8-2022

Environmental noise exposure and its association with elementary standardized testing scores and adult mental ill-health in Louisville, Kentucky.

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ENVIRONMENTAL NOISE EXPOSURE AND ITS ASSOCIATION WITH ELEMENTARY STANDARDIZED TESTING SCORES AND ADULT MENTAL ILL-HEALTH IN LOUISVILLE, KENTUCKY

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A Dissertation
Submitted to the Faculty of the
School of Public Health and Information Sciences of the University of Louisville
in Partial Fulfillment of the Requirements
for the Degree of

Doctor of Philosophy
in Public Health Sciences:
Specialization in Epidemiology

Department of Epidemiology and Population Health
University of Louisville
Louisville, Kentucky

August 2022

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A Dissertation Approved on

July 13, 2022

By the following Dissertation Committee

Dr. Natalie C. DuPré, Chair

Dr. Kira C. Taylor

Dr. Brian Guinn

Dr. Ray Yeager

Dr. Jeremy Gaskins

DEDICATION

This dissertation is dedicated to the younger version of myself; the part of me that endured and conquered more than a child ever should. There's a quote that sticks out to me – "be the person you needed when you were younger." It sounds silly, but when I picture my younger self, she was desperate to be loved unconditionally in the way that any human would love a stranger. The kind of love built on empathy, compassion, and understanding rather than a love solely based on being good enough, or the fact that she was someone's child. My younger self needed who I am today. My younger self grew to be exactly what would've fulfilled her – someone who fights for the rights of all living beings, someone who holds no barriers on acceptance, someone who finds beauty in going against social norms, someone who believes that everyone should be treated with respect until a reason for otherwise is given, someone who thinks that most people are good but holds accountable those who are not. This dissertation is dedicated to her, to the little girl who grew up and didn't conform to the person that statistics predicted she would become. This is dedicated to her, and to being the anomaly. You are amazing, I am proud of you, and I love you.

ACKNOWLEDGMENTS

There are many people for whom I have incredible gratitude that made this dissertation possible, and they deserve my sincerest appreciation. First and foremost, my committee has graciously extended their endless support and guidance, and each member has made innumerable contributions to this dissertation and to my growth as a researcher:

Dr. Ray Yeager, thank you for sparking my interest in and contributing to my knowledge of cartography and spatial analysis. Through the years that we have been working together, you have inspired me to be and molded me into another “health geographer.” The knowledge I have gained from you will undoubtedly contribute to having a successful career, and I am forever grateful for you.

Dr. Jeremy Gaskins, throughout this dissertation, you have challenged me more than any other, but in the best way possible. You never failed to make me think about things that I would never have thought of on my own; somewhat embarrassingly, I often spent hours working my way through some unfamiliar biostatistical concept that you brought to my attention. Ultimately, your feedback and contributions helped me grow as an epidemiologist, and I cannot thank you enough.

Dr. Brian Guinn, over the years, you have been my colleague, my mentor, my teacher, my friend, and my hype-man. Your contributions to my journey through the MS and PhD program go far beyond just this dissertation, and I can confidently say that I would not be where I am today without you. Thank you for everything.

Dr. Kira C. Taylor, my day-one mentor. You have remained a constant support in my graduate career, from a “bright-eyed and bushy-tailed” first-year MS student through completion of the PhD program. Thank you for choosing me and for investing so much of yourself in me. I only hope that I have made you proud.

Finally, my chair, Dr. Natalie C. DuPré. There are many great things that I could say about how much I’ve learned from you, the immeasurable ways you have contributed to my education, or how I would not be where I am without you. And while all those things are true, and I will spend an eternity being grateful for those things, I also want to highlight and thank you for another quality of your mentorship. The past three years, while under your mentorship, have been some of the most challenging years of my life; I was diagnosed of two mental illnesses, an auto-immune disease, and concurrently lived through unprecedented historical events like the COVID-19 pandemic, a civil rights movement, the ever impending threat of climate change, countless mass shootings, an attempted coup of the American government, and most recently, the overruling of a precedented law that established the rights of women to their own bodies. There were so many days that I did not believe that I could go on, that the weight of the

world and living within it was all too much for me overcome or endure. Whether you know it or not, you have single-handedly talked me through and out of more mental breakdowns than I can count. You have been an unwavering support to me, you have advocated for my physical and mental well-being, and you have believed in me when I could not do those things for myself. It is so rare to have a mentor that not only cares about who you are as a professional, but also cares about who you are as a human-being, and I am so thankful to have found that in you. Please know that the time and energy you have invested in me did not go unnoticed, and that I will spend the rest of my career and my life striving to be to others what you have been to me. I could never thank you enough for the past three years, so I will simply say that I am infinitely grateful to have had you as a mentor and as a friend.

There are several others who deserve acknowledgement. Drs. Joy Hart and Kandi Walker have been the best supervisors a research assistant could hope to have. Much of my CV is credited to working on their team, and I am so grateful to have had the experiences I have with them. They are fiercely supportive, caring, incredible mentors, genuinely kind, and some of the strongest women I have ever met. They have been my family in a place where I had none for four-and-a-half years, and I will carry them with me for the rest of my life.

Included in my work on the Hart-Walker team is my involvement with the American Heart Association's VAPERACE Center and the University of Louisville's Superfund Research Center (SRC), Christina Lee Brown Envirome Institute (EI), and Green Heart Louisville (GHL) project, all of which have contributed to my education by providing funding for nearly my entire graduate career, allowing for my interest in environmental epidemiology to flourish beyond the classroom, presenting learning opportunities for community engagement and research translation that cannot be taught in the classroom, and by sharing data utilized in this dissertation.

From the many researchers on the SRC, EI, and GHL team, Dr. Jay Turner and his graduate students, Maryssa Loehr and Pradeep Prathibha, deserve a special shoutout. These three have graciously and patiently offered their resources, knowledge, and time to contribute to nearly everything I know about noise mechanics, data collection of noise, and land use regression modeling, all of which laid the foundation for this dissertation. It has been such a pleasure to collaborate with researchers who are not only brilliant, but incredibly kind and genuinely as excited about my work as I am.

This dissertation would not have been possible without HMB Professional Engineers Inc., specifically Mark Gavula and Mitch Green, for lending me a noise meter not only once, but twice, for six weeks at a time. Were it not for your willingness to entrust me with a very expensive piece of equipment, I would not have been able to build and execute the dissertation of my dreams. Further, I want to thank the 15 volunteers, and several others who offered, who allowed me to have full access to their backyards for 48+ hours to collect noise data. Each of you have quite literally made my dissertation dreams come true. I also have much appreciation for Bob Slattery from Louisville International Airport who, after a single phone call, kindly shared the Noise Exposure Map shapefiles that aided in the development of all LURs. Your generosity made this dissertation even stronger than I had originally dreamed.

I want to extend thanks to the many colleague-friends in the Department of Epidemiology and/or on the Hart-Walker team: in the order in which I met them, Delvon Mattingly, T'Shura Ali, Jack Pfeiffer, Lindsay K. Tompkins, Savanna Kersteins, Madeline M. Tomlinson, Lyndsey Blair, Kolbie Vincent, and Stephie Abraham have all, at some time or another, made me feel much less lonely.

I also have several friends who deserve my acknowledgement. Shelby Carter, Jade Nyugen, and Kellyn Kennerly; it's because of your endless and unwavering support that I was even halfway sane most of the time. You are my chosen family, and I am forever thankful for the unshakeable bonds I have built with each of you. Special thanks to Mark Gavula for first introducing me to noise work and teaching me all the basics. Also, thank you for being my best friend and for being there throughout this entire journey. I promise to never become one those who are stuck in the ivory towers, and I hope you are proud of me the way that Drake is proud of Nicki Minaj. Oh, and fun-Lindsey is back!

To my family – Mom, John, Bubba, and Mama Jean – it is the four of you who have been the resolute foundation on which I stand. I would be nothing without each of you. I love you so much.

Finally, I want to acknowledge the many medications that have maintained my mental and physical stability while writing this dissertation: Humira, Remicaid, Amitriptyline, Adderall, and Escitalopram. It is no secret that the culture of

academia often ostracizes those with mental or physical disabilities. During my tenure as a PhD candidate, I was diagnosed with two mental illnesses and a debilitating auto-immune disease, all of which greatly altered the way I function and my own understanding of self. I am lucky enough to have invisible disabilities – and to have incredibly considerate and understanding mentors – which protected me from experiencing any explicit ableism. However, I cannot deny that the pressures and expectations of academia were considerably more difficult to meet as a disabled individual, and I feel that it is important to be transparent about these difficulties to increase awareness of academic stigma towards disability. I challenge my fellow academics to continue working towards ensuring that their own academic environments are welcoming to and accepting of those with disability. We are talented and brilliant, and our experiences and perspectives are ones from which all branches of academia could benefit.

ABSTRACT

ENVIRONMENTAL NOISE EXPOSURE AND ITS ASSOCIATION WITH ELEMENTARY STANDARDIZED TESTING SCORES AND ADULT MENTAL ILL-HEALTH IN LOUISVILLE, KENTUCKY

Lindsey A. Wood

July 13, 2022

Background and Aim: The current body of literature on the associations of environmental noise exposure with varying psychological outcomes is inconclusive, with many conflicting findings. Limitations include exposure measurement error and lack of investigation of effect modification by important factors. This dissertation aims to expand on the current understanding of these relationships by limiting exposure measurement error and by assessing effect modification.

Methods: We estimated the distribution of total environmental noise in Louisville, Kentucky for several time-periods using land use regression (LUR) methodologies. Additionally, through multiple regression models, we estimated the association of environmental noise during relevant time-periods with childhood cognition using standardized testing scores at the school-level, and mental health outcomes of adults at the census-tract and individual levels. We assessed effect modification of these associations by several demographic, socioeconomic, and health behavioral factors. Data linkage of several sources was utilized throughout analyses.

Results: Environmental noise in Louisville was louder in areas where the majority of the population is non-white or lower income. Generally, louder noise was not associated with school-level standardized testing scores. At the census-tract level, louder noise was significantly associated with higher prevalence of mental ill-health. Also, individuals with the loudest environmental noise exposures had significantly higher odds of depression than those exposed to the quietest exposures. However, results suggest that socioeconomic and health behavioral factors – like race, income, stress, and sleep – may confound or modify these associations. Findings suggest that white, higher income, and less stressed individuals living within louder, less-white, low-income, high-stress areas are the most negatively impacted by louder environmental noise in relation to psychological outcomes.

Conclusion: Non-white, lower income, and more stressed individuals living within these areas may have higher baseline allostatic loads, such that the effects of louder noise may be negligible. However, noise mitigation efforts will need to be implemented at large, neighborhood levels to effectively break the cycle of environmental health disparities from environmental noise, especially among underserved Louisville communities that endure the loudest environmental noise exposures.

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INTRODUCTION

Environmental noise exposure is rapidly becoming a public health concern, particularly in urban areas in which there are many noise polluters – such as airports, roadways with high traffic volume, railway, and construction. The World Health Organization (WHO) has reported that noise exposure is responsible for 45,000 disability-adjusted life years for childhood cognitive impairment.[1] Further, in 1999, the WHO recognized environmental noise exposure for its potential to harm the mental health of adults.[2] Nearly ten years later, in 2018, the WHO published guidelines for environmental noise, which recommended noise levels for road-traffic, railway, aircraft, wind turbine, and even leisure noise.[3] In developing guidelines, WHO considered evidence of noise associations with several adverse health outcomes, including cognitive impairments of children and mental health.[3] However, evidence of the association between environmental noise with childhood cognition[4] and with mental ill-health[5] was not strong enough to be considered when developing the WHO guidelines.

Although several studies exist on the relationships of environmental noise with childhood cognition[6–22] and mental ill-health in adults,[23–37] effect estimates and levels of confidence are inconsistent and vary widely. The inconsistency in findings is partially attributable to the varying definitions of cognition and mental ill-health. Childhood cognition definitions include reading comprehension,[6–16] varying types of memory,[6–10,17] and attention.[7–11,18] Although it may important to understand the relationship between environmental noise and specific facets of cognition, it may be more meaningful to determine the association with cognitive proxies that predict later-life outcomes, such as standardized testing scores.[38] To date, few studies utilize standardized testing scores as proxies of cognition.[19–22] For adult mental ill-health, definitions include diagnosed mental illness,[23–25] questionnaires that assess mental illness symptomology,[25–31] self-assessments of mental health,[36] emergency admissions due to mental illnesses,[37] suicide rates,[37] and medication use.[31–35] The varying definitions of mental ill-health affect the interpretation of effect estimates. For instance, emergency admissions and suicide rates capture those with the most severe mental illness and medication use captures those being treated, whereas questionnaires and self-reports may capture those who are not truly mentally ill or miss those who are being treated.

Further, environmental noise is generally defined as source-specific noise, such as road traffic or aircraft noise, which may not be fully representative of total environmental noise exposures. Additionally, there is a general lack of accounting for spatial-temporal movements of individuals, which determines individual noise exposures.[36,39] Consider that noise at one's home may be quieter than at one's work location, and noise at all locations may vary by the hour. As such, estimations of environmental noise exposure should account for the location of individuals and the hours during which individuals are at specific locations. Although the fool-proof method of estimating an individual's noise exposure is through personal noise monitors, their cost limits the ability of researchers to conduct concurrent exposure assessments of large-enough samples that are required for powerful epidemiologic analyses.[36,40,41] Additionally, personal noise monitors may be a nuisance for individuals to wear for extended periods of time, and therefore prohibits long-term exposure assessments.[36,40,41]

Noise modeling via land use regression (LUR) may be a useful tool to estimate total environmental noise exposure. LUR is a spatial statistics method used to estimate exposures based on geographical characteristics. LUR has been widely used and consistently successful in modeling air pollutants.[42] More recent studies have tested LUR in modeling environmental noise and have shown that LUR is a reliable method to estimate noise exposures,[43–45] and the application of LURs has been specifically recommended for estimating total environmental noise exposure in epidemiologic studies.[44] What's more, multiple LUR models can be used to estimate environmental noise distributions for specific time-periods, such as the times that individuals would be at their work locations versus at their homes.

To date, there are no studies of environmental noise in association with childhood cognition and adult mental ill-health based in the US, but Louisville, Kentucky is an urban US area in which such a study could be conducted. Environmental noise is abundant in Louisville, with numerous roadways, including five interstate systems, and railways, as well as the Muhammad Ali International Airport (SDF) (Figure 0.1), all of which are located in or around residential areas (Figure 0.2), raising concern for the health of Louisville residents. SDF is home of the United Postal Service (UPS) Worldport, which is responsible for hundreds of low-flying aircrafts (Figure 0.3) a day, many of which occur at times during which residents are likely asleep; a total of 260 UPS flights arrived to and departed from SDF between 10:00 PM to 7:00 AM on August 10-11.[46] Additionally, environmental noise in Louisville is likely not geographically homogenous, with many areas being absent of large noise polluters, and others being in close proximity to more than one large noise polluter; Figure 0.4 illustrates transportation noise in Louisville, with some areas having sound pressure levels above 100 decibels (equivalent to a gas lawn mower running from three feet away) and others having less than 35 decibels.

At a localized level, variations in noise exposure are present in Louisville neighborhoods. Data collected by the Green Heart Louisville study, conducted in South Louisville neighborhoods, suggests that 24-hour environmental noise varies between two collection sites, of which are roughly 1.2 miles apart, as displayed in Figure 0.5. The difference in 57.7 decibels at Site A and 52.1 decibels at Site B is 5.6 decibels. For context, 57.7 decibels is about the same loudness of a microwave from one foot away, while 52.1 decibels is about the same loudness of a microwave from nine feet away. Further, changes in noise of three decibels are barely perceivable to humans, whereas changes of five decibels are readily perceivable, and changes in 10 decibels are perceived as double or half the amount of loudness.[47] Therefore, one would be able to readily perceive the differences in noise exposure after traveling only 1.2 miles, from Site A to Site B.

In terms of standardized testing scores in Louisville, the standardized testing scores of 3^{rd}, 4^{th}, and 5^{th} graders in 2019 in Reading and Math are considerably lower when compared to all elementary schools in the state of Kentucky; 54.6% and 48.6% of elementary schoolers in Kentucky reached Proficient or Distinguished scores in Reading and Math, respectively, while only 45.5% and 39.7% meet these standards in Lousiville.[48] In the same year, it was estimated that 17.2% of Kentuckians would experience 14+ days in the past 30 days in which their mental health would not be good.[49] Louisville mental ill-health statistics were comparable to Kentucky, with an estimated 16.1% experience 14+ poor mental health days in the past month.[50] However, the prevalence of mental ill-health varies widely within Louisville, with census-tract level prevalence estimations ranging from 8.2% to 27.4% of the population experiencing 14+ bad mental health days within a month.[50]

In brief, the abundance and variation of noise sources, the relatively low standardized testing scores of elementary schools, and the variation in census-tract level estimated prevalence of mental ill-health justify investigation of the association of environmental noise levels with standardized testing scores and mental ill-health in Louisville. Therefore, the purpose of this dissertation is to estimate the total environmental noise distribution in Louisville and to assess the association of environmental noise with standardized testing scores of elementary schools, and with adult mental ill-health at an ecological and individual level. Importantly, environmental noise exposures will be representative of total noise rather than source-specific noise. Further, multiple estimations of noise will represent noise levels during varying seasons and varying time-periods within the 24-hour day.

Specific Aims

AIM 1: Develop and validate noise models of Louisville using land-use regression (LUR) by collecting noise readings throughout the city and integrating with various datasets on noise predictors including elevation, distance from major noise sources (e.g. roadways, trains, airports), land use, and other environmental factors. Separate LUR models will estimate environmental noise during different seasons (i.e. spring/summer and fall/winter) and times of day to capture noise during school-time and home-time.

Hypotheses: Noise will be higher in the downtown, West, and South ends of Louisville; winter months will have louder environmental noise than spring months.

AIM 2: Determine the association of spring school-time and home-time noise estimates on standardized testing scores at the school-level using a linear regression adjusted for various student-, teacher-, and school-related factors. Spring environmental noise will most closely represent noise exposure at the time of standardized testing that occurs in April; further the 7-hour school-time equivalent (9:00 AM to 4:00 PM) will represent noise exposure at school when tests would be administered, whereas the 17-hour home-time equivalent (4:00 PM to 9:00 AM) will represent noise exposure while students are at home during the testing season.

Hypotheses: Schools with higher 7-hour school-time environmental noise will have lower testing scores, and schools with higher 17-hour home-time environmental noise will have lower testing scores.

AIM 3: Determine the association of winter and spring 16-hour (5:00 PM to 9:00 AM) home-time noise estimates on adult mental ill-health parameters using a regression adjusted for demographics and socioeconomic factors, as well as other community characteristics predictive of mental ill-health.

SUBAIM 3A: Examine the association of seasonal home-time environmental noise estimates with census-tract level prevalence of adult mental ill-health using the CDC PLACES Study.

SUBAIM 3B: Determine the association of spring home-time environmental noise with depression status in the Green Heart Louisville cohort.

Hypothesis: Higher environmental noise will be associated with higher estimates of mental ill-health.

