

Article

Regional EEG Responses from Exposures to Virtual Urban Green Spaces

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Abstract

Exposure to urban green spaces has been associated with mental wellbeing, but the neural responses to specific visual properties of urban green spaces remain unclear. This study investigated regional electroencephalogram (EEG) responses to latent visual dimensions of virtual urban green space exposures. This study used a quantitative scene-based approach that extracted 41 visual metrics to capture the heterogeneous structural properties of 24 panoramic urban green images. EEG recordings were analyzed from 150 participants, each of whom viewed eight randomly selected images repeated three times. Dimension-wise factor analysis with varimax rotation was used to derive latent factor scores for four conceptual dimensions: naturalness, complexity, coherence, and visual scale. These factors were then used as predictors in crossed mixed-effects models of regional EEG relative power changes. The hypothesis-driven primary analysis showed a significant and positive association between parietal alpha–theta activity and a naturalness factor reflecting green–grey scene compositions. Exploratory frontal associations with a terrain-related visual scale factor reached nominal significance but did not survive false discovery rate correction. Overall, the findings support a quantitative, feature-based approach for linking urban green space structure with regional neurophysiological responses. This study provides a methodological step toward more evidence-informed assessment of smart and sustainable urban environments.

Keywords: urban landscape; electroencephalogram (EEG); environmental neuroscience; factor analysis; mixed-effects modelling; representational similarity analysis



Academic Editor: Alexandros A. Lavdas

Received: 29 April 2026

Revised: 22 May 2026

Accepted: 9 June 2026

Published: 10 June 2026

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1. Introduction

Urbanization has transformed the visual environments in which people live. At the same time, the relationship between urban green space exposure and human mental wellbeing has attracted growing scientific interest. Previous studies have reported associations between exposure to urban green spaces and favourable psychological outcomes, including reduced stress, improved mood, and enhanced attention [1–5]. A more recent review further suggests that the quality of urban green space is also important for understanding

these associations [6]. These behavioural findings raise an important further question of how such effects are represented in the brain. Two complementary theoretical frameworks are relevant to this question. Attention Restoration Theory (ART) [7] proposes that natural environments can help restore directed attention by engaging attention in a relatively effortless way. Meanwhile, Stress Recovery Theory (SRT) [8] emphasizes affective and physiological recovery, proposing that natural environments can reduce stress-related responses and promote more positive affective states. In the present study, ART and SRT provide a broad framework for interpreting neural responses to urban green space exposure. However, because the study did not include direct behavioural measures of attention restoration or stress recovery, these theories were used to guide interpretation rather than to test restoration or stress reduction directly.

To address this, environmental neuroscience studies have increasingly used electroencephalography (EEG) to investigate neural responses to nature-related and urban visual exposure. Recent syntheses suggest that nature exposure is associated with measurable neurophysiological changes, including shifts towards alpha/theta dominated states and attentional restoration [9]. However, systematic reviews of urban and mobile EEG studies also emphasize substantial heterogeneity across laboratory, field, and visual paradigms, as well as across exposure definitions and outcome measures [10]. Empirical studies likewise suggest that environmental exposure can modulate EEG across multiple regions and frequency bands. These effects are likely to be region- and band-specific. Posterior and parietal alpha activity is commonly linked to visual processing and visual cortex excitability [11]. Lower parietal alpha is often interpreted as stronger engagement with visual input [12]. Frontal theta activity, in contrast, is commonly linked to executive attentional demand and cognitive control [13]. Therefore, environmental EEG effects should not be expected to appear uniformly across all scalp regions or frequency bands. For example, passive viewing of contemplative landscapes has been associated with higher right temporal beta activity, while predicted frontal alpha symmetry effects were not consistently observed [14]. In situ work further suggested higher frontal alpha asymmetry in greener urban sites than in a busy downtown control, although variation across views remained substantial [15]. Other studies have reported stronger occipital alpha–theta oscillations and alpha–theta synchronization during restorative exposure [16], increased alpha during nature video viewing [17], and lower frontal midline theta after a 40 min nature walk than after an urban walk [18]. Posterior and parietal alpha activity may be particularly relevant to visual environment exposure: Hopman et al. reported lower posterior alpha power during prolonged real-world nature exposure than during urban comparison sessions [19], while McDonnell et al. found lower parietal alpha power during nature image viewing than urban image viewing, consistent with greater visual engagement [20]. Indoor nature studies have also reported higher perceived restoration and working-memory performance together with lower delta–theta, delta–alpha, theta–beta, and alpha–beta responses in greener settings [21]. Taken together, these studies suggest that EEG is sensitive to environmental experience, but the reported effects remain mixed across paradigms, tasks, exposure formats, and outcome definitions.

A key limitation of the existing EEG literature is that environments are still commonly defined using broad categorical contrasts, such as nature versus urban or contemplative versus non-contemplative scenes. Although such contrasts are useful for demonstrating general environmental sensitivity, they make it difficult to determine which specific visual properties of complex urban green spaces are most relevant to neural responses. This limitation is increasingly recognized in the broader urban greenery exposure literature, where recent methodological reviews argue for more human-scale, visibility-based, and multidimensional measures that better reflect what people actually see in everyday life [22–24]. Related recent work has further shown that panorama-based computational

metrics can explain and predict restorative potential in urban landscapes, supporting the use of interpretable scene descriptors rather than simple binary labels alone [25].

In landscape research, this question has been approached through the concept of Landscape Visual Quality (LVQ), which concerns how the visual character of a landscape is perceived and evaluated [26]. Tveit et al. [27] proposed a theory-based framework for analyzing visual landscape character, in which visual quality is described through concepts, dimensions, landscape attributes, and potential indicators rather than broad labels alone. Ode et al. [28] further developed this line of work by linking theoretical concepts in landscape esthetics to measurable visual indicators. More recent quantitative LVQ research has extended this by quantifying visual landscape structure using 3D spatial metrics. In particular, Qi et al. [29] showed that naturalness, complexity, coherence and visual scale can be represented as physically quantifiable dimensions. In a later study of residential green space in Singapore [30], the same group showed that these four dimensions could differentiate urban landscapes in ways that were meaningfully related to perceived restorative quality. These studies suggest that urban environments can be described as multidimensional visual stimuli with interpretable structural properties. However, these dimensions have so far been used mainly to explain visual quality, rather than to test how specific aspects of urban landscape structure are reflected in neural activity during viewing.

In this context, combining computational scene metrics with EEG may provide one way to examine how measurable properties of urban green spaces relate to neurophysiological responses during visual exposure. Smart city approaches increasingly use computational tools to describe, simulate, and evaluate urban environments. Urban digital twins are one example, as they can support urban modelling, scenario comparison, and sustainable planning decisions [31]. However, recent work also highlights the need to connect these tools with human perception and citizen response. For example, digital twin platforms have been used to collect citizen feedback on proposed buildings and green spaces [32]. Additionally, perception-informed urban digital twins have been proposed to integrate visual perception into planning assessment [33]. Building on this direction, the present study links computational descriptions of urban green space structure with EEG responses during controlled visual exposure. This offers a methodological step toward more neurophysiologically informed urban green space assessment.

