

Spatiotemporal patterns and socioeconomic inequalities of noise and sound sources in Accra, Ghana

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Declaration of originality

I declare that the work contained in this thesis is my own. All other work has been appropriately cited and referenced. This work has benefited from the guidance of my supervisors and collaborators which is acknowledged below.

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Abstract

The urban environment is made up of mixtures of mechanical, human, animal, and natural sounds with diverse acoustical qualities. Epidemiological evidence has shown that noise pollution - generally understood as loud, unwanted sound – can have adverse effects on multiple health states and outcomes. In growing sub-Saharan African (SSA) cities, noise pollution is an emerging public health concern. Yet limited local information on spatiotemporal variations and inequalities of sound environments is a barrier to the formulation and evaluation of environmental policies and management strategies.

My PhD research helps fills this data and information gap in a growing sub-Saharan African metropolis. I characterized and modelled the spatiotemporal patterns and socioeconomic inequalities of the outdoor sound environment and its sources in Accra, Ghana.

I designed and implemented a large-scale 1-year measurement campaign (April 2019 - June 2020) to collect data on sound sources and levels with audio recorders and sound level meters at 146 representative road-side locations (136 weeklong and 10 yearlong) in the Greater Accra Metropolitan Area (GAMA, ~5 million people, 1500 km²). To detect different types of urban sounds, such as road-transport, air-transport, music, human speech, nature, and animals, I applied a pre-trained deep learning acoustic classifier to the audio recordings. I used descriptive statistics and land use regression (LUR) methods to characterize and predict trends in sound levels (dBA), sound intermittency (Intermittency Ratio: % of sound energy from events) and the presence of different types of sounds (i.e., sources) across space and multiple time scales. I then linked aggregated census data at the enumeration area level (i.e., small census tracts) to estimate population exposures to, and socioeconomic (SES) inequalities in, the urban sound environment in Accra Metropolis, the main city area (~2 million people). SES metrics included household consumption, higher educational attainment, and unemployment.

Road transportation was the most identified source of environmental noise and was pervasive throughout Accra Metropolis. However, mixtures of different sound types were prevalent in different places and times of the day, such as animal and insect sound in peri-urban as well as higher SES areas in Accra Metropolis. Additionally, outdoor music and human speech sounds were more common in lower SES, high-density residential neighbourhoods, particularly during the daytime. Nature-based sounds were relatively uncommon, but more prevalent in peri-urban areas.

Measured and model predicted day-evening-night (L_{den}) and night-time (L_{night}) equivalent continuous sound levels surpassed local¹ and international² guidelines almost everywhere in the GAMA, with significant spatial variations in magnitude. In Accra Metropolis, enumeration area L_{den} and L_{night} followed a socioeconomic gradient; the lowest SES enumeration areas had higher median L_{den} and L_{night} compared with higher SES areas. Furthermore, areas in the GAMA which had both high L_{night} (≥ 50 dBA) and intermittent night-time sound ($IR_{night} \geq 50\%$), were predominantly found in the city's poorest residential neighbourhoods.

The measured sound environment did change throughout the city during periods of extreme disruption or planned traditional festivals. Significant reductions in measured sound levels were observed during the COVID-19 pandemic lockdown (~ 6 dBA median reduction) in April 2020. Reductions were also observed at two of the long-term high-density residential sites during an annual 1-month ban on 'drumming and noise making' preceding the celebration of the *Homowo* festival (~ 3 dBA median reduction).

Sound levels in Accra Metropolis were generally higher than in cities in North America and Europe, and similar to a major city in South America, with estimates from either LUR or propagation-based models. Stronger noise policy is needed to ensure that permissible limits, which

are in place to safeguard public health, are met. Furthermore, equitable city-level actions and interventions in relation to urban infrastructure (e.g., road-networks, buildings, parks) and services (e.g., transportation) are needed to reduce noise from specific sources and improve sound environments in Accra that could also have broader benefits for health and wellbeing.

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List of abbreviations

AD: Asylum Down

AMA: Accra Metropolitan Area

ASH: Ashaiman

BRT: Bus Rapid Transit

CBI: Commercial, business, industrial

EA: Enumeration area

EL: East Legon

EPA: Environmental Protection Agency

GAMA: Greater Accra Metropolitan Area

HR: Hazard Ratio

IQR: Interquartile range

IR: Intermittency Ratio

IHD: Ischemic Heart Disease

JT: Jamestown

LAeq: A-weighted Equivalent Continuous Sound Level. Can be calculated at different intervals such as LAeq_{1min}, LAeq_{1hr}, LAeq_{24hr}

L_{day}: A-weighted Equivalent Continuous Sound Level during the day

L_{den}: A-weighted evening and night penalized Equivalent Continuous Sound Level

LA_{FMax}: A-weighted instantaneous maximum sound level (Fast response)

L_{night}: A-weighted Equivalent Continuous Sound Level during the night

L10: Sound level which is exceeded 10% of the time for the duration of a measurement

L90: Sound level which is exceeded 90% of the time for the duration of a measurement

LA: Labadi

LUR: Land use regression

MAE: Median absolute error

ME: Mean error

ML: Machine learning

N1: N1 West Motorway at Lapaz

NN: Neural network

NSRT: Noise Sentry Sound Level Meter

OR: Odds ratio

RE: Random effect

RF: Random Forest

RR: Relative Risk

SD: Standard deviation

SES: Socioeconomic status

SLM: Sound Level Meter

SSA: Sub-Saharan Africa

TMW: Tema Motorway

UGH: University of Ghana Hill

WHO: World Health Organization

Chapter 1 Introduction

1.1 Rationale

Just over half of the world's population now live in cities³. Urban living can improve livelihood and health through increased access to infrastructure, technology and services. However, environmental pollution can also erode these health benefits and worsen the quality of life of urban residents⁴. Furthermore, health burdens and life expectancies are not equitably distributed across and within cities^{5,6}, and inequalities in exposure to environmental pollution^{7–16} can widen this gap. In SSA, cities are experiencing multiple burdens of pollution in the air, water, and soil^{11,17–19}. Noise pollution in particular, has garnered recent attention as an emerging environmental health risk in SSA cities^{20–27}. Numerous epidemiological studies, primarily in Europe and North America, have shown that environmental noise exposure can lead to a range of auditory and non-auditory health effects including cardiometabolic disease, sleep disturbance, impaired cognitive function, stress and annoyance^{28–33}. Though, soundscape studies in these regions have also highlighted how certain sound environments can also be considered as tranquil, pleasant, or restorative³⁴. Nature-based and animal sounds (e.g., birdsong) in particular have been found to reduce physical markers of stress (e.g., heart rate, blood pressure, cortisol) and perceived pain, and improve mood and cognitive ability in mostly laboratory or hospital-based settings^{35–37}. Unlike in Europe^{38–42}, and increasingly in North America and Asia^{43–50}, there is a lack of measurement and modelling of the magnitude and characteristics of noise and different types of sounds found in urban SSA environments, especially in high spatial and temporal resolution^{24,26}. Such data could support future noise epidemiological research as well as effective and equitable noise policy and soundscape promotion in the region.

1.2 Research aims and objectives

The aim of my PhD research is to model and characterize the spatiotemporal patterns and socioeconomic inequalities of the urban sound environment and its sources in the West African city of Accra. To achieve my research aim, I had the following objectives:

1. Design, pilot, and implement a large-scale 1-year measurement campaign of the urban sound environment and sources in the Greater Accra Metropolitan Area (GAMA) using sound level meters, audio recorders, weather meters, street-level imagery, and survey tools.
2. Descriptively characterize, model, and predict the spatiotemporal patterns of sound level and intermittency metrics across the GAMA and estimate the percentage of the population exposed to varying levels.
3. Descriptively characterize, model and predict the spatiotemporal patterns of the presence and frequency of different types of sounds from a range of sources identified from audio recordings across the GAMA.
4. Descriptively characterize the socioeconomic inequalities of the urban sound environment in high-spatial resolution in the GAMA.

1.3 Thesis structure

Chapter 2 provides an overview and a critical review of the relevant literature. Chapter 3 lays out the design and implementation of the measurement campaign in the GAMA. Chapter 4 presents a descriptive and graphical characterization of the spatiotemporal patterns of different types of sounds, their levels and intermittency. Chapters 5 and 6 contain the spatiotemporal land use regression (LUR) modelling of sound metrics and sound types, and prediction for all locations, in the GAMA. In addition, Chapter 5 presents estimates of the percentage of the population exposed to varying noise levels in Accra Metropolis. Chapter 7 characterizes the socioeconomic inequalities of the urban sound environment in Accra Metropolis, based on multiple SES metrics. Finally, Chapter 8 gives a final discussion and conclusion.

Chapter 2 Background

2.1 Health in cities

In 1875, a British physician and sanitarian, Sir Benjamin Ward Richardson, described his dream of a healthy city as ‘quiet’ and ‘noiseless’. The city he imagined was called ‘*Hygeia*’ and the streets were paved and wide and transportation went underground^{51,52}. Since Sir Richardson wrote about *Hygeia*, cities have swelled and undergone massive transformations³. Currently, over 55% of the world lives in cities (4.2 billion people)³. Urban living can remarkably improve livelihood and health through increased access to urban infrastructure, technology, energy, and services⁴. Though, environmental pollution in cities can also erode these health benefits and worsen the quality of life of urban residents⁴ in highly unequal ways. With increasing demand for energy, transport, agriculture and manufactured goods, environmental pollution has become a common fixture of urban life. Pollutants in the form of material substances or energy can contaminate the sounds we hear, the air we breathe, water we drink and the food we eat⁵³.

2.1.1 Unequal pollution in cities

Within-city distributions of pollution are often not random. Government policy making, urban planning, private enterprise, and community mobilization, all have a role to play in making decisions which shape urban built environments and delivery of services, and their equitable distributions⁵⁴. The distribution of pollution is often patterned by socioeconomic inequalities, power imbalances, and histories of racial and social segregation⁵⁴. This can result in poor, marginalized, and ethnic minority communities exposed to sometimes dangerous levels of waterborne, airborne, and chemical pollutants^{9,28,54–60}. Unequal decision making also extend to the creation, placement, and restoration of urban parks and greenspace which could shield urban residents from pollution by improving local air quality, lowering local temperatures, and creating nature-based sound environments⁶¹.

Health inequalities created from environmental inequalities persist even in countries with sophisticated social programs and universal healthcare but are amplified in countries without these social safety nets. For decades, environmental justice research in North America and Europe has documented disparities in environmental risks including proximity to hazardous waste sites, polluting industries, agricultural pesticides, and vehicle traffic, by ethnicity, class and SES^{54,55,62,63}. In SSA, while urban dwellers consistently outperform their rural counterparts on multiple health indicators⁴, disparities in pollution exposure and health between and within cities exist^{5,11,64–68}. The 200 million slum dwellers in SSA cities are exposed to the extremes of environmental pollution⁶⁹, including inadequate water supply, sanitation, drainage and rubbish collection. Unstable and temporary housing structures and insufficient access to clean fuels can result in higher levels of indoor (and community) air pollution⁶. Since slums are often near areas of work⁶, residents may be exposed to outdoor air and noise pollution from busy roads or other occupational activities.

2.2 Noise pollution

Perception of sound is integral to everyday human functioning as it helps us to navigate and interact with our physical and social environments. Sound can also create a sense of place and an emotional attachment to our surroundings⁷⁰. Depending on the context and one's personal control over the source, sounds of engines, drilling, honking, grinding, lawn mowing, barking, music, talking, church bells and/or construction could be perceived as noise. More specifically, noise pollution can be defined as unwanted⁷¹ and/or harmful sound⁷². Environmental noise pollution, in particular, is defined by the European Environmental Agency as unwanted outdoor sound created by human activity, such as transportation or industrial sources⁷¹, while the operational definition of environmental noise in the latest WHO guidelines (2018) casts a wider net and states 'noise emitted from all sources except sources of occupational noise exposure in workplaces'². With the rapid

pace of population growth in the 21st century, and a reliance on machinery for transportation, energy, building, computing and other purposes, noise has become a common fact of modern day life, particularly in dense cities⁵². Even protected natural spaces, such as national parks, are becoming louder with anthropogenic sounds over time³⁷.

2.3 Urban noise sources

The urban acoustical environment is the sum of a diverse set of sound sources acting upon the environment⁷³. In Europe and North America, sources of environmental noise are often cited as arising from transportation (road, rail and aircraft traffic⁵²), and in some places, industrial activities and wind turbines⁷⁴. As discussed in *Section 2.11.2*, minimal research has been conducted on the diversity of noise sources in other places of the world, such as SSA. From the few studies that have been conducted in the region, urban noise sources have not just been limited to transportation but include community sources such as religious activities, street celebrations and festivals, restaurants, bars, commercial centers and markets, music shops, and large- and small-scale informal industry^{21,22,75–84}. These other noise sources often do not feature in the noise and health literature from Europe and North America but are the subject of research scholarship, and have appeared in the local news and policy debates, in SSA countries^{21,22,25,79,80,85}.

2.4 Noise pollution and health

Noise is often talked about as a nuisance, but it can have a myriad of detrimental impacts on psychological wellbeing and physical health. Epidemiological studies conducted primarily in high-income countries in Europe and North America² have shown that noise from transportation sources (road, rail, or aircraft traffic) are associated with a range of health outcomes^{2,86–90}. In Europe, the majority of people exposed to environmental noise are exposed to road-traffic noise pollution⁷¹, and the epidemiological evidence is strongest for road, rail, and aircraft sources. However, an

emerging evidence base shows some evidence of associations with wind-turbine and low-frequency sound and annoyance^{2,91}. The epidemiological evidence of an association between environmental noise and health is further supported by experimental studies examining biological plausibility and mechanisms^{89,92}.

2.4.1 Sleep disturbance and annoyance

Noise exposure can disturb sleep patterns and have a downstream short and long-term impact on cognitive and emotional responses, elevation of blood pressure and stress hormones, and induce changes to appetite and glucose dysregulation^{71,93}. The 2018 WHO-commissioned systematic review and meta-analysis found significant odds ratios for being highly sleep disturbed with respect to a 10 dB increase in L_{night} for road (2.13), rail (3.06), and aircraft (1.94) noise exposure, and the exposure-response curve is highest for aircraft noise⁹³. Polysomnographic studies undertaken in controlled laboratory conditions also found that the acute effects of exposure to transportation noise events were also significant (Range of odds ratios for a 10 dBA increase in indoor L_{max} : 1.35 – 1.36)⁹³.

Exposure to noise can also impact mental wellbeing, and cause people to become highly annoyed^{71,94}. The exposure response relationships are non-linear, and the odds ratios relating to the percent of the population highly annoyed with a 10 dBA increase in road, rail, and aircraft noise range from 3.03, 3.51 and 4.78, respectively^{2,94}. However, it is well known that non-acoustic factors account for a large proportion of the variation in community annoyance levels, such as (i) attitudes, concerns and expectations of the noise source, (ii) noise sensitivity, (iii) perceived control over the source, (iv) trust in authorities and perceived fairness, and (v) other area-level and contextual factors, such as access to a quiet side of a dwelling or green space⁹⁵. Noise exposure is also associated directly, or mediated through annoyance, with anxiety⁹⁶ and depression⁹⁷.

2.4.2 Cardiovascular effects

Environmental noise is associated with cardiovascular diseases. Exposure can activate stress responses in the body, affecting the autonomic nervous and endocrine system, which in turn can impact blood pressure, heart rate, blood fats and endothelial dysfunction, which are risk factors for hypertension and atherosclerosis and serious conditions such as ischaemic heart disease (IHD) and stroke^{88,98}. The noise and cardiovascular link may also be a product of impaired sleep quality⁷¹. Meta-analyses of epidemiological studies have shown positive associations between exposure to road-traffic noise and IHD. The 2018 WHO systematic review and meta-analysis found a Relative Risk (RR) estimate of 1.08 [95% CI 1.01 – 1.15] for the incidence of IHD with a 10 dBA increase in road-traffic noise, though another systematic review published a year later, which included several additional studies found a much smaller RR at 1.02 [95% CI 1.00 – 1.04]^{30,99}. The 2018 WHO review also found a positive association between road-traffic noise and the prevalence of hypertension (RR: 1.05 [95% CI 1.02-1.08] per 10 dB, n=26 studies), however all of the studies were cross-sectional. In a large pooled 2021 Scandinavian study (n=136,000 participants), there was a statistically robust increase in risk of stroke with long-term exposure to road-traffic noise (hazard ratio: 1.06 [95% CI 1.03, 1.08 per 10-dB higher 5-year mean exposure])³². Even though the exposure distribution of road-traffic air pollution can be correlated with noise, associations of noise and cardiovascular outcomes seem to be relatively independent of air pollution^{30,32,100,101}.

2.4.3 Metabolic effects

Recent evidence points to an association between noise exposure and metabolic health⁸⁹. The suggested physiological pathways are through the stimulation of the endocrine system, hormone imbalance and glucose dysregulation^{102–104}. Interrupted sleep also acts on similar pathways including effects on appetite and energy expenditure¹⁰⁵. The relative risk of diabetes incidence from exposure to road-traffic noise was relatively consistent in five cohort studies in Canada and Europe, with a pooled effect estimate of 1.11 [95% CI 1.08-1.15] per 10 dB³⁰. Recent evidence from four

longitudinal cohort studies in Switzerland and Scandinavia also suggest that there is an association between road-traffic noise and adiposity markers or obesity⁸⁹.

2.4.4 Neurodegenerative effects

Data from epidemiological studies is suggestive of an association between environmental noise exposure and Alzheimer's disease and dementia^{106,107}. Long-term chronic exposure to environmental noise may have neurotoxic effects on older adults and lead to inflammatory processes and oxidative stress in the brain¹⁰⁸. As an example, a recent cohort study in Chicago (USA) found 29% higher odds [95% CI 1.08-1.55] of Alzheimer's disease with 10 dB increments of chronic noise exposure, even after controlling for residential air pollution (NO_x) and other confounders¹⁰⁷.

2.4.5 Health effects in children

Environmental noise is associated with annoyance and a range of health outcomes in children. There is a robust association between exposure and cognitive development in children, particularly through exposure in the classroom²⁹. Environmental noise can lower children's motivation, reduce speech intelligibility, and impair reading comprehension^{33,71,109,110}.

2.4.6 Health burden

From the epidemiological evidence of environmental noise in Europe (road, rail, aircraft, industry), it was estimated that long-term exposure to environmental noise caused 12,100 premature deaths and contributed to 48,000 new cases of ischaemic heart disease per year in Europe (estimated for 2017)⁷¹. Furthermore, 6.5 million people experienced chronic sleep disturbance and 22 million suffered from chronic annoyance as a result of exposure to environmental noise⁷¹. Exposure to road-traffic noise accounted for the largest proportion of the health burden: 17 million people

suffering chronic annoyance, 4.5 million people suffering from sleep disturbance, 40 thousand new cases of IHD, and 10 thousand premature deaths. 12,400 European school children also suffered from learning impairment from exposure to aircraft noise⁷¹. In regions of the world such as SSA, there is very limited epidemiological research on noise¹¹¹, and thus limited information on exposure-response relationships, which may be specific to these geographies and populations.

2.4.7 Urban sounds can be health promoting

Urban sounds are more than just noise and can be a resource to promote good health and mental wellbeing^{112,113}. Investigations into the perceived or objective health benefits of acoustic environments have been conducted in mostly small-scale experimental or cross-sectional studies in laboratory, hospital, or field-based settings¹¹⁴. A recent study from London even developed a mobile phone application (Urban Mind project) to crowd source data from a large participant pool¹¹⁵. From these studies, sounds such as those from natural sources (i.e., running water, rustling foliage) or bird songs were generally described as a comforting, pleasant, desirable or tranquil soundscapes^{115–118}. Changes in physical markers following exposure to these soundscapes have been put to the test in generally small-scale experimental or cross-sectional studies¹¹⁴. For example, Swedish subjects who underwent a stress test and were placed in a virtual reality showed signs of stress recovery based on cardiovascular data and saliva cortisol when they were exposed to nature sounds¹¹⁹. Additionally, hospital patients who listened to rustling leaves and birdsongs during surgery had lower salivary alpha-amylase levels (biomarker of decreased sympathetic activity), compared to regular sounds in the operating room¹²⁰. Furthermore, a study in Sweden (n=59 participants) found that nature sounds were described as ‘pleasant’ and promoted recovery among patients undergoing rehabilitation for stress-related mental disorders¹²¹. A recent meta-analysis (18 studies, mean sample size: 150 participants) estimated that exposure to nature-based sounds relative to comparison groups resulted in a -0.60 (95% CI -0.97, -0.23) effect size reduction in stress and annoyance outcomes, which included decreased pain, heart rate and blood pressure¹¹⁴. Bird sounds

specifically had the largest mean effect size for reducing stress and annoyance outcomes¹¹⁴. However, the results among these studies are not always consistent^{114,120,122} and can vary by geography, demographics and sociocultural factors^{116,123}.

2.5 Measurement of the urban sound environment

2.5.1 Acoustics and instrumentation

Sound level meters (SLMs) are used to directly measure acoustical energy. Specifically, SLMs record sound pressure levels relative to a standard threshold, which is the threshold of human hearing¹²⁴. As the human ear can detect a wide range of sound pressure levels, the unit of measurement is on the logarithmic scale (decibels, dB)¹²⁴. Sound waves propagate at the same speed through a medium, but the number of waves per second is the frequency (measured in Hertz (Hz)). The human ear can only detect sounds within the frequency range of 20 Hz – 20 kHz and is not equally sensitive to all frequencies. Thus, measuring or weighting sounds at certain frequencies may be more relevant for environment health studies compared with sounds that the human ear is less sensitive to. There is a frequency weighting approach, called A-weighting, which is commonly applied in environmental health studies. This approach weights mid- and higher-range frequencies more heavily than lower frequency sounds^{124,125}.

Sound level meters come in different forms and can cost upwards of a thousand pounds per SLM or be purchased for a few hundred. What typically sets the cost of SLMs apart is the microphone technology and the ability for frequency decomposition and analysis. For example, lower cost SLMs with lower quality microphones are generally less sensitive and thus unlikely to accurately detect very low sound pressure levels (i.e., <30 dB)¹²⁴. International standards classify SLMs into types, such as *Type 1* or *Type 2*. *Type 1* SLMs are generally more expensive than *Type 2* and are recommended for use when precise measurements are needed, such as when assessing compliance with regulations. *Type 2* SLMs are useful for large-scale, city-wide campaigns where extreme

precision at any one location and time point is not required¹²⁴. These SLMs are particularly attractive when planning environmental monitoring campaigns which require many sensors that may also need to be deployed for long periods of time.

Instantaneous sound pressure level measurements can be used to derive a multitude of metrics which describe the urban sound environment. The A-weighted equivalent continuous sound pressure level ($L_{Aeq,T}$) represents the sound level equivalent to the average of the fluctuating sound energy over some time period T ^{124,126}. Time periods by which A-weighted equivalent continuous sound levels are integrated in environmental health studies are typically for the daytime (L_{day}), night-time (L_{night}), and 24-hour ($L_{Aeq,24hr}$) periods. Another common metric is the day-evening-night weighted sound level (L_{den}), which penalizes sound in the evening and night-time compared with the daytime¹²⁶. Measured sound can also be described in terms of percentiles: L_{10} is the A-weighted level that is exceeded 10% of the time and L_{90} is the A-weighted level exceeded 90% of the time. Another characteristic of environmental sound, which is particularly health relevant, is eventfulness or intermittency. The frequency and magnitude of sound events can be characterized with the maximum sound levels (L_{Amax} (fast or slow response)) recorded over some time interval¹²⁴. As well, new metrics have been proposed such as the intermittency ratio (IR), which discriminates between sound environments with marked peaks and without¹²⁷.

2.5.2 Spatial and temporal patterns of urban outdoor sound

Levels and other characteristics of sound vary spatially within cities^{128–130} due to the non-uniform distribution of sources and attenuators (e.g., trees, buildings)¹³¹ as well as the rapid rate at which sound levels decay with increasing distance from a source^{132,133}. Furthermore, there is typically a strong diurnal pattern to urban sound levels as a result of daytime movement and activities around cities¹³⁴.

A city-wide survey of the urban sound environment requires measurements to be conducted at a sufficient number of locations and time periods which are representative for that area^{43,135}. For example, studies of environmental noise in Dublin (Ireland), New York (USA), Boston (USA), Montreal (Canada), Toronto (Canada), Taichung (Taiwan), and Cape Town (South Africa) did measurements in a diversity of neighborhoods across 13 to 767 locations^{26,42–45,49,136–139}. Some studies have also used mobile monitoring to collect measurements along pre-defined routes, such as in Philadelphia (USA)¹⁴⁰. Nonetheless, due to logistical and cost constraints of conducting city-wide measurements, trade-offs between the number of monitoring locations, the duration of monitoring, and the number of repeated measurements, often have to be made. For instance, studies in Montreal and Cape Town covered 87 and 134 locations, respectively, but conducted continuous weeklong measurement at all of them^{26,45}. Meanwhile, a study from Boston conducted single 10-min long measurements, but at 400 locations⁴⁴. Studies that collect short-term measurements (<24 hours of monitoring) often make the assumption that the data represent long-term levels. This assumption is likely met in cities where road-traffic is the primary source of noise^{136,141–143} - but may not be met in rapidly urbanizing cities in low-income countries where spatial and temporal distributions of sound source profiles may differ. As well, meteorological conditions which vary day to day (e.g., wind speed, temperature), can affect the temporal representativeness of short-term measurements¹⁴⁴.

2.5.3 Measurement and classification of sound types in the urban environment

Research on the classification of different types of sounds in the urban environment (e.g., road traffic, construction, animals) have increased in the past decade¹⁴⁵, largely through the use of low-cost sensors to collect data and machine learning techniques for processing^{146,147}. As an illustration, a team of researchers at New York University deployed a network of sensors in New York City¹⁴⁸, published a labelled dataset of audio recordings of environmental sounds (SONYC – UST)^{149,150}, and developed machine learning models to classify and predict the types of sounds from audio

recordings¹⁴⁶. Research teams in London have also built open-source machine learning models to classify anthropogenic and biotic sounds from audio recordings collected in parks¹⁵¹, and characterized how the urban sound environment changed during the COVID lockdown¹⁵². In England, a tool was developed to classify and map areas across the entire country on a tranquility scale based on audio-visual stimuli^{153,154}.

Audio recorders are common measurements tools in some research fields, and ecologists in particular have used them to characterize animal species presence and abundance¹⁵⁵. Their potential for large-scale deployment in cities as a measurement tool for the urban sound environment is promising^{148,156–158}. However, in some countries, laws regarding the collection of certain types of data that could infringe on personal privacy, such as audio recordings, may limit their use. Certain safeguards could be put in place when collecting urban audio, such as recording short audio clips instead of continuous data, safely and securely storing data, or even using software which can process the data in real-time so that audio recordings are not stored.

2.6 Modelling urban sound at city-scale

Mapping metrics and characteristics of the urban sound environment is a useful resource for policy makers and urban planners to work towards reducing noise pollution and promoting specific sound environments through policy and intervention. These maps can raise public awareness about noise and highlight social and spatial inequalities in exposure across neighbourhoods^{59,144}. Many cities in Europe already have published noise maps¹⁵⁹ (primary indicator is day-evening-night weighted sound (L_{den})) as part of an European Environmental Agency objective (END directive) to reduce noise pollution from transportation sources by 2020¹⁶⁰. However, modelling and mapping metrics that capture additional characteristics of sound at city-scale, such as intermittency or the diversity of sound types/sources, in both space and time is limited^{39,150,153,161}. Below, I describe approaches to urban sound/noise modelling which include propagation and statistical approaches.

2.6.1 Propagation modelling

Propagation modelling (also called dispersion or determinist modelling) has been widely used for modelling noise from road-, rail-, and aircraft-traffic sources, particularly in European cities ¹⁵⁹. Propagation models are based on the mathematical description of source emissions and propagation of sound through the environment in order to derive estimates¹⁶². The information that is needed on sources that also has spatial, and sometimes even temporal, granularity generally include road-networks, road traffic volume, vehicle fleet compositions, building heights and footprints, land use, and depending on the model's purpose, airport locations, aircraft traffic and railway networks. Propagation modelling can be a cost-effective approach to modelling noise from specific sources as it relies primarily on secondary data without physical field measurements of sound levels. However, model predictions should still be validated with field measurements, especially when models have been imported to new locations or when using lower-resolution data inputs^{38,159}.

A challenge for implementing propagation models in many regions of the world is that national governments or even international corporations do not routinely collect much of the data that are needed for the models^{26,40,144}. Furthermore, these models were designed within a European/North American context where transportation are the primary sources of noise, and thus are emphasized in the models. However, as I describe in *Section 2.11.2*, the sources of noise in other cities, such as those in SSA, may be more diverse^{79,80,163,164}. Thus, transferring transportation-focused propagation models to cities in SSA or elsewhere without adaptation, may actually underestimate the total environmental noise levels and limit the scope of policy recommendations that could be made about potential sources¹⁴⁴.

2.6.2 Statistical modelling

Statistical modelling of the urban sound environment, primarily through land use regression (LUR) models¹⁶⁵, has increased in recent years^{26,40,42,45,48–50,136,137,139,166}. To date, most applications of LUR have been for air pollution in high income countries¹⁶⁵, with a growing number of noise models developed for middle and high-income cities in North America, Europe, Asia and South America^{40,42,44,45,47–49,136,137,139,166}. Currently, only one environmental noise LUR model has been developed in SSA, for informal settlements in South Africa¹⁶⁷. LUR models depend upon geospatial data which are used as predictors^{159,165}. Such data are increasingly available globally; such as satellite derived land use measures¹⁶⁸ or locations of road networks and human activities from OpenStreetMap or Google^{169,170}. LUR models can also incorporate elements of time such as predictor variables with temporal characteristics (e.g., hourly weather conditions)^{44,47}. The relationship between the measured pollutants and spatiotemporal predictors are then estimated within the statistical model^{159,165}. If resulting models explain sufficient variability, they can be used for prediction at unmeasured locations where predictor data exist. Recently, one study in Toronto, Canada even combined LUR and propagation model estimates in a hybrid approach⁵⁰. Previous LUR studies used sound level data that came from a range of monitoring durations (Table 1), from as short as 5-minutes in Vancouver (Canada)⁴⁹ and Taichung (Taiwan)¹³⁷ to as long as one year in Dublin (Ireland)⁴². As well, the number of measurement sites varied substantially between studies, from as low as 13 in Dublin (Ireland)⁴² to as high as 767 in Toronto (Canada)¹³⁹.

A variety of statistical sound level LUR models have been developed with linear and non-linear relationships, in addition to more recent machine learning approaches (Table 1). Previous studies modelled daily-scale metrics of equivalent continuous sound levels, such as $L_{Aeq24hr}$, L_{den} , L_{day} or L_{night} . Studies often only modelled one metric (Table 1). However, studies from Boston (USA) and Taichung (Taiwan) did additionally model frequency specific sound levels^{44,137}, which is important when considering health impacts and annoyance to noise with varying characteristics^{34,171,172}. Other

characteristics, such as the degree of intermittency and level fluctuations, are important to characterize, particularly with regard to disturbed sleep and awakenings during the night^{173,174}. Though to my knowledge, urban sound intermittency has not been modelled for a city within a statistical LUR framework.

Table 1. Urban noise land use regression modelling studies.

Study lead author, year	City (country)	Period	Monitoring duration	Number of sites	Sound level metric	Types of predictor variables considered	R ²	Error metric (value(s))
Xie et al., 2011	Dalian (China)	May 2008 & Feb 2009	--- (6am to 10pm)	202	LAeq	Land use; road networks	---	Average of the relative errors (5.8%-6.2%)
Aguilera et al., 2015	Girona (Spain) Basel (Switzerland) Grenoble (France)	2011	20 mins	60 (Bas) 40 (Giro) 41 (Gren)	LAeq _{24hr} estimated from 20-min measurements	Land use; traffic volume; road networks; bus networks; population density; building density	0.66 to 0.84*	RMSE (2.47 to 3.81* dBA)
Ragettli et al., 2016	Montreal (Canada)	2010 & 2014	7 days	87	LAeq _{24hrs} , L _{night} , L _{den}	Land use; road networks; traffic volume; rail networks; aircraft flight path; vegetation	LAeq _{24hr} : 0.68 L _{night} : 0.59 L _{den} : 0.69	RMSE (3.54 dBA LAeq _{24hr}) RMSE (3.97 dBA L _{night}) RMSE (3.71 dBA L _{den})
Sieber et al., 2017	Informal settlements in Western Cape (South Africa)	2015 to 2016	7 days	134	L _{den}	Land use; road networks; distance to airport; rail networks; building density; vegetation; distance to POIs (church, police station, hospital)	0.13	---
Walker et al., 2017	Boston (USA)	2015 to 2016	10 mins	400	LAeq _{10min} at multiple frequencies	Land use; road networks; vehicle counts; rail networks; bus networks; building density; POIs (restaurants, fire station, police station); vegetation; meteorological conditions; temporality	0.59 to 0.69*	MAPE (4.25-9.25 %*)
Harouvi et al., 2018	Tel Aviv (TA) & Beer Sheva (BS) (Israel)	July to Aug (2015) & Dec to Feb (2015 to 2016)	20 mins	99 (TA) 73 (BS)	LAeq _{20min}	Land use; road networks; traffic volume; bus networks; building density	0.52 and 0.79*	RMSE (2.67 to 4.33* dBA)
Drudge et al., 2018	Toronto (Canada)	June (2012) to October (2013)	30 mins (10am to 5pm) & 7 days	751 (30 mins) & 16 (7 days)	L _{night}	Land use; road networks	---	---
Chang et al., 2019	Taichung (Taiwan)	2013 to 2014	30 mins	50	LAeq _{24hr} , L _{night} estimated from 30-min measurements	Land use; road networks; traffic volume; meteorology	0.83	RMSE (2.09 dBA LAeq _{24hr} *) RMSE (2.80 dBA L _{night} *)
Fallah-Shorshani et al., 2018	Toronto (Canada)	---	20 mins (7am to 7pm) multiple times at each site	92	LAeq _{20mins}	Land use; road networks; traffic; rail networks; bus networks; rail networks; building density; population; distance from airport; vegetation and water; meteorological conditions	0.44 to 0.64	NMSE (<6* dBA)
Liu et al. 2019	Montreal (Mon), Longueuil (Lon), Toronto (Tor),	2003 (Mon), 2010 (Long)	5 minutes (Van)	188 (Mon) 71 (Long) 220 (Tor) 104 (Van) 48 (Hal)	LAeq _{24hr}	Land use; road networks; road-traffic volume; rail networks; bus networks; NEF30 airport sources; POIs (cinemas, health	All five cities: 0.47 to 0.58*	RMSE (3.56 to 5.37 dBA*)

levels across and within cities^{13,40,59,60,71,175}. A limited number of studies have also shown that these inequalities were sometimes patterned by socioeconomic factors^{13,59,60,71,175}. Particularly, when SES indicators were based on deprivation indices or material income, lower SES groups tended to have higher levels of exposure^{13,60,71}. Similarly in Hong Kong (China), it was found that there was within-city socioeconomic inequalities (lower educational attainment and income) in road-traffic noise¹⁷⁶, though the association was weak.

Studies in New York City (USA), Minneapolis and St. Paul (USA), and Montreal (Canada) showed that noise levels (specifically traffic noise in Minneapolis/St. Paul) were associated with race/ethnic makeup of neighbourhoods – specifically, positively associated with the percentage of non-white residents^{175,177,178}. A nation-wide study in the USA at a larger spatial aggregation (the census block level), found that night-time and daytime noise levels were higher in census blocks with higher proportions of non-white and lower SES residents⁵⁹.

The relationships between socioeconomic factors and exposure to health-positive soundscapes within and across cities, is less clear. Research on access to urban green space might shed some light on this relationship. In both high and low-income countries around the world^{179–182}, there appears to be clear socioeconomic gradients between who has access to green (and blue) spaces and who does not. Considering that green spaces - particularly quality ones - can facilitate and promote ‘positive’ sound environments such as natural (e.g., water, wind) and animal sounds (e.g., birdsong)^{116,180,183}, inequalities in access likely also pattern exposure to some degree.

2.8 International noise guidelines

The World Health Organization (WHO) first published a set of guidelines on community noise in 1999, followed by night noise guidelines for Europe in 2009¹⁸⁴. More recently (2018), the WHO Regional Office for Europe published a region specific guideline for Europe². Notably, the WHO

does not have noise guidelines for any other region of the world, though states that these guidelines ‘in terms of their health implications, the recommended exposure levels can be considered applicable in other regions and suitable for a global audience’². The WHO guideline states that there is a strong recommendation that above 53 dB (L_{den}) and 45 dB (L_{night}) for road-traffic noise, above 54 (L_{den}) and 44 dB (L_{night}) for railway noise, and above 45 dB and 40 dB for aircraft noise, there is an association with adverse health effects and effects on sleep. The guideline also provides recommendation, with conditional strength for wind turbine noise and leisure noise (e.g., noise from personal listening devices, pubs, nightclubs, concerts, sporting events, etc).

2.9 Policy for urban noise reduction and healthy soundscape creation

The first known noise ordinance was credited to Julius Caesar in 44 B.C. in an attempt to control the time at which wagons could enter Rome in an effort to reduce the clanking sound of wagon wheels on cobble stone¹⁸⁵. In the eighth century B.C., the ancient Greeks of Sybaris banned blacksmiths, potters, carpenters, and even roosters from the city to control noise¹⁸⁶. Since those times, noise has still proven difficult to manage and control. The definition of whether noise is a public versus a private problem has made noise abatement ever more difficult, and the majority of the responsibility has fallen on individuals¹⁸⁷. Amidst these challenges, standards/guidelines, compliance testing, exposure assessment and interventions for mitigation are implemented at regional⁷¹, national^{1,188}, and municipal levels¹⁸⁹ around the world. In Europe, the European Commission oversees regional noise policy, with particular emphasis on road-, rail-, and aircraft-traffic sources. In 2002, a Directive of the European Parliament was created for the assessment and management of environmental noise¹⁹⁰. One of the features is that member states are required to produce strategic noise maps on a 5-year basis for all major roads, railways, airports, and urban agglomerations using a set of standardized noise indicators⁷¹. Individual countries also make their own noise policies, though the standards/guidelines, relevant land use zones, times of the day, and noise limits can vary between countries^{1,191–193}.

