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Spatial-scale dependent risk factors of heat-related mortality: A multiscale geographically weighted regression analysis

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ABSTRACT

Extreme heat is a leading cause of weather-related human mortality throughout much of the world, posing a significantly heavy burden on the development of healthy and sustainable cities. To effectively reduce heat health risk, a better understanding of where and what risk factors should be targeted for intervention is necessary. However, little research has examined how different risk factors for heat-related mortality operate at varying spatial scales. Here, we present a novel application of the multiscale geographically weighted regression (GWR) approach to explore the scale of effect of each underlying risk factor using Hong Kong as a case study. We find that a hybrid of global and local processes via multiscale GWR yields a better fit of heat-related mortality risk than models using GWR and ordinary least squares (OLS) approaches. Predictor variables are categorized by the scale of effect into global variables (i.e., age and education attainment, socioeconomic status), intermediate variables (i.e., work place, birth place and language), and local variables (i.e., thermal environment, low income). These findings enrich our understanding of the spatial scale-dependent risk factors for heat-related mortality and shed light on the importance of hierarchical policy-making and site-specific planning processes in effective heat hazard mitigation and climate adaptation strategies.

1. Introduction

Climate change mitigation and adaptation are essential to attaining sustainable development (United Nations, 2016). In fact, sustainability is increasingly threatened by climate change-induced extreme weather events, such as severe typhoons, intense flooding, droughts, and heat waves (The Emergency Event Database (EM-DAT) 2020; The United Nations Office for Disaster Risk Reduction (UNDRR 2015)). As a leading cause of weather-related loss and damage as the climate warms, extreme heat events pose huge societal, economic and ecological burdens on global cities (Benmarhnia, Kihal-Talantikite, Ragettli & Deguen, 2017; Gasparrini et al., 2015; McMichael, Montgomery & Costello, 2012; Wilhelmi & Hayden, 2010), including devastating heat waves, such as the 2003 European heat wave, which caused 70,000 deaths (Robine et al., 2008), and the 2010 Russian heat wave, which killed an estimated 55,000 people (Dole et al., 2011). Aside from the heat wave events that occurred in temperate regions, these abnormal weather patterns and their associated excess deaths are increasingly becoming more severe and frequent in the tropics (Borzino, Chng, Mughal & Schubert, 2020; Zhao et al., 2019) and subtropics (Ingole et al., 2017; Ng et al., 2016; Yilmaz, Toy, Demircioglu Yildiz & Yilmaz, 2009), especially in densely populated cities where heat stress is further aggravated by the local hot and humid climate and the urban heat island effect, such as Hong Kong, the focus of the present case study (Hua, Zhang & Ren, 2020; Song, Huang, Kim, Wen & Li, 2020; Hong Kong Observatory (HKO) 2020). In addition, extreme heat events are projected to increase in frequency, duration, and intensity (Qing & Wang, 2021; Intergovernmental Panel on Climate Change (IPCC 2018)), which are likely to exacerbate their heat-related impacts in most of the world (Gasparrini et al., 2015; McMichael et al., 2012; Muthers, Laschewski & Matzarakis, 2017; Wilhelmi & Hayden, 2010).

Extreme heat has a range of impacts on ecosystems and human society, including crop failures (Wegren, 2011), wildfires (Shaposhnikov et al., 2014), and infrastructure damage and disruption (García-Herrera, Díaz, Trigo, Luterbacher & Fischer, 2010). More importantly, extreme heat has significantly increased population health risk and mortality (Guo et al., 2016). A multicountry observational study demonstrated that 4.2 out of every 1000 deaths were attributable to hot temperatures

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(Gasparrini et al., 2015), and all selected countries would experience a sharp surge in heat-related excess mortality under the high CO_2 emission scenario (Gasparrini et al., 2017). As such, the health effects of extreme heat should be an urgent issue to address. To minimize the worldwide health burden imposed by such extreme weather events, scientists have called for adaptation strategies for reducing heat health risks and enhancing heat resilience, thus prompting wide interest in heat health risk research (Bakhsh, Rauf & Zulfiqar, 2018; Benmarhnia et al., 2017; Keramitsoglou et al., 2017; McGregor, Bessemoulin, Ebi, & Menne, 2015). Currently, time-series studies on the day-to-day associations between temperature and human health risk are already at the "mature stage" and have facilitated the development of early heat warning systems (Gasparrini et al., 2015; Guo, Barnett & Tong, 2012; Hajat et al., 2010; (Hajat et al., 2006)). However, geographical studies of socio-environmental influences on human health are still being investigated (Wong, Ho & Tse, 2020), and far less attention has been given to differentiating their scales of effect.

This paper presents a case study in Hong Kong, the world's fourth most densely populated city, which is under increasing threat of extreme heat events owing to the combined effects of the urban heat island effect and global warming (Hua et al., 2020; Liu et al., 2020). By presenting the case of Hong Kong, we aim to build on the existing literature in three ways. First, this study includes both social and environmental factors in the analysis and thus provides a more comprehensive understanding of underlying risk factors associated with heat-related mortality risk. Second, this study extends the existing heat health research by identifying at which specific spatial scales those risk factors present the most significant associations with heat-related mortality and how those relationships vary over space. Third, along with the top–down heat hazard mitigation interventions outlined in the Hong Kong Climate Action Plan 2030+, this study provides an evidence basis for joint geographically targeted strategies and action plans to mitigate climate change-induced health risks and impacts locally and globally.

To present this study, this paper begins with a review of past geographical studies on heat health risk. Then, a description of the data used and the measures and methods adopted is provided. The subsequent sections present the major findings of this study and the practical implications for health interventions, heat hazard mitigation and climate adaptation strategies. The paper concludes with a discussion on the limitations of this study and recommendations for future work.

2. Review of past geographical studies on heat health risks

A comprehensive assessment is required to identify areas of high risk and thus prioritize interventions in heat action plans (Ho, Knudby, Walker & Henderson, 2017; (Wolf et al., 2015); (Hondula et al., 2015); (O'Neill & Ebi, 2009)). To delineate the spatial variability of heat health risk, scientists have devised a number of heat vulnerability and risk indices ((Zhang et al., 2019a); (Chen et al., 2018); Di Napoli, Pappenberger & Cloke, 2018; (Aubrecht and Özceylan, 2013)Buscail, Upegui & Viel, 2012; Wolf & Mcgregor, 2013). Some of these indices are further validated against heat-related morbidity and mortality data at both the city and subcity levels (Harlan, Declet-Barreto, Stefanov & Petitti, 2013; Hu, Yang, Zhong, Fei & Qi, 2017; Wolf, Mcgregor & Analitis, 2014; Zhang et al., 2019; (Reid et al., 2012)). These studies are particularly important because they can help local policy makers identify areas at higher risk of mortality during heat wave events (Conlon et al., 2020; Ho, Knudby & Huang, 2015; Jänicke et al., 2019). However, most of these indices have not had a substantial influence on policymaking or prevention action, probably because some useful information may be buried in aggregates based on an equal-weighting scheme (Mallen, Stone & Lanza, 2019; Wolf, Chuang & Mcgregor, 2015). Although areas at high risk can be highlighted in maps of these composite indices, the underlying causes of the risk remain unknown. Without this crucial information, public health authorities often have trouble recognizing appropriate measures and developing cost-effective plans (U.S. Environmental Protection Agency (U.S. EPA 2018); (American Planning Association 2021)).

