Cartographies of Immersive Fractality

An exploration of collective emotive responses in urban settings through Machine Learning

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Recent advances in machine learning technologies offer avenues for a more efficient analysis of large photographic and text-based datasets, facilitating a deeper understanding of the fundamental characteristics inherent in the immersive representation of the urban environment. It is known that automatic fractal processing in the human visual system triggers positive emotive responses to the environment. The project explores the correlation among fractal aesthetics, visual perception, and emotional responses in urban settings, developing an integrated evaluation method that uses the data-scraping of existing online photographic media from Flickr and Google Street View (GSV). Taking the area of Southbank in London (UK) as a case study, the study initially employed a sentiment analysis method rooted in the Lexical dictionary from TextBlob. Further, an extensive online GSV urban scenery dataset was built via Google API. The photographic dataset was then evaluated by fractal dimension as a quantitative index to measure the complexity of fractal patterns. Concurrently, to enhance the comprehension of the composition of urban form, a semantic segmentation method for image analysis was implemented. A comparative evaluation of the data collected indicated the key role of fractal patterns described by vegetation in the generation of positive emotional responses, underscoring with methodological rigour the potentially transformative impact of the experience of fractal patterns and green infrastructures in open urban spaces.

Keywords: *Visual perception, Sentiment analysis, Psychogeography, Fractal aesthetics, Machine Learning.*

INTRODUCTION

Psychogeography suggests that individuals, as active participants within urban environments, ought to engage in subjective and dynamic urban exploration, incorporating multisensory experiences (Rose and Samuels, 2021). The advent of contemporary psychogeographic methods heralds a fresh approach to urban mapping aimed at visualising the subjective emotions and experiences of individuals within urban spaces, which draws from the groundbreaking work of Kevin Lynch (1960) and Guy Debord (1956). Since 2004, Nold (2018) has worked on an approach to emotional cartography that includes the collection of human emotional feedback in urban settings through the collection of situated Galvanic Skin Response (GSR), an indicator of physiological arousal that measures the electrical conductivity of the skin. Further explorations of situated GSR collection and visualisation for urban analysis (Papeschi, 2020) illustrate how, within participatory settings, emotional mapping may become critical to effectively capturing individual insights for the construction of collective knowledge. By considering the many individual responses to specific settings and by exploring their significance within the context of group discussions, such an approach reveals how we can gain a more nuanced and inclusive understanding of the collective experience of our cities. Advancements in machine learning (ML) and artificial intelligence (AI) present unprecedented opportunities to gather text and spatial image datasets to further enable the qualitative assessment of collective emotions within urban settings.

The project explores the use of ML methods to quantitatively measure visual perception and emotive responses, facilitating a comprehensive analysis of the relationship between emotions and urban space. For this purpose, it draws on the positive emotional effect produced by fractal pattern processing in the human visual system (Brielmann et al., 2022), employing machine learning methods and computer vision algorithms to systematically assess the impact of fractal pattern processing on the shared emotional experience of our cities.

FRACTALS: A MEASURE OF ENVIRONMENTAL WELLBEING

According to Kaplan and Kaplan (1989) and Han (2010), the complexity and coherence of our surroundings, as experienced by visual perception, increase our attraction toward our environments. Also, numerous healthcare studies show that the visual complexity exhibited by natural environments might help people feel less anxious (Heerwagen, 1990) and recover from illness more quickly (Ulrich, 2002).

Fractal patterns, renowned for their intricate organisation across varying scales, hierarchies, and self-similarities, epitomise such complexity and coherence. As posited by Robles et al. (2021), fractal patterns have the potential to combat the negative effects of our environments and create a more positive experience for those occupying these spaces. Neuroscientist Chatterjee (2014) also supports the thesis of a positive connection between the experience of fractal patterns and mental well-being by outlining how, when fractal patterns with high self-similarity in the environment capture human attention, the neurons in the limbic regions of the brain are stimulated, which can be attributed to the brain's inherent preference for certain visual stimuli resembling those found in nature.

Vision, being the primary sensory modality, plays a pivotal role in shaping our experiential landscape. Through a comprehensive review of current research on visual urban perception, Brielmann et al. (2022) reveal that when humans walk in urban environments, they are exposed to a plethora of visual stimuli, prompting a process of automatic fractal processing that triggers the peaks of emotional response to the environmental stimuli. A novel visual simulation software was employed to forecast eye-tracking fixations, revealing that eye-movement visual scans tend to allocate minimal perceptual attention to low-fractal architecture (Brielmann et al., 2022). The study demonstrates how, as visual perception processes undergo repeated cycles, it becomes increasingly evident that the appeal of urban forms significantly influences user emotions to a greater extent than previously acknowledged.

