CENSE Project: general overview

Arnaud Can[1], Judicaël Picaut[1], Jérémy Ardouin[2], Pierre Crépeaux[3], Erwan Bocher[4], David Ecotière[5], Mathieu Lagrange[6], Catherine Lavandier[7], Vivien Mallet[8], Christophe Mietlicki[9], Marc Paboeuf[10]

[1] UMRAE, Univ Gustave Eiffel, IFSTTAR, Cerema, Bouguenais, France
(arnaud.can@univ-eiffel.fr, judicaël.picaut@univ-eiffel.fr)
[2] Wi6Labs
[3] Ville de Lorient
[4] Lab-STICC, CNRS, UBS, Vannes, France
[5] UMRAE, Cerema, Univ Gustave Eiffel, IFSTTAR, F-67035 Strasbourg, France
[6] LS2N CNRS Centrale Nantes, Nantes, France
[7] ETIS, CY Cergy Paris Université, ENSEA, CNRS, Cergy Pontoise, France
[8] ANGE, INRIA, Paris, France
[9] BruitParif
[10] Bouygues E&S

Abstract

The CENSE project, funded by the French Research National Agency from 2017 to 2021, aimed at proposing a new methodology for the production of more realistic noise maps. CENSE stands for "Characterization of urban sound environments: Modelling, noise sensors network and open data". The project relied on a dense network of low-cost sensors deployed in an experimental site in the city of Lorient (France), and data assimilation techniques between simulated and measured data. Beyond the production of physical indicators, the project was also positioned on the characterization of sound environments. The project, which is drawing to a close, has produced advances on noise modelling, low-cost sensor network technologies, data assimilation techniques applied to sound levels prediction, urban sound recognition, and perception. This first presentation, of a series of five, will give a general overview of the project comprehensive approach and framework, and its operational outcomes.

Keywords: Dynamic noise maps, sensor networks, data assimilation, sound recognition, soundscape.

1 Introduction

The reduction of the noise exposition represents both societal and environmental concerns, in particular for cities that are subjected to a multitude of noise sources and that count *de facto* numerous exposed people. In this context, noise mapping is acknowledged as a relevant tool to diagnose urban sound environments, to propose action plans to reduce noise annoyance, as well as to communicate with city dwellers. Nowadays, noise maps are essentially elaborated by means of numerical simulations, with high spatial precision, from a census of noise sources (mainly road, railway and air traffic, and the biggest industries), followed by a sound propagation modelling [1]. However, this method has some well-known limitations especially concerning the inaccuracy of input data, the simplified emission and propagation modelling [2][3][4][5], and, lastly, the inadequacy of classical output noise indicators to describe the perceived sound environments [6][7][8]. In parallel, noise observatories have been deployed in some cities, which give locally access to the time variations of the real sound levels, but entail high operational costs that forbid their dense deployment, limiting the number of observation points to few units [9]. Given the recent developments in noise measurement technologies and computational methods, it is now possible to combine these two approaches in order to benefit from the advantages of each method [10][11]. This would be a significant advance in the development of predictive noise models, and would open many opportunities for assessment and improvement of urban soundscapes.
The CENSE project, funded by the French Research National Agency from 2017 to 2021, aimed at improving the characterization of urban sound environments, by combining *in situ* observations and

numerical noise predictions. The project relied on a dense network of low-cost sensors deployed in an experimental site in the city of Lorient (France), and data assimilation techniques between simulated and measured data. Beyond the production of physical indicators, the project was also positioned on the characterization of sound environments based on sound recognition and perceptual assessments. The project involved ten partners, namely University Gustave Eiffel, Wi6labs, Ville de Lorient, Lab-STICC (CNRS), Cerema, LS2N (CNRS), ETIS (Cergy Paris Université), INRIA, BruitParif and Bouygues E&S.
The combination of modelling and measurements within a common modelling framework has been investigated in few recent projects, among which:

