Development of a Perception-Based Urban Quality of Life Index Using Street View Imagery and Deep Learning: The Case of Metro Manila, Philippines

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Abstract

Urban quality of life (QoL) assessments often rely on objective spatial indicators such as infrastructure access, land use, and environmental conditions. However, these metrics may overlook how residents subjectively perceive their surroundings. This disconnect signifies a methodological deficiency within urban studies: the lack of inclusive frameworks that integrate both objective and perceptual aspects of urban quality. In response, this study introduces a perception-based urban quality of life index (PUQLI) derived from street view imagery and deep learning and compares it against a composite objective indicator built from 13 spatially measured indicators across seven QoL domains. Each indicator was normalized and spatially joined to a hexagonal grid system. Pearson correlation revealed only modest associations between PUQLI and individual objective indicators, suggesting partial alignment. A mismatch was computed to quantify perception–provision gaps, revealing statistically significant and spatially patterned divergences ($t = -10.535$, $p < 0.0001$). Areas of under-perception and over-perception were examined, which provide critical spatial insights for the formulation of planning interventions. These findings underscore the necessity of integrating subjective perceptions into urban assessment frameworks to ensure that the provision of infrastructure effectively translates into tangible enhancements in urban quality. The mismatch index serves as a pragmatic diagnostic tool for perception-informed urban development.

1. Introduction

Urban Quality of Life (UQoL) serves as a critical metric for evaluating urban livability, inclusivity, and sustainability. It pertains to the welfare of urban individuals and communities, integrating both the physical environment and lived experiences (Al-Qawasmi, 2020). This concept includes tangible elements such as infrastructure and environmental quality, as well as intangible factors like safety, neighborhood identity, and emotional connections to places.

Although Quality of Life has been extensively studied, its measurement remains methodologically fragmented and conceptually contested (Prutkin and Feinstein, 2002). A recurring tendency in existing frameworks is to emphasize objective indicators because they are easier to quantify and standardize. However, such indicators do not necessarily reflect how residents actually experience urban environments, and prior studies have shown that measurable urban conditions and subjective evaluations do not always align.

This focus often overlooks subjective factors impacting urban residents' perceptions. Empirical studies reveal a gap between objective and subjective quality of life indicators (McCrea et al., 2006), implying that objective metrics may inadequately capture lived experiences. The incorporation of subjective data encounters challenges in collection, standardization, and scalability through conventional surveys, which are labor-intensive and difficult to standardize across diverse urban environments (Merschdorf et al., 2020). These issues sustain a significant divide between the physical and experiential dimensions of urban quality.

Recent advances in geospatial analytics and artificial intelligence propose innovative methodologies for bridging this divide. Researchers have initiated the estimation of subjective perceptions derived from street-level imagery employing machine learning algorithms trained on crowdsourced datasets (Biljecki and Ito, 2021). Notably, the Place Pulse 2.0 dataset provides global evaluations of urban scenes across various perceptual categories, enabling scalable and spatially explicit urban perception modeling.

In response, this study develops the Perception-Based Urban Quality of Life Index (PUQLI), a spatial composite index constructed from deep learning-derived perception scores across Metro Manila using street view imagery. PUQLI aggregates visual perception scores related to beauty, safety, vibrancy, wealth, boredom, and depression, following the Place Pulse 2.0 framework. The study has four objectives. First, it develops a perception-based representation of urban quality from street-level imagery using deep learning. Second, it constructs a composite perceptual index that captures the experiential dimension of urban quality across Metro Manila. Third, it examines the spatial distribution and clustering of perceived urban quality. Fourth, it compares PUQLI with conventional objective indicators in order to identify areas where measured provision and perceived experience converge or diverge.

By integrating perceptual modeling with spatial analysis, this research presents an innovative, data-informed methodology for assessing urban quality from a human-centered perspective. It connects both objective and subjective metrics, providing essential insights for urban stakeholders in fostering more equitable and perception-driven urban environments.

2. Literature Review

2.1 Approaches to Measuring Urban Quality of Life

Urban Quality of Life (QoL) is a multidimensional construct in urban research that encompasses both objective indicators which are quantifiable elements like infrastructure and environmental quality and subjective indicators which correspond to residents' perceptions and satisfaction (McCrea et al., 2006).

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Theme	Representative Studies	Approach	Data Type
Global/Institutional Indices	Economist Intelligence Unit (2016), Mercer (2016), Monocle (2018), OECD (2024), UN-Habitat (2015)	Scoring, benchmarking, indicator sets	Objective
Urban and Environmental Quality	Dobrowolska et al. (2024), Patil and Sharma (2022), Zhalehdoost et al. (2025),	GIS, statistical indicators, accessibility models	Objective
Subjective-Only Assessments	Huynh et al. (2023), Mouratidis (2021), Mouratidis and Yiannakou (2022), Salleh and Badarulzaman (2012)	Perception surveys, resident-based scoring	Subjective
Integrated / Mixed Methods	Al-Qawasmi et al. (2021), Li et al. (2021), Garau and Pavan (2018), McCrea (2007), Merschdorf et al. (2020)	Objective + subjective indicators, perception + spatial/quantitative	Objective-Subjective

Table 1. Summary of Urban QoL Studies by Data Type and Approach

As summarized in Table 1, the current literature shows a clear disproportionate emphasis on objective indicators. This includes global benchmarking tools developed by institutions (e.g., EIU, Mercer, CPI), as well as urban studies using GIS, accessibility modeling, and statistical techniques (Giap et al., 2014). Recent comparative reviews similarly note that existing QoL indices lack consistency and often omit resident-centered dimensions (Al-Qawasmi et al., 2021).

