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Deep Learning–Based Semantic Segmentation for Evaluating Urban Environmental Quality and Walkability in Dongdaemun

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Abstract

This study evaluates environmental quality and urban walkability in the Dongdaemun district through geospatial semantic segmentation of street-view imagery. A DeepLab ResNet101 model, pre-trained on the ADE20K dataset and implemented using the GluonCV framework, was applied to Google Street View images collected at 40-meter intervals in four cardinal directions. Pixel-level segmentation was used to quantify key environmental features such as greenery, sky visibility, pavement, and road surfaces. Based on these visual attributes, composite indicators representing comfort, convenience, and safety were derived, leading to the calculation of an Integrated Visual Walkability index. The results reveal clear spatial variations in walkability across the study area, highlighting areas with favorable pedestrian environments and zones requiring improvement. Although the analysis is constrained by image quality and spatial coverage, the findings demonstrate the effectiveness of deep learning–based semantic segmentation for large-scale environmental assessment. This approach provides a scalable and data-driven framework to support evidence-based urban planning and sustainable city development.

Keywords: Deep Learning, Geospatial Data, Semantic Segmentation, Urban Sustainability, Walkability.

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1. Introduction

Walkability is widely recognized as an important factor influencing physical activity, public health, and overall urban livability. Despite the well-documented health benefits of regular physical activity, many adults in developed countries still do not engage in sufficient physical activity (Dyck et al. 2011). To promote active living, it is important to understand the multidimensional factors that shape walking behavior. Recent studies have shown that objectively measured neighborhood attributes—such as residential density, street connectivity, and land use mix—are strongly associated with walking levels and broader physical activity patterns (Handy et al. 2002; Saelens et al. 2003; Owen et al. 2007; Sallis et al. 2009; Dyck et al. 2011). Adults living in environments with well-connected streets, diverse land uses, and higher residential density tend to exhibit more pedestrian activity than those in low-walkable neighborhoods. Consequently, researchers and urban planners emphasize the development of highly walkable environments to support physical activity and improve public health outcomes. In addition to physical characteristics, neighborhood perception also affects residential satisfaction and overall well-being. Prior research indicates that neighborhood satisfaction is associated with happiness, mental health, and quality of life (Michael et al. 2006; Van Dyck et al. 2010). Furthermore, studies have found that social and leisure activities within neighborhoods—such as participation in local events or informal social interactions—can positively influence neighborhood satisfaction (Wilson et al. 2004; Forum 2007). These findings highlight the importance of considering both physical and perceptual aspects when evaluating urban environments.

Traditional assessments of walkability have relied on field surveys, manual audits, or subjective perception questionnaires, which are often time-consuming, resource-intensive, and limited in spatial coverage. Recent advances in computer vision have enabled automated and scalable analysis of the urban visual environment using street-view imagery. In particular, deep learning–based semantic segmentation allows pixel-level identification of environmental components such as buildings, vegetation, sky openness, pavement surfaces, and physical obstacles. These visual characteristics directly influence pedestrian comfort, safety, and spatial experience, making them valuable indicators for evaluating walkability. In this study, a DeepLab semantic segmentation model is applied to Google Street View images to quantify key urban environmental features throughout the Dongdaemun district of Seoul. From the extracted visual attributes, composite indicators representing comfort, convenience, and safety are derived and integrated into an Integrated Visual Walkability (IVW) index. The resulting spatial evaluation provides detailed insights into environmental quality and walkability patterns, offering practical guidance for urban planning, environmental management, and policy decision-making.

2. Related Work

Recent research has increasingly leveraged street view imagery (SVI) and deep learning–based semantic segmentation to assess urban environments and walkability, moving beyond traditional surveys and site audits. These methods allow scalable, objective extraction of visual features that influence pedestrian experience and walkability patterns. For instance, Choi et al. (2024) applied semantic segmentation to Google Street View panoramas to model urban visual composition, defining typologies such as greenness, openness, and enclosure based on pixel-level imagery data. Ghose and Rai (2025) demonstrated a GeoAI approach for integrated visual walkability assessment, quantifying greenery, openness, pavement, and crowdedness across Kolkata, revealing significant intra-city variations in pedestrian infrastructure. Yu (2024) employed deep learning to evaluate temporal changes in walkability indicators (e.g., greenery, sidewalk coverage) in downtown Orlando, illustrating how visual characteristics evolve with urban development. Similarly, Smith et al. (2025) integrated objective street-level features with subjective assessments using deep CNNs to capture safety, aesthetics, and accessibility for walkability evaluation.

Several studies focused on perceptual aspects of walkability. Choi and Kang (2025) modeled and explained perceived walkability in urban environments using semantic segmentation and explainable AI, extracting fine-grained visual features to identify which elements most strongly influence pedestrian judgments. Yang et al. (2025) developed a framework combining GeoAI and human perceptions to estimate walkability scores, highlighting the importance of integrating subjective perceptions with objective urban measures. Harmonizing semantic features with spatial predictors has been shown to improve urban visual composition modeling and walkability assessment (Pradana et al. 2025), while Li et al. (2025) demonstrated that spatiotemporal contrast learning can enhance street-view representation for urban analysis. Generative AI approaches, such as SAGAI (Perez and Fusco 2025), have also emerged to automate the mapping of streetscape elements into structured walkability indicators. Automated sidewalk mapping and urban feature extraction have further enhanced neighborhood-scale walkability analysis. Hamim et al. (2024) mapped sidewalks using street view imagery, while Hwang et al. (2024) applied regression models to spatial image features to predict walkability levels. Mushkani and Koseki (2026) proposed a participatory AI framework that integrates resident feedback with machine learning for inclusive walkability assessment. Zhang et al. (2025) used GeoAI-based semantic segmentation to quantify greenery and walkability metrics at the city scale. Huang et al. (2024) integrated streetscape images, machine learning, and space syntax to enhance walkability analysis in Seoul, demonstrating practical application in a dense urban context.

Recent studies have also explored dynamic and temporal dimensions. Alvarez and Garcia (2025) evaluated walkability using objective street-view measures with regression models, while Nguyen et al. (2025) quantified visual indicators for walkability through semantic segmentation. Brown and Green (2025) assessed visual crowdedness using automated street-level image analysis, highlighting areas of high pedestrian obstruction. Wilson and Taylor (2025) analyzed sidewalks and greenery to assess pedestrian safety and comfort, and Chen et al. (2025) applied deep learning and street-view analytics to measure perceived walkability in dense urban areas, emphasizing both physical and perceptual components. Collectively, these advances demonstrate the growing integration of AI, deep learning, and semantic segmentation in walkability research. However, relatively few studies have applied pixel-level semantic segmentation specifically to Seoul's urban environment. This motivates the present study, which applies these methods to the Dongdaemun district to generate detailed insights into urban environmental quality and walkability patterns.

3. Methodology

This study adopts a systematic methodology grounded in recent advances in geospatial and urban analytics (Zhang et al. 2019), Google Street View–based environmental data extraction and sampling strategies (Zhang et al. 2019; Liu et al. 2020), and deep learning–based semantic segmentation techniques for urban feature analysis (Cheng et al. 2022; Minaee et al. 2022) to evaluate urban environmental characteristics and walkability in the Dongdaemun district of Seoul, South Korea. The methodology is designed to ensure rigor, reproducibility, and spatial representativeness. It is divided into four main components: data collection and preprocessing, multi-directional sampling and data structuring, system architecture, and semantic segmentation with feature extraction, each contributing to building a structured and interpretable dataset for urban analysis.

3.1 Data Collection and Preprocessing

The first stage of this study focuses on acquiring high-quality geospatial and street-level imagery, which forms the basis for all subsequent analyses. Accurate data collection is critical to ensure the reliability of semantic segmentation and the validity of derived indicators. This phase also establishes a reproducible spatial framework that allows consistent alignment between image pixels and real-world locations, a key factor in quantitative urban assessment. The research begins with acquiring high-resolution geospatial and satellite imagery of the study area. The area was delineated using QGIS, where sampling points were systematically generated at 40-meter intervals to maintain uniform spatial coverage. This spatial framework ensures precise alignment between image pixels and real-world locations, supporting reproducibility and consistency in subsequent analyses.

Figure 1 illustrates the spatial extent of the study area, showing the distribution of sampling points across Seodaemun-gu (yellow) and Dongdaemun (blue), with Dongdaemun serving as the primary focus for detailed geospatial analysis. The systematic placement of sampling points ensures uniform spatial coverage during data acquisition and processing. Each coordinate point was programmatically linked to the Google Street View (GSV) API (https://developers.google.com/maps/documentation/streetview), enabling automated retrieval of panoramic street-view images. To capture a complete 360° view of each location, four images were obtained per point at 0°, 90°, 180°, and 270°. From 620 sampling points, a total of 2,480 images were generated, of which 2,370 high-quality images were retained after removing blurred, distorted, or obstructed frames.

Preprocessing steps included resizing images to 512×512 pixels, color normalization (RGB values scaled to [0,1]), cropping to remove redundant upper and lower frame regions, and quality control to eliminate images with obstructions such as vehicles or construction barriers. The processed images were systematically renamed according to coordinate ID and orientation (e.g., P123_90.jpg) and compiled into a Pandas DataFrame linking each image to its geographic coordinates and viewing direction. These procedures establish a reliable foundation for subsequent semantic segmentation and quantitative urban analysis.

