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The Impact of Building and Land Use Characteristics on Land Surface Temperature in Urban Areas*

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Abstract

This study examined the impact of urban building and land use characteristics on land surface temperature (LST) by using a dataset defined at the zip-code district level. Zip-code districts are a suitable unit of analysis, as they are determined based on similarities in land use and building properties, which define urban development characteristics. Analyses using spatial regression models showed that the increase in the values of variables related to the heights of the buildings was associated with lower LST values in both summer and winter. In addition, the proportion of green areas was negatively correlated with the summer LST, when plants had the largest leaf areas, whereas it did not significantly correlate with the winter LST. Meanwhile, building density and the proportion of commercial area contributed to the increased LST of districts. Such results indicate that the LST in an apartment complex, which is a common housing type in South Korea, is normally lower than that in areas with detached single-family housing. The research findings provide implications for establishing sustainable urban development plans.

Keywords Land Surface Temperature (LST), Building Characteristics, Land Use Characteristics, Spatial Regression Model

주제어 지표면 온도, 건물 특성, 토지이용 특성, 공간회귀분석

Ⅰ. Introduction

A city is a geographical space where human activities and artificial structures used for them are concentrated. These physical characteristics of urban spaces are known to have an impact on the urban thermal environment. A representative example is "urban heat island" (UHI), which is defined as a phenomenon in which the temperature inside a city developed through urbanization processes is higher than that of the surrounding (Oke, 1982). Major factors affecting UHI include human activities such as industrial and transportation activities that occur within cities (Halder et al., 2021) as well as land use and land cover and physical characteristics of buildings in cities (Herold et al., 2003; Yuan et al., 2020; Santos et al., 2021).

In the current situation in which the intensification of climate change and response thereto are considered as important policy goals, the temperature distribution within cities is attracting attention from various perspectives. For example, with the rise of the global average temperature, the number of heat wave days and the number of patients suffering from heat-related illnesses in summer are increasing (Chae et al., 2022). Urban environments with a high ratio of developed areas and a low ratio of natural environment

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areas such as trees and green spaces are unavoidably vulnerable to heat wave disasters (Savić et al., 2018), so attention is required regarding methods of urban planning and development that can reduce the intensity of UHI in summer. In addition, a large amount of energy is used in cities, and the energy used for cooling and heating is closely related to the temperature distribution within a city. In the current situation where efficient use of energy is emphasized to reduce greenhouse gas emissions, the knowledge of structural and physical characteristics that affect the temperature distribution within a city is a necessary element for the planning and development of sustainable cities.

To identify the physical characteristics that affect the temperature distribution within a city, such as UHI, studies have been conducted to predict temperature changes within a city caused by physical changes in urban spaces through modeling-based simulation (Wang et al., 2016), or to analyze differences in temperature distribution according to differences in physical characteristics using statistical methods (Guo et al., 2020).

The data used in the relevant studies to measure the temperature distribution within a city broadly divides into two types: one is the atmosphere temperature (AT) data based on the temperature measured at observatories built on the ground; the other is the land surface temperature (LST) data in grid units based on the satellite observation data. Although there are differences depending on the purpose of the study and the characteristics of the analysis method, when the spatial unit subject to analysis is large, such as an administrative district, the actual AT data measured around the observation point is used (Cho et al., 2014; Je and Jeong, 2018), while studies targeting more detailed spatial units tend to use the LST data that allows to utilize grid-level data (Kim et al., 2015; Guo et al., 2020; Lee and Lim, 2022). In the present study, the unit of analysis was set to be the state basic district (hereinafter referred to as basic district), which is comparable to zip-code district in other countries, and the factors that affect the temperature distribution within a city were analyzed. According to Article 2, Paragraph 8 of the Road Name Address Act, the basic district is defined as "a district divided smaller than the areas of Eup/Myeon/Dong upon setting certain boundaries, based on road name addresses." As of 2020, a total of 5,665 basic districts have been designated in Seoul, which is more than 10 times as many as the number of legally designated Dongs (467 Dongs). Therefore, in the present study, the temperature distribution within a city was measured using the LST data.

The LST data has the advantage of providing temperature distribution across a city with a high spatial resolution (Sheng et al., 2017). Since practically applicable LST data is provided in the form of a grid of at least tens of meters, it is often the case that a grid of tens to hundreds of meters is set as a unit of analysis for research that uses the data (Kim and Yeom, 2012; Yoon et al., 2013; Ahn et al., 2017; Kim, 2021; Jin et al., 2021; Li et al., 2019). In most of the studies conducted in South Korea by setting the grid as the analysis unit, the land cover characteristics of the analysis unit, such as impervious area, building coverage ratio, and normalized difference vegetation index (NVDI), were mainly considered as the urban spatial characteristics that affect the LST (Kim and Yeom, 2012; Yoon et al., 2013; Ahn et al., 2017; Jin et al., 2021). On the other hand, there are not many studies analyzing the impact of building characteristics (floor area ratio, building coverage ratio, building density, etc.), which are main structures characterizing urban spaces, on the LST distribution (Li et al., 2019). This may be because most of the data related to building characteristics are provided at the administrative district level, which is larger than grid-type analyses units.

The basic district, which is set to be the unit of analysis in this study, is the most detailed spatial classification unit of the state. The district is partitioned in consideration of the distribution of population, business employees, building use, and zoning classifications of the area (Article 32 of the Enforcement Decree of the Road Name Address Act), and thus the similarity in urban planning and physical attributes within the district is considered to be high. In addition, the basic district is the smallest spatial unit in South Korea for which reliable data on building characteristics can be obtained. These characteristics of the basic district are advantageous for assessing the impact of building and land use characteristics on the LST compared to methods that set administrative districts or spatial ranges of an arbitrary size (e.g., grid) as a unit of analysis. When different building or land use characteristics are included within a single analysis unit, which usually is the case when setting analysis unit with administrative districts, the impact of each factor on the LST is likely to be underestimated. In addition, when the boundaries of the analysis unit are arbitrarily set, in the form such as a grid, and the size of the analysis unit is very small, units with missing variable values could be created in processing the values of the data provided from different spatial ranges to be fit to the analysis unit.

