Environmental Research 220 (2023) 115029

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Using multi-sourced big data to correlate sleep deprivation and road traffic noise: A US county-level ecological study

Huan Tong [a,b,*], Joshua L. Warren [c,**], Jian Kang [b,***], Mingxiao Li [d,****]

[a] School of Architecture, Harbin Institute of Technology, Shenzhen, China
[b] Institute for Environmental Design and Engineering, The Bartlett, University College London, London, UK
[c] Department of Biostatistics, Yale School of Public Health, Yale University, New Haven, CT, USA
[d] School of Architecture and Urban Planning, Shenzhen University, Shenzhen, China

A R T I C L E I N F O

Keywords:
Large scale
Noise policy
Bayesian spatial model
Urban sprawl pattern
Road traffic noise

A B S T R A C T

Background: Road traffic noise is a serious public health problem globally as it has adverse psychological and physiologic effects (i.e., sleep). Since previous studies mainly focused on individual levels, we aim to examine associations between road traffic noise and sleep deprivation on a large scale; namely, the US at county level.
Methods: Information from a large-scale sleep survey and national traffic noise map, both obtained from government's open data, were utilized and processed with Geographic Information System (GIS) techniques. To examine the associations between traffic noise and sleep deprivation, we used a hierarchical Bayesian spatial modelling framework to simultaneously adjust for multiple socioeconomic factors while accounting for spatial correlation.
Findings: With 62.90% of people not getting enough sleep, a 10 dBA increase in average sound-pressure level (SPL) or L_s10 (SPL of the relatively noisy area) in a county, was associated with a 49% (OR: 1.49; 95% CrIs:1.19–1.86) or 8% (1.08; 1.00–1.16) increase in the odds of a person in a particular county not getting enough sleep. No significant association was observed for L_s90 (SPL of the relatively quiet area). A 10% increase in noise exposure area or population ratio was associated with a 3% (1.03; 1.01–1.06) or 4% (1.04; 1.02–1.06) increase in the odds of a person within a county not getting enough sleep.
Interpretation: Traffic noise can contribute to variations in sleep deprivation among counties. This study suggests that policymakers could set up different noise-management strategies for relatively quiet and noisy areas and incorporate geospatial noise indicators, such as exposure population or area ratio. Furthermore, urban planners should consider urban sprawl patterns differently in terms of noise-induced sleep problems.

1. Introduction

Road traffic noise is a serious public health concern and environmental nuisance. According to the World Health Organization (WHO), at least one million healthy life-years are lost annually because of traffic-related noise in Western Europe (World Health Organization, 2011). To reduce the adverse impacts of noise on human health, a series of policies and actions have been implemented by various organisations, such as the WHO Environmental noise guidelines (World Health Organization, 2018), the Environmental Noise Directive in Europe (European Union, 2002), the Environmental Protection Act in Canada (Government of Canada, 2019). In the US, after the adoption of the National Environmental Policy Act in 1969, the Office of Noise Abatement and Control made considerable efforts on the development of noise policies which are largely ineffective due to the lack of funding (Andrews, 1976; Kang et al., 2001). Among these policies, administrative levels, such as cities, regions, even the whole country are regarded as significant subjects when policies are created and implemented. Therefore, understanding the association between noise and human health at the large-scale administrative level is important from policy and planning perspectives.

* Corresponding author.
** Corresponding author.
*** Corresponding authors.
**** Corresponding author.
E-mail addresses: huan.tong.18@ucl.ac.uk (H. Tong), joshua.warren@yale.edu (J.L. Warren), j.kang@ucl.ac.uk (J. Kang), limx@lreis.ac.cn (M. Li).

https://doi.org/10.1016/j.envres.2022.115029
Received 26 June 2022; Received in revised form 6 December 2022; Accepted 7 December 2022
Available online 8 December 2022

Road traffic noise has adverse health effects including hearing loss, sleep deprivation, and cardiovascular disease (e.g., Basner et al., 2014; Dratva et al., 2012; Hériter et al., 2018; Kang et al., 2023; Kryter, 1972; Münzel et al., 2021; Pirrera et al., 2010; Von Lindern et al., 2016; Tong et al., 2021). There is a growing body of evidence concerning the health consequences of traffic noise. We searched PubMed from database inception up to May 1, 2022 for articles published in English, with combinations of the search terms "sleep", "traffic noise", and "public health". A total of 283 papers have been published, while 79 studies were found to investigate the impacts of road traffic on sleep. These studies, mainly from laboratory or field experiments, found that the sleep quality and quantity for individuals can be compromised by road traffic noise. However, we did not find any ecological study especially at a large scale to quantify associations between sleep and geospatial traffic noise indicators. Also, no study considered characteristics of urban sprawl patterns or spatial variations. Large-scale ecological research at administrative levels is still lacking, which is the fundamentals for public policymaking and implementation. In addition, in the era of big data, such research has become possible. While big data from multiple sources have been combined and studied in the environmental health setting previously, such as air quality and thermal environment (e.g., Kuo et al., 2018; Li et al., 2019), less attention has been given to studying the impacts of sound environment on health.

