Pol. J. Environ. Stud. Vol. 31, No. 5 (2022), 4623-4639
DOI: *10.15244/pjoes/150383* ONLINE PUBLICATION DATE: 2022-08-02

Original Research

Prediction and Evaluation of Park Sound Comfort Based on Back Propagation Neural Network

Qindong Fan*, Yujie He, Chenming Zhang, Xiaoyu Yang

School of Architecture, North China University of Water Resources and Electric Power, Zhengzhou 450046, China

Received: 26 April 2022
Accepted: 24 May 2022

Abstract

Park soundscape construction is an important method to improve the quality of urban environments. At present, the studies on soundscape mostly focus on the evaluation of soundscape indexes and the accuracy analysis of model simulations of actual sites, but the research on small-scale soundscape characteristic spaces is inadequate. Based on a Back Propagation(BP) neural network model, we predict and evaluate the sound comfort in a park. The results show that: (1) The distribution trends of measured and predicted sound comfort values in different scenes (space type, plant type, functional area and sound source type) are relatively consistent. (2) A sound comfort of the park is space dependent. The sound landscape design of small-scale characteristic space is of great significance to improve the environmental quality. (3) The evaluation of emotional acoustics has obvious correlation with sound comfort. (4) The soundscape planning process based on BP neural network is clearly proposed. The research results are of great significance to promote soundscape evaluation and planning based on the evaluation results.

Keywords: BP neural network, park, sound comfort, evaluation, prediction

Introduction

With the rapid progress of urbanization, the pressure of urban life on residents has become increasingly prominent [1]. Parks, owing to their good environmental quality and as important components of a city, have crucial effects on the physical and mental health of urban residents [2]. The good park space can improve the quality of urban environment, relieve the pressure of urban residents, and ensure the physical and mental health of residents. How to create such a park environment has attracted extensive attention of scholars at home and abroad [3]. Currently, the research on urban parks focuses on users' perceptions and experiences through multiple senses, as opposed to vision alone. Among these senses, hearing, as a perceptive route next only to visual perception, has gradually attracted scholars' attention [4, 5]. The soundscape design of parks has become an important means to break the visual design and improve the overall quality of a park's environment.

ISO defines "soundscape" as the "the acoustic environment as perceived or experienced and/or understood by a person or people, in context" [6]. The current research on soundscape is mainly focused on the acoustic environment and acoustic perception. The studies on acoustic environment mainly analyze acoustic environments by quantifying sound sources,

*e-mail: fanqindong@126.com

sound pressure levels, and other acoustic indices. The studies on acoustic perception mainly focus on how and the extent to which people perceive sound environments. The factors considered for specific soundscape include sound source characteristics [7], sound preferences [8-10], semantic characteristics of sound [11, 12], acoustic scene perception [13, 14], acoustic scene evaluation [15-17], and acoustic scene prediction [18, 19]. Among these factors, soundscape evaluation is considered an important basis for solving acoustic-environment-related problems and guiding the design of acoustic environments. There are four types of traditional soundscape evaluation methods: 1) the Subjective evaluation method based on society and psychology, which mainly analyzes people's subjective feelings to soundscape through questionnaire survey [20-25]; 2) the objective evaluation method based on acoustic physical parameters, which mainly describes the soundscape based on the measured acoustic parameters [26-30]; 3) the method of combining subjective perception with objective physical parameters [31-35]; 4) the Method based on physiology, which mainly evaluates the soundscape by measuring the response of human physiological indexes to soundscape [36].

The traditional methods mainly use on-site index measurement and questionnaire survey to evaluate the soundscape. These methods are limited by their time-consuming nature, considerable energy consumption, and low efficiency. In recent years, researchers have been developing prediction models to overcome the shortcomings of the traditional evaluation methods [37, 38]. A soundscape prediction model predicts how people perceive an acoustic environment without measuring the full range of soundscape indicators to reduce the workload of field research. The general objective of prediction is to predict the acoustic measurement data associated with an acoustic environment [39, 40] and quantify people's perceptions of the acoustic environment [41-43]. Acoustic prediction models were initially used to assess the presence and effects of urban traffic noise [44]. With the expansion of this research field, a subjective perception factor has been included in the new model indicators, and the cases of subjective acoustic evaluation and prediction are increasing [45, 46]. Research on soundscape has emerged as a hot topic in the environmental field. The evaluation indexes of model prediction mainly include perception index and acoustic index. The perceptual indicators generally include sound source significance evaluation [47], sound source subjective preference [21-23], sound pressure level subjective loudness evaluation [48], and higher-level emotional acoustics evaluation (such as sound pleasure [49,50] and sound comfort [51]). The acoustic indicators mainly include equivalent sound pressure level, occurrence and duration [52], fluctuation [53], peak [53], spectrum [54], frequency [55], and a few environmental and crowd indicators (such as user information [56], crowd characteristics [38, 56], and physical measurement of an environment [57]). The process of establishing a soundscape prediction model can be divided into three parts: index, prediction method, and rule set (linear or nonlinear) (Fig. 1). Mapping can be performed using linear regression methods or nonlinear mapping methods, such as fuzzy logic [58], support vector regression (SVR) [59-61], and artificial neural network (ANN) [46, 60]. Compared with the traditional methods, the artificial neural network model can predict big data and realize bidirectional operation. It also has the advantages of high stability, convergence and fault tolerance, and quickly becomes the mainstream research method [36]. Consequently, ANNs have emerged as a mainstream research method [36]. Currently, ANNs are used for soundscape index prediction [40], soundscape perception prediction [36, 60, 61], sound source preference prediction [62], and simulation of soundscape evaluation [51].

As an important public space, the parks can provide healthy environmental resources for residents, and they are also the main place for people to enjoy the soundscape. The current research of soundscape in urban parks focuses on the relationship between soundscape and landscape factors. For example, the influence of plant landscape on soundscape perception [62], the influence of landscape space and composition characteristics on soundscape perception [63], the influence of landscape materials on soundscape [64], the influence of human behavior factors on soundscape experience [65], and the soundscape design strategy based on landscape factors [62, 65]. The existing soundscape research methods are numerous and comprehensive. However, most of them focus on the large-scale space such as city and street, and there is still a lack of research on the design of small-scale characteristic space, such as the influence of different space functions, landscape settings and sound source structure on the soundcape of small space. In addition, it has been proved that the artificial neural network model is more accurate than the mathematical statistical model in the evaluation and prediction of soundscape.

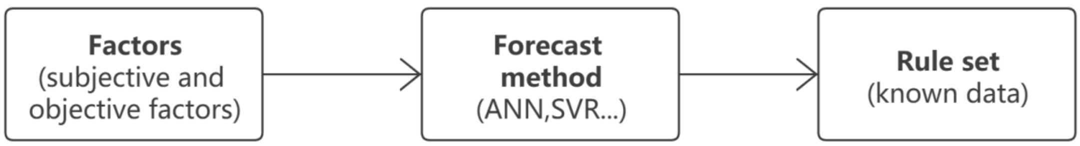

Fig. 1. Modelling flowchart.

but the prediction results have not been applied adequately. At present, most artificial neural network prediction results are only used to evaluate the accuracy of the model. However, it is still uncertain whether the predicted values can be used to guide the multi-angle soundscape evaluation and the construction on large-scale soundscape.

In this study, from the perspective of sound comfort considering the characteristics of sound environment and different landscape functional areas, a BP ANN model is used to predict and evaluate sound comfort. By comparing the measured and predicted values of each factor pertaining to sound comfort, the evaluation and application of soundscape in large-scale spaces and soundscape design in small-scale characteristic spaces are explored in an attempt to provide a useful reference for the construction of urban park soundscape. In the following sections, we first establish the BP neural network comfort prediction model, then compare the effects of various kinds of space environment, functional zoning and emotional acoustic perception on the measured and predicted comfort values, and finally discuss the soundscape construction method based on BP neural network model.

Material and Methods

Selection of Research Sites and Measurement Points

In this study, the Longzihu Beach Park in the Zhengdong New District of Zhengzhou City was used as the research area (Fig. 2). The Longzihu Beach Park is located within Longzihu University Park, Zhengzhou City, Henan Province, China. The 17,000 m² beach park is a part of the Longzi Lake Park, located in the west of Longzi Lake. Presently, the landscape effect of the park is good, with a large, stable flow of people. Considering the different types of sound sources, space types, and space functions, sample collection was performed at 15 measurement points in the beach park, and another 15 measurement points in similar types of spaces were selected. The BP neural network model was used to predict the soundscape comfort value in the park. The 30 measurement points were distributed relatively evenly throughout the beach park, and they essentially covered the soundscape characteristics of the entire park.

