Urban Planning and Public Health:
A Sound Environment Perspective with a Data-driven Approach

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Declaration

I, Huan Tong, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

The impact of the sound environment on human health has become a growing concern among the general public, policymakers, and urban planners worldwide. However, previous studies focus on individuals rather than cities/areas when investigating sound environment planning and health issues. Further research at a large scale or population level remains lacking. Therefore, this research aims to examine the relationships between urban planning and public health from a sound environment perspective at three large scales, including city/micro, regional/meso, and national/macro scales. It is achieved by a data-driven approach. Specifically, massive geo-spatial data from governmental open data platforms are processed based on GIS technique and used for statistical analysis, including hypothesis tests, Spearman correlation, ridge regression, and Bayesian model.

This research provides evidence of the critical importance of urban planning on noise-induced public health problems (involving noise complaints, sleep deprivation, and mental health) at large scales. At city/micro and regional/meso scales, the results show that the noise complaint is not only related to urban spatial morphology, but also to socio-economic conditions. Contextual urban factors play a more significant role in affecting noise perception than the actual noise level. At the national/macro scale, traffic noise can significantly contribute to variations in sleep deprivation and mental health problems among counties. The finding also indicates that urban sprawl patterns play a significant role rather than the magnitude of urbanisation with respect to adverse health effects of sound environment; furthermore, linear cities could confront more serious noise-induced health problems.

These findings have valuable theoretical and practical implications. It herein could be used to identify urban planning factors that should receive more attention when addressing noise-induced public health issues. Furthermore, the results are useful for achieving healthier cities by developing more effective noise management strategies and establishing a better planning layout.

Impact statement

With rapid urbanisation, the significance of urban planning in determining human well-being is increasingly valued. Urban planning plays an important role in sound environments, which, in turn, have significant impacts on health (i.e., noise complaints, sleep, and mental health). However, previous studies mainly focus on individuals rather than cities/areas. Research on large-scale administrative levels, which are significant subjects for policymaking and urban planning, remains insufficient. To the best of my knowledge, this research conducts the first large-scale analysis of noise-induced health problems at administrative levels and provides evidence regarding the vital role of urban planning factors on such issues. It is found that the sound environment can be harmful to public health in general, not only to individuals. From a method perspective, data-driven approach used in this research proves helpful in expanding understanding of urban sound environment at large scales. Big data and Geographic Information System (GIS) techniques are utilised to extend sound environment research from an individual level to a population level.

This research examines how the prevalence and nature of noise-induced health problems, as measured by noise complaints, sleep deprivation, and mental health, differ depending on urban planning factors. The findings suggest an important role for urban planning and design in promoting a healthy city from a sound environment perspective. To this end, this research identifies strategies that can be tailored for specific urban patterns when making or implementing policies and developing urban planning with respect to mitigating the harmful effects of sound environments. Therefore, the results of this research can be useful for reducing the negative impacts of environmental noise, improving the quality of life, and ultimately, achieving a healthy city.

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Contents

List of abbreviations

ACS	American Community Survey
BRFSS	Behavioral Risk Factor Surveillance System
CDC	Centers for Disease Control and Prevention
CrI	Credible Interval
DALY	Disability Adjusted Life Year
dB	Decibel
dB(A)	Decibel (A-weighted)
DEFRA	Department of Environment, Food and Rural Affairs
Esri	Environmental Systems Research Institute
END	Environmental Noise Directive
FHWA	Federal Highway Administration
TNM	Traffic Noise Model
FOI	Freedom of Information
GIS	Geographic Information System
GDP	Gross Domestic Product
GVA	Gross Value Added
IEEE	Institute of Electrical and Electronics Engineers
IMD	Index of Multiple Deprivation
ISO	International Organisation for Standardisation
km	Kilometre(s)
km^2	Square Kilometre(s)
km/h	Kilometre(s) per Hour
L_{Aeq}	A-weighted Equivalent Continuous Sound Level
L_{den}	Day Evening Night Sound Level
L_{ave}	Average Sound Pressure Level

L_s10	Sound Pressure Level Exceeded for 10% in a Particular Area
L_s90	Sound Pressure Level Exceeded for 90% in a Particular Area
m	Metre(s)
MCMC	Markov Chain Monte Carlo
NHS	National Health Service
NYC	New York City
OR	Odds Ratio
PCA	Principal Component Analysis
PLUTO	Primary Land Use Tax Lot Output
SPSS	Statistical Package for Social Sciences
UHI	Urban Heat Island
UK	United Kingdom
US	United States
WHO	World Health Organisation
°C	degree centigrade

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Chapter 1

Introduction

This chapter contextualises the research by providing background information on healthy city, the impact of sound environment, and big data area in Section 1.1. Section 1.2 defines the overall research aims and three research questions. Subsequently, Section 1.3 illustrates the overview of the research methodology. Finally, this chapter is concluded by outlining the main structure of the thesis in Section 1.4.

1.1. Research background

1.1.1. Healthy city

The pursuit of health has been recognised since ancient times. In the ancient period, Aristotle and other sages began discussing and studying urban problems. In Politics, Aristotle states that the consideration of health is the foremost concern in a city and goes on to state that “we have to consider the health of the inhabitants, and this depends upon the place being well situated both on healthy ground and with a healthy aspect” (Downey, 1976; Rackham, 1944). Similarly, in Ten Books on Architecture, Vitruvius argues that “in setting out the walls of a city, the choice of a healthy situation is of the first importance” (Alberti et al., 1955). At that time, there was a widespread consensus that “we must take great care to select a very temperate climate for the site of our city, since healthfulness is, as we have said, the first requisite” (Morgan,1914). Thus, it is evident that urban construction is closely related to health since ancient times. Urban planning has developed in association with human health since the earliest stages.

Subsequently, after the industrial revolution, a healthy built environment was emphasised, and the concept of a healthy city was first proposed. Additionally, urban planning as an intervention method to create a built environment attracted considerable attention in response to environmental degradation, population overcrowding, and public health issues during the rapid industrialisation process. To promote the development of healthy cities, World Health Organisation (WHO) Regional Office for Europe launched the Healthy Cities project. The Healthy City concept provides a human-centred research perspective and considers human health states as a reference and objective. The construction of healthy cities involves various fields, such as public health, medicine, economics, sociology, architecture, and urban planning, and requires the coordination of all fields. The purpose of building a healthy city through urban planning is to create and improve physical and social environments, which, in turn, promote the mental and physical health of people. With rapid urbanisation, it is estimated that two-thirds of the world's population will be living in urban areas by 2050 (United Nations, 2014). The built environment has become the main place where human beings live and work. As an essential part of the urban built environment, the sound environment is a global public health concern.

1.1.2. Impacts of sound environment

The impact of the sound environment is increasingly recognised as a common and severe problem worldwide. According to WHO, in European countries, one out of five people are exposed to harmful noise and external costs of noise to society, ranging from 0.2% to 2% of the Gross Domestic Product (GDP) (European Commission, 1996; WHO, 2011). In the United Kingdom (UK), it is estimated that the social cost of road noise is approximately seven billion pounds to ten billion pounds annually (DEFRA, 2014). Noise pollution is acknowledged as a significant public health issue by international agencies and regulatory bodies such as the United Nations, WHO, and European Union. This form of environmental pollution is linked to increased minor and major physical and mental problems, ranging from an increased risk of sleep disturbance and noise annoyance to cardiovascular diseases and psychiatric disorders (Basner et al., 2014; Dzhambov & Dimitrova, 2016a; Mouratidis, 2019; Schreckenberg et al., 2010; Van de Schoot et al., 2021; Welch et al., 2013;).

According to a WHO report, at least one million disability adjusted life years (DALYs) are lost annually due to environmental noise exposure in European A-member states. Most of these DALYs can be attributed to noise-induced sleep disturbances and annoyance (WHO, 2011). A total of 903,000 and 654,000 DALYs were lost from noise-induced sleep disturbance and annoyance, respectively, for people in European Union towns with more than 50,000 inhabitants (WHO, 2011). To reduce the negative impacts of the sound environment, a series of policies and actions have been implemented globally, such as the Environmental Noise Directive (END) in Europe (European Union, 2002), Planning Policy Guidance 24: Planning and Noise in the UK (Adams et al., 2006), Noise Regulation Law in Japan (Ministry of the Environment, 2000), and Environmental Protection Act in Canada (Government of Canada, 2019). Among these policies, administrative levels, such as cities, regions, and even entire nations, are regarded as significant subjects with respect to policymaking and implementation. Therefore, understanding the sound environment health problems at the large-scale administrative level is important from the policymaking and planning perspectives. A number of studies have explored the impact of the sound environment on psychological and physiological health, both from physical properties of sound and sound perception perspectives. However, previous research has focused on individuals rather than on cities/areas or administrative levels when investigating the relationships between urban sound environment planning and human health. Further analysis at a large scale or population level remains lacking. This could be due to the limitations of data and techniques, which have significantly improved in recent years.

1.1.3. Big data era

In recent decades, the advent of the information revolution has provided a new way of thinking about healthy urban environment planning and design, namely, using information data to explore urban problems. Data science is incorporated into built environment planning to help planners understand the city from a macro perspective and lead to rational and effective solutions. With the development of information and communication technology, vast amounts of information and data are constantly generated. According to the Digital Global Study, the total amount of global information doubles every two years. By 2025, a total of 35 trillion gigabytes of data will be created worldwide (Gantz & Reinsel, 2012; Patrizio, 2018). Massive digital data provide the possibility of capturing the characteristics of human activity. This indicates that the era of using big data for urban studies has arrived. In the big data era, the research paradigm has shifted from the traditional research based on mathematical models to data-driven scientific research (Hey et al., 2009). Digital data drive changes in the ways of thinking and research in urban studies. According to the theory of the data science research paradigm, the data-driven approach to explore urban laws will become a new and essential aspect for future urban studies (Bibri & Krogstie, 2020; DeLyser & Sui, 2014; Mayer-Schönberger & Cukier, 2013; Park & Nagy, 2018).

More importantly, a series of policies and actions have been implemented to promote open data, such as the Freedom of Information Act 2000 (FOI) in the UK, Open Data Law in New York, and open data action plan in New Zealand (Okamoto, 2016; UK Government, 2000; Stats NZ, 2018). With the promotion of open data action worldwide, a number of open data platforms are being built and open data are largely available, including but not limited to business, city government, education, environment, and health data. The open data ambiance has facilitated urban studies and lowered the barriers to accessing datasets. Urban planning researchers and practitioner can discover meaningful information from the growing body of urban open data. Especially, open spatiotemporal data provide significant support for urban planning and design. Regarding research on the urban built environment, especially the acoustic environment, traditional studies mostly use physical measurements or questionnaire surveys, which limit the depth and breadth of research. The development of information and communication technology and the prevalence of ubiquitous geo-spatial data provide data support for a larger scale and broader coverage of urban research. In this context, open data-driven urban studies have attracted the attention of numerous scholars from multiple disciplines. The data-driven approach is applied to some extent in climate change and environmental research fields such as air quality, thermal environment, and urban ventilation. However, the application of emerging technologies and massive open data in acoustics research, especially research involving the subjective perception and health impacts of sound, is still in a relatively preliminary stage.

1.2. Research questions

As discussed above, urban planning was originally an intervention method for creating a built environment that developed in consideration of public health. As a vital part of the built environment, the impact of the sound environment has become a growing concern both the general public and policymakers worldwide. However, previous studies mainly focus on individuals rather than cities/areas. Large-scale administrative level research is still lacking. Therefore, the overall aim of this research is to study the relationships between urban planning and human health from the sound environment perspective at three large scales, including city/micro, regional/meso, and national/macro scales. To this end, the following research questions are addressed:

(1) For the city/micro scale studies, the overall research question is: what is the relationship between urban morphology and sound perception citywide?

(2) For the regional/meso scale studies, the overall research question is: what is the relationship between urban planning parameters and perceptual sound in terms of noise complaints region-wide?

(3) For the national/macro scale studies, the overall research question is: what is the relationship between sound environment and human health nationwide?

Corresponding to the above research questions, the objectives of this thesis are:

(1) To explore the relationship between urban morphology and noise complaints, considering the different areas within a city and different periods to gain insight into the soundscape.

(2) To examine the relationship between noise complaints and comprehensive urban planning parameters, grouped into socio-economic factors and urban development pattern factors.

(3) To the study the associations between road traffic noise, sleep deprivation, as well as mental health.

This thesis extends sound environment research with a larger scale and broader coverage. It is expected that this research can help in understanding urban planning and public health from sound environment perspectives at a large administrative level. The results are expected to be used to help different tiers of local authorities to build liveable and healthy cities through public policy and urban planning.

For the purposes of this thesis, the city/micro scale means that the study area is the whole city and focuses on the variations within the city (e.g., London). The region/meso scale means that the study focuses on the whole region (e.g., England), which is a part of a country with definable characteristics and includes several cities. The national/macro scale is the largest scale, which covers a whole country (e.g., the UK).

1.3. Research methodology overview

A data-driven approach is adopted to answer the research questions mentioned above. Previous studies on the sound environment mainly use questionnaires, interviews, field surveys, and clinical measurements. Collecting data through these methods to achieve a large-scale study requires inordinate amounts of time and resources. With the various, massive, and normative open data largely available, a data-driven approach is employed to answer the research questions, significantly reducing the costs and time needed. Therefore, in this thesis, the open data-driven approach is adapted to move the research on urban sound environment to a larger scale and broader coverage. Specifically, governmental open data are used in this thesis. The detailed datasets and methods used in this research are as follows:

(1) To answer the first research question of the relationship between urban morphology and noise complaints at the city/micro scale, New York City (NYC) and London are taken as examples. Data are obtained from the open data platforms of these two cities and processed based on GIS technique. Hypothesis tests and Spearman correlation are employed.

(2) To answer the second research question of the relationship between urban planning parameters and perceptual sound in terms of noise complaints at the regional/meso scale, all cities in England are considered as the cases. Data are obtained from Public Health England, Census, and Strategi Map and analysed using Spearman correlation and ridge regression.

(3) To answer the third research question of the relationship between traffic noise and human health in terms of sleep deprivation and mental health at the national/macro scale, the United States (US) is taken as the case. National traffic noise maps and large-scale health surveys from the US Department of Transportation and Centers for Disease Control and Prevention (CDC) are used and combined with a hierarchical Bayesian spatial regression model.

With the development of techniques, massive available datasets make large-scale urban sound environment investigations possible. Governmental open data, which are credited in terms of accuracy and authenticity and do not require expensive or time-consuming data collection, are used in this research, although it is limited by the data availability. The data-driven approach promotes moving the research on the sound environment from the individual level to a large/population scale.

1.4. Thesis structure

Figure 1.1 presented the diagram of the thesis structure. The thesis is organised as follows. Chapter 1 gives an introduction of this research. Then, in Chapter 2, the context of this research topic is defined, and the current related literature is reviewed. Chapter 3 presents the methodology employed in this thesis. The research questions are answered in three parts: city/micro, regional /meso, and national/macro scale studies. Each part has two chapters. Therefore, Part I (Chapters 4 and 5), Part II (Chapters 6 and 7), and Part III (Chapters 8 and 9) present the analysis results from the studies on three scales, respectively. Each analysis chapter is based on published/publishing journal papers. Finally, Chapter 10 summarises all the results to provide suggestions on policymaking, urban planning, and city management. A brief summary of each chapter is presented as follows:

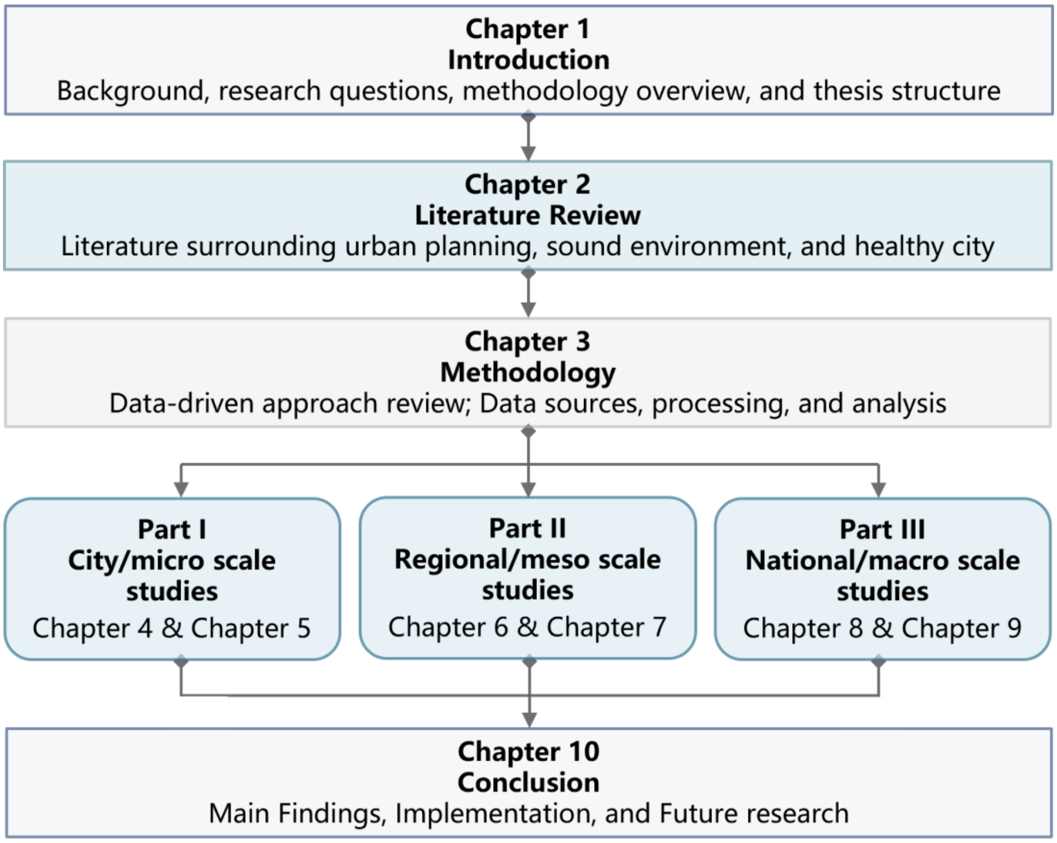

Figure 1.1 Research framework of this thesis

Chapter 2 discusses the context of urban planning, including the aim (healthy city), object (built environment), and approach (data science) of urban planning. Then, the literature surrounding urban planning, sound environment, and health are reviewed. Finally, a short conclusion is presented to summarise the current research trends and the research gaps.

Chapter 3 introduces the overall research methodological framework, which is split into a review, data sources, data processing, and data analysis. The review focuses on a data-driven approach to urban studies and environmental planning. The open data sources, GIS technique used for data processing and statistical analysis, including hypothesis tests, Spearman correlation, ridge regression, and Bayesian model, are illustrated in this chapter.

The key chapters are grouped into three parts. Each of them presents results relating to one of the research questions, generally, Part I city/micro scale studies, Part II regional/meso studies, and Part III national/macro scale studies.

In Part I, namely city/micro scale studies, Chapters 4 and 5 examine the first research question of the relationships between urban morphology and noise complaints at the micro/city scale. These chapters are published in two journal papers. Chapter 4 illustrates the characteristics of the spatiotemporal distribution of noise complaints across boroughs in NYC and explores the effects of urban morphology, including transport network, land use, and building morphology on noise complaints in different urban densities. Chapter 5 goes to an insight into soundscape and explores noise complaints during the lockdown period due to the COVID-19 pandemic. Specifically, this chapter illustrates the change in noise complaints received by local authorities in London because of the lockdown measures and the degree to which these changes are mediated by other factors related to urban and socio-economic characteristics of the local environment, including housing, demographics, transport, and traffic noise levels.

In Part II, namely regional/meso scale studies, Chapters 6 and 7 investigate the second research question of the relationships between urban planning parameters and perceptual sound in terms of noise complaints at the meso/regional scale. More comprehensive urban planning parameters are involved and grouped into socio-economic factors and urban development patterns, which are investigated in Chapters 6 and 7, respectively. These chapters are based on two published journal papers. Chapter 6 presents the relationships between the rate of noise complaints and various socio-economic factors, including demographic, job-related, property, and deprivation indicators, at the city level in England. Chapter 7 examines the relationships between noise complaint matters and urban development patterns, including population, industrial structure, built-up area, transport network, commuting, and natural landscape. The results provide a fundamental understanding of such relationships and their strengths, which helps form effective noise management strategies.

In Part III, namely national/macro scale studies, Chapters 8 and 9 explore the final research question of the relationships between traffic noise and human health in terms of sleep deprivation and mental health at the national/macro scale. Chapter 8 visualises the spatial variations of sleep deprivation nationwide, and then estimates its association with traffic noise indicators. Additionally, there is a discussion of the results in the context of urban sprawl patterns and public policy. By examining the same study area, Chapter 9 focuses on mental health problems. This chapter characterises the spatial pattern of mental health status and explores its relationships with noise-level indicators, considering neighbourhood effects.

Finally, Chapter 10 summarises the research findings in the thesis and discusses the possible implementations of the results from policy, planning, and governance perspectives. In addition, several suggestions for future research on public health and other environmental nuisances are included.

Chapter 2

Literature review

This chapter reviews the literature on the themes and keywords identified in Chapter 1 as being central to the research problems. Figure 2.1 shows structure of literature review. It can be seen that the review covers literature surrounding urban planning, sound environment, and health and is composed of four sections. Section 2.1 reviews the literature regarding trends in the discipline of urban planning from the perspectives of the aims (2.1.1 Urban planning and public health), objects (2.1.2 Urban planning and environment), and approaches (2.1.3 Urban planning and data science) of urban planning. Section 2.2 considers the relationships between urban planning (including socio-economic factors and urban morphology) and the sound environment, ranging from environmental noise to soundscape. Section 2.3 illustrates the relationships between the sound environment and health. In this section, the overall impacts of the sound environment on health are first introduced in Section 2.3.1. Then, in Section 2.3.2, 2.3.3, and 2.3.4, the impacts of the sound environment on sleep, noise annoyance, and mental health, respectively, are further discussed. Section 2.4 summarises current research trends and points out research gaps.

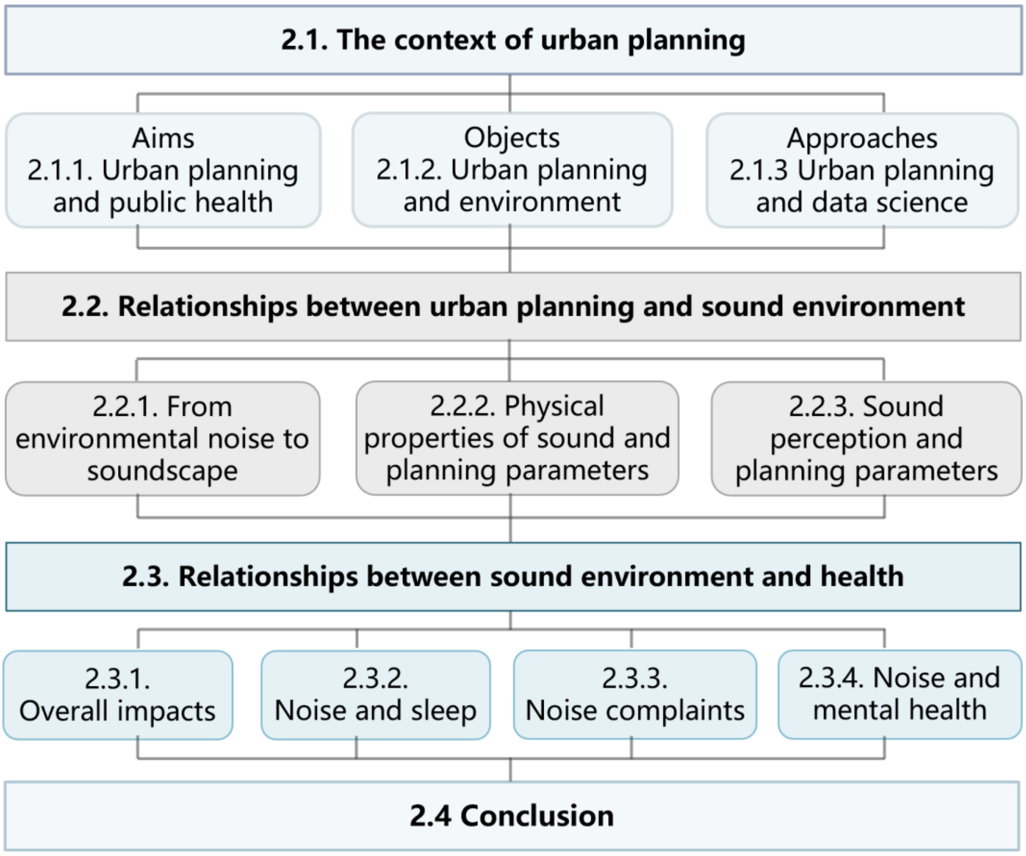

Figure 2.1 Structure of literature review

2.1. The context of urban planning

2.1.1. Urban planning and public health

According to WHO, health is defined as “a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity” (WHO, 1948). A good health status includes not only good physical health but also mental and social well-being. Health involves various aspects, such as physical, spiritual, emotional, intellectual, environmental, social, economic and occupational well-being. Public health is defined as the art and science of preventing disease, prolonging life and promoting health through organised efforts of society (Acheson, 1988). Public health pays greater attention to the health of communities and the health outcomes of groups of individuals. Many public health activities are targeted at populations (WHO, 2012; WHO, 2021).

There are numerous factors affecting public health, including individual factors (e.g., genetics, gender, age, etc.) and living environment (e.g., environmental pollution).

Through the process of urbanisation, cities have become the main habitat of human beings. Urban planning, as an intervention method intended to create a built environment, has a long history and was originally developed alongside public health. Modern urban planning began as a response to overcrowding and public health issues caused by environmental degradation, sanitation shortages, and air pollution during the period of rapid industrialization and urbanization in the late 19th century. The 1848 Public Health Act was published as a first step towards improving public health. This act required drainage, sewerage, and street paving projects to be undertaken and guidelines for urban planning and architecture to be provided subsequently to improve the urban environment and promote public health. Early theorists and practitioners identified the concept of healthy cities or public health as one of the key goals of urban development. Benjamin Ward Richardson published Hygeia: A City of Health and proposed his vision of a health city (Richardson, 1876). In 1898, Howard proposed the idea of a Garden City that would combine the conveniences of an urban living environment with the available natural elements in rural settings as a response to the need to promote human well-being in the city (Howard, 1898). Since the 20th century, the quality of urban life has been influenced by congestion and overcrowding caused by uncontrolled growth, and urban public health problems have grown increasingly serious. The Housing and Town Planning Act, as the first modern urban planning legislation, was passed in 1909 to promote health (Sutcliffe, 1988). Sir Edwin Chadwick first proposed the concept of a healthy city in the report on the Sanitary Condition of the Labouring Population of Great Britain (Chadwick, 1965), and thus the Health of Towns Association was born. Chadwick suggested that public health is to a large extent an environmental matter, not merely a medical matter (Dormandy, 1999). Thus, concern for public health was a key driver of the early development of modern urban planning.

Before the advent of germ theory in the 1860s, there was no specialised understanding of sanitation and sanitation facilities, and public health and urban planning had the same goal, as they both sought to address the common problems of overcrowding and deteriorating sanitation (Richmond, 1954). However, with the advent of germ theory and the development of the links between disease and pathogens, public health has gradually shifted from a generally engineering-based affair to a highly specialised effort focusing on combating pathogens. Public health shifted to the field of laboratory-based clinical medicine, while urban planning shifted to focus on the design of physical spaces and socio-economic development; thus, public health and urban planning went their separate ways. Meanwhile, until the establishment of the Ministry of Town and Country Planning in 1943, the Ministry of Health was responsible for town and country planning (Duhl et al., 1999).

The worldwide economic recession of the early 1980s had a serious impact on urban development, leading to deteriorating habitats, increasing social exclusion, and challenges to public health. In 1986, the WHO Regional Office for Europe launched Healthy Cities projects, which led to a reintegration of public health and urban planning in practice. In the same year, Hancock and Duhl (1986) defined a “healthy city” for the WHO as “one that is continually creating and improving those physical and social environments and expanding those community resources which enable people to mutually support each other in performing all the functions of life and in developing to their maximum potential. ” Thus, urban planning and public health have been closely reunited. Meanwhile, numerous cities have been involved in this project, including Liverpool (UK), Copenhagen (Denmark), and Toronto (Canada) (Flynn, 1996;

Tsouros, 1995). Recently, with the outbreak of COVID-19, increasing attention has been paid to the notion of healthy cities. Human well-being is the fundamental purpose of urban planning, and the question of how to promote public health through urban planning has become one of the foremost scientific issues in current planning research and practice.

2.1.2. Urban planning and environment

Urban planning can be described as “planning”, “town planning”, “city planning”, “spatial planning”, and “environmental planning”. The definitions of planning are not the same in all parts of the world and have changed over time. Urban planning and urban design are often conflated. Urban planning pays more attention to an overall strategy of development, taking into account economics, policies, laws, demographics, and other factors. Urban designers focus on detailed plans and spatial morphology (e.g., plans for roads, buildings, transportation, or parks). Urban planning and urban design are similar and always presented together. In this thesis, the term urban planning is used to refer to both urban planning and design. Planning control is the process of managing the development of land and buildings. Planning involves different scales from the micro- to the macrolevel and designates a particular area as a planning subject, such as a city, region, or even a whole country. Early opinions defined urban planning in terms of physical design enforced through land use control (Cullingworth & Nadin, 2006). Namely, the core of urban planning is a concern with spatial morphology or a physical environment. These opinions were reflected in early urban planning theories and regulations. For instance, as mentioned in the previous section, the 1909 Housing and Town Planning Act, banned “back-to-back” housing, which has insufficient ventilation and provides poor levels of health and sanitation (Sutcliffe, 1988). The Garden City movement developed new fundamentals of architectural design and city layout (such as designing a concentric pattern and planning satellite cities) to create spacious, tree-lined avenues of houses for the working class, combining the advantages of town and country (Howard, 1898). The City Beautiful movement, spurred by Georges-Eugene Haussmann, reconfigured the boulevards in the Paris city centre to be wider in order to provide lighter and air and allow for easier mobility by vehicles (Hall, 2002; Gandy, 1999). The establishment of urban planning and design as a profession began with these ideas. From these ideas, it can be seen that urban planning and design can change the physical environment and ultimately benefit human health. During the early development of urban planning, the discipline focused on optimising the spatial or physical environment. As socio-economic development progressed throughout the late 20th century, urban planning significantly enriched its pool of expert knowledge due to the contributions of sociology (Pinson, 2004). The connotations of urban planning have expanded further, and the objects of urban planning have grown to include more aspects than simply physical spaces such as buildings, environmental beautification, and facility support. The objects of planning have become more comprehensive and corresponding policies related to social, economic, ecological and cultural aspects have been carried out. The 1977 White Paper Policy for the Inner Cities and the 1978 Inner Urban Areas Act brought about significant changes. These pieces of legislations aimed to provide additional powers to local authorities to solve city issues (such as poverty and unemployment) via urban planning (Cullingworth & Nadin, 2006).

Thus, the content and scope of urban planning has been expanded and enriched. Types of urban planning now include (but are not limited to) strategic planning, infrastructure planning, regional/metropolitan planning, economic development, and environmental planning (Marshall, 2000). Urban planning is a technical and political process focused on the construction, growth, and development of settlements ranging from single buildings or hamlets and villages to cities and regions. Meanwhile, urban planning involves many aspects, such as the configuration of physical space, socio-economic development, and policy decisions. Urban planning and related professions play an essential part in shaping environmental, social and economic conditions; in turn, those conditions in cities can have both positive and negative influences on human health, ranging from physical disease to mental problems (Duhl et al., 1999).

To date, the relationships between built environments and urban planning have been widely discussed from the perspectives of spatial morphology and socio-economic factors. For instance, regarding the air environment, Stone (2008) tested urban sprawl and air quality in large US cities and found that the spatial attributes of density and connectivity are strongly related to ozone exceedances. Likewise, Silva (2016) investigated the relationships between urban forms and PM_{10} concentrations and found that higher levels of sky-view factors and higher ratios of open space lead to decreases in PM_{10} concentrations. Meanwhile, the impacts of urban planning on thermal, acoustic, and other environments have also been discussed. Urban heat island (UHI) is a major area of interest within the field of the built environment. It has a pivotal role in public health and energy consumption, especially in high density areas. In Hong Kong, a typical high-density city, the finding shows UHI in the order of 1.5 °C within an estate, and 1.0 °C between estates. The UHI effect is affected by urban planning factors, such as open space, building rooftops, water surface albedo, sky view factor (Chun & Guldmann, 2014; Giridharan et al.,2015; Hu et al., 2016). Urban greenery can mitigate the UHI effect in heavily built areas (Tan et al., 2016). For instance, most pocket parks can result in the reduction in UHI intensity at micro scale. Planting trees is more effective than shrubs (Lin et al., 2017). Meanwhile, UHI phenomena typically co-exist with urban noise pollution geographically. Urbanisation can not only lead to UHI phenomena. The increased population density inevitably contributes to excessive noise incidences because of the heavy traffic and dense urban planning in urban areas. Therefore, city centres are significantly nosier than rural areas and thus can be understood as urban noise islands (Kousis & Pisello, 2020). Both UHI and urban noise pollution issues can be mitigated by several same approaches, such as urban tree design and building façade design (Attal et al., 2021; Tan et al., 2016; Wong et al., 2010). More research on sound environments and urban planning is further discussed in Section 2.2.

2.1.3. Urban planning and data science

With the development of technology, the approach to urban planning has also changed. In the late 19th and early 20th centuries, early urban planning tended to be focused on a static picture depicting a rosy picture of the future of the city. At this stage, the approach to urban planning could be understood as an expanded form of architectural design and was dominated by hand drawing, scale modelling, and hand calculations. Many early urban planners also had backgrounds as landscape architects, architects, and engineers. During this period, the linear city, which was developed by Soria Y Mata, was one of the most representative urban forms (Doxiadis, 1967). Probably inspired by Soria, the French architect Tony Garnier developed the "industrial city", an ideal city intended to meet the needs of industrial development. Garnier divided the elements of the "industrial city" into clear functional areas. The heart of the city is the city centre, with museums, assembly halls, sports facilities, and other public buildings. The residential area is long and narrow, and the health and medical centre is located on the sunny side of an upper slope to the north. An industrial zone next to a train station is located to the southeast of the residential area. Each zone is segregated by a green belt (Doxiadis, 1967; Wiebenson, 1960). Thus, in the early stage, urban planning and design were based on planners' imagination and simple calculations and presented in the form of hand-drawn plans.

After the early 20th century and its proliferation of urban laws, scholars from multiple disciplines joined together to promote research into practice of urban planning and produced a considerable amount of research concerning urban populations, economy, ecology, environmental pollution, transportation and other issues. Planners proposed new urban planning and design paradigms from different disciplinary perspectives. Patrick Geddes, a Scottish biologist, sociologist, geographer, philanthropist and pioneering planner, developed a new approach to regional and town planning based on the integration of people and their habitat, which is known as the triad “place-work-folk”. Geddes believed that before planning, a detailed survey was needed, including at least investigations of the climate, geography, flora, fauna, economic condition, and geology (Geddes & Tyrwhitt, 1947). Furthermore, Geddessian bioregionalism and modernist social-aesthetic ideals inspired contemporary ecological urbanism and sustainable urbanism (Pepler, 1955; Shoshkes, 2017; Welter, 2002). In the mid-20th century, a more systematic, scientific, and rational approach to urban planning received an increasing amount of emphasis. Comprehensive rational planning, which is a strategy for dealing with complex urban problems, developed over time. In addition, there have been significant advances in science and technology. Computer technology have provided powerful tools for urban information collection and analysis. Urban planning and design have evolved from manual drawing to computer-aided design (e.g., using Autodesk CAD, Adobe Photoshop, and other software). Electronic statistical tables have also been applied to the urban planning and analysis process. Furthermore, geographic information science has also progressed. Geo-spatial mapping and analysis techniques are used in urban planning and design processing.

Dramatic changes have occurred throughout the last decade. Due to the ongoing development of information and communications technology, urban internet stations and the large number of smart devices that access the internet, such as smartphones, constantly generate and disseminate huge amounts of information and data. It is estimated that the total amount of global information doubles every two years. A total of 175 zettabytes of data will have been created and copied worldwide by 2025 (Gantz & Reinsel, 2012; Patrizio, 2018). Digital data also offer the possibility to capture a large number of characteristics of human activity.

A vision of a "fourth paradigm" has been pointed out to separate data science from its third paradigm (computer simulation) as a separate research paradigm because this new approach differs from traditional research based on mathematical models in that it emphasises data-driven scientific research (Hey et al., 2009). Digital data drive changes in modes of thinking and research and have advantages in the context of investigating associations between urban factors. Data-driven research concerning urban development laws have become a new and essential aspect for future urban studies (DeLyser & Sui, 2014; Mayer-Schönberger & Cukier, 2013). To date, data science has been applied in the field of urban studies. Based on social media data, mobile phone data, smart card data, and sensor data, urban vitality, population predictions, and human mobility have been widely investigated (e.g., Abbasi et al., 2015; Sulis et al., 2018; Zhao et al., 2016). Furthermore, in terms of urban climate environment planning, based on data from monitoring stations, street view data, and urban geo-spatial data (road networks, building footprints, etc.), air pollution, energy performance, urban heat islands, and other environmental issues have also been examined (e.g., Apte et al., 2017; Jain et al., 2020; Kanjo, 2009; Naeher et al., 2000). More details concerning environmental planning and data science are discussed in Section 3.1.

2.2. Relationships between urban planning and sound environment

2.2.1. From environmental noise to soundscape

Sound is a critical element of any ecosystem. The term “environment” can be simply understood as “surroundings”, which may be defined as a community of interacting organisms together with their physical surroundings (Daley & Kent, 2013; Smithson et al., 2008). As one element of surroundings, sound generated from all vibrations passes through and around us all the time. Sound is used by organisms like humans and animals to communicate and perceived by the auditory system and hence affects human beings. The urban sound environment, as one aspect of physical surroundings in an urban context, describes the acoustic situation in an urban setting and includes both wanted and unwanted sound. The objectives of research concerning sound pertain to each kind of sound, and research regarding noise is a key component in this field. Noise, defined as “unwanted sound”, is perceived as an environmental stressor and nuisance (Stansfeld & Matheson, 2003). Noise is one of the most important urban environmental health concerns and is primarily caused by traffic or industrial and domestic activities. In the European Union (except Cyprus and Malta), over 210 million people are exposed to traffic noise levels that are directly harmful to health (Den Boer & Schroten, 2007). Previous studies have indicated that the social cost of transportation noise alone ranges between 0.2% and 2% of GDP (European Commission, 1996). According to a WHO report, it is estimated that at least one million healthy life years are lost annually due to traffic-related noise in Western European countries (WHO, 2011). The DEFRA in the UK suggests that the social cost of road noise could be as much as approximately seven-ten billion pounds annually (DEFRA, 2014).

A number of studies have demonstrated fundamental physical properties of sound, such as the physical properties of sound waves, sound sources, and acoustic materials. Furthermore, previous studies have investigated sound propagation in an urban context. Based on the fundamentals of urban sound propagation, many countries have developed noise models. For instance, the US Department of Transportation developed the Federal Highway Administration Traffic Noise Model (FHWA TNM), which has been widely applied (Bureau of Transportation Statistics, 2017). The Ministry of Ecology and Environment in China has also taken the FHWA TNM as a reference. In Germany, RLS-90 (Richtlinien für den Lärmschutz an Straben), a national model, is an improved version of RLS-81 released by the Ministry of Transport (Alfredo Calixto et al., 2003). The UK Department of Transport developed Calculation of Road Traffic Noise (CRTN 88) as its traffic noise prediction model (UK Department of Transport, 1988). These models can predict the urban sound environment and provide support for decisionmakers. However, research into techniques alone cannot solve growing urban noise pollution problems. Correspondingly powerful noise control strategies are needed. In 1999, the WHO published evidence-based policy guidance with limit values as Guidelines for Community Noise, which has been widely used as a reference for sound environment management strategy (WHO, 1999). For nocturnal noise, the WHO released Night Noise Guidelines for Europe (WHO, 2009). To promote public awareness and facilitate public understanding of noise hazards, the document Burden of Disease from Environmental Noise: Quantification of Healthy Life Years Lost in Europe was published, which took into consideration sleep disturbance, annoyance, ischaemic heart disease, cognitive impairment among children, and tinnitus as health outcomes. The European Commission released a green paper, Future Noise Policy, which aimed to encourage policymakers to treat noise abatement as a higher priority (European

Commission, 1996). The END, which was related to the assessment and management of environmental noise, is the main tool used in the European Union to identify noise pollution levels and point out necessary actions. The directive requires European Union Member States to adapt noise maps and noise management action plans every five years. A wide range of noise management strategies have been adapted for use in Europe. In addition to Europe, the Ministry of the Environment in Japan authorised the Noise Regulation Law (Ministry of the Environment, 2000), and the Canadian government approved the Environmental Protection Act (Government of Canada, 2019). In the US, there is also a road traffic noise control policy. In 1972, the Noise Control Act was approved as a national policy to prevent harm to the health and well-being of all Americans from noise nuisance. The act authorised the Environmental Protection Agency to issue noise emission regulations to address sources of noise, including motor vehicles, machinery, appliances, and other commercial products.

The research concerning the physical properties of sound and the implementation of noise policies listed above has led to a decrease in sound pressure levels to some extent. However, De Ruiter (2000) and Schulte-Fortkamp (2001) found that a decrease in sound pressure levels does not necessarily contribute to a higher level of acoustic comfort in urban areas. For instance, when the sound pressure level decreases to a certain value, subjective evaluation of acoustic comfort becomes disconnected from the sound level, whereas demographics and socio-economic status as well as the type of sound sources involved play a vital role in this evaluation (Ballas, 1993; Gaver, 1993; Maffiolo et al., 1997; Dubois, 2000; Yang & Kang, 2005). These studies refer to the term “soundscape”, which is defined as the acoustic environment perceived, experienced and/or understood in a particular context by a person or people (International Organisation for Standardisation (ISO), 2014). In early research into soundscape, the pioneering work of Schafer can be traced back to the 1960s (Schafer, 1977a & 1977b). Subsequently, scholars have discussed soundscape and sound comfort in urban public spaces from different perspectives, such as the perspectives of description, evaluation, or design, and in different contexts, such as those of the sound itself, the listeners, and the surroundings. A number of studies concerning soundscape have been conducted based on laboratory experiments and field work. In terms of sound sources, a large number of studies have been published that investigated noise (such as road traffic, railway traffic, aircraft, industry, commercial, or ventilation noise) and positive sounds (such as natural sounds, birdsongs, and ripples) (e.g., Jones, 2005; Smith, 2001). In terms of the physical characteristics of sound sources, there have also been several studies concerning frequency, reverberation, tone, and impulse characteristics (e.g., Lubman, 2002; Zhang & Yang, 2021). In terms of listeners, studies concerning soundscape have considered people from different demographic groups, including children, the elderly, and blind or hearing-impaired people. The impacts of social and demographic features have also been examined (e.g., Fields & Walker, 1982; Lim et al., 2006; Licitra et al., 2016; Pennig et al., 2012). In addition, it is necessary to investigate different locations. Scholars have conducted research in the context of urban streets, public spaces, parks, stations, cycle paths, temples and interior spaces, such as commercial pedestrian streets (e.g., Aletta et al., 2018; Meng & Kang, 2015).

The body of literature in soundscape studies is growing and intersects with many research fields, such as environmental protection, psychology, social culture, public policy, and medicine. Among soundscape research topics, the intersection between urban soundscape and health is one of the most important aspects and have received increased attention from a number of disciplines in recent years. For instance, Skånberg and Öhrström (2002) discussed adverse health effects in relation to urban residential soundscape. Meanwhile, soundscape can also promote human health. Quiet soundscape can benefit restoration and health and contribute to human well-being (Booi & Van den Berg, 2012; Öhrström et al., 2006; Shepherd et al., 2013). Therefore, to prevent harm to human health, the END pointed out that it is necessary to protect quiet areas against an increase in noise (European Union, 2002). Aletta et al. (2018) systemically reviewed the impacts of soundscape on positive health and stated that soundscape should be investigated more at the levels of planning and design in the broader context of environmental research and public health. To promote health via soundscape, the Soundscape Support to Health program was put into effect between 2000 and 2007 by the Swedish Foundation for Strategic Environmental Research (Chalmers University of Technology, 2021; Skånberg & Öhrström, 2002). This program claimed that in residential areas, a positive soundscape can benefit human health, and it proposed a new method of “soundscape thinking” that can be used to plan and build new housing areas or improve the sound environment in existing residential environments (Chalmers University of Technology, 2021; Skånberg & Öhrström, 2002).

It is noted that in recent decades, electric car technology has developed rapidly and received considerable attention across a number of disciplines, including the sound environment research field. Electric cars can diminish fuel consumption and reduce the emission of polluting gases (Cerovsky & Mindl, 2008). Another significant feature of electric cars is their electric engines are relatively quiet which lead to less traffic noise and the noise pollution decrease. The cities become quieter by using electric and hybrid motor vehicles. Jabben et al. (2013) estimated that the urban noise level will decrease by 3 to 4 dB if the electric and hybrid motor vehicles instead of conventional cars in the Netherlands. In the report of National Institute for Public Health and the Environment in the Netherlands, hybrid cars would decrease the urban traffic noise by 1 to 3 dB. This corresponds to a decrease in the number of annoyed residents by one fifth in the urban area. Meanwhile, fully electric cars would contribute to reduce urban traffic noise by 3 to 4 dB. A reduction of the number of annoyed residents by one third would be caused(Verheijen & Jabben, 2010). This report also indicated that at speeds below 20 km/h, the noise emission from electric cars is significantly lower. However, at higher speeds, the benefit from electric cars is limited. It is due to the dominant contribution of rolling noise at higher speeds (Campello-Vicente et al., 2017; Verheijen & Jabben, 2010).

From another perspective, low-noise and electric vehicles can also lead to the absence of acoustic warning signals. It can increase the number of traffic accidents, especially for the older people who rely on both auditory and visual warning signals to detect approaching vehicles. At low speeds in particular, a conventional car is better detectable than an electric vehicle (Grosse et al., 2013). Especially, cyclists who always talk on the phone or listen to music will have limited auditory input of electric cars in the future and have a higher risk of traffic accidents (Stelling-Konczak at al., 2017). Under this circumstance, a new warning sound design for electric vehicles could be needed to prevent people from traffic accidents in urban areas (Brand et al., 2013). Bike lanes separated from the motor lane and corresponding visual signal design should receive more attention during the urban planning progress. Also, corresponding traffic management strategies can be adjusted appropriately. However, the research on the impact of electric cars on ambient sound and urban planning is still lacking. Insufficient evidence and research are difficult to provide suggestions for local authorities.

Overall, due to the impacts of noise on human health, there have been a number of studies concerning fundamental physical properties of sound, such as the sound pressure level. However, researchers found that a decrease in sound pressure level does not necessarily contribute to a higher level of acoustic comfort. In recent decades, there has been a surge of interest in sound perception or soundscape. Subsequently, there is a growing body of research that explores soundscape and sound perception in an urban context from different perspectives. It is noted that the prevalence of electric cars is a challenge to research on sound environment.

2.2.2. Relationships between physical properties of sound and planning parameters

As mentioned previously, the physical properties of sound are an essential topic of acoustic research. Previous studies have discussed the effects of planning parameters, including urban morphology and socio-economic factors, on the physical properties of sound, such as sound pressure level. Margaritis and Kang (2016 & 2017) investigated relationships between green space-related morphology and noise environments based on noise mapping techniques at three scales (including agglomeration, city, and kernel scale levels). They found that cities with higher green-space coverage had lower noise levels and that radial cities are more likely to be “quieter” than linear cities. To date, the research by Margaritis and Kang (2017) remains relatively large scale, especially at the agglomeration level, which has rarely been investigated by other research. At the city level, a comparative study by Wang and Kang (2011) demonstrated that there are significant differences in spatial noise-level distribution between high- and low-density cities. Moreover, areas containing the most densely and heavily built types of urban structure are likely to have higher noise levels (Sakieh et al., 2017). More studies have focused on streets, buildings, or other small locations. In terms of urban street configuration, Kang (2001) calculated the sound propagation in urban street canyons and demonstrated that an increase in the street width/height ratio can lead to more energy being reflected out of street canyons and lower the overall sound pressure level in the streets. Hupeng et al. (2017) explored the associations between urban street morphology and sound propagation in a high-density city, suggesting that when the cross-sectional enclosure degree and the plan enclosure degree increase or vehicle lane width decreases, sound attenuation decreases. In terms of specific locations within a city, such as traffic infrastructure and residential areas. Hao and Kang (2014) analysed the relationships between urban morphology and the spatial noise level attenuation of flyover aircraft, finding the latter to be correlated primarily to the building frontal area index. Zhou et al. (2016) investigated traffic noise distribution and street morphology in urban residential blocks based on acoustic propagation modelling. Those authors found that the ground space index is significantly negatively related to the ground and building facade average noise level, while street interface density is significantly negatively related to the standard deviation of ground and building facade noise. Furthermore, at the block or building levels, numerous studies have examined various building design parameters and physical characteristics of sound. Salomons and Pont (2012) found that in closed building blocks, the noise level of quiet façades is lower than that of open building blocks. In addition, façade shapes and materials can also influence noise level (Badino et al., 2019; Sanchez et al., 2016). Furthermore, sustainable vegetated façades can reduce noise levels by two dB at the pedestrian level in street canyons (Jang et al., 2015).

