The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-5/W4-2025
Philippine Geomatics Symposium (PhilGEOS) 2025 "Enhancing Human Quality of Life through Geospatial Technologies",
24–25 November 2025, Quezon City, Philippines

Analyzing Urban Visual Environments through Spatial Patterns of Color from Street View Imagery

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Keywords: Urban color, street-view imagery, semantic segmentation, color metrics, spatial analysis

Abstract

Urban environments are experienced not only through their density, land use, and spatial layout but also through their visual character. Color, for instance, is a prominent feature of façades and streetscapes, affecting the perception, memory, and value of cities. Nevertheless, despite its significance, widespread patterns of urban color have been understudied, and their relationship with urban function has rarely been systematically explored. This study provides a methodology combining street-view imagery, deep learning-based semantic segmentation, and perceptual color indices to evaluate façade colors in Quezon City, Philippines. From 42,942 Google Street View images, façades were segmented with the SegFormer model, and four indices—vibrancy, harmony, tone balance, and entropy—were computed to capture complementary dimensions of visual character. The results show clear functional signatures: commercial areas are marked by high vibrancy and entropy, residential areas show higher harmony, institutional complexes show homogeneous color schemes, and industrial parks show muted tones. Road types also show variation, with trunk and tertiary roads showing visual diversity, while motorways and service roads show homogeneity. Furthermore, hotspot analysis shows contrasts between informal settlements, upscale subdivisions, and industrial corridors. These results demonstrate that color provides valuable information on the interdependence of visual character and urban function. By placing color in the position of a quantifiable dimension of urban form, the study highlights its ability to inform planning and design policies to support livable, unique, and sustainable urban environments.

1. Introduction

Cities are complex visual environments where architectural form, spatial organization, and surface materials together shape visual character (Laurie, 2022). Classical urban analysis has mainly focused on characteristics like density, land use pattern, transport accessibility, and morphological indicators of compactness or sprawl, with a tendency to overlook color as a valuable dimension of visual character. Existing metrics capture greenery (e.g., GVI, NDVI) and built form (e.g., floor area ratio, building footprints), yet there is a discernible lack of systematic ways of quantifying color (Chen and Kong, 2021). This is a critical gap, since color has a strong influence on the visual appearance of the streetscape, impacting imageability, attractiveness, continuity, and residents' sense of comfort and attachment (Gorzaldini, 2016). In addition, how color patterns relate to urban functions also remains insufficiently understood, particularly in terms if they form similar patterns within a city. Developing quantitative methods for analyzing urban color is therefore vital to bring visual character more fully into discussions of urban form and function.

Recent advances in street-view imagery (SVI) and computer vision provide a means to address this gap (Zhang et al., 2023). Unlike aerial imagery, SVI offers information on the built-up environment in ground-level views that better capture human experience and allow multimodal visual perception analysis. Google Street View and similar services already offer effectively continuous observation of major portions of major urban areas around the world and hence constitute a rich data source for visual analytics. At the same time, computer vision has been transformed in a fundamental way by deep learning in the form of transformer-based architectures like SegFormer (Xie et al., 2021), which reach state-of-the-art performance in semantic segmentation. These models can successfully deal with complex visual features in different urban scenes, overcoming multiple limitations that accompany previous convolutional designs.

Considering this, the paper examines the color composition of Quezon City, Philippines, a highly heterogeneous urban environment. The aim of the study is to examine the contribution of color to the city's visual character, to analyze the variation in its spatial distribution across different urban environments, and to quantify the correlation between these patterns and urban functions. Utilizing systematic extraction of façade colors from street-view imagery, we produce city-scale maps of four particular indices—vibrancy, harmony, tone balance, and entropy—that capture distinctive features of urban color. Utilizing these metrics to analyze visual character, spatial distribution, and function, the current study enables the holistic analysis of the contribution of color to urban form and the implications for planning practice.

The contribution of this paper is threefold. First, it develops a methodological workflow that combines street-view imagery, deep learning–based semantic segmentation, and perceptually grounded color indices within a unified workflow. Second, it applies this workflow to Quezon City, a big and socio-spatially heterogeneous urban area in a third world country, thus contributing to a research corpus that has been predominantly concerned with areas in North America, Europe, and East Asia. Third, it demonstrates the utility of urban color in planning through correlation of color indices with functional attributes of urban form, that is, land-use categories and road typologies. Taken together, these contributions position color not as a trivial or decorative feature of the city, but as a quantifiable dimension of visual identity and one that encodes underlying socio-economic conditions, regulatory regimes, and cultural practices, and hence warrants more serious attention in urban analysis and planning.

2. Related Literature

2.1 Urban color analysis

Urban color analysis increasingly emphasizes quantitative methods, leveraging computer vision and perceptual modeling to convert what was once qualitative into measurable form. Li et al. (2019) combined machine learning and perceptual analysis by semantically segmenting 10,396 Changsha panoramas using SegNet, applying batch white balancing, and classifying pixels into three façade colors. From these, they derived HSV-based statistics, a "color complexity" index, and a harmony score based on average pairwise differences in hue, saturation, and value (ΔH, ΔS, ΔV). Another study examined color relationships directly. Yang et al. (2024) analyzed 1,058 historic buildings in Shanghai using a harmony tool involving image normalization, automatic white balancing in HSV space, and FCN-based façade segmentation. RGB clusters were grouped by a cognitive vision service, converted to HSV, and evaluated on a 12-sector hue wheel to detect relational patterns (e.g., monochromatic, analogous, complementary). This approach quantified "combination quality" beyond the mere frequency of individual colors.

