

# Noise footprint from personal land-based mobility

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## Abstract

A large part of the world population is exposed to noise levels that are unhealthy. Yet noise is often neglected when impact assessment studies are conducted and when policy interventions are designed. In this study, we provide a way to calculate the noise footprint of citizens directly determined by their use of private and public transport on land. The study combines the results of the large transport simulation model MATSim applied to Switzerland, with a noise characterization model, N-LCA, developed in the context of life cycle assessment. MATSim results allow tracking the use of private and public transportation by agents in the model. The results after characterization provide a consumption-based noise footprint, thus the total noise and impacts that are caused by the private mobility demand of the citizens of Switzerland. Our results confirm that road transportation is the largest contributor to the total noise footprint of land-based mobility. We also included a scenario with a full transition to an electrified car fleet, which showed the potential for the reduction of impacts, particularly in urban areas, by about 55% as compared to the modeled regime with combustion engines.

## KEYWORDS

agent-based modeling, industrial ecology, life cycle assessment, noise, private mobility demand, transportation

## 1 | INTRODUCTION

Environmental noise pollution is considered as one of the most affecting yet neglected environmental issues of the modern world (Stewart & Bronzaft, 2011). The World Health Organization (WHO) states that one in five Europeans is regularly exposed to noise levels that could significantly damage their health (Fritschi, Brown, Kim, Schwela, & Kephelopoulou, 2011), and tens of millions of Americans suffer from a range of adverse health outcomes that are due to noise exposure, such as sleep disturbance and ischemic heart disease (Hammer, Swinburn, & Neitzel, 2014). Comparative burden studies suggest that, after particulate matter, noise is the second major cause of disability adjusted life years (DALYs) lost in Europe (Babisch, Beule, Schust, Kersten, & Ising, 2005; Dratva et al., 2012; Stansfeld, 2015). The DALYs attributed to noise are more than those attributed to, for example, lead, ozone, and dioxins (Stansfeld, 2015).

Life cycle assessment (LCA) considers a broad set of impact categories from global warming to acidification and eutrophication (Hauschild & Huijbregts, 2015). Even though noise impacts have been high on the agenda of LCA developers for decades (see, e.g., Guinée, 2001), noise impacts have been for a large part excluded from regular LCA studies (see Cucurachi, Heijungs, & Ohlau, 2012 for a review).

A number of approaches to quantify the impacts of noise on humans are available in the context of LCA. Althaus (2012) and Althaus, De Haan, and Scholz (2009) provided an endpoint methodology developed from the case of land-based transportation in Switzerland. Further elaborations of this work can be found in Franco, Garraín, and Vidal (2010). The application of the model is data-intensive, but provides a good interpretation of the physics of sound and of the impact of noise on humans measured using the DALY scale. However, it does not allow for a straightforward inclusion of the impact category noise in case studies that do not focus only on road transportation.

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Ongel (2016) and Ongel and Sezgin (2016) also proposed a noise evaluation model that borrows the typical characterization structure of LCA in a non-LCA context. The method focuses on road transportation and was applied to the case of the city of Istanbul in Turkey. As in Cucurachi et al. (2012), the impact assessment model considers the physical features of the propagation of sound and relates them through exposure and effect to endpoints in DALY. However, no generic or spatially explicit characterization factors are provided for other cases than the main roads of Istanbul (Heijungs & Cucurachi, 2017).

The noise impact life cycle assessment (N-LCA, hereafter) model developed by Cucurachi and Heijungs (2014) and Cucurachi et al. (2012) allows accounting for the physical properties of sound propagation and for the sensitivity of humans exposed to sound emissions in various contexts (e.g., noisy urban areas, quiet night) and to sound emissions at various frequencies [e.g. 32 to 512 hertz (Cucurachi & Heijungs, 2014)]. At the life cycle inventory (LCI) stage, N-LCA allows linearizing sound emissions and translating them in units of sound energy (joule), thus making it finally possible to shift away from the nonlinear decibel units of previous noise models, and to apply the model in full-scale LCA studies. N-LCA allows, in principle, to account for sound emissions and the related noise impacts not only in the transportation phase of a life cycle, but also considering any static or dynamic sources across the full life cycle that emit sound energy (Cucurachi, van der Giesen, Heijungs, & de Snoo, 2016). N-LCA is a so-called midpoint method (Hauschild et al., 2013), and impacts on humans are expressed in physical units of sound pressure. The results express the amount of sound pressure that affect each exposed person every second sound is emitted by a certain source (e.g., a wind turbine).

The above features make N-LCA suitable for a direct coupling with a large-scale simulation model as performed in this contribution. Simulation models can be combined with LCA to feed in the necessary inventory information to run the analysis, thus allowing the focus of LCA to shift from a single product system, to a wider system perspective (Dijkema & Basson, 2009), and overcoming some of the recognized limits of traditional static LCA studies (Haes, Heijungs, Suh, & Huppel, 2004). Simulation models can be also used to track spatial and temporal changes and detect patterns and specific behaviors that can provide more representative inventory data (Davis, Nikolić, & Dijkema, 2009). Even in the presence of complex characterization models that take into account physical properties and exposure dynamics of environmental stressors, inventory data may still be a crucial limiting factor. In the case of noise, lack of suitable inventory data de facto limits the possibility of accurately considering the effects of sound emissions that are by nature short-lived and have a local effect.

We show here an example of such joint application of LCA impact assessment and a large-scale simulation model. N-LCA is coupled with the MATSim simulation model, a framework that implements large-scale agent-based transport simulations (Horni, Nagel, & Axhausen, 2016). We use the implementation of MATSim for Switzerland (see Bauer, Cox, Heck, Hirschberg, & Hofer, 2016 for the model details) to feed the inventory of N-LCA and perform the noise assessment. The agents of the model are statistical representations of the Swiss population. The agents and their plans were created based on detailed statistical and empirical data regarding, for example, personal work timetables and use of the road network (Bauer et al., 2016; Swiss Federal Statistical Office, 2000, 2010). However, only 10% of the population was effectively simulated in order to lower the computational burden. Therefore, the simulation results were subsequently extrapolated to the whole of Switzerland in an extra step. The demand patterns resulting from the agent-based simulation were used to simulate private land-based mobility, to identify the spatial and temporal location of emissions, and to track per capita noise emissions. The demand triggered by the agents in combination with the N-LCA model allowed calculating for the first time a consumption-based noise footprint.

The MATSim and N-LCA models were linked directly using an ad hoc Python (van Rossum, 1995) implementation. We extracted detailed information from MATSim related to specific parameters of the agents involved in the simulation (e.g., context of the emission), and additionally extracted data about sound emitted and noise caused by land-based mobility, thus including cars, trams, buses, and trains in the analysis. Motorbikes, scooters, and other two-wheeled vehicles were not included in the analysis. Vehicle-specific features (e.g., the propulsion noise and rolling noise of cars and their influence on the frequency of the sound emission) as well as specific technical features (e.g., the track gauge for trains) were considered in the assessment. The resulting assessment is an LCA-based noise footprint assessment quantifying the impacts that are triggered by land-based private mobility demand in Switzerland.

