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USING MACHINE LEARNING APPROACHES TO ENHANCE HEATWAVE MEASUREMENT FOR VULNERABILITY ASSESSMENT AND TIMELY MANAGEMENT OF HEAT-RELATED HEALTH SERVICES

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KEYWORDS

Vulnerability assessment, heatwave measurement, machine learning

ISSUES:

Climate change is one of the most critical challenges facing Australia and the global community today. Data from the Australian Bureau of Meteorology (BoM) indicates that Australia has been experiencing rising temperatures, particularly since the late 20th century. The frequency, duration, and intensity of heatwaves are projected to continue increasing [1-4]. Since national records began in 1910, Australia has warmed by an average of 1.47°C (±0.24°C), with the highest official temperature recorded at 50.7 degrees Celsius in Onslow, Western Australia (WA), on January 13, 2022. Furthermore, a recent unprecedented high temperature of +41.6°C was recorded during winter on August 26, 2024, in Yampi Sound, WA. Among all natural disasters in Australia, heatwave (HW) represents a leading silent killer and pose a significant public health threat [4, 5]. However, innovative methods for assessing vulnerability for HW-related health services remain limited.

Machine Learning (ML), a branch of artificial intelligence within computer science, employs data and algorithms to replicate human cognitive functions and enhance accuracy. Its application has surged across various scientific disciplines; ML research publications indexed in Web of Science have increased over 110 times in the past two decades alone. It is noteworthy that most studies utilising ML methodologies originate from engineering or computer science fields; only approximately 0.2% pertain specifically to health policy services.

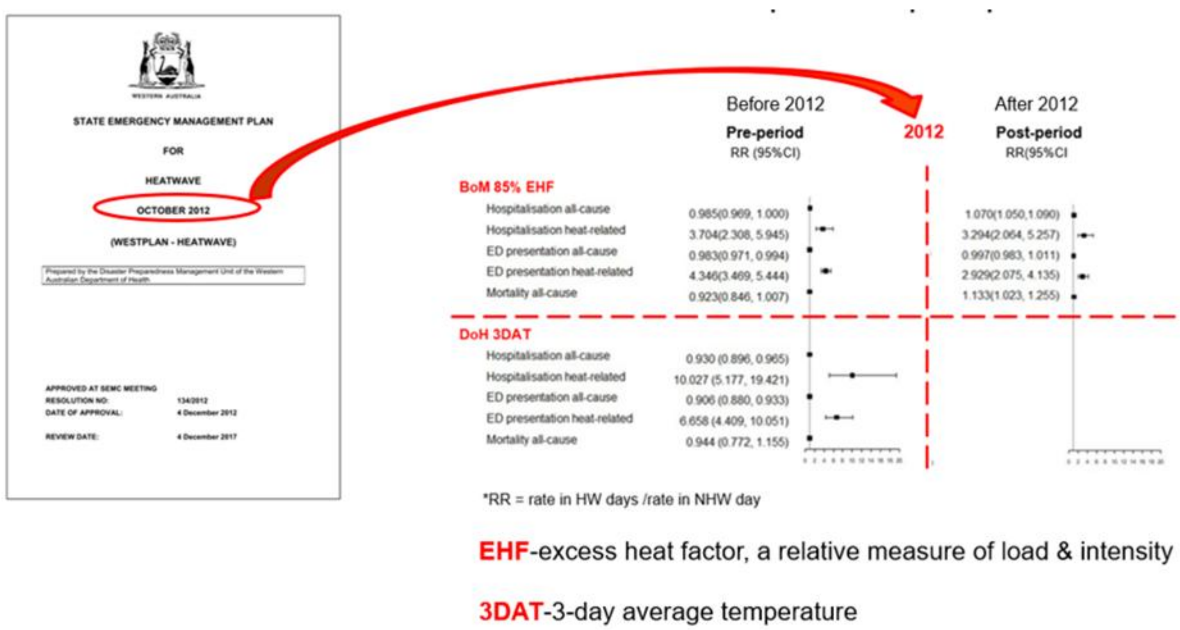
APPROACHES AND KEY FINDINGS:

A research study was conducted in WA aimed to develop innovative methods for assessing vulnerability to facilitate timely management of heat-related health service demands through mixed-methodologies incorporating ML techniques.

