This is the Accepted Manuscript version of an article published by Elsevier in the journal *Cities* in 2024, which is available at:
`https://doi.org/10.1016/j.cities.2023.104704`
Cite as: Wang Z, Ito K, Biljecki F (2024): Assessing the equity and evolution of urban visual perceptual quality with time series street view imagery. *Cities*, 145: 104704.

Assessing the Equity and Evolution of Urban Visual Perceptual Quality with Time Series Street View Imagery

Zeyu Wang[a], Koichi Ito[a], Filip Biljecki[a,b,*]

[a]*Department of Architecture, National University of Singapore, Singapore*
[b]*Department of Real Estate, National University of Singapore, Singapore*

Abstract

The well-being of residents is considerably influenced by the quality of their environment. However, due to the lack of large-scale quantitative and longitudinal evaluation methods, it has been challenging to assess residents' satisfaction and achieve social inclusion goals in neighborhoods. We develop a novel cost-effective method that utilizes time series street view imagery for evaluating and monitoring visual environmental quality in neighborhoods. Unlike most research that relies on site visits or surveys, this study trains a deep learning model with a large-scale dataset to analyze six perception indicators' scores in neighborhoods in different geographies and does so longitudinally thanks to imagery taken over a period of a decade, a novelty in the body of knowledge. Implementing the approach, we examine public housing neighborhoods in Singapore and New York City as case studies. The results demonstrated that temporal imagery can effectively assess spatial equity and monitor the visual environmental qualities of neighborhoods over time, providing a new, comprehensive, and scalable workflow. It can help governments improve policies and make informed decisions on enhancing the design and living standards of urban residential areas, including public housing communities, which may be affected by social stigmatization, and monitor the effectiveness of their policies and actions.

Keywords: Residential Quality, Public Housing, Environmental Quality, Spatial Equity, Street View Imagery, Visual Environment

*Corresponding author
Email addresses: wangzeyu@u.nus.edu (Zeyu Wang), koichi.ito@u.nus.edu (Koichi Ito), filip@nus.edu.sg (Filip Biljecki)

Paper submitted to Cities *December 8, 2023*

1. Introduction

The continuously evolving nature of the built environment can significantly impact the human perception of the city, resulting in spatial inequalities and changes over time (Salesses et al., 2013). Studies have reported increased attention towards discovering the relationship between housing and neighborhood qualities and their effects on the well-being of residents (Wang et al., 2023). Most of them have found that poor housing quality and distressed neighborhoods negatively affect both individual and civic life (Greene et al., 2020; Jeon and Woo, 2023; Ma et al., 2018). However, the absence of quantitative and large-scale evaluation methods to monitor the built environment changes within the neighborhood and the effectiveness of neighborhood upgrades can result in continuing low levels of resident satisfaction (Hananel, 2017; Kumar, 2019). The varying quality of residential neighborhoods poses a challenge for policymakers in ensuring a satisfactory living environment citywide.

With the rapid advancement of map services, a vast number of images depicting the urban environment with accompanying geographic information have become publicly accessible (Liu et al., 2015; Biljecki and Ito, 2021). Through reviews and empirical studies, it has been demonstrated that when combined with deep learning, street view imagery, SVI (also known as street-level imagery) can be used to automatically estimate human perceptions of diverse built environment attributes at a large-scale and rapidly, outperforming traditional field surveys and similar methods (Liu et al., 2017; Zhang et al., 2018). Despite the advancements in using SVI to identify differences in built environment attributes, studies have concentrated on identifying spatial disparities, with little attention paid to assessing or monitoring temporal variations (Zhou et al., 2019; Jeon and Woo, 2023; Ito and Biljecki, 2021). Further, residential neighborhoods have not been in particular focus of such studies, which is a notable omission considering their importance in urban planning.

To bridge these gaps, we present a novel approach that utilizes deep learning models and time series street view imagery to estimate the visual environmental quality of neighborhoods both spatially and temporally, thereby enabling governments to identify communities in need of environmental enhancement and improve the satisfaction and quality of life of residents in a timely manner. Our method can replace or supplement the existing approaches by providing a large-scale, timely, and automatic inspection of the visual environmental quality of neighborhoods. Specifically, we aim to answer two main questions: first, what are the differences in the quality of neighborhoods located in different parts of the city during the same period of time, and second, whether there is an improvement in the environmental quality of the neighborhoods over time. Subsequently, the study adopted a deep learning model proven effective in similar studies for assessing environmental quality based on six key subjective human perception aspects: safety, liveliness, beauty, wealth, depression, and boredom. These aspects were selected for their established predictive accuracy and their comprehensive representation of urban experience. Safety and wealth provide insights into the socio-economic dynamics, while liveliness and beauty reflect the vibrancy and aesthetic appeal of cities. Depression and boredom are crucial for understanding mental health challenges in urban settings. This holistic approach allows the model to derive nuanced scores for each aspect, facilitating a detailed comparison of environmental quality across neighborhoods and over time, aligning with indicators used in comparable research (Zhang et al., 2018; Wu et al., 2020; Liu and Ma, 2021; Huang and Du, 2015).

In our work, for the implementation, we zero in on public housing, which has gained attention recently (Won and Lee, 2020; Widya et al., 2023), and enables us to focus on neighborhoods that are comparable. Public housing programs, which are operated by the government for public welfare, are often considered an effective solution to provide affordable housing for relatively disadvantaged households (Beck, 2019). However, they are more susceptible to the effects of political, social, and economic factors leading to a lack of effective maintenance and environmental enhancement (Power et al., 2020; Hananel et al., 2021). The standardized and less-designed built environment in public housing neighborhoods affects the physical and mental health of residents to some extent and limits their quality of life (Apparicio et al., 2008; Jones-Rounds et al., 2014). Therefore, compared to other types of residential neighborhoods, those with predominantly public housing deserve more attention.

2. Related work

2.1. Empirical evaluation of neighborhood quality and resident satisfaction

Studies examining the quality of neighborhoods and resident satisfaction usually consider housing and infrastructure conditions, neighborhood characteristics, access to amenities, and socio-economic conditions (Adamkiewicz et al., 2011; Burgos et al., 2013; Diaz Lozano Patino and Siegel, 2018; Howden-Chapman et al., 2007; Mohit and Azim, 2012; Crawford and Sainsbury, 2017). Among these, neighborhood environment or characteristics have been identified as one of the most crucial determinants of residential satisfaction (Liu and Ma, 2021; Ibem et al., 2017; Huang and Du, 2015). Indicators commonly used to estimate the environmental quality of residential neighborhoods include green spaces, sanitation, quietness, security, space design, maintenance, and landscape (Wu et al., 2020; Liu and Ma, 2021; Huang and Du, 2015). It should be acknowledged that the indicators used to assess the environmental quality of residential neighborhoods are frequently assessed based on the perceptions of a chosen group of residents, their personal experiences, or memories, or evaluated by a selected group of experts. However, it is essential to note that these approaches, including questionnaires, interviews, and expert scoring, have limitations that need to be considered. One limitation is that the data collected may have a restricted scale of application and may not reflect the diversity of experiences and perspectives among residents. Another limitation is the potential subjectivity in the ratings, which may impact the validity and reliability of the findings.

As highlighted above, researchers have long aimed to improve the representativeness of the data to gain a better understanding of residents' satisfaction with the neighborhood environment (Wu et al., 2020). To address the limitations, this study aims to improve the representativeness and coverage of the data by adopting a novel dataset of time series SVI and using machine learning to estimate human perceptions of the residential neighborhood environment.

2.2. Street view imagery and quantification of the urban environment quality

Recent studies and reviews have shown that utilizing SVI in combination with deep learning can offer a highly effective approach for automated estimation of human perceptions regarding diverse built environment attributes at a large scale.

Street view imagery is a collection of spatially sequential images that capture ground-level views on public roads and highways (Anguelov et al., 2010; Hou and Biljecki, 2022). With the rapid development of map services providers and volunteered geographic information (VGI) platforms (Yan et al., 2020; Ding et al., 2021; Juhász and Hochmair, 2016; Quinn and León, 2019), a large number of geotagged images have become publicly available. SVI is now available in over 100 countries worldwide and covers about half of the world's population (Goel et al., 2018). Moreover, studies have shown that SVI can accurately portray the built environment of a city and it is more consistent with people's actual vision and perspective than other spatiotemporal data such as remote sensing imagery (Helbich et al., 2019; Liu et al., 2015; Chen and Biljecki, 2023).

Nowadays, SVI is widely used for reliably assessing various built environments. Numerous studies have utilized Google Street View (GSV) to assess different types of built environments, such as greenness differentiation of residential streets (Li et al., 2015), walkability (Jeon and Woo, 2023; Wang and Yang, 2019; Zhou et al., 2019), bikeability (Ito and Biljecki, 2021), street space quality differentiation (Naik et al., 2014), urban open space quality (Edwards et al., 2013), urban function (Zhang et al., 2023), and overall neighborhood environmental conditions (Charreire et al., 2014).

To date, deep learning has become the primary instrument for analyzing SVI due to its ability to learn and identify patterns from large and complex datasets.

However, traditional image processing methods and computer vision may not be sufficient to handle the diversity and variability of SVI (Li et al., 2022b). The Place Pulse 2.0 dataset (Dubey et al., 2016) provides an opportunity to develop deep learning models that can predict urban perceptions based on visual features of the environment. The dataset contains over 1.17 million pairwise comparisons for approximately 110,988 images from cities worldwide, along with their corresponding perception scores at 6 perceptual dimensions such as safety, liveliness, boredom, wealth, depression, and beauty (Dubey et al., 2016). This dataset can replace previous low-throughput survey methods such as questionnaires, providing a rapid and large-scale estimate of residents' true perceptions of the environmental quality of their neighborhoods (Dadvand et al., 2016; Kabisch et al., 2015). The dataset has been used in various studies to explore the relationship between the urban environment's visual quality and perception. For example, by using pre-trained scene understanding algorithms on GSV images, Zhang et al. (2021) inferred the perception of safety scores of streetscapes for each census block group and explore the relationship between crime rates and perception of safety in the city of Houston; Zhang et al. (2018) proposed a deep learning-based approach to predict human perceptions of the physical setting of a place using the Place Pulse 2.0 dataset, and investigated the connections between urban visual elements and perceptions using multivariate regression analyses to understand place sentiments and semantics in a large-scale urban environment. It has been demonstrated to be a valuable resource for researchers seeking to understand how people perceive the visual quality of urban environments and can inform urban design and policy decisions aimed at improving the quality of life in these communities (Kang et al., 2023).

