Clinical paper

Spatiotemporal variation in the risk of out-of-hospital cardiac arrests in Queensland, Australia

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Abstract

Background: Spatiotemporal analysis of out-of-hospital cardiac arrest (OHCA) risk is essential to design targeted public health strategies. Such information is lacking in the state of Queensland and Australia more broadly.

Methods: We developed a spatiotemporal Bayesian model accounting for spatial and temporal dimensions, space-time interactions, and demographic factors. The model was fit to data of all OHCA cases attended by paramedics in Queensland between January 2007 and December 2019. Parameter inference was performed using the integrated nested Laplace approximation method. We estimated and thematically mapped area-year risk of OHCA occurrence for all 78 local government areas (LGAs) in Queensland.

Results: We observed spatial variability in OHCA risk among the LGAs. Areas in the north half of the state and two areas in the south exhibited the highest risk; whereas OHCA risk was lowest in the west and south west parts of the state. Demographic factors did not have significant impact on the heterogeneity of risk between the LGAs. An overall trend of modestly decreasing risk of OHCA was found.

Conclusions: This study identified areas of high OHCA risk in Queensland, providing valuable information to guide public health policy and optimise resource allocation. Further research is needed to investigate the specifics of the areas that may explain their risk profile.

Keywords: Bayesian, Out-of-hospital cardiac arrest, Spatiotemporal model

Introduction

Out-of-hospital cardiac arrest (OHCA) is a life-threatening event which has a substantial impact on morbidity and mortality globally.[1] Across Australia, some 25,000 cases of OHCA occur each year with an overall rate of survival to hospital discharge less than 10%.[2–4] Emerging data both within Australia and internationally suggest significant regional variation in OHCA risk due to region-specific demographic and geographic factors.[2]

Spatiotemporal analysis can highlight sources of heterogeneity underlying patterns in the distribution of health risk and outcomes, and consequently is useful to guide public health interventions. Such an analysis has been widely performed in other health problems; however, application in OHCA is limited. A number of studies have investigated national and regional distribution of OHCA.[5–10] However, those studies are subject to a number of limitations, including an exclusive focus on the spatial domain without accounting for the temporal dimension,[5,6] a focus on a single urban area,[6,7,9,10] and the exclusion of population demographic data.[7–10] To our knowledge, Peluso et al.[11] and Auricchio et al.[12] are the only studies in the setting of OHCA that account for both spatial and temporal dimensions, rural and urban areas, and demographic features, overcoming the limitations of previous studies. However, Peluso et al.[11] and Auric-

chio et al.,[12] and the methods developed in these studies, have to date been applied only to the region of Canton Ticino, Switzerland. Given the well-established regional variation in risk factors, management and outcomes of OHCA, setting-specific spatiotemporal insights are of paramount importance to guide public health interventions and emergency response. As such, spatiotemporal evaluation of OHCA in a broader range of geographic contexts is desirable.

Having a vast landmass (1.73 million km^2) and a population density (3 people per km^2) below the national average in one of the world's most sparsely populated countries, the state of Queensland (Australia) is faced with unique challenges in the management of OHCA.[13,14] With 65 of the 78 local government areas (LGAs) being classified as either regional or remote, Queensland represents a very different context to the existing literature on spatiotemporal variation in OHCA risk (and other health problems in general), in having a wide range of population sparseness from urban to rural parts of the state.[15] In fact, population densities in the state vary from as low as 0.003 to as high as 934 people per km^2 and exhibit an inverse relationship with land mass (Supplementary Fig. S1). Furthermore, it is estimated that people living in regional and remote Queensland experience an increase in both years of life lost (1.7 times) and disability-adjusted life years (1.4 times) compared to their metropolitan counterparts.[16] It is therefore imperative to identify region-specific risks of OHCA so that interventions (e.g. public training in cardiopulmonary resuscitation, public-access defibrillators) and resource allocation can be targeted and optimised. In this study, we estimated and thematically mapped the risk of OHCA for all regions in Queensland using a Bayesian hierarchical model that accounted for temporal and spatial heterogeneity, space-time interactions, and demographic features.