Therefore, the aim of this study is first to visualise the spatial variations of sleep deprivation at the administrative level, then estimate its association with traffic noise indicators. We will also discuss which kind of urban sprawl pattern had a higher risk of noise-induced sleep problems, and consider whether other unexplanatory factors still exist. To answer these questions, multiple geospatial noise indicators were calculated at the US county level based on the nationwide noise map and connected to sleep deprivation data obtained from the largest health survey system. Hierarchical Bayesian spatial regression models were used to quantify the associations of interest while accounting for spatial correlation in the data. Finally, significant indicators were identified and more effective noise-management strategies were explored. It is expected that our findings can inform policymakers and urban planners to protect people from noise nuisance and build a healthier city.

2. Methods

2.1. Data sources

We conducted the large-scale ecological study by investigating counties from the 48 contiguous states in the US. Open-sourced big data (including noise maps, sleep deprivation, and social-economic data) were obtained and aggregated to the county level.

This study used the self-reported sleep data, which was obtained from the Behavioral Risk Factor Surveillance System (BRFSS) developed by the Centers for Disease Control and Prevention (CDC, 2021). BRFSS from 2010, as the latest sleep data that has county code information, was used in this study (CDC, 2021). Sleep deprivation, measured as sleep insufficiency in this study, is based on the question from the survey: "How many days did you not get enough sleep in past 30 days?". The answers include "Number of days", "None", "Don't know/Not sure", "Refused", and "Not asked or Missing". Using this information, we created a binary sleep deprivation outcome variable for each respondent in order to estimate the deprivation at the county level; sleep deprivation (i.e., >0 days of not enough sleep) vs. no sleep deprivation (i.e., 0 days of not enough sleep). In the dataset, each respondent has been labelled by county code. The individual sleep data were aggregated to the county level based on county code labels. In total, 451,075 people were interviewed. Of these, 9085 persons were excluded since they did not respond to this question.

Noise levels were obtained from the noise maps which is an efficient tool in the environmental plan and provide a visual presentation of the distribution of sound-pressure levels (European Environment Agency, 2014). The US national noise map was produced by the US Department of Transportation using an A-weighted 24-h equivalent SPL metric based on the Federal Highway Administration Traffic Noise Model version 2.5 (Bureau of Transportation Statistics, 2017). The national noise map is only available and feasible to process in the big data era with high computational capability. The available map dates to 2014, which is used in this study, since the changes in road network could be negligible between 2010 and 2014 in the US, a developed country (Barrington--Leigh and Millard-Ball, 2020; Rodrigue et al., 2016). The road traffic noise map in Tag Image File Format was imported in ArcGIS Pro 2.7 and converted to a raster file of 30 m grid resolution, which is the finest available spatial resolution. The value of pixels from the raster map presents the value of SPLs. There are more than ten billion pixels in total. To make the data processing feasible and fast, the whole map was divided into smaller maps then processed separately. Meanwhile, the accuracy of SPL is reduced to 1 dBA from 0.001 dBA. Subsequently, we developed a Python program and applied spatial statistics function in ArcGIS Pro 2.7 to calculate geospatial noise indicators. Based on previous studies, geospatial noise indicators were widely used in the field of urban sound environment (Cai et al., 2019; Casey et al., 2017; Lam and Chung, 2012; Xie and Kang, 2009). Studying the health effects of noise from a spatial and macro perspective, can help with managing and allocating resources towards more effective urban planning layouts and noise management strategies. Through a literature review, seven indicators were extracted to describe the county traffic noise, as shown in Table 1.

Since previous studies have indicated that the impacts of noise on health are related to social-economic status, we extracted data on 19 county-level descriptors from the American Community Survey as control variables; including population, sex ratio, median age, percentage of Black or African American, unemployment rate, old-age dependency ratio, mean travel time to work (in minutes), percentage of married-couple family households, average household size, median income, percentage of people with bachelor's degree, graduate or professional degree, percentage of renter-occupied housing units, median number of rooms, median housing value, percentage of households with no vehicle, percentage of detached or attached houses, percentage of households below 149 percent of the poverty level, and population density. Due to high correlation between the variables, a principal components analysis was conducted to extract less correlated combined components that explained a large proportion of the original variability. These factor scores were then used in the regression modelling.

