An International Journal of Optimization and Control: Theories & Applications
ISSN: 2146-0957 eISSN: 2146-5703
Vol.16, No.1, pp.265-282 (2026)
https://doi.org/10.36922/IJOCTA025350148

RESEARCH ARTICLE

A StyleGAN2-based framework for generating and evaluating urban color landscapes and street vitality

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ARTICLE INFO

Article History:
Received: August 27, 2025
1st revised: November 4, 2025
2nd revised: November 11, 2025
3rd revised: November 20, 2025
Accepted: November 21, 2025
Published Online: January 7, 2026

Keywords:
Adversarial networks
StyleGAN2
Urban colorscape generative
Visual analytics
Vitality assessment

AMS Classification 2010:
90B23, 90B56

ABSTRACT

Urban color landscapes play a significant role in shaping perceptual experience and street vitality. We proposed a style-based generative adversarial network 2 (StyleGAN2)-inspired generative framework for creating urban colorscapes and quantitatively assessing their vitality. The approach integrated advanced data preprocessing, generator–discriminator architecture, and hyperparameter optimization using a non-saturating logistic loss function. Vitality was evaluated through three chromatic indicators—saturation, contrast, and diversity—and validated against behavioral (pedestrian volume) and socioeconomic (point-of-interest density) data via correlation analysis (r = 0.47–0.68). The model achieved theoretical convergence (Fréchet Inception Distance < 15) and optimality, while ablation experiments with a deep convolutional GAN, Wasserstein GAN with gradient penalty, and StyleGAN3 confirmed its superior generative performance. The synthesized images exhibited an 18.2% increase in saturation and a 10.5% increase in diversity relative to real-world scenes, suggesting a strong positive association with urban vitality, as established in our correlation analysis. Computational efficiency was enhanced through mixed-precision training, reducing total processing time. Empirical and perceptual validations confirmed the framework's robustness, offering a reproducible pathway for artificial intelligence-driven urban color planning.

1. Introduction

1.1. Research background and significance

The city's color scheme, as a main element of the cityscape, plays an important role in shaping residents' psychological feelings, improving their quality of life, and thereby raising the attractiveness of the city. [1] Colors in a city are not only an aesthetic concern; they also influence human emotions, behavior, and activities. They also play significant roles in making a city vibrant. Ongoing rapid global urbanization has led to a shift in city landscape planning from focusing solely on functional and infrastructural concerns to adopting a more holistic approach that embraces the cityscape, culture, and city characteristics from the perspective of human and social interactions. [2] Colors, in this regard, can be considered an important element of human visual perception. Colors can evoke emotional responses by enhancing experiences related to urban activities, vibrancy, and aesthetics. [3] The use of vibrant color schemes can make city squares, business districts, or residential districts lively by leveraging site or community values. Ill-planned color schemes may compromise the city's visual integrity, creating visual eyesores that reduce urban attractiveness or appeal. Such visual degradation can also negatively affect residents' well-being. [4]

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Despite the importance of color schemes, conventional urban color planning practices have typically relied on subjective approaches, such as designers' or planners' experience and intuition, which cannot be scaled or reproduced. The procedures cannot grasp the subtlety and complexity of modern urban conditions, whose varying cultural, historical, and functional situations demand site-specific solutions. [5] Moreover, the absence of data-driven quantitative methods in color planning limits the ability to objectively measure the effect of color on urban vitality and to predict the effect of the color scheme under varying urban conditions. This inadequacy underlines the need for innovative instruments and techniques that provide creative, analytical solutions for urban color landscape design.

Over the past few years, advances in artificial intelligence—particularly the development of generative adversarial networks (GANs)—have opened new possibilities for overcoming conventional limitations in urban color analysis. [6] Among these, style-based GAN2 (StyleGAN2) has gained considerable attention for its capacity to generate high-definition, photorealistic images with exceptional flexibility and structural detail. [7] By leveraging its superior architecture, [8] which implements a style-based generator to control image features across multiple scales, it becomes possible to construct versatile and realistic urban color landscapes within specific spatial contexts. Recent studies have further demonstrated StyleGAN2's adaptability for architectural and urban design applications, enabling realistic façade and city-scene generation without conditional inputs, while allowing fine-grained attribute control through latent-space manipulation. [9,10] Building upon these advances, we propose a StyleGAN2-based model for generating urban color landscapes and introduce a vitality evaluation framework to assess their impact on urban dynamism. This integrative approach connects generative modeling with urban-vitality theories, linking visual parameters—such as saturation, contrast, and diversity—to perceptual and behavioral indicators established in prior studies. [11,12] Through this synthesis, the model unites aesthetic design with scientific evaluation, enabling a measurable analysis of urban vitality through chromatic criteria. The purpose of the model is to integrate aesthetic design with scientific evaluation by generating high-fidelity images of cities and assessing vitality using measurable criteria, such as color saturation, contrast, and diversity. [13]

The merit of this study is that it can transform urban color planning from an intuitive art form into a quantitative science. [14] By developing a systematic framework for generating and evaluating urban color landscapes, the study fills a significant gap in quantitative research on urban vitality and beauty. [15] The model not only facilitates the development of variable, locally specific urban landscape imagery but also provides researchers and policymakers with a substantive framework for assessing the impact of color characteristics on urban vitality. [16] By comparing variables, such as contrast and saturation, the model can establish the effect of high-brightness vs. dull color schemes on the perceived vitality of a community space or streetscape. [17] It provides an objective, fact-based decision-making guide for urban designers and planners to guarantee that color schemes achieve optimal visual appeal and social functionality. [18] Moreover, integrating deep learning and the aesthetics of cities is part of the broader effort of smart city development and supports the transition towards sustainable city planning by optimizing resources and improving citizens' quality of life. [19]

By advancing the application of artificial intelligence in urban planning, this study promotes creativity across multiple disciplines by merging computer science, urban planning, and environmental psychology to create vibrant, inclusive, and sustainable urban spaces. [5] Moreover, the proposed StyleGAN2 approach can generate urban colorscapes that directly support applications, including the optimization of street design layouts to improve pedestrian engagement, urban color policy-making, [9] and color management initiatives by the community. For instance, the model's ability to simulate high-saturation, high-contrast landscapes can assist planners in revitalizing commercial districts to boost economic activity or in designing calming residential areas with cooler tones to promote community well-being. [10] By providing data-driven visual simulations, the model enables urban designers and policymakers to test and refine color schemes before implementation, reducing costs and enhancing the aesthetic and functional quality of urban spaces. [20] This study bridges aesthetic intuition and computational intelligence by integrating StyleGAN2 with measurable vitality indicators, transforming color design from an art into a quantitative science.

1.2. Global and China-specific research developments

Urban color landscape studies and generative models have progressed considerably in recent years, with significant developments at both global and local scales. [21] At the global level, research on urban color landscapes and GANs has developed substantially over the past decade. Since their introduction, GANs have gained immense popularity for image synthesis applications ranging from photorealistic faces to architecture visualization. StyleGAN2 is distinguished by the creation of a style-based generator with fine-grained freedom over image features, achieving heretofore undocumented realism and diversity for generated images. [22] In urban landscape planning applications, researchers have employed GAN frameworks, including StyleGAN2, to generate building façades, urban textures, and volumetric configurations that complement specific architectural contexts. [10,23]

Such approaches have proven effective in historical urban renovation and diverse architectural design tasks, ranging from façade style transfer to semantic segmentation–based generative modeling. [24] The opportunities these models offer have highlighted the potential of generative models to automate urban planning.

