Highlights

From Perception to Appraisal: Hierarchical Brain Responses to Natural and Built Features in Urban Environments

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- Higher proportions of greenery in urban environments lead to more positive responses across a variety of subjective rating scales.
- More urban greenery elicited more pronounced P1 amplitudes, replicating previous findings.
- Earliest visual processing (P1) responds to natural elements of the environment, before processing of visual features characteristic of artificial elements (N1).
- Later ERP components (P3, LPP) predict subjective scene appraisal of higher level and aesthetic evaluation, revealing a hierarchical separation between perceptual and evaluative processes.

From Perception to Appraisal: Hierarchical Brain Responses to Natural and Built Features in Urban Environments

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Abstract

Exposure to urban rather than natural environments has been linked to elevated stress and diminished well-being, prompting interest in the underlying mechanisms and influences of specific urban elements. This study investigated how semantic and lower-level visual characteristics of urban scenes influence subjective experience and underlying neural processes. A total of 63 adults viewed street-level photographs depicting Berlin environments with varying proportions of vegetation, buildings, vehicles, and sky visibility while electroencephalography (EEG) was recorded. Subjective ratings indicated that urban scenes with more greenery compared to built elements were consistently perceived as more positive. In terms of lower-level image features, images with higher non-straight edge density also led to scenes being perceived as more positive. In contrast, more visible sky area and a higher mean metric depth led to more negative scene appraisal. On a neural level, urban scenes with higher greenery/built ratios enhanced visual evoked P1 amplitudes, while higher straight-

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edge density led to more pronounced N1 amplitudes. Further analysis showed that later P3 and LPP components predicted subjective ratings on higher-level evaluative but not basic affective dimensions. These results partially replicate previous studies, suggesting that urban greenery exerts an effect on subjective well-being and influences early visual processing. Moving forward, neurourbanism research should employ more diversified stimuli and leverage immersive or in situ paradigms to refine our understanding of the relationship between greenery in urban environments and well-being to inform evidence-based urban design strategies.
Keywords: Neurourbanism, Environmental Neuroscience, EEG, Event-Related Potentials, Green Restoration, Lower-level visual features

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1. Introduction

1.1. Associations between mental health and the living environment

Urban environments are increasingly recognized as powerful determinants of mental health. Today, more than half of the global population resides in cities, and this proportion is projected to rise substantially in the coming decades (United Nations, 2019) as cities offer advantages like dense infrastructure, education, and cultural life (Cohen, 2006). Yet, these benefits come with a high concentration of stressors such as traffic noise, air pollution, and heat-island effects (Feng et al., 2023; Moore et al., 2003). These ambient stressors converge with psychosocial pressures, including anonymity, weakened social ties, and intensified social competition (Gruebner et al., 2017). Epidemiological evidence, primarily derived from WEIRD (Western, educated, industrialized, rich, and democratic) populations, indicates that urban living is associated with an increased risk of depression and anxiety (Peen et al., 2010), as well as a dose–response relationship between urbanicity and schizophrenia (Gruebner et al., 2017). These risks are unevenly distributed due to structural inequalities,

with socioeconomically disadvantaged and migrant populations experiencing disproportionate exposure through residential concentration in areas with inadequate infrastructure and limited protective resources (Christie-Mizell, 2022; Feldman and Steptoe, 2004; Rethy et al., 2021). Individual characteristics also modulate how urban life is experienced: women and gender minorities frequently report greater fear of crime and reduced perceptions of safety (Beebeejaun, 2017), while personality traits such as extraversion and emotional stability are linked to lower stress appraisals and more positive affective responses (Ebstrup et al., 2011; Şahin and Çetin, 2017). Taken together, these findings highlight the ambivalent impact of urban environments and how they shape mental health through a complex interplay of structural, social, and individual factors.

1.2. Neuroimaging Evidence of Environmental Impact

Neurourbanism (Adli et al., 2017), an emergent domain within the wider research field of Environmental Neuroscience (Berman et al., 2019; Kühn and Gallinat, 2024), seeks to unravel how specific features of the built and natural environment modulate stress and restoration processes. By shaping affective responses, these mechanisms provide a crucial link between urban exposures and long-term physical as well as mental health outcomes. Leveraging neuroimaging tools such as electroencephalography (EEG) and magnetic resonance imaging (MRI) allows for investigating how urban exposures shape brain structure, function, and dynamics to provide empirical evidence guiding a health-promoting future urban development (Beyer et al., 2024; Grassini, 2024). Previous MRI studies provide evidence that urban upbringing is associated with heightened perigenual anterior cingulate cortex (pACC) activity and reduced pACC–amygdala connectivity, indicating impaired top-down regulation of affective stress (Lederbogen et al., 2011). In addition, urban upbringing was shown

to be associated with attenuated connectivity between the dorsal attention network (DAN) and default mode network (DMN) when participants viewed environmental photographs, reflecting a sustained state of hyper-vigilance (Kühn et al., 2021). These effects are assumed to result from continuous exposure to urban stressors such as high social and traffic density, environmental pollution (noise, light), and reduced access to restorative greenery, leading to an imbalanced neuroimmune response (Hahad et al., 2019; Liu et al., 2023; Miller and Raison, 2016).

1.3. EEG evidence in frequency and time domains.

EEG studies corroborate these findings by documenting differential brain activity during exposure to natural versus built environments. Natural scenes are consistently rated as more relaxing, restorative, and fascinating than urban scenes (Elsadek et al., 2020; Hassan et al., 2018; Mahamane et al., 2020). Frequency-domain analyses further indicate that viewing nature increases alpha power (8–12 Hz), which is interpreted as increased resting-state activity and internally directed attention (Klimesch et al., 2007; Laufs et al., 2003; Pfurtscheller et al., 1996), with effects observed in frontal and occipital regions (Elsadek et al., 2019, 2020; Hassan et al., 2018; Olszewska-Guizzo et al., 2018; Mavros et al., 2022; note that some of these studies are methodologically flawed; Gramann, 2024). Frontal alpha asymmetry and posterior alpha differences also distinguish green, i.e., more natural, from grey, i.e., more manmade, environments when participants passively observe different environments (Hopman et al., 2020; Olszewska-Guizzo et al., 2020). Increased alpha power during nature exposure is often accompanied by beta (12-30 Hz) suppression, interpreted as reflecting reduced mental load (Chang et al., 2008; Hassan et al., 2018; Ulrich, 1981; Zou et al., 2021). Conversely, urban stimuli tend to enhance theta and beta activity, potentially reflecting greater attentional engagement and cognitive ef-

fort (Karandinou and Turner, 2018; Olszewska-Guizzo et al., 2018). Some studies additionally report modulation in gamma and delta frequency bands during nature exposure (Jiang et al., 2020; Grassini et al., 2019), though results remain heterogeneous. Indeed, recent reviews highlight inconsistent and sometimes contradictory findings (Senkler et al., 2025), partly due to methodological limitations (Gramann, 2024).

In the EEG time domain, event-related potential (ERP) studies show that natural scenes elicit enhanced amplitudes of the early (P1) components, potentially reflecting facilitated perceptual (Grassini et al., 2019). By contrast, urban scenes evoke more negative-going early posterior components (EPN/N1) and enhanced P3 responses, with more pronounced amplitudes in these components being traditionally interpreted as indicative of enhanced automatic attention capture encoding elementary stimulus features and greater cognitive effort during context updating, respectively (Grassini et al., 2019; Kok, 1997; Luck and Kappenman, 2011; Rushby et al., 2005). For the late positive potential (LPP), contradictory results were reported: While Grassini et al. (2019) observed enhanced amplitudes in response to natural environments, Mahamane et al. (2020) reported elevated amplitudes occurring in response to built environments, yielding conflicting interpretations about emotional processing and sustained affective engagement.

1.4. Limitations of prior studies

Despite these important insights, studies in the field of Neurourbanism often come with several limitations. They usually maximize the contrast between green and built settings by presenting extreme stimuli (e.g., bamboo forest vs. dense inner-city environments; Hassan et al., 2018) rather than capturing the mixed and continuous nature of real urban environments. However, cities typically present a complex mixture

of built and natural features, further modulated by factors such as sky view, vehicle presence, and social density. Sky views can reduce perceived stress while enhancing fascination and openness (Asgarzadeh et al., 2014; Kühn et al., 2023), whereas vehicle presence might increase arousal and diminish preference (Knöll et al., 2019). High social density has been shown to be associated with heightened arousal, negative affect, and increased theta–beta ratios, though these effects might be buffered by sky openness or opportunities for movement (Evans, 1979; Mavros et al., 2022). Additionally, other studies have shown that the openness/enclosure or physical built density of urban environments also have an influence on participants' well-being and preferences (Shi et al., 2014; Trossman Haifler and Fisher-Gewirtzman, 2024).

A further limitation of previous studies is the lack of systematic attention to low-level visual features (LLVFs) such as spatial frequency, color, texture, straight edge density (SED), or fractal patterns (e.g., Hagerhall et al., 2008). Beyond the semantic contents of an urban scene, these low-level visual properties shape rapid 'gist' extraction of a scene (Oliva, 2005), which might impact the scene appraisal through efficient feature prioritization (Groen et al., 2016) more than extensive inspection (Sander et al., 2024). Recent empirical work shows that measures such as hue, saturation, lightness, entropy, or sky/green pixel ratios predict perceived naturalness and restorativeness (Celikors and Wells, 2022; Ma et al., 2023; Samaan et al., 2024), though predictive strength varies across contexts.

2. Methods

The current EEG study addresses limitations observed in previous studies by investigating human brain responses to authentic urban scenes with varied proportions of vegetation and built structures. To this end, we integrated semantic segmentation with gist-based feature analysis and accounted for individual variation by including

gender and personality dimensions in the analyses. Additionally, we explored the connection between subjective scene appraisal and early neural responses immediately following their perception. Using previously tested real-world images of different urban scenes in Berlin, Germany (Sander et al., 2024), we expected that scenes with greater amounts of greenery and sky would be rated as less arousing and less stressful, more positive in valence, and higher in beauty, fascination, and openness. Similarly, we expected to find higher ratings for hominess, feelings of control, and safety with more greenery in an image. We further examined LLVFs as independent predictors, hypothesizing they might exert distinct influences beyond their correlation with semantic categories. Regarding neural responses, based on the previous results reported by Grassini et al. (2019), we predicted larger P1 amplitudes with increasing amounts of natural elements in a scene, more negative-going N1 amplitudes and enhanced P3 amplitudes for scenes with more urban as compared to natural elements, and more pronounced LPP amplitudes for more restorative environments.

2.1. Participants

For this study, 72 participants were recruited via TU Berlin's participant recruitment portal. The sample consisted of students and citizens signing up to participate in research studies. Participation was reimbursed with either study credits or 12 EUR per hour. To qualify, participants had to be 18 years or older, fluent in English or German, and have normal or corrected-to-normal vision with contact lenses. Four participants had to be excluded due to technical problems during data recording and two participants were excluded as they did not adhere to the instructions (falling asleep or excessively looking away from the screen). Finally, three participants were excluded due to poor EEG data quality (more than 20% of channels rejected in preprocessing or over 75% of epochs rejected). The final analysis was thus performed

on a sample of 63 participants (age $M = 29.16$ years, $SD = 7.53$, range = 19–61 years; 29 male, 33 female, 1 non-binary). Ethical approval was obtained from the Ethics Board of the Institute of Psychology and Ergonomics at Technische Universität Berlin (ethics protocol BPN_GRA_230,415).

An a priori simulation-based power analysis was calculated using the approach suggested by Kumle et al. (2021). Simulations used the smallest effect sizes of interest based on effect sizes observed in a previous online study with a very similar experimental protocol (Sander et al., 2024). The results indicated a power of 0.81, 0.88, and 0.76 for the three fixed effects built density, greenery, and cars, respectively, with a sample size of n = 60. The sample size recruited based on these power simulations should thus have been sufficiently powered to observe the hypothesized effects.

2.2. Design

The experiment used a within-person design with independent variables being images of different urban areas varying in built, green, and social density, operationalized as image area covered by different object classes (i.e., buildings, greenery, sky, cars, persons). Participants rated each stimulus on nine scales. We used the Self Assessment Manikin (SAM) with a 9-point Likert scale to assess the three dependent variables dominance, arousal, and valence (Bradley and Lang, 1994). In addition, six subjective measures assessing perceived stress, openness, safety, beauty, hominess, and fascination used 5-point Likert scales. We also used the Ten Item Personality Measure (TIPI) (Gosling et al., 2003) in the original version and its validated German translation (Muck et al., 2011) to measure the Big-5 personality traits extraversion and emotional stability, which were included in the analyses as control variables. The city size where participants spent the first 15 years of their life was recorded with a 5-point scale by number of inhabitants ($<$ 5.000; 5.000 – 20.000; 20.000 –

100.000; 100.000 – 1 million; >1 million). Additionally, participants' brain activity was recorded throughout the experiment using EEG. While we also recorded electrodermal activity (EDA), electrocardiography (ECG), and eye tracking, the current study focuses on the EEG data only.

