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Noise indicators for sleep disturbance and how to model them

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ABSTRACT

In epidemiological research, L_{night} has been used as an indicator to assess the impact of sound on sleep. The predictive superiority of noise events and their level has nevertheless been shown in laboratory sleep studies. Therefore, developing a novel indicator for sleep disturbance that captures noise events might be an asset. However, although such an indicator might have a higher biological validity, its practical applicability might be hindered by the complexity and cpu-time requirements of its simulation. Therefore, the new sleep disturbance indicator (SDI) that we propose is flanked by an efficient model grounded in machine learning to estimate it at any dwelling in Europe. The model is trained on a vast number of numerical simulations for distinct locations and road traffic situations. It is applied to a dataset of children’s non-targeted sleep problems and health, collected in the Alpine region, showing that the model can predict L_{night} and SDI sufficiently accurately to explain at least as much of the variance in sleep problems as detailed noise estimation models. Moreover, it highlighted the importance of the quiet side of the building.

Keywords: Noise, Sleep, Indicator, Machine Learning

INTRODUCTION

The neighbourhood physical environment is an important determinant of children's sleep quality and sleep duration. Studies on transportation noise have shown well-known direct short-term effects on sleep, annoyance, and cognition in both, adults and children. Less is known about the long-term effects of sleep disturbance by noise on children and adolescents, although some evidence points to effects of impaired sleep on cognitive, mental and physical health outcomes [1]. However, these studies have inherent shortcomings. The hitherto used exposure characterisation is very crude (i.e., average sound levels) and has not considered the role of soundscape and the wider context of the neighbourhood built environment. Moreover, existing studies have methodological shortcomings, as analyses related to the potential mediating role of sleep impairment on health outcomes have not been seriously considered.

New indicators relevant for sleep disturbance by traffic sound, capture noise events and therefore cannot be as easily modelled as an equivalent sound level that only depends on the overall exposure dose and thus the overall amount of traffic. Micro traffic simulations of the route of individual cars that assign a realistic range of levels have been constructed. However, such models are cpu-time intensive and above all require significant time to set up [2,3]. They therefore cannot be easily applied to large scale health effects studies.

In the present study, we attempted to improve the prediction of sleep disturbance and potential long-term health effects in children and adolescents with a superior exposure characterisation, the sleep disturbance index (SDI). We employed machine learning that only uses open data available across Europe. This model can therefore easily be run with extremely limited initial setup time. To validate both the new indicator and the model used to calculate it and evaluate its predictive performance, we applied it to an Alpine cohort.

MATERIALS AND METHODS

Sleep Disturbance Index (SDI), an indicator for effects of noise on sleep

The indicator for sleep disturbance has already been presented in [4]. It is grounded in laboratory and field results on sleep disturbance by sound events. Hence, the definition of an event is considered first.

The start of a sound event is detected when the indoor loudness exceeds a given threshold, $N_{1sec,indoor} > T_{NA}$, and when, at the same time, loudness is increasing, dN>0. Masking is implicitly included in the calculation of loudness and hence an additional criterion based on relative level like in the calculation of the intermittency ratio [5] is avoided. The event is thought to continue until the N_{1sec} drops 5 dB below its maximum level or when the level drops below the 15-minute 90 percentile value of loudness, N_{90}.

Once an event is detected, the probability of sleep disturbance P_{SD} is calculated. Sleep disturbance can be detected via noise induced cardiac responses [6], changes in sleep stages [7], etc. For the purpose of constructing the indicator, all these outcomes are pooled and the main trends with respect to exposure are extracted: (1) probability of sleep disturbance shows an S-like curve with a threshold around 35 dBA (1-sec average) and a saturation point between 60 and 75 dBA; (2) the type of sound plays a role and recognition may play a role as well, yet the strongest evidence is found for an increase in probability of sleep disturbance with rise time [8] [9]; (3) spectral content may be important but as most studies consider A-weighted levels rather than loudness, this evidence is inconclusive [8] [10] [11]. Based on the above $P_{SD} = f(N, dN)$ is proposed. The pattern of subsequent noise events may be important for determining sleep disturbance and Markov-style models have been proposed to account for this [12]. When the indicator is calculated based on measurements or a traffic micro-simulation [3], this approach could allow for observing the effect of platooning or traffic lights, but as most simulations will treat vehicle passages as a random Poisson process, preference is given to treating sleep disturbing events as independent and hence:

$$P_{SD,Tk} = \sum_{i=1}^{Tk} P_{SD,i} \prod_{j=1}^{i-1} \left(1 - P_{SD,j}\right),$$

where |Tk| is the time duration of sleep epochs, which is set to 10 minutes, inspired by [13].