Building on this motivation, the present study tested whether latent dimensions of urban green space structure are associated with regional EEG responses during sustained viewing. Rather than comparing broad scene categories, this study used a feature-based approach. Each panoramic urban green image was first quantified using 41 computational scene metrics. These metrics were then reduced through dimension-wise factor analysis. This produced latent factors within four conceptual domains: naturalness, complexity, coherence, and visual scale. This approach allows urban green spaces to be analyzed in continuous rather than categorical terms. It also reduces a large and potentially collinear set of visual descriptors into a more interpretable latent structure. Crossed mixed-effects models were then used to estimate scene effects while accounting for repeated observations across both participants and images.

Based on the prior evidence on posterior/parietal alpha responses to nature-related exposure, this study hypothesized that the latent naturalness factor reflecting green–grey scene composition would be associated with parietal alpha-related activity during sustained viewing. Specifically, because lower posterior/parietal alpha power has been reported during nature exposure and nature image viewing compared with urban exposure [19,20], this study expected relatively greener and greyer scenes to differ in parietal alpha-related responses. Because the present study used baseline-normalized alpha-minus-theta as a derived regional feature, this hypothesis was tested as an association between the green–

grey naturalness factor and parietal alpha–theta relative power change. This was treated as the primary hypothesis-driven test using a two-sided $p < 0.05$ threshold. For the remaining LVQ dimensions, this study formulated exploratory research questions. First, this study asked whether latent complexity, coherence, and visual scale factors were associated with regional EEG responses. These analyses were exploratory because current evidence does not yet provide clear directional predictions for these dimensions or their regional EEG correlates. They were also evaluated with correction for multiple comparisons. Representational Similarity Analysis (RSA) was also used as a secondary exploratory analysis. It was used to test whether similarity relations in scene structure were reflected in similarity relations in regional EEG responses. In this sense, this study contributes to smart and sustainable urban research by combining computational scene metrics with neurophysiological measures.

2. Materials and Methods

2.1. Study Participants

This study included 152 adult participants. The sample consisted of 83 females (54.6%) and 69 males (45.4%). The mean age was approximately 43.0 ± 13.2 years, estimated from age-group midpoints. Education levels were distributed as follows: bachelor's degree, 61 participants (40.1%); high school, 46 participants (30.3%); master's degree, 18 participants (11.8%); trade school, 12 participants (7.9%); prefer not to say, 11 participants (7.2%); and Ph.D. or higher, 4 participants (2.6%). After EEG quality control, 150 participants were retained for the main EEG analysis. Participants were required to be right-handed and aged 21 years or above. Recruitment was conducted with the assistance of the Policy Institute at the Lee Kuan Yew School of Public Policy, National University of Singapore.

All participants provided informed consent before participation. The study was approved by the Institutional Review Board at the National University of Singapore (IRB Reference NUS-IRB-2022-445, initial approval obtained on 8 October 2022, amended on 5 December 2022). The EEG data analysis component conducted at the Institute for Info-comm Research, Agency for Science, Technology and Research, Singapore was additionally reviewed and granted exemption from full review by the A*STAR Institutional Review Board, Singapore (IRB Reference: 2023-108, approval obtained on 23 August 2023).

2.2. Stimulus Set and Scene Metrics

The stimulus set contains 24 panoramic urban green images (Figure 1) depicting environments with varying combinations of vegetation, grey built surfaces, spatial clustering, openness, colour composition and terrain variation. Each image was quantified using 41 computational 3D scene metrics derived from the underlying landscape visual quality framework. These metrics were selected to capture multiple aspects of scene composition and spatial organization, rather than the amount of greenery alone.

Following the underlying LVQ framework, the metrics were grouped a priori into four conceptual dimensions: naturalness, complexity, coherence, and visual scale. Naturalness included indicators of the relative presence of green, grey, and blue components, such as volumetric and area ratios. Complexity reflected heterogeneity in three-dimensional arrangement, including horizontal, vertical, and distance-based diversity as well as shape irregularity. Coherence described the extent to which scene elements formed organized or clustered spatial patterns, represented by cluster number, density, size, and spacing. Visual scale captured broader perceptual properties of openness, depth, colour richness, and terrain variation, including view distance, sky exposure, slope, and gradient variation. Detailed definitions and computational procedures of these metrics are provided in Zhang et al. [34]. This organization provided an interpretable basis for the subsequent factor

analysis and allowed each urban green space to be represented as a multidimensional visual stimulus.



Figure 1. The 24 panoramic urban green images used as stimuli in the study.

2.3. Study Design and EEG Data Acquisition

EEG was recorded using a Brain Products actiCAP Xpress dry-electrode EEG system (Brain Products GmbH, Zeppelinstraße 7, 82205 Gilching, Germany) with 16 channels. The montage included Fp1, Fp2, F3, F4, F7, F8, T7, T8, C3, C4, P3, P4, P7, P8, O1, and O2. Signals were recorded at a sampling rate of 2000 Hz. The dry-electrode setup enabled a relatively rapid setup for a large participant sample. It also preserves a practical recording workflow suitable for visually guided environmental-exposure studies.

Participants were seated in front of the projected panoramic stimuli throughout the task. Each participant was randomly assigned 8 images from the full 24 image set, and each assigned image was presented three times in a random order, producing 24 stimulus trials per participant (Figure 2). This produced a partially crossed participant-by-image design. Each participant viewed 8 of the 24 images, while each image was viewed by approximately 50 participants on average. This design reduced participant burden during sustained EEG viewing, while still allowing each image to be observed across multiple participants. Each trial consisted of a 15 s fixation period followed by 30 s of image viewing. A 60 s resting baseline recording was also collected before the experimental trials.

The projector-based presentation was used to provide a controlled and standardized visual exposure across all participants. This reduced variation in viewing conditions and allowed the same urban green space scenes to be compared across participants. However, this format did not reproduce the full sensory, spatial, and embodied experience of real-world urban green space exposure. It was also less immersive than virtual reality. Therefore, the paradigm adopted by this study should be interpreted as controlled visual exposure

to virtual urban green space images, rather than as a direct substitute for real-world environmental exposure.

