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The Seasonal and Diurnal Influence of Surrounding Land Use on Temperature: Findings from Seoul, South Korea

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Abstract: There is a growing interest in understanding how the built environment affects temperature in cities. This study explores the impact of land use on temperature and how it varies by season and time of day in Seoul, South Korea. Unlike other studies that rely on extracted data from remotely sensed information, this study uses land use data from local GIS and near-ground temperature data from a network of state-run weather stations. To deal with multicollinearity among the land use variables, partial least squares regression models were used for analysis. Results suggest that residential and commercial uses and roads increase the temperature while open spaces decrease it. In detail, central commercial use, high-density residential use, and roads were influential heaters, while greenery was an influential cooler throughout the year. This study suggests the need for place-based planning and design solutions that help build climate resilience of cities.

Keywords: land use; temperature; partial least squares regression; Seoul

1. Introduction

Urban researchers are increasingly becoming interested in the city's role in determining the temperature that is sensed by citizens [1–4]. In addition to understanding the city as a major generator of greenhouse gas that causes climate change [5,6], discussions on how the built environment influences surface or near-ground temperature in cities are moving ahead. Critics argue that these discussions help understand how the planning of cities shape urban climate [7–12] to adapt to the rising temperatures, mitigate any negative impacts, and in the long term build resilience [13–15].

Among studies on the relationship between the built environment and temperature in cities, some focus on the contribution of buildings on the rising temperature and its mitigation by adopting green or cool roofs [16–20], green walls [21], and cool pavements [22]. Others adopt a three-dimensional approach by examining the impact of sky view factor which is the amount of free sky uninterrupted by buildings, structures, or vegetation at a specific location [23–28]. A second focus is on urban density. Several studies based on the American context report that low-density residential areas discharged more heat [29,30]. Another from a tropical Asian city finds that urban areas with higher built-up ratio experienced cooler daytime and warmer nighttime conditions [31].

Perhaps the most investigated element of the built environment is the land cover conditions, or land use/land cover (LULC) as termed by environmental scientists. Researchers extract various information from remotely sensed satellite imagery such as Light Detection and Ranging (LIDAR) and Landsat. They pay attention to the cooling effects of green elements in the city such as vegetation, landscaping, and greenery [32–43]. Others investigate the impact of water bodies [44–48] and impervious land surface [49–52].

Another body of literature looks into how land use in cities affect local temperature [53–58], which may benefit local planning practice. However, many of these studies tend to oversimplify land use information; for example, Weng et al. [58] classified local land use into three types that seem to be broad: commercial and industrial, residential, and green. These studies depend entirely on abstracted land use information from satellite imagery without consideration of actual conditions on the ground. Rather, only a small number of studies make use of local land use or zoning details derived from geographic information system (GIS) data [59–61].

Similar applies to studies that rely on computed values from satellite imagery for producing city-wide surface temperature maps. Algorithms and models that support such a process are becoming more supplicated and comprehensive, but the values they generate are essentially estimates subject to errors. Only a handful of studies use data collected at the ground-level weather stations [44,62–64], as not many cities have enough weather stations to support research. Some researchers design, build, and operate a mobile station of their own to collect temperature data [26,59,65,66], but end up with short-term observations that range up to weeks at the most, which may seem too instantaneous for making planning decisions that often look years ahead.

This study explores how the surrounding land use conditions affect near-ground temperatures in Seoul, South Korea. It also analyzes whether there are seasonal and diurnal variations observed in the influences. It differentiates from other studies in two ways. First, it does not rely on satellite imagery but on GIS data that reflect actual land use and temperature data measured and recorded at weather stations. Second, it adopts partial least square (PLS) regression models that safely deal with the peculiar nature found among the independent variables used in this study. The outcome of this study may help unveil the relationship between the built and thermal environments and support local land use practice, which takes environmental challenges such as climate change into serious consideration.

2. Methods

2.1. Study Area

Seoul (37°34′ N and 126°58′ E) sits in the central part of the Korean Peninsula, which extends southward from the east coast of Eurasian continent. Accommodating a stable population of 10 million, it is the capital city of South Korea, a world leading per capita carbon emitter. The Köppen climate classification places the city under the continental climate zone which experiences hot, humid summers and cold, dry winters. Seoul is one of many cities around the world where rising temperatures have become an obvious trend over the past decades and will remain in the coming future. Readings at the city's main weather station report that its annual average temperature has increased 2.0 °C, from 11.5 °C to 13.5 °C between 1910 and 2010 [67]. In accordance with the regional climate projections made by the Intergovernmental Panel on Climate Change (IPCC) that estimates extensive warming across East Asia [68], local meteorologist forecast that by 2100 Seoul's annual average temperature will range between 15.5 °C and 17.9 °C, which is 2.5 °C to 4.9 °C higher than that of 13.0 °C between 2001 and 2010, and argue for an active adoption of relevant land use policies and climate action plans [69].

Local meteorologists present observations of temperature rise and the intensifying of urban heat islands (UHIs) in Seoul [70–73]. Cha et al. [74] measured the effects of LULC characteristics on surface temperature in Seoul but did not provide lessons for local planning practice.

2.2. Data

2.2.1. Temperature Data

This study used temperature data that come from a dense system of weather stations run by the Korea Meteorological Administration (KMA), a state-run entity responsible for collecting nation-wide meteorological information and providing weather forecasts. As shown in Figure 1, the KMA operates 29 automated weather stations (AWSs) in Seoul today that log air temperature, wind speed and direction, relative humidity, and many other meteorological data at the near-ground level. While several studies report problems with poorly located weather stations for research [75,76], these stations in Seoul are set up mostly on publicly owned land at locations with minimal interference from most immediate surrounding conditions [77].

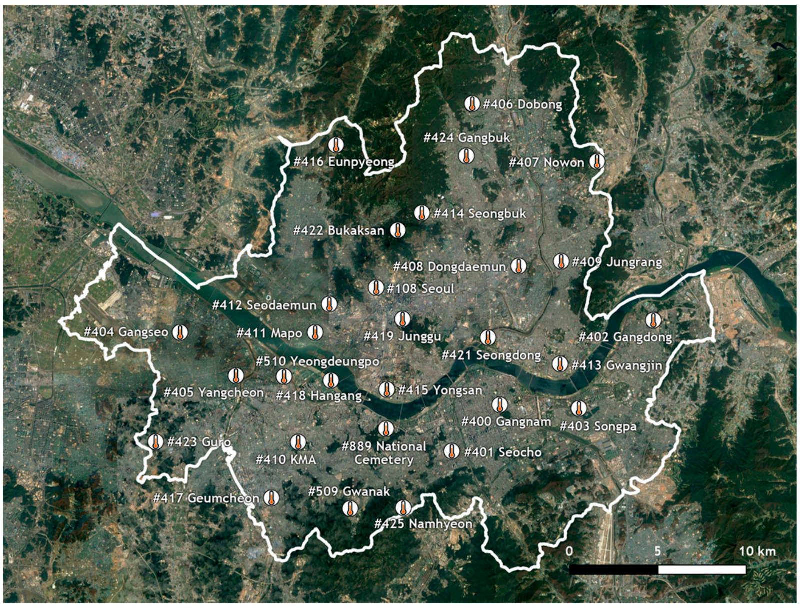

Figure 1. Locations and names of 29 automated weather stations operated by KMA in Seoul.