- The IDEA project (Intelligent Distributed Environmental Assessment), which hosted the development of local, intelligent measurement networks for noise and UFP (ultra-fine particulate matter) [12][13]. The collected data were used to feeding models for short-term prediction, by updating noise maps through parameter model tuning [10];
- The DYNAMAP project, which aimed at developing a dynamic noise mapping system able to detect and represent in real time the acoustic impact of road infrastructure, based on customized low-cost sensors and a software tool implemented on a general purpose GIS platform [14][15][16];
- The SONyC project, which aims to create technological solutions for: (1) the systematic, constant monitoring of noise pollution at city scale; (2) the accurate description of acoustic environments in terms of its composing sources; (3) broadening citizen participation in noise reporting and mitigation; and (4) enabling city agencies to take effective, information-driven action for noise mitigation [17][18][19].

The CENSE projects distinguished from these previous works by the proposed integrated approach, mainly based on the use of assimilation methods, novel sensor network technologies, consideration of uncertainties on noise prediction from input data, and sound recognition and perceptual assessments, all in order to predict more accurate and relevant noise assessment in urban areas. The project, which is drawing to a close, has produced advances on noise modelling [20], low-cost sensor network technologies [21], data assimilation techniques applied to sound levels prediction [22], urban sound recognition, and perception [23], each topic corresponding to a specific Work Package of the project. This first presentation, of a series of five, will give a general overview of the project comprehensive approach and framework, and its operational outputs. The project advances are described from sections 2 to 5, then more in-depth in articles [20][21][22][23]. Section 6 discusses the advances of the project as well as the encountered difficulties, so as to draw the further research and development avenues for the years to come as regarding the characterization and monitoring of urban sound environments.

2 Improvement of city noise map production processes and sensitivity analysis to noise models inputs

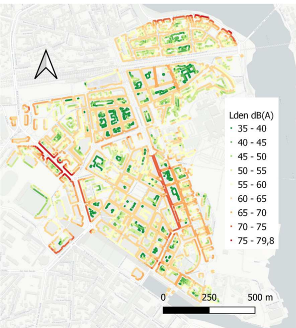
2.1 Improvement of city noise map production processes

Collecting input data for noise mapping is often a difficult task, and obtaining good quality for this data is certainly even more difficult. A specific process for noise mapping was developed under the CENSE project, based on the coupling between an open source noise mapping software and an open source spatial database that can provide most of the input data for noise mapping.
All noise mapping achieved under the CENSE project relied on the NoiseModelling software, which has been improved and subject to a new release during the project [24]. It is a free and open-source software dedicated to environmental noise maps on large-scale outdoor spaces. It can be used as a Java library or be controlled through a web interface [25]. The CNOSSOS-EU model is implemented for the estimation of road traffic emissions, as well as for the calculation of its attenuation along propagation paths [1]. NoiseModelling allows information to be stored at three levels: the noise sources and their sound levels, the geometry of the propagation paths and finally the transfer matrix for each of the source/receiver pairs. This choice was made because the computation time of such a software is essentially concentrated into the pathfinding algorithm. A groovy script manages interactions between NoiseModelling libraries and a spatial database (PostGIS or

H2GIS) for getting most input parameters. Simulation can be performed using a configuration file containing the values on the input parameters, and results are stored in dedicated compressed folders. All the framework is open-source and available on GitHub to ensure the research is reproducible and adaptable to other case studies. Most input data of NoiseModelling came from OpenStreetMap (OSM) data, and are requested, processed and formatted by means of the opensource geospatial toolbox GeoClimate. Details on input data can be found in [20]. OSM-based noise predictions were compared to a noise map of a part of Paris, calculated with reference input data. Noise maps show a moderate agreement, with nearly 40% of the receivers with a deviation lower than 2.5%. Discrepancies might be attributed to road pavement classifications [20].