National and city governments have increasingly recognized that healthy cities with health promoting urban acoustics require more than just the absence of unwanted sound. Cities in Europe are increasingly incorporating soundscape science and evidence into urban planning and noise policy¹⁹⁴. For example, the *London Plan* (2021) from the Mayor's office makes specific reference to the fact that 'managing noise includes improving and enhancing the acoustic environment and promoting appropriate soundscapes'¹⁸⁹ and the *City of London Noise Strategy* (2016-2026) recognizes that vibrant noise in a certain context can be iconic to the space¹⁹⁵. Another example is the Welsh Government's *Noise and Soundscape Action plan* (2018-2023), which recognises the need to create appropriate soundscapes within national policy¹⁹⁶.

The urban sound environment can be enhanced or mitigated by policies and interventions affecting sound emission, propagation, and attenuation^{31,197,198}. Studies have found that interventions for aircraft noise, specifically, building or closing infrastructure (e.g., flight path), resulted in changes in reported annoyance levels, sleep disturbance, and cognition in children³¹. Similarly, interventions aimed at reducing road-traffic noise at the source or along the transmission path generally resulted in reductions in noise levels and observed changes in reported annoyance³¹. For example, policies that target source emissions could focus on regulating vehicle engines¹⁹⁹, banning excessive vehicle honking, or restricting access of heavy vehicles to densely populated areas^{199–201}. Implementing direct changes to the urban environment such as modifying pavement material^{199,202} could also reduce road-traffic noise, particularly on higher-speed roads²⁰³. Strategic changes to urban design²⁰⁴, placement of key services, safety measures and public messaging that inspire modal shifts towards cycling and walking and mass transit, can also be used as a mechanism to reduce road-traffic noise in cities. These modal shifts could also achieve co-benefits with regards to improvement in air quality and potential increases in active transport (physical activity)²⁰⁵.

Expanding and caring for quality green and blue spaces can create sound environments often described as ‘positive’, ‘pleasant’ or ‘tranquil’^{34,194} from the presence of natural (e.g., running water, rustling leaves) and/or biotic sounds (e.g., birdsong). Vegetation is a natural noise attenuator^{131,191} and quiet parklands can serve as a refuge from the mechanical sounds of the city^{117,119,183,191,206}. A significant number of cities in Europe have defined and designated ‘quiet areas’, such as parkland⁷¹. For example, in the 2021 *Plan for London* published by the Mayor’s office, there is explicit mention of ‘improving and enhancing the acoustic environment and promoting appropriate soundscapes (including quiet areas and spaces of relative tranquility)’ and mention is made of deliberately introducing natural and biotic sounds¹⁸⁹.

2.10 Urbanisation in sub-Saharan Africa

Future population growth is projected to occur predominantly in developing country cities³. SSA is currently the world’s fastest urbanising region, with the number of urban dwellers having increased by over 400% since 1980³. SSA alone accounts for 13% of the world’s urban population³. As SSA rapidly urbanizes, and demand for energy, housing, transportation, and commercial enterprise increase, environmental pollution is becoming ever more pervasive in cities^{11,12,23,67,83,207–209}. Pollution also often disproportionately impacts the poor and people living in slums^{6,11,209,210}. While urban dwellers in SSA generally have better health than their rural counterparts^{4,211}, environmental pollution and poor living conditions contribute to the health gap within cities⁶. Furthermore, 76% of the urban workforce in Africa is informal²¹². This makes the regulation and mitigation of pollution generated from such activities difficult²¹³.

Demand for transport to access jobs, healthcare and services has increased substantially as populations and the spatial extents of SSA cities grow. Private vehicles, privately owned mini buses (known locally as Tro tro in Ghana; Matatu in Kenya; Danfo/Molue in Nigeria; Combi in South Africa; Ndiaga Niaye in Senegal), and commercial motorbikes are the main means of getting

around and contribute to long traffic delays, congestion, and noise and air pollution²¹⁴. Though some major cities have built underground or overground alternative transportation systems including metro (Addis Ababa, Ethiopia; Abuja, Nigeria) and bus rapid transit (Dar es Salaam, Tanzania; Lagos, Nigeria).

2.11 Noise pollution and sound environments in sub-Saharan African cities

Environmental noise pollution is common to countries globally, and is quickly becoming a public health topic of concern in SSA, as evidenced by news articles^{20,21,25,215}, government reports and guidelines^{1,192,216,217}, and scientific research^{22,85,164,218} on the topic. However, the lack of local high-quality data and information on the spatial and temporal patterns and sound sources poses a barrier for generating public and political demand for noise policies and regulations in the region. As well, the characteristics and patterns of noise and sources may be different in SSA compared to other regions of the world²¹⁹.

2.11.1 Data on the urban sound environment in sub-Saharan Africa

Compared to European and North American cities^{71,188,220}, there is very little research on the urban sound environment in SSA cities, which may be characterized by different mixtures of sources that also vary differently in within cities and over time^{83,221,222}. The majority of the information on sound levels in SSA comes from small-scale studies conducted in Nigerian cities, however, several measurement-based studies conducted in Cameroon, Ethiopia, Ghana, Kenya, Tanzania, South Africa, and Uganda populate the literature as well^{23,24,26,79,82,83,85,218,221,223–228}. With the exception of a larger study from South Africa²⁶, most of the previous studies in SSA collected measurements over a short duration (median across studies: 30 minutes) and at few locations (median across studies: 35 locations), which were not representative of the target city (often done in high-road traffic exposure areas, such as along highways/major road). Furthermore, most measurements were

conducted during the day-time hours, while few conducted nighttime measurements, which is an important exposure time window for time-dependant health outcomes such as sleep disturbance.

There are no environmental noise guidelines for Africa by the World Health Organization (WHO), though the WHO 2018 has guidelines for the European region and some countries have their own national guidelines or standards^{1,192,216,217}. Comparing findings from several SSA studies with night-time measurements to the WHO Environmental Noise Guidelines for the European Region, measured L_{night} generally exceeded^{26,83,164,228} the corresponding guidelines for road-traffic noise exposure (<45 dBA)². However, this comparison should be made with caution as the monitoring locations were generally representative of high road-traffic exposure situations, the duration of the measurements were short (<1 hr)^{83,164,228} and did not cover the entire nighttime range (10pm – 6am)^{83,164,228}, and thus may not truly represent average L_{night} in these areas.

2.11.2 Noise sources in sub-Saharan Africa

Unlike in many North American and European cities, where the predominant sources of ambient noise are transportation related, noise pollution in SSA sometimes emerges from a mixture of community sources including street festivals/funerals²²⁹, religious activities^{22,226}, formal and informal commercial activities, street hawkers²²⁹, and large and small-scale industrial activities^{23,80,163,201,224,230}. For example, the streets of Accra (Ghana) are dotted with loudspeakers used for commercial purposes and to broadcast religious messages^{21,25,27}, while in England, it is an offence to use loudspeakers at any time in the street to advertise entertainment, trade, or business²³¹. Several previous studies measured sound levels at a variety of sources in SSA, including: inside restaurants in Tanzania (range of L_{Aeq} : 60 to 73 dBA)⁷⁹ and public-sector buses in Nairobi, Kenya (mean L_{Aeq} : 86 dB)⁸²; near churches (range of L_{night} : 65 to 91 dBA)¹⁶³ and mosques in Ashaiman, Ghana (range of L_{night} : 75 to 86 dBA)¹⁶³, music shops in Benin City, Nigeria ($>90\%$ of measurements were above 85 dBA)⁸⁰, electricity generators in Nigeria²³², festivals and events in

Kumasi, Ghana⁷⁵, an industrial port in Tema, Ghana⁷⁶; and around an airport in Dar es Salaam, Tanzania (range of $L_{Aeq_{1min}}$: 45 to 99 dBA)²²⁴. Furthermore, in some neighbourhoods in cities in SSA, the road-network is more than a space for transportation and can accommodate economic (e.g., food sales) and recreational activities (e.g., games, sports (e.g., football)) that will impact the overall acoustic profile of the area²³³. Spatial and temporal variations in the presence of these sound sources could shape the spatial distribution of sound related health outcomes and perceptions of wellbeing. However, space-time variations in sound types and their sources have not been thoroughly characterized in SSA.

2.11.3 Urban sound research gaps in sub-Saharan Africa

As described in *Section 2.11.1*, there is a lack of data and research characterizing the spatial and temporal variations in noise pollution within SSA, which is needed for policy and planning, exploring relationships between noise exposures and health, and quantifying health burdens. Additionally, to my knowledge, no previous studies compared within-city socioeconomic inequalities in noise pollution within SSA¹³. However, previous research conducted in Accra, Ghana found inequalities in neighbourhood concentrations of outdoor ambient particulate matter air pollution between neighbourhoods of lower and higher socioeconomic status¹¹. I am also unaware of research conducted in SSA cities characterizing the magnitude and spatial distribution of different types of sounds within cities, such as anthropogenic and natural sounds. Though a review study has shown that the most marginalized communities in countries in the Global South, including SSA, most often have less access to urban green spaces in cities¹⁸¹ which might pattern exposures to nature-based acoustic environments. Understanding space-time variations of a variety of potential health-promoting sounds in SSA is important in addition to characterising the patterns of potentially harmful ones for healthy city soundscape planning and creation.

2.12 Accra, Ghana

The Greater Accra Metropolitan Area (GAMA, 1500 km²) is the most densely populated area in Ghana and the political, economic, and administrative capital. While these sectors drive urban economic growth, vast inequalities in income, housing and environmental quality remain^{11,12,64}. Accra is also a city with a large a diversity of languages, ethnicities, and demographic make-up, driven by the massive migration into the city from other parts of Ghana and West Africa. Accounting for over a fifth of the urban population (~ 5 million people, 2019 estimates), this metropolitan region includes Accra Metropolis at its core (~ 2 million people), Tema Metropolitan Area (large shipping port and industrial area) to the east and the expanding suburban municipalities to the north east and north west²³⁴. As the population and economic activities have expanded over the years in the GAMA, demand for transportation has increased^{235,236}, with private vehicles or privately owned minibuses (tro tros) as the main means of getting around^{236,237}. There is no train or tram service, and formal transit bus services are limited. Ride-shares such as Uber and Bolt, and motorcycle-taxis ('Okada'), are more recently being used to complement the need for public transport²³⁸. At the same time, urban growth has resulted in the re-development of natural lands, effectively decreasing the percentage of forested areas in the GAMA from 34% of land area in 1992 to 6.5% in 2015²³⁹.

2.12.1 Why noise exposure research is needed in Accra, Ghana

As described in *Section 2.11.3*, city-wide characterization of urban sound environments is urgently needed in SSA cities, and particularly in Accra Ghana to (1) support local noise policy creation and formulation, (2) provide exposure data for planned environmental epidemiological analyses in the city, and (3) provide a baseline to evaluate the real-world impacts of policies and interventions that will affect the acoustic environment.

In Accra, noise pollution has been highlighted as a public health concern in research¹⁶³, international agency reports²⁴⁰ and increasingly in the local news and social media^{25,27,241}. Noise pollution also appears to be a concern for the residents of Accra as it is consistently one of the top citizen complaints received by the Ghana Environmental Protection Agency each year²⁴². While urban noise has had less direct policy attention than other environmental hazards, such as air pollution, the municipal government has taken some steps to try and reduce levels from religious activities^{27,243} such as (unsuccessfully) asking Mosque's to use the WhatsApp messaging application for call to prayer²⁷ and enforcing fines on Churches that make excessive noise. The Ghana Standards Authority also published a set of nation-wide guidelines for ambient noise in 2018¹. However, a commonly cited barrier to the creation of noise policy, and the enforcement of regulation, is a lack of government capacity and funding for noise monitoring in Accra²⁴⁴. Effective management of noise requires a thorough understanding of patterns, and thus information on daily, weekly and seasonal trends and their consistency across urban areas can help aid prioritization. As well, estimation of population exposures to noise and potential socioeconomic inequalities, could also be an effective advocacy tool for generating local demand for equitably distributed policies and interventions. Finally, as urban soundscape creation is more than just noise reduction, identification of areas in the city that are abundant in nature-based sounds with 'good' acoustic qualities could also help local policy makers in Accra to identify areas worthy of preservation and protection⁷¹.

Another reason why it is timely to conduct noise and urban sound exposure research in Accra is because there are several planned and upcoming environmental epidemiological studies in the city. For example, there is a new birth cohort which will conduct an epidemiological study on the health impacts of exposure to environmental pollution, including noise. The study will follow mothers and new-born babies longitudinally, and capture data on birth outcomes (e.g., low birthweight), self-reported and objective sleep quality measures, annoyance, and blood pressure. As well, there

is a concurrent environmental epidemiological study which will characterize environmental exposures for children (Grades 1-2) at school and at home and link these exposures to a range of cardiovascular markers and sleep quality. These studies are first of its kind type of research in an urban African setting, and very much needed to diversity and enhance the representativeness of the global literature on noise and health effects.

Evidence of the effectiveness of interventions to mitigate noise or enhance pleasant and tranquil sound environments from Europe and other regions of the world can help shape future policies in Accra, however, local research is also needed to develop contextually relevant approaches²⁴⁵. Studies in Accra and other African cities could treat changes to road-networks, transportation services, and/or transport policies as natural experiments to investigate the potential noise level and health impacts in these settings. For example a study in Cairo, Egypt published in 2003 found that honking restrictions in the downtown core resulted in large noise reductions between 9-10 dBA²⁴⁵. In Accra, if the previously failed Bus Rapid Transport (BRT) system is eventually implemented²⁴⁶, a study could investigate its potential impact on road-traffic noise (i.e., by boosting the use of mass transit and thereby reduce the number of private vehicles on the road). As well, Accra Metropolis recently announced a new program of initiatives to reduce air pollution in the city²⁴⁷, which includes reducing air pollutants through vehicular and industrial sources, which may have indirect effects on noise as well. However, in order to estimate changes in noise over time, baseline measurements and models are needed. Therefore, characterization of the baseline urban sound environment in Accra can serve as a starting point for future intervention/policy evaluation studies.

2.13 Working definition of noise

Within my thesis, I use the terminology ‘environmental noise’ as a working definition to describe noise emitted from all sources except sources of occupational noise exposure in workplaces, in line with the WHO’s 2018 guidelines operational definition². I note however, that the Ghana Standards

Authority uses the terminology ‘environmental noise and ‘ambient noise’ almost interchangeably¹. When describing noise from road, rail, and/or aircraft sources, I use the terminology ‘transportation noise’. When describing noise from non-transportation sources found within communities, such as noise from commercial, leisure, religious, or industrial activities, I use the terminology ‘community noise’. Throughout my thesis, when referring to sound level measurements without specific reference to a source (e.g., road-traffic), I use the terminology ‘sound levels’ or ‘sound environments’, so as not to place a value judgement on the level of sound alone being indicative of noise.

Chapter 3 Measurement of the urban sound environment in Accra, Ghana

This chapter has been adapted from the open access (CC BY) published paper “Clark et al. High-resolution spatiotemporal measurement of air and environmental noise pollution in sub-Saharan African cities: Pathways to Equitable Health Cities Study protocol for Accra, Ghana. 2020” in BMJ Open²⁴⁸. I am the first author on the paper. I hereby give credit to this work without citing the work in every instance in the text.

3.1 Overview and objectives

Sub-Saharan Africa is currently the fastest urbanizing region of the world³, and while urban sound levels are currently surpassing local guidelines^{22–24,83,223,228}, large scale monitoring activities, as are seen in Europe and North America, are severely lacking^{22–24,83,223,228}. In this Chapter, I describe how I designed and implemented a large-scale measurement campaign to characterize the space-time variability of the urban sound environment in the Greater Accra Metropolitan Area (GAMA), Ghana. I co-designed this work with members of the *Pathways to Equitable Healthy Cities* air pollution measurement and monitoring team. As one of the only measurement campaigns which can characterize the urban sound environment at fine spatial and temporal resolution in a SSA city, the protocol set forth in this chapter can serve as a prototype for measurement in other SSA cities.

3.2 Measurement timeline and approach

The overall aim of the monitoring campaign was to measure the sound environment, air pollution (PM_{2.5}, NO₂), and their sources. However, the air pollution component of this work will not be covered by my thesis. Environmental monitoring occurred over the span of approximately one year in the GAMA, beginning on April 10th 2019. A long and short-term monitoring approach was taken

to capture the full temporal variation in urban sound (daily, weekly, seasonal) as well as the spatial variation due to local sources across the area's geographic extent. Specifically, myself and the team set up monitors to continuously run for ~12 months at 10 fixed sites to capture yearly temporal variability in environmental exposures. 136 rotating sites, which monitored for weeklong periods, captured spatial variability in urban sound and sources across Accra while also covering multiple seasons. The campaign was originally scheduled to finish 12 months after it started, with a target end date of April 10th 2020. However due to the interruption of the COVID-19 lockdown in Accra, which took place between April 1st and April 20th 2020, field work was suspended on March 29th 2020 (monitors at fixed sites were left to run until batteries ran out a week later). Field work and monitoring was resumed from May 20th to June 11th 2020 to capture a final 3 weeks of fixed site data and cover an additional 12 (weekly) rotating sites.

3.3 Measurement site selection

Potential sites for both fixed (1 year) and rotating (7 days) monitoring were chosen to maximize the space-time variability in urban sound, air pollution, temperature, and their sources in the GAMA (Figure 1). This timescale (> 1 week) is also in line with the classification of high quality measurements of noise exposure within WHO commissioned systematic reviews². To select locations for rotating-sites, I used a stratified random sampling approach^{43,44}. The GAMA was stratified by a 20m-by-20m land cover dataset from 2014 with four classes. The classes included informal residential areas which are generally high-density neighborhoods with small, crowded, irregular buildings and narrow unidentifiable unpaved roads such as in shantytowns and slums; formal residential areas which are generally low or medium density neighborhoods with small regular planned buildings; industrial, commercial, business, government which are areas with large buildings that can be used for commercial, industrial, office, or warehouse purposes; and peri-urban 'other' areas that are generally peri-urban but have either dense vegetation (i.e., forest, grassland), barren land (i.e., sand, soil, dirt), or water²⁴⁹. As well, I over-sampled in the main metropolitan

area (Accra Metropolis) which is the most densely populated area. Point locations were randomly selected within strata without replacement. I recognize that there are other approaches for selecting measurement sites for noise studies, such as stratifying by road-network type, especially where traffic is the dominant source of noise²⁵⁰. After target locations were selected, I verified their suitability by plotting them in Google Earth and Google Maps. If the target point locations were sampled in an unsuitable or restricted area (e.g., military base), I re-sampled their locations to be as near as possible to the original location. From March 2019 to the end of the measurement campaign, the field team conducted on-site visits to find actual measurement locations at, or as near as possible to, the target locations and they made an attempt to retain the same land cover characteristics for sites (Figure 2).



Figure 1. Illustration of the diversity of local sound sources found along the roadside in Accra.
Photo credit: Sierra Clark.

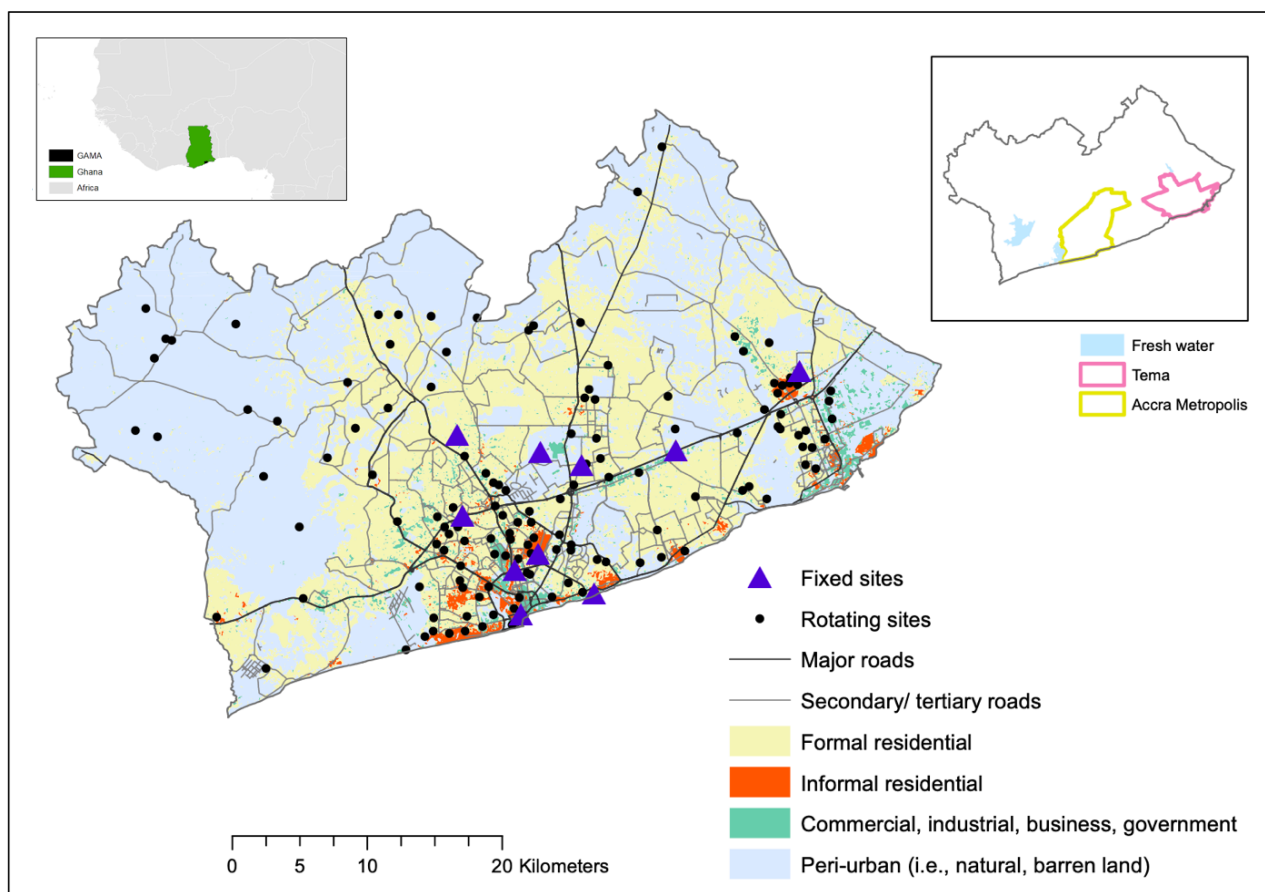


Figure 2. The Greater Accra Metropolitan Area (GAMA) and the measurement locations of the fixed and rotating sites.

The road network data is from OpenStreetMap (from 2019)²⁵¹, the land cover data is from the World Bank (2014)²⁴⁹, the administrative boundaries are from the Ghana Statistical Service (2010 census), and the base maps of Africa and Ghana are from Esri. Informal residential areas: generally high-density neighbourhoods with small, crowded, irregular buildings and narrow unidentifiable unpaved roads such as in shantytowns and slums. Formal residential areas: generally low or medium density neighbourhoods with small regular planned buildings. Industrial, commercial, business, government: Areas with large buildings that can be used for commercial, industrial, office, or warehouse purposes. Peri-urban: ‘other’ areas that are generally peri-urban but have either dense vegetation (i.e., forest, grassland), barren land (i.e., sand, soil, dirt), or water.

In collaboration with the air pollution team, we purposefully selected the 10 fixed sites using substantial local knowledge of the area and aided by data on key features like geography, population density²⁵², transportation networks²⁵¹, neighbourhood SES²⁵² and community biomass fuel use. Additional consideration was made to co-locate with existing or new regulatory air pollution monitoring sites (e.g., reference monitor installed at the United States embassy), and re-visit sites used in a previous air pollution study (2006-2007)¹¹. N1 West at Lapaz (N1) and Tema Motorway (TMW) are at the west and east ends of the multi-lane N1

motorway; Asylum Down (AD) is on the Central Ring Road; Jamestown (JT) and Nima (Nima) are poor, densely populated neighbourhoods in south and middle of Accra Metropolis; Taifa (Taifa) is an emerging medium-density neighbourhood north of the city; Labadi (La) is an indigenous Ga community along on the Coast; East Legon (EL) is an affluent neighbourhood east of the University of Ghana Campus - previously residential streets in EL now host large corporate, commercial and small business ventures; Ashaiman (Ash) is an emerging low-density residential neighbourhood next to the port city of Tema; and University of Ghana Hill (UGH) is located on top of the quiet, forested Legon Hill.

3.4 Measurement methods and equipment

The logistical constraints of conducting high quality environmental monitoring are numerous in most settings and are further complicated in cities in SSA. Availability of electricity for monitors is lacking and extreme weather, such heavy rainstorms, heat and seasonal dust storms, can create conditions which make measurement impossible and damage equipment. Thus, I systematically selected measurement instruments which had sufficient memory for logging data, battery life, and were rugged enough to withstand the elements, all while capturing high-quality data.

I collected measurements of sound levels, weather conditions, audio, and time-lapse imagery with sound level meters, weather meters, audio recorders, and camera traps (Table 2, Figure 3). The monitors underwent a process of selection and testing to meet ruggedness, power, memory and data validity requirements.



Figure 3. Sound level meter, audio recorder, weather meter, and time lapse camera.
Figure is adapted from my open-access first-author paper²⁴⁸. Photo credit: Sierra Clark.

Table 2. Features, dimensions, and prices of the monitors/sensors

Monitor	Cost per unit (USD \$)	Weight (g)	Dimensions (cm)	Battery/ power requirements	Memory requirements	Recording/ measurement interval	Measured parameters
Noise Sentry sound level meter	306	100	7.6x3.9 x5.9	Internal chargeable battery	Internal memory (USB connection)	1 minute	Noise levels (dBA)
AudioMoth audio recorder	70	95	6.2x5.0x2.2	AA batteries	Micro SD	10 seconds every 10 minutes	Audio (.WAV file)
Kestrel weather meter	310	120	12.7x4.5x2.8	AA batteries	Internal memory (USB connection)	1 minute	Temperature; relative humidity; wind speed; wind direction
Moultrie camera trap	150	500	13.1x8.1x6.6	AA batteries	SD	5 minutes	Time-lapse imagery (.jpeg file)

dBA: Decibels A-weighted

3.4.1 Sound level meter

I used the Noise Sentry sound level meter (SLM) to measure sound levels (dBA) (Convergence Instruments, Canada). The Noise Sentry has a digital MEMS microphone that complies with *Type I* precision standards²⁵³. The SLMs were set to integrate and log A-weighted equivalent continuous sound levels every minute. They also recorded the minimum and maximum sounds levels for every minute, set to *Fast* response. The Noise Sentry is rugged in design, built to withstand high temperatures (-20°C to 60°C), and the microphone is protected against water and dust, which is necessary for a setting like Accra. The accuracy of the Noise Sentry's were validated in a separate

aircraft noise study conducted in San Francisco against a more sophisticated Type I instrument (DUO 01dB)²⁵⁴, and the agreement was high (mean and median second by second $L_{Aeq_{1sec}}$ difference between the instruments was -0.42 and -0.38 dBA, respectively) and similarly for number of peak counts. I had also conducted short-term measurements co-locating a Type 1 sound level meter (Cirrus Optimus Red) with my Noise Sentry SLM prior to the commencement of the field campaign to assess agreement at multiple sites in London. Like the San Francisco study, I found good agreement: the difference in L_{Aeq} 's between the Cirrus and the Noise Sentry was between 0.09 and 0.81 dBA.

3.4.2 Audio recorder

I co-located audio recorders with the SLMs to capture other features of the urban sound environment. Specifically, the data were used in Chapter 4 to classify different types of urban sounds from a variety of sources (e.g., road-traffic, animals). I used the AudioMoth audio recorder which was developed by Open Acoustic Devices (Oxford, UK). The AudioMoth is a low-cost, full spectrum, acoustic logger. The AudioMoth was programmed to record for 10 seconds every 10 minutes and saved recordings in separate files; this was due to memory and battery capacity of the recorders, but also to preserve the privacy of human conversations nearby.

3.4.3 Time lapse camera

Time-lapse imagery was captured by one or two night-vision camera traps mounted at each site (Moultrie-50 camera trap, purchased from PERDIX wildlife, UK). The cameras were programmed to take a time-stamped image every 5 minutes. Images are captured silently (no click) with 20 mpxl quality in a 36.7° field of view. The imagery were used to identify sources of air and noise pollution with high temporal granularity with deep learning techniques in a project separate from my thesis. However, I mention the measurement protocol as I led most of the logistics of image capture; specifically, camera selection and purchase, camera deployment in the field, and imagery data

management. Results on the spatiotemporal patterns of objects identified from imagery with deep learning models are documented elsewhere²⁵⁵.

3.4.4 Weather monitor

The Kestrel 5500 weather meter (Nielsen-Kellerman Inc., Boothwyn, PA, USA) was utilized to record weather data every minute. The Kestrel is a hand-held monitor that tracks several weather parameters, including temperature, relative humidity, and wind speed. The Kestrel has low power consumption, large memory capacity and is dust-and waterproof. According to factory specifications, the accuracy of the instrument is 0.5°C for temperature and 2% for relative humidity.

3.4.5 Custom enclosure

To house the monitors, myself and the air pollution team custom designed an integrated enclosure using weather protective Seahorse (SE-300) cases. The cases were designed, and weather tested, to securely house each monitor. They were mounted on poles/trees of different sizes using ratchet straps and a curved foam backing. The cameras were mounted on the outside of the enclosure with rotational multi-access brackets. The audio recorders were placed outside of the main enclosure in their own separate weather protective plastic case.

3.5 Equipment deployment and field work logistics

The air pollution team and I trained three local university graduates to be our field assistants. We also hired a local taxi driver to provide transport for the team. I gave the team specific training prior to the pilot and the main measurement campaign to understand the site selection criteria and to collect sound level, audio, and imagery data. Each member was also provided with their own data and instrument handling protocols for reference. I visited Accra several times over the course of the campaign, staying between two weeks and a month at a time, to provide training and support.

The field team identified potential measurement locations at or near the computer-generated ones. The team approached residents, owners, or managers, and explained the study rationale and sought approval to install equipment for 1-year (fixed sites) or 7-days (rotating sites) on their properties. The team also worked with local community members to establish trust and facilitate entry into that neighborhood. The site was then prepared, and the equipment mounted on metal poles out of direct reach of passersby (Figure 4), in front of the most exposed façade. My target height for placing monitors was 4 meters off of the ground¹⁹⁰. While the logistics of finding a suitable site meant that the team was not always able to install at the target height, they aimed to be within ± 1 meter of it. The team additionally recorded the height of the monitors with a laser measuring meter. The SLM and audio recorder microphones were installed such that there were no obstructions in between the microphones and the sound sources. As well, monitors were placed at least 2 meters away from the nearest façade to mitigate reflection effects, installed on either poles or trees mounted on the ground, on a small pole mounted on a rooftop, or on a pole mounted on a balcony. One or two cameras were installed at each site based on whether one or two fields of view would be needed to capture the public streetscape²⁵⁵. Finally, one fixed site near the ocean did not receive an audio recorder as the contact of the airborne sea-salt with the exposed circuit board damaged the equipment.



Figure 4. Equipment deployment.

Figure is adapted from my open-access first-author paper²⁴⁸. Photo credit: Sierra Clark.

During deployment and equipment retrieval, the field team filled out a short questionnaire about the site location and the equipment. As well, the team recorded by consensus, the land use classification of the site based on a set criterion and adapted from the city-wide dataset used to select site locations²⁴⁹. The four classes included medium- or low-density residential areas, high-density residential areas, peri-urban ‘background’ areas (e.g., forest, agricultural land), and commercial, business, and industrial (CBI) areas. A detailed description of the land use classifications is in the Appendix Table A1 and Table A2.

For the rotating sites, the team returned 7-days after initial set-up to take down the equipment and bring to the lab for cleaning and data download. The fresh equipment was then re-deployed 48 hours later at new locations. For the fixed sites, the team brought replacement monitors or replacement batteries and SD cards to the site so as not to have a disruption in continuous monitoring.

While weather conditions can affect the propagation and attenuation of sound waves^{256–258}, similar to other long-term monitoring studies^{26,45}, I did not take weather conditions into account when planning the measurement schedule, as is recommended by ISO 1996-2 for long-term measurements. Data from the weather monitors are incorporated into the modelling in Chapter 5. As well, with regard to the identification of different types of sounds with the audio recorders, identifying natural sounds, such as rainfall and wind, are of explicit interest in my study.

3.6 Quality assurance and control

Prior to each field deployment day, the field team calibrated the SLMs prior to each monitoring session with a CA114 sound calibrator at 94.0 dB $\pm$ 0.3 dB and 1000Hz $\pm$ 0.5% (Convergence Instruments, Canada). If an instrument consistently gave a calibration offset $\pm$ 0.5 dBA, the SLM

was pulled out of commission and tested and the data from that monitoring session considered invalid.

I conducted a SLM monitor-monitor precision tests prior to the field campaign. The pre-campaign test of SLM monitor-monitor precision showed good agreement. There was only a 0.5 dBA difference between the monitoring period median values (LA_{eq1min}) for 50% of monitors within the interquartile range (IQR) bounds around the overall median. The monitor-monitor precision test was done in Accra over a period of 16 hrs. Additionally, to ensure that the SLMs were in agreement with each other throughout the campaign, every week the team set up a duplicate SLM monitor at one of the measurement locations to cover 16% of sites. Duplicates were in agreement; we found that the median difference between duplicate LA_{eq1min} was -0.1 dBA. Furthermore, the median absolute difference between duplicate LA_{eq1min} was 0.74 dBA (Appendix Figure A1).

The SLM data was inspected weekly as it was downloaded from the instruments. Potential implausible values were identified by inspecting all values that were 5-standard deviations above or below the site and day specific mean value. The log sheets were also checked to see if any information on instrument malfunction or other irregularities was noted. Values deemed erroneous were dropped from analysis. I identified potential outlier weeks of data by plotting timeseries of a month worth of data to identify any potential 'implausible' data and conducted instrument checks, reviewed log sheets and dropped data as needed. Finally, all SLMs had their first five minutes of data dropped to allow the instruments to stabilize and the data further trimmed to match the exact monitoring session start and end date and time as recorded by the field team on the data log forms.

3.7 Ethics

As the study did not recruit or enrol human participants and was solely interested in monitoring what is in the environment, I was exempt from seeking ethical approval at Imperial College London

and the study received ethical approval from the University of Ghana. Monitors were placed far field off of the ground so that conversations picked up by the audio recorders were relatively unintelligible. Additionally, I only recorded audio clips for 10 second intervals every 10 minutes, rather than continuously, to preserve bystander privacy.

3.8 Summary

As urban dwellers in SSA are increasingly exposed to noise pollution, data is required to help formulate policy options. To address this need, I developed, piloted, and implemented a large-scale measurement campaign to collect high-quality data on urban sounds and sources in Accra. The information gained from the year-long monitoring in Accra can support and inform strategic evidence-based environmental policies and urban planning decisions in Accra. The measurement protocol itself is also well positioned to be transferred to other SSA cities to support vital work on urban sound environment characterisation and noise monitoring.

Chapter 4 Space-time characterisation of the urban sound environment in Accra

This chapter has been adapted from the open-access (CC BY) published paper ‘Clark et al. Space-time characterization of community noise and sound sources in Accra, Ghana. 2021’ in Scientific Reports. I am the first-author on the paper²²². I hereby give credit to this work without citing the work in every instance in the text.

4.1 Overview and objectives

Information on the spatiotemporal characteristics of the urban sound environment in SSA is lacking^{22–24,83,223,228}. In this Chapter, I used high-resolution data collected over one year to descriptively and graphically characterize the spatial and temporal patterns of urban sound levels and intermittency, as well as a variety of sound types/sources, across the Greater Accra Metropolitan Area.

4.2 Data cleaning

After cleaning the data described in Chapter 3, I had 952-site days of sound level measurements from rotating sites (n=136) and 3,320 site-days from fixed sites (n=10). Four of the fixed sites each lost a week of data due to equipment malfunction. I used 1,232,640 site-seconds and 1,370,880 site-seconds of audio data from rotating (n=121 sites) and fixed sites (n=9). Missing data was due to equipment malfunction, damage, or theft.