Further, electroencephalogram signals were employed to gauge human physiological markers of visual contentment across various spatial simulations within the virtual reality realm, including open landscapes, semi-open areas, and enclosed spaces, to infer the influence of diverse environments on productivity (Li et al., 2020). Also, Yin et al. (2020) utilized biomonitoring sensors to measure the physiological indicators of stress responses among participants within a virtual office environment, proving the effectiveness of biophilic design elements in impacting stress recovery and anxiety. Additionally, Li et al. (2016) propose an alternative methodology that integrates geographic information systems with wristband sensors developed by *Bodymonitor* to record the skin conductivity and temperature of the experimenter and assess the relationship between individuals' emotional responses and urban characteristics, including visual fractals and isovist parameters. Although this approach extends beyond virtual environments, the small sample size of participants limited the generalizability of its findings and the comprehensive understanding of emotional perceptions in urban spaces.

PROCESSING IMMERSIVE PERCEPTION

The development of global positioning systems has enabled mapping service companies to amass vast situated image datasets freely accessible online, serving as a valuable resource for investigating the interplay between human visual perception and urban space.

Machine learning, and in particular deep learning models, have emerged recently as powerful tools for analysing these extensive datasets. Zhang et al. (2018) trained a deep learning model to predict the human perception score of each Tencent Street View image based on six perceptual indicators. The study correlates human visual perception with the presence of visual elements and concludes that walls are a negative element in urban scenes. By combining deep learning technology with semantic segmentation analysis of Baidu Street View images, a conceptual framework of visual walkability was proposed by Zhou et al. (2019) to explore the inequality of social environments, especially socioeconomic status. These studies demonstrate the feasibility of utilizing street view data for analysing how urban environments are perceived. Drawing on the above methodology, Chen et al. (2022) proposed the collection of residents' perceptions through questionnaires, utilising the urban images combined with machine learning techniques to explore the impact of street elements on residents' emotions. This approach suggests the possibility of intersecting the evaluation of the visual dataset with emotive scoring.

Despite the advancements outlined in the study of immersive urban perception through machine learning, the possibility of demonstrating quantitatively the positive influence of fractal aesthetics on human visual and emotional perception remains overlooked. This paper builds on the stream of AI-based urban research described above to constitute the precedent for an analytical method, combining machine learning techniques for street view image analysis and fractal pattern recognition with geolocated social media sentiment analysis to explore more comprehensively the relationship between visual perception and emotion in the urban environment.

METHODOLOGY

This paper describes a three-step methodology: (1) the production of a social media-based geolocated sentiment analysis; (2) the production of a geolocated street-view fractal dimension analysis; and (3) the production of a semantic segmentation analysis describing the composition of the street-view dataset.

Step 1: Cartographies of Sentiment

Social media platforms might provide valuable insights into the collective emotional state of urban populations. Papeschi et al. (2022) utilised nearly 260,000 posts gathered from the social media platform Flickr to investigate urban residents' emotional ties to specific locations, using immersive visualisation methods (VR) and the gathering of live emotive feedback (Galvanic Skin Response). Gao et al. (2022) described urban collective emotions by extracting a substantial volume of geotagged posts from the *Sina Weibo* social platform and subsequently conducting a machine learning-based sentiment analysis to evaluate the collective positive and negative emotional valences associated with specific locations.

Sentiment analysis, a natural language processing (NLP) technique, is employed to ascertain the sentiment or emotional tone conveyed in text-based media. *TextBlob,* a Python library built on top of the NLTK (Natural Language Toolkit) and Pattern libraries, offers a ready-to-use sentiment analysis tool that allows users to analyse the sentiment of text data. *TextBlob* sentiment analysis module employs a pre-trained machine learning model that utilises computational linguistics techniques to classify text into positive, negative, or neutral sentiment categories based on words and phrases present in the text and their association with sentiment polarity in the training data.

Taking the area of Southbank in London (UK) as a case study, the team used QGIS to interact with the *Flickr API* and automatically obtained 5,056 Flickr information points (posts) uploaded in 2020. Each information point included associated tags and geographical coordinates. *TextBlob* sentiment analysis was then conducted on the tag attribute of the dataset, and the information extracted was visualised into a map and a 3D diagram to illustrate the emotive weighting of the photographic database (Figure 01).

