Landscape and Urban Planning 241 (2024) 104917

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Quantifying threshold effects of physiological health benefits in greenspace exposure

Xihan Yao [a], Zhaowu Yu [a,*], Weiyuan Ma [a], Junqi Xiong [a], Gaoyuan Yang [b,*]

[a] Department of Environmental Science and Engineering, Fudan University, Shanghai 200438, China
[b] School of Environmental and Geographical Sciences, Shanghai Normal University, Shanghai 200234, China

HIGHLIGHTS

- The PHB threshold model was proposed which includes the concepts of efficiency and benefit threshold.
- The PHB threshold model was tested in a case study and found to be influenced by various factors.
- 4 min for the efficiency threshold and 12 min for the benefit threshold in the pilot study have been revealed.
- The proposed framework based on "reality-virtual" and "subject-object" dimensions needs further studies.

ARTICLE INFO

Keywords:
Greenspace exposure
Physiological health effect
Benefit threshold
Efficiency threshold

ABSTRACT

Despite the existence of discussions regarding the dose-response relationship between greenspace exposure (GE) and physiological health benefits (PHB), the threshold effects of GE have not been adequately addressed. Here we present the hypothesis of a PHB threshold model for GE, which introduces the concepts of efficiency threshold and benefits threshold and incorporates calculations of the area under the curve of the ground (AUCg) and the area under the curve of the increase (AUCi). To test the validity of this model, a pilot study was conducted over four days in a typical greenspace during the spring and summer seasons. Electroencephalogram was continuously measured as the physiological indicator, while meteorological and demographic factors were collected. The results suggest that (1) the PHB threshold model is applicable across different experimental groups and seasons, while also being influenced by multiple factors (such as meteorological factors). (2) Case study had shown that the efficiency threshold can be reached within 4 min and the benefit threshold within 12 min, demonstrating that the thresholds for GE can be achieved within a short period of time. Moreover, the mean AUCg and AUCi were lower in summer compared to spring, and meteorological factors such as lower heat stress index were found to be associated with higher PHB. (3) Besides, the proposed conceptual framework based on the "reality-virtual" dimension and the "subject-object" perspective needs further investigation to explore GE thresholds. The model provides insights into the optimal and maximum PHB that can be achieved through GE and also enriches the theoretical basis of research on GE.

1. Introduction

Considerable research has demonstrated that greenspace exposure (GE) can effectively reduce the risk of disease and overall mortality among populations (Kasdagli et al., 2020), as well as enhance residents' sense of belonging and participation, thereby promoting social health (Hartig et al., 2014; Zhang et al., 2020b). In fact, GE has been shown by numerous studies to have a positive impact on physiological health, including brain waves, heart rate, blood pressure, and salivary gland secretion (Lin et al., 2019; Veitch et al., 2022; Zhao et al., 2022). Besides, related studies are also focusing on the factors and potential mechanisms that influence the health benefits of residential greenspace exposure, and indicating that these effects may be mediated through various pathways and intermediaries (Browning et al., 2022; Marselle et al., 2021; WHO, 2016). While greenspaces are beneficial for human health, the intensifying process of urbanization poses increasing pressure and

* Corresponding authors at: Study about Urban Ecology, Exposure Ecology, Urban Climate, and Eco-Environment Remote Sensing (Z. Yu); Study about Landscape Ecology and Planning (G. Yang).
E-mail addresses: zhaowu_yu@fudan.edu.cn (Z. Yu), gaoyuan@shnu.edu.cn (G. Yang).

https://doi.org/10.1016/j.landurbplan.2023.104917
Received 19 April 2023; Received in revised form 23 September 2023; Accepted 29 September 2023
Available online 3 October 2023

threats to greenspaces in cities, including the decline of urban greenspaces and their unequal spatial distribution (Gong et al., 2019; Yu et al., 2019a; Zhang et al., 2020a). This, in turn, results in a series of ecological and environmental problems and a reduction in the frequency and duration of GE (McDonnell and MacGregor-Fors, 2016; Yu et al., 2019b). Meantime, with the accelerated pace of modern life leading to more time constraints on people's exposure to greenspace, it has become necessary to study how to maximize the health benefits of GE in a limited period of time (Ibes and Forestell, 2020).

Dose-response assessment refers to the likelihood and degree of human health effects under certain levels and conditions of exposure to greenspace (Shanahan et al., 2015). As a powerful tool in the field of health science, this method has brought a qualitative-to-quantitative shift in the study of PHB of GE and often provides behavioral guidance for enhancing health outcomes in populations (Hartig et al., 2014; Jiang et al., 2014; Nieuwenhuijsen et al., 2022). Research has shown that the dose-response curve for the health benefits of GE may not be linear, meaning that the effect does not increase or decrease in a fixed proportion as the dose increases (Shanahan et al., 2015; Symonds, 2019). Shanahan et al. (2015) identified four forms of dose-response relationships between nature exposure and health outcomes: rapid/slow improvement followed by a plateau/decline. Similarly, Jiang (2017) suggested that there may be three forms of dose-response relationships: U-shaped & inverted U-shaped, power function-shaped, and mutation forms.

However, despite the potential advantages of simplification and quantification, the concept of dose-response is less explicitly used in the context of the greenspace-physiological health linkages (Shanahan et al., 2015; Zhan et al., 2020). In limited studies, some research on the PHB of GE has found that residents' mental health may improve rapidly when exposed to greenspace for a short time, but the health benefits may remain stable or show a declining trend over time (Barton and Pretty, 2010; Mao et al., 2022; Shanahan et al., 2015). For example, Cox et al. (2017) found that the optimal benefits to mental health were achieved when residents visited gardens four to five times a week (with limited additional benefits thereafter). Symonds (2019) suggested that exposure to natural environments for 120 min per week can effectively promote health and enhance well-being, but beyond that time, the marginal benefits show a declining trend. Recently, Kondo et al. (2020b) also found that emotional changes in response to GE were more significant within 10 min compared to within 30 min, indicating that the relationship between GE and emotional changes may be temporary. Overall, health benefits tend to increase with increasing GE, reaching a peak at some point and then stabilizing or declining. The point at which the peak is reached is of particular importance, as is the point at which the growth rate of the curve reaches its maximum before slowing down.

Meanwhile, it is important to note that the health effects of GE, as well as dose-response effects and thresholds, will inevitably be influenced by a range of factors (Shanahan et al., 2015). Population-level studies show that demographic factors such as gender are critical to GE effects on the health (Hartig et al., 2014; Jiang et al., 2014; White et al., 2013). In addition, original mental health status and the frequency of original GE can have an impact on the recovery and health effects of individuals (Shanahan et al., 2015). For outdoor experiments, the seasonal dynamics of greenspaces have not been investigated in many studies, and the impact of seasonal changes and thus changes in meteorological factors such as temperature, humidity, and wind speed on GE and health outcomes (Zhou et al., 2022).

However, although some studies have reported changes in health indicators in response to GE, few have employed continuous monitoring of physiological indicators to assess the health benefits of GE. Further, there is limited research investigating specific trends in the dose-response relationship and considering threshold effects to scientifically define and quantify the physiological health benefit thresholds of GE. Therefore, here we propose the concepts of "efficiency threshold" and "benefit threshold" and present a threshold model to quantify the impact of GE on physiological health. Through a pilot study, this paper aims to explore two scientific questions: (1) Is this model feasible? That is, does the threshold of PHB from GE exist? (2) What factors may affect this threshold model? The proposal of this model can not only enrich and improve the theoretical knowledge of GE and related health effects but also provide practical suggestions for the public to conduct more targeted and efficient greenspace rehabilitation activities.

2. Methodology

2.1. Definition of efficiency threshold and benefit threshold

Thresholds are typically associated with the concepts of cost-benefit analysis and economics. In situations where resources are limited, thresholds are an important consideration for maximizing benefits. Currently, thresholds have been widely applied in fields such as medical health and urban ecology and planning (Hass and Ellis, 2019; Knox et al., 2013; Lamarche et al., 2017).

In studying the relationship between GE and health benefits, we propose the definitions of efficiency threshold and benefit threshold to determine the fastest and greatest health benefits from GE (Fig. 1). Drawing on the definition of the threshold value of efficiency (TVoE) in urban greenspace cooling by Yu et al. (2017), we also define the efficiency threshold and benefit threshold using the concept of diminishing marginal benefits. Assuming the PHB with exposure time is a continuously differentiable function $y = f(x)$, the curve represents that as x increases, the y value also increases (or decreases), and then at some point, the slope of the curve gradually decreases. This means that with the increase of x, the benefit gained gradually decreases. We can define this point as the efficiency threshold point (Formula 1). The efficiency threshold refers to the point at which the benefit growth is the fastest during GE, which is the point where the absolute value of the slope is the maximum. After the efficiency threshold point, the growth rate of the curve will slow down (the absolute value of the slope will decrease).

$$|f'(x_1)| = \max_{i=1}^{n} |f'(x_i)| \tag{1}$$

The benefit threshold refers to the point at which the physiological health benefit $f(x)$, reaches its maximum (or minimum) or stabilizes, which means that at some point, its slope equals 0 (Formula 2). The benefit threshold point indicates that the optimal benefit of GE has been achieved at that point, and after prolonged exposure, the benefit will stabilize or decrease.

$$|f'(x_2)| = 0 \tag{2}$$

Here, x_1 represents the time point at which the efficiency threshold is reached, and $f(x_1)$, represents the physiological health benefit value achieved when the efficiency threshold is reached. Similarly, x_2 represents the time point at which the benefit threshold is reached, and $f(x_2)$ represents the physiological health benefit value achieved when the benefit threshold is reached.

