Urban soundscape maps modelled with geo-referenced data

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Abstract: The noise maps that are currently proposed as part of the EU Directive are based on the calculation of the Lday, Levening and Lnight. These levels are calculated from emission and propagation models that are expensive in time. These noise maps are criticized for being distant from the perception of city users. Thus, calculation models of sound quality have been proposed, for being closer to city users' perception. They are either based on perceptual variables, or on acoustic measurements, or on geo-referenced data, the latter being often already integrated into the Geographic Information Systems of most French metropolises. Considering 89 Parisian situations, this article proposes to compare the sound quality really perceived, with those from models using geo-referenced data. It also looks at the modeling of perceptual variables that influence the sound quality, such as perceived loudness, the perceived time ratio of traffic, voices and birds. To do this, such geo-referenced data as road traffic, the presence of gardens, food shops, restaurants, bars, schools, markets, are transformed into core densities. Being quick and easy to calculate, these densities predict effectively sound quality in the urban public space. Visualization of urban soundscape maps are proposed in this paper.

Keywords: sound quality map; kernel density; soundscape modelling

1 Introduction

The current maps on traffic noise in urban areas [1] are based on the DENL indicator (weighted average of the Day-Evening-Night sound Levels). Yet, this indicator, which is supposed to characterize the noise exposure of populations affected by road traffic, is poorly understood by city users for being distant from their felt experience. Moreover, the dB scale is difficult to understand at first. Thus, calculation models of soundscape descriptors, that are closer to the perception of users, have been proposed by soundscape researchers in the recent decade (for a review, see the paper of Aletta and his colleagues [2]). In their common approach, the soundscape has been defined as the "acoustic environment as perceived or experiences and/or understood by a person or people in context" [3]. In the context of soundscape studies, the overall loudness is not the only perceptual dimension which characterizes the pleasantness of a sonic environment. The evaluation of identified sources is important too [4]. Three different types of sounds (natural, human and technological) which are common to most previously proposed taxonomies [5–8] were evaluated in this study. Generally, the identification of the traffic negatively influences the perceived pleasantness, whereas the identification of the natural sounds positively influences it [10, 11]. Dubois [12] and Nilsson and Berglund [10] found a neutral impact of human sounds on the soundscape quality. For natural sounds, it seems that bird songs have a positive influence whatever the context but water sounds with temporal variability may have a positive influence whereas water sounds with high loudness and low temporal variability may have a negative influence on pleasantness [13–16]. In that frame, several researches studied the link between soundscape quality and relevant perceptual dimensions with regression models [17–21]. Among these studies, the Cart_ASUR project (Cartographic representation of urban sound quality) proposed an indicator of sound quality (pleasantness of the urban sound environment) that is constructed on perceptual variables and which takes into account not only the overall perceived loudness, but also the various sound sources composing the soundscape (for example birds or voices [22]). A global sound quality indicator, modelled from 3409 points of perceptual data collected through the use of mobile phones [23] was thus proposed on a scale from 1 (unpleasant) to 11 (pleasant) with a linear regres-

***Corresponding Author: Catherine Lavandier:** Labo MRTE, Université de Cergy Pontoise 5 Mail Gay Lussac, 95031 Cergy Pontoise Cedex France; Email: catherine.lavandier@u-cergy.fr
Pierre Aumond: Labo MRTE, Université de Cergy Pontoise 5 Mail Gay Lussac, 95031 Cergy Pontoise Cedex France.
Saul Gomez, Catherine Dominguès: IGN, Université Paris-Est COGIT 73 avenue de Paris, 94160 Saint-Mandé, France.

sion model (R1):

$$\begin{aligned}\text{Pleasantness} = {} & 8.11 - 0.38 \cdot (\text{Overall Loudness}) \\ & + 0.20 \cdot (\text{Time Ratio of Voices}) \\ & + 0.15 \cdot (\text{Time Ratio of Birds}) \\ & - 0.14 \cdot (\text{Time Ratio of Traffic})\end{aligned} \quad (1)$$

In this model, the sound "Pleasantness" concerns an outdoor urban location, where:

- the "Overall Loudness" corresponds to the perceived loudness of the situation, evaluated by a listener on an 11-point scale "Quiet (1) – Noisy (11)"
- the "Time Ratio of Voices" (respectively the "Time Ratio of Birds" and the "Time Ratio of Traffic") corresponds to the perceived time ratio of voice presence (respectively of bird song presence and of traffic noise), evaluated on an 11-point scale "Rarely heard (1) – Continuously heard (11)".

In the Cart_ASUR project, this indicator allowed to explain 34% of the individual variance of participants (correlation of 0.58 between the 3409 individual real sound pleasantness and the pleasantness predicted by the model). This correlation reached a value of 0.89 if the average values of the sound pleasantness for each of the 204 urban assessed situations were compared with the proposed model values, which were constructed from the averages of the influential perceptual variables. Axelsson *et al.* [17] showed that the pleasantness of sound environments ranked on a pleasantness matching scale can be explained with an adjusted variance of 0.55 by the loudness and by the identification of technological, human and natural dominant sounds.

It is therefore interesting to represent this sound quality indicator (pleasantness of the acoustic environment) through sound quality maps and make them available to city users. Liu *et al.* [24, 25] proposed maps of urban soundscape as well as Hong and Jeon [26, 27] or Aletta and Jang [28], with simple visualization of the perceptual collected data [26], with global and local modelling of perceptual data [27], or with Kriging interpolation method [28]. For all of these studies, the maps are built on perceptual variables collected during soundwalks. Because they are not built on predictive soundscape models, they cannot be applied to the entire city.

In contrast, this paper focuses on predictive models. It proposes predictive soundscape maps built on geo-referenced data. There exist emission and propagation models that allow predicting noise levels from road traffic [29], but the same is not true regarding the propagation of human or natural sounds. Furthermore, the use of these models is very time consuming in terms of calculation. So, the decision was made to test soundscape predictive models directly through geo-referenced data already integrated into the GIS of most metropolises, without any physical model. To do so, the pleasantness dependent variable and the independent perceptual variables (overall loudness, and the three time ratios for traffic, voices and birds) which were collected in the Cart_ASUR project during the day period of the week days were used in this study (70 Parisian situations in the 13^{th} and 14^{th} districts). To increase the validity of the models, a new campaign was carried out on 19 new situations in the same districts during the GRAFIC project (Cartographic representation of urban sound quality for locations and for paths), collecting the same perceptual data than the Cart_ASUR project. For this study, a total of 89 urban situations were evaluated (Figure 1) by about 20 persons for each location.

In this paper, these perceptual data are modelled with the geo-referenced data in order to be predicted wherever the locations in the public space are. The final aim of this study is then to propose predictive sound quality maps that can be built by any city which has these geo-referenced data already collected in its GIS. First of all, in section 2, the kernel density method which is used to distribute georeferenced data on each mesh of the map is presented, and the kernel density calculation is applied for traffic, garden and voice densities. In section 3 predictive regressions which explain the perceptual variables (overall loudness, and the three time ratios for traffic, voices and birds) with the densities calculated in section 2 are then proposed. In this section, the predictive models of the overall loudness and of the perceived time presence of traffic built on densities are compared with the predictive models built on the Lday indicator simulated with the classical physical model [29]. The section 4 is dedicated to the prediction of the sound pleasantness. The first model is based on perceptual variables, the second one is based on densities, and the last one is based on the classical Lday indicator (Equivalent sound level calculated in dB(A) for a continuous traffic between 6AM till 6PM). Finally, in section 5 the predictive models based on densities are used to propose soundscape maps which should allow better communication with city users.