Data Source

The data were divided into subjective evaluation data and objective measurement data. The subjective data were used to provide a subjective score of the comfort level due to the sound scene in the beach park based on human perception experience, and the objective physical acoustic data were used to measure the sound pressure level in the beach park.

(1) Subjective data: The subjective data were obtained by administering a soundscape comfort research questionnaire (Appendix 1). The physical data were measured, and the respondents were asked to fill in the questionnaire between 29 September 2020 and 14 October 2020. A total of 600 questionnaires were issued, and 498 valid questionnaires were recovered. For each measurement point, at least 30 evaluation data points were used as the sample training data, and for each prediction point, at least 3 evaluation data points were used as the basic prediction data. Consequently, 453 sample training data points and 45 sample prediction data points were obtained. Based on field interviews, the questionnaire was created considering three main aspects: space environment, sound source, and sound environment. Under the first aspect, basic space information was used to explore the influences of different spatial function types on sound comfort. Under the second aspect, the main sound sources were evaluated. The frequency and degree of preference of each source were evaluated, and the influence of the frequency of the main source and the preference of the sound source on the evaluation of the sound comfort is explored. Under the third aspect, information of the park's sound environment was evaluated, and a subjective evaluation of the quietness, pleasure, and annoyance of the entire acoustic environment was performed to clarify the effect of various emotional acoustics on sound comfort. Responses to the formal field survey questionnaire were obtained on a five-point Likert scale. In the questionnaire survey, the evaluation is divided into five levels, and the respondents determine the score according to their subjective feelings, as shown in Table 1.

(2) Objective data: Sound pressure levels at the measurement points were obtained to clarify the impact of specific sound pressure level data on the evaluation of soundscape comfort. During the filling of each questionnaire, three investigators measured the ambient sound pressure level data by using GM1351 sound level meters. The measurements were conducted under sunny conditions to the extent possible, duration of each measurement was 2 min, and average value of each measurement point was taken as the final result. Finally, 498 effective data points were obtained.

Data Pre-Processing

Input Factor Selection

In total, 17 final input factors were selected (Table 2), including 13 quantitative factors and 4 qualitative factors. The types and selection bases of the qualitative factors are summarized in Table 3.

Qualitative Data Coding and Sample Screening

In addition to quantitative data, qualitative data, such as space type and plant type, were set. Such

Fig. 2. Pictures of the measurement points.

Table 1. Rating table of quiet, pleasure, and annoyance.

Project	Exceedingly bad	Bad	Medium	Good	Exceedingly good
Quiet	-2	1	0	1	2
Pleasure	-2	1	0	1	2
Annoyance	-2	1	0	1	2

Table 2. Selection of input factors.

Space environment	Sound source	Sound environment feeling
Environmental satisfaction	Water sound preference	Sound pressure level
Space type	Water sound frequency	Annoyance degree
Plant type	Children's sound preference	Pleasure degree
Landscape function areas	Children's sound frequency	Quiet degree
Sound source structure	Birdsong preference	
	Birdsong frequency	
	Mechanical sound preference	
	Mechanical sound frequency	

Table 3. Classification of qualitative factors.

	Type	Classification basis
Space type	Private space	Such a space usually has only one entrance, smaller scale, and poor accessibility due to high walls, hedges, fences, and other types of boundaries.
	Semi-open space	Such a space usually has a sense of enclosure, but the vision is transparent, and people's activities are relatively limited, such as a pavilion or a small garden.
	Open space	An open space offers a large sense of scale and the provision for various activities, and it a certain enclosure at its boundary, for example, a square or grass.
Types of landscape functional areas	Viewing Area	Such spaces are meant for viewing and sightseeing, and most people stay in them for periods shorter than 10 min.
	Activity area	Such spaces can be used to participate in various activities, and most people stay in them for periods longer than 30 min.
	Rest Area	Most people stay in these spaces for periods longer than 10 min but shorter than 30 min.
Plant type	A layer of plant landscape	Such a space has one plant layer, such as a lawn or ground cover.
	Two layers of plant landscape	Such a space has two layers of plants, such as grassland and shrubs.
	Three or more layers of plant landscape	Such a space has three or more layers of plants, such as grassland, shrubs, and trees.
Sound source structure	Mainly natural sound	The sounds originate mainly from animals, plants, and their physical phenomena.
	Mainly life sound	The sounds originate mainly from human activities.
	Mainly mechanical sound	The sounds originate mainly from mechanical sources.

qualitative data have discrete attributes, and they are processed by means of hot coding. In addition, in the generation of predictions using ANNs, missing data directly affect the calculation and selection of the network. Therefore, in the input data pre-processing step, the data with missing values were deleted. The sample size after removing the data with missing values was 453 in this study.

Research Methods

Establishment of BP Neural Network Prediction Model

To facilitate data processing and ensure program convergence during operation, the probability distribution of the statistics between 0 and 1 was normalized using the MATLAB 2019 platform.

The parameters of an ANN directly affect its prediction results. Because the convergence rate of the model used herein was fast in all parameter tests, the number of iterations was set to 300, and the learning function was used as the default setting. We mainly studied the selection of training samples, layers, and training functions of the BP neural network.

In the first step, the training samples were selected. Training samples accounting for 65%, 70%, 75%, 80%, and 85% of the total sample were used, and each group was trained 10 times. The accuracy of the prediction model is shown in Fig. 3. When the training samples accounted for more than 70% to 80% of the total sample, the accuracy of the model increased, but when the training samples accounted for more than 85% of the total sample, the accuracy of the model decreased. When the training sample accounted for 75% of the total sample, the training accuracy was the highest and the most stable. Therefore, in the model considered herein, the training sample accounting for 75% of the total sample was used.

In the second step, the number of network layers were determined. In this paper, 17 factors were selected as the input variables, including 13 quantitative factors and 4 qualitative factors. After exclusive hot coding, the number of qualitative input nodes was 12, so the number of input layer nodes was 25. Comfort was taken as the output variable, so the number of output layer nodes was 1 (Fig. 4). Based on extant research [55, 60, 66], two hidden layers were set, and the number of hidden layer nodes was determined as 13 by using empirical values and the trial-and-error method. Finally, a three-layer "25-13-13-1" network structure was constructed (Fig. 5).

The third step is function selection. 1) Transfer function. The training samples used for the two models accounted for 75% of the total sample, the topological structure of the two models is the same as that in step (1). It can be seen from Fig. 6 that when the transfer function is Tan-Sigmoid + purelin, the accuracy of the prediction model is higher. Therefore, Tan-Sigmoid + purelin is the best choice of transfer function.

2) Training function. Taking the prediction model of sound comfort in Beach Park as an example, three groups of training functions traincgb (Fig. 7 a), traingdm (Fig. 7 b) and trainlm (Fig. 7 c) were selected for a comparative study. The training samples of the two groups of models accounted for 75% of the total sample, topological structure is the above settings, and the transfer function is Tansig + purelin. As can be inferred from Fig. 8, when the training function is traincgb, the model accuracy is higher.

The fourth step, model validation. The above model is used to train the data for 10 times, and there is no fitting phenomenon in the training process. The average accuracy of the 10 training results is 0.91 and the average mean square deviation is 0.07. The maximum

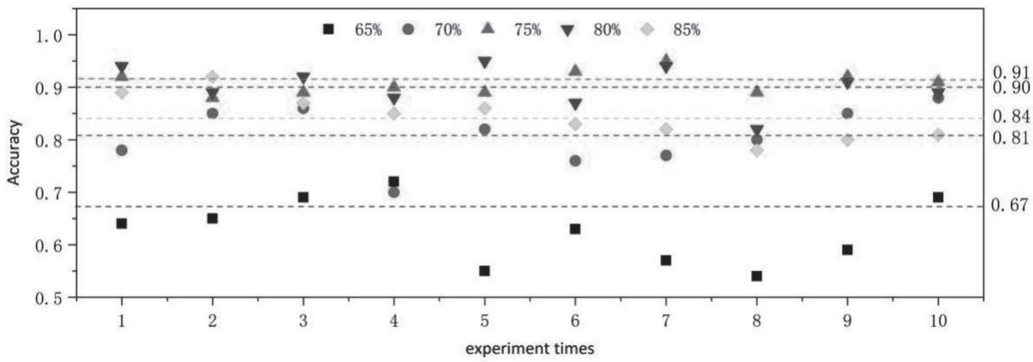

Fig. 3. Test results corresponding to different training sample numbers.

