Green Space and Deaths Attributable to the Urban Heat Island Effect in Ho Chi Minh City

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Objectives. To quantify heat-related deaths in Ho Chi Minh City, Vietnam, caused by the urban heat island (UHI) and explore factors that may alleviate the impact of UHIs.

Methods. We estimated district-specific meteorological conditions from 2010 to 2013 using the dynamic downscaling model and calculated the attributable fraction and number of mortalities resulting from the total, extreme, and mild heat in each district. The difference in attributable fraction of total heat between the central and outer districts was classified as the attributable fraction resulting from the UHI. The association among attributable fraction, attributable number with a green space, population density, and budget revenue of each district was then explored.

Results. The temperature–mortality relationship between the central and outer areas was almost identical. The attributable fraction resulting from the UHI was 0.42%, which was contributed by the difference in temperature distribution between the 2 areas. Every 1-square-kilometer increase in green space per 1000 people can prevent 7.4 deaths caused by heat.

Conclusions. Green space can alleviate the impacts of UHIs, although future studies conducting a heath economic evaluation of tree planting are warranted. (*Am J Public Health.* 2018;108:S137–S143. doi:10.2105/AJPH.2017.304123)

See also Hondula et al., p. S62.

The urban heat island (UHI) is a well-documented phenomenon[1] in which the temperature of an urban area is warmer than that of the surrounding rural area. The factors that cause the UHI effect include differences in land use (e.g., green space, impermeable space),[2] surface properties (e.g., surface roughness, albedo, emissivity), geometry,[3] and anthropogenic heat release[4] between urban and surrounding rural areas. The UHI effect can also be observed within a city (i.e., when the inner city is warmer than the outer city). People living in urban areas, especially the inner areas of cities, are subsequently exposed to excessive heat. From a health perspective, this is concerning because it can increase heat-related mortality and morbidity risks. More than half of the global population lives in urban areas, and this proportion is expected to rise to 85% by 2100.[5] Therefore, the impact of UHIs on human health could be substantial and will likely be amplified in the future.

In this study, we focused on the UHI effect within a city. Previous studies have investigated heat-related mortality variations within particular cities; however, they either lack spatial temperature data at finer scales (such as at the district level within a city)[6–8] or neglect district-specific mortality.[9] This has hindered their ability to compare the mortality–temperature association between the central and outer districts of the same city. In addition, to our knowledge no study has directly quantified the magnitude of the UHI effect on mortality (i.e., the number of deaths attributable to the UHI effect). City authorities are now considering some UHI mitigation activities, such as land-use planning and tree planting.[10] These activities, however, need to be supported by empirical studies that can answer questions such as "To what extent does the UHI effect cause mortality?" and "To what extent can the planting of trees/green space prevent deaths caused by the UHI effect?" Here, we examine these questions by quantifying the deaths attributable to the UHI effect in Ho Chi Minh (HCM) City, Vietnam, and exploring factors that may alleviate UHI impacts. HCM City is a tropical megacity undergoing rapid urbanization, and it is the most populous city in Vietnam; thus, it offers an interesting setting for this study.

METHODS

HCM City, located in southern Vietnam, is one of Vietnam's most populous cities, with more than 7 million inhabitants, accounting for 8.4% of Vietnam's total population in 2012. HCM City has an extremely dense population, with about 2660 people per square kilometer. According to the Köppen–Geiger classification, HCM City has a tropical wet and dry climate, experiencing high annual average temperatures and 2 distinct seasons: the rainy season and the dry season. The rainy season occurs from May to November, with an average rainfall of about 1800 millimeters and about 150 rainy days per year.[11] The dry season occurs from December to April. The annual average temperature is 28°C, with little variation throughout the

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year, and the city experiences between 2400 and 2700 hours of sunshine per year.[11]

Data Source and Quality

In 1992, Vietnam introduced a national system for collecting mortality data: the A6 Mortality Reporting System. The A6 mortality system has been described in detail elsewhere.[12] Put simply, in the A6 system the mortality data are first collected at a community health center level and are then forwarded to district, provincial, and central levels. Previous studies have validated the data from the A6 system, demonstrating that they are of good quality.[13,14] In this study, we obtained data from the HCM City health department for January 1, 2010, through December 31, 2013, which included data from 322 community health centers in 24 districts of HCM City. The data contain 101 897 mortalities, with information about the date of death, sex, age, and cause of death as classified by the *International Classification of Diseases, 10th Revision* (http://apps.who.int/classifications/icd10/browse/2016/en).

