Enhanced functional connectivity properties of human brains in nature scenes

Zheng Chen, Yujia He, Yuguo Yu

In this study, we investigated the impact of in-situ nature and urban exposure on human brain activities and their dynamics. We randomly assigned 32 healthy right-handed college students (mean age =20.6 years, SD= 1.6; 16 males) evenly to a 20-minute in-situ sitting exposure to either a nature or an urban-built environment, and measured their EEG signals. Analyses revealed that a brief in-situ nature experience may induce more efficient brain connectivity with enhanced small-world properties and stronger global functional connectivity than a stressful urban-built experience Exposure to nature may also induce stronger long-term correlated activity across different brain regions with a right lateralization. These findings enhance our understanding of the impact of different in-situ environmental exposures on subsequent brain activity, implying that a nature or nature-like environment may benefit cognitive performance and mental well-being. These results may foster the construction of large-scale cortical network models to mimic cognitive computation in real natural situations.

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1 Introduction

41 Real-world society and the surrounding environment may be critical in shaping cognitive functions
42 and brain performance. Evidence has suggested that social pressure and an intense workload can
43 suppress cognitive performance (Juster et al. 2010; Kuhlmann et al. 2005; Takahashi et al. 2004).
44 More recent studies, however, have demonstrated improvements in working memory and attention
45 shortly after a short-term nature experience (Berman et al. 2008; Lee et al. 2015; Taylor & Kuo
46 2009). In one example, a brief nature walk, as revealed in a recent empirical study, significantly
47 reduced anxiety-related neural activity in the subgenual prefrontal cortex (Bratman et al. 2015b),
48 enhancing positive cognitive performance and emotion regulation as well (Bratman et al. 2015a).
49 This phenomenon suggests that the natural environment in addition to social pressure may be
50 another key factor influencing human cognitive performance. However, only limited evidence
51 exists of environmental impact on human cognitive activity (Bowler et al. 2010).
52   Previous studies have suggested that 1/f characteristics in the log-log power spectrum (a
53 unique statistical feature of natural signals widely observed in natural environments but rare in
54 urban-built ones) may be potential key factors in shaping cognitive functions during natural
55 adaptation and evolution. More and more studies have revealed that mammalian brains can
56 perform more efficiently in response to naturalistic signals than artificial ones(Simoncelli &
57 Olshausen 2001). A perfect nature-like signal should contain a high-order statistic of a $1/f^\beta$-like
58 power spectrum. For example, a natural sound, which is one-dimensional, is close to a power
59 distribution of $1/f^1$ while a two-dimensional natural image is close to a distribution of $1/f^2$ and a
60 three-dimensional natural video is close to $1/f^3$ (Chen 2012). In-vivo evidence has demonstrated
61 that mammalian sensory systems (Gal & Marom 2013; Yu et al. 2005) can process natural signals
62 more efficiently than artificial ones. This characteristic of cognitive functioning may impact the
63 efficiency of neural networks (He 2011) and eventually define global cognitive performance.
64   The evidence above, therefore, suggests a new hypothesis: specifically, signal statistics
65 may be one critical factor driving human brains to perform more efficiently in nature settings than
66 more urban-built ones. Hence, in this paper, we examine the following questions: Do nature and
67 constructed artifacts differ significantly in their statistics of visual stimuli? Do human brains
68 respond differently to these different statistics? What are the significant differences in the brain
69 when responding to the two types of environmental signals? Although visual signals are probably
70 among the most important stimuli in the two types of environments, we believe that they only
71 partially capture the differences between the two. To fully capture the holistic environmental
72 experience, multisensory immersion is crucial. Therefore, we adopted in-situ exposure instead of
73 pictorial representation. To minimize the external variables that an in-situ experimental design can
74 present, we intentionally controlled the thermal comfort, including temperature, humidity, wind
75 chill, and other conditions, to ensure that the two treatments occurred within equivalent
76 circumstances.
77   Indeed, our new hypothesis is supported by a recent analysis of auditory perception. This
78 study found that music sound with a 1/f property, comparing to random noise, induced an enhanced
79 brain connectivity with efficient information flow across brain regions featuring a small-world
80 complex network property (Wu et al. 2013; Wu et al. 2012b). Small-world networks are
81 hierarchical structures with more efficient and well-connected hubs, which are widely found in
82 biological, ecological, social, world-wide web, molecular and neuronal networks (Watts &
83 Strogatz 1998b). The small-world network, because of these hubs, usually entails a large clustering
84 coefficient and short path length, enabling more efficient flow of information than that found in

85 randomly ordered nonhierarchical networks. In this study, we examined the EEG functional
86 connectivity during in-situ nature and urban experiences, including functional correlation, small-
87 world network statistics, 1/f statistics and their lateralization.
88   Experiment-observed functional network connectivity could be valuable for constructing
89 large-scale neural network models underlying cognitive computation and cortical information
90 processing (Ampazis et al. 2015; Ding et al. 2013; Gao et al. 2014; Sun 2013). In many existing
91 computational designs, networks are generally studied with the resting state as the default mode,
92 which is not the actual state in which brains execute behavior. Our study of how brain functional
93 connectivity changes, both temporally (e.g., 1/f statistics) and spatially (e.g., small-world statistics
94 and correlation) in response to sensory stimuli, may inspire alternative designs for cognitive
95 computation such as reservoir computing and attractor networks (Gros 2009).
96