2 Calculation of the kernel density

The aim of this project is to offer at any point in the city a value of sound pleasantness. This value can be modelled by four perceptual variables (see Eq. (1)) that should

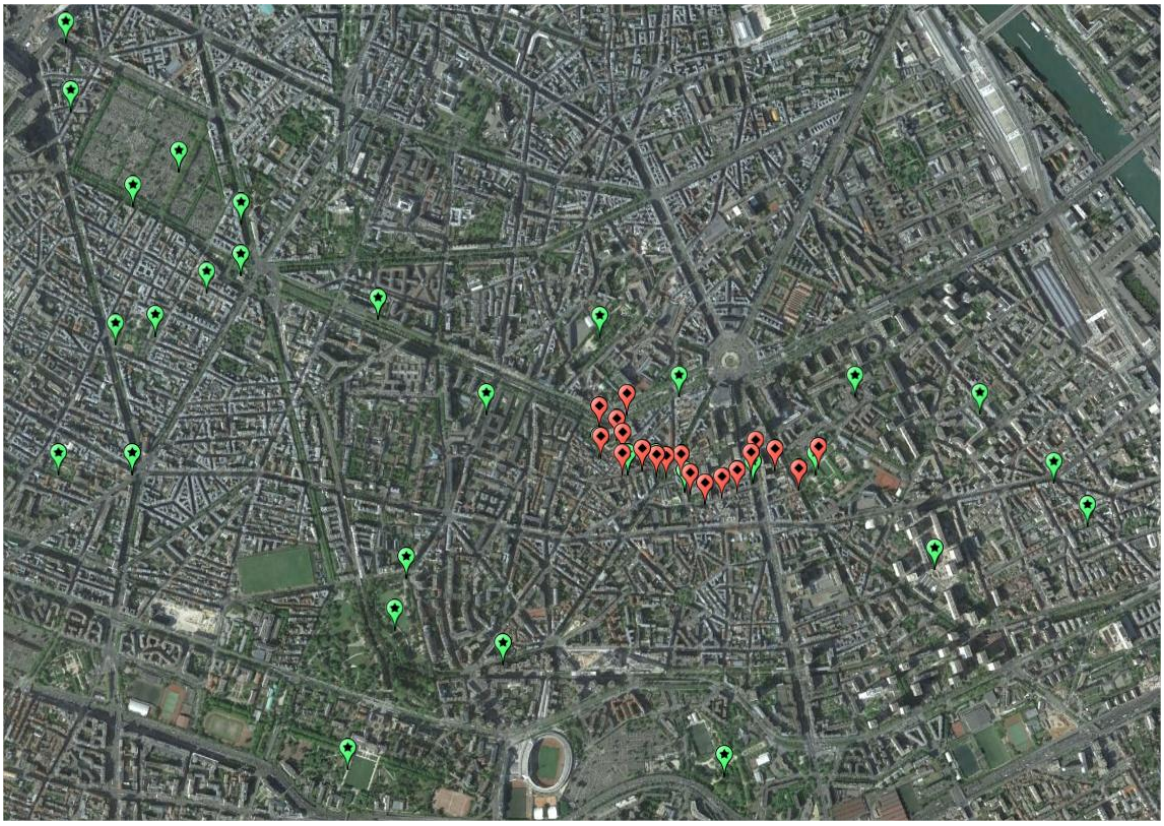


Figure 1: Locations of the evaluated situations. The red dots correspond to the 19 locations assessed in March 2015. The green dots correspond to the 29 locations evaluated at different moments of the day (35 different situations) between September 2013 and February 2014 (winter period), and correspond also to the same 35 situations assessed between March 2014 and September 2014 (summer period).

be predicted at any point on the map. In this work, it is proposed to estimate these variables thanks to the use of various geographic layers integrated into the GIS. Yet the geographic data are often vector, punctual or linear ones. In order to be able to anticipate variable values at every point in the city, these vector data have to be transformed into data on each mesh of the map (called "raster"). To do so, and throughout the rest of this work, the kernel density tool will be used [30]. The goal here is to distribute the influence of a punctual data (for example the number of vehicles per hour at a point on a street) on a neighboring area which value will decrease according to the distance. There are different kernel functions in literature for the distribution of a punctual data such as Gaussian, quartic, uniform or triangular functions [31]. In this paper, the QGIS software which proposes Gaussian and quartic functions only was used for calculations and visualizations. As a first approximation, the simplest fixed Gaussian kernel function has been chosen because it is proposed in most of the open source GIS which can be used by any city.

The value is cancelled beyond the smoothing window (or the search radius R). For more than one point, the values of density are simply the sum of the individual density for each point. Then, these values have no absolute meaning, but only a relative one, because they depend on several parameters, such as the radius parameter and the distance between points. Figure 2 shows an example of the creation of a density map for an urban element with a value of 10, with a search radius of 3 meshes. In this study the size of the grid which corresponds to the size of the mesh is 5 m × 5 m. The open source QGIS software was used for calculations and visualizations.

2.1 Traffic density

The purpose is to transform the traffic data used in traditional cartography (number of vehicles per hour during the day) into punctual data. The process is based on the creation of points on traffic lines by defining a constant distance between each point. The value of the points was chosen as the number of vehicles per hour on the section. The equidistance as well as the radius have been optimized by calculating, for the 89 points, the correlation between the

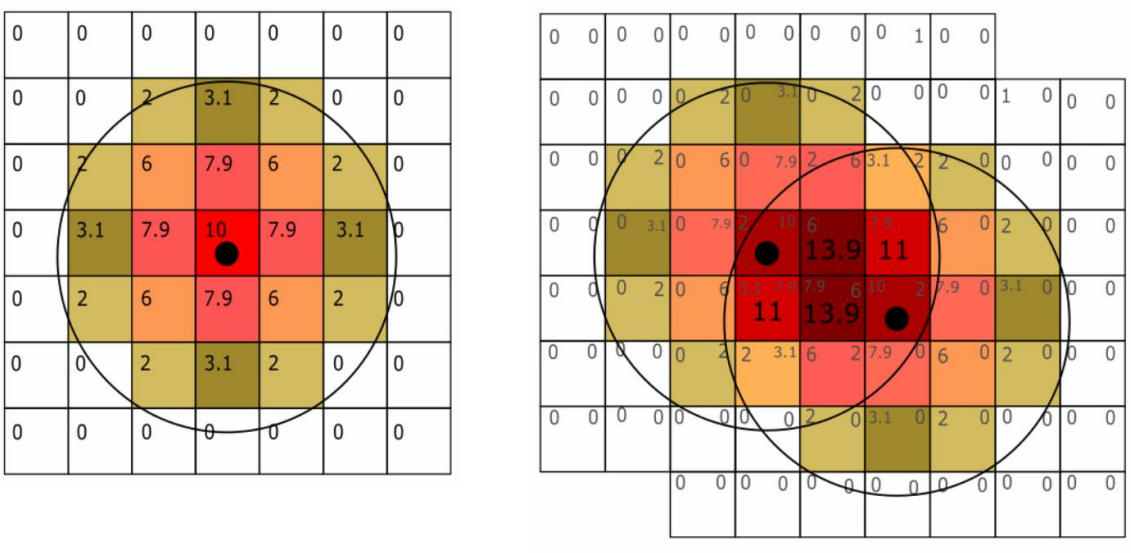


Figure 2: Example of a kernel density, calculated with the Gaussian distribution of the value 10 on the surrounding meshes (search radius, R = 3 meshes), (a) for a single point, (b) for two points.

average of the perceived traffic time ratio, and the traffic density calculated by the kernel density (Table 1).

A large equidistance reduces the correlation as well as a large radius. The equidistance of 10 m for traffic density means that a value of traffic is taken into account in the calculation every two meshes. The optimum radius of 75 m appears as a good compromise. Actually, this distance permits to take into account the propagation distance of traffic noise, while avoiding the masking phenomenon which inevitably happens when sound meets a building, often beyond the 75 m compared to the position of the source.

2.2 Density of gardens

The density map of gardens was created in order to represent the more or less significant presence of birds (variable D_gardens) at any point of the map. It is noteworthy that these birds are better perceived in the center of the garden than at its periphery [32]. The data layer "gardens" of the IGN's[1] BD TOPO® French database was used. This is a polygonal vectorial layer. A particular transformation was proposed to show that the density is low on the perimeter, increasingly significant inside the garden, but with a degree of stability when getting closer to its center.

Figure 3 shows three parameters. When we progress inward from the garden:

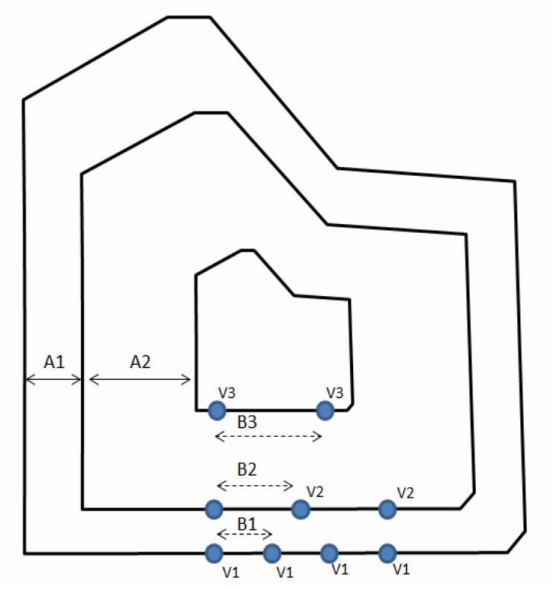


Figure 3: Construction of the punctual values of gardens, from the outline of the gardens.