While a diverse array of tools and indices has emerged to assess QoL, their structure and scope vary substantially. A critical review of 26 global assessment tools by Mittal et al. (2019) highlights this fragmentation, noting that despite covering multiple aspects of urban life, few tools adopt a holistic perspective—and most lean heavily toward top-down, objective measures. Qualitative, perception-based approaches remain limited, and neighborhood-scale variation is often overlooked (Abbate et al., 2001).

In light of this fragmented landscape, Wesz et al. (2023) provide a useful synthesis by identifying dimensions that frequently recur across empirical studies, even in the absence of a unified framework. Their systematic review suggests that seven thematic areas—urban services, economy, culture and recreation, urban mobility, conviviality, security, and environmental comfort, emerge as common threads in the literature. While these dimensions are not universally adopted, they represent a flexible yet coherent structure through which both objective and subjective aspects of urban life may be interpreted and evaluated.

Despite such developments, the overall trend remains skewed. As Mittal et al. (2019) argue, most QoL assessments still conceptualize the city as a homogenous entity and overlook the variability of experiences across urban neighborhoods. This signals a critical research gap: the need for more perception-driven, bottom-up QoL assessments that better reflect the nuances of how urban life is experienced on the ground.

2.2 Approaches to Measuring Urban Quality of Life

The growing recognition of the limitations of objective-only QoL assessment has opened space for new approaches that better reflect lived experiences. Recent developments in computational technologies, extensive image datasets, and crowdsourced perceptual surveys offer novel avenues for systematically and expansively capturing the subjective attributes of urban environments.

Place Pulse 2.0, an MIT initiative, collected over 1.1 million street view evaluations across six dimensions: safety, wealthy, beautiful, lively, boring, and depressing (Dubey et al., 2016). These evaluations serve as proxies for personal urban quality experiences based on visual perceptions. The method is subjective, focusing on emotional and cognitive urban design reactions rather than fixed metrics. In contrast to traditional, costly data collection methods, Place Pulse utilizes a standardized visual interface for systematic perception gathering. When integrated with deep learning, these scores facilitate the scaling of subjective urban experiences using street-level imagery.

These perceptual dimensions, although not initially designed to correspond with conventional QoL categories have subsequently been examined in numerous studies as indicators of subjective urban experience and have demonstrated strong associations with quantifiable urban outcomes (Salesses et al., 2013). When compared to Wesz et al.'s seven thematic dimensions of Urban QoL, perceptual categories from datasets like Place Pulse 2.0 reveal significant conceptual overlaps. For example, the perceived safety dimension directly correlates with urban security concerns and actual crime rates, as evidenced by several studies (Zhou et al., 2024). Perceptions of wealth or depression reflect socioeconomic conditions and urban service quality, aligning with economy and urban service dimensions. Similarly, perceptions of vibrancy or dullness relate to public activity and social interaction, linking to culture and recreation and conviviality dimensions (Sammakieh and Mohammed, 2024). Ultimately, aesthetically appealing streetscapes, associated with visual attractiveness and greenery, can signify environmental comfort (Cirino et al., 2024).

The six perceptual categories used in this study were adopted from the Place Pulse 2.0 framework and represent visually interpretable dimensions of urban experience (Salesses et al., 2013; Zhang et al., 2018). They are not treated as exhaustive measures of UQoL, but as scalable visual-perceptual proxies derived from street-level imagery. Their ability to capture spatial nuance and emotional resonance makes them valuable for urban QoL modeling, especially in cities where fine-grained subjective data is difficult to obtain through surveys alone.

Building on these insights, this study systematically aligns Place Pulse perceptual categories with the seven objective quality of life dimensions and investigates their integration into a composite, perception-based quality of life index, thereby addressing existing methodological deficiencies in quality-of-life research.

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3. Data and Methodology

3.1 Study Area

Metro Manila, composed of 16 cities and 1 municipality, serves as the study area (Figure 1). It covers a densely populated urban landscape of 619.6 square kilometers and housing over 13 million residents. This region is characterized by a mix of dense commercial areas, residential zones, and informal settlements, making it an ideal setting for studying urban landscapes through human perception.