In addition to urban spatial morphology, socio-economic factors are another essential factor affecting the physical properties of sound in urban settings. There have been two relatively systematic studies of the relationships between socio-economic factors and noise level based on noise mapping techniques. Xie and Kang (2009) investigated National Health Service (NHS) hospital environmental noise and 28 socio-economic factors via noise maps. The results of this study also indicated that unemployment rates are lower and pupil/teacher ratios are higher in relatively quieter areas. The noise levels of NHS hospitals are also relevant to household size, population density, total fertility rate, and crude death rate. In subsequent research in 2010, Xie and Kang (2010) carried out a more comprehensive study to examine the associations between environmental noise levels and socio-economic factors, focusing on neighbourhood and borough levels across London. Apart from the direct relationships examined, socio-economic inequality is also considered and discussed as a mediating factor in noise pollution studies (Lam & Chan, 2008; Margaritis & Kang, 2016). There have been few studies concerning the relationships between the physical properties of sound and socio-economic factors. However, the impact of socio-economic factors on sound perception have been widely examined, a point which is further discussed in the following section.

2.2.3. Relationships between sound perception and planning parameters

In the context of soundscape, sound perception is an essential research topic with respect to urban sound environments. In terms of urban morphology and sound perception, Hao et al. (2015) investigated the integrated impacts of urban morphology on birdsong loudness in low-density residential areas, indicating that the masking effects of birdsong could be considered a soundscape design technique. Through a case study in Seoul, Korea, Hong and Jeon (2017) suggested that in high-density areas, low-frequency sound content and lower sharpness values are more common than in low-density areas. Liu et al. (2014) examined the impact of landscape spatial patterns on sound perception in a multifunctional urban area and suggested that major sound indicators are associated with a number of planning indices, such as road density, the types of roads in the area, and distribution. Liu and Kang (2018) evaluated soundscape at the street level, finding negative relationships between acoustic comfort and street width, building height, and width-to-height ratio. Furthermore, it is difficult to ignore the effects of the thermal environment on sound perception. By investigating the effects of air temperature on noise perception, it is found that the loudness, annoyance, noisiness and acoustical preference are significantly related to temperature and noise level (Yang et al., 2019). Furthermore, in the urban soundscape, water sound can improve traffic noise perception (Jeon et al., 2010). However, the impact of water sounds on traffic noise perception is different according to the temperature. Specifically, in warm conditions, water sounds enhanced pleasantness, calmness, naturalness, and acoustic comfort, while in cool conditions, water sounds increased noisiness, loudness, and annoyance (Yang & Moon, 2019a). Also, acoustic comfort is affected by the perception of the thermal environment in addition to the temperature (Yang & Moon, 2019b). Alternatively, the thermal comfort level is different according to the acoustic environment. Specifically, people in a perceptually quiet outdoor environment show higher thermal tolerance and lower thermal sensitivity (Zhou et al., 2022). Overall, the interaction effects between the thermal and acoustic environment on human perception can be not negligible. It is more effective to improve quality of life and human health by considering such effects.

The studies discussed above focused on the link between urban morphology and sound perception, but sound perception is related not only to urban morphology but also to socio-economic factors. More studies concerning the relationships between socio-economic factors and sound perception have been conducted through small-scale investigations performed to examine locations such as areas of traffic infrastructure, residential areas, commercial areas and parks. In terms of traffic infrastructure, in a relatively early study, Fields and Walker (1982) examined the impact of approximately 35 demographic factors on the annoyance arising from railway noise by using a combined questionnaire and noise measurement survey in Great Britain. The results showed that noise annoyance is related to older dwellings, older respondents, and residents' lifetime. Apart from railway noise, several studies have investigated annoyance resulting from road noise in terms of demographics, residential satisfaction, and other socio-economic factors (Bolte et al., 2009; Miedema & Vos, 1999; Urban & Máca, 2013). Other research has analysed the impacts of personal factors and noise level on annoyance in the vicinity of airports (Babisch et al., 2009; Rylander et al., 1972). In addition, Fields (1993) investigated the effect of demographic and situational variables on noise annoyance in residential areas. The results showed that, in this case, demographic factors, including age, gender, income, socio-economic status, education, homeownership, and type of dwelling, have weak relationships with noise annoyance. Yu and Kang (2008) and Rey Gozalo et al. (2018) focused on subjective evaluations of the sound level in an urban open space by means of questionnaires or interviews. Aletta et al. (2018) analysed the effect of demographic factors on sound perception using the case study of a cycling path by interviewing 181 participants.

From another perspective, it can be concluded that a wide range of socio-economic factors are related to sound perception based on the studies discussed above. In terms of demographic factors, the results regarding the effect of age vary. Apart from age, sex is another basic demographic variable. In terms of sound preference, there are differences between males and females. Females' preferences for music played on the street by church bells, water and certain other sounds are stronger compared to those expressed by males (Kang, 2006). Meanwhile, previous studies have shown that residents with higher levels of education express more annoyance with noise (Miedema & Vos, 1999). Sound perception is also related to marital status and family size. For instance, Fields and Walker (1982) indicated that marital status might affect noise annoyance. Miedema and Vos (1999) suggested that residents who live in a large family are more annoyed by noise than residents who live alone. In addition to demographic factors, DiPasquale and Glaeser, (1999), Fields (1993), Tonin (1996), and Yano et al. (2002) found evidence that the type and tenure of accommodations may have an impact on noise annoyance. Sound perception has also been proven to be affected by economic factors such as income and type of occupancy (Fields, 1993; Tonin, 1996). For instance, Miedema and Vos (1999) found that residents with higher occupational status are more likely to report noise annoyance to some extent. Finally, the impacts of numerous other factors have been studied, including general state of health, length of residence, and time spent at home (Dzhambov & Dimitrova, 2016a; Sato et al., 1999; Schreckenberg et al., 2010; Schulte-Fortkamp, 1996; Welch et al., 2013; Wothge et al., 2017). A wide range of socio-economic factors have been identified that have relationships with sound perception based on questionnaires and interviews at the individual level and small scale.

2.3. Relationships between sound environment and health

2.3.1. Overall impacts of sound environment on health

The urban environment is an increasingly important area in human health. Environmental pollution can cause a burden of disease and reduce healthy life years. For instance, ambient air pollution has critical effects on lung cancer, chronic bronchitis and other respiratory diseases (Kampa & Castanas, 2008). Urban heat islands have effects on liveability in cities (Yang et al., 2015). The warming effect of urbanisation has effects on health and wellbeing, such as affecting thermal comfort and afflicting thermal stress on residents (Grimmond, 2007; Mohajerani et al., 2017). Light pollution has significant consequences for ecological systems, including negative impacts on animal and human health.

The sound environment is an important component of the urban environment system and plays a key role in public health. Many studies have shown that environmental noise has significant impacts on physical and psychological health, including annoyance, effects on sleep, cardiovascular disease, and hearing loss (Dzhambov & Dimitrova, 2016a; Mouratidis, 2019; Schreckenberg et al., 2010; Welch et al., 2013).

Hearing loss is one of the directed effects of noise, which is caused by one-time exposure to an intense sound impulse or by long-term exposure to high sound pressure levels, such as in the context of industry. Hearing loss caused by occupational or social noise exposure is highly prevalent and is considered to be a public health threat (Twardella et al., 2011; Verbeek et al., 2012). In addition to noise exposure, noise-induced hearing loss is also related to age (Davis et al., 2007). Furthermore, Daniel (2007) and Śliwińska and Zaborowski (2017) reviewed the effect of noise on hearing loss and found that temporary and permanent hearing impairments are becoming more common among young adults and children.

Apart from the auditory effects of noise (e.g., hearing loss), many studies have shown that noise is a primary contributor to certain risk factors related to extra-auditory health problems, such as annoyance, cardiovascular disease, cognitive performance, and sleep disturbance (Basner et al., 2014). In terms of cardiovascular disease, numerous studies have suggested that the incidence and mortality of cardiovascular diseases is higher for individuals with higher rates of noise exposure (Davies & Van Kamp 2012; Gan et al., 2012; Huss, 2010; Sørensen et al. 2012; Sørensen et al. 2011; Van Kempen et al., 2002; Tomei et al., 2010). Specifically, research concerning the exposure–response link in the context of transportation noise shows that an increase in L_{Aeq} leads to an increase in the risk of cardiovascular diseases, including hypertension and myocardial infarction (Babisch, 2008; Babisch & Kamp, 2009; Van Kempen & Babisch, 2012). In terms of cognitive performance, the negative effects of environmental noise exposure on children's learning outcomes and cognitive performance have been well documented (Basner et al., 2014). These effects include communication difficulties, increased arousal, learned helplessness, and impaired attention (Evans, 2006; Stansfeld et al., 2000). Noise-induced health problems are related to socio-economic factors, such as age, gender, deprivation index and other characteristics (Öhrström et al., 2006). According to the WHO report, approximately 45,000 annual DALYs losses were estimated to result from environmental noise exposure for children aged 7-19 years in Western European countries (WHO, 2011). Noise can also contribute to heart rate increase as the sound pressure level increases from all sources as well as to physiological stress, impairments to sleep quality or mental health, and annoyance (Baum & Grunberg, 1995; Grunberg & Singer, 1990; Nassur et al., 2019).

Among the impacts of noise on health mentioned above, sleep and annoyance are considered to be the most serious side effects of environmental noise. According to the WHO report, at least one million healthy life years are lost annually due to environmental noise exposure in European A-member states. Most of these lost DALYs can be attributed to noise-induced sleep disturbance and annoyance (WHO, 2011). Figure 2.2 presents lost DALYs attributed to environmental noise in Europe. It can be seen that a total of 903,000 and 654,000 DALYs were lost due to noise-induced sleep disturbance and annoyance among the European Union population living in towns of >50,000 inhabitants.

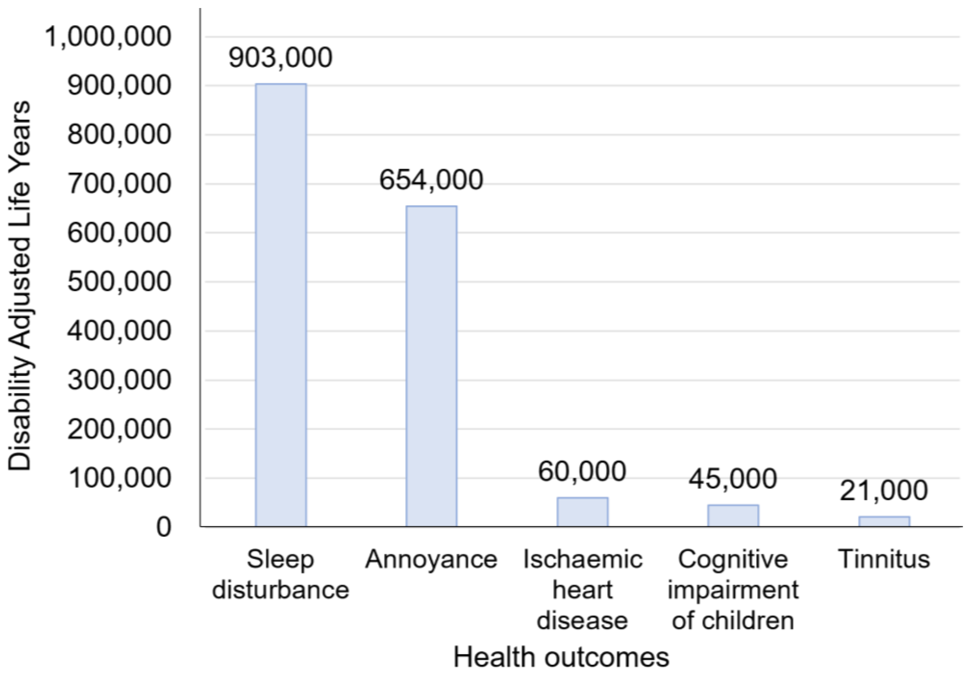

Figure 2.2 Lost DALYs attributed to environmental noise exposure in Europe, with data adopted from WHO (2011)

To reduce the negative effects of the sound environment on health, a series of policies and guidelines have been implemented. Loss of sleep and annoyance are considered to be the main negative impacts of noise in the context of these policies. For instance, the END acknowledges the need to prevent or reduce environmental noise levels that may negatively affect human health, including via annoyance and sleep disturbance (European Union, 2002). The European Environment Agency published a technique report called the Good Practice Guide on Quiet Areas and noted that the purpose of preserving quiet areas is to protect human health, including protecting people from noise annoyance, sleep disturbance, and negative phycological status (European Commission, 1996).

Overall, the sound environment has significant impacts on annoyance, sleep, cardiovascular disease, adverse birth outcomes, cognitive impairment, phycological health, hearing impairment and tinnitus. Among these negative impacts, sleep and disturbance are recognised as the most harmful effects of noise and are widely considered in the development of policy and research. In the context of soundscape, it is also noted that a sound environment can have positive effects on human health (Aletta et al., 2018). Nature sounds promote faster recovery from stress (Alvarsson et al., 2010; Ulrich et al., 1991). Experience with pleasant soundscape aids in recovery from psychological stressors, while exposure to unpleasant soundscape during rest produces greater stress than pleasant soundscape (Medvedev et al., 2015). Quiet soundscape can promote restoration and health and contribute to psychological and physiological well-being (Booi & Van den Berg, 2012; Öhrström et al., 2006; Shepherd et al., 2013)

2.3.2. Noise and sleep

Sleep deprivation is generally considered to be one of the most harmful effects of environmental noise, and a quiet environment is an important requirement for getting a good night's sleep (National Sleep Foundation, 2013). Basner et al. (2014) reviewed English-language articles, and claimed that sleep disturbance is considered to be the most harmful extra-auditory effect of noise. Sleep disturbance, which is mostly related to road traffic noise, is the main burden resulting from environmental noise in western Europe (WHO, 2011). Sufficient sleep is needed for good performance, good quality of life, and well-being. Generally, both sleep quality and quantity can be compromised for individuals living in areas with high noise exposure (Evandt et al., 2017). Even while asleep, human beings perceive, evaluate, and react immediately to environmental sounds. Sleep quality also impacts daytime functioning, such as thoughts and alertness. Therefore, the impacts of noise on sleep could follow noise exposure immediately or occur subsequently during the next day or after a few days (Muzet, 2007). Immediate effects can be measured objectively through clinical experiments (e.g., via polysomnographic measurements), while subsequent effects can be self-reported or measured via daytime performance.

For immediate effects, it is obvious that intrusive noise with a high sound pressure level can wake people from sleep immediately. For instance, the ringing of a church bell increases the likelihood of additional arousal responses that would not have occurred if the ringing of the bell had been suspended during the night (Brink et al., 2011). Awakening from sleep depends on complicated physical characteristics of the sound environment (e.g., sound sources, the intermittency ratio, and the significance of sound), not merely sound pressure level. By an investigation of 72 subjects, Basner et al. (2011) examined the effects of different traffic noise sources on sleep and recuperation via a polysomnographic laboratory study over 11 nights and found that road traffic noise led to the strongest changes in sleep structure and continuity.

Consideration has also been given to the intermittency ratio, a metric reflecting short-term temporal variations in sound (Wunderli et al., 2016). With the same average noise level, highly intermittent noise has adverse effects on sleep quality, as found by an examination of 21 participants in a laboratory study (Thiessen et al., 2018). Apart from the physical characteristics of sound, the significance of sound is also a key factor. For instance, spoken names might awaken sleepers momentarily and more easily than louder sounds that lack any particular meaning for sleepers (Brain, 1958; Oswald et al., 1960). In addition to awakening from sleep, exposure to noise can reduce the length of sleep duration. Noise is associated with difficulties falling asleep and waking up too early; hence, total sleep time is reduced (Evandt et al., 2017). Öhrström (1988) indicated that intermittent noise with peak sound pressure levels of 45 dB(A) and higher can cause an increase in the time required to fall asleep ranging from a few minutes to 20 minutes. Intermittent noise impacts sleep duration and causes sleep stage modification simultaneously (Carter, 1996). In addition to the impacts of noise on sleep time and stage, exposure to nocturnal noise can also trigger autonomic responses such as pulse changes, vasoconstrictions, and heart rate changes (Croy et al., 2013). Measured by electrocardiography or heart rate monitoring, heart rate increases with increasing vibration amplitude or when sound pressure level exceeds 90% of the measurement period (Nassur et al., 2019; Smith et al., 2013). Maximum sound pressure levels as low as 33 dB can lead to an autonomic response (e.g., tachycardia and cortical arousal) (Basner et al., 2010; Muzet, 2007). Not only can nocturnal noise exposure induce sleep disorders, the experience of noise during the daytime can also impacts sleep. Based on a quasi-experiment of 48 participants, Lin et al. (2018) suggested that participants working in a nosier location have a lower percentage of slow wave sleep and lower sleep efficiency. Additionally, daytime sleepiness, next-day tiredness, and the need for rest can be effects of exposure to nocturnal noise and the experience of sleep deprivation (Fields, 1986; Gualezzi, 1998). These subsequent effects are often measured by subjective evaluation of sleep quality via questionnaires or interviews.

The impacts of noise on sleep are broad and complicated. Self-reported sleep quality can reflect long-term feelings regarding noise-induced sleep. Subjective evaluation of sleep has also been widely applied via questionnaires and interviews. From the perspective of clinical medicine, objective measurements in the laboratory have often been applied. Given the soundscape context, from an acoustic comfort perspective, subjective evaluation has a wider scope of application. For instance, via questionnaire surveys of hundreds of respondents conducted in three residential areas in Sheffield and Taipei, Yu and Kang (2013) found that traffic noise ranked highest among the factors influencing sleep deprivation. Objective and subjective evaluation methods can also be combined and used simultaneously. Halperin (2014) stated that nocturnal noise pollution significantly impairs sleep both objectively and subjectively. Combined with questionnaires and clinical measurements, Öhrström and Skånberg (2004) assessed the effects of different types of noise exposure on sleep and found that traffic noise is more disturbing to sleep quality than ventilation noise. Research on noise and sleep has attracted attention. However, previous studies focus on individual sleep problems rather than population health.

2.3.3. Noise complaints

The WHO defined health as complete mental and social well-being. Therefore, a high level of annoyance caused by environmental noise is considered to be an environmental health burden and thus taken into calculation (WHO, 2011). A total of 654,000 DALYs were lost due to noise-induced annoyance in European Union member states and other Western European countries (WHO, 2011). Annoyance is the most prevalent community response from a population that is exposed to environmental noise. Noise annoyance can be caused by noise interfering with daily activities, thoughts, and feelings, and it might entail negative responses, such as displeasure, anger, anxiety, and stress-related symptoms (Miedema & Oudshoorn, 2001). Complaining about noise is rooted in residents' annoyance with noise and depends on both individual attitudes and perceptions and objective noise levels (Kang, 2006). Reporting noise complaints is a part of noise policy. For instance, in England, noise complaints are reported under environmental legislation, providing a dataset that can be referenced by government decision-makers (Public Health England, 2018). Noise complaints typically dominate the amount of environment-related complaints that local authorities have to deal with (Kang, 2006). A general assumption is that not everyone who experiences noise issues complains; however, noise complaints can serve as useful indications of areas where people are highly annoyed by noise (Public Health England, 2018).

There has been much less research on noise complaints. In terms of early research, Guski (1977) analysed the noise sources related noise complaints, showing that complaints regarding traffic noise comprise the greatest proportion of noise complaints, constituting 37.5% of such complaints. Among traffic noise sources, road traffic and air traffic are the main sources of annoyance. Following traffic noise, sounds caused by trade or business account for 33.5% of noise complaints. Liu et al. (2019) mapped the spatial distribution of each complaint type (including noise complaints) in Brisbane, Australia. They claimed as a limitation of their work that the relationships between neighbour complaints and socio-economic characteristics had not been examined. However, such relationships were mentioned by the research conducted by Gillen and Levesque (1994). Those authors examined the relationships between airport complaints and socio-economic factors, finding that noise complaints are positively related to income and house age and negatively related to tenancy, education, and mobility. Ethno-racial diversity is also associated with the number of complaint calls, as reported by a sociological investigation. In addition to acousticians or sociologists, research into noise complaints has attracted the attention of data scientists and other scholars. Using noise complaint data alongside social media, road network data, and points of interest, Zheng et al. (2014) developed a model to examine the noise situation throughout NYC. Hong et al. (2019) treated the noise complaint rate as an indicator of urban development. They examined the spatiotemporal relationships between urban development and noise complaints and found that a one-unit increase in construction activity was associated with an approximately 6% higher incidence rate of noise complaints by consulting longitudinal administrative data from 2011 to 2016. From an urban conflict perspective, Méndez and Otero (2018) investigated the complex relationships between socio-spatial inequalities and neighbourhood conflicts (involving annoying noise). Their results showed that the incidence of these conflicts is not solely associated with individual socio-economic circumstances, suggesting that such conflicts instead form part of a common framework of intersectional vulnerabilities.

Since the COVID-19 pandemic outbreak, reports have started to appear in the news claiming that noise complaints were on the rise in the UK, Japan and South Korea (BBS, 2020; Choon, 2021; KYODO NEWS, 2020). Research concerning noise complaints has received more attention. A significant increase in noise complaint rates during lockdown was also observed in New York (US) (Azad & Ghandehari, 2021; Schiff, 2021), while a reduction was surprisingly found in Dallas (US) (Yildirim & Arefi, 2021). Schiff (2021) also found that monthly noise complaint rate is positively associated with monthly median rent in every borough and subdistrict of New York. Regarding the economic situation, in subsequent research, Ramphal et al. (2021) pointed out that during the COVID-19 pandemic, economic disparities in noise complaint increases were magnified, as were seasonal disparities. However, research on noise complaints is still at a preliminary stage and related-influencing factors remains insufficient.

2.3.4. Noise and mental health

Mental health is a general term referring to a state of emotional and psychological well-being (Van Kamp & Davies, 2008). Interest in mental health has been increasing, as demonstrated by the inclusion of mental health in the United Nations' Sustainable Development Goals (United Nations, 2020). Many published studies have described the link between an individual sound environment and mental health status. Previous surveys have indicated that long-term noise exposure has relationships with mental health problems, such as anxiety, depression, stress response, and other emotions, in both adults and children (Stansfeld et al., 2000; Stansfeld & Matheson, 2003). For adults, it is generally suggested that a high level of ambient noise is related to psychiatric symptoms. Specifically, Carbone et al. (2005) found that residents who are exposed to noise are likely to have a higher risk of generalised anxiety disorder and anxiety disorder not otherwise specified. Wallenius (2004) indicated that noise is related to individual stress levels a questionnaire.

However, many studies have argued that environmental noise is not related to mental health (Meis & Schreckenberg, 2007; Stansfeld, 2007; Van Kamp et al., 2007). With respect to children, Lercher et al. (2002) examined the effect of ambient neighbourhood noise on children's mental health and found that ambient noise was related to a small decrease in children’s mental health. Wålinder et al. (2007) conducted a study among schoolchildren and found that L_{Aeq} were significantly related to an increased prevalence of fatigue symptoms based on questionnaires and daily measurement of sound level. However, Haines and Stansfeld (2003) and Goodman (2001) found no relationship between noise and children’s mental health. In addition to mental health problems, it has also been proven that psychological wellbeing, such as emotional state, could be affected by the sound environment. For instance, Cain et al. (2013) explored the links between the soundscape of built environments and emotional reactions via a lab-based experiment. Moscoso et al. (2018) investigated the associations between individual emotional status and local soundscape. Those authors found from interviews that natural sounds were associated with positive emotions, whereas mechanical and industrial sounds were linked to negative emotions. To date, evidence for the impact of noise on mental health is weak, and the associations between these two factors remain inconclusive and contradictory.

2.4. Concluding remarks

In summary, urban planning was originally developed alongside public health. Urban planning and design can change the sound environment and ultimately impact human health. A number of studies have investigated the relationships between urban planning, including socio-economic factors and spatial morphologies, and the sound environment based on field measurements, acoustic propagation modelling, and questionnaires. Furthermore, a considerable amount of literature has been published that focuses on the impact of the sound environment on health from both auditory and nonauditory perspectives. Specifically, many studies have attempted to recognise the serious side effects of environmental noise, including its effects on sleep, annoyance and mental health, based on clinical analysis and questionnaires.

However, previous research has focused on individuals rather than on cities/areas (i.e., spatial units) or administrative levels when investigating the relation between sound environment planning and human health. Further analysis at a large scale remains lacking. Research on noise complaints, mental health, and sleep deprivation has not fully investigated. It is worthwhile to shift the research from a focus on individual health to an emphasis on population health. Therefore, this research aims to study the relationships between urban planning and public health from the sound environment perspective at a large scale, as indicated in Chapter 1 (see Section 1.2).

Chapter 3

Methodology

This chapter begins with the overall methodology and justifications for choosing it in Section 3.1. Section 3.2 reviews the literature on the data-driven approach to urban studies and environmental issues. Open data sources used in this research are introduced in Section 3.3. Subsequently, Section 3.4 presents the GIS technique applied for data processing, and Section 3.5 illustrates the statistical analysis used in this research, including hypothesis tests, Spearman correlation, ridge regression, and Bayesian model. Finally, a summary of the methodology is covered in Section 3.6.

3.1. Overall workflow

Against the background of the big data area, the data-driven approach has been drawing considerable interests; it is a way of collecting and analysing data to derive solutions. As indicated in Chapter 2 Literature review, previous studies on sound environments have mainly used questionnaires, interviews, physical measurements, and clinical analysis. For instance, the impact of noise on sleep have been examined via polysomnography measures and self-reported surveys. For noise annoyance, the extent of noise annoyance has been measured using a designed questionnaire and interview. However, this research focuses on urban planning and health from the sound environment perspective at a large scale. Collecting data through questionnaires, clinical measurements, or filed surveys to conduct a large-scale study consumes considerable time and resources. Therefore, the data-driven approach is adapted to achieve the research aims, which mainly focuses on large-scale urban sound environment studies. Specifically, massive, various, and spatiotemporal datasets from governmental open data platforms which are credible in terms of accuracy and authenticity are used. These datasets are processed based on GIS technique and used for statistical analysis, including hypothesis tests, Spearman correlation, ridge regression, and Bayesian model. The overall workflow is shown in Figure 3.1.

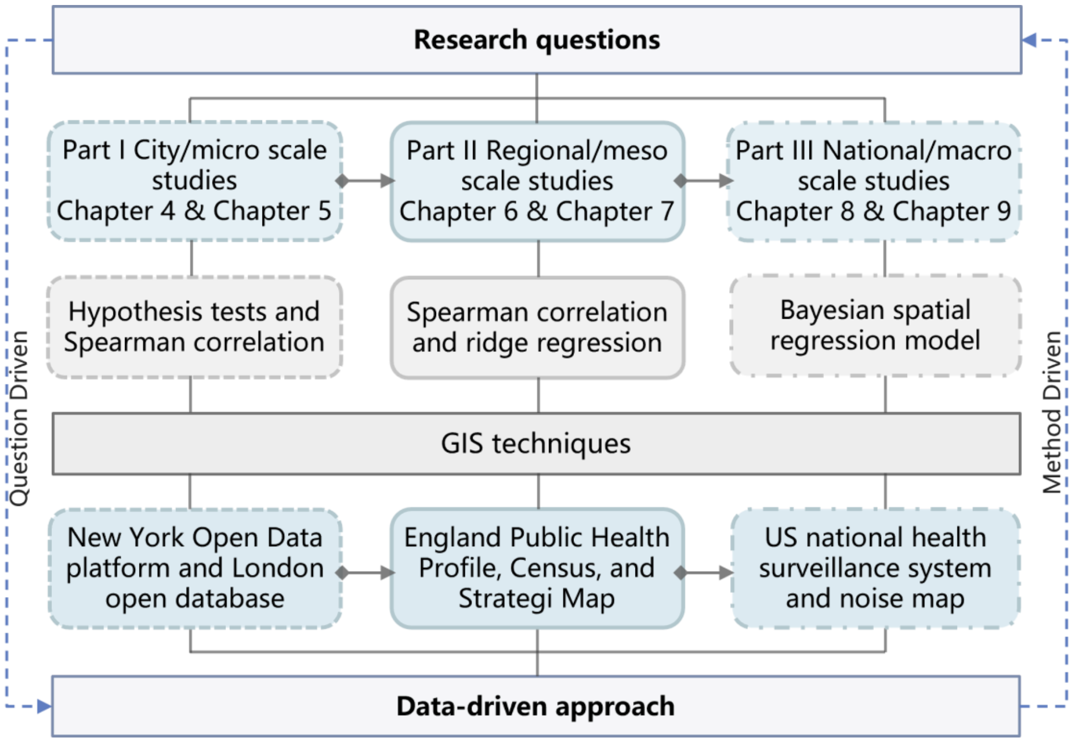

Figure 3.1 Overall workflow

As shown in Figure 3.1, to investigate the relationship between urban morphology and sound perception in terms of noise complaints at the city/micro level in Part I, the dataset was sourced from the NYC Open Data platform and the London open database, which are recognised statistical platforms. In Part II, all of England was taken as the case study to understand the relationship between urban planning parameters and noise complaints at the regional/meso level. Data from the Public Health Profile, Census, and Strategi Map were used.

For Part III, to examine the relationships between the sound environment and health problems at the national/macro level, the entire country (i.e. the US) was selected. Data were extracted from the CDC's national health surveillance system and transportation department's noise maps. The detailed data sources for the three scale studies are illustrated in Section 3.3. Section 3.3 also provides a brief introduction for open data. Subsequently, to clean and process these datasets, the GIS technique was applied; GIS is recently developed and has advantages in dealing with geo-spatial data and integrating location information and descriptive data. The development of the GIS technique and the operations process—including the geoprocessing module, joining attributes, spatial statistics, and the proximity toolset based on ArcGIS—are illustrated in Section 3.4. Finally, the processed data were imported into statistical software (i.e. Statistical Package for Social Sciences (SPSS) and R language) for further analysis. Hypothesis tests, Spearman correlation, ridge regression, and Bayesian model are utilised and are introduced in Section 3.5.

It is noted that this research is driven by governmental open data, and it seems fair to assume that data availability should be an important factor affecting the feasibility of conducting such research. As the foundation of research, this thesis relies on data more than other research rooted in conventional techniques of gathering data, such as using questionnaire surveys and clinical measurements. Moreover, in terms of data analysis, statistical analysis is powerful enough to seek laws from numerical data. However, the relationship is not grounded in causality. Statistics are unable to clarify the complex mechanism of the effects behind the relationships. Explanation and causality cannot be solved through the data-driven approach, which requires theoretical support and further development. Furthermore, data-driven research has received increasing attention and discussion. However, the interaction between the data-driven approach and urban studies lacks a professional methodology and systematic theoretical support.

3.2. The data-driven approach to urban planning

Data are a type of information that help with decision-making (New Zealand Government, 2021). With the development of techniques and the arrival of the big data era, massive available datasets have been applied to a wide range of multidisciplinary fields such as geography, economics, epidemiology, and sociology. In particular, there are numerous urban studies carried out from a variety of perspectives by using massive, various, and spatiotemporal data. Cities have been treated as complex systems due to the intricate interactions between land use, environment, populations, and transport (Batty, 2009). Due to city complexity, it is difficult to understand cities comprehensively based on conventional approaches or limited sample sizes. The changes from a data-scarce to a data-rich environment make it easier to understand how cities function. Such rich and massive data have propelled a number of urban studies. The data-driven approach is supported by sets of factual information-not just observations. The meaning of data-driven entails collecting and analysing data to derive insights and solutions.

Among the data-driven research on urban studies, mobile phone data, smart card data, volunteered geographic information, GPS data, and sensor data have been used to examine transportation planning, population growth, urban economic expansion, and urban function divisions. In terms of smart card data, studies on the analysis of urban spatial structure by smart card data have mainly focused on urban spatial structure and public transport planning. For instance, smart card data have been applied to investigate the spatiotemporal dynamics of bus passenger travel behaviour (i.e., Chakirov & Erath, 2011; Egu & Bonnel, 2020; Tao et al., 2014). Zhang et al. (2021) explored structural evolution based on long-term smart card records in Greater London. Long and

Shen (2015) identified the public transportation community structure in Beijing using large-scale smart card data. In terms of mobile phone data, substantial studies have used mobile phone data to investigate urban commuting (i.e., Frias-Martinez et al., 2012; Liu et al., 2020; Yang et al., 2018). For research on individual commuting behaviour, GPS log data have been employed and regarded as the early stage of big data application in urban studies (Hao et al., 2015, Zheng et al., 2008). Volunteered geographic information generated from online service platforms that provide geo-spatial location (such as Facebook, Twitter, Foursquare, and the NYC311 App) has been mined to extract text, pictures, frequency, and positional data to understand land use configuration, infrastructure planning, urban deprivation, environmental planning, social inequality, and other urban research topics (i.e., Abbasi et al., 2015; Sulis et al.,2018; Zhao et al., 2016). With the gradual improvement of sensing infrastructure construction, available sensor data have been integrated for urban environmental monitoring (Resch et al., 2009). In addition, massive data are generated all the time in cities. Hence, various big data have significantly expanded the body of research on urban affairs and enabled the large-scale studies.

Urban environmental issues pose a serious public health concern and form the primary cause of a series of psychological and physical problems. In terms of urban environment studies, many studies have described the links between urban planning factors and environmental issues, and have been driven by open big data such as air pollution and the thermal environment. The number of data-driven studies on air pollution is enormous, and data mining is increasingly being applied in air pollution epidemiology (Bellinger et al., 2017). Kuo et al. (2018) examined the effects of air pollution and season on childhood asthma hospitalisation in cities with differing urban patterns using governmental open data. Apte et al. (2017) mapped high-resolution air pollution by exploring big data with Google street view cars. Further, to assess pollution exposure, GPS data and mobile phone data have been applied (Li et al., 2019; Park & Kwan, 2017; Yoo et al., 2015). In terms of the thermal environment, researchers have extensively used satellite images from remote sensing data to study land-surface temperature or urban heat island problems (Lee & Yoon, 2020; Zhou et al., 2011). For broader environmental pollution issues, there have also been numerous studies driven by data science.

More specifically, the discussion of research on the sound environment with open big data has increased. For instance, Kanjo (2009) monitored and mapped urban noise using a real-time mobile phone platform, NoiseSPY. Gasco (2019) evaluated noise perception through online social networks and designed a noise-event alarm system based on social media content through a text mining approach. Hong et al. (2019) investigated the spatiotemporal relationships between urban growth and noise annoyance by leveraging crowdsourced big data provided freely by the Canadian government. Meanwhile, based on open data from the NYC311 app, Legewie and Schaeffer (2016) examined noise complaints at the census tract level. Zheng et al. (2017) developed a model to recover the noise situation throughout New York, where they also employed 311 noise complaint data, together with social media, road network data, and points of interest. During the national lockdown period due to COVID-19, NYC311 data have gained a wider application (Azad & Ghandehari, 2021; Ramphal et al., 2021)

In sum, there are a number of urban studies propelled by diversely sourced data. However, the data-driven research regarding urban sound environments, especially for the perceptual sound environment or its impacts on health, is still at a preliminary stage. Moreover, the development of big data makes it possible to investigate large-scale sound environments; this has been lacking for a long time due to the limitations of data. It is worth attempting to conduct data-driven research on urban sound environment at the large scales. More importantly, with the various, massive, and normative open data largely available, researchers can access these data easily and conveniently, which significantly lowers the source costs and time required compared to questionnaires, interviews, and field measurements, which necessitate considerable workforce costs and expensive equipment. Hence, for this thesis, the open data-driven approach was adapted to shift the research on urban sound environments to a larger scale and broader coverage, although it is limited by data availability.

3.3. Data sources

3.3.1. Open data

As mentioned in Section 3.1, in this study, massive data obtained from governmental open data platforms were used. With the implementation of open data-related laws and regulations, a number of open data platforms have been built and largely open data are available. Open data means anyone can access, use, and share data with full permission (New Zealand Government, 2021). According to the Open Knowledge Foundation, the key features of openness are availability and access (a convenient and modifiable form of data), reuse and redistribution (a machine-readable data format), and universal participation (open to everyone without discrimination) (Abdelrahman, 2021). Governments or non-governmental organisations around the world actively promote open data action. For instance, in the UK, data.gov.uk was established in 2010 to develop an open data environment and to maximise the value of governmental open data (UK Government, 2021). In addition, the FOI was passed in the UK, which provides public access to information held by public authorities (UK Government, 2000). The open data action plan in New Zealand aimed to help the public look for and use governmental open data (Stats NZ, 2018).

Meanwhile, data.govt.nz was created to support government publishers in maintaining data and helping people use data. In terms of establishing open data platforms at the city level, the Open Data Law in New York is worth mentioning. Under the Open Data Law, a single web portal was built where all public data are available such as information on businesses, city governments, education, environment, and health (Okamoto, 2016). Specifically, there are open data platforms concentrating on the environment. For instance, to prevent residents from suffering from noise nuisances, the END requires European Union member states to prepare and publish noise maps, which are always available from the local transportation or environmental department (European Union, 2002). In the US, the National Aeronautics and Space Administration and a series of agencies made available a large number of satellite images and sensor monitoring data for environmental management.

The application of governmental open data is significantly increasing with the creation of open data platforms. The launch of open data platforms provides researchers with new ideas and perspectives to try to solve problems that were difficult to investigate in the past. In this thesis, the research questions at the three scales are answered based on three corresponding government tier open-data platforms. In other words, for city/micro studies, the datasets were mainly obtained from city-level data platforms. For regional/meso studies, the datasets were downloaded from regional open databases. For the national/macro studies, the datasets were obtained from a national open data system. Accordingly, the datasets are illustrated in the following sections, including Sections 3.3.2, 3.3.3, and 3.3.4. More details for these datasets are also presented in the key chapters. More specifically, the data across three levels of studies were drawn from various databases, including noise maps, health surveillance systems, non-emergency line systems, censuses, and fundamental urban spatial morphology data. All datasets used in this thesis have geo-spatial references and detailed data sources are discussed below.

3.3.2. Data sources at the city/micro scale (Part I)

In terms of the city/micro scale studies from Part I (chapters 4 and 5), NYC was chosen as the case study to investigate the associations between noise complaints and urban morphology at the city/micro level. In addition, to understand noise complaints during the lockdown period, London was chosen as the case study. All the datasets were obtained from NYC and London open data platforms.

In Chapter 4, NYC 311, a LION geographic base file, and the Primary Land Use Tax Lot Output (PLUTO) data file obtained from the NYC Open Data platform were used. The noise complaint was extracted from NYC 311, which is NYC's government non-emergency service system. The 311 system records data on each complaint, including the time it happened, case type, and the reporter's location. The service handles complaints related to noise, air pollution, health, public safety, and 15 other problem categories (NYC 311, 2019b; NYC 311, 2019c). Based on a literature review and open data from New York, urban planning indicators were categorised into three groups: road transport networks, land use, and building morphology. In this study, transport network features were extracted from a LION geographic base file, which is maintained by the Department of City Planning. In this dataset, the single line was used to represent the city's streets. The lines/streets contain geo-spatial information that can be reflected in the map from NYC, as well as the unique ID, width, and name (NYC Planning, 2019b). Land use and building morphology data were extracted from the PLUTO data file, which was produced by the Department of City Planning. The PLUTO data file contains extensive land use and spatially morphologic data (NYC Planning, 2019c). The data sources are also addressed in Chapter 4, which presents the detailed indicators.

In Chapter 5, the noise complaint dataset is applied from the London Borough authorities under the FOI. The FOI was passed on 30 November 2000 and provides the public access to information held by most UK public authorities such as government departments, police forces, local authorities, the NHS, and state schools (UK Government, 2000). Urban planning factors were extracted from the London Ward Profile and Atlas, which were downloaded from the London Datastore (Greater London Authority, 2015). The ward profiles and atlas provide a range of demographic and related data at the ward level in Greater London. The dataset aims to provide an overview of the population at the ward level by displaying a large amount of data for numerous aspects including population, life expectancy, housing, crime, benefits, diversity, households, deprivation, land use, and employment (Greater London Authority, 2015). Noise level data were extracted from noise maps obtained from the DEFRA (2018) for Greater London. Noise levels were calculated from a 3 Dimensions computer model as part of implementing the European Union's END. The map provides strategic noise maps that are available for noise pollution from major road and rail sources, and presents links to detailed GIS noise datasets.

3.3.3. Data sources at the regional/meso scale (Part II)

In terms of Part II (including chapters 5 and 6), to understand the relationships between noise complaints and urban planning factors (including socio-economic factors and urban development patterns) at the regional/meso scale, , data obtained from Public Health England, Census, and Strategi Map were used.

First, noise complaint data were extracted from the Public Health Profile, which is an open data platform that provides public access to a large number of data sources tied to a range of health and wellbeing topics. The dataset was created to improve public health and reduce inequality (Dobras, 2021). Data on noise complaint rates are available from 2010 to 2015 when the research was conducted. Since the census of 2011 has the most recent and detailed socio-economic dataset, and because the most recent urban development pattern dataset available is from 2011, the 2011 rate of noise complaints was selected for statistical analysis.

Second, Census 2011 was used to extract the majority of socio-economic indicators and a minor portion of urban development pattern factors. The census is a comprehensive investigation, which includes detailed information for each person. Further, Census 2011 is published by the Office of National Statistics, which is the largest recognised statistical institute in the UK (Office of National Statistics, 2016). The census in the UK is conducted every ten years. When this study was performed, the Census 2011 was the most recent version. On the basis of the literature review and data availability, comprehensive factors were selected to be inputted into the analysis. The detailed indicators are presented in Chapter 6.

Third, the Strategi map was the source employed to identify urban development pattern factors. A Strategi map is produced from data used to create Ordnance Survey's 1:250 000 scale graphic mapping, with a resolution of 1 m (Ordnance Survey, 2015). This dataset comprises digital vector data and contains settlements, water, wood, land use, and positioned geographic names, among other urban elements. Detailed indicators are described in Chapter 7.

3.3.4. Data sources at the national/macro scale (Part III)

To understand the relationships between traffic noise and sleep problems at the national/macro scale in Part III, national traffic noise maps and large-scale health surveys from the US Department of Transportation and CDC were combined and used.

National online noise maps were produced by the US Department of Transportation (Bureau of Transportation Statistics, 2017). The maps cover all the counties in the US. The national transportation noise inventory was formulated using a L_{Aeq} for 24 hours noise metric based on the FHWA TNM 2.5. Like many other noise prediction models, the FHWA TNM 2.5 computes a predicted noise level through a series of adjustments to a referenced sound level. In the TNM, the reference level is the vehicle noise emissions level. Adjustments are then made to the emissions level to account for traffic flow, distance, and shielding (Bureau of Transportation Statistics, 2017). For the current research, the latest available public data are from 2014.

The self-reported sleep and mental health data for this study were obtained from the Behavioural Risk Factor Surveillance System (BRFSS) established by CDC in 1984. The BRFSS is the nation’s premier system of telephone surveys that collects data about US residents’ health-related risk behaviours, chronic health conditions, and use of preventive services. It is the largest conducted health survey system in the world, founded in 1984 (CDC, 2014). In this survey, sleep and mental health problems were one of the most important topics. BRFSS 2010 contains the latest data that covers the state and county levels. Further descriptions of the datasets are presented in Part III.

3.4. Data processing

During the historical development of urban planning and design, the approach and tools for urban studies have changed significantly. In the early stage, urban planning and design primarily relied on hand drawings, scale models, and hand calculations. With the emergence of the computer era, a series of software programs was developed to aid in design, planning, and mapping (e.g., Autodesk CAD and Adobe Photoshop). Such software was used to process graphical data, while statistical or descriptive data were processed by other software programmes separately, such as Microsoft Excel. However, the city is a complex system. It is necessary to integrate location information and descriptive data. In the 1960s, the Canadian GIS was developed when Canada conducted the national land resources survey (Loukes & McLaughlin, 1991). A GIS is a system that creates, manages, analyses, and maps all types of data. Subsequently, at the end of the 20^{th} century, GIS technology developed rapidly and has typically been applied to land registration, real estate tax assessment, infrastructure management, and other city governance work. With the prevalence of personal computers, GIS has been widely used including in health care, disaster prevention, environmental pollution management, logistics management, and other urban planning affairs (Campagna,2005; Sui, 1994; Wang, 2006). In urban studies, there are numerous research based on the GIS technique. For instance, overlay analysis, which allows for the integration of different datasets or elements according to spatial references, can be used to assess land suitability (e.g., Azem & Terzi, 2018; Mallik et al., 2021; Yalew et al., 2016). Density analysis maps certain elements according to their quantity at each location and the spatial relationships between the locations; they can be used to create heatmaps for human activity or urban crises (Chen et al., 2011; Loo et al.,2011). In addition, the GIS technique has been applied for accessibility analysis, environmental pollution mapping, and optimal infrastructure siting (Briggs et al., 1997; Liu & Zhu, 2004; Liu et al., 2006; Sumathi et al., 2008).

In this research, the GIS was applied to deal with data throughout all three parts of this thesis. The data used in this research have geographic labels and plenty of descriptive information. Hence, the GIS technique was used because it has advantages in connecting data to a map, combining location data with descriptive information, and dealing with massive data. There are several mature software programmes for GIS technique, such as ArcGIS produced by Environmental Systems Research Institute (Esri), and the free and open-sourced system-QGIS. In this research, ArcGIS platform was used throughout the data processing and authorised by University College London licence.

In this research, there are several function modules embedded in ArcGIS that were used to handle data. First, the geoprocessing module, as the fundamental function, was applied for the initial processing of the data, such as extracting the study areas. The geoprocessing module includes buffer, clip, intersect, union, merge, and dissolve tools, which can be used individually or in combination. The clip tool is for cutting out an input feature (points, lines, or polygons) with a defined boundary (polygons) (Esri, 2016). As such, for each dataset, the clip tool was applied to extract the exact study area. The intersection tool is similar to the clip tool, which was employed to divide continuous features (i.e., large-scale national parks and rivers) according to the administrative boundary involved (Esri, 2016). Second, in addition to the geoprocessing module, joining attributes is also a fundamental and powerful GIS function. As mentioned above, GIS has advantages in combining location information and descriptive data. This can be achieved by joining attributes, which integrates several datasets according to a key field (i.e., city name) or geo-spatial reference. Joining attributes allows for massive urban data to be added to geographic units for subsequent indicator calculation. Third, spatial statistics, as well as proximity toolsets, were mostly used for the indicator calculation. Spatial statistics enabled us to summarise the characteristics of a feature in a certain area. This tool can calculate the sum, mean, maximum, minimum, range, standard deviation, count, first, and last. In this research, for instance, the length of rivers in a city can be summarised via spatial statistics (Rodgers et al., 2007; Scott & Janikas, 2010). The proximity toolset is used to determine the proximity of features between two feature layers (Esri, 2021). For instance, the distance between the cross and the location of noise complaints can be computed via the near tool in proximity analysis. Finally, ArcGIS can be used to visualise spatial data by styling layers and creating meaningful visualisations for maps and scenes. All the maps in this research were created with ArcGIS platform.

Across all the analytical parts, the above GIS functions were used in combination. However, not all data processing steps can be achieved through functions embedded in ArcGIS, such as the calculation of certain noise level (e.g., L_S10). Thus, based on the ArcGIS platform, the Python programme was developed to achieve the remaining analysis. In this section, the overall GIS technique and introduction for key GIS functions used in this research are presented. More details and operational procedures are shown in chapters 4 through 9.

3.5. Data analysis

Following the data processing, data analysis is an important part of data-driven approach. To analyse data, quantitative and qualitative methods are the two main research methodologies. Quantitative methods centre on exploring how and why things have happened, while quantitative methods are employed to understand the measurable reality (Taylor, 2005). Quantitative research collects numerical data and examines the data using mathematical and statistical methods. Quantitative techniques involve collecting text data via interviews, focus groups, and observations, and analysing them by summarising, categorising, and interpreting (Sandelowski, 2000). Qualitative methods have been used in small-scale urban planning and design (e.g., public participation). However, this research focuses on a large scale and is driven by data. Therefore, the quantitative research framework and theory were applied throughout the entire study. Specifically, statistical analysis, including hypothesis tests, Spearman correlation, ridge regression, and Bayesian model, was utilised. Statistical methods have advantages in understanding data, analysing numerical data, and summarising laws; however, they do not explain causality, which needs to be further discussed in combination with theories.