- The distances of successive buffers (A1, A2, etc.) are becoming greater;
- The equidistance between the points on the buffer lines (B1, B2, etc.) is becoming longer;
- The value of each core, according to its position in the garden (V1, V2, etc.), is increasingly greater.

In the same way as traffic density, the optimization of garden density parameters is done by correlating these densities with the mean perceived presence of birds on the

1 http://professionnels.ign.fr/sites/default/files/DC_BDTOPO_2-1.pdf

Table 1: Correlations between perceived traffic time ratio and traffic densities. The nomenclature of density maps (Cd) is as follow: Cd (equidistance between points in meters) _ (search radius in meters). The equidistance and the search radius correspond to several numbers of meshes. The data for a search radius of 75 m are in bold.

Equidistance → ↓ Search radius	10 meshes	7 meshes	5 meshes	3 meshes	2 meshes
40 meshes					Cd 10_200 0.611
20 meshes	Cd 50_100 0,754	Cd 35_100 0,794	Cd 25_100 0,790	Cd 15_100 0,800	Cd 10_100 0,792
15 meshes			**Cd 25_75 0,813**	**Cd 15_75 0,827**	**Cd 10_75 0,838**
10 meshes			Cd 25_50 0,775	Cd 15_50 0,796	Cd 10_50 0,800
5 meshes					Cd 10_25 0,556

89 perceptually evaluated points. The search radius is limited to 50 m this time slightly reducing the spatial impact of the garden regarding the sound perception, compared to the search radius of 75 m used for traffic. After testing several values, the values used to offer the best correlation (r = 0.76) with the perceptual variables are presented in Table 2.

Table 2: Construction parameters of points for the calculation of garden density (* buffer distance, ** edge of garden).

Rings (A1, A2...) *	0m**	10m	30m	60m
Equidistance (B1, B2...)	15m	20m	25m	30m
Value (V1, V2...)	2	5	10	20

2.3 Density of voices

This map is created from several sources of information, seeking all urban activities that could generate voices in the urban space. Five elements were taken into account:

- Food shops (bakeries, fishmongers, etc.), (Base BD COM 2001 - APUR)
- Bars, cafés and restaurants (Base BD COM 2001 - APUR)
- Schools and sports areas (Base BD TOPO®)
- Markets (linear data constructed from the website data of the municipality of Paris)
- Play areas (BD Base TOPO®)

2.3.1 Food Shops and restaurants

These data have a point layout. No transformation is therefore necessary, but the localization is done using the geocodes based on the official address of the shop. To avoid some addressing problems, a "cleaning" tool has been used to only leave one point on businesses accumulation places.

2.3.2 Schools and sports areas

Information on schools comes from two layers: the surface of schools and that of buildings. There is no information about the localization of schools exits (as well as for sports areas), but it is possible to locate a recreation area (or the sports area) where voices are mainly present. To locate the recreation area, we can directly remove all the building surfaces from the school ones. We consider that inside the buildings the voice level is low as the pupils take their classes. Then, on this free surface, an interior buffer can be created with a distance of 4 meters, thus indicating that an area of less than 16 square meters (4m × 4m) is not likely to be a place of recreation. Finally, on the edges of these interior surfaces, points are created with an equidistance of 10 meters (Figure 4).

2.3.3 The markets

The layer of markets has been digitized from the information provided by the city of Paris. This information details the existing markets for each district. The digitization is

done first in linear and then in point form. The equidistance between the points is of 10 meters.

2.3.4 Play areas

The layer "play areas" of the BD TOPO® is a point vector layer. No transformation is required to integrate this data in the calculation of the density of these areas.

2.3.5 Construction of the density of voice (variable D_Voice)

Once all the urban elements likely to be noise sources are transformed into point geometry, they are included in a same layer to create one voice density map. As a first approximation, all the points have the same value, and this value is arbitrarily set at 10. The search radius is 50 meters.

3 Modelling of perceptual variables

The perceptual variables that were found to have an influence on the quality of the sound environment were presented in the introduction, and there are four: (1) the perceived overall loudness, (2) the time ratio of traffic, (3) the time ratio of voices, and (4) the time ratio of birds. These variables have been evaluated by approximately 20 people, between 10AM and 18PM and at 89 situations (Figure 1). In literature different kind of predictive models have been chosen to explain perceptive sound quality. Non-linear predictive models such as Artificial Neural Networks are sometimes chosen [33, 34], but they are often considered as "black boxes" and are very difficult to understand by naïve population. Furthermore Brocolini showed that non-linear ANN models do not improve the explained variance in a significant way compared to linear regression models [35]. So, sometimes linear regressions are preferred [17, 22, 36]. In this study linear regressions have been chosen. All the linear regressions were calculated on the average of evaluations and optimized using a step-by-step top-down process. Only significant ($p<0.05$) and uncorrelated ($r<0.5$) variables are present in the selected models. In order to evaluate the explanatory power of a model, the adjusted R-squares (R^2adj.) is calculated. This is the proportion of the variance explained by the multiple regression model compared to the total variance of data. In order to estimate the mean difference between values predicted by a model and the values actually observed, the root mean square error (RMSE) is calculated.

3.1 Overall loudness

Several regressions were tested to predict the quiet or noisy character of the urban public space (Table 3). The regression only build on the traffic density R2 can explain 60% of the variance in perceived overall loudness (Figure 5a). Yet, the perceived loudness is not only due to traffic [37]. If the variable D_Voices is added to the regression (regression R3 - Figure 5b), it is significant ($p<0.01$) and the variance explained by the model is improved ($R^2 = 0.66$). Figure 5a reveals the logarithmic character of the perception of loudness regarding traffic flow. A new regression was therefore envisaged between perceived loudness and the logarithm of traffic density. This transformation is problematic for places of urban space that have a zero traffic density (or a very low one, generally at the center of a park). For 9 situations in this study, the logarithm of the density was replaced either by the smallest value of the densities of small parks, that is to say 2 (Cd_10_75 corrected = 100 for the regression R5 – Figure 5d), or by the average of densities in small parks, that is to say 2.7 (Cd_10_75 corrected = 297 for the regression R4 – Figure 5c). If this last substitution is chosen, the middle of a large park could have a higher value of traffic density (297) than a boundary value. Even if the regression R4 (Eq. 4 Table 3) has a better adjustment with perceptual data than the R5 regression (Eq. 5 Table 3), the corresponding substitution does not seem relevant. So the substitution with the minimum value has been chosen for the regression models selected for visualization of final maps (see §5.2 and §5.3). Moreover the regression R5 is more easily automated as part of a mapping study. Here, no added density variable (D_Voices or D_Gardens) improves regression as none of them is significant.

Presently, the only tool that local communities offer about noise levels in the cities is the Lday indicator. So, it is interesting to compare the calculation of the loudness from the Lday (calculated by the city of Paris and accessible on the internet) with the R4 or R5 models. Interestingly, the corresponding regression R6 (Figure 6) then explains a lower part of the variance (56%) despite a much greater calculation time.

It is important to remain that the perceived loudness was assessed on a scale from 1 (quiet) to 11 (loud). Whatever the models, the root mean square errors (RMSE) are about 1 (Table 3), which means that the precisions of the loudness models are about 10%.

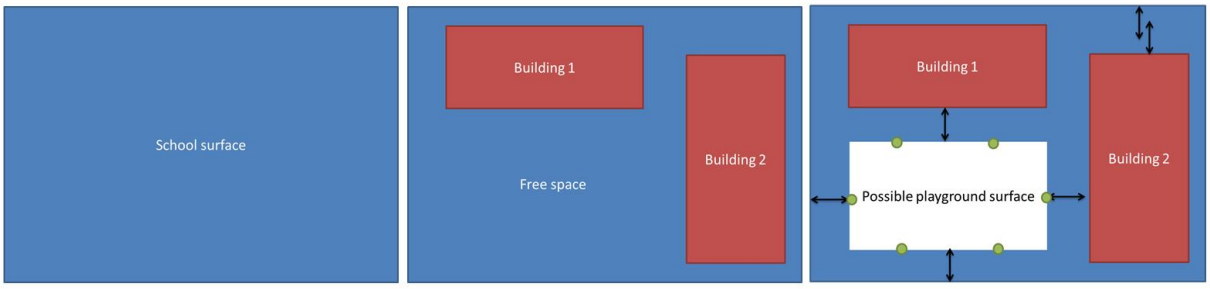


Figure 4: Construction of the source points for the presence of children's voices in schools at recreation times.

