

Research Article

Jian Kang*, Francesco Aletta, Efstathios Margaritis, and Ming Yang

A model for implementing soundscape maps in smart cities

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Abstract: Smart cities are required to engage with local communities by promoting a user-centred approach to deal with urban life issues and ultimately enhance people's quality of life. Soundscape promotes a similar approach, based on individuals' perception of acoustic environments. This paper aims to establish a model to implement soundscape maps for the monitoring and management of the acoustic environment and to demonstrate its feasibility. The final objective of the model is to generate visual maps related to perceptual attributes (e.g. 'calm', 'pleasant'), starting from audio recordings of everyday acoustic environments. The proposed model relies on three main stages: (1) sound sources recognition and profiling, (2) prediction of the soundscape's perceptual attributes and (3) implementation of soundscape maps. This research particularly explores the two latter phases, for which a set of sub-processes and methods is proposed and discussed. An accuracy analysis was performed with satisfactory results: the prediction models of the second stage explained up to the 57.5% of the attributes' variance; the cross-validation errors of the model were close to zero. These findings show that the proposed model is likely to produce representative maps of an individual's sonic perception in a given environment.

Keywords: GIS; environmental noise; soundscape mapping; soundwalk

1 Introduction

The process of increasing urbanisation over the last few decades has led to the spread of highly complex urban agglomerations all around the world. Such a densification of cities meant a cumulative need of management resources and prompted urban policies' responses to community demands, in which information and communication technology (ICT) played a key role. Nowadays, with ICT support, it is possible to cope in real time with a number of functions across the physical and social structures of the cities, to improve the efficiency of single buildings or more complex urban systems [1, 2]. The so-called 'smart' cities are indeed capable of collecting, processing and providing feedback on data coming from multiple networks at different scales, in order to promote sustainability and improve people's quality of life [3]. This has been shown to be a crucial aspect in environmental management and for sustainable development strategies [4]. Furthermore, it has also been noted that the concept of smart cities is not only focused on technological aspects, and is gradually evolving into a broader idea including components strongly connected to people and community [5]. The sonic environment has often been disregarded within this framework, although it is one of the main components of the human experience in urban contexts and it is directly related to human health and well-being. Therefore, in recent years it has attracted more and more attention, both from the computational [6] and the perceptual viewpoint, with the soundscape approach (e.g., [7, 8]).

How are, in general, acousticians and soundscape researchers trying to make cities 'smarter'? It is generally acknowledged that static noise mapping, as stipulated by the Environmental Noise Directive [9], provides a limited range of information regarding the actual perception of the sound environment, as it only takes into account a given set of noise sources (e.g. traffic, industry) and is far from representing real-time noise conditions. Researchers are trying to overcome this approach by investigating more dynamic ways of representing information, such as noise monitoring networks [10–12], or participatory sensing [13–16]. However, noise mapping is meant to provide insights

***Corresponding Author: Jian Kang:** UCL Institute for Environmental Design and Engineering, University College London, WC1H 0NN London, United Kingdom; Email: j.kang@ucl.ac.uk

Francesco Aletta: School of Architecture, University of Sheffield, S10 2TN Sheffield, United Kingdom; Department of Information Technology, Ghent University, 9052 Ghent, Belgium; Email: francesco.aletta@ugent.be; Tel.: +32-926-43323

Efstathios Margaritis: School of Architecture, University of Sheffield, S10 2TN Sheffield, United Kingdom; Email: e.margaritis@sheffield.ac.uk

Ming Yang: School of Architecture, University of Sheffield, S10 2TN Sheffield, United Kingdom; Email: mingkateyang@163.com

on noise exposures for aggregated groups of population from principal noise sources. From the smart cities perspective, the “quality” of the acoustic environment for the listener is more relevant [17]. Thus, methods to provide information about how acoustic environments are actually perceived at a local scale and individual level are being explored and researchers are gradually shifting their attention from ‘noise’ to ‘sound’ [18–23].

In smart cities, a strong governance-oriented approach is required in order to emphasise the role of social assets and human relations in the urban context [24]. The challenge for smart cities is to engage with citizens and promote a user-centred approach to the urban realm, in order to inspire the desired changes. Considering this issue from the perspective of acoustics, the centrality of the individuals –or rather the users– is definitely within the scope of soundscape, defined as: “*the acoustic environment as perceived or experienced and/or understood by a person or people, in context*” [25]. Therefore, it is appropriate to define a model for implementing the soundscape approach in smart cities, both for the ‘smart’ concept and the soundscape focus on how individuals perceive and experience the (sound) environments. To achieve such a goal, it is necessary to make the perception of the sonic environment (*i.e.* the soundscape) ‘viewable’ and ‘communicable’ on a city-scale.

There are several studies that are seeking to engage with more qualitative aspects of the sound environment and the way it is perceived [26–29]. Most of them are crowd-sourced and consist of georeferenced audio samples, usually combined with individual assessments of the acoustic environment. While acknowledging the high potential of such initiatives in terms of community awareness, it is worth noting that this approach raises at least two significant issues: (1) crowd-sourced perceptual assessments could be biased by the lack of instructions that are usually provided to the participants by experts, during controlled individual data collection sessions (*e.g.* soundwalks), and (2) data are collected in a highly fragmented and discrete way (punctual samples), making the corpus of recordings less relevant from the management and planning perspective.

This paper therefore proposes a model for a systematic characterisation of soundscape in urban contexts. The focus of the research is the development of a protocol for predicting and mapping emotional dimensions and qualitative aspects of urban environments from recorded sounds. The final soundscape mapping is achieved through a continuous process based on: (1) the sound sources recognition and profiling, (2) the prediction of the sonic perceptual attributes according to the sound source profiles

and (3) the generation of soundscape maps based on measured values. Such a three-step process is likely to lead to a simple input-output model based on audio recordings (input) providing soundscape maps (output). The rationale for this research is that in the future it should be possible to map with an acceptable level of reliability some perceptual attributes of the acoustic environment, without the need to involve human participants. Therefore, the accuracy of the above-mentioned process is explored and discussed.

