Tokyo Nihonbashi Visual Walkability Analysis

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Abstract:

Tokyo is one of the most densely populated cities in the world, and the high population density of urban areas requires special measures to make these areas sustainable, attractive, safe, and friendly to residents. This study combines the methods of GSV and extensive GIS data to assess the walkability of an urban area in Nihonbashi, Tokyo. These measures help us better understand the impact of street-level urban design features on the walkability of healthy urban design and planning. Signboards and greenery play a critical role in improving the visual appearance and sustainability of urban areas. However, the management and monitoring of these elements can be a challenging task for city authorities due to their vast number and geographical spread. The Google Street View (GSV) Image API provides a solution that can enhance the efficiency and effectiveness of managing these elements in the city. This proposal aims to explore how GSV can be used to achieve this objective.

Introduction:

Nihonbashi is a historic district in the heart of Tokyo that has undergone significant redevelopment in recent years. The area is a mix of traditional and modern architecture, including the famous Nihonbashi Bridge, which has connected the eastern and western parts of Tokyo since the 17th century. In recent years, the local government and community organizations in Nihonbashi have been working to improve the pedestrian environment in the area by creating more pedestrian-friendly streets, improving public transportation, and promoting bicycle use.

Visual walkability is an important concept that refers to the visual qualities of streets and neighborhoods that make them attractive and safe for pedestrians to walk. Research has shown that visual walkability is an important factor in promoting walking behavior (Li et al.,2022). For example, a study by Frank and Engelke (2001) found that people are more likely to walk in neighborhoods with aesthetically pleasing environments. Similarly, a study by Southworth and Ben-Joseph (2003) found that streets with visually attractive buildings and sidewalks had higher levels of pedestrian activity than streets with less attractive features. These findings suggest that visually appealing environments can encourage walking behavior and promote physical activity.

In addition to promoting walking behavior, visual walkability has been linked to various health benefits. A study by Chaparro et al. (2019) found that neighborhoods with high levels of visual appeal were associated with lower levels of obesity and higher levels of physical activity. The study suggested that visually appealing environments may encourage people to walk and engage in other physical activities, which can lead to better health outcomes.

Visual walkability has also been found to have social benefits. A study by Zhang et al. (2021) found that streets with visually interesting buildings and landscapes were associated with increased social interaction among pedestrians. Similarly, a study by Chen et al. (2021) found that streets with visually attractive and human-scaled design were more conducive to social interactions and community engagement. These findings suggest that visually appealing environments can promote social cohesion and community building.

Moreover, visual walkability has been linked to economic benefits. A study by Sohn et al. (2012) found that sideways with visually appealing views were more likely to sell at a higher price than houses without such views. The study suggested that visual walkability can have a positive effect on property values and local economic development.

The impact of signboards on vision:

In recent years, there has been a great deal of interest in the problems faced by public spaces due to the design of commercial signs. From the perspectives of architecture, planning, and psychology, people have studied the negative effects of commercial signs on the visual quality of urban areas and people's quality of life. (Adriana, 2014). Signboard traditionally provides store information to help consumers make purchase decisions when they are visiting a city or engaging in consumer activities. Therefore, a signboard is an important part of a commercial street and one of the most effective ways to convey information. Studies have shown that randomly designed signs have a negative visual impact on the streetscape, with aesthetic value decreasing as the number and type of signs increase, and a decrease in the number of signs appears to increase pleasantness (Kim&Park, 2020).

Several studies have shown that signboards increase the cognitive load of pedestrians, causing them to pay less attention to their surroundings and increasing the likelihood of accidents (Decker et al., 2015). Billboards can have a significant impact on walkability and visual aesthetics in urban environments. While billboards can be effective in promoting products and services, they can also create visual clutter, obstruct views, and detract from the aesthetics and coherence of the surrounding environment (Adam et al, 2022). The next part of this paper assesses the distribution and visual impact of signboards in the area.

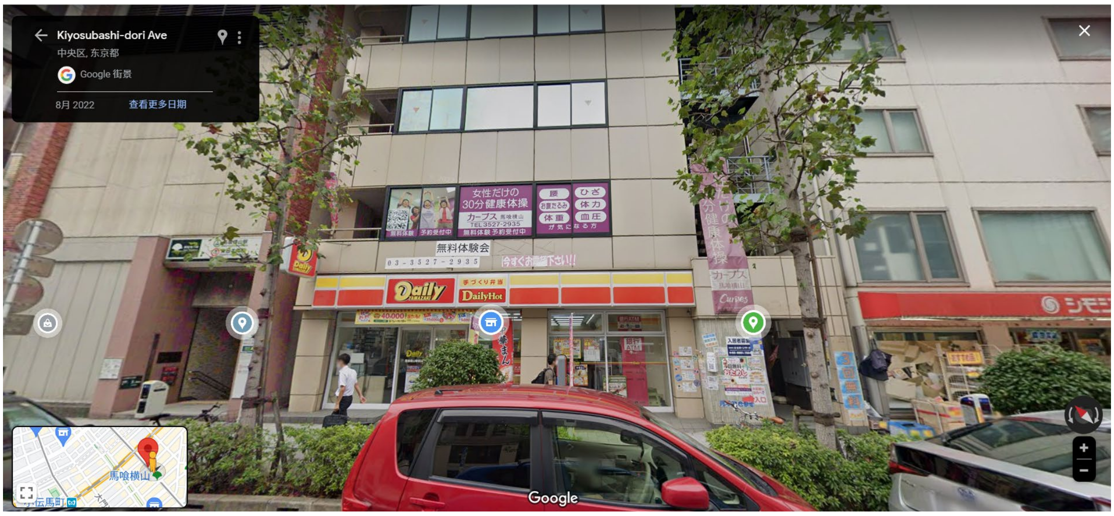


Figure:1. (Source: Google Map)

