Heat exposure assessment based on individual daily mobility patterns in Dhaka, Bangladesh

Abstract

Despite a growing body of evidence indicating increasing health impacts from heat exposure secondary to climate change, previous studies have assessed heat exposure based only on the residential locations of individuals. Such assessments may be imprecise as they do not reflect the impact of people's daily mobility patterns. Furthermore, most studies have focused on urban areas in developed countries, whilst relatively little is known about the situation in developing nations, particularly a tropical climate region where heat exposure is severe for residents. As a case study in Dhaka, Bangladesh, we conducted a heat exposure assessment by integrating individual mobility data which was obtained from a questionnaire survey. Estimates of heat exposure were made using remotely sensed land surface temperature data. Population exposures based on residential locations were compared to a dynamic exposure model that incorporated mobility. Especially for people in suburban areas, we found the traditional assessment method based on the static residential model underestimated exposure compared to the dynamic model owing to the fact that some residents migrate into the city center each day where they tend to experience higher temperatures. We found small differences in heat exposure levels between social groups stratified by gender, age, and income based on the dynamic and static models. These results demonstrate that integration of mobility patterns may be important when comparing exposure levels between urban and suburban populations. Our findings may raise issues regarding new remediation measures against urban heat islands, such as reviewing the distribution of health resources or generating a risk map.

Keywords:

Population mobility, Heat exposure assessment, Geographic information systems, Remote sensing, Bangladesh

1. Introduction

Epidemiological studies have repeatedly demonstrated that heat exposure has an adverse effect on human health, with high temperatures being associated with both increased mortality and morbidity (Bassile and Cole 2010, Åström et al. 2011). For example, cardiovascular and respiratory diseases (Almeida et al. 2010), diarrhea (Hashizume et al. 2007) as well as mental health problems (Hansen et al. 2008) have been shown to be associated with elevated temperature. The mechanisms by which heat impacts health are largely associated with the triggering of often pre-existing chronic conditions (Vandentorren et al. 2006). These effects are evident in a range of international settings, including Asia (Pudpong and Hajat 2011), Europe (Michelozzi et al. 2009), North America (Kestens et al. 2011), and Oceania (Schaffer et al. 2012).

Urban heat islands (UHIs) are the phenomenon of a modified thermal climate generally caused by urbanization, and the urbanized area is often warmer than the surrounding non-urbanized area (Voogt and Oke 2003). UHIs are defined for different layers of the urban atmosphere, or for a range of types of surfaces and subsurface (Oke 1995). In this research, we specifically focused on surface urban heat islands (SUHI) which can be observed as the spatial patterns of upwelling thermal radiance captured by a remote sensor (Voogt and Oke 2003). In SUHI, warming is mostly caused by the modification of land surfaces using materials that effectively store short wave radiation, with waste heat from energy creation being a secondary contributor.

There is a growing concern that the effects of UHIs may increase the magnitude of population exposure to heat (Patz et al. 2005). Coupled with the effects of global warming, studies suggest that UHIs may magnify the severity, duration, and frequency of extreme climate events such as heat waves in urban areas (Åström et al. 2011). There is a consequent pressing need to accurately assess population exposure to heat in order to establish efficient preventive measures (Almeida et al. 2010).

Previous research on heat exposure assessment suffers from two main limitations. Firstly, most studies have focused on urban areas in developed countries, whilst little is currently known about the situation in developing nations, largely due to a lack of data (Hashizume et al. 2009). Secondly, typical assessments of human heat exposure are based solely on the residential locations of individuals. Thus, they may be imprecise as they do not reflect the impact of people's daily mobility patterns on heat exposure.

The development of Geographic Information Systems (GIS) has enabled us to capture and model human mobility (Sekimoto et al. 2013) providing the potential to update the methods used in the field of environmental exposure assessment. Their use has typically focused on air pollution exposure (e.g., Hatzopoulou and Miller 2010, Dhondt et al. 2012). Several studies found that environmental exposure assessment which integrates population mobility substantially alters estimated pollutant exposure levels compared to assessment which assumes people are static at their homes (e.g., Beckx et al. 2009a).

Research suggests that individual mobility is constrained and characterized by two major factors: physical and socio-cultural circumstances (Briggs 2005, Hagerstrand 1970). Physical circumstance, particularly where an individual lives, is an important determinant of people's daily travel patterns (Hagerstrand 1970, Dhondt et al. 2012, Beckx et al. 2009a). For example, those who reside in suburbs often travel into the urban core to work or study, or for other purposes (Brainard et al. 2002), and this may substantially affect the magnitude of their exposure to environmental risks. Dhondt et al. (2012) conducted health impact assessments using measurements of population exposure to air pollutants which integrated people's mobility estimated through agent-based simulation framework in regions of Belgium. They found integrating population mobility models altered estimated exposure levels to NO_2 and ozone at the municipal level, and better predicted health outcomes compared to exposure assessment based solely on residential locations.