The remainder of the article is organized as follows. In Section 2, we briefly describe the main features of N-LCA and provide technical details of coupling MATSim with noise emission data. In Section 3, we present the noise footprints induced by the households' mobility demand, and we provide results for a scenario in which the entire car fleet of Switzerland is modeled as powered by electricity. A discussion on the implication of the accurate quantification of noise impacts on humans and the benefits of the noise footprint and of agent-based modeling in combination with LCA close the article.

## 2 | MATERIALS AND METHODS

### 2.1 | Inventory modeling

The Common Noise Assessment Methods in Europe (CNOSSOS) reference report of the European Commission (Kephalopoulos, Paviotti, & Ledee, 2012) provides detailed information on the calculation of the sound power level for a number of static and dynamic sound-emitting sources. Sound power is the rate at which sound energy is emitted, reflected, transmitted, or received, per unit time, and is expressed in units of Watt (Joule/s; Thompson & Taylor, 2008). The corresponding sound power level is expressed in units of decibel relative to a reference value. Source-specific technical parameters defined in CNOSSOS allow quantifying the sound power level for all the land-based sources used by the agents in the MATSim

model. Cucurachi, van der Giesen, et al. (2016) provide detailed information on the way the sound power level in decibels may be transformed into units of sound energy to be inventoried at the LCI stage for different archetypal contexts of emissions. We considered land-based private and public transportation, and the speeds they travelled in the simulated environment. Thereby, we distinguished between private cars, regional and long-distance trains, urban/metropolitan trains, trams, and regular/urban and trolley buses. Additional details related to the modeled transport (e.g., average occupation of vehicles) were included following the specifications for transport services as defined in the ecoinvent database (Spielmann & Bauer, 2007; see Supporting Information S1 and S2).

The sound power level calculated according to CNOSSOS in decibels may be back-converted to the physical unit of Watt as in:

$$W_{ftls} = 10^{-12} \times 10^{\frac{Lw_{ftls}}{10}}, \quad (1)$$

where  $Lw$  is the sound power level in units of decibel calculated following CNOSSOS (Kephalopoulos et al., 2012), and  $W$  is the equivalent sound power expressed in units of Watt. The sound power is frequency- (index  $f$ ; e.g., 63 Hz), time- ( $t$ ; e.g., night), location- ( $l$ ; e.g., urban), and source-specific ( $s$ ; e.g., car) and was calculated for all the transportation means used in the MATSim model.

For each location, the average speed corresponding to the context of emissions was used for the calculation of the sound power. Therefore, the corresponding changes in sound emissions related to different velocities were also incorporated, whereas changes in velocity (acceleration and deceleration) and the impacts of peak velocities were not considered. The differentiation at the inventory level facilitates the later classification and characterization phases.

We imported from the MATSim simulation the information related to the distance driven in passenger-km (pkm). We used the speeds of alternative transportation means at specific locations in the MATSim simulation to obtain the duration  $d_{ftls}$ . This quantity allows determining the mobility demand for each vehicle used by agents in the simulation in units of seconds. Information on the time and location of emissions was also recorded for passenger cars. The resulting sound energy was calculated as:

$$m_{ftls} = W_{ftls} \times d_{ftls}. \quad (2)$$

The quantity  $m_{ftls}$  is the calculated sound energy inventoried for all transportation means and is expressed in joules (J). The inventoried quantity can then be coupled with the N-LCA model.

## 2.2 | N-LCA model

In Cucurachi et al. (2012), the formula for the calculation of the midpoint characterization factor (CF) is defined as follows:

$$CF_{ftls} = \frac{20}{\sqrt{Wamb_{ftl}}} \times Nf_{tl} \times 10^{\frac{(D_f - A_{att}_{ftls})}{20}} \times 10^{\frac{(\alpha_f s + \beta_t)}{20}}, \quad (3)$$

where the indices  $f$ ,  $t$ ,  $l$  represent, respectively, the octave center-frequency band, the time of the day, the archetypal location of the emission.  $Wamb$  represents the environmental sound power at the emission compartment, thus assuming that some sound emissions are already present in the environment,  $Nf$  represents the average number of human beings that are exposed to the sound power at a certain time of the day and location,  $D$  is a directivity factor that determines the direction of propagation,  $A_{att}$  defines a series of attenuations factors that intervene and limit the propagation of sound waves between emitting source and receiver,  $\alpha$  is a specific factor related to the frequency of emission,  $\beta$  refers to a penalty added according to the time of the day the emission takes place. All physical aspects of sound propagation (e.g., frequency of propagation of sound waves), and physical parameters related to the fate and effect of sound emissions from emission location to receiver (e.g., conformation of the pavement) were modeled following standard literature on sound and noise impacts. We refer the reader to Supporting Information S1 and S2 and previous work on N-LCA (see, e.g., Cucurachi et al., 2012) for additional details on the individual parameters. The parameters and attenuation factors represent the typical European situation of exposure and can be assumed to be valid also for the region under consideration in the current study. The unit of CF is person  $\times$  pascal/Watt. At the midpoint level, the characterization factors are not source specific.

Archetypes as defined in Cucurachi and Heijungs (2014) were matched to the specific locations and temporal conditions of emission. Additionally, the N-LCA model further differentiates the archetypes for each of the eight major octave band center frequencies, thus covering the full frequency spectrum of sounds emissions on land. Frequency specifications were also used, where possible, to take into account the full frequency spectrum of sound emitted by the different transport modes. In total, 216 archetypal characterization factors are defined in the N-LCA model. From these, a selection was made based on the context of the emission obtained from the simulation. Therefore, emissions taking place in an urban context during the day were matched to the urban day archetype, and the full frequency spectrum was then considered from 63 to 8000 Hz.

The midpoint human-noise impact score ( $midHN_{ftls}$ ) is obtained as:

$$midHN_{ftls} = CF_{ftls} \times m_{ftls}, \quad (4)$$

where  $m$  (see Equation (2)) represents the inventoried sound emission in J and the index  $s$  refers to the source of the emission. The unit of the noise impact score after characterization is person  $\times$  pascal  $\times$  second. Additionally, we translated the midpoint noise footprint into a damage score

in units of DALY, using an ad hoc calculated mid-to-endpoint conversion factor,  $\theta^{EU}$ , translating person  $\times$  pascal  $\times$  second into units of DALYs (see Supporting Information S1).

## 2.3 | Extraction of data from MATSim and coupling of N-LCA with MATSim

In order to derive the mobility demand per household, we expanded on the methodology described in Saner and Heeren (2013). The application of the MATSim framework to Switzerland is based on the National Census (Swiss Federal Statistical Office, 2000) and the Mobility and Transport Microcensus of Switzerland (Swiss Federal Statistical Office, 2010) and simulates the mobility behavior of synthetic agents that are a representative 10% sample of the Swiss population. For each agent, the driven kilometers, velocities, and the chosen traffic mode were extracted from the MATSim results and used to calculate the time driven in seconds with each specific vehicle type as described in Equation (2).