Step 2: Quantifying Fractal Experience

According to Li (2016), the fractal dimension of an image can demonstrate the level of complexity of visual experiences. Also, the complexity of urban scenery can be measured by its fractal dimensions (Jiang and Brandt, 2016). The fractal dimension of an image is a mathematical measure used to quantify the irregularity of geometric shapes, which can be applied to various natural and artificial objects, from coastlines and clouds to biological organisms and urban landscapes. In the context of the urban environment, numerous features, including the layout of city streets, the distribution of buildings, and the patterns of green spaces, often exhibit fractal-like characteristics, displaying self-similarity and hierarchical structures across varying scales, characteristics that can be represented by their fractal dimension.

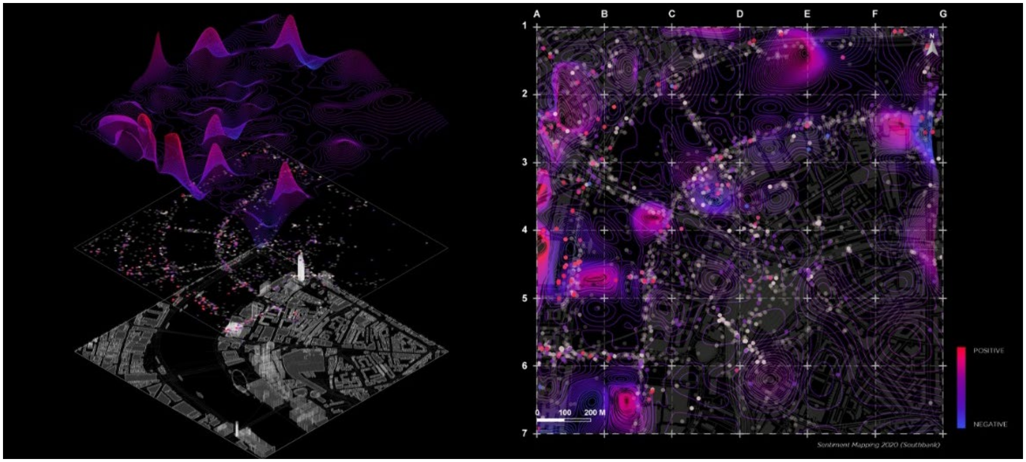


Figure 01 Sentiment Mapping 2020 (Southbank)

FracLac, a plugin for ImageJ, a popular open-source image processing program used for analysing and processing scientific images, enables researchers to investigate fractal dimension and associated parameters, allowing for multifaceted fractal analyses that include methodologies such as box counting, box covering, and Fourier methods. Particularly in urban settings where conventional mathematical techniques may encounter limitations in estimating fractal dimensions accurately, the box-counting method emerges as a valuable and adaptable approach, offering a robust means to characterise the spatial complexity and self-similarity prevalent within urban structures and landscapes (MAA EPADEL, 2020).

As the Flickr entries initially downloaded included many close-up pictures not relevant to the purpose of this investigation, the team proceeded to create a new dataset of medium-shot imagery extracted from *Google Street View*. A data cleaning procedure was implemented on the vast amount of geo-location data collected through the *Flickr API*, effectively eliminating duplicate entries. A Python script was developed to automatically retrieve through the *Google API* sets of 4 images taken at the cardinal directions at each of the specified geolocations. Built upon *Google Street View* (GSV) imagery, the new urban scenery dataset served as the basis for a subsequent fractal dimension analysis via the box-counting method. The information extracted was again visualised as a map and 3D diagram illustrating the fractal dimension of the Southbank as informed by the GSV imagery extracted at locations matching the Flickr database (Figure 02).

Step 3: Quantifying Urban Composition

To further explore the interplay among immersive urban perception, the fractal dimension of space, and situated emotional responses, an in-depth examination of the composition of the urban environment was undertaken via semantic segmentation analysis. By segmenting images at the pixel level and assigning semantic labels, semantic segmentation algorithms enable machines to perceive and comprehend visual information accurately, providing a detailed understanding of the scene. In recent years, a subset of machine learning techniques, such as deep learning and convolutional neural networks, have made significant progress in the field of image semantic segmentation.