Meteorological data were collected from the 7 weather stations of the Hydro-Meteorological Data Center of Vietnam. Weather data, including air temperature, relative humidity, wind speed, wind direction, and air pressure, were collected during April of each year from 2009 to 2011. Meteorological data were used to evaluate the performance of the dynamic downscaled model, and the result of this validation is presented elsewhere.[15]

Dynamic Downscaling With a Regional Weather Model

We used the Weather Research and Forecasting (WRF) model to dynamically downscale the meteorological conditions of HCM City. The WRF model is a next-generation, mesoscale numerical weather prediction model, designed for both atmospheric research and weather forecasting.[16] The model can simulate a wide range of atmospheric phenomena at scales ranging from meters to thousands of kilometers, using real data (observations and analyses) as initial and boundary conditions. In our study, the initial and boundary conditions were generated from final operational global analysis data from the National Centers for Environmental Prediction.

In addition, the WRF model was coupled with the single-layer urban canopy model (UCM).[17] The UCM is specially designed to represent the physical processes on urban surfaces, and a combination of the UCM and the WRF model has been successfully used to simulate UHI phenomena in megacities.[18,19] In this study, the WRF–UCM was conducted under the nesting model at the finest possible resolution, 2 × 2 kilometers, which is enough to capture the district level of HCM City. We included geographic characteristics (e.g., near a lake), land use (e.g., green space and impermeable space), surface properties (e.g., surface roughness, albedo, and emissivity), and anthropogenic heat release data in the WRF–UCM to estimate weather variables from 2010 to 2013, which is consistent with the period of daily mortality. For the technical details of the WRF–UCM used in this study, please refer to our previous publications.[15,18]

Statistical Methods

Steps for analysis. First, we calculated the daily mean surface air temperature from 2010 to 2013 for each district within HCM City using the simulated results of the WRF–UCM.

Second, for each district, we examined the association between daily spatial temperature and mortality, following a 2-stage model (details are provided in the "Two-stage model" section); we then calculated the attributable fraction (AF) and attributable number (AN) of mortalities resulting from total heat, extreme heat, and mild heat, using the method described by Gasparrini and Leone.[20] For a given temperature exposure intensity x, a general definition of AFx and ANx is as follows:

$$AFx = 1 - \exp(-\beta x) \quad (1)$$

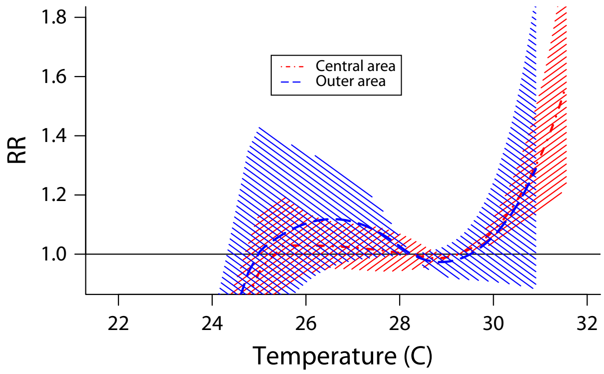
$$ANx = n^{*}AFx, \quad (2)$$

where n is the total number of cases and βx is obtained from a regression model that refers to the risk associated with exposure intensity, x, compared with a reference value, x_0. In this study, we used the 75th percentile of temperature as x_{00}, and x ranged from the 75th to the 99th percentile when calculating the AF and AN resulting from mild heat. The 75th percentile is a good estimate of the minimum mortality temperature in the pooled temperature and mortality curve (Figure 1). We chose the 99th percentile as x_0, and x ranged from the 99th to the 100th percentile when calculating the AF and AN resulting from extreme heat. Then, the total heat of AF and AN were the sum of mild and extreme AF and AN heat, respectively. The advantage of this method[20] is that we could consider the lag effect of temperature on mortality when calculating the AF and AN. For example, the AF of high temperature today (i.e., the 99th percentile of temperature) compared with the 75th percentile temperature at lag 0–2 would be estimated by $1 - exp[-(B_0 + B_1 + B_2)]$, where B_i is the risk of today's temperature causing mortality at $i = 0, 1, 2$ days ahead. The AN of today's temperature would then be estimated by AF ∗ the average of number of deaths 3 days before the current day.

