Urban Public Space Soundscapes of the COVID-19 Lockdown: An application of predictive soundscape modelling

Andrew,[1] Tin,[1] Francesco Aletta,[1] Magdalena Kachlicka,[1] Matteo Lionello,[1] Mercede Erfanian,[1] and Jian Kang[1]
Institute for Environmental Design & Engineering, The Bartlett, University College London, London, United Kingdom[a)]

(Dated: 9 July 2021)

The unprecedented lockdowns enforced around the world to fight the COVID-19 pandemic in the first half of 2020 triggered a change in human activities in public spaces and acoustic environment in cities. This study was conducted to characterise the resulting change in the sound environment as it would potentially be perceived by people. As people were not present in the public spaces to be surveyed, an online listening test was conducted and a linear multi-level predictive model was applied to determine the change in sound sources and to predict the expected perception, respectively. Building on an existing database of soundscape surveys and binaural recordings collected in 13 urban public spaces across London ($N = 11$) and Venice ($N = 2$) during 2019, new recordings were made in the same locations during the lockdowns in spring 2020. Making use of these 30-second-long binaural recordings, the model is used to predict the likely pleasant and eventful rating of the soundscape within the circumplex, and the expected change in soundscape is plotted for each location. Results indicate: 1) human sounds were perceived as less dominant across all the locations, 2) natural sounds were perceived more dominant, 3) the perception shifted towards less eventful for most locations 4) the perception shifted towards more pleasant for typically traffic dominated locations, but not for human- and natural-dominated locations. The framework tested in this study has the potential for use in soundscape quality assessment of locations which are hard to survey. The study demonstrates the potential usefulness of predictive soundscape modelling and indicates the importance of considering contextual information when discussing the impacts of sound level reductions on the soundscape.

 [http://dx.doi.org(DOI number)]

[XYZ] Pages: 1–14

I. INTRODUCTION

The global emergency caused by the COVID-19 pandemic in early 2020 required national lockdown measures across the world, primarily targeting human activity. In the United Kingdom, construction and transport were allowed to continue, but a decrease in activity was observed (Hadjidemetriou *et al.*, 2020). In other countries, such as Italy, the restrictions were more severe and even included limiting people's movement to a certain radius from their place of residence. The explorations in environmental acoustics of lockdown conditions across the world have revealed various degrees of impact on the acoustic environment, both at a city-scale (Bonet-Solà *et al.*, 2021; Munoz *et al.*, 2020; Rumpler *et al.*, 2021) and at a more local, public space-scale (Aletta *et al.*, 2020; Alsina-Pagès *et al.*, 2021; Bonet-Solà *et al.*, 2021; Manzano *et al.*, 2021). In general, these studies have revealed a decrease in urban noise levels, although the latter group indicated a difference in the amount the level decreased depending on the type of area investigated and the type of human activity characteristic for the area.

Aletta *et al.* (2020) explored the impacts of the COVID-19 lockdowns on the acoustic environment in London in particular, through many short-term (30s) binaural recordings. This study revealed that average reductions in the various locations considered ranged from 10.7 dB (L_{Aeq}) to 1.2 dB, with an overall average reduction of 5.4 dB. This metric-reporting focused approach left some key questions unanswered: how would people have perceived these spaces as a result of this change in acoustic environment, and would these sound level reductions result in improvements to the soundscape of the spaces?

These questions arise out of the soundscape approach, which is characterised by prioritising the perceptual effect of an acoustic environment by taking into account the interaction of sound sources, context, and the person perceiving it (International Organisation for Standardization, 2014; Truax, 1999), bringing together objective and subjective factors. The soundscape approach to noise mitigation and management is being recognised as a response to arising environmental requirements on noise

[a)] j.kang@ucl.ac.uk;

pollution and sustainability, such as the regulation of quiet areas in Europe (European Environment Agency., 2020; Kang and Aletta, 2018; Radicchi *et al.*, 2021).

Soundscape research is therefore traditionally rooted in environmental acoustics and environmental psychology, typically dealing with outdoor spaces (Torresin *et al.*, 2020) and urban open spaces, where parks and squares are often used as case study sites (Kang, 2007). A soundscape assessment typically requires people to be surveyed but the presence of people at a location influences assessment (Aletta and Kang, 2018) and 'quiet places' usually require low numbers of users to remain quiet, which limits the possibility of an assessment. Even in a crowded public space, soundscape surveys are demanding as they require significant resources to carry out at scale, limiting their widespread application (Mitchell *et al.*, 2020). Therefore, a need for a predictive model arises to overcome this limitation and improve the implementation of the soundscape approach into everyday planning and management practices.

According to a recent review of predictive soundscape models from Lionello *et al.* (2020), the degree of employing auditory and non-auditory factors in soundscape prediction varies with some studies relying on contextual (Kajihara *et al.*, 2017), personal/demographic (Erfanian *et al.*, 2020; Tarlao *et al.*, 2021) or social media (Aiello *et al.*, 2016) data entirely to predict and generate soundscape features. Some methods also incorporate perceptually-derived features, such as subjective sound level and visual pleasantness (Lionello *et al.*, 2020), however these features must also be collected via a survey and therefore are unsuitable for predictive modelling where surveys are not possible. This indicates the necessity for considering and accounting for the influence which contextual factors in a space have on the relationship between the sound environment itself and the listener's perception of it (i.e. the soundscape).

Therefore, a first research question arises: what is the potential of a soundscape prediction model based on comprehensive acoustic on-site measurements and contextual features for assessing locations with low social presence or in situations where conducting surveys is impractical (RQ1).

A standardization approach to reporting subsequent changes in soundscape was proposed, focused around the L_{Aeq} (Asensio *et al.*, 2020). However, those studies were not able to reveal the perceptual impact of such conditions in public spaces mainly because of: 1) the lack of subjective data for the exact or comparable locations in previous years; and 2) the lack of participants present in public spaces during the lockdown, hence the inability to collect soundscape data in situ. Attempts have been made to bridge this gap by using social networks to source subjective data but resulted in focus on indoor conditions following the shift in the citizens' behavior, i.e. spending a much more significant amount of time indoors (Bartalucci *et al.*, 2021; Lee and Jeong, 2021). To the best of the authors' knowledge, the only study published at the time of writing looking closely at the perception of environmental sounds during the lockdown in public spaces didn't feature the comparable data available for the normal period but focused on different stages of the lockdown condition (Lenzi *et al.*, 2021). Although numerous studies have reported on the physical changes in urban spaces during the lockdowns through a mostly environmental acoustics lens, little can so far be said about how the soundscapes of these spaces were affected during this period.

Making use of a soundscape database created throughout 2019 containing both detailed acoustic measurements and subjective perceptual surveys (Mitchell *et al.*, 2020) and the subsequent acoustic data collection campaign conducted during the lockdown period as reported previously in Aletta *et al.* (2020), this study aims to answer the following research questions by developing and applying the prediction model based on acoustic features: what is the effect of human activities on the perception of an acoustic environment in general, and how would the change in acoustic environment during the lockdown in spring 2020 have been perceived, compared to the same period in 2019 (RQ2). Because, although it is clear that the levels went down (Aletta *et al.*, 2020), it is less clear if that change is enough to enhance an acoustic environment of an open public space, and if that works equally across all locations.

II. MATERIALS AND METHODS

This study was conducted via initial onsite data collection campaigns in Central London and Venice in 2019 before the outbreak of COVID-19 as part of the Soundscape Indices (SSID) project (Mitchell *et al.*, 2020) and in 2020 during the strictest part of the lockdowns (Aletta *et al.*, 2020), including objective acoustic data and subjective responses. Using both 2019 and 2020 binaural recordings, an online listening experiment was conducted to provide an understanding about the change in sound source composition. A predictive model was developed to reveal the change in the perceived pleasantness and eventfulness using objective acoustic data and location to predict subjective responses. Due to the nature of this study as being a reaction to the strict movement and activity restrictions, sites selected were those locations included in the initial SSID data collection for which additional measurement campaigns could be undertaken during the spring of 2020.

