Ecological Indicators 154 (2023) 110729

Contents lists available at ScienceDirect

Ecological Indicators

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

Can acoustic indices reflect the characteristics of public recreational behavioral in urban green spaces?

Weicong Fu [a,b], Chengyu Ran [a], Jingkai Huang [a], Zhu Chen [c], Shiyuan Fan [a], Wenqiang Fang [a], Miaojun Ye [a], Jiaying Dong [d], Xiong Yao [e], Ziru Chen [a,e,*]

[a] College of Landscape Architecture and Art, Fujian Agriculture and Forestry University, Fuzhou 350002, China
[b] Collaborative for Advanced Landscape Planning, The University of British Columbia, Vancouver V6T 1Z4, BC, Canada
[c] Institute of Environmental Planning, Leibniz University Hannover, Herrenhäuser Str. 2, 30419 Hanover, Germany
[d] College of Architecture, Arts and Humanities, Clemson University, Clemson 29630, SC, United States
[e] College of Architecture and Urban Planning, Fujian University of Technology, Fuzhou 350118, China

ARTICLE INFO

Keywords:
Soundscape
Acoustic index
Recreational behavior
Spatial and temporal variation

ABSTRACT

Acoustic indicators serve as an effective means of assessing the quality of urban green space soundscape. The informative, easy accessibility and non-invasive nature of acoustic monitoring renders it an excellent tool for studying the interaction among the natural environment, wildlife, and human activities. Urban green space is essential in the urban ecosystem and constitutes the primary location for public outdoor recreation. However, the existing methods for monitoring public recreational behavior, such as on-site observation, drone observation, or questionnaire interviews, require significant labor or professional expertise. All of these methods have their limitations, so there is still much to be researched in the acoustic indices and recreational behavior. As a result, the potential for using acoustic characteristics to monitor public recreational behavior remains underexplored. To address this gap, this study investigates the potential of 5 widely used acoustic indices and acoustic intensity for monitoring public recreational behavior: Acoustic Complexity Index (ACI), Acoustic Diversity Index (ADI), Acoustic Richness (AR), Normalized Difference Soundscape Index (NDSI), and Power Spectral Density (PSD). Data were collected from 35 monitoring points in urban green spaces during the opening hours (6:00–22:00) to analyze the relationship between these indices and public recreational behavior. The findings indicate that (1) ACI, ADI, and AR daily exhibited multi-peak daily variation characteristics similar to those of public recreational behavior, displaying a "W" shape, while NDSI exhibits opposite variation characteristics; (2) the spatial variation characteristics of ACI, ADI, and AR change in response to the green space, and these changes align with public recreational behavior; (3) the correlation analysis and generalized linear mixed model construction further demonstrate that acoustic indices are effective in capturing the dynamic activities of visitor behavior; and (4) PSD undergoes significant temporal dynamic changes along the frequency gradient, with different frequency intervals reflecting the activity information of different recreational behaviors. In conclusion, this research highlights the effectiveness of using acoustic indices to analyze both the spatial and temporal variation characteristics of public recreational behavior in urban green spaces. The results can provide valuable data support for the enhancement and renovation of urban green spaces.

1. Introduction

Recreational behavior is crucial for promoting physical and mental health of urban populations. Studies have demonstrated that an increase in public use of green spaces can effectively reduce the risk of public illness. As a result, improving urban public space to meet the recreational needs of individuals has become a popular research topic as well as a key strategy for planning and design. Direct observation of recreational behavior is considered the most reliable and accurate method for obtaining information about recreational behavior for designers and managers. SOPARC (System for Observing Play and Recreation in Communities) is a scientific and effective observation system that has been validated by research experiments (Baran et al. 2014). However, direct observation has high requirements for observers, who must be

* Corresponding author at: College of Architecture and Urban Planning, Fujian University of Technology, Fuzhou 350118, China.
E-mail address: fjchenziru@fjut.edu.cn (Z. Chen).

https://doi.org/10.1016/j.ecolind.2023.110729
Received 5 May 2023; Received in revised form 1 July 2023; Accepted 24 July 2023
Available online 8 August 2023

trained to collect various data from visitors and must be able to record large amounts of visitor data instantly into text or images (Marquet et al. 2019). To improve the effectiveness of public recreation observation, new methods have been developed, such as video recording, GPS tracking, and drone observation (Arnberger et al. 2005; Engelhard et al. 2001; Park and Ewing 2017). These methods align with the development of science and technology. However, each method has its limitations. For instance, video recording has a limited observation area (Guillén et al. 2008); GPS tracking method requires high capital investment (Matisziw et al. 2016), and often yields a small sample size (Zhao et al. 2019); and drone observation is subject to regulations restricting its use and is limited by rainy day (Park and Ewing 2017). Most research on observing visitors' recreational behavior focused on daytime observation periods, with little attention has been given to nighttime observations, which are often preferred by urban residents (Zhong and Wang 2019). This knowledge gap raises the question of whether a mature and efficient observation method can be employed to analyze public recreational behavior during different time periods. See (Table 1).

In the late 1960 s, the pioneering Canadian composer Raymond Murray Schafer initiated the "World Soundscape Project," which paved the way for the establishment of the field of acoustic ecology. This field recognizes the significance of sound in the environment and its interactions with human activities (Schafer 1969, 1970). Research in acoustic ecology mainly focused on describing the soundscape dynamics in terrestrial ecosystems (Krause et al. 2011), facilitate wildlife research (Lillis et al. 2014), habitat quality assessment (Gómez et al. 2018), biodiversity assessment (Pieretti et al. 2011), conservation effectiveness assessment (Bobryk et al. 2016), and the impacts of human activities on biodiversity (Krause and Farina 2016; Zhao et al. 2020). The efficacy of acoustic indicators in quantifying geo-, bio-, and artificial sounds has been confirmed, offering high application value with low intrusion (Zhao et al. 2021), low cost, and increased information. Although acoustic characteristics are well-suited for studying visitor behavior, which is the main component of artificial sound (Bai et al. 2021), the utilization of acoustic indices to analyze public recreational behavior remains an unexplored area in the existing literature.

This study aims to investigate the potential of acoustic indices in reflecting the features of public recreational behavior. Specifically, the study collects recreational sounds in Jinshan Park, Fuzhou City, using recording equipment and obtains temporal and spatial distribution data of visitors' recreational behavior using the SOPARC tool. The spatial and temporal relationships among 5 commonly used acoustic indices, namely, Acoustic Complexity Index (ACI) (Farina et al. 2011), Acoustic Diversity Index (ADI) (Villanueva-Rivera et al. 2011), Acoustic Richness (AR) (Depraetere et al. 2012), Normalized Difference Soundscape Index (NDSI) (Kasten et al. 2012), and Power Spectral Density (PSD) (Joo et al. 2011), and visitors' recreational behavior were analyzed. This study seeks to address the gap in the application of acoustic indices for examining recreational behavior. Moreover, the research endeavors to introduce a novel and cost-effective monitoring approach for analyzing public recreational behavior in urban green spaces. The findings of the study could contribute to the understanding and advancement of public recreational behavior in urban green spaces and ultimately improve public health. See (Table 2).

Table 1
4 acoustic indices used in this study.

Acoustic indices	Details	Reference
Acoustic Complexity Index (ACI)	This index measures changes in amplitude between adjacent frequency bands, reflecting the variability and irregularity of acoustic intensity. The index is relatively unaffected by a constant intensity of a sustained sound. The following parameters are used in this study:max_freq = 2000, min_freq = 1000, fft_w = 1024, no_cores = 2. The higher the ACI value, the higher the variability of the acoustic intensity in the audio.	Farina et al. 2011
Acoustic Diversity Index (ADI)	The spectrogram is divided into frequency bands (default 10), and the percentage of sounds in each band that exceed the threshold (default −50dBFS) is calculated using the Shannon index. The following parameters are used in this study: max_freq = 2000, db_threshold = -50, freq_step = 1000, no_cores = 2. The higher the ADI value, the higher the diversity of sounds in the audio.	Villanueva-Rivera et al. 2011
Acoustic Richness (AR)	The index is obtained based on temporal entropy (Ht) and the median of the amplitude envelope (M). It can assess vocal animal diversity and acoustic activity levels. This index ranges from 0 to 1 and is calculated using the default parameters in this study. The higher the AR value, the higher the complexity of the sound changing in time.	Depraetere et al. 2012
Normalized Difference Soundscape Index (NDSI)	NDSI is assessed by calculating the ratio of anthrophony (1–2 kHz) to biophony (2–11 kHz). The formula is NDSI = (biophony - anthrophony) / (biophony + anthrophony). The range is from −1 to 1 and is calculated using the default parameters in this study. A high NDAI value means that animal communication is dominant in that habitat and vice versa for human activities.	Kasten et al. 2012

2. Study area and methods

2.1. Study location

Jinshan Park is a comprehensive park in the Cangshan District of Fuzhou City. Located adjacent to the Wulong River, the park is surrounded by primarily residential communities and educational institutions, thereby providing a broad and diverse pool of subjects for experimental studies. Jinshan park takes the form of a belt-like configuration and spans an area of approximately 31.6 ha from north to south. Within its territory, 16 ha are dedicated to green space, while the remaining 13.2 ha are characterized by water bodies, augmenting the park's recreational appeal and accommodating a wide range of recreational activities.

