Individual level heat risk evaluation using GPS towards smart navigation system

Takahiro Yoshida[a,] *, Yoshiki Yamagata[a], Daisuke Murakami[a, b]

[a] *National Institute for Environmental Studies, Japan, yoshida.takahiro@nies.go.jp, yamagata@nies.go.jp*
[b] *The Institute of Statistical Mathematics, Japan, dmuraka@ism.ac.jp*

* Corresponding Author

Abstract: Urban heat risk management is an urgent issue in Japan. Although it is difficult to evaluate heat risk at spatially fine scale due to measurement data restrictions, heat risk varies depending on the location of the people. As a first step of developing smart navigation system for managing heat risk, we try to evaluate personal heat risk by combining ground surface temperature observed from an aircraft and people location acquired from mobile phones at the same time. G star statistic is used to detect high risk areas considering instantaneous co-occurrence of high temperature distribution and walking people density.

Keywords: Heat Risk, Exposure, Hazard, Vulnerability, G star statistic, Global Positioning System

1. Introduction

Due to urban heat island effect and global warming, health damages caused by heat waves are rising in the world as well as in Japan. In fact, heat strokes caused by large-scale heat waves have been reported in recent years (Rooney et al., 1998; Beniston, 2004; Le Tertre et al., 2006; Hajat et al., 2006; Clark et al., 2010; Steffen, 2014; Richardson, 2015; Klinenberg, 2015; Lemonsu et al., 2015; Mora et al., 2017; Zampieri et al., 2017; Sailor et al., 2019). Improving urban resilience against heat risk is an urgent task (Solecki et al., 2005; Gill et al., 2007; Milan et al.,2015). It is especially important to take measures against heat risks during the summer Olympic Games in 2020 Tokyo.

The heat waves impacts on human health, such as dehydration and dysfunction, become serious when people are exposed to heat for a long time (Rooney et al., 1998; Richardson, 2015). So, to evaluate the heat stress of individual people, it is necessary to know not only heat intensity (i: hazard) but also how people were exposed to the heat (ii: exposure). As temperature changes greatly by location due to the surrounding surface conditions and each individual walking patters are different, it is not easy to evaluate both (i) heat hazard and (ii) exposure of each individual at the same time with conventional methods.

Regarding (i) hazard, the ground surface temperature data is useful to know heat environment in each place. In fact, ground surface temperatures reflect heating on concrete and cooling on parks/grassland more sensitively than air temperatures (Richardson, 2015). The ground surface temperature data observed by the satellite, such as ASTER (Advanced Spaceborne Thermal Emission and Reflection radiometer; Spatial Resolution: 90m) and MODIS (MODerate resolution Imaging Spectroradiometer; Spatial Resolution: 1km), are publicly available in these days. These data would be valuable to analyze thermal condition in a local spatial scale.

Regarding (ii) exposure, collecting and managing location information of people has been done through mobile sensing in recent years. For example, Agoop Co., Ltd. (`https://www.agoop.co.jp/`) provides location information logs obtained from applications of smartphones. The logs are acquired by every 30 minutes intervals or 500m to 1km moves. This Global Positioning System (GPS)'s information will be useful to know movement of individual people, which determines exposure to heat. To find an area in which people are highly exposed to heat hazard, it is necessary to consider spatial cluster of people flows.

Given these backgrounds, as the first step of developing smart navigation system to reduce heat risk of individual people, this study attempts to quantify heat stress of each people by employing ground surface temperature data and mobile sensing data. Furthermore, spatial hots spots of people's heat stress is detected using an approach, which we will develop later, based on the G star (G^*) statistic (Getis and Ord, 1992), which is a cluster detection approach, which is well-known in spatial statistics (Fischer and Getis, 2009).

The reminder of this study is as follows. Section 2 introduces G^* statistic and discusses how to apply this statistic to people flow data. In Section 3, we apply G^* statistic to the analysis of heat stress. Finally, in Section 4 we show the future direction of research.

