Building and Environment 243 (2023) 110645

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Exploring the impact of urban factors on land surface temperature and outdoor air temperature: A case study in Seoul, Korea

Tageui Hong, Yeonsook Heo *

School of Civil, Environmental and Architectural Engineering, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul, 02841, Republic of Korea

ARTICLE INFO

Keywords:
Urban heat island (UHI)
Land surface temperature (LST)
Outdoor air temperature (OAT)
Urban characteristics
Pedestrian-level temperature

ABSTRACT

Land surface temperature (LST) and outdoor air temperature (OAT) have been widely used to investigate urban heat island (UHI) phenomena. Although LST and OAT were reported to show a substantial correlation, whether urban factors play a consistent role in both LST and OAT has not been well addressed in the existing literature. To fill this gap, this study examined the effects of urban factors on both LST derived from satellite image data and OAT measured at the pedestrian-level through a case study in Seoul, Korea. Two different temperature datasets were used for the same days in summer and winter, and corresponding urban spatial characteristics were calculated on the basis of geographic information system (GIS) data. The effects of urban variables were analyzed using the Genizi and partial correlation methods. The results from the Genizi method revealed that land use characteristics (i.e., building coverage and pervious ratios) were important factors influencing LST, whereas urban morphological characteristics (i.e., building height) had a greater influence on OAT. The partial correlation results confirmed these separate sets of urban factors above are key factors for LST and OAT. In addition, the partial correlation analysis demonstrated that the pervious ratio showed a negative correlation with LST and the building height consistently showed a significant influence on OAT in both seasons. In contrast, the canyon ratio showed a contrasting effect on OAT depending on the season, underscoring that urban factors can affect temperatures differently depending on the meteorological conditions. This study highlights the different effects of urban factors depending on temperatures.

1. Introduction

Urban heat islands (UHI) are serious environmental problems caused by urbanization. The UHI phenomenon has resulted from a rapid increase in urban structures such as residential buildings, commercial buildings, and roads in urban areas. The UHI effect is represented by the outdoor air temperature difference between an urban area and a surrounding rural area. The effect is attributed to changes in land cover, various urban factors, anthropogenic heat, and air pollutants in the urban area [1,2]. The scale and intensity of the UHI effect continue to increase in many urban areas worldwide. The UHI intensity in a region of Chicago, USA, was measured to be 2.34 °C [3], and the highest and lowest daily maximum UHI intensity in Seoul were 4.8 °C and 3.5 °C in autumn and summer, respectively [4]. Furthermore, China's megacities, including Beijing, Shanghai, and Guangzhou, showed an annual average surface UHI intensity (SUHII) exceeding 2 °C, especially in the summer, with the highest average of 3.39 °C in Beijing [5]. The rise in the air temperature of urban areas due to UHI has not only increased the energy consumption in buildings but has also been regarded as a risk factor for diminished public health [6].

Land surface temperature (LST) has been widely used in urban climate research owing to the availability of data over large areas worldwide. LST data were obtained from satellite images and used to investigate the surface UHI (SUHI). SUHII represents the radiative temperature difference between urban and non-urban surfaces, and it is quantified primarily on the basis of satellite remote sensing data [7]. Peng et al. [8] investigated the SUHII in 419 global big cities and found that the average annual daytime SUHII was higher than the annual nighttime SUHII across these cities. They highlighted the key role of vegetation in mitigating the SUHII. Bechtel et al. [9] analyzed the temporal and spatial variations in LST in 50 cities for SUHI analysis. Schwarz et al. [10] compared various indicators for quantifying SUHI and emphasized the need for using multiple indicators, particularly those that enable capturing diurnal and seasonal patterns, to gain a better understanding of SUHI. LST data were used to investigate the relationships between various urban variables and the surface UHIs.

* Corresponding author.
E-mail address: yeonsookheo@korea.ac.kr (Y. Heo).

https://doi.org/10.1016/j.buildenv.2023.110645
Received 23 May 2023; Received in revised form 18 July 2023; Accepted 19 July 2023
Available online 20 July 2023

Land use-related variables, particularly the building coverage ratio and greenspace ratio, are typically used to indicate the man-made and natural portions of urban areas. The building coverage ratio was selected as the dominant predictor of LST and was found to have a significant positive relationship with LST [11]. On the contrary, the greenspace ratio has been reported to reduce LST [12], and a recent study further investigated the effects of greenspace size and pattern on LST [13,14]. Song et al. [15] found a strong negative relationship between the proportion of water and vegetation and LST and a strong positive relationship between the proportion of impervious surfaces and LST.

Outdoor air temperature (OAT) is a direct measure to quantify the UHI. Typically, a limited number of automatic weather stations (AWS) are installed in urban areas, and the number of OAT measurements is limited compared to LST measurements. In addition to existing AWS data, additional field measurements were collected from various urban locations and used to analyze UHI. Tong et al. [16] measured the air temperature at a 2.5-m height in 46 locations with various urban contexts in China and developed multiple linear regression (MLR) models for predicting OATs (maximum, minimum, daytime-average, and nighttime-average) in relation to building height, road width, and green plot ratio. Similarly, Jin et al. [17] developed MLR models on the basis of field measurement data from 27 locations in Singapore and investigated the effects of the green plot ratio, building plot ratio, percentage of pavement, sky view factor, distance to park, and distance to water on OAT. However, those studies considered the effect of urban factors on OAT under the same day or a few days with comparable weather conditions, and did not consider the effect of anthropogenic heat. Most studies, including the references mentioned above, were based on OAT measurements from a limited number of urban locations. Kim et al. [18] pointed out the limitation of the availability of urban weather measurements and the installation of a sufficient number of OAT sensors due to budget constraints as a key obstacle in UHI research.

Owing to the easy access to LST data, LST data have been used to infer OAT. In principle, LST is completely different from atmospheric temperature in terms of observational principles and altitudes [7]. SUHI was measured on the basis of LST data, whereas UHI was measured on the basis of OAT data. Nevertheless, OAT and LST data on the basis of the MODIS product were found to show a substantial correlation in many studies [10,19–21]. Furthermore, several studies developed methods to estimate OAT on a local scale using remote sensing data for areas with low observing station densities [22–24]. The availability of LST data is also limited because LST measurements are highly affected by atmospheric conditions, particularly cloud conditions. The issue of missing data owing to the cloud conditions has been acknowledged as a major limitation in examining spatial and temporal variations in large urban areas [25,26].

This study questioned whether individual urban factors play a consistent role in both LST and OAT. This research question was addressed by quantifying the effects of urban factors on these two temperatures through a case study in Seoul. In addition to LST data from satellite images, OAT data from 1,019 sensors across the Seoul area were utilized to sufficiently cover the entire Seoul area with varying urban characteristics. The effects of individual urban factors on LST and OAT were analyzed for summer and winter using the following steps: First, urban spatial variable values corresponding to LST and OAT measurements were estimated on the basis of Seoul GIS data. In order to determine the effects of the urban variables under different seasons, their overall effects were verified using data from all summer and winter days available in LST and OAT datasets. In addition, in the selection of the date, a clear day without precipitation was selected to reduce the effect of the weather conditions. The variable importance and relationship to each temperature were analyzed by quantitatively calculating the effects of individual variables through the Genizi and partial correlation methods. This study enhances the understanding of the impact of urban factors on two different temperatures, especially air temperature at the pedestrian-level.

2. Methodology

Fig. 1 shows the research framework used to investigate the impact of urban spatial characteristics on two different temperatures, namely, land surface temperature (LST) and outdoor air temperature (OAT), during summer and winter through a case study of the Seoul area. The datasets used in this study are two temperature measurement data and GIS data for extracting urban spatial characteristics. LST is the surface temperature measured from satellite images at a 1 km-by-1km grid and represents the average surface UHI effect. LST has been used to investigate the relationships between urban spatial variables and surface UHI effect for the daytime and nighttime on specific summer and winter days [27]. In addition, this study used the outdoor air temperature measured using sensors installed at the pedestrian level. GIS data were used to calculate the spatial characteristics of urban locations corresponding to the two temperature datasets. This study used GIS data, including building, road, greenspace, water-space, and subway information. GIS data were obtained from NSDI (http://www.nsdi.go.kr), and urban spatial variables were calculated using ArcMap10.1 and MATLAB.

We employed Genizi and partial correlation methods to investigate the effect of urban spatial variables on temperatures. As urban spatial variables might potentially show substantial parameter correlations, the Genizi method and partial correlation method were used to reflect the parameter correlations. The Genizi method has been used to quantify the contribution of individual variables under various conditions of other variables in the presence of correlated variables. The Genizi method was used to quantify the importance of correlated urban factors on building energy use in London [28] and on LST in London and Seoul [27]. The partial correlation method is used to evaluate the correlations while controlling for the relationship between target variables and eliminating the influence of the remaining variables. Shi et al. [29] performed a partial correlation analysis and demonstrated that the partial correlation and Pearson's correlation analyses resulted in opposite relationships between urban factors and OAT, and the partial correlation results were consistent with existing findings. This comparison highlighted the importance of considering parameter correlations in urban microclimate study.