2.3. Materials

The stimuli used in this study consisted of 56 street view images, which were a subset of the most extremely rated images from a set of 100 stimuli used in the previous study from our group (Sander et al., 2024). All images were of locations in Berlin, Germany, with varying levels of building height, greenery, and traffic. Images were taken as screenshots from high-resolution 360-degree street-level imagery (Apple Lookaround; Apple Inc., 2022).

2.4. Procedure

The experiment was presented on a 27" (diagonal) monitor with a 60Hz refresh rate at a resolution of 2560x1440p using Psychtoolbox (Brainard, 1997) for MATLAB (The Mathworks Inc., Version 2023b). During the experiment, participants were presented with different urban stimuli and had to subsequently rate them on the nine subjective rating scales (arousal, valence, dominance, stress, openness, safety, beauty, hominess, and fascination). Each of the 56 stimuli was rated on each of the nine scales, resulting in 504 trials. The stimulus-scale combinations were randomized individually for each participant and presented across two blocks of 28 stimuli each, separated by a break. Each experimental trial consisted of participants being presented with a word pair for 1000ms, priming them to the scale they would be presented with (arousal: excited – calm; valence: happy – unhappy; dominance: controlled – in control; stress: relaxed – stressful; openness: narrow – open; safety:

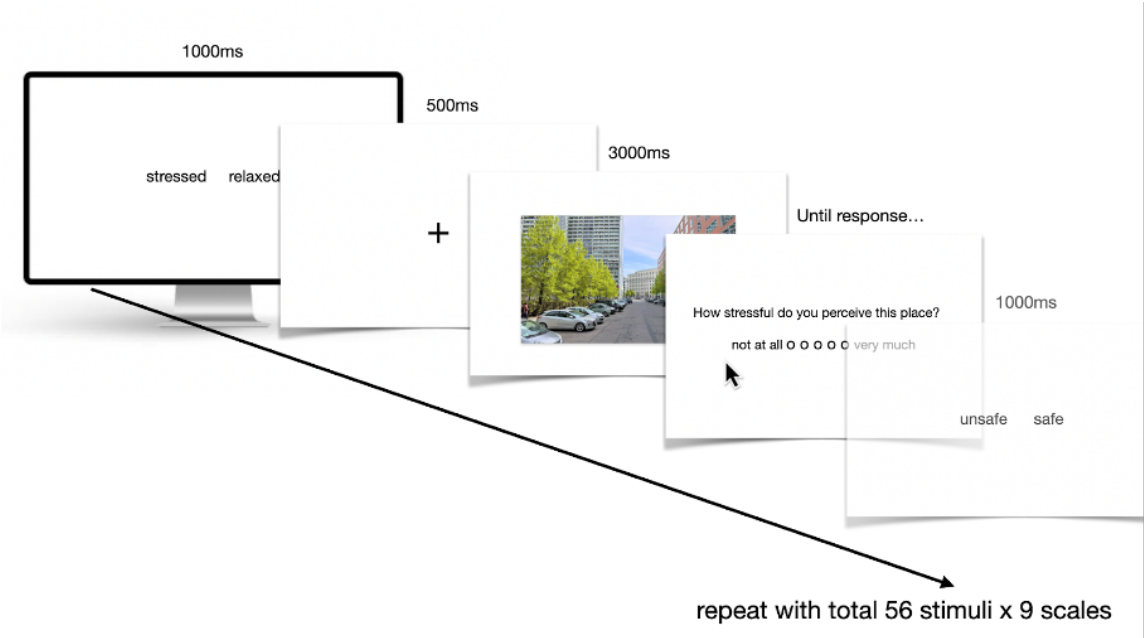

Figure 1: Schematic representation of the experimental trial structure. Each trial began with a word-pair primer indicating the rating dimension, followed by a fixation cross, an urban scene image, and a rating scale. The sequence was repeated for 56 stimuli across nine rating dimensions

unsafe – safe; beauty: ugly – beautiful; hominess: alienated – at home; fascination: boring – fascinating). Subsequently, a fixation cross appeared for 500ms, followed by a stimulus for 3000ms. After the stimulus disappeared, the rating scale was presented until participants logged their rating using the computer mouse. At the beginning and end of the experiment, there was a 3 min baseline recording in which participants were looking at a white screen with an instruction to keep eyes open and directed at the monitor. For an overview of the experimental procedure, see Figure 1.

2.5. Electroencephalography

Continuously recorded physiological data and event streams were synchronized and recorded using the Lab Streaming Layer (LSL; Kothe et al., 2025). EEG data was recorded continuously throughout the experiment from 64 actively amplified gel-based Ag/AgCl electrodes placed according to the extended 10% system (Chatrian et al., 1985) with FCz as reference and Fpz as ground. The data was sampled at 500 Hz with a 16-bit resolution using BrainAmp DC amplifiers from BrainProducts (BrainProducts GmbH, Gilching, Germany) with a 0.016 Hz high-pass filter during data acquisition. After fitting the cap, all electrodes were filled with conductive gel to ensure proper conductivity. Electrode impedances were kept below 10kΩ where possible.

2.5.1. Preprocessing

Preprocessing was performed using the 'BeMoBIL Pipeline' (Klug et al., 2022; `https://github.com/BeMoBIL/bemobil-pipeline`, v2.0.0, accessed 30.04.2024) implemented via the EEGLAB toolbox (Delorme and Makeig, 2004) for MATLAB (The Mathworks Inc., Version 2023b). After merging the two experimental blocks and removing non-experimental sections from the data, the EEG was filtered with a 125 Hz low-pass filter and downsampled to 250Hz. Subsequently, the data was subjected to the ZapLine-Plus function to remove spectral noise using the default automatic detection settings (Klug and Kloosterman, 2022). We then used the pipeline's 'bemobil_detect_bad_channels' functions using default settings but lowering the maximum time during which a channel may be broken before it gets rejected to 30% for a more aggressive detection approach due to overall good data quality. Rejected channels ($M = 2.53$, $SD = 2.73$) were subsequently interpolated using spherical spline interpolation in EEGLAB, and the data was rereferenced to the average of

all channels, including the reconstruction of the original reference channel FCz. After applying a high-pass filter at 1.5 Hz, we used the BeMoBIL wrapper functions to perform Adaptive Mixture Independent Component Analysis (AMICA; Palmer et al., 2011) using the default parameters for AMICA, including 2,000 iterations and the sample rejection option. The high-pass filter and rejection were only applied to the data for AMICA computations. Equivalent dipoles were fitted for each of the resultant Independent Components (ICs) using the 'dipfit' toolbox of EEGLAB with default settings. The computed AMICA data and dipole models were copied back to the initial preprocessed dataset without any high-pass filter or rejected data. ICs were labeled using the ICLabel default popularity classifier, which assigns ICs one of seven labels ("brain," "eye," "muscle," "heart," "line noise," "channel noise," or "other") (Pion-Tonachini et al., 2019). The final datasets were cleaned with ICA by removing ICs labeled as eye sources, and the data was lastly high-pass filtered with a 0.2Hz finite response filter.

2.6. Data Analysis

2.6.1. Event-Related Potentials

The preprocessed EEG data was epoched using a time window of –200 to +1200ms relative to stimulus onset. Baseline correction was applied using the interval from –200 to 0ms. To reduce artifacts, noisy epochs were excluded if the amplitude exceeded $\pm 100\mu$V in any channel, thereby removing trials contaminated by excessive transient signal fluctuations. To identify relevant ERP components, grand average waveforms were initially plotted and visually inspected. For early components (P1, N1), the grand-averaged signals were examined at posterior electrodes POz, Oz, O1, and O2, consistent with observed visual processing topographies (Colombari et al., 2024). For later components (P3, LPP), the centro-parietal and parietal

electrodes CPz, Pz, P3, and P4 were considered. This choice aligns with established findings that P3 and LPP components typically reach their peak amplitudes at centro-parietal and parietal sites (Barry et al., 2020; Schupp et al., 2000). For the early components P1 and N1, grand average peak/trough latencies were extracted based on these visual inspections, serving to define component-specific search time windows of ±20ms around the identified maxima or minima: The P1 component (peak at ∼105ms) was analyzed within 85–125ms, and the N1 component (peak at ∼152ms) within 132–272ms after stimulus onset. Component-specific peak detection was performed by automatically identifying the local maximum (P1) or minimum (N1) using a min/max search function. To improve robustness and mitigate the influence of single-point fluctuations, the final peak amplitude was calculated as the average across the identified peak and its two adjacent sample points (i.e., ±1 sample point or ±4ms). For the later, more slowly varying components P3 and LPP, average amplitudes were extracted around the maxima identified from the grand average ERP waveform: P3 (maximum at ∼364ms) within 339–389ms, and the LPP (maximum at ∼535ms) within 485–585ms after stimulus onset.

2.6.2. Quantification of Image contents

To obtain continuous quantification of the stimulus images' contents, the images were first downsized to 1024x612px and then semantically segmented using the SegFormer-B5 model (Xie et al., 2021) pretrained on the ADE20K dataset (Zhou et al., 2017). Semantic segmentation is a machine-learning technique that assigns a class label to each pixel of an input image, effectively dividing the image into segments that represent various object classes. This allows for extracting the sums of pixels classified as being a specific object, in this case buildings, greenery, cars, persons, and sky. Example outputs of the segmentation can be found in Figure 2.

In the present analyses, the proportion of greenery was operationalized as a ratio of the sum of pixels classified as trees, plants, and grass relative to pixels classified as built structures (i.e., roads, sidewalks, towers, and buildings). This methodological decision was based on the observation of a pronounced negative correlation between the absolute pixel numbers of greenery and buildings, which would introduce multicollinearity into the linear models. Specifically, these two predictors represented mutually exclusive spatial features within a fixed two-dimensional image frame, resulting in a strong structural dependency. An analysis based on z-standardized values (N = 56) revealed a Pearson correlation coefficient of -0.81 (95% CI [-0.82, -0.80], $p < .001$), indicating a close inverse relationship. Variance inflation factors (VIFs) consistently exceeded the acceptable threshold of 5 (greenery: 5.15 – 5.63; buildings: 5.89 – 6.31), indicating problematic multicollinearity. To address this issue and obtain statistically interpretable estimates, we therefore computed a ratio of greenery relative to built structures. This relative metric reduces redundancy between predictors while retaining the ecological interpretability of the greenery variable.

2.6.3. Low-Level Visual Features

Besides segmenting the images regarding the pixels occupied by built structures, greenery, cars, persons, and sky, we analyzed LLVFs to provide insights into which aspects of the environment contribute to subjective experiences (Celikors and Wells, 2022; Samaan et al., 2024). A hierarchical model of scene processing suggests that early visual processing is primarily driven by LLVFs, which are basic image properties such as color information, contrast, and edge orientation, whereas later stages rely more heavily on object recognition and categorical representations (Groen et al., 2016). These LLVFs serve an adaptive function by facilitating rapid recognition and guiding navigational behavior in complex environments.

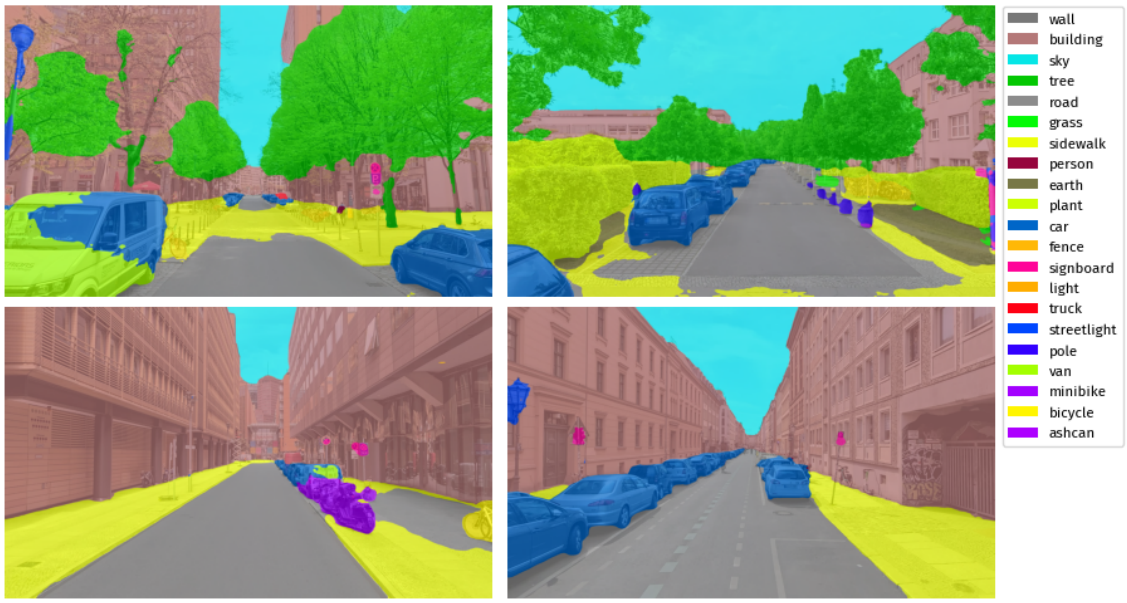

Figure 2: Example of four stimuli with varying levels of greenery and built density, sky, and traffic, shown with overlays of their respective semantic segmentation outputs. Top row, left: high greenery, high built density. Top row, right: high greenery, low built density. Bottom row, left: low greenery, high built density. Bottom row, right: low greenery, low built density.