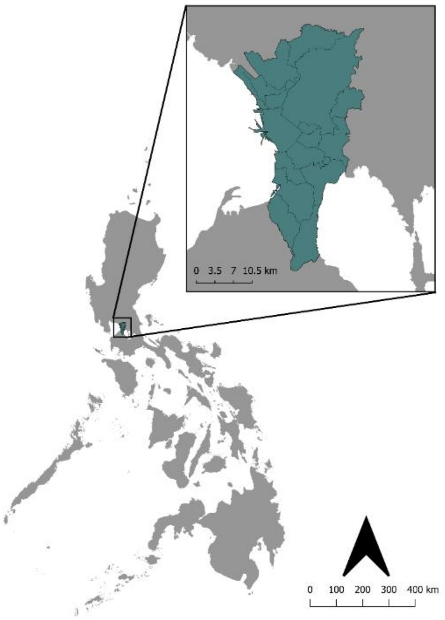

Figure 1. Study Area (Metro Manila)

3.2 Research Framework

This study introduces a perception-driven methodology for evaluating Urban Quality of Life through the integration of street-level imagery, deep learning models, and spatial analytics. The research framework encompasses four interconnected phases, as depicted in Figure 2. These phases are designed to systematically transform raw perceptual data into a composite perception-based index and analyze its spatial patterns in relation to conventional objective indicators:

1. **Perceptual Feature Modeling**: Deep learning algorithms are utilized on the Place Pulse 2.0 dataset to extract perceptual cues from urban imagery, with a Vision Transformer (ViT) classifying perceptual dimensions, SegFormer segmenting urban features, and a Random Forest model integrating results to predict perceptual scores.

2. **PUQLI Index Construction and Calculation:** The models are applied to street-level imagery in Metro Manila to derive perception scores across six dimensions, which are subsequently synthesized into a Perception-Based Urban Quality of Life Index (PUQLI).

3. **Spatial Pattern Analysis of PUQLI**: The spatial distribution of PUQLI is examined using spatial statistics such as Getis-Ord Gi* to uncover hotspots and neighborhood-level disparities in perceived urban quality.

4. **Comparative Assessment with Objective Indicators**: PUQLI is compared against conventional objective indicators to evaluate alignment to reveal areas where perceived and measured urban conditions diverge or align.

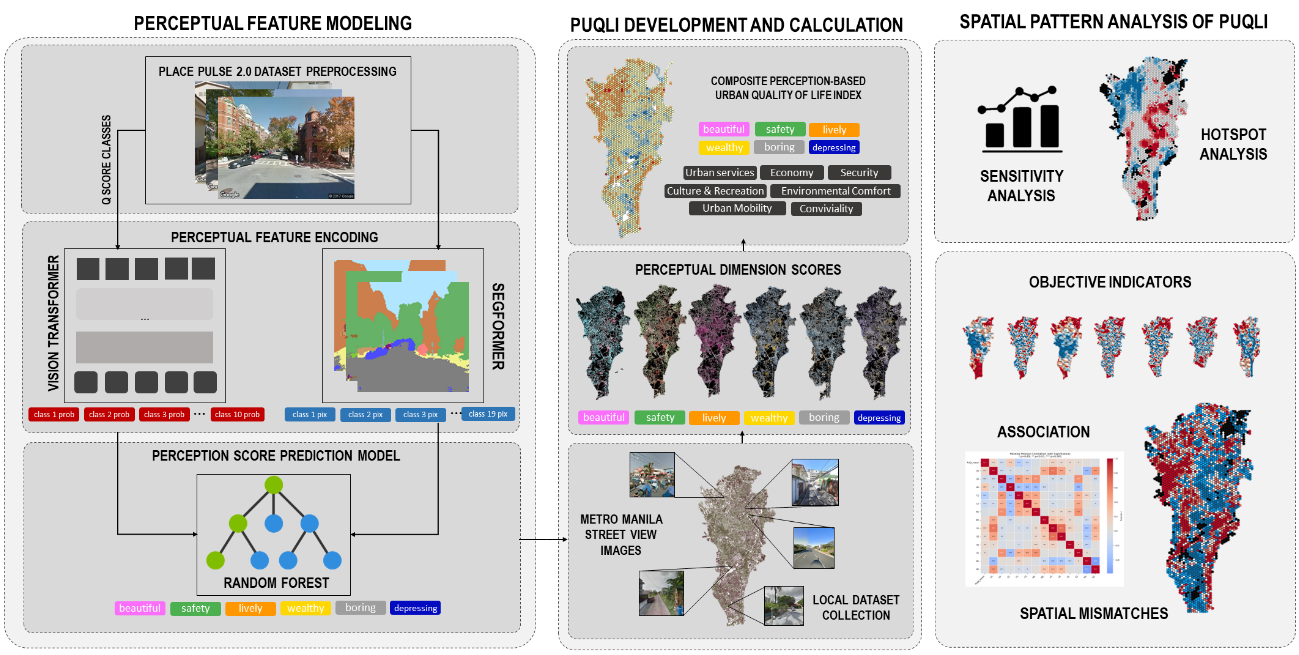

Figure 2. Research Framework

3.2.1. Perceptual Feature Modeling

The street-level imagery used was sourced from Google Street View. A uniform sampling strategy was applied by generating points at approximately 50 m intervals along the road network extracted from OpenStreetMap. A total of 168,547 images were retrieved across the metropolitan area, each at a nominal resolution of 640 × 640 pixels. Images were filtered to remove duplicates, obstructions, or non-navigable views.