EEG Experimental Setup

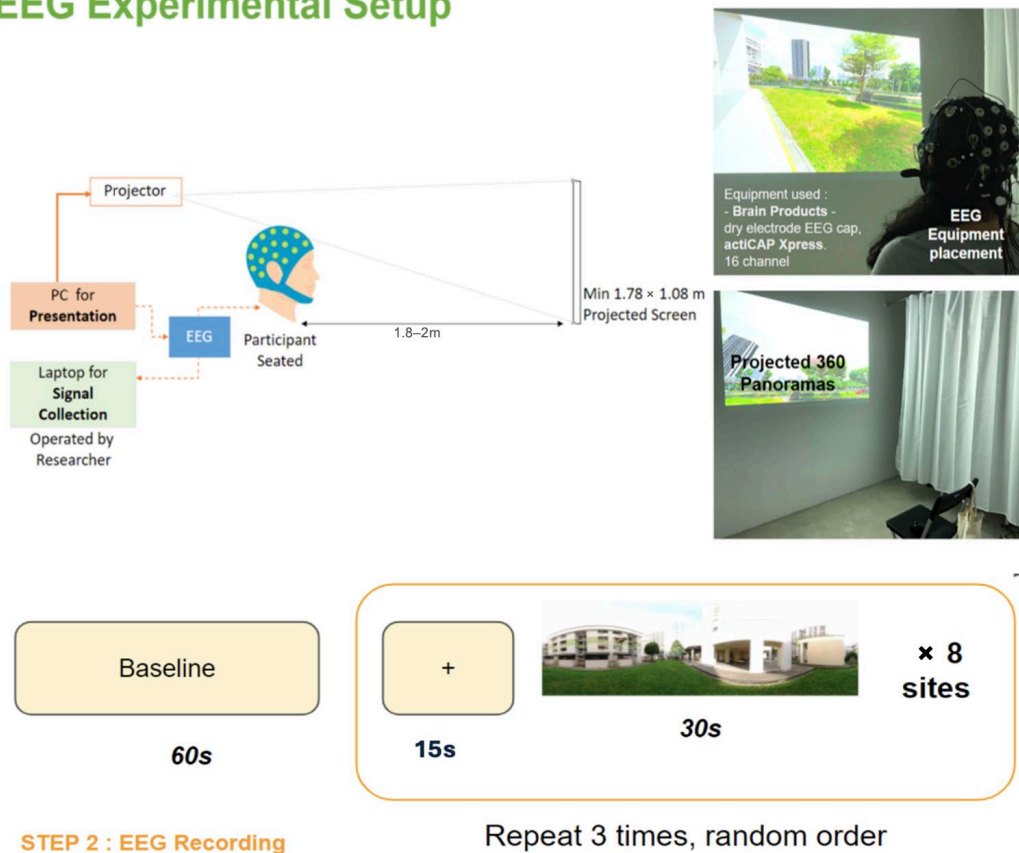


Figure 2. Experimental setup and stimulus presentation protocol.

2.4. EEG Preprocessing and Epoch Preparation

The EEG recordings underwent dataset cleaning to correct event-marker inconsistencies, align stimulus annotations with the experimental sequence, and identify channels with invalid or out-of-range impedance values. The cleaned recordings were then imported into MNE-Python 1.11.0 for further analysis. The 16 EEG channels were renamed to standard scalp labels (Fp1, Fp2, F3, F4, F7, F8, T7, T8, C3, C4, P3, P4, P7, P8, O1, O2) and assigned a standard Brain Products montage. Channels identified as unreliable during the cleaning stage were marked as bad.

Continuous EEG was notch filtered at 50 Hz and band-pass filtered from 1 to 80 Hz. Stimulus-related epochs were extracted from 15 s before to 45 s after image onset. A separate baseline epoch was extracted from 30 s before the marker denoting the end of the initial resting baseline period up to the marker. The epoched data formed the input to the subsequent analysis pipeline.

Independent Component Analysis (ICA) was not performed. This decision was made because the dataset used a 16-channel dry-electrode montage, which provides limited spatial information for stable component separation. Instead, preprocessing focused on event-marker correction, bad-channel identification and filtering.

2.5. Regional EEG Feature Extraction

Trial-level EEG outcomes were quantified as relative power change (RPC) in decibels, computed as:

$$RPC = 10 \log_{10} \left(\frac{P_{stim}}{P_{base}} \right)$$

where P_{stim} is the band-limited power during the stimulus interval and P_{base} is the corresponding baseline power from -10 to 0 s within each stimulus epoch. Band power was estimated during multitaper spectral decomposition after resampling the epochs to 250 Hz.

Five post-stimulus windows were defined: 0–5 s (start), 5–10 s (early), 10–20 s (mid), 20–30 s (late), and 5–30 s (mean). For the current analysis, the primary baseline was the within-epoch inter-trial interval from -10 to 0 s. This baseline was chosen because it provided a trial-specific reference and helped reduce the influence of slow changes across the recording session. However, because this interval occurred immediately before image presentation, it may include anticipatory attentional activity. The resulting RPC values should therefore be interpreted as changes relative to the immediately preceding fixation period, rather than as changes relative to a neutral resting state. A separate 30 s baseline epoch was additionally used for individual alpha frequency estimation where required.

Alpha power was estimated using individualized alpha limits centred on each subject's baseline peak alpha frequency, with a half-width of 1.5 Hz and bounds constrained to 6–16 Hz when a valid estimate was available. When an individualized alpha peak could not be estimated, a fixed 8–12 Hz alpha band was used. Theta and beta bands were defined as 4–7 Hz and 13–30 Hz, respectively. In addition to these conventional bands, two derived contrast features were computed: alpha-minus-theta and theta-minus-beta. These contrast features were included to capture relative shifts in oscillatory balance that may be less evident when alpha, theta, and beta are analyzed separately. For each trial and time window, the alpha-minus-theta feature was computed by subtracting theta RPC from alpha RPC, whereas theta-minus-beta was calculated by subtracting beta RPC from theta RPC. Because all bands were first expressed as power changes in decibels with baseline normalization, these contrasts can be interpreted as log-ratio measures of relative band power change. This preserves the directional information of a conventional alpha/theta ratio while providing a more symmetric and model-friendly feature for linear modelling.

To examine spatial variation in the EEG response, the same extraction pipeline was applied to predefined channel groups within the 16-channel montage: frontal (Fp1, Fp2, F3, F4, F7, F8), central (C3, C4), temporal (T7, T8), parietal (P3, P4, P7, P8), occipital (O1, O2) and posterior (P3, P4, P7, P8, O1, O2). The present study used predefined time-windowed spectral summaries rather than a full time-frequency analysis. This choice was made because the main predictors were image-level scene factors, and the primary aim was to estimate stable scene-associated EEG responses at the subject–image level. Trial-level band-limited relative power change was therefore aggregated within predefined post-stimulus windows. The late 20–30 s window was selected as the primary analysis window to focus on sustained viewing responses rather than stimulus-onset activity.

To assess whether the highlighted associations were specific to this late window, a focused temporal sensitivity analysis was conducted across the predefined 0–5 s, 5–10 s, 10–20 s, 20–30 s, and 5–30 s windows. This analysis was restricted to the hypothesis-driven primary association and the two nominal exploratory trends, rather than rerunning the full exploratory model family across all time windows.

2.6. Dimension-Wise Factor Analysis of Scene Metrics

Because each conceptual dimension was represented by several related computational metrics rather than a single direct measure, the metrics within a dimension were often

correlated and partially overlapping in meaning. To address this, factor analysis was used to derive a smaller set of latent variables from the original metric set. This allowed shared variance among related metrics to be captured in a more compact form, reducing redundancy and making the dimension structure easier to interpret [35]. As a result, each urban green space could be represented using a smaller number of high-level latent dimensions. This provides a more compact representation of scene structure without discarding the main information contained in the original measures.

The factor analysis was conducted at the image level, with the 24 images serving as cases. The relevant ratio was therefore the number of images to the number of scene metrics within each LVQ dimension. The number of metrics was 6 for Naturalness, 15 for Complexity, 14 for Coherence, and 6 for Visual Scale. This corresponded to image-to-variable ratios of 4.0:1, 1.6:1, 1.7:1, and 4.0:1, respectively. Given this limited image-level sample, the factor analysis was not intended as an independent validation of the LVQ factor structure. Instead, it was used as a theory-guided descriptive reduction in correlated scene metrics within the present stimulus set. The retained factors were therefore interpreted as latent scene descriptors specific to this study.