Previous studies have highlighted various underlying factors that can be targeted for interventions to reduce heat health risks. Chen, Huang and Zhou (2015) emphasized the fair distribution of heat vulnerability factors in terms of the disparity in heat health risks between urban and rural areas. Eisenman et al. (2016) argued that socioeconomic factors have a closer relationship with heat-related illness than built environments, especially during extremely hot days. He et al. (2019) explored the spatial variability of mortality risks due to extreme heat in Shanghai and argued that adaptation factors are relatively more important than heat exposure and sensitivity factors. However, previous studies have demonstrated that relationships between heat-related mortality risks and certain influencing factors have local variations. Specifically, heat-related mortality risks in urban areas are influenced by drivers that have little importance in rural areas (Hattis, Ogneva-Himmelberger & Ratick, 2012; Hu et al., 2019b; Kovach, Konrad II & Fuhrmann, 2015; Rey et al., 2009). Such spatial disparity in factors associated with heat-related death is further evidenced in six cities in Japan (Ng et al., 2014) and seven U.S. cities (Hondula, Davis, Saha, Wegner & Veazey, 2015) using city-specific models. Chien, Guo and Zhang (2016) found that the effects of heat and heat waves on elderly individuals in Texas, USA, vary across affected areas, and these effects are relatively more severe in Northwest Texas and parts of West Texas. In view of these pieces of evidence, a universal policy or action plan may be unsuitable to address the heterogeneity of local risks and impacts (Wilhelmi & Hayden, 2010). To be able to respond appropriately to localized heat burden, scientists, policy makers, and urban planners must understand where these targeted interventions are needed and how to appropriately prioritize heat management strategies to achieve effective policy implementation (Heaton et al., 2014; (Price, Perron, & King, 2013)).

The need to develop local-specific action plans has prompted widespread interest in incorporating spatial context into the analyses and modeling of heat-related mortality risks (Declet-Barreto, Knowlton, Jenerette & Buyantuev, 2016; Lehnert, Wilt, Flanagan & Hallisey, 2020; Pramanik, Punia, & Chakraborty, 2020; Wang, Fan, Zhao & Myint, 2020). In particular, geographically weighted regression (GWR) is a well-established spatial regression technique to model spatially varying relationships in heat risk studies. Via GWR, Kovach, Fuhrmann, Konrad II and Harrison (2012) found that heat-related hospital admissions in communities in North Carolina have spatially varying relationships with factors of land use and housing conditions. Sun, Yun, & Ling, 2019 estimated the spatially varying weights of environmental, demographic, and health-related risk factors in contributing to spatial heat health vulnerability in Western Austria. (Cao et al., 2020) revealed that spatial clusters of heat health risks in a district of Guangzhou City in China are strongly associated with social activity locations and time periods.

Given that heat-related health outcomes are treated as a complex interplay of sociodemographic conditions and the physical environment (O'Neill & Ebi, 2009), the underlying factors of heat health risks in various domains may differ in their scales of effect. Yang and Jensen (2017) discovered that the association between mortality and social condition is spatially stationary, whereas that between mortality and climatic conditions is not. These findings raise the concern that a universal model, such as GWR, which assumes all processes operate at the same spatial scale ((Fotheringham, Brunsdon, & Charlton, 2003)), may not be appropriate in predicting heat-related mortality risks. In contrast, the recently developed multiscale geographically weighted regression (MGWR) allows the effects of various predictor variables, each of which varies at a specific spatial scale, to be modeled simultaneously ((Fotheringham et al., 2017)). For MGWR, its mathematical details are provided in the work of Fotheringhan et al. (2017), its Python implementation in Oshan, Li, Kang, Wolf and Fotheringham (2019) and the inference in Yu et al. (2020). Thus far, this method has been applied in research on air pollution ((Fotheringham, Yue, & Li, 2019)), obesity (Oshan, Smith & Fotheringham, 2020), and road fatalities ((Iyanda &

Osayomi, 2020)), but its applicability in heat health research should be further demonstrated in empirical studies.

Against the background presented above, the goal of this paper is to explore multiscale processes associated with heat-related mortality and the scale of effect of each underlying risk factor in a specific domain via MGWR. In relation to this overarching aim, we address the following specific questions.

(1) For risk factors in different domains, do their associations with heat-related mortality vary over space?
(2) Do different risk factors associate with heat-related mortality at varying spatial scales?
(3) How do the associations between different risk factors, each operating at a specific spatial scale, and heat-related mortality vary over space?

3. Data, measures and methodology

3.1. Measures of heat-related mortality risk

Heat-related mortality refers to deaths associated with dehydration or volume depletion (the International Classification of Disease Tenth Revision (ICD-10), E86), cardiovascular diseases (ICD-10, I00-I99), respiratory diseases (ICD-10, J00-J99), hyperpyrexia (ICD-10, R50.9), effects of heat and light (ICD-10, T67), heat stroke (ICD-10, X30) and exposure to sunlight (ICD-10, X32) during the summer season (Hu et al., 2019a; (Hu et al., 2019b); Eisenman et al., 2016). Daily mortality data in Hong Kong during the summer season (May to October) from 2015 to 2017 are provided by the Hong Kong Census and Statistics Department (HKSCD). The daily deaths of residents are tabulated for each tertiary planning unit (TPU) according to the place of residence (in 3-digit TPU code). The TPU is a geographic reference system demarcated by the Planning Department of the Territory of Hong Kong; TPUs with small populations are merged with adjacent ones to form small TPUs—the smallest census units with publicly available and accessible data of the 2016 Hong Kong Census Statistics. To match the scale units of the census statistics, the TPU-level mortality data are recounted for each small TPU. Given the incoherent boundaries of some small TPUs before and after 2016, we merge units sharing changed boundaries for a new one and then recount mortality for each newly merged unit. Finally, a total of 209 small TPUs with complete data are included in this study for analysis. Regarding the small numbers associated with a rare event, we calculated the odds ratio of heat-related death and included the population size to control for the number of people at risk in each small TPU (Burkart et al., 2016; Harlan et al., 2013; Nordio, Zanobetti, Colicino, Kloog & Schwartz, 2015).

The calculated heat-related mortality risk is visualized as shown in Fig. 1. The highest risk units are found to be clustered within the Kowloon Peninsula (i.e., Sham Shui Po, Kowloon City, Wong Tai Sin), whereas the low-risk clusters are within the New Territories (i.e., Yuen Long, Tai Po, etc.) (see Figure A1 in Appendix A). The heat-related mortality risk therefore depends greatly upon the location, allowing us to further explore its spatial variance.

3.2. Demographic and socioeconomic variables

Predictor variables in this domain include age, education, income, place of birth, language, occupation and place of work. Age is considered a risk factor for heat-related mortality because the elderly are usually the first to be influenced, probably due to their weak thermoregulatory mechanisms and existing medical conditions (Fuhrmann, Sugg, Konrad & Waller, 2016). In a population-based analysis of heat risk in Houston, a 1% increase in the elderly percentage within a block group led to a 5.66% increase in the relative risk of nonaccidental mortality within that block (Heaton et al., 2014). The age variable is also found to be a significant predictor of heat-related deaths of census block groups in Phoenix, Arizona (Uejio et al., 2011).

A lower education level was found to be at higher heat risk in the U.S. at the ZIP code level (Gronlund, Berrocal, White-Newsome, Conlon & O'Neill, 2015; Hondula et al., 2015) and at the census tract level (Mallen et al., 2019) and in China at the county level (Chen et al., 2016). A probable explanation for this might be that a well-educated population tends to have more chances to learn knowledge and skills to adapt to heat stress. Therefore, communities with larger proportions of highly educated populations are expected to be less heat vulnerable.

Lower income was associated with elevated heat risk across many

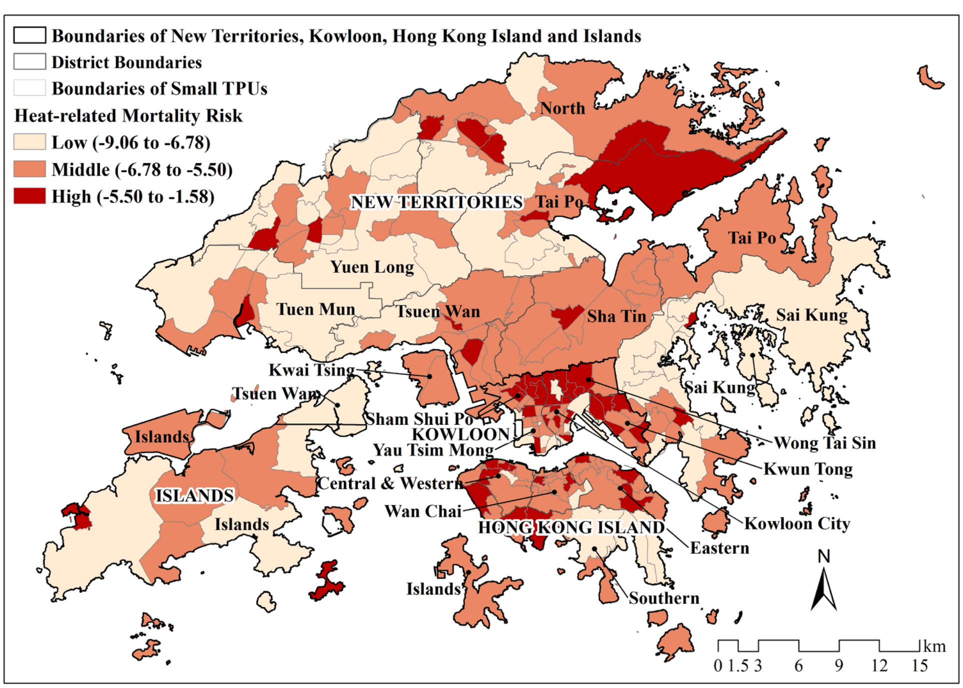

Fig. 1. Map of Heat-related Mortality Risk.