In addition to image creation, foreign researchers have conducted additional quantitative assessments of urban vitality. [25] Researchers have explored how color characteristics, including saturation, hue, and contrast, affect urban attractiveness. Often, socioeconomic factors, such as population density and economic activity, are included in assessments of urban vitality. [1] For example, color schemes in vibrant commercial areas have been associated with high pedestrian flow and economic activity, whereas dull residential area colors may nurture quietness and community bonding. [26] However, those studies often focus on isolated aspects of urban scenes, such as specific buildings or streetscapes, and lack an integrated framework for examining the relationship between color landscape and urban vitality under diverse urban environments. Furthermore, those models have limited generalization ability because they are often trained on specific datasets that cannot capture the diversity of global urban environments, with morphological genes failing to generalize well across distinct regions due to varied climatic, geographic, and infrastructural conditions. [27,28]

China is highlighted separately because it has produced an especially large and diverse body of research on urban color landscapes, driven by rapid urban development and substantial adoption of deep learning in urban planning. Local research in China has gathered momentum in recent years, particularly in the application of deep learning for urban landscape generation and vitality evaluation. [29] Researchers have utilized deep neural networks to synthesize urban night landscapes, green patches, and cultural scenes, and have studied residents' emotional experiences and perceptions of urban scenery regarding color. [30,31] Specifically, it has been found that warm-toned light at night in urban areas can evoke feelings of warmth and security, while green-dominant scenery can evoke feelings of relaxation and ecological affection. In vitality evaluations, Chinese researchers have used image analysis techniques to derive color information from urban sceneries and combined these with questionnaires/surveys to measure felt vitality. [32] These are typically context-specific, e.g., ancient districts or modern commercial districts, and provide interesting insights into color's emotional and social impact.

Despite these advances, domestic research on generative models still faces several methodological and contextual challenges. [9] Adapting generative models to highly variable, multi-scenario urban environments remains difficult, as existing models are mostly trained on relatively standardized datasets that cannot adequately reflect the rich cultural heritages, eclectic architectural styles, and diverse functional demands of Chinese cities. [24,33] In addition, vitality evaluation methods employed in domestic studies often rely on anecdotal or perceptual data, such as user questionnaires, whose subjectivity may introduce biases and reduce objectivity. Only a few systematic studies integrating advanced generative models, such as StyleGAN2, with comprehensive vitality evaluation frameworks have been reported, indicating a significant research deficiency. [34]

Based on Chinese and international research, we anticipate that by optimizing the StyleGAN2 model for generating urban color landscapes and by building an effective vitality index system, it is possible to address key deficiencies in prior research. [35] The proposed model enhances the output image's realism and diversity by tuning the StyleGAN2 model to extract specific color characteristics across urban environments, from highly urbanized cities and towns to tranquil suburban regions. Meanwhile, the vitality evaluation framework applies objective indicators, such as color saturation, contrast, and spatial distribution, to convert the impact of color landscapes on urban dynamism into quantitative expressions. [36,37] Through these combined efforts, the present study aims to provide an innovative, science-driven way of planning an urban color landscape, offering urban planners an effective tool for designing bright, practical, and aesthetically appealing cityscapes compatible with the philosophy of smart, sustainable city development. [38]

2. Theoretical basis and technical framework

2.1. The relationship between urban color landscape and urban vitality

As a primary visual determinant of the urban environment, color profoundly influences psychological states, social interaction patterns, and aesthetic perception. [20] The role of cityscape color in the city is far from superficial. Colors in the cityscape play an active role shaping the urban scene's perception; they often convey emotional states that energize or numb the vitality of space. Color characteristics, including saturation, contrast, and diversity, have been shown to play a definitive role in elevating the level of dynamism or vitality of urban space. [39] Warm, highly saturated colors, particularly reds and oranges, have frequently been associated with increased pedestrian activity or commercial districts, creating an environment rich in trade transactions and convivial meetings. Cooler tones, such as blues or greens, can create an environment of meditative reflection, potentially leading to increased feelings of relaxation and, in some cases, may be associated with reduced levels of activity or vitality. [40] Thus, the emotional mediation of color becomes a critical pathway linking chromatic properties to urban vitality. These perceptual responses can be further explained through color psychology, in which hue, brightness, and saturation systematically evoke affective states linked to pleasure, arousal, and dominance. [41] Such findings align with environmental psychology perspectives, suggesting that urban color compositions act as affective stimuli that modulate behavioral activation and spatial engagement.

Urban vitality can thus be conceived as the complex manifestation of economic, social, or cultural activities, ranging from trade or communal celebrations to artistic expression or communal engagement. [42] Therefore, by carefully enriching the color landscape, that is, by deliberate color, tone, or palette selection and application, it is possible to impact the civic engagement in communal efforts. By using vibrant colors in, for example, parks or town squares, it is possible to influence casual engagement, outdoor activities, or communal functions, thereby increasing the overall civic or communal vitality of the towns. [43] The key design principles of the urban color landscape can thus draw significant insights from environmental psychology, which asserts that color affects human behavior primarily through visible stimuli or activation. [11,12] For example, highly stimulating or vibrant colors, such as yellow or vivid purple, can evoke heightened excitement or activation, leading to increased activity and engagement on the streets, shops, and overall commercial levels of vitality.

Regarding this issue, the city's color scheme is considered an important input variable in vitality assessment, as it serves as the foundation for analyzing the role of visual information in the overall vitality of urban areas. [34] By employing generative models that can simulate an ever-wider range of color schemes, from the simplest range of monochromatic to highly colorful color schemes, we examine the quantitative effect of the changes on vitality measures, including activity density, user interest, and perceptual beauty. This research methodology not only elucidates the role of color distribution in urban functionality, including how highly concentrated vibrant colors in mixed-use developments can contribute to multi-use functionality, but also provides quantitative optimization strategies for urbanization that can be applied from building façades renovations to landscapes. [44]

Moreover, the urban colorscape–vitality relationship is highly susceptible to various variables, including cultural sensitivity, climate, or seasonal characteristics, making color planning more intricate. For instance, in tropical megacities with abundant sunlight and dense vegetation in their tropical megacities, vibrant color schemes can increase seasonal vitality by creating beneficial spaces that reflect local cultural patterns and designs, attracting tourists.

Conversely, in regions with limited sunlight and cold climates, neutral color schemes or earth-toned patterns can help maintain social contact by creating a sense of warmth. [8] As various variables, including multiple perspectives, are evaluated in the research task, the assessment framework established within it aims to examine the particular role of color in enhancing urban vitality, thereby introducing more scientific aspects into urban aesthetic planning. The assessment ensures universality and effectiveness of planning strategies, as it can work efficiently across multiple regions with varied climates, with fewer trial-and-error efforts during implementation.

