ANALYSIS OF THE EFFECTS OF PERVIOUS SURFACE DISTRIBUTIONS ON AIR TEMPERATURES USING FIELD MEASUREMENT RESULTS AND SOCIAL MEDIA DATA

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KEY WORDS: Spatial continuity, Tweet data, Movement

ABSTRACT: Pervious surfaces such as green spaces distributed in urban areas are expected to contribute to air temperature reduction against an urban heat island (UHI) phenomenon. The pervious surfaces have the effect of reducing the air temperatures and it is pointed out that their effect is further enhanced on the condition that the distributions of isolated pervious surfaces are spatially continuous. We have developed the method of detecting the spatial continuity of the pervious surface distributions using remotely sensed data. Furthermore, through verification using air temperature data derived from in-situ observations, it was suggested that the air temperatures dropped around the detected areas. In order to analyze the details of the UHI phenomenon, meteorological observation stations should be arranged more densely. By using the air temperature data observed more densely, the effects of the pervious surface distributions on the air temperature would be clarified. Moreover, there is a possibility that information related to the hot environments for humans would be included in the observed data because they are obtained along the daily movement of people. On the other hand, with the widespread use of social media, people began to share contents: circumstances, events, emotions and thoughts on social network structure. Social media data with location information shows human sensibility, mobility and activity, which are also affected by the hot environments. In this study, we examine the effects of pervious surface distributions on the air temperatures using high densely observed air temperature data. In addition, we apply social media data to the spatial analysis of the relationship between the effect of pervious surface distributions and the human interest in the air temperatures.

1. INTRODUCTION

An urban heat island (UHI) phenomenon has become more pronounced. It has been pointed out that UHI phenomenon occurrence is caused mainly by the replacement of previous surfaces with impervious surfaces, i.e. substituting concrete and asphalt surfaces for grass lands, woods, and bare lands. The higher air temperatures also increase impacts on the comfort and health of urban dwellers (Inter-Ministry Coordination Committee to Mitigate Urban Heat Island, 2004).

Pervious surfaces are expected to contribute to air temperature reduction against UHI phenomenon. Evapotranspiration and radiational cooling generated by pervious surfaces drop the air temperatures, and the air around the pervious surfaces produces cooling through its diffusion. In addition, it is pointed out that their effect is further enhanced on the condition that the distributions of isolated pervious surfaces are spatially continuous. We have developed the method of detecting the spatial continuity of the pervious surface distributions using remotely sensed data (Kumagai et al. 2012). Furthermore, through verification using air temperature data derived from in-situ observations, it was suggested that the air temperatures dropped around the detected areas.

In order to analyze the details of the UHI phenomenon, meteorological observation stations should be arranged more densely. By using the air temperature data observed more densely, the effects of the pervious surface distributions on the air temperature would be clarified. Moreover, there is a possibility that information related to the hot environments for humans would also be included in the observed data because they are obtained along the daily movement of people.

On the other hand, since the UHI phenomenon causes health damage, the analysis of the hot environment for humans is also important. With the widespread use of social media, people have begun to share contents: circumstances, events, emotions and thoughts on social network structure. Social media data with location information shows human sensibility, mobility and activity, which are also affected by the hot environments.

In this study, we examine the effects of pervious surface distributions on the air temperatures using high densely observed air temperature data. In addition, we apply social media data to the spatial analysis of the relationship between the effect of pervious surface distributions and the human interest in the air temperatures.

2. DATA AND METHODOLOGY

2.1 Study Area

In this study, the urban area of the Kyoto city was adopted as the area of interest. This area is located in the Kansai district in the western part of Japan. It covers about 300 km^2 and contains 11 wards. The urbanized areas are formed in a basin surrounded by hills on three sides, so that UHI phenomenon occurs remarkably.

2.2 Remotely Sensing Data

Landsat OLI data from July 2013 was adopted as basic data for this research. The data covers the whole area of interest since the observation swath of Landsat OLI is wide enough (185 km). We applied atmospheric corrections based on the MODTRAN for this study. We calculated the ratio of the pervious surface based on the mixture pixel analysis from the Landsat OLI data as the percentage of pervious surfaces occupying within one pixel. Figure 1 shows Landsat OLI data and the ratio of the pervious surface derived from the corrected data.