Comprehensive daily data spanning ten years were collected on health indicators such as emergency department (ED) presentations, hospitalizations, and mortality alongside environmental factors (temperature, air pollutants PM2.5, PM10, CO, SO2, NO2, and O3, and fire events) from various official sources. Appropriate sensitive measures for assessing vulnerability were identified, which included assessing optimal HW exposure indicators (Excess Heat Factor (EHF) [6] vs. 3-day average temperature (3DAT)) [7] along with other environmental factors, sociodemographic factors (socioeconomic status (SES), age, ethnic groups, and geographic locations), and health indicators related to sensitivity and adaptive capacity.

Since 2012, WA Health has implemented a state-wide HW management policy [7]. Within this policy framework, the HW exposure indicator of 3-day average temperature (3DAT) was assessed in comparison to EHF, a relative measure of HW load and intensity, introduced by BoM in 2013. Quasi-experimental analyses compared health indicators during pre-implementation and post-implementation periods. Results presented in Figure 1 demonstrate that BoM's EHF is more effective at identifying health service utilisations associated with HWs than 3DAT across both periods; thus, indicating that EHF is a more sensitive HW exposure indicator than 3DAT.

FIGURE 1. HEALTH EFFECTS DURING HW DAYS COMPARED WITH NON-HW DAYS BY BOM'S 85TH PERCENTILE EHF AND WA HEALTH'S 3DAT IN THE PRE- AND POST-PERIODS.



Sensitivity analysis utilising various EHF cut-offs (70th to 95th percentiles) revealed that EHF could detect increased health service utilisations—including ED presentations and hospitalisations—even during mild HW events. Conversely, severe and extreme events (>80% EHF) correlated significantly with increased mortality rates.

Subsequently, predictive models were developed with their goodness-of-fit evaluated using ML approaches. The Random Forest (RF) algorithm integrates predictions from multiple decision trees (DT) into a single model while effectively managing large datasets and minimising overfitting; this makes it one of the most accurate machine learning algorithms available.

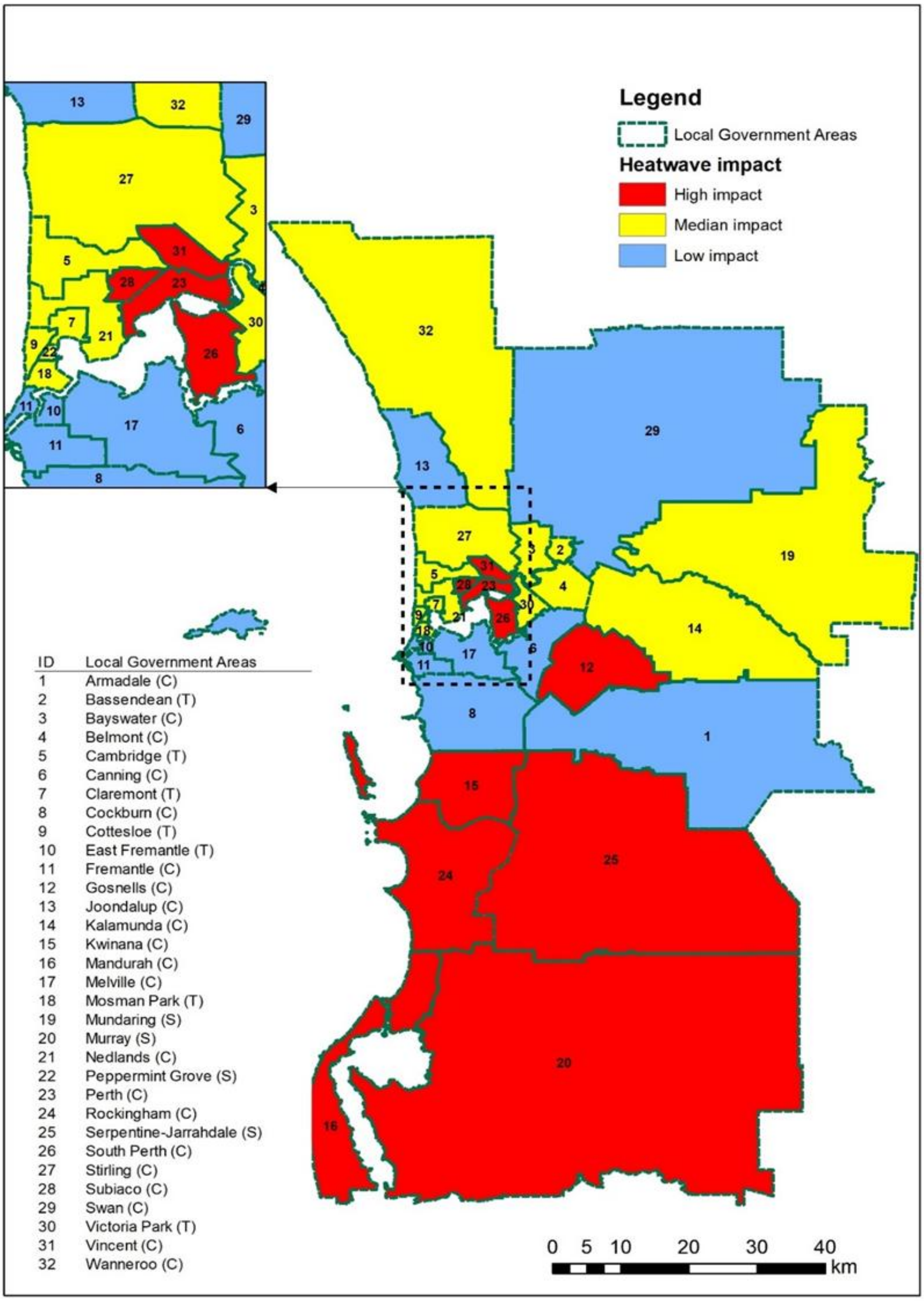
In our study, 500 decision tree models were employed to construct the RF model. The RF outperformed four other models due to its lowest error rates making it the optimal method for our analysis. In addition to cross-validation conducted during RF model development, construct validation was performed by comparing actual ED presentations against predicted numbers generated by the RF model. The R2 reached 0.953 indicates strong agreement between observed data and predictions made by the model.