Field research questions found (signboards):

Regarding the urban environment of Nihonbashi, it is a historically significant area of Tokyo with a blend of traditional and modern architecture. The visual quality of the area is heavily influenced using signage, billboards, and other signage. In some parts of Nihonbashi, such as the area around the "Kilometer Zero" monument, the signage is tasteful and informative, providing historical and cultural context for visitors without detracting from the visual impact of the area's landmarks.

Figure:2. (Source: Author shot)

In other areas of the Nihonbashi, however, large and ornate signboards have been erected that can obscure views of important landmarks and diminish the visual quality of the area. For example, the advertisements floating on the facades of commercial streets in the photo below distract pedestrians from measures and distractions, especially when walking through the historic district. These advertisements can disrupt the visual coherence of the area and detract from the visitor and pedestrian experience. In conclusion, while these signboards are a great provider of commercial interest, we should consider the negative impact of large, flashy advertisements on the historic culture and visual quality of the area.

Figure:3. (Source: Author Shot)

The impact of greenery on vision:

Studies on the effects of greenery on visual walking have found that increased vegetation has a positive impact on the perceived quality of the walking environment. The presence of street trees promotes pedestrian perceptions of safety and walkability of the area (Alicia et al., 2021). People's observation of street greening is also an important sensory function (Li et al, 2015). Urban street greening contributes significantly to the attractiveness and walkability of residents and visitors. The presence of vegetation usually increases people's aesthetic evaluation of urban scenes (Lindemann-Matthies et al, 2010).

Field research questions found (greenery):

Nihonbashi is a densely populated area with a mix of commercial and residential buildings and many cultural landmarks such as “Nihonbashi” and the Mitsui Memorial Museum. Moreover, the historical development of Nihonbashi has resulted in limited greenery in the area. Nihonbashi is a traditional commercial district and has not undergone several major updates like other districts such as Shibuya and Shinjuku. This traditional commercial business model was designed primarily for commercial use, with little consideration given to providing open space and greenery. As a result, there is a lot of pressure on land use in the area, and the need for commercial and residential space often takes precedence over the need for green space. As a result, the availability of open space and green space is limited, and many streets and public areas are dominated by concrete and sidewalks.

Figure:4. (Source: Author Shot)

The use of GSV in evaluating urban visibility:

Several studies have used GSV to assess visibility in different contexts. GSV was used to assess the visibility of street intersections, finding that the visibility of intersections was associated with the frequency of pedestrian accidents (Li et al.,2022). GSV has also been used to assess the visual quality of urban environments, such as the aesthetics of buildings, streets, and public spaces. For example, in a study by Lu. (2019), GSV was used to assess the visual quality of neighborhoods in Hongkong, finding that visual disorder and blight were negatively associated with physical activity and well-being.

Additionally, GSV has been used to assess the visual accessibility of public spaces, such as parks. For example, in a study by Yang et al. (2021), GSV was used to assess the visual accessibility of parks in Hongkong, finding that the visibility of parks was positively associated with their use by children and adults.

Data Access:

1. Use of Google Street View in research:

Google Street View has been widely used in research to study a variety of topics, including urban planning, transportation, public health, and environmental justice. Researchers have used the Street View Image API to extract and analyze visual features of the built environment, such as building facades, street signs, and green spaces.

2. Technical aspects of the Google Street View Image API:

The Google Street View Image API is a RESTful web service that provides a simple interface for accessing Street View images. Developers can use the API to retrieve still images of Street View panoramas, as well as metadata about the images, such as the latitude and longitude of camera locations. The API also supports various parameters such as image size, caption, and spacing, allowing developers to customize the retrieved images.

3. Methods used in this study:

The GSV images in this study were identified and downloaded using the following method, firstly the center of the road and the effective location for the presence of google street image shot were selected based on the road network of Nihonbashi area and the shapefile of each block. Secondly, the camera is set up at 30m intervals so that the line of sight is parallel to the road section. For the intersection of the four directions to shoot, to obtain a 360 ° image of the location, for the street, according to the direction of the road to obtain the two ends of the scene. All other parameters were set to default values. The program was applied to all streets, and alleys in the study area. to calculate the parameters needed to download the street view images through the GSV Application Programming Interface (API) with 640*640 pixels per image. covering the entire study area.

