buildings

Article

Analyzing Electricity Consumption Factors of Buildings in Seoul, Korea Using Multiscale Geographically Weighted Regression

Hanghun Jo and **Heungsoon Kim** *

Department of Urban Planning and Engineering, Hanyang University, Seoul 04763, Korea; hh0228@hanyang.ac.kr
* Correspondence: soon@hanyang.ac.kr

Abstract: The recent increase in energy consumption worldwide has accelerated global warming. Thus, developed countries are aiming to reduce energy consumption in cities and promote eco-friendly policies. Buildings account for most of the energy used in a city. Therefore, it is necessary to identify the factors that affect electrical energy consumption in urban buildings. In this study, we use multiscale geographically weighted regression (MGWR) to analyze these urban characteristic factors at the global and local scales in Seoul, Korea. It is found that population and household characteristics, outdoor temperature, green and water areas, building area according to building usage, and construction age significantly affect the electrical energy consumption of buildings. In addition, the influences of these variables change with the region. Variables with different coefficients by region are winter temperature, green and water area, and households with three or more persons. The results confirm that even within a city, the influence of the aforementioned factors varies in terms of spatial distribution and patterns. This study is significant as it carried out basic research for energy consumption reduction in buildings by deriving related influencing factors.

Keywords: energy consumption; building energy; spatial autocorrelation; multiscale geographically weighted regression (MGWR)

check for updates

Citation: Jo, H.; Kim, H. Analyzing Electricity Consumption Factors of Buildings in Seoul, Korea Using Multiscale Geographically Weighted Regression. *Buildings* **2022**, *12*, 678. https://doi.org/10.3390/buildings12050678

Academic Editors: Haijun Bao, Liyin Shen and Jorge Ochoa

Received: 26 April 2022
Accepted: 17 May 2022
Published: 19 May 2022

1. Introduction

Recently, global warming owing to an unprecedented increase in energy consumption has emerged as a growing concern. According to predictions made using the Shared Socioeconomic Pathways (SSP) scenario linked to socioeconomic activities in terms of population, economy, land use, energy use, and carbon emissions, the global average temperature will increase by 1.5 °C by 2040 compared to preindustrial levels, regardless of the scenario [1]. Climate change is the reality we are faced with. Therefore, efforts have been undertaken by various organizations and governments to develop carbon-neutral cities. Given increasing urban population and the development of high-rise buildings, buildings now use 2.5 times more electricity than they did in the past [2]. In addition, global building energy consumption accounts for 40% of the total global energy consumption. Owing to continuous urbanization, high-density, high-rise buildings are the primary residential constructions in cities [3]. In light of this, many studies have been conducted to elucidate the causes and consequences of global warming. The literature suggests that anthropogenic activities have accelerated warming of the atmosphere, ocean, and land [4]. To cope with climate change, the European Union (EU) has initiated various environmental policies and proposed to reduce energy consumption and carbon emissions from human activities by 40% by 2030 [5]. Similarly, various efforts have been undertaken to reduce the energy consumption of buildings in cities for mitigating the environmental toll of urbanization [6]. In this context, various physical factors that affect the energy consumption of buildings have been studied [7–9]. Furthermore, to reduce the energy consumption of cities, it is crucial to identify the primary causes and phenomena affecting the energy consumption of buildings [10,11].

Several researchers have studied the electrical energy consumption of buildings [12–17]. In addition, numerous studies have reported that the electrical energy consumption of buildings has a spatial correlation [18–21]. Similarly, in this study, the urban characteristics of buildings in Seoul, Korea, and their correlation with the energy consumption of these buildings were explored. Buildings in cities are spatially distributed, and buildings with similar level characteristics appear in a dense form [22]. According to the first law of geography, each building exhibits spatial autocorrelation owing to this distribution [23]. Therefore, the energy consumption of these buildings, too, must exhibit spatial autocorrelation owing to the spatial pattern of buildings. Considering the aforementioned factors, in this study, the distribution of spatial patterns and the local relationships of each factor are analyzed using a geo-weighted model, which is a known spatial analysis technique.

Seoul is a large city with a population of 10 million. It is expected that the characteristics of each region within Seoul vary because the city has a large urban and green areas, and the Han River runs through the city from east to west. As such, Seoul has peculiar spatial patterns of energy use, but the existing studies reflecting the urban characteristics of Seoul are insufficient. Although many researchers have analyzed the energy consumption of Seoul, they have not considered the influence of spatial patterns [24–28]. In addition, these researchers considered only partial variables in the analysis. By contrast, variables mentioned as significant or important are considered comprehensively in the present study. Among the previous studies on Seoul's energy consumption, the geographically weighted regression (GWR) model was used to analyze energy consumption in only one study [29]. However, even in this study, carbon dioxide emissions were used to measure energy consumption, which is an indirect method. In light of these points, we conduct a more developed study based on spatial analysis and variables that considers the characteristics of Seoul.

The objective of this study is to identify the variables that affect the electrical energy consumption of buildings by performing spatial regression analysis. Moreover, we attempt to determine the effects of significant variables on electrical energy consumption in urban spaces. GWR is a representative model for performing spatial analysis. It can be used to examine the influence of each regression formula considering the bandwidth corresponding to the analysis unit. Thus, the GWR model can provide results that are relevant to the objective of this study. Herein, the effect of diverse variables on electrical energy usage is examined comprehensively by using the multiscale geographically weighted regression (MGWR) model, which can check the local part among models that consider spatial influence. The MGWR model is based on the GWR model, and it sets the bandwidth differently for each independent variable. The characteristic that the spatial distribution of each variable is different is reflected in the analysis. Therefore, the MGWR model facilitates more accurate local unit analysis. Consequently, this analysis method that considers space is expected to yield significant results in this study. Finally, the analysis results of this study can be used as basic building energy consumption data at the local level to achieve the energy reduction goal set by the city in the future.

The remainder of this paper is organized as follows. Section 2 discusses the previous studies related to the use of electrical energy and spatial characteristics of buildings. Section 3 describes the methodology used in the present study. The dependent and independent variables constructed to provide spatial and temporal explanations and a description of the analysis target are provided. In addition, the analysis methods used herein, namely GWR and MGWR, are discussed. Section 4 describes the basic statistical results, as well as the results of ordinary least squares (OLS) and MGWR analyses. Section 5 discusses the policy implications of this study based on the results presented in Section 4. Section 6 describes the significance and limitations of this study (Figure 1).

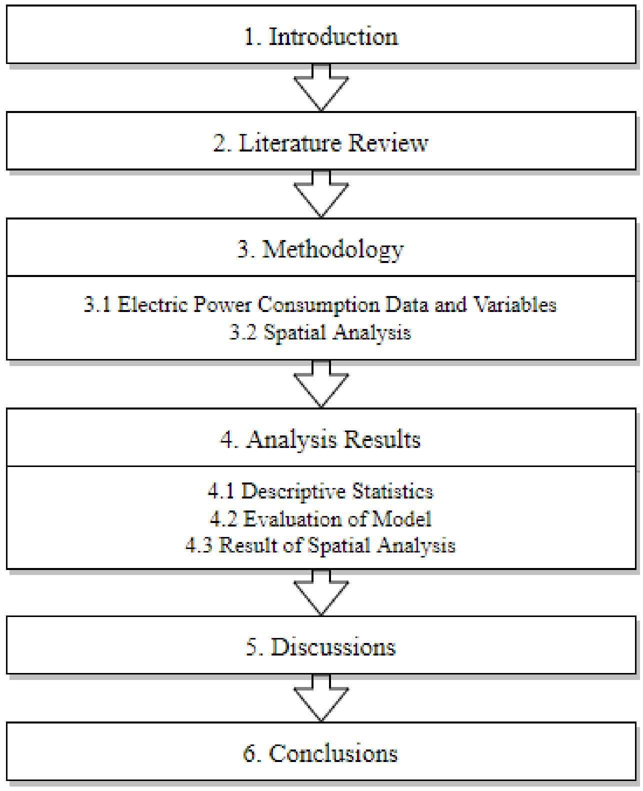

Figure 1. Flowchart of research methodology.

2. Literature Review

In this section, previous studies on the electrical energy consumption of buildings are discussed. Several studies have analyzed the electrical energy consumption of buildings based on their spatial characteristics and derived urban-characteristic factors that affect electrical energy usage in buildings. The characteristic factors considered include physical, socioeconomic, and environmental factors. Among them, studies on physical factors have made the most significant contributions to the literature. In these studies, it has been reported that various physical factors, such as the area, density, height, age of construction, and building materials, affect the electrical energy consumption of buildings [7–14]. In addition, more electrical energy is used for heating and cooling in high-density and high-rise buildings owing to solar radiation and restricted airflow around such buildings [30–32]. Furthermore, as the total floor area of buildings increases, the amount of electrical energy required increases. Several studies [33,34] have reported the use of glass windows and insulation materials as critical factors that influence the power consumption of buildings. It has been observed that older buildings have a weaker insulation effect. Therefore, they require more energy for heating and cooling.