Others analyze how tones and variety shape street atmospheres at the district scale. Zhai et al. (2023) processed 25,337 Baidu SVIs in Changning, segmented façades using PSPNet, and extracted seven dominant colors per scene via mini-batch k-means, computing harmony in CIELAB with Ou–Luo's model and diversity as a fractal dimension—capturing "how colors go together" versus "how many kinds there are." They found that residential and commercial streets exhibit higher chromatic heterogeneity, while industrial areas show uniform palettes. Extending this, Hu et al. (2023) introduced CEP-KASS, integrating k-means color extraction and SegNet-based parsing with a human–machine adversarial scoring process and SVM regression, linking HSV features from 109k SVIs in Xuzhou to perceived "interesting" and "safety" scores, where lighter, low-saturation tints were rated as more engaging and darker tones as less safe. Zhang et al. (2021) further demonstrated citywide color standardization by mapping HSV values from 77,448 façade samples in Nanjing to a 258-chip color card, revealing dominant grey and khaki tones, especially in conservation zones with low-saturation regulations, thereby associating urban color identity with planning frameworks.

Together, these implementations suggest that four basic dimensions consistently emerge from empirical observation rather than from subjective impression: (i) vibrancy, as characterized by saturation and value statistics after sensitive calibration and façade masking; (ii) harmony, as a relational attribute involving hue/lightness/chroma—either via HSV angular arrangements or CIELAB-derivative perceptual arrangements; (iii) tonal balance, as an interpretation of the value–saturation pairing distribution that separates muted from bold palettes; and (iv) diversity, as measured by summary variation measures (e.g., complexity based on dominant-color fractions or fractal dimensionality of the palette). These four dimensions—vibrancy, harmony, tonal balance, and diversity—emerge as commonalities across methodologies, and as such, they offer a coherent foundation for systematically analyzing how color affects the character and perception of urban space. This research fills certain dimensions neglected by the existing literature by applying all four indices through a single analytical framework. By doing so, we move beyond one-dimensional descriptors of "colorfulness" toward a richer understanding of how vibrancy, harmony, tone, and diversity interact.

3. Materials and Methods

3.1 Study Area

The study area, Quezon City is largest city in Metro Manila, Philippines, covering 166.2 km² with a population exceeding 2.9 million as of 2020. The city's diverse land uses including residential, commercial, industrial, and institutional zones make it an ideal case for examining variations in urban form and color.

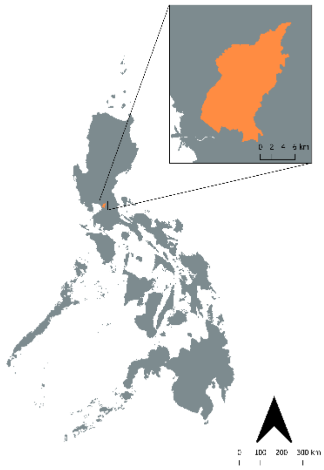

Figure 1. Study Area

3.2 Research Framework

The study follows a five-stage workflow: image extraction, preprocessing, segmentation, color metric computation, and spatial analysis (Figure 2). Segmented urban features from street-view images were analyzed using perceptual color indices and mapped to examine spatial patterns and relationships with urban functions of land use and road types.

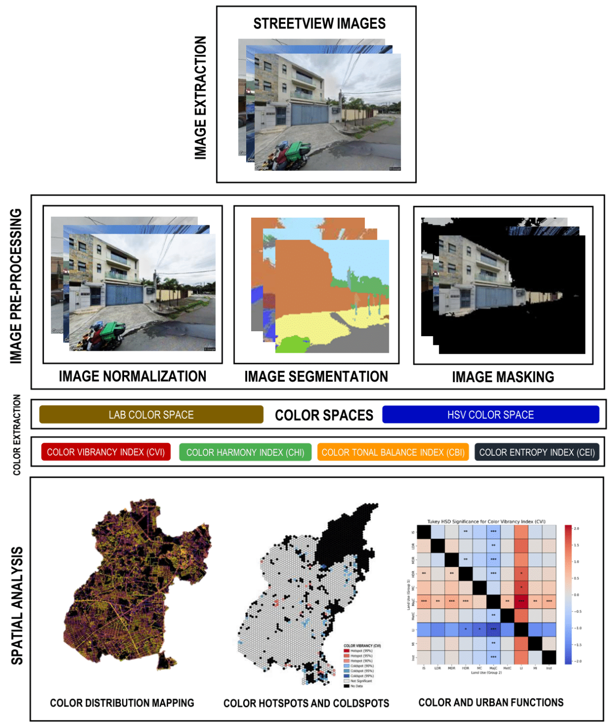

Figure 2. Research Framework

3.2.1 Data Acquisition: Land-use data were collected from the Quezon City Planning and Development Department, which classifies land lots into different uses, including residential (low-, medium-, and high-density), commercial (minor, major, metropolitan), industrial (light, medium), institutional, and informal settlement areas. Road data were collected from OpenStreetMap (OSM) and also reclassified into road categories like motorway, trunk, primary, secondary, tertiary, residential, service, cycleway, footway, and path.