Specifically, in Part I, hypothesis tests and Spearman correlation were used. A hypothesis test can help to determine if there are significant differences between two or more sets of data. Hypothesis tests, including the chi-square test, Mann-Whitney U test, and Kruskal-Wallis test, were used. The chi-square test is a non-parametric tool designed to scrutinise differences when the dependent variable is measured (McHugh, 2013). In this part, the chi-square test was employed to identify the difference in noise complaints among boroughs and types. The Kruskal-Wallis test and Mann-Whitney U test assess significant differences on a continuous dependent variable via a categorical independent variable (Kruskal & Wallis,1952; McKight & Najab, 2010); it was used to determine if there were statistically significant differences between different periods regarding noise complaints in this part. The major difference between the Mann-Whitney U and the Kruskal-Wallis test is that the Mann-Whitney U test was used to compare differences between two groups, while the Kruskal-Wallis test can accommodate more than two groups. Further, because the variables are not normally distributed, Spearman correlation was also used to explore the associations between urban planning factors and noise complaints in this part. The process was also conducted based on the SPSS 26 (Landau & Everitt, 2003).

In Part II, Spearman correlation and ridge regression were applied. Pearson correlation and Spearman correlation are broadly used correlation analyses as measures of how things are related. Pearson correlation is used to examine linear relationships between normally distributed variables, while Spearman correlation is a non-parametric test and does not require normality. Therefore, to explore the relationships between urban planning factors and noise complaints, Spearman correlation was used. In this part, the rate of noise complaints is not normally distributed, according to the Shapiro-Wilk test (Ghasemi & Zahediasl, 2012; Yap & Sim, 2011). Thus, Spearman correlation was applied to measure the relationships between urban planning factors and noise complaints while refraining from making any assumption about the distribution of the variables (Hauke & Kossowski, 2011). The process was carried out using the SPSS 26 (Landau & Everitt, 2003). In addition to Spearman correlation, for the multiple regression analysis, considering sample size, unknown causality, the requirements of interpretability and multicollinearity problems among the variables, a ridge regression model was applied to model the relationships between the noise complaints and multiple urban planning factors. Ridge regression is an improved regression model and specialises in data that suffer from multicollinearity problems by adding a degree of bias (Hoerl & Kennard, 1970; Marquaridt, 1970). In addition, compared to other modelling methods, this model is analytical with the explanatory contribution of each variable. The process can be conducted using the R language (Friedman et al., 2010).

In Part III, a hierarchical Bayesian spatial regression model is applied. Bayesian statistics is a statistical paradigm for data analysis and parameter estimation based on Bayes' theorem. A unique aspect of Bayesian statistics involves updating the probability for a hypothesis as more evidence becomes available (Van de Schoot et al., 2021). Bayesian statistics has found application in a wide range of research, such as image analysis and disease mapping (Besag, 1989; Lawson, 2018). For this section, to understand the relationships between sleep deprivation and traffic noise, a hierarchical Bayesian spatial regression framework was built. The first level of the hierarchy is a logistic regression framework, where sleep deprivation and mental health problems are treated as separate outcomes and road traffic noise, socio-economic factors, and spatial correlation are the covariances. The spatial correlation was modelled at the second level of the hierarchy by a set of random effects. All models were adopted in the Bayesian setting using Markov chain Monte Carlo (MCMC) sampling algorithms within R statistical software using the CARleroux function within the CARBayes package (Lee et al., 2018; R Core Team, 2020). The regression equations with built and detailed model parameters are shown in Part III.

3.6. Concluding remarks

Previous studies have investigated urban sound environments and human health based on questionnaires, field measurements, and clinical analyses. The obtained sample size is generally limited by having researchers themselves collect data based on the above methods, especially for large-scale studies. With the arrival of the big data era, a data-driven approach is currently the most popular method for urban studies. Advances in the data-driven approach can also facilitate the investigation of urban sound environments. With the establishment of open data platforms, massive and various datasets are available, which significantly lowers costs and time consumption. Therefore, the study in this thesis followed an open data-driven approach that makes it feasible to examine a large-scale sound environment.

Specifically, the research data in this thesis were drawn from national noise maps, health surveillance systems, and other governmental open data sources, which has advantage in credibility, accuracy, and consistency. Subsequently, the GIS technique, which is good at dealing with geo-spatial data, was applied to process the data. Finally, statistical analysis, including hypothesis tests, Spearman correlation, ridge regression, and Bayesian model, was utilised to examine urban planning and public health from the sound environment perspective. This research, using a data-driven approach, is significantly limited by data availability compared with designing questionnaires or interviews.

It is noted that all data used in this research are anonymous and publicly available non-sensitive data. According to University College London Research Ethics Committee regulations, by using such data, this research is exempt from the need for ethics approval (University College London, 2021).

PART I

CITY/MICRO SCALE STUDIES

The research starts with city/micro scale studies from Part I (Chapters 4 and 5). This part examines the noise complaints and urban planning factors at the city/micro level, and considers the different areas within a city and the different periods. Chapter 4 focuses on the associations between urban morphology and noise complaints, with an in-depth consideration of different density areas within a city. Chapter 5 turns its research attention to a particular period, namely the lockdown period. Environmental noise level significantly decreased globally due to the limitations of human activities during the lockdown period. This offers a good opportunity and a novel perspective to think about the urban soundscape. Therefore, Chapter 5 considers the changes in noise complaints during lockdown due to the COVID-19 pandemic and explores their relationships with urban factors.

Chapter 4

Characteristics of noise complaints and the associations with urban morphology: A comparison across densities[1]

For the city/micro scale studies in Part I, the primary purpose of this chapter is to summarise the spatiotemporal distribution of noise complaints, ascertain the associations between urban morphology and noise complaints, and compare such associations in different density areas within a city. Section 4.1 introduces the background of noise complaints in urban sound environment research. Section 4.2 illustrates the reason for choosing NYC as the case study area, data sources, and the analysis method. Section 4.3 presents the results of the spatiotemporal distribution characteristics of noise complaints and their associations with urban morphology across densities. Section 4.4 includes a discussion of the implications of the findings and future research. Section 4.5 provides a brief summary of this chapter.

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[1] This chapter has been published as: Tong, H., & Kang, J. (2021a). Characteristics of noise complaints and the associations with urban morphology: A comparison across densities. Environmental Research, 197. In order to ensure the fluency of content and consistency, the title of this chapter is kept the same as the published paper, and text is also kept largely unchanged. No attempt has been made to rewrite, apart from slight wording changes to correspond to other chapters.

4.1. Introduction[2]

Exposure to noise is an increasingly common and serious problem globally because of rapid urbanisation. Noise complaints top the list of environment-related complaints and along with the influence of urban planning on the sound environment, have received increased research attention across a number of disciplines (Kang, 2006). Current estimates predict that two-thirds of the world's population will be living in urban areas by 2050 (United Nations, 2014), and urban density as a factor of urban planning is an important consideration from a psychological and sociological point of view (Hui, 2001). It has been shown that high-density, crowded, and stressful urban environments might negatively impact residents' health because of factors such as air pollution and noise problems (WHO, 2019).

Numerous studies have been conducted on urban environment and urban morphology, with the comparison across densities. For instance, Naeher et al. (2000) found that $PM_{2.5}$ and CO were significantly higher in high-density villages. Yuan et al. (2014) showed that low urban permeability in high-density areas could reverse air flow near the ground, allowing air pollutants to disperse into the windward area of the pollutant sources. Guo et al. (2016) presented a regression model for land surface temperature based on building height, where the model performance varies depending on whether the building density is above or below 0.16.

A number of studies have examined the associations between urban morphology and environmental noise issues in different density areas. Wang

[2] As explained in footnote 1, to have a better narrativity of this chapter and keep the flow for this chapter, this introduction section (4.1) is kept the same as the published paper, and no attempt has been made to change the text even there might are some slight repetitions with Chapter 2.

and Kang (2011) examined the relationships between noise level distribution and urban morphology based on two representative cities, suggesting that there were significant differences in spatial noise-level distribution between high and low-density cities. Zhou et al. (2016) investigated traffic noise distribution and street morphology in urban residential blocks. They found that the floor space index showed a significant positive correlation with the standard deviation of ground and building façade noise only in small low-rise blocks. Hupeng et al. (2017) analysed the relationships between urban street spatial parameters and sound propagation in the high-density city, demonstrating that when the cross-sectional enclosure degree and the plan enclosure degree increased, or vehicle lane width decreased, sound attenuations decreased. Hao and Kang (2014) studied the associations between urban morphology and the spatial noise level attenuation of flyover aircraft in low-density areas, finding it to be mainly correlated to the building frontal area index and the horizontal distance of the first-row building to the flight path.

In terms of noise perception, Meng et al. (2017) investigated acoustic perception based on crowd density characteristics in high-density urban open spaces. Hao et al. (2015) examined the relationships between traffic noise resistance and urban morphology in low-density residential areas. Consideration has also been given to soundscape, Hong and Jeon (2017) examined the effect of urban morphology on the spatiotemporal variability of soundscape in Seoul, Korea. They found that high-density commercial areas have lower sharpness values compared with low-density commercial areas. However, in terms of noise complaints which are strongly related to noise annoyance, indicative of the areas where residents are highly annoyed with noise, there is still a lack of research taking into account the associations with urban morphology. A direct comparison between areas of different densities in terms of noise complaints would be of great interest. Meanwhile, with the arrival of the big data era, such data from multiple sources has been applied on environmental research, such as air quality and the thermal environment (Cao et al., 2020; Zheng et al., 2019). However, little research has occurred on open big data from various sources to study the associations between urban morphology and sound environment.

Therefore, the aim of this chapter was to examine the distribution characteristics of noise complaints in different urban densities, and how they are influenced by urban morphology. NYC was selected as the study area, as its five boroughs have a considerable range of density. A statistical analysis was performed on crowdsourced noise complaints and urban morphology datasets from the NYC governmental open data sources. More specifically, the research questions were: (1) What are the characteristics of spatial and temporal distribution of noise complaints in different urban densities? (2) What are the associations between noise complaints and urban morphology, including transport network, land use, and building morphology in different urban densities?

4.2. Methods

4.2.1. Case study area

With the aim of identifying characteristics of noise complaints and the associations with urban morphology across high- and low-density areas, NYC was selected for analysis, including five boroughs: Manhattan, Brooklyn, Bronx, Queens, and Staten Island (Figure 4.1). Manhattan is a highly developed borough with an extremely high population density of 27,560 people/km^2. The urban environment is also highly developed in terms of buildings and roads. Brooklyn and Bronx have a population density of 14,350 people/km^2 and 13,000 people/km^2, approximately half that of Manhattan. The population density in

Queens is 8,140 people/km^2. Staten Island has the lowest density, with 3,130 people/km^2. Manhattan has a relatively high prevalence of office and commercial areas, and the proportion of residential areas is about 20% lower than in other boroughs (NYC Planning Labs, 2019).

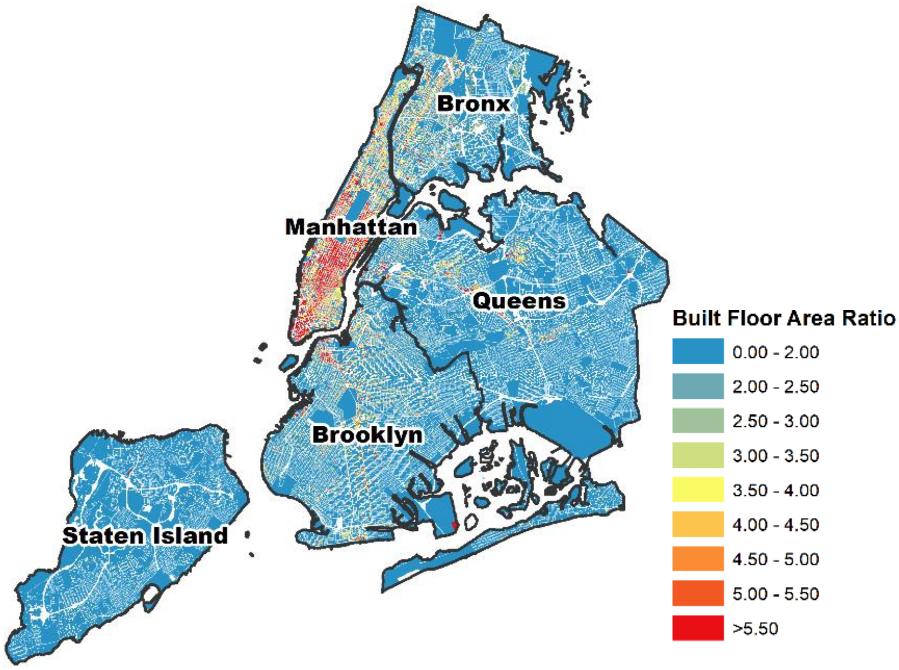

Figure 4.1 The distribution of built floor area ratios in New York City

4.2.2. Crowdsourced noise complaints dataset

Noise complaint data can be understood as a crowdsourced dataset which is collected via a participatory method of building a dataset with the help of a large group of people. NYC 311 is NYC's governmental non-emergency service number. The 311 system records data on each report, including time, case type, and reporter's location. The service handles complaints related to noise, air pollution, health, public safety, and other problem categories (New York City, 2019).

According to 311 data from 2010 to 2018, there were 2.92 million noise complaints in total. There were ten types of noise complaints in the original dataset: “Collection Truck Noise”, “Noise”, “Noise-Commercial”, “Noise-

Helicopter", "Noise-House of Worship", "Noise-Park", "Noise-Residential", "Noise-Street/Sidewalk", "Noise-Vehicle", and "Noise Survey". The noise complaint types are classified based on where the noise comes from or is generated by. For instance, Noise-Residential refers to noise that comes from inside a residential building, such as TV shows. Noise-Streets/Sidewalk is noise coming from the street or sidewalk, such as loud talking. In this chapter, "Noise-unclassified" is used to refer to "Noise" above. "Noise Survey" was eliminated since there was no "Noise Survey" data in 2018.

Apart from year-changing analysis, noise complaints for the whole 2018 were selected for this chapter (for year changing, data from 2010–2018 was used). There were 436,692 complaints in 2018, of which 2,287 were eliminated due to missing information. Finally, 434,395 complaints were retained for analysis. Subsequently, these were imported into ArcGIS 10.3 for spatial analysis and visualisation, based on the longitude and latitude information of each noise complaint. In this chapter, noise complaint rate (the number of complaints per thousand people) was calculated for analysis.

4.2.3. Urban morphology dataset and indicators

There are considerable urban morphology indicators related to the sound environment (Margaritis & Kang, 2016; Gozalo, 2016; Souza & Giunta, 2011; Zhou et al., 2016). Based on literature review and datasets from the Department of City Planning in NYC, urban morphology indicators were mainly categorised into three groups: road transport network, land use, and building morphology. In this chapter, transport network features were extracted from a LION geographic base file, which is maintained by the Department of City Planning. In this dataset, the single-line was used to represent the city's streets. The lines/streets contain geographic spatial information, which can be reflected on the NYC map, as well as the unique ID, width, and name (NYC Department of

City Planning, 2019a). Land use and building morphology data were extracted from the PLUTO data file, which contains extensive land use and geographic data (NYC Department of City Planning, 2019b).

In terms of the road transport network, there are two aspects considered in this chapter: the average distance between noise complaints and the nearest road crossing, and the road density (the length of road per spatial unit). To calculate these indicators, a fishnet was created in ArcGIS 10.3 by dividing the study area into smaller rectangular cells (i.e., spatial analysis units), each with a unique code. A large cell size will hardly capture spatial variability or yield an adequate sample size, where a small cell size will result in many noise complaints projected onto cells without any roads, and will increase the computational cost. Therefore, in this chapter, 500 m*500 m rectangular cells were selected as spatial analysis units by considering the space type, building density, road distribution pattern, road type, and land use (Guo et al., 2016; Wang & Jian, 2011). This method allowed us to calculate the transport network indicators in each cell, as well as land use and building morphology indicators. Meanwhile, noise complaint rate was also calculated in each cell for further statistical analysis.

In term of land use, it included building floor area for each type of land use (including commercial, residential, office, retail, garage, storage, factory, park, and others), land value (including assessed land value and assessed total value), and residential units (including residential units and total units). These indicators were originally derived from PLUTO. Total units were the sum of residential units and non-residential units; assessed land value was calculated by multiplying the estimated full market land value, determined as if vacant and unimproved, by a uniform percentage for the property's tax class; and assessed total value was calculated by multiplying the estimated full market land value by a uniform percentage for the property's tax class (NYC Department of City

Planning, 2019b). Building morphology included lot area, building area, number of building floors, frontage ratio (building frontage/block frontage), depth ratio (building depth/block depth), and floor area ratio. These indicators, originally from PLUTO, were also calculated by creating the fishnet as mentioned above.

4.2.4. Data analysis

In terms of the characteristics of spatial and temporal distribution of noise complaints, apart from the descriptive statistics, the inferential statistics including chi-square test and Kruskal-Wallis test were also used. The chi-square test is a non-parametric tool designed to analyse differences (McHugh, 2013). In this chapter, the chi-square test was applied to identify the difference in noise complaints among boroughs and types. Kruskal-Wallis test assess for significant differences on a dependent variable by a categorical variable (Kruskal & Wallis, 1952; McKight & Najab, 2010). It was used to determine if there are statistically significant differences between different periods on noise complaints in this chapter.

To explore the associations between noise complaints and urban morphology, including transport network, land use, and building morphology, Spearman correlation were used. In this chapter, the rate of noise complaints was not normally distributed, according to the Shapiro-Wilk test (Ghasemi & Zahediasl, 2012; Yap & Sim, 2011). Therefore, Spearman correlation was applied, since it does not make any assumption about the distribution of the variables (Hauke & Kossowski, 2011). The process was conducted using the SPSS 26 (Landau & Everitt, 2003).

4.3. Results

4.3.1. Temporal and spatial distribution characteristics of noise complaints

4.3.1.1. Spatial distribution

The distribution of the locations of reported noise complaints is shown in Figure 4.2 and the rate of noise complaints by type and boroughs is displayed in Table 4.1. Overall, the difference in noise complaint rate across boroughs was significant (p<0.01) via the chi-square test. It is clear that the distribution of the various types of noise complaints was not even (Figure 4.2). Table 4.1 clearly shows that the highest noise complaint rate was observed in Manhattan; the value was 93.19 per thousand people. It can be explained by that the rate of top four noise complaint types, including residential, street/sidewalk, unclassified, and commercial noise complaints, were considerably higher than that in other boroughs in the dataset. Then, in Brooklyn the noise complaint rate was 76.25. Subsequently, the noise complaint rate was similar in Bronx and Queen, with the values of 33.22 and 34.88, respectively. The lowest noise complaint rate was observed in Staten Island, at 24.08.

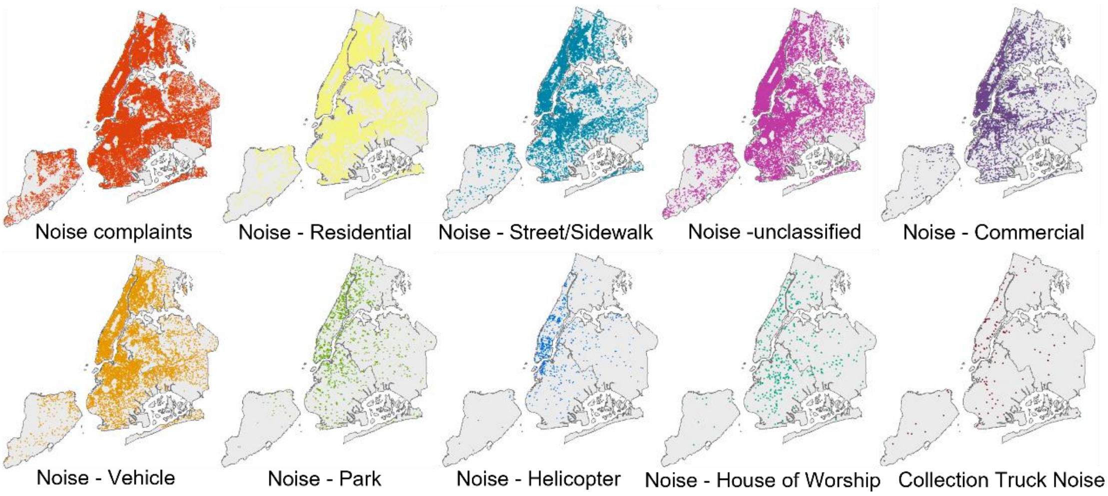

Figure 4.2 The distribution of noise complaints by types (each point represents a noise complaint)

Table 4.1 Noise complaint rate by types and boroughs

Noise complaint types	Noise complaint rate in different boroughs					
	New York City overall	Manhattan	Brooklyn	Bronx	Queens	Staten Island
All type of noise complaints	51.72	93.19	76.25	33.22	34.88	24.08
Noise - Residential	25.81	33.43	38.14	21.66	19.16	15.05
Noise - Street/Sidewalk	8.78	20.68	12.70	6.12	2.94	1.87
Noise - Unclassified	7.09	19.46	9.71	1.21	4.88	3.46
Noise - Commercial	5.31	11.99	9.11	1.59	3.39	1.67
Noise - Vehicle	4.01	6.35	5.22	2.31	4.05	1.87
Noise - Park	0.49	0.79	0.97	0.27	0.30	0.10
Noise - Helicopter	0.12	0.39	0.16	0.02	0.07	0.02
Noise - House of worship	0.09	0.08	0.22	0.04	0.07	0.03
Collection Truck Noise	0.02	0.03	0.02	0.00	0.01	0.02

The proportion of noise complaint by type, in terms of complaint rate, is displayed in Table 4.2. In overall NYC, the noise complaints with higher percentages were residential (49.90%), unclassified (13.72%), commercial (10.27%), street/sidewalk (16.97%), and vehicle noise (7.75%). The remainder of noise complaints represent less than 2% of the total. In Manhattan, the proportion of street/sidewalk, unclassified, commercial, and helicopter noise, was higher than in other boroughs. Vehicle, house of worship, and residential noise complaints in Manhattan had lower values. The highest proportion of vehicle noise complaints was observed in Queens, with a value of 11.61% which was significantly higher than other boroughs. Meanwhile, the highest percentage of residential noise complaints was seen in Bronx, at 65.20%, which was significantly higher than that in Manhattan (approximately twice the value for Manhattan). Bronx has the smallest number of commercial and helicopter noise complaints. The highest proportion of noise complaints about houses of worship and parks occurred in Brooklyn. Staten Island had three extreme values: highest collection truck noise complaints at 0.09%, lowest park noise complaints at 0.41%, and lowest street/sidewalk noise complaints at 7.75%.

Table 4.2 Proportions of noise complaint rate by types

Noise complaint types	Proportions of noise complaint rate in different boroughs					
	New York City overall	Manhattan	Brooklyn	Bronx	Queens	Staten Island
Noise – Residential (%)	49.9	35.87	50.02	65.20	54.94	62.49
Noise – Street/Sidewalk (%)	16.97	22.19	16.66	18.43	8.43	7.75
Noise – Unclassified (%)	13.72	20.88	12.74	3.64	13.99	14.38
Noise – Commercial (%)	10.27	12.86	11.94	4.78	9.72	6.91
Noise – Vehicle (%)	7.75	6.81	6.84	6.96	11.61	7.76
Noise – Park (%)	0.95	0.84	1.27	0.81	0.87	0.41
Noise – Helicopter (%)	0.24	0.42	0.21	0.05	0.19	0.10
Noise – House of worship (%)	0.17	0.08	0.29	0.11	0.21	0.11
Collection Truck Noise (%)	0.03	0.04	0.03	0.01	0.04	0.09
Total (%)	100	100	100	100	100	100

Highest proportion for each type of noise complaint is highlighted in orange, the lowest in blue.

Overall, in the high-density borough of Manhattan, there were four types of highest noise complaints and three types of lowest noise complaints. It is remarkable that in Manhattan, with the highest population and building density, residential noise complaints accounted for the highest percentage of complaints among all types, although it was at least 15% lower than in any other borough. This could be the result of the difference in land use: Manhattan has the lower proportion of residential areas as mentioned in Section 4.2.1 . Another notable result is that the proportion of street/sidewalk noise complaints in Manhattan (22.19%) was three times higher than that of Staten Island (7.75%). It is possible that, in a typical high-population and high-building density area like Manhattan, pedestrian traffic would be more crowded than in Staten Island, a sparsely populated area.

4.3.1.2. Temporal distribution

Figure 4.3 shows changes in the rate of noise complaints by type. It can be seen the rate of noise complaints increased from 2010 to 2018. Correspondingly, the rate of noise complaints increased approximately 2.10 times from 24.66 per thousand people to 51.72 per thousand people. The tendency of noise complaints by season within every year was similar. For noise complaint types, the tendency was more dramatic for streets/sidewalks, followed by vehicle, unclassified, park, and commercial noise complaints, while it was relatively less dramatic for residential noise complaints. In terms of park and street noise complaints, in all boroughs, the lowest noise complaint rate was always in winter, while in the other three seasons the rate of noise complaints was significantly higher, with the value in summer being slightly lower. The tendency of vehicle noise complaint rate was similar to that of park and street noise complaints, while the difference between seasons was less obvious. Unclassified and commercial noise complaints had two significant peaks, autumn and spring, whereas the rate of unclassified and commercial noise complaints was lowest in winter and summer, in all five boroughs.

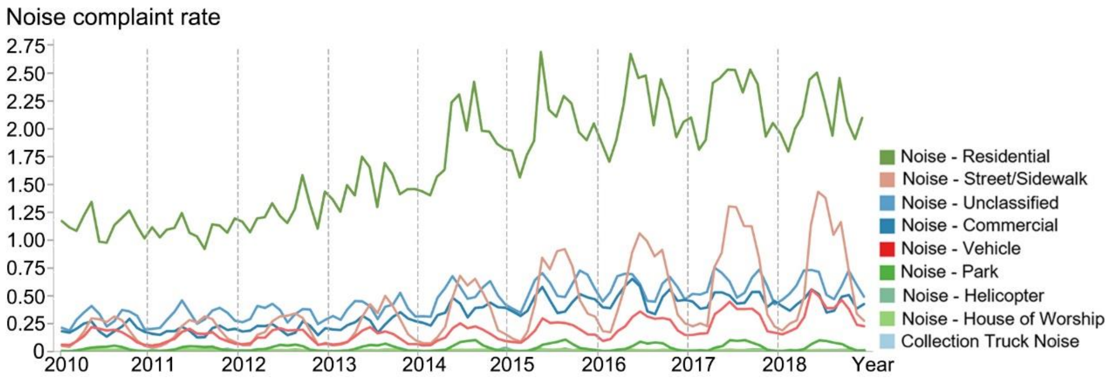

Figure 4.3 Changes in the rate of noise complaints by type from 2010 to 2018

Two factors could contribute to the difference between seasons. The first plausible reason is the temperature, causing fewer outdoor activities, such as walking in the street and attending outdoor retail markets. This could partly explain the change in park, street, unclassified, and commercial noise complaints, as these obviously change with the seasons. The second possible explanation is open windows during summer. Residents are likely to close their windows when it is cold outside, consequently reducing the noise, which could partly explain the change in vehicle noise complaints.

From hourly changes perspective, changes in the rate of noise complaints by hours of the day are shown in Figure 4.4. In all five boroughs, the highest rate of noise complaints appeared at 23:00 with a value of 4.88, followed by 22:00

with a value of 4.49. WHO (2018) provides recommendations for noise levels for protecting human health from exposure to environmental noise originating from various sources. Hence, the different types of noise complaints were further discussed. During the daytime, the noise complaint rates per hour for residential, commercial, street/sidewalk, and vehicle noise complaints were 0.72, 0.12, 0.24, and 0.15, respectively, compared with the value of 1.78, 0.41, 0.61, 0.21 during the night. It can be seen that all these noise complaint types increased, perhaps due to the impacts of noise on sleep disturbance. Significant difference was found between different hours in noise complaints via Kruskal-Wallis test with $p<0.01$. Overall, noise complaints started to plummet from around 8:00 with a value of 1.23 (approximately half the value for 7:00), except for Manhattan, where the decrease was more gradual. A second small peak of complaints appeared in the afternoon at 15:00 with a value of 1.78. Among the five boroughs, the trend of complaint rate about vehicles was similar to most types of noise complaints; however, in Queens, vehicle complaints increased from 9:00.

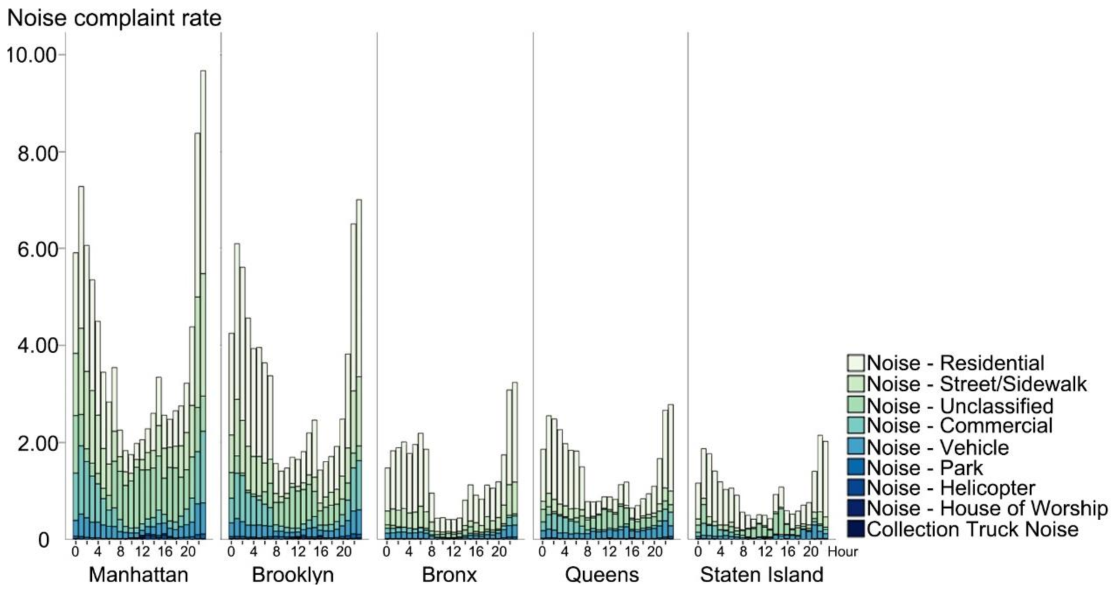

Figure 4.4 Changes in the rate of noise complaints by hours of the day

4.3.2. Associations with urban morphology

4.3.2.1. Transport network

Table 4.3 shows the relationships between noise complaint rate and transport network by borough. It can be seen that in Brooklyn, Bronx, and Queens, distance to the nearest road crossing was significantly negatively related to the rate of noise complaints. No significant relationship was found in Manhattan and Staten Island. This finding is in line with the research of Gozalo et al. (2016), who found that the number of crossings was positively related to noise level. This could be due to traffic volumes: closer proximity to road crossings means experiencing the effects of more than one road.

Table 4.3 Correlation coefficients between noise complaint rate and transport network

Transport network indicators	Correlation coefficients in different boroughs					
	New York City overall	Manhattan	Brooklyn	Bronx	Queens	Staten Island
Distance to road crossing	0.073**	-0.006	-0.179**	-0.109*	-0.109**	-0.061
Total road density	0.370**	0.015	0.203**	0.352**	0.192**	0.465**
0-20 m road density	-0.118**	-0.152**	-0.139**	-0.133**	-0.001	-0.144**
20-40 m road density	0.345**	0.121	0.413**	0.317**	0.212**	0.509**
40-60 m road density	0.289**	0.035	-0.099*	0.271**	0.114**	0.257**
60-80 m road density	0.167**	-0.080	-0.154**	0.283**	0.064*	-0.004
>80 m road density	-0.062**	-0.030	-0.179**	-0.045	-0.016	-0.016

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

For noise complaint rates, all boroughs except Manhattan, were positively related to road density, as shown in Table 4.3. Specifically, in Manhattan, noise complaint rate was only negatively related to 0-20 m-wide road density with the magnitudes being -0.152. In Brooklyn, among all widths of road, only 20-40 m road density was positively related to the rate of noise complaints, with a coefficient value of 0.413. Noise complaint rate was negatively related to other classifications of road, with lower coefficients around -0.100. In Bronx, noise complaints had negative relationships with 0-20 m width, and positive relationships with 20-40 m, 40-60 m, and 60-80 m roads. In Queens, there were positive relationships in 20-40 m, 40-60 m, and 60-80 m road densities, whereas no significant correlation was found in 0-20 m and greater than 80 m road widths. In Staten Island, a negative relationship also appears for 0-20 m road density and positive relationships in 20-40 m and 40-60 m road densities.

Generally, noise complaints occurred in areas with a high density of 20-60 m roads, especially in areas with 20-40 m roads, which had higher coefficient values. Generally speaking, this finding is broadly consistent with that of Margaritis and Kang (2016), who found that primary road length has an impact on noise levels. Across all five boroughs, the least significant relationships were found in Manhattan, where even the significant relationships were weaker than in other boroughs. The results could be explained by the fact that the high and dense buildings in Manhattan limit the effect strength of road density, hence the correlation coefficients were near zero.

4.3.2.2. Land use

Table 4.4 shows the relationships between noise complaints and land use, including land function, residential unit, and land value. In terms of land function, the rate of noise complaints in NYC overall was positively related to all functions of land, except for parks. Among these functions, the relationship between residential floor area and noise complaint rate was higher than other functions of land, followed by retail floor area. However, in Manhattan, noise complaints were only related to residential, retail, and storage floor area at 0.01 significance level, with lower coefficient values than in other boroughs. For park, the significant negative relationship was only observed in Staten Island. To some extent, this result is in line with studies that found that the impacts of sound and visual interaction on perception. For instance, greenery could reduce noise annoyance (Sanchez et al., 2017; Van Renterghem et al., 2015). However, the negative association was only found in Staten Island, lowest density area in NYC.

Table 4.4 Correlation coefficients between noise complaint rate and land use

Land use indictors	Correlation coefficients in different boroughs					
	New York City overall	Manhattan	Brooklyn	Bronx	Queens	Staten Island
Commercial floor area	0.481**	0.085	0.398**	0.351**	0.288**	0.278**
Residential floor area	0.588**	-0.174*	0.457**	0.534**	0.448**	0.621**
Office floor area	0.456**	0.134*	0.268**	0.421**	0.314**	0.311**
Retail floor area	0.537**	0.225**	0.392**	0.470**	0.426**	0.430**
Garage floor area	0.412**	-0.068	0.297**	0.298**	0.224**	0.213**
Storage floor area	0.386**	0.233**	0.295**	0.290**	0.316**	0.201**
Factory floor area	0.268**	0.132	0.249**	0.193**	0.250**	0.129**
Other floor area	0.456**	0.134*	0.268**	0.421**	0.314**	0.311**
Park area	0.010	-0.130	0.059	-0.039	-0.015	-0.136**
Assessed land value	0.347**	-0.109	0.265**	0.352**	0.105**	0.124**
Assessed total value	0.520**	-0.059	0.440**	0.458**	0.252**	0.366**
Residential units	0.619**	-0.086	0.506**	0.560**	0.498**	0.660**
Total units	0.631**	-0.025	0.519**	0.564**	0.509**	0.674**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Regarding assessed land value and assessed total value, significant positive relationships between these and noise complaint rate were found in NYC overall, Brooklyn, Bronx, Queens, and Staten Island. However, in Manhattan, no significant relationship was found between the rate of noise complaints and assessed land value. In terms of residential units, noise complaint rate had positive relationships with residential units and total units, with coefficient values of 0.619 and 0.631 in NYC overall. These relatively strong relationships also appeared at borough level, except for Manhattan, where the relationships were not significant. The difference could be explained by the fact that, because of the high building density in Manhattan, with the addition of each residential unit, the increase of noise complaints would be limited.

4.3.2.3. Building morphology

The relationships between noise complaints and building morphology are shown in Table 4.5. In terms of lot area and building area, in NYC overall, as well as Bronx, Queens, and Staten Island, negative relationships were found between noise complaint rate and lot area, while there was a positive relationship with building area, with higher values around 0.5. The results indicate that the lower the built area/lot area ratio, the lower the noise complaint rate. This is partly because a lower ratio of built area indicates there is a garden or yard in the lot, which could impact residents' perception and noise absorption (Sanchez et al., 2017; Liu & Kang, 2018). In Manhattan, no significant relationship was observed for lot area or building area; in Brooklyn the relationship was significant only for building area. Noise complaint rate had positive relationships with the number of building floors in NYC overall and in every borough except for Manhattan. This means that, as the number of floors increases, the rate of noise complaints is likely to increase.

Table 4.5 Correlation coefficients between noise complaint rate and building morphology

Building morphology indicators	Correlation coefficients in different boroughs					
	New York City overall	Manhattan	Brooklyn	Bronx	Queens	Staten Island
Lot area	-0.221**	-0.091	-0.003	-0.189**	-0.090**	-0.184**
Building area	0.608**	-0.009	0.500**	0.532**	0.457**	0.623**
Number of floors in building	0.613**	-0.106	0.494**	0.593**	0.481**	0.614**
Frontage ratio	0.507**	0.149*	0.321**	0.498**	0.383**	0.509**
Depth ratio	0.554**	0.167*	0.300**	0.600**	0.408**	0.403**
Floor area ratio	0.605**	0.007	0.486**	0.527**	0.459**	0.606**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

In terms of front ratio and depth ratio, the front ratio is equal to the building's frontage (along the street) divided by the lot frontage, while depth ratio is equal to the building's depth (which is the effective perpendicular distance) divided by lot depth. The rate of noise complaints was positively related to front ratio and depth ratio in each borough. However, in Manhattan, the significant level was only at 0.05 which was lower than in others. The associations between front ratio and depth ratio and noise complaint rate could probably be explained by the fact that traffic noise is one of dominant noise sources on daily life and attracts more attention. Residents in street-facing buildings are exposed to more traffic noise and can probably see more vehicles, which increases the possibility that they report noise issues (Van Renterghem et al., 2015). The last indicator is floor area ratio, which is a typical measure of area density. It was positively related to the rate of noise complaints in NYC overall and in all boroughs, except for Manhattan.

Overall, the more enclosed and denser the blocks are, the higher noise complaint rate is likely to be. The relationships between building morphology and noise complaints vary from different density areas; they were weaker in Manhattan than in other boroughs. To some extent, the results confirm Wang and Kang's research (2011), which also showed different relationships between building coverage and noise level in different density cities, where the relationship was significantly negative in high density areas while the correlation tended to be positive in low density area.

4.4. Discussions

In the field of urban sound environment, previous research has mainly focused on the noise level. Recently, noise perception has received more attention. By considering the perception of sound, the influence of urban sound environment on human well-being could be studied better. However, the chapter of noise perception is insufficient in the urban scale due to limited sample size. Hence, spatiotemporal big data, GIS technique, and statistical method were utilized and combined in this chapter which filled the gap. The present results are broadly significant in environment issues. First, from the noise pollution perspective, noise is a primary contributor to certain risk factors related to physical and mental health, such as loss of hearing, sleep disorder, and stress (Schreckenberg et al., 2010). Noise complaints can give a useful indication for the area where residents are highly annoyed with environmental noise. This chapter depicted characteristics of the spatial and temporal distribution of noise complaints and clarified its relation to urban morphology parameters. These results could be helpful for reducing environmental noise pollution by urban planning. For instance, policymakers could set up the different noise level criteria during different time periods in 24 hours or different seasons in a year. Planners could focus on layout on 20-40 m roads where noise complaints occur more. Second, with urban sprawl, the issues for divisive urban density have a critical importance for sustainability (Newman, 2014). This chapter analysed the difference of noise complaints in various urban densities. Due to the environment pollution and conflicting interests, it would be important for policymakers to make the policy efficient and effective considering various urban densities. While in literature it is shown greenery could reduce noise annoyance (Sanchez et al., 2017), based on the results from this chapter, an increase on park density did not have a significant effect on decreasing noise complaints in high density areas, while in a low-density area, reducing noise pollution would benefit more from using and protecting parks. Third, neighbourhood conflicts appear to be a growing phenomenon and are a key feature of contemporary urban living. They have significant effects on the quality of life for residents, as well as on the level of health and neighbourhood cohesion (Ellaway et al., 2001; Mouratidis, 2019). Noise complaints, as a type of neighbourhood conflicts, are more serious in high-density areas. In addressing urban conflicts, high density cities should therefore be emphasised. Overall, the results of this chapter can therefore be useful for reducing the negative impacts of environmental noise and improving the quality of life.

Future studies on the current topic are recommended. First, while this chapter considered only the transport network, land use, and building morphology, future studies could involve more socio-economic conditions, since the relationships between noise complaints and socio-economic spatial inequalities are significant (Xie & Kang, 2010). From this perspective, more socio-economic indicators are further investigated in Chapter 6 (Part II). Second, this chapter presented and discussed the relationships between urban morphology and noise complaint rates in different urban densities. However, the complex causality of these relationships remains undiscussed and is worth exploring in further research. Finally, this chapter primarily focuses on noise complaints; to develop an integrated understanding of environmental complaints, research on other types of complaints is needed, such as air pollution, wastewater, and odour.

4.5. Conclusions

Using NYC boroughs with different urban densities as case study sites, this chapter examined the characteristics of noise complaints and examined the relationships between noise complaints and urban morphology. This chapter indicates that urban planning parameters could be applied to achieve better sound environment. Such results could be useful to develop more effective noise-management strategies. The findings are as follows:

(1) In NYC, the noise complaints are not evenly distributed spatially across the whole city; rather, they are clustered around the highest density area (i.e. Manhattan). The rate of noise complaints increases every year, with an annual peak in autumn and another in spring.

(2) Noise complaint rate is generally negatively related to the distance to the nearest road crossing. Meanwhile, it is higher in areas with a high density of 20-40 m roads.

(3) Noise complaint rate is positively related to all types of land use, except for parks. The significant relationship between noise complaints and park density is only observed in lowest density area (Staten Island).

(4) The more enclosed and denser blocks are, the higher the noise complaint rate is. The relationships between noise complaints and building morphology are weaker in high-density boroughs than in other boroughs.

Chapter 5

Increases in noise complaints during the COVID-19 lockdown in Spring 2020: A case study in Greater London, UK[1]

In order to contain the spread of COVID-19, many cities have claimed that the enforcement of lockdown measures and the corresponding limitations of human activities led to reduced environmental noise levels. This provides an opportunity to think about the soundscape and whether it is impacted by urban planning. Therefore, this chapter aims to examine how noise complaints changed during the first stages of the lockdown implementation, and how urban factors, including housing, demographics, transport, and traffic noise, may have influenced these changes. Section 5.1 introduces the background of COVID-19 and research during the lockdown period. Section 5.2 points out the aims and scopes of this chapter. Section 5.3 describes the data and statistical methods (including Mann-Whitney U test and Spearman correlation) utilised in this chapter. In Section 5.4, the variations in noise complaints in terms of quantity and type are presented and their relation to urban factors are analysed. Section 5.5 discusses the reasons for the changes in noise complaints and the limitations. Section 5.6 gives a brief summary and implications of the findings.

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[1] This chapter has been published as: Tong et al., (2021). Increases in noise complaints during the COVID-19 lockdown in Spring 2020: A case study in Greater London, UK. Science of the Total Environment, 785. In the interest of fluency and readability, this chapter maintains the original title, text, and structure of the published paper. Only slight changes are made to correspond to other chapters.

5.1. Introduction[2]

The coronavirus disease 2019 (COVID-19) was first identified in December 2019 and quickly started to affect many regions of the world in the following months. In January 2020, the WHO declared the outbreak a “Public Health Emergency of International Concern”, and subsequently escalated it to a “pandemic” in March 2020 (Brown & Horton, 2020). In order to prevent and slow down the spread of the virus, many countries adopted a series of policies and actions, which in the most restrictive scenarios were commonly identified as “national lockdowns”.

In general, lockdown measures involved “staying at home” recommendations, social distancing, stopping non-essential commercial activities, banning public gatherings, limiting traffic mobility and alike. Specifically, the UK Government passed the Health Protection (Coronavirus, Restrictions) (England) Regulations 2020, which were put into force at 1:00 pm on 26th March 2020 (Public Health England, 2020). Under these restrictions, the public were only allowed to leave their homes once per day for essential activities and exercise. All offices and shops selling non-essential goods were told to close, gatherings of more than two people in public were banned, and individuals were advised to only interact with members of their own household. These restrictions were set to be reviewed by the Secretary of State at least once every 21 days and would continue indefinitely until they were no longer necessary to prevent the spread of infection in England. In practice the lockdown continued through the spring of 2020 and was first partially eased on 1st of June, with school children in England returning to school, but the broader lockdown continued throughout the summer.

[2] To have a better narrativity and keep the flow for this chapter, Section 5.1. Introduction is included and kept the same as the published paper.

Such measures at global scale were unprecedented and suddenly changed human behaviours and communities' life around the world, with considerable impacts on society. For instance, from psychological perspectives, acute panic, anxiety, obsessive behaviours, paranoia, and depression can be produced (Ausín et al., 2021; Dubey et al., 2020; Dzhambov et al., 2021). The socio-economical condition can also be impacted, where financial uncertainty, decrease in income, fear of job loss, and food insecurity are some major challenges (Ali et al., 2020; Rasheed et al., 2021). Yet, in spite of the adverse societal and economic implications, the lockdown implementations to contain the COVID-19 outbreak led to some improvements in the urban environment, particularly in terms of air quality and noise pollution. For instance, In the US, NO_2 levels declined by 25.5% during the COVID-19 pandemic compared to historical data, and $PM_{2.5}$ levels declined in urban counties and those instituting early business closures (Berman & Ebisu, 2020). In China, because of the lockdown, NO_2 emissions dropped by 30%; CO_2 emissions decreased by 25% (Dutheil et al., 2020). Furthermore, early reports in China show that the improved air quality avoided a total of 12,125 NO_2 and $PM_{2.5}$ -related deaths during the lockdown period (Chen et al., 2020).

Noise pollution followed similar decreasing trends, with environmental noise levels dropping particularly in urban contexts, due to the lack of human activities in public spaces and overall reduction of traffic volumes. In Paris (France), since the lockdown measures were implemented, the noise levels from road traffic reduced by 7.6 dB(A) (L_{den}) on average, and aircraft noise reduced by 21.5 dB(A) (L_{den}) (Bruitparif, 2020). In Barcelona, the noise pollution levels dropped by 9 dB(A) (L_{Aeq} for the 12-hour day period) after one week of lockdown, and an additional 2 dB reduction after two weeks was observed (Ajuntament de Barcelona, 2020). In Athens (Greece), noise levels (L_{den}) reductions of up to 6 dB(A) and 8 dB(A) were measured on road networks and in proximity of the Athens International Airport, accordingly, as a consequence of the lockdown restrictions (Vogiatzis et al., 2020). In London (UK), an average reduction of 5.4 dB (L_{Aeq}) was observed across 11 sampled locations by comparing a dataset of noise measurements from Spring 2019 and one from Spring 2020, during the UK lockdown (Aletta et al., 2020).

The cases mentioned above are just examples: the reduction in environmental noise levels observed in these cities is likely to be common also to other urbanised areas of the world, for which monitoring data is not yet available. Consequently, one could reasonably expect that since there was a reduction in noise pollution levels, the general attitude of the public towards the urban acoustic environments would have improved during the lockdown confinements. However, focusing merely on the "physical" acoustic environment rather than how it is experienced and perceived by people is a major issue that needs further discussion, for the manifold implications that noise annoyance can have on people's lives. Indeed, focusing on the UK context, soon after the national lockdown was implemented on March 26th 2020, reports started to appear in news outlets claiming that noise complaints were on the rise in many UK councils (BBC, 2020). The underlying reasons seemed to be that since people were spending more time at home to comply with lockdown restrictions, they would become more sensitive to neighbourhood-related noise sources. Some city councils had to release specific guidance on possible coping strategies and/or special "noise advice" (Royal Borough of Greenwich, 2020). An excerpt from the Gateshead Council website on the "Neighbour noise advice during the Coronavirus (COVID-19) pandemic" page stated: "A considerable number of people will need to work from home and children will be doing school work at home […] that means we will probably be seeing and hearing more of our neighbours than we are used to. In some situations, this may lead to frustrations or annoyance with noise we do not want to hear. With this in mind, we urge everyone to be considerate of their neighbours by thinking about how noise from your home could be causing problems and upset to others. For the same reason, we urge everyone to be more tolerant and patient with noise and activity that they won't be used to hearing" (Gateshead Council, 2020). The rationale for this chapter is ascertaining whether such informal claims were indeed supported by noise complaints data, using Greater London as a case study.