Three years of hourly temperature data operation, between January 2012 and December 2014, collected at 28 of 29 AWSs are used. Following an approach from previous studies [26,63], one AWS, #108 Seoul, is designated as a reference point and is not include in the data for analysis, except its temperature data to calculate differences between the 28 other stations. Located in the heart of Seoul, the station has served for decades as the main weather station of the city and is being perceived as a key reference point by locals. Land use conditions surrounding this station today are close to average when compared to those for other stations, rather than being predominantly developed or kept green.

The temperature data were grouped into eight groups—four seasons and two times of day—and averaged. In the South Korean climate context, spring ranges from March to May, summer from June to August, fall from September to November, and winter from December to February. This study considered daytime hours as being from 09:00 to 17:00 and nighttime hours from 21:00 to 05:00.

2.2.2. Land Use Data

Parcel-level GIS data were acquired from the National Geographic Information Institute (NGII) of South Korea, which keeps a regular update of the country's spatial information. A thorough review was carried out to verify whether the data reflect the actual land use conditions, and revisions were made when necessary.

Land use types were reorganized into two generalized classifications for analysis. One is a relatively broad classification of Seoul's land use in seven types: residential (RE), commercial (CO), civic (CI), industrial (IN), open space (OS), road (RO), and water (WA). This resembles approaches of environmental science studies on LULC, as previously introduced. The other is a much finer classification that is in line with what is usually found in local land use maps. It subdivides some of the seven types from Classification I into eleven and incorporates density. They are low-density residential (RL), medium-density residential (RM), high-density residential (RH), neighborhood commercial (CN), central commercial (CC), civic (CI), industrial (IN), park (PA), greenery (GE), road (RO), and water (WA). Among these, PA typically accommodates natural habitat and spaces for recreation such as paved fields, structures, and buildings. GE refers to areas populated by trees or bushes that are protected or reserved.

This study focuses on the land use conditions of surrounding parcels within one kilometer from each weather station, as exemplified in Figure 2. It is a common approach found in the literature that examines the impact of the surrounding land use on the environmental condition of a given location [63,74,78,79]. From the one-kilometer radius circles, data were drawn in percentages for the land use types in Classification II, and then combined into those in Classification I. Table 1 lists the land use types of the two classifications and the summary statistics of each land use type for the 28 AWSs selected for analysis in this study, in comparison with the reference station.

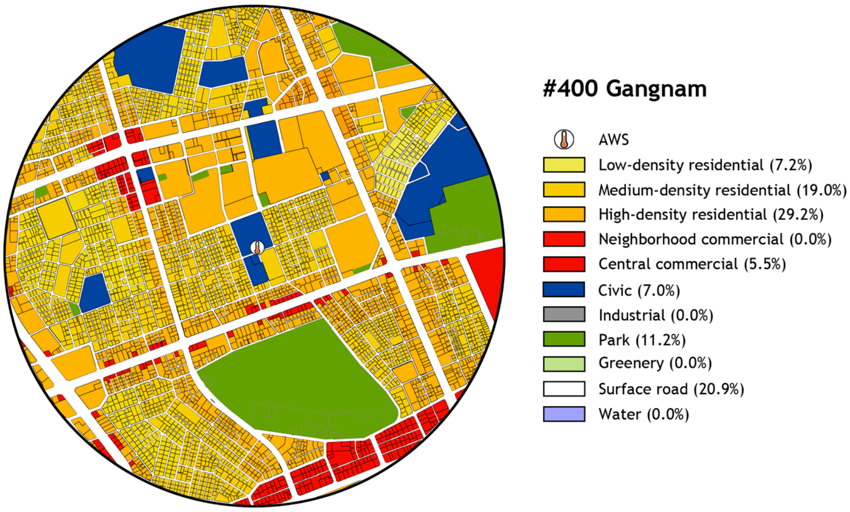

Figure 2. Land use conditions surrounding AWS #400 Gangnam and the percentages of each land use based on Classification II. The station is located at the center of the one-kilometer radius circle.

Table 1. Land use types of Classifications I and II and their summary statistics for 28 AWSs in comparison with the reference station (#108).

Classification	Land Use Types	Summary Statistics			Reference Station (#108)
		Min.	Max.	Mean.	
Classification I	Residential (RE)	0.0%	64.2%	34.3%	50.4%
	Commercial (CO)	0.0%	15.1%	3.2%	7.7%
	Civic (CI)	0.1%	56.5%	7.1%	8.8%
	Industrial (IN)	0.0%	24.6%	2.9%	0.0%
	Open Space (OS)	2.7%	93.7%	31.2%	12.9%
	Road (RO)	0.2%	27.5%	15.0%	20.1%
	Water (WA)	0.0%	51.9%	6.3%	0.0%
Classification II (Permissible floor area ratio [1] and lot coverage ratio [2])	Low-density residential (RL) (1.5 and 0.5)	0.0%	20.5%	4.8%	11.6%
	Medium-density residential (RM) (2.0 and 0.6)	0.0%	41.1%	15.2%	18.6%
	High-density residential (RH) (4.0 and 0.6)	0.0%	35.7%	14.3%	20.2%
	Neighborhood commercial (CN) (6.0 and 0.6)	0.0%	1.5%	0.2%	0.0%
	Central commercial (CC) (10.0 and 0.6)	0.0%	15.1%	3.0%	7.7%
	Civic (CI) [3]	0.1%	56.5%	7.1%	8.8%
	Industrial (IN) (4.0 and 0.6)	0.0%	24.6%	2.9%	0.0%
	Park (PA) (0.5 and 0.2)	0.0%	52.8%	7.2%	4.8%
	Greenery (GR) (0.5 and 0.2)	0.0%	93.6%	24.1%	8.2%
	Road (RO)	0.2%	27.5%	15.0%	20.1%
	Water (WA)	0.0%	51.9%	6.3%	0.0%

[1] Floor area ratio = (Total floor area)/(Site area); [2] Lot coverage ratio = (Building area)/(Site area); [3] Permissible floor area ratios for this category is subject to site-specific regulations.