Third, assuming that the heat effect is same between central districts (central area) and outer districts (outer area), we defined the difference between mean AF resulting from total heat between the 2 regions as AF resulting from the UHI effect. This definition was adopted from the previous definition, which stated that the UHI index is the difference between urban and rural air temperatures.[1] To determine whether the UHI effect is statistically significant, we produced a linear regression model with AF of total heat as the dependent variable and UHI category as the independent variable. The formula for this is $AF_i = \alpha + B{*}UHI$, where i is the district number (ranging from 1–24), and the *UHI* variable has 2 values (center or outer).

Finally, we conducted linear regression analysis among AF, AN with a green space area in square kilometers, green space fraction, population density, and budget revenue (i.e., the revenue of the government from domestic production, business and service establishments or citizens, and other revenue from abroad) of each district. The green space area was identified from satellite images with a resolution of 30 × 30 meters. The green space fraction was the percentage of the total district area occupied by green space.

Two-stage model. In the first stage, we used a standard time-series quasi-Poisson regression linking daily mortality (i.e., response or outcome) with daily average temperature



Note. RR = relative risk. The red line is the pooled estimate for the central districts, and the blue line is the pooled estimate for the outer districts. The shaded area is the 95% confidence interval.

FIGURE 1—Heat-Related Mortality Risk Functions Between Central vs Outer Area in Ho Chi Minh City, Vietnam, 2010–2013

(i.e., exposure) to produce an overall cumulative exposure–response curve for each district.[21] To adjust this curve for a long-term trend and seasonality, we used natural cubic spline smoothing for the time variable, with 7 degrees of freedom per year. In addition, to account for a potential nonlinear relationship between temperature and health, we applied a distributed lag nonlinear model using a cross-basis function for multiple lag-day temperatures.[22,23] The parameters of this cross-basis function followed specifications from a previous study,[24] which included a quadratic B-spline with 4 degrees of freedom in the exposure–response dimension and a natural cubic B-spline with 5 degrees of freedom in the lag–response dimension. The maximum lags allowed in this study were up to 21 days, considering that the effects of hot temperatures were acute and could have been affected by mortality displacement.[25]The general model is as follows:

$$(3)\quad Y_t \sim quasi-Poisson(\mu_t)$$
$$\text{Log}(Y_t) = \alpha + \beta_1{}^*\text{T}_{t,l} + \beta_2{}^*DOW_t + \beta_3{}^*NCS(time,\ 7\ df/year),$$

where Y_t is the daily death count on day t and l is the lag day. $T_{t,l}$ is a matrix obtained by applying the cross-basis distributed lag nonlinear model functions to temperature. *DOW* is the day of the week, *NCS* is the natural cubic spline function, and *time* is a variable that takes consecutive numbers ranging from 1 on the day on which observations began to 1461 on the final day of the observation period (2010–2013). We also conducted a sensitivity analysis to test the robustness of the model, in which we simplified the lag structure by fitting the moving average of the temperature series over lags 0 to 3 and 0 to 21 and by including the humidity variable in Equation 3.

In the second stage of the analysis, we reduced and pooled the estimated district-specific cumulative exposure–response curves using a multivariate meta-analytical model, separating the data into central districts and outer districts.[26] This 2-stage model was recently used in multicity, multicountry studies.[27] The central and outer districts were categorized on the basis of their locations on the map (Figure A, available as a supplement to the online version of this article at http://www.ajph.org) and population density (districts with population density < 8000 persons per square kilometer were classified as outers).

All analyses were performed using R software version 3.2.2 (R Core Team, http://www.R-project.org). The R code to reproduce the results of this study can be obtained by contacting the first author (T. N. D.).