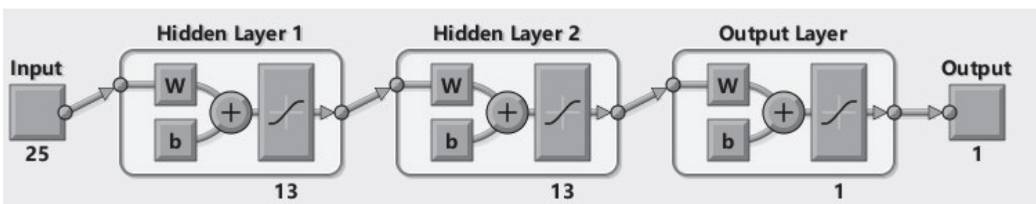

Fig. 4. Topological structure of BP neural network.

difference between the accuracy of 10 times and the average value is 0.06, indicating that the accuracy calculated by the model is relatively stable.

Ordinary Least Squares Regression Analysis

By comparing the distribution trends of the measured and predicted values of overall sound comfort through the gis10.2 platform, based on the consistent trend, the ordinary least squares (OLS) regression model was used to analyze the influences of the measured and predicted values of each factor of sound comfort, and the usability of the predicted value was confirmed. The formula is as follows:

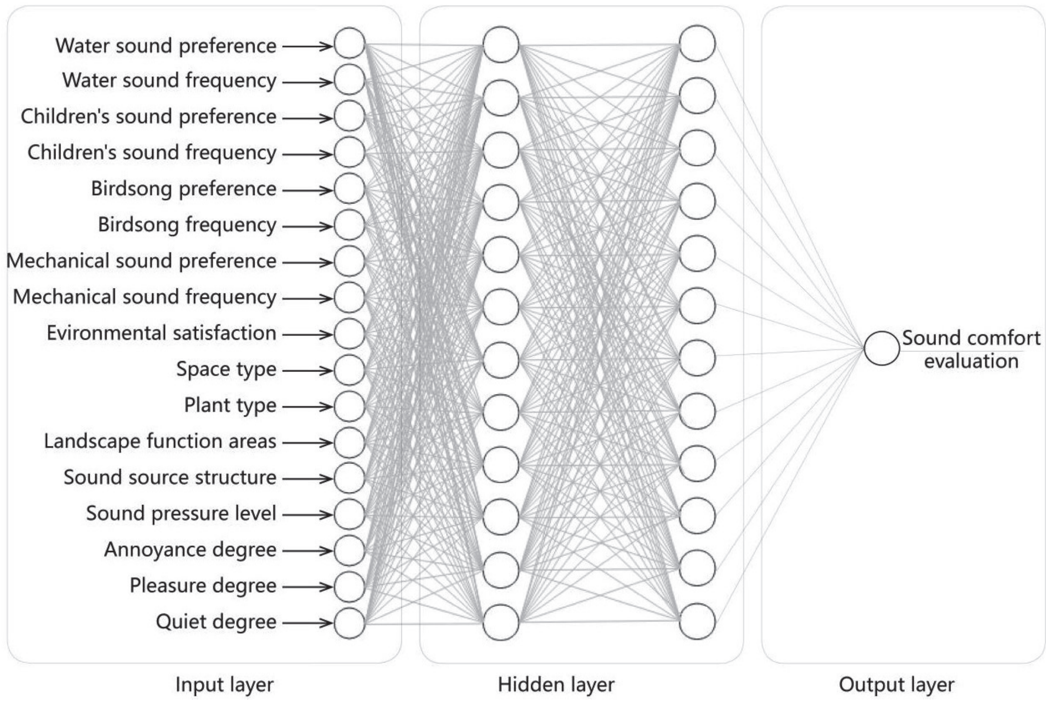

Fig. 5. Topological structure of BP neural network for Beach Park.

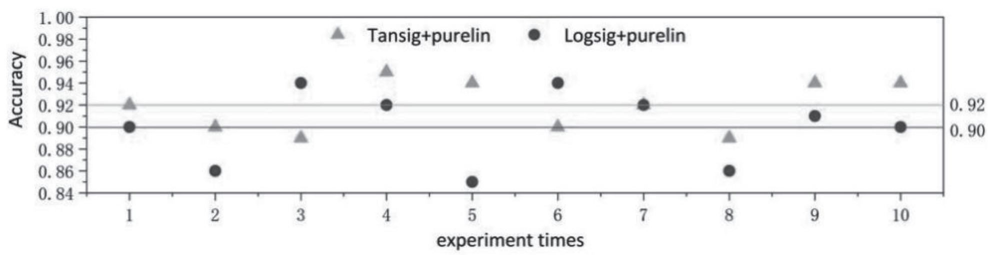

Fig. 6. Accuracy of transfer function.

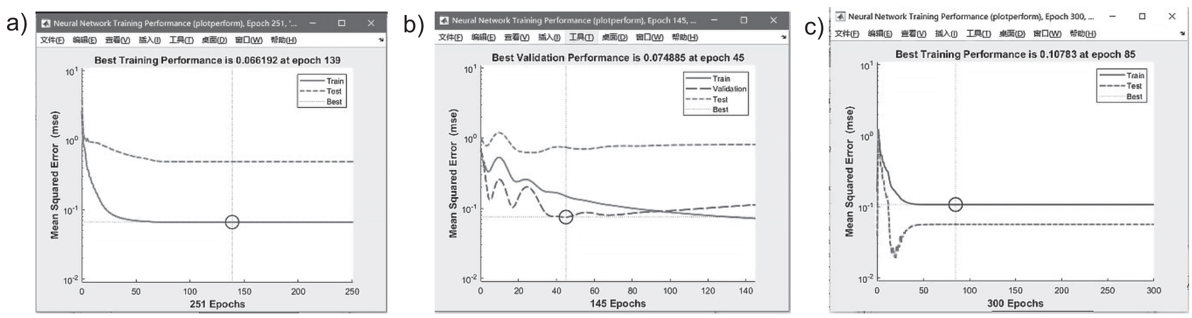

Fig. 7. Three groups of training functions traincgb a), traingdm b) and trainlm c).

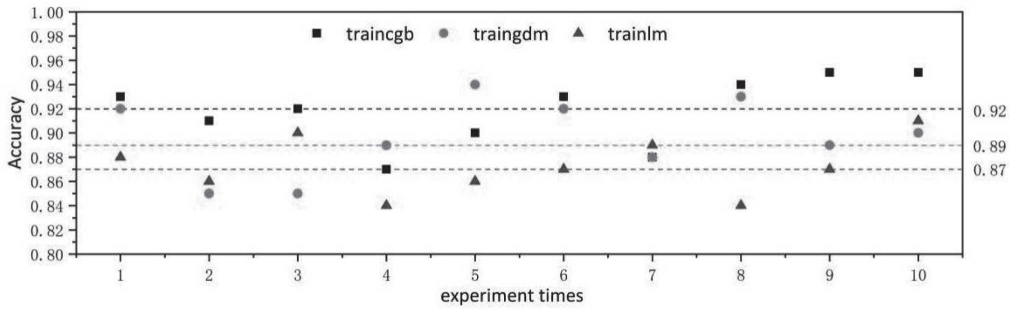

Fig. 8. Accuracy of training function.

$$Y_i = \beta_0 + \sum_k \beta_k X_{ik} + \varepsilon_i \quad (1)$$

where Y_i is the value of the dependent variable at point i, β_0 is the intercept, and X_{ik} is the value of the K explanatory variable at point i.βk is the slope or regression coefficient of the K explanatory variable, and εi is the residual.

Results and Discussion

Results

Sound Comfort and Space Environment

By using the gis10.2 platform, the comfort distribution maps of the 15 measured points (Fig. 9a) and 15 predicted points (Fig. 9b) were drawn by using the inverse distance weighting method. The overall sound comfort values of the park tended to be high in the West and low in the East, which indicate that the distribution trends of the measured and predicted sound comfort values in the park are essentially consistent.