2   Methods

98 In this study, we compared the brain performance of 32 healthy right-handed participants (mean
99 age=20.6, SD=1.6, 16 males) during a 20-minute in-situ sitting exposure to nature and to a
100 constructed environment. We utilized a portable wireless EEG recording device in addition to self-
101 report psychological scales. This study was approved and supervised by the Ethics Committee of
102 Tongji University (no. 2015yxy103).
103   No significant neurotic personality was found among the participants as indicated by scores
104 (mean = -1.58~1.33 on a 7-point Likert scale) from the neuroticism subscale of the NEO
105 Personality Inventory (Costa & McCrae 1992). Participants reported small everyday stresses
106 (mean= 0.29, SD=1.90 on a 7-point Likert scale) and slightly stress-reducing living environments
107 (mean=0.32, SD=1.40 on a 7-point Likert scale). They were generally well rested (sleeping
108 hours=6.90, SD=1.33) with a broad range of work (studying hours = [1.5, 15], mean=8.06,
109 SD=3.25) and entertainment (hours=[1,11], mean=3.25, SD=2.35) schedules, besides moderate
110 exercise (mean hours=0.73, SD=0.49) and exposure to nature (mean hours=0.83, SD=0.68) on a
111 daily basis.

2.1. Site Selection

113 Because this study was designed to examine the extent to which unique statistics of natural signals
114 induce more efficient brain functioning, we used the β values in the 1/f statistics of visual stimuli
115 as criteria for site selection. Research has shown that the β values of nature images are likely to be
116 close to 2 (Szendro et al. 2001; West & Shlesinger 1990) due to an appropriate distribution between
117 low-frequency contours (e.g., shapes of trees, mountains) and high-frequency details (e.g., fractal
118 edges, random texture and lines). This implies a moderate long-term correlation level across image
119 components of all frequency ranges. With increasingly uniform materials (e.g., concrete) and
120 limited high-frequency detail, urban-built scenes may be more likely to reveal a larger β, but we
121 were less confident before verification.
122   To find a typical nature and urban-built environment, we first examined a large number of
123 photographs. Because of limited confidence in the β estimation for built scenes, we intentionally
124 investigated a larger sample of photographs of urban-built scenes (n=135) than nature scenes
125 (n=80). All of the photos had been captured and reviewed by professional landscape architects and

126 architects. Both nature and urban photos revealed a normal distribution of β (Fig. 1c and d), with
127 means of 2.30 (SD=.22) and 2.61 (SD=.18), respectively (Fig. 1a). These results were consistent
128 with those from a previous study (Braun et al. 2013) which documented an average β of 2.24
129 (SD=.19) for nature scenes and 2.53 (SD=.24) for buildings, amidst sample sizes of 200 photos
130 each.
131   Therefore, we intentionally selected two typical sites with representative β slopes: a
132 wooded campus garden (β= 2.24) for the nature scene and a traffic island under an elevated
133 highway (β=2.62) for the urban-built scene (Fig. 1b). Specifically, the nature scene consisted of
134 89% visible green and water along with 4% visible buildings and paved areas from where
135 participants were seated while the urban-built scene consisted of 8% visible green with 56% visible
136 buildings and paved areas (Fig. 2). To control for external variables such as thermal comfort levels,
137 all experiments were conducted in May and June in a comfortable temperature of 22 degrees
138 centigrade (difference within ±5), 81 percent humidity (difference within±13), an acoustic level of
139 72 db (difference within±12), and a wind speed of 0.8 m/s or slower.

140 **2.1. Procedure and Data Validity Control**

141 The experiment was taken via a structured procedure (Fig. 3). After first signing a written consent
142 form containing a written explanation of the experimental procedure and risks, participants
143 completed a two-page pretest questionnaire. Portable EEG electrodes were positioned onto
144 participants' scalps, and they were then asked to sit facing a wall to temporarily exclude visual
145 information. Participants were instructed to alternate keeping their eyes open and closed in four
146 one-minute cycles. After this pre-experimental phase, participants were told to turn and face the
147 environment for 20 minutes[1]. Participants were asked to sit either in a built environment (i.e., a
148 traffic island under an elevated highway), or in a natural environment (i.e., a heavily wooded
149 campus garden) facing a designated view. After viewing the environment, participants completed
150 a posttest questionnaire and a short interview. To prevent their minds from wandering or becoming
151 drowsy, participants were told to count from 1 to 1000 soundlessly at a speed which was slow
152 enough not to interrupt the environmental experience.
153   We specifically adopted eye-opened and eye-closed pretests in the beginning of the
154 experiment to verify the reliability/stability of electrode recording across the 20 minutes of
155 environment exposure. We examined the power distribution and 1/f statistics of two electrodes at
156 the primary visual cortex (O1 and O2) during the two pretests. The results revealed a clear 1/f
157 statistic in both the nature and built environments (Fig. 3b~c). At both sites, there was also a clear
158 bump at the top of the 1/f slope near logf=1 (the location of the alpha range) during the eye-closed
159 session, while the bump dropped towards the slope during the eye-open session. This bump-
160 dropping effect during the eye-open session is called alpha-blocking (Könönen & Partanen 1993).
161 The successful capture of 1/f statistics (arrhythmic firing) and alpha-blocking (rhythmic
162 oscillation) as expected supports the validity of the data.

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[1] EEG of the entire 20-minute exposure was measured for the latter 16 participants (8 nature) while only the latter half (10 minutes) of the exposure was measured for the first 16 participants (8 nature). Paired t-test revealed no significant differences between the first half (10 minutes) and the latter half (10 minutes) of exposure for the 16 participants whose EEG was recorded for the entire 20 minutes in terms of EEG correlation and β exponent, except for two individuals in the built environment groups (see supporting materials). Therefore, the full recording length from both groups (10 minutes for first half and 20 minutes for the latter half) was used for analyses.