For the case of the transportation demand by car, also the information about the time (i.e., day, evening or night) and the context where the travel took place (e.g., urban) were obtained from the MATSim simulation and used for the analysis and directly implemented in the noise footprint calculation using the most appropriate archetype (see previous section). The extraction of the same information for the public transport modes was not possible due to the specific modeling assumptions of MATSim (Bauer et al., 2016). Therefore, in all cases in which the transport demand was triggered by public transport, the context and time were based on expert judgment (see details in Supporting information S1 and S2). We considered for each transport mode the specific speed of travel extracted from the simulation model, and matched it to the average vehicle load using information provided in the standard LCA database ecoinvent (Spielmann & Bauer, 2007). The related noise emission was calculated comparing the sound emitted at a reference speed following the reference report CNOSSOS (Kephalopoulos et al., 2012), with the sound emitted at the speed of the vehicles modeled in the simulation. The sound power  $L_w$  defined in Equation (1) was calculated as follows (Kephalopoulos et al., 2012; we refer the reader to detailed modeling details in the SI):

$$L_{w_{f_{tfs}}} = AR_{f_{tfs}} + BR_{f_{tfs}} \times \log \left( \frac{v_s}{v_{s,ref}} \right), \quad (5)$$

where,  $AR_{f_s}$  and  $BR_{f_s}$  are frequency- and source-specific coefficients given in CNOSSOS (Kephalopoulos et al., 2012), and also location- and time-specific.  $v_s$  is the reference speed of the means of transportation considered, and  $v_{s,ref}$  is the reference speed (e.g., 70 km/h for road vehicles) as specified in Kephalopoulos et al. (2012). Acceleration and deceleration were considered as penalties in the calculation defined in CNOSSOS and not considered dynamically in the model. For the rail-based emissions, the specific values of sound power can already be found in CNOSSOS for every frequency spectra and were directly implemented in the calculations. Using Equations (1) and (2) and based on the speed, the distance travelled by agents over the period of 1 year, the time needed to cover a certain distance, the frequency spectra for each transport mode, and the related sound power, we calculated the specific inventory sound energy for each agent.

We proceeded with estimating the mobility demand of individual Swiss households as provided by MATSim. We then matched the synthetic agents to household members, using personal characteristics (comprising age, gender, and geographical location) provided by the National Census (Swiss Federal Statistical Office, 2014) as matching criteria. By doing so, we are using implicitly the simulated agents as archetypes whose mobility behavior can be allocated to real household members. The mobility behavior of a specific household is thus the sum of the mobility needs of all household members. Using the mobility demand for one full year for all households in the simulation as a functional unit for the LCA-based noise footprint is reasonable because many trips of household members serve the household as a whole (e.g., going for shopping or for work).

This extrapolation of the MATSim results to the national census allowed deriving the mobility demand of the entire country of Switzerland considering approximately 8 million residents, and 3,540,525 households in 2,352 municipalities. The municipalities are divided across 26 cantons (i.e., Swiss administrative divisions comparable to counties, provinces, or states in other countries).

The extraction and the matching were both implemented using the programming language Python (van Rossum, 1995). For the calculation of the noise footprint, a calculator was created for handling the large amount of data. Also here, Python was used as a basis with help of its extensions pandas (McKinney, 2010) and NumPy (van der Walt, Colbert, & Varoquaux, 2011); and an example of the calculation is reported in Supporting Information S1. For all vehicle types, every possible scenario was calculated. In addition to the average fuel-powered cars, a scenario with an entirely electrical driven fleet was calculated using data from CNOSSOS and an adapted noise model (Kephalopoulos et al., 2012). The total noise footprint was calculated summing up contributions of individual households per municipality across frequency ranges.

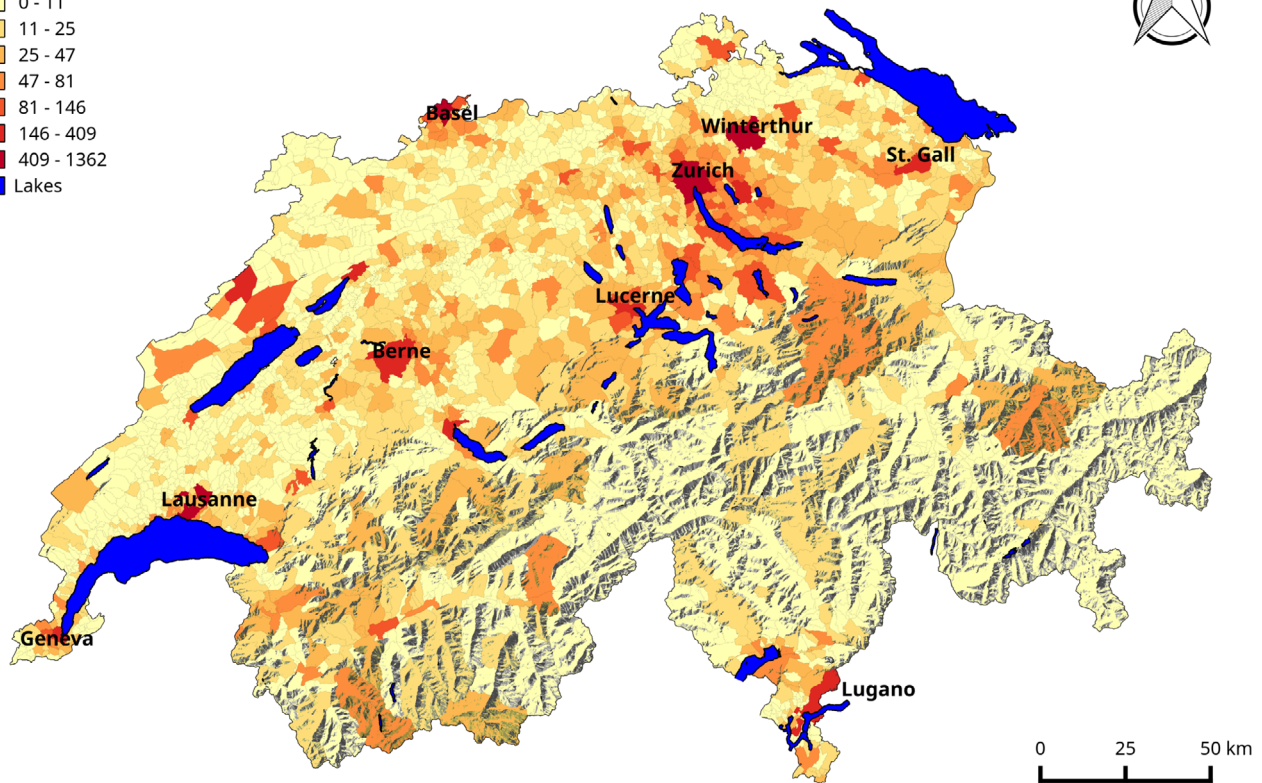
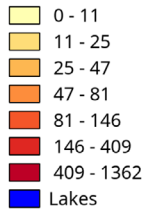
## 3 | RESULTS

### 3.1 | Noise footprint

The total yearly noise footprint of Switzerland resulted in  $3,915 \times 10^{16}$  person  $\times$  pascal  $\times$  second for all inhabitants and for all transport modes. The noise footprint of each municipality in the analysis is determined from a consumption perspective, thus the total resulting noise footprint is the sum of individual noise footprints induced by the inhabitants of the municipality (e.g., the noise footprint of an inhabitant of St. Gallen using a tram in Zurich is allocated to St. Gallen).

