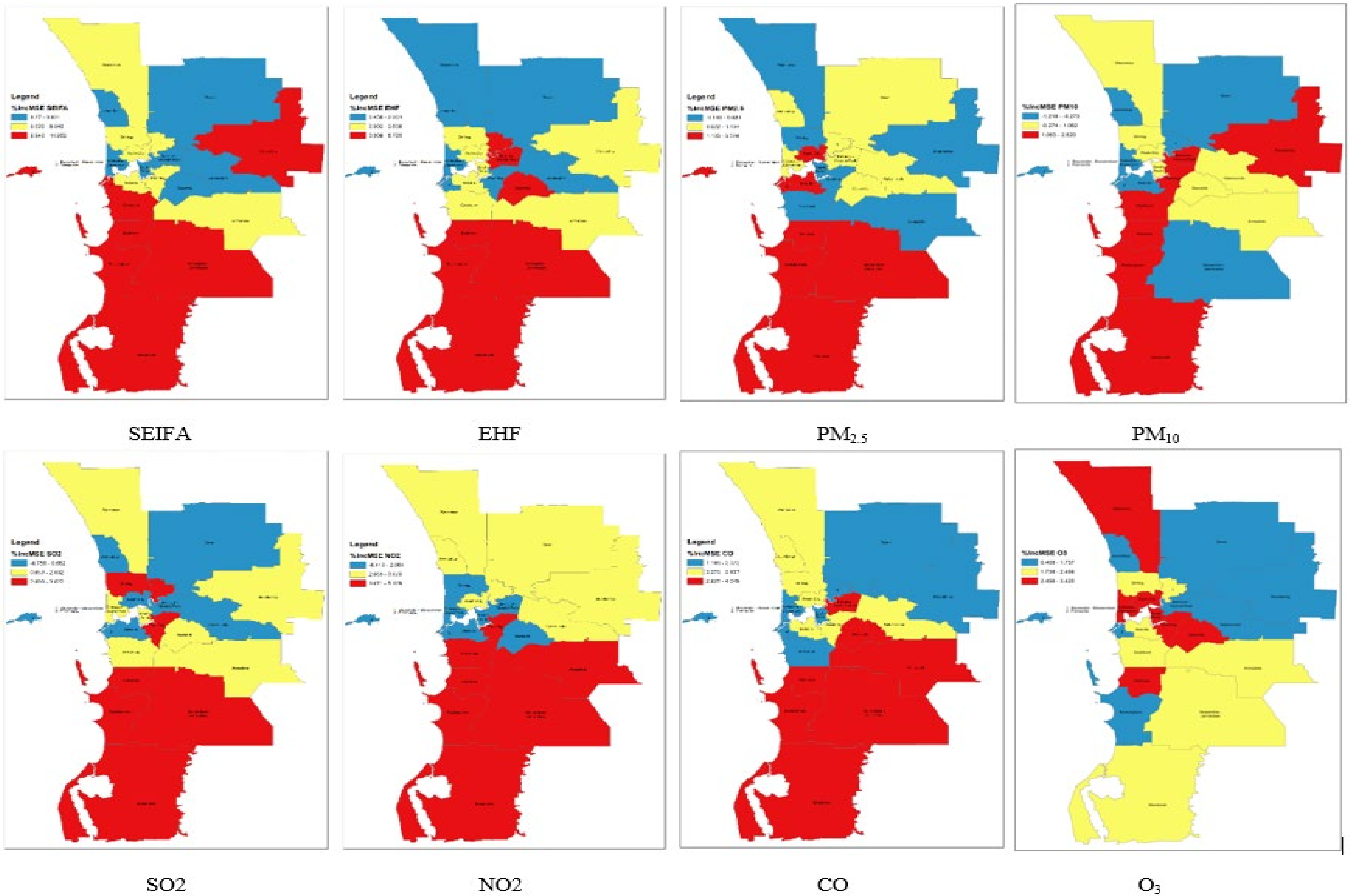

Figure 13 Importance rank (red>yellow>blue) of SEIFA, HWs and air quality measures in GRF models by SA3s in 0–4-year age group

d) Impact of HWs on prediction of ED presentations in local government areas for children 0–14 years

To make the GRF results more useful and practicable for local government agencies, the overall EHF ranking results for children 0–14 years from the GRF models were calculated and further aggregated evenly into three levels (i.e., high, middle, and low levels, and each level included seven SA3 areas), and then converted from SA3s to corresponding local government areas (LGAs) in a HW impact map format and LGA boundaries. The map is presented in Figure 14. The detailed results on average EHF for each SA3 and concordance between SA3 and LGA from ABS 2011 are included in Appendices 28–29.

From the map (Figure 14), the HW hotspots for children (0–14 years) on ED presentations are highlighted. The hotspots are mainly located in the southern LGAs, such as Mandurah, Serpentine-Jarrahdale, Kwinana, and Rockingham, with some in the middle of the Perth metropolitan area, such as Subiaco, Vincent, South Perth, and Perth City.

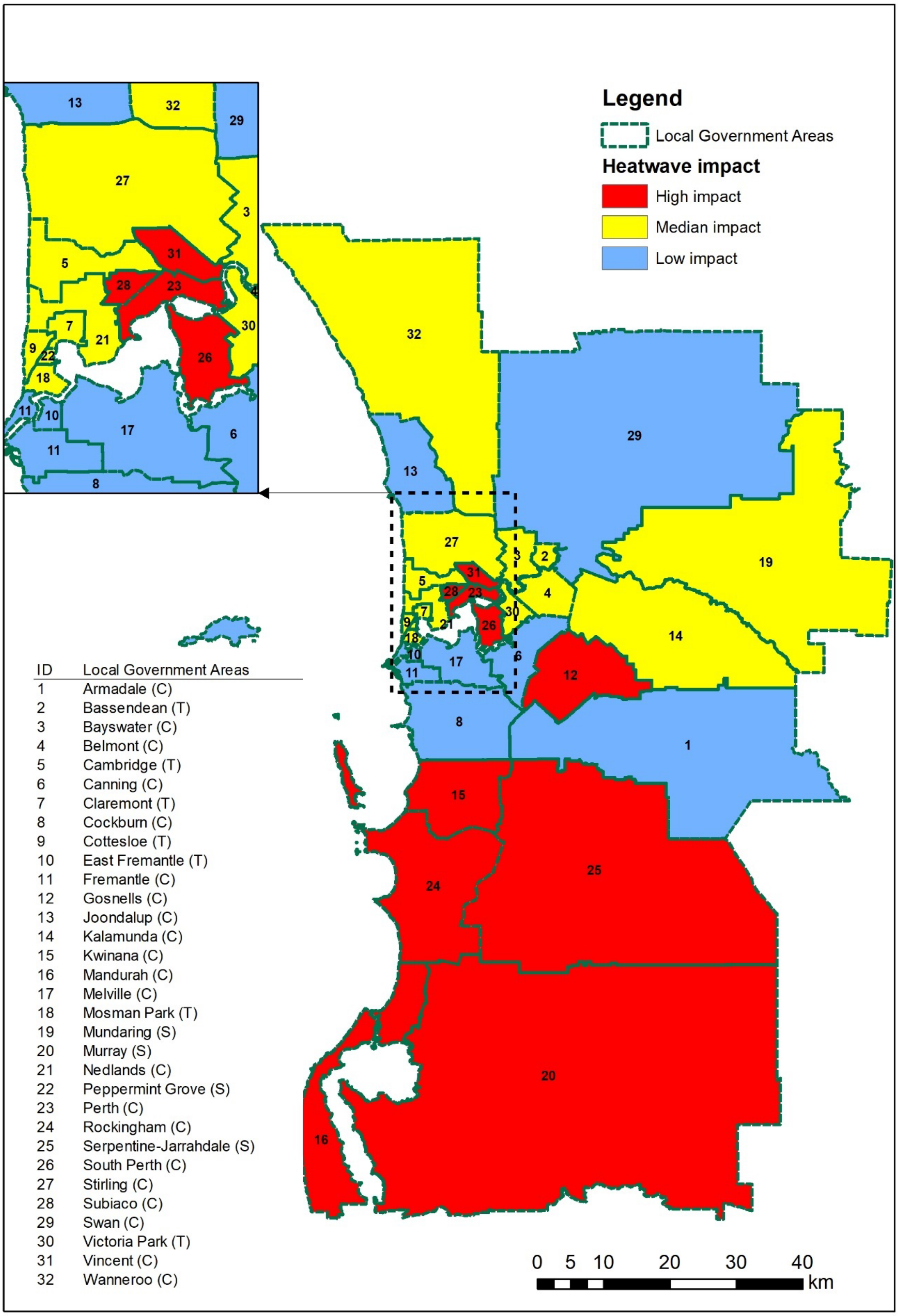

Figure 14 Spatial variations (LGAs) of the impact of HWs on children 0–14 years in Perth Metropolitan area

4. DISCUSSION

Public health authorities across Australia have identified the need for a coordinating approach to establish a public HW warning system to facilitate timely interventions and mitigate the health risks associated with extreme weather conditions. Such a system would ensure appropriate heat warnings and guidance are provided, promoting protective behaviours for at-risk populations and locations.

This study not only examined the individual effects of HWs and air quality on ED presentations, but also investigated their joint effects across different age groups, particularly focusing on children under 15 years of age. Additionally, the study evaluated spatial variations in the impact of HWs and air quality on ED presentations as well as the impact of SES as one of the most stable and important predictors. Furthermore, machine learning approaches were used to predict ED presentations by identifying the most important predictors.

4.1. HW and Air Quality

We found that during the 10-year study period, 2011 and 2012 experienced the highest frequency of HW events (Table 1), whereas 2007 recorded the most intense HW occurrences (Table 2). This suggests that years with frequent HW events do not necessarily coincide with those characterised by severe intensity.

Interestingly, despite overall air quality in Western Australia remaining within Australian ambient standards (Tables 3 and 4), median levels of air pollutants increased on HW days as compared to non-HW days (Table 55), with CO being an exception. This result was consistent with a study conducted in Birmingham, UK, evaluating the relationship between temperature and air quality, which found that during HW days, the level of air pollutants (NO_2, O_3, and PM_{10}) increased with the increase in temperature [42]. Similarly, an early study conducted in Athens, Greece between June and July 2007 also observed an increased level of air pollutants attributable to hot weather during summer's HW events [70].

Pearson correlation analysis (Table 7) revealed a significant positive relationship between air quality measures and HWs, except for CO. Among all air quality measures, the strongest relationship observed was with O_3, followed by PM_{10} and $PM_{2.5}$. A similar result was found in a study conducted in 213 US counties for 12.5 million people who were Medicare beneficiaries, which found a positive association between temperature and air pollutants (median: O_3, 0.39; PM_{10}, 0.42; $PM_{2.5}$, 0.45) in the correlation analysis [71]. Another study conducted in Brisbane, Australia, found that the maximum temperature was positively associated with PM_{10}, O_3, and NO_2 during summers [41]. One study in Athens, Greece, also found a positive association between heat load index values and O_3 and SO_2 in both the June and July HWs [39]. The variations found between different studies might be related to the levels of these air quality indicators in these countries and regions.

4.2. Impact of HWs on ED Presentations

The current study showed the ED presentation rate increased with the increase of HW events from 2006 to 2012 and reached its peak in 2012, except for 2009 (Figure 2). Generally, along with the increase in population, the ED presentation counts will increase each year. However, the ED presentation counts in December 2012 were higher than those in December 2013 (Table 6). This unusual phenomenon or pattern was possibly related to more frequent HW events in December 2012.

4.2.1. Lag Effect of HWs on ED Presentations

Very few studies have analysed the lag effect of HW on emergency health services (EHS). In this study, we found both all-cause and heat-related ED presentations had maximum lag effects on the third day of an HW event (Table 8). In some previous studies, short period lags (0-3 day lag) after the HW onset were reported to have the maximum detrimental effect on health and increased utilisation of EHS [22, 41, 71, 72]. However, one study conducted in 200 counties of the United States found that extreme heat (apparent temperature above the 95th percentile for 2–8 days) was related to an increase of 3% (95% CI: 2%, 4%) in all-cause emergency hospital admissions over the subsequent 8 days for individuals aged 65 years and older [73]. Therefore, it is important to assess the lag effect before assessing the HW effect on EHS to identify the most appropriate lag days where the strongest association between heat exposure and EHS demand exists. Consequently, it is worthwhile to explore the different lag effects of HWs on different health outcome measures in different climatic or geographic areas. Exploring the most appropriate and standardised HW exposure definition worldwide is a challenge but also important to enable comparisons between studies in different countries and regions.

4.2.2. Cause-related HW Vulnerability

We found (Tables 8-9 and 11) that the all-cause ED presentation rate was significantly higher on HW days than that on non-HW days in Perth (the crude rate increased by 3.8% and the adjusted rate increased by 4.2%). We also found (Tables 10 and 12) that the heat-related ED presentation rate was much higher than the all-cause rate of ED presentations (the crude rate increased by 184% and the adjusted rate increased by 301%). Using different HW definitions and analysis methods, some previous studies in Australia and overseas also found that HWs significantly increased ED presentations [16, 21, 73-77]. Such as a HW study in Canada found [78] a 4% (3,400 extra ED presentations) increase in the crude all-cause ED presentation rate during a HW period compared to the reference period. One study conducted in the Netherlands found a positive relationship between increasing temperatures above 32°C and ED presentations for heat-related diseases, with RR ranges between 1.15 and 1.19 among different age groups [17]. Another study observed that during HWs, heat-related ED presentations increased with RR = 6.30 (95% CI: 5.67, 7.01) across California, especially in the central coastal region, which includes San Francisco [79].

The current study also observed a significant effect of HWs on ED presentations due to renal failure (Table 8). This was consistent with a study conducted in Atlanta, US, which found the strongest relationship between ED presentations due to acute renal failure and HWs with an RR of 1.17 (95% CI: 1.04, 1.31) [76]. Another study conducted in Brisbane, Australia, observed a similar effect of HWs on ED presentations due to renal diseases with an OR of 1.41 (95% CI: 1.09, 1.83) [22]. Moreover, a previous study conducted in Perth, Australia [80] and Adelaide, Australia [81] also observed a higher risk of HWs on renal associated ED presentations.

However, we did not observe significant effects of HWs on ED presentations due to stroke, cardiac conditions, respiratory diseases, circulatory diseases, and hypertensive conditions. Similar to the results in the current study, a study conducted in the UK did not observe a significant rise in ED presentations due to disease of the circulatory system during HWs [18]. Another study conducted in 200 counties in the US did not observe the effect of HWs on ED presentations associated with cardiac diseases [73]. But two other studies in the USA found increased respiratory-related ED presentations increased by 4.3% (95% CI: 3.8%, 4.8%) with HWs [71] and a strong association between ischemic stroke and HWs, with an RR = 1.17 (95% CI: 1.02, 1.34) [76].