The sites were selected to provide a mixture of sizes and uses, varying in typology ranging from paved squares to small and large parks to waterside spaces across both cities. Throughout the text they are indexed via a LocationID based on the location's name (e.g. CamdenTown, SanMarco), while a more in-depth overview of each is given in supplementary files. London is presumed to be representative of a typical large city while the Venice sample provides a unique look at spaces with typically very high human activity levels and no road traffic activity.

The ISO/TS 12913 (International Organisation for Standardization, 2018) series were consulted for reporting on soundscape data. As the details on the SSID database have not been published yet in a comprehensive way, a more detailed description of the 2019 survey campaigns is featured throughout the paper and in the supplementary files / database reference.

This study was approved by departmental UCL IEDE Ethics Committee on 17th July 2018 for onsite data collection and on the 2$^{\text{nd}}$ of June 2020 for the online listening experiment and is conducted in adherence to the ethical requirements of the Declaration of Helsinki (noa, 2013).

A. Onsite data collection: questionnaires, binaural measurements, and recordings

The initial onsite data collection featured both questionnaire data collected from the general public and acoustic measurements, conducted across thirteen urban locations (in London $N = 11$, in Venice $N = 2$) between the 28$^{\text{th}}$ of February and the 21$^{\text{st}}$ of June 2019, with additional sessions in July and October 2019. A total of 1,318 questionnaire responses were collected from the general population across the measurement points during 1 – 3 hour-long campaigns in both cities in 2019, accompanied by 693 approximately 30-second long 24-bit 44.1 kHz binaural recordings. Each of the 13 locations was characterised by between 14 to 80 recordings and between 89 to 155 questionnaire responses. Mean age of the participants was 33.9 (45% male, 53.8% female, 0.4% non-conforming, 0.9% prefer-not-to-say).

The subsequent measurement campaign in 2020 mimicked the binaural recording strategy applied in the initial campaign and was performed between the 6th and the 25th of April 2020 in both cities, this time excluding the questionnaire. An additional 608 binaural recordings were collected on-site in 2020.

1. Questionnaires

The 2019 data collection was performed across all the locations using the protocol based on the Method A of the ISO/TS 12913-2: 2018 (International Organisation for Standardization, 2018), as described in (Aletta *et al.*, 2020; Mitchell *et al.*, 2020), collected either via handheld tablets or paper copies of the questionnaire. The full questionnaire and data collection procedure are given in Mitchell *et al.* (2020), however the key parts used for this study are those addressing sound source dominance and perceived affective quality (PAQ).

Participants are first asked to rate the perceived dominance of several sound sources, as assessed via a 5-point Likert scale, coded from 1 (Not at all) to 5 (Dominates completely). The sound sources are split into four categories: Traffic noise, Other noise, Human sounds, and Natural sounds and each is rated separately. Next are the 8 PAQs which make up the circumplex model of soundscape (Axelsson *et al.*, 2010): pleasant, chaotic, vibrant, uneventful, calm, annoying, eventful, and monotonous. These are assessed on a 5-point Likert scale from 1 (Strongly disagree) to 5 (Strongly agree). In order to simplify the results and allow for modelling the responses as continuous values, the 8 PAQs undergo a trigonometric projection to reduce them onto the two primary dimensions of pleasant and eventful, according to the procedure outlined in Part 3 of the ISO 12913 series (International Organisation for Standardization, 2019). In order to distinguish the projected values from the Likert-scale PAQ responses, the projected values will be referred to as ISOPleasant and ISOEventful and can be considered to form an x-y coordinate point (x = ISOPleasant, y = ISOEventful) as explained in detail in Lionello *et al.* (2021).

2. Binaural recordings

The calibrated binaural device SQobold with BHS II by Head Acoustics was used in both campaigns at all the locations by various operators to capture acoustic data, as mentioned in the acknowledgements. Following the before mentioned onsite protocol (Mitchell *et al.*, 2020), in case of participants being in a group and filling their responses simultaneously, a single binaural recording was used to capture their experience. The purpose behind this sampling strategy was to obtain data from the perspective of a typical user, corresponding to a range of individual experiences available within an urban open space. These recordings are indexed by a GroupID such that the recording for each group is matched up to each of the corresponding respondents and their individual survey responses.

B. Field Data Analysis

1. Data cleaning

The cleaning of the samples was conducted using the ArtemiS SUITE 11. The researcher discarded or cropped whole recordings, or its parts affected by wind gusts or containing noises and speech generated by the recording operator by accident or for the purpose of explaining the questionnaire to a participant. This resulted in 1,291 binaural recordings then processed further, as described in the section B.2. Psychoacoustic analyses and shown in supplementary files/database.

In order to maintain data quality and exclude cases where respondents either clearly did not understand the PAQ adjectives or intentionally misrepresented their answers, surveys for which the same response was given for every PAQ (e.g. 'Strongly agree' to all 8 attributes) were excluded prior to calculating the ISO projected values. This is justified as no reasonable respondent who understood the questions would answer that they 'strongly agree' that a soundscape is pleasant and annoying, calm and chaotic, etc. Cases where respondents answered 'Neutral' to all PAQs are not excluded in this way, as a neutral response to all attributes is not necessarily contradictory. In addition, surveys were discarded as in-complete if more than 50% of the PAQ and sound source questions were not completed.

The site characterization as per International Organisation for Standardization (2018) is available in the supplementary files / SSID database and features notes about sound sources, typical use of each location and pictures taken during the survey sessions.

2. Psychoacoustic analyses

The binaural recordings were analyzed in ArtemiS SUITE 11 to calculate the following suite of 11 acoustic and psychoacoustic features to be used as initial predictors (additional information is given in Appendix B):

1. Loudness (N_5, sones, per ISO 532-1:2017)
2. Sharpness (acum, per ISO 532-1:2017)
3. Roughness (asper)
4. Impulsiveness (iu)
5. Fluctuation Strength (vacil)
6. Tonality (tuHMS)
7. Zwicker Psychoacoustic Annoyance (per Zwicker and Fastl (2007))
8. L_{Aeq}, 30s (dB)
9. $L_{A10} - L_{A90}$ (dB)
10. $L_{Ceq} - L_{Aeq}$ (dB)
11. Relative Approach (per Genuit (1996))

The (psycho)acoustic predictors investigated were selected in order to describe many aspects of the recorded sound – in particular, the goal was to move beyond a focus on sound level, currently present in the existing literature on the acoustic effects of lockdowns noted in Section I. In all, they are expected to reflect the sound level (L_{Aeq}), perceived sound level (N_5), spectral content (Sharpness, $L_{Ceq} - L_{Aeq}$, Tonality), temporal character or predictability (Impulsiveness, Fluctuation Strength, Relative Approach), and overall annoyance (Psychoacoustic Annoyance). These metrics are have been proposed as indicators to predict perceptual constructs of the soundscape (Aletta *et al.*, 2017, 2016) and have shown promise when combined together to form a more comprehensive model applied to real-world sounds (Orga *et al.*, 2021). Each of these predictors was calculated from the 30s binaural recordings using Artemis. The maximum value from the left and right channels of the binaural recording are used, as suggested in ISO/TS 12913-2 (International Organisation for Standardization, 2019).

Table 1 shows the Pearson correlation coefficient between each of the candidate acoustic features and the outcome pleasantness and eventfulness. For *ISOPl*, we can perhaps see three tiers of correlations: the more highly correlated tier ($|r| > 0.28$) consists of RA, L_{Aeq}, R, N_5, and PA; the low correlation tier consists of $L_{A10} - L_{A90}$, T, and I; while $L_{Ceq} - L_{Aeq}$, I, and S show no correlation. For *ISOEv*, these tiers are: RA, L_{Aeq}, T, R, and N_5 comprise the most correlated tier ($|r| > 0.30$); $L_{Ceq} - L_{Aeq}$, $L_{A10} - L_{A90}$, FS, and PA show low correlations; I and S show no correlation.

