



Mortality risk of a future heat event across a subtropical city: implications for community planning and health policy

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Abstract

In this study, we applied the Weather Research and Forecasting model to project 2050 urban and rural temperature. We applied a time-stratified analysis to compare it with mortality between 2001 and 2014 and between 2011 and 2014, to estimate the elevated risk of a 2050 heat event. We included change in daytime versus nighttime and urban versus rural temperatures as factors to project mortality, to evaluate the potential influence of climate change on mortality risk. Increases of 2.9 °C and 2.6 °C in maximum and minimum air temperature are projected in a 2050 heat event, with a day and a night that will have respective temperatures 9.8 °C and 4.9 °C higher than 2001–2014. Significantly higher mortality risk is forecasted in 2050 compared to 2001–2014 (IRR 1.721 [1.650, 1.796]) and 2011–2014 (IRR 1.622 [1.547, 1.701]) without consideration of temperature change. After consideration of changing temperature, change in maximum temperature in rural areas will induce the highest mortality risk during 2050, possibly due to rapid urbanization across the city, and with the second highest mortality risk induced by the change in minimum temperature in urbanized areas, possibly because local people in the city have been adapted to the maximum level of urban thermal stress during a summer day. Improvements to heat warning systems and sustainable planning protocols are urgently needed for climate change mitigation.

Keywords Projected mortality · Extreme heat · WRF · Urban health risk · Community planning · Policy implications

1 Introduction

One aspect of climate change is localized increases in the frequency, severity and intensity of extreme heat, resulting in higher population health risk in the past few decades. For better health planning in order to mitigate the effects of extreme heat, previous studies have

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projected mortality data to estimate future heat risk (Guo et al. 2016; Kim et al. 2016). However, previous studies mainly focused on discussing whether heat mortality on normal summer days declines or increases. These studies usually applied multiple assumptions for projecting mortality, for example, including factors related to acclimatization and future population in modeling. These techniques can facilitate the comparison of urban environments with and without improvement in adaptive capacity (e.g., use of air conditioners), to understand whether long-term decline will occur when humans have adapted to extreme heat. Some studies with strong focus on climate projection and modeling have also observed that long-term decline will soon occur in multiple cities or countries (Bobb et al. 2014; Gasparrini et al. 2015; Hondula et al. 2015). However, previous studies may have limitations in two aspects: (a) representativeness of tropical and subtropical cities with extensive current climate adaptation practices and (b) representativeness of extreme scenarios. It is important to note that some tropical and subtropical cities, especially the cities in high-income countries, have comprehensive strategies for extreme heat mitigation, for example, extensive use of cooling systems and application of heat warning systems (Ho et al. 2017b). Although the populations in these cities have experience with high daily temperatures, acclimatization and adaptability to extreme heat caused by high infrastructure resilience among these populations are also high. In other words, projecting mortality of normal summer days to describe excess mortality in the future may not be useful, since the mortality risk during these normal summer days may have been reduced after the first installation of heat warning systems and first application of climate change mitigation, while the key factor influencing mortality in the future should be isolated extreme heat events that can dramatically increase health risks because of a lack of public awareness and disaster risk reduction. These studies of extreme events have also been recommended by the United Nations Office for Disaster Risk Reduction (UNDRR), because past catastrophic environmental hazards such as earthquakes across China have demonstrated to the public that a lack of preparation will dramatically increase the mortality. More importantly, similar fatal effects due to extreme heat events have been discussed extensively in historical studies (Ho et al. 2017a; Heaviside et al. 2016; Krstic et al. 2017). For example, a heat wave across Europe during 2003 increased mortality by 70% in Paris and 20% in London (Mitchell et al. 2016), and an extreme heat event in 2009 caused 40% more deaths in Vancouver within a 7-day period (Kosatsky et al. 2012). Under the influence of climate change (Lee et al. 2014; Li et al. 2017; Sun et al. 2014), more health problems are expected during extreme heat events before human adaptation, when local populations lack comprehensive plans for disaster risk reduction.

In addition, past studies have generally used temperature results of macroscale models, such as climate projections using a general circulation model (GCM), to predict future heat mortality risk (Mitchell et al. 2016; Guo et al. 2016). Due to the coarse spatial resolution (> 15 km), GCM models are unable to consider the urban heat island (UHI) effect, which exacerbates the human thermal stress across an urban region, and thus inadequately analyze the relationship between an urban environment and health risk during an extreme heat event. Since the UHI effect can be enhanced through the difference between daytime and nighttime temperature, missing data such as daytime and nighttime temperature information from the modeling can result in failure to estimate the mortality risk during an extreme heat event appropriately. It is important to note that understanding the key temperature influencing future mortality is essential for developing a better public health surveillance system, because the previous literature on historical heat events has observed the importance of using a key temperature for establishing heat health warnings and for identifying vulnerable areas that need to apply sustainable planning (Chau et al. 2009). More importantly, mortality projections with different

temperature metrics and retrieved from urban versus rural stations are expected to be different, while the representativeness of these projections for heat mortality estimation has not yet been investigated. These issues have been discussed in previous studies of historical heat events, in which using different temperature metrics to evaluate heat mortality may influence the results (Barnett et al. 2009; Davis et al. 2016; Hajat et al. 2010; Zhang et al. 2012).