4.3 Data analysis

4.3.1 Sound level and intermittency metrics

I calculated the following sound level and intermittency metrics for each site and date of measurement^{126,127,259}:

- Equivalent continuous hourly sound levels (LA_{eq1hr} (dBA));
- Equivalent continuous daily sound levels (LA_{eq24hr} (dBA));
- Equivalent continuous daytime sound levels between 6:00 – 21:59 hours (L_{day} (dBA));
- Equivalent continuous nighttime sound levels between 22:00 - 5:59 hours (L_{night} (dBA));
- Daily intermittency ratio (IR_{24hr} (%))
- Daytime intermittency ratio between 6:00 – 21:59 hours (IR_{day} (%))
- Nighttime intermittency ratio 22:00 - 5:59 hours (IR_{night} (%))
- Maximum sound level with fast time weighting during measurement (LA_{Fmax})

I calculated sound metrics for each site and date of measurement so that variability within-and between sites over time could be characterized. The maximum sound level (LA_{Fmax}) is the maximum level recorded. The equivalent continuous sound level represents the steady sound level that has the same total energy as the fluctuating sound over a given period of time. In contrast, the intermittency ratio (IR) expresses the amount of intermittent sound in a defined period of time. Essentially, the IR discriminates between sound environments with marked peaks and without. Intermittent environmental noise in particular has been found to have a larger effect on sleep disturbance than continuous noise, particularly from events that emerge from the background level^{173,174}. The IR is defined as the percentage of sound energy in the total energetic dose that is created from distinct sound events that exceed a certain threshold¹²⁷. By definition, the IR is bounded between 0% and 100%. To define a sound ‘event’, equivalent continuous sound levels recorded for each minute of measurement (LA_{eq1min}) had to surpass a fixed cut-off of three dBA

above the site and date specific daily, daytime or nighttime equivalent continuous sound level. Three dBA was chosen as it has been shown to produce IRs that can distinguish between situations with different degrees of intermittency¹²⁷. As a secondary analysis, I computed IRs using alternative fixed cut-offs of +4 and +5 dBA. IR's that were calculated with C=3, C=4, and C=5 were correlated (C(3) and C(4): r=0.99; C(3) and C(5): r=0.95) across measurement sites and days, though the absolute values of IRs were lower when C=5 and 4.

$$L_{eq,T,Tot} = 10 * \log_{10}\left(\frac{1}{T} \int_0^T 10^{0.1L(t)} dt\right) [dB]$$

$$K = L_{eq,T,Tot} + C [dB]$$

$$L_{eq,T,Events} = 10 * \log_{10}\left(\frac{1}{T} \int_0^T H(L(t) - K) 10^{0.1L(t)} dt\right) [dB]$$

$$IR = \frac{10^{0.1L_{eq,T,Events}}}{10^{0.1L_{eq,T,Tot}}} * 100$$

Equation 1. Intermittency Ratio.

Legend: *IR*: Intermittency Ratio¹²⁷; $L_{eq,T,Tot}$: Overall sound pressure level for time T; $L_{eq,T,Events}$: Event-based sound pressure level for time T; $L(t)$: Continuous sound pressure level at the receiver position; K : Threshold for which $L(t)$ would contribute to $L_{eq,T,Events}$; C : Fixed offset above $L_{eq,T,tot}$; H : Heaviside step function.

4.3.2 Sound type classification

To classify the different types of sounds present in the GAMA, I applied a pre-trained neural network attention model (DEEP-Hybrid DataCloud project^{260,261}) to my outdoor audio recordings. This is an open source model that was pre-trained on the *Audio Set* dataset published by Google²⁶². *Audio Set* consists of 5,800 hours of 10-second manually labelled YouTube videos and a structured hierarchical ontology of 527 sound classes. *Audio Set* is *weakly labelled* meaning that only the presence or absence of audio events are known in a clip. The neural network is a Multi-level Attention Model as described by Yu et al²⁶¹, which takes a spectrogram of each audio clip as an input to several, sequential fully connected layers, whose final and intermediate outputs provide inputs in turn to several “attention” modules, designed to selectively ignore irrelevant sound

segments such as background sound while attending to those segments of the sound most relevant to classification after training. The final classification is derived from the concatenation of the outputs from the attention modules.

I applied my audio recordings from Accra to the pre-trained neural network model. As is expected in an urban sound environment, the presence of different types of sounds within each audio recording was not mutually exclusive but often overlapping (e.g., bus, car, motorcycle, engine, bird, dog bark, etc.). For each 10-second recording, the neural network returns the top 5 predicted sub-category sound classes ranked based on the probability that they are in the recording (i.e., the neural network's confidence that the sound class is present, which is a function of clarity, loudness, but also the features the neural network was trained on). A more formal definition of the probability score is that it is a confidence score indicating the extent to which the features identified from a given data set correspond to the features learned by the network for identifying a given category. For this descriptive analysis, I retained the model's top 3 sub-category sound classes within each recording to reduce potential misclassification error given the lower probabilities of presence for the 4th and 5th placed sound classes (Probabilities in Appendix Table A3, Appendix Figure A2). For interpretability, I then grouped the sub-category sound classes into super-category sound types that were adapted from ISO standards for acoustic environment characterization²⁶³: road-transport sounds (e.g., motorized vehicles), animal and insect sounds (e.g., wildlife or domesticated animals), outdoor music, human speech, airplane sounds, nature sounds (e.g., wind, rain, thunder), and 'other' sounds. I did not separately categorize railway sounds as Accra's between-city railway line is largely out of use and the measurement sites were not located near the tracks. A visual representation of this process is shown in Figure 5. The terminology sound type is generally synonymous with sound source (e.g., dog bark (type); dog (source)). However, here I use the terminology sound type to reflect the fact that a sound source may be physically present in a location, but not emitting any sound. Or a sound source may be present and emitting sound, but

due to potential masking effects of other more prominent or more identifiable sounds in a recording, the sound source may not be identified by the acoustic classifier. Though, if the quiet sound of a trickling stream is masked out by the loud sounds of nearby road-traffic, the fact that the stream is present from a purely auditory perspective likely does not have much of an impact on the human experience of that place at that time, which would instead be dominated by road-traffic.

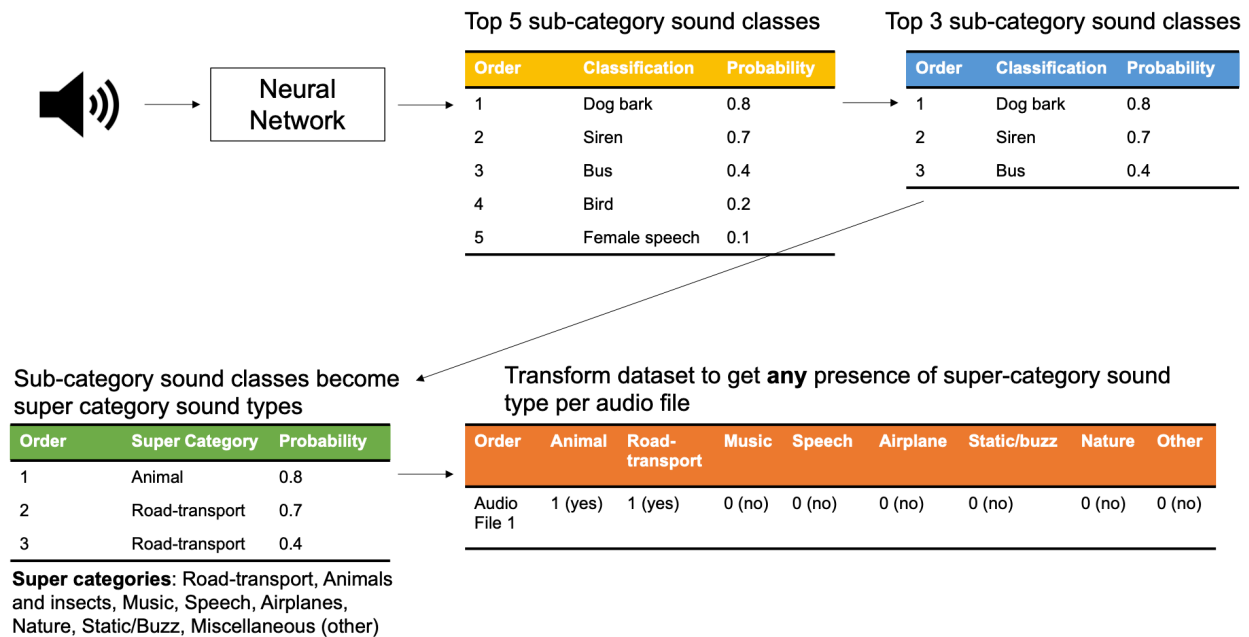


Figure 5. Graphical example of the pre-processing steps for sound classification within an audio file.

425 different sound classes were identified in the entire Accra dataset by the neural network, of which 3 (vehicle, engine, speech) occupied 30% of the data.

The accuracy of the neural network model's predictions in each sound type super category was tested by comparing agreement against my manual sound labels from 150 randomly selected audio files. I was blinded to the model results when labeling the audio files. The accuracy of model predictions was high for music sounds (93%), and moderate-high for speech (80%), animal and insects (79%), and road-transport sounds (76%). Nature sounds had moderate-high accuracy (87%), though the frequency at which this sound type was present in the audio files was low (4 audio clips out of 150). Airplane sounds had a moderate-high accuracy value (82%), though the positive-predictive value was low, only 4%. I also investigated whether airplane sound predictions were more common near the airport by separating sites that were within 1-kilometer around the

Accra's Kotoka International airport (KIA) flight path and sites that were outside of the flightpath. The flight path for this analysis represented the landing/ take off trajectory of low-flying planes into and away from the airport only. Further details on model accuracy testing are in the Appendix Table A4.

4.3.3 Descriptive summaries

I report summary statistics on the spatial and temporal trends in sound level and intermittency metrics from the fixed and rotating sites separately. I assessed spatial trends by mapping the data to each site's coordinate location (Lat/ Lon) and by stratifying the data on land use characteristics (described in Chapter 3) as well as road-network information, specifically major roads in the city²⁵¹. Temporal trends were evaluated at multiple time periods, including minute by minute, hourly, daily, weekly, and monthly aggregates. The sound level and event metric data were summarized as medians and interquartile ranges (IQR) in aggregate and within spatial and temporal strata.

I also summarized the prevalence of sound types across multiple time intervals within the GAMA, in Accra Metropolis, within land use areas, and near major roads. The percentage of time a particular sound type was present (i.e., prevalence) at any given site was calculated as the ratio between the number of audio recordings that had the sound type predicted as present (yes=1, no=0) over the total number of audio recordings collected during the monitoring period at that site, multiplied by 100. For summaries where sites were pooled into strata (e.g., land use), I considered the prevalence to be a measure of site-time as audio files captured across different time periods and locations (sites) were included in the overall metric.

In order to characterize the co-occurrence of sound levels and sound types in the GAMA, I linked the sound type and sound level data by site, date, and time of measurement. Specifically, I linked the sound level data, which was continuously recording and integrated sound levels every minute,

to the audio recordings, which were collected for a period of 10-seconds once every 10-minutes. For a given audio recording, the nearest sound level by minute of measurement was linked to it. I then categorized the sound level data into fixed intervals (e.g., LA_{eq1min} : 51-55 dBA, 56-60 dBA), and for each sound type and land use area separately, calculated the percentage of site-time that the sound type was present within intervals of LA_{eq1min} .

Finally, I assessed whether random days of measurement were representative of average yearly trends at fixed sites. This information is useful for informing the validity of urban sound/noise monitoring studies, particularly in SSA, that aim to characterize long-term trends with short-term measurements. I selected 50 random days of LA_{eq24hr} measurements ($n=5$ dates from each of the 10 fixed sites) and calculated the dBA and percent (%) difference between the randomly sampled LA_{eq24hr} ($n=5$ for each site) and the average yearly LA_{eq24hr} , for each fixed site separately.

4.4 Results

4.4.1 Spatial patterns

The median daily A-weighted equivalent continuous sound level (LA_{eq24hr}) across the GAMA at rotating sites was 62 dBA (inter-quartile range (IQR): 58, 67) and 66 dBA (IQR: 61, 70) in Accra Metropolis (i.e., main urban centre of the GAMA). The median of the maximum sound level (LA_{Fmax}) recorded for each date and across sites in the GAMA was 96 dBA (IQR: 92, 100), and 98 (IQR: 94, 102) in the Accra Metropolis. There was variability in measured sound levels between and within land use categorizations. Commercial, business, and industrial (CBI) areas had the highest median daily sound level (69 dBA, IQR: 66, 71) and highest daily recorded LA_{Fmax} (102 dBA) and peri-urban areas in the north, northwest and northeast of the GAMA the lowest (56 dBA, IQR: 54, 59) (Table 3). High-density residential areas had higher median daily sound levels compared with medium/low-density residential areas. In general, the difference in daily sound levels (LA_{eq24hr}) at the 25th and 75th percentiles of the distribution within land use areas ranged

from 5-6 dBA (Table 3). In the daytime, the variability was greatest within residential areas and lowest within CBI areas. In the night-time the variability was highest within high-density residential areas and lowest in peri-urban areas. Figure 6 also shows the spatial patterns of sound levels mapped at the site-level across the GAMA. The lowest daily sound levels were measured at sites in the outlying geographic areas of the GAMA, and the highest at sites in the city-core (Accra Metropolis), to the east near Tema and Ashaiman, and along major road networks. For the sites along major roads (highways, motorways, trunk roads), median day-time sound levels (L_{day}) were as high as 74 dBA (IQR: 73, 75) and remained elevated at night (median 68 dBA (IQR: 67, 70)).

Table 3. Measured sound metrics in the Greater Accra Metropolitan Area and across land use areas.

Metrics Unit	$L_{Aeq24hr}$ dBA	L_{day} dBA	L_{night} dBA	IR_{24hr} %	IR_{day} %	IR_{night} %
Rotating sites						
Greater Accra Metropolitan Area	62 (58, 67)	63 (59, 68)	55 (51, 61)	53 (37, 64)	46 (32, 59)	52 (35, 67)
Accra Metropolis	66 (61, 70)	67 (62, 71)	58 (53, 64)	49 (31, 60)	40 (25, 53)	51 (39, 66)
Land use area						
Peri-urban background	56 (54, 59)	57 (55, 60)	50 (49, 53)	60 (51, 68)	58 (47, 67)	40 (20, 58)
Medium/low-density residential	61 (58, 64)	62 (59, 66)	54 (51, 57)	55 (42, 64)	48 (35, 59)	57 (38, 69)
High-density residential	67 (63, 69)	68 (64, 70)	60 (54, 64)	51 (35, 64)	43 (29, 57)	57 (39, 68)
Commercial, business, industrial	69 (66, 71)	70 (68, 72)	63 (60, 67)	36 (27, 54)	30 (18, 44)	50 (36, 65)
Fixed sites*	69 (63, 72)	70 (64, 73)	64 (58, 68)	33 (19, 49)	23 (11, 40)	41 (30, 54)

Data are expressed as medians and inter-quartile ranges (IQR). Each of the 136 rotating sites have 7-days of measurement, and fixed sites have data spanning 12-months.

$L_{Aeq24hr}$: A-weighted equivalent continuous 24-hour sound level; L_{day} and L_{night} : A-weighted equivalent continuous sound levels in the day and night-time; IR_{24hr} : 24-hour Intermittency Ratio; IR_{day} and IR_{night} : Day- and night-time Intermittency Ratios.

*10 fixed sites had 3 CBI areas along major motorways, 2 sites in high-density residential neighborhoods, 4 sites in medium/low-density residential areas and one at a peri-urban location.

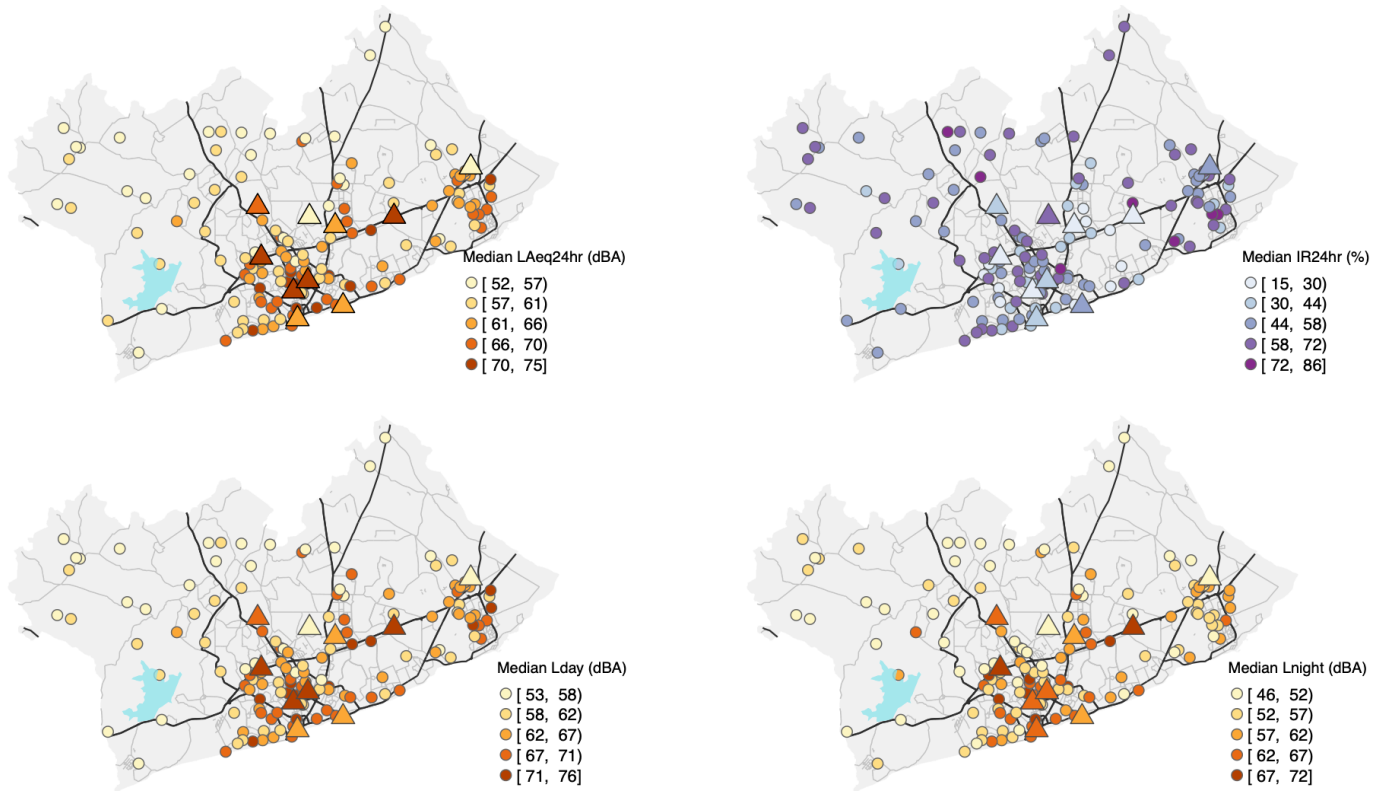


Figure 6. Median measured sound level and intermittency metrics for rotating and fixed site locations in the GAMA.

Legend: Circles: rotating sites; Triangles: Fixed sites; Major roads: Black lines, Secondary roads: grey lines. For the color legend scales, a bracket means that the value in the range is included, and a parenthesis means that the value in the range is not included. LA_{eq24hr} : A-weighted equivalent continuous 24-hour sound level; L_{day} and L_{night} : A-weighted equivalent continuous sound levels in the day and night-time; IR_{24hr} : 24-hour Intermittency Ratio. Road network is from OpenStreetMap and the Greater Accra Metropolitan Area (GAMA) boundary from Ghana Statistical Service. A waterbody is depicted on the map in light blue. This figure is adapted from my open access peer-reviewed paper where I am first author²²². The interactive map version is available here: <https://sierraclark16.github.io/Noise-pollution-in-Accra/Interactive-maps.html>

I found that the median Intermittency Ratio in the GAMA, which expresses the amount of intermittent sound in a defined period of time, was ~50% for both the day and night-time (Table 3), when a fixed cutoff of 3 dBA above the site and date specific day and night-time sound level was used. Intermittency Ratios also varied between and within land use areas. Peri-urban areas had the highest median daily Intermittency Ratios (60%, IQR: 51, 68), while CBI areas had the lowest (36%, IQR: 27, 54). Additionally, sites along major roads had a low median Intermittency Ratio (7%, IQR: 5, 12) in the daytime and moderate-low in the night-time (31%, IQR: 26, 32); at night-time, background ambient sound decreases, and sound events (such as vehicles pass by) can be more clearly identified. As expected, when higher fixed thresholds were used to calculate the daily

Intermittency Ratios (i.e., +4, +5), the median levels were reduced to 46% (with +4 dBA) and 39% (with +5 dBA). Though the IR_{24hr} calculated with varying fixed thresholds was highly correlated (Pearson correlation coefficient (r) > 0.96).

As determined from the neural network, the most prevalent type of sound identified across sites in the GAMA was road-transport, which was present 64% of site-time among rotating sites (Table 4). Within CBI areas, road transport sound dominated (present 85% of site-time) and were the least prevalent within peri-urban areas (40% of site-time). Animal and insect sounds were also fairly common within medium and low-density residential and peri-urban areas (present 43% and 65% of site-time) but generally at lower sound levels (Figure 7). Within high-density residential areas, human speech and outdoor music were fairly prevalent (present 33% and 15% of site-time) and generally at higher sound levels (Figure 7). The prevalence of airplane sounds appears to be over-estimated (see Methods section on model performance), though the neural network did predict a higher percentage closer to the airport than elsewhere. Nature sounds were uncommon across all land use areas (overall 4% of site-time present) and all sound levels.

Table 4. Detection of sound type prevalence across land use areas in the Greater Accra Metropolitan Area.

	Road-transport	Animals and insects	Outdoor music	Human speech	Nature	Aircraft (within flight path)*	Aircraft (outside flight path)*	Other
Rotating sites								
Greater Accra Metropolitan Area	64%	39%	10%	23%	4%	29%	14%	39%
Accra Metropolis	78%	24%	13%	29%	2%	29%	15%	35%
Land use area								
Peri-urban background	40%	65%	4%	8%	9%	-	-	41%
Medium/ low-density residential	64%	43%	10%	22%	3%	-	-	40%
High-density residential	71%	30%	15%	33%	2%	-	-	40%
Commercial, business, industrial	85%	16%	9%	28%	1%	-	-	31%
Fixed sites**	82%	16%	16%	29%	1%	-	-	32%

Data are expressed as the percentage (%) of site-time present.

* Within/outside of 1km of take-off/ descent flight path for Kotoka airport (n=7 rotating and n=1 fixed site near flight path)

** 9 fixed sites had 3 CBI areas along major motorways, 2 sites in high-density residential neighborhoods, 3 sites in medium/low-density residential areas and one at a peri-urban 'background' location.

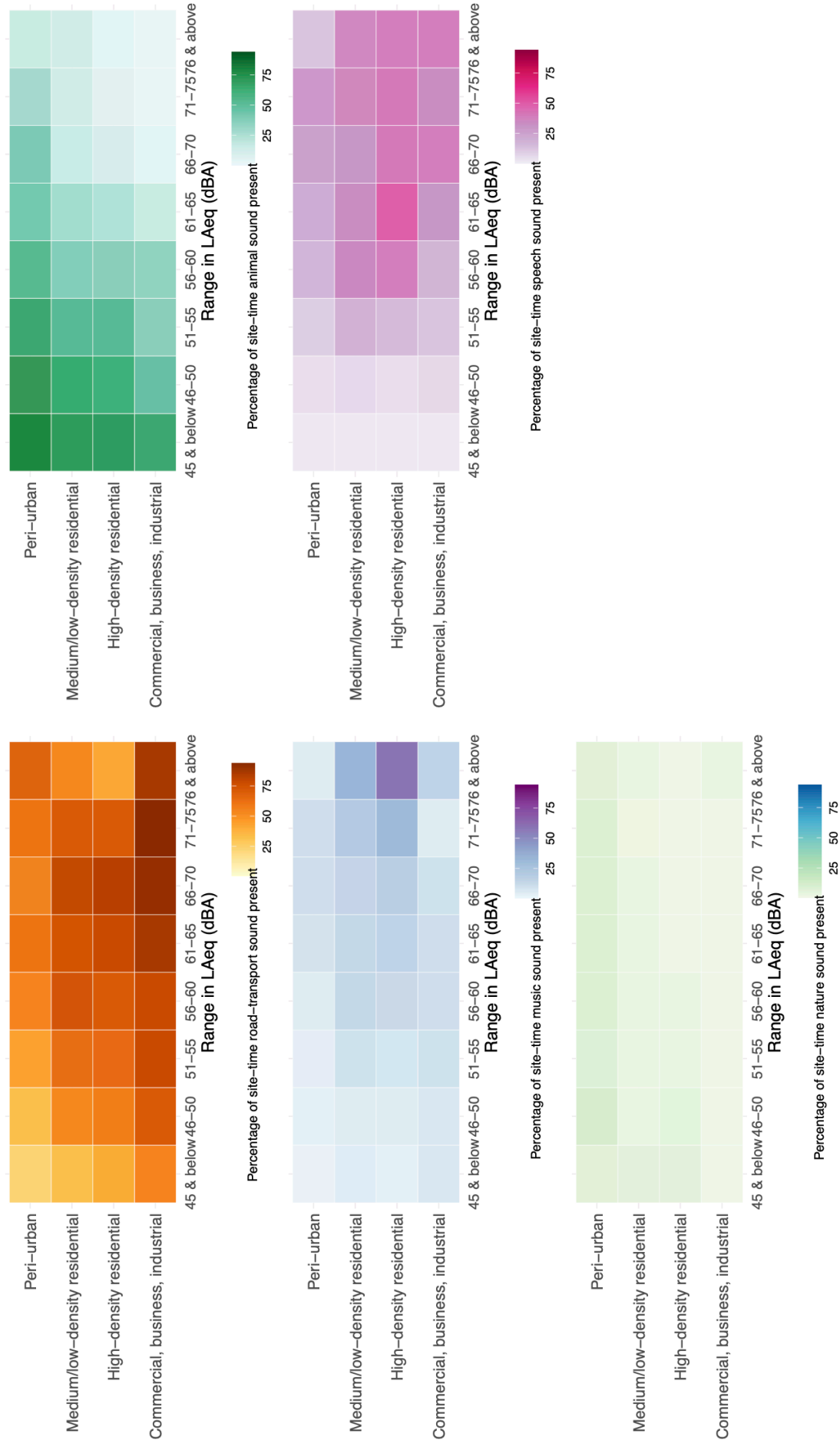


Figure 7. Prevalence of identified sound types within land use areas and at fixed sound level intervals (LA_{eq1min}) in the Greater Accra Metropolitan Area.

Data from rotating sites. Legend: The percentage of site-time that each sound type was present was calculated from the data within each land use area and sound level interval separately.

4.4.2 Temporal patterns

4.4.2.1 Diurnal

Sound levels were generally lowest between midnight and 4am and highest between 8am and 8pm across all land use areas (Figure 8). However, the difference between L_{day} and L_{night} ($L_{\text{day}} - L_{\text{night}}$) varied across land use areas (Figure 8). There was also no singular daytime hour which consistently had the highest or lowest sound levels. The prevalence of road-transport sounds within the GAMA was higher in the daytime (71% site-time present) compared with the nighttime (53% site-time present) (Figure 4) though the day and night-time differences varied by land use area. The prevalence of animal and insect sounds was highest during nighttime, most notably in peri-urban areas (present 71% of site-time at night). Human speech sounds and outdoor music increased in the morning and declined in the evening, most evidently within residential areas (Figure 9).

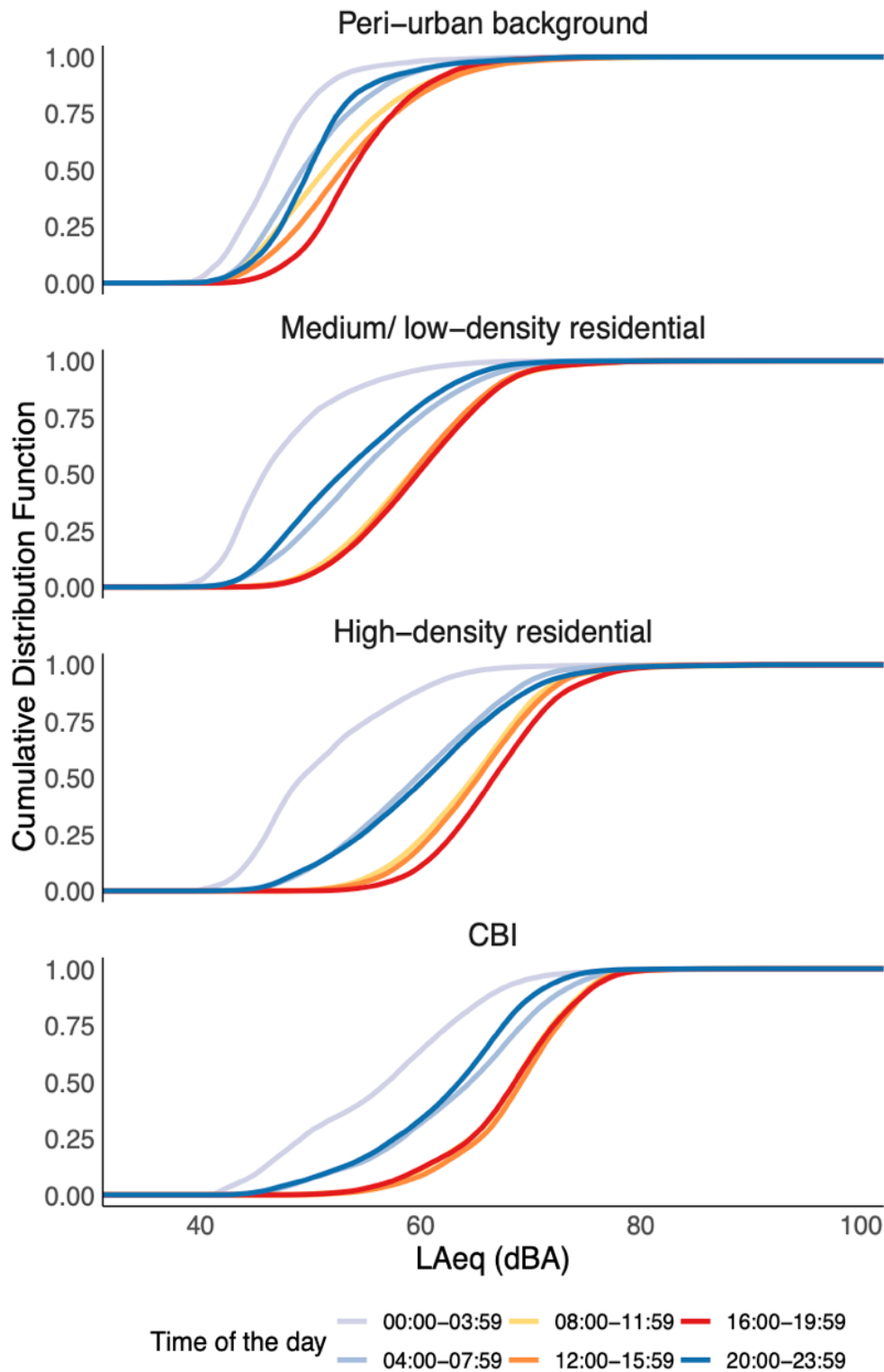


Figure 8. Cumulative density functions (CDF) of 1-minute measured sound levels (dBA) across a 24-hour day period in the Greater Accra Metropolitan Area.

Legend: Data from rotating sites. Blue lines represent time periods in the nighttime and early morning (8pm-8am) and red/ orange lines represent periods in the daytime (8am-8pm). CBI: Commercial, business, industrial areas; LAeq: 1-minute A-weighted equivalent continuous sound levels; dBA: A-weighted decibels. This figure is re-used from my open access peer-reviewed paper where I am first author²²².

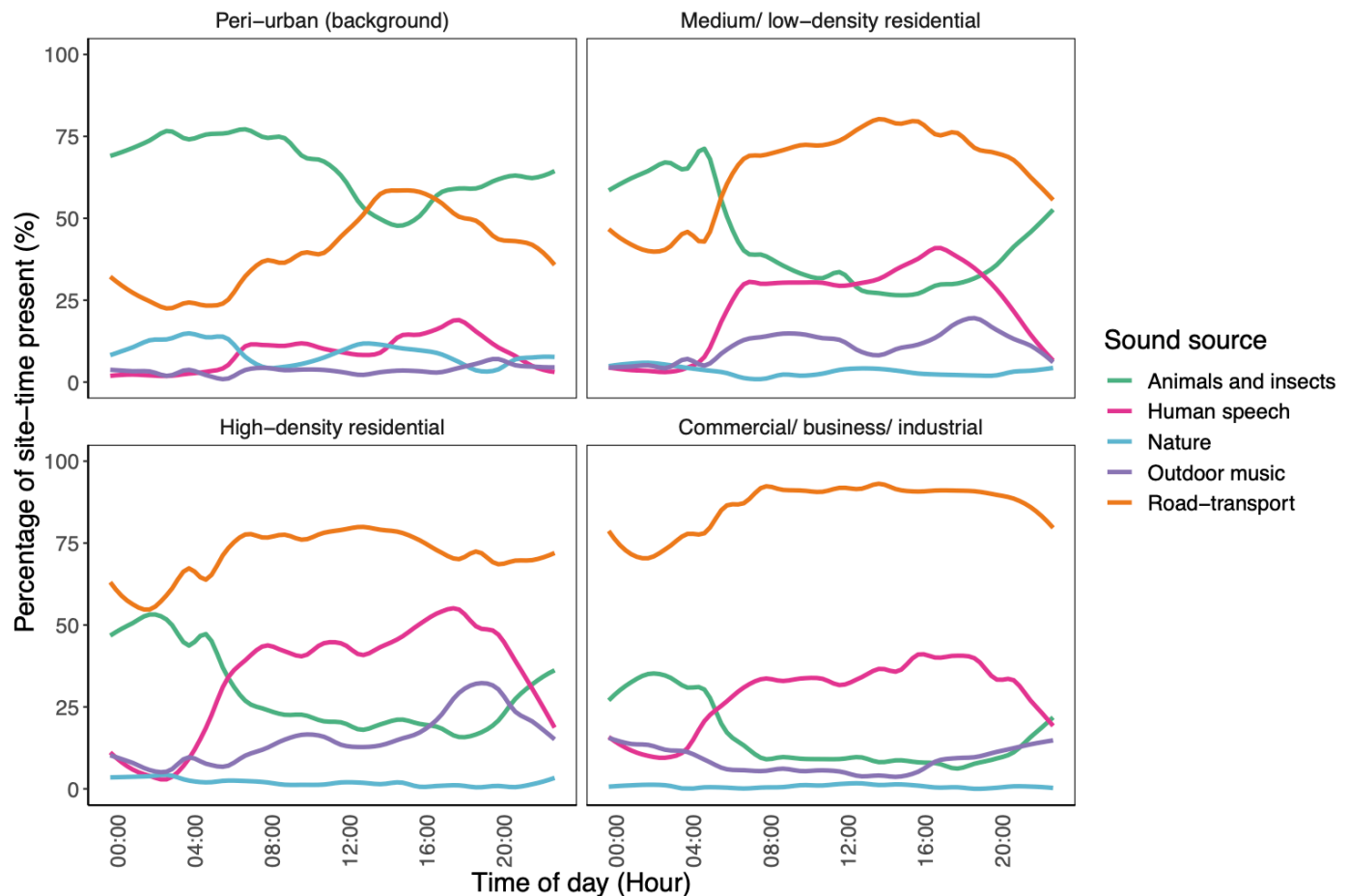


Figure 9. Diurnal patterns of the percentage of site-time that identified road-transport, animal and insect, human speech, outdoor music, and nature, sound types were present for each hour of the day and within land use areas in the Greater Accra Metropolitan Area.

Legend: Data are from rotating sites, but fixed sites had similar trends. Only sound types which were in the top three identified in each 10-second audio clip are included. This figure is adapted from my open access peer-reviewed paper where I am first author²²².

4.4.2.2 Day of the week

In general, the distribution of hourly sound levels (L_{Aeq1hr}) was similar across days of the week (Monday-Sunday) and between weekdays versus weekends across land use areas and for each of the 10 fixed sites (Appendix Figure A3). Though, there were a couple of small deviations, notably one of the high-density residential sites (Nima) had higher median day-time sound levels on Wednesdays, which are market days. As well, I found minimal difference between the percent of time that sound types were present across different days of the week. However, the prevalence of

outdoor music sounds was higher on Sundays (12% site-time present) compared to other days of the week (Appendix Figure A4).

4.4.2.3 Season

I found no clear seasonal or month-month pattern to daily sound levels when the year-long fixed sites were stratified by land use (Figure A5). In general, there was also no clear seasonal pattern to the prevalence of most sound types, though human speech sounds were more prevalent between April to July compared with other months, and animal and insect sound prevalence reduced at two sites during the summer months (Appendix Figure A6).

4.4.2.4 Sound levels during and after the COVID-19 pandemic lockdown and during the 1-month ban on drumming in Accra

The lockdown of Accra in response to the COVID pandemic was announced on March 28th 2020 to take effect on April 1st 2020. The lockdown lasted until April 20th 2020. In Accra, all individuals were advised to stay at home and were only permitted to leave for essential items such as food, medicine, and water. Additionally, inter-city travel for private and commercial purposes, except for essential goods and services, was suspended. Between city travel vehicles had to reduce their capacity and social distancing was imposed. Finally, international travel was banned, and airports significantly reduced their capacity. Daily life and activities largely returned to normal after April 20th, with social distancing and mask mandates imposed in most places.

When the lockdown was announced on March 28th, the field team visited the 10 fixed sites on March 29th to install and leave a fresh batch of equipment to monitor for one week during the lockdown period (April 1 – 8th 2020). Field work resumed on May 20th, and the field team collected

3 weeks of data at fixed sites (May 20th to June 11th 2020), which represented the post-lockdown period. Pre-lockdown refers to the period from April 10th 2019 to March 28th 2020.

Across the 10-fixed sites, pre-lockdown median LAeq_{1min} was 65 dBA, while during lockdown it was 59 dBA, representing a difference of ~6 dBA. Urban sound levels largely returned to normal post-lockdown with median LAeq_{1min} of 64 dBA across all sites (Figure 10). Jamestown (JT) was the only site where post-lockdown measured sound remained at lockdown levels. Jamestown is a poor, densely populated Indigenous Ga neighbourhood in the south of Accra Metropolis.