Meanwhile, in South Korea, studies on temperature distribution within a city were mainly conducted using summer data (Park et al., 2016; Ahn et al., 2017; Ko and Park, 2019; Kim, 2021; Jin et al., 2021). However, the impact of the same factor on temperature distribution within a city may vary depending on the season, and the relative importance of each factor may also do so (Peng et al., 2018; Huang et al., 2019; Wu et al., 2021). This information may be handled importantly when considering urban sustainability, especially in view of cooling and heating energy use. Therefore, in the present study, the impact of factors on temperature distribution was compared and analyzed using the LST data measured in summer and winter.

In summary, this study aims to analyze the impact of building and land use characteristics of urban space on temperature distribution within a city. For this purpose, the basic district was set as the unit of analysis, and the factors related to LST were analyzed using statistical methods. In addition, the effects of each factor by seasonal differences were compared using summer and winter data.

Ⅱ. Review of Previous Studies

Among previous studies that analyzed factors that affect temperature distribution within a city, the major influencing factors presented in studies using the LST data, as in the present study, can be classified into land cover characteristics factors and land use characteristics factors.

In this regard, it is generally known that land cover characteristics with high vulnerability to heat, such as being unable to reflect heat and easily absorbing it, may have an impact on the increase of the LST (Ki and Lee, 2009; Kim and Kim, 2018). Kim and Kim (2018) suggested that the increase of the impervious area ratio and the decrease of green area due to the public housing land development project promoted in Seoul increased the LST in the areas where the project was implemented.

In a similar context, a significant number of previous studies have shown that reducing the land cover area that is vulnerable to heat and increasing the land cover area that is capable of reflecting heat are effective ways to reduce the temperature within a city (Yoon et al., 2013; Kim et al., 2014; Kim et al., 2018; Kim, 2021; Li et al., 2019; Yang et al., 2021). In this regard, it has been suggested that green spaces, such as small parks located in urban areas, and rivers may alleviate the LST increase in not only those spaces but also the surrounding areas. Yang et al. (2021) categorized urban spaces based on the local climate zone (LCZ) classifications and analyzed the impact of the urban physical characteristics on the temperature in each category. They suggested that among the various influencing factors, both green spaces and waterside environments located in a city, regardless of their type, can contribute to reducing the temperature inside the city. In addition, Kim (2021) suggested that it is important to provide green spaces in an urban space to alleviate the temperature increase inside a city, but that increasing the NDVI of green spaces is more effective than simply providing green spaces.

Analyses have shown that land use characteristics also affect temperature distribution within a city (Kim et al., 2018; Ko and Park, 2019; Jin et al., 2021). Kim et al. (2018) analyzed the LST differences according to land use characteristics and showed that residential and commercial areas had the second highest LST after roads. They further analyzed the cooling effect of green spaces to lower the temperature inside the city by each land use type and found that the effect was greater in residential areas than in commercial areas (Kim et al., 2018). Ko and Park (2019) reported that the temperature inside a city was relatively higher in areas with a higher proportion of residential areas. However, the study showed that the temperature inside the city could be decreased when the proportion of buildings with a high total floor area, such as large-scale high-rise apartments, is high in residential areas, because the parks and green spaces within the residential complexes such as high-rise apartments may have contributed to the decrease of the LST in the nearby areas (Ko and Park, 2019).

In addition to land cover and land use characteristics, studies have been conducted to analyze the impact of regional socioeconomic characteristics and physical characteristics of buildings on the LST (Ko and Park, 2019; Jo et al., 2019; Yin et al., 2018; Li et al., 2019). In particular, Cho et al. (2019) showed that, in addition to land cover and land use characteristics, the LST tended to be relatively high in areas where the proportion of socio-economically vulnerable groups, such as the national basic livelihood beneficiaries and the elderly people living alone, is high. Yin et al. (2018) showed that the higher the building density within a city, the lower the heat circulation inside the city, which can lead to the intensified UHI, and concluded that it is important to regulate the density of buildings within a city in order to reduce the temperature inside a city. With regard to the physical characteristics of buildings, Li et al. (2019) showed that the higher the building area, total floor area, and sky view factor, the higher the LST, while the higher the level of surface roughness of buildings, the lower the LST. Yang et al. (2021) suggested that the impact of building density on temperature inside a city may vary depending on the type of LCZ of the urban space where the building is located. The study showed that in areas where mid-rise buildings are distributed at a relatively low density, the impact of building density on temperature increase in the city was the lowest, while in areas where mid-rise buildings are located at a high density, the impact was the highest (Yang et al., 2021).

Building characteristics were considered major influencing factors in studies in which air temperature and heat index were measured and analyzed in addition to the LST (Je and Jeong, 2018; Kim and Kang, 2018; Yoo and Bae, 2023; Lin et al., 2017). Je and Jeong (2018) reported that the air temperature was relatively high in commercial and business areas within a city and in particular, the air temperature tended to be relatively high in areas with a high building density among the residential and commercial areas. Similarly, Yoo and Bae (2023) showed that, during the day, temperature was high in areas with a high density of low-rise residential buildings, and low in multi-family housings areas with a relatively low building density. On the other hand, Lin et al. (2017) presented results that areas with a high density of high-rise buildings exhibited a relatively low temperature distribution, and suggested that shades formed around high-rise buildings may contribute to temperature decrease in the surrounding area (Lin et al., 2017). Similarly, Emmanuel et al. (2007) also suggested that in areas where high-rise buildings are densely located, the buildings may contribute to blocking heat from the sun by forming shades in the surrounding area.