Therefore, we should focus on studying future heat mortality with: (1) application of finer-resolution spatial information to represent variations in temperature and UHI; (2) prediction of elevated mortality during an extreme heat event in the future without consideration of temperature influence; and (3) comparison of the elevated mortality risk of this extreme heat event when influence of temperature change is considered.

2 Study area

This paper reports on a study with the three perspectives above, with Hong Kong selected as our case. Hong Kong and its surrounding areas have recently been found to have an increasing number of extremely hot days (> 35 °C) and significant heat mortality (Chan et al. 2012; Ho et al. 2017b; Ma et al. 2014; Wei and Chen 2009; Yi and Chan 2015). Air temperature and UHI effect have also been predicted to be much higher across the city in the future (Nichol et al. 2014). Due to the high-density environment of this subtropical city, the UHI effect has highly influenced the mortality in urban areas in Hong Kong during extremely hot days (Goggins et al. 2012), while variation in daytime and nighttime temperatures may also influence heat mortality across this city (Tam et al. 2009). In general, higher daytime temperature may be found in rural areas across Hong Kong, while urban areas in Hong Kong can be much hotter than rural areas during the night. Distributions of daytime and nighttime temperature are also changing across the years due to climate change and urbanization. Therefore, future scenarios in Hong Kong (e.g., a heat wave in 2050) may be very different than such scenarios at present.

In order to target our study to a Hong Kong scenario particularly, our objectives included: (1) prediction of hourly air temperature within a 14-day extreme heat event in 2050; (2) projection of the mortality relevant to the selected extreme heat event; (3) estimation of the excess mortality during this extreme heat event through comparison with current years; and (4) evaluation of the temperature–mortality relationship influenced by temperature at different times and locations (e.g., urban and rural). The reason for choosing 2050 as our case study is that the World Health Organization (WHO) has forecast 250 000 additional deaths per year due to climate change between 2030 and 2050, including 38,000 additional deaths caused by extreme heat events among older people. Recent studies have also documented that heat waves in 2050 will cause increasing heat-related deaths (Stone et al. 2014; Wang et al. 2018). Therefore, the ultimate goal of this study is to conduct a complete survey with the objectives above that can be applied to develop protocols of public health surveillance.

3 Data and methods

3.1 Temperature projection for future heat wave

In this study, air temperature of an extreme heat event in 2050 across Hong Kong was predicted by the Weather Research and Forecasting (WRF) model. WRF is an advanced climatic model that can be used for both research and operational forecasting, especially to map air temperature with moderate spatial resolution (1 km) that is more appropriate for a city-level study compared to GCM models (Chen et al. 2014; Nemunaitis-Berry et al. 2017). Particularly, we used the WRF model to dynamically downscale Community Earth System Model version 1 (CESM1) projections.

This study first adopted CESM1 climate data from phase 5 of a Coupled Model Inter-comparison Experiment (CMIP5) under a RCP forcing scenario 8.5 (Monaghan et al. 2014); scenario 8.5 represents a very extreme meteorological case, and the use of this scenario helps analyze the impacts of intensive fossil fuel consumption with excessive emissions of greenhouse gases, under the condition of limited computational resources such as not processing data with cloud computing. The CESM1 data are interpolated to 26 vertical pressure levels, are at approximately one-degree grid spacing, and are available at 6-h intervals. In addition, we followed Bruyère et al. (2014) to bias-correct all variables using the European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Reanalysis (ERA-Interim) fields for 1981–2005.

In order to estimate the air temperature under the UHI effect, we applied the WRF model (version 3.8) coupled with a single-layer urban canopy model (Miao et al. 2011; Tewari et al. 2010; Wyszogrodzki et al. 2012). This single-layer urban canopy model (SLUCM) can represent the thermal dynamic effects of urban areas by including urban geometry as a variable in its surface energy budgets and wind shear calculations (Kusaka and Kimura 2004). The SLUCM was coupled to the Noah land surface model, which can provide surface sensible and latent heat fluxes as well as surface skin temperatures as the lower boundary conditions to the WRF model (Chen and Dudhia 2001). Other physical parameterizations were also used in WRF modeling, including the Yonsei University (YSU) planetary boundary layer (PBL) scheme (Noh et al. 2003), Dudhia shortwave radiation scheme (Dudhia 1989), and RRTM longwave radiation scheme (Mlawer et al. 1997).