We extracted eight low-level visual features that have been shown to significantly influence natural scene perception in previous studies (Celikors and Wells, 2022; Ma et al., 2023; Samaan et al., 2024). Extraction of Straight (SED) and Non-Straight Edge Density (NSED), as well as entropy was adapted from Berman et al. (2014), with entropy serving as a measure of visual complexity. Color features were derived from the HSV color space. We computed the number of pixels in each image that fell into the green (60-180°) hue spectrum to quantify the images' green color properties linked to natural elements. To extract only pixels that can be reasonably considered perceptible as chromatic (i.e., colorful or different from gray/black/white), we set a

perception cut-off according to the true color weight function ($W_H(S, I)$) proposed by Vadivel et al. (2008), which models color perception based on pixels' saturation and intensity values and includes perceptual tuning parameters based on human color perception. Pixels with true color weight values larger than 0.6 were considered reasonably perceivable for this analysis. We also included mean saturation (saturation)values, as well as saturation's standard deviation (SDsaturation). We additionally extracted images' Fractal Dimension (FD), a non-integer value quantifying the complexity and self-similarity of a pattern. Stimuli's mean spatial depth was estimated using the Depth Anything V2 model (Yang et al., 2024), specifically the outdoor-scene variant optimized for metric depth estimation.

Together, this set of extracted features balances LLVF's perceptual cues with higher-order spatial and textural information, laying the groundwork for linking continuous scene characteristics to neurophysiological evidence.

2.6.4. Statistical Models

To examine the influence of visual stimulus features and individual differences on both subjective ratings and ERPs, a series of linear mixed models (LMMs) were computed using the lme4 package (Bates et al., 2015) in R (version 4.2.2; R Core Team, 2022). We focused the analyses on nine subjective outcome variables: arousal, valence, dominance, stress, safety, beauty, hominess, fascination, and openness, as well as amplitudes of four ERP components: P1, N1, P3, and LPP. Separate models were estimated for each dependent variable.

A total of 26 LLMs were fitted: two models for each dependent variable, one using predictors extracted from stimuli via semantic segmentation (greenery/built ratio, sky, car, person), and one using 8 measures of the stimuli's LLVFs (saturation, SD of saturation, number of green pixels, entropy, SED, NSED, fractal dimension, mean

of metric depth). To investigate the connection between neural processes and subsequent subjective ratings, we also fitted nine linear models with the subjective ratings of interest as outcomes and mean ERP amplitudes as predictors. Each model additionally included individual-level control variables as fixed effects previously shown to influence appraisal of urban areas: gender, size of the city where the respondents spent the first 15 years of their life, extraversion, and emotional stability (Sander et al., 2024). The gender variable was binarized to male and non-male due to a single participant reporting their self-identified gender as non-binary, which did not allow for separate statistical analysis. All continuous predictors were z-scaled prior to analysis due to differences in scales.

To account for the repeated measures design, we included random intercepts for both participant and stimulus (Judd et al., 2012). Where supported by model comparison, random slopes for key visual predictors were added to improve fit. For nested models, comparisons were conducted using likelihood-ratio tests (LRT, $p < .05$). The final model choice was guided by LRT results. Statistical significance of fixed effects was assessed using the Satterthwaite approximation for degrees of freedom, as implemented in the lmerTest package (Kuznetsova et al., 2017).

3. Results

We examined the relationships between all semantic image contents, visual low-level features, and outcome variables (see Figure 3).

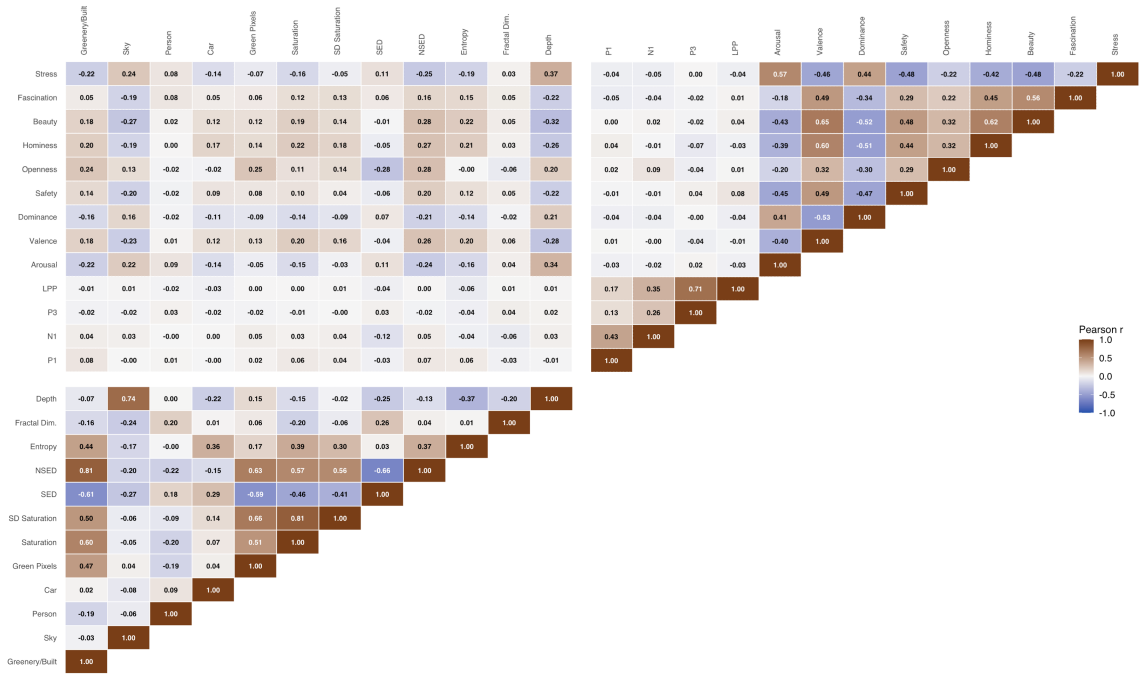

Figure 3: Correlation matrix showing Pearson correlations between all variables used in the study. The matrix includes semantic image features (greenery/built ratio, sky, person, car), low-level visual features (green pixels, saturation, SD of saturation, straight edge density [SED], non-straight edge density [NSED], entropy, fractal dimension, mean metric depth), ERP components (P1, N1, P3, LPP), and subjective ratings (arousal, valence, dominance, safety, openness, hominess, beauty, fascination, stress). Color coding ranges from blue (r = -1.0) to brown (r = 1.0). Strong correlations are highlighted in darker shades.

3.1. Subjective Measures

We report analyses for nine dimensions examining how visual and individual-level variables influence subjective evaluations. Overall, the image ratings were approximately normally distributed with mean ratings close to the means of the respective Likert scales (see Figure 4).

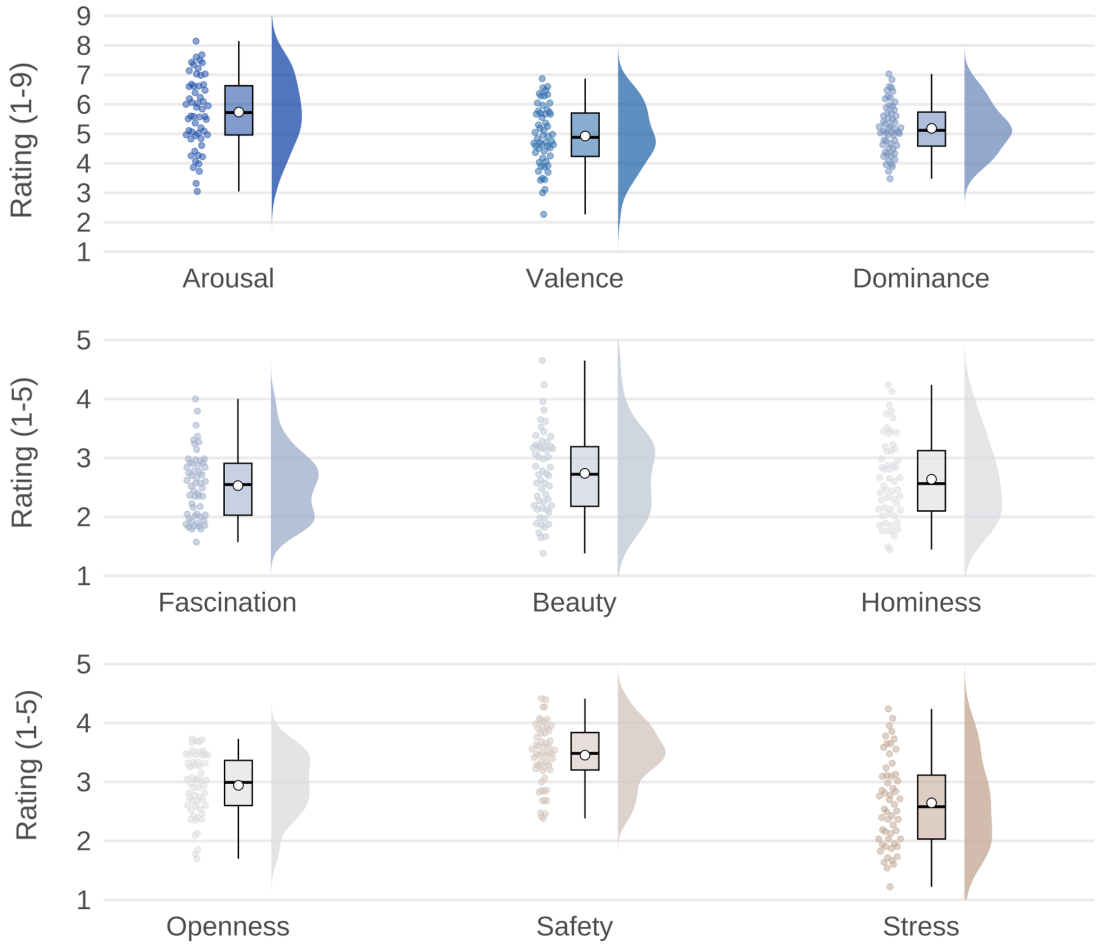

Figure 4: Raincloud plots of subjective ratings for SAM scales and Likert scales. Individual data points represent stimulus means aggregated across participants, boxplots show median and mean, and density distributions illustrate the variability across stimuli.

3.1.1. Semantic Image Contents

The results of all LMMs using semantic segmentation categories as predictors and subjective ratings as outcomes are summarized in Tables 1 and 2. All p-values

were adjusted for multiple hypothesis testing using the Benjamini-Hochberg procedure (FDR) (Benjamini and Hochberg, 1995).

The model for the *arousal ratings* showed that higher greenery/built ratios led to stimuli being rated as significantly more calm (β = -0.41, p = .02). Conversely, the amount of sky area in images had the opposite effect, with more sky area leading to higher arousal ratings (β = 0.43, p = .014). The size of the city participants grew up in also had a significant main effect (β = -0.15, p = .02), suggesting that individuals with more urban upbringing reported lower arousal overall. All other predictors did not significantly influence arousal ratings (all $p \geq .099$).

Similar effects were observed for *valence ratings*. Greenery/built ratios exhibited a positive effect (β = 0.38, p = .011), suggesting that images containing more natural and less artificial elements were associated with more positive emotional evaluations. Sky area had a negative effect on valence ratings (β = -0.44, p = .002). None of the other predictors demonstrated effects on valence ratings (all $p \geq .137$)

The *dominance ratings* assessed participants' feeling of being in control vs. controlled. The selected final model again showed that greenery/built ratios had a significant negative effect on perceived dominance (β = -0.35, p = .005), indicating that scenes with a higher proportion of vegetation compared to buildings and roads elicited stronger feelings of being in control. Sky area had a positive effect on perceived dominance ratings (β = 0.32, p = .005), reflecting higher feelings of being controlled. No other predictor showed effects on dominance ratings (all $p \geq .081$.).

Safety ratings were significantly influenced only by the amount of sky in the images, with larger sky areas being perceived as less safe (β = -0.22, p = .004). No other predictor revealed an impact on safety ratings (all $p \geq .062$).