Table 1
County-level traffic noise indicator descriptions.

Indicators	Descriptions
L_{ave} (dBA)	Average sound-pressure levels
L_s10 (dBA)	Sound-pressure levels of relatively noisy area in a county (sound-pressure levels exceeded for 10% of the county)
L_s90 (dBA)	Sound-pressure levels of relatively quiet area in a county (sound-pressure levels exceeded for 90% of the county)
Exposure area (km^2)	Area exposed to traffic noise
Exposure area ratio (%)	The percentage of area exposed to traffic noise
Exposure population (thousand people)	Population exposed to road noise
Exposure population ratio (%)	The percentage of population exposed to road noise

2.2. Statistical analysis

We model the probability that an individual living in a specific county did not get enough sleep at some point in the past 30 days as a function of county-level road traffic noise, socioeconomic factors, and spatially correlated random effects using a hierarchical Bayesian spatial logistic regression framework. The statistical model is given as

$$Y_k|p_k \sim \text{Binomial}(n_k, p_k), k = 1, \ldots, n;$$

$$\text{logit}(p_k) = \beta_0 + \beta_1 {}^*\text{noise}_k + \sum_{j=1}^{m} \text{fs}_{jk} {}^* \gamma_j + \varphi_k$$

where Y_k is the observed number of people not getting enough sleep in county k out of the n_k people who were surveyed in the county; n is the total number of counties included in the study; p_k is the probability that a person in the county does not get enough sleep; noise_k is the measure of road traffic noise in the county (multiple metrics were tested in separate models due to high correlation between them); fs_{jk} is the factor loading from the j^{th} principal component in the county ($m = 6$, six total factors were retained); and φ_k is the spatially correlated random effect specific to the county.

The spatially correlated random effects account for unexplained spatial variability in the data and help to ensure that statistical inference for the primary noise associations is accurate. Failing to account for spatial correlation can potentially lead to different conclusions from the model and may need further investigations (Bravo et al., 2022; Gunasekera et al., 2020; Warren et al., 2022). To model this correlation, we used the Leroux version of the conditional autoregressive model (Leroux et al., 2000) where the prior mean for a county-specific random effect is a weighted average of its neighbours' random effect values with a variance that depends on the number of neighbours. Specifically, the model is given as

$$\varphi_k \left| \boldsymbol{\varphi}_{-k}, \rho, \tau^2 \sim \text{N}\left(\frac{\rho \sum_{j=1}^{n} w_{kj} \varphi_j}{\rho \sum_{j=1}^{n} w_{kj} + 1 - \rho}, \frac{\tau^2}{\rho \sum_{j=1}^{n} w_{kj} + 1 - \rho} \right) \right.$$

where $\boldsymbol{\varphi}_{-k}$ is a vector of all random effects other than the one from county k; $\rho \in [0, 1)$ describes the level of spatial correlation in the random effects with values near zero suggestive of spatial independence and values near one suggestive of strong spatial correlation; τ^2 is the variance parameter for the effects; and w_{kj} is a binary variable describing whether counties k and j are neighbours (i.e., touching borders). By definition, a county is not a neighbour of itself so that $w_{kk} = 0$ for all k.

To complete the model specification, we assigned weakly informative prior distributions to the introduced model parameters, allowing the data to drive the inference rather than our prior beliefs. Specifically, all regression parameters were assigned $\text{N}(0, 100, 000)$ distributions, $\rho \sim \text{Uniform}(0, 1)$, and $\tau^2 \sim \text{Inverse Gamma}(1, 0.01)$. All models were adopted in the Bayesian setting using Markov chain Monte Carlo (MCMC) sampling algorithms within R statistical software (R Core Team, 2020) using the "CARleroux" function within the "CARBayes" package (Lee et al., 2018). We discarded 100,000 samples prior to convergence of the algorithm. The total number of MCMC samples collected post-convergence of the model was 1,000,000. We thinned these samples by a factor of 100, resulting in 10,000 less correlated posterior samples with which to make statistical inference. Convergence for each model was assessed through visual inspection of trace plots and calculation of Geweke's convergence diagnostic for all model parameters.

3. Results

In the US, 62.90% of people reported that they did not get enough sleep to different extents. On average, they did not get enough sleep for 7.66 days in last 30 days. The spatial distribution of the modelled percentages of people not getting enough sleep across every county is shown in Fig. 1, based on the model that used L_{ave} as the noise covariate. In counties without observed survey data, the statistical model allowed us to estimate these percentages based on county covariate values and spatial correlation. It can be seen the percentage of people not getting enough sleep varied considerably over counties.