Table 2
Acoustic intensity used in this study.

Acoustic intensity	Details	Reference
Power Spectral Density (PSD)	PSD was calculated in 1-kHz frequency intervals based on the Welch algorithm, which computes modified periodograms of overlapping segments using the Fast Fourier transform (FFT) to estimate the average power spectral density. A Hamming window of size 512 with 50% overlap was used between segments. Then output an energy value (PSD) for each of 11 frequency intervals. The numerical values resulting from this process provided a quantitative measure of how energy is distributed across the acoustic spectrum. The higher the PSD value, the higher the acoustic intensity in the audio.	Joo et al. 2011

2.2. Data collection

2.2.1. Soundscape data collection

According to previous studies, the feasible distance between recording equipment is 100 m (Hao et al. 2021; Zhang 2020). To enhance soundscape monitoring accuracy, 35 monitoring points were established by dividing the grid into 70*70 m equally spaced sections, taking into account both practical considerations and specific characteristics of the park. (see Fig. 1). Data were collected in two clear and breezy days in June and July of 2022, during the park opening hours (6:00–22:00). At each of the 35 monitoring points, Sony PCM-D100 recording equipment was positioned simultaneously. The recording parameters were set to a sampling frequency of 44.1 kHz, a resolution of 16 bits, and stereo sampling, with audio format saved in the WAV format. A total of 560 min of audio recordings were acquired through the collection of two-minute sound clips every two hours randomly (Gage and Axel 2014). If the center of the grid was inaccessible, appropriate adjustments were made to ensure data acquisition.

2.2.2. Recreational behavior data collection

During the soundscape data collection, panoramic data were simultaneously gathered from the 35 monitoring points using an Insta360-°one X camera device. The camera is equipped with two F2.0 fisheye lenses and offers various modes, including HDR and night shot. The observation was conducted at a height of 3 m, and the resulting panoramic photos have a resolution of 6080 by 3040 pixels. Examples of the panoramic images are shown in Fig. 2. For each two-minute period of soundscape data acquisition, panoramic photos were taken every 5 s, resulting in a total of 7,000 panoramic images. These images were subsequently analyzed to identify the characteristics of public recreational behavior (Huang et al. 2022).

2.3. Data analysis

2.3.1. Soundscape data analysis

Based on previous research, biological sounds typically fall within the 2–11 kHz frequency range, while artificial sounds fall within the 1–2 kHz range. Earth sounds, on the other hand, can span the entire sound spectrum of 1–11 kHz (Pijanowski et al. 2011). The spectrograms of the audio files collected in Jinshan Park indicated that most recreational sounds were within the 1–2 kHz frequency range. However, certain sounds such as conversations, music, and radio equipment extended to the 1–5 kHz range. Other sounds, including footsteps, ball tapping, running and jumping, and even laughing, and coughing, covered the full range of 0–11 kHz, although most of these sounds still fell within the 1–2 kHz range. To account for operational considerations, data within the 0–1 kHz range were excluded to avoid potential distortions caused by wind sounds (Bradbury and Vehrencamp 1998). Therefore, the

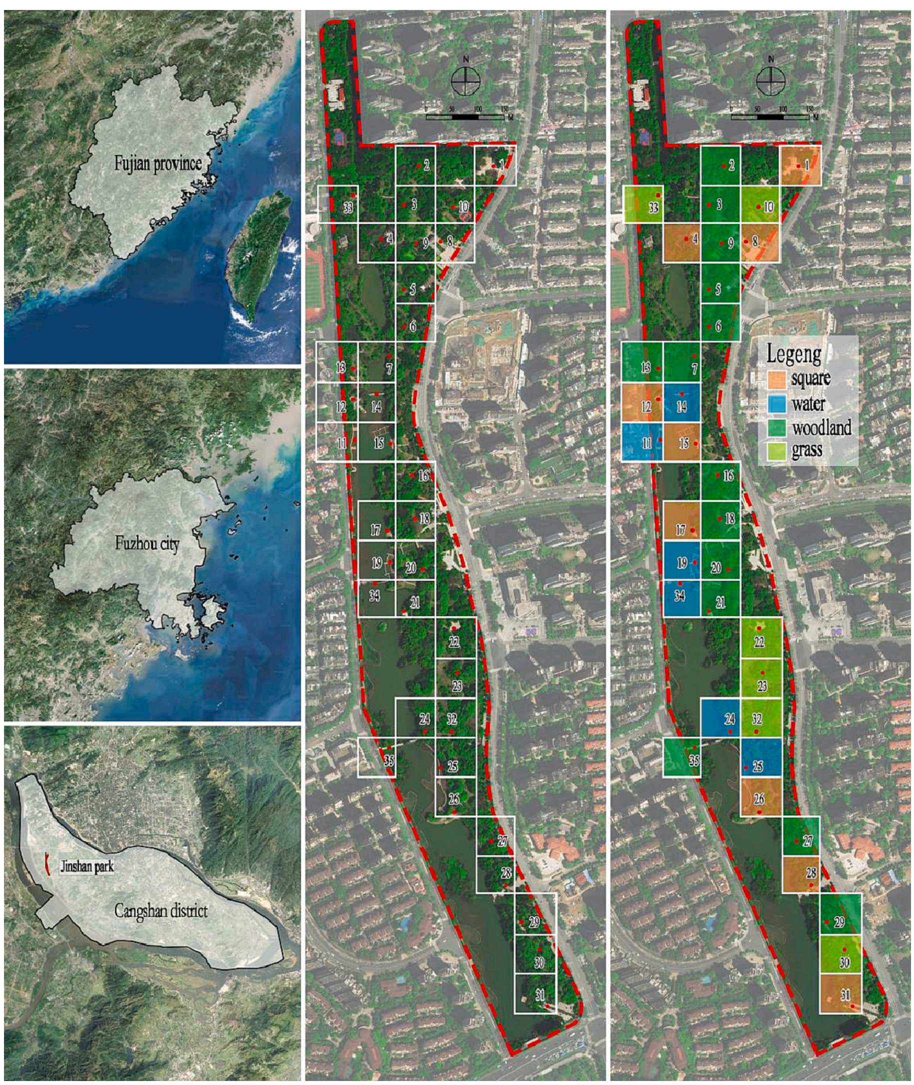


Fig. 1. Grid and sampling sites location.

Fig. 2. Panoramic overview of monitoring sites.

calculation of acoustic indices in this study were restricted exclusively to the 1–2 kHz frequency range.

The analysis of the soundscape data was carried out using the R programming language. To compute and present 280 sound samples of 560 min in the 1–11 kHz frequency range, the 'multipe sounds' function in the 'soundecology' package and 'sewave' package were utilized in the RStudio software. In this paper, four acoustic indices and one acoustic intensity index are used.

(1) Acoustic index calculation

The present study employs four well-established acoustic indices commonly employed in landscape research: the Acoustic Complexity Index (ACI), the Acoustic Diversity Index (ADI), the Acoustic Richness (AR), and the Normalized Difference Soundscape Index (NDSI). These indices have been extensively utilized in prior studies to monitor the α-diversity index of green space soundscape, showcasing robust analytical techniques and producing reliable findings (Zhao et al. 2021; Zhao et al. 2020). Given that the 1–2 kHz frequency range is sensitive to almost all recreational sounds, the acoustic indices for 35 sample sites in Fuzhou Jinshan Park were calculated using data within this range. The resulting data were then averaged and visualized to depict the daily variations of the acoustic indices in Fuzhou Jinshan Park from 6:00 to 22:00.

(2) Acoustic intensity calculation

The automated calculation of Power Spectral Density (PSD) was performed using the C++ programming language. The recorded audio files were analyzed within the frequency range of 0–11 kHz, with data from 0 to 1 kHz being excluded. Recreational sounds can span multiple frequency bands and typically exceed 7 kHz, thus minimizing interference from biological sounds. Consequently, the power spectral density of each frequency band can be utilized to identify recreational behavior. To this end, all audio files were segmented into frequency intervals, specifically ranging from 1 to 2 kHz, 2–3 kHz, and so on up to 10–11 kHz, within the overall range of 0–11 kHz. The power spectral density of each frequency interval was calculated using Matlab software. The resulting PSD values can provide a quantitative description of the relative contribution of sound power variation across time and frequency (Joo et al. 2011).

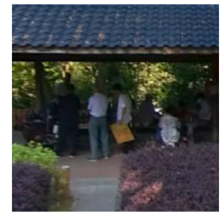
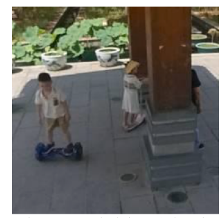
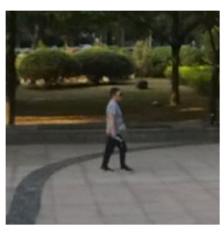
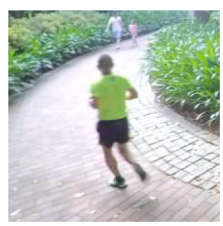
2.3.2. Recreational behavior data analysis

Panoramic images were used to capture public recreational behavior data, including information on gender, age, type of behavior, and location of the subject. Th data collection process employed the SOPARC (System for Observing Play and Recreation in Communities) recording method. To suit the specific research requirements, modifications were made to the original SOPARC record content-based localization, and the classification of recreational behavior types was refined according to observation results. Subsequently, the activity types of visitors were then categorized into three groups: static, dynamic, and passing-by (as detailed in Table 3) for further calculation and analysis (Huang et al. 2022).