A detailed understanding of the role of color will also help unravel the inherent subjectivity of traditional urban planning methods by shifting the paradigm from intuition-driven approaches to intelligent optimization. Urban planners can thus overcome their experience-driven approaches by using data models that predict vitality outcomes based on color compositions.

The mutual mechanism between vitality and the urban colorscape is realized at multiple scales, ranging from the micro-scale of individual architectural elements, such as signage and building façades, to the macro-scale of districts and the entire city. At each of these scales, aesthetic balance, in the form of color integration, is critical to generate a composite impression of vitality while ensuring that urban places appear cohesive and attractive rather than disconnected. [45] Empirical research, for instance, has confirmed that augmenting color contrast in street-level compositions can boost pedestrian dwell times, encouraging lingering behaviors and, subsequently, boosting economic vitality through consumer expenditure and casual interactions. Conversely, a lack of color diversity may create spatial monotony, diminishing the social appeal of places and possibly leading to underutilization or urban decay. [14] Using GAN technology, the research explores innovative color landscape simulation and experiments with vitality response curves—the graphical plots that connect changes in color controls to changes in the vitality metric. The simulation is translated into actionable visual feedback, enabling designers to predict and fine-tune transformation initiatives before physical realization, thereby reducing costs and stakes. Such methodical advancement not only extends the theoretical boundaries of urban vitality research by embracing computational aesthetics but also provides policymakers with practical tools to encourage inclusive urban environments amenable to diverse populations and to support sustainable development. Through that interlinked methodology, the research enables a robust and dynamic urban future in which color is incorporated as strategic capital amenable to bolstering quality of life. Recent empirical studies have demonstrated that urban color environments evoke distinct emotional responses, which in turn shape perceptual engagement and spatial vitality. In particular, Zhang et al. [32] examined community outdoor spaces through the affective circumplex model and found that color attributes—specifically hue, saturation, and brightness—showed strong associations with positive affective states among elderly residents. Complementing this evidence, façade-based studies in visual perception revealed that higher saturation and hue variability, when balanced by appropriate brightness contrast, enhanced spatial engagement and vitality cues in urban scenes. [46,47] Collectively, these empirical findings directly inform the present study's selection of saturation, contrast, and diversity as the core chromatic metrics for modeling urban vitality. Building upon these insights, the present study conceptualizes these chromatic attributes as perceptual and behavioral proxies for vitality, thereby integrating color–emotion theory with spatial vitality assessment. This integration provides a comprehensive understanding of how visual design parameters contribute to affective urban experience.

2.2. Style-based generative adversarial network 2 model principle and application

StyleGAN2 is a sophisticated GAN architecture. Its essence is to generate high-definition images with fine details by decomposing the mechanisms of noise input and style control (Figure 1). The model framework is divided into a mapping network, synthesis network, and discriminator: the mapping network changes the randomly generated noise vector into an intermediate latent space w to achieve nonlinear style representation; the synthesis network injects styles with varying scales through adaptive instance normalization (AdaIN) to gradually construct image features; the discriminator adopts a projection structure and progressive growth strategy to facilitate the enhancement of training stability and generation quality. [15] Compared to earlier-generation models, StyleGAN2 adopts path length regularization and weight demodulation technology to reduce the likelihood of artifacts and mode collapse, ensuring the output images' realism and diversity. At the application level, StyleGAN2 is widely used for image synthesis tasks, such as art style transfer and virtual scene construction. In urban colorscape generation, it can simulate complex textures and color distributions, providing high-fidelity urban images. [16] We used the style injection feature of StyleGAN2 to customize the design of urban colorscapes. By adjusting latent space parameters to control color saturation and contrast, we enabled the generation of urban colorscapes related to different vitality levels.

The training process of this model adopted a non-saturating logistic loss function, combined with mini-batch discrimination and R1 regularization, to enhance convergence speed and generation stability, laying the foundation for subsequent vitality evaluation. To ensure theoretical rigor, we analyzed the convergence properties of StyleGAN2. The non-saturating loss, defined as Equations (1) and (2):

$$L_G = -\mathbb{E}_{z\sim P_z}[\log D(G(z))] \tag{1}$$

for the generator and

$$L_D = -\mathbb{E}_{x\sim P_r}[\log D(x)] - \mathbb{E}_{z\sim P_z}[\log(1 - D(G(z)))] \tag{2}$$

promoted stable adversarial training by balancing the generator and discriminator updates. Following Borji [48] and Kynkäänniemi et al., [49] both quantitative (Fréchet inception distance [FID] and inception score [IS]) and perceptual metrics (learned perceptual image patch similarity [LPIPS]) were considered for robustness, providing a comprehensive evaluation framework for generative performance. R1 regularization, expressed as Equation (3):

$$\mathcal{R}_1 = \frac{\gamma}{2}\mathbb{E}_{x\sim P_r}[\|\nabla D(x)\|_2^2] \tag{3}$$

penalized large discriminator gradients, ensuring Lipschitz continuity and mitigating mode collapse. Convergence was monitored via the FID, which empirically stabilizes below 15 after approximately 1.2 million iterations, indicating robust convergence to a local equilibrium. For optimality, the StyleGAN2 architecture leveraged path length regularization to minimize distortion in the latent space mapping, ensuring that generated images aligned closely with the target distribution. Theoretical optimality was supported by the model's ability to approximate the true data distribution P_r through iterative adversarial updates, as evidenced by the low FID scores. These enhancements provided a robust theoretical foundation for the generation of urban colorscapes. The application scalability of StyleGAN2 is further demonstrated when it is combined with domain adaptation techniques. However, recent studies emphasize that relying solely on a single quantitative measure, such as FID, may not comprehensively capture perceptual quality or diversity in generative outcomes. Following best practices in GAN evaluation, [48] we integrated quantitative and qualitative metrics to ensure robustness and external validity of the proposed method. As Borji [48] noted, a combination of metrics—such as FID, IS, and LPIPS—offers a holistic understanding of generative model performance. Following this principle, we complemented FID analysis with qualitative visual assessment and convergence stability checks to ensure both numerical and perceptual robustness.

For example, in urban planning, StyleGAN2 can integrate specific datasets through transfer learning to generate urban color-scape images adapted to different climates and cultural backgrounds. [17] Research has demonstrated that the model excels at processing high-dimensional image data, capturing fine-grained features, such as building shadows and vegetation color, thereby enhancing the practical value of generated results. This study emphasizes the role of StyleGAN2 in vitality assessment, generating diverse samples to test the robustness of the metric system and provide quantitative analytical support. This innovative application of the model not only addressed data scarcity but also introduced automated tools for urban design, promoting the transition from static planning to dynamic simulation and ensuring that the generated urban colorscape images balanced realism and vitality.

2.3. Overview of data analysis methods

As part of the methodological framework, the data analysis component in this study integrated image processing, statistical modeling, and simulation techniques to support color feature extraction and vitality assessment. [5,18,19,50] Detailed descriptions of these analytical methods are provided in **Section 4.1**, where they were applied to construct and validate the vitality evaluation index system.