2.2 Sensitivity analysis of noise mapping modeling

When producing a noise map, it is essential to be able to identify the most influential input data and parameters in order to prioritize them in the data collection and modelling process. In order to help this prioritization, a methodology for sensitivity analysis built on an open-source modeling framework has been proposed under the CENSE project, relying on the Morris method; see [26] for details. The total procedure was repeated 50 times for a group of 15 inputs, resulting in 800 simulations. To ensure that the space of exploration did not favor any area, 500 trajectories were drawn and only the fifty trajectories that maximize exploration were retained. Figure 1 shows the chosen parameters and ranges of variation. All ranges of variation and parameters chosen are specific to this study and should be adapted to any other case study. Above all, the aim was to propose a methodology that can be replicated, including long-distance sound propagation for example.



Parameter	Variation	Step	Parameter	Variation	Step
Total Veh. Flow Rate on major road (>1000 veh./h)	[0.7;1.3]	0.2 (*)	Buildings absorption coef.	[0.5;1.5]	0.33 (*)
Total Veh. Flow Rate on medium road (300–1000 veh./ h)	[0.7;1.3]	0.2 (*)	Temperature (C)	[6;18]	4 (+)
Total Vehicle Flow Rate on small road (<300 veh./h)	[0.7;1.3]	0.2 (*)	Humidity (%)	[20;80]	20 (+)
Heavy Vehicle Ratio)	[0.5;1.5]	0.33 (*)	Order of Reflection	[0;1]	1 (+)
Medium Vehicle Ratio	[2;8]	2 (+)	Horizontal diffraction	[true/false]	–
2 Wheels Vehicle Ratio	[2.7;3.3]	0.2 (+)	Vertical diffraction	[true/false]	–
Favorable meteo conditions	[0.7;1.3]	0.2 (*)	Max Propagation distance	[300;750]	150 (+)
Wind direction (°)	[60;60]	30 (+)			

Figure 1 – Left: Study area of the analysis. 14,343 receivers are represented on the map. The color represents the median L_{den} value at each receiver over the 800 simulations. Right: Sensitivity analysis parameters, related topic reference codes, ranges of variation and step types (multiplicative * or additive +)

The study area retained all along the CENSE project is the city of Lorient. It covers an area of about 2 km^2, in which 14,343 receivers (around 1772 buildings) were selected to serve as a support for the sensitivity analysis. The influent input parameters are a compilation of data collected from Cerema, IGN (the French National Institute of Geographic and Forest Information) and the Lorient city council. Figure 1 shows an example of results through the median L_{den} value of the 800 simulations in dB(A) representing 9672 inhabitants. Approximatively 24% of them are exposed to road traffic L_{den} values above 65 dB(A).

Results are detailed in [26]. In brief, the sensitivity to the input parameters of the CNOSSOS-EU model highly depends on the location of the receivers. The most influential parameter is whether diffraction over horizontal edges is considered or not, regardless of the indicator observed: average sound level over the area or ratio of the population exposed to more than 65 dB(A). This can be easily explained by the fact that some receivers may not be reached by a propagation path until this parameter is introduced in the calculation. When model configuration parameters are excluded from the analysis, it can be shown that for most receivers, the most influent parameters are linked with the emission part of the CNOSSOS-EU model, and concern the mean flow rates of the road category the closest to the receiver.

3 A high density network of low cost acoustic sensors based on wired and airborne transmission of spectral data

The CENSE network, currently deployed in the downtown area of the city of Lorient, is described in this section. More details are given in [21].

3.1 Network

Following a literature review [27], the CENSE network considered a hybrid communication scheme where each node of the network is a sensor with acoustic monitoring capability. Those nodes can be leaf nodes. In this case the sensor is energetically autonomous and sends wirelessly the data to the other types of nodes, the gateway nodes. A gateway node is wired both in terms of power and network connectivity. The degree of precision of the measure can vary greatly from device to device. As discussed in [28], this degree of precision is balanced with the cost of the sensors. While high precision sonometers are of great interest for metrologic use, we believe that low cost sensors based on the MEMS technology has the potential of allowing the use of large scale and dense network of sensors at a reasonable price. Following the constraints of the project, the specifications of the microphone have been defined and more than 20 MEMS microphones have been considered [29]. The Invensense ICS-43432 MEMS microphone is selected because of its good overall performance and the fact that it offers an I2S fully digital interface, thus reducing the risk of any electrical noise addition to the audio data.