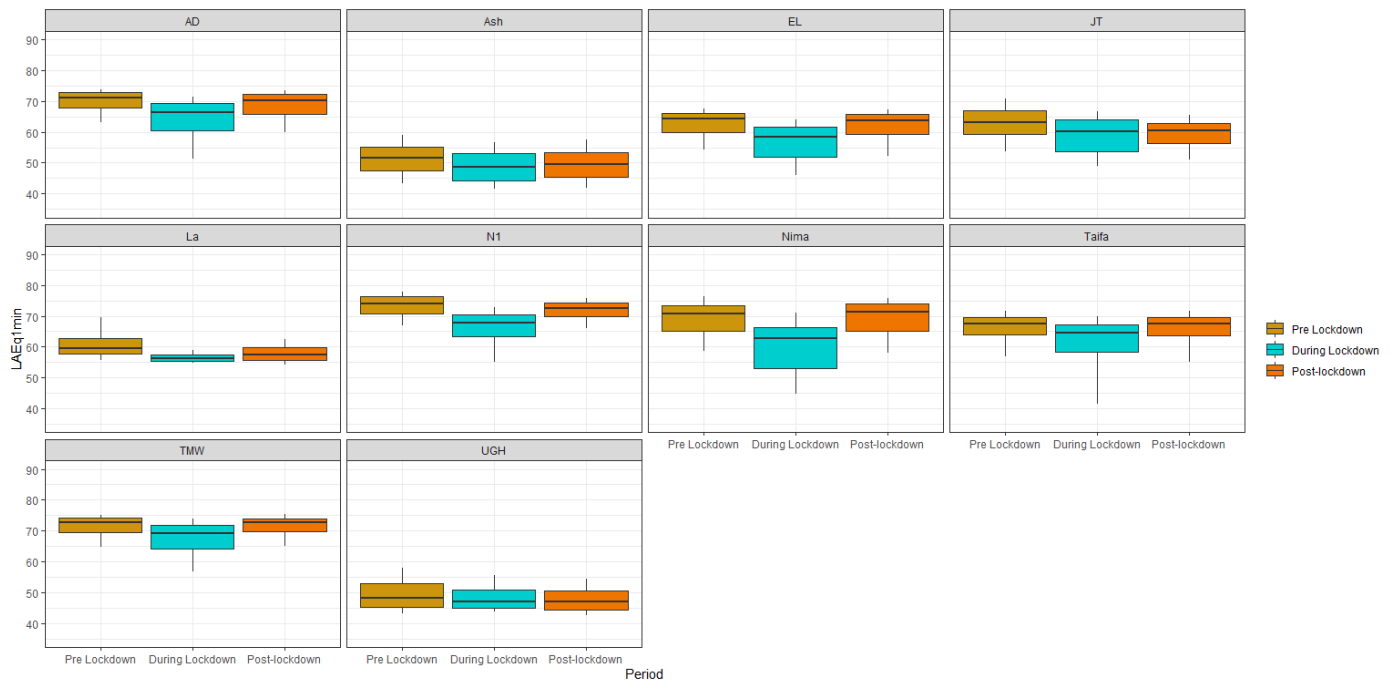


Figure 10. Distribution of pre-, during, and post-COVID-19 lockdown LAeq_{1min} at 10-fixed sites in the Greater Accra Metropolitan Area.

Plots show the 10th and 90th percentiles as the upper and lower limits of the vertical black lines, the 25th and 75th percentiles (IQR) as the upper and lower limits of the box and the median as the horizontal line within the box²²². N1 West at Lapaz (N1) and Tema Motorway (TMW) are at the west and east ends of the multi-lane N1 motorway; Asylum Down (AD) is on the Ring Road Central; Jamestown (JT) and Nima (Nima) are poor, densely populated neighbourhoods in the south and middle of Accra Metropolis; Taifa (Taifa) is an emerging neighbourhood north of the city; Labadi (La) is an indigenous Ga community along on the Coast; East Legon (EL) is an affluent neighbourhood next to the University of Ghana Campus. Previously residential streets in EL now host large corporate, commercial and small business ventures; Ashaiman (Ash) is an emerging neighbourhood next to the port city of Tema; and University of Ghana Hill (UGH) is located on top of the quiet, forested Legon Hill.

During the annual 1-month ban on ‘drumming and noise-making’ in the city as part of the traditional *Homowo* festival (May 13 – June 13 2019), I found minimal changes in median hourly sound levels ($L_{Aeq_{1hr}}$) at yearlong fixed sites along major traffic routes and in medium/low-density and peri-urban residential areas. However, the exception the two high-density residential sites, had reductions of median levels during the ban of 2.7 dBA.

4.4.2.5 Short-term sound level measurements (generally) represent long-term trends

To evaluate whether my short-term sound level measurements in Accra could characterize longer-term trends, I assessed whether daily sound levels from randomly sampled days were representative of yearly trends for each fixed site separately. The median dBA difference and percent difference between random days and the average for the year was -0.04 dBA and -0.06%, respectively. The median absolute dBA difference and absolute percent difference was 0.72 dBA and 1.03%, respectively. The magnitude of the deviation from the yearly average did vary between fixed sites and there were some outlier days. For example, my three CBI fixed sites situated along major roads/highways were the most temporally stable; each had median differences of 0.19 dBA, -0.16 dBA, and -0.63 dBA, respectively. Conversely, the sites with the greatest deviation between short-term samples and long-term averages were the high-density residential sites, each with median differences of 2.59 dBA and -0.58 dBA, respectively.

4.5 Discussion

In this chapter, I descriptively characterized the spatiotemporal patterns of the urban sound environment across the Greater Accra Metropolitan Area using data from a large-scale, 1-year measurement campaign. Median L_{day} and L_{night} across the GAMA was 63 and 55 dBA and the degree of sound intermittency varied considerably between sites. Road-transport sound presence

dominated in most locations, though mixtures of sounds were present in different areas and times of the day.

I found that the majority of measured day and night-time sound levels exceeded the Ghana Standards Authority limits for ambient noise in comparable areas (Appendix Table A5). At the regional level, there are no environmental noise guidelines set for Africa by the World Health Organization (WHO), though the guidelines for the European region have global relevance as the evidence base which underpin the recommendations are from Europe, North America, and Asia². When compared to the WHO guidelines for the European region, 98% of night-time sound measurements (L_{night}) in the GAMA and 99% in Accra Metropolis were higher than the guidelines for long-term exposure to L_{night} from road-transportation sources (guideline: <45 dB)². An important distinction to make is that the Ghana Standards Authority limits are environment specific (e.g., residential, mixed-use areas, etc) while the WHO guidelines are source specific.

Across the measurement sites in the GAMA, IR_{night} levels varied widely (IQR: 35%, 67%), though the median level was lower than what was previously reported among a Swiss cohort of adults exposed to road-traffic noise (median IR_{night} : 73%)²⁶⁴, likely as a result of the higher overall noise levels observed in Accra. Though along major traffic routes, low-levels of day-time IR were similar to a study in Milan (Italy)²⁶⁵. I can only interpret my results within the context of the fixed event cutoff that was used. If I had interpreted my main results with stricter cutoffs, the intermittency of urban sound in the GAMA would be lower.

I found significant reductions in urban sound levels at the high-density yearlong sites during a 1-month ban on noise making and drumming (~ 3 dBA reduction) and at almost all yearlong sites during the COVID-19 pandemic lockdown of the city (reduction of ~ 6 dBA). Reductions in this

week were lower than what was observed in Barcelona (~9-11 dBA decrease in L_{day})²⁶⁶ and Lima (~8 dBA decrease in L_{den})²⁶⁷ but similar to London (5.4 dBA decrease in L_{Aeq} (range 1.2 to 10.7 dBA))¹⁵². Between city differences could be due to different lockdown measures applied as well as enforcement and adherence, especially in a setting where opportunity for remote work is limited.

I found that daily sound level measurements at the majority of the fixed sites were generally representative of an entire year, as has been found elsewhere^{141,143}, though some outlier days did show deviation from the yearlong average. This finding is useful for future studies, particularly in SSA, as the sampling duration could be reduced from what we conducted in Accra. Sites with the most variability, such the high-density residential sites, had the greatest differences in daily sound levels between short-term measurements and yearlong averages. While sites with the least variability, such as those along major traffic routes, were largely consistent. In a city like Accra, multiple sequential or random days of measurements at each site would ideally ‘average out’ sound levels captured on outlier days. Previous studies have even shown that repeated short-term measurements conducted for several minutes/hours can represent long-term trends¹⁴³. Future work is needed in SSA cities to verify if that finding applies in this setting, given that there may be contextual differences impacting sound types and their temporal variations.

Road-traffic sounds are generally considered noise³⁴, and exposure has been associated with a variety of adverse health outcomes in populations, such as sleep disturbance, annoyance and stress, and cardiovascular disease^{31,93,199,268,269}. In the Accra, road-transport sounds were prevalent throughout the day and night. Recent road-traffic air pollution control measures in Ghana, such as the regulation and taxes imposed on the import of old (and often noisy) vehicles into the country, may have an indirect impact on reducing noise from road-transport in Accra²⁷⁰. However, in general, reduction of road transport noise is not currently prioritized by local policy actions.

Another source of transportation-related noise comes from overflights around airports^{161,224,271,272}, and has been linked to numerous adverse health outcomes and particularly sleep disturbance^{93,269,271}. Although the neural network over predicted airplane sounds in Accra with a high degree of error, it still predicted a higher prevalence near the airport. Aircraft traffic near Kotoka International Airport (KIA) may already be a source of noise pollution for the people who live and work in the area²⁷³ and is likely to only get worse as the city grows around the airport and demand for air travel increases. According to ISSER (2018), Ghana's open skies policy and expansion of KIA have resulted in aircraft movement (international) increasing from 17,481 in 2008 to 26,726 in 2017²⁷⁴. As well, at a Pathways project engagement meeting (March 1st, 2021) with key policy stakeholders in Accra representing a diversity of government departments and divisions, airplane noise was discussed by participants as a problem already plaguing two neighbourhoods in the city (Cantonments and some areas in East Legon).

While the focus in North America and Europe has primarily been on transport-related sources of noise, outdoor music and human speech sounds were quite common in residential areas in Accra. Loud music and even human speech sounds from a variety of sources, such as small scale business and shops, festivals and events, religious activities, bars, nightclubs and restaurants are commonplace in Accra and other SSA cities^{79,80,83}. Previous studies found that perceptions of these sounds varied widely between countries^{112,116} and were intricately linked to social, cultural, and contextual factors related to the time and place in which the sound was perceived, as well as personal preferences and demographics³⁴. For example, in the city of Sheffield (UK), music in three different contexts - on the street, from a store, and from passing by vehicles - yielded very different preferences³⁴. As well with relation to music, it was found that users of outdoor public spaces were easily able to notice music sounds, thus making the perceived sound louder³⁴. Beyond

a few small studies in SSA related to religious noise making^{22,164}, and music from commercial shops⁸⁰, there is scarce information to ascertain whether human speech and outdoor music are considered unwanted, neutral, or tranquil sound environments by the local population. In Accra, religious activities in particular can generate high-levels of outdoor human speech and music sounds and has received local and international press attention^{20–22,25}.

In general, people tend to favour nature-based over humanmade sound environments^{34,118,120}. Geophonic nature (e.g., running water, rain) and some animal sounds (e.g., birdsong) are generally considered as a ‘comforting’ or ‘tranquil’ soundscapes^{112,116,117,275}. These sounds have also been linked to enhanced feelings of wellbeing and markers of physiological stress recovery in experimental studies^{115,117,119,276–278}. This had led to local and national governments to increasingly incorporate positive soundscape planning into urban design and policy^{189,194,196}. In SSA, there are limited studies, though one small report identified that these sounds were perceived as ‘pleasant’ among 21 adult participants in Cape Coast, Ghana²⁷⁵.

From my Accra audio recordings, nature sounds were rarely identified by the neural network. This could be influenced by the fact that the area of urban public parkland Accra is a fraction of what exists in other high-income cities, such as in England or Wales^{279–281}. Furthermore, animal sounds were classified most often in quieter peri-urban and medium/low-density residential areas. It is possible that the inverse relationship between animal sound presence and measured sound levels is due to animals avoiding locations with noise and human activity²⁸² as well as features of the peri-urban environment which is less built up than other areas of the city. This is further confirmed by analyses that myself and *Pathways* colleagues conducted on visual objects identified from time-lapse imagery²⁸³. The analyses confirmed that the spatial patterning of the visual presence of animals in the GAMA largely followed the sound type presence²⁸³. Though, it is also possible that

part of this observed relationship is due to the masking effects²⁸⁴ of other louder sounds picked up by the neural network.

4.6 Summary

From a large-scale measurement campaign, I descriptively characterized the spatiotemporal patterns of the urban sound environment across the large and diverse Greater Accra Metropolitan Area. Through the application of a neural network, I further characterized the major sources contributing to the sound environment in the city. Day and night-time sound levels surpassed national and international health-based guidelines at almost all the measurement sites, and road-transport sounds dominated the overall sound environment.

Chapter 5 Geospatial modelling of sound levels and intermittency in Accra, Ghana

5.1 Overview and objectives

Modelling the sound environment within cities can help aid city governments in creating action plans to reduce noise and tackle the key sources in specific areas. These models can also help to identify the number of people exposed and whether exposure is inequitably distributed across cities. I used data collected as described in Chapter 3, and presented graphically in Chapter 4, to model, predict and map sound level and intermittency metrics across the Greater Accra Metropolitan Area in high-resolution with geostatistical land use regression models. I further estimated associations with urban features and services as well as the percentage of the population exposed to varying levels of urban sound in Accra Metropolis (~ 2 million people).

5.2 Modelling approach

I took a land use regression (LUR) approach to model and predict sound metrics across the GAMA. I use the term ‘sound metrics’ as opposed to ‘noise metrics’, because, as I showed in Chapter 4, the sound level meters captured sound generated from mixtures of sources, some of which may not be perceived as noise. LUR models have become common for the estimation of spatial variability in air pollution within cities¹⁶⁵ and increasingly have been applied to noise/sound in high and middle-income countries^{40,42,44,45,47–49,136,137,139,166}. An urban sound LUR model regresses spatially, and sometime temporally, heterogenous sound data on geospatial predictors that represent a range of factors in the urban environment associated with the emission, propagation, and attenuation of sound.

5.3 Sound data

The sound data have been described in detail in Chapters 3 and 4. For the models, I used hourly A-weighted equivalent continuous sound levels (LA_{eq1hr}) for each site and date of measurement as Chapter 3 showed substantial diurnal patterns. As a secondary sound metric, I used intermittency ratios for the day (IR_{day}) and night-time (IR_{night}).

5.4 Spatial and temporal predictor variables

I collected and collated spatial and temporal predictor variables that reflected factors in the urban environment associated with the emission, propagation, and attenuation of sound. Details of each predictor variable and its source are included in Table 5. To capture land use/land cover, I used a raster dataset at 20m resolution that mapped four land cover classes across the GAMA from Spot 5 imagery attributed to the year 2014. The land cover classes were (i) formal residential neighbourhoods with small regular planned buildings, (ii) informal residential neighbourhoods (e.g., shantytowns, slums) with small irregular buildings, (iii) industrial and business areas, with large buildings and, and (iv) other areas (e.g., parks, forests, water, grass land)²⁴⁹. To characterize vegetation in Accra, I calculated the Normalized Difference Vegetation Index (NDVI) from the spectral signatures of green vegetation from 30m resolution satellite imagery²⁸⁵. I obtained a Landsat 8 satellite product held on the U.S. Geological Survey department website attributed to a cloud free day (cloud cover: 0.02%) in January 2020. January was also considered as a mid-point in the measurement campaign. Other days with Landsat 8 imagery were unusable for this purpose due to cloud cover over the area. However, there was minimal temporal variability of NDVI levels throughout the year due to Accra's location near the equator. The Normalized Difference Vegetation Index (NDVI) was calculated from raster bands 4 and 5. To estimate building density, I made use of a high-resolution spatial dataset of building footprints attributed to the year 2019/2020 from Maxar/ECOPIA²⁸⁶. To estimate human population density, I used population

information from the most recent Ghana census summarized within census enumeration areas (EAs)²⁵². Census EAs are small geographic units with average population of 750-800 people and area 0.03-0.04 km² within the GAMA. To capture road-traffic sources of sound, I used a road-network shapefile from OpenStreetMap (OSM) downloaded in 2019²⁵¹. Road-types were grouped as (i) major roads (includes highways, motorways, trunk roads), (ii) secondary and tertiary roads (iii) minor roads, and (iv) all roads. OpenStreetMap is an open-source editable global database of urban geographic information which has grown rapidly over the years. The data is crowdsourced and input into the database by registered users. While globally OSM is largely complete (i.e., 83% of roads are covered²⁵¹), the data is less complete in low-income compared with high-income countries. For example, in the GAMA, the northwest region is missing several minor and secondary roads in the OSM dataset which are known to exist from visual inspection of satellite imagery. To capture aircraft noise, I obtained the location and spatial boundaries of the international Kotoka airport from Google Earth. To capture locations of human activity, I obtained the latitude and longitude locations of churches, mosques, hospitals, primary and secondary schools, restaurants, shopping centres and markets, bars, pubs, and nightclubs from Google Places/Maps in 2019. I also obtained locations of bus stations/terminals from Google Places/Maps as an indicator of both human activity and road-transport sources. Preliminary comparisons with OSM data indicated that the Google data were more complete (i.e., by comparing presence/absence with known locations in Accra). However, I could not find a quantitative study investigating the completeness of Google data in the scientific literature, which remains an area of uncertainty in this analysis. Finally, I retrieved data on elevation above sea level from a digital elevation model (DEM) for Africa at 90m resolution²⁸⁷ and data on waterways from OSM (2019). I did not retrieve or use the locations of railway terminals or routes from OSM as the railway line in Accra is almost entirely out of use.

Table 5. Candidate predictor variables for LUR models.

Variable type	Categories	Spatial calculation	Source (Date dataset created)
Land cover (<i>raster</i>)	Commercial, business, industrial (CBI); informal high-density residential; formal residential; other non-built-up areas (e.g., forest, water, grassland)	Area (m ²) within buffer	World Bank (2014) 20m x 20m ²⁴⁹ from Spot 5 imagery
Road-network (<i>Spatial line</i>)	Major roads; secondary/ tertiary roads; minor roads; all roads	Total length within buffer (m); Euclidean distance and square root distance to nearest (m)	OpenStreetMap (2019) ²⁵¹
Airport (<i>Spatial polygon</i>) *	--	Euclidean distance and square root distance to nearest (m)	Google Earth
Locations of human activity (<i>Spatial point</i>)	Schools, hospitals, bus stations/ terminals, restaurants, bars and nightclubs, churches, mosques, shopping centres	Presence/ absence within buffer; Count within buffer	Google Places/Maps (2019)
Normalized Difference Vegetation Index (<i>raster</i>)	--	Average NDVI value within buffer	United States Geological Survey (2020) – Landsat 8 imagery - 30m x 30m ²⁸⁵
Human population density within enumeration areas (<i>Spatial polygon</i>)	--	Average (pop/km ²) within buffer	Ghana census (2010) data ²⁵²
Building footprints (<i>Spatial point</i>)	--	Count within buffer	Maxar/Mapbox.ai (2020)
Rivers/ waterways (<i>Spatial line</i>)	--	Total length (m) within buffer	OpenStreetMap (2019) ²⁸⁸
Elevation above sea level (<i>raster</i>)	--	--	U.S Geological Survey DEM (2017) (~90m) ²⁸⁷
Height of monitor off the ground (meter) **	--	--	Measurement campaign ²⁴⁸

* Aircraft traffic at Kotoka airport (~ 1.8 million passengers a year)²⁸⁹ is a fraction of what it is at other large airports in major cities such as Heathrow in London (~ 80 million passengers/ year)²⁹⁰ or Schiphol in Amsterdam (~ 71 million passengers/ year)²⁹⁰.

**SLM instruments were installed at a target height of 4 meters off of the ground. Though due to field work logistical constraints, 4 meters was not always achieved. Therefore, the height of the monitor was added into the models to account for potential differences in sound levels across sites due to monitor height. For the dataset used for prediction (unmeasured locations), I set the height at 4 meters.

Variations in weather patterns can affect acoustic wave propagation^{133,257}, be sources of sound (e.g., rainfall), or affect human behaviours leading to an increase or decrease in sound generation²⁹¹. Thus, I also incorporated time-resolved data on temperature (Celsius degree), wind speed (m/s), and relative humidity (%), collected at six of the fixed (~yearlong) measurement sites, into the

analysis (measurement described in Chapter 3). I also collated data on daily rainfall (mm) from the Ghana Meteorological Agency (GMA).

I created multiple buffers around the measurement sites which were based on the noise LUR literature^{40,45}: 50 meters, 100 meters, 200 meters, and 500 meters. I mapped the spatial predictors to each buffer, centred by the coordinate location of the measurement site, through spatial overlay. I then clipped the spatial predictors so that only the features of the spatial predictors overlapping with each buffer remained. I then calculated various zonal statistics within each buffer, depending on the spatial predictor variable type. For example, I calculated the total length of each road category, rivers and waterways; the total number of bus stations/terminals, places of human activities, and buildings; the total land cover area; and the average NDVI and population density. For the gridded spatial predictors with values representing a feature of the space (e.g., NDVI, population density), if multiple values corresponding to multiple grids fell within one buffer, an unweighted average was taken. As well, due to the computational complexity of working with the building footprints dataset, the number of buildings was estimated by summing the number of building centroids (points) found within each buffer. Additionally, I calculated the distance of each monitoring site to the nearest major and secondary road and to the airport location and applied an additional transformation by taking the square root of the values to capture non-linear trends.

5.5 Model building and evaluation

I used linear mixed-effects LUR to model sound levels and intermittency in the GAMA (Table 6). This approach allowed me to (i) interpret the mean associations of sound metrics with predictors and (ii) predict sound metrics for unmeasured areas in the GAMA. I modelled the hourly LA_{eq1hr} (dBA), and as a secondary analysis, the day and night-time intermittency ratios (IR_{day} , IR_{night} , %), as dependent variables. I fit separate models for the day and night times. I checked for linear

relationships between the dependent variables and the predictors with bivariate scatter plots and included random intercepts for hour of the day in the LA_{eq1hr} models to account for diurnal correlation of measured sound levels collected repeatedly throughout the day. All models included random intercepts for sites to account for correlation among repeated measurements taken at each site over multiple days and for any site-specific unmeasured variations.

Table 6. Overview of land use regression models for A-weighted equivalent continuous sound levels and intermittency ratios in the Greater Accra Metropolitan Area.

Model	Dependent variable	Timescale data aggregated on	Random effects	Outputs
I	Equivalent continuous sound levels during the daytime	Hourly (LAeq _{1hr})	Random intercepts for hour and measurement site	Predicted LAeq _{1hr} for each hour in the day-time*
II	Equivalent continuous sound levels during the nighttime	Hourly (LAeq _{1hr})	Random intercepts for hour and measurement site	Predicted LAeq _{1hr} for each hour in the night-time *
III	Intermittency ratios for the daytime	Day-time (IR _{day})	Random intercepts for measurement site	Predicted IR _{day}
IV	Intermittency ratios for the nighttime	Night-time (IR _{night})	Random intercepts for measurement site	Predicted IR _{night}

*Predicted LAeq_{24hr}, L_{den}, L_{day}, and L_{night} were calculated from the 24, hourly predicted surfaces of LAeq_{1hr}.

My model selection process was aimed at identifying parsimonious and generalizable models that also maximized predictive accuracy. I first chose the buffer radii for each predictor variable that had the highest correlation with sound levels and intermittency ratios in the day and night. I also considered the direction of the correlation coefficient if I had an *a priori* hypothesis^{26,40,45,136,292}. This approach has shown to reduce sound LUR model error previously¹³⁶. I then used a stepwise forward model selection process to choose models that had a reduced set of spatial predictor variables^{26,40,293}, starting with the variables that had the strongest associations with the dependent variables. The process was stopped when the coefficient of determination (R^2) of the fixed effect component of the model was no longer improved by at least 1%^{40,47}. I considered removing a predictor variable if its 95% confidence interval around the slope coefficient crossed zero; specifically, if the magnitude of the coefficient and the width of the confidence interval were large, I considered the estimate to be unstable and dropped the variable from the final model. The final models were then challenged by adding in, and removing, all omitted variables one by one. If during this process the addition of a predictor variable resulted in an increase in the R^2 by at least 1%, and the variable was statistically significant, it was included. I also assessed whether there was

collinearity present among predictor variables in the model ($r > 0.8$), and if so, the predictor variable that was more correlated with the sound metric was retained. A variable representing the height of the monitors off the ground was included in all models to control for any slight differences in measured sound levels between sites which might have been impacted by monitor height.

I evaluated the accuracy of the predictions of the final models with cross validation. I ran 10-fold cross-validation holding out data from 10% of random measurement sites 10 times ($CV_{10\%sites}$) and leave one site out cross validation (LOOCV). From the cross-validations, I calculated the median absolute errors, mean absolute errors, the mean errors, and the correlation of predicted and observed values. Furthermore, I evaluated whether model assumptions were upheld using diagnostic plots to see whether the residuals were normally distributed and had random and constant variance. I also checked for any temporal and spatial patterns in the residuals. I checked for residual spatial dependence by visualizing the residuals in variogram plots and I calculated the Moran's I statistic of spatial autocorrelation. Finally, I ran the final models with splines applied to the continuous predictor variables to allow for non-linear associations. I found that model fit did not improve with splines (results in the Appendix Table A6), therefore, I continued to model the data as linear relationships with the additional advantage of enhanced interpretation.

After model evaluation, predictions were made for the whole of the GAMA at a spatial grid resolution of 50m x 50m. Predictions of LA_{eq1hr} were made for each hour of the day representing long-term hourly averages and then LA_{eq24hr} , L_{den} , L_{day} , and L_{night} were calculated from the 24, hourly predicted surfaces of LA_{eq1hr} . IR_{day} and IR_{night} were predicted directly from the IR models.

Since the primary aim of this analysis was to predict annual average sound metrics across the GAMA, I could not use the weather data for spatial prediction as I only collected it at certain sites

in the city. However, I conducted sensitivity analyses to estimate the associations of sound levels with time-resolved weather conditions, specifically wind speed, temperature, relative humidity, and rainfall, and to investigate whether their inclusion in the main spatial models improved predictive accuracy. I additionally modelled the final predictor variables sets with Random Forest models as a sensitivity analysis for the choice of model infrastructure. Random Forest models have been shown previously to improve predictive accuracy over linear regression in a noise LUR study conducted in Canadian cities⁴⁹.

5.6 Population exposure to urban sound levels in Accra Metropolis

I estimated the percentage of the population exposed to varying L_{den} and L_{night} levels in Accra Metropolis, as that information can be useful for estimating attributable burdens of disease due to noise. As I will show in the upcoming Chapter 6, road-transport sounds dominated the sound environment in Accra Metropolis and were highly prevalent in both the day and night-time. Therefore, herein, I refer to population exposures to noise levels within this analysis. I spatially overlaid the predicted L_{den} and L_{night} surfaces onto a map of EAs from the 2010 census (see Figure 17 in Chapter 7). EAs reflect the location of residence at the time of the census and the smallest spatial administrative unit in Ghana. The median size and population of EAs in Accra Metropolis are $\sim 0.03 \text{ km}^2$ and 800 people. I then calculated average noise levels within each EA and estimated the number of people exposed to varying levels of 5 dBA increments (e.g., 50-54 dBA, 55-59 dBA, etc.) based on the population distribution in 2010.

5.7 Results

The final models included between four and six spatial predictors (Table 7). LA_{eq1hr} was positively associated with road-traffic predictors (length of major roads (buffer size: 100m), length of secondary/tertiary roads (buffer size: 200m)) and the presence of restaurants (buffer size: 100m),

and negatively associated with variables representing vegetation (NDVI, buffer size: 50m) and formal low/medium residential land use (buffer size: 200m). Population density was additionally positively associated with day-time $LAeq_{1hr}$ (buffer size: 500m). The variables which explained the most variance in the fixed effect component of the $LAeq_{1hr}$ models were NDVI and length of major roads. The intermittency ratio was negatively associated with road-traffic related variables (length of major roads (buffer size: 100m), length of secondary/tertiary roads (buffer size: 200m)) and night-time IR was positively associated with population density (buffer size: 200m) and formal residential areas (buffer size: 100m). NDVI was negatively associated with the intermittency ratio in the night-time, but positively associated with it in the daytime, possibly due to the low background sound levels in areas with higher vegetation in the day-time, and thus the ability of day-time sound events to emerge from the background.

The median absolute errors (MAEs) of the final $LAeq_{1hr}$ models ranged from 2.9 – 3.4 dBA with $CV_{10\%sites}$ and the correlation of predicted and observed values (r) ranged from 0.72 – 0.74 (r^2 : 0.51 – 0.54). The mean error (ME), a measure of bias, was less than 1, indicating no systematic under or over prediction (Table 8). The MAEs of the final IR models ranged from 8.7 – 9.3% with $CV_{10\%sites}$. The correlation of predicted and observed values was much higher for IR_{day} (0.60) compared with IR_{night} (0.37). The ME was less than 1% for IR_{day} , but at 3.6% for IR_{night} , indicating an upward bias in the average estimate (Table 8). Results from LOOCV were very similar.

Table 7. Mean associations of sound metrics with spatial predictor variables in the final LUR models.

Model dependent variables	Predictor variables	Predictor variable unit	Buffer size	Slope coefficient [95% confidence interval]
L_{Aeq}_{1hr} (day-time, dBA)	<i>Intercept</i>	-	-	65.2 [64.2, 66.3]
	Total length of major roads	Standardized (meters)	100	2.5 [1.2, 3.7]
	Total length of secondary/ tertiary roads	Standardized (meters)	200	1.8 [0.9, 2.8]
	Formal low/ medium residential area	Standardized (meters ²)	200	-0.8 [-1.5, -0.1]
	Normalized difference vegetation index	Standardized (value)	50	-2.8 [-3.7, -2.0]
	Number of restaurants	Count	100	1.4 [0.5, 2.4]
	Population density	Standardized (people/km ²)	500	0.8 [-0.4, 2.0]
L_{Aeq}_{1hr} (night-time, dBA)	<i>Intercept</i>	-	-	57.2 [55.2, 59.2]
	Total length of major roads	Standardized (meters)	100	3.0 [1.7, 4.4]
	Total length of secondary/ tertiary roads	Standardized (meters)	200	2.2 [1.2, 3.3]
	Formal low/ medium residential area	Standardized (meters ²)	200	-1.3 [-1.9, -0.5]
	Normalized difference vegetation index	Standardized (value)	50	-2.2 [-2.9, -1.5]
	Number of restaurants	Count	100	1.8 [0.8, 2.9]
IR_{day} (%)	<i>Intercept</i>	-	-	38.4 [35.6, 41.2]
	Total length of major roads	Standardized (meters)	100	-7.3 [-11.1, -3.5]
	Total length of secondary/ tertiary roads	Standardized (meters)	200	-7.2 [-10.2, -4.3]
	Normalized difference vegetation index	Standardized (value)	100	3.6 [1.5, 5.7]
	Number of restaurants	Count	100	-1.9 [-4.9, 1.1]
IR_{night} (%)	<i>Intercept</i>	-	-	47.5 [44.8, 50.3]
	Total length of major roads	Standardized (meters)	100	-3.7 [-7.4, -0.1]
	Total length of secondary/ tertiary roads	Standardized (meters)	200	-2.5 [-5.3, 0.4]
	Normalized difference vegetation index	Standardized (value)	100	-4.1 [-6.6, -1.6]
	Population density	Standardized (people/km ²)	200	3.3 [-1.0, 7.7]
	Formal low/ medium residential area	Standardized (meters ²)	100	2.5 [0.5, 4.4]

IR: Intermittency Ratio; L_{Aeq}: Equivalent continuous sound level (A-weighted). Models adjusted for monitor height off the ground.

I did not find evidence that model assumptions were violated, and model residuals were randomly distributed. Furthermore, the Moran's I statistic for the residuals indicated a tendency towards spatial randomness (Range of model's Moran's I values: -0.06 to 0.05). As a sensitivity analysis, I used Random Forest models to generate predictions using the final predictor variable sets and found no improvement in model accuracy (Table A8 in Appendix). As an additional sensitivity analysis, I included time-resolved weather variables into the final spatial models and found some significant associations between weather variables and LAeq_{1hr}, but no improvement in the accuracy of predicted sound levels (Table A9 in Appendix).

Table 8. Final LUR model prediction accuracy from 10-fold 10% random site hold-out cross validation (CV_{10%sites}).

	r	r²	Median absolute error	Mean absolute error	Mean error
LAeq_{1hr} - day	0.74	0.54	2.92 dBA	3.60 dBA	-0.33 dBA
LAeq_{1hr} - night	0.72	0.51	3.38 dBA	4.01 dBA	-0.41 dBA
IR_{day}	0.60	0.35	8.65 %	10.81 %	-0.72 %
IR_{night}	0.37	0.14	9.32 %	12.39 %	3.58%

Observed and predicted values were summarized as medians for each site and hour of the day to generate accuracy statistics which were reflective of the timescale at which model predictions were made and results were presented. r² approximates R².

5.7.1 Spatial patterns of sound metrics

Spatial patterns of day and night-time sound levels in the GAMA were nearly the same, though day-time sound levels were higher by approximately 7 to 8 dBA (Table 9, Figure 11). Accra Metropolis, the most populated and urbanized area of the GAMA, had some of the highest predicted L_{den} (median: 64 dBA), as well as the port city of Tema in the east (median: 62 dBA) (Figure 12). The peri-urban periphery in the north and west of the GAMA had the lowest levels of L_{den} (median: 58 dBA). The spatial patterns of sound levels and intermittency differed, particularly in the daytime. There was an inverse day-time spatial correlation between predicted sound levels and intermittency ratios (correlation coefficient (r) = -0.89), indicating that daytime sound in quieter

areas in the GAMA was more intermittent. This contrast was particularly stark along major road-traffic routes within the GAMA, where there were high predicted sound levels (median L_{day} : 66 dBA), but low predicted IRs (median IR_{day} : 34%). This result indicates that these areas had a more constant (as opposed to intermittent) stream of high sound levels occurring. Areas which had both high ($L_{\text{night}} \geq 50$ dBA) and intermittent night-time sound ($IR_{\text{night}} \geq 50\%$), were predominantly found in residential neighborhoods, and accounted for $\sim 30\%$ of all areas. Furthermore, areas with intermittent and louder sound ($L_{\text{night}} \geq 55$ dBA) were predominantly found in high-density low-income neighborhoods such as some of the major slums in Accra Metropolis and to the east of the GAMA. These areas accounted for $\sim 6\%$ of all areas in the GAMA with predictions.

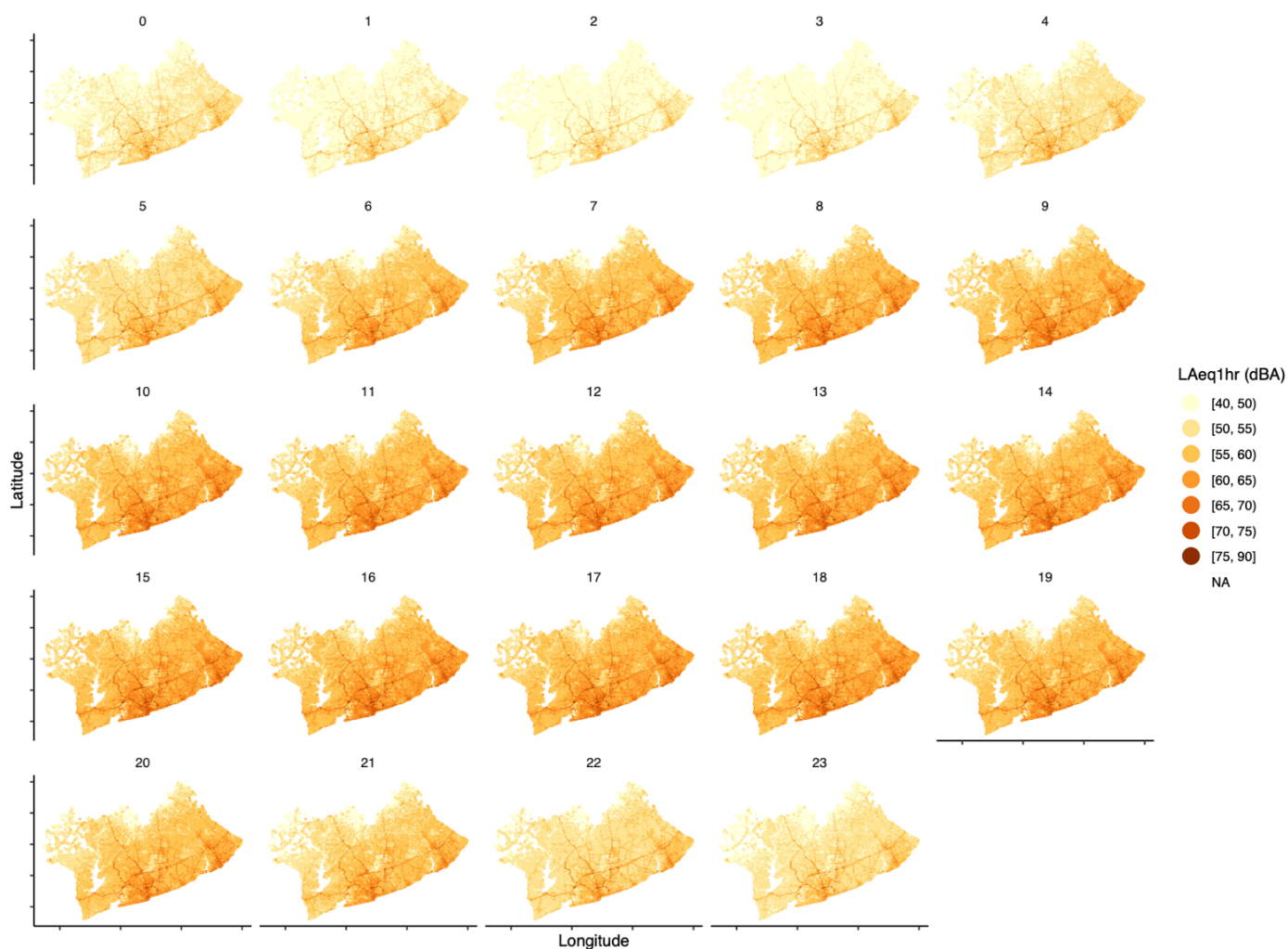


Figure 11. Predicted annual average $LAeq_{1hr}$ for each hour of the day.