populations and regions, such as Seoul in Korea (Jänicke et al., 2019; (Kim & Joh, 2006)), Boston in the U.S. (Hondula et al., 2015), and six cities in Japan (Ng et al., 2014). Poor response to warnings (Kalkstein & Sheridan, 2007), lack of ready access to cooler locations (Sampson et al., 2013) and medical care (Zhang, Nitschke & Bi, 2013) might explain the association of low income with high vulnerability in the face of extreme heat events.

Birth place has been associated with heat-related mortality at both the community level (Eisenman et al., 2016) and the neighborhood level (Kovach et al., 2015). We gather data on the place of birth at the small TPU level and use the variable to capture the potentially vulnerable populations in Hong Kong, such as immigrants who lived in a distinct climate before (i.e., temperate climate) and thus cannot adapt well to the local hot and humid climate or immigrants who are experiencing social and cultural isolation (Sampson et al., 2013; Yardley, Sigal & Kenny, 2011).

The effects of language barriers are not consistent among studies of different geographical regions. In the U.S., most emergency alerts are issued in English, placing limited English-proficient populations at an increased vulnerability (Nayak et al., 2018). In contrast, in most international metropolises, such as Hong Kong, where multilingual emergency alerts and official documents are often provided, language barriers are reduced for foreigners; native speakers who can only communicate in Cantonese are instead more vulnerable since they are more likely to be less educated and have a shortage of risk awareness and risk reduction capability (Song et al., 2020).

The heat-related mortality risk also exhibits a disparity by occupation. While the population employed in administrative and managerial positions often represents a socially affluent population group and has a higher adaptive capacity to heat risk (Yang & Jensen, 2017), mutual workers such as service, sales, craft and related workers tend to have low income and low educational attainment and could be more susceptible to heat health risk (Gubernot, Anderson & Hunting, 2014; Wong, Peng, Zou, Shi & Wilson, 2016).

Poor working conditions could lead to higher occupational heat exposure and thus increase the heat risk of the working population (Spector, Masuda, Wolff, Calkins & Seixas, 2019). Communities are assumed to suffer higher heat risk if there is a higher proportion of people who work in areas with crowded buildings using higher albedo materials (i.e., reflecting materials) and have longer communing distances to their workplaces (Hoffmann, Fischereit, Heitmann, Schlünzen & Gasser, 2018; Schrijvers, Jonker, De Roode & Kenjereš, 2016).

Information on age, education, low income, place of birth, language, occupation and place of work are extracted from the 2016 Hong Kong Census Data published by HKSCD at the small TPU level (214 small TPUs in 2016). To match the scale units of mortality data (209 small TPUs including the newly merged units), we recalculated the data and corresponding variables for each merged unit.

3.3. Variables of heat hazard and built environment

Land surface temperature (LST) during extreme heat events is used as a proxy for heat hazards. We collected LST data from two widely used satellite image products, the Moderate Resolution Imaging Spectroradiometer (MODIS), MOD11A1 (daytime) and MYD11A1 (nighttime), which have been used as alternative data sources for heat risk studies (Estoque et al., 2020; Zhang et al., 2019). The heat hazard is thereby captured by the LSTs during very hot days (maximum temperature ≥ 33 °C) and hot nights (minimum temperature ≥ 28 °C) recorded from 2015 to 2017 by the Hong Kong Observatory (HKO). As LSTs within built-up areas are highly associated with residents' heat health risk (Song et al., 2020), we then extracted daytime and nighttime LSTs only within built-up regions and calculated the mean value of LSTs at each pixel using the cell statistics tool in ArcGIS 10.5. To match the scale units of demographic and socioeconomic variables from census data, we aggregated pixel values for maps at the small TPU level using the zonal statics tool in ArcGIS 10.5.

The built environment can impact microclimatic thermal conditions and the risk of heat-related mortality (Eisenman et al., 2016; Yardley et al., 2011). In this study, variables of built-up land, transport land and building density are included as proxies of the built environment. Built-up areas tend to have a long-lasting effect of heat stress due to the large amounts of concrete and asphalt (Madrigano, Ito, Johnson, Kinney & Matte, 2015a) and have reduced evapotranspiration due to a lack of vegetation and surface moisture (Hart & Sailor, 2009). This can contribute to the urban heat island (UHI) effect, which further exacerbates heat waves (Reid et al., 2009) and increases the urban-rural disparity of heat-related health risks (Chen et al., 2016; Hu et al., 2019a). The heavy traffic flows in areas used for transport emit large amounts of anthropogenic heat and air pollutants, in which the former has a direct negative influence on thermal comfort (Hart & Sailor, 2009) while the latter can deteriorate the thermal environment as a confounder of the UHI (Madrigano, Jack, Anderson, Bell & Kinney, 2015b). Therefore, a high percentage of traffic land is assumed to contribute to adverse heat health outcomes. Building density was linked to heat health risk in earlier studies (Uejio et al., 2011) and could be a key factor in crowded cities such as Hong Kong. We calculate the building density using the kernel density tool first and then aggregate the pixel-based values for each small TPU in ArcGIS 10.5.

Data on land use are drawn from the Hong Kong Land Use (HKLU) database at a spatial resolution of 30 m^2s in 2016 and are aggregated to calculate the percentages of various land use types at a small TPU level. In the end, we include thirteen variables that may explain the heat-related mortality risk of 209 small TPUs. Information on the selected variables is summarized in Table 1.

3.4. Multivariable predictive model

Data preprocessing. To detect influencing factors of heat-related mortality risk, this study screens selected variables exhibiting significant associations with heat-related mortality risk for inclusion in the multivariate analyses (Uejio et al., 2011). The variables included are treated as potential contributors to heat-related mortality risk. Spearman's correlation coefficients are then calculated, by which high correlations are detected between some of those included variables. To reduce the duplicate messages and potential multicollinearity that might affect the final estimation results, we adopt principal component analysis (PCA) to eliminate redundant information and create independent factors for inclusion in further regression analysis (Song et al., 2020). A varimax rotation is used to minimize the number of original variables that load highly on any one factor and increase the variation among factors (Mallen et al., 2019). We retain factors based on a combination of standard criteria: the proportion of each variable's variance (i.e., communality) and that of the total variance that can be explained by the factors (say above 0.8 for each). Factor scores were computed using estimated factor score coefficients in the factor analysis tool in IBM SPSS Statistics 23 software. The resulting factor scores are normalized to have a mean of 0 and a standard deviation of 1.

Multiscale geographically weighted regression model. Unlike global regressions, local regressions can detect spatial heterogeneity in a process (i.e., GWR) (Fotheringham, Brunsdon, & Charlton, 2003); varying-scale methods can further take into account different spatial scales of predictor variables, such as those following the most recently developed MGWR (Fotheringham, Yang & Kang, 2017; Yu et al., 2020). This study thereby predicts heat-related mortality risk through MGWR, which adopts the function expressed below (Eq. (1)).

$$y_i = \sum_{j=1}^{k} \beta_{bwj}(\mu_i, \upsilon_i) x_{ij} + \varepsilon_i \quad (1)$$

where y_i indicates the heat-related mortality risk at unit i, x_{ij} is the jth predictor variable of unit i, and $\beta_{bwj}(\mu_i, \upsilon_i)$ denotes the coefficient of unit

Table 1
Data summary of the selected variables.