While SVI has been used extensively to identify spatial disparities in the built environment, there has been limited attention paid to the temporal variations in the urban landscape. The urban environment is not static and changes over time due to many factors such as urbanization, public policies, urban redevelopments, and economic development. These changes can have a considerable impact on the well-being of its residents, making it important to monitor and assess them. Historical (or time series) SVI provides an attractive opportunity to track and monitor such changes in the built environment over time. With the increasing availability of SVI from different time periods, there is growing interest in developing algorithms that can automatically detect and classify changes in the built environment. Based on our knowledge, there are very few studies that utilized historical SVI to monitor the changes in the urban environment attributes (Li et al., 2022a; Liang et al., 2023), and none for this purpose. Furthermore, there has not been any study that adopted the Place Pulse 2.0 dataset to train a Deep Convolutional Neural Networks (DCNN) model that is able to estimate the human perception of visual environment quality changes overtime at scale, a gap that is bridged by this study.

3. Methodology

3.1. Study Area

Public housing programs in New York City and Singapore have received global recognition for providing affordable and high-quality housing on a large scale (Hananel et al., 2021; Beck, 2019; Tamura and Fang, 2022). In recent years, city governments have been paying more attention to providing a decent and sustainable living environment for public housing residents (Hagelskamp et al., 2020; Polyakov et al., 2022). For example, New York City has allocated a greater proportion of its discretionary capital budget to public housing communities through participatory budgeting (Hagelskamp et al., 2020), while the Singapore Government has introduced major upgrading programs and home improvement schemes to enhance the quality of living in public housing neighborhoods (Glass and Salvador, 2018). Since the 1930s, New York City's public housing has played a critical role in the city's social infrastructure, with over 400,000 residents living in more than 2,500 buildings (Li and Shamsuddin, 2022). In Singapore, the Housing and Development Board (HDB) was established in 1960 to address the city-state's rapidly growing population and urbanization. Today, more than 80 percent of Singapore's population resides in HDB flats (Lin-Heng, 2020). Despite the challenges that come with maintaining and enhancing public housing, both cities have remained steadfast in their commitment to providing affordable and comfortable homes to their citizens. Their success has made them models for other cities worldwide, inspiring similar public housing initiatives in other countries.

As for the spatial distribution of public housing, in New York City, public housing is primarily located in the boroughs of Brooklyn, the Bronx, and Manhattan. These areas are characterized by high-rise buildings, often surrounded by green spaces and community facilities (Wyly and DeFilippis, 2010). In contrast, Singapore's public housing is strategically distributed throughout the city-state, with many HDB flats clustered around transit nodes and regional centers. Despite these differences, both public housing programs share the same mission of providing safe, affordable, and well-designed housing for their residents and have contributed to the social and economic development of their respective cities.

Therefore, we chose these two cities from different parts of the world and social-economical backgrounds as the focus of this study.

3.2. MIT Place Pulse dataset

We used two main datasets in this study. The Place Pulse 2.0 dataset was used to train the DCNN model to predict human perception (Dubey et al., 2016). In 2013, the MIT Media Lab introduced a web-based platform known as 'Place

Pulse 2.0' (Dubey et al., 2016). The purpose of this platform is to gather people's opinions about urban areas by presenting them with two street view images from different cities side-by-side. Participants are asked to select the image that they believe best represents a particular quality, such as 'beautiful', 'safe', 'lively', 'wealthy', 'boring' or 'depressing'. The platform's goal is to collect data on how individuals perceive different aspects of urban environments. The dataset contains 110,988 street view images captured between 2007 and 2012 covering a diversity of 56 cities across 6 continents, e.g. New York, Singapore, Kyoto, and Glasgow. The images were randomly and densely sampled from each city's spatial region, and the dataset includes meta-data such as geo-coordinates and camera heading degrees. As of October 2016, the dataset had collected 1,169,078 pairwise comparisons from 81,630 online participants (Dubey et al., 2016).

3.3. Street view images for public housing neighborhoods of New York City and Singapore

Corresponding to the Place Pulse 2.0 dataset, a custom dataset was prepared. This dataset was used as input for a pre-trained DCNN model that aims to predict the human perception of targeted neighborhoods within New York City and Singapore. To ensure that all images accurately depicted the environment within public housing neighborhoods, sample points for retrieving GSV images were generated every 300 meters along residential or similar categories of road networks (e.g., service road, tertiary road) from OpenStreetMap (OSM). This was done for both cities. Those sample points were inputted into the GSV Application Programming Interface (API) to download the related panorama images. The metadata for each panorama image contained a unique panorama ID, latitude, longitude, timestamp (year and month it was taken), and input latitude and longitude data indicating which sample point the image was retrieved from. A total of 141,294 images were retrieved for New York City, and 45,247 images for Singapore.

Quality check for the custom dataset. Given the nature of the Google Street View (GSV) platform, it is possible that not all targeted neighborhoods within a city will be covered in a particular year due to the image capture schedule. This poses a challenge in ensuring the representativeness of the dataset for analysis. Therefore, it is necessary to perform a quality check to assess the spatial and temporal distribution of all retrieved panorama images. The quality check process involves evaluating the availability of panorama images across different neighborhoods and time periods, to ensure that the dataset is not heavily biased towards a particular region or period. This approach helps to ensure that the dataset is representative of the targeted neighborhoods and provides a reliable basis for analysis. To illustrate the results of the quality check, Fig. A.12a for New York City and fig. A.12b for

Singapore are presented and can be found in Appendix. Upon examining these figures, it was found that the year 2015 to 2023 showed a relatively higher spatial coverage of GSV images compared to other years. This suggests that these years have a more comprehensive representation of the targeted neighborhoods, and are therefore more suitable for use in our study. As a result, the year 2015 to 2023 was chosen as the time frame for this study.

Custom dataset prepossessing. The street view images are captured from a panoramic perspective, allowing for different directional views to be captured from the same location. To meet the requirements of the machine learning model and minimize distortion in the analyzed images, the panoramic images will be divided into six planar images, corresponding to the front, back, left, right, top, and bottom directions. The top and bottom images will be excluded as they represent the sky and ground, respectively, and are not relevant to this study. After segmentation, each panoramic image was divided into four images with distinct orientations, and each of these four images was assigned a score, in line with the usual practices (Biljecki et al., 2023).

3.4. Deep learning of street view images to estimate neighborhood quality

The previous subsection outlined how the dataset for modeling and predicting human perception of the urban environment was prepared. In the following subsection, the modeling process for human perception will be described. The goal of the machine learning model is to predict the human perception score of a given image along six perceptual indicators, which include, 'safety', 'liveliness', 'boredom', 'wealth', 'depression', and 'beauty'.

Selection of deep learning model. Among all the models that can extract information from nature images, deep convolutional neural network (DCNN)-based models have better performance than others, as they are able to extract high-level information (Zhang et al., 2021). In this study, a DCNN model based on the deep residual network (ResNet) was used, which has been successfully employed in similar studies (Zhang et al., 2018; Wei et al., 2022). While most similar studies use ResNet50, this study will employ ResNet101, which is one of the best-performing convolutional neural network (CNN) models for image recognition tasks. ResNet101 is a deep neural network with 101 layers, making it capable of learning complex and high-level features from input images. The additional layers allow the model to extract more abstract and nuanced features, which can be particularly useful for predicting human perception scores.

Model training and human perception prediction. The ResNet101 architecture was visualized in Fig.1 for use in binary classification. The labels for the dataset were assigned based on the first and last 5 percentiles of scores, with samples scoring greater than 95% labeled as positive and those scoring less than 5% labeled as negative. The intermediate scores were excluded from the labeling approach, in order to avoid errors due to perceptual differences. Inverted labels were used for two specific negative perceptual indicators, 'depressing' and 'boring', samples were labeled as positive with a score less than 5%, and negative with a score greater than 95%. Therefore, to avoid confusion, the label 'depressing' will be changed to 'cheerful', and 'boring' will be rephrased as 'interesting'. With this labeling approach, a well-defined dataset was created for training and testing the ResNet101 architecture.

The training set consisted of 70% of the data, while the test set consisted of the remaining 30%. The model has shown promising accuracy rates in predicting human perception across various aspects. In particular, it performed well in assessing safety (73.3%), liveliness (73.0%), and beauty (71.0%). While the accuracy was slightly lower for other aspects, the results are still comparable to similar studies (Zhang et al., 2018). The model achieved an accuracy of 68.6% for wealth, 64.1% for cheerfulness, and 61.2% for interestingness. In general, the findings suggest that the model is a reliable tool for predicting human perception, with high accuracy rates in several important domains.

3.5. Spatial and Temporal Analytical Methods for the Model Output

3.5.1. Model output and selection of spatial analysis units

Data structure of the model output. As mentioned previously, to optimize machine learning and reduce distortion, panoramic street view images were divided into six planar images, including front, back, left, right, top, and bottom, but only the first four were used and assigned scores. Each of these four views was scored separately by the model in 6 aspects to provide a more comprehensive analysis of the scene. To reduce potential scoring errors, the four sets of scores for each image are then averaged together. This process helped to smooth out any inconsistencies or biases that may be present in individual scores and to provide a more accurate overall score for each image. Additionally, the averaging is performed at the level of the parent image ID. This means that all four scores for each panoramic image captured at the same coordinate were grouped together and averaged to provide a single score for that location. This further helps to reduce scoring errors and provides a more accurate representation of the scene at each coordinate. Subsequently, each scored panorama ID was associated with its corresponding coordinates and timestamp to facilitate subsequent analysis.