Initial and boundary conditions for the outermost domain covering our study area were obtained from the CESM1 dataset above. The simulations were made over four-nesting domains with grid spacing of 27, 9, 3 and 1 km, and 118×112 , 109×91 , 91×73 and 139×139 grid points, respectively. There were 31 vertical sigma levels up to 100 hPa and 8 levels below 1 km to better resolve the processes in the planetary boundary layer. In addition, the MODIS global land cover products (MOD12) with 500-m resolution were used to represent the distribution of rapidly urbanized areas for modifying the UHI effect, and an anthropogenic heat of 50 W m^{-2} was set in this study because this value was reported as an important factor to better capture the spatial variance of surface temperature for WRF simulation (Miao et al. 2011; Zhong and Yang 2015). The resulting air temperature of this WRF simulation was in 1-km resolution covering the whole Pearl River Delta region. The predicted map was validated with observed air temperature data, and our result was found to have high accuracy. Mean bias (MB), root mean square error (RMSE), and normalized mean error (NMS) of this model were $0.01 \text{ }^\circ\text{C}$, $0.53 \text{ }^\circ\text{C}$, and 0.14% , respectively. Based on the WRF result, the dates between Jul. 4–17, 2050, were identified as days with a predicted extreme heat

event, and therefore, this time period was selected for our case study. We extracted the urban and rural hourly temperatures based on the locations of Hong Kong Observatory and Ta Kwu Ling's weather station for further analyses.

3.2 Mortality risk estimation

Mortality data were retrieved from the Hong Kong Census and Statistics Department, specifically the variables of date of death and causes of death (ICD-10). Since the heat warning system of Hong Kong was first established in 2000, we only used summer mortality data (Jun.–Sept.) of 2001 through 2014, to minimize the bias of the data projection (Chau et al. 2009). In addition, missing information of date of death was replaced with the remarked information (e.g., date of certified death) to maintain the statistical accuracy of the “big data” for mortality projection. This forms a mortality dataset with 166,473 decedents, which was merged with the hourly temperature data from Hong Kong Observatory based on the date of death.

In addition, there are four types of temperature of interest in this study, including: (1) urban daytime temperature ($T_{\text{urban-max}}$), (2) urban nighttime temperature ($T_{\text{urban-min}}$), (3) rural daytime temperature ($T_{\text{rural-max}}$), and (4) rural nighttime temperature ($T_{\text{rural-min}}$). Daytime temperature was represented by the daily maximum temperature, and nighttime temperature was represented by the minimum temperature. Urban temperature was measured by the weather station at the headquarters of the Hong Kong Observatory located in the urban center, while rural temperature was measured at the Ta Kwu Ling station (Fig. 1).

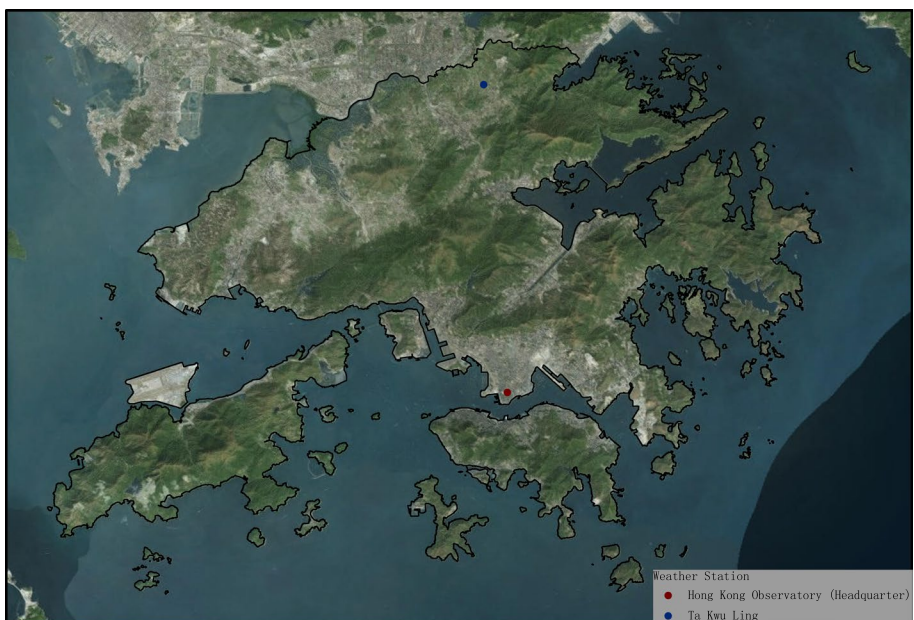


Fig. 1 Study area. Area within the black boundary indicates the location of Hong Kong. Red dot indicates the urban station at headquarters of the Hong Kong Observatory. Blue dot indicates the rural station at Ta Kwu Ling

We projected the mortality to a 2050 scenario based on a multivariate linear regression with all-cause mortality data during summer (Jun.–Sept.) of 2001 through 2014, excluding 14 days with missing weather information:

$$\text{Death Count}(t) = \beta_0 + \beta_1 \text{Day} + \beta_2 \text{Month} + \beta_3 \text{Year} + \beta_4 \text{Ta}(t) + \beta_5 \text{Weekday/Weekend}(t).$$

where death count is the total number of deaths on a summer day (t) between June and September, Day, Month, and Year are the day, month, and year of the summer date, Ta is the temperature of interest, and Weekday/Weekend is a binary variable to control for the weekday–weekend effect.