In this study, we employed the Genizi method to determine the relative importance of various urban spatial variables in explaining variations in LST and OAT. As a variance decomposition technique, the Genizi method is designed for handling highly correlated variables [28]. The Genizi measure is calculated based on the decomposition proposed in the Genizi method [30–32]. The Genizi method is initiated by orthogonalizing the predictor matrix (X) that represents the urban spatial variables. In the orthogonalized matrix (Z), transformed from the predictor matrix, each component (v_i) is calculated as the product of the correlation between the original and the transformed regressors ($a_{ij} = \rho(x_i, z_j)$) and the correlation between the response variable (Y –LST and OAT in this case) and the transformed regressors ($c_j = \rho(y, z_j)$). This computation can be represented as:

$$v_i = \sum_j a_{ij}^2 c_j^2, \tag{1}$$

The sum of these components provides a unique decomposition of R^2:

$$\sum_i v_i = R^2 \tag{2}$$

The Genizi method satisfies the orthogonal compatibility criterion, which indicates that the sum of the importance scores equals the overall variance in temperature measurements. In other words, the relative importance of each urban spatial variable can be compared directly using the percentage of R^2 contributions. However, it should be noted that the Genizi method primarily evaluates the relative importance of variables and does not provide the direction of relationships among the variables. To supplement this limitation, additional partial correlation

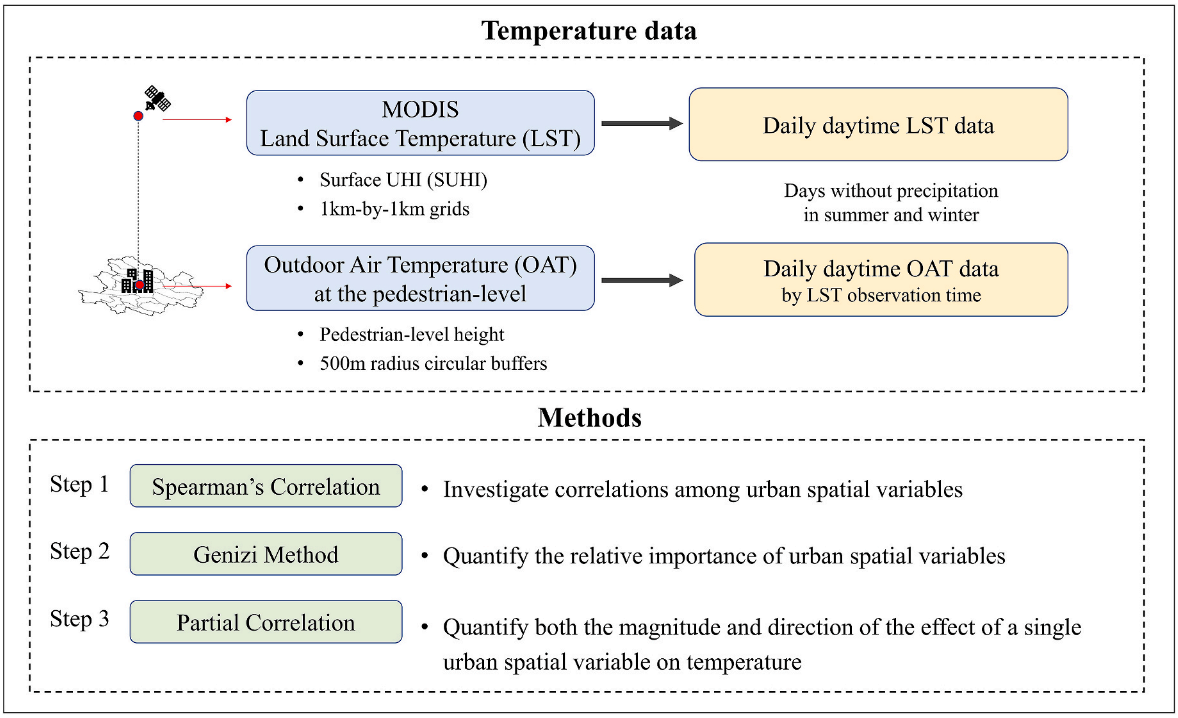

Fig. 1. Research framework.

analyses are usually performed to gain insights into the relationships between the urban spatial variables and temperature measurements.

Next, we employed the partial correlation method to assess the relationship between the individual urban spatial variables and temperature (LST and OAT), whilst controlling the effects of all the other urban variables. The partial correlation method computes a partial correlation efficiently; it ranges from −1 to 1, representing perfect negative and positive correlation, respectively, with 0 indicating no correlation. This method allowed us to isolate the relationship between each independent variable and the dependent variable. The partial correlation coefficient, R, is computed using the formula:

$$R_{YX_i.X_j} = \frac{\left(R_{YX_i} - \sum R_{YX_j} \cdot R_{X_iX_j}\right))}{\sqrt{\left(1 - \sum R^2_{YX_j}\right) \cdot \left(1 - \sum R^2_{X_iX_j}\right)}} \tag{3}$$

where Y is a dependent variable, and X_i is an independent variable. The partial correlation coefficient ($R_{YX_i.X_j}$) quantifies the direct correlation between Y and X_i by removing the influence of correlations with all other variables (X_j, for all $j \neq i$). R_{YX_i}, R_{YX_j}, and $R_{X_iX_j}$ were the correlation coefficients between X_i *and* Y, X_j *and* Y, and X_i *and* X_j, respectively.

In this study, the effects of urban characteristics were examined separately using a series of statistical analyses of LST and OAT. First, correlation analyses were performed to investigate the correlations among urban spatial variables. Spearman's correlation analysis is a nonparametric method that shows a simple rank-based relationship [27]. This is an essential step in inspecting the presence of high correlations among urban variables, which will be used as predictors in further analyses. Second, the Genizi method was applied to quantify the relative importance of the urban spatial variables with respect to LST and OAT. The function 'genizi' provided in the R studio package 'relaimpo' was used in this step. This function computes the relative importance of regressors in linear models and evaluates the coefficient of determination as a positive term through variance decomposition of the contribution of individual variables. In other words, the Genizi method offers a comprehensive indication of the importance of individual variables with full consideration of other variable settings. The results of the Genizi method were used to identify important urban factors for LST and OAT, separately. Finally, partial correlation analyses were performed to identify the direction of the relationship between urban factors and temperatures.

3. Case description

3.1. Study area

The study area was Seoul, a highly dense city with a high population density and numerous high-rise buildings. Geographically, the Han River flows through the center of the city and is a basin-shaped city surrounded by mountains. Seoul has four distinct seasons, hot and humid summers and cold and dry winters, each of which exhibits different UHI phenomenon [4,33]. This study used temperature data from 2021 to compare LST and OAT. According to the Korea meteorological administration (KMA), the average outdoor air temperatures for June, July, and August (summer) in 2021 were 22.8 °C, 28.1 °C, and 25.9 °C, with the highest temperatures reaching 31.6 °C, 36.5 °C, and 33.7 °C, respectively. In winter, the average temperatures for January, February, and December were −2.4 °C, 2.7 °C, and 0.6 °C, with the highest temperatures reaching 13.9 °C, 17.4 °C, and 13.3 °C, respectively. Precipitation was high and frequent in summer and drastically reduced in winter. LST and OAT data used in our analysis were selected from days without precipitation to exclude the effect of precipitation on the underlying relationships between urban factors and temperatures.

3.2. Temperature data

LST data used in this study were obtained from the moderate resolution imaging spectroradiometer (MODIS) MOD11A data product (earthdata.nasa.gov). This product provides daytime and nighttime LST data at different observation times. We used daytime LST data observed between 10:00 a.m. and 12:00 p.m. Korean local time. Because the MODIS dataset was obtained from satellite images, empty data points existed depending on sky cloud conditions. We selected three days in summer and winter in 2021, which showed almost no empty data points within the Seoul region: three summer days from June to August and three winter days from December to February. Hence, 699 LST data points were used for each day in the case study. In 2021, precipitation occurred for 23 of 31 days in August; therefore, the selected days in summer were limited to June and July. Table 1 summarizes the meteorological conditions for the selected days as provided by the KMA. The selected days were clear days with no precipitation and few clouds in common, but showed slightly different weather conditions within the same season.

The same days selected for LST were used to obtain OAT data and to compare OAT with LST under identical meteorological conditions. In addition, the same daytime duration (10 a.m.–12 p.m.) was used to calculate the daytime average OAT corresponding to the daytime LST. OAT data used in this study were provided by 1,019 smart Seoul city data sensors (S-DoT) installed at the pedestrian level across the Seoul area (data.seoul.go.kr). S-DoT sensors collect 17 types of environmental information data, including temperature, noise, and particulate matter. This data is collected using IoT sensors at a frequency of every 2 min, and the public data is made available in an hourly format. The sensors are distributed throughout Seoul, covering different administrative districts, residential areas, commercial zones, open spaces, and areas of policy interest (S-DoT information provided from the website, smart.seoul.go.kr). The S-DoT sensors are installed on utility poles, CCTV poles, and building exteriors as shown in Fig. 2. The heights of the installed sensors ranged from 0 to 6 m, with the average height of 3.59 m above the ground. The literature review by Kim and Brown [34] defined the categories of UHIs based on vertical height. The urban canopy layer (UCL), at the height of the average building roof, is a relatively high-level layer and may not represent pedestrian-level outdoor thermal comfort. In contrast, building canopy layer (BCL), closer to the surface, is considered to better represent human thermal comfort between street canyons. Since the majority of S-DoT sensors (around 91%) are concentrated at 2.5–4.5 m, below 10 m used to define the BCL, we assume that the S-DoT sensors effectively capture pedestrian-level temperatures and are referred to the pedestrian-level temperature.

