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► **To cite this version:**

Pierre Aumond, Arnaud Can, Mathieu Lagrange, Felix Gontier, Catherine Lavandier. Multidimensional analyses of the noise impacts of COVID-19 lockdown. *Journal of the Acoustical Society of America*, 2022, 151 (2), pp.911-923. 10.1121/10.0009324 . hal-03584844v1

HAL Id: hal-03584844

<https://hal.science/hal-03584844v1>

Submitted on 2 Mar 2022 (v1), last revised 23 Feb 2022 (v2)

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Multidimensional analyses of the noise impacts of COVID-19 lockdown

Pierre AUMOND¹; Arnaud CAN¹; Mathieu LAGRANGE²; Felix GONTIER²; Catherine
LAVANDIER³

¹UMRAE, Univ Gustave Eiffel, IFSTTAR, CEREMA, F-44344 Bouguenais, France

²LS2N, UMR CNRS 6004, Ecole Centrale de Nantes, F-44321 Nantes, France;

³ETIS UMR 8051, CY Cergy Paris Univ, ENSEA, CNRS, F-95000, Cergy-Pontoise, France

ABSTRACT

As part of the ANR CENSE project, a questionnaire was sent in January 2019 to households in a 1 km² study area in the city of Lorient, France, to which about 318 responded. The main objective of this questionnaire was to collect information about the inhabitants' perception of the sound environments in their neighborhood, in their street, and in their dwelling. In the same study area, starting mid-2019, about 70 sensors were continuously positioned, and fifteen of them were selected for testing sound source recognition models. The French lockdown due to the COVID-19 crisis occurred during the project, and the opportunity was taken to send a second questionnaire during April 2020. About 31 of the first 318 first survey respondents answered to this second questionnaire. This unique longitudinal dataset, both physical and perceptual, allows us to undertake an analysis from different perspective of such a period. The analysis reveals the importance of integrating source recognition tools, soundscape observation protocol, in addition to physical level analysis, in order to accurately describe changes in the sound environment.

Keywords: Soundscape, Noise annoyance, covid-19 lockdown, sound recognition, holistic approach

I. INTRODUCTION

The emergence and the spread of Covid-19 pandemic from late 2019 to 2020 impacted all continents. It forced governments to undertake unprecedented social distancing measures to slowdown the virus propagation, from which the most emblematic was the lockdown imposed in a large number of countries in the spring of 2020. Severe restrictions on ground transportation and flights, as well as population lockdown measures, had an immediate and dramatic impact on urban activity and thus on sound environments. City dwellers in many cities around the world have collectively experienced a sudden reduction of noise levels, as well as a modification in the distribution of sound sources

¹ pierre.aumond@ifsttar.fr

31 dominating urban sound mixtures. Newspapers quickly reported on these sudden changes in urban
32 sound environments and their impact on perceptions (Bui and Badger, 2020). From a research point
33 of view, this unprecedented event questions the ways in which both the physical modifications in
34 urban sound environments during this period can be witnessed and objectified, as well as their
35 perception by populations. This question is crucial to understand the impact of such a crisis, which is
36 likely to modify perceptions and expectations regarding noise in the long term. It is also important in
37 order to propose protocols that are able to capture and understand the impact of slower and less
38 obvious modifications in sound environments.

39

40 Despite initiatives to homogenize observations such as the one proposed by Asensio *et al.* (Asensio,
41 Aumond, Can, Gascó, Lercher, Wunderli, Lavandier, de Arcas, Ribeiro, Muñoz, and Licitra, 2020),
42 the observation protocols in the recent literature on the topic of the change of sound environment due
43 to the Covid-19 lockdown are very disparate. We have chosen to refer to about 17 studies that we
44 consider to be the most representative.

45 First, cities equipped with noise measurement networks capturing continuously noise levels have
46 been quick to consistently point out the drop-in noise levels. An equivalent sound level reduction of
47 about 4 to 7 dB(A) has been reported on average in Rio (Gevú, Carvalho, Fagerlande, Niemeyer,
48 Cortês, and Torres, 2021), Montreal (Steele and Guastavino, 2021), Lyon (Munoz, Vincent, Domergue,
49 Gissing, Guillot, Halbwachs, and Janillon, 2020), Madrid (Asensio, Pavón, and de Arcas, 2020),
50 Milan (Zambon, Confalonieri, Angelini, and Benocci, 2021), Girona (Alsina-Pagès, Bergadà, and
51 Martínez-Suquía, 2021) or Paris (BRUITPARIF, 2020), based on 21 to more than a hundred fixed
52 sensors. Numerous short-term measurements were carried out in London in (Aletta, Oberman,
53 Mitchell, Tong, and Kang, 2020), through a series of 30-second binaural recordings pre-lockdown and
54 during-lockdown (481 samples) at 11 locations, which highlighted a similar tendency. This sound
55 level decrease is however not homogeneous in both space and time. The London study showed that
56 active areas were affected the most, followed by traffic-dominated areas and quiet areas. Similar
57 trends were found in Madrid, although less pronounced (Asensio, Pavón, and de Arcas, 2020) or into
58 the Brazilian study (Gevú, Carvalho, Fagerlande, Niemeyer, Cortês, and Torres, 2021), which
59 complements its measurements with modeling approach. These slight discrepancies between the two
60 studies may be due to a different classification between the site categories. The observed noise
61 decrease has even reached 20 dB(A) near work site areas and 30 dB(A) near airports in Paris
62 (BRUITPARIF, 2020), revealing the difference in the “lockdown sound experience” between
63 populations. In Montreal, special emphasis is being placed on dramatically reducing noise at festivals
64 and events in public spaces during the summer of 2020 (Steele and Guastavino, 2021). In Temporal
65 structures of sound environments were also impacted. Basu *et al.* showed that minimum hourly sound
66 levels $L_{\min,1h}$ dramatically decreased, which were attributed to reductions in both road and air traffic
67 movements (Basu, Murphy, Molter, Sarkar Basu, Sannigrahi, Belmonte, and Pilla, 2021). In Madrid,
68 Asensio *et al.* showed a significant variation in the daily noise patterns, with the activity starting

69 earlier in the morning and decreasing significantly in the afternoon (Asensio, Pavón, and de Arcas,
70 2020).

71 While very useful for understanding which populations were most impacted by the reduction of
72 noise levels based on their residential location, and on a national scale based on government decisions,
73 these studies fail to qualify the modification of noise environments in terms of sound sources. The
74 shift in daily noise patterns observed in (Asensio, Pavón, and de Arcas, 2020) could for instance be
75 hypothesized as the result of the emergence in natural sound sources. In (Derryberry, Phillips,
76 Derryberry, Blum, and Luther, 2020), Derryberry *et al.* showed that white-crowned sparrows shifted
77 their song frequency, in response to the disappearance of traffic sounds, benefiting this new emptied
78 acoustic space in order to enhance communication. These results underline the importance of being
79 able to recognize the sources composing the sound mixtures within the sensor networks for a better
80 understanding of the balances between anthropogenic and biophonic sound sources. The Dynamap
81 project in Italy also studied the differences in sound environment caused by the lockdown due to
82 COVID-19 in Italy (period 2019 vs 2020) (Pagès, Alías, Bellucci, Cartolano, Coppa, Peruzzi,
83 Bisceglie, and Zambon, 2020). Their ANED (Anomalous Noise Events Detection) algorithm identifies
84 non-traffic related sounds using binary identifier classifications. It showed a distinct change in ANEs
85 during the night in Rome and, to a lesser extent, in Milan.

