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Data Article

Aggregated hedonic dataset with a green index: Busan, South Korea

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A R T I C L E I N F O

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A B S T R A C T

We provide an aggregated dataset for investigating the association between hedonic variables and property prices in the Busan Metropolitan City of South Korea. This hedonic dataset includes various factors that influence property prices such as property characteristics, environmental amenities, local built environments, local demographic characteristics, and seasonal controls. In this dataset, we introduce the green index, which quantifies the degree of urban street greenness exposed to residents and pedestrians using images from Google Street View. In addition, the spatial interpolation method is employed to resolve the nonuniform distribution issue of the source images. To encourage the reusability of the dataset, we provide data and code files in a convenient manner. Therefore, the aggregated hedonic dataset can be readily benchmarked in property appraisal and urban studies and utilized in geographic information system fields.

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Specifications Table

Subject	Economics, Econometrics and Finance, Social Sciences
Specific subject area	Geography, Real Estate Economics, Econometrics
Type of data	Table
Data collection	A total of 306,425 street view images were collected using the Google Street View download tool to quantify street greenery. Images featuring artificial greenness, such as those of playgrounds or green-painted tunnels, were excluded. Green indices were incorporated into the hedonic dataset using spatial interpolation. Housing transaction records and other hedonic data were manually sourced from public data repositories, while additional housing information was obtained from three private real estate companies. The aggregated dataset was refined through exploratory data analysis and descriptive statistics.
Data source location	Daum Real Estate: realty.daum.net Google Street View: https://svd360.istreetview.com Housing Transaction Data: rt.molit.go.kr Kookmin Bank: kbland.kr Naver Financial: land.naver.com Spatial Information Portal: www.nsdi.go.kr Statistic Korea: www.kostat.go.kr Korea Transport Database: www.ktdb.go.kr Statistical Geographic Information Service: sgis.kostat.go.kr
Data accessibility	Repository name: Zenodo Data identification number: 10.5281/zenodo.11092589 Direct URL to data: https://zenodo.org/records/11092589
Related research article	An, S., Jang, H., Kim, H., Song, Y. & Ahn, K. (2023). Assessment of street-level greenness and its association with housing prices in a metropolitan area. Scientific Reports, 13(1), 22577. https://doi.org/10.1038/s41598-023-49845-0 [1].

1. Value of the Data

- This dataset includes urban greenery information regarding proximity to green spaces and the degree of urban street greenness exposed to residents, which are useful instruments in the fields of real estate and urban studies.
- The green index is quantified based on a large amount of panoramic Google Street View (GSV) images and pixel-wise computer vision algorithms so that the measure can precisely reflect the urban greenness in the three-dimensional view.
- The aggregated dataset consists of a variety of housing factors such as property characteristics, environmental amenities, local built environments, local demographic characteristics, and seasonal controls, enabling the synthetic comprehension of the association between housing factors and property prices.
- Investigators can readily utilize our dataset encapsulated in a convenient format, and researchers can also interpret the impacts of hedonic variables on housing prices through the statistical modeling.
- Geographers can benchmark this dataset in analyzing spatial patterns of property values and distributions of the urban infrastructure such as transportation and environmental amenities.

2. Background

Since the Industrial Revolution, a rapid urbanization has led to the tradeoff of natural environmental resources for built environments in urban areas. Recently more attention has been paid to green cities prioritizing environmental health [2]. Many studies presented positive financial incentives of the urban greenness in relation to housing prices such as the promotion of physical activity and mitigation of pollution [3–5].

To measure the urban greenness, the normalized difference vegetation index (NDVI) calculated from satellite images has been utilized [6–8]. However, NDVI measures the urban greenness only at the canopy level, which potentially overestimates the extent of greenness [5,9,10] and differs from actual observations of residents [11]. Hence, the greenery measure at human eye level can be considered by reflecting pedestrians' views.

