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The influence of forest characteristics on psychological well-being: an analysis based on immersive virtual reality

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ABSTRACT

This study investigates the influence of forest characteristics and seasonality on psychological well-being, based on survey data collected in real forest and administered to interviewees through immersive virtual environment. Grounded in the context of "forest bathing" and "forest therapy" research, the work explores how environmental parameters interact with individual responses and contribute to the restorative effects of forest environments. The analysis considers various forest typologies, species compositions, seasons, greenness indices, brightness levels, forest densities, and dendrometric variables. Psychological well-being was assessed using the Restorative Outcome Scale (ROS). The findings confirm the positive impact of forest environments on individual health and well-being, highlighting the significant roles of the greenness index (Vegetative Index – VEG), seasonality, and brightness in shaping ROS scores. Furthermore, statistical analyses reveal a clear seasonal modulation of VEG effects, suggesting complex, non-additive interactions among environmental factors. The study also identifies preliminary patterns indicating potential social influences on ROS responses and outlines directions for future research.

1. Introduction

The role of forests in supporting psychological well-being is an increasingly relevant topic in scientific literature (Siah et al., 2023). Starting from the studies on Attention Restoration Theory (Kaplan and Kaplan, 1989), several researchers have quantitatively highlighted that immersion in forest environments aids in stress recovery and alleviates the effects of mental fatigue (Berto, 2014; White et al., 2023). In Japan, the concept of Shinrin-yoku – known internationally as "forest bathing" – was introduced in the 1980s as a restorative practice that combines relaxation with immersion in the scents and sounds of nature (Paletto et al., 2024a). Documented psychological effects of this practice include an overall improvement in emotions and mood (Miyazaki et al., 2011).

Recent research has used validated psychometric tools – e.g., the Profile of Mood States (POMS) – to assess the impact of forest bathing on negative mood and emotional tension (Ochiai et al., 2015; Park et al., 2022). Scales – e.g., the State-Trait Anxiety Inventory (STAI) and the Positive and Negative Affect Schedule (PANAS) – applied to the forest bathing practice have shown a significant decrease in anxiety levels and an increase in positive emotions after exposure to natural environments (Takayama et al., 2014; Chun et al., 2017; Park et al., 2017; Song et al., 2020). Notably, the psychological benefits derived from contact with forests have been found to surpass those achieved in urban environments (Song et al., 2016).

Despite this scientific evidence, there is a significant gap in the literature on understanding the forest variables that contribute most to these psychological effects, as highlighted by Paletto et al. (2024b). Forest variables such as forest type, stem density, brightness, greenness indices, seasonality, or other dendrometric parameters could significantly influence individual preferences and mental well-being. However, they have not been adequately studied in an integrated way. This study aims to fill the gap by exploring the relationship between forest variables and perceived psychological benefits. The primary objective is to identify the characteristics that have the most significant impact on well-being, providing insights into more targeted forest management strategies to promote individuals' mental and physical health. To this

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end, a questionnaire-based approach was adopted using the Restoration Outcome Scale (ROS) to measure the subjective perception of relaxation and restoration (Tsunetsugu et al., 2013; Tyrväinen et al., 2014).

Participants experienced a virtual forest environment through immersive virtual reality to investigate different forest variables in controlled trials; immersive virtual reality applied to forest bathing positively impacts socio-affective behavior, indicating the potential use in stress reduction (Abdullah et al., 2021; Lopes et al., 2024).

The paper is structured as follows. Section 2 provides an overview of how single forest characteristics have been investigated in the literature concerning psycho-physiological well-being. Section 3 introduces the material and methods applied in the analysis. The work results have been highlighted in Section 4, with a discussion of the main findings and the strengths and limits of the application reported in Sections 5 and 6.

2. Theoretical framework

Forest characteristics, such as tree species composition, stem density, canopy cover, brightness and greenness indices, or seasonality, play a crucial role in determining the psychological impact of immersion in natural environments.

2.1. Tree species composition

Regarding tree species composition, Lee et al. (2011) demonstrated that participants exposed to a broadleaf forest reported a greater sense of calm, serenity, and freshness than those in an urban environment. This result highlights how broadleaf forests' visual and sensory characteristics – such as the wide canopy and seasonal color variations – can evoke a strong positive emotional response. In a similar context, coniferous forests – dominated by evergreen trees such as pine, spruce and fir species – stand out for their contribution to psychological well-being. Li (2010) conducted experiments in coniferous forests in Japan, finding not only an improvement in participants' psychological responses but also positive effects on the immune system, such as an increase in natural killer (NK) cell activity due to the emission of Biogenic Volatile Organic Compounds (BVOCs).

2.2. Seasonality

Seasonality adds a fundamental dimension to the psychological impact of forests, profoundly influencing both visual perception and emotional responses from visitors. During summer, forests are characterized by environments with lush vegetation and intensely saturated colors. These factors create visually stimulating landscapes that have the potential to improve mood, reduce stress levels, and promote psychological recovery, according to many studies (Mao et al., 2012). Green vegetation and abundant sunlight foster general well-being, creating an atmosphere that facilitates relaxation and emotional regeneration.

Recent studies have highlighted that the experience of "forest bathing" during the greener seasons (e.g., spring and summer) shows significant effects in improving emotions, reducing inflammation, and boosting the body's antioxidant defenses (Huang et al., 2022). Antihypertensive and relaxing effects observed in camphor tree (*Cinnamomum camphora* (L.) J. Presl) forests were more pronounced during these seasons compared to the winter months. Similarly, Mao et al. (2017) investigated during summer the effects of forest bathing on elderly patients with chronic heart failure, finding a reduction in negative feelings and an improvement in mood after the experience. Peterfalvi et al. (2021) detected a lower activation of NK cells in winter with respect to the spring session of experiments in Hungary. However, seasonal influence does not seem to follow a uniform pattern. Broadleaf forests – characterized by more exuberant vegetation in spring and summer – do not lose their positive impact even during winter when the vegetation is bare. For instance, Bielinis et al. (2018a) found that the restorative effect of broadleaf trees was stronger during winter than in spring, suggesting that the presence of living woody plants continues to exert a positive effect even during less floriferous seasons. Those authors demonstrated how short winter interaction with forest had a substantial emotional and restorative on individuals. This result suggests that, although summer is generally the most favorable season for psychological well-being, forests can offer benefits during other seasons, depending on the tree species and environmental context. Positive physiological and psychological responses from walking in and viewing autumn forests have also been demonstrated (Joung et al., 2015; Wu et al., 2023; Pratiwi et al., 2024).

2.3. Greenness index

Another relevant aspect of well-being perception is the greenness index, defined as the level of vegetation and color saturation in an environment. Grilli et al. (2022) emphasized that green intensity significantly influences individuals' psychological and physiological responses. The study's results suggested that the degree of vegetation can directly impact psychological recovery and general well-being. Areas with a high greenness index seem particularly favorable for improving mood and reducing stress.

2.4. Stem density, dendrometric characteristics, and brightness

Stem density (number of trees per unit of surface) and canopy cover (percentage of forest area occupied by the vertical projection of tree crowns) represent other factors potentially influencing the psychological impact of forests. Dense vegetation, characterized by a high number of trees and thick canopies, can create environments that foster a greater sense of security and intimacy, reducing the perception of external stimuli, facilitating psychological relaxation, emotional recovery and stress reduction (Kobayashi et al., 2019). Conversely, Takayama et al. (2017) found that the decrease in stem density due to the thinning does not directly influence the mood index and emotions of the participants. An et al. (2004) reported improvement in the physiological trend of decreasing forest density in coniferous stands and a U-shaped profile of EEG and pulse rate for broadleaves stands from 100 % to 30 % of density. Wang et al. (2020) show in a neuroscientific experiment how bamboo forests with a higher canopy density could significantly decrease α waves (directly correlated with relaxation). High β and low β waves (inversely correlated with relaxation) showed more significant decreases, with tension reduced more effectively when bamboo forests have a low tilt ratio and neat undergrowth.

Less dense vegetation, which offers more open spaces and visibility, may have different psychological effects. Forests with lower tree density are often associated with more panoramic landscapes, which stimulate feelings of freedom and expansiveness but may be less effective in reducing stress perception or inducing sensations of intimacy (Berman et al., 2008).