In brief, this method is designed to reduce potential bias of assumptions (e.g., future population) for mortality projection. It has been observed by census that Hong Kong has a fast growing population due to immigration and socioeconomic change; therefore, assuming future population in projecting mortality for such a city with high-population dynamics is not practical. As an alternative, the year of the summer date is to control for the potential increase in mortality due to undefined socioeconomic change; while month is a control for seasonal change, which has also been observed to be a factor associated with community health issues. Day of a month is a control of occupational factor, in which the human behavior due to the work cycle of a month may also affect health.

We repeatedly projected the mortality based on all temperatures of interest, and these projected data above were then compared with the baseline mortality estimated without consideration of change of temperature, as below.

$$\text{Death Count}(t) = \beta_0 + \beta_1 \text{Day} + \beta_2 \text{Month} + \beta_3 \text{Year} + \beta_5 \text{Weekday/Weekend}(t)$$

Based on all projected mortality datasets, we applied a time-stratified analysis to estimate the elevated mortality risk of each scenario. Time-stratified analysis is a common method for estimating excess mortality during an extreme weather event, especially to study mortality risk based on isolating a specific heat wave period (Bell et al. 2008; Kosatsky et al. 2012). Following previous studies to reduce selection bias of the control period, we estimate the excess mortality during Jul. 4–17, 2050 (case), by comparing it with two sets of control periods: (1) the same calendar weeks as the case period of 2001 through 2014 and (2) the same calendar weeks as the case period of 2011 through 2014 under the recent climate impact. A Poisson generalized linear regression run with the `glm2` package of R software was used in this time-stratified analysis:

$$\text{logit}(\text{Death Count}) = \beta_0 + \beta_1 \text{Case}$$

where death count is the total number of deaths on a summer day within the case and control periods and case is a binary variable indicating case days or control days. Weekday/weekend effect is not included as a confounder because our study period was a 14-day period that inclusively controlled for such an effect (Kosatsky et al. 2012). Incidence rate ratio (IRR) and its 95% confidence intervals were used to estimate the elevated mortality during the 2050 period compared to the control periods.

In this study, the IRRs estimated by projected data with consideration of temperature were compared with the IRR of the baseline scenario without inclusion of temperature change in the projection. For IRR and CIs higher than the baseline, we considered this to be the scenario with significantly higher mortality risk contributed by temperature change.

4 Results

4.1 Temperature variations of 2050 heat event and control period (2001–2014)

During Jul. 4–17, 2050, T_{\max} and T_{\min} averaged from two representative weather stations (Hong Kong Observatory and Ta Kwu Ling) will be 34.8 °C and 28.9 °C, respectively. These T_{\max} and T_{\min} are expected to be on average 2.9 °C and 2.6 °C higher than the same calendar days of 2001 through 2014 and on average 2.8 °C and 2.6 °C higher than the same calendar days of 2011 through 2014 under the impact of recent climate change (Fig. 2). The strongest effect of heat wave is expected to occur during the night of Jul. 16, 2050, with overall T_{\min} (average of two representative stations) 4.4 °C higher than the lowest overall T_{\min} of this 2050 extreme heat event, resulting in an extremely high daytime temperature (overall T_{\max} 41.3 °C) on Jul. 17, 2050, that is 7.9 °C higher than the lowest overall T_{\max} within these 14 days. In addition, overall T_{\min} on Jul. 16, 2050, is 4.9 °C higher than the average of overall T_{\min} of Jul. 16, 2001 through 2014, while overall T_{\max} on Jul. 17, 2050, is 9.8 °C higher than the average of overall T_{\max} of Jul. 17, 2001 through 2014.

In addition, a significant difference in urban and rural temperatures is projected within this 14-day extreme heat event. Based on the urban and rural stations, we found that $T_{\text{urban-max}}$ is usually lower than $T_{\text{rural-max}}$ between 2001 and 2014 and during 2050 (predicted), while $T_{\text{urban-min}}$ is generally much higher than $T_{\text{rural-min}}$. This is consistent with a previous study which showed that nighttime temperature in Hong Kong is more representative of the urban heat island than is the daytime temperature (Nichol and To 2012), possibly due to the effect of energy absorption and release across high-density and high-rise built environment across this compact city (Ho et al. 2019; Peng et al. 2017). During the forecast 2050 extreme heat event, $T_{\text{urban-min}}$ is on average 1.9 °C higher than $T_{\text{rural-min}}$, while the difference of urban and rural temperatures may be even more significant in various locations, based on the landscape and elevation (Fig. 3).