Meanwhile, some studies have shown that the level of influence of land cover and land use characteristics and physical characteristics of buildings on temperature distribution inside a city may vary depending on the season (Peng et al., 2018; Huang et al., 2019; Wu et al., 2021). Wu et al. (2021) reported that in spring and summer, when the temperature is relatively high, the distance to rivers and green spaces had the greatest impact on the level the LST, while in winter, the impact of the variable was relatively small. Similarly, Huang et al. (2019) also showed that green spaces created in areas where urbanization has occurred rapidly play a role in alleviating rapid increase of the temperature inside a city, but this effect tended to decrease in winter compared to spring and summer.

Compiling previous studies that analyzed factors that affect temperature distribution within a city, it can be seen that land cover and land use characteristics were investigated as the major influencing factors in studies using the LST data in South Korea. In other countries, many studies have been conducted to analyze the impact of building characteristics in urban spaces on the LST (Lin et al., 2017; Yang et al., 2021), but a limited number of studies have been conducted by targeting cities in South Korea (Li et al., 2019). With regard to the effect that building characteristics have on the temperature distribution inside a city, studies have considered variables such as building height and building density the major influencing factors. Regarding building density, it has been generally reported that higher building density was associated with higher temperature in the surrounding area (Je and Jeong, 2018; Kim and Kang, 2018; Yoo and Bae, 2023), but some studies have suggested that when high-rise buildings are densely located, shades formed in the surrounding areas may help reduce the temperature (Emmanuel et al., 2007; Lin et al., 2017). In studies conducted in other countries, there were cases where geographical ranges in which the properties of buildings were similar were set as a unit of analysis by classifying spaces within a city into LCZs, or analyzing sites that were representative of specific properties (Emmanuel et al., 2007; Lin et al., 2017; Yang et al., 2021). However, in the studies conducted with the cities in South Korea, the unit of analysis was set to be the administrative Dong (Je and Jeong, 2018) or a grid having an arbitrary size (Li et al., 2019), so the unit of analysis had limitations in considering building characteristics.

In the present study, in consideration of the limitations of previous studies conducted in the cities of South Korea, a basic district with high similarity in urban planning and physical properties of spatial structure was determined as the unit of analysis, and both land use characteristics and building characteristics were taken into account to analyze their relationships with the LST in the basic district.

Ⅲ. Methods

The present study was conducted in Seoul, which has the highest level of urbanization among the cities in South Korea. LST calculated using the satellite observation images was used to establish the temperature distribution data within the city. When analyzing the relationships of the variables representing building and land use characteristics with LST, statistical methods were used.

1. Unit of Analysis

In the present study, the basic district was set as the unit of analysis. As of 2020, a total of 34,443 basic districts have been designated across South Korea, and a total of 5,665 basic districts have been designated in Seoul. As described in the Introduction, since the population, number of business employees, building use, and zoning classifications are taken into consideration when establishing a basic district boundary, it can be assumed that the land use and building characteristics, which are of interest in this study, are similar within a basic district. (see the left image of 〈Figure 1〉). This feature of the basic district is more advantageous than setting a spatial scope larger than the basic district as the unit of analysis (e.g. administrative Dong, legal Dong) in deriving implications related to the development of urban spaces based on the obtained analytical results. When different building characteristics or land use characteristics are included within a single unit of analysis, the impact of each factor on the LST is likely to be underestimated. In addition, when the boundaries of the unit of analysis are arbitrarily set in the form of a grid or the like, if the size of the analysis unit is very small, there is a possibility that many sample deviations may occur in processing the values of the data provided from different spatial ranges to be fit to the analysis unit. For example, the National Geographic Information Institute provides building characteristics information such as floor area ratio and building coverage ratio at a grid of at least 100 meters, but the data includes more than 50% of missing values. When the unit of analysis is set sufficiently large to avoid this problem, problems that different urban spatial characteristics are included in a single unit of analysis, as described above, could occur. In this study, it was attempted to overcome these problems by setting the basic district as the unit of analysis because the basic district is a spatial division that has similar urban planning and physical properties, and reliable data can be obtained therefrom.