To address this, we introduce a green index that captures three-dimensional street greenness and provide an aggregated hedonic dataset. This dataset offers additional value in exploring the relationship between green amenities and housing prices, alongside variables commonly used in housing price assessment models. An et al. [1] analyzed this dataset and demonstrated that both proximity to green spaces and the green index could jointly explain the relationship between green amenities and housing prices.[1]

3. Data Description

3.1. Data repository and format

To enhance the availability of the dataset, we have uploaded the aggregated hedonic dataset to Zenodo (https://zenodo.org/records/11092589) [13] and GitHub (https://github.com/Quantitative-Finance-Lab/Green-Index), which was examined by An et al. [1]. The dataset, titled "Property Price and Green Index.xlsx," is available for free download in Microsoft Excel format. It includes 52,644 observations and 27 variables, making it a valuable resource for benchmarking or exploring urban and real estate studies. Researchers can easily access and cite the dataset using the unique identifier (10.5281/zenodo.11092589), which facilitates accessibility and citation. In addition, we encourage the reuse of our dataset and methodology by offering detailed guidance on calculating the green index and implementing spatial interpolation to address the issue of nonuniform image distribution.[2] The refined hedonic dataset is accessible through our GitHub repository (https://github.com/Quantitative-Finance-Lab/Green-Index), which facilitates its usage for other researchers. Furthermore, the dataset is available for unrestricted use under the MIT license, ensuring broad applicability and ease of access.[3]

3.2. Data structure

The dataset consists of property prices and various hedonic variables, which are categorized into five groups, namely, such as property characteristics, environmental amenities, local built environment, local demographics, and sales period controls. Demographic variables are measured at the administrative level called dong, which is equivalent to a Census district in the United States. The green index is classified under environmental amenities.

Table 1 summarizes the hedonic variables, including their names, scales, and details. Variable column presents the column names of the variables in the hedonic dataset (Property Price and Green Index.xlsx) and the denominated names in the descriptive statistics. Scale stands for the measurement scale, and Detail describes each variable. Table 2 presents the descriptive statistics for the green index and other hedonic variables.

4. Experimental Design, Materials and Methods

4.1. Acquisition of source dataset

We chose Busan as the study area because of its diverse characteristics, including a large population and various environmental amenities such as waterfronts, seashores, and natural parks.

[1] We provide additional information by comparing our aggregated hedonic dataset to the existing dataset provided by Song et al. [12]. The results are represented in Appendix A.

[2] Specifically, we provide sample data and images on GitHub to facilitate the step-by-step execution of the code, thereby promoting reusability.

[3] The MIT license is a straightforward and permissive open-source license that permits users to freely use and modify the code, provided the original license and copyright notice are retained.

Table 1
Delineation for green index and hedonic variables.

Variable	Scale	Detail
Property prices[a]	Ratio	Log-transformed Korean won per square meter (won/m^2)
Longitude	Ratio	Longitude in the Cartesian coordinate system
Latitude	Ratio	Latitude in the Cartesian coordinate system
Property Characteristics		
Size	Ratio	Unit size aggregated in square meters (m^2)
Floor	Interval	A floor of transacted property
Highest Floor	Ratio	Highest floor in an apartment complex
Units	Ratio	Number of households in an apartment complex
Parking	Ratio	Number of parking spaces divided by the number of households
Heating	Nominal	A heating type of each housing: city gas = 0; others = 1
Year	Date	Year of construction of each apartment complex
Environmental Amenities		
Dist. Green[a]	Ratio	Log-transformed network distance to the nearest park, hill, or mountain in meters
Dist. Water[a]	Ratio	Log-transformed network distance to the nearest river, stream, pond, or seashore in meters
Green Index	Ratio	Degree of street greenness exposed to pedestrians
Local Built Environment		
Dist. Subway[a]	Ratio	Log-transformed network distance to the nearest subway station in meters
Bus Stop	Ratio	Number of bus stops within a 400-meter radius of a property
Dist. CBD	Ratio	Network distance to the city hall in meters
Top Univ.	Ratio	Number of Seoul National University entrants from high schools within a 5-km radius of properties
High School	Ratio	Number of high schools within a 5-km radius of a property
Local Demographics		
Sex Ratio	Ratio	Percentage of the number of men divided by the number of women
Population	Ratio	Number of people in a neighborhood
Pop. Density	Ratio	Number of people per square kilometer (km^2)
Higher Degree	Ratio	Percentage of the number of people with a higher degree divided by the number of people aged 15 years or older
Young Population	Ratio	Percentage of the number of people aged less than 15 years divided by the total population
Median Age	Ratio	Percentage of the number of people aged 15 to 65 years divided by the total population
Old Population	Ratio	Percentage of the number of people aged 65 years or older divided by the total population
Seasonality Control		
Spring	Nominal	Seasonal dummy indicating that a transaction occurred in March, April, or May
Fall	Nominal	Seasonal dummy indicating that a transaction occurred in September, October, or November
Winter	Nominal	Seasonal dummy indicating that a transaction occurred in December, January, or February