The prediction results are consistent with the measured values in terms of the mean values of spatial type, plant type, functional area, and sound source classification. The average results of specific comfort are presented in Fig. 10: 1) In terms of space type, private space > open space > semi open space. 2) In terms of plant types, three or more layers of plant landscape > two layers of plant landscape > one layer of plant landscape. 3) In terms of the types of landscape functional areas, viewing area > activity area > rest area. 4) In terms of the types of sound source structure, mainly natural sound > life sound > mechanical sound. The predicted values can also be used to analyze the influences of space type, plant type, functional area, and sound source type on sound comfort.

Sound Comfort and Sound Source Perception Frequency

Under the ArcGIS platform, the Kriging method was used to draw the spatial distributions of the four sound sources (Fig. 11). The occurrence frequency of mechanical sounds in the west of the park is the highest, and the sound comfort in this area is the lowest. The eastern part of the park, which houses a dense forest, is the main rest area. In this part, the frequency of birdsong is the highest, and the sound comfort in this part is high. The south part of the park is close to the water, and it is the main activity area. The occurrence frequencies of children's playing sounds and underwater sounds are high, and the sound comfort in this area is moderate.

OLS regression analysis was performed to explore the influence of perceived frequency of each sound source in different functional areas of the park (Fig. 12), and the predicted value of comfort value is compared with the measured value (Table 4).

The regression model summarized in Table 4 indicates that the prediction model and the measurement

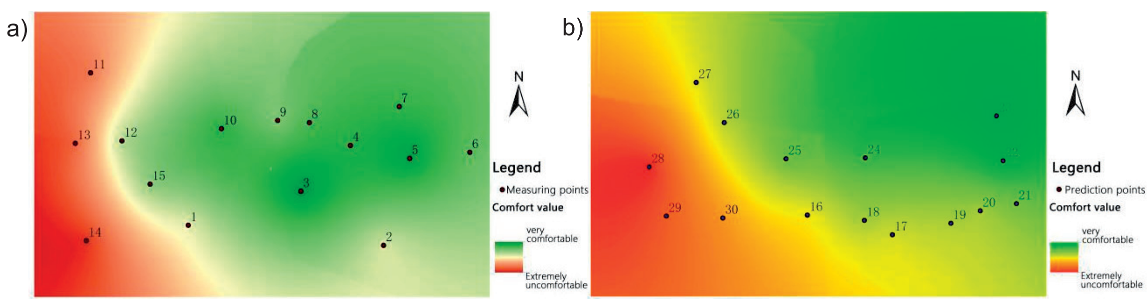

Fig. 9 Measured and predicted comfort values at measurement points: a) Measured comfort values at measurement points, b) Predicted comfort values at measurement points.

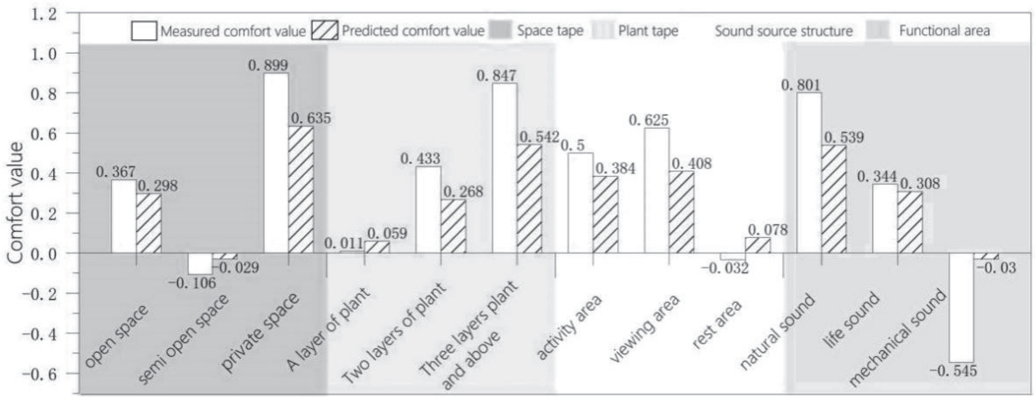

Fig. 10. Average values of various comfort levels.

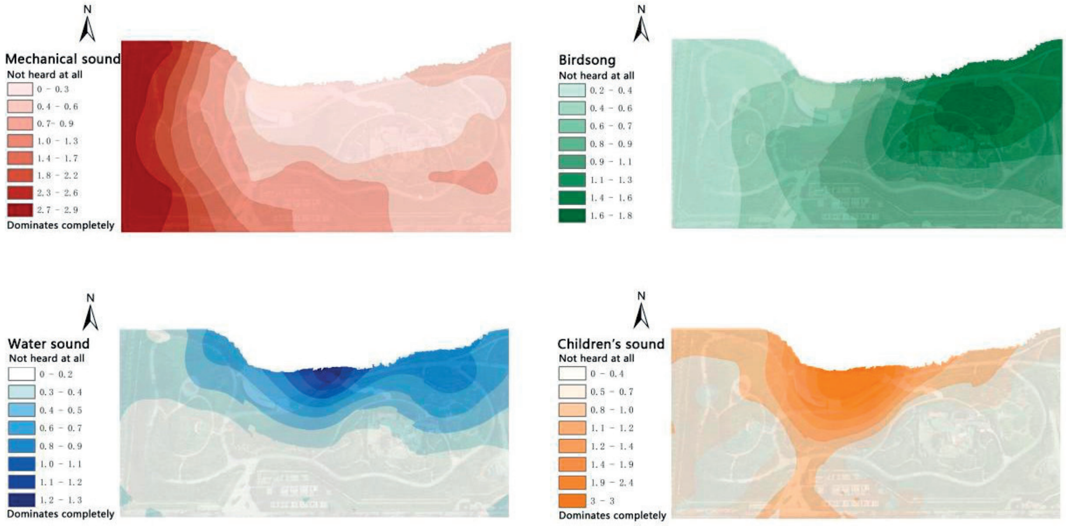

Fig. 11. Spatial distribution of sound sources.

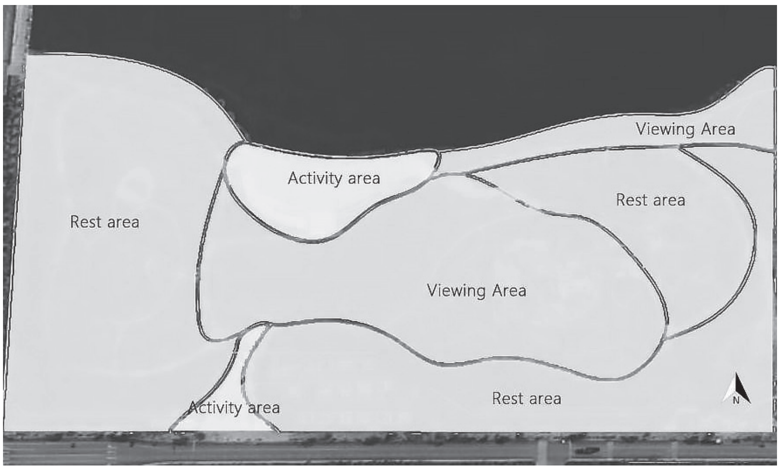

Fig. 12. Classification of functional areas.

model pass the F-test. According to the results, the influence trends of the four sound source sensing frequencies on the sound comfort in the active area are consistent with the predicted trends. The occurrence frequencies of mechanical sounds, birdsong, and water sound at the venue are not significant, meaning that they do not affect the sound comfort in the activity area. The occurrence frequency of children's playing sounds

Table 4. Regression model of sound comfort in the activity area.

Measured comfort in activity area			Prediction of comfort in activity area		
	Regression coefficient	*p*		Regression coefficient	*p*
Constant	0.020	0.872	Constant	-0.054	0.605
Mechanical sound frequency	-0.028	0.931	Mechanical sound frequency	-0.017	0.946
Birdsong frequency	-0.297	0.120	Birdsong frequency	-0.201	0.141
Water sound frequency	0.120	0.138	Water sound frequency	0.103	0.098
Children's playing sound frequency	0.532	0.000**	Children's playing sound frequency	0.559	0.000**
R^2	0.923		R^2	0.901	
Adjust R^2	0.899		Adjust R^2	0.884	
F□	F (4,310) = 64.961, p = 0.000		*F*□	F (4,314) = 75.352, p = 0.000	
Dependent variable: measured comfort value at some points in the activity area			Dependent variable: predicted comfort value at some points in the activity area		
D-W: 1.896			D-W: 1.967		
* p<0.05 ** p<0.01			* p<0.05 ** p<0.01		

Table 5. Regression model of degree of comfort in the viewing area.