This study adopts a collaborative perception modeling framework, following Huang et al. (2023), which integrates subjective judgments and physical features using machine learning. Perceptual labels derived from Place Pulse 2.0 are integrated with transformer-based models to derive both semantic and perceptual attributes from street-level imagery.

The Place Pulse 2.0 dataset provides pairwise comparisons of urban images across six perceptual categories: safe, wealthy, beautiful, lively, boring, and depressing. To ensure reliability, only images with at least five comparisons were retained. Q-scores (ranging from 0 to 10) were computed per image and category using normalized winning and losing ratios then discretized into 10 bins for classification, as discretization provides a more robust intermediate representation of noisy and subjective pairwise labels.

$$\mathrm{W_{i,u}} = \frac{\mathrm{w_{i,u}}}{\mathrm{w_{i,u} + l_{i,u} + t_{i,u}}}, \ \mathrm{L_{i,u}} = \frac{\mathrm{l_{i,u}}}{\mathrm{w_{i,u}+l_{i,u}+t_{i,u}}} \tag{1-2}$$

$$\mathrm{Q}_{i,u} = \frac{10}{3}\left(\mathrm{W}_{i,u} + \frac{1}{n_i^w}\sum_{j_1=1}^{n_i^w} W_{j_1 u} - \frac{1}{n_i^l}\sum_{j_2=1}^{n_i^l} L_{j_2 u} + 1\right) \tag{3}$$

where n_i^w and n_i^l represent the number of images that image i was preferred over and not preferred over, respectively. These Q-scores range from 0 to 10 and were discretized into 10 score bins for classification.

A Vision Transformer (ViT) was adapted for image classification. ViT divides images into segments and employs self-attention for spatial relationship analysis. A pre-trained model was enhanced through data augmentation, cosine annealing, and early stopping to bolster generalization. To extract urban features, SegFormer was used for semantic segmentation, classifying each pixel into one of 19 categories (e.g., vegetation, buildings, road). These pixel-level distributions serve as structured descriptors of the scene.

The combined outputs of ViT and SegFormer, specifically class probabilities and feature distributions, were used as inputs to a Random Forest regression model to predict continuous perceptual scores. The model (256 trees, depth = 8) was regularized using minimum split and leaf constraints and evaluated using RMSE and MAE on a validation set. This framework combines classification, segmentation, and regression to estimate perceptual scores from urban imagery.

3.2.2. PUQLI Index Construction and Calculation

The Perception-Based Urban Quality of Life Index (PUQLI) was developed by mapping perceptual scores from Place Pulse onto seven commonly identified QoL dimensions. These dimensions were operationalized by combining perceptual categories based on the literature-established associations discussed in Section 2.2 and the thematic framing of Urban QoL dimensions (Wesz et al., 2023). The mapping of perceptual categories to QoL dimensions reflects well-documented links between visual cues and urban outcomes, such as the associations between perceived safety and crime, greenery and environmental comfort, and vibrancy and social activity. These established relationships provide the basis for the mapping used in the study. Table 2 summarizes the mapping strategy.

QoL Dimension	Mapped Perceptual Indicators	Dimension Score
Urban Services	Wealthy, Depressing	(Wealthy + (10 − Depressing)) / 2
Economy	Wealthy	Wealthy
Culture and Recreation	Lively, Boring, Beautiful	(Lively + (10 − Boring) + Beautiful) / 3
Urban Mobility	Safe, Lively	(Safe + Lively) / 2
Conviviality	Lively, Boring	(Lively + (10 − Boring)) / 2
Security	Safe	Safe
Environmental Comfort	Beautiful, Depressing	(Beautiful + (10 − Depressing)) / 2

Table 2. Mapping of Perceptual Indicators to Urban QoL Dimensions

Each perceptual score ranged from 0 to 10 and was linearly combined based on the formulas above to produce dimension-specific sub-scores. The final PUQLI was computed as the unweighted mean of all seven dimensions:

$$\mathrm{PUQLI} = \frac{1}{7}\sum_{d-1}^{7} Score_d \tag{4}$$

This equal-weighting method aligns with index development practices favoring equal weighting when preferences are ambiguous or when minimizing subjectivity in weighting is needed. Sensitivity analysis was implemented to identify the extent to which variations in individual indicator weights could influence the overall PUQLI scores and spatial patterns. This step ensures the robustness of the index construction and highlights whether equal weighting yields stable outcomes. The PUQLI scores were aggregated to 500-meter hexagonal grid cells to optimize detail at a local scale while ensuring analytical stability. A 500-meter cell size is sufficient to capture detail at a local scale, such as streetscape perception, but limits noise associated with image-level detail and density.