Category	Data Source	Characteristics	Variables	Mean	(Std. Dev)
Demographic and socioeconomic variables	HK census (2016)	Age	% population >= 65 years of age	16.15	(4.50)
		Education	% population >= 15 years of age with educational attainment only at primary and below	18.33	(8.25)
		Low income	% working population with monthly income from main employment below 10,000 Hong Kong Dollars.	28.42	(7.75)
		Place of birth	% population who are born in Hong Kong	60.49	(8.77)
		Language	% population >= 5 years of age, whose usual spoken language is Cantonese	83.51	(13.38)
		Occupation [a]	% managers and administrators of the working population	12.56	(7.16)
			% service, sales, craft and related workers of the working population	19.90	(8.99)
		Place of work a	% working population who work on Hong Kong Island	24.09	(15.85)
			% working population who work in the New Territory	22.89	(15.42)
Heat hazard and build environment	HKLU (2016)	Building density	Kernel density of buildings	21.58	(14.24)
		Transportation	% roads and traffic facilities (i.e., roads, railways, etc.)	12.81	(9.21)
		Built-up land	% built-up area	53.47	(34.82)
	MODIS (2015–2017)	Land surface temperature (LST) [a]	Average nighttime LST within built-up area during hot nights at the small TPU level	26.03	(0.80)

[a] Some categories of variables of occupation, place of work, and LST are not listed because those categories were found to have no significant associations ($p > 0.05$) with heat-related mortality risk, including unlisted categories of occupation (i.e., professionals, associate professionals, etc.), place of work (i.e.,% working population who work in Kowloon), and LST (i.e., average daytime LST within built-up area during very hot days at a small TPU scale level).

i for location (μ_i, υ_i), in which *bwj* represents the i^{th} optimal bandwidth.

MGWR is calibrated using a back-fitting algorithm under a generalized additive model (GAM) framework. In the MGWR algorithm, every additive term in each step is fitted using a GWR estimator, and local parameter estimates are location-specific and are realized by specifying spatial weight matrices that allow neighborhoods closer to unit i to have stronger impacts on local parameter estimations at location (μ_i, υ_i) (Eq. (2)).

$$\widehat{\beta}_{bwj}(\mu_i, \upsilon_i) = \left(X_j{}' W_{bwj}(\mu_i, \upsilon_i) X_j\right)^{-1} X_j{}' W_{bwj}(\mu_i, \upsilon_i) y \tag{2}$$

where $\widehat{\beta}_{bwj}(\mu_i, \upsilon_i)$ denotes the vector of local estimates, X_j denotes the y^{th} predictor variable, y denotes the observation of the dependent variable, and $W_{bwj}(\mu_i, \upsilon_i)$ denotes the j^{th} spatial weights matrix at unit i.

Each spatial weights matrix is characterized by a kernel function and a bandwidth designed to control the weighting intensity or data-borrowing (i.e., spatial scale). Instead of the fixed Gaussian kernel function, the adaptive bi-square kernel function is particularly used in this study. There are two reasons for selecting such a data-borrowing scheme. First, the Gaussian kernel function assumes that all observations have nonzero weights regardless of how far they are from the target location; however, in most cases, this is not in line with reality. Instead, the bi-square kernel function estimates each local regression based on data of the nearest neighborhoods but regardless of the influences of other observations. This makes it possible to detect the optimal bandwidth that could serve as a proxy of spatial scale and thus is selected ((Iyanda & Osayomi, 2020); Oshan et al., 2019). Second, in comparison with the Euclidean distance–based measure of proximity, the nearest-neighbors measure used in the adaptive kernel function is more robust to irregular spatial sampling (Fotheringham et al., 2017). The bandwidth is thereby used to predefine the number of nearest neighbors that influence the local parameter estimation and is thus involved in estimating the coefficient of each variable at each location. In MGWR models, each bandwidth represents a unique spatial scale for parameter estimation and can be used to explain the rate of change of coefficients in space, which indicates the scale of spatial heterogeneity. The larger the bandwidth is, the more stable the influence of the variable in space, and vice versa. A corrected Akaike information criterion (AICc) is used to detect the optimal bandwidth, where the smallest value of AICc signals the optimal bandwidth.

All local parameter estimates and optimal bandwidths in MGWR are evaluated based on the GAM through a back-fitting algorithm that allows for estimating the globally consistent effects and spatially varying effects of predictor variables simultaneously (Fotheringham et al., 2017; Yu et al., 2020). For calibrations of the MGWR model, the parameter estimates of the GWR model are used to initiate the GAM and for a quick convergence; the convergence of the model calibration is diagnosed by the score of change (SOC) in the GWR smooth functions between consecutive back-fitting iterations (i.e., terminate if SOC-f<10^{-5}) (Yu et al., 2020; Iyanda et al. 2020). We used MGWR software (v2.2, 2020, Spatial Analysis Research Center, Tempe, the U.S.) to derive all the results in this study (https://sgsup.asu.edu/sparc/mgwr).

Model comparison and visualization. To further explore which model could favorably fit the data, we compare the ordinary least squares (OLS), GWR and MGWR models based on a combination of standard criteria: the goodness of fit (R-squared), AICc, and the residual sum of squares (RSS) (Oshan et al., 2020; (Fotheringham, Yue, & Li, 2019)). A higher value of R-squared indicates a larger amount of random variance that could be explained and thus signals a preferred model. For AIC, the rule of thumb is that when the difference between two AICs is greater than 10, the optimal model is the one with the smaller AIC (Burnham & Anderson, 2004). The study refers to the rule of thumb for AIC and applies it to AICc. For the RSS, it measures the amount of variance in the dependent variable that is not explained by a regression model; a model with a smaller value of RSS represents the model that fits the empirical data better. We further compared the GWR and MGWR, as suggested in prior research, by mapping the local condition number of each model (Oshan et al., 2020; (da Silva & Fotheringham, 2016)). The map is used to show the pattern of local multicollinearity in each model. To visualize the spatial heterogeneity detected by the optimal model, we visualized each variable's parameter estimates that were statistically nonzero and displayed them in color using a choropleth map.

4. Results

According to the results of PCA with a varimax rotation, six factors were created as potential predictor variables of heat-related mortality risk (Table 2). The derived factors explain more than 80% of the variance of each original variable and over 90% of the total variance of all variables.

The thermal environment measure consists of four variables in the heat hazard and built environment domains, collectively indicating that

Table 2
List of predictor variables and derived factors after principal component analysis.

Derived Factors\Potential predictor variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Explained variance of each variable
	Thermal Environment	**Socioeconomic status**	**Work-place**	**Birth place and language**	**Age and education attainment**	**Low income**	
% of the total variance explained	*33.46*	*26.96*	*13.01*	*8.45*	*5.63*	*4.52*	–
Kernel density of buildings	**0.91**	−0.06	−0.13	−0.01	0.07	0.16	*0.89*
% roads and traffic facilities (i.e., roads, railways, etc.)	**0.86**	0.05	−0.25	−0.24	−0.06	−0.15	*0.88*
% built-up area	**0.94**	0.05	−0.16	−0.05	−0.03	−0.04	*0.91*
Average nighttime LST within built-up area during hot nights at the small TPU level	**0.85**	0.12	0.30	0.02	0.01	−0.04	*0.82*
% population >= 65 years of age	0.02	0.31	−0.01	0.02	**0.94**	0.02	*0.99*
% population >= 15 years of age with educational attainment at primary and below	−0.09	**0.74**	0.25	0.16	**0.54**	−0.04	*0.93*
% population who are born in Hong Kong	−0.25	0.00	0.16	**0.91**	0.00	−0.19	*0.96*
% population >= 5 years of age, whose usual spoken language is Cantonese	0.14	**0.53**	0.21	**0.70**	0.12	−0.25	*0.91*
% managers and administrators of the working population	0.00	**−0.95**	−0.08	−0.14	−0.17	0.01	*0.95*
% service, sales, craft and related workers of the working population	0.16	**0.95**	0.13	−0.04	0.09	−0.08	*0.95*
% working population who work on Hong Kong Island	0.03	−0.12	**−0.96**	−0.10	0.02	0.00	*0.95*
% working population who work in the New Territory	−0.28	0.29	**0.74**	0.27	0.11	−0.23	*0.85*
% working population with monthly income from main employment below 10,000 HKD.	−0.03	−0.08	−0.10	−0.26	0.02	**0.95**	*0.98*

higher densities of buildings, traffic land and built-up land, and higher land surface temperatures during hot nights are associated with greater health risks to heat stress. Variables loading on the factor of socioeconomic status suggest that service, sales, craft and related work positions are more likely to be occupied by less educated individuals, while managerial and administrative work positions are more likely to be occupied by highly educated individuals. Thus, socioeconomic status is expected to contribute positively to heat-related mortality risk. The factor of workplace involves variables of percent population work on Hong Kong Island and the New Territories, capturing the increased risk caused by poor thermal environment in the workplace and long commuting distance. Variables of birth place and language have highly loaded on the same factor, whose effects are mixed in terms of past research and should be investigated further. The dominant variables of age and education factor indicate that the elderly and the less educated are closely associated with each other and collectively represent a group of people who are vulnerable to heat stress. The low-income factor is extracted with a single heavy-loaded variable and thus represents the corresponding effect modification independently.