2.3.3. Statistical analysis

A quantitative approach was utilized to investigate the correlation between the acoustic index of green spaces and recreational behavior and how they overlap. Temporal variation was visually represented using line graphs generated by Excel software, while spatial variation was analyzed using the inverse distance weighting method in ArcGIS software, resulting in the generation of a visualization map. Spearman

Table 3
Content of the SOPARC record.

Record content				
Sampling sites	1	2	...	35
	Static behaviors	 Relaxation (sitting, reading, closing eyes during meditation, etc.)	 Contact with nature (enjoying nature, listening to sounds such as birdsong and running water, etc.)	 Social interaction (drinking tea, chatting, partying, playing chess, etc.)
Type of activity	Dynamic behaviors	 Facility activities (activities dependent on various park facilities)	 Sports activities (sports-related activities such as ball games, dance, etc.)	 Leisure activities (chasing games, taking care of children, picnicking, etc.)
	Passing-by behaviors	 Walking	 Jogging	 Other forms of Passing-by behaviors (bicycles, electric bikes, skateboards, etc.)

correlation analysis was performed on the original data to examine the relationship between different types of recreational behavior and acoustic indices and acoustic intensity, with the results visualized on ChiPlot. For comparison purposes, the acoustic intensity is presented together with the acoustic indices. The discrete data were fitted to the Poisson distribution (Zhang et al. 2018). Thus, a Generalized Linear Mixed Model (GLMM) was developed based on the count of public recreational data, aiming to evaluate the prediction power of acoustic indices on public static, dynamic, and passing-by recreational behavior. Prior to modeling, the data were standardized, and response variables were public static, dynamic, and passing-by recreational behaviors. Random effects were accounted for using sample points. 5 acoustic indices and acoustic intensity (ACI, ADI, AR, NDSI, PSD) and the power spectral intensity of 10 frequency intervals (1–2 kHz, 2–3 kHz…10–11 kHz) were calculated as fixed effects. To avoid multicollinearity among the explanatory variables, the variance inflation factor (VIF) was calculated for each variable, and those with VIF > 10 were excluded from the analysis. The McFadden R-squared of the model and the Akaike information criterion (AIC) were used to assess the model's goodness of fit (Grueber et al. 2011).

3. Results

3.1. Temporal variation characteristics of acoustic indices and public recreational behavior

3.1.1. Temporal variation characteristics of acoustic indices

Fig. 3 depicts the temporal variation patterns of four acoustic indices (ACI, ADI, AR, and NDSI) during the park opening hours (06:00–22:00) in summer. The data is presented in a normalized format to facilitate

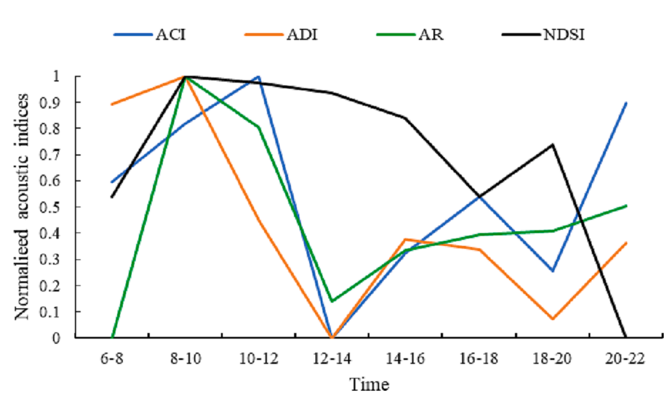


Fig. 3. Temporal variation characteristics of each acoustic index after normalization.

comparisons (Zhao et al. 2021). The daily patterns of ACI, ADI, and AR indices followed a "W"-shaped multi-peak variation pattern. These indices demonstrated a rising trend during the morning hours, reaching their highest between 8:00–10:00. Subsequently, they gradually declined, reaching the lowest points during 12:00–14:00, followed by a slow increase until 18:00–20:00 and a further rise until the park's closing time at 22:00. Conversely, the NDSI index displayed different temporal variations compared to other three indices. Its values remained consistently above zero from 06:00–20:00, indicating a predominance of biological sounds during this period. However, during 20:00–22:00, recreational sounds surpassed biological sounds, revealing the dominance of recreational behavior. This observation was negatively correlated with the overall variation characteristics the other indices.

The distribution of PSD average values is illustrated in Fig. 4, showing a concentration within the 0–0.3 w/kHz. A bimodal distribution of PSD is evident with fluctuations. After the park opens, there was an increase in the sound power spectrum density, followed by a slight decrease, and then peaking at 20:00–22:00. The main sources of recreation sound were detected in the 1–2 kHz range, although some recreational sounds extended to 2–5 kHz, such as conversations, children's play, and equipment sounds. The temporal variations of power spectral density in these four frequency intervals corresponded to the overall temporal variations observed in Fig. 7. Moreover, the temporal variation of power spectral density within the 5–11 kHz range exhibited a similar trend to that in the 1–5 kHz range but demonstrated a more pronounced increase at night.

3.1.2. Temporal variation characteristics of recreational behavior

Fig. 5 displays the overall temporal variation characteristics of visitors, which exhibit a bimodal distribution. The first peak was observed during the period of 8:00–10:00, followed by a gradual decrease and a sharp drop to the lowest value at 12:00–16:00. The number of visitors then steadily increased, reaching the highest peak at 20:00–22:00. The lowest number of visitors was recorded from 12:00–16:00, possibly due to the high summer temperatures and lunch breaks. Differences were observed in the temporal changes of different recreational behaviors. Dynamic behavior tended to be minimal from 12:00–18:00, followed by a rapid increase towards 22:00 after 18:00. The change of static behavior coincided with the overall change in the number of visitors from 6:00–16:00, but the frequency of static behaviors decreased after 16:00. Passing-by behavior was the most frequent recreational behavior, and its temporal change trend mirrored that of total number of visitors. However, the rate of increase in passing-by behavior during 20:00–22:00 is comparatively lower.

3.1.3. Comparison of acoustic indices and temporal variation characteristics of recreational behavior

The similarities in trends between the acoustic indices and the recreational behaviors are evident in Fig. 6. Specifically, the diurnal variation of the ACI, ADI, and AR indices closely resembled the trends observed in the three types of recreational behaviors and the total number of visitors. Notably, only the NDSI index exhibited a different change pattern from 8:00–12:00 compared to the other indices. Similarly, only the dynamic behavior from 14:00–20:00 showed a distinct trend compared to other behaviors. When comparing the temporal variation characteristics of the acoustic indices and the number of recreational behaviors, there was a significant overlap between them, suggesting that both can serve as reliable indicators of visitors' behavioral activities.

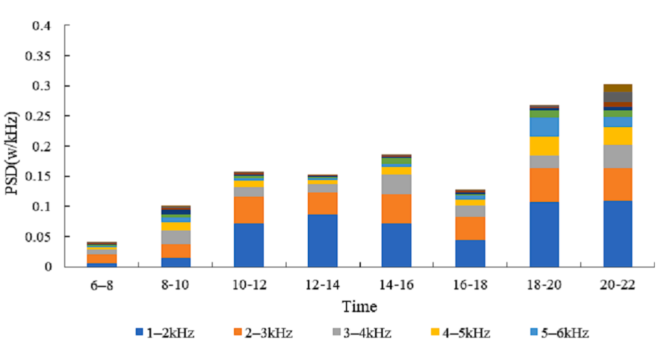


Fig. 4. Temporal variation characteristics of power spectral density in 10 frequency intervals.

3.2. Spatial distribution characteristics of acoustic index and public recreational behavior

3.2.1. Spatial distribution characteristics of acoustic index

According to Fig. 7, areas with high vegetation coverage, such as forest nodes, tend to have higher ACI and ADI indices, as they offer rich bio-acoustic and artificial sounds, diverse sound sources, and a highly complex spectrum that covers all frequency acoustic intensity. In contrast, plazas and hard nodes that lack bioacoustics and artificial sound tended to have lower ACI and ADI indices. Areas with a higher AR index were typically active nodes with rhythmic and highly varied artificial sounds, such as musical sounds, while quieter natural nodes had lower AR indices. Natural nodes with less human activity and abundant natural sound tended to have higher NDSI indices, whereas large hard-paved nodes like plazas, dominated by artificial sound, tended to have lower NDSI indices.

Additionally, landscape spaces with high PSD values (PSD $\geq$ 0.4w/kHz) were typically located near open water or uncovered squares, where there was less vegetation and more human activities. In these areas, wind, insects, and recreational sounds were the main contributors to the sound power spectrum density. Conversely, sites with low PSD values (PSD $\leq$ 0.01w/kHz) tended to be enclosed and covered areas with abundant vegetation and little human activity. In such locations, bird calls and footsteps were the primary contributing factors to the power spectral density.