Figure 2 - The leaf (left) and gateway (middle) sensors. Right: Deployment in the City of Lorient

The installation of the sensors was planned in two phases on an experimental site in the heart of the city of Lorient in France. The first phase consisted of the installation of 78 gateway nodes, then in a second phase, the installation of 65 nodes. The maintenance of the network is a crucial element of the project. The entire network was developed specifically by the project partners, from scratch, be it for the design of the sensors, the installation of the network, and the implementation of an IT infrastructure for data management. On one hand, it allowed rapid intervention; on the other hand, numerous skills from very different technical areas were required to cope with unforeseen issues. Among the difficulties encountered were: the failure of some sensors after installation (a few units); the multiplicity of risks of measurement stoppage due to malfunctioning of either the sensors themselves, or the Citybox ®, or the controller, or the router; the maintenance of the servers. In spite of these difficulties inherent to the initial choices for the development of the network, the whole network was successfully implemented during the first months of the study, allowing the acquisition of a large amount of data and the experimentation of different sound analysis.

3.2 Acoustic sensitivity and robustness analysis

In order to study the acoustic behavior of the developed sensors, several tests were performed in an acoustic test room, which evaluated the linearity, directivity, sensitivity and background noise characteristics. The tests were limited to values measured in one-third octave bands over a frequency range from 20 Hz to 12500 Hz. Concerning the background noise of the sensor, results obtained showed that the CENSE sensor has a threshold of about 22 dB, over all the frequency bands concerned. The frequency sensitivity was very good for the octave bands from 250 Hz to 4000 Hz, with a difference of less than 0.5 dB. For the 125 Hz, 8k Hz and 12.5k Hz octave bands, the differences were a little larger, from 1 to 2 dB. For the 2 lowest octave bands

(31.5 Hz and 63 Hz), the differences were much more important (from 4 to 10 dB approximately). Finally, the linearity was tested: from 125 Hz to 12.5 kHz, the slope measured for the sensor was very close to unity, which is the expected theoretical behavior. The conclusion of these tests is that the sensor results appear to be acceptable for the frequency bands between 400 Hz and 5000 Hz.
The reliability, accuracy and robustness of the developed acoustic sensors has been qualified under various meteorological conditions in a climate chamber in order to check the potential sensor drift according to both the temperature and relative humidity. Results are detailed in [30]. In brief, both temperature and humidity have a weak effect on the acoustic measurements, except for one of the six sensors, and uncertainties for these two environmental parameters fulfill specifications of class I sound level meter. Results demonstrate the satisfying accuracy of the implemented acoustic sensors for the targeted purpose.

3.3 Data archiving

Each node produces acoustic data, pressure level statistics, and third octave spectral data, that are sent every 10 seconds. Control information, such as temperature and humidity inside the sensor are sent every 60 seconds. If the sensor is a leaf node, information about battery voltage and connectivity are also sent every 5 minutes. Acoustic pressure statistics are the L_{Aeq} and L_{eq} computed every second (520 bytes). Third octave spectra with frequency range 20Hz-12500Hz are computed every 125 ms using a rectangular window Fast Fourier Transform (15 kbytes). Bandwidth testing showed a bandwidth consumption of 1769 bytes per second. Each gateway node is responsible for sending its data through the internet to an archiving architecture using the opensensorhub protocol.
The storage architecture of the CENSE project was designed to maintain high availability. To this end, the data are distributed on 2 distinct sites (see [21]). The archiving system should therefore be operational even if one site is no longer reachable.
Each gateway node collects data through its sensors then aggregates into an embedded OpenSensorHub instance. This aggregated data is transferred to a random server through a secured http request using the open source Elasticsearch interface. The receiving server then duplicates the data to another Elasticsearch server for data safety (https://github.com/elastic/elasticsearch). Archived data can be accessed using low level request protocol using the Elasticsearch engine as it allows database replication for further data processing purposes by serving json files. For example, the acoustic data is pushed to the servers of bruitparif (https://www.bruitparif.fr) that services a range of display tools available at the following url: https://rumeur-lorient.bruitparif.fr. Higher level data visualization and monitoring can also be performed using a Kibana interface. Finally, by recording spectral data, the CENSE project aims at allowing the automatic estimate of those quantities using deep learning techniques (see section 5). Coding schemes have been proposed in that respect [31][32]. Figure 3 shows the presence of three sources of interest: traffic, voice and birds.