## Total Noise Footprint

[Terapascal\*second\*person]



**FIGURE 1** Noise footprint of Switzerland in terapascal  $\times$  second  $\times$  person

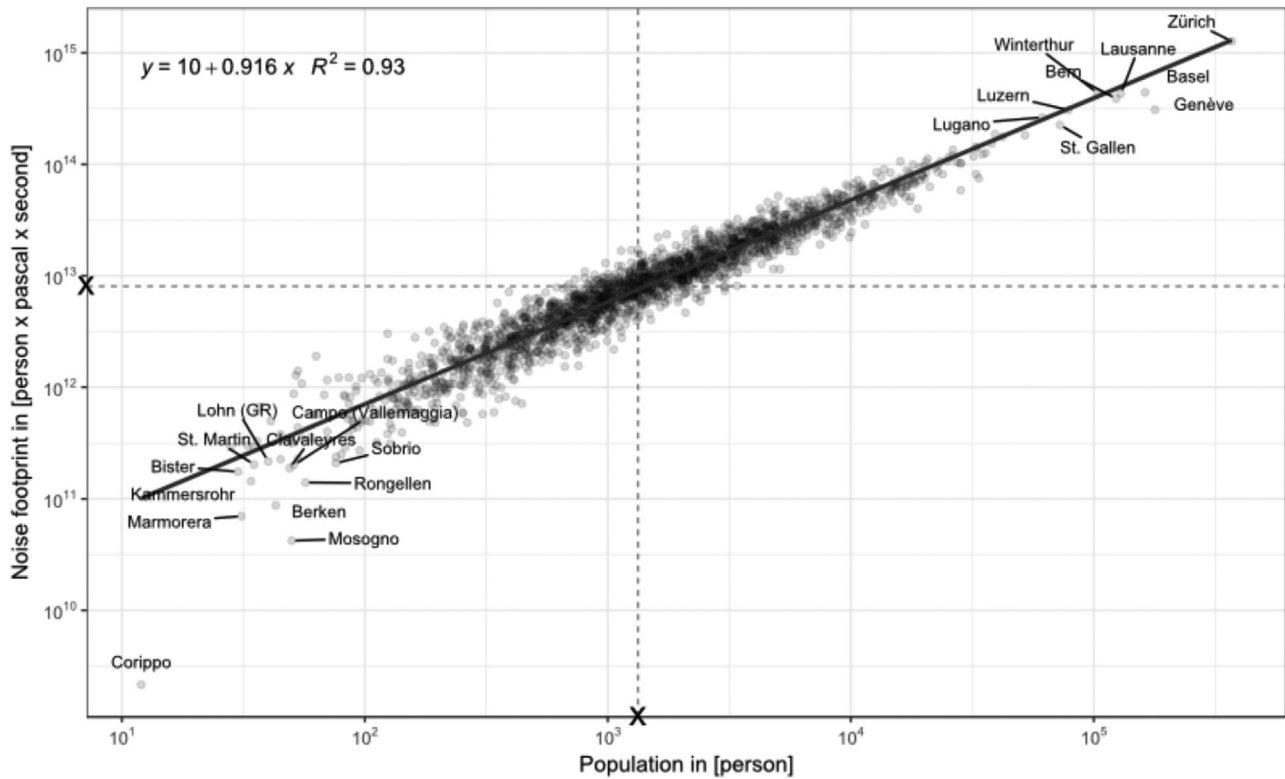
Transportation by passenger car (see Figure 1 and Supporting Information S1 for detailed results; geographical boundaries obtained from Federal Office of Topography swisstopo, 2016) dominated the impacts accounting for 95% of the total impacts (mean score per municipality  $5,78 \times 10^{12}$ ) followed, respectively, by metropolitan train (approximately 2% of total impacts), train, bus, tram, trolley bus, and long-distance train all combined accounting for the remainder of the impact. Lower frequencies contributed the most to the final impact for road-based mobility. For the case of rail mobility also frequencies at 8 kHz, usually associated with squeaking sounds due to wheels on the rail, contributed significantly to the impact.

The per capita comparisons of results (see Supporting Information S1 and S2) show that municipalities with a small number of residents have relatively higher impacts per capita. Looking at the total score, the city of Zurich (4.6% of the Swiss population) accounted for approximately 4% of the total noise impacts, whereas the canton of Zurich (17.5% of the Swiss population) accounted for about 18% of total emissions. The major 10 cities by population (together 16.7% of the Swiss population) accounted for approximately 12% of total noise emissions.

A cluster analysis using the clustering large applications algorithm (CLARA; Kaufman & Rousseeuw, 2008) was performed on the results (see Supporting Information S1 and S2), using population, total noise footprint, noise footprint by car transportation, and noise footprint by regular bus as inputs. The results of such analysis allow for a grouping of municipalities by similar features, thus can be used as support for policy making in other contexts in which noise impacts need to be quantified. Based on their noise footprints, municipalities may be grouped in four clusters, of 703 (the medoid for this cluster was Murgenthal; see Supporting Information S1 and S2 for additional data on these municipalities), 203 (medoid Muri bei Bern), 1,410 (medoid Tomils), and nine municipalities (medoid Winterthur), respectively. The analysis of the medoids allows roughly characterizing the clusters as: rural area, commuting to other municipalities; middle density, small city, part of an agglomeration, commuting from and to this town; very small village, rural, low density; large urban center with availability of all transportation means, and with high density of infrastructure. No major differences by geophysical features (e.g., elevation) could be identified.

An additional statistical analysis of the correlations among noise footprints and population data of municipalities was performed. Population positively correlated with transportation by passenger car, train, and metropolitan train. A correlation of 0.97 was found with the car noise footprint, 0.8 with metropolitan and long distance trains, and 0.6 with the noise footprint determined by bus transportation. Lower correlations values were found with trolley bus and regional train (0.3) and tram (0.4; see correlation plot in Figure S9 in Supporting Information S1).

Overall, population provides a good estimate of the total noise footprint and footprint determined by passenger cars for most of the municipalities ( $R^2 = 0.93$ ,  $P$ -value  $< 2 \times 10^{-16}$ ; see Figure 2 and Supporting Information S1). The noise footprint for the large cities is pretty much on the regression line (e.g., see the case of Zurich), while there are small village outliers that have an underproportional footprint.



**FIGURE 2** Relationship between total noise footprint determined by the use of private cars and population in 2,352 municipalities. Dashed lines and crosses placed at median values for noise footprint and population

The results depend on the availability of infrastructure at a certain location, and are, therefore, affected by the distribution of such transportation means in the area of study. Moreover, a number of agents in the model commute to areas in which there is a greater availability of certain modes of public transport (e.g., transportation by tram for people that commute to Zurich). The results are also affected by the way in which the MATSim model defines public transportation in large cities (Bauer et al., 2016).