2.2. Calculation of AUCg and AUCi

The calculation of the area under the curve (AUC) is a commonly used method in endocrinology research and neuroscience, and can be used to evaluate dose-response relationships (O'Brien et al., 1996). Pruessner et al. (2003) subsequently introduced the concepts of AUCg and AUCi on the basis and noted that the trapezoid rule can be used for calculation. This metric has been applied in studies investigating the relationship between GE and health, such as Veitch et al. (2022), who used AUCg and AUCi to explore differences in physiological indicators such as salivary sebaceous gland activity and heart rate during walking in greenspaces versus urban areas. As this study utilized fitted curves, we calculated AUCg and AUCi by the integration method based on the

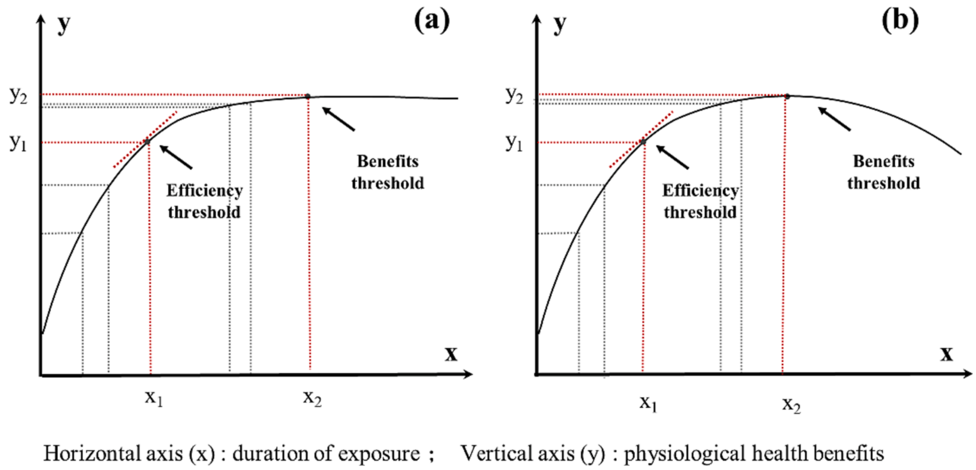
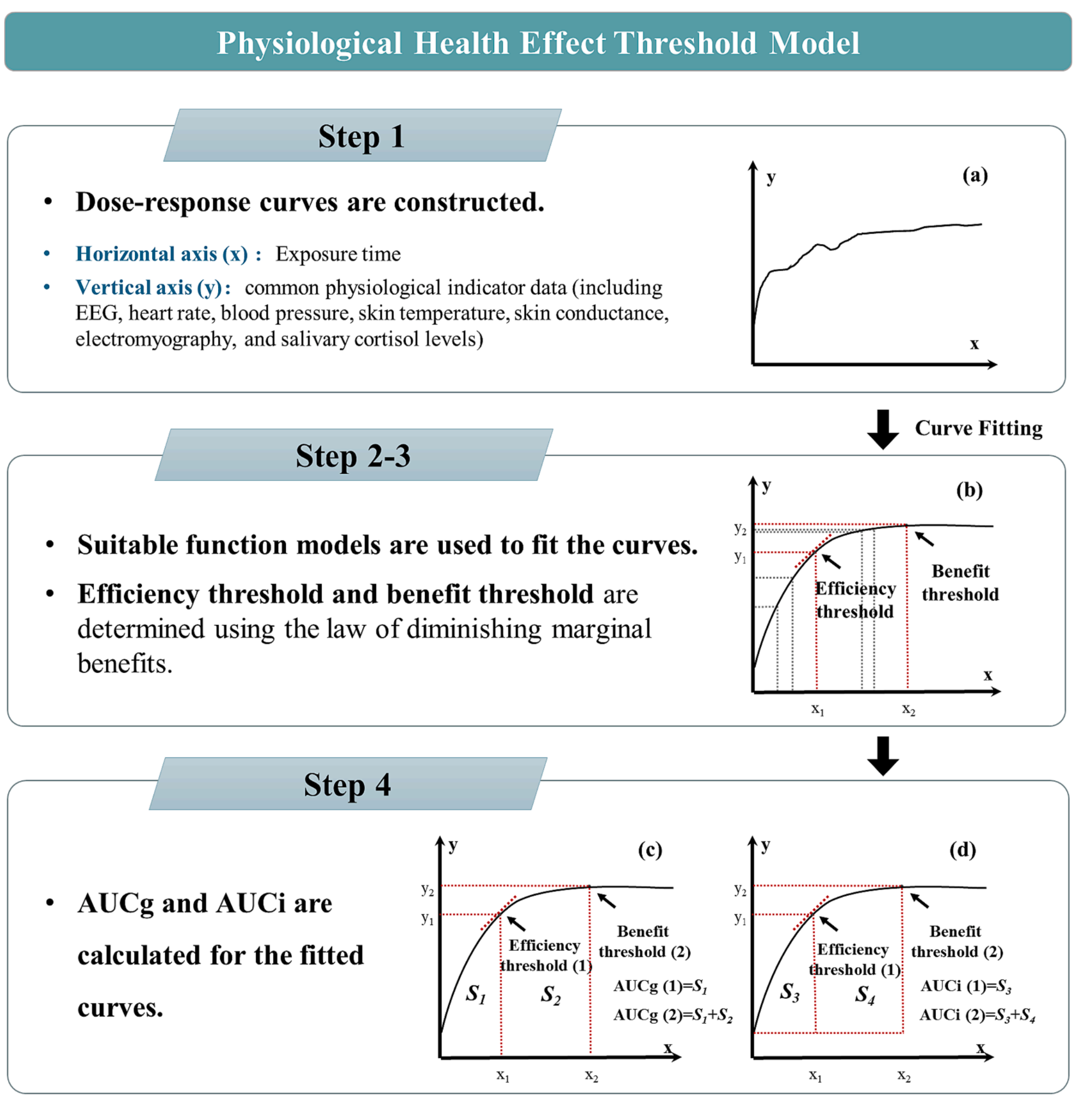


Fig. 1. Conceptual diagram of the efficiency threshold and benefit threshold definitions. (a) represents a growth-stable curve shape; (b) represents a growth-decline curve shape.



Notes: It should be noted that our study focuses mainly on the short-term physiological health indicators of GE.

Fig. 2. Conceptual diagram of the physiological health effect threshold model (using a growth-stabilization curve type as an example): (a) the initial dose-response curve; (b) calculation of the efficiency threshold and benefit threshold after curve fitting; (c) calculation of AUCg; (d) calculation of AUCi.

trapezoidal rule.

For a continuously differentiable function $f(x)$ over the interval [a, b], the calculation of AUCg can be represented by Formula (3):

$$AUCg = \int_a^b f(x)dx \tag{3}$$

AUCi can be expressed as Formula 4:

$$AUCi = \int_a^b f(x)dx - \min(f(a),f(b))^*(b-a) \tag{4}$$

Here, $f(x)$ represents the value of the physiological indicator at x for the fitted curve, and dx is a small horizontal length.

It is important to note that since different physiological indicators are used as dependent variables, the overall trend of the curve after exposure to greenspaces may either increase or decrease. Therefore, it is necessary to determine the values of $f(a)$ and $f(b)$ when calculating AUCi.

2.3. Physiological health effect threshold model

In summary, we have established a quantifiable physiological health effect threshold model of GE (Fig. 2). The specific steps of this model are as follows: (1) First, dose-response curves are constructed using time as the x-axis and common physiological indicator data (including EEG, heart rate, blood pressure, skin temperature, skin conductance, electromyography, and salivary cortisol levels) as the y-axis. (2) Suitable function models are used to fit the curves with different shapes, such as growth/decrease-stable type, U-shaped, or inverted U-shaped. (3) Threshold points, including the efficiency threshold and benefit threshold, are determined using the law of diminishing marginal benefits. (4) AUCg and AUCi are calculated for the fitted curves. It should be noted that our study mainly focuses on the short-term physiological health indicators of GE. The long-term impact of greenspace on human health, such as the microbial hypothesis and other related theories, require longitudinal studies throughout the lifespan and are beyond the scope of our discussion.

3. Case study

To validate the model of the physiological health threshold effect, a pilot experiment was conducted. The experimental site was located within a forested greenspace at a university in Xi'an, Shaanxi Province, China (108°5′18′E, 34°15′44′N) (Fig. 3). The sky view factor (SVF) (Oke, 1988), visible green index (VGI) (Aoki, 1987), and perceived restoration scale (PRS) (Hartig et al., 1997) scores of the site indicated that it possessed typical characteristics of greenspace and demonstrated favorable restorative effects (details, see Text.S1, Table S1, and Fig. S1, Appendix A).