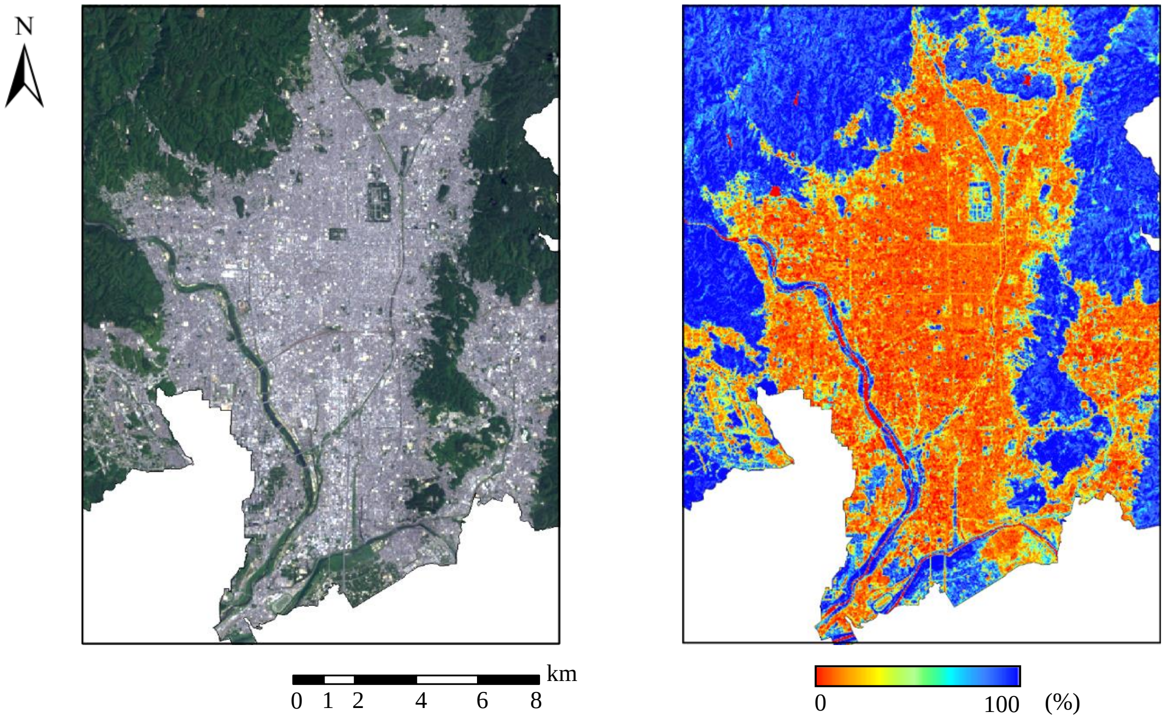
2.3 Air Temperatures Data

In order to analyze the effects of pervious surface distributions on the air temperatures, we use air temperature data observed densely. In this study, we carried out the field measurements of the air temperatures. For the field measurements, we installed thermo-hygrometers with data loggers at the elementary school's instrument shelters in the area of interest. In advance, 52 elementary schools were selected from the verification of measurement conditions: the general condition of the instrument shelter, sky factor, land cover and the source of artificial exhaust heat around the shelter. Figure 2 shows observation points. The measurement period was from late July 2016 to early October 2016 and the air temperatures and humidity were measured at interval of 10 minutes.

We then focused on climatic conditions where radiational cooling was likely to occur. The air temperature data corresponding to fine weather days in August 2016 was extracted from the results of measurement. The representative days were defined as the fine days where their sunshine duration showed 8 hours or more and their daily precipitations were below 1mm, observed by the Automated Meteorological Data Acquisition System of Japan (AMeDAS). We use the air temperature data observed during the 16 days meeting the selection criteria.

2.4 Social Media Data

In this study, tweet data was adopted for the analysis of the relationship between the effect of pervious surface distributions and the human interest in the air temperatures. We obtained 44,143 tweet data with location information in the area of interest using twitter API. From the obtained data, we selected 23,665 tweets on the representative days. Then, we detected the tweet data including a Chinese character “hot” from the selected data. The Chines character is usually used in sentences related to the air temperatures. Thus, tweet data including “hot” are regarded as the human interest in the air temperatures.