Socio-cultural circumstance, specifically population characteristics such as age, gender, and socio-economic circumstance, also has a role to play determining individual mobility patterns (Briggs 2005, Hagerstrand 1970). Beckx et al. (2009b) showed large intra-day differences in air pollution exposure estimates between gender and socio-economic classes in the Netherlands. They suggested to target exposure reductions at the most critical places and times for particular social groups for more efficient policy measures, considering different mobility patterns between these groups (Beckx et al. 2009b).

Focusing on social groups and their mobility-based exposure has another important aspect. Several particular social groups, such as the very young, the elderly, and the poor, are relatively vulnerable to heat exposure (Yardley et al. 2011, Chan et al. 2012). Furthermore, some case studies have shown that these vulnerable groups are more prone to be exposed to heat (e.g., Wong et al 2016, Huang et al. 2011). Most previous studies which focused on disparities in environmental exposure have been based on static assessment, but neglected effect of population mobility on the exposure level, and thus the magnitude of disparity found might be biased if estimates are poorest for the most mobile members of the population.

A mobility-based heat exposure analysis, as a rare case study, was conducted in Leipzig, Germany (Schlink et al. 2014). They found that the different algorithms which simulated population mobility generate substantially different mobility patterns and levels of heat exposure. This indicated that integrating mobility patterns has the potential to advance assessment of thermal burden compared to the traditional static assessment. Nevertheless, the effect of physical circumstances (i.e. urban v.s. suburb areas) and social groups on mobility-based heat exposure have not been widely examined in previous research. Further, the situation in a developing country, particularly a tropical climate region where heat exposure is severer for residents, is still not well known.

Dhaka is the capital city of Bangladesh with high temperatures and where only limited work on heat exposure has been undertaken. The setting is important because the development of UHIs in Dhaka is being accelerated by a reduction in green spaces and increases in impervious surfaces associated with uncontrolled land development from rapid population growth (Raja and Neema 2013). In Bangladeshi cities there is particular concern that heat-related health problems may be magnified by poor adaptive capacities (Patz et al. 2005), as well as by the limited availability of medical care (Byomkesh et al. 2012). In this research we examined if and how incorporating individual daily mobility data might provide improved exposure assessment (hereafter termed "dynamic exposure assessment") compared to analyses based on traditional measurements of heat exposure (hereafter "static exposure assessment") , as a case study in Dhaka.

In this work we aimed to determine the factors affect mobility-based population exposure, and how the models may inform possible remediation measures against thermal burdens.

For this, we firstly evaluated how our findings vary by urban setting (i.e., urban core v.s. suburbs), hypothesizing that places of people's residences and destinations of daily travel may have a significant effect on the heat exposure of individuals. Secondly, we analyzed if heat exposure varies between different social groups and how the integration of mobility patterns might alter any estimated inequalities in exposure.

2. Methodology

2.1. Study area

Dhaka consists of the Dhaka Metropolitan Area (DMA) and its surrounding suburbs, located in the central part of the country (Figure 1). While Bangladesh is recognized as an economically impoverished south Asian country (Lewis 2011), several urban areas, including Dhaka city, are currently accomplishing strong and stable economic growth (Muzzini and Aparicio 2013, Lewis 2011). These economic developments are resulting in rapid urbanization of the city (Muzzini and Aparicio 2013) but are simultaneously generating a range of environmental issues, including UHI (Muzzini and Aparicio 2013, Byomkesh et al. 2012).