4.2.3. Vulnerable Populations to HWs

Using Poisson regression analysis, we found that the relative risk of ED presentations was different in different age groups. Young children aged 0–4 years and senior people aged 60 years and above were among the highest risk groups for all-cause ED presentations, and the young children group was also the most vulnerable population for heat-related ED presentations (Tables 11 and 12). Several studies conducted in Australia, China, and the Netherlands [16, 17, 23] observed increased risk among older people. While there were few reports on the vulnerability of children for ED presentations, one study in 58 counties in California found the greatest risk of HWs in young children (0–4 years old) with an RR of 1.05 (95% CI: 1.04, 1.07) [79]. A hand, foot, and mouth disease study for children under 15 years of age in Japan concluded that an increase of 1°C in the mean weekly temperature resulted in an increase in the number of cases of 12.1% (95% CI: 3.9, 20.8) in those aged 0–4 years [82]. Another study from Spain found [26] that mortality among children under one year of age increased by 25% on hot days, with acute (lag 0, i.e., same day) effects observed. A connection between age and heat can be explained by suboptimal thermoregulation [83]. Children are vulnerable to HWs due to their poor adaptive behaviour [75]. Thermoregulation helps a person survive in hot weather by losing heat from the body. When it fails during HWs, this results in the onset of heat illnesses, such as heat stress, heat exhaustion, and heatstroke.

In this study, we found that males had significantly higher ED presentation rates [RR: 4.3%, (95% CI: 4.2%-4.5%) for all-cause and 26.8% (95% CI: 20.0%-34.1%) for heat-related] than females during HWs, although both sexes were affected by HWs. In comparison, a study in Shanghai, China, found an insignificantly increased risk of ED presentations during HWs among males [RR:1.81%, 95% CI: 1.08%, 2.54%)] in comparison to females [RR: 1.75% (95% CI: 1.03%, 2.49%)] [84]. A descriptive study conducted in France found a significant excess mortality during HW for male children aged less than one year, with a ratio of observed to expected mortality of 1.3 (95% CI: 1.0, 1.6) [25]. Another study in Brisbane, Australia, found that male children and children aged 0–4 years were most vulnerable to heat effects for ED presentations for childhood asthma [24]. However, female and Indigenous children appeared particularly vulnerable to the temperature effect on ED presentations for pneumonia, with a relative risk of 2.02 (95% CI: 1.11, 3.66), and 4.20 (95% CI: 1.03, 8.16), respectively [27].

The current study found that Aboriginal residents had a higher risk of all-cause ED presentations during HWs [RR=1.901 (95% CI: 1.894, 1.908)] than that of non-Aboriginal residents. This is consistent with two other studies that showed Indigenous people were at higher risk of ED presentations as compared to non-Indigenous people [27, 85]. This phenomenon may be linked to a higher rate of homelessness among Indigenous population relative to that observed within the reference group in WA [86], making them more vulnerable to HWs. In addition, they have also been shown to be vulnerable to climate change because of their lower socio-economic condition and poor health status compared with non-Aboriginal people [87]. However, in this study, the observed relative risk of heat-related ED presentations was just the opposite; the non-Aboriginal population had a higher rate than the Aboriginal population. We identified only 21 cases of Aboriginal individuals for heat-related ED presentations on HW days, in contrast to 30,367 observed in the all-cause analysis. It is possible that the analyses regarding heat-related impacts on the Aboriginal population were affected by small sample sizes, thus, resulting data may lack reliability. One study conducted in Brisbane reported a similar finding: heat-related ED visits were higher in non-Aboriginal populations than in Aboriginal people. The authors were concerned that the identified patterns could stem from coding issues—specifically due to a higher prevalence of other conditions (e.g., diabetes, cardiovascular, and renal conditions) leading to categorisation of heat-related illnesses as underlying conditions or because Indigenous communities might utilise ED services at elevated rates compared to others [75]. Therefore, further studies assessing heat-related ED presentations need to extend the study period to include more cases and obtain more accurate and reliable outcomes.

One important finding from this study was the association of SES and ED presentations with HW exposure. Using spatiotemporal approaches, we demonstrated in all models (Tables 9-12) that people living in the most disadvantaged area were at the highest risk of all-cause and heat-related ED presentations during HWs as compared to other subcategories (i.e., the middle or the least disadvantaged area). Even in child-only analysis (Appendix 6), using the least disadvantaged area as the reference group, children who live in the most disadvantaged areas were also at the highest risk of heat-related ED presentations during HWs [RR = 2.402 (95% CI: 2.133, 2.7040)] compared with those lived in the middle area [RR = 1.380 (95% CI: 1.194, 1.5950)], and those in the least disadvantaged area (RR = 1). SES was also identified as the most important predictor in machine learning approaches, and details were presented in RF and GRF models (Tables 15 and17, and Appendices 16-21). There were limited studies on SES as a predictor for heat-related mortality and morbidity in Australia. A study conducted in Hong Kong [7] showed that people with low SES were more vulnerable to heat-related mortality, perhaps due to chronic health problems or their inability to afford air conditioners or their greater reluctance to use air conditioners due to the electricity costs. The affordability of good housing, air-conditioning, and a higher living standard make higher SES groups less likely to die during HWs. Another study of HWs in Brisbane, Australia, found a significant increase in ED presentations, with a cumulative RR of 1.11 (95% CI: 1.02, 1.20) in the most disadvantaged areas and of 1.05 (95% CI: 1.02, 1.08) in the least disadvantaged areas during HWs [88]. Overall, populations with lower SES and poor accessibility to services or air conditioning that are not affordable have a higher vulnerability to HWs for ED presentations.

In addition, this study found that people who lived in coastal areas were at greater risk of ED presentations during HWs, including children. The results of the current study contrast with findings suggesting that living near the coast may reduce the dangerous effects of HWs due to the cooling effect of the sea [89]. Coastal areas are influenced by marine climates and sea breeze convergence, which is common in Perth. However, one HW study found that those aged 75 years and older had the highest excess rates of all-cause ED visits during an exceptional 8-day HW event along the central coast of New South Wales in 2011 [23]. Australia is the biggest country in the world surrounded by oceans, with the longest coastline. As major cities have been built and most populations live near coastal areas, one possible explanation might be that the high density of population in cities tends to be affected by the urban heat island effect more than people living in rural areas. In addition, some coastal areas are popular leisure and tourist areas, such as Mandurah and Rockingham, which have a high proportion of elderly populations or children and are therefore more vulnerable to HWs. Coastal residents may also underestimate the severity of coastal HWs, assuming cooler conditions due to proximity to the ocean so may engage more in outdoor activities during heatwaves, increasing the likelihood of heat-related illnesses.

Moreover, we found that the risk of ED presentations on HW days was higher during holidays and weekends. This might be due to the onset of HW days aligning with holidays and weekends or because people are more likely to engage in recreational activities, celebrations, social gatherings, travel, or outdoor activities such as hiking, swimming, and beach tanning. Other possible reasons include the reduced availability of primary care during holidays and weekends or delayed seeking of medical attention due to travel plans or festivals, leading to worsening conditions that necessitate ED visits. As there is a lack of studies reporting such an association, further studies may need to confirm the outcomes found in this study on a broader scale.

4.3. Impact of Air Quality on ED Presentations

The current study observed that air pollution has an adverse impact on ED presentations (Tables 9-12). Exposure to middle or high-level air pollutants was associated with increased ED presentation rates compared to low level exposure. O_3, PM_{10}, and $PM_{2.5}$ played an important role in the increased ED presentation rate and showed dose-response relationships with adjusted relative risks of all-cause and heat-related ED presentations (Tables 11 and 12). Ambient air pollution is a significant risk factor for people's health [30, 90, 91]. WHO estimated that in 2012, 3.7 million people died prematurely due to the effects of air pollution [92]. Moreover, a meta-analysis was conducted for the impact of air pollution on ED presentations and hospital admissions due to chronic obstructive pulmonary disease. The study observed that an increase in 10μg/m^3 of $PM_{2.5}$ and NO_2 was related to 2.5% (95% CI: 1.6, 3.4%) and 4.2% (95% CI: 2.5, 6.0%) of the increase in morbidity, respectively [93]. Another study showed that the risk of ED presentations for myocardial infarction (MI) was increased with an OR of 1.48 (95% CI: 1.09, 2.02) and 1.69 (95% CI: 1.13, 2.34) for the increase of every $PM_{2.5}$ in 25μg/m^3 for the 2 hours before the onset of MI and every 20μg/m^3 $PM_{2.5}$ for the 24 hours before the onset of MI [29]. Exposure to CO, SO_2, NO_2, O_3, and $PM_{2.5}$ for children younger than 19 years of age observed a significant increase in ED presentations [94].

4.4. Joint Effects of HW and Air Quality on ED Presentations

The final Poisson regression model used interaction analysis, and results showed (Table 11) that increasing levels of $PM_{2.5}$ showed a significant positive joint effect with HWs on all-cause ED presentations after adjusting for other risk factors, including other air pollutants [high level RR = 1.038 (1.027, 1.050), and middle level RR = 1.007 (0.998, 1.016)]. Such a dose-response relationship was statistically significant. The interaction between $PM_{2.5}$ and HWs on heat-related ED presentation rates showed a non-significant increase with an RR of 1.202 (0.954, 1.515) at the high level and 1.064 (0.986, 1.397) at the middle level, compared with low level exposure to $PM_{2.5}$.

Three previous studies conducted in Australia observed that increasing concentrations of air pollutants in the environment could increase ED presentations during HWs. One study found a significant increase in ED presentations during HWs with relatively high levels of O_3, NO_2, and $PM_{2.5}$ [80]. Another observed a significant increase in ED presentation rates adjusted with O_3, NO_2, and PM_{10} (ORs ranged from 1.03 to 1.18) during HWs [95].

The third study found that correlations between temperatures above certain thresholds and ED presentation rates were significant when adjusting for O_3 and PM_{10} [96]. However, these three studies did not conduct interaction analysis. A study conducted in Shanghai, China, reported that with a 10μg/m^3 increase in concentrations of $PM_{2.5}$ and PM_{10}, the risk of emergency and outpatient visits for cardiovascular disease increased by 0.50% (95% CI: 0.46%, 0.55%) and 0.251% (95% CI: 0.221%, 0.282%), respectively, during warm seasons [97]. It is worth noting that the average daily concentration of $PM_{2.5}$ and PM_{10} in the Shanghai study was 56.3 μg/m^3 and 76 μg/m^3, but all air pollutant levels observed in this current study were lower than the Australian national standards summarised in Table 4 [98]. The maximum concentration of particulates in the atmosphere observed in this current study occasionally exceeded the national standards, such as $PM_{2.5}$ and PM_{10}. The overall low level of air pollutants in the Perth atmosphere could partly explain the different outcomes of this current study compared with other studies in other regions and countries. $PM_{2.5}$ is smaller in size and can penetrate the lungs more easily while breathing. This may have an adverse impact on respiratory health. However, due to a limited number of studies in the area, epidemiological evidence of the joint effect between HW and air quality on health, in particular, ED presentations, is insufficient.

It is possible that HW and air quality interact with each other and increase their impact on health. On the one hand, temperature and other weather parameters (i.e., rainfall, wind speed, and direction) may have a significant impact on air quality [99-101]. For example, a study conducted in multiple cities in China in different seasons found that among the various meteorological factors, temperature had the strongest influence on the concentration of $PM_{2.5}$ nationwide in all seasons [102]. Another study conducted in China found that the mean ultrafine particle concentration was estimated to increase by 4,983 particles/cm^3 for a one-degree increase in temperature (°C) [100]. On the other hand, air pollutants may also have a significant effect on HWs or higher temperatures [103]. During periods of extreme heat, stagnant air accumulates pollutants within the environment [104]. Consequently, air quality deteriorates during high-temperature episodes as sunlight interacts with atmospheric components while chemical compounds remain suspended within it. During fires, the generation of particulates increases significantly [105]. This creates a smog effect, making the air uncomfortable for breathing, subsequently leading to a rise in the utilisation of emergency health services due to heightened respiratory distress.

This study conducted in Perth to investigate the joint effect of HWs and air quality on ED presentations is novel. This research assessed ED presentations by using EHF (values extracted from the gridded cell) as a HW indicator, which is more sensitive compared with traditional temperature indicators [13], (a separate evaluation report comparing the two indicators is presented elsewhere). The outcomes of this study increase knowledge regarding the impact of HWs on ED presentations, in particular the knowledge of the joint effects of HWs and air pollution on ED presentations. This study also examined the vulnerability of Perth populations to HW conditions, which can be used by the state and local governments to develop HW management plans to protect vulnerable populations.

4.5. Spatial Variations in HW-related ED Presentations

Identifying the geospatial patterns of vulnerable populations and the impact of important predictors on the local environment has the potential to direct targeted public health interventions to mitigate associated morbidity [106]. Spatial variations of HWs on all-cause mortality among elder people aged 65 and over were reported in Sydney, Australia [107] and medical dispatch calls in Ontario, Canada [43], but never studied in WA. In the current study, three methodologies were used to explore the spatial variations of ED presentations related to HW exposure: traditional statistical analysis (e.g., a crude ED rate by HW indicator, or an adjusted ED rate by Poisson regression), GWR, and GRF models.

Initial analysis for the effect of HWs on adjusted ED rates for SA3 areas was conducted using Poisson regression and included the spatial variable SA3. After adjusting for other risk factors, including air quality indicators, we found that the relative risk of ED presentations significantly increased in all 20 SA3 areas during HW days as compared to the Melville area and all SA3s during non-HW days (Appendix 9). Additionally, different SA3 areas in Perth had different degrees of impact of HWs on the relative risks of ED presentations during HWs (Appendices 9-10), with the southern areas having a higher impact of HWs on the ED presentations, such as Mandurah, Armadale, Kwinana, and Rockingham compared to other areas of Perth. Overall, the HW impact pattern on the relative risk of all-cause ED presentations across the whole Perth geographical area was similar and significant in both age group models (Figure 3), with some variations mainly observed in the north and centre areas of Perth. Air quality influenced ED presentations, with most measures displaying significant dose-response relationships in both age models. The joint effect of HWs and SA3s was observed and significantly varied in more than half of the SA3s in Perth. HW hotspots were important, which require more detailed HW planning to protect the most vulnerable populations in the most vulnerable areas to reduce ED presentations during hot weather.

The GWR model is better than the traditional regression method (Table 13), in which the spatial variation is applied to the regression model (described in the methodology section). However, due to the limitations of the resources, including the ArcGIS Pro version on the types of data and the volume of data records that can be included to run the GWR models, we were only able to use one year data to obtain the impact and pattern of HWs on ED presentations over each of the five years (i.e., 2007, 2009, 2011, 2013, and 2015, Figure 5). Looking at the trend of ED presentations over these five years, there were large variations in the impact of HWs on the ED presentations in different SA3s and/or the same SA3s, such as the Stirling area being highly affected by HWs in 2009, 2011, 2013, and 2015 after adjusting for the other predictors in the GWR model (Figure 5). Other areas with high impact from HWs included Rockingham (in 2009, 2011, and 2015), Mandurah (in 2011 and 2013), and Swan (high in 2009 and 2015). The GWR models and the ArcGIS Pro application need to be further improved to enable a larger dataset and more types of data to be used to generate reliable outcomes.

We then explored the usefulness of GRF models for spatial analysis. We found that the GRF model performed better than the GWR model. Thus, further analysis for children used GRF models. Detailed discussions on GRF outcomes were included in Section 4.7.