2. Methodology

2.1 G* Statistic

The G^* statistic is a popular test statistic to detect hot spot, such as high-risk area, economically agglomerated area, and ecological community, on a geographical space (Getis and Ord, 1992). The G^* statistic for a sample site $i \in \{1, \ldots, n\}$ is defined as follows:

$$G_i^* = \frac{\sum_{j=1}^n w_{i,j} y_j}{\sum_{j=1}^n y_j}, \qquad (1)$$

where where y_j represents the observation at j-th site. $w_{i,j}$ represents the spatial proximity between the sample sites i and j. The proximity can be defined by a variable indicating 1 if the distance between the sites i and j is shorter than a threshold distance, and 0 otherwise. Alternatively, the proximity may be given by a distance-decay function.

The G_i^* takes a non-negative value. A large G_i^* suggests a concentration of large y_j values nearby the site j. For example, if y_j represents ground temperatures at the site j, the large G_i^* value means a considerably high ground temperatures nearby that site. The statistical significance can be evaluated analytically, or numerically e.g. using a bootstrap approach. See Getis and Ord (1992) for further details.

Unfortunately, the original G_i^* statistic assumes samples distributed over a 2-dimensional space. In other words, the statistic is not readily applicable to our GPS data (Figure 1). The next section explains how to apply it to our data.
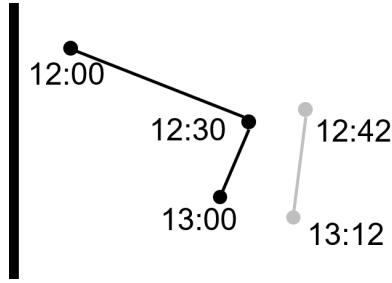

Figure 1. Image of our people flow data

To apply the G^* statistic to our data , we need to define the proximity $W_{I,J}$ between the flow I and J. The resent spatial statistical papers such as Tao and Thill (2016) and Ermagun and Levinson (2018) have studied proximity between people flows. Based on their discussions, we defined the proximity $W_{I,J}$ as follow:

$$W_{I,J} = \frac{1}{n_I n_J} \sum_{i \in I} \sum_{j \in J} w_{I,J}. \tag{2}$$

In Equation (2), $w_{i,j}$ denotes the spatial proximity between a GPS point i, which is in I-th flow, and a point, which is in J-th flow. We defined the proximity using an exponential decay function $\exp(-d_{i,j})$, where $d_{i,j}$ is the Euclidean distance separating these points. Equation (2) evaluates the proximity between flows I and J by averaging the proximities between GPS points in the I-th flow and those in the J-th flow (see Figure 2).
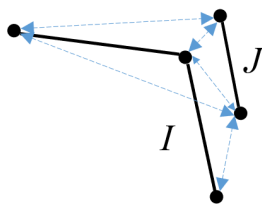

Figure 2. Image of the proximity between people flow I and J

Spatial concentration of large y_I values can be quantified using Equation (3), which is given by substituting Equation (2) into Equation (1):

$$G_I^* = \frac{\sum_{J=1}^{N} W_{I,J} y_J}{\sum_{J=1}^{n} y_J}. \tag{3}$$

In our analysis, the G^* statistic for flow data (Equation (3)) is used to detect hot spots of people's heat stress. The heat stress of J-th people is defined as

$$y_J = \sum_{j \in J} t_j \delta[g_j > 30](g_j - 30), \tag{4}$$

where g_j is the ground temperature at the j-th GPS point, and t_j is the estimated time spent at the point, which we assume 0.5 (= 30 minutes), $\delta[\bullet]$ is an indicator returning 1 if

$\bullet$ is satisfied, and 0 otherwise. y_J quantifies how long J-th people walk on hazardous heat areas, which are defined by areas with the mean ground temperatures being more than 30 degrees at the target period. Equation (3) indicates a large value in areas with many people being suffered from hazardous heats. That is, Equation (3) detects high risk heat areas considering individual people's behavior. Because Equation (3) is identical to the standard G^* statistic, the statistical inference for the original G^* statistic is readily available.