The results from the statistical modelling are presented in Table 2, which shows the estimated associations on the odds ratio (OR) scale (i.e., posterior medians and 95% equal tailed quantile based credible intervals (CrIs)) between the probability of not getting enough sleep and substantial noise indicators. We highlighted results for those variables

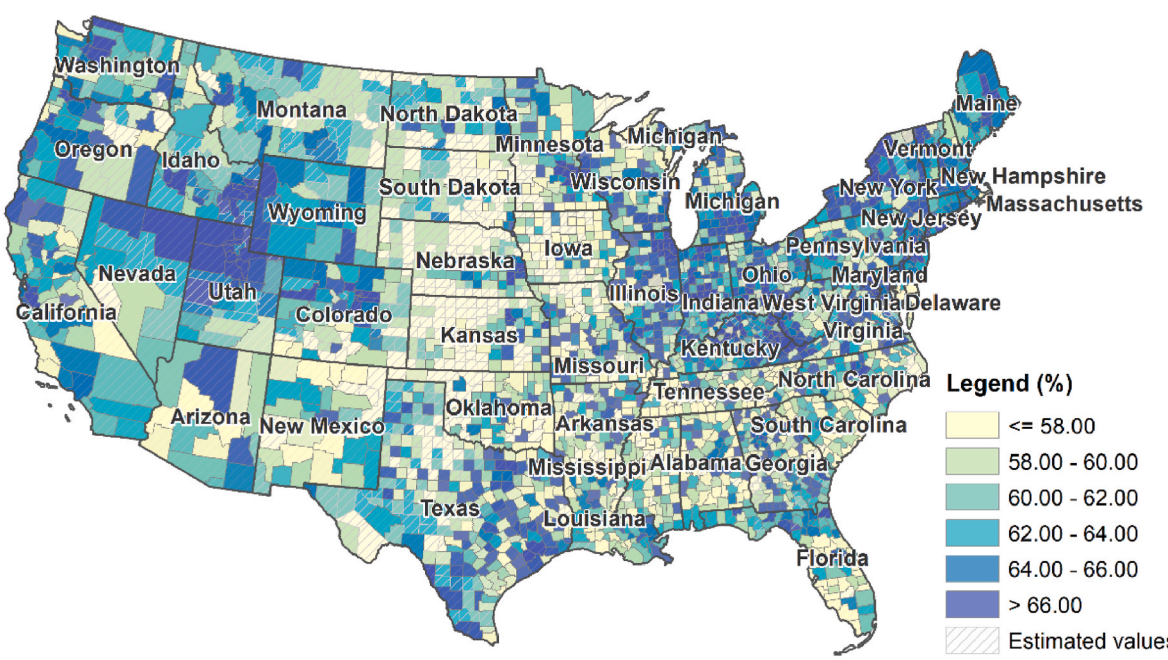

Fig. 1. The modelled percentage of people not getting enough sleep at the county level based on the statistical model using L_{ave} as the noise covariate.

Table 2
Odd ratio and 95% credible interval (CrI) for sleep deprivation associated with overall indicators for noise.

Indicators	Odd Ratio		
	Posterior Median	95% CrI (Posterior Quantiles)	
		2.5%	97.5%
L_{ave} (10 dBA)	**1.49**	**1.19**	**1.86**
L_s10 (10 dBA)	**1.08**	**1.00**	**1.16**
L_s90 (10 dBA)	1.46	0.80	2.65
Exposure area (km^2)	1.00	1.00	1.00
Exposure area ratio (10%)	**1.03**	**1.01**	**1.06**
Exposure population (thousand people)	1.00	1.00	1.00
Exposure population ratio (%)	**1.04**	**1.02**	**1.06**

with 95% CrIs that exclude 1.00 in bold. Overall, considerable positive relationships were observed. A 10 dBA increase in L_{ave} at the US county level resulted in a 49% increase in the odds of a person in that county not getting enough sleep (OR: 1.49; 95% CrIs: 1.19–1.86). Furthermore, L_s10 and L_s90 indicating spatial percentile SPLs were examined. The results showed that a 10 dBA increase in county-level L_s10 was associated with an 8% increase in the odds of a person not getting enough sleep (1.08; 1.00–1.16) while the CrIs for L_s90 were not statistically significant. Also, for absolute exposure area and exposure population, no significant association was observed. However, when we examined the exposure area ratio and exposure population ratio, they were positively associated with sleep deprivation. Specifically, a 10% increase in exposure area ratio was associated with a 3% increase in the odds of a person not getting enough sleep (1.03; 1.01–1.06). A 10% increase in exposure population ratio has a correlation with a 4% higher probability of a person not getting enough sleep (1.04; 1.02–1.06).