Fig. 3 shows LST and S-DoT datapoint locations and corresponding buffer areas (fishnet grids and circular buffers, respectively) used to calculate the urban variable values. For the selected days, 699 LST datapoints and 1,019 S-DoT datapoints were used for the case study. Each LST datapoint provided in the MOD11A data product represented the average surface temperature corresponding to each fishnet grid cell, whereas each S-DoT sensor datapoint was a point measurement of OAT. As shown in Fig. 3, LST was provided for the entire Seoul divided into 699 grid cells, with a spatial resolution of 1km × 1 km. Accordingly, the same fishnets were used to calculate the urban characteristics corresponding to LST datapoints. The spatial buffer area of OAT datapoints was assumed to be the same as that of LST grid, and a circular buffer shape with a radius of 500 m was used to reflect the surrounding urban characteristics at the same effective distance from the measured sensor data points.

Fig. 4 and Table 2 show the distribution and statistical summary of LST and OAT datapoints for the same selected days during summer (left) and winter (right). The two datasets were not measured at the same location and LSTs were area-averaged values while OATs were point measurements. Overall, LSTs were higher than OATs and were much higher during summer. In both the summer and winter, OATs showed a reduced frequency of high peak temperatures compared to LSTs. In addition, OATs showed a two-mode distribution with the highest frequency in the higher-temperature mode, whereas LSTs showed the highest frequency around the middle of the distribution.

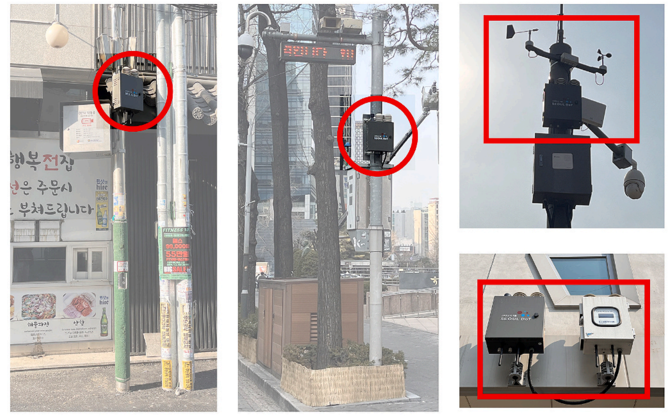

Fig. 2. Images of S-DoT sensors and their installation locations.

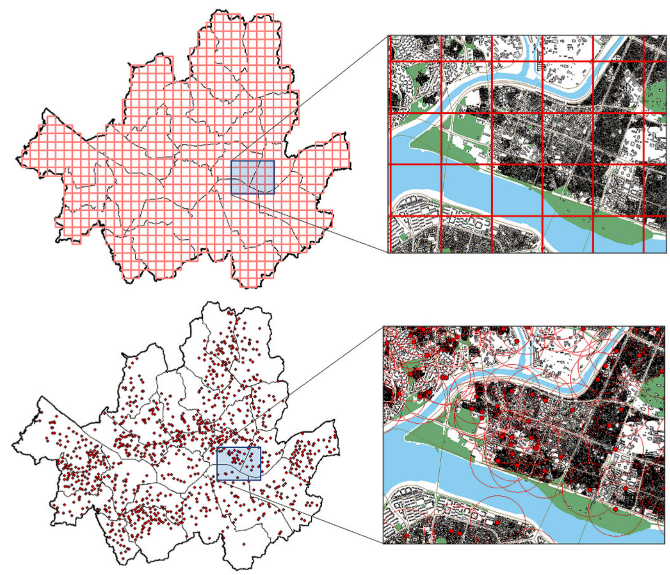

Fig. 3. LST fishnet grid cells (top), S-DoT sensor locations, and associated buffers (bottom) for Seoul.

3.3. Urban spatial variables

Urban variables are broadly categorized into urban morphology,

Table 1
Weather conditions for six selected time durations in 2021 by the KMA.

2021		Mean. air temperature (°C)	Min. air temperature (°C)	Max. air temperature (°C)	Mean. wind speed (m/s)	Total insolation (MJ/m^2)	Mean. total cloudiness (of 10)
Summer	June 21	23.6	19.2	28.5	2.2	25.72	3.3
	July 23	31.2	27.2	35.8	1.8	26.91	2.3
	July 26	31.2	27.4	35.4	2.4	29.3	1.6
Winter	January 19	−6.3	−11.6	−0.2	1.8	12.48	0.0
	February 12	6.5	0.6	14.0	1.7	14.72	4.0
	December 22	2.2	−2.6	8.2	1.7	10.21	0.0

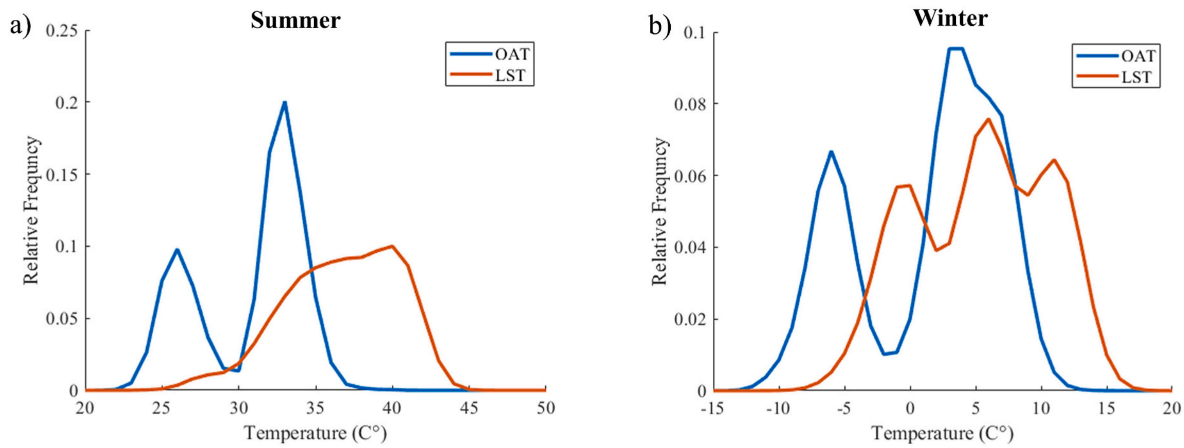

Fig. 4. Distributions of LST and OAT on selected days.

Table 2
Statistical summary of LST and OAT for six days in 2021.

2021		LST			OAT		
		Mean (°C)	Min (°C)	Max (°C)	Mean (°C)	Min (°C)	Max (°C)
Summer	June 21	33.8	24.4	39.1	26.2	22.2	33.3
	July 23	38.0	30.6	43.2	33.0	29.1	39.7
	July 26	38.0	29.4	43.8	33.1	28.6	39.9
Winter	January 19	−0.81	−6.13	3.31	−5.99	−11.2	−0.20
	February 12	10.9	6.77	14.0	6.56	1.55	12.7
	December 22	5.59	2.41	7.29	2.99	−1.7	8.00

land use, and anthropogenic heat. Table 3 summarizes the set of urban variables selected for the case study. Among the various urban morphological variables, building height and canyon ratio have been investigated as key variables that play a major role of urban morphology characteristics in UHI [35–37]. In addition, the building coverage ratio and pervious ratio have been used to explain the dominant land cover types that impact UHI [12–14]. The building coverage ratio is the ratio of the sum of building footprint areas within a buffer area to the total buffer area. The pervious ratio represents the ratio of green and water space areas to the total buffer area. Anthropogenic heat generated by human activities has been shown to have a significant impact on urban microclimate [38–40]; however, direct measurements of anthropogenic heat generation are not available. Hence, the number of subway stations is considered a potential surrogate indicator to represent anthropogenic heat from human activities; in fact, Seoul has more than 300 subway stations heavily used for daily transportation. Finally, an additional variable, the sensor height, is considered only for OAT dataset to reflect differences in the measurement height and, ultimately, vertical differences in air temperature. In addition to the aforementioned variables, the thermo-physical properties of construction materials were found to play a substantial influence on the UHI [39,41,42]. However, this information is typically not available (also for the case area of Seoul). Hence, this study focused on urban spatial variables that can be derived from the GIS data.