Li et al. (2019) found that participants immersed in low-density forests exhibited less stress reduction than those exploring denser forests. These results suggest that forest density can influence an individual's psychological experience during immersion in a natural environment.

Additionally, stem density can interact with other variables, such as tree species and seasonality, creating combined effects on mood and psychological well-being. The effect of a dense coniferous forest may be even more pronounced in summer when the vegetation is particularly lush compared to a less dense broadleaf forest, which might be less psychologically favorable during certain times of the year (Li et al., 2020).

The effects of brightness were also analyzed in the scientific literature: a finding from the study of Li et al. (2020) was that exposure to the natural light of medium brightness could significantly reduce stress, compared to overly bright or overly dark levels.

3. Materials and methods

3.1. Stimuli selection and processing

A total of 24 forest stimuli were recorded. Stimuli registration included 12 winter videos (registered in February – March 2024) and 12 summer videos (registered in June – July 2024). The selected forests belonged to three Italian inland areas in the Alpine, Apennine, and Mediterranean regions (Fig. 1). In the Italian context, inland and mountainous areas represent an interesting case study to promote diversification of forest activities and emerging markets based on cultural ecosystem services provided by forests (Guardini et al., 2023; Marino et al., 2024).

Spherical videos of forests were recorded using the Insta360 camera, equipped with two 180° lenses. These lenses capture two separate video streams, which are merged during post-production using Insta360 Studio software. For each forest, four filming locations were identified based on two specific criteria: tree species composition (pure or mixed forest) and stem density (high: density>350 trees/ha or low: density<=350 trees/ha). A uniform distribution of deciduous/evergreen and broadleaves/conifers typology among stimuli was also guaranteed. Field visits were conducted to both register stimuli and collect dendrometric and structural characteristics of each forest (average diameter at breast height, DBH - cm -, basal area - m^2/ha -, and illuminance at viewing level - lx). Table 1 provides the details of the selected stimuli.

Two video sequences (T1 and T2), each with 12 videos, were created. The sequences were processed with CapCut software, which allowed for video trimming, the addition of a uniform audio track (forest sounds) to eliminate auditory variables, and the integration of explanations and questions directly visible during an immersive virtual reality experience. For visualization, the Oculus Meta Quest 2 virtual reality headset was used.

3.2. Sample, experimental tasks, and interviews

The sample consisted of 67 participants (33 males and 34 females), evenly distributed across the two sequences. Each participant evaluated only one sequence (T1 or T2) for a total of 12 forest videos individually assessed. Thirty-five participants evaluated sequence T1 (17 males and 18 females), while 32 participants evaluated sequence T2 (16 males and 16 females). Participants were voluntary students, primarily enrolled in undergraduate and graduate programs at the University of Florence (course of Urban and Regional Planning, 69 %) and the University of Trento (course of Economics and Management, 31 %).

Upon arrival at the laboratory, participants completed a preliminary questionnaire collecting information on gender, age, education level, residence, and frequency of visits to natural areas, among other data. Then, the Ishihara test (Birch, 1997) was administered to detect any color vision deficiencies. The test consists of a series of Ishihara plates, each composed of a circle of colored dots varying in size, which may initially appear random (Birch, 1997; Ekhlasi et al., 2021). Participants were asked to identify the numbers embedded within the figures.

The experiment lasted approximately 24 min. After the first Restorative Outcome Scale (ROS) questionnaire administration and an introductory description to immersive virtual reality experiment, participants underwent a stress test, which involved counting backward in steps of 13, starting from 1687. This test aimed to assess potential differences in physiological responses, comparing a "baseline" level to those observed during forest video exposure.

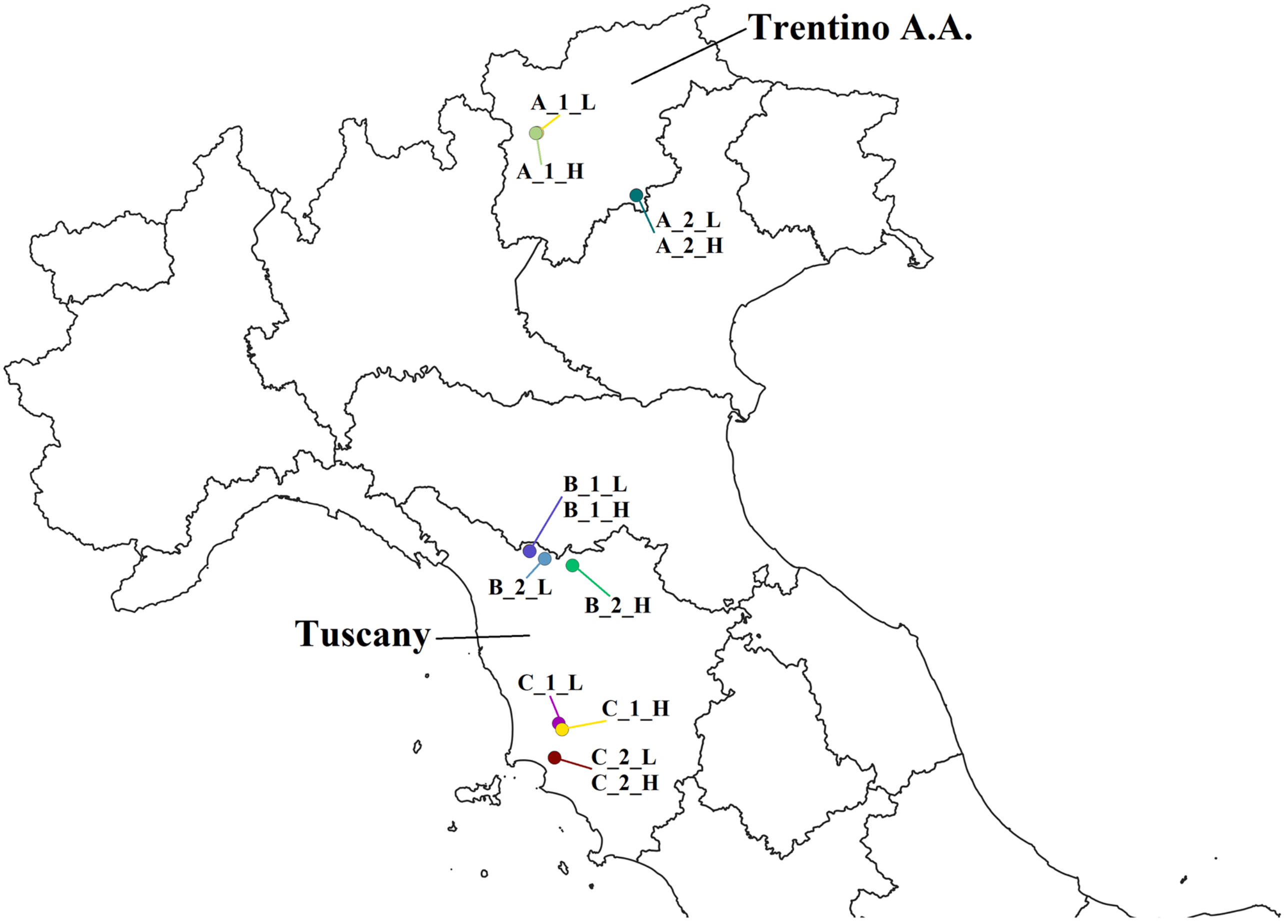

Fig. 1. Location of study areas (for recodification of stimuli, see Table 1).

Table 1

Description of the selected areas and stimuli. Each stimulus was identified by a descriptive code where the first letter indicates the location (*A*= Alpine, *B*= Apennine, *C*= Mediterranean); the number represents the tree species composition (1= pure, 2= mixed); the third character defines the stem density (*L*= low, *H*= high); the fourth element indicates the season (sum= summer, win= winter).