2.3. Analysis

The independent variables of this study are the percentages of each land use type of Classifications I and II within the one-kilometer circle around the 28 AWSs. The dependent variables are the mean temperature differences (ΔT_{mean}), which are calculated by subtracting the mean temperature of the reference station from the mean temperate from each of the 28 stations for the four seasons and two times of the day. Figure 3 summarizes these variables.

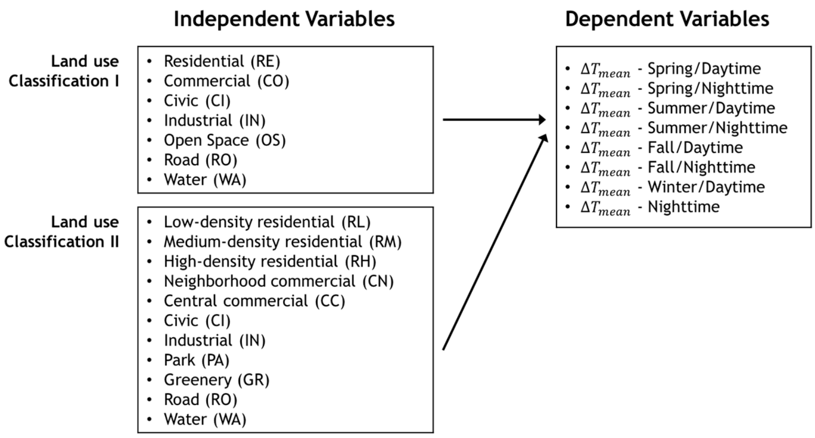

Figure 3. Independent and dependent variables of this study.

Application of multiple regression models based on ordinary least squares seems like an obvious method for analysis in this case. However, studies report the problem of multicollinearity frequently exhibited among land use variables [59,79] and adopt alternative approaches. Some use bivariate correlation to measure the direction and strength of the impact of each land use type [37,42,49]. Another group uses simple linear regression models so that the impact of each type on temperature can be quantified individually [80–82]. Others take best subset regressions that selectively incorporate land use types into the regression model to obtain the best fitted curve [26,38,47,74].

The PLS regression model is adopted in studies that examine the impact of land use on various environmental conditions [83–85]. The model is a robust multivariate regression method that predicts the dependent variable by extracting from the independent variables a set of orthogonal factors called latent variables which have the best explanatory power [86]. It is favored by environmental scientists for effectively dealing with independent variables that yield high multicollinearity. However, the model has been introduced to only a small number of urban researchers such as Liu and Shen [87] and Zhao et al. [88]. Unlike other regression models that generate the p value to represent significance level, the PLS regression model generates the variable importance for projection (VIP) value for each independent variable to reflect its importance. A VIP value between 0.8 and 1.0 suggests moderate influence of the independent variable on predicting the dependent variable, while a value larger than 1.0 yields high influence [89]. The goodness-of-fit statistics are R^2 as the explanatory capacity of the model and Q^2 as the cross-validated goodness of prediction.

3. Results

3.1. Testing for Multicollinearity

The first step was to check whether multicollinearity among the independent variables is evident. Tables 2 and 3 present bivariate correlation results between the land use types in Classifications I and II, respectively. They commonly suggest that there are a number of statistically significant ($p < 0.05$) and strong correlations ($|r| > 0.6$). This demonstrates that multicollinearity is present in both classifications and that an alternative model such as PLS regression is required.

Table 2. Bivariate correlation results between Classification I land use types.

Land Use	RE	CO	CI	IN	OS	RO	WA
RE	1						
CO	0.181	1					
CI	−0.175	−0.178	1				
IN	−0.025	0.347	−0.161	1			
OS	−0.710 **	−0.501 **	−0.034	−0.278	1		
RO	0.703 **	0.497 **	−0.353	0.358	−0.797 **	1	
WA	−0.279	0.129	−0.186	−0.087	−0.228	0.007	1

** $p < 0.01$.

Table 3. Bivariate correlation results between Classification II land use types.

Land Use	RL	RM	RH	CN	CC	CI	IN	PA	GR	RO	WA
RL	1										
RM	−0.076	1									
RH	−0.317	0.334	1								
CN	0.022	0.386 *	0.067	1							
CC	−0.300	−0.130	0.555 **	−0.221	1						
CI	0.084	−0.148	−0.174	0.000	−0.176	1					
IN	−0.197	0.086	−0.037	0.331	0.310	−0.161	1				
PA	0.423 *	−0.029	−0.068	0.005	−0.070	−0.155	−0.143	1			
GR	0.045	−0.535 **	−0.576 **	−0.259	−0.399 *	0.035	−0.194	−0.396 *	1		
RO	−0.252	0.530 **	0.725 **	0.307	0.460 *	−0.353	0.358	0.111	−0.780 **	1	
WA	−0.323	−0.174	-0.109	−0.161	0.142	−0.186	−0.087	−0.003	−0.208	0.007	1

* $p < 0.05$; ** $p < 0.01$.

3.2. Land Use Classification I

Table 4 shows estimation of ΔT by season (spring, summer, fall, and winter) and time of day (daytime and nighttime) with the land use types in Classification I using PLS regression models. First, RE, CO, and RO turned out to be influential heaters while OS was an influential cooler in all seasons during both daytime and nighttime. This suggests that areas with a larger degree of residential or commercial development served by more roads are generally hotter, while those with more open spaces are cooler throughout the year. Second, the absolute values of coefficients of these four land use types were bigger during nighttime than daytime, indicating that their influences are more evident at night. Third, among the three heaters, CO was the most impactful in all cases, followed by RO and RE. The coefficients of CO remained relatively constant during daytime (0.019 to 0.028) and nighttime (0.051 to 0.067). Those of RO and RE showed similar trends around the year. These suggest that, regardless of the season and time of day, the impact of residential, commercial, and road uses are generally fixed. Fourth, the coefficient of OS, the cooler, was relatively stable during daytime (−0.006 to −0.005) and nighttime (−0.013 to −0.011). Fifth, the absolute values of OS's coefficients were considerably smaller than those of RE, CO, and RO. It can be interpreted as the per area cooling capacity of open spaces is outperformed by the heating capacity of commercial areas and roads. Lastly, CI and IN showed mixed results, and WA was an unexpected heater in all cases. However, none of these three were identified as influential, as their VIP values did not exceed 0.8. Figure 4 visually presents the impacts of statistically influential land use types of this classification on the temperature with respect to their size.

Table 4. PLS regression models between land use Classification I and ΔT by season and time of the day.