[a] The variables with asterisk were transformed with logarithm.

This diversity allows researchers to explore a wide range of urban resource-related aspects. The Ministry of Land, Infrastructure and Transport (MLIT) provides apartment transaction records that include transaction prices, property addresses, and related characteristics. We focused on the condominium as the representative housing type because the MLIT supplies geographic coordinates[4] for transaction points, facilitating spatial analyses, and apartments serve as the predominant housing type in South Korea [14,15]. Using the provided data source, we manually col-

[4] Because apartments often share the same spatial location, individual transactions may have identical latitude and longitude coordinates; however, these transactions can be distinguished by a set of unique features, such as the area,

Table 2
Descriptive statistics of the variables.

Property prices[a]	Mean	Std.	Min.	Max.
	10.187	0.568	6.908	12.934
Property Characteristics: Unit-related				
Size	77.820	28.916	12.488	269.680
Floor	11.819	8.201	−1.000	77.000
Property Characteristics: Complex-related				
Units	937.087	885.506	4.000	5239.000
Buildings	9.227	8.910	1.000	77.000
Year	2003.496	10.153	1969.000	2019.000
Heating	0.093	0.291	0.000	1.000
Parking	1.101	0.619	0.000	77.000
Highest Floor	23.249	10.347	2.000	84.000
Environmental Amenities				
Dist. Green[a]	7.277	2.222	0.808	10.714
Dist. Water[a]	6.268	1.181	−0.170	8.601
Green Index	10.733	2.098	4.163	18.927
Local Built Environment				
Dist. Subway[a]	6.892	1.016	3.366	9.978
Bus Stop	18.105	10.840	0.000	63.000
Dist. CBD	237377.312	192493.328	243.860	398856.132
Top Univ.	11.179	6.442	0.000	27.000
High school	14.274	7.295	0.000	30.000
Local Demographics				
Population	25888.373	14125.007	1208.000	83116.000
Pop. Density	13220.993	10687.626	1.003	118181.818
Higher Degree	30.303	9.847	10.356	61.289
Young Population	12.120	4.121	3.151	26.285
Old Population	16.325	4.455	5.712	33.292
Medium Age	42.603	3.637	32.700	55.4000
Sex Ratio	95.750	4.656	81.024	124.508
Sales Period Control				
Spring	0.215	0.411	0.000	1.000
Fall	0.343	0.475	0.000	1.000
Winter	0.243	0.429	0.000	1.000

[a] This variable is log-transformed.

lected raw data about all apartment transaction records in Busan for the years 2018 and 2019. After excluding missing values and outliers through exploratory data analysis (EDA) and descriptive statistics analysis, we constructed the aggregated hedonic dataset with a total of 52,644 observations, including property prices and other hedonic variables. For the green index, we used GSV images, which have proven to be a reliable and promising source to examine urban areas, especially when compared to less developed or rural regions [1].