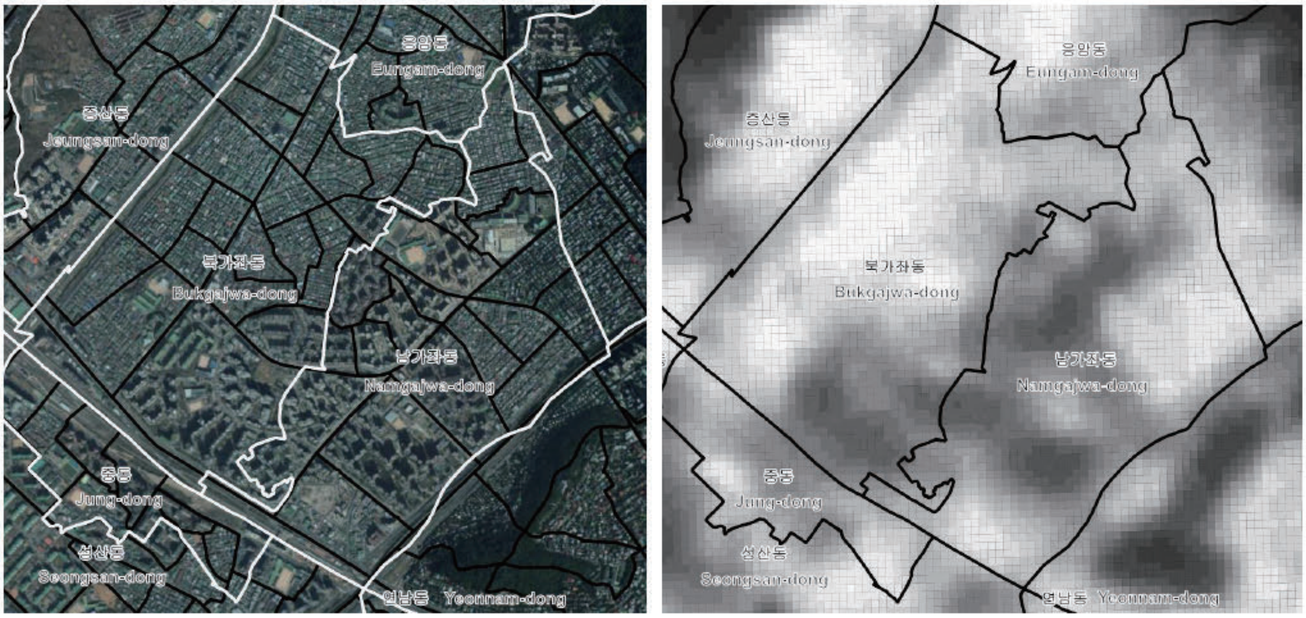

Figure 1. Zip-code district boundaries (left, black solid lines) and land surface temperature (right, darker pixels indicate lower values, black solid lines represent the boundaries of Dong) around Gajwa-dong, Seodaemun-gu, Seoul.

2. Research Data

1) Dependent Variable (LST)

This study was performed using the LST to measure the temperature distribution inside the city. The Landsat 8 Collection 2 level 2 Science Product (L2SP) data, which is the satellite observation images, was used to calculate the LST. The data can be collected through the Earth Explorer website operated by the United States Geological Survey (USGS). Among Landsat 8 L2SP data, Band 10 images provide the LST information on a 30 m square grid, which can be converted to Celsius temperature values using the equation below (Park and Kim, 2021):

$$\begin{aligned} &LST(℃) = MLBST + AL - 273.15 \\ &ML : \text{multiplicative rescaling factor } (0.00341802) \qquad (1) \\ &AL: \text{additive rescaling factor } (149.0) \end{aligned}$$

In this study, Landsat 8 satellite observation data from the region corresponding to path 116, row 34, which includes the observation area of Seoul, the subject of analysis, was obtained for 2013 to 2021. Since the Landsat 8 satellite observes the same point once every 16 days (shooting time is around 11:10 a.m.), a total of 22 to 23 images can be obtained each year. However, the LST calculated through the satellite observation is affected by atmospheric phenomena such as clouds. Therefore, the Landsat 8 L2SP data provides a Pixel Quality Assessment band (QA_PIXEL) representing the state of each observation grid through a code value generated by entering information such as clouds, water, snow, and shades in a binary format (USGS, 2022). For analysis, Band 10 images for days satisfying following criteria were extracted: among the grids within the boundaries of Seoul (a total of 672,967 grids), data in which the proportion of grids with a quality assessment code value of 21824, representing 'clear with lows set,' was more than 90%. As a result, a total of 37 images were extracted for the data collection period, but there were only three images observed in summer (July to August) and one image in winter (December to February), respectively, which were very few. The available images were taken on August 2, 2014, July 4, 2015, and August 26, 2017 for summer and on February 26, 2021 for winter. The observation data on February 26, 2021 was used to calculate the winter LST, and on August 26, 2017 was used to calculate the summer LST, as the date was closest in time to the winter data.

The two images of the Landsat 8 L2SP Band 10 data to be used in the analysis were processed in the following steps. First, Equation (1) was applied to calculate the LST for each of the 30 m grids, which was then converted to Celsius temperature. Afterwards, the average of the LST was calculated for each basic district, which was the unit of analysis of this study. When calculating the average for each basic district, only grids containing the center point within the boundary of each basic district were used. The average LST value for each basic district calculated in this manner was used as a dependent variable for a regression models in the statistical analysis process. The right image of 〈Figure 1〉 shows the distribution of the LST calculated for the area of Gajwa-dong, Seodaemun-gu as an example, from which it can be seen that there is a large LST deviation within a legal Dong boundary. Furthermore, when compared to the image on the left, it can be seen that the LST is related to the spatial characteristics divided by the basic districts.

2) Explanatory Variables (Building Characteristics and Land Use Characteristics)

In the present study, factors that may affect the LST distribution were divided into building characteristics and land use characteristics, and variables representing the specific status of each factor were used in the analysis. The variables used in the analysis are listed in 〈Table 1〉.

To construct the variables representing building characteristics, the data provided by the National Statistical Map of the National Land Information Platform operated by the National Geographic Information Institute was used. The National Statistical Map provides data related to population, buildings, land, etc. by the basic district. Among these, data on building height, floor area ratio, building coverage ratio, and number of buildings were downloaded and used to construct the related variables. The building height is the average height of the buildings located within the basic district, and the floor area ratio and building coverage ratio are the average values of them for each lot within the basic district. The number of buildings refers to the total number of buildings located within the basic district, and in the present study, a building density variable was created by dividing this by the area of the basic district. Because the LST data

Table 1. Variables used for the analyses

Category	Variable (unit)	Description	Source
Surface temperature	ST_summer (℃)	Average surface temperature of 26 August 2017	Landsat 8 L2SP Dataset[2]
	ST_winter (℃)	Average surface temperature of 26 February 2021	
Building characteristics	Height (m)	Average height of buildings	National Statistics Map[3]
	FAR (%)	Average floor-to-area ratio of buildings	
	Building_cover (%)	Average Building coverage ratio of buildings	
	Building_density (Buildings / km^2)	Total number of buildings / area of zip-code district	
Land Cover characteristics	% residential (%)	Total area of residential buildings[1]	Land Cover Map[4]
	% multi_family (%)	Total area of lands for multi-family housings[1]	
	% commercial (%)	Total area of commercial buildings/facilities[1]	
	% transport (%)	Total area of transportation facilities[1]	
	% green (%)	Total area of green areas[1]	
	% forest (%)	Total area of forests[1]	
	% water (%)	Total area of waterbodies[1]	

Note 1: The value was divided by the area of zip-code district to create the variable.
Note 2: https://earthexplorer.usgs.gov/
Note 3: https://map.ngii.go.kr/ms/map/NlipMap.do?tabGb=statsMap
Note 4: https://egis.me.go.kr/

observed at different periods were used in the present (August 26, 2017 and February 26, 2021), variables were constructed using data obtained for November 2017 and October 2020, which were close to the LST observation periods.