Income, real estate, tax, and the number of household members are the socioeconomic factors that significantly influence energy consumption. In general, it is observed that the more affluent a region, the higher is the consumption of electrical energy. Similarly, income significantly influences energy consumption [35,36]. Studies on the effects of socioeconomic factors on energy consumption have analyzed the energy consumption of buildings based on their purpose [35–37]. It has been reported that the amount of energy consumed by a building varies depending on the primary use of the building. Therefore, the characteristics and electrical energy consumption patterns of residential, commercial, and industrial buildings differ [12–14,17]. The electricity consumption of a household is correlated to taxes, real estate prices [38], number of household members, and income [35]. In commercial buildings, factors such as population, income, building type, and amount of heating and cooling influence the amount of energy consumed [39]. The amount of electricity consumed based on building type can be ordered as follows: retail > office >

restaurant > school. While the aforementioned order can differ somewhat depending on building characteristics in each country, retail and business buildings consume the highest amounts of energy.

Environmental factors, such as indoor and outdoor temperature, climate, wind speed, humidity, and vegetation, have various effects on energy consumption. Among the environmental factors, temperature has the most significant effect on electrical energy consumption [17,31,40–45]. In general, in a city with hot weather, owing to the strong heat island effect, electricity consumption is related to cooling. Similarly, in a city with cold weather, electricity consumption is related to heating. In general, owing to the heat island phenomenon, more energy is used for cooling in summer, but less energy is consumed for heating in winters [40,41]. Therefore, it can be concluded that temperature outside a building plays a significant role in determining the amount of energy required to maintain the internal temperature of the building. Many studies [35–47] have reported that vegetation is one of the factors that reduces the heat island effect in cities and, therefore, energy consumption, by lowering the ambient temperature. Therefore, green spaces, such as urban parks, vegetation zones, and water systems, need to be promoted in urban environments.

Our review of previous studies confirmed that various city-specific factors influence the electrical energy consumption of buildings. Recent studies have suggested that to reduce the energy consumption of buildings, it is necessary to check the energy consumption patterns of multiple buildings [7,13]. Given that these energy consumption patterns change according to the characteristics of cities, various other factors must be considered as well [18,35–37]. Characteristics such as demographic factors indicate that humans consume energy when engaging in social activities, which seem to follow a certain spatial pattern [35]. However, the spatial correlations of and changes in all variables are not equal. The unique spatial patterns of each variable affect energy consumption in various manners. Therefore, it is crucial to identify unique spatial patterns for identifying the factors affecting energy consumption [18]. Although several studies have considered spatial autocorrelation in the use of electrical energy, studies that comprehensively address urban characteristic factors are lacking. In light of this, this study uses a more advanced model than the GWR model and comprehensively accounts for the variables employed in the literature.

In sum up, our literature review confirmed the existence of various factors affecting the energy consumption of buildings, such as demographic factors, socioeconomic factors, environmental factors, and building characteristics. However, previous studies have not considered the spatial autocorrelation that may occur when analyzing these factors individually or in complex analyses. Therefore, in this study, the aforementioned factors are analyzed comprehensively.

3. Methodology

3.1. Electric Power Consumption Data and Variables

In this study, the GWR model was used to identify the urban characteristic factors that affected the electrical energy consumption of buildings in 424 administrative districts in Seoul in 2020. The electrical energy consumption data of these buildings in Seoul were used as the dependent variables. The values obtained by taking the natural logarithm of the total amount of electrical energy used in the buildings in each administrative dong were used as the dependent variables. The electrical energy consumption data of the buildings in question was provided by the Korea Real Estate Agency. The independent variables were composed based on the variables considered as the factors influencing the electrical energy consumption in buildings in previous studies (Figure 2).

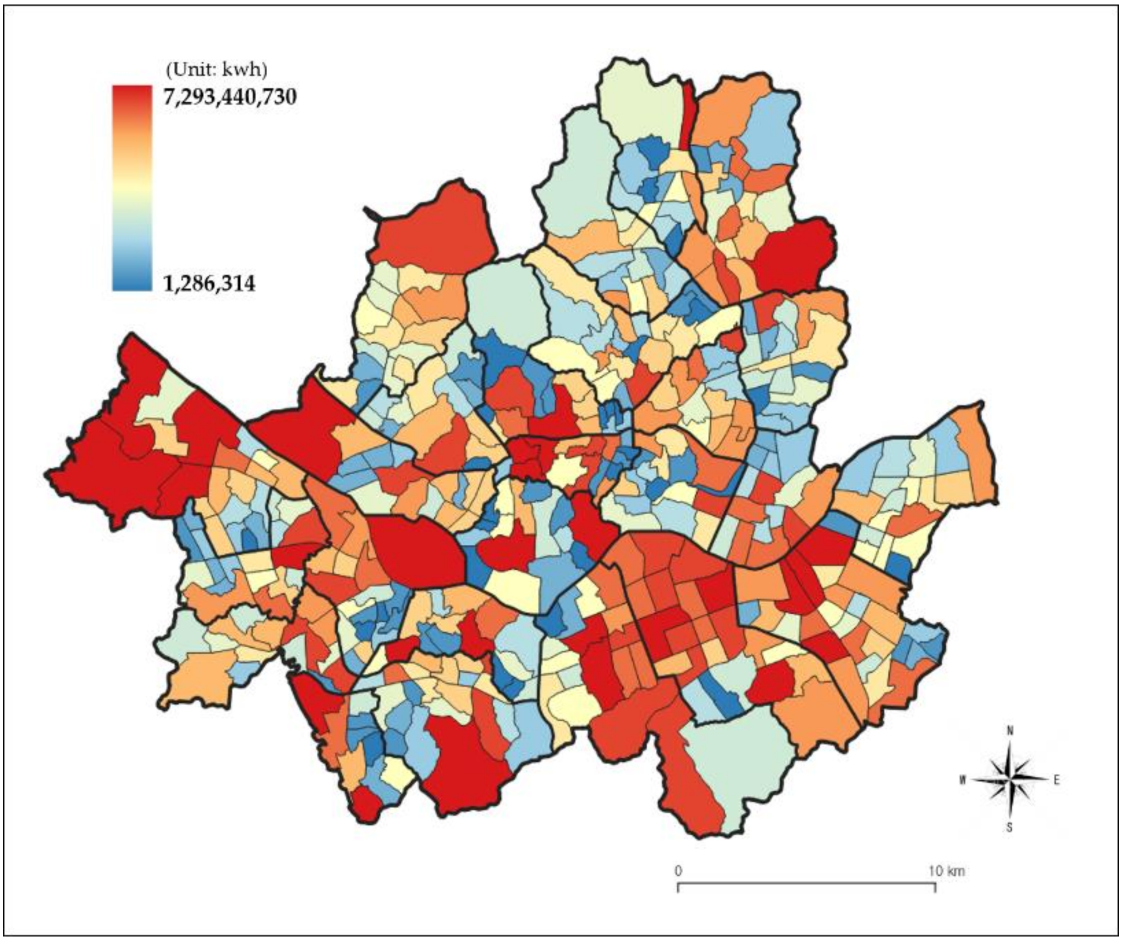

Figure 2. Electrical energy consumption by administrative dong in Seoul in 2020.

First, a set of variables related to temperature, a factor that significantly affects the energy consumption of buildings, was constructed. The average temperatures during spring, summer, autumn, and winter were constructed as variables because the temperature changes across these four seasons are distinct in Korea. In addition, because the temperature in the city is affected by vegetation, the total area covered by vegetation and water bodies was constructed as a variable. Next, as the population and household variables, the living population and the numbers of single-person households, two-person households, and three or-more-person households were selected as variables. Considering that electricity consumption is generally high in regions with large active populations, living population data that aggregate the active population in a region were used instead of resident population data. Smartphone communication data from an area were used to derive the living population data. According to previous studies, the energy consumption per person increases as the number of household members decreases. In this study, the variables were set by categorizing the households into one-, two-, and three-or-more-person households based on the number of household members. Household income, which has been considered a significant factor affecting electricity consumption in previous studies [35,36], was considered in this study as well. In previous studies, the physical characteristics of buildings and building types were considered significant factors affecting electrical energy consumption. Therefore, in this study, the average number of floors; average age of buildings in administrative dongs (the smallest administrative district in Korea); and total floor areas of apartments, detached houses, commercial facilities, education facilities, and business facilities were considered as building type variables. Given that most of the industrial facilities in Seoul are light industries (Table 1), industrial facilities were not considered as a separate variable.

Table 1. Definition of variables.