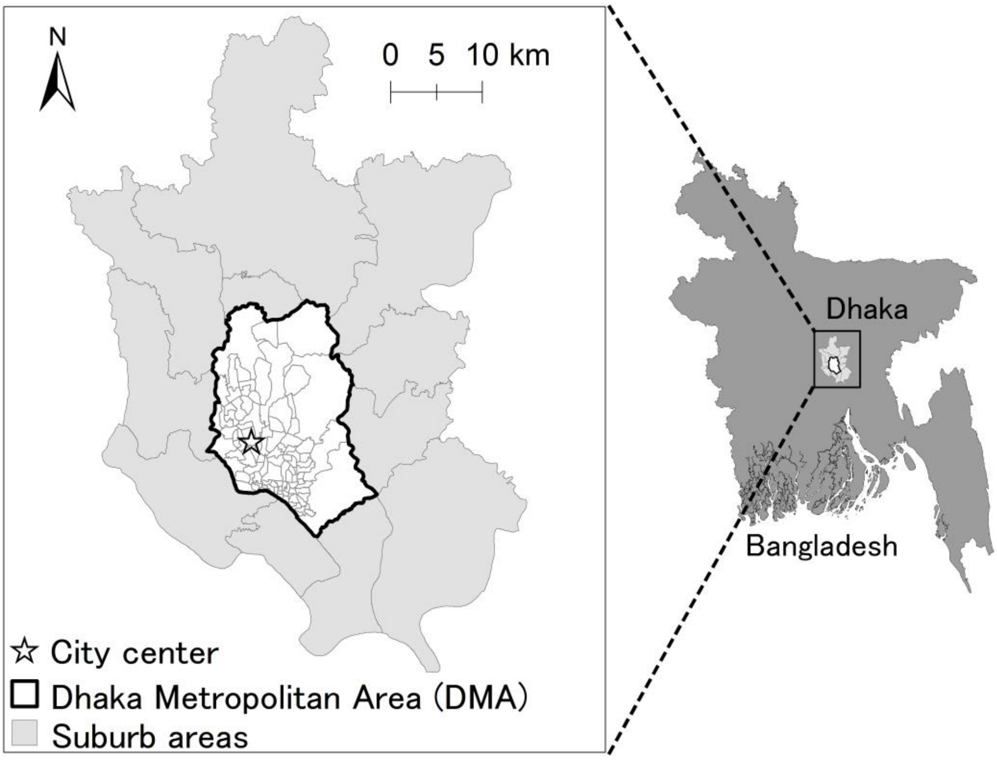


Figure 1. Study area: Dhaka Metropolitan Area (DMA) and surrounding suburban areas, Bangladesh

2.2. Population mobility data

Two principal datasets (questionnaire-based mobility data and remotely sensed land surface temperature data) were used for this study. The estimates of population mobility were constructed as follows: a survey was conducted by the Japan International Cooperation Agency (JICA) in the study area (Sekimoto et al. 2013, JICA 2010). The study area covers 108 zones (Figure 1), and 1% of the population in each zone was randomly selected from a list of names of electors collected by the Dhaka City Council. The zones were administrative boundaries within the city –"wards" in DMA, and "thana" and subdivided thana outside the DMA (see Figure 1). Wards are the smallest administrative boundaries in Bangladeshi urban areas (Zinia and McShane 2018). A thana is defined as a sub-district in the country in terms of police jurisdiction units.

Because some thana are substantially larger than others, those large thanas were subdivided into smaller zones for more comprehensive sampling for the questionnaire survey.

JICA conducted face-to-face interviews by visiting the selected households' residences in 2009. All household members were asked questions on their daily travel pattern of the working day immediately before the survey date. The questions included the departure place of each trip and destination (e.g., a workplace or school), the departure and arrival times of the trip, how long they stayed at their destination, and their modes of transport. We assumed that the initial departure places are their residential locations. The survey also requested information on the socio-demographic characteristics of the respondents (e.g., age, sex, and income level). In Dhaka, many workers are non-regular employment and regularly change their income. Therefore, each person's monthly income of the month immediately before the survey date of the questionnaire was requested to provide a more stable measure. The population mobility data was called "person trips" (Sekimoto et al. 2011). The overall available sample population from the person trip data was 42,114 individuals and each individual had one recoded trip within a day.

We developed a mobility model using the person trip data (Sekimoto et al. 2011, Sekimoto et al. 2013). The address information on the home location and trip destination of each participant in the person trip data was only available at the level of 108 zones. So as to more precisely estimate starting point and end point of each trip, we used Landscan, which provided data on spatial distribution of population at 1km^2 level. Two steps were employed. Firstly, using the zone boundary GIS map provided by JICA, zones corresponding to the home and destination of each trip were identified. Secondly, the Landscan was used to estimate both locations within each corresponding zone. Landscan provides information on spatial distribution of both the daytime and nighttime population of Dhaka city. These were estimated through a model based on characteristics of land cover, road networks, slopes (as an indicator of suitability for residences) and settlement locations identified through high resolution imagery analysis (for the details, see GIST, 2015). In order to locate trip start points the zone boundaries, and associated residential populations, were overlaid on the resampled Landscan data and estimates of the likely population of each 100m cell were made based on the boundaries within which the cell fell along with the corresponding area population count. The population quotient was used as a probability to estimate trip origins. Likewise trip end points were estimated using the population estimates as well as end point locations reported at the zone level in the questionnaire.

The route taken between the origin and destination was computed using the Dijkstra method (a minimum route-search process) (Sekimoto et al. 2011). It was assumed that individuals would travel at a constant speed, which was computed as the mean of the speeds associated with the different travel modes reported.