	Spring				**Summer**				**Fall**				**Winter**			
	Day	**VIP**	**Night**	**VIP**	**Day**	**VIP**	**Night**	**VIP**	**Day**	**VIP**	**Night**	**VIP**	**Day**	**VIP**	**Night**	**VIP**
	Land Use Coefficient															
RE	0.006 ††	1.129	0.012 ††	1.063	0.006 ††	1.091	0.010 †	0.976	0.004 †	0.836	0.010 †	0.829	0.004 †	0.877	0.011 †	0.961
CO	0.019 †	0.847	0.055 ††	1.055	0.025 ††	1.027	0.051 ††	1.103	0.028 ††	1.169	0.067 ††	1.234	0.022 †	0.996	0.052 ††	1.075
CI	−0.002	0.240	−0.006	0.325	−0.003	0.272	−0.007	0.399	−0.001	0.100	−0.007	0.358	0.000	0.031	−0.005	0.266
IN	−0.001	0.043	0.012	0.382	0.002	0.132	0.014	0.492	0.007	0.462	0.021	0.614	0.006	0.387	0.015	0.494
OS	−0.005 ††	1.471	−0.012 ††	1.508	−0.006 ††	1.487	−0.011 ††	1.482	−0.006 ††	1.523	−0.013 ††	1.484	−0.006 ††	1.544	−0.012 ††	1.533
RO	0.021 ††	1.618	0.043 ††	1.416	0.022 ††	1.504	0.038 ††	1.390	0.020 ††	1.448	0.040 ††	1.266	0.021 ††	1.567	0.040 ††	1.390
WA	0.003	0.408	0.008	0.476	0.003	0.436	0.008	0.549	0.004	0.544	0.012	0.693	0.004	0.499	0.009	0.570
	Goodness-of-fit Statistics															
R^2	0.405		0.721		0.477		0.790		0.392		0.669		0.357		0.670	
Q^2	0.259		0.679		0.342		0.755		0.260		0.621		0.223		0.614	

† VIP > 0.8; †† VIP > 1.0.

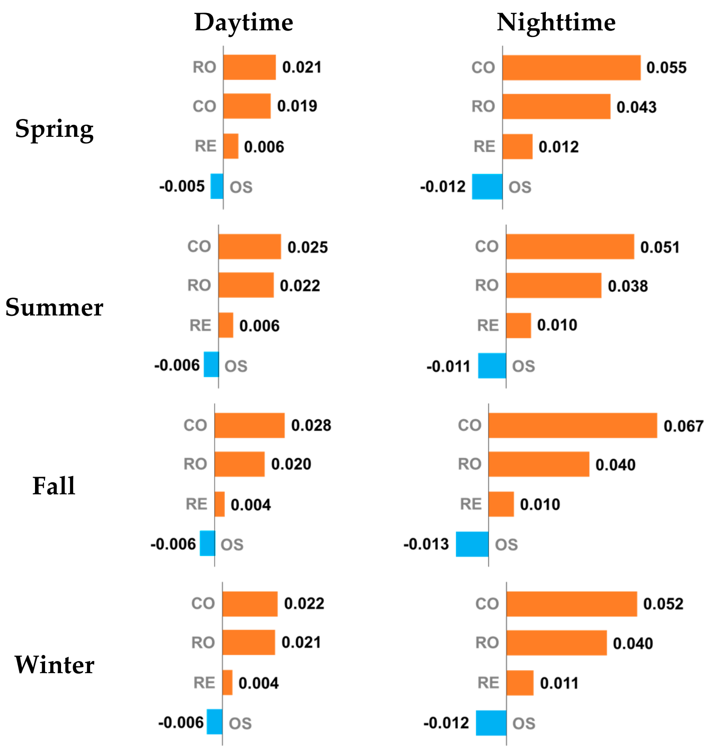

Figure 4. Visualization of the impacts of statistically influential land use types of Classification I on the temperature with respect to their size.

3.3. Land Use Classification II

PLS regression models that estimate ΔT with the land use types Classification II are provided in Table 5. A first observation is that CC, RO, and RH performed as influential heaters. It can be interpreted that urban areas with more high-density residential or central commercial uses and roads experience higher temperatures. Among the three heaters, CC was the most impactful in most cases as its coefficients were generally the largest during daytime (0.015 to 0.023) and nighttime (0.042 to 0.056). It was followed by RO (0.018 to 0.019 during daytime and 0.033 to 0.038 during nighttime) and RH (0.011 to 0.012 during daytime and 0.020 to 0.024 during nighttime). A plausible interpretation is that concentrations of high-rise buildings that dominate CC and RH areas trap heat and hinder ventilation, resulting in higher temperatures. Second, GR played the role of an influential cooler in all seasons at both times of day, and RL was a stronger cooler during daytime in all seasons than GR but not influential during nighttime. Our interpretation is that areas surrounded by more greenery experience lower temperatures at all times, and those by low-density residential enjoy lower temperatures during daytime. The coefficients of GR remained relatively constant during daytime (-0.004) and nighttime (-0.008 to -0.009) in all four seasons. RL presented more impactful coefficients (-0.011 to -0.016). It can be interpreted as RL, unlike RH, provides room for ventilation and minimizes heat trapped between buildings during daytime. Third, absolute values of the coefficients of the heaters were generally larger than those of the coolers, and their differences were much bigger during nighttime than daytime. Especially, the influence of GR was much smaller than those of the heaters, suggesting the relatively limited cooling performance by GR as opposed to the heating effect of high-density development patterns. The larger absolute values observed during nighttime suggest the larger influences of these land uses, as well as the intensification of UHI during nighttime. Lastly, no other land uses were found to be influential. Figure 5 is a visual representation of the impacts of statistically influential land use types from Classification II on the temperature with respect to their size.

Table 5. PLS regression models between land use Classification II and ΔT by season and time of the day.