Factor analysis was conducted separately within each conceptual domain using the relevant subset of image-level metrics. Metric values were checked for numeric validity and standardized prior to factor extraction. Maximum-likelihood factor analysis was then applied within each dimension. It was followed by orthogonal varimax rotation to improve interpretability of the loading structure [36]. In the current study, factor retention was evaluated using multiple criteria, including eigenvalues from the metric correlation matrix, scree-plot inspection, Horn's parallel analysis, interpretability of the rotated loading patterns, and consistency with the a priori LVQ framework. These diagnostics were used to guide an interpretable factor-retention decision rather than to maximize the number of retained factors.

The rotated factor loadings indicate the extent to which each original metric contributed to each latent factor, whereas the factor scores indicate the position of each image along these latent dimensions. In other words, the standardized metric profile of each image was transformed into coordinates in the rotated latent factor space. These image-level factor scores were then entered as continuous predictors in the subsequent mixed-effects models. Thus, the factor analysis served not only as a procedure to reduce dimensionality, but also as a way of representing each urban green space using a smaller set of interpretable latent variables.

2.7. Crossed Mixed-Effects Modelling

The primary inferential analysis tested whether image-level factor scores predicted regional EEG outcomes using crossed mixed-effects models. For each EEG outcome and factor score, a univariate model was fitted. Each model included random intercepts for subject and image. Based on the experimental design, the dataset had a repeated-measures structure in which each participant contributed responses to multiple images, and each image was viewed by multiple participants. Mixed-effects modelling was therefore appropriate because it accounted for variation at both the participant and image levels.

The model was specified as:

$$Y_{ij} = \beta_0 + \beta_1 X_j + u_i + v_j + \varepsilon_{ij}$$

where Y_{ij} denotes the EEG outcome for subject i viewing the image j , and X_j denotes the image-level factor score for image j . The term u_i represents the subject-specific random intercept, and v_j represents the image-specific random intercept. The term ε_{ij} denotes the residual error.

Models were fitted in statsmodels using restricted maximum likelihood estimation. Fixed effects were summarized using regression coefficients and two-sided p values. The analysis was performed on aggregated subject–image outcomes rather than all repeated trials directly. In practice, this means that repeated measurements from the same participant viewing the same image were first combined into a single outcome value for that subject–image pair. This reduced pseudo-replication, that is, the treatment of non-independent repeated observations as if they were independent, and ensured that the level of analysis matched the image-level nature of the predictors.

Since the predictors were defined at the image level, the number of unique scene-level predictor values was limited to 24. The repeated participant observations improved estimation of EEG responses, but they did not increase the number of independent image-level predictor values. The mixed-effects results were therefore interpreted as associations within the present stimulus set, rather than as population-level estimates for all possible urban green scenes. The partially crossed participant-by-image design was handled by modelling the observed subject–image cells with random intercepts for both participants and images.

The mixed-effects screening analysis was restricted to frontal and parietal regions and to the two derived EEG contrast features, alpha–theta and theta–beta. This restriction was used to align the inferential model family with the study focus on regional EEG responses most relevant to visual scene processing and oscillatory balance, while avoiding an unnecessarily large number of tests across all extracted features. The reported screening family therefore contained 32 models, corresponding to 2 regions, 2 EEG contrast features, 4 LVQ domains, and 2 retained factors per domain.

To address multiple comparisons, the hypothesis-driven primary test was separated from the exploratory screening analysis. The primary hypothesis-driven test was the association between Naturalness F1 and parietal alpha–theta relative power change. This test was evaluated using a two-sided $p < 0.05$ threshold. All other mixed-effects models were treated as exploratory. For these exploratory models, p -values were adjusted using the Benjamini–Hochberg False Discovery Rate (FDR) procedure [37]. Both uncorrected p -values and FDR-adjusted q -values were reported. Exploratory effects with $q < 0.05$ were interpreted as FDR-corrected associations, whereas effects with $p < 0.05$ but $q \geq 0.05$ were interpreted as nominal trends.

Additionally, to evaluate whether the highlighted mixed-effects associations were specific to the late post-stimulus window or extended across time, a focused temporal sensitivity analysis was conducted. This analysis was restricted to the hypothesis-driven primary association and the nominal exploratory trends identified in the main mixed-effects screening analysis.

For each highlighted association, the same crossed mixed-effects model was refitted separately for the predefined 0–5 s, 5–10 s, 10–20 s, 20–30 s, and 5–30 s windows. Window-specific subject–image outcomes were reconstructed using the same baseline filtering and within-cell median aggregation used in the main analysis. Standardized coefficients were obtained by z-scoring both the EEG outcome and predictor before refitting the model. Benjamini–Hochberg q -values were calculated across the temporal sensitivity checks as a supplementary reference.

2.7.1. Minimum Detectable Effect-Size Analysis

The sample size was determined by the parent EEG study, and no formal a priori power analysis was conducted before data collection. Therefore, a post hoc minimum detectable effect size analysis was conducted for the hypothesis-driven primary mixed-effects model.

Both the scene predictor and EEG outcome were standardized, so the fixed-effect coefficient could be interpreted as a standardized effect size.

The minimum detectable standardized effect size was estimated using the observed standard error of the standardized fixed effect. For 80% power at a two-sided alpha level of 0.05, the minimum detectable effect size was calculated as $MDES_{80\%, \alpha=0.05} = (z_{0.975} + z_{0.80})SE_{\beta} \approx 0.066$. A brief derivation of the minimum detectable effect-size calculation has been added to the Supplementary Methods.

2.7.2. Leave-One-Out Robustness Analysis

Associations were selected for focused follow-up if they showed nominal evidence of association in the main mixed-effects screening analysis ($p < 0.05$). Their stability was assessed using leave-one-image-out (LOIO) and leave-one-subject-out (LOSO) procedures. Under each procedure, the crossed mixed-effects model was repeatedly refitted after excluding one image or one participant at a time. This allowed the robustness of the association to be evaluated against the influence of any single image or subject.

For the same focused follow-up associations, an image-level permutation test was also implemented in which the focal image-level factor scores were shuffled across the 24 images and then reassigned to all subject–image rows belonging to each image, while the EEG outcomes and crossed subject–image structure were left unchanged. The crossed mixed-effects model was refit for 2000 permutations.

2.8. Representational Similarity Analysis (RSA)

RSA was implemented as a secondary exploratory analysis using LVQ-domain model representational dissimilarity matrices (RDMs). One model RDM was constructed for each a priori LVQ dimension: Naturalness, Complexity, Coherence, and Visual Scale. Each model RDM was computed from all standardized scene metrics within that dimension using pairwise Euclidean distance between images across the full 24-image stimulus set. This allowed the RSA to test whether image similarity within each LVQ domain was reflected in similarity of EEG response patterns.

For this analysis, epochs were cropped to the sustained-viewing interval from 5 to 25 s and resampled to 128 Hz. The EEG feature spaces were aligned with the mixed-effects screening analysis. RSA was conducted for frontal alpha–theta, frontal theta–beta, parietal alpha–theta, and parietal theta–beta responses. For each participant, the relevant rows and columns of the corresponding LVQ-domain model RDM were extracted for the eight images viewed by that participant. Subject-specific neural RDMs were then computed using correlation distance between the EEG feature vectors for the corresponding subject–image cells. RSA values were computed as Spearman correlations between the upper-triangular off-diagonal entries of the model and neural RDMs [38]. Group-level inference was performed using sign-flip permutation tests with 2000 permutations. For each EEG feature-space analysis, p -values across the four LVQ-domain RDMs were adjusted using the Benjamini–Hochberg False Discovery Rate procedure. Because each participant viewed only 8 of the 24 images, and because RSA was used as a secondary representational analysis, these results were interpreted as exploratory.