Four days with distinct climatic characteristics were selected for the experiment in spring (March 19th and March 23rd, 2022) and summer (June 24th and June 27th, 2022), and the duration of each day lasted from 9:00 to 18:30. The multi-factor ANOVA results indicate significant differences in meteorological conditions between spring and summer (details, see Table S2, Appendix A). To investigate the differences between open-eye (OE) and blindfolded (BF) conditions and verify the proposed physiological health benefit threshold model's applicability, each trial of the experiment involved two participants: one in the OE group and the other in the BF group. At the end of the experiment, 61 volunteers were recruited, meeting the numerical requirements for experimental studies that utilize binary designs (Berman et al., 2021; Veitch et al., 2022). Due to some missing EEG data, the experiment finally obtained data from 59 participants (details, see Table S3, Appendix A).

3.1. Data collection and pre-processing

3.1.1. Physiological indicators (EEG)

EEG provides a non-invasive, direct measurement of neural

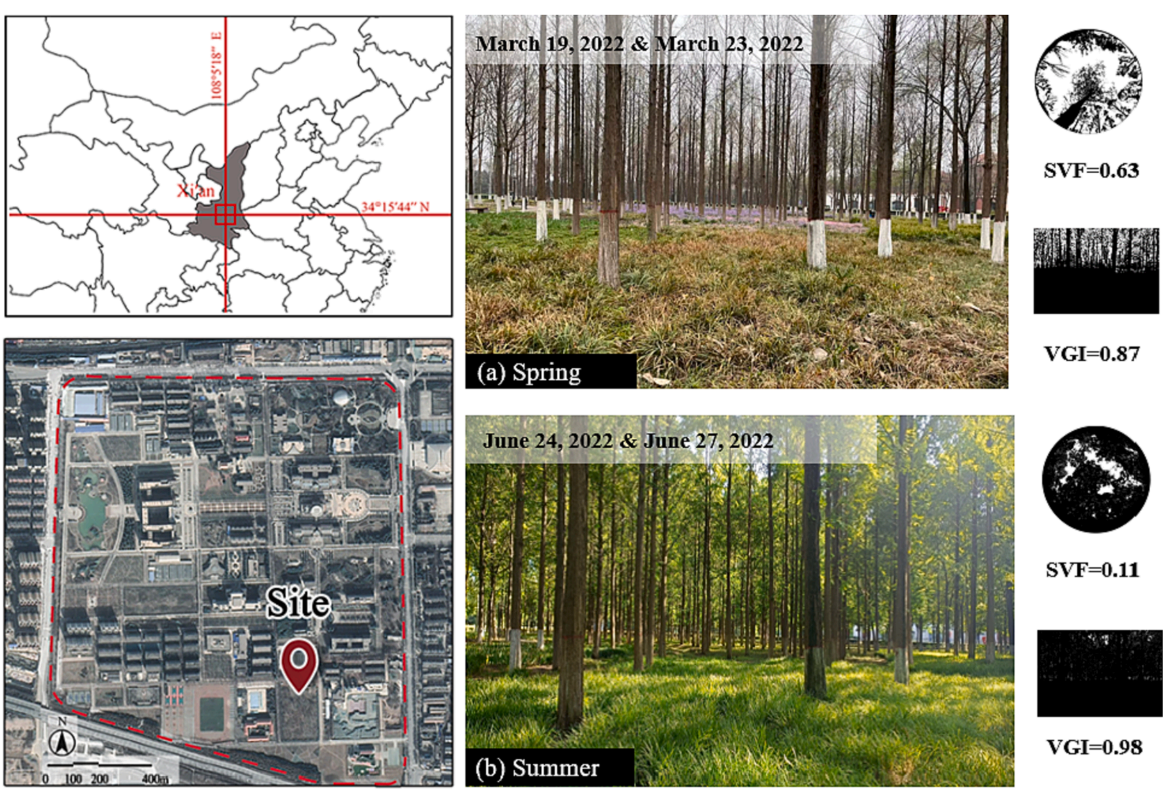


Fig. 3. Experimental site: photos of forested greenspace in (a) spring and (b) summer were taken from the participant's viewpoint, with the experiment date marked on the photos.

activities, offering insights into immediate physiological responses to greenspace exposure with high temporal resolution for capturing rapid changes (Ancora et al., 2022; Khosla et al., 2020). Its reliability as a tool for studying the effects of greenspace exposure on health has been established (Lin et al., 2019; Liu et al., 2022). Therefore, in this case study, EEG served as a physiological indicator to evaluate the short-term response. EEG measurement was performed using a non-invasive Emotiv EPOC + EEG headset (EMOTIV Inc., USA), which boasts 14 channels (AF4, AF3, F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1, O2) aligned with the international 10–20 position system, and has electrode impedance below 5 kΩ for accurate brain response data recording at 128 Hz (0.0078 sec sampling time). The recorded data was transmitted wirelessly to the relevant computer, and the headset's reliability and accuracy have been proven in previous studies (Lin et al., 2019; Neale et al., 2017; Tilley et al., 2017). Participants were instructed to remain motionless and refrain from speaking in the green environment to minimize potential external factors that could affect their brainwaves during EEG measurements.

3.1.2. *Meteorological data and participants' basic information*

Kestrel 5500 (Nielsen-Kellerman Co., USA) was used for meteorological data collection. During the experiment, the instrument was fixed at a height of 1.1 m, and it would continuously record the peripheral meteorological data at 1-minute intervals, including air temperature (Ta), relative humidity (RH), wind speed (Ws), and heat stress index (HSI).

The participants' basic information questionnaire was divided into three sections: demographics (including gender, age, BMI, and major), the World Health Organization Well-Being Index (WHO-5), and greenspace exposure frequency (details, see Text.S2, Appendix A).

3.1.3. *EEG index pre-processing process*

The EEG frequency bands can be classified according to power spectrum analysis: 1–4 Hz (Delta), 4–7 Hz (Theta), 7–13 Hz (Alpha), 13–30 Hz (Beta), and 30–50 Hz (Gamma). Based on the case study and the characteristics of the different EEG bands, we selected several common EEG indicators for analysis (details, see Text.S3, Appendix A): (1) relative power of different frequency bands (relative α, β, and θ); (2) β/α index; and (3) relative ($\alpha + \theta$) index. Among them, higher α waves are associated with relaxation, while higher β waves are associated with alertness; a lower β/α ratio indicates that the subject is in a more relaxed and calm state (Suh and Yim, 2018); higher slow brain waves (α and θ) indicate deeper levels of inner contemplation (Delorme and Makeig, 2004).

The EEG data were preprocessed using the EEG Lab toolbox in MATLAB R2021b (Delorme and Makeig, 2004) (details, see Text.S4, Appendix A). This process included electrode positioning, frequency filtering, and independent component analysis (ICA). The original EEG data were then transformed into the frequency domain using discrete Fourier transform (DFT) for subsequent analysis (Higgins, 1976).

3.2. *Experimental procedure*

Prior studies found health indicators may stabilize within 5–10 mins of GE (Barton and Pretty, 2010; Kondo et al., 2020a; Wang, 2019). To more accurately examine the threshold effect, this pilot study extended EEG monitoring to 30 min, with 26 min of GE. In Stage 1, participants should wear the Emotiv EPOC + EEG headset and fill out questionnaires with basic personal information. In Stage 2, participants were asked to complete a 4-minute pressure test. The pressure test required participants to perform complex calculations under time pressure and noise disturbance, without the help of a calculator (Jiang et al., 2014; Medvedev et al., 2015; Zhang et al., 2021). In Stage 3, participants were exposed to greenspace for 26 min in a seated position, with the OE group viewing the greenspace through a viewfinder at 1.1 m to control variables and ensure standardized visual exposure among the volunteers, and the BF group wearing a blindfold. The experiment in each period lasted about 50 min (Fig. 4).

3.3. *Data analysis*

We utilized MATLAB R2021b to split the preprocessed EEG data into two stages: Stage 2 (pressure test) from 0 to 4 min, and Stage 3 (GE) from 4 to 30 min. To achieve higher accuracy in curve fitting, calculations were performed every 30 s during Stage 2 (0–4 min) and every 1 min during Stage 3 (4–30 min) of the data. Subsequently, line graphs were drawn to preliminarily analyze the shapes of different EEG indicators (details, see Fig. S2, Appendix A). The relative θ index was excluded from further analysis as it showed no significant change between Stage 2 and Stage 3.