Spatial unit for analysis. To analyze the data, a spatial unit is required as the scores are spatially distributed in the form of points. A hexagonal grid of 300×300 meters (Singapore) and 500×500 meters (New York City) was created to accommodate the points. In the case of Singapore, as there is no official public housing neighborhood boundary provided, the grid was generated based on the 200-meter buffer coverage of public housing car park locations provided by the Housing Development Board (HDB). Car parks are provided in every public housing neighborhood in Singapore, with 2-3 blocks each having a car park. Hence, using the car park buffer is the best way to ensure the generated hexagon covers all public housing neighborhoods. In Singapore, a total of 2,101 research units were generated. As for New York City, the neighborhood boundary was readily available and provided by the NYC Housing Authority (NYCHA) in the open data portal. Hence, this boundary was directly utilized to generate the hexagonal grid. A total of 705 research units were created in New York City.

3.5.2. Spatial variations: Getis-Ord Gi Statistic*

To investigate whether public housing neighborhoods have equal environmental quality, this study calculated the average human perception score across six different aspects from 2015 to 2022. To identify spatial clustering of high and low scores, the Getis-Ord Gi* statistic was used. This statistic produces Z-scores and P-values, which help to determine the statistical significance of the clustering of higher values (hotspots) for each aspect of human perception scores (Ghodousi et al., 2020).

For statistically significant positive Z-scores, larger Z-scores indicate stronger clustering of higher values (hotspots). These hotspots identify neighborhoods that perform remarkably better than others in terms of human perception of visual environmental quality. Conversely, lower Z-scores indicate stronger clustering of lower values (coldspots), which identify neighborhoods that perform remarkably worse than others.

3.5.3. Spatial-temporal variations: Calculation of the Changing Score

To answer the second research question, we analyzed the change in multiple perception indicators over time, aggregated by different periods of time. Based on the analysis of the time distribution of the images captured in Singapore and New York City, it is apparent that the years 2015, 2018, and 2021 have the highest density of images (Figure A.12). Consequently, to perform a more detailed temporal analysis for this study, the time frame has been subdivided into three distinct periods: period 1, which spans from 2015 to 2017; period 2, which encompasses 2018 to 2020; and period 3, which ranges from 2021 to 2023. This categorization tackles temporal variations in data availability and allows for a more refined analysis of the changes that have occurred in Singapore and New York City over time.

To assess the visual environment quality of public housing neighborhoods, a calculation was performed to determine the difference in quality indicators between the current period and the previous period. The indicators of interest are denoted by $L_{i,m}$, where i represents the observation and m is the index of the indicator. Let P_j denote the periods, where $j = 1, 2, 3$, and let Ik denote the unique group identifiers (e.g., id). The objective is to compute the average difference in each indicator, Li, m, between consecutive periods for each group I_k. To achieve this, we first calculated the average value of each indicator within each period for every group. Next, we computed the differences between the averages of consecutive periods. Finally, we calculated the overall mean of these differences for each indicator. The formula to calculate the average difference for the m-th indicator between consecutive periods (1, 2, and 3) for each group is as follows:

$$\overline{\Delta L_m} = \frac{1}{N} \sum_{k} \sum_{j=2}^{3} \left(\frac{1}{n_{kj}} \sum_{i \in I_k, P_j} L_{i,m} - \frac{1}{n_{k(j-1)}} \sum_{i \in I_k, P_{j-1}} L_{i,m} \right) \tag{1}$$

In this formula, N is the total number of unique group identifiers, and n_{kj} is the number of observations for group k in period j. The outer summation iterates over all unique group identifiers I_k, while the inner summation covers the periods P_j from 2 to 3. The formula computes the mean of the differences in the m-th indicator values between consecutive periods for each group.

The output for each perception aspect was then used to determine whether a neighborhood was experiencing a decline, improvement, or was stable in terms of visual environment quality. Specifically, a neighborhood was considered to be in a possible decline if the ΔL_m was below -0.1, an improvement if it was above 0.1, and a stable situation if it fell between -0.1 and 0.1.

To summarise all the sections above, the overall workflow of our study is shown in Fig. 1.

4. Results

The focus of this section is on the analysis of the output human perception scores produced by the Deep Convolutional Neural Network (DCNN) model. We utilized several methods to analyze them at both spatial and temporal scales. By examining these scores using different methods and scales, the variations and changes

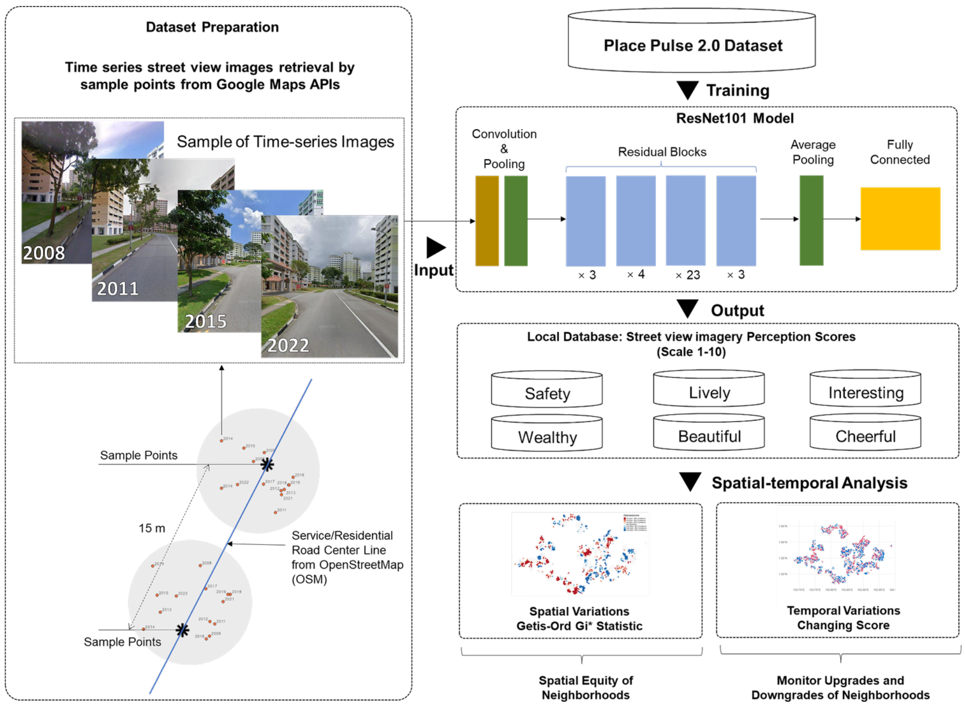


Figure 1: Overall framework of the study. Source of the imagery: Google Street View.

within targeted public housing neighborhoods in both cities were effectively captured and analyzed. Through this analysis, insights into the features and characteristics of these neighborhoods were identified to be useful for making informed policy decisions and improving the quality of life for public housing residents.

4.1. *Spatial Equity of Public Housing neighborhoods*

4.1.1. *High/low Clustering Analysis of Different Visual Environmental Quality Variables*

First, we focused on understanding the equity of neighborhoods. The findings presented in Fig. 2 and Fig. 3 are informative, as they indicate the diverse human perceptions of neighborhoods across Singapore and New York City respectively. In particular, these results revealed that distinct neighborhoods elicit unique perceptions across multiple dimensions.

For the Singapore case, one observation is that neighborhoods in the eastern part of the city tend to be perceived as more intriguing and lively compared to their western counterparts. This trend is evident in the perception scores for interestingness and liveliness, which display a clustering of higher scores in the east. More-

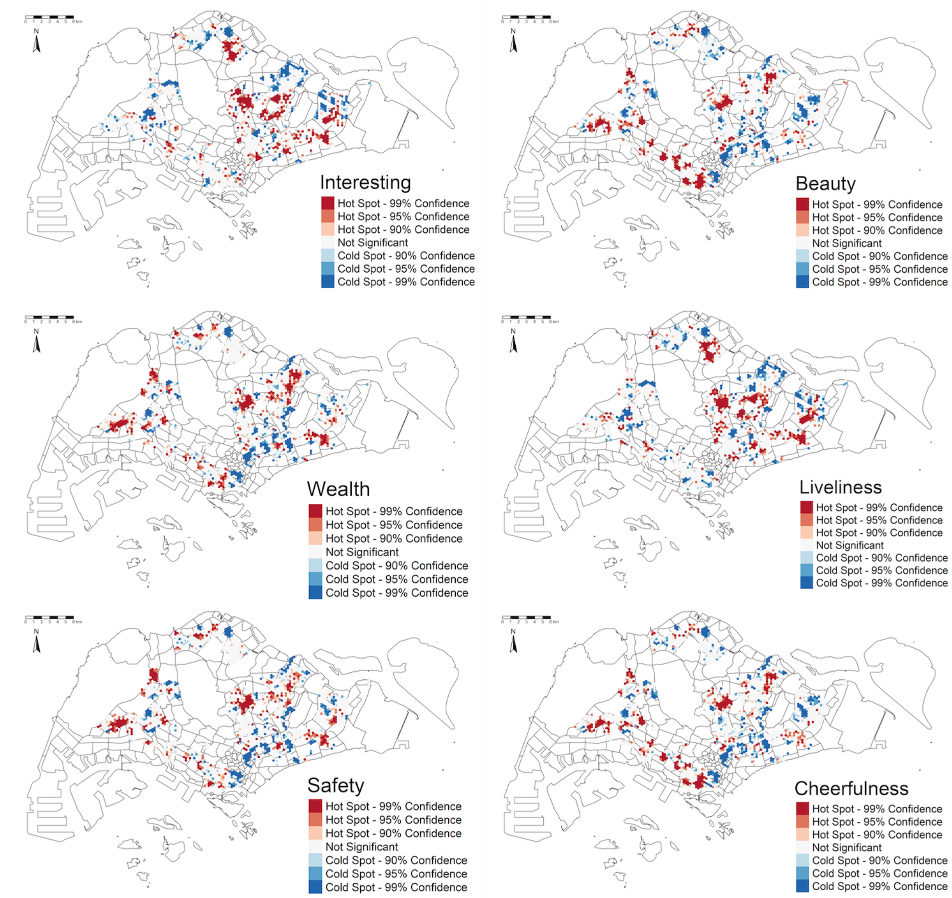


Figure 2: Result of Getis-Ord Gi* statistic that shows the hot and cold spot for each indicator in Singapore

over, this finding also reveals a clear association between the perceived beauty of a neighborhood and its perceived level of cheerfulness. The clustering pattern of perception scores for these two dimensions is highly similar, indicating that neighborhoods perceived as more 'beautiful' are also perceived as 'cheerful'. This insight suggests that aesthetic qualities and mental well-being are perhaps intertwined and that enhancing the visual appeal of a neighborhood could create positive impacts on the mental health of its residents. Additionally, the perception scores for wealth and safety also demonstrate a similar clustering pattern, indicating that neighborhoods perceived as wealthier are also perceived as safer. This finding might underscore the importance of a neighborhood's visual appearance in shaping perceptions of its safety and prosperity.