4.6. Prediction of ED Presentations by RF Models

One novel aspect of this study involves the use of a machine learning approach to predict ED presentations in the Perth metropolitan area. Machine learning gives better outcomes as the model is trained by using a training dataset and testing the trained model on the validation dataset. This way, the machine learning model learns the pattern from the training data, and it will generalise well on the validation dataset. The validated optimal model will automatically rank the importance of all predictors in comprehensive large datasets, thus ensuring the prediction is more accurate and the advice on protective measures is timely and appropriate. This approach enabled the selection of the optimal model, thus enhancing the fitness of the model for ED presentation prediction. The results from this study indicated that demographic variables, such as age groups and SES, were the two most important predictors. Air quality measures are important predictors in the prediction. Temporal variables such as weekends and holidays were on the list but contributed less than others mentioned above. HWs contributed to the model to a moderate extent. The established machine learning approach can be applied to assess the impact of extreme weather and other environmental factors on other health service indicators. In addition, the prediction model for ED presentations established in this study could play an important role in better supporting HW planning, air pollution related health risk assessment, and improving early warning systems.

In the past, some of the most commonly used statistical methods to assess the relationship between HWs and health services include generalised estimating equations [34, 96], the Poisson regression model [72, 73], and the logistic regression model [15]. Some studies used machine learning methods to develop spatial models of air pollutants [50] and define the HW threshold [51]. However, there is a lack of studies that use machine learning approaches to derive optimal models for predicting the impact of environmental factors and their joint effects on health outcomes. The current study used not only Poisson regression but also RF and GRF models to assess and predict the effects of HWs and air quality and their joint effect on ED presentations. Additionally, spatial variations of these two environmental factors were also examined.

To our knowledge, no published literature has employed machine learning techniques to investigate the joint effect of HWs and air quality alongside other predictors (risk factors) on ED presentations. The current study found that the goodness of fit (R^2) of the RF model was 0.953, indicating an excellent simulation of real-world conditions by this model [108]. Few studies using such techniques have predicted adverse health effects related to HWs. Notable exceptions include research conducted in China using RF method and a study in Europe using an age-specific linear regression method [44, 109].

Exploring potential predictive factors and their importance was vital to the model's development. One of the benefits of using the RF model is that it can include large datasets with multiple variables (potential predictors or risk factors) and determine the importance ranking of these predictors in the RF model automatically and much more efficiently. Results from RF models showed that age contributed the most to the prediction. Some previous studies reported that age was an important risk factor for ED presentations, such as one study in California, USA, which identified that children (0–4 years of age) and the elderly (≥ 65 years of age) were at greatest risk for ED visits during two HW events [110]. The SEIFA was ranked as the second most important predictive variable in the RF model. When the analysis was stratified by age groups, the SEIFA was ranked as the most important predictor for ED presentation rates in all models (e.g., 0–4 years, 5–9 years, and 10–14 years), and this result is consistent among all models used in this study. These results confirmed that age and SES of the population were the two most important predictors for ED presentations compared to the meteorological and air quality variables. This study also showed that the number of landscape fire events was also an important predictor after age and SEIFA. Although there were few studies that examined mortality and SES [111, 112], it was rare for studies to explore SES and HW-related morbidity, in particular ED presentations. Our study was the first to use GRF models to confirm that SES was among the most important predictors for predicting EHS (ED presentations) in either the all-age model or the child-only model.

Air quality measures ranked higher in model importance analysis as compared to HWs, indicating the necessity of including air quality in the model. Among all air pollutants, the particulate matter was among the most important predictors in both all-age and child-only models. There were a few other studies that observed the significant adverse effects of HWs and air quality on health by using different methods such as cross-correlation, GLM, and the GEE model [34, 39, 40]. But the only published RF model study did not include air quality to adjust the outcomes [44]. The current study demonstrated the importance of air quality while estimating the effects of HWs on ED presentations in the RF model.

4.7. Prediction of ED presentations by GRF Models

Although RF is a highly flexible and nonlinear algorithm, it does not account for spatial heterogeneity. In contrast, the GRF model considers nonlinear relationships between explanatory and dependent variables while effectively demonstrating spatial heterogeneity alongside insights into the local performance of these explanatory variables. Consequently, GRF models can provide information on the importance of predictors influencing ED presentations across various locations.

In addition to Poisson regressions applied to SA3 areas and GWR models, the GRF models developed in this study simulated reality remarkably well for geographic variation for three child group models, yielding R^2 values of 0.975, 0.934, and 0.899, respectively (Table 16). Using these established GRF models allowed us to observe spatial variations regarding the importance of each predictor for all three child groups across the 21 study areas (SA3s) (Table 17, Figures 13-14 and Appendix 26-27). Furthermore, we observed spatial interactions between EHF, SEIFA, and $PM_{2.5}$ on ED presentations across different child groups. Notably, SEIFA and EHF were the two most important predictors for predicting demand for ED presentation among children — particularly pronounced in southern areas compared to other study areas.

Several studies have reported the adverse impacts of HWs on children's health in countries such as Austria [113], Australia [24, 27], South Korea [114], Hong Kong, China [115], Brazil [116], and Spain [117]. However, these studies did not include SES as a predictor nor consider the geographic variations. A limited number of studies have explored spatial heterogeneity in linear models such as GWR for investigating heat related mortality or assessing relationships between temperature and environmental risk factors [107, 118]. Nevertheless, this study's approach — investigating spatial variation by appropriately addressing heterogeneity while assessing ED presentation demands using GRF models—represents a novel methodology that has only recently been established for alternative purposes [48].

The established GRF method in this study offers a cost-effective approach to mitigating potential adverse consequences for children affected by environmental risk factors, such as HWs and air pollution. This is achieved by focusing on at-risk areas and critical variables (risk factors/predictors).

4.8. Strengths and Limitations

This study presents several advantages. Firstly, the use of ED presentations as the dependent variable rather than mortality provides insights into the immediate joint effect of HWs and air quality on ED presentations. Secondly, the research employs a comprehensive long-term dataset spanning 10 years alongside nonconventional predictive models (i.e., RF and GRF) to evaluate the impact of environmental factors (i.e., HWs and air quality) on emergency health service demand and spatial variations across the entire Perth metropolitan area, yielding satisfactory results. Thirdly, the machine learning approach applied in this study is represents a pioneering effort in modelling the prediction of health service demands associated with HW exposure. This approach is capable of modelling nonlinearities and interactions among various predictors within large datasets, thereby improving model fit when compared to traditional regression approaches. Finally, the importance ranking of predictors has been validated among an extensive array of candidate independent variables—including demographic data, air quality metrics, weather-related information, area-specific characteristics, and time-dependent variables—which substantially contributed to improving model predictions.

However, there are limitations associated with this study. Firstly, Perth has a limited number of air quality observation stations and weather stations. The measurements obtained from these stations were not uniform; different locations collected data on various air pollutants starting from different time periods. Although this study employed the IDW method [119] to improve estimations of air quality across the entire Perth region, some uncertainty remains regarding the accuracy of these estimated measurements. Furthermore, this study only explored a few models utilising machine learning methodologies.

5. CONCLUSIONS

As the frequency and intensity of HWs increase, there has been a corresponding rise in the utilisation of EHS worldwide, including an increase in ED presentations. The adverse impact of air pollution further complicates these effects. Findings from this study indicate that the rate of ED presentation serves as a critical and sensitive indicator for promptly evaluating emergency morbidity or EHS utilisation related to HW exposure.

Using a sensitive HW exposure indicator (EHF), this research has revealed that the most significant impact on all-cause and heat-related ED presentations occurs over a cumulative three-day period. Children under five years old and individuals aged 60 years and older are among the most vulnerable age groups for heat-related ED presentations. Air quality can directly influence or indirectly modify the effect of HWs—through joint effects—on ED presentations. The most important air quality measures include particulate matter ($PM_{2.5}$ and PM_{10}) and ozone. Through age-stratified analysis, SES has been consistently identified as the most important predictor and predictor for ED presentations across all models examined. Aboriginal populations, individuals residing in the most disadvantaged areas, coastal areas, and southern areas of Perth face the highest risk for all-cause ED presentations during HWs. The relative risk of heat-related ED presentations surpasses that of all-cause ED presentations, further confirming the impact of HWs on excess ED presentations. Additionally, renal failure related ED presentations exhibit a significantly increase during HWs with varying lag effects. Public holidays and weekends are two critical time periods associated with excess ED presentations during HWs.

In terms of methodological innovation, this study is pioneering in its application of machine learning approaches to develop RF and GRF models aimed at identifying important predictors or risk factors associated with heat-related ED presentations while achieving high goodness-of-fit results. GRF can effectively pinpoint geographic variations in HW and air quality across different areas. This model is valuable for identifying vulnerable hotspots for HWs, as well as vulnerable populations such as young children, thereby facilitating the targeted allocation of resources and excess EHS to these specific demographics and locations.

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Appendices

Appendix 1 Pearson correlation between air quality, EHF, and ED presentation rate (/100,000/day) by kriging method

		NO_2	O_3	PM_{10}	$PM_{2.5}$
EHF	r value	0.0135	0.2399	0.1787	0.0485
	P value	<.0001	<.0001	<.0001	<.0001
Rate	r value	-0.0018	0.0012	0.0008	0.0015
	P value	<.0001	0.0052	0.0536	0.0006

CO: carbon monoxide; EHF: excess heat factor; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micrometres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micrometres; r value: Pearson correlation coefficient value; SO_2: Sulphur dioxide

Appendix 2 ICD-10-AM codes used for related ED conditions

Condition	ICD-10-AM Codes
Respiratory	MDB=3B or MDC=4
Cardiac diseases	MDB=3A or MDC=5
Circulatory diseases	I00-I99, G45
Hypertensive	I10-I13, I15
Stroke	I60-I64
Renal failure	N17-N19
Heat related	T67, L55, X30, X32, L59, L74

MDB: Major Diagnostic Block; MDC: Major Diagnostic Category

Appendix 3 Description of the variables used in machine learning models

Variable name	Description
Age_grp	5 age groups; 1=0-4, 2=5-9, 3=10-14, 4=15-59, 5=60+ year
SEIFA	3 categories; socio-economic index for areas; 1= disadvantaged and most disadvantaged, 2=middle, 3= least disadvantaged and less disadvantaged
Bunrs_day	Number of landscape fire burns per day
co_cat	3 categories of carbon monoxide; 1=low, 2=middle, 3=high
so2_Cat	3 categories of sulphur dioxide; 1=low, 2=middle, 3=high
no2_Cat	3 categories of nitrogen dioxide; 1=low, 2=middle, 3=high
o3_cat	3 categories of ozone; 1=low, 2=middle, 3=high
pm10_cat	3 categories of particulate matter with aerodynamic diameter ≤10 micro metres; 1=low, 2=middle, 3=high
pm25_cat	3 categories of particulate matter with aerodynamic diameter ≤2.5 micro metres; 1=low, 2=middle, 3=high
holiday	2 categories; 1=holiday and 0=non-holiday
weekend	2 categories; 1=weekend and 0=weekday
ehf_flag	2 categories; 1=heatwave and 0=non-heatwave

Appendix 4 Effects of HW & sociodemographic factors on adjusted relative risk of all-cause ED presentations

Variable	Subcategory	RR (95% CI)	P value
HW	HW day	1.032 (1.030,1.035)	<.0001
	Non HW day*		
Age group	0-4y	2.307 (2.299,2.316)	<.0001
	60+y	1.487 (1.482,1.492)	<.0001
	15-59y	1.068 (1.064,1.071)	<.0001
	5-9y	1.072 (1.067,1.077)	<.0001
	10-14y*		
Sex	Male	1.043 (1.042,1.045)	<.0001
	Female*		
Aboriginal status	Aboriginal	1.899 (1.892,1.906)	<.0001
	Non-Aboriginal *		
SEIFA	Disadvantaged	1.713 (1.710,1.716)	<.0001
	Middle	1.300 (1.298,1.303)	<.0001
	Advantaged*		
Weather zone	Coastal	1.146 (1.144,1.148)	<.0001
	Inlands*		
Holiday	Holiday	1.120 (1.117,1.124)	<.0001
	Non-Holiday*		
Weekend	Weekend	1.065 (1.063,1.067)	<.0001
	Weekday*		

CI: confidence interval; ED: emergency department; HW: heatwave; RR: relative risk; SEIFA: socio-economic index for areas; * reference category

Appendix 5 Effects of HW & sociodemographic factors on adjusted relative risk of heat-related ED presentations

Variable	Subcategory	RR (95% CI)	P value
HW	HW day	2.787 (2.609,2.977)	<.0001
	Non HW day*		
Age group	0-4y	1.561 (1.372,1.776)	<.0001
	60+y	0.480 (0.419,0.548)	<.0001
	15-59y	0.792 (0.711,0.883)	<.0001
	10-14y	1.309 (1.143,1.498)	<.0001
	5-9y*		
Sex	Male	1.269 (1.200,1.342)	<.0001
	Female*		
Aboriginal status	Aboriginal	0.718 (0.584,0.882)	0.002
	Non-Aboriginal *		
SEIFA	Disadvantaged	1.847 (1.733,1.968)	<.0001
	Middle	1.235 (1.144,1.333)	<.0001
	Advantaged*		
Weather zone	Inlands	1.059 (1.001,1.121)	0.046
	Coastal*		
Holiday	Holiday	1.446 (1.297,1.613)	<.0001
	Non-Holiday*		
Weekend	Weekend	1.226 (1.155,1.301)	<.0001
	Weekday*		

* Reference category. CI: confidence interval; ED: emergency department; HW: heatwave; RR: relative risk; SEIFA: socio-economic index for areas.