	Spring				Summer				Fall				Winter			
	Day	**VIP**	**Night**	**VIP**	**Day**	**VIP**	**Night**	**VIP**	**Day**	**VIP**	**Night**	**VIP**	**Day**	**VIP**	**Night**	**VIP**
Land Use Coefficient																
RL	−0.012 †	0.909	−0.020	0.685	−0.011 †	0.807	−0.019	0.747	−0.016 ††	1.162	−0.017	0.578	−0.016 ††	1.173	−0.018	0.672
RM	0.005	0.774	0.010	0.761	0.005	0.748	0.009	0.722	0.003	0.530	0.008	0.589	0.004	0.568	0.009	0.715
RH	0.011 ††	1.723	0.024 ††	1.605	0.012 ††	1.695	0.020 ††	1.516	0.011 ††	1.570	0.020 ††	1.330	0.011 ††	1.577	0.020 ††	1.460
CN	0.061	0.337	0.202	0.495	0.045	0.227	0.164	0.448	0.044	0.219	0.147	0.353	0.097	0.499	0.184	0.487
CC	0.015 †	0.894	0.045 ††	1.168	0.021 ††	1.137	0.042 ††	1.231	0.023 ††	1.251	0.056 ††	1.430	0.018 ††	1.014	0.043 ††	1.199
CI	−0.002	0.267	−0.006	0.381	−0.002	0.312	−0.006	0.469	−0.001	0.110	−0.007	0.432	0.000	0.033	−0.004	0.313
IN	−0.001	0.048	0.011	0.447	0.002	0.152	0.013	0.578	0.006	0.511	0.019	0.741	0.005	0.419	0.013	0.582
PA	0.000	0.057	−0.003	0.234	−0.001	0.201	−0.003	0.271	−0.002	0.327	−0.001	0.072	−0.001	0.145	−0.001	0.065
GR	−0.004 ††	1.477	−0.009 ††	1.521	−0.004 ††	1.480	−0.008 ††	1.482	−0.004 ††	1.408	−0.009 ††	1.614	−0.004 ††	1.474	−0.009 ††	1.631
RO	0.018 ††	1.798	0.038 ††	1.657	0.019 ††	1.725	0.033 ††	1.632	0.018 ††	1.602	0.036 ††	1.527	0.018 ††	1.696	0.035 ††	1.637
WA	0.002	0.453	0.007	0.557	0.003	0.499	0.007	0.645	0.004	0.602	0.011 †	0.836	0.003	0.540	0.008	0.672
Goodness-of-fit Statistics																
R^2	0.451		0.730		0.503		0.795		0.450		0.637		0.424		0.665	
Q^2	0.266		0.663		0.349		0.737		0.253		0.567		0.213		0.591	

† VIP > 0.8; †† VIP > 1.0.

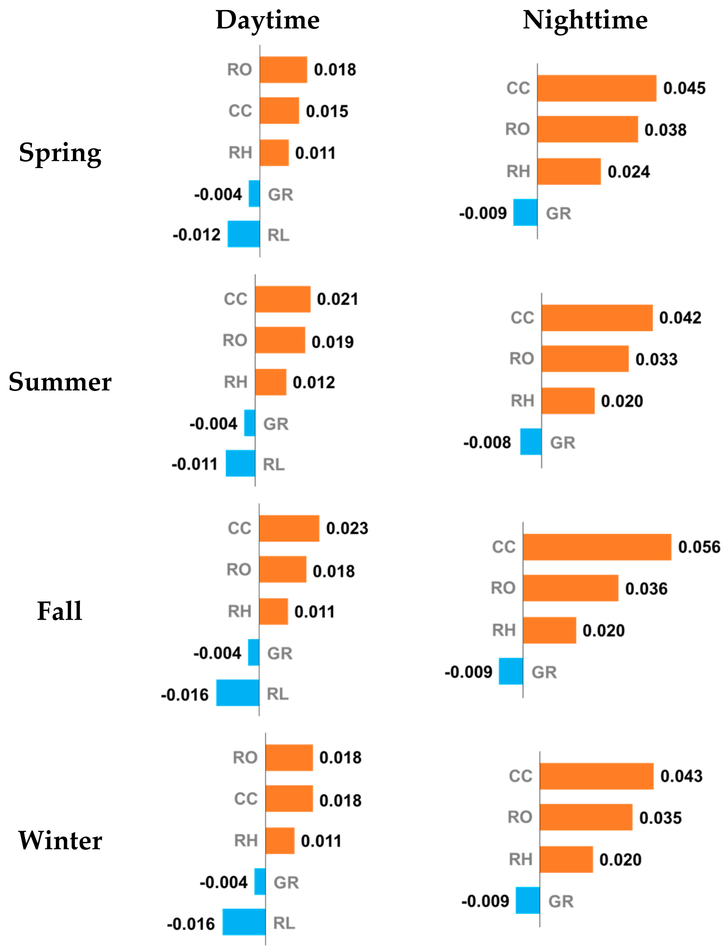

Figure 5. Visualization of the impacts of statistically influential land use types of Classification II on the temperature with respect to their size.

4. Discussion and Implications

Review of the two PLS regression models incites further discussion. In general, Classification II, a finer break down of Seoul's land use, unveils what Classification I does not. First, the heating impact of RE in Classification I throughout the year is in fact mostly driven by RH in Classification II. This suggests that the widely spread high-density living in Seoul may not be a preferred solution from the temperature perspective. Intense use of land to accommodate ten million residents, but over-dependency on high-density residential environment could result in higher temperatures. Alternative planning and design guidelines for high-density residential environments that promote cooling could be incorporated.

Similarly, the heating effect by CO in Classification I can be attributed to CC in Classification II. This implies the existence of UHI that forms around commercial cores of the city. As the cores inherently concentrate people, goods, and traffic, it may be almost impossible to expect commercial areas not to warm up. However, again, alternative approaches may provide guidance to establishing cooler commercial areas of the city.

Third, this research reconfirms the fact that roads are the main actors that warm up the city. The current practice of relying on asphalt or concrete for paving will keep boosting temperatures. Our findings call for a new approach, such as cool or green paving to be implemented.

Lastly, it is quite alarming to find that, while OS in Classification I was identified as an influential cooler, PA and GR in Classification II showed differing results. Of the two, GR presented consistent cooling performance at all times, but the cooling impact of PA was not at all statistically influential.

This is somewhat contrary to common sense that parks help cities cool down. Rather, greenery was identified to be impactful in cooling.

Overall, the thermal performances of land use and their seasonal and diurnal variability propose further challenges that may alarm planners and designers. Near-ground temperatures affected by the surrounding land use would result in increased cooling or heating loads in peak seasons. They may also discourage people from engaging in outdoor activities by negatively influencing their perceived thermal comfort.

5. Concluding Remarks

This study examined how the surrounding land use conditions affect the near-ground temperatures in Seoul, South Korea. Specifically, it analyzed the impacts of various land use types on temperature and their variations by season and time of the day. Findings suggest that, among those from a coarser classification of local land use, residential and commercial uses and roads increase the temperature while open space decreases it at all times. From a much finer classification, high-density residential and central commercial uses and surface roads were found as influential heaters, while greenery was an influential cooler all year round and low-density residential during daytime.

There are several shortcomings in this study. The samples size (N = 28) may not seem be large enough. Findings of this study may apply only to Seoul and not be transferred to other cities or generalized. The analysis incorporated a subset of variables on the built environment at the ground level without much consideration of climate and topography at a more regional scale, as well as socio-economic conditions.

However, this study makes several contributions. First, the nature of data used in this study, which come from local GIS information and meteorological measurements at publicly run weather stations, enhances reliability of the findings as opposed to studies based on estimates. Second, rather than developing knowledge that is transferrable or generalizable, it sounds more plausible to state that the impacts of land use on temperature would depend on the specific conditions within each city. Further exploration of the varying impacts of land use on temperature in cities around the world and coming up with place-based solutions may be a more urgent task for planning practice and research in the coming future.