Methods

Study setting and data

The state of Queensland (1.73 million km^2, 5.23 million people, population density 3 people per km^2) is located in north-east Australia (Supplementary Fig. S2) and divided into 78 LGAs (Supplementary Fig. S3).[17] The south-east region of Queensland, which includes the capital city Brisbane, is the most densely populated area of the state. The Queensland Ambulance Service (QAS) is a single, state-wide, government-funded emergency ambulance service that serves the entire state of Queensland. The QAS OHCA database is a state-wide, population-based database that prospectively collects data of all OHCA patients attended by QAS paramedics. Detailed description of the database can be found in our previous publications.[18,19] Location and datetime of arrest were the only two variables from the QAS OHCA database that were used in this study.

The present study included all OHCA cases that occurred in Queensland and attended by paramedics between 1 January 2007 and 31 December 2019. Annual data on total population, as well as composition by age and sex, of the 78 LGAs from 2007 to 2018 were obtained from the Australian Bureau of Statistics.[20] LGA-specific populations for 2019 were not available from the Australian Bureau of Statistics, and were obtained from the Queensland Government Statistician's Office.[21] LGA-specific age and sex composition for 2019 was not available, and was estimated by fitting non-linear models to data of the preceding years using the nonlinear least-squares approach (Supplementary Fig. S4). Supplementary

Table S1 shows the annual total population of each LGA; and Supplementary Fig. S5 and Fig. S6 display the sex composition, and age composition by sex, respectively, of each LGA for each year during the study period. This study was approved by the Royal Brisbane and Women's Hospital Human Research Ethics Committee (LNR/2019/QRBW/54899). Informed consent was waived by the ethics committee.

Bayesian analysis

We employed the models of Peluso et al.[11] and Auricchio et al.[12] that accounted for spatial heterogeneity, temporal heterogeneity, space-time interactions and demographic features. We chose LGA boundaries to be the spatial cells, motivated by the fact that annual demographic data on total population and age composition by sex were available and complete at the LGA level. A finer grid, for example at suburb level, would have posed challenges with regards to missing suburb-specific demographic data, extensive computation times, and overcrowded maps. The Bayesian analysis is described in detail in Supplementary Materials. Briefly, the model takes the following form:

$$\log(\text{OHCA relative risk of a specific LGA in a specific year})$$
$$= (intercept) + (covariates) + (structured\ spatial + unstructured\ spatial) +$$
$$(structured\ temporal + unstructured\ tempotal) + (spatiotemporal)$$

$$(1)$$

The relative risk (RR) quantifies whether a specific LGA in a specific year has higher (RR > 1) or lower (RR < 1) risk of OHCA occurrence than the overall state-wide risk. The intercept represents the overall OHCA risk in the state, common to all LGAs and years. All other variables in the model describe how OHCA risk varies between LGAs and over time. The covariates are demographic covariates, including male/female population proportions, and sex-specific proportions of the age groups for each LGA in each year. We considered three age groups 0–14, 15–64 and 65+ years old, representing children, working-age population and senior citizens, respectively, according to the Queensland Government Statistician's Office and the Australian Bureau of Statistics.[20,21] The spatial component consists of two random effects: structured and unstructured. The structured component models spatially-correlated heterogeneity in OHCA risk; whereas the unstructured component models spatially-uncorrelated heterogeneity. To account for possible temporal variability in the distributions of OHCA risk, temporal effects were modelled through a temporally structured component and temporally unstructured component. The spatiotemporal component models space-time interactions. This interaction term represents the difference between the global temporal trend and the area-specific trend.

The parameters of the model can be conveniently inferred using the integrated nested Laplace approximation (INLA) method.[11,22] This method was proposed by Rue et al.[22] as a more efficient alternative to traditional Markov chain Monte Carlo algorithm for parameter inference for Bayesian hierarchical spatiotemporal models. INLA was implemented in the INLA package for the R programming language (the R-INLA package).