Among the correlations for the psychoacoustic metrics considered for inclusion as input features, we can see several highly correlated features. As expected, RA, L_{Aeq}, and N_5 are highly correlated, meaning that careful consideration is paid to these features to ensure they do not contribute to multicollinearity in the final model.

C. Modelling

Two linear multi-level models (MLM) were computed to predict: 1) ISOPleasant, and 2) ISOEventful. The inherent grouped structure of the SSID database necessitates a modelling and analysis approach which considers the differing relationships between the objective acoustic features and the soundscape's perceived affective quality ratings across the various locations and contexts. The individual-level of the models is made up of the acoustic features calculated from the binaural recordings made during each respondent's survey period, while the group-level includes the categorical 'LocationID' variable indicating the location in which the survey was taken, acting as a non-auditory contextual factor.

A separate backwards-step feature selection was performed for each of the outcome models in order to identify the minimal feature set to be used for predicting each outcome. In this feature selection process, an initial model containing all of the candidate features was fit, then each feature was removed from the model one at a time, then the best-performing model which is selected and the procedure continues step-wise until no improvement is seen by removing more features. This process is carried out first on the location-level features (including the potential to remove all features including LocationID, resulting in a 'flat' or standard multivariate linear regression model), then on the individual-level features. The performance criterion used for this process was the Akaike Information Criterion (AIC) (Akaike, Hirotugu, 1974). To check for multicollinearity among the selected features, the variance inflation factor (VIF) was calculated and a threshold of VIF ¡ 5 was set. Any features which remained after the forwards stepwise selection and exceeded this threshold were investigated and removed if they were highly collinear with the other features.

All of the input features are numeric values, in the units described above. Before conducting feature selection, the input features are z-scaled to ensure proper comparison of their effect sizes. After the feature selection, the scaled coefficients are used in the text when reporting the final fitted models to facilitate discussion. The unscaled model coefficients are reported in Appendix **??** to enable the models to be applied to new data. In order to properly assess the predictive performance of the model, an 80/20 train-test split with a balanced shuffle

TABLE I. Pearson correlation coefficients between candidate acoustic features and ISOPleasant and ISOEventful across all 13 locations

Parameter	**ISOPl**	**ISOEv**	**PA**	N_5	**S**	**R**	**I**	**FS**	**T**	L_{Aeq}	$L_{A10} - L_{A90}$	$L_{Ceq} - L_{Aea}$
ISOPleasant												
ISOEventful	-0.24**											
PA	-0.28**	0.24**										
N5	-0.37**	0.33**	0.94**									
S	0.01	0.04	0.71**	0.56**								
R	-0.36**	0.32**	0.63**	0.74**	0.11**							
I	-0.03	0.03	-0.10**	-0.03	-0.37**	0.24**						
FS	-0.11**	0.14**	0.37**	0.43**	0.04	0.46**	0.55**					
T	-0.21**	0.30**	0.58**	0.63**	0.12**	0.54**	0.16**	0.52**				
L_{Aeq}	-0.34**	0.37**	0.84**	0.93**	0.56**	0.72**	-0.09**	0.37**	0.57**			
$L_{A10} - L_{A90}$	-0.18**	0.15**	0.21**	0.33**	-0.20**	0.31**	0.36**	0.44**	0.40**	0.23**		
$L_{Ceq} - L_{Aeq}$	0.04	-0.20**	-0.49**	-0.49**	-0.54**	-0.31**	0.02	-0.27**	-0.28**	-0.61**	-0.22**	
RA	-0.34**	0.31**	0.60**	0.74**	0.18**	0.71**	0.31**	0.63**	0.58**	0.73**	0.23**	-0.14**

across LocationIDs was used. The z-scaling and feature selection was performed on the training set only in order to prevent data leakage. To score the performance of the model on the training and testing sets, we use the mean absolute error (MAE), which is in the scale of the response feature - for ISOPleasant this means our response can range from -1 to +1. However, since the end-goal of the model is to predict the soundscape assessment of the location as a whole, rather than the individual responses, we also assess the performance of the model in predicting the average response in each location. To do this, the R^2 accuracy across LocationIDs is reported for both the training and testing sets.

D. Online Survey

An online listening test was conducted using the Gorilla Experiment Builder (`www.gorilla.sc`) (Anwyl-Irvine *et al.*, 2020). The participants were exposed to a random selection of 78 binaural recordings (39 from 2019 and 39 from 2020, 6 recordings per each location). Each participant could have chosen to evaluate 1 or 2 sets of 6 recordings randomly assigned between 13 stimuli sets. Mp3 files, converted at 256 kBps were used due to the requirements of the Gorilla platform.

No visual stimuli were used in the experiment. The experiment consisted of: 1) an initial exercise to enhance chances of participants complying to the instructions and wearing headphones; 2) training set using two randomly chosen binaural recordings from the dataset; 3) soundscape characterization questionnaire starting with an open-ended question about perceived sound sources and featuring the same questions as the one used in situ, looking into the perceived sound source dominance of the following four types: traffic noise, other noise, human sounds and natural sounds; 4) questionnaire on the basic demographic factors. The questionnaire used in the Part 3 of the online experiment is reported in Appendix A.

Having in mind the remote nature of the study and to ensure a minimum level of robustness for reliable sound source recognition, an initial exercise was performed consisting of a headphone screening test (Woods *et al.*, 2017) and a headphone reproduction level adjustment test (Gontier *et al.*, 2019). The level adjustment was performed using an eleven-second-long pink noise sample matched to the lowest and the highest L_{A90} values from the experimental set. Participants were asked to adjust their listening level to clearly hear the quieter sample while keeping the level low enough, so they don't find the louder sample disturbing. The headphones screening test followed, featuring a stereo signal of one-second-long 100 Hz sine tone, generated with Izotope RX 6 application, played at a 3 dB difference where one of the equally loud pairs had its phase inverted. A 100 Hz sine was used because the pilot tests revealed the 200 Hz sine tone proposed by Woods *et al.* (2017) created a higher uncertainty varying across different laptop models and would likely contribute to the chances of a participant fooling the test. It was expected that participants using speakers would not be able to either hear the sine wave or would be fooled by the inverted phase effect and therefore not able to pass the trials, unless they were indeed using headphones. The participant needed to recognise the quietest of the 3 samples in a trial of 6 attempts. Only participants correctly answering 5 or more out of 6 trials were allowed to proceed with the experiment. Participants were asked not to change their audio output settings during the rest of the experiment. (This was introduced to ensure that a participant is using a headphones playback system which allows a listener to clearly recognise a 3 dB difference at 100 Hz as a proxy for sufficient audio quality playback.)

Online questionnaire data was collected between the 9th of June and the 9th of August 2020. Within the Gorilla Experiment Builder, a total of 250 attempts to complete the experiment were recorded, where 165 participants were excluded either on the basis of not passing the headphones screening ($N = 79$) or for not completing the experiment, usually before engaging into the screening ($N = 83$). Out of a total of 88 participants who completed the test, 2 participants were excluded as outliers as they provided uniform answers across all the questions and commented on not being able to properly hear the stimuli, despite their successful completion of the training tests. The participants of the online experiment were of mean age 32.42, 45.1% male, 54.9% female.

III. RESULTS

The results of the onsite surveys, online experiment and the model are reported here in their dedicated subsections. They are reported following the structure of the ISO/TS 12913 series, revealing the perceived sound source dominance and key perceptual attributes (ISOPleasant and ISOEventful).

A. Perceived sound source dominance

1. 2019 sound source composition per location

Descriptives to support the Interpretation of movement??