(a) Landsat-8 OLI data

(b) Ratio of the pervious surface

Figure 1 Area of interest: the urbanized area of the Kyoto city

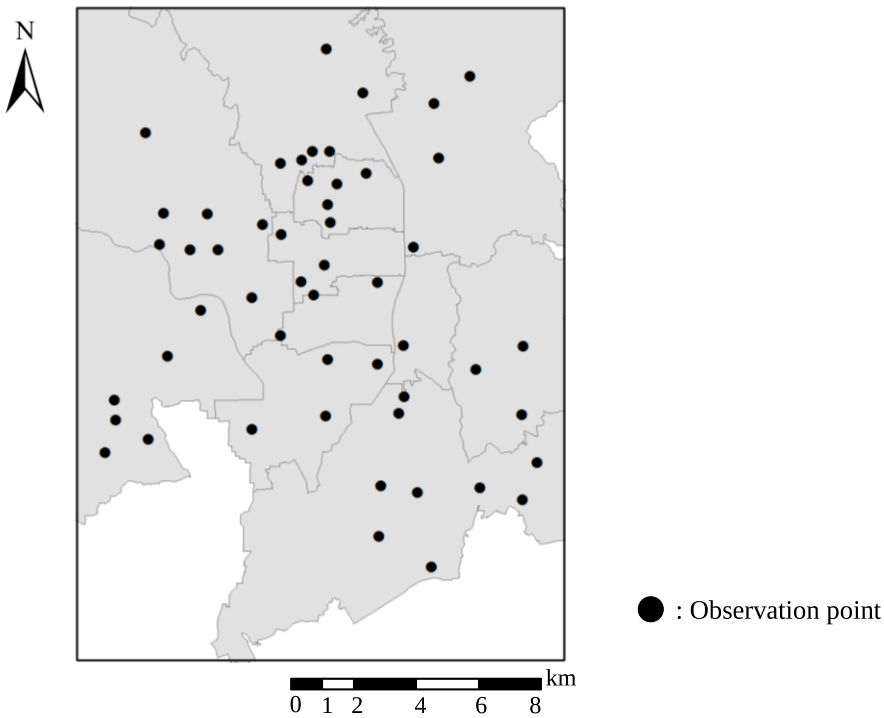


Figure 2 Observation points in the area of interest

2.5 Methodology

The spatial analysis method of pervious surface distribution we have developed is composed of a spatial autocorrelation analysis, an overlay analysis, and a hydrological analysis (Kumagai et al. 2012). The spatial autocorrelation method is described as

$$G_i(d)=\frac{\sum_{j=1}^{n} w_{ij}(d)x_j}{\sum_{j=1}^{n} x_i} \tag{1}$$

where G is G statistics, x is a spatial variable of interest, n is the number of spatial variables, w_{ij} is a symmetric binary spatial weight matrix with ones for all links defined as being within distance d of a given i; all other links are coded zero, including the link of a point i to itself. We assigned the ratio of the pervious surface to variable x. If the null hypothesis is that the set of x values (ratio of the pervious surface) within d of location i is a random sample, then we obtained a negative spatial autocorrelation. As the result of the statistical tests with a significance level of 10%, the area of interest was divided into the two kinds of results: a negative spatial autocorrelation and no spatial autocorrelation.

We focused attention on the relationship between d and the negative autocorrelation areas: the negative areas were expanding as d was increasing. The convergence of the expansion of the negative autocorrelation areas was also confirmed, so that the range of d was defined. We then overlaid the negative autocorrelation areas generated with the fluctuation of d: from a widest range to a narrowest range. The area which consists of the multiple layers of the negative autocorrelation area has been called the Spatial Scale of Clumping of pervious surface distributions (SSC). Figure 3 shows the basic generation of the SSC. The SSC has a layer structure of negative spatial correlation areas. The top layer of the SSC (e.g. (a) in Figure 3(ii)) means that a dense distribution area of high impervious surface occupation exists from the narrowest range to the widest range, while the outskirts of the SSC (e.g. (b) in Figure 3(ii)) denotes that the dense distribution area of high impervious surface exists solely within the widest range.

We also detected the valley lines from the SSC as the backbones of the high spatial continuity of the pervious surface distributions by interpreting the SSC as topographic features (see Figure 3(ii)). The valley lines play an important role in acting as bridges between the widely dense distribution areas and sparse areas of pervious surface.