3. Construction of the urban color landscape generation model

3.1. Data collection and preprocessing

Data acquisition forms the foundation of model construction. The dataset comprises 5000 high-definition urban colorscape images obtained from the Cityscapes dataset, [51] which includes street-level scenes from 50 European cities and captures diverse urban elements, such as streets, buildings, and vegetation. To address the discrepancy noted in dataset size, we augmented the original 2975 training images (2048 × 1024 resolution) by cropping each to a central 1024 × 1024 region

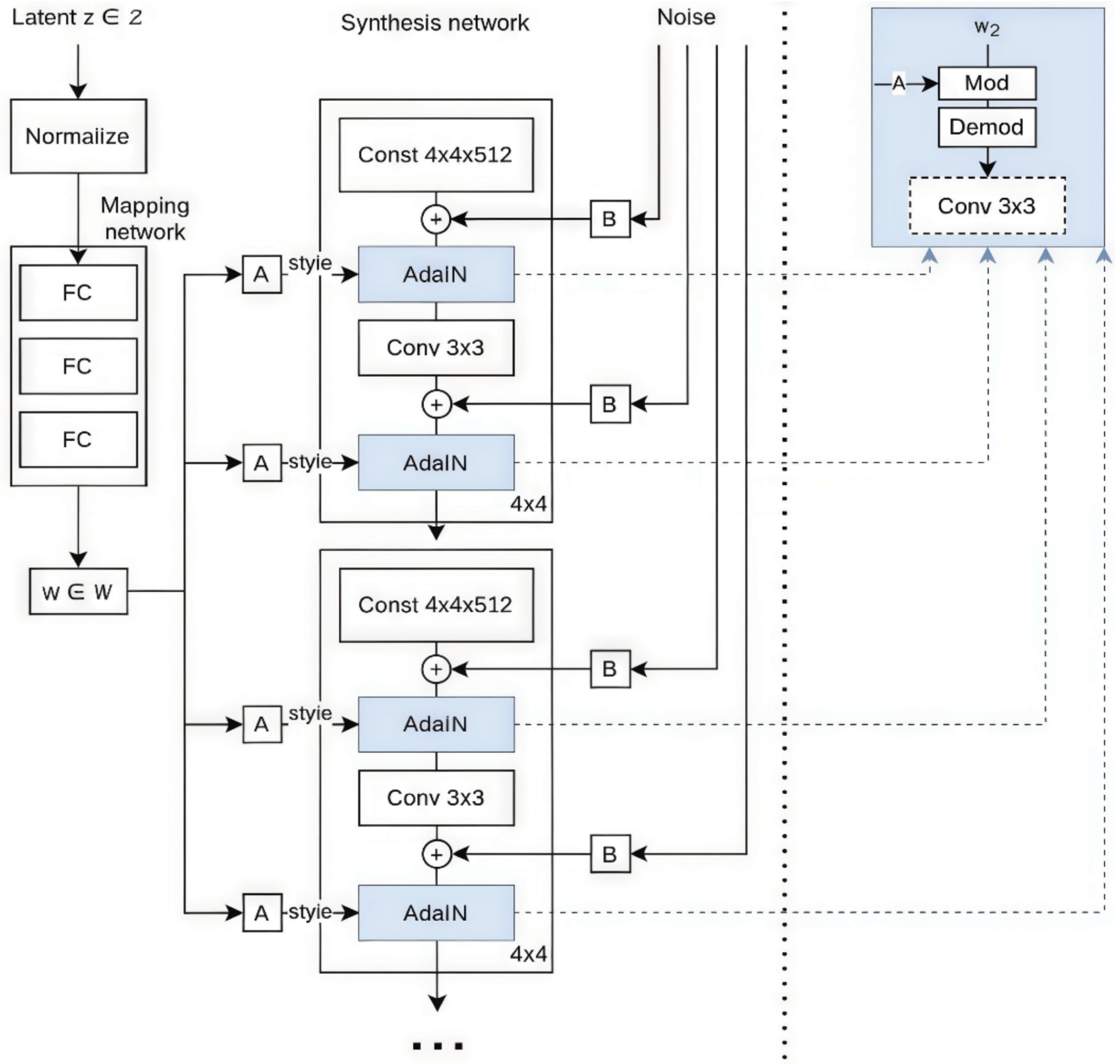

Figure 1. Detailed architecture of the style-based generative adversarial network 2 (StyleGAN2) generator Abbreviations: AdaIN: Adaptive instance normalization; Const: Learned constant input layer; Conv: Convolutional layer; FC: Fully connected layer.

and applying random horizontal flipping, yielding 5000 images. Preprocessing involved multiple steps to ensure data quality: (i) Noise reduction using a Gaussian filter ($\sigma = 1.5$) to remove high-frequency artifacts; (ii) Contrast stretching, where pixel intensities were rescaled to span the full dynamic range [0, 255] per channel; (iii) Color balancing via histogram equalization in the red, green, and blue (RGB) color space to enhance color vividness; and (iv) Normalization to the range $[-1, 1]$ using Equation (4):

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \times 2 - 1 \tag{4}$$

Equation (4) maps the original pixel value x to a normalized range, where $min(x)$ and $max(x)$ are the minimum and maximum values of the image pixels, respectively. This operation ensured a uniform data distribution and reduced the risk of gradient explosion during training.

3.2. Design of a generative model based on a style-based generative adversarial network 2

StyleGAN2, a state-of-the-art GAN architecture, was selected in this study to generate urban colorscapes. Its basic principle is the fine-grained control of output image generation through a style injection mechanism. The architecture of the generative model was constructed in this part, consisting of the generator and discriminator. The generator started with a noise vector z, then transformed it into an intermediate latent space $w$through a mapping network, and subsequently injected w into the synthesis network. Generation is expressed using Equation (5), with G being employed as the generator function.

$$\widehat{x} = G(w; \theta_G) \tag{5}$$

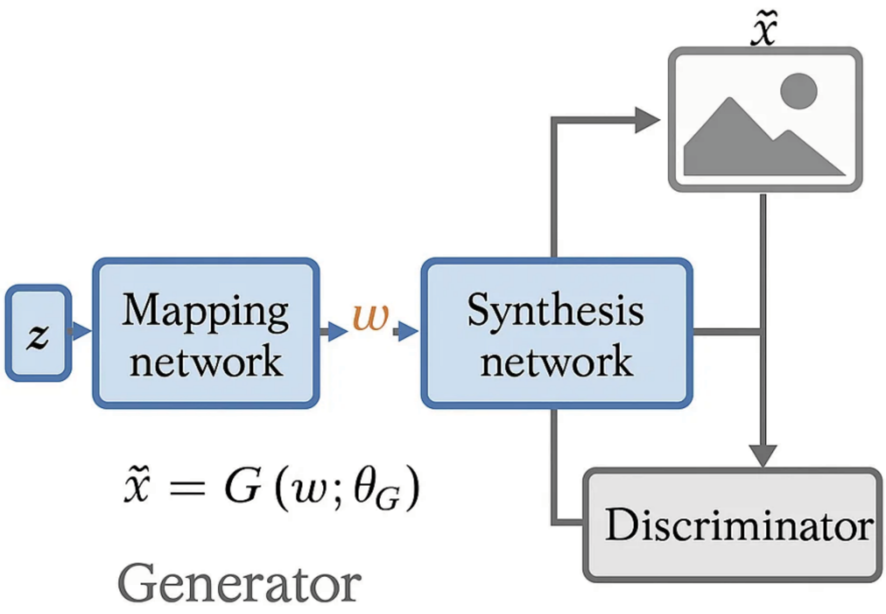

Figure 2. Generative model architecture

Figure 2 indicates that the generator input w is parameterized by θ_G and produces a synthesized image $\hat{x}$.