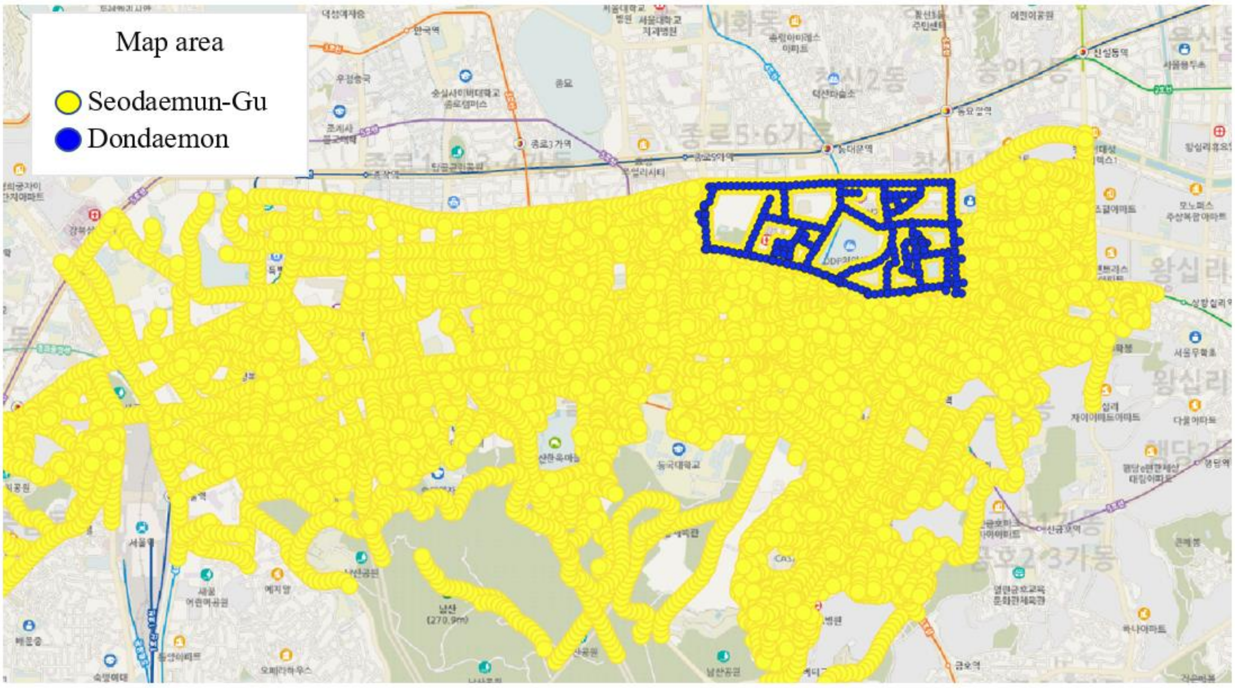


Figure 1: Extract The Study Area from The Map Using QGIS

3.2 Multi-Directional Sampling and Data Structuring

To fully capture the urban visual environment, a multi-directional sampling strategy was adopted, providing a comprehensive 360° perspective for each location. This approach ensures that key environmental attributes such as greenery, sky openness, and building enclosure are accurately represented. Systematically structuring these images with spatial metadata enables reproducibility and integration into machine learning pipelines for subsequent semantic analysis.

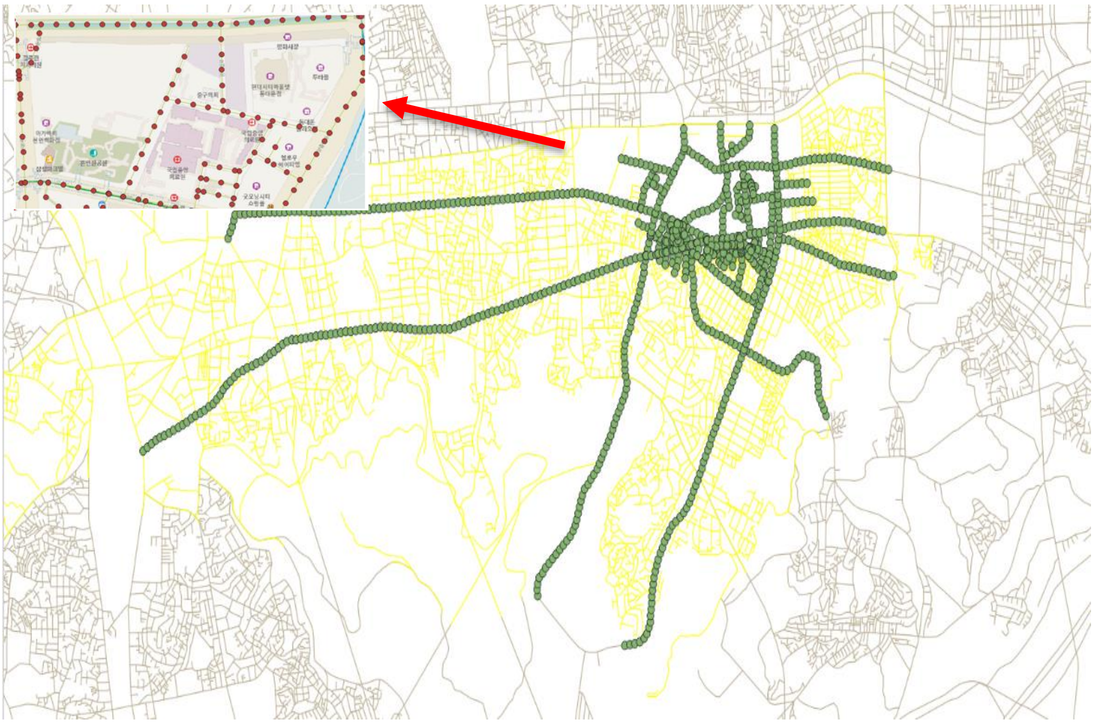


Figure 2: Road Network and Sampling Points of Dongdaemun, Seoul, South Korea (40 m Intervals)

Figure 2 illustrates the spatial configuration of the road network and the systematically distributed 40-meter sampling points within the Dongdaemun district. Figure 2 illustrates the spatial configuration of the road network and systematically distributed sampling points within Dongdaemun. Each point represents a fixed geographic coordinate and forms the basis of the study's conceptual framework, linking geospatial sampling to semantic segmentation for urban environmental assessment. The multi-directional sampling strategy ensures that each location captures the surrounding environment comprehensively, including greenery coverage, sky openness, pedestrian infrastructure, and building enclosure, which are key indicators for evaluating urban livability and walkability. The collected images provide a rich visual dataset, supporting a robust and representative analysis of street-level environmental conditions.

Figure 3: Example of Street View Image Samples (SVIs) at Different Viewing Angles. Each image represents the same location, captured from four viewing directions to ensure comprehensive visual

coverage. The numbers indicate the data collection angles from the same point: 0° (front view), 90° (right view), 180° (back view), and 270° (left view)

Figure 3 presents representative SVIs captured at 0°, 90°, 180°, and 270° from the same location, illustrating the multi-directional sampling approach for complete 360° visual coverage. Preprocessed SVIs served as inputs for semantic segmentation using the DeepLab ResNet101 model, pre-trained on the ADE20K dataset, and implemented with the GluonCV framework. The model performs pixel-level classification, automatically labeling features such as buildings, roads, trees, sky, and sidewalks. Post-processing involved computing pixel-wise class distributions, which were normalized and stored as numerical attributes in a structured analytical dataset. The tools used at this stage included GluonCV for model implementation, Python (NumPy, Pandas, Matplotlib) for post-processing and visualization, and QGIS for spatial alignment. These semantic attributes form the basis for constructing the Integrated Visual Walkability Index (IVW) and its sub-indicators, linking visual environmental composition with geospatial analysis.

3.3 System Architecture

The system architecture integrates geospatial data processing, machine learning, and quantitative analysis into a unified framework for urban environmental evaluation. This framework ensures that image acquisition, preprocessing, and semantic segmentation are aligned and reproducible. It also establishes a workflow for deriving measurable indicators from complex visual data, allowing rigorous assessment of walkability and environmental quality. Figure 4 illustrates the systematic analytical workflow integrating geospatial data processing, semantic segmentation, and quantitative spatial analysis. The process begins with downloading the location file for the study area, extracting the area of interest in QGIS, and generating 40-meter interval sampling points. Using the GSV API, panoramic images were retrieved based on latitude and longitude coordinates, and then processed through the DeepLab ResNet101 semantic segmentation model to classify pixels into urban features, including buildings, roads, trees, sky, and walkways. This allowed for the precise extraction of visual attributes, including greenery coverage, sky openness, pavement visibility, and street enclosure, essential for evaluating urban form and environmental quality. From these segmented outputs, four sub-indicators were computed: Psychological Greenery (G-level), Visual Crowdedness (C-level), Outdoor Enclosure (S-level), and Visual Pavement (D-level). These were aggregated into the Integrated Visual Walkability Index (IVW), reflecting the overall environmental quality and pedestrian experience. The IVW is further decomposed into three dimensions: Comfort (greenery and sky visibility), Safety (open space and unobstructed visibility), and Convenience (accessibility and spatial continuity). Spatial visualization using QGIS and Python tools (Matplotlib, Seaborn) produced maps depicting walkability across Dongdaemun. This structured and reproducible workflow integrates geospatial data processing, machine learning–based segmentation, and quantitative analysis within a coherent methodological framework.