3.2.2. Spatial distribution characteristics of recreational behavior

According to Fig. 8, passing-by behavior emerges as the most prevalent and widely distributed type of recreational behavior. A correlation was observed between its occurrence and the accessibility of park nodes, with nodes situated along main roads and landscape roads exhibiting more passing-by behaviors. In contrast, nodes at the end of cut-off roads demonstrated fewer instances of passing-by behaviors. Nodes with high levels of dynamic behavior typically encompass large hard surfaces, such as plazas. Conversely, nodes with a higher concentration of static behavior featured resting areas furnished with pavilions or seats, thereby suggesting that fixed recreational facilities, such as pavilions and promenades, play a role in shaping the occurrence of static behavior among park visitors.

3.2.3. Comparison of acoustic index and spatial variation characteristics of recreational behavior

The spatial distributions of acoustic indices and recreational behavior were compared in Fig. 7 and Fig. 8. Results showed a consistency between the distribution of the PSD index and dynamic behavior. Similarly, the ACI index's distribution aligned with the pattern of passing-by behavior and the total number of visitors. However, other acoustic indices and recreational behavior exhibited comparable characteristics at specific locations. This suggests that acoustic indices can effectively represent the acoustic landscape information of urban parks, highlighting notable spatial dynamics, and can reasonably reflect the dynamic activities of park visitors.

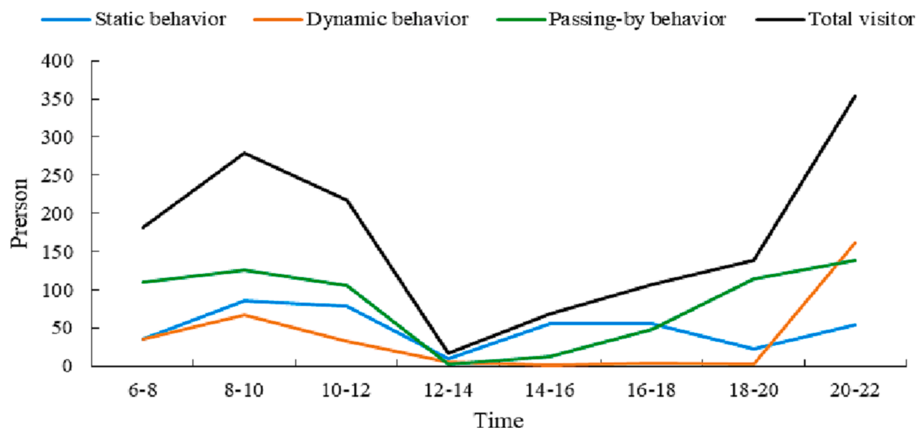


Fig. 5. Temporal variation characteristics of recreational behavior.

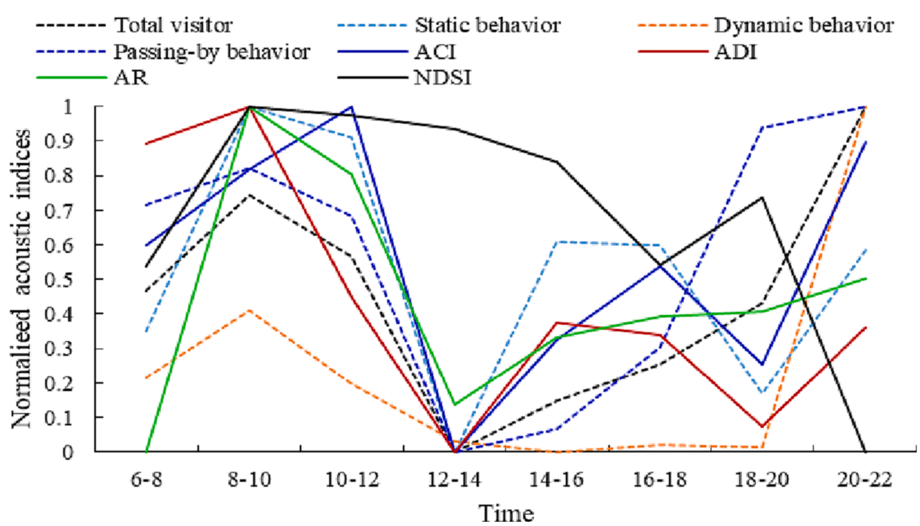


Fig. 6. Normalized temporal variations in acoustic indices and recreational behavior.

3.3. Correlation analysis and model construction

3.3.1. Correlation analysis of acoustic index and public recreational behavior

Fig. 9 illustrates strong positive correlations between ACI, ADI, AR, and each behavior type, including total behavior. Notably, both ACI and AR showed extremely significant positive correlations with all types of behavior, including dynamic behavior, static behavior, passing-by behavior, and total visitors ($p < 0.01$). ADI showed significant positive correlations with dynamic behavior and passing-by behavior ($p < 0.05$), and extremely significant positive correlations with total visitors and static behavior ($p < 0.01$). Additionally, NDSI exhibited a significant positive correlation only with static behavior ($p < 0.05$), implying that locations with a higher occurrence of biological sounds are more appealing for static public behavior. In contrast, NDSI lacks significant connections with other types of public recreational behavior.

According to Fig. 10, the PSD values in the 5–6 kHz, 6–7 kHz, 9–10 kHz, and 10–11 kHz frequency intervals all showed significant negative correlations ($p < 0.05$) with the total visitor count. The PSD values in the 4–5 kHz and 7–8 kHz frequency intervals showed a significant negative correlation with passing-by behavior ($p < 0.05$), while the PSD values in the 5–6 kHz, 6–7 kHz, 8–9 kHz, 9–10 kHz, and 10–11 kHz frequency intervals showed an extremely significant negative correlation with passing-by behavior ($p < 0.01$). These results indicate that the passing-by behavior significantly affects the PSD values in each frequency interval within 4–11 kHz. In other words, an increase in passing-by behaviors corresponds to lower PSD values within the 4–11 kHz frequency band.

3.3.2. Model construction of acoustic index and recreational behavior

When constructing the regression models for acoustic indices and recreational behavior, no evidence of multicollinearity was observed, as indicated by variance inflation factors (VIF) values of each variable being<10. The results are presented in Table 4, showing the significance of all indices. Specifically, static behavior displayed significant positive correlations with ACI, ADI, and AR indices and a significant negative correlation with the NDSI index. Dynamic behavior exhibited a significant positive correlation with ADI and NDSI indices only. Passing-by behavior showed a significant positive correlation with ACI index, while displaying a significant negative correlation with NDSI and overall PSD index. Furthermore, when fitting acoustic indices to types of recreational behaviors, the results showed that the fit of acoustic indices to passing-by behavior ($R^2 = 0.524$, $\triangle AIC_C = 2.641$) was better than the fit of acoustic indices to dynamic behavior ($R^2 = 0.478$, $\triangle AIC_C = 2.679$) and static behavior ($R^2 = 0.453$, $\triangle AIC_C = 3.513$).

Table 5 displays the correlation coefficients between the PSD values in different frequency intervals and recreational behaviors. Static behavior showed a significant positive correlation with PSD values in the 1–2 kHz, 3–4 kHz, 4–5 kHz, 7–8 kHz, and 8–9 kHz frequency intervals. Dynamic behavior showed a significant positive correlation with PSD values in the 8–9 kHz frequency interval only. In contrast, passing-by behavior showed a significant positive correlation with PSD values in