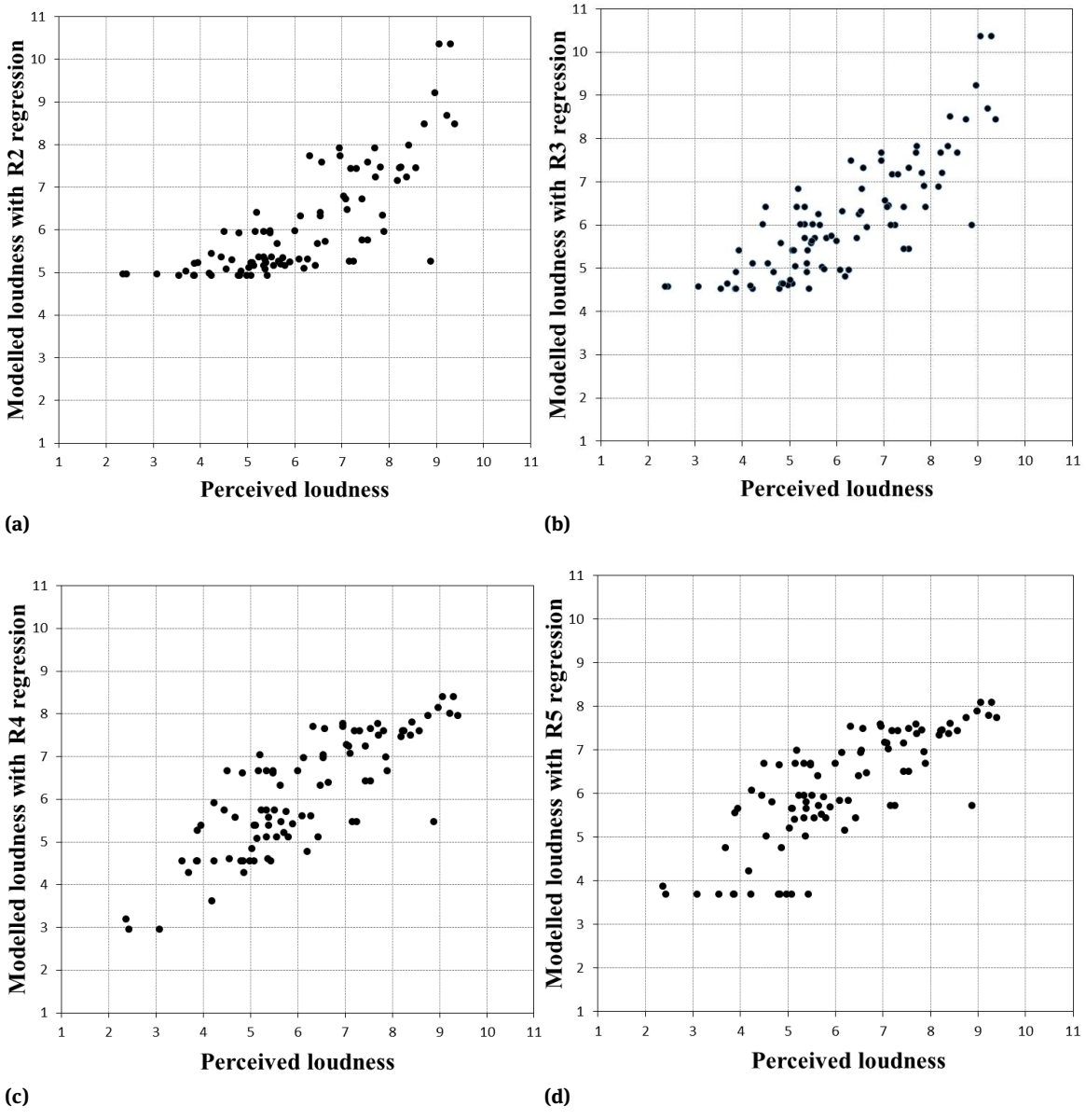


Figure 5: Relations between perceived and modelled loudness with the different regressions.

Table 3: Adjusted R-squared values, Root mean square errors and Correlations between perceived and modelled loudness for different linear regressions.

Regressions	Models of perceived loudness		R^2adj.	RMSE	Correlation between perceived and modelled loudness
R2	$4.93 + 2.7x10^{-4} \cdot$ Cd_10_75	(2)	0,60	1,03	0.78
R3	$4.52 + 2.9x10^{-4} \cdot$ Cd_10_75 + 0.016 · D_Voice	(3)	0.66	0.96	0.82
R4	−1.98 + 2.42 · log (Cd_10_75 corrected with 2.7)	(4)	0.67	0.95	0.82
R5	−0.21 + 1.93 · log (Cd_10_75 corrected with 2)	(5)	0.61	1.02	0.79
R6	−6.94 + 0.21 · Lday	(6)	0.56	1.09	0.75

Table 4: Correlations between perceived and modelled traffic time ratio for different linear regressions.

Regressions	Models of perceived loudness		R^2adj.	RMSE	Correlation between perceived and modelled traffic time ratio
R7	$3.93 + 4.3x10^{-4} \cdot$ Cd_10_75	(7)	0,70	1,30	0.84
R8	−6.09 + 3.55 · log (Cd_10_75 corrected 2.7)	(8)	0.68	1.33	0.82
R9	−2.76 + 2.60 · log (Cd_10_75 corrected 2)	(9)	0.53	1.62	0.73
R10	−13.86 + 0.32 * Lday	(10)	0.60	1.49	0.78

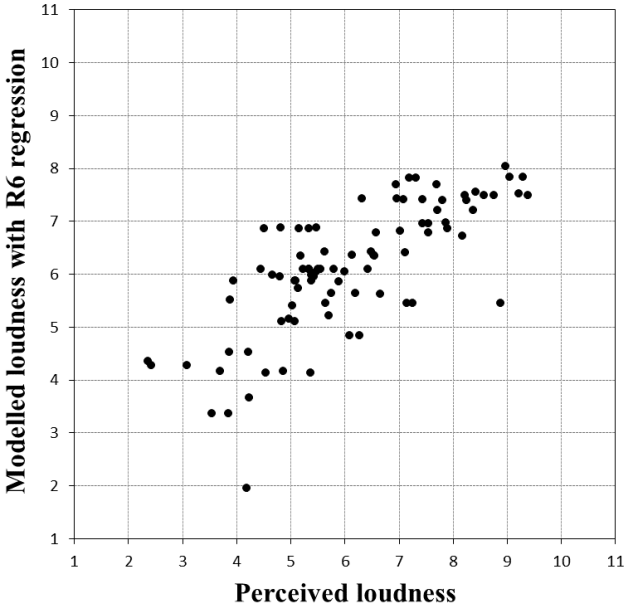


Figure 6: Relation between perceived and modelled loudness with the Lday.

3.2 Traffic time ratio

The traffic time ratio is close in concept to traffic density. It is therefore logical to seek a link between this perceptive variable and the Cd_10_75 traffic density which allowed the optimization of the kernel density (see §2.1).

The linear density traffic model explains 70% of the variance, with an average error of 1.30 compared with the actually perceived traffic time ratio (Table 4). If we try to model this time by the logarithm of traffic density (corrected with the smallest value 2), the model then only explains 53% of the variance, with an average difference of 1.62, which is not as good as the linear model.

In the same way as in the previous paragraph, it is interesting to seek a relationship between the perceived traffic time ratio and the Lday, as both should be correlated. The latter model explains 60% of the variance (r = 0.78), with an average error of 1.49. The Lday is slightly better correlated to the perceived traffic time ratio (r = 0.78) than to the perceived loudness (r = 0.75). This is not surprising because the Lay does not include noises other than road traffic.