2.3. Heat exposure assessment

The magnitude of heat exposure was then estimated using remotely sensed land surface temperature (LST) data derived from satellite images captured by a Moderate Resolution Imaging Spectroradiometer (MODIS) equipped on Tera and Aqua American satellites launched in 1999 and 2002 respectively by the National Aeronautics and Space Administration (NASA) (Rajasekar and Weng 2009, Østby et al. 2014). LST has been widely measure of heat exposure level in research. For example, Laaidi et al. (2012) found that areas with high LST were associated with a higher mortality rate among elderly populations when a heatwave occurred in Paris, France in 2003. The frequency of image capture of Dhaka by MODIS is four times daily 1:30 am, 10:30 am, 1:30 pm, and 10:30 pm; and the spatial resolution of the images was 1 km^2.

We computed three different metrics to measure magnitudes of heat exposure: the maximum LST exposure ('max exposure') between the four time points, which was defined as the highest exposure on each individual experienced within a day; the minimum LST exposure ('min exposure') between the four time points; and the 'exposure gap' which was the difference in temperature between the maximum and minimum LST exposure during each day. All of these are previously established indicators of heat exposure risks (Gosling et al. 2009, Laaidi et al. 2012), and they were computed for both the dynamic and static assessment models.

April 2009 was chosen as the target period. April was appropriate month for this study because, in Dhaka, the hottest months are April, May, and June (Hashizume et al. 2007), and LST data for May and June is poorer due to images being frequently obscured by cloud cover during the rainy season. The year 2009 was chosen since the mobility data described below are based on the questionnaire survey conducted in year 2009.

Using a GIS, the magnitude of heat exposure on each individual at each time point (i.e., 1:30 am, 10:30 am, 1:30 pm, and 10:30 pm) on each day was calculated according to the LST value where the individual was at the corresponding time. Therefore, in the static assessment, the individuals' exposure levels were consistently assumed to be the LST value in their residential locations, whilst in the dynamic assessment the exposure level of each individual depended on where that person was located (at home, commuting, or at work/school). Because LST values of some 1 km^2 grids are not available for April due to the cloud cover, we calculated monthly average of max, min, and gap of LST exposure values on each individual, and the values were used as the heat exposure metrics in the subsequent analyses.

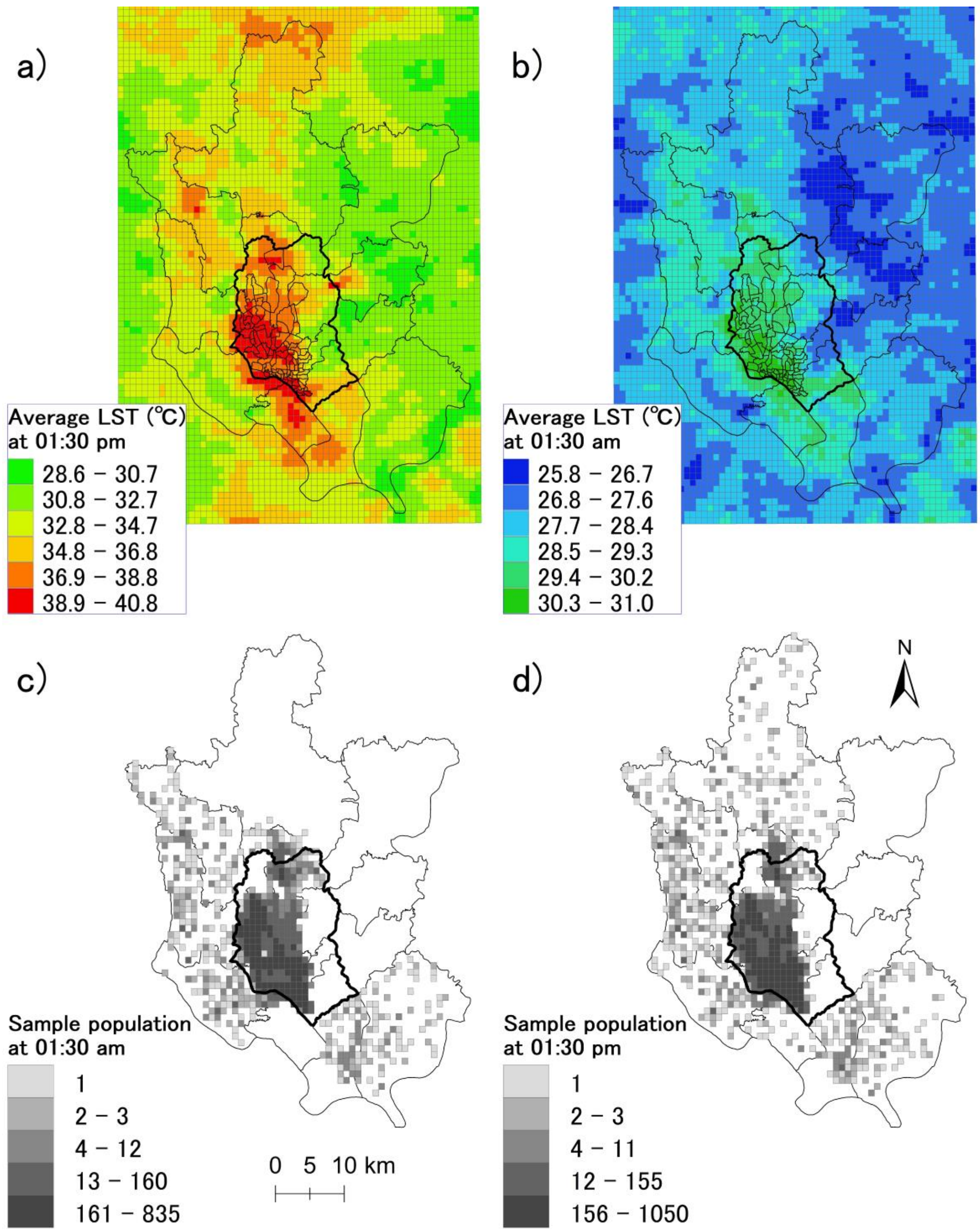
To describe how dynamic assessment alters heat exposure levels compared to the static one, we present results according to the location of individuals (location based analysis) as well as social group (social group analysis). For the location based analysis we divided the sample into four groups: those who live within the DMA and stay there all day, those who live within the DMA but commute into the suburbs during the daytime, those from the suburbs who remain there all day, and those from suburbs who migrate into the DMA during the daytime. For the social group analysis, we present results according to an aggregation by gender, age, and monthly income. Paired 2-sided t-tests were conducted to test the statistical significance of the difference between dynamic exposure and static exposure estimates for each mobility group and each social group.