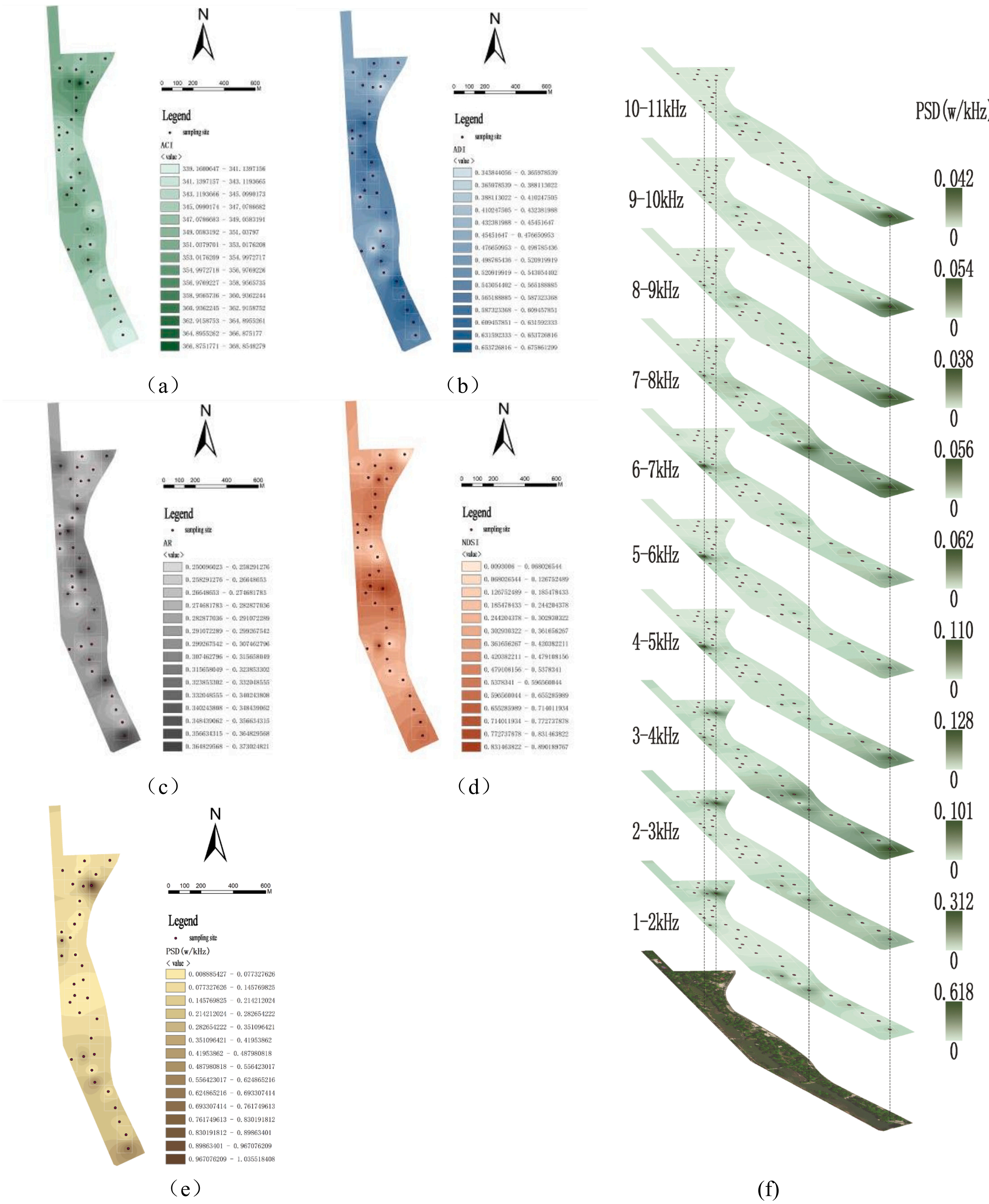


Fig. 7. Spatial distribution characteristics of different acoustic indices (a) Spatial distribution characteristics of ACI; (b)Spatial distribution characteristics of ADI; (c) Spatial distribution characteristics of AR; (d) Spatial distribution characteristics of NDSI; (e) Spatial distribution characteristics of PSD; (f)Spatial distribution characteristics of PSD in each frequency interval.

the 3–4 kHz, 4–5 kHz, 5–6 kHz, 8–9 kHz, 9–10 kHz, and 10–11 kHz frequency intervals. Furthermore, the regression results indicated that the fit of acoustic intensity to passing-by behavior ($R^2 = 0.544$, $\Delta AIC_C = 7.937$) outperforms the fit of acoustic intensity to dynamic behavior ($R^2 = 0.505$, $\Delta AIC_C = 8.446$) and static behavior ($R^2 = 0.104$, $\Delta AIC_C = 10.280$).

4. Discussion

4.1. Comparison of traditional observation and acoustic monitoring

The composition of recreational behaviors identified by acoustic monitoring in this study is approximately the same and demonstrates a considerable overlap (90%) with those recorded by traditional observation method. However, each method has its own advantages and weakness which are summarized in Table 6. Given the specific

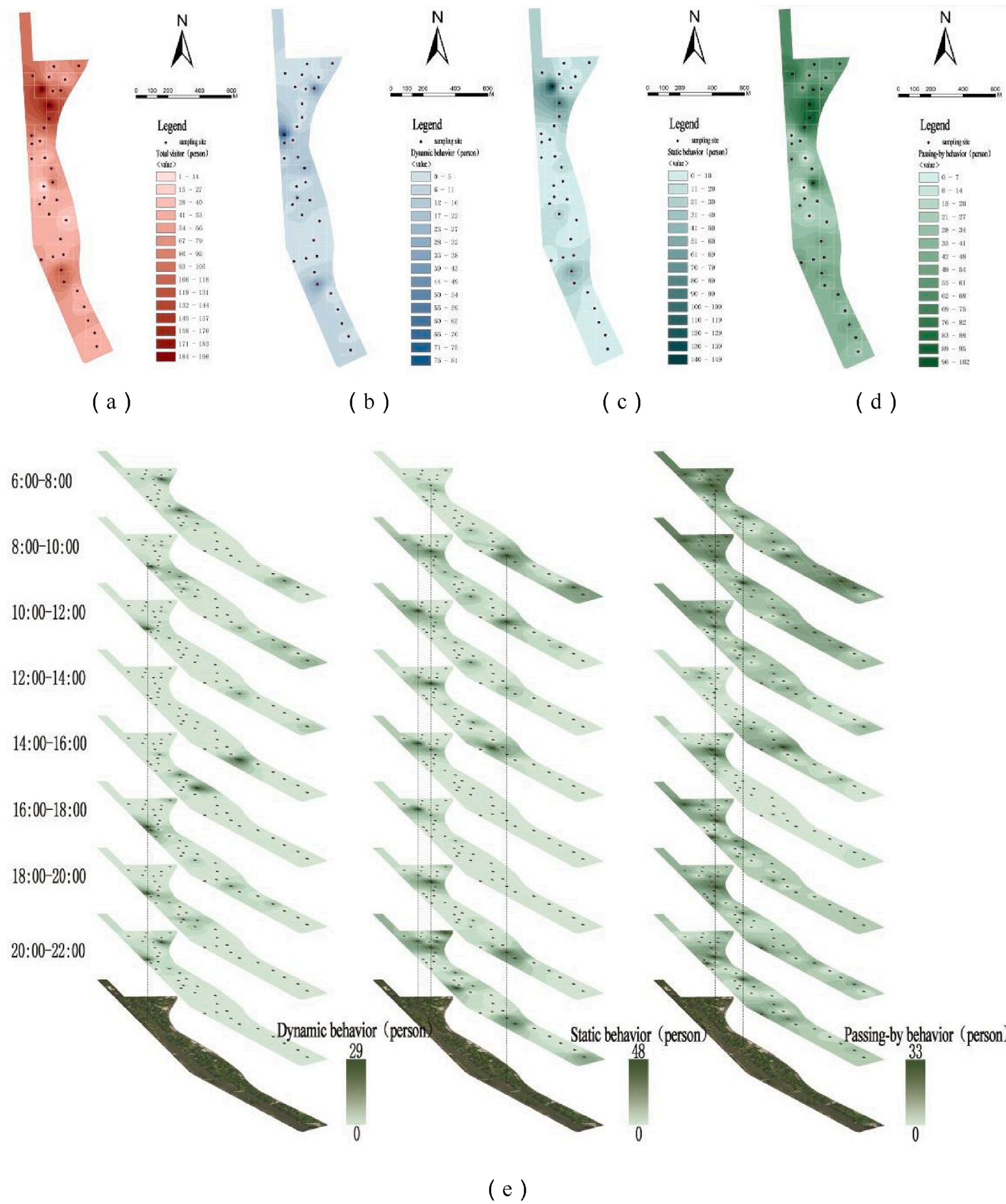


Fig. 8. Spatial distribution characteristics of recreational behavior (a) Spatial distribution characteristics of total visitors; (b)Spatial distribution characteristics of dynamic behavior; (c) Spatial distribution characteristics of static behavior; (d) Spatial distribution characteristics of passing-by behavior; (e) Spatial and temporal variation of various recreational behaviors.

objectives of the study, researchers can leverage the unique strengths of each method and combine them to obtain more comprehensive statistical data on public recreational behavior, depending on the purpose of the study. In this study, both types of observation were conducted simultaneously to ensure the consistency and reliability of the experimental data, but acoustic monitoring was more advantageous in long-term detection. The recording equipment supports continuous day and night operations for long periods of time at different locations without requiring human intervention. This frees up labor and facilitates the collection of more complete and comprehensive data. The long-term nature of acoustic monitoring allowed for the effective capture of uncommon recreational behaviors and enabled the analysis of dynamic changes in public recreational behavior over time.