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References

1. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2014.
2. Bulkeley, H. *Cities and Climate Change*, 1st ed.; Routledge: New York, NY, USA, 2013; ISBN 978-0-415-59705-0.
3. Ewing, R.; Bartholomew, K.; Winkelman, S.; Walters, J.; Chen, D. *Growing Cooler: The Evidence on Urban Development and Climate Change*; Urban Land Institute: Washington, DC, USA, 2008; ISBN 978-0-87420-082-9.
4. Stone, B. *The City and the Coming Climate: Climate Change in the Places We Live*, 1st ed.; Cambridge University Press: New York, NY, USA, 2012; ISBN 978-1-107-60258-8.
5. Hickman, R.; Banister, D. *Transport, Climate Change and the City*; Routledge: London, UK; New York, NY, USA, 2015; ISBN 978-0-415-66003-7.
6. Newman, P.; Beatley, T.; Boyer, H.M. *Resilient Cities: Responding to Peak Oil and Climate Change*, 1st ed.; Island Press: Washington, DC, USA, 2009; ISBN 978-1-59726-499-0.

7. Deilami, K.; Kamruzzaman, M. Modelling the urban heat island effect of smart growth policy scenarios in Brisbane. *Land Use Policy* **2017**, *64*, 38–55. [CrossRef]
8. Giridharan, R.; Lau, S.S.Y.; Ganesan, S.; Givoni, B. Urban design factors influencing heat island intensity in high-rise high-density environments of Hong Kong. *Build. Environ.* **2007**, *42*, 3669–3684. [CrossRef]
9. Givoni, B. *Climate Considerations in Building and Urban Design*; Van Nostrand Reinhold: New York, NY, USA, 1998; ISBN 0-442-00991-7.
10. Lenzholer, S. *Weather in the City: How Design Shapes the Urban Climate*; nai010 Publishers: Rotterdam, The Netherlands, 2015; ISBN 978-94-6208-198-7.
11. Mitchell, D.; Enemark, S.; van der Molen, P. Climate resilient urban development: Why responsible land governance is important. *Land Use Policy* **2015**, *48*, 190–198. [CrossRef]
12. Taylor, P.J. Cities in climate change. *Int. J. Urban Sci.* **2017**, *21*, 1–14. [CrossRef]
13. Calthorpe, P. *Urbanism in the Age of Climate Change*, 2nd ed.; Island Press: Washington, DC, USA, 2013; ISBN 978-1-59726-721-2.
14. Desouza, K.C.; Flanery, T.H. Designing, planning, and managing resilient cities: A conceptual framework. *Cities* **2013**, *35*, 89–99. [CrossRef]
15. Jabareen, Y. Planning the resilient city: Concepts and strategies for coping with climate change and environmental risk. *Cities* **2013**, *31*, 220–229. [CrossRef]
16. Santamouris, M. Cooling the cities—A review of reflective and green roof mitigation technologies to fight heat island and improve comfort in urban environments. *Sol. Energy* **2014**, *103*, 682–703. [CrossRef]
17. Susca, T.; Gaffin, S.R.; Dell'Osso, G.R. Positive effects of vegetation: Urban heat island and green roofs. *Environ. Pollut.* **2011**, *159*, 2119–2126. [CrossRef] [PubMed]
18. Takebayashi, H.; Moriyama, M. Surface heat budget on green roof and high reflection roof for mitigation of urban heat island. *Build. Environ.* **2007**, *42*, 2971–2979. [CrossRef]
19. Wong, J.K.W.; Lau, L.S.-K. From the "urban heat island" to the "green island"? A preliminary investigation into the potential of retrofitting green roofs in Mongkok district of Hong Kong. *Habitat Int.* **2013**, *39*, 25–35. [CrossRef]
20. Zinzi, M.; Agnoli, S. Cool and green roofs. An energy and comfort comparison between passive cooling and mitigation urban heat island techniques for residential buildings in the Mediterranean region. *Energy Build.* **2012**, *55*, 66–76. [CrossRef]
21. Alexandri, E.; Jones, P. Temperature decreases in an urban canyon due to green walls and green roofs in diverse climates. *Build. Environ.* **2008**, *43*, 480–493. [CrossRef]
22. Santamouris, M. Using cool pavements as a mitigation strategy to fight urban heat island—A review of the actual developments. *Renew. Sustain. Energy Rev.* **2013**, *26*, 224–240. [CrossRef]
23. Chen, L.; Ng, E.; An, X.; Ren, C.; Lee, M.; Wang, U.; He, Z. 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.* **2012**, *32*, 121–136. [CrossRef]
24. Chun, B.; Guhathakurta, S. Daytime and nighttime urban heat islands statistical models for Atlanta. *Environ. Plan. B Plan. Des.* **2015**. [CrossRef]
25. Chun, B.; Guldmann, J.-M. Spatial statistical analysis and simulation of the urban heat island in high-density central cities. *Landsc. Urban Plan.* **2014**, *125*, 76–88. [CrossRef]
26. Coseo, P.; Larsen, L. How factors of land use/land cover, building configuration, and adjacent heat sources and sinks explain Urban Heat Islands in Chicago. *Landsc. Urban Plan.* **2014**, *125*, 117–129. [CrossRef]
27. Svensson, M.K. Sky view factor analysis—Implications for urban air temperature differences. *Meteorol. Appl.* **2004**, *11*, 201–211. [CrossRef]
28. Yuan, C.; Chen, L. Mitigating urban heat island effects in high-density cities based on sky view factor and urban morphological understanding: A study of Hong Kong. *Archit. Sci. Rev.* **2011**, *54*, 305–315. [CrossRef]
29. Middel, A.; Häb, K.; Brazel, A.J.; Martin, C.A.; Guhathakurta, S. Impact of Urban Form and Design on Mid-Afternoon Microclimate in Phoenix Local Climate Zones. *Landsc. Urban Plan.* **2014**, *122*, 16–28. [CrossRef]
30. Stone, B.; Rodgers, M.O. Urban Form and Thermal Efficiency: How the Design of Cities Influences the Urban Heat Island Effect. *J. Am. Plan. Assoc.* **2001**, *67*, 186–198. [CrossRef]
31. Jamei, E.; Jamei, Y.; Rajagopalan, P.; Ossen, D.R.; Roushenas, S. Effect of built-up ratio on the variation of air temperature in a heritage city. *Sustain. Cities Soc.* **2015**, *14*, 280–292. [CrossRef]