4.2 Projected mortality and future heat risk

There is a moderate increasing trend of mortality from 2001 through 2014 (Fig. 4). Based on the mortality projection, each year will have 1.7 more deaths on a summer day (p value < 0.05) controlling for the day, month, and weekday/weekend effects, while approximately 2413 deaths are expected within 14 days of this 2050 extreme heat event, without considering the temperature in the projection. After separately including $T_{\text{urban-max}}$, $T_{\text{urban-min}}$, $T_{\text{rural-max}}$, and $T_{\text{rural-min}}$ in the mortality projection, the expected number of decedents between Jul. 4 and Jul. 17, 2050, changes to be approximately 2413, 2423, 2746, and 2417 deaths.

Resulting from the time-stratified analysis, all-cause mortality risk of this extreme heat event will be significantly higher than that of 2001–2014 (Table 1), even without considering temperature change in the mortality projection (IRR 1.721 [1.650, 1.796]). There will also be significantly higher mortality during 2050 compared to the years of 2011 through 2014 under the impact of recent years (IRR 1.622 [1.547, 1.701]). These IRRs above are defined as the baseline increase in heat risk without considering the climate change in mortality projection.

When we consider the impact of temperature change across the city in the mortality projection, a significant difference in mortality risk is found. In brief, change

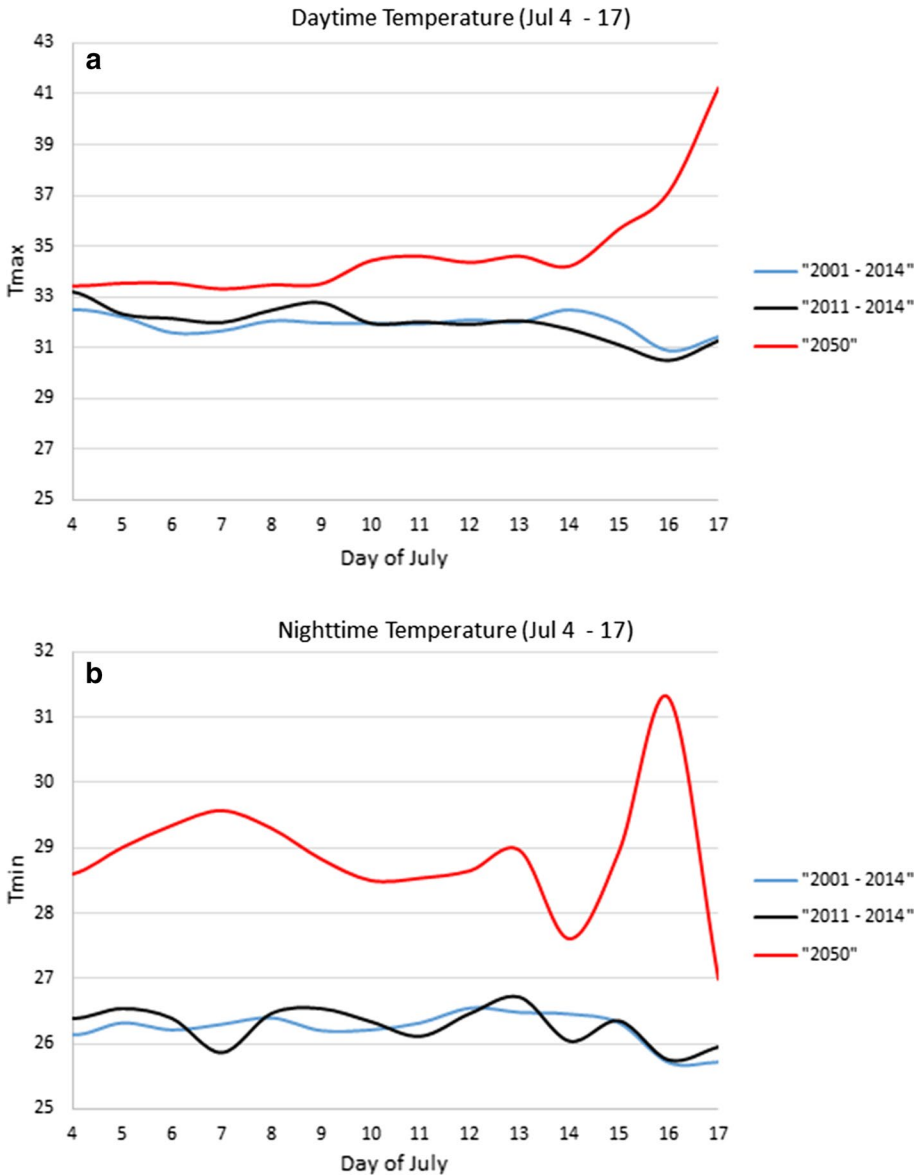


Fig. 2 Comparison of daytime and nighttime temperature between 2050 and 2001–2014. **a** (top) shows the daytime temperature during Jul. 4–17. **b** (bottom) shows the nighttime temperature during Jul. 4–17. Red lines of all figures show the trend of temperature during Jul. 4–17, 2050. Blue lines show the trend of temperature during Jul. 4–17, 2001 through 2014. Black lines show the temperature trend during Jul. 4–17, 2011 through 2014

in $T_{\text{rural-max}}$ through the years can result in the highest influence on heat risk during this future extreme heat event. Based on the time-stratified analysis, IRRs estimated by the projected mortality data including influence of $T_{\text{rural-max}}$ for comparisons with mortality between 2001–2014 and 2011–2014 were 1.959 [1.882, 2.031] and 1.846