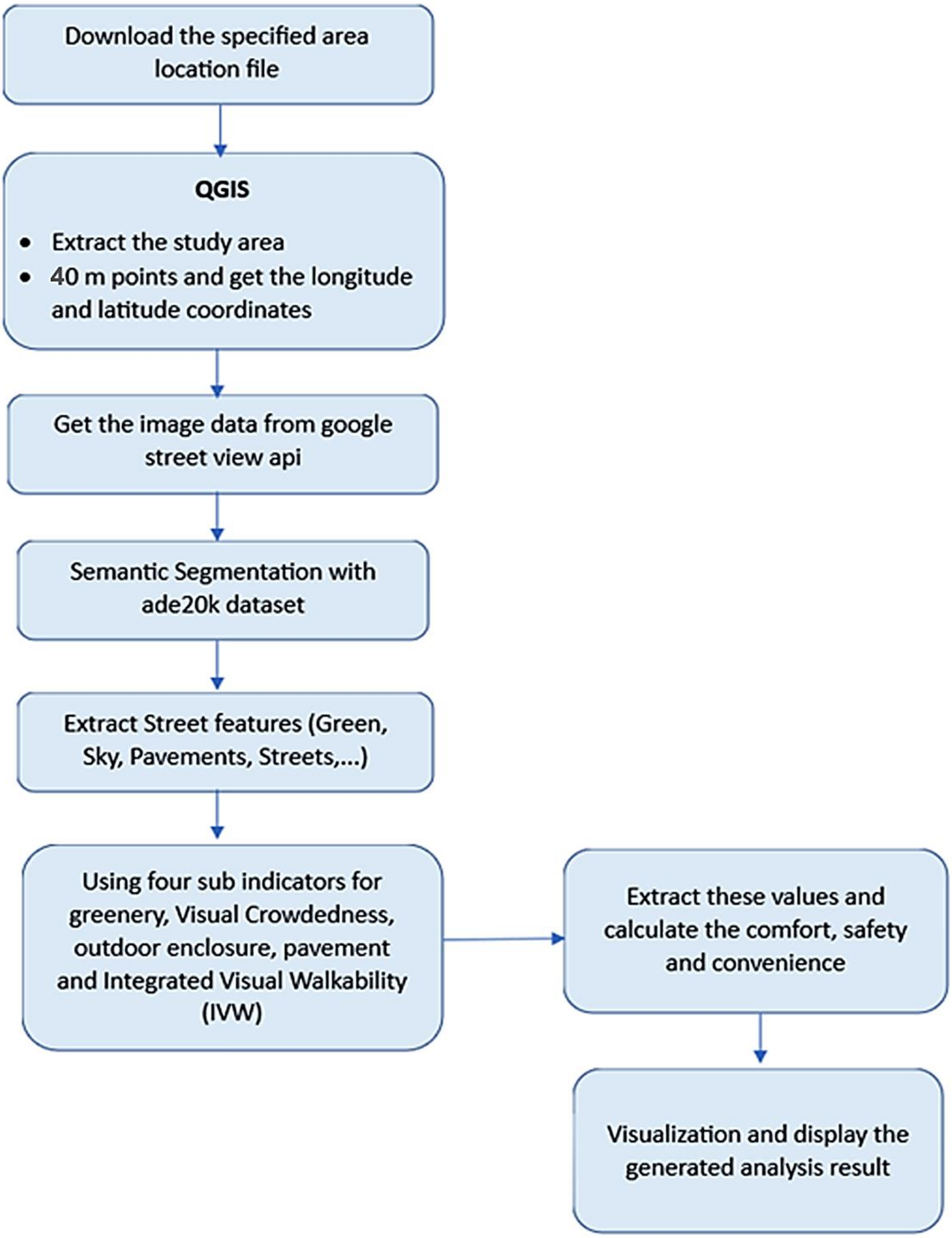


Figure 4: Workflow of the Data Processing and Analysis for the Integrated Visual Walkability Index (IVW)

3.4 Semantic Segmentation and Feature Extraction

Semantic segmentation and feature extraction convert visual information into structured, interpretable data, enabling quantitative evaluation of urban environmental quality. Accurate segmentation ensures that pixel-level measurements of buildings, roads, greenery, and other elements are reliable. This stage bridges the machine learning outputs with geospatial analysis, forming the foundation for deriving environmental indicators that inform the IVW.

Figure 5 shows a representative segmented output generated using the ADE20K dataset. Each object and surface—including buildings, trees, sky, roads, sidewalks, and other elements—is color-coded according to its semantic label. The legend associates each hue with its corresponding feature for intuitive interpretation. The segmentation demonstrates the model's precision in differentiating built and natural elements, revealing spatial arrangements and proportional dominance of urban features. The derived pixel-level data are used to compute sub-indicators for comfort, safety, and convenience, forming the foundation of the IVW. By converting visual information into structured numerical data, this step effectively links machine learning outputs with geospatial analysis, enabling detailed evaluation of environmental quality and walkability in urban areas.

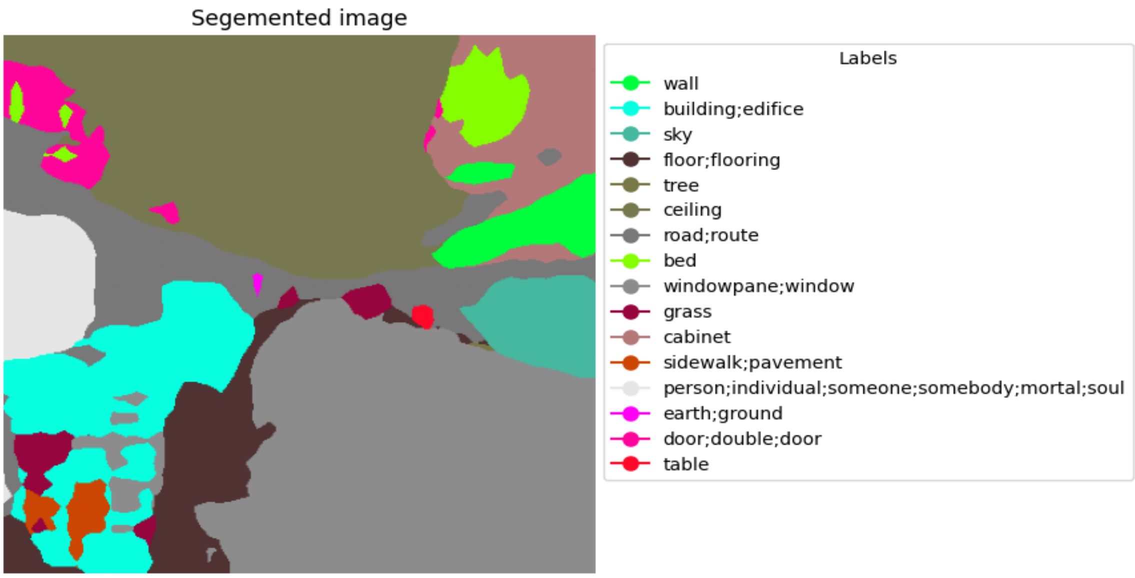


Figure 5: Segmented Image and Ade20k Color Label Visualization

This visualization demonstrates the model's capability to accurately differentiate between built and natural elements, highlighting the spatial arrangement and relative dominance of urban features. The precise separation of surfaces such as walls, roads, trees, and sky ensure the reliability of subsequent quantitative pixel-level analyses, which are used to compute the sub-indicators for comfort, convenience, and safety. By converting visual information into structured semantic data, this process establishes a solid foundation for integrating machine learning outputs into the broader analytical framework for evaluating urban environmental quality and walkability.

4. Results

This study provides a detailed evaluation of environmental attributes through semantic segmentation analysis, offering a comprehensive understanding of the urban landscape in the Dongdaemun area of Seoul, South Korea. During the segmentation process, the model assigned specific class labels to individual pixels, enabling semantic identification of every element within each image. This pixel-level classification allowed the systematic compilation of pixel distribution data, which served as the foundation for subsequent quantitative analyses. A structured Pandas DataFrame was developed to store the segmented class distributions, representing the proportional ratio of pixels assigned to each class relative to the total image size. These normalized values were essential for examining the spatial composition and visual characteristics of the urban environment.

The Integrated Visual Walkability Index (IVW) was calculated using RGB attributes extracted from the segmentation results through a custom Python program. Four sub-indicators—Psychological Greenery (G-level), Visual Crowdedness (C-level), Outdoor Enclosure (S-level), and Visual Pavement (D-level)—were measured for each street segment by averaging the coverage of street features across six vision boxes. Each sub-indicator was categorized into five levels, where higher levels represented more favorable environmental conditions. The integrated IVW values ranged from 20 to 200, reflecting the overall degree of pedestrian comfort, safety, and accessibility.

The Outdoor Enclosure score captured the degree of spatial confinement created by vertical structures, while the IVW index integrated the combined effects of greenery, pavement-to-street ratio, obstacle density, and enclosure to provide a holistic measure of walkability. Safety was evaluated based on obstacle-related features such as vehicles and pedestrians, which may restrict movement. A quantile-based scoring approach enabled detailed analysis across multiple zones within Dongdaemun, revealing spatial variations in comfort, convenience, and safety. Each location was evaluated to produce a total score integrating the three main indicators—comfort, convenience, and safety. Higher scores indicated more pedestrian-friendly and environmentally favorable conditions, while lower scores highlighted areas with limited accessibility or environmental challenges. The comfort score was derived from sky and greenery proportions, representing openness and natural visibility. Convenience incorporated crowd density, Outdoor Enclosure, and IVW measurements, reflecting accessibility and spatial continuity. Safety was assessed by obstacle density, identifying locations prone to congestion. The total score provided a comprehensive measure of livability and walkability, combining multiple environmental variables that influence pedestrian experience.

4.1 Segmentation Class Distribution

Figure 6 illustrates the relative sizes of the segmentation classes extracted from the analyzed street-view images. Each color segment corresponds to a semantic class, with proportions indicating the pixel coverage within the dataset. The dominant categories are ‘road, route’ (28.1%) and ‘ceiling’ (25.6%), showing that road surfaces and open-sky elements occupy the largest portions of the visual scenes. These features reflect the openness and exposure characteristic of Dongdaemun’s street environment. Other major components include ‘seat’ (10.1%) and ‘wall’ (9.9%), defining pedestrian and vehicular boundaries. ‘Floor, flooring’ (5.9%) and ‘building, edifice’ (5.8%) further describe the dense urban morphology, while smaller elements—such as ‘windowpane, window’ (3.9%), ‘bag’ (3.3%), ‘awning, sunshade, sunblind’

(2.8%), and ‘signboard, sign’ (2.2%)—represent commercial and human-activity features essential to streetscape characterization. These segmentation outcomes provide the foundational dataset for analyzing comfort, convenience, and safety indicators. The proportional pixel ratios were aggregated and reclassified into thematic variables, ‘greenery’, ‘sky’, ‘pavement’, and ‘street’—forming the basis for computing the Integrated Visual Walkability Index (IVW) and its sub-indicators.