SVI was downloaded through the Google Street View API at 50 m sampling interval over the available road network, yielding 42,942 images (Figure 3). Prior research (Zepeng, 2023; Yang et al., 2021) uses similar sampling intervals to trade off spatial coverage and computational practicability. Every image was captured at resolution 1024×512, field of view 120°, pitch 0°, and search radius 20 m to achieve the highest façade visibility. While coverage was extensive, data gaps occurred in gated subdivisions and private roads.

Figure 3. Sampling points along the road network

3.2.2 Image Preprocessing: Lighting, shading, and varying effects of weather conditions of street view images create unbalanced effects on perceived building colors, walls, and fences. This research mitigated such challenges by adopting a sequence of color normalization and correction processes of image standardization that reduced such artefacts to a minimum.

The first preprocessing step was white balancing, which was performed with the SimpleWB algorithm from the OpenCV library. The procedure is a preprocessing technique that normalizes the color temperature of all input images, thus producing neutral shades of gray and reducing the effect of lighting differences, thus improving color uniformity in the dataset. After white balancing, gamma correction with a gamma of 1.2 was performed. A lookup table (LUT) was used to dynamically scale pixel intensity values in a bid to correct tonal distribution and improve detail in areas that were under- or overexposed. This helped improve both tonal balance and color accuracy.

Figure 4. Image Normalization (a) Raw; (b) Normalized

3.2.3 Image segmentation: SegFormer, a transformer architecture-based semantic segmentation model (Xie et al., 2021), was employed to separate façade elements from street-view images. For the purpose of this study, Hugging Face's version of SegFormer, pretrained on the Cityscapes data (Xie et al., 2021), was employed to separate façade elements from the street-view imagery. This Cityscapes-pretrained version can identify 19 classes of urban scenes, including roads, buildings, walls, fences, poles, vegetation, sky, and vehicles. For analytical purposes, only the façade-related classes—i.e., buildings, walls, and fences—were kept and merged into a single façade mask per image.

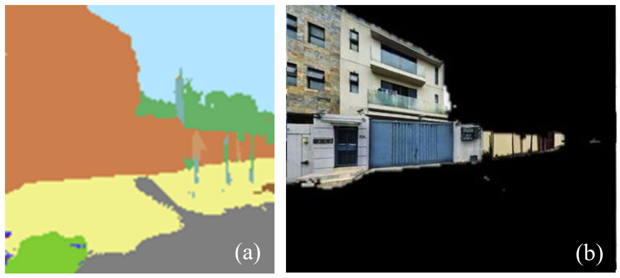

Figure 5. (a) Image Segmentation and (b) Masking

To measure segmentation quality quantitatively, a random stratified test set of 300 images was acquired. Images were sampled over 10 land-use strata. Annotated façade annotations within the subset were taken as the reference masks against which model predictions were measured. Standard accuracy measures such as pixel accuracy, F1-score, and mean Intersection-over-Union (mIoU) were subsequently computed to measure model reliability.

3.2.4 Color Metric Computation: Color values were extracted from façade objects that were recognized by masks created with SegFormer. Wall, building, and fence pixels were extracted, and façade objects like sky, vegetation, and vehicles were eliminated. Color values extracted from the highlighted façade objects served as the basis for the remaining analyses.

To ensure robust analysis, two complementary color spaces were employed. The LAB color space, suggested by the International Commission on Illumination, presents a perceptually uniform model with three dimensions: L (lightness, 0–100), a (red–green chromaticity), and b (blue–yellow chromaticity). The HSV color space is a cylindrical coordinate description of colors: Hue (0–360°), Saturation (0–100%), and Value (0–100%), and is generally preferred for its intuitive interpretability.

To capture urban facade color's structural and perceptual nature, four complementary measures were employed: the Color Vibrancy Index (CVI), the Color Harmony Index (CHI), the Color Tone Balance Index (CBI), and the Color Entropy Index (CEI).

3.2.4.1 Color Vibrancy Index (CVI): The Color Vibrancy Index quantifies the richness and intensity of colors, reflecting how saturated or "energetic" a façade appears. It was calculated in the LAB color space as:

$$\mathrm{CVI} = \sqrt{(\sigma_a^2 + \sigma_b^2)} + 0.3 \cdot \sigma_L \tag{1}$$

where σ_a and σ_b are the standard deviations of the chromaticity channels (a*, b*) and σ_L is the standard deviation of the lightness channel (L*). Higher values indicate vivid and dynamic tones, while lower values correspond to muted or monotonous shades (Hasler, et al, 2003).