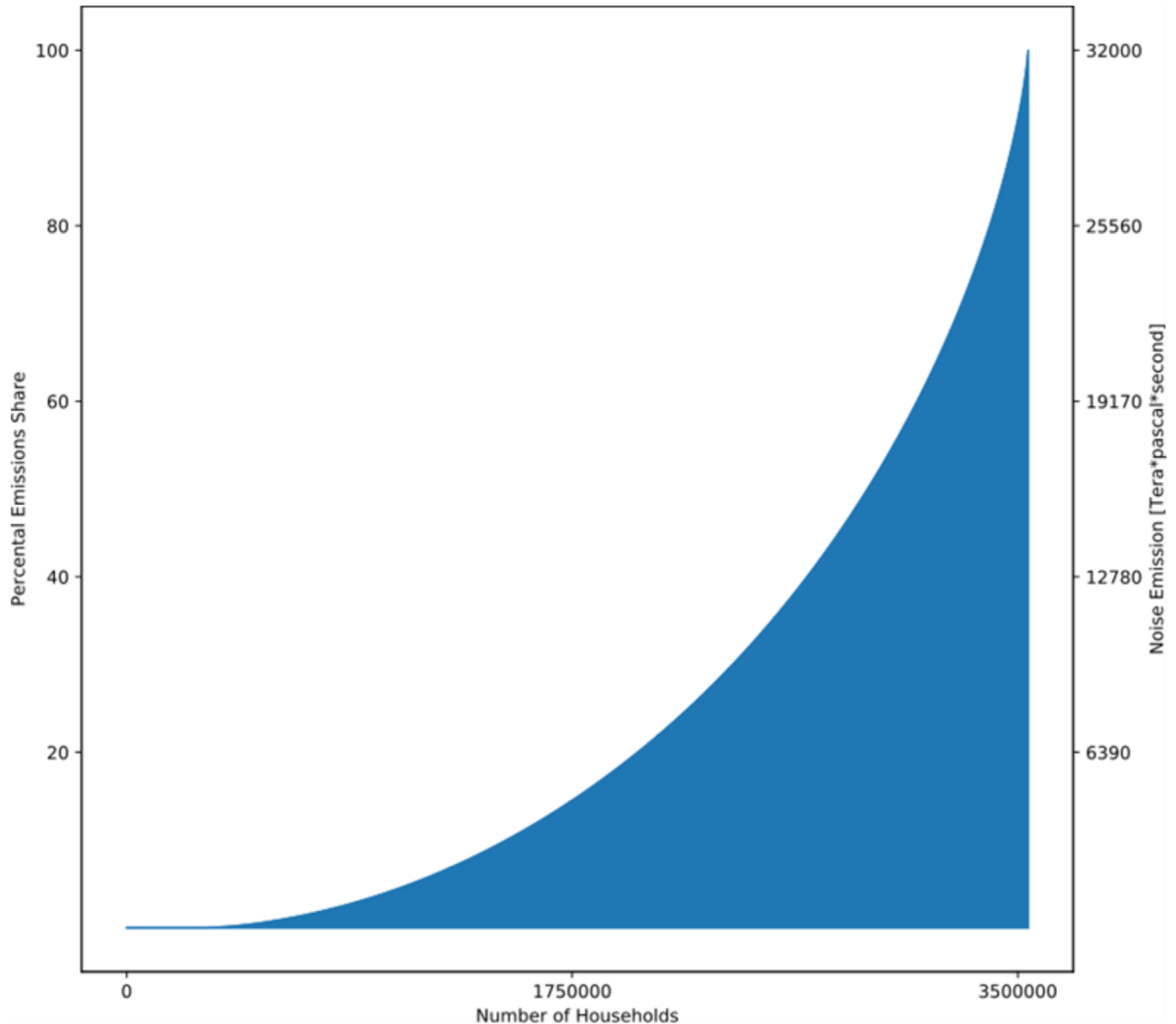
Results in Figure 3 show the distribution of noise impacts by household, and show that 25% of the population causes more than 60% of the impact.

Using an endpoint conversion factor (see section 6 in Supporting Information S1), we attempted to translate the midpoint noise footprint into an endpoint footprint in DALY. The results provide a preliminary assessment of noise damage in Switzerland (see Section 4 for a comparison of results with the literature). Using the defined conversion factor, we obtained that a total number of 23,172 DALYs were lost in Switzerland yearly, 67% due to annoyance, and the remainder due to sleep disturbance (see Figures S4–S8 in Supporting Information S1). The average Swiss citizen lost in the modeled year 0.003 DALYs, or 83 days per person per lifetime.

### 3.2 | Electric vehicles scenario

Propulsion noise is a major component of sound emitted and noise impacts caused by cars with combustion engines travelling at speeds lower than 50 km/h. Currently, electrical cars registered in Switzerland correspond to about 0.32% of the entire fleet and 2% of the newly registered vehicles are electric cars (European Automobile Manufacturers Association, 2017). Thus, the calculation with an entire electrical car fleet is a hypothetical scenario, even though an increase of the electrical mobility is to be expected due to increased efforts in Switzerland to adopt clean vehicle technologies and to reduce energy consumption and carbon dioxide emissions in the transportation sector. In the creation of the electric fleet scenario, we assumed that the usage of electric cars would be the same as that of cars with combustion engines, as modeled by MATSim. The scenario did not include considerations related to the necessity to adapt the existing infrastructure to accommodate a growing electric fleet, and did not attempt to account for the influence that changes would have on mobility behavior. The propulsion noise of electric cars and its reduction at low speeds can be calculated and apportioned to different levels of frequency following the extension of the CNOSSOS report to electric cars provided by Pallas et al. (2016), as described in detail in Supporting Information S1 and S2.

The total reduction in impacts following this scenario resulted in about 55% as compared to the modeled regime with combustion engines (see Figure S4 in Supporting Information S1). The total noise footprint considering the electrified fleet would be  $2.16 \times 10^{16}$  person  $\times$  pascal  $\times$  second (see Figure 4). The reduction is due to use of average speeds for all three contexts modeled in this contribution. In urban locations, the average speed is 20.5 km/h. The change in noise impact of vehicles driving at low speeds in urban contexts has, as a consequence, the highest influence