Location	Inland area (province, region)	Tree species composition	Specie(s)	Density (trees/ha)	Stimuli ID	Average DBH (cm)	Basal area (m^2/ha)	Illuminance (lx) (winter, summer)
Alpine	Val di Sole (Trento, Trentino A.A.)	Pure forest	Larch	Low	A_1_L_win, A_1_L_sum	81	50	41,000, 4500
			Larch	High	A_1_H_win, A_1_H_sum	43	58	21,000, 3500
	Tesino (Trento, Trentino A.A.)	Mixed forest	Beech, Silver fir, Spruce fir	Low	A_2_L_win, A_2_L_sum	35	36	11,700, 2500
			Beech, Silver fir, Spruce fir	High	A_2_H_win, A_2_H_sum	36	34	12,300, 1000
Apennine	Pistoia’a Apennine (Pistoia, Tuscany)	Pure forest	Beech	Low	B_1_L_win, B_1_L_sum	46	56	15,500, 900
			Beech	High	B_1_H_win, B_1_H_sun	27	43	26,000, 1700
	Pistoia’a Apennine (Pistoia, Tuscany)	Mixed forest	Douglas fir and Silver fir	Low	B_2_L_win, B_2_L_sum	64	77	2500, 1700
	Pistoia’a Apennine (Pistoia, Tuscany)	Mixed forest	Douglas fir and Silver fir	High	B_2_H_win, B_2_H_sum	43	63	2400, 700
Mediterranean	Colline Metallifere (Grosseto, Tuscany)	Pure forest	Turkey oak	Low	C_1_L_win, C_1_L_sum	34	33	22,000, 7800
			Turkey oak	High	C_1_H_win, C_1_H_sum	28	46	21,500, 650
	Colline Metallifere (Grosseto, Tuscany)	Mixed forest	Umbrella pine and Cork oak	Low	C_2_L_win, C_2_L_sum	31	25	12,350, 4600
			Umbrella pine and Cork oak	High	C_2_H_win, C_2_H_sum	33	37	15,300, 26,000

Participants then watched 12 forest videos in the randomized sequences. At the end of each video, they verbally responded to six statements based on the ROS. These statements assessed their psychological state and perceived well-being, including “I feel restored and relaxed”, “I feel calm”, “I have enthusiasm and energy for my everyday routines”, “I feel focused and alert”, “I can forget everyday worries”, “My thoughts are clear”. Participants rated their agreement with each statement using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

The experimental workflow and the corresponding time in seconds are illustrated in Fig. 2.

3.3. *Quantification of greenness index*

The Greenness Index (GI) is a quantitative parameter used to measure the presence and distribution of vegetation within an image. This index was calculated by analyzing the values of the RGB (Red, Green, and Blue) color components, which indicate the intensity of these three primary colors for each pixel in still frames extracted from the recorded videos. The RGB values for each stimulus (reported in Supplementary material, table A.1) allowed for identifying location color and distribution variations.

The GI was employed to investigate the relationship between vegetation cover and the perception of environmental well-being, as the green level seems to influence the sense of comfort significantly. Mul-

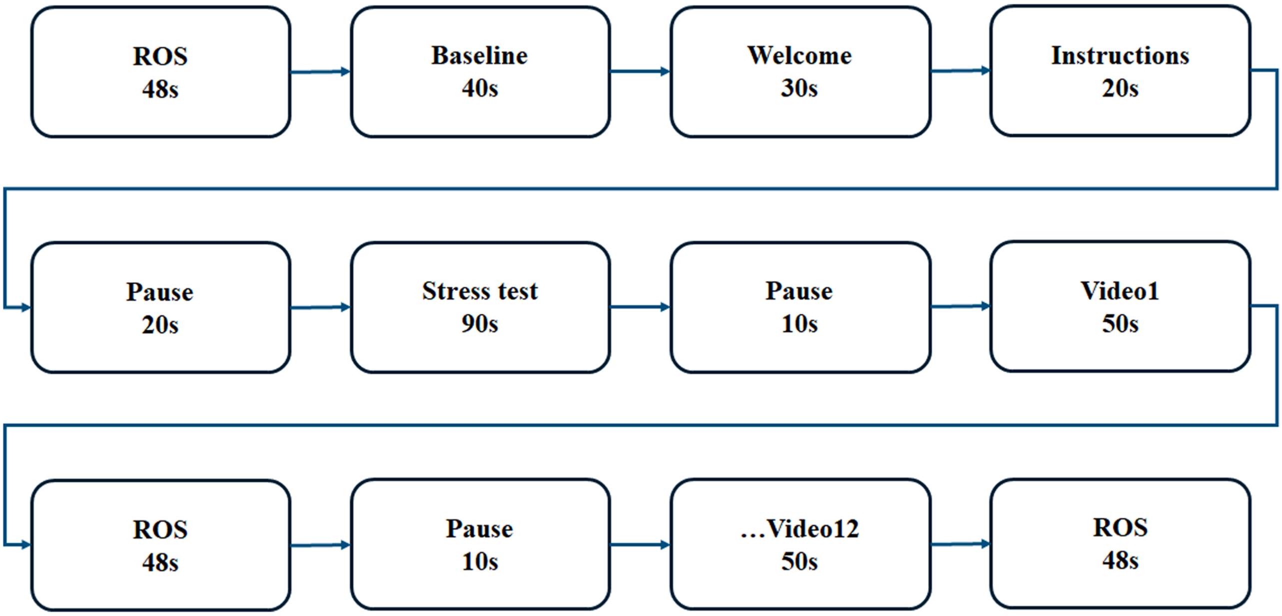

Fig. 2. Experimental workflow.

tiple GIs were calculated for the analysis to determine the most suitable and relevant one. The analyzed GIs, along with their respective formulas, are the following:

- Excess Green (ExG) (Woebbecke et al., 1995):

$$\text{ExG} = 2 * G - R - B \tag{1}$$

- Green Red Vegetation Index (GRVI) (Motohka et al., 2010):

$$\text{GRVI} = \frac{G - R}{G + R} \tag{2}$$

- Vegetative Index (VEG) (Hague et al., 2006):

$$\text{VEG} = \frac{G}{R^{0,667} * B^{0,334}} \tag{3}$$

A non-parametric correlation analysis was conducted using Spearman's method to identify the most effective index suitable for non-normally distributed data.

3.4. Data analysis

Data analysis was conducted using R software to examine how forest characteristics influence the average scores of the ROS, which serves as the dependent variable in this study. First, the Shapiro–Wilk normality test was performed to assess the distribution of the average ROS scores. Given that the data did not meet the normality assumption, the non-parametric Kruskal–Wallis test was selected to compare group differences. Dunn's post-hoc test with Bonferroni correction was also applied. In this case, the independent variable was the forest characteristics set, such as tree species composition (pure or mixed forests), season (winter or summer), stem density, greenness index, brightness, average DBH, and basal area.

A predictive model was implemented to further explore forest variables' influence on ROS scores. The analytical workflow originated with an exploratory phase, in which data distributions and patterns of potential multicollinearity among independent variables were examined. Subsequently, a Random Forest (RF) analysis was employed to evaluate the relative importance of predictors; the relative importance was applied to select representative variables and potential interactions among variables to be considered in further modelling stages. Guided by these preliminary insights, linear mixed-effects models were constructed, integrating (i) fixed effects for environmental and ecological variables, (ii) interaction among variables suggested by RF exploratory analyses, and (iii) random intercepts to account for repeated measures within subjects. Model assumptions were assessed through standard residual diagnostics, including visual inspections of residual distributions and quantile-quantile plots. Finally, the significance of predictors and interactions was evaluated using *t*-tests with Satterthwaite's approximation method and Type III Analysis of Variance.

The RF regression model was employed to evaluate the relative predictive importance of each variable. The RF model can be formally expressed through the following equation, which summarizes its general predictive framework:

$$\begin{aligned}\text{ROS} &= f\,(\mathit{Season},\ \mathit{GI}(s),\ \mathit{Brightness},\ \mathit{Basal\ area},\ \mathit{Density},\\ &\quad \mathit{DBH},\ \mathit{Species},\ \mathit{Composition})\ +\ \varepsilon\end{aligned} \tag{4}$$

where f represents the non-linear predictive function estimated by the RF algorithm, and ε denotes the residual error. This approach effectively captures complex, non-linear relationships among variables without imposing restrictive assumptions on their functional form. The model was built using 500 "trees", with two variables tried at each split.

The importance of each predictor was quantified using two standard metrics: the percentage increase in Mean Squared Error (%IncMSE), representing how much prediction accuracy decreases when a predictor is removed, and the increase in node purity (IncNodePurity), reflecting the cumulative reduction in residual sum of squares attributed to splits on a particular predictor.

Finally, a linear mixed-effects model based on the outcomes of the preliminary RF analysis was implemented to assess the potential correlation among variables.