GIS data were used to estimate urban characteristics corresponding to LST and OAT buffer areas. In the GIS data of Seoul, buildings, greenspaces, and water spaces are represented by polygons, roads are represented by polylines, and subway stations are represented by points. As for the building height, for some polygons that did not provide information about building height but only about the number of floors, the building height was calculated by multiplying the average floor height in Seoul (3.72 m) by the number of floors. The canyon ratio, originally derived from the homogeneous urban canyon concept, was difficult to derive correctly from the uneven, irregular relationships between streets and buildings. In this study, the building-occupied ratio, introduced by Liao et al. [27], was factored into the calculation of the canyon ratio. The calculation processes for extracting urban variable values from GIS data are provided in Ref. [27]. The average values of the urban variables were calculated based on GIS data for each LST and OAT buffer areas.

Table 4 presented a statistical summary of the urban variable values corresponding to LST and OAT data. In addition, histograms of the building height, canyon ratio, building coverage ratio, and pervious ratio were shown in Fig. 5. Overall, the urban characteristics of the buffer areas associated with LST and OAT showed a similar range of values although LST presented wider ranges of values for the pervious

Table 3
Urban spatial variables.

No.	Variables	Categories	Note
1	Building height (BH)	Urban morphology	–
2	Canyon ratio (CR)	Urban morphology	–
3	Building coverage ratio (BCR)	Land use	–
4	Pervious ratio (PR)	Land use	–
5	Number of subway stations (NSS)	Anthropogenic heat	–
6	Sensor height (SH)	Measurement height	Only for OAT data

Table 4
Statistical summary of urban spatial variables at selected time points.

		BH (m)	CR	BCR	PR	NSS	SH (m)
LST	**Mean**	14.31	1.85	0.17	0.29	0.42	–
	Min.	3.72	0.00	0.00	0.00	0.00	–
	Max.	74.74	4.88	0.43	1.00	4.00	–
	Std.	9.30	1.05	0.12	0.29	0.60	–
OAT	**Mean**	14.08	1.97	0.25	0.14	0.83	3.59
	Min.	4.40	0.00	0.00	0.00	0.00	0.00
	Max.	64.29	6.75	0.45	1.00	6.00	6.00
	Std.	6.92	0.71	0.09	0.14	0.97	0.69

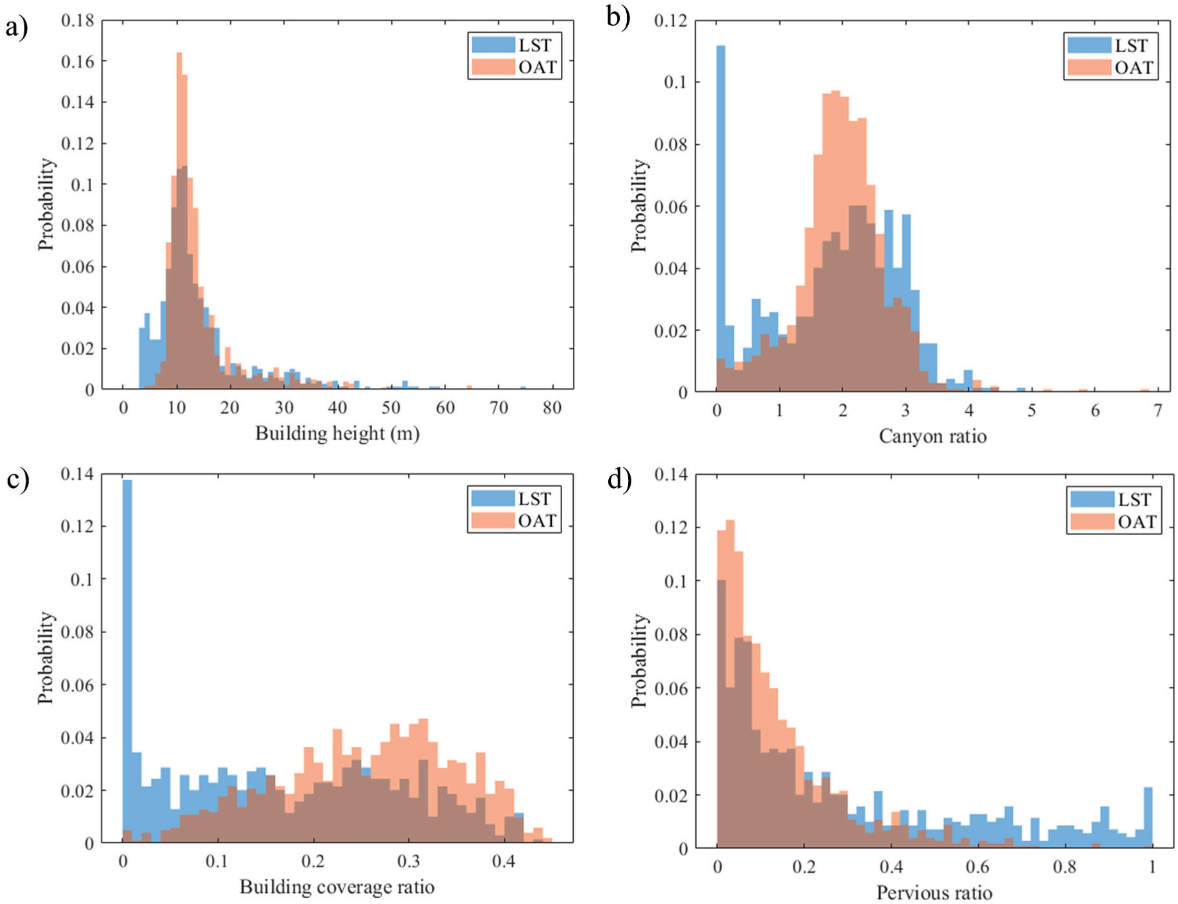

Fig. 5. Histogram of urban spatial variables: a) building height, b) canyon ratio, c) building coverage ratio, d) pervious ratio.

ratio and building height. Since most of OAT sensors were installed on pedestrian streets between buildings, OAT had relatively smaller the pervious ratio values than LST data, which covered the periphery of Seoul area with very large green spaces.

4. Results

4.1. Correlations among spatial variables

Fig. 6 summarized the Spearman's correlation coefficients among the spatial variables for LST and OAT data locations. Although differences in the magnitudes of the coefficients existed, the same pairs of urban

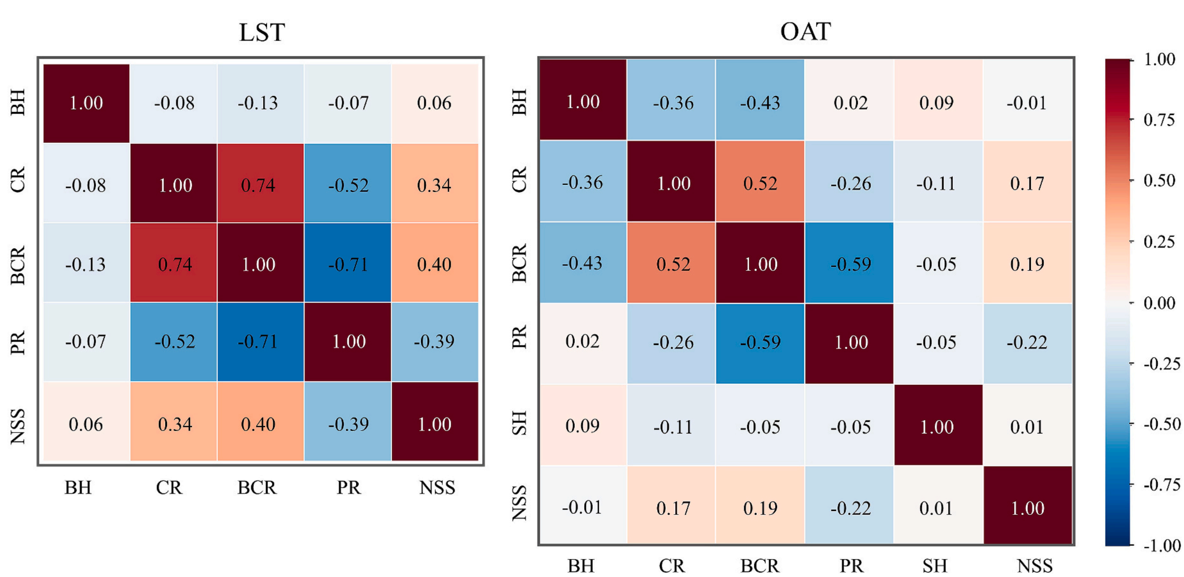

Fig. 6. Correlations among urban spatial variables.

variables showed substantial correlations in both LST and OAT data locations. A strong positive correlation between the building coverage ratio and canyon ratio and a strong negative correlation between the building coverage ratio and pervious ratio were observed for both LST and OAT data locations. The high positive correlation between the building coverage and canyon ratios indicated that the canyon ratio increased as the building footprint area increased. A strong negative correlation between the building coverage and pervious ratios was expected because a higher building coverage ratio implies a larger impervious area and, accordingly, less pervious area within the buffer area. LST generally showed higher magnitudes of correlation coefficients than OAT.