3.2.3. Spatial Pattern Analysis of PUQLI

Spatial statistical techniques were used to identify localized patterns in the gridded scores. The Getis-Ord Gi* statistic detected clusters of high and low PUQLI values which revealed neighborhood-scale disparities that may not be evident in the raw index. The standardized hexagonal units further supported consistent spatial comparison across the metropolitan area.

3.2.4. Comparative Assessment with Objective Indicators

To evaluate the alignment between perception-based urban quality and conventional measures, quantitative indicators corresponding to the seven QoL dimensions of PUQLI were identified, normalized, and integrated (Table 3). Each indicator was min–max normalized and aggregated by dimension. Pearson correlation was then used to assess the associations between PUQLI and individual objective indicators.

To further examine perception–provision gaps, a mismatch index was computed at the hexagonal grid level as the difference between PUQLI and the composite objective urban quality index, with both indices aligned in direction and expressed on the same 0–10 scale. This index identified areas where perceived urban quality exceeded or fell below objective conditions. Mismatch values were classified into five quantile-based categories, from very negative (under-perceived) to very positive (over-perceived), and mapped to visualize their spatial distribution.

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QoL Dimension	Code	Indicator	Description	Source
Urban Services	U1	Access to basic utilities	% of households with piped water and electricity as proxy for service coverage	PSA
	U2	Proximity to nearest healthcare facility	Euclidean distance to the nearest health facility	OSM
Economy	E1	Night-time light intensity	Proxy for economic activity and consumption levels	VIIRS
Culture and Recreation	C1	Proximity to parks	Euclidean distance to nearest green/leisure space	OSM
	C2	Proximity to cultural or recreational facilities	Euclidean distance to museums, gyms, or cultural sites	OSM
Urban Mobility	M1	Proximity to public transport stop	Euclidean distance nearest bus/train/jeepney stop	GTFS, OSM
	M2	Road density	Total road length per km², proxy for connectivity	OSM
Conviviality	V1	Population density	Proxy for potential human interaction and social vibrancy	PSA
	V2	Building density	Built-up density per unit area	OSM
Security	S1	Crime incidence rate	Number of index crimes per 1,000 population	PNP
	S2	Proximity to police stations	Euclidean distance to nearest police precinct	OSM
Environmental Comfort	N1	NDVI	Normalized Difference Vegetation Index as proxy for greenness	Landsat
	N2	PM2.5 concentration	Fine particulate matter level as proxy for air quality	Sentinel/GEOS

Table 3. Objective Indicators per QoL Dimension

4. Results and Discussion

4.1 Modeling and Validation of Perception-Based Urban Quality Index (PUQLI)

The integration of Vision Transformer (ViT), SegFormer, and Random Forest (RF) formed a robust pipeline for predicting perceptual scores from urban street-level imagery. ViT effectively captured abstract visual cues, particularly for more distinct categories such as depressing, which reached training accuracies exceeding 78%, indicating the model’s capability to internalize features reflective of negative urban impressions. SegFormer provided pixel-level semantic segmentations across 19 urban land cover classes (e.g., buildings, vegetation, roads), adding spatial structure and context essential for perception-based modeling.

Using both the ViT category probabilities and SegFormer-derived spatial features, the RF model predicted perceptual scores across six dimensions. The model excelled in identifying cues for depressing (RMSE: 0.913), lively (RMSE: 0.945), and safety (RMSE: 0.951) which indicates its proficiency in recognizing stable urban characteristics. Error rates were higher in more subjective categories, beautiful (RMSE: 1.128), wealthy (RMSE: 1.079), and boring (RMSE: 1.023), suggesting the challenges of modeling perceptions shaped by cultural and socioeconomic interpretations.

To assess the robustness of PUQLI, a sensitivity analysis was performed by sequentially excluding each input variable and calculating its correlation with the original composite. The greatest drop in correlation was observed when removing boring ($\rho = 0.9413$), followed by depressing ($\rho = 0.9203$), and wealthy ($\rho = 0.6908$), indicating their significant contributions to the index. These findings confirm that PUQLI is not only empirically grounded but also resilient to changes in component structure, making it a reliable and interpretable measure of human-centered urban quality

4.2 Spatial Patterns and Clustering of Perceived Urban Quality

The spatial patterns of the Perception-Based Urban Quality Index (PUQLI) show significant variation across the study area which indicates the different ways by which the urban environment is perceived visually about aspects of safety, vibrancy, beauty, etc. Figure 3 shows the spatial patterns of the six perceptual dimensions, their corresponding histograms, and the spatial clustering of the PUQLI using the Getis-Ord Gi* method.