To construct variables representing land use characteristics, the sub-categorized land cover map data was used. The Environmental Geographic Information Service operated by the Ministry of Environment provides land cover maps, and the nationwide sub-categorized land cover maps provide updated data every year since 2019. The sub-categorized land cover map divides land cover into a total of 41 types, and a total of 36 land cover types are included within the boundaries of Seoul, which is the study area. Based on the data for 2021, 〈Table 2〉 shows the land cover types of the study area and the area and the area proportion of each type (For the types of which area proportion is less than 2%, their total area proportion is given in the 'Others' category.).

Table 2. Area by the land cover types

Land cover type	Area (km^2)	Area proportion (%)
Single-detached housings	45.73	7.55
Multi-family housings	32.60	5.38
Commercial/Business facilities	45.10	7.45
Roads	164.91	27.23
Deciduous forests	97.33	16.07
Coniferous forests	25.81	4.26
Mixed forests	19.15	3.16
Artificial green areas	66.10	10.91
Bare lands	17.75	2.93
Rivers/Streams	31.27	5.16
Others	59.93	9.93

The related variables were calculated using the land cover maps for 2020 (used for analysis of summer LST data) and 2021 (used for analysis of winter LST data) that were produced based on the aerial orthoimages taken on December 31, 2018 and December 30, 2020, respectively (based on Seoul area). The calculated variables are the proportions of residential area, multi-family housing area, commercial area, transportation area, green area, forest area, and inland water area to the area of basic district. Among these, the residential area, commercial area, transportation area, and inland water area were calculated by applying the middle-level land cover classification criteria, green area and the forest area were calculated by applying the high-level land cover classification criteria, and the multi-family housings area was calculated by applying the low-level land cover classification criteria.

3. Analytical Model

In this study, factors influencing the LST were analyzed through a linear regression analysis using the variables presented above. First, a linear regression model was estimated using Ordinary Least Squares (OLS), and then the Variance Inflation Factor (VIF) values were calculated to diagnose multicollinearity of the independent variables. Afterwards, the Moran test was performed to determine whether a spatial autocorrelation exists in the estimated regression residuals. When it is diagnosed that there is a significant spatial autocorrelation in the residuals, a spatial regression analysis is performed.

For spatial regression analysis, the Lagrange Multiplier (LM) test was performed to select a more appropriate model between a spatial lag model and a spatial error model. The selected model is then estimated using a generalized spatial two-stage least squares (GS2SLS) method. The GS2SLS method has an advantage of providing robust estimates even when the normality assumption of errors is violated. The row-standardized Queen Contiguity weighted matrix was used in the Moran test and the spatial regression analysis.

Ⅳ. Results and Discussion

1. Descriptive Statistics

As of 2020, a total of 5,665 basic districts (5,668 basic districts as of 2017) have been designated in Seoul. However, due to the missing values in the raw data, the analysis was performed using information of a total of 5,332 basic districts for winter LST model (2020) and 5,326 basic districts for summer LST model (2017). 〈Table 3〉 shows the average LST by land cover types. This confirms that the LST varies depending on the land cover type, and so it is necessary to control the effect of the land cover types in order to analyze the effect of the development characteristics on the LST. Meanwhile, it was found that the LST was significantly lower in the forest areas and inland waters than in other land cover types. Therefore, in the present study, the analysis was separately performed with all the samples and with samples that did not include forest areas and inland waters within the boundary of the basic district. Since the basic districts that do not include forest areas and inland waters could be considered to have the characteristics of an urbanized area that does not include natural environmental factors that affect temperature, hereinafter these samples will be separately referred to as 'urbanized sample.' Among the basic districts classified as urbanized samples, the total number of samples used for the analysis was 3,872 for the winter LST model and 3,879 for the summer LST model.

Table 3. Average (standard deviation) land surface temperature by the land cover types

Land cover type	Date of Observation	
	26-AUG-2017	26-FEB-2021
Single-detached housings	38.45 (1.62)	14.72 (1.26)
Commercial/Business facilities	38.36 (2.12)	14.48 (1.60)
Multi-family housings	36.92 (1.97)	13.78 (1.41)
Roads	36.91 (2.42)	14.12 (1.64)
Bare lands	35.22 (2.46)	13.84 (2.01)
Artificial green areas	34.94 (2.71)	14.32 (1.98)
Deciduous forests	30.31 (2.91)	14.29 (2.19)
Coniferous forests	29.98 (3.16)	13.36 (2.12)
Mixed forests	29.86 (3.16)	14.06 (2.08)
Rivers/Streams	25.21 (3.28)	7.50 (3.06)

Note: Only types with area proportion greater than 2% are included.