163 **2.2. Measures**

164 Participant affective status was measured both before and after the environmental exposure using
165 the Profile of Mood State questionnaire (Curran et al. 1995). In this questionnaire, participants
166 were asked to rate the extent to which 40 descriptive words captured their affective status on a 7-
167 point Likert scale.
168 An Emotiv wireless headset (Dekihara & Iwaki 2014) and accompanying software was used to
169 measure EEG. The headset consists of 14 sensors positioned on the wearer's scalp according to
170 the international 10–20 system: antero-frontal (AF3, AF4, F3, F4, F7, F8), frontocentral (FC5,
171 FC6), occipital (O1, O2), parietal (P7, P8) and temporal sites (T7, T8). Brain waves are measured
172 in terms of amplitude (10–100 microvolts) and frequency (1–70 Hz). EEG data were analyzed via
173 Matlab and EEGlab. Data were first filtered (<0.5Hz or >50 hz) using EEGlab and adjusted for
174 artifacts using Adjust 1.1 (Mognon et al. 2011).
175 The signal was first analyzed via Fast Fourier Transformation and then categorized into five
176 frequency bands: delta (1–4 Hz), theta (5–8 Hz), alpha (9–12 Hz), beta (13–25 Hz), and gamma
177 (26-45 Hz). Total mean power by frequency bands and brain connectivity were calculated.
178
179 *Correlations*
180   Correlations between signals at different electrodes were calculated using the following
181 equation:

$$r(x) = C_{AB}(x)/(C_{AA}C_{BB}) \qquad \textbf{(1)}$$

182 where the cross-covariance between signals A and B was noted as C_{AB} while the auto-covariances
183 of signals A and B were noted as C_{AA} and C_{BB}, respectively (Guevara & Corsi-Cabrera 1996).
184
185 *Small-World Network Statistics* (Watts & Strogatz 1998b; Wu et al. 2013)
186   We used a small-world characteristic value C_{mean}/ L_{mean} to measure the small-world
187 network propriety, where L_{mean} is the averaged shortest path length and C_{mean} is the clustering
188 coefficient. A higher small-world characteristic value C_{mean}/ L_{mean} indicates a higher clustering
189 effect at smaller path lengths, which is therefore indicative of more distinct small-world
190 characteristics. The clustering coefficient of an electrode v_i was calculated as
191

$$C_{v_i} = \begin{cases} 0 & k \leq 2 \\ \dfrac{2n}{k(k-1)} & k > 2 \end{cases} \qquad \textbf{(2)}$$

193 where k denotes the number of electrodes of an EEG correlation with the electrode v_i higher than
194 a given threshold, and n denotes the number of paths with a correlation higher than the threshold
195 between the k electrodes that it is connected to (where n equals C_k^2 in a saturated scenario). The
196 averaged clustering coefficient for an individual is then calculated as

$$C_{mean} = \frac{1}{14}\sum_{i=1}^{14} C_{v_i} \qquad \textbf{(3)}$$

198   The shortest path length was calculated from the shortest of all total paths from v_i to v_j
199 for a pair of electrodes v_i and v_j, using the Floyd algorithm. The path length between two immediate
200 neighbors was coded as 0 (to itself), 1 (beyond threshold) or 13 (below threshold). For each
201 individual,
202

203
$$L_{mean} = \frac{1}{C_{14}^2} \sum_{\substack{i=1, j=1 \\ i<j}}^{14} L_{v_i, v_j} \qquad\qquad \textbf{(4)}$$

204 where $L_{vi,vj}$ denotes the shortest path length between a pair of electrodes v_i and v_j.
205
206 *1/f Statistics*
207   The 1/f statistics were calculated as the regression slope β (absolute value) of the log power
208 over the log frequency in a $1/f^β$ power spectrum. The β values were first calculated at each electrode
209 for each individual and then linearly combined as electrode and individual global means.
210 Lateralization was calculated as log(R)-log(L), where R and L represent the right and left
211 symmetrical pairs (i.e., AF4/AF3, F8/F7, F4/F3, FC6/FC5, T8/T7, O2/O1), respectively.
212
213 *Statistical Test*
214   As we were primarily interested in documenting how brain regions responded to
215 environmental stimuli, all differences were tested against electrode variance using T test paired by
216 electrodes, with an exception of small-world network property which was tested against individual
217 variances using independent T test.

218 **3   Results**

219 **3.1. Impact on Affect and EEG Power**

220 To investigate the impact of environmental exposures on affect, we linearly combined the
221 constructs on a 7-point Likert PMOS psychological scale reported by participants. All participants
222 sitting in front of nature, after a 20-minute exposure, reported a more positive affective status than
223 those sitting in front of a built environment. Specifically, nature-exposed participants reported less
224 fatigue (nature=-2.38, SD=4.65; built=1.69, SD= 4.73; p=.020), as well as better-maintained vigor
225 (nature=-.50, SD=4.65; built=-4.08, SD=3.18; p=.045) and less negative mood disturbance
226 (nature=-.394, SD=11.29; built =9.64, SD=15.07; p=.007).
227 To investigate the impact of environmental exposures on EEG power, we performed a two-way
228 ANCOVA on EEG power in five frequency bands (delta, theta, alpha, beta and gamma) in two
229 conditions (nature and built environment exposures) with their eye-open pretest baselines
230 controlled. ANCOVA confirmed a significant overall power difference between nature and built
231 environment (F(1,129)=4.175 p=.043), with a higher power found during nature exposure in all
232 frequency bands confirmed by T-test paired by channels (all p<.001, compared at a Bonferroni
233 correction of .05/5=.01).