3.3 Time ratio of birds

The best regression predicting the time ratio of birds with significant geo-referenced data ($p<0.05$) and independent data (correlations <0.5) is as follows:

$$\begin{aligned}\text{Time Ratio of Birds} = {} & 5.28 + 0.07 \cdot \text{D\_Gardens} \\ & - 0.01 \cdot \text{D\_Voices} \\ & - 0.92 \cdot \log(\text{Cd\_10\_75\_cor\_2})\end{aligned} \quad (11)$$

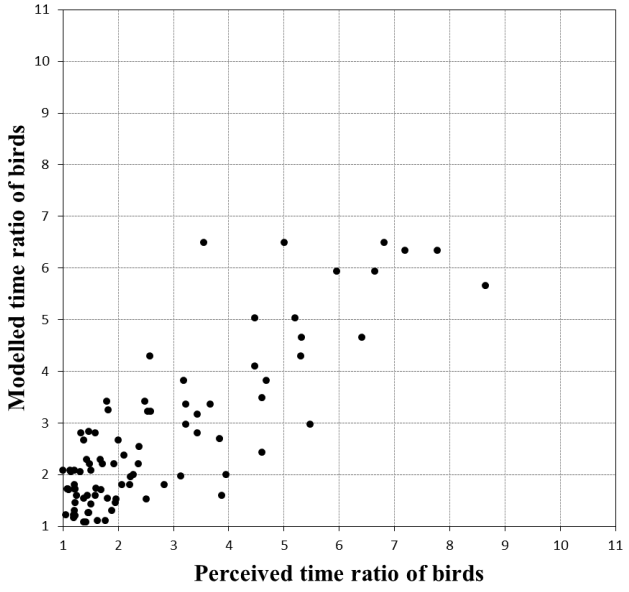


Figure 7: Relation between the perceived time ratio of birds and this time ratio modelled by the Eq. (11).

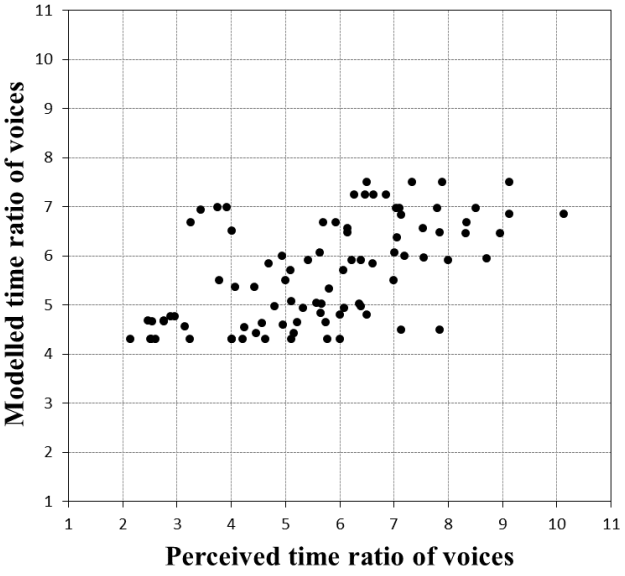


Figure 8: Relation between the perceived time ratio of voices and this time ratio modelled by the Eq. (12).

This regression can explain 67% of the variance with an average error of 1.02. It shows that birds are mainly present in the gardens. These birds can be heard only when traffic density is low, as well as the voice density characterizing the human presence in the place. On the 89 points, the time ratio of birds is usually very low (TR_Birds < 4 for 83% of the evaluated situations), except for some special locations that have been evaluated in Parisian gardens (Figure 7).

3.4 Time ratio of voices

The best regression found to model the time ratio of voices is as follows:

$$\text{Time Ratio of Voices} = 4.3 + 0.05 \cdot \text{D\_Voices} + 0.04 \cdot \text{D\_Gardens} \quad (12)$$

This equation reflects the fact that voices are not only present around shops, restaurant and such places (§2.3), but are also present in the gardens. This regression only explains 31% of the variance, with an average error of 1.52 on a scale from 1 to 11. On Figure 8, it can be seen that the perceived time ratio of voices varies from 2 to 10, but the predicted values are limited to the range of 4 to 8. Further researches are needed to develop potential improvements on the prediction of voices, by weighting the different geo-referenced layers which allowed constructing the voice density variable, by adding such elements as subway exits, or by optimizing the many parameters that allow the calculation of kernel densities.

4 Modelling of urban sound quality

4.1 From perceptual variables

We have seen in the introduction (Eq. 1) that pleasantness could be predicted from 4 independent perceptual variables. This equation was established from 3409 individual perceptual measures through the Cart_ASUR project on 204 different places at specific times (day, evening, night, weekend, etc.), but in the day and during the week, only 70 situations (plus 19 situations evaluated in GRAFIC project), on average of 20 measures, could be crossed with the geo-referenced data. Of these 89 situations, the "Traffic" variable is strongly correlated with the "Loudness" variable ($r = 0.77$). One of these two variables then had to be excluded from our model, in order to find the optimal variance of the perceptual reference model. It was decided to use the "Loudness" variable because it is better correlated to the pleasantness ($r = 0.85$) than to the traffic time ratio ($r = 0.81$). Equation 13 provides the optimal perceptual regression for the 89 studied situations.

$$\text{Sound pleasantness} = 8.71 - 0.74 \cdot (\text{Overall Loudness}) + 0.33 \cdot (\text{Time Ratio of Voices}) + 0.18 \cdot (\text{Time Ratio of Birds}) \quad (13)$$

This linear regression explains 90% of the adjusted variance (correlation r = 0.94 between the predicted quality of the acoustic environment and the really perceived quality) with an average error from the actual value of pleasantness RMSE = 0.51 (on a range scale from 1 to 11).

4.2 From the density variables

From all the density variables that we have at our disposal, we can construct the following linear regressions:

$$\text{Sound pleasantness} = 12.7 - 2.00 \cdot \log(\text{Cd\_10\_75corrected2.7}) + 0.03 \cdot \text{D\_Gardens} + 0.01 \cdot \text{D\_Voices}. \quad (14)$$

$$\text{Sound pleasantness} = 11.3 - 1.62 \cdot \log(\text{Cd\_10\_75corrected2}) + 0.02 \cdot \text{D\_Gardens} + 0.01 \cdot \text{D\_Voices}. \quad (15)$$

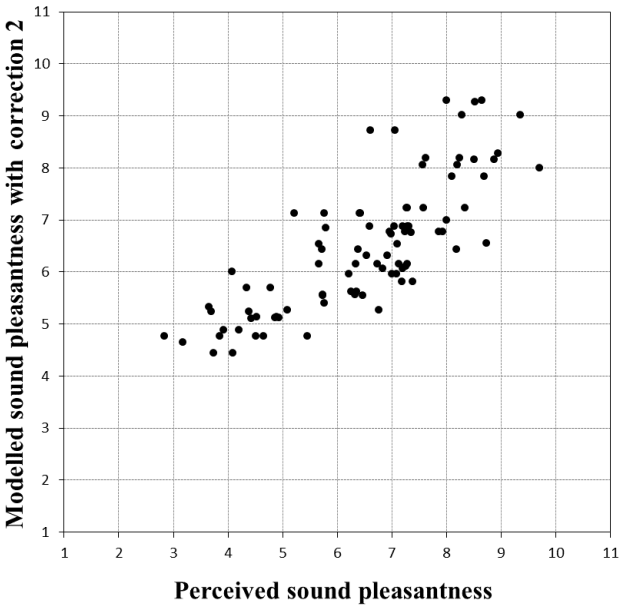
These regressions are actually coherent with the perceptive regression considered in the previous paragraph. The first model explains 68% of the adjusted variance of pleasantness (respectively 62% for the second one), with an average error of 0.89 (respectively 0.97), and a correlation between the perceived and modelled pleasantness of 0.83 (respectively 0.79). We notice that a decision on the correction of the logarithm for very low traffic density values (for high pleasantness) has a significant influence on the degree of variance explained by the models.

4.3 From the Lday

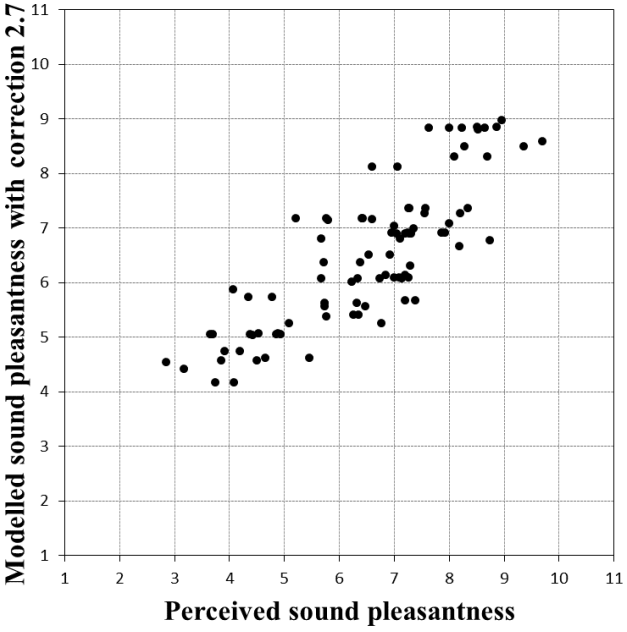
Again, it is tempting to test the intersection of sound quality with the Lday, the only indicator currently available to citizens to appraise the sound quality of a place. The regression (Eq. (16)) explains 65% of the variance, with an average error of 0.93. It therefore corresponds to a correlation of 0.80 between the two variables.

$$\text{Sound pleasantness} = 19.9 - 0.22 \cdot \text{Lday} \quad (16)$$

The Lday is surprisingly better correlated to the sound quality than to the perceived loudness, or even to the traffic time ratio. It is however less correlated to sound quality than a linear combination of core densities, which is much faster to be calculated. On Figure 10, it can be observed that the sound quality modelled linearly by the Lday overestimates the perceived pleasantness for the extreme rankings corresponding to the quiet areas and to the noisy boulevards.