The model for *beauty ratings* showed a significant effect of greenery/built ratio

with images with more greenery compared to built areas being rated as more beautiful ($\beta = 0.22$, $p = .028$). On the other hand, larger sky areas made the images appear less beautiful (β = -0.31, $p = .001$). Beauty ratings were also influenced by participants' extraversion ($\beta = 0.04$, $p = .040$) and gender, with non-male identifying participants rating urban images as generally less beautiful (β = -0.30, $p = .002$). All other predictors did not significantly influence beauty ratings (all $p \geq .083$).

As for *hominess ratings*, significant effects were found for greenery/built ratios with higher ratios positively influencing hominess ratings ($\beta = 0.25$, $p = .030$). Conversely, sky area had a negative effect on perceived hominess (β = -0.22, $p = .032$). Additionally, larger amounts of image areas covered by cars lead to participants perceiving the scenes as homier ($\beta = 0.20$, $p = .042$). All other predictors did not significantly influence hominess ratings (all $p \geq .056$).

Openness ratings showed significant positive effects of greenery/built ratios (β = 0.30, p $<$ .001), as well as sky area ($\beta = 0.16$, $p = .026$). Aside from image characteristics, perceived scene openness was also positively affected by the size of the city participants grew up in ($\beta = 0.11$, $p = .008$). All other predictors did not significantly influence openness ratings (all $p \geq .051$).

Of the semantic image contents, *fascination ratings* were only significantly affected by sky area, with more visible sky leading to lower fascination ratings (β = -0.23, p =0.007). Additionally, there was an effect of gender with non-male identifying participants generally perceiving scenes as less fascinating (β = -0.30, $p = .045$). All other predictors did not significantly influence fascination ratings (all $p \geq .343$).

The final LMM analyzing the influence of visual features on *stress ratings* also showed a significant negative effect of greenery/built ratios (β = -0.41, $p = .020$), showing images with proportionally more greenery compared to buildings and roads being rated as less stressful. Sky area had the opposite effect, suggesting more

visible sky area to be perceived as more stressful (β = 0.43, p = .014). Among the sociodemographic predictors, city size emerged as having the only significant effect (β = -0.15, p = .020), implying that participants from larger cities reported slightly less stress in response to the stimuli.All other predictors had no significant effects (all $p \geq .064$).

Table 1: Results of LMMs predicting subjective ratings from semantic image contents(1/2).

	Arousal				Valence				Dominance				Stress			
Predictors	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}
(Intercept)	5.61	0.46	4.71–6.52	<0.001	4.65	0.45	3.76–5.55	<0.001	5.74	0.63	4.50–6.98	<0.001	5.61	0.46	4.71–6.52	<0.001
greenery/built ratio	-0.41	0.15	-0.69– -0.12	**0.020**	0.38	0.13	0.13–0.62	**0.011**	-0.35	0.10	-0.55– -0.14	**0.005**	-0.41	0.15	-0.69– -0.12	**0.020**
sky	0.43	0.14	0.16–0.70	**0.014**	-0.44	0.12	-0.67– -0.22	**0.002**	0.32	0.10	0.13–0.50	**0.005**	0.43	0.14	0.16–0.70	**0.014**
car	-0.26	0.14	-0.53–0.01	0.099	0.21	0.11	-0.02–0.43	0.137	-0.20	0.09	-0.38– -0.02	0.081	-0.26	0.14	-0.53–0.01	0.099
person	0.16	0.14	-0.12–0.44	0.304	0.06	0.12	-0.17–0.28	0.701	-0.07	0.09	-0.25–0.12	0.609	0.16	0.14	-0.12–0.44	0.304
Gender [Non-male]	0.15	0.17	-0.17–0.48	0.358	-0.30	0.17	-0.63– -0.02	0.137	0.12	0.23	-0.34–0.58	0.696	0.15	0.17	-0.17–0.48	0.358
City size first 15 years	-0.15	0.06	-0.26– -0.04	**0.020**	0.06	0.06	-0.05–0.17	0.381	-0.09	0.08	-0.24–0.07	0.410	-0.15	0.06	-0.26– -0.04	**0.020**
extraversion	-0.04	0.03	-0.09–0.02	0.274	0.04	0.03	-0.01–0.10	0.211	-0.07	0.04	-0.15–0.01	0.182	-0.04	0.03	-0.09–0.02	0.274
emotional stability	-0.06	0.03	-0.12– -0.01	0.064	-0.00	0.03	-0.06–0.06	0.992	-0.01	0.04	-0.09–0.07	0.819	-0.06	0.03	-0.12– -0.01	0.064
Observations	3528				3528				3528				3528			
Marginal R^2 / Conditional R^2	0.128 / 0.459				0.104 / 0.395				0.072 / 0.384				0.128 / 0.459			

Table 2: Results of LMMs predicting subjective ratings from semantic image contents(2/2)

	Safety				Beauty				Hominess				Openness				Fascination			
Predictors	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}
(Intercept)	2.79	0.34	2.13–3.46	<0.001	2.44	0.24	1.97–2.91	<0.001	2.36	0.27	1.83–2.89	<0.001	1.92	0.29	1.34–2.50	<0.001	2.50	0.33	1.86–3.14	<0.001
greenery/built ratio	0.15	0.06	0.03–0.28	0.062	0.22	0.09	0.05–0.39	**0.028**	0.25	0.09	0.07–0.42	**0.030**	0.30	0.06	0.18–0.42	**<0.001**	0.08	0.08	-0.07–0.22	0.467
sky	-0.22	0.06	-0.34– -0.10	**0.004**	-0.31	0.08	-0.47– -0.16	**0.001**	-0.22	0.08	-0.38– -0.06	**0.032**	0.16	0.06	0.04–0.28	**0.026**	-0.23	0.07	-0.36– -0.09	**0.007**
car	0.08	0.06	-0.03–0.20	0.254	0.12	0.08	-0.03–0.28	0.169	0.20	0.08	0.04–0.35	**0.042**	-0.03	0.06	-0.13–0.08	0.643	0.04	0.07	-0.10–0.17	0.741
person	-0.02	0.06	-0.14–0.10	0.753	0.04	0.08	-0.12–0.19	0.728	0.02	0.08	-0.14–0.18	0.802	0.05	0.06	-0.06–0.16	0.475	0.09	0.07	-0.04–0.23	0.343
Gender [Non-male]	0.06	0.12	-0.18–0.30	0.718	-0.30	0.09	-0.47– -0.14	**0.002**	-0.05	0.10	-0.24–0.14	0.719	-0.08	0.11	-0.29–0.14	0.549	-0.30	0.12	-0.54– -0.07	**0.045**
City size first 15 years	0.06	0.04	-0.02–0.15	0.254	0.06	0.03	-0.00–0.11	0.083	0.03	0.03	-0.03–0.10	0.507	0.11	0.04	0.04–0.19	**0.008**	0.05	0.04	-0.03–0.13	0.343
extraversion	0.01	0.02	-0.03–0.06	0.696	0.04	0.02	0.01–0.07	**0.040**	0.04	0.02	0.00–0.07	0.056	0.04	0.02	0.01–0.08	0.051	-0.01	0.02	-0.05–0.03	0.741
emotional stability	0.03	0.02	-0.01–0.08	0.254	-0.01	0.02	-0.04–0.02	0.737	-0.01	0.02	-0.05–0.02	0.507	0.03	0.02	-0.01–0.07	0.164	0.01	0.02	-0.04–0.05	0.741
Observations	3528				3528				3528				3528				3528			
Marginal R^2 / Conditional R^2	0.076 / 0.430				0.134 / 0.450				0.104 / 0.444				0.116 / 0.403				0.064 / 0.381			

3.1.2. Lower-level visual Features

Tables 3 and 4 show the results of all models using LLVFs as predictors and subjective ratings as outcomes. All p-values were adjusted for multiple hypothesis testing using FDR.

Arousal ratings showed significant effects of metric depth of the urban scenes. A higher mean depth of a scene also led to significantly higher arousal ratings ($\beta = 0.70$, $p < .001$). All other LLVFs had no significant effect on subjective arousal (all $p \geq .084$).

The model for *valence ratings* showed that participants reported themselves significantly happier in scenes with higher non-straight edge density ($\beta = 0.61$, $p = .004$), indicating a positive impact of more unstructured (natural) edges in the scenes. Additionally, metric depth once again had a significant effect; higher mean depth sig-

nificantly increased valence ratings (β = -0.43, p = .004). None of the other LLVFs had a significant effect on valence ratings (all $p \geq .094$).

Similar to valence ratings, *dominance ratings* were also significantly affected by scenes' mean metric depth and non-straight edge density. Higher non-straight edge density led to participants reporting to be more in control (β = -0.44 , p = .027), while higher depths were associated with higher feelings of being controlled (β = 0.38 , p = .007). Other LLVFs had no effects on dominance ratings (all $p \geq .593$)

Safety ratings were significantly affected by non-straight edge density and mean metric depth. More non-straight edges led to higher perceived safety (β = 0.28 , p = .035), while higher mean metric depth led to lower safety ratings (β = -0.21 , p = .027). No other LLVF showed significant effects on scenes' safety ratings (all $p \geq$ .188).

For *beauty ratings*, the model showed a significant positive effect of both straight edge density (β = 0.34 , p = .015) and non-straight edge density (β = 0.47 , p = .002). Additionally, beauty ratings were significantly influenced by mean metric depth, with higher depths in images leading to lower beauty scores (β = -0.29 , p = .003). No other LLVF showed significant effects on perceived beauty (all $p \geq .345$).

None of the LLVFs had significant effects on *hominess ratings* (all $p \geq .058$).

The model for perceived *openness ratings* revealed a significant positive effect of non-straight edge density (β = 0.37 , p $<$ .001) as well as mean metric depth (β = 0.23 , p $<$ .001). Other LLVFs had no significant effect (all $p \geq .382$).

Fascination ratings, similar to beauty ratings, were positively affected by both straight- (β = 0.34 , p = .008) and non-straight edge density (β = 0.35 , p = .008). The model also showed a significant negative effect of mean metric depth (β = -0.18 , p = .039). Other LLVFs, again, had no significant effect (all $p \geq .576$).

Lastly, *stress ratings* were once more only significantly impacted by mean metric

depth: higher depths in images led to participants rating them as more stressful ($\beta = 0.46$, $p = .007$).All other LLVFs had no significant effects on stress ratings (all $p \geq .265$).

In summary, of all eight extracted LLVFs, only edge density measures and mean metric depth significantly affected subjective scene perception.

Table 3: Results of LMMs predicting subjective ratings from LLVFs of images (1/2). *Note: CI are 95% confidence intervals; p-values were adjusted using FDR method; all predictors were z-scaled.*

	Arousal				Valence				Dominance				Stress			
Predictors	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}
(Intercept)	5.59	0.46	4.70–6.49	<0.001	4.73	0.46	3.83–5.62	<0.001	5.66	0.63	4.43–6.90	<0.001	3.50	0.25	3.02–3.98	<0.001
Green Hue	-0.09	0.19	-0.47–0.28	0.749	0.14	0.16	-0.17–0.45	0.549	-0.08	0.14	-0.35–0.19	0.717	-0.08	0.12	-0.31–0.14	0.717
Saturation	-0.23	0.23	-0.69–0.23	0.425	0.23	0.19	-0.14–0.61	0.425	-0.15	0.17	-0.48–0.18	0.603	-0.13	0.14	-0.41–0.14	0.603
SD of Saturation	0.51	0.24	0.04–0.97	0.084	-0.15	0.19	-0.53–0.23	0.568	0.19	0.17	-0.14–0.52	0.593	0.29	0.14	0.01–0.57	0.593
Straight Edge Density	0.06	0.21	-0.35–0.48	0.765	0.39	0.17	0.05–0.72	0.094	-0.14	0.15	-0.43–0.16	0.603	0.06	0.13	-0.19–0.31	0.603
Non-Straight Edge Density	-0.47	0.21	-0.89– -0.05	0.084	0.61	0.17	0.27–0.95	**0.004**	-0.44	0.15	-0.74– -0.14	**0.027**	-0.24	0.13	-0.49–0.01	0.265
Entropy	0.05	0.15	-0.24–0.34	0.765	-0.06	0.12	-0.29–0.18	0.718	0.04	0.11	-0.17–0.25	0.776	0.00	0.09	-0.17–0.18	0.776
Fractal Dimension	0.21	0.14	-0.06–0.47	0.255	-0.05	0.11	-0.27–0.17	0.718	0.07	0.10	-0.12–0.26	0.699	0.11	0.08	-0.05–0.27	0.699
Mean metric depth	0.70	0.15	0.41–1.00	**<0.001**	-0.43	0.12	-0.67– -0.19	**0.004**	0.38	0.11	0.17–0.60	**0.007**	0.46	0.09	0.28–0.63	**0.007**
Gender binary [Non-male]	0.17	0.17	-0.15–0.49	0.425	-0.29	0.17	-0.62–0.04	0.230	0.11	0.23	-0.35–0.57	0.768	0.06	0.09	-0.12–0.23	0.768
City size first 15 years	-0.15	0.06	-0.26– -0.04	**0.042**	0.06	0.06	-0.05–0.17	0.521	-0.10	0.08	-0.26–0.05	0.511	-0.07	0.03	-0.13– -0.01	0.511
extraversion	-0.04	0.03	-0.09–0.02	0.339	0.04	0.03	-0.02–0.10	0.409	-0.07	0.04	-0.15–0.01	0.331	-0.04	0.02	-0.07– -0.01	0.331
emotional stability	-0.06	0.03	-0.12– -0.01	0.084	-0.00	0.03	-0.06–0.06	0.915	0.00	0.04	-0.08–0.08	0.964	-0.03	0.02	-0.06–0.00	0.964
Observations	3528				3528				3528				3528			
Marginal R^2 / Conditional R^2	0.201 / 0.473				0.154 / 0.377				0.090 / 0.380				0.221 / 0.482			