2.9. Software

All analyses were implemented in Python 3.11.14 using MNE-Python 1.11.0, NumPy 2.3.5, pandas 3.0.0, SciPy 1.17.0, scikit-learn 1.8.0, statsmodels 0.14.6, and matplotlib 3.10.8.

3. Results

3.1. Latent Factor Structure of the Scene Metrics

Factor-retention diagnostics are reported in Supplementary Table S1 and Supplementary Figure S1. The diagnostics supported a low-dimensional structure across the LVQ domains, although the suggested number of factors varied by domain. For visual scale, parallel analysis supported a two-factor solution. For naturalness, the eigenvalue > 1 criterion supported two factors, while parallel analysis suggested one factor. For complexity and coherence, the diagnostics indicated that additional factors may also be present. Considering the diagnostic results, the limited number of images, and the need for comparable predictors across LVQ domains, a two-factor representation was adopted for each domain. This provided a compact and interpretable summary of the scene-metric structure for downstream mixed-effects modelling. The resulting factors were therefore interpreted as study-specific latent scene descriptors rather than definitive latent constructs. Quantitative rotated loading matrices are provided in Table 1, which reports the loading of each original scene metric on F1 and F2. Because factor sign is arbitrary, interpretation focused on the strongest absolute loading patterns rather than on the sign of the factor alone.

Table 1. Summary of retained LVQ factor structures and representative high-loading scene metrics.

LVQ Domain	Cumulative Two-Factor Variance	Factor	Variance Explained	Representative Metrics
Naturalness	0.745323	F1	0.525972	Green area ratio (−0.98); Grey area ratio (+0.98); Green volumetric ratio (−0.78); Grey volume (+0.71)
		F2	0.21935	Blue area ratio (+1.00); Green volumetric ratio (+0.34)
Complexity	0.455142	F1	0.193585	Vertical diversity (Green) (+0.99); Vertical diversity (Whole) (+0.97); Horizontal, vertical, and distance diversity (Green) (+0.82)
		F2	0.261557	Horizontal, vertical, and distance diversity (Whole) (+0.95); Horizontal, vertical, and distance diversity (Grey) (+0.93); Distance diversity (Grey) (+0.64); Horizontal diversity (Whole) (+0.62)
Coherence	0.478812	F1	0.22894	Distance of clusters (Whole) (−0.98); Distance of clusters (Green) (−0.82); Cluster number (Green) (−0.58); Cluster size (Green) (+0.57)
		F2	0.249872	Cluster density (Green) (+0.91); Cluster density (Whole) (+0.82); Cluster size (Whole) (−0.70); Distance of clusters (Grey) (−0.57)
Visual Scale	0.642057	F1	0.337966	Front background ratio (−0.98); Distance to green (−0.66); View distance (Whole) (−0.61); Distance to grey (−0.48)
		F2	0.304091	Slope (+0.98); Gradient variation (+0.86)

Within the naturalness domain, the first factor (F1) captured a clear green–grey composition axis. It loaded negatively on Green area ratio and Green volumetric ratio, and positively on Grey area ratio and Grey volume, such that higher scores reflected relatively

greyer scenes. The second factor (F2) was dominated primarily by Blue area ratio. It was therefore interpreted more cautiously as a blue content factor, rather than as a broad naturalness category. The retained two factors explained 74.5% of the variance in the naturalness metrics.

Within the complexity domain, the retained factors captured complementary aspects of scene heterogeneity and structural form. F1 was driven mainly by vertical diversity measures, particularly those derived from the whole scene and green components, whereas F2 was more strongly associated with combined horizontal and vertical distance diversity and landscape shape metrics. Together, these two factors explained 45.5% of the variance in the complexity metrics.

Within the coherence domain, the factor structure was defined primarily by indices of cluster-based organization. F1 loaded most strongly on distance between clusters and cluster number, whereas F2 was dominated by cluster density and cluster size measures. These factors therefore appeared to reflect latent differences in the spatial grouping and dispersion of scene elements. The retained coherence solution explained 47.9% of the variance.

Within the visual scale domain, F1 was defined mainly by front–background ratio and depth-related distance measures. It suggests variation in scene openness and perceived depth. F2 was dominated by slope and gradient variation, and was therefore interpreted as a visual scale factor related to terrain. These two factors explained 64.2% of the variance in the visual scale metrics.

The retained two-factor solutions were not intended to maximize explained variance alone, but to capture the most interpretable and conceptually meaningful latent structure within each domain. Overall, the findings support the view that the stimulus set forms a multidimensional scene space. It is not well described by a simple binary contrast. The factor solutions also provided a more interpretable basis for the later mixed-effects analysis.

3.2. Mixed-Effects Associations Between Latent Scene Factors and Regional EEG Responses

The reported mixed-effects screening family contained 32 models across combinations of region, EEG feature, LVQ domain, and retained factor (Figure 3). For each model, raw coefficient, standardized coefficient, 95% confidence intervals, *p*-values, FDR-adjusted *q*-values, marginal R^2 and conditional R^2 are reported in Supplementary Table S2. A compact summary of the hypothesis-driven primary association and nominal exploratory trends is provided in Table 2.

Table 2. Hypothesis-driven primary association and nominal exploratory trends from the crossed mixed-effects models.

Region	EEG Feature	LVQ Factor	Raw β	Standardized β	Marginal R^2	Conditional R^2	<i>p</i>	<i>q</i>
Parietal	alpha–theta	Naturalness F1	0.113	0.070	0.005	0.678	0.003	-
Frontal	theta–beta	Visual Scale F2	−0.101	−0.050	0.003	0.697	0.023	0.719
Frontal	alpha–theta	Visual Scale F2	0.070	0.049	0.002	0.669	0.046	0.719

The hypothesis-driven primary association was Naturalness F1 predicting parietal alpha–theta relative power change. This association was positive and met the planned significance threshold (raw $\beta = 0.113$, standardized $\beta = 0.070$, $p = 0.003$, marginal $R^2 = 0.0049$, conditional $R^2 = 0.678$). Since Naturalness F1 loaded positively on grey metrics and negatively on green metrics, this means that relatively greyer scenes were associated with larger parietal alpha–theta responses than relatively greener scenes.