Appendix 6 Variables including air quality for all-cause ED presentations for children, Perth, WA, 2006-2015

Variable	Category	Joint effect	RR (95% CI)	P value
HW	HW day		0.985 (0.958,1.012)	0.277
	Non HW day*			
Age group	0–4y		**2.314 (2.305,2.323)**	<.0001
	5–9y		**1.073 (1.068,1.078)**	<.0001
	10–14y*		1.000	
Sex	Male		**1.203 (1.199,1.206)**	<.0001
	Female*		1.000	
Aboriginal status	Aboriginal		**1.206 (1.198,1.215)**	<.0001
	Non-Aboriginal *		1.000	
SEIFA	Disadvantaged		**1.458 (1.453,1.464)**	<.0001
	Middle		**1.180 (1.175,1.185)**	<.0001
	Advantaged*		1.000	
Weather zone	Coastal		**1.043 (1.040,1.046)**	<.0001
	Inlands*		1.000	
Holiday	Holiday		**1.112 (1.104,1.119)**	<.0001
	Non-Holiday*		1.000	
Weekend	Weekend		**1.075 (1.072,1.079)**	<.0001
	Weekday*		1.000	
CO	High		**1.096 (1.090,1.101)**	<.0001
	Middle		**1.059 (1.055,1.064)**	<.0001
	Low*		1.000	
O_3	High		**1.085 (1.079,1.090)**	<.0001
	Middle		**1.068 (1.064,1.073)**	<.0001
	Low*		1.000	
PM_{10} × HW	High	HW day	**1.044 (1.019,1.069)**	0.000
	Middle	HW day	**1.034 (1.012,1.056)**	0.002
	Low*	HW day*	1.000	
	High*	Non HW day*	1.000	
	Middle*	Non HW day*	1.000	
	Low*	Non HW day*	1.000	

Appendix 7 Variables including air quality for heat-related ED presentations for children, Perth, WA, 2006-2015

Variable	Category	Joint effect	RR (95% CI)	P value
HW	HW day		**2.521 (1.251,5.080)**	0.0097
	Non HW day*		1.000	
SO_2	High		**1.402 (1.167,1.685)**	0.0003
	Middle		**1.210 (1.034,1.417)**	0.0173
	Low*		1.000	
O_3	High		**1.395 (1.173,1.658)**	0.0002
	Middle		0.884 (0.765,1.021)	0.0941
	Low*		1.000	
PM_{10}	High		**1.867 (1.489,2.342)**	<.0001
	Middle		**1.509 (1.254,1.816)**	<.0001
	Low*		1.000	
$PM_{2.5}$	High		**1.165** (0.921,1.472)	0.2012
	Middle		**1.080** (0.901,1.294)	0.4005
	Low*		1.000	
CO × HW	High	HW day	**1.363** (0.802,2.315)	0.2512
	Middle	HW day	**1.139** (0.786,1.651)	0.4884
	Low*	HW day*	1.000	
	High	Non HW day*	1.000	
	Middle	Non HW day*	1.000	
	Low*	Non HW day*	1.000	
SO_2 × HW	High	HW day	**1.119** (0.716,1.750)	0.6187
	Middle	HW day	**1.276** (0.859,1.894)	0.2262
	Low*	HW day*	1.000	
	High	Non HW day*	1.000	
	Middle	Non HW day*	1.000	
	Low*	Non HW day*	1.000	
$PM_{2.5}$ × HW	High	HW day	**1.786** (0.923,3.455)	0.0846
	Middle	HW day	**1.399** (0.780,2.511)	0.2592
	Low*	HW day*	1.000	
	High	Non HW day*	1.000	
	Middle	Non HW day*	1.000	
	Low*	Non HW day*	1.000	
Age group	0-4y		**1.553 (1.365,1.768)**	
	10-14y		**1.313 (1.147,1.504)**	
	5-9y*		1.000	
Sex	Male		**1.188 (1.072,1.317)**	
	Female*		1.000	
Aboriginal status	Aboriginal		0.663 (0.492,0.894)	
	Non-Aboriginal*		1.000	
SEIFA	Disadvantaged		**2.402 (2.133,2.704)**	
	Middle		**1.380 (1.194,1.595)**	
	Advantaged*		1.000	
Weather zone	Coastal		**1.049** (0.942,1.169)	
	Inlands*		1.000	
Holiday	Holiday		**1.347 (1.084,1.674)**	
	Non-Holiday*		1.000	
Weekend	Weekend		**1.278 (1.144,1.428)**	
	Weekday*		1.000	

Appendix 8 Crude all-cause ED presentation rate, AR, and RR (/100,000/day) by SA3s for all age groups on HW days and non-HW days in Perth, 2006-2015

Area	HW indicator	ED count	ED rate	AR	RR (95% CI)
Rockingham	HW day	64,083	113.26	**3.61**	**1.032 (1.024,1.041)**
	Non HW day*	578,755	109.65		
Melville	HW day	23,612	43.14	**0.46**	1.010 (0.997,1.024)
	Non HW day*	219,702	42.68		
Kwinana	HW day	16,584	117.20	**5.32**	**1.047 (1.030,1.064)**
	Non HW day*	146,698	111.88		
Fremantle	HW day	15,532	81.98	**3.87**	**1.049 (1.032,1.067)**
	Non HW day*	138,214	78.10		
Cockburn	HW day	29,084	68.56	**2.12**	**1.031 (1.019,1.044)**
	Non HW day*	263,981	66.44		
South Perth	HW day	11,418	50.33	**0.84**	1.016 (0.997,1.036)
	Non HW day*	106,279	49.49		
Serpentine- Jarrahdale	HW day	8,445	92.73	**4.82**	**1.054 (1.031,1.078)**
	Non HW day*	78,844	87.90		
Kalamunda	HW day	19,020	66.79	**2.09**	**1.032 (1.017,1.047)**
	Non HW day*	179,272	64.70		
Gosnells	HW day	46,059	80.44	**2.80**	**1.036 (1.026,1.046)**
	Non HW day*	421,811	77.64		
Canning	HW day	26,255	54.41	**1.68**	**1.031 (1.018,1.045)**
	Non HW day*	242,257	52.73		
Belmont- Victoria Park	HW day	26,412	76.59	**2.96**	**1.040 (1.027,1.053)**
	Non HW day*	241,400	73.63		
Armadale	HW day	38,982	119.12	**5.77**	**1.050 (1.040,1.061)**
	Non HW day*	360,235	113.35		
Wanneroo	HW day	61,002	80.41	**4.00**	**1.052 (1.043,1.061)**
	Non HW day*	550,314	76.41		
Stirling	HW day	67,313	68.23	**2.68**	**1.040 (1.032,1.049)**
	Non HW day*	607,960	65.56		
Joondalup	HW day	53,768	62.86	**3.48**	**1.058 (1.049,1.068)**
	Non HW day*	472,161	59.38		
Swan	HW day	45,394	83.34	**2.26**	**1.027 (1.018,1.037)**
	Non HW day*	432,926	81.08		
Mundaring	HW day	16,690	74.99	**3.10**	**1.043 (1.026,1.059)**
	Non HW day*	148,805	71.89		
Bayswater- Bassendean	HW day	29,966	72.07	**2.06**	**1.029 (1.017,1.041)**
	Non HW day*	277,210	70.01		
Perth City	HW day	34,217	66.73	**1.79**	**1.027 (1.016,1.039)**
	Non HW day*	310,688	64.94		
Cottesloe - Claremont	HW day	17,712	49.30	**1.71**	**1.035 (1.020,1.052)**
	Non HW day*	161,001	47.59		
Mandurah	HW day	57,946	132.82	**5.31**	**1.041 (1.032,1.050)**
	Non HW day*	538,400	127.51		

RR: relative risk; AR: Attributable rate; CI: confidence interval; ED presentations: emergency department attendances; HW: heatwave; * reference category

Appendix 9 Crude all-cause ED presentation rate, AR, and RR (/100,000/day) by SA3s for children on HW days and non-HW days in Perth, 2006-2015

Area	HW indicator	ED count	ED rate	AR	RR (95% CI)
Rockingham	HW day	14,403	114.10	-3.02	0.974 (0.957,0.991)
	Non HW day*	138,346	117.12		
Melville	HW day	4,942	54.33	-2.57	0.954 (0.927,0.983)
	Non HW day*	48,859	56.90		
Kwinana	HW day	3,925	118.41	**3.40**	1.029 (0.996,1.084)
	Non HW day*	35,388	115.01		
Fremantle	HW day	2,192	75.51	-1.85	0.976 (0.934,1.020)
	Non HW day*	21,016	77.35		
Cockburn	HW day	6,366	74.11	-1.29	0.982 (0.957,1.008)
	Non HW day*	60,763	75.40		
South Perth	HW day	2,708	84.94	**2.58**	1.031 (0.991,1.073)
	Non HW day*	24,933	82.36		
Serpentine- Jarrahdale	HW day	2,073	98.97	**2.15**	1.022 (0.977,1.089)
	Non HW day*	20,062	96.82		
Kalamunda	HW day	4,194	75.55	**0.09**	1.001 (0.989,1.033)
	Non HW day*	40,877	75.46		
Gosnells	HW day	10,551	87.82	-0.91	0.989 (0.970,1.009)
	Non HW day*	101,596	88.73		
Canning	HW day	5,729	71.46	-2.82	0.962 (0.936,0.988)
	Non HW day*	56,916	74.27		
Belmont- Victoria Park	HW day	5,937	114.56	**2.33**	1.020 (0.993,1.048)
	Non HW day*	55,558	112.23		
Armadale	HW day	8,549	123.01	-2.31	0.981 (0.959,1.003)
	Non HW day*	84,997	125.32		
Wanneroo	HW day	16,572	90.89	-0.06	0.999 (0.983,1.015)
	Non HW day*	157,588	90.96		
Stirling	HW day	15,732	95.05	**0.45**	1.004 (0.988,1.021)
	Non HW day*	147,657	94.60		
Joondalup	HW day	11,844	72.94	-1.01	0.986 (0.967,1.005)
	Non HW day*	112,038	73.95		
Swan	HW day	11,230	91.34	-1.16	0.987 (0.968,1.006)
	Non HW day*	111,721	92.50		
Mundaring	HW day	3,329	78.76	**1.32**	1.017 (0.981,1.054)
	Non HW day*	30,501	77.44		
Bayswater- Bassendean	HW day	6,340	94.65	-0.17	0.998 (0.972,1.024)
	Non HW day*	60,744	94.81		
Perth City	HW day	6,152	93.56	-5.36	0.945 (0.921,0.971)
	Non HW day*	60,894	98.92		
Cottesloe - Claremont	HW day	4,001	63.01	-1.71	0.973 (0.942,1.005)
	Non HW day*	38,775	64.72		
Mandurah	HW day	11,010	134.70	**0.80**	1.005 (0.986,1.025)
	Non HW day*	106,024	133.90		

RR: relative risk; AR: Attributable rate; CI: confidence interval; ED presentations: emergency department attendances; HW: heatwave; * reference category

Appendix 10 Adjusted relative risk of ED presentations by SA3 areas for all-age population in Perth, 2006-2015

Variable	Subcategory	Joint effect	RR (95% CI)	P Value
HW	HW day		1.004 (0.991,1.018)	0.52
	Non HW day*		1.000	
SA3	Armadale		**2.609 (2.595,2.622)**	<.0001
	Kwinana		**2.540 (2.523,2.556)**	<.0001
	Mandurah		**2.847 (2.832,2.861)**	<.0001
	Serpentine - Jarrahdale		**2.040 (2.023,2.057)**	<.0001
	Wanneroo		**1.743 (1.734,1.752)**	<.0001
	Fremantle		**1.803 (1.791,1.815)**	<.0001
	Rockingham		**2.495 (2.483,2.507)**	<.0001
	Joondalup		**1.376 (1.369,1.383)**	<.0001
	Mundaring		**1.670 (1.659,1.681)**	<.0001
	Belmont - Victoria Park		**1.714 (1.704,1.724)**	<.0001
	Gosnells		**1.806 (1.797,1.815)**	<.0001
	Stirling		**1.493 (1.486,1.501)**	<.0001
	Swan		**1.889 (1.879,1.898)**	<.0001
	Cockburn		**1.560 (1.551,1.569)**	<.0001
	Kalamunda		**1.495 (1.486,1.504)**	<.0001
	Bayswater - Bassendean		**1.616 (1.607,1.625)**	<.0001
	Perth City		**1.519 (1.510,1.527)**	<.0001
	Cottesloe - Claremont		**1.091 (1.085,1.099)**	<.0001
	Canning		**1.243 (1.236,1.250)**	<.0001
	South Perth		**1.160 (1.151,1.168)**	<.0001
	Melville*		1.000	
Age group	0-4y		**2.320 (2.311,2.329)**	<.0001
	60+y		**1.499 (1.494,1.505)**	<.0001
	15-59y		**1.073 (1.069,1.076)**	<.0001
	5-9y		**1.071 (1.066,1.076)**	<.0001
	10-14y*		1.000	
CO	High		**1.049 (1.046,1.051)**	<.0001
	Middle		**1.029 (1.027,1.031)**	<.0001
	Low*		1.000	
SO2	High		**1.036 (1.033,1.038)**	<.0001
	Middle		**1.031 (1.029,1.033)**	<.0001
	Low*		1.000	
NO2	High		0.911 (0.909,0.914)	<.0001
	Middle		0.959 (0.957,0.961)	<.0001
	Low*		1.000	
O3	High		**1.056 (1.054,1.059)**	<.0001
	Middle		**1.033 (1.031,1.035)**	<.0001
	Low*		1.000	
PM10	High		0.967 (0.964,0.969)	<.0001
	Middle		0.989 (0.987,0.991)	<.0001

	Low*		1.000	
PM2.5	High		**1.013 (1.010,1.016)**	<.0001
	Middle		**1.006 (1.004,1.009)**	<.0001
	Low*		1.000	
SA3 × HW	Armadale	HW day	**1.041 (1.023,1.059)**	<.0001
	Kwinana	HW day	**1.035 (1.014,1.057)**	0.001
	Mandurah	HW day	**1.029 (1.013,1.045)**	0.000
	Serpentine - Jarrahdale	HW day	**1.044 (1.017,1.072)**	0.001
	Wanneroo	HW day	**1.039 (1.023,1.056)**	<.0001
	Fremantle	HW day	**1.039 (1.017,1.061)**	0.000
	Rockingham	HW day	**1.016 (1.000,1.032)**	0.040
	Joondalup	HW day	**1.045 (1.028,1.062)**	<.0001
	Mundaring	HW day	**1.027 (1.005,1.048)**	0.012
	Belmont - Victoria Park	HW day	**1.028 (1.010,1.048)**	0.003
	Gosnells	HW day	**1.025 (1.008,1.042)**	0.003
	Stirling	HW day	**1.027 (1.011,1.043)**	0.001
	Swan	HW day	1.010 (0.994,1.027)	0.211
	Cockburn	HW day	**1.021 (1.003,1.040)**	0.019
	Kalamunda	HW day	1.016 (0.995,1.036)	0.121
	Bayswater - Bassendean	HW day	1.014 (0.996,1.032)	0.123
	Perth City	HW day	1.015 (0.997,1.033)	0.090
	Cottesloe - Claremont	HW day	**1.025 (1.004,1.046)**	0.015
	Canning	HW day	**1.022 (1.004,1.041)**	0.017
	South Perth	HW day	1.006 (0.983,1.030)	0.594
	Melville*	HW day*		
	All SA3*	Non HW day*		

RR: relative risk; AR: Attributable rate; CI: confidence interval; ED presentations: emergency department attendances; HW: heatwave; CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micro metres; $PM_{2.5}$: particulate matter with aerodynamic diameter ≤2.5 micro metres; * reference category; Green shade areas: similar outcomes observed in child-only model