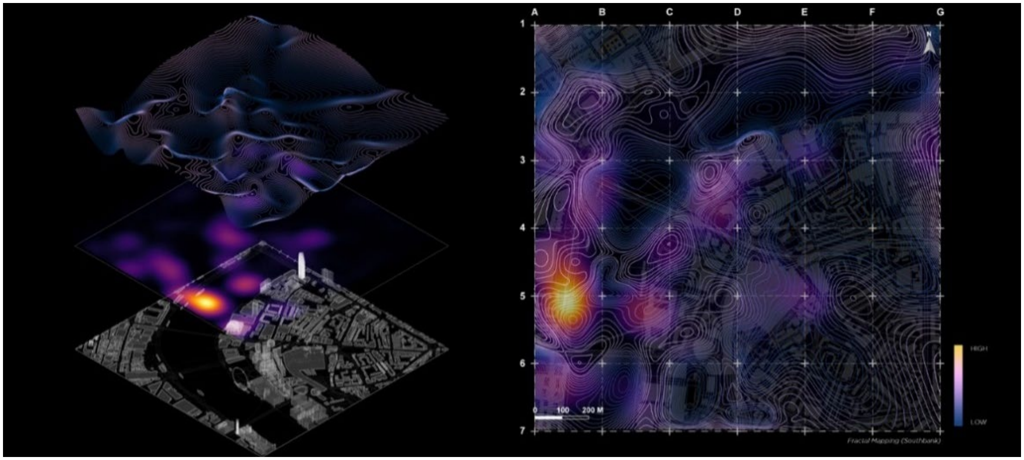


Figure 02
Fractal Mapping
(Southbank)

TensorFlow, a currently popular machine learning framework developed by *Google Brain*, provides a flexible and scalable platform that facilitates the creation and training of various machine learning models, including neural networks. To train the ML model, the *CityScape* dataset (Cordts et al., 2016) was utilized as the input dataset. The *CityScape* dataset comprises high-quality urban scenery images captured from various cities and annotated with pixel-level semantic labels for objects such as roads, buildings, pedestrians, vehicles, and vegetation.

Using the urban scenery dataset as the basis of the fractal dimension analysis described above, a semantic segmentation analysis was carried out, and a new matching dataset of urban imagery with semantic segmentation information was extracted, providing the basis for a comprehensive comparative analysis of the urban environment's composition, the sentiment analysis results, and the fractal analysis results. To further explore the interplay among immersive urban perception, the fractal dimension of space, and situated emotional responses, an in-depth examination of the urban environment's composition was undertaken via semantic segmentation analysis.

CARTOGRAPHIES OF IMMERSIVE FRACTALITY

With the visual perception and urban emotion elicited by urban scenes being quantified and visualised in cohesive maps and 3D diagrams (Figures 01 and 03), the relationship between sentiment score and fractal dimension was considered. A preliminary analysis of the cartographies produced outlines how the areas along the river exhibit more positive sentiment, accompanied by a higher degree of irregularity, self-similarity, and hierarchical organisation within the urban fabric. This comparison also shows a generally positive relationship between sentiment score and fractal dimension score, indicating that urban emotion is highly influenced by the immersive experience of spatial fractality.

To discern the primary environmental composition factors influencing the fractal dimension index and therefore their potential impact on eliciting positive emotional responses, the team proceeded to develop further analysis that integrated the localised results of the semantic segmentation analysis. Based on the lexical source of *TextBlob* named *Natural Language Toolkit* (NLTK), the sentiment information extracted was further identified into 4 categories: Great, Love, Relaxed, and Afraid & Terrible (Figure 03). The *Google Street View* and the matching semantic segmentation datasets were then subdivided into 4 sub-catalogues for comparison, analysis, and visualisation (Figures 04, Figures 05, and Figures 06).

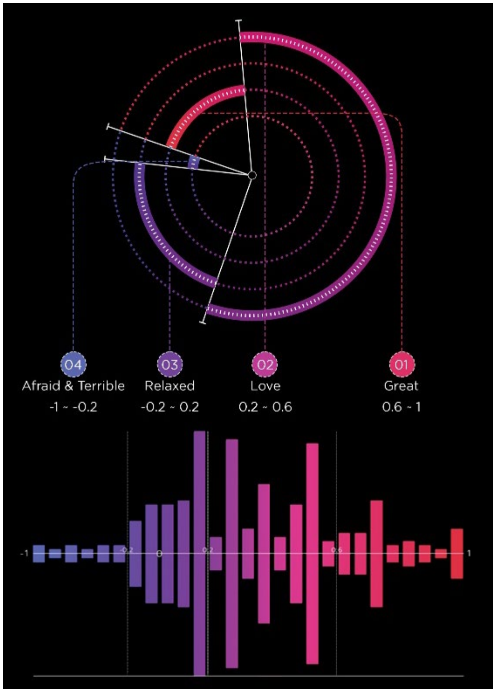


Figure 03
Identification of Different Sentiments

Figure 04
Urban Scene
dataset
(Southbank)