RESULTS

Table 1 contains descriptive statistics. Overall, central districts experienced higher temperatures and drier conditions than outer districts. The mean average temperature of the central area was 0.9°C higher than that of the outer area (28.4°C vs 27.5°C), and the mean average humidity was 68.6% in the central area and 75.1% in the outer area. In addition, the mean number of hot days (average temperature ≥ 30°C) was higher in the central area than in the outer area (108 days vs 42 days). A total of 101 897 mortalities were recorded during the study period.

The main result (Figure 1) is the relationship between heat-related mortality risk and the central and outer areas. The slope of heat-related mortality risk in the 2 areas was almost identical, which indicates that the level of vulnerability to heat between the 2 areas is the same. The range of heat exposure, however, was higher in the central area than in the outer area.

The AFs of heat by extreme and mild temperature and by central and outer area are presented in Figure 2. On average, the AFs resulting from total, extreme, and mild heat were 1.42%, 0.3%, and 1.12%, respectively, in the central area and 1%, 0.26%, and 0.74%, respectively, in the outer area. Therefore, the AF resulting from the UHI effect is the difference in total heat AF between the central area and the outer area, which was 0.42% (95% confidence interval = 0.11%, 0.73%).

Figure 3 presents the linear relationships among green space, population density, and district budget and mortality AF attributable to total heat. The AF had a positive relationship with population density and a negative relationship with green space, but it had no relationship with district budget. Therefore, we created a new variable: green square kilometers per 1000 people (green space in square kilometers per population in 2011, multiplied by 1000). This was then related to the AN of mortalities resulting from heat in a linear regression model to calculate the protective effect of green space in reducing the AN of mortalities resulting from heat. Every increase in green space of 1 square kilometer per 1000 people can prevent 7.4 mortalities (95% confidence interval = 1.3, 13.5) attributable to heat in HCM City.

We also conducted a sensitivity analysis to determine whether the results were dependent on modeling choices (i.e., changing lag structure and the inclusion of the humidity variable); the alternative models are presented in Figure B (available as a supplement to the

TABLE 1—Demographic Comparison of Central and Outer Districts in Ho Chi Minh City, Vietnam, 2010–2013