The derived factors are involved as predictor variables in regression models against the calculated heat-related mortality risk based on death records. A total of three models are estimated: OLS (global estimates), GWR (local estimates with the same bandwidth for all parameters) and MGWR (local estimates with a specified bandwidth for each parameter). The results of the estimations in the global model (OLS) are first summarized to provide a context for those of the GWR and MGWR models. Then, the model fits metrics for all three models and the map for comparing the results of GWR and MGWR. As the MGWR favorably predicts the heat-related mortality risk over OLS and GWR, we focus on the estimation results of MGWR. Since the dependent variable is transformed by the natural log, estimates of independent variables that are in the form of a natural log can be interpreted as elasticity.

The OLS serves as the baseline, whereas the GWR and MGWR models serve as comparisons acknowledging the possibility of the spatial variability of parameter estimates. The goodness of fit of OLS shows moderate to low explanatory power ($R^2 = 0.29$). Accordingly, almost all factors except for birth place and language have a t-value over the threshold of 1.96 and thus are statically nonzero (Table 3). Due to data standardization of variables, as expected, the intercept is not significant. The parameter estimates of the global model illustrate that factors of socioeconomic status and thermal environment have the highest influences on heat-related mortality risk, followed by factors of low income, age and education attainment. The factor of workplace is the only factor with a significant negative estimated coefficient, implying that residents in the New Territories working in their residence would have lower heat health risk than those working on Hong Kong Island.

Different from the global model, which assumes that all processes are spatially stationary across the analysis units, the GWR and MGWR models allow spatial variability in parameter estimates. In comparison with the fit metrics of OLS (Table 4), the R-squared is increased in GWR (0.46) and is almost doubled in MGWR (0.51); the AICc is reduced by over 20 in GWR and is reduced even more (by almost 35) in MGWR; the RSS is also decreased in GWR (113.51) and is even smaller in MGWR (102.85). In a comparison of GWR and MGWR, the maps of the local condition number in the two models show that MGWR has much lower condition number values than GWR over space and thus is less prone to multicollinearity (Fig. 2). All model indices and maps show that models incorporating spatial variability outperform the global model, and MGWR fits the empirical data even better than GWR. The results indicate that the relationships between predictor variables and heat-related mortality risk are always spatially constant, and some of them could

Table 3
Parameter estimates of the global model.

Predictor variable	Coefficient	t-value
Intercept	−0.00	−0.00
Thermal environment	0.29	4.83
Socioeconomic status	0.30	5.05
Workplace	−0.23	−3.96
Birth place and language	0.03	0.45
Age and education attainment	0.12	1.96
Low income	0.23	3.93

Table 4
The model fit metrics for OLS, GWR and MGWR.

Model Index	OLS	GWR	MGWR
Goodness of fit (R-squared)	0.29	0.46	0.51
Corrected Akaike information criterion (AICc)	537.24	516.40	503.27
Residual sum of squares (RSS)	147.67	113.51	102.85

vary across different spatial scales.

Such variation in the scale of the effect can be reflected by the optimal bandwidth detected by MGWR for each individual predictor variable (Table 5). In comparison with the single bandwidth of 139 nearest neighbors in GWR, the bandwidths for predictor variables in MGWR can be categorized into three groups: global variables with large bandwidths (age and education attainment, socioeconomic status) indicating almost all analysis units are included for parameter estimation; variables yielding relatively small bandwidths (workplace, birth place and language); and local variables with small bandwidths (thermal environment, low income) implying processes operating at local spatial scales. Different from the global model, the intercept in MGWR effectively shows a global effect on the heat-related mortality risk with a bandwidth of 208.

To exhibit the estimation results of the optimal model, the spatial heterogeneity for each group in MGWR is further visualized in Fig. 3. Colored areas represent units with significant local parameter estimates, where positive estimates are in red and negative estimates are in blue. Estimates in gray units are not significantly different from zero. In terms of the estimate surfaces, the effects of global variables (i.e., age and education attainment, socioeconomic status) are significantly positive across the entire study area but with little to no spatial variations (Fig. 3a & b). The resulting visualization patterns are in concordance with the results of the global model and further illustrate the global nature of those processes.

The surfaces of variables with relatively smaller bandwidths demonstrate a moderate number of significant estimates, and both display spatial variations (Figs. 3c & 2d). For the variable of workplace, the estimated surface has a single cluster in the north New Territories. The birth place and language variables manifest in two clusters: a negative one in the northwest corner of the New Territories and a positive one in Kowloon and its surrounding areas. This is interesting because the birth place and language variables are not significantly different from zero in the global model, and the direction of their effect is not uniform across the study area. Further investigation of this result is needed to determine the possible reasons behind this result.

The estimated surfaces of the two local variables exhibit distinct spatial patterns (Fig. 3e & f). The effects of thermal environment conditions are significant across almost all units within the New Territories and Islands and have obvious spatial heterogeneity, including a hot spot in the center of the north New Territories. The surface of low income only has a small number of statistically nonzero estimates, which are clustered in the southeast corner.

Different from the global model, the intercept estimates are found to be significant across the entire study area (Fig. 3g). However, spatial variations are rarely detected at the surface except for the slightly higher estimates in the western regions of Hong Kong Island. The intercept here could represent the effects of undetected variables accounting for residual spatial variance after controlling for existing predictor variables in the model.

5. Discussion

5.1. Results analysis and key findings

To our knowledge, little research has simultaneously involved both demographic and socioeconomic variables and variables of heat hazards and the built environment in the examination of spatial variations in heat-related mortality risk. Even less research has employed MGWR to explore at which specific spatial scales those risk factors present the most significant associations with heat mortality risk and how those relationships vary over space. This may mislead the formulation of effective policy interventions and climate action plans. This paper aims to advance existing research in those aspects.

The findings can answer three research questions posed at the outset. This study proposes questions on whether the associations between heat-related mortality and risk factors in different domains vary over space and vary at different spatial scales. As both GWR and MGWR exhibit a better fit to the empirical data than OLS, the spatial context should be incorporated in the exploration of dominant factors of heat-related death risk. The even better fit of MGWR over GWR further illustrates that the associations differ in spatial scale. The findings are consistent with those in a U.S. case (Yang & Jensen, 2017). In addition to the global nature of social conditions detected in that case, our study extends the previous findings by identifying the geographically unstable effects of workplace, birth place and language at relatively smaller scales and those of thermal environment and low income at even local scales.

Our third question is about how those predictor variables, each associated with heat death at a specific spatial scale, contribute to or mitigate the risk of heat-related mortality. A set of interesting findings is detected in the estimated surfaces. Variables of age and education attainment and socioeconomic status are found to be associated with heat-related death risk to similar degrees over the entire area, which is in concordance with existing research (Cupido, Fotheringham & Jevtic,

Table 5
Bandwidths for predictor variables in GWR and MGWR.