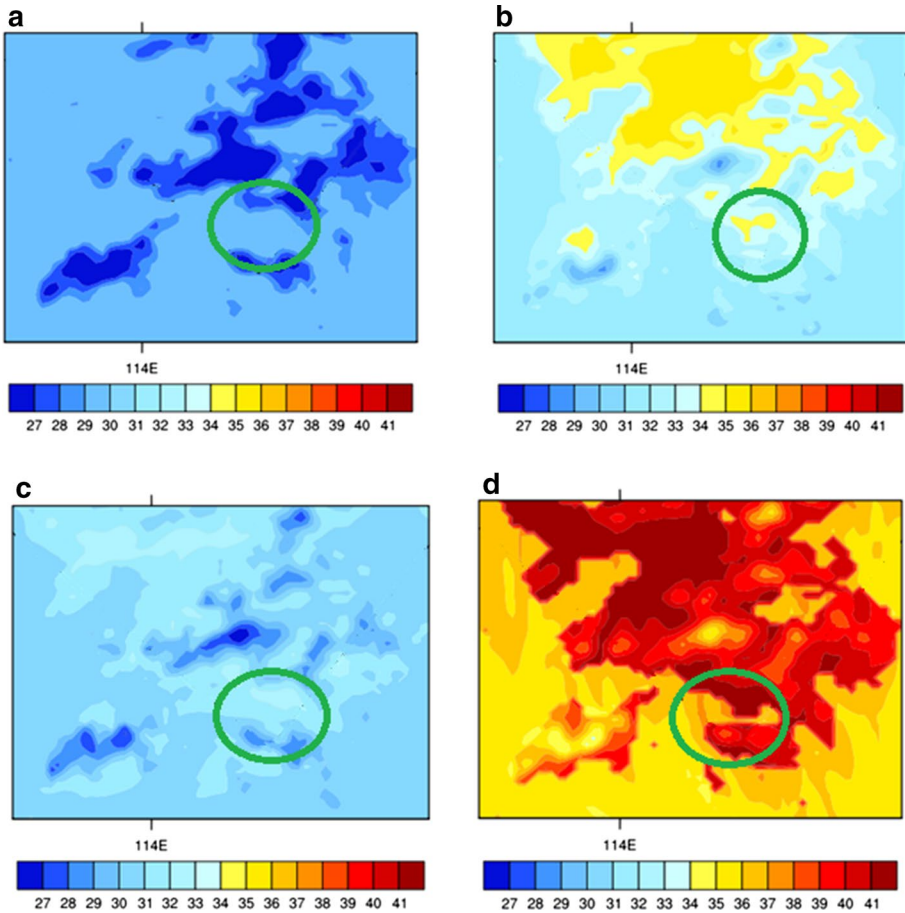


Fig. 3 Air temperature distribution predicted by WRF model. **a** (left top) shows the average minimum temperature of Jul 4–17, 2050. **b** (right top) shows the average maximum temperature of Jul 4–17, 2050. **c** (left bottom) shows the minimum temperature of Jul 16, 2050. **d** (right bottom) shows the maximum temperature of Jul 17, 2050. Green circles indicate the urban areas of Hong Kong

[1.764, 1.931], and both were significantly higher than the baseline mortality risk. There is also a significant urban/rural difference in the temperature–mortality relationship. While increasing daytime temperature across rural areas will result in the highest risk, mortality risk in urbanized areas is shown to have a stronger relationship with the increase in minimum temperature. Compared with the mortality data between 2001–2014 and 2011–2014, IRRs estimated based on mortality data with influence of $T_{\text{urban-min}}$ were 1.728 [1.656, 1.802] and 1.628 [1.553, 1.707], which were significantly higher than the baseline mortality risk. In contrast, mortality risk estimated based on the projected data with the effect of $T_{\text{urban-max}}$ change had no significant difference on the baseline mortality risk.