Division	Variable	Description	Source
Population and household factors	Living population	Total population of administrative dong estimated using public big data and communication data	Seoul Open Data Plaza
	One-person household	Number of households with one member	Seoul Commercial Analysis Service
	Two-person household	Number of households with two members	
	Three-or-more-person household	Number of households with three or more members	
Socioeconomic factors	Household income	Average household income in administrative dong	
Building characteristic factors	Average number of floors	Average number of floors in a building	EAIS (Electronic Architectural Administration Information System)
	Average building age	Average number of years of a building	
	Apartment area	Total floor area of an apartment	
	Detached house area	Total floor area of a single house	
	Commercial building area	Total floor area of a commercial building	
	Education building area	Total floor area of an educational building	
	Office building area	Total floor area of an official building	
Environmental factors	Spring temperature	Average air temperature in spring	Meteorological Agency in Korea
	Summer temperature	Average air temperature in summer	
	Fall temperature	Average air temperature in fall	
	Winter temperature	Average air temperature in winter	
	Green and water areas	Total area covered by vegetation and water bodies within an administrative dong	EGIS (Environmental Geographic Information Service)

3.2. Spatial Analysis

3.2.1. GWR

General regression analysis methods do not consider spatial influence relationships and they describe only global relationships among variables [48]. GWR applies spatial weights to the existing OLS model to facilitate local spatial analysis. Hence, spatial autocorrelation and heterogeneity were considered through spatial weights. Spatial weights were applied to the GWR model by using the coordinates (u, v) of each spatial analysis unit [49] according to the following Equation (1).

$$y_i = \sum_{j=0}^{m} \beta_j(u_i, v_i)x_{ij} + \varepsilon_i \tag{1}$$

In the above equation, y_i represents the electrical energy consumption of an administrative dong i, and β_j is the coefficient of the j independent variables of administrative dong i. The coordinates of each administrative dong u_i, v_i were applied to each space, as expressed in (1). A regression equation was derived for as many administrative dongs as possible, and the statistical analysis results of each target site were checked. In this study, the geographic weight of the GWR model was applied to the kernel function. Subsequently, a fixed kernel randomly selected by the authors and a statistically manipulated adaptive kernel were used. Because GWR yields local regression results, the spatial correlations and heterogeneity that conventional OLS cannot consider were accounted for. However, the GWR model is vulnerable to multicollinearity [50]. Various GWR models have been developed to mitigate this problem [51].

3.2.2. Multiscale GWR

The general GWR model is limited, in that it applies only one spatial scale. It considers only a single fixed bandwidth value in the analysis model. Thus, the model is vulnerable to multicollinearity. Additionally, each independent variable has global or local characteristics depending on the characteristics of the overall data. Therefore, considering the characteristics of the variables and the limitations of the GWR model, GWR analysis methods that apply a bandwidth suitable for each variable have been developed. Among such methods, mixed GWR separates global and local independent variables, and the multiscale GWR

(MGWR) sets the local coefficient value that has the optimal Akaike Information Criterion (AICc) value in the analysis model [52].

Thus, the best model is selected based on the AICc value. In this study, the MGWR model was applied using a backfitting algorithm (Figure 3). In general, the initial local coefficient of the MGWR model is based on the results of GWR analysis, and the subsequent local coefficients are estimated through corrections. The local coefficients are estimated repeatedly until they reach the desired levels, and the same method is repeated for all independent variables. *SOC-RSS* (Residual Sum of Squares) (2) are used as the iterative work termination criteria. The coefficient values are estimated using the proportionality of the residual sum of squares (RSS) and the *SOC-f* method (3), which corrects the GWR analysis results. Therefore, in this study, we used the *SOC-f* method. When the *SOC-f* value was less than 0.0005, the next independent variable was set. The adaptive kernel function was applied to each independent variable to select the bandwidth value. In addition, the model in which AICc attained the minimum value was selected by combining the bandwidth values [53].

$$SOC_{RSS} = \frac{|RSS_{new} - RSS_{old}|}{RSS_{new}} \tag{2}$$

$$SOC_f = \sqrt{\frac{\sum_{j=1}^{p} \frac{\sum_{i=1}^{n}\left(f_{ij}^{new} - f_{ij}^{old}\right)^2}{n}}{\sum_{i=1}^{n}\left(\sum_{j=1}^{p} f_{ij}{}^{new}\right)^2}} \tag{3}$$

where *SOC-RSS* is the proportional change in the residual sum of squares, and *SOC-f* is the change in the GWR smoother.

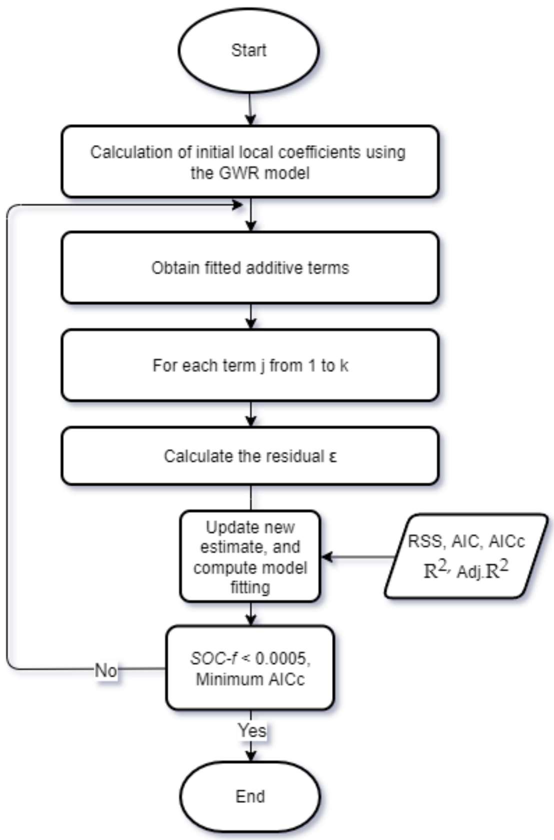

Figure 3. Data flow diagram of multiscale geographically weighted regression back-fitting calibration.

4. Analysis Results

4.1. Descriptive Statistics

The reliability of the data constructed for analysis is confirmed through basic statistical analysis. In addition, the basic statistics serve as a starting point for conducting spatial regression analysis by displaying data distributions and patterns in this study. The descriptive statistics of the independent variables used in the analysis and the electrical energy consumption of buildings by administrative dong, the dependent variable in this study, are as follows: first, the number of administrative dongs in Seoul, which is the analysis target, is 424; the administrative dong is the unit of analysis in this study. Because the existing distribution of electrical energy consumption does not exhibit a general linear form, it is converted to a linear form by taking its natural logarithm. Among seasonal temperatures, the temperatures in spring and autumn are similar, as can be observed from the overall statistical values. By contrast, the summer and winter temperatures are noticeably different. The temperature distribution used in this study reflects the seasonal characteristics of Korea, which has four distinct seasons. Based on the results reported in previous studies, we considered temperature a significant factor affecting the amount of electrical energy required for heating and cooling in buildings. The average number of floors in each administrative dong varied from 2 to 18. The average building age in each dong ranged from 5 to 55 years. Among the variables pertaining to each building type, the areas of detached houses and education and business facilities are zero in several administrative dongs because these dongs house densely populated buildings of the same type. Household income levels ranged from 1836 USD per month to 5714 USD per month, and the average household income was 2849 USD per month (Table 2).

Table 2. Descriptive statistics of variables.

Division	Variable	Minimum	Maximum	Mean	Standard Dev.	Variance	VIF
Dependent	Log of building electrical energy consumption	14.07	22.71	18.11	0.97	0.94	-
Independent	Living population	57106.00	1253928.00	298939.89	142864.43	20410244485.88	3.593
	One-person household	115.00	16971.00	4192.66	2457.34	6038503.79	2.968
	Two-person household	20.00	6152.00	2187.68	881.79	777547.92	2.318
	Three-or-more-person household	29.00	11217.00	3875.65	1848.23	3415942.81	2.298
	Household income	2230710.00	6945812.00	3460789.90	1019302.25	1038977085862.02	2.005
	Average number of floors	2.00	18.00	4.11	2.08	4.33	2.170
	Average building age	5.00	55.00	28.08	6.20	38.45	1.771
	Apartment area	527.00	28482642.00	803712.85	1707951.48	2917098242892.06	1.081
	Detached house area	0.00	560122.00	138281.46	104137.33	10844584450.76	2.384
	Commercial building area	2063.00	1340807.00	161112.39	148799.38	22141254757.75	2.312
	Education building area	0.00	1766866.67	83258.86	156400.18	24461015913.75	1.193
	Office building area	0.00	4472947.89	156292.92	404878.90	163926920148.92	2.057
	Spring temperature	13.58	21.27	17.98	1.38	1.91	4.701
	Summer temperature	19.56	28.50	24.08	1.59	2.53	1.365
	Fall temperature	14.15	19.92	17.40	1.06	1.12	4.801
	Winter temperature	−1.56	2.75	1.24	0.67	0.45	1.451
	Green cover and water areas	548.24	3834250.60	126512.09	314705.56	99039587845.58	1.220

4.2. Evaluation of Model

According to the literature [18–21], there exists a spatial effect on the consumption of electrical energy in buildings. Therefore, a GWR analysis considering spatial autocorrelation was conducted. Before spatial regression analysis, the dependent variable, that is, the electrical energy consumption of each administrative dong, was examined to identify spatial autocorrelations. Moran's index was calculated by performing Moran's I analysis of ArcGIS to examine global spatial autocorrelations and spatial distribution patterns. A Moran's index value of 0.1153, which represents a significant level, was obtained in the analysis. This indicated a positive spatial autocorrelation. Furthermore, the Z-Score value indicated that the degree of clustering was 6.249, meaning that the spatial pattern was extremely clustered (Table 3). Moran's Index was calculated using the MGWR residual to determine whether the spatial autocorrelation was controlled by the MGWR model. The value of Moran's Index was −0.0278, which was lower than the Moran's Index value obtained using the OLS model. In addition, the probability for spatial autocorrelation of the MGWR model was not significant, meaning that spatial autocorrelation was controlled.