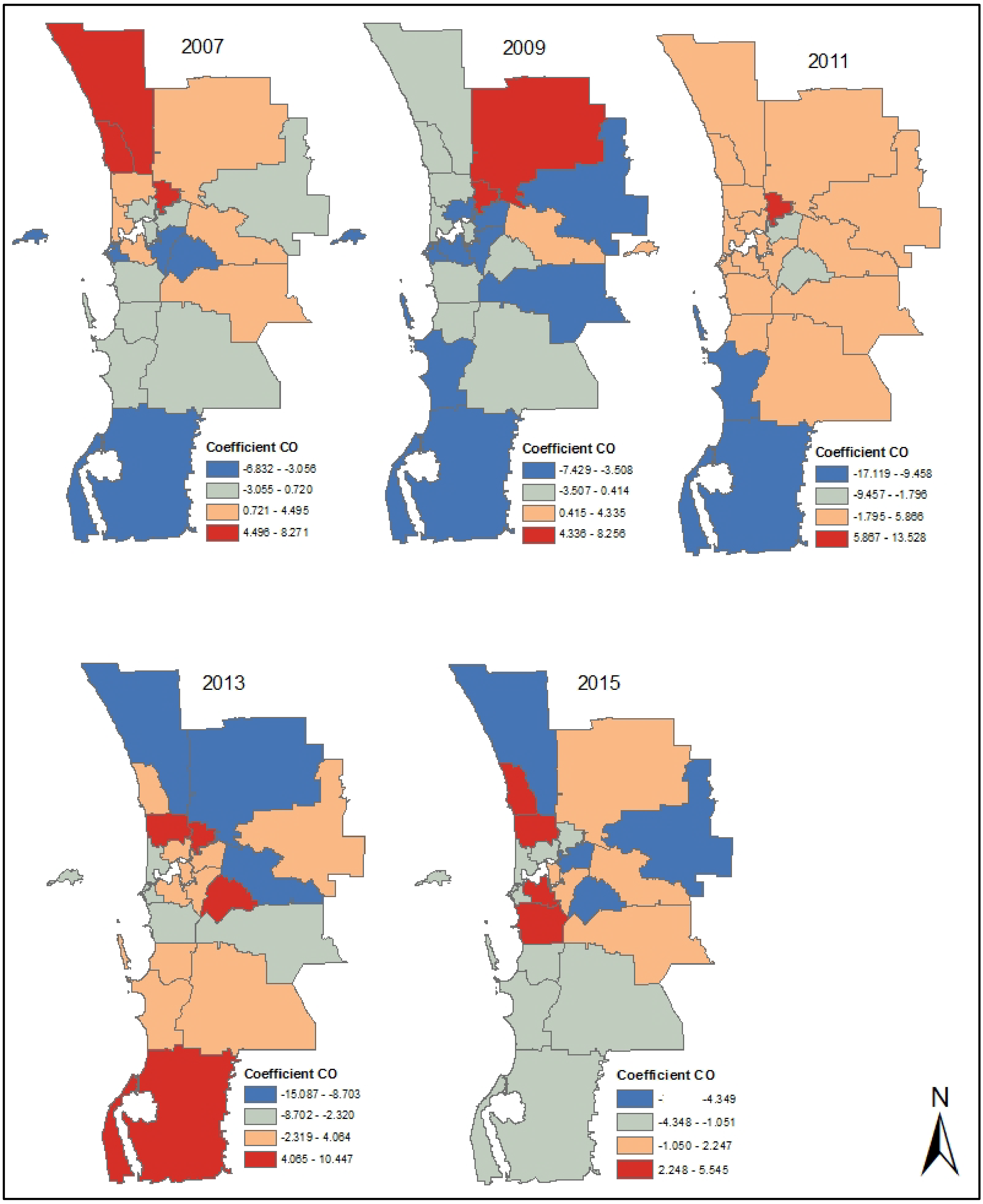
Appendix 11 Adjusted relative risk of ED presentations by SA3 areas for children in Perth, 2006-2015

Risk factor	Subcategory	Joint effect	RR (95% CI)	P value
HW	HW day		0.950 (0.923,0.979)	0.001
	Non HW day*			
SA3	Armadale		**2.077 (2.054,2.100)**	<.0001
	Kwinana		**1.857 (1.831,1.882)**	<.0001
	Mandurah		**2.274 (2.250,2.299)**	<.0001
	Serpentine - Jarrahdale		**1.666 (1.639,1.693)**	<.0001
	Wanneroo		**1.494 (1.479,1.510)**	<.0001
	Fremantle		**1.293 (1.272,1.314)**	<.0001
	Rockingham		**1.952 (1.932,1.973)**	<.0001
	Joondalup		**1.262 (1.249,1.276)**	<.0001
	Mundaring		**1.360 (1.340,1.379)**	<.0001
	Belmont - Victoria Park		**1.775 (1.753,1.796)**	<.0001
	Gosnells		**1.486 (1.470,1.502)**	<.0001
	Stirling		**1.525 (1.509,1.541)**	<.0001
	Swan		**1.568 (1.551,1.584)**	<.0001
	Cockburn		**1.265 (1.250,1.280)**	<.0001
	Kalamunda		**1.294 (1.277,1.311)**	<.0001
	Bayswater - Bassendean		**1.539 (1.521,1.557)**	<.0001
	Perth City		**1.566 (1.547,1.584)**	<.0001
	Cottesloe - Claremont		**1.145 (1.130,1.160)**	<.0001
	Canning		**1.273 (1.257,1.288)**	<.0001
	South Perth		**1.373 (1.352,1.394)**	<.0001
	Melville*			
Age group	0-4y		**2.316 (2.307,2.324)**	<.0001
	5-9y		**1.072 (1.067,1.077)**	<.0001
	10-14y*			
CO	High		**1.058 (1.053,1.064)**	<.0001
	Middle		**1.032 (1.028,1.036)**	<.0001
	Low*			
SO_2	High		**1.026 (1.021,1.031)**	<.0001
	Middle		**1.032 (1.027,1.036)**	<.0001
	Low*			
NO_2	High		0.934 (0.929,0.939)	<.0001
	Middle		0.966 (0.962,0.970)	<.0001
	Low*			
O_3	High		**1.072 (1.066,1.077)**	<.0001
	Middle		**1.055 (1.051,1.060)**	<.0001
	Low*			
PM_{10}	High		0.942 (0.936,0.948)	<.0001
	Middle		0.979 (0.974,0.983)	<.0001
	Low*			

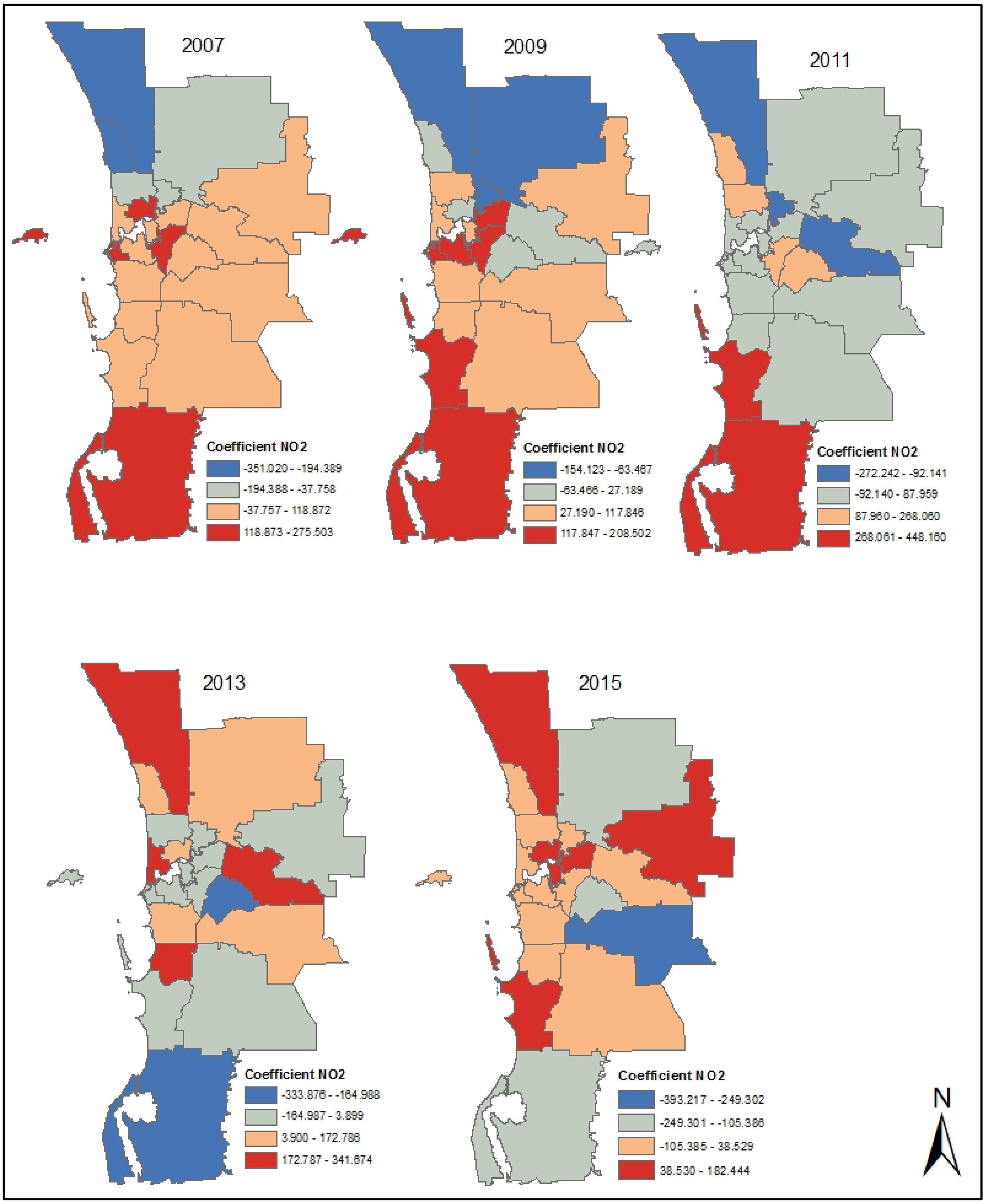
$PM_{2.5}$	High		0.996 (0.990,1.003)	0.308
	Middle		0.988 (0.983,0.992)	<.0001
	Low*			
Area × HW	Armadale	HW day	1.030 (0.993,1.068)	0.111
	Kwinana	HW day	**1.078 (1.031,1.126)**	0.001
	Mandurah	HW day	**1.053 (1.016,1.091)**	0.004
	Serpentine - Jarrahdale	HW day	**1.073 (1.017,1.133)**	0.01
	Wanneroo	HW day	**1.047 (1.013,1.083)**	0.006
	Fremantle	HW day	1.026 (0.973,1.081)	0.337
	Rockingham	HW day	1.017 (0.983,1.052)	0.323
	Joondalup	HW day	1.032 (0.996,1.068)	0.076
	Mundaring	HW day	**1.062 (1.014,1.113)**	0.01
	Belmont - Victoria Park	HW day	**1.068 (1.027,1.112)**	0.001
	Gosnells	HW day	**1.038 (1.002,1.075)**	0.037
	Stirling	HW day	**1.051 (1.016,1.087)**	0.003
	Swan	HW day	1.029 (0.993,1.066)	0.106
	Cockburn	HW day	1.029 (0.990,1.070)	0.145
	Kalamunda	HW day	**1.044 (1.000,1.090)**	0.047
	Bayswater - Bassendean	HW day	**1.041 (1.001,1.083)**	0.04
	Perth City	HW day	0.990 (0.952,1.030)	0.636
	Cottesloe - Claremont	HW day	1.022 (0.979,1.068)	0.311
	Canning	HW day	1.010 (0.971,1.051)	0.603
	South Perth	HW day	**1.081 (1.029,1.136)**	0.002
	Melville*	HW day*		
	All SA3s*	Non HW day*		

RR: relative risk; AR: Attributable rate; CI: confidence interval; ED presentations: emergency department attendances; HW: heatwave; CO: carbon monoxide; SO_2: sulphur dioxide; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micro metres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micro metres; *reference category; Green shade areas: similar outcomes observed in all-age model

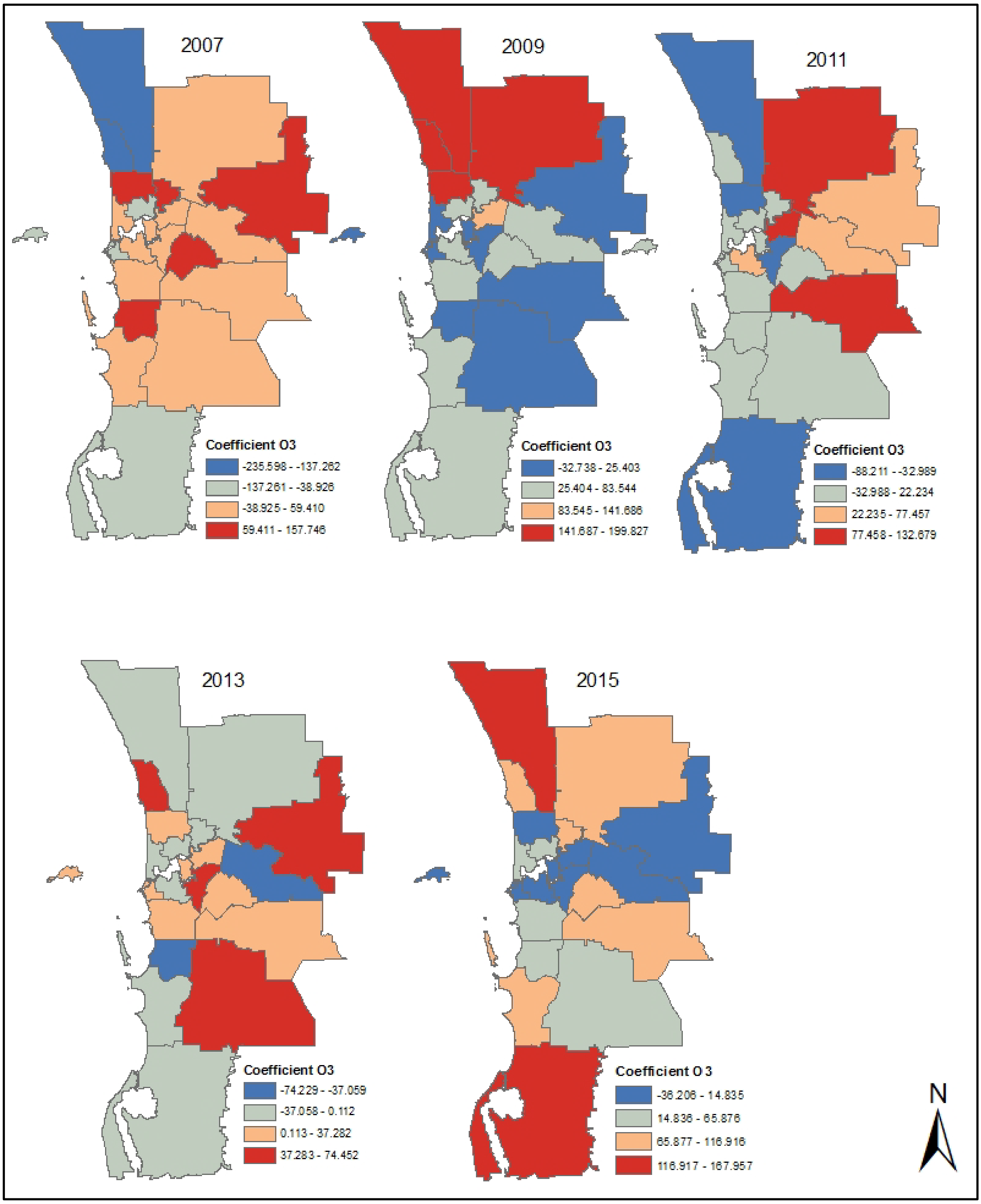
Appendix 12 The impact of carbon monoxide (CO) on all-cause ED presentation rates for each of the 5 years in GWR models