With advancements in smart technology, various big data sources for local landscapes have become available. GSV images are particularly valuable owing to their comprehensive panoramic landscape information. For our dataset, we retrieved 409,390 GSV images from within Busan's administrative boundary using the GSV download tool (https://svd360.istreetview.com), all generated in 2017 and 2018. During the image collection, we included location tokens with geographical information, such as latitude and longitude, to facilitate the spatial interpolation based on geographic coordinates. Subsequently, we filtered out images with artificial greenness, such as those depicting playgrounds or tunnels painted green, resulting in 306,425 cleaned GSV images. This cleaning procedure was essential to accurately assess the impact of natural greenness [1]. Next, we performed image processing by converting the images to the hue, saturation, and value (HSV) color space and setting upper and lower boundaries to identify natural greenness. We

floor, transaction price, transaction date, and other property characteristics. To determine whether each transaction can qualify for an individual observation, we compared these overlapping property characteristics.

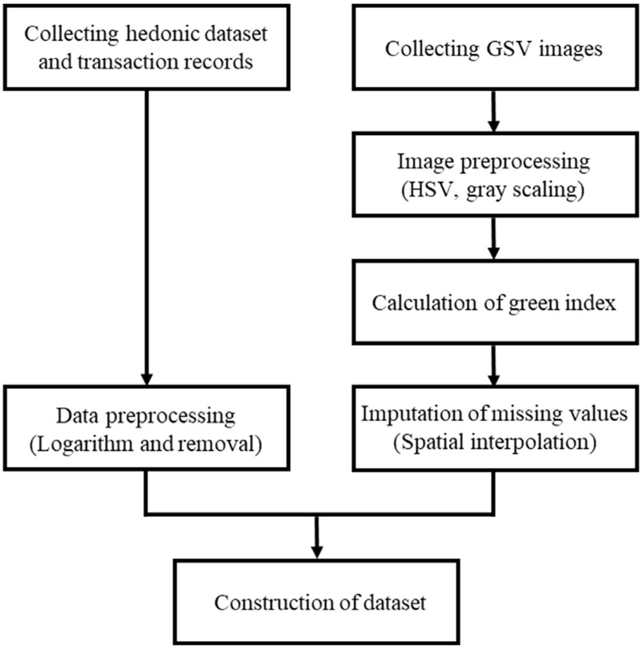

Fig. 1. Flowchart illustrating the procedure for constructing the hedonic dataset.

used gray scaling to determine whether each pixel falls within these boundaries. We then calculated the green index for each GSV image. Finally, we conducted spatial interpolation to address missing values and integrated the calculated green indices into the aggregated hedonic dataset. In summary, we used a four-step approach to construct the green index data: GSV image collection, color space conversion and masking, green index calculation, and spatial interpolation.[5]

In addition to GSV images, we aggregated and cleaned property data for the years 2018 and 2019. The resulting dataset encompasses transaction records and other hedonic variables sourced from public data repositories, including the Korea Transport Database, Statistics Korea, MLIT, and the Spatial Geographic Information Service. Supplementary property information was also obtained from the websites of three private real estate companies: kbland.kr, land.naver.com, and realty.daum.net. During the data collection process, each transaction record was treated as an individual observation. The compiled transaction records included geographic coordinates and property-specific variables such as the property price, address, year built, floor, floor area, and transaction date. Next, we collected data on environmental amenities, local built environment, and local demographic variables for each property. Specifically, we calculated distance variables based on road network distances from each housing unit to the nearest environmental amenity or subway station. The highly skewed variables are transformed into a logarithmic scale to be close to a normal distribution. Additionally, the variable for bus stops was calculated to reflect the number of bus stops within a 400-m radius buffer around each housing unit using the ArcMap. Fig. 1 is a flowchart that illustrates the construction procedure of the aggregated dataset.[6] Specifically, the study derived property prices from transaction data for apartments sourced from the MLIT, because it provides geographical coordinates unlike other types of housing. We visualize the spatial distribution of aggregated GSV images and property transaction records on the basis of their longitudes and latitudes (Fig. 2).

[5] The method for calculating the green index is provided step-by-step in Appendix B.