Table 3. Analysis of spatial autocorrelation.

Criteria	OLS	MGWR
Moran's Index	0.1153	−0.0278
Expected Index	−0.0023	−0.0023
Variance	0.0003	0.0003
Z-score	6.2490	−1.3575
p-value	0.000 0	0.17461

Subsequently, the fits of three models were compared, namely, the global OLS, spatial GWR, and MGWR models, considering various criteria. In this study, the residual sum of squares (RSS), AIC, AICc, R^2, and adjusted R^2 were considered to identify the most suitable model. The RSS, AIC, and AICc values decreased gradually in the order of OLS, GWR, and MGWR. This indicates that MGWR had the best model fit. In addition, the R^2 of the OLS model was 0.555. However, the R^2 of the GWR model was 0.661, R^2 of the MGWR model was 0.74, and adjusted R^2 of the MGWR model was 0.685. Thus, it can be concluded that the MGWR model had the highest explanatory power. Consequently, iterative work was performed to determine the optimal model fit and bandwidth of the MGWR model. Through iteration, the model with the lowest AICc was selected as the final model. In this study, 36 iterations were performed to determine the final model (Table 4).

Table 4. Model fit summary of OLS, GWR, and MGWR models.

Criteria	OLS	GWR	MGWR
RSS	186.38	143.92	109.671
AIC	894.76	863.36	784.07
AICc	899.06	882. 88	818.87
R^2	0.5 55	0.661	0.74 0
Adj. R^2	0.536	0.607	0.685
No. of iteration	-	-	36

In general GWR analysis, the adjusted R^2 value indicates the explanatory power of the entire global model, and the local R^2 value representing each variable locally is presented separately. In this study, the adjusted R^2 value of the MGWR analysis model was 0.685. The region with the lowest local R^2 value of 0.63 was located toward the northeast and southeast of Seoul. The region with the highest explanatory power was the southwestern region. Note that the closer it is to the region, the higher is its explanatory power. The region with the strongest explanatory power had an R^2 value of 0.78, indicating the existence of regions with explanatory powers higher than 0.685, which was the overall explanatory power of the model (Figure 4).

4.3. Result of Spatial Analysis

In this study, the bandwidth value applied to each independent variable in the MGWR model differed from that in the GWR model. According to the spatial distribution of the data of each variable, iterative work was performed using an appropriate bandwidth value. As mentioned above, a total of 36 operations were performed. Variables representing 423 of the bandwidth values that appeared had the characteristics of global variables rather than local variables. Other variables included variables with strong local characteristics, such as summer temperature, winter temperature, households with three or more people, green and water-covered areas, average building age, average apartment area, average educational facility area, and average business facility area (Table 5).

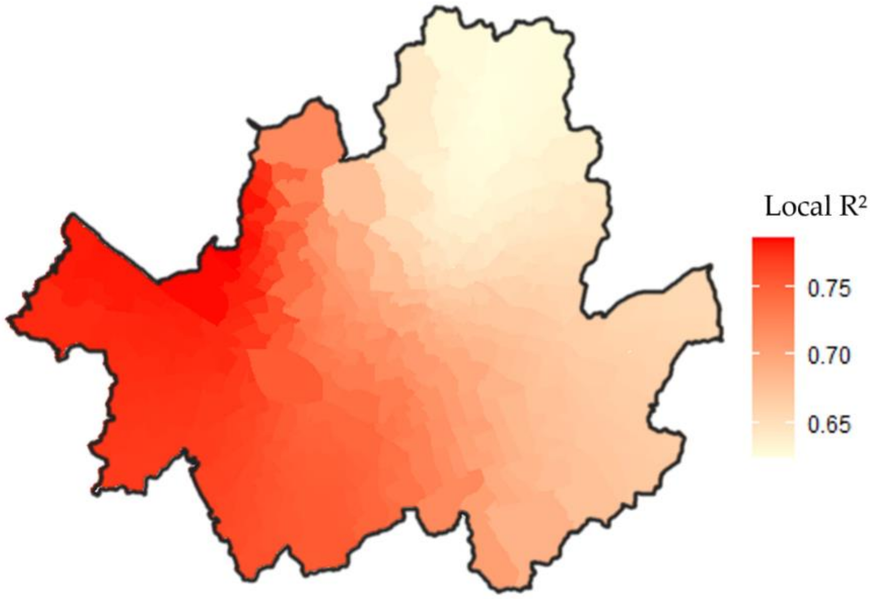

Figure 4. Local R^2 values of multiscale geographically weighted regression.

Table 5. Optimal bandwidth of each parameter in GWR and MGWR analyses.

Division		**Bandwidth**	
	Variable	**GWR**	**Multiscale GWR**
Intercept	Intercept	264	58
Population and household factors	Living population	264	423
	One-person household	264	423
	Two-person household	264	423
	Three-or-more-person household	264	103
Socioeconomic factors	Household income	264	423
Building characteristic factors	Average number of floors	264	423
	Average building age	264	418
	Apartment area	264	314
	Detached house area	264	423
	Commercial building area	264	423
	Education building area	264	145
	Office building area	264	334
Environmental factors	Spring temperature	264	423
	Summer temperature	264	235
	Fall temperature	264	423
	Winter temperature	264	78
	Green and water areas	264	109

The analysis results obtained using the global OLS model and the MGWR model were compared and reviewed. Firstly, the analysis results were reviewed centering on the variables significantly derived from OLS. The summer temperature exhibited a significant influence at 0.111, and the winter temperature exhibited a significant influence at −0.106. In the MGWR analysis, the average values of the local coefficients of these two variables had a positive influence. However, in terms of the minimum, median, and maximum values of winter temperature, there were regions with local negative and positive effects. In the OLS analysis results, living population had a significant positive influence, and in the MGWR results, it also had a positive influence globally. This finding is consistent with the results of previous studies, which indicated that the larger the population in an area, the greater the electrical energy consumption. Next, green and water areas had a significant positive influence. In general, green and water areas play a significant role in alleviating the urban heat island phenomenon. Furthermore, they have a negative influence on electrical energy consumption for cooling. However, note that green and water areas alone do not reduce the heat island phenomenon. The heat island phenomenon is additionally affected by the permeability, density, and surrounding environment of an area [42]. However, the OLS results obtained in this study showed their positive effect, which is contrary to the results obtained in a previous study. This can be attributed to the factors other than green and water areas that significantly reduced electrical energy consumption.

In terms of building area, significant positive results were observed for apartments, education buildings, and business buildings. According to the OLS and MGWR analysis results, the building areas of apartments and business buildings had a global positive effect. Regarding the area of educational buildings, the OLS result was positive, but the MGWR results found regions with a negative influence. In addition, both the OLS and MGWR analyses showed the significant positive influence of household income (Table 6).

Table 6. Factors affecting the consumption of electrical energy in buildings: OLS and MGWR analysis results.

Division	Variable	OLS	Multiscale GWR				
			Mean	Standard Deviation	Min	Median	Max
-	Intercept		−0.023	0.161	−0.394	0.001	0.342
Population and household factors	Living population.	0.388 ***	0.411	0.005	0.399	0.411	0.421
	One-person household	0.036	0.033	0.004	0.024	0.033	0.042
	Two-person household	−0.023	−0.027	0.013	−0.054	−0.022	−0.009
	Three-or-more-person household	−0.011	0.005	0.08	−0.158	−0.003	0.204
Socioeconomic factors	Household income	0.156 ***	0.215	0.001	0.212	0.216	0.217
Building characteristic factors	Average number of floors	0.028	−0.024	0.01	−0.044	−0.025	0.002
	Average building age	0.030	0.042	0.004	0.034	0.041	0.052
	Apartment area	0.107 ***	0.1	0.045	0.044	0.08	0.169
	Detached house area	−0.055	−0.077	0.009	−0.086	−0.082	−0.053
	Commercial building area	0.066	0.089	0.004	0.08	0.088	0.102
	Education building area	0.215 ***	0.199	0.104	−0.015	0.2	0.404
	Office building area	0.094 *	0.14	0.02	0.098	0.144	0.169
Environmental factors	Spring Temperature	0.031	0.091	0.007	0.079	0.089	0.108
	Summer Temperature	0.111 ***	0.071	0.071	−0.043	0.054	0.225
	Fall Temperature	0.015	0.01	0.014	−0.006	0.003	0.039
	Winter Temperature	−0.106 ***	−0.101	0.119	−0.481	−0.086	0.163
	Green and water areas	0.076 *	0.103	0.142	−0.105	0.085	0.363

* $p < 0.1$, *** $p < 0.01$.