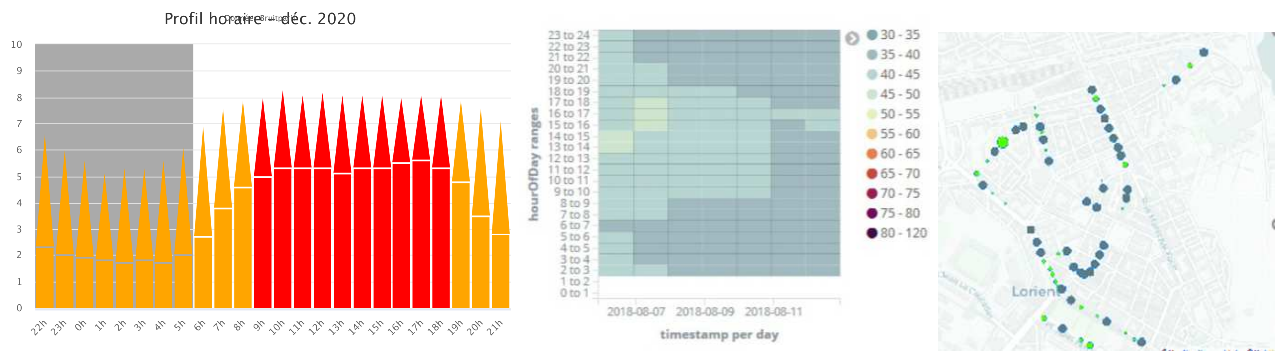


Figure 3 – Left: The Harmonica profile for a given sensor of the CENSE network for the month of December 2020. Center: Evolution of the L_{Aeq} over a week for a given sensor using the Kibana dashboard. Right: Estimation of the time of presence of birds (green) from spectral data using deep learning techniques.

4 Faster and more accurate noise mapping combining meta-modeling and data assimilation

The CENSE project relied on a two steps approach to combine measurements and modeling, in order to go towards faster and more accurate noise mapping:

- A meta-model (also sometimes called surrogate model) is built to statistically reproduce the behavior of the reference simulation software, NoiseModelling in this case;
- The meta-model is then employed to assimilate acoustic measurements from 16 locations. State estimation, inverse modeling and joint state-parameter estimation are compared and evaluated using cross validation.

This section summarizes the results of the CENSE project in terms of meta-modelling and data assimilation. The reader can refer to [22], or to the following papers for more details [33][34][35].

4.1 Material and methods

For phasing and data availability reasons, the model was built on data produced on the City of Paris, and not on the Lorient measurement network of the CENSE project. The study area is located in the 13th district of Paris, France and covers an area of 3 km2, and is described in details in [36]. It consists of an array of 25 microphones that has been deployed across the study area in 2015, from which 16 have been selected for the present study.

4.1.1 Meta-model

Due to the large number of model calls in the optimization algorithm, data assimilation techniques are made practicable only after replacing the noise mapping software with a meta-model, i.e., a statistical emulation of the noise mapping software that can compute similar maps at a much lower computational cost. The meta-model is built in three steps:

- The generation of the training sample. Here, the training sample is made of 2000 simulations run with model input parameters defined a so-called design of experiment;
- The dimension reduction, through a PCA, which aims to select a reduced amount of maps that explain most of the variance of the noise maps of the training sample;
- The kriging, which interpolates with a statistical method the projected values of the training sample onto the basis vectors of the reduced subspace.