4. Results

4.1. Descriptive analysis of the sample

Most participants (55 %) were between 18 and 24 years old, 32 % were in the 25–39 age range, and the remaining 13 % were between 40 and 60 years old. Regarding place of residence, 81 % of respondents lived in a medium-big city with >25,000 inhabitants, 12 % in a small city (between 2500 and 25,000 inhabitants), and 7 % in a rural area or small village (<2500 inhabitants). Finally, 46 % of the sample reported frequent or occasional visits to natural areas, while 51 % visited them only once a month or less, and 3 % rarely (less than once a year).

According to the Ishihara test, all participants were found to have normal color vision.

Table 2 highlights the improvement of the ROS average for all variables from baseline to forest stimuli. The magnitude of ROS enhancement is relevant for males vs. females and, particularly, taking into account the place of residence: moving from rural areas to medium/big cities, the score difference between forest and baseline increases.

4.2. Statistical analysis

4.2.1. Baseline vs. forest exposure

The first analysis compared the participants' baseline state (before the experiment) with their state after watching the forest videos to examine the differences between pre- and post-forest exposure and between the two groups (T1 and T2 sequences). The results of the Kruskal–Wallis test confirmed the preliminary evaluation reported in Table 2. In particular, the results revealed a significant difference between the "Baseline" responses (average: 4.35) and the "Forest" responses (average: 5.41) concerning the mean ROS scores ($\chi^2 = 38.47$, $p < 0.001$). The post-hoc Dunn test confirmed that the difference between

Table 2
ROS average for sample variable (baseline value and average of forest stimuli).

Variable *Gender*	Baseline	Forest	ROS difference (forest –baseline)
Female	4.28	5.28	1.01
Male	4.44	5.54	1.10
Place of residence	Baseline	Forest	ROS difference (forest –baseline)
Rural area / Small village (<2500 inhabitants)	5.57	5.71	0.14
Small cities (2500<=inhabitants< 25,000)	4.54	5.46	0.92
Medium-big cities (>=25,000 inhabitants)	4.25	5.27	1.02
Frequency of visits to natural areas	Baseline	Forest	ROS difference (forest –baseline)
Very often (once or twice a week)	4.93	5.80	0.87
Often (three or four times a month)	4.47	5.47	1.00
Sometimes (max once a month)	4.35	5.32	0.97
Rarely (less than once a year)	4.09	4.83	0.75
University	Baseline	Forest	ROS difference (forest –baseline)
University of Florence	4.07	5.43	1.37
University of Trento	4.99	5.35	0.36

the two groups was statistically significant (Z = -6.20, p = 2.78e-10).

Subsequently, individual videos were analyzed to identify the most preferred and relaxing. The results of the Kruskal–Wallis test showed significant differences between them, with a χ^2 value of 115.08 and an extremely low p-value (7.235e-14), indicating significant differences among stimuli. The post-hoc Dunn test was then conducted to analyze the pairwise comparisons between stimuli, confirming significant differences between many pairs.

The comparisons showing particularly marked and highly significant differences ($p < 0.001$) were those between A_1_H_win - C_1_H_sum ($Z = -4.47$, p = 3.89E-06) and between A_1_H_sum - A_1_H_win (Z = 4.23, p = 1.16E-05). Other comparisons showed high significance ($0.001 < p < 0.01$), such as the comparison between A_1_H_win - C_2_H_sum ($Z = -3.03$, p = 0.0012) and A_1_H_sum -B_2_H_win (Z = 3.01, p = 0.0013). Some comparisons yielded more moderate significance ($0.01 < p < 0.05$). An example of this is the evaluation between B_2_L_win - C_2_L_sum ($Z = -2.32$, p = 0.0102) and B_1_H_sum - C_2_H_win (Z = 2.31, p = 0.0104). Finally, some comparisons were found to be non-significant ($p > 0.05$), such as the comparison between A_1_L_sum - A_1_L_win (Z= -0.96, p = 1.6853e-01) and A_1_H_sum - A_2_L_sum (Z = 0.76, p-value= 2.2260e-01).

The mean ROS values for each stimulus and forest typology are reported in Tables 3 and 4.

4.2.2. *Tree species composition*

The analysis conducted for tree species composition shows no significant differences between pure and mixed forests. The results of the non-parametric Kruskal-Wallis test support this observation, with a χ^2 value of 1.579 and a p-value equal to 0.208. Furthermore, the post-hoc Dunn test further confirmed the absence of significant differences, with a Z value of -1.25 and a p-value of 0.1044.

4.2.3. *Seasonality*

The analysis of seasonality, conducted through the non-parametric Kruskal–Wallis test, shows statistically significant differences in the average well-being perception across the different seasons. The test returned a χ^2 value of 45.468 and a p-value of 1.552e-11. The post-hoc test highlighted a significant difference between the summer and winter seasons, with a Z of 6.743 and a corrected p-value of 7.758e-12.

The results suggest that the summer season has a more positive impact on well-being perception than the winter. Fig. 3 displays the comparative boxplots of the two seasons.

Table 3
Average ROS values for single stimulus.

ID_Stimuli	ROS average
C_1_H_sum	6.042
A_1_H_sum	5.983
B_1_L_sum	5.912
A_2_L_sum	5.755
A_2_H_sum	5.638
C_2_L_sum	5.631
C_2_H_sum	5.605
B_2_H_sum	5.578
B_1_L_win	5.568
B_1_H_sum	5.553
B_2_L_sum	5.509
A_1_L_win	5.485
A_2_L_win	5.438
C_1_L_sum	5.386
B_2_H_win	5.245
A_1_L_sum	5.223
C_1_H_win	5.219
A_2_H_win	5.181
B_1_H_win	5.172
C_2_L_win	5.089
C_1_L_win	5.028
C_2_H_win	5.005
B_2_L_win	4.900
A_1_H_win	4.700
Baseline	4.356

Table 4
Average ROS values for forest typology.

Forest typology	ROS average
Silver fir, spruce, beech	5.71
Beech	5.60
Turkey oak	5.60
Larch	5.49
Umbrella pine and Cork oak	5.43
Silver fir and Douglas fir	5.40

Table 5 confirms statistical analysis showing a regular trend in the difference between ROS scores in summer and winter (apart for A_1_L stimuli). Outputs for deciduous/evergreen and broadleaves/conifers are also reported: the same tendency between summer and winter analysis is confirmed for these categories.

4.2.4. *Greenness indices*

The results about seasonality indicate a potential influence of GIs in ROS score elicitation. An in-depth analysis of GIs was thus provided. The values of examined GIs are shown in Table 6.

Table 7 shows additional information on the three indices (i.e. correlation coefficients with ROS and p-values).

The outputs (Table 7) indicated that the Vegetative Index (VEG) exhibited the highest correlation coefficient and a significantly lower p-value than the other indices. Consequently, VEG was recognized as the most effective parameter, displaying the strongest correlation with ROS.

The Kruskal-Wallis test performed on VEG (χ^2= 80.307, $p < 0.001$) revealed highly significant differences between stimuli. Specifically, post-hoc Dunn comparisons showed that all significant differences occurred between summer and winter stimuli, emphasizing the crucial role of summer vegetation in promoting relaxation and well-being.

4.2.5. *Stem density, dendrometric characteristics and brightness*

The analysis of stem density did not reveal any significant differences between areas with low and high density. The Kruskal-Wallis test results, with a χ^2 value of 0.1386 and a p-value of 0.7097, suggest the absence of statistically relevant variations between the analyzed groups.

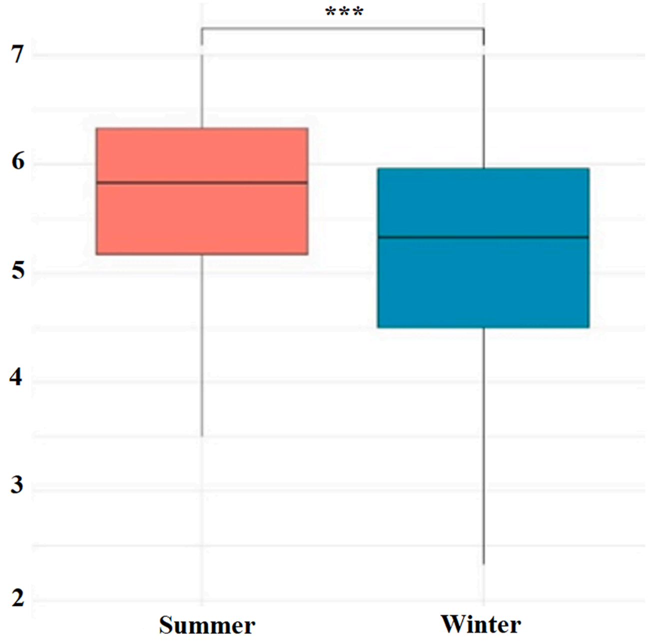

Fig. 3. Boxplots with the median value of ROS score in summer and winter stimuli.