The local results of the variables that appear significantly in the MGWR analysis results are as follows. Summer temperature had significant positive effects in most of the regions. These results were similar to those of the related studies in which MGWR was used, and the higher the summer temperature, the stronger the influence on energy consumption [54]. Electrical energy consumption due to cooling is high in summer. Therefore, it was identified to have a positive effect across the city [45]. The bandwidth used for summer temperature was 235. Therefore, summer temperature was shown to be a variable that influenced a large area of the city. This indicates that the summer temperature across administrative dongs in Seoul was similarly high overall. In addition, it was observed that the closer a region was to Gangnam, the more significant the effect of summer temperature on energy consumption in that region. Notably, this result confirmed that the influence of summer temperature was weaker in regions closer to Mt. Bukhan, which is in the northern part of Seoul. This reflects the spatial characteristics of a region with small building areas and large mountainous areas (Figure 5a). Winter temperature also had significant positive effects. However, it had a negative influence on the CBD areas, Gangnam, and Jongro. The bandwidth used for winter temperature was 78. Thus, winter temperature had a smaller bandwidth than summer temperature, indicating a regional temperature difference, and we can conclude that the energy used for heating increases as the temperature outside buildings in a region decreases (Figure 5b). These results suggest a relationship between seasonal temperature and energy usage, and it was confirmed that energy usage differs depending on the region owing to the temperature differences stemming from the heat island effect or density [31].

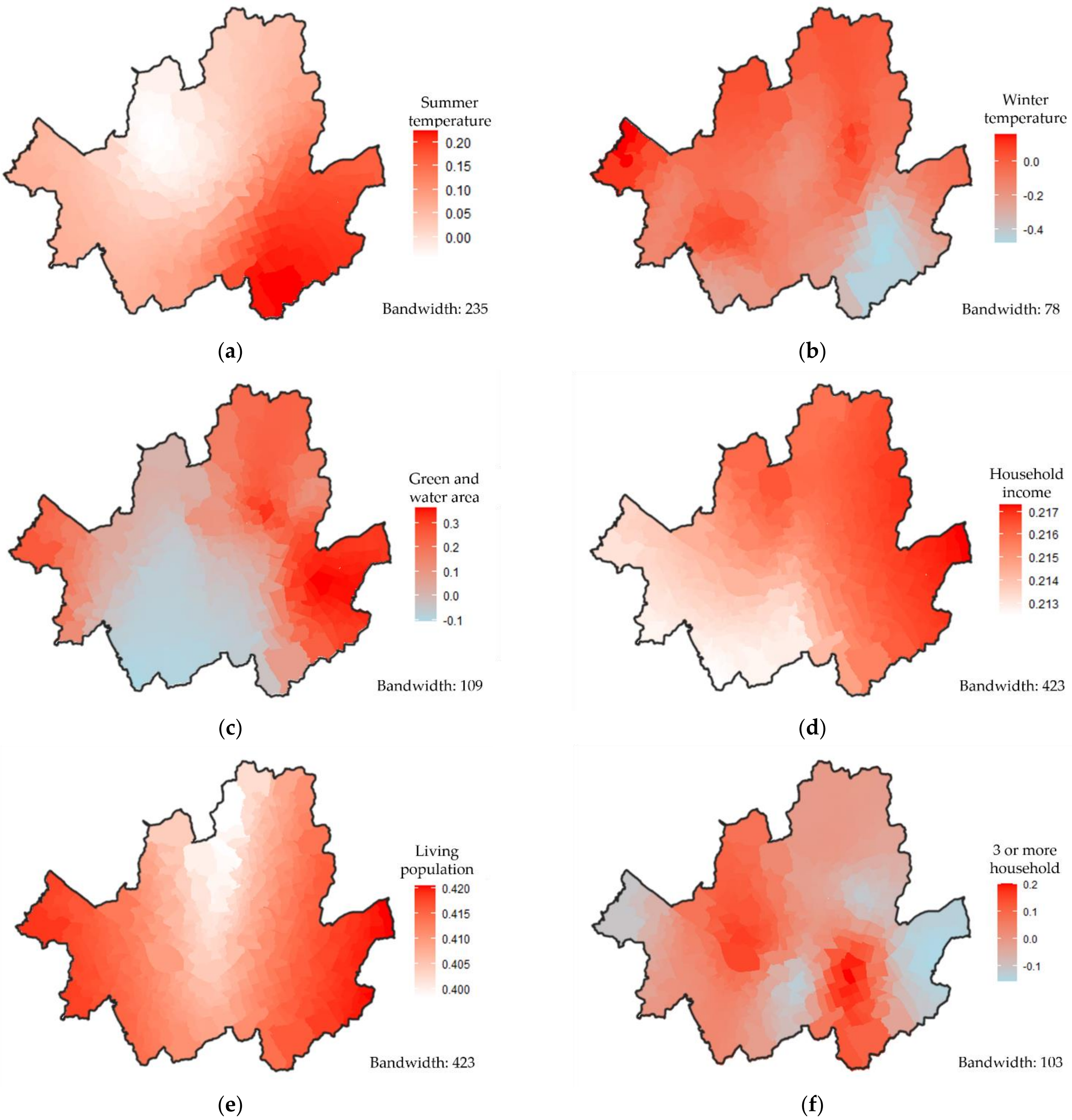

Figure 5. Multiscale geographically weighted regression results of local coefficients: (**a**) summer temperature; (**b**) winter temperature; (**c**) green and water area; (**d**) household income; (**e**) living population; (**f**) three-or-more-person household.

Previous studies have reported that green and water areas alleviate the urban heat island phenomenon and reduce electrical energy consumption by maintaining the temperature in the city at a comfortable level [42]. However, in contrast to the results of previous studies, the analysis results of this study confirmed that the average coefficient value had a positive influence on electric energy consumption. A related study using MGWR confirmed that all variables related to green areas had positive effects, unlike the analysis results of this study [54]. By contrast, we assumed that green areas may have local effects depending on the region and that there may be differences in influence depending on the area, as mentioned in the Introduction. In addition, by checking the local coefficient of green and water areas, it can be inferred that the green and water areas had a weak negative influence on Seoul overall. However, strong positive effects were observed in the Gangnam and Gangseo areas (Figure 5c). The bandwidth of the green and water area variable was 109. Thus, the effect of green and water areas in Seoul is more local than city-wide. Therefore, it can be concluded that a strong positive influence was observed for a high average local coefficient value. This result can be attributed to the high building density and high electrical energy consumption, despite the large-scale green and water areas. The Gimpo Airport (8.63 km^2) in Gangseo consumes the highest amount of electrical energy among all of the administrative dongs in Seoul. In the Jamsil district, which corresponds to the Songpa area, there are large green areas, such as Seokchon Lake and Olympic Park. In addition, many high-rise buildings, such as the Jamsil Lotte Tower and Lotte World, are located in this area. However, Eunpyeong and Gwanak, the regions in which Mt. Bukhan and Mt. Gwanak are located, respectively, and Yeongdeungpo and Yongsan, which are close to Mt. Gwanak and the Han River, were found to be negatively affected. We assumed that the green and water areas in these regions reduced the use of electrical energy by maintaining the temperature at a relatively comfortable level. These results show that superficial green and water areas alone cannot significantly affect energy reduction, as mentioned in previous studies (Figure 6).