We also calculated the posterior probabilities of RR estimates being greater than a given threshold value. A threshold of 1.5 was used as suggested in the literature.[23] These probabilities are called exceedance probabilities and are useful to identify areas where there is an unusual elevation of risk. We validated the model by comparing the differences between model-estimated and observed numbers of events. All analysis was performed in R (version 3.6.1).

Table 1 – Posterior mean and 95% credible interval for estimates of fixed effect parameters.

Parameter	Posterior mean	95% Credible interval
μ	7.247	(−24.400; 38.560)
Male	0.587	(−1.916; 3.083)
Male 0–14 years	0.972	(−13.863; 15.839)
Male 15–64 years	1.995	(−12.847; 16.873)
Male 65+ years	3.560	(−11.278; 18.435)
0–14 years, regardless of sex	−8.200	(−37.994; 21.754)
15–64 years, regardless of sex	−10.415	(−40.212; 19.539)
65+ years, regardless of sex	−6.769	(−36.413; 23.040)

Results

Description of data

A total of 61,279 cases of OHCA were recorded for all 78 LGAs combined for the entire study period between January 2007 and December 2019, with an average number of cases per year per LGA ranging from 0 to 946. Supplementary Fig. S7 shows the average event counts per year and average incidence rate per 1000 population per year for each LGA across the study period. As expected, data on event counts show a spatial concentration of cases in more populated LGAs situated on the east coast of the state, especially the south-east corner, reflecting the patterns of population distribution in Queensland (Supplementary Fig. S7 panel A). The spatial distribution of event counts markedly differed to that of incidence rates, which was higher in less populated LGAs (Supplementary Fig. S7 panel B). There visually appears to be an inverse relationship between incidence rate and population density (Supplementary Fig. S7 panel C). LGA-specific event counts and incidence rate for individual years are shown in Supplementary Tables S2 and S3.

Bayesian analysis

Bayesian inference of fixed effect parameters is displayed in Table 1, which shows that the 95% credible intervals of the estimates of all fixed effect parameters contained zero. This suggests that demographic factors did not have major impact on the heterogeneity of OHCA risk.
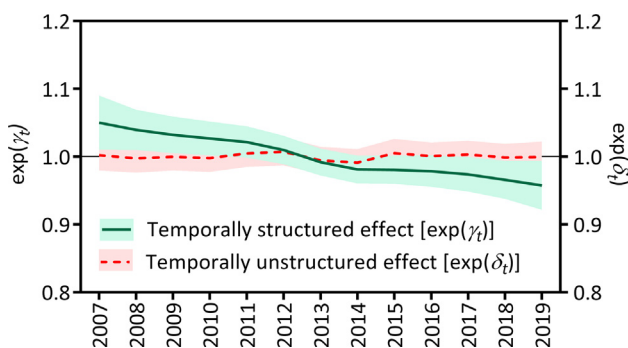

Fig. 1 – Posterior temporal trend for the risk of out-of-hospital cardiac arrest in Queensland. Solid line is temporally structured effect [exp (c$_t$)]; broken line is temporally unstructured effect [exp (d$_t$)]. The lines represent the posterior means, and the shaded areas represent 95% credible intervals.

Fig. 1 shows the posterior mean, together with 95% credible interval, of the global temporal effect. The figure reveals a modestly decreasing trend in OHCA risk for the temporally structured effect over the years, while the temporally unstructured effect fluctuated closely around one. Fig. 2 shows the map of the spatial pattern of OHCA risk for the 78 LGAs with darker colours corresponding to relatively higher risk. The risk is highest in the northern and north-western parts of the state as well as two southern LGAs. Fig. 3 displays the space-time interactions (spatiotemporal) for four selected years between 2007 and 2019, which suggests that such interactions were negligible (the numbers in the maps are very close to 1). The spatiotemporal effect for each individual year across the entire study period (13 years) is shown in Supplementary Fig. S8.

The RR (sum of all effects) of OHCA over time for each LGA is shown in Fig. 4 (maps of four selected years), Supplementary Fig. S9 (maps of all years) and Supplementary Fig. S10 (trend lines over time by LGA). The risk was generally stable across the years for the majority of LGAs (no noticeable change in colour over the years). Across the study period, the highest RR was observed throughout the northern half of the state and a few areas in the south (darker colours). The western areas of the state generally exhibited the lowest RR (lighter colours).