Measured comfort in activity area			Prediction of comfort in activity area		
	Regression coefficient	*p*		Regression coefficient	*p*
Constant	0.148	0.609	Constant	0.402	0.099
Mechanical sound frequency	-0.300	0.319	Mechanical sound frequency	-0.493	0.090
Birdsong frequency	0.332	0.006**	Birdsong frequency	0.229	0.033*
Water sound frequency	0.700	0.009**	Water sound frequency	0.794	0.012*
Children's playing sound frequency	-0.297	0.284	Children's playing sound frequency	-0.419	0.142
R^2	0.870		R^2	0.834	
Adjust R^2	0.796		Adjust R^2	0.761	
F□	F (4,302)= 36.392,p = 0.000		*F*□	F (4,298)= 21.663,p = 0.000	
Dependent variable: Measured comfort value at some points in the viewing area			Dependent variable: Predicted comfort value at some points in the viewing area		
D-W: 1.954			D-W: 1.967		
* p<0.05 ** p<0.01			* p<0.05 ** p<0.01		

has a significant positive effect on sound comfort in the activity area.

According to the regression model summarized in Table 5, the prediction model and the measurement model pass the F-test. According to the results, the influence trend of the four sound source sensing frequencies on the sound comfort in the viewing area is consistent with the predicted value. The occurrence frequencies of mechanical sounds and children's playing sounds at the venue were not significant, meaning that they do not affect sound comfort in the viewing area. The occurrence frequencies of birdsong and water sound have a significant positive impact on sound comfort in the viewing area.

The regression model summarized in Table 6 indicates that both the prediction model and the measurement model pass the F-test. According to the results, the influence trends of the four sound source

Table 6. Regression model of degree of comfort in the tourist area.

Measured comfort in activity area			Prediction of comfort in activity area		
	Regression coefficient	*p*		Regression coefficient	*p*
Constant	0.666	0.002**	Constant	0.746	0.000**
Mechanical sound frequency	-0.589	0.000**	Mechanical sound frequency	-0.657	0.000**
Birdsong frequency	0.035	0.831	Birdsong frequency	0.117	0.085
Water sound frequency	0.121	0.060	Water sound frequency	-0.095	0.567
Children's playing sound frequency	0.027	0.860	Children's playing sound frequency	0.074	0.694
R^2	0.964		R^2	0.955	
Adjust R^2	0.947		Adjust R^2	0.940	
F□	F (4,287) = 100.767, p = 0.000		F□	F (4,295) = 72.337, p = 0.000	
Dependent variable: Measured comfort value at some points in the rest area			Dependent variable: Predicted comfort value at some points in the rest area		
D-W: 2.438			D-W: 2.559		
* p<0.05 ** p<0.01			* p<0.05 ** p<0.01		

sensing frequencies on sound comfort in the rest area are consistent with the predicted values. The frequency of birdsong, water sound, and children's playing sounds are not significant, meaning that they do not affect sound comfort in the rest area. The occurrence frequency of mechanical sounds has a significant negative impact on sound comfort in the rest area.

The OLS model was established by comparing the comfort model of the measured area and the predicted area in terms of the occurrence frequencies of mechanical sound, water sound, birdsong, and children's playing sounds to explore the influence of sound source frequency on different functional areas. The results indicate that the influences of measured comfort and the predicted comfort on the sound source frequency in each functional area are essentially the same.

Sound Comfort and Sound Environment

An acoustic environment has four indicators: sound pressure level, degree of quietness, degree of annoyance, and degree of pleasure. The sound pressure level is an objective measurement index, and the degrees of quietness, annoyance, and pleasure are emotional acoustic indexes. The specific values of these indexes are shown in Fig. 13. The measured comfort value and the predicted sound comfort value were used as the independent variables, and the degrees of quietness, annoyance, and pleasure and the sound pressure level were used as the independent variables in the OLS regression analysis.

The regression model summarized in Table 7 indicates that both the prediction model and the measurement model pass the F-test.

According to the results, the analysis results of the four factors influencing the predicted and measured values of comfort in the acoustic environment are consistent: annoyance and pleasure have a significant positive impact on acoustic comfort in the site; sound pressure level has a significant negative impact on acoustic comfort; and silence has no effect on acoustic comfort in the site. The possible reasons are analyzed

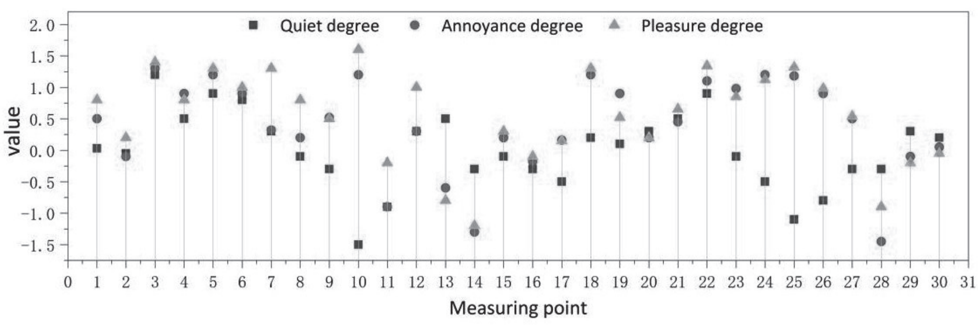

Fig. 13. Values of quietness, annoyance, and pleasure.

Table 7. Regression model of comfort in acoustic environment.

Measured comfort in activity area			Predicted comfort in activity area		
	Regression coefficient	p		Regression coefficient	p
Constant	2.538	0.082	Constant	1.646	0.006**
Quietness degree	-0.218	0.051	Quietness degree	-0.033	0.579
Annoyance degree	0.349	0.000**	Annoyance degree	0.118	0.007**
Pleasure degree	0.303	0.001**	Pleasure degree	0.461	0.000**
Sound pressure level	-0.047	0.000**	Sound pressure level	-0.032	0.005**
R^2	0.945		R^2	0.914	
Adjust R^2	0.923		Adjust R^2	0.901	
F□	F (4,301) = 33.961, p = 0.000		F□	F (4,298) = 90.146, p = 0.000	
Dependent variable: comfort value of measured points			Dependent variable: comfort value of prediction points		
D-W: 1.626			D-W: 1.967		
* p<0.05 ** p<0.01			* p<0.05 ** p<0.01		

by taking measurement point 10 as an example. The sound comfort value at measurement point 10 is higher; the degrees of annoyance and pleasure are positive, but the subjective degree of quietness is negative. These results can be ascribed to the fact that point 10 is in the main activity area of Beach Park, and the subjective loudness is high. However, people are in a happier mood when they are active, and they are not upset by noise in the environment, meaning that sound tranquillity has no effect on the sound comfort in this area.

Discussion

Application of Soundscape Simulation and Evaluation Results Based on BP Neural Network

The BP neural network has been used for soundscape simulation, and in most of the relevant cases, the measured and predicted values of soundscape indexes in the same sample plot have been compared to determine the simulation accuracy [36, 40, 61]. For example, Meng Qi [40] used a BP neural network to establish the acoustic comfort evaluation model of an underground business based on a study of the relationship between acoustic comfort and various indicators; they compared the accuracy of the model with that of the sequential logical regression method. Their results confirmed that the prediction accuracy of the BP neural network was higher than that of the sequential logical regression model. Kumar, P [48] used a BP ANN to predict traffic noise and compared its results with those of regression analysis; the BP ANN passed the statistical t test at the 5% significance level, which further verified the degree of fit between the BP neural network model and the field data, as well as the effectiveness of the model. However, in the soundscape planning and management of large sites, it is often unable to cover the entire soundscape research site. It is difficult to cover every area in a soundscape evaluation, which has emerged as a practical problem in soundscape planning based on the evaluation results. In this study, based on an evaluation of a soundscape, 15 measurement points in similar spaces were selected, and a BP ANN was used to simulate the soundscape. Different from other studies, we selected different measuring points with similar characteristics from the measured and predicted values for comparative analysis, that is, we used the soundscape data of a known area to simulate the soundscape of an unknown area. These results indicate that the predicted values are consistent with the measured values in terms of comfort distribution, space type, functional area, plant type, sound source structure, sound source frequency, annoyance, quietness, and pleasure. Therefore, it can be confirmed that the predicted values can be used as real data instead of the measured values in actual soundscape analysis, which can greatly reduce the workload associated with soundscape research and promote the application of acoustic landscape planning.