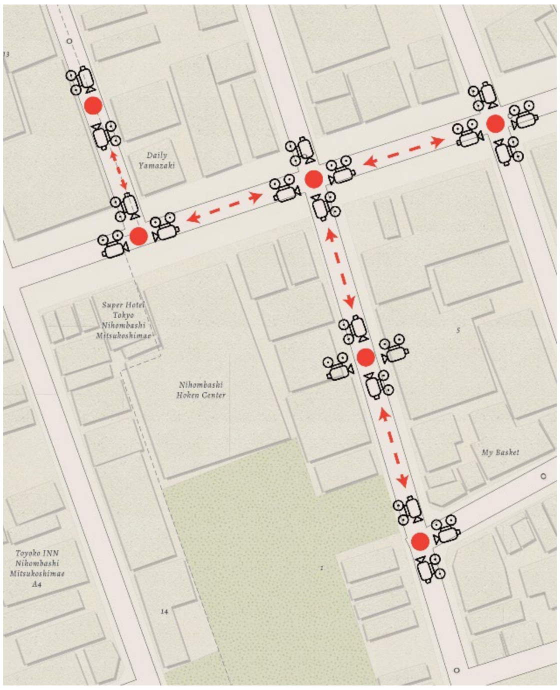


Figure:5. Camera position and angle

The Google Street View images in this study were downloaded between the months of August and September. Climatic conditions play a significant role in a tree's blooming. Temperature, humidity, and rainfall are some of the climatic factors that can affect a tree's flowering. The number of trees in Google Street View images is representative of the real situation during most of the year, as August to September is the season when Japanese trees flourish, based on rainfall and temperature conditions.

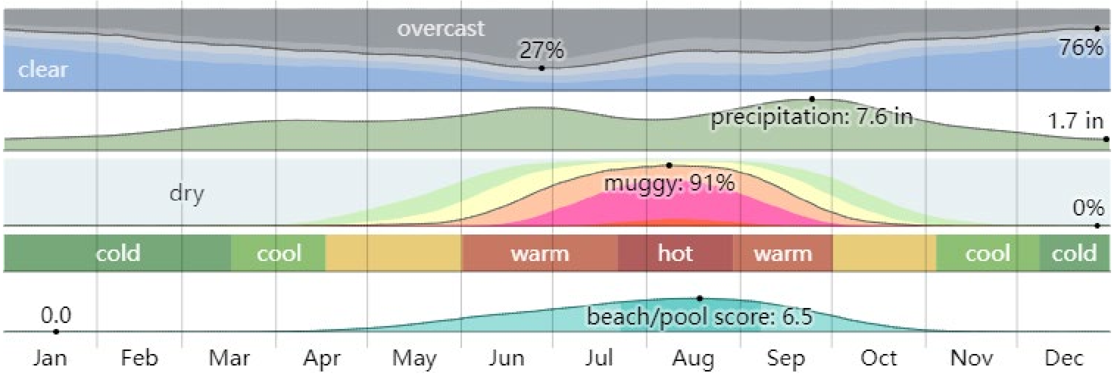
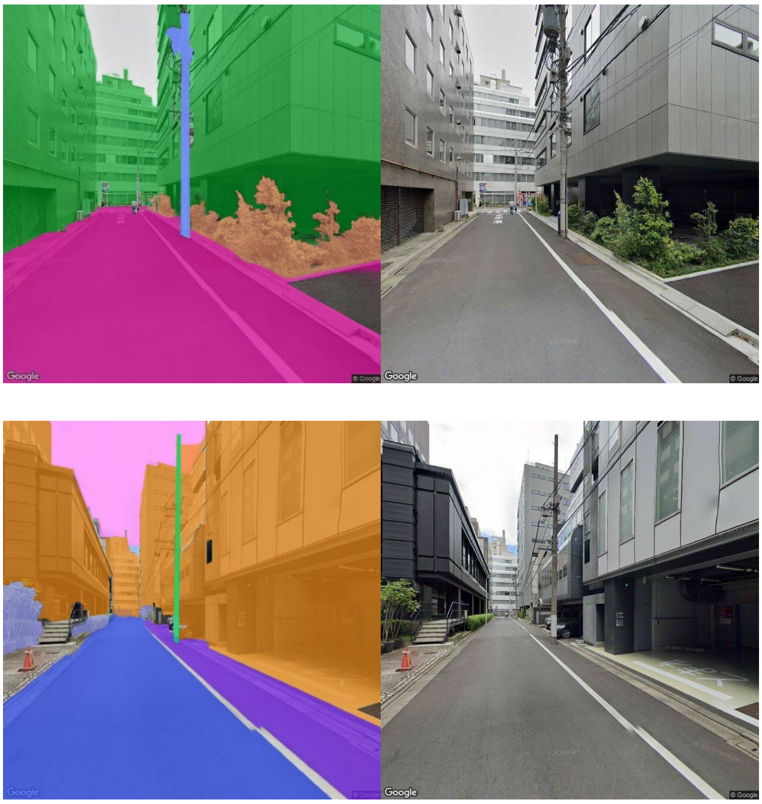


Figure:6. Source: Weather Spark Japan(https://weatherspark.com/y/143809/Average-Weather-in-Tokyo-Japan-Year-Round)

To analyze the images I collected, I employed a semantic segmentation model called PSPNet. PSPNet was developed by Zhao et al. (2017) and is based on the complete convolutional network structure proposed by Long (2015). Using pre-trained weights, the model processes the original image and predicts the category with the highest probability for each pixel. The weights used by PSPNet were pre-trained on ADE20K, a database of annotated images consisting of 150 categories created by Zhou et al. in 2017.