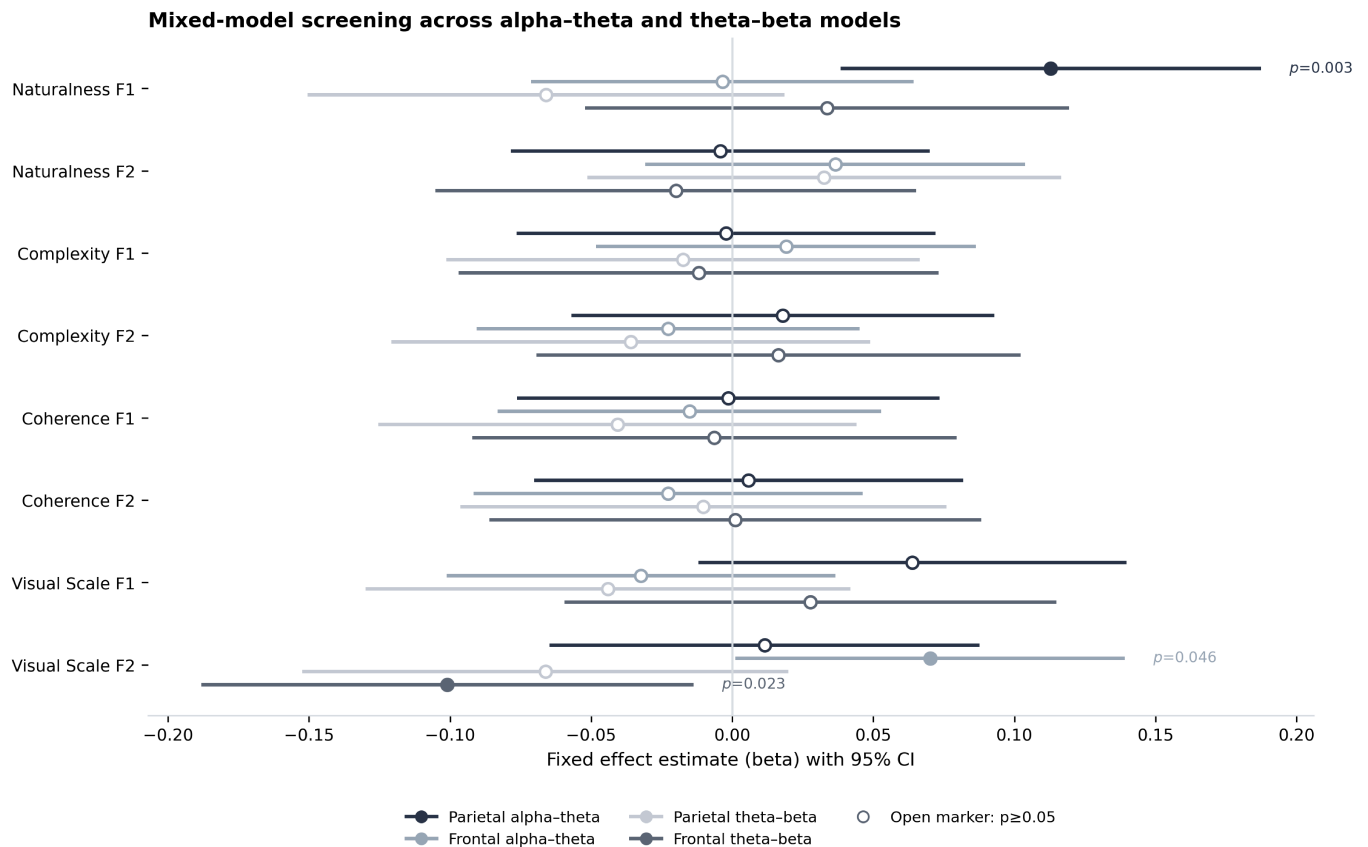


Figure 3. Mixed-effect associations between latent scene factors and regional EEG contrast features.

The remaining 31 models were treated as exploratory and corrected using the Benjamini–Hochberg FDR procedure. Two exploratory models reached the nominal uncorrected threshold of $p < 0.05$. Visual Scale F2 showed a nominal negative association with frontal theta–beta relative power change (raw $\beta = -0.101$, standardized $\beta = -0.050$, $p = 0.023$, $q = 0.719$, marginal $R^2 = 0.0025$). Visual Scale F2 also showed a nominal positive association with frontal alpha–theta relative power change (raw $\beta = 0.070$, standardized $\beta = 0.049$, $p = 0.046$, $q = 0.719$, marginal $R^2 = 0.0024$). However, no exploratory model survived FDR correction. These frontal visual Scale F2 associations were therefore interpreted as nominal exploratory trends rather than FDR-corrected effects.

Across the full screening family, standardized effect sizes were small. The largest absolute standardized β was 0.070, and marginal R^2 values were also low, with a maximum value of 0.0049. In contrast, conditional R^2 values were larger, ranging from 0.652 to 0.697. The low marginal R^2 values indicate that the fixed scene-factor effects explain a small proportion of EEG outcome variance. The larger conditional R^2 values suggest that participant and image level differences accounted for much of the modelled variability.

3.3. Robustness of Highlighted Mixed-Effects Associations

Leave-one-out robustness analyses were conducted for the hypothesis-driven primary association and the two nominal exploratory trends. These analyses tested whether the highlighted associations were driven by any single image or participant.

For the hypothesis-driven primary association between Naturalness F1 and parietal alpha–theta relative power change, both leave-one-image-out and leave-one-subject-out analyses showed consistent effect direction across folds. The image-level test also remained significant. This supports the stability of the primary association within the present stimulus set.

The two frontal Visual Scale F2 associations also showed directional stability in leave-one-out analyses. The frontal alpha–theta association showed complete sign stability, although directional replication was less consistent. The frontal theta–beta association showed complete sign stability and stronger directional replication across folds. The corresponding image-level permutation tests also remained significant.

These robustness checks suggest that the highlighted associations were not driven by a single image or participant. However, the two frontal Visual Scale F2 associations did not survive FDR correction in the exploratory screening family. They were therefore retained as nominal exploratory trends with some evidence of directional stability, rather than interpreted as corrected effects.

3.4. Representational Similarity Analysis

The RSA provided a complementary test of whether domain-level scene similarity was reflected in regional EEG similarity structure. The results were summarized in the heatmap below (Figure 4). The strongest uncorrected correspondences were observed for Complexity and Visual Scale, although the overall RSA effects were weak.

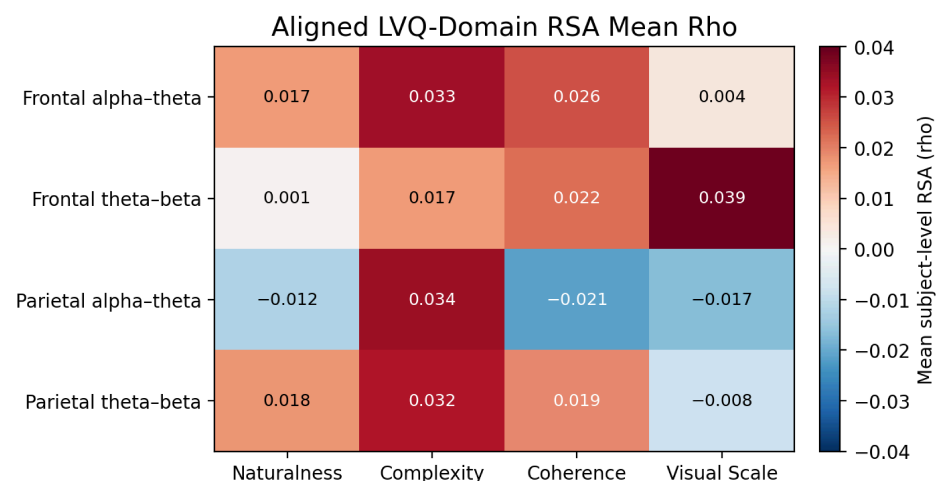


Figure 4. Representational Similarity Analysis (RSA) results for LVQ domain model RDMs and regional EEG feature spaces.