The two temperature datasets showed different correlation results for the building height. LST data locations showed almost no correlation of the building height with the canyon ratio and the building coverage ratio, whereas OAT locations showed a higher negative correlation between these pairs. The sensor height, applicable only to OAT dataset, showed weak correlations with the other urban variables. The differences in the correlation results were, of course, attributed to the two data being measured at different locations, which potentially had different urban characteristics. Although some degree of difference in the correlation of urban variables was present between the two temperature datasets, they overall showed a consistent correlation trend.

4.2. Relative importance of urban variables for LST and OAT

Fig. 7 showed the relative importance of the urban spatial variables computed by the Genizi method for LST and OAT in summer and winter. The boxplot displayed all Genizi measures representing the proportional contribution of each variable to the variation in temperature data, which summarized the significance of individual urban variables over feasible combinations of other variable values. Genizi measures were obtained per selected day for summer and winter, separately. For both seasons, the most important variable for LST was the pervious ratio, followed by the building coverage ratio and the canyon ratio. On the contrary, the building height, along with the sensor height, was identified to be as important or more important than the pervious ratio and the building coverage ratio for OAT. These results suggested that LST was more affected by the configuration of land use, whereas OAT was affected more by urban morphological characteristics. In addition, the building coverage and pervious ratios had noticeable impacts on both LST and OAT. The number of subway stations was relatively insignificant for LST, whereas it was a more important for OAT.

Regarding LST, the pervious ratio accounted for 35.5% of LST variations on average during the summer and 51.7% of LST variations in the winter much higher than in the summer. In the summer, the building coverage ratio and canyon ratio were responsible for 32.1% and 24.3% of LST variations, respectively, and their influence on LST was considered comparable to the pervious ratio. However, in the winter, these two variables accounted for 25.1% and 16.1% of LST variations, respectively, marking a significant reduction in their importance relative to the pervious ratio. This comparison suggested that the influence of important urban variables on LST, particularly the pervious ratio, varied depending on the season and underscored the increased significance of the pervious ratio in explaining LST variations during the winter season. For OAT, the building height and the sensor height were important or more important than the pervious ratio and the building coverage ratio. The sensor height, used only for OAT, contributed to OAT variations by 25.5% in summer and 26.5% in winter. The building height contributed to 20.8% in summer and 28.9% in winter on average. In addition to these two top variables, the building coverage ratio and the pervious ratio explained 15.6% and 19.3% of OAT variations in summer and 24.7% and 12.0% in winter, respectively. The effects of the pervious ratio in summer and the building coverage ratio in winter were nearly as important as the building height. Although the NSS also showed the lowest effect on OAT on average, it should be noted that the upper

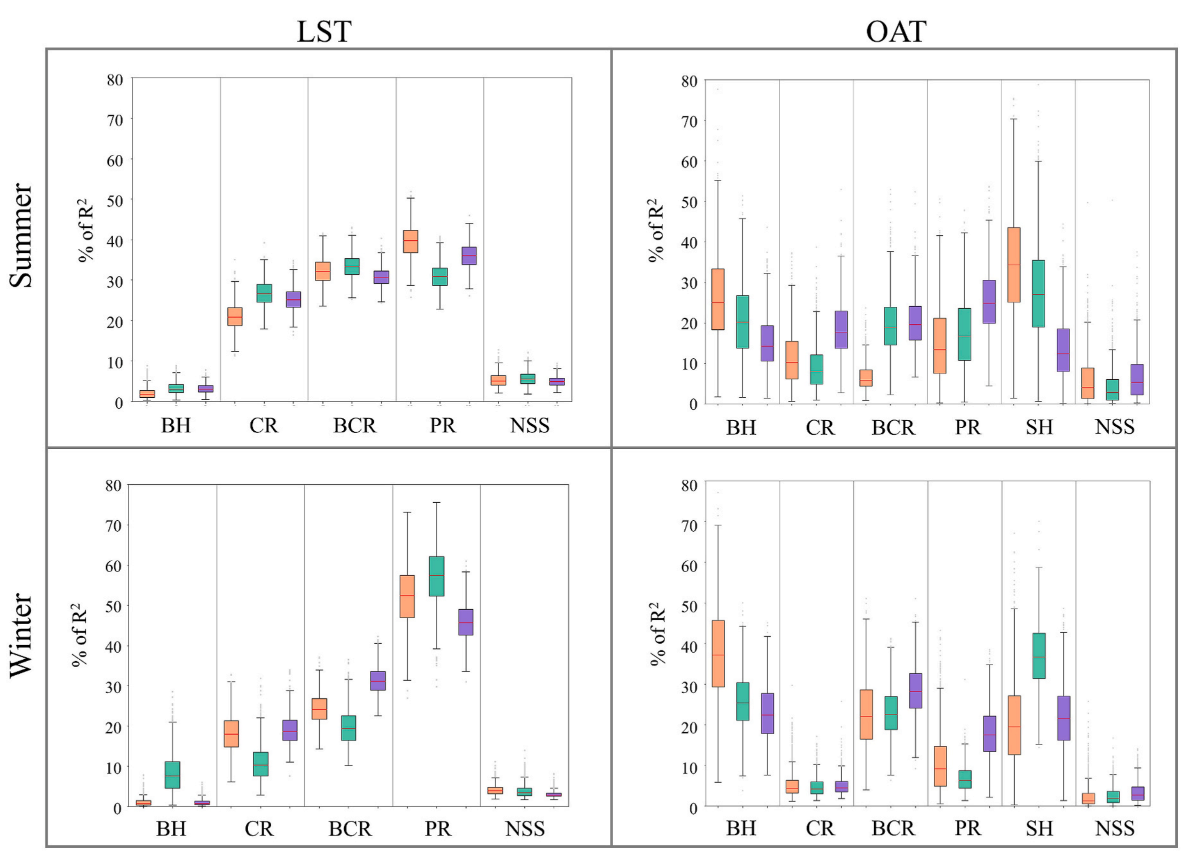

Fig. 7. Relative importance of spatial variables by the Genizi method.

whisker (maximum values excluding outliers) and the interquartile range (IQR) of the NSS were relatively wider for OAT than LST.

A key difference between LST and OAT was that LST showed a substantially reduced effect of the building height in comparison to OAT. Indeed, the building height impacts urban albedo, including the shading effect and air flow within an urban canyon. Chen et al. [43] showed that an increase in building height changes substantially decreased the average urban albedo, which may potentially decrease the UHI effect. Taller buildings was reported to lower potential temperatures due to their shading effects [36], and in case of buildings below 20 floors, every 10 m increase in the building height was reported to decrease the daytime temperature by 0.06 °C [35]. Additionally, an increase in building height led to a decrease in LST through building shadows, which effectively reduced solar radiation. Furthermore, the alteration of wind flow around high-rise buildings might create turbulence, which could improve the local thermal environment [44]. Another major difference was that the pervious ratio had a much more dominant effect on LST than on OAT. Indeed, in many existing studies, green spaces were found to play a significant role in mitigating the UHI by absorbing heat and cooling the air through evapotranspiration [11,45,46]. Although both LST and OAT were substantially affected by the pervious ratio, LST was much more influenced by the land use type, particularly the fraction of green and water surfaces, which directly determined the surface temperature.

The building coverage and canyon ratios appeared to be important variables for both LST and OAT, with the exception of the canyon ratio for OAT on winter days. The building coverage ratio has been used as an indicator of building density and has been shown to have a fairly linear relationship with LST [47]. Zhou et al. [11] also found that the composition of land use, particularly the building coverage ratio, had the greatest effect on LST. Similarly, OAT was also shown to have a positive relationship to the building coverage ratio [18,48]. In addition to the building coverage ratio, the canyon ratio (H/W) has been used as a major factor that affects solar heat gains, shading effects, local airflow, and ultimately, UHI [49–51]. On the one hand, an increase in the canyon ratio resulted in a decrease in the canyon, wall, and ground temperatures, which potentially had a positive effect on mitigating UHI [49]. On the other hand, the increase in the canyon ratio was reported to result in an increase in the UHI effect because the heat energy trapped by the long-wave radiation was much higher than the cooling effect due to shading [50].

The number of subway stations had a relatively smaller effect on LST and OAT than the other urban variables. In this study, the number of subway stations was used as a surrogate variable for anthropogenic heat. The major sources of anthropogenic heat are cooling and heating in buildings, manufacturing, and transportation [38]. In existing studies, statistical data on energy consumption were used to infer anthropogenic heat production for each sector [52]. Instead, information about subway station locations, obtained from GIS data, was used in this case study, and the number of subway stations within a buffer area was assumed to be correlated to the population density and, consequently, heat emissions from buildings and transportation within the buffer area. In LST, the importance of the number of subway stations was small; however, in OAT, the whiskers of the Genizi measure approximately appeared up to 20% in summer and up to around 10% in winter. Although the number of subway stations has been used as one of predictors in the analysis of UHI [53,54], the relevance of using this variable to represent anthropogenic heat has not yet been verified because of the lack of reliable data sources for anthropogenic heat. Based on our results, we highlight the cautions that should be taken when concluding the effect of anthropogenic heat flux on LST and OAT.