3. RESULTS AND DISCUSSION

3.1 Detection of Spatial Continuity

Figure 4 shows the results of the analysis. SSC appears in the urbanized areas and its valley lines are extended from the suburban areas to the urbanized areas (see Figure 1).

3.2 Statistical Verification of Air Temperatures around the Valley Lines

To verify the effect of the valley lines on the air temperature, the analysis of the air temperature data statistics around the valley lines was carried out. We calculated the test statistics for the difference of the averages of the air temperatures between the area within and the area located outside of the range d in Figure 5 by varying d which was done from the widest range to the narrowest range.

Figure 6 indicates the results of the analysis. The distance from the valley lines is shown in the horizontal axis, while the times of day are in the vertical axis. The statistics of the test between the inside and outside of range d are indicated by gradation in Figure 6. In the case where the statistics of the test show a value above 0, the average of the air temperature within the range d is less than that of the air temperature beyond distance d. The statistics of the test showing a value below 0 mean that the average of the air temperature within the range d is greater than that of the air temperature beyond distance d. From 0 o'clock to 5 o'clock and from 21 o'clock to 0 o'clock on the following day, the statistics of the test show high value, i.e. the effect of air temperature dropping during the nighttime is suggested.

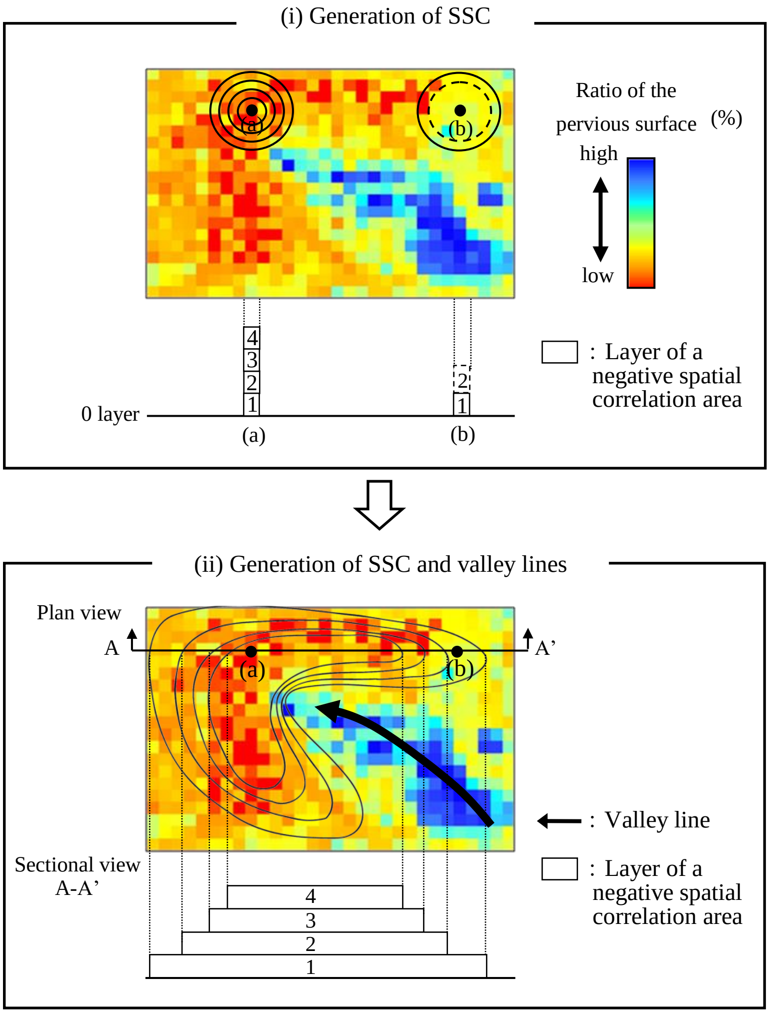


Figure 3 Procedure of the spatial analysis of pervious surface distributions :the basic generation of the SSC and its valley lines

