New Environmental Indicators for Sustainable Cities of Varying Size Scale: The Use Case of France

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Abstract. Nowadays, more and more data about our environment are available. Those data might be of various sources and types such as quality of life, energy consumption or any other domain that may have an impact on people's environment. However, when it comes to evaluating the quality of our environment, a lot of approaches exist which are not easy to use. Hence, this paper introduces a new methodology to calculate an environmental score for cities which takes into account pollution (water and air) indicators, energy consumption, soil uses and artificialization and habitat insulation. This method compares those data with social indicators such as unemployment rate and our purpose is to help city leaders to understand the statement of their city on the environmental topics. Moreover, the methodology that is proposed in this paper can be applied by all French cities, regardless of their size, since it only uses free open source verified data. The calculated scores are available on 31 cities of different size from the Occitanie region in France. As a finding of this paper, we identified that bigger cities have a smaller environmental score while smaller cities get higher scores. Environmental low score for big cities is most often due to low air quality, artificialization of soils and high electrical consumption. With the smaller cities, unemployment and poverty rates are lower, as well as drinkable water quality, mostly due to the chlorine quantity in water.

Keywords: Environment governance · Cities environment indicators · Sustainable smart cities · Air pollution · Water pollution

1 Introduction

Many data are collected nowadays about air quality, energy consumption, quality of life… To address environmental issues, their interpretation and the way they are exploited need to be optimized to obtain proper indicators for citizens and city leaders. Those indicators are useful not only to inform the population but also to provide them clues on which directions they need to improve for city development. Those indicators must be accessible and exhaustive. Our objective is to provide a methodology to produce scores with different indicators related to environmental topics, to improve cities development

S. Paiva et al. (Eds.): SmartCity360° 2021, LNICST 442, pp. 381–391, 2022.
https://doi.org/10.1007/978-3-031-06371-8_25

and increase citizens involvement. Ease of use is the core of this methodology: based only on existing and available governmental data and national goals and laws, it is a low-cost solution, and therefore can be available for any city, regardless its size and its state of development.

In order to get citizens involved in environmental change, it is important to provide them not only with detailed and trustworthy information, but also to make them understand the impact of environmental issues on other aspects of their daily life. In fact, giving indicators may prove to be unsuccessful if citizens can't link them to social dimension. The methodology result should be a final score, which could help cities to focus on the main aspects to improve.

2 State of the Art

This study assumes that global warming must be slow down, and citizens want more ecology in their cities. The Intergovernmental Panel on Climate Change (IPCC) reports on climate change 2021 [1] indicate that GHG (Green House Gases) increased in atmosphere since 1750 and mostly for CO_2 (47%), CH_4 (156%) and NO_2 (23%). This human impact influences global surface temperature (+0.8 °C to + 1.3 °C from 1850–1900 to 2010–201911), land precipitation has likely increased, sea level increased by 3.7 mm/yr between 2006 and 2018. In order to include environment protection int their programs, city leaders have to be familiar with those topics.

Sustainability was defined in the 1987 Brundtland report as "the balance of economic, social and environmental development" [2]. More than 413 indicators already exist to evaluate sustainability [3] and ecological impact [4] of cities. The problem with cities sustainability is the citizens and city leader vision of environmental indicators. They receive wrong information about prices, regulations and controls, and indicators are not sufficiently linked to specific environmental effects [5]. Studies suggested environment indicators on many topics like Impervious surface coverage [6].

These environment indicators must be linked to economical. institutional and social indicators [7]. A detailed method to define social indicators for a sustainable smart city was presented in [8].

In France, standards exist for air and water pollution [9, 10], air pollution [11, 12] and insulation of buildings [13] for example, but standards and thresholds is not always understandable for citizen and city leaders. A method based on North of France already exists, it is a study case to determine an environmental score [11] but it requires data which are difficult to obtain, such as "low level of education" or "no access to car" for the 36 000 French cities. The second point is that this method has been developed for mapping representation and not to determine a distinct score for each city. Therefore, we propose a new approach for measuring different indicators related to different topics linked to environment and make them interpretable for anybody.

3 Methodology

Based on literature recommendations, a new methodology was built using existing open access data. The case study is the Occitanie region of France, where interactions and feedbacks from city leaders are at the core of the elaboration of our smart city study. We started with cities which air pollution data were available, as it is not the case for many cities in Occitanie region.