**FIGURE 3** Cumulative impacts determined by households in the simulation

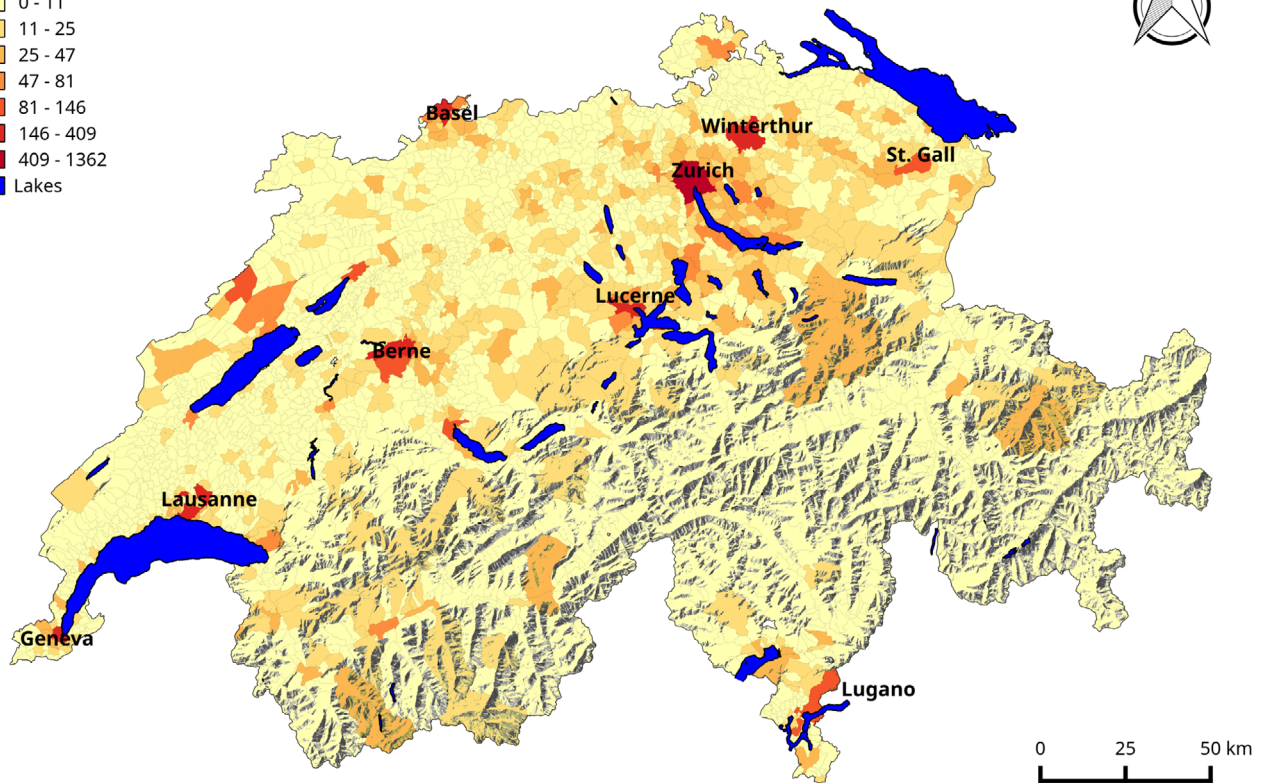
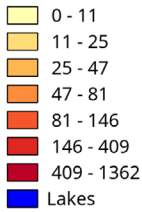
on the final result. This is in line with the literature on sound emissions of electric vehicles, which confirms that electric vehicles driving at low speeds have lower sound emissions than similar vehicles with combustion engines (see, e.g., Iversen, Marbjerg, & Bendtsen, 2013). By contrast, the reduction in sound emissions and noise impacts related to the suburban and rural contexts are negligible, as the road-based noise emissions are dominated by the rolling component of the sound emissions and by tire-road noise, rather than by the propulsion component.

#### 4 | DISCUSSION

We calculated for the first time the noise footprint of a full country, considering the impacts on humans determined by the use of private and public land-based transportation. The noise footprint method allows accounting for noise impacts on humans using an LCA impact assessment model combined with a large-scale simulation model, MATSim. The current model obviates the limitations of available methodologies and expands on the benefits of the LCA noise model introduced in Cucurachi and Heijungs (2014) and Cucurachi et al. (2012). This is especially interesting for assessments in which not only transportation but also other relevant elementary flows that emit sound are considered in a full LCA study. The comparison of the noise-footprint results with the spatial noise database of Switzerland SonBase (Bundesamt für Umwelt, 2009; Karipidis, Vienneau, & Habermacher, 2014) corroborates our results, as areas of impacts overlap, and urban centers are the highest contributors to the impacts in the analysis of SonBase, and the highest contributors to emissions in our assessment. We compared the noise footprint results to the distribution of population at different locations, and with the availability of infrastructure at the locations where emissions took place and impacts

## NF with Electrical Cars

[Terapascal\*second\*person]



**FIGURE 4** Noise footprint of Switzerland in terapascal  $\times$  second  $\times$  person under the electric fleet scenario

were measured. As our results are at the level of municipalities, further comparisons with other statistics at the local and national level are possible as needed by policy makers.

We focused in the current study on land-based sound-emitting sources, and, in particular, on a full multimodal assessment including a variety of transport modes. We also accounted for the way different sources differently affect humans based on the physical properties of sound (e.g., frequency and power) and the location, time of the day, and human perception of sound emitted. For the system under study, with the exception of a limited set of assumptions regarding public transportation, we were able to precisely map the time and location of the emission in the area. Our results confirm that road noise from cars and buses is the dominating source of impact on human health among land-based traffic modes. The scenario considering the electrification of the car fleet provides additional information for policy-making. The ideal situation of a full conversion of the car fleet in Switzerland from combustion engines to electric cars shows the potential for a significant reduction in noise emissions. These reductions were especially relevant in the urban context that we considered in this analysis, as the noise benefits of electrification occur particularly at low velocities, while at higher speeds the noise of tires rolling on the road surface dominates the sound composition (Emadi, Lee, & Rajashekar, 2008; Kephelopoulos et al., 2012).

The results are affected by a number of sources of variability and uncertainty. Uncertainty analyses and sensitivity analyses were conducted on the models merged in this contribution in previous publications, independently. The matter of the combined assessment of uncertainty in the results can only be addressed here qualitatively due to the complexity of the models that are integrated. Further research is needed to address these issues. In a study by Cucurachi, Boronovo, and Heijungs (2016) related to the characterization of the uncertainty of N-LCA, the authors showed how the exact location, time, and the number of people exposed to sound were the key inputs in driving the uncertainty of the model output. In this study, the possibility of closely following where agents in the simulation model operated allowed for reducing the uncertainty of the results determined by the use of N-LCA. The combination of MATSim detailed data and N-LCA allows improving the matching of emission data to archetypes, due to the use of time and location data, and population exposure data, thus reducing the influence of the inventory data on the output uncertainty. Improvements of N-LCA to include more spatialized characterization factors for Switzerland would allow to further minimize the uncertainty due to the typical inability of LCA analysts to pinpoint location and time of emissions.

The availability of inventory data elaborated from an agent-based model allowed for a more precise assessment of the noise footprint. The specificity of emission patterns defined per household allowed calculating per capita noise footprints that can provide a good picture of the mobility-induced noise of households and the variability between households (see Figure 3). The use of the detailed plans for the single agents in MATSim



reduced the uncertainty of the current results and allowed to better assign inventoried emissions to the most suitable characterization factors and archetypes.

This study allows adding noise to the list of impact categories that can be assessed and combined with simulation models, thus providing a complete picture of the sources of impacts. We focused our assessment only on annoyance and sleep disturbance, but further sophistications of the characterization model could be considered to include tinnitus, cognition impairment, or with adequate control of confounding variables, also heart-related diseases. Additionally, when considering the specific implications of noise exposure to human health, at the endpoint, the study of model uncertainty would also require to address the influence of the dose–effect relationships between exposure to sound and noise impacts. These relationships are considered as a major source of uncertainty in any noise assessment by the WHO (Kim et al., 2012), and would require specific knowledge of the epidemiological implications of noise exposure. Therefore, these are out of the scope of the current paper. A specific analysis of further implications of uncertainty while calculating noise footprints will be the object of future research.