Areas with high perceptual values for beauty, safety, and liveliness are found primarily in the central business districts (Makati, Bonifacio Global City, Alabang), academic zones

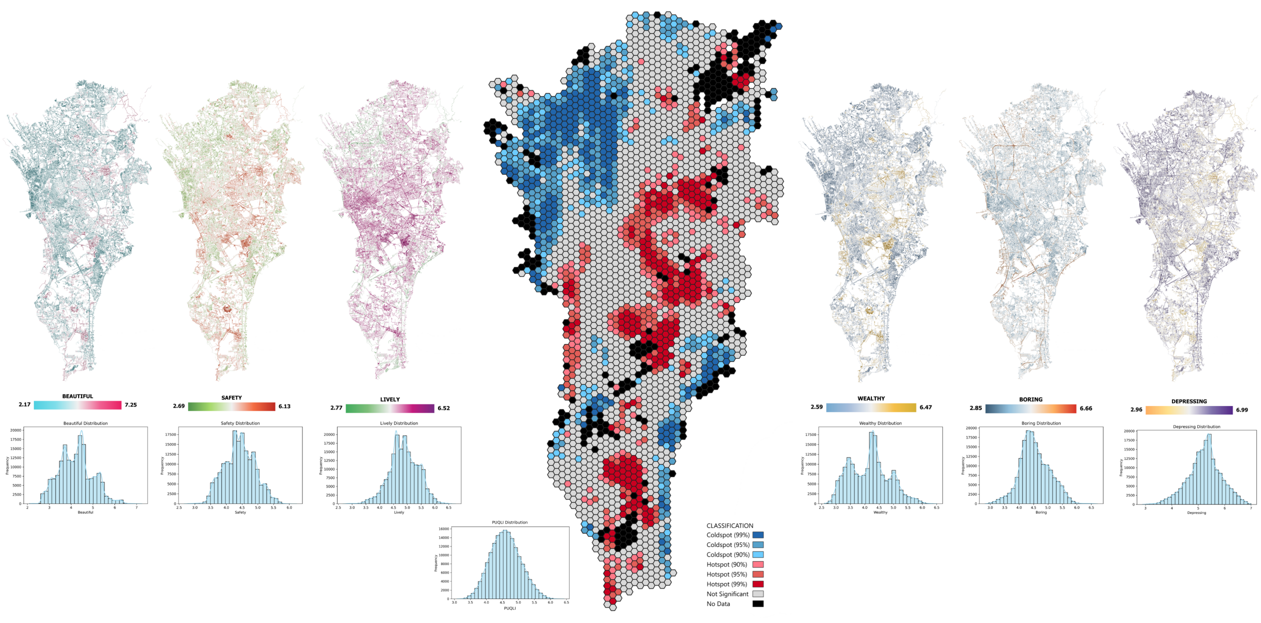

Figure 3. Spatial Patterns of Predicted perceptual dimensions and hotspots of composite perception-based urban quality of life

(UP Diliman, Quezon City), and mixed-use areas, while low perceptual values are found primarily in the periphery, including CAMANAVA and Taguig City. This center-periphery pattern is common in studies of urban environments.

The use of visual-based perceptual scores shows how people intuitively understand the differences in the environment. High perceptual values for safety and liveliness are found primarily in dense, walkable, and visually maintained environments, while high perceptual values for boredom and depression are found primarily in visually monotonous environments. The histograms show that the perceptual values for safety, liveliness, and depression are close to normal, while the perceptual values for beauty and wealth show skewed or multi-modal patterns, possibly due to the subjectivity of beauty and wealth.

The Getis-Ord Gi* map in Figure 3 reveals distinct spatial clustering, with PUQLI hotspots in central urban areas and coldspots in peripheral zones. While individual dimensions reflect specific perceptual traits, the composite PUQLI provides a broader representation of perceived urban quality that generally aligns with spatial patterns observed in the objective indicators.

4.3 Association of Objective and Subjective Indicators

The spatial distribution maps in Figure 5 show that PUQLI and the corresponding objective indicators across the seven urban quality of life domains do not always follow the same spatial pattern. To quantify these relationships, a correlation analysis was done between PUQLI and the 13 objective indicators which suggests a partial but meaningful alignment between subjective perceptions and measurable urban conditions (Figure 4). While most associations were statistically significant, effect sizes were generally modest ($|r| < 0.3$). Rather than weakening the value of PUQLI, this pattern supports the study’s central premise that urban provision does not directly equate to urban perception. Although perceived urban quality is influenced by objective spatial conditions, it is not fully reducible to them. If provision and perception were equivalent, substantially stronger correlations would be expected across domains.

The most pronounced alignment was identified with C1 (proximity to parks) ($r = 0.256$, $p < 0.001$) and E1 (nighttime light intensity) ($r = 0.210$, $p < 0.001$), indicating that accessibility to recreational facilities and economically vibrant areas positively influences perceived quality of life. Positive correlations were also found for N1 (greenness) ($r = 0.155$, $p < 0.001$), C2 (proximity to cultural or recreational facilities) ($r = 0.136$, $p < 0.001$), M2 (road density) ($r = 0.092$, $p < 0.001$), and U2 (proximity to health services) ($r = 0.090$, $p < 0.001$), indicating that environmental quality and access-related urban features contribute, albeit modestly, to perceived urban quality.