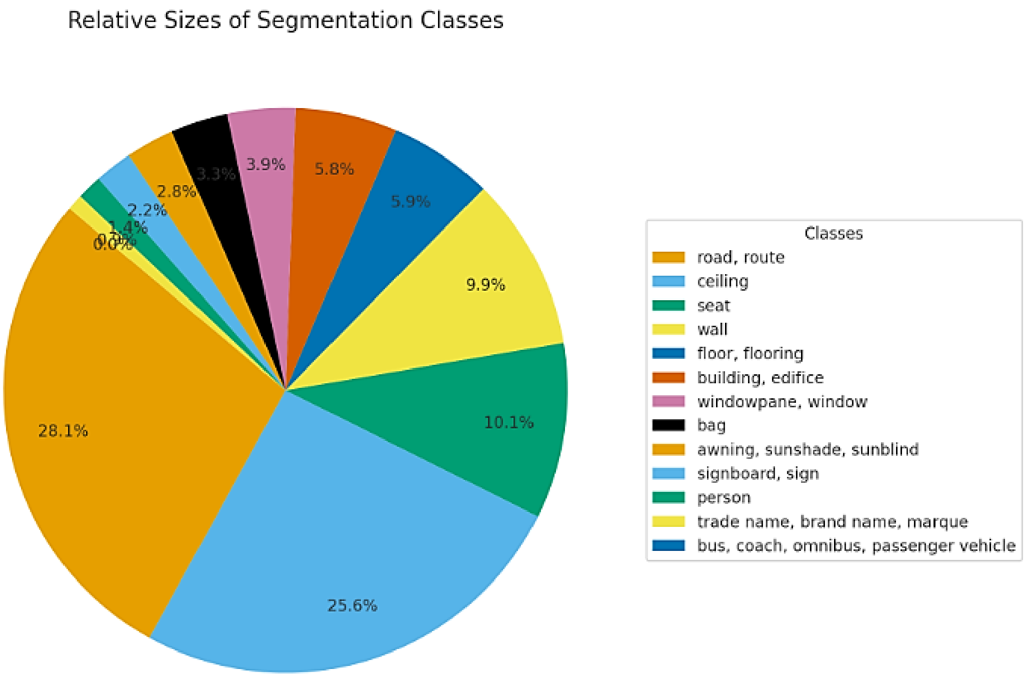


Figure 6: Relative Sizes of Segmentation Classes

4.2 IVW Indicators and Formula

Table 1 summarizes the indicators, their definitions, formulas, and explanations used in calculating the IVW. The IVW integrates four primary sub-indicators—Psychological Greenery (G), Visual Crowdedness (C), Outdoor Enclosure (S), and Visual Pavement (D)—each capturing a unique aspect of the visual and physical urban environment influencing pedestrian comfort, safety, and accessibility. The Psychological Greenery

Table 1: Indicators And Definition, Formula, and Explanation (Zhou *et al.* 2019)

Indicators and their definition, formula and explanation.

Indicators	Definition	Formula	Explanation
Psychological Greenery	Extent to which the visibility of street vegetation can influence pedestrian psychological feelings	$G_i = \frac{(\sum_1^6 Tn)}{6*Sum}$	T_n is the number of tree pixels; Sum is the total pixel number;
Visual Crowdedness	Extent to which the visibility of obstacles can influence pedestrian experiences	$C_i = \frac{(\sum_1^6 Cn)}{6*Sum}$	C_n is the number of obstacles pixels; Sum is the total pixel number;
Outdoor Enclosure	How the room-like outdoor space is (the ratio of vertical objects to horizontal features)	$S_i = \frac{\sum_1^6 Bn + \sum_1^6 Tn}{\sum_1^6 Pn + \sum_1^6 Rn + \sum_1^6 Fn}$	B_n is the number of building pixels; T_n is the number of tree pixels; P_n refers to the number of pavement pixels; R_n refers to the number of road pixels; F_n refers to the number of fence pixels
Visual Pavement	Psychological impacts of the proportion of road and sideway on pedestrian experience	$D_i = \frac{\sum_1^6 Pn + \sum_1^6 Fn}{\sum_1^6 Rn}$	R_n refers to the number of road pixels; P_n refers to the number of pavement pixels; F_n refers to the number of fence pixels;
Integrated Visual Walkability (IVW)	Integrated Visual Walkability index	IVW = (G-level + C-level + S-level + D-level)*5	

(G) indicator reflects how visible vegetation improves psychological well-being; Visual Crowdedness (C) measures the presence of obstacles affecting walkability; Outdoor Enclosure (S) expresses the balance between vertical and horizontal spatial features, revealing openness or confinement; and Visual Pavement (D) quantifies the proportion of walkable surfaces.

The IVW is calculated using the following formula:

$$IVW=(G\text{-level}+C\text{-level}+S\text{-level}+D\text{-level})\times 5 \tag{1}$$

This composite score ranges from 20 to 200, where higher values indicate safer, more accessible, and visually comfortable pedestrian environments. Sub-indicator values were computed using RGB pixel segmentation in Python and aggregated by averaging across six vision boxes per street segment. Each indicator was normalized and categorized into quantile-based levels (G-, C-, S-, and D-level), facilitating detailed comparison between locations. The combination of these indicators establishes a quantitative and replicable framework for assessing visual walkability and environmental quality within dense urban areas.

4.3 Spatial Distribution of Comfort, Convenience, and Safety

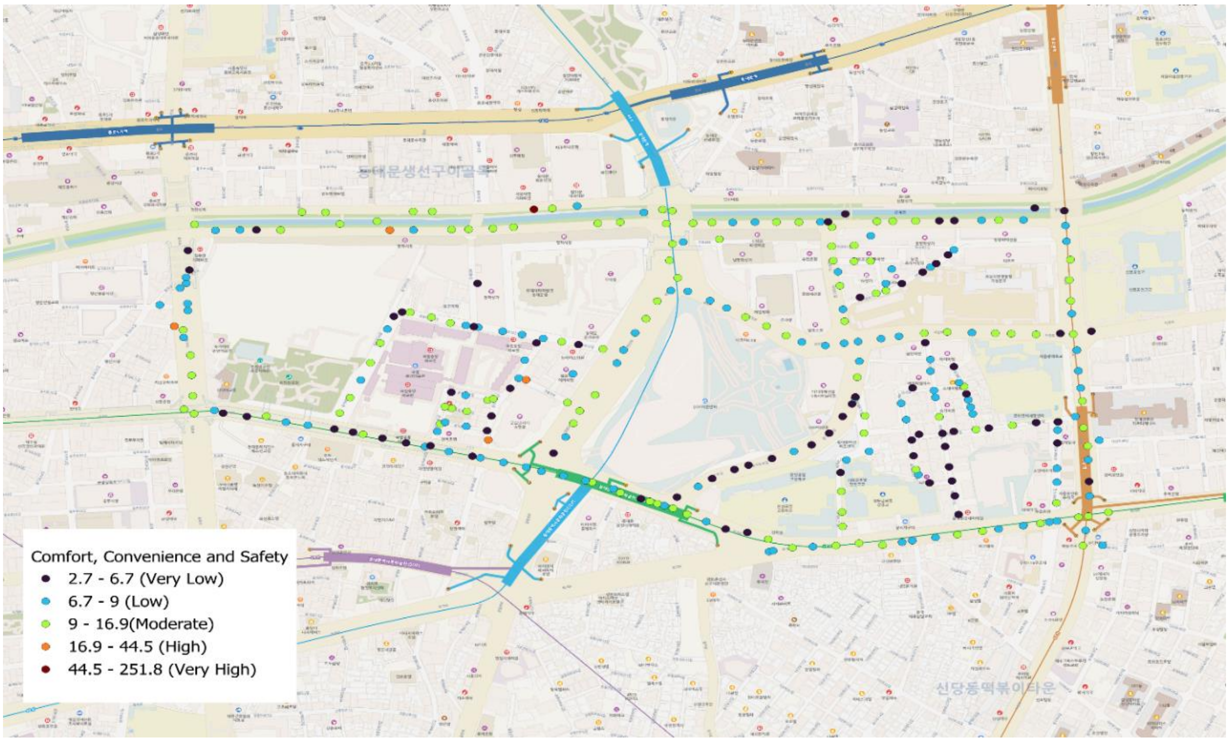
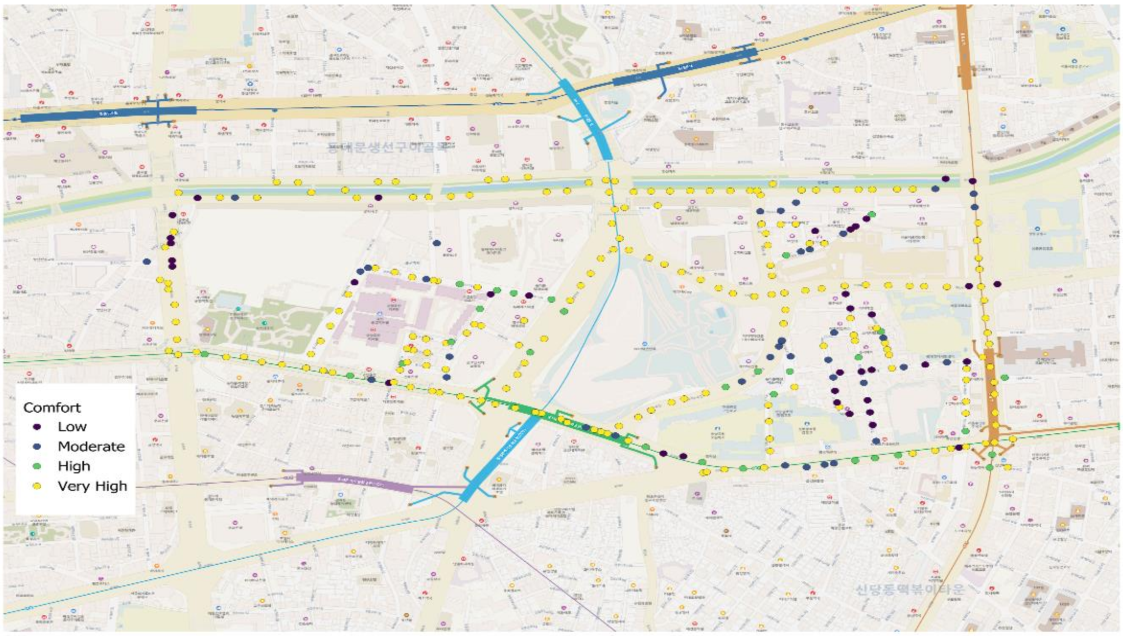
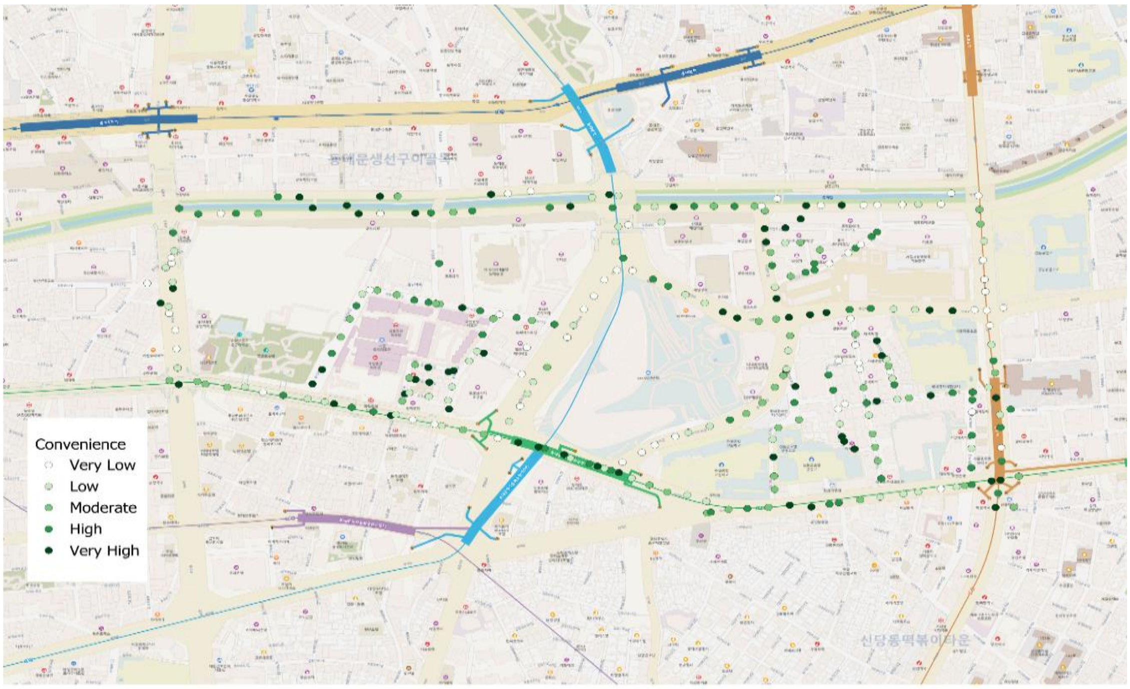