Predictions were made onto a 50m x 50m spatial resolution grid at a fixed height of 4 meters off the ground. White 'NA' areas are excluded from prediction as they are considered out of sample (e.g., water bodies, forests, grasslands). Numbers above maps refer to the hour of the day based on the 24-hour clock (e.g., 2: 2am).

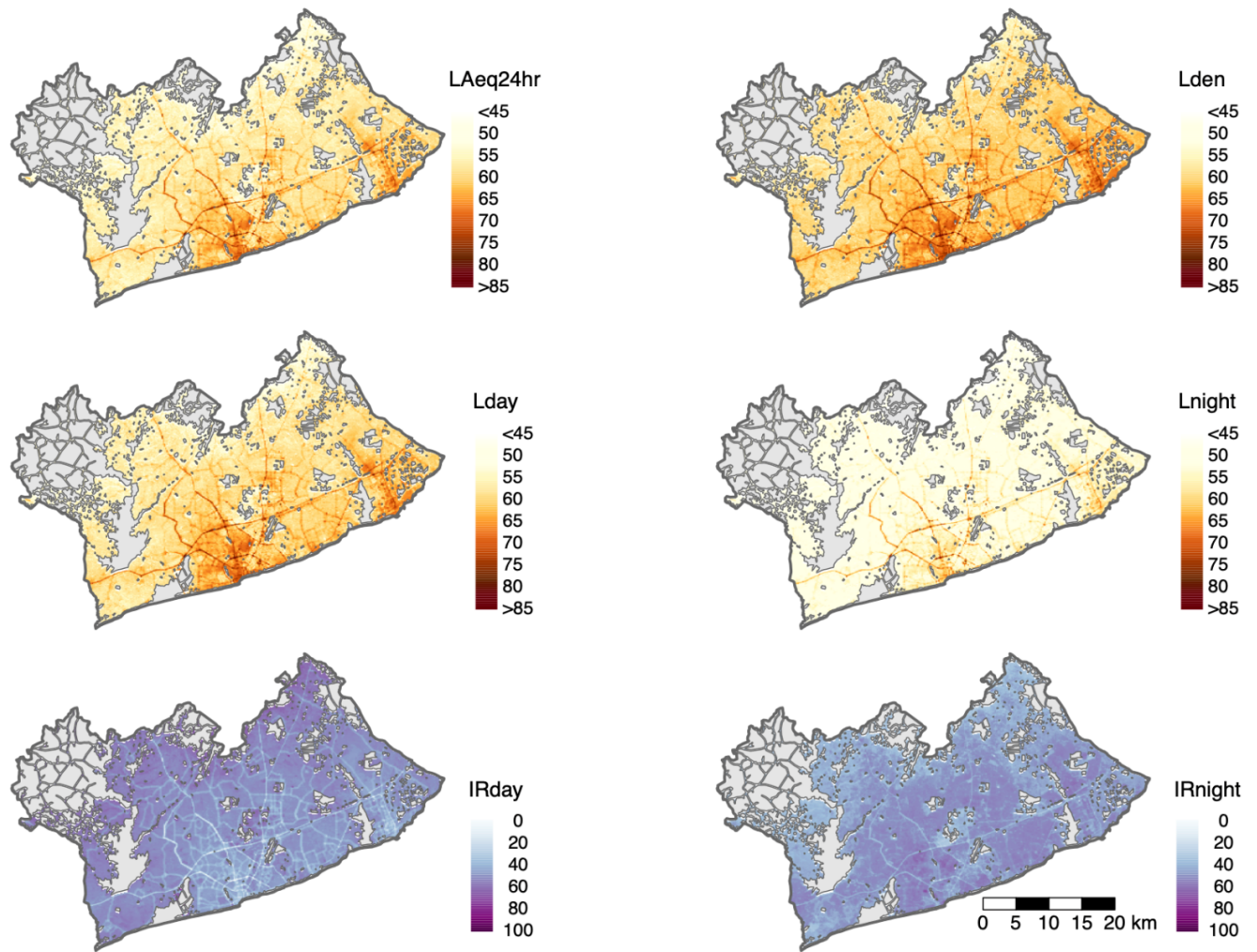


Figure 12. Predicted daily sound metrics in the Greater Accra Metropolitan Area.

Predictions were made for a fixed height of 4 meters off the ground onto a 50m x 50m grid of the city and calculated from the 24 surfaces of long-term hourly averages (Figure 11). Grey areas on the map represent areas excluded from prediction as they were considered to be out of sample (e.g., water bodies, forest/grassland with no roads nearby). **Legend:** **LAeq_{24hr} (dBA):** 24-hour equivalent continuous A-weighted sound level; **L_{den} (dBA):** Day-evening-night equivalent continuous A-weighted sound level; **L_{day} (dBA):** Day-time equivalent continuous A-weighted sound level (6am-9:59 pm); **L_{night} (dBA):** Night-time equivalent continuous A-weighted sound level (10:00pm-5:59 am); **IR_{day} (%):** Day-time intermittency ratio (6am-9:59 pm); **IR_{night} (%):** Night-time intermittency ratio (10:00pm-5:59 am).

Table 9. Predicted sound metrics in the Greater Accra Metropolitan Area (GAMA), Accra Metropolis and stratified by road-networks.

	L_{Aeq24hr} (dBA)	L_{den} (dBA)	L_{day} (dBA)	L_{night} (dBA)	IR_{day} (%)	IR_{night} (%)
GAMA	57.0 (54.8, 59.3)	60.2 (58.2, 62.4)	58.5 (56.1, 60.7)	51.2 (49.6, 53.3)	51.4 (47.6, 54.6)	46.9 (41.0, 50.9)
Roads						
Major roads	65.0 (61.8, 68.1)	68.4 (65.2, 71.6)	66.4 (61.1, 69.3)	59.8 (56.6, 63.1)	33.6 (26.4, 40.4)	41.4 (37.4, 45.4)
Secondary/ tertiary roads	59.0 (57.1, 62.8)	63.0 (60.5, 65.9)	61.3 (58.4, 62.1)	54.1 (52.3, 56.9)	43.9 (39.5, 48.0)	47.0 (40.7, 50.3)
Minor roads	57.0 (55.1, 59.4)	60.3 (58.5, 62.4)	58.5 (56.4, 60.8)	51.3 (50.2, 53.4)	51.3 (47.4, 54.3)	47.6 (41.8, 51.2)
Accra Metropolis	60.9 (58.1, 63.6)	63.9 (61.1, 66.6)	62.3 (59.4, 64.9)	54.6 (52.0, 57.5)	45.9 (39.2, 50.0)	49.6 (44.4, 52.0)

Data summarized as median and interquartile ranges (IQR). 100-meter buffer was created arounds roads in order to stratify results.

5.7.2 Population exposure to urban sound levels

Almost the entire population in the Accra Metropolis (99%), ~1.66 million people based on the most recent (2010) census estimates, lived in EAs where the average predicted L_{den} and L_{night} noise levels exceeded the WHO-Europe's guidelines for road-traffic noise ($L_{den} < 53$ dB; $L_{night} < 45$ dB)² (Figure 13). Furthermore, 98% of the population lived in areas exceeding 55 dBA L_{den} . The majority of the population lived in EAs with average L_{den} between 60-64 dBA (38%, ~621,000 people) and 65-69 dBA (51%, ~843,000 people) (Table 10). Moreover, almost two thirds of the 2010 Accra population lived in EAs where L_{night} exceeded 55 dBA (~70%). With a recent projection of around 2 million people in Accra Metropolis in 2019, I expect the current number of people exposed to elevated outdoor sound to be higher than these estimates.

Table 10. The number of people and percentage of the population living in enumeration areas (EA) with varying levels of average EA L_{den} and L_{night} in Accra Metropolis.

dBA	L_{den}	Number of people	L_{night}	Number of people
	Percentage of the population		Percentage of the population	
40-44 dBA	0%	-	Less than 1%	485
45-49 dBA	Less than 1%	485	Less than 1%	14,220
50-54 dBA	Less than 1%	2,527	30%	502,188
55-59 dBA	2%	40,025	56%	919,103
60-64 dBA	38%	621,739	12%	192,560
65-69 dBA	51%	842,657	1%	19,832
70-74 dBA	8%	132,674	Less than 1%	5,479
75+ dBA	Less than 1%	13,760	0%	-

Population estimates are from the most recent (2010) 100% sample of the national census. The sound environment in Accra Metropolis was dominated by road-traffic sounds in the day and night-time (Chapter 6 results).

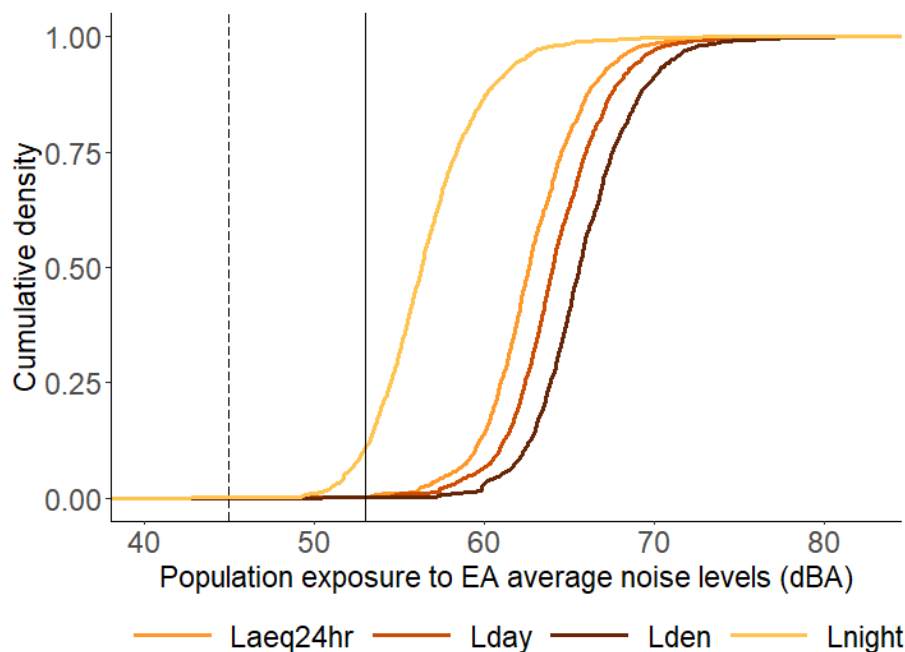


Figure 13. Cumulative densities of the proportion of the Accra Metropolis population living in enumeration areas with varying average noise levels.

The solid grey vertical line and the dashed black vertical line shows the L_{den} and L_{night} limits for road-traffic noise based on WHO guidelines for the European region, respectively². Note that the guidelines have global relevance². The sound environment in Accra Metropolis was dominated by road-traffic sounds in the day and night-time (Chapter 6 results).

5.8 Discussion

Nearly all areas in the GAMA and Accra Metropolis had L_{den} and L_{night} levels which exceeded international guidelines, though levels were not equally spread across neighborhoods. My models of sound levels were more accurate than the sound intermittency models, and variables which represented road-traffic and vegetation explained the most variation in the models.

The accuracy of the sound level LUR models in Accra were within range of reported accuracy metrics from previous LUR studies in Toronto (Canada)¹³⁶, five Canadian cities⁴⁹, Dublin (Ireland)⁴², Giron, Basel, and Grenoble (Europe)⁴⁰, Tel Aviv and Beer Sheva (Israel)¹⁶⁶ but lower than a study conducted in Taiwan (Root mean squared error (RMSE): 2.1 to 2.8 dBA)⁴⁷ and in Boston, USA (Mean absolute percent error (MAPE): 7.0 %)⁴⁴. The median predicted L_{den} (63.9 dBA), $L_{Aeq24hr}$ (60.9 dBA), L_{day} (62.3 dBA) and/or L_{night} (54.6 dBA) in Accra Metropolis was higher than city-wide levels predicted from LUR studies in Dalian (China)⁴⁸, Dublin (Ireland)⁴², Toronto (Canada)^{49,139}, Halifax (Canada)⁴⁹, Vancouver (Canada)⁴⁹, Boston (USA)⁴⁴, Tel Aviv and Beer Sheva (Israel)¹⁶⁶, and in informal settlements in South Africa²⁶. Median predicted L_{night} from a LUR study in Sao Paulo (Brazil) was the same as in Accra Metropolis (55 dBA), though L_{den} was slightly higher in Sao Paulo (Median: 65 dBA)²⁹³. Finally, while not directly comparable, median predicted sound levels in Accra Metropolis from the LUR models were lower than what was reported from weeklong measurements conducted in New York City (USA) (Mean L_{dn} : 74.1 dBA (range: 62.6, 85.3))⁴³.

Predicted sound levels from the LUR models were positively associated with traffic-related variables, particularly major roads (highways, motorways), similar to previous LUR studies in North America^{44,45,49,136}, Europe^{40,42}, Asia, the Middle East^{47,137,166}, and SSA²⁶. Multi-lane and higher-speed roads can facilitate higher traffic volumes, and attract a fleet composition with a higher percentage of heavy vehicles that can produce higher noise levels in these areas¹⁹⁹. The mechanisms by which motor vehicles generate noise is multi-faceted²⁸⁴ and include engine sounds, tire contact with the road and driver behavior such as honking²⁰⁰.

Predicted sound levels were generally higher in the city-core (i.e., Accra Metropolis) and in industrial (i.e., Tema Metropolis) areas^{26,45,139,166} compared with outlying peri-urban and formal residential areas, where vegetation, which is a natural sound attenuator¹³¹, was more abundant. Previous research from SSA showed that noise sources extend beyond road-transportation and can include religious activities, formal and informal commercial activities, restaurants, and large and small-scale industrial activities^{22,77,79}, which is likely reflected in the generally high predicted sound levels in Accra Metropolis and where the population is most dense. From the Accra LUR models, the number of restaurants in an area, which is a proxy for commercial activity, was also consistently positively associated with sound levels⁷⁹.

Almost the entire area of the GAMA had predicted sound levels (99%) which exceeded the World Health Organization guidelines (for the European region) for road traffic noise (L_{den} (>53 dB), L_{night} (>45 dB))². Reviews of the largely European epidemiological evidence highlight how chronic exposure to road-traffic noise beyond these thresholds is associated with adverse health effects including sleep disturbance, annoyance, and CVDs². Though, I must acknowledge the limitation of comparing population noise exposures in Accra, Ghana to a guideline set for a different region of the world. Though the WHO does state that while the guidelines were published by the European Regional Office for Europe, they are suitable for a global audience as a large body of the evidence used to form the recommendations was derived from research in Europe, America, Asia, and Australia².

Compared to urban areas in Europe, there seems to be a much higher percentage of the population in the GAMA exposed to L_{den} above 55 dB ($>98\%$) – in Europe, it was estimated that $\sim 20\%$ of the urban European population lives in areas where noise levels are considered harmful to health. However, there is large variation in the proportion of the exposed population across cities and

countries in Europe⁷¹. Though I make this comparison with caution as the measured and modelled sound levels in Accra are not directly comparable to European city estimates. Specifically, measurements in Accra were conducted along the roadside, and while road-transport sounds were prominent in many areas (Chapter 4), SLMs picked up sound energy from community sources as well, while the European noise maps were derived from source-specific propagation models, namely from road, rail, and aircraft sources.

My analysis is the first to my knowledge to model and map the intermittency ratio metric with a LUR model. However, the out of sample predictive accuracy of my day-time intermittency ratio model was moderate, and unfortunately the night-time model was low. Future work can focus on improving models of intermittency ratios for epidemiological analyses. Modelling and mapping sound intermittency in cities is important as loud and intermittent noise has been shown to have a larger effect on sleep disturbance than continuous noise at the same levels^{173,174}. Recent evidence from Switzerland also suggests that for night-time road-traffic noise above 60 dBA, higher intermittency ratios can modify the exposure response-curve of the probability to be highly sleep disturbed in a positive direction¹⁶¹. Similar evidence was found within the same cohort for L_{den} road-traffic noise exposure and diabetes risk²⁹⁴. In Accra, the areas of the city which had both loud ($L_{night} > 55$ dBA) and intermittent ($IR_{night} > 50\%$) night-time sound were predominantly found within the high-density, low-income neighbourhoods of Nima, Ussher Town, James town, and Ashaiman, as well as along the coast in Indigenous Ga communities.

5.9 Summary

This chapter presents one of the first LUR models of sound levels and intermittency in a SSA city. The predicted sound levels exceeded international health-based guidelines almost everywhere. It is probable that common health impacts of noise, such as annoyance, sleep disturbance, and CVD,

are experienced within the city. Sound levels and intermittency varied widely across the city, and the highest levels were in the densely populated Accra Metropolis and near major roads. City-level actions are needed to tackle this environmental exposure in Accra through changes in transportation infrastructure, urban services and environmental noise regulations, which cover a multi-faceted group of sources, including but not limited to road-traffic.

Chapter 6 Geospatial modelling of different sound types across Accra, Ghana

6.1 Overview and objectives

The urban sound environment is a mixture of mechanical, human, animal, and natural, sounds varying in space and time⁷³. These sounds in isolation or in combination can create sound environments which are detrimental to physical and psychological health, neutral, or even beneficial^{28,116,117,183}. In this chapter, I use collected audio data described in Chapter 3 and graphically described in Chapter 4 to model, predict and map a diversity of identified sound types across the city of Accra. Additionally, I combine information on city-wide predicted sound levels (Chapter 5) to better understand the spatiotemporal patterns of multiple sound characteristics in the city. While this work is not a soundscape study, as I do not incorporate information on perception, this work is influenced by the soundscape paradigm which suggests ‘assessing all sounds perceived in an environment in all its complexity’²⁶³.

6.2 Methods

6.2.1 Data sources and pre-processing

The pre-processing steps to identify sound types from the audio recordings have been described in detail in Chapter 4 (*Section 4.3.2*) with a few adaptations for this analysis. First, I ran each 10-second audio recording through the pre-trained neural network (described in *Section 4.3.2*). The neural network then provided and ranked the top 5 sub-category sound classes based on the neural network’s given probability of each sound class being present in the audio recording (see *Section 4.3.2* for details). For this LUR analysis, I used all 5 sub-category sound classes, instead of restricting to the top 3; I did this to reduce the chance of unintentionally censoring the data, as the likelihood that a sound class makes it into the top 5 is dependent on the neural network probability,

but also the probabilities of all other sound classes. I then grouped the sub-category sound classes into super category sound types: road-transport, animal and insect, music, speech, and nature. A description of sub- vs super-categories is in *Chapter 4, Section 4.3.2*.

To prepare the data for the LUR models, I calculated the average percentage of time (prevalence) in the day (06:00 – 21:59) and night (22:00- 05:59) that each super category sound type (referred to here after as just ‘sound types’) was identified by the neural network at each measurement site. Unlike the sound level and intermittency LUR models (Chapter 5), where I included daily sound data into the models, I aggregated the sound type data across all days at each site. I did this because the purpose of the analysis was to generate spatial annual average predictions, and the modelling infrastructure (Random Forest models described below in *Section 6.2.2*), does not include random effects which could account for within-site temporal correlations. Finally, as shown in Figure A4 in the Appendix, the percentage of time sound types were present was fairly consistent between different days of the week.

The frequency of identified sound types is slightly sensitive to how one interprets the value of the neural network’s given probabilities of sound type presence (i.e., model confidence) within each audio recording (described in *Section 4.3.2*) (Table A3 in Appendix). For example, there was a 4% absolute difference in the percentage of audio files where music sound types were identified as present when the top 5 vs the top 3 sub-category sound classes were retained within each file (Differences in Table A10 in Appendix). Thus, I additionally modelled audio data retaining (i) the top 3 sub-category sound classes within each recording (based on neural network probabilities), and (ii) all sub-category sound classes which had a neural network probability above a fixed cut off of 0.25 (which retains 30-40% of the data with the highest probabilities), as comparative sensitivity analyses.

A table of spatial predictor variables (Table 5) and their pre-processing with buffers (50m, 100m, 200m, 500m) and transformations are described in Chapter 5. I additionally included the median day (L_{day} , dBA) and night-time (L_{night} , dBA) measured sound levels at each site as predictors.

6.2.2 *Geospatial sound type modelling*

Similar to the sound level and intermittency models in Chapter 5, I used a land use regression (LUR) approach to model and predict the frequency of different types of sounds across the GAMA. For this analysis I used Random Forest (RF) regression models²⁹⁵. Random Forest is an ensemble learning method, made up of combinations of uncorrelated decision trees. Single decision trees are highly sensitive to being overfit, though Random Forests overcome this drawback by combining multiple trees, which are made up of bootstrapped observations and a random subset of predictor variables²⁹⁵.

Random Forest models have been used more recently to model and predict air and noise pollution within a LUR framework, often achieving high accuracy results^{49,296,297}. I used Random Forest models for this analysis, as opposed to linear mixed effect regression (used in Chapter 5), because Random Forests are robust to the inclusion of many variables with little or no importance and are non-parametric modelling methods (distributions in Appendix Figure A7)²⁹⁵, which is important as the sound type data distributions are highly skewed. As well, Random Forests will not predict out of the training dataset range (unlike linear regression), ensuring that sound type data (expressed as percent of time present) will not be predicted below 0% or above 100%. Finally, the primary aim of this analysis was prediction, not the interpretation of associations, as was one of the goals in Chapter 5.

I constructed 10 different models. Five models for each sound type and separate models for the day and night-time. Same as the approach I took in Chapter 5, I first selected the buffer radii (50m, 100m, 200m, or 500m) for each spatial predictor variable and corresponding model which reduced model error the most. I did this with the random permutation method. This method provides a robust measure of the importance of predictors in a Random Forest model²⁹⁸ and has been used by previous spatial noise modelling studies using Random Forest⁴⁹. This method generates a random permutation of a variable and calculates the difference in model predictive accuracy when the random permutation is made compared with when the variable's true values are used. If a buffer radii size is important, random permutations will result in a larger decrease in model accuracy compared to permutations of the same predictor variable with alternate buffer radii sizes. After identifying the best buffer size for each predictor variable for each of the day and night-time Random Forest models and verifying that buffer sizes made physical sense in relation to each predictor, I investigated whether any of the predictors were collinear (correlation coefficient (r) >0.8). If two or more predictor variables were collinear, the variable that was the least important in each model was dropped.

I fitted Random Forest models with 500 trees each to the sound type variables and a suite of spatial predictor variables. I evaluated the external predictive accuracy of the final models with 10-fold cross validation holding out 10% of random sites. Metrics of model evaluation are described in *Section 5.5*. The importance of each predictor variable in each model was assessed with the same method used to choose the best buffer size, the Random Permutation method. To check for residual spatial autocorrelation, I visually inspected maps of model error across measurement sites and generated Moran's I statistics with the model's residuals. I also combined the residuals across models to see if there was any clustering of model prediction error present in a combined way. Specifically, I first took the absolute value of the residuals from all models and then standardized

them to have the same range, between 0 and 1. I then summed the standardized absolute residuals across the sound type models, for the day and night separately.

I generated predictions for the identified sound types (expressed as the percentage of time present) for the day and night-time separately, resulting in predicted surfaces covering unmeasured locations in the GAMA at a spatial grid resolution of 50m x 50m. The predictions were restricted to areas of the GAMA with some level of human activity/inhabitation, so that I did not predict out of sample (the same approach was taken in Chapter 5). For example, I did not predict for areas covering open bodies of water or dense forests. In addition to mapping the predicted prevalence of identified types of sounds, I also summarized the median, interquartile range (IQR), minimum and maximum values within the GAMA and across spatial sub-groups such as within Accra Metropolis and by proximity to major, secondary/tertiary, and minor roads. Finally, to show the combined spatial distribution of sound levels and sound types, I spatially overlaid and jointly summarized the prediction surfaces for sound levels (Chapter 5) with sound types.

6.2.2.1 Additional analyses

I constructed LUR models, and made predictions, using alternative definitions of sound type presence within each audio file (described in *Section 6.2.1*). I compared the predicted values from the main models to the models with the alternative definitions with scatterplots.

6.3 Results

6.3.1 Random Forest model accuracy and variable importance

As described in *Methods Section 6.2.2*, vegetation (NDVI) was an important predictor in almost all models using the random permutation method. Predictor variables representing road-traffic sources of sound (e.g., road-networks), and day and night-time sound levels, were important in the road-

transport and animal and insect sound models. The most consistently important predictors in the music, speech, and nature sound models were related to population and building density and NDVI (Table 11).

Table 11. The top three most important predictor variables within each Random Forest sound type model. Variables are listed in order of importance.

	Day-time	Night-time
Road-transport sound models	Square root distance to major road NDVI L_{day}	Length of minor roads Length of secondary roads L_{night}
Animal and insect sound models	NDVI Length of secondary/tertiary roads L_{day}	Length of secondary/tertiary roads Length of Major roads L_{night}
Music sound models	Population density Building density Land use area (informal residential settlements)	Population density Building density Land use area (non-built up, barren, or vegetated land)
Speech sound models	NDVI Building density Land use area (non-built up, barren, or vegetated land)	Population density NDVI L_{night}
Nature sound models	NDVI Building density L_{day}	NDVI Building density Land use area (non-built up, barren, or vegetated land)

NDVI: Normalized Difference Vegetation Index

Model external predictive accuracy with $CV_{10\%sites}$ was fairly good for the road-transport, animal and insect, and speech sound models and, on average, predictions were unbiased (Table 12). The median absolute errors (MAEs) of the road-transport day and night models ranged from 8.8 – 16.7%. The correlation of predicted and observed values ranged from 0.61– 0.69. The median absolute errors (MAEs) of the animal and insect day and night models ranged from 9.7 – 14.4%. The correlation of predicted and observed values ranged from 0.66 - 0.83. The MAEs of the speech models ranged from 5.5 – 14.9%. The correlation of predicted and observed values ranged from 0.54 – 0.65. The music models were more accurate at predicting low levels than they were at predicting higher levels since there were limited data points at the higher ends of the distribution for the model to train on. This is reflected in the fact that the MAE was relatively low (6.5 – 8.5%), driven down by the majority of observations at the lower end of the distribution, yet the correlation

between the observed and predicted values was moderate-low (0.41 – 0.46). In general, the nature models, particularly night-time, could not generalize to new locations when the values were greater than 0%, as the distribution of nature sounds at the sites were highly skewed towards zero. I thus do not present city-wide night-time nature sound predictions. The mean error (ME), which is a measure of bias, was less than absolute 1. I did not find evidence of residual spatial autocorrelation in model residuals and the Moran's I statistic of spatial autocorrelation indicated a tendency towards spatial randomness of the residuals (statistic near 0) and was not statistically significant (p-value > 0.05).

Table 12. Random Forest sound type LUR model external predictive accuracy with 10-fold cross-validation of 10% random sites (CV_{10%sites}).

Average % of time sound type was present [Range: 0-100%]	Normalized median absolute error*	Median absolute error	Mean absolute error	Mean error	r	r ²
Day-time models						
Road-transport	0.34	8.8 %	11.5 %	0.6 %	0.69	0.48
Animal and insect	0.18	9.7 %	12.5 %	-0.3 %	0.83	0.70
Music	0.40	8.5 %	11.3 %	-0.9 %	0.46	0.21
Speech	0.34	14.9 %	16.5 %	-0.6 %	0.65	0.42
Nature	0.48	3.4 %	5.0 %	-0.2 %	0.30	0.10
Night-time models						
Road-transport	0.36	16.7 %	18.6 %	1.0 %	0.61	0.37
Animal and insect	0.29	14.4 %	17.5 %	-0.2 %	0.66	0.44
Music	0.57	6.5 %	7.9 %	-0.7 %	0.41	0.17
Speech	0.45	5.4 %	8.1 %	-0.6 %	0.54	0.30
Nature	0.84	3.6 %	7.7 %	-0.5 %	0.02	0.00

*Normalized by dividing the median absolute error by the interquartile range of the observed values.

6.3.2 Spatial patterns of predicted sound type prevalence

The median percentage of the time that road-transport sounds were predicted as present across all locations in the GAMA was 63% in the daytime, and 42% in the night-time (Table 13). However, there was substantial spatial variation in the predicted percentage of time that road-transport sounds were present, which also varied to some degree between the day and the night-time (Figure 14). The lowest levels were observed in the northern peri-urban residential areas where predicted daytime levels were generally <30% and night-time levels <10% (Figure 15). Conversely road-

transport sounds were most frequent near major roads (median across locations: 85% of the daytime; 69% of the night-time), and in the most densely populated areas including Accra Metropolis (median across locations: 81% of the daytime; 62% of the night-time) and in the eastern urban centres of Tema and Ashaiman (median across locations: 76% of the daytime; 53% of the night-time) (Figure 15).

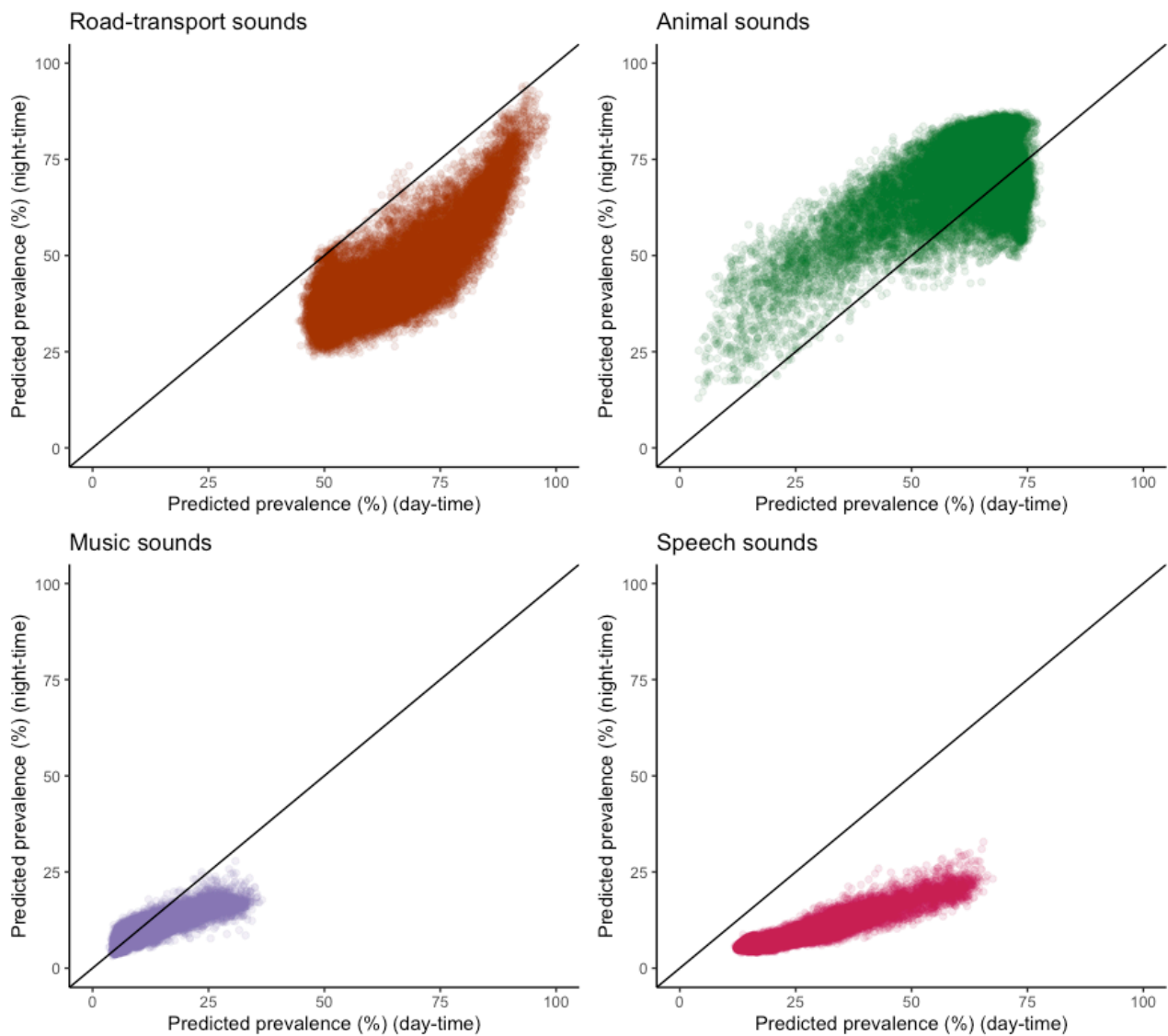
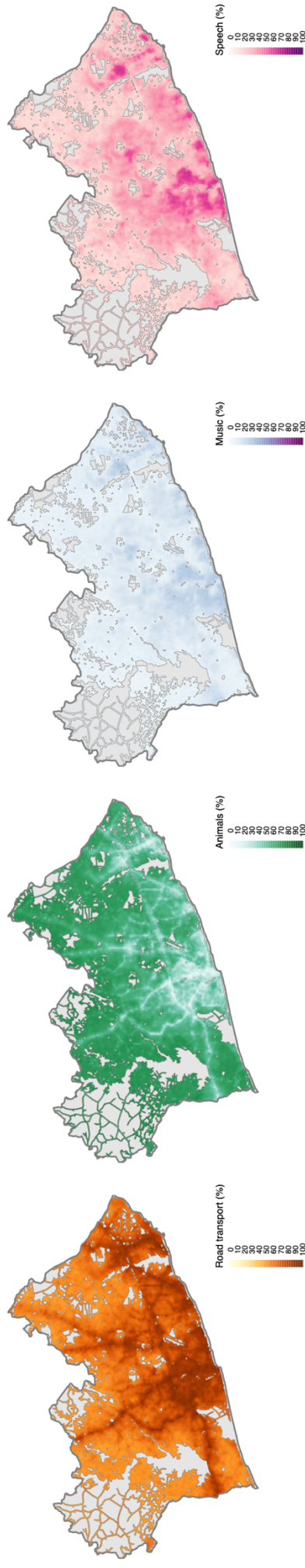


Figure 14. Correlation between the predicted percentage of time (prevalence) that sound types are present in the day and night across the GAMA.

Day-time



Night-time

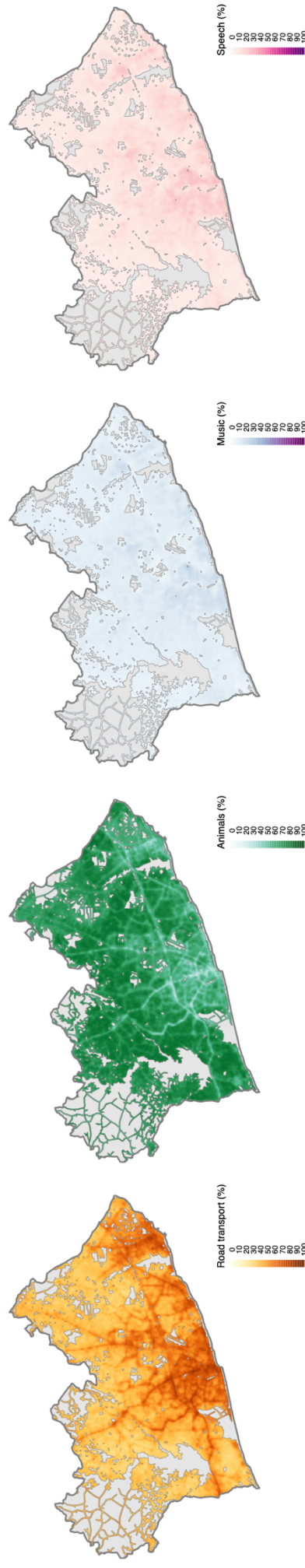


Figure 15. Predicted percentage of road-transport, animal and insect, music, and speech sounds in the day and night-times (%).

Predictions were made onto a 50m x 50m spatial resolution grid covering the city. Grey areas on the map represent areas excluded from prediction as they are considered out of sample (e.g., water bodies, forest/grassland with no human settlement and no roads).

Table 13. Predicted percentage of time that sound types were present in the Greater Accra Metropolitan Area (GAMA) and in Accra Metropolis.

	GAMA		Accra Metropolis	
	Day-time	Night-time	Day-time	Night-time
Road-transport sounds (%)	62.5 (52.9, 74.9)	41.7 (36.0, 52.5)	81.4 (73.6, 86.2)	61.6 (52.8, 70.5)
Animal and insect sounds (%)	64.7 (54.2, 69.6)	71.0 (63.1, 78.1)	42.6 (30.3, 54.7)	59.1 (49.8, 66.5)
Music sounds (%)	9.3 (6.7, 14.1)	9.2 (7.3, 14.3)	17.7 (11.5, 25.1)	13.2 (9.8, 16.5)
Speech sounds (%)	23.1 (17.7, 33.2)	8.1 (6.5, 11.3)	38.3 (29.4, 50.4)	14.9 (10.7, 19.4)
Nature sounds (%)*	10.0 (6.7, 13.6)	-	6.4 (5.1, 10.3)	

Data are summarized as median and interquartile ranges (IQR).