District Name	Category	Average Temperature, °C (Range)	Average Relative Humidity, % (Range)	Days ≥ 30°C	Population Density, People/km²	Total Deaths	Area, km²	Green Area, km²	Budget Revenues,[a] Million VND	Urban Fraction, %
Dist1	Center	28.4 (22.6–31.4)	68.7 (43.2–87.0)	89	24 025	5 067	7.7	2.6	827 769	0.66
Dist3	Center	28.6 (22.6–31.5)	67.9 (42.5–86.9)	118	38 394	4 314	4.9	0.9	565 613	0.81
Dist4	Center	28.4 (22.6–31.4)	68.8 (43.1–86.6)	91	43 788	4 420	4.2	0.8	369 801	0.81
Dist5	Center	28.5 (22.7–31.5)	68.6 (42.3–87.3)	101	41 034	4 118	4.3	0.6	558 499	0.86
Dist6	Center	28.5 (22.7–31.7)	68.5 (41.4–87.9)	124	35 035	5 327	7.2	0.7	521 119	0.91
Dist8	Center	28.2 (22.5–31.4)	70.4 (43.3–88.7)	68	21 978	7 283	19.2	7.3	607 863	0.62
Dist10	Center	28.5 (22.6–31.5)	68.1 (42.1–87.6)	111	40 942	4 612	5.7	1.1	493 542	0.81
Dist11	Center	28.6 (22.7–31.7)	67.7 (41.2–87.5)	142	45 582	4 618	5.1	0.6	434 728	0.88
Dist12	Center	28.3 (22.7–31.7)	69.1 (43.8–90.0)	102	8 559	3 412	52.8	27.6	552 227	0.48
Binhtan	Center	28.3 (22.3–31.8)	69.8 (42.1–90.2)	90	11 778	3 541	51.9	22.8	614 754	0.56
Binhthanh	Center	28.2 (22.2–31.2)	69.7 (44.7–88.3)	72	23 109	7 174	20.8	9.4	733 707	0.55
Govap	Center	28.4 (22.3–31.5)	68.2 (43.2–89.2)	105	28 423	5 547	19.7	5.6	753 719	0.72
Phunhuan	Center	28.7 (22.6–31.6)	67.3 (42.0–87.2)	150	35 990	3 712	4.9	0.4	366 162	0.91
Tanbinh	Center	28.6 (22.5–31.6)	67.7 (42.1–88.6)	138	19 229	5 676	22.4	6.4	772 753	0.72
Tanphu	Center	28.7 (22.6–31.9)	67.5 (40.8–88.7)	160	26 104	3 631	16.1	2.4	788 945	0.85
Thuduc	Center	28.2 (22.3–31.3)	69.5 (44.4–89.0)	75	9 936	4 029	47.8	24.5	501 133	0.49
Dist2	Outer	27.6 (22.4–30.7)	74.1 (49.7–89.9)	26	2 744	1 781	49.7	27.1	387 410	0.31
Dist7	Outer	27.8 (22.6–30.8)	74.4 (50.1–90.2)	28	7 453	3 271	35.7	13.3	745 409	0.46
Dist9	Outer	27.3 (22.3–30.4)	76.2 (52.1–91.7)	15	2 360	2 882	114.0	68.8	481 232	0.19
Binhchanh	Outer	27.6 (22.0–31.3)	73.8 (46.4–91.2)	52	1 841	4 311	252.7	221.0	737 431	0.13
Cangio	Outer	26.8 (22.1–30.3)	80.9 (51.1–95.1)	1	100	1 123	705.0	578.6	526 659	0.01
Cuchi	Outer	27.7 (21.7–31.7)	72.3 (43.6–92.2)	105	834	6 015	434.6	381.0	812 387	0.12
Hocmon	Outer	28.0 (22.0–31.9)	70.7 (43.6–91.2)	104	3 326	4 526	109.2	82.9	832 258	0.24
Nhabe	Outer	27.2 (22.5–30.3)	78.6 (52.3–92.6)	8	1 095	1 507	100.4	66.1	374 976	0.10

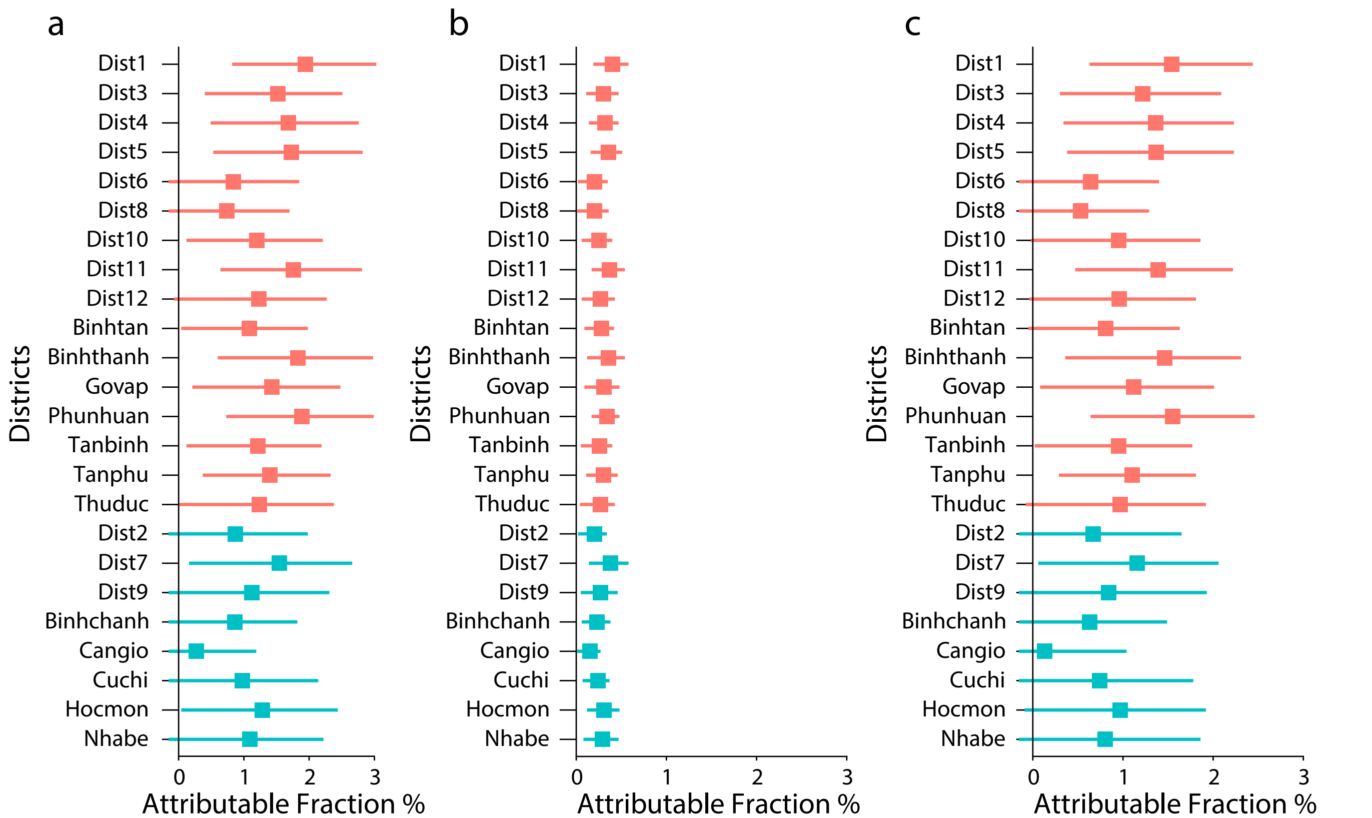
Note. Dist = district; VND = Vietnamese dong.
[a]The revenue of the government from domestic production, business and service establishments, or citizens and other revenues from abroad.