Figure 7: Visualization of the Total Proportion of Comfort, Convenience, and Safety in The Dongdaemun Area

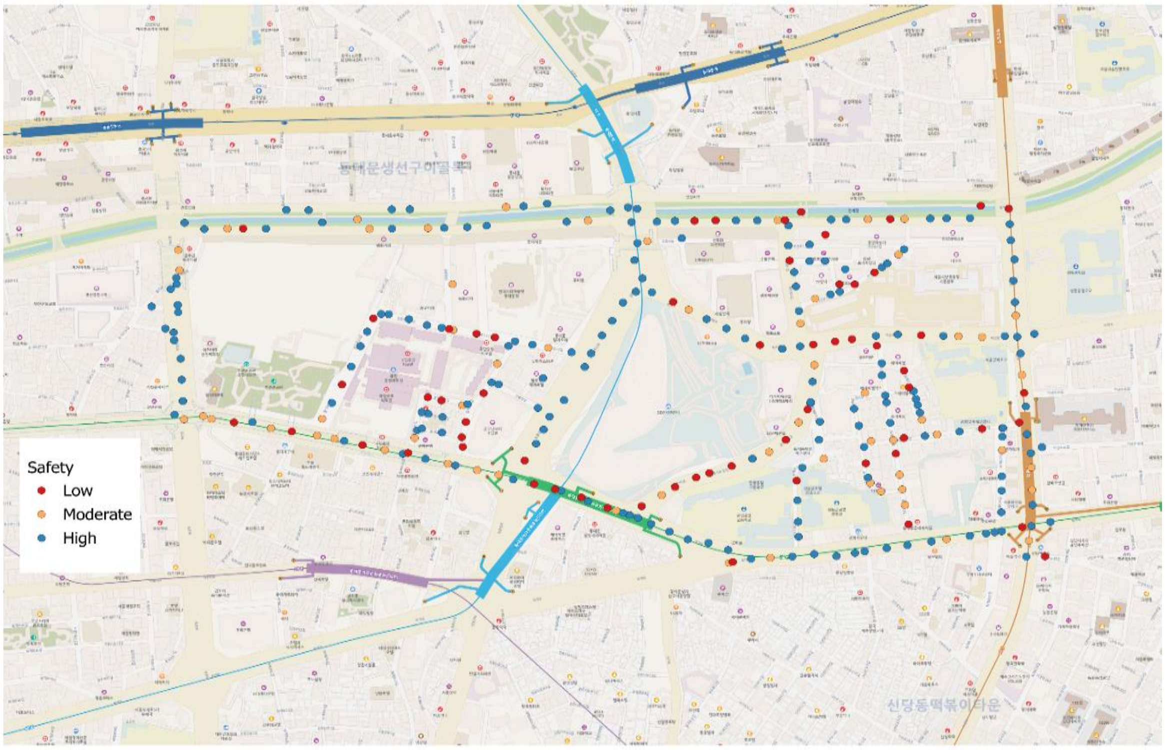
Figures 7 and 8 illustrate the spatial distribution of the Integrated Visual Walkability Index (IVW) and its three sub-indicators—comfort, convenience, and safety—across the Dongdaemun area. The results reveal distinct spatial variations in environmental quality and walkability. Figure 7 visualizes the total proportion of comfort, convenience, and safety scores derived from the IVW across the study area. The map clearly depicts variations in environmental quality, with color-coded points representing the aggregated scores at each street site. Streets with very low to low scores (2.7–9), shown in dark and light blue, are mainly concentrated along inner residential alleys and narrow passageways, reflecting areas with limited greenery, poor visibility, and higher obstacle density. In contrast, moderate to high values (9–44.5), indicated by green and orange points, are found along main streets and open public areas where pedestrian conditions are more favorable. A few segments display very high scores (44.5–251.8), marked in red, located near parks, public facilities, and wide sidewalks—signifying the most comfortable and safest walking environments.



(a)



(b)

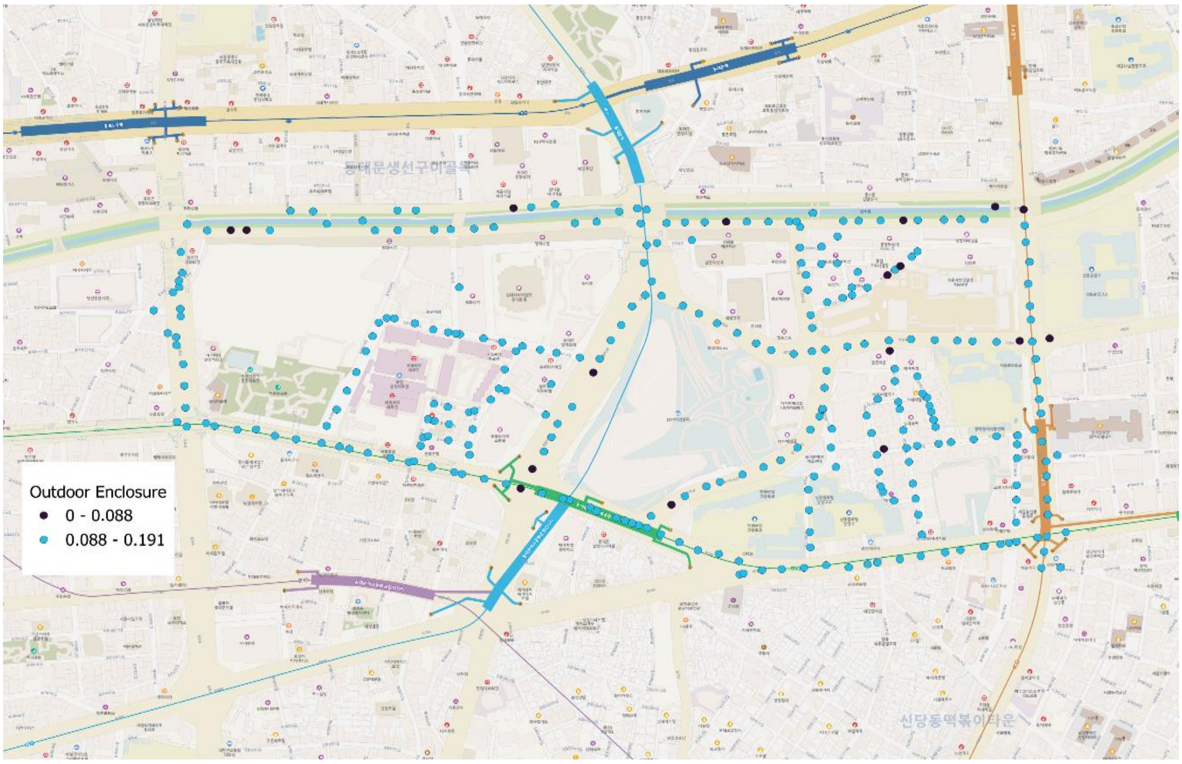


(c)