5.2. Aims and scopes

Greater London has approximately an 8.9 million population and a population density of 64.16 per hectare. There are 32 boroughs divided into inner London and outer London (Butler et al., 2008). There are three reasons that London is well-suited as a case study: the noise complaint, noise level and urban factors datasets are all available in London; the lockdown measures were consistent across all London boroughs; and it includes areas with various urban factors (such as housing, transport, demographics, and noise sources). In England, reporting noise complaints is carried out under environmental legislation and managed by the local authority. This noise complaint dataset can provide a basis for the government decision-making. In this context, if residents have a problem with noise, they can report through service hotlines, websites, or in-person to the local council, which can then seek to address this problem.

Noise complaints typically dominate the amount of environment-related complaints that local authorities have to deal with (Kang, 2006). The topic has received increased research attention across several disciplines, such as psychology, sociology, and urban studies (Kang & Aletta, 2018). For instance, Nieuwenhuis et al. (2013) examined negative relationships between neighbours and proposed that property ownership is not correlated to neighbour conflicts, involving noise annoyance complaints. Legewie and Schaeffer (2016) examining 311 noise complaints datasets in NYC, found that ethno-racial diversity is positively associated with the number of complaint calls. Hong, Kim and Widener (2019) found that construction activities were associated with higher volumes of noise complaints. Noise complaints depend on individual attitudes, perceptions, and objective noise levels (Hong et al., 2019; Public Health England, 2018). It seems apparent that the amount of noise complaints would be related to noise level, particularly road traffic and rail sources. However, the perception of noise and the act of filing a complaint might also be affected by a number of urban planning parameters involving demographic, transport, housing factors. For instance, the road network is the main source of noise, primarily affecting the sound pressure level, which can be characterised through urban planning factors such as road density and the mode for commuting (Calixto et al., 2003; Tong & Kang, 2020). Secondly, the influence of demographic factors such as population density, age, occupation, education level, and health states on sound evaluation have been broadly studied (Aletta et al., 2018; Licitra et al., 2016; Miedema & Vos, 1999; Rey et al., 2018; Yu & Kang 2008). Finally, housing factors such as price, housing size, house type, and ownership have been proved to have a relation to the sound environment and evaluation (Fields, 1993). However, the changing patterns of noise complaints during the lockdown and the effect of such urban factors have not been investigated in detail yet.

The aim of this chapter is to examine how noise complaints changed during the first stages of the lockdown implementation during Spring 2020, both locally and at city scale, and how urban factors, including housing, demographic, transport, and traffic noise level band, may have been influencing them. More specifically, the research questions are:

(1) How did the noise complaints received by local authorities in London change because of the lockdown measures?

(2) Did this change in noise complaints during the lockdown vary depending on the noise complaint type (i.e., categories of noise sources)?

(3) To what degree are these changes mediated by other factors related to urban and socio-economic characteristics of the local environment, including

housing, demographic, transport, and traffic noise level band?

For this purpose, a case study in Greater London was considered. Noise complaint datasets were requested from London's Borough Councils for the years 2019 and 2020 in order to compare the noise complaints received during the lockdown in Spring 2020 and the noise complaints received during the same period from the previous year.

5.3. Methods

5.3.1. London noise complaint dataset

The noise complaint dataset was applied for from the local Borough authorities under the FOI, which provides public access to information held by public authorities (UK Government, 2000). As of the 16th of July 2020, noise complaint datasets from 24 boroughs were received by the researchers: 22 datasets without missing data or a crucial missing field (e.g., date) were used for this analysis. The data includes received date, complaint type, and location information for the single complaint record. The geographic location information of noise complaints is based on the coordinate points, postcode, or ward, depending on the reporting policies of the various boroughs. Amongst them, ward level was selected to get the same level of geographic labelling across all of the provided data (i.e., if postcode and coordinate points information were available, these were assigned to the corresponding ward). Wards are the administrative level below boroughs, which are the local government areas within Greater London (Figure 5.1).

Figure 5.1 Borough and ward boundary in London

The datasets received from some local authorities include other environmental complaints in addition to noise complaints. These include complaints related to odours, anti-social behaviours, dust, etc. These complaints were identified based on the type label and were excluded from this analysis in order to focus solely on noise complaints.

The classification for the type of noise complaint was not consistent among the London boroughs: some would use multiple-answer options with pre-defined categories, others a free-text field for users to fill; thus, a further categorisation step was necessary to handle the complaints type variable in a meaningful way. From the original database, a set of 484 unique labels used to characterise the type of noise complaint was extracted. These were then manually screened and sorted into 4 categories: Industry (36 labels), Construction (29 labels), Neighbourhood (373 labels), and Undefined (46 labels) (Table B-1 in Appendix B). The rationale for clustering the labels in this way was being aligned as much as possible with the WHO categorisation for community noise, defined as "noise emitted from all sources except noise at the industrial workplace […] including: road, rail and air traffic, industries (i.e., "Industry" label in this chapter), construction and public work (i.e., "Construction" label in this chapter), and the neighbourhood (i.e., "Neighbourhood" label in this chapter). […] Typical neighbourhood noise comes from premises and installations related to the catering trade (restaurant, cafeterias, discotheques, etc.); from live or recorded music; sport events including motor sports; playgrounds; car parks; and domestic animals such as barking dogs" (WHO, 1999). So the first category would essentially cover transportation and industries; the second category have a connotation of "public" works, as opposed to construction noise from a neighbour's flat for instance (as that would fall into the following category); the third category is possibly the broadest in scope, yet, from the perspective of the person complaining, the main difference between category 1-2 and category 3 is whether the complaint is directed towards an "infrastructural element" (for which local authority is accountable most likely) or towards a clearly identifiable person/group/premises generating the noise (thus the conflict is between to private subjects). The fourth category ("Undefined") does not indicate missing data, but rather lack of clear category, as sometimes the labels in the database did not allow classification (e.g., "other noise"; "noise"; or alike). Unique labels for the noise complaints with the category to which they were assigned were presented in Table B-2 in Appendix B.

5.3.2. The spring 2020 lockdown period

For the purpose of analysing the data, it was decided to compare the same period of the year in 2019 and 2020; that is: 27th March 2019-31st May 2019 (Spring 2019), and 27th March 2020-31st May 2020 (Spring 2020), the latter capturing the start and development of the UK lockdown period. This resulted in 43,186 complaints being analysed. Only for the analysis of the temporal variations in noise complaints, the periods considered range from 1st January to 31st May, both in 2019 and 2020, because of the need to detect potentially sudden changes (i.e., transitioning from a non-lockdown to a lockdown scenario).

5.3.3. Urban factors

To explore affecting urban factors causing the difference in noise complaints changing among London boroughs, housing, demographics, transport, and traffic noise level bands were discussed. Generally, (high) noise levels are expected to lead to increased noise complaints in any given area, therefore the possible influences of the exposure to road and rail traffic noise sources on the noise complaints change rate were explored. To test this, L_{den} values were extracted at a ward level from the noise pollution datasets obtained from the DEFRA (2018) for Greater London. The two indicators, namely road L_{den} and rail L_{den}, were selected as they are the main parameters represented in noise maps (Figures A-1 & A-2 in Appendix A). Using ArcGIS 10.3, L_{den} data at ward level was extracted and each ward was assigned a rank (0-5) automatically based on the percentage of its area covered by a certain noise level band (split by 5 dB). Amongst 383 wards covered by noise complaint data, 373 wards were covered by the road L_{den} data and 295 were covered by the rail L_{den} data. They received ranks from 0 to 2 for road and from 0 to 1 for rail noise, with rank 0 representing a ward ranked to a noise level band below 55 dB(A), and rank 2 representing a ward ranked in the noise level band of 60-64.9 dB(A) (Figures A-3 & A-4 in Appendix A). For instance, the ward of Barnsbury in the borough of Islington features a total area of 83 ha, with 7.1 ha (8.5%) of which is covered by data modelled for road L_{den} above 55 dB(A). The amount of area covered by each noise level band in Barnsbury is as follows: 3% in the 55-59.9 dB(A), 1.6% in the 60-64.9 dB(A), 1% in the 65-69.9 dB(A), 1.9% in the 70-74.9 dB(A), 1% in the area covered by the noise level band above 75 dB(A) and 91.5% of the area left uncovered by any noise level band, meaning the L_{den} exposure was modelled below 55 dB(A) for the most of the ward’s footprint. Therefore, Barnsbury was assigned the rank of 0 for road noise.

In addition, according to previous studies, the decrease in noise levels during the enforcement of lockdown measures varies in different types of areas (Aletta et al., 2020). However, the noise complaint or perception might be also affected by other factors like a number of urban planning parameters involving housing, demographic, and transport factors as mentioned in the introduction. Apart from considering factors mentioned above, the data availability is also considered when selecting the urban planning parameters. London Ward Profile is the main data source used, downloaded from the London Datastore (Greater London Authority, 2015). In this dataset, all the indicators have been aggregated to the ward level. For instance, the mean age is the average age for all residents in the ward; “cars per household” means the average number of cars per household in the Ward. Meanwhile, in this dataset, the tax band codes from A to H, were categorised into three groups (A or B; C, D or E; F, G or H) by Department for Communities and Local Government and indicate the tax rate from lowest to highest (UK Government, 2020). Finally, 18 indicators were selected and grouped into four categories - housing, demographics, transport, and noise level bands (detailed parameters are in Table 5.1).

It is worth noting that some urban factors show significant inter-correlations. Significant correlations exist both within and between categories, such as between qualification and household income. This multicollinearity should be paid attention to when building and selecting a regression model. However, as this chapter focuses on the correlation between each individual urban factor and noise complaints, rather than the inter-relationship between the factors this is not considered a primary concern. The coefficient values given are the Spearman correlation strength between noise complaint change rate and each individual urban factor.

5.3.4. Statistical analysis

In order to characterise how the noise complaints changed across the boroughs and wards investigated, the rate by which noise complaints changed from Spring 2019 to Spring 2020 was calculated. The equation for this change rate is shown as follows:

$$R = (N_{spring\ 2020} - N_{spring\ 2019})/N_{spring\ 2019} * 100 \quad (5.1)$$

where R is the change rate of noise complaints in percentage; $N_{spring\ 2019}$ is total number of noise complaints during spring 2019; $(N_{spring\ 2020}$ is total number of noise complaints during spring 2020. The results return to positive and negative values. Negative values mean the number of noise complaints decreased, while the positive values mean increase (Kenton & Mansa, 2020). The change rate of noise complaints in three wards were extremely high and identified as outliers, namely Gospel Oak and Highgate in the borough of Camden and Heathfield Ward in the borough of Richmond upon Thames. These were considered outliers due to their very low number of noise complaints in Spring 2019 (which may itself be an anomaly for year-over-year numbers in that borough), meaning a relatively small increase in absolute numbers of complaints results in a very high percentage change. They were not considered in further analyses.

The variables in this chapter are not normally distributed, according to the Shapiro-Wilk test (Ghasemi & Zahediasl, 2012; Yap & Sim, 2011). Therefore, Spearman correlation, which does not assume normal distributions, was applied to measure the correlations between the urban factors and noise complaints (Hauke & Kossowski, 2011). This process was conducted using SPSS software (version 25) (Landau & Everitt, 2003). The correlation analysis was conducted at ward level, as all indicators are available at ward level. Meanwhile, the Mann-Whitney U test, as a non-parametric test, was used to compare differences in the number of noise complaints between Spring 2020 and Spring 2019 for each borough and source breakdown individually.

5.4. Results

During the Spring 2020 lockdown period (27th March – 31st May), local authorities experienced a significant increase of noise complaints compared to the same time period in the previous year (p<0.001 via Mann-Whitney U test). In total during the lockdown, there were 25,740 noise complaints reported, with approximately 4.29 complaints per thousand people. During the same period in 2019, there were 17,446 and 2.97, respectively.

To investigate the effects of the containment measures on the amount of noise complaints received, the time series of total daily noise complaints for the first half-year of 2019 and 2020 is shown in Figure 5.2. To better demonstrate the general trends, a seven-day rolling average window is applied, accounting for observed weekly patterns in received noise complaints. In general, 2019 exhibits a relatively stationary pattern with small fluctuations above and below 250 daily noise complaints, showing no clear increasing or decreasing pattern during this period. Likewise, the pre-lockdown period of 2020 also exhibits a stationary trend with fluctuations around 250 daily noise complaints. However, shortly after the imposition of a national lockdown on 26th of March, there is a marked increase of the 2020 trend. Within two weeks the number of daily noise complaints has nearly doubled compared to the same time period in 2019 and continues to grow throughout the lockdown period.

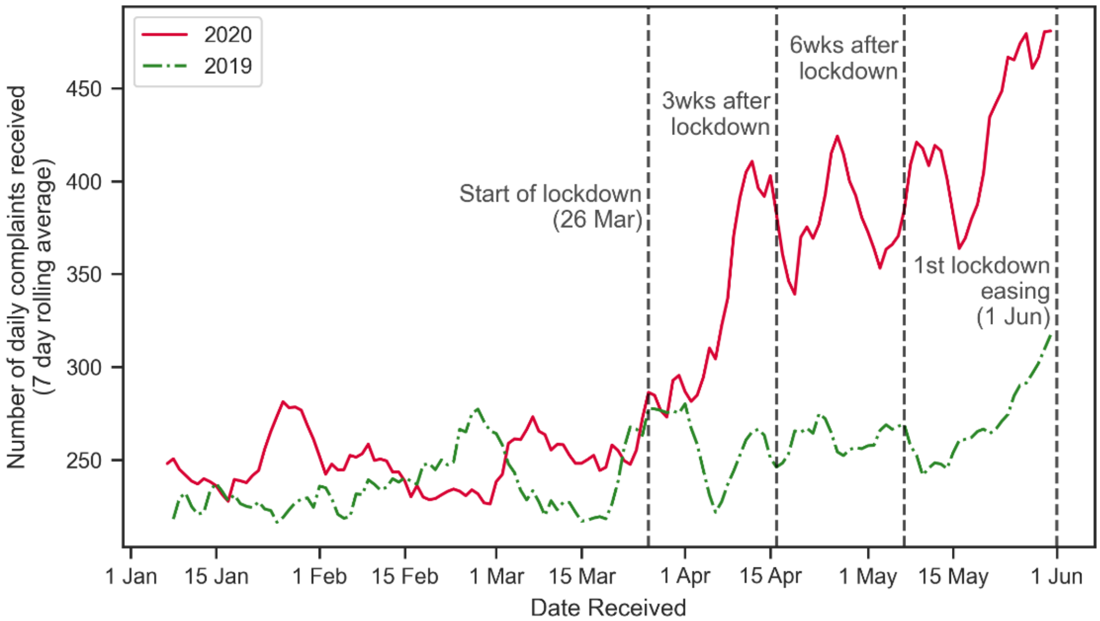


Figure 5.2 Time series of the number of noise complaints in the first half year in 2019 and 2020. A 7-day rolling average window is applied to account for weekly patterns in noise complaint reporting

In the month before the start of lockdown, local authorities received an average of 282 new complaints per day and 8,454 noise complaints in total. In the first month after the start of the lockdown, these numbers had increased significantly with 402 new cases every day and 12,071 reports in total, representing an increase of 42.55% for the whole of London. For the second month since enforcing lockdown, this rate of increase began to slow, with local authorities receiving 442 reports per day, an increase of 10% compared to the first month.

5.4.1. Variations in noise complaints at borough level

To explore more characteristics of the variation in noise complaints due to the implementation of lockdown measures among boroughs, the spatial distribution of the change rate of noise complaints during the lockdown compared with Spring 2019 was mapped, as shown in Figure 5.3. This figure shows the change rate of noise complaints between Spring 2020 and Spring 2019, by borough (the change rate of noise complaints at ward level is shown in Figure A-5 in Appendix A). In 21 of the 22 boroughs for which data of noise complaint were available, the rate of complaints increased during the lockdown. The increases were significant in 15 of the 21 boroughs (the details were shown in Table A-5 in Appendix A).

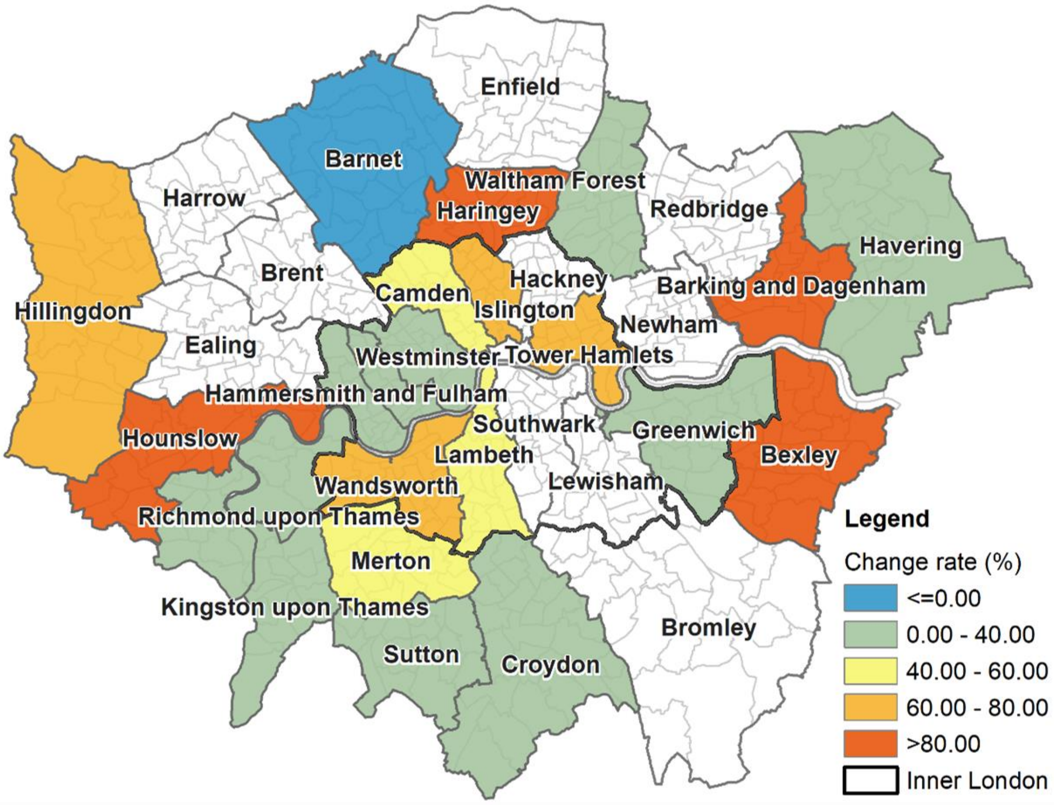


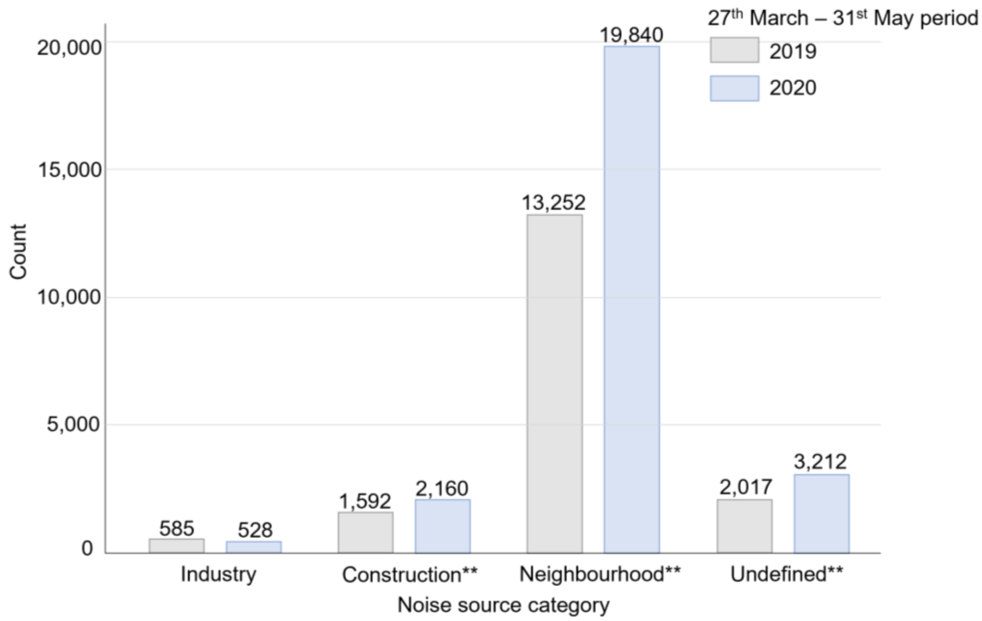
Figure 5.3 Change rate of noise complaints by boroughs

On the other hand, Haringey, which is adjacent to Barnet, has the highest increase in noise complaints (+175.36%), followed by Barking and Dagenham (+104.2%), Hounslow (+84.46%), and Bexley (+84.32%), all located in Outer London. Apart from Barnet, the lowest change rate was observed in Waltham Forest (+6.31%), followed by Kensington and Chelsea (+11.23%), Greenwich (+15.59%), and Croydon (+18.08%). The change rate was substantially lower across inner London (+38.67%) compared to outer London (+66.37%). Indeed, the difference in change rate is also more dramatic for the first month of the lockdown. Overall, it can be observed that the number of noise complaints increased significantly after the lockdown measures were implemented and the change rate of noise complaints was distributed unevenly across London.

5.4.2. Variation by types of noise complaints

In order to further investigate the driving factors in the general increase in noise complaints during the lockdown period, the data are analysed according to the type of noise complaints. Figure 5.4 shows the number of complaints received during the lockdown period and the same period in 2019, across all boroughs, for the four types of noise source (Industry, Construction, Neighbourhood, and Undefined). These categories were aggregated from the various tags provided by the borough data, as described in Section 5.3.1.

The most common noise complaints category in both 2020 and 2019 is Neighbourhood, followed by Undefined, then Construction and Industry. Interestingly, in this last category, which includes transportation noise, complaints remained at approximately the same level with only a slight decrease (ca. -9%), despite road traffic and other noise-generating industrial activities being dramatically reduced during the lockdown. Indeed, the decrease in Industry noise complaints did not show significance (p=0.126). All other categories reported significant increases: Construction (+36%), Neighbourhood +50%, Undefined +59% (p values<0.001 via Mann-Whitney U test).



* Difference is significant at the 0.05 level. ** Difference is significant at the 0.01 level.

Figure 5.4 Differences in the number of noise complaints between Spring 2019 and Spring 2020 by noise source category

5.4.3. The effect of urban factors on noise complaint increase

From the previous results (Figure 5.2), it can be concluded that the change rate of noise complaints varies across Greater London. Hence, urban planning factors such as housing, demographic, transport, and traffic noise level bands may be contributing factors to this variation. The Spearman correlation coefficients between these urban planning factors and the change rate across wards are shown in Table 5.1. Regarding housing factors, several significant relationships are revealed with noise complaints. Median house price and median household income, which reflect the economic status of the family, are negatively related to the change rate of noise complaints, with coefficient values of -0.108 and -0.140, respectively. This result means that the number of noise complaints in rich areas had increased less since the lockdown was enforced. As for property ownership, the change rate of noise complaints was positively related to the percentage of households that social rented. For instance, the noise complaints in Westbourne ward with a relatively high social rented housing rate (48.5%) has increased by 118%. Secondly, for the dwelling in council tax bands, bands C, D or E had positive relationships with noise complaints, while F, G or H were negatively related. No significant difference was found for bands A or B. Therefore, the results of dwellings in council tax bands further support, as previously mentioned, that noise complaints from residents living in expensive housing had increased less during the lockdown period. In a word, the noise complaints increased less in areas with a higher proportion of expensive houses.

Table 5.1 Spearman correlation coefficients between the change rate of noise complaints and urban planning factors

Factors	Indicators	Correlation coefficients
Housing	Median House Price (£)	-0.108*
	Median Household income estimate	-0.140**
	% Households Owned	-0.078
	% Households Social Rented	0.160**
	% Households Private Rented	-0.073
	% dwellings in council tax bands A or B	0.087
	% dwellings in council tax bands C, D or E	0.134**
	% dwellings in council tax bands F, G or H	-0.131*
Demographic	Population density	0.059
	Mean Age	-0.066
	Unemployment rate	0.114*
	% with no qualifications	0.129*
	Life Expectancy	-0.123*
	Subjective well-being average score	-0.016
Transport	Road density	-0.080
	Cars per household	-0.064
	Average Public Transport Accessibility score	-0.043
	% travel by bicycle to work	0.119*
Noise level band	Road L_{den} rank	-0.114*
	Rail L_{den} rank	0.006
	% in the highest noise level band (road L_{den}≥75dB(A))	-0.082
	% in the highest noise level band (rail L_{den}≥75dB(A))	-0.068

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

In terms of demographic factors, no significant relationships were found with population density, mean age, or subjective well-being average score. The change rate of noise complaints was positively related to unemployment rate, and the percentage of residents with no qualifications. In contrast, it is negatively related to life expectancy. For transport factors, no significant relationship was found with road density, cars per household, and average public transport accessibility score. Noise complaints were positively correlated with the percentage of residents who travel by bicycle to work.

In particular, it seems fair to assume that actual noise exposure should be an important factor causing noise complaints and negative noise perception; however, significant correlation (ρ=-0.114, p=0.05) was observed only between the noise complaint growth rate and road L_{den} noise level band. No statistically significant correlations were observed between the other data derived from noise level bands and complaints (Table 5.1). These findings indicate that no relationship between noise from road and noise complaints.

5.5. Discussions

This chapter investigated the variation of noise complaints in London during the COVID-19 lockdown period and tried to explore affecting factors causing the difference in noise complaints changing across London boroughs. Having so many people staying home because of the lockdown-related restrictions created unprecedented scenarios and forced people to adjust to their new surrounding (indoor) acoustic environment, raising questions on how they relate to it and to its sound sources (e.g., neighbours, construction noise, etc.). Recent literature on the topic is identifying some emerging trends. Lee and Jeong (2021) conducted an online survey about noise annoyance in London in May 2020, with 183 participants, before the lockdown eased. They reported that neighbour noise was more annoying than outdoor noises during the lockdown, suggesting that this type of noise source is more problematic than other typical sources of community noise, when considered in the context of an enforced “stay home” policy. This brought other researchers to question what the positive role of indoor soundscape could be to promote well-being in times of social distancing (Andargie et al., 2021; Dzhambov et al., 2021).

5.5.1. Changes in noise complaints by numbers, types and affecting factors

5.5.1.1 The number of noise complaints increase during lockdown

Overall, it can be observed that the number of noise complaints increased significantly after the lockdown measures were implemented, indicating that residents have been more annoyed with noise during the lockdown, hence the negative impact on psychology well-being could be more serious. This impact is not one-directional - the COVID-19 pandemic has caused a crucial effect psychologically, such as anxiety, depression, and annoyance as mentioned in the introduction. In turn, these negative psychological states could make residents more annoyed with noise and trigger them to report a noise complaint. On the other hand, during lockdown, more family members could stay in the house, hence more noise could be produced, particularly with children kept at home due to school closures. These results are in line with a previous study, where Miedema and Vos (1999) suggested that residents living in a large family are more annoyed by noise than residents living alone. However, during the lockdown period, noise-inducing human activities reduced dramatically, as did the traffic volumes. Therefore, the urban environmental noise levels decreased in several cities worldwide, as reported by studies on environmental noise levels during the COVID-19 lockdowns which show decreases in the 5-15 dB range (Arenas, 2020; Aletta et al., 2020; Asensio et al., 2020; Bartalucci et al., 2020). Thus, combining these results with the previous research, it can be pointed out that, noise complaints are not only driven by noise events, there should be other factors impacting the noise complaints/perception.

The 2020 lockdown has sparked further discussion on future patterns of people working from home for a higher percentage of time. The results of this chapter indicate that large proportions of the population permanently working from home could result in a considerable and lasting increase in noise disturbance, even as urban noise levels decrease. In new dwelling developments, sound insulation is more important and need to be increased, such as soundproof window and materials. However, it is unclear to what extent this effect would remain under a non-lockdown scenario when people have more options for managing and changing their environment.

5.5.1.2. Results from type of noise complaints

The increase in absolute numbers of complaints across London by type shows patterns that are expected when considering the experiences of people spending more time at home. The results seem to confirm that neighbourhood noise is the main trigger for complaints and the one that witnessed a dramatic increase during lockdown. This could be a direct consequence of people spending more time at home, thus being exposed to noises they would not normally experience if they were at the workplace. It is also likely that Neighbourhood noise sources are perceived as being closer and/or more easily identifiable (e.g., a neighbour, a domestic animal, catering premises, etc.), so that a complaint would be meaningful, as from the perspective of the person complaining it would be easier for a local authority to enforce compliance (compared, for instance, with road traffic noise from a highway). Indeed, neighbourhood is the most common noise complaints category in both 2020 and 2019. This result is in line with Section 4.3.1 which found that the proportion of residential/neighbourhood noise complaints was approximately 50% in NYC.

Construction noise complaints, which here include public works or perceived-to-be public works (i.e., excluding DIY and small construction/refurbishment noises coming from neighbouring flats), show a significant increase. The construction industry did not fully stop during the lockdown measures as UK Government policy was to assimilate it to “critical activities” and prioritize its re-start (Mayor of London, 2020). So, in a relatively quieter background noise (less traffic, fewer people on the streets, etc.) it is likely that construction noises became more salient also because of their spectral and temporal features (e.g., very different sound sources, unsteady, often impulsive noises, etc.).

In the Industry category (which included transportation noise sources) the slight, and possibly negligible decrease, in noise complaints contrasts with considerable decreases in traffic noise levels seen in other studies. In new dwelling developments, sound insulation is more important and need to be increased, such as soundproof window and materials. The lack of an observable impact of the lockdown measures and the low absolute numbers of transportation-related noise complaints compared to other categories, indicates that traffic noise is not a major driver of community noise complaints, when considering aggregated data at ward level or higher. This is further confirmed by the lack of any relationship between the relative level of traffic noise within a ward (as derived from the DEFRA noise map) and the change rate of noise complaints. However, this does not necessarily indicate a complete decoupling between traffic noise levels and complaints. It may be that transportation-related complaints are driven by cases and locations of extremely disturbing traffic noise (e.g., only at major intersections and exposure to major motorways). Aletta et al. (2020) showed that traffic-dominated locations in London (Camden Town and Euston Road intersection) experienced only a limited decrease in noise levels (4.5 dB, L_{Aeq}) during the lockdown period, which may not be enough to drive a noticeable decrease in noise complaints.

5.5.1.3. The effect of urban planning factors on noise complaint increase

By examining potential affecting factors on the change of noise complaints, (high) noise levels are expected to lead to increased noise complaints in any given area. However, the noise level (as characterised by noise bands derived from noise maps) did not show significant correlations with change rate of noise complaints. Especially, according to Aletta et al. (2020) during the lockdown, it is highly likely that the road L_{den} values across Greater London were lower than presented in the noise maps. The observed lack of correlation between the increase in noise complaints and the noise ranks assigned to wards could be explained by hypothesising that noise complaints are driven more by single noise events than the overall levels represented by $L_{den.}$

Furthermore, housing factors show a significant relationship with noise complaints. The result that noise complaints increased less in the area with expensive houses could be explained that the expensive houses could have more bedrooms and yards. Hence, the residents are able to choose a quiet room to stay and the green space in the yard could reduce noise annoyance (Bodin et al., 2015). As for property ownership, in this chapter, the change rate of noise complaints was positively related to the percentage of households that social rented. This result contradicts Nieuwenhuis et al. (2013), who proposed that ownership is not correlated to neighbour complaints. However, it is supported by other previous studies. For instance, Gillen and Levesque (1994) suggested complaint probabilities appear to be higher in the areas with high tenancy rate. Michaud et al. (2016) also indicated that ownership can contribute to differences in high noise annoyance. Indeed, housing policy and target are a key difference between inner and outer London (Butler et al., 2008). For instance, density of dwellings in outer London (16.3 per hectare) is lower than in inner London (46.7 per hectare) (the detailed density of dwellings was shown in Table C-2 in Appendix C). These results could support the finding that the change rate of noise complaints was distributed unevenly in London; in detail, the four boroughs with the highest change rates were located in outer London area. This difference could be correlated with the base value before the lockdown. Boroughs in inner London have relatively high number of noise complaints in Spring 2019, which means an increase in absolute numbers of complaints results in a relatively low percentage change. In addition, the high complaint levels of inner London in 2019 could be explained by the density and diversity. Legewie and Schaeffer (2016) found that residents living between racial enclaves tend to complain more about noise than those who live within clearly defined racial boundaries. Nieuwenhuis et al. (2013) also indicated religious diversity lead to a higher likelihood for negative relationships between neighbours. In addition, during normal periods, high density areas have more noise complaints or higher noise annoyance level (Liu et al., 2019; Zheng et al., 2014). Compared with previous study findings, this chapter found that the effect of several urban planning factors on change rate of noise complaints during lockdown is different from its effect on noise complaint/annoyance at normal times. For instance, normally population density and road density have strong positive correlations with the rate of noise complaints, as showing in Section 4.3.2. While population density didn’t prove to be a significant factor, another explanation behind this phenomenon might simply be the number of residents who were spending more of their time in their homes during the lockdown, as outer London has higher population than the inner. In terms of the positive correlations between noise complaints and the percentage of residents who travel by bicycle to work, it could be explained that cyclists are especially strongly exposed to noise in urban environments, particularly because of their proximity to road traffic (Jérémy & Apparicio, 2019). From a demographic perspective, the positive relationships between residents with no qualification and the change rate of noise complaint rate is supported by Gillen and Levesque (1994), who found that areas with high education level are less likely to exhibit complaint activity. Indeed, the results from the housing and demographic factors are consistent; higher unemployment rate and low qualification are always related to low quality of house and income. All these factors are likely to increase the change rate of noise complaints. This finding is also in line with the other chapter (see Section 6.3.2); in normal time, cities with higher unemployment rates are also likely to receive more noise complaints.

Overall, it can be concluded that in such extraordinary circumstances, such as a nation-wide lockdown, contextual urban factors proved to be more significant for the increase in noise complaints than the actual noise exposure to road and rail traffic noise. Even though the noise level decreased during lockdown, the number of noise complaints increased significantly. It is expected that the findings can inform policymakers from the perspective of acoustic impacts and urban factors, allocating resources more effectively and leading to noise management strategies during the lockdown. For instance, a number of actions have been carried out to prevent noise pollution from road noise, such as noise barriers and noise level limitations for trucks. However, from the finding of housing factors impacting on noise complaints, the noise abatement for housing which focus on more than road noise and simultaneously prevent transfer from out-to-in could be paid more attention, such as the use of sustainable sound absorbing material. During the lockdown, the house is the main place where residents live, work and sleep, and it appears that increased working from home will continue to be a trend in the future. Therefore, the home environment will likely play an increasingly important role in human wellbeing. From previous studies, green spaces have been proven to have relationships with noise perception, applying an absorption or scattering effect on noise propagation and influencing individual perception of noise (Hao et al., 2015; Margaritis & Kang, 2017). From an urban planning perspective, the accessibility and visibility of green space from houses could be emphasised, such as utilising fragmented parks/yards.

5.5.2. Limitations of the study

The first aspect to consider is certainly related to the noise complaints dataset. The goal was to provide an overview for the Greater London area, by aggregating data from its boroughs since they are the local authorities responsible for handling such complaints. However, there could be some inconsistencies and/or deviations due to how single boroughs gather and process noise complaints records. For instance, sudden peaks or lows in numbers of complaints may be due to how easy (or difficult) it is to approach the local authority (e.g., via an app, a dedicated telephone line, etc.). The pandemic itself is likely to have affected the borough environmental departments' operations and ability to react to complaints (e.g., reduced staffing, increased remote working, etc.). Taking the Borough of Barnet as an example, where a 21% decrease in noise complaints rate was observed between 2019 and 2020, the information provided on its website states that during the lockdown "The council will continue to run a Noise Line Service, but with a reduced response capacity. You can still call to report ongoing noise by calling [telephone number]" (Barnet Council, 2021). Information is not explicitly available on this matter for all boroughs, but it is fair to assume similar circumstances apply. On the other hand, in boroughs where particularly high increase rates were observed, it could be that complaints could be filed via different channels (thus streamlining the process for the user), like in the case of Haringey, which accepted complaints both online and via telephone (Haringey Council, 2021; Havering Council, 2021). While this is certainly a possible limitation, this chapter considers that, in the aggregate, such issues are averaged out and the trends are observed are still representative of the 2019-2020 variations.

Related to this, it is the fact that this analysis is based on a comparison to only one year of past data. It is therefore potentially impacted by anomalous or random fluctuations in the noise complaints received during the investigated period in 2019. This, as well as year-to-year changes in boroughs' complaint collection methods, could be addressed in future studies by comparing to an average of multiple years of previous noise complaint data. This issue is also common to other studies being conducted on similar topics, but different context. For instance, Yildirim and Arefi (2021) compared the noise complaints in Dallas (US) after the COVID-19 outbreak, from March to December 2020 and the same period in 2019. The authors in this case surprisingly observed reduced noise complaints during the COVID-19 period by about 14% compared to the pre-COVID-19 period. It seems reasonable to assume that there could be a lag to the effect that lockdown policies have on noise complaints, and this lag time can be difficult to distinguish from normal levels of week-to-week variations. In the Dallas case, it appears there was not enough time for the lockdown effect to show up, at least when compared to 2019 levels alone, before regulations were changing again. Thus, it is generally difficult to observe these patterns with such recent data, yet it is worth to extract preliminary information to inform possible future policies.

The analysis is of course affected by the categorisation of noise complaints performed in Section 5.3.1. While this chapter tried to adhere to the framework provided by the WHO about community noise to define the categories in this chapter, there is still Undefined category showing the highest increase proportionally, and, in absolute numbers, being larger than two other categories (i.e., Industry and Construction). During the categorisation it was not possible to allocate these items with certainty to any other category; many occurrences refer to complaints where the type was inputted manually as a free-text by the complainants and the label was too generic (e.g., “noise” or “other noise”). Following a statistical approach, the Undefined complaints could be allocated either proportionally or evenly to the remaining three categories. In both cases, this would not change the patterns which have been observed, so it is considered as a minor methodological limitation.

For the other data types (i.e., non-noise complaint data), this chapter only considered basic housing, demographic, and transportation factors. Therefore, if datasets are available, it would be useful to consider more urban pattern indicators which is explored in Chapter 7 (Part II). In addition, the sampling strategy at the ward level resulted in the low effect of the highest noise level bands on the analyses as most of the wards were ranked in the low bands. The ward area covered in the noise level band above 75 dB(A) is typically below 1% and the ward coverage of the noise map data (above 55 dB(A)) for road L_{den} is typically below 50% and 30% for rail noise. Hence, no ward received a rank above 2. This approach was used as it was not possible to acquire the representative number of noise complaints at a level more detailed than a ward.

5.6. Conclusions

Taking Greater London as a case study, this chapter investigated the change of noise complaints in terms of their spatial and temporal distributions in London during the lockdown period and tried to explore affecting factors causing the difference in noise complaints changing across London boroughs. The results are shown as following:

(1) During the COVID-19 lockdown the number of noise complaints increased significantly after the lockdown was implemented, with an overall increase of 47.54%. This change rate of noise complaints was distributed unevenly across the Greater London area, with the top four boroughs with the highest change rates located in outer London. Outer London in general experienced a higher change rate compared to inner London.

(2) In terms of noise sources, complaints about construction and neighbourhood reported significant increases, with the values of 36% and 50%, respectively.

(3) Finally, the change rate of noise complaints is higher in areas with higher unemployment rates, more residents with no qualifications, and low house price. Meanwhile, no significant difference in the change rate was observed across traffic and rail noise level bands as derived from the DEFRA noise map. It can be inferred that in such extraordinary circumstances, such as a nation-wide lockdown, contextual urban factors proved to be more significant for the increase in noise complaints than the actual noise exposure to road and rail traffic noise.

While this chapter has focused on the first lockdown in Spring 2020, at the time of writing the pandemic (unfortunately) continues, and lockdown measures are still being frequently enforced. This work provided a cross-sectional dataset, but it would be interesting to examine the effect of longer-term lockdown policy on noise complaints. Meanwhile, to get a comprehensive picture of environmental noise complaints, other types of complaints such as odours, air pollution, and dust, as well as inter-relationships among them need to be further investigated. In addition, the specific lockdown measures vary from country to country, so it would be worth comparing noise complaint variations across regions, if the data is available.

Despite the contingent lockdown measures, the dramatic events of 2020 did change the way people look at “working from home”, probably for good, and it is likely this will become an increasingly common practice in the future. Noise complaints (and particularly from neighbourhood sources) will then be an even more crucial factor in the context of public health and human well-being. It is expected that this chapter could inform government about the pattern of noise complaints and help with allocating resources more effectively and achieve a better urban environment.

PART II

REGIONAL/MESO SCALE STUDIES

Following the city/micro studies, studies in this part, namely Part II (Chapters 6 and 7), moves this thesis forward to larger-scale studies (i.e. regional/meso scale studies). These studies discuss noise complaints with broader coverage. In the city/micro studies, some urban factors are found to be related to noise complaints. In this part, more comprehensive urban planning parameters are examined as opposed to considering variations in different periods. In total, 150 indicators, which describe almost all aspects of a city, are examined. These indicators are categorised into socio-economic factors and urban development patterns, which are investigated in Chapters 6 and 7, respectively. These chapters follow the same structure and apply the same methods.

Chapter 6

Relationships between noise complaints and socio-economic factors in England[1]

Socio-economic conditions are the fundamental characteristics of a city. Therefore, this chapter aims to examine the relationships between noise complaints and socio-economic factors. First, Section 6.1 gives a brief overview of the recent research on sound environment and socio-economic factors. Then, Section 6.2 illustrates the specific methods by which the research and analyses are conducted, including the Spearman correlation and ridge regression. Next, Section 6.3 presents and discusses the results of this chapter. Finally, Section 6.4 concludes this chapter, highlights the implications of the findings, and identifies areas for further research.

6.1. Introduction

Acoustic environmental quality has become a critical factor for improving urban sustainability. Noise has significant negative impacts on health and well-being which is one of the essential goals for developing sustainable cities (European Commission, 2020; United Nations, 2020; Yuan et al, 2019). The effects of

[1] This chapter was partially published as: Tong, H., & Kang, J. (2021b). Relationships between noise complaints and socio-economic factors in England. Sustainable Cities and Society, 65, 102573. In order to have a better narrativity, the structure of this chapter follows that of the published paper and the title of this chapter is also kept the same. No attempt has been made to rewrite, apart from changes in format of the figures and tables to correspond to other chapters.

noise involve sleep disorder, loss of hearing, cardiovascular disease, and other physiological disease (Moudon, 2009; Münzel et al., 2018). Apart from that, noise is also a primary contributor to psychological issues, such as stress, anxiety, and depression (Dzhambov & Dimitrova, 2016a; Ouis, 2001). In Europe, environmental noise is estimated to cause more than 10,000 premature deaths per year (European Commission, 2020). To reduce the impact of noise, a series of policies and actions have been carried out, such as END in Europe (European Union, 2002), Planning Policy Guidance 24: planning and noise in the UK (Adams et al., 2006), Noise Regulation Law in Japan (Ministry of the Environment, 2000), and Environmental Protection Act in Canada (Government of Canada, 2019). Among these, legislation regarding complaints is an important part. Among environment-related neighbour complaints, the volume of complaints about noise is the greatest. Complaining about noise is a behaviour based on residents' annoyance with noise.

A number of studies have examined the link of noise annoyance to physical characteristics of sound and socio-economic factors. From the physical characteristics of sound perspective, residents are annoyed with a series of noise sources, such as traffic and construction (Brambilla et al., 2017; Zambon et al., 2020). In the last decade, wind turbine noise annoyance has received increased research attention as installed global wind power increasing (Janssen at al., 2011; Fredianelli et al., 2019; Licitra & Fredianelli, 2013; Pedersen & Persson Waye, 2004). Apart from noise source, other acoustic indices, such as sound pressure level, Intermittency Ratio and Harmonica index, also have significant impacts on annoyance (Praščević et al., 2017; Wunderli et al., 2016). For instance, the intermittency ratio is explored to describe the urban road traffic noise which is strongly related to annoyance (Brambilla et al., 2019; Brambilla et al., 2020).

Noise annoyance is not only related to physical characteristics of noise but also socio-economic factors. This point has been examined by a considerable amount of research through small-scale investigations, such as at locations of traffic infrastructure and in parks. For railway, the effects of socio-economic factors on annoyance from railway have been widely discussed (Lim et al., 2006; Licitra et al., 2016; Pennig et al., 2012). For instance, Licitra et al. (2016) conducted a long-term survey involving demographic factors of participants when evaluating annoyance due to overall railway noise and vibration in Pisa urban areas. Using a combined questionnaire and noise measurement survey in Great Britain, Fields and Walker (1982) conducted research to examine the impact of about 35 demographic factors on annoyance arising from railway noise. The results show that there are significant relationships between noise annoyance and older dwellings, older respondents, and life-time residents. Apart from railway noise, several studies investigated annoyance from road noise in terms of demographics, residential satisfaction, and other socio-economic factors (Bolte et al., 2009; Miedema & Vos, 1999; Urban & Máca, 2013). Other research analysed the impact of personal factors and noise level on annoyance near airports (Babisch et al., 2009; Bröer, 2007; Licitra et al., 2014; Lim et al., 2008; Rylander et al., 1972; Vogiatzis & Remy, 2015). In addition, Fields (1993) investigated the effect of demographic and situational variables on noise annoyance in residential areas. The results showed that, in this case, demographic factors including age, gender, income, socio-economic status, education, homeownership, and type of dwelling have weak relationships with noise annoyance. Yu and Kang (2008) and Rey Gozalo et al. (2018) focused on subjective evaluations of the sound level in an urban open space. Aletta et al. (2018) analysed the effect of demographic factors on sound perception using a case study of a cycling path. A range of correlations have been revealed through such small-scale research.

Although the relationships between socio-economic factors and noise annoyance have been investigated, the relationships between socio-economic factors and noise complaints have not been adequately explored, especially on a larger scale. Kang (2006) stated that noise complaints are strongly related to noise annoyance and indicate the areas where residents are highly annoyed with noise, when he analysed noise standards and regulations in Europe. Furthermore, Legewie & Schaeffer (2016) found that the relationships between ethno-racial diversity in a neighbourhood and the number of noise complaints calls was significant. Méndez and Otero (2018) investigated the complex relationships between social inequality and urban conflicts, involving annoying noise, use of parking lots, and other conflicts, in Santiago, Chile. The results showed that the conflicts between neighbours are not only related to individual socio-economic circumstances, it suggested that they form a part of a common framework of intersectional vulnerabilities. Liu et al. (2019) mapped the spatial distribution of each complaint type (including noise-related complaints) across 218 suburbs in Brisbane, Australia, and stated as a limitation of their work that the relationships between neighbour complaints and socio-economic characteristics had not been examined.

Therefore, the aim of this chapter is to examine the relationships between various socio-economic factors and the rate of noise complaints. Based on the literature review and data availability, in this chapter, socio-economic factors are categorised into four groups: demographic, job-related, property, and deprivation factors. This chapter uses noise complaints and socio-economic datasets from the governmental open data sources at the district and unitary authority levels across England. While acknowledging that this chapter focuses on the relationships between noise complaints and socio-economic factors, rather than causality, its results are expected to provide a fundamental understanding of such relationships and their strengths, which is helpful in forming effective noise management strategies.

6.2. Methods

6.2.1. Geographic samples

In England, there are different levels of geographical units, such as local authorities, output areas, and postcode areas. However, in terms of noise complaint data, only local authority levels are available, namely county and unitary, and district and unitary, as shown in Figure 6.1. To obtain a larger sample size, the district and unitary authority levels were selected for analysis. The term of “city”, as a strategic and political level of administration and policy making, is used to refer to district and unitary authorities. With the aim to analyse at city level, this chapter took cities as the analysis objects, with a total of 325 samples (excluding the Isles of Scilly as noise complaint data is not available).