A choropleth map of the random effect (φ_k) estimates from the model which associated L_{ave} and sleep deprivation is shown in Fig. 2. Maps of estimates from other regression models show similar patterns. It can be seen that several areas (e.g., counties in Michigan) continued to have high residual risk of people not getting enough sleep even after adjustment for noise and socioeconomic factors. This suggests that the covariates are not perfectly describing risk in these areas and there is unexplained variation remaining in the data. The results also suggest that the unexplained variability in the data was primarily driven by strong spatial correlation instead of non-spatial random variation, as indicated by the estimate of ρ (0.98; 0.94–1.00). From the map, it can be seen that the counties with positive residual values are mainly clustered in the northeast and northwest of the US (e.g., Michigan & Montana). This suggests that the risk of sleep deprivation in these counties tends to be elevated after adjustment of predictors in the model. The counties with negative values are located at the southwest and southeast, which means that the remaining risk is lower after adjustment of predictors.

4. Discussions

Based on the multi-sourced data analysis and spatial visualisation, considerable people (62.90%) are suffering from sleep deprivation in the US, and they are not distributed evenly at the county level. The problem seems to have been reduced slightly, compared with 69.4% of adults experiencing lack of sleep in 2009 based on the same survey (Liu et al., 2013). We used the Bayesian spatial model to predict percentage of people not getting enough sleep in the counties without observed survey data. The results can be used to identify which areas have more serious sleep deprivation issues in the US and allocate more resources when dealing with such issues.

With the Bayesian spatial regression modelling, it can be concluded that substantial noise indicators can contribute to variations in sleep deprivation among counties in the US, however, the noise management strategies have not received the US government's significant attention. Overall, the risk of not getting enough sleep would be higher when there is an increase in the average SPL of a county. While this finding is excepted and in keeping with previous studies where it has been shown that both quality and quantity of sleep can be compromised for individuals (Kim et al., 2012; Lee et al., 2018). It is interesting to note that among different spatially referenced noise indicators (L_s10 and L_s90), only SPL of the relatively noisy area (L_s10) can increase the risk of sleep deprivation. L_s90, as SPL of relatively quiet area, was not correlated with sleep significantly. Hence, environment noise policymakers should consider the spatial variations within a county (i.e., difference between relatively noisy and quiet areas) that current policies failed to consider.

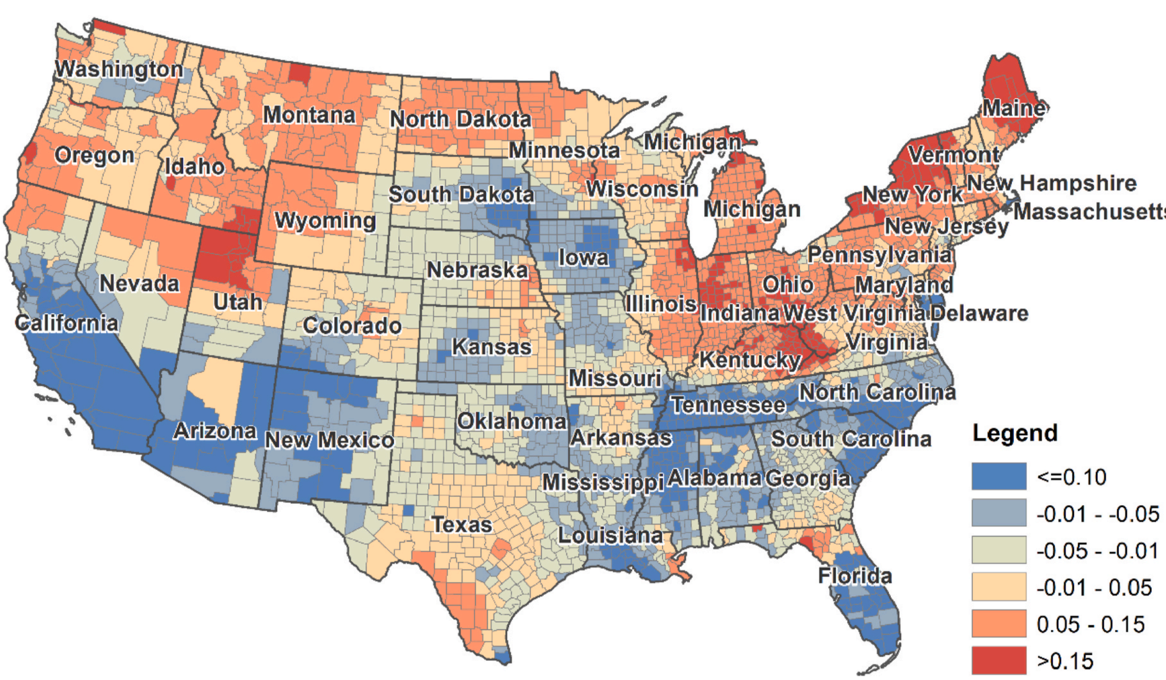

Fig. 2. Posterior means of the spatial random effects from the regression model for L_{ave}. Large positive random effect values represent elevated risk of sleep deprivation after adjustment of predictors in the model. Large negative values indicate the opposite.