2 The model

The proposed model aims at mapping perceptual attributes of the sonic environment. The rationale for developing such a model is its potential to represent with an acceptable level of plausibility how the sonic environment would be perceived, starting from some of its measurable features. This research acknowledges that this process originates in the acoustic environment (*i.e.* the mix of all sounds from all sound sources as modified by the environment), whose geographical information should be recorded. The subsequent processing aims to extract from the recorded data a soundscape ‘profile’, which is meant as the dominance of a number of sound sources. Afterwards, a linear regression model is used to predict the score of a set of perceptual attributes according to the detected soundscape profiles. Eventually data related to the predicted soundscape perceptual attributes can be imported into a Geographical Information Systems (GIS) platform, in order to produce soundscape maps. Therefore, the proposed procedure is based on three main stages:

- Sound sources recognition and profiling
- Prediction of the soundscape’s perceptual attributes
- Soundscape maps implementation

The first stage is related to the identification of sound sources in recorded sound data, to provide the input data for the predictive model. Recognition techniques for identifying sound sources/events in soundscapes were researched by a number of studies over the past decade. Earlier techniques related to environmental sound sources mainly included those typically used in speech and musical instrument recognition, whereas more algorithms specifically aiming at soundscapes have now been developed. The recognition accuracy ranged from ~ 40% to above 90%, varying among studies based on different situations, sound samples and statistical methods of accuracy calculation [30–34]. This paper describes the recent

methods of automatic recognition of environmental sound sources.

The second stage aims to establish a predictive model using as input data the sound source profiles from the previous stage to determine some perceptual attributes of the investigated sonic environment. Lavandier and De-fréville [35] previously defined an unpleasantness model based on the profiling of audio recordings according to their sound sources' characterisation. Their perceptive descriptor was based on the level and the identification of sound sources for the assessment of the 'unpleasantness of sound'. The descriptor was analytically defined through a linear regression where the variables were the global level and the relative time of appearance of the categories of sound sources. This research has a similar focus, but aims to explore what other perceptual attributes are likely to be predicted, depending on the context.

The third stage of the model deals with how to make the results of the perceptual prediction visible and for this purpose a GIS-based procedure is implemented. The use of GIS has already been proposed in soundscape studies. Liu *et al.* [36] used a GIS tool to map the spatial and temporal variability of different types of sound sources (*i.e.* anthrophony, biophony and geophony) in a multifunctional urban area in Rostock (Germany). Similarly, Hong and Jeon [37] used GIS techniques to map the perceived loudness of traffic noise together with human and natural sounds, and looked for correlations between those rates and acoustic as well as landscape indices.

Each stage of the above mentioned process includes a number of sub-processes as shown in Figure 1. Sound recognition and profiling is a broad topic *per se*. Overall, previous research has shown that it is possible to identify sound sources in the context of general urban sound environments. The recognition algorithms, which are computationally inexpensive, showed their potential and feasibility for large-scale practical applications [38, 39]. While acknowledging that the first stage of this model is propaedeutic to provide input data for the proposed model, this paper will particularly focus on Stages 2 and 3, with corresponding methods and accuracy analysis of the results, with an overall description and discussion about Stage 1 on general approach and procedure for sound source recognition and profiling. The sections below aim to prove the methodological feasibility of the model in principle and to offer insights on how to implement soundscape maps for the visualization of perceptual attributes about the acoustic environments in urban contexts.

3 Sound sources recognition and profiling

3.1 General approach

Sound sources need to be identified from recorded sounds through sound recognition models. This is because sound sources profiles will form the input of the predictive model proposed in Section 4. Sound source recognition techniques in general involve two stages: (1) the feature extraction (or parameterisation) stage, which produces a set of characteristic features for sound to reduce the complexity of the data using measures such as the Mel Frequency Cepstral Coefficients (MFCCs) [40] that have often been used for speech and music recognition, spectral contributions, and psychoacoustic features [41]; and then (2) classification stage, which recognises the sound based on the extracted features, using the techniques of learning vector quantization, k nearest neighbours, hidden Markov models, Gaussian mixture models, and artificial neural network (ANN). Also, a preliminary source separation algorithm to the feature extraction and classification stages is often involved in the case of multiple sound sources presenting simultaneously as in real-world environments, which is usually implemented by the successive frame decomposition in time domain, calculation of source localization through inter-aural phase/intensity/time difference, or signal extraction from the spectro-temporal gram.

In previous research of Yang [45] psychoacoustic and music-related metrics were used for feature extraction [38, 42], like loudness, pitch, timbre, rhythm, and $1/f$ noise indicators [43, 44], according to the corresponding characteristics of various environmental sounds. Such metrics considered both spectral and temporal auditory perceptions that are critical in human abilities in distinguishing acoustic events of everyday environments [46]. Using ANNs for classification led to a recognition accuracy of 98% (cases correctly identified) for the category of a set of natural and urban sound sources (water, wind, birdsong, human voice, traffic, etc.), with sound recordings (duration of 30s and sample rate of 44.1 kHz) in which a single sound source was predominantly present [45]. Focusing particularly on the simplicity of recognition algorithms to meet the requirement for large-scale practical applications in the real environment, Yang and Kang [39] used only a small number of specific indicators (such as peak frequency/amplitude in spectrum, and peak/peaks in spectral flux [47] for the sources to be recognised) to characterise the different sound sources, simple evaluation according to given indicators classification thresholds, and