3.2.4.2 Color Harmony Index (CHI): CHI evaluates the compatibility of dominant color groupings, based on LAB color clusters. The index incorporates differences in chromaticity, lightness, and hue, and was computed as:

$$CHI = 1.3 - 0.07C\Delta + 2.2 + 0.03L_{sum} + 0.92 - 0.05\Delta L + H'(h1) + H'(h2) - 1.1 \tag{2}$$

where CΔ represents chromatic difference, L_{sum} the combined lightness, ΔL, the lightness difference, and $H'(h1), H'(h2)$ is hue-related effects. High values indicate cohesive and aesthetically consistent color schemes, while low values denote dissonance. High harmony scores indicate visually cohesive and appealing color combinations, while lower scores suggest dissonance (Ou, 2006).

3.2.4.3 Color Balance Index (CBI): CBI captures the relationship between hue and saturation in the HSV color space:

$$\mathrm{CBI} = \frac{\text{Mean Hue}}{\text{Mean Saturation}} \tag{3}$$

Lower values are associated with bold, saturated tones, whereas higher values correspond to muted or pastel-like schemes. This index reflects the tonal subtlety or intensity that characterizes urban palettes.

3.2.4.4 Color Entropy Index (CEI): CEI measures the complexity of color distributions by quantifying randomness in luminance values:

$$\mathrm{CEI} = -\sum_{i=1}^{n} p(i)\ \log_2 p(i) \tag{4}$$

where $p(i)$ is the normalized frequency of pixel intensity i. High entropy values indicate diverse and visually complex scenes, while low values reflect uniformity and simplicity (Shannon, 1948).

3.2.5 Spatial and Statistical Analysis: Color metrics were linked to street-view points and aggregated along road network segments to produce citywide maps of vibrancy, harmony, tone balance, and entropy. Local patterns were examined using the Getis-Ord Gi* statistic, which identified significant clusters of high and low values ($p < 0.05$), interpreted as hotspots of aesthetic intensity and coldspots of visual uniformity. Differences across land-use types and road classes were tested with Tukey's HSD for pairwise contrasts, and results were summarized in heatmaps highlighting statistically significant variations.

4. Results and Discussion

4.1. Image segmentation results

The initial step of the analysis was to delineate the façade objects from the 42,942 street-level images of Quezon City with the pre-trained SegFormer-B0 model in the Cityscapes dataset. The model was chosen due to its effectiveness and performance for semantic segmentation tasks but was used here without domain-specific fine-tuning.

Quantitative evaluation was performed on a stratified sample of 300 images, evenly split across land-use classes. Human annotations were used as ground truth against which estimated masks were checked. Result delivered a pixel accuracy of 0.79, an F1-score of 0.74, and mIoU of 0.63 on binary separation of façade and non-façade areas. These scores are consistent with expectations for an Cityscapes-pretrained model applied out-of-domain, and while they indicate room for improvement, they provide sufficient reliability for city-scale analysis.

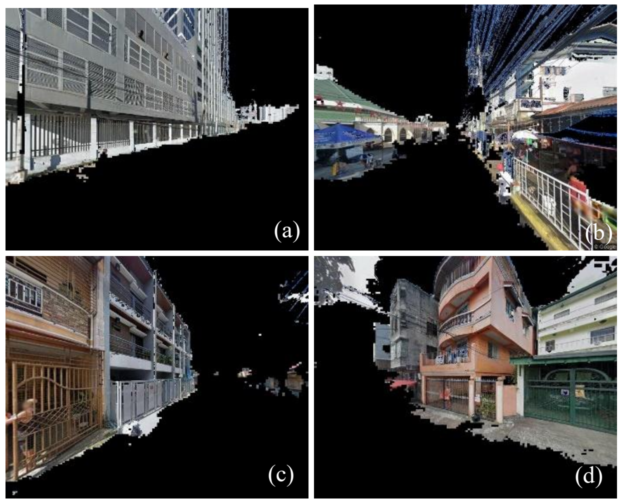

Figure 6. Image segmentation sample results

Results were also contextualized by visual inspection. In commercial districts and institutional, segmentation was typically crisper, with façades and walls cleanly separated from neighboring categories (Figure 6a). In high-density residential neighborhoods and narrow alleys, however, façades tended to look fragmented. Overhead electric wires were occasionally mistaken for façades, and thin strips of sky along roof edges were occasionally included in building boundaries at times (Figure 6b). Partial occlusions by people also introduced small but consistent errors in façade delineation (Figure 6c). Sidewalks with wall-like textures adjacent were also occasionally included in the façade category at times (Figure 6d). These problems were most evident in visually difficult residential settings, where irregular roof geometries, mixed materials, and a wide range of colors made the model's predictions difficult.

Despite these limitations, segmentation accuracy was sufficient for the purposes of this study. At the city scale, localized errors—such as wires or small sky fragments—accounted for only a minor fraction of façade pixels and were unlikely to systematically affect color vibrancy or harmony. Façade deterioration in dense residential areas may have slightly increased entropy values, suggesting a minor overestimation of chromatic diversity. While these imprecisions are not negligible, they remain acceptable for the study's objectives.