〈Table 4〉 shows the descriptive statistics of the samples used in the analysis for the total samples and the urbanized samples, respectively. As the descriptive statistics of the

Table 4. Descriptive statistics of the variables

Variable	Total (N=5.332)		Urbanized (N=3,872)	
	Mean	Std. Dev.	Mean	Std. Dev.
ST_summer	37.22	2.39	38.04	1.50
ST_winter	14.12	1.28	14.12	1.14
Height	18.68	13.91	18.98	14.62
FAR	188.31	106.19	202.03	108.50
Building_cover	26.57	18.09	29.96	17.65
Building_density	1,901.02	1,538.39	2,230.26	1,536.26
% residential	23.64	18.80	26.77	18.90
% multi_family	8.76	8.24	9.55	8.44
% commercial	14.81	13.07	18.05	12.85
% transport	38.14	14.08	41.35	12.30
% green	8.31	9.85	6.73	9.17
% forest	6.00	16.79	-	-
% water	1.01	5.88	-	-

explanatory variables, only the values calculated using the data of the year 2020 are presented, and the values of data of the year 2017 are not significantly different from the values presented in 〈Table 4〉. It can be confirmed that the average values of most variables related to the development characteristics of urban spaces, including the summer LST, are larger in the urbanized samples than in total samples. On the other hand, the average value of the winter LST was not different between the two samples, and the mean of % green was smaller in the urbanized samples. Among the explanatory variables, Height was log-transformed to be used in the regression models, considering the linearity of the variable's relationship with the dependent variable. As a result of performing a correlation analysis to pre-diagnose the collinearity between the explanatory variables, the Pearson correlation coefficient calculated between % residential and the Building_density was as large as about 0.8 in all the samples (Year 2020 data: 0.812, Year 2017 data: 0.784). As can be seen in 〈Table 3〉, even among residential areas, there is a difference in the LST between land types of single-detached housings and multi-family housings. Therefore, only % multi_family, which can better show the effect on the LST of the type of residential building, was employed in the regression models.

2. Results of OLS Estimation

〈Table 5〉 shows the results of OLS estimation of the linear regression model for the total and the urbanized samples with the summer and winter LST as dependent variables. The table shows the estimated regression coefficient, significance probability, and standardized regression coefficient (Beta) values of explanatory variables. The calculated VIF values of the explanatory variables were smaller than 5 in all the models, so it was determined that there was no need to exclude the explanatory variables due to multicollinearity problems.

It can be confirmed that the size and statistical significance of the estimated regression coefficients significantly vary according to the dependent variable (summer and winter LST). In the models using summer LST as a dependent variable (Models 1 and 3), most of the explanatory variables had significant regression coefficients, while in models using winter LST as a dependent variable (Models 2 and 4), some explanatory variables had regression coefficients that were not significant at $p < 0.05$ level. In particular, the results indicated that in models using total samples (Models 1 and 2), the % forest, which had the greatest impact on the summer LST (with the largest absolute value of the standardized regression coefficient), had a regression coefficient that was not significant in the winter model. This may be

Table 5. Results of OLS estimation for linear regression model

Variables	Total						Urbanized					
	D.V.: ST_summer (Model 1)			D.V.: ST_winter (Model 2)			D.V.: ST_summer (Model 3)			D.V.: ST_winter (Model 4)		
	Coef.	P>t	Beta	Coef.	P>t	Beta	Coef.	P>t	Beta	Coef.	P>t	Beta
Height (Log)	-0.307	0.000	-0.064	-0.942	0.000	-0.371	-0.412	0.000	-0.137	-1.018	0.000	-0.449
FAR	-0.0029	0.000	-0.126	-0.00003	0.916	-0.003	-0.0028	0.000	-0.201	0.00035	0.288	-0.033
Building_cover	0.013	0.000	0.058	-0.0040	0.067	-0.036	0.012	0.001	0.065	-0.0072	0.016	-0.055
Building_density	0.00034	0.000	0.225	0.00013	0.000	0.157	0.00027	0.000	0.284	0.00015	0.000	0.206
% multi_family	-0.015	0.000	-0.051	-0.020	0.000	-0.128	-0.018	0.000	-0.097	-0.014	0.000	-0.105
% commercial	0.026	0.000	0.142	0.0097	0.000	0.099	0.023	0.000	0.195	0.010	0.000	0.117
% transport	0.0087	0.001	0.052	-0.0022	0.326	-0.024	0.0020	0.497	0.017	0.00013	0.955	0.001
% green	-0.027	0.000	-0.111	0.015	0.000	0.113	-0.027	0.000	-0.164	0.010	0.000	0.084
% forest	-0.076	0.000	-0.536	0.00059	0.775	0.008	-	-	-	-	-	-
% water	-0.130	0.000	-0.320	-0.064	0.000	-0.296	-	-	-	-	-	-
Constant	37.51	0.000	-	16.74	0.000	-	38.33	0.000	-	16.79	0.000	-
N / Adj. R^2	5,326 / 0.756			5,332 / 0.315			3,879 / 0.467			3,872 / 0.305		

Note: Significance probability values were estimated based on the robust standard errors.

because of changes in the leaf area, which is related to the seasonal activities of trees. The main mechanisms of temperature reduction effects by trees are solar radiation blocking and evapotranspiration (Lee et al. 2018), which are related to changes in leaf area. It has been reported that among the seasons, evapotranspiration is most active in summer when the leaf area is the largest (Han et al., 2021), and the solar radiation blocking effect is also greatest in this season. On the other hand, this effect is greatly reduced in winter. As can be seen in 〈Table 2〉, in the forest area of the study area, deciduous forests, of which the leaf area changes greatly by season, occupy a much larger area than coniferous forests. Therefore, it is understood that the effect of % forests on the LST decrease significantly varies depending on the season.

Variable regression coefficients significant both for summer and winter LST were found to have generally the identical sign. However, % green had a negative (-) relationship with the summer LST and a positive (+) relationship with the winter LST both for models with total and the urbanized samples. These results may also be due to the differences in the seasonal activities of the plants that make up the green area. Meanwhile, in the models using the dependent variable calculated from the LST data measured on the same day, the regression coefficients of variables significant at $p < 0.05$ level had similar magnitude in models with different samples (Total/Urbanized).