Fig. 5 shows the maps of the probabilities of RR estimates being greater than 1.5 for four selected years with darker colours corresponding to relatively higher exceedance probabilities. The maps provide evidence of excess risk within individual areas. We observed that LGAs in the northern half of Queensland and two southern LGAs had the highest exceedance probabilities, consistent with the RR map (Fig. 4). Maps of the exceedance probabilities for all years are presented in Supplementary Fig. S11.

The comparison of estimated and observed numbers of events is shown in Supplementary Fig. S12, indicating an excellent agreement between model estimates and observations. All plots of year-specific and LGA-specific observations versus corresponding model estimates fall onto or are very close to the line of equality. Furthermore, most of the absolute differences between model estimates and observations were zero or only a few cases.

Discussion

This study is the first in Australia and among the few in the world that estimates and maps the risk of OHCA using a Bayesian hierarchical model with the INLA method that accounts for temporal and spatial heterogeneity, space-time interactions, and demographic factors. Despite its widespread use in other health problems, spatiotemporal
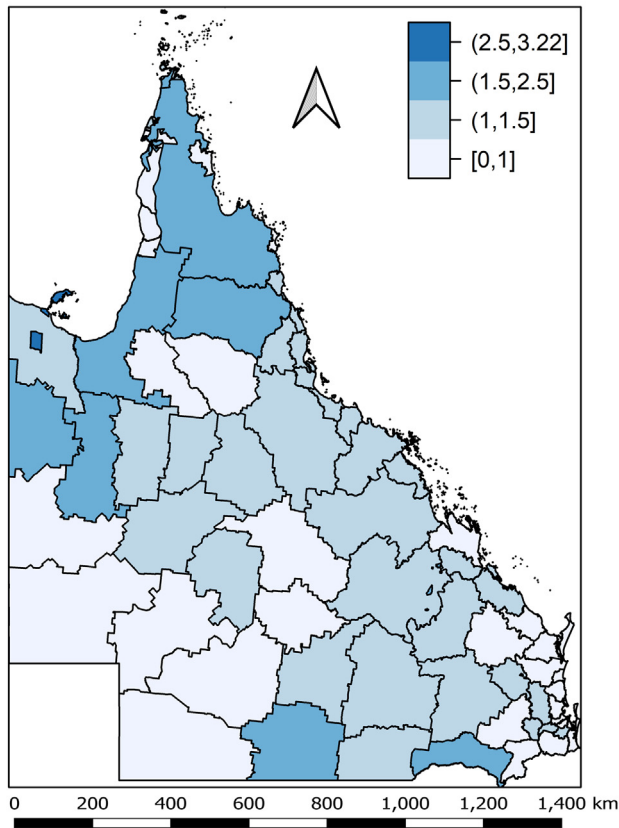
Fig. 2 – Posterior mean for the spatial pattern of the risk of out-of-hospital cardiac arrest in Queensland.