For curve fitting, the drc package in R 4.2.2 and RStudio was employed, which is a popular tool for dose-response studies (Ritz et al.,

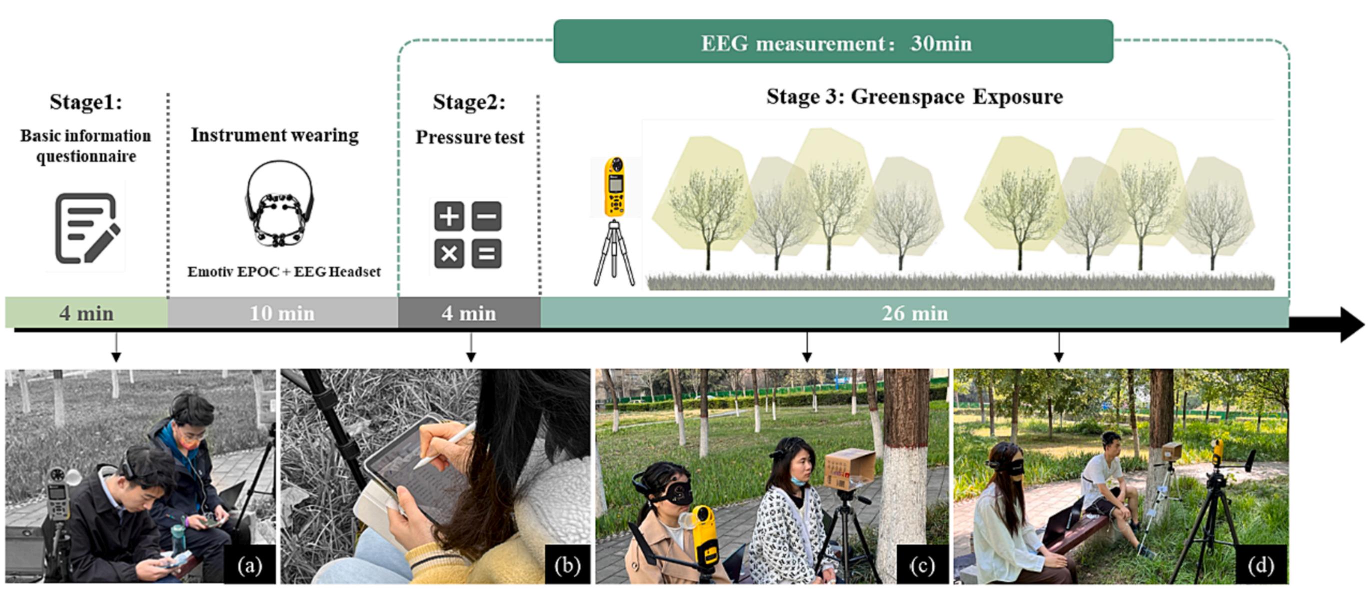


Fig. 4. Experimental procedure: a) fill out personal information questionnaire (Stage 1); b) pressure test (Stage 2); c) & d) two participants were exposed in the greenspace for 26 min with eyes open/blindfolded (Stage 3).

2015). Due to the initial line plot indicating an S-shaped curve for the response change, we employed a fourth-order logistic function for data fitting, which proved to be effective. To account for the challenge of attaining a slope of 0 during the stable phase of the curve, we adjusted the benefit threshold point to 0.0005. Given the relatively larger absolute value of the β/α index compared to other indicators, using 0.005 as the benefit threshold point would have been more suitable.

Additionally, we performed a multifactorial analysis of variance (multi-factor ANOVA) to examine significant correlations between AUCg and AUCi across various groups and seasons. We also utilized the Spearman correlation method to investigate the factors influencing the threshold model for PHB derived from GE. Meanwhile, we removed some of the data that could not be fitted and data where the x value of the efficiency threshold was higher than the x value of the benefit threshold. All statistical analyses were conducted using IBM SPSS Statistics 25 software.

3.4. Results

3.4.1. Physiological health effect threshold in different groups and seasons

In spring, for both OE and BF groups, all four indicators showed a positive effect (except for the OE group's relative (α + θ) index, which did not change significantly) (details, see Table.S4, Appendix A). Research suggests that slow brain waves (α and θ) dominate during meditation-like internal deep thinking, and as a result, some of the relative α index and relative (α + θ) index trends in the OE group may not exhibit significant changes. For fitted curves with insignificant changes in trend, we did not calculate threshold points. The results in spring showed that the efficiency threshold for the OE group was the 1st minute, and the benefit threshold was between the 4th and 8th minutes; the efficiency threshold for the BF group was the 4th minute, and the benefit threshold was between the 6th and 12th minutes. Similarly, in summer, the efficiency threshold for the OE group was between the 2nd and 3rd minutes, and the benefit threshold was between the 8th and 12th minutes; the efficiency threshold for the BF group was between the 1st and 4th minutes, and the benefit threshold was between the 5th and 11th minutes (Fig. 5, Fig. 6, and Table 1).

We also conducted a calculation of AUCg and AUCi, and analyzed the discrepancies between OE and BF groups as well as between spring and summer (Table 2). The results indicated that during summer, the mean AUCg and AUCi were lower compared to the spring season, indicating that the total PHB of GE during the summer season are lower than those during the spring season. Furthermore, the OE group showed marked differences in some of the AUCg indices (such as the relative β index and β/α index). Notably, the BF and OE groups showed significant differences in various AUCg indices (such as relative α index and β/α index) and AUCi indices (such as relative α index) during both spring and summer seasons.

3.4.2. Factors influencing the physiological health benefit threshold model

Overall, meteorological factors remain the influencing factors of the threshold model for the physiological health of GE (Fig. 7, details, see Table S5). It can be observed that, in general, Ta and HSI are negatively correlated with numerous physiological indicators, while RH and Ws are mainly positively correlated and exhibit significant correlations. This phenomenon is more pronounced in the spring BF group, as evidenced by significant correlations between the four meteorological factors and multiple related indicators of the relative α index and relative (α + θ) index. This suggests that lower Ta, higher RH, higher Ws, and lower HSI can lead to higher PHB for participants, but may also lead to slower attainment of the benefit threshold and efficiency threshold points. In terms of demographic factors, the profession may also be a factor influencing this physiological health benefit threshold model, as participants majoring in landscape architecture and environmental design may take longer to reach the relative α index and relative (α + θ) index, while the efficiency threshold and benefit threshold may also be got relatively lower.