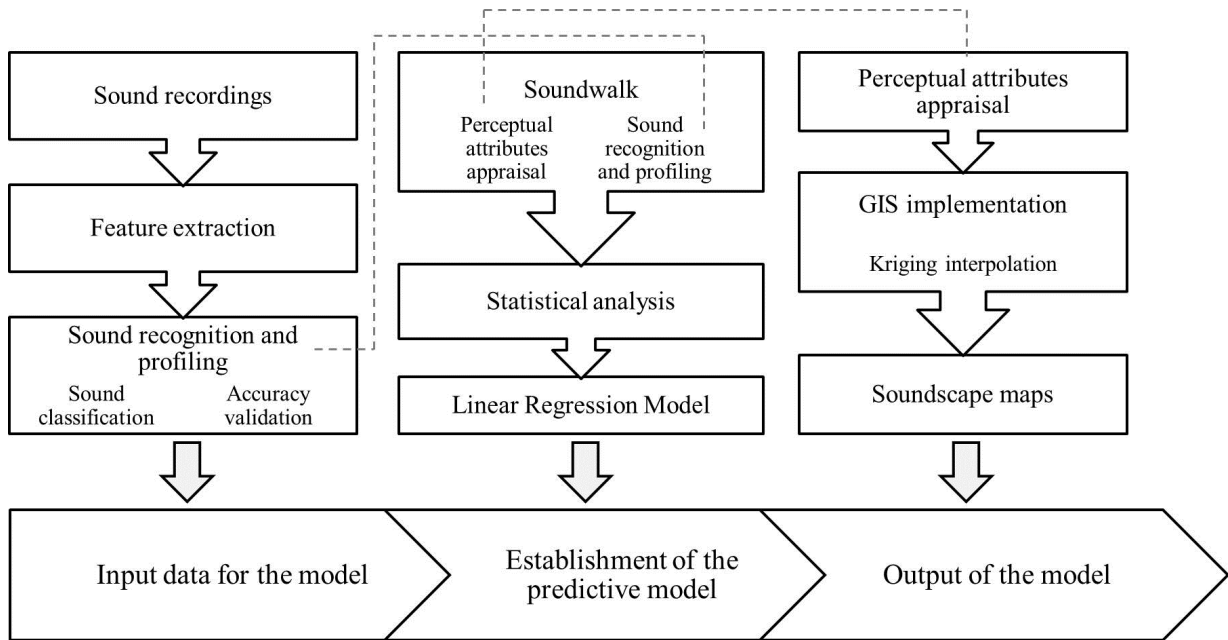


Figure 1: Flowchart of the proposed model for implementing soundscape mapping in smart cities

frame decomposition for the prior source separation. Using this computationally inexpensive algorithm, the recognition accuracy achieved 78-94%, depending on the different sources, in the studied case of recognition of various construction noise sources in overall soundscape, even though the quality of sound recordings used was not high (frequency responses from ~10 Hz to 2.8 kHz and sample rate of 22.05 kHz). These previous studies showed that it is possible to achieve very high levels of accuracy for automatic recognition of sound sources in soundscape.

3.2 Procedure

Sound recordings should be acquired at single spots. For the sake of the mapping process, several recording points will be needed to interpolate data. The number, locations and relative distances between points would highly depend on the spatial configuration of the investigated environment, as well as on the detail needed and purpose of the specific study. Can *et al.* [11] used a 20-meter grid for a similar application, but this study will show that lower spatial resolution (*i.e.*, >100 m) can still be suitable. While environmental noise monitoring systems terminals are usually located several meters above the ground, it is expected that for soundscape applications sound recording spots would be located at average human height (*e.g.*, 1.6 m off the ground) to better represent the acoustic environment as experienced by human listeners.

Within the framework of implementing such methods into smart cities, the sound data could be collected through a grid of small sensors, such as low-cost wireless sensing units, which has already been proved feasible for noise and other environmental data (*e.g.* [12, 48, 49]).

Once data is stored, ideally on remote servers, it can be processed. Indicators such as those described in Section 3.1 can be computed via calculation programs or software packages [50–53]. Trained ANN models are conventionally used for classification.

To form the input of the predictive model proposed in Section 4, data should be in the format of sound sources categories (*e.g.* traffic sound, natural sounds, sounds of individuals) associated to a ‘prominence’ scale. The concept of prominence might vary depending on what is needed for the area of interest. A conventional interpretation of this dimension is that of prominence of a sound source over time, which is computed through the intensities and occurrences of frames where a specific sound source is present, normalising data between 0 and 10. The previous recognition algorithms described in Section 3.1 could be further extended for identifying other sound sources in urban environment, and involve more indicators and/or articulated classification methods, in case of more complex environmental conditions. Even if these processes have not been presented in this work (they are beyond of the scope of the paper), they could easily be applied if needed.

4 Prediction of the perceptual attributes of soundscape

4.1 The rationale and procedure of the prediction model

It is acknowledged that it is necessary to measure the relationship between the soundscape assessment and the objective parameters. This relationship has been thoroughly investigated over the years. Nevertheless, despite several attempts to identify a relationship between perceptual factors and acoustic indices *e.g.* [51, 54, 55], the traditional approach in acoustics, investigating the statistical correlations between the perceptual measurements and sets of predefined acoustic indices, does not always lead to results that are likely to be generalised, because the quality and the ‘meaning’ of sounds are mostly important.

The assumption of the model proposed in this research is that it is possible to predict some of the perceptual attributes of the sonic environment, according to the prominence of the sound sources composing the sonic environment itself. For the purpose of this study, the prominence of a sound source is conceived as a characteristic involving both the intensity and the duration over time of the specific sound source (or sound sources’ type), with respect to the other sound sources.

In order to establish such a prediction model, an on-site campaign was carried out, using the soundwalk method [56]. Data collected from individual responses were then used as input variables for a set of linear regression models.

4.2 The study area

The case study area where the model was applied is located in the Valley Gardens area of Brighton and Hove (UK). It stretches for 1.5 km from the Level (North) to King’s Road (South), adjacent to the Old Steine roundabout on the seaside (Figure 2). This part of the city is highly congested by road traffic, including private cars and public transportation. The green infrastructure in the area remains unexploited with the park serving mostly as a transition corridor in the city and not as an inclusive place for the residents. In total eight key points were chosen to be explored in this area [57], with a view to account for the spatial and acoustic variability in a representative way. Figure 2 presents the exact locations, namely: the Seafront (1), the Old Steine (2), the Royal Pavilion (3), the area next to the statue in Victoria Gardens South (4), the Mazda

Fountain in Victoria Gardens South (5), Victoria Gardens North (6), St. Peter’s Church (7) and the Level (8).

4.3 Soundwalk and binaural recordings

Five women and sixteen men ($M_{age} = 38.7$ years, $SD = 11.5$) comprised the group of 21 people who participated in the soundwalk. This took place on a Monday of October 2014 from 09:30 to 10:30 am. All participants were led through the study area and made consecutive stops at the eight selected points starting from the Sea Front (1) and ending up at the Level (8). Following the conventional soundwalk methods, participants were required to listen to the acoustic environment for two minutes and fill in a structured questionnaire divided in two sections. The question in the first section (Q1) was relevant to sound sources and precisely: “*To what extent do you presently hear the following five types of sounds?*” with five different options for the potential sound sources [58]. These included: a) traffic noise (*e.g.* cars, buses, trains, airplanes), b) other noise (*e.g.* sirens, construction, industry, loading of goods), c) sounds of individuals (*e.g.* conversation, laughter, children at play), d) crowds of people (*e.g.* passers, restaurants, sport events, festivals) and e) natural sounds (*e.g.* singing birds, flowing water, wind in vegetation). Participants had to put a mark on a ten-centimetre continuous scale ranging from ‘do not hear at all’ (0) to ‘dominates completely’ (10). For the second Section (Q2) participants were required to assess eight attributes [59] – namely: pleasant, chaotic, vibrant, uneventful, calm, annoying, eventful and monotonous – by putting again a mark on a ten-centimetre continuous scale ranging from ‘strongly disagree’ (0) to ‘strongly agree’ (10).