In the frontal alpha–theta analysis, the largest correspondence was observed for Complexity ($\rho = 0.033$, $p = 0.088$, $q = 0.321$). In the frontal theta–beta analysis, the largest correspondence was observed for Visual Scale ($\rho = 0.039$, $p = 0.068$, $q = 0.272$). In the parietal alpha–theta analysis, the largest correspondence was again observed for complexity ($\rho = 0.034$, $p = 0.097$, $q = 0.388$). No clear domain-level correspondence was observed in the parietal theta–beta analysis.

The parietal alpha–theta feature space was most closely aligned with the hypothesis-driven primary mixed-effects model. In this RSA, the Naturalness-domain RDM was not reliably associated with EEG representational structure ($\rho = -0.012$, $p = 0.439$, $q = 0.439$). This suggests that the primary mixed-effects association with Naturalness F1 reflected a directional response-magnitude relationship, rather than a broader pairwise similarity structure across the full Naturalness domain.

After FDR correction, none of the LVQ-domain RSA associations remained reliable. The RSA results were therefore interpreted as exploratory and complementary to the mixed-effects findings, rather than as independent confirmatory evidence.

3.5. Temporal Sensitivity Analysis

A focused temporal sensitivity analysis was conducted for the hypothesis-driven primary association and the two nominal exploratory trends. The analysis examined the predefined 0–5 s, 5–10 s, 10–20 s, 20–30 s, and 5–30 s windows using the same crossed mixed-effects specification as the main analysis. Full results are reported in Figure 5.

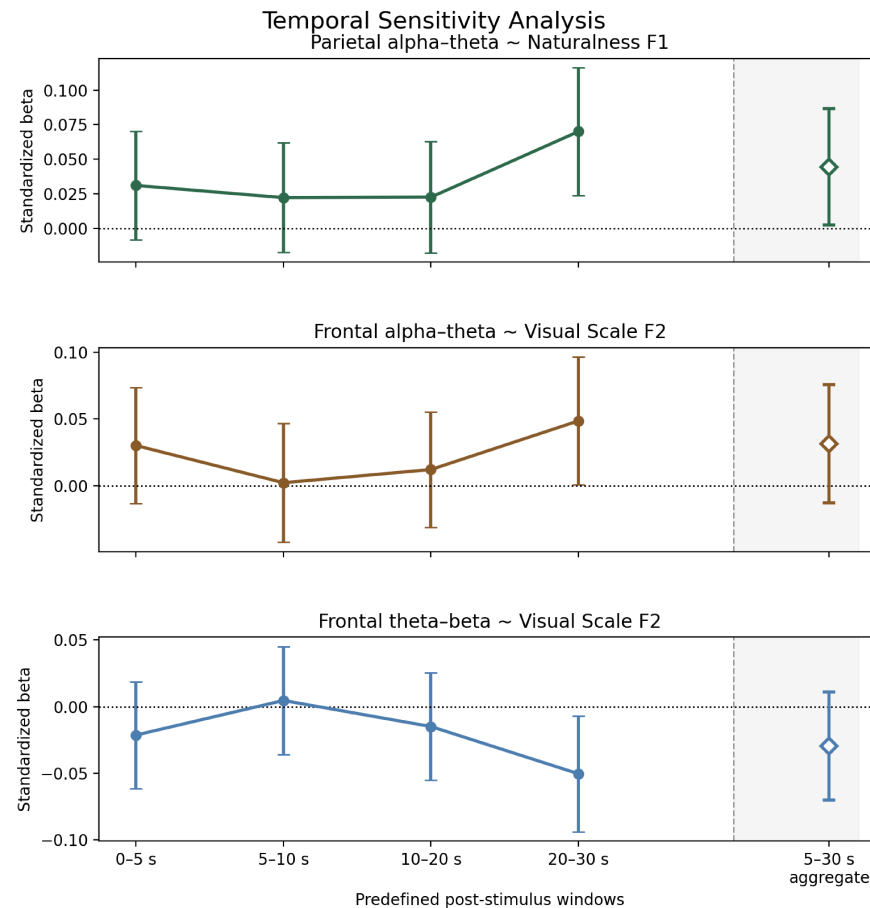


Figure 5. Temporal sensitivity analysis of the hypothesis-driven primary association and nominal exploratory trend across predefined post-stimulus windows.

For the hypothesis-driven primary association between Naturalness F1 and parietal alpha–theta relative power change, the strongest effect was observed in the late 20–30 s window. Earlier windows showed smaller positive estimates with confidence intervals overlapping zero. The 5–30 s aggregate was also positive but weaker than the late-window estimate. The two frontal Visual Scale F2 associations showed a similar late-window pattern. The frontal alpha–theta association was strongest in the 20–30 s window. The frontal theta–beta association was also strongest in the 20–30 s window. These exploratory temporal checks did not remain reliable after supplementary FDR correction.

Overall, the temporal sensitivity analysis suggested that the highlighted associations were concentrated in the late sustained-viewing window rather than emerging consistently across earlier windows. These findings support the use of the 20–30 s window as the primary analysis window, while the temporal checks are interpreted as descriptive sensitivity analyses rather than new time-window discovery tests.

4. Discussion

This study investigated whether latent visual properties of urban green spaces were associated with regional EEG responses during sustained scene viewing. The clearest

finding was the hypothesis-driven primary association between parietal alpha–theta activity and the first naturalness factor, which captured a green–grey scene composition axis. This effect was statistically significant in the primary model and remained stable in LOIO, LOSO, and image-level permutation test. However, the standardized effect size and marginal R^2 were small. A weaker secondary association was observed between frontal alpha–theta and theta–beta activity with the second visual scale factor, which was defined mainly by slope and gradient variation. The two frontal Visual Scale F2 associations reached nominal uncorrected thresholds, but did not survive FDR correction. The temporal sensitivity analysis suggested that the highlighted associations were strongest in the late 20–30 s window. The RSA did not provide strong evidence that LVQ-domain scene similarity was reflected in regional EEG similarity structure.

The multiple-comparison structure is important for interpreting these results. The Naturalness F1 to parietal alpha–theta association was evaluated as the hypothesis-driven primary test. The remaining mixed-effects models were treated as exploratory and corrected using the Benjamini–Hochberg False Discovery Rate procedure. No exploratory association survived FDR correction. Therefore, the frontal Visual Scale F2 associations should be interpreted as nominal exploratory trends rather than corrected effects. This supports a focused interpretation of the findings, with the clearest evidence coming from the planned parietal Naturalness F1 association.

Additionally, the EEG frequency contrasts used in this study should be interpreted as regional spectral summaries rather than markers of a single psychological process. Alpha, theta, and beta activity are multifunctional and can reflect several overlapping processes, including visual engagement, attentional state, arousal, and task context. The alpha–theta contrast was used to summarize relative shifts in slower oscillatory activity during scene viewing, while theta–beta was used as a complementary measure of relative theta and beta modulation.