Locations	Traffic	Human	Natural	Other
CamdenTown	3.8	3.3	1.3	2.7
EustonTap	3.7	2.6	1.7	3.0
MarchmontGarden	2.7	2.7	2.6	2.5
MonumentoGaribaldi	1.9	3.4	3.0	2.0
PancrasLock	2.4	2.5	2.4	3.3
RegentsParkFields	2.4	2.9	3.1	1.9
RegentsParkJapan	1.9	2.5	4.0	1.5
RussellSq	2.8	3.0	3.3	2.1
SanMarco	1.4	4.0	2.2	1.9
StPaulsCross	2.6	3.3	2.3	2.1
StPaulsRow	2.5	3.4	1.7	2.3
TateModern	2.5	3.6	2.6	2.1
TorringtonSq	3.2	3.3	1.9	2.8

FIG. 1. Caption

2. Overall change in the perceived sound source dominance

The results from the listening tests deployed online were analysed using the SPSS Statistics v. 25.

1803 words describing the sound sources present in the 2019 recordings and 1395 words related to the 2020 recordings were inputted by participants in response to the open-ended question Q1 (see Appendix A). The frequency of occurrence, generated using the WordClouds web app, is shown in the Figure 1, for the 2019 and the 2020 sets respectively. The most frequent words in from both 2019 and 2020 groups are: noise, car/traffic, bird/birds, talk/voice and (foot)steps.

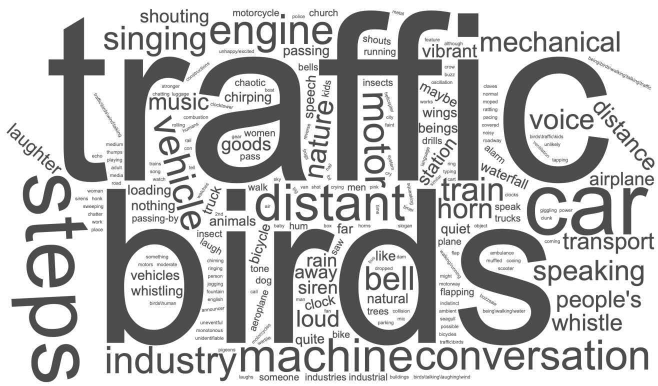

FIG. 2. A graphic illustrating the frequency of occurrence of the sound sources reported by the participants of the online study, shown for recordings from the 2019 (above) and 2020 (below).

Levene's test for equality of variances resulted in highly statistically significant values for all 4 sound sources investigated (less than .001). Therefore, a Mann-Whitney U-test test was used as a non-parametric equivalent to the T-test to investigate the change in the perceived dominance of the four sound source types (McKnight and Najab). The results for traffic sounds indicated higher perceived dominance in 2020 (M=2.56), than in 2019 (M=2.51), U=80,568.00, p=939. A similar result was found for other noise sources (higher in 2020, but not statistically significant). However, the results for human sounds indicated that the perceived dominance was greater for the 2019 sample (M=3.82), than for the 2020 sample (M=2.62), U=41,656.00, p¡.001. The results for natural sounds indicated the perceived dominance increased from 2019 (M=2.00) to 2020 (M=2.54), U=63,797.00, p¡.001.

TABLE II. Mann-Whitney U-Test results for the change in the perceived sound source dominance between the 2019 and 2020 sample

Sound source type	Traffic	Other	Human	Natural
Mann-Whitney U	80568	73696.5	41656	63797
Wilcoxon W	169821	162949.5	114809	153897
Z	-.08	-2.2	-12.2	-5.4
Asymp. Sig. (2-tailed)	.94	.03	<0.001**	<0.001**

TABLE III. Mean values and standard deviation for the perceived dominance of sound sources, assessed via an online survey

Sound source type	Campaign	N	Mean	Std. Dev.	Std. Error Mean
Traffic	2019	422	2.51	1.369	.067
	2020	383	2.56	1.525	.078
Other	2019	422	2.00	1.182	.058
	2020	382	2.23	1.333	.068
Human	2019	423	3.82	1.143	.056
	2020	382	2.62	1.346	.069
Natural	2019	424	2.00	1.307	.063
	2020	380	2.54	1.441	.074

B. Model outcomes, specification, and performance

1. ISOPleasant Model Selected

Following the feature selection, the ISOPleasant model (given in Table IV has N_5 as the fixed effect with a scaled coefficient of -0.06, and L_{Aeq}, $L_{A10} - L_{A90}$, and $L_{Ceq} - L_{Aeq}$ as coefficients which vary depending on the LocationID. The training and testing MAE are very similar, indicating that the model is neither over- nor under-fitting to the training data ($MAE_{train} = 0.259$; $MAE_{test} = 0.259$). The model performs very well at predicting the average soundscape assessment of the locations ($R^2_{train} = 0.998$; $R^2_{test} = 0.85$).

The high intraclass correlation ($ICC = 0.90$) demonstrates that the location-level effects are highly important in predicting the pleasantness dimension. Within this random-intercept random-slope model structure, these effects include both the specific context of the location (i.e. the LocationID factor), but also the L_{Aeq}, $L_{A10} - L_{A90}$, and $L_{Ceq} - L_{Aeq}$ features whose effects vary across locations. These slopes are given in Figure 3. This point highlights the need to consider how the context of a location will influence the relationship between the acoustic features and the perceived pleasantness.

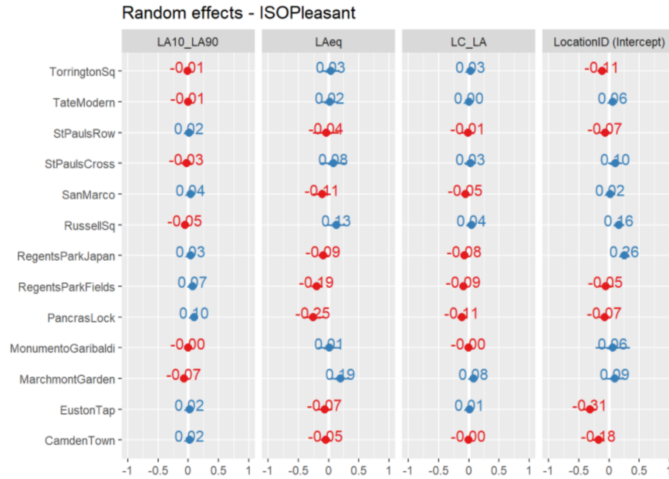

FIG. 3. Location-level scaled coefficients for the ISOPleasant model.

2. ISOEventful Model Selected

Through the group-level feature selection, all of the group-level coefficients were removed, including the LocationID factor itself. Therefore the final ISOEventful model is a 'flat' multi-variate linear regression model, rather than a multi-level model. The ISOEventful model is a linear combination of S, FS, T, L_{Aeq}, and $L_{Ceq} - L_{Aeq}$. The training and testing MAE are very similar, indicating that the model is not over-fit to the training data ($MAE_{train} = 0.233$; $ME_{test} = 0.231$). The model performs slightly worse than the ISOPleasant at predicting the mean location responses, but still performs well ($R^2_{train} = 0.873$; $R^2_{test} = 0.715$).

3. Application to Lockdown data

Once the two models were built and assessed, they were then applied to the lockdown recording data in order to predict the new soundscape ISO coordinates. Figure 4(a) shows the pre–lockdown ISO coordinates for each location and Figure 4(b) shows how the soundscapes are predicted to have been assessed during the lockdown period. As in the model assessment process, the predicted responses are calculated for each recording individually, then the mean for each location is calculated and plotted on the circumplex.

In 2019 the majority of locations in the dataset fall within the 'vibrant' quadrant of the circumplex, particularly those which are primarily dominated by human activity (e.g. San Marco, Tate Modern). Camden Town and Euston Tap, which are both in general visually and acoustically dominated by traffic, are the only two to be rated as 'chaotic', while no locations are overall considered to be 'monotonous'. During the 2020 lockdown, there is general positive move along the 'pleasant' dimension and general negative move along the 'eventful' dimension, but several different patterns of movement

TABLE IV. Scaled linear regression models of ISOPleasant and ISOEventful for 13 locations in London and Venice. The ISOPleasant model is a multi-level regression model with one level for individual effects and a second level for LocationID effects, while the ISOEventful model is a 'flat' multi-variate linear regression with no location effects.