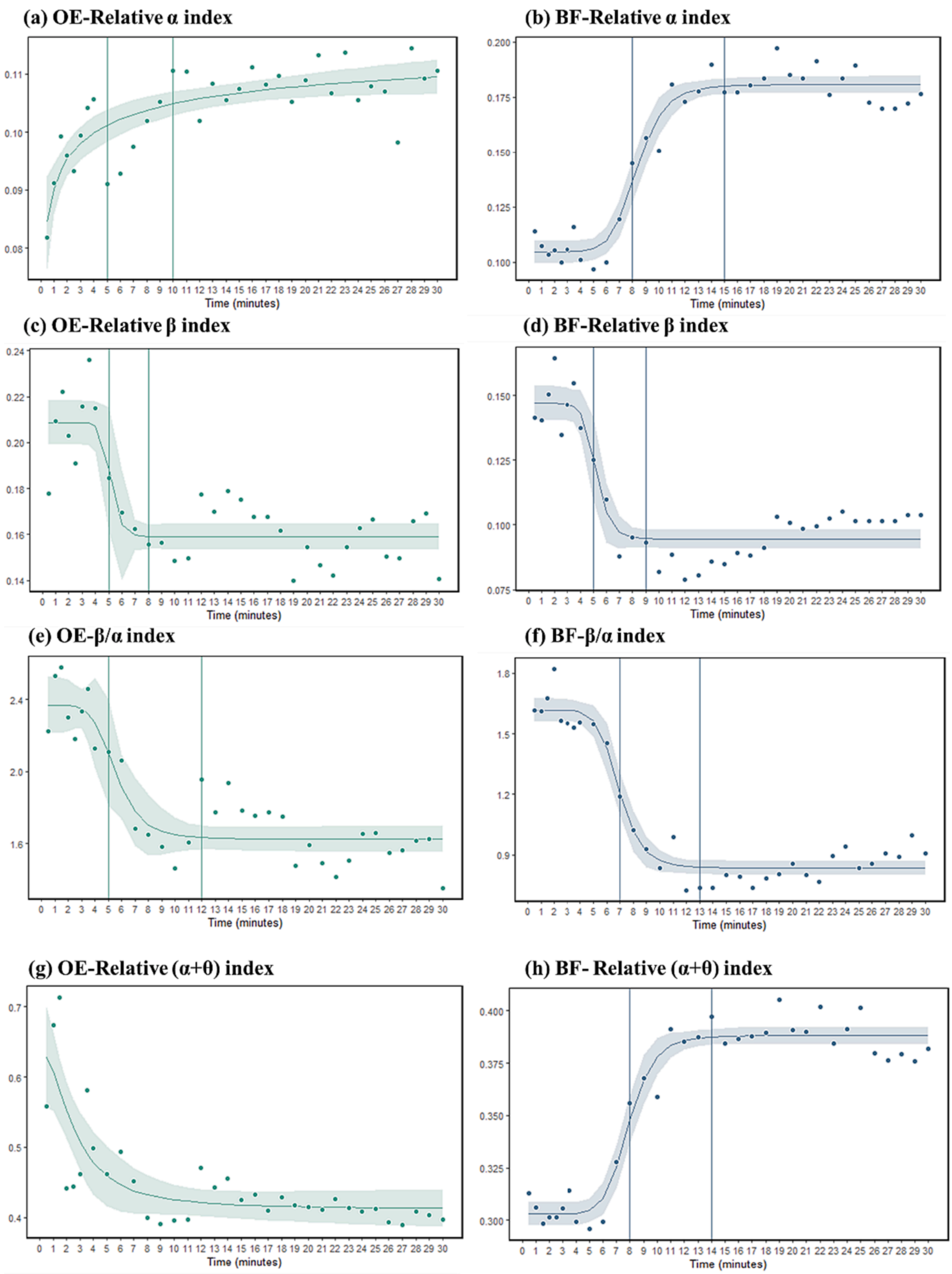
4. Discussion

4.1. Significance of physiological health effect threshold model in greenspace exposure

Threshold models have wide-ranging applications in fields such as medical health and urban ecology and planning (Hass and Ellis, 2019; Knox et al., 2013; Lamarche et al., 2017). GE has emerged as a new area of interest in the study of the coupling of urban ecology and resident health, with the potential to address health outcomes "upstream" rather than "downstream" (Galster et al., 2006), making further quantitative studies of GE and health of additional importance. The PHE threshold model in GE is a theoretical framework that helps to explain how GE can impact an individual's physiological health. The threshold model also provides a quantitative assessment of the optimal dose of GE, moving the focus from the question of whether greenspaces are good for health to the question of what level of GE is most beneficial. The model proposed in this study offers a systematic and scientific approach to identifying the most efficient and beneficial ways to expose oneself to greenspace, providing researchers with a more comprehensive understanding of the relationship between GE and health effects. Overall, the physiological health effect threshold model has significant theoretical implications for understanding the complex relationship between GE and human health, and it provides a framework for future research to better understand the mechanisms underlying this relationship.

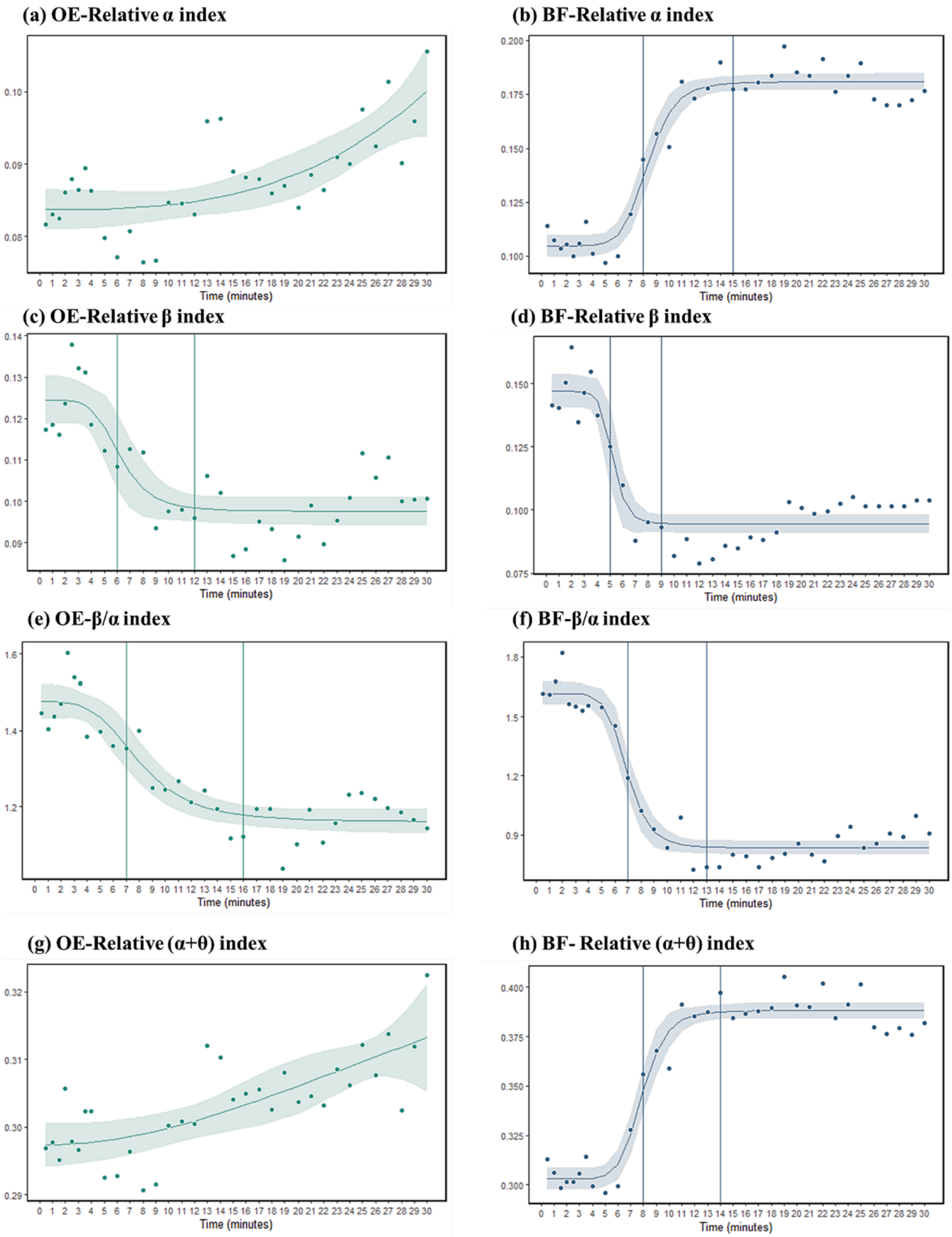
Through preliminary experiments, we have discovered the presence of efficiency and benefit thresholds for achieving PHB through GE. These thresholds can be reached in a short time period, with the efficiency threshold being achieved within 4 min and the benefit threshold being achieved within 12 min. This is consistent with the results of many studies, which suggest that the relationship between GE and health benefits may be transient (Barton and Pretty, 2010; Kondo et al., 2020b; Shanahan et al., 2015). The study also discovered that the efficiency threshold, benefit threshold, AUCg, and AUCi varied between seasons and experimental groups, and investigated the factors that influenced these differences. In the spring, the OE group reached the efficiency and benefit thresholds earlier than the BF group, potentially because they were more sensitive and responsive to the natural environment during GE. However, in the summer, the OE group reached the benefit threshold later than the BF group. Additionally, the AUCg and AUCi were lower in the summer than in the spring, likely because the weather conditions were unfavorable, such as high temperature and humidity, causing more fatigue and discomfort in the human body. Thus, it can be inferred that during the summer, the OE group may require more time to reach the benefit threshold due to unfavorable external conditions, while the BF group may be more focused on their own feelings and reactions (Barry and De Blasio, 2017). Furthermore, it can be observed that in the OE group, relative α index and relative (α + θ) index may not demonstrate significant changes; For the relative α index, BF and OE groups in both spring and summer showed noticeable differences in AUCg and AUCi indices. This may be attributed to the predominance of α brainwaves under blindfolded conditions (Barry and De Blasio, 2017).

The study also revealed that various meteorological factors, such as lower Ta, higher RH, higher Ws, and lower HSI, can result in higher PHB. This aligns with previous research showing the impact of environmental meteorological factors on an individual's physical and mental well-being (Yao et al., 2008; Zhang et al., 2021). For example, Zhang et al. (2021) found that with increasing air temperature, globe temperature, and mean radiant temperature, positive emotions (PA) showed an inverted U-shaped trend, while negative emotions (NA) exhibited the opposite trend, indicating that participants' health status is influenced by meteorological parameters. Such findings not only contribute to our understanding of the complex interplay between meteorological data and physiological health but also underpin the potential interaction



Notes: "OE" refers to the open-eye group, and "BF" corresponds to the blindfolded group

Fig. 5. The shape of the curve after fitting in spring (the first line in the figure represents the efficiency threshold, and the second line represents the benefit threshold).



Notes: "OE" refers to the open-eye group, and "BF" corresponds to the blindfolded group

Fig. 6. The shape of the curve after fitting in summer (the first line in the figure represents the efficiency threshold, and the second line represents the benefit threshold).

Table 1
The efficiency threshold and benefit threshold in different groups and seasons.

Season	Group	EEG index	Efficiency Threshold		Benefit Threshold	
			x (min)	y	x (min)	y
Spring	OE	Relative α index	1	0.101	6	0.105
		Relative β index	1	0.188	4	0.159
		β/α index	1	2.105	8	1.634
		Relative (α + θ) index	/	/	/	/
	BF	Relative α index	4	0.124	12	0.195
		Relative β index	4	0.145	6	0.136
		β/α index	4	1.608	10	0.980
		Relative (α + θ) index	4	0.322	12	0.401
Summer	OE	Relative α index	/	/	/	/
		Relative β index	2	0.112	8	0.098
		β/α index	3	1.360	12	1.178
		Relative (α + θ) index	/	/	/	/
	BF	Relative α index	4	0.136	11	0.180
		Relative β index	1	0.126	5	0.095
		β/α index	3	1.204	9	0.839
		Relative (α + θ) index	4	0.348	10	0.388

Notes: "OE" refers to the open-eye group, and "BF" corresponds to the blindfolded group.

between the threshold effects of PHB resulting from GE. Additionally, demographic factors, including major, were found to influence the threshold model for GE and PHB, indicating the complexity of the model and its susceptibility to various factors. For instance, participants majoring in landscape architecture and environmental design may exhibit a longer time to reach the efficiency threshold and benefit threshold, while with relatively lower values. This may be due to the fact that these participants may have greater sensitivity to GE and take longer to reach the threshold due to their familiarity with nature. These findings highlight the importance of considering meteorological variations and individual differences when evaluating the physiological health effects of GE and suggest that different intervention strategies may be needed for different populations under different meteorological conditions.