Data used to develop this methodology come from open databases, and are mostly provided by the French governmental data platform [14]. All data sources are available in the tab "Data sources" of the **Supplementary Materiel 1**, which link is in the Acknowledgement. The key points of the methodology are: (1) Available data: they must be easy to find and free; (2) Indicators built from understandable data measures; (3) Any French city, regardless of its size and number of citizens, can apply this method.

First, we studied raw data to identify trends between environmental data, eco-social data, and size of cities. Second, we proposed various scores for different selected indicators before comparing them. All indicators, data, scores and sources for selected cities are available in the "Cities data and scores" tab of the **Supplementary Materiel 1**.

For environmental score, indicators were selected from different categories: water contamination, air pollution, habitat insulation, electrical consumption, gas consumption and natural and artificial surfaces. Those categories include different indicators. For example, air pollution is composed of 12 indicators on $PM_{2.5}$, O_3, NO_2 and SO_2 concentration in the air.

For eco-social conditions, we selected unemployment rate and poverty rate. Finally, cities were classified in three categories: less than 20 000 people (category "Cities 1"), between 20 000 and 100 000 people (category "Cities 2") and more than 100 000 people (category "Cities 3").

Detailed scores are calculated with different methods. For unemployment and poverty, the score is based on unemployment rates (%) and poverty rate (%). This rate is then normalized to 40% for poverty, meaning that 40% of poverty gives a score of 0/100 and 0% of poverty gives a score of 100/100. The 40% value is defined with the maximum values observed. The same method is used for unemployment but with a normalization of 30%.

For water and air pollution, scores are determined based on comparison between measured concentrations and standard concentrations. Standard values for air pollution [9] are 10 $\mu g/m^3$ (on average per day) for $PM_{2.5}$, 120 $\mu g/m^3$ for O_3, 40 $\mu g/m^3$ for NO_2 and 50 $\mu g/m^3$ for SO_2.

For water pollution, we chose many indicators with standard values for most of them [10] except for taste and look, total chlorine and revivable air bacteria at 22 °C in 68 h. For taste and look, a "no comment" gives a 100/100 score, and any special observation gives 0/100. For total chlorine, 0 mg/l gives 100/100 and >1 mg/l gives 0/100. The 1 mg/l limit for chlorine is chosen with the maximum concentration observed and is discussed in detail in the discussion part of this publication. For the revivable air bacteria at 22 °C in 68 h, <1 mg/l gives 100/100 when ≥ 1 mg/l gives 0/100. The other scores (bacteria, pH, ammonium and aluminum) are calculated thanks to the standard values, defining the 0/100 scores.

Scores for the EPD (Energetic Performance Diagnostic of buildings) depend on two criteria for which the insulation of buildings show an estimated consumption (from <51 $kWhEP/m^2.yr$ to >450). The second criteria is the estimated GHG emissions (from <5 $kg_{eqCO2}/m^2.yr$ to >80).

Electrical and gas consumption scores are all calculated from consumptions in different sectors that are Residential (R), Tertiary (T), Industrial (I), Agricultural (A) and Other (X). Final scores for those aspects are composed of two calculated scores which are the Per capita electric average consumption for R area (standardized) and for all sectors (standardized). Normalization is defined with the maximum observed values.

Finally, the Total land score is composed of two scores that are the rate of artificial soils and the rate of natural soils. The natural soil score is calculated by adding Forest and semi-natural soil rate, Wetland rate, Water surfaces rate and Natural soil rate.

4 Results and Environmental Scores

First, we analyzed data which can help cities for environmental transition.