86 Studies based on perceptual approaches and questionnaires have also underlined the impact of the
87 lockdown on the perceived sound environments. In Argentina, a study of a thousand people showed
88 that most participants preferred the new acoustic environment, and especially in large cities, where
89 mechanical sounds dominate the sound environment (Maggi, Muratore, Gaetán, Zalazar-Jaime, Evin,
90 Pérez Villalobo, and Hinalaf, 2021). Analyses in noise complaints in London showed an increase in
91 noise complaints of 48%, mainly due to construction and neighborhood noise (Tong, Aletta, Mitchell,
92 Oberman, and Kang, 2021). In (Munoz, Vincent, Domergue, Gissinger, Guillot, Halbwachs, and
93 Janillon, 2020), (BRUITPARIF, 2020) and (Bartalucci, Bellomini, Luzzi, Pulella, and Torelli, 2021),
94 questionnaires were distributed to residents, spread respectively over the French and Italian countries.
95 The analysis of those questionnaires underlined the perceived modification in the sound environments,
96 namely a decrease in transportation and mechanical sound sources and an increase in natural sound
97 sources. Questions relative to the period before and during the lockdown period were answered
98 simultaneously. This could have introduced memory and cognitive biases. Finally, Lenzi *et al.*
99 provided a comprehensive analysis of the sound environment at one location in the city of Gexto,
100 based on audio recordings and annotations of perceived sounds, diary notes, and evaluation of
101 soundscape quality (Lenzi, Sádaba, and Lindborg, 2021). The study revealed that bioacoustic indices
102 such as eventfulness, acoustic complexity, and acoustic richness increased significantly over the
103 lockdown period, while the amount of technological sounds decreased.

104 While studies on noise levels on one side and studies on perception on the other side have their
105 respective merits, we believe that performing both at the same time and location can shed a new light
106 on the topic under study. For that purpose, in this paper, an innovative protocol is proposed to relate,

107 with a great level of detail, the physical and perceptual modifications of the sound environments
 108 during this period. It associates a measurement network coupled with an automatic sound source
 109 recognition module, and questionnaires distributed before and during lockdown. The objective here
 110 is not to define a universal characterization of the impact of lockdown, but to demonstrate the
 111 relevance of such a protocol to characterize such an event. The protocol of this study follows closely
 112 the recommendations described in the "triangulation" section of the ISO/TS 129313-3:2019
 113 soundscape standard, and aims to test/demonstrate its value.

114 This paper is organized as follows. Section 2 presents the questionnaires and the measurement
 115 network that includes a sound recognition module. Section 3 presents the perceptual analysis as well
 116 as the analyses of the sound levels and of the perceived time of presence for different sound sources.
 117 This section finishes with a cross analysis of those indicators. A discussion of these results is then
 118 given in Section 4.

119 II. MATERIAL AND METHODS

120 A. Questionnaire

121 During the second week of January 2019, a questionnaire was sent to approximately 2000
 122 households in a 1 km² wide study area in the city of Lorient, France. Until March 15, 2019, residents
 123 were allowed to return a paper version of the questionnaire or to complete it through a web platform.
 124 The questionnaire was designed to take about 20-25 minutes to complete and is composed of 5 sections
 125 detailed below. A second questionnaire was sent to participants of the first questionnaire during the
 126 lockdown period in 2020, from early April until mid of May. It was identical in every aspect
 127 concerning the first two sections. 318 people completed the first questionnaire and about 50 of these
 128 participants also completed the 2nd questionnaire (31 complete questionnaires).

129
 130 In the first section of the questionnaire, the respondents had first to assess the quality of the sound
 131 environment in their neighborhood and second in their street (when walking or cycling home). The
 132 evaluation relied on 5 bipolar semantic scales (7 levels) inspired by the Swedish protocol (Axelsson,
 133 Nilsson, and Berglund, 2012). Table 1 presents the French semantic elements as well as a proposal for
 134 translation into English.

135
 136 Table 1 – Elements of the bipolar scales (1 to 7). The last column corresponds to their codification

<i>Désagréable</i>	Unpleasant	<i>Agréable</i>	Pleasant	Pl
<i>Inerte, Amorphe</i>	Inert	<i>Animé, mouvementé</i>	Eventful	Ev
<i>Bruyant</i>	Noisy	<i>Silencieux</i>	Silent	Si
<i>Ennuyeux, Inintéressant</i>	Boring	<i>Stimulant, Intéressant</i>	Exciting	Ex
<i>Agité, Chaotique</i>	Chaotic	<i>Calme, Tranquille</i>	Calm	Ca

161 how much does
 162 - global noise
 163 - noise from (noise sources from Table 2)
 164 bother, disturb, or annoy you: Extremely, Very, Moderately, Slightly or Not at all?"

165
 166 In the third section of the questionnaire, four free paragraph boxes allowed respondents to share
 167 free expressions regarding remarkable environments (pleasant, unpleasant, conducive to walking and
 168 conducive to rest) of their neighborhood.

169
 170 In the fourth section of the questionnaire, personal information was collected: noise sensitivity of
 171 the inhabitants based on the 6-item Weinstein's noise sensitivity scale (WNSS) (Kishikawa, Matsui,
 172 Uchiyama, Miyakawa, Hiramatsu, and Stansfeld, 2006), gender, age, socio-professional category,
 173 membership (or not) to an association fighting against noise.

174
 175 In the fifth and last section of the questionnaire, residents were invited to provide information on
 176 where they live: the exact location, so that the questionnaires can be linked with the acoustic
 177 measurements or simulations made in the area, and a set of questions on housing type (Table 3).
 178

179 Table 3 – Questions about the housing of participants

Tenant / Owner	Courtyard or garden area? (yes/no)	Has quiet room? (yes /no)
House/Apartment	Living space overlooking the street? (yes/no)	Double glazing? (yes /no)
Time of occupancy? (<1 year, 1-3 year, >3 year)	Living space with a view on natural elements? (no, a little, a lot)	Insulation of the facade <10 years ago? (yes/no)

180
 181 Under this fifth section, the respondents also had to give their level of satisfaction (5 levels) on
 182 four dimensions:

- 183 • Acoustic insulation of their housing;
- 184 • To what extent they are globally satisfied with their (home/street/neighborhood) as a place to
 185 live.

186 More information can be found in the conference papers (Aumond, Can, and LAVANDIER, 2019;
 187 Aumond and Lavandier, 2019).