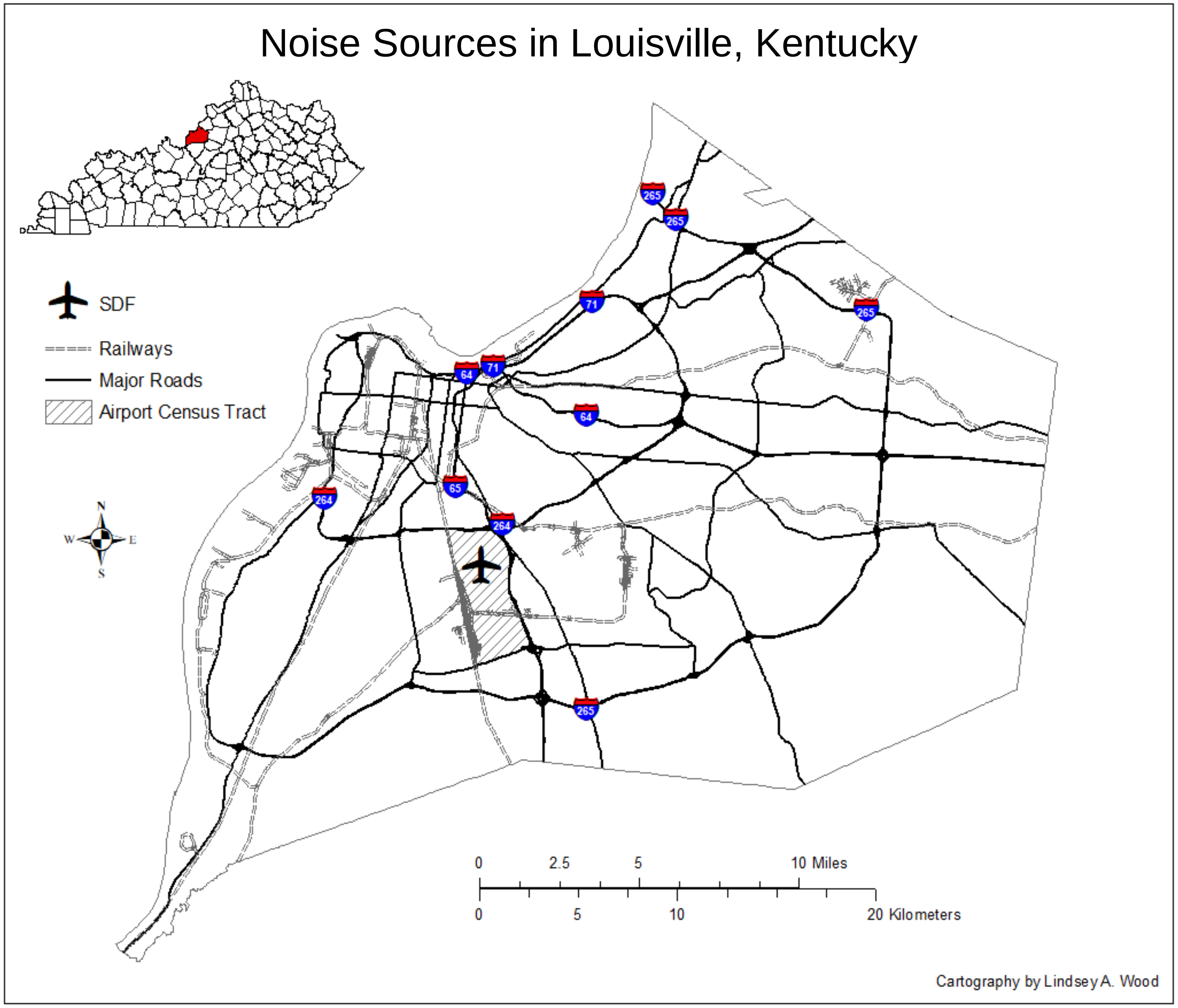

Figure 0.1: Noise sources in Louisville, Kentucky.

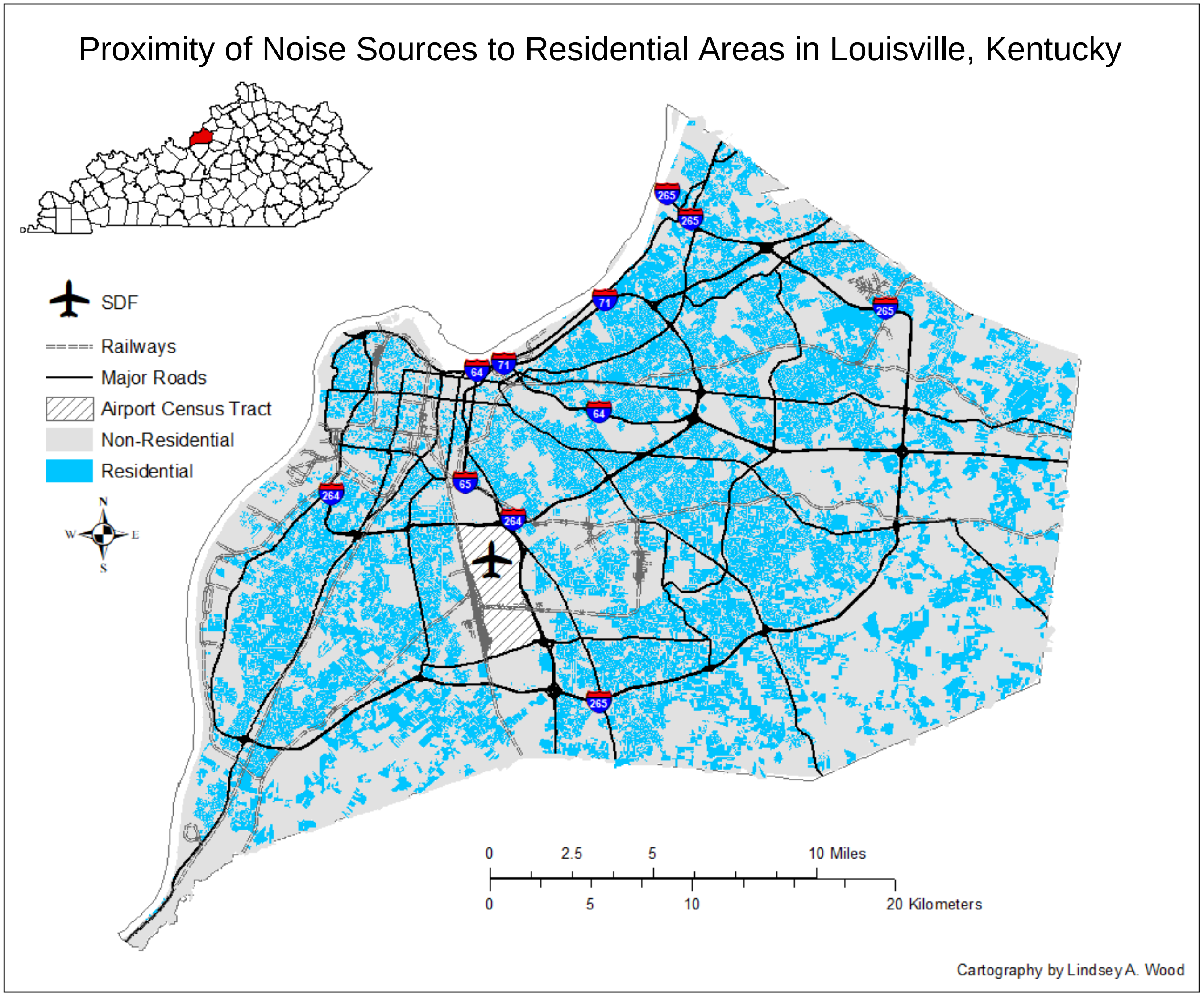

Figure 0.2: Proximity of noise sources to residential areas in Louisville, Kentucky.

Figure 0.3: Low-flying aircraft as seen from University of Louisville. (Photo by Dr. Brian Guinn.)

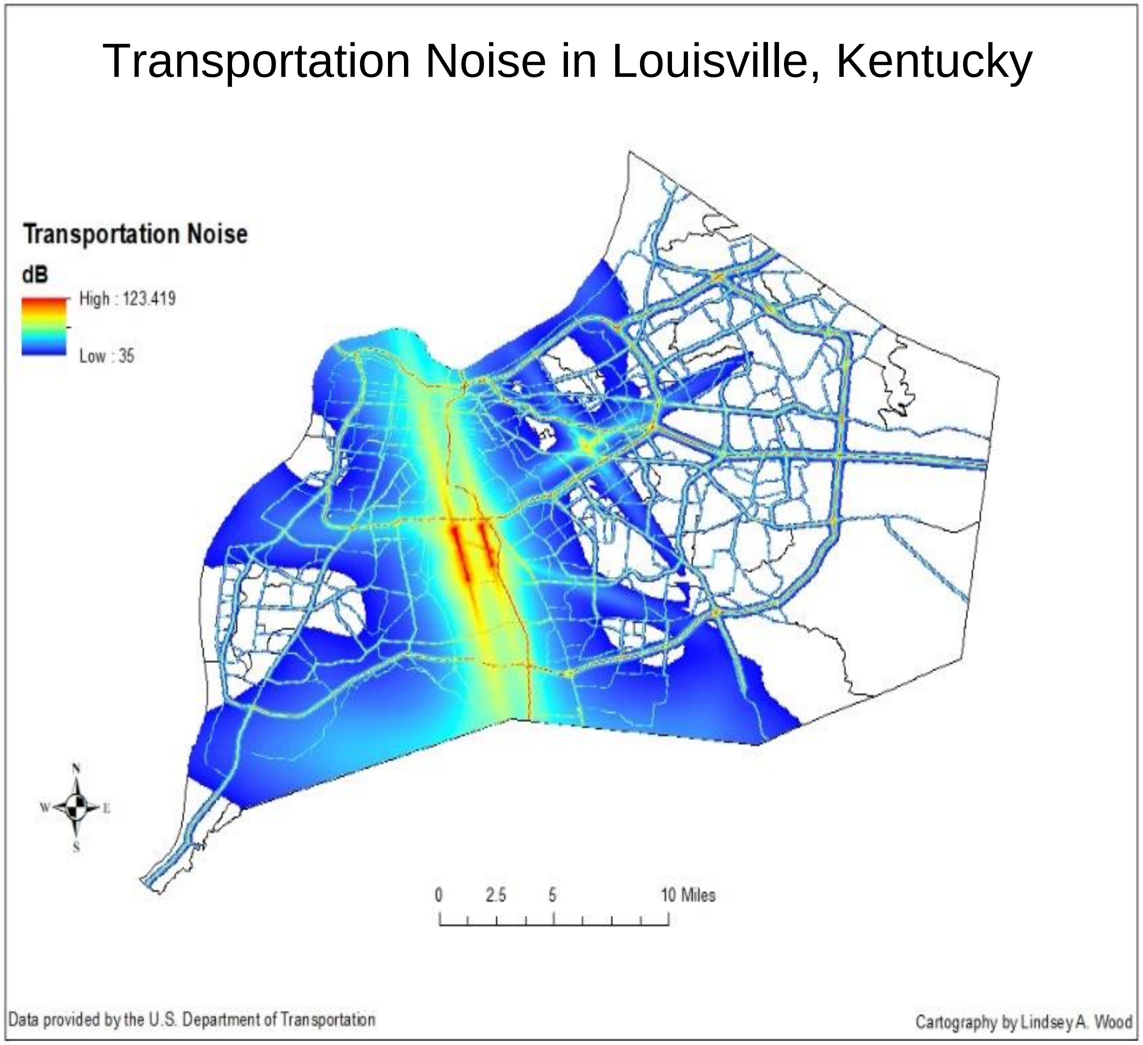

Figure 0.4: Transportation noise in Louisville, Kentucky.

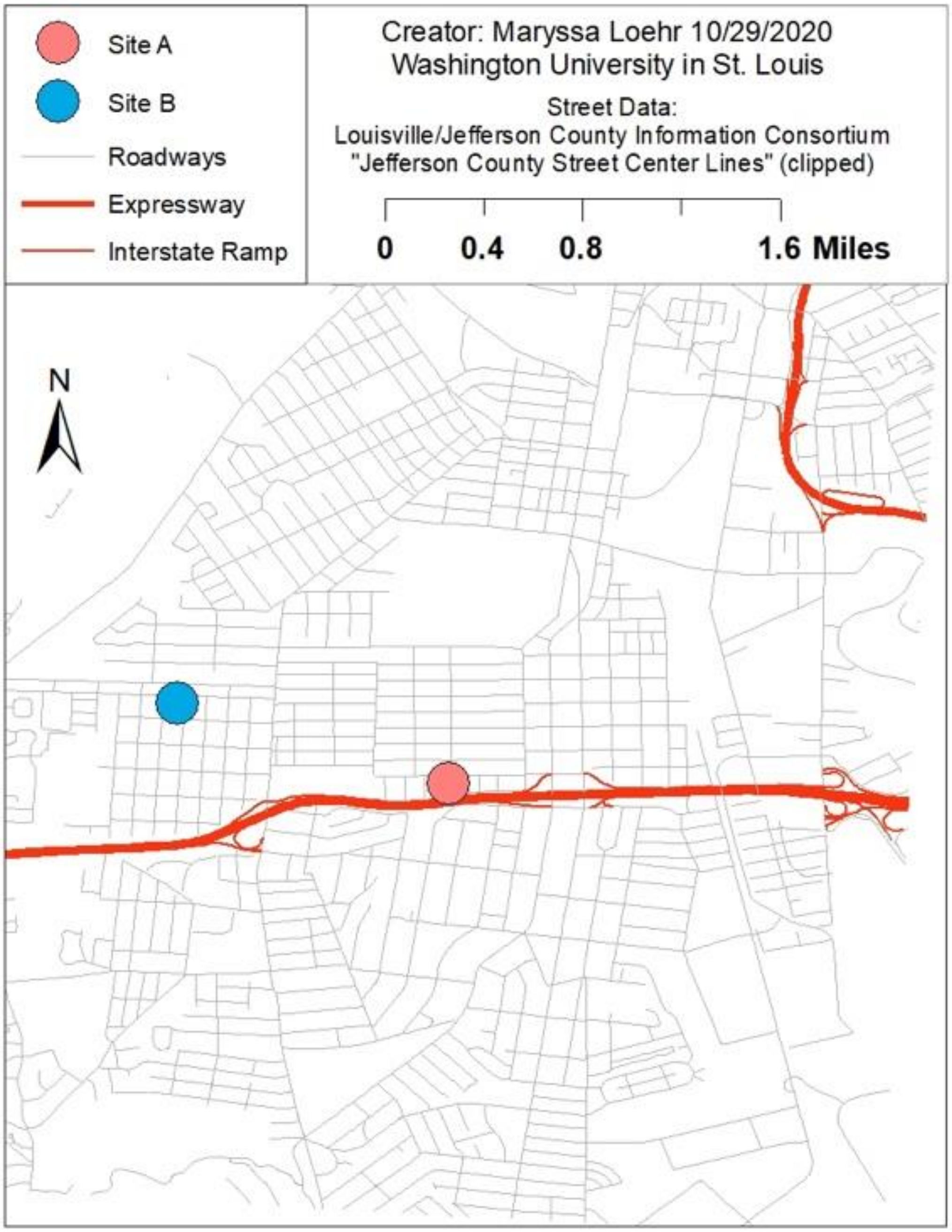

Figure 0.5: Noise meter sites in South Louisville, Kentucky.

AIM 1. ESTIMATION OF SEASONAL ENVIRONMENTAL NOISE LEVELS IN LOUISVILLE, KENTUCKY USING LAND USE REGRESSION MODELING[a]

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Acknowledgments: We would like to thank the participants who volunteered their land/yards for noise collection and HMB Professional Engineers, Inc. for loaning the noise monitor used in data collection. The University of Louisville Center for Integrative Health Sciences NIEHS P30 ES030283 (ND), University of Louisville Superfund Research Center NIEHS P42 ES023716 (LW, RY, JT), and University of Louisville Green Heart Louisville Project NIEHS R01 ES029846 (LW, RY, JT) supported researchers on this project.

Competing Financial Interests Declaration:
The authors declare that they have no actual or potential competing financial interests.

Introduction

Exposure to environmental noise, or noise pollution, is a growing concern for public health, particularly in urban areas consisting of loud noise polluters (e.g., airports, busy roadways, construction) that contribute to urban areas generally being 20 decibels louder than rural areas.[51] Notably, the World Health Organization (WHO) has published several extensive reports regarding noise exposure and its association with varying facets of health including cardiovascular and metabolic illnesses,[52] adverse birth outcomes,[53] hearing loss and tinnitus,[54] and annoyance.[55] Further, there is now enough evidence for adverse health outcomes attributable to noise exposure that WHO has estimated the burden of disease from environmental noise in high-income western European countries as 60,000 disability-adjusted life years (DALYs) for ischemic heart disease, 21,000 DALYs for tinnitus, 654,000 DALYs for annoyance, 903,000 DALYs for sleep disruption, and 45,000 DALYs for childhood cognitive impairment.[1]

Assessing the association of environmental noise with health outcomes requires large epidemiologic studies with individual-level exposure assessment of environmental noise. Individual-level noise exposure is dependent on the movement of an individual and the duration of time spent at a single location by an individual. Therefore, individual exposure assessment of environmental noise can be performed with the use of personal noise monitors that capture the variation of noise an individual is exposed to as they move through space and time. Recent epidemiological studies that have utilized personal noise monitoring have included relatively short duration of sampling times of 5 hours, 48 hours, and 7 days, with sample sizes of 46, 117, and 78, respectively.[36,40,41] However, this method can be expensive and generally prohibitive for long-term exposure assessment or sample sizes large enough to precisely determine effects of noise exposure on health outcomes.

Land Use Regression (LUR) techniques are a potentially useful tool in conducting exposure assessment of noise for large populations. LUR has been widely successful in modeling air pollutants.[42] More recently, LUR has been utilized in modeling environmental noise in urban areas, though all have been conducted outside of the United States.[43–45,56–60] Several studies have demonstrated LUR as a reliable and valid method to estimate noise exposures, with R^2 values ranging from 0.44 to 0.93 and prediction errors within five decibels.[43–45,56–62] Throughout the literature, noise is generally defined by specific sources (e.g. road traffic)[43,44,61–63] or by cumulative environmental noise.[43,45,56–60] For those estimating cumulative environmental noise, common predictors retained in LUR models include various road traffic measures such as length of roads, traffic volume, and distance from roads; distance to aircraft flyovers or airport noise contours; area of green spaces or other estimates of vegetation like Normalized Difference Vegetation Index (NDVI); area of building coverage and industrial, residential, and commercial land uses.[43,45,56–60]

Often, noise estimates from LUR studies represent the average noise levels within 24 hours. Commonly used measures are the average A-weighted (representative of the sensitivity of human hearing) sound pressure level of day-evening-night (LA_{den}) that more heavily weights evening and night noise and the average A-weighted sound pressure level of 24 hours (LA_{eq}24).[56–60] When these estimates are applied as individual exposure assessment to an individual's home address, the spatial and temporal movement of individuals is ignored, as the average person is not at their home for 24 hours a day. Ryu et al., applying the logic that most individuals stay in their residence during the nighttime, estimated road traffic noise for nighttime only.[61]

Further, seasonal differences in environmental noise may be present in urban areas. Daigle et al. demonstrates that atmospheric conditions, such as temperature, can affect sound pressure levels heard from a distant noise source.[64] When atmospheric conditions are cooler, sound waves travel farther than when atmospheric conditions are warmer. For a stationary listener, noise sources from further distances will be better heard when the air is cooler. Additionally, patterns of road traffic – an important predictor of environmental noise – vary throughout the year, with higher traffic volumes in warmer seasons and lower volumes in cooler seasons.[65] Therefore, for accurate noise exposure assessments, seasonal LUR models should be considered.

To the best of our knowledge, LUR methodologies in the context of cumulative environmental noise have yet to be applied to urban areas in the United States. In Louisville, Kentucky (Louisville Metro area), noise exposure is likely not geographically homogenous. One major factor that could lead to variation in noise exposure is the Louisville Muhammad Ali International Airport (SDF), which is located in the central part of the county. In the 2020 calendar year, SDF operated 151,641 in- and out-bound flights.[66] In 2019, SDF was ranked second in the United States and fourth in the world for cargo movement.[67] The amount of cargo transported through SDF is attributable to the main air hub of the United Parcel Service (UPS) being located at SDF. UPS estimates a daily average of 387 in- and out-bound flights at SDF.[68] A majority of these flights are arriving to and departing from the airport during night-time hours. For example, from 10:00 PM on August 10, 2021 to 7:00 AM on August 11, 2021, UPS had 133 flights arrive and 127 flights depart from SDF, totaling 260 flights.[46] Additionally, five busy interstate systems (I-65, I-64, I-71, I-264, and I-265) and several major roads weave through Louisville, contributing to Louisville's 2019 rank as the 110th most congested city in the United States and 597th in the world.[69] In 2019, the annual average daily traffic in Louisville was 10,922,711 vehicles traveling cumulatively on all roads.[70] Some major roadways as well as the airport are located in or near residential areas, creating both a concern about the impact of environmental noise exposure on the health of the population and a need for estimations of environmental noise.

The purpose of this study was to apply LUR methodologies to estimate cumulative and geographically specific environmental noise exposure throughout residential areas of Louisville, Kentucky for varying times of day and seasons, and assess geographic predictors of noise exposure. Models were developed to represent evening and nighttime noise (5:00 PM to 9:00 AM) in both the winter and spring seasons and daytime noise (9:00 AM to 4:00 PM) in the spring season.

Methods and Materials

Noise Data Collection

Convenience sampling, through personal contacts, was used to determine 15 noise collection sites across residences in multiple regions in Louisville, Kentucky (Figure 1.1) at two time points: January/February 2021 and April/May 2021. The distance between nearest locations ranged from 1.40 and 5.51 miles (2.25 and 8.88 kilometers). At each location, collection consisted of a 24-hour noise reading with noise levels recorded every ten seconds using a Class 1 noise meter (Type 2236, Brüel & Kjær, Naerum, Denmark). The noise meter was attached to a tripod – which was weighted down to prevent any moving or falling – and connected to an external power source (Figure 1.2). Two collection periods occurred at each site: one 24-hour collection in January or February 2021 to represent environmental noise in the winter season, and another 24-hour collection in April or May to represent environmental noise in the spring season. Collection was avoided on days with 1) a thick blanket of snow on the ground because thick snow absorbs sound waves,[71] 2) precipitation rates greater than 0.05 inches per hour, and 3) consistent wind speeds greater than 10 miles per hour or 5 kilometers per second.[56] Importantly, collection in the spring season was completed before the 2021 emergence of the Brood X cicadas in Kentucky.