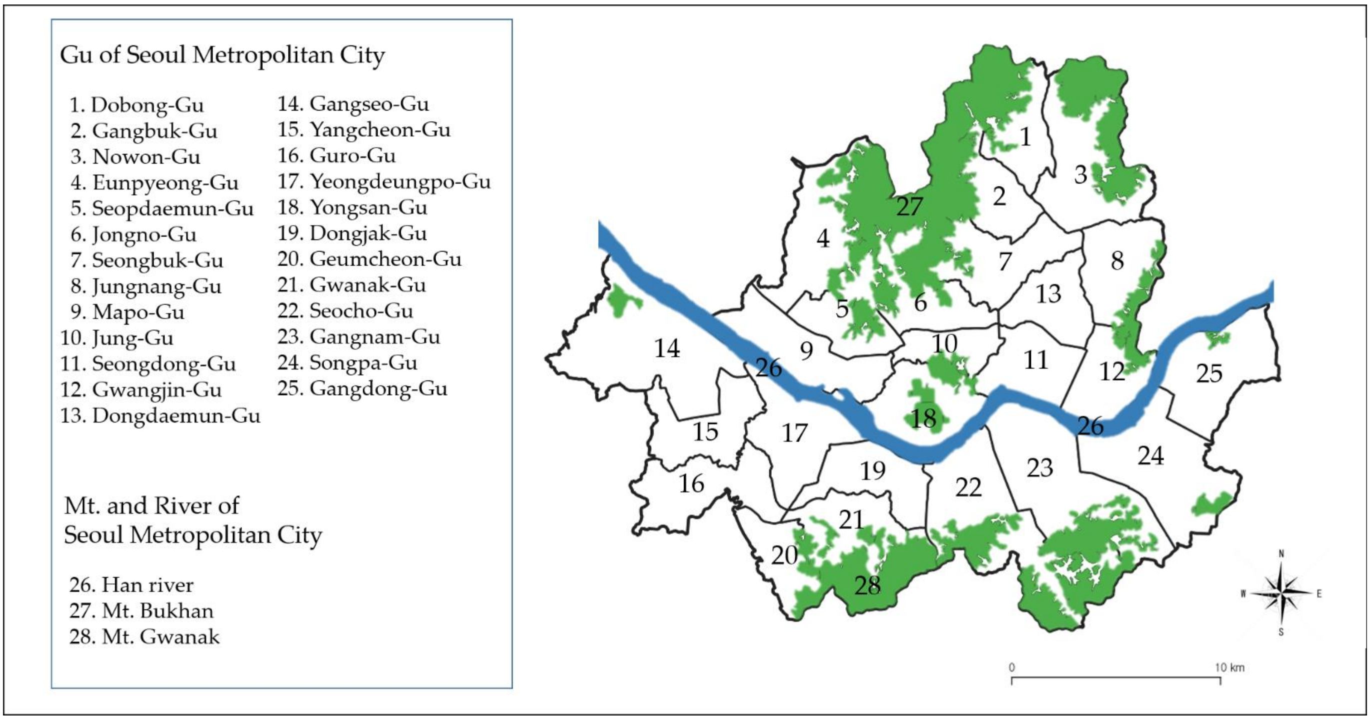

Figure 6. Administrative boundary of Gu, and mountains and rivers of Seoul.

In the case of household income, significant positive effects were confirmed in all regions except Gangseo. A study conducted using GWR yielded the same results as the present study, with a positive impact across the city [55]. This result is consistent with the social belief that high-income people use more electrical energy than low-income people. This was confirmed by the fact that a greater amount of electrical energy was consumed in Gangdong and Gangnam in 2020, where the average household income is relatively high, compared to that in Gangseo, where the average household income is relatively low. In a related study conducted using MGWR, energy consumption increased as income increased across the city. Moreover, as the interregional income difference increased, the influence increased, as reported in a previous study [56] (Figure 5d).

Living population had no significant influence on the Gangbuk region around Mt. Bukhan. However, the closer a region was to Gangnam and Gangseo, the more significant the positive influence. This is consistent with the results of previous studies, in which it was demonstrated that the electrical energy consumption of buildings increases in areas with a high density of buildings and more floating populations than that in mountainous terrain [3,4]. In another study conducted using MGWR, the effect of population differed depending on the region, but it was found to have a positive effect overall. This is consistent with the general conclusion that the higher the population density, the higher is the energy consumption [57]. In addition, the analysis results indicated that the impact of living population on Seoul is large (Figure 5e). In addition, various local factors affect households with three or more persons in Seoul. The bandwidth used for households with three or more persons was 103. In other studies conducted using MGWR, the influence of regional differences was different from that in the present study. Previous studies have mentioned households as an important variable. Moreover, the previous studies reported consistent results throughout the city with no regional differences [54,58]. Unlike previous studies, we identified differences in influence due to the regional characteristics mentioned in the introduction. Living population had a positive influence in the Gangnam, Yeouido, Mapo, and Yongsan regions. Thus, it can be inferred that in these areas, the higher the number of households with three or more persons, the higher the electricity consumption. This was validated by the fact that these regions have households with relatively high income levels in Seoul. Therefore, they possibly use a large amount of electrical energy. By contrast, a negative influence was observed in Gangseo, Jungnang, Gwanak, Gangdong, and the entire city, meaning that the higher the number of households with three or more people, the lower the electrical energy consumption. These results indicate that as the number of household members increases, the amount of energy consumed by one person per unit area in a building decreases. Moreover, previous studies have demonstrated that an increase in the number of household members leads to a decrease in energy consumption because it increases the population density [38]. Thus, it can be concluded that in general, an increase in the number of household members leads to a reduction in energy consumption (Figure 5f).

Among building types, apartment buildings had a significant positive influence in the Gangdong and Gangbuk regions, but no significant effect in the Gangseo region. In the case of apartment buildings, given that multiple households reside in one building, the amount of electrical energy used by the building is higher than that used in other types of housing. This claim was validated by the results of the present study (Figure 7a). By contrast, detached houses had a negative influence. Unlike apartments, a detached house is often inhabited by a single household. Hence, compared to an entire apartment building, the amount of energy consumed is lower because the total floor area of a detached house is lower than that of an apartment building (Figure 7b). Educational buildings had a significant positive influence, except in the Gangnam, Eunpyeong, and Mapo regions. The bandwidth used for educational buildings was 145. In the Gwanak region, where Seoul National University is located, educational buildings had the strongest influence. This indicates that universities consume a large amount of electrical energy (Figure 7c). Among educational buildings, the amount of energy used by each school level was different, but university buildings used large amounts of energy [59]. Furthermore, it was found that building age had a significant positive effect. OLS analysis did not yield any significance, but MGWR analysis yielded some significance in the city center, which houses relatively old buildings. Thus, as reported in a previous study [60], the results of this study confirmed that building age affects the insulation and energy consumption of buildings. Therefore, old buildings should be repaired to reduce electrical energy consumption and increase energy efficiency (Figure 7d).

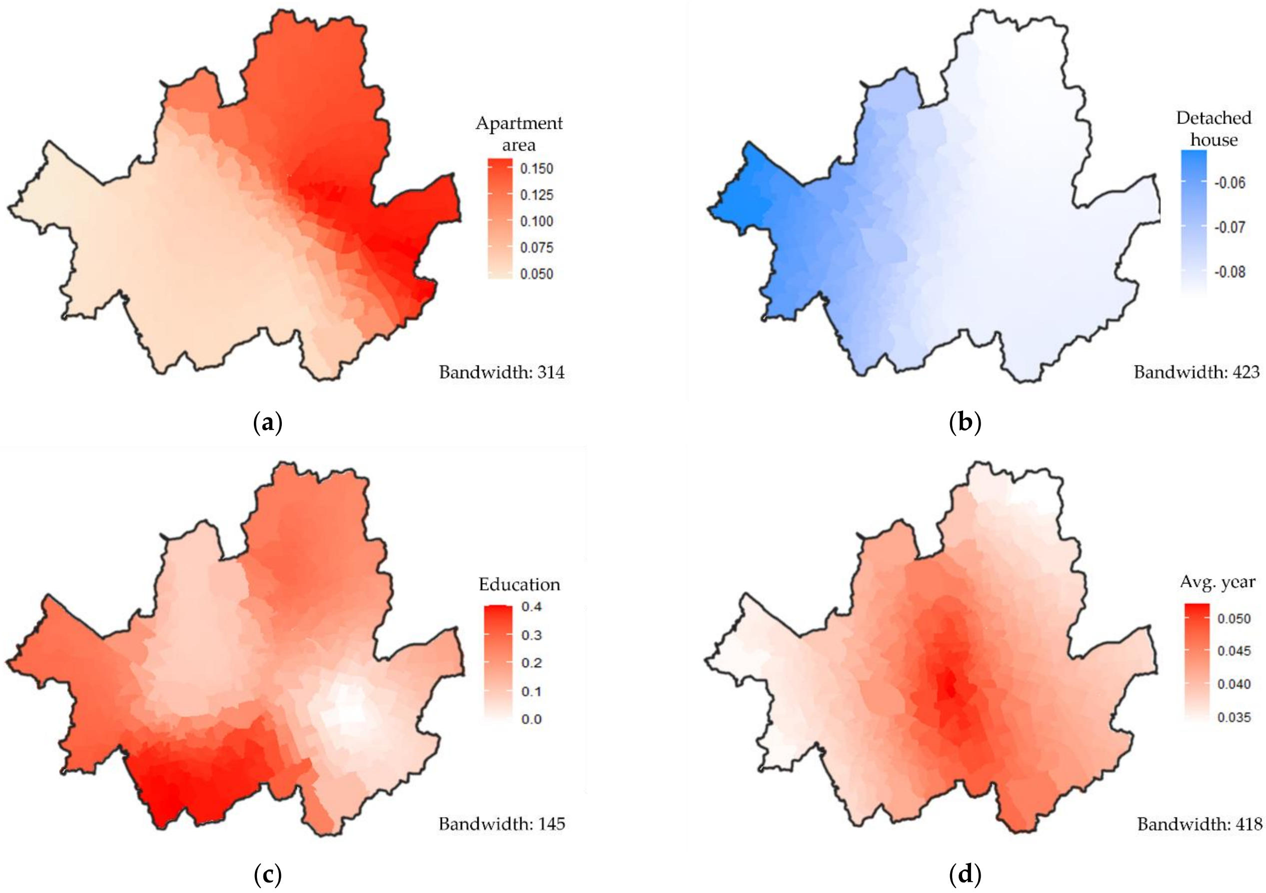

Figure 7. Multiscale geographically weighted regression results of local coefficients: (**a**) apartment; (**b**) detached house; (**c**) education; (**d**) average building age.