Model\Predictor Variable	GWR	MGWR
Intercept	139	208
Thermal environment	139	81
Socioeconomic status	139	185
Workplace	139	160
Birth place and language	139	104
Age and education attainment	139	208
Low income	139	87

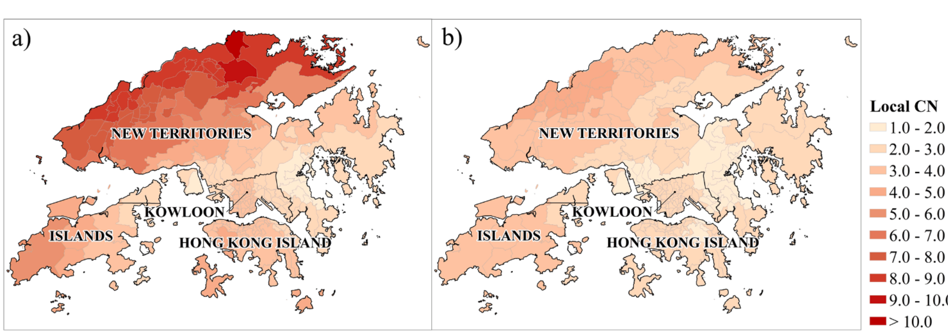

Fig. 2. Maps of the local condition numbers (CNs) in a) GWR and b) MGWR.

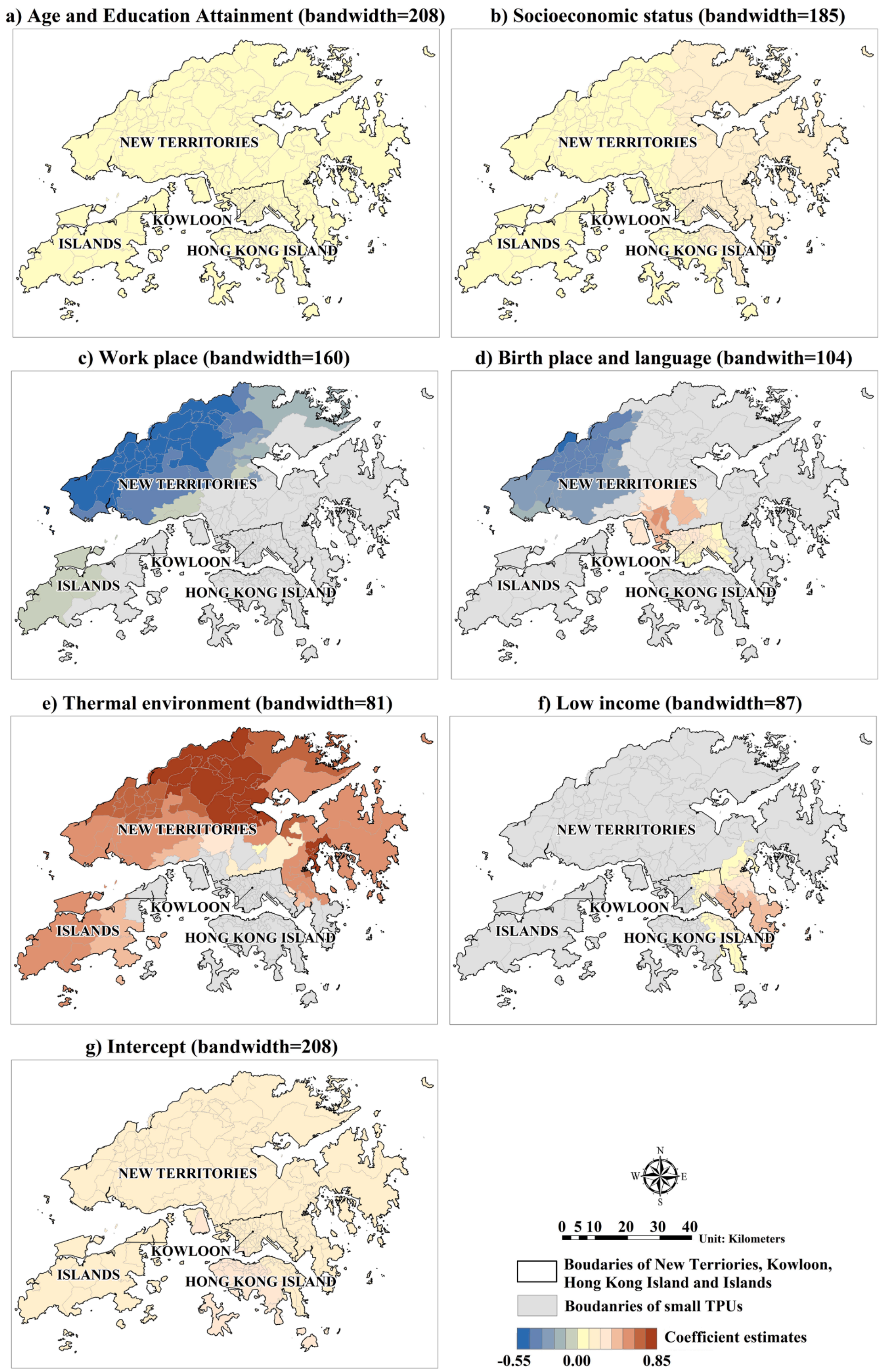

Fig. 3. Surfaces of significant local parameter estimates for predictor variables of heat-related mortality risk.

2021; Regidor et al., 2015; (Borrell et al., 2014) Martikainen, Kauppinen & Valkonen, 2003). The thermal environment conditions are found to play a dominant role in almost all regions of the New Territories and the Islands (Fig. 3e). This fact could be partially explained by the different occupation compositions in the four main regions. The percentage of people working in their residence in each of the main regions is shown in Table A1 (see Appendix A), which could represent the "net" heat exposure in each region since part of the heat exposure of the population with a separation of work and residence is eliminated. Accordingly, as managers and administrators often work in air-conditioned indoor offices (Yang & Jensen, 2017) while manual workers often work in comparatively poor thermal conditions and suffer higher heat exposure (Gubernot et al., 2014), the prevalence of manual workers in the Islands, New Territories and Kowloon regions should exacerbate local heat vulnerability in comparison with Hong Kong Island. However, some areas in the New Territories and almost the whole Kowloon area are found to be exceptions where the effects of the thermal environment are not significant. For the exceptions in the New Territories, the reason might be due to other variables in the model accounting for the local variations (Oshan et al., 2020); for example, in some areas (i.e., the small TPUs in red in Fig. 3d), the variables of birth place and language are found to be the dominant predicator variables, whereas in other areas (i.e., the small TPUs in color in Fig. 3f), the low-income variable is found to be most significant. For the exceptions in the Kowloon area, this trend may be due to the small variations in the thermal environment (see Figure A2 in Appendix A). As such, the local heat-related mortality risk in those areas is more likely to depend on the social context of the surrounding area (i.e., the prevalence of less educated native speakers who tend to have language barriers and have fewer chances to educate themselves on heat risk reduction), as discussed in a recent study (Song et al., 2020).

Another interesting finding is that the positive effects of birth place and language do not remain consistent over space and even flip in direction in the northwest New Territories. The negative effects of birth place and language indicate that the prevalence of Hong Kong residents in these areas is associated with reduced heat health risk, justifying the proposed immigrant vulnerability in past research (Kovach et al., 2015). However, this study further targeted this process to certain clusters in the study area (Fig. 3d). Moreover, according to a past study, immigrant vulnerability is attributable to language barriers and cultural isolation (Hondula et al., 2012; Nayak et al., 2018); in contrast, immigrant vulnerability here is more likely due to the lower adaptive capacity of foreigners to local weather and climate in regards to the significant effect of the thermal environment in the same area (Fig. 3e).

The estimated surface also illustrates that where people work is the underlying factor of their heat-related mortality risk. This fact has been discussed in recent studies (Hoffmann et al., 2018; Schrijvers et al., 2016). However, this research provides preliminary evidence that such a relationship might be less prevalent. This finding arouses particular concerns in some specific areas, such as the three districts of Tuen Mun, Yuen Long and North in the northern New Territories. Several reasons could explain the resulting pattern. First, for residents in the New Territories, as the overall environment is better than those in Kowloon and Hong Kong Island (see Figure A2 in Appendix A), working in the regions of their residences might lead to less heat hazard that the working population may experience during their working time; in contrast, working on Hong Kong Island should require even longer commuting distances than in Kowloon and other regions, leading to extra heat exposure; things may get even worse if the workers' residences are located in the three northernmost districts, which are a substantial distance from Hong Kong Island. Second, in comparison with other districts in the New Territories, the Tuen Mun, Yuen Long and North districts have larger proportions of residents working on Hong Kong Island engaged in vulnerable occupations (i.e., service, sales, craft and related workers) but employ fewer in managerial and administrative positions (see Figure A3 in Appendix A). As people working in vulnerable occupations are more sensitive to outdoor thermal environments, the comparatively poor thermal environment on Hong Kong Island should be less friendly to those people and probably strengthens the impact of health stress on them.