Relationship between Acoustic Landscape Quality and Space

Soundcape quality has a certain spatial dependence [67]. Hong J.Y. and Jeon J.Y. established a perceptual soundscape quality model through regression analysis by using sound source perceptual frequency, psychoacoustic parameters, and soundscape quality map, and they analyzed the influence of sound source frequency, acoustics, and other data on soundscape quality in urban spaces with different functions (such as urban parks and squares, high-density commercial areas, and residential areas). Therefore, we propose that urban soundscape planning should be combined with different urban spatial characteristics. As a typical urban space, most studies have evaluated the soundscape of a park as a whole and arrived at a few universal conclusions. For example, increasing the amount of natural sound and reducing the amount of mechanical sound can improve soundscape comfort. On this basis, the present study further divided the functional areas of a park, analyzed the influence of sound source perception frequency on sound comfort in different functional areas of the park, and proved the small-scale spatial dependence of sound comfort. The study of small-scale soundscape comfort may be more meaningful because it is the most direct environmental space for park users. Moreover, this study puts forward the idea of soundscape based on different functional spaces (Appendix 1).

Conclusions

Based on an investigation of current situation in Beach Park, we used a BP ANN to predict the sound comfort value at certain measurement points, verified the practicability of using the predicted values as a guidance in soundscape construction, and offered suggestions for further construction and optimization of soundscape in the park. The main conclusions are as follows:

(1) The values predicted using the BP ANN used in this paper are consistent with the measured values in terms of the effects of space type, plant type, space function, sound source structure, sound source frequency, and degrees of annoyance, pleasure, and quietness on sound comfort, which proves that the values predicted by the model have good usability. The results show that in actual park soundscape analysis, the use of predicted values instead of measured values can greatly reduce the workload associated with soundscape research and promote large-scale soundscape design.

(2) The sound comfort in a park is space dependent. Therefore, the soundscape design of small-scale characteristic spaces is highly significant for improving the environmental quality of a park. In different areas of a park, the effects of the same sound source on sound comfort are different. An effective method for improving the sound comfort in a park is adjusting

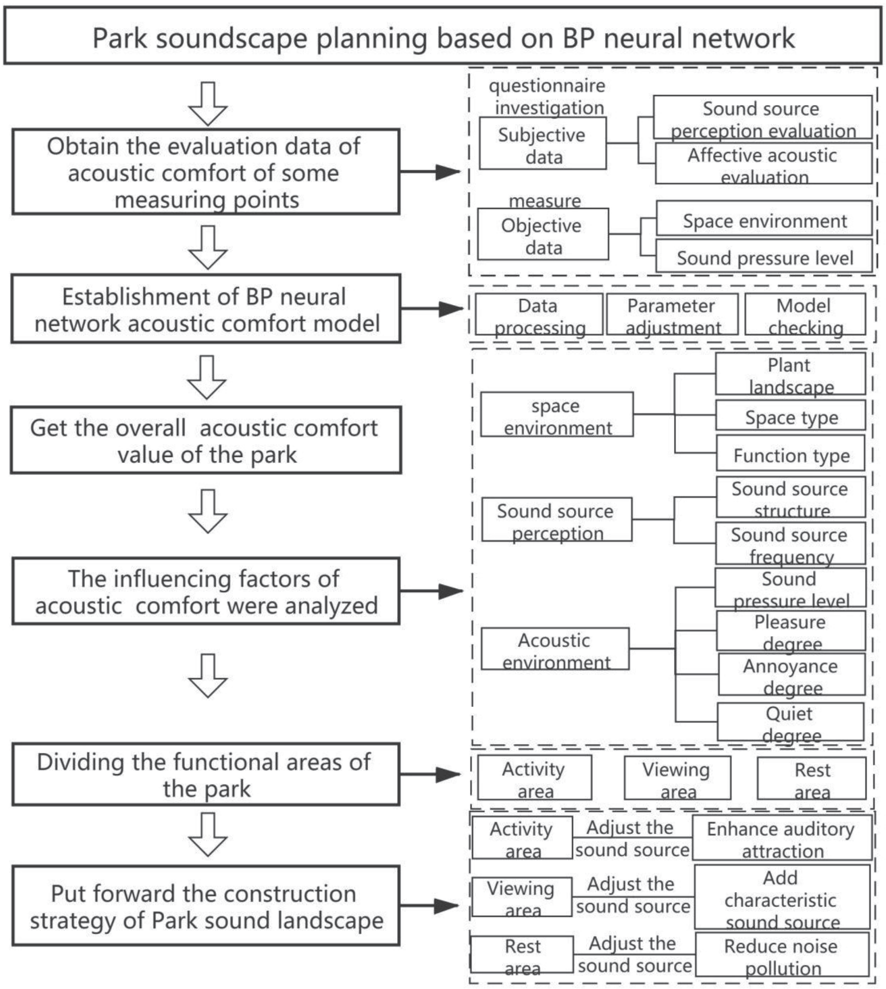

Fig. 14. Soundscape planning process based on the BP ANN.

the advantages of various sound sources in different park areas. Taking the park studied herein as an example, reducing the frequency of mechanical sound and birdsong in the activity area can improve sound comfort. In the viewing area, increasing the frequency of birdsong and water sound can improve sound comfort. Reducing mechanical sound frequency in the rest area can improve sound comfort.

(3) The evaluation of affective acoustics is related to sound comfort. Taking the research area considered herein as an example, improving sound pleasure and reducing sound annoyance can improve sound comfort. Therefore, in the later stages of park optimization design, we can focus on the evaluation results of people's emotional acoustics to guide the construction of soundscape.

(4) Under the background of these discussions, we propose soundscape planning process based on the BP ANN (Fig. 14).

Appendix

Appendix 1. Sound comfort evaluation of Longzi Lake Beach Park

1. What's your age[[single choice]*

○ 20 years old

○ 20-30 years old

○ 31-40 years old

○ 41-50 years old

○ 51-60 years old

○ 60 years old

2. How often do you come to the beach park[[single choice]*

○ Very few

○ Once a week

○ 2-3 times a week

○ Almost every day

3. Please choose whether you can hear the following sounds in the park, and how much you like them[[multiple topics]* (choose one of the sounds you have never heard, heard occasionally, or heard frequently; Choose one of favorite, average or dislike)

	Never heard of it.	Heard of it once in a while.	Often heard	Love it	No feeling	Dislike it
Water sound	□	□	□	□	□	□
Birdsong	□	□	□	□	□	□
Children's playful	□	□	□	□	□	□
Mechanical sound (vehicle sound, construction sound, garbage cleaning sound, plant pruning sound, etc.)	□	□	□	□	□	□

4. What do you think of the quietness of the environment[[single choice]*

Very quiet ○ 2 ○ 1 ○ 0 ○ –1 ○ –2 Very noisy

5. Do you think the sound of this environment can make you feel happy[[single choice]*

Very pleasant ○ 2 ○ 1 ○ 0 ○ –1 ○ –2 Very unpleasant

6. Do you think the sound of this environment bothers you[[single choice]*

Not disturb ○ 2 ○ 1 ○ 0 ○ –1 ○ –2 Very disturbing

7. Do you think the sound of this environment makes you feel comfortable? [single choice]*

Very comfortable ○ 2 ○ 1 ○ 0 ○ –1 ○ –2 Great discomfort

8. Do you think the overall environment makes you feel comfortable? [single choice]*

Very satisfied ○ 2 ○ 1 ○ 0 ○ –1 ○ –2 Very dissatisfied

Appendix 2: Soundscape optimization design of Beach Park

Table 8. Design methods for different functional areas.