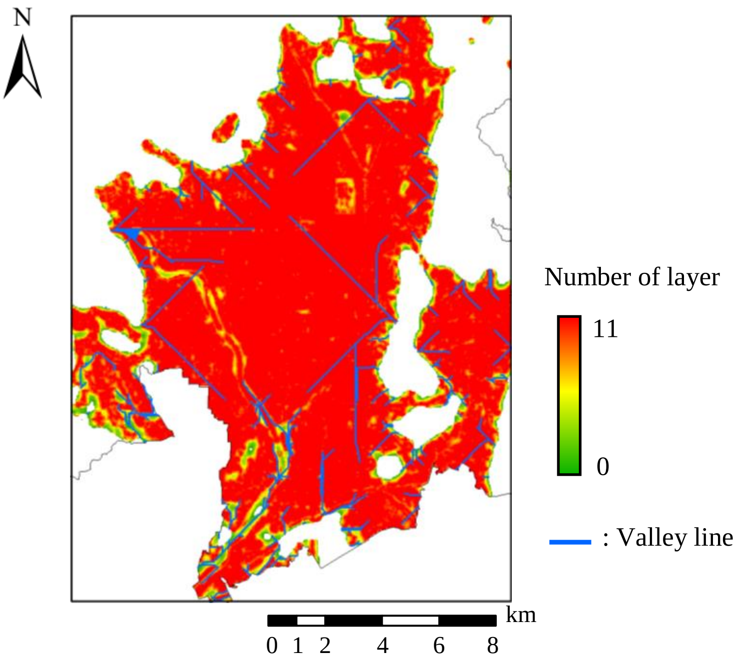


Figure 4 Results of the analysis

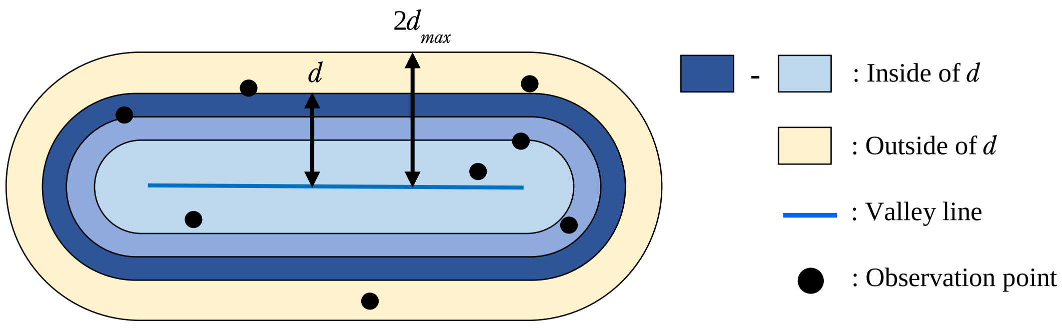


Figure 5 Concept of reviewing the air temperature reduction around the valley line