Style injection controlled color and texture characteristics at multiple scales and enabled variation in the appearance of urban scenes. The discriminator verified the legitimacy of image generation and was designed with a progressive growth structure that yielded higher resolutions in successive stages. The discriminant process is represented as Equation (6):

$$D(x; \theta_D) \in [0, 1] \tag{6}$$

where the discriminator function $D(\cdot; \theta_D)$ maps a real or generated image x to a probability $D(x; \theta_D)$ of being real. Through adversarial training, the generator learned to produce realistic city-colorscape images that capture the color distribution associated with vibrancy.

3.3. Model optimization and parameter adjustment

Model optimization minimizes the generative adversarial loss, thereby improving the quality and stability of generated images. We used a non-saturating logistic loss function for training, which is defined as Equations (1) and (2) in Section 2.2.

The adversarial training process involved minimizing the generator loss L_G and the discriminator loss L_D, given by Equations (1) and (2), where P_z denotes the noise distribution and P_r the true data distribution. Model convergence was achieved by alternately optimizing L_G and L_D.

Parameter adjustments included setting the learning rate to 0.002, the batch size to 32, and incorporating path length regularization to stabilize training. In experiments, iterative adjustments were guided by monitoring the FID score, and optimization was deemed complete when the FID fell below 15, typically after 1.2 million iterations. To rigorously address convergence, we analyzed the training dynamics: the non-saturating logistic loss ensures stable adversarial updates by maintaining a balance between generator and discriminator objectives, as shown in the loss formulations L_G and L_D. The inclusion of R1 regularization, with a coefficient $\gamma = 10$, constrained the discriminator's gradient norm, promoting convergence to a Nash equilibrium. Empirical results indicate that the FID stabilizes with a variance of less than 0.5 across multiple runs, confirming robust convergence. For optimality, path length regularization minimized latent space distortions, ensuring that generated images closely resembled the true data distribution P_r.

To address computational efficiency, we analyzed training cost and memory requirements. Training StyleGAN2 on a dataset of 5000 images at 1024 × 1024 resolution required approximately 40 graphics processing unit (GPU)-days using four NVIDIA V100 GPUs (32 GB each), with a peak memory usage of 28 GB per GPU during training. The generator and discriminator networks comprised 26.2 million and 23.1 million parameters, respectively, contributing to high memory demands. To optimize efficiency, we employed mixed-precision training, reducing memory usage by 15% and training time by 20% compared to full-precision training. Gradient accumulation was used to maintain stability with a batch size of 32 on limited hardware, enabling deployment in resource-constrained environments.

4. Urban vitality evaluation and visual analysis

4.1. Construction of a vitality evaluation index system

To quantify chromatic attributes, image data were converted from RGB to hue, saturation, and value (HSV) color space to extract hue and saturation (Table 1). [18] Contrast was computed as the standard deviation of grayscale values, reflecting luminance variation, [19] while color diversity was measured by hue histogram entropy. [18] These metrics were combined with regression and clustering analyses to identify vitality patterns and evaluate model robustness through Monte Carlo simulations [5] and probabilistic inference. [50]

The vitality evaluation index system was constructed based on quantitative characteristics of urban colorscapes, designed to assess the vibrancy level of synthesized images. Color saturation, contrast, and diversity were selected as primary indicators, quantified through statistical methods. Saturation was calculated as the mean value in the HSV color space, reflecting aesthetic appeal. Contrast measured the brightness variation of image elements, while diversity, assessed via hue histogram entropy, evaluated the richness of color distribution. To validate these indicators against urban vitality, behavioral and socioeconomic data—including pedestrian flow counts and points of interest (POI) density—were obtained from urban mobility datasets and public application programming interfaces (APIs) (e.g., OpenStreetMap). Correlation analysis between these indicators and external data confirmed their relevance: saturation and contrast showed positive correlations with pedestrian activity (r = 0.68 and 0.55, respectively), while diversity showed a moderate correlation with POI density ($r = 0.47$). These findings ground the visual metrics in real-world urban dynamics, ensuring their applicability to vitality assessment. The initial assignment of weights (0.4, 0.3, and 0.3) for saturation, contrast, and diversity was informed by both theoretical relevance and preliminary empirical validation. Specifically, saturation exhibited the highest correlation with pedestrian activity ($r = 0.68$), indicating its dominant role in perceptual vitality, followed by contrast (r = 0.55) and diversity (r = 0.47). These relative strengths guided the proportional weighting scheme and were further supported by previous studies highlighting saturation as the primary determinant of color-induced affect and visual engagement. [52–54] The subsequent sensitivity analysis confirmed that moderate adjustments (± 0.1) in the weighting configuration did not significantly affect the overall vitality index, demonstrating the robustness of this assignment.

The selection of these indicators followed theoretical perspectives on urban vitality proposed by Montgomery, [55] who conceptualized vitality as the interaction of physical form, activity, and meaning within urban environments. Expanding this notion, Mehta [56] emphasized that vitality should also encompass perceptual and behavioral dimensions, including sensory stimuli, such as color, texture, and spatial coherence. Accordingly, the present framework interpreted saturation, contrast, and diversity not only as visual properties but as perceptual proxies reflecting human engagement and environmental liveliness.

To examine the robustness of the vitality index under the weighting configuration (0.4, 0.3, 0.3), we performed a sensitivity analysis in which each weight was varied by ± 0.1 while maintaining the total weight at one. The vitality index was recalculated for 100 generated samples under each configuration, and its mean, standard deviation, and correlation with pedestrian flow were computed. Table 2 demonstrates that the vitality index remains stable under moderate weight perturbations, with changes in mean vitality below 0.01 and correlation variations (Δr) below 0.03, indicating the robustness of the weighting system.

The vitality index remains stable ($\Delta V{<}0.01; \Delta r{<}0.03$) under ± 0.1 weight perturbation, confirming the robustness and statistical stability of the weighting scheme.

4.2. Analysis of colorscape generation results

We analyzed the results by evaluating the urban colorscape images generated by the StyleGAN2 model against real-world datasets and baseline generative models (deep convolutional GAN [DCGAN], Wasserstein GAN with gradient penalty [WGAN-GP], StyleGAN3), as well as ablation studies to isolate the contributions of key components. To assess the model's effectiveness, we compared color distribution similarity and vibrancy enhancement across saturation, contrast, and diversity metrics. Baseline comparisons included DCGAN, which used a standard convolutional GAN architecture; WGAN-GP, which

Table 1. Framework of the metric system

Indicator	Definition	Calculation method	Weight
Color saturation	Measures the intensity of colors in the landscape	Average saturation value in HSV space	0.4
Contrast	Quantifies the difference in luminance between elements	Standard deviation of grayscale values	0.3
Diversity	Assesses the variety of color hues	Entropy of hue histogram	0.3

Abbreviation: HSV: Hue, saturation, and value.