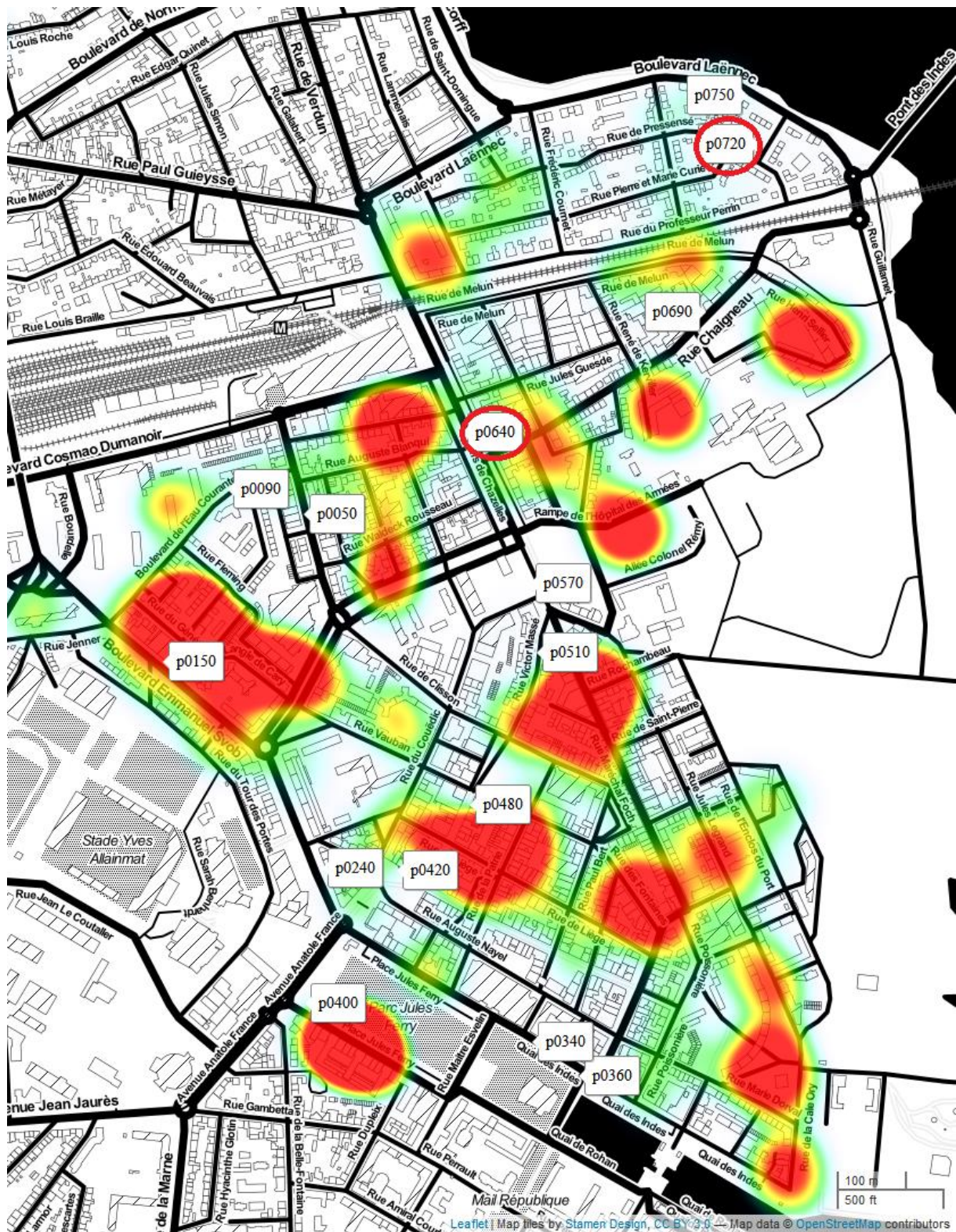
188 B. MEASUREMENT NETWORK

189 Specific low-cost noise monitoring sensors have been developed by the CENSE project in order to
 190 be integrated in a large measurement network (Ardouin, Baron, Charpentier, Ecotière, Fortin, Gontier,

191 Guillaume, Lagrange, Libouban, Picaut, and Ribeiro, 2021; Picaut, Can, Fortin, Ardouin, and
192 Lagrange, 2021). The complete network planned is 123 noise sensors with 70 sensors currently
193 connected to the cloud through a hybrid communication network based on wireless and public street
194 lamp network equipped with power-line communication systems. The sensors have been specifically
195 designed and developed to consider urban sound environment constraints. They transmit acoustic
196 indicators continuously thanks to wireless communications based on 802.15.4 modulation with
197 6LoWPAN MAC layer as described by IEEE RFC4944. The microphones used are MEMS
198 microphones, and recording and transmitting systems are based on STM32L4 microcontrollers or on
199 small single-board computers Raspberry-Pi. Real-time audio processing is included in both type of
200 sensors in order to perform the calculation of the $L_{Aeq,1s}$ and $L_{Zeq,1s}$ acoustic indicators, as well as the
201 acoustic spectrum every 125 ms, using third octave bands from 20 Hz to 12.5 kHz. The recording
202 sampling rate is 32 kHz.

203

204 In April 2020, about 70 sensors were installed in the study area. Among these sensors we
205 strategically select 15 of them that reliably transmitted data over the study periods and that are
206 spatially distributed to match the areas of living of the respondents of the questionnaires. To facilitate
207 the processing of the data, only the first 10 minutes of each hour is analysed under the assumption
208 suggested in (Brocolini, Lavandier, Quoy, and Ribeiro, 2013) that they are representative of the entire
209 homogeneous corresponding period. Figure 1 shows the comparison between the locations of the
210 measurement points (labelled pins) and the spatial distribution of the responses to the questionnaires
211 (heatmap).



212

213 Figure 1 – CENSE study area. Labels correspond to the selected sensors (n=15). Labels circled in red

214 correspond to the stations we focus on more during the analysis. The heat map displays the density of

215 responses to the questionnaire first call (n = 318).

216 C. SOUND RECOGNITION

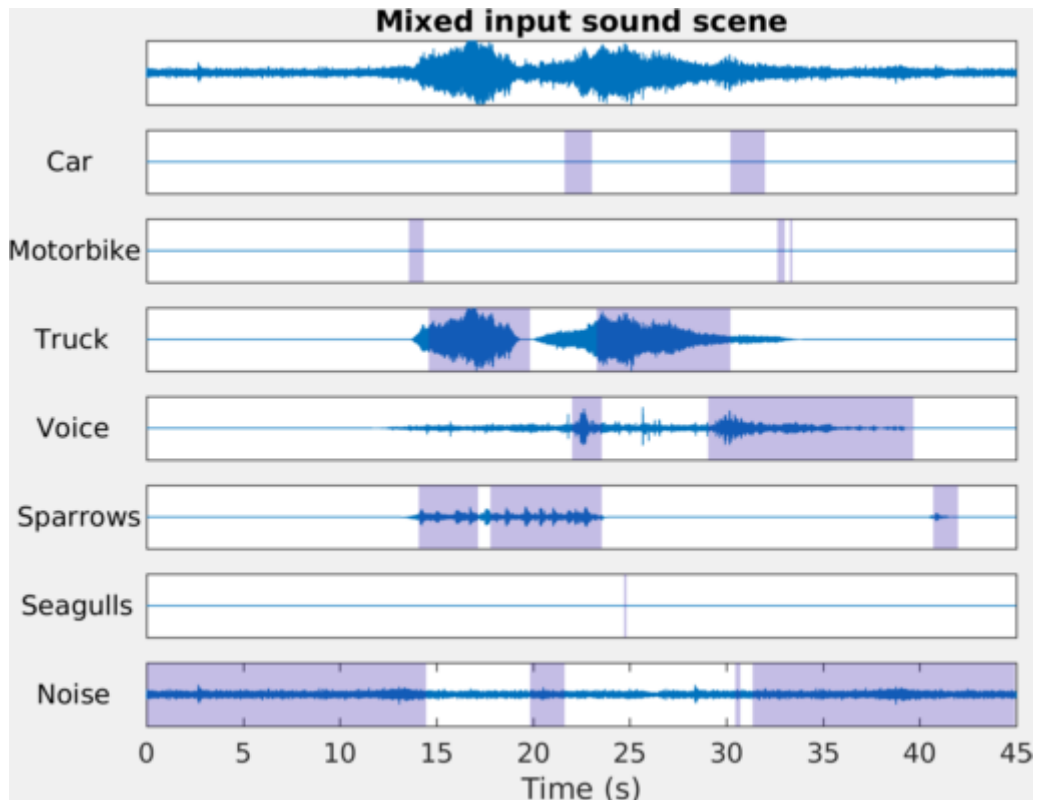
217 In addition to the analysis of subjective assessments and acoustic indicators, we investigated
218 variations in the content of sound environments through automatic sound source recognition.
219 Specifically, a deep neural network has been designed to identify cars, trucks, motorcycles, voices,
220 small birds, seagulls, and background noise activities from CENSE sensor measurements.

221
222 Source identification is conducted on short segments of 8 fast third-octave frames ($8 \times 125\text{ms} = 1\text{s}$).
223 To do so, a deep convolutional architecture first extracts time-frequency patterns relevant to the
224 identification of sound sources from each 1s third-octave segment. It is composed of 6 layers with
225 3×3 filters and 64, 64, 128, 128, 256, and 256 output channels respectively. Convolutional layers are
226 followed by batch normalization (Ioffe and Szegedy, 2015) and rectified linear unit activations.
227 Maximum pooling layers down sample the hidden representation in time and frequency by a factor of
228 2 after each set of two convolutional layers. Then, a single-layer gated recurrent unit (Cho, van
229 Merriënboer, Gulcehre, Bahdanau, Bougares, Schwenk, and Bengio, 2014) with 128 neurons draws
230 predictions on each 1s segment from the current output of the convolutional architecture as well as its
231 recurrent internal state, which aggregates past information. The step duration between subsequent 1s
232 segments processed by the network is 125ms. At inference, presence or absence labels predicted for
233 each sound source are averaged over time to obtain the time of presence in third-octave measurements
234 of arbitrary duration².

235
236 The model is trained on a fully synthetic set of 400 sound scenes of 45s each as described in
237 (Gontier, Lostanlen, FORTIN, Lagrange, Lavandier, and Petiot, 2021). Sound scenes are simulated
238 with the simScene Matlab library³ by combining background noise recordings and extracts
239 representing sound events from up to three sources of interest. The source categories, signal-to-noise
240 ratios, and inter-onsets characteristics of sound events are drawn semi-randomly from normal
241 distributions. The corresponding parameters, as well as the overall sound level of each scene, are
242 conditioned on a desired type of sound environment: quiet street, noisy street, very noisy street, park,
243 or square. All background and event extracts appearing in the synthetic training set are recorded in
244 the city of Lorient. The ground truth composition, i.e. separate channels for each active sound source,
245 is known for synthetic scenes. This enables automatically labeling source presence in order to train
246 the deep neural architecture in a supervised approach. Synthetic scene generation and automatic
247 annotation processes are further detailed in (Gontier, LAVANDIER, Aumond, Lagrange, and Petiot,
248 2019). Figure 2 shows an example of source identification by the trained model. Only the third-octave
249 spectrogram of the mixed scene (top) is visible to the network.