The Moran test was performed on OLS models, and it was diagnosed that the residuals of all the models were spatially autocorrelated (Model 1 – chi2: 3,854, p > chi2: 0.000; Model 2 – chi2: 3,334, p > chi2: 0.000; Model 3 – chi2: 2,804, p > chi2: 0.000; Model 4 – chi2: 2,110, p > chi2: 0.000). Therefore, a spatial regression analysis was performed for each model, and the results are described in the next section.

3. Results of Spatial Regression Model Analysis

The LM test was performed to select a spatial regression model suitable for spatial regression analysis, and the calculated LM and robust LM statistics are presented in 〈Table 6〉.

All statistics presented in 〈Table 6〉 were significant at the level of $p < 0.01$, and it can be confirmed that in all the models, the calculated values of the Robust LM-error statistics were significantly larger than those of the Robust LM-lag statistics. Therefore, a spatial regression analysis was performed using a spatial error model.

Table 6. Results of the LM test

Model	LM-lag	LM-error	Robust LM-lag	Robust LM-error
Model 1	865.88	3907.58	103.94	3145.64
Model 2	1731.57	3377.46	22.70	1668.59
Model 3	195.62	2839.39	23.05	2666.82
Model 4	412.84	2302.61	7.13	1896.91

The estimation results for the spatial error model are shown in 〈Table 7〉. In all the models, the coefficient for spatial error term (λ) was significant at $p < 0.05$ level, and the statistical significance and sign of the regression coefficient of the explanatory variables were generally similar to those in the model estimated by OLS (see 〈Table 5〉).

Based on the estimated coefficients of Model 5, the effect of explanatory variables' value change on changes in summer LST could be calculated as follows (The range of change in the explanatory variables' value is presented in consideration of the standard deviation of the variable): A 1% increase in the building height (Height) and a 100%p increase in FAR are related to a decrease in the average LST of the basic district by around 0.42℃ and 0.18℃, respectively. On the other hand, an increase of 1,000 buildings per 1 km^2 (Building_density) is related to an increase in the average LST of the basic district by about 0.22℃. Regarding land use characteristics, when the % commercial increased by 10%p, the average LST in the basic district tended to increase by about 0.16℃, and a 10%p increase in % green and % forest tended to decrease the LST by about 0.33 °C and 0.68℃, respectively. In addition, a one unit (1%p) increase in % water was associated with a decrease in the average LST of the base district by approximately 0.13℃.

It can be confirmed that, among the variables representing building characteristics, building height and floor area ratio have a negative relationship with the LST. The reason for this result may be the effect of shades created by buildings. A decrease in heat absorption by artificial structures when buildings cast a shade on the ground or adjacent buildings has been reported in previous studies (Javanroodi et al., 2018; Lima et al., 2019). Previous studies also have empirically suggested that the shades formed between buildings in urban areas can contribute to the reduction of

Table 7. Results of spatial regression model estimation

Variables	Total						Urbanized					
	D.V.: ST_summer (Model 5)			D.V.: ST_winter (Model 6)			D.V.: ST_summer (Model 7)			D.V.: ST_winter (Model 8)		
	Coef.	P>|z|	Beta	Coef.	P>|z|	Beta	Coef.	P>|z|	Beta	Coef.	P>|z|	Beta
Height (Log)	-0.421	0.000	-0.088	-0.685	0.000	-0.270	-0.632	0.000	-0.210	-0.873	0.000	-0.385
FAR	-0.0018	0.000	-0.078	-0.00048	0.012	-0.040	-0.0014	0.000	-0.098	-0.00004	0.849	-0.004
Building_cover	0.0029	0.048	0.013	-0.0024	0.081	-0.021	-0.0010	0.607	-0.005	-0.0092	0.000	-0.071
Building_density	0.00022	0.000	0.148	0.00008	0.000	0.094	0.00016	0.000	0.172	0.00009	0.000	0.115
% multi_family	-0.0092	0.000	-0.031	-0.020	0.000	-0.131	-0.0071	0.000	-0.039	-0.014	0.000	-0.101
% commercial	0.016	0.000	0.088	0.0026	0.068	0.027	0.016	0.000	0.134	0.036	0.009	0.040
% transport	0.011	0.000	0.064	-0.0037	0.013	-0.041	0.0063	0.225	0.052	0.00083	0.591	0.009
% green	-0.033	0.000	-0.133	0.00029	0.877	0.002	-0.033	0.000	-0.197	-0.0025	0.208	-0.020
% forest	-0.068	0.000	-0.480	-0.0038	0.004	-0.050	-	-	-	-	-	-
% water	-0.129	0.000	-0.317	-0.068	0.000	-0.312	-	-	-	-	-	-
Constant	38.31	0.000	-	16.43	0.000	-	39.34	0.000	-	16.87	0.000	-
lambda (λ)	0.768	0.000	-	0.699	0.000	-	0.764	0.000	-	0.690	0.000	-
N / Pseudo R^2	5,326 / 0.750			5,332 / 0.308			3,879 / 0.451			3,872 / 0.296		

cooling energy consumption (Yang et al., 2011; Futcher et al., 2013; Chen et al., 2018).

On the other hand, it can be confirmed that building density has a positive relationship with the LST. This may be due to the tendency that ventilation performance in urban spaces decreases as building density increases. The spacing between buildings is known to affect wind speed distribution and ventilation performance in urban spaces, and dense building spacing prevents the air heated in the vicinity of the ground surface from spreading by the wind (Marciotto et al., 2010; Wang & Akbari, 2014).