Additionally, the proposed threshold model has practical implications for guiding residents' GE. By scientifically quantifying the threshold of PHB, it can provide recommendations for the optimal GE dose to maximize residents' health benefits in a short period of time. Moreover, identifying factors that may affect the threshold model can assist urban planners and policy makers in making informed decisions in creating and maintaining greenspaces. Overall, the proposed threshold model can contribute to both theoretical and practical aspects of GE and health-related research, providing valuable insights into the relationship between GE and PHB.

4.2. Further studies

In this study, we have constructed a conceptual framework for exploring the threshold of GE for residents based on the "reality-virtual" dimension and the "subject-object" perspective (Fig. 8). The "subject" threshold refers to the exposure duration and frequency threshold of the residents, while the "object" threshold refers to the greenspace composition and configuration threshold. It should be noted that this case study only focuses on exploring the threshold of "subject" GE for residents in the real world. However, some studies have investigated the health effects of greenspace by altering the coverage, composition, and arrangement of different vegetation types, and have found that these indicators exhibit a reverse U-shaped trend in terms of stress reduction and physiological health (Hedblom et al., 2019; Jiang et al., 2014; Zhu et al., 2021). Therefore, the threshold model can be extended to the "object" threshold level, such as the blue-green ratio, tree-shrub-grass ratio, and tree cover percentage. Additionally, recent related research has also started to use virtual reality and other technologies to analyze the impact of exposure to virtual greenspace on the physical and mental health of residents (Browning et al., 2022; Frumkin et al., 2017; Tabrizian et al., 2020; Yang et al., 2021). Hence, the study of the "virtual" dimension can also be included in the scope of the threshold model. The existence of the "subject" (time and frequency, etc.) and "object" (blue-green ratio, tree-shrub-grass ratio, and tree cover percentage, etc.) thresholds for GE in both "reality" and "virtual" settings, as well as their influencing factors, are areas for future studies.

In summary, the threshold model for physiological health effects of GE is an emerging research field with great application potential. Analysis from the "subject" perspective of the "reality-virtual" dimension can help formulate public health guidelines for individual optimal exposure, while the combination of the "reality-virtual" dimension and the "object" perspective can provide scientifically-based recommendations for greenspace planning. Further studies should delve deeper into this field and broaden the scope of research to better evaluate the impact of GE on human health and provide effective advice for individuals in contact with urban greenspace planning.

5. Limitations

Limitations of this study need to be mentioned. (1) The physiological health effect threshold model may not be applicable to all situations, as in the case of irregular curve shapes where the model may not accurately capture the relationship between environmental factors and health. Furthermore, the model predominantly depends on data collected through experimentation, which is susceptible to inherent biases and inaccuracies. (2) The absence of baseline EEG data may influence the interpretation of the physiological responses associated with greenspace exposure. Additionally, the omission of an assessment of participants'

Table 2
Multi-factor ANOVA of AUCg and AUCi for different groups and seasons in greenspace exposure (* $p < 0.05$; ** $p < 0.01$).

EEG indicators	Spring		Summer		OE vs BF				Sping vs Summer			
	OE	BF	OE	BF	Spring		Summer		OE		BF	
	mean	mean	mean	mean	F	p	F	p	F	p	F	p
AUCg												
Relative α index	3.151	5.26	2.673	5.004	11.141	0.003**	6.383	0.017*	0.3	0.588	0.074	0.787
Relative β index	4.796	4.08	2.961	2.9	0.777	0.386	0	0.99	6.423	0.017*	3.547	0.071
β/α index	49.812	33.028	35.766	27.122	5.124	0.032*	4.219	0.05*	5.956	0.021*	1.279	0.269
Relative (α + θ) index	12.53	11.281	9.025	11.12	0.202	0.657	1.446	0.239	0.96	0.336	0.022	0.882
AUCi												
Relative α index	0.216	2.866	0.16	1.858	21.715	0**	7.406	0.011*	0.443	0.511	2.653	0.115
Relative β index	−1.426	−0.505	−0.71	−1.41	0.475	0.497	1.73	0.199	2.721	0.11	3.497	0.073
β/α index	−18.715	−26.791	−8.052	−21.131	1.113	0.301	0.152	0.699	1.389	0.249	1.266	0.271
Relative (α + θ) index	−2.406	2.983	0.093	2.021	3.86	0.061	1.786	0.192	0.571	0.456	1.555	0.224

Notes: "OE" refers to the open-eye group, and "BF" corresponds to the blindfolded group.

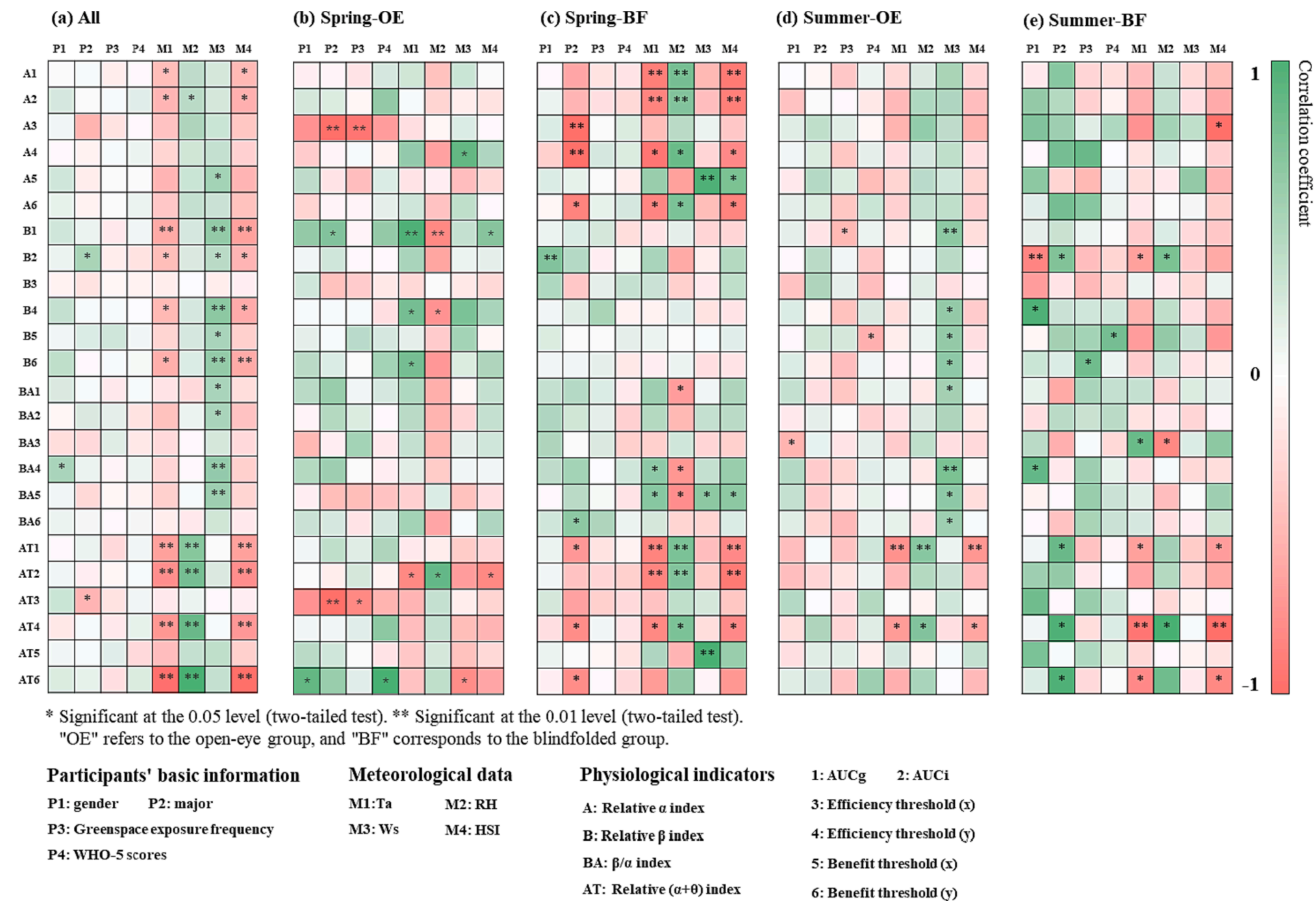


Fig. 7. Heat map of Spearman correlation analysis of factors influencing the physiological health effect threshold model.