In children, loudness perception itself may be deviant from loudness perception in adults, yet there is little direct evidence on this, neither from EEG based studies nor from behavioural research. Yet it is known that hearing threshold peaks at 6 to 8kHz in young children rather than at 500 Hz to 4kHz in adults. Moreover pure-tone hearing threshold is higher in young children [14].

There is some evidence that the effect threshold for sleep disturbance may increase with decreasing age although there are some differences depending on the outcome where EEG based sleep stages show a stronger dependence than cardiovascular response [15] [16].

Considering the above and in absence of further evidence, an increase in effect threshold of 10 dB for the age range 0-3 yrs. and of 5 dB for the age range 3-6 yrs. is used as a working hypothesis.

Sound measurements are often conducted outdoors, on the one hand, because of privacy reasons and practical considerations, and, on the other hand, because of the uncertainty in the origin of the sound measured indoors. Simulations result in outdoor levels that need correcting to account for sound insulation of the bedroom and orientation of the bedroom in relation to the source. Hence, some hypotheses have to be made regarding this insulation and orientation.

In [17], it was found that sleep disturbance of children correlates better with the equivalent noise level at the least exposed façade. This may reflect the choice of parents to orient the children's sleeping room towards the quiet side as a form of coping. In [18] it was found that sound insulation of the façade with windows closed depends on the level outside. This is partly due to a coping mechanism but in Switzerland (and some other countries) the insulation of new buildings is related to the outdoor level.

Taking this evidence together, several forms of coping, all depending on average outdoor noise levels (closing windows, insulating for sound, reorienting bedrooms), are summarized in an assumed frequency-dependent sound insulation index D(f), loosely fitted on data from [18], is given by:

$$D(f) = \min(58;\ 31 * log10(150 + f) - 30) + 0.55 * 10 * log10\left(10^{\frac{Lnight}{10}} + 10^{\frac{35}{10}}\right) - 60$$

There exists a complex interplay between the diurnal pattern of exposure and the sensitivity to sleep disturbance. To account for the changing sensitivity over the night, a weighting w_k is introduced in the calculation of the nightly accumulated sleep disturbance index (SDI) where k refers to the sleep time interval. This weight is linearly increasing from 5:00 until 7:00 from 1 to 2 to account for the lack of remaining bed time, preventing deep sleep after being woken by an early morning noise event. The instantaneous probability of noise related sleep disturbance is expected to be relevant if it exceeds a natural sleep disruption probability, $P_{nat,Tk}$, which is kept independent of the time of the night T_k and fixed at 0.1 in the current implementation of the model.

$$SDI = \frac{1}{|T_{sleep}|} \sum_{k \epsilon Tsleep} ReLu(P_{SD,Tk} - P_{nat,Tk}) w_k$$

Children sleep longer and usually during earlier hours of the night [19,20]when traffic noise is still high. In the age dependent definition of the SDI, this is accounted for by adjusting the duration of the night to 14 hours for age range 0-3 yrs., 12 hours for 3-6 yrs, 10.5 hours for 6-12 yrs., 9 hours for 12-18 yrs. This may be adjusted for the actual sleep duration in the specific sample one wants to analyse. Sleep patterns may change with age making children of different ages more vulnerable to sound events that occur at different times during the night.

Example of SDI values calculated on measurements and their comparison to L_{night} can be found in [4].

A machine learning model to calculate advanced noise exposure indicators

Traffic noise models that include the contributions of individual cars to the sound level at any given location, and thus allow to calculate indicators such as the SDI described above, have the disadvantage that they take a high amount of CPU time and very long setup times. Therefore, they are not suitable for estimating exposome for a large population. So called surrogate models have been proposed as a solution since many years, yet it is with the advent of deep neural networks that they have seen a revival.