2.2 G^* Statistic for People Flow Data

The GPS data we will study is a collection of people locations (2D coordinates) by 30 minutes (see Figure 1), or by 500m or 1000m of movement for moving people. We focus not on individual GPS points but on flow of individual people indexed by $I \in \{1, \ldots, N\}$. I-th flow is composed of a set of n_I spatial coordinates, which we will index by $i \in \{1, \ldots, n_I\}$.

3. Results and Discussion

3.1 Approach

For ground surface temperatures data, we used thermal image observed from a helicopter (spatial resolution: 5 m; observation period: 11:30–13:00, August 5, 2016; weather: sunny), which is shown in Figure 3. For a data of individual people movement, we used Agoop's "Point type floating population data". We analyze individual level heat stress by applying the approach we developed in the previous section. The target area is the center of Tokyo shown in Figure 3.

Regarding exposure, our targets are pedestrians. This is because pedestrians are directly exposed to high temperatures and solar radiations. Unfortunately, because the abovementioned people flow data do not have attributes such as traffic modes, we need to classify the GPS data into walk, and other transportation modes (see Figures 4 and 5). The criterion of walk is that the average moving speed is less than 6km/h in each movement. 6km/h is equivalent to 1.5 times faster than 4km/h which is often assumed as average walking speed. In addition, when the movement before and after movement at 6km/h is less than 6km/h, it is divided into two people flows data (Yamagata et al., 2019). In this
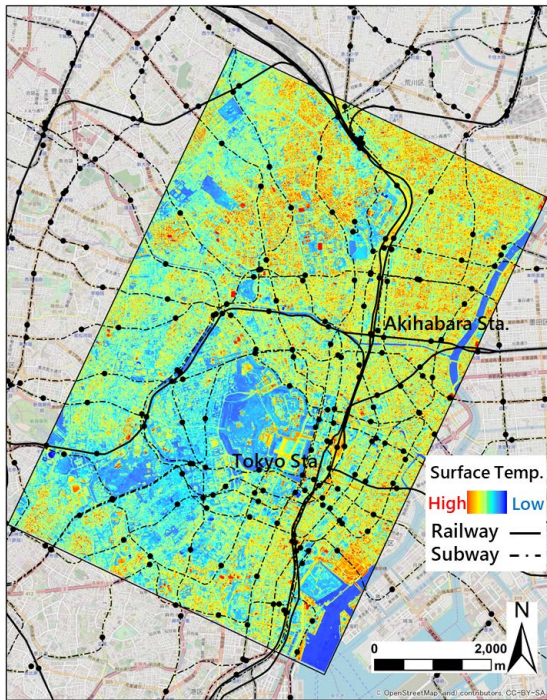
Figure 3. Surface temperature

Figure 4. GPS data Classification results

research, we analyze only people flow tagged by walk extracted by the above assumption. Refinement of the pedestrian identification method is an important subjects in the future.

3.2 Results

Figure 6 shows spatial clusters of pedestrians with heat stress evaluated by G_I^* in Equation (3). G_I^* is small in areas nearby Tokyo station and Shinbashi station. The result suggests that the heat stress of pedestrians in these two areas is relatively small.

As shown in Figure 3, the ground surface temperature in this two areas is relatively low. Therefore, this result is reasonable. Moreover, it is found that pedestrians with high heat stress are concentrated in near Akihabara Station, Suidobashi Station, Jimbo-cho Station, Hamamatsu-cho Station. This is probably because the walking distance tends to become longer in these areas where the station density is relatively low. The result suggests that considering the traveling time of pedestrians is important to properly evaluate the heat stress.

4. Concluding Remarks

This study developed a new approach to detect high heat risk areas considering people exposure to heat stress using people location information observed by GPS. Then, the proposed approach is tested for the city center area of Tokyo. The result suggests that locational heat stress of individual people changes street by street level. This kind of GPS-based heat risk evaluation approach will be an important step to use geo-sensors towards personal navigation system which could be a very important tool for managing heat risk as well as an adaptation measure to climate change.