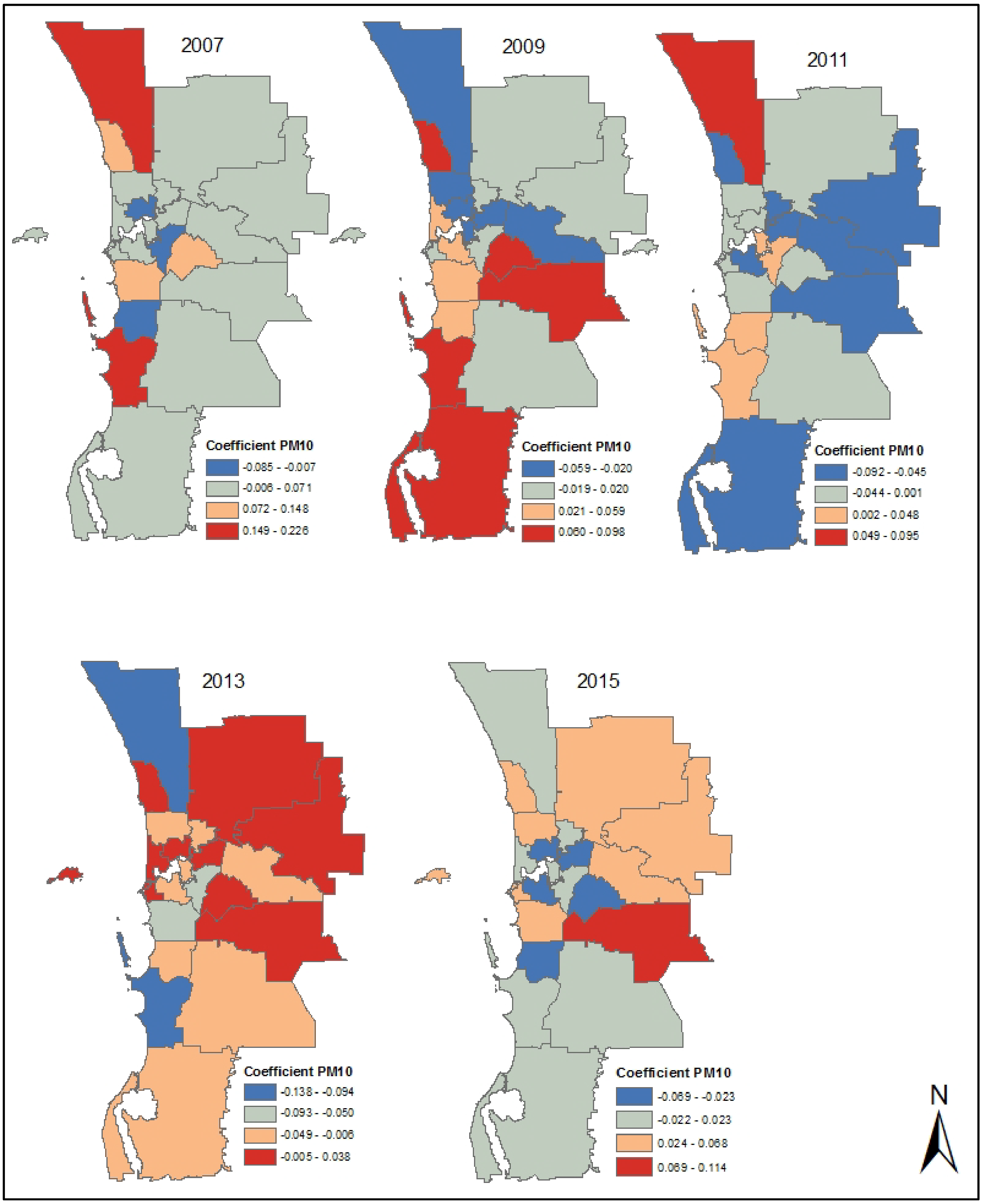
Appendix 13 The impact of nitrogen dioxide (NO_2) on all-cause ED presentation rates for each of the 5 years in GWR models



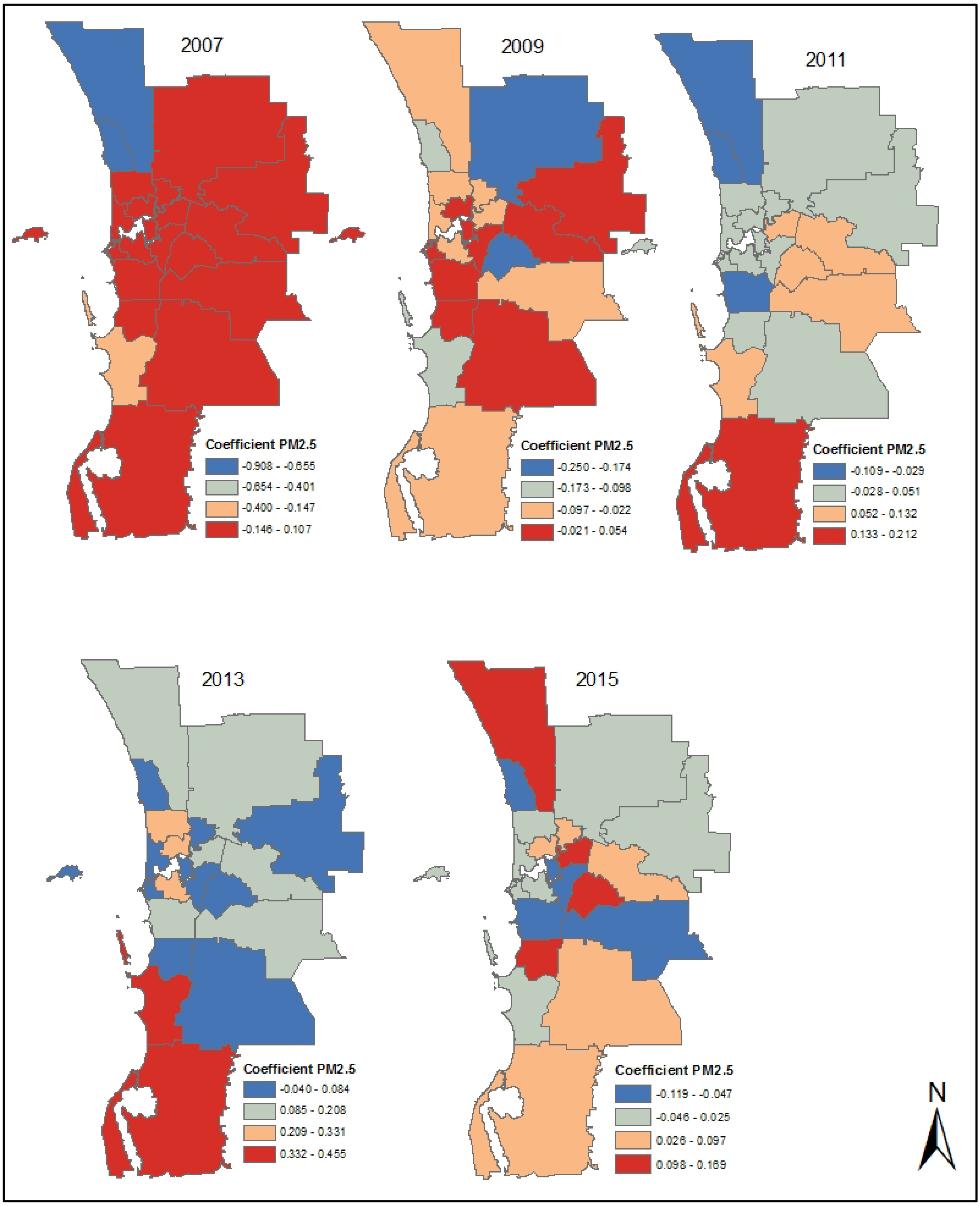
Appendix 14 The impact of ozone (O_3) on all-cause ED presentation rates for each of the 5 years in GWR models



Appendix 15 The impact of PM_{10} on all-cause ED presentation rates for each of the 5 years in GWR models



Appendix 16 The impact of PM2.5 on all-cause ED presentation rates for each of the 5 years in GWR models



Appendix 17 Summary of the important risk factors based on IncNodePurity from RF model

Order[#]	0-4 years model	5-9 years model	10-14 years model	All- age model
1	-	-	-	5 age groups
2	SEIFA	SEIFA	SEIFA	SEIFA
3	Burns	Burns	Burns	Burns
4	CO	CO	CO	CO
5	SO_2	O_3	PM_{10}	SO_2
6	O_3	SO_2	$PM_{2.5}$	$PM_{2.5}$
7	NO_2	PM_{10}	O_3	O_3
8	$PM_{2.5}$	$PM_{2.5}$	SO_2	PM_{10}
9	PM_{10}	NO_2	NO_2	NO_2
10	weekend	weekend	weekend	weekend
11	holiday	EHF	EHF	EHF
12	EHF	holiday	holiday	holiday

CO: carbon monoxide; EHF: excess heat factor; IncNodePurity: increase in node purity; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 micro metres; $PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 micro metres; PPM: parts per million; SEIFA: socio-economic index for areas; SO_2: sulphur dioxide; #: 1 means the most important variable and 12 means the least important variable

Appendix 18 Importance of CO, SO_2, NO_2, O_3, PM_{10}, $PM_{2.5}$, and SEIFA (%IncMSE) for 0–4-year age group in different areas (SA3) by GRF

Area	EHF	CO	SO_2	NO_2	O_3	PM_{10}	$PM_{2.5}$	SEIFA
Mandurah	4.443	3.044	3.822	3.603	2.456	1.309	1.624	11.680
Cottesloe	1.155	1.712	1.491	1.913	2.533	-1.099	0.811	9.021
Perth City	3.808	2.937	0.504	2.461	2.748	0.368	1.144	9.635
Bayswater	3.964	1.919	3.129	2.954	1.740	-0.735	1.134	9.500
Mundaring	3.199	1.710	0.717	2.603	1.228	2.620	0.161	10.367
Swan	0.456	2.072	0.366	3.024	1.093	-0.741	0.634	8.628
Joondalup	2.633	2.279	0.599	2.881	1.563	-1.218	0.649	8.270
Stirling	3.569	2.153	2.234	2.064	1.884	0.073	-0.331	9.334
Wanneroo	2.704	2.675	1.684	3.070	2.609	-0.152	-0.084	9.942
Armadale	3.198	3.408	1.321	3.096	2.353	0.526	-1.143	9.725
Belmont	4.413	3.933	-0.755	-0.413	1.282	1.879	0.777	8.365
Canning	1.303	2.923	2.305	3.319	2.843	2.126	0.621	9.550
Gosnells	4.656	4.048	0.810	1.405	2.700	0.223	0.728	8.984
Kalamunda	2.901	2.918	0.652	2.390	0.408	1.062	1.123	8.762
Serpentine	5.725	3.369	3.307	3.56	2.369	-0.273	3.526	10.251
South Perth	3.572	1.992	2.092	0.759	3.420	0.220	-0.529	8.581
Cockburn	3.365	1.288	1.542	3.349	1.806	1.502	-1.103	9.956
Fremantle	1.820	1.166	0.468	1.502	1.703	-1.182	1.790	10.212
Kwinana	5.588	3.754	2.821	5.328	3.163	1.412	2.594	11.962
Melville	3.043	2.491	0.188	1.989	2.286	-0.386	1.498	9.637
Rockingham	4.719	3.294	2.914	4.905	1.737	1.644	2.702	11.492

%IncMSE: percentage increase in mean squared error; CO: carbon monoxide; SO2: sulphur dioxide; μg/m3: NO2: nitrogen dioxide; O3: ozone; PM10: particulate matter with an aerodynamic diameter ≤10 micro metres; PM2.5: particulate matter with an aerodynamic diameter ≤2.5 micro metres; SEIFA: socio-economic index for areas

Appendix 19 Importance of CO, SO_2, NO_2, O_3, PM_{10}, $PM_{2.5}$, and SEIFA (%IncMSE values) for 5–9-year age group in different areas (SA3) by GRF

Area	EHF	CO	SO_2	NO_2	O_3	PM_{10}	$PM_{2.5}$	SEIFA
Mandurah	8.709	1.248	4.413	6.281	3.530	3.177	2.652	10.395
Cottesloe	7.792	3.004	2.204	6.340	4.828	5.057	2.708	7.500
Perth City	6.783	0.410	2.586	6.134	3.671	3.101	0.500	9.006
Bayswater	7.204	1.370	2.396	5.664	5.279	3.035	1.993	8.782
Mundaring	7.252	-0.170	2.582	5.966	5.597	3.617	2.690	8.378
Swan	7.896	0.517	2.368	5.282	4.329	5.248	1.436	8.367
Joondalup	6.477	1.544	2.667	4.093	3.457	3.858	3.142	8.656
Stirling	5.603	0.739	1.626	4.919	5.212	4.297	1.157	8.930
Wanneroo	7.859	2.236	2.569	5.420	4.106	3.425	1.391	9.162
Armadale	5.915	1.555	1.928	4.490	4.836	3.405	2.335	8.532
Belmont	5.540	1.339	4.030	2.970	2.417	2.198	1.825	8.433
Canning	6.810	1.114	1.122	5.543	4.384	4.311	0.609	7.779
Gosnells	7.223	0.191	1.119	5.221	4.413	2.494	2.079	8.107
Kalamunda	6.946	0.380	1.932	5.198	4.554	1.763	0.050	8.596
Serpentine	8.713	1.745	5.032	5.083	3.231	5.080	3.459	9.237
South Perth	7.858	-0.334	3.486	5.756	4.517	2.748	2.491	8.250
Cockburn	5.732	-1.941	0.244	4.918	3.207	4.186	1.022	8.806
Fremantle	5.837	0.446	2.657	5.724	3.117	1.817	2.222	7.975
Kwinana	8.056	1.346	4.016	5.059	4.983	1.217	1.489	10.401
Melville	6.652	1.204	1.860	5.248	4.619	4.735	1.536	8.638
Rockingham	7.225	1.004	5.071	4.489	4.016	2.641	3.155	10.477

%IncMSE: percentage increase in mean squared error; CO: carbon monoxide; SO2: sulphur dioxide; µg/m3: NO2: nitrogen dioxide; O3: ozone; PM10: particulate matter with an aerodynamic diameter ≤10 micro metres; PM2.5: particulate matter with an aerodynamic diameter ≤2.5 micro metres; SEIFA: socio-economic index for areas

Appendix 20 Importance of CO, SO_2, NO_2, O_3, PM_{10}, $PM_{2.5}$, and SEIFA (%IncMSE values) for 10–14-year age group in different areas (SA3) by GRF