Once the meta-model is built, each call with new input parameters takes a very small amount of time (100 ms versus ~ 1 h for the complete model). For more details about the meta-model construction, the reader can refer to [33].

4.1.2 Data assimilation methods

Data assimilation is the process of combining a noise model simulation and field observations, in order to build an improved representation of the real noise levels, at least at simulated points. In our context, the data assimilation makes use of a model or a model simulation (simulated noise map) and field observations at a given time, in order to produce another noise map closer to the real noise map. It can be seen as a correction on the simulated noise map, induced by the additional information brought by the observations. Among all the data assimilation approaches, we compared state estimation, inverse modeling and a joint state-parameter estimation:

- The state estimation applies a direct correction on a simulation map. It assumes the simulated map is an a priori map with some unknown error at every point of the map. The so-called best linear unbiased estimator (BLUE) is computed, which is an improved noise map whose error has minimum variance.
- Another approach is called inverse modeling (IM). In this case, we do not correct directly the simulated noise map, but instead the input parameters of the noise model, or in our case, of the meta-model. The method allows to determine better parameters, which with the simulated map gets closer to the observations.

- Joint state-parameter estimation (JSPE) combines both approaches: the parameters are improved and also a correction of the resulting noise map is corrected. This allows for further flexibility and gives more room for improvement.

Both methods, IM and JSPE, can work with or without prior knowledge of the input parameters; four optimization algorithms are therefore analyzed. If satisfying results are obtained with optimization algorithms that do not need a priori parameters, then it is possible to expand the inverse modeling data assimilation processes to a wider range of urban areas where the input parameters values are not known.

4.2 Results

Methods are compared through a leave-one-out cross validation, which consists in removing the observations of a given microphone from the data assimilation process. Results are detailed in [35]. In brief, the inverse modeling shows similar results as the data assimilation method BLUE (Best Linear Unbiased Estimator) only, whereas the JSPE always has a lower RMSE value than the state estimation only. The performance of IM and JSPE without a priori parameters remains very similar to the performance with these parameters. The most accurate noise map is generated computing a JSPE algorithm without a priori knowledge about traffic and weather and shows a reduction of the RMSE from 3.5 dB to 2.6 dB compared to the reference meta-model noise map with 16 microphones over an area of 3 km^2. This means that the operators who wish to obtain a dynamic noise mapping for a given area can get a satisfying level of accuracy without the need to get real-time traffic and weather data, and extend the availability of dynamic noise mapping to areas where no traffic measurement is available.

5 Characterizing the sound environment through an automatic assessment of traffic, voice and bird presence ratios

Going further than just the sound levels, the data collected through the urban sensor network allow to perceptually characterize the soundscape as it is defined in the ISO standard as the "acoustic environment as perceived or experienced and/or understood by people, in context" [37], as soon as acoustic measurements could correspond to perceptual data. In the continuity of previous works that were interested in the outdoor [38][39] or indoor [40] perceived sound quality, in the CENSE project, we focused on the perceived sound quality and on noise annoyance for pedestrian point of view (soundscape characterization) as well as for resident point of view (at home situation). As these perceptual characteristics depend on perceived sources, we also focused on the possibility to measure automatically the sound source presence ratios on the sensors, in addition to classical level indicators.

5.1 Questionnaire campaign

The sound quality and the noise annoyance has been assessed for both the pedestrian and inhabitant points of view thanks to a questionnaire that has been sent by postal mail to about 2000 inhabitants in the city center of Lorient between January and March 2019. It was divided into four parts:

- The first one concerned the sound environment quality: it concerned the Short-Term (ST) assessment on 7 levels semantic differential scales of variables such as pleasantness, eventfulness, etc.;
- The second part focused on the perceived time of presence ratio and loudness of 13 sound sources, such as road traffic, rail traffic, calm voices, expressive voices, small birds, gulls, etc.;
- The third part concerned the Long-Term (LT) annoyance for both points of view;
- A last part was dedicated to collect personal data, such as noise sensitivity, gender, age, socio-professional category, etc.