During the soundwalk, a non-participant operator carried out some binaural recordings by means of two 1/8” in-ear microphones (DPA, frequency range 20 Hz – 20 kHz) connected to a portable high-resolution audio recorder (722 Sound Devices). The operator attended the soundwalk together with the other participants and recorded a two-minute audio sample at each of the eight selected locations. The eight audio samples were afterwards collected and the main statistical sound levels were calculated.

4.4 Sound levels

For descriptive purposes, the main statistical noise levels (L_{Aeq} , L_{min} , L_{max} , L_{10} , L_{50} , and L_{90}) were calculated from the binaural recordings and are reported in Table 1. Furthermore, Figure 3 shows the frequency spectra of the

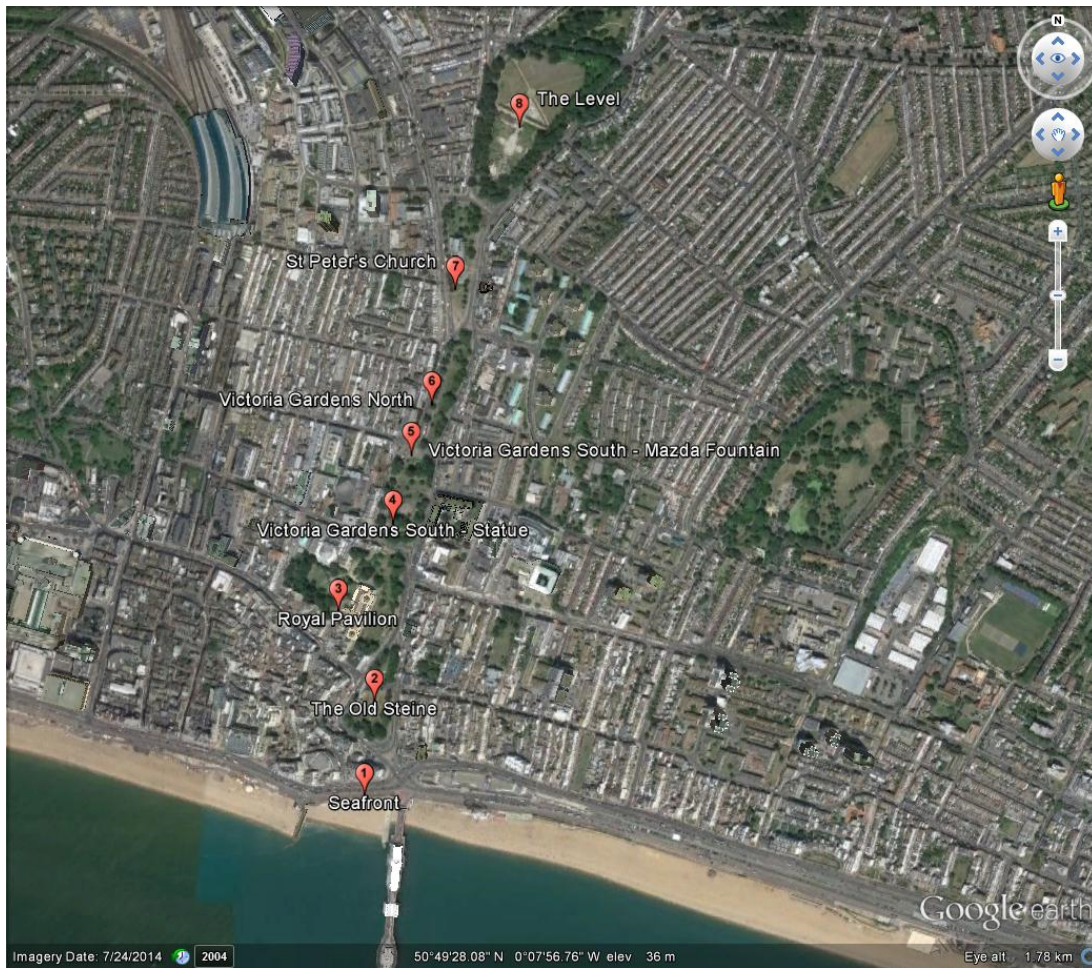


Figure 2: The eight locations selected for the soundwalk and the binaural recordings

eight selected locations on average over the two-minute period of recording.

4.5 Individual responses

The individual responses provided by the 21 participants for Q1 and Q2 were averaged into single values for each of the eight locations. Considering all the variables, visual inspection of their histograms and normal Q-Q plots showed that the scores across the eight locations were approximately normally distributed [60]. Figure 4 shows that ‘traffic noise’ was by far the most dominant sound source during the soundwalk, except in locations (3) and the (8) where the contribution from ‘natural sounds’ and ‘sounds of individuals’ was more relevant. These two locations indeed were not directly exposed to the traffic flows circulating across the study area. In particular, they correspond to the entrance of the historical site (Royal Pavilion) facing a

green area and a small urban park close to a children playground (the Level).