[6] We summarize the details of constructing a hedonic dataset, including sources and methods used in Appendix C.

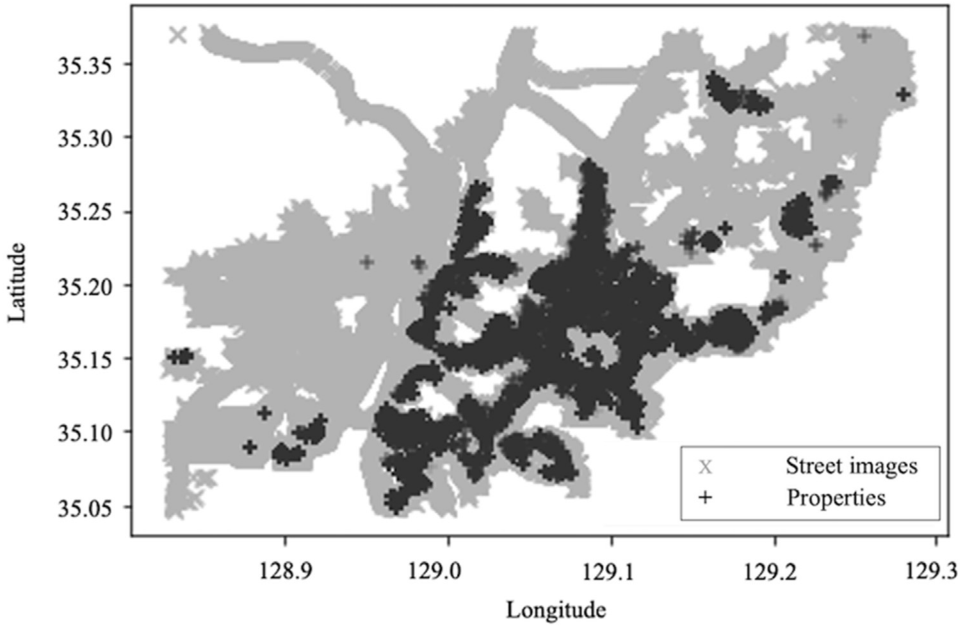

Fig. 2. Spatial distribution of street images and property units (sourced from An et al. [1]). This map was created using Matplotlib library (https://matplotlib.org/stable/index.html), version 3.7.1.

4.2. Calculation of the green index

Traditional greenness indices, such as those derived from NDVI or satellite imagery, have been widely used to assess urban greenness [6–8]. However, NDVI only measures greenness at the canopy level, which does not necessarily reflect the actual experience of pedestrians and residents [11]. Additionally, NDVI may overestimate the extent of green areas [5,9,10], leading to inaccuracies in evaluating street-level greenness. In contrast, the green index, as quantified through the previous steps, uses GSV images captured from a three-dimensional perspective. This approach allows us to assess the degree of natural greenness visible to pedestrians. Furthermore, the iStreetView tool's API facilitates the efficient collection of a large volume of images, which is essential for accurately quantifying the green index.

For quantifying the degree of urban street greenness, we conduct a four-step process with street view images and employ the spatial interpolation strategy for mitigating the nonuniform distribution of the obtained images. Fig. 3 depicts that the quantification for the green index from GSV images takes a four-step approach, namely, the GSV image collection; the conversion of color space and masking process; the calculation of the green index; and the spatial interpolation.

After collecting street view images, we transform each of the GSV images from a red, green, and blue color space to the HSV color space to improve image clarity [16,17]. Next, we set the upper and lower boundaries to capture natural greenness based on the HSV color space. We then scrutinize all images according to whether or not each of the pixels falls between boundaries. If a pixel value is out of boundaries, then we mask the pixel by assigning a value of zero (Fig. 4). Therefore, the green index of each GSV image can be calculated as follows:

$$Green\ index_i = pixel_{non-zero}/pixel_{total} \times 100,$$

where $pixel_{non-zero}$ denotes the number of non-zero pixels and $pixel_{total}$ represents the total number of pixels in an image; hence, $Green\ index_i$ is the fraction of natural greenness to i-th