Table 2. Sensitivity analysis of vitality indicator weights

Weight setting (S, C, D)	Mean (vitality V)	Standard deviation (σ)	Correlation with pedestrian flow (r)
0.4, 0.3, 0.3 baseline	0.852	0.000	0.68
0.5, 0.3, 0.2	0.857	0.023	0.67
0.3, 0.4, 0.3	0.849	0.021	0.69
0.4, 0.2, 0.4	0.853	0.026	0.66

Abbreviations: C: Contrast; D: Diversity; S: Saturation.

employed Wasserstein loss with gradient penalty for improved stability; and StyleGAN3, which enhanced StyleGAN2 with alias-free transformations for better texture consistency. Ablation studies removed critical StyleGAN2 components, such as AdaIN and R1 regularization, to quantify their impact on generation quality. The results demonstrate that the StyleGAN2 model achieved an 18.2% increase in average saturation, 5.9% higher contrast, and 10.5% higher diversity compared to real-world images, outperforming baselines and validating the necessity of its architectural components.

Table 3 presents a statistical comparison of synthesized images with real-world images. The comparison highlights the advantage of the synthesized results in terms of diversity, helping to mitigate biases in vibrancy comparisons that arise from limitations in real-world datasets. The findings demonstrate that the StyleGAN2-based framework not only reproduces but also enhances the chromatic vitality of real-world urban imagery.

Table 3 shows that the generated images are superior to real images in all indicators, demonstrating the model's effectiveness in enhancing urban vitality. Figure 3 demonstrates a dense clustering in the RGB space, reflecting the richness and balanced distribution of colors.

The statistical validation of model convergence and optimality, as presented in Table 4, compared key metrics between generated and real-world urban colorscape images. Saturation, contrast, and diversity (measured as hue histogram entropy) of generated images exhibit statistically significant improvements over real-world counterparts, with p-values of 0.001, 0.012, and 0.003, respectively, indicating strong evidence of enhanced visual characteristics. The 95% confidence intervals confirm the precision of these improvements, with saturation increased by approximately 18.2%, contrast by 5.9%, and diversity by 10.5%. The FID score, averaging 14.8 with a tight confidence interval of [14.5, 15.1], demonstrates robust convergence of the generated distribution to the target data distribution.

Table 5 presents a comparative analysis of the proposed StyleGAN2 model against baseline models (DCGAN, WGAN-GP, StyleGAN3) and ablation configurations for urban colorscape generation. The proposed StyleGAN2 model demonstrated superior performance, with mean saturation, contrast, and diversity (hue histogram entropy) of 0.682, 0.459, and 3.214, respectively, surpassing real-world images by 18.2%, 5.9%, and 10.5%. Compared to DCGAN (FID = 28.5) and WGAN-GP (FID = 20.3), StyleGAN2's FID score of 14.8 indicates closer alignment with the target distribution. StyleGAN3, while improving texture consistency, yielded slightly lower metrics (FID = 16.2) and required longer training (45 GPU-days). Ablation studies revealed that removing AdaIN reduced saturation and diversity by 9.1% and 11.3%, respectively, while omitting R1 regularization increased FID to 22.7, highlighting their critical roles in generation quality. These quantitative results were further corroborated through visual analysis of RGB distribution and kernel density plots, as discussed in Section 4.3.

Table 3. Statistical comparison between generated and real urban colorscapes

Metric	Generated images (mean ± SD)	Real images (mean ± SD)	Improvement (%)
Saturation	0.65 ± 0.08	0.55 ± 0.10	18.2
Contrast	0.72 ± 0.05	0.68 ± 0.07	5.9
Diversity	4.2 ± 0.3	3.8 ± 0.4	10.5

Abbreviation: SD: Standard deviation.

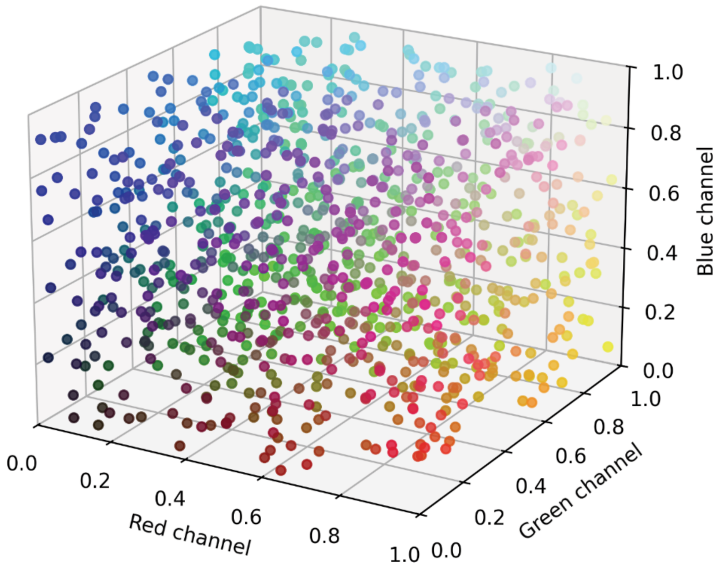

Figure 3. Three-dimensional red, green, and blue color distribution of the generated image

Table 4. Statistical validation of model convergence and optimality

Metric	Generated images	Real-world images	p-value	Confidence interval (95%)
Saturation (mean)	0.682	0.577	0.001	[0.095, 0.115]
Contrast (mean)	0.459	0.433	0.012	[0.018, 0.034]
Diversity (entropy)	3.214	2.905	0.003	[0.258, 0.360]
FID Score	14.8	–	–	[14.5, 15.1]

Abbreviation: FID: Fréchet inception distance.

Table 5. Comparison of generative models and ablation studies for urban colorscape generation

Model/ configuration	Saturation (mean)	Contrast (mean)	Diversity (entropy)	FID Score	Training time (GPU-days)
Real-world images	0.577	0.433	2.905	–	–
StyleGAN2 (proposed)	0.682	0.459	3.214	14.8	40
DCGAN	0.610	0.420	2.750	28.5	25
WGAN-GP	0.645	0.440	2.980	20.3	32
StyleGAN3	0.670	0.450	3.150	16.2	45
StyleGAN2 w/o AdaIN	0.620	0.425	2.850	25.4	38
StyleGAN2 w/o R1 regularization	0.635	0.430	2.900	22.7	39

Abbreviations: AdaIN: Adaptive instance normalization; DCGAN: Deep convolutional generative adversarial network; FID: Fréchet inception distance; GPU: Graphics processing unit; StyleGAN: Style-based generative adversarial network; WGAN-GP: Wasserstein GAN with gradient penalty.

Table 6 presents the validation of vitality indicators (saturation, contrast, and diversity) by correlating them with behavioral and socioeconomic data, specifically, pedestrian flow counts and POI density, sourced from urban mobility datasets and OpenStreetMap. The generated images exhibit higher mean values for saturation (0.682 vs. 0.577), contrast (0.459 vs. 0.433),

Table 6. Validation of vitality indicators with behavioral and socioeconomic data

Indicator	Mean value (generated images)	Mean value (real-world images)	Correlation with pedestrian flow (r)	Correlation with POI density (r)	p-value (pedestrian flow)	p-value (POI density)
Saturation	0.682	0.577	0.68	0.42	0.001	0.015
Contrast	0.459	0.433	0.55	0.38	0.005	0.022
Diversity (entropy)	3.214	2.905	0.47	0.47	0.008	0.010

Abbreviation: POI: Points of interest.