	ISOPleasant			**ISOEventful**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.24	0.15 - 0.33	**<0.001**	0.14	0.12 - 0.16	**<0.001**
N_5	-0.06	-0.10 - -0.02	**<0.001**			
S				-0.08	-0.11 - -0.06	**<0.001**
FS				-0.02	-0.05 - -0.00	**0.033**
T				0.04	0.01 - 0.07	**0.002**
L_{Aeq}				0.14	0.11 - 0.17	**<0.001**
$L_{Ceq} - L_{Aeq}$				-0.03	-0.05 - 0.00	0.052
Random Effects						
σ^2	0.11					
τ_{00}	$0.03_{LocationID}$					
τ_{11}	$0.02_{LocationID.L_{Aeq}}$					
	$0.00_{LocationID.L_{A10}-L_{A90}}$					
	$0.00_{LocationID.L_{Ceq}-L_{Aeq}}$					
ICC	0.90					
N	$13_{LocationID}$					
Observations	914			914		
MAE Test, Train	0.259	0.259		0.233	0.231	

can be noted. These are investigated further in the Discussion section below.

IV. DISCUSSION

A. Implications: Model selection results

The application of the model reflected the two expected general connections: 1) the reduction in human sound sources leads to lower eventfulness and 2) the reduction in level leads to increased pleasantness. Further, the analyses of the model structure reveals the amount in which auditory and non-auditory factors contribute to soundscape.

The most immediately interesting result of the model-building and feature selection process is the apparent irrelevance of location context to the ISOEventful dimension. The multilevel model structure was chosen since the starting assumption was that soundscape perception is heavily influenced by contextual factors, such as expectations of the space and visual context (references). For this modelling, these factors can be considered as location-level latent variables at least partially accounted for by the inclusion of the LocationID as the second-level factor. While this assumption certainly held true for ISOPleasant, our results indicate that these types of contextual factors are not significant for ISOEventful, and do not affect the relationship between the acoustic features of the sound and the perception.

In particular this result may herald a shift in modelling approach for soundscapes – where previous methods, in both the soundscape and noise paradigms, have mostly focused on deriving acoustic models of annoyance (in other words have focused on the ISOPleasant dimension) perhaps they should instead consider the acoustic models as primarily describing the eventfulness dimension when considered in situ. In addition this study takes the approach of modelling responses at an individual level in order to derive the soundscape assessment of the location. Rather than either attempting represent the predicted response of an individual person – which is less useful in this sort of practical application – or to base the model on average metrics of the location, the goal is instead to characterise the location itself, through the aggregated predicted responses of individuals. The authors believe this modelling approach better addresses the practical goal of predictive soundscape modelling and reflects the structure of the data collection.

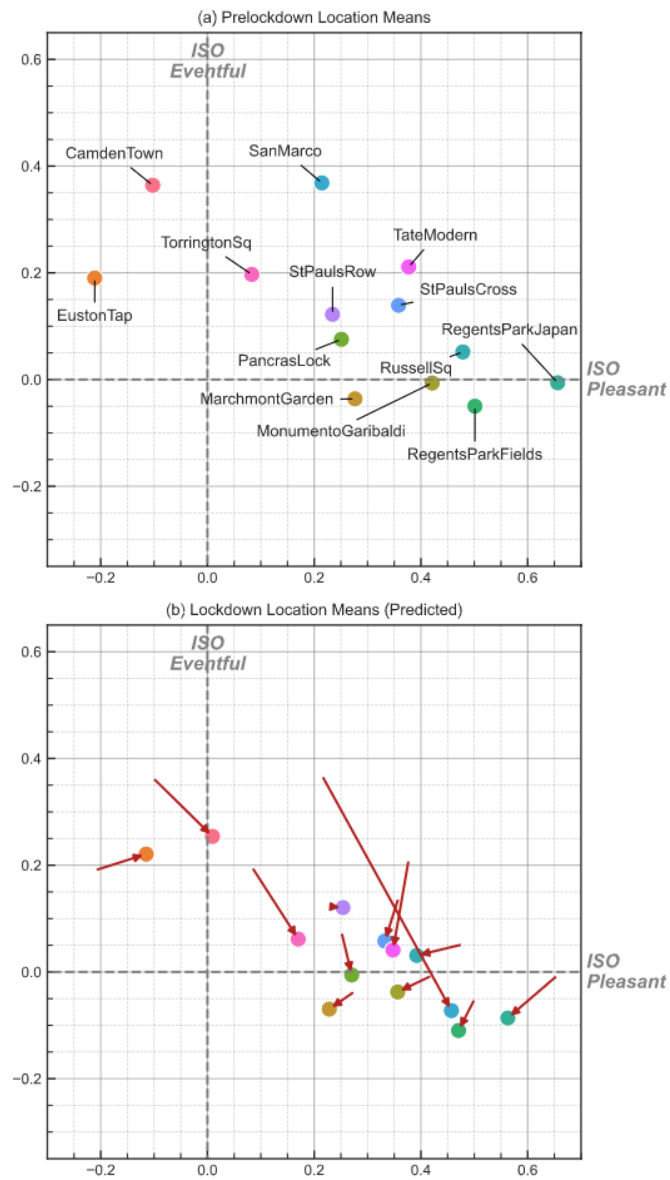

FIG. 4. Soundscape circumplex coordinates for (a) the mean ISOPleasant and ISOEventful responses for each location; and (b) the mean predicted responses based on recordings made during the lockdown and the location's movement in the circumplex.

B. Interpretation of the results

1. Change in the soundsource composition

The open-ended question about sound sources hasn't revealed a change in sound source types but rather confirmed that all types were still present in both conditions. The sound source composition question taken from the Method A of the International Organisation for Standardization (2018) revealed a statistically significant reduction in human sound sources and a significant increase in the perceived dominance of natural sound sources. (This has implications for the ISO 12913 series.)

The most frequent sound sources detected from the open-ended question correspond to the main four sound source types investigated, which indicated that all types remained present in the lockdown condition (at all the locations). While traffic intensity might have gone down, where the results of the Mann-Whitney U-test were inconclusive, but supported by the psychoacoustic measurements (Aletta *et al.*, 2020), traffic-related sound sources were still clearly present.

Sound source composition of an outdoor acoustic environment is extremely complex. Removing one component from it, such as human sounds, has implications on the whole (Gordo *et al.*, 2021). Testing this in the wild is not straight forward. Therefore, interpreting this study in line with 'what is the impact of human sounds' needs to be taken with a grain of salt as this was not the only condition that changed and it is likely that it triggered other changes itself. However, looking at the overarching picture, the lockdown condition was the perfect case study of this 'what happens if' kind of exercise to understand the impact human activities can have on soundscape perception of urban open spaces.

2. Movement of soundscapes

In order to interpret how the change of the acoustic environment at the locations examined would have been perceived, and to answer RQ2, movement vectors within the circumplex space are shown in Figure 5. This clearly shows a few different patterns of movement due to the effects of the 2020 lockdown. These can be further looked into depending on 1) the magnitude of change; 2) the direction of change; 3) shift between the quadrants shown in Figure 4; 4) sound source composition.

The largest change is seen in Piazza San Marco, with a predicted increase in pleasantness of 0.24 and a decrease in eventfulness of 0.44, enough to move the soundscape out of the 'vibrant' quadrant and into 'calm'. This extreme change (relative to the rest of the locations) is exactly what would be expected given the unique context of the measurements taken in 2019 – the measurement campaign corresponded with Carnevale, a yearly festival which centres around the square. By contrast, due to the particularly strict measures imposed in Italy, during the lockdown measurement period, the square was almost entirely devoid of people. What is promising is that, without any of this contextual information about the presence or absence of people, our model is able to capture and reflect what may be considered a reasonable and expected direction and scale of movement within the soundscape circumplex.