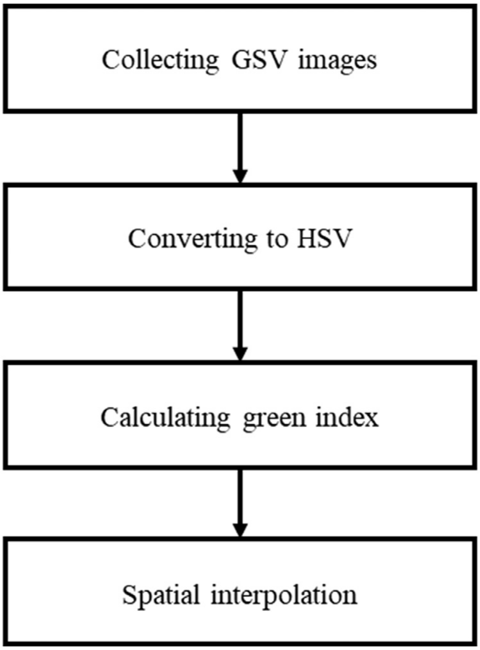

Fig. 3. Four-step process for quantifying the green index.

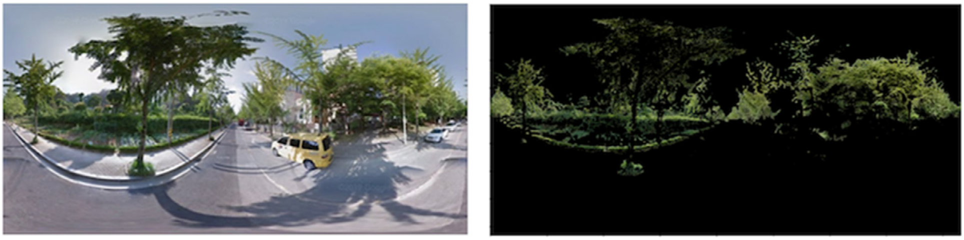

Fig. 4. Original (left) and converted (right) images with masked pixels (sourced from An et al. [1]).

GSV image. GSV images are basically captured in three-dimensional view; thus, the green index can measure the degree of natural greenness exposed to pedestrians.

4.3. Spatial interpolation

Notably, less GSV images are taken of city outskirts, because natural barriers, such as mountains, rivers, and forests, frequently determine administrative boundaries, such that city outskirts tend to have a smaller number of street images. This scenario indicates that the use of GSV images can potentially suffer from uneven spatial distribution, which leads to a biased quantification of the green index.

To address this issue, we used spatial interpolation to transform point data into areal information. Li and Heap [18] demonstrated that spatial interpolation can effectively handle environmental variables at unsampled locations using point data. This method is versatile and has been applied in various fields, such as identifying locations for renewable energy sources [19]

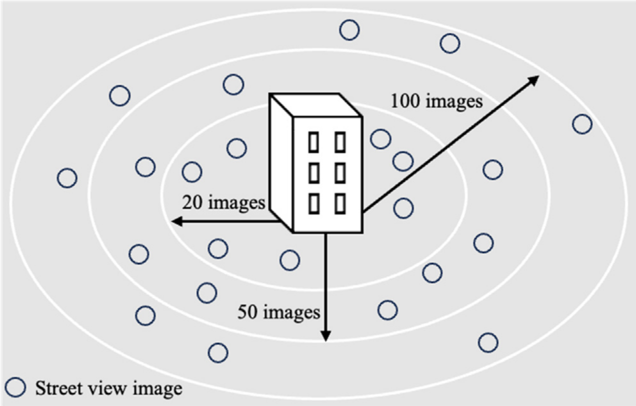

Fig. 5. Graphical description of spatial interpolation (sourced from An et al. [1]).

and integrating mobile phone data [20]. This relies solely on longitude and latitude information, making it accessible for spatial analysis and urban studies. The spatial interpolation assumes that adjacent properties are likely to exhibit similar levels of street greenness.