Table 4: Results of LMMs predicting subjective ratings from LLVFs of images (2/2). *Note: CI are 95% confidence intervals; p-values were adjusted using FDR method; all predictors were z-scaled.*

	Safety				Beauty				Hominess				Openness				Fascination			
Predictors	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}
(Intercept)	2.81	0.34	2.15–3.47	<0.001	2.44	0.24	1.98–2.91	<0.001	2.35	0.27	1.83–2.88	<0.001	1.94	0.30	1.36–2.52	<0.001	2.50	0.32	1.87–3.14	<0.001
Green Hue	0.10	0.09	-0.08–0.28	0.528	0.12	0.11	-0.09–0.33	0.345	0.08	0.12	-0.16–0.32	0.701	0.07	0.06	-0.05–0.19	0.451	0.04	0.09	-0.14–0.23	0.810
Saturation	0.10	0.11	-0.12–0.32	0.528	0.14	0.13	-0.12–0.39	0.345	0.13	0.15	-0.16–0.43	0.626	-0.07	0.07	-0.22–0.07	0.474	0.00	0.11	-0.22–0.23	0.994
SD of Saturation	-0.22	0.11	-0.44–0.00	0.188	-0.15	0.13	-0.41–0.11	0.345	-0.07	0.15	-0.36–0.23	0.745	-0.03	0.08	-0.18–0.11	0.711	0.08	0.12	-0.15–0.31	0.701
Straight Edge Density	0.10	0.10	-0.10–0.29	0.528	0.34	0.12	0.11–0.57	**0.015**	0.22	0.13	-0.05–0.48	0.289	0.00	0.07	-0.13–0.13	0.969	0.34	0.10	0.14–0.55	**0.008**
Non-Straight Edge Density	0.28	0.10	0.08–0.48	**0.035**	0.47	0.12	0.24–0.71	**0.002**	0.35	0.14	0.09–0.62	0.058	0.37	0.07	0.24–0.51	**<0.001**	0.35	0.10	0.15–0.56	**0.008**
Entropy	-0.05	0.07	-0.19–0.09	0.591	-0.05	0.08	-0.21–0.11	0.570	-0.00	0.09	-0.19–0.18	0.961	-0.03	0.05	-0.12–0.06	0.609	-0.05	0.07	-0.20–0.09	0.701
Fractal Dimension	-0.02	0.07	-0.15–0.11	0.770	-0.08	0.08	-0.23–0.06	0.345	-0.05	0.09	-0.23–0.12	0.701	-0.06	0.04	-0.14–0.03	0.382	-0.07	0.07	-0.20–0.06	0.576
Mean metric depth	-0.21	0.07	-0.35– -0.07	**0.027**	-0.29	0.08	-0.46– -0.13	**0.003**	-0.23	0.09	-0.42– -0.05	0.058	0.23	0.05	0.13–0.34	**<0.001**	-0.18	0.07	-0.32– -0.04	**0.039**
Gender binary [Non-male]	0.04	0.12	-0.21–0.28	0.770	-0.29	0.09	-0.46– -0.13	**0.003**	-0.04	0.10	-0.23–0.15	0.745	-0.09	0.11	-0.30–0.13	0.563	-0.30	0.12	-0.54– -0.07	**0.039**
City size first 15 years	0.06	0.04	-0.02–0.14	0.392	0.06	0.03	-0.00–0.11	0.113	0.03	0.03	-0.04–0.09	0.626	0.11	0.04	0.04–0.19	**0.011**	0.05	0.04	-0.03–0.13	0.417
extraversion	0.02	0.02	-0.03–0.06	0.591	0.04	0.02	0.01–0.07	**0.044**	0.04	0.02	0.01–0.08	0.058	0.05	0.02	0.01–0.08	0.058	-0.01	0.02	-0.05–0.03	0.810
emotional stability	0.03	0.02	-0.01–0.07	0.392	-0.01	0.02	-0.04–0.02	0.710	-0.02	0.02	-0.05–0.02	0.626	0.03	0.02	-0.01–0.07	0.308	0.01	0.02	-0.04–0.05	0.810
Observations	3528				3528				3528				3528				3528			
Marginal R^2 / Conditional R^2	0.102 / 0.437				0.212 / 0.438				0.143 / 0.428				0.173 / 0.389				0.118 / 0.361			

3.2. EEG

Grand average potentials across all images and participants revealed clear and pronounced ERP components with a visual evoked P1-N1 complex over occipital

sites and a P3 component followed by an LPP complex over centro-parietal sites (See figure 5). To evaluate the influence of visual and person-related predictors on neural responses to environmental stimuli, these four ERP components were analyzed. For each component, hierarchical LMMs were fitted in the same way as was done for the subjective outcome measures. All p-values for models with shared predictor sets were adjusted for multiple hypothesis testing using FDR.

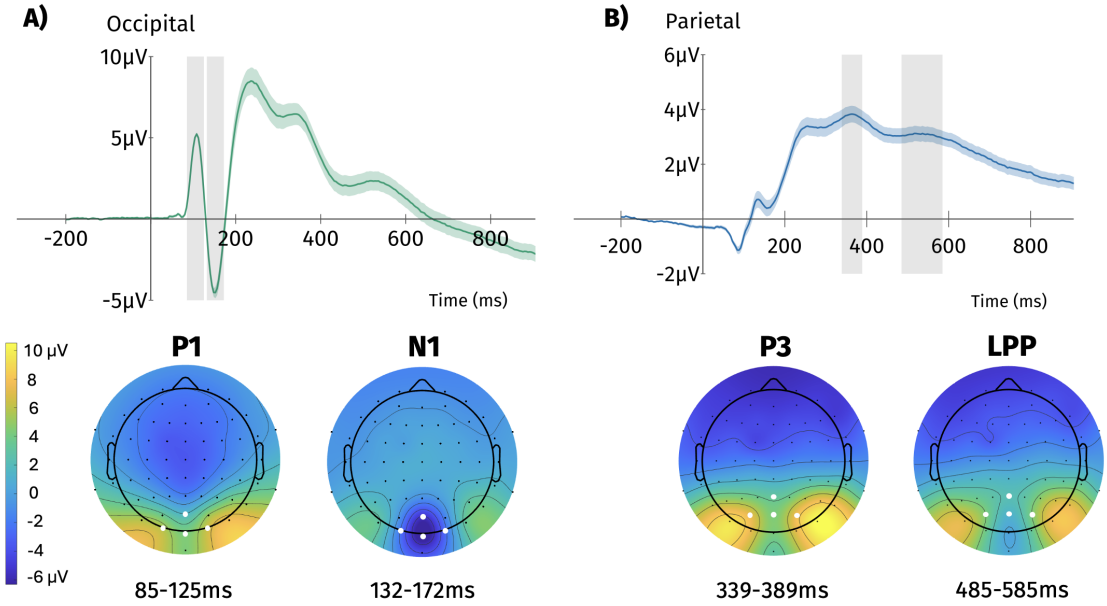

Figure 5: Grand Average ERP waveforms (averaged across all participants and stimuli) at onset of urban scene stimuli for the (A) occipital and the (B) parietal cluster. Color-shaded areas represent $\pm$ 1 standard error of the mean (SEM). (C) Bottom of Figure shows topographical plots of averaged amplitude activity (in μV) during the time windows (indicated by the grey-shaded time periods) of the four extracted ERP components. *Note differences in scale of y-axes!*

3.2.1. Semantic Image Contents

The LMM showed a significant effect of greenery/built ratio on occipital *P1-amplitudes* ($\beta = 0.54$, $p = .001$). Higher proportions of natural compared to artificial elements were associated with more pronounced P1-amplitudes. All other stimuli or participant characteristics had no significant effects on P1 amplitudes (all $p \geq .256$).

The subsequent *N1 component* did not reveal any significant effects (all $p \geq .433$) regarding the semantic image contents. However, N1 amplitudes demonstrated a gender effect, with non-male participants exhibiting significantly more negative N1-amplitudes than male participants (β = -4.79, p = .047), indicating a possible gender-based modulation of the N1 component. Other sociodemographic variables were not significant.

For the *P3 and LPP components* at the centro-parietal electrode cluster, none of the image contents, nor personal characteristics of participants reached statistical significance (all $p \geq .724$). Full results can be found in Table 5.

Table 5: Results of LMMs predicting ERP component amplitudes from semantic image contents. *Note: CI are 95% confidence intervals; p-values were adjusted using FDR method; all predictors were z-scaled.*

	mean P1				mean N1				mean P3				mean LPP			
Predictors	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}
(Intercept)	13.95	3.16	7.75–20.16	<0.001	-7.78	4.42	-16.44–0.89	0.376	4.35	1.70	1.03–7.68	0.115	1.76	1.54	-1.26–4.79	0.762
greenery/built ratio	0.54	0.14	0.26–0.81	**0.001**	0.37	0.26	-0.15–0.89	0.433	-0.06	0.09	-0.24–0.12	0.752	-0.04	0.10	-0.23–0.15	0.873
sky	0.01	0.12	-0.23–0.26	0.905	0.28	0.26	-0.22–0.78	0.461	-0.08	0.09	-0.26–0.10	0.752	0.02	0.10	-0.17–0.20	0.878
car	-0.05	0.12	-0.29–0.20	0.806	0.04	0.26	-0.46–0.54	0.882	-0.07	0.09	-0.25–0.11	0.752	-0.10	0.10	-0.29–0.09	0.762
person	0.18	0.13	-0.07–0.43	0.288	0.07	0.26	-0.44–0.58	0.880	0.07	0.09	-0.11–0.26	0.752	-0.05	0.10	-0.24–0.14	0.873
Gender binary [Non-male]	0.54	1.18	-1.78–2.86	0.806	-4.79	1.65	-8.03– -1.55	**0.047**	-0.90	0.63	-2.14–0.34	0.724	-0.56	0.58	-1.69–0.57	0.762
City size first 15 years	-0.57	0.40	-1.36–0.22	0.288	0.74	0.56	-0.36–1.84	0.433	0.00	0.22	-0.42–0.42	0.991	0.25	0.20	-0.14–0.63	0.762
extraversion	0.10	0.21	-0.31–0.51	0.806	0.22	0.29	-0.36–0.79	0.590	-0.02	0.11	-0.24–0.20	0.991	0.07	0.10	-0.13–0.27	0.873
emotional stability	-0.37	0.21	-0.79–0.04	0.256	-0.31	0.30	-0.89–0.28	0.461	0.00	0.11	-0.22–0.23	0.991	0.02	0.10	-0.19–0.22	0.878
Observations	3528				3528				3493				3493			
Marginal R^2 / Conditional R^2	0.053 / 0.660				0.116 / 0.792				0.020 / 0.580				0.026 / 0.543			

3.2.2. Lower-level visual Features

The models with LLVFs as predictors revealed only one significant effect: higher straight edge density led to more pronounced *N1 amplitudes* (β = -1.22, p = .024).

None of the other LLVFs had a significant effect on any of the other three ERPs (all $p \geq 0.075$). For full results see Table 6.