234 **3.2. Impact on Functional Connectivity and Signal Correlation**

235 We analyzed the averaged correlations of EEG power at different frequency bands to understand
236 the functional connectivity (Fig.4). A channel-wise two-way ANCOVA was performed on EEG
237 power correlation in five frequency bands (delta, theta, alpha, beta and gamma) and in two
238 conditions (nature and built environment exposures) with their eye-open pretest baselines
239 controlled. We observed a significant higher overall power correlation during nature exposure

240 compared at that during built environment exposure (F(1,129)=85.09, p<.001), with a higher
241 power found during nature exposure observed in delta (p=.008<.01, compared at a Bonferroni
242 correction of .05/5=.01), theta, alpha and beta (all p<.001<.01).
243 We then analyzed the averaged correlations of EEG power to analyze the difference across
244 electrodes. A participate-wise two-way ANOVA was performed on mean EEG power correlation
245 in 14 electrodes and in two conditions (nature and built environment exposures) with their eye-
246 open pretest baselines controlled. Again, we observed a significant a significant higher overall
247 power correlation during nature exposure compared at that during built environment exposure
248 (F(1,419)=15.32, p<.001), but no significant difference at individual electrode using independent
249 T test after Bonferroni correction.

250 **3.4. Impact on Small-World Network**

251 At the beginning, we calculated the average shortest path length L_{mean} and network clustering
252 coefficients C_{mean} to quantify the information flow efficiency within the network. We observed
253 that L_{mean} was slightly smaller in the nature scene condition than in the urban environment (Fig.
254 5a), although there was no significant difference observed across all threshold values. The
255 clustering coefficients were significantly higher in the nature scene condition than the urban
256 condition for the medial threshold values (Fig. 5b), indicating a better small-world property. To
257 see this clearly, we defined a new measure C_{mean}/L_{mean} to directly quantify the small-world
258 characteristic to evaluate the impact of environmental exposure on brain functional network
259 connectivity. We observed higher values for C_{mean}/L_{mean} for almost all thresholds (Fig. 5c) for the
260 nature scene (the t-test against participant variances indicated significance at .50 with p=.041, .60
261 with p=.046 and .095 with p=.044, respectively). Hence, participants sitting in the nature scene
262 may have had more efficient information communication because of a better small-world network
263 property.

264 **3.5. Impact on the temporal long-term correlation (1/f characteristic) of EEG**

265 To investigate the 1/f statistics during the two environmental exposures, we first investigated the
266 global β value averaged across the β values of all electrodes. We found, as expected, a significant
267 difference during the viewing of the two scenes (p=.033, t-test paired by electrode, Fig. 6a). To
268 further investigate the spatial variation of 1/f statistics, six brain regions were studied: the left
269 (AF3, F7 and F3) and right antero-frontal (AF4, F8 and F4), left (FC5 and T7) and right
270 temporal/frontocentral (FC6 and T8), left (P7 and O1) and the right parietal/occipital (P8 and O2).
271 A trend towards larger β slopes in these brain regions was observed during the nature experience
272 (Fig. 6*b*). After noticing a possible lateralization effect of β during the above brain region analysis,
273 we compared the lateralization of β between nature and built environment exposure. The two
274 environments revealed distinct lateralization in β values. Specifically, a right lateralization (a
275 larger β slope in the right) was found at F8/F7 (p=.030, t-test against participant variance),
276 FC6/FC5 (p=.005) and T8/T7 (p<.001) in the nature experience while a right lateralization at
277 T8/T7 (p=.002) and P8/P7 (p<.001) was instead found for the built environment (Fig. 6*c*).
278
279

280   **4   Discussion**

281   While studies have emphasized that the social pressures of urban life can induce cognitive decline
282   and discomfort (Lederbogen et al. 2011), our study revealed that the distinct statistical properties
283   of the artificial built environment relative to those from the natural scenes also induce different
284   macro statistical properties of brain EEG signals, which may therefore lead to cognitive decline
285   and discomfort. Growing experimental and theoretical evidence supports the notion that human
286   and animal visual systems are adapted to represent natural scenes efficiently (Simoncelli &
287   Olshausen 2001). The statistics of natural images are typically characterized by the scale-invariant
288   power spectra, with the slope of the frequency-power relationship in a log-log plot close to 2 (the
289   so called $1/f^2$ statistics) (Ruderman 1997; Ruderman & Bialek 1994). The slope of 2 suggests the
290   presence of long-term correlations among picture pixels in different scales. Because brain vision
291   systems have evolved in the natural world, it has been strongly suggested (Olshausen & Field
292   1996; Simoncelli & Olshausen 2001) that early visual pathways were adapted to de-correlate the
293   correlational structure of the input signals efficiently and then pool all the encoded information
294   together in the higher level cortex to formulate internal pictures of the outward natural world.
295   Hence, brain sensory systems may function more efficiently in response to the natural scene's
296   characteristics and consume less energy in their visual processing of natural signals (Laughlin
297   2001; Olshausen & Field 1997; Simoncelli & Olshausen 2001). As stated in our previous study of
298   primates (Yu et al. 2005), the visual function of cortical neurons may be designed to tune to $1/f$
299   characteristics for efficient coding, which induce a preference in the visual system for natural
300   signals in the natural environment. In addition, a recent study (Torralba & Oliva 2003) reported
301   that cardinal (horizontal and vertical) orientations are more prevalent in sample image statistics of
302   man-made artifacts (e.g., urban buildings, streets, highway infrastructures) than in images of
303   natural scenes. In addition, there are more low frequency components and less high frequency
304   components in built artificial views, resulting in a larger slope (>=2.5) in the power spectra of
305   urban images (Braun et al. 2013; Torralba & Oliva 2003). This raises a nontrivial issue. That is,
306   after prolonged exposure to built artifacts with signal statistics distinct from nature, could human
307   neural responses differ in terms of statistical properties and therefore become overstressed and
308   uncomfortable (Penacchio & Wilkins 2015)? Actually, recent studies have documented a
309   significant drop in both self-reported rumination and neural activity in the subgenual prefrontal
310   cortex of healthy participants after a 90-min walk in a natural environment, while no such effect
311   was observed for an urban walk (Bratman et al. 2015b).
312   Our study here examined the above issues and observed several new statistical properties
313   of brain EEG responses for humans set in nature or urban environments. First of all, as expected,
314   analysis of the questionnaire forms reported that all the participants reported more pleasant feelings
315   and less stress in nature than in the urban-built environment. Second, when observers were sitting
316   within nature, their brain EEG activities were more strongly correlated (almost among all
317   frequency bands) across the whole brain globally than those sitting in an urban environment. This
318   suggests that different cortical regions may be in more organized functional states. This idea has
319   been supported by recent behavior studies which revealed that performance on working memory
320   tasks improved shortly after a nature experience (Berman et al. 2008; Bratman et al. 2015a; Taylor
321   & Kuo 2009). The lower global functional EEG connectivity observed during the urban experience
322   may imply that our neural network may be less efficient at perceiving and reconstructing urban
323   environment and built artifacts. However, further studies are needed to verify this tentative
324   hypothesis.