Once collection was completed at each site, the data were transmitted from the noise meter to a computer using Protector Software (Type 7825, Brüel & Kjær, Naerum, Denmark). An example of transmitted data is shown in Figure 1.3, where the y-axis represents noise (dB) and the x-axis represents time. Noise data are represented as ten second A-weighted equivalent sound level (LA_{eq}) throughout the 24-hour collection period.

Geographic Data Collection for Environmental Noise Predictors

Collection sites were geocoded, and several buffers of varying radii were created around each site. Buffer radii included 50, 100, 150, 300, 500, 750, 1,000, 1,500, 2,000, and 2,500 meters (Supplemental Figure 1.1). We considered 14 variables that are thought to be considered predictors of environmental noise including: being within one kilometer of the airport's 60-decibel Noise Exposure Map (NEM) contour; length of local roads, major roads, railroads, and streams; area of building coverage, industrial land use, residential land use, and commercial land use; traffic volume; Normalized Difference Vegetation Index (NDVI); and distance to nearest hospital, fire station, and police station. These geographic characteristics were calculated within buffer zones for each collection site (Table 1.1) and are described below. All geographic data were computed in ArcGIS 10.7.1.

Data for length of local and major roads, railroads, and streams; building coverage; industrial, residential, and commercial land use; and hospital, fire station, and police station locations were obtained from The Louisville/Louisville Information Consortium (LOJIC). Local and major roads data from 2018 were measured by the Kentucky Transportation Cabinet (KYTC), while railroad and stream data from 2019 were collected and measured – using photogrammetrically interpreted polygons – by LOJIC. Local and major roads, railroad, and stream data were represented as line features. For these line variables, we determined the total length in meters of each characteristic that was present within buffer sizes. LOJIC and the Louisville/Louisville Metropolitan Sewer District (MSD) photogrammetrically interpreted polygons to derive building coverage data for 2020. The Louisville Metro Planning and Design Services derived land use data for 2017 parcel property class, aerial photography, and field surveys. Building coverage and land use data were represented as polygon features and we determined the total area in meters^2 of building coverage and of each land use type within buffer sizes. Hospital location data from 2021 were collected by the Kentucky Cabinet for Health & Family Services (CHFS) and the Kentucky State Health Operations Center (SHOC). Fire station location data from 2015 were collected by the Louisville Fire Department. Police station location data from 2014 were collected by the Louisville Metro Police Department. Hospitals, fire stations, and police stations were represented as point features. Distance in meters from collection sites to the nearest hospital, fire station, and police station were calculated in ArcGIS (Generate Near Table tool).

Traffic volume data for 2020 were collected by and obtained from KYTC. Annual average daily traffic (AADT) data were estimated by KYTC by computing monthly average daily traffic for each month based on available traffic counts within some temporal period (i.e. one hour, 5 minutes, 1 minute).[72] These 12 monthly averages were then used to calculate the AADT.[72] For all roads, the AADT for the prior year (2019) was multiplied by the length (meters) of the road, which represented the total number of meters traveled on each roadway. We calculated the cumulative number of meters traveled on all roadways within buffer sizes as an estimate of traffic volume.

Due to the SDF airport and its housing of the UPS hub, aircraft noise is a large contributor to environmental noise in Louisville. Therefore, we considered proximity to the 60-decibel NEM contour that serves as a proxy for the aircraft noise attributable to the major commercial and cargo flyovers in Louisville. NEMs display noise contours surrounding airports in five decibels increments based on aircraft traffic. In the United States, NEMs represent noise levels in decibels based on yearly averages of Day-Night Sound Levels (DNL), which includes a 10 decibels correction applied during nighttime hours (10:00 PM to 7:00 AM).[73] These noise levels are predicted based on varying characteristics (i.e. aircraft type, elevation of the aircraft, flight paths, time of flights) of aircraft traffic coming into and out of the airport. NEMs are used to identify land use surrounding an airport that may be affected by noise exposure from air traffic. The 60-decibel contour was chosen for two reasons: 1) the 60-decibel contour is the lowest predicted contour and therefore includes land use located within higher noise contours (i.e. 65 dB, 70 dB, 75 dB); 2) Goudreau et al. utilized the Noise Exposure Forecast (NEF) 25 contour in Canada,[58] which is equivalent to the 60-decibel NEM contour.[73] The 2016 NEM Forecast contour data for SDF were obtained from the Airport Authority's Noise Officer (NEM for SDF shown at https://www.flylouisville.com/wp-content/uploads/2019/06/2021-NEM.pdf). These contours include a five-year forecast of NEM contours for 2021, which were the contours used for this analysis. Distance from collection sites to the 60-decibel

NEM contour was calculated in ArcGIS. As no collection sites were within the 60-decibel NEM contour, sites were then categorized into two groups – a method used by Goudreau et al.[58] – as 1) being within one kilometer of the 60-decibel NEM contour, or 2) being further than one kilometer to the 60-decibel NEM contour.

NDVI was calculated using bands obtained from Landsat8 from the United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center Science Processing Architecture (ESPA) On Demand Interface[74] using EarthExplorer.[75] NDVI is a representation of the amount of greenness and/or the density of vegetation within an area. Vegetation absorbs visible red (R) light wavelengths and reflects invisible near-infrared (NIR) light wavelengths.[76] The amount of these wavelengths being absorbed and reflected on land surfaces are measured by satellite sensors.[76] These satellite data can then be translated to NDVI values by calculating the ratio of R to NIR values using the equation: $NDVI = (NIR - R) / (NIR + R)$.[76,77] The NDVI scale ranges from -1 to +1; spaces with low vegetation (i.e. barren areas, rocks, sand, snow, water) typically have NDVI values between 0 to at or below 0.1, spaces with sparse vegetation (i.e. areas with bushes, crops, or residential neighborhoods) typically have values between 0.2 and 0.5, and spaces with highly dense vegetation (i.e. temperate forests, tropical forests, peak crops) typically have values greater than 0.6;[76] negative NDVI values represent water. R and NIR bands from January 6th, 2020 (cloud coverage of 6.09%) were used to represent winter NDVI, while R and NIR bands from August 17th, 2020 (cloud coverage of

1.05%) were used to represent spring NDVI. Bands 4 – representing R wavelengths – and 5 – representing NIR wavelengths – for each season were used to create the seasonal NDVI rasters using the established equation: NDVI = (Band 5 – Band 4) / (Band 5 + Band 4), which is appropriate for Landsat8 data.[77] Average NDVI within buffers was calculated using ArcGIS (Zonal Statistics tool).

Statistical Analyses

Noise Data and Reproducibility

Multiple time-equivalents for each season were calculated by averaging the noise levels within the time windows: 16 hours (5:00 PM to 9:00 AM) and 7 hours (9:00 AM to 4:00 PM). Due to unforeseen intermittent monitor malfunctions, data for short periods of time were sometimes missing from the 24-hour reading (0.01% of winter data; 1.46% of spring data). In these cases, data were imputed with the average noise level. Paired t-tests were utilized to determine if noise levels in the same timeframe varied by season or if noise levels within the same season varied by timeframe.

Reproducibility of noise collection measures was assessed by intraclass correlation coefficients (ICC). During the winter collection, four sites were sampled for an additional 24-hour collection, resulting in four sites with two measurements contributing to the winter ICC calculation. Due to the oncoming emergence of the Brood X cicadas in May 2021, time allowed for only two sites to be sampled for an additional 24-hour collection in the spring, resulting in two sites with two measurements each contributing to spring ICC calculations.

Land Use Regression (LUR) Modeling

We utilized LUR models to estimate the A-weighted equivalent sound level (LA_{eq}) at the 15 locations for the following different times of day and seasons:

1) Winter 16-hour (5:00 PM to 9:00 AM) equivalent ($LA_{eq}16_{winter}$) to represent environmental noise during winter months and during the times that most adults would presumably be at home,

2) Spring 16-hour (5:00 PM to 9:00 AM) equivalent ($LA_{eq}16_{spring}$) to represent environmental noise while most adults are home during the spring,

3) Spring 7-hour (9:00 AM to 4:00 PM) equivalent ($LA_{eq}7_{spring}$) to represent the spring season during the times that school children would be in school.

Linear LUR models were built using the geographic characteristics as predictor variables and the continuous time-equivalent noise values for each of the 15 sites as the outcome. We took two approaches to build the LUR models. 1) We used a widely practiced supervised forward selection method that strongly relies on statistical tests[78] and can be underpowered with small sample sizes; for this paper, we have coined this approach as the "Conventional Approach." 2) We used an *a priori* approach based on our *a priori* knowledge of the current literature on community noise predictors[43,45,56–60] that is coined here as the "*A Priori* Approach". Variables tested in LUR modeling and considered for the *A Priori* Approach are shown in Table 1.1.

For the Conventional Approach, the order of variables to be entered into models were determined by their R^2 values in univariate linear regression analysis, where the variable with the largest R^2 value had a higher priority of model inclusion. For each variable with buffers, we selected a single buffer size to include in models based on the highest R^2 value in univariate analysis. (Supplemental Table 1.1 displays univariate results from $LA_{eq}16_{spring}$ as an example of the variable selection process.) To assess if more explanation of variance within the Conventional Approach models was possible, other buffer sizes of each variable included were tested in place of the original buffer size. Pearson correlation coefficients between all included variables were estimated; however, due to the small sample size, correlation coefficients were heavily influenced by random error. Therefore, strong correlation between variables was not used as a justification for predictor exclusion. For transparency, we report the Pearson correlation coefficients for variables included in all final models in Supplemental Table 1.2.

For the *A Priori* Approach, a subset of predictors was identified for consideration of model inclusion based on their consistent association with noise in prior literature. Similar to the Conventional Approach, the order of inclusion was determined by their R^2 values in univariate analyses. However, if a variable entered into the LUR model did not match the expected sign of the β coefficient (see Table 1.1; positive coefficients expected for length of local roads, major roads, and railroads; traffic volume; area of building coverage and industrial land use; negative coefficients expected for increased distance from the 60-decibel NEM contour, NDVI, length of streams, area of residential and commercial land use, and distance to nearest hospital, fire station, and police station), other buffer zones or variables were used in its place as an attempt to have an exhibition of the β coefficient that agrees with not only previous literature but with acoustical physics and noise dynamics. Additionally, if an added variable resulted in incongruous signs of β coefficients for variables already in the model, the added variable was dropped (so long as other buffer sizes of the added variable did not correct the issue).

For all models, regardless of the Approach, unstandardized and standardized β coefficients and 95% confidence intervals were used to determine the strength and significance of association between variables and noise. Although multicollinearity was assessed for all models, the small sample size limited the ability of relying upon condition indexes and variance decomposition proportions. For this reason, multicollinearity of predictor variables was not used as a driving factor in modeling decisions – an approach that mimics that of Goudreau et al.[58] However, for transparency, we report the condition indexes for final LUR models. The performance of the final models was evaluated based on their R^2 value. All statistical analyses were performed using SAS Software (version 9.4).

Validation of the LUR-estimated Noise

For model validation, the leave-one-out cross-validation (LOOCV) method was performed on each LUR model to assess model reliability. LOOCV consists of comparing a built model against the observed data while excluding a single observation and repeating this process multiple times. The number of permutations of LOOCV that were computed for each LUR model was equal to the number of observations included in each model. The prediction error of the final models was quantified based on their LOOCV root mean square error (RMSE).

Determining Final LUR Models

In modeling $LA_{eq}16_{winter}$ via the *A Priori* Approach, being within one kilometer of the 60-decibel NEM contour, traffic volume, NDVI, and length of streams were considered for inclusion. However, due to an incongruous sign for traffic volume, the variable was replaced with the length of major roads in the 1500-meter buffer. For two of the 15 collection sites, there were no major roads present in the 1500-meter buffer, resulting in only 13 collection sites being used in modeling.

During Conventional Approach modeling for $LA_{eq}16_{spring}$, two models were built; Conventional model 1 included NDVI in the 1,000-meter buffer, while Conventional model 2 included NDVI within the 150-meter buffer. In *A Priori* Approach modeling, variables considered for inclusion were being within one kilometer of the 60-decibel NEM contour, traffic volume in the 750-meter buffer, NDVI in the 1,000-meter buffer, and length of streams in the 2,000-meter. Both traffic volume in the 750-meter buffer and NDVI in the 1,000-meter buffer had β coefficients with the incongruous sign. Ultimately, after testing all buffer sizes, *A Priori* model 1 included the 500-meter buffer for traffic volume and the 300-meter buffer for NDVI. *A Priori* model 2 was built and included length of major roads in the 1,500-meter buffer in the place of traffic volume in the 500-meter buffer.

For $LA_{eq}7_{spring}$, variables considered for inclusion in the *A Priori* Approach were being within one kilometer of the 60-decibel NEM contour, traffic volume in the 750-meter buffer, NDVI in the 150-meter buffer, and length of streams in the 2,000-meter were considered for inclusion. For the length of streams in the 2,000-meter buffer, the β coefficient consisted of the incongruous sign. Inclusion of all other buffer sizes for the length of streams did not correct the sign of the streams β coefficient. Therefore, length of streams was dropped from the model altogether.

When models from both approaches – the Conventional Approach and *A Priori* Approach – were built and validated, the R^2 values and LOOCV RMSE values were compared to determine the most reasonable model for each time equivalent.

Estimating and Mapping Noise in Louisville, Kentucky

The final LUR models were then applied to predict noise throughout the entirety of Louisville. All shapefiles for included variables were converted to rasters with a 10-meter x 10-meter resolution. After rasters for all retained variables were created, the Raster Calculator tool was used to apply the LUR equation to the variable rasters. The 10-meter by 10-meter raster layer output predicted noise levels throughout the county based on the LUR equation. Noise estimation and mapping were computed in ArcGIS 10.7.1.

Applying Certain LUR Models to Other Time-equivalents

To determine if models were appropriate for the same period of time between seasons, the selected model predictors for $LA_{eq}16_{winter}$ noise were tested on the $LA_{eq}16_{spring}$ noise data and vice versa. Further, the selected model predictors for $LA_{eq}16_{spring}$ were tested on the $LA_{eq}7_{spring}$ data to determine if the model was appropriate for a different period of time within the same season.

Results

The ICC for $LA_{eq}16_{winter}$, $LA_{eq}16_{spring}$, and $LA_{eq}7_{spring}$ were 0.986 (n=4 sites, 8 samples), 0.857 (n=2 sites, 4 samples), and 0.968 (n=2 sites, 4 samples), respectively. Descriptive statistics of noise data at the 15 collection sites for each time equivalent are shown in Table 1.2. Mean noise levels at the 15 collection sites for $LA_{eq}16_{winter}$, $LA_{eq}16_{spring}$, and $LA_{eq}7_{spring}$ were 49.81 decibels (SD=4.8), 52.21 decibels (SD=4.8), and 55.05 decibels (SD=5.0), respectively. Within the spring season, noise was significantly louder in the daytime ($LA_{eq}7_{spring}$) than the time window that included nighttime hours ($LA_{eq}16_{spring}$; $t(14)=5.52$, $p<0.01$). Similarly, when comparing the same time of day across seasons, noise was louder in the spring season ($LA_{eq}16_{spring}$) than in the winter season ($LA_{eq}16_{winter}$), albeit non-significantly ($t(14)$ -1.87, $p=0.08$).

Table 1.3 displays descriptive statistics of predictor variables and buffers that were retained in final models. In univariate analysis, all predictor variables were associated with noise in the direction of which they were expected.

$LA_{eq}16_{winter}$ LUR Modeling Results

The resulting Conventional model for $LA_{eq}16_{winter}$ included being within one kilometer of the 60-decibel NEM contour, traffic volume in the 2,500-meter buffer, NDVI in the 150-meter buffer, length of railroads in the 2,500-meter buffer, and length of streams in the 2,000-meter buffer. This model had an R^2 value of

0.4387 and an LOOCV RMSE value of 5.85 decibels. For the *A Priori* model (n=13), the R^2 and LOOCV RMSE values were 0.7341 and 2.98 decibels, respectively. The *A Priori* model 1 (n=13), accounted for more variance in noise and had a lower prediction error than the Conventional. Therefore, the final LUR model (shown in Table 1.4) for $LA_{eq}16_{winter}$ had a sample of 13 collection sites and included being within one kilometer of the 60-decibel NEM contour, length of major roads in the 1500-meter buffer, NDVI in the 150-meter buffer, and length of streams in the 2000-meter buffer.

Compared to being within one kilometer of the 60-decibel NEM contour, living further than one kilometer resulted in lower $LA_{eq}16_{winter}$ noise estimates (β=-4.86, 95% CI: -11.67, 1.95; standardized β=-0.43, 95% CI: -0.86, 0.14). A 10-kilometer increase in length of major roads resulted in a higher noise estimate (β=1.54, 95% CI: -3.32, 6.41; standardized β=0.17, 95% CI: -0.33, 0.64). NDVI was inversely associated with noise, with a 0.1 increase resulting in lower noise estimates (β=-2.01 95% CI: -9.60, 5.59; standardized β=-0.17, 95% CI: -0.68, 0.40). An increase of 100 kilometers in the length of streams resulted in lower estimates of noise (β=-4.06, 95% CI: -13.04, 4.93; standardized β=-0.30, 95% CI: (-0.81, 0.31). Based on the standardized beta coefficients, being within one kilometer compared to being further than one kilometer of the 60-decibel NEM contour had the strongest association with predicted noise than other predictors. As mentioned prior, the R^2 value of the final model was 0.7341 with an LOOCV RMSE value of 2.98 decibels, indicating that the model was well fit and had a low prediction error. The condition index for the model was 26.03. When this model was applied to Louisville (shown in Figure 1.4), estimated noise ranged from 47.53 decibels to 66.37 decibels.

$LA_{eq}16_{spring}$ LUR Modeling Results

Conventional model 1 for $LA_{eq}16_{spring}$ included being within one kilometer of the 60-decibel NEM contour, traffic volume in the 750-meter buffer, NDVI in the 1,000-meter buffer, length of railroads in the 2,500-meter buffer, and length of streams in the 2,000-meter buffer. This model had an R^2 value of 0.5430 and an LOOCV RMSE value of 6.16 decibels. Conventional model 2, which utilized NDVI in the 150-meter buffer, had an R^2 value of 0.5719 and an LOOCV RMSE value of 5.92 decibels. The resulting *A Priori* model 1 had an R^2 value of 0.3738 and a LOOCV RMSE value of 9.87 decibels, while *A Priori* model 2 resulted in an R^2 value of 0.4478 and an LOOCV RMSE value of 8.03 decibels. Both *A Priori* models had lower R^2 values and higher LOOCV RMSE values than the Conventional models. Of the two Conventional models, model 2 had the highest explanation of variance and lowest prediction error. Therefore, the Conventional model 2 was chosen as the final model for $LA_{eq}16_{spring}$.

Compared to being within one kilometer of the 60-decibel NEM contour, living further than one kilometer resulted in lower noise estimates (β=-3.73, 95% CI: -30.04, 22.59; standardized β=-0.27, 95% CI: -2.20, 1.65). A 1,000,000-kilometer increase in traffic volume resulted in higher noise estimates (β=4.16, 95% CI: -121.79, 130.11; standardized β=0.07, 95% CI: -1.93, 2.06). NDVI was inversely associated with noise, with a 0.1 increase resulting in lower noise estimates (β=-2.92, 95% CI: -11.36, 5.52; standardized β=-0.22, 95% CI: -0.84, 0.41). As the length of railroads increased by 10 kilometers, the noise estimates also increased (β=2.50, 95% CI: -2.46, 7.46; standardized β=0.39, 95% CI: -0.38, 1.15). An increase of 100 kilometers in the length of streams resulted in a lower estimate of noise (β=-0.16, 95% CI: -13.02, 12.89; standardized β=-0.01, 95% CI: -0.81, 0.79). Based on the standardized beta coefficients, length of railroads had the strongest association with predicted noise relative to other predictors. The final model had an R^2 value of 0.5719 and an LOOCV RMSE value of 6.49 decibels, indicating that the model had a satisfactory fit and prediction error. The model resulted in a condition index of 78.75. When this model was applied to Louisville (shown in Figure 1.5), estimated noise ranged from 49.73 decibels to 80.16 decibels.