5.2. Practical implications

This paper also provides important practical implications for hierarchical policy-making and site-specific planning in health interventions, heat hazard mitigation and climate adaptation strategies.

Hierarchical Policy-making. Heat-related mortality is spatially heterogeneous, and the associated factors vary at the global, regional and local scales, thereby requiring scalable interventions (Table 6). At the *global* scale, this study finds that areas with higher proportions of elderly individuals, less-educated individuals and those engaged in vulnerable occupations are at higher risk of heat-related mortality. This finding aids efforts to protect the population groups most at risk for heat-related death and supports corresponding strategies proposed in city-level climate action plans (i.e., Hong Kong's Climate Change Strategy and Action Agenda, Hong Kong's Climate Action Plans 2030+). In addition to these plans, the local government can consider broadening conventional adaptive strategies to include targeted interventions, such as additional healthcare institutions and medical personnel for the elderly (Benmarhnia et al., 2017; Yardley et al., 2011), regular workshops, and public talks on the knowledge of heat risk reduction for less-educated individuals ((Frumkin and McMichael, 2008); (McGregor, Bessemoulin, Ebi, & Menne, 2015)), as well as protective actions for those engaged in vulnerable occupations (i.e., adjustment of working hours, high temperature allowance, etc.) (International Labor Organization (ILO), 2019). At the *regional* scale, the findings shed light on the disparities in the health benefits of city cooling practices among the main regions. This result is important, as it demonstrates the necessity of targeted physical heat management strategies (Vargo, Stone, Habeeb, Liu & Russell, 2016). Some large cities (i.e., Los Angeles and Philadelphia in the USA and Athens in Greece) demonstrate the effectiveness of large-scale enhanced vegetation cover and surface reflectance in reducing ambient temperatures (Stone et al., 2014; Synnefa, Dandou, Santamouris, Tombrou & Soulakellis, 2008). Green and cooling strategies can be implemented in other cities, such as Hong Kong, and are likely to be most effective in specific regions (i.e., the New Territories and the Islands in Hong Kong). At the *district* level, the associations between working location and mortality risk clearly vary across districts even within the same region (Fig. 4). The precise mechanisms of the underlying processes require further exploration. However, this finding is important, as it reveals the fact that in some districts, working individuals with residences separate from their workplaces also belong to populations most at risk, thereby calling for district-based protective efforts. Increasing connectivity and accessibility is an applicable practice because it could shorten the commuting distance and thus reduce the heat exposure of workers on the way to and from their workplaces. This research also extends the mortality-income associations detected in a past study in Hong Kong (Chan, Goggins, Kim & Griffiths, 2012) by determining the *local* nature of such a relationship that exists only at a small number of subdistrict units (Fig. 4). This preliminary finding highlights the importance of these subdistricts of community-oriented adaptation programs, which have often been viewed as an economical alternative to government programs and have been led by local stakeholders (Wilhelmi & Hayden, 2010; Yardley et al., 2011). Extra outreach visits to such vulnerable populations and their evacuation (in extreme cases) are suggested, where community centers, health agencies, volunteer groups, etc. could initially implement the practices ((Kovats and Kristie, 2006)).

Site-specific Action Plans. This study also provides valuable guidance to existing climate action plans by introducing more targeted health interventions to respond to local determinant factors and to support the most vulnerable populations. In terms of the resulting

Table 6
Effective scale of predictor variables of heat-related mortality risk.

Predictor variables	Effective scale [a]	Targeted administrative level [b]
Age and education attainment	Global	Whole city
Socioeconomic status	Global	Whole city
Thermal environment	Local	Main region [c]
Work place	Local	District
Birth place and language	Local	Subdistrict [d]
Low income	Local	Subdistrict [d]

[a] Effective scale presents the extent to which the corresponding variable significantly affects heat-related mortality risk.
[b] Targeted administrative level indicates at which administrative level the strategies and action plans could be conducted in the most effective way.
[c] Main region indicates the level at which the four main regions are located, including the New Territories, Kowloon, Hong Kong Island and the Islands.
[d] Subdistrict indicates the administrative level below district and specifically refers to the small TPU level here.

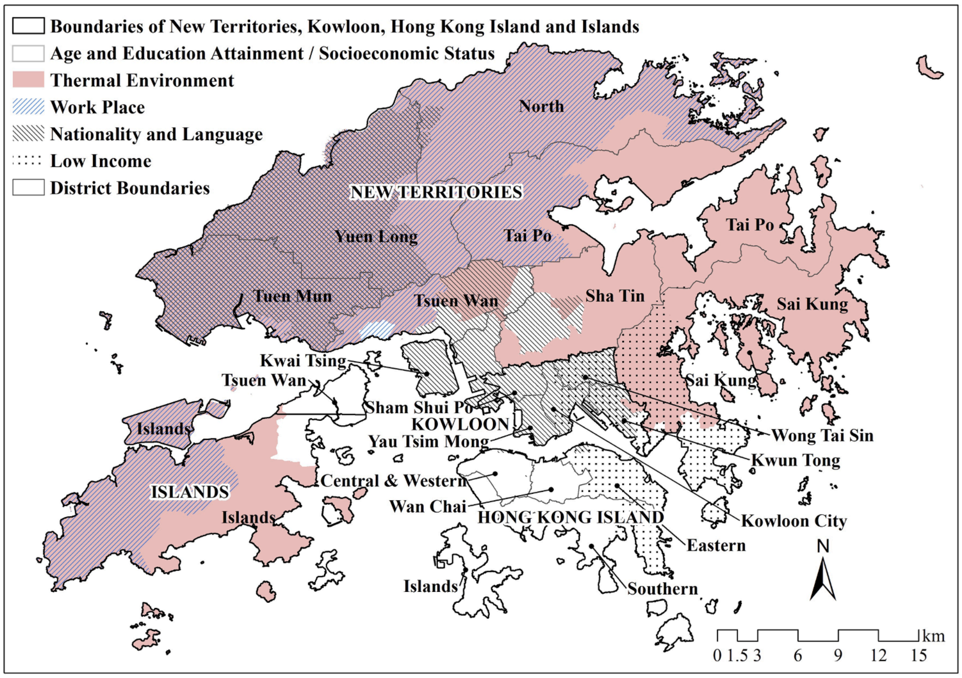

Fig. 4. Boundaries of the estimated surfaces and administrative units at different levels.