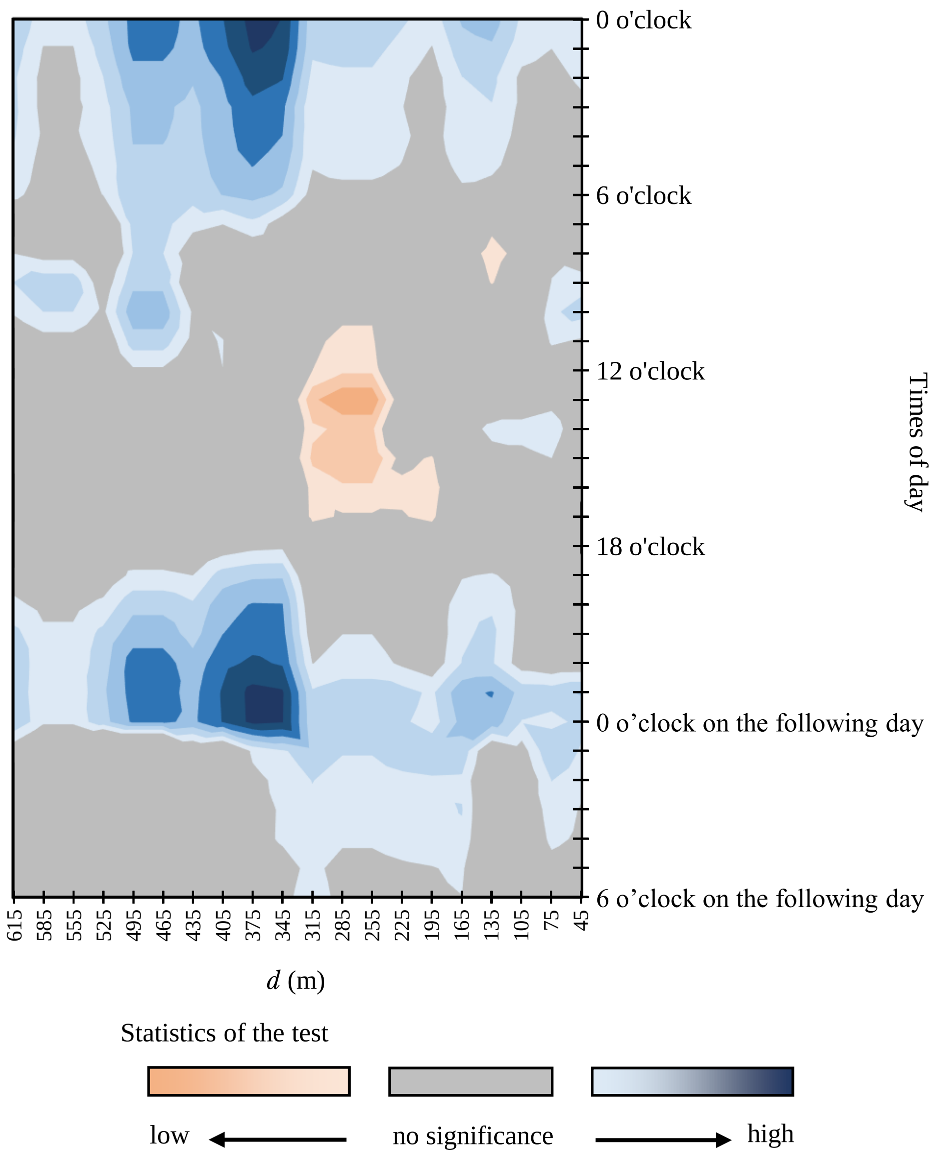


Figure 6 Results of the statistical test for the difference of the averages of the air temperature in the representative days between the inside and outside of the distance *d*

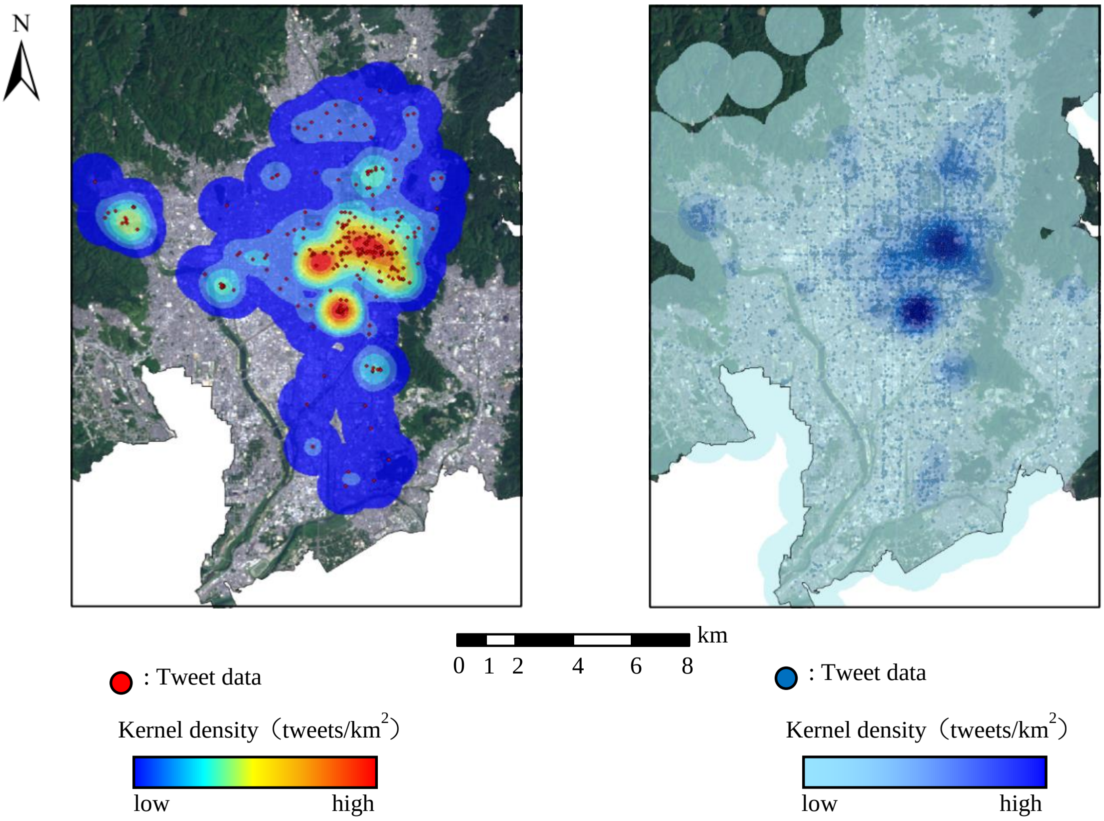
3.3 Spatial Distribution of the Tweet Data