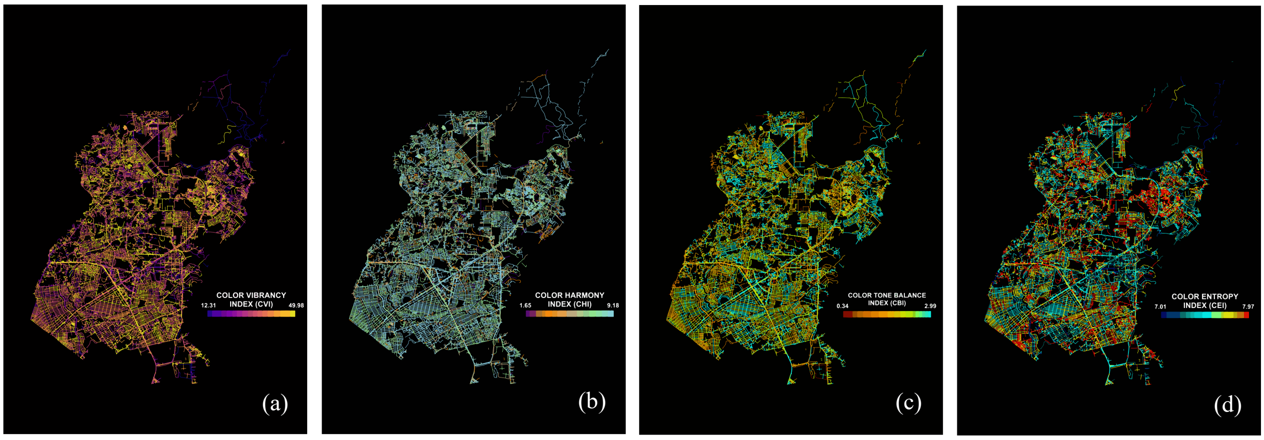

Figure 7. Spatial distribution of color metrics across Quezon City derived from street-view imagery: (a) Color Vibrancy Index (CVI), (b) Color Harmony Index (CHI), (c) Color Tone Balance Index (CBI), and (d) Color Entropy Index (CEI).

The results also suggest the scope for methodological improvement. Upgrading the SegFormer model with locally obtained annotations should enhance façade detection, particularly in contexts plagued by skews and visual complexity. Nevertheless, even with modest validation scores, the present model provides a consistent and replicable means o f isolating façades at scale. Its outputs form a sufficiently robust basis for analyzing urban color metrics, and the statistical effects of random errors are diluted across tens of thousands of images.

4.2. Citywide Distribution of Color Metrics

A color metric analysis in Quezon City provides rich information regarding the overall visual character of the metropolis, combining required values from LAB and HSV base color spaces and specific metrics—most especially the Color Vibrancy Index (CVI), Color Tone Balance Index (CBI), Color Harmony Index (CHI), and Color Entropy Index (CEI)—to account for the aesthetic appeal of the cityscape (Table 1). A mean Perceptual Lightness (L*) value of 129.83 shows that the cityscape is largely composed of medium tones, thereby providing a consistent brightness among its buildings. Such balance is also emphasized by the low variability (std = 21.39). The chromaticity components of Red-Green and Blue-Yellow both provide means of 129.58 and 129.30, respectively, and show a neutral color scheme, with little tendency towards warmer or cooler tones. Such neutrality in chromaticity suggests aesthetically pleasing design, most probably because of the consistency of materials utilized within the cityscape.

Color Metric	Mean	Std	Min	Max
Perceptual Lightness (L*)	129.83	21.39	65.94	196.39
Red-Green (a*)	129.58	2.05	123.88	135.41
Blue-Yellow (b*)	129.30	3.99	118.07	140.39
Hue (H)	66.93	17.15	19.47	117.06
Saturation (S)	56.88	13.38	21.09	95.22
Color Value (V)	135.71	22.27	71.06	202.84
Color Vibrancy Index (CVI)	38.65	4.46	24.90	50.00
Color Tone Balance Index (CBI)	1.24	0.44	0.24	2.53
Color Harmony Index (CHI)	2.88	0.74	0.88	4.92
Color Entropy Index (CEI)	7.69	0.15	7.24	7.97

Table 1. Summary Statistics of Color Metrics in Quezon City

Derived indices provide context for these root metrics. The Color Vibrancy Index (mean = 38.65) describes a richness level that ma y be described as moderate, reflecting an urban landscape that is neither too dull nor too saturated. The Color Tone Balance Index (mean = 1.24) demonstrates a stable hue-saturation relationship, avoiding extremes of either vividness or dullness. The Color Harmony Index (mean = 2.88) suggests cohesive color relationships are generally present, so even though there is visual diversity, the prevailing tones often complement each other. At the same time, the Color Entropy Index (mean = 7.69, std = 0.15) highlights a consistently high degree of diversity in luminance and chromatic distribution across the city. Taken together, these indices suggest a landscape of moderate vibrancy, balanced tonal relationships, and a persistent but not overwhelming visual complexity.