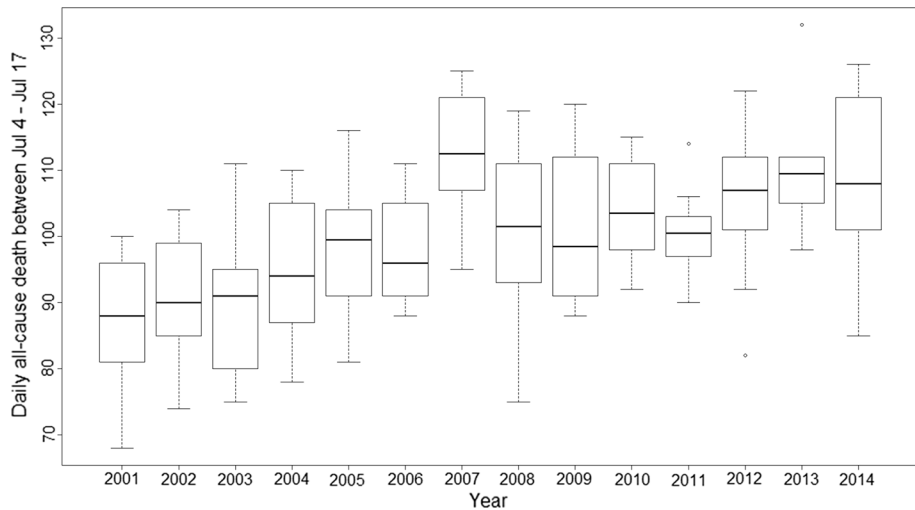


Fig. 4 Boxplot of daily mortality change (Jul. 4–Jul. 17) of 2001 through 2014. The Y-axis indicates the variation in daily mortality between Jul. 4 and Jul. 17 of each year, and X-axis indicates the variation between 2001 and 2014

Table 1 Heat risk estimated by projection of mortality data with daytime and nighttime temperatures of urban weather station at Hong Kong Observatory and rural weather station at Ta Kwu Ling

Mortality risk based on projected data	OR (2050 compared to 2001–2014)	OR (2050 compared to 2011–2014)
Without inclusion of temperature	1.721 [1.650, 1.796]	1.622 [1.547, 1.701]
Including $T_{\text{urban-max}}$ for projection	1.721 [1.650, 1.795]	1.622 [1.547, 1.701]
Including $T_{\text{urban-min}}$ for projection	1.728 [1.656, 1.802]	1.628 [1.553, 1.707]
Including $T_{\text{rural-max}}$ for projection	1.959 [1.882, 2.038]	1.846 [1.764, 1.931]
Including $T_{\text{rural-min}}$ for projection	1.724 [1.653, 1.798]	1.625 [1.550, 1.703]

All odds ratios (OR) and 95% confidence intervals were estimated

5 Discussion

5.1 Summary of results

This study demonstrated an assessment of the combining results of WRF modeling and mortality projection to estimate future heat risk during an isolated heat event in 2050. There are significant increases in both temperature and mortality during 2050. Without consideration of the temperature increase, the baseline mortality risk is still 72.1% higher than the years of 2001 through 2014 and 62.2% higher than the years 2011 to 2014, if the trend of population growth of the control period (e.g., immigration, socioeconomic change) will continue in the future. While temperature change is included in the mortality projection, increase in daytime temperature across rural areas is shown to be the factor that can induce the highest mortality risk (IRR 1.959 [1.882, 2.038]), while projected mortality with the inclusion of increase in daytime temperature across urbanized areas as a factor has no significant difference in the baseline mortality. As Hong Kong has been well

recognized as a city with high infrastructure resilience (Sim et al. 2018), these projected results may be due to the consequences of human behavior, in which the population in a high-density city has been adapted to the maximum level of urban thermal stress during a summer day. It is also related to the rapid urbanization of the city and a progressive formation of urban agglomeration (“Guangdong-Shenzhen-Hong Kong”), in which (1) maximum temperature across a suburban/rural area is increasing much faster than the ability of human adaptation and (2) urban minimum temperature is also increasing due to the nighttime UHI effect resulting in an increasing minimum level of urban thermal stress higher than the level of resilience. Therefore, change in urban maximum temperature may not have a significant influence on health burden among local citizens, while change in urban minimum temperature (also representing the baseline of thermal distress across urbanized areas) can induce a higher health burden on an urban population. Based on these findings, a better health-planning protocol is needed in order to mitigate the heat mortality risk before the occurrence of the next extreme weather event.