Bayesian analysis with the INLA method in OHCA is limited. Peluso et al.[11] and Auricchio et al.[12] claimed to be the first to adopt INLA methodology to estimate OHCA risk of a region (both studies were in Switzerland). Based upon the models developed by Peluso et al.[11] and Auricchio et al.,[12] our study presents another important example of the application of INLA in the evaluation of spatiotemporal distribution of OHCA risk. More importantly, we applied the methods to a different and unique geographic context, across a very broad range of population densities (from 0.003 to 934 people per km^2) and localities. Furthermore, our study included all paramedic-attended OHCA cases regardless of aetiology of arrest, unlike Peluso et al.[11] and Auricchio et al.[12] which included only arrests of cardiac aetiology. Another point of difference between our model and those of Peluso et al.[11] and Auricchio et al.[12] is that we modelled observed counts using a Poisson distribution with mean being a product of the expected counts and RR; whereas in Peluso et al.[11] and Auricchio et al.,[12] the Poisson mean was a product of the resident populations and incidence rates. While inference on incidence rates provides information about disease burden, incidence rates are subject to high random variation due to the small number of cases occurring in areas with sparse populations as is the case of rural LGAs in Queensland (Supplementary Fig. S1). In many instances, areas with small populations can appear to have particularly high incidence rates purely by chance. Those areas are often the largest in land mass and can dominate a map visually. Therefore, mapping incidence rates can be misleading. Inference on and mapping of RR overcomes this limitation, and provides a more reliable picture of the distribution of disease risk.
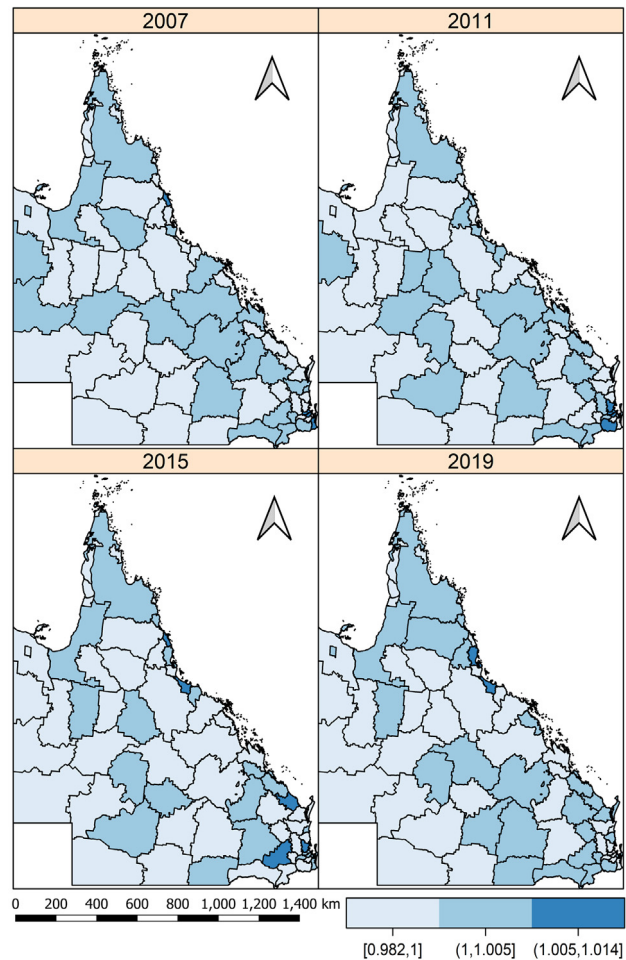

Fig. 3 – Posterior mean of the space-time interactions for the risk of out-of-hospital cardiac arrest in Queensland. For readability, only maps of 4 out of the 13 years are shown. Spatiotemporal effect for each individual year across the entire study period (13 years) is shown in Supplementary Fig. S8.

Apart from Peluso et al.[11] and Auricchio et al.,[12] other studies have also investigated national and regional distribution of OHCA and resource allocation.[5–10] Lin et al.[5] evaluated accessibility and identified gaps between demand and supply for allocating automated external defibrillators (AEDs) in the city of Kaohsiung, Taiwan. However, only 3 years of historical data were available, and the temporal effect was neglected. Chocron et al.[6] assessed ambulance density and OHCA outcomes (return of spontaneous circulation on hospital arrival) in an urban area (Paris, France) using a generalised linear mixed model. This study did not account for temporal effects and was limited to a single urban area. Similarly, Sun et al.[10] modelled and optimised AED placements in a single urban area (Toronto, Canada). By explicitly incorporating the time dimension and population demographic factors, as well as including both urban and rural areas, our study (and Peluso et al.[11] and Auricchio et al.[12] from which the method we adopted) overcomes those limitations and significantly expands knowledge in developing OHCA risk maps.