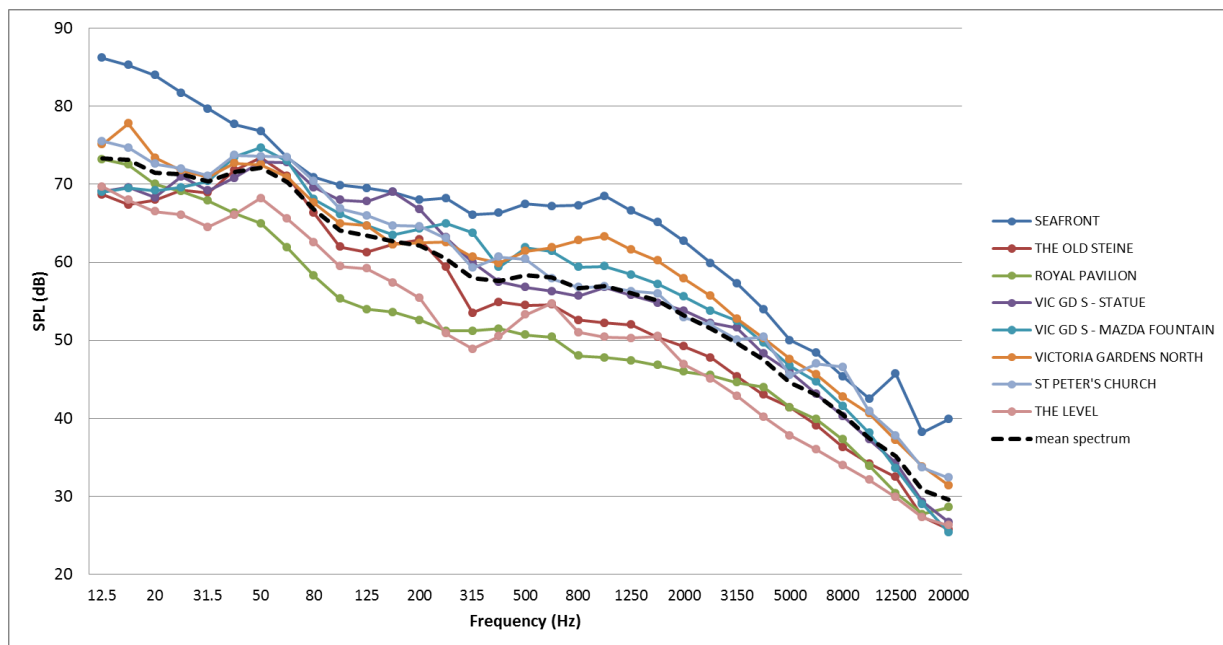
Likewise, considering the assessment of the emotional components, Figure 5 shows that the locations (3) and the (8) are found in the “Pleasant-Calm-Uneventful” area of the model depicted by Axelsson *et al.* [59], while the rest of the locations tend to converge towards the “Eventful-Chaotic-Annoying” region.

4.6 Establishment of the predictive model

The focus of the proposed model is on predicting perceptual features of the soundscape itself, rather than the perceived loudness of a given set of sound sources. Previous research has thoroughly investigated the perceptual dimensions underlying the soundscape appraisal, *e.g.* [59, 61]. For the purpose of predicting the affective qualities of soundscape, the eight perceptual attributes reported in the “circumplex” model, as defined by Axelsson *et al.* [59]

Table 1: Statistical noise levels for the eight selected locations (average of left and right channel)

Site	SPL (dB)					
	L_{Aeq}	L_{Amin}	L_{Amax}	L_{A10}	L_{A50}	L_{A90}
(1) SEAFRONT	75.7	67	81.5	78.6	74.7	70.7
(2) THE OLD STEINE	62.8	58	71.5	64.6	61.7	59.5
(3) ROYAL PAVILION	58.5	53.4	67.4	60.5	57.4	55.2
(4) VIC GD S - STATUE	66.8	59	83.7	69.7	65.6	61.8
(5) VIC GD S - MAZDA FOUNTAIN	68.9	64.8	72.6	70.8	68.3	66.1
(6) VICTORIA GARDENS NORTH	70.6	61.3	78.4	74.3	68.2	63.6
(7) ST PETER'S CHURCH	67.2	58.6	77.9	69	65.6	61.4
(8) THE LEVEL	60.5	54.8	71.9	61.7	58.9	57.6

**Figure 3:** Frequency spectra for the eight selected locations and mean spectrum (average of left and right channel)

were used, namely, pleasant (PL), annoying (AN), eventful (EV), uneventful (UN), calm (CM), monotonous (MN), vibrant (VB), and chaotic (CH).

Eight stepwise multiple linear regression analyses were conducted, using PL, AN, EV, UN, CM, MN, VB and CH as dependant variables and the complete set of sound sources as independent variables (SPSS 22 for Windows), considering all the 168 records (*i.e.*, 21 participants * 8 locations) for each model. The sound sources types were: traffic noise (TR*), other noise (OT*), sounds of individuals (IN*), crowds of people (CR*) and natural sounds (NS*). Out of the eight stepwise multiple linear regressions, only four models explained at least 30% of the variance in the investigated variables; these were: PL, AN, CM and CH. Table 2 presents the best predictors, the standardised regression coefficients (β) and the explained variance for

these four models. In order to test the potential presence of highly inter-correlated predictor variables in the regression models, a collinearity diagnostics was performed. The Variance Inflation Factor (VIF) for all independent variables resulted to be smaller than 10, therefore severe multicollinearity was discarded [62].

The 54.6% of the variance in PL was explained by TR* and NS*. The negative relationship between 'pleasant' and 'traffic noise' shows that there was a better assessment of the acoustic environments associated to a smaller prominence of traffic sounds. In general, this suggests that the traffic noise source was considered inappropriate for the acoustic environment of the place, which is in line with the concept that natural sounds should prevail in urban parks [63, 64]. The AN model explained a similar amount of variance (52.4%) using the same predictors as the PL

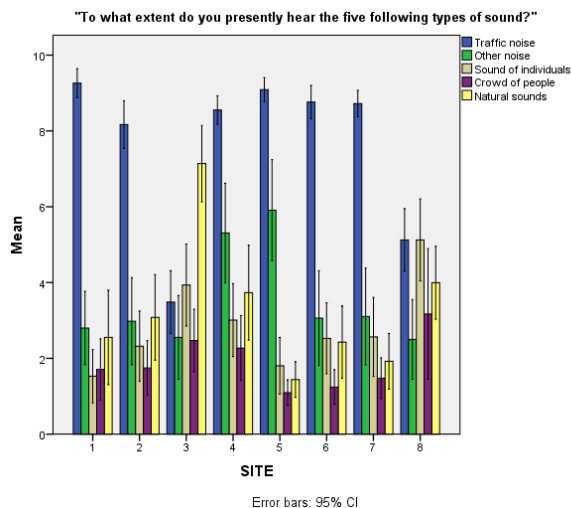


Figure 4: Mean values and 95% CI of the individual responses for Q1

Table 2: Multiple linear regression models for the eight considered variables

Model	Predictor	<i>t</i>	Sig.	β	R^2
PL	TR*	-9.428	$p < 0.001$	-0.577	0.499
	NS*	4.117	$p < 0.001$	0.252	0.047
AN	TR*	10.219	$p < 0.001$	0.64	0.509
	NS*	-2.304	$p = 0.022$	-0.144	0.015
CM	TR*	-9.519	$p < 0.001$	-0.582	0.527
	NS*	3.989	$p < 0.001$	0.24	0.036
	OT*	-2.112	$p = 0.036$	-0.111	0.012
CH	TR*	5.853	$p < 0.001$	0.437	0.309
	OT*	3.482	$p = 0.001$	0.223	0.04
	NS*	-2.068	$p = 0.04$	-0.152	0.017

model: this was expected since ‘pleasant’ and ‘annoying’ represent the two extremes of the ‘pleasantness’ dimension according to the circumplex model by Axelsson *et al.* [59]. Interestingly, TR*, NS* and OT* explained 57.5% of the variance in CM. The negative relationships between ‘traffic noise’, ‘other noises’ and ‘calm’ show that calmer sound environments are associated with a lesser prominence of both traffic noise and eventful sounds (e.g. sirens, construction, industry, loading of goods). Other models for calmness perception were proposed in the literature which included sound level as predictor, e.g. [65, 66]. However, such models compensate the lack of ‘qualitative’ information on the sound component (i.e. semantic contribution of the sound sources) by taking into account the effects of other non-acoustical factors (e.g. visual cues).