Figure 7 presents the spatial p attern of Quezon City's color metrics, revealing a heterogeneous, contrasted urban landscape of chromatically vibrant centers and muted peripheries. Highest vibrancy (Figure 7a) and diversity (Figure 7d) levels are found along major corridors and central business districts like Cubao and the QC CBD, where dense building, mixed architectural styles, and full street life reflect the relationship of chromatic vibrancy to economic activity and transport networks. The concentration of high values along main roads like EDSA serves to highlight the dual function of these corridors as functional transport conduits and visually prominent urban buildings that link the city's most dynamic and strategically important places.

On the other hand, government complexes around Quezon City Circle appear less vibrant and diverse which reflect functional yet restrained design approaches. Peripheral areas such as Novaliches and Balintawak also show lower values due to reduced activity densities and a more homogeneous urban form that restricts chromatic richness. Harmony (Figure 7b) is more uniformly distributed, indicating generally consistent color compatibility, though isolated or fast-developing zones tend to lack it. Tonal balance (Figure 7c) remains moderate to high along major corridors like EDSA and Quezon Avenue, supporting their role in linking dynamic centers with quieter residential areas and maintaining contrast between vivid and subdued tones. Overall, the distribution of color metrics distinguishes vibrant, diverse corridors from more subdued institutional and residential landscapes. These preliminary patterns highlight areas of heterogeneity and homogeneity that will be refined through further hotspot and coldspot analyses.

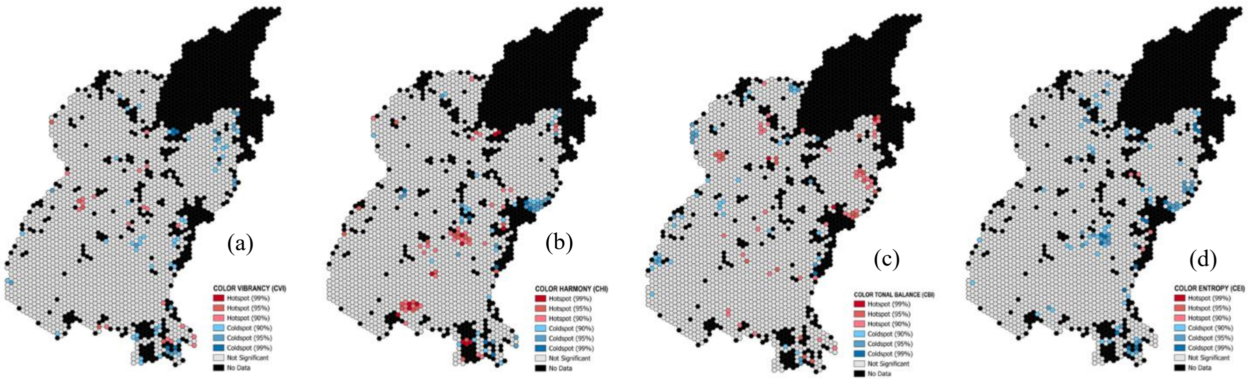

Figure 8. Hotspot and Coldspot Analysis of Color Metrics in Quezon City: (a) Color Vibrancy Index (CVI); (b) Color Harmony Index (CHI); (c) Color Tone Balance Index (CBI); (d) Color Entropy Index (CEI)

4.3. Citywide Distribution of Color Metrics

Hotspot and coldspot analysis across the four indices (Figure 8) highlights clear spatial contrasts in Quezon City. Hotspots such as Capitol Hills (Figure 9a), and New Manila (Figure 9b) show elevated Color Harmony (CHI) and Tone Balance (CBI), reflecting deliberate beautification, community upkeep, and heritage architecture that strengthen visual quality.

Figure 9. Sample Streetview images of areas in color hotspots

In contrast, coldspots are evident in industrial areas and some residential suburbs. Bagong Silangan registers low Color Vibrancy (CVI) and Entropy (CEI), where utilitarian design and limited resources reduce visual appeal (Figure 10a). Even exclusive enclaves like Vista Real (Figure 10b) and Loyola Grand Villas score low in CEI, their controlled and uniform designs prioritizing consistency over diversity. Industrial districts in the northwest similarly exhibit weak CVI and CEI, emphasizing function over aesthetics.

Figure 10. Sample Streetview images of areas in color coldspots

Overall, the juxtaposition shows how land use drives differences in visual quality. Hotspots tied to residential prestige, institutions, or mixed-use activity display higher CHI and CBI, while coldspots—whether densely utilitarian or tightly regulated—reflect lower CVI and CEI, underscoring the uneven distribution of urban vibrancy and diversity across the city.

4.4. Color and Urban Function

Color metrics and urban function were investigated as interdependent by correlating CVI, CHI, CBI, and CEI with land-use and road types. This study implies the way in which visual qualities like vibrancy, harmony, and diversity systematically change with function and indicates the city's aesthetic and functional character.