Tweet data including the Chinese characters "hot" and all tweet data on the representative days were applied to the Kernel Density Estimation Method. Figure 7 shows the results of the applications. Both in Figures 7(i) and 7(ii), there seem to be high density areas around the main stations and the tourist spots in the city. We therefore calculated the ratio of these results, and then we defined the ratio as an Air Temperature Tweet Ratio (ATTR). Figure 8 indicates the results of the calculation.

We calculated the test statistics for the difference of the averages of ATTR between the area within and the area located outside of the range d by using the method shown in Figure 5. Figure 9 indicates the results of the calculation. The distance from the valley lines is shown in the horizontal axis, while the statistics of the test between the inside and outside of range d was plotted in the vertical axis. In the case where the statistics of the test show a value above 0, the average of ATTR within the range d is greater than that of ATTR beyond distance d. When the distance from the valley lines is 315m, the statistics of the test satisfies the positive significant level of 10%. As the distance from the valley lines is decreasing, it is confirmed that the statistic of the test is increasing.

3.4 Movement Derived from the Tweet Data around the Valley Lines

The influence of heat stress on the body increases generally when a change of the air temperature occurs rapidly (Fukuoka et al. 2008). There is a possibility that the interest in the air temperature is affected by the change of the surroundings in daily life. Particularly, as the air temperature changes through the one's movement (e.g. from a point A to a point B), the air temperature is noticed after the movement (at the point B). We then compared the movements derived from the tweet data around the valley lines. Initially, we defined the range of keen interests in the air temperature based on the features of the relationship between ATTRs and the distances to the valley lines in Figure



(i) Tweet data including Chinese character "hot"

(ii) All tweet data

Figure 7 Application results of the Kernel Density Estimation

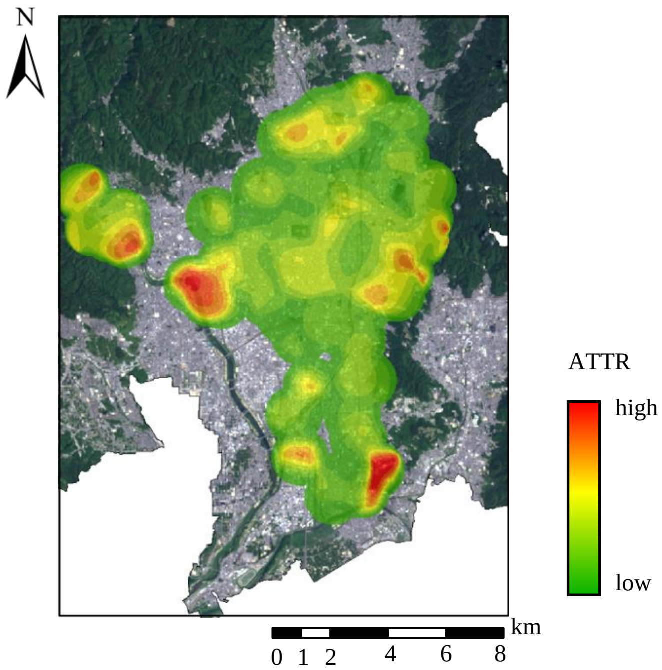


Figure 8 Distributions of the air temperature tweet ratio (ATTR)