Table 5
ROS scores in winter and summer seasons for stimulus and forest classification.

Stimuli	ROS winter	ROS summer	Difference (summer-winter)
A_1_L	5.49	5.22	-0.26
A_1_H	4.72	5.98	1.26
A_2_L	5.44	5.76	0.32
A_2_H	5.18	5.64	0.46
B_1_L	5.57	5.91	0.34
B_1_H	5.17	5.55	0.38
B_2_L	4.90	5.51	0.61
B_2_H	5.25	5.58	0.33
C_1_L	5.03	5.39	0.36
C_1_H	5.22	6.04	0.82
C_2_L	5.09	5.63	0.54
C_2_H	5.00	5.61	0.60
Deciduous	5.20	5.68	0.48
Evergreen	5.14	5.62	0.48
Broadleaves	5.25	5.72	0.48
Conifers	5.13	5.62	0.48

Table 6
Values of greenness indices.

Sequence	Stimuli	ExG	GRVI	VEG
T1	A_1_L_sum	42	0.043	1.166
	B_1_H_win	-1	0.006	0.997
	C_1_L_sum	42	0.033	1.158
	A_2_H_win	2	-0.024	0.985
	B_2_L_sum	46	0.089	1.237
	C_2_H_win	3	-0.016	0.992
	A_1_L_win	2	-0.028	0.982
	B_1_H_sum	54	0.070	1.238
	C_1_L_win	-2	-0.027	0.974
	A_2_H_sum	57	0.076	1.281
	B_2_L_win	12	0.003	1.026
	C_2_H_sum	6	-0.018	1.004
T2	C_2_L_win	10	0.003	1.018
	B_2_H_sum	9	-0.011	1.025
	A_2_L_win	-1	-0.029	0.975
	C_1_H_sum	58	0.095	1.293
	B_1_L_win	5	0.040	1.033
	A_1_H_sum	37	0.030	1.142
	C_2_L_sum	17	0.004	1.054
	B_2_H_win	6	0.012	1.019
	A_2_L_sum	58	0.072	1.248
	C_1_H_win	12	-0.011	1.011
	B_1_L_sum	67	0.085	1.302
	A_1_H_win	-1	-0.026	0.977

Table 7
Correlation and p-value of greenness indices.

Greenness indices	Correlation coefficient	*p*-value
ExG	0.212	1.19e-09
GRVI	0.186	1.03e-07
VEG	0.217	4.63e-10

These results were further confirmed by the post-hoc Dunn test, which returned a Z value of 0.3723 and a corrected p-value of 0.3548 for the direct comparison between high and low density, indicating the lack of significance. This implies that stem density seems not to be a discriminating factor for the analyzed parameter. However, to further explore the data, the stimuli were divided into summer and winter groups to explore seasonal differences. The Kruskal-Wallis and Dunn tests revealed significant differences only in the summer but not in winter. In the summer, the Dunn test revealed a significant difference between the high-density (H) and low-density (L) groups, with a corrected p-value of 0.0458. This result indicates that the average ROS scores are significantly higher in the high-density (H) group compared to the low-density (L) group in summer. In contrast, during the winter season, the Dunn test confirmed no significant differences between the high-density (H) and low-density (L) groups, with a *p*-value of 0.1584.

The analysis of dendrometric characteristics (average DBH and basal area) and brightness did not reveal any statistical significance for correlation with ROS. A summary of these variables for stimulus is reported in Table 8.

4.2.6. Random Forest analysis and predictive models

The performance of the RF indicated a mean squared residual error of 1.07 and explained approximately 41.7 % of the variance. Results from RF about variable importance are summarized in Table 9.

Among predictors, Season (5.78 %), VEG (4.82 %), and Brightness (4.22 %) showed the most significant influence on model performance according to %IncMSE, indicating their strong predictive relevance. Basal area, Density, DBH, and Species demonstrated relatively lower importance, whereas Composition showed minimal predictive contribution.

The linear mixed-effects model was formulated based on the outcomes of the preliminary RF analysis, as reported in Section 3.4. According to the RF results, predictors demonstrating higher relative importance – specifically Season, greenness index (VEG), and Brightness – were prioritized for inclusion as fixed effects. Given that RF analysis also highlighted potential interactions, two interaction terms, VEG × Season and VEG × Brightness, were incorporated to capture context-dependent effects. The mixed-effects model thus included fixed effects for these selected variables (Season, VEG, Brightness), additional covariates of theoretical interest (Species, Density, DBH, and Basal area), and interaction between VEG and Season as well as VEG and Brightness. Moreover, the model featured a random intercept for each participant to account for repeated measurements within individual participants and the resulting correlated residuals.

Formally, the mixed-effects model was specified as follows:

$$\begin{aligned} ROS_{ij} = \; & \beta_0 + \beta_1 VEG_{ij} + \beta_2 Season_{ij} + \beta_3 Brightness_{ij} + \beta_4 Species_{ij} + \\ & \beta_5 Density_{ij} + \beta_6 DBH_{ij} + \beta_7 Basal\_area_{ij} + \\ & \beta_8 \left(VEG_{ij} \times Season_{ij} \right) + \beta_9 \left(VEG_{ij} \times Brightness_{ij} \right) + u_j + \epsilon_{ij} \end{aligned} \tag{5}$$

where ROS_{ij} represents the restorative outcome scale score for observation *i* within participant *j*, β_0 is the fixed intercept, β_1 to β_9 represent fixed-effect coefficients, $u_j \sim N(0, \sigma_u^2)$ is the random effect of the

Table 8
Brightness, average DBH, and basal area for stimulus.

Stimuli	Brightness (lx)	DBH (cm)	Basal area (m^2/ha)
A_1_H_sum	3500	43	58
A_1_H_win	21,000	43	58
A_1_L_sum	4500	81	50
A_1_L_win	41,000	81	50
A_2_H_sum	1000	36	34
A_2_H_win	12,300	36	34
A_2_L_sum	2500	35	36
A_2_L_win	11,700	35	36
B_1_H_sum	1700	27	43
B_1_H_win	26,000	27	43
B_1_L_sum	900	46	56
B_1_L_win	15,500	46	56
B_2_H_sum	700	43	63
B_2_H_win	2400	43	63
B_2_L_sum	1700	64	77
B_2_L_win	2500	64	77
C_1_H_sum	650	28	46
C_1_H_win	21,500	28	46
C_1_L_sum	7800	34	33
C_1_L_win	22,000	34	33
C_2_H_sum	26,000	33	37
C_2_H_win	15,300	33	37
C_2_L_sum	4600	31	25
C_2_L_win	12,350	31	25

Table 9
Variable importance from Random Forest regression.

Variable	%IncMSE	IncNodePurity
Season	5.78 %	23.13
VEG	4.82 %	24.49
Brightness	4.22 %	20.31
Basal area	1.86 %	10.55
Density	1.78 %	9.02
DBH	1.71 %	8.98
Species	1.63 %	9.75
Composition	0.53 %	2.07

participant, and $\epsilon_{ij} \sim N(0, \sigma^2)$ is the residual error.

All continuous predictors (e.g., VEG, Brightness, DBH, Basal area) were standardized to have mean= 0 and SD= 1 prior to fitting the model, in order to facilitate comparison of effect sizes and model convergence. The linear mixed model results (Table 10) report a random intercept variance of 0.647 (SD= 0.805) highlighting noticeable individual differences in ROS scores among participants. The residual variance was 0.415. While no formal significance test was performed on the random effect, the non-zero variance and improved model fit (as assessed by residual diagnostics) justifying the use of a mixed-effects approach. Overall, the model demonstrated satisfactory goodness of fit, with a marginal R^2 of 0.27 (variance explained by fixed effects) and a conditional R^2 of 0.64 (variance explained by both fixed and random effects), which are considered appropriate values for mixed-effects models in psychological and environmental research (Rights and Sterba, 2019). In the linear mixed model formulation the categories, represented by group of variables, are automatically treated with a "dummy coding". This means that each category with k variables is represented by $k-1$ dummy variables. In the "dummy coding" the first level (a variable defined manually) is indicated as the reference (Ref.) to compute statistical trend of the other variables belonging to the same category. In our case study, the categories are Season (variables "summer" and "winter") as well as Species (variables "silver fir, spruce, and beech", "turkey oak", "Douglas fir and silver fir", "beech", "larch", "umbrella pine and cork oak"). For each category, the selected Ref. variables are respectively, "summer" and "silver fir, spruce, and beech".