$LA_{eq}7_{spring}$ LUR Modeling Results

The Conventional model for $LA_{eq}7_{spring}$ included being within one kilometer of the 60-decibel NEM contour, traffic volume in the 750-meter buffer, NDVI in the 150-meter buffer, and length of railroads in the 2,500-meter buffer. The R^2 value was 0.4897 and the LOOCV RMSE value was 6.77 decibels. The resulting *A Priori* model had an R^2 value of 0.5005 and an LOOCV RMSE value of 5.83 decibels. These values indicated that the *A Priori* model was better fit and had a lower prediction error than the Conventional model and was therefore chosen as the final model.

For $LA_{eq}7_{spring}$, being further than one kilometer resulted in lower noise estimates when compared to being within one kilometer of the 60-decibel NEM contour (β=-0.99, 95% CI: -19.49, 17.50; standardized β=-0.07, 95% CI: -1.36, 1.22). A 1,000,000-kilometer increase in traffic volume resulted in an increased noise estimate (β=20.41, 95% CI: -72.03, 112.85; standardized β=0.64, 95% CI: -1.09, 1.71). A 0.1 increase in NDVI resulted in a lower noise estimate (β=-5.97, 95% CI: -14.23, 2.30; standardized β=-0.42, 95% CI: -1.01, 0.16). The final model had a satisfactory fit and prediction error, with an R^2 value of 0.5005 and an LOOCV RMSE value of 6.47 decibels. The condition index value was 52.31. When this model was applied to Louisville (shown in Figure 1.6), estimated noise ranged from 42.57 decibels to 74.12 decibels.

Application of Certain LUR Models to Other Time-equivalents

When applying the selected $LA_{eq}16_{winter}$ model to $LA_{eq}16_{spring}$ noise data (Table 1.5), the R^2 was lower and the LOOCV RMSE value was higher than those of the selected $LA_{eq}16_{spring}$ model. This indicated that the model built to predict noise from 5:00 PM to 9:00 AM in the winter was not as well fit for predicting noise from the same hours in the spring as the model built for $LA_{eq}16_{spring}$. Additionally, the length of major roads and noise were inversely associated in the spring when applying the winter model, which violated the rule of having β coefficients with the correct expected sign. Upon testing all other buffer sizes for the length of major roads, the sign remained in the incongruous direction. Similarly, the selected $LA_{eq}16_{spring}$ model was not a good fit for the $LA_{eq}16_{winter}$ noise data (Table 1.6). When applied to the $LA_{eq}16_{winter}$ data, the $LA_{eq}16_{spring}$ model resulted in a similar LOOCV RMSE value but a much lower R^2 value than that of the $LA_{eq}16_{winter}$ built model. An inverse association was detected between traffic volume and noise and the inclusion of other buffer sizes did not correct the sign. Therefore, it was determined that models built for specific hours in one season could not be applied to the same subset of hours in the opposite season and that individual LUR models were needed for $LA_{eq}16_{winter}$ and $LA_{eq}16_{spring}$.

Applying the selected $LA_{eq}16_{spring}$ model to $LA_{eq}7_{spring}$ noise data (Table 1.6) resulted in a similar R^2 value but higher LOOCV RMSE value than that of the selected $LA_{eq}7_{spring}$ model, indicating that the $LA_{eq}16_{spring}$ model contained more error in predicting $LA_{eq}7_{spring}$ noise than the selected $LA_{eq}7_{spring}$ model. Further, two predictors, traffic volume and length of streams, were associated with noise in the incongruous direction. Replacing the buffer sizes of these predictors with other buffer sizes did not correct the issue. Therefore, the model built for predicting noise in daytime hours could not be used for predicting noise in nighttime hours, even within the same season; individual models $LA_{eq}16_{spring}$ and $LA_{eq}7_{spring}$ were required.

Discussion

Although varying models were applied to varying time equivalents, distance to the 60-decibel NEM contours and NDVI were consistent predictors of noise across seasons and time windows, which is consistent with findings from other studies. Other predictors, such as traffic volume and length of streams, were retained in multiple models, again consistent with extant literature. However, the strength of the association for these common predictors of noise varied across time equivalents.

Most notably, spring noise during the daytime was more strongly associated with traffic volume ($LA_{eq}7_{spring}$ standardized β=0.64, 95% CI: -1.09, 1.71) than spring nighttime noise ($LA_{eq}16_{spring}$ standardized β=0.07, 95% CI: 95% CI: -1.93, 2.06). While both are not statistically significant, these differing strengths of association with noise for traffic volume across times of day is likely due to the increased activity of traffic in the daytime compared to nighttime. Conversely, noise was more strongly determined by proximity to the 60-decibel NEM contour during the nighttime ($LA_{eq}16_{spring}$ standardized β=-0.27, 95% CI: 2.20, 1.65) than in the daytime ($LA_{eq}7_{spring}$ standardized β=-0.07, 95% CI: -1.36, 1.22). These varying coefficient estimates are likely attributable to frequency of UPS aircraft flyovers during the nighttime. The current observation emphasizes the need for varying models to be applied to varying time-equivalents, especially when considering urban areas in which environmental noise exposure may have a large temporal variance within 24 hours. Some cumulative environmental noise exposure assessment studies[59,60] have used LA_{den} estimates of noise, which is a measure of the average noise within a 24-hour day but includes a five decibels penalty for the evening hours and a 10 decibels penalty for the night hours. This measure of noise is useful in that the average noise level of the full 24 hours is weighted more heavily by evening noise and even more heavily by nighttime noise, which can account for the relative impacts of noise exposure at different times of the day. However, since LA_{den} is a single estimate of averaged noise, the noise exposure within varying time periods throughout the day cannot be assessed. The current study proposes the idea that environmental noise exposure assessments should include the use of multiple noise estimating LUR models to represent varying times of day. When these time equivalent noise estimates are extracted by the location of an individual during these times, the true noise exposure of individuals may be better reflected. Future studies, especially those of which use LUR models as a means of exposure assessment of noise, should seek to improve noise estimating LUR modeling for specific time equivalents that may be important for assessing impacts on health outcomes.

Interestingly, during model building traffic volume was chosen for only spring noise, while length of major roads was chosen for winter noise. Although neither were significantly associated with noise levels, it was expected that the same variable – either traffic volume or major road length – would be associated with noise in both seasons. The unanticipated discordance in chosen variables between seasons may be attributable to the timing of noise data collection. During the January/February 2021 noise collection, strict social restrictions in response to the COVID-19 pandemic were still in place, with many in Louisville still working and attending school from home.[79] This likely led to a lower-than-normal amount of traffic volume in the winter and potentially a lower-than-normal amount of environmental noise being produced by traffic. As the traffic volume data was represented by the annual average of 2019 – a year in which no extenuating circumstances were affecting traffic in Louisville – it is likely that the traffic volume variable was not an adequate reflection of traffic volume in January/February 2021 but was a better predictor of the April/May 2021 season when social restrictions were beginning to be lifted as result of vaccination efforts.[79] Further, when comparing counts in 2021 to the pre-pandemic year of 2019, traffic in the US declined by 65%.[80] Regardless, when comparing the 5:00 PM to 9:00 AM time window between seasons, the strength of association between traffic volume in the spring season ($LA_{eq}16_{spring}$ standardized β=0.07) was less than that of the major road length in the winter season ($LA_{eq}16_{winter}$ standardized β=0.17).

Similar to the findings of the current study, Goudreau et al. – who modeled summer and winter environmental noise via LUR in Montreal, Canada – reported models that varied by two seasons.[58] Common predictors of both summer and winter noise reported by the authors included: NDVI; area of residential, industrial, and commercial land use; the length of highways and bus lines; and proximity to airport noise contours.[58] Although the current study confirmed the importance of NDVI, roadway variables (e.g. traffic volume or length of major roads), and proximity to airport noise contours, future studies should seek to further explicate these seasonality differences in noise exposure.

In the current study, several predictors of noise were not retained in any LUR models. These predictors include the length of local roads; the area of building coverage; the area of industrial, residential, and commercial land use; and the distance to the nearest hospital, fire station, and police station. Length of local roads may not have been contributing to noise levels as strongly as length of major roads due to the reduced speed limit on local roads relative to major roads. Indeed, the faster a vehicle is moving, the louder it will be as it passes.[81] For their respective chosen buffer zones for the $LA_{eq}16_{winter}$ data, the area of building coverage in the 1,000m buffer was highly correlated with the length of local roads in the 1,000m buffer (Pearson Rho=0.82, p-value<0.001). However, it appears that the strength of correlation between the two predictors decreases as the difference in their buffer sizes increases ($LA_{eq}7_{spring}$: area of building coverage in the 150m buffer and length of local roads in the 300m buffer, Pearson Rho=0.57, p-value=0.03; $LA_{eq}16_{spring}$: area of building coverage in the 1,000m buffer and length of local roads in the 150m buffer, Pearson Rho=0.31, p-value=0.26). This is plausible since the value for one predictor will increase directly with increased buffer zone. Regardless of the statistics, it seems reasonable that the area of building coverage and the length of local roads would be correlated, as most buildings would be located near local roads. If local roads were contributing to increased noise, buildings can potentially attenuate the loudness of local roads by acting as a barrier; essentially, the two predictors may "cancel out" the other's effect on noise.[47,82]

Regarding, the area of industrial and commercial land use, the lack of consistent presence throughout the county may have contributed to their non-retention in modeling; for all site locations, the amount of commercial and industrial land in surrounding areas was low. The opposite was true for the amount of residential land surrounding site locations. This is because all site locations were homes in residential areas. The lack of variability in the area of these land uses may have led to an incapability of detecting their associations with noise. Since all site locations were within residential areas, the distance to the nearest hospital, fire station, and police station, may have been so far removed from site locations that noise generated at/around these locations by their respective response vehicles was negligible. In Louisville, there are two fire stations (range of distance from sites to nearest fire station: 404 to 8,678 meters) and no police stations (range of distance from sites to nearest police: 511 to 5,623 meters) or hospitals (range of distance from sites to nearest hospital: 877 to 10,778 meters) in residential areas. Future studies should aim for higher variability within all potential predictor variables. Further, there may be high variability in the presence of conditions requiring fire, police, and/or ambulance vehicle response in any given 24-hour period; a larger sample with multiple or longer collections per site are likely needed to capture the patterns of emergency response by fire, police, or ambulance vehicles.

The statistical methods –namely the supervised forward stepwise approach – that have been used in prior investigations of LUR-estimated noise[44,56,57,59,60,63] were applied in the current study; however, the resulting estimates of noise for the county were not as reasonable for some time equivalents as the alternative *A Priori* Approach estimates that were based on our knowledge of noise from the current body of literature. This observation is consistent with that of Fallah-Shorshani et al., who note that multiple approaches to building noise-estimating LUR models may be necessary.[57] The authors report that the noise-estimating LUR models built using the conventional approach included incongruous signs of some coefficient estimates and benefitted from manual modification of predictor variables included.[57] The modification efforts included exchanging buffer sizes of a predictor variable.[57] This modification approach was implemented in the current study during the model building process; however, we expand the use of manual modifications by applying *a priori* knowledge of important predictor variables to build separate LUR models.

Limitations and Strengths

The current study has limitations that should be considered during interpretation of results. First, the use of convenience sampling may have resulted in less-than-desirable variation of noise exposure throughout the study area. Other techniques, such as algorithmic selection of collection site locations, may result in a larger variance of environmental noise. However, the range of noise levels throughout the three time-equivalents were sufficiently broad; $LA_{eq}16_{winter}$, $LA_{eq}16_{spring}$, and $LA_{eq}7_{spring}$, consisted of ranges of 15.50 decibels, 17.33 decibels, and 15.77 decibels, respectively. Considering that an increase in noise of 10 decibels results in a two-times greater perceived loudness,[47] even the smallest range of 15.50 decibels results in the loudest location being perceived as 2.5 times louder than the quietest location. The perceived difference of 15 decibels is equivalent to the difference in loudness of conversational speech from 3 feet away (60 decibels) and a vacuum cleaner from 10 feet away (85 decibels), or in the difference of a vacuum cleaner from 10 feet away (85 decibels) and a gas lawn mower from 3 feet away (100 decibels).

The current study was also limited by the use of only one noise monitor during noise collection, which resulted in a 24-hour collection from each collection site on different days. Ideally, multiple noise monitors would be deployed concurrently for several days at a time across all sites. Using one monitor for 24-hour collection periods resulted in a lack of temporally concurrent noise measurements, which may be problematic if environmental noise is variable from day-to-day. Day-to-day variability of environmental noise in an urban area was found to be present by Geraghty and O'Mahony, who reported that noise levels by the day were statistically significantly different from each other and followed no clear pattern.[83] Therefore, the noise estimates of the current study may not accurately represent long-term noise exposure. For best practice, environmental noise monitoring at multiple locations should be concurrent in nature and be deployed for longer than 24 hours at a time.

Further, the sample size of the current study (N=15) was rather small, which may have impacted the specificity and variability of noise data. Due to this, modeling statistics such as correlation coefficients, multicollinearity diagnostics, and β coefficient p-values could not be fully relied upon. In most LUR modeling strategies, predictor variables are only retained in models if they are statistically significant predictors of noise at the 0.05 level. In the case of having only 15 collection sites, no predictor variables were detected to be statistically significantly associated with noise at the 0.05 level and 95% confidence intervals were extremely wide. Additionally, a small sample size limits the number of predictor variables that can be included in the model before the data becomes too sparse; in the current study, there exists the potential of models being overfit. The presence of multicollinearity in models indicates this overfitting, and the inability to reduce multicollinearity between variables resulted in inflated standard errors of beta coefficients such that significance could not be detected. The lack of confidence likely explains the unexpected directions of beta coefficients in Conventional models. As such, our *A Priori* Approach may not be necessary for larger samples that allow for models to have a greater number of predictors and less sensitive beta coefficient estimates that may swing in the expected direction.

Further, the small sample size could also have led to a limited amount of complexity in the combination of predictor variables. This is made evident by the relatively large R^2 values (range: 0.5005 – 0.7341) of the final LUR models presented; Basagaña et al. suggest that, in LUR models of air pollution, R^2 values will be lower with increased site locations due to an increased amount of complexity in predictor combinations being captured.[84] Additionally, high R^2 values may be an indication that models are overfit, which likely exists in the current study; however, the estimation of prediction error via LOOCV RMSE values limits the likelihood of high R^2 values as a result of overfitting. Other studies of LUR modeling of cumulative environmental noise with larger sample sizes have reported comparable R^2 values, ranging from 0.83 – which utilized 99 noise collection site locations in Tel Aviv, Israel – to 0.40 – based on noise collected during the winter from 62 site locations in Montreal, Canada.[43,58] Further, Chang et al. and Wang et al. utilized 50 site locations for LUR modeling of noise in Taichung, Taiwan[62,63] – an area of 855 square miles – yielding 17.1 square miles per site; 15 sites in Louisville, an area of 398 square miles, results in 26.5 square miles per site. Although comparable, this larger ratio of study area to number of collection sites may contribute to a more limited distribution of geographic data, such that the presence of certain geographic variables could only be detected in larger buffer sizes. For example, data on length of streams and major roads were present for 15 sites only within the 2,000-meter buffer and when smaller buffer sizes were utilized, there was not sufficient variability in the data (ex. all sites had values of 0). Similarly, the dichotomous nature of the being within 1 kilometer of the airport 60-decibel NEM contour created a spatially instantiation in estimates, which may not accurately represent the influence of aircraft flyovers in some areas. It may also be possible that resulting predictors of noise may not act as noise producers, but rather as proxies of other noise sources; for example, estimated coefficients of NDVI may indicate fewer producers of noise rather than indicating the noise mitigation potential of greenness.

There are also strengths of this study. One strength is that noise monitoring during data collection only occurred on days of which extreme weather was not present. Intense wind speeds, heavy rains, and thick blankets of snow were avoided so that collection would be as representative as possible of normal weather conditions. This allowed for the exclusion of weather variables as predictors of environmental noise since there was an absence of highly variable weather conditions. Additionally, noise estimates of Louisville from the varying LUR models resulted in a fine spatial resolution of 10 meters. This resolution is more specific than the 20-meter,[58,59] 50-meter,[44] 100-meter,[43] and 200-meter[45] resolutions of estimated noise from similar studies. Higher resolution allows for higher accuracy in spatial features (i.e., estimated noise) which is beneficial when applying LUR-estimated noise levels as an exposure assessment of individuals. Further, to date, studies regarding the utilization of LUR modeling for estimating cumulative environmental noise have been conducted in Ireland,[56] Israel,[43] Canada,[57–59] South Africa,[60] and China.[45] To the best of our knowledge, the current study is the first-of-its-kind to be conducted in the United States.

Conclusion

The current study utilized the application of two approaches to LUR modeling of cumulative environmental noise and demonstrated that the use of *a priori* modeling strategies may be just as useful as the conventional approach. Although the strongest predictors of environmental noise were transportation related – whether road-traffic, distance to aircraft flyovers, or railways – the effects of each on predicted noise varied by time of day and season. Therefore, we highlight the use of multiple noise estimating LUR models to represent varying times of day and seasons. Future investigations of cumulative environmental noise estimation should consider the use of multiple models for varying time equivalents, especially when applying the noise estimates as an exposure assessment for epidemiologic investigations of cumulative environmental noise exposure during specific seasons and times of day in relation to health outcomes of individuals.

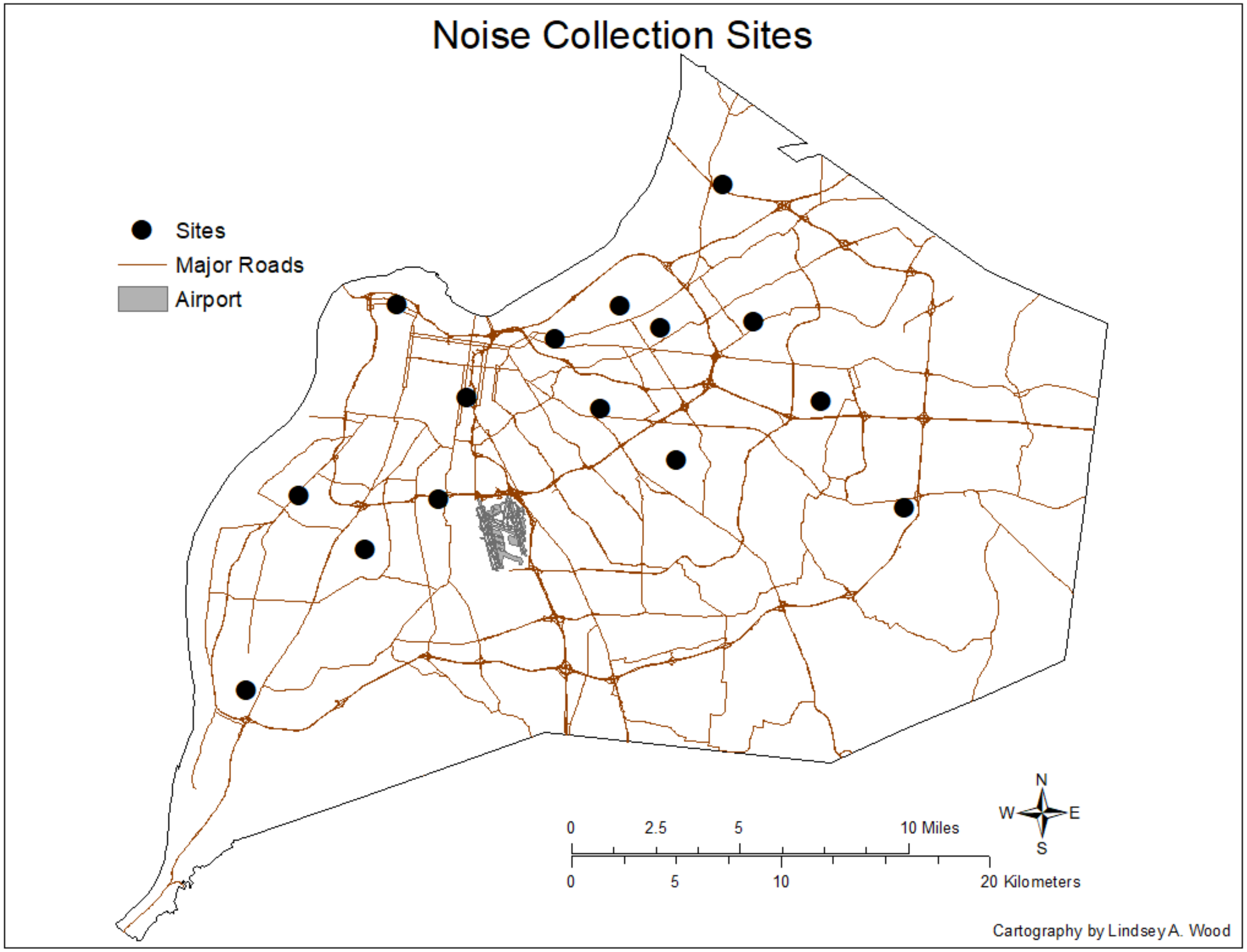


Figure1.1: Noise collection sites in Louisville, Kentucky for winter and spring 2021 noise collections.