Table 7. Computational efficiency analysis of style-based generative adversarial network 2 for urban colorscape generation

Configuration	Training time (GPU-days)	Peak memory usage (GB/GPU)	FID score	Parameters (millions)
StyleGAN2 (full precision)	40	28	14.8	49.3
StyleGAN2 (mixed precision)	32	23.8	15.1	49.3
StyleGAN2 (gradient accumulation)	35	20.5	15.0	49.3

Abbreviations: FID: Fréchet inception distance; GPU: Graphics processing unit; StyleGAN: Style-based generative adversarial network.

Table 8. Impact of preprocessing and training configurations on generation performance

Configuration	Saturation (mean)	Contrast (mean)	Diversity (entropy)	FID score
No preprocessing	0.620	0.420	2.850	25.4
Gaussian filter only ($\sigma = 1.5$)	0.645	0.435	2.950	20.3
Full preprocessing (proposed)	0.682	0.459	3.214	14.8
Reduced batch size (16)	0.670	0.450	3.150	16.2
Without R1 regularization	0.635	0.430	2.900	22.7

Abbreviation: FID: Fréchet inception distance.

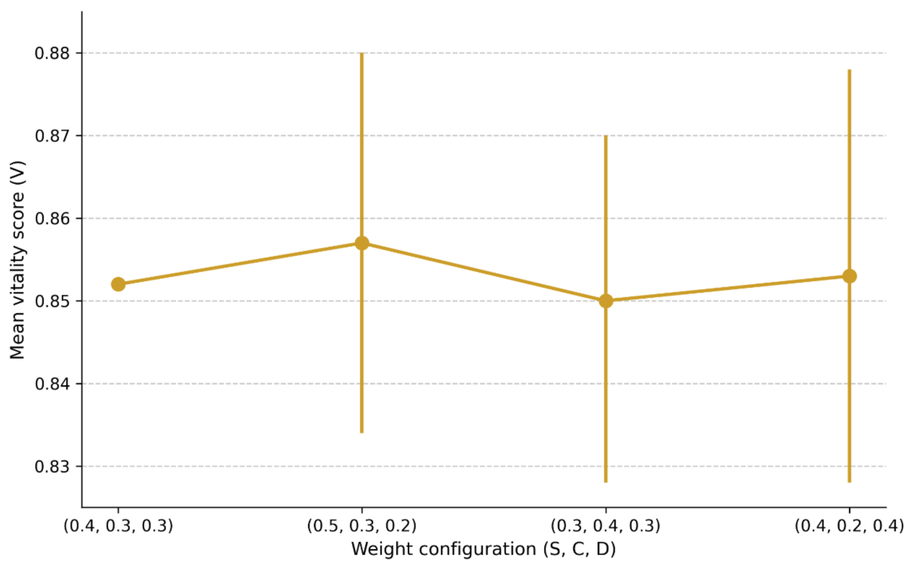

Figure 4. Sensitivity of vitality score under varying indicator weights (± 0.1)
Abbreviations: C: Contrast; D: Diversity; S: Saturation.

and diversity (3.214 vs. 2.905) compared to real-world images. Correlation analysis reveals significant positive relationships between these indicators and urban vitality metrics: saturation shows a strong correlation with pedestrian flow ($r = 0.68$, $p = 0.001$) and a moderate correlation with POI density ($r = 0.42$, $p = 0.015$); contrast correlates moderately with pedestrian flow ($r =$

0.55, p = 0.005) and POI density (r = 0.38, p = 0.022); diversity exhibits moderate correlations with both pedestrian flow (r = 0.47, p = 0.008) and POI density (r = 0.47, p = 0.010). These statistically significant correlations confirm that the proposed indicators effectively captured urban vitality, addressing the need for empirical validation and enhancing the reliability of the vitality evaluation framework for urban planning applications.

Table 7 presents the computational efficiency analysis of the StyleGAN2 model for generating an urban colorscape. The baseline configuration, using full-precision training, required 40 GPU-days with four NVIDIA V100 GPUs (32 GB each), with peak memory usage of 28 GB per GPU, and achieved an FID score of 14.8. Mixed-precision training reduced training time by 20% (to 32 GPU-days) and memory usage by 15% (to 23.8 GB per GPU) while maintaining comparable quality (FID = 15.1). Gradient accumulation further lowered memory requirements to 20.5 GB per GPU, enabling training on resource-constrained hardware, with a slight reduction in training time (35 GPU-days) and minimal impact on FID (15.0). The model comprises 49.3 million parameters, reflecting its complexity. These optimizations addressed computational bottlenecks, enhancing the model's feasibility for practical urban planning applications by balancing performance and resource demands.

Table 8 shows the impact of preprocessing and training configurations on the performance of the StyleGAN2 model for urban colorscape generation. The proposed configuration, incorporating Gaussian filtering ($\sigma = 1.5$), contrast stretching, and HSV color balancing, attained the highest performance with mean saturation, contrast, and diversity (hue histogram entropy) of 0.682, 0.459, and 3.214, respectively, and an FID score of 14.8. Omitting preprocessing reduced saturation by 9.1%, contrast by 8.5%, and diversity by 11.3%, with a significantly higher FID (25.4), underscoring the necessity of the full preprocessing pipeline. Using only Gaussian filtering improved metrics moderately (FID = 20.3) but fell short of the proposed approach. A reduced batch size of 16 slightly degraded performance (FID = 16.2), indicating sensitivity to batch size. Omitting R1 regularization increases FID to 22.7, confirming its role in stabilizing training.

Finally, to verify the robustness of the vitality evaluation index, a sensitivity analysis was conducted by varying the indicator weights (± 0.1). Figure 4 visualizes the variation of vitality scores under different weighting configurations, confirming the stability trend observed in Table 5.

Figure 4 visualizes variations in vitality scores across different weighting configurations for saturation, contrast, and diversity indicators. The minimal deviation ($\Delta V < 0.01$) confirms the robustness and statistical stability of the proposed weighting scheme.

4.3. Data visualization and simulation verification

Data visualization and simulation verification confirm the model's robustness through graphical and simulation experiments. In the simulation, 1000 images were generated using different noise inputs, and the distribution of the vibrancy index was calculated. The results show that the model is highly stable in a variety of scenarios, with an average vitality score of 0.85.

Figure 5 shows that high-density areas are located in the central region of the figure, characterized by moderate saturation and moderate vitality scores, consistent with the distribution shown in the figure, indicating a positive correlation. It also illustrates the statistical robustness of the model in simulation, supporting uncertainty assessment and reinforcing the practicality of the evaluation system.