Table 10
Results of the mixed model[a].

Variable	Estimate (β)	Std. error	t-value	*p*-value
(Intercept)	5.715	0.175	32.587	<0.001***
VEG	-0.351	0.173	-2.033	0.042*
Season (winter)	-0.024	0.253	-0.096	0.923
Brightness	-0.198	0.141	-1.411	0.159
Density	<0.001	<0.001	0.108	0.914
Species (turkey oak)	-0.131	0.095	-1.386	0.166
Species (Douglas fir and silver fir)	-0.442	0.205	-2.159	0.031*
Species (beech)	-0.119	0.111	-1.068	0.286
Species (larch)	-0.383	0.149	-2.571	0.010*
Species (umbrella pine and cork oak)	-0.273	0.102	-2.675	0.008**
Basal area	0.038	0.066	0.580	0.562
DBH	0.050	0.077	0.651	0.515
VEG × Season (winter)	0.859	0.376	2.287	0.022*
VEG × Brightness	-0.375	0.148	-2.543	0.011*

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

[a] : the model was fitted on $N = 804$ observations ($n = 67$ participants). Marginal $R^2 = 0.27$; Conditional $R^2 = 0.64$. Statistical significance for fixed effects was assessed via Type III ANOVA with Satterthwaite's method. The REML criterion at convergence was 1855.2. Random intercept variance (Participant): 0.647; residual variance: 0.415.

The analyses highlighted significant differences in ROS among the different forest typologies. In particular, "larch" ($\beta = -0.258$, $p = 0.004$), "Douglas fir and silver fir" ($\beta = -0.442$, $p = 0.031$), and "umbrella pine and cork oak" ($\beta = -0.181$, $p = 0.043$) show significantly lower values of ROS than the reference species, indicating a potential influence of the forest typology on the analyzed variable.

The interaction analysis highlighted a significantly seasonally dependent relationship between VEG and ROS. During summer (reference category), a significant negative effect of VEG on ROS was observed ($\beta = -0.351$, $p = 0.042$). However, this relationship changed direction during winter, becoming positive (interaction VEG × Season winter: $\beta = 0.859$, $p = 0.022$). In addition, as light intensity increases, the effect of VEG on ROS is significantly reduced ($\beta = -0.375$, $p = 0.011$). These results indicate a precise seasonal modulation of VEG effects, suggesting that the relationship between vegetation and ROS cannot be generalized to all seasons (they are not simply additive) but must be temporally contextualized.

The other variables (Density, Basal area, DBH) did not show significant effects and could be excluded in simplified models.

In-depth screening of sample characteristics (gender, place of residence, frequency of visits in natural areas) confirms potential importance of the VEG index on ROS elicitation. In fact, a particular trend is revealed focusing on female sample residents in rural areas: in this case, a regression model combining both VEG and brightness shows a relatively low statistical significance with ROS but is interesting for future additional evaluations of individual characteristics (R^2: 0.35; VEG, positive correlation, $p < 0.05$; brightness, negative correlation, $p < 0.05$).

5. Discussion

The present research explored the role of forests in promoting psychological well-being, focusing on forest variables that favor such healthy status. Our results confirmed this relationship by comparing psychological states before and after exposure to natural stimuli. The data showed a significant effect, suggesting that viewing natural landscapes positively impacts psychological and mental well-being, with a restorative effect of nature.

The forest stimuli perceived as the most relaxing belong to summer situations. For example, the pure Turkey oak (*Quercus cerris* L.) forest with high density in the Tuscan Mediterranean area and the pure European larch (*Larix decidua* L.) forest with high density in the Trentino Alpine area are ranked as the ones with higher ROS scores. Generally, the lowest scores were recorded for winter stimuli as established also in other studies (Kim and Lee, 2023). Some exceptions due to other relevant environmental peculiarities are reported: mountainous landscape and/or snow covering seem to be additional parameters influencing perception, as confirmed by Bielinis et al. (2021). These results highlighted how seasonal conditions (summer vs. winter) are crucial in the perception of psychological well-being associated with forest environments.

Summer stimuli recorded the highest average ROS values, regardless of the geographical area, tree species composition, brightness, stem density, or dendrometric variables. This trend is closely related to one factor: the higher greenness indices of summer environments. This output supports the (few) existing literature about relation between greenness indices and well-being (see e.g. Hwang et al., 2019; Grilli et al., 2022). The greenness indices are strong indicators of the relaxing function of the forest landscape. Vegetative Index (VEG) was considered the most correlated GI with ROS score. The better performances of summer stimuli for all forest categories, such as deciduous/evergreen or broadleaves/conifers, suggest that the GI should not be evaluated only for canopy cover. Areas with a higher GI are associated with more lush vegetation, including ground-level growth such as grass, shrubs, seedlings, and saplings. The imagery evaluated (video, picture etc.) should therefore consider green amount in the whole visualization of the environment inside the forest (defined as “in-stand scenic”; Ribe, 2009) and not only the green relate to canopies.

The analysis of tree species composition (pure vs. mixed forest) did not reveal significant differences between the two categories. The outputs on stem density and dendrometric indices, such as average DHB and basal area, did not directly impact perceived well-being in contrast with references reported in Section 2.4. The light variable does not correlate with ROS; however, a multi-regression model focused on females living in rural areas seems to associate ROS with VEG and brightness with a certain statistical significance; a linear mix-effects model shows the inverse correlation of VEG with brightness.

The descriptive analysis of ROS responses reported in Section 4.1 indicates future additional insights to be investigated with *ad hoc* research. In particular, minor differences are stressed between males and females in the sample (with a higher well-being improvement from baseline to forest for males). Interesting evidence is the substantial increment of ROS from baseline to forest for subjects living in medium-big urban areas with respect to those living in rural areas and small villages: the trend seems to be correlated with town dimensions. Inhabitants of rural areas and small villages assign high ROS scores (>5) even at the baseline level (before the forest video), suggesting a possible dose-response effect of forest or green areas due to residence. A similar assumption (potential dose-response effect due to people background) emerges from the focus on the frequency of visits to natural areas. Both baseline and forest-associated ROS scores decrease from a "very often" item to a "rarely" level of visits. Given the output from Section 4.1, further research should calibrate a stratified sample of respondents to explore ROS elicitation in respect of their background (i.e. different level of contact with rural and forested areas due to place of residence, frequency of visits to natural areas etc.) to statistically verify the above trends (Russo, 2024).

Results reported in Section 4.2 suggest that psychological well-being is influenced by a complex interplay of factors, with seasonality and GIs assuming a predominant role. Due to high correlation between season and GI (VEG in our case study) some concerns about the independent role of the variables can arise. However, seasonality captures non-visual sensory elements (e.g., heat, humidity, biodiversity cues) that VR cannot fully simulate. Thus, seasonality may act as a contextual “frame” influencing psychological responses even in VR and explaining the independent role in respect to VEG index. Forest environments that are summer-like represent a potential tool for promoting psychological well-being. This finding paves the way for further research on optimizing natural experiences for mental health support.