4.4.1 Color and Land Use: The color metric analysis covered ten land-use categories—Informal Settlements (IS), Low-, Medium-, and High-Density Residential (LDR, MDR, HDR), Minor, Major, and Metropolitan Commercial (MinC, MajC, MetC), Light and Medium Industrial (LI, MI), and Institutional (Inst)—and there are some stark contrasts. High-Density Residential areas show highest Color Variability Index (CVI) (mean = 38.66, SD = 4.38), reflecting highly vibrant visual surroundings, and Light Industrial areas show lowest CVI (mean = 37.09, SD = 5.38), as per their functional characteristics. Tukey heatmaps (Figure 11) show these pair-wise contrasts, whereas red and blue colors represent positive and negative contrasts, respectively, and asterisks represent levels of significance ($p < 0.05$, $p < 0.01$, $p < 0.001$).

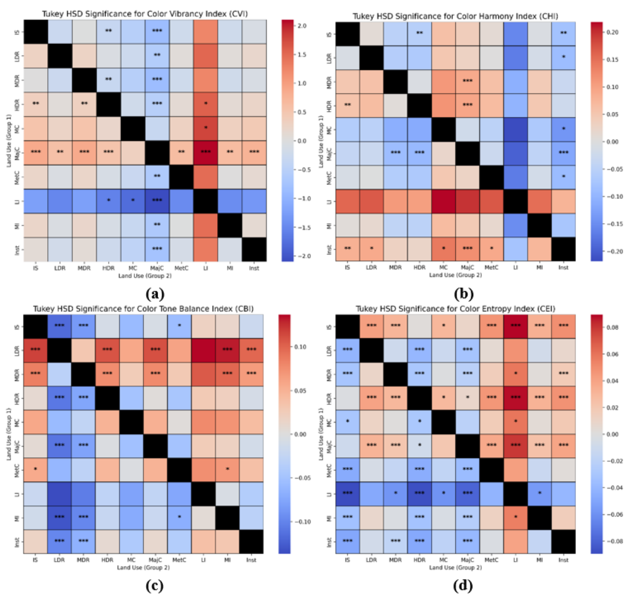

Figure 11. Tukey HSD significance heatmaps for color metrics across land use types

Commercial areas become the most vibrant, with MajC boasting the highest CVI (39.19), far above LI ($\Delta = 2.10$, $p < 0.001$) and IS ($\Delta = 0.86$, $p < 0.001$) (Figure 11a). This reflects their role in provoking attention in the shape of colorful facades, signage, and branding that move business. But this vibrancy is at the expense of cohesion, as their low CHI (mean = 2.80) indicates, where multiple advertisements and varied architectural expression reduce visual cohesion. MetC areas, highly vibrant as well (CVI = 38.55), exhibit slightly greater cohesion (CHI = 2.83), reflecting some balance between spectacle and order.

Industrial districts reflect the opposite trend. Light-Industrial (LI) districts exhibit the lowest vibrancy (CVI = 37.09) and diversity (CEI = 7.61), which is consistent with their dependence on dull functional materials, i.e., steel and concrete. Nevertheless, these districts obtain a relatively high CHI (mean = 3.00), which corresponds to the homogeneity of warehouse and factory buildings. Medium-Industrial (MI) zones, with a slightly higher CVI (38.55) and CEI (7.67), are consistent with their dual function as production and functionality; yet, they still have the typical grayness and uniformity of industrial buildings.

Institutional zones integrate function and aesthetics more successfully. With moderate vibrancy (CVI = 38.42) and tonal balance (CBI = 1.24), they nonetheless record stronger harmony (CHI = 2.92), significantly higher than MajC ($\Delta = 0.12$, $p < 0.001$) and MetC ($\Delta = 0.09$, $p < 0.05$) (Figure 11b). This coherence reflects the planned, consistent character of government and academic campuses.

Together, these observations demonstrate how visual metrics capture functional intention: commercial areas maximize vibrancy and variety but at the cost of coherence; industrial zones maximize order at the expense of richness of color; and institutional zones balance visual restraint against aesthetic compatibility. Domestic and informal settlements fall between these poles, with HDR zones achieving higher vibrancy while informal areas exhibit moderate entropy challenging visual disorder clichés—potentially due to constraints of street-view imagery in capturing dynamic features such as signage, temporary structures, or human presence.

Overall, the relationship between color and land use demonstrates that chromatic patterns are not merely aesthetic markers but also reveal the socio-spatial logic of urban functions. Recognizing how commercial districts use vibrancy and diversity to generate economic vitality, how institutional areas employ coherence to project stability and authority, and how industrial zones rely on uniformity to emphasize utility allows planners and designers to better align visual quality with functional goals. Such insights are beneficial not only for diagnosing existing conditions but also for informing strategies that balance vibrancy with coherence in commercial spaces, enhance livability through well-managed residential palettes, and introduce greater diversity in industrial landscapes without sacrificing efficiency. By systematically linking color metrics to land use, urban environments can be understood, compared, and improved in ways that support both functional performance and aesthetic experience.