The implementation of spatial interpolation involves two major steps: calculating the haversine distance and averaging the green index. First, we used longitude and latitude information to calculate the distances between target properties and all green indices using the haversine formula. This formula is commonly used to calculate the distance between two points based on their longitude and latitude coordinates [21]. The haversine formula accounts for the Earth's spherical shape, providing a more accurate distance measurement compared to the simple Euclidean distance formula [22]. The mathematical expression for the haversine formula is as follows:

$$d_{haversine} = 2 \times R \times arcsin\left(\sqrt{\sin^2\left(\frac{\Delta lat}{2}\right) + \cos\left(lat_p\right) \times \cos\left(lat_g\right) \times \sin^2\left(\frac{\Delta lng}{2}\right)}\right),$$

where R is the Earth's radius, set at $6,371$ km; Δlat is the difference between the latitude of the target property (lat_p) and the latitude of the green index (lat_g); and Δlng is the difference in longitudes between the target property and the green index. Next, we arranged the calculated haversine distances in ascending order and assigned the mean values of the green indices to each property unit by aggregating the values of a specific number of the nearest green indices. At the averaging stage, the number of nearest green indices can be adjusted as a parameter. We experimented with different numbers of nearest images, specifically 50, 100, and 150. An et al. [1] focused on using 50 nearest images to explore the relationship between urban greenness and property prices. Fig. 5 graphically illustrates the spatial interpolation strategy employed.

The Spatial interpolation effectively imputes missing values by considering the spatial distribution of data points. Li and Heap [18] demonstrated that this method was effective for estimating environmental variables at unsampled sites using point observation data. Additionally, the spatial interpolation avoids the modifiable areal unit problem, which is often criticized for introducing statistical bias [8,23]. This technique also improves spatial accuracy and has been successfully applied in various fields, such as identifying potential sites for renewable energy sources [16] and integrating mobile phone data [20]. Besides the target variable to be imputed, our spatial interpolation approach only requires two locational parameters—longitude and latitude—making it easy for potential users to apply and reuse our methodology.

4.4. Potential application

We provide the materials, including the refined dataset, data descriptions, and code snippets, on reputable repositories to enhance accessibility and reproducibility. The aggregated hedonic dataset can serve as a benchmark for geography and urban studies examining the effects of urban resources—such as street greenness and subway networks—on housing prices. The spatial interpolation method detailed in our work can be broadly applied in geography and geoinformatics studies that require managing missing values to improve data quality. Additionally, the visualization code provided enables users to gain visual insights into the overall spatial distribution of variables.[7]

Limitations

We collected the raw dataset of actual apartment transaction records and other hedonic variables, focusing on Busan for the years 2018 and 2019 from reliable sources such as MLIT, the Korea Transport Database, and Statistics Korea. However, potential systematic errors, such as outliers and missing values, may occur owing to measurement errors or inaccuracies in the data recorded by information recorders, potentially leading to erroneous results [24]. To address these issues, we performed EDA and descriptive statistics analysis to refine the aggregated hedonic dataset. This indicates that while the raw data collection approach is robust, supplementary procedures such as descriptive statistics and EDA are necessary to validate and enhance the credibility of the final dataset.

Ethics Statement

All authors have read and followed the ethical requirements for publication in Data in Brief. The current work does not involve human subjects, animal experiments, or any data collected from social media platforms.

Data Availability

Property Price and Green Index.xlsx (Original data) (Zenodo).

CRediT Author Statement

Sihyun An: Investigation, Writing – original draft, Methodology; **Seongeun Bae:** Investigation, Writing – original draft, Data curation, Visualization; **Yena Song:** Conceptualization, Writing – review & editing, Supervision; **Kwangwon Ahn:** Conceptualization, Writing – review & editing, Supervision.

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[7] We also provide delineations for data visualization of green indices in Appendix D.

Declaration of Competing Interest

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

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.dib.2024.111009.

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