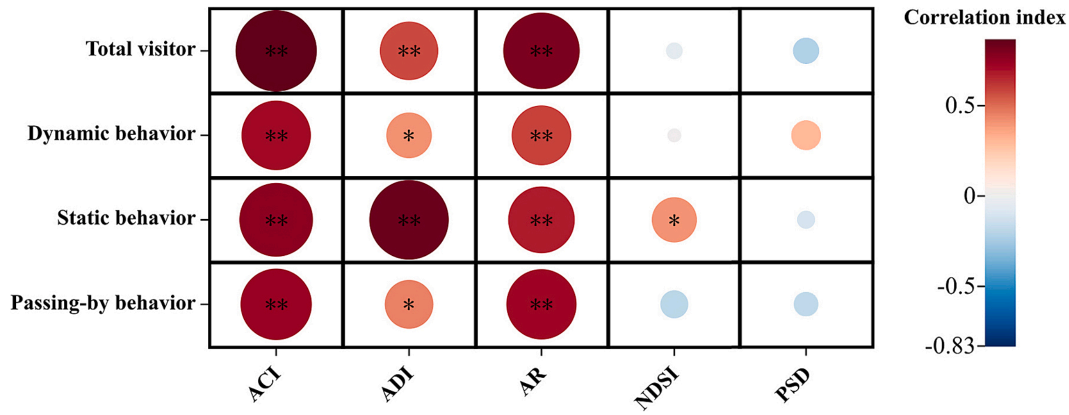


Fig. 9. Visual heat map of the correlation between the acoustic index and public recreational behavior. The color scheme used in the graphs assigns red to signify a positive correlation and blue to represent a negative correlation. The size and color intensity of the graphs directly correspond to the magnitude of the correlation index, with larger and darker graphs indicating a stronger correlation. *At the 0.05 level (two-tailed), the correlation is significant; **at the 0.01 level (two-tailed), the correlation is significant. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

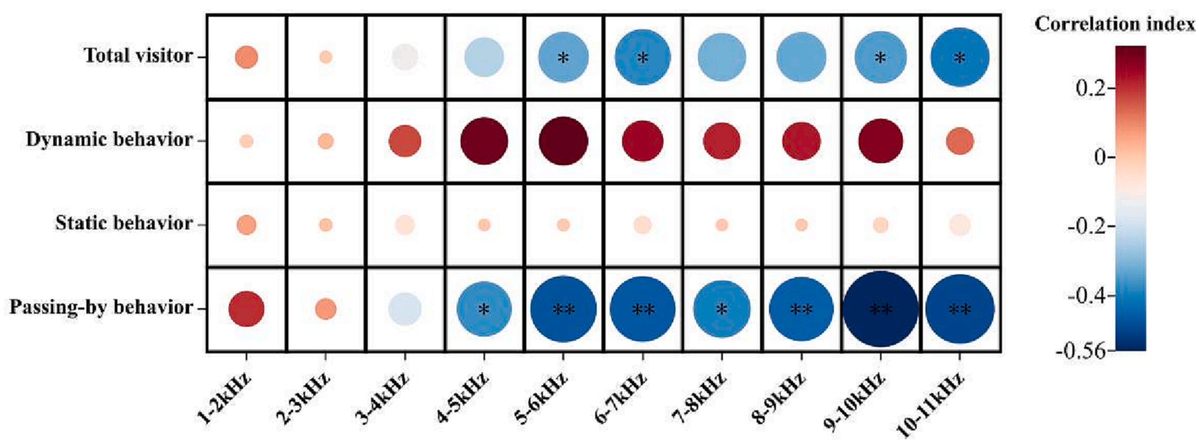


Fig. 10. Visual heat map of the correlation between acoustic intensity and public recreational behavior. The color scheme used in the graphs assigns red to signify a positive correlation and blue to represent a negative correlation. The size and color intensity of the graphs directly correspond to the magnitude of the correlation index, with larger and darker graphs indicating a stronger correlation. *At the 0.05 level (two-tailed), the correlation is significant; **at the 0.01 level (two-tailed), the correlation is significant. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. *Spatial and temporal variation characteristics of acoustic indices*

Some studies have reported that the highest value of the PSD index occurs in the evening (16:00–18:00) (Zhao et al. 2022), while another study proposed that the peak occurs in the low-frequency band in the early morning (6:00–8:00) (Zhao et al. 2021). In contrast, our study found that the peak of the PSD index occurs during the night hours (20:00–22:00). These inconsistent results may be attributed to the potential influence of multiple sources of interference in the urban environment that may bias the results. Regarding spatial variations in acoustic indices, our study reveals that the ACI and ADI indices were positively correlated with dense vegetation, indicating that higher vegetation density and coverage were related to higher ACI and ADI value. These findings are consistent with prior research (Zhao et al. 2021). Conversely, the AR and PSD indices depended on open areas, as higher AR and PSD values were found in areas with more open space and less vegetation coverage. This pattern may be attributed to the influence of urban traffic noise in the open fields of the urban park (Margaritis et al. 2018).

4.3. *Spatial and temporal characteristics of public recreational behavior*

During summer, visitor activity in urban parks peaks in the morning and evening, potentially due to the high temperatures during the afternoon that discourage outdoor recreation. Previous studies have found that individuals tend to engage in more indoor activities in hot summer weather (Qi et al. 2022; Qi et al. 2023), and lifestyle habits like napping may also contribute to this phenomenon (Wang et al. 2023). Notably, during the nighttime, dynamic behavior becomes the dominant type of activity, which aligns with the findings of Liu et al. (2017)., who proposed that the number of park visitors is sensitive to microclimate changes. Furthermore, it was observed that long-term recreational activities are primarily walking-based, with passing-by behaviors concentrated on park paths. Dynamic behaviors tend to occur on large hard surfaces, while static behaviors were more common around fixed park recreational facilities. These results confirm that various landscape elements influence recreational behaviors, highlighting the importance of designing well-considered landscape elements to meet the needs of visitors in urban parks (Zhang, 2022).

4.4. *Correlation between acoustic index and public recreational behavior*

Of the acoustic indices evaluated in this study, the ACI index appears to be the most robust in capturing the complexity of bio-acoustic signals in urban environments. The ACI index shows an extremely significant positive correlation with all recreational behavior types, highlighting its

Table 4
Parameter estimates for the average model of visitor recreational behavior.

Response variable	Explanatory variable	Estimate	Standard Error	value	P
Static behavior	(Intercept)	−67.600	3.485	−19.398	<0.001 ***
	ACI	0.193	0.009	21.325	<0.001 ***
	ADI	3.145	0.814	3.863	<0.001 ***
	AR	6.639	1.685	3.939	<0.001 ***
	NDSI	−3.260	0.292	−11.163	<0.001 ***
	PSD	0.447	0.177	−2.526	0.011 *
Dynamic behavior	(Intercept)	1.167	4.484	0.260	0.795
	ACI	−0.017	0.012	−1.397	0.162
	ADI	6.115	0.947	6.455	<0.001 ***
	AR	0.790	1.513	2.800	0.005 **
	NDSI	0.440	0.282	3.889	<0.001 ***
	PSD	1.167	0.113	0.260	0.795
Passing-by behavior	(Intercept)	−10.849	2.458	−4.414	<0.001 ***
	ACI	0.039	0.007	5.948	<0.001 ***
	ADI	−0.260	0.567	0.459	0.646
	AR	0.057	1.078	0.314	0.754
	NDSI	−0.596	0.181	−4.419	<0.001 ***
	PSD	−10.849	0.135	−4.414	<0.001 ***

Note: *P ≤ 0.05, **P ≤ 0.005, ***P ≤ 0.001.

applicability in urban parks. Additionally, the ADI, AEI, and AR indices were also found to be correlated with recreational behaviors. The ADI and AR indices showed significant positive correlations with each type of behavior, while the AEI index decreased as recreational behavior increased. On the other hand, the NDSI index, which indicates the impact of human activities on the soundscape, was significantly correlated only with static behavior. This suggests that people prefer quiet and natural environments for rest and the static activity has the least impact on the soundscape, consistent with previous studies (He 2022). The analysis of spatiotemporal variation characteristics of the NDSI index reveals errors occur during the time periods of 8:00–12:00 due to the high frequency of biological sounds above 2 kHz and the influence of other traffic noises, indicating that the NDSI index is not suitable for environments with strong disturbances. However, the changing trend of NDSI index in other periods matches the changing trend of public recreational behavior. When the NDSI index fell to a negative value, it coincides with the time when public recreational behavior is most abundant. This suggests that the NDSI index can effectively capture diversity of recreational behavior and that the acoustic index can quickly assess the recreational condition of urban parks.

4.5. Correlation between acoustic intensity and public recreational behavior

In this study, the effectiveness of acoustic intensity was investigated as an indicator of passing-by, dynamic, and static behaviors in urban parks. However, it is important to acknowledge that disturbing factors such as traffic and construction noise, which fall within the same frequency range, can potentially affect the correlation results for recreational behavior. In contrast, sound sources in the high-frequency power value range, such as footsteps in passing-by behavior, and sounds related to ball tapping, running, and jumping sounds in dynamic behavior, were more accurate in predicting recreational behavior. Specifically, the PSD values within the 4–11 kHz frequency range were inversely correlated with passing-by behavior, with footsteps being the most frequent sound

Table 5
Parameter estimates for the average model of visitor recreational behavior.