(a)



(b)

Figure 9: Relation between the perceived sound quality and the sound quality modelled by the Eq. 14 (9a) and Eq. 15 (9b).

5 Soundscape mapping

Thanks to the geo-referenced data, it is possible to easily predict the loudness and other influent variables as well as the sound pleasantness of an urban situation. It is therefore possible to propose loudness maps or sound quality maps, at any point of the urban area, and even to predict

the importance of the perceptual variables that allowed building this quality. In the following section, all the models will use the variable Cd_10_75 with the correction of very low values of traffic fixed to 2. Even if the models are a little bit less good than models with a 2.7 correction, they are more relevant for large parks. These maps can be proposed by any city which has geo-referenced data from traffic, gardens and shops.

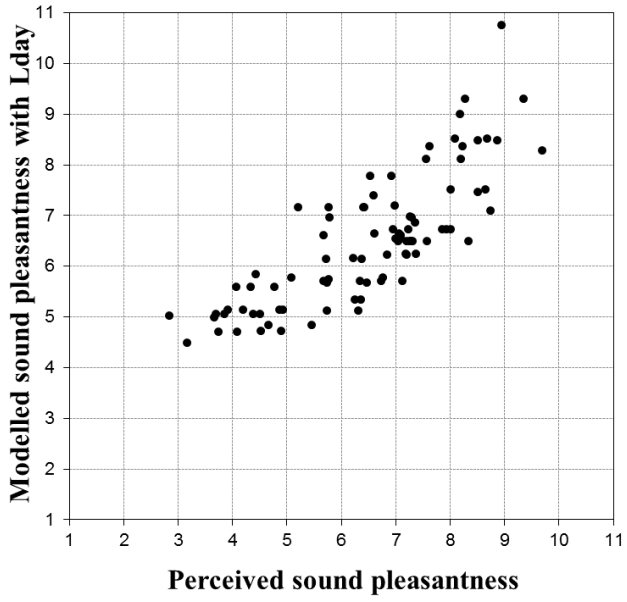


Figure 10: Relationship between perceived sound quality and this quality modelled by Eq. 16.

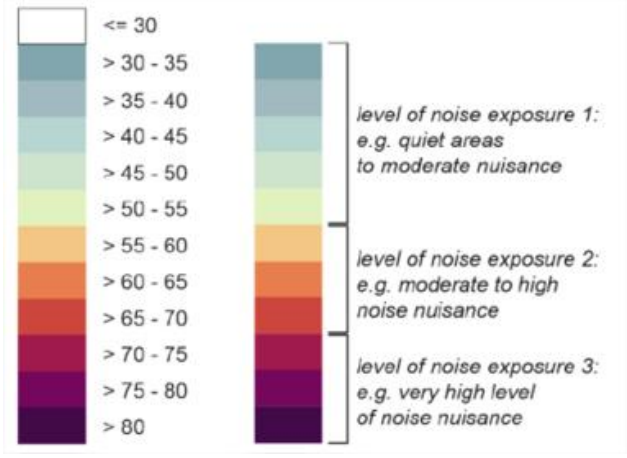


Figure 11: Proposed color scale in [38] by B. Weninger.

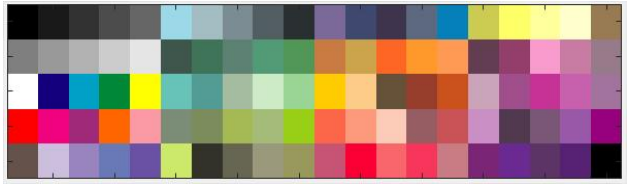


Figure 12: Color table presented to participants on Internet.

5.1 Choice of colors for mapping

According to recent works on color for sound level cartography, the standard color scale used for European noise maps is not suitable [38] and a new scheme was proposed for digital uses (Figure 11).

In this study, the final aim is to propose both soundscape pleasantness and loudness map. In urban context, if high levels of noise are always correlated with a high level of annoyance or unpleasantness, it is not the case for lower levels of noise. For example, high levels can be present in parks due to the presence of human voices and activities. Nevertheless this kind of place may be associated to high soundscape quality.

In order to differentiate pleasantness and loudness variables, a new color scheme has to be proposed. A quick online survey has been done on Internet in December 2015 and 150 persons participated. They had to select 3 colors from a color table (see Figure 12), which ones are appropriate, according them, to describe a pleasant soundscape and then, a silent soundscape. The results are presented on Figure 13.

The final color is defined as follow: (1) the weighted barycentric color coordinates *r, g, b* of the full colorset is calculated (see Eq. 17); (2) the furthest color of the barycentric coordinates, calculated with Euclidien distance, is eliminated of the colorset; (3) new barycentric coordinates are calculated; (4) the final color correspond to the last color present in the colorset.

$$\text{Barycentric Color}(r_b, g_b, b_b) \begin{cases} r_b = \dfrac{\sum_{i=1}^{n} \alpha_i r_i}{\sum_{i=1}^{n} \alpha_i} \\ g_b = \dfrac{\sum_{i=1}^{n} \alpha_i g_i}{\sum_{i=1}^{n} \alpha_i} \\ b_b = \dfrac{\sum_{i=1}^{n} \alpha_i b_i}{\sum_{i=1}^{n} \alpha_i} \end{cases} \tag{17}$$

with r, g, b the red, green and blue coordinates of each color and α the number of times the participants selected a color.

Interestingly, the final color calculated for silent soundscape is very near of the color selected by B. Weninger. However, it can also be observed that a lot of participants chose white, or very light colors. This suggest that the absence of polluant (noise in our case) could also be represented by the absence of colorization on the map.

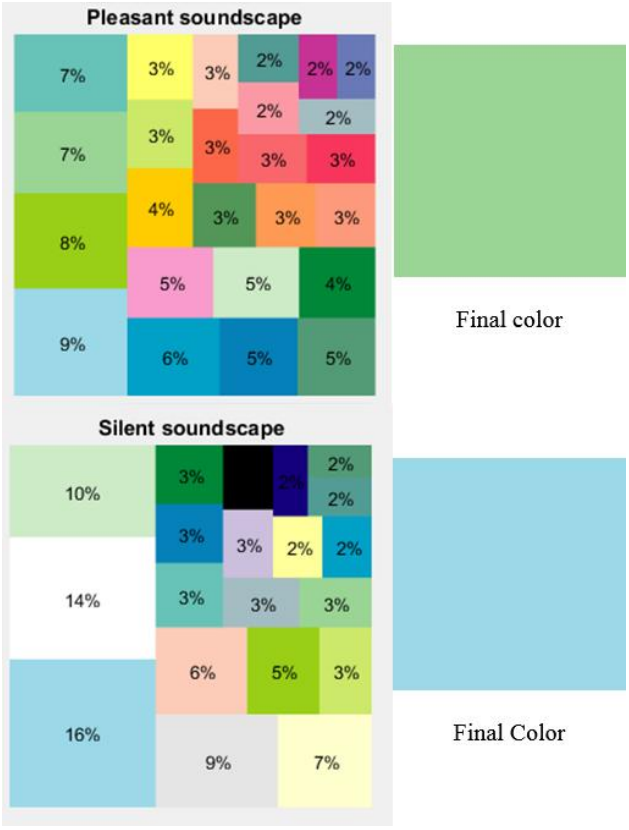


Figure 13: Results of the Internet color study for a pleasant soundscape and for a silent soundscape.