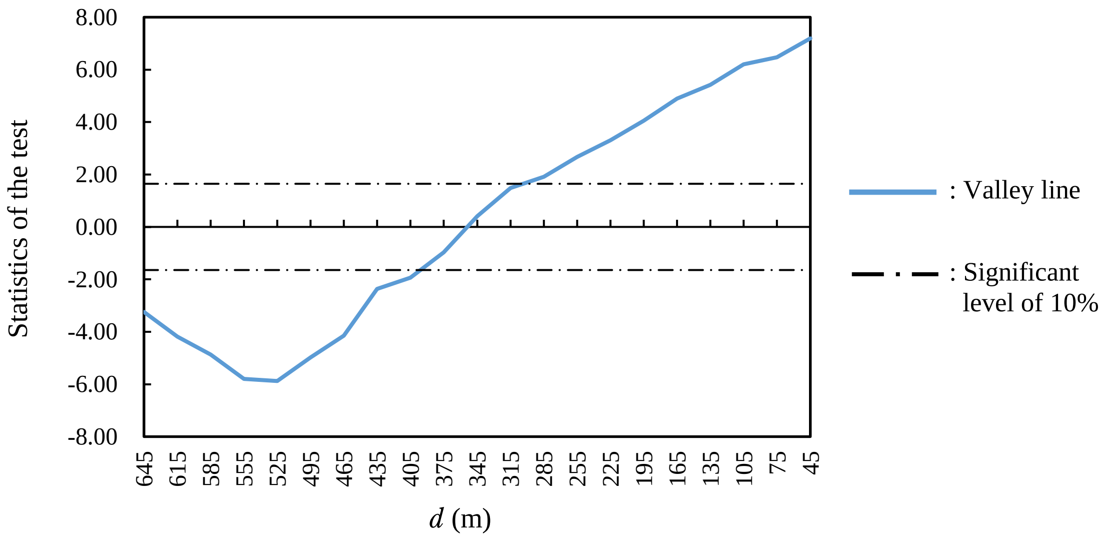


Figure 9 Results of the statistical test for the difference of the averages of ATTR between the inside and outside of the distance *d*

9; the range of distance is 315m. We focused on the pair of tweet data tweeted consecutively by a same id (a same twitter user). We assumed that the pair of tweet data shows the movement of the user. The movements were classified into three patterns: remaining within the range (Rem), entering from outside the range (Ent) and leaving the range (Lev). We also detected 2 kinds of the pair of tweet data in the movements: one contains short sentences including “hot” after the movement, the other is free from “hot”. We designated the former as IncH, and the latter as FreH. The averages of the number of these six patterns were calculated for each the valley lines. Then, we calculated the statistics of the test for the difference of the averages of the numbers between IncH and FreH.

Table 1 shows the results of the calculation. In the case where the statistics of the test show a value above 0, the averages of the numbers of IncH movement is greater than those of FreH. In 7 cases among 9 combinations, the statistics of test shows a value below 0. Their p-values also are less than 10%. It is suggested that the movements of

Table 1 Results of comparison for each movement patterns

		FreH		
		Rem	Ent	Lev
IncH	Rem	-2.77	-6.23	-5.82
	Ent	2.35	-3.27	-2.76
	Lev	2.42	-4.84	-4.34

FreH occur more frequently than those of IncH in general. The statistic of test between Ent in IncH and Rem in FreH, however, shows a value above 0. Between Lev in IncH and Rem in FreH, the statistic similarly shows a value above 0. Significant differences exist between these movements in whether or not to tweet "hot" because their p-values are less than 10%. The results in these combinations also show that the movements across the range of the keen interest in the air temperatures seem to happen more often than the movements within the range. Consequently, the one's interest in the air temperature seems to be rose by the one's movement across the range.

4. CONCLUSIONS

We compared the differences of the air temperatures around the valley lines using the air temperature data observed densely. From 0 o'clock to 5 o'clock and from 21 o'clock to 0 o'clock on the following day, the air temperature reduction around the valley lines was statistically clarified.

We also compared Air Temperature Tweet Ratios (ATTRs) around the valley lines. The averages of ATTR within 315m of the valley lines were significantly greater than those of ATTR beyond 315m. We defined the areas within 315m as the range of keen interest in the air temperatures. We then compared the movements derived from tweet data around the range. Consequently, the one's interest in the air temperature seemed to be rose by the one's movement across the range.

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