Area name	EHF	CO	SO_2	NO_2	O_3	PM_{10}	$PM_{2.5}$	SEIFA
Mandurah	11.170	3.341	6.469	3.754	1.286	0.908	1.921	10.018
Cottesloe	9.403	3.551	6.117	3.004	2.604	0.439	0.625	9.111
Perth City	8.624	0.110	4.599	2.915	2.841	0.806	-0.381	9.807
Bayswater	7.837	1.661	3.780	2.401	1.989	1.138	1.005	10.083
Mundaring	8.481	1.615	4.796	3.090	3.175	0.812	-0.717	8.025
Swan	8.784	2.067	5.216	2.148	3.828	1.762	1.231	8.793
Joondalup	8.463	0.884	4.285	2.990	2.464	-0.389	-0.603	8.446
Stirling	8.858	0.623	4.296	4.567	3.614	2.835	1.152	9.329
Wanneroo	7.474	1.770	5.437	4.277	3.412	2.336	-0.196	9.097
Armadale	8.088	1.083	3.451	2.511	3.613	1.498	-0.930	8.313
Belmont	8.532	2.476	5.149	0.214	3.307	1.886	0.906	9.598
Canning	8.085	2.121	6.314	1.789	2.334	2.291	2.661	8.448
Gosnells	7.519	-0.013	6.129	3.181	2.890	2.343	1.229	9.625
Kalamunda	8.949	0.521	4.756	2.689	3.257	2.318	1.076	8.130
Serpentine	8.988	2.408	6.954	3.935	2.802	0.460	1.335	11.348
South Perth	7.800	1.515	5.352	2.755	2.957	4.246	1.853	8.820
Cockburn	7.773	3.181	6.352	3.394	1.812	1.678	1.407	9.168
Fremantle	9.235	2.339	3.705	2.048	4.453	3.044	-0.684	8.966
Kwinana	9.626	2.499	7.815	2.593	2.393	1.327	2.237	10.458
Melville	8.191	0.340	4.014	1.857	1.346	2.291	0.855	9.550
Rockingham	9.794	2.261	6.676	4.431	2.917	0.380	2.395	11.716

%IncMSE: percentage increase in mean squared error; CO: carbon monoxide; SO2: sulphur dioxide; µg/m3: NO2: nitrogen dioxide; O3: ozone; PM10: particulate matter with an aerodynamic diameter ≤10 micro metres; PM2.5: particulate matter with an aerodynamic diameter ≤2.5 micro metres; SEIFA: socio-economic index for areas

Appendix 21 Importance of CO, SO_2, NO_2, O_3, PM_{10}, $PM_{2.5}$, and SEIFA (IncNodePurity values) for 0–4-year age group in different areas (SA3) by GRF

Area name	EHF	CO	SO_2	NO_2	O_3	PM_{10}	$PM_{2.5}$	SEIFA
Mandurah	2.15E-07	1.37E-07	1.68E-07	2.40E-07	1.17E-07	1.08E-07	1.24E-07	3.33E-07
Cottesloe	1.50E-07	1.03E-07	1.11E-07	1.33E-07	9.53E-08	1.24E-07	1.23E-07	2.24E-07
Perth City	1.46E-07	1.09E-07	1.21E-07	1.35E-07	9.52E-08	1.22E-07	1.02E-07	2.30E-07
Bayswater	1.50E-07	9.21E-08	1.04E-07	1.41E-07	1.03E-07	1.04E-07	1.20E-07	2.38E-07
Mundaring	1.41E-07	9.72E-08	1.11E-07	1.39E-07	1.13E-07	1.17E-07	1.13E-07	2.42E-07
Swan	1.34E-07	9.21E-08	1.22E-07	1.42E-07	1.08E-07	1.27E-07	1.02E-07	2.25E-07
Joondalup	1.23E-07	1.23E-07	1.02E-07	1.24E-07	9.66E-08	1.23E-07	1.27E-07	2.37E-07
Stirling	1.49E-07	9.04E-08	1.14E-07	1.27E-07	9.23E-08	1.18E-07	1.22E-07	2.25E-07
Wanneroo	1.43E-07	9.97E-08	1.12E-07	1.39E-07	8.54E-08	1.23E-07	1.19E-07	2.36E-07
Armadale	1.45E-07	1.05E-07	9.56E-08	1.42E-07	1.09E-07	1.04E-07	9.64E-08	2.51E-07
Belmont	1.72E-07	1.10E-07	1.13E-07	1.41E-07	9.47E-08	1.05E-07	1.08E-07	2.26E-07
Canning	1.47E-07	1.04E-07	1.14E-07	1.37E-07	9.35E-08	1.06E-07	1.13E-07	2.39E-07
Gosnells	1.40E-07	1.25E-07	1.08E-07	1.31E-07	9.99E-08	1.25E-07	1.15E-07	1.92E-07
Kalamunda	1.44E-07	1.22E-07	1.02E-07	1.34E-07	9.85E-08	1.14E-07	1.22E-07	2.50E-07
Serpentine	2.37E-07	1.30E-07	1.88E-07	2.19E-07	1.17E-07	1.22E-07	1.26E-07	3.11E-07
South Perth	1.46E-07	9.25E-08	1.12E-07	1.25E-07	9.41E-08	1.28E-07	1.18E-07	2.14E-07
Cockburn	1.43E-07	1.08E-07	9.17E-08	1.41E-07	1.04E-07	1.24E-07	1.13E-07	2.35E-07
Fremantle	1.48E-07	9.16E-08	1.10E-07	1.38E-07	8.33E-08	1.16E-07	1.09E-07	2.68E-07
Kwinana	2.19E-07	1.50E-07	1.87E-07	2.07E-07	1.15E-07	1.10E-07	1.31E-07	3.25E-07
Melville	1.43E-07	1.02E-07	1.23E-07	1.21E-07	9.50E-08	1.14E-07	1.22E-07	2.44E-07
Rockingham	2.25E-07	1.54E-07	2.03E-07	1.91E-07	1.12E-07	1.08E-07	1.22E-07	3.24E-07

IncNodePurity: increase in node purity; CO: carbon monoxide; SO2: sulphur dioxide; μg/m3: NO2: nitrogen dioxide; O3: ozone; PM10: particulate matter with an aerodynamic diameter ≤10 micro metres; PM2.5: particulate matter with an aerodynamic diameter ≤2.5 micro metres; SEIFA: socio-economic index for areas

Appendix 22 Importance of CO, SO_2, NO_2, O_3, PM_{10}, $PM_{2.5}$, and SEIFA (IncNodePurity values) for 5–9-year age group in different areas by GRF

Area name	EHF	CO	SO_2	NO_2	O_3	PM_{10}	$PM_{2.5}$	SEIFA
Mandurah	5.84E-08	1.64E-08	4.21E-08	4.50E-08	2.63E-08	2.62E-08	2.36E-08	6.50E-08
Cottesloe	4.24E-08	1.40E-08	1.87E-08	2.81E-08	1.92E-08	2.40E-08	1.83E-08	3.59E-08
Perth City	3.21E-08	1.03E-08	2.19E-08	2.70E-08	2.65E-08	2.31E-08	1.92E-08	4.11E-08
Bayswater	3.58E-08	1.09E-08	2.12E-08	2.77E-08	2.54E-08	2.32E-08	1.98E-08	4.27E-08
Mundaring	3.61E-08	1.29E-08	2.14E-08	3.24E-08	2.57E-08	2.29E-08	1.91E-08	3.39E-08
Swan	3.80E-08	1.22E-08	1.82E-08	3.06E-08	2.67E-08	2.32E-08	1.90E-08	3.97E-08
Joondalup	3.59E-08	1.22E-08	1.90E-08	2.36E-08	2.65E-08	2.38E-08	1.71E-08	3.89E-08
Stirling	3.80E-08	1.15E-08	2.06E-08	2.90E-08	2.31E-08	2.04E-08	1.81E-08	3.86E-08
Wanneroo	3.65E-08	1.18E-08	1.88E-08	2.68E-08	2.35E-08	2.46E-08	1.91E-08	4.21E-08
Armadale	3.65E-08	1.10E-08	1.93E-08	3.07E-08	2.92E-08	2.18E-08	1.80E-08	3.65E-08
Belmont	3.34E-08	1.47E-08	2.17E-08	2.45E-08	2.68E-08	2.18E-08	1.87E-08	3.86E-08
Canning	3.88E-08	1.13E-08	1.79E-08	2.96E-08	2.70E-08	2.33E-08	1.84E-08	4.15E-08
Gosnells	3.87E-08	1.24E-08	2.03E-08	2.97E-08	2.35E-08	2.17E-08	1.93E-08	3.84E-08
Kalamunda	3.38E-08	1.34E-08	1.94E-08	2.88E-08	2.57E-08	1.93E-08	1.92E-08	4.39E-08
Serpentine	6.73E-08	1.96E-08	4.06E-08	4.20E-08	2.69E-08	2.16E-08	2.25E-08	6.86E-08
South Perth	4.14E-08	1.16E-08	1.99E-08	2.83E-08	2.37E-08	2.22E-08	1.64E-08	4.00E-08
Cockburn	3.87E-08	1.32E-08	2.18E-08	2.90E-08	2.33E-08	2.18E-08	1.96E-08	3.86E-08
Fremantle	3.93E-08	9.73E-09	2.06E-08	2.82E-08	2.53E-08	2.27E-08	2.04E-08	3.90E-08
Kwinana	5.81E-08	1.46E-08	4.48E-08	4.65E-08	2.79E-08	2.47E-08	2.27E-08	6.53E-08
Melville	3.35E-08	1.26E-08	2.11E-08	2.90E-08	2.82E-08	2.18E-08	1.92E-08	3.65E-08
Rockingham	5.90E-08	1.96E-08	4.67E-08	4.64E-08	3.04E-08	2.15E-08	2.28E-08	6.80E-08

IncNodePurity: increase in node purity; CO: carbon monoxide; SO2: sulphur dioxide; μg/m3: NO2: nitrogen dioxide; O3: ozone; PM10: particulate matter with an aerodynamic diameter ≤10 micro metres; PM2.5: particulate matter with an aerodynamic diameter ≤2.5 micro metres; SEIFA: socio-economic index for areas

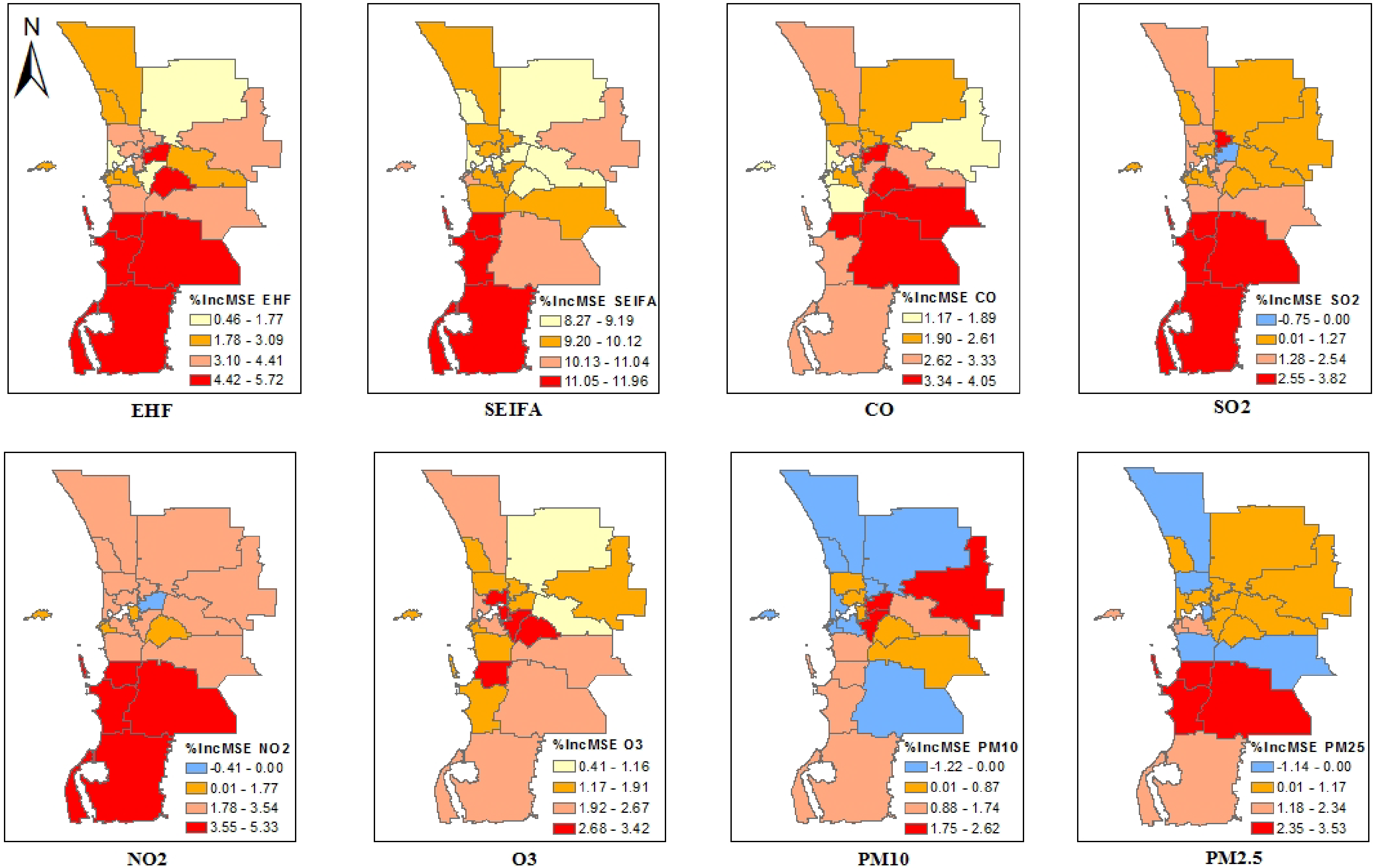
Appendix 23 Importance of CO, SO_2, NO_2, O_3, PM_{10}, $PM_{2.5}$, and SEIFA (IncNodePurity values) for 10–14-year age group in different areas by GRF