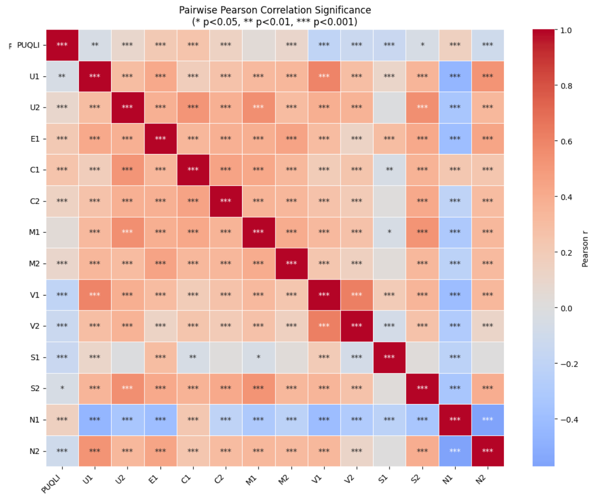

Figure 4. Correlation of subjective and objective indicators

In contrast, negative correlations were observed for V1 (population density) ($r = -0.194$, $p < 0.001$), S1 (crime incidence) ($r = -0.146$, $p < 0.001$), V2 (building density) ($r = -0.134$, $p < 0.001$), and N2 (PM2.5 concentration) ($r = -0.099$, $p < 0.001$). These results suggest that denser, more polluted, or less secure environments tend to be perceived less favorably. Weak negative correlations were also found for U1 (access to utilities) ($r = -0.054$, $p < 0.01$) and S2 (proximity to police stations) ($r = -0.050$, $p < 0.05$), indicating that the mere presence of infrastructure or services does not always translate into more positive urban perceptions.

The generally weak correlations should not be interpreted as a limitation of PUQLI, but rather as evidence that objective provision and subjective perception capture related yet distinct dimensions of urban quality (McCrea et al., 2006; Wesz et al., 2023). While measurable urban conditions such as access, economic activity, greenness, and density help shape perception, they do not fully determine how places are experienced. This helps explain why several indicators show only modest or inverse associations with PUQLI despite their expected contribution to urban quality.

Taken together, these findings show that the relationship between subjective and objective indicators is partial, selective, and nuanced. While some spatial features, particularly those related to access to amenities, economic activity, and environmental quality, align with perceived urban quality, others show weak or inverse associations. This reinforces the view that provision and perception are related but not equivalent, and that perception captures additional experiential, contextual, and affective dimensions not fully represented by conventional objective spatial indicators.

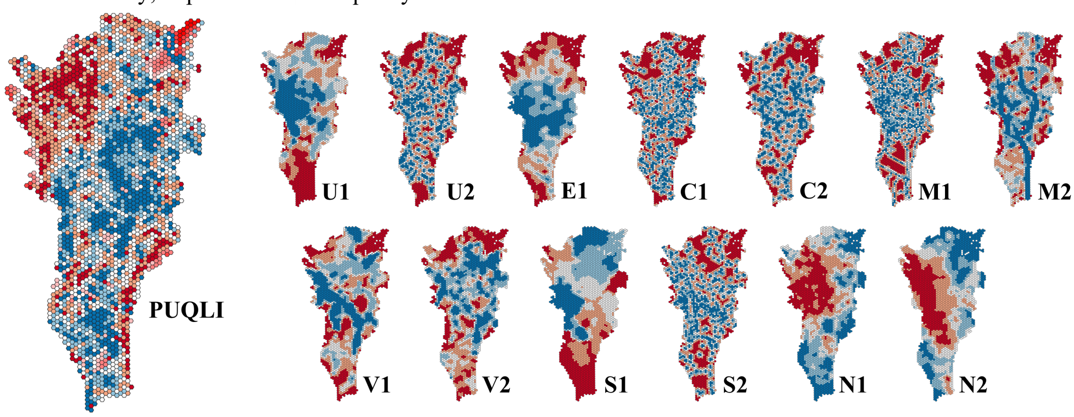

Figure 5. PUQLI and objective indicators across 7 identified domains (blue: high urban QoL; red: low urban QoL)

4.4 Spatial Mismatch Between Perceived and Objective Urban Quality

The mismatch analysis further shows that perceived urban quality does not always align with objectively measured urban conditions. To quantify this divergence, a mismatch index was computed at the hexagonal grid level as the difference between PUQLI and the composite objective urban quality index. Positive values indicate areas where perceived urban quality exceeds what objective provision would suggest, while negative values indicate the reverse. This provides a spatially explicit view of the perception–provision gap identified in the correlation analysis. The mismatch map in Figure 6 shows the spatial distribution of under-perceived and over-perceived areas across Metro Manila.