All analyses were implemented using ArcGIS10.1 (ESRI Inc.) and R (Version 3.0.1, package "maptools"). All statistical analyses in this study were performed using PASW statistics 18 and R (Version 3.0.1).

3. Results

Figures 2a and b demonstrate the distributions of the monthly averages of LST at 1:30 pm and 1:30 am respectively in April 2009. As anticipated, both in the daytime and at night, the areas surrounding the city center had the highest LST values, while relatively low LSTs were observed in the suburbs. These spatial variations in LST clearly showed that an UHI existed in the study area.

The spatial distributions of the sample population at 1:30 am and 1:30 pm are shown in Figures 2c and 2d respectively. During both day and night time, southern and western areas in the DMA were the most populated. In the suburbs surrounding the DMA, the nighttime population was sparse, whereas the daytime population increased somewhat and dispersed.



285 **Figure 2.** Distribution of land surface temperature (LST) and population changes within

one day in Dhaka, Bangladesh. a) Distribution of LST at 1:30 pm (monthly average for April 2009). b) Distribution of LST at 1:30 am (monthly average for April 2009). c) Sample population at 1:30 am. d) Sample population at 1:30 pm

Table 1 illustrates the averages of the heat exposure assessments for the four mobility groups for the max and min exposure and exposure gap estimates based on the dynamic and static models. To compare the differences between the exposure levels based on the dynamic model and those of the static model, we subtracted the static estimates from the dynamic estimates.

The four groups of mobility patterns showed clear trends. Firstly, for the three exposure metrics, the two groups who stayed in either within DMA or suburbs all day had little difference in estimated exposures when comparing the dynamic and static estimates. On the other hand, for max exposure and exposure gap the suburban group migrating to the city center during the daytime had large differences (2.01 ℃ and 1.9 ℃ respectively), and these were statistically significant. This suggests that the static model systematically underestimated actual heat exposures for these migrating suburban populations. Furthermore, max exposure and the exposure gap for the group who move from the DMA to the suburbs were overestimated (i.e., around -2.44 ℃ and -2.42 ℃ for max exposure and exposure gap values respectively) when the static model was applied, and again this was statistically significant.

On the other hand, for min exposure, the difference was consistently small for all mobility groups because people are likely to experience min exposure around their home locations, even if the mobility pattern was integrated, although differences were still statistically significant.

Figures 3 illustrates the spatial distribution of differences between the dynamic and static assessments for max exposure values for the four mobility groups. There was large variation across the zones. For example, for the suburban population who migrate to the city center, the differences in values were between -1.94 ℃ and 9.10 ℃ (Figure 3-d), whilst differences for the group moving from the DMA to the suburbs were between -6.71 ℃ and 3.59 ℃ (Figure 3-b).