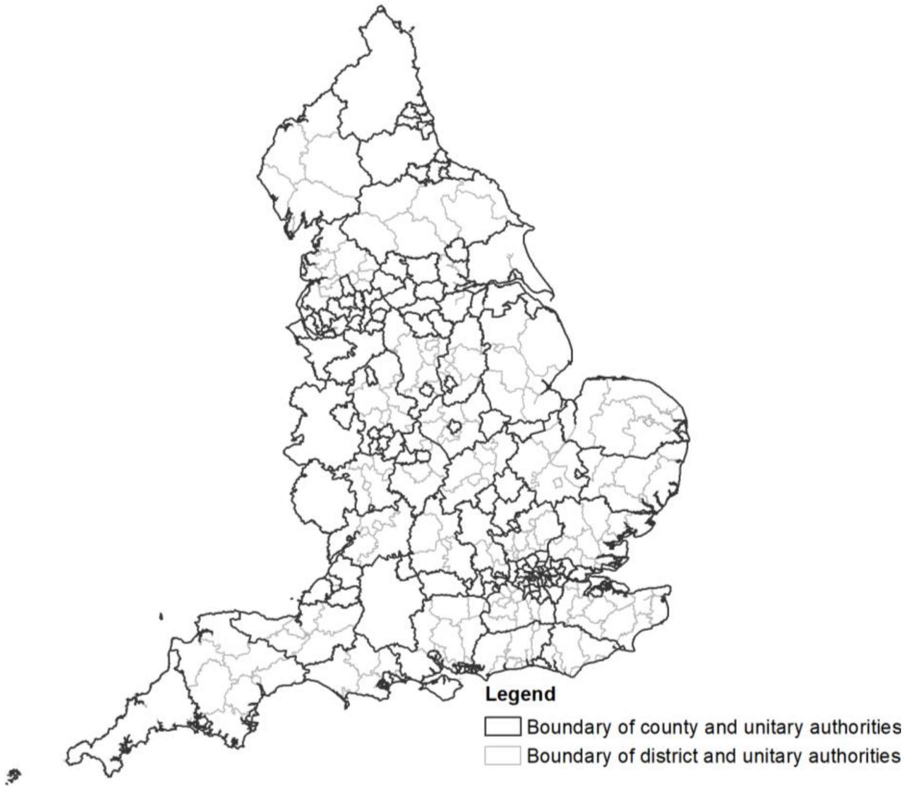


Figure 6.1 The boundary of local authorities in England

6.2.2. Noise complaint dataset

The reporting of noise complaints is carried out in England as a part of environmental legislation in the context of government policy on sustainable development (Public Health England, 2018). Reporting a noise complaint is a direct action that residents can take when they are affected by environmental noise, such as road and railway noise, and the complaint is reported to their local authority. Thereafter, the data at city level are recorded and released by the local authority. Since the decision to complain is an individual choice, the value of the noise complaint rate for cities cannot be treated as the effect of noise, as not all residents complain. However, this indicator provides a reflection of how many people feel sufficiently affected by noise to cause them to report it (Public Health England, 2018). The noise complaint data can be downloaded from Public Health England, which is an executive agency of the Department of Health and Social Care. Rate and number are the indexes included in the noise complaint dataset.

The rate of noise complaint data was selected to conduct the correlation analysis, with the aim of comparing a large number of cities across various scales. The rates are calculated using the number of complaints, which is collated by the Chartered Institute of Environmental Health, divided by population. The latter value is based on the relevant reference year and mid-year population estimates, multiplied by a factor of 1,000 (Public Health England, 2018). Data on noise complaint rates are available from 2010 to 2015. As the census of 2011 has the most recent and detailed socio-economic dataset, the 2011 rate of noise complaints was selected for the statistical analysis. Overall, there were 399,112 noise complaints reported across all cities in England in 2011. The average number of noise complaints for each city in that year was 1,228, and the average rate was 6.7 per thousand people per city (Figure 6.2). These noise complaints have been aggregated into 325 cities, which are samples in this chapter.

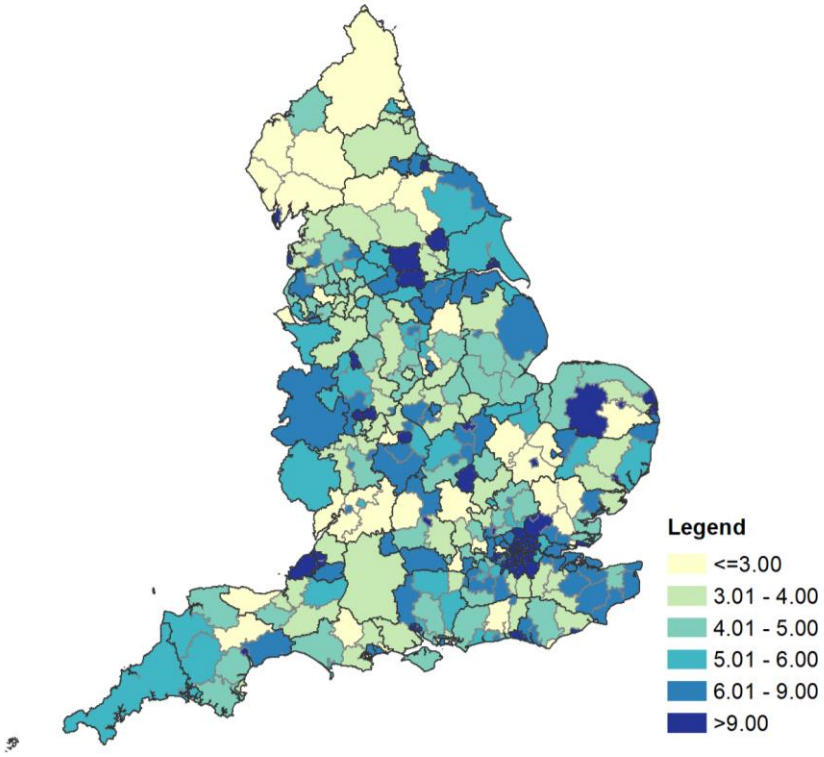


Figure 6.2 The spatial distribution of noise complaint rate for 2011 in England

6.2.3. Socio-economic factors dataset

As previous studies argue, there is a wide range of socio-economic factors that can have an impact on sound environment evaluation. On the basis of the literature review and data availability, 76 factors were selected to conduct the correlation analysis. They were categorised into four groups: demographic, job-related, property, and deprivation factors. The detailed factors are shown in Table 6.1.

Table 6.1 Indicators of socio-economic factors.

Factors' category	Indicators	Variables	Regression coefficient	Code
Demographic factors	Population	Population density	0.008**	A1
	Age	Mean age	-0.025**	A2
		Median age	-0.015**	A3
		The percentage of underage people	-0.007	A4
		The percentage of young people	0.020**	A5
		The percentage of old people	-0.015**	A6
	Sex	Males	-0.014	A7
		Females	0.014	A8
	Marital status	Singe	0.014**	A9
		Married	-0.018**	A10
	Qualification	No qualifications	-0.002	A11

		Level 1 qualifications	-0.017	A12
		Level 2 qualifications	-0.039**	A13
		Apprenticeship	-0.073**	A14
		Level 3 qualifications	-0.044*	A15
		Level 4 qualifications and above	0.003	A16
		Other qualifications	0.062**	A17
	Health	Good	0.002	A18
		Fair	-0.013	A19
		Bad	0.016	A20
		Day-to-day activities limited (all residents)	-0.009*	A21
		Day-to-day activities limited (workers)	0.016	A22
		Provides no unpaid care	0.079**	A23
		Provides 50 or more hours unpaid care a week	-0.051	A24
	Religious diversity	Religious diversity	0.371**	A25
	Ethnic diversity	Ethnic diversity	0.816**	A26
Job-related factors	Economic activity	Part-time	-0.039**	A27
		Full-time	-0.006	A28
		Self-employed	0.001	A29
		Unemployed	0.067**	A30
		Unemployed male	-0.021**	A31
		Unemployed female	0.022**	A32
		Retired	0.079**	A33
		Student	0.021	A34
		Looking after home or family	0.186**	A35
		Long-term sick or disabled	0.041**	A36
		Other	0.111**	A37
	Hours worked	Less than 15	-0.014	A38
		16 to 30	-0.016	A39
		31 to 48	-0.014*	A40
		More than 49	0.021**	A41
	Occupation	Managers, directors and senior officials	0.013	A42
		Professional occupations	0.000	A43
		Associate professional and technical occupations	0.026**	A44
		Administrative and secretarial occupations	-0.028	A45
		Skilled trades occupations	-0.019*	A46
		Caring, leisure and other service occupations	-0.032	A47
		Sales and customer service occupations	-0.013	A48
		Process plant and machine operatives	-0.014	A49
		Elementary occupations	0.018*	A50
Property factors	Accommodation size and central heating	Average number of rooms per household	-0.235**	A51
		Average number of bedrooms per household	-0.540**	A52
		Central heating	-0.026	A53
	Car or van availability	No car or van	0.012**	A54

		The average number of cars or vans	-0.004**	A55
	Accommodation type	Whole house or bungalow	-0.011**	A56
		Whole house or bungalow: detached	-0.004**	A57
		Whole house or bungalow: semi-detached	-0.018**	A58
		Whole house or bungalow: terraced	0.000	A59
		Flat, maisonette or apartment	0.011**	A60
		Flat, maisonette or apartment: purpose-built block of flats or tenement	0.013**	A61
		Flat, maisonette or apartment: part of a converted or shared house	0.048**	A62
		Flat, maisonette or apartment: in a commercial building	0.028	A63
		Caravan or other mobile or temporary structure	-0.013	A64
	Accommodation tenure	Owned	-0.014**	A65
		Shared ownership	0.088	A66
		Social rented	0.020**	A67
		Private rented	0.022**	A68
		Rent free	-0.021	A69
Deprivation factors	Deprivation factors	Total deprivation index	-0.001**	A70
		Barriers to housing and services	-0.001*	A71
		Crime	-0.001**	A72
		Employment	0.000**	A73
		Health	0.000	A74
		Living environment	-0.001*	A75
		Income	-0.001**	A76

*Coefficients are significant at the 0.05 level. ** Coefficients are significant at the 0.01 level.

The main open database, used in this chapter, is Census 2011. The census is a comprehensive investigation, which includes detailed information for each person and Census 2011 is the most recent version published by the Office of National Statistics and taken in March 2011 (Office of National Statistics, 2016). All socio-economic factors were extracted from Census 2011, except the Index of Multiple Deprivation (IMD). IMD, as the official measure of relative deprivation for areas in England, is produced by Department for Communities and Local Government. It is common to describe how relatively deprived a small area is. The IMD ranks every city in England from 1 (most deprived area) to 326 (least deprived area). Detailed values are available only for 2010 and 2015 (Department for Communities & Local Government, 2015). Because there are very strong relationships between IMD 2010 and IMD 2015, the IMD Rank 2010 has been selected for correlation analysis, along with the noise complaints data from 2011. Additionally, a similar result is shown after correlation analysis between IMD 2015 and noise complaints in 2015. The result, using IMD 2010 and noise complaints in 2011, is presented in this paper in order to match other parts of this chapter.

In terms of ethnicity and religion for cities, the diversity is calculated using Simpson's Diversity Index, which is universally accepted (Gorelick, 2006; Lande, 1996). The formula is:

$$D = \sum_{i=1}^{S} \left(\frac{N_i}{N}\right)^2 \tag{6.1}$$

where D is Simpson's Diversity Index; N_i is the population by ethnicity or religion i. Religions comprise Christianity, Buddhism, Hinduism, Judaism, Islam, Sikhism, and Other. Ethnic groups comprise White, Mixed/Multiple, Asian/Asian British, Black/African/Caribbean/Black British, and Other. N is the total population. S is the number of ethnicity or religion.

It should be noted that significant correlations are also found between socio-economic factors. For instance, the percentage of old people is related to sex. However, as this chapter focuses on the impact of individual socio-economic factors on noise complaints, rather than the inter-relationship between the factors. Principle Component Analysis (PCA), as a popular multivariate statistical technique, was provided to get an overall for correlations among variables, and to exact principle component which can partly explain the variance (Abdi & Williams, 2010). Overall, a number of significant inherent correlations exists among the variables. Table for total variance explained, and component matrix were obtained from PCA (Tables C-3 and C-4 in Appendix C). With the principle components exacted from PCA, the top three components can explain the 72 % of the variance. From the component matrix, it can be summarised that Component 1, describing 35.98 % of the data variability, is relatively strongly associated with demographic factors. Component 2, describing 26.90 % of the data variability, can be associated with job-related factors, whereas Component 3, describing 9.13 % of the data variability, which can be associated with property factors. These results support the categories of socio-economic variables as mentioned above, to some extent. Apart from these three components/categories, deprivation factors, as a synthetic indicator, were presented as an individual category and give an overall assessment of the impact of socio-economic situation on noise complaints.

6.2.4. Statistical analysis

To compare cities across various scales, all other indicators are presented by percentage, such as the percentage of females, excluding deprivation factors, which are shown as rank, mean age, median age, car or van availability, and religious and ethnic diversity. In this chapter, Shapiro-Wilk test was used to check normality (Ghasemi & Zahediasl, 2012; Yap & Sim, 2011). For 76 socio-economic variables, only 8 variables are normally distributed (Table C-5 in Appendix C). In particular, the key indicator, noise complaint rate, does not follow a normal distribution. Therefore, Spearman correlation, as a nonparametric test, was applied to measure the relationships between two variables since it does not make any assumption about the distribution of the variables (Hauke & Kossowski, 2011). The process was conducted using SPSS (Landau & Everitt, 2003). Spearman correlation coefficient is interpreted based on the standard published by Quinnipiac University (Akoglu, 2018).

In terms of multivariable analysis, considering sample size, unknown causality, and multicollinearity between variables, a ridge regression model was applied to predict the rate of noise complaints. Ridge regression is a technique for analysing multiple regression data. Compared with regular multiple regression, it is an improved regression model that is useful for dealing with the problem of multicollinearity by adding a degree of bias (Hoerl & Kennard, 1970; Khalaf & Shukur, 2005; Marquaridt, 1970). In addition, compared to other modelling methods, this model is analytical with the explanatory contribution of each variable. Hence, it is helpful for the government organisations prioritising resources to dealing with noise pollution in terms of the socio-economical aspect. The core idea of ridge regression is to add a degree bias λ to the regression estimates for reducing the standard errors. In the modelling process, a five-fold cross-validation is used to determine the value of λ. Specifically, all samples are divided into the training set (80%) and test set (20%) randomly. The training set is used to generate the model, while the test data is to predict the errors of the model. Finally, a value is obtained to indicate the model error. The whole process is achieved via the package of the R language (Friedman et al., 2010; Hastie & Efron, 2011; Khalaf & Shukur, 2005; Simon et al., 2011).

The whole process can be easily realised via the package of the R language (Friedman et al., 2010; Hastie & Efron, 2011; Khalaf & Shukur, 2005; Simon et al., 2011). The results are primarily presented in Table 6.1 and further analysed in Results and discussion section.

6.3. Results and discussions

6.3.1. Demographic factors

The correlation analysis results of noise complaint rate with population density, age composition, and sex are shown in Table 6.2. Overall, population density is positively related to rate of noise complaints, with coefficient value of 0.489. The rate of noise complaints has relatively strong negative correlations with mean and median age, with coefficients of about -0.5. When residents' ages are grouped into three categories, the percentage of underage and young people for cities show positive relationships with noise complaints, with 0.144 and 0.470 as the correlation coefficients, respectively. Old people have a similar correlation coefficient level as young people, but show a negative relationship. The results might be because young people are the primary work force in urban developments. The high percentage of young people implies that the city is productive and prone to noise. Another possible explanation is that old people prefer to live in a relatively quiet city (Yu & Kang, 2014).

Table 6.2 Correlation coefficients of noise complaint rate with population density, resident age and sex

Indicators for population density, resident age and sex	Coefficients
Population density	0.489**
Mean age	-0.497**
Median age	-0.508**
The percentage of underage people	0.144**
The percentage of young people	0.470**
The percentage of older people	-0.478**
The percentage of males	0.146**
The percentage of females	-0.146**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Apart from age, sex is another basic demographic variable (Table 6.2). The results indicate that noise complaints have a positive relationship with the proportion of males, indicating that a city with a higher proportion of males tends to receive more noise complaints. However, the effect of sex composition of cities on noise complaints has low coefficient values, which reflects the results of previous studies that show that the impact of sex on noise perception is unimportant, to a certain degree (Fields, 1993; Tonin, 1996).

In terms of marital status, a strong positive relationship is found between noise complaints and the proportion of single residents, with a higher coefficient value at 0.529 at a 0.01 significance level, and an adverse relationship with married residents, with a similar coefficient value. Thereby, cities with a higher proportion of couples tend to receive fewer noise reports. It is noteworthy that in terms of noise annoyance, these are controversial results. Miedema and Vos (1999) suggested that residents living in a large family are more annoyed by noise than residents living alone.

Significant correlations are found between residents' highest level of qualification and noise complaints, as shown in Table 6.3. The percentage of residents with either Level 2 qualifications or an apprenticeship present negative relationship, with coefficient values of -0.221 and -0.308. The percentage of residents with other qualifications have positive relationships with noise complaints, with coefficient values of 0.508. Thus, the cities with a higher percentage of residents with a lower education tend to receive less noise nuisance reports.

Table 6.3 Correlation coefficients between the percentage of residents with various qualification levels and the rate of noise complaints

Qualification levels	Coefficients
No qualifications	-0.003
Level 1 qualifications	-0.012
Level 2 qualifications	-0. 221**
Apprenticeship	-0.308**
Level 3 qualifications	-0.101
Level 4 qualifications and above	0.050
Other qualifications	0.508**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

The impact of sound environment on health problems has been intensively investigated (e.g., Dzhambov & Dimitrova, 2016b; Sato et al., 1999; Schreckenberg et al., 2010; Welch et al., 2013; Wothge et al., 2017). There are three indicators of health: general health, long-term health problems or disability, and provision of unpaid care. The relationships among noise complaints and these indicators are shown in Table 6.4. General health is a self-assessment of a person's general state of health (University of Durham, 2018a). No significant correlation is seen in terms of the percentage of residents with a good health condition. The percentage of residents with fair health is negatively related to noise complaints, with a coefficient value of -0.117. Bad health problems show a positive relationship. Noise complaints have a negative relationship with the proportion of residents with a limiting long-term illness, and they have a positive relationship with working residents with a limiting long-term illness. One of the possible explanations for the reverse relationship might be that long-term health problems or disability includes problems that are related to old age. As previously mentioned, the results reinforce the idea that the percentage of old people has a negative correlation with noise. In terms of provision of unpaid care, noise complaints positively relate to the percentage of residents who provide no unpaid care, with a coefficient value of 0.387. No statistically significant correlation is observed between the percentage of residents who provide 50 or more hours of unpaid care a week and noise complaint rates. It is difficult to explain the relationships between health and noise complaints as health is affected by multiple factors.

Table 6.4 Correlation coefficients between health factors and the rate of noise complaints

Health factors		Coefficients
General Health	Good	0.030
	Fair	-0.117*
	Bad	0.128*
Long-term health problem or disability	Day-to-day activities limited (all residents)	-0.144**
	Day-to-day activities limited (workers)	0.181**
Provision of unpaid care per week	No unpaid care	0.387**
	50 or more hours	-0.074

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Both ethnic and religious diversity have strong positive relationships with noise complaints (the correlation coefficients are 0.453 and 0.433 at a 0.01 significance level). In a diverse society, therefore, there could be more conflicts. Residents from different ethnic, cultural, and religious groups are more likely to complain about the noise produced by each other. This finding is consistent with that of Legewie and Schaeffer (2016), who found that residents living between racial enclaves tend to complain more about noise than those who live within clearly defined racial boundaries.

6.3.2. Job-related factors

There are three categories of job-related factors: economic activity, hours worked, and occupation. Economic activity is an indicator of residents' status of employment. The relationships between noise complaints and the percentage of usual residents aged 16–74 in England classified by economic activity are presented in Table 6.5. In terms of being economically active, the percentage of residents with part-time and self-employed jobs has negative relationships with the rate of noise complaints, with coefficients of -0.331 and -0.222, respectively. Noise complaints do not show correlation with the percentage of residents having full-time jobs. As for the percentage of unemployed residents, the rate of noise complaints is positively related, with coefficient values of 0.441. A difference is found between unemployed males and females. The coefficient values of unemployed males are lower than that of females; therefore, the relationship between noise complaints and unemployed females is stronger than that between noise complaints and males. As for economically inactive residents, a significant negative relationship is found between noise complaints and the percentage of retired residents, with a coefficient of -0.444. Positive relationships are found between noise complaints and all remaining factors, including the percentage of students and disabled residents. The results indicate that cities with a higher proportion of unemployed residents might be facing more serious noise complaint problems.

Table 6.5 Correlation coefficients between economic activity status and the rate of noise complaints

Economic activity status			Coefficients
Economically active	Part-time		-0.331**
	Full-time		0.003
	Self- employed		-0.222**
	Unemployed	Total	0.441**
		Unemployed male	0.406**
		Unemployed female	0.473**
Economically inactive	Retired		-0.444**
	Student		0.365**
	Looking after home or family		0.349**
	Long-term sick or disabled		0.244**
	Other		0.447**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

In terms of the number of hours worked, Table 6.6 indicates that noise complaints are generally related to this variable. The percentage of residents who work less than 15 hours have a negative relationship with noise complaints, with a coefficient value of -0.183. A weak positive relationship is found for residents who work from 31 to 48 hours, with a coefficient value of 0.246. There is no significant correlation between 16–30 hours worked and noise complaints. The percentage of residents who worked more than 49 hours is negatively related to noise complaints, with a low coefficient value of -0.162.

Table 6.6 Correlation coefficients between the percentage of residents' hours of work and the rate of noise complaints

Hours worked	Coefficients
Less than 15	-0.183**
16 to 30	-0.093
31 to 48	0.246**
More than 49	-0.162**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

In terms of residents' occupations, the relationships with noise complaints are shown in Table 6.7, organised top to bottom from professional to entry-level or blue-collar occupations. The proportion of residents with professional or senior occupations have negative relationships with noise complaints, while residents with entry-level or blue-collar occupations have a positive relationship. As the share of managers, directors, senior officials, and skilled trade occupations increases, the rate of noise complaints decreases. In contrast, occupations such as sales, customer service, and elementary occupations have negative values in terms of noise complaint rates. The remaining occupations do not show statistically significant correlations. Overall, noise complaints have a negative relationship with the percentage of residents in professional-level occupations. This result is contrary to the findings of Miedema and Vos (1999), who found that residents with higher occupational status are more likely to report noise annoyance, to some extent.

Table 6.7 Correlation coefficients between the occupation of residents (percentage) and the rate of noise complaints

Occupation	Coefficients
Managers, directors, and senior officials	-0.289**
Professional occupations	0.010
Associate professional and technical occupations	0.027
Administrative and secretarial occupations	-0.035
Skilled trades occupations	-0.293**
Caring, leisure, and other service occupations	-0.041
Sales and customer service occupations	0.229**
Process plant and machine operatives	-0.010
Elementary occupations	0.204**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

6.3.3. Property factors

There were generally significant correlations between property factors and noise complaints. Table 6.8 shows that noise complaints have a negative relationship with the average number of rooms and bedrooms per household, with coefficient values of -0.528 for rooms and -0.487 for bedrooms. In terms of central heating, the percentage of centrally heated households is negatively related to the rate of noise complaints, with a correlation coefficient value of -0.169 (the household's accommodation is classified as having central heating if it is present in some or in all rooms). In terms of the correlation analysis between car or van availability and noise complaints, the noise complaint rate has a positive relationship with the percentage of households without a car or a van, with a slightly higher coefficient value of 0.482. In addition, as the average number of car or van per household increases, the noise complaint rate tends to decrease.

Table 6.8 Correlation coefficients between accommodation condition and the rate of noise complaints

Accommodation condition	Coefficients
Average number of rooms per household	-0.528**
Average number of bedrooms per household	-0.487**
Central heating	-0.169**
No car or van	0.482**
The average number of cars or vans	-0.481**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Fields (1993), Tonin (1996), and Yano et al. (2002) have found evidence that the type and tenure of accommodation may have impacts on noise annoyance. The correlation coefficients between accommodation type and tenure and noise complaints are shown in Table 6.9. In terms of accommodation type, negative relationships are found between the proportion of residents living in a whole house or bungalow and noise complaints, with a coefficient value of -0.433. Detached and semi-detached dwellings also have negative relationships with noise complaints, with lower coefficient values of -0.482 and -0.173, respectively. Noise complaints, however, are positively related to the proportion of residents living in terraced houses. Similar relationships appear for flats: noise complaints are generally positively related to the proportion of residents living in a flat, with coefficient values of 0.455, 0.336, and 0.217, for purpose-built blocks of flats or tenements, for part of a converted or shared house, and for commercial buildings, respectively. To some extent, terraced houses are more similar to flats in spatial patterns as the rooms are contiguous, although they are categorised under whole house or bungalow. Therefore, they show similar relationships with noise. As for the last variable, caravan or other mobile or temporary structure, it is positively related to noise complaints. The results show that cities with more residents living in flats have an increasing rate of complaint activity. This result may be because a higher percentage of residents living in flats indicates that the city is a high-density area. Because of high traffic volumes in high-density areas, there is likely to be a more extreme noise environment in locations with a high percentage of residents living in flats. Another possible reason is that residents living in flats are more influenced by noise nuisance caused by residents living in the same block or building.

Table 6.9 Correlation coefficients between accommodation type and tenure, and the rate of noise complaints

Accommodation type and tenure		Coefficients
Accommodation type	Whole house or bungalow	-0.433**
	Detached	-0.482**
	Semi-detached	-0.173**
	Terraced	0.309**
	Flat, maisonette, or apartment	0.442**
	Purpose-built block of flats or tenement	0.455**
	Part of a converted or shared house	0.336**
	In commercial building	0.217**
	Caravan or other mobile or temporary structure	-0.320**
Tenure	Owned	-0.509**
	Shared ownership	0.145**
	Socially rented	0.368**
	Privately rented	0.452**
	Rent free	-0.145**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

The results of tenure are shown in Table 6.9. It can be clearly seen that there is a significant and strong inverse relationship between noise complaints and the percentage of a household that owns the accommodation it occupies, with a coefficient value of -0.509. However, noise complaints appear to be positively related to the percentage of households who share ownership with others, with a lower coefficient value of 0.145. Households living in rented accommodation are classified by the type of landlord who owns or manages the accommodation. The rate of noise complaints has positive relationships with the percentage of households that rents from social and private properties, with higher coefficient values of 0.368 and 0.452, respectively. “Socially rented” means that the accommodation is rented from the council and other landlords, and this type is cheaper than privately rented property. A higher proportion of socially rented dwellings implies that the residents’ income might be lower. The results show that cities with a higher proportion of households living in socially rented dwellings receive more noise complaints. The result corresponds to Xie and Kang’s (2010) study, which reports that people’s median income is generally higher in noisier boroughs.

In relatively quiet cities, there are fewer tenants. A possible explanation is that residents are more likely to invest in dwellings in a relatively quiet area. Owners pay more attention to the surroundings of the dwelling than those who rent, since tenants have a lower transaction cost of relocation compared with homeowners. This means that if the dwelling is owned by the resident, it is more likely to be located in an area with a better environment (DiPasquale & Glaeser, 1999). Another possible reason is that areas with more renters may imply greater intentions to leave; therefore, they are likely to have a negative relationship with their neighbours. However, the finding is contrary to the study of Nieuwenhuis et al. (2013), which suggests, to some extent, that there is no significant difference between renters and owners in terms of relationships with neighbours.

6.3.4. Deprivation factors

In terms of deprivation factors, Table 6.10 shows the correlation analysis results between noise complaints and the IMD Rank, including total deprivation, income deprivation, employment deprivation, health deprivation, barriers to housing and services deprivation, crime deprivation, and living environment deprivation. The first-ranked cities represent the most deprived cities, namely disadvantaged areas. The results show a negative relationship between total deprivation and noise complaints, with a coefficient value of -0.378, indicating that more deprived cities tend to have more noise complaints. In terms of barriers to housing and services, crime, living environment, and income deprivation all have negative relationships with noise complaints, with similar coefficient values, compared to total deprivation. Employment and health are also negatively related to noise complaints, but with lower coefficient values.

Table 6.10 Correlation coefficients between deprivation factors and the rate of noise complaints

Deprivation factors	Coefficients
Total deprivation index	-0.378**
Barriers to housing and services	-0.143**
Crime	-0.543**
Employment	-0.272**
Health	-0.278**
Living environment	-0.251**
Income	-0.396**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

The results suggest that areas with higher rates of people who die prematurely or whose quality of life is impaired by poor health or who are disabled are likely to report more noise issues, and it might be more difficult for those residents to access local services such as shops, general practitioners, schools, and post offices in such areas. The findings are consistent with Xie & Kang (2009), who found a negative relationship between deprivation indexes and noise level at neighbourhood level.

6.3.5. Ridge regression model

After figuring out relationships between the rate of noise complaints and 76 individual socio-economic factors, a multivariate model was developed to predict the noise complaint rate. Based on the ridge regression model, the mean square error of this model is 0.369, which, in this chapter, is better than most other models such as hierarchical regression, path analysis and lasso regression. The prediction equation based on the ridge regression model is as follows:

$$The\ rate\ of\ noise\ complaints = \sum_{i=1}^{n} RC_i * A_i + a \quad (6.2)$$

where A_i represents the indicators of socio-economic factors and the RC_i indicates the corresponding regression coefficient value of each variable as shown in Table 6.1. a indicates the regression intercept. In this chapter, the value of a is 10.22. In terms of the model application, for instance, Bristol is a major city in South West England with 39.10 persons per hectare and population size of 428,074. The noise complaint rate of Bristol is 10.18 per thousand persons, with the prediction value of 9.78. In terms of cross-validation to examine the model accuracy, 260 samples were used for training the model, with 65 samples for validation. This model can help the government organisations to prioritise resources for dealing with noise pollution from the socio-economical aspect.

6.4. Conclusions

The noise complaints and socio-economic datasets from the governmental open data provide input for statistical analysis across all districts and unitary local authorities in England. This chapter used governmental open data from various sources rather than questionnaire or interview which are widely applied in sound environment research. The usage of such geo-spatial data enables us to analyse urban issues at a larger scale and broader spatial coverage. Based on statistical analysis, this chapter examines the relationships between noise complaints and socio-economic factors, including demographic, job-related, property, and deprivation factors.

In general, various aspects of socio-economic factors have effects on noise complaints. Individually, first, from the perspective of demographic factors, complainants are likely to live in an area with diverse religions and ethnicities. From the results, it can be inferred that cities with a higher proportion of single individuals are prone to receive more noise complaints. Moreover, if the unemployment rate of the cities is higher, residents tend to report more noise issues. The results show unemployment rate of females has a stronger relationship with noise complaints than that of males. Furthermore, as for property factors, if there are more flats or rented houses in an area, noise problems become considerably significant. Finally, more deprived cities tend to have more noise complaints in terms of each aspect in the deprivation index: housing and services, crime, employment, health, environment, and income.

This chapter has revealed the strengths of the relationships between each socio-economic factor and noise complaints, and it can contribute a multivariate model to predict the noise complaint rate. From these results, profiles of cities can be drawn up from the perspective of noise complaints and socio-economic factors. Furthermore, these results can help government organisations to build a liveable and sustainable city by prioritising resources in terms of ambient noise, both geographically and socio-economically. For instance, if a city has a higher unemployment rate, it tends to have a higher noise complaint rate. Therefore, more resources could be allocated in such cities.

This chapter suggests a number of possibilities for future research. First, although the relationships between socio-economic factors and noise complaint rates have been identified, the causality of these relationships remains undiscussed. With more data on complainants' characteristics, such as sex, occupation, qualification, and other socio-economic factors, the causality and motivation for complaints could be better understood. Second, the present study has considered only the district and local authority levels. To develop a comprehensive understanding of noise complaints, additional studies based on other scales are required. For instance, location information of individual complaints could be used to examine the impact of urban morphology on noise complaint rates. Third, this chapter has primarily focused on noise complaints, which is a behaviour, instead of noise level and noise exposure. A noise map could facilitate this study. However, they are mostly only available in cities with more than 100,000 inhabitants (European Union, 2002). If the dataset is systematically available, future studies could focus on the links between noise complaints and other aspects of noise research.

Chapter 7

Relationship between urban development patterns and noise complaints in England[1]

After the investigation on socio-economic factors in Chapter 6, this Chapter aims to examine the relationships between noise complaints and urban development patterns, which is the main focus of urban studies. Further, this Chapter works on the same scale as in Chapter 6 (i.e., England). The structure of this chapter is similar to that of Chapter 6, including the introduction, method, results and discussions, and conclusions. Section 7.1 presents the research on urban planning and environmental noise issues in terms of noise level and sound perception. Section 7.2 illustrates the data sources and analysis methods. The sources and methods are slightly similar to Chapter 6 and kept unchanged to make this chapter more readable. Section 7.3 presents and discusses the results from Spearman correlation and ridge regression. Lastly, Section 7.4 provides a brief summary and critique of the findings.

7.1. Introduction

With the rapid increase in urbanisation, exposure to noise is increasingly

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recognised as a common and serious problem worldwide. Many studies have shown that noise is a primary contributor to certain risk factors related to physical and mental health, such as loss of hearing, sleep disorder, and stress (Dzhambov & Dimitrova, 2016a). A series of policies and actions have been implemented to reduce the impact of noise. In the European Union, various noise action plans following on the END have been introduced, among which legislation regarding complaints is an important part. Noise complaints have been reported to be the single most common type of environment-related complaints; in addition, partly as a result of urbanisation, the role of urban planning in the sound environment of cities is receiving increased research attention across a number of disciplines (Kang, 2006).

A number of studies have examined the link between urban planning and environmental noise issues in terms of noise level and sound perception (Alberti, 1999; Zhou et al., 2016). From a noise level perspective, a comparative study by Wang and Kang (2011) demonstrated that there are significant differences in the spatial noise level distribution between high- and low-density cities. Margaritis and Kang (2017) focussed on the relationships between green-space-related morphology and noise pollution, and found that at the urban and kernel scale, cities with higher green-space coverage were found to have lower day-evening-night noise levels. Through analysis of a noise map, Margaritis and Kang (2016) found that linear cities have a higher probability of being noisier, and that dispersed patterns are related to lower noise levels. Moreover, areas with the most densely and heavily built urban structure types are likely to have a higher noise level (Sakieh et al., 2017). Salomons and Pont (2012) examined the correlations of façade noise level and traffic volume with urban densities. They found that the average sound level in urban areas decreases with increasing building density, but it increases with rising road network density and vehicle. Hao and Kang (2014) analysed the relationships between urban morphology and the spatial noise level attenuation of flyover aircraft, finding it to be mainly correlated with the building frontal area index. Salomons and Pont (2012) found that in closed building blocks, the noise level in quiet façades is lower than in open building blocks. In addition, façade shapes and materials can influence the noise level as well. For instance, the general shape of buildings can be important for pedestrians. Flat façades inclined upwardly are most efficient for noise reduction; flat vertical façades and concave shapes are also beneficial (Sanchez et al., 2016). Badino et al. (2019) found that the sound level over the façade can be reduced by up to 6.5 dB by absorbing balconies and loggias and by 10 dB with entirely absorbing sound façades. Furthermore, sustainable vegetated façades can reduce noise levels by 2 dB at pedestrian level in the street canyon (Jang et al., 2015).

Noise/sound perception has been another aspect of research on sound environments. Hao et al. (2015) investigated the integrated impacts of urban morphology on birdsong loudness, indicating that the masking effects of birdsong could be considered a soundscape design technique. From a case study in Seoul, Korea, Hong and Jeon (2017) suggested that in high-density areas, there is more low-frequency content of sound and lower sharpness values compared with low-density areas. Liu et al. (2014) examined the impact of landscape spatial patterns on soundscape perception. Their results showed that major sound indicators are associated with a number of planning indices, such as road density. Thus far, a range of urban planning parameters have been identified that have impacts on noise level and sound perception, mostly based on a small scale and/or a relatively limited sample size.

Reporting noise complaints as a part of noise policy depends on individual attitudes and perceptions as well as objective noise levels (Kang, 2006). Gillen and Levesque (1994) examined relationships between airport complaints and socio-economic factors, suggesting that noise complaints are positively related to population. From their dataset, it can also be seen that the day complaints are greater than the night ones. Meanwhile, Liu et al. (2019) analysed the spatial patterns of neighbour complaints based on GIS technique, including noise-related complaints. Zheng et al. (2014) developed a model to recover the noise situation throughout NYC where they used noise complaint data. Hong et al. (2019) found, using longitudinal administrative data from 2011 to 2016, that an increase in construction activity of one-unit in a cell based on heat maps was associated with an approximately 6% higher incidence rate of noise complaints. However, the research on how urban planning affects noise complaints is currently inadequate.

According to the above considerations, for urban planners and policymakers, the relationships between urban development patterns and noise complaint matters is still lacking, especially at a large scale. Therefore, this chapter aims to examine relationships between urban development patterns and noise complaints at the city level. For this purpose, the indicators of urban development patterns relating to planning and landscape are categorised into six groups: population, industrial structures, built-up areas, transport networks, commuting, and natural landscapes.

7.2. Methods

7.2.1. Geographic samples

In England, there are 152 counties and unitary authorities, as well as 326 district and unitary authorities. To obtain a large sample size for this study, district and unitary administrative levels were selected. Another reason for this choice is because this chapter analyses the relationships between urban development patterns and noise complaints, and district and unitary administrations have local authorities for urban governance. In total, 325 samples were examined from across England (all districts and unitary administrations were selected excluding the Isles of Scilly, for which noise complaint data were absent).

7.2.2. Noise complaint dataset

In England, noise complaints are reported under environment legislation, providing a database for government decision making. Making a noise complaint is a behaviour related to noise level and perception. Noise complaints can give useful indications regarding those areas in which people are bothered by noise (Hong et al., 2019; Public Health England, 2018). Two variables for noise complaints are included in the dataset: the raw number of noise complaints and the rate of noise complaints per local authority per thousand people (Public Health England, 2018). For this chapter, the noise complaint rate was selected for correlation analysis allowing comparison across the scale of cities. Data regarding noise complaint rates were available for the years 2010–2015. As this research seeks to study general rules rather than current issues, the noise complaint rate data for 2011 were selected for analysis, since the most recent urban development pattern data set is available in 2011.

7.2.3. Urban development pattern indicators

There are many urban development pattern indicators related to the sound environment (Badino et al., 2019; Zhou et al., 2016). Through literature reviews, 75 indicators were selected and categorised them into six groups: population, industrial structures, built-up areas, transport networks, commuting, and natural landscapes. Details of the indicators are provided in Table 7.1 and described below:

(1) Population is a basic characteristic of cities and, hence, a common and essential factor in urban studies research. Population factors include population size and density.

(2) Industrial structures describe the relative size of each industrial sector, which reflects the nature of the local urban economy. Changes in industrial structure result from increases in urbanisation and expansion of urban areas.

With urban development, cities gradually change from agriculture-dominated to service-dominated societies (Moir, 1976; Schnore, 1961).

(3) Built-up areas are where the majority of the population reside. Thus, the characteristics of this area can have considerable effects on human well-being and are essential components of urban patterns. The indicators of built-up areas describe different dimensions of urban patterns, such as evenness, clustering, and fragmentation (Alberti, 1999; Sudhira et al., 2004).

(4) Transport networks are an indicator of local connectivity, which is an important measure of the evenness of urban patterns. Moreover, the noise generated by vehicular traffic is one of the most annoying sources of noise, which could have a strong relationship with noise complaints (Calixto et al., 2003).

(5) Commuting comprises indicators concerning residents' methods of travelling to work and the distance they travel to work. Commuting patterns (i.e., the length, mode choice, etc.) gradually change as an area matures (Sultana & Weber, 2013; Zhao et al., 2010). The percentage of residents using public transport and commuting distance are crucial indicators for a compact city, as well as the integration of urban land use (OECD, 2012).

(6) Natural landscapes are examined because they have been proven to impact noise perception and diffusion (Hao et al., 2015; Margaritis & Kang, 2017).

Table 7.1 Indicators of urban development patterns and their regression coefficient on noise complaints based on the ridge regression model

Factors	Detailed variables		Regression Coefficients	Code
Population	Population density		0.002**	B1
	Population size		0.000**	B2
Industrial structure	Proportion of GVA per industry	GVA	0.000**	B3
		Per capita	0.000	B4
		Industry A,B,D,E	-0.004**	B5
		Industry C	-0.002**	B6
		Industry F	-0.005**	B7

		Industry G,H,I	-0.001	B8
		Industry J	0.003**	B9
		Industry K	0.002**	B10
		Industry L	-0.001	B11
		Industry M,N	0.004**	B12
		Industry O,P,Q	0.001	B13
		Industry R,S,T	0.011**	B14
	Proportion of residents employed in each industry	Industry A	-0.010**	B15
		Industry B	-0.008	B16
		Industry C	-0.005**	B17
		Industry D	-0.029**	B18
		Industry E	-0.061**	B19
		Industry F	-0.014**	B20
		Industry G	-0.006**	B21
		Industry H	0.000	B22
		Industry I	0.009**	B23
		Industry J	0.007**	B24
		Industry K	0.008**	B25
		Industry L	0.044**	B26
		Industry M	0.006**	B27
		Industry N	0.022**	B28
		Industry O	-0.005**	B29
		Industry P	-0.002	B30
		Industry Q	-0.004*	B31
		Industry R, S, T ,U	0.018**	B32
Built-up area	Area metrics	Number of settlement patches	-0.002**	B33
		Settlement density	-0.019**	B34
		Total settlement size	0.007**	B35
		Mean settlement size	0.055**	B36
		Settlement size standard deviation	0.000*	B37
		Largest settlement size	0.039**	B38
	Edge metrics	Edge density	-0.010**	B39
	Nearest-neighbour metrics	Total nearest-neighbour distance	0.000**	B40
		Mean nearest-neighbour distance	0.000**	B41
Transport network	Road density by classification	Total road density	0.034**	B42
		Motorway density	-0.168**	B43
		Primary road density	0.220**	B44
		A road density	0.098**	B45
		B road density	-0.025	B46
		Minor road density	-0.054**	B47
	Kernel density	Kernel density for road network at the 1,000-cell-size level	0.001**	B48
		Kernel density for road network at the 500-cell-size level	0.001**	B49
	Railway density		0.133**	B50
Commuting	Proportion of residents using each commuting method examined	Work at or from home	-0.007**	B51
		Underground, metro, light rail, tram	0.007**	B52

		Train	0.003**	B53
		Bus, minibus or coach	0.011**	B54
		Taxi	0.076**	B55
		Motorcycle, scooter, or moped	0.066**	B56
		Driving a car or van	-0.004**	B57
		Passenger in a car or van	-0.020**	B58
		Bicycle	0.012**	B59
		On foot	0.001	B60
	Proportion of residents commuting each distance examined	0–2	0.000	B61
		2–5	0.003**	B62
		5–10	0.003**	B63
		10–20	-0.002**	B64
		20–30	-0.005**	B65
		30–40	-0.007**	B66
		40–60	-0.006**	B67
		> 60	-0.008**	B68
		Total distance	0.000	B69
		Average distance	-0.009**	B70
Natural elements	National park density		0.023*	B71
	Woodland density		-0.201**	B72
	Lake density		0.204	B73
	Coast density		0.016*	B74
	River density		-0.082**	B75

*Coefficients are significant at the 0.05 level. ** Coefficients are significant at the 0.01 level.

In this chapter, there are two main open databases used: the UK Census (produced by the UK Office for National Statistics) and Strategi (produced by the UK Ordnance Survey). The data set for population, industrial structures, and commuting was sourced from the UK Office for National Statistics (2019). Data for all indicators in these three sections (excluding gross value added (GVA)) were extracted from the 2011 Census, which is the only survey that provides a detailed picture of the entire population (Office for National Statistics, 2018). The built-up area, transport network, and natural landscape data sets were sourced from Strategi, which is produced from data that are used to create the UK Ordnance Survey's 1:250,000 scale topographic mapping with a resolution of 1 m (Ordnance Survey, 2015). This data set comprises digital vector data and contains settlements, water, woods, land use, and positioned geographic names, among other urban elements. These data are sufficiently precise for calculating urban development pattern indicators. All data sets, including the noise complaints, UK Census and Strategi, are from 2011 for the correlation analysis. Overall, 75 variables describing urban development patterns were obtained (Table 7.1).

To illustrate the industrial structures, statistics for the proportion of GVA and residents employed per industrial classification were used. Table 7.2 shows the industry classification and codes according to the Standard Industrial Classification of Economic Activities 2007. These industrial classifications are listed from primary (approximately from Industries A to B) to secondary (approximately from Industries C to H) and third (approximately from Industries I to U) (Fisher, 1935; Fisher, 1939; Lindsay, 2009).

Table 7.2 Indexes of the standard industrial classification of economic activities

Code	Industry classification
Industry A	Agriculture, forestry, and fishing
Industry B	Mining and quarrying
Industry C	Manufacturing
Industry D	Electricity, gas, steam, and air conditioning supply
Industry E	Water supply; sewerage, waste management and remediation activities
Industry F	Construction
Industry G	Wholesale and retail trade; repair of motor vehicles and motorcycles
Industry H	Transport and storage
Industry I	Accommodation and food service activities
Industry J	Information and communication
Industry K	Financial and insurance activities
Industry L	Real estate activities
Industry M	Professional, scientific and technical activities
Industry N	Administrative and support service activities
Industry O	Public administration and defence; compulsory social security
Industry P	Education
Industry Q	Human health and social work activities
Industry R, S, T	Recreation, household, and other service activities
Industry U	Activities of extraterritorial organisations and bodies

Sourced from Lindsay (2009)

The majority of built-up area indicators and their equations were sourced from FRAGSTATS, which is a spatial-pattern-analysis program developed to quantify landscape structure. FRAGSTATS is applied widely in urban and landscape studies and includes comprehensive indicators (McGarigal & Marks, 1995). Built-up areas comprise the area, edge, and nearest-neighbour metrics. The indicators of area metrics describe the size and distribution of settlements, accounting for city size, fragmentation, clustering and evenness. Settlement density is calculated by dividing the number of settlements by the area of cities. Finally, the nearest-neighbour metrics illustrate the distance between two individual built-up areas (i.e. settlements) and, thus, describe the sprawl and dispersal of built-up areas.

Regarding transport network factors, roads and railways are considered. Among various urban noise sources, traffic noise generally attracts the most attention because of two characteristics: it is usually loud and very widespread (Van Renterghem & Botteldooren, 2010). The total density of roads, that of each road subcategory, and that of railways, can be calculated by dividing the total length of roads and railways (in kilometre (km)) by the area of the city in question (in square kilometre (km^2)). To determine the spatial distribution of road networks, kernel density, which calculates magnitude-per-unit cell from road features using a kernel function, was applied.

Natural landscape factors have been proven to have relationships with sound environments, applying an absorption or scattering effect on noise propagation and influencing individual perception of noise (Hao et al., 2015; Margaritis & Kang, 2017). Using the Strategi dataset, the natural elements of national parks, woodlands, lakes, coasts, and rivers were selected as water and green factors. The density of each natural element was calculated by dividing the area/length of the natural element by the area of the city.

It is worth noting that some urban development pattern factors show significant correlations. The significant correlations exist, such as the population density and population amount. However, as this chapter focuses on the impact of urban development patterns on noise complaints, rather than the interrelationship between the factors, no further correlation analysis was made. Nevertheless, the ridge regression model was applied to deal with the multicollinearity problem.

7.2.4. Data analysis

The Strategi map was processed in ArcGIS 10.4 to calculate the values of the indicators and the urban development patterns. A correlation analysis was subsequently conducted in SPSS on the noise complaint data and urban development pattern indicators, in order to understand relationships between each indicator and the noise complaint rate (IBM Corp, 2015). The choice of correlation analysis is based on the type and distribution characteristics of the variables. In this chapter, all the variables are continuous. Pearson correlation is widely used for examining the relationship between two continuous variables. However, the statistical results of variable distribution do not all conform to a normal distribution according to the Shapiro-Wilk test. The Spearman correlation, as a nonparametric test, does not assume normal distributions. Therefore, the Spearman correlation was applied to measure the correlations between the noise complaint rates and each urban development pattern indicator separately (Hauke & Kossowski, 2011). In terms of sample size, the size of 325 samples meets sample size requirements for Spearman correlation (Bonett & Wright, 2000). Furthermore, a correlation analysis was also conducted with 80% of the samples to validate the robustness of the correlation. The correlation coefficients, listed in Appendix C (Table C-6), did not show a significant difference. Thus, the Spearman correlation results in this chapter were robust.

As for the multiple regression analysis, considering sample size, unknown causality, the requirement of interpretability, and the multicollinearity problem among the variables, a ridge regression model was applied to model the relationships between the noise complaint rates and urban development pattern indicators. Ridge regression is an improved regression model and specialises in data that suffer from the multicollinearity problem by adding a degree of bias (Hoerl & Kennard, 1970; Marquaridt, 1970). In addition, compared to other modelling methods, this model is analytical with the explanatory contribution of each variable. Hence, it is helpful for government organisations prioritising resources to deal with noise pollution in terms of urban development pattern aspects. Cross-validation was used to validate the ridge regression model errors during the training process. This step is to divide all samples into a training set (80%) and a test set (20%) randomly. The training set is used to generate the model, while the test data are used to predict the errors of the model. Finally, a value is obtained to indicate model error. The process can be conducted using the R language. The results are primarily presented in Table 7.1 and further analysed in the Section 7.3.7.