The next locations of interest are those which, in the 2019 survey data, were rated as being dominated by traffic noise: Euston Tap, Camden Town, Torrington Square, and Pancras Lock. These are the only locations (besides San Marco) which show a predicted increase in pleasantness. Of these traffic-dominated spaces, the two which were most heavily dominated by traffic noise (Camden

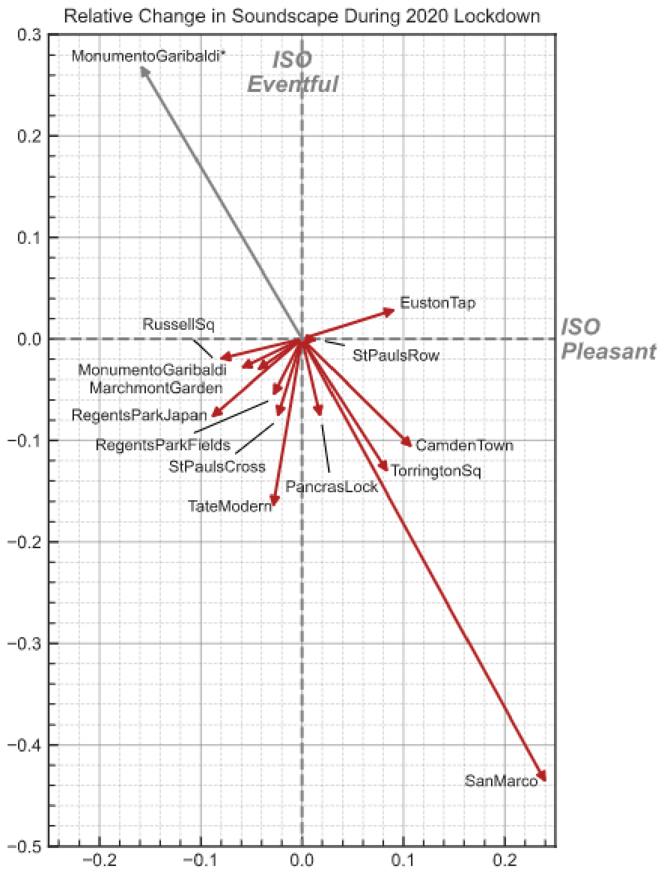

FIG. 5. The relative movement of soundscape perception in the circumplex due to the COVID-19 lockdowns, represented as vectors centred on the origin. *The lawn mower dominated session is shown separately as MonumentoGaribaldi* with a grey arrow to indicate that this is distinct from the effects of the lockdown changes.

Town and Euston Tap) showed the most increase in pleasantness, with Torrington Square having slightly less of an increase. Pancras Lock, which was also rated as having high levels of both Human and Natural sounds shows only a modest improvement in pleasantness.

Among the locations which are predicted to experience a negative effect on pleasantness we see a mix of spaces which were assessed as being dominated by Human (St Pauls Cross and Tate Modern) and Natural (Regents Park Japan, Regents Park Fields, Russell Square) sounds before the lockdown. It is hard to discern a pattern of difference between these two groups, although it appears that the Human-dominated spaces saw a greater reduction in eventfulness, compared to the Natural-dominated spaces.

In general, we note that most of the spaces experience some degree of reduction in eventfulness. This pattern is particularly consistent with what would be expected from a reduction in human presence in these spaces (Aletta and Kang, 2018), as reflected by the observation that, in general, those spaces which had the most human sounds prior to the lockdown showed the greatest reduction in eventfulness during the lockdown.

An unexpected result is that Euston Tap is predicted to experience an increase in eventfulness and it is unclear whether this accurately reflects the real experience people would have had in the space. Normally, Euston Tap is a mostly-outdoor drinking venue located at the entrance to the Euston Train station and situated directly along a very busy central London road. During the 2020 survey, the researchers noted that the music and chatter of people from the pub was noticeably missing, but that the perceived reduction in road traffic was minimal. Based on the theory of vibrancy which would suggest it is driven by human presence and sounds (Aletta and Kang, 2018), we would not therefore expect a shift in the vibrant direction as indicated here. This discrepancy may reveal a weakness in the context-independent ISOEventful model, or it may in fact be indicating that, at certain thresholds of traffic noise, a reduction in level – and therefore a reduction in energetic masking – will allow other aspects of the sound to influence the perception.

Finally, special attention should be paid to the results shown for Monumento Garibaldi, which in 2019 was perceived as a pleasant and slightly calm green space featuring a gravel walkway. During the first measurement session during the lockdown in 2020, the researcher noted that the soundscape was dominated by landscaping works, in particular noise from strimmers (or weed whackers). In order to gain a sample which was more representative of the impact of the lockdowns, the researcher returned another day to repeat the measurements without interference from the works.

To examine the impact of these two scenarios separately, the prediction model was fitted to the data from the two sessions independently and the session which was impacted by the landscaping works is shown in Figure 5 in gray and labelled MonumentoGaribaldi*, while the unaffected session is shown in red. In the latter case, the predicted change in soundscape as a result of the lockdown fits neatly into what would be expected and closely matches the predicted behaviour of similar locations in London (i.e. Marchmont Garden and Russell Square). On the other hand, the session which was dominated by noise from the strimmers is predicted to have become much more chaotic, with a decrease in pleasantness of 0.16 and an increase in eventfulness of 0.27. This indicates that, although the model has no contextual information about the type of sound and in fact the training data never included sounds from similar equipment, just based on the psychoacoustic features of the sound it is able to reasonably predict the expected change in soundscape.

As a whole, the primary impact of the 2020 lockdowns on the soundscapes in London and Venice was an overall decrease in eventfulness. With the exception of Euston Tap, all of the sessions show some degree of reduction in eventfulness, reflecting the general decrease in sound levels and human sound sources across the locations. The impact of the lockdowns on pleasantness is more mixed and less directly related to the overall sound level reductions.

C. Limitations of the study

The onsite sampling method was initially not intended as the ultimate characterisation of a location's soundscape but rather as a tool for model development. Therefore, the change observed does not necessarily represent the ground truth about the site's soundscape, if such a thing exists. Further, the online listening tests took a relatively small but random sample from the available database and haven't included any contextual information. This proved to be sufficient for the purpose of detecting a change in sound source composition, however the relatively small sample of recordings included in the online study does limit how representative they are of the location's sound environment as a whole.

The surveys and recordings taken represent only a snapshot of the soundscape or sound environment for a short period in time. This is a flaw in most soundscape sampling methods presented both in the literature and in ISO/TS 12913-2. To truly be said to characterise the soundscape of a space, long-term monitoring and survey methods will need to be developed in order to capture the changing environmental and contextual conditions in the space. Models of the sort presented here, which are based on measurable quantities, could prove to be useful in this sort of longterm monitoring as they could take continuous inputs from sensors and generate the likely soundscape assessment over time.

Further, the lockdown condition is likely to cause distortions of the circumplex soundscape perception model. Therefore, it is important to acknowledge that all the predictions were made for the people with no experience of the pandemic and its psychological effects. Future research might look into potential perception changes in the post-pandemic world.

V. CONCLUSION

This study demonstrates an application of predictive modelling to the field of soundscape studies. The model building results reveal that, within this dataset, an approach based on psychoacoustics can achieve $R^2 = 0.85$ for predicting the pleasantness of locations and $R^2 = 0.715$ for predicting the eventfulness. A modelling-focused method of this sort is a key component to the potential scalability of the soundscape approach to applications such as smart city sensing, urban planning, and cost-effective, sustainable design. To demonstrate the usefulness and feasibility of such an approach, we apply our predictive model to a unique case study in which traditional soundscape survey methods were impossible.

By applying this predictive model to recordings collected during the 2020 lockdown, the change in perception of the urban soundscapes is revealed. In general, soundscapes became less eventful, and those locations which were previously dominated by traffic noise became more pleasant. By contrast, previously human- and natural-dominated locations are in fact predicted to become less pleasant despite the decrease in sound levels. Although these results are limited in that they represent one snapshot of the soundscape of the spaces, the success of the model in responding to new and disturbing sound events demonstrates its potential usefulness in long-term monitoring of urban soundscapes.