Figure 1.2: Set up of noise monitor.

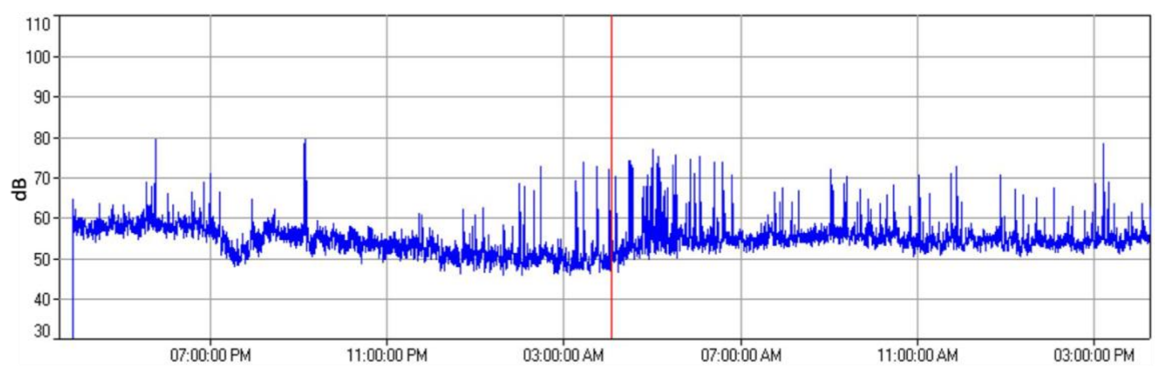


Figure 1.3: Example of transmitted noise data.

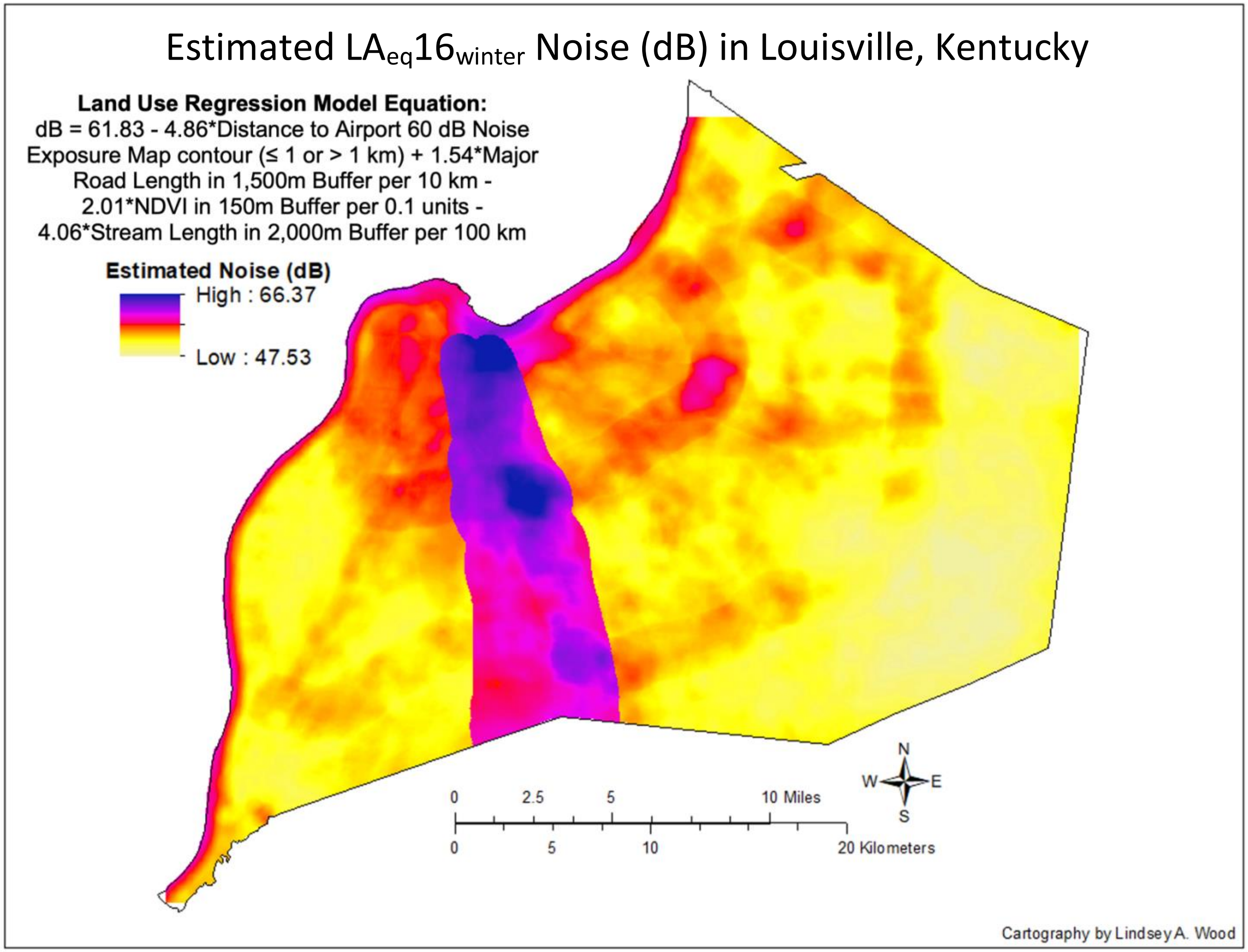


Figure 1.4: Noise estimation in decibels for winter season 16 hour (5:00 PM – 9:00 AM) in Louisville.

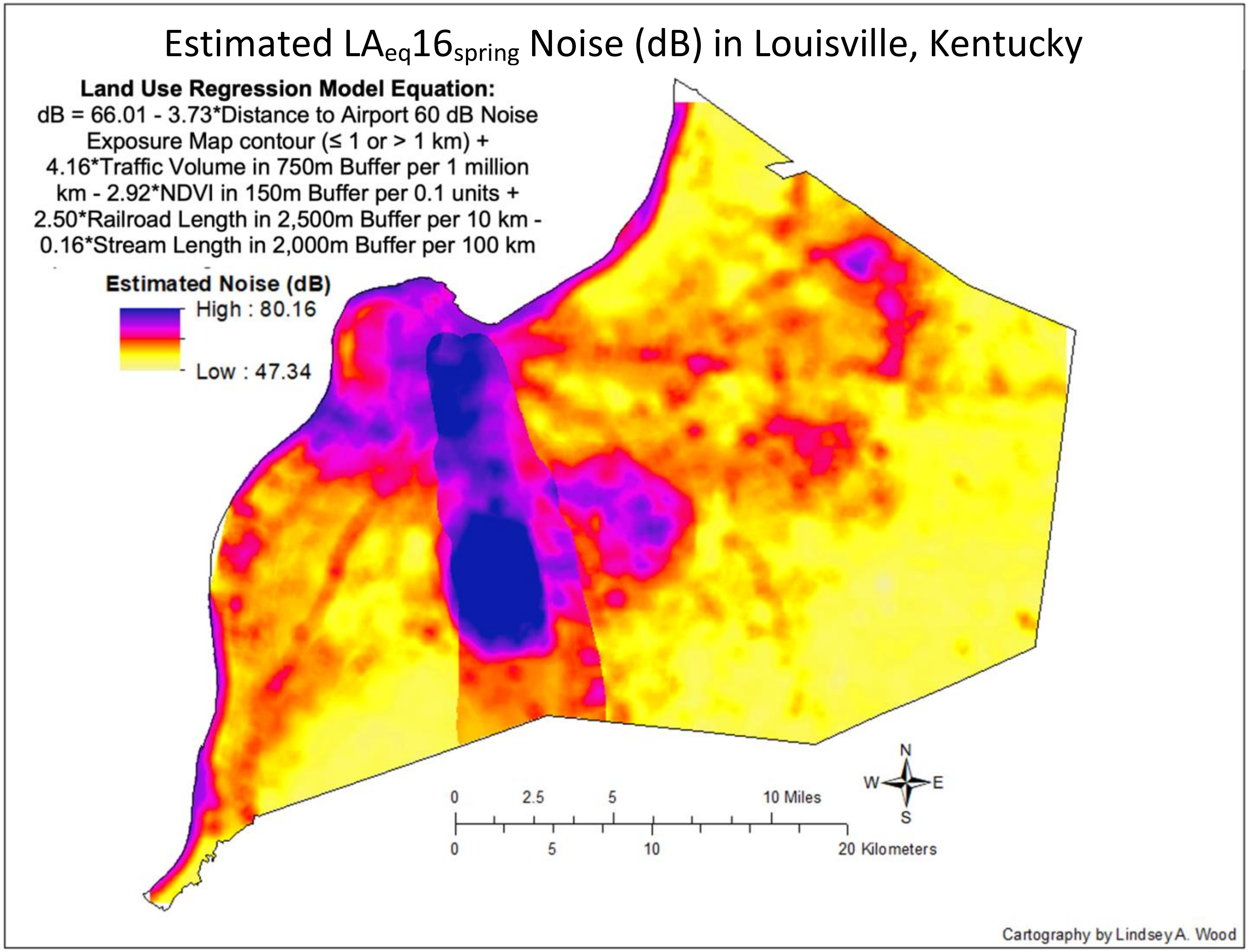


Figure 1.5: Noise estimation in decibels for spring season 16 hour (5:00 PM – 9:00 AM) in Louisville.

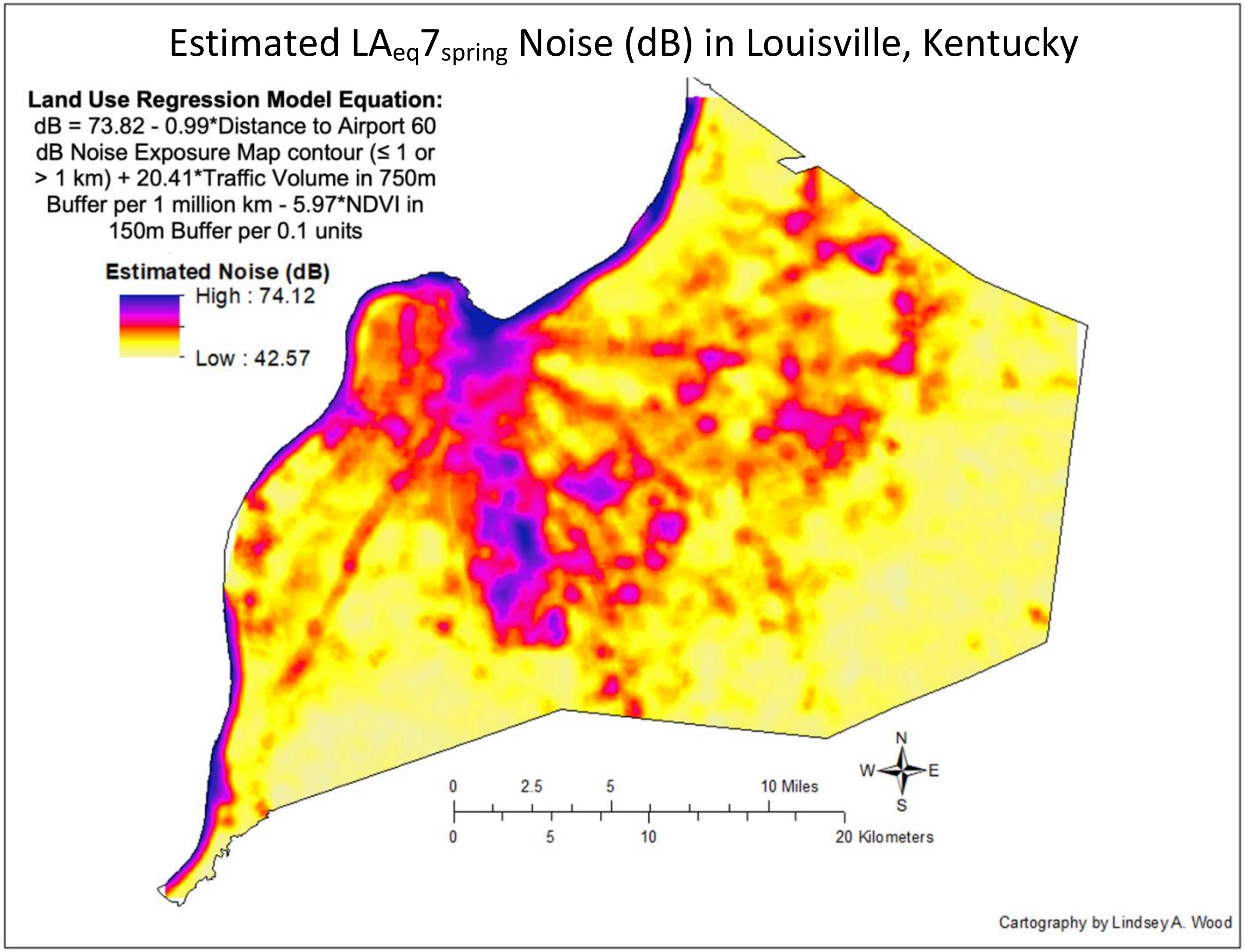


Figure 1.6: Noise estimation in decibels for spring season 7 hour (9:00 AM – 4:00 PM) in Louisville.

Table 1.1: Variables and buffer sizes considered for LUR modeling.

Geographic Variable	Buffer Radii (meters)	Expected Sign	Considered for the *A Priori* approach
Within 1 km of the Airport 60-dB NEM contour, yes/no	NA	-	Yes
Local Roads Length within the Buffer, meters	50/100/150/300/500/750/1,000	+	Yes
Major Road Length within the Buffer, meters	1,500/2,000/2,500	+	Yes
Traffic Volume within the Buffer, meters traveled	50/100/150/300/500/750/1,000	+	Yes
Average NDVI	50/100/150/300/500/750/1,000	-	Yes
Railroad Length within the Buffer, meters	1,500/2,000/2,500	+	Yes
Stream Length within the Buffer, meters	750/1,000/1,500/2,000	-	Yes
Industrial Land Use Area within the Buffer, meters^2	1,000/1,500/2,000	+	Yes
Residential Land Use Area within the Buffer, meters^2	50/100/150/300/500/750/1,000	-	No
Commercial Land Use Area within the Buffer, meters^2	750/1,000/1,500	-	No
Building Coverage Area within the Buffer, meters^2	50/100/150/300/500/750/1,000	+	No
Distance to nearest hospital, meters	NA	-	No
Distance to nearest fire station, meters	NA	-	No
Distance to nearest police station, meters	NA	-	No

Table 1.2: Descriptive statistics for noise time-equivalents based on data from the 15 collection sites.

Time-Equivalent	Min	Max	Mean (SD)	Median (IQR)
$LA_{eq}16_{winter}$	42.00	57.50	49.81 (4.76)	49.10 (46.80 – 55.20)
$LA_{eq}16_{spring}$	47.11	64.44	52.21 (4.81)	51.03 (48.44 – 54.92)
$LA_{eq}7_{spring}$	50.68	66.45	55.05 (5.03)	52.37 (51.53 – 59.03)

Data are expressed as decibels (dB).

Table 1.4: Estimated beta coefficients (95% confidence intervals) for the final LUR models for $LA_{eq}16_{winter}$, $LA_{eq}16_{spring}$, and $LA_{eq}7_{spring}$.

	$LA_{eq}16_{winter}$ (5:00 PM – 9:00 AM) (n=13)		*$LA_{eq}16_{spring}$ (5:00 PM – 9:00 AM) (n=15)*		*$LA_{eq}7_{spring}$ (9:00 AM – 4:00 PM) (n=15)*	
R^2	*0.7341*		*0.5719*		*0.5005*	
LOOCV RMSE	*2.98*		*5.92*		*5.83*	
Range of Estimated Noise in Louisville	*47.53 dB – 66.37 dB*		*47.73 dB – 80.16 dB*		*42.57 dB – 74.12 dB*	
	Unstandardized β (95% CI)	Standardized β (95% CI)	Unstandardized β (95% CI)	Standardized β (95% CI)	Unstandardized β (95% CI)	Standardized β (95% CI)
Intercept	61.83 (45.42, 78.24)	0.00 (-0.59, 0.13)	66.01 (1.41, 130.62)	0.00 (-0.48, 0.48)	73.82 (20.08, 127.56)	0.00 (-0.46, 0.46)
Distance to Airport 60-dB NEM contour ≤ 1 kilometer	REF		REF		REF	
> 1 kilometer	-4.86 (-11.67, 1.95)	-0.43 (-0.86, 0.14)	-3.73 (-30.04, 22.59)	-0.27 (-2.20, 1.65)	-0.99 (-19.49, 17.50)	-0.07 (-1.36, 1.22)
Major Road Length in 1,500m Buffer, per 10 kilometers	1.54 (-3.32, 6.41)	0.17 (-0.33, 0.64)	-		-	
Traffic Volume in 750m Buffer, per 1,000,000 kilometers	-		4.16 (-121.79, 130.11)	0.07 (-1.93, 2.06)	20.41 (-72.03, 112.85)	0.31 (-1.09, 1.71)
NDVI in 150m Buffer, per 0.1 units	-2.01 (-9.60, 5.59)	-0.17 (-0.68, 0.40)	-2.92 (-11.36, 5.52)	-0.22 (-0.84, 0.41)	-5.97 (-14.23, 2.30)	-0.42 (-1.01, 0.16)
Railroad Length in 2,500m Buffer, per 10 kilometers	-		2.50 (-2.46, 7.46)	0.39 (-0.38, 1.15)	-	
Stream Length in 2,000m Buffer, per 100 kilometers	-4.06 (-13.04, 4.93)	-0.30 (-0.81, 0.31)	-0.16 (-13.20, 12.89)	-0.01 (-0.81, 0.79)	-	

Notes. 95% CI = 95% confidence interval.

Table 1.5: Applying the $LA_{eq}16_{winter}$ LUR model to the $LA_{eq}16_{spring}$ data.

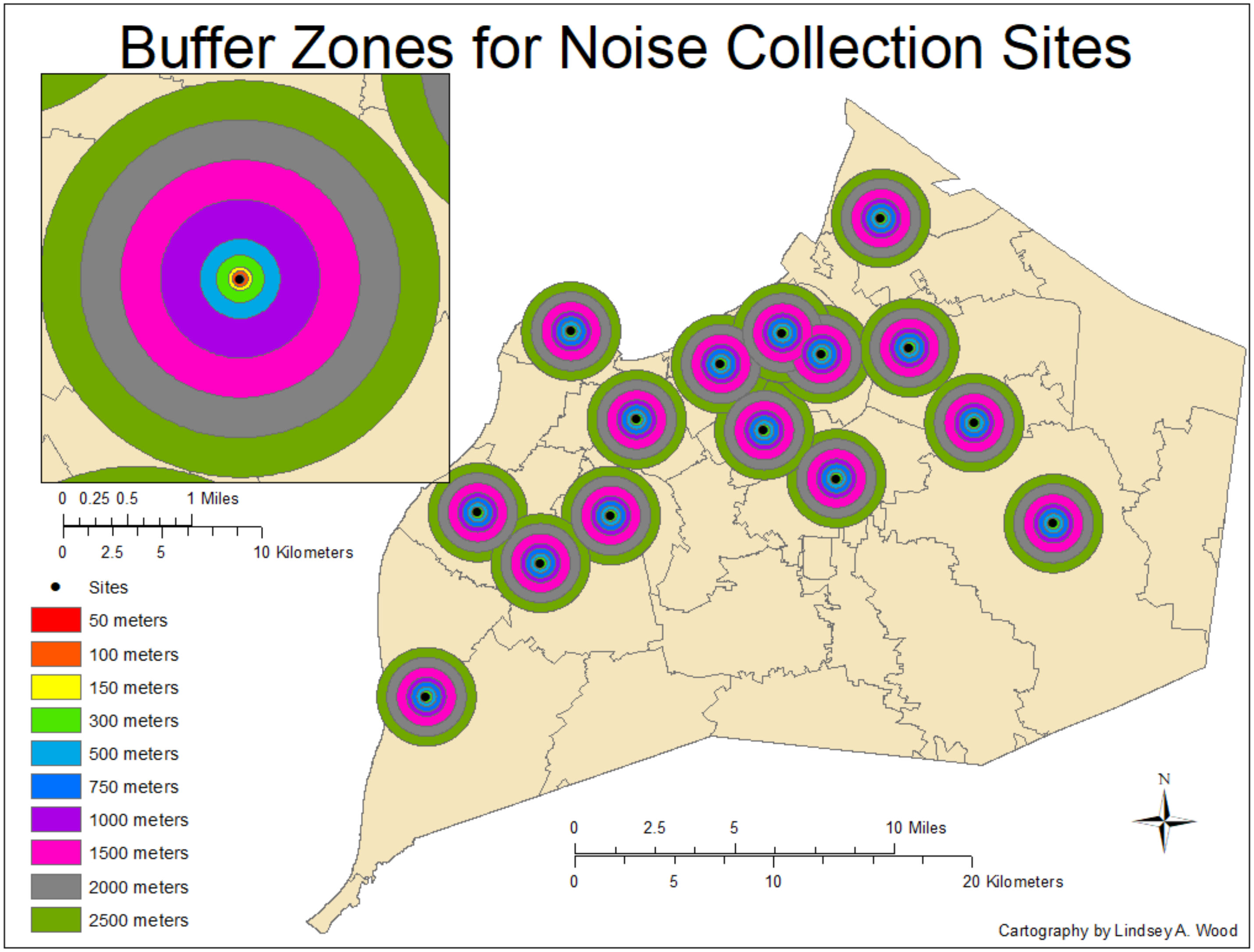
	***$LA_{eq}16_{winter}$* (5:00 PM – 9:00 AM) (n=13)**	***$LA_{eq}16_{spring}$* (5:00 PM – 9:00 AM) (n=13)**
R^2	***0.7341***	***0.4640***
LOOCV RMSE	***4.57***	***7.82***
Range of Outcome in Louisville	***47.53 dB – 66.37 dB***	***50.16 dB – 73.04 dB***
	Unstandardized β (95% CI)	Unstandardized β (95% CI)
Intercept	61.83 (45.42, 78.24)	74.33 (23.25, 125.41)
Distance to Airport 60-dB NEM contour ≤ 1 kilometer	REF	REF
> 1 kilometer	-4.86 (-11.67, 1.95)	-5.98 (-17.45, 5.50)
Major Road Length in 1,500m Buffer, per 10 kilometers	1.54 (-3.32, 6.41)	-0.272 (-10.56, 10.01)
NDVI in 150m Buffer, per 0.1 units	-2.01 (-9.60, 5.59)	-3.15 (-17.43, 11.13)
Stream Length in 2,000m Buffer, per 100 kilometers	-4.06 (-13.04, 4.93)	-2.46 (-16.01, 11.09)

Notes. 95% CI = 95% confidence interval.