Table 6: Results of LMMs predicting ERP component amplitudes from LLVFs. *Note: CI are 95% confidence intervals; p-values were adjusted using FDR method; all predictors were z-scaled.*

	mean P1				mean N1				mean P3				mean LPP			
Predictors	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}
(Intercept)	13.49	3.10	7.40–19.57	<0.001	-7.63	4.25	-15.97–0.71	0.336	4.35	1.63	1.16–7.54	0.123	1.76	1.48	-1.14–4.67	0.639
Green Hue	-0.21	0.19	-0.58–0.16	0.441	-0.19	0.34	-0.85–0.48	0.602	-0.11	0.14	-0.38–0.15	0.746	-0.12	0.14	-0.39–0.16	0.639
Saturation	0.29	0.23	-0.16–0.74	0.441	-0.67	0.41	-1.48–0.14	0.361	0.10	0.17	-0.22–0.43	0.764	-0.03	0.17	-0.37–0.30	0.873
SD of Saturation	-0.13	0.23	-0.59–0.33	0.571	0.63	0.42	-0.20–1.46	0.368	0.07	0.17	-0.27–0.40	0.910	0.15	0.17	-0.19–0.49	0.639
Straight Edge Density	0.19	0.21	-0.22–0.59	0.449	-1.22	0.37	-1.95– -0.49	**0.024**	0.19	0.15	-0.11–0.48	0.472	-0.23	0.15	-0.54–0.07	0.639
Non-Straight Edge Density	0.55	0.21	0.14–0.96	0.075	-0.24	0.38	-0.99–0.50	0.602	0.11	0.15	-0.19–0.41	0.764	-0.07	0.16	-0.38–0.24	0.770
Entropy	0.18	0.15	-0.10–0.47	0.441	-0.14	0.26	-0.65–0.38	0.602	-0.16	0.11	-0.37–0.04	0.472	-0.21	0.11	-0.42–0.00	0.639
Fractal Dimension	-0.14	0.13	-0.40–0.12	0.441	-0.31	0.24	-0.79–0.16	0.378	0.14	0.10	-0.05–0.33	0.472	0.08	0.10	-0.12–0.27	0.639
Mean metric depth	0.17	0.14	-0.11–0.44	0.441	-0.24	0.25	-0.74–0.26	0.503	0.13	0.10	-0.07–0.33	0.472	-0.08	0.11	-0.29–0.12	0.639
Gender binary [Non-male]	1.03	1.16	-1.25–3.30	0.449	-4.72	1.59	-7.84– -1.60	**0.027**	-0.90	0.61	-2.09–0.29	0.472	-0.56	0.55	-1.64–0.53	0.639
City size first 15 years	-0.73	0.39	-1.50–0.04	0.300	0.72	0.54	-0.34–1.78	0.378	0.00	0.21	-0.40–0.41	0.990	0.25	0.19	-0.12–0.62	0.639
extraversion	0.12	0.21	-0.28–0.53	0.571	0.21	0.28	-0.34–0.77	0.587	-0.02	0.11	-0.23–0.19	0.990	0.07	0.10	-0.13–0.26	0.646
emotional stability	-0.31	0.21	-0.72–0.10	0.441	-0.31	0.29	-0.87–0.25	0.447	0.00	0.11	-0.21–0.22	0.990	0.02	0.10	-0.18–0.21	0.873
Observations	3528				3528				3493				3493			
Marginal R^2 / Conditional R^2	0.067 / 0.638				0.134 / 0.776				0.025 / 0.561				0.033 / 0.524			

3.3. Associations between ERPs and Ratings

To explore possible connections between ERPs and subjective ratings, indicating an effect of perceptual processing of visual urban stimuli as well as subsequent appraisal processes on subsequent ratings, we calculated nine LMMs with the amplitudes of the four ERP components as predictors and subjective ratings as outcomes. All LMMs contained a random intercept per subject, as well as the same personal characteristics as the previous models as covariates. All p-values were adjusted for multiple hypothesis testing using FDR. For full results see Tables 7 and 8.

The ERP components P1 and N1 at occipital electrodes did not significantly predict subjective ratings (all $p \geq 0.303$). In contrast, the models revealed a significant effect of the parietal components P3 and LPP on subjective ratings. Increasing P3 amplitudes predicted decreasing beauty ratings (β = -0.03, p = .009), as well as lower perceived openness (β = -0.03, p = .047) and fascination (β = -0.03, p = .017). Conversely, LPP amplitudes significantly predicted perceived safety (β = 0.03, p =

.017), beauty ($\beta = 0.03$, $p = .009$), and fascination ($\beta = 0.04$, $p = .009$), with higher amplitudes leading to higher subjective ratings.

Table 7: Results of LMMs predicting subjective ratings from ERP component amplitudes (1/2). *Note: CI are 95% confidence intervals; p-values were adjusted using FDR method.*

	Arousal				Valence				Dominance				Stress			
Predictors	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}
(Intercept)	4.25	0.24	3.78–4.71	<0.001	5.28	0.23	4.83–5.72	<0.001	4.81	0.25	4.32–5.31	<0.001	2.73	0.14	2.46–3.00	<0.001
LPP	-0.03	0.02	-0.06–0.00	0.217	0.02	0.02	-0.01–0.06	0.347	-0.04	0.02	-0.07– -0.00	0.128	-0.01	0.01	-0.03–0.00	0.349
P3	0.01	0.02	-0.02–0.04	0.581	-0.04	0.02	-0.07– -0.01	0.078	0.03	0.02	-0.00–0.06	0.224	0.01	0.01	-0.01–0.02	0.679
N1	-0.00	0.01	-0.02–0.01	0.832	-0.01	0.01	-0.02–0.01	0.581	0.01	0.01	-0.01–0.03	0.418	0.00	0.00	-0.01–0.01	0.788
P1	-0.00	0.01	-0.02–0.01	0.747	0.00	0.01	-0.02–0.02	0.889	-0.01	0.01	-0.03–0.01	0.534	-0.01	0.00	-0.02–0.00	0.303
Gender binary [Non-male]	0.14	0.17	-0.20–0.48	0.581	-0.38	0.18	-0.73– -0.03	0.128	0.36	0.25	-0.13–0.85	0.363	0.06	0.09	-0.12–0.24	0.658
City size first 15 years	-0.21	0.08	-0.38– -0.05	0.078	0.10	0.09	-0.08–0.27	0.466	-0.14	0.12	-0.38–0.10	0.466	-0.10	0.05	-0.19– -0.01	0.124
extraversion	-0.10	0.08	-0.26–0.06	0.458	0.06	0.08	-0.11–0.23	0.624	-0.11	0.12	-0.35–0.12	0.543	-0.11	0.04	-0.20– -0.03	0.078
emotional stability	-0.20	0.08	-0.37– -0.03	0.119	-0.04	0.09	-0.21–0.14	0.119	0.05	0.12	-0.20–0.29	0.769	-0.07	0.05	-0.16–0.02	0.303
Observations	3493				3493				3493				3493			
Marginal R^2 / Conditional R^2	0.024 / 0.432				0.012 / 0.340				0.013 / 0.333				0.021 / 0.444			

Table 8: Results of LMMs predicting subjective ratings from ERP component amplitudes (2/2). *Note: CI are 95% confidence intervals; p-values were adjusted using FDR method.*

	Safety				Beauty				Hominess				Openness				Fascination			
Predictors	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}	Est	SE	CI	p_{adj}
(Intercept)	3.45	0.14	3.18–3.71	<0.001	2.87	0.13	2.61–3.13	<0.001	2.63	0.14	2.35–2.90	<0.001	3.01	0.13	2.76–3.26	<0.001	2.69	0.14	2.42–2.96	<0.001
LPP	0.03	0.01	0.01–0.04	**0.017**	0.03	0.01	0.02–0.05	**0.009**	0.02	0.01	0.00–0.04	0.128	0.01	0.01	-0.01–0.03	0.418	0.04	0.01	0.02–0.05	**0.009**
P3	-0.02	0.01	-0.04– -0.00	0.124	-0.03	0.01	-0.05– -0.01	**0.009**	-0.02	0.01	-0.04– -0.01	0.066	-0.03	0.01	-0.04– -0.01	**0.047**	-0.03	0.01	-0.05– -0.01	**0.017**
N1	-0.00	0.00	-0.01–0.01	0.604	-0.01	0.00	-0.01–0.00	0.432	-0.00	0.00	-0.01–0.01	0.581	-0.00	0.00	-0.01–0.01	0.581	-0.01	0.01	-0.02–0.00	0.462
P1	-0.00	0.00	-0.01–0.01	0.792	0.00	0.00	-0.01–0.01	0.927	0.01	0.01	-0.00–0.02	0.459	0.00	0.01	-0.01–0.01	0.624	-0.00	0.01	-0.01–0.01	0.769
Gender binary [Non-male]	-0.05	0.13	-0.30–0.21	0.786	-0.33	0.09	-0.50– -0.16	**0.009**	-0.11	0.10	-0.31–0.09	0.467	-0.16	0.11	-0.38–0.06	0.369	-0.33	0.12	-0.57– -0.09	0.066
City size first 15 years	0.08	0.06	-0.05–0.20	0.446	0.07	0.04	-0.02–0.15	0.303	0.05	0.05	-0.04–0.15	0.472	0.17	0.05	0.07–0.28	**0.026**	0.07	0.06	-0.05–0.18	0.466
extraversion	0.04	0.06	-0.09–0.16	0.679	0.09	0.04	0.01–0.17	0.128	0.09	0.05	-0.00–0.18	0.217	0.11	0.05	0.01–0.22	0.128	-0.02	0.06	-0.14–0.09	0.769
emotional stability	0.05	0.07	-0.08–0.17	0.624	-0.03	0.04	-0.11–0.06	0.670	-0.06	0.05	-0.16–0.04	0.462	0.07	0.06	-0.04–0.18	0.458	0.01	0.06	-0.11–0.12	0.927
Observations	3493				3493				3493				3493				3493			
Marginal R^2 / Conditional R^2	0.012 / 0.390				0.027 / 0.392				0.012 / 0.382				0.041 / 0.340				0.023 / 0.337			

4. Discussion

The present study investigated the influence of semantic contents as well as LLVFs of urban images on subjective and neural responses.

4.1. Subjective Ratings of Urban Scenes

Greenery in urban images consistently exhibited beneficial effects across several psychological dimensions. Images with higher greenery/built ratios were associated

with lower arousal and stress ratings, more positive valence, stronger feelings of control, and higher perceived beauty and hominess.

In contrast to previous studies reporting a further positive impact of sky area on affective responses to urban scenes (Asgarzadeh et al., 2014; Peng et al., 2025; Rhee et al., 2023), our results predominantly demonstrated a negative impact of increasing sky areas in the displayed scenes. More sky area in an image was associated with higher arousal and stress ratings, lower valence ratings, and reduced feelings of control and safety, as well as lower beauty, hominess, and fascination ratings. This pattern challenges the assumption that openness and visual access to sky are inherently restorative. As would be expected, when considering LLVFs of the images, a strong positive correlation of visible sky area with spatial depth was observed. Like sky area, depth in images showed a similar negative impact on ratings, suggesting that the negative influence of visible sky area in an image is closely related to the spatial openness of an urban scene. This negative impact on sky area on subjective experience might be explainable with the Prospect-Refuge Theory (Appleton, 1975), which proposes that humans evolved preferences for environments offering an optimal balance between visibility and concealment. While extensive sky visibility can appear empty, unwelcoming, or unsafe in general (Cui et al., 2023), open spaces with extensive sky maximize prospect but minimize refuge, potentially resulting in feelings of exposure and vulnerability in urban settings (Dosen and Ostwald, 2016). This is supported by research on spatial enclosure suggesting that excessive enclosure but also excessive openness are detrimental (Fisher-Gewirtzman, 2018). Some stimuli in the present study may have contained disproportionately wide sky views, resulting in depth and exposure exceeding levels of comfort and control. As, contrary to our findings, sky visibility in natural landscapes is often associated with positive responses and aesthetic appreciation (Franěk, 2023), the appraisal of openness ap-

pears to be context-dependent. This suggests that the affective influence of openness may depend on surrounding factors. In urban settings, particularly those dominated by built structures and lacking vegetative refuge, the same openness may signal barrenness or insufficient environmental complexity to sustain interest. Additionally, openness in urban environments often coincides with large streets and intersections, which might also play a significant role in their affective and aesthetic appraisal.

4.2. Neural Dynamics of Urban Scene Perception

The positive impact of greenery in urban scenes in our study was reflected in a modulation of the visual evoked P1 component approximately 105ms after scene onset. Higher proportions of natural elements in the presented images elicited significantly increased P1 amplitudes. While in this study, the effect was specific only to the semantic category of greenery but not to related LLVFs, the effect of NSED (which is characteristic of greenery) approached significance. It is thus reasonable to consider that there might also be preferential early visual processing for LLVFs that are characteristic of natural elements, but that the effect did not survive multiple hypothesis correction and a resulting loss of power in the present study design.

These results are theoretically significant, as they replicate previous findings (Grassini et al., 2019) and provide converging evidence for some form of preferential early visual processing of natural environmental features. They may also explain previous behavioral findings which suggest approach biases and faster reaction times in response to natural as compared to urban scenes (Schiebel et al., 2022). This early differentiation may set the stage for subsequent affective processing, though our data revealed no direct connection between early neural responses and subjective appraisal, hinting at a more complex relationship.