The findings of this study confirm that the impacts of noise level and sound source reductions vary according to the character of the urban space. Therefore, different soundscape design aims need to be set for different types of urban open spaces, depending on the sound source composition and context. In addition, this study demonstrates the potential of predictive soundscape models based on objective acoustic features for the assessment and design of urban spaces.

ACKNOWLEDGMENTS

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (Grant Agreement No. 740696, project title: Soundscape Indices – SSID). More information and related publications can be found at the CORDIS webpage of the project: https://cordis.europa.eu/project/rcn/211802/factsheet/en.

The authors would like to thank Zhongzhe Li for conducting binaural recordings at Euston Station and Torrington Square in 2019. The authors would like to thank Meihui, Nicolas Assiotis, Veronica Rugeles Allan, Yu Wang and Hua Su for their help in conducting on-site surveys during the spring and the autumn of 2019.

On-site study data were collected and managed using REDCap electronic data capture tools hosted at University College London (UCL).

APPENDIX A: ONLINE QUESTIONNAIRE

APPENDIX B: MODEL RESULTS

Table VI presents the unscaled coefficients for the ISOPleasant and ISOEventful predictive models. The scaled coefficients are presented in the body of the text to facilitate comparisons between the various factors. However, we feel it is important to present unscaled coefficients such that these models could be implemented and compared for future work.

(**2013**). "World Medical Association Declaration of Helsinki: Ethical Principles for Medical Research Involving Human Subjects," JAMA **310**(20), 2191, http://jama.jamanetwork.com/article.aspx?doi=10.1001/jama.2013.281053, doi: 10.1001/jama.2013.281053 number: 20.

TABLE V. Questionnaire deployed via the Gorilla Experiment Builder

Q1	**While listening, please note any sound sources you can identify in this sound environment:**
Q2	**To what extent have you heard the following four types of sounds?**
	Traffic noise (e.g. cars, buses, trains, airplanes)
	Not at all / A little / Moderately / A lot / Dominates completely
	Other noise (e.g. sirens, construction, industry, loading of goods)
	Not at all / A little / Moderately / A lot / Dominates completely
	Sounds from human beings (e.g. conversation, laughter, children at play, footsteps)
	Not at all / A little / Moderately / A lot / Dominates completely
	Natural sounds (e.g. singing birds, flowing water, wind in vegetation)
	Not at all / A little / Moderately / A lot / Dominates completely

Aiello, L. M., Schifanella, R., Quercia, D., and Aletta, F. (**2016**). "Chatty maps: constructing sound maps of urban areas from social media data," Royal Society Open Science **3**(3), 150690, https://royalsocietypublishing.org/doi/10.1098/rsos.150690, doi: 10.1098/rsos.150690 number: 3.

Akaike, Hirotugu (**1974**). "A New Look at the Statistical Model Identification," IEEE Transactions on Automatic Control **19**(6), 716–723 number: 6.

Aletta, F., Axelsson, Ö., and Kang, J. (**2017**). "Dimensions underlying the perceived similarity of acoustic environments," Frontiers in Psychology **8**(JUL), 1–11, doi: 10.3389/fpsyg.2017.01162.

Aletta, F., and Kang, J. (**2018**). "Towards an Urban Vibrancy Model: A Soundscape Approach," International Journal of Environmental Research and Public Health **15**(8), 1712, http://www.mdpi.com/1660-4601/15/8/1712, doi: 10.3390/ijerph15081712 number: 8.

Aletta, F., Kang, J., and Axelsson, Ö. (**2016**). "Soundscape descriptors and a conceptual framework for developing predictive soundscape models," Landscape and Urban Planning **149**, 65–74, doi: 10.1016/j.landurbplan.2016.02.001.

Aletta, F., Oberman, T., Mitchell, A., Tong, H., and Kang, J. (**2020**). "Assessing the changing urban sound environment during the COVID-19 lockdown period using short-term acoustic measurements," Noise Mapping **7**(1), 123–134, https://www.degruyter.com/view/journals/noise/7/1/article-p123.xml, doi: 10.1515/noise-2020-0011 number: 1.

Alsina-Pagès, R. M., Bergadà, P., and Martínez-Suquía, C. (**2021**). "Changes in the soundscape of Girona during the COVID lockdown," The Journal of the Acoustical Society of America **149**(5), 3416–3423, https://asa.scitation.org/doi/10.1121/10.0004986, doi: 10.1121/10.0004986 number: 5.

Anwyl-Irvine, A. L., Massonnié, J., Flitton, A., Kirkham, N., and Evershed, J. K. (**2020**). "Gorilla in our midst: An online behavioral experiment builder," Behavior research methods **52**(1), 388–407.

Asensio, C., Aumond, P., Can, A., Gascó, L., Lercher, P., Wunderli, J.-M., Lavandier, C., de Arcas, G., Ribeiro, C., Muñoz, P., and Licitra, G. (**2020**). "A Taxonomy Proposal for the Assessment of the Changes in Soundscape Resulting from the COVID-19 Lockdown," International Journal of Environmental Research and Public Health **17**(12), 4205, https://www.mdpi.com/1660-4601/17/12/4205, doi: 10.3390/ijerph17124205 number: 12.

Axelsson, , Nilsson, M. E., and Berglund, B. (**2010**). "A principal components model of soundscape perception," The Journal of the Acoustical Society of America **128**(5), 2836–2846, http://asa.scitation.org/doi/10.1121/1.3493436, doi: 10.1121/1.3493436 number: 5.

Bartalucci, C., Bellomini, R., Luzzi, S., Pulella, P., and Torelli, G. (**2021**). "A survey on the soundscape perception before and during the COVID-19 pandemic in Italy," Noise Mapping **8**(1), 65–88, https://www.degruyter.com/document/doi/10.1515/noise-2021-0005/html, doi: 10.1515/noise-2021-0005 number: 1.

Bonet-Solà, D., Martínez-Suquía, C., Alsina-Pagès, R. M., and Bergadà, P. (**2021**). "The Soundscape of the COVID-19 Lockdown: Barcelona Noise Monitoring Network Case Study," International Journal of Environmental Research and Public Health **18**(11), 5799, https://www.mdpi.com/1660-4601/18/11/5799, doi: 10.3390/ijerph18115799 number: 11.

Erfanian, M., Mitchell, A., Aletta, F., and Kang, J. (**2020**). "Psychological Well-being, Age and Gender can Mediate Soundscapes Pleasantness and Eventfulness: A large sample study," preprint , http://biorxiv.org/lookup/doi/10.1101/2020.10.16.341834, doi: 10.1101/2020.10.16.341834.

European Environment Agency. (**2020**). *Environmental noise in Europe, 2020.* (Publications Office, LU), https://data.europa.eu/doi/10.2800/686249.

Genuit, K. (**1996**). "Objective evaluation of acoustic quality based on a relative approach," in *Proceedings-Institute of Acoustics*, Vol. 18, pp. 3233–3238, iSBN: 0309-8117.

Gontier, F., Lavandier, C., Aumond, P., Lagrange, M., and Petiot, J.-F. (**2019**). "Estimation of the Perceived Time of Presence of Sources in Urban Acoustic Environments Using Deep Learning Techniques," Acta Acustica united with Acustica **105**(6), 1053–1066, https://www.ingentaconnect.com/content/10.3813/AAA.919384, doi: 10.3813/AAA.919384 number: 6.

Gordo, O., Brotons, L., Herrando, S., and Gargallo, G. (**2021**). "Rapid behavioural response of urban birds to COVID-19 lockdown," Proceedings of the Royal Society B: Biological Sciences **288**(1946), 20202513, https://royalsocietypublishing.org/doi/10.1098/rspb.2020.2513, doi: 10.1098/rspb.2020.2513 number: 1946.

Hadjidemetriou, G. M., Sasidharan, M., Kouyialis, G., and Parlikad, A. K. (**2020**). "The impact of government measures and human mobility trend on COVID-19 related deaths in the UK," Transportation Research Interdisciplinary Perspectives **6**, 100167, https://linkinghub.elsevier.com/retrieve/pii/S2590198220300786, doi: 10.1016/j.trip.2020.100167.