Examples of Google Street View images and their output from the computer vision processing by PSPNet

The final step was to select objects from 150 categories that affected walkability and visuality. I chose the following objects: (1) the measurement factors previously used in most of the literature: sky, buildings, houses, vehicles, sidewalks, and plants (2) the factors I found from Google Street View that have an impact on visuals: bicycles, signboards. The final detection objects are cars, buildings, houses, sidewalks, plants, bicycles, and signboards. Based on literature on urban design, environmental transportation, and walkability measurement. I have developed the following indicators:

Greenspace=%tree pixels+%grass pixels +%plant pixels

Visual Walkability= (Greenspace+%Sidewalk pixels)/ (%Car pixels+%Building pixels+%House pixels+% Bicycle pixels)

After completing the scene parsing with PSPNet, I computed the number of pixels per category in each image. Check the input of PSPNet and remove the abnormal images, such as those inside subway stations and indoors. For intersections download the images from four viewpoints and average the pixels in the images. For street and alley, the images are downloaded for both ends according to the direction of the road (OSM road data).

Figure:7. Visualization of greenery values for selected locations

The number of pixels per image is 640*640, and the visualization of the result is obtained by dividing the percentage of greenery (trees + grass + flowers) at each location by the total number of pixels. The visual percentage of greenery for each location is obtained. From the size of the dots in the figure, we can get the content of the greenery share for each location. Combining the average value between the two points, the greenery index of the whole street can be evaluated.

Looking at the street through Google Street Image, I found that the placement of bicycles, which take up most of the street, and have a negative visual impact. It makes the already narrow street area even smaller. So, I tried to count the number of bicycles on the street by the same means to evaluate the number and its distribution.

Figure:8. (Source: Google Map)

Using the same method, I evaluated the number of signboards and bikes in the area. I randomly selected one of the larger points back to google street view to check, the picture at the bottom is an interception of the real image, we can see that the higher the index is in the picture, the higher the number percentage is, which also indirectly affects the visual impact on our daily life. As we know from the real Google Street View images, some signboards are very exaggerated or repetitive in appearance, which has a significant impact on our daily travels. They occupy most of the area in narrow alleyways or streets and have a visual impact.

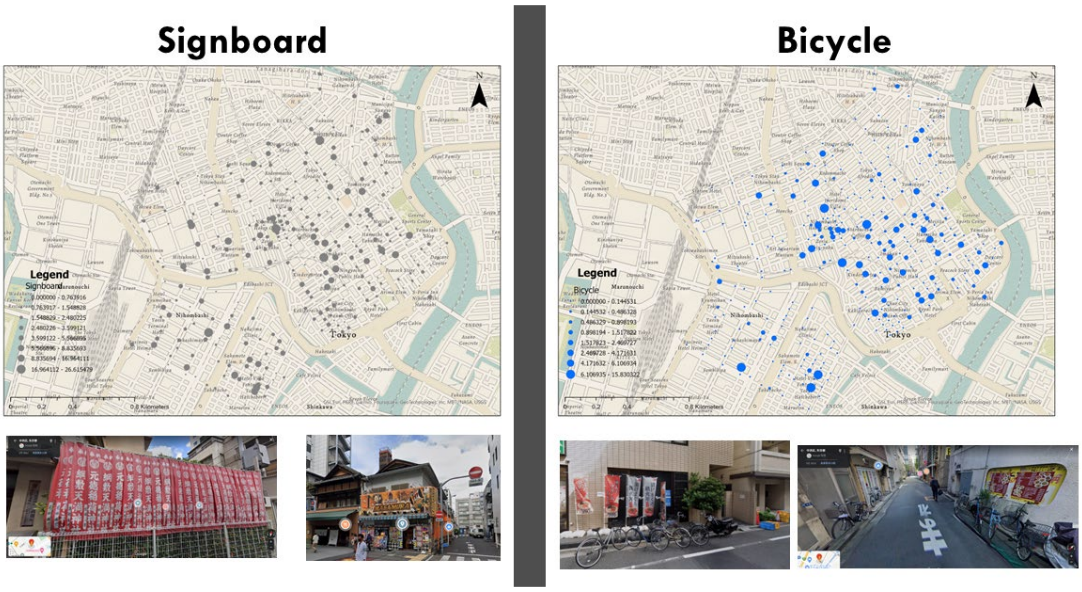


Figure:9. Visual impact visualization of signboards and bicycles in the area

Results:

The spatially joined point data obtained after GSV output is used to evaluate the number of green plants within each block in the study area. To do this, the points within each block are averaged, and the resulting values are used to sort the blocks into five ranks. However, it was observed that there are many blank areas in the study area. Given the special situation of Japanese neighborhoods and alleyways, the walkability of an area cannot be solely measured based on the percentage of green plants. Therefore, to better understand the distribution of green plants, we combined the number of signboards in each block with the distribution map of green plants. Our analysis showed that areas with high signboard density had a smaller number of green plants. This is due to the need to save floor space for buildings in commercial areas, which reduces the space available for planting greenery. The final results showed that the number of green plants in the study area ranged from 0.09 to 14.23, with most blocks falling within the medium level (19 blocks on average). However, we recommend increasing the number of green plants in the blank areas for visual improvement.