The remaining four models (i.e. EV, UN, VB, MN) explained limited amounts of variance (from 3% to 9%). A possible explanation for this is that not all perceptual di-

mensions are always likely to emerge at a given place, since soundscape appreciation will strongly depend on the sound sources composition of the acoustic environment. Thus, it is worth observing that the linear regression models defined within the present study are only valid for the investigated test site. However, the proposed method can be easily adapted for different cases and more generic relations can be established. It is expected that the applicability of the possible linear regression models will be context-dependent; that is, for example: it is more likely that a ‘calm’ regression model will be considered for an urban park or a residential area, rather than a context highly exposed to road traffic, while a ‘vibrant’ regression model might be considered for commercial districts or pedestrian areas.

5 Soundscape map implementation

The main aim of the present model is to provide the user with visual maps depicting the spatial variation of the selected perceptual attributes across the study area. For this purpose, a GIS-based methodology was used.

5.1 Soundscape mapping method using GIS

Several interpolation methods are currently available [67]; however, all of them are applied under two main conditions: (a) the mean value of the examined variable is the same throughout the entire area and (b) the correlation between two variables solely depends on the distance that separates them, signifying that nearby elements tend to be more similar than others that are far. Some interpolation methods such as ‘Kriging’ and ‘Inverse Distance Weighting’ (IDW) have previously been used for noise mapping purposes [11]. In the current study, in order to capture the general surface trend, an ordinary kriging interpolation method (spherical semivariogram) was applied. This kind of geostatistical technique is using the statistical properties of the sample points quantifying the spatial autocorrelation among them [68].

The input data for the current implementation were based on the mean values of the individual responses provided by the 21 people during the soundwalk described above, who assessed the perceptual attributes and sound sources’ profiles throughout the area. Specifically, the mean values of the attributes pleasant, calm, uneventful, monotonous, annoying, chaotic, eventful and vibrant were used as input variables for the kriging algorithm, in

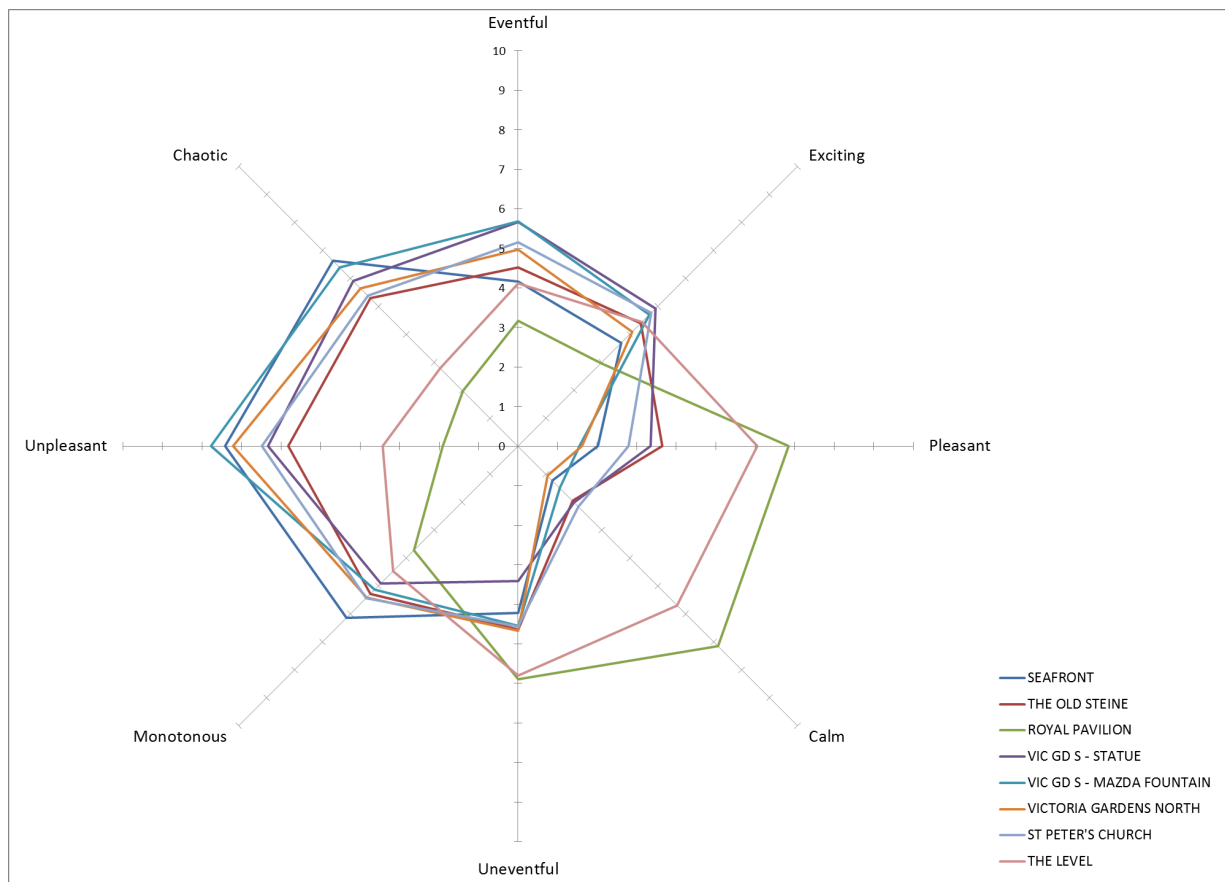


Figure 5: Mean values of the individual responses for Q2, represented according to Ref. [59]

order to produce the corresponding prediction maps using the Spatial Analyst tool.