*Omitted prediction for nature sounds in the night-time due to poor model fit

The spatial patterning of animal and insect sound predicted prevalence's were inversely correlated with road-transport (Pearson correlation coefficient (r): -0.88 day-time and -0.80 night-time). In the daytime, animal and insect sounds were present 43% of the time (median across locations) within Accra Metropolis and 33% of the time near major roads. Night-time prevalence's of animal and insect sounds was generally higher at all locations (Figure 14), particularly in peri-urban areas in the north (Figure 15). The spatial patterning of music and speech sounds were similar to each other (correlation coefficient: 0.82 (night) to 0.92 (day)), with the highest predicted prevalence's observed in neighbourhoods with higher population and building densities, and particularly in the Accra Metropolis (Figure 15).

As a sensitivity analysis, I built LUR models and made predictions when the sound type modelling dataset was constructed with alternative definitions of 'presence' in each audio file (see Sections 6.2.1 and 6.2.2.1 for details). Retaining the top 3 and the top 5 sound classes in each audio file, based on neural network acoustic classifier probabilities, yielded similar LUR models and city-wide predictions (see Appendix Figure A8). However, absolute levels and some spatial patterns

differed when I used an audio dataset which further restricted the top 5 sound classes to those in which the neural network probability exceeded a cut off of 0.25. (see Appendix Figure A9).

6.3.3 Predicted sound levels and types

In areas with higher day and night-time sound levels (> 65 dBA), predicted road-transport sounds were prevalent, generally over 75% of the time (Figure 16 and Figure 17). Predicted speech and music sounds were also more prevalent in areas with higher sound levels, particularly in the daytime, but overall, less prevalent than road-transport sounds. The quieter areas in the city ($L_{\text{day}} < 55$ dBA and $L_{\text{night}} < 50$ dBA) had a high prevalence of predicted animal and insect sounds in the day and night-time ($> 50\%$ of the time present), and relatively lower prevalence of predicted road-transport, music, and human speech sounds (Figure 16 and Figure 17).

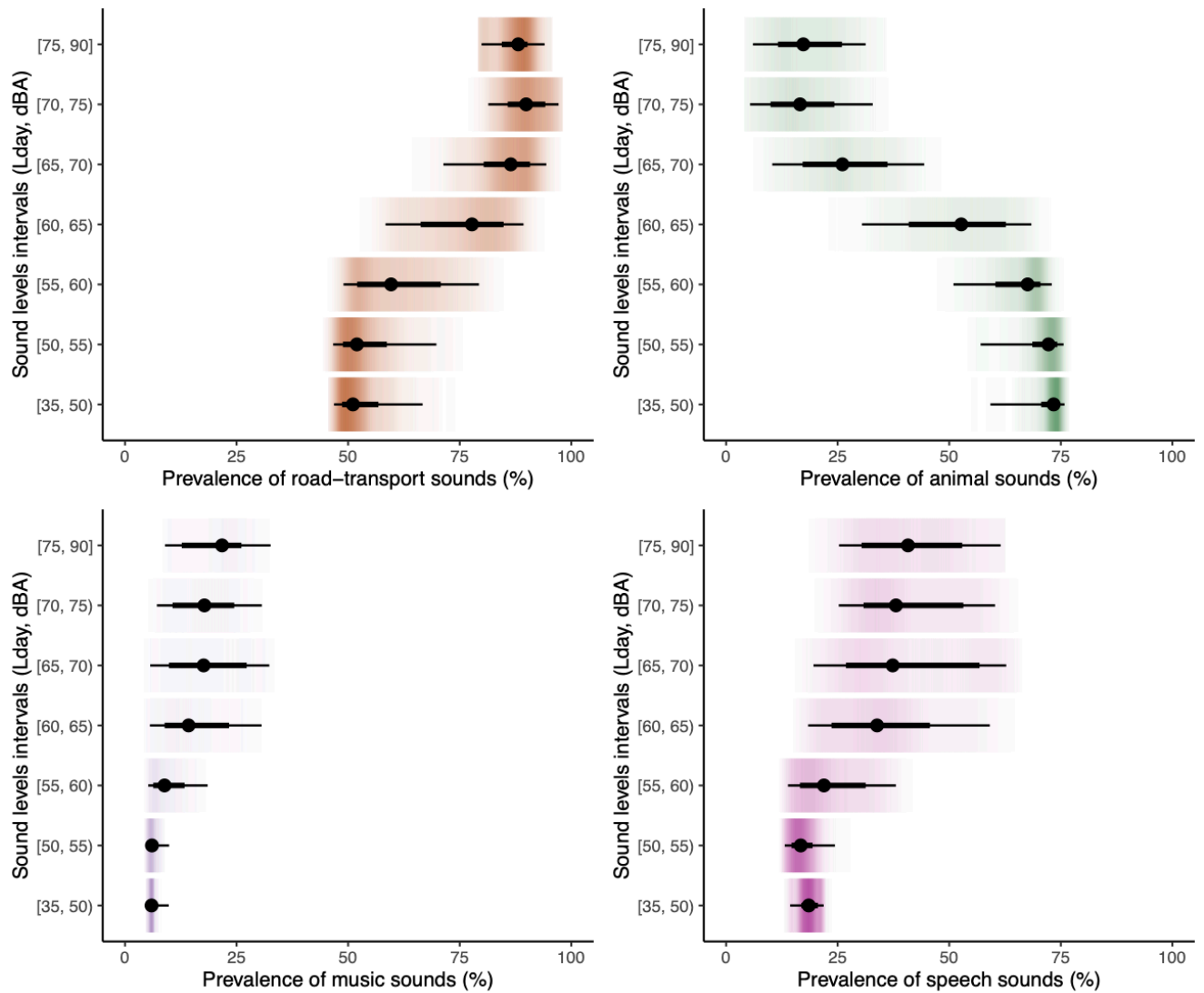


Figure 16. Distributions of daytime predicted sound type prevalence (% of time present) across areas with varying predicted sound levels (L_{day} , dBA).
 Sound levels for each area in the GAMA were predicted from a LUR model described in Chapter 5. Circular points represent the sample median, black horizontal lines the quartile range, and the coloured regions the density of the sample distribution.

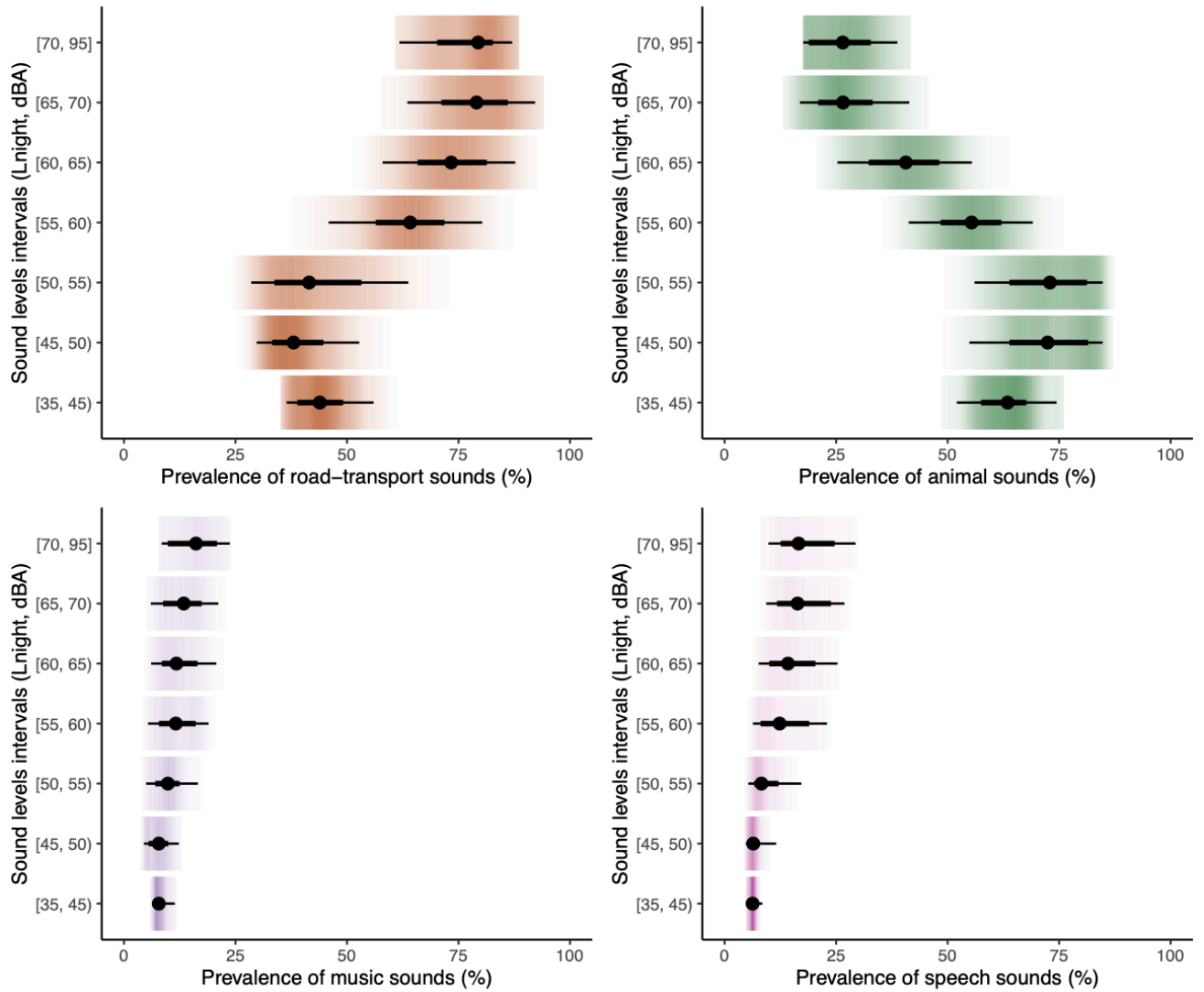


Figure 17. Distributions of night-time predicted sound type prevalence (% of time present) across areas with varying predicted sound levels (L_{night} , dBA).

Sound levels for each area in the GAMA were predicted from a LUR model described in Chapter 5. Circular points represent the sample median, black horizontal lines the quartile range, and the coloured regions the density of the sample distribution.

6.4 Discussion

Few previous studies have used audio recordings to classify and characterize the complexity of the urban sound environment at city-scale^{147,150–152}, and even fewer have used the processed data within a modelling framework for city-wide prediction of the sound environment^{153,158}. Low-cost audio recording devices²⁹⁹ that can passively monitor the urban sound environment can help fill this measurement gap in other cities¹⁵⁸. Furthermore, recent developments in deep learning sound classification neural networks^{150,151,261,300} and geospatial models are opening up this field of

research on a larger scale. The approach that I took for audio classification and sound type LUR modelling is not without its limitations however, which are discussed in greater detail in *Section 8.4*. The random forest model was not able to accurately predict night-time nature-based sounds above 0% due to the lack of representation of the model training data at levels higher than 0%. In the future, additional audio measurements in targeted nature-based spaces in Accra could be collected, classified, and included in the random forest model to improve the spatial prediction performance.

Environmental epidemiological studies have largely evaluated the adverse health effects of exposure to noise from multiple transportation sources (road traffic, airplanes, rail traffic)^{31,93,94}. However, the adverse health effects of exposure to non-transportation noise sources (e.g., loud outdoor music), have scarcely been evaluated at a large population scale^{22,85,301}. This also extends to the potential health benefits of exposure to tranquil sound environments, such as biotic or nature-based sounds. In this chapter, I showed how data from audio recordings can be combined with geospatial models to predict the different types of sounds prevalent across a city in the day and night-time. Exposure scientists and environmental epidemiologists can leverage the aforementioned approaches to generate city-scale data on multiple parameters of the acoustical environment. This would then allow the inclusion of a rich source of information in future epidemiological studies on the adverse, as well as potentially beneficial, health effects of exposure to different types of sounds as well as their acoustic properties (i.e., loudness, intermittency).

6.5 Summary

As has been demonstrated in this chapter, data from audio recordings can be combined with geospatial models to predict and characterize the spatial and temporal distributions of different types of sounds within an African urban environment in high-resolution. In Accra, predicted road-

transportation sounds were pervasive and generally accompanied with higher sound levels. Predicted music and human speech sounds were more prevalent in high-density residential areas, while animal and insect sounds were most prevalent in outlying peri-urban areas. To further build off of this work, future soundscape research is needed in Accra to understand perceptions and preferences of exposure to different sound types within this context. Perception data is critical for informing local policy making and urban planning efforts to identify the sound sources which are worthy of preservation, and those which should be regulated and mitigated.

Chapter 7 Socioeconomic inequalities of the urban sound environment in Accra

7.1 Overview

Inequalities in exposure to environmental pollutants persist between and within cities around the world^{7–13}, and these inequalities can further widen urban health inequalities^{8,9,59,63,67,302}. For decades, environmental justice research in North America and Europe has documented that it is often societies poorest and most marginalized communities which are exposed to environmental risks including proximity to hazardous waste sites, polluting industries, agricultural pesticides, and vehicle and aircraft traffic^{7,54,55,62,63}. These trends extend to the African continent as well^{6,11,12,66,181,303,304}. A limited number of studies from mostly high-income countries have sometimes shown that within-city or region inequalities in exposure to environmental noise were also correlated with socioeconomic factors and race/ethnicity^{13,59,60,71} (further discussion in *Section 2.7*). In this chapter, I conducted an analysis of the socioeconomic patterns of the urban sound environment, including sound levels and types, in Accra Metropolis. This is the first analysis of its kind in a SSA city. The spatial unit of analysis was the enumeration area level (Figure 18), which is the smallest administrative entity in Ghana.

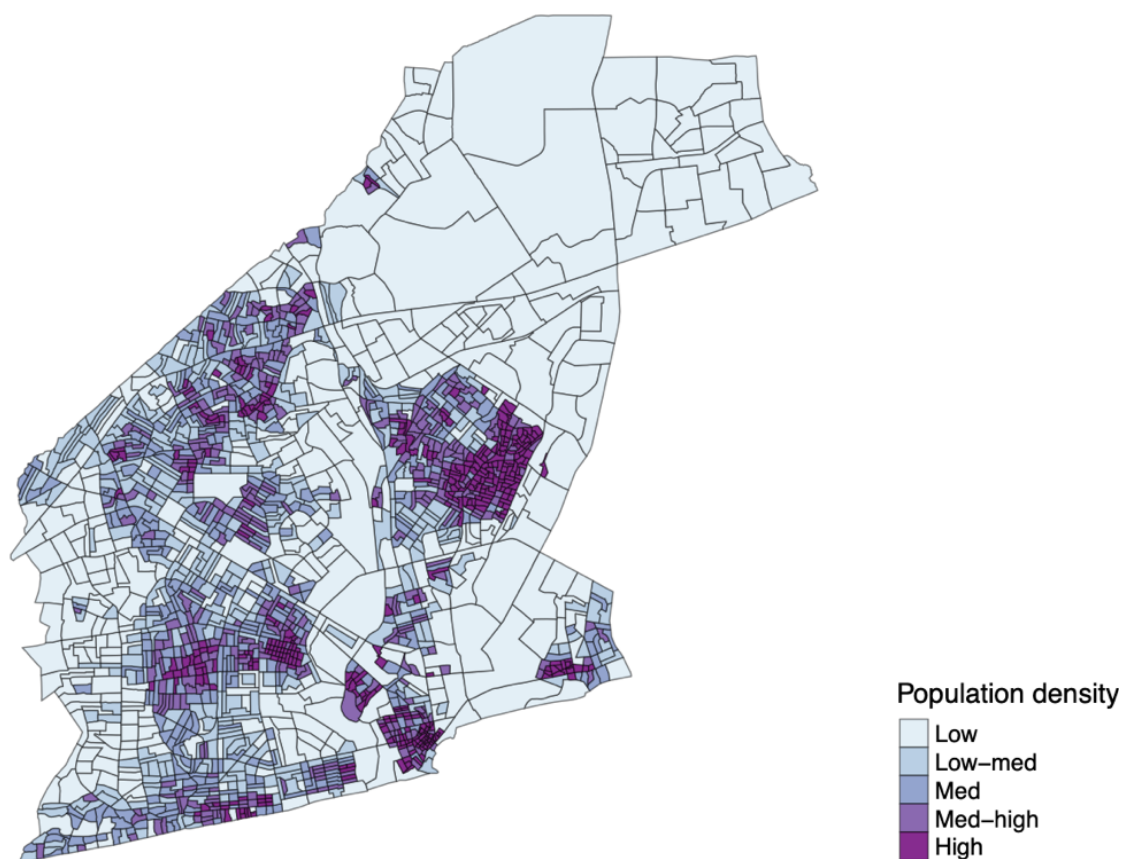


Figure 18. Quintiles of population density (population/km²) within enumeration areas (Average size: 0.03 km², average number of people: 800) in Accra Metropolis (population ~ 2 million in 2019).

7.2 Methods

7.2.1 Socioeconomic status (SES)

Socioeconomic status is not only defined by money, but is also related to opportunity (e.g., employment), access (e.g., healthcare, education), security, empowerment (e.g., who has a voice), and living environments and quality of services (e.g., healthcare, education)⁵⁶. Measures of consumption levels (\$) ^{305,306} and inequalities in consumption may be a cause of, and/or a result of, physical and social environments, opportunities, access, security, and empowerment within households and communities. Importantly, consumption is a reflection of what people can afford and can access. SES can also be operationalized as education (any or level), employment prestige, and social standing, for example. For this analysis, I used consumption levels, post-secondary

educational attainment, and unemployment as measures of SES, with the former being the primary measure, aggregated at the enumeration area level.

7.2.2 Data

The data and modelling methods for sound levels and sound types are described in detail in Chapters 4-6. For this analysis, I use the predicted surfaces of L_{den} (dBA) and L_{night} (dBA) and the prevalence of identified road-transport, animal and insects, music and human speech sounds in the day- and night-times (average percentage of time present (%)) from the LUR models (Chapters 5-6).

The creation of small area-level measures of SES in Accra was led by my colleagues on the *Pathways to Equitable Healthy Cities (Pathways)* project (<http://equitablehealthycities.org/>) and is described in detail in a previous report³⁰⁷. In brief, my primary measure of SES was median log equivalized household consumption (Ghanaian Cedi (GH¢)) within each census enumeration area (EA). Household consumption was derived from total annual real household expenditures including rent captured within the 2012-2013 Ghana Living Standards Survey (GLSS) (93% response rate) (list of expenditures in Appendix Table A11). Equivalization is a way to account for the economies of scale in household consumption; *Pathways* colleagues used a method which weights by the square root of household size. To then estimate median household consumption within all EAs in the GAMA, *Pathways* colleagues combined the GLSS with the 100% sample of the most recent census (2010) in small area estimation models^{308,309} which derived relationships between median household consumption, area and other factors such as asset ownership, education, employment, housing quality, and sociodemographics (full list of variables in Appendix Table A12). As secondary SES measures, I used census data on the number and percentage of individuals within each EA with post-secondary education (education measure) and the number and percentage

of unemployed individuals within each EA (unemployment measure). These measures are aggregates of household level SES, individual education and unemployment, summarized at the enumeration area-level, and represent proxies for area-level SES measures.

7.2.3 Analysis

I conducted this analysis for Accra Metropolis, the capital city and the most populated area in the GAMA. Within each EA, I calculated the average L_{den} and L_{night} (dBA) as well as the average prevalence of sound types (%) in the day and night. Given the high prevalence of road-traffic sounds in all areas of Accra Metropolis in the day and night-time (Table 13; Figure 15), I herein refer to L_{den} and L_{night} exposures and inequalities as ‘noise’ within this Chapter. I estimated Pearson correlations between EA SES metrics with noise levels and sound type prevalence. I then summarized the distributions of EA noise levels and sound type prevalence across quintiles of EA SES metrics (5 groups, 20% of EAs in each group) (Figure 19). I investigated whether differences between groups were statistically significant using difference-in-means tests with a p-value cut-off of <0.05 . Distributions within each group were checked for normality. Of note is that the datasets used to estimate consumption levels were independent of the data used to predict noise levels and sound types.

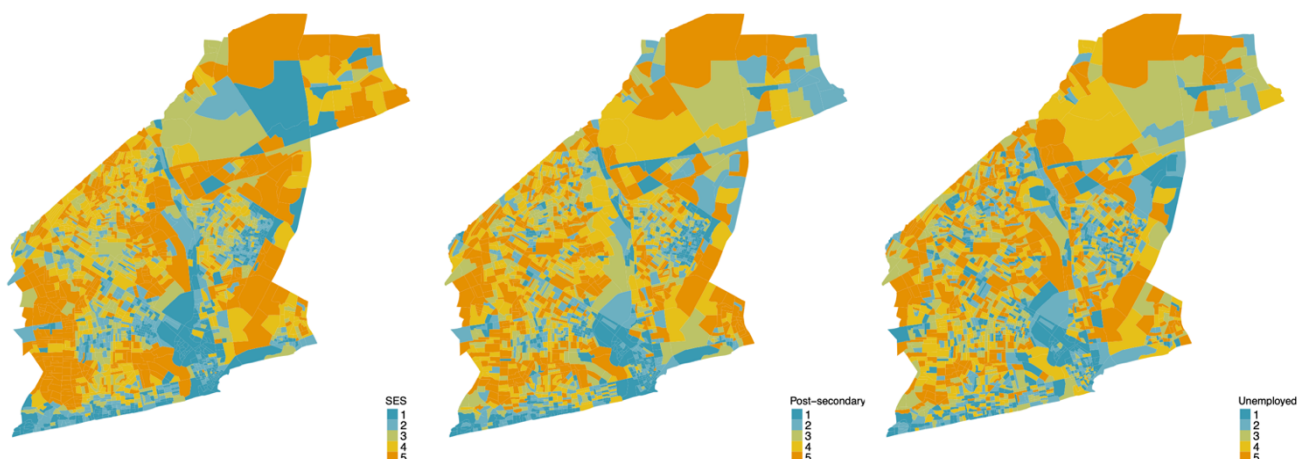


Figure 19. Spatial distribution of enumeration area (EA) socioeconomic status (SES, based on median household consumption), number of individuals with post-secondary education (post-secondary) and number of individuals unemployed (unemployed) in Accra Metropolis. SES measures are colored based on quintiles of the distribution. A value of 1 represents the lowest quintile along the distribution (e.g., low SES, low numbers of individuals with post-secondary education), and a value of 5 represented the highest quintile along the distribution.

7.3 Results

With data from the most recent national census and the Ghana Living Standards Survey, the median number of individuals and households within EAs in Accra Metropolis was 801 people and 225 households. EA median log equivalized household consumption was normally distributed across EAs in Accra Metropolis, with a median of 8.92 (IQR: 8.81, 9.01). The average and median number of individuals with post-secondary education in each EA was 16 and 13 people, respectively, though the distribution was highly skewed (min: 0 people, max: 128 people). EAs had on average 33 people unemployed, though the distribution was also skewed (min: 0 people, max: 178 people).

There was an inverse relationship between EA noise levels and SES (median household consumption) in Accra Metropolis (Table 14). The poorest EAs (bottom 20% of SES distribution) had statistically significant ($p < 0.01$) higher L_{den} and L_{night} compared with the wealthiest EAs in the top 20% with a stepwise gradient for EAs in between. There was a difference of ~ 3 dBA between the mean and the median EA L_{den} levels for the EAs in the highest and lowest SES quintiles (Figure

20). Even within the same wealth quintile, there were considerable inequalities in noise level exposures. For example, within the same SES quintile, there was a 6-7 dBA difference for L_{den} levels between EAs at the 10th and 90th percentiles of the distribution.

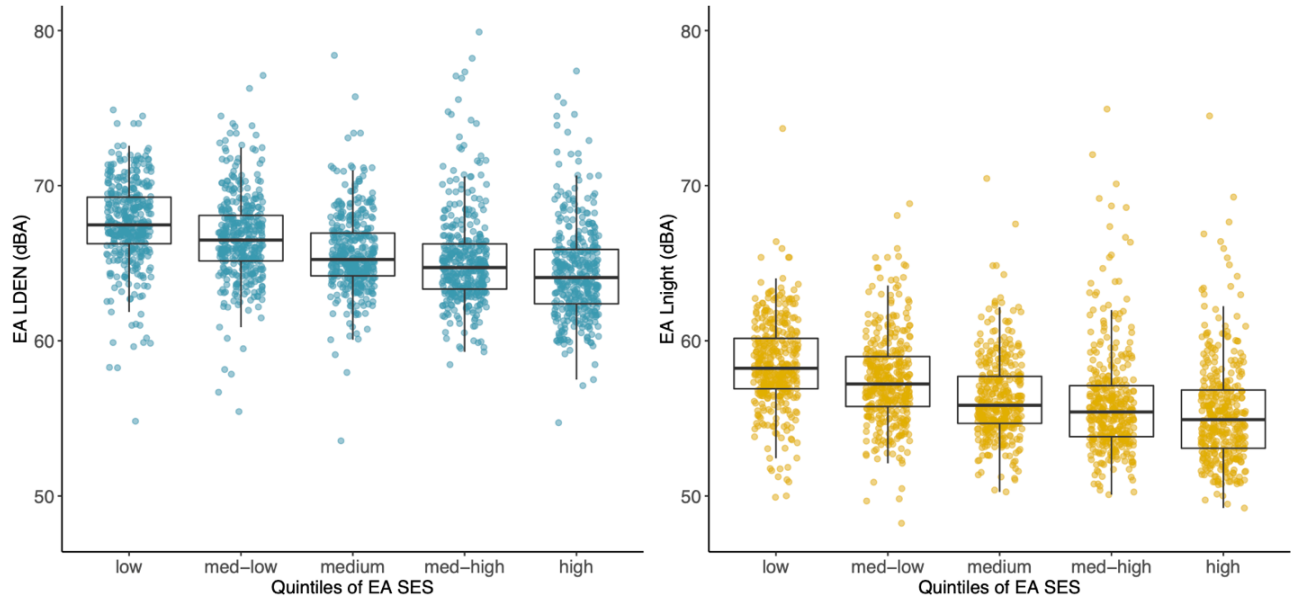


Figure 20. Distribution of enumeration area (EA) L_{den} and L_{night} across quintiles (20% increments) of EA socioeconomic status (SES) in Accra Metropolis.

SES: EA median log equivalized household consumption. The upper and lower limits of the black box represent the interquartile range of the distribution and the horizontal line within the box represents the median. Each colored point represents an EA average sound level (dBA).

While higher SES EAs generally had lower L_{den} and L_{night} levels, a few EAs were outliers. Four EAs with mid-high or high SES had L_{night} above 70 dBA. These small EAs were all along major highways and overpasses, receiving high levels of road-traffic exposure. Conversely, the three low SES EAs with L_{night} less than 50 dBA encompass a fishing community and are found along the ocean front.

There was an inverse, but weaker, relationship between sound levels and the number and percentage of individuals with post-secondary education (Table 14). Specifically, there was a difference of ~ 2 dBA between the mean and the median EA L_{den} levels for the EAs in the highest

and lowest post-secondary quintiles. The weakest relationship was found for the number and percentage of unemployed individuals within each EA (Table 14).

Table 14. Correlation of enumeration area (EA) predicted noise levels and sound type prevalence with socioeconomic status metrics in Accra Metropolis.

Table shows Pearson correlations and 95% confidence intervals around estimates.

	Median log equivalized household consumption (primary SES metric)	Number of individuals with post- secondary education*	Number of unemployed individuals*
L _{den} (dBA)	-0.34 [-0.37, -0.30]	-0.25 [-0.29, -0.21]	-0.16 [-0.20, -0.12]
L _{night} (dBA)	-0.32 [-0.36, -0.27]	-0.24 [-0.28, -0.19]	-0.15 [-0.19, -0.11]
Road-transport sounds - day (%)	-0.16 [-0.20, -0.12]	-0.06 [-0.10, 0.01]	-0.01 [-0.06, 0.03]
Road-transport sounds - night (%)	-0.20 [-0.24, -0.15]	-0.14 [-0.19, -0.09]	-0.08 [-0.12, -0.04]
Animal and insect sounds - day (%)	0.37 [0.33, 0.41]	0.24 [0.20, 0.29]	0.14 [0.09, 0.18]
Animal and insect sounds - night (%)	0.22 [0.17, 0.26]	0.16 [0.12, 0.20]	0.09 [0.05, 0.13]
Music sounds - day (%)	-0.40 [-0.44, -0.36]	-0.25 [-0.29, -0.21]	-0.18 [-0.23, -0.14]
Music sounds - night (%)	-0.33 [-0.37, -0.29]	-0.19 [-0.23, -0.14]	-0.11 [-0.16, -0.07]
Speech sounds - day (%)	-0.44 [-0.47, -0.39]	-0.31 [-0.35, -0.27]	-0.20 [-0.24, -0.16]
Speech sounds - night (%)	-0.33 [-0.37, -0.29]	-0.26 [-0.29, -0.21]	-0.14 [-0.18, -0.09]

* The percentage of individuals with post-secondary education within each EA were similarly negatively correlated with L_{den} (r: -0.22) and L_{night} (r: -0.20). The percentage of individuals unemployed were not correlated with L_{den} (r: -0.07) and L_{night} (r: -0.07). Person correlations with sound type prevalence were similar to results in table above.

Enumeration area SES based on household consumption had a positive correlation with the prevalence of music and human speech sounds (Figure 21, Figure 22), with highest SES's having significantly lower median levels of music and human speech sound prevalence's compared with all other SES quintiles (p<0.01). The prevalence of music and speech sounds were also negatively correlated with the number and percentage of individuals with post-secondary education. There was a weak negative correlation between the EA prevalence of road-transport sounds and SES (household consumption), reflecting the overall pervasiveness of this type of sound in the city. The prevalence of animal and insect sounds were positively correlated with SES (household consumption) and the number and percentage of individuals with post-secondary education more strongly in the daytime compared with the night-time.

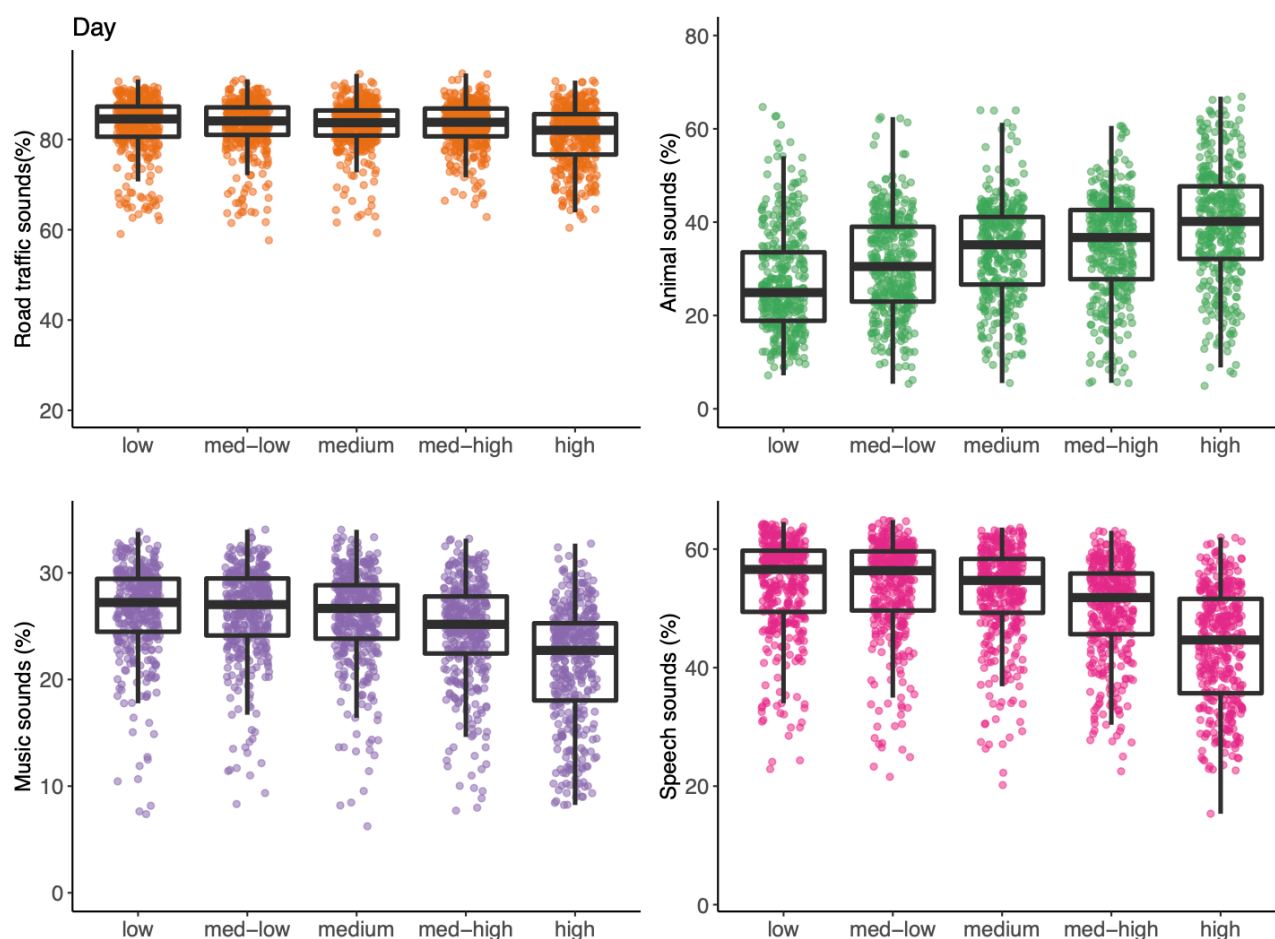


Figure 21. Distribution of enumeration area (EA) road-transport, animal and insect, music, and speech sound prevalence (%) across quintiles (20% increments) of EA socioeconomic status (SES) in the Accra Metropolis during the daytime.

SES: EA median log equivalized household consumption. The upper and lower limits of the black box represent the interquartile range of the distribution and the horizontal line within the box represents the median. Each colored point represents an EA sound type prevalence.

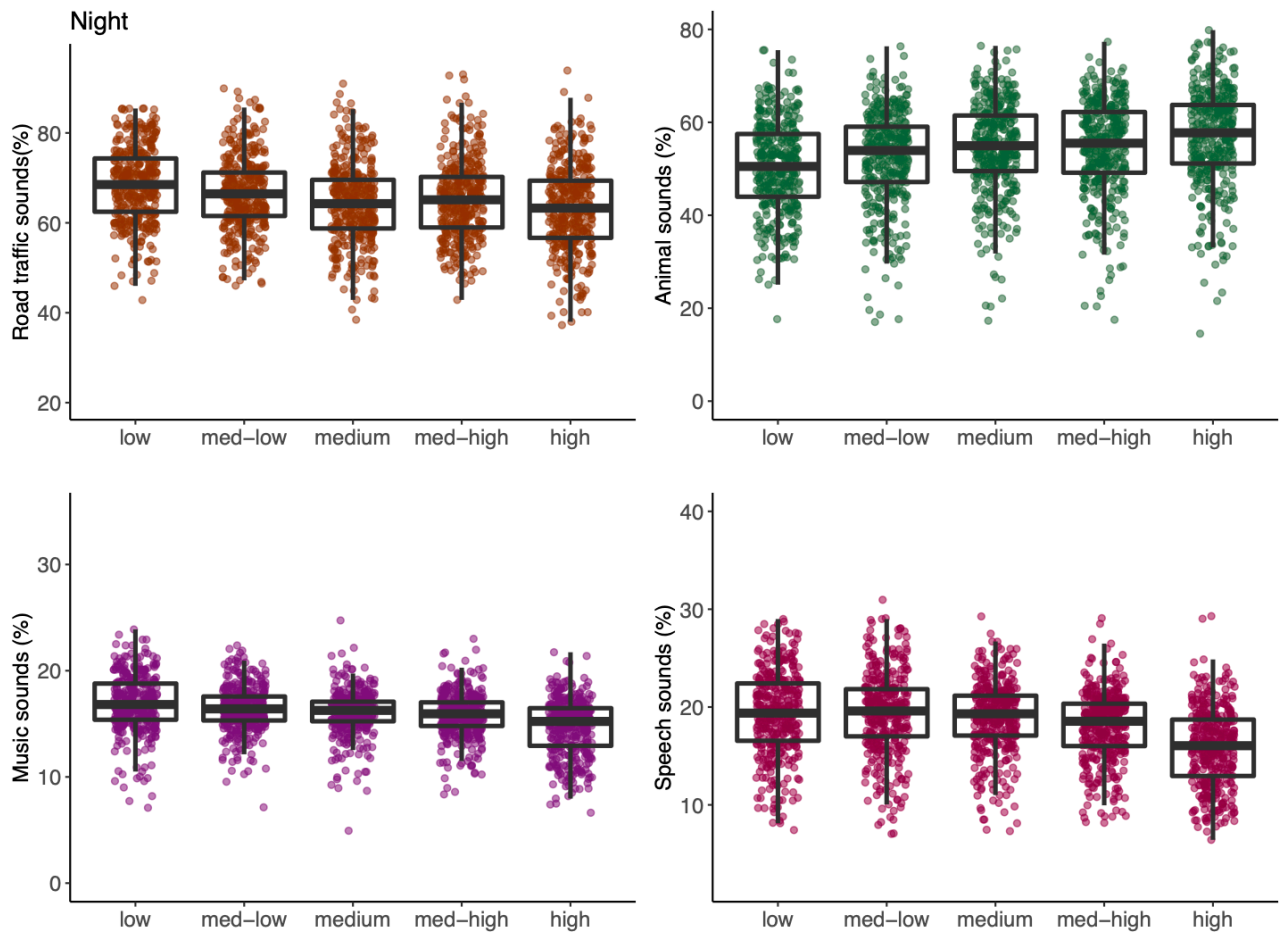


Figure 22. Distribution of enumeration area (EA) road-transport, animal and insect, music, and speech sound prevalence (%) across quintiles (20% increments) of EA socioeconomic status (SES) in the Accra Metropolis during the nighttime.