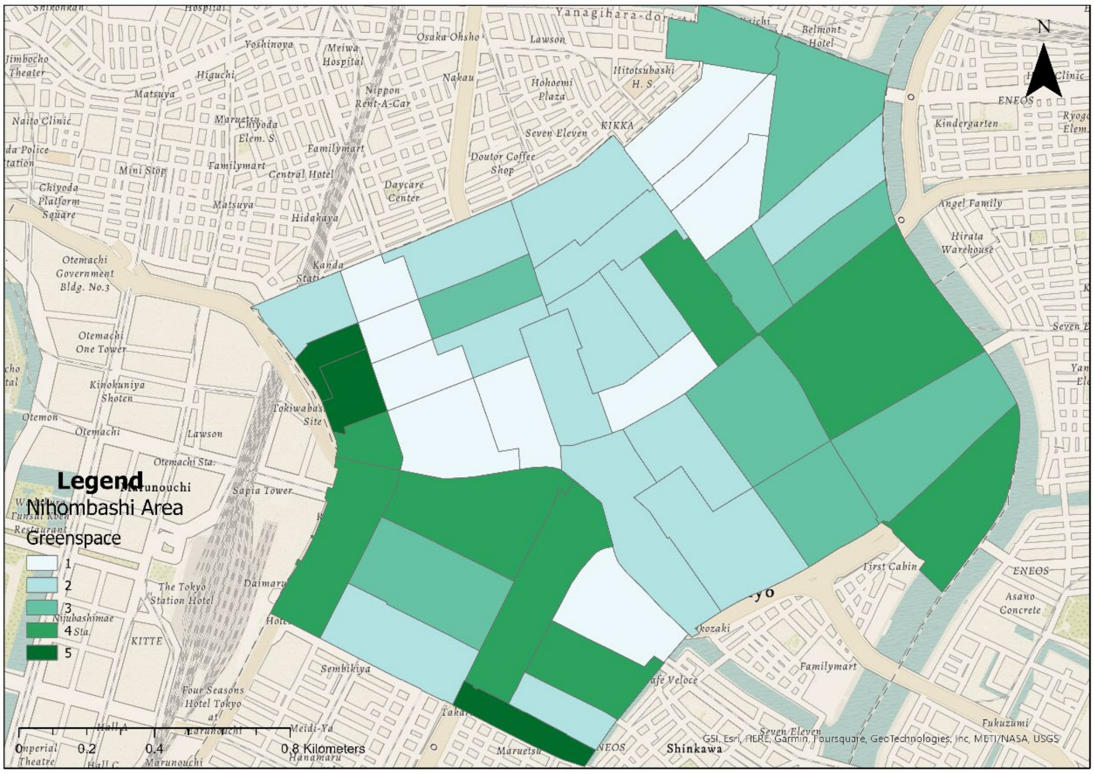


Figure:10. Greenery area distribution map

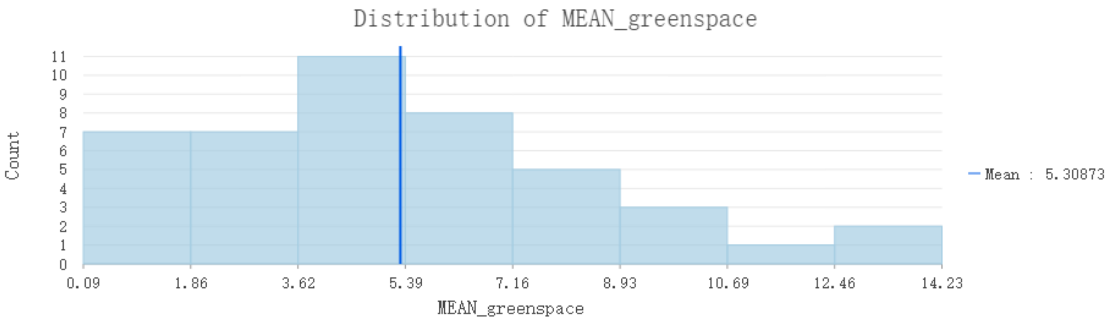


Figure:11. Distribution of mean greenspace

There are certain drawbacks to the evaluation of the overall block, for example, some blocks have a large area but fewer data are acquired, some locations with plants do not have cameras set up, or the camera positions set up are far away from the greenery points, resulting in much less pixel acquisition than the real situation, or the value of a particular point is particularly large, raising the average value of the whole area. All these may affect the determination of the final result. If the calculation is done according to the density points, the overall evaluation error can be reduced, and the evaluation based on the size and density of the values can be more in line with the visual impact of the greenery distribution on people.

This figure shows the spatial distribution of green space in the Nihonbashi area, and the areas with high and low greenery density are indicated by dark and light colors, respectively. The analysis shows that the areas with the highest green space density are located in the eastern and southern parts of the study area, while the northern areas have lower green space density. This analysis can inform planning decision-makers related to greenspace planting and management, with a focus on protecting and enhancing these areas to maintain healthy and coherent greenspace.