² The full code and databases will be made available upon publication

³ <https://bitbucket.org/mlagrange/simscene>



250

251 Figure 2 – Example of predicted source activity for a simulated sound scene. From the mixed scene (top),

252 the model infers the presence of seven sound sources along time (shaded areas). Separated waveform

253 contributions for each source are shown for illustrative purposes and are hidden to the predictor.

254

255 D. MATCHING MEASUREMENTS TO QUESTIONNAIRES

256 1. Temporal match

257

258 Table 4 represents the timeline of the different periods concerned by this study:

- 259 • The first questionnaire was sent out in early January 2019 and responses poured in until
- 260 early March 2019 (although most arrived within the first few weeks). This period will be
- 261 called hereafter Q1;
- 262 • The second questionnaire was sent out in early April 2020 and responses poured in until
- 263 mid-may 2020 (although most arrived within the first few weeks). This period will be
- 264 called hereafter Q2;
- 265 • Since the measurements from the sensors are only available since the end of 2019, we
- 266 chose the period between January 11 and February 11, 2020 as the "out of lockdown"
- 267 period called M1 and the period from April 11 to May 11, 2020 as the "during lockdown"
- 268 period called M2.

269

270 The analyses are done on the period out of lockdown called P1, which will relate results from the
 271 beginning of the year 2019 (Q1) to the beginning of the year 2020 (M1), assuming that the sound
 272 environments remain similar over these two time periods.

273 Table 4 - Timeline of the time periods considered in the study to gather data.

	January 2019	March 2019	January 2020	February 2020	March 2020	Mid of April 2020	Mid of May 2020
French Lockdown	Before Lockdown				After Lockdown		
Questionnaire	Q1					Q2	
Measurement			M1			M2	
Cross analysis	P1					P2	

274
 275 The period during the lockdown called P2 relates the responses to the questionnaires (Q2) to
 276 measurements (M2) over the same time period (April-May 2020).

277

278 2. Spatial match

279

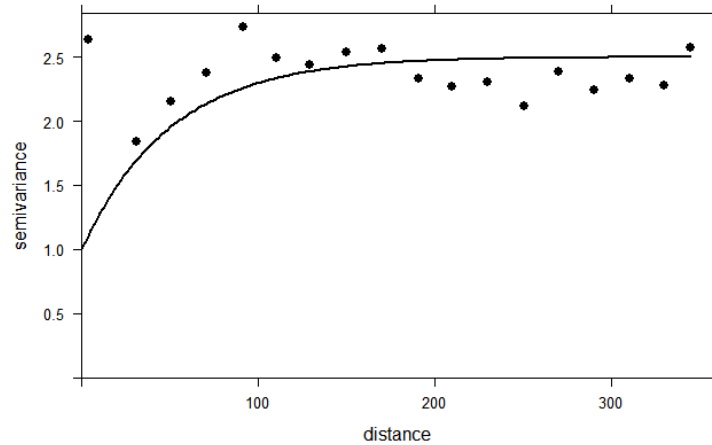
280 There are no direct spatial links that can be established between the sensors and the questionnaires,
 281 as the sensors were not positioned in the gardens or right in front of each house of the respondents.
 282 We thus propose to interpolate the results of the questionnaires and calculate an aggregated value for
 283 each of the sensor locations. For this purpose, a spatial Kriging algorithm is used, following the
 284 protocol used in (Aumond, Can, Mallet, De Coensel, Ribeiro, Botteldooren, and Lavandier, 2018).

285

286 The Kriging method is a well-known interpolation method that has been used in a variety of
 287 applications, particularly in the environmental field. It bears resemblance with classical data
 288 assimilation methods that have been applied to environmental forecasting, particularly at the urban
 289 scale for air pollution and noise pollution. The approach is relevant when a meaningful function can
 290 fit the empirical variogram of a value to interpolate. The variogram and kriging algorithms presented
 291 in this study are applied using the “variogram”, “vgm” and “gstat” functions of the “gstat” R package
 292 (Pebesma, 2004).

293

294 The parameter used to calculate the empirical variogram is the perceived sound level "Sil",
 295 evaluated in the first part of the questionnaire. The variogram is calculated over a distance of 350
 296 meters. The exponential covariance model is used to calculate the best fit of the experimental
 297 variogram. This regression curve fitting estimates the 3 following standard parameters: “nugget” (1.0),
 298 “range” (50 m), and “sill” (1.5). Figure 3 present the empirical variogram and the fitted curve.



299

300 Figure 3 – Empirical variogram of the “Sil” parameter along the Euclidian distance. The fitted parameters

301 are “nugget” (1.0), “range” (50 m), and “sill” (1.5).

302 III. RESULTS

303 A. PERCEPTUAL ANALYSIS

304 It can be expected that the lockdown had a drastic impact on the overall sound levels but also on
 305 the sound sources activity in the urban sound environment, and we expect that this impact can be
 306 measured from the gathered data. Table 5 shows the variation on their respective scales of a set of
 307 questionnaire variables between January 2019 and March 2020 (respectively Q1 and Q2). The
 308 statistical information is extracted from 2-sample nonparametric studentized permutation test for
 309 paired data (Brunner-Munzel test) from R package “nparcomp” (Konietschke, Placzek, Schaarschmidt,
 310 and Hothorn, 2015). The Brunner Munzel test (also called the Generalized Wilcoxon Test) is a non-
 311 parametric statistical test for stochastic equality of two samples. The null hypothesis for the test is H_0
 312 = 0.5, which implies stochastic equality. If the estimated relative effect “hat” is superior to 0.5, greater
 313 values occur in the second group and conversely.

314

315 Table 5. Brunner-Munzel Test (n=31-Q1/31-Q2) between Q1 and Q2; hat: estimated relative effect;
 316 Lower: Lower limit of the confidence interval; Upper: Upper limit of the confidence interval; T:
 317 studentized test statistic; p val: p-value for the hypothesis. *** p-value < 0.01, ** p-value < 0.05, *
 318 p-value < 0.1

	Lower	hat	Upper	T	p val		Lower	hat	Upper	T	p val
Brd	0,71	0,80	0,89	6,89	***	Pl	0,81	0,89	0,97	9,93	***
Tra	0,06	0,17	0,28	-6,11	***	Ex	0,49	0,64	0,80	1,87	**
CaV	0,32	0,44	0,57	-0,91		Ca	0,75	0,85	0,95	6,98	***
ExV	0,07	0,18	0,29	-6,03	***	Ev	0,07	0,17	0,27	-6,83	***
ChV	0,26	0,41	0,57	-1,15		Sil	0,73	0,83	0,94	6,38	***
Gul	0,43	0,57	0,71	1,01		Ad	0,60	0,71	0,82	3,66	***

2Wh	0,12	0,27	0,43	-3,01	***						
------------	------	------	------	-------	-----	--	--	--	--	--	--

319

320 As expected, we observe an important and significant decrease in the perceived sound level (Sil)
 321 as well as in the presence time of road traffic (Tra) and two-wheelers (2Wh). We also notice a
 322 significant increase in the time of presence of birds (Brd). Nevertheless, this result must be put into
 323 perspective, as this increase can be due to the lockdown effects but also to the spring seasonal effect
 324 (P1 is in winter and P2 in spring). There is a significant decrease in the perceived time of presence of
 325 expressive voices (ExV), nevertheless the assessment of calm voices (CaV) did not change
 326 significantly.

327

328 More generally, the perceptual assessments allow a rather detailed description of what happened
 329 in the sound environment of Lorient, as it mixes affects and description of sound source activities.
 330 However, it is difficult to capture the subjective part of the phenomenon. For example, people
 331 probably spent more time passively or actively listening to the sound environment than in the first
 332 questionnaire and at different periods of the day. Variations in the evaluation may then come from
 333 changes in the mode of perception rather than from the sound environment per se. In addition, the low
 334 temporal resolution of the perceptual data makes it difficult to evaluate the impact of the moment at
 335 which the respondent does the evaluation, and his/her ability to mentally project himself/herself on
 336 an average value of the period under evaluation.