The primary parietal association suggests that EEG responses varied along the green–grey composition axis during sustained viewing. The parietal location of this association is relevant because parietal regions are involved in visuospatial attention, spatial integration, and scene-related processing [39,40]. One possible interpretation is that differences in green–grey scene composition were associated with differences in posterior visuospatial processing demand. However, this interpretation should remain cautious. Alpha–theta activity is not process-specific, and the low marginal R^2 indicates that the fixed scene factor explained only a small proportion of EEG outcome variance. In addition, Naturalness F1 may covary with low-level image properties such as luminance, contrast, and colour saturation. These properties were not explicitly controlled in the present analysis. The 16-channel dry-electrode montage also supports regional scalp-level analysis but does not provide sufficient spatial resolution for reliable source localization. The finding should therefore be interpreted as a scalp-level association with the measured green–grey scene factor, rather than as direct evidence of a specific neural source, perceptual mechanism, or restorative process.

The frontal findings appeared specifically for visual scale F2. Higher visual scale F2 scores, reflecting greater terrain slope and gradient variation, were associated with both higher frontal alpha–theta values and lower frontal theta–beta values. These results suggest that terrain-related scene properties may have modulated frontal oscillatory balance during sustained viewing. One possible interpretation is that these effects may reflect differences in scene processing more broadly [41]. The concurrent changes in frontal alpha–theta and theta–beta therefore suggest a modest shift in frontal oscillatory dynamics associated with visually more structured terrain.

Additionally, instead of testing whether a scene factor predicts the magnitude of a neural response, RSA tests whether the similarity structure among stimuli is mirrored in the similarity structure of neural patterns. That is a more demanding analysis, and its success depends strongly on the stability of both the stimulus representation and the neural representation. In the present dataset, each participant contributed only eight images, so each subject-level neural RDM was based on a relatively small number of pairwise image comparisons. This is likely to have reduced the stability of the RSA estimates.

Taken together, these findings suggest that urban green space structure was reflected in EEG, but that the effects were selective and subtle rather than widespread across all factors and regions. This pattern is broadly consistent with wider literature showing that visual landscape can influence cognitive and psychological processes [42]. Furthermore, the current findings also highlight that the effects of environmental features are heterogeneous and depend on how “nature” is defined and measured [43]. This perspective is relevant to urban planning because health and wellbeing are increasingly being treated as explicit planning targets rather than only downstream outcomes [44]. Recent work on healthy urban design has shown growing interest in spatial indicators that integrate environmental quality, green space accessibility, and human wellbeing within urban evaluation frameworks [45,46]. In relation to psychophysical wellbeing, the present data support a limited conclusion. They show that measurable visual properties of urban green scenes were associated with regional EEG responses during controlled viewing, but they do not directly show changes in restoration, stress, preference, or wellbeing. Therefore, the psychophysical relevance of these EEG associations should be treated as a future hypothesis to be tested with subjective and behavioural outcome measures.

There are several limitations to the current study. First, the stimulus set was relatively small, which constrains both factor estimation and representational analysis. Although the retained factors were interpretable, some accounted for only moderate proportions of variance. Also, the exact loading structure depends partly on the current image sample. Second, the literature on the physiological meaning of the EEG relative power change remains limited. As noted above, alpha and theta are multifunctional bands whose interpretation depends on region, task context, and temporal structure. The 16-channel dry-electrode montage also supports regional scalp-level analysis, but does not provide sufficient spatial resolution for reliable source localization. The parietal association should therefore be interpreted as a scalp region finding rather than as source-level evidence. Thirdly, the study did not include direct behavioural or subjective measures of restoration, stress or preference. For that reason, the findings should not be overstated as evidence for restorative experience in a strong psychological sense. A more cautious conclusion is that regional EEG responses were sensitive to latent visual properties of urban green spaces. This stance is also in line with broader reviews, which note both the promise of nature-exposure research and the need for stronger mechanistic designs and clearer implementational scope [47–49].

These limitations also point to several directions for future research. A larger and more diverse image set would allow more stable factor solutions and further analysis. Future studies could also use denser EEG montages to support more precise spatial analysis and source-level modelling. Low-level image properties, including luminance, contrast, and colour saturation, should be measured and included as covariates or controlled through stimulus matching. Future work could also build on the present scene-metric and EEG analysis pipeline by adding new behavioural experiments informed by ART [7] and SRT [8]. For example, subjective ratings of restoration, perceived stress, affective state, or attentional recovery could be collected alongside EEG responses to test whether spectral responses to latent properties of urban scenes are associated with behavioural or experiential outcomes. Finally, the present paradigm of using a projector could be extended to more immersive

designs, such as virtual reality or real-world exposure, where scene perception is presented in richer and more ecologically valid ways [50–52]. These steps could help clarify whether the observed associations reflect general properties of scene composition or more specific features of the current viewing paradigm. If supported by further work, this type of framework could contribute to emerging urban analytics that aim to integrate environmental quality, neurophysiological responses, and direct wellbeing indicators into digital planning systems. Recent work on urban digital twins has argued that these platforms should move beyond physical infrastructure alone and incorporate citizen-oriented wellbeing metrics as part of urban evaluation [53,54]. Hence, the current study points towards one possible neurophysiological component for future urban assessment.

5. Conclusions

This study provides evidence that latent visual properties of urban green spaces are associated with regional EEG responses during sustained viewing. The most robust effect was a parietal alpha–theta association with a green–grey naturalness axis, while nominal exploratory frontal alpha–theta and theta–beta associations were observed for a terrain-related visual scale factor. Taken together, the findings support a multidimensional and feature-based approach to urban green space analysis. They show that neural variation during urban green space perception is not fully explained by binary categories alone. Instead, continuous latent dimensions of landscape structure provide a more informative account. More specifically, this study shows the value of combining computational scene metrics, factor analysis, and regional EEG analysis to test how specific structural properties of urban environments are associated with neural responses. Overall, the work contributes a quantitative and feature-based framework for linking urban green space structure with human neurophysiological responses.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16125882/s1>. The following supporting materials are attached: Supplementary Methods S1: Post-hoc minimum detectable effect-size calculation for the hypothesis-driven primary mixed-effects model; Supplementary Figure S1: Scree plots of the factor-retention diagnostics; Supplementary Table S1: Factor-retention diagnostics for each LVQ domain; Supplementary Table S2: Full crossed mixed-effects screening results for all 32 tested combinations of region, EEG feature, LVQ domain, and retained factor.

Author Contributions: Conceptualization, Y.X., Z.Y.C., R.W., X.Z., J.Q., L.G., E.S.L. and K.K.A.; methodology, Y.X., Z.Y.C., R.W., X.Z., J.Q., L.G., E.S.L. and K.K.A.; software, Y.X. and Z.Y.C.; validation, Y.X.; formal analysis, Y.X.; investigation, Y.X.; resources, Y.X.; data curation, Y.X., Z.Y.C., R.W., X.Z., J.Q., L.G. and E.S.L.; writing—original draft preparation, Y.X.; writing—review and editing, Y.X., Z.Y.C., X.Z. and K.K.A.; visualization, Y.X.; supervision, K.K.A.; project administration, J.Q., L.G., E.S.L. and K.K.A.; funding acquisition, J.Q., L.G., E.S.L. and K.K.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by (1) the National Research Foundation (NRF), Ministry of National Development (MND), and National Parks Board (NPB), Singapore, under the Cities of Tomorrow (CoT) Research Programme (Award No. CoT-V5-2024-3); and (2) Ministry of Education Academic Research Fund (AcRF) Tier 2 (Award No. MOE2019-T2-2-184).

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request. Access to the data is subject to ethical restrictions and local data protection regulations to ensure participant privacy, and may require a signed Data Use Agreement.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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