online version of this article at http://www.ajph.org). The pooled temperature–mortality curves of the alternative models were similar, which suggests that our results are robust and not likely to be affected by modeling choices. We also validated the dynamic downscaled model for simulating spatial temperatures, and the result is presented in Figure C (available as a supplement to the online version of this article at http://www.ajph.org). The correlation between spatial hourly temperatures, estimated from the dynamic downscaled weather model and observed temperatures at 7 ground monitoring sites, was very high (correlation coefficients ranged from 0.79–0.92). This suggests that the downscaled weather model simulates spatial temperatures well with respect to the temperatures recorded at monitoring sites.

DISCUSSION

This study directly quantifies the impacts of the UHI effect on mortality in HCM City between 2010 and 2013. We used dynamic downscaling with a regional model to estimate the daily spatial temperature of each district; similarly, we also calculated the AF and AN of mortality attributable to total, extreme, and mild heat between the central and outer districts. We found that the AF of mortality resulting from the UHI effect was substantial, amounting to 0.42% (from 1.42% AF of mortality resulting from total heat in the central area). Thus, we can assume that the number of mortalities resulting from the UHI accounted for 0.42/1.42 = 30% of the total mortalities resulting from heat in HCM City. Heaviside et al.[9] found that the UHI contributed to around 50% of the total heat mortalities during the 2003 heat wave in the West Midlands, Unite Kingdom, which is higher than our estimate. This suggests that the effect of the UHI can be larger in temperate regions or amplified during heat waves.

Our study also found that every increase in green space by 1 square kilometer per 1000 people can prevent 7.4 mortalities resulting from heat. Such information is extremely helpful in city planning for climate change. Wolf et al. conducted a systematic review of 37 studies using geospatial techniques to assess human vulnerability to heat. They used a survey of the lead authors to understand interactions between researchers, as scientific



Note. Dist = district. Central districts are in red, and outer districts are in green.