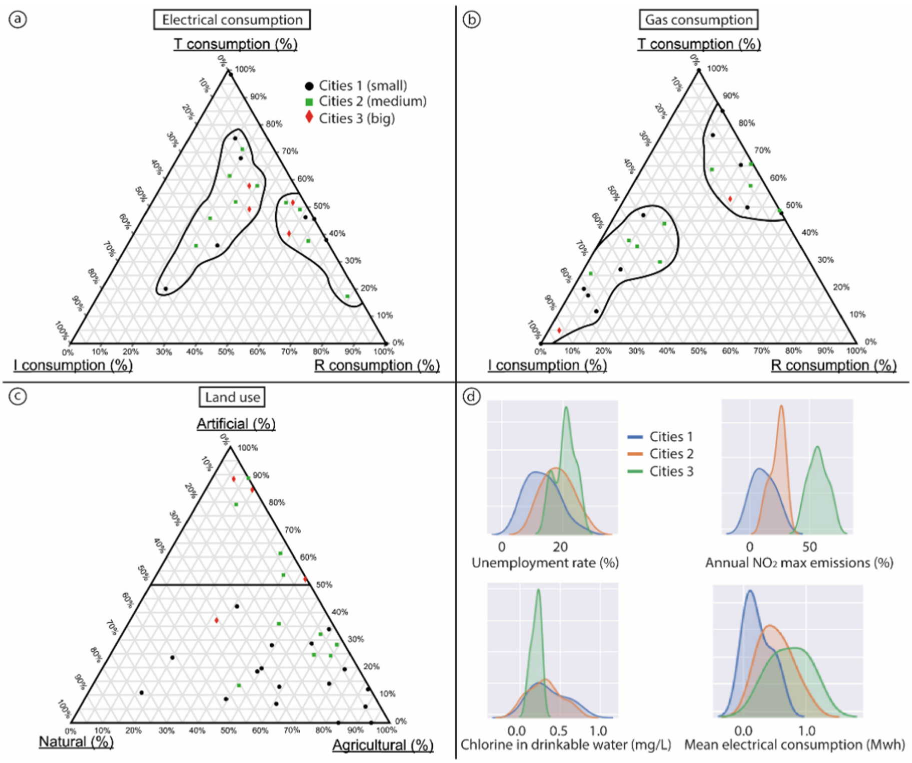

Fig. 1. Available data about **a)** Electrical consumption distribution in the city: rates of Tertiary (T), Industrial (I) and Residential (R) sectors; **b)** Gas consumption distribution in the city: rates of T, I and R sectors; **c)** Land use distribution: rates of artificial, natural, and agricultural lands; **d)** Histogram distribution depending on the cities size are obtain using pandas and seaborn Python libraries. Indicators are unemployment rate (%), annual NO_2 emission comparing to the limit standard of emission (%), total chlorine in the drinkable water (mg/L) and mean consumption per citizen for the Residential sector (Mwh).

As energy is a very important aspect in environmental transition, we first studied electrical and gas consumption in cities (Fig. 1a and 1b). Electrical consumption presents two patterns (Fig. 1a): one showing less than 35% of Residential (R) consumption and a distribution of the major component between Industrial (I) and Tertiary (T) consumption. The second one is share between R and T consumption, with a majority of R consumption.

For gas consumption (Fig. 1b), each city shows less than 55% of R contribution, and a majority with less than 30%. Electrical and gas consumption distribution show the major contribution of non-residential activities in the total consumption.

Land use on cities territory (Fig. 1c) is divided into three categories: artificial, agricultural, and natural. This indicator is important for environmental aspect, but also for risk prevention because land use has major impact on it. Flood risks could increase by 255% in 2030 [15] and the reduction of artificial land surfaces could reduce this risk. The distribution of values (Fig. 1c) shows a clear distinction between small cities with a distribution mostly between agricultural and natural land, with a majority on agricultural. For medium and big cities, artificial and agricultural components are the highest with a majority of artificial land. Most of those cities are composed of less than 20% of natural land.

To present the results of social, air pollution, water pollution and electrical consumption, we chose a histogram distribution based on the city size (Fig. 1d). We can observe on those diagrams that unemployment rate, annual NO_2 max emission and mean electrical consumption are growing with the number of citizens in a city. However, chlorine in drinkable water is clearly lower for bigger cities (Cities 3).

The second part of this study is about the calculated scores, their analysis and review, and linkage between them.

Table 1 introduces scores that we calculated for every group of cities. As it is shown, we calculated two main scores that are Unemployment-Poverty and Environmental scores. Those scores are calculated as the average of their sub-scores which have not been weighted for our approach. All scores are calculated on a scale of 0 to 100.

Unemployment-Poverty score is calculated from both unemployment and poverty sub-scores and a higher score indicates good social conditions and a lower one poverty and unemployment.