7.3. Results and discussions

7.3.1. Population

The results show that the rate of noise complaints is strongly related to population density, with a correlation coefficient of 0.489 ($p < 0.01$). Furthermore, it is also related to population amount, albeit with a lower value at 0.287 ($p < 0.01$). Thus, the noise complaint rate increases as the population grows. These results correspond to the findings of Xie and Kang (2010), who revealed that noise levels have positive relationships with population density and total population change in London at the borough level. However, our results are somewhat contrary to those of Méndez and Otero (2018), who reported in an investigation conducted in Santiago, Chile, a negligible impact of population density on noise complaints. It is possible that their research was focused on the neighbourhood level.

7.3.2. Industrial structures

Industrial structures are an essential index for economic development that affects the change and composition of land use. It shows that the rate of noise complaints is positively related to total GVA, with a coefficient of 0.301, while it is negatively related to GVA per capita (Table 7.3). The GVA proportions of industries ABDE, C, F and L have negative relationships with noise complaints. Namely, as the proportional GVA of industries ABDE, C, and F increases, the noise complaint rate in the city tends to decrease. For another, the industries J, K, OPQ, and RST have statistically significant positive relationships. No significant correlation was found in other industries. Table 7.3 shows that the negative relationships are clustered in the primary and secondary industries, such as mining and manufacturing; in contrast, the industries that are positively related to noise complaints are largely tertiary industries, such as financial, recreation, and insurance activities. A possible reason for this is that primary and secondary industries are clustered in specific spaces, such as industrial zones and suburbs, due to lower land cost and noise regulations (Sonobe & Otsuka, 2006). This means that these industries tend, to some extent, to be located relatively far from highly populated places. However, tertiary industries are located close to residences and, consequently, may impact residents. In other words, cities with a higher proportion of tertiary industries tend to have higher noise complaint rates.

Table 7.3 Correlation coefficients between the proportion of GVA per industry and noise complaint rate

Industry category	Coefficients	Industry category	Coefficients
GVA	0.301**	Industry J	0.208**
Per capita	-0.126*	Industry K	0.215**
Industry ABDE	-0.213**	Industry L	-0.216**
Industry C	-0.264**	Industry MN	0.106
Industry F	-0.191**	Industry OPQ	0.157**
Industry GHI	-0.03	Industry RST	0.136*

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Table 7.4 shows the relationships between noise complaints and the share of residents who work in each industry. Here, the noise complaint rate is related to 15 industry categories (18 industries examined). The table shows negative relationships between noise complaints and the proportion of residents in that occupation for industries A, B, C, D, E, and F. Industry O also have negative relationships with the rate of complaints. Conversely, the proportion of residents employed in industries H, I, J, K, and N has positive relationships with noise complaints. These results reveal that cities with higher rates of residents employed in primary and secondary industries are more likely to have less noise complaints. In contrast, resident occupations are clustered in tertiary industries, leading to an increased likelihood of noise complaints.

Table 7.4 Correlation coefficients between the proportion of residents' employed in specific industries and noise complaint rate

Industry category	Coefficients	Industry category	Coefficients	Industry category	Coefficients
Industry A	-0.417**	Industry G	-0.055	Industry M	0.012
Industry B	-0.144**	Industry H	0.170**	Industry N	0.319**
Industry C	-0.222**	Industry I	0.196**	Industry O	-0.118*
Industry D	-0.178**	Industry J	0.150**	Industry P	-0.106
Industry E	-0.189**	Industry K	0.208**	Industry Q	-0.024
Industry F	-0.209**	Industry L	0.022	Industry R, S, T, U	0.081

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Overall, our analysis of GVA and occupation per industry indicates that as the percentage of GVA and employment in the service industry increases, the noise complaint rate also increases. From the perspective of economic development history, with urbanisation, this structural change might cause environmental issues. In addition, residents are more likely to report noise nuisances as they become increasingly aware of the negative impact that noise has on health (Kang, 2006). Meanwhile, economic centres, which are generally dominated by tertiary services across the country, might also generate more noise complaints and sound environment issues as a result of their proximity to residences.

7.3.3. Built-up areas

The results in Table 7.5 show that the number of settlement patches and settlement density has a negative relationship with the noise complaint rate. These results suggest that if settlement patterns in cities are fragmented, the rate of noise complaints tends to be reduced. All other indicators that describe the size of the settlements are positively related to the noise complaint rate.

The total and mean settlement size are positively related, with coefficients of 0.378 and 0.443. These results suggest that when the share of built-up area or the average area of the settlement is greater, residents are more likely to report noise complaints. Standard deviations of settlement size and the largest settlement size were also examined, and this showed that there were positive relationships between those variables and noise complaints. The coefficient for the settlement size standard deviation, which represents the difference in settlement areas, was 0.319, while the coefficient for the largest settlement size was slightly higher, at 0.400. The settlement size standard deviation indicates the evenness of cities; the results suggest that a more uneven city is likely to receive more noise complaints. The largest settlement size indicates the clustering of the city, which concerns the degree to which development has been grouped to minimise the amount of land used for residential or non-residential aspects. The main settlement area might be the city centre or where the local authority is located. The results also show that a more clustered city tends to have more noise complaints. This may because clustered cities can have high densities of buildings, larger traffic volumes, and lower degrees of natural landscapes. All these factors can increase resident annoyance regarding noise and, hence, increase complaints (Hao et al., 2015).

Indeed, edge density has a negative relationship with the rate of noise complaints. This indicates that where the edge length per unit area is smaller, the rate of noise complaints increases. This result may be explained by the fact that a higher edge-density value means that the settlement shape is ragged, suggesting that the area touching the natural landscape could be enlarged along the edge. Previous studies have provided evidence that visibility of natural elements such as forests contributes to relieving noise annoyance, thereby reducing the noise complaint rate (Van Renterghem et al., 2015).

Table 7.5 Correlation coefficients between settlement indicators and the rate of noise complaint rate

Settlement indicators		Coefficients
Area metrics	Number of settlement patches	-0.446**
	Settlement density	-0.319**
	Total settlement size	0.378**
	Mean settlement size	0.433**
	Settlement size standard deviation	0.319**
	Largest settlement size	0.400**
Edge metrics	Edge density	-0.376**
Nearest-neighbour metrics	Total nearest-neighbour distance	-0.455**
	Mean nearest-neighbour distance	-0.319**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Regarding the distance between settlements in a city, there are two indicators: total nearest distance and average nearest distance. Higher values in either or both indicate that the distance between settlements is longer. Both the total distance and average distance are negatively related with the noise complaint rate. Nearest-neighbour metrics can indicate, to some extent, the dispersion of cities; therefore, these results suggest that a more dispersed city has a lower noise complaint rate.

Overall, noise complaints have positive relationships with built-up area size metrics, such as the total settlement size, the settlement size standard deviation, and the largest settlement size. They also have negative relationships with the number of settlement patches and settlement density. In addition, they are also negatively related to edge and distance metrics, such as edge density, total nearest-neighbour distance, and mean nearest-neighbour distance. These results suggest that if a city is large, clustered, and/or uneven, a ragged boundary, fragmented distribution, and high distance between settlements are likely to reduce noise complaints.

In other words, it is possible to infer that sound environments in cities with fragmented patterns are better than those in an integrated city; a decentralised city might have less noise pollution than a centralised city; a dispersed city might have a better sound environment than a clustered city; and cities that have grown discontinuously might have a better sound environment than those that have grown contiguously.

7.3.4. Transport networks

Most road and railway network indicators are related to the rate of noise complaints (Table 7.6). The rate of noise complaints is related to total road density. Motorway density is not related to the rate of noise complaints; motorways are normally not close to residential settlements and consequently have less influence on residents' activities. Primary road density and A road density have positive relationships with the rate of noise complaints, as they are close to residential areas and thus have negative impacts on the living experience. B and minor road density is not related to the rate of noise complaints although these roads also interact with residential areas, they are relatively narrow and have light traffic, and their speeds also tend to be low.

With regard to kernel density, which is an indicator of the overall spatial distribution of the road network, the relationships between the noise complaint rate and road network kernel density at both 1000 and 500 cell-size level are positive. This suggests that a city with a dispersed and even network has fewer noise complaints; uneven networks, in contrast, tend to lead residents to report noise nuisances. Therefore, these results provide further support for the previous analysis indicating that an uneven city tends to have more complaints.

Table 7.6 Correlation coefficients between transport-network indicators and noise complaint rate

Transport-network indicators		Coefficients
Road density by classification	Total road density	0.325**
	Motorway density	-0.069
	Primary road density	0.383**
	A road density	0.410**
	B road density	0.012
	Minor road density	-0.054
Road kernel density	Kernel density for road network at the 1,000-cell-size level	0.355**
	Kernel density for road network at the 500-cell-size level	0.357**
Railway density	Railway density	0.444**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Railway density is correlated with the rate of noise complaints, with a value of 0.444. Thus, as the density of railway infrastructure increases, the noise complaint rate also increases. From a historical perspective, the development of a railway might prompt immigration to the core area, and hence, cause unevenness in development (Kotavaara et al., 2011). The result also supports that uneven cities are likely to have more serious noise pollution issues.

Among the factors analysed in this research, the transport network was found to have the strongest relationship with noise complaints. These results, to some extent, verify the findings of other studies, which reported that traffic noise is one of the main urban noise sources and has a serious impact on human well-being (Asdrubali & Costantini, 2005). From these results, it is obvious that not all road classes, but only roads that pass through residential areas, are positively related to the noise complaint rate. From another perspective, a linear pattern is an urban growth form that is developed along transport routes such as roads and railways (Clawson, 1962; Sultana & Weber, 2013). The results indicate that cities developing along the transport routes can have more serious sound environment problems, to some extent.

7.3.5. Commuting

The relationships between proportions of residents with different commuting methods and noise complaints are shown in Table 7.7. The percentages of residents who travel to work by underground, train, bus, taxi, or motorcycle/scooter/moped have positive relationships with noise complaints. In contrast, the percentages of residents who drive a car or van are negatively related to noise complaints, and the coefficient is higher than those of other modes: the value is −0.425. The percentage of residents riding a bicycle to work is positively related to noise complaints. No statistically significant correlation was observed between noise complaints and residents who walk to work. From these results, it appears that cities with higher percentages of residents taking energy-efficient transport modes to work tend to have more noise complaints.

Table 7.7 Correlation coefficients for the percentages of different commuting methods and noise complaint rate

Commuting methods	Coefficients
Work at or from home	-0.342**
Underground, metro, light rail, tram	0.137**
Train	0.176**
Bus, minibus or coach	0.408**
Taxi	0.319**
Motorcycle, scooter, or moped	0.192**
Driving a car or van	-0.425**
Passenger in a car or van	-0.020
Bicycle	0.158**
On foot	0.085

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

The relationship between noise complaints and commuting distance is shown in Table 7.8. The proportion of residents who travel less than 2 km is not related to noise complaints. Residents might walk such a short distance to work and, thus, this finding corresponds to Table 7.8, which shows no relationship between the percentage of residents who travel to work on foot and noise complaints. The proportion of residents who travel 2-5 km to work has positive relationships with noise complaints. These distances are suitable for cycling; therefore, this also corresponds to the results shown in Table 7.7. The proportion of residents who travel from 10 to over 60 km is generally negatively related to noise complaints, with coefficients of approximately 0.2-0.3.

Table 7.8 Correlation coefficients between distance travelled to work and noise complaints

Distance travelled to work and noise complaints (km)	Coefficients
0–2	-0.081
2–5	0.397**
5–10	0.047
10–20	-0.193**
20–30	-0.259**
30–40	-0.285**
40–60	-0.296**
> 60	-0.201**
Total distance	0.150**
Average distance	-0.398**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Overall, noise complaints have a negative relationship with the average commuting distance. Areas in which workplaces and residences are mixed tend to have more noise complaints and to be relatively noisy, while areas with separated workplaces and residences show fewer noise complaints. It could be caused by the land use of workplaces (i.e., commercial or industrial), where the intensity of activities and noise levels are both high during the daytime. Therefore, residents tend to complain (Gillen & Levesque, 1994; Nadaraja et al., 2010). In addition, cities with short average commuting distance and a higher percentage of residents using public transport might be clustered and integrated, meaning that a compact city is likely to have more noise complaints.

7.3.6. Natural landscapes

A number of studies have found that natural landscape features, such as vegetation and water bodies, can have significant impacts on sound environments (e.g., Hao et al., 2015; Margaritis & Kang, 2017). It can be seen from Table 7.9 that natural elements are generally related to noise complaints. National park density has a negative relationship with noise complaints. The coefficient is −0.238 ($p < 0.01$). Thus, cities with national parks are likely to have less noise complaints, and as national park density increases, the noise complaint rate reduces. Woodland density also has a negative relationship with noise complaints. This result seems to be consistent with other research, which found that forests may strongly decrease nighttime noise levels. Noise annoyance, therefore, could be reducing (Van Renterghem et al., 2015).

No statistically significant correlation was observed between lake density and noise complaints; this might be because lake areas are relatively small and, thus, have little effect on residents. It could be also partly explained from an accessibility perspective. The average nearest distance from residential areas to the lake is 4,473.51 m. Accessibility to the lake is low for residents. Hence, the effect of lakes is limited.

Table 7.9 Correlation coefficients between natural-element indicators and noise complaints

Natural elements	Coefficients
National park density	-0.238**
Woodland density	-0.255**
Lake density	0.104
River density	-0.199**
Coast density	0.118**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

River density is negatively related to the noise complaint rate, with a coefficient of −0.199. For coastlines, a positive relationship is shown, with a coefficient of 0.118. Cities developing along coastlines are another linear pattern, apart from developing along roads as previously mentioned. The finding, to some extent, indicates that cities developing along coastlines also have more serious noise pollution, which is in accordance with recent studies implying that cities developing along the coastline have lower noise levels (Margaritis & Kang, 2016).

Overall, natural elements are negatively related to noise complaints, with the sole exception being coasts, but the coefficients are small. Consistent with the literature, this chapter confirms that natural scenery has a positive impact on the perception of sound environments (Liu et al., 2014). There are several possible explanations for this finding. Noise can be absorbed by vegetation, and waterscapes can also reduce noise annoyance. In addition, the impacts of sound and visual interaction on perception have been confirmed in previous research (Van Renterghem et al., 2015). Therefore, it is to be expected that natural landscapes can mitigate noise complaint rate issues. The result also suggests that a dispersed city with prevalent natural elements could have a better sound environment. This finding is consistent with previous studies that have suggested that an increase in green patches can possibly be correlated with a decrease in noise levels and that green space provides more positively experienced sound (Gunnarsson et al., 2017; Van Herzele & Wiedemann, 2003).

7.3.7. Ridge regression model

After determining the relationships between the noise complaint rate and 75 individual urban development pattern factors, a multivariate model was developed to predict the noise complaint rate. The regression equation is shown as follows

$$NCR = \sum_{j=1}^{m} \gamma_j * B_j + b \quad (7.1)$$

where NCR indicates noise complaint rate of certain area, B_j indicates the j^{th} variable used in the regression, γ_j indicates the corresponding regression coefficient of B_j(Table 7.1), b indicates the regression intercept. In this chapter, the variables used in regression are the urban development pattern factors whose regression coefficient is remarkable at the 0.05 level, and the regression intercept is 6.852. In terms of cross-validation to examine the model accuracy, 260 samples were used for training the model, with 65 samples for validation. The prediction results were evaluated with the root mean square error. The root mean square error is 0.623 in this case study, which is better than the regression results of linear regression and path analysis.

In terms of the model application, for instance, Nottingham is located in the centre of England with 41.00 persons per hectare and a population size of 303,899. The noise complaint rate of Nottingham is 8.10 per thousand persons (a case from the test set), with the prediction value of 7.38. However, the application of this model to other countries needs further discussion. From an urban development pattern and culture background perspective, generally speaking, cities in Europe could apply this model as they are similar to those in England, although previous research has shown that the tolerance level to noise also varies in different countries (Yang & Kang, 2005). In contrast, the model has limitations for cities that are significantly different from those in England, such as typical high-density areas like Manhattan. Indeed, the relationships between the sound environment and urban morphology vary with different densities (see Section 4.3.2). High-density areas have more low frequency content of sound and lower sharpness values compared with low-density areas (Hong & Jeon, 2017), whereas in low-density areas, birdsong has a masking effect on noise (Hao et al., 2015).

7.4. Conclusions

This thesis examined the relationships between noise complaints and urban development patterns through a large-scale analysis of England. The findings are as follows:

(1) Cities with high population densities tend to have a higher noise complaint rate. In addition, it is strongly related to population density and weakly related to total population. High-density cities have higher probability of a poorer sound environment.

(2) Regarding industrial structures, service-dominated cities have more noise complaints than cities dominated by primary and secondary industries.

(3) Larger and more uneven cities tend to have more noise complaints, as do clustered cities. However, cities with dispersed and fragmented patterns and ragged boundaries are likely to have lower noise complaint rates.

(4) Regarding transport networks, overall, cities with higher road and railway densities are likely to receive more noise complaints. However, not all road classes, but only primary and A-class roads have a positive relationship with noise complaints. In addition, uneven road networks lead residents to report noise nuisances. Linear urban patterns along a road might have serious noise pollution problems.

(5) Also related to transport networks, commuting factors show that cities in which residences are separated from workplaces are prone to have fewer noise complaints, and vice versa. Furthermore, from a commuting pattern perspective,

a compact city is likely to have a higher noise complaint rate.

(6) Cities with more natural elements, including greenery and bodies of water, tend to have lower noise complaint rates.

This chapter provides a basic analysis for the understanding of relationships between noise complaints and urban development patterns, and it illustrates the impact of the latter on the former. These findings could be used to predict the rate of noise complaints, clarify the cities that might have more serious noise complaint issues, and identify the factors that should receive more attention when addressing these issues (e.g. when utilising and protecting the natural landscape). This research indicates that urban planning parameters can be applied to achieve better sound environments, and can, to some extent, inform urban planners from the perspective of acoustic impacts, potentially leading to more effective noise management strategies and planning progress.

This chapter primarily focussed on noise complaints, which is a behaviour as opposed to a noise perception. A considerable literature exists with regards to the latter, so the links between noise complaints and perception can be researched further. Another limitation is that this chapter focused on noise complaints in England and generated a regression model based on datasets from England. It would be interesting to explore situations in other countries with different urban morphological features, population density, and cultural backgrounds.

PART III

NATIONAL/MACRO SCALE STUDIES

Studies in this part, namely Part III (Chapters 8 and 9), moves this thesis forward to the largest scale, namely, the national/macro scale. Following a comprehensive investigation of regional/meso studies, this part focuses on ambient noise indicators and their relation to health problems at a broad coverage. Specifically, this part discusses the sound environment and health from both sleep deprivation and mental health perspectives driven by the data. Accordingly, Chapter 8 focuses on sleep deprivation, while Chapter 9 focuses on mental health problems. The data sources and methods are the same in Chapters 8 and 9. To make each chapter more readable, the method sections of both chapters are repeated slightly.

Chapter 8

Using multi-sourced big data to correlate sleep deprivation and road traffic noise: A national scale spatial analysis[1]

The aim of this chapter is to visualise the spatial variations of sleep deprivation at the administrative level and then estimate its association with traffic noise indicators, considering the neighbourhood effects. This chapter starts with an introduction (Section 8.1) including the background on noise policy, a brief systemic review on sleep and traffic noise, and the aim of this chapter. Section 8.2 considers both the data sources and statistical methods of this chapter, including the US national noise map, health survey, and hierarchical Bayesian spatial regression models. Section 8.3 presents the data gathered and analysed. Section 8.4 addresses each of the research questions and discusses the results in the context of urban patterns. Additionally, practical implications and suggestions for future research are included in this section. Lastly, Section 8.5 summarises the findings. This chapter has been submitted to a journal for publication.

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[1] This chapter is in preparation for publication as: Tong et al., (2022). Using multi-sourced big data to correlate sleep deprivation and road traffic noise: A national scale spatial analysis. In the interest of fluency and readability, this chapter maintains the title and most text. Structure is changed slightly to correspond to other chapters.

8.1. Introduction[2]

Road traffic noise is a serious public health concern and environmental nuisance. According to the WHO, at least one million healthy life-years are lost annually because of traffic-related noise in Western Europe (WHO, 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 (WHO, 2018), the END in Europe (European Union, 2002), the Environmental Protection Act in Canada (Government of Canada, 2019), and the National Environmental Policy Act in the US (Andrews, 1976). 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.

Road traffic noise has adverse health effects including hearing loss, sleep deprivation, and cardiovascular disease (e.g., Basner et al., 2014; Münzel et al., 2021; Pirrera et al., 2010). Among them, sleep deprivation is generally considered to be the most serious side effect of environmental noise (Öhrström et al., 2006; WHO, 2011) and numerous studies have shown that sleep quality can be compromised by the environmental noise (Basner et al., 2014; Muzet, 2007). PubMed was searched from database inception up to 24th November 2021 for articles published in English, with combinations of the search terms "sleep", "traffic noise", and "public health". A total of 236 papers have been published, while 74 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

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[2] To have a better narrativity of this chapter and keep the flow for this chapter, this introduction is elaborated and kept the same as the paper in preparation.

noise. However, any ecological study especially at a large scale to quantify sleep and geo-spatial traffic noise indicators was not found. Also, no study considered characteristics of urban sprawl patterns and spatial variations. Large-scale ecological research at administrative levels is still lacking, which is the fundamentals for public policymaking and implementation. 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 (e.g., air quality and thermal environment (e.g., Kuo et al., 2018)), less attention has been given to studying the impacts of sound environment on health.

Therefore, the aim of this thesis is first to visualise the spatial variations of sleep deprivation at the administrative level, then estimate its association with traffic noise indicators. This chapter will also discuss which kind of urban sprawl pattern had a higher risk of noise-induced sleep problems, also consider whether other unexplanatory factors still exist. To answer these questions, multiple spatial 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 relating to urban sprawl patterns 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.

8.2. Methods

8.2.1. Data sources

The large-scale ecological study was conducted by investigating counties from the 48 contiguous states in the US. Open big data were obtained and aggregated to the county level.

This chapter used the self-reported sleep data, which was obtained from the BRFSS developed by the CDC (CDC, 2021). BRFSS from 2010, as the latest sleep data that has county code information, was used in this chapter (CDC, 2021). Sleep deprivation, measured as sleep insufficiency in this chapter, 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, a binary sleep deprivation outcome variable for each respondent was created 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 total, 451,075 people were interviewed. Of these, 9,085 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 level (European Environment Agency, 2014). The US national noise map was produced by the US Department of Transportation using an L_{Aeq} for 24 hours metric based on the FHWA TNM 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 & Millard-Ball, 2020, Rodrigue et al., 2016). The road traffic noise map in .tiff 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 sound pressure levels. 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 sound pressure level is reduced to 1 dB(A) from 0.001 dB(A). Subsequently, a Python program was developed and applied spatial statistics function in ArcGIS Pro 2.7 to calculate geo-spatial noise indicators. Through a literature review, seven indicators were extracted to describe the county traffic noise, as shown in Table 8.1.

Table 8.1 County-level traffic noise indicators

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

Since the impacts of noise on health are associated to social-economic status, this study also extracted data on 19 county-level descriptors from the American Community Survey (ACS) 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 (minutes), percentage of married-couple family household, average household size, median income, percentage of people with bachelor's degree or 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 house, percentage of household below 149 percent of the poverty level, and population density. Due to high correlation between the variables, a PCA 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.

8.2.2. Statistical analysis

This chapter modelled 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, socio-economic factors, and spatially correlated random effects using a hierarchical Bayesian spatial logistic regression framework. The statistical model is given as:

$$Y_k|p_k \sim \text{Binomial}(n_k, p_k), k = 1, \ldots, n; \tag{8.1}$$

$$logit(p_k) = \beta_0 + \beta_1 * \text{noise}_k + \sum_{j=1}^{6} \text{fs}_{jk} * \gamma_j + \phi_k \tag{8.2}$$

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 (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. To model this correlation, the Leroux version of the conditional autoregressive model (Leroux et al., 2000) was used, 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

$$\phi_k|\boldsymbol{\phi}_{-k}, \rho, \tau^2 \sim \text{N}\left(\frac{\rho \sum_{j=1}^{n} w_{kj}\phi_j}{\rho \sum_{j=1}^{n} w_{kj} + 1 - \rho}, \frac{\tau^2}{\rho \sum_{j=1}^{n} w_{kj} + 1 - \rho}\right) \tag{8.3}$$

where $\boldsymbol{\phi}_{-k}$ 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, weakly informative prior distributions were assigned to the introduced model parameters, allowing the data to drive the inference rather than our prior beliefs. Specifically, all regression parameters were assigned $\mathrm{N}(0, 100{,}000)$ distributions, $\rho \sim \mathrm{Uniform}(0{,}1)$, and $\tau^2 \sim \mathrm{Inverse\ Gamma}(1, 0.01)$. All models were adopted in the Bayesian setting using MCMC sampling algorithms within R statistical software (R Core Team, 2020) using the “CARleroux” function within the “CARBayes” package (Lee et al., 2018). 100,000 samples prior to convergence of the algorithm were discarded. The total number of MCMC samples collected post-convergence of the model was 1,000,000. These samples were thinned 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 (Geweke, 1992).

8.3. 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 Figure 8.1, based on the model that used L_{ave} as the noise covariate. In counties without observed survey data, the statistical model allowed us to predict these percentages based on the county’s covariate values and spatial correlation. It can be seen the percentage of people not getting enough sleep varied considerably over counties.

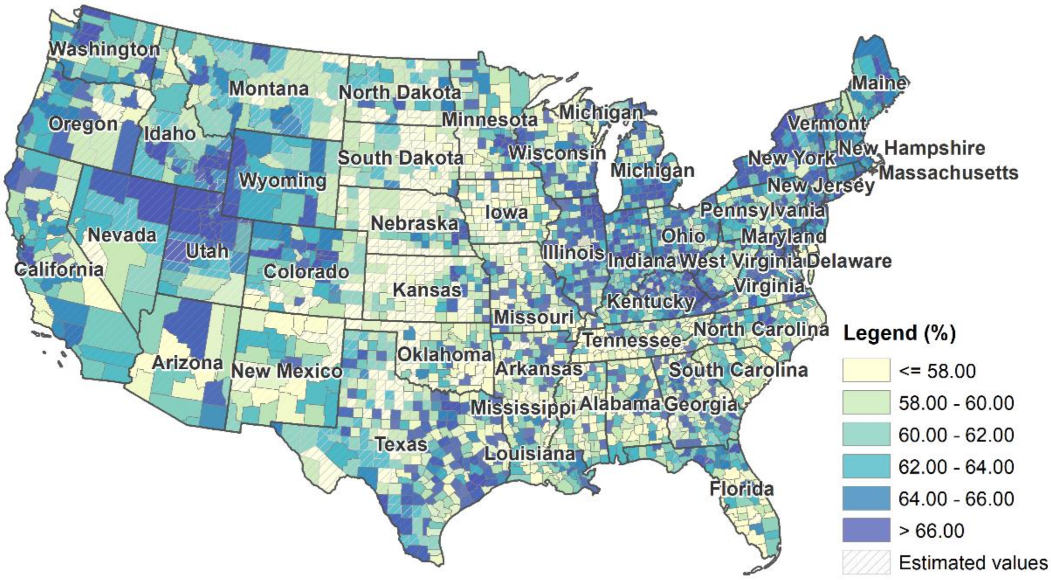

Figure 8.1 The modelled/predicted percentage of people not getting enough sleep at the county level based on the statistical model using L_{ave} as the noise covariate

The results from the statistical modelling are presented in Table 8.2, 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. Results for those variables with 95% CrIs that exclude 1.00 were highlighted in bold. Overall, considerable positive relationships were observed. A 10 dB(A) increase in L_{ave} at the county level resulted in a 49% increase in the odds of a person in that county not getting enough sleep (OR: 1.49; 95% CrI: 1.19-1.86). Furthermore, L_s10 and L_s90 indicating spatial percentiles sound pressure levels were examined. The results showed that a 10 dB(A) 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 associations were observed. However, when the exposure area ratio and exposure population ratio was examined, 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).

Table 8.2 Odd ratio and 95% credible interval (CrI) for sleep deprivation associated with overall indicators for noise

Indicators	Odds Ratio		
	Posterior Median	95% CrI (Posterior Quantiles)	
		2.5%	97.5%
L_{ave} (10 dB(A))	**1.49**	**1.19**	**1.86**
L_s10 (10 dB(A))	**1.08**	**1.00**	**1.16**
L_s90 (10 dB(A))	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**

A choropleth map of the random effect (ϕ_k) estimates from the model which associated L_{ave} and sleep deprivation is shown in Figure 8.2. 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 socio-economic 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 and 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.

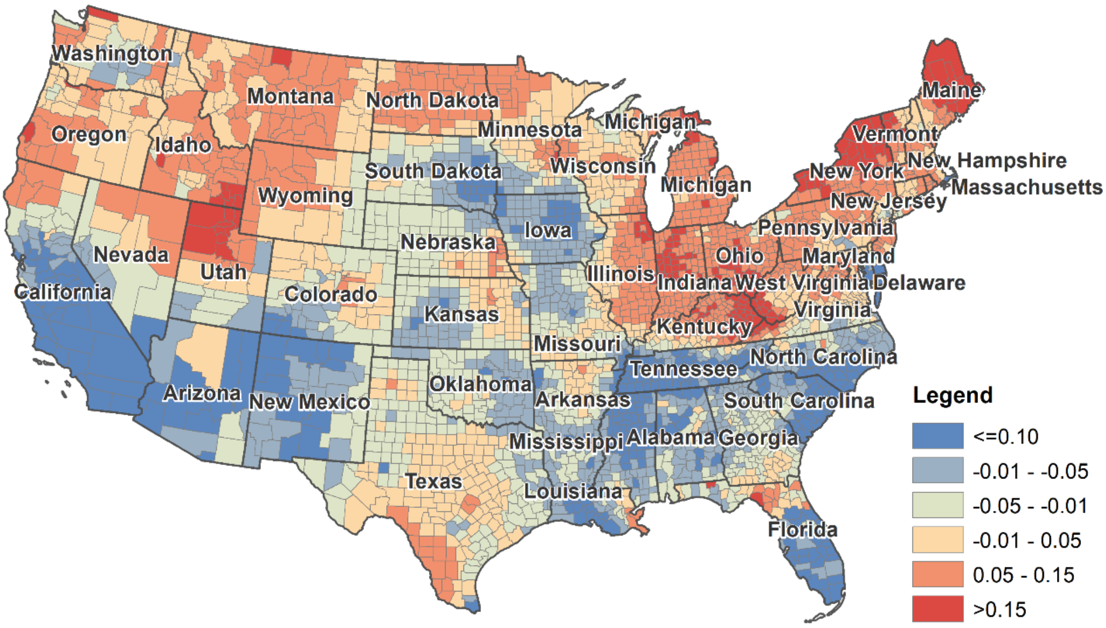

Figure 8.2 Posterior means of the spatial random effects from the regression model for L_{ave}. Large positive random effect values represent elevated risk of sleep deprivation after adjustment of predictors in the model. Large negative values indicate the opposite

8.4. 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 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).

With the Bayesian spatial regression modelling, it can be concluded that substantial noise indicators can contribute to variations in sleep deprivation among counties. Overall, the risk of not getting enough sleep would be higher when there is an increase in the average sound pressure level 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; Lin et al., 2018). It is interesting to note that among different spatially referenced noise indicators (L_s10 and L_s90), only sound pressure level of the relatively noisy area (L_s10) can increase the risk of sleep deprivation. L_s90, as sound pressure level of relatively quiet area, was not correlate with sleep significantly. Hence, noise policymakers should consider the spatial variations within a county (namely difference between relatively noisy and quiet areas) which current policies failed to consider. It is suggested that in the relatively noisy areas and quiet areas, the noise-management strategies could be different rather than uniform. For instance, in a relatively quiet area, more tolerant sound pressure level limits could be set. In the relatively noisy area, noise management could be more severe for population health. Furthermore, for population health, it is worth to protect "Quiet Areas" which has been paid much attention in Europe (European Environment Agency, 2014). The noise map used in this chapter can be also used to identify the "Quiet Areas". It is also suggested that policymakers could take L_s10 into consideration at county-level noise control guidelines and urban planners should place more emphasis on the layout on highway (where L_s10 always occurs) than other classifications of roads.

This chapter also found that exposure area ratio and exposure population ratio are associated 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 which considering the high-precision distribution of population in the county, can also increase the risk of sleep deprivation. A higher exposure population ratio means human settlements are located around the transportation network, which is a typical linear city as one of the urban sprawl patterns (Marshall & Gong, 2009). Therefore, the result also indicates that linear 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 the findings of Chapter 7, which showed that in urbanised or linear cities, the negative impacts of noise on residents is more serious. Previous studies focus more on physically acoustical indicators such as sound pressure level, however, did not fully take administrative level geo-spatial 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. Big data also makes it possible to conduct research at larger scale and broader coverage, for example, at the European Union 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. For instance, linear cities should be placed more emphases on when dealing with noise-induced sleep problems.

This chapter suggests a number of possibilities for future research. First, previous research has shown that subjective perception of noise varies in different countries (Yang & Kang, 2005), while this chapter 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 (ISO, 2014). This chapter 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. Finally, it is 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. Hence, it is worth exploring additional reasons, such as noise policy and building regulation. Correspondingly, collective actions are needed to deal with public environmental health issues across counties, especially the geographical proximity counties.

8.5. 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. This chapter 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. Among the geo-spatial noise indicators, only L_s10 (sound pressure level of the relatively noisy area in a county) can increase the risk of sleep deprivation, while L_s90 (sound pressure level of the 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 increase in the odds of a person within a county not getting enough sleep. This chapter suggests that policymakers could set up different noise-management strategies for quiet and noisy areas (i.e., different limiting sound pressure levels) and incorporate large scale geo-spatial noise indicators, such as exposure population or area ratio when formulating noise policies. Furthermore, urban planners can pay more attention to different urban sprawl patterns, like linear city. In future studies, it is worth exploring additional reasons for remaining unexplained variations which is driven by spatial correlation.

Chapter 9

Using multi-sourced big data to correlate mental health and road traffic noise: A national scale spatial analysis[1]

In addition to sleep deprivation, this chapter discusses the impact of noise on health from another perspective, namely mental health status, which is also driven by the convenience and availability of data. Section 9.1 contextualises the research background and introduces the augments of the impact of sound environment on mental health. Section 9.2 illustrates Bayesian spatial regression methods utilised to examine the correlations between noise and mental health in the US. The data sources and analysis methods used in this chapter are same as the previous chapter. In Section 9.3, the results are presented and discussed. Finally, Section 9.4 gives a brief summary and critique of the findings. This chapter is in preparation for publication.

9.1. Introduction

Road traffic noise is a growing environmental health problem that has a significant impact on human well-being. Noise is a primary contributor to certain risk factors related to human health. For instance, temporary or permanent loss of hearing, loss of sleep, stress, and irritability can be caused by noise exposure

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[1] This chapter is in preparation for publication: Tong et al., (2022). Using multi-sourced big data to correlate mental health and road traffic noise: A national scale spatial analysis. In the interest of fluency and readability, this chapter maintains the title and most text, apart from changes in method section(9.2.4).

(e.g., Dzhambov & Dimitrova, 2016a; Welch et al., 2013; Wothge et al., 2017). In recent years, there is a growing academic interest in the factors affecting mental health. Many studies show that noise is related to adverse effects on mental health, including stress, discomfort, and negative psychological status (e.g., Lercher et al., 2002; Wålinder et al., 2007). For instance, Carbone et al. (2005) and Wallenius (2004) indicated that noise exposure is related to increased individual stress levels and psychological diseases. Based on questionnaires, Sygna et al. (2014) found that noise has a weak positive relationship with psychological distress. Lercher et al. (2002) found that ambient noise was related to a small decrease in children's mental health. It can be seen that the evidence on the impact of noise on mental health remains weak. Furthermore, previous studies primarily focus on the individual level at a small scale. In the big data era, data from various sources have been applied to environmental research, such as air quality and the thermal environment (e.g., Naeher et al., 2000; Yuan et al., 2014; Zheng et al., 2019). In particular, massive amounts of data enable large-scale research on environmental health. However, little research is conducted using open data to study the impact of the sound environment on health.

Therefore, this chapter aims to characterise the spatial pattern of mental health status at the county level based on open big data and explore its relationships with road traffic noise by considering neighbourhood effects. To investigate the research question, this chapter takes the US as the study area and applies open data from various sources, based on the GIS technique and hierarchical Bayesian spatial model, at the county level.

9.2. Methods

9.2.1. Geographic samples

To explore the mental health status and its relation to road traffic noise at a large scale, the US, which has a population of approximately 332 million people, is considered as the study area. The dataset has two geographic labels: state and county. County levels were examined to obtain more samples. Meanwhile, all indicators were calculated at the county level. Due to limited data availability, 48 contiguous states were selected for analysis (i.e., excluding Alaska and Hawaii). In addition, the measurement of traffic noise and mental health status are consistent across the continental US, making it feasible to compare across counties.

9.2.2. Mental health data sources

Numerous studies measured the factors affecting mental health, and subjective evaluation of mental health status is a well-recognized method that is widely used. This chapter used self-reported health status data as well. Data for this study were obtained from BRFSS developed by CDC in 1984. BRFSS is the nation's premier system of telephone surveys that collect data on US residents' health-related risk behaviours, chronic health conditions, and use of preventive services. Established in 1984, it is the largest health survey system in the world (CDC,2014). In this survey, health status is one of the most important topics. BRFSS 2010 is the latest dataset with county labels. The mental health status in this chapter is measured based on the following question from the survey: "how many days during the past 30 days was your mental health not good?" The answers include: "Number of days", "None", "Don't know/Not sure", "Refused", and "Not asked or Missing". A total of 451,075 persons were surveyed. The effective response rate of this question is 98.07% because 8,723 persons were not sure or refused to answer or were not asked.

9.2.3. Traffic noise data sources and processing

The data source for noise levels lies in the online noise maps produced by the US Department of Transportation (Bureau of Transportation Statistics, 2017).

The national transportation noise inventory is developed based on the FHWA TNM 2.5. Similar to many other noise prediction models, the FHWA TNM 2.5 computes a predicted noise level through a series of adjustments to a reference sound level. In the TNM, the reference level is the vehicle noise emission level. Adjustments are made to the emission level to account for traffic flow, distance, and shielding (Bureau of Transportation Statistics, 2017). The results are L_{Aeq} that represent the approximate average noise energy due to road noise over a 24-hour period. For the current study, the latest available public data dates to 2014.

The road traffic noise map was imported into ArcGIS Pro 2.7 and converted to a raster file with 30 m grid resolution, which is the finest available spatial resolution. The same grid size was used for the original noise maps. The value of the pixels from the raster represents the road noise level. As there are 153,609 × 96,498 pixels in total, it exceeds the available computational ability. To combat this problem, the raster was split and reclassified to make data processing feasible, and the noise map was reconstructed as a new raster dataset by splitting the raster into 400 smaller raster maps. These 400 raster maps were batch-processed. The original accuracy of the noise level values was 0.001 dB(A), and the accuracy of the noise level was reduced to 1 dB(A) to improve the computing efficiency.

After reconstructing the noise map data, detailed indicators of road traffic noise were calculated. This includes the average sound pressure level (L_{ave}), sound pressure level of relatively noisy areas in a county (L_s10), sound pressure level of relatively quiet areas in a county (L_s90), area exposure to traffic noise (Exposure area (km^2)), the percentage of an area exposed to traffic noise (Exposure area ratio (%)), population exposed to road noise (Exposure population (in thousands)), and the percentage of population exposed to road noise (Exposure population ratio (%)). It should be noted that L_s10 and L_s90 generally represent the level of noise exceeding 10% or 90% for the specified measurement period, whereas, in this chapter, they are used to represent a spatial rather than temporal distribution. In other words, if the noise level values obtained for an area are sorted in descending order, then L_s10 and L_s90 are the 10th and 90th noise levels, respectively.

All the indicators were extracted based on the reconstructed noise map. A Python program was developed to extract L_s10 and L_s90. For other noise indicators, the calculation is conducted with the help of the "Zonal Statistics" tool, which makes it feasible to summarise the area of noise pixels per noise level value within the county. In terms of population exposure, the noise map data allows viewing potential exposure at the county level as well. Population exposure assessments can be a valuable tool for evaluating current and future noise conditions. Population exposure is measured by the number of people affected by road noise. First, the population in each noise pixel is calculated, then the "Zonal Statistics" tool was used to summarise the number of people affected by noise. Population data are obtained from the US census 2010, which is the most comprehensive demographic survey available for the US population. The spatial reference of the census 2010 is based on the census block group, which has the finest resolution.

9.2.4. Statistical analysis

This chapter modelled the probability that, in a specific county, an individual's mental health status was not good at some point in the past 30 days as a function of county-level road traffic noise, socio-economic factors, and spatially correlated random effects using a hierarchical Bayesian spatial logistic regression framework. The statistical model is as follows:

$$Z_l|q_l \sim \mathrm{Binomial}(m_l, q_l), l = 1, \dots, m; \tag{9.1}$$

$$logit(q_l) = \alpha_0 + \alpha_1 * \mathrm{noise}_l + \sum_{g=1}^{6} \mathrm{fs}_{gl} * \mu_g + \phi_l \tag{9.2}$$

where Z_l is the observed number of people with not good mental health status in county *l* out of the m_l people who were surveyed in the county; *m* is the total number of counties included in the chapter; q_l is the probability that a person in the county does not have a good mental health status; noise_l is the measure of road traffic noise in the county (multiple metrics were tested in separate models due to the high correlation between them); fs_{gl} is the factor loading from the g^{th} principal component in the county (six factors were retained); and ϕ_l is the spatially correlated random effect specific to the county. The calculation of ϕ_l is adapted the equation for ϕ_k in Chapter 8 (see section 8.2.2). Six principal components were extracted from a number of socio-economic factors via PCA to reduce the high autocorrelation among these factors. The socio-economic factors obtained from ACS include population, sex ratio, median age, percentage of black or African Americans, 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 a bachelor's, 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. To complete the model setting, the same prior distributions were assigned as Chapter 8 (see Section 8.2.2).

9.3. Results and discussions

In the US, 31.08% of people reported that their mental health was not good to different extents in the last 30 days. On average, their mental health was not in good status for 11.07 days.

Figure 9.1 presents the percentage of people not getting good mental health at the county level. It shows that there are considerable differences in percentage of people who reported a not good mental health status among counties.

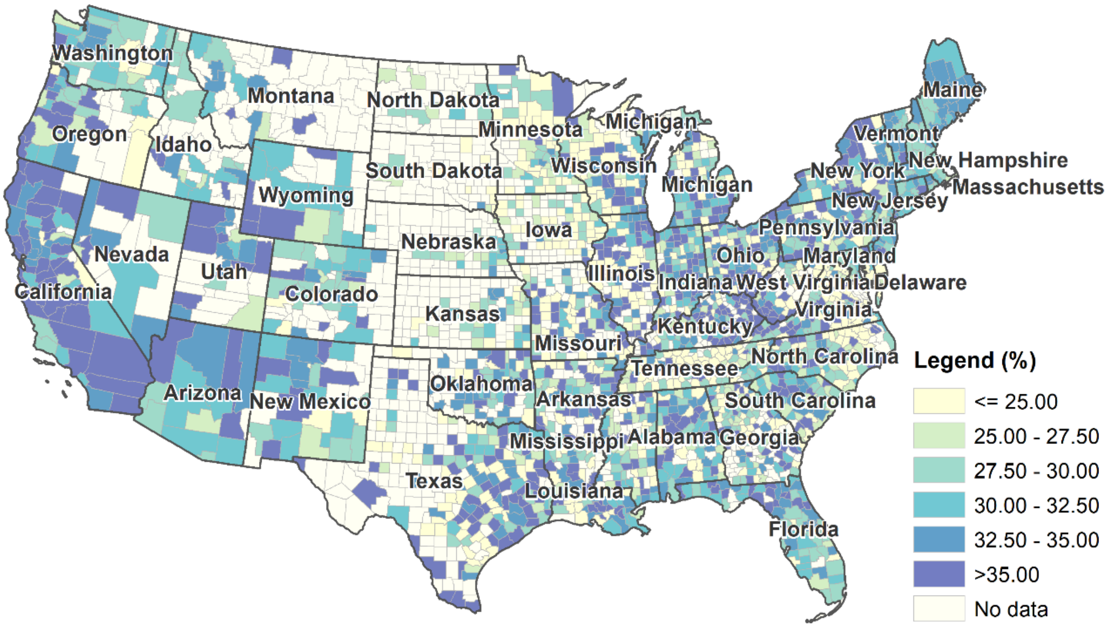

Figure 9.1 The percentage of people not getting good mental health at the county level

The results from the statistical modelling are presented in Table 9.1. The table shows the estimated associations on the OR scale (i.e., posterior medians and 95% CrIs) between the probability of not having a good mental health status and substantial noise indicators. The results for those variables with 95% CrIs that exclude 1.00 were highlighted in bold. Overall, traffic noise can contribute to variations in mental health problems among counties. The changes in geo-spatial noise level, including L_{ave}, L_s10, and L_s90 at the county level, were not associated to the odds of a person in that county having a not good mental health status in the past 30 days. No significant association was observed between mental health and the absolute exposure area, as well as exposure population. Turning to the exposure area ratio and exposure population ratio, the results show that a 10% increase in exposure population ratio was associated with a 3% increase in the odds of a person reporting not good mental health (1.03; 1.01-1.04). It can be concluded among the seven noise indicators, only the exposure population ratio has a positive relationship with mental health status. The findings support the results from observations on individuals that ambient noise is weakly associated to mental health from the psychological distress perspective (Sygna et al., 2014). The results from the exposure population ratio and absolute exposure population indicate that urban sprawl patterns play a more significant role than city size. Furthermore, a higher exposure population ratio indicates that human settlements are located around the transportation network, which is the linear city, a typical urban sprawl pattern (Marshall & Gong, 2009). Therefore, the findings suggest that linear cities may be more prone to serious mental health problems due to sound environments.

Table 9.1 Odd ratio and 95% credible interval (CrI) for sleep deprivation associated with overall indicators for noise

Indicators	Odds Ratio		
	Posterior Median	95% CrI (Posterior Quantiles)	
		2.5%	97.5%
L_{ave} (10 dB(A))	1.12	0.89	1.23
L_s10 (10 dB(A))	0.97	0.90	1.05
L_s90 (10 dB(A))	1.15	0.68	1.96
Exposure area (km^2)	1.00	1.00	1.00
Exposure area ratio (10%)	1.00	0.99	1.01
Exposure population (thousand people)	1.00	1.00	1.00
Exposure population ratio (%)	**1.03**	**1.01**	**1.04**

Figure 9.2 displays a choropleth map of the random effect (ϕ_k) estimates from the model that associated the exposure population ratio and mental health. It can be seen that several areas (e.g., counties in California) continued to have a high residual risk for people without a good mental health status even after adjustment for noise and socio-economic factors. This suggests that the covariates cannot explain all the variances among counties, and there is unexplained variation in the data. The results further suggest that the unexplained variation in the data was primarily driven by strong spatial correlation instead of non-spatial random variation, as indicated by the estimate of ρ (0.99; 0.97-1.00). This means that apart from traffic noise, the variations between counties are driven by neighbourhood effects as well. Hence, when dealing with noise-induced mental health problems, discussion forums and collective actions are needed across counties, especially in geographically close counties. Additionally, this rationale can be applied to broader public environmental health issues. Furthermore, it is worth exploring additional

reasons for unexplained variations, such as noise policy and building regulations.

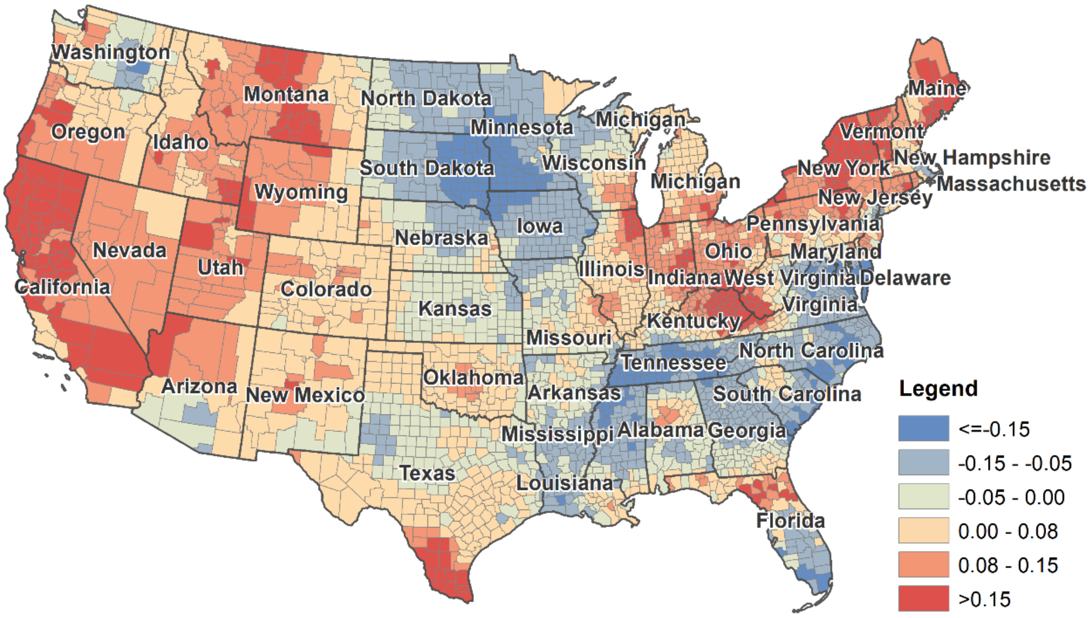

Figure 9.2 Posterior means of the spatial random effects from the regression model for exposure population ratio. Large positive (negative) random effect values represent elevated (lowered) risk of mental health after adjustment of predictors in the model.