337

338 The literature often mentions perceptual models that link two main perceptual dimensions
 339 (pleasantness and eventfulness) to the sound sources birds, traffic and voices (perceived time of
 340 presence) (Aumond, Can, De Coensel, Botteldooren, Ribeiro, and Lavandier, 2017; Ricciardi, Delaitre,
 341 Lavandier, Torchia, and Aumond, 2015). A statistical analysis using the R package ‘multcomp’ (Bretz,
 342 Hothorn, and Westfall, 2010) allows us to extract the multilevel components of this type of model. It
 343 is a question of evaluating which part of the variance proportion in the model can be attributed to the
 344 individuals (associated to different locations) and which part to the analysis period (Q1/Q2). Table 6
 345 shows the results of the multi-level linear regressions for both independent variables pleasantness (Pl)
 346 and eventfulness (Ev).

347

348 Table 6 - Multi-level linear regression of the independent parameters pleasantness (Pl) and
 349 eventfulness (Ev) and the dependent parameters presence time of birds (Brd), traffic (Tra) and calm
 350 voices (CaV) and expressive voices (ExV). The random effects are associated to the individuals or the
 351 questionnaire period (Q1/Q2).

n=62	Pl	Ev
Interc	6.6***	2.0**
Brd	0.3***	0.0
Tra	-0.5***	0.3***
CaV	0.0	0.09
ExV	-0.1	0.11
	R ² total = 67%	R ² total = 37%

	R ² fixedeffects = 52%	R ² fixedeffects = 15%
Random effect :	Std.Dev.	Std.Dev.
Individuals	0.6	0
Questionnaire period (Q1/Q2)	0.1	0.7

352

353 The time of presence of birds and traffic have a significant impact over the estimation of the
354 pleasantness. The random effect is quite small and mainly due to the disparity between individuals.
355 The model and its strength are very close to the literature (Aumond, Can, De Coensel, Botteldooren,
356 Ribeiro, and Lavandier, 2017; Aumond and Lavandier, 2019; Ricciardi, Delaitre, Lavandier, Torchia,
357 and Aumond, 2015). For example, for the city of Paris with quite different experimental conditions
358 but with a similar questionnaire (Aumond, Can, De Coensel, Botteldooren, Ribeiro, and Lavandier,
359 2017), the best perceptual model is:

360

$$361 \quad PI = 8,11 - 0,38*(OL) - 0,15*Tra + 0,20*Voi + 0,15*Brd \quad (4)$$

362

363 with “Voi”, the perceived time presence of voices and the overall loudness “OL” corresponds to
364 (10-Si) of this paper and explain 58% of the global variance ($R_{adj}^2 = 58\%$). In (Lavandier, Aumond,
365 Can, Gontier, Lagrange, and Petit, 2021), readers can also find more comparison between these similar
366 models on different study cases. Multi-level linear regression also reveals that the variation of the
367 pleasantness depends much more on the individual differences (*e.g.* different locations) than on
368 differences in the different periods.

369

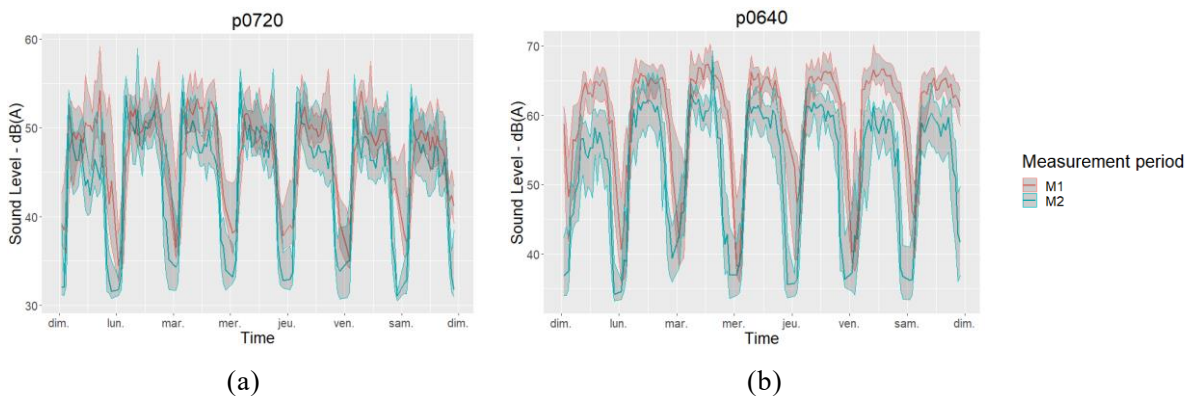
370 We find that the time of presence of traffic is the only one that has a significant impact on the
371 estimation of the eventful character. The total explained variance is much lower ($R^2 = 37\%$). We can
372 also observe a significant random effect due to the period of the questionnaire. This is in line with the
373 fact that the Q2 period is much calmer than the Q1 period, and with the fact that the calm dimension
374 is opposed to the eventful dimension in the circumflex model (Axelsson, Nilsson, and Berglund, 2012).
375 The literature consistently highlights the instability of the definition of this parameter according to
376 the translations (Jeon, Hong, Lavandier, Lafon, Axelsson, and Hurtig, 2018; Nagahata, 2018). For
377 example, Jeon et al. state in their study “The perceived dominance of sound of human activities shows
378 a positive relationship with Eventfulness scores in Korea and Sweden, while the same relationship is
379 not statistically significant in France.” (Jeon, Hong, Lavandier, Lafon, Axelsson, and Hurtig, 2018).
380 Also, due to the ambivalence of this term in French, a semantic shift may have occurred when there
was very little traffic during the lockdown period.

381 B. SOUND LEVEL ANALYSIS

382

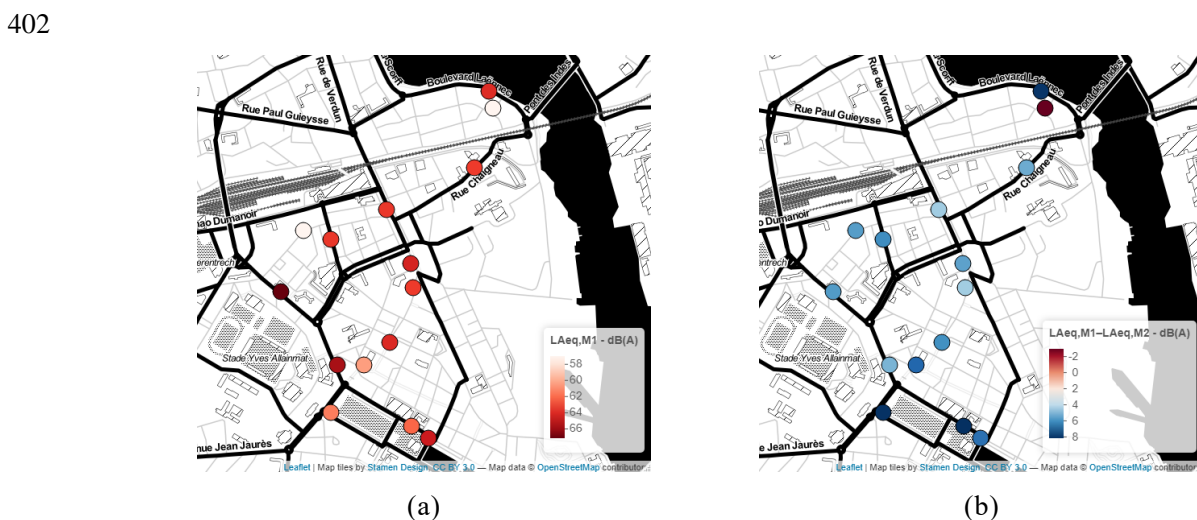
383 Figure 4 shows the median and interquartile range of $L_{Aeq,1s}$ (10 minutes every hour correspond to
384 600 values of $L_{Aeq,1s}$) for the 7 days of the week and for the two stations respectively located on a
385 boulevard and in a quiet residential area for each period of measurement M1 and M2 ($n_{1h} = 2400 L_{Aeq,1s}$

386 values for 4 weeks).
 387
 388



389 Figure 4 – Median and interquartile range of $L_{Aeq,1s}$ (10 min, every hours) for the 7 days of the
 390 week and for the two focus stations respectively located (a) in a quiet residential area and (b) on a
 391 boulevard for each period of measurement M1 and M2.