Response variable	Explanatory variable	Estimate	Standard Error	value	P
Static behavior	(Intercept)	2.789	0.057	49.231	<0.001 ***
	1–2 kHz	11.392	2.664	4.276	0.023 *
	2–3 kHz	27.351	5.557	4.922	0.135
	3–4 kHz	32.002	8.246	3.881	0.007 **
	4–5 kHz	54.855	16.249	3.376	<0.001 ***
	5–6 kHz	98.122	30.256	3.243	0.286
	6–7 kHz	49.558	41.535	1.193	0.058.
	7–8 kHz	89.738	21.941	4.090	<0.001 ***
	8–9 kHz	186.360	83.358	2.236	<0.001 ***
	9–10 kHz	246.794	86.067	2.867	0.851
	10–11 kHz	277.216	107.491	2.579	0.196
Dynamic behavior	(Intercept)	1.959	0.080	24.407	<0.001 ***
	1–2 kHz	0.873	2.882	0.303	0.762
	2–3 kHz	4.478	6.146	0.729	0.466
	3–4 kHz	12.389	8.351	1.484	0.138
	4–5 kHz	24.212	15.815	1.531	0.126
	5–6 kHz	9.818	35.934	0.273	0.785
	6–7 kHz	37.286	54.784	0.681	0.496
	7–8 kHz	2.753	35.119	0.078	0.938
	8–9 kHz	187.341	89.456	2.094	0.036 *
	9–10 kHz	140.860	110.594	1.274	0.203
	10–11 kHz	136.844	145.072	0.943	0.346
Passing-by behavior	(Intercept)	3.225	0.046	70.091	<0.001 ***
	1–2 kHz	6.455	1.935	0.303	0.762
	2–3 kHz	13.186	3.994	1.531	0.126
	3–4 kHz	−7.945	4.146	−3.153	0.002 **
	4–5 kHz	−46.875	7.799	−6.011	<0.001 ***
	5–6 kHz	−53.032	16.487	−3.217	0.001 **
	6–7 kHz	−2.674	23.704	−0.113	0.910
	7–8 kHz	−5.964	13.209	−0.452	0.652
	8–9 kHz	−301.283	54.650	−5.513	<0.001 ***
	9–10 kHz	−166.609	57.228	−2.911	0.003 **
	10–11 kHz	303.094	79.332	−3.821	<0.001 ***

Note: *P ≤ 0.05, **P ≤ 0.005, ***P ≤ 0.001.

source within the high-frequency power value interval. These findings suggest that acoustic intensity at high-frequency power values can serve as useful tool for quickly assessing the recreational conditions of urban parks. In addition, the present study found that both dynamic and static behaviors were positively correlated with the PSD values of the full frequency band, indicating that larger PSD values in each frequency interval were linked with increased occurrences of these two behaviors. Conversely, the insignificant correlation with dynamic behaviors may be due to smaller sample size and its less frequent occurrence compared to the other two behavior types.

4.6. Limitations and potential of acoustic indices for assessing visitor recreational behavior in urban parks

Acoustic indices are affected by various sounds present in the environment. Many domestic and international studies have pointed out that the predictive power of acoustic indices and landscape intensity models can be negatively interfered with by insects, weather, and other human activity noise, resulting in a reduction in their effectiveness (Buxton et al. 2018). However, it should be acknowledged that our analysis cannot completely exclude the presence of non-focal organisms' sounds. Furthermore, the selection of acoustic indices can impact the predictive ability of a model. Consequently, it is imperative for future research to explore ways to select the appropriate acoustic ecological indexes that

Table 6
Comparison of traditional observation and acoustic monitoring.

	Traditional observation	Acoustic monitoring	Reference
Advantage	One of the most commonly used recreational behavior survey methods. Easy to implement and easy to randomize or systematize. The observation process provides direct access to the type of entertainment and the specific number of each behavior of visitors, with efficiency and flexibility. Suitable for complex or fragmented research sites	The operation is simple and repeatable, and supports simultaneous large-scale, long-term, continuous dynamic monitoring and tracking. Recordings are permanently stored and can be monitored repeatedly to reduce recognition bias. The continuous development of acoustic indices and machine learning helps to quickly assess recreational behavior. Spectrograms can visualize sound, can effectively assist in identification, and their results are objective It is also possible to record the duration of recreational behavior at the same time, providing data reference for more in-depth study of public recreation preferences.	Darras et al. 2019; Zhao et al. 2022; Zhang et al. 2018
Weakness	The limited number of observations does not guarantee the synchronization of multiple points, and the period affects the reliability of the results. When visibility is low or obstructions obscure, it makes it difficult to identify the behavior of the visitors and can lead to speculative results. When the number of visitors is too high, the limited energy of the observer may lead to some missing records. Observers, especially those with equipment, entering the study site can affect visitors' recreational behavior.	The challenge of big data. Long-term recording generates huge audio files, requiring consideration of big data storage and processing, battery capacity and replacement costs, etc. Manual recognition takes a lot of time, and current automatic recognition techniques are still subject to interference from background noise and sound overlap, leading to biased results. Behavior in excessively noisy areas and non-vocal behavior cannot be recognized.	Darras et al. 2019; Huang et al. 2022; Bian et al. 2023

can enhance model-fitting efficacy. This study verifies the feasibility of acoustic monitoring in urban parks, where audio-based manual recognition of recreational behavior can yield comparable results to panoramic camera photography. As future research progresses, the potential of acoustic detection in analyzing public recreational behavior, and even landscape gardening, can be further explored. The continuous innovation of science and technology portends a promising application prospect for acoustic monitoring. However, it should be noted that the study did not compare multiple acoustic indices or conduct larger-scale testing due to time and content constraints. It is possible that methodological issues may emerge over time and require further investigation.

5. Conclusion

The application of acoustic indices in analyzing recreational behavior offers numerous benefits, including cost-effectiveness and non-invasiveness. This research investigates the spatial and temporal variation characteristics of acoustic indices, acoustic intensity, and public recreational behavior by simultaneously recording both metrics at 35 monitoring points located in urban green spaces during park operating hours from 6:00 to 22:00. The study aims to examine the possibility of using acoustic indicators to reflect public recreational behavior. Findings reveal that: (1) the ACI, ADI, AR, and NDSI acoustic indices have substantial overlap with the spatial and temporal variation characteristics of recreational behavior, and can reflect tourist behavioral activities to a certain degree; (2) the daily variation characteristics of the three acoustic indices (ACI, ADI, and AR) are similar to those of public recreational behavior, displaying multi-peak daily variation patterns in a "W" shape, and their spatial variation characteristics are also analogous; (3) the acoustic intensity shows significant variation across the frequency gradient, and different frequency intervals can reflect activity information of different recreational behaviors, particularly the power spectral density in the high-frequency interval, which possesses great capacity for assessing passing-by behavior; (4) regarding the three recreational behaviors, the acoustic index model and the acoustic intensity model exhibit better assessment ability for passing-by behavior than for dynamic behavior and static behavior; (5) based on correlation analysis and model construction, acoustic indices can be used to analyze the spatial and temporal variation characteristics of public recreational behavior in green spaces, providing data support for urban green area renovation and enhancement. Overall, acoustic monitoring, either as an independent or complementary tool, holds excellent potential for development and application in visitor activity research. This study supports the inclusion of acoustic indices such as ACI, ADI, AR, and the PSD values within high-frequency intervals in existing monitoring methods. By incorporating these acoustic indicators, researchers can gain a more comprehensive understanding of public recreational behavior. Furthermore, the application of data analysis techniques, such as machine learning and pattern recognition, facilitates the analysis of large volumes of acoustic data, allowing for the extraction of meaningful insights and the identification of behavioral patterns in a more efficient and systematic manner. This contributes to the improvement of monitoring methods and enhances our ability to assess and manage public recreational behaviors in urban parks. Finally, integrating acoustic monitoring as a constituent element of park management strategies is recommended. The recorded acoustic data provides valuable information for formulating targeted interventions and allocating resources effectively. By leveraging these insights, park managers can enhance visitor experiences while minimizing environmental impacts. Implementing these suggestions will lead to improvements in existing public behavior monitoring methods, resulting in a more comprehensive and effective understanding of public behavior in urban green spaces.

Funding

This work was supported by National Natural Science Foundation of China (NSFC): Green Urbanization across China and Europe: Collaborative Research on Key technological Advances in Urban Forests, (Grant No. 2021YFE0193200); Horizon 2020 strategic plan: CLEARING HOUSE—Collaborative Learning in Research, Information sharing, and Governance on How Urban tree-based solutions support Sino-European urban futures, (Grant No. 821242).

CRediT authorship contribution statement

Weicong Fu: Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Chengyu Ran:** Conceptualization, Data curation, Investigation. **Jingkai Huang:** Methodology, Data curation, Investigation. **Zhu Chen:** Methodology, Data curation. **Shiyuan Fan:** Data curation, Writing – review & editing. **Wenqiang Fang:** Writing – review & editing. **Miaojun Ye:** Writing – review &

editing. **Jiaying Dong:** Writing – review & editing, Supervision. **Xiong Yao:** Writing – review & editing, Supervision. **Ziru Chen:** Conceptualization, Validation, Writing – review & editing, Supervision.

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.

References

Arnberger, A., Haider, W., Brandenburg, C., 2005. Evaluating visitor-monitoring techniques: A comparison of counting and video observation data. Environ. Manag. 36 (2), 317–327.

Bai, Z., Wang, C., Zhao, Y., Hao, Z., Sun, Z., 2021. Characteristics and temporal variation of spring anthrophony in urban park in Beijing. Chinese Landscape Architecture 37 (04), 99–104.