The subsequent N1 component, in contrast to the P1, showed selective sensitivity

to SED, with higher rectilinearity in an image predicting more negative amplitudes. Straight Edges mainly occur in built/man-made structures, suggesting that N1 modulation reflects sensitivity to the geometric properties of scenes. This effect may help explain previous findings (Grassini et al., 2019) which showed that urban scenes elicit stronger N1 responses than natural scenes. This effect, contrasting with the earlier P1 component, suggests that different stages of early visual processing might prioritize different aspects of the visually perceived environment. During scene perception, features that are characteristic of natural elements seem to be preferentially processed before those characteristic of artificial/built elements.

4.3. Neural Correlates of Scene Appraisal

Another central finding of our study is the relationship between later ERP components and subjective ratings. While early visual evoked components over the occipital cortex reflected automated processing of natural categories and artificial lower-level features, amplitudes of the P1-N1-complex did not predict the subjective rating of urban scenes. Conversely, the later P3 and LPP components demonstrated no modulation by environmental features, but a systematic association with subjective ratings.

The P3 component, a positive deflection in the ERP waveform occurring that, depending on the task, appears roughly 300–800 ms after stimulus onset, and exhibits a broad, also task-dependent scalp distribution (Polich, 2007). The P3 is among the most thoroughly investigated ERP signatures, appearing across a wide range of paradigms. Although it has been linked to diverse cognitive operations such as context updating (Donchin, 1981) and surprise processing (Polich, 2007), its precise functional role remains debated. The observed negative relationship between P3 amplitude and ratings of openness, beauty, and fascination may indicate more

effortful attentional processing. Since larger P3 amplitudes are generally thought to reflect greater allocation of attentional resources (Polich, 2012), this pattern could suggest that less pleasant scenes demand increased cognitive effort for processing and evaluation.

A complementary explanation, which might be consistent with this effort-related interpretation, is that positively experienced environments are processed more efficiently, whereas potentially negative or less inviting environments require more extensive accumulation of sensory evidence. In decision-making research, the amplitude of the centroparietal P3 has been shown to increase systematically with the accumulation of sensory evidence (Kelly and O'Connell, 2013; O'Connell et al., 2012). If the P3 amplitude reflects the amount of evidence required to reach a decision threshold, our results may indicate that appraising unpleasant scenes involves more effortful evidence gathering and thus more demanding evaluative processing.

The subsequent LPP is associated with sustained attention to motivationally relevant stimuli and more elaborate processing (Cuthbert et al., 2000; Schupp et al., 2000) and has been linked to emotional and motivational significance, with larger amplitudes indicating deeper processing of salient content (Hajcak and Foti, 2020). The positive association between LPP and ratings of safety, beauty, and fascination supports this interpretation. Individuals showing larger LPP amplitudes may have engaged more elaborately in scene evaluation, investing greater attentional resources in aesthetic appraisal.

Together, our results regarding P3 and LPP amplitudes appear to capture complementary but distinct aspects of environmental appraisal. While both components are related to evaluations of aspects of the environment, they likely index different processing stages. The P3 component might reflect earlier, effort-related attentional engagement, while the LPP might reflect later, more elaborative motivational pro-

cessing. The two components also show partially selective associations with scene attributes, suggesting at least partially independent contributions to the perception of urban environments.

4.4. Individual Differences

Among personal predictors, the size of the city participants grew up in showed a significant impact on subjective ratings. Participants raised in larger cities reported lower arousal and stress in response to urban stimuli, while perceiving scenes as more open. This pattern contrasts with neuroimaging work showing heightened stress-related brain activity in urbanized individuals during social stress tasks (Lederbogen et al., 2011; Winz et al., 2022). While stress reactivity may be heightened, our findings suggest adaptation or desensitization to visual urban stressors (Frissen et al., 2014), at least on the level of subjective ratings. Individuals raised in cities may have developed habituated responses to urban stressors. Urban upbringing has also been linked to altered spatial perception and more global scene processing strategies (Koivisto and Grassini, 2023), potentially reducing sensitivity to specific environmental cues.

Gender differences emerged in both subjective ratings and ERPs. Non-male participants exhibited more negative N1 amplitudes, consistent with prior demonstrations of gender differences in early visuo-spatial processing (Mikhailova et al., 2012). Non-male identifying participants also provided lower ratings of beauty and fascination. These differences could reflect biological factors in attention allocation or sociocultural differences in aesthetic preferences and task engagement (Vessel et al., 2012). However, the present results do not indicate a general gender-related difference in neural activity during the processing or appraisal of environmental scenes. While the P3 and LPP components significantly predicted beauty and fascination

ratings, their amplitudes were unaffected by gender. Conversely, the N1 component showed a clear gender difference but did not predict subjective ratings. This pattern is noteworthy, as no prior studies have reported robust gender differences in the N1 component specifically related to urban scene processing. Future research should therefore explore potential gender-specific influences of urban features on early perceptual mechanisms. Importantly, the observed gender differences in N1 amplitudes and in aesthetic ratings do not appear to be linked through later evaluative processes indexed by the P3 and LPP components.

4.5. Limited Effects of Predictors

A pattern across our findings is the limited number of significant effects for LLVFs and semantic image contents. Among eight extracted LLVFs that have previously been shown to significantly affect our outcome variables (Celikors and Wells, 2022; Ma et al., 2023; Samaan et al., 2024), our results could only replicate the effects of edge density measures and depth, while the effects of green pixels, saturation, brightness, entropy, and fractal dimensions failed to be replicated. Similarly, among semantic categories, only greenery/built ratios and sky area showed robust effects, while the presence of cars and people had no significant influence on any outcome measures. This finding contrasts with our previous study using the same experimental protocol and stimuli (Sander et al., 2024), where these predictors showed small but significant effects. This discrepancy can possibly be explained by originally small effects combined with reduced statistical power in our selected subset of stimuli. Additionally, in the present study, a larger number of models led to stronger multiple hypothesis correction, causing many predictors to fail to achieve statistical significance. Beyond these considerations, the limited predictor effects likely stem from the visual complexity inherent in ecologically valid urban scenes (Sander et al., 2024).

In naturalistic urban scenes, environmental features are embedded in multivariate contexts where numerous properties covary, making it difficult to isolate individual feature contributions. Prior research demonstrating the effects of specific features often used controlled and simplified stimuli where the feature of interest was the primary varying dimension. In our ecologically more valid approach, single quantifiable features may be overshadowed by a multitude of other properties.

4.6. Limitations and Future Directions

The stimulus material of the present study was selected for ecological validity and captures the actual visual complexity people encounter in urban scenes. This realism, however, also reproduces the inherent relationships and co-occurrences among various environmental features. Such interdependencies make it challenging to isolate the specific contribution of individual factors using simple linear models and global image statistics. Consequently, our analytical approach may have been overly reductive for the complex stimulus set, and subtle feature effects may have been masked by uncontrolled variability within the scenes. Additionally, the high multicollinearity between semantic predictors and LLVFs further complicates interpretation, reflecting natural co-occurrence patterns that cannot be experimentally disentangled without artificial stimulus manipulation. This limitation constrains causal inference and leaves open whether observed effects reflect truly distinct influences or correlated properties. Moreover, global image properties such as mean saturation and total sky area may be too coarse to capture what humans actually attend to. Viewers might not experience scenes as uniform averages but selectively attend to salient regions in the stimulus. Region-specific analyses might therefore better predict responses (Fernandes and Castelhano, 2021). Future studies jointly analyzing EEG and eye-tracking could provide insights about what aspects of a scene participants focused on and,

hence, which image properties were actually processed.

In general, static images might not allow for capturing the dynamic aspects of real-world experiences, and future research should address the issue of complex naturalistic stimuli through complementary approaches. Virtual reality (VR) experiments could create highly realistic but systematically manipulated urban scenes where specific features vary independently, enabling more reliable interpretations while preserving the immersive experience. Alternatively, exploration of fringe-case urban environments and careful selection of pre-quantified scenes might enable the use of naturalistic stimuli by assuring sufficient independence while maintaining variability in predictors. Finally, field studies with mobile EEG could validate laboratory findings in real-world contexts.

4.7. Conclusion

The present study investigated subjective and neural responses to urban environments presented as static images. Subjectively, greenery in the scenes consistently promotes positive outcomes while sky and depth show negative effects, challenging oversimplified assumptions about perceived openness and sky view, and underscoring the importance of context. This study demonstrates that neural responses to urban environments reveal both early categorical differentiation and later evaluative processes. Modulations of the visual evoked P1 by natural greenery suggest preferential early processing of biophilic content before artificial or built aspects of environments as reflected in N1 modulations. Later event-related components likely reflect evaluative properties, with the P3 component potentially reflecting evidence accumulation for the subsequent response, reflecting differences in response thresholds for different aesthetic evaluations, and the LPP indexing sustained engagement with the stim-

uli. The disconnect between early visual processing and later evaluative processes predicting specific ratings suggests a complex relationship and potential mediating processes between perception and appraisal. The specifics of this relationship remain elusive. To better understand human responses to urban scenes and their specific characteristics, neural, behavioral, and personal data must be integrated to enable fine-grained analysis of perception-related brain activity. This should best be done in the real world to achieve the highest ecological validity possible to serve as the baseline for controlled laboratory replications.

CRediT authorship contribution statement

Carolina Zähme: Writing – original draft, Writing - review & editing, Formal analysis, Data curation, Investigation, Visualization, Software. **Isabelle Sander:** Writing – original draft, Writing – review & editing, Investigation, Formal Analysis, Visualization, Conceptualization, Methodology, Data curation. **Aleksandrs Koselevs:** Writing – review & editing, Software, Formal Analysis. **Simone Kühn:** Writing - review & editing, Conceptualization. **Klaus Gramann:** Writing – review & editing, Supervision, Methodology, Conceptualization, Validation, Resources, Funding Acquisition.

Declarations

Data availability statement

The data analyzed in this study is available in the BIDS format in an OpenNeuro repository (doi:10.18112/openneuro.ds006850.v1.0.0). The full stimulus set used in the experiment, along with the code for experimental implementation, is available at `https://github.com/BeMoBIL/urban_appraisal-experiment`. All analysis scripts

can be found at: https://github.com/BeMoBIL/perception2appraisal_analyses.

Declaration of competing interest

The authors declare no conflicts of interest.

AI declaration statement

Generative AI (ChatGPT-5) has been used only to improve the readability and language of parts of the work.