We have to address many issues before actually test this system operationally. Firstly, we need to improve the
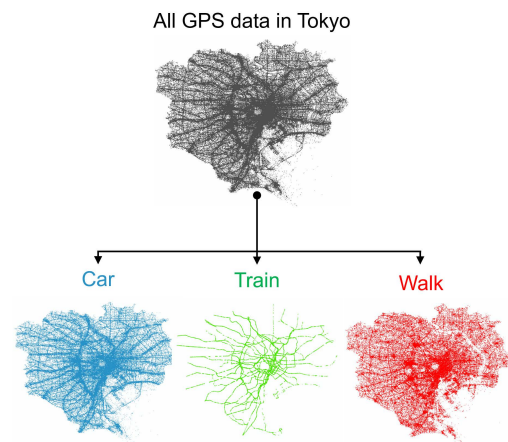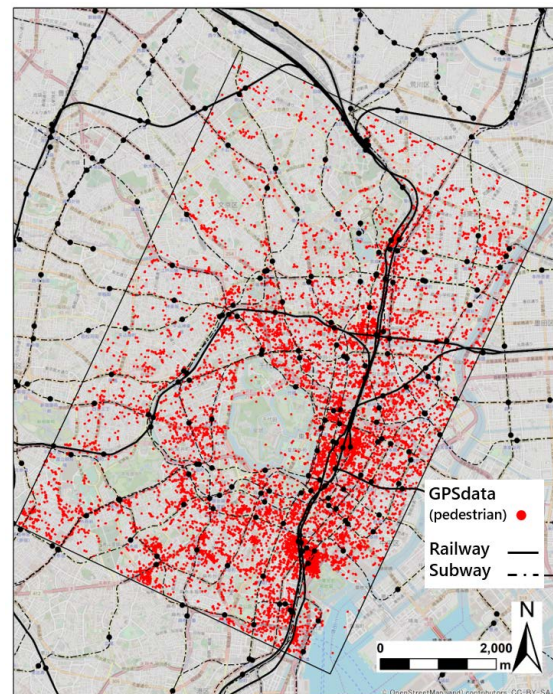

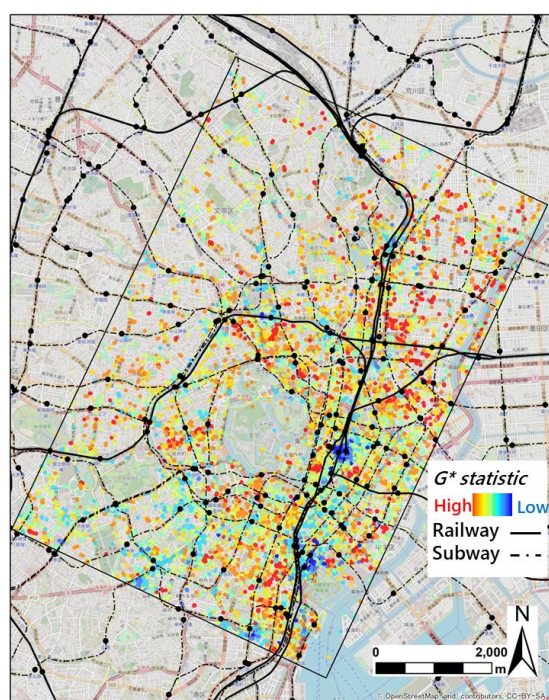Figure 5. GPS data points of estimated walking pedestrians

Figure 6. Evaluated G^* statistic

pedestrian detection accuracy. For that purpose, supervised machine learning techniques to classify actual pedestrian counts using new GPS sensors will be useful to increase the accuracy. Secondly, we need to improve the data on vulnerability of each individual people. Elders are likely to be more vulnerable to heats than young people (Gonzalez et al., 2008; Worfork, 2000). In fact, combination of improved GPS and socioeconomic data such as age distribution and income are anticipated in the near future. In fact, the use of quasi-zenith satellites is expected to improve the precision of GPS information; the location error is expected to be at most 1 m for mobile user (Inaba et al., 2009; Hsu et al., 2016; Guo et al., 2017). Thirdly, as heat conditions change dynamically over space and time. A spatiotemporal modeling is needed to predict heat and people behaviors by using multi-scale observations and people sentiments data such as tweets (Yamagata et al., 2015; Murakami et al., 2016).

5. Acknowledgment

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