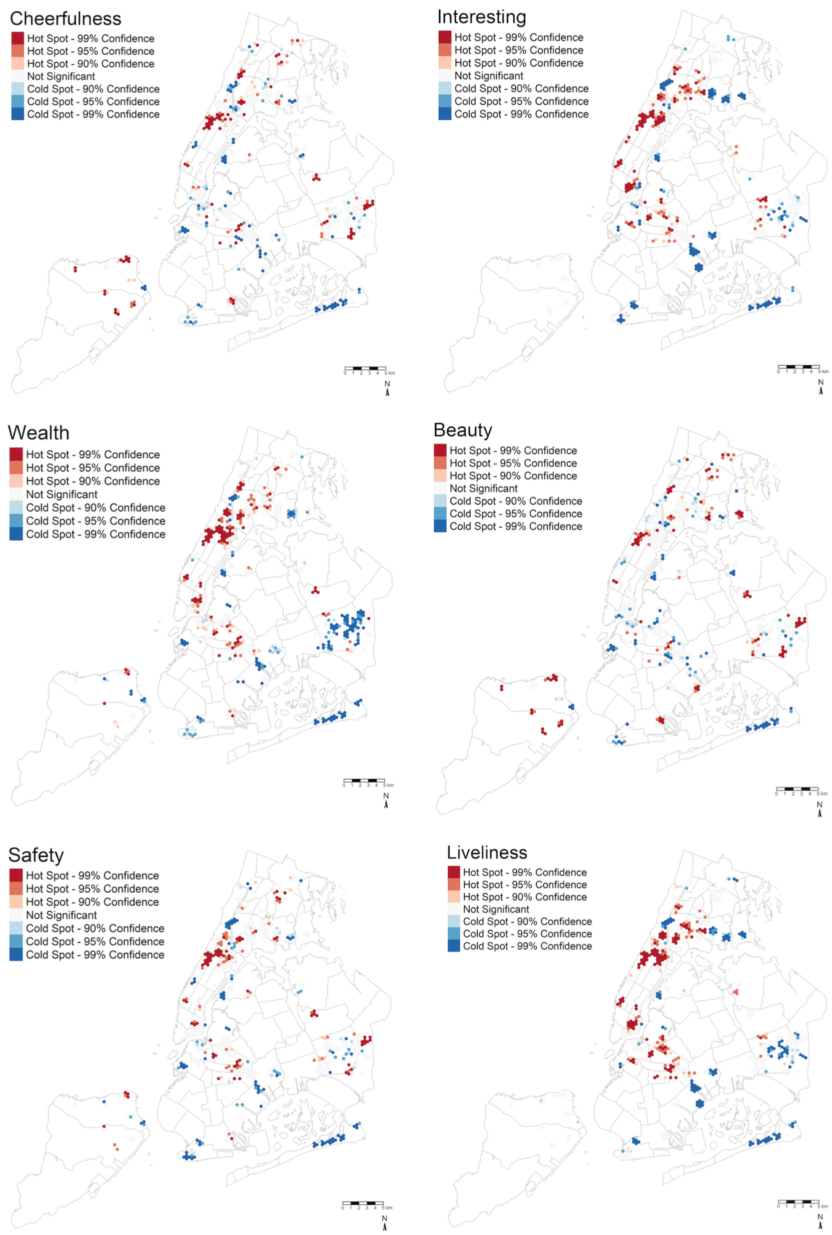


Figure 3: Result of Getis-Ord Gi* statistic that shows the hot and cold spot for each indicator in New York City

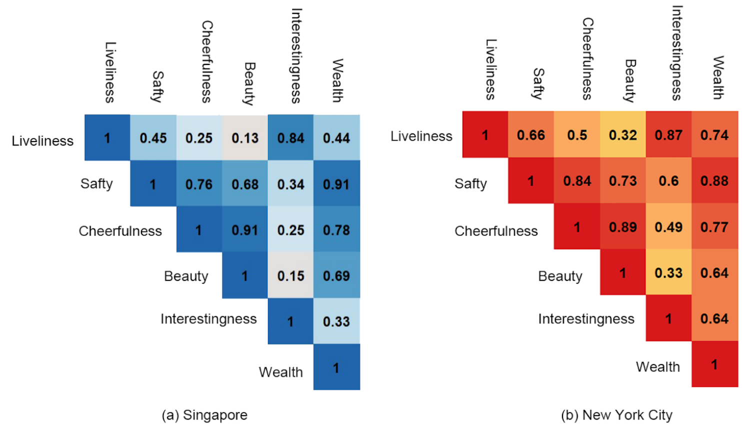


Figure 4: Correlation Matrix for each human perception aspect for each neighborhood.

As for the perception indicators in New York City, it is clear that a noticeable number of residential neighborhoods situated in the borough of Manhattan and the northern section of Brooklyn exhibit clustering of higher scores. While the clusters of lower scores were mostly observed in the north-eastern part of the Bronx and the south-eastern part of Queens.

A correlation matrix was used to further support the above-mentioned findings. Based on the correlation matrix (Fig. 4), it was found that public housing neighborhoods in both cities that are perceived as lively are more likely to be considered as ‘interesting’ but may not necessarily be ‘beautiful’. Similarly, neighborhoods perceived as safe may perform equally well in being ‘cheerful’, ‘beautiful’, and ‘wealthy’, but may be considered less ‘interesting’. On the other hand, neighborhoods perceived as ‘cheerful’ are also likely to score higher in terms of beauty and wealth. These findings suggest that there are plausibly complex and nuanced relationships between different perceptions of neighborhood qualities, and further research is needed to fully understand these relationships.

4.2. Spatio-temporal evolution of public housing neighborhood visual environmental quality

Section 4.1 explores spatial differences in the quality of the visual environment in public housing neighborhoods. This section introduces the temporal scale to further investigate how the visual environment quality evolves over time and space. Temporal scales play an important role in assessing the visual environment qualities of public housing neighborhoods, as some may deteriorate due to a lack of maintenance over time. Government or stakeholder-led projects that aim to upgrade and enhance public housing neighborhoods take several years to implement, and their effectiveness needs to be continuously monitored and evaluated after completion. Therefore, we compared differences in the visual environment quality scores of individual neighborhoods between different time periods calculated by 1 for both cities and evaluate the spatial extent of the Singapore Government's neighborhood upgrading programs to assess whether they have improved the visual environment quality of neighborhoods. Additionally, the study aims to explore outstanding factors that may have influenced the visual environment quality scores, to guide future neighborhood upgrading programs.

4.2.1. Getting Better or Worse Over Time: Evidence from the Scores

Singapore Case. Fig. 5 depicts changes in visual environment quality indicators for Singapore's public housing neighborhoods from 2015 to 2023, both over time and space. The analysis of the indicators, including 'interesting', 'cheerful', and 'beautiful', suggests that, visually, most public housing neighborhoods in Singapore have remained stable over the period. The graph provides visual evidence that there were no notable changes in these indicators for most neighborhoods between 2015 and 2023, implying that residents in these neighborhoods likely experienced consistent levels of these indicators over the period. However, the other three indicators of 'wealth', 'vibrancy', and 'safety' show relatively large fluctuations in neighborhood scores over time for different areas. Notably, for all three indicators, the spatial distribution of neighborhoods with worsening and improving visual environment quality shows some similarities. Improvements are more likely to be found in relatively young neighborhoods, such as Canberra, the north-western part of Punggol, and the western part of Bukit Batok, where development was mostly completed in 2015 or later. On the other hand, visually worsened neighborhoods are concentrated in older areas, such as Boon Lay, Ang Mo Kio, Bukit Merah North, and Tampines West. In summary, Fig. 5 demonstrates that visual environment quality indicators have remained stable in most public housing neighborhoods in Singapore, while indicators related to wealth, vibrancy, and safety have fluctuated over time and across different locations. The result suggests that the age of the neighborhood and the timing of development may influence changes in these indicators.

To further illustrate these changes, Fig. 6 displays original SVIs of neighborhoods that experienced noticeable improvements or declines in specific indicators. For instance, in Singapore, the neighborhoods of Canberra and Punggol demonstrated noticeable enhancements in greenery and infrastructure, while neighborhoods such as Tampines and Boon Lay showed no noticeable changes in the built environment, with evident wear and tear in the road surface and building facades.

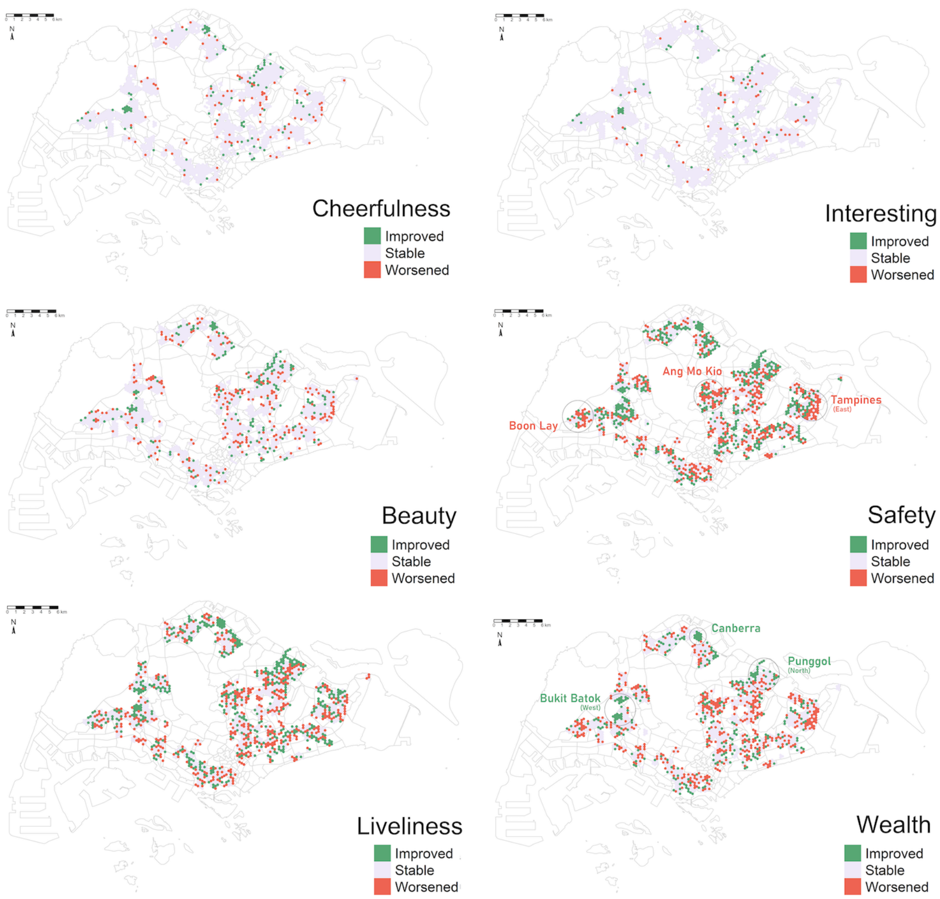


Figure 5: Temporal changes in Singapore public housing neighborhoods.