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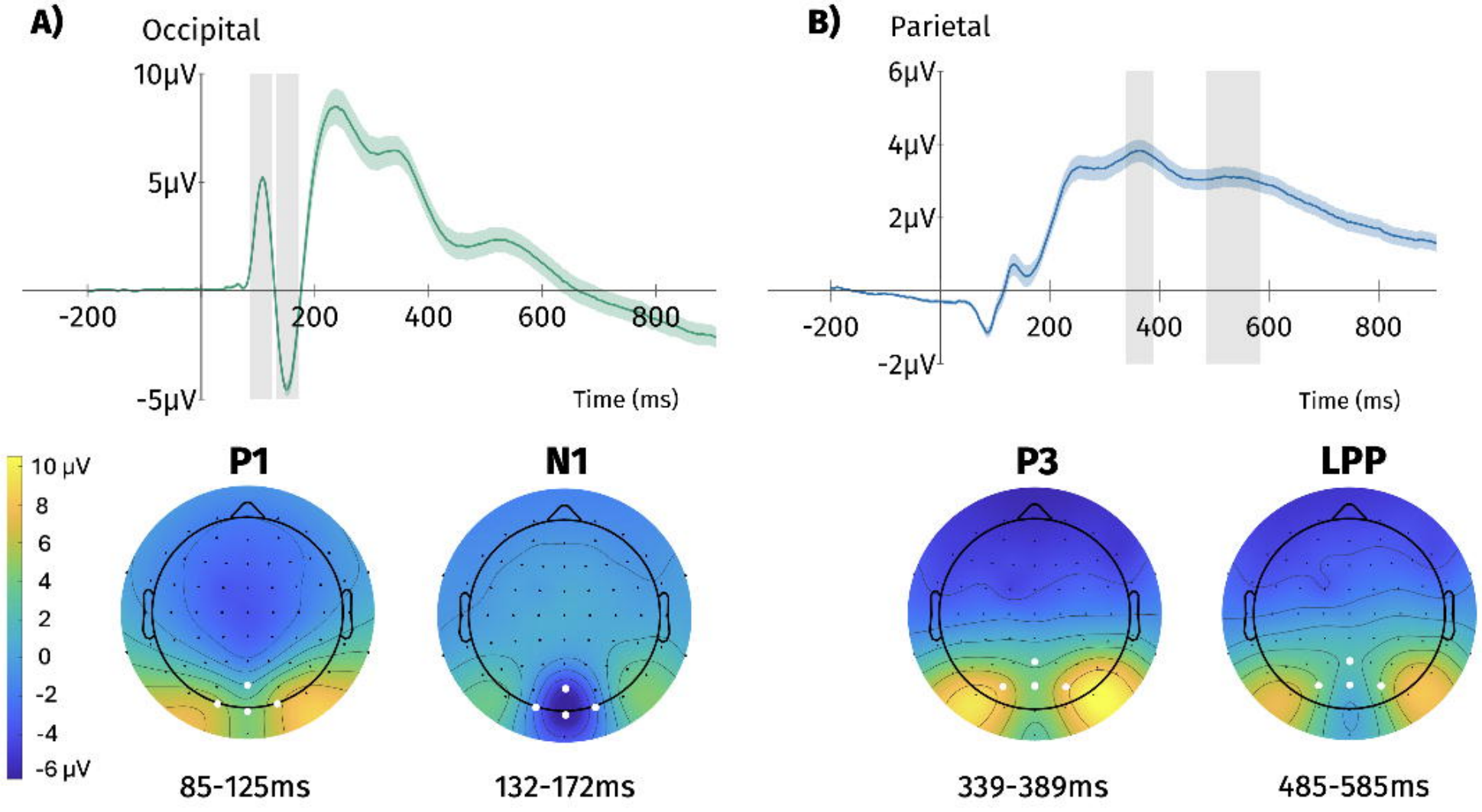
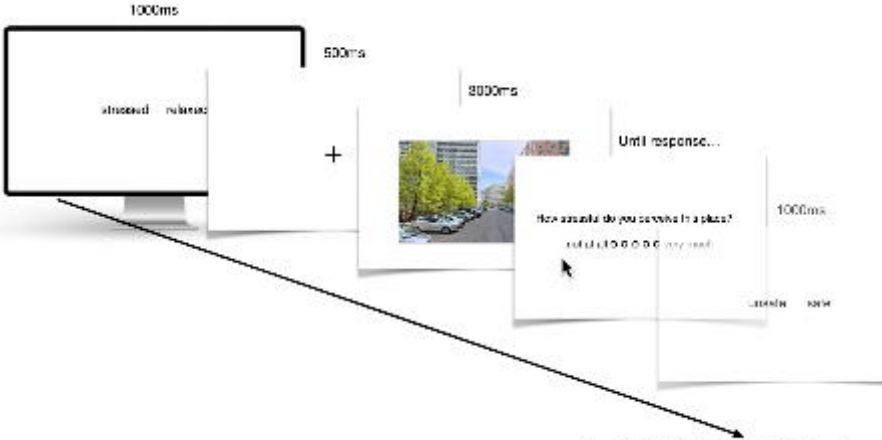
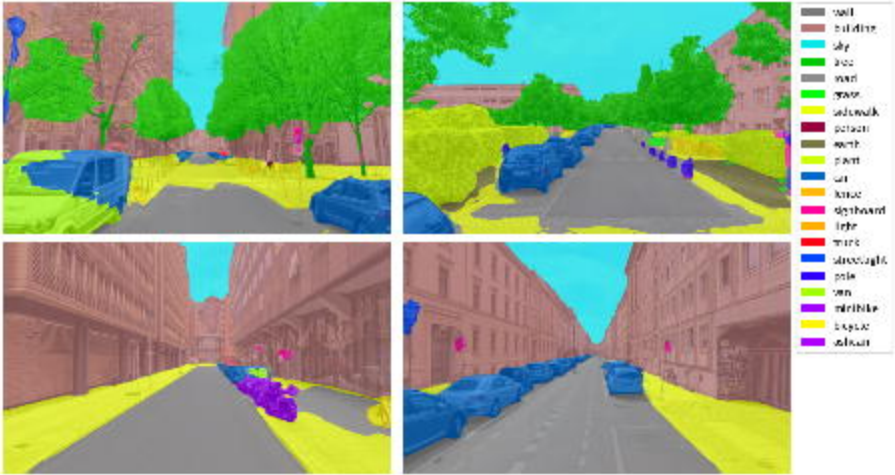
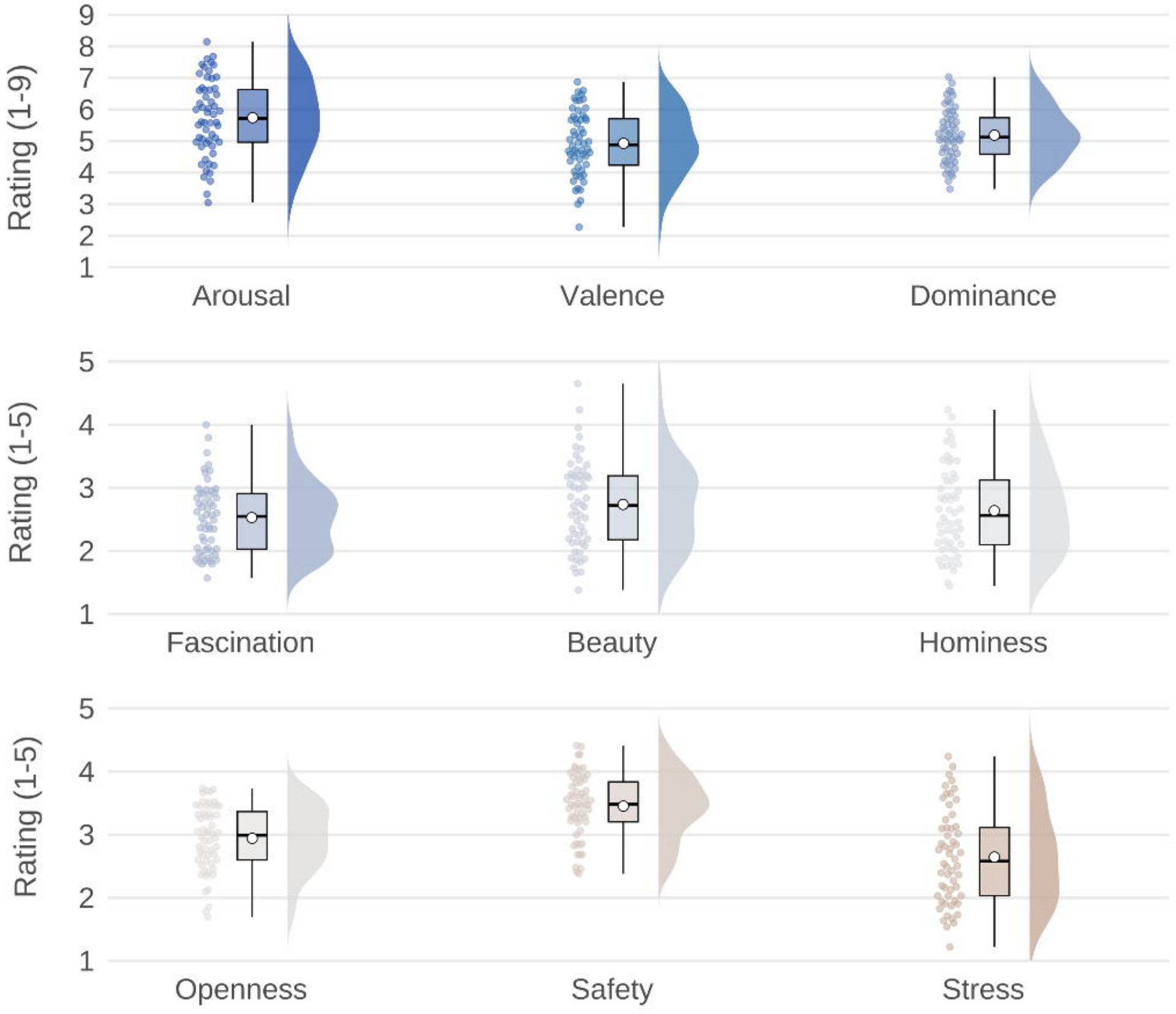
	Greenery/Built	Sky	Person	Car	Green Pixels	Saturation	SD Saturation	SED	NSED	Entropy	Fractal Dim.	Depth	P1	N1	P3	LPP	Arousal	Valence	Dominance	Safety	Openness	Hominess	Beauty	Fascination	Stress
Stress	-0.22	0.24	0.08	-0.14	-0.07	-0.16	-0.05	0.11	-0.25	-0.19	0.03	0.37	-0.04	-0.05	0.00	-0.04	0.57	-0.46	0.44	-0.48	-0.22	-0.42	-0.48	-0.22	1.00
Fascination	0.05	-0.19	0.08	0.05	0.06	0.12	0.13	0.06	0.16	0.15	0.05	-0.22	-0.05	-0.04	-0.02	0.01	-0.18	0.49	-0.34	0.29	0.22	0.45	0.56	1.00	
Beauty	0.18	-0.27	0.02	0.12	0.12	0.19	0.14	-0.01	0.28	0.22	0.05	-0.32	0.00	0.02	-0.02	0.04	-0.43	0.65	-0.52	0.48	0.32	0.62	1.00		
Hominess	0.20	-0.19	0.00	0.17	0.14	0.22	0.18	-0.05	0.27	0.21	0.03	-0.26	0.04	-0.01	-0.07	-0.03	-0.39	0.60	-0.51	0.44	0.32	1.00			
Openness	0.24	0.13	-0.02	-0.02	0.25	0.11	0.14	-0.28	0.28	-0.00	-0.06	0.20	0.02	0.09	-0.04	0.01	-0.20	0.32	-0.30	0.29	1.00				
Safety	0.14	-0.20	-0.02	0.09	0.08	0.10	0.04	-0.06	0.20	0.12	0.05	-0.22	-0.01	-0.01	0.04	0.08	-0.45	0.49	-0.47	1.00					
Dominance	-0.16	0.16	-0.02	-0.11	-0.09	-0.14	-0.09	0.07	-0.21	-0.14	-0.02	0.21	-0.04	-0.04	-0.00	-0.04	0.41	-0.53	1.00						
Valence	0.18	-0.23	0.01	0.12	0.13	0.20	0.16	-0.04	0.26	0.20	0.06	-0.28	0.01	-0.00	-0.04	-0.01	-0.40	1.00							
Arousal	-0.22	0.22	0.09	-0.14	-0.05	-0.15	-0.03	0.11	-0.24	-0.16	0.04	0.34	-0.03	-0.02	0.02	-0.03	1.00								
LPP	-0.01	0.01	-0.02	-0.03	0.00	0.00	0.01	-0.04	0.00	-0.06	0.01	0.01	0.17	0.35	0.71	1.00									
P3	-0.02	-0.02	0.03	-0.02	-0.02	-0.01	-0.00	0.03	-0.02	-0.04	0.04	0.02	0.13	0.26	1.00										
N1	0.04	0.03	-0.00	0.00	0.05	0.03	0.04	-0.12	0.05	-0.04	-0.06	0.03	0.43	1.00											
P1	0.08	-0.00	0.01	-0.00	0.02	0.06	0.04	-0.03	0.07	0.06	-0.03	-0.01	1.00												
Depth	-0.07	0.74	0.00	-0.22	0.15	-0.15	-0.02	-0.25	-0.13	-0.37	-0.20	1.00													
Fractal Dim.	-0.16	-0.24	0.20	0.01	0.06	-0.20	-0.06	0.26	0.04	0.01	1.00														
Entropy	0.44	-0.17	-0.00	0.36	0.17	0.39	0.30	0.03	0.37	1.00															
NSED	0.81	-0.20	-0.22	-0.15	0.53	0.57	0.56	-0.56	1.00																
SED	-0.61	-0.27	0.18	0.29	-0.59	-0.46	-0.41	1.00																	
SD Saturation	0.50	-0.06	-0.09	0.14	0.56	0.81	1.00																		
Saturation	0.66	-0.05	-0.20	0.07	0.51	1.00																			
Green Pixels	0.47	0.04	-0.19	0.04	1.00																				
Car	0.02	-0.08	0.09	1.00																					
Person	-0.19	-0.06	1.00																						
Sky	-0.03	1.00																							
Greenery/Built	1.00																								

Pearson r
1.0
0.5
0.0
-0.5
-1.0


A)
Occipital
10μV
5μV
-5μV
-200
200
400
600
800
Time (ms)
B)
Parietal
6μV
4μV
2μV
-2μV
-200
200
400
600
800
Time (ms)
10 μV
8
6
4
2
0
-2
-4
-6 μV
P1
N1
P3
LPP
85-125ms
132-172ms
339-389ms
485-585ms


1000ms
500ms
3000ms
Until response...
1000ms
repeat with total 56 stimuli x 9 scales


wall
building
sky
tree
road
grass
sidewalk
person
earth
plant
car
fence
signboard
light
mark
streetlight
pole
van
minibike
bicycle
saloon


Rating (1-9)
9
8
7
6
5
4
3
2
1
Arousal
Valence
Dominance
Rating (1-5)
5
4
3
2
1
Fascination
Beauty
Hominess
Rating (1-5)
5
4
3
2
1
Openness
Safety
Stress