To train a machine learning model to predict detailed noise indicators obtained from measurements, a huge number of measurements (thousands of locations) would be needed. Such measurements should be detailed enough to extract the additional indicators. As a minimal requirement, the 1/3 octave band spectral resolution combined with a temporal resolution of 8 times per second could be set. Such measurements are unfortunately not available. Hybridisation, however, could be an alternative. Running a model based on physics for thousands of locations and training the ML model could learn to understand and mimic these physical laws using a convolutional deep neural network (shown in blue in Figure 1). Here, this is done for 7000 locations and three traffic scenarios. Still, if some measurements are available the model can be fine-tuned for a local situation by adding additional layers in the model.

The input features used in the model are derived from the OpenStreetMap and include different types of streets with their estimated traffic intensity and buildings. At short distance, the direction of streets, and possibly shielding and reflecting buildings, are taken into account. At longer distances, only average traffic and average build up area are considered. The estimation is based on two assumptions: (1) It is assumed that roads are built in a logical way, which means that the number of lanes, and the categorization of the road are appropriate for the expected traffic volume; (2) It is assumed that roads are used more when they connect to other roads. The latter is measured by the "edge betweenness" of the road segment in the graph.

The indicators predicted by the model are SDI, L_{night} (for reference), and related statistics on sound events. For training and testing during model development, indicators calculated on 15-minute time intervals are used. On this time scale, equivalent levels are predicted within 3 dBA and P_{SD} within 0.1 of their value obtained from detailed models. It should however be noted that a large part of this deviation is due to the stochastic nature of the detailed calculations, leading to changes in these levels between multiple realizations of the 15- minute traffic. Over a whole night, this randomness averages out and correlation between the detailed model and the machine learning approximation of SDI has an r^2 around 0.9.

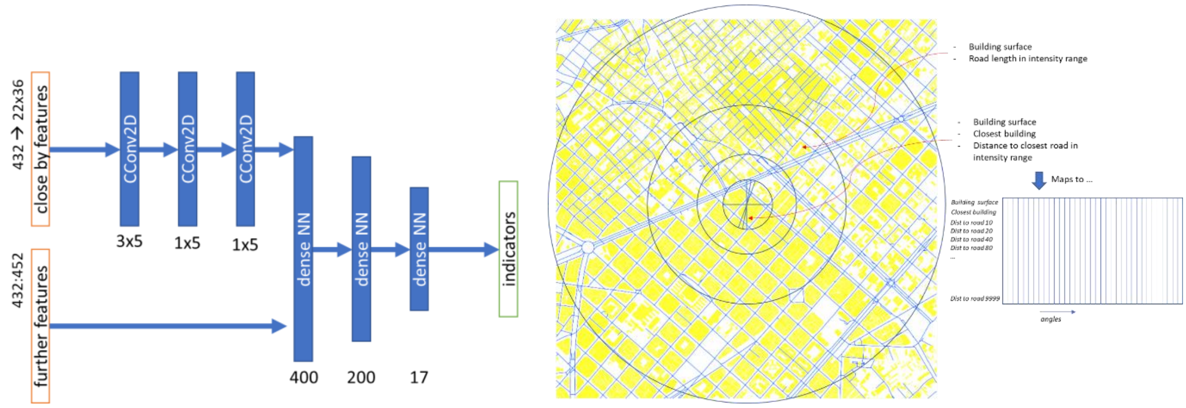

Figure 1. Machine learning surrogate model (left) and the environmental features it uses (right)

Validation data set, Alpine.

The data used for validation was collected in 2004-2005 for the Brenner Base Tunnel Study. The sample included 1251 8-12 year-olds recruited from 49 public schools in the Tyrol region of Austria and Italy (Lower Inn, Wipp, and side valleys). Ethical approval was obtained from the Ethics committee of the Medical University Innsbruck (Ethics commission number 2105/2004).

Children answered three questions about problems falling asleep, uneasy sleep, and feeling tired in the morning. Reponses were provided on a 5-point scale from never to very often.