SES: EA median log equivalized household consumption. The upper and lower limits of the black box represent the interquartile range of the distribution and the horizontal line within the box represents the median. Each colored point represents an EA sound type prevalence.

7.4 Discussion

In Accra, the lowest SES EAs had higher median L_{den} and L_{night} noise levels compared with their wealthier counterparts, based on household consumption. This trends was also found in previous studies from Europe, North America, and Hong Kong (China) where SES measures were derived from material income or deprivation indices^{59,60,71,176}. Furthermore, EAs with a larger population who obtained a level of higher education generally had lower noise levels, which may reflect both income and behavioral factors. A similar result with education was found in a study in Montreal Canada⁶⁰. Though this relationship had mixed results among studies with individual-level data in

Europe¹³. There was a weak correlation between EA noise levels and the number of individuals unemployed, that was additionally not in the expected direction. This weak correlation was further diminished when the metric was transformed into the percentage of individuals unemployed. It is possible that area-level unemployment in a city like Accra does not reflect the same socioeconomic characteristics as what is conventionally considered in Western countries.

Enumeration areas with the lowest SES (consumption) and number of individuals with post-secondary education generally had higher prevalence of human speech and music sounds. In Accra, the highest density neighborhoods in terms of human, building, and activity density, are also often the poorest areas (Figure 18)^{310,311}. The negative association between road-transport sounds and SES, albeit weak, can be partly explained by the fact that a higher percentage of low SES EAs are situated near a major road/highway (13%) compared with the highest SES EAs (5%). Though the strength of the association likely reflects the general pervasiveness of road-transport sounds in Accra Metropolis (Figure 15), which was also confirmed in our analysis of street view imagery collected in Accra²⁵⁵. Though it could also be affected by the detection of sounds within the audio clips, which does not distinguish between the number of sources of the same type (e.g., 1 car vs 5 cars) or loudness. Therefore, it is likely that the negative SES association seen with noise levels (Figure 20) may be a better reflection of the magnitude of road-transport noise exposure, in addition to other loud street sounds (e.g., music, human activity). Finally, the EAs in the highest SES quintile had higher median animal and insect sound prevalence's compared with lower SES EAs. As many of the detected animal and insect sounds are nature based (i.e., wild birds) and they rely on vegetation and trees as natural habitat, this association could be supported by the higher availability of green spaces within these EAs along with a higher proportion of personal residences that can accommodate private gardens^{249,312}. Notably, average NDVI, a measure of the abundance

of green vegetation, was 2-fold higher in EAs in the highest SES quintile compared with EAs in the lowest.

7.5 Summary

Chapter 7 presented the first study on SES inequalities of the urban sound environment in SSA. In Accra Metropolis, EA L_{den} and L_{night} noise levels followed a socioeconomic gradient based on multiple SES metrics, particularly for consumption levels and higher educational attainment. The lowest SES EAs also had the highest prevalence's of music and human speech generated sounds. In the highest SES EAs, animal sounds, which may be considered a desirable soundscape (e.g., birdsong), were more common compared with the lowest SES EAs. It is possible that inequalities in exposure to the urban sound environment, compounded with socioeconomic inequalities, could impact health inequalities in Accra.

Chapter 8 Discussion and conclusion

8.1 Summary

I modelled and characterized the spatiotemporal patterns and socioeconomic inequalities of the urban sound environment in Accra, Ghana. I first implemented a large-scale 1-year campaign (Chapter 3) to collect measurements of sound levels, audio recordings, and other environmental features. I descriptively and graphically characterized measured sound levels, sound intermittency, and the prevalence of different sound types across spatial, land use, and temporal strata (Chapter 4). I then combined measurements with geospatial data to model and predict sound metrics and sound types across the GAMA in high-resolution with LUR models (Chapters 5 and 6). Finally, I examined whether characteristics of the urban sound environment were patterned across the city by socioeconomic factors (Chapter 7).

Road traffic noise was pervasive, particularly in Accra Metropolis. However, mixtures of different sound types were prevalent in specific places and times of the day, such as music and human speech sounds in high-density residential neighbourhoods during the daytime. Measured and model predicted L_{den} and L_{night} levels surpassed local¹ and international² guidelines almost everywhere in the GAMA. Lower SES EAs, based on consumption and education, generally had higher L_{den} and L_{night} compared with their wealthier counterparts. Furthermore, louder and intermittent sounds were predominantly located within high-density lower SES neighbourhoods. Lower SES neighbourhoods in Accra Metropolis also generally had a lower prevalence of biotic sounds (animals and insects) during the daytime. Finally, large reductions in urban sound levels were observed during periods of extreme disruption and change, such as during the COVID-19 pandemic lockdown of the city and the 1-month *Homowo* festival.

8.2 Impact and implications for public health and policy

The protocol I designed for urban sound, audio, and imagery measurement in Accra can serve as a guide for scaling up similar campaigns in other SSA cities and thus help fill the gap in city-wide noise pollution research in the region²⁴⁸. The specific approach, including the systematic selection of instruments (e.g., battery and memory capacity, durability, accuracy/precision), site installation, and the custom design of the weather protective enclosure, ensured the collection of high-quality data within the unique West African urban environment. I also showed that short-term measurements could generally represent longer-term averages in Accra. Therefore, it is plausible that the current protocol could be lightened with regard to monitoring durations in future campaigns in other SSA cities with similar source profiles. However, given the presence of some days with outlier sound levels, my results do indicate that multiple measurements at the same location across several days may still be warranted in this setting. The 1-year Accra campaign provides what is currently the largest dataset of urban sound levels and sources within SSA and can support future environmental epidemiological research and local environmental decision-making processes in Accra.

Local governments have powers and resources to alter built and information environments and use regulation to reduce environmental pollution^{31,272,313}. Local governments can also promote healthy environments through the protection and implementation of places with such qualities, such as the construction or revitalization of parks and natural spaces. As such, the detailed information that I gathered on the urban sound environment, and their spatial and temporal patterns, will be of interest to regulators, policy makers, and the general public in Accra. In SSA cities, such as in Accra, there is scarce data on environmental noise to stimulate and inform policy. Also, in such settings, the determinants and variations of noise may differ from other places of the world, as was shown for other environmental pollutants like air pollution^{314,315}. Thus, understanding and characterizing the

patterns and sources over space and time provides new information and data to guide policy and public health decision making in this understudied setting. I found that measured and modelled sound levels largely surpassed local and international guidelines, and road-transportation was the predominant source of sound. At these levels, it is likely that common health impacts of exposure to road-transport noise, such as annoyance, sleep disturbance, and IHD are experienced among the population in Accra. However, environmental noise can be reduced in Accra, as was seen through the widespread reductions in measured ambient sound levels during the COVID-19 lockdown and during the 1-month ban on noise making leading up to the *Homowo* festival (in high-density residential locations). While the city-wide lockdown during the pandemic does not serve as a realistic framework for how noise can be reduced in the city - as the lockdown came with economic hardship and isolation for many of the city's citizens - it serves as an example of the opportunities available for urban sound reduction in Accra.

Classification of audio recordings (Chapter 4) and results from the LUR models (Chapter 5 and 6) revealed that road-transportation was an important and pervasive source of noise in Accra, affecting almost all communities. Interventions to reduce road-traffic noise can take on many forms, including vehicle emissions reduction (e.g., modifications to engines and tire materials), land use planning (e.g., separation between road and buildings), transport management, modification or creation of noise barriers or vegetation^{199,284} and behavioral change interventions (i.e., ban on horns/honking)^{200,201,316}. In Accra Metropolis, 20% of roads (mostly minor) are still unpaved, particularly in the poorer neighborhoods³¹⁷; thus modifying pavement material^{199,202} could potentially curb some road-transport noise, particularly at higher speeds. Noise barriers are common along highways in many places of the world, though often unfeasible measures on city streets. Noise barriers may have adverse economic impacts on people who rely on access to commuters for informal road-side commercial activities, as is the case in Accra. As well, given the

dominance of transport by private vehicles, the Accra government could consider changes to urban design and infrastructure (e.g., sidewalks), placement of key services, safety measures (e.g., separate bike lanes), pricing (e.g., congestion zones) and public messaging that inspire modal shifts towards cycling, walking and mass transit, as a mechanism to reduce traffic volume and thus noise in the city³¹⁸. Successful examples of this include the large increases in bike share trips observed in Bogota (Columbia), Barcelona (Spain), Paris (France) and Berlin (Germany) following the construction of bicycle facilities and sharing programs³¹⁹. As well in Paris, the planning of the ‘15-minute city’ encourages active transportation by making key services assessable and walkable and through the re-purposing of street space for pedestrians and cyclists³²⁰. These aforementioned interventions also have co-benefits for air pollution reduction, climate change (reduction in climate forcing pollutants) and an increase in physical activity^{205,318}. Currently, noise reduction from road transport is not prioritized by local policy actions in Accra. Though, recent measures to curb air pollution from motor vehicles in Ghana, such as the regulation and taxes imposed on the import of old (and often noisy) vehicles into the country, may have an indirect impact on noise by upgrading the vehicle fleet on the road.

Historically, the focus in Europe and North America has been on the characterization, regulation, and mitigation of noise from road, rail, and aircraft transport^{2,321,322}. By extension, epidemiological research and international noise guidelines have also largely focused on the adverse health effects of exposure to transportation-related noise^{2,33,93,94,268}. However, in many cities around the world, transport-noise often coexists with street noise from human and other mechanical activities, such as construction works, formal and informal industrial activities, bars and restaurants, road-side commercial activities and even loud, pervasive music from religious activities^{21,22,25,27,78–81}. In Accra, I found that there is a diversity of sound environments, with mixtures of sources varying in space and time, as illustrated in Chapters 4-6. Though the distribution of these sound types was not

always equitably spread across the city; outdoor music sounds for example was most often detected in high-density residential locations, co-occurring with high recorded sound levels. Therefore, meaningful reductions in environmental noise will likely only be achieved from a multi-source approach and engagement of multiple government sectors, institutions, and community and religious groups ³²³. Furthermore, the process I took to quantify the prevalence of a variety of different types of sounds at city scale through the combination of audio recorders, a neural network, and land use regression modelling, can be used to support, and be incorporated in, future epidemiological noise and sound environment research elsewhere.

From my audio recordings, I found that outdoor human speech and music sounds were most often detected in lower SES, high-density residential locations, which may have been generated, among other sources, from religious activities. In Accra, religious activities can generate high-levels of outdoor human speech and music sounds and has received local and international press attention as a source of noise pollution, particularly for people living in residential areas nearby^{20–22,25}. Enforcement of noise from religious activities has proven to be difficult as cities need to monitor thousands of places of worship^{21,22,25,164} that can range from small informal activities on the side of the road to mega congregations²¹. Furthermore, policy makers need to carefully balance considerations around religious freedom of expression and infringement of public order and public health²². Some SSA cities have tried to enforce the removal of external speakers from religious buildings and building codes for soundproofing²¹.

Urban sounds can be created and enhanced in such a way that they can be a resource for improving public health in outdoor and indoor spaces. Importantly, nature and animal sounds (e.g., often birdsongs) have been linked to enhanced feelings of wellbeing and markers of stress reduction in experimental studies^{117,119,183,324}. In Accra, identified nature and animal sounds were classified

most often in quieter peri-urban and medium/low-density residential areas in the GAMA (Chapter 4 and 6), as well as in higher SES EAs in Accra Metropolis (animal sounds only) (Chapter 7). These areas also typically had a higher density and availability of green vegetation (Appendix Table A2, Section 7.4). Vegetation can facilitate tranquil/desirable sounds as providing a habitat for birds (typically tall trees) as well as be a source of sound itself (e.g., rustling leaves). Vegetation can also reduce noise from other sources in the surrounding environment by acting as a natural attenuator through absorption and diffusion¹⁹¹. In Chapter 5, I found that NDVI, which is a measure of green vegetation abundance, was consistently and significantly negatively associated with sound levels in the Accra LUR models. In previous studies, it had been demonstrated that tall trees with dense foliage and a depth of 15-40m can offer noise attenuation of around 6-8 dB at both low and high frequencies³²⁵. Urban planners in Accra can consider ways to increase and enhance natural and vegetated spaces within the city, particularly in the urban center, by ‘greening’ the streets with trees or protecting and increasing public parklands which can be home to birds and other animal species.

The spatial and social inequalities in neighbourhood sound environments in Accra further highlight the need for local government to consider the equity impacts of urban planning and policy decision making. Improvements in the sound environment in Accra will, on average, most likely provide a population health benefit. However, attention must also be paid to improving the lives of those who are most affected and vulnerable. In the case of Accra, communities with the highest noise level exposures were also the most socioeconomically disadvantaged and burdened by other unhealthy environments¹², including air pollution^{11,66,326}.

8.3 Strengths and novelty

My thesis depicts a large-scale and comprehensive characterization of the urban sound environment in a SSA city. The combination of fixed (10 sites for 1 year) and rotating (136 sites for 7 days) monitoring sites allowed for the assessment of both the temporal and spatial variability of urban sound and sources in Accra, Ghana, and comparison of measured levels with other cities/regions around the world. The campaign produced millions of sound level and audio records covering every hour of the day, day of the week, and month of the year at diverse locations in the city. My systematic selection of monitoring equipment that were cost-effective, energy-efficient and battery powered, lightweight, and socially unobtrusive optimized data collection and was less labour intensive in a setting with unreliable electricity. In addition, the ruggedness of the equipment and the design of the equipment enclosure ensured that the instruments could collect high-quality data while surviving the climatic elements in West Africa which include hot and humid climate, seasonal torrential rains, and Harmattan dust storms.

In Chapter 4, my estimates of the intermittency ratio, in addition to the more commonly reported energy average metrics (i.e., LAeq), provided a broader picture of the characteristics of the urban sound environment in Accra. The application of a deep learning neural network to my outdoor audio recordings, achieving accuracies between 76-93%, also provided the first city-scale information on the spatiotemporal patterns of a diversity of sound types in a SSA city.

The LUR models of sound metrics in Chapter 5 and sound types in Chapter 6 included a variety of geospatial covariates covering land use features, vegetation, traffic related information, population and building densities, and locations of human activities. The models also accounted for temporal structures within the sound level, IR and sound type data through stratified day and night-time models and random effects to account for correlations across temporal strata. While previous sound

level LUR studies modelled energy average metrics (i.e., LAeq), I additionally modelled the sound intermittency as this characteristic is an important determinant of noise annoyance and is associated with health outcomes, such as sleep disturbance^{173,174}. Modelling sound types at city scale using audio recording classifications and LUR models, is to my knowledge, the first attempt to do so in any study. The use of Random Forest modelling techniques ensured efficient and accurate prediction of many of the sound types.

The analysis in Chapter 7 represents, to my knowledge, the first characterization of socioeconomic inequalities of the urban sound environment in a SSA city. Strengths include (i) using socioeconomic data from the 100% sample of the most recent census, the (ii) diversity of socioeconomic factors evaluated and the (iii) representations of the urban sound environment evaluated by SES, including levels and sound types.

8.4 Limitations

8.4.1 Measurement campaign

As discussed in Chapter 3, data collection was limited by some factors that reflect logistical realities of conducting field research. For example, some trade-offs between ideal and actual measurement site locations were inevitable to accommodate factors such as sites located within restricted areas (airports, military barracks/zones), site safety and accessibility, and property owner's reluctance to provide a space for the equipment. Furthermore, even with advances in measurement and sensor technology, human resources were still needed for site identification and preparation, data download, and equipment maintenance. In such a large-scale campaign as this one, the monetary and time cost was nontrivial. I used affordable SLMs so that I could purchase enough units to conduct detailed spatial and temporal analysis, though I was limited in that I could not conduct a detailed frequency analysis as is done with more sophisticated, higher cost instruments. This is an

area warranting future work in SSA cities. Finally, the data collection campaign was interrupted due to the disruption that the COVID-19 pandemic caused, which resulted in 12 additional sites to be sampled a month after the lockdown lifted (May-June 2020). Though, I expect the measurements at these 12 sites to represent normal conditions as analysis of sound levels from fixed sites showed that measured sound post-lockdown returned to pre-lockdown levels (Figure 10).

8.4.2 Capturing urban audio recordings

As described in Chapter 4, for storage and privacy reasons, I collected 10-second audio clips every 10-minutes (i.e., 6 times in an hour, every day for a week or almost a year). I thus had to make the assumption that the systematic temporal sampling strategy provided an adequate representation of the underlying distribution of sound type frequency over time³²⁷. Furthermore, my approach to identifying sound types through the collection of urban audio recordings may not be feasible in all research settings with different privacy frameworks and laws.

8.4.3 Audio classification of sound types

The different types of sound classes which are identified in each audio recording by the neural network is partly a function of how *clear* the recording is; how *loud/prominent* the specific sound is in the recording; but also the neural network itself and the unique nature of the training dataset. It is also the case that sometimes sound types are not identified within an audio recording because they are masked by other sounds (e.g., road-traffic masking out sounds of rustling leaves). However, I believe that masking effects do not have a major impact on the descriptive (Chapter 4 results) and modelled prevalence's (Chapter 6 results) across space and time for the following reasons: The accuracy of the neural network based on human labels was good - between 76%-93% for road-traffic, animals and insects, human speech, and music – and the relatively small percentage of non-accurate labels could be from either masking or misclassification; also the spatial patterning

of sound sources that were identified visually from analysis of time-lapse camera imagery collected at the same locations²⁵⁵ largely followed the same patterning found with audio analysis. Finally, I was interested in those sounds which were clearly identifiable by the network, and supposedly by the human ear also, as I believe that that more accurately reflects the human experience of the sound environment at each place and time.

8.4.4 Land use regression modelling

The LUR models, described in Chapter 5 and 6, have several limitations worth mentioning. While I did utilize a wide variety of spatial predictor variables, I was not able to obtain spatially and/or temporally resolved information on traffic flow, volume and fleet composition. Inclusion of this information could have improved model predictive accuracy, particularly from traffic-related sources. Further, I was not able to capture and characterize potential small-scale variations in sound propagation due to sound reflection or absorption in the built environment as I did not have data on building height, building material or ground material citywide²⁸⁴. I also made the assumption that the spatial predictors were stationary in time and representative of the period when the sound measurements were taken. This assumption may not be true for all spatial predictors as the census data which was used to estimate population counts was generated in 2010 and the dataset used to estimate land cover dates to 2014. The temporal misalignment of some of the predictor variables may be especially relevant for an urbanizing area such as the GAMA and particularly its peripheries.

The predictive accuracy of my day-time IR model (Chapter 5) was moderate, and the night-time model was low. The challenge of modelling a metric, such as the IR, with predictor variables that are temporally static, makes it difficult to capture intermittency which is inherently more random over time. Predictors which varied in both time and space may have allowed the capture of sound

intermittency better. Furthermore, the medium-low predictive accuracy of the IR models could be due to the measurement of the metric itself. I calculated IR with SLM data integrated every minute; thus, I would have lost some sound events/peaks in the integration.

Like any classification problem, how the presence and absence of different types of sounds are defined within each audio recording has an impact on the observed prevalence's in the raw data, as well as LUR model predictions (Chapter 6). The neural network acoustic classifier that I used provided the top 5 identified sub-class sound classes within each audio recording, ranked based on their probabilities of presence within the audio file (*Section 4.3.2*). This then leaves open to interpretation which sound classes, of the top 5, should be retained and classified as present. For the LUR modelling and prediction, I retained all 5 sound classes within each audio file. However, as a sensitivity analysis, I built LUR models and generated predictions for alternative definitions of presence within each audio file, specifically: the top 3 sound classes and sound classes with neural network probabilities exceeding a fixed cut off. The overall levels and spatial patterns of the prevalence's of sound types in the raw data, and LUR predictions, were slightly different but very similar when I defined presence as being in the top 5 compared with the top 3. The levels and patterns differed more when I compared retaining the top 5 with setting a fixed probability cut off of 0.25.

Furthermore, with regard to the sound type LUR models (Chapter 6), as I only collected 6 10-second audio recordings each hour at each site, the temporal measurement resolution was too limited to summarize and model the data at the hourly level for each date, as was done with the sound level models (Chapter 5). Therefore, I aggregated the sound type data for the day (06:00-21:59) and night-times (22:00-05:59) to achieve more stability in the estimates using a larger sample size of audio recordings (day: 96 recordings; night: 48 recordings). I thus could not model

and predict the hourly spatial patterns, which are shown descriptively in Chapter 4. As well, Random Forest models do not have random effect structures which could account for temporal correlation of repeated measurements (across days) at each site; therefore, I averaged the daily estimates for each site, thus building purely spatial models. If spatial patterns are time dependent (e.g., day, month), this would not be captured in the annual average spatial prediction maps. Though in the initial stages of model building, I fitted sound type LUR models with data aggregated at the daily scale and included ‘day of the week’ and ‘month’ as predictor variables. I found no improvement in model fit when those variables were included versus excluded from the models.

8.4.5 Estimating population exposures and socioeconomic inequalities of the urban sound environment

My analysis was at the aggregate EA level, representing a proxy of area-level SES, and I recognize that associations at the individual level may be different. There is also a temporal misalignment between the noise level, sound type prevalence, and the SES data; I used SES metrics estimated from the 2012 GLSS and the 2010 census as they were the most recent data of its kind, though the SLM and audio data were collected in 2019/2020. It is possible that the spatial distribution of SES in some parts of the GAMA, based on consumption, education, and unemployment metrics, differ to present day realities (2019/2020). Though I expect this to be minimal in the city core (Accra Metropolis) where I conducted the SES analysis, as the major changes to within city migration, land use, and urban planning, are taking place at the peripheries of the GAMA²³⁹. Furthermore, while the absolute levels of SES change over time, the spatial patterns are likely to do so more gradually. Future work incorporating the 2020 census is warranted to verify if trends have remained the same or changed. The 2020 census was delayed due to the COVID-19 Pandemic but may be completed and data released in a few of years.

8.4.6 Comparison to international guidelines

Finally, I recognize that I made comparisons to a road-traffic-specific noise guideline in Chapters 4 and 5, and while my sound level measurements were collected along the roadside, and road-traffic dominated as a prevalent sound source, the SLMs ultimately captured sound levels generated from a mixture of transportation and community sources. I also recognize the limitation of making a comparison to a guideline produced for a different region of the world (European Region). Notably, while studies which informed the recommendations were from the United States, Australia, and Asia, in addition to Europe, there were no studies from SSA. It is even possible that the exposure-response relationships between road-transport noise and health outcomes may be different among SSA urban populations, and thus the threshold and response for observed health effects might differ from the WHO-European guidelines; possibly as a result of heterogeneous characteristics of road-traffic, such as traffic composition (e.g., older vehicle fleet in Accra²³⁶), road material (pavement vs gravel³¹⁷), road-traffic patterns (e.g., daily road-traffic peaks at 6am in Accra²⁵⁵), and/or societal attitudes towards honking of car horns³²⁸, which would affect noise characteristics beyond dB level, such as frequency and eventfulness. There could also be potential differences due to differences in population sensitivities or perceptions which might modify the associations with road-traffic noise^{34,329}. For instance, studies have shown how perceptions of noise, including road-traffic noise³⁴, can be affected by sociocultural factors and vary across countries/regions. Furthermore, a recent study found that environmental noise sensitivities differed between Swiss and South African adults³²⁹; though this is an area of research which is severely understudied and local epidemiological research in SSA is needed. This point is particularly relevant for noise annoyance, and the WHO recommends using locally derived exposure-response relationships whenever possible when assessing the specific relationships between noise and annoyance for burden of disease calculations².

8.5 Future work

My LUR models used urban landscape and transport predictors which were static in time. Future modelling studies could incorporate highly time-resolved information on sound sources captured within the street-view imagery from the Accra campaign, to potentially explain more temporal variation in the sound data and its contributing sources. In fact, myself and *Pathways* project researchers have already applied objective detection deep learning models to 2.10 million street-view images captured in the Accra Campaign (imagery described in Chapter 3)²⁸³ to identify the spatial and temporal distributions of people (persons and market vendors), large vehicles (lorries, vans, buses and tro tros (local name for minibuses commonly used for public transportation)), small vehicles (cars, taxis and pick-up trucks), two wheelers (bicycles and motorcycles), objects from the market and street vending which are common in African cities (market stalls, umbrellas, cookstoves, cooking pots/bowls, food and loudspeakers), refuse (debris and trash), and animals, at each of the measurement sites. The types of objects we were able to detect in the images, may also be able to explain more localized small-scale sources of sound that are not captured with traditional LUR modelling datasets (e.g., roads, land use), such as the presence of loudspeakers on the street.

I inferred the perceived pleasantness/unpleasantness of different sound types based on the global soundscape literature. However future work needs to be done within a SSA context as sound perceptions can vary across geographies and sociocultural contexts³⁴. Given the growing mobile phone usage in SSA³³⁰, there is potential for citizen science approaches to support future soundscape research in this setting, by using mobile phone applications to gather information on sound perceptions^{115,194}. This information is useful as it can help guide strategic policy making and urban planning in Accra to protect those soundscapes which are most tranquil/pleasant or reduce sound source emissions which are perceived locally as the most harmful/ annoying¹⁹⁴.

Noise epidemiological studies are needed in SSA cities to diversify and strengthen the global literature on this topic. Local research is needed as the nature of noise sources, sensitivities to noise³²⁹, and population perceptions³⁴ may not be exactly the same as in other places, such as Europe, where the vast majority of noise epidemiology evidence is produced. Notably, there is a new birth cohort in Accra which will conduct an epidemiological study on the health impacts of exposure to environmental noise and air pollution, using measured and modelled data from my thesis dissertation. The study will follow mothers and new-borns longitudinally, and capture data on birth outcomes (e.g., low birthweight), self-reported and objective sleep quality measures, annoyance, and blood pressure. Large-scale epidemiological investigations and environmental policy have also largely focussed on the negative aspects of the urban sound environment¹⁹⁴. Therefore, the data and information generated from my thesis dissertation is well positioned to support future population-level investigations in the SSA context on the potential health benefits (e.g., mental health) of different sound environments, such as those with a high prevalence of natural and/or biotic sounds.

Future studies in Accra and other African cities²⁰¹ could treat changes to road-networks, transportation services, and/or transport policies as natural experiments to investigate the potential impacts on noise and health in these settings. For example, Accra attempted, but failed, to implement a World Bank funded Bus Rapid Transport (BRT) system to boost the use of long-distance mass transit and reduce the number of private vehicles on the road. If the BRT system is eventually executed³³¹, a study could investigate its impact on road-traffic noise in the city using quasi experimental research designs. These types of scenario-based studies can have a major impact on influencing policy decisions.

Now with information from my thesis on the proportion of the population exposed to varying noise levels (Chapter 5), and with established exposure response relationships from the literature^{30,93,94,99}, the burden of disease attributable to noise can be estimated in the Accra⁴¹ at the EA level. For example, the percentage of the population estimated to be highly sleep disturbed (%HSD) and annoyed (%HA) can be calculated directly at the EA level. However, baseline information on incidence of IHD is not available at the EA-level to estimate the population attributable risk of IHD. Though the caveat of this approach is that assumptions would have to be made that the population distribution of noise exposure in Accra is entirely due to the distribution of road-traffic noise, as road-traffic exposure response relationships would be used.

Finally, noise is currently not included as an environmental risk factor in the Global Burden of Disease studies (GBD)³³², and thus it's impact on health is under-estimated on a global scale. While burden of disease estimates from road, rail and aircraft noise exposure have been generated for European countries⁷¹ (annoyance, sleep disturbance, IHD, premature mortality, cognitive impairment in children), a major limitation to the inclusion of noise in the GBD studies is the lack of exposure estimates in low and middle income countries. Future research needs to prioritize a scalable approach for generating noise exposure estimates in cities in underrepresented regions such as SSA. While measurements can provide accurate local estimates, their efficient scalability is limited. Though, transportation-based propagation noise modelling is also currently limited in SSA due to the lack of data required for the models (e.g., traffic flows/volume, vehicle fleets, building footprints, building heights, etc). Current research is being undertaken at Imperial College to estimate traffic flow information from high-spatial and temporal resolution satellite imagery. This innovation could prove essential for opening the door to scalable road traffic noise modelling in SSA cities and other LMICs and the eventual inclusion of road-traffic noise in the GBD.

8.6 Conclusion

Like many other SSA cities, Accra is impacted by pollution, including noise pollution. For my thesis, I measured, modelled, and characterized the spatiotemporal patterns and socioeconomic inequalities of the sound environment in the Greater Accra Metropolitan Area. My data collection approach can be applied to other cities in SSA and globally to support noise management strategies and to provide additional characterization for application to epidemiologic studies. My thesis sheds light not only on urban sound levels, which largely surpassed local and international noise guidelines, but also on spatial variations in intermittency and corresponding sound types, which sometimes followed a socioeconomic gradient in Accra Metropolis. Road transport-related sources were the main noise contributor, though mixtures of different types of sounds were present in different places and times of the day. Stronger regulation and enforcement are needed in Accra to ensure that permissible limits, which are in place to safeguard public health, are met. Furthermore, equitable city-level actions and interventions in relation to urban infrastructure (e.g., road-networks, buildings, parks) and services (e.g., transportation) are needed to reduce noise and improve sound environments that could also have broader benefits for health and wellbeing. Lastly, my thesis provided a basis for future research in the city, which should focus on noise epidemiology and soundscape research to provide essential local information on health effects, health burdens, and population perceptions of sound environments in this understudied part of the world.

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Appendix

Table A1. Land use classifications. Images are from Google Street View, Google Earth, and the Accra campaign cameras. (Table and images re-used from my open-access first author publication Clark et al. SR. 2021²²²).

Land use area	Descriptions	Street view and arial images	
Peri-urban ‘background’ areas	Areas with an abundance of forest land, grass land, shrubs, barren lands, water, formal and informal parks. Can have unpaved or paved roads with very low traffic volume. If residential homes exist, there are few. <i>Example areas: University of Ghana hill or the Water Research Institute.</i>	 	 
Medium/ low-density residential areas	Formal residential areas. Roads can be paved or unpaved and double or single lane. Houses can have yards, fences, walls, and/ or driveways and often there is a clear demarcation of where one home ends and another begins. Houses can be sparse or close together and it is mostly residential buildings. <i>Example locations: East Legon, Cantonments, Taifa.</i>	 	 
High-density residential areas	Largely informal residential areas such as shantytowns or slums. Houses often crowded with a high population density (# people/ rooms, e.g., >2 people per room). Narrow, sometimes unidentifiable, paved or unpaved roads. Small building structures with often no clear		

	demarcation of where one home ends and another begins. <i>Example locations: Jamestown, Nima, Old Fadama.</i>		
Commercial, business, and industrial areas	Can be commercial buildings, industrial buildings, government buildings, warehouses, factories, markets, office buildings. Can be along major motorways or highways with generally large buildings. <i>Example locations: Lands Commission.</i>	 	  

The following number of sites fell within each land use category: commercial, business, industrial (rotating: 25, fixed: 3), high-density residential (rotating: 30, fixed: 2), medium/low-density residential (rotating: 52, fixed: 4), peri-urban (rotating: 29, fixed: 1). To provide additional contextual information on the land use areas, and in particular how built up and populated they are, I overlaid the locations of the measurement sites onto city-wide geographic datasets of population density and vegetation in the GAMA (Table A2). Specifically, population density (people/km²) within census enumeration areas was obtained from the most recent Ghana National Population Housing census²⁵². This is the most up to date and reliable record of population distribution within Accra at the small-area level²⁵². I obtained estimates of vegetation by calculating the Normalized Difference Vegetation Index (NDVI) from 30m spatial resolution Landsat 8 satellite imagery collected at the mid-point of the campaign in January 2020. This imagery also had the lowest

amount of cloud cover in the potential set²⁸⁵. NDVI values close to zero indicate no green vegetation (mostly built-up areas), and values close to +1 indicate a high abundance of available green vegetation.

Table A2: Population density and vegetation at measurement sites. Data are summarized as means and standard deviations.

	High-density residential	Medium/low- density residential	Commercial, business, industrial	Peri-urban (background)
Normalized Difference Vegetation Index (NDVI) (value range: 0-1)*	0.09 (0.03)	0.13 (0.04)	0.10 (0.03)	0.22 (0.06)
Population density (people/ km²)	35,833 (42,011)	6,881 (9,612)	7,966 (9,220)	1,701 (3,867)

*To capture vegetation not just at the site but in the area, I created a 200m radius buffer around the site and calculated the average NDVI within it. Note that NDVI values range from -1 to +1 whereby -1 indicates water. But as my measurements were conducted on land, I did not have an NDVI value below zero.

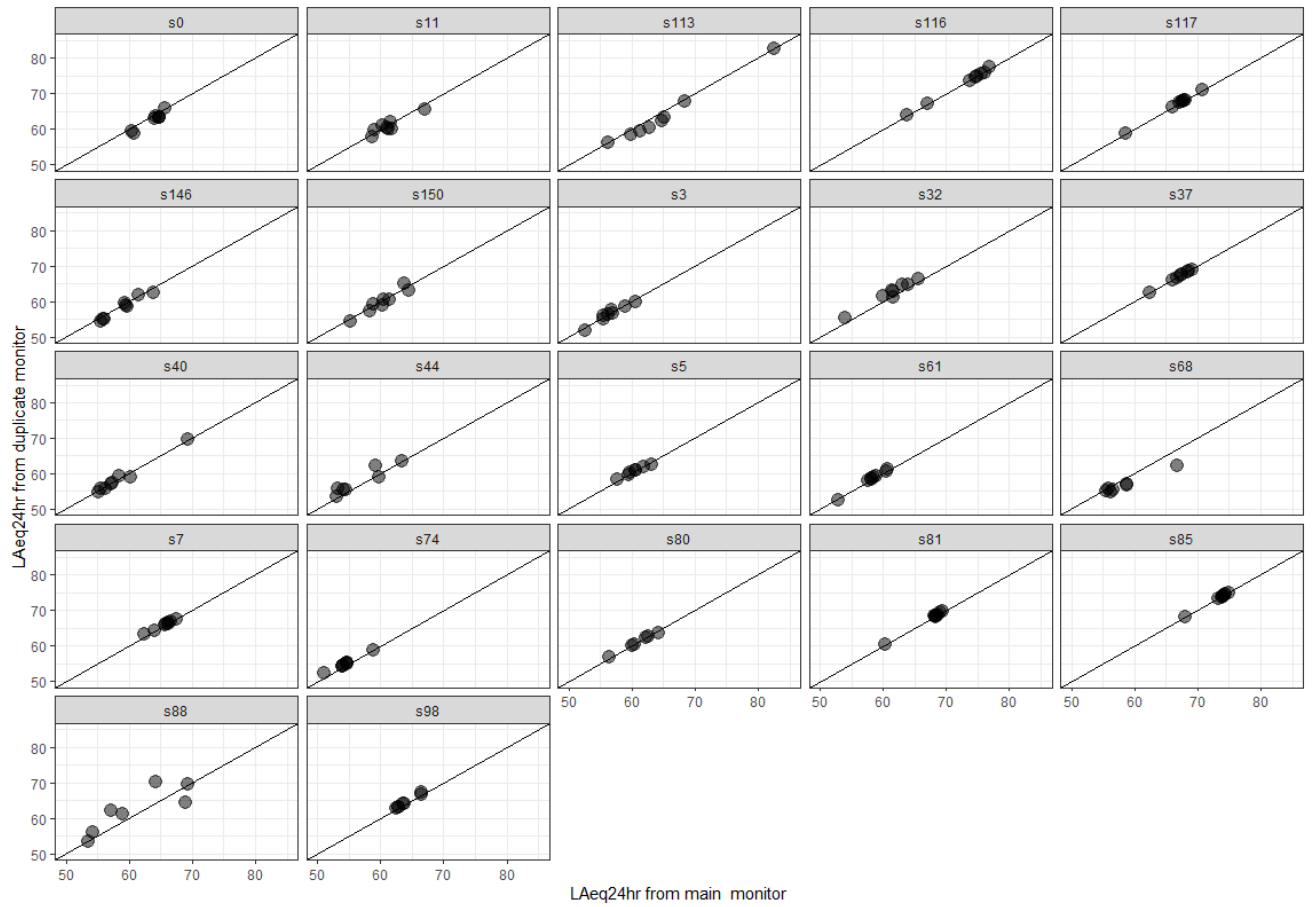


Figure A1. Correlation between duplicate daily LAeq_{24hr} estimates at 22 rotating sites. Site s88 was found to have a malfunctioning duplicate monitor and was subsequently pulled from the field and fixed.

Table A3. Mean and range of neural network acoustic classifier probabilities of presence for the top 1-5 sound classifications in each audio file.