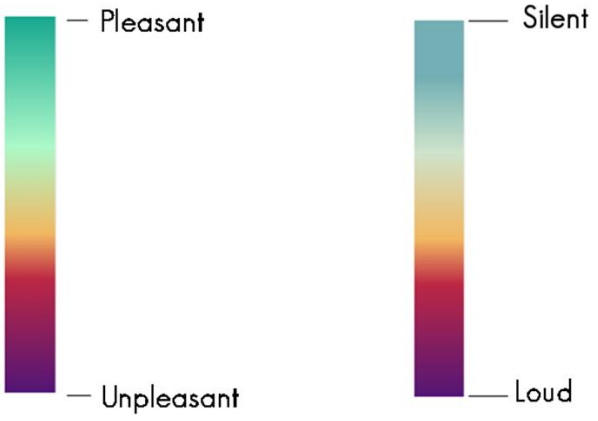


Figure 14: Final color scales for the loudness and the pleasantness of the sound environment.

By contrast, a pleasant soundscape is linked to intense colors, which is in line with the bipolar type of the variable "pleasant" (pleasant/unpleasant). The final chosen scheme scales were obtained from a mix between our results and those presented in [38] (Figure 14).

5.2 Overall loudness mapping

On Figure 15, a map of overall loudness for the 13th district of Paris is proposed. It should, however, be made clear that the modelled variables are only valid in an "urban open space", because the geo-referenced model does not take into account the masking phenomena caused by buildings. These areas most often correspond to public spaces, closed spaces being mostly private spaces. Thus the maps predicted by geo-referenced data should not include the interior courtyard of buildings. A 3m buffer is thus applied around each building to close very small spaces, and then the visualization of these closed spaces is deleted. If Figure 15 shows the map calculated from the predicted model of the overall loudness (Eq. 5) at any mesh except those under buildings only, Figure 16 shows the same map where closed spaces are also not visualized. In Figures 15 and 16, the points represent the mean values of the actually perceived loudness by participants.

First of all the range of the modeled loudness corresponds quite well to the actual perceived loudness, especially along the boulevards. It may be noted that low intensities are generally overestimated by the selected model (in small streets or in garden). This is probably due to the masking phenomenon which is not taken into account by this model.

5.3 Urban sound quality mapping

The final aim of this study is to predict and propose urban sound quality maps that are easily understand by city users. Figure 17 presents the sound quality of the district of Paris which has been perceptively evaluated. It can be noticed that the unpleasantness of some boulevards is sometimes underestimated by the model. For example, the two red dots on the upper west side of the map (Figure 18) correspond to a location where a market takes place on the Tuesdays between 11AM and 1PM. These two locations have been assessed during a Monday and a Tuesday in the frame of the GRAFIC project without the presence of this market, and the ranking of the sound pleasantness is limited to 3.7 and 4.1. On the same boulevard, on the right side, the assessment has been done during the market in the frame of the Cart_ASUR project, and the human presence made the ranking increased to 6.3 and 6.4. It is clear that the identification of voices here has a positive effect on the sound quality. The model which takes into account the presence of the market along this boulevard overestimates the sound quality compared to the period when the market is not there.

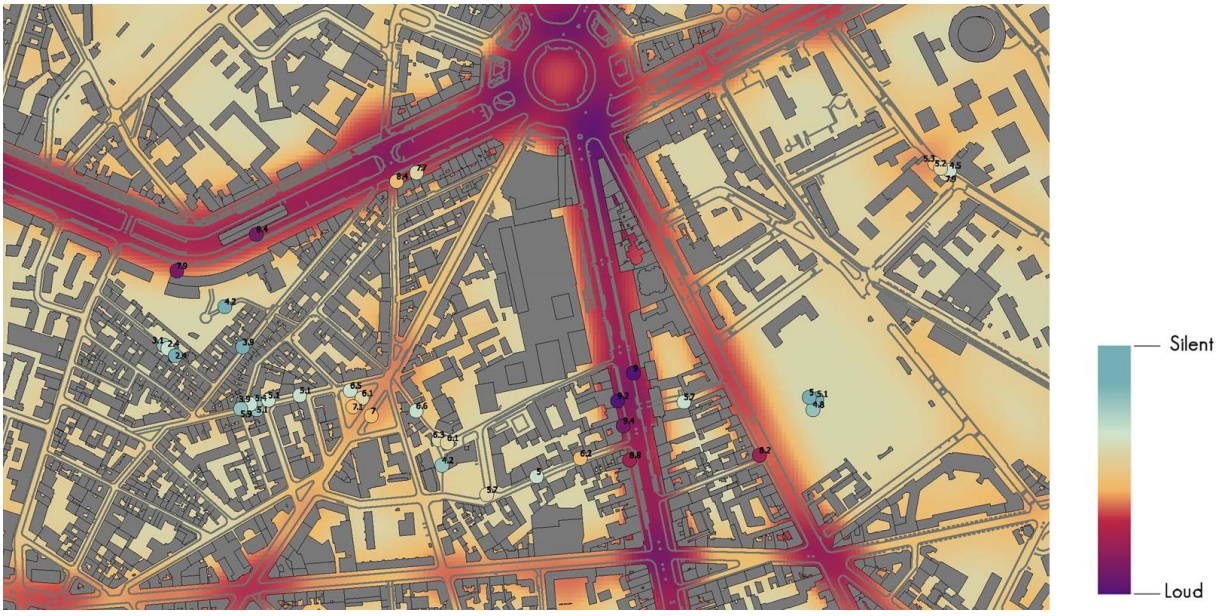


Figure 15: Mapping of loudness modelled on open and closed spaces (Eq. 5).The circles represent the mean values of perceived loudness evaluated by participants.

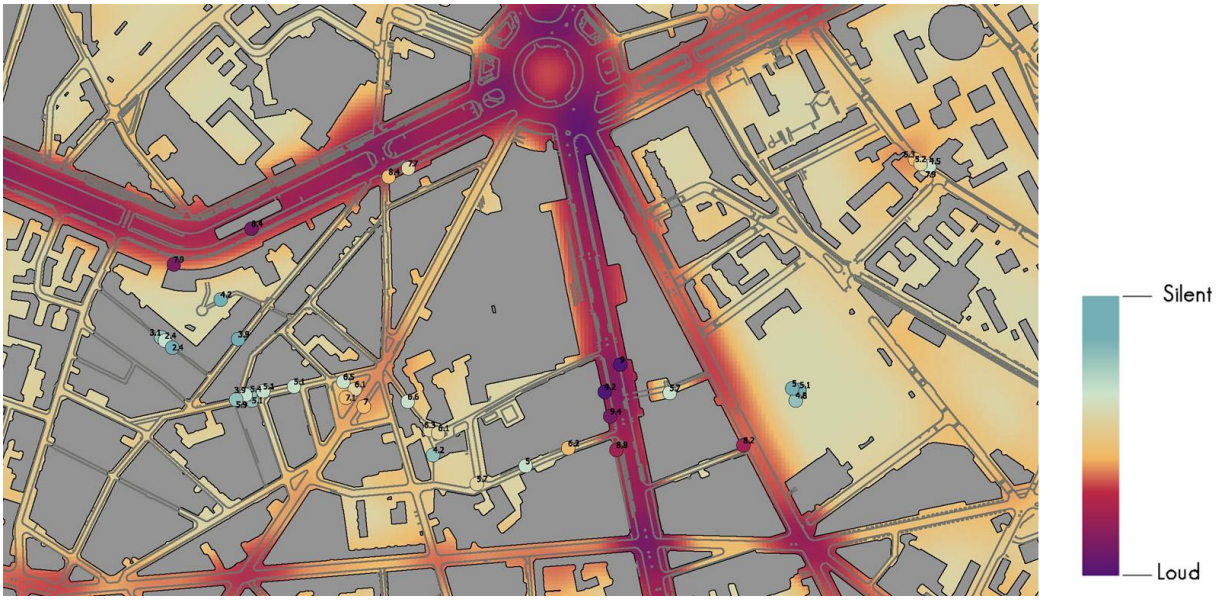


Figure 16: Mapping of loudness represented only on open spaces (Eq. 5).The circles represent the mean values of perceived loudness evaluated by participants.

It is also interesting to show in Figure 19 the time presence of the different sources modelled with the densities (Eq. 9 for traffic, Eq. 11 for birds and Eq. 12 for voices). The representation should specify the period of the evaluation (week or week-end, day, evening or night). The button "details" can be used to give the values (if needed by the reader) of the influent variables such as the loudness, and the perceived time of source presence.