Environmental score is calculated on a scale of 0 to 100, and a good score means low pollution, consumption, and natural land. This environmental final score is the average of six intermediate scores which are as follows:

- Water quality score evaluates quality of water in cities. Big cities have better scores due to lower concentration of chlorine, aluminum and ammonium and higher number of indicators.
- Air pollution score evaluates quality of air in cities. For this score, SO_2 is quite difficult to analyze because of a lack of available data. NO_2 score is the most discriminating and is often exceeding thresholds as it is the case for $PM_{2.5}$.
- EPD (Energetical Performance Diagnostic) score evaluates energy performance of people housing. This indicator doesn't present any trend at first sight.
- Electrical consumption score shows clearly lower scores for bigger cities, and mostly for the Residential sector.

Table 1. Scores average, median and standard deviation (SD) for the 3 city groups. EPD (Energetical Performance Diagnostic); GHG (Green House Gases); consumption R (Residential); consumption AS (All Sectors)

City size (1, 2, 3)	Cities 1 (small)			Cities 2 (medium)			Cities 3 (big)		
Statistical indicators	Average	Median	SD	Average	Median	SD	Average	Median	SD
Unemployment score	55.6	59.3	17.5	38.9	40.3	16.5	30.9	30.0	12.2
Poverty score	65.5	67.5	14.3	46.5	50.0	15.6	31.3	28.8	13.9
Total Poverty-unemployment score	*59.7*	*59.3*	*15.3*	*42.7*	*45.2*	*15.1*	*31.1*	*29.4*	*13.0*
Bacteria in water score	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
Water taste and look score	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
Chlorine in water score	63.5	72.0	22.0	68.2	66.5	20.5	79.0	77.5	5.9
Water pH score	67.9	70.0	17.7	55.0	55.0	13.5	63.8	62.5	10.3
Water ammonium score	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
Water aluminum score	78.1	79.5	17.2	75.2	72.5	16.9	82.8	82.8	11.0
Water Revive 22 °C bacteria score	68.8	100.0	47.9	70.0	100.0	48.3	75.0	100.0	50.0
Number of water indicator score	86.6	85.7	17.1	94.3	100.0	10.0	92.9	92.9	8.2
Total water quality score	**82.2**	**84.0**	**9.2**	**83.3**	**86.6**	**8.0**	**86.7**	**89.2**	**7.5**
$PM_{2.5}$ air pollution score	41.5	40.2	7.7	34.4	24.6	19.1	32.3	33.7	4.8
O_3 air pollution score	70.2	70.1	3.2	70.0	69.3	4.6	71.9	71.4	1.3
NO_2 air pollution score	91.6	93.1	7.5	82.3	80.3	4.6	53.9	53.6	9.3
SO_2 air pollution score	89.9	89.9	12.5						
Total air pollution score	**70.3**	**69.6**	**13.1**	**71.1**	**75.7**	**10.4**	**52.7**	**53.7**	**4.7**
EPD GHG score	58.0	74.7	28.9	49.1	45.6	13.7	58.5	58.7	4.2
EPD consumption score	42.8	56.6	27.6	34.6	33.1	13.9	45.6	46.4	5.9
Total EPD Score	**50.4**	**66.7**	**28.0**	**41.8**	**38.8**	**13.3**	**52.1**	**52.4**	**4.5**
Electrical consumption R score	78.1	83.7	18.7	51.7	54.7	23.5	31.4	30.3	28.1
Electrical consumption AS score	72.4	79.7	27.3	56.6	63.9	22.5	45.3	53.8	25.3

(*continued*)

Table 1. (*continued*)

City size (1, 2, 3)	Cities 1 (small)			Cities 2 (medium)			Cities 3 (big)		
Statistical indicators	Average	Median	SD	Average	Median	SD	Average	Median	SD
Total electrical consumption score	**75.2**	**78.1**	**19.2**	**54.1**	**58.0**	**19.0**	**38.3**	**43.2**	**25.5**
Artificial land score	83.2	85.8	11.7	55.9	66.0	25.3	34.5	31.7	24.9
Natural land score	23.8	23.0	20.3	10.2	6.5	11.7	10.5	2.9	17.0
Total land use score	**53.5**	**52.9**	**11.8**	**33.0**	**36.9**	**16.5**	**22.5**	**16.2**	**19.4**
Gas consumption R score	62.6	93.9	47.6	90.8	95.1	12.6	98.1	98.1	2.4
Gas consumption AS score	66.4	97.3	45.3	97.5	97.3	2.3	99.3	99.3	0.4
Total gas consumption score	**64.5**	**95.6**	**46.3**	**94.2**	**96.2**	**7.4**	**98.7**	**98.7**	**1.4**
Total environmental score	***66.4***	***67.2***	***5.9***	***62.4***	***63.1***	***4.9***	***54.7***	***54.1***	***7.0***

- Gas consumption score is difficult to interpret since gas is less used in big cities than in rural cities.
- Land use score evaluates the usage of land especially by analyzing how much natural land is available for population. The biggest cities present more artificial lands and thus, lower scores.