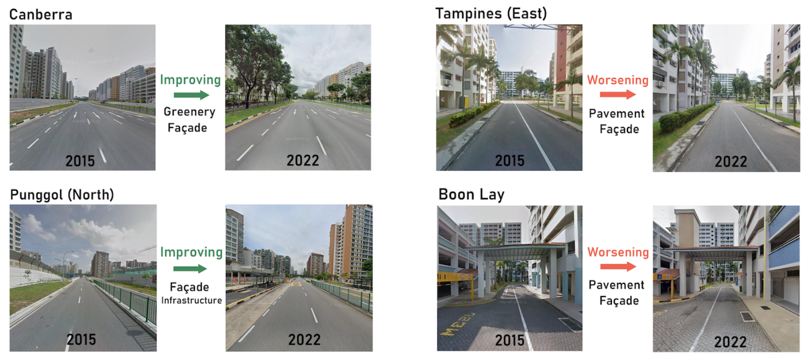


Figure 6: Examples of selected improving and worsening neighborhoods in Singapore. Source of the imagery: Google Street View.

NYC Case. Figure 7 displays the changes in indicators of visual environmental quality for public housing neighborhoods in New York City from 2015 to 2023, taking into account both time and space. A consistent pattern was observed in both the upgrading and downgrading trends of the six perception indicators, with neighborhoods experiencing similar changes being located in the same geographic areas. Those neighborhoods classified as downgraded were typically situated in the northern and eastern regions of the Bronx, with a few estates in Staten Island, while the improving or stable neighborhoods were mainly located in the southern part of the Bronx, Manhattan, and the northern part of Brooklyn.

To further illustrate these changes, Fig. 8 shows the original SVIs of neighborhoods that experienced considerable improvements or losses in visual environmental quality. For example, improvements in some estates in the southern part of Manhattan can be seen in the form of newly paved roads with marked cycle paths and widened pavements. Similarly, neighborhoods located in the northern part of Brooklyn have undergone upgrades to their facades and pavements. Conversely, some neighborhoods in the east and north of the Bronx, classified as downgraded, show broken road surfaces.

In conclusion, our workflow makes it feasible and straightforward to identify whether there are positive or negative changes occurring in a given area.

4.2.2. Monitor the effectiveness of Public Housing Neighborhood Upgrading Program: the Singapore case

As mentioned in the previous section, the age of public housing neighborhoods may have an impact on their visual environment quality indicators. To address this, the Singapore government has introduced the Neighborhood Renewal Programme

Figure 7: Examples of selected improving and worsening neighborhoods in New York City. Source of the imagery: Google Street View.

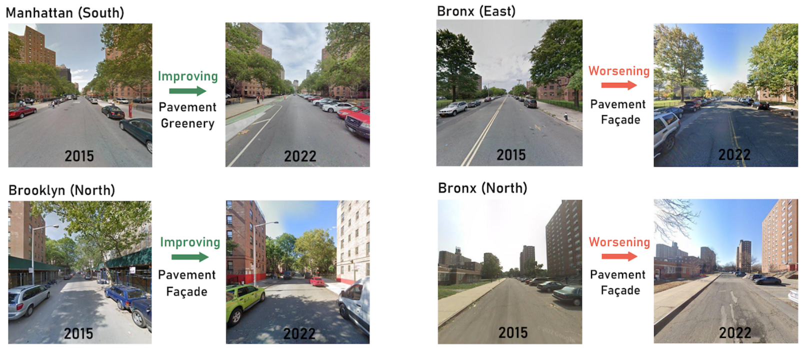


Figure 8: Examples of selected improving and worsening neighborhoods in New York City. Source of the imagery: Google Street View.

(NRP), which focuses on block and precinct improvements and is fully funded by the government. Eligible blocks include those built up to 1995, and each NRP project involves two or more precincts, allowing for comprehensive improvements with better coordination and integration across neighboring precincts (Housing & Development Board, 2015). The NRP aims to provide a greater variety of enhancements to meet the needs of residents, and improvements will be made at both the block and precinct levels. Major improvements include adding seating areas at void decks, covered linkways, new footpaths, jogging tracks, and general landscaping to improve barrier-free accessibility. In general, the NRP is an important initiative in improving the visual environment quality indicators of relatively older public housing neighborhoods in Singapore. This section aims to evaluate the effectiveness of the NRP using an established workflow and identify specific improvements that have a noticeable impact on the visual environmental quality within public housing neighborhoods using Singapore as a case study.

The Singapore Open Data Portal publicly provides all the spatial boundaries of neighborhoods that have undergone or are planned to undergo the Neighborhood Renewal Programme (NRP) as of 2020. This dataset includes the status of each targeted neighborhood, indicating whether it is a proposed or under-construction project, as well as other information such as the start and estimated end dates of the project. Between 2014 and 2022, a total of 92 neighborhoods have undergone or planned to undergo NRP, with 56 of them classified as under construction and set to be completed by 2022. However, to minimize the negative impact of the construction periods on scoring, only the neighborhoods that started improvement in 2017 and ended in 2020 will be considered and analyzed in the following paragraphs as a case study. The scores generated from images taken between 2015 and

2017 will be used to describe the condition before the NRP, while scores generated from images taken between 2020 and 2022 will be used to describe the condition after the NRP. Out of the 56 neighborhoods, 23 were eligible for inclusion in the analysis.

To investigate the impact of the NRP on the comprehensive visual environmental quality of neighborhoods, a control group consisting of all the neighborhoods eligible for NRP (built before 1995) but not yet implemented was established. The key to quantifying the overall environmental quality of neighborhoods is to aggregate the scores across different indicators (on a scale of 0 to 10), each indicator was given the same weight, resulting in a general score that can range from 0 to 60. The results are presented in the form of violin plots (Fig. 9), which compare the overall environmental quality scores (on a scale of 0-60) for the neighborhoods that have undergone NRP and those that have not, before and after the NRP implementation. In addition, we have employed the Wilcoxon Rank-Sum Test to ascertain whether there is a significant distinction between the score distributions before and after the NRP within both the ”Treated” and ”Non-Treated” groups. The results show that there was a certain degree of decline in the average scores of neighborhoods that did not undergo NRP (Wilcoxon Rank-Sum Test, p-value 3.367e-11). Specifically, the number of neighborhoods with high scores (35-40) noticeably decreased, and the median score decreased substantially. Interestingly, the frequency distribution of overall scores for neighborhoods that underwent NRP became more concentrated (Wilcoxon Rank-Sum Test, p-value 0.004942), and although the median score decreased to some extent, the frequency of neighborhoods with low scores (25-30) decreased substantially. This indicates that the implementation of NRP can partially prevent the deterioration of the neighborhood's visual environment and reduce the differences between neighborhoods, but it may also lead to most neighborhoods converging towards a similar score probably due to its standardized renovation scheme.

A noticeable improvement in overall scores across various indicators (greater than before by more than 3) was achieved by neighborhoods that underwent the NRP, which were subsequently identified. This finding affirms the validity of our approach, as its results are consistent with the improvement program. To better understand the factors that contributed to this improvement, the original street view images of these neighborhoods were traced back and analyzed, as shown in Fig. 10. It can be observed from these examples that the visual environmental quality of public housing neighborhoods in Singapore was enhanced through improvements in three aspects, namely, enhanced greenery, repainted facades, and upgraded pavements, which has been confirmed automatically with our method. For future research, it would be interesting to integrate SVI with demographic and socio-economic data, exploring the socio-economic profiles of selected neighborhoods for the NRP compared to those not selected and potential factors that have associations with the degree of observed improvements.

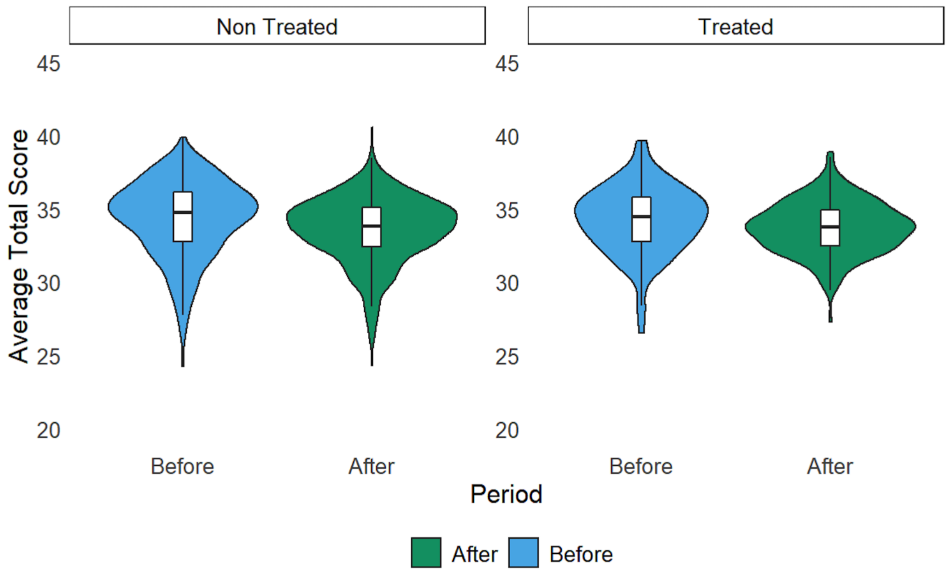


Figure 9: Comparing neighborhoods treated with improvement program and those without. Our approach is able to confirm the improvements.