Table 1. Average differences in heat exposure levels between four mobility groups based on the dynamic and static models a)those who live within the DMA and stay there all day. b) those who live within the DMA but commute into the suburbs during the daytime. c) those from the suburbs who remain there all day. d) those from suburbs who migrate into the DMA during the daytime.

Mobility type	Max exposure			Min exposure			Exposure gap			Sample size	Male (%)	Age groups (%)	
	Dynamic	Static	Difference	Dynamic	Static	Difference	Dynamic	Static	Difference				
a)	36.94	36.96	-0.03**	24.64	24.63	0.01**	12.3	12.33	-0.03**	40542	53.4%	Under 15:	20.0%
	±0.81	±0.87	±0.8	±0.25	±0.26	±0.07	±0.83	±0.87	±0.79			15-39:	53.5%
												40-64:	24.4%
												Over 64:	2.1%
b)	34.55	36.99	-2.44**	24.57	24.58	-0.01	9.97	12.41	-2.43**	345	78.0%	Under 15:	2.6%
	±1.76	±0.91	±1.92	±0.27	±0.28	±0.11	±1.79	±0.91	±1.91			15-39:	53.9%
												40-64:	41.2%
												Over 64:	2.3%
c)	34.59	34.65	-0.06	23.32	23.3	0.02**	11.28	11.35	-0.08	917	48.4%	Under 15:	30.2%
	±1.74	±1.92	±1.68	±0.68	±0.69	±0.16	±1.64	±1.63	±1.67			15-39:	50.6%
												40-64:	18.3%
												Over 64:	0.9%
d)	36.78	34.78	2.01**	23.41	23.3	0.1**	13.38	11.47	1.9**	310	64.2%	Under 15:	11.6%
	±1.03	±2.11	±2.12	±0.71	±0.74	±0.3	±1.14	±1.68	±2.07			15-39:	58.1%
												40-64:	27.4%
												Over 64:	2.9%