It is suggested that in the relatively noisy areas and quiet areas, the noise-management strategies could be different rather than uniform (e.g., setting up different limiting SPLs). Furthermore, it is worth protecting 'Quiet Areas' for population health. In Europe, the definitions, economic effects, and evaluation methods for quiet areas have been widely discussed, and there are guidelines published and practice conducted among Member States of European Union (European Environment Agency, 2014). In the US, Quiet Communities Act was developed by the US Environmental Protection Agency and introduced in the US Congress, but it was essentially unfunded (Environmental Protection Agency, 2021). Compared to Europe, noise policy implementation and environment noise research in the US are not well studied. Indeed, the US has advantages in 'Quiet Areas' protection since the well-established national noise map used in this study can also be applied to identify and evaluate the 'Quiet Areas'.

This study also found that exposure area ratio and exposure population ratio are related to sleep deprivation. The finding of exposure area ratio suggested that the risk of sleep deprivation is higher in a highly urbanised city. Beyond exposure area ratio, the exposure population ratio as a crucial factor considering the high-precision distribution of population in the county can also increase the risk of sleep deprivation. The exposure population ratio can reflect how population density is distributed spatially, which indicates the urban sprawl patterns (Johnson, 2001; Masum et al., 2021; OECD, 2018). A higher exposure population ratio means that human settlements are located around the transportation network, which is a typical urban sprawl pattern (Marshall and Gong, 2009). Therefore, the result indicates that such cities could confront a higher risk of sleep deprivation. It is noticeable that exposure population ratio has a higher odd ratio compared to the exposure area ratio. This means that urban sprawl patterns play a more important role in noise-induced sleep issues than the magnitude of urbanisation. To some extent, the results are in line with the research of Margaritis and Kang (2016) and Tong and Kang (2021), which showed that in highly urbanised cities, the negative impacts of noise on residents is more serious. Previous studies focused more on physically acoustical indicators such as SPL, however, did not fully take administrative level geospatial indicators into investigation, which can be used to describe both urban sprawl patterns and sound environment. With the open big data largely available, it is feasible to access these datasets and calculate county-level indicators. Especially in the US, these geospatial indicators can be calculated in a convenient way since the national noise map has been established across the whole country. Big data also makes it possible to conduct research at larger scale and broader coverage, for example, at the European Union and the US level. Finally, it is suggested that large-scale noise indicators could be incorporated when formulating noise policies, and different urban sprawl patterns should be treated strategically rather than uniformly.

This study suggests a number of possibilities for future research. First, previous research has shown that subjective perception of noise varies in different countries (Yang and Kang, 2005), while this study only examined noise-induced sleep problems in the US. From this perspective, it would also be useful to investigate other countries and compare them with the US. Second, consideration has also been given to soundscape, defined as the acoustic environment perceived or experienced and/or understood by a person or people (International Organization for Standardization, 2014). This study just discussed sleep deprivation from noise, namely the adverse health effects from the sound. With soundscapes attracting research attention, the positive effects of sound on health are worth to be discussed. Third, this study used noise maps in 2014. Although, the change in noise maps could be negligible between 2010 and 2014 in the US, it would be better to use the noise map in 2010 for the analysis if the data was available. Finally, we found that the variations in sleep deprivation among counties are also driven by spatial correlation, namely the neighbourhood effects, apart from noise and socio-economic factors. It indicated that the sleep deprivation was affected by adjacent county characteristics. Hence, it is worth exploring additional reasons, such as noise policy and building regulation. Correspondingly, discussion forums and collective actions are needed to deal with environmental health issues and implement related policies across counties in the US, especially the geographical proximity counties.