325   Furthermore, we also calculated the small-world property of all the brain EEG recording
326   sites (Smit et al. 2008; Watts & Strogatz 1998a). Network measures were calculated as a function
327   of a certain Pearson correlation threshold value. There was a larger small-world network
328   characteristic value C_{mean}/L_{mean} in the nature than in the urban condition, with a significantly larger
329   clustering coefficient C_{mean} at thresholds of .50 (p=.041), .60 (p=.046) and .95(p=.044). The
330   enhanced small-world network in nature exposure suggests a more optimized configuration and a
331   higher efficiency of information transfer across the brain regions than that in the urban-built
332   environment. This enhanced small-world property has also been observed in the context of music
333   perception (Wu et al. 2012a) when compared to noise listening.
334   In addition, we have also studied the power spectrum properties of EEG signals and
335   observed that they demonstrated a reversed power law phenomenon, called $1/f^{\beta}$ statistics in the
336   frequency domain, indicating a power law distribution of frequencies. The $1/f^{\beta}$ statistics suggest
337   long-term correlations in the time domain. A large β value means that any two time events in the
338   EEG signal have a relatively large correlation time constant. A $1/f^{\beta}$ power spectrum, with power
339   tending to fall off with increasing frequency, indicates no particularly dominating periodic
340   oscillatory dynamic. Hence, a pure $1/f^{\beta}$ phenomenon is indicative of arrhythmic activity. Because
341   EEG signals are also well-known to be characterized by the different oscillatory bands, e.g., δ (0-
342   3Hz), θ (4-7Hz), α (8-12Hz) and β (13-30Hz), frequency bands that are correlated with some
343   special brain behavior state, the above observations suggest that brain activities are a combination
344   of oscillatory activity and arrhythmic activity. For decades, research has concentrated on the
345   former and discarded the latter as pure noise. Not until recently did evidence reveal that the latter
346   was more than just noise and may be intimately related to brain functioning(Ray & Maunsell
347   2011). In this study, we observed a larger β value for brain EEG in the natural scene than was
348   observed in the urban environment. The larger power-law exponent β suggests a higher time-
349   lagged autocorrelation, indicating that the past dynamics of the system have a stronger influence
350   on its future dynamics, i.e., the system has more long-range memory. A reduced power-law
351   exponent might indicate enhanced working task behavior, as observed in an ECoG study during a
352   visual detection task of unpredictable stimuli(He et al. 2010). Therefore, our observation here of a
353   larger β value for brain EEG in the natural scene may suggest more relaxed and associated brain
354   states than what exists in urban environments. However, identifying the best range of β values for
355   the brain in the best performance or most pleasant state requires a better designed task in the future.
356   The general observation that brain signals contain long-term correlation and oscillatory
357   components might reflect interactions between bottom-up information process and top-down
358   cognitive feedback. This requires further investigation to deepen our understanding of cognitive
359   computation processes within the brain. It will be interesting to construct large-scale cortical
360   circuit models to investigate the biophysical mechanism of the 1/f response and the oscillation
361   characteristics as revealed in this study. These brain response features, potentially important to
362   brain functioning (He 2014; Watts & Strogatz 1998b), have barely been considered in current
363   cognitive computational models. Moreover, the preference of brain sensory system for the 1/f
364   characteristic may also require further investigation of cortical computational modeling to reveal
365   the biophysical mechanism underlying cortically efficient coding. The experimental investigation
366   of the relationship between environmental statistics and cognitive processing could be valuable for
367   number of reasons. First, it may deepen our understanding of the functional properties of brain
368   sensory systems. Second, it may foster the derivation of new cortical computation models based
369   on environmental statistics for efficient coding. It might also be helpful in the design of new forms
370   of stochastic experimental protocols and stimuli for probing different brain sensory systems.