Unit of exposure:℃
Plus-minus values are average ±SD

**P < 0.01

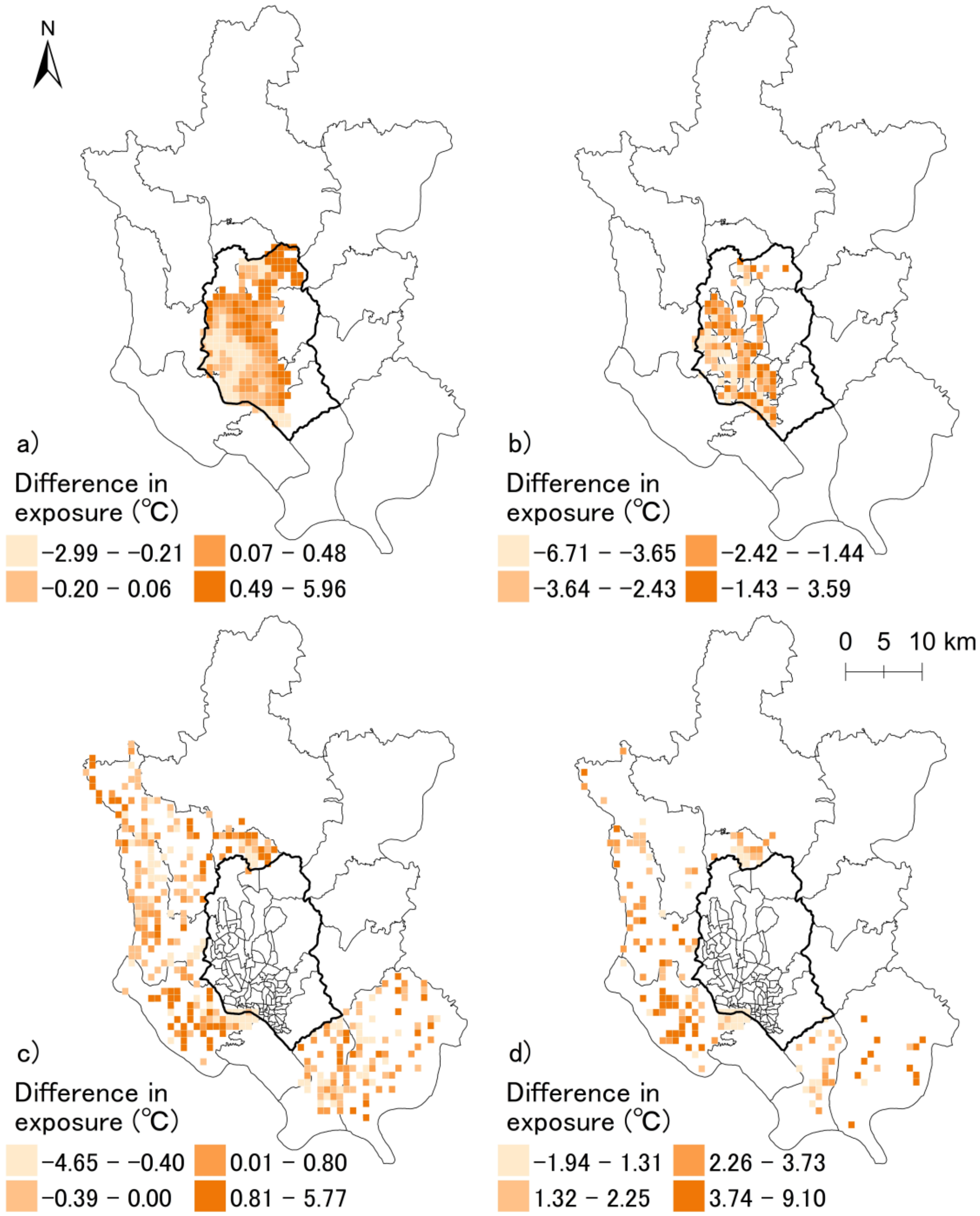


Figure 3. Spatial distribution of differences between the dynamic and static assessments for max exposure values for the four mobility groups. a) those who live
330 within the DMA and stay there all day. b) those who live within the DMA but commute into the suburbs during the daytime. c) those from the suburbs who remain there all day. d) those from suburbs who migrate into the DMA during the daytime.

Table 2 shows the results of the social group analyses. We found that males and adults are more mobile than the rest of the population. Income level was positively related to travel distance. However only small differences were found between static and dynamic exposures in the three exposure estimates; all of the differences in estimated exposure were less than 0.2℃, although most were statistically significant. Comparing the groups, we also found very weak evidence of disparity of heat exposure for both dynamic and static assessments with very small disparities for all of the three exposure metrics.

Table 2. Result of the social group analysis: Differences in heat exposure levels between different social groups (stratified by gender, age and monthly income) based on the dynamic and static models

Population characteristics	Median travel distance (km)	Max exposure			Min exposure			Exposure gap			Sample size
		Dynamic	Static	Difference	Dynamic	Static	Difference	Dynamic	Static	Difference	
Gender											
Male	9.1	36.85±0.93	36.9±0.99	-0.05±1**	24.6±0.35	24.59±0.35	0.01±0.08**	12.25±0.91	12.31±0.91	-0.05±0.99**	22541
Female	6.4	36.88±0.96	36.89±1	-0.01±0.79**	24.6±0.35	24.59±0.36	0.01±0.08**	12.28±0.91	12.3±0.92	-0.02±0.78**	19570
Age											
Under 15	3.7	36.88±0.98	36.87±1.04	0.01±0.68	24.59±0.37	24.58±0.38	0.01±0.08**	12.29±0.9	12.28±0.93	0±0.66	8441
15 - 39	8.6	36.86±0.94	36.9±0.99	-0.03±0.94**	24.6±0.35	24.59±0.36	0.01±0.08**	12.26±0.91	12.3±0.92	-0.04±0.93**	22512
40 - 64	10.2	36.86±0.94	36.92±0.96	-0.07±0.98**	24.61±0.34	24.6±0.34	0.01±0.08**	12.25±0.92	12.32±0.91	-0.07±0.97**	10290
Over 64	9	36.87±0.88	36.88±0.95	-0.02±0.96	24.6±0.32	24.59±0.34	0.01±0.09**	12.27±0.88	12.3±0.9	-0.03±0.93	871
Monthly Income (taka)											
0	7.4	36.89±0.95	36.89±1.01	0±0.79	24.6±0.35	24.59±0.36	0.01±0.08**	12.29±0.9	12.3±0.93	-0.01±0.78	17539
1 - 100,00	8.4	36.82±0.94	36.86±0.99	-0.04±0.98**	24.58±0.37	24.57±0.37	0.01±0.09**	12.24±0.92	12.29±0.91	-0.04±0.97**	6275
100,01 - 200,00	12.2	36.86±0.89	36.93±0.94	-0.07±1.08**	24.61±0.33	24.61±0.33	0.01±0.08**	12.25±0.86	12.33±0.89	-0.08±1.07**	4975
>200,00	14.9	36.79±0.97	36.94±0.96	-0.15±1.16**	24.61±0.32	24.6±0.33	0.01±0.08**	12.18±0.96	12.34±0.91	-0.16±1.14**	4884

Unit of exposure:℃ Plus-minus values are average ±SD ** $P < 0.01$
3 samples have no information on their gender
Monthly income were only stated for people aged 15 or over

4. Discussion

This study conducted two different heat exposure assessments as a case study in Dhaka, Bangladesh, where UHIs are common (Raja and Neema, 2013). Population-based exposures to heat using only residential locations were compared to a dynamic exposure model that incorporated mobility to better explore public health implications.