6 Discussion and conclusion

The aim of this study is to propose predictive sound quality maps. The first assumption is that the urban sound quality, which is perceptively measured by the sound pleasantness of an urban situation, is based on relevant perceptual variables. The perceptual variables in this study were collected through field studies in 89 Parisian situations in the 13th

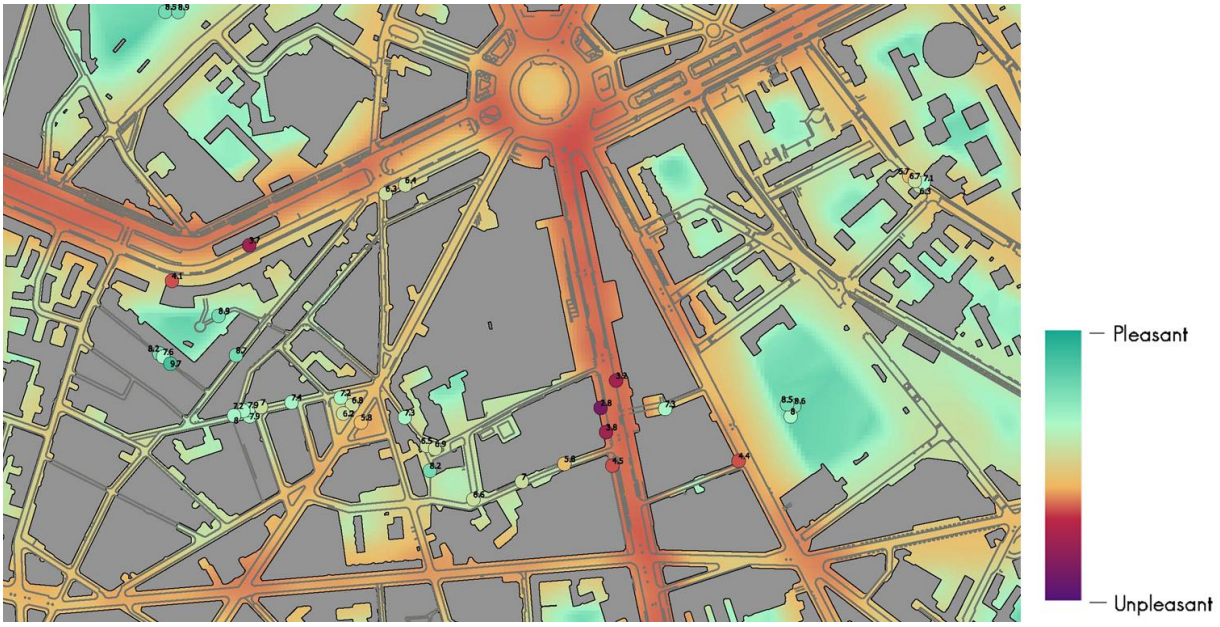


Figure 17: Mapping of sound quality modelled on public space (Eq. 15).The circles represent the mean values of the pleasantness evaluated by participants.

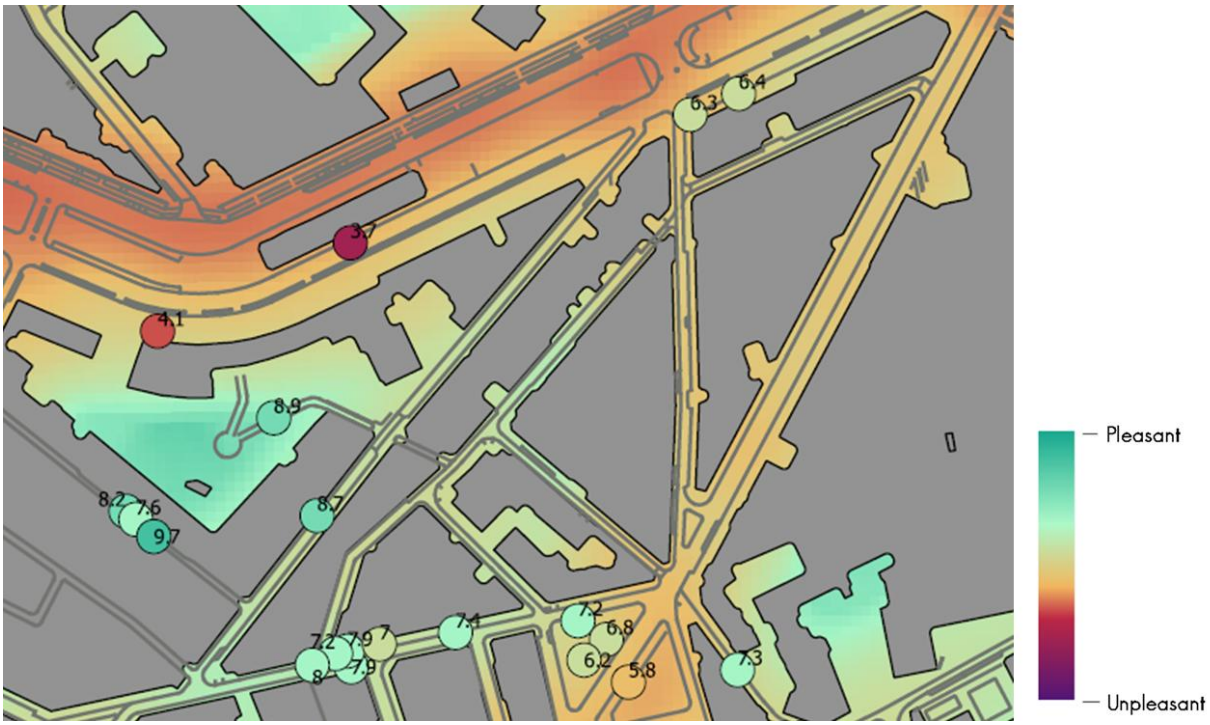


Figure 18: Modelled sound quality around the Boulevard Blanqui (on the top of the map) during a market day. The circles represent the mean values of the assessed pleasantness. The red dots on the boulevard correspond to the mean assessments carried out on a day without the presence of the market. The light green dots on the same boulevard correspond to the mean assessments during a market day.

and 14th districts during the day period and on week days. The global loudness is correlated to the perceived presence of traffic, and has a negative impact of the sound pleasantness. On the contrary, bird songs have a positive impact. This is perfectly in line with literature (see the introduction section). Although an evaluation about the water sounds was asked to the participants, the final perceptual regressions for sound quality (Eq. 1 for the Cart_ASUR project,

Figure 19: Final representation of the sound quality with visualization of sound source presence and visualization of the period of the selected map (buttons in black).

and Eq. 13 for this study) are not based on this particular sound source. This is likely because there were almost no fountain sound in the sonic environment of the selected Parisian situations during the experiment. The presence of voices has a positive impact which is not always the case in literature. The positive effect of voices is due to the pleasantness of streets with bars and restaurants. This corresponds to the point of view of passerby's for who liveliness is appreciated. It does not correspond to the point of view of the inhabitants who live along these streets and suffer about noise during the evening or during the night. So the proposed sound quality model in this study cannot be extrapolated to any kind of urban context without care.

This study has shown that it is possible to anticipate sound pleasantness in all places of a city based on geo-referenced data already available in large cities. The proposed method is very fast to compute, and a full map of a city as Paris can be easily computed in some minutes on a standard computer. This prediction is optimized for sound perception in public space only.

It is therefore possible to provide the population with soundscape maps, as well as maps showing the presence of traffic, birds and voices. These maps are close to the felt experience and allow the reader to better apprehend the sound environment in the places. Also the chosen scale is easier to understand to non-expert than dB scale. These maps could be proposed as a complement to the more expert and technical view of the standardized noise traffic maps.

This work must still be pursued because the models constructed on geo-referenced variables currently predict 68% of the variance of the perceived sound quality, while the perceptual model explains 88%. Progress should be made by optimizing models.

A first optimization could concern the choice of the kernel function and its parameters (point and radius values). In that paper, a fixed Gaussion kernel function has been chosen for all the data as it has been already chosen for previous study about soundscape [27] but this distribution is most adapted for regular distribution of data in

space. If it seems well adapted for traffic density, it should have been different for example for shops and schools. It should have been possible to choose an adaptive radius instead of a fixed bandwidth, defining the number of data to include within a circle centered on each point, and taking the radius of this circle as the bandwidth around that point. A different choice of parameters for the kernel function or a different choice of GIS data could optimize the voice prediction model, as this one is poorly efficient.

A second optimization could concern the substitution of the null values of traffic densities in middle of parks, with low traffic density values. For traffic densities inside parks, the search radius could be increased or adapted in order to smooth the decrease of this density from boundary values to central low values.

This work should also be continued to provide maps that are adapted to evening periods, and why not to nighttime. Finally, a proper work on interactive web development should be done so that the reader enjoys reading these new maps.

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