Geographic Random Forrest (GRF) is an extension of RF that specifically addresses spatial heterogeneity. Both RF and GRF models demonstrated excellent goodness-of-fit results. During the development of the RF model, a percentage increase in mean squared error was generated, serving as an informative accuracy metric across all predictive models; higher values indicate greater predictor importance. The results indicated that age and socioeconomic status (SES) ranked as the two most important predictors for increased ED presentations on HW days. In contrast, the importance ranking for predictors in GRF models revealed that SES and HWs were prioritised among all predictors, followed by air quality indicators across all three child age groups (0-4, 5-9, and 10-14 years). Vulnerable populations at heightened risk from HWs include children under five years old, adults over sixty years old, males, Aboriginal people, and residents in disadvantaged or coastal areas.

Air quality during HW days was generally poor. Significant dose-response relationships between ED presentations and air quality indicators such as O3 and PM2.5 were demonstrated. A significant interaction between HWs and PM2.5 was also observed ($P<0.05$).

The identification of vulnerable hotspots for heat-related ED presentations among children under 15 years old—primarily concentrated in southern Perth metropolitan area including Mandurah, Kwinana, and Serpentine-Jarrahdale—is illustrated in Figure 2.

FIGURE 2. SPATIAL VARIATIONS OF THE IMPACT OF HWS ON CHILDREN 0–14 YEARS IN PERTH METROPOLITAN AREA



IMPACT FOR PRACTICE

A departmental report published in 2022 [8] informed policy decisions and received endorsement from the Assistant Director General, Public and Aboriginal Health.

Currently the Disaster Preparation and Management Directorate is using EHF with its 85% trigger to activate the new HW management plan in WA.

As a pioneering study of its kind, this research demonstrates how machine learning can enhance our understanding of environmental health impacts from HWs and air quality while supporting evidence-based policymaking.

This study provides evidence-based support for preparing initiatives aimed at protecting vulnerable populations and locations affected by HW-related health issues in Perth with potential applicability across WA.

The findings and recommendations from the study can help develop cost-effective strategies for allocating limited resources to mitigate adverse health effects of heatwaves, aligning with the WA Health's climate change adaptation priorities.

DECLARATION

This work was supported by the Telethon-Perth Children's Hospital Research Fund 2016 (Round 5), Western Australia, Australia. Ethics approval for this research has been received from the Western Australia Department of Health Human Research Ethics Committee (NO:2015/44). The reciprocal ethics approval was received from the Curtin University Ethics Committee (HRE2016-0079-05). All the health data was obtained from de-identified administrative databases. The research findings were only presented using aggregated data so that the confidentiality of the data was kept.

The authors declare they have no actual or potential conflict of interests that could have appeared to influence the work reported in this paper.

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