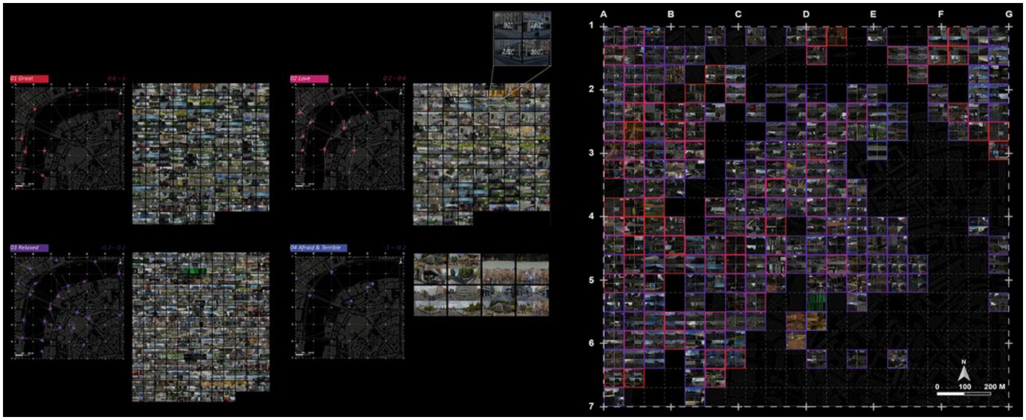


Figure 05
Urban Scene
Fractal Dimension
Dataset
(Southbank)

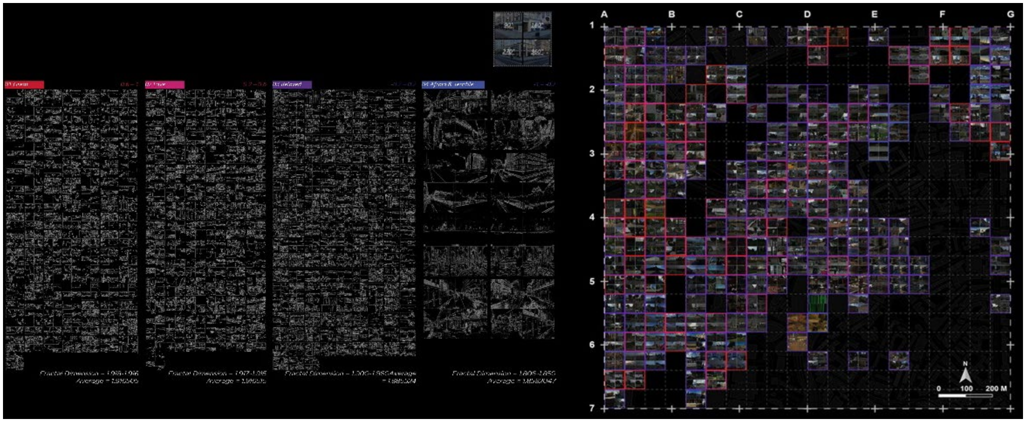
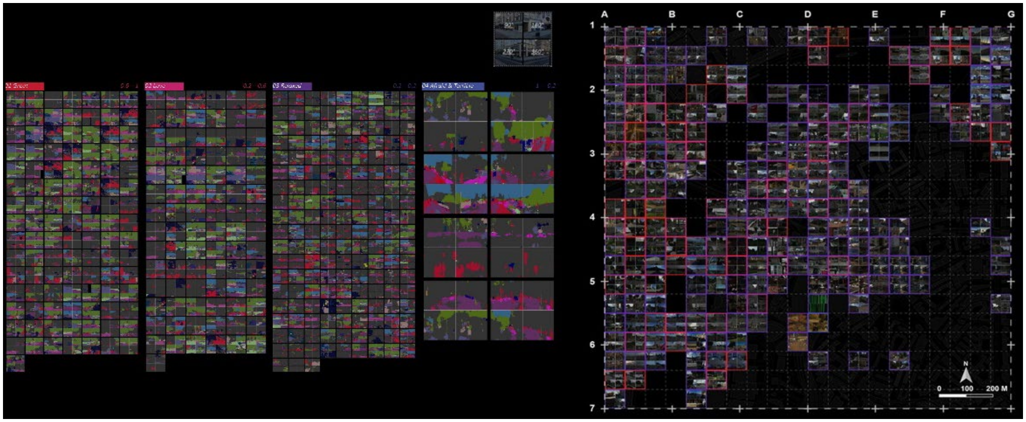