5. Discussion

5.1. Significance and applications

Public housing neighborhoods have often been overlooked despite being home to disadvantaged populations that are more vulnerable to the effects of political and socio-economic factors that may lead to a lack of maintenance and environmental enhancement. Such may be worth more attention than other housing types. The lack of a quantitative and large-scale evaluation method to continuously monitor and analyze neighborhoods may result in continuing low levels of resident satisfaction, which can have negative impacts on their well-being. To address this issue, we developed a workflow that leverages time series street view imagery and deep learning technologies to enable a large-scale and longitudinal estimation of the visual environmental quality of neighborhoods in different cities, focusing on public housing as a case study. By doing so, the workflow used in this study provides a comprehensive and objective evaluation of the built environment that can facilitate evidence-based decision-making in urban planning and design, ultimately improving the well-being of residents. Empirically, it was found that for Singapore and

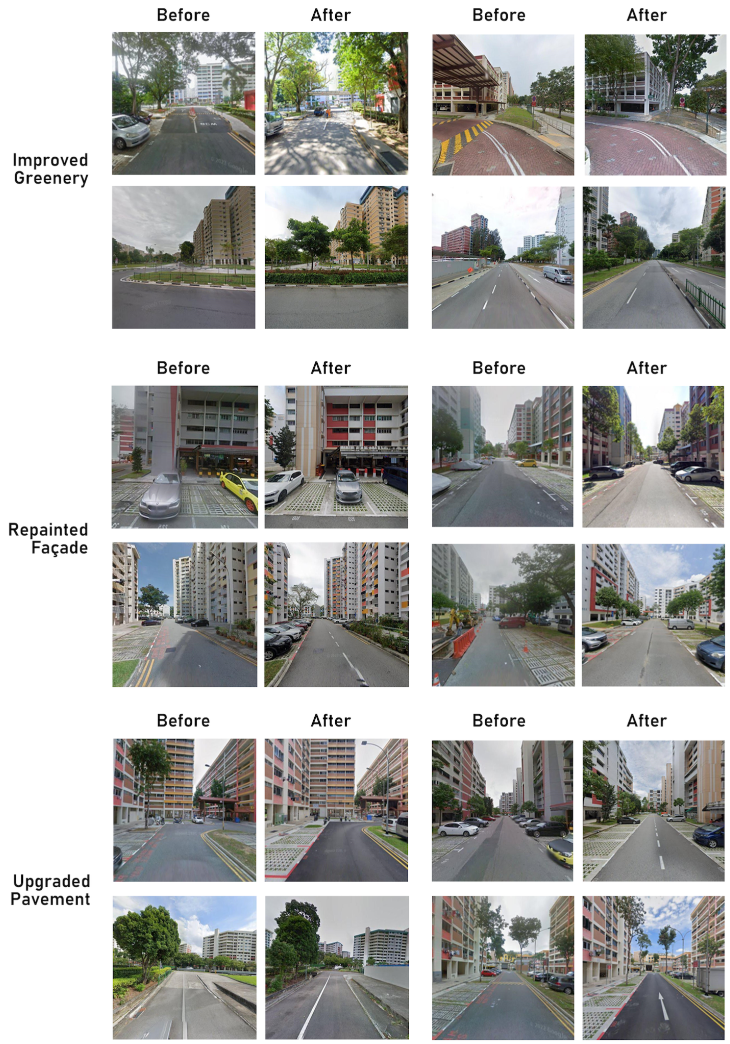


Figure 10: Evidence what are the factors that may contribute to the improvement based on the model that we used. Source: Google Street View.

New York City, public housing neighborhoods exhibit distinct differences over both space and time, and the workflow of our study demonstrated to be able to detect the changes at the neighborhood level and, in a way, be an effective alternative to the exiting inspecting methods such as field observations or surveys.

5.2. Challenges and limitations

Bias in Place Pulse 2.0 dataset and DCNN model accuracy. In this study, the DCNN model was trained using the Place Pulse 2.0 dataset, which is publicly available. While the dataset encompasses various countries and regions of the world and recruited participants from all over the world to rate the provided SVI, the lack of disclosure of participants' demographic information, such as age and nationality, may lead to biased models for particular countries (Kang et al., 2023). In addition, the model lacks local knowledge as well. To improve the accuracy of the model, we adjusted the ratio of the training set to the test set, but the prediction accuracy of the model still remains low for the three indicators of wealth, cheerfulness, and interestingness. The low accuracy of the model leads to a lack of differentiation in the predicted scores of some indicators, such as the 'cheerful' and 'interesting' indicators, as shown in Fig. 5 of this paper. This issue affects the strength of the interpretation of the model prediction results. Nevertheless, our primary focus was to demonstrate a model-agnostic approach to assess residential neighborhoods' visual qualities at a large scale, and we believe that the methodology and results presented in this study provide a foundation for future research to improve the accuracy and applicability of such DCNN models. While it is important to acknowledge the potential drawbacks and limitations of any dataset, it is equally crucial to recognize the significant impact that Place Pulse has had on the field. Numerous studies, including (Rossetti et al., 2019), (Zhang et al., 2018), and (Larkin et al., 2021), have relied on this dataset to uncover valuable insights into urban environments, social dynamics, and perception biases.

Perception scores may be biased due to weather conditions or similar factors. Apart from the accuracy concerns mentioned earlier, the model's performance may also be impacted by biases when scoring the new input data set. As depicted in Fig. 11, for the same location, a neighborhood in Singapore that has not undergone noticeable visual changes, but due to weather variations (clear in 2022 and cloudy in 2015) results in a considerably higher score in 2022 than in 2015. There are instances where a neighborhood in New York City may not have undergone any visible changes, but the images taken during winter may receive a lower score compared to those taken during summer due to differences in greenery conditions. This may undermine the reliability of the time series variation results to some extent. However, we have taken steps to address this issue by averaging the scores for the same location from neighboring years, with each period usually consisting of three years. Additionally, to further minimize the bias caused by different image conditions, a single panorama image is divided into four different directions, and each direction is rated individually before being averaged. These measures have been taken to ensure that our results are as reliable and accurate as possible.

Transferability to other cities. Time series SVI is not available everywhere for all periods. In this study, we used data from Google Street View in Singapore and New York City. In previous sections, we analyzed the temporal and spatial availability of them in both cities. The analysis showed that there were years in which some city areas had no collected images. To mitigate the impact of missing images on our study results, we divided the period between 2015 and 2023 into three three-year cycles based on image availability and averaged the image scores from different areas across the three cycles. However, for future research aiming to improve temporal resolution (e.g., using one-year cycles), a more complete dataset with better temporal and spatial coverage will be needed. Additionally, both Singapore and New York City have public roads that provide access to public housing neighborhoods, allowing us to capture images within the neighborhoods. However, for cities without public roads leading into public housing neighborhoods, Google Street View images used in this study may not cover the interior of these neighborhoods. For such cities, crowdsourced SVI platforms, such as Mapillary or KartaView, which collect images not limited to motor vehicle lanes (Chen and Biljecki, 2023), may be used instead.

Drawbacks of the use of SVI indicators only. In this study, we focused solely on the SVI indicators as a means of assessing the visual environmental qualities of public housing neighborhoods. However, we recognize that non-SVI indicators, such as POI data, could provide valuable insights into the vibrancy of a neighborhood and contribute to a more comprehensive understanding of its overall visual environmental quality. As such, in future studies, we recommend developing a more comprehensive index system that includes both SVI and non-SVI indicators to provide a more complete and nuanced picture of the visual environment in public housing neighborhoods.

6. Conclusion

In previous studies, it has been a challenge to monitor and evaluate residential neighborhood environmental qualities over space and time in a timely and low-cost manner. There is a very limited number of studies that have used time series SVI and deep learning techniques, and none of them has quantitatively and automatically scored the environmental qualities of residential neighborhoods. The study demonstrated that it is possible to use time series street view imagery and deep learning models to monitor the environmental quality improvement within public housing neighborhoods in Singapore and New York City.

The research questions that were addressed in this study focused on differences in the quality of public housing neighborhoods located in different parts of the city

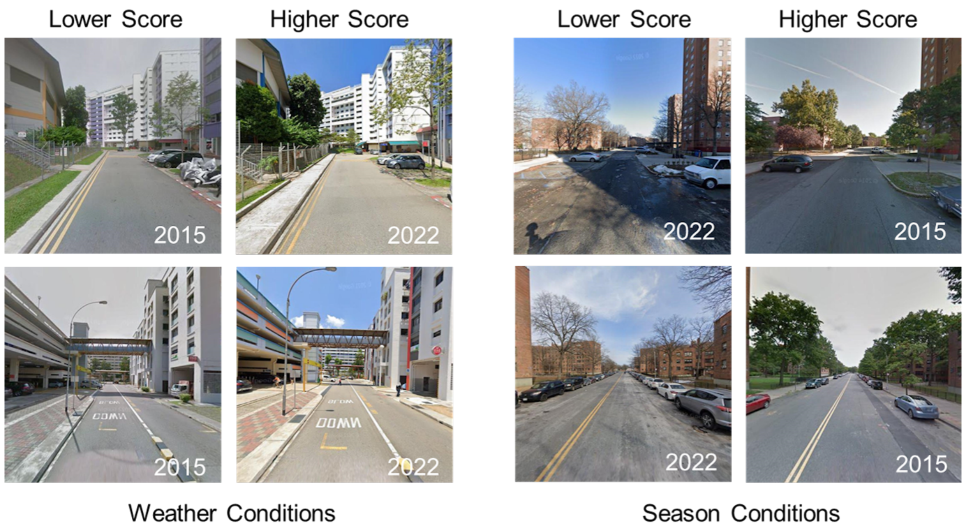


Figure 11: Evidence that there may be biased by the weather and seasonal conditions. In the case of these locations, which were not subject to any significant change, the model outputs different scores due to different cyclical conditions affecting the visual perception.

during the same period of time and whether there was an improvement in the environmental quality of the same public housing neighborhoods over time. The study yielded several findings. First, for spatial variation, it was found that neighborhoods in the eastern part of Singapore tend to be perceived as more intriguing and lively compared to their western counterparts. This trend is evident in the perception scores for boredom and liveliness, which display a noticeable clustering of higher scores in the east. For New York City, different patterns across boroughs also be observed. Secondly, for spatial-temporal variation, the study found that visual environment quality indicators such as 'interesting', 'beautiful', and 'cheerful' have remained stable in most public housing neighborhoods in Singapore, while indicators related to wealth, vibrancy, and safety have fluctuated over time and across different locations. While for New York City, all indicators show a similar spatial-temporal pattern. In addition, the implementation of the Neighborhood Renewal Programme (NRP) prevented the deterioration of the neighborhood's visual environment, reduced the differences between neighborhoods, and led to most neighborhoods converging towards a similar score. The visual environmental quality of public housing neighborhoods in Singapore was enhanced through improvements in three aspects, namely, enhanced greenery, repainted facades, and upgraded pavements.