32. Aflaki, A.; Mirnezhad, M.; Ghaffarianhoseini, A.; Ghaffarianhoseini, A.; Omrany, H.; Wang, Z.-H.; Akbari, H. Urban heat island mitigation strategies: A state-of-the-art review on Kuala Lumpur, Singapore and Hong Kong. *Cities* **2017**, *62*, 131–145. [CrossRef]
33. Alavipanah, S.; Wegmann, M.; Qureshi, S.; Weng, Q.; Koellner, T. The Role of Vegetation in Mitigating Urban Land Surface Temperatures: A Case Study of Munich, Germany during the Warm Season. *Sustainability* **2015**, *7*, 4689–4706. [CrossRef]
34. Armson, D.; Stringer, P.; Ennos, A.R. The effect of tree shade and grass on surface and globe temperatures in an urban area. *Urban For. Urban Green.* **2012**, *11*, 245–255. [CrossRef]
35. Bowler, D.E.; Buyung-Ali, L.; Knight, T.M.; Pullin, A.S. Urban greening to cool towns and cities: A systematic review of the empirical evidence. *Landsc. Urban Plan.* **2010**, *97*, 147–155. [CrossRef]
36. Chang, C.-R.; Li, M.-H. Effects of urban parks on the local urban thermal environment. *Urban For. Urban Green.* **2014**, *13*, 672–681. [CrossRef]
37. Chen, A.; Yao, X.A.; Sun, R.; Chen, L. Effect of urban green patterns on surface urban cool islands and its seasonal variations. *Urban For. Urban Green.* **2014**, *13*, 646–654. [CrossRef]
38. Connors, J.P.; Galletti, C.S.; Chow, W.T.L. Landscape configuration and urban heat island effects: Assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona. *Landsc. Ecol.* **2013**, *28*, 271–283. [CrossRef]
39. Feyisa, G.L.; Dons, K.; Meilby, H. Efficiency of parks in mitigating urban heat island effect: An example from Addis Ababa. *Landsc. Urban Plan.* **2014**, *123*, 87–95. [CrossRef]
40. Gill, S.; Handley, J.; Ennos, A.; Pauleit, S. Adapting Cities for Climate Change: The Role of the Green Infrastructure. *Built Environ.* **2007**, *33*, 115–133. [CrossRef]
41. Park, J.-H.; Cho, G.-H. Examining the Association between Physical Characteristics of Green Space and Land Surface Temperature: A Case Study of Ulsan, Korea. *Sustainability* **2016**, *8*, 777. [CrossRef]
42. Shih, W. Greenspace patterns and the mitigation of land surface temperature in Taipei metropolis. *Habitat Int.* **2017**, *60*, 69–80. [CrossRef]
43. Hanamean, J.R., Jr.; Pielke, R.A., Sr.; Castro, C.L.; Ojima, D.S.; Reed, B.C.; Gao, Z. Vegetation greenness impacts on maximum and minimum temperatures in northeast Colorado. *Meteorol. Appl.* **2003**, *10*, 203–215. [CrossRef]
44. Chen, Y.-C.; Tan, C.-H.; Wei, C.; Su, Z.-W. Cooling Effect of Rivers on Metropolitan Taipei Using Remote Sensing. *Int. J. Environ. Res. Public Health* **2014**, *11*, 1195–1210. [CrossRef] [PubMed]
45. Hathway, E.A.; Sharples, S. The interaction of rivers and urban form in mitigating the Urban Heat Island effect: A UK case study. *Build. Environ.* **2012**, *58*, 14–22. [CrossRef]
46. Steeneveld, G.J.; Koopmans, S.; Heusinkveld, B.G.; Theeuwes, N.E. Refreshing the role of open water surfaces on mitigating the maximum urban heat island effect. *Landsc. Urban Plan.* **2014**, *121*, 92–96. [CrossRef]
47. Sun, R.; Chen, L. How can urban water bodies be designed for climate adaptation? *Landsc. Urban Plan.* **2012**, *105*, 27–33. [CrossRef]
48. Han, S.-G.; Huh, J.-H. Estimate of the Heat Island and Building Cooling Load Changes due to the Restored Stream in Seoul, Korea. *Int. J. Urban Sci.* **2008**, *12*, 129–145. [CrossRef]
49. Xiao, R.; Ouyang, Z.; Zheng, H.; Li, W.; Schienke, E.W.; Wang, X. Spatial pattern of impervious surfaces and their impacts on land surface temperature in Beijing, China. *J. Environ. Sci.* **2007**, *19*, 250–256. [CrossRef]
50. Yuan, F.; Bauer, M.E. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sens. Environ.* **2007**, *106*, 375–386. [CrossRef]
51. Gallo, K.; Xian, G. Application of spatially gridded temperature and land cover data sets for urban heat island analysis. *Urban Clim.* **2014**, *8*, 1–10. [CrossRef]
52. Gallo, K.; Xian, G. Changes in satellite-derived impervious surface area at US historical climatology network stations. *ISPRS J. Photogramm. Remote Sens.* **2016**, *120*, 77–83. [CrossRef]
53. Amiri, R.; Weng, Q.; Alimohammadi, A.; Alavipanah, S.K. Spatial—Temporal dynamics of land surface temperature in relation to fractional vegetation cover and land use/cover in the Tabriz urban area, Iran. *Remote Sens. Environ.* **2009**, *113*, 2606–2617. [CrossRef]
54. Buyantuyev, A.; Wu, J. Urban heat islands and landscape heterogeneity: Linking spatiotemporal variations in surface temperatures to land-cover and socioeconomic patterns. *Landsc. Ecol.* **2010**, *25*, 17–33. [CrossRef]