5. Discussions

In this study, we conducted an MGWR analysis to identify the factors affecting electrical energy consumption, especially the factors that were not detected in OLS analysis. The analysis results confirmed that the influence of the factors considered here may differ across regions. Therefore, we propose several suggestions for reducing the electrical energy consumption of buildings based on the analysis results.

We found that the outdoor temperature during winter and summer has a significant effect on electrical energy consumption. In summer, electricity consumption increases throughout the city because of an increase in cooling demand. This is consistent with the results of previous studies [10,38,54]. By contrast, several regions consumed more electrical energy during winter to maintain a relatively comfortable temperature in the building. This result confirmed the existence of regional differences in electrical energy consumption used for heating in winter, which did not appear in other studies. The area with the highest electrical energy consumption had a high density of buildings. It was found that this area used plenty of electrical energy for heating and cooling to maintain comfortable temperatures inside buildings. Thus, the application of technology that maintains indoor temperatures can reduce the electrical energy required for heating and cooling in winter and summer, respectively.

Furthermore, the OLS analysis results indicated that the green and water areas have a positive influence. However, the MGWR results show that the degree of influence differs across regions. This indicates that green and water areas do not necessarily affect the electrical energy consumption within a city. However, in some regions, green and water areas can somewhat influence electrical energy consumption. Even in the areas with plenty of green areas and water bodies, we found areas with high temperatures depending on solar orientation. Likewise, even in areas with a high density of green areas, some patches may not be significantly influenced by green cover. Therefore, a novel method is required for assessing the relationship between energy consumption and the density and degree of influence of green and water areas.

In the case of the influence of population, the analysis results showed that the higher the absolute population, the higher the energy consumption; this result is consistent with the existing perception that a compact city is more suitable for reducing energy consumption.

Studies have reported that older buildings consume more electrical energy, which is consistent with our analysis results. Therefore, the insulation effect of old buildings should be improved through repair and reconstruction. The Jongro region of Seoul has many aging buildings, and their energy efficiency is low. Hence, active redevelopment and repair work is required in Seoul to increase the electrical energy efficiency of these buildings.

6. Conclusions

In this study, characteristic urban factors affecting the energy consumption of buildings were analyzed across the administrative districts in Seoul in 2020. The local influences of variables were determined using the MGWR model, a local spatial regression model. This model was used to consider the spatial autocorrelations of the electrical energy consumption of buildings by applying a backfitting algorithm to the GWR model. Consequently, the resulting model confirmed that the influences of the factors affecting electrical energy usage varies by region.

Moreover, the analysis results confirmed that summer and winter temperatures affect the electrical energy consumption of buildings. In addition, they confirmed that in some regions, green and water areas reduce electrical energy consumption by alleviating the heat island phenomenon, as reported in previous studies. However, in regions with large-scale facilities or buildings, the influence of large green areas or water areas was not significant. Hence, the relationship between green and water areas and electrical energy consumption warrants further investigation. In the case of population and households, the analysis results showed that the number of household members had a significant effect on the use of electrical energy. An increase in the number of household members reduced electrical energy consumption. In addition, electricity consumption varied according to building type. Furthermore, it was confirmed that the influence of building type on electrical energy consumption differed across regions.

Variables with different influences across regions were identified using the MGWR model. The variables with differing influence across regions were winter temperature, green and water areas, and households with three or more members. This result did not appear in previous studies, and it could not be confirmed by the results of OLS analysis. Therefore, it is reasonable to use the MGWR model, which can reflect the spatial distribution characteristics of variables.

The present work is significant as a fundamental study for reducing the energy consumption of buildings by analyzing various factors that affect their electrical energy consumption. However, this study has a few limitations. First, this case study targeted Seoul, a city with an annual gross regional domestic product (GRDP) of 360 billion US dollars and one of the most active global economic centers. Moreover, Seoul is a densely populated metropolis with approximately 10 million inhabitants. In terms of natural environment, the city has large natural green areas, and Han River runs from east to west across the city. In addition, the built-up areas house numerous high-rise buildings. It is difficult to generalize the results of this study to all cities in the world because of the peculiar spatial characteristics of Seoul. Second, we did not consider indoor temperature, unlike previous studies, owing to data limitations. Because approximately 82% of the buildings in Seoul are made of reinforced concrete, we did not consider building materials as a variable. These are different from other previous studies in this study. Therefore, subsequent studies will be able to generate superior results by adopting a variety of variables depending on their unique situations.

Author Contributions: Conceptualization, H.J. and H.K.; methodology, H.J.; software, H.J.; validation, H.J.; formal analysis, H.J.; investigation, H.J.; resources, H.J.; data curation, H.J.; writing—original draft preparation, H.J.; writing—review and editing, H.K.; visualization, H.J.; supervision, H.K.; project administration, H.K.; All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the research fund of Hanyang University (HY-2021).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. IPCC. Climate Change 2021: The Physical Science Basis. *IPCC Sixth Assess. Rep.* **2022**, *12*, 142.
2. Mostafavi, F.; Tahsildoost, M.; Zomorodian, Z. Energy efficiency and carbon emission in high-rise buildings: A review (2005–2020). *Build. Environ.* **2021**, *206*, 108329. [CrossRef]
3. Steemers, K. Energy and the city: Density, buildings and transport. *Energy Build.* **2003**, *35*, 3–14. [CrossRef]
4. Chen, H.; Zhu, Q.; Peng, C.; Wu, N.; Wang, Y.; Fang, X.; Gao, Y.; Zhu, D.; Yang, G.; Tian, J.; et al. The impacts of climate change and human activities on biogeochemical cycles on the Qinghai-Tibetan Plateau. *Glob. Change Biol.* **2013**, *19*, 2940–2955. [CrossRef] [PubMed]
5. Amanatidis, G. European Policies on Climate and Energy towards 2020, 2030 and 2050. *Policy Commons* **2019**, *631*, 47.
6. Global Alliance for Buildings and Construction. International Energy Agency and the United Nations Environment Programme 2019 global status report for buildings and construction: Towards a zero-emission, efficient and resilient buildings and construction sector. *United Nations Environ. Programme* **2019**, *10*, 2265.
7. Nord, N. Building energy efficiency in cold climates. *Encycl. Sustain. Technol.* **2017**, 149–157.
8. Chen, Y.; Hong, T. Impacts of building geometry modeling methods on the simulation results of urban building energy models. *Appl. Energy* **2018**, *215*, 717–735. [CrossRef]
9. Li, C.; Song, Y.; Kaza, N. Urban form and household electricity consumption: A multilevel study. *Energy Build.* **2018**, *158*, 181–193. [CrossRef]
10. Ahn, Y.; Sohn, D.W. The effect of neighbourhood-level urban form on residential building energy use: A GIS-based model using building energy benchmarking data in Seattle. *Energy Build.* **2019**, *196*, 124–133. [CrossRef]
11. Sena, B.; Zaki, S.A.; Rijal, H.B.; Alfredo Ardila-Rey, J.; Yusoff, N.M.; Yakub, F.; Ridwan, M.K.; Muhammad-Sukki, F. Determinant factors of electricity consumption for a Malaysian household based on a field survey. *Sustainability* **2021**, *13*, 818. [CrossRef]
12. Swan, L.G.; Ugursal, V.I. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renew. Sustain. Energy Rev.* **2009**, *13*, 1819–1835. [CrossRef]
13. Choi, I.Y.; Cho, S.H.; Kim, J.T. Energy consumption characteristics of high-rise apartment buildings according to building shape and mixed-use development. *Energy Build.* **2012**, *46*, 123–131. [CrossRef]
14. Woo, Y.E.; Cho, G.H. Impact of the surrounding built environment on energy consumption in mixed-use building. *Sustainability* **2018**, *10*, 832. [CrossRef]
15. Qiao, R.; Liu, T. Impact of building greening on building energy consumption: A quantitative computational approach. *J. Clean. Prod.* **2020**, *246*, 119020. [CrossRef]
16. Zhao, J.; Zhu, N.; Wu, Y. The analysis of energy consumption of a commercial building in Tianjin, China. *Energy Policy* **2009**, *37*, 2092–2097. [CrossRef]
17. Campagna, L.M.; Fiorito, F. On the Impact of Climate Change on Building Energy Consumptions: A Meta-Analysis. *Energies* **2022**, *15*, 354. [CrossRef]
18. Zhang, J.; Zhang, K.; Zhao, F. Research on the regional spatial effects of green development and environmental governance in China based on a spatial autocorrelation model. *Struct. Change Econ. Dyn.* **2020**, *55*, 1–11. [CrossRef]
19. Fonseca, J.A.; Schlueter, A. Integrated model for characterization of spatiotemporal building energy consumption patterns in neighborhoods and city districts. *Appl. Energy* **2015**, *142*, 247–265. [CrossRef]
20. Wang, H.; Pan, X.; Zhang, S. Spatial autocorrelation, influencing factors and temporal distribution of the construction and demolition waste disposal industry. *Waste Manag.* **2021**, *127*, 158–167. [CrossRef]
21. Tian, W.; Song, J.; Li, Z. Spatial regression analysis of domestic energy in urban areas. *Energy* **2014**, *76*, 629–640. [CrossRef]
22. Mostafavi, N.; Heris, M.P.; Gándara, F.; Hoque, S. The Relationship between Urban Density and Building Energy Consumption. *Buildings* **2021**, *11*, 455. [CrossRef]