Figure 06
Urban Scene
Semantic
Segmentation
Dataset
(Southbank)



The resulting diagram (Figure 07) describes the proportion of each environmental component in each sub-catalogue, illustrating a clear inverted tendency in which a higher sentiment score consistently accompanies higher percentages of vegetation and lower percentages of built scenery. The analysis results reveal that there is a positive correlation between urban emotion and the environment's fractal dimension. In particular, fractal patterns found in vegetation are more significant in fostering positive sentiment compared to fractal patterns observed in man-made structures within the built environment. This suggests that natural fractals contribute more significantly to the mental well-being of individuals.

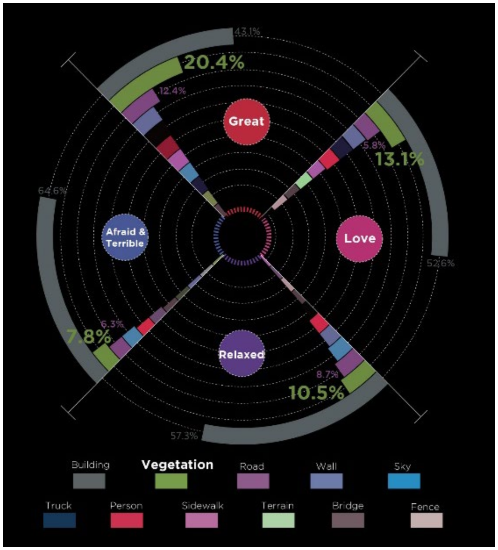


Figure 07 Color Ratio Diagram for Each Catalogue

CONCLUSIONS

The study illustrates how, by synthesizing the findings from the analysis of urban scenery through GSV imagery and the emotional responses extracted from social media, the correlation between urban features, fractal aesthetics, and emotional experiences within the cities can be elucidated. The analysis of emotional responses elicited by urban scenes illustrated a positive correlation between higher fractal dimensionality and increased positive emotional valence, with higher levels of visual complexity often associated with greater emotional appeal and satisfaction. Further analysis of urban scene composition reveals the critical contribution of vegetation to the experience of fractal patterns in the city, suggesting a potential correlation between the presence of vegetation and the overall perception of an area, with greener environments likely contributing to more positive sentiments.

Building upon ML techniques, the analytical approach described in this paper enables us to identify key determinants driving variations in fractal dimensionality across different environmental elements and assess their significance in shaping the emotional responses of individuals within urban environments. However, it is important to note that the content of textual data taken from social media in the initial stage, as well as the subjective interpretation throughout the successive extraction of analytical metrics, might have introduced bias into the approach. Future endeavours should contemplate the adoption of a more comprehensive methodological framework and an automated workflow to enhance the tool's efficacy and impartiality.

Concurrently, it is important to consider the potential impact of such a methodology beyond the analytical realm and into the domain of design, particularly given the opportunity that this process provides to integrate empirical insights on collective sentiment into the creative process. By bridging the gap between quantitative analysis and design synthesis, such an integrated pathway would indeed facilitate an evidence-based approach to urban design, which, by leveraging a deeper understanding of the collective emotive experience of urban space, could support novel prospective avenues for the design of open space and green infrastructures with transformative potential.

ACKNOWLEDGEMENTS

The work illustrated in this paper is part of the Fractal Aestheti(c)ity project by Akbar Agniputra, Daijia Ke, Zhaoyan Feng and Ilin Wu. The project was developed at the Research Cluster 15, Master in Urban Design, The Bartlett School of Architecture, University College London, in 2022-23, supervised by Ilaria Di Carlo, Annarita Papeschi, Soungmin Yu (Design Tutors) and Vincent Nowak (Skills Tutor). The project's authors are immensely thankful to Qiuyi Zhang and Joshua Chi for their help with some of the technical issues faced. We acknowledge the use QuillBot (Open AI, https://quillbot.com/) as a grammar checker.

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