Perceptual maps in Figure 6 cover an interpolation surface of 0.375 km^2 . The borders of the interpolation (convex hull region) are always defined based on the coordinates of the marginal points. The colour scale ranges from 1 to 8 (maximum spread of the original 0–10 scale for the average values of the perceptual attributes). For graphical purposes the colour ramp was divided in 14 equal segments, corresponding to 14 colours (*i.e.*, two colours for each step of the 1–8 scale). In that way all the maps were rendered comparable to each other with graphically visible variations.

Interpolation techniques and in general stochastic processes can only offer predictions and error assessments based on a group of control points. In this case, the aim was simply visualising the perceptual variability of the acoustic environment. For this reason interpolation techniques should not be confused with the physics of sound propagation or any kind of acoustic filtering. Similar approaches can be retrieved in the literature [36, 37, 72].

5.2 Soundscape maps of the study area

Out of the eight perceptual attributes, two were excluded from further analysis (“vibrant”, “uneventful”) as not spatially autocorrelated [73]. From the remaining six - presented in Figure 6 - the highest variability was detected in “pleasant”, “calm” and “annoying” ranging between 1.0 and 7.8. Points in the middle of the study area followed the same pattern in terms of the first two variables being characterised as poorly “pleasant” or “calm”. Among points (4) and (7) (Figure 6a, 6b) none of these two variables managed to score above 3.3 with $\text{MIN}_{\text{Pleasant}} = 1.6$ and $\text{MIN}_{\text{Calm}} = 1.0$. On the contrary, points (3) and (8) were unanimously voted as the most pleasant and calm with average values over 6.8 for point (3) and over 5.7 for point (8). The surrounding greenery in both locations possibly enhanced the overall assessment.

Following the previous outcomes, “annoying” presented an opposing pattern towards “pleasantness” and “calmness”. As shown in Fig.6d points (1), (5) and (6) presented the highest values between 7.2 and 7.8 characterising an environment highly aggravated by traffic noise.

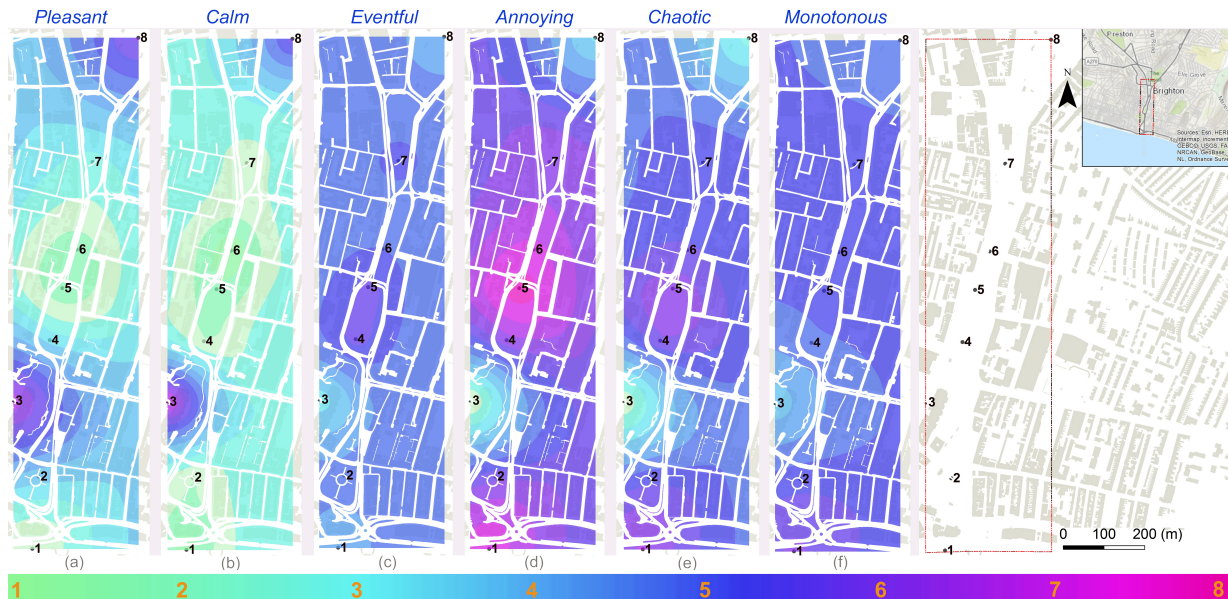


Figure 6: Measurement points and soundscape maps within the study area in Brighton according to the selected perceptual attributes: a) Pleasant, b) Calm c) Eventful, d) Annoying, e) Chaotic, f) Monotonous. The colour ramp ranges between 1 and 8.

The sea front occasionally suffers from strong winds which could make the sound environment unpleasant. This is the reason why “chaotic” (Figure 6e) recorded its maximum value (6.6) in the same place, with the second highest (6.4) at point (5). In all cases, participants assessed “chaotic” lower than “unpleasant”; however both of them followed the same spatial variations in the eight points. Another way to visualise the incessant activity of the study area is to examine Figure 6c, which represents the extent of “eventfulness”. As expected the tranquillity in places (3) and (8) reduced the level of eventfulness compared to the other points, where it presented average values between 4.2 and 5.7 with a bull’s-eye effect around points (4) and (5). Finally, “monotonous” presented a very good correlation with “chaotic” and “annoying” ($R^2 = 0.77$) showing once more that traffic dominates in the area. On the other hand, the average variability of this parameter was an evidence of the diverse nature of the sound environment coupled with the activities that take place in the area.

To sum up, the overall values from the six perceptual parameters show that the majority of the points in the study area were heavily exposed to the surrounding traffic with just two places to constitute the pleasant outliers. A future policy for a local regeneration plan should therefore aim at decreasing the noise levels and use additional masking techniques to mitigate traffic noise at points (1,2) and (4–7).

5.3 Accuracy of the GIS implementation of soundscape maps

The accuracy of the kriging model was validated using the cross-validation process [69, 70]. A data point is omitted consecutively and the predicted values at the location of the omitted point are compared with the actual values using the remaining points. For all points, cross-validation compares the known and predicted values. For the quality assessment we used the following error parameters and their optimal values as shown in Table 3.