23. Miller, H.J. Tobler's first law and spatial analysis. *Ann. Assoc. Am. Geogr.* **2004**, *94*, 284–289. [CrossRef]
24. Noh, S. Analysis of Energy Consumption and CO_2 Emissions Structure in Household Sector. *Korea Spat. Plan. Rev.* **2014**, *81*, 157–183.
25. Jung, J.; Yi, C.; Lee, S. An Integrative Analysis of the Factors Affecting the Household Energy Consumption in Seoul. *J. Korea Plan. Assoc.* **2015**, *50*, 75–94. [CrossRef]
26. Kim, K.J.; Lee, C.H. A Study on the Difference of Cooling Energy Consumption by Building Use. *Seoul Stud.* **2019**, *20*, 91–103.
27. Lee, G.; Jeong, Y.; Moon, Y.D. The Relation of between the Architectural and Urban Form, Microclimate Factors and Buildings Energy Consumption. *Asia-Pac. J. Multimed. Serv. Converg. Art Humanit. Sociol.* **2019**, *9*, 923–934.
28. Lee, S.; Kim, K.; Lee, S. Empirical Analysis of Mutual Influential Relationship between Urban Temperature and Building Energy Consumption Using Simultaneous Equation—Focused on Seoul, Korea. *Seoul Stud.* **2019**, *20*, 33–44. [CrossRef]
29. Kim, D.H.; Kang, K.Y.; Sohn, S.Y. Spatial Pattern Analysis of CO_2 Emission in Seoul Metropolitan City based on a Geographically Weighted regression. *J. Korean Inst. Ind. Eng.* **2016**, *42*, 96–111.
30. Mohammadi, N.; Taylor, J.E. Urban infrastructure-mobility energy flux. *Energy* **2017**, *140*, 716–728. [CrossRef]
31. Santamouris, M.; Cartalis, C.; Synnefa, A.; Kolokotsa, D. On the impact of urban heat island and global warming on the power demand and electricity consumption of buildings—A review. *Energy Build.* **2015**, *98*, 119–124. [CrossRef]
32. Lee, J.; Kim, J.; Song, D.; Kim, J.; Jang, C. Impact of external insulation and internal thermal density upon energy consumption of buildings in a temperate climate with four distinct seasons. *Renew. Sustain. Energy Rev.* **2017**, *75*, 1081–1088. [CrossRef]
33. Aditya, L.; Mahlia, T.M.I.; Rismanchi, B.; Ng, H.M.; Hasan, M.H.; Metselaar, H.S.C.; Muraza, O.; Aditiya, H.B. A review on insulation materials for energy conservation in buildings. *Renew. Sustain. Energy Rev.* **2017**, *73*, 1352–1365. [CrossRef]
34. Sadrzadehrafiei, S.; Mat, K.S.S.; Lim, C. Energy consumption and energy saving in Malaysian office buildings. *Models Methods Appl. Sci.* **2011**, *75*, 1392–1403.
35. Bhattacharjee, S.; Reichard, G. Socio-economic factors affecting individual household energy consumption: A systematic review. *Energy Sustain.* **2011**, *54686*, 891–901.
36. Wiedenhofer, D.; Lenzen, M.; Steinberger, J.K. Energy requirements of consumption: Urban form, climatic and socio-economic factors, rebounds and their policy implications. *Energy Policy* **2013**, *63*, 696–707. [CrossRef]
37. Duan, H.; Chen, S.; Song, J. Characterizing regional building energy consumption under joint climatic and socioeconomic impacts. *Energy* **2022**, *245*, 123290. [CrossRef]
38. Fabbri, K.; Tronchin, L.; Tarabusi, V. Real Estate market, energy rating and cost. Reflections about an Italian case study. *Procedia Eng.* **2011**, *21*, 303–310. [CrossRef]
39. Lee, K.; Baek, H.J.; Cho, C. The estimation of base temperature for heating and cooling degree-days for South Korea. *J. Appl. Meteorol. Climatol.* **2014**, *53*, 300–309. [CrossRef]
40. Li, L.; Sun, W.; Hu, W.; Sun, Y. Impact of natural and social environmental factors on building energy consumption: Based on bibliometrics. *J. Build. Eng.* **2011**, *37*, 102136. [CrossRef]
41. Vardoulakis, E.; Karamanis, D.; Fotiadi, A.; Mihalakakou, G. The urban heat island effect in a small Mediterranean city of high summer temperatures and cooling energy demands. *Sol. Energy* **2013**, *94*, 128–144. [CrossRef]
42. Huang, J.; Gurney, K.R. The variation of climate change impact on building energy consumption to building type and spatiotemporal scale. *Energy* **2016**, *111*, 137–153. [CrossRef]
43. Shen, P. Impacts of climate change on US building energy use by using downscaled hourly future weather data. *Energy Build.* **2017**, *134*, 61–70. [CrossRef]
44. Pérez-Andreu, V.; Aparicio-Fernández, C.; Martínez-Ibernón, A.; Vivancos, J.L. Impact of climate change on heating and cooling energy demand in a residential building in a Mediterranean climate. *Energy* **2018**, *165*, 63–74. [CrossRef]
45. Skelhorn, C.P.; Levermore, G.; Lindley, S.J. Impacts on cooling energy consumption due to the UHI and vegetation changes in Manchester, UK. *Energy Build.* **2016**, *122*, 150–159. [CrossRef]
46. Mcpherson, E.G., III. Effects of vegetation on building energy performance. Doctoral dissertation. *State Univ. N. Y. Coll. Environ. Sci. For.* **1987**, *25*, 1245.
47. Raji, B.; Tenpierik, M.J.; Van Den Dobbelsteen, A. The impact of greening systems on building energy performance: A literature review. *Renew. Sustain. Energy Rev.* **2015**, *45*, 610–623. [CrossRef]
48. Li, Z.; Fotheringham, A.S. Computational improvements to multi-scale geographically weighted regression. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 1378–1397. [CrossRef]
49. Oshan, T.M.; Li, Z.; Kang, W.; Wolf, L.J.; Fotheringham, A.S. MGWR: A Python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 269. [CrossRef]
50. Hong, I.; Yoo, C. Analyzing spatial variance of Airbnb pricing determinants using multiscale GWR approach. *Sustainability* **2020**, *12*, 4710. [CrossRef]
51. Fotheringham, A.S.; Oshan, T.M. Geographically weighted regression and multicollinearity: Dispelling the myth. *J. Geogr. Syst.* **2016**, *18*, 303–329. [CrossRef]
52. Li, Z.; Fotheringham, A.S.; Oshan, T.M.; Wolf, L.J. Measuring bandwidth uncertainty in multiscale geographically weighted regression using Akaike weights. *Ann. Am. Assoc. Geogr.* **2020**, *110*, 1500–1520. [CrossRef]
53. Fotheringham, A.S.; Yang, W.; Kang, W. Multiscale geographically weighted regression (MGWR). *Ann. Am. Assoc. Geogr.* **2017**, *107*, 1247–1265. [CrossRef]

54. Chen, H.C.; Han, Q.; De Vries, B. Modeling the spatial relation between urban morphology, land surface temperature and urban energy demand. *Sustain. Cities Soc.* **2022**, *60*, 102246. [CrossRef]
55. Sultana, S.; Pourebrahim, N.; Kim, H. Household energy expenditures in North Carolina: A geographically weighted regression approach. *Sustainability* **2018**, *10*, 1511. [CrossRef]
56. Tan, S.; Zhang, M.; Wang, A.; Zhang, X.; Chen, T. How do varying socio-economic driving forces affect China's carbon emissions? New evidence from a multiscale geographically weighted regression model. *Environ. Sci. Pollut. Res.* **2021**, *28*, 41242–41254. [CrossRef]
57. Moore, D.; Webb, A.L. Evaluating energy burden at the urban scale: A spatial regression approach in Cincinnati, Ohio. *Energy Policy* **2022**, *160*, 112651. [CrossRef]
58. Fotheringham, A.S.; Yue, H.; Li, Z. Examining the influences of air quality in China's cities using multi-scale geographically weighted regression. *Trans. GIS* **2019**, *23*, 1444–1464. [CrossRef]
59. Pereira, L.D.; Raimondo, D.; Corgnati, S.P.; Da Silva, M.G. Energy consumption in schools–A review paper. *Renew. Sustain. Energy Rev.* **2014**, *40*, 911–922. [CrossRef]
60. Aksoezen, M.; Daniel, M.; Hassler, U.; Kohler, N. Building age as an indicator for energy consumption. *Energy Build.* **2015**, *87*, 74–86. [CrossRef]