9.4. Conclusions

In the US, approximately one-third of the residents reported that their mental health was not good in the past 30 days. Further, these residents are unevenly spatially distributed across the whole country. To examine the associations between traffic noise and mental health status, a hierarchical Bayesian spatial modelling framework was used to simultaneously account for spatial correlations. Among the examined indicators, only the exposure population ratio was associated to the increase in the risk of a person reporting not good mental health in a particular county. No significant association was found for the absolute exposure area. In addition, various sound pressure level indicators were not associated to sleep deprivation. Notably, this chapter indicates that apart from traffic noise, the variations between counties are driven by neighbourhood effects as well.

The present results have broad implications for public health issues from the perspectives of city governance and resource allocation. This finding of mental health inequalities in spatial distribution could be used to determine which areas have more severe mental health issues and to provide decision support for policymakers. For instance, policymakers could set different noise standards or guidelines in different cities. Meanwhile, more resources could be allocated to severer areas. Moreover, this chapter also explains the impacts of different noise indicators on mental health from the perspective of urban planning and policy implementation. These results could help promote mental health by reducing noise pollution. For instance, exposure population ratio could be treated as a priority indicator resource allocation and noise pollution prevention.

In this chapter, mental health was analysed as an integrated indicator. Specific mental health problems are not addressed. In future studies, it might be possible to investigate specific problems related to mental health, such as stress, depression, and anxiety. Furthermore, given the consideration of soundscapes, Alvarsson et al. (2010) and Ulrich et al. (1991) stated that exposure to natural sounds facilitates recovery after psychological stress. The positive impact of sound on mental health would be worthwhile to explore in future studies. Furthermore, the health data used in the analysis are subjectively reported health status. It could be argued that self-reports may deviate from the findings of physiological and medical examinations. Although self-reported health is widely used in environmental health research, which is strongly related to clinical data (Bowlin et al., 1993, Heliovaara et al., 1993, Molenaar et al., 2007). Using clinical data may improve the analysis.

Chapter 10

Conclusions

This chapter is composed of three themed sections by main findings, implementation, and future research. Section 10.1 summarises the findings of the research, and answer the three key research questions proposed in the introduction chapter. Then Section 10.2 discusses the implication of the main findings. Finally, Section 10.3 identifies limitations and directions for further research.

10.1. Main findings

Healthy cities have long been a question of great interest in a wide range of academic fields, especially in urban planning and environmental research. With rapid urbanisation, determining the impacts of the sound environment in an urban context on human health is essential for the future of constructing healthy cities. However, research on the urban sound environment at a large administrative scale is still insufficient. With the advent of big data era, large-scale studies have become feasible by using massive and various open data. Therefore, following the data-driven approach framework, this research uses governmental open data with statistical analyses based on GIS technique to examine the relationships between urban planning and human health from the sound environment perspective, at three large scales, including city/micro, regional/meso, and national/macro scales. Overall, this research extents literature with a substantial body of evidence that urban patterns play an essential role in noise-induced public health problems at all three large scales.

Regarding the three research questions posed at the beginning of this thesis, the main findings are as follows:

(1) For the city/micro scale studies, the overall research question was: what is the relationship between urban morphology and sound perception citywide?

Based on hypothesis tests and Spearman correlation using data obtained from New York City and London open data platforms, an examination of the noise complaints at the city/micro scale in Part I reveals that urban planning factors can significantly contribute to the variations in noise complaints between different areas within a city or in different periods. Contextual urban factors play a more significant role in determining noise perception as compared to the actual noise level.

Specifically, noise complaints increase every year and are unevenly spatially distributed (Chapter 4). The noise complaint rate is generally significantly related to the transportation network and all land use types, except for parks. A significant relationship between noise complaints and park density is only found in the lowest-density areas. Moreover, the more enclosed and denser the blocks, the higher the noise complaint rate. However, the relationships between noise complaints and building morphology are weaker in high-density boroughs than in other boroughs.

Turning to the lockdown period, the number of noise complaints increased significantly after the lockdown was implemented in Greater London, with an overall increase of 47.54% (Chapter 5). The change rate of noise complaints is generally related to housing and demographic factors but is not significantly related to the traffic noise level. It can be inferred that in such extraordinary nationwide lockdown circumstances, contextual urban factors proved to be more significantly associated with the increase in noise complaints than the actual noise exposure to traffic noise.

(2) For the regional/meso scale studies, the overall research question was:

what is the relationship between urban planning parameters and perceptual sound in terms of noise complaints region-wide?

Based on Spearman correlation and ridge regression using data obtained from Public Health England, Census, and Strategi Map across all cities in England, regional/meso scale studies reveal that a large number of urban planning parameters are related to noise complaints. The noise complaint rate is not only associated with urban morphologic features, but also the socio-economic status of a city, which reflects the importance of the soundscape. More specific findings are as follows:

As a key component of urban planning parameters, various socio-economic status aspects are generally related to noise complaints. The results show that cities with a higher proportion of young and single residents tend to have more noise complaints, as do cities with diverse ethnicities and religions. Moreover, high-density cities with higher unemployment rates are likely to receive more noise complaints. It can be concluded that more deprived or unstable cities tend to have more noise complaints.

Urban development patterns as another essential component of urban planning parameters have been also examined, with results showing that large and uneven cities tend to have more noise complaints, as do clustered cities. However, dispersed, fragmented, and/or cities with ragged boundaries are likely to have fewer noise complaints. These findings are supported by the analysis of transport networks and commuting factors. Furthermore, cities with more natural elements, including greenery and bodies of water, tend to have lower noise complaint rates.

(3) For the national/macro scale studies, the research question was: what is the relationship between sound environment and human health nationwide?

Based on a hierarchical Bayesian spatial regression model using national traffic noise maps and large-scale health surveys, the findings of this research indicate that traffic noise can significantly contribute to health inequality among counties. Furthermore, the urban sprawl pattern plays a more significant role in noise-induced health problems than the magnitude of urbanisation. Notably, this research indicates that apart from traffic noise, the variations between counties are driven by neighbourhood effects as well. More specific findings are as follows:

In terms of sleep deprivation, it is found that a large group of people suffer from sleep deprivation in the US (Chapter 8). These results confirm that traffic noise can contribute to variations in sleep deprivation among counties. Specifically, the sound pressure level of the relatively noisy area in a county is associated to the increase in the risk of sleep deprivation, whereas that of relatively quiet area cannot. Moreover, the noise exposure population ratio is associated with sleep deprivation, with a higher odd ratio than the noise exposure area ratio. Considering the distribution characteristics of traffic noise levels, the results indicate that urban sprawl patterns play a more critical role in noise-induced sleep issues than the magnitude of urbanisation. Furthermore, noise-induced sleep deprivation varies with different urban sprawl patterns. Residents in linear cities could suffer serious sleep problems due to noise.

From mental health perspective, the results from Chapter 9 show that, in the US, around one-third of the residents reported their mental health status are not good. The links between traffic noise and mental health are weak. Among the noise indicators extracted from the noise map, a higher percentage of the population exposed to road traffic noise tends to increase the risk of a person reporting poor mental health. No significant association is observed for other traffic noise indicators. The results further support the findings in Chapter 8, which shows that residents in a linear city could suffer serious noise-induced health problems.

10.2. Implementation

This research adds a body of evidence of the relationships between urban planning and public health from the sound environment perspective at three large scales. To the best of the author's knowledge, this research provides the first comprehensive assessment of the urban sound environment at large administrative levels. The results can be used to achieve healthy cities based on the impacts of the sound environment on human health. The findings are expected to inform different tiers and departments of local authorities from urban planning and design, policymaking, and city government perspectives. These findings have significant implications as following:

City/micro scale studies provide a deep insight into noise complaints within a city. This study examines the prevalence and nature of various types of noise complaints in NYC and London during normal and lockdown periods. Its significance lies in the fact that this study identifies strategies that can be tailored for specific urban morphologies when implementing policies or designing areas with respect to the negative impacts of noise. For instance, policymakers could set up the noise level criteria during different periods of twenty-four hours or different seasons in a year. Due to the higher number of vehicle noise complaints in the summer, more traffic noise management regulations could be implemented, such as stricter speed limitations or whistle bans. From the transportation network perspective, planners could focus on the layout of 20-40 m wide roads where noise complaints occur more frequently than minor roads or high-level motorways. This recommendation is also supported by Margaritis and Kang (2016), who found that primary road length impacts noise levels. It is noted that the results from this study and research from Margaritis and Kang (2016) are both based on the statistical analysis, which only reveals correlation rather than the casual effects. Furthermore, while in literature, it is shown greenery could reduce noise annoyance (Echevarria Sanchez et al., 2017), based on the results from this study, an increase in park density is only related to noise complaints in a low-density area. It would be important to consider various urban densities when using and protecting parks to mitigate noise annoyance. By an examination of noise complaints during the lockdown period, the findings of this research provide insights for future patterns of people working from home, which will likely become an increasingly common practice in the future. Noise complaints will then be an even more crucial factor in the context of human well-being, although the environment is quieter. It is expected that this study could cause the government and policymakers' attention about the importance of soundscape and the unexpected impacts of future life and work patterns.

The findings of the regional/meso scale studies could help create a better sound environment through urban development planning. This study has raised important questions about the nature of noise complaints and illustrates the relationships between noise complaints and comprehensive urban planning parameters. From regional/meso scale studies, profiles of cities/regions can be drawn up from the perspective of noise complaints and urban planning factors. These findings could identify the regions with more severe noise complaints. For instance, a high-density, uneven city with a higher unemployment rate tends to have a higher noise complaint rate. Therefore, more resources can be allocated to such cities. Furthermore, this study can be applied to identify the urban planning factors that should receive more attention when addressing these issues (e.g., when utilising and protecting the natural landscape). It is noted these recommendations are made based on the statistical analysis. The correlations are revealed, but the complicated causality is not built. To build causality and make further suggestions, it is worth examining the demographic factors and psychological states of complainants for more analysis. Overall, it is expected that this study could inform the government about the pattern of noise complaints and help allocate resources more effectively to achieve a better urban environment.

As for the national/macro scale study, it is one of the first attempts at a nationwide analysis of noise-induced sleep and provides evidence on the critical importance of urban sprawl patterns in such issues. It is expected that this study can attract the government's attention to noise-induced health problems and promote noise policy implementation. The results could be used to identify which areas have more serious sleep deprivation or mental health issues in the US and provide decision support for policymakers to protect people from noise nuisance. This study suggests that governments pay more attention to administrative-level noise indicators and urban sprawl patterns from public policy and urban planning perspectives. For instance, the policymakers should emphasise the protection of quiet areas and set up different noise-management strategies for relatively quiet and noisy areas in a county (i.e., different limiting sound pressure levels). 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'. Moreover, large-scale geo-spatial noise indicators, such as exposure population ratio, could be incorporated when formulating noise policies. Furthermore, urban sprawl patterns play an important role; hence, different urban sprawl patterns should be treated strategically in different ways, and linear cities should be paid particular attention due to the high noise impacts.

In addition, from a methodological perspective, the data-driven approach used in this research proves helpful in expanding our understanding of the urban sound environment at a large scale. This thesis is one of the first attempts to apply open data and GIS techniques to conduct large-scale sound environment research. It is expected that the data-driven approach will serve as a basis for future studies. Taken together, these findings suggest that urban planning and design may play a crucial role in promoting a healthy city from a sound environment perspective. It is expected that this research can inform urban planners and policymakers from the perspective of acoustic impacts, leading to more effective noise management strategies and planning. Therefore, the results of this research can be useful for reducing the negative impacts of environmental noise, improving the quality of life, and ultimately, achieving a healthy city.

10.3. Future research

Due to time constraints on this thesis, this thesis has several limitations that may be addressed by future studies on the current topic. Taken together, it is recommended that further research should be undertaken in the following areas.

First, this thesis primarily focuses on noise complaints, sleep problems, and mental health. To develop an integrated understanding of the impacts of the sound environment on human health, more research on other health problems is needed. For instance, according to a WHO report, it is estimated that DALYs lost from environmental noise leading to cardiovascular diseases amounts to 61,000 years. Accordingly, it would be useful to research cardiovascular diseases and other diseases in this context. Furthermore, the sound environment has positive effects on human health. For instance, quiet soundscape can promote health restoration and contribute to psychological and physiological well-being. A future study investigating the positive impacts of the urban sound environment on health would be very interesting.

Second, this research only considers the perspective of the sound environment to establish the relationships between urban planning and public health. Additional studies from other perspectives, such as air pollution and the thermal environment, are needed to develop a full picture of a healthy city and built environment. For instance, ambient air pollution has critical effects on respiratory diseases. It is worth conducting future research on urban ventilation in the context of a healthy city.

Third, this research primarily concentrates on the urban sound environment in the UK and the US. Further research should be undertaken to investigate the sound environment issues in emerging countries, such as Vietnam, China, and other countries. For instance, previous research has shown that the tolerance level to noise also varies in different countries (Yang & Kang, 2005). By an investigation in Ho Chi Minh City, Vietnam, the findings suggested that residents in Vietnam are more tolerant of road traffic noise. Specifically, the response is similar to the curve recommended by the European Commission when the noise levels increased by 5-10 dB (Gjestland et al., 2015). Therefore, it is worth investigating the sound environment issues in emerging countries. A further study with more focus on comparing emerging countries and developed countries is also suggested. However, from the applicability of the methodology perspective, there are still some limitations to extending this research to emerging countries. In the UK and the US, environment noise-related data have been largely available for the public, but the emerging countries have lagged behind in this field. For instance, by checking the governmental open data platforms, the noise complaints data collection and open is relatively late in emerging countries than in the UK and the US. Also, the accuracy, duration, and coverage of noise complaint data in emerging countries are relatively lower (DEFRA, 2015; NYC Department of Health and Mental Hygiene, 2014; Public Health England, 2018). For noise maps, currently, large-scale noise maps are available in the US and European cities with more than 100,000 inhabitants (Bureau of Transportation Statistics, 2017; European Union, 2002). The development of noise maps in emerging countries (e.g. China) is in progress. In the future, with more datasets available in emerging countries, the data-driven approach to sound environment research will benefit and move forward.

Fourth, the prevalence of electric cars is also a major challenge to noise map techniques. Currently, to create a noise map, the traffic noise model in the US, Germany, and other countries are calculated based on the noise emission of conventional cars. For instance, the national/macro scale studies in this research use the US national noise maps created by FHWA TNM 2.5, which computes a predicted noise level through a series of adjustments to the conventional vehicle noise emissions level by default. However, the emergence of traffic flow with electric cars would change the environmental acoustic conditions. For instance, Campello-Vicente et al. (2017) evaluated the expected noise effects of electric cars on noise maps based on the French Noise Prediction Model. They estimate that electric cars at speeds of 30 km/h in a free field lane lead to a 2 dB decrease. At speed above 50 km/h, the changes could be negligible because tyre-road noise becomes the dominant noise source. Currently, the research on effects of electric car fleet on noise maps is still lacking. In the future scenarios of hybrid and/or electric car fleet, the pattern of noise map could change (e.g., the decrease in noise level in low-speed zones) and it would be interesting to re-evaluate the impacts of traffic noise on sleep deprivation, mental health, and other diseases. In addition, it is noteworthy that the distribution of traffic noise complaints as a key component of noise complaint types would also vary with the change of noise map.

Lastly, this research uses statistical methods to answer the research questions. However, statistics can only be applied to explore the relationships and cannot measure the complex causality. Further work needs to be done to establish causality by combining qualitative and quantitative analyses. For instance, although the characteristics of the spatiotemporal distribution of noise complaints and their relations to urban planning parameters have been identified, the causality and motivation for complaints remain unexplored. With more data on complainants' characteristics, such as occupation, qualification, social class, the willingness to use the complaint platform, and other demographic factors, the causality and motivation for complaints could be better understood from psychological and social behaviour perspectives.

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Appendix A

Supplementary London noise maps

This appendix provides supplementary London noise maps for Chapter 5. The supplementary maps include road and rail noise level maps, road and rail noise ranks, and the change rate of noise complaints at the ward level.

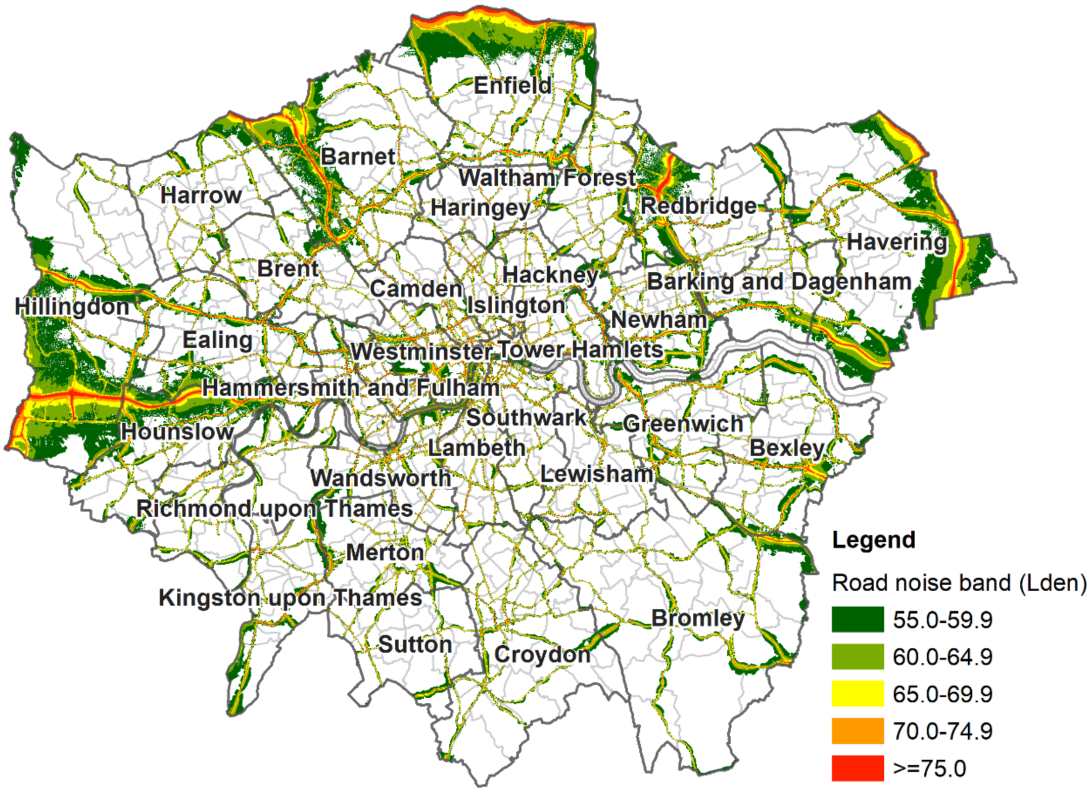

Figure A-1 Road noise level in London

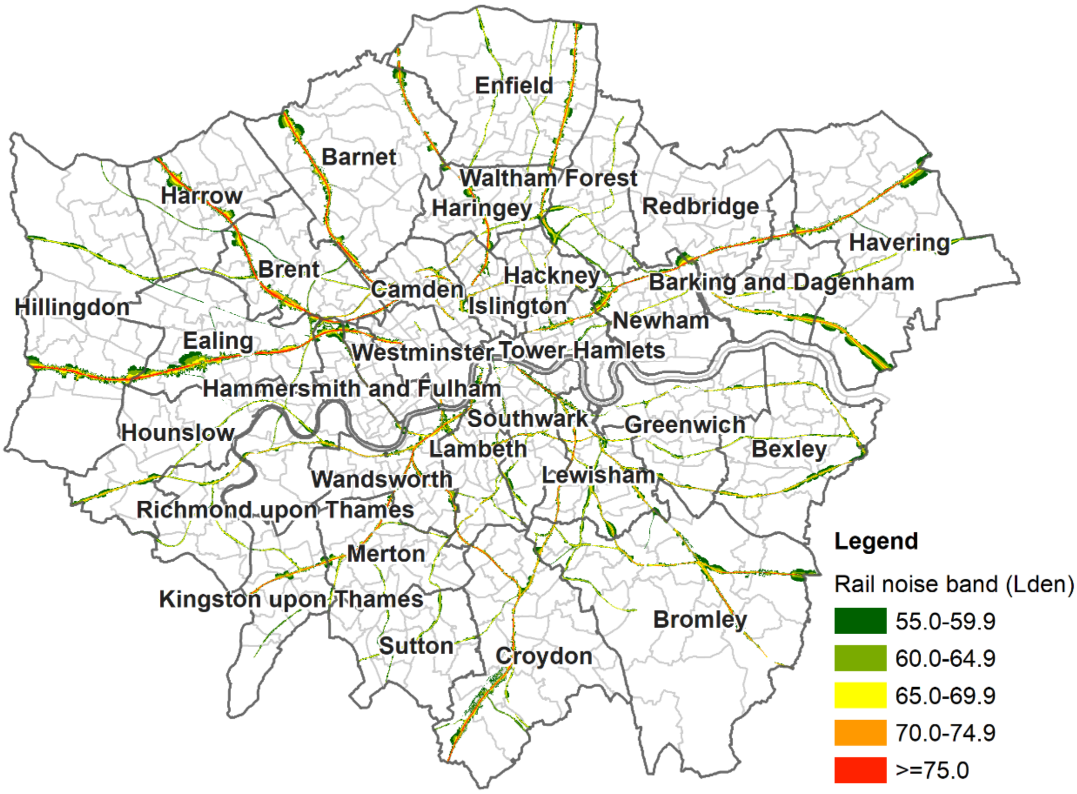

Figure A-2 Rail noise level in London

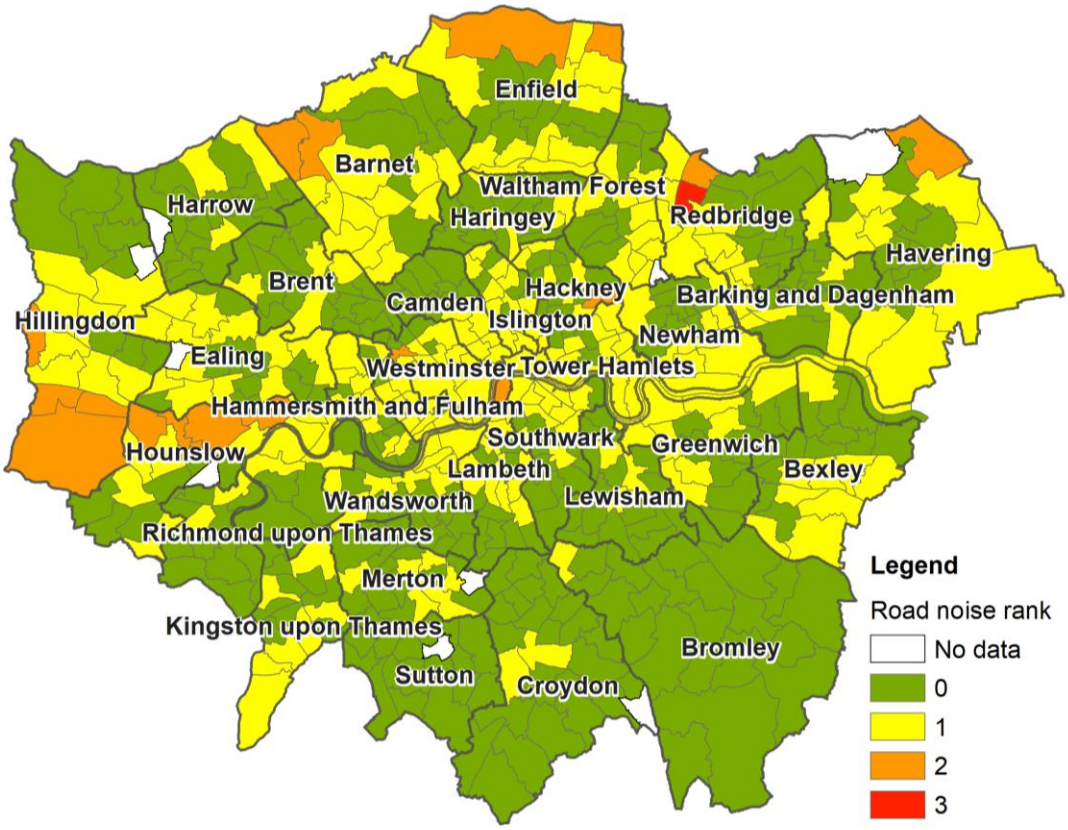

Figure A-3 Road noise ranks at ward level in London

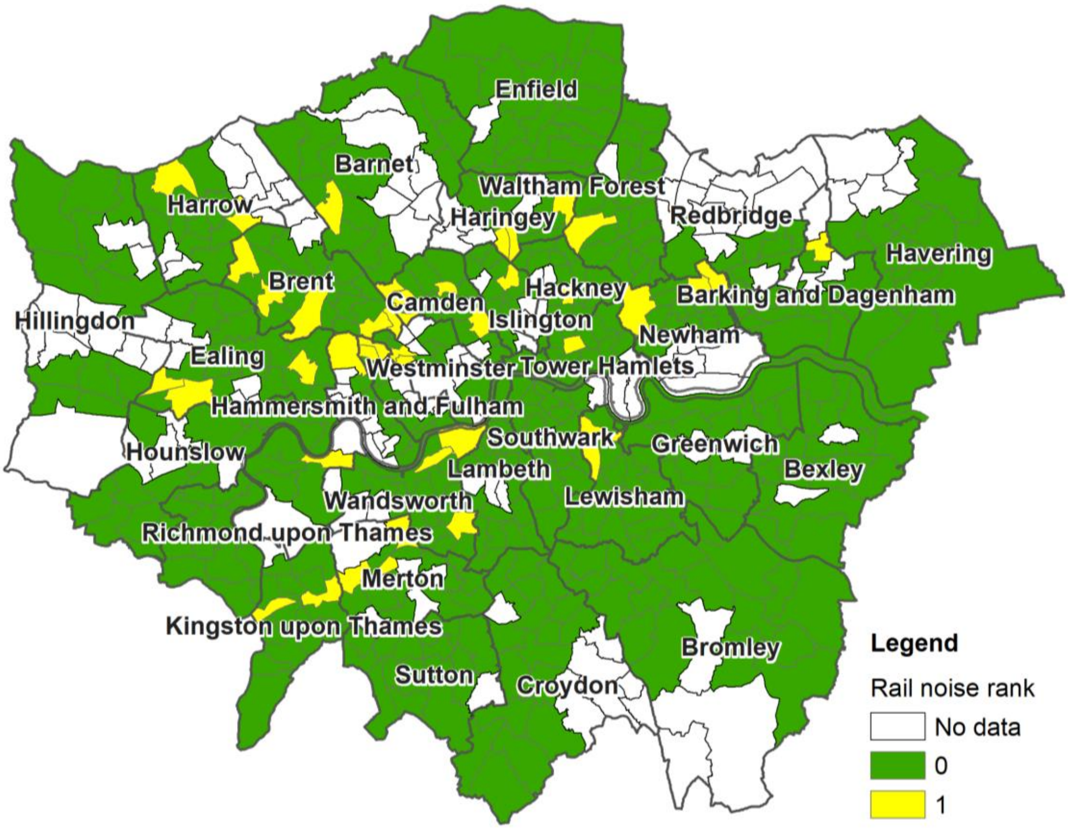

Figure A-4 Rail noise ranks at ward level in London

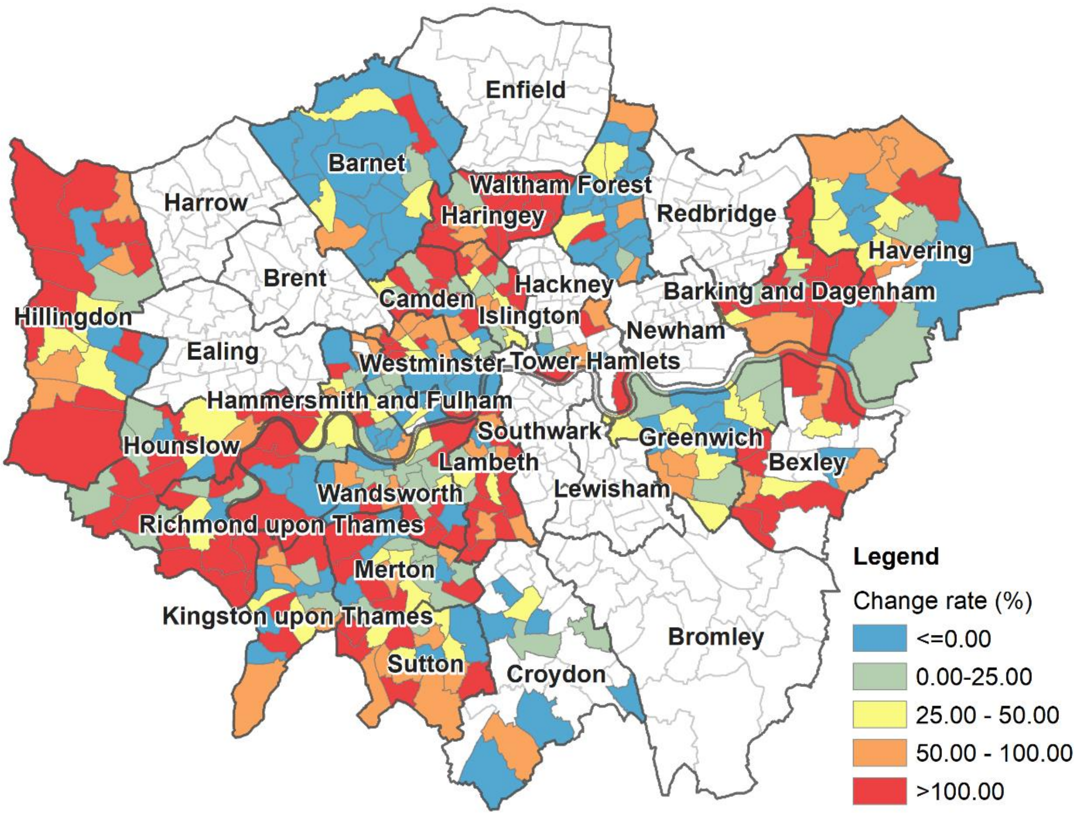

Figure A-5 Change rate of noise complaints by wards

Appendix B

Labels and categories for noise complaints

This appendix, including two tables, illustrates labels and categories for noise complaints for Chapter 5. Specifically, Table B-1 gives a summary of the labels for noise complaints. Table B-2, based on the teamwork, presents unique labels and assigned categories for the noise complaints.

Table B-1 Summary of the unique labels for noise complaints, grouped according to the five main categories used in this study.

cat_num	Category	N	%
1	Industry	36	7.4%
2	Construction	29	6.0%
3	Neighbourhood	373	77.1%
4	Undefined	46	9.5%
5	Non-noise	246	50.8%
	Total	484	100.0%

Table B-2 Unique labels for the noise complaints extracted from aggregated database of the 22 London boroughs that returned data, with the category to which they were assigned.

Unique noise complaint label	cat_num	Category
Building site	**2**	Construction
Residential noise	**3**	Neighbourhood
Smoke and fumes	**5**	Non-noise
Birds	**3**	Neighbourhood
Noise in the street	**3**	Neighbourhood
Noise from commercial premises	**1**	Industry
Street works	**2**	Construction
Basement construction - noise and dust	**3**	Neighbourhood
Busker complaint	**3**	Neighbourhood
Dog	**3**	Neighbourhood

Appendix B. Labels and categories for noise complaints

OOH requests - street works	**2**	Construction
Odours and smoke	**5**	Non-noise
Burglar/fire alarm	**3**	Neighbourhood
Grit and dust	**5**	Non-noise
Crossrail complaint	**1**	Industry
Complaint Stage 1 (Noise Team Only)	**4**	Undefined
Proactive Noise Team Job	**4**	Undefined
Car alarm	**3**	Neighbourhood
Insects	**5**	Non-noise
People Noise	**3**	Neighbourhood
Barking Dogs	**3**	Neighbourhood
Music and Voices	**3**	Neighbourhood
Machinery and Equipment	**3**	Neighbourhood
Section 61 Building Site Prior Consent	**2**	Construction
Noisy Neighbours-Music	**3**	Neighbourhood
Parties/Raves	**3**	Neighbourhood
Noisy Neighbours-People	**3**	Neighbourhood
ASB Crime and Policing Act 2014	**4**	Undefined
Domestic - Loud Amplified Music	**3**	Neighbourhood
Domestic - Construction and Demolition	**3**	Neighbourhood
Construction/Roadworks	**2**	Construction
Licensed Prem Noise-People	**3**	Neighbourhood
Domestic noise DIY	**3**	Neighbourhood
Dog Barking/Other Animal Noise	**3**	Neighbourhood
DIY	**3**	Neighbourhood
Domestic noise other	**3**	Neighbourhood
Domestic noise music	**3**	Neighbourhood
Alarm Noise	**3**	Neighbourhood
Smoke / Bonfire	**5**	Non-noise
Noisy party	**3**	Neighbourhood
Service REQUEST Noise and Nuisance	**4**	Undefined
Party	**3**	Neighbourhood
Noise Pollution Case	**4**	Undefined
Domestic - Voices, Singing, Banging etc	**3**	Neighbourhood
Highways - In Car Entertainment stereo	**3**	Neighbourhood
Commercial - Construction and Demolition	**3**	Neighbourhood
Commercial - Fixed Air Handling Units	**3**	Neighbourhood
RS - Domestic - Bonfires, vehicle, etc	**5**	Non-noise
Commerical noise	**3**	Neighbourhood
TV / Radio	**3**	Neighbourhood
Premises alarm	**3**	Neighbourhood

Appendix B. Labels and categories for noise complaints

Building works noise	**2**	Construction
Miscellaneous Noise	**4**	Undefined
Construction site	**2**	Construction
ENVIRONMENTAL PROTECTION ACT 1990	**4**	Undefined
Nuisance other	**4**	Undefined
Machinery Fixed	**3**	Neighbourhood
Other / Unidentified	**4**	Undefined
Domestic - Misc (Anything Else)	**3**	Neighbourhood
Mobile plant	**3**	Neighbourhood
Dust nuisance	**5**	Non-noise
Vehicle Noise (Deliv/Collect)	**3**	Neighbourhood
Construction/demolition	**2**	Construction
OOH other EH	**5**	Non-noise
Domestic - Generators	**3**	Neighbourhood
Noise - Planning Application	**3**	Neighbourhood
NAMP - Noise from amplified music	**3**	Neighbourhood
NBUI - Building Site Noise	**2**	Construction
NVME - Vehicle, Machine & Equip Noise	**3**	Neighbourhood
Odour/smoke nuisance	**5**	Non-noise
Plant (Mobile)	**3**	Neighbourhood
Amplified Music	**3**	Neighbourhood
N01 Domestic Noise - Music	**3**	Neighbourhood
N02 Domestic Noise - Other	**3**	Neighbourhood
Highways - Misc (Anything Else)	**1**	Industry
NOTH - Noise - Other	**4**	Undefined
Barking Dog	**3**	Neighbourhood
Alarm	**3**	Neighbourhood
Other	**4**	Undefined
Fixed machinery	**3**	Neighbourhood
Streetworks	**2**	Construction
N99 Noise advice	**4**	Undefined
Commercial - Loud Amplified Music	**3**	Neighbourhood
Domestic - Barking Dog	**3**	Neighbourhood
Noise in Street Car Alarms	**3**	Neighbourhood
Vehicle Repairs	**3**	Neighbourhood
N03 Animal Noise	**3**	Neighbourhood
(NSE) CIEH - People Noise (e.g. footsteps, talking, shouting etc)	**3**	Neighbourhood
(NSE) Noise (CIEH stats)	**4**	Undefined
Domestic - Non amplified musical instr	**3**	Neighbourhood
Noise Other	**4**	Undefined
Noise Domestic Music	**3**	Neighbourhood

N22 Vehicle Alarm	**3**	Neighbourhood
RS - Domestic Pol - Misc (Anything Else)	**5**	Non-noise
Licensed Premises Noise-Music	**3**	Neighbourhood
TV/Radio	**3**	Neighbourhood
(NSE) CIEH - TV / Radio	**3**	Neighbourhood
(NSE) CIEH - DIY	**3**	Neighbourhood
Domestic - Do it Yourself	**3**	Neighbourhood
RS - Domestic - Odours, fumes and gas	**5**	Non-noise
Commercial - Industrial Noise	**1**	Industry
NDOG - Noise from barking dog(s)	**3**	Neighbourhood
Buskers	**3**	Neighbourhood
Noise - domestic,neighbours	**3**	Neighbourhood
Vip Complaint (Noise Team Only)	**4**	Undefined
N20 Intruder alarm	**3**	Neighbourhood
Highways - Roadworks	**2**	Construction
Noise - barking dogs	**3**	Neighbourhood
Noise In the Street - NOT ALARMS	**3**	Neighbourhood
Noise commerical - deliveries	**3**	Neighbourhood
Noise - building sites	**2**	Construction
NNH Noise-People	**3**	Neighbourhood
NNT LA2003 Consultation - Public Nuisance	**4**	Undefined
E17 Fly-tipping - private land	**5**	Non-noise
N11 DIY On Premises - Domestic	**3**	Neighbourhood
A20 Smell nuisance - other	**5**	Non-noise
D01 Bonfires - Domestic	**5**	Non-noise
N09 Licensing Enquiry	**5**	Non-noise
N10 Industrial / Commercial Noise	**1**	Industry
N14 Construction Site Noise	**2**	Construction
Oth Invalid code	**5**	Non-noise
N08 Car Alarms on Street-Dom	**3**	Neighbourhood
E10 Accumulation - domestic	**5**	Non-noise
062 Private Land	**5**	Non-noise
E01 Blocked/Defective Drain	**5**	Non-noise
C57 Abandoned Vehicles	**5**	Non-noise
A15 Pollution Enquiry	**5**	Non-noise
(NSE) CIEH - Music	**3**	Neighbourhood
(NSE) CIEH - Barking Dogs	**3**	Neighbourhood
Highways Street Speakers,buskers etc	**3**	Neighbourhood
Domestic - Car Alarms all vehicles	**3**	Neighbourhood
N01 Construction	**2**	Construction
N47 Equipment/ Plant - Domestic	**3**	Neighbourhood

Appendix B. Labels and categories for noise complaints

Dog barking	**3**	Neighbourhood
Commercial noise -other	**3**	Neighbourhood
Noise - commercial,shops,clubs,pubs	**3**	Neighbourhood
N13 Human Noise - Domestic	**3**	Neighbourhood
E26 Covid-19	**5**	Non-noise
N38 Planning App. Consultation	**5**	Non-noise
NNI Noise-Music	**3**	Neighbourhood
054 Other	**5**	Non-noise
C23 Fly Tipping	**5**	Non-noise
E11 Accumulation - commercial	**5**	Non-noise
C65 Trees	**5**	Non-noise
E25 Domestic Waste On Landings	**5**	Non-noise
A17 Fumes - Commercial	**5**	Non-noise
NALA - Noise from a burglar alarm	**3**	Neighbourhood
NNG Noise-Plant/machinery (mobile) e.g. construction site	**2**	Construction
NNB Noise-Barking Dog	**3**	Neighbourhood
NNF Noise-Machinery (fixed) e.g. fans, boiler	**3**	Neighbourhood
N16 Music - Domestic	**3**	Neighbourhood
601 Homelessness	**5**	Non-noise
N10 Road Works	**2**	Construction
L07 Out of hours noise - domestic music	**3**	Neighbourhood
N02 Domestic noise (banging/shouting)	**3**	Neighbourhood
I01 Rats	**5**	Non-noise
E12 Accumulation - private land (	**5**	Non-noise
(NSE) CIEH - Alarm (e.g. House, Car, Fire etc)	**3**	Neighbourhood
Commercial - Aircraft Noise	**1**	Industry
Domestic - Audible Intruder Alarm etc	**3**	Neighbourhood
Noise Pollution Street Record	**4**	Undefined
N18 Equipment/Plant - Commercial	**5**	Non-noise
Noise Construction Demolition	**2**	Construction
N50 Human Noise - Street	**3**	Neighbourhood
UA0 Drug / substance misuse & dea	**5**	Non-noise
ASBIT Noise	**4**	Undefined
N51 Human Noise - Commercial	**3**	Neighbourhood
N19 Light Motor Vehic./ Street-Com	**5**	Non-noise
N15 Parties - Domestic	**3**	Neighbourhood
UP0 Intimidation / harassment	**5**	Non-noise
A09 Odour from Mogden	**5**	Non-noise
N17 Music - Commercial	**3**	Neighbourhood
(NSE) CIEH - Party	**3**	Neighbourhood
N35 Railway Noise-Engineering Wor	**1**	Industry

Extractor Fan/Airconditioning Unit	**3**	Neighbourhood
A16 Fumes - Domestic	**5**	Non-noise
L02 Out of Hours noise - domestic (banging/shouting)	**3**	Neighbourhood
N20 Noise in street	**3**	Neighbourhood
N46 Noise - commercial (other)	**3**	Neighbourhood
N25 Noise adv/info	**3**	Neighbourhood
N13 Noise - commercial construction/demolition	**2**	Construction
N07 Domestic noise (music from stereo)	**3**	Neighbourhood
N05 Domestic noise (other)	**3**	Neighbourhood
N12 Commercial and domestic alarm	**3**	Neighbourhood
N14 Domestic noise (DIY)	**3**	Neighbourhood
UIT Illegal Traveller Incursions	**5**	Non-noise
(NSE) CIEH - Mechanical (fixed) e.g., fan, pump, boiler	**3**	Neighbourhood
(NSE) CIEH - Vehicle Noise	**3**	Neighbourhood
Commercial - Misc (Anything Else)	**5**	Non-noise
Noise Domestic Other	**3**	Neighbourhood
NN NOISE COMPLAINTS	**4**	Undefined
N59 Licensing Consultation	**5**	Non-noise
Res - Asb Impact Noise (alleged Deliberate Banging)	**3**	Neighbourhood
Res - Loud Music / Tv / Entertainment /games Console/radio	**3**	Neighbourhood
E08 Light Nuisance - Domestic	**3**	Neighbourhood
N55 Jumping/Stamping on Floor	**3**	Neighbourhood
Res - Raised Voices, Shouting, Screaming	**3**	Neighbourhood
N33 Noise Non S61 street works for TFL/Highways decision	**2**	Construction
N26 Noise from vehicle/property alarm	**3**	Neighbourhood
N21 Noise from aircraft	**1**	Industry
L13 Out of Hours Noise - construction/demolition sites	**3**	Neighbourhood
UA3 Discarding needles / drug par	**5**	Non-noise
(NSE) CIEH - Vehicle Repairs	**3**	Neighbourhood
(NSE) CIEH - Plant (mobile) (e.g. construction equipment)	**3**	Neighbourhood
RS - Domestic - Security Flood lights	**5**	Non-noise
NCDN - Noise - Domestic	**3**	Neighbourhood
MUSC Music	**3**	Neighbourhood
PNSA Shouting / Arguing	**3**	Neighbourhood
BPLA Building Services Plant Noise	**1**	Industry
MISC Miscellaneous	**5**	Non-noise
SMLN Smell Nuisance	**5**	Non-noise
BSIT Building Site Noise	**2**	Construction
TVRD TV / Radio	**3**	Neighbourhood
BUSK Buskers in Street	**3**	Neighbourhood
ACON Air Conditioning	**3**	Neighbourhood

DIY D.I.Y.	**3**	Neighbourhood
SMOK Smoke	**5**	Non-noise
ALAR Alarm (burglar,car,fire)	**3**	Neighbourhood
Construction Bond Building Site	**3**	Neighbourhood
PNFT Footsteps / Talking	**3**	Neighbourhood
PART Party	**3**	Neighbourhood
Cmls - Commercial Unlicenced Premises (machinery, Refridg, Air Con)	**3**	Neighbourhood
Ph Noise Complaint	**4**	Undefined
NNO Noise-Vehicles	**3**	Neighbourhood
Res - House Party	**3**	Neighbourhood
Res - Household Appliances (eg Hoover)	**3**	Neighbourhood
N21 Noise on street	**3**	Neighbourhood
N34 Noise Non S61 site works application	**2**	Construction
N42 Noise - residential constuction/renovation	**3**	Neighbourhood
N23 Noise from river/water activity	**3**	Neighbourhood
A19 Dust - Commercial	**5**	Non-noise
RS - Commercial - Bonfires, vehicle, etc	**5**	Non-noise
PA system	**3**	Neighbourhood
Noise Commercial Intruder Alarms	**3**	Neighbourhood
Underground (tube/station)	**1**	Industry
Bonfire	**3**	Neighbourhood
COVID Corona Virus	**5**	Non-noise
BONF Bonfires	**3**	Neighbourhood
Noise - Premises Alarm	**3**	Neighbourhood
Devlliveries	**3**	Neighbourhood
Cndm - Building Works - Large Development	**2**	Construction
061 Council Owned land	**5**	Non-noise
Res - Barking Dog(s)	**3**	Neighbourhood
C36 Litter	**5**	Non-noise
N10 Noise from music (other)	**3**	Neighbourhood
C80 Commercial Waste Enforcement	**5**	Non-noise
Drunken behaviour	**5**	Non-noise
N46 Noise Pollution Advice/Enquir	**4**	Undefined
N56 Television/Radio	**3**	Neighbourhood
Noise Commercial Retail	**3**	Neighbourhood
Vehicle alarm noise	**3**	Neighbourhood
NMSC Noise Miscellaneous	**4**	Undefined
ELDN Early/ Late Delivery Noise	**3**	Neighbourhood
DOMA Domestic Appliance noise	**3**	Neighbourhood
UQ0 Criminal damage / vandalism	**5**	Non-noise

N32 Equipment(Loudspeakers)-Stree	**3**	Neighbourhood
N08 Noise from voice (singing)	**3**	Neighbourhood
L14 Out of Hours noise - domestic (DIY)	**3**	Neighbourhood
E07 Light Nuisance - Commercial	**5**	Non-noise
Commerial - Voices, Singing, Banging etc	**3**	Neighbourhood
CONTROL OF POLLUTION (AMEND) ACT 1989	**5**	Non-noise
S26 Working Hours	**5**	Non-noise
NASB - Noise Anti Social Behaviour	**3**	Neighbourhood
Other Animals & Birds	**3**	Neighbourhood
Cmls - Leisure Premises (eg Football, Sports, Play)	**3**	Neighbourhood
E09 Music	**3**	Neighbourhood
E08 People Noise	**3**	Neighbourhood
Cndm - Diy Noise / Build Work	**3**	Neighbourhood
E10 Party	**3**	Neighbourhood
Noise-Music	**3**	Neighbourhood
Noise-Plant/machinery (mobile) e.g. construction site	**2**	Construction
Noise-People	**3**	Neighbourhood
N06 Car Alarms on Prems-Dom	**3**	Neighbourhood
UE1 Loitering	**5**	Non-noise
E07 Mobile Plant	**5**	Non-noise
N06 Commercial noise - music (club/pub/restaurant)	**3**	Neighbourhood
RS - Highways Pol - Misc (Anything Else)	**5**	Non-noise
Cndm - Building Works - Single House/small Site (eg Single House Renovation, Extension)	**3**	Neighbourhood
E02 Barking Dogs	**3**	Neighbourhood
Noise-Unidentified/other	**4**	Undefined
Noise-Party	**3**	Neighbourhood
E01 Alarms	**3**	Neighbourhood
E13 Vehicle Noise	**3**	Neighbourhood
RS - Domestic - Air Pollution	**5**	Non-noise
Mice	**5**	Non-noise
Noise-TV/Radio	**3**	Neighbourhood
0	**5**	Non-noise
N01 Domestic noise (children running)	**3**	Neighbourhood
E15 DIY	**3**	Neighbourhood
E06 Fixed Machinery	**3**	Neighbourhood
E24 Littering - street	**5**	Non-noise
W-Vehicle-related	**3**	Neighbourhood
Noise Domestic Dogs and other animals	**3**	Neighbourhood
Noise Anti Social Behaviour	**3**	Neighbourhood
Dust/Fumes/Smoke	**5**	Non-noise