371 Certainly, the results here can also lead to fundamental improvements in the design of naturalistic
372 urban architecture that strengthens brain cognitive performance and computation.
373   In sum, while many studies have emphasized the impact of urban social pressure (e.g.,
374 unemployment, poverty) as being one of the critical stressors on human health and wellbeing
375 (Seresinhe et al. 2015; Tost et al. 2015), a brief walk or sitting in a natural environment, e.g., pure
376 natural woods, could benefit brain cognitive performance and alleviate the negative stressors. Our
377 studies suggest that a nature environment, as characterized by the long-term correlation statistics
378 in their visual signals, can evoke different brain oscillatory activity and arrhythmic activity, which
379 may help place brain functioning in a more pleasant and less-stressful state. In other words, brains
380 generate more memory-like effects of auto-correlated electrical signals when we are watching
381 nature than when we are watching a busy built environment. This might be an indication of better
382 memory formation in the natural environment than in the urban environment. Moreover, it may be
383 possible that this "redundant" autocorrelation, which is seen in many natural phenomena as well
384 as neuronal signals, could be important to our resilience and mental wellbeing. This idea requires
385 further careful investigation.

386 **4  Summary**

387   In last decades, there are increased experimental evidences reported that animal sensory
388 neurons process natural signals more efficiently than artificial signals (Lewen et al. 2001; Rieke
389 et al. 1995). Computational studies revealed that the structure and function of sensory neurons and
390 network may be designed to efficient coding to signals in natural environment due to long-term
391 adaptation and natural evolution. Our study designed in an early stage to examine whether the
392 human brain function more efficiently in a natural environment than in urban environment. The
393 answer and underlying mechanism related to this issue may be critical to understanding the
394 operating principle of human brains.
395   Previous experiments have revealed that a short walk in purely natural wooded area may
396 greatly refresh the brain's cognitive performance and alleviate negative stressors. Our study
397 revealed that in additional to the social pressures found in urban environments, the distinct
398 statistical properties of the built artifacts may also shape the human brain response properties
399 differently, and thus, further stress human brains. Additional investigations are needed to more
400 precisely examine the performance differences observed between these two types of environments.
401   This study revealed the presence of a more efficient brain network during a nature
402 experience than during an urban one. Specifically, stronger global functional connectivity was
403 observed in nature, as well as a more enhanced small world property with a higher small-world
404 characteristic value (C_{mean}/L_{mean}) and higher mean clustering coefficients (C_{mean}) at .50, .60 and
405 .95. The more efficient brain network in nature may help explain the better affective states reported
406 in this study and the potential cognitive improvements exhibited shortly after a nature experience
407 as observed elsewhere in the research literature (Berman et al. 2008; Bratman et al. 2015a; Taylor
408 & Kuo 2009).
409   This study also documented some relevant changes to long-term correlation characteristics
410 of human EEG signals during in-situ environmental exposures to nature and to a built environment.
411 We found a larger β exponent in the $1/f^{\beta}$ frequency spectrum during the nature experience, as well
412 as a larger β in the right hemisphere during the exposures to nature and to the built environments
413 with distinct differences. This may be among the earliest studies of changes in the 1/f power
414 spectrum exponent β of human EEG signals as a function of different environmental experiences.

415 A larger sample size and repeated experiments are needed to further investigate the key properties
416 intrinsic within the nature-related that impact the resulting EEG signal statistics. Greater
417 understanding of the functional connectivity characteristics observed in this study in response to
418 different environmental stimuli will be beneficial in constructing better cognitive computational
419 models.
420