Based on the results presented on Table 3 the average difference in absolute values between the measured and the predicted values (MPE) was between 0.01 and 0.27. However, it is already known [70] that MPE is a weak diagnostic for kriging, scale-dependent and insensitive to the variogram changes. For this reason additional indicators to validate the model are needed. The bias assessment was further checked with the MSE, which was very close to zero in all the six perceptual attributes. However, the main indicator to assess the model accuracy is the RMSPE, which should be as close to zero as possible.

The kriging model presented values ranging between 0.77 and 2.61. A better understanding of this error’s extent can be drawn if combined with the standard deviation (SD) of the respective perceptual parameters mentioned in Table 4 as well. For example, “pleasantness” varies almost up to two degrees from the measured values in the 1-8 scale used in this study. Differences above two degrees in the

Table 3: Error types used in the cross-validation model

Error type (ideal values)	Description	Mathematical type
Mean Prediction (MPE) (≈ 0)	Averaged difference between the measured and the predicted values	$\frac{\sum_{i=1}^n (\hat{Z}(s_i) - z(s_i))}{n}$
Mean Standardised Error (MSE) (≈ 0)	The average of the standardized errors	$\frac{\sum_{i=1}^n (\hat{Z}(s_i) - z(s_i)) / \sigma(s_i)}{n}$
The Root Mean Squared Prediction Error (RMSPE) (≈ 0)	Specifies how closely the model predicts the measured values	$\sqrt{\sum_{i=1}^n \frac{(\hat{Z}(s_i) - z(s_i))^2}{n}}$
Average Standard Error (ASE) (\approx RMSPE)	Average of the prediction standard errors	$\sqrt{\frac{\sum_{i=1}^n \sigma^2(s_i)}{n}}$
Root Mean Square Standardized Error (RMSSE) (≈ 1)	RMSSE $< 1 \rightarrow$ overestimation RMSSE $> 1 \rightarrow$ underestimation	$\sqrt{\frac{\sum_{i=1}^n \hat{Z}((s_i) - z(s_i)) / \sigma(s_i)}{n}}$

RMSPE can be found when assessing the level of “annoyance” or “calmness” which had the highest variability in the study area. Nevertheless, this variability was slightly “overestimated” (RMSSE <1) when assessing, apart from “annoyance”, how “pleasant” or “eventful” was the place. A close examination of the RMSPE showed that the highest errors were detected in the outlier points, which were very calm or quiet in the study area. Therefore, it comes as a natural conclusion that the effectiveness of group soundwalks - when collecting data for mapping purposes - can be maximised based on both *a priori* and on-site selection of the sampling points. The main disadvantage of group soundwalks is the limited duration [71], which inevitably will affect the number of measurement points. Therefore, preliminary knowledge of the study area can help to address this challenge.

6 Discussion and conclusions

The proposed model relies on three main stages, namely: (1) sound sources recognition and profiling, (2) prediction of the soundscape’s perceptual attributes, and (3) implementation of soundscape maps. Ideally, each stage provides the input data for the following one. This work focused on the last two stages, showing that the model can be applied in everyday life situations, and described what kind of data would be needed in the first stage and how to gather them.

For the second stage of the model, the sound source profiles proved to be valuable input data for predicting perceptual attributes of the acoustic environment. Within the

framework of this research, the individual responses related to the sound source profiles and the perceptual attributes were collected in a test site in Brighton & Hove and used to establish a set of linear regression models. The source types ‘traffic noise’ and ‘natural sounds’ explained 54.6% of the variance for the sonic environment attribute ‘pleasant’. Likewise, ‘traffic noise’, ‘natural sounds’ and ‘other sounds’ source types explained 57.5% of the variance for the attribute ‘calm’. These results are not likely to be generalised to any situation, due to the limited number of participants and the specific features of the investigated site. However, they show that it is possible to use soundscape profiles to predict perceptual attributes of the acoustic environment. Specific models might be defined in the future, according to the different urban contexts (e.g. urban parks, commercial districts) and the predictive sound source types shall consequently vary.

The third stage of the proposed model showed how to represent the predicted perceptual attributes with a GIS technique, offering a suitable process to visualise the outcomes of the soundscape mapping process. The accuracy of the proposed methodology was shown to be adequate according to the various errors reported in Table 4, even with an average intra-point distance of 175 m for the eight points. However the RMSPE and the individual errors suggest that for certain points (e.g. point (3) having an error of -3.56 for ‘pleasant’) a higher grid resolution might be more appropriate. The grid size in this study (i.e. 175 m) is greater than those conventionally used for physical noise indicators. For instance, Can *et al.* [11], used a 20-meter grid. A possible explanation for the model still having a reasonable accuracy is that perceptual attributes in a relatively homogenous urban context present smaller varia-

Table 4: Cross-validation process: analysis of all the error descriptors (mean values) and the standard deviation (SD) for all perceptual attributes

Errors	Pleasant	Annoying	Calm	Chaotic	Eventful	Monotonous
MPE	-0.27	0.22	-0.23	0.16	0.13	0.01
MSE	-0.08	0.07	-0.07	0.06	0.1	-0.01
RMSPE	1.92 (1.99)	2.26 (2.07)	2.61 (2.28)	1.93 (1.69)	0.96 (0.86)	0.77 (0.72)
ASE	2.02	2.24	2.47	1.80	0.97	0.75
RMSSE	0.9	0.98	1.03	1.05	0.99	1

tions compared to noise levels, which are significantly affected by the physics of sound propagation. As a result, the current sample size can be considered adequate for such urban contexts.

Taken together, the three stages of the proposed model define a process for which it is possible to associate a predicted value of a perceptual attribute to a given audio recording of an acoustic environment. When this process is replicated in a systematic way and applied to a number of points that are spatially connected within a reasonable distance, it is possible to generate soundscape maps.

The proposed tool is mostly relevant from the planning viewpoint, since it offers new insights into the individual's perception and understanding of the sonic environment and provides the basis for the implementation of perceptual sound maps; these can be further combined with classic outputs derived from noise control engineering techniques. Research is currently oriented to such an approach, which is highly desirable as a complementary qualitative description of urban sound environments [74, 75].

Cities are really 'smart' when they are able to evolve continuously according to the citizens' needs, enhancing their participation and engagement. The soundscape philosophy has its focus on the community perception of the acoustic environment: such perception in urban contexts is extremely volatile and it is evolving over space and time; therefore it is essential that smart cities adopt the soundscape approach to provide qualitative data about the acoustic environment. This research suggests that there is room for implementing new dynamic tools in smart cities for soundscape purposes.

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