Functional area	Spatial characteristics	Main sound source	Soundscape demand	Design method
Activity area	It is mainly used by people for various activities, and people generally stay here for long durations.	Sounds of vehicles, conversations, play, and movement	The activity area is a landscape area with high requirements for environmental atmosphere, meaning that it has high requirements in terms of the attraction and pleasure of the soundscape.	1) Enhance the visual and auditory attraction of the environment and increase people's participation in activities. 2) Through the vegetation planning activity route and activity space, in order to form the flow of people scattered. 3) For this study, we can design a variety of children's landscapes to attract children to participate in activities and increase the perception frequency of children's playing sounds.
Viewing area	It is mainly used by people to enjoy their time and rest	Sounds of conversations, birds, motor vehicles, and water	Viewing area is a landscape area with high requirements for environmental quality in functional zoning, meaning that it has high requirements in terms of the characteristics of the soundscape.	1) Add characteristic sound source to setoff different landscape features. 2) At this research site, the perception frequency of birdsong and underwater sound can be appropriately improved.
Rest area	It is mainly used by people to rest and talk.	Sounds of birds, motor vehicles, conversations, and water	In the rest area, people's perception of sound is more sensitive, so the requirement of environmental quietness is high.	1) Through the site enclosure, plant landscape planning to create a quiet and natural sound environment. 2) At this research site, it is necessary to reduce the perceived frequency of mechanical sound and improve the perception advantage of other sound sources.

Acknowledgments

This study is financed by 2022 Key R&D and Promotion Projects in Henan Province (No. 222102320064), 2022 Henan Science and Technology Think Tank Research Project (HNKJZK-2022-51B), and we would like to express our thanks.

Conflict of Interest

The authors declare no conflict of interest.

References

1. XU J., WANG F., CHEN L., ZHANG W. Perceived urban green and residents' health in Beijing. SSM - Population Health, **14**, 100790, **2021**.
2. LI X., LIU L., ZHANG Z., ZHANG W., LIU D., FENG Y. Gender Disparity in Perceived Urban Green Space and Subjective Health and Well-Being in China: Implications for Sustainable Urban Greening. Sustainability, **12** (24), 10538, **2020**.
3. ENGEL M.S., FIEBIG A., PFAFFENBACH C., FELS J.A Review of Socio-acoustic Surveys for Soundscape Studies. Current Pollution Reports, **4** (3), 220, **2018**.
4. BATES V., HICKMAN C., MANCHESTER H., PRIOR J., SINGER S. Beyond landscape's visible realm: Recorded sound, nature, and wellbeing. Health & Place, **61**, 102271, **2020**.
5. CAN A., L'HOSTIS A., AUMOND P., BOTTELDOOREN D., COELHO M.C., GUARNACCIA C., KANG J. The future of urban sound environments: Impacting mobility trends and insights for noise assessment and mitigation. Applied Acoustics, **170**, 107518, **2020**.
6. International Organization for Standardization. Acoustics Soundscape Part1: Definition and Conceptual Framework ISO 12913-1:2014. Geneva: International Organization for Standardization, Switzerland, **2014**.
7. KOGAN P., ARENAS J.P., BERMEJO F., HINALAF M., TURRA B.A Green Soundscape Index (GSI): The potential of assessing the perceived balance between natural sound and traffic noise. Science of the Total Environment, **642**, 463, **2018**.

8. DENG L., LUO H., MA J., HUANG Z., SUN L.X., JIANG M.Y., ZHU C.Y., LI X. Effects of integration between visual stimuli and auditory stimuli on restorative potential and aesthetic preference in urban green spaces. Urban Forestry & Urban Greening, **53**, 126702, **2020**.
9. LI J., BURROUGHS K., HALIM M.F., PENBROOKE T.L., SEEKAMP E., SMITH J.W. Assessing soundscape preferences and the impact of specific sounds on outdoor recreation activities using qualitative data analysis and immersive virtual environment technology. Journal of Outdoor Recreation and Tourism-Research Planning and Management, **24**, 66, **2018**.
10. ZUO L., ZHANG J., ZHANG R.J., ZHANG Y., HU M., ZHUANG M., LIU W. The Transition of Soundscape in Tourist Destinations from the Perspective of Residents' Perceptions: A Case Study of the Lugu Lake Scenic Spot, Southwestern China. Sustainability, **12** (3), 1073, **2020**.
11. FIEBIG A., JORDAN P., MOSHONA C.C. Assessments of Acoustic Environments by Emotions - The Application of Emotion Theory in Soundscape. Frontiers in Psychology, **11**, 3261, **2020**.
12. PAYNE S.R., GUASTAVINO C. Exploring the Validity of the Perceived Restorativeness Soundscape Scale: A Psycholinguistic Approach. Frontiers in Psychology, **9**, 2224, **2018**.
13. HONG J.Y., JEON J.Y. Comparing associations among sound sources, human behaviors, and soundscapes on central business and commercial streets in Seoul, Korea. Building and Environment, **186,** 107327, **2020**.
14. ROZALO G.R., MORILLAS J.M.B., GONZALEZ D.M., MORAGA P.A. Relationships among satisfaction, noise perception, and use of urban green spaces. Science of the Total Environment, **624**, 438, **2018**.
15. JIA Y., Ma H., KANG J. Characteristics and evaluation of urban soundscapes worthy of preservation. Journal of Environmental Management, **253**, 109722, **2020**.
16. LEE H.M., LIU Y., LEE H.P. Assessment of acoustical environment condition at urban landscape. Applied Acoustics, **160**, 107126, **2020**.
17. LI H., LAU S.K. A review of audio-visual interaction on soundscape assessment in urban built environments. Applied Acoustics, **166**, 107372, **2020**.
18. YU L., KANG J. Using Ann to study sound preference evaluation in urban open space. Journal of Environmental Engineering and Landscape Management, **23** (3), 163, **2015**.
19. MENG Q. Soundscape research and prediction of Underground Commercial Street. Harbin Institute of technology, Harbin, China, **2010**. https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CDFD0911&filename=1011278957.nh
20. BILD E., PFEFFER K., COLER M., BERTOLINI L. An Exploratory Study on the Influence of Activities on Public Space Users' Descriptions of Their Auditory Environments on Site: The Case of Amsterdam. Acta Acustica United with Acustica, **105** (3), 449, **2019**.
21. BILD E., PFEFFER K., COLER M., RUBIN O., BERTOLINI L. Public Space Users' Soundscape Evaluations in Relation to Their Activities. An Amsterdam-Based Study. Frontiers in Psychology, **9**, 1593, **2018**.
22. HERMIDA L., PAVON I., LOBO S.A.C., Luis Bento-Coelho J. On the Person-Place Interaction and Its Relationship with the Responses/Outcomes of Listeners of Urban Soundscape (Compared Cases of Lisbon and Bogota): Contextual and Semiotic Aspects. International Journal of Environmental Research and Public Health, **16** (4), 551, **2019**.
23. HO H.M., NOH S.H., JIN X., DAO Z. Semantic Structure and Importance of Visual Landscape and Soundscape in University Campus: Focusing on Chonnam National University's Yongbong Campus. Korean Journal of Converging Humanities, **8** (1), 169, **2020**.
24. JO H.I., JEON J.Y. The influence of human behavioral characteristics on soundscape perception in urban parks: Subjective and observational approaches. Landscape and Urban Planning, **203**, 103890, **2020**.
25. KITAPCI K., GALBRUN L. Perceptual analysis of the speech intelligibility and soundscape of multilingual environments. Applied Acoustics, **151**, 124, **2019**.
26. DE SOUZA T.B., ALBERTO K.C., BARBOSA S.A. Evaluation of noise pollution related to human perception in a university campus in Brazil. Applied Acoustics, **157**, 107023, **2020**.
27. FARINA A. Ecoacoustics: A Quantitative Approach to Investigate the Ecological Role of Environmental Sounds. Mathematics, **7** (1), 21, **2018**.
28. MANCINI S., MASCOLO A., GRAZIUSO G., GUARNACCIA C. Soundwalk, Questionnaires and Noise Measurements in a University Campus: A Soundscape Study. Sustainability, **13** (2), 841, **2021**.
29. MITCHELL A., OBERMAN T., ALETTA F., ERFANIAN M., KACHLICKA M., LIONELLO M., KANG J. The Soundscape Indices (SSID) Protocol: A Method for Urban Soundscape Surveys-Questionnaires with Acoustical and Contextual Information. Applied Sciences-Basel, **10** (7), 2397, **2020**.
30. YANG M., KANG J. Psychoacoustic Evaluation of Natural and Urban Sounds in Soundscapes. Journal of the Acoustical Society of America, **134** (1), 840, **2013**.
31. HONG J.Y., LAM B., ONG Z.T., OOI K., GAN W.S., KANG J., YEONG S., LEE I., TAN S.T. Effects of contexts in urban residential areas on the pleasantness and appropriateness of natural sounds. Sustainable Cities and Society, **63**, 102475, **2020**.
32. HONG X., WANG G., LIU J., LAN S. Cognitive persistence of soundscape in urban parks. Sustainable Cities and Society, **51**, 101706, **2019**.
33. JASZCZAK A., MALKOWSKA N., KRISTIANOVA K., BERNAT S., POCHODYLA E. Evaluation of Soundscapes in Urban Parks in Olsztyn (Poland) for Improvement of Landscape Design and Management. Land, **10** (1), 66, **2020**.
34. JEON J.Y., JO H.I. Effects of audio-visual interactions on soundscape and landscape perception and their influence on satisfaction with the urban environment. Building and Environment, **169**, 106544, **2020**.
35. LU X., TANG J., ZHU P., GUO F., CAI J., ZHANG H. Spatial variations in pedestrian soundscape evaluation of traffic noise. Environmental Impact Assessment Review, **83**, 106399, **2020**.
36. LI Z., KANG J., BA M. Influence of distance from traffic sounds on physiological indicators and subjective evaluation. Transportation Research Part D-Transport and Environment, **87**, 102538, **2020**.
37. CHEN J., MA H. A Conceptual Model of the Healthy Acoustic Environment: Elements, Framework, and Definition. Frontiers in Psychology, **11**, 2814, **2020**.
38. HONG J.Y., JEON J.Y. Influence of urban contexts on soundscape perceptions: a structural equation modeling approach. Landscape Urban Plan, **141**, 78, **2015**.