estimate surfaces, we find that the city of Hong Kong can be divided into 10 areas (Fig. 5) differing in prior concerns for heat health risk reduction. This finding helps illustrate, for specific areas, the action plans that could maximally benefit population health when under extreme heat stress. In Fig. 5, the 10 areas have been labeled 1 to 10 in the center map, and each corresponds to a small figure (labeled A1 to A10) showing the site-specific predictor variables sorted by priority. Where the thermal environment plays a leading role, such as in A2, A5, A8, A9 and, to a lesser extent, A6, physical heat management strategies designed to improve the thermal environment are expected to produce greater population health benefits than other strategies. Specific strategies focused on enhanced vegetation and surface reflectance (i.e., green walls, sidewalk greenways, reduced-albedo sidewalks and street trees), as demonstrated by previous work with great cooling effects (Park, Lee & Hyun, 2019; Zhang et al., 2019), can be the primary interventions in these hot spots. While most adaptive plans often emphasize protective strategies for people most at risk of heat-related death, our work sheds light on the spatially varying effectiveness of these plans for particular populations. The local government should extend the conventional people-based action plans that focus on heat-associated impacts on different groups of people to consider people- and place-based adaptive strategies (Wilhelmi & Hayden, 2010). Analyses such as this one, which are based on more accurate and robust results using MGWR, help delineate the vulnerable "hot spots" of different population groups. As a result of this pattern (Fig. 5), the working individuals with a residence separate from their workplace are probably more sensitive to extreme heat in A3, A5 and A9 than the other vulnerable population groups (i.e., the elderly, less-educated people, etc.). Thus, protective strategies for particular groups of workers, such as high temperature allowance and adjustment of working hours in hot seasons (Xiang, Bi, Pisaniello, & Hansen, 2013), may be most effective in reducing the local heat-related death risk. While past studies have demonstrated the importance of reducing immigrant vulnerability to heat stress (Hondula et al., 2012; Nayak et al., 2018), the present study illustrates that protective strategies for immigrants are likely to function only at specific sites (i.e., A9). Areas in A4, A6 and, to a lesser extent, A10 provide a strong counterpoint to A9, with prior concerns on the dialect speakers instead. This fact sheds light on site-specific protective actions for people suffering language barriers in response to heat stress, including more complete heat warning systems and interventions (i.e., multilingual early warnings using different methods such as online videos, booklets and warning signs) (Nastos & Matzarakis, 2012; (Reid et al., 2009); Sheridan, 2007). For low-income people, the most vulnerable groups in A7 and A8, more public spaces and free facilities such as indoor open spaces with air conditioners (i.e., libraries, community lounges) could be an adaptive option to improve their thermal comfort ((Zografos, Anguelovski, & Grigorova, 2016); Song et al., 2020). To respond to the combined effects of the thermal environment and heat vulnerability of the prevalent low-income people in A8, the local population's health could be maximally benefited by increasing the vegetative cover and albedo, which has been found to be most protective of low-income populations in past research (Vargo et al., 2016).

6. Conclusion

This study presents a novel application of MGWR to characterize the spatial context of multidimensional risk factors for heat-related mortality using the city of Hong Kong as a case study. The results show that MGWR, which considers both spatial heterogeneity and scale differences of determinant risk factors, presents a best fit of heat-related death in comparison with both GWR and OLS. While the relationships between some risk factors and heat-related mortality are invariant to location, others may vary at more regional scales, and some may vary at very local scales. These findings could help with hierarchical policy-making and site-specific planning for more targeted health interventions, heat hazard mitigation and climate adaptation strategies.

Several limitations should be acknowledged in this study. First, some variables that are treated as important factors in previous studies of other geographic regions are not included. For example, air conditioning is not included since no data are available in Hong Kong. However, due to the prevalence of air conditioners in Hong Kong, there is no significant spatial variance in air conditioning use across communities. Therefore, the corresponding variables may have limited predictive power for the spatial variance of heat-related mortality. Similar findings have been evident in some cities in Japan where air conditioner prevalence exhibits no effect modification in daily heat-related mortality (i.

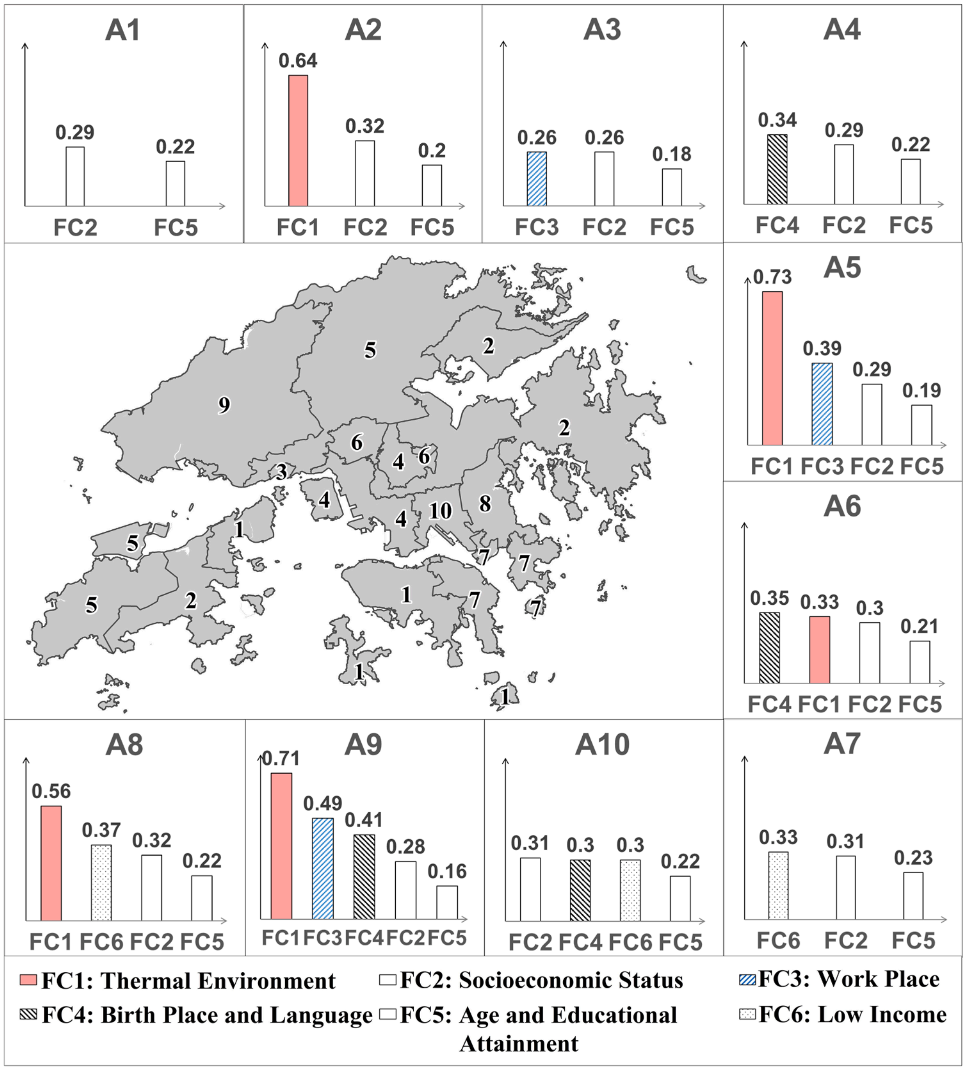

Fig. 5. Site-specific predictor variables sorted by priority: the city of Hong Kong is divided into 10 areas labeled 1 to 10 in the center map, and each corresponds to a small figure labeled A1 to A10, showing the site-specific predicator variables sorted by priority. In A1 to A10, the coefficient estimates are aggregated for the average of each area; negative coefficients are transferred to positive ones for easier comparisons of strength with the others.

e., cardiovascular, respiratory) (Ng et al., 2014). In addition, this study does not consider the effect of humidity due to the sparse distribution of monitoring stations. However, some investigations in Hong Kong have found that the effect of relative humidity was not as significant as expected (Goggins, Chan, Ng, Ren, & Chen, 2012). Air quality is another variable that was omitted from the analysis but needs further investigation in the future. Air pollutants are found to be positively associated with nonaccidental mortality. The combined effects of air pollutants and heat are also evident in past empirical research (Hu et al., 2018; Knowlton et al., 2008). However, the air pollutant monitors in Hong Kong are sparse, within which some are far away from residential areas and some are near traffic roads. The local pollutant level is unlikely to be characterized by sparsely distributed monitors in an accurate way (Heaton et al., 2014); therefore, we opted to omit pollutants from this analysis but will investigate their impacts in our future studies. As this research aims to determine the influencing factors of heat-related mortality risk and their spatial context rather than construct a perfect predictive model, omitting certain variables is not a huge issue. Second, it leaves opportunities to improve the MGWR model. Specifically, covariate-specific bandwidths and bandwidth uncertainty could be introduced to further investigate the multiscale spatial processes associated with heat-related mortality risk (Oshan et al., 2019). Third, as this study is the first attempt to apply the recent MGWR model in exploring the influencing factors of heat-related mortality risk, more empirical case studies are needed to validate and generalize the conclusions achieved here. These avenues of future work could advance our knowledge of the spatial context of heat-related mortality risk and help policy makers and urban planners build up and optimize climate action plans to address climate change-induced health risks and construct sustainable and healthy cities.

Declaration of Competing Interest

The authors report no declarations of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2021.103159.

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