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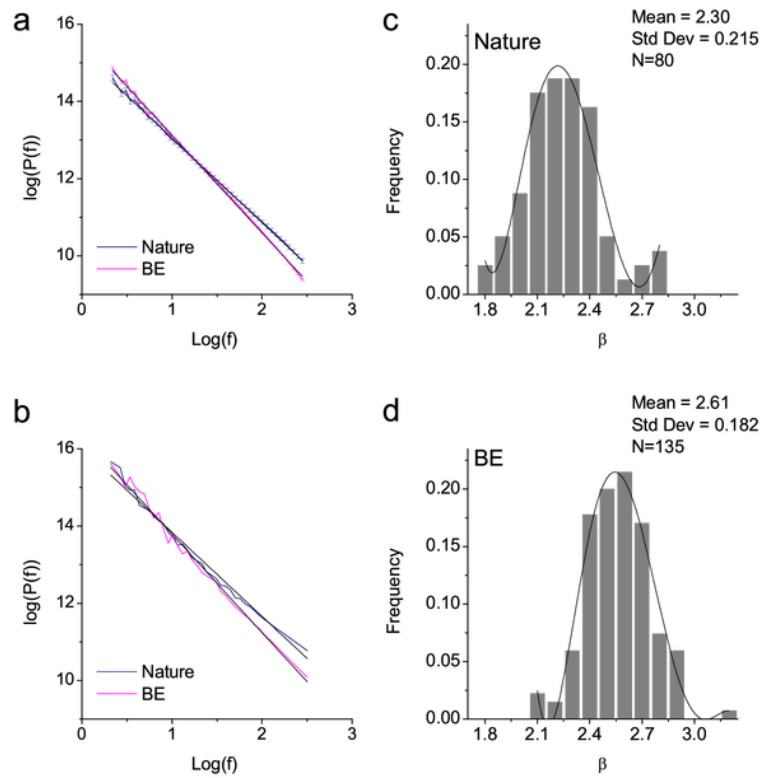
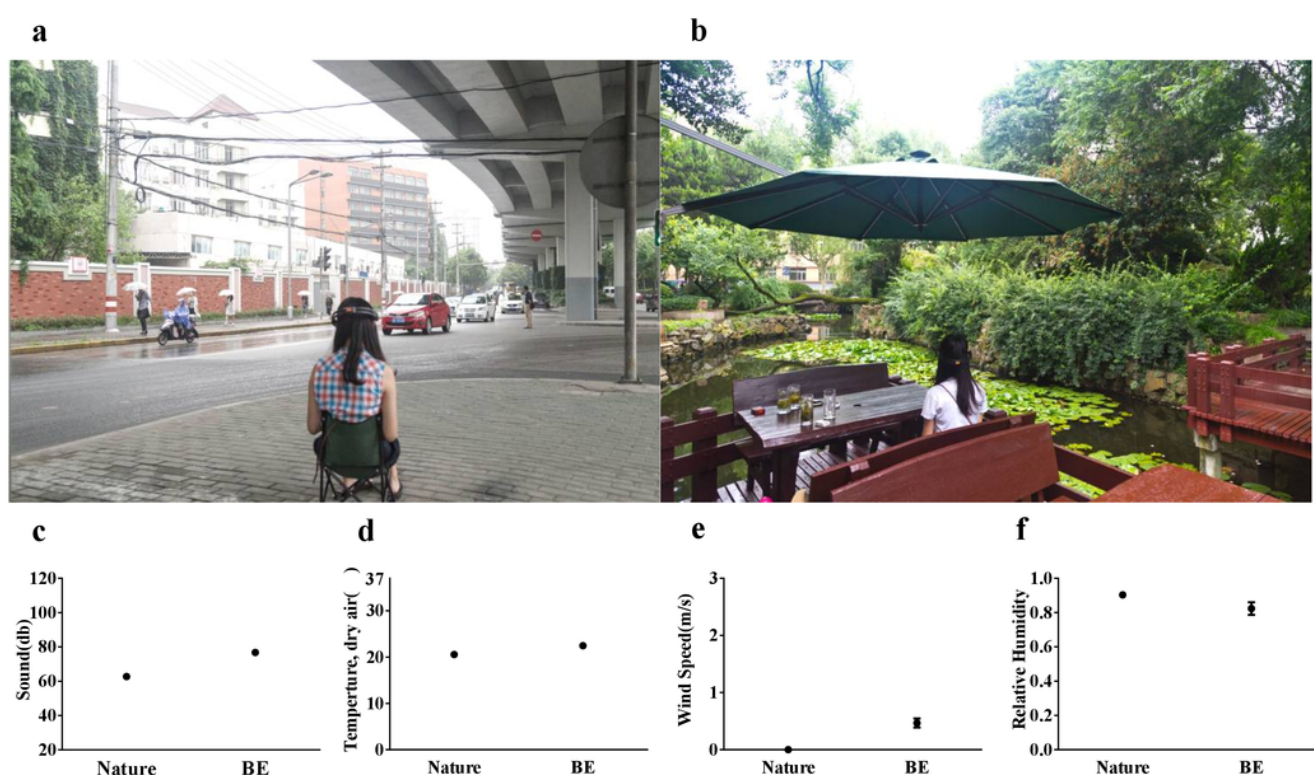
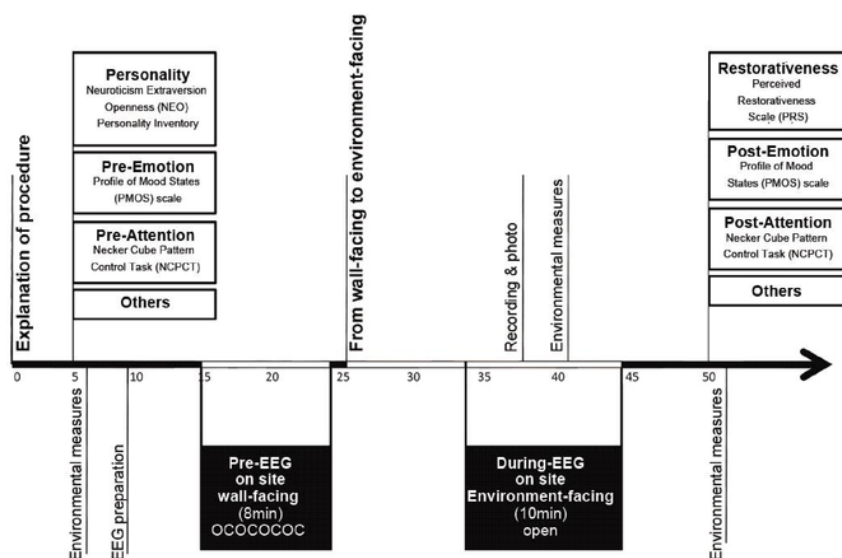
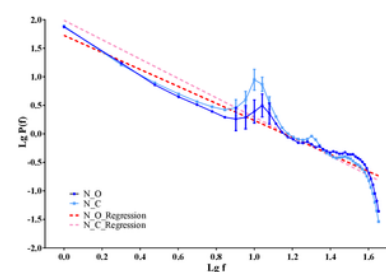
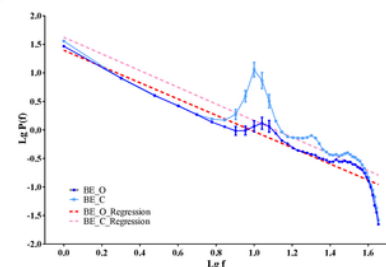
1

The 1/f statistics of visual stimuli in the nature and urban-built scenes.