The model here developed allows not only modeling the status quo, but more interestingly allows looking at alternative scenarios and at the effects of political measures or changes in consumption behavior, thus providing decision makers at local and national levels with a means to drive change using policy interventions. Noise is, in fact, a serious burden to the quality of life of individuals across the globe. In Switzerland, the country on which our study is focused, about two thirds of the population consider themselves as annoyed by noise (Karipidis, Vienneau, & Habermacher, 2014). We show that a considerable part of noise impacts is determined by the use of transport, being it private or public. Other sources of noise disturbance (e.g., noise from freight transport) need to further be evaluated for a complete assessment of the Swiss soundscape. Furthermore, survey data show (Stewart & Bronzaft, 2011) that not only transportation and traffic are the major source of complaint but also noise produced by neighbors. The matter of personal subjectivity to noise has been incorporated to a certain extent in the characterization model, but may be further expanded to include a more detailed assessment of people preferences.

The spatial composition of the demand is accounted for at the characterization stage. The characterization factors used to calculate the noise footprint use an archetypal representation of typical situations of emission/exposure that fit with the related context of emission in MATSim. The further use of spatially explicit characterization factors at a finer level of specification was not possible as specific characterization factors for Switzerland are not yet available. The model also allows considering future demand scenarios and future composition of the transportation fleet, as shown in the example of a fully electric car fleet. Up to 55% of the impacts could be, in principle, reduced by the electrification of the car and public transport fleet and a 1:1 conversion from combustion engines to electric engines.

The use of an agent-based simulated environment could also be used in the future to calibrate the characterization models, and to put archetypes to the test, helping, when needed, to redefine and improve the archetype definitions. Agent-based models could also incorporate the capability of directly applying specific characterization factors to the demand of agents, adapting them also to the conditions of exposure of the agents in the model. In this way, characterization factors would not be, as they usually are, fixed precalculated values, but they would be calculated on the fly based on the local condition of emission/exposure. Such an approach would highly improve the assessment of emissions such as sound emissions that are highly localized, and that disappear without deposition soon after they happen. Such dynamic assessment model overlaying the personal demand of agents with, for example, the physics of sound propagation and the human perception of noise impacts could significantly reduce the uncertainty of the results of an LCA study.

The noise footprint of Switzerland was quantified in units of sound pressure. Additionally, an attempt to translate results into the DALY scale is included. The translation of results to the DALY scale in the context of a full LCA study also allows a comparison across environmental impacts calculated at the endpoint level, and in principle allows comparing results to national or global statistics. However, such translation inevitably adds uncertainty to the results, as the transition from the midpoint N-LCA model required the setting of a conversion factor  $\vartheta^{EU}$  (see Section 6 in Supporting Information S1) that translates midpoint noise impacts on humans into endpoint damages on human health.

In order to test the conversion factor and identify whether the results are in line with available information, we proceeded with comparing the impacts here calculated with international statistics and previous efforts in the field of LCA. The WHO estimated the total amount of 1.0–1.6 million DALYs lost in Europe in 2010 (Fritschi et al., 2011) due to noise from all sources combined, thus 0.014–0.022 DALY per capita per year. Sleep disturbance and annoyance accounted together for 92% of the total DALY caused by environmental noise in Western Europe (Fritschi et al., 2011). The noise footprint per capita per year for Switzerland calculated in this contribution using the newly calculated  $\vartheta^{EU}$  factor is of 0.003 DALY. This suggests that the model seems to underestimate the overall impact of noise, as compared to the WHO statistics.

A comparison of results with contributions addressing the issue of noise impacts in LCA seems to suggest that discrepancies are due to an underestimation of impacts due to sleep disturbance as a consequence of noise emission at night. The combination of the demand data extracted from MATSim with the Swiss EPA method (Müller-Wenk, 2004) yields, respectively, a total of 11,747 DALYs lost during the day, and 46,243 at night. Directly applying the method described in Althaus et al. (2009), we obtain a total of 10,572 DALYs lost during the day, and 23,806 at night, against a total of 23,172 DALYs for day and night combined in our analysis. The discrepancies in the results among models are due to differences in the physical characterization of sound emissions, differences in country coverage, temporal extent, and geographical extent of the analyses, and double counting of annoyance/sleep disturbance effects, among others.

For the above reasons, while the endpoint results of this contribution partially improve on the limitations of the N-LCA model highlighted by Meyer, Benetto, Igos, and Lavandier (2017), additional work is needed to further refine the mid-to-endpoint conversion factor, and to more closely assess potential sources of discrepancies. Until then, the midpoint results of this contribution can be used as a suitable tool to support decision

making and planning around noise and land-based transportation. The possibility to define a narrow range for the conversion factor can further help guiding future research efforts.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