The relative importance of the urban variables was found to substantially vary for different days in the same season. This variation suggested that the magnitude of the impact of urban characteristics on LST and OAT might differ depending on regional meteorological conditions (e.g., outdoor temperature, solar radiation, and wind speed). Furthermore, the wide whiskers of the Genizi measure within the same day indicated that the effect of individual urban variables on the UHI might substantially differ depending on the overall urban characteristics (a combination of all urban variables). In particular, OAT showed much wider whiskers of the Genizi measure than LST for all urban variables. In OAT, the sensor height was the top influential variable, which confirmed a substantial temperature gradient along the vertical height ranging between 0 and 6 m.

4.3. Partial correlations of urban variables with LST and OAT

This section summarized the results of the partial correlation between the urban variables and temperatures (LST and OAT) in summer and winter as shown in Fig. 8. Partial correlation coefficients were displayed as bars. *R* measure was used to indicate the strength and direction of the correlation. Significance was determined by p-values, and non-significant relationships ($p > 0.05$) were represented as white bars without color. Overall, the results obtained from partial correlation analyses closely aligned with the relative importance of urban spatial variables derived from the Genizi method. Variables with a high relative importance exhibited significant partial correlations, while those with lower importance demonstrated non-significant partial correlations. For all selected days in summer and winter, the partial correlation analyses yielded the pervious ratio and the sensor and building heights as the dominant factors affecting LST and OAT, respectively, which were confirmed to be statistically significant.

In summer, LST showed significant partial correlations with all urban variables ($p < 0.01$), except for the NSS. In winter, only the pervious ratio consistently showed a significant correlation with LST ($p < 0.01$). In contrast, OAT presented significant correlations with the building height, pervious ratio, and sensor height in summer and with the building height and sensor height in winter. The previous ratio showed a significantly negative effect on LST: an average partial correlation coefficient of −0.262 for selected summer days and −0.279 for selected winter days, respectively. The building height, along with the sensor height, showed a significantly negative effect on OAT for all selected days: the average coefficients of the sensor height ranging between −0.122 and −0.161 in winter and the building height ranging between −0.091 and −0.128 for summer and winter.

Except for LST on selected summer days, the partial correlation results were not statistically significant to some extent. Different directions of correlation were observed not only between LST and OAT but also between seasons with the same temperature indicator. Since the three days may not be sufficient to analyze the overall effect of urban factors, partial correlation analyses were further performed with an extensive set of winter days for LST and summer and winter days for OAT. The extensive set of LST data for winter covered 20 days, including the three days used in the earlier analyses. The extensive OAT dataset covered 31 days in summer and 42 days in winter. Similar to earlier analyses, a partial correlation analysis between the urban variables and temperature was performed per day, and all partial correlation coefficients of all summer or winter days were summarized as displayed in Figs. 9 and 10. Fig. 9 showed the range of partial correlation coefficient values for the 20 winter days of LST data ($p < 0.05$), and Fig. 10 showed that for the 31 summer days and 42 winter days of OAT data. Only partial correlation results with statistical significance were included and, consequently, different numbers of results were presented per urban variable.

Overall, although the number of days showing a statistically significant result differed per urban variable, the direction of the partial correlation results with statistical significance was consistent for most urban variables. Regarding LST data, the pervious ratio showed the most dominant and significant negative correlation with LST (also shown in Figs. 8a and 9). Specifically, its average partial correlation coefficients were −0.26 in summer and −0.27 in winter, which were almost two to three times greater than those of other variables. In addition, the canyon

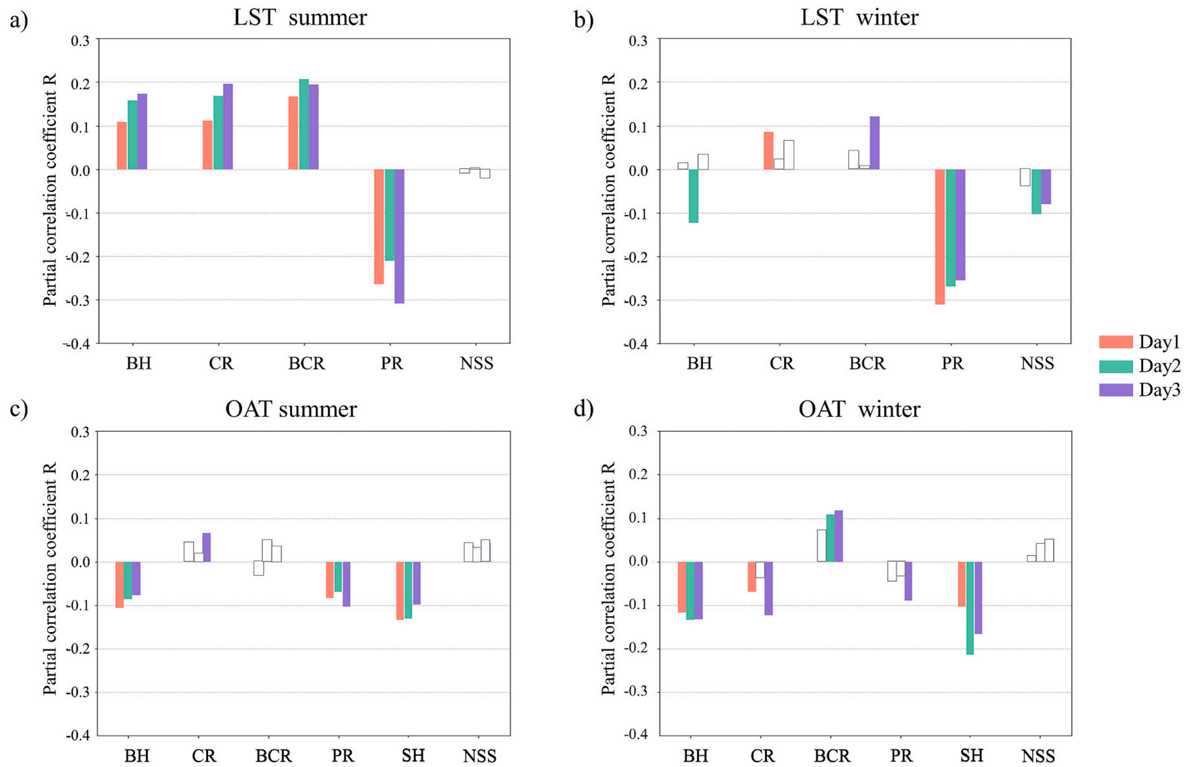

Fig. 8. Partial correlations between urban variables and a) LST summer, b) LST winter, c) OAT summer, d) OAT winter.

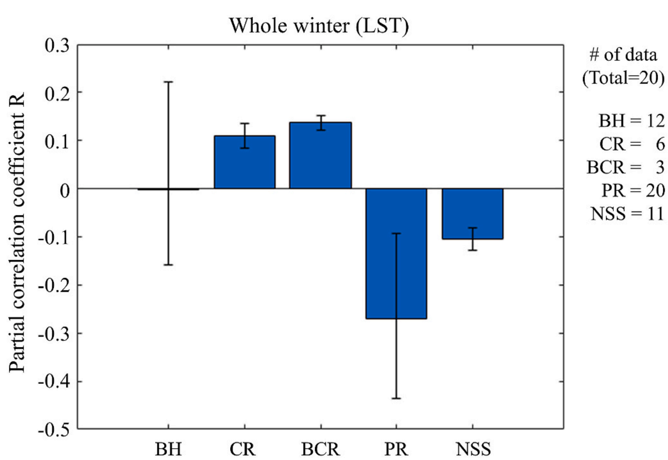

Fig. 9. Partial correlation coefficients between urban variables and LST for the whole winter.

ratio and the building coverage ratio showed a positive correlation with LST in both summer and winter. While the building height was positively correlated with LST on the three selected summer days, it showed a wide range of correlation coefficients from −0.16 to 0.22, including both positive and negative effects, for the whole winter days. Regarding OAT, the building and sensor heights showed a negative correlation with OAT for the whole summer and winter periods. The building coverage ratio mostly showed a positive correlation with OAT in both seasons, whereas the pervious ratio showed a negative correlation with OAT. Moreover, the canyon ratio showed a contrasting correlation direction in different seasons for OAT: a positive effect in summer (R = 0.09) and a negative effect in winter (R = −0.09). Particularly in OAT, the NSS consistently showed a positive correlation in both seasons, with an average coefficient of roughly 0.10, comparable to that of the canyon ratio although it showed the insignificant effect for the selected days in