5.2 Implications of community planning and health policies

In order to reduce the heat health risk, there are already plans to enhance adaptive capacity in both Hong Kong and other cities around the world, for example, extensive use of cooling systems (e.g., air conditioners), urban greening, and application of heat warning systems to monitor extreme temperatures. However, there are some worldwide issues of using such adaptive strategies, and thus, these strategies should be improved before the occurrence of future heat events. For example, it has been widely discussed that the representative weather stations of a city may not be able to appropriately indicate extreme heat across urbanized areas, especially for airport-based weather stations (Basu 2009). There are also studies showing that air temperature of representative weather stations can be much lower than the temperature in urbanized areas with high population (Ho et al. 2014; Stewart et al. 2017). These studies are also consistent with our findings, in which temperature reported by urban and rural stations in Hong Kong can result in significant differences in heat risk prediction. Therefore, future planning should examine the appropriate locations to measure air temperature across a city in the future, for the purpose of developing a better heat warning system that can be of greater benefit to the city population. There is also a need to re-examine the uses of different temperature metrics for heat warning systems as carried out in previous studies (Davis et al. 2016; Ho et al. 2017a), because different types of temperature change have had different results in terms of mortality risk based on mortality projection. Using Hong Kong as an example, we may need a heat warning system with multiple representative stations that can detect heat risks in both urban and rural areas, with a focus on using $T_{\text{urban-min}}$ to estimate urban heat severity in order to accurately predict health risk across high-population areas. Following advances in technology, innovative applications such as “Smart City” and volunteered geographic information (VGI) should be applied to the city for community planning and real-time monitoring (Al-Hader and Rodzi 2009; Goodchild 2007). There have been cases in Asia (e.g., Tainan, Taiwan; and Singapore) in which multiple real-time sensors have been implemented across a city for a “top-down” (top-to-bottom) strategy in air quality monitoring along the “Smart City” guideline. This application can be used in other high-density cities such as Hong Kong for better monitoring of ambient temperature along different districts. Apart from that, Hong Kong Observatory has applied different strategies for improving the spatiotemporal coverage of weather stations, for example, to develop the “Hong Kong Community Weather Information

Network” with schools and local communities. However, how it can be integrated with better protocols for disaster risk governance may prove to be a greater challenge, including integration with the “Smart City” concept so that citizens can receive accurate and near real-time weather information for their location(s) by way of the location-based service of mobile phones and a comprehensive weather network.

In addition, it is also necessary to have urban redevelopment with sustainable planning protocols before 2050 for climate change mitigation, for example, improvement in urban greenery, enhancement of air ventilation systems, and relocation of emergency facilities. Specifically, further study should be conducted based on the perspective above, by re-projecting the air temperature with different urban morphological settings under sustainable urban plans. New temperature projections based on different sustainable plans can be used to re-estimate heat health risks in 2050. By comparing the heat risks predicted by the current study and such new research, we can determine which sustainable urban plan(s) can more greatly reduce the health burdens during an extreme heat event in the coming decades.

5.3 Limitations

Finally, there are limitations of our study. One is that we did not include air pollutants as confounding factors to predict future mortality. This is because projecting air pollution is limited by existing methods (e.g., GCM), so the projected pollution can only represent a macroscale scenario. However, previous studies have shown significant variation in air pollution across a high-density environment (Lee et al. 2017; Shi et al. 2018). This indicates that using macroscale modeling for air pollution projection may induce statistical biases in heat risk prediction. A well-developed study projecting fine-scale air pollution should be conducted before integrating the pollution information for mortality estimation.

Another limitation of this study is the consideration of the population at all ages instead of only seniors or the aging population, which are commonly identified as the groups vulnerable to heat mortality. This is due to the limitation of the demographic structure in current years in Hong Kong, in which immigration has been a major part of the growing population recently. Therefore, stratifying the aging population for mortality projection may not be appropriate. In addition, a local study has previously found that young seniors, not older seniors, were the vulnerable population group in Hong Kong (Chan et al. 2012). Therefore, simply projecting the aging population may induce bias in mortality estimation. As an alternative, future research should re-examine the association of vulnerable population(s) and heat risk every five years, and re-define which vulnerable population should be used in projections for disaster risk reduction.

6 Conclusion

In this study, we studied the mortality risk during a forecast extreme heat event in 2050. Higher mortality risk during an extreme heat event is forecasted if additional plans for climate change mitigation are not applied to this subtropical, high-density and urbanized city. Particularly, we included change in daytime versus nighttime and urban versus rural temperatures as factors to project mortality and to evaluate the potential influence of climate change on mortality risk. Based on the analyses, increases of 2.9 °C and 2.6 °C in maximum and minimum air temperature are projected in a 2050 heat event, with a day and a night that will have respective temperatures 9.8 °C and 4.9 °C higher than 2001–2014. Significantly

higher mortality risk is forecasted in 2050 compared to 2001–2014 (IRR 1.721 [1.650, 1.796]) and 2011–2014 (IRR 1.622 [1.547, 1.701]) without consideration of temperature change. After consideration of changing temperature, change in maximum temperature in rural areas will induce the highest mortality risk during 2050, possibly due to rapid urbanization across the city, and with the second highest mortality risk induced by the change in minimum temperature in urbanized areas, possibly because local people in the city have been adapted to the maximum level of urban thermal stress but not the minimum level of urban thermal stress during a summer day. Based on these results, it is observed that a heat warning system with multiple representative stations is needed in order to measure heat risk in both urban and rural areas appropriately, and a sustainable urban planning protocol following the guidelines of Smart City with climate change mitigation strategies should be conducted before 2050 to reduce heat mortality in such high-population urbanized areas.

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