Area name	EHF	CO	SO_2	NO_2	O_3	PM_{10}	$PM_{2.5}$	SEIFA
Mandurah	9.94E-08	2.77E-08	6.30E-08	6.39E-08	3.29E-08	2.46E-08	3.43E-08	8.76E-08
Cottesloe	7.04E-08	2.03E-08	4.47E-08	3.25E-08	2.95E-08	3.09E-08	2.73E-08	5.62E-08
Perth City	6.56E-08	1.95E-08	4.09E-08	3.61E-08	2.82E-08	2.96E-08	2.79E-08	6.27E-08
Bayswater	6.93E-08	2.08E-08	4.04E-08	3.57E-08	2.95E-08	2.75E-08	2.89E-08	6.49E-08
Mundaring	5.88E-08	1.88E-08	3.82E-08	3.80E-08	3.46E-08	3.00E-08	2.80E-08	5.99E-08
Swan	5.87E-08	2.31E-08	3.97E-08	3.56E-08	3.51E-08	2.61E-08	2.85E-08	6.42E-08
Joondalup	7.70E-08	2.19E-08	3.94E-08	3.49E-08	2.66E-08	2.26E-08	2.88E-08	5.91E-08
Stirling	6.59E-08	1.97E-08	3.91E-08	3.30E-08	3.36E-08	3.14E-08	2.76E-08	5.72E-08
Wanneroo	6.03E-08	2.02E-08	4.19E-08	3.92E-08	3.22E-08	2.69E-08	2.60E-08	6.52E-08
Armadale	6.88E-08	1.91E-08	4.08E-08	3.60E-08	3.22E-08	2.74E-08	2.95E-08	5.68E-08
Belmont	6.83E-08	2.18E-08	4.13E-08	3.48E-08	2.77E-08	3.14E-08	2.56E-08	6.42E-08
Canning	7.23E-08	2.30E-08	4.40E-08	3.27E-08	3.18E-08	2.96E-08	2.70E-08	5.59E-08
Gosnells	7.07E-08	1.34E-08	3.98E-08	3.75E-08	2.90E-08	2.58E-08	2.71E-08	6.90E-08
Kalamunda	6.82E-08	1.93E-08	4.28E-08	3.37E-08	3.29E-08	2.51E-08	3.02E-08	6.26E-08
Serpentine	9.26E-08	2.70E-08	6.98E-08	5.08E-08	3.71E-08	2.74E-08	2.77E-08	9.89E-08
South Perth	5.84E-08	1.58E-08	4.14E-08	3.71E-08	3.00E-08	3.35E-08	2.88E-08	6.85E-08
Cockburn	6.59E-08	2.01E-08	4.72E-08	4.01E-08	2.97E-08	2.83E-08	2.74E-08	5.53E-08
Fremantle	7.87E-08	1.81E-08	3.93E-08	3.35E-08	3.15E-08	3.07E-08	2.61E-08	5.47E-08
Kwinana	9.83E-08	2.99E-08	7.37E-08	5.14E-08	3.25E-08	2.50E-08	2.54E-08	9.14E-08
Melville	6.63E-08	2.15E-08	4.54E-08	3.61E-08	2.82E-08	2.42E-08	2.80E-08	6.35E-08
Rockingham	9.62E-08	2.62E-08	6.93E-08	6.03E-08	3.19E-08	2.77E-08	2.86E-08	1.04E-07

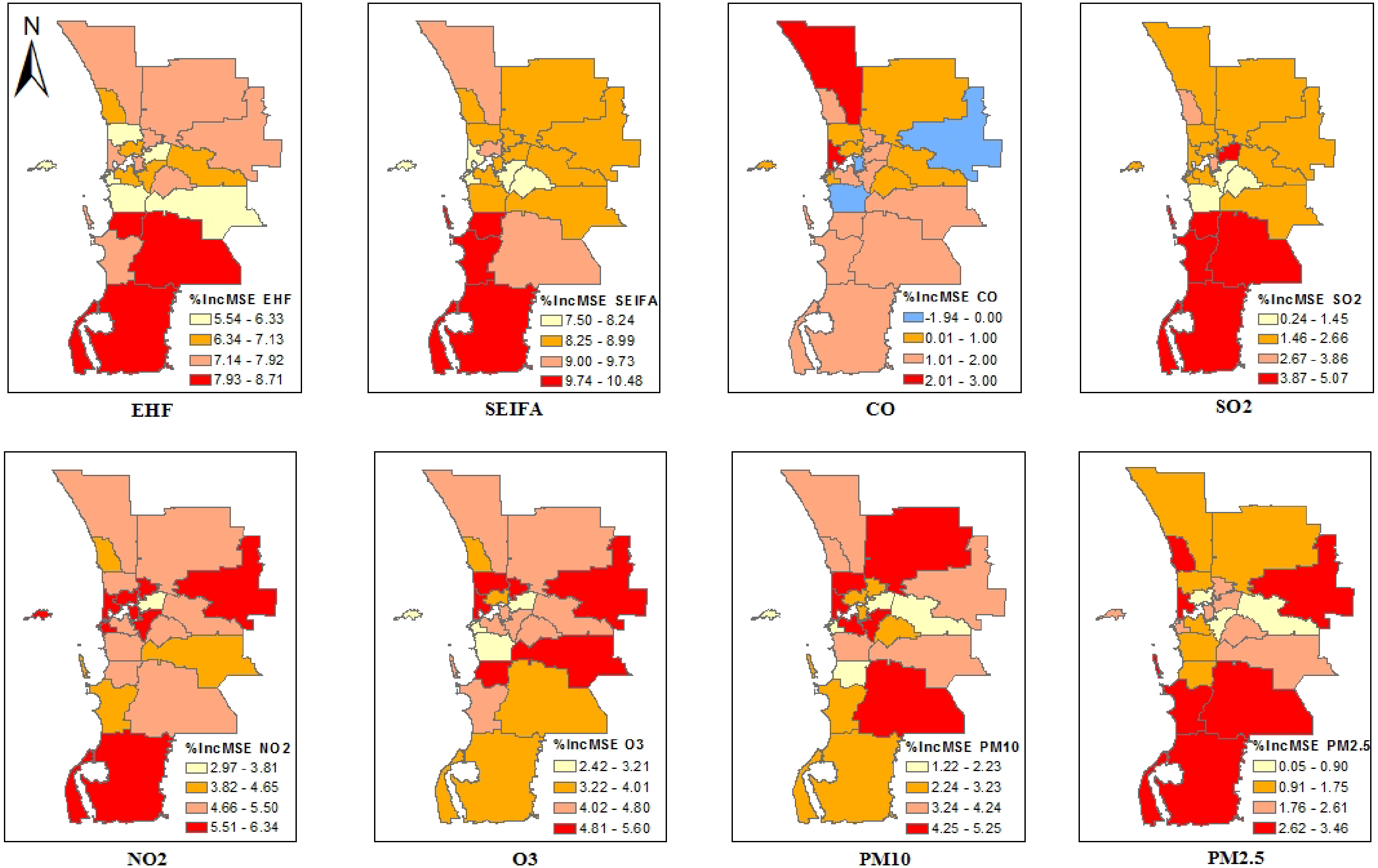
IncNodePurity: increase in node purity; CO: carbon monoxide; SO2: sulphur dioxide; μg/m3: NO2: nitrogen dioxide; O3: ozone; PM10: particulate matter with an aerodynamic diameter ≤10 micro metres; PM2.5: particulate matter with an aerodynamic diameter ≤2.5 micro metres; SEIFA: socio-economic index for areas

Appendix 24 Legends for 8 predictors by importance rank in Figure 13

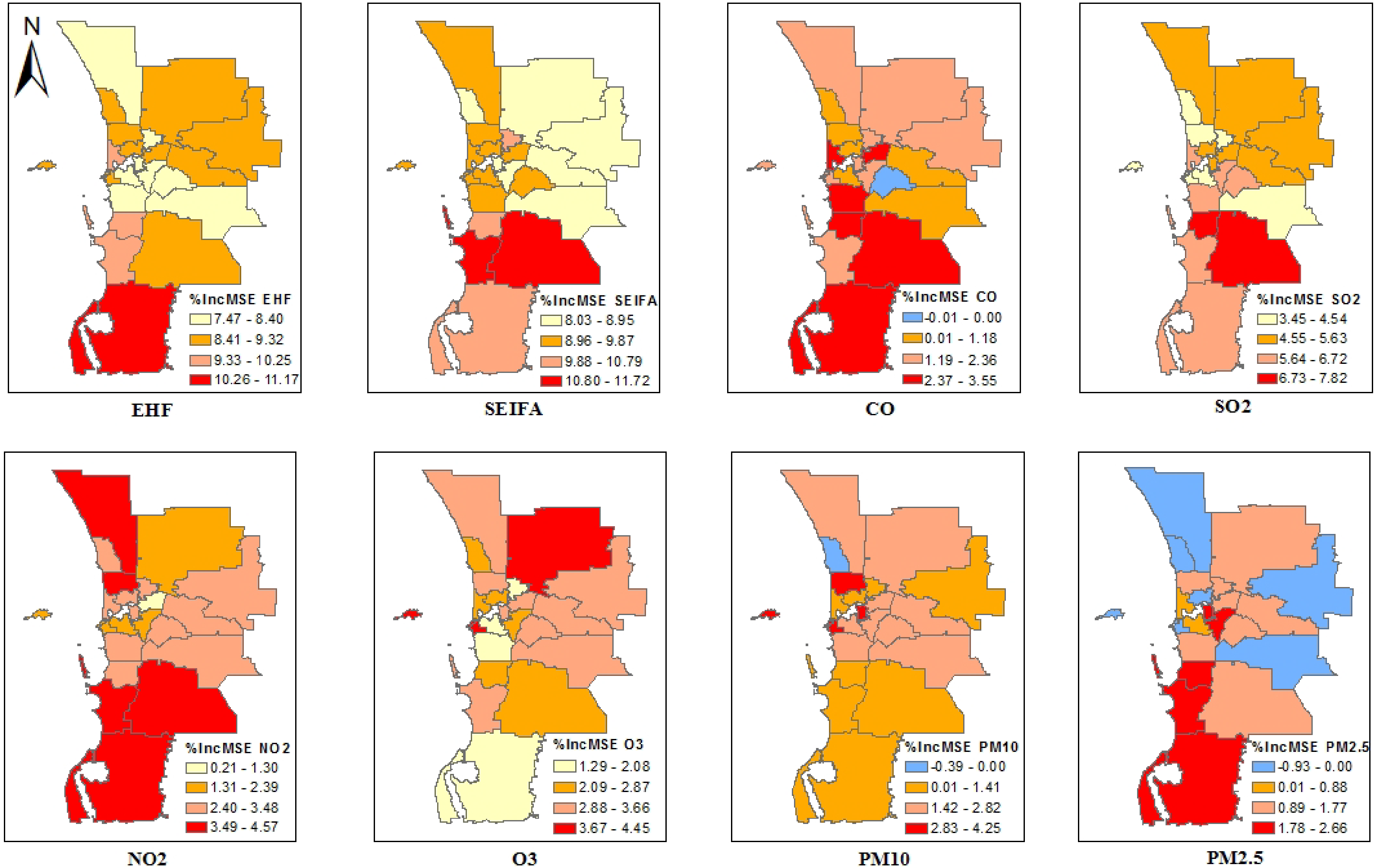
%IncMSE	Low	Middle	High
SEIFA	8.270-9.021	9.022-9.942	9.943-11.982
EHF	0.456-2.901	2.902-3.808	3.809-5.762
PM2.5	-1.143-0.621	0.522-1.134	1.135-3.520
PM10	-1.218-0.273	-0.274-1.062	1.063-2.620
SO2	-0.756-0.652	0.653-2.092	2.093-3.422
NO2	-0.413-2.064	2.065-2.070	3.071-5.320
CO	1.166-2.072	2.073-2.937	2.938-4.048
O3	0.408-1.737	1.738-2.456	2.457-3.420



Appendix 25 Important risk factors (%IncMSE) in different geographic locations (SA3) for 0–4-year age group from the GRF model



Appendix 26 Important Predictors (%IncMSE) in different geographic locations (SA3) for 5–9-year age group from the GRF model



Appendix 27 Important Predictors (%IncMSE) in different geographic locations (SA3) for 10-14-year age group from the GRF model

Appendix 28 Average HW impact (3-level) on children 0-14y in different SA3s

HW impact	SA3_code	Area name	Average EHF
	50201	Mandurah	8.11
	50606	Serpentine	7.81
	50703	Kwinana	7.76
High	50705	Rockingham	7.25
	50604	Gosnells	6.47
	50607	South Perth	6.41
	50302	Perth City	6.41
	50401	Bayswater	6.34
	50402	Mundaring	6.31
	50605	Kalamunda	6.27
Median	50602	Belmont	6.16
	50301	Cottesloe	6.12
	50503	Wanneroo	6.01
	50502	Stirling	6.01
	50704	Melville	5.96
	50501	Joondalup	5.86
	50601	Armadale	5.73
Low	50403	Swan	5.71
	50702	Fremantle	5.63
	50701	Cockburn	5.62
	50603	Canning	5.4

Appendix 29 Perth concordance of SA3 and LGA area from ABS 2011

SA3_Code	SA3_Name	Percentage	LGA_Code	LGA_Name
50201	Mandurah	100.00	55110	Mandurah (C)
50201	Mandurah	94.64	56230	Murray (S)
50301	Cottesloe - Claremont	51.74	51310	Cambridge (T)
50301	Cottesloe - Claremont	100.00	51750	Claremont (T)
50301	Cottesloe - Claremont	100.00	52170	Cottesloe (T)
50301	Cottesloe - Claremont	100.00	55740	Mosman Park (T)
50301	Cottesloe - Claremont	99.37	56580	Nedlands (C)
50301	Cottesloe - Claremont	100.00	56930	Peppermint Grove (S)
50301	Cottesloe - Claremont	5.85	57080	Perth (C)
50301	Cottesloe - Claremont	16.07	57980	Subiaco (C)
50302	Perth City	1.19	50420	Bayswater (C)
50302	Perth City	48.26	51310	Cambridge (T)
50302	Perth City	0.63	56580	Nedlands (C)
50302	Perth City	94.15	57080	Perth (C)
50302	Perth City	8.83	57910	Stirling (C)
50302	Perth City	83.93	57980	Subiaco (C)
50302	Perth City	100.00	58570	Vincent (T)
50401	Bayswater-Bassendean	100.00	50350	Bassendean (T)
50401	Bayswater-Bassendean	98.81	50420	Bayswater (C)
50401	Bayswater-Bassendean	1.29	58050	Swan (C)
50402	Mundaring	98.18	56090	Mundaring (S)
50402	Mundaring	4.19	58050	Swan (C)
50403	Swan	1.82	56090	Mundaring (S)
50403	Swan	94.48	58050	Swan (C)
50501	Joondalup	100.00	54170	Joondalup (C)
50501	Joondalup	0.01	58760	Wanneroo (C)
50502	Stirling	91.17	57910	Stirling (C)
50503	Wanneroo	0.04	58050	Swan (C)
50503	Wanneroo	99.99	58760	Wanneroo (C)
50601	Armadale	100.00	50210	Armadale (C)
50602	Belmont - Victoria Park	100.00	50490	Belmont (C)
50602	Belmont - Victoria Park	88.17	58510	Victoria Park (T)
50603	Canning	99.40	51330	Canning (C)

50603	Canning	11.61	58510	Victoria Park (T)
50604	Gosnells	100.00	53780	Gosnells (C)
50605	Kalamunda	99.99	54200	Kalamunda (S)
50606	Serpentine - Jarrahdale	0.39	56230	Murray (S)
50606	Serpentine - Jarrahdale	100.00	57700	Serpentine-Jarrahdale (S)
50607	South Perth	100.00	57840	South Perth (C)
50607	South Perth	0.22	58510	Victoria Park (T)
50701	Cockburn	97.47	51820	Cockburn (C)
50702	Fremantle	0.13	51820	Cockburn (C)
50702	Fremantle	100.00	53150	East Fremantle (T)
50702	Fremantle	100.00	53430	Fremantle (C)
50703	Kwinana	100.00	54830	Kwinana (T)
50704	Melville	0.60	51330	Canning (C)
50704	Melville	2.40	51820	Cockburn (C)
50704	Melville	100.00	55320	Melville (C)
50705	Rockingham	100.00	57490	Rockingham (C)