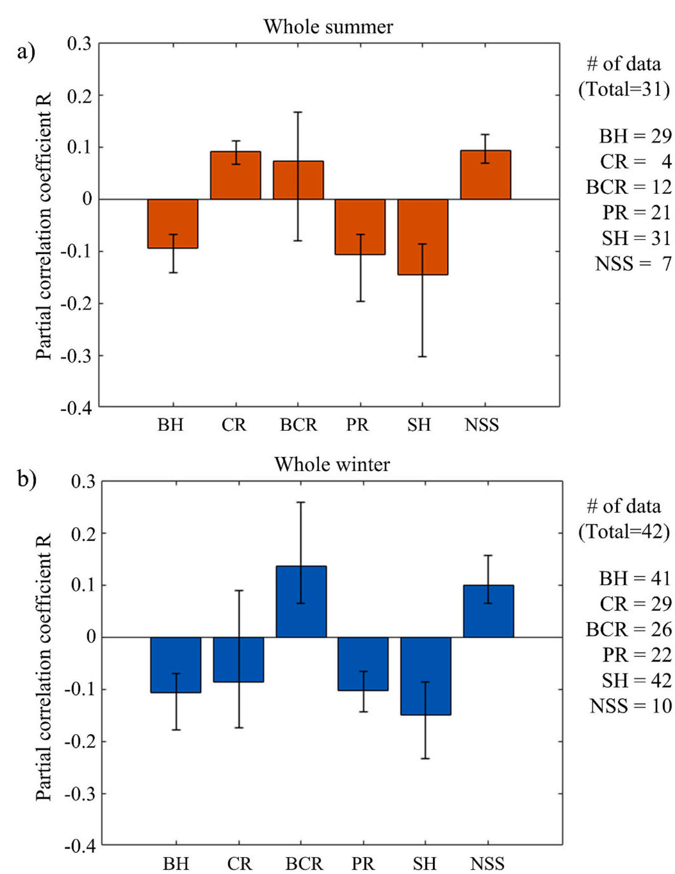

Fig. 10. Partial correlation coefficients between urban variables and OAT for the whole summer and winter.

the earlier analysis. This additional analysis indicates the importance of considering anthropogenic heat generation for OAT.

Except for the pervious ratio and the building coverage ratio, the other variables showed different directions of relationship depending on the temperature indicator and season. The building height had both positive and negative correlations with LST but only a negative correlation with OAT. Previous studies showed that increasing the building height resulted in lower daytime air temperatures [35,36,43]. Some studies reported inconsistent results regarding LST. Some studies showed that taller buildings led to higher LSTs [41,55], whereas other studies found that the building height had a negative effect on LST due to the shading effect between buildings [56,57]. This collection of existing evidence aligned with our results regarding the effects of building height on different temperatures.

Overall, LST showed a positive correlation with the canyon ratio in both summer and winter, while OAT showed a positive correlation with the canyon ratio in summer and a negative correlation in winter. Previous studies have explained the effects of urban canyons on UHI or temperature in two main ways: trapping heat energy and cooling effect of creating shadows. Theeuwes et al. [50] found that the UHI was controlled by two counteracting processes: trapping long-wave radiation and creating shadows. A higher canyon ratio led to more long-wave radiation being trapped, resulting in a higher temperature rise in the canyon. However, as the street narrows, less solar radiation penetrated into the canyon. In this study, the combined effects of the increased the canyon ratio were found to increase LST and OAT for both seasons except OAT in winter. In particular, during winter, when short-wave radiation was limited, trapping of long-wave radiation might dominate the relationship between the canyon ratio and UHI, particularly air temperature. Liang et al. [58] found that when the street canyon became narrower, the sky view factor decreased and was inversely proportional to daytime intra-urban air temperature in summer.

5. Conclusions

This study investigated the effects of urban factors on two temperature data, LST and OAT. The study calculated the average values of urban variables in the grids and buffers of the two temperatures. Using daytime LST and the corresponding pedestrian-level OAT, the study investigated the individual effects of urban variables in temperature data with different characteristics. Through the correlation analysis of urban spatial variables, the similarity of urban spatial variables in different datasets was discovered. Based on representative summer and winter days, the study used the Genizi method to analyze the relative importance of urban variables for each temperature. Partial correlation analysis was used to identify the relationship direction between urban spatial variables and the two temperatures. In addition to representative summer and winter days, the analysis was performed using all available days in summer and winter to clarify the direction of the relationship.

The findings of this study highlighted the importance of evaluating urban spatial variables at the pedestrian level to understand the UHI effect on people. By using Genizi method and partial correlation analysis, this study was able to quantify the discrepancy in the impact on LST and OAT, and to distinguish the importance of urban variables and their influence on OAT. Especially, LST was mainly affected by land use characteristics, while OAT reflected the importance of urban morphology. Also, the sensor height was the most significant factor affecting OAT. However, to fully understand the UHI effect of the potential factors depending on vertical height, it is necessary to examine the urban temperatures of both lower and upper levels. In addition, there were variables that showed a consistent role in both summer and winter, but some variables were also identified that had seasonal differences. Nevertheless, in this study, S-DoT data, temperature data close to the pedestrian-level, are sufficiently available to provide knowledge for estimating the effects of urban spatial characteristics on the temperature between street canyons. This study represents an initial step in evaluating pedestrian-level UHI and can provide valuable insights for urban planners and policymakers in devising effective strategies for mitigating UHI.

Despite the valuable insights provided by this study, there are still some limitations to consider and directions for future research. First, this study only examined average urban characteristics, and consideration of urban heterogeneous factors is needed to highlight the intricate nature of urban morphology. Second, the study only focused on the relationship between urban spatial characteristics and UHI, without examining the impacts of other factors such as meteorological factors or human behavior. Third, the study was conducted in a specific urban area, and the findings may not be generalizable to other regions with different urban forms or climatic conditions. Therefore, future research should consider these limitations and explore further the relationships between UHI and various factors in different urban contexts.

CRediT authorship contribution statement

Tageui Hong: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yeonsook Heo:** Supervision, Methodology, Conceptualization, Funding acquisition, Investigation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (2020R1A2C1003751).

References

[1] A.M. Rizwan, L.Y. Dennis, L.I.U. Chunho, A review on the generation, determination and mitigation of Urban Heat Island, J. Environ. Sci. 20 (1) (2008) 120–128.
[2] M.E. Hulley, The urban heat island effect: causes and potential solutions, in: Metropolitan Sustainability, Woodhead Publishing, 2012, pp. 79–98.
[3] P. Coseo, L. Larsen, How factors of land use/land cover, building configuration, and adjacent heat sources and sinks explain Urban Heat Islands in Chicago, Landsc. Urban Plann. 125 (2014) 117–129.
[4] S.H. Lee, J.J. Baik, Statistical and dynamical characteristics of the urban heat island intensity in Seoul, Theor. Appl. Climatol. 100 (2010) 227–237.
[5] Y. Hu, M. Hou, G. Jia, C. Zhao, X. Zhen, Y. Xu, Comparison of surface and canopy urban heat islands within megacities of eastern China, ISPRS J. (2019).
[6] C. Heaviside, H. Macintyre, S. Vardoulakis, The urban heat island: implications for health in a changing environment, Curr. Environ. Health Rep. 4 (2017) 296–305.
[7] J.A. Voogt, T.R. Oke, Thermal remote sensing of urban climates, Rem. Sens. Environ. 86 (3) (2003) 370–384.
[8] S. Peng, S. Piao, P. Ciais, P. Friedlingstein, C. Ottle, F.M. Bréon, R.B. Myneni, Surface urban heat island across 419 global big cities, Environ. Sci. Technol. 46 (2) (2012) 696–703.
[9] B. Bechtel, M. Demuzere, G. Mills, W. Zhan, P. Sismanidis, C. Small, J. Voogt, SUHI analysis using Local Climate Zones—a comparison of 50 cities, Urban Clim. 28 (2019), 100451.
[10] N. Schwarz, S. Lautenbach, R. Seppelt, Exploring indicators for quantifying surface urban heat islands of European cities with MODIS land surface temperatures, Rem. Sens. Environ. 115 (12) (2011) 3175–3186.
[11] W. Zhou, G. Huang, M.L. Cadenasso, Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes, Landsc. Urban Plann. 102 (1) (2011) 54–63.
[12] R. Sun, L. Chen, Effects of green space dynamics on urban heat islands: mitigation and diversification, Ecosyst. Serv. 23 (2017) 38–46.