We found that especially for suburban populations who move into the city center in the daytime, the traditional assessment method based on the static residential model underestimated the magnitude of heat exposure compared to the dynamic model. From both policy and public health perspectives, consideration needs to be taken of the fact that the victims of heat exposure from UHI reside not only within the city center, but also in the suburbs. On the other hand, we also found that the static model overestimated the LST exposure level of people from several other areas in the DMA.

The sample sizes of mobility type b) and d) were relatively small compared to the sample size of a) and c) (residents in the city core) (see Table 1), but our methodology is adaptable into different contexts (see Dhondt et al. 2012 for example). For example, Japan is known as the country where many workers have long commutes from suburban districts to the central business district (OECD 2011), and Japanese urban areas also suffer from the heat island phenomena. In this context, our methodology may be useful to better understand population heat exposure patterns in such settings.

Over the different social groups, we found only weak evidence of a disparity in heat exposure estimation for both the dynamic assessment and the static assessment. This result does not accord with previous studies which found disparity, although all are from outside Bangladesh and did not integrate mobility (e.g. Wong et al. 2016, Huang et al.

2011). However, Dhaka is rapidly growing city in terms of population and urbanization, and there are serious concerns of magnification of UHI and urban poverty (Lewis 2011). Therefore, any disparity in heat exposure whereby vulnerable groups are more likely exposed still may have potential to be apparent in the study area. Like many other developing countries, census records are not available in Bangladesh, and thus questionnaire surveys such as that we used have an important role to play to identify the distribution of social groups as well as disparities in environmental exposure levels.

Although we did not attempt to directly estimate health impacts of the estimated heat exposure levels, there is some evidence available from past studies. Laaidi et al. (2012) found that a 0.4℃ increase at nighttime in LST exposure significantly elevated the risk of mortality in the elderly in Paris, France, based on data from the heat wave in 2003. Although this study did not integrate the effect of individual mobility patterns, this suggests that a small difference in LST might have significant health effect.

There are several caveats to this work. The first limitation is related the nature of remotely sensed LST data. Whilst the LST data allows to assess outdoor heat exposure with relatively high spatial resolution, we could not integrate data regarding the effects of indoor environments on heat exposure, especially the effects of air conditioning in residences, offices, or schools. Nevertheless, we believe that the effects of air conditioners may be relatively limited in Bangladeshi cities compared to cities in developed countries, owing to the poor diffusion rate and quality of cooling facilities, as well as the frequent occurrence of electricity outages (Muzzini and Aparicio, 2013). Further, the heat exposure metrics were calculated based on where the individual was at each of the four single time points of capturing the satellite images, and thus length of stay outside of these time points was not fully considered.

Second, the daily mobility data was based on a questionnaire survey that may not capture any unusual travel patterns. Therefore, our model may potentially overestimate heat exposure compared to the actual personal exposure if people exhibit different migration patterns to normal in particularly hot weather. Additionally, the questionnaire only asked about the travel pattern on working days; and thus, the mobility of the individuals during weekends and holidays is not known.

Third, since we resampled the original 108 zones data into the 1km^2 Landscan grid, there may be some distortion of the spatial distribution of the starting and ending points of trips compared to the actual distribution, and this effect may be magnified if the zone is geographically larger.

Fourth, there is also no information of rejection rate in the questionnaire survey which was based on a quote sample. The representativeness of the sample, in terms of travel behavior, to the general population is untested. In addition, the slum dwellers, one of the most economically deprived groups, may be underrepresented on the electors list, the sample ledger of this study. Slum dwellers often informally settle in Dhaka (Nazrul 2003).

Population mobility data can play a significant role in updating environmental exposure assessments. This study has demonstrated that mobility data shows potential in enabling refinements in heat exposure assessments, although the magnitude of differences observed between the static and dynamic assessments were relatively small in this case. This type of assessment could be also applied for measuring exposure to other environmental burdens, such as noise (Brainard et al. 2004), which is also recognized as an important environmental risk in the urban areas of most countries.

Another concern is commuting time itself; some studies showed that long commuting time may have potential to negative health effect on the commuters (Oliveira et al. 2015, Wang and Yang 2019). Mobility data may contribute to clarify the distribution of this exposure across population groups and possible negative health impacts. The findings gained from revised exposure assessments for a range of environmental risks may in turn raise new urban planning issues like the need for reallocation of health resources such as emergency clinics and cooling stations to help mitigate thermal burdens (Johnson and Wilson 2009). A risk map may also contribute as a communication tool and may even have the potential to change mobility patterns amongst high-risk individuals (Johnson and Wilson 2009).

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