After those observations on the different topics, we decided to study correlations between our different scores (Fig. 2) to highlight noticeable relationships between them.

As data were originally collected by hand and stored in a datasheet, performing statistics calculation was not possible because of heterogeneity of the original datasheet. We first separated all data by topics or subtopics in different datasheets and ensured homogeneity concerning names and format conventions. Only raw data were extracted, and scores calculation has been automatized with Python code, and then applied to fill our new datasheets. That way, scores can be calculated automatically whenever new data is added and new cities are interesting by this method. Once this step was realized, it was possible to perform correlations.

Correlation used in this method was the Pearson correlation, used to determine whether a linear relationship exists between two variables. Concerning EPD scores, we noticed that it has a moderate positive correlation with the unemployment-poverty score. A city with low unemployment and poverty tends to have a better EPD score. An unexpected finding is that the correlation between EPD and electric scores is very low, even though we could expect electric consumption to be strongly related to EPD. A focus on $PM_{2.5}$ score highlights two interesting correlations: a moderate positive correlation with water quality and a strong positive correlation with the land use score. The first correlation proves that $PM_{2.5}$ and water quality scores increase in parallel, which means air quality and water quality hold the same priority for cities leaders.

However, the correlation between chlorine score and $PM_{2.5}$ is moderately negative, indicating that the good quality of drinkable water in small cities is probably due to an important chlorine quantity. The second correlation shows that when more natural land is available, $PM_{2.5}$ score is better, as air is cleaner than in cities. The strongest correlation is between the NO_2 score and the number of inhabitants of a city with a $R = -0.84$: this very strong negative correlation demonstrates that a rise of the population is linked to a decrease in the NO_2 score. Two other interesting correlations are the ones between population, land use and electricity scores. The negative moderate correlations show that when population increases, the two scores decrease. To sum up, a growing number of inhabitants tends to be incompatible with an improvement of air quality score, land use score and electricity score, which is consistent with the fact that it is difficult to favor city expansion while improving environmental issues: NO_2 production increases, as well as land artificialization and energy consumption.

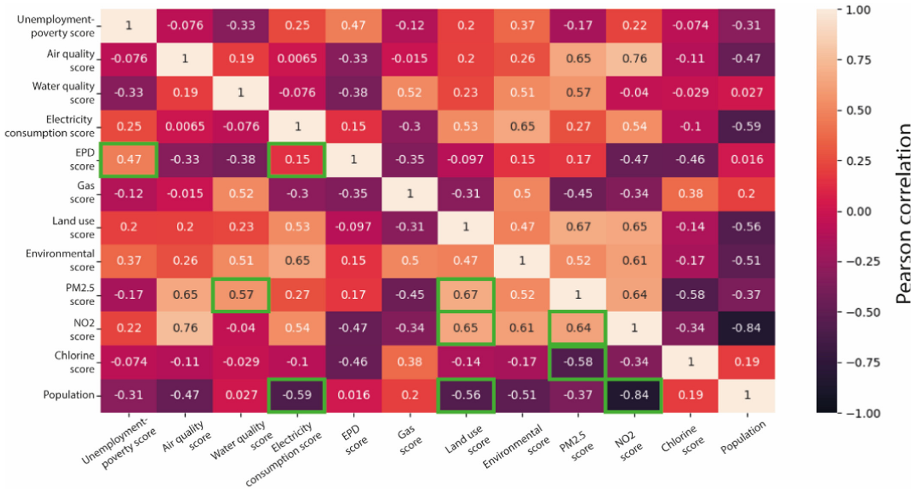

Fig. 2. Pearson correlations between scores. A high absolute value indicates a high correlation when a low absolute value indicates a low correlation. A positive value indicates a positive correlation when a negative value indicates a negative correlation. Green framed values are the most interesting and comment values. (Color figure online)

5 Discussion and Conclusion

In this paper, we proposed a new methodology to calculate an environmental score of cities compared with eco-social score. We built this methodology with the goal to use only open-source accessible data to make it as generic as possible.