4.4.2 Color and Road Types: When measures of colour are compared across road classes—Motorway (MTR), Trunk (TRK), Primary (PRI), Secondary (SEC), Tertiary (TER), Residential (RES), Service (SRV), Footway (FTW), Cycleway (CYC), and Path (PTH)—there are significant differences. Motorways, through their functional planning, always have the lowest ratings across all measures (CVI = 36.60, CBI = 0.92, CHI = 2.75, CEI = 7.58), suggesting environments that prioritize safety and efficiency over visual aspects. Primary and secondary roads are more colourful and richer, as necessary given the dominance of commercial and mixed-use activity on major roads. Residential, tertiary, and service roads fall in between, registering moderate richness while also suggesting more harmony and balance of tones characteristic of more stable and localized settings. At the most detailed scale, footways, cycleways, and paths show patchy areas of chromatic richness characteristic of human-scale settings and social interaction and illustrate the role of small-scale circulation spaces to overall visual richness in the urban setting.

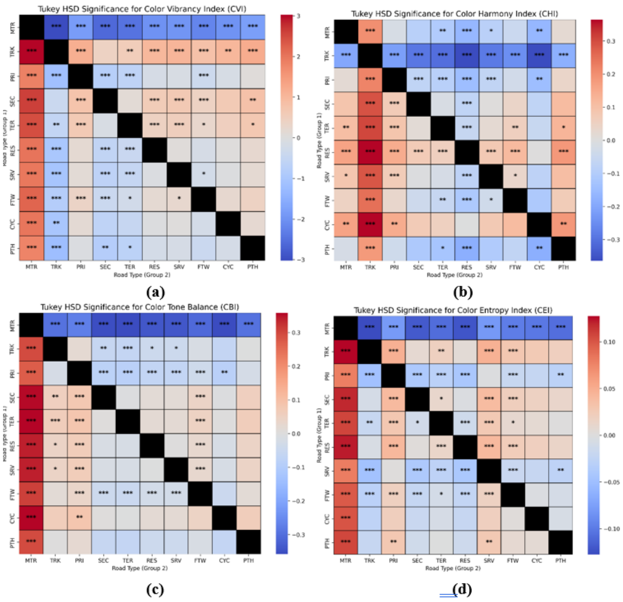

Figure 12. Tukey HSD significance heatmaps for color metrics across road types

Trunk roads (TRK), such as EDSA, have the highest vibrancy (CLI = 39.65) and entropy (CEI = 7.71) values, reflecting their critical role as metropolitan arteries connecting disparate land uses, building types, signage classes, and traffic control systems. Their low harmony value (CHI = 2.56), however, reflects the difficulty of visual coherence derived from their congested and diversified nature. Residential streets (RES), cycleways (CYC), and footways (FTW) have higher harmony (CHI = 2.93, 2.91, and 2.82, respectively) and higher vibrancy (CLI ≈ 38.6–38.8), reflecting cohesive environments for pedestrian activity represented by homogeneous pavements and orderly signage. Secondary (SEC) and tertiary (TER) roads have a balanced profile, reflecting high vibrancy (CLI = 39.20 and 39.06) and tonal balance stability (CBI = 0.35 and 0.36), reflecting double roles as functional connectors and visually cohesive environments. Service roads (SRV) and pathways (PTH) have moderate vibrancy and entropy (CLI ≈ 38.4–38.6, CEI ≈ 7.7) and relatively uniform harmony (CHI ≈ 2.8), but low tonal balance (CBI = 0.29 and 0.22), which reveal a utilitarian purpose rather than utilitarian priority.

In brief, color metrics establish that different kinds of roads take on different visual and functional roles: trunk and tertiary roads are dynamic but visually separated activity thoroughfares, residential and pedestrian-oriented streets emphasize harmony and stability, and service roads and paths also emphasize functional simplicity. These distinctions establish how color qualities align with roadway functions, so that different urban planners can have a useful tool for assessing not just mobility and connectivity but also the experiential and aesthetic dimensions of city streets.

5. Conclusion and Recommendations

This study developed a systematic framework that combines street-view photography, deep learning-based semantic segmentation, and color indices to evaluate visual attributes of urban areas. When applied to Quezon City, Philippines, the framework enabled large-scale façade color extraction, which was then evaluated for vibrancy, harmony, tone balance, and entropy. The results show that color is not randomly distributed; rather, it adheres to systematic differences based on varying land uses and road types, thus providing a replicable approach to city-scale color mapping.

The findings highlight that color goes beyond mere aesthetic appeal and is a strong indicator of urban functionality. Commercial areas were marked by greater vibrancy and entropy, while residential areas were marked by greater harmony. Industrial areas, however, presented dull and uniform color palettes, and institutional buildings presented systematic consistency. In addition, varying types of roads showed different properties, with trunk and tertiary roads showing a combination of diversity and activity, while motorways and service roads showed uniformity and efficiency. These findings suggest that color measures can be employed as diagnostic tools that show both perceptual properties and functional arrangement, and hence place color as a useful addition to conventional measures like density, greenspace, and accessibility.

Recommendations are made on three levels. Methodologically, locally trained models should be developed to improve façade detection in visually difficult locations such as informal settlements. Analytically, follow-up research could utilize this framework to temporal comparisons to see how urban color evolves under redevelopment or regulation. Practically, the integration of color metrics into planning instruments would enable policies that balance vibrancy and cohesion in commercial corridors, livability in residential neighborhoods, and bring more diversity in industrial precincts. By making color at once measurable and meaningful, planners and designers can better understand visual character and more effectively match urban settings to functional and social requirements.

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