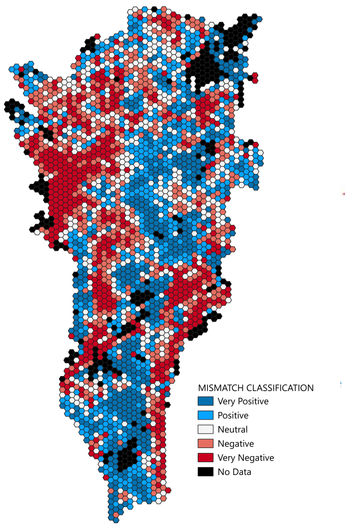

Figure 6. Objective and Subjective UQoL mismatch

The positive mismatch clusters are concentrated in areas that have established or developing mixed-use urban centers within the increasingly polycentric structure of Metro Manila (Rau and Corpuz, 2012). Some of the areas where the positive mismatch is concentrated include Makati, the Ortigas-Mandaluyong urban corridor, Bonifacio Global City in Taguig, growth centers in Quezon City, the Bay City reclamation area in Pasay, and Alabang in Muntinlupa. In urban planning and urban development literature, these areas have been recognized as the most important business, growth, or mixed-use urban centers of Metro Manila. These areas have the most pronounced centrality, activity, and urban legibility, which may have partly contributed to their more favorable perception compared to the objective provision. Marikina, on the other hand, is recognized as a well-ordered, livable, and community-oriented urban area, suggesting a role for urban identity and perceived urban order in addition to infrastructure provision.

The negative mismatch regions are primarily concentrated in Manila and CAMANAVA. A negative mismatch indicates a perceived urban quality lower than the composite index. This implies that despite the comparatively favorable urban provision, the urban experience in this area is less favorable. This is consistent with the urban stressors documented in the literature for this area. In Manila, for example, documented informality and multidimensional deprivation may contribute to less favorable lived urban conditions despite the availability of some urban services (Singh and Gadgil, 2017). In CAMANAVA, this area is recognized in the literature as a low-lying coastal and riverine zone frequently subject to flooding, inadequate drainage, tidal action, and pollution-related urban stressors (Muto et al., 2010). Thus, the issue is not simply whether infrastructure or service access exists, but whether such
provision is sufficient to offset the cumulative burdens that shape lived urban experience.

Statistical analyses further support these spatial patterns. A one-sample t-test showed that the mean mismatch was significantly different from zero ($t = –10.535$, $p < 0.0001$), with the negative mean indicating that perceived urban quality generally falls below what objective provision alone would suggest. The slight left skew of the mismatch distribution likewise indicates a greater prevalence of under-perceived areas. Taken together, these results point to a structural perception–provision gap: urban environments may perform relatively well in measurable terms yet still be experienced less positively in everyday life. This suggests that infrastructure or service access alone does not automatically translate into favorable urban perception.

These findings have important implications for urban planning. They reinforce the need to complement objective indicators with subjective assessments, since measurable provision alone may overestimate livability and obscure localized experiential deficits. The identified mismatch zones also provide spatially explicit points for intervention: positive-mismatch areas may reflect places where identity, legibility, or activity intensity strengthen perception beyond formal provision, while negative-mismatch areas suggest that provision may be undermined by congestion, environmental stress, insecurity, weak maintenance, or limited public trust. More broadly, improving urban quality requires not only expanding infrastructure and services, but also ensuring that they translate into favorable lived experience.

4.5 Limitations and Scope of Interpretation

Several limitations should be considered in interpreting the findings. Firstly, the results are limited by the availability and road-based viewing perspective of Street View data, which may unevenly represent urban environments. In addition, PUQLI only measures the visual perceptual aspect of urban quality, without including other non-visual dimensions such as noise, odors, thermal comfort, cost, governance, and life satisfaction. Third, the perceptual labels are derived from the Place Pulse framework, whose meanings may vary across sociocultural contexts and may not fully correspond to local interpretations in Metro Manila. Finally, the predicted perception scores are model-based estimates, not direct resident-reported perceptions.

5. Conclusion and Recommendation

This study developed a Perception-Based Urban Quality of Life Index (PUQLI) using street-level imagery and deep learning and compared it with objectively measured urban conditions in Metro Manila. The results showed that both subjective and objective urban quality are related but not interchangeable, as indicated by the low correlations and spatial mismatches between provision and perception. The significantly negative mean mismatch further confirmed this perception-provision gap, indicating that there are areas that are less favorably perceived than their objective urban conditions. Overall, the findings show that well-being is shaped not only by material conditions, but also by how communities are perceived and experienced, which are not fully captured by objective indicators alone.

These results highlight the importance of integrating perception into urban quality assessment. The mismatch index offers a useful tool for identifying areas where technical provision does not align with lived experience and where more context-sensitive intervention may be needed. For planning and policy, this suggests that improving urban quality requires not only expanding infrastructure and services, but also ensuring that these translate into favorable everyday experience. Future research may strengthen the framework by incorporating locally grounded perceptual surveys, non-visual experiential variables, and temporal analysis.

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