RESULTS

Both the sleep disturbance index (SDI) and L_{night} were calculated for road traffic with the machine learning model that only uses the OpenStreetMap data as a source of information. Note that no local traffic intensity information is used in this calculation. Overall sleep problems which are a combination of problems falling asleep, uneasy sleep and tiredness after sleeping is used as an outcome variable. The questionnaire used to assess this does not refer to noise explicitly. Therefore, one usually expects a lower degree of explained variance. Figure 2 shows a trend analysis for the insomnia score versus SDI and L_{night} calculated at the most ("m") and least ("l") exposed façade of the dwelling. The plots represent smoothed estimates of x vs. y, using the lowess function in the Hmisc-library [21] and do not include information on the direction that the child's bedroom is facing.

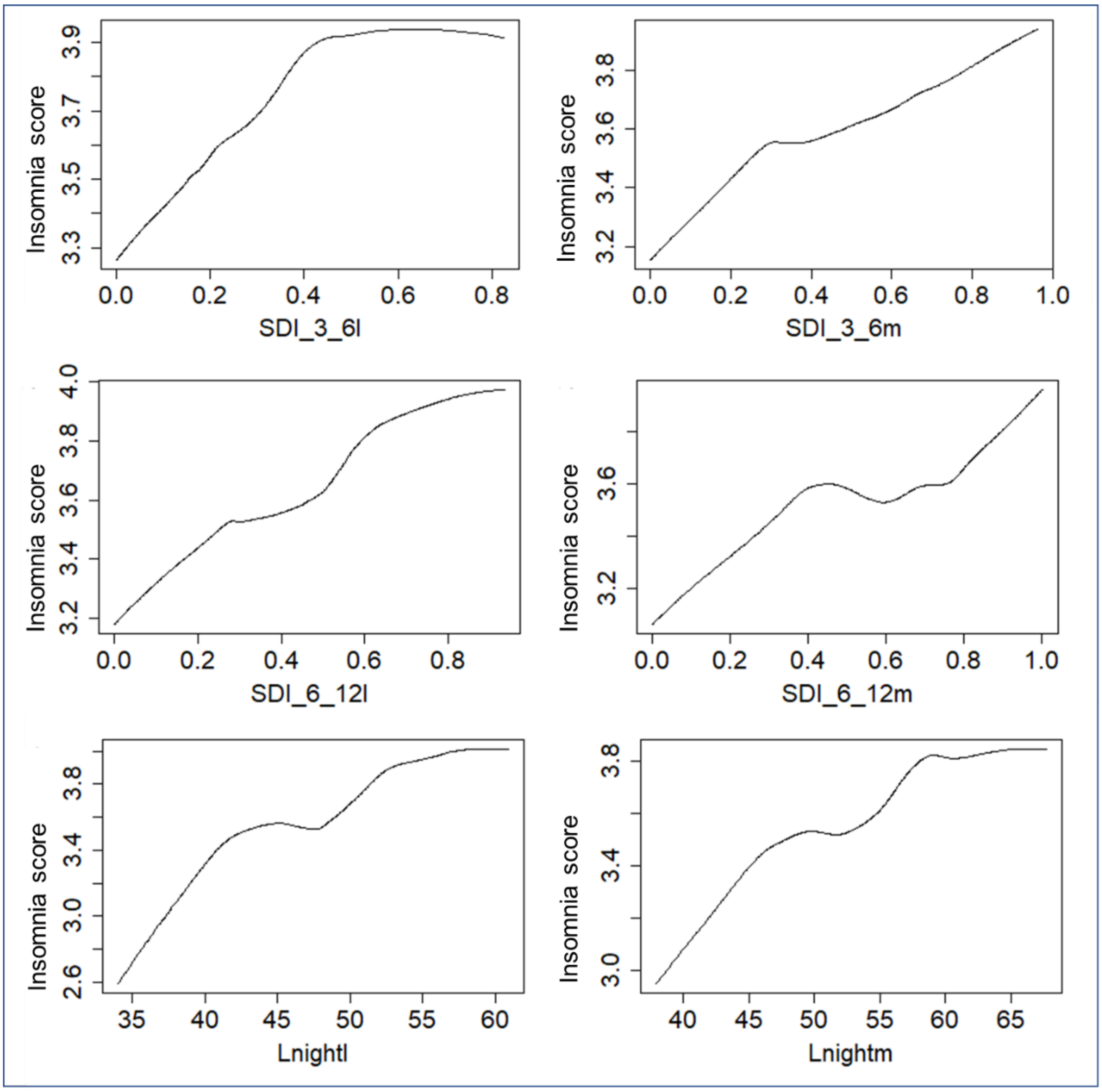

Figure 2. Trends for sleep problems experienced by the study population versus road traffic noise Lnight (lower) at the least exposed (left) and the most exposed façade (right); upper: similar for the sleep disturbance score with the SDI.