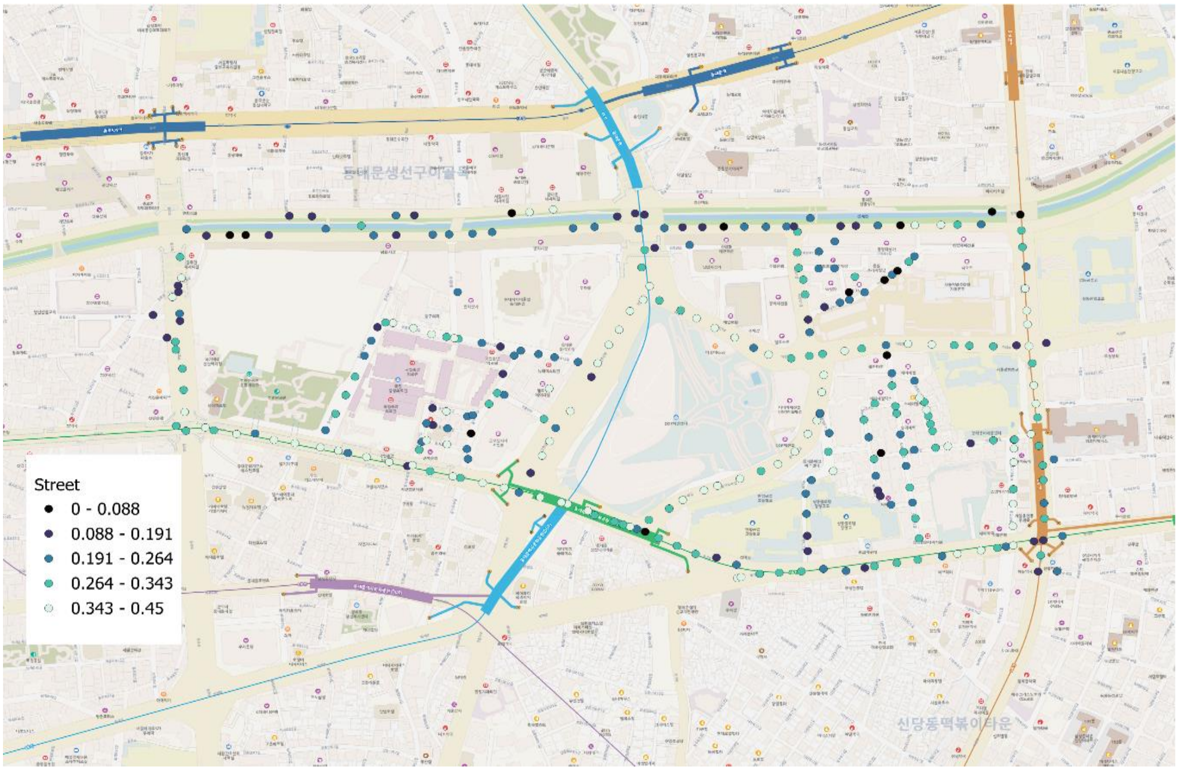
Figure 8: Comfort, Convenience, and Safety Results on the Analysis of Dondaemun Area

These visual patterns demonstrate clear spatial differences in walkability within Dongdaemun. Major roads and open zones tend to provide better comfort, convenience, and safety, while inner streets and crowded alleys show lower scores. Such spatial insights are valuable for urban planners in identifying priority areas that require improvement through enhanced greenery, lighting, and pedestrian infrastructure. Figure 8(a) indicates that high comfort levels are concentrated along open streets and park surroundings with abundant vegetation and wide pedestrian paths, whereas low-comfort areas are mainly found in dense built-up zones. Figure 8(b) reveals that convenience is higher along main transportation corridors and intersections where pedestrian access and infrastructure continuity are stronger, while less connected interior streets show low convenience levels. Figure 8(c) shows that safety is greatest along unobstructed and well-designed streets but decreases in areas with heavy traffic and pedestrian congestion. These spatial patterns emphasize the uneven distribution of walkability across Dongdaemun and the importance of targeted improvements—such as adding greenery, expanding sidewalks, and enhancing lighting—to achieve a safer, more comfortable, and accessible urban environment.

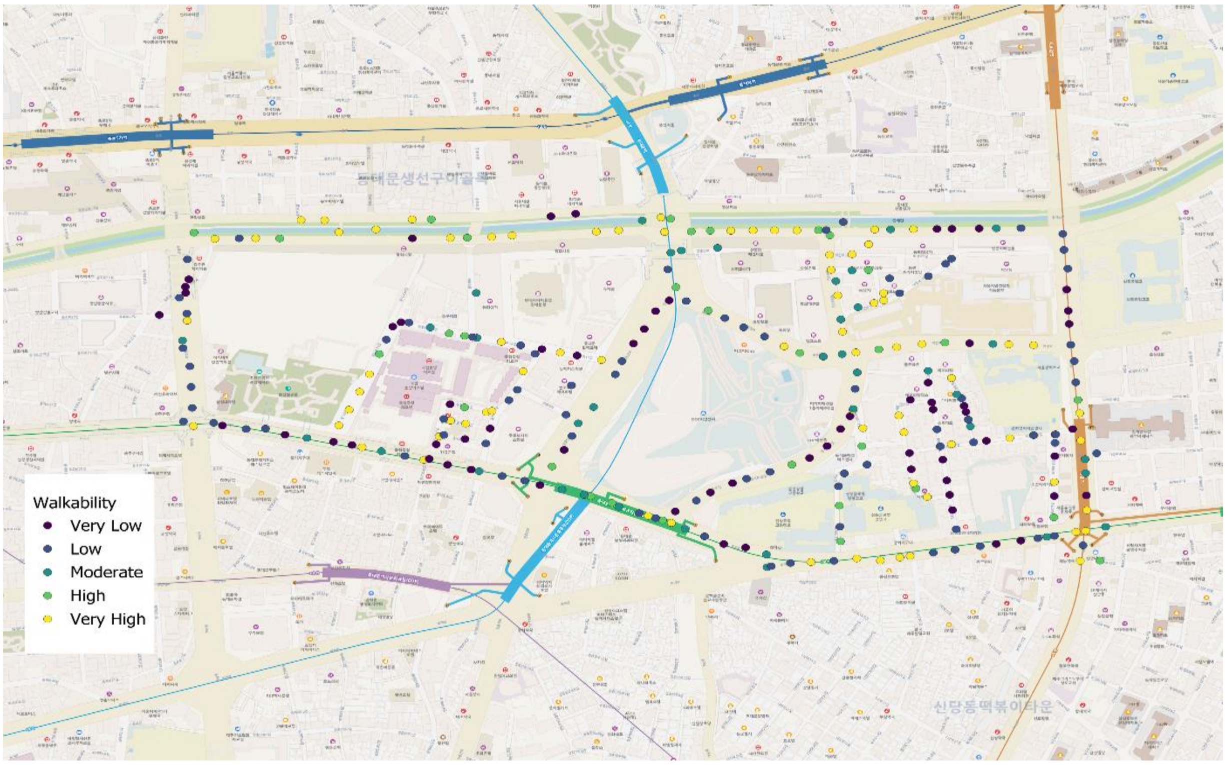
4.4 Feature-Specific Spatial Indicators



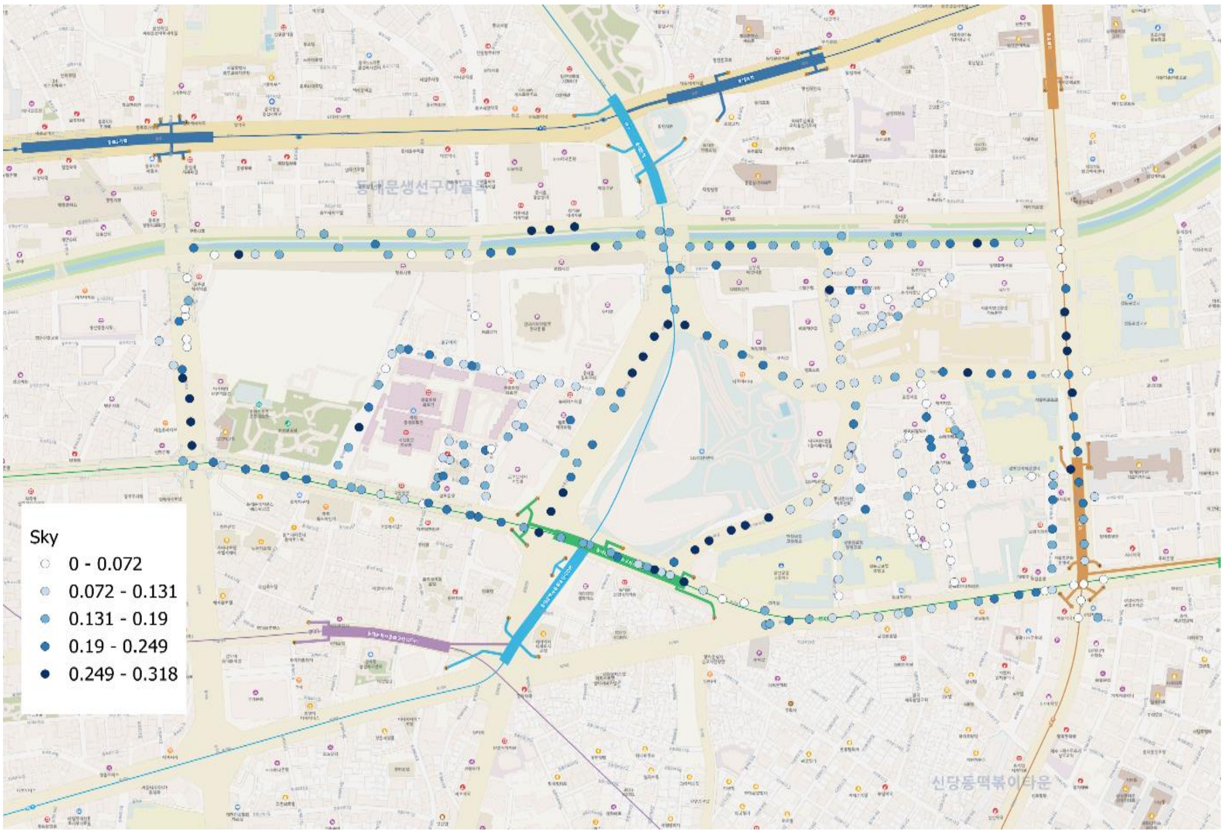
(a)