Outdoor pleasantness and outdoor annoyance models were built (see [23] or [41] for details). Overall Loudness (rated on the Noisy/Silent scale) appears in all models at the first place showing that this variable is the most influent one. Sound sources such as road and air traffic, expressive voices and birds also appear in the regressions. Long-term inside annoyance models are also built, which make a distinction between calm voices (perceived positively) and expressive voices (perceived negatively). Finally, it is found that Noise Sensitivity and Age increase the adjusted explained variance of the models.

5.2 Sound identification

The calculation of the source presence ratios has been automatically implemented on the low-cost sensors, for relevant sources such as Road traffic, 2-wheel motor vehicles, Voices and Birds for examples. The source identification is realized every second for each source of interest on each sensor. Source identification is conducted using a deep convolutional architecture that first extracts time-frequency patterns relevant to the identification of sound sources from each 1s third-octave segment. At inference, presence or absence labels predicted for each sound source are aggregated over time to obtain the time of presence over the first 10 minutes of each hour. The model is trained on a fully synthetic set of 400 sound scenes of 45s each as described in [42]. Synthetic scene generation and automatic annotation processes are further detailed in [43]. Results are in accordance with expectations (see [23] for details), highlighting for instance an increase of the time of presence of birds in the morning corresponding to the sunrise birds chorus, an increase of voices on Wednesdays and week-ends, and a cars evolution following the rhythms of the days.

5.3 The cartographic web portal

To highlight the results on a map, a cartographic portal has been set up. Publicly available at http://cense.noise-planet.org/, this website allows users to navigate the map (with the classic zoom and address search functions) and to consult the calculated indicators in detail. Figure 4 illustrates some screenshots of layers accessible to the user.

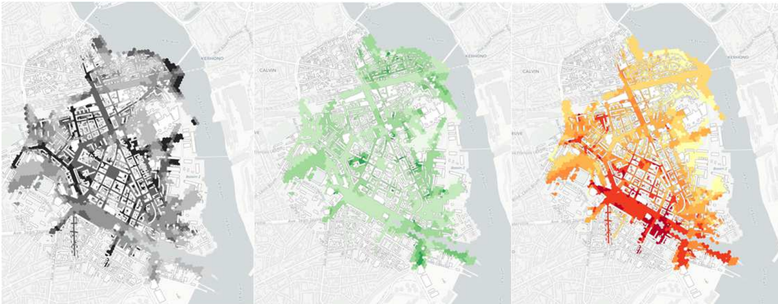


Figure 4 – Traffic (left), birds (middle), and expressive voices (right) layers, which represent the presence ratios of different sources.

6 Conclusion

The CENSE project, funded by the French Research National Agency from 2017 to 2021, aimed at improving the characterization of urban sound environments, by combining *in situ* observations and numerical noise predictions. The project, which is drawing to a close, has produced advances on:

- Enhancing the noise production process and proposing a sensitivity analysis for noise mapping [20];
- Designing and deploying a low-cost sensor network, as well as a data archiving [21];
- Proposing data assimilation techniques applied to sound levels prediction [22];
- Characterizing urban sound environments through sound recognition and perception advances [23].

The reader can refer to the corresponding Euronoise papers, or to the literature produced during the project, for in-depth results. The main encountered limitation consisted of the technical difficulties linked to the sensor network maintenance, which has desynchronized part of the perceptual study from the physical data collected, and necessitated that the work on data assimilation be done on another measurement network. However, this in no way calls into question the scientific results of the project. The CENSE network being now operational, it will allow researchers to answer many scientific and technological questions regarding the characterization of the urban sound environment. Finally, the CENSE project opens up many avenues of research, for example on the enrichment of the input data with other sources of traffic and acoustic data, on the production of perceptual noise maps, or on the use of sensor networks for decision making.

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