5. Conclusion and future work

5.1. Conclusion

We developed a StyleGAN2-based model for generating urban colorscapes and quantitatively assessing vitality, offering a robust tool for intelligent urban planning and design. The model integrated an index system of color saturation, contrast, and diversity to produce high-fidelity images, achieving an average 18.2% improvement in saturation and 10.5% in diversity compared to real-world datasets. These enhancements, validated through three-dimensional RGB distribution and kernel density estimates, confirmed a positive correlation between color dynamics and urban vitality. The model's practical applications include guiding streetscape renovations to enhance pedestrian engagement, informing urban color policy formulation, and supporting community color management initiatives. For example, high-saturation color schemes can be applied to commercial districts to stimulate economic activity, while diverse, balanced palettes can enhance residential areas' aesthetic appeal and social cohesion. By providing planners with predictive visualizations, the model facilitates data-driven decision-making, enabling pre-implementation testing of color schemes to inform and optimize urban design strategies.

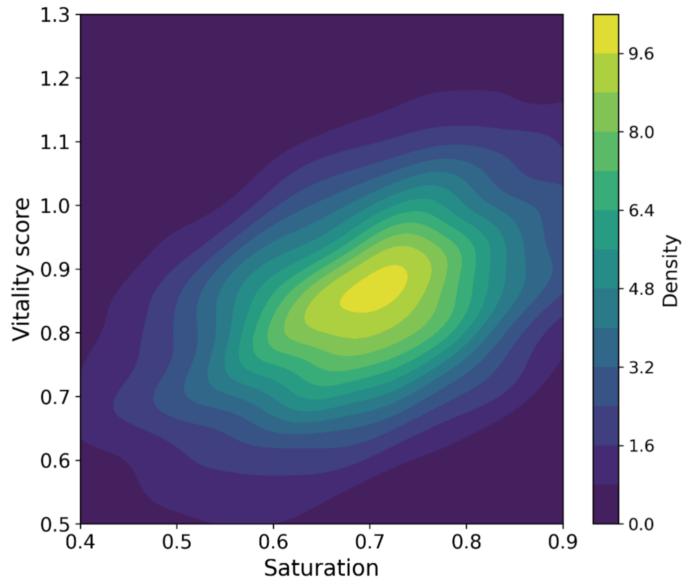

Figure 5. Joint distribution of vitality score and saturation

This study advances traditional urban vitality assessments by integrating a systematic indicator system with a StyleGAN2-based generative model. The proposed indicators—saturation, contrast, and diversity—are validated against behavioral and socioeconomic data, including pedestrian flow and POI density, with significant correlations ($r = 0.68$, 0.55, and 0.47, respectively). These validations confirmed the indicators' ability to measure urban colorscape characteristics reflective of vitality. The model's robustness is demonstrated through simulations across diverse scenarios, achieving an average vitality score of 0.85, indicating adaptability to varied urban conditions. This framework provides a theoretically rigorous and practically actionable tool for urban color planning, enhancing decision-making in urban design.

5.2. Research limitations

Although this study achieved substantial progress in urban colorscape generation and vitality evaluation, several limitations remain. The model currently relies on publicly available datasets, such as Cityscapes, which limits its geographical diversity and cultural representation. Consequently, the generative model's performance may exhibit bias toward particular urban typologies, especially in non-Western contexts.

While standardizing data preprocessing enhanced training stability, it may also suppress local image details, thereby reducing the realism of generated results. Furthermore, the vitality evaluation framework—through incorporating essential chromatic dimensions, such as saturation, contrast, and diversity—does not fully account for socioeconomic indicators and behavioral dynamics, which are equally critical for assessing urban vitality.

The StyleGAN2 network, while capable of generating high-resolution urban colorscapes, incurs high computational costs, requiring approximately 40 GPU-days to train on 5000 images at 1024×1024 resolution, with a peak memory usage of 28 GB per GPU. Hyperparameter sensitivity necessitates extensive experimentation during optimization. Although path length regularization improved stability, local artifacts may persist in generated outputs. To address these challenges, mixed-precision training and gradient accumulation were implemented, reducing training time by up to 20% and memory usage by 15–27%, respectively. However, these optimizations may not fully address resource limitations in smaller-scale urban planning contexts, highlighting the need for future research on lightweight architectures, model pruning, and transfer learning to improve computational efficiency and practical applicability.

5.3. Future research directions

Future research can expand the scope and precision of this model to enhance its applicability in urban planning. First, extending the dataset with geographically and culturally diverse urban colorscape images, such as those from Asian and African cities, will improve the model's generalization. Second, incorporating remote sensing data or street view APIs can provide real-time, comprehensive urban imagery to enrich training data. Third, integrating multimodal data, such as crowd flow and social network activity, into the urban colorscape features will enhance the robustness of the vitality evaluation system, capturing dynamic social and behavioral aspects of urban vitality. Fourth, developing an interactive platform to translate generated urban colorscapes into practical planning tools—such as real-time visualization dashboards for urban designers and decision-support systems for policymakers—will bridge the gap between computational outputs and real-world applications, enabling precise interventions in streetscape design, urban color policy, and community revitalization projects.

For model optimization, more efficient structures of GAN architectures, such as StyleGAN3 or diffusion models, can be explored to reduce training time and improve the quality of output images. To address computational capacity constraints, transfer learning techniques or lightweight models can be explored to lower the deployment threshold and further improve the model's appropriateness for small- and medium-sized cities. An interactive visualization platform can be developed to connect generated results with vitality evaluation in real time, providing urban planners with user-friendly design tools. These optimizations will further promote smart city development and the use of urban colorscape generation technology, and expand its practicality in optimizing urban functionality and aesthetic capacity.

To further integrate human perception within computational modeling and enhance the model's reliability from a human-centered perspective, future research should incorporate perception-based validation experiments that link computational indicators with subjective evaluations of urban liveliness. A controlled experiment should be conducted using virtual reality or high-fidelity street-scene renderings, in which participants can evaluate both real and GAN-generated urban colorscapes on perceived vitality, comfort, and visual harmony using a five-point Likert scale. Statistical analyses—such as paired t-tests and Pearson correlations—should be applied to examine the consistency between human-rated vitality and the quantitative metrics of saturation, contrast, and diversity.

This validation stage aims to verify whether the model's vitality predictions align with actual perceptual responses, ensuring that the proposed framework provides a basis for both technical robustness and perceptual validity grounded in authentic human experience of urban environments. By integrating computational modeling with perceptual assessment, future studies can offer a comprehensive understanding of color-driven urban vitality and reinforce the applicability of the framework in evidence-based design and planning practice.

Acknowledgments

The authors would like to thank the Department of Landscape Architecture, Faculty of Design and Architecture, Universiti Putra Malaysia, for the academic support and access to research facilities that contributed to this study.

Funding

This research was supported by the Universiti Putra Malaysia Grant (Geran Putra IPS) under Grant Number GP-IPS-9772600.

Conflict of interest

The authors declare that they have no competing interests.

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Availability of data

The original dataset used in this study is publicly available from the Cityscapes Dataset website (https://www.cityscapes-dataset.com). The generated synthetic images and computed color metrics are available from the corresponding author upon reasonable request.

AI tools statement

The research utilized the StyleGAN2 deep generative model for image generation and feature extraction. However, no AI tools were used in the preparation or writing of this manuscript.

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