This study contributes to the broader body of knowledge by providing evidence that it is possible to use time series street view imagery and deep learning models to monitor and evaluate changes in the environmental qualities of residential neighborhoods over space and time. In addition, we have found that the weather or seasonal conditions shown in the input images will influence the judgment of the model, seconding similar findings in other domains that use SVI (Chiang et al., 2023; Han et al., 2023). Based on the findings and limitations of this study, future research should focus not only on overcoming the challenges discussed in the previous section but also on finding a comprehensive index system that does not solely rely on SVI indicators to monitor the visual environmental quality of residential neighborhoods, which allows for less bias and a more comprehensive understanding.

Acknowledgements

We thank the members of the NUS Urban Analytics Lab for the discussions. The second author has been funded by the Agency for Science, Technology, and Research (A*STAR) and the National University of Singapore (NUS) through the Singapore International Graduate Award (SINGA) scholarship. This research is part of the project Large-scale 3D Geospatial Data for Urban Analytics, which is supported by the National University of Singapore under the Start Up Grant R-295-000-171-133.

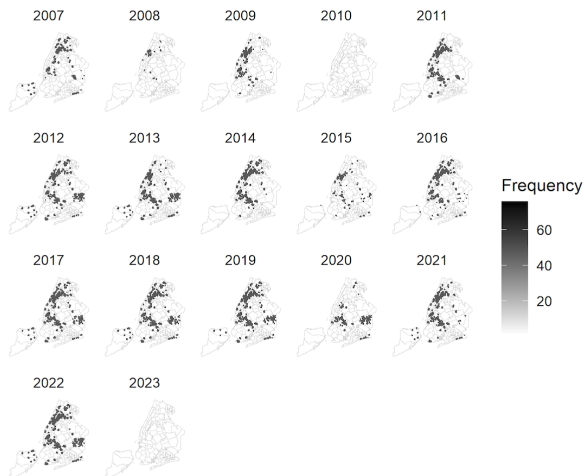
Appendix A. Quality check of the custom data set

Figure A.12 shows the spatio-temporal distribution of images retrieved from Google Street View, an important part of our data exploratory analysis.

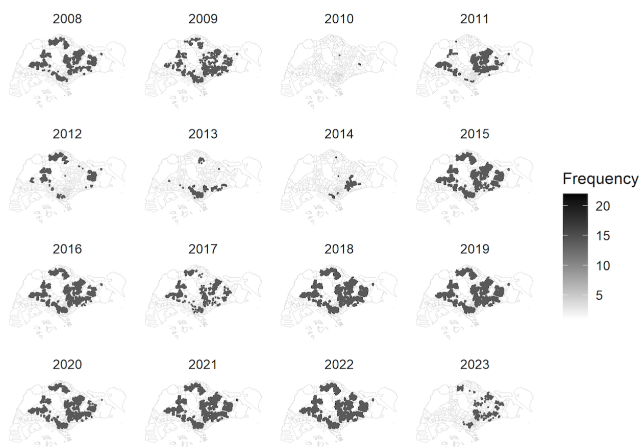
References

Adamkiewicz, G., Zota, A. R., Fabian, M. P., Chahine, T., Julien, R., Spengler, J. D., and Levy, J. I. (2011). Moving Environmental Justice Indoors: Understanding Structural Influences on Residential Exposure Patterns in Low-Income Communities. *American Journal of Public Health*, 101(S1):S238–S245. Publisher: American Public Health Association.

Anguelov, D., Dulong, C., Filip, D., Frueh, C., Lafon, S., Lyon, R., Ogale, A., Vincent, L., and Weaver, J. (2010). Google Street View: Capturing the World at Street Level. *Computer*, 43(6):32–38. Conference Name: Computer.



(a) New York City



(b) Singapore

Figure A.12: Spatial and temporal distribution of retrieved historical SVIs. The frequency represents the number of images in each cell.

Apparicio, P., Séguin, A.-M., and Naud, D. (2008). The Quality of the Urban Environment Around Public Housing Buildings in Montréal: An Objective Approach Based on GIS and Multivariate Statistical Analysis. *Social Indicators Research*, 86(3):355–380. Company: Springer Distributor: Springer Institution: Springer Label: Springer Number: 3 Publisher: Springer Netherlands.

Beck, K. (2019). Trust and the Built Environment in New York City's Public Housing. *Sociological Perspectives*, 62(1):120–138. Publisher: SAGE Publications Inc.

Biljecki, F. and Ito, K. (2021). Street view imagery in urban analytics and GIS: A review. *Landscape and Urban Planning*, 215:104217.

Biljecki, F., Zhao, T., Liang, X., and Hou, Y. (2023). Sensitivity of measuring the urban form and greenery using street-level imagery: A comparative study of approaches and visual perspectives. *International Journal of Applied Earth Observation and Geoinformation*, 122:103385.

Burgos, S., Ruiz, P., and Koifman, R. (2013). Changes to indoor air quality as a result of relocating families from slums to public housing. *Atmospheric Environment*, 70:179–185.

Charreire, H., Mackenbach, J. D., Ouasti, M., Lakerveld, J., Compernolle, S., Ben-Rebah, M., McKee, M., Brug, J., Rutter, H., and Oppert, J. M. (2014). Using remote sensing to define environmental characteristics related to physical activity and dietary behaviours: A systematic review (the SPOTLIGHT project). *Health & Place*, 25:1–9.

Chen, S. and Biljecki, F. (2023). Automatic assessment of public open spaces using street view imagery. *Cities*, 137:104329.

Chiang, Y.-C., Liu, H.-H., Li, D., and Ho, L.-C. (2023). Quantification through deep learning of sky view factor and greenery on urban streets during hot and cool seasons. *Landscape and Urban Planning*, 232:104679.

Crawford, B. and Sainsbury, P. (2017). Opportunity or Loss? Health Impacts of Estate Renewal and the Relocation of Public Housing Residents. *Urban Policy and Research*, 35(2):137–149. Publisher: Routledge _eprint: https://doi.org/10.1080/08111146.2016.1140033.

Dadvand, P., Bartoll, X., Basagaña, X., Dalmau-Bueno, A., Martinez, D., Ambros, A., Cirach, M., Triguero-Mas, M., Gascon, M., Borrell, C., et al. (2016). Green spaces and general health: roles of mental health status, social support, and physical activity. *Environment international*, 91:161–167.

Diaz Lozano Patino, E. and Siegel, J. A. (2018). Indoor environmental quality in social housing: A literature review. *Building and Environment*, 131:231–241.

Ding, X., Fan, H., and Gong, J. (2021). Towards generating network of bikeways from Mapillary data. *Computers, Environment and Urban Systems*, 88:101632.

Dubey, A., Naik, N., Parikh, D., Raskar, R., and Hidalgo, C. A. (2016). Deep Learning the City: Quantifying Urban Perception at a Global Scale. In Leibe, B., Matas, J., Sebe, N., and Welling, M., editors, *Computer Vision – ECCV 2016*, Lecture Notes in Computer Science, pages 196–212, Cham. Springer International Publishing.

Edwards, N., Hooper, P., Trapp, G. S. A., Bull, F., Boruff, B., and Giles-Corti, B. (2013). Development of a Public Open Space Desktop Auditing Tool (POSDAT): A remote sensing approach. *Applied Geography*, 38:22–30.

Ghodousi, M., Sadeghi-Niaraki, A., Rabiee, F., and Choi, S.-M. (2020). Spatial-temporal analysis of point distribution pattern of schools using spatial autocorrelation indices in bojnourd city. *Sustainability*, 12(18):7755.

Glass, M. R. and Salvador, A. E. (2018). Remaking singapore's heartland: sustaining public housing through home and neighbourhood upgrade programmes. *International Journal of Housing Policy*, 18(3):479–490.

Goel, R., Garcia, L. M. T., Goodman, A., Johnson, R., Aldred, R., Murugesan, M., Brage, S., Bhalla, K., and Woodcock, J. (2018). Estimating city-level travel patterns using street imagery: A case study of using Google Street View in Britain. *PLOS ONE*, 13(5):e0196521. Publisher: Public Library of Science.

Greene, G., Fone, D., Farewell, D., Rodgers, S., Paranjothy, S., Carter, B., and White, J. (2020). Improving mental health through neighbourhood regeneration: the role of cohesion, belonging, quality and disorder. *European Journal of Public Health*, 30(5):964–966.

Hagelskamp, C., Silliman, R., B. Godfrey, E., and Schleifer, D. (2020). Shifting Priorities: Participatory Budgeting in New York City is Associated with Increased Investments in Schools, Street and Traffic Improvements, and Public Housing. *New Political Science*, 42(2):171–196. Publisher: Routledge _eprint: https://doi.org/10.1080/07393148.2020.1773689.

Han, Y., Zhong, T., Yeh, A. G., Zhong, X., Chen, M., and Lü, G. (2023). Mapping seasonal changes of street greenery using multi-temporal street-view images. *Sustainable Cities and Society*, 92:104498.

Hananel, R. (2017). From central to marginal: The trajectory of Israel's public-housing policy. *Urban Studies*, 54(11):2432–2447. Publisher: SAGE Publications Ltd.