[13] F. Kong, H. Yin, P. James, L.R. Hutyra, H.S. He, Effects of spatial pattern of greenspace on urban cooling in a large metropolitan area of eastern China, Landsc. Urban Plann. 128 (2014) 35–47.
[14] X. Li, W. Zhou, Z. Ouyang, Relationship between land surface temperature and spatial pattern of greenspace: what are the effects of spatial resolution? Landsc. Urban Plann. 114 (2013) 1–8.
[15] J. Song, S. Du, X. Feng, L. Guo, The relationships between landscape compositions and land surface temperature: quantifying their resolution sensitivity with spatial regression models, Landsc. Urban Plann. 123 (2014) 145–157.
[16] S. Tong, N.H. Wong, S.K. Jusuf, C.L. Tan, H.F. Wong, M. Ignatius, E. Tan, Study on correlation between air temperature and urban morphology parameters in built environment in northern China, Build. Environ. 127 (2018) 239–249.
[17] H. Jin, P. Cui, N.H. Wong, M. Ignatius, Assessing the effects of urban morphology parameters on microclimate in Singapore to control the urban heat island effect, Sustainability 10 (1) (2018) 206.
[18] M. Kim, K. Lee, G.H. Cho, Temporal and spatial variability of urban heat island by geographical location: a case study of Ulsan, Korea, Build. Environ. 126 (2017) 471–482.
[19] C. Vancutsem, P. Ceccato, T. Dinku, S.J. Connor, Evaluation of MODIS land surface temperature data to estimate air temperature in different ecosystems over Africa, Rem.Sens. Environ. 114 (2) (2010) 449–465.
[20] T. Hengl, G. Heuvelink, M. Perčec Tadić, E.J. Pebesma, Spatio-temporal prediction of daily temperatures using time-series of MODIS LST images, Theor. Appl. Climatol. 107 (1) (2012) 265–277.
[21] N. Janatian, M. Sadeghi, S.H. Sanaeinejad, E. Bakhshian, A. Farid, S. M. Hasheminia, S. Ghazanfari, A statistical framework for estimating air temperature using MODIS land surface temperature data, Int. J. Climatol. 37 (3) (2017) 1181–1194.
[22] A. Benali, A.C. Carvalho, J.P. Nunes, N. Carvalhais, A. Santos, Estimating air surface temperature in Portugal using MODIS LST data, Rem.Sens. Environ. 124 (2012) 108–121.
[23] G.V. Mostovoy, R.L. King, K.R. Reddy, V.G. Kakani, M.G. Filippova, Statistical estimation of daily maximum and minimum air temperatures from MODIS LST data over the state of Mississippi, GIScience Remote Sens. 43 (1) (2006) 78–110.
[24] W. Zhu, A. Lű, S. Jia, Estimation of daily maximum and minimum air temperature using MODIS land surface temperature products, Rem.Sens. Environ. 130 (2013) 62–73.
[25] S.N. Williamson, D.S. Hik, J.A. Gamon, J.L. Kavanaugh, S. Koh, Evaluating cloud contamination in clear-sky MODIS Terra daytime land surface temperatures using ground-based meteorology station observations, J. Clim. 26 (5) (2013) 1551–1560.
[26] X. Li, Y. Zhou, G.R. Asrar, Z. Zhu, Creating a seamless 1 km resolution daily land surface temperature dataset for urban and surrounding areas in the conterminous United States, Rem.Sens. Environ. 206 (2018) 84–97.
[27] W. Liao, T. Hong, Y. Heo, The effect of spatial heterogeneity in urban morphology on surface urban heat islands, Energy Build. 244 (2021), 111027.
[28] W. Tian, Y. Liu, Y. Heo, D. Yan, Z. Li, J. An, S. Yang, Relative importance of factors influencing building energy in urban environment, Energy 111 (2016) 237–250.
[29] Y. Shi, Y. Xiang, Y. Zhang, Urban design factors influencing surface urban heat island in the high-density city of Guangzhou based on the local climate zone, Sensors 19 (16) (2019) 3459.
[30] A. Genizi, Decomposition of R^2 in multiple regression with correlated regressors, Stat. Sin. (1993) 407–420.
[31] J. Bi, A review of statistical methods for determination of relative importance of correlated predictors and identification of drivers of consumer liking, J. Sensory Stud. 27 (2) (2012) 87–101.
[32] U. Grömping, Variable importance in regression models, Wiley Interdiscipl.Rev.: Comput. Stat. 7 (2) (2015) 137–152.
[33] Y.Y. Lee, J.T. Kim, G.Y. Yun, The neural network predictive model for heat island intensity in Seoul, Energy Build. 110 (2016) 353–361.
[34] S.W. Kim, R.D. Brown, Urban heat island (UHI) variations within a city boundary: a systematic literature review, Renew. Sustain. Energy Rev. 148 (2021), 111256.
[35] J. Zhang, P. Cui, H. Song, Impact of urban morphology on outdoor air temperature and microclimate optimization strategy base on Pareto optimality in Northeast China, Build. Environ. 180 (2020), 107035.
[36] K. Perini, A. Magliocco, Effects of vegetation, urban density, building height, and atmospheric conditions on local temperatures and thermal comfort, Urban For. Urban Green. 13 (3) (2014) 495–506.
[37] R.A. Memon, D.Y. Leung, C.H. Liu, Effects of building aspect ratio and wind speed on air temperatures in urban-like street canyons, Build. Environ. 45 (1) (2010) 176–188.
[38] P. Shahmohamadi, A.I. Che-Ani, K.N.A. Maulud, N.M. Tawil, N.A.G. Abdullah, The Impact of Anthropogenic Heat on Formation of Urban Heat Island and Energy Consumption Balance, Urban Studies Research, 2011, 497524, 2011.
[39] H. Taha, Urban climates and heat islands: albedo, evapotranspiration, and anthropogenic heat, Energy Build. 25 (2) (1997) 99–103.
[40] D.J. Sailor, A review of methods for estimating anthropogenic heat and moisture emissions in the urban environment, Int. J. Climatol. 31 (2) (2011) 189–199.
[41] X. Yang, Y. Li, The impact of building density and building height heterogeneity on average urban albedo and street surface temperature, Build. Environ. 90 (2015) 146–156.
[42] H. Taha, H. Akbari, A. Rosenfeld, J. Huang, Residential cooling loads and the urban heat island—the effects of albedo, Build. Environ. 23 (4) (1988) 271–283.
[43] Y. Chen, J. Wu, K. Yu, D. Wang, Evaluating the impact of the building density and height on the block surface temperature, Build. Environ. 168 (2020), 106493.
[44] M. Wang, H. Xu, The impact of building height on urban thermal environment in summer: a case study of Chinese megacities, PLoS One 16 (4) (2021), e0247786.
[45] X. Cao, A. Onishi, J. Chen, H. Imura, Quantifying the cool island intensity of urban parks using ASTER and IKONOS data, Landsc. Urban Plann. 96 (4) (2010) 224–231.
[46] Q. Weng, D. Lu, J. Schubring, Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies, Rem. Sens. Environ. 89 (4) (2004) 467–483.
[47] J. Yang, Y. Yang, D. Sun, C. Jin, X. Xiao, Influence of urban morphological characteristics on thermal environment, Sustain. Cities Soc. 72 (2021), 103045.
[48] H. Xu, H. Chen, X. Zhou, Y. Wu, Y. Liu, Research on the relationship between urban morphology and air temperature based on mobile measurement: a case study in Wuhan, China, Urban Clim. 34 (2020), 100671.
[49] S.H. Lee, H. Lee, S.B. Park, J.W. Woo, D.I. Lee, J.J. Baik, Impacts of in-canyon vegetation and canyon aspect ratio on the thermal environment of street canyons: numerical investigation using a coupled WRF-VUCM model, Q. J. R. Meteorol. Soc. 142 (699) (2016) 2562–2578.
[50] N.E. Theeuwes, G.J. Steeneveld, R.J. Ronda, B.G. Heusinkveld, L.W.A. Van Hove, A.A.M. Holtslag, Seasonal dependence of the urban heat island on the street canyon aspect ratio, Q. J. R. Meteorol. Soc. 140 (684) (2014) 2197–2210.
[51] R.A. Memon, D.Y. Leung, C.H. Liu, Effects of building aspect ratio and wind speed on air temperatures in urban-like street canyons, Build. Environ. 45 (1) (2010) 176–188.
[52] D.J. Sailor, A review of methods for estimating anthropogenic heat and moisture emissions in the urban environment, Int. J. Climatol. 31 (2) (2011) 189–199.
[53] L. Lin, L. Meng, Y. Mei, W. Zhang, H. Liu, W. Xiang, Spatial–temporal patterns of summer urban islands and their economic implications in Beijing, Environ. Sci. Pollut. Control Ser. 29 (2022) 33361–33371.
[54] S.A. Benz, P. Bayer, K. Menberg, S. Jung, P. Blum, Spatial resolution of anthropogenic heat fluxes into urban aquifers, Sci. Total Environ. 524 (2015) 427–439.
[55] G. Guo, X. Zhou, Z. Wu, R. Xiao, Y. Chen, Characterizing the impact of urban morphology heterogeneity on land surface temperature in Guangzhou, China, Environ. Model. Software 84 (2016) 427–439.
[56] Z. Zheng, W. Zhou, J. Yan, Y. Qian, J. Wang, W. Li, The higher, the cooler? Effects of building height on land surface temperatures in residential areas of Beijing, Phys. Chem. Earth, Parts A/B/C 110 (2019) 149–156.
[57] M. Wang, H. Xu, The impact of building height on urban thermal environment in summer: a case study of Chinese megacities, PLoS One 16 (4) (2021), e0247786.
[58] L. Chen, E. Ng, X. An, C. Ren, M. Lee, U. Wang, Z. He, Sky view factor analysis of street canyons and its implications for daytime intra-urban air temperature differentials in high-rise, high-density urban areas of Hong Kong: a GIS-based simulation approach, Int. J. Climatol. 32 (1) (2012) 121–136.