DISCUSSION

The L_{night} and SDI show a clear relationship with reported sleep problems even though traffic data for the specific site has not been used to obtain them. The relationship with L_{night} caused by road traffic shows a double trend. At very low levels, there is a linear increase, while around 45 to 50 dBA, a plateau can be seen, followed by a further increase. It should be noted that in the main Alpine valley, the railroad and highway run almost in parallel and direct line-of-sight sound propagation towards the slopes is most often possible. Hence the further decrease of sleep disturbance below L_{Aeq}=40dBA might be due to exposure to railway noise, which will include higher noise peaks at the same L_{Aeq} and L_{night} by road traffic is only a proxy. It can also be observed that the levels at the least exposed façade seem to explain a larger range of sleep problem levels. This might indicate that children most often sleep at the least exposed façade of the house, which might be a way of coping with exposure to noise.

Two values of the SDI for road traffic noise corresponding to an age range 3 to 6 years (SDI_3_6) and to an age range 6 to 12 years (SDI_6_12) have been used in a similar one-dimensional analysis. The latter age range corresponds to the actual age of the children included in this study. The reader should remember that the differences between these indicators are caused by at the one hand a different threshold for disturbance by single events, at the other hand longer sleeping hours. Figure 2 left column that focusses on the least exposed façade, shows an almost linear regression between SDI_6_12 the insomnia score, for values above 3.2. This level of insomnia score corresponds to an L_{night} just below 40 dBA. This is in line with the hypothesis in the previous paragraph that sleep disturbance at the lower level could be cause by other sources. Turning to the SDI_3_6, it can be seen that the range of insomnia scores is covered to a lesser extend and that the curve saturates, indicating that a further increase in expected sleep disturbance is not reflected in the insomnia score. Thus the higher threshold and earlier sleeping times assumed for these younger children does not match the observations for the 8 to 12 year olds, as expected.

The trend between SDI_6_12 at the most exposed façade shows a double trend. Th breakpoint lies at an insomnia score of 3.6. A possible hypothesis for this is that at this degree of sleep disturbance the sleeping room of children is moved to the least exposed façade as a coping mechanism. It can also be observed that at very low SDI at the most exposed façade, a lower insomnia score is predicted than for the SDI at the least exposed façade.

One should also keep in mind that sleep quality could also be lost for other reasons than road traffic noise at night. Hence, even at low SDI, sleep quality is not perfect as it can be influenced by other noise sources or non-noise disturbances at night. One of them could be noise exposure during the evening. A restorative period in the evening (calculated as L50<50dB) reduces the sleep problems from 4.0 to 3.5 when considered it as a single parameter (figure not shown). Yet, before drawing strong conclusions from this, one should keep in mind that dwellings that lack a restorative period in the evening will probably be exposed to high noise levels at night. Reversely, the lower insomnia score for low SDI at the most exposed façade could be related to these restorative periods during the eveneing.

An extended structural equation model (SEM) is also being developed with these data, but will be reported elsewhere.**Error! Reference source not found.** Briefly, that model will include f urther environmental, perceptual, and sociodemographic variables (grey/green space/air pollution, environmental disturbance, restorative quality of the environment, education, density). Preliminary tests show that both indicators (L_{night}, SDI) keep their predictive value also in this SEM and that, when combined with an indicator that also includes railway noise peaks, SDI has a slightly stronger predictive power than L_{night}.

CONCLUSIONS

We have introduced a possible indicator for sleep disturbance by traffic noise that includes more field knowledge obtained from various studies than L_{night}. At the same time, we have introduced a surrogate model to efficiently calculate such an indicator as the lack of models may hinder its application in epidemiological research. Finally, we have applied the indicator and model to a sleep study in the Alpine area and show that plausible results are obtained.

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