5. Conclusions

In conclusion, in the US, a large group of people were suffering from sleep deprivation and variations in sleep deprivation among counties were found. We conducted an ecological analysis to explain patterns in this variability across the US based on hierarchical Bayesian spatial logistic regression models. Overall, a number of noise indicators can significantly contribute to variations in sleep deprivation among counties in the US, while the noise management strategies have not received considerable attention from the US government. Among the geospatial noise indicators, only L_s10 (SPL of relatively noisy area in a county) can increase the risk of sleep deprivation, while L_s90 (SPL of relatively quiet area) cannot. In terms of other large-scale noise indicators, the increase in noise exposure area or population ratio in a county was associated with an increase in the odds of a person within a county not getting enough sleep. This study fills the gap in public health and noise issues at the large scale and promotes noise-related health research in the US and beyond. This study points out the importance of the 'Quiet Areas' protection and suggests that policymakers set up different noise-management strategies for quiet and noisy areas (e.g., different limiting SPLs). Moreover, when formulating noise policies, large scale geospatial noise indicators, such as exposure population or area ratio, can be incorporated, which are easy to calculate based on the well-established national noise map. Furthermore, urban planners can pay more attention to different urban sprawl patterns. In future studies, it is worth exploring additional reasons for remaining unexplained variations which are driven by spatial correlation.

Author contributions

All authors contributed to the concept and design of the study. HT and ML collected, prepared, and cleaned the datasets. HT and JLW did the statistical analysis and drafted the manuscript. All authors edited and revised the draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the European Research Council (ERC) Advanced Grant (no. 740696) on "Soundscape Indices" (SSID).

References

Andrews, R.N., 1976. Environmental Policy and Administrative Change. Implementation of the National Environmental Policy Act. United States. https://www.osti.gov/biblio/7330294.

Barrington-Leigh, C., Millard-Ball, A., 2020. Global trends toward urban street-network sprawl. Proc. Natl. Acad. Sci. USA 117 (4), 1941–1950.

Basner, M., Babisch, W., Davis, A., Brink, M., Clark, C., Janssen, S., Stansfeld, S., 2014. Auditory and non-auditory effects of noise on health. Lancet 383 (9925), 1325–1332.

Bravo, M.A., Warren, J.L., Leong, M.C., Deziel, N.C., Kimbro, R.T., Bell, M.L., Miranda, M.L., 2022. Where is air quality improving, and who benefits? A study of