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## REFERENCES

- Althaus, H. (2012). Inventories and impact assessment for road transport noise in generic life cycle assessment. ETH Zurich. Retrieved from <https://doi.org/10.3929/ethz-a-007583857>
- Althaus, H. J., De Haan, P., & Scholz, R. W. (2009). Traffic noise in LCA: Part 2: Analysis of existing methods and proposition of a new framework for consistent, context-sensitive LCI modeling of road transport noise emission. *International Journal of Life Cycle Assessment*, 14(7), 676–686.
- Babisch, W., Beule, B., Schust, M., Kersten, N., & Ising, H. (2005). Traffic noise and risk of myocardial infarction. *Epidemiology*, 16(1), 33–40.
- Bauer, C., Cox, B., Heck, T., Hirschberg, S., & Hofer, J. (2016). *Opportunities and challenges for electric mobility: An interdisciplinary assessment of passenger vehicles: Final report of the THELMA project in co-operation with the Swiss Competence Center for Energy Research*. "Efficient technologies and systems for mobility." Retrieved from [www.research-collection.ethz.ch/bitstream/handle/20.500.11850/122825/2/ab1221.pdf](http://www.research-collection.ethz.ch/bitstream/handle/20.500.11850/122825/2/ab1221.pdf). Accessed December 8, 2017.
- Bundesamt für Umwelt. (2009). *SonBase-The GIS Noise Database of Switzerland*. Retrieved from [www.bafu.admin.ch/bafu/en/home/topics/noise/state/gis-laermdatenbank-sonbase.html](http://www.bafu.admin.ch/bafu/en/home/topics/noise/state/gis-laermdatenbank-sonbase.html). Accessed November 28, 2018.
- Cucurachi, S., Borgonovo, E., & Heijungs, R. (2016). A protocol for the global sensitivity analysis of impact assessment models in life cycle assessment. *Risk Analysis*, 36(2), 357–377.
- Cucurachi, S., & Heijungs, R. (2014). Characterisation factors for life cycle impact assessment of sound emissions. *Science of the Total Environment*, 468–469, 280–291.
- Cucurachi, S., Heijungs, R., & Ohlau, K. (2012). Towards a general framework for including noise impacts in LCA. *International Journal of Life Cycle Assessment*, 17(4), 471–487.
- Cucurachi, S., van der Giesen, C. C., Heijungs, R., & de Snoo, G. (2016). No matter—How? Dealing with matter-less stressors in LCA of wind energy systems. *Journal of Industrial Ecology*, 21(1), 70–81.
- Davis, C., Nikolić, I., & Dijkema, G. (2009). Integration of life cycle assessment into agent-based modeling. *Journal of Industrial Ecology*, 13(2), 306–325.
- Dijkema, G. P. J., & Basson, L. (2009). Complexity and industrial ecology. *Journal of Industrial Ecology*, 13(2), 157–164.
- Dratva, J., Phuleria, H. C., Foraster, M., Gaspoz, J. M., Keidel, D., Künzli, N., ... Schindler, C. (2012). Transportation noise and blood pressure in a population-based sample of adults. *Environmental Health Perspectives*, 120(1), 50–55.
- Emadi, A., Lee, Y., & Rajashekara, K. (2008). Power electronics and motor drives in electric, hybrid electric, and plug-in hybrid electric vehicles. *IEEE Transactions on Industrial Electronics*, 55(6), 2237–2245.
- European Automobile Manufacturers Association. (2017). *Electric vehicle incentives per country in Europe*. Retrieved from <http://www.acea.be/statistics/article/interactive-map-electric-vehicle-incentives-per-country-in-europe>
- Federal Office of Topography swisstopo. (2016). *Boundaries of Switzerland*. Retrieved from [map.geo.admin.ch](http://map.geo.admin.ch)
- Franco, V., Garraín, D., & Vidal, R. (2010). Methodological proposals for improved assessments of the impact of traffic noise upon human health. *The International Journal of Life Cycle Assessment*, 15(8), 869–882.
- Fritschi, L., Brown, L., Kim, R., Schwela, D., & Kephapopolous, S. (2011). *Burden of disease from environmental noise: Quantification of healthy life years lost in Europe*. Geneva, Switzerland: WHO.
- Guinée, J. (2001). *Handbook on life cycle assessment—Operational guide to the ISO standards*. Dordrecht, The Netherlands: Kluwer Academic Publishers.
- Haes, H. A. U., Heijungs, R., Suh, S., & Huppes, G. (2004). Three strategies to overcome the limitations of life-cycle assessment. *Journal of Industrial Ecology*, 8(3), 19–32.
- Hammer, M. S., Swinburn, T. K., & Neitzel, R. L. (2014). Environmental noise pollution in the United States: Developing an effective public health response. *Environmental Health Perspectives*, 122(2), 115–119.
- Hauschild, M. Z., Goedkoop, M., Guinée, J., Heijungs, R., Huijbregts, M., Joliet, O., ... Pant, R. (2013). Identifying best existing practice for characterization modeling in life cycle impact assessment. *International Journal of Life Cycle Assessment*, 18(3), 683–697.
- Hauschild, M. Z., & Huijbregts, M. A. J. (2015). *Life cycle impact assessment*. Berlin, Germany: Springer.
- Heijungs, R., & Cucurachi, S. (2017). Life cycle assessment of noise emissions: Comment on a recent publication. *Environmental Modeling & Assessment*, 22(2), 183–184.
- Horni, A., Nagel, K., & Axhausen, K. (2016). *The multi-agent transport simulation MATSim*. London, England: Ubiquity Press.

- Iversen, L. M., Marbjerg, G., & Bendtsen, H. (2013). Noise from electric vehicles—'State of the art' literature survey. In *INTER-NOISE and NOISE-CON Congress and Conference Proceedings* (Vol. 247, pp. 267–271). Washington, DC: Institute of Noise Control Engineering.
- Karipidis, I., Vienneau, D., & Habermacher, M. (2014). Reconstruction of historical noise exposure data for environmental epidemiology in Switzerland within the SIRENE project. *Noise Mapping*, 1(1). <https://doi.org/10.2478/noise-2014-0002>
- Kaufman, L., & Rousseeuw, P. J. (2008). Clustering large applications (program CLARA). In *Finding groups in data: An introduction to cluster analysis* (pp. 126–163).
- Kephalopoulos, S., Paviotti, M., & Ledee, F. A. (2012). *Common Noise Assessment Methods in Europe (CNOSSOS-EU)*. Retrieved from [ec.europa.eu/jrc/en/publication/reference-reports/common-noise-assessment-methods-europe-cnossos-eu](http://ec.europa.eu/jrc/en/publication/reference-reports/common-noise-assessment-methods-europe-cnossos-eu). Accessed December 8, 2017.
- Kim, M., Chang, S. I., Seong, J. C., Holt, J. B., Park, T. H., Ko, J. H., & Croft, J. B. (2012). Road traffic noise: Annoyance, sleep disturbance, and public health implications. *American Journal of Preventive Medicine*, 43(4), 353–360.
- McKinney, W. (2010). Data structures for statistical computing in python. In *Proceedings of the 9th Python in Science Conference* (Vol. 445, pp. 51–56), Austin, TX.
- Meyer, R., Benetto, E., Igos, E., & Lavandier, C. (2017). Analysis of the different techniques to include noise damage in life cycle assessment. A case study for car tires. *The International Journal of Life Cycle Assessment*, 22(5), 744–757.
- Müller-Wenk, R. (2004). A method to include in LCA road traffic noise and its health effects. *The International Journal of Life Cycle Assessment*, 9(2). <https://doi.org/10.1007/BF02978566>
- Ongel, A. (2016). Inclusion of noise in environmental assessment of road transportation. *Environmental Modeling & Assessment*, 21(2), 1–12.
- Ongel, A., & Sezgin, F. (2016). Assessing the effects of noise abatement measures on health risks: A case study in Istanbul. *Environmental Impact Assessment Review*, 56, 180–187.
- Pallas, M. A., Berengier, M., Chatagnon, R., Czuka, M., Conter, M., & Muirhead, M. (2016). Towards a model for electric vehicle noise emission in the European prediction method CNOSSOS-EU. *Applied Acoustics*, 113, 89–101.
- Saner, D., & Heeren, N. (2013). Housing and mobility demands of individual households and their life cycle assessment. *Environmental Science & Technology*, 47(11), 5988–5997.
- Spielmann, M., & Bauer, C. (2007). Transport services (*Ecoinvent Report No. 14*). Dübendorf: Swiss Centre for Life Cycle Inventories.
- Stansfeld, S. A. (2015). Noise effects on health in the context of air pollution exposure. *International Journal of Environmental Research and Public Health*, 12(10), 12735–12760.
- Stewart, J., & Bronzaft, A. (2011). *Why noise matters: A worldwide perspective on the problems, policies and solutions*. Oxon, England: Routledge.
- Swiss Federal Statistical Office. (2000). *Eidgenössische Volkszählung (VZ)*. Neuchatel, Switzerland: Author.
- Swiss Federal Statistical Office. (2010). *Ergebnisse des Mikrozensus Mobilität und Verkehr 2010*. Neuchatel, Switzerland: Author.
- Swiss Federal Statistical Office. (2014). *STATPOP 2013 - Statistik der Bevölkerung und Haushalte*. Neuchâtel, Switzerland: Author.
- Thompson, A., & Taylor, B. N. (2008). *Use of the international system of units (SI)* (Vol. 81). Gaithersburg, MD: NIST Special Publication.
- van der Walt, S., Colbert, S. C., & Varoquaux, G. (2011). The NumPy array: A structure for efficient numerical computation. *Computing in Science & Engineering*, 13(2), 22–30.
- van Rossum, G. (1995). *Python tutorial* (Technical Report CS-R9526). Amsterdam, The Netherlands: Centrum voor Wiskunde en Informatica (CWI).

## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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