Baran, P.K., Smith, W.R., Moore, R.C., Floyd, M.F., Bocarro, J.N., Cosco, N.G., Danninger, T.M., 2014. Park use among youth and adults: examination of individual, social, and urban form factors. Environ. Behav. 46 (6), 768–800.

Bian, Q., Wang, C., Cheng, H., Han, D., Zhao, Y., Yin, L., 2023. Exploring the application of acoustic indices in the assessment of bird diversity in urban forests. Biodivers. Sci. 31 (1), 22080.

Bobryk, C.W., Rega-Brodsky, C.C., Bardhan, S., Farina, A., He, H.S., Jose, S., 2016. A rapid soundscape analysis to quantify conservation benefits of temperate agroforestry systems using low-cost technology. Agrofor. Syst. 90 (6), 997–1008.

Bradbury, J.W., Vehrencamp, S.L., 1998. Principles of animal communication. Sinauer Associates.

Buxton, R.T., McKenna, M.F., Clapp, M., Meyer, E., Stabenau, E., Angeloni, L.M., Crooks, K., Wittemyer, G., 2018. Efficacy of extracting indices from large-scale acoustic recordings to monitor biodiversity. Conserv. Biol. 32 (5), 1174–1184.

Darras, K., Batáry, P., Furnas, B., Grass, I., Mulyani, Y., Tscharntke, T., 2019. Autonomous sound recording outperforms human observation for sampling birds: a systematic map and user guide. Ecol. Appl. 29, e01954.

Depraetere, M., Pavoine, S., Jiguet, F., Gasc, A., Duvail, S., Sueur, J., 2012. Monitoring animal diversity using acoustic indices: implementation in a temperate woodland. Ecol. Ind. 13 (1), 46–54.

Engelhard, S., Stubbs, J., Weston, P., Fitzgerald, S., Giles Corti, B., Milat, A.J., Honeysett, D., 2001. Methodological considerations when conducting direct observation in an outdoor environment: our experience in local parks. Aust. N. Z. J. Public Health 25 (2), 149–151.

Farina, A., Pieretti, N., Piccioli, L., 2011. The soundscape methodology for long-term bird monitoring: a Mediterranean Europe case-study. Eco. Inform. 6 (6), 354–363.

Gage, S., Axel, A., 2014. Visualization of temporal change in soundscape power of a Michigan lake habitat over a 4-year period. Ecological Information 21, 100–109.

Gómez, W.E., Isaza, C.V., Daza, J.M., 2018. Identifying disturbed habitats: a new method from acoustic indices. Eco. Inform. 45, 16–25.

Grueber, C.E., Nakagawa, S., Laws, R.J., Jamieson, I.G., 2011. Multimodel inference in ecology and evolution: challenges and solutions. J. Evol. Biol. 24 (4), 699–711.

Guillén, J., García-Olivares, A., Ojeda, E., Osorio, A., Chic, O., González, R., 2008. Long-term quantification of beach users using video monitoring. J. Coast. Res. 24 (6), 1612–1619.

Hao, Z., Wang, C., Sun, Z., van den Bosch, C.K., Zhao, D., Sun, B., Xu, X., Bian, Q.i., Bai, Z., Wei, K., Zhao, Y., Pei, N., 2021. Soundscape mapping for spatial-temporal estimate on bird activities in urban forests. Urban For. Urban Green. 57.

He, Y., 2022. Research on park soundscape evaluation and planning: Taking Longzihu park as an example. North China University of Water Resources and Electric Power, M.S.

Huang, Z., Dong, J., Chen, Z., Zhao, Y., Huang, S., Xu, W., Zheng, D., Huang, P., Fu, W., 2022. Spatiotemporal characteristics of public recreational activity in urban green space under summer heat. Forests 13 (8), 1268.

Joo, W., Gage, S.H., Kasten, E.P., 2011. Analysis and interpretation of variability in soundscapes along an urban–rural gradient. Landsc. Urban Plan. 103 (3–4), 259–276.

Kasten, E.P., Gage, S.H., Fox, J., Joo, W., 2012. The remote environmental assessment laboratory's acoustic library: an archive for studying soundscape ecology. Eco. Inform. 12, 50–67.

Krause, B., Farina, A., 2016. Using ecoacoustic methods to survey the impacts of climate change on biodiversity. Biol. Conserv. 195, 245–254.

Krause, B., Gage, S.H., Joo, W., 2011. Measuring and interpreting the temporal variability in the soundscape at four places in Sequoia National Park. Landsc. Ecol. 26 (9), 1247–1256.

Lillis, A., Eggleston, D.B., Bohnenstiehl, D.R., 2014. Soundscape variation from a larval perspective: the case for habitat-associated sound as a settlement cue for weakly swimming estuarine larvae. Mar. Ecol. Prog. Ser. 509, 57–70.

Liu, J., Zhang, L., Lu, G., 2017. An analysis on the relationship between micro-climate comfort and visitor's behaviors in city park: a case study in the city of Huzhou. Journal of Huzhou University 39 (11), 93–101.

Margaritis, E., Kang, J., Filipan, K., Botteldooren, D., 2018. The influence of vegetation and surrounding traffic noise parameters on the sound environment of urban parks. Appl. Geogr. 94, 199–212.

Marquet, O., Hipp, J.A., Alberico, C., Huang, J., Fry, D., Mazak, E., Lovasi, G.S., Floyd, M. F., 2019. Use of SOPARC to assess physical activity in parks: do race/ethnicity, contextual conditions, and settings of the target area, affect reliability? BMC Public Health 19, 1–11.

Matisziw, T.C., Nilon, C.H., Stanis, S.A.W., LeMaster, J.W., McElroy, J.A., Sayers, S.P., 2016. The right space at the right time: the relationship between children's physical activity and land use/land cover. Landsc. Urban Plan. 151, 21–32.

Park, K., Ewing, R., 2017. The usability of unmanned aerial vehicles (UAVs) for measuring park-based physical activity. Landsc. Urban Plan. 167, 157–164.

Pieretti, N., Farina, A., Morri, D., 2011. A new methodology to infer the singing activity of an avian community: the Acoustic Complexity Index (ACI). Ecol. Ind. 11 (3), 868–873.

Pijanowski, B.C., Villanueva-Rivera, L.J., Dumyahn, S.L., Farina, A., Krause, B.L., Napoletano, B.M., Gage, S.H., Pieretti, N., 2011. Soundscape ecology: the science of sound in the landscape. Bioscience 61 (3), 203–216.

Qi, J., Ding, L., Lim, S., 2022. A decision-making framework to support urban heat mitigation by local governments. Resour. Conserv. Recycl. 184.

Qi, J., Ding, L., Lim, S., 2023. Application of a decision-making framework for multi-objective optimisation of urban heat mitigation strategies. Urban Clim. 47.

Schafer, R., 1969. The New Soundscape. Berandol Music Limited.

Schafer, R., 1970. The Book of Noise. Price Print.

Villanueva-Rivera, L.J., Pijanowski, B.C., Doucette, J., Pekin, B., 2011. A primer of acoustic analysis for landscape ecologists. Landsc. Ecol. 26 (9), 1233–1246.

Wang, M., Chen, Z., Hu, Y., Li, Q., 2023. Spatio-temporal characteristics of daily leisure activities of the elderly in small and medium-sized cities: A case study of Wuling district, Changde city. J. Chinese Ecotourism 13 (01), 169–182.

Zhang, G., 2020. Application of soundscape mapping technology in soundscape optimization of urban open space: A case study in Beijing park. Shenyang Jianzhu University, M.S.

Zhang, Y., Li, L., Li, D., Wu, G., 2018. Evaluation of habitat suitability based on patches of the Sichuan snub-nosed monkey (Rhinopithecus roxellana) in Shennongjia. Hubei Province. 38 (11), 3784–3791.

Zhang, L., A, l., 2022. Research on preferences of tourists in ethnic village landscape space based on GPS data: Taking Sichuan Taoping Qiang village as an example. Chinese Landscape Architecture 38 (11), 52–57.

Zhao, Y., Shen, X., Li, S., Zhang, Y., Peng, R., Ma, K., 2020. Progress and prospects of research in soundscape ecology. Biodivers. Sci. 28 (7), 806.

Zhao, Y., Bai, Z., Wang, C., Yin, L., Sun, Z., Zhang, C., Sun, R., Xu, S., Bian, Q., Sun, B., 2021. Urban parks soundscape and its relationship with vegetation structure: A pilot study. Acta Ecologica Sinica.

Zhao, X., Xu, J., Liu, X., Zhu, X., 2019. Observations of winter physical activities in urban park s using UAVs: a case study of four city park in Harbin. Chinese Landscape Architecture 35 (12), 40–45.

Zhao, Y., Xu, S., Huang, Z., Fang, W., Huang, S., Huang, P., Zheng, D., Dong, J., Chen, Z., Yan, C., Zhong, Y., Fu, W., 2022. Temporal and spatial characteristics of soundscape ecology in urban forest areas and its landscape spatial influencing factors. Forests 13 (11), 1751.

Zhong, W., Wang, D., 2019. A study on spatial characteristics of nighttime vitality in the center of Shanghai. City Plan. Rev. 43 (6).