Table 1.6: Applying the $LA_{eq}16_{spring}$ LUR model to the $LA_{eq}16_{winter}$ and $LA_{eq}7_{spring}$ data.

	***$LA_{eq}16_{spring}$* (5:00 PM – 9:00 AM) (n=15)**	***$LA_{eq}16_{winter}$* (5:00 PM – 9:00 AM) (n=15)**	***$LA_{eq}7_{spring}$* (9:00 AM – 4:00 PM) (n=15)**
R^2	***0.5719***	***0.4318***	***0.5149***
LOOCV RMSE	***6.49***	***4.55***	***7.56***
Range of Outcome in Louisville	***49.73 dB – 76.43 dB***	***43.80 dB – 73.55 dB***	***48.6 3 dB – 91.81 dB***
	Unstandardized β (95% CI)	Unstandardized β (95% CI)	Unstandardized β (95% CI)
Intercept	66.01 (1.41, 130.62)	75.26 (31.60, 118.91)	86.43 (14.53, 158.33)
Distance to Airport 60-dB NEM contour ≤ 1 kilometer	REF	REF	REF
> 1 kilometer	-3.73 (-30.04, 22.59)	-9.53 (-29.57, 10.51)	-7.52 (-36.80, 21.77)
Traffic Volume in 750m Buffer, per 1,000,000 kilometers	4.16 (-1217.91, 1301.08)	-28.27 (-129.57, 73.03)	-7.88 (-148.05, 132.29)
NDVI in 150m Buffer, per 0.1 units	-2.92 (-11.36, 5.52)	-4.49 (-13.73, 4.75)	-6.57 (-15.97, 2.82)
Railroad Length in 2,500m Buffer, per 10 kilometers	2.50 (-2.46, 7.46)	1.45 (-3.17, 6.07)	1.26 (-4.26, 6.78)
Stream Length in 2,000m Buffer, per 100 kilometers	-0.16 (-13.20, 12.89)	-9.53 (-29.57, 10.51)	4.39 (-10.13, 18.91)

Notes. 95% CI = 95% confidence interval.



Supplemental Figure 1.1: Buffer zones for 15 Louisville, Kentucky noise collection sites.

Supplemental Table 1.1: R^2 values from univariate analyses of individual variables with the $LA_{eq}16_{spring}$ estimate.

Variable	R^2
Traffic Volume in 750m Buffer	0.4437
Railroad Length in 2,500m Buffer	0.4062
Distance to Airport 60-dB NEM contour (≤ 1 km or > 1 km)	0.3925
NDVI (spring) in 1,000m Buffer*	0.3531
Building Coverage Area in 1,000m Buffer	0.2732
Industrial Land Use Area in 1,000m Buffer	0.2601
Stream Length in 2,000m Buffer	0.2106
Residential Land Use Area in 100m Buffer	0.2100
Commercial Land Use Area in 1,000m Buffer	0.1689
Distance to Nearest Police Station	0.0722
Distance to Nearest Hospital	0.0597
Major Road Length in 1,500m Buffer	0.0469
Distance to Nearest Fire Station	0.0113
Public Land Use Area in 500m Buffer	0.0047

*Variable was not chosen to remain in model upon implementing manual manipulation methods.

Supplemental Table 1.2: Correlation matrix of Pearson correlation coefficients.

	Distance to Airport 60-dB NEM contour (≤ 1 km or > 1 km)	Major Road Length in 1,500m Buffer	Traffic Volume in 750m Buffer	NDVI (winter) in 150m Buffer	NDVI (spring) in 150m Buffer	Railroad Length in 2,500m Buffer	Stream Length in 2,000m Buffer
Distance to Airport 60-dB NEM contour (≤ 1 km or > 1 km)	1						
Major Road Length in 1,500m Buffer	Rho=-0.41 p=0.13	1					
Traffic Volume in 750m Buffer	Rho=-0.92 p<0.01	NA	1				
NDVI (winter) in 150m Buffer	Rho=0.51 p=0.05	Rho=-0.37 p=0.18	NA	1			
NDVI (spring) in 150m Buffer	Rho=0.41 p=0.12	NA	Rho=-0.54 p=0.04	NA	1		
Railroad Length in 2,500m Buffer	Rho=-0.44 p=0.10	NA	Rho=0.58 p=0.02	NA	Rho=-0.40 p=0.14	1	
Stream Length in 2,000m Buffer	Rho=0.62 p=0.01	Rho=-0.08 p=0.77	Rho=-0.48 p=0.07	Rho=0.56 p=0.03	Rho=0.29 p=0.30	Rho=-0.48 p=0.07	1

TRANSITION 1

The preceding chapter assessed geographic predictors of environmental noise and described the environmental noise distribution in Louisville, Kentucky. Particularly, we determined the distribution of spring environmental noise during the seven hours between 9:00 AM and 4:00 PM and the 17 hours between 4:00 PM and 9:00 AM (not shown in Aim 1 manuscript).

Evidence exists to suggest that environmental noise exposure is associated with impaired cognition in children. In the following chapter, we utilize the 7-hour and 17-hour environmental noise distributions modeled in Aim 1 to determine the association of school-level environmental noise exposures during school hours and at-home hours with school-level performance on Math, Reading, Science, and Writing standardized tests among elementary schools in Louisville, Kentucky.

AIM 2. THE ASSOCIATION OF ENVIRONMENTAL NOISE LEVELS WITH ELEMENTARY STANDARDIZED TESTING SCORES: A SCHOOL-LEVEL STUDY IN LOUISVILLE, KENTUCKY[b]

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Acknowledgments:
The University of Louisville Center for Integrative Health Sciences NIEHS P30 ES030283 (ND), University of Louisville Superfund Research Center NIEHS P42 ES023716 (LW, RY), and University of Louisville Green Heart Louisville Project NIEHS R01 ES029846 (LW, RY) supported researchers on this project.

Competing Financial Interests Declaration:
The authors declare that they have no actual or potential competing financial interests.

Introduction

Cognitive ability consists of sensation and perception, motor skills and construction, attention, memory, executive functioning, processing speed, and language/verbal skills.[85] Cognitive ability in childhood is an important predictor of later-life health, and lower childhood cognition is associated with increased odds of coronary heart disease,[86] mental illness,[87–90] brain pathologies,[91,92] and health behaviors like alcohol intake,[93] food consumption,[94] and physical activity.[94] Standardized testing scores are often used as a proxy of cognition,[95–98] and scores in childhood may be associated with later life social determinants of health, such as educational attainment and income.[99,100]

However, the World Health Organization (WHO) recognizes environmental noise exposure attributing to 45,000 disability-adjusted life years (DALYs) for cognitive impairment in children,[3] relying on evidence suggesting that environmental noise exposure is associated with significant declines in various cognitive skills in children.[10,15,17,101] Associations have been observed between environmental noise exposure and standardized testing scores of primary and elementary school-children,[19–22,102] but noise exposure is usually defined as source-specific noise, such as aircraft[20,21,102] or road traffic noise.[22] Few studies have assessed *ambient* or *total* environmental noise exposure in relation to early-childhood standardized testing scores.[19,102] Further, Pujol et al. observed that ambient noise exposure at home was negatively associated with children's standardized testing scores,[19] but investigation of at-home noise exposure in relation to testing scores has yet to be repeated. Moreover, Sharp et al. reported on ambient environmental noise in relation to testing scores of children attending schools surrounding the 50 largest airports in the United States (US)[102] and observed that aircraft noise exposure was more strongly associated with testing scores among non-disadvantaged children compared to disadvantaged children.[102] However, analyses of total environmental noise at localized levels do not exist in the US, and effect modification by socioeconomic status on the relationship between *total* environmental noise and testing scores has not been done.

Louisville, KY, which was included in the Sharp et al. analysis, presents as an urban US area in which to conduct such analysis. The purpose of this study was to determine the association of total environmental noise at school and at home with the distribution of standardized testing scores of elementary schools in Louisville, KY. Additionally, we assessed effect modification by race, family income, and income of surrounding neighborhoods of schools.

Methods and Materials

Exposure Data – 7-hour and 17-hour Environmental Noise

Detailed descriptions of noise data are documented elsewhere (see Aim 1 manuscript). Briefly, noise data were collected during April/May 2021 at 15 sites throughout Louisville. At every site, noise was recorded every 10 seconds for 24 hours using a Class 1 noise meter (Type 2236, Brüel & Kjær, Naerum, Denmark) and averaged for two time-periods: 7-hour (9:00 AM and 4:00 PM) chosen to represent times when children would be in school and 17-hour (4:00 PM and

9:00 AM) when children would most likely be home. Both the 7-hour and 17-hour noise distributions in Louisville, KY were estimated using land use regression (LUR) models with several geographic characteristics of sites used as the predictors of noise (e.g., normalized difference vegetation index, distance to airport flyovers, annual average road traffic, length of streams). The 7-hour model resulted in a R^2 of 0.70 and leave-one-out cross-validation (LOOCV) root mean square error (RMSE) of 6.47 decibels, and the 17-hour model resulted in a R^2 of 0.59 and a LOOCV RMSE of 6.25 decibels, indicating that both models consisted of satisfactory fit and prediction error. Noise at each elementary school during the school hours was determined by extracting the 7-hour LUR-estimated noise distribution at the school address. To represent noise exposure of students at their residences during non-school hours, the average 17-hour noise was estimated for each ZIP code, and a school-level weighted average of ZIP-code level noise was calculated based on the proportion of students residing within each ZIP code.

Outcome Data – School Percentage of Proficient or Distinguished Scores

Data for standardized testing scores at elementary schools (N=91) were obtained from publicly available reports from Jefferson County Public Schools (JCPS).[103] JCPS reports standardized testing scores at each school as the percentage of students who scored Novice, Advanced, Proficient, Distinguished, and Proficient or Distinguished for each subject.

We retained the 2019 percentages of Proficient or Distinguished scores at each school for the state-standardized Math and Reading tests. From the school profile webpages,[104] we further retained the combined percentage of students who scored Proficient or Distinguished on Math or Reading tests (n=90; one school was closed by the time of data collection and no longer had a school profile webpage, and the combined percentage cannot be derived from individual subject percentages). Math and Reading tests are taken by all 3rd, 4th, and 5th graders, resulting in a total of 21,607 tests taken for Math and for Reading in, and 42,980 tests taken for combined Math and Reading. Due to the large number of students taking Math and Reading tests, within school error was minimal. Therefore, Math, Reading and combined Math and Reading were the primary outcomes of this analysis.

We also retained the 2019 percentages of Proficient or Distinguished scores at each school for the state-standardized Science and Writing tests. Science tests are only taken by 4th graders, resulting in 7,154 tests taken, while Writing tests are only taken by 5th graders, resulting in 7,353 tests taken. Due to these tests being taken by fewer students, likely contributing to higher within school error, Science and Writing scores were analyzed as secondary outcomes.

To match the year during which exposure data was collected, we additionally retained data on 2021 percentages of Proficient or Distinguished scores at each school for all subjects. However, large portions of testing scores were missing for the 2021 testing year (n=63 for Math, n=89 for Reading, n=31 for Science, and n=43 for Writing) and combined Math or Reading scores were not available for 2021 testing year. Due to missing data for 2021, subject scores represent 11,367 tests taken for Math, 14,713 for Reading, 2,092 for Science, and 2,899 for Writing. Therefore, 2021 scores were used as outcomes for sensitivity analysis. Percent of Proficient or Distinguished scores between 2019 and 2021 for each subject were strongly correlated (Supplemental Table 2.1).

Covariate Data

A directed acyclic graph (Figure 2.1) was constructed to guide variable selection for regression modeling and to aid in the visualization of the school-level relationship between environmental noise and standardized testing scores. Given the ecological nature of the current study, the DAG is not meant to imply causation, but rather display how the exposure, the outcome, and school characteristics may be related. According to the DAG, potential school-level confounders of the association between environmental noise and school-level standardized testing scores are student aptitude, student race, student family income, student absences, teacher quality, school resources, median income of the school ZIP code, and school safety events to enrollment ratio.

Student-, teacher-, and school-related data for covariates and potential confounders were obtained from publicly available JCPS data. Student variables considered for model inclusion included aptitude variables, such as percentages of Gifted and Talented, Advanced Program, and mentally or physically disabled students; race/ethnicity variables, such as percentages of black, Hispanic (JCPS reports Hispanic as a race rather than an ethnicity), white, or other race, and limited English proficient students; percentage of male students; family income variables, such as percentages of free and reduced lunch participation and homeless students; and percentage of chronically absent students. Teacher quality variables included the percent of full-time teachers with a master's degree or higher and the average years of experience of full-time teachers. School variables included those related to resources – such as per pupil spending ($USD) and receiving Title 1 grants (yes/no) – as well as safety events to enrollment ratio. Additionally, median income of the school ZIP code, obtained from the 2015-2019 American Community Survey 5-year estimates, was also considered for model inclusion.

Statistical Analyses

To better understand the school-level difference in noise exposures during school hours and at-home, we plotted the bivariate distributions of school-level 7- and 17-hour environmental noise exposures. School-level descriptive characteristics were assessed by tertiles of 7-hour and 17-hour environmental noise levels. To limit issues of multicollinearity, we selected individual variables to represent student aptitude, student race, student family income, teacher quality, and school resources. For student aptitude variables, the Advanced Program was strongly correlated with the percentage of Gifted and Talented students (Supplemental Table 2.2) and had a larger distribution than did the percentage of disabled students, so the percentage of Advanced Program students was chosen to represent student aptitude. Due to the majority student population most often being white, we selected the percentage of white students to represent the distribution of race/ethnicity of students. The student family income variables were strongly correlated with each other (Supplemental Table 2.2), and the percentage free and reduced lunch participation was chosen to represent student family income. Similarly, the teacher quality variables were strongly correlated with each other (Supplemental Table 2.2), and the average years of teacher experience was selected as the teacher quality variable. Finally, school-level per pupil spending was chosen to represent school resources since nearly all JCPS elementary schools were eligible for Title 1 grants regardless of whether a school was receiving grants. Therefore, the variables selected to be tested in modeling were the percentage of Advanced Program students, the percentage of white students, the percentage of students participating in free and reduced lunch, percentage of chronically absent students, average years of teacher experience, per pupil spending, median income of the school ZIP code, and school safety events to enrollment ratio. Correlation coefficients between all variables chosen for model inclusion are reported in Supplemental Table 2.3.

To determine the association of louder school and at-home noise with testing scores, we utilized multivariable linear regression with continuous 7-hour or 17-hour environmental noise as the exposure and the percentage of Proficient or Distinguished scores for each subject as the outcome. The above covariates were added into models to determine how variables altered the strength of the association between noise and testing scores. Final models were achieved when further addition of covariates did not materially change the noise β coefficient. Performance of final models was determined by R^2 values, and presence of multicollinearity was indicated by condition indexes greater than 30. When multicollinearity was present, the variables were centered on their mean where appropriate.

We assessed effect modification for several variables using the fully adjusted models. Based on our previous findings (see the Aim 3A Manuscript) and that of others', variables of interest included the percentage of students with free and reduced lunch[102] and percentage of white students. Additionally, we considered median income of school ZIP code as an effect modifier due to evidence that suggests that neighborhoods around high-scoring schools are more expensive than low-scoring schools,[105] and that low-income students perform better in schools with middle- or high-income student populations compared to low-income students in schools with low-income student populations.[105] Median income of school ZIP code was dichotomized by the median to create a low and high group. Tertiles were created for percentages of free and reduced lunch and white students based on their one-third percentiles. The significance of effect modification was determined by the Wald X^2 p-value upon inclusion of noise*binary effect modifier, or the Likelihood Ratio Test p-value with 2 degrees of freedom upon inclusion of noise*tertiary effect modifier.

Due to the lack of temporality between the exposure and the outcome, we conducted a sensitivity analysis using 2021 testing scores as the outcome. As mentioned previously, the sample sizes for the 2021 scores were much lower than those of 2019. Additionally, changes in JCPS reporting between 2019 and 2021 prevented the use of identical covariates in 2021 models. Therefore, we used two sets of covariates for the 2021 models: 1) many covariates from 2019 (i.e., percentage Advanced Program students, percentage of chronically absent students, safety events to enrollment ratio, and average experience in years of full-time teachers) to be comparable to the main results, but the data on percentages of white students and free and reduced lunch students from the 2021 school year to reflect the 2021 testing population, and 2) covariates from 2021 school data that are similar to 2019 covariates but not always identical (i.e., percentage of white students, percentage of free and reduced lunch students, percentage of Gifted and Talented students, percentage of chronically absent students, safety events to enrollment ratio, percentage of full-time teachers with a Master's degree or higher), and 2019 data for per pupil spending and school ZIP code median income. All statistical analyses were performed using SAS Software (version 9.4).

Results

Figure 2.1 displays the bivariate distributions of school-level 7- and 17-hour environmental noise exposures. Of the 91 schools, nine had louder 17-hour environmental noise exposures than 7-hour exposures by five decibels or more, whereas four schools had louder 7-hour exposures than 17-hour exposure by five decibels or more. Descriptive student-, teacher-, and school-related characteristics of the 91 elementary schools by tertiles of 7-hour and 17-hour environmental noise are displayed in Table 2.1. Schools with louder 7-hour and 17-hour noise had lower percentages of Proficient or Distinguished testing scores for all subjects in the 2019. Schools with louder noise had lower percentages of Gifted and Talented (17-hour only) and Advanced Program students, higher percentage of disabled students, lower percentages of white and higher percentages of black or other race, lower family income (i.e., had higher percentages of free and reduced lunch participation and homelessness), and higher chronic absentees. Full-time teachers at schools with louder noise were less likely to have a Master's degree or higher and had fewer years of experience. Schools with louder noise spent more money per student, were located in ZIP codes with lower median incomes, and had higher safety events to enrollment ratios. School-level percentages of male or Hispanic students did not vary meaningfully across noise tertiles. Schools with louder 7-hour noise had lower percentages of limited English proficient students, but schools with louder 17-hour had higher percentages of limited English proficient students. Further, there was no meaningful variation in reception of Title 1 grants across 7-hour noise tertiles, but schools with louder 17-hour noise were more likely to be receiving Title 1 grants.