Energy consumption analysis of cities shows that tertiary and industrial sectors represent the biggest part of energy, compared with residential consumption. It is an important indicator for cities if they want to reduce consumption. However, scores are even more distant to each other for the residential sector with higher consumption for the bigger cities, showing a clear difference of citizens consumption depending on the size of the city.

Scores computed on 31 cities in the Occitanie region of France show that the increase in citizens number is correlated with an increase in NO_2 and $PM_{2.5}$ air pollution, artificialization of land and electric consumption (Fig. 2). The very low correlation between EPD and electric consumption shows that cities with a good insulation of buildings do not present lower electrical consumption. This is maybe because the higher correlation of unemployment-poverty score is with EPD score, indicating that richer cities have good insulation but high consumption.

Our scores were built considering that each aspect (energy consumption, air pollution, unemployment…) holds an equivalent weight in the final environmental and social scores. But it is possible that each of them may have a different influence and should be weighted differently in our calculation in order to obtain finer-grain results. This solution will be explored in the future.

To discuss standards and limits of pollution and environment, we want to discuss the adherence to current standards and the absence of standards for some of the pollutants. Current standards in air pollution are not met for most pollutants and it is even more true for $PM_{2.5}$ (standard is 10 $\mu g/m^3$) with maximum one-day average of 75.6 $\mu g/m^3$ and NO_2 (standard is 40 $\mu g/m^3$) with maximum one-day average of 105.4 $\mu g/m^3$. The second observation is that the bigger is the city, the higher is the $PM_{2.5}$ and mostly NO_2 pollution. Finally, there are very few stations measuring SO_2 concentration (maximum one-day average of 89 $\mu g/m^3$) and even fewer measuring H_2S concentration (maximum one-day average of 24.6 $\mu g/m^3$) [16]. The number of stations measuring those sulfur gases should increase for a more detailed analysis.

Some pollutants do not have standards in France, and the best example is chlorine in drinkable water. Chlorine used as a disinfectant has impacts on transmission of antibiotic-resistant genes [17]. Standards indicate impact on human health for concentrations of free chlorine >2 mg/l [18–20] but the major part of chlorine studies are old and a more recent study suggests a limit of 0.2 mg/l [21], 10 times lower. A recent detailed study could be interesting to identify potential effects of chlorine on human health in intermediary concentrations (<2 mg/l).

Data in this study reveal concentrations between 0.03 and 0.78 mg/l with clearly lower concentration for Cities 3 (Fig. 1d). This difference is probably due to a difference of water disinfectant method: medium and small cities do not have the same water treatment plants as the big cities and compensate with additional chlorine.

To discuss actual standards, bacterial standard for drinkable water is set to ≤ 0 n/(100mL). The problem is that detection methodologies do not reach this precision, and most measurements indicate <1 n/(100mL) and the standard should be changed.

Now that our methodology is available, we should confront it to more cities from other regions. With more data, we will be able to carry out further studies and confirm whether correlation exists between our scores, because performing correlations now will lead to non-significant results as there are too few data for big cities (Cities 3). Because we need to provide more results for comparison and performance evaluation sake, the future work on this topic will be to collect needed data to calculate those scores on the 36 000 French cities. To assess the relevance of our scores, we will also collect feedback from cities on their usability. To progress further, we are developing an automated solution written in Python language with a web site interface. This tool will allow all citizens and city leaders to see environmental scores on all French cities. The main differences with other existing scores [11] is the reproducibility aspect of our method which can be calculated for all French cities, the easy access of the required data and the understandable scores.

With Covid-19 epidemic, lots of CO_2 sensors are installed everywhere, and many data will soon be available to study evolution of concentrations of gas in closed spaces. Thus, we could complete our study with an indoor air quality score.

Acknowledgment. The authors acknowledge the financial support by the Digital Factory (Altran part of Capgemini) and we greatly appreciated the assistance of Martine Aubret and David Barret.
The **Supplementary Materials 1** is shared and made freely available on the open-access repository Mendeley Data (https://doi.org/10.17632/j66797tdw9.2 and link: https://data.mendeley.com/datasets/j66797tdw9/draft?a=e3608fb5-fe27-4e07-b9e8-afeb90488b11).

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