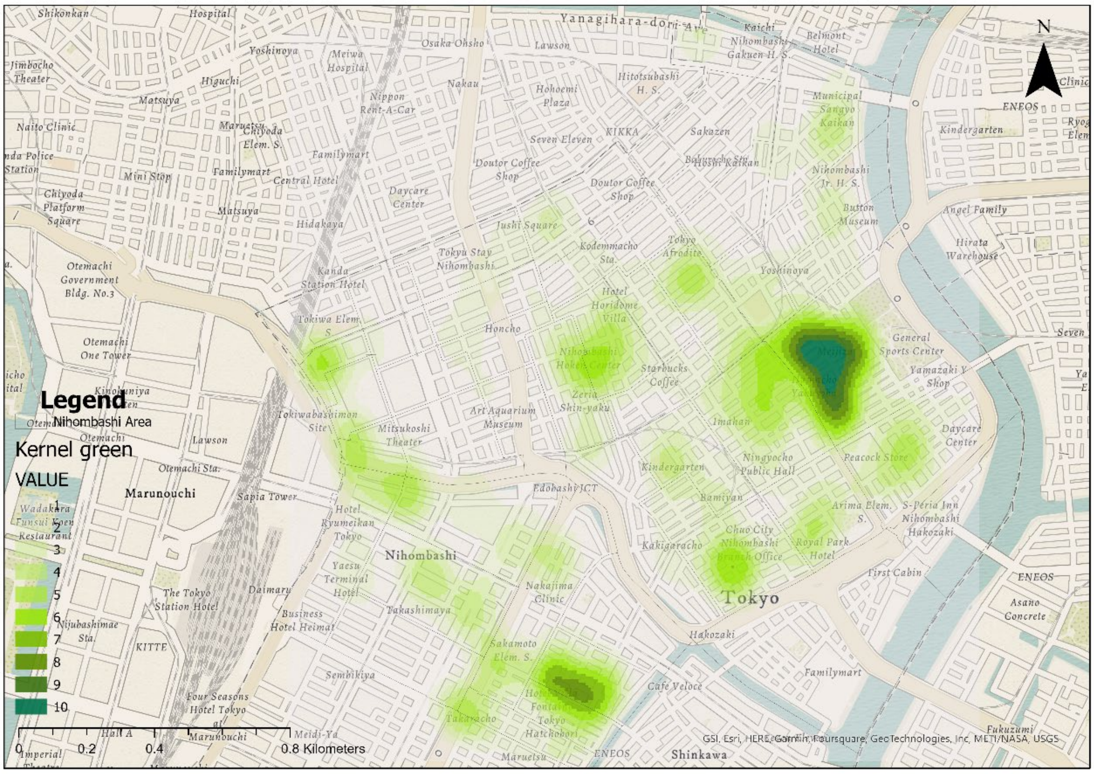


Figure:12. Kernel greenspace analyze.

Using the same method, I averaged the number of signboards per neighborhood to comprehensively assess the impact of signboards in the visuals for the entire area. From the overall situation, only two blocks have an excessive number of signboards. Most of the blocks are in the middle (value=3) but considering Nihonbashi is a large commercial and cultural complex, the 4% (2/45) of the area with too many signboards does not pose any impact on the life of ordinary visitors and residents.