Linear regression modeling results for the association between 7-hour and 17-hour environmental noise with the percent of Proficient or Distinguished 2019 scores in Math, Reading, and combined Math or Reading are shown in Table 2.2. In crude models, a one-decibel increase in 7-hour noise was nonsignificantly associated with lower percentages of Proficient or Distinguished scores in Math (β=-1.10, 95% CI: -2.56, 0.36), Reading (β=-0.92, 95% CI: -2.33,0.49), combined Math or Reading (β=-1.20, 95% CI: -2.55, 0.15), scores by 1.10, 0.92, and 1.20, percentage points, respectively. Variables retained in fully adjusted models were the percentage of students that are of white race, percentage of students who participate in free and reduced lunch, percentage of students who are in

Advanced Placement classes, percentage of chronically absent students, median income of the ZIP in which the school is located, safety events to enrollment ratio, average experience in years of full-time teachers, and per pupil spending. After all adjustments, one-decibel louder 7-hour noise was not associated with percentages of Proficient or Distinguished scores in Math (β=-0.20, 95% CI: -0.83, 0.43), Reading (β=0.03, 95% CI: -0.48, 0.53), or combined Math or Reading (β=-0.20, 95% CI: -0.73, 0.33). Similar null associations were observed between 17-hour noise and percentages of Proficient or Distinguished scores in Math (β=-0.24, 95% CI: -1.31, 0.82), Reading (β=0.29, 95% CI: -0.57, 0.1.14), and combine Math or Reading (β=-0.20, 95% CI: -1.10, 0.69). R^2 values for Math, Reading, and combined Math or Reading were 0.83, 0.89, and 0.87 for 7-hour final models, and 0.85, 0.89, and 0.86 for 17-hour models, indicating that the models were explaining most of the variance in the testing score outcomes. Condition index values for fully adjusted models were 102.7 for 7-hour noise with all three outcomes, and 158.1 for 17-hour noise with all three outcomes, indicating that multicollinearity was present. However, in all models, variance decomposition proportions indicated that the multicollinearity was driven by the noise exposure variable and the model intercept, not between covariates. As such, noise exposure variables were centered on their mean values, and all results presented represent models in which multicollinearity was eliminated.

Using the fully adjusted model, results of effect modification analysis of Math, Reading, and combined Math or Reading are presented in Table 2.3 Among the schools with the lowest free and reduced lunch participation, louder

7-hour noise by one decibel was significantly associated with lower percentages of Proficient or Distinguished Math scores by 1.22 percentage points (low free and reduced lunch participation, β=-1.22, 95% CI: -2.25, -0.19), which varied significantly from the null associations observed among schools with moderate or high free and reduced lunch participation (moderate β=0.11, 95% CI: -1.08, 1.31; high β=0.84, 95% CI: -0.40, 2.07; LRT p-value=0.040). The percentage of white students was a significant effect modifier of the association between 17-hour noise and the percentage of Proficient or Distinguished Reading scores (LRT p-value=0.041), but the associations were generally null across schools with low, moderate, and higher percentages of white students (low β=-1.02, 95% CI: -2.18, 0.15; moderate β=0.79, 95% CI: -0.38, 1.97; high β=-0.34, 95% CI: -1.31, 0.63).

In the fully adjusted models, one-decibel louder 7-hour noise was not associated with Science nor Writing scores (Science β=-0.02, 95% CI: -0.67, 0.63; Science R^2=0.80; Writing β=0.07, 95% CI: -0.81, 0.94; Writing R^2=0.73; Supplemental Table 2.4). Similarly, one-decibel louder 17-hour noise was not associated with Writing but was significantly associated with higher percentages of Proficient or Distinguished scores in Science (Science β=1.30, 95% CI: 0.23, 2.37; Science R^2=0.81; Writing β=-0.15, 95% CI: -1.63, 1.33; Writing R^2=0.73; Supplemental Table 2.4). Additionally, significant effect modification of the association between 7-hour noise and percentage of Proficient or Distinguished Writing scores was observed by the median income of school ZIP codes, but the associations were null for lower and higher school ZIP-code level median income (low β=0.88, 95% CI: -0.15, 1.91; high β=-1.28, 95% CI: -2.69, 0.14; X^2 p-value=0.014; Supplemental Table 2.5).

When considering the sensitivity analysis using the 2021 testing scores, regardless of the set of covariates used for models (i.e., 2019 covariates or 2021 covariates), associations between 7-hour noise and 17-hour noise with testing scores were generally null and comparable to the main results, indicating that the effect estimates were not sensitive to variable selection. However, the association between 17-hour noise and percentage of Proficient or Distinguished scores in Science was comparable to the main results when 2019 covariates were used, but were null when 2021 covariates were used (2019 covariate model β=1.57, 95% CI: 0.08, 3.05; 2021 covariate model β=1.65, 95% CI: -0.19, 3.49; Supplemental Table 2.6), indicating that the effect estimate was sensitive to the included confounders.

Discussion

The current study examined the association of school-level total environmental noise during school-time hours and during the non-school time hours with school-level standardized testing scores among public elementary schools in Louisville, Kentucky. After adjusting for several confounders, we observed no association between neither 7-hour nor 17-hour environmental noise with school-level standardized testing scores of Math, Reading, combined Math or Reading, or Writing. Furthermore, schools with lower percentages of students participating in free and reduced lunch had stronger inverse associations between 7-hour noise and Math scores than schools with moderate or high percentages of students participating in free and reduced lunch. Similarly, schools with lower percentages of white students had stronger inverse associations between 17-hour noise and Reading scores than schools with moderate or high percentages of white students, and schools located in ZIP codes with higher median incomes had strong associations between 17-hour noise and Writing scores than schools in lower income ZIP codes.

The null findings in the current study is congruent with the previous null findings of the association between individual-level aircraft noise and standardized testing scores of 11,000 6th graders[20] and between reduced aircraft noise and elementary school-level verbal test failure rates.[21] With the use of *total* environmental noise in the current study, the null findings may be due in part to the noise exposure levels used, which were estimated from land use regression models built from a small sample of 15 sites. Although this small sample may have negatively impacted the reliability and validity of noise estimates, samples had acceptable levels of intra-class correlation and models resulted in acceptable levels of prediction error (see Aim 1 manuscript). Additionally, all 15 sampling sites were located in residential areas and noise estimates most closely represent areas of similar land use, which may not accurately reflect noise at school locations that may not be located in residential areas. Further, the lack of significance may be partially attributed to the presence of multicollinearity between covariates in models, as multicollinearity can inflate standard errors of effect estimates and therefore inflate p-values and widen confidence intervals.

The null results of this study are not congruent with the Sharp et al. observation of a significant 3-4 percentile decrease in state-standardized test ranking for a 10-decibel increase in total environmental noise.[102] However, percentile-rankings of schools between states ignores the inherent rigorousness of state-standardized tests, and a 3-4 percentile decrease in ranking says little about student competency. Pujol et al., who reported on 586 children in 31 schools and mutually adjusted for school-level noise and individual-level at-home noise, observed a significant inverse association between school-level ambient environmental noise with French scores by 0.48 points and Math scores by 0.44 points, but null associations between at-home noise with French and Math scores.[19] However, school-level noise may not have been representative of noise exposure at schools, as school-level noise was representative of 6:00 AM to 6:00 PM, which includes times during which children would not be in school.

We observed that school racial composition modified the association of 7-hour school noise with Math scores, and school percentages of students participating in free and reduced lunch modified the association of 17-hour at-home noise with Reading scores. These findings may be due to chance, as the sample size in each category was rather small (n=31 or 30 for the three categories of each variable). However, black children and children living in poverty have been observed to experience higher levels of chronic stress than white children and children from families with higher incomes.[106] It may be possible that the effects of noise on stress and allostatic load[107–117] may be more impactful for children with lower stress levels, whereas the impacts of noise on stress may not be meaningful for children with high levels of stress; certain racial and income groups, such as non-white and lower-income populations, disproportionately experience additional stressors compared to other racial and income groups, like white and higher-income populations.[118,119] However, further work is needed to better understand the potential of modified associations between noise and testing scores for schools with varying racial and socioeconomic distributions of student populations.

Limitations and Strengths

The current study has some limitations that should be considered. First, the study was ecological in nature, and individual-level noise exposures and testing scores were unknown. Therefore, findings should not be interpreted as individual-level associations. Additionally, there lacked temporality between the 2021 noise exposure estimates and 2019 testing scores outcome, and analyses of 2021 noise exposure with 2021 testing scores are cross-sectional. As such, causation cannot be inferred from the findings. Further, this study consisted of a sample of 91 elementary schools, which limits the power associated with calculating effect estimates and may contribute to the largely null results observed in this study.

The outcomes and exposures included in this analysis may have consisted of measurement error. All students in 3rd through 5th grades take Math and Reading tests, so the number of these tests taken were relatively large, yielding stable distributions of testing scores within schools. On the contrary, Science tests are only taken by 4th graders and Writing tests by only 5th graders, and the number of tests taken for these subjects is rather smaller, such that distributions of testing scores may not be stable enough to accurately reflect Science or Writing scores for the school, as shown by the lower R^2 values of the Science and Writing models compared to the Math and Reading models. Inherent limitations of noise estimates, such as a non-concurrent collection and the small sample of 15 collection sites, may have contributed to exposure measurement error, and findings of the current study may be due to chance. Further, the school-level 17-hour at-home noise exposure was determined by a weighted average of ZIP-code level environmental noise based on the full enrollment (K – 5) distribution of students residing in each ZIP code, which may not be representative of test-taking students, and therefore limits the interpretation of the effect estimates, especially for Science and Writing models. Hence, measurement error may erroneously contribute to the significant findings of the association between 17-hour at-home noise with Science testing scores and effect modification by the median income of school ZIP code on the association between 17-hour noise with Writing scores, and findings should be interpreted with caution. Also, it is possible that all variables, which are representative of the full enrollment, may not be representative of student enrollment in test-taking grades. As such, results should be interpreted at the school-level rather than at specific grade-levels.

Despite these limitations, the study has several strengths. Rather than source-specific noise, we utilized total environmental noise as the exposure, which may be more important to testing scores of elementary school children, as

Sharp et al. observed that total noise exposure was more strongly associated with state-rank of standardized testing scores than aircraft noise exposure alone.[102] Further, we individually assessed the associations of school-hour environmental noise and at-home environmental noise with standardized testing scores of schools that allowed for noise estimates based on the times in which children would likely be located at either location. Similarly, the land use regression models utilized to determine noise exposure levels were built from noise collections that occurred during April or May, which are representative of the season in which standardized tests are taken. Finally, although there lacked temporality between the noise exposure and testing scores outcome, the distribution of 2019 and 2021 scores were highly correlated, and the sensitivity analysis indicated that the associations of noise levels were not sensitive to the year in which tests were taken.

Conclusion

The current study generally observed no associations between school-level total environmental noise, either during school hours or at home, and the percentage of students who scored Proficient or Distinguished on standardized testing scores in varying subjects. However, certain associations of noise between testing scores did vary by racial composition of the school, the percentage of the students that participate in free and reduced lunch, and the median income of the school. To gain a better understanding of the relationship between environmental noise exposure and standardized testing scores of elementary school children, individual-level analyses are needed.

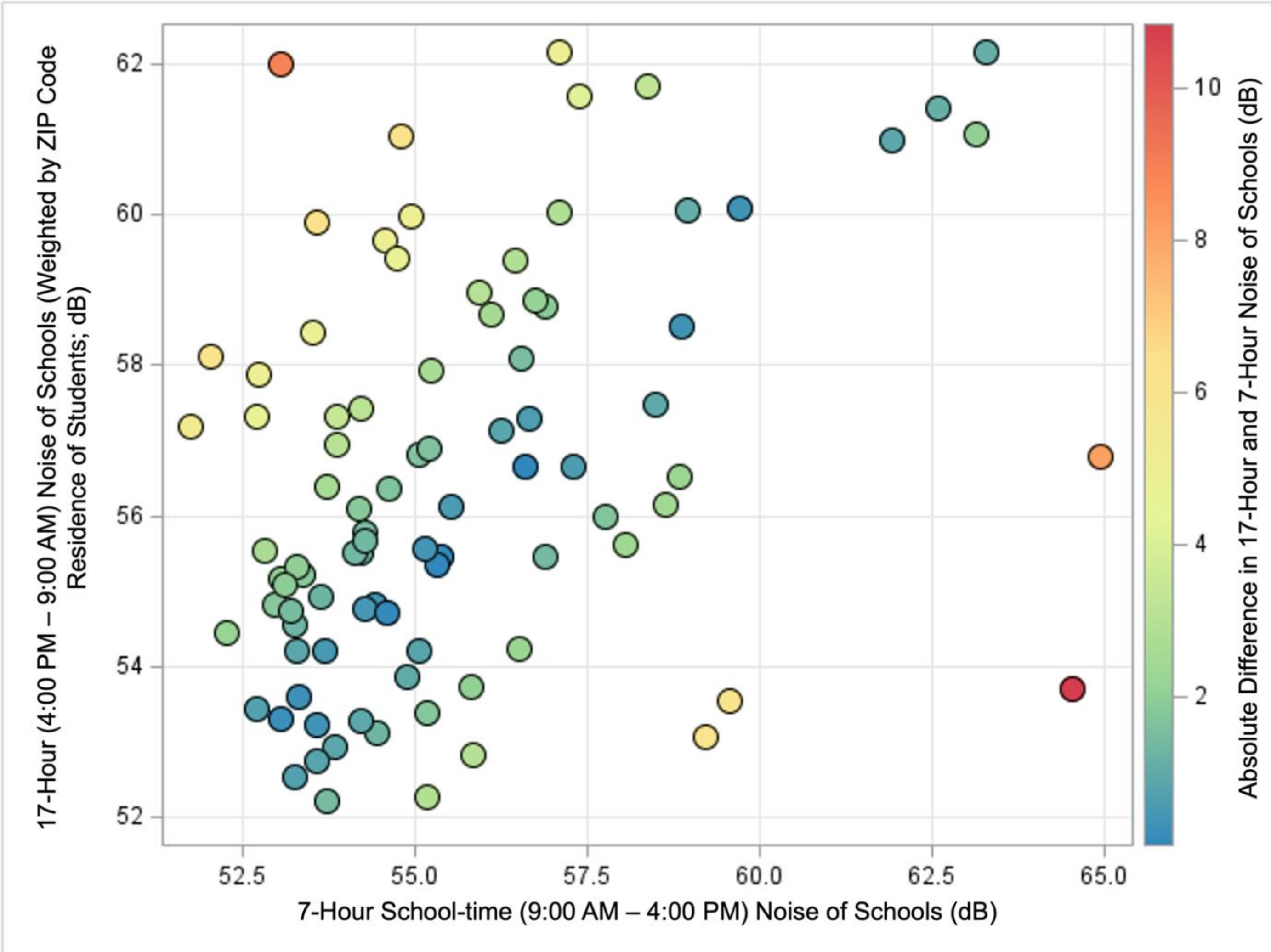

Figure 2.1: Bivariate distribution and absolute difference of 17-hour (4:00 PM – 9:00 AM) and 7-hour (9:00 AM – 4:00 PM) noise of schools.

Table 2.1: Descriptive Characteristics of Elementary Schools by Noise Exposure Levels (N=91).

	Average 7-Hour School-time (9:00 AM – 4:00 PM) Noise of Schools			Average 17-Hour (4:00 PM – 9:00 AM) Noise of Schools (Weighted by ZIP Code Residence of Students)		
	Low: 51.75 – 54.14 dB (n=31)	Moderate: 54.20 – 56.10 dB (n=30)	High: 56.26 – 64.93 dB (n=30)	Low: 52.22 – 55.09 dB (n=31)	Moderate: 55.17 – 57.29 dB (n=29)	High: 57.33 – 62.15 dB (n=31)
Percentage of Proficient or Distinguished Scores						
Math 2019	40.5 (21.4)	41.2 (19.2)	32.1 (19.3)	51.3 (18.1)	41.5 (16.4)	21.4 (13.1)
Reading 2019	46.3 (19.6)	47.1 (17.7)	38.0 (20.4)	56.3 (15.9)	48.9 (16.3)	26.5 (12.1)
Science 2019	20.9 [7.8,32.9]	21.4 [10.5,41.7]	13.9 [6.5,29.1]	32.1 [18.6,50.6]	24.6 [13.3,41.1]	8.1 [4.5,11.5]
Writing 2019	34.9 [20.6,49.4]	35.2 [19.0,52.3]	21.8 [12.9,48.2]	46.7 [34.9,63.4]	36.9 [21.4,53.1]	16.4 [8.8,29.3]
Student Variables, Percentage of Students						
Aptitude						
Gifted and Talented	9.3 [5.5,13.8]	11.5 [7.0,18.0]	9.6 [5.0,10.9]	11.8 [9.2,16.3]	9.9 [5.0,15.0]	7.0 [4.3,10.4]
Advanced Placement	3.9 [2.2,7.3]	5.0 [2.7,10.4]	2.6 [1.1,4.6]	7.3 [3.2,12.4]	3.9 [1.8,10.0]	2.3 [1.1,3.7]
Disability	12.6 (3.1)	12.9 (3.5)	14.9 (4.5)	12.3 (2.8)	12.3 (3.8)	15.7 (3.9)
Race & Ethnicity						
White race	44.9 [24.5,59.5]	46.1 [29.4,59.2]	27.3 [15.8,46.9]	59.5 [47.6,64.7]	44.9 [31.0,51.1]	15.8 [7.7,27.1]
Black race	26.1 [13.9,42.0]	27.4 [19.0,35.8]	43.8 [34.2,62.5]	18.7 [12.5,22.2]	32.7 [26.3,41.4]	58.0 [44.4,79.4]
Hispanic “race”*	12.7 [6.0,21.1]	8.1 [6.4,20.6]	7.2 [4.2,15.6]	9.0 [6.0,17.6]	7.2 [4.6,22.2]	10.2 [4.5,20.6]
Other race (2 or more, AAPI, Native)	11.8 [7.1,14.7]	10.0 [7.9,14.2]	9.1 [6.6,13.3]	13.3 [9.6,15.2]	10.3 [8.0,12.9]	7.1 [5.4,11.9]
Limited English Proficient	17.6 [6.9,28.3]	8.3 [4.3,27.8]	7.7 [3.0,22.1]	9.3 [5.0,21.3]	9.9 [3.1,28.2]	16.8 [3.1,38.2]
Male	52.5 (2.5)	50.8 (3.4)	50.1 (3.4)	51.5 (2.8)	50.5 (4.6)	51.4 (2.1)

Table 2.1: Descriptive Characteristics of Elementary Schools by Noise Exposure Levels (N=91).

	Average 7-Hour School-time (9:00 AM – 4:00 PM) Noise of Schools			Average 17-Hour (4:00 PM – 9:00 AM) Noise of Schools (Weighted by ZIP Code Residence of Students)		
	Low: 51.75 – 54.14 dB (n=31)	Moderate: 54.20 – 56.10 dB (n=30)	High: 56.26 – 64.93 dB (n=30)	Low: 52.22 – 55.09 dB (n=31)	Moderate: 55.17 – 57.29 dB (n=29)	High: 57.33 – 62.15 dB (n=31)
Family Income						
Free and Reduced Lunch	73.5 [57.5,84.0]	69.6 [45.9,80.0]	83.6 [50.2,87.6]	58.2 [35.0,70.2]	68.7 [46.5,80.1]	85.7 [81.0,89.2]
Homeless	4.3 [2.8,9.7]	5.3 [3.4,6.8]	7.3 [3.9,12.4]	3.9 [1.6,6.2]	4.3 [2.8,6.4]	10.8 [7.2,13.4]
Chronically Absent	15.6 (6.6)	15.2 (6.4)	18.1 (8.8)	12.8 (6.6)	14.5 (6.8)	21.4 (5.9)
Full Time Teacher Quality						
Percent with Master's Degree or Higher	83.7 [78.8,92.1]	80.7 [71.9,92.6]	78.4 [63.6,88.2]	89.3 [81.5,92.9]	81.0 [76.7,90.6]	74.1 [59.4,82.1]
Average Years of Experience	11.6 (3.4)	11.7 (2.8)	9.8 (3.4)	12.7 (2.9)	11.7 (3.4)	8.7 (2.3)
School Variables						
Resources						
Per Pupil Spending, thousands ($USD)	15.28 [14.42,17.13]	15.41 [14.69,16.00]	15.82 [14.55,17.91]	14.61 [14.01,15.63]	15.28 [14.73,16.39]	17.46 [15.48,18.45]
Title 1 School Receiving Grants, %(n)	67.7 (21)	63.3 (19)	66.7 (20)	41.9 (13)	58.6 (17)	96.8 (30)
School ZIP Code Median Income, thousands $USD	31.85 [30.44,37.71]	33.59 [30.74,41.42]	25.85 [21.54,36.75]	37.29 [31.22,41.42]	32.77 [29.37,37.96]	25.85 [21.46,30.75]
Safety Events to Enrollment Ratio	0.2 [0.0,0.3]	0.2 [0.1,0.4]	0.3 [0.1,0.9]	0.1 [0.0,0.3]	0.2 [0.1,0.4]	0.5 [0.2,1.0]

Values are means(SD) or medians[IQR] for continuous variables; %(n) for categorical variables.