This research has some limitations that could be addressed in future studies. Firstly, the analysis focused only on two seasons, summer and winter, excluding spring and autumn, which may provide further insights into the seasonal dynamics of psychological well-being as suggested by international scientific literature (Bielinis et al. 2018a, 2018b, Chen et al. 2023). In relation to seasonality influence on mood responses, Chen et al. (2023) highlighted the so-called seasonal deviation i.e. the interaction between the season during which stimuli (photos, videos etc.) are taken and the season in which photos are viewed. Seasonal deviation suggests a forward preference for the coming season, an aspect to be further investigated. Additionally, the lack of a “medium density” category limits understanding the effects of intermediate forest density, which could represent an optimal balance between vegetative cover and landscape perception. In this sense, Ramanpong et al. (2024) reported how medium-density plantation forests demonstrated a more significant relaxation effect on reducing the heart rate compared to high and low-density plantations. However, those authors – as emerged in the study presented – stressed that regardless of stand density, restorative components were similar among the four experimental settings (high, medium, and low density, as well as control). Medium-density levels can also affect perception and emotional responses related to light and brightness: Li et al. (2024) found an inverted U-shaped trend of mood and perceived safety due to natural light brightness levels in virtual reality forests. The choice to focus on specific tree species composition also represents a limitation, as other structures might influence well-being in different ways, such as vertical stand structure (uneven--aged forests vs. even-aged forests) or forest management (coppices vs. high forests). Apart the numerous advantages in the use of VR (controlled variables, reduced costs of interviews etc.; Lopes et al., 2024) the use of this technique can limit validity of responses due to lacking of thermal, olfactory, tactile, air quality, humidity, wind and other feedbacks. Real forests involve multisensory experiences that could modulate well-being independently from visual feature. Future studies can try to compare responses between VR and real forests to statistically quantify uncertainty related to laboratory experiments. A relevant parameter influencing health status and immune system responses is the release of Biogenic Volatile Organic Compounds (BVOCs) emitted by plants (Donelli et al., 2023). This variable, strictly related with thermal comfort, and additional logistics, facilities, artificial/natural peculiarities, and risk factors should be integrated into a unique multicriteria framework to depict optimal forest areas suitable for forest bathing activities.

6. Conclusions

The study highlighted the key role forests play in promoting psychological well-being, thanks to a combination of different environmental factors, such as seasonality and greenness indices. The summer forest environment is particularly effective in facilitating stress recovery. Conversely, tree forest composition, stem density, and dendrometric variables did not emerge as a determinant factor for well-being (at least in the ranges applied in the study). The Greenness Index (VEG), either on its own or combined with specific social characteristics of respondents and/or brightness levels, should reveal additional insights into the investigation of well-being.

The results of this study may have practical implications for decision-makers (forest managers and planners) in maximizing the restorative potential of forests. Promoting visits and activities in forests during the summer, capitalizing on the lush vegetation, could be an effective strategy to promote psychological well-being. Similarly, the design of natural spaces could incorporate areas with high greenness indices, providing greater comfort and protection. For winter tourism, snow-covered and mountainous landscapes could represent a unique attraction with significant visual and psychological value, but in this sense, further investigations are needed.

These recommendations, integrated with future suggested lines of research, can form a basis for integrating forest management with human well-being objectives, highlighting the role of natural resources as tools for health and well-being.

CRediT authorship contribution statement

S. Sacchelli: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **E. Barbierato:** Writing – original draft, Investigation, Formal analysis, Data curation. **S. Baldessari:** Writing – review & editing, Investigation, Formal analysis. **F. Becheri:** Methodology. **A. Cerutti:** Writing – review & editing, Investigation. **S. Notaro:** Writing – review & editing, Supervision, Investigation. **S. Righi:** Writing – review & editing, Methodology, Conceptualization. **A. Paletto:** Writing – review & editing, Investigation, Formal analysis, Conceptualization. **I. Bernetti:** Writing – review & editing, Validation, Formal analysis, Data curation.

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.

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Supplementary materials

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Data availability

Data will be made available on request.

References

Abdullah, S.S.S., Rambli, D.R.A., Sulaiman, S., Alyan, E., Merienne, F., Diyana, N., 2021. The impact of virtual nature therapy on stress responses: a systematic qualitative review. Forests 12 (12), 1776.

An, K.W., Kim, E., Jeon, K.S., Setsu, T., 2004. Effects of forest stand density on Human's physiophychological changes. J. Fac. Agric. Kyushu Univ. 49 (2), 283–291.

Berman, M.G., Jonides, J., Kaplan, S., 2008. The cognitive benefits of interacting with nature. Psychol. Sci. 19 (12), 1207–1212.

Berto, R., 2014. The role of nature in coping with psycho-physiological stress: a literature review on restorativeness. Behav. Sci. 4 (4), 394–409.

Bielinis, E., Omelan, A., Boiko, S., Bielinis, L., 2018a. The restorative effect of staying in a broad-leaved forest on healthy young adults in winter and spring. Balt. For. 24 (2), 218–227.

Bielinis, E., Takayama, N., Boiko, S., Omelan, A., Bielinis, L., 2018b. The effect of winter forest bathing on psychological relaxation of young Polish adults. Urban. For. Urban. Green. 29, 276–283.

Bielinis, E., Janeczko, E., Takayama, N., Zawadzka, A., Słupska, A., Piętka, S., Lipponen, M., Bielinis, L., 2021. The effects of viewing a winter forest landscape with the ground and trees covered in snow on the psychological relaxation of young Finnish adults: a pilot study. PLoS. One 16, e0244799.

Birch, J., 1997. Efficiency of the Ishihara test for identifying red-green colour deficiency. Ophthalmic Physiol. Opt. 17 (5), 403–408.

Chen, R., Gao, Y., Zhang, R., Zhang, Z., Zhang, W., Meng, H., Zhang, T., 2023. How does the experience of forest recreation spaces in different seasons affect the physical and mental recovery of users? Int. J. Environ. Res. Public Health 20 (3), 2357.

Chun, M.H., Chang, M.C., Lee, S.J., 2017. The effects of forest therapy on depression and anxiety in patients with chronic stroke. Int. J. Neurosci. 127 (3), 199–203.

Donelli, D., Meneguzzo, F., Antonelli, M., Ardissino, D., Niccoli, G., Gronchi, G., Baraldi, R., Neri, L., Zabini, F., 2023. Effects of plant-emitted monoterpenes on anxiety symptoms: a propensity-matched observational cohort study. Int. J. Environ. Res. Public Health 20 (4), 2773.

Ekhlasi, A., Ahmadi, H., Molavi, A., Saadat, N., M, Nasrabadi, A.M., 2021. EEG signal analysis during Ishihara's test in subjects with normal vision and color vision deficiency. Biomed. Phys. Eng. Express. 7 (2), 33445166.

Grilli, G., Barbierato, E., Capecchi, I., Sacchelli, S., 2022. Application of stated-preferences methods and neuroscience for the valuation of dynamicity in forest cultural ecosystem services. J. Environ. Plann. Manage. 65 (3), 398–417.

Guardini, B., Secco, L., Moè, A., Pazzaglia, F., De Mas, G., Vegetti, M., Perrone, R., Tilman, A., Renzi, M., Rapisarda, S., 2023. A three-day forest-bathing retreat enhances positive affect, vitality, optimism, and gratitude: an option for green-care tourism in Italy? Forests 14 (7), 1423.

Hague, T., Tillett, N.D., Wheeler, H., 2006. Automated crop and weed monitoring in widely spaced cereals. *Precis. Agric.* Berlin 7 (1), 21–32.

Huang, R., Li, A., Li, Z., Chen, Z., Zhou, B., Wang, G., 2022. Adjunctive therapeutic effects of forest bathing trips on geriatric hypertension: results from an on-site experiment in the Cinnamomum camphora forest environment in four seasons. Forests 14 (1), 75.

Hwang, J.H., Lee, H.J., Park, J.H., Kim, D.M., Lee, K.M., 2019. The impact of program improvement using forest healing resources on the therapeutic effect: focused on improving index of greenness for adolescents. J. People Plants Environ. 22 (6), 691–698.

Joung, D., Kim, G., Choi, Y., Lim, H., Park, S., Woo, J.M., Park, B.J., 2015. The prefrontal cortex activity and psychological effects of viewing forest landscapes in Autumn season. Int. J. Environ. Res. Public Health 12 (7), 7235–7243.

Kaplan, R., Kaplan, S., Brown, T., 1989. Environmental preference: a comparison of four domains of predictors. Environ. Behav. 21 (5), 509–530.

Kim, E., Lee, H., 2023. Effects of short-term urban forest experiences by season on stress and affective response of university students. J. People Plants Environ. 26 (4), 433–444.

Kobayashi, H., Song, C., Ikei, H., Park, B.J., Kagawa, T., Miyazaki, Y., 2019. Combined effect of walking and forest environment on salivary cortisol concentration. Front. Public Health 7, 376.

Lee, J., Park, B.J., Tsunetsugu, Y., Ohira, T., Kagawa, T., Miyazaki, Y., 2011. Effect of forest bathing on physiological and psychological responses in young Japanese male subjects. Public Health 125 (2), 93–100.