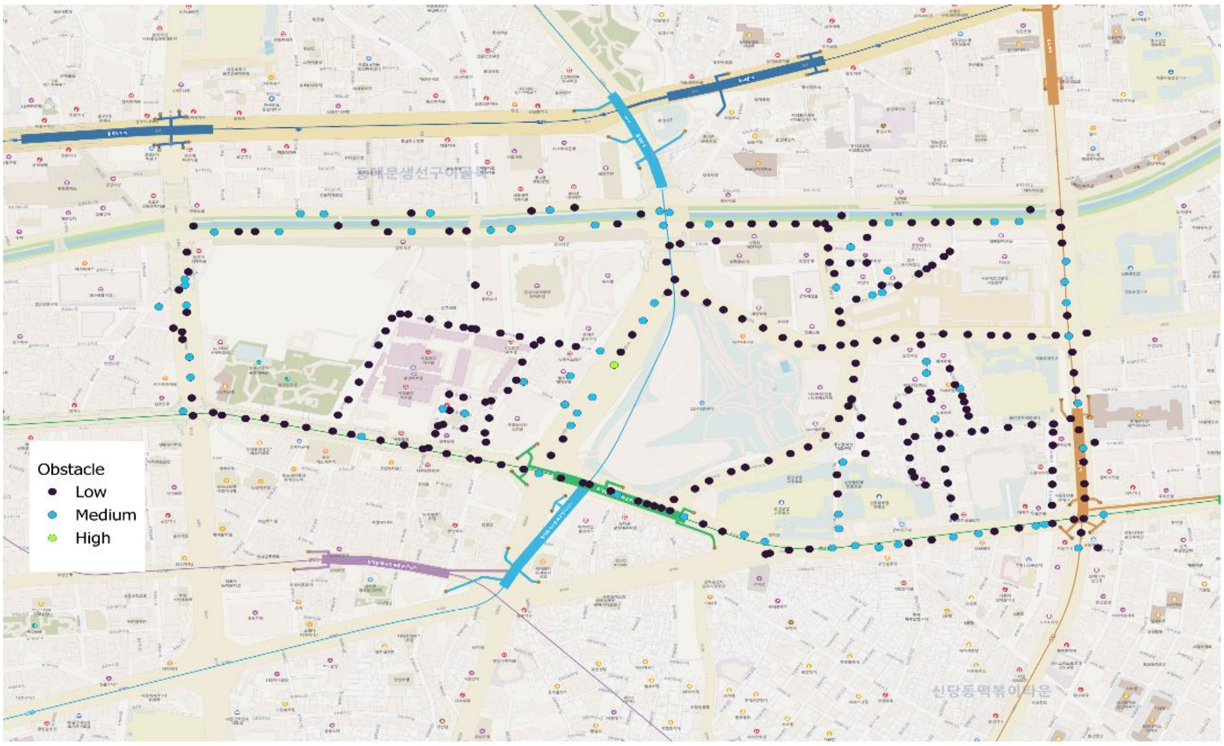
(b)


Walkability
Very Low
Low
Moderate
High
Very High

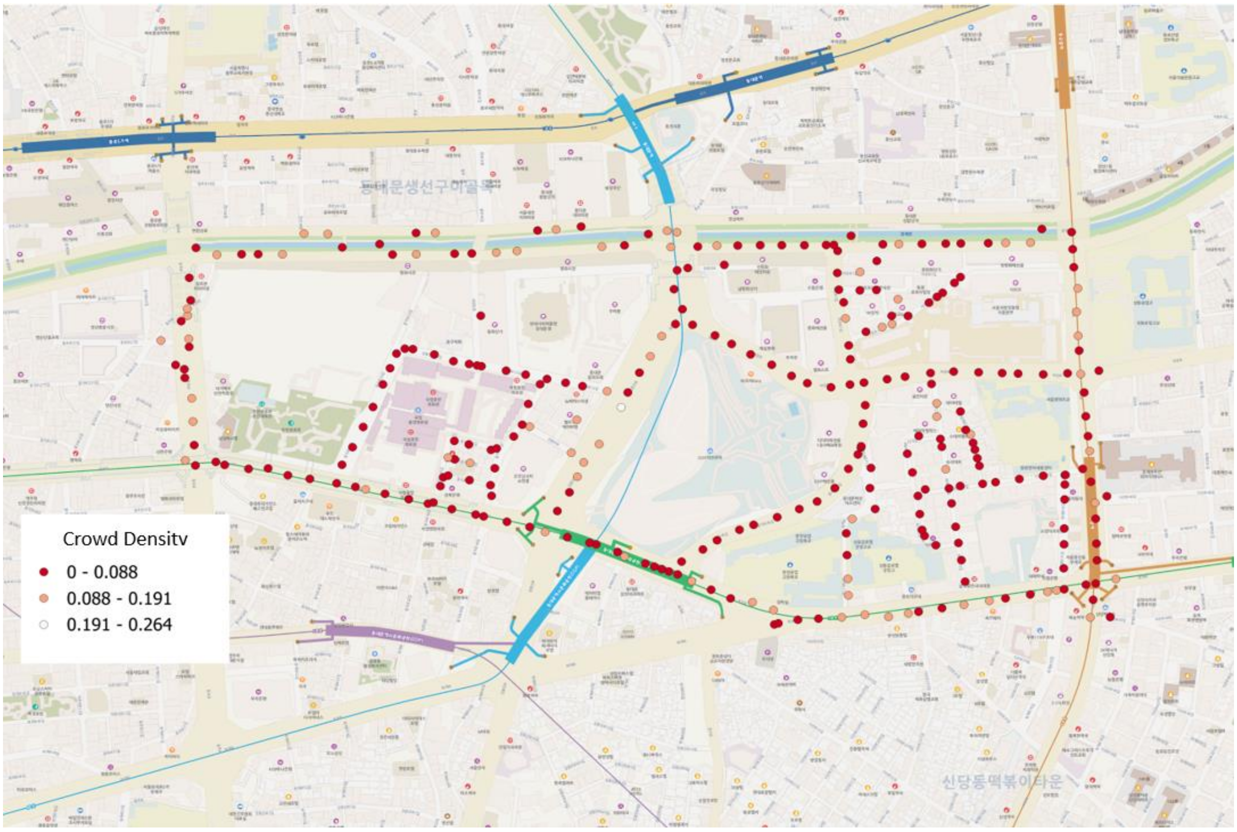
(c)


Sky
0 - 0.072
0.072 - 0.131
0.131 - 0.19
0.19 - 0.249
0.249 - 0.318

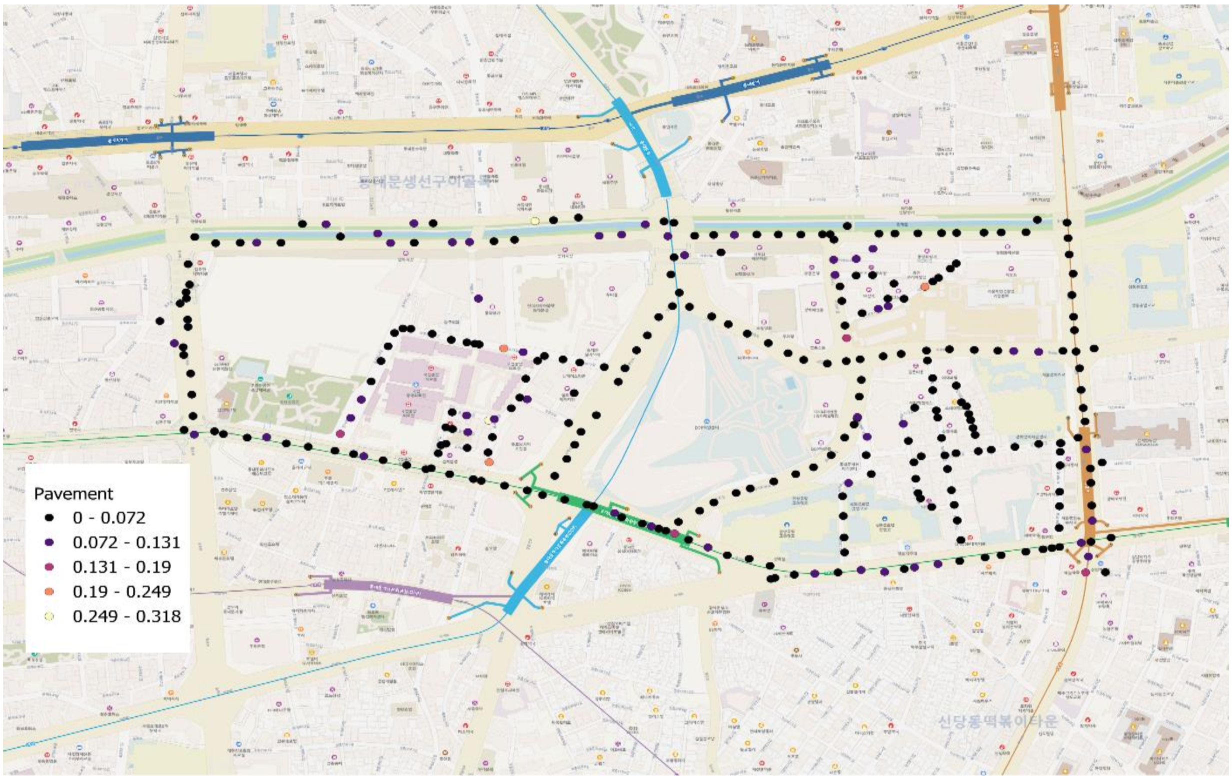
(d)