Top 1-5 in order	Mean probability	Range of probabilities
1 st	0.51	0.04-0.99
2 nd	0.27	0.03-0.99
3 rd	0.19	0.03- 0.99
4 th	0.15	0.00- 0.89
5 th	0.12	0.00-0.71

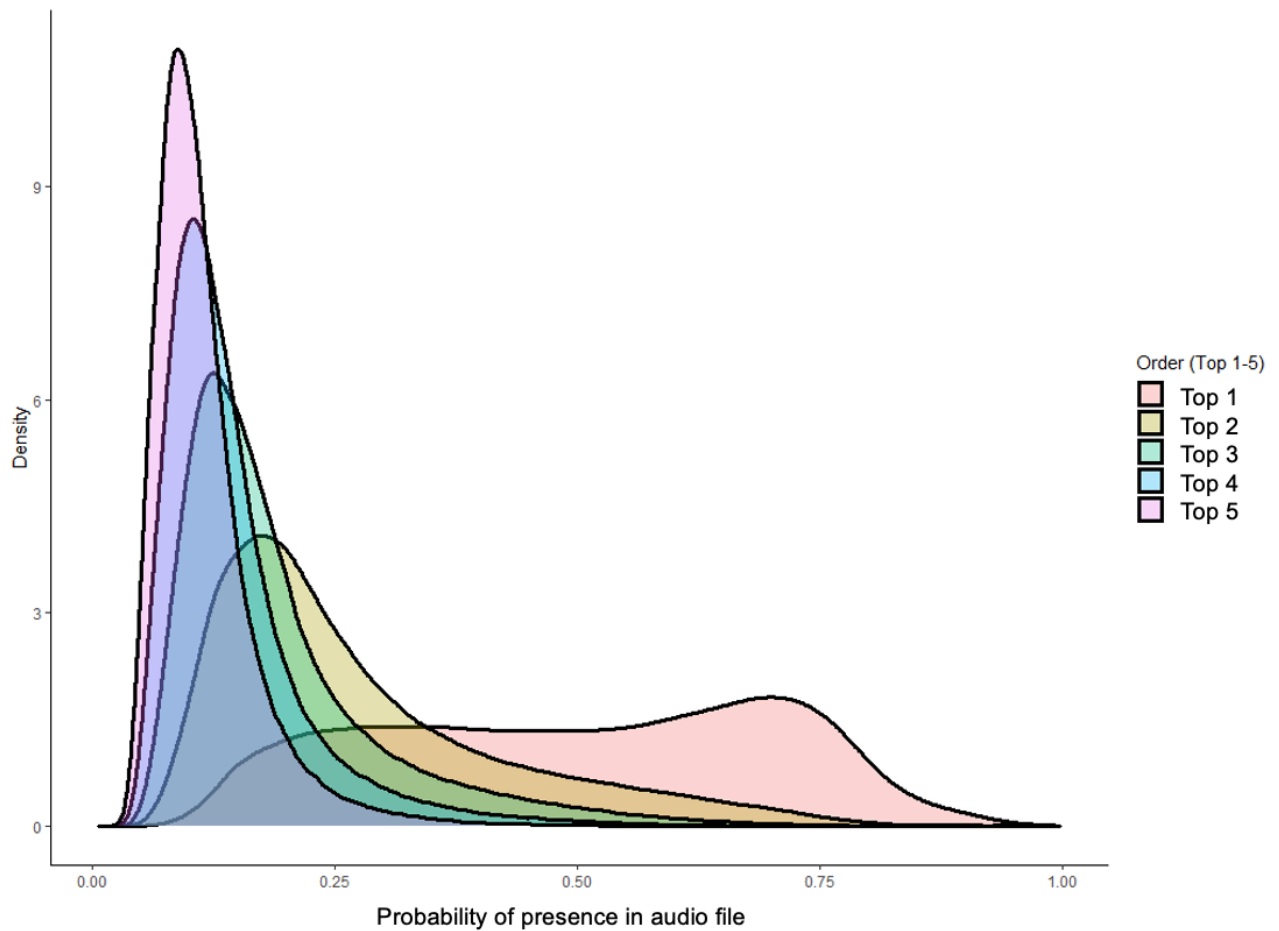


Figure A2. Distribution of neural network acoustic classifier model probabilities of presence for the top 1-5 sound classifications within each audio file.

Table A4. Acoustic classifier model accuracy, positive predictive values, and negative predictive values when applied to the Accra campaign data²²². Testing dataset consisted of 150 randomly selected audio files.

Sound type category	Accuracy	Positive predictive value	Negative predictive value
Road-transport	76%	76% (n=93/ 123)	78% (n=21/27)
Animals and insects	79%	97% (n=30/31)	74% (n=88/119)
Music	93%	71% (n=18/25)	97% (n=121/125)
Speech	80%	83% (n=39/47)	79% (n=81/103)
Airplane	82%	4% (n=1/26)	99% (n=123/124)
Nature	87%	100% (n=4/4)	83% (n=126/146)

%; percentage; n: number of audio files

Accuracy: (True positive + True negative) / Total observations

Positive predictive value: True positive/ (True positive + False positive): Percentage of audio files where the sound type was labelled as present by the researcher given that it was predicted as present by the model.

Negative predictive value: True negative/ (True negative + False negative): Percentage of audio files where the sound type was labelled as not present by the researcher given that it was predicted not to be present by the model.

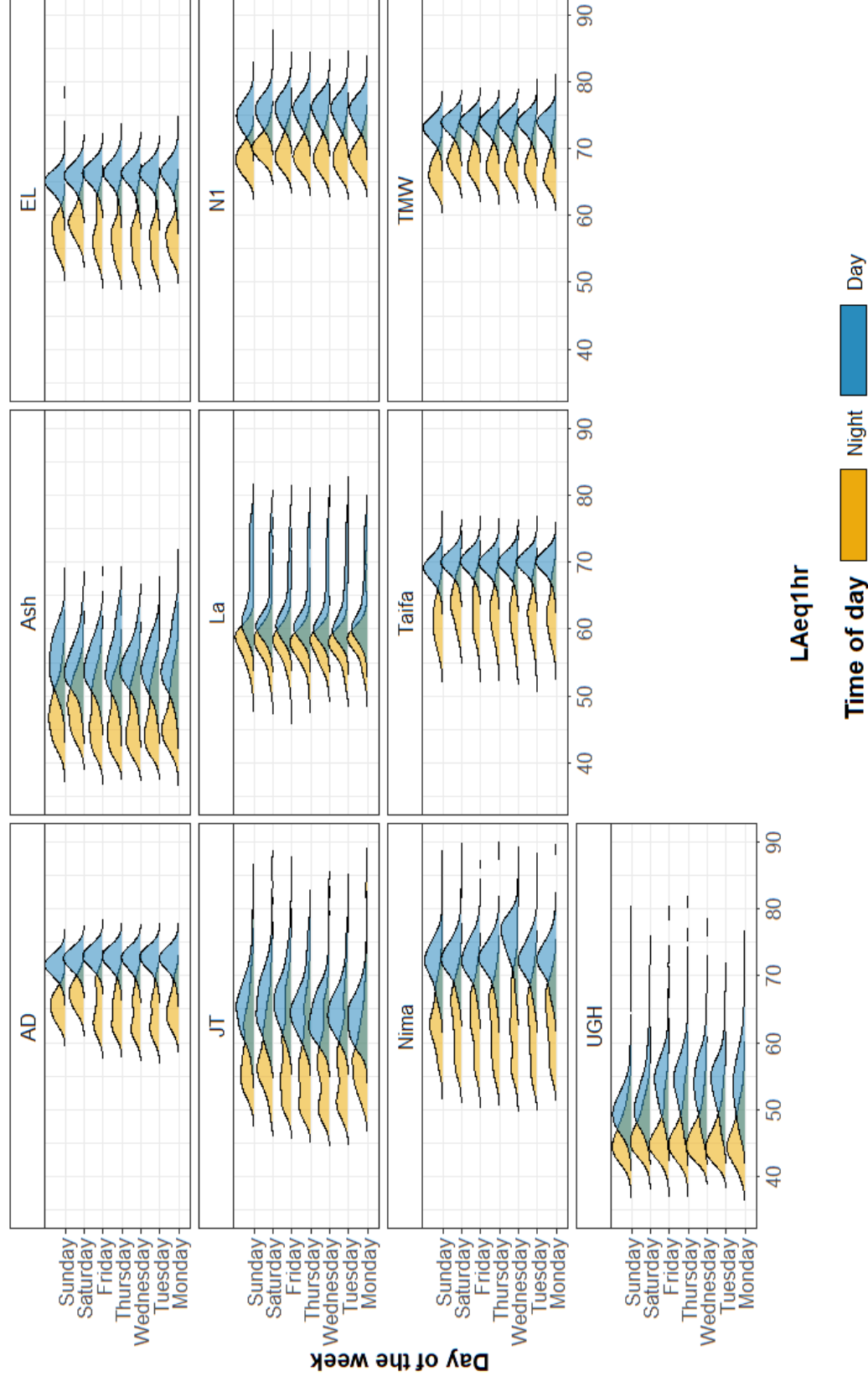


Figure A3. Distribution of day and night-time hourly sound levels (LAeq1hr) across days of the week and each of the 10 fixed sites in the Greater Accra Metropolitan Area. N1 West at Lapaz (N1); Tema Motorway (TMW); Asylum Down (AD); Jamestown (JT); Nima (Nima); Taifa (Taifa); Labadi (La); East Legon (EL); Ashaiman (Ash); University of Ghana Hill (UGH) Figure re-used from my first author open-access publication²²².

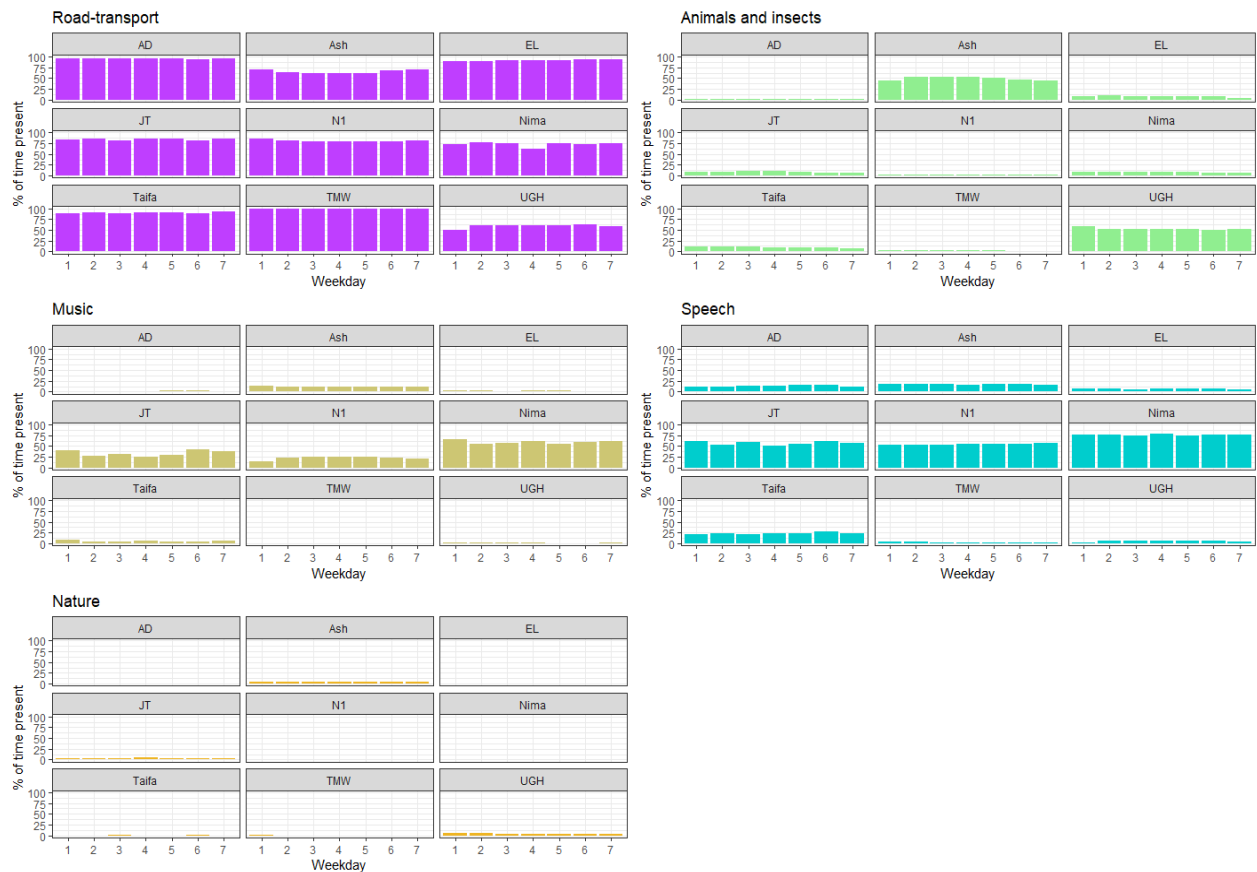


Figure A4. Identified sound type prevalence (% of time present) across days of the week for each fixed site. N1 West at Lapaz (N1); Tema Motorway (TMW); Asylum Down (AD); Jamestown (JT); Nima (Nima); Taifa (Taifa); Labadi (La); East Legon (EL); Ashaiman (Ash); University of Ghana Hill (UGH). Sunday (1), Monday (2), Tuesday (3), Wednesday (4), Thursday (5), Friday (6), Saturday (7). Figure re-used from my first author open-access publication²²².

Fixed sites had relatively consistent prevalence of identified sound type presence across different days of the week. Though, the prevalence of music sounds were slightly higher on Sundays, particularly in the high-density residential areas (Nima, JT) and in Taifa.

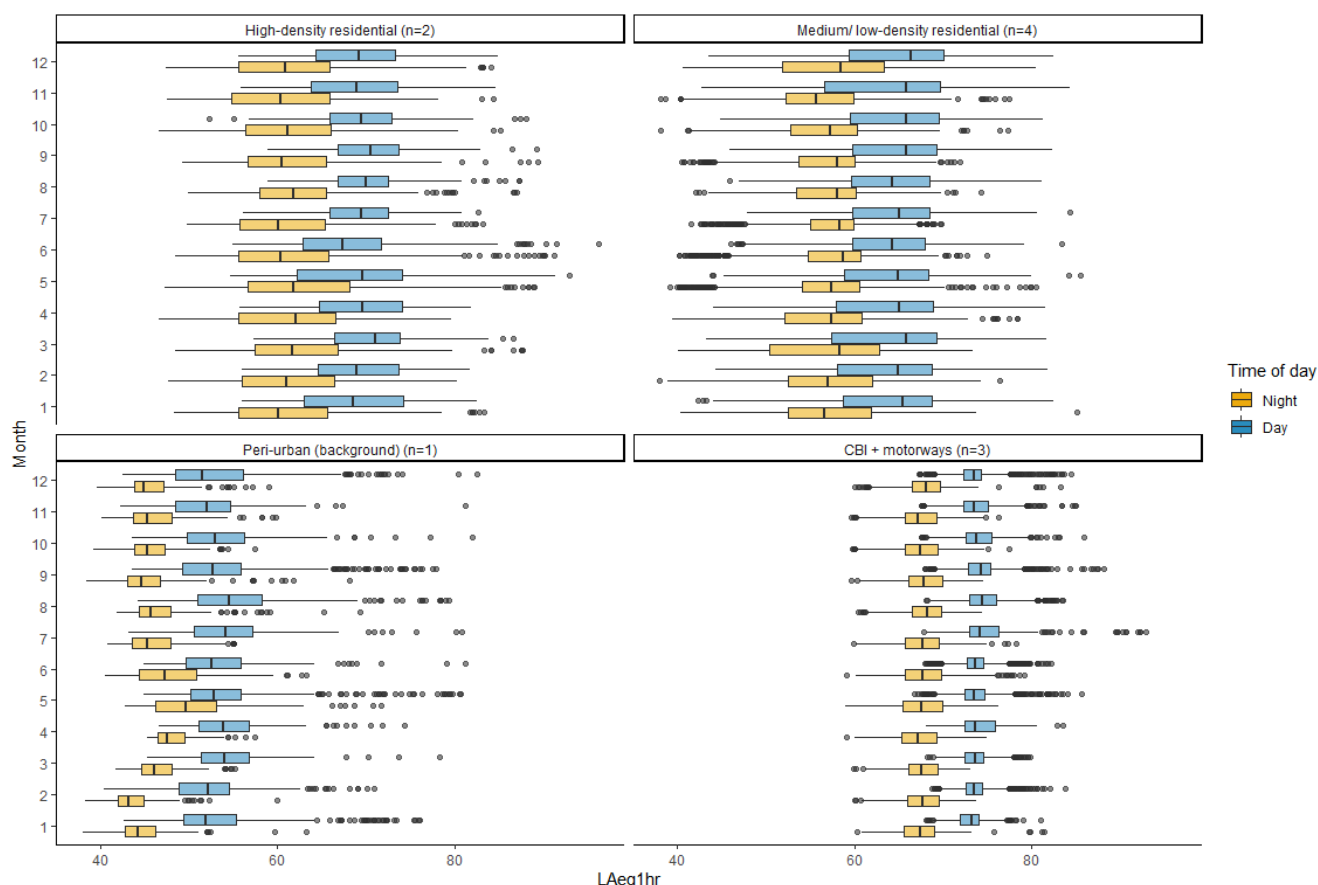


Figure A5 Distribution of day and night-time hourly sound levels (LA_{eq1hr}) across months of the year stratified by land use category. Data from 10 yearlong fixed sites. ‘n’ represents the number of sites in each land use category. The box and whiskers plot shows the median, interquartile ranges, and outlier data in the distribution. Figure re-used from my first author open-access publication²²².

The majority of land use areas had relatively consistent day and night-time measured hourly sound levels across different months of the year. The least within and between month variation was at the commercial, business, and industrial (CBI) sites along major motorways (n=3). UGH is a secluded forested area with few buildings and a one lane road. The increase in median hourly sound levels between April and June is possibly due to university graduation and commencement activities which take place around this time of the year near the administrative building on University Hill, close to where the monitors are located.



Figure A6. Identified sound type prevalence (% of time present) across months of the year for each fixed site. N1 West at Lapaz (N1); Tema Motorway (TMW); Asylum Down (AD); Jamestown (JT); Nima (Nima); Taifa (Taifa); Labadi (La); East Legon (EL); Ashaiman (Ash); University of Ghana Hill (UGH). Figure re-used from my first author open-access publication²²².

The prevalence of road-transport sounds was fairly constant at fixed sites throughout the year, though UGH site appeared to have a higher prevalence during the months of April – July. Similarly, animal and insect sound during these months at UGH were lower than other months, possibly as a result of animals avoiding vehicles or a potential masking effect of louder road-transport sounds in the audio recordings. There wasn't a clear seasonal pattern of music sounds, though some minimal month-to-month random variation. The prevalence of speech sounds was noticeably higher at Nima, N1, JT, Taifa, Ash, AD, and EL between April and July. There was little month-to-month variability in nature sounds.

Table A5. Ghana Standards Authority permissible limits for environmental sound¹.

Zones defined by the Ghana Standards Authority	Permissible L_{day}, L_{night} limits*
Residential areas	55, 48 dBA
Mixed use areas	60, 55 dBA

* L_{day} : covers daytime hours from 6:00am to 9:59pm; L_{night} : covers nighttime hours from 10:00pm to 5:59am.

I compared measurements at peri-urban sites to the Ghana Standards Authority ‘Residential area’ zones and I found that 79% of site-days of day-time sound levels (L_{day}) surpassed the guideline limit. As well, 83% of site-days of night-time sound levels (L_{night}) surpassed the limit. As well, I compared measurements at medium/low-density residential areas to the Ghana Standards Authority ‘Residential area’ zones and found that 95% of site-days of day-time sound levels (L_{day}) surpassed the guideline limit. As well, 94% of site-days of night-time sound levels (L_{night}) surpassed the limit. Finally, I compared measurements at high-density residential areas to the Ghana Standards Authority ‘Residential area’ zones and ‘Mixed area’ zones as these areas are typically both residential and contain a high density of mixed activities. I found that 99% of site-days of both day-time and night-time sound levels surpassed the guideline limit for ‘Residential areas’. As well, 93% of site-days of day-time sound levels and 71% of night-time sound levels surpassed the limits set for ‘Mixed use areas’.

Table A6. Metrics of sound level and intermittency ratio model fit* for mixed-effect models with splines (knots=3).**

	R²	Median absolute error	Mean error
L _{Aeq1hr} - Day (dBA)	0.84	1.43 dBA	<0.001 dBA
L _{Aeq1hr} – Night (dBA)	0.84	1.69 dBA	<0.001 dBA
IR _{day} (%)	0.73	5.52 %	<0.001 %
IR _{night} (%)	0.38	8.11 %	<0.001 %

L_{Aeq1hr}: Hourly Equivalent Continuous Sound levels; IR: Intermittency ratio

*Model fit estimated from the full dataset (no cross validation conducted).

**Random effects and predictor variable sets are the same as the final main models (mixed effect linear regression), however non-linear functions are applied to predictor variable associations with splines.

Adding splines into the L_{Aeq1hr} models to allow for non-linear relationships did not improve model R² or error metrics (MAE, ME). Though the marginal portion for the fixed effect R² did improve minimally by 0.03. The IR models had similar results.

Table A7. R² of the final mixed-effect linear regression models of sound levels and intermittency ratios.

Model dependent variable	Variance (R ²) explained by the fixed factors	Variance (R ²) explained by the fixed and random factors
Daytime LAeq _{1hr} (dBA)	0.60	0.83
Nighttime LAeq _{1hr} (dBA)	0.55	0.83
IR _{day} (%)	0.51	0.72
IR _{night} (%)	0.15	0.38

LAeq_{1hr}: Hourly Equivalent Continuous Sound levels; IR: Intermittency ratio; Random effects included 'site' to account for the correlation of repeated measurements at the same location, and 'hour' (LAeq_{1hr} models only) to account for diurnal patterns of sound levels throughout the day.

*Model R² estimated from the full dataset (no cross validation).

Table A8. Random Forest sound level and intermittency ratio LUR model predictive accuracy*.

	Full dataset		CV _{10%sites} cross-validation	
	Median absolute error	Mean error	Median absolute error	Mean error
Daytime LAeq _{1hr} (dBA)	1.4	<0.01	3.7	0.10
Nighttime LAeq _{1hr} (dBA)	1.7	<0.01	4.0	0.11
IR _{day} (%)	7.3	-0.02	11.5	3.24
IR _{night} (%)	8.0	0.01	15.9	0.32

*Predictor variable sets were the same as the final main models (mixed effect linear regression). The variable for 'hour' was included as a fixed effect in the LAeq_{1hr} models.

Table A9. Mean associations of hourly sound levels (LAeq_{1hr}) with hourly temperature, relative humidity and wind speed and daily rainfall in bivariate and multivariable mixed-effect linear regression models. All models have random intercepts for site and hour of the day.

	Unadjusted mean associations (bivariate models)		Adjusted mean associations (multivariable models with weather predictor variables)		Adjusted mean associations (multivariable models with spatial * and weather predictor variables)	
	Day-time	Night-time	Day-time	Night-time	Day-time**	Night-time***
	Slope coefficient [95% CI]	Slope coefficient [95% CI]	Slope coefficient [95% CI]	Slope coefficient [95% CI]	Slope coefficient [95% CI]	Slope coefficient [95% CI]
Hourly temp <i>Standardized (degrees Celsius)</i>	-0.44 [-0.48, -0.40]	-0.12 [-0.17, -0.07]	-0.15 [-0.21, -0.10]	-0.01 [-0.06, 0.04]	-0.15 [-0.20, -0.09]	-0.01 [-0.06, 0.04]
Hourly relative humidity <i>Standardized (%)</i>	0.36 [0.33, 0.40]	0.12 [0.07, 0.16]	0.18 [0.13, 0.23]	0.06 [0.02, 0.11]	0.18 [0.13, 0.23]	0.06 [0.02, 0.11]
Hourly wind speed <i>Standardized (m/s increase)</i>	0.43 [0.39, 0.46]	0.26 [0.22, 0.31]	0.36 [0.33, 0.39]	0.24 [0.19, 0.29]	0.36 [0.33, 0.39]	0.24 [0.19, 0.28]
Daily rainfall <i>Standardized (mm)</i>	0.12 [0.09, 0.15]	0.09 [0.04, 0.13]	0.06 [0.04, 0.09]	0.05 [0.01, 0.10]	0.06 [0.04, 0.09]	0.05 [0.01, 0.09]

95% CI: 95% confidence interval; Standardized: Weather variables standardized by subtracting each value by the data mean and dividing by the data standard deviation.

*Spatial variables were those chosen for the main models from the selection procedure.

**Day-time model spatial predictor variables: NDVI, length of major roads, number of restaurants, length of secondary/ tertiary roads, formal residential land use area, population density, height of monitor off the ground.

***Night-time model spatial predictor variables: Length of major roads, NDVI, number of restaurants, length of secondary/ tertiary roads, formal residential land use area, height of monitors off the ground.

Data on hourly temperature, wind speed, and humidity that I collected at the 6 fixed measurement sites were averaged across the sites to obtain a single date specific hourly value for the study area.

I also used daily rainfall data from the Ghana Meteorological Agency that represented the entire area. I first estimated the unadjusted mean associations between hourly sound levels (LAeq_{1hr}) and hourly average temperature, relative humidity, and wind speed and daily average rainfall, matched on date and time of measurement. I then added the weather variables into the main spatial models and estimated the adjusted mean associations with LAeq_{1hr}. I also investigated whether the predictive accuracy of the main spatial models improved with the inclusion of the weather variables.

The ways in which atmospheric conditions can affect measured sound levels are complex. Previous research shows that atmospheric propagation of sound waves can be impacted by wind speed,

temperature, and humidity²⁸⁴. As well, sound from other sources can be amplified under certain atmospheric conditions, such as how motor vehicle sounds from the contact of tires with the road-material is amplified in wet conditions²⁸⁴. Finally, atmospheric conditions such as high winds or rain can be sources of sound energy themselves, and they can influence human behaviours/activities that result in sound generation²⁹¹.

Wind speed, rainfall, and humidity were positively associated with LAeq_{1hr}, while temperature had the inverse relationship. In all cases, the magnitude of the associations between LAeq_{1hr} and weather variables in the day and night-time were fairly minimal, which is supported by the fact that atmospheric attenuations of short-range sound propagation are minimal²⁸⁴. Among the various weather parameters considered, wind speed had the largest magnitude of effect. This is expected as for short-range sound propagation, the effects of wind structure (i.e., wind speed) are more important than other atmospheric conditions²⁸⁴. Higher winds could be (i) assisting in the propagation of sound from sources towards the sound level meters (receivers)¹³³, or the sound level meters could be picking up the sound of wind as a source of sound itself. The positive association between relative humidity and LAeq_{1hr} that I observed, has been found in a previous noise LUR study in Taichung (Taiwan), but only at a higher frequency level (8000 Hz for LAeq_{24hr})⁴⁷. The relationship between sound wave attenuation and relative humidity is complex as the relationship changes with temperature and sound frequency. Though at higher relative humidity levels (i.e., >70 % as is the case in Accra), increasing humidity has been shown to lead to a decrease in atmospheric attenuation²⁵⁶. This relationship has been found at higher temperature levels, 25-35 degrees Celsius²⁵⁶, as is the case in Accra.

Inclusion of time-resolved weather data did not improve the predictive accuracy of the main models. The median absolute prediction error (MAE) of the main spatial day and night-time

$LAeq_{1hr}$ models only changed by 0.01 dBA when weather predictor variables were included. The coefficients of the spatial variables remained relatively unchanged with the inclusion of the weather variables.

Table A10. Absolute difference in the percentage of audio files where sound types were identified by the neural network when the top 5 compared with the top 3 sound classifications were retained in each audio file.

	Difference
Road-transport	6%
Animals and insect	5%
Music	4%
Speech	7%
Nature	3%

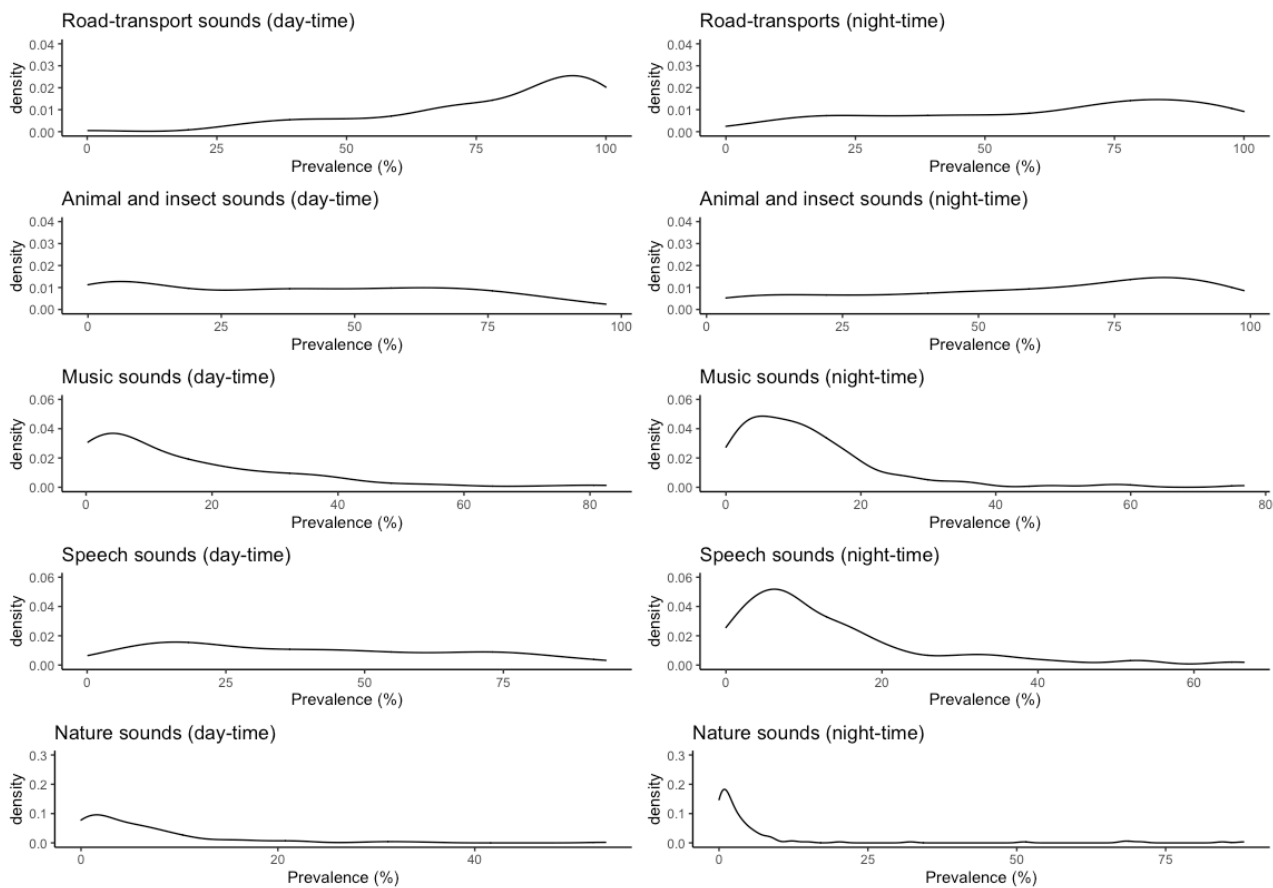


Figure A7. Distributions (densities) of the percentage of time in the day and night that identified sound types were present (%) at each measurement site. Figure represents the raw data distributions at the measurement sites, when the top 5 classifications within each audio file were retained.

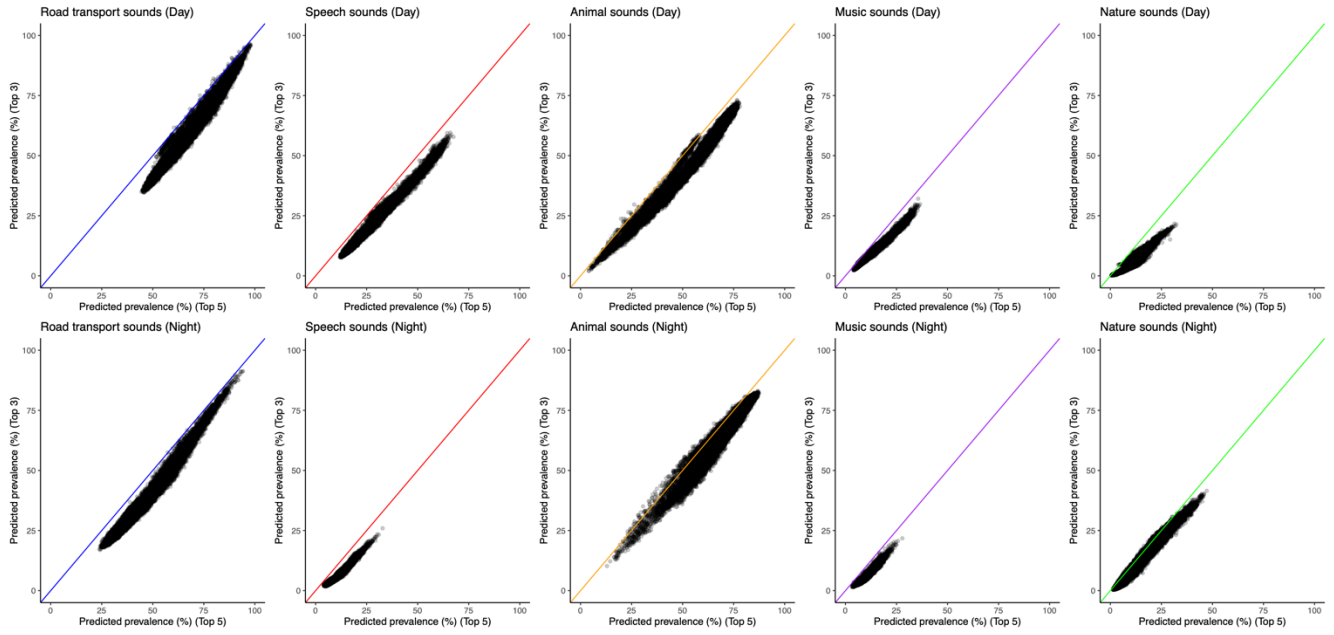


Figure A8. Correlations of the predicted percentage of time that sound types were present (prevalence) at each location in the GAMA when the sound type dataset for the LUR models was constructed by retaining the top 5 compared with the top 3 sound classes within each audio file.

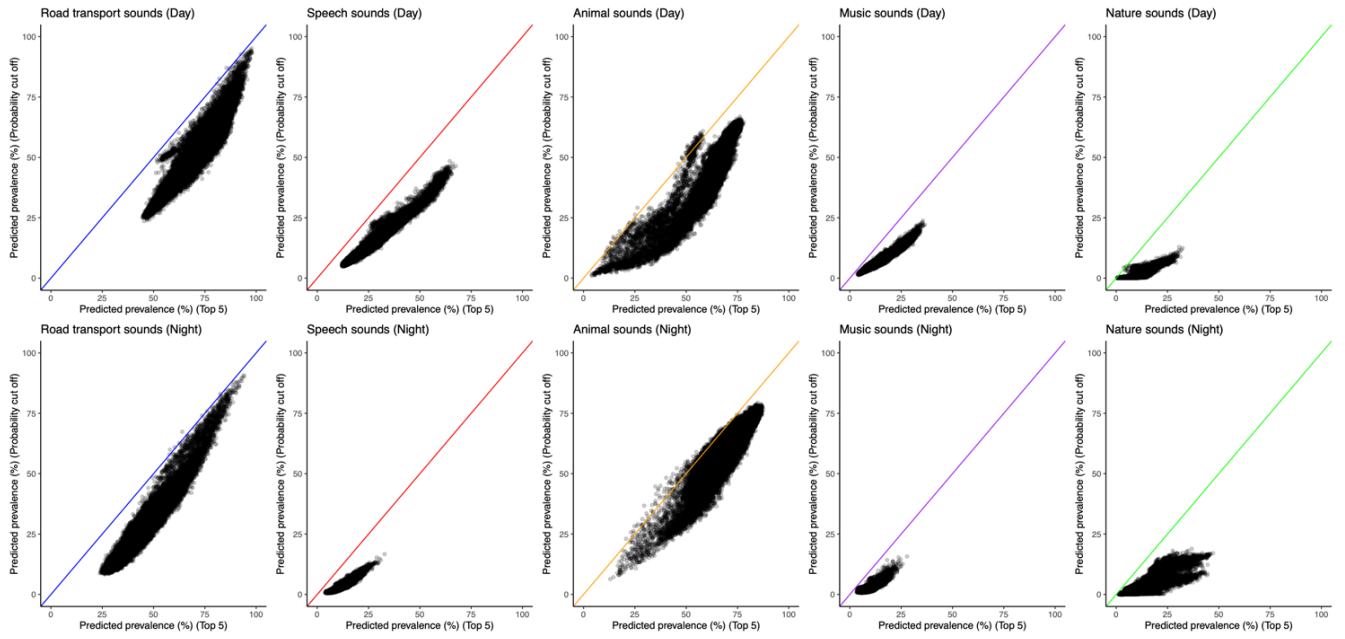


Figure A9. Correlations of the predicted percentage of time that sound types were present (prevalence) at each location in the GAMA when the sound type dataset for the LUR models was constructed by retaining the top 5 sound classes within each audio file compared with when a fixed probability cut-off was applied (probability >0.25).

Appendix Table A11. List of expenditure items included in consumption variable³⁰⁷.

Total annual real household expenditures	Food, beverages and alcohol, tobacco, clothing and footwear, housing, electricity, water, gas and other fuels, furnishings, equipment, routine maintenance, health, transport, communications, recreation and culture, education, hotels, cafes and restaurants, and miscellaneous goods and services
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Appendix Table A12. Predictor variables used in small-area models to estimate consumption for all enumeration area's in the GAMA³⁰⁷.

Covariates	Topic
Household owns computer	Assets
Household is connected to the web	Assets
Proportion of household with middle school education	Education
Proportion of household with secondary education	Education
Head of the household has post-secondary education	Education
Head of the household works as a manager	Employment
Proportion working in the tertiary sector	Employment
Agricultural household	Employment
Drinking water is piped inside	Housing
Tenure (renting)	Housing
Rubbish sent to public dump	Housing
Number of rooms in household	Housing
fuel gas for cooking	Housing
Gas torch for lighting	Housing
No toilet facilities	Housing
Rubbish is burned	Housing
Rubbish is collected	Housing
Urban vs rural	Housing
Charcoal for cooking fuel	Housing
Dependency ratio (0-14 + 65 and over)/(15-64)	Socio-Demographic
Proportion married	Socio-Demographic
Head of the household born in eastern Ghana	Socio-Demographic
Number of people in the household of Ghanaian nationality	Socio-Demographic