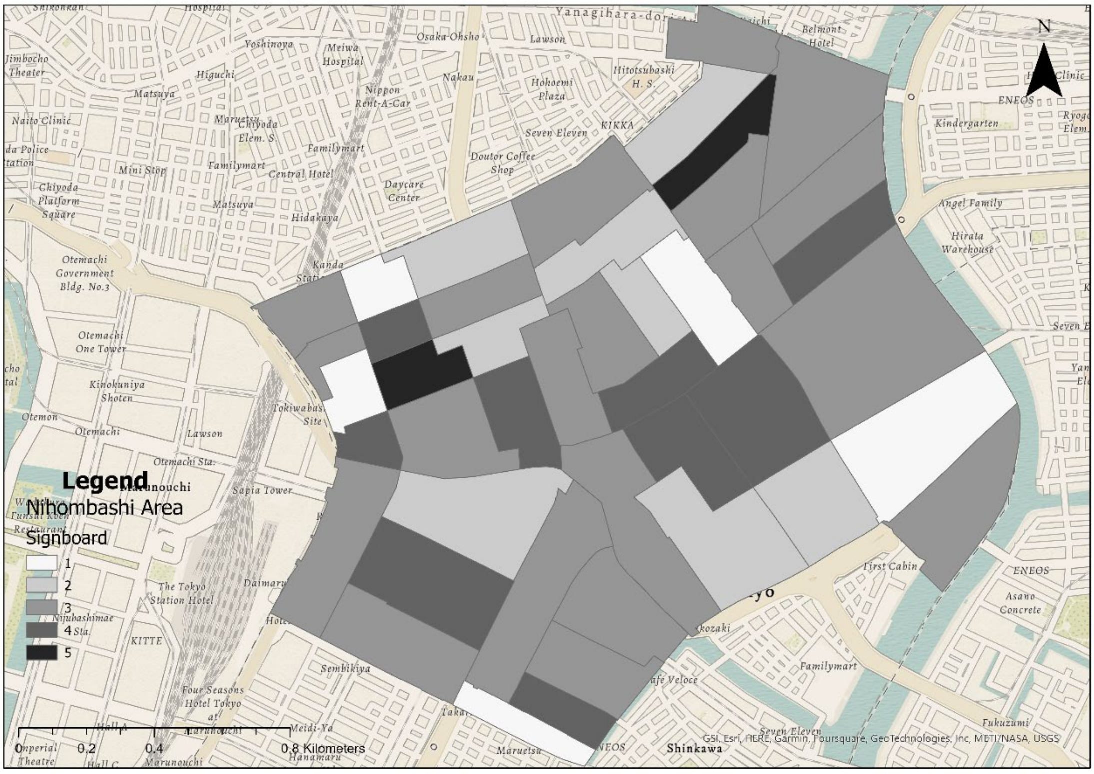


Figure:13. Signboards distribution map

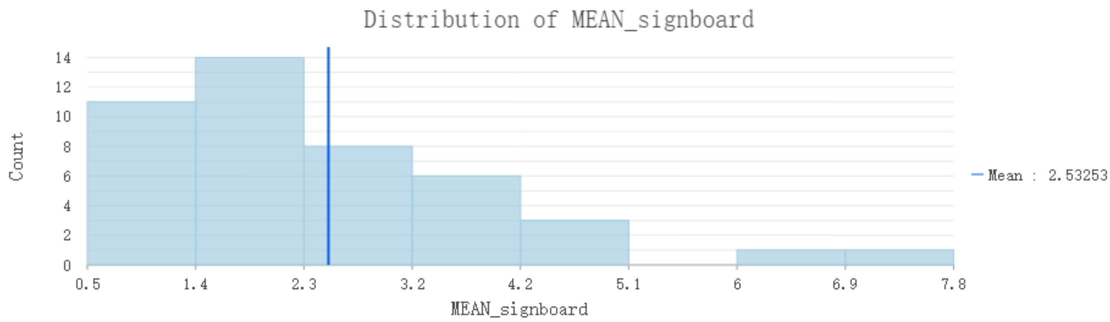


Figure:14. Distribution of mean signboards

The map depicts the distribution of signboards in the study area, with dark and light colors representing areas of high and low signboard density, respectively. Interestingly, the analysis shows that the highest concentration of signboards is not on the main commercial streets in the area, but in narrow lanes and alleyways close to residential areas. This suggests that signboards on these everyday commercial streets play a more prominent role in creating visual impact, given the high density of foot traffic and limited space. In contrast, the largest commercial streets in the Nihonbashi area may have a lower density of signage and less visual impact due to their wider and less crowded nature.

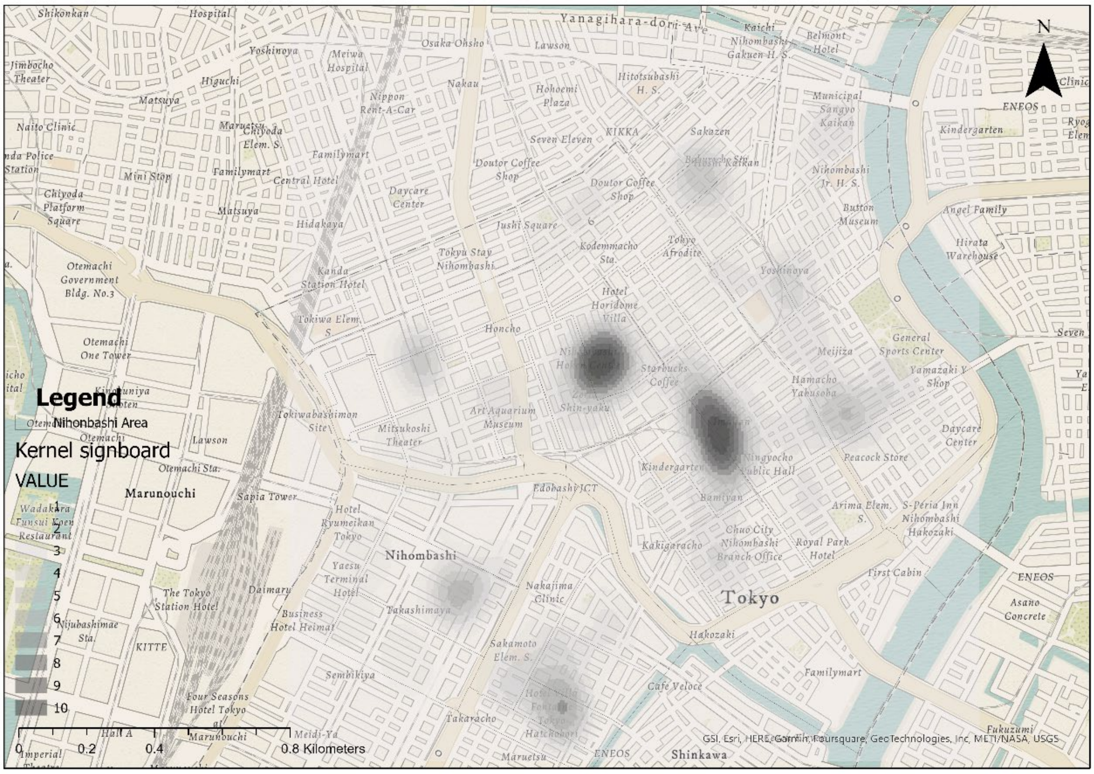


Figure:15. Kernel signboards analyze.

Figure:16. (Source: Author Shot)

The visual walkability calculated by the Google Street View algorithm mentioned above reflects some extent of walkability in the area: First, the three areas with the highest visual walkability rating include two parks in the Nihonbashi area. Second, for the two areas with the highest density of signboards, the visual walkability is lower, which confirms the overall assessment accuracy. This is a suggestion for the future improvement of visual walkability in the Nihonbashi area.