PM2.5 and ozone in North Carolina over 15 years. Am. J. Epidemiol. 191 (7), 1258–1269.
Bureau of Transportation Statistics, 2017. National Transportation Noise Map. https://www.bts.gov/newsroom/national-transportation-noise-map.
Cai, M., Lan, Z., Zhang, Z., Wang, H., 2019. Evaluation of road traffic noise exposure based on high-resolution population distribution and grid-level noise data. Build. Environ. 147, 211–220.
Casey, J.A., Morello-Frosch, R., Mennitt, D.J., Fristrup, K., Ogburn, E.L., James, P., 2017. Race/ethnicity, socioeconomic status, residential segregation, and spatial variation in noise exposure in the contiguous United States. Environ. Health Perspect. 125 (7), 077017.
CDC, 2021. The behavioral risk factor surveillance system- about BRFSS. https://www.cdc.gov/brfss/about/index.htm.
Dratva, J., Phuleria, H.C., Foraster, M., Gaspoz, J.M., Keidel, D., Künzli, N., et al., 2012. Transportation noise and blood pressure in a population-based sample of adults. Environ. Health Perspect. 120 (1), 50–55.
Environmental Protection Agency, 2021. EPA History: Noise and the Noise Control Act. https://www.epa.gov/history/epa-history-noise-and-noise-control-act.
European Environment Agency, 2014. Good Practice Guide on Quiet Areas. Publications office of the European Union, Luxembourg.
Government of Canada, 2019. Canadian Environmental Protection Act. https://www.canada.ca/en/environment-climate-change/services/canadian-environmental-protection-act-registry/guidelines-objectives-codes-practice/guidelines-objectives.html.
Gunasekera, K.S., Zelner, J., Becerra, M.C., Contreras, C., Franke, M.F., Lecca, L., Murray, M.B., Warren, J.L., Cohen, T., 2020. Children as sentinels of tuberculosis transmission: disease mapping of programmatic data. BMC Med. 18 (234), 1–7.
Héritier, H., Vienneau, D., Foraster, M., Eze, I.C., Schaffner, E., Thiesse, L., et al., 2018. Diurnal variability of transportation noise exposure and cardiovascular mortality: a nationwide cohort study from Switzerland. Int. J. Hyg Environ. Health 221 (3), 556–563.
International Organization for Standardization (ISO), 2014. ISO/FDIS 12913-1.
Johnson, M.P., 2001. Environmental impacts of urban sprawl: a survey of the literature and proposed research agenda. Environ. Plann. 33 (4), 717–735.
Kang, J., Aletta, F., Oberman, T., Mitchell, A., Erfanian, M., Tong, H., Chen, X., 2023. Supportive soundscapes are crucial for sustainable environments. Sci. Total Environ. 855, 158868.
Kang, J., Grasby, P., Derrick, M., Franks, L., Williams, P., Flindell, I., Harsham, K., 2001. Environmental Performance: Noise and Acoustic Management Engineering - Group Guidelines. BP report, London.
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. Am. J. Prev. Med. 43 (4), 353–360.
Kryter, K.D., 1972. Non-auditory effects of environmental noise. Am. J. Publ. Health 62 (3), 389–398.
Kuo, C., Pan, R., Chan, C., Wu, C., Phan, D., Chan, C., 2018. Application of a time-stratified case-crossover design to explore the effects of air pollution and season on childhood asthma hospitalization in cities of differing urban patterns: big data analytics of government open data. Int. J. Environ. Res. Publ. Health 15 (4), 647–661.
Lam, K.C., Chung, Y.T.T., 2012. Exposure of urban populations to road traffic noise in Hong Kong. Transport. Res. Transport Environ. 17 (6), 466–472.
Lee, D., Rushworth, A., Napier, G., 2018. Spatio-temporal areal unit modeling in R with conditional autoregressive priors using the CARBayesST package. J. Stat. Software 84 (9), 1–39.
Leroux, B.G., Lei, X., Breslow, N., 2000. Estimation of Disease Rates in Small Areas: a New Mixed Model for Spatial Dependence. Statistical Models in Epidemiology, the Environment, and Clinical Trials. Springer, New York, NY, pp. 179–191.
Li, M., Gao, S., Lu, F., Tong, H., Zhang, H., 2019. Dynamic estimation of individual exposure levels to air pollution using trajectories reconstructed from mobile phone data. Int. J. Environ. Res. Publ. Health 16 (22), 4522.
Liu, Y., Croft, J.B., Wheaton, A.G., Perry, G.S., Chapman, D.P., Strine, T.W., et al., 2013. Association between perceived insufficient sleep, frequent mental distress, obesity and chronic diseases among US adults, 2009 behavioral risk factor surveillance system. BMC Publ. Health 13 (1), 1–8.
Margaritis, E., Kang, J., 2016. Relationship between urban green spaces and other features of urban morphology with traffic noise distribution. Urban For. Urban Green. 15, 174–185.
Marshall, S., Gong, Y., 2009. WP4 Deliverable Report: Urban Pattern Specification. University College London, London, UK.
Masum, M.H., Pal, S.K., Akhie, A.A., Ruva, I.J., Akter, N., Nath, S., 2021. Spatiotemporal monitoring and assessment of noise pollution in an urban setting. Environmental Challenges 5, 100218.
Münzel, T., Sørensen, M., Daiber, A., 2021. Transportation noise pollution and cardiovascular disease. Nat. Rev. Cardiol. 1–18.
OECD, 2018. Rethinking Urban Sprawl: Moving towards Sustainable Cities. OECD Publishing, Paris.
Pirrera, S., De Valck, E., Cluydts, R., 2010. Nocturnal road traffic noise: a review on its assessment and consequences on sleep and health. Environ. Int. 36 (5), 492–498.
R Core Team, 2020. A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna.
Rodrigue, J.P., Comtois, C., Slack, B., 2016. The Geography of Transport Systems. Routledge.
Tong, H., Kang, J., 2021. Relationship between urban development patterns and noise complaints in England. Environment and Planning B: Urban Analytics and City Science 48 (6), 1632–1649.
Tong, H., Aletta, F., Mitchell, A., Oberman, T., Kang, J., 2021. Increases in noise complaints during the COVID-19 lockdown in Spring 2020: a case study in Greater London, UK. Sci. Total Environ. 785, 147213.
European Union, 2002. Directive 2002/49/EC Relating to the Assessment and Management of Environmental Noise. Official Journal of the European Communities No. L 189/12.
Von Lindern, E., Hartig, T., Lercher, P., 2016. Traffic-related exposures, constrained restoration, and health in the residential context. Health Place 39, 92–100.
Warren, J.L., Cai, J., Johnson, N.P., Deziel, N.C., 2022. A discrete kernel stick-breaking model for detecting spatial boundaries in hydraulic fracturing wastewater disposal well placement across Ohio. J. Roy. Stat. Soc. C 71 (1), 175–193.
World Health Organization, 2011. Burden of disease from environmental noise: quantification of healthy life years lost in Europe. In: Regional Office for Europe. World Health Organization.
World Health Organization, 2018. Environmental Noise Guidelines for the European Region.
Xie, H., Kang, J., 2009. Relationships between environmental noise and social–economic factors: case studies based on NHS hospitals in Greater London. Renew. Energy 34 (9), 2044–2053.
Yang, W., Kang, J., 2005. Acoustic comfort evaluation in urban open public spaces. Appl. Acoust. 66 (2), 211–229.