Res - Alarm - House Alarm	**3**	Neighbourhood
B33 Suspected banned breed	**5**	Non-noise
S13 Noise	**4**	Undefined
063 Highways	**1**	Industry
N21 Light Motor Vehic./Prem.-Comm	**3**	Neighbourhood
Loitering	**5**	Non-noise
Noise Domestic TV	**3**	Neighbourhood
Noise Domestic Intruder Alarms	**3**	Neighbourhood
D07 Bonfires - Demolition/Constru	**3**	Neighbourhood
E11 TV/Radio	**3**	Neighbourhood
Vm - Delivery / Loading Activities From Vehicle	**3**	Neighbourhood
Vm - Engine Noise	**3**	Neighbourhood
CLEAN NEIGHBOURHOODS & ENV ACT 2005	**5**	Non-noise
Helicopter and aircraft movements	**1**	Industry
LITE Light Pollution	**5**	Non-noise
E03 Other Animals/Birds	**3**	Neighbourhood
Noise-Barking Dog	**3**	Neighbourhood
Res - Noise Other (eg High Freq, Other Misc, Snoring)	**3**	Neighbourhood
I25 Pigeons	**5**	Non-noise
B16 Dogs - Noise - Domestic	**3**	Neighbourhood
I18 Oak Processionary Moth	**5**	Non-noise
Commercial - Generators	**5**	Non-noise
ASB - Vulnerable Victims	**5**	Non-noise
Commercial - Audible Intruder Alarm etc	**3**	Neighbourhood
017 Pro-active	**5**	Non-noise
Noise in Street Machinery	**3**	Neighbourhood
Noise Domestic DIY	**3**	Neighbourhood
DOGB Dogs Barking	**3**	Neighbourhood
Noise Domestic Building Works	**3**	Neighbourhood
D02 Bonfires - Commercial	**3**	Neighbourhood
Commercial - Do it Yourself	**3**	Neighbourhood
N14 Garden Equipment - Domestic	**3**	Neighbourhood
E12 Fireworks	**3**	Neighbourhood
Vm - Busker / Street Peformer With Equipment	**3**	Neighbourhood
N12 DIY Activities - on Street	**3**	Neighbourhood
A18 Dust - Domestic	**5**	Non-noise
E16 Litter - private land	**5**	Non-noise
Highways - - Car Alarms all vehicles	**3**	Neighbourhood
Artificial light pollution	**5**	Non-noise
UK4 Hooliganism / loutish behavio	**5**	Non-noise
NNC Noise-Other Animals and Birds	**3**	Neighbourhood

Appendix B. Labels and categories for noise complaints

NNA Noise-Alarm	**3**	Neighbourhood
Noise-Machinery (fixed) e.g. fans, boiler	**3**	Neighbourhood
Noise-Burglar Alarm	**3**	Neighbourhood
N05 Intruder Alarms -Commercial	**3**	Neighbourhood
N20 Light Motor Vehic./Street-Dom	**3**	Neighbourhood
Traffic noise	**1**	Industry
Service ENQUIRY Noise and Nuisance	**4**	Undefined
Email complaint	**5**	Non-noise
PSH HMO - Mechanical Noise within the Home	**3**	Neighbourhood
Noise-Vehicles	**3**	Neighbourhood
N62 Sct 61 Applications	**3**	Neighbourhood
Res - Transmittion Of Footfall (impacts)	**3**	Neighbourhood
NCAR - Noise - Car Alarm	**3**	Neighbourhood
Busking	**3**	Neighbourhood
NNR Noise-Low frequency	**3**	Neighbourhood
N26 Motorbikes - on Street	**3**	Neighbourhood
E19 Commercial Waste - private la	**5**	Non-noise
POTH - Pollution - Other	**5**	Non-noise
N11 People Noise (e.g. footsteps,	**3**	Neighbourhood
N02 Car Alarm	**3**	Neighbourhood
N05 Construction Noise	**2**	Construction
N07 Music	**3**	Neighbourhood
Noise from Fireworks	**3**	Neighbourhood
N04 Intruder Alarms - Domestic	**3**	Neighbourhood
ASBIT Seeking Prior Consent for Noise (Section 61)	**3**	Neighbourhood
D05 Chimney - Commercial	**5**	Non-noise
K02 Fly-tipping	**5**	Non-noise
Vm - Alarm - Vehicle	**3**	Neighbourhood
Vm - Music From Vehicle In Street	**3**	Neighbourhood
C30 Dumped Fridges/Freezers	**5**	Non-noise
N52 Industrial Noise	**1**	Industry
Domestic - Fixed Air Handling Units	**3**	Neighbourhood
N30 Deliveries/Collections	**3**	Neighbourhood
N17 Party	**3**	Neighbourhood
N24 Buskers / Street Performers	**3**	Neighbourhood
N13 Burglar/Fire Alarm	**3**	Neighbourhood
N23 Roadworks	**2**	Construction
TRCA Traffic / Car Noise	**1**	Industry
NSAN Noisy Animals/Birds (Not dogs)	**3**	Neighbourhood
GDFU Grit/Dust/Fumes	**5**	Non-noise
Bus/commercial - Intruder Alarm	**3**	Neighbourhood

(NSE) CIEH - Other / Unidenitified	**4**	Undefined
N27 Other	**4**	Undefined
N01 Machinery (fixed) e.g fan, pu	**3**	Neighbourhood
L25 OOH noise from vehicle/property alarm	**3**	Neighbourhood
L01 Out of Hours noise - domestic (children running)	**3**	Neighbourhood
N18 Rave	**3**	Neighbourhood
N44 Fire Alarm - Commercial	**3**	Neighbourhood
A12 Smell nuisance - Rest./Takeaw	**5**	Non-noise
NDIY - Noise from DIY activities	**3**	Neighbourhood
Rats	**5**	Non-noise
Low Frequency	**4**	Undefined
UB1 Street drinking	**5**	Non-noise
C85 Graffiti - Other	**5**	Non-noise
N03 Domestic noise (loud TV)	**3**	Neighbourhood
UA1 Taking drugs	**5**	Non-noise
N12 DIY	**3**	Neighbourhood
RWNS Railway Noise	**1**	Industry
E17 Other/Unidentified	**4**	Undefined
Noise-DIY	**3**	Neighbourhood
N41 High Frequency Noise	**4**	Undefined
RS Commercial Pol - Misc (Anything Else)	**5**	Non-noise
(NSE) CIEH - Other Animals and Birds	**5**	Non-noise
Civil dispute	**5**	Non-noise
E05 Exhumation	**5**	Non-noise
N22 Noise from rail	**1**	Industry
Vm - Machinery Or Equipment Noise In Street (eg Generator, Roadworks/utilities)	**3**	Neighbourhood
N45 Fire Alarm - Domestic	**3**	Neighbourhood
X15 Waste/Dumping	**5**	Non-noise
Commercial - Railway Traffic	**1**	Industry
Dog - Other	**3**	Neighbourhood
N10 Amplified sound (TV/Radio/Mus	**3**	Neighbourhood
NNK Noise-TV/Radio	**3**	Neighbourhood
NNJ Noise-Party	**3**	Neighbourhood
Noise-Public Address Systems	**3**	Neighbourhood
N25 Motorbikes - on Land	**3**	Neighbourhood
L20 Our of Hours noise in the street	**3**	Neighbourhood
Noise Commercial Sports and Leisure	**3**	Neighbourhood
N06 Delivery / Collection	**3**	Neighbourhood
N04 Animals noise	**3**	Neighbourhood
Covid-19 Licensing related enquiries	**5**	Non-noise

D03 Bonfires - Open Land	**5**	Non-noise
N03 Site	**5**	Non-noise
UH1 Inconvenient / illegal parkin	**5**	Non-noise
Commercial - Car Alarms all vehicles	**3**	Neighbourhood
QAD Other Complaint or Enquiry	**5**	Non-noise
Domestic - Vibration	**3**	Neighbourhood
UL6 Impeding access to communal a	**5**	Non-noise
RS - Commercial - Odours, fumes and gas	**5**	Non-noise
Domestic - Sound Insulation	**3**	Neighbourhood
HIGHWAYS ACT 1980	**5**	Non-noise
L03 Out of Hours noise - domestic (loud TV)	**3**	Neighbourhood
Fireworks	**3**	Neighbourhood
Res - Musical Instrument (non Amplified)	**3**	Neighbourhood
N63 Other	**4**	Undefined
OTH Other	**5**	Non-noise
Shouting and swearing	**3**	Neighbourhood
K07 Hazardous waste	**5**	Non-noise
N08 Plant / Equipment (mobile)	**3**	Neighbourhood
Public Address System	**3**	Neighbourhood
Noise - Car Alarms	**3**	Neighbourhood
C68 Grass Cutting	**3**	Neighbourhood
N21 Noise on street (can't deal)	**3**	Neighbourhood
C58 Overhanging Vegetation	**5**	Non-noise
E04 Bells	**3**	Neighbourhood
Commercial - Vibration	**3**	Neighbourhood
S21 Hazardous Substances	**5**	Non-noise
PADS Public Address System	**3**	Neighbourhood
NNQ Noise-DIY	**3**	Neighbourhood
PSMC - Non Domestic bonfire	**3**	Neighbourhood
PSMO - Domestic Smoke	**5**	Non-noise
Licensing request	**5**	Non-noise
Uncontrolled Animals	**5**	Non-noise
UE2 Pestering residents	**3**	Neighbourhood
C24 Other Refuse - Domestic	**5**	Non-noise
C11 Dumped/Accum. - Street/Land	**5**	Non-noise
N12 Aircraft Noise	**1**	Industry
W-Drug-and-drink	**5**	Non-noise
Light Pollution	**5**	Non-noise
L04 Our of Hours noise - domestic (sewing machine)	**3**	Neighbourhood
N09 Noise from music in studio	**3**	Neighbourhood
L28 Out of Hours noise - domestic (hard flooring)	**3**	Neighbourhood

D04 Chimney - Domestic	**5**	Non-noise
UK3 Drunken behaviour	**5**	Non-noise
UF2 Indecent exposure	**5**	Non-noise
Noise - Alarm	**3**	Neighbourhood
UP2 Verbal abuse	**5**	Non-noise
UH0 Vehicle related nuisance & In	**5**	Non-noise
B14 Poultry/Cockerels	**3**	Neighbourhood
UP1 Groups or individuals making	**5**	Non-noise
Refuse Dumping	**5**	Non-noise
Hooliganism/loutish behaviour	**5**	Non-noise
Highways - Non amplified musical instr	**3**	Neighbourhood
Refuse Collection - Domestic/Trade	**5**	Non-noise
RS - Commercial - Air Pollution	**5**	Non-noise
Light nuisance	**5**	Non-noise
N09 Car Alarms on Street-Comm	**3**	Neighbourhood
Noise - Religious Establishment	**3**	Neighbourhood
R33 Bollard Over	**5**	Non-noise
L11 Out of Hours noise - domestic alarm	**3**	Neighbourhood
L06 Out of Hours noise - commercial music	**3**	Neighbourhood
L05 Out of Hours noise - domestic (other)	**3**	Neighbourhood
N01 Commercial	**3**	Neighbourhood
N22 Light Motor Vehic./Prem.-Dom.	**3**	Neighbourhood
C41 Leaf	**5**	Non-noise
C53 Encroachment/footway obstruct	**5**	Non-noise
RS - Domestic - Dust Pollution	**5**	Non-noise
Commercial - Barking Dog	**3**	Neighbourhood
Noise Commercial Deliveries	**3**	Neighbourhood
C54 Builders materials	**5**	Non-noise
C35 Litter Bins	**5**	Non-noise
BSRA Building site rapids	**5**	Non-noise
Animal (not dogs)	**5**	Non-noise
Domestic incident	**5**	Non-noise
W-Nuisance behaviour	**5**	Non-noise
N02 Residential	**3**	Neighbourhood
Noise-Vehicle repairs	**3**	Neighbourhood
V05 Anti-Social Behaviour	**5**	Non-noise
M31 Domestic waste - put out late	**5**	Non-noise
Highways - Road, Traffic, Vehicles etc	**1**	Industry
G14 Noise Limits	**4**	Undefined
N27 Motorbikes - on Premises	**3**	Neighbourhood
L29 Out of Hours noise from car sound system	**3**	Neighbourhood

Appendix B. Labels and categories for noise complaints

NTC TEN Licensing consultation	**5**	Non-noise
N14 Instrument	**3**	Neighbourhood
Noise Commercial Pubs Clubs Entertmt	**3**	Neighbourhood
Noise Commercial Food Premises	**3**	Neighbourhood
Noise Place of Worship	**3**	Neighbourhood
L18 Out of Hours noise - barking dog	**3**	Neighbourhood
Entertainment noise (Pub, Licensed prem)	**3**	Neighbourhood
PLAN Planning Enquiry	**5**	Non-noise
000 General Housing Inspection	**5**	Non-noise
V08 Other - specify in text line	**5**	Non-noise
Noise Task	**4**	Undefined
Cml - Licensed Prem (pubs, Clubs, Rests)	**5**	Non-noise
016 Non Urgent	**5**	Non-noise
N53 Slamming Doors	**3**	Neighbourhood
E09 Blocked Drain/Sewer - Council	**5**	Non-noise
LONDON LOCAL AUTHORITES ACT 1990	**5**	Non-noise
Commercial - Non amplified musical instr	**3**	Neighbourhood
NNE Noise-Public Address Systems	**3**	Neighbourhood
Noise-Low frequency	**4**	Undefined
Begging/Vagrancy	**5**	Non-noise
Boat Noise	**1**	Industry
C87 "A" Advertising Boards	**5**	Non-noise
RS - Highways - Bonfires, vehicle, etc	**5**	Non-noise
E02 Blocked/Defective Public Sewe	**5**	Non-noise
N20 Railway	**1**	Industry
H&S Smoking	**5**	Non-noise
L10 Out of Hours noise- music (other)	**3**	Neighbourhood
Aircraft noise	**1**	Industry
N42 Low Frequency Noise	**4**	Undefined
CGD Grimebuster dumped rubbish	**5**	Non-noise
R13 Noise (res)	**3**	Neighbourhood
Domestic - Other Animals	**3**	Neighbourhood
N09 Vehicle / Traffic/Aircraft	**1**	Industry
B22 Dogs Fouling - Garden	**5**	Non-noise
L31 Out of Hours noise - vehicle alarm	**3**	Neighbourhood
B01 Dogs Fouling - On Street	**5**	Non-noise
Complaint Stage 2 (Noise Team Only)	**4**	Undefined
UA5 Presence of dealers or users	**5**	Non-noise
015 Urgent	**5**	Non-noise
N54 Moving Furniture	**3**	Neighbourhood
UA4 Crack houses	**5**	Non-noise

Comments on variations to lic premises	**5**	Non-noise
V07 Unlicensed Premises/Traders	**5**	Non-noise
H07 Obstruction on the Highway	**5**	Non-noise
E00 Blocked/Defec.- Gully Soakawa	**5**	Non-noise
FIRW Fireworks	**3**	Neighbourhood
N02 Demolition Site	**2**	Construction
FLTH Filthy & Verminous Premises	**5**	Non-noise
(NSE) CIEH - Low Frequency	**4**	Undefined
N13 Railway Noise	**1**	Industry
N15 Speakers/Public address syste	**3**	Neighbourhood
F46 Spillage/Littering	**5**	Non-noise
Highways - Construction and Demolition	**2**	Construction
N39 Explosives/Fireworks	**3**	Neighbourhood
Commercial - Sports and Leisure	**3**	Neighbourhood
N33 Equipment (Loudspeakers)-Prem	**3**	Neighbourhood
N04 Noise From Party	**3**	Neighbourhood
RS - Commercial - Security Flood lights	**5**	Non-noise
X08 Houses in Multiple Occupation	**5**	Non-noise
L30 Out of Hours noise from raves	**3**	Neighbourhood
E16 Low Frequency Noise	**4**	Undefined
I27 Foxes	**5**	Non-noise
UQ6 Damage to trees / plants / he	**5**	Non-noise
E03 Blocked Drains/Private Sewer	**5**	Non-noise
C31 Hazardous Waste	**5**	Non-noise
Noise-Other Animals and Birds	**3**	Neighbourhood
(NSE) CIEH - Public Address Systems	**3**	Neighbourhood
Loud party/gathering	**3**	Neighbourhood
B05 Dogs Stray - On Street	**5**	Non-noise
E22 Accumulation - CPN - domestic	**5**	Non-noise
B25 Dog Missing	**5**	Non-noise
B17 Dogs - Noise - Commercial	**3**	Neighbourhood
UDO Prostitution	**5**	Non-noise
Discarded condoms	**5**	Non-noise
UL7 Games in restricted / inappro	**5**	Non-noise
UF0 Sexual acts	**5**	Non-noise
C67 Trees to be Removed	**5**	Non-noise
Noise-Fireworks	**3**	Neighbourhood
RP TEST	**5**	Non-noise
M19 Clinical waste - missed dome	**5**	Non-noise
C81 Suspected Fly-tippers	**5**	Non-noise
BELL Bells	**3**	Neighbourhood

S06 H&S - Miscellaneous	**5**	Non-noise
NSIN - Noise (Sound Insulation)	**3**	Neighbourhood
N19 Underground	**1**	Industry
Noise Commercial Industrial	**1**	Industry
E05 PA Systems	**3**	Neighbourhood
E23 Invasive plants	**5**	Non-noise
L12 Out of Hours noise - domestic and commercial alarm	**3**	Neighbourhood
Railway noise (not construction)	**1**	Industry
A14 Spraying Vehicles - Commercia	**3**	Neighbourhood
Oi - Other Industry Eg. Cement/glass Works	**1**	Industry
E14 Vehicle Repairs	**3**	Neighbourhood
Highways - Industrial Noise	**1**	Industry
N60 Noise - Smoking outside Premi	**3**	Neighbourhood
N24 Heavy Motor Vehic./Street-Com	**3**	Neighbourhood
A13 Spraying Vehicles - Domestic	**3**	Neighbourhood
Noise from Parked Vehicle	**3**	Neighbourhood
UK2 Fighting	**5**	Non-noise
RS - Domestic - Water Pollution	**5**	Non-noise
Waste accumulation	**5**	Non-noise
Amplified music from cars	**3**	Neighbourhood
G01 Night Time Flying-Sleep Depri	**5**	Non-noise
K15 Street Cleansing - general	**5**	Non-noise
K06 Clinical waste - Dumped needl	**5**	Non-noise
A06 Motor Engine Exhaust	**5**	Non-noise
(NSE) CIEH - Fireworks	**3**	Neighbourhood
Highways - Mobile refrigeration plant	**3**	Neighbourhood
I38 Requests for Information	**5**	Non-noise
Noise Domestic Fireworks	**3**	Neighbourhood
H09 Damage to the Highway	**5**	Non-noise
SERC Service Complaint	**5**	Non-noise
Noise - Licensing Case	**4**	Undefined
ASB - Commercial - Dust emissions	**5**	Non-noise
N11 Traffic Noise	**1**	Industry
N23 Heavy Motor Vehic./Prem.-Comm	**3**	Neighbourhood
L27 Out of Hours noise from smoking outside commercial premises	**3**	Neighbourhood
Vm - Aircraft Noise	**1**	Industry
Commercial - Karaoke	**3**	Neighbourhood
K24 Overflowing litter bins	**5**	Non-noise
C84 Graffiti - Council	**5**	Non-noise
L23 Out of Hours noise - river/water activity	**3**	Neighbourhood
S18 Lighting	**5**	Non-noise

Animal nuisance	**5**	Non-noise
(NSE) CIEH - Boat Noise (all forms of water transport)	**1**	Industry
UP4 Following people	**5**	Non-noise
S08 Asbestos	**5**	Non-noise
PEDI Noise and Disturbance from Pedicabs	**3**	Neighbourhood
V06 Street Trading - Unauthorised	**5**	Non-noise
NLIC - Noise from licensed premises	**3**	Neighbourhood
K10 Glass	**5**	Non-noise
G11 Vortex/Physical Damage(eg.ice	**5**	Non-noise
UP9 Menacing gestures	**5**	Non-noise
Noise Events	**4**	Undefined
C83 Graffiti - Racist/Offensive	**5**	Non-noise
CCU Community Clean Up	**5**	Non-noise
W-Agressive behaviour	**5**	Non-noise
CARN Carnival	**3**	Neighbourhood
AQPG Air Quality Not Traffic	**5**	Non-noise
L22 Out of Hours noise - rail	**1**	Industry
J01 Asbestos Land	**5**	Non-noise
Cmls - Party Boats (eg Music On Thames)	**3**	Neighbourhood
PSH HS - Mechanical noise within the home	**3**	Neighbourhood
Section 61 prior consent	**3**	Neighbourhood
Cmls - Gym - Mixed Use Development (only Gyms In Resi Blocks)	**3**	Neighbourhood
CWE Other waste education/enforce	**5**	Non-noise
VREP Vehicle Repair Noise	**3**	Neighbourhood
MFE Flats above shops - enquiry	**5**	Non-noise
Noise-Bells (e.g. Church/Phone)	**3**	Neighbourhood
N06 Noise from HMO	**3**	Neighbourhood
Carnival	**3**	Neighbourhood
G17 Vibration	**4**	Undefined
W08 CCTV - Non-LBH	**5**	Non-noise
W21 PROW - General Enquiry	**5**	Non-noise
Animals	**5**	Non-noise
ASB - Commercial - Industrial noise(factory/plant)	**1**	Industry
N16 Low frequency (hums)	**4**	Undefined
ISMO Individual Smoking	**5**	Non-noise
PREVENTION OF DAMAGE BY PESTS ACT 1949	**5**	Non-noise
C69 Vehicle to pound	**5**	Non-noise
UL3 Inappropriate use of firework	**5**	Non-noise
ASB - Commercial - Construction noise	**2**	Construction
N05 Noise Loud Music	**3**	Neighbourhood
F20 Recycling collections - items	**5**	Non-noise

Appendix B. Labels and categories for noise complaints

I07 Bedbugs	5	Non-noise
UH4 Joyriding	5	Non-noise
NVR Vehicle repairs	3	Neighbourhood
ASB - Commercial - Music noise	3	Neighbourhood
D06 Cable Burning	5	Non-noise
Highways - Generators	5	Non-noise
Bells	3	Neighbourhood
B09 Dangerous/Worrying Dog -Stree	5	Non-noise
B32 Dog acting Aggressively	5	Non-noise
E21 Accumulation - CPN - commerci	5	Non-noise
Advice and Queries	5	Non-noise
C51 Damage/deposits on highway	5	Non-noise
B28 Dog Fouling-Communal Area Ext	5	Non-noise
Noise-Boats	1	Industry
E20 Education - environmental pro	5	Non-noise
Commercial - In Car Entertainment stereo	3	Neighbourhood
B15 Pet Animals Noise (Not Dogs)	3	Neighbourhood
Cllr/MP Enquiry Noise	4	Undefined
N43 Funfairs	3	Neighbourhood
Individual Smoking Shisha	5	Non-noise
V01 Licensing - Advice Requested	5	Non-noise
C37 Street Cleansing - General	5	Non-noise
CTW GM/Trees/Weeds	5	Non-noise
K14 Weeds	5	Non-noise
RS - Commercial - Dust Pollution	5	Non-noise
MBR Replacement bin - lost/damage	5	Non-noise
R43 Out - Not working At All	5	Non-noise
RS - Highways - Air Pollution	5	Non-noise
F41 Garden waste sack sales	5	Non-noise
O08 Private	5	Non-noise
701 Call Centre	5	Non-noise
R16 L/col. - Lighting Out	5	Non-noise
B13 Feral Cats	5	Non-noise
(NSE) CIEH - Bells (e.g. church, telephone)	3	Neighbourhood
N07 Car Alarms on Prems-Comm	3	Neighbourhood
N04 Domestic noise (sewing machine)	3	Neighbourhood
Drainage defect	5	Non-noise
NNS Noise-Unidentified/other	4	Undefined
SASB Asbestos	5	Non-noise
K20 Fouling	5	Non-noise
Noise - Advice Only	4	Undefined

Barking Dogs	**3**	Neighbourhood
Fireworks	**3**	Neighbourhood
Music	**3**	Neighbourhood
People Noise(i.e Talking/Shout	**3**	Neighbourhood
Machinery - Fixed(i.e Fan/Pump	**3**	Neighbourhood
Alarm (house/Car/fire/etc)	**3**	Neighbourhood
Plant- Mobile(i.e. const.equip	**3**	Neighbourhood
DIY	**3**	Neighbourhood
TV/Radio	**3**	Neighbourhood
Other/Unidentified	**4**	Undefined
Party	**3**	Neighbourhood
Vehicle Noise	**3**	Neighbourhood
Other Animals & Birds	**3**	Neighbourhood
Vehicle Repairs	**3**	Neighbourhood
Section 61	**3**	Neighbourhood
Loud Music Residential	**3**	Neighbourhood
Cockerels	**3**	Neighbourhood
Construction	**2**	Construction
House Alarm	**3**	Neighbourhood
Commercial Alarm	**3**	Neighbourhood
People Noise - Movement	**3**	Neighbourhood
Loud Music Commercial	**3**	Neighbourhood
People Noise - Vocal	**3**	Neighbourhood
D I Y	**3**	Neighbourhood
Deliveries or Collections	**3**	Neighbourhood

This table is based on the teamwork.

Appendix C

Additional statistical results

This appendix provides additional statistical results for Chapters 5, 6, and 7. Section C.1 presents the results from PCA and the normal distribution test for each indicator for Chapter 5. Section C.2 illustrates Mann-Whitney U test results and a summary of dwelling density by borough for Chapter 6. Section C.3 shows more statistical analysis results (i.e., Spearman correlation with partial samples) for Chapter 7.

C.1. Mann-Whitney U test results and dwelling density for Chapter 5

Table C-1 Significant level of differences in the number of noise complaints between 2019 and 2020 by boroughs and noise source categories via Mann-Whitney U test

Borough	Significance level (*p* value)	Mann-Whitney U	Z	Median 2019	Median 2020
All boroughs	0.000**	319.000	-8.461	285.50	431.00
Barking and Dagenham	0.000**	331.000	-8.410	16.00	33.00
Barnet	0.008**	1606.500	-2.640	3.50	1.50
Bexley	0.000**	965.000	-5.553	3.00	6.00
Camden	0.006**	1572.500	-2.762	6.50	11.00
Croydon	0.096	1814.000	-1.666	4.00	5.50
Greenwich	0.126	1842.500	-1.532	9.00	11.00
Hammersmith and Fulham	0.015*	1645.500	-2.426	16.00	19.00
Haringey	0.000**	315.500	-8.483	7.50	22.00
Havering	0.075	1791.000	-1.783	2.50	3.00
Hillingdon	0.000**	1272.500	-4.131	7.50	10.00
Hounslow	0.000**	335.500	-8.389	18.50	41.50
Islington	0.000**	607.000	-7.152	27.00	46.50
Kensington and Chelsea	0.001**	1454.500	-3.296	34.00	41.00
Kingston upon Thames	0.260	1939.500	-1.125	1.00	2.00
Lambeth	0.002**	1506.500	-3.059	17.50	23.50
Merton	0.074	1788.000	-1.785	3.00	6.00
Richmond upon Thames	0.002**	1510.000	-3.061	3.00	5.00

Sutton	0.002**	1512.500	-3.051	4.00	6.00
Tower Hamlets	0.000**	1300.500	-4.001	8.50	14.00
Waltham Forest	0.954	2165.500	-0.058	6.50	5.00
Wandsworth	0.000**	907.000	-5.792	8.50	14.50
City of Westminster	0.000**	803.500	-6.258	53.00	68.00
Industry	0.126	1936.000	-1.105	8.00	7.00
Construction	0.000**	1318.000	-3.916	25.50	33.50
Neighbourhood	0.000**	398.500	-8.099	201.00	304.00
Undefined	0.000**	717.500	-6.649	30.00	47.00

* Difference is significant at the 0.05 level. ** Difference is significant at the 0.01 level.

Table C-2 Dwelling density by borough

Inner London boroughs	Density of dwellings (per hectare)	Outer London boroughs	Density of dwellings (per hectare)
City of London	20.7	Barking and Dagenham	20.1
Camden	48.5	Barnet	17.6
Hackney	58.6	Bexley	15.3
Hammersmith and Fulham	52.0	Brent	27.9
Haringey	37.0	Bromley	9.3
Islington	69.8	Croydon	18.6
Kensington and Chelsea	70.8	Ealing	24.4
Lambeth	51.9	Enfield	15.4
Lewisham	36.3	Greenwich	22.7
Newham	30.3	Harrow	18.2
Southwark	45.5	Havering	9.0
Tower Hamlets	56.3	Hillingdon	9.6
Wandsworth	42.0	Hounslow	18.0
Westminster	56.9	Kingston upon Thames	18.2
		Merton	22.5
		Redbridge	18.5
		Richmond upon Thames	14.6
		Sutton	19.1
		Waltham Forest	26.7
Inner London	46.7	Outer London	16.3

C.2. PCA and normal distribution test results for Chapter 6

Table C-3 Total variance explained by Principal Component Analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	27.344	35.979	35.979	27.344	35.979	35.979
2	20.443	26.899	62.879	20.443	26.899	62.879
3	6.935	9.125	72.004	6.935	9.125	72.004
4	3.184	4.190	76.194	--	--	--
5	2.812	3.699	79.893	--	--	--
6	2.597	3.417	83.310	--	--	--
7	1.595	2.099	85.408	--	--	--
8	1.230	1.618	87.027	--	--	--
9	1.034	1.361	88.387	--	--	--
10	.879	1.156	89.543	--	--	--

11	.742	.976	90.519	--	--	--
12	.706	.929	91.449	--	--	--
13	.641	.843	92.292	--	--	--
14	.530	.697	92.988	--	--	--
15	.493	.649	93.637	--	--	--
16	.472	.621	94.258	--	--	--
17	.398	.524	94.782	--	--	--
18	.324	.427	95.209	--	--	--
19	.313	.412	95.620	--	--	--
20	.278	.366	95.987	--	--	--
21	.260	.342	96.329	--	--	--
22	.249	.328	96.657	--	--	--
23	.226	.297	96.954	--	--	--
24	.223	.294	97.247	--	--	--
25	.190	.250	97.497	--	--	--
26	.179	.236	97.733	--	--	--
27	.171	.225	97.958	--	--	--
28	.157	.206	98.165	--	--	--
29	.123	.161	98.326	--	--	--
30	.117	.154	98.480	--	--	--
31	.110	.145	98.625	--	--	--
32	.098	.129	98.754	--	--	--
33	.089	.117	98.871	--	--	--
34	.089	.117	98.988	--	--	--
35	.077	.101	99.089	--	--	--
36	.073	.096	99.186	--	--	--
37	.070	.092	99.278	--	--	--
38	.065	.085	99.363	--	--	--
39	.056	.073	99.436	--	--	--
40	.050	.066	99.502	--	--	--
41	.046	.061	99.563	--	--	--
42	.043	.057	99.620	--	--	--
43	.037	.049	99.668	--	--	--
44	.034	.044	99.713	--	--	--
45	.027	.035	99.748	--	--	--
46	.026	.034	99.782	--	--	--
47	.021	.028	99.810	--	--	--
48	.019	.025	99.835	--	--	--
49	.018	.024	99.859	--	--	--
50	.017	.022	99.881	--	--	--
51	.014	.018	99.899	--	--	--
52	.013	.017	99.917	--	--	--
53	.010	.014	99.930	--	--	--
54	.010	.013	99.943	--	--	--
55	.008	.010	99.954	--	--	--
56	.007	.010	99.963	--	--	--
57	.007	.009	99.972	--	--	--
58	.006	.008	99.980	--	--	--
59	.005	.006	99.987	--	--	--
60	.003	.004	99.991	--	--	--
61	.003	.003	99.994	--	--	--
62	.002	.002	99.996	--	--	--
63	.001	.002	99.998	--	--	--

64	.001	.001	99.999	--	--	--
65	.001	.001	100.000	--	--	--
66	4.084E-5	5.374E-5	100.000	--	--	--
67	1.243E-5	1.636E-5	100.000	--	--	--
68	1.168E-15	1.537E-15	100.000	--	--	--
69	8.371E-16	1.101E-15	100.000	--	--	--
70	5.956E-16	7.837E-16	100.000	--	--	--
71	2.305E-16	3.032E-16	100.000	--	--	--
72	1.333E-17	1.754E-17	100.000	--	--	--
73	-3.374E-17	-4.439E-17	100.000	--	--	--
74	-3.959E-16	-5.209E-16	100.000	--	--	--
75	-5.392E-16	-7.095E-16	100.000	--	--	--
76	-9.706E-16	-1.277E-15	100.000	--	--	--

Table C-4 Component matrix from Principal Component Analysis

Factors' category	Indicators	Variables	1	2	3
Demographic factors	Population	Population density	-0.901	-0.029	-0.120
	Age	Mean age	0.853	-0.051	-0.474
		Median age	0.878	-0.053	-0.406
		The percentage of underage people	-0.157	0.152	0.733
		The percentage of young people	-0.915	-0.096	0.218
		The percentage of older people	0.861	0.026	-0.469
	Sex	Males	-0.416	-0.151	0.146
		Females	0.416	0.151	-0.146
	Marital status	Singe	-0.937	0.082	-0.028
		Married	0.876	-0.275	0.146
	Qualification	No qualifications	0.230	0.899	-0.022
		Level 1 qualifications	0.487	0.524	0.413
		Level 2 qualifications	0.810	0.294	0.229
		Apprenticeship	0.740	0.362	0.056
		Level 3 qualifications	0.078	0.080	0.112
		Level 4 qualifications and above	-0.400	-0.831	-0.193
		Other qualifications	-0.757	-0.056	0.023
	Health	Good	-0.193	-0.898	0.327
		Fair	0.388	0.820	-0.340
		Bad	-0.094	0.901	-0.271
		Day-to-day activities limited (all residents)	0.363	0.810	-0.396
		Day-to-day activities limited (workers)	-0.165	0.917	-0.183
		Provides no unpaid care	-0.773	-0.429	0.264
		Provides 50 or more hours unpaid care a week	0.302	0.876	-0.191
	Religious diversity	Religious diversity	-0.876	-0.159	0.148
	Ethnic diversity	Ethnic diversity	-0.755	-0.150	0.108
Job-related factors	Economic activity	Part-time	0.827	0.344	0.039
		Full-time	-0.141	-0.499	0.608
		Self-employed	0.216	-0.698	-0.456
		Unemployed residents	-0.602	0.700	0.118
		Retired	0.867	0.219	-0.389
		Student	-0.673	-0.021	-0.035

		Looking after home or family	-0.494	0.159	0.253
		Long-term sick or disabled	-0.264	0.886	-0.163
		Other	-0.766	0.291	-0.045
		Unemployed male	-0.518	0.757	0.098
		Unemployed female	-0.699	0.576	0.140
	Hours worked	Less than 15	0.448	-0.255	-0.301
		16 to 30	0.383	0.735	-0.279
		31 to 48	-0.357	0.405	0.706
		More than 49	-0.068	-0.764	-0.389
	Occupation	Managers, directors and senior officials	0.207	-0.830	-0.235
		Professional occupations	-0.449	-0.721	-0.086
		Associate professional and technical occupations	-0.439	-0.735	-0.024
		Administrative and secretarial occupations	0.127	0.053	0.541
		Skilled trades occupations	0.716	0.389	-0.250
		Caring, leisure and other service occupations	0.336	0.713	-0.188
		Sales and customer service occupations	-0.122	0.796	0.218
		Process plant and machine operatives	0.226	0.769	0.207
		Elementary occupations	-0.070	0.769	0.089
Property factors	Accommodation size and central heating	Average number of rooms per household	0.887	-0.253	0.158
		Average number of bedrooms per household	0.821	-0.253	0.270
		Central heating	0.199	-0.239	0.521
	Car or van availability	No car or van	-0.889	0.291	-0.250
		The average number of cars or vans	0.862	-0.389	0.217
	Accommodation type	Whole house or bungalow	0.851	0.285	0.328
		Whole house or bungalow: detached	0.834	-0.311	-0.076
		Whole house or bungalow: semi-detached	0.451	0.427	0.403
		Whole house or bungalow: terraced	-0.347	0.494	0.234
		Flat, maisonette or apartment	-0.857	-0.278	-0.318
		Flat, maisonette or apartment: purpose-built block of flats or tenement	-0.849	-0.278	-0.250
		Flat, maisonette or apartment: part of a converted or shared house	-0.711	-0.205	-0.402
		Flat, maisonette or apartment: in a commercial building	-0.551	-0.326	-0.563
		Caravan or other mobile or temporary structure	0.509	-0.283	-0.189
	Accommodation tenure	Owned	0.927	-0.123	0.161
		Shared ownership	-0.359	-0.371	0.219
		Social rented	-0.747	0.314	0.049
		Private rented	-0.820	-0.086	-0.334
		Rent free	-0.031	-0.232	-0.522
Deprivation	Deprivation factors	Total deprivation index	0.537	-0.770	0.222

factors	Barriers to housing and services	0.287	0.342	0.411
	Crime	0.685	-0.436	-0.311
	Employment	0.332	-0.883	0.191
	Health	0.384	-0.804	0.157
	Living environment	0.560	-0.269	0.422
	Income	0.533	-0.773	0.146

Table C-5 Test for normal distribution

Factors' category	Indicators`	Variables	Shapiro-Wilk	Distribution
	Noise complaint rate		0.000	Not normal distribution
Demographic factors	Population	Population density	0.000	Not normal distribution
	Age	Mean age	0.097	Normal distribution
		Median age	0.000	Not normal distribution
		The percentage of underage people	0.000	Not normal distribution
		The percentage of young people	0.000	Not normal distribution
		The percentage of older people	0.111	Normal distribution
	Sex	Males	0.000	Not normal distribution
		Females	0.000	Not normal distribution
	Marital status	Singe	0.000	Not normal distribution
		Married	0.000	Not normal distribution
	Qualification	No qualifications	0.486	Normal distribution
		Level 1 qualifications	0.000	Not normal distribution
		Level 2 qualifications	0.000	Not normal distribution
		Apprenticeship	0.000	Not normal distribution
		Level 3 qualifications	0.000	Not normal distribution
		Level 4 qualifications and above	0.000	Not normal distribution
		Other qualifications	0.000	Not normal distribution
	Health	Good	0.013	Not normal distribution
		Fair	0.287	Normal distribution
		Bad	0.000	Not normal distribution
		Day-to-day activities limited (all residents)	0.001	Not normal distribution
		Day-to-day activities limited (workers)	0.000	Not normal distribution
		Provides no unpaid care	0.000	Not normal distribution
		Provides 50 or more hours unpaid care a week	0.004	Not normal distribution
	Religious diversity	Religious diversity	0.000	Not normal distribution
	Ethnic diversity	Ethnic diversity	0.000	Not normal distribution
Job-related factors	Economic activity	Part-time	0.000	Not normal distribution
		Full-time	0.551	Normal distribution
		Self-employed	0.001	Not normal distribution
		Unemployed residents	0.000	Not normal distribution
		Retired	0.014	Not normal distribution
		Student	0.000	Not normal distribution
		Looking after home or family	0.000	Not normal distribution
		Long-term sick or disabled	0.000	Not normal distribution

		Other	0.000	Not normal distribution
		Unemployed male	0.000	Not normal distribution
		Unemployed female	0.000	Not normal distribution
	Hours worked	Less than 15	0.777	Normal distribution
		16 to 30	0.000	Not normal distribution
		31 to 48	0.005	Not normal distribution
		More than 49	0.000	Not normal distribution
	Occupation	Managers, directors and senior officials	0.000	Not normal distribution
		Professional occupations	0.000	Not normal distribution
		Associate professional and technical occupations	0.000	Not normal distribution
		Administrative and secretarial occupations	0.000	Not normal distribution
		Skilled trades occupations	0.000	Not normal distribution
		Caring, leisure and other service occupations	0.000	Not normal distribution
		Sales and customer service occupations	0.279	Normal distribution
		Process plant and machine operatives	0.001	Not normal distribution
		Elementary occupations	0.192	Normal distribution
Property factors	Accommodation size and central heating	Average number of rooms per household	0.000	Not normal distribution
		Average number of bedrooms per household	0.000	Not normal distribution
		Central heating	0.000	Not normal distribution
	Car or van availability	No car or van	0.000	Not normal distribution
		The average number of cars or vans	0.000	Not normal distribution
	Accommodation type	Whole house or bungalow	0.000	Not normal distribution
		Whole house or bungalow: detached	0.000	Not normal distribution
		Whole house or bungalow: semi-detached	0.000	Not normal distribution
		Whole house or bungalow: terraced	0.000	Not normal distribution
		Flat, maisonette or apartment	0.000	Not normal distribution
		Flat, maisonette or apartment: purpose-built block of flats or tenement	0.000	Not normal distribution
		Flat, maisonette or apartment: part of a converted or shared house	0.000	Not normal distribution
		Flat, maisonette or apartment: in a commercial building	0.000	Not normal distribution
		Caravan or other mobile or temporary structure	0.000	Not normal distribution
	Accommodation tenure	Owned	0.000	Not normal distribution
		Shared ownership	0.000	Not normal distribution
		Social rented	0.000	Not normal distribution
		Private rented	0.000	Not normal distribution
		Rent free	0.000	Not normal distribution
Deprivati	Deprivation	Total deprivation index	0.000	Not normal distribution

on factors	factors	Barriers to housing and services	0.000	Not normal distribution
		Crime	0.000	Not normal distribution
		Employment	0.000	Not normal distribution
		Health	0.000	Not normal distribution
		Living environment	0.000	Not normal distribution
		Income	0.000	Not normal distribution

C.2. Additional correlation results for Chapter 7

Table C-6 Spearman correlation coefficients between noise complaints and urban development patterns with population and 80% samples

Factors	Detailed indicators		Spearman correlation (population)	Spearman correlation (80% samples)
Population	Population density		0.489**	0.486**
	Population size		0.287**	0.259**
Industrial structure	Proportion of GVA per industry	GVA	0.301**	0.269**
		Per capita	-0.126*	0.109
		Industry A,B,D,E	-0.213**	-0.205**
		Industry C	-0.264**	-0.271**
		Industry F	-0.191**	-0.209**
		Industry G,H,I	-0.030	0.094
		Industry J	0.208**	0.196**
		Industry K	0.215**	0.211**
		Industry L	-0.216**	-0.218**
		Industry M,N	0.106	0.079
		Industry O,P,Q	0.157**	0.167**
		Industry R,S,T	0.136*	0.106
	Proportion of residents employed in each industry	Industry A	-0.417**	-0.406**
		Industry B	-0.144**	-0.201**
		Industry C	-0.222**	-0.202**
		Industry D	-0.178**	-0.128*
		Industry E	-0.189**	-0.169**
		Industry F	-0.209**	-0.208**
		Industry G	-0.055	0.111
		Industry H	0.170**	0.217**
		Industry I	0.196**	0.226**
		Industry J	0.150**	0.132*
		Industry K	0.208**	0.178**
		Industry L	0.022	-0.044
		Industry M	0.012	-0.042
		Industry N	0.319**	0.325**
		Industry O	-0.118*	-0.124*
		Industry P	-0.106	-0.101
		Industry Q	-0.024	0.048
		Industry R, S, T, U	0.081	0.050
Built-up area	Area metrics	Number of settlement patches	-0.446**	-0.457**
		Settlement density	-0.319**	-0.393**
		Total settlement size	0.378**	0.377**

		Mean settlement size	0.433**	0.436**
		Settlement size standard deviation	0.319**	0.333**
		Largest settlement size	0.400**	0.403**
	Edge metrics	Edge density	-0.376**	-0.377**
	Nearest-neighbour metrics	Total nearest-neighbour distance	-0.455**	-0.457**
		Mean nearest-neighbour distance	-0.319**	-0.298**
Transport network	Road density by classification	Total road density	0.325**	0.325**
		Motorway density	-0.069	-0.042
		Primary road density	0.383**	0.364**
		A road density	0.410**	0.394**
		B road density	0.012	0.027
		Minor road density	-0.054	0.004
	Kernel density	Kernel density for road network at the 1,000-cell-size level	0.355**	0.336**
		Kernel density for road network at the 500-cell-size level	0.357**	0.340**
	Railway density		0.444**	0.450**
Commuting	Proportion of residents using each commuting method examined	Work at or from home	-0.342**	-0.349**
		Underground, metro, light rail, tram	0.137**	0.105
		Train	0.176**	0.149*
		Bus, minibus or coach	0.408**	0.396**
		Taxi	0.319**	0.298**
		Motorcycle, scooter, or moped	0.192**	0.157*
		Driving a car or van	-0.425**	-0.396**
		Passenger in a car or van	-0.020	0.013
		Bicycle	0.158**	0.147*
		On foot	0.085	0.097
	Proportion of residents commuting each distance examined	0–2	-0.081	0.124*
		2–5	0.397**	0.409**
		5–10	0.047	0.024
		10–20	-0.193**	-0.244**
		20–30	-0.259**	-0.258**
		30–40	-0.285**	-0.254**
		40–60	-0.296**	-0.258**
		> 60	-0.201**	-0.149*
		Total distance	0.150**	0.129*
		Average distance	-0.398**	-0.382**
Natural elements	National park density		-0.238**	-0.256**
	Woodland density		-0.255**	-0.223**
	Lake density		0.104	-0.086
	Coast density		0.118**	0.102
	River density		-0.199**	-0.169**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

Appendix D

Publications by the candidate during doctoral study

This appendix lists the publications by the candidate during doctoral study, as well as the papers in preparation. Published/publishing papers mentioned in Chapters 4-9 are also presented correspondingly in this appendix. This appendix is subdivided into three sections: publications directly related to this thesis (Section D.1), papers in preparation (Section D.2), and other published papers (Section D.3).

D.1. Publications directly related to this thesis

Tong, H., & Kang, J. (2022). A Spatial-Temporal Big Data Analysis on Urban Planning and Public Health from the Perspective of Sound Environment (in Chinese). Time Architecture,1, 70-73.

Tong, H., & Kang, J. (2021). Relationship between noise complaints and urban density across cities of different levels of density: a crowd-sourced big data analysis. The Lancet, 398, S86.

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. Science of the Total Environment, 785, 147213. (Corresponding to Chapter 5)

Tong, H., & Kang, J. (2021). Characteristics of noise complaints and the associations with urban morphology: A comparison across densities. Environmental Research, 197. (Corresponding to Chapter 4)

Tong, H., & Kang, J. (2021). Relationships between noise complaints and socio-economic factors in England. Sustainable Cities and Society, 65, 102573. (Corresponding to Chapter 6)

Tong, H., & Kang, J. (2020). Relationship between urban development patterns and noise complaints in England. Environment and Planning B: Urban

Analytics and City Science, 48(6). 1632-1649. (Corresponding to Chapter 7)

D.2. Papers in preparation directly related to this thesis

Tong, H., Warren, JL., Kang, J., & Li M. (2022). Using multi-sourced big data to correlate sleep deprivation and road traffic noise: A national scale spatial analysis. In preparation. (Corresponding to Chapter 8)

Tong, H., Warren, JL., Kang, J., & Li M. (2022). Using multi-sourced big data to correlate mental health and road traffic noise: A national scale spatial analysis. In preparation. (Corresponding to Chapter 9)

D.3. Other published papers

Xu, C., Oberman, T., Aletta, F., Tong, H., & Kang, J. (2021). Ecological Validity of Immersive Virtual Reality (IVR) Techniques for the Perception of Urban Sound Environments. Acoustics, 3(1), 11-24.

Kang, J., Aletta, F., Oberman, T., Mitchell, A., & Tong, H. (2021). Acoustic environments and soundscapes in London during the Spring 2020 Lockdown. The Journal of the Acoustical Society of America, 149(4), A27-A27.

Gao, X., Cao, M., Zhang, Y., Liu, Y., Tong, H., & Yao, Q. (2021). Towards sustainability: An assessment of an urbanisation bubble in China using a hierarchical-Stochastic multicriteria acceptability analysis-Choquet integral method. Journal of Cleaner Production, 279, 123650.

Xu, C., Tong, H., & Kang, J. (2021). Perceived width evaluation on interpolated line sources in a virtual urban square. In 2021 Immersive and 3D Audio: from Architecture to Automotive (I3DA). IEEE. 1-4

Aletta, F., Oberman, T., Mitchell, A., Tong, H., & Kang, J. (2020). Assessing the changing urban sound environment during the COVID-19 lockdown period using short-term acoustic measurements. Noise Mapping, 7(1), 123-134.

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. International Journal of Environmental Research and Public Health, 16(22), 4522.

Mougan, C., Fu, Q., Kolath, J., Tong, H., Dixit, S., Geffert, L., ... & Gale, E. (as a group) (2020). Get Bristol moving: tackling air pollution in Bristol city centre. In Turing Network Data Study Group Bristol. Zenodo.