Meanwhile, variables related to building characteristics exhibited differences in significance and size of the regression coefficient depending on the dependent variable (season). However, it is unreasonable to interpret that a specific factor has a greater or lesser impact in a specific season based on the absolute value of the estimated regression coefficient. Instead, standardized regression coefficients can be used to compare the impact of factors calculated from each model. The standardized regression coefficient is a value that expresses the degree to which the dependent variable changes when the value of an explanatory variable changes by one standard deviation as a ratio to the standard deviation of the dependent variable. Therefore, by multiplying the standardized regression coefficient of a variable with the standard deviation of the dependent variable, the standardized size of the effect of that variable on the dependent variable can be calculated. The results of comparing the magnitude of the impact of the two variables (Height and FAR), that contribute to the reduction of the average LST of the basic district, by season using the standardized regression coefficients are described below. In Model 5, the summer model, the standardized regression coefficients of building height and floor area ratio are -0.088 and -0.078, respectively. Multiplying these values by the standard deviation of the dependent variable (ST_summer) of 2.39 (see Table 4) and adding the resulting values gives a value of –0.396. In Model 6, the winter model, multiplying the standardized regression coefficient values of the two variables -0.270 and –0.040 by the standard deviation of the dependent variable (ST_winter) of 1.28 and adding the resulting values gives a value of -0.395. When the same procedure is applied to the models estimated for the urbanized sample, a larger effect size is calculated for the summer model (Model 7, -0.736) than for the winter model (Model 8, -0.496). In addition, in the case of the Building_density, the calculated standardized regression coefficient is smaller in the winter model (Model 6, Model 8), where the standard deviation of the dependent variable is smaller, than in the summer model (Model 5, Model 7). Therefore, the effect size of this variable on the LST becomes smaller in winter than in summer. Through this, it can be determined that the impact of building characteristic factors on the LST is generally greater in summer than in winter.

The first notable analytical result related to land cover characteristics is that % multi_family and the LST have a negative relationship. This may be understood in the context of the above-mentioned relationship that the building height and floor area ratio variables have with the LST. In areas with a high proportion of multi-family housings, the LST was relatively low probably because the building height was relatively high compared to areas where detached single-family housings were dense and so the cooling effect of shades was relatively large. Lee et al. (2021) classified the physical characteristics of urban space into LCZ types and reported that under the same building density conditions, higher heat island intensity was found in an LCZs with low building heights compared to an LCZs with high building heights. Meanwhile, green areas formed through artificial landscaping contribute to effectively lowering the LST during high-temperature periods. As mentioned above, the vegetation that makes up green areas is known to have the effect of lowering the temperature of the surrounding area through evapotranspiration. However, when vegetation is affected by excessive solar radiation, the effect of reducing temperature through evapotranspiration is reduced due to stomata control caused by moisture stress (Lee et al., 2018). Therefore, it is assumed that providing green areas in locations that can be affected by shades from nearby buildings in developed urban areas will allow for efficient utilization of the cooling effect of summer solar radiation blocking and evapotranspiration of vegetation.

In urban development practices, the combined effects of the factors discussed above tend to occur. In South Korea, there are many cases of redeveloping aged low-rise residential areas into high-rise apartment complexes. In this case, the height and floor area ratio of buildings in the area increases, and green areas are often supplied by landscaping within the complex. In addition, the proportion of detached single-family housings in the area will naturally decrease. Since all of these changes can contribute to the LST decrease, the temperature-reducing effect resulting from the development activities can be relatively large. Therefore, this development method may effectively prevent high heat island intensity from occurring inside a city during summer. In the area shown in 〈Figure 1〉, an LST difference of up to about 7 °C was observed between the apartment complex area and the surrounding low-rise residential area (as of August 26, 2017). On the other hand, this development method could result in a lower LST in winter compared to the surrounding areas. Lee et al. (2021) also suggested that a negative heat island intensity may occur in winter in developed areas with high building heights. Therefore, further studies may need to be conducted to determine how temperature within urban spaces, which is affected by structural and physical characteristics of urban development, influences various fields such as disaster occurrence (heat waves, cold waves, etc.) and energy consumption.

V. Conclusions

In the present study, the basic district was set as the unit of analysis for Seoul to analyze the impact of building and land use characteristics on the LST distribution within the city.

The characteristics of buildings, which are major artificial structures that make up an urban space, may affect the LST. A relationship was derived in which the LST decreases as the building heights increase. On the other hand, an increase in building density is related to an increase in the LST of the basic district. This relationship means that regardless of the season, the LST may be lower in areas such as apartment complexes than in areas where low-rise housing units are dense. Therefore, developing areas of high-density low-rise buildings into areas with low-density high-rise buildings can contribute to lowering the intensity of heat islands in summer. On the other hand, in winter, areas where this development method is applied may have lower LST compared to other areas. Meanwhile, the analysis showed that the increase of proportion of green areas increased by parks and landscaping areas supplied during the (re)development process contributes to the decrease in the LST in summer. It was also confirmed that increasing the green areas proportion did not reduce the LST in winter. Therefore, providing green areas in urbanized area can be a possible way to produce a effect of alleviating summer heat islands without any negative effect of lowering the temperature in winter.

Although the present study is significant as an empirical study that analyzed the impact of building and land use characteristics on the LST and its seasonal differences, limitations also exist. In particular, the data used to calculate the LST only provide observations during daylight hours of the day and have a long observation cycle. Therefore, the data may not be used to analyze factors affecting the temperature distribution at night, when the heat island intensity is known to be greater than during the day. In addition, due to the lack of available observation data in summer and winter, which are of major interest regarding the temperature distribution within a city, it is difficult to present generalized results based on analysis of multiple measurement data. To overcome these limitations, data such as the S-DoT data of Seoul, which provides temperature measurement data for each hour with a high spatial resolution, could be utilized.

Additionally, based on the analysis of the impact of urban space development characteristics on temperature distribution within the city, further studies need to be conducted to analyze how they affect overall urban sustainability. It is necessary to consider both seasonal gains and losses in the impact of development characteristics on temperature. For example, when it is assumed that a specific form of development has an effect of reducing cooling energy consumption in summer by contributing to local temperature decrease, a comparative study may be conducted to examine whether the resulting benefits are offset by an increase in heating energy consumption in winter.

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