Hananel, R., Krefetz, S. P., and Vatury, A. (2021). Public Housing Matters: Public Housing Policy in Sweden, the United States, and Israel. *Journal of Planning Education and Research*, 41(4):461–476. Publisher: SAGE Publications Inc.

Helbich, M., Yao, Y., Liu, Y., Zhang, J., Liu, P., and Wang, R. (2019). Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing, China. *Environment International*, 126:107–117.

Hou, Y. and Biljecki, F. (2022). A comprehensive framework for evaluating the quality of street view imagery. *International Journal of Applied Earth Observation and Geoinformation*, 115:103094.

Housing & Development Board (2015). Neighbourhood renewal programme (nrp). `https://www.hdb.gov.sg/residential/living-in-an-hdb-flat/sers-and-upgrading-programmes/upgrading-programmes/types/neighbourhood-renewal-programme-nrp`. Retrieved March 9, 2023.

Howden-Chapman, P., Matheson, A., Crane, J., Viggers, H., Cunningham, M., Blakely, T., Cunningham, C., Woodward, A., Saville-Smith, K., O'Dea, D., Kennedy, M., Baker, M., Waipara, N., Chapman, R., and Davie, G. (2007). Effect of insulating existing houses on health inequality: cluster randomised study in the community. *BMJ*, 334(7591):460. Publisher: British Medical Journal Publishing Group Section: Research.

Huang, Z. and Du, X. (2015). Assessment and determinants of residential satisfaction with public housing in Hangzhou, China. *Habitat International*, 47:218–230.

Ibem, E. O., Opoko, P. A., and Aduwo, E. B. (2017). Satisfaction with Neighbourhood Environments in Public Housing: Evidence from Ogun State, Nigeria. *Social Indicators Research*, 130(2):733–757.

Ito, K. and Biljecki, F. (2021). Assessing bikeability with street view imagery and computer vision. *Transportation Research Part C: Emerging Technologies*, 132:103371.

Jeon, J. and Woo, A. (2023). Deep learning analysis of street panorama images to evaluate the streetscape walkability of neighborhoods for subsidized families in Seoul, Korea. *Landscape and Urban Planning*, 230:104631.

Jones-Rounds, M. L., Evans, G. W., and Braubach, M. (2014). The interactive effects of housing and neighbourhood quality on psychological well-being. *J Epidemiol Community Health*, 68(2):171–175.

Juhász, L. and Hochmair, H. H. (2016). User Contribution Patterns and Completeness Evaluation of Mapillary, a Crowdsourced Street Level Photo Service. *Transactions in GIS*, 20(6):925–947.

Kabisch, N., Qureshi, S., and Haase, D. (2015). Human–environment interactions in urban green spaces—a systematic review of contemporary issues and prospects for future research. *Environmental Impact assessment review*, 50:25–34.

Kang, Y., Abraham, J., Ceccato, V., Duarte, F., Gao, S., Ljungqvist, L., Zhang, F., Näsman, P., and Ratti, C. (2023). Assessing differences in safety perceptions using GeoAI and survey across neighbourhoods in stockholm, sweden. *Landscape and Urban Planning*, 236:104768.

Kumar, V. (2019). User centric facility maintenance model for public housing. *Facilities*, 37(11/12):839–859.

Larkin, A., Gu, X., Chen, L., and Hystad, P. (2021). Predicting perceptions of the built environment using gis, satellite and street view image approaches. *Landscape and Urban Planning*, 216:104257.

Li, M., Sheng, H., Irvin, J., Chung, H., Ying, A., Sun, T., Ng, A. Y., and Rodriguez, D. A. (2022a). Marked crosswalks in US transit-oriented station areas, 2007–2020: A computer vision approach using street view imagery. *Environment and Planning B: Urban Analytics and City Science*, page 23998083221112157. Publisher: SAGE Publications Ltd STM.

Li, X. and Shamsuddin, S. (2022). Housing the poor? a comparative study of public housing provision in new york, hong kong, and shenzhen. *Housing Policy Debate*, 32(4-5):678–696.

Li, X., Zhang, C., Li, W., Kuzovkina, Y. A., and Weiner, D. (2015). Who lives in greener neighborhoods? The distribution of street greenery and its association with residents' socioeconomic conditions in Hartford, Connecticut, USA. *Urban Forestry & Urban Greening*, 14(4):751–759.

Li, Y., Peng, L., Wu, C., and Zhang, J. (2022b). Street View Imagery (SVI) in the Built Environment: A Theoretical and Systematic Review. *Buildings*, 12(8):1167. Number: 8 Publisher: Multidisciplinary Digital Publishing Institute.

Liang, X., Zhao, T., and Biljecki, F. (2023). Revealing spatio-temporal evolution of urban visual environments with street view imagery. *Landscape and Urban Planning*, 237:104802.

Lin-Heng, L. (2020). Public housing in singapore: a success story in sustainable development. In *The Impact of Environmental Law*, pages 128–153. Edward Elgar Publishing.

Liu, L., Silva, E. A., Wu, C., and Wang, H. (2017). A machine learning-based method for the large-scale evaluation of the qualities of the urban environment. *Computers, Environment and Urban Systems*, 65:113–125.

Liu, Y., Liu, X., Gao, S., Gong, L., Kang, C., Zhi, Y., Chi, G., and Shi, L. (2015). Social Sensing: A New Approach to Understanding Our Socioeconomic Environments. *Annals of the Association of American Geographers*, 105(3):512–530. Publisher: Routledge _eprint: https://doi.org/10.1080/00045608.2015.1018773.

Liu, Z. and Ma, L. (2021). Residential experiences and satisfaction of public housing renters in beijing, china: A before-after relocation assessment. *Cities*, 113:103148.

Ma, J., Dong, G., Chen, Y., and Zhang, W. (2018). Does satisfactory neighbourhood environment lead to a satisfying life? An investigation of the association between neighbourhood environment and life satisfaction in Beijing. *Cities*, 74:229–239.

Mohit, M. A. and Azim, M. (2012). Assessment of Residential Satisfaction with Public Housing in Hulhumale', Maldives. *Procedia - Social and Behavioral Sciences*, 50:756–770.

Naik, N., Philipoom, J., Raskar, R., and Hidalgo, C. (2014). Streetscore - Predicting the Perceived Safety of One Million Streetscapes. pages 779–785.

Polyakov, M., Iftekhar, M. S., Fogarty, J., and Buurman, J. (2022). Renewal of waterways in a dense city creates value for residents. *Ecological Economics*, 199:107468.

Power, E. R., Rogers, D., and Kadi, J. (2020). Public housing and COVID-19: contestation, challenge and change. *International Journal of Housing Policy*, 20(3):313–319. Publisher: Routledge _eprint: https://doi.org/10.1080/19491247.2020.1797991.

Quinn, S. and León, L. A. (2019). Every single street? Rethinking full coverage across street-level imagery platforms. *Transactions in GIS*, 23(6):1251–1272.

Rossetti, T., Lobel, H., Rocco, V., and Hurtubia, R. (2019). Explaining subjective perceptions of public spaces as a function of the built environment: A massive data approach. *Landscape and Urban Planning*, 181:169–178.

Salesses, P., Schechtner, K., and Hidalgo, C. A. (2013). The collaborative image of the city: mapping the inequality of urban perception. *PloS one*, 8(7):e68400.

Tamura, J. and Fang, K. (2022). Quality of Public Housing in Singapore: Spatial Properties of Dwellings and Domestic Lives. *Architecture*, 2(1):18–30. Number: 1 Publisher: Multidisciplinary Digital Publishing Institute.

Wang, H. and Yang, Y. (2019). Neighbourhood walkability: A review and bibliometric analysis. *Cities*, 93:43–61.

Wang, J., Chow, Y. S., and Biljecki, F. (2023). Insights in a city through the eyes of Airbnb reviews: Sensing urban characteristics from homestay guest experiences. *Cities*, 140:104399.

Wei, J., Yue, W., Li, M., and Gao, J. (2022). Mapping human perception of urban landscape from street-view images: A deep-learning approach. *International Journal of Applied Earth Observation and Geoinformation*, 112:102886.

Widya, A. T., Kusuma, H. E., and Lubis, H. A. (2023). Exploring housing quality perception and attitude groups through annoyance on vertical public-housing: online user review: case study—apartment in bandung city, indonesia. *Journal of Housing and the Built Environment*, pages 1–38.

Won, J. and Lee, J.-S. (2020). Impact of residential environments on social capital and health outcomes among public rental housing residents in seoul, south korea. *Landscape and Urban Planning*, 203:103882.

Wu, F., Liu, Y., Zeng, Y., Yan, H., Zhang, Y., and Li, L.-H. (2020). Evaluation of the Human Settlements Environment of Public Housing Community: A Case Study of Guangzhou. *Sustainability*, 12(18):7361. Number: 18 Publisher: Multidisciplinary Digital Publishing Institute.

Wyly, E. and DeFilippis, J. (2010). Mapping public housing: the case of new york city. *City & Community*, 9(1):61–86.

Yan, Y., Feng, C.-C., Huang, W., Fan, H., Wang, Y.-C., and Zipf, A. (2020). Volunteered geographic information research in the first decade: a narrative review of selected journal articles in GIScience. *International Journal of Geographical Information Science*, 34(9):1–27.

Zhang, F., Fan, Z., Kang, Y., Hu, Y., and Ratti, C. (2021). "Perception bias": Deciphering a mismatch between urban crime and perception of safety. *Landscape and Urban Planning*, 207:104003.

Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H. H., Lin, H., and Ratti, C. (2018). Measuring human perceptions of a large-scale urban region using machine learning. *Landscape and Urban Planning*, 180:148–160.

Zhang, Y., Liu, P., and Biljecki, F. (2023). Knowledge and topology: A two layer spatially dependent graph neural networks to identify urban functions with time-series street view image. *ISPRS Journal of Photogrammetry and Remote Sensing*, 198:153–168.

Zhou, H., He, S., Cai, Y., Wang, M., and Su, S. (2019). Social inequalities in neighborhood visual walkability: Using street view imagery and deep learning technologies to facilitate healthy city planning. *Sustainable Cities and Society*, 50:101605.