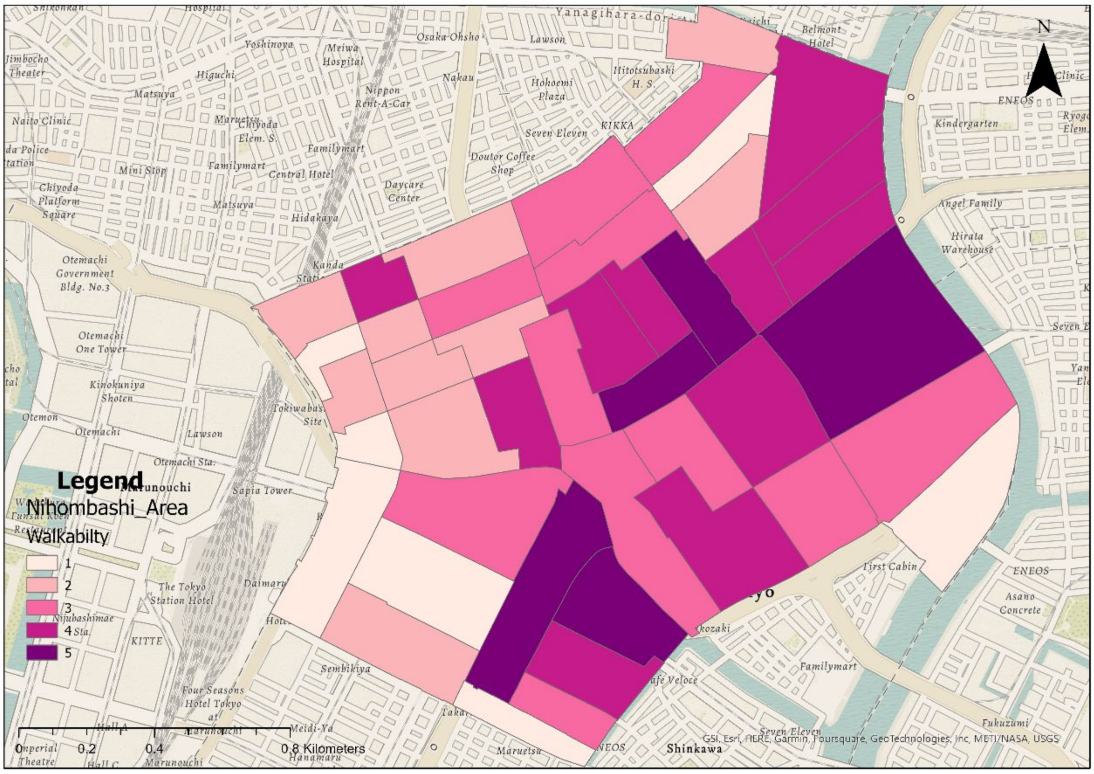


Figure:17. Visual Walkability Assessment Map

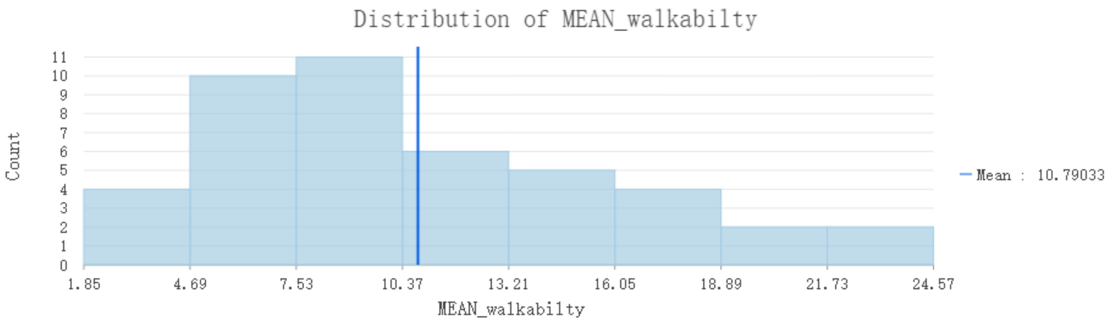


Figure:18. Distribution of mean visual walkability

Discussions:

An important limitation of Google Street View is its inability to capture the full range of weather conditions and seasonal changes that may affect the streetscape of a location. Images in the Google Street View database are typically taken at specific times of the year, which means that they may not accurately reflect conditions that exist at other times of the year. For example, if a location was taken in the summer, the image may not accurately represent what that location looks like in the winter when snow and ice cover the ground. Similarly, if a location was taken on a particularly sunny day, the image may not accurately represent what that location looks like on a rainy or cloudy day. Another limitation of Google Street View is its inability to capture the passage of time. Images in the database are typically static and do not change over time, which means they cannot capture the impact of events or changes at a location over time (usually updated every three years). For example, if a building is demolished or a new building is constructed, Google Street View images may not accurately reflect the current state of that location.

There are other limitations of using Google Street View for analysis. One of these limitations is the traffic conditions in the images; Google Street View images may not accurately reflect the actual traffic conditions at a location, especially if the images were taken during rush hour. Although this paper deliberately reduces the importance and proportion of car pixels in the calculation, it is still an important factor that cannot be avoided. During rush hour, some narrow roads or alleyways that normally do not have vehicles will also have cars in the image, which greatly affects the evaluation of the actual situation. The traffic time variable cannot be represented in Google Images. This greatly affects the accuracy of the analysis that considers traffic flow and patterns. In addition, the images taken from a fixed viewpoint may not capture all angles or areas of the location, which may affect the accuracy of analyses that rely on a comprehensive understanding of location characteristics. For example, in the analysis of the number of signboards in this paper, many signboards are hanging on high buildings or at negative angles on both sides of the road, which are not captured by the Google Street View camera. The specific pixel index cannot be clearly identified due to the low pixel count (640*640), which can be a factor in the results.

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