International Organisation for Standardization (**2014**). "ISO 12913-1:2014 Acoustics — Soundscape — Part 1: Definition and conceptual framework" https://www.iso.org/standard/52161.html.

International Organisation for Standardization (**2018**). "ISO/TS 12913-2:2018 Acoustics — Soundscape — Part 2: Data collection and reporting requirements" https://www.iso.org/standard/75267.html.

International Organisation for Standardization (**2019**). "ISO/TS 12913-3:2019 Acoustics — Soundscape — Part 3: Data analysis" https://www.iso.org/standard/69864.html.

Kajihara, Y., Dozono, S., and Tokui, N. (**2017**). "Imaginary Soundscape: Cross-Modal Approach to Generate Pseudo Sound Environments," in *31st Conference on Neural Information Processing Systems*, Long Beach, CA, USA, https://nips2017creativity.github.io/doc/Imaginary_Soundscape.pdf.

Kang, J. (**2007**). *Urban sound environment* (Taylor & Francis, London ; New York), oCLC: ocm65301511.

Kang, J., and Aletta, F. (**2018**). "The Impact and Outreach of Soundscape Research," Environments **5**(5), 58, http://www.mdpi.com/2076-3298/5/5/58, doi: 10.3390/environments5050058.

Lee, P. J., and Jeong, J. H. (**2021**). "Attitudes towards outdoor and neighbour noise during the COVID-19 lockdown: A case study in London," Sustainable Cities and Society **67**, 102768, https://linkinghub.elsevier.com/retrieve/pii/S2210670721000603, doi: 10.1016/j.scs.2021.102768.

Lenzi, S., Sádaba, J., and Lindborg, P. (**2021**). "Soundscape in Times of Change: Case Study of a City Neighbourhood During the COVID-19 Lockdown," Frontiers in Psychology **12**, 570741, https://www.frontiersin.org/articles/10.3389/fpsyg.2021.570741/full, doi: 10.3389/fpsyg.2021.570741.

Lionello, M., Aletta, F., and Kang, J. (**2020**). "A systematic review of prediction models for the experience of urban soundscapes," Applied Acoustics **170**, 107479, https://linkinghub.elsevier.com/retrieve/pii/S0003682X20305831, doi: 10.1016/j.apacoust.2020.107479.

TABLE VI. Unscaled linear regression models of ISOPleasant and ISOEventful for 13 locations in London and Venice.

	ISOPleasant			**ISOEventful**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.39	0.28 - 0.50	**<0.001**	-0.77	-1.05 - -0.48	**<0.001**
N_5	-0.01	-0.01 - -0.00	**<0.001**			
S				-0.17	-0.23 - -0.12	**<0.001**
FS				-1.36	-2.61 - -0.11	**0.033**
T				0.24	0.08 - 0.39	**0.002**
L_{Aeq}				0.02	0.02 - 0.02	**<0.001**
$L_{Ceq} - L_{Aeq}$				-0.01	-0.02 - 0.00	0.052
Random Effects						
σ^2	0.11					
τ_{00}	$1.01_{LocationID}$					
τ_{11}	$0.00_{LocationID.L_{Aeq}}$					
	$0.00_{LocationID.L_{A10}-L_{A90}}$					
	$0.00_{LocationID.L_{Ceq}-L_{Aeq}}$					
ICC	0.90					
N	$13_{LocationID}$					
Observations	914			914		

Lionello, M., Aletta, F., Mitchell, A., and Kang, J. (**2021**). "Introducing a Method for Intervals Correction on Multiple Likert Scales: A Case Study on an Urban Soundscape Data Collection Instrument," Frontiers in Psychology **11**, 602831, https://www.frontiersin.org/articles/10.3389/fpsyg.2020.602831/full, doi: 10.3389/fpsyg.2020.602831.

Manzano, J. V., Pastor, J. A. A., Quesada, R. G., Aletta, F., Oberman, T., Mitchell, A., and Kang, J. (**2021**). "The "sound of silence" in Granada during the COVID-19 lockdown," Noise Mapping **8**(1), 16–31, https://www.degruyter.com/document/doi/10.1515/noise-2021-0002/html, doi: 10.1515/noise-2021-0002 number: 1.

McKnight, P. E., and Najab, J. (). "Mann-whitney u test," in *The Corsini Encyclopedia of Psychology*, edited by I. B. Weiner and W. E. Craighead (John Wiley & Sons, Inc.), p. corpsy0524, http://doi.wiley.com/10.1002/9780470479216.corpsy0524, doi: 10.1002/9780470479216.corpsy0524.

Mitchell, A., Oberman, T., Aletta, F., Erfanian, M., Kachlicka, M., Lionello, M., and Kang, J. (**2020**). "The Soundscape Indices (SSID) Protocol: A Method for Urban Soundscape Surveys—Questionnaires with Acoustical and Contextual Information," Applied Sciences **10**(7), 2397, https://www.mdpi.com/2076-3417/10/7/2397, doi: 10.3390/app10072397 number: 7.

Munoz, P., Vincent, B., Domergue, C., Gissinger, V., Guillot, S., Halbwachs, Y., and Janillon, V. (**2020**). "Lockdown during COVID-19 pandemic: impact on road traffic noise and on the perception of sound environment in France," Noise Mapping **7**(1), 287–302, https://www.degruyter.com/document/doi/10.1515/noise-2020-0024/html, doi: 10.1515/noise-2020-0024 number: 1.

Orga, F., Mitchell, A., Freixes, M., Aletta, F., Alsina-Pagès, R. M., and Foraster, M. (**2021**). "Multilevel annoyance modelling of short environmental sound recordings," Sustainability **13**(11), https://www.mdpi.com/2071-1050/13/11/5779, doi: 10.3390/su13115779.

Radicchi, A., Cevikayak Yelmi, P., Chung, A., Jordan, P., Stewart, S., Tsaligopoulos, A., McCunn, L., and Grant, M. (**2021**). "Sound and the healthy city," Cities & Health **5**(1-2), 1–13, https://www.tandfonline.com/doi/full/10.1080/23748834.2020.1821980, doi: 10.1080/23748834.2020.1821980.

Rumpler, R., Venkataraman, S., and Göransson, P. (**2021**). "Noise measurements as a proxy to evaluating the response to recommendations in times of crisis: An update analysis of the transition to the second wave of the CoViD-19 pandemic in Central Stockholm, Sweden," The Journal of the Acoustical Society of America **149**(3), 1838–1842, https://asa.scitation.org/doi/10.1121/10.0003778, doi: 10.1121/10.0003778 number: 3.

Tarlao, C., Steffens, J., and Guastavino, C. (**2021**). "Investigating contextual influences on urban soundscape evaluations with structural equation modeling," Building and Environment **188**, 107490, https://linkinghub.elsevier.com/retrieve/pii/S036013232030857X, doi: 10.1016/j.buildenv.2020.107490.

Torresin, S., Albatici, R., Aletta, F., Babich, F., Oberman, T., Siboni, S., and Kang, J. (**2020**). "Indoor soundscape assessment: A principal components model of acoustic perception in residential buildings," Building and Environment **182**, 107152, https://linkinghub.elsevier.com/retrieve/pii/S0360132320305266, doi: 10.1016/j.buildenv.2020.107152.

Truax, B. (**1999**). *Handbook for Acoustic Ecology* (Cambridge Street Publishing, Cambridge, MA), https://www.sfu.ca/sonic-studio-webdav/handbook/index.html.

Woods, K. J. P., Siegel, M. H., Traer, J., and McDermott, J. H. (**2017**). "Headphone screening to facilitate web-based auditory experiments," Attention, Perception, & Psychophysics **79**(7), 2064–2072, http://link.springer.com/10.3758/s13414-017-1361-2, doi: 10.3758/s13414-017-1361-2 number: 7.

Zwicker, E., and Fastl, H. (**2007**). *Psychoacoustics: facts and models*, third ed. ed. (Springer, Berlin ; New York), https://link.springer.com/book/10.1007/978-3-540-68888-4.