To our knowledge, Straney et al.[24] was the only spatial analysis on Australian OHCA data (in the state of Victoria). However, this study was limited to arrests of cardiac aetiology aged greater than
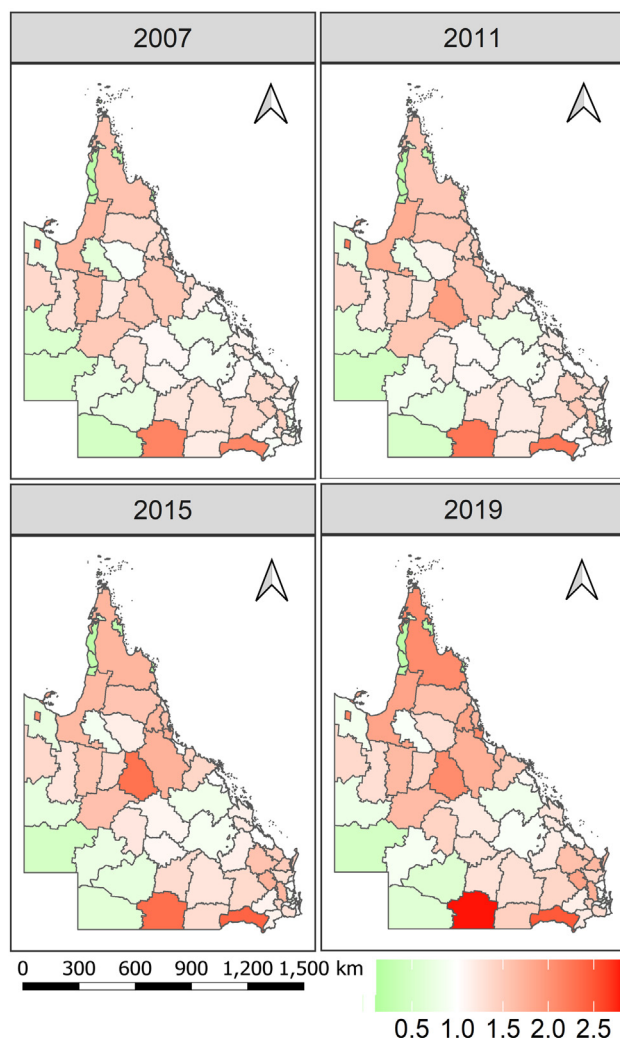
Fig. 4 – Posterior mean of the relative risk of out-of-hospital cardiac arrest for each of the 78 local government areas (LGAs) over time. For readability, only maps of 4 out of the 13 years are shown. Maps of each individual year across the entire study period (13 years) are shown in Supplementary Fig. S9; and trend lines over time by LGA are shown in Supplementary Fig. S10.
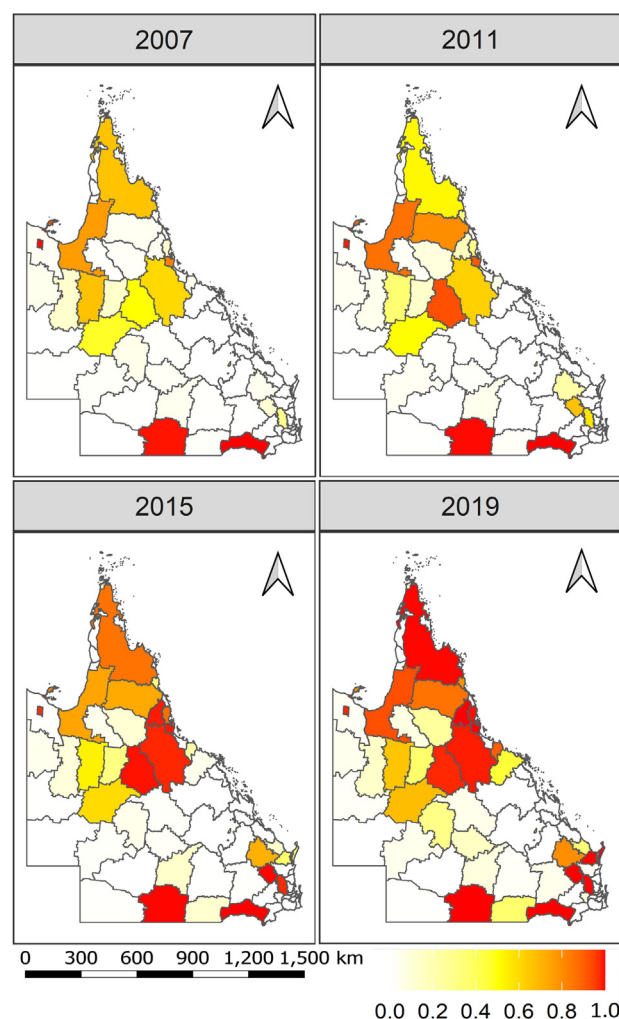
Fig. 5 – Map of exceedance probabilities (threshold = 1.5). For readability, only maps of 4 out of the 13 years are shown. Maps of each individual year across the entire study period (13 years) are shown in Supplementary Fig. S11.