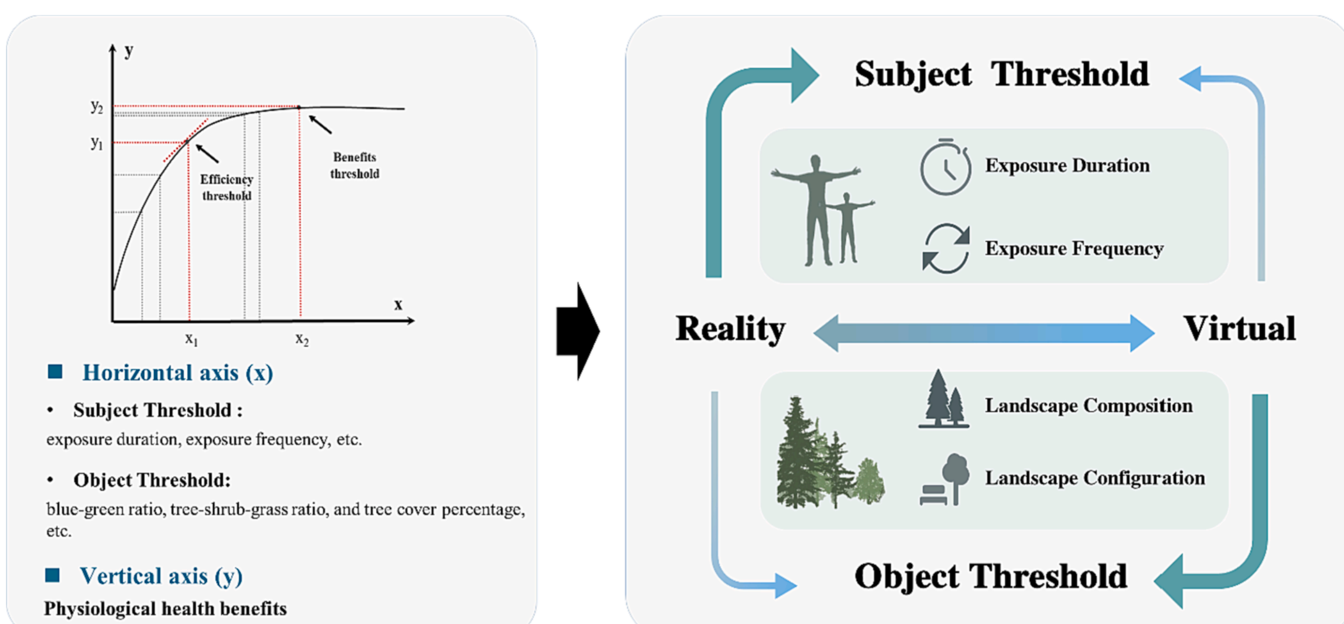


Fig. 8. A further study framework based on the “reality-virtual” dimension and the “subject-object” perspective.

attitudes towards greenspaces could further impact the discernment of the physiological reactions to such environments. (3) This pilot study had a limited scope with only 61 young participants recruited from a typical forest greenspace. Although the sample size is sufficient to support the development of the threshold model, future studies should increase the sample size to improve the accuracy of the model. Besides, the case study only used EEG as a physiological indicator and only considered meteorological data and basic participant information as influencing factors for the threshold model. Future studies should consider using additional physiological indicators and exploring other potential factors that may influence the threshold model.

6. Conclusions

This study presents the physiological health effect threshold model, which defines the efficiency threshold and benefit threshold using the method of diminishing marginal benefits and further adds and optimizes the calculation of AUCg and AUCi. Through a typical forest understory greenspace case study, different exposure groups (OE group and BF group) were set to verify the threshold effect model of PHB during static GE and explore relevant influencing factors. The following conclusions were drawn:

(1) The study found that there is a threshold effect of PHB in GE. The results showed that in the spring, the efficiency threshold of the OE group was the 1st minute, and the benefit threshold was the 4th-8th minute; the efficiency threshold of the BF group was the 4th minute, and the benefit threshold was the 6th-12th minute. Similarly, in the summer, the efficiency threshold of the OE group was the 2nd-3rd minute, and the benefit threshold was the 8th-12th minute; the efficiency threshold of the BF group was the 1st-4th minute, and the benefit threshold was the 5th-11th minute. Additionally, the AUCg and AUCi in the summer were generally lower than those in the spring.

(2) The physiological health effect threshold model of GE is influenced by multiple factors. Meteorological factors still affect the physiological health threshold model of GE. Lower Ta, higher RH, higher Ws, and lower HSI can lead to higher PHB for participants, but at the same time, it may take longer to reach the benefit and efficiency threshold points. Demographic factors may also be influencing factors in this threshold model, but more detailed influencing factors need to be further explored.

(3) We further established a conceptual framework based on the "reality-virtual" dimension and the "subject-object" perspective to explore the threshold of GE for residents. Further experimental and research are needed in the future to better understand the physiological and health benefits threshold effects of GE under different perspectives and dimensions. These experiments should cover various types of greenspaces and different exposed populations, and should include detailed measurements and analysis of physiological and health effects to establish a threshold effect database under different conditions. In addition, further research is needed to explore the relationship between more detailed influencing factors and thresholds, providing more scientific and accurate guidance for urban planning and greenspace design.

In conclusion, the physiological and health benefits threshold effects model of GE is still in the preliminary stage and requires further experimentation and research to improve and validate. The proposal of this model can enrich and improve the theoretical knowledge of GE and related health effects. The conclusions of this model can provide practical suggestions for the public to conduct more targeted and efficient greenspace rehabilitation activities.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The study was supported by the National Natural Science Foundation of China (Grant No. 42171093), Scientific and Innovative Action Plan of Shanghai (Grant No. 21ZR1408500), Shanghai Pujiang Program (Grant No. 21PJ1401600) and Shanghai Urban Trees Ecology Application Engineering Technology Research Center.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104917.

References

Ancora, L. A., Blanco-Mora, D. A., Alves, I., Bonifácio, A., Morgado, P., & Miranda, B. (2022). Cities and neuroscience research: A systematic literature review. *Frontiers in Psychiatry, 13*, Article 983352.
Aoki, Y. (1987). Relationship between perceived greenery and width of visual fields. *J. Jpn. Inst. Landsc. Archit, 51*(1), 1–10.
Barry, R. J., & De Blasio, F. M. (2017). EEG differences between eyes-closed and eyes-open resting remain in healthy ageing. *Biological Psychology, 129*, 293–304.
Barton, J., & Pretty, J. (2010). What is the best dose of nature and green exercise for improving mental health? *A multi-study analysis, Environmental science & technology, 44*(10), 3947–3955.
Berman, M. G., Cardenas-Iniguez, C., Meidenbauer, K. L., 2021, An Environmental Neuroscience Perspective on the Benefits of Nature, in: *NATURE AND PSYCHOLOGY: BIOLOGICAL, COGNITIVE, DEVELOPMENTAL, AND SOCIAL PATHWAYS TO WELL-BEING* (A. R. Schutte, J. C. Torquati, J. R. Stevens, eds.), pp. 61-88.
Browning, M. H. E. M., Rigolon, A., McAnirlin, O., & Yoon, H. (2022). Where greenspace matters most: A systematic review of urbanicity, greenspace, and physical health. *Landscape and Urban Planning, 217*, Article 104233.
Cox, D. T. C., Shanahan, D. F., Hudson, H. L., Fuller, R. A., Anderson, K., Hancock, S., & Gaston, K. J. (2017). Doses of Nearby Nature Simultaneously Associated with Multiple Health Benefits. *International Journal of Environmental Research and Public Health*.
Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of neuroscience methods, 134*(1), 9–21.
Galster, J. C., Pazzaglia, F. J., Hargreaves, B. R., Morris, D. P., Peters, S. C., & Weisman, R. N. (2006). Effects of urbanization on watershed hydrology: The scaling of discharge with drainage area. *Geology, 34*(9), 713–716.
Gong, P., Li, X., & Zhang, W. (2019). 40-Year (1978–2017) human settlement changes in China reflected by impervious surfaces from satellite remote sensing. *Science Bulletin, 64*(11), 756–763.
Hartig, T., Kaiser, F. G., & Bowler, P. A. (1997). Further development of a measure of perceived environmental restorativeness. *Institutet för bostads-och.* urbanforskning.
Hartig, T., Mitchell, R., De Vries, S., & Frumkin, H. (2014). Nature and health. *Annual review of public health, 35*, 207–228.
Hass, A. L., & Ellis, K. N. (2019). Using wearable sensors to assess how a heatwave affects individual heat exposure, perceptions, and adaption methods. *International journal of biometeorology, 63*(12), 1585–1595.
Hedblom, M., Gunnarsson, B., Iravani, B., Knez, I., Schaefer, M., Thorsson, P., & Lundström, J. N. (2019). Reduction of physiological stress by urban green space in a multisensory virtual experiment. *Scientific reports, 9*(1), 1–11.
Higgins, R. J. (1976). Fast Fourier transform: An introduction with some minicomputer experiments. *American Journal of Physics, 44*(8), 766.
Ibes, D. C., & Forestell, C. A. (2020). The role of campus greenspace and meditation on college students' mood disturbance. *Journal of American College Health, 70*(1), 99–106.
Jiang B., 2017, Measuring Impacts of Ordinary Green Landscapes on Human Health and Transforming Research Findings into Design Solutions Four Important Issues, *Time + Architecture* (05):34-37.
Jiang, B., Chang, C.-Y., & Sullivan, W. C. (2014). A dose of nature: Tree cover, stress reduction, and gender differences. *Landscape and Urban Planning, 132*, 26–36.
Kasdagli, M.-I., Katsouyanni, K., de Hoogh, K., Lagiou, P., & Samoli, E. (2020). Associations of air pollution and greenness with mortality in Greece: An ecological study. *Environmental.* Research:110348.
Khosla, A., Khandnor, P., & Chand, T. (2020). A comparative analysis of signal processing and classification methods for different applications based on EEG signals. *Biocybernetics and Biomedical Engineering, 40*(2), 649–690.
Knox, E. C. L., Webb, O. J., Esliger, D. W., Biddle, S. J. H., & Sherar, L. B. (2013). Using threshold messages to promote physical activity: Implications for public perceptions of health effects. *European Journal of Public Health, 24*(2), 195–199.
Kondo, M. C., Triguero-Mas, M., Donaire-Gonzalez, D., Seto, E., Valentin, A., Hurst, G., … Nieuwenhuijsen, M. J. (2020a). Momentary mood response to natural outdoor

environments in four European cities. *Environmental International, 134*, Article 105237.