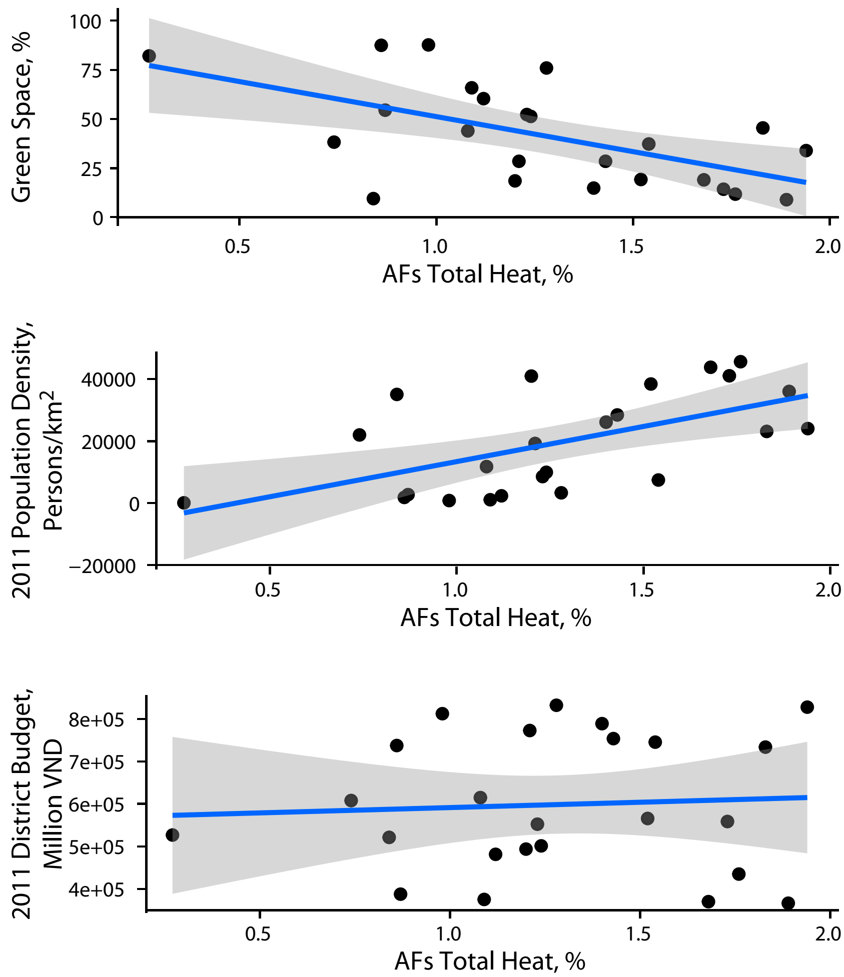
FIGURE 2—Attributable Fractions (%) and Their 95% Empirical Confidence Intervals of Districts Grouped Into Central and Outer Area for (a) Total Heat, (b) Extreme Heat, and (c) Mild Heat: Ho Chi Minh City, Vietnam, 2010–2013

information producers, and local authorities, as information users.[28] They found that none of the 37 studies had a successful or substantial influence on policymaking or preventive action. Many factors can contribute to this phenomenon, but one possibility is that the summary of the risk report may be in a form that hinders communication with policymakers. This study used a novel method (i.e., a method specifically developed for temperature–mortality time-series studies[20]) to directly calculate mortalities attributable to the UHI effect, which is more meaningful and easier to communicate to policymakers responsible for intervention.[29]

HCM City has experienced strong economic growth since the Doi Moi period (the economic reforms initiated in Vietnam in 1986), but this, together with population growth, has caused urban encroachment into adjacent agricultural and rural regions. The urbanization process of HCM City, however, is unbalanced because it is concentrated in the center of the city.[30] Consequently, the green space of the central districts of HCM City has been replaced by urban infrastructures. Our results demonstrated that the area of green space in the outer districts was significantly higher than that in the central districts (Table 1), and there was a negative relationship between AF total heat and green space (Figure 3). To prevent future mortalities resulting from excess heat in the central districts, we recommend that the HCM City government campaign to increase the population's awareness of the impacts of UHI on health. We also believe that interventions at an individual level, such as green or white roofs, are one of the best strategies to reduce the impacts of the UHI in highly urbanized cities.[31]

It is evident that the variation in the heat slope of the temperature–mortality curve depends on latitude.[32] The manner in which the heat slope varies within a city is, however, unclear. Previous studies found that the heat slope was higher in the UHI area than in the non-UHI areas.[7,8] However, in this study, the heat slope was identical between the central (UHI) and outer (non-UHI) areas (Figure 1). A possible explanation for this is that previous studies did not use spatial temperatures[6–8] or district-specific mortality in estimating the heat slope,[9] whereas this study used both district-specific temperature measurements and mortality. This allowed us to sufficiently compare the heat slopes between the central and the outer areas of HCM City.