동대문생선구이골목
Obstacle
Low
Medium
High
신당동떡볶이타운

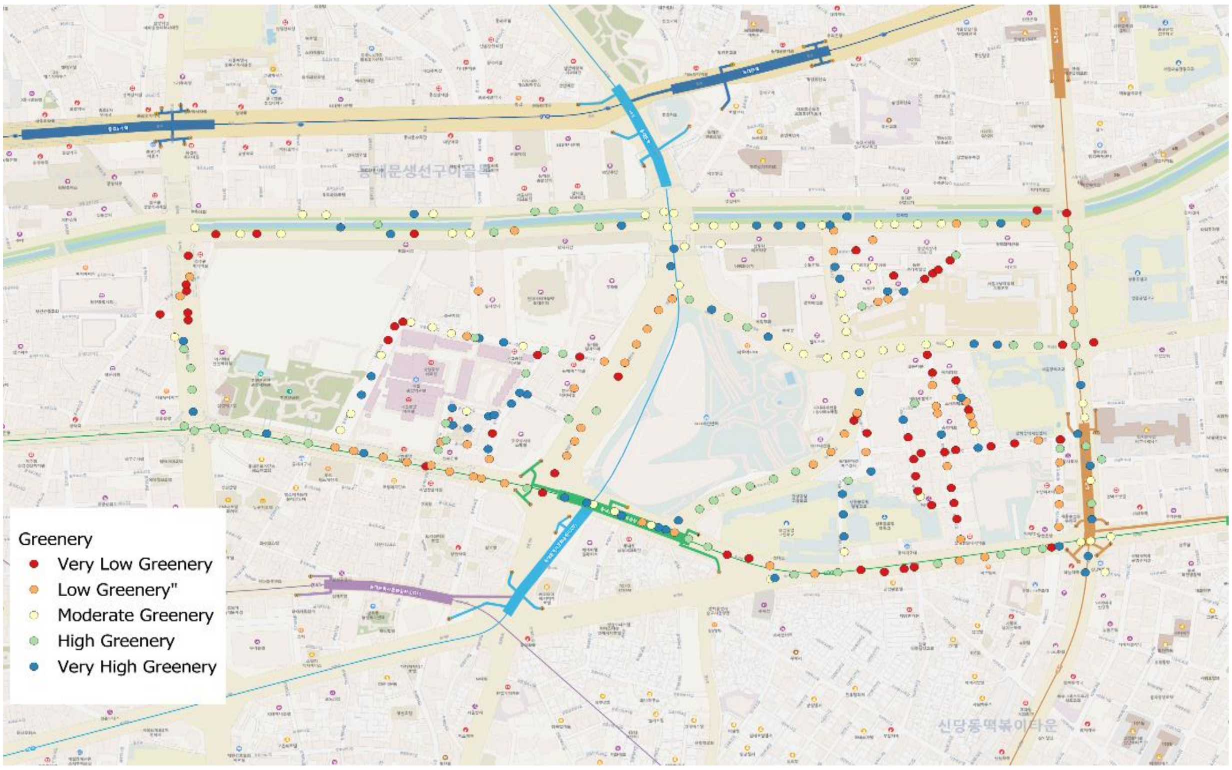
(e)


동대문생선구이골목
Crowd Density
0 - 0.088
0.088 - 0.191
0.191 - 0.264
신당동떡볶이타운

(f)



(g)



(h)

Figure 9: Outdoor Enclosure, Street, Walkability, Sky, Obstacles, Crowd Density, Pavement, Greenery, Proportion of Dongdaemun Area

Figure 9(a) illustrates the Outdoor Enclosure, showing that higher enclosure values occur along major roads and building corridors where structural walls define the pedestrian space, while lower values appear near open areas and parks, offering greater visual openness. Figure 9(b) presents the Street feature, highlighting that high street proportions align with primary circulation routes and intersections, reflecting strong connectivity and accessibility within the urban network. Figure 9(c) displays Walkability, indicating that high walkability levels are concentrated along main streets and open spaces, where pedestrian conditions and accessibility are more favorable. Low walkability zones are clustered in inner alleys with narrow paths and limited vegetation. Figure 9(d) shows the Sky proportion, where high values correspond to open spaces and intersections with clear vertical visibility, while low ratios are found in dense built-up environments.

Figure 9(e) represents the Obstacle distribution, identifying areas with varying levels of potential pedestrian obstruction. High obstacle density occurs near crowded or traffic-heavy zones, while low values correspond to open and safer walking areas. Figure 9(f) depicts Crowd Density, revealing high pedestrian concentrations around transportation hubs and commercial streets, and lower densities in residential or park-side streets. Figure 9(g) illustrates Pavement coverage, with high values indicating well-maintained, wide sidewalks, and low values observed in narrow or poorly developed street segments. Figure 9(h) visualizes Greenery, where the highest levels are observed around parks, open green corridors, and public spaces, while built-up commercial areas exhibit low greenery levels. These spatial patterns collectively highlight the interaction between built form, natural elements, and pedestrian infrastructure in determining the environmental quality and walkability of the Dongdaemun area. The integration of these indicators offers valuable insights for improving comfort, accessibility, and safety in urban planning and design.

4.5 Model Accuracy and Validation

To ensure the reliability of the semantic segmentation process, a validation test was conducted on a subset of randomly selected Google Street View images from the Dongdaemun dataset. Although the DeepLab ResNet101 model was pre-trained on the ADE20K dataset, its performance was re-evaluated within the local urban context to verify segmentation consistency and class-level precision. Manual annotations were prepared for 50 representative street-view samples encompassing diverse urban settings, including residential alleys, open roads, green corridors, and commercial streets. Model performance was quantitatively assessed using three standard metrics: Pixel Accuracy (PA), Mean Class Accuracy (mCA), and Mean Intersection over Union (mIoU).

- PA measures the overall proportion of correctly classified pixels in the entire image set.
- mCA reflects the average classification accuracy across all semantic classes.
- mIoU quantifies the mean overlap between the predicted and ground-truth regions for each class, providing a balanced measure of model precision.

Table 2: Model Performance Evaluation on the Dongdaemun Dataset

Metric	Definition	Result
Pixel Accuracy (PA)	Ratio of correctly classified pixels to total pixels	**0.88**
Mean Class Accuracy (mCA)	Average per-class accuracy	**0.82**
Mean Intersection over Union (mIoU)	Average intersection-over-union across all classes	**0.74**

Table 2 presents the quantitative evaluation of the DeepLab ResNet101 model's performance on the Dongdaemun dataset using three standard semantic segmentation metrics: Pixel Accuracy (PA), Mean Class Accuracy (mCA), and Mean Intersection over Union (mIoU). The Pixel Accuracy of 0.88 indicates that 88% of all image pixels were correctly classified into their respective semantic categories, while the Mean Class Accuracy of 0.82 reflects consistent performance across different urban classes, including less represented features such as vegetation and sidewalks. The Mean Intersection over Union of 0.74 demonstrates the model's strong segmentation precision, effectively distinguishing between overlapping regions like buildings, roads, sky, and greenery. Overall, these results confirm that the DeepLab ResNet101 model achieved satisfactory accuracy even in complex urban scenes. Minor performance reductions observed in narrow pedestrian alleys and shaded regions were primarily due to visual overlaps between walls and pavements. Nonetheless, the model's segmentation accuracy was sufficient to extract reliable environmental sub-indicators for computing the Integrated Visual Walkability (IVW) index, thereby ensuring the robustness and reliability of subsequent spatial and environmental analyses.

4.6 Visual Validation and Reliability

Visual inspection confirmed that thematic maps produced by the model closely aligned with real-world street conditions. High greenery and sky ratios corresponded to open spaces, while obstacle and crowd density aligned with commercial and transit areas. No random artifacts or irregular patterns were observed, demonstrating spatial coherence and reliable boundary delineation. These outcomes confirm the robustness of the segmentation framework and support the use of derived indicators for evaluating comfort, convenience, and safety.

5. Discussion

The results highlight significant spatial variation in walkability across Dongdaemun. High walkability areas were concentrated along major streets, public open spaces, and park surroundings, where greenery, sky visibility, and pedestrian-friendly infrastructure improved comfort and accessibility. Conversely, narrow alleys and dense commercial corridors exhibited low walkability due to limited openness, higher obstacle density, and constrained pedestrian space.The strong model performance (PA = 0.88, mIoU = 0.74) demonstrates that DeepLab ResNet101 effectively captured complex urban structures, enabling reliable extraction of environmental indicators. Although minor misclassifications occurred in visually congested areas, these had minimal influence on aggregated IVW outcomes.The observed spatial patterns align with existing literature emphasizing the importance of greenery, openness, and unobstructed pedestrian routes for enhancing urban walkability. The IVW framework developed in this study provides a scalable and reproducible method for evaluating visual walkability. These insights are valuable for urban planners seeking to improve pedestrian environments through targeted interventions such as increasing vegetation, widening sidewalks, reducing obstacles, and enhancing lighting.

6. Conclusion

This study aimed to assess the urban environmental quality of the Dongdaemun area through geospatial semantic segmentation, addressing the research problem of how street-level visual data can be translated into meaningful indicators for urban planning and environmental assessment. By applying a deep learning–based DeepLab ResNet101 model to Google Street View imagery, key visual elements such as greenery, sky openness, pedestrian pathways, and road surfaces were quantified to derive composite measures of comfort, safety, and convenience, culminating in the Integrated Visual Walkability (IVW) index. The findings demonstrate that semantic segmentation enables pixel-level understanding of environmental patterns, offering valuable insights for evidence-based decision-making, policy development, and sustainable urban design. The approach effectively bridges visual data analysis and spatial planning, identifying specific locations where improvements—such as enhanced vegetation, lighting, or pedestrian infrastructure—can improve livability. However, the study is limited by its reliance on Google Street View imagery, which may not fully capture temporal variations or areas with incomplete coverage. Future research should incorporate temporal datasets, expand to broader metropolitan areas, and enhance segmentation accuracy through multi-modal or higher-resolution imagery to strengthen applicability and generalizability.

Author Contributions

Conceptualization, S.M.T.; methodology, S.M.T.; software, S.M.T. and validation, S.M.T.; formal analysis, investigation, S.M.T.; resources, data curation, writing—original draft preparation, S.M.T.; writing— review and editing, S.M.T.; visualization, S.M.T. All authors have read and agreed to the published version of the manuscript.

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