55. Stathopoulou, M.; Cartalis, C. Daytime urban heat islands from Landsat ETM+ and Corine land cover data: An application to major cities in Greece. *Sol. Energy* **2007**, *81*, 358–368. [CrossRef]
56. Svensson, M.K.; Eliasson, I. Diurnal air temperatures in built-up areas in relation to urban planning. *Landsc. Urban Plan.* **2002**, *61*, 37–54. [CrossRef]
57. Viegas, C.V.; Saldanha, D.L.; Bond, A.; Ribeiro, J.L. D.; Selig, P.M. Urban land planning: The role of a Master Plan in influencing local temperatures. *Cities* **2013**, *35*, 1–13. [CrossRef]
58. Weng, Q.; Lu, D.; Schubring, J. Estimation of land surface temperature—Vegetation abundance relationship for urban heat island studies. *Remote Sens. Environ.* **2004**, *89*, 467–483. [CrossRef]
59. Hart, M.A.; Sailor, D.J. Quantifying the influence of land-use and surface characteristics on spatial variability in the urban heat island. *Theor. Appl. Climatol.* **2009**, *95*, 397–406. [CrossRef]
60. Jusuf, S.K.; Wong, N.H.; Hagen, E.; Anggoro, R.; Hong, Y. The influence of land use on the urban heat island in Singapore. *Habitat Int.* **2007**, *31*, 232–242. [CrossRef]
61. Rinner, C.; Hussain, M. Toronto's Urban Heat Island—Exploring the Relationship between Land Use and Surface Temperature. *Remote Sens.* **2011**, *3*, 1251–1265. [CrossRef]
62. Santamouris, M. On the energy impact of urban heat island and global warming on buildings. *Energy Build.* **2014**, *82*, 100–113. [CrossRef]
63. Steeneveld, G.J.; Koopmans, S.; Heusinkveld, B.G.; van Hove, L.W.A.; Holtslag, A.A.M. Quantifying urban heat island effects and human comfort for cities of variable size and urban morphology in the Netherlands. *J. Geophys. Res. Atmos.* **2011**, *116*, D20129. [CrossRef]
64. Szymanowski, M. Interactions between thermal advection in frontal zones and the urban heat island of Wrocław, Poland. *Theor. Appl. Climatol.* **2005**, *82*, 207–224. [CrossRef]
65. Busato, F.; Lazzarin, R.M.; Noro, M. Three years of study of the Urban Heat Island in Padua: Experimental results. *Sustain. Cities Soc.* **2014**, *10*, 251–258. [CrossRef]
66. Wong, N.H.; Yu, C. Study of green areas and urban heat island in a tropical city. *Habitat Int.* **2005**, *29*, 547–558. [CrossRef]
67. Seoul Metropolitan Government. *Atmospheric Environment Conditions of Seoul*; Seoul Metropolitan Government: Seoul, Korea, 2017.
68. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2013: The Physical Science Basis*; Cambridge University Press: New York, NY, USA, 2013.
69. Korea Meteorological Administration. *Climate Change Projection Report—Seoul, Incheon, and Gyeonggi*; Korea Meteorological Administration: Seoul, Korea, 2012.
70. Kim, Y.-H.; Baik, J.-J. Daily maximum urban heat island intensity in large cities of Korea. *Theor. Appl. Climatol.* **2004**, *79*, 151–164. [CrossRef]
71. Kim, Y.-H.; Baik, J.-J. Spatial and Temporal Structure of the Urban Heat Island in Seoul. *J. Appl. Meteorol.* **2005**, *44*, 591–605. [CrossRef]
72. Kim, Y.-H.; Baik, J.-J. Maximum Urban Heat Island Intensity in Seoul. *J. Appl. Meteorol.* **2002**, *41*, 651–659. [CrossRef]
73. Lee, S.-H.; Baik, J.-J. Statistical and dynamical characteristics of the urban heat island intensity in Seoul. *Theor. Appl. Climatol.* **2010**, *100*, 227–237. [CrossRef]
74. Cha, Y.-H.; Kim, H.-Y.; Heo, T.-Y. The Effects of Urban Land Use and Land Cover Characteristics on Air Temperature in Seoul Metropolitan Area. *Seoul City Res.* **2009**, *10*, 107–120.
75. Pielke, R., Sr.; Nielsen-Gammon, J.; Davey, C.; Angel, J.; Bliss, O.; Doesken, N.; Cai, M.; Fall, S.; Niyogi, D.; Gallo, K.; et al. Documentation of Uncertainties and Biases Associated with Surface Temperature Measurement Sites for Climate Change Assessment. *Bull. Am. Meteorol. Soc.* **2007**, *88*, 913–928. [CrossRef]
76. Fall, S.; Watts, A.; Nielsen-Gammon, J.; Jones, E.; Niyogi, D.; Christy, J.R.; Pielke, R.A. Analysis of the impacts of station exposure on the U.S. Historical Climatology Network temperatures and temperature trends. *J. Geophys. Res.* **2011**, *116*, D14120. [CrossRef]
77. Korea Meteorological Administration. *Guidelines for Surface Meteorological Observation*; Korea Meteorological Administration: Seoul, Korea, 2011.
78. Kim, Y.; Guldmann, J.-M. Land-use regression panel models of NO_2 concentrations in Seoul, Korea. *Atmos. Environ.* **2015**, *107*, 364–373. [CrossRef]
79. Ross, Z.; Jerrett, M.; Ito, K.; Tempalski, B.; Thurston, G.D. A land use regression for predicting fine particulate matter concentrations in the New York City region. *Atmos. Environ.* **2007**, *41*, 2255–2269. [CrossRef]

80. Mallick, J.; Singh, C.K.; Shashtri, S.; Rahman, A.; Mukherjee, S. Land surface emissivity retrieval based on moisture index from LANDSAT TM satellite data over heterogeneous surfaces of Delhi city. *Int. J. Appl. Earth Obs. Geoinf.* **2012**, *19*, 348–358. [CrossRef]
81. Onishi, A.; Cao, X.; Ito, T.; Shi, F.; Imura, H. Evaluating the potential for urban heat-island mitigation by greening parking lots. *Urban For. Urban Green.* **2010**, *9*, 323–332. [CrossRef]
82. Xiao, H.; Ji, W. Relating landscape characteristics to non-point source pollution in mine waste-located watersheds using geospatial techniques. *J. Environ. Manag.* **2007**, *82*, 111–119. [CrossRef] [PubMed]
83. Sampson, P.D.; Richards, M.; Szpiro, A.A.; Bergen, S.; Sheppard, L.; Larson, T.V.; Kaufman, J.D. A regionalized national universal kriging model using Partial Least Squares regression for estimating annual PM2.5 concentrations in epidemiology. *Atmos. Environ.* **2013**, *75*, 383–392. [CrossRef] [PubMed]
84. Woldesenbet, T.A.; Elagib, N.A.; Ribbe, L.; Heinrich, J. Hydrological responses to land use/cover changes in the source region of the Upper Blue Nile Basin, Ethiopia. *Sci. Total Environ.* **2017**, *575*, 724–741. [CrossRef] [PubMed]
85. Yan, B.; Fang, N.F.; Zhang, P.C.; Shi, Z.H. Impacts of land use change on watershed streamflow and sediment yield: An assessment using hydrologic modelling and partial least squares regression. *J. Hydrol.* **2013**, *484*, 26–37. [CrossRef]
86. Abdi, H. Partial least square regression (PLS regression). In *Encyclopedia for Research Methods for the Social Sciences*; SAGE Publications, Inc.: Thousand Oaks, CA, USA, 2003; pp. 792–805.
87. Liu, H.-L.; Shen, Y.-S. The Impact of Green Space Changes on Air Pollution and Microclimates: A Case Study of the Taipei Metropolitan Area. *Sustainability* **2014**, *6*, 8827–8855. [CrossRef]
88. Zhao, J.; Deng, W.; Song, Y. Ridership and effectiveness of bikesharing: The effects of urban features and system characteristics on daily use and turnover rate of public bikes in China. *Transp. Policy* **2014**, *35*, 253–264. [CrossRef]
89. Wold, S. Exponentially weighted moving principal components analysis and projections to latent structures. *Chemom. Intell. Lab. Syst.* **1994**, *23*, 149–161. [CrossRef]