392
 393 The typical daily and weekly pattern is maintained for both periods studied. A difference of up to
 394 -15 dB(A) is observed between the period before and during lockdown for the station p0640. A multi-
 395 level linear regression ($n=470992$, groups: 15 stations) indicates that the fixed effect related to the
 396 period (M1 vs M2) is 7.4 dB(A) (std: 0.03; t-value: -279.70). This dramatic decrease is in accordance
 397 with the literature (Asensio, Pavón, and de Arcas, 2020; BRUITPARIF, 2020; Munoz, Vincent,
 398 Domergue, Gissinger, Guillot, Halbwachs, and Janillon, 2020). The random effects related to the
 399 stations have a significant variance of 12 dB(A), which reflects a fairly large variability on the selected
 400 stations. Figure 5 shows the $L_{Aeq,M1}$ computed from $L_{Aeq,1s}$ (10min every hour) and its difference (pre,
 401 $L_{Aeq,M1}$ and during lockdown, $L_{Aeq,M1} - L_{Aeq,M2}$) for the 15 stations.



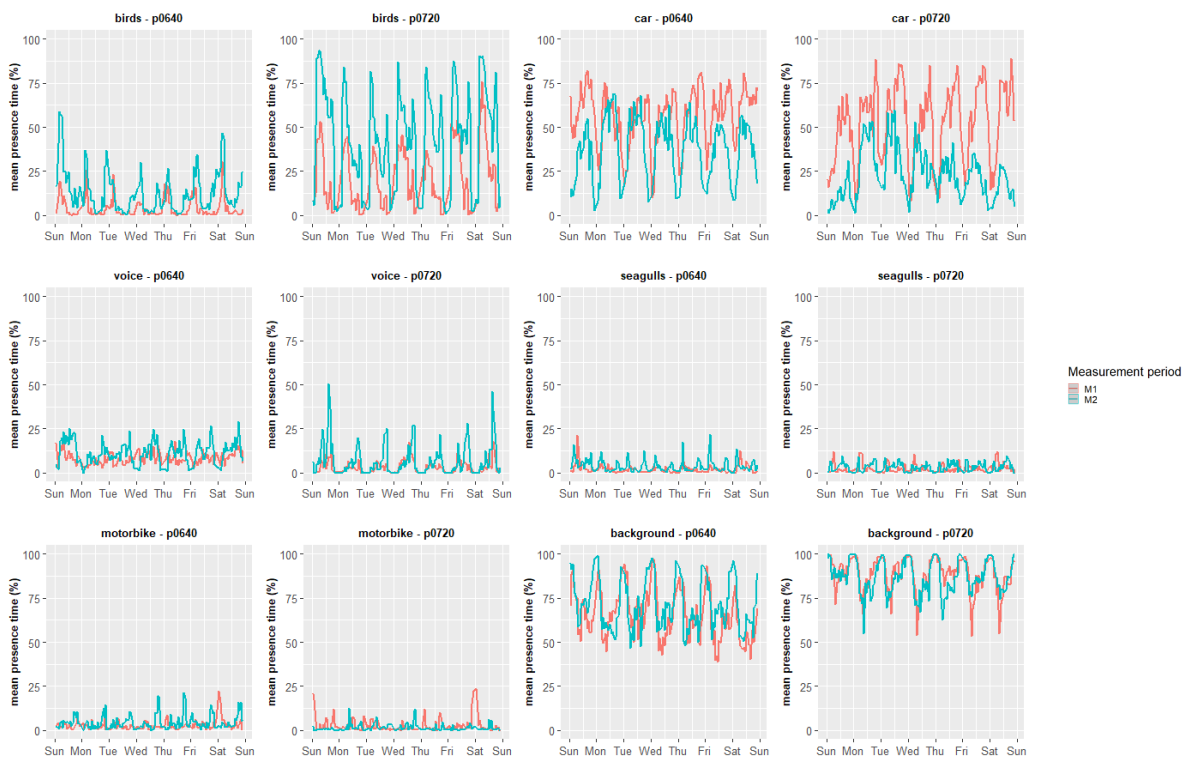
403 Figure 5 - For the 15 stations, (a) the pre-lockdown $L_{Aeq,M1}$ and (b) its difference with the period
 404 during the lockdown $L_{Aeq,M1} - L_{Aeq,M2}$.

405

406 The Pearson correlation coefficient, calculated between $L_{Aeq,M1}$ and $L_{Aeq,M1} - L_{Aeq,M2}$, shows that
 407 the most noise-exposed sensors are generally those with the greatest decrease in noise level ($r = 0.4$,
 408 $p < 0.01$). The most drastic decrease was in the downtown area around Jules Ferry Park. It is the center
 409 of the city with a lot of animation, road traffic, bars, restaurants, etc. during the non-lockdown period.
 410 Only one sensor has seen its level slightly increase, it is the sensor p0720 near the Scorff River located
 411 in a residential area, possibly due to an increase in naturally occurring sounds and the presence of
 412 local residents walking during the M2 period in a very quiet area.
 413

414 **C. SOUND RECOGNITION ANALYSIS**

415 Figure 6 shows the average hourly median of the perceived time of presence estimated for the 6
 416 different parameters from the algorithm presented in Section 2.3, for the 7 days of the week and for
 417 the 2 stations. The two focus stations selected are again p0640 as representative of a boulevard and
 418 p0720 as representative of a residential area.
 419



420
 421 Figure 6 - Average hourly median of the presence time of the 6 estimated parameters for the 2
 422 focus stations over the week period (left column, boulevard, right column quiet residential area) and
 423 for the presence time of the 6 estimated parameters.
 424

425
 426 First, the expected general diurnal and weekly behavior is observed for most of the variables (*e.g.*
 427 the morning bird songs peak at sunrise), which strengthen our confidence in the source recognition