20 years over a shorter time period of 6 years. Spatial models were applied separately to each spatial cell with years dichotomously divided into two periods (2008–2010, 2011–2013). In contrast, our study included OHCA cases of all aetiology and all age over a much longer period of 13 years.

By providing data on the spatiotemporal distribution of OHCA that are specific to Queensland taking into account the state's unique geographic features, our study generates an important risk map that can serve for guiding targeted interventions and optimal allocation of resources. A spatial disparity in OHCA risk was found, where in general there was higher risk in the northern half of the state of Queensland, and this pattern remained consistent over the years. The LGAs in the western and south western parts of the state exhibited the lowest risk. Our results show that in the entire study period, the state was divided into two risk groups of geographic regions: those with

a significant excess of risk (more than 150%) in the northern half part, and those with lowered risk in the remaining parts of the state with a few exceptions in the south and south-east. These findings highlight that public education (e.g. public training in cardiopulmonary resuscitation, public-access AEDs) and a targeted approach in high-risk communities would help reduce differences in risk experienced across areas. Although outside the scope of this study, our model can be extended to accommodate analysis of optimising resource allocation such as AED placements. A potential optimisation method is to use an exponential decay function to model the distance between AEDs and OHCA as described in Lin et al.[5] and Tierney et al.,[25] enabling evaluation of AED accessibility and priority ranking. Such an analysis requires data on geolocations of AEDs. Using data from Canton Ticino (Switzerland), Tierney et al.[26] found that relocating existing AEDs using optimisation models can improve OHCA coverage by 38%. Chan et al.[8] also reported similar finding for Toronto (Canada).

While spatial pattern reveals interesting findings, it is not possible to clearly establish the risk factors. Here we provide some hypothe-

ses about factors related to OHCA risk. In general, most of high risk LGAs have a relatively higher percentage of rural population and low population density.[15] Limited access to medical care in those sparse areas may in part explain their higher risk of OHCA. Furthermore, we speculate that people in these areas have specific risk factors that make them more prone to cardiovascular risk including Aboriginal and Torres Strait Islander status, socioeconomic disadvantage level, and labour force composition.[27] Further research is needed to investigate the specifics of the areas that may be attributable to their risk profile.

This study has several limitations. We did not account for several other factors that may influence spatiotemporal variability in OHCA risk such as racial distribution, socioeconomic factors, level of education and occupation composition. Lifestyle and health-related characteristics such as drug and alcohol use were also not included. Furthermore, as this was an ecological study, no individual-level covariates such as patient comorbidities were used.

Conclusions

We developed a spatiotemporal model to construct OHCA risk maps for Queensland using a Bayesian hierarchical model that accounted for temporal and spatial heterogeneity, space-time interactions, and demographic factors. The model identifies high risk areas and provides valuable information to guide public health policy by directing interventions and resources to areas with elevated risk.

Ethics information

This study was approved by the Royal Brisbane and Women's Hospital Human Research Ethics Committee (LNR/2019/QRBW/54899). Informed consent was waived by the ethics committee.

Conflicts of interest

None.

Funding

None.

CRediT authorship contribution statement

Tan N. Doan: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft. **Daniel Wilson:** Conceptualization, Writing – original draft. **Stephen Rashford:** Conceptualization, Supervision. **Stephen Ball:** Conceptualization, Writing - review & editing. **Emma Bosley:** Conceptualization, Supervision, Writing - review & editing.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resplu.2021.100166.

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