39. FAIRBRASS A.J., FIRMAN M., WILLIAMS C., BROSTOW G.J., TITHERIDGE H., JONES K.E. CityNet-Deep learning tools for urban ecoacoustic assessment. Methods in Ecology and Evolution, **10** (2), 186, **2015**.
40. BRAVO M.L., LUCIO N.J., PAVON G.I., MOSQUERA R. Neural based contingent valuation of road traffic noise. Transportation Research Part D: Transport and Environment, **50**, 26, **2017**.
41. LIONELLO M., ALETTA F., KANG J. A systematic review of prediction models for the experience of urban soundscapes. Applied Acoustics, **170**, 107479, **2020**.
42. GONTIER F., LAVANDIER C., AUMOND P., LAGRANGE M., PETIOT J.F. Estimation of the Perceived Time of Presence of Sources in Urban Acoustic Environments Using Deep Learning Techniques. Acta Acustica United with Acustica, **105** (6), 1053, **2019**.
43. NTALAMPIRAS S. Emotional quantification of soundscapes by learning between samples. Multimedia Tools and Applications, **79** (41-42), 30387, **2020**.
44. KUMAR P., NIGAM S.P., KUMAR N. Vehicular traffic noise modeling using artificial neural network approach. Transportation Research Part C: Emerging Technologies, **40**, 111, **2014**.
45. BOES M., FILIPAN K., DE COENSEL B., BOTTELDOOREN D. Machine Listening for Park Soundscape Quality Assessment. Acta Acustica United with Acustica, **104** (1), 121, **2018**.
46. ROMERO V.P., MAFFEI L., BRAMBILLA G., CIABURRO G. Modelling the soundscape quality of urban waterfronts by artificial neural networks. Applied Acoustics, **111**, 121, **2016**.
47. FILIPAN K., DE COENSEL B., AURNOND P., CAN A, LAVANDIER C., BOTTELDOOREN D. Auditory sensory saliency as a better predictor of change than sound amplitude in pleasantness assessment of reproduced urban soundscapes. Building and Environment, **148**, 730, **2019**.
48. MA K.W., MAK C.M., WONG H.M. Effects of environmental sound quality on soundscape preference in a public urban space. Applied Acoustics, **171**, 107570, **2021**.
49. GALE T., EDNIE A., BEEFTINK K., ADIEGO A. Beyond noise management: exploring visitors' perceptions of positive emotional soundscape dimensions. Journal of Leisure Research, **52** (2), 129, **2021**.
50. EKMAN M.R., LUNDEN P., NILSSON M.E. Similarity and pleasantness assessments of water-fountain sounds recorded in urban public spaces. Journal of the Acoustical Society of America, **138** (5), 3043, **2015**.
51. YU L., KANG J. Modeling subjective evaluation of soundscape quality in urban open spaces: An artificial neural network approach. The Journal of the Acoustical Society of America, **126** (3), 1163, **2009**.
52. CIFUENTES E., VELEZ G.J., BUTLER S.J. Relationship between acoustic indices, length of recordings and processing time: a methodological test. Biota colombiana, **22** (1), 26, **2021**.
53. DE SOUSA I.P., DOS SANTOS L.G.Z., SOUSA L.R., CORSO G. Scale-free and characteristic time in urban soundscape. Physica a-Statistical Mechanics and Its Applications, **530**, 121557, **2019**.
54. DOSER J.W., FINLEY A.O., KASTEN E.P., GAGE S.H. Assessing soundscape disturbance through hierarchical models and acoustic indices: A case study on a shelterwood logged northern Michigan forest. Ecological Indicators, **113**, 106244, **2020**.
55. METCALF O.C., BARLOW J., DEVENISH C., MARSDEN S., BERENGUER E., LEES A.C. Acoustic indices perform better when applied at ecologically meaningful time and frequency scales. Methods in Ecology and Evolution, **12** (3), 421, **2021**.
56. KOU L., KWAN M.P., CHAI Y. The effects of activity-related contexts on individual sound exposures: A time-geographic approach to soundscape studies. Environment and Planning B-Urban Analytics and City Science, **48** (7), 2073, **2020**.
57. KIM Y.H., HWANG I.H., HONG J.Y., LEE S.C. Effects of vegetation on soundscape of an urban religious precinct: Case study of Myeong-dong cathedral in Seoul. Building and Environment, **155**, 389, **2021**.
58. MARISTANY A., LOPEZ M.R., RIVERA C.A. Soundscape quality analysis by fuzzy logic: a field study in Cordoba, Argentina. Applied Acoustics, **111**, 106, **2016**.
59. YAMAMOTO K. Method for Estimating the Number of Sound Sources Using SVM in Sound Source Separation. Ieice Technical Report Speech, **102**, 19, **2002**.
60. SHIN H.K., PARK S.H., KIM K.W. Inter-floor noise classification using convolutional neural network. Plos One, **15** (12), e0243758, **2020**. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0243758
61. TORIJA A.J., RUIZ D.P., RAMOS R.A.F. A Tool for Urban Soundscape Evaluation Applying Support Vector Machines for Developing a Soundscape Classification Model. Science of the Total Environment, **482**, 440, **2014**.
62. SONG X., LV X., YU D., WU Q. Spatial-temporal change analysis of plant soundscapes and their design methods. Urban Forestry & Urban Greening, **29**, 96, **2018**.
63. ZHAO Z., WANG Y., HOU Y. Residents' Spatial Perceptions of Urban Gardens Based on Soundscape and Landscape Differences. Sustainability, **12** (17), 6809, **2020**.
64. ALETTA F., KANG J., ASTOLFI A., FUDA S. Differences in soundscape appreciation of walking sounds from different footpath materials in urban parks. Sustainable Cities and Society, **27**, 367, **2016**.
65. LIU J., YANG L., XIONG Y., YANG Y. Effects of soundscape perception on visiting experience in a renovated historical block. Building and Environment, **165**, 106375, **2020**.
66. JO H.I., JEON J.Y. The influence of human behavioral characteristics on soundscape perception in urban parks: Subjective and observational approaches. Landscape and Urban Planning, **203**, 103890, **2020**.
67. HONG J.Y., JEON J.Y. Exploring spatial relationships among soundscape variables in urban areas: A spatial statistical modelling approach. Landscape and Urban Planning, **157**, 352, **201**.