Although the AF and AN depend on risk (β in Equation 1) and the number of days that present the risk (n in Equation 2), we have demonstrated that the difference in temperature distribution between the central and outer areas caused the differences in the mortality AF and AN. To our knowledge, global heat-related mortality projections have not included the UHI effect in their models.[33,34] Our study suggests that the



Note. VND = Vietnamese dong. Each point represents a district.

FIGURE 3—Linear Relationship Between Mortality Attributable Fractions (AFs) Resulting From Total Heat and (a) Green Space, (b) Population Density, and (c) District Budget: Ho Chi Minh City, Vietnam, 2010–2013

impact of the UHI on health is substantial; therefore, future global heat-related mortality projections should consider the UHI effect to reduce underestimation. As mentioned earlier, the heat slope was similar between the central and the outer areas; it is therefore reasonable to choose the same heat slope for different districts within a city, but this necessitates district-specific temperature measurements in the global heat-related mortality projection model.

Limitations

This study has several limitations. First, the study was only conducted in HCM City, which is a tropical city undergoing rapid urbanization. Therefore, the results of this study cannot be generalized to cities in cold or temperate climates, or that are not undergoing the same pace of urbanization as HCM City. Second, we need to consider that this study may cause exposure misclassification because people move between locations (e.g., from the surrounding area to the urban area for work). Elderly people aged 65 years or older accounted for 58.2% (59 348 people) of all mortalities. Most of these elderly people are retired and usually do not go to work; therefore, the exposure misclassification in this study is small.

The location of death could be another source of misclassification. For example, a person could become sick as a result of temperature exposure at home and then die at the hospital. Exposure misclassification will occur if the location of that person's death is registered as the hospital. Fortunately, in this study deaths were registered at people's place of usual residence, which can avoid this type of exposure misclassification. Finally, the definition of AF resulting from UHI (i.e., the difference in the mean AF resulting from total heat between the central and outer districts) appears crude because other factors, including socioeconomic status, demographic differences, and housing factors (such as air conditioning), could contribute to these differences. In this study, a key assumption for the definition of AF resulting from UHI is that vulnerability to heat should be the same between central and outer districts. Previous studies estimated 2 parameters as measures of the vulnerability of a population to heat: the heat threshold (or minimum temperature mortality) and the heat slope.[35] The result demonstrated that the slope of the risk curve and the heat threshold are almost identical between the 2 areas. This suggests that vulnerability to heat of the central district is the same as that of the outer district. Socioeconomic status and housing data were unavailable, so we could not further explain the factors that contribute to differences in heat-related mortality between the central and outer districts. Future studies that investigate the association between socioeconomic status, housing, and AF total heat are warranted.

Public Health Implications

This study identified a difference in weather conditions and mortality AF resulting from the heat components in central and outer districts. The AF resulting from the UHI effect in HCM City was substantial at 0.42%, and every increase in green space of square kilometers per 1000 people can prevent 7.4 deaths resulting from heat. This information will be valuable for authorities, considering the extent to which the UHI effect on mortality may be minimized by implementing appropriate planning and intervention. However, future studies regarding the health economics of interventions are warranted. AJPH

CONTRIBUTORS

T. N. Dang originated the study and analyzed the data. D. Q. Van and H. Kusaka collected meteorological data and provided the dynamic downscaling model technique. X. T. Seposo assisted with data analyses. Y. Honda supervised the whole project and provided technical support. T. N. Dang, X. T. Seposo, and Y. Honda interpreted findings. All authors contributed to the writing of the article.

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HUMAN PARTICIPANT PROTECTION

This study was approved by the Human Research Ethics Committee of the University of Medicine and Pharmacy at Ho Chi Minh City, Vietnam.

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