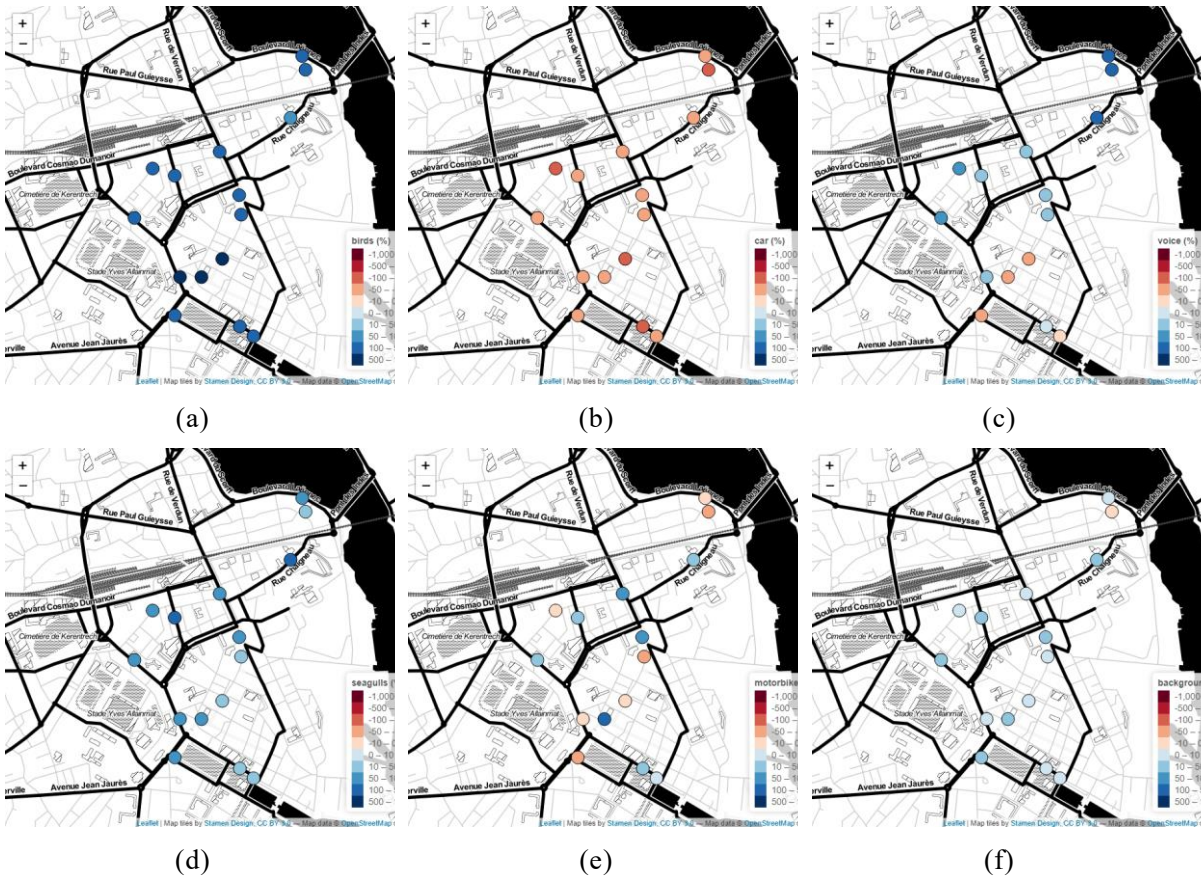
428 model. Concerning voices, there is a significant increase during the afternoons of the M2 period and
 429 especially for the station in the quiet area and during the week-ends. This is probably due to the
 430 outings in the urban outdoor space (the lockdown rule in France allowed an exit of 1 hour possible).
 431 In France, the weather was particularly good during this period, probably reinforcing this effect. The
 432 difference between the M1 and M2 periods is less noticeable on Wednesdays (in France, children have
 433 the afternoon off on this day) and on Sundays. As concerning motorcycles, in the M1 period, there
 434 was a peak in the Friday and Saturday evenings. In the M2 period this peak seems to occur more
 435 frequently at the end of the day. Several hypotheses discussed in Section 4 can account for this
 436 phenomenon. As expected, the "Background" parameter is inversely correlated with the number of
 437 events recognizable by the algorithm and its level is generally higher in the M2 period and for the
 438 station located in the quiet area. Finally, birds are increasingly noticed during M2 at both locations,
 439 what is in accordance with (Aletta, Oberman, Mitchell, Tong, and Kang, 2020; Gordo, Brotons,
 440 Herrando, and Gargallo, 2021).

441
 442 Table 7. Brunner-Munzel Test (n=154/154); hat: estimated relative effect; Lower: Lower limit of
 443 the confidence interval; Upper: Upper limit of the confidence interval; T: studentized test statistic; p
 444 val: p-value for the hypothesis. *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

	Lower	hat	Upper	T	p val		Lower	hat	Upper	T	p val
Bird	0,88	0,90	0,93	28,06	***	Seagulls	0,67	0,72	0,77	8,88	***
Car	0,11	0,14	0,18	-18,66	***	MotorBike	0,43	0,49	0,55	-0,35	
Voice	0,49	0,55	0,60	1,70	*	Background	0,56	0,60	0,64	5,28	***

446
 447 We complete this analysis with a non-parametric post-hoc test (Brunner-Munzel). Table 7 shows
 448 the difference (and related significance) of the 6 estimated variables between M1 and M2. Also, Figure
 449 7 shows the relative change of the mean value during the periods M1 and M2 (reference period M1)
 450 for relevant estimated parameter and each station. Both Figures 6 and 7 and the statistical evaluation
 451 show a strong increase in the estimated presence time of birds and Seagulls, and a decrease of the
 452 presence time of road vehicles, recognized by the algorithm. There is also a decrease in the estimated
 453 presence time of voices during the lockdown period (M2) in the hyper center and near the bars, but
 454 an increase in the small streets or on the ballade of the Scorff. Figure 7(f) shows the slight increase
 455 of the "background" estimation during the M2 period everywhere except close to the Scorff river.
 456 Figure 7(e) shows spatial variability in changes in "motorbike" estimates that is difficult to relate in
 457 an obvious way to any spatial features.

458



459
460
461
462

Figure 7. Relative change between the average estimated time presence of sound sources between the periods M1 and M2 $(M2-M1)/M1$

463 D. CROSS-COMPARISON OF THE DIFFERENT EVALUATION METHODS

464 1. Preamble

465

466 All the methods presented provide complementary information for the analysis of the change in
467 the sound environment. In this section, we now propose to cross-reference these data in order to
468 highlight, or not, the consistency between these perspectives. Section 2.4 presents the spatial and
469 temporal methods used to link the measurement stations to the different questionnaires.

470

471 2. Global analysis

472

473 First, the comparison of the results of Tables 5 and 7 shows a very good agreement between the
474 decrease of source presence as measured by questionnaires and by automatic source recognition tools
475 for birds (hat value of 0.8 and 0.9) and for road traffic (hat value of 0.14 and 0.17).

476

477 The analysis for voice is less straightforward. The questionnaire introduced a discrimination

478 between expressive voices, calm voices and children voices that is not accessible through the sound
 479 recognition model. The algorithm learning database being mainly conversational voices, one can
 480 assumes that the algorithm refers primarily to calm voices. Then, both forms of analysis converge on
 481 a very small change in calm voices times of presence.

482

483 Lastly, the decrease of presence of motorcycles is much higher for the questionnaires than in the
 484 source recognition estimates. A first hypothesis would be that when the traffic noise is low, the noise
 485 of the 2-wheelers propagates further before being masked. Thus, the estimated presence time of this
 486 parameter decreases only slightly from the algorithm point of view but the perceived time of presence
 487 by inhabitants decreases more strongly due to the decrease in the number of vehicles.

488 Another hypothesis could be that the type of two-wheeled noise sources and driver behavior may
 489 have changed between the two periods. Many delivery vehicles appeared during the P2 period (small
 490 engines and moderate acceleration) and there may have been a decrease in recreational or long-
 491 distance use of two-wheelers. The recognition algorithm does not identify the difference between
 492 these two types of vehicles, but their noise characteristics and the perception induced for the
 493 inhabitants may be very different.

494

495 3. Spatial analysis

496

497 Using the method described in Section 2.4, it is possible to interpolate the perceived values at the
 498 location of each of the sensors in the area. Then, the spatio-temporal correlations between the sensor
 499 estimates and the questionnaires for P1 and P2 periods and each location can be performed. Table 8
 500 shows Pearson correlation coefficients with their respective significance (p-value inferior to certain
 501 thresholds) between the variables from the questionnaire, the source recognition, but also the physical
 502 indicators directly calculated from the sensors.

503

504 Table 8 - Pearson correlation coefficients between perceived (interpolation), physical and source
 505 recognition parameters for the periods P1, P2 and P1&P2. *** p-value < 0.01, ** p-value < 0.05, * p-
 506 value < 0.1

507

Perceptual assessments	Recognized times of presence	Physical indicators	P1 (spatial) n=15	P2 (spatial) n=15	P1&P2 temporal) n=30	(spatio-temporal)
Sil		L _{Aeq}	-0,36	-0,44*		-0,78***
Sil		L _{A50}	-0,37	-0,51**		-0,83***
Tra		L _{Aeq}	0,34	0,35		0,76***
Tra		L _{A50}	0,32	0,18		0,81***
	Car	L _{Aeq}	0,34	0,65***		0,63***

	Car	L _{A50}	0,26	0,44*	0,56***
Brd	Birds		0,30	-0,23	0,63***
Tra	Car		-0,08	0,34	0,47***
CaV	Voice		0,53***	-0,01	0,27
ExV	Voice		0,72***	0,13	0,19
ChV	Voice		0,51**	-0,44*	0,20
Gul	Seagulls		0,33	-0,20	0,52***
2Wh	Motorbike		0,28	0,04	-0,01
Sil	Background		0,46**	0,09	0,37***

508

509 First, it should be pointed out that these correlation coefficients reflect a link between the observed
510 variables, but also the spatial and/or temporal dynamics of these variables. Weak dynamics will
511 probably lead to a more difficult link to highlight between two variables.