Li, Q., 2010. Effect of forest bathing trips on human immune function. Environ. Health Prev. Med. 15, 9–17.

Li, D., Chiang, Y.C., Sang, H., Sullivan, W.C., 2019. Beyond the school grounds: links between density of tree cover in school surroundings and high school academic performance. Urban. For. Urban. Green. 38, 42–53.

Li, C., Sun, C., Sun, M., Yuan, Y., Li, P., 2020. Effects of brightness levels on stress recovery when viewing a virtual reality forest with simulated natural light. Urban. For. Urban. Green. 56, 126865.

Li, C., Ge, S., Jiang, Y., 2024. Effects of simulated natural light brightness on visual perception in virtual reality forests: an eye-tracking study. J. Environ. Psychol. 99, 102446.

Lopes, M.K.S., Falk, T.H., 2024. Audio-visual-olfactory immersive digital nature exposure for stress and anxiety reduction: a systematic review on systems, outcomes, and challenges. Front. Virtual. Real. 5, 1252539.

Mao, G.X., Cao, Y.B., Lan, X.G., He, Z.H., Chen, Z.M., Wang, Y.Z., Hu, X.L., Lv, Y.D., Wang, G.F., Yan, J., 2012. Therapeutic effect of forest bathing on human hypertension in the elderly. J. Cardiol. 60 (6), 495–502.

Mao, G., Cao, Y., Wang, B., Wang, S., Chen, Z., Wang, J., Xing, W., Ren, X., Lv, X., Dong, J., Chen, S., Chen, X., Wang, G., Yan, J., 2017. The salutary influence of forest bathing on elderly patients with chronic heart failure. Int. J. Environ. Res. Public Health 14 (4), 368.

Marino, D., Barone, A., Marucci, A., Pili, S., Palmieri, M., 2024. The integrated analysis of territorial transformations in inland areas of Italy: the link between natural, social, and economic capitals using the ecosystem service approach. Land 13 (9), 1455.

Miyazaki, Y., Lee, J., Park, B.J., Tsunetsugu, Y., Matsunaga, K., 2011. Preventive medical effects of nature therapy. Jpn. J. Hyg. 66 (4), 651–656.

Motohka, T., Nasahara, K.N., Oguma, H., Tsuchida, S., 2010. Applicability of green-red vegetation index for remote sensing of vegetation phenology. Remote Sens. 2 (10), 2369–2387.

Ochiai, H., Ikei, H., Song, C., Kobayashi, M., Miura, T., Kagawa, T., Li, Q., Kumeda, S., Imai, M., Miyazaki, Y., 2015. Physiological and psychological effects of a forest therapy program on middle-aged females. Int. J. Environ. Res. Public Health 12 (12), 15222–15232.

Paletto, A., Notaro, S., Sergiacomi, C., Di Mascio, F., 2024a. The economic value of forest bathing: an example case of the Italian Alps. Forests 15, 543.

Paletto, A., Notaro, S., Pavaleanu, C., 2024b. Forest bathing: a quantitative exploration of emerging trends, patterns, and growth areas. J. Forest Research 29 (4), 239–245.

Park, B.J., Shin, W.S., Shin, C.S., Yeon, P.S., Chung, C.Y., Lee, S.H., Park, C.E., 2022. Effects of forest therapy on psychological improvement in middle-aged women in Korea. J. Prev. Med. Public Health 55 (5), 492.

Park, S.H., Yeon, P.S., Hong, C.W., Yeo, E.H., Han, S.M., Lee, H.Y., Kim, Y.H., 2017. A study on the effect of the forest healing programs on teachers' stress and PANAS. Korean J. Environ. Ecol. 31 (6), 606–614.

Peterfalvi, A., Meggyes, M., Makszin, L., Farkas, N., Miko, E., Miseta, A., Szereday, L., 2021. Forest bathing always makes sense: blood pressure-lowering and immune system-balancing effects in late spring and winter in central Europe. Int. J. Environ. Res. Public Health 18 (4), 2067, 1–20.

Pratiwi, P.I., Xiang, Q., Xie, Z., 2024. Physiological and psychological effects of walking in and viewing autumn forests in urban park in Japanese and Indonesian adults. IOP Confer. Series: Earth Environ. Sci. 1384 (1), 012014.

Ramanpong, J., Yin, J., Zhang, C.J., Chen, H.T., Tsai, M.J., Spengler, J.D., Yu, C.,P., 2024. The effects of viewing forests with different planting densities on physiological and psychological responses: a between-subject experiment. Trees. For. People 16, 100551.

Ribe, R.G., 2009. In-stand scenic beauty of variable retention harvests and mature forests in the U.S. Pacific Northwest: the effects of basal area, density, retention pattern and down wood. J. Environ. Manage. 91, 245–260.

Rights, J.D., Sterba, S.K., 2019. Quantifying explained variance in multilevel models: an integrative framework for defining R^2 measures. Psychol. Methods 24 (3), 309–338.

Russo, A., 2024. Renaturing for Urban wellbeing: a socioecological perspective on green space quality, accessibility, and inclusivity. Sustainability 16 (13), 5751.

Siah, C.J.R., Goh, Y.S., Lee, J., Poon, S.N., Ow Yong, J.Q.Y., Tam, W.S.W., 2023. The effects of forest bathing on psychological well-being: a systematic review and meta-analysis. Int. J. Ment. Health Nurs. 32 (4), 1038–1054.

Song, C., Ikei, H., Miyazaki, Y., 2016. Physiological effects of nature therapy: a review of the research in Japan. Int. J. Environ. Res. Public Health 13 (8), 781.

Song, C., Ikei, H., Park, B.J., Lee, J., Kagawa, T., Miyazaki, Y., 2020. Association between the psychological effects of viewing forest landscapes and trait anxiety level. Int. J. Environ. Res. Public Health 17 (15), 5479.

Takayama, N., Korpela, K., Lee, J., Morikawa, T., Tsunetsugu, Y., Park, B.J., Kagawa, T., 2014. Emotional, restorative and vitalizing effects of forest and urban environments at four sites in Japan. Int. J. Environ. Res. Public Health 11 (7), 7207–7230.

Takayama, N., Saito, H., Fujiwara, A., Horiuchi, M., 2017. The effect of slight thinning of managed coniferous forest on landscape appreciation and psychological restoration. Prog. Earth. Planet. Sci. 4, 17.

Tsunetsugu, Y., Lee, J., Park, B., Tyrväinen, L., Kagawa, T., Miyazaki, Y., 2013. Physiological and psychological effects of viewing urban forest landscapes assessed by multiple measurements. Landsc. Urban Plan. 113, 90–93.

Tyrväinen, L., Ojala, A., Korpela, K., Lanki, T., Tsunetsugu, Y., 2014. The influence of urban green environments on stress relief measures: a field experiment. J. Environ. Psychol. 38, 1–9.

Wang, Y., Jiang, M., Huang, Y., Sheng, Z., Huang, X., Lin, W., Chen, Q., Li, X., Luo, Z., Lv, B., 2020. Physiological and psychological effects of watching videos of different durations showing urban bamboo forests with varied structures. Int. J. Environ. Res. Public Health 17 (10), 3434.

White, M.P., Hartig, T., Martin, L., Pahl, S., van den Berg, A.E., Wells, N.M., Costongs, C., Dzhambov, A.M., Elliott, L.R., Godfrey, A., Hartl, A., Konijnendijk, C., Litt, J.S., Lovell, R., Lymeus, F., O'Driscoll, C., Pichler, C., Pouso, S., Razani, N., Secco, L., Steininger, M.O., Stigsdotter, U.K., Uyarra, M., van den Bosch, M., 2023. Nature-based biopsychosocial resilience: an integrative theoretical framework for research on nature and health. Environ. Int. 181, 108234.

Woebbecke, D.M., Meyer, G.E., Bargen, K.V.O.N., Mortensen, D.A., 1995. Color indices for weed identification under various soil, residue, and lighting conditions. *Trans. ASAE*, Michigan 38 (1), 259–269.

Wu, L., Luo, S., Li, D., Chen, Q., Li, J., Wen, J., 2023. Effects of deciduous forests on adolescent emotional health in urban areas: an example from the autumn Ginkgo forest in Chengdu. Forests 14 (6), 1099.