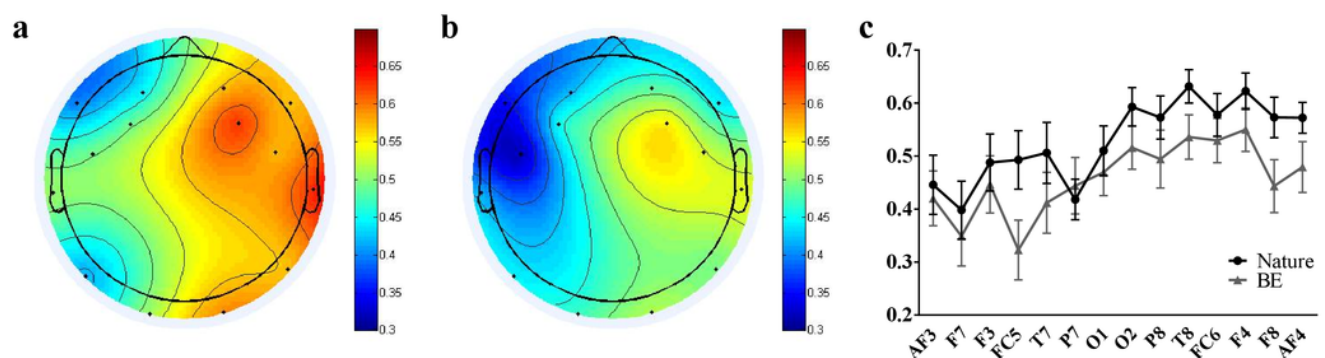
Eighty nature images and 135 urban-built environment (BE) images were analyzed, yielding distinct β slopes (*a*) in the nature (mean=2.30, SD=.22) and urban-built environment (mean=2.61, SD=.18, p<.001). The β distributions of the analyzed nature (*c*) and urban-built (*d*) environments are shown. We then selected two sites (*b*) with visual 1/f statistics representative of a nature (β=2.24) and urban-built environment (β=2.62). Error bars denote SEM.

Environmental conditions of the experiment.

A shaded traffic island as a built environment site (*a*) and a campus garden as a nature site (*b*). Acoustic conditions (*c*), temperatures (*d*), wind speed (*e*) and relative humidity (*f*) were intentionally documented and controlled. Error bars denote SEM.

3

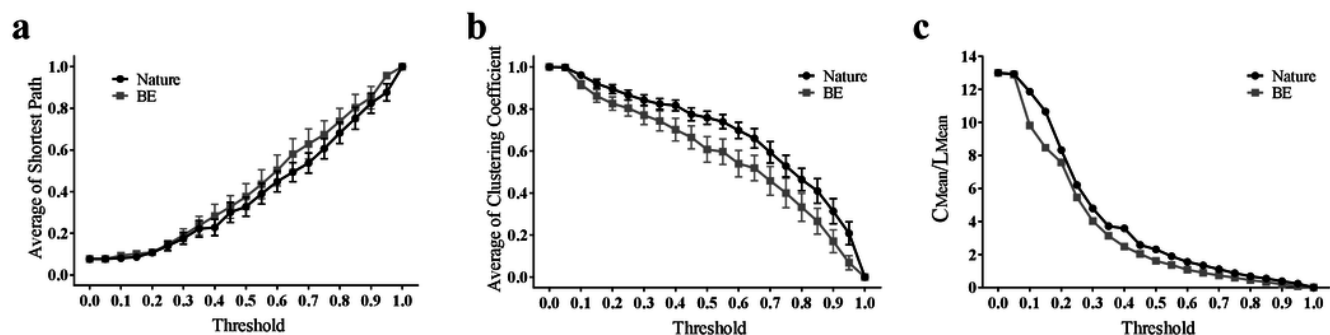
Experiment procedure and data validity.

Experiment procedure (*a*) was illustrated. The EEG log-transformed power distribution, as observed at the occipital lobe (O1 and O2) during the pre-test eye-open sessions and compared to the eye-closed session in both the nature (*b*) and built (*c*) environment sites, revealed a clear 1/f statistic and alpha-blocking effect. Error bars denote SEM.

4

EEG functional connectivity.

A higher global EEG correlation (p<.001, paired t-test by electrode) was found during nature experience (*a*) relative to the urban experience (*b*) while no significant difference was found in the eye-open baselines (p=.314, paired t-test by electrode). Average correlation coefficients ranged from 0.3 (blue) to 0.7 (red) at the 14 electrodes (*c*). Error bars denote SEM.

5

EEG small-world network statistics.

The average shortest path lengt h (L_{mean}) and average clustering coefficients (C_{mean}) in the nature and built environment experience. Although L_{mean} was comparable between the two exposures (*a*), a higher C_{mean} (*b*) was observed during the nature experience at a threshold of .50 (p=.041, t-test against participant variance), .60 (p=.046) and .95 (p=.044) . A higher C_{mean}/L_{mean} coefficient was consistently observed at virtually all thresholds (*c*). Error bars denote SEM.

6

The 1/f statistics of EEG.

EEG signals during the nature experience revealed a larger global β exponent than in the built environment (*a*, p=.033, t-test paired by electrode). The β values in the sub-brain regions are illustrated (*b*). A larger β in the right hemisphere (calculated by β lateralization , i.e., β_{right}-β_{left}) was found during the nature experience at F8/F7 (p=.030, t-test against participant variance), FC6/FC5 (p=.005) and T8/T7 (p<.001) while the built environment experience revealed a different right lateralization at T8/T7 (p=.002) and P8/P7 (p<.001) . Error bars denote SEM.