512

513 The indicators L_{Aeq} and L_{A50} correspond to the average value of all the L_{A50,10min}, L_{Aeq,10min}
514 calculated respectively on the periods P1 and P2. As expected, the perceived silence (Sil) and the
515 measured sound level indicators L_{Aeq} and L_{A50} are significantly inversely correlated ($r_{\text{Sil/LAeq}} = -0.78$;
516 $r_{\text{Sil/LA50}} = -0.83$). These variables for the periods P1 are significantly inversely correlated ($r_{\text{Sil/LA50}} = -$
517 0.36 ; $r_{\text{Sil/LA50}} = -0.37$) and P2 ($r_{\text{Sil/LA50}} = -0.44$; $r_{\text{Sil/LA50}} = -0.51$). The equivalent or median sound level
518 is again a good physical indicator of the perceptual variable "Silent to Noisy". The correlation
519 coefficients may seem rather weak, but the perception of the residents is based on memory and not on
520 a judgment of a sound environment that they listen to. Also, low density of sensors analyzed in the
521 area and therefore to the large distances between sensors and questionnaires can explain these low
522 values.

523

524 Exactly the same dynamics are observed when comparing the measured sound level L_{Aeq} and L_{A50}
525 and the perceived traffic presence time (Tra). We also observe that the correlations are slightly weaker
526 for this perceived variable, which reflects the part of the overall noise level that is not related to road
527 traffic. The gap between the time of presence of road traffic and the noise level is confirmed by looking
528 at the correlation coefficients between noise levels and the presence time of cars as estimated by the
529 algorithm at each sensor ($r_{\text{cars/LA50}} = 0.63$; $r_{\text{cars/LA50}} = 0.56$).

530

531 Even if the correlation coefficients between the perceived time of presence of traffic and birds
532 (recognized by the algorithm and perceptual assessed) is not significantly spatially correlated over the
533 periods P1 ($r_{\text{Brd/Birds}} = 0,30$; $r_{\text{Tra/cars}} = -0,08$) and P2 ($r_{\text{Brd/Birds}} = -0.23$; $r_{\text{Tra/cars}} = 0.34$), the spatio-temporal
534 correlation coefficients are significant for these two observables ($r_{\text{Brd/Birds}} = 0.63$; $r_{\text{Tra/cars}} = 0.47$), which
535 confirms that the perceptual and algorithmic methods lead to the same observations.

536

537 The perceived time of presence of voices is significantly correlated to the estimation from source
538 recognition only for the periods P1 ($r_{CaV/Voice}=0.53$; $r_{ExV/Voice}=0.72$; $r_{ChV/Voice}=0.51$). During the period
539 P2, people were restricted to go out in a radius of one kilometer around their home. The resulting loss
540 of spatial dynamics for this variable thus may prevent the measurement/perception correlation from
541 being revealed.

542
543 Lastly, we observe a significant spatial correlation on the period P1 of the perceived sound level
544 "Sil" and the variable "background" of the algorithm ($r_{Sil/Background}=0.46$). On the P2 period, the
545 dynamics of this last variable is probably too weak to reveal any difference ($r_{Sil/Background}=0.09$). Over
546 the period P1+P2, the spatio-temporal correlation of this variable is significant ($r_{Sil/Background}=0.37$).
547 This variable thus seems to correctly reveal the absence of sound sources in the environment.

548 IV. DISCUSSION

549
550 First of all, the overall results are consistent with the existing literature: we observe an overall
551 decrease in noise levels in comparable ranges with respect to those of other cities, and this decrease
552 is all the more important near the main roads. We also observe an emergence of natural sound sources,
553 and a drastic decrease of mechanical noise, both reflected by questionnaires and sensors.

554
555 When crossing the physical and perceptual analysis methods, two main limitations arise. The
556 small number of sensors spatially close to participant questionnaires does not allow a direct link
557 between a questionnaire and a nearby measurement station. The chosen interpolation method
558 alleviates this issue but introduces approximations. Nevertheless, the average proximity between
559 stations and questionnaires remains acceptable to justify the methodology (median = 108 m, 80% <
560 155 m). From a temporal point of view, technical limitations forced us to choose periods spaced one
561 year apart for the unconfined period (M1 vs Q1). Despite these approximations, the proposed protocol
562 allows us to evaluate the performance of the source recognition algorithm, on site and at scale with
563 an applied scenario, and to confront its prediction with the citizens' appreciation.

564
565 Regarding the questionnaire and co-factors influencing perception, an important aspect of the
566 housing questions is whether respondents live alone or with others in their homes, as investigated in
567 Torresin et al. (Torresin, Albatici, Aletta, Babich, Oberman, Stawinoga, and Kang, 2022). This
568 question is particularly relevant in the context of COVID-19-related lockdown. Unfortunately, this
569 variable was not collected in our questionnaire.

570
571 Our analysis of the perceptual results indicates that individuals/places are more important in the
572 evaluation of pleasantness than the difference between periods. In a context such as the lockdown
573 with very high variation in the sound environment, even in the most unpleasant locations in the city,

574 one could hypothesize that this observation also partly reflects non-acoustic factors (e.g., visual
575 context (Jeon and Jo, 2020; Jeon, Lee, Hong, and Cabrera, 2011)) that cannot be captured by the
576 sensors (and thus by the model).

577

578 In this study, the perceptual assessment provides a fairly accurate description of what happened in
579 the Lorient sound environment during the lockdown period. We could hypothesize that there is no bias
580 in the perceptual assessment and that it accurately reflects the sound environment. But the lockdown
581 period could have implied a modification of the perceptions, such as an overestimation of the time of
582 presence of the birds or of the decrease of the road noise exacerbated by the sensations of the moment
583 or by the surprise to discover such a peaceful urban sound environment. It would therefore be
584 interesting to go further by conducting a contextual analysis or an analysis according to the
585 psychosocial characteristics of the individuals interviewed, but the sample size of our study was not
586 sufficient.

587

588 Different from that of the questionnaire, which can induce biases in the comparison, the method
589 linked to source recognition allows a very detailed temporal follow-up. For example, the low
590 correlation coefficient between the perceived time of presence of the 2-wheelers and the
591 measurements can be partly explained by the very different temporal resolution of these two
592 observation methods. Indeed, the presence of the 2-wheelers has a very specific behavior, in particular
593 at the time of the lockdown in the evening between 6 pm and 8 pm which can probably be attributed
594 to food deliveries. It is difficult to estimate how this behavior translates into perceptual assessments
595 over the period linked to the questionnaire.

596 **V. Conclusion**

597 In this paper, three methods of sound environment analysis were jointly considered over periods before
598 and during the lockdown related to the COVID-19 crisis in the city of Lorient, France. The analysis of sound
599 levels reflects the results of many other studies on the subject, namely an average decrease in equivalent
600 sound level of about 5-10 dB(A). The analysis of the questionnaire results allows us to go into detail about
601 the changes in the perceived time of presence of certain sources, like as expected, the drastic decrease of the
602 road traffic and the increase of the birds' songs perceived presence.

603

604 This study also introduced a protocol of integration of the analysis of the presence of sound sources from
605 questionnaires and from automatic estimation using deep convolutional network algorithms. The analysis of
606 the latter reveals a temporal detail on the presence of sources that is very complementary to the questionnaires
607 one. The differences between the questionnaires and the algorithm also make it possible to question the
608 perceptual or algorithmic biases that may be present.

609

610 The lockdown related to COVID-19 allowed us to validate the relevance of the proposed approach, as

611 strong assumptions on the expected behaviors of the analysis variables could be made. Despite some
612 methodological and technical limitations that could be improved in the future, this paper demonstrates the
613 interest of introducing multidisciplinary analyses, as proposed in the "triangulation" section of the ISO/TS
614 129313-3:2019 soundscape standard, to account for the short-term and long-term evolutions of urban sound
615 environments and their appraisal. With further validation in order to increase our confidence in the
616 performance of the recognition algorithm, we believe that this kind of cross analysis will allow us to highlight
617 perceptual biases that are particularly revealing of the modes of perception of sound environments considered
618 by citizens.

619 **ACKNOWLEDGEMENTS**

620 The authors want to thank the city of Lorient and in particular J.C. Baron and P. Crépeaux from
621 “le pôle cadre de vie et développement durable” (the life and sustainable development center). This work
622 was funded under the ANR project CENSE No. ANR-16-CE22-0012.

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