Kondo, M. C., Triguero-Mas, M., Donaire-Gonzalez, D., Seto, E., Valentín, A., Hurst, G., … Nieuwenhuijsen, M. J. (2020b). Momentary mood response to natural outdoor environments in four European cities. *Environment International, 134*, Article 105237.

Lamarche, D. T., Meade, R. D., D'Souza, A. W., Flouris, A. D., Hardcastle, S. G., Sigal, R. J., … Kenny, G. P. (2017). The recommended Threshold Limit Values for heat exposure fail to maintain body core temperature within safe limits in older working adults. *Journal of occupational and environmental hygiene, 14*(9), 703–711.

Lin, W., Chen, Q., Jiang, M., Zhang, X., Liu, Z., Tao, J., … Zeng, Q. (2019). The effect of green space behaviour and per capita area in small urban green spaces on psychophysiological responses. *Landscape and Urban Planning, 192*, Article 103637.

Liu, L., Qu, H., Ma, Y., Wang, K., & Qu, H. (2022). Restorative benefits of urban green space: Physiological, psychological restoration and eye movement analysis. *Journal of Environmental Management, 301*, Article 113930.

Mao, Y., He, Y., Xia, T., Xu, H., Zhou, S., & Zhang, J. (2022). Examining the Dose-Response Relationship between Outdoor Jogging and Physical Health of Youths: A Long-Term Experimental Study in Campus Green Space. *International Journal of Environmental Research and Public Health, 19*(9), 5648.

Marselle, M. R., Hartig, T., Cox, D. T. C., de Bell, S., Knapp, S., Lindley, S., … Bonn, A. (2021). Pathways linking biodiversity to human health: A conceptual framework. *Environment International, 150*, Article 106420.

McDonnell, M. J., & MacGregor-Fors, I. (2016). The ecological future of cities. *Science, 352*(6288), 936–938.

Medvedev, O., Shepherd, D., & Hautus, M. J. (2015). The restorative potential of soundscapes: A physiological investigation. *Applied Acoustics, 96*, 20–26.

Neale, C., Aspinall, P., Roe, J., Tilley, S., Mavros, P., Cinderby, S., … Thompson, C. W. (2017). 2017, The Aging Urban Brain: Analyzing Outdoor Physical Activity Using the Emotiv Affectiv Suite in Older People (vol 94, pg 869. *Journal of Urban Health-Bulletin of the New York Academy of Medicine, 94*(6), 881.

Nieuwenhuijsen, M. J., Dadvand, P., Márquez, S., Bartoll, X., Barboza, E. P., Cirach, M., … Zijlema, W. L. (2022). The evaluation of the 3–30-300 green space rule and mental health. *Environmental Research, 215*, Article 114387.

O'Brien, J. T., Ames, D., Schweitzer, I., Mastwyk, M., & Colman, P. (1996). Enhanced adrenal sensitivity to adrenocorticotrophic hormone (ACTH) is evidence of HPA axis hyperactivity in Alzheimer's disease. *Psychological medicine, 26*(1), 7–14.

Oke, T. R. (1988). Street design and urban canopy layer climate. *Energy and buildings, 11*(1–3), 103–113.

Pruessner, J. C., Kirschbaum, C., Meinlschmid, G., & Hellhammer, D. H. (2003). Two formulas for computation of the area under the curve represent measures of total hormone concentration versus time-dependent change. *Psychoneuroendocrinology, 28*(7), 916–931.

Ritz, C., Baty, F., Streibig, J. C., & Gerhard, D. (2015). Dose-response analysis using R. *PLoS One1, 10*(12), e0146021.

Shanahan, D. F., Fuller, R. A., Bush, R., Lin, B. B., & Gaston, K. J. (2015). The Health Benefits of Urban Nature: How Much Do We Need? *Bioscience, 65*(5), 476–485.

Suh, Y. A., & Yim, M. S. (2018). "High risk non-initiating insider" identification based on EEG analysis for enhancing nuclear security. *Annals of Nuclear Energy, 113*, 308–318.

Symonds M., 2019, Faculty Opinions recommendation of Spending at least 120 minutes a week in nature is associated with good health and wellbeing, in: *Faculty Opinions – Post-Publication Peer Review of the Biomedical Literature*, Faculty Opinions Ltd.

Tilley, S., Neale, C., Patuano, A., & Cinderby, S. (2017). Older People's Experiences of Mobility and Mood in an Urban Environment: A Mixed Methods Approach Using Electroencephalography (EEG) and Interviews. *International Journal of Environmental Research and Public Health, 14*(2).

Veitch, J., Timperio, A., Salmon, J., Hall, S. J., Abbott, G., Flowers, E. P., & Turner, A. I. (2022). Examination of the acute heart rate and salivary cortisol response to a single bout of walking in urban and green environments: A pilot study. *Urban Forestry & Urban Greening, 74*, Article 127660.

Wang, Q. (2019). *Effects of Different Campus Greenland Landscape Types on College Students' Health, Northwest Agriculture &*. Forestry University.

White, M. P., Alcock, I., Wheeler, B. W., & Depledge, M. H. (2013). Would you be happier living in a greener urban area? *A fixed-effects analysis of panel data, Psychological science, 24*(6), 920–928.

WHO, 2016. Urban green spaces and health - a review of evidence (Andrey I. Egorov, Pierpaolo Mudu, Matthias Braubach, M. Martuzzi, eds.), WHO Regional Office for Europe, WHO Regional Office for Europe, UN City, Marmorvej 51, DK-2100 Copenhagen Ø, Denmark.

Yao, Y., Lian, Z., Liu, W., & Shen, Q. (2008). Experimental study on physiological responses and thermal comfort under various ambient temperatures. *Physiology & Behavior, 93*(1), 310–321.

Yu, Z., Guo, X., Jørgensen, G., & Vejre, H. (2017). How can urban green spaces be planned for climate adaptation in subtropical cities? *Ecological Indicators, 82*, 152–162.

Yu, Z., Yao, Y., Yang, G., Wang, X., & Vejre, H. (2019a). Spatiotemporal patterns and characteristics of remotely sensed regional heat islands during the rapid urbanization (1995–2015) of Southern China. *Science of The Total Environment, 674*, 242–254.

Yu, Z., Yao, Y., Yang, G., Wang, X., & Vejre, H. (2019b). Strong contribution of rapid urbanization and urban agglomeration development to regional thermal environment dynamics and evolution. *Forest Ecology and Management, 446*, 214–225.

Zhan, Y., Liu, J., Lu, Z., Yue, H., Zhang, J., & Jiang, Y. (2020). Influence of residential greenness on adverse pregnancy outcomes: A systematic review and dose-response meta-analysis. *Science of the Total Environment, 718*, Article 137420.

Zhang, J., Yu, Z., Cheng, Y., Chen, C., Wan, Y., Zhao, B., & Vejre, H. (2020a). Evaluating the disparities in urban green space provision in communities with diverse built environments: The case of a rapidly urbanizing Chinese city. *Building and Environment, 183*, Article 107170.

Zhang, J., Yu, Z., Zhao, B., Sun, R., & Vejre, H. (2020b). Links between green space and public health: A bibliometric review of global research trends and future prospects from 1901 to 2019. *Environmental Research Letters, 15*(6), Article 063001.

Zhang, T., Su, M., Hong, B., Wang, C., & Li, K. (2021). Interaction of emotional regulation and outdoor thermal perception: A pilot study in a cold region of China. *Building and Environment, 198*, Article 107870.

Zhao, Y., Bao, W.-W., Yang, B.-Y., Liang, J.-H., Gui, Z.-H., Huang, S., … Chen, Y.-J. (2022). Association between greenspace and blood pressure: A systematic review and meta-analysis. *Science of The Total Environment, 817*, Article 152513.

Zhou, Y., Yang, L., Yu, J., & Guo, S. (2022). Do seasons matter? Exploring the dynamic link between blue-green space and mental restoration. *Urban Forestry & Urban Greening, 73*, Article 127612.

Zhu, H., Yang, F., Bao, Z., & Nan, X. (2021). A study on the impact of Visible Green Index and vegetation structures on brain wave change in residential landscape. *Urban Forestry & Urban Greening, 64*, Article 127299.