*JCPS reports Hispanic or Latino as a race rather than as an ethnicity distinct from race.

Table 2.2: Beta coefficients for a one-decibel increase in 7-hour and 17-hour noise on the school-level 2019 percent of proficient or distinguished scores in Math, Reading, and combined in Math or Reading in various models (n=91 schools).

	Math (21,607 tests taken)			Reading (21,607 tests taken)			Combined Math or Reading (N=90; 42,980 tests taken)*		
Model	R^2	β Coefficient (95% CI)	p-value	R^2	β Coefficient (95% CI)	p-value	R^2	β Coefficient (95% CI)	p-value
7-Hour Noise (9:00 AM – 4:00 PM)									
Crude	0.02	-1.10 (-2.56, 0.36)	0.139	0.02	-0.92 (-2.33, 0.49)	0.201	0.03	-1.20 (-2.55, 0.15)	0.083
Model 1	0.52	-0.01 (-1.07, 1.04)	0.980	0.56	0.18 (-0.79, 1.15)	0.714	0.84	-0.09 (-1.04, 0.86)	0.857
Model 2	0.80	-0.31 (-0.99, 0.36)	0.365	0.85	-0.11 (-0.67, 0.45)	0.695	0.87	-0.33 (-0.89, 0.23)	0.243
Model 3	0.84	-0.16 (-0.78, 0.45)	0.602	0.89	-0.01 (-0.48, 0.48)	0.996	0.87	-0.21 (-0.72, 0.30)	0.416
Model 4	0.84	-0.29 (-0.92, 0.34)	0.371	0.89	-0.05 (-0.55, 0.44)	0.833	0.87	-0.27 (-0.79, 0.26)	0.322
Model 5	0.85	-0.20 (-0.83, 0.43)	0.528	0.90	0.03 (-0.48, 0.53)	0.921	0.88	-0.20 (-0.73, 0.33)	0.455
17-Hour Noise (4:00 PM – 9:00 AM; weighted by proportion of student ZIP residence from each school)									
Crude	0.42	-4.94 (-6.14, -3.75)	<0.001	0.44	-4.87 (-6.00, -3.73)	<0.001	0.45	-4.81 (-5.91, -3.70)	<0.001
Model 1	0.54	-1.89 (-3.49, -0.28)	0.021	0.58	-1.68 (-3.16, -0.20)	0.026	0.58	-1.89 (-3.34, -0.44)	0.011
Model 2	0.80	-0.31 (-1.41, 0.79)	0.585	0.85	-0.12 (-1.03, 0.79)	0.797	0.84	-0.45 (-1.36, 0.46)	0.332
Model 3	0.84	0.26 (-0.77, 1.28)	0.624	0.89	0.40 (-0.40, 1.19)	0.326	0.87	-0.02 (-0.87, 0.83)	0.961
Model 4	0.84	0.03 (-1.05, 1.10)	0.960	0.89	0.33 (-0.52, 1.17)	0.447	0.87	-0.11 (-1.01, 0.79)	0.810
Model 5	0.85	-0.24 (-1.31, 0.82)	0.655	0.90	0.29 (-0.57, 1.14)	0.511	0.88	-0.20 (-1.10, 0.69)	0.653

The Crude model includes only noise.
Model 1 includes the Crude model plus percentage of students that are of white race.
Model 2 includes Model 1 plus percentage of students who participate in free and reduced lunch.
Model 3 includes Model 2 plus percentage of students who are in Advanced Placement classes and percentage of chronically absent students.
Model 4 includes Model 3 plus median income of the ZIP in which the school is located.
Model 5 includes Model 4 plus safety events to enrollment ratio, average experience in years of full-time teachers, and per pupil spending.
*No data available for one school.

Table 2.3: Effect modification of the association of a one-decibel increase in 7-hour or 17-hour noise and the school-level 2019 percent of proficient of distinguished scores in Math, Reading, and combined in Math or Reading using model 5.*

Effect Modifier	Math (21,607 tests taken)		Reading (21,607 tests taken)		Combined Math or Reading (N=90; 42,980 tests taken)[+]	
	β Coefficient (95% CI)	X^2 or LRT p-value	β Coefficient (95% CI)	X^2 or LRT p-value	β Coefficient (95% CI)	X^2 or LRT p-value
7-Hour Noise (9:00 AM – 4:00 PM)						
Median Income of School ZIP Code		0.099		0.711		0.332
< $31, 854.00 (n=45)	0.22 (-0.53, 0.98)		0.13 (-0.48, 0.74)		0.04 (-0.61, 0.68)	
≥ $31, 854.00 (n=46)	-0.85 (-1.89, 0.19)		-0.07 (-0.91, 0.78)		-0.49 (-1.37, 0.38)	
Percentage of Students with Free and Reduced Lunch		0.040		0.404		0.089
13.40% - 61.20% (n=31)	-1.22 (-2.25, -0.19)		-0.40 (-1.23, 0.43)		-0.95 (-1.83, -0.07)	
64.40% - 81.30% (n=30)	0.11 (-1.08, 1.31)		0.03 (-0.93, 0.99)		0.04 (-0.98, 1.06)	
81.40% - 98.40% (n=30)	0.84 (-0.40, 2.07)		0.49 (-0.50, 1.49)		0.58 (-0.50, 1.67)	
Percentage of Students that are White		0.406		0.621		0.090
2.15% - 27.43% (n=31)	0.23 (-0.66, 1.12)		0.16 (-0.57, 0.89)		0.45 (-0.28, 1.19)	
27.96% - 49.88% (n=30)	-0.15 (-1.19, 0.89)		0.26 (-0.59, 1.11)		-0.65 (-1.50, 0.20)	
50.21% - 78.48% (n=30)	-0.17 (-0.93, 0.58)		-0.05 (-0.67, 0.57)		0.07 (-0.55, 0.69)	
17-Hour Noise (4:00 PM – 9:00 AM; weighted by proportion of student ZIP residence from each school)						
Median Income of School ZIP Code		0.621		0.655		0.637
< $31, 854.00 (n=45)	0.07 (-1.11, 1.25)		0.21 (-0.69, 1.19)		0.02 (-0.98, 1.02)	
≥ $31, 854.00 (n=46)	-0.31 (-1.72, 1.09)		0.53 (-0.59, 1.64)		-0.28 (-1.45, 0.89)	
Percentage of Students with Free and Reduced Lunch		0.643		0.671		0.853
13.40% - 61.20% (n=31)	-1.34 (-3.47, 0.99)		0.86 (-0.89, 2.61)		-0.34 (-2.24, 1.55)	
64.40% - 81.30% (n=30)	-0.26 (-1.75, 1.24)		0.03 (-1.14, 1.21)		-0.50 (-1.77, 0.77)	
81.40% - 98.40% (n=30)	0.02 (-1.70, 1.73)		-0.02 (-1.37, 1.33)		-0.02 (-1.52, 1.48)	
Percentage of Students that are White		0.238		0.041		0.676
2.15% - 27.43% (n=31)	-1.12 (-2.57, 0.34)		-1.02 (-2.18, 0.15)		-0.21 (-1.48, 1.05)	
27.96% - 49.88% (n=30)	0.55 (-0.92, 2.01)		0.79 (-0.38, 1.97)		-0.67 (-1.91, 0.56)	
50.21% - 78.48% (n=30)	-0.77 (-1.99, 0.45)		-0.34 (-1.31, 0.63)		-0.06 (-1.10, 0.98)	

*Model covariates include percentage of students that are of white race, percentage of students who participate in free and reduced lunch, percentage of students who are in Advanced Placement classes, percentage of chronically absent students, median income of the ZIP in which the school is located, safety events to enrollment ratio, average experience in years of full-time teachers, and per pupil spending.

[+]No data available for one school.

Supplemental Table 2.1: Spearman correlation coefficients of percentage of proficient or distinguished testing scores between subject within the same year and between years within the same subject.

		2019				2021			
		Math (N=91)	Reading (N=91)	Science (N=91)	Writing (N=91)	Math (n=63)	Reading (n=89)	Science (n=31)	Writing (n=43)
2019	Math (N=91)	1							
	Reading (N=91)	0.95	1						
	Science (N=91)	0.89	0.93	1					
	Writing (N=91)	0.82	0.84	0.78	1				
2021	Math (n=63)	0.87				1			
	Reading (n=89)		0.88			0.97	1		
	Science (n=31)			0.79		0.89	0.92	1	
	Writing (n=43)				0.67	0.59	0.69	0.40	1

Supplemental Table 2.2: Spearman correlation coefficients for variables within categories of variables representing a similar construct.

		Student Aptitude			Student Family Income		Full Time Teacher Quality	
Construct	Construct Variables	Percent Gifted and Talented	Percent Advanced Program	Percent Disabled	Percent Free and Reduced Lunch Participation	Percent Homeless	Average Years of Experience	Percent with Master's degree or Higher
Student Aptitude	Percent Gifted and Talented	1						
	Percent Advanced Program	0.67	1					
	Percent Disabled	-0.20	-0.33	1				
Student Family Income	Percent Free and Reduced Lunch Participation				1			
	Percent Homeless				0.84	1		
Full Time Teacher Quality	Average Years of Experience						1	
	Percent with Master's degree or Higher						0.71	1

Supplemental Table 2.3: Spearman correlation coefficients between variables chosen for model inclusion.

	Percent Advanced Program Students	Percent White Students	Percent Free and Reduced Lunch Student Participants	Percent Chronically Absent Students	Average Years of Experience of Full Time Teachers	Per Pupil Spending	School ZIP Code Median Income	Safety Events to Enrollment Ratio
Percent Advanced Program Students	1							
Percent White Students	0.61	1						
Percent Free and Reduced Lunch Student Participants	-0.64	-0.71	1					
Percent Chronically Absent Students	-0.53	-0.50	0.80	1				
Per Pupil Spending	0.54	0.54	-0.72	-0.64	1			
Average Years of Experience of Full Time Teachers	-0.36	-0.48	0.66	0.62	-0.42	1		
School ZIP Code Median Income	0.33	0.53	-0.45	-0.43	0.34	-0.32	1	
Safety Events to Enrollment Ratio	-0.37	-0.49	0.56	0.61	-0.40	0.55	-0.38	1

Supplemental Table 2.4: Beta coefficients for a one-decibel increase in 7-hour and 17-hour noise on the school-level 2019 percent of proficient or distinguished scores in Science and Writing in various models (n=91 schools).

	Science (7,154 tests taken)			Writing (7,353 tests taken)		
Model	R^2	β Coefficient (95% CI)	p-value	R^2	β Coefficient (95% CI)	p-value
7-Hour Noise (9:00 AM – 4:00 PM)						
Crude	0.01	-0.70 (-2.02, 0.62)	0.298	0.01	-0.62 (-2.14, 0.91)	0.428
Model 1	0.49	0.26 (-0.71, 1.23)	0.596	0.35	0.33 (-0.93, 1.58)	0.611
Model 2	0.79	-0.01 (-0.64, 0.62)	0.970	0.70	-0.02 (-0.87, 0.84)	0.969
Model 3	0.80	0.01 (-0.61, 0.62)	0.993	0.72	0.12 (-0.71, 0.95)	0.776
Model 4	0.80	-0.05 (-0.69, 0.59)	0.865	0.73	0.03 (-0.83, 0.89)	0.948
Model 5	0.80	-0.02 (-0.67, 0.63)	0.958	0.73	0.07 (-0.81, 0.94)	0.880
17-Hour Noise (4:00 PM – 9:00 AM; weighted by proportion of student ZIP residence from each school)						
Crude	0.31	-3.83 (-5.00, -2.66)	<0.001	0.32	-4.47 (-5.80, -3.13)	<0.001
Model 1	0.49	-0.53 (-2.05, 0.99)	0.495	0.38	-2.20 (-4.12, -0.27)	0.025
Model 2	0.80	1.02 (0.02, 2.02)	0.046	0.70	-0.38 (-1.76, 1.01)	0.593
Model 3	0.81	1.27 (0.29, 2.26)	0.011	0.72	0.06 (-1.32, 1.43)	0.937
Model 4	0.81	1.30 (0.25. 2.34)	0.015	0.73	-0.17 (-1.62, 1.29)	0.819
Model 5	0.81	1.30 (0.23, 2.37)	0.017	0.73	-0.15 (-1.63, 1.33)	0.840

The Crude model includes only noise.
Model 1 includes the Crude model plus percentage of students that are of white race.
Model 2 includes Model 1 plus percentage of students who participate in free and reduced lunch.
Model 3 includes Model 2 plus percentage of students who are in Advanced Placement classes and percentage of chronically absent students.
Model 4 includes Model 3 plus median income of the ZIP in which the school is located.
Model 5 includes Model 4 plus safety events to enrollment ratio, average experience in years of full-time teachers, and per pupil spending.

Supplemental Table 2.5: Effect modification of the association of a one-decibel increase in 7-hour or 17-hour noise and the school-level 2019 Percent of Proficient of Distinguished Scores in Science and Writing using Model 5.*

	Science (7,154 tests taken)		Writing (7,353 tests taken)	
Effect Modifier	β Coefficient (95% CI)	X^2 or LRT p-value	β Coefficient (95% CI)	X^2 or LRT p-value
7-Hour Noise (9:00 AM – 4:00 PM)				
Median Income of School ZIP Code		0.722		0.014
< $31, 854.00 (n=45)	0.09 (-0.70, 0.89)		0.88 (-0.15, 1.91)	
≥ $31, 854.00 (n=46)	-0.15 (-1.24, 0.93)		-1.28 (-2.69, 0.14)	
Percentage of Students with Free and Reduced Lunch		0.063		0.945
13.40% - 61.20% (n=31)	-1.03 (-2.01, -0.04)		-0.23 (-1.65, 1.20)	
64.40% - 81.30% (n=30)	0.10 (-1.05, 1.24)		0.11 (-1.54, 1.76)	
81.40% - 98.40% (n=30)	0.81 (-0.37, 1.99)		0.08 (-1.63, 1.78)	
Percentage of Students that are White		0.816		0.794
2.15% - 27.43% (n=31)	0.20 (-0.74, 1.15)		0.42 (-0.85, 1.69)	
27.96% - 49.88% (n=30)	0.08 (-1.02, 1.18)		-0.08 (-1.56, 1.40)	
50.21% - 78.48% (n=30)	0.01 (-0.80, 0.80)		0.17 (-0.91, 1.24)	
17-Hour Noise (4:00 PM – 9:00 AM; weighted by proportion of student ZIP residence from each school)				
Median Income of School ZIP Code		0.858		0.834
< $31, 854.00 (n=45)	1.23 (0.05, 2.41)		-0.06 (-1.69, 1.58)	
≥ $31, 854.00 (n=46)	1.38 (-0.03, 2.78)		0.17 (-1.78, 2.11)	
Percentage of Students with Free and Reduced Lunch		0.512		0.700
13.40% - 61.20% (n=31)	0.70 (-1.38, 2.77)		0.02 (-2.95, 2.99)	
64.40% - 81.30% (n=30)	0.80 (-0.59, 2.19)		-0.10 (-2.09, 1.90)	
81.40% - 98.40% (n=30)	1.77 (0.17, 3.37)		-1.11 (-3.40, 1.17)	
Percentage of Students that are White		0.980		0.669
2.15% - 27.43% (n=31)	1.06 (-0.46, 2.58)		-0.96 (-3.05, 1.12)	
27.96% - 49.88% (n=30)	1.10 (-0.43, 2.64)		0.14 (-1.96, 2.24)	
50.21% - 78.48% (n=30)	1.15 (-0.12, 2.42)		-0.52 (-2.26, 1.21)	

*Model covariates include percentage of students that are of white race, percentage of students who participate in free and reduced lunch, percentage of students who are in Advanced Placement classes, percentage of chronically absent students, median income of the ZIP in which the school is located, safety events to enrollment ratio, average experience in years of full-time teachers, and per pupil spending.

Supplemental Table 2.6: Beta coefficients for a one-decibel increase in 7-hour and 17-hour noise on the school-level 2021 Percent of Proficient or Distinguished Scores in Math and Reading.

	Math (N=63; 11, 367 tests taken)		Reading (N=89; 14, 713 tests taken)		Science (N=31; 2, 092 tests taken)		Writing (N=43; 2, 899 tests taken)	
Model	β Coefficient (95% CI)	p-value	β Coefficient (95% CI)	p-value	β Coefficient (95% CI)	p-value	β Coefficient (95% CI)	p-value
7-Hour Noise (9:00 AM – 4:00 PM)								
Model A*	-0.37 (-1.02, 0.27)	0.259	0.05 (-0.37, 0.47)	0.815	0.71 (-0.93, 2.34)	0.398	-1.02 (-2.23, 0.20)	0.102
Condition Index	100.34		101.87		165.22		99.06	
R^2	0.73		0.89		0.69		0.61	
Model B[+]	-0.10 (-1.00, 0.19)	0.185	-0.01 (-0.43, 0.41)	0.971	-0.06 (-1.78, 1.66)	0.943	-0.73 (-1.94, 0.49)	0.240
Condition Index	103.32		97.81		186.14		107.55	
R^2	0.77		0.88		0.62		0.59	
17-Hour Noise (4:00 PM – 9:00 AM; weighted by proportion of student ZIP residence from each school in 2021)								
Model A*	-0.07 (-1.32, 1.19)	0.916	0.23 (-0.47, 0.93)	0.522	1.57 (0.08, 3.05)	0.038	-0.88 (-3.01, 1.24)	0.415
Condition Index	174.84		158.80		160.89		151.97	
R^2	0.72		0.89		0.72		0.60	
Model B[+]	0.47 (-0.74, 1.68)	0.444	0.10 (-0.34, 0.83)	0.797	1.65 (-0.19, 3.49)	0.078	-0.88 (-3.12, 1.36)	0.442
Condition Index	185.32		158.98		203.72		152.19	
R^2	0.76		0.88		0.65		0.58	

*Models utilize many covariates from 2019 (i.e., percentage of students who are in Advanced Placement classes, percentage of chronically absent students, safety events to enrollment ratio, and average experience in years of full-time teachers) to be comparable to the main table results, but the percentage of students that are of white race and percentage of students who participate in free and reduced lunch are from 2021 school data.

[+]Models utilize covariates from 2021 school data (i.e., percentage of students that are of white race, percentage of students who participate in free and reduced lunch, percentage of students who are in Gifted and Talented, percentage of chronically absent students, safety events to enrollment ratio, percent of full-time teachers with a Master’s degree or higher) that are similar to 2019 covariates but not always identical, 2019 data for per pupil spending and school ZIP code median income.

TRANSITION 2

There are several reports that environmental noise exposure is associated with various facets of mental ill-health. In Aim 1, we estimated the distribution of environmental noise during the 16 hours between 5:00 PM and 9:00 AM during the winter and spring seasons. These estimates, which represent the times during which most adults would be at their homes, are utilized in the following subaims to examine the association of environmental noise with mental ill-health outcomes among adults in Louisville, Kentucky.

In Aim 3A, we determine the association between census-tract level winter and spring environmental noise with census-tract level prevalence of mental ill-health. In Aim 3B, we assess spring environmental noise in relation to odds of depression among participants in a South Louisville cohort.

AIM 3A. THE ASSOCIATION OF SEASONAL ENVIRONMENTAL NOISE LEVELS WITH ADULT MENTAL ILL-HEALTH PREVALENCE: A CENSUS-TRACT LEVEL STUDY IN LOUISVILLE, KENTUCKY[c]

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Acknowledgments:
The University of Louisville Center for Integrative Health Sciences NIEHS P30 ES030283 (ND), University of Louisville Superfund Research Center NIEHS P42 ES023716 (LW, RY), and University of Louisville Green Heart Louisville Project NIEHS R01 ES029846 (LW, RY) supported researchers on this project.

Competing Financial Interests Declaration:
The authors declare that they have no actual or potential competing financial interests.

Introduction

Mental illness, or mental ill-health, is a broad term used to describe a variety of conditions with varying levels of severity. As of 2019, the National Institute of Mental Health estimates that 51.5 million United States (US) adults are living with a mental illness, accounting for 20.6% of the US adult population.[120] The development of mental ill-health is multicausal, with no single factor acting as the determinant of any mental illness.[121] A growing body of evidence suggests that environmental exposures, such as the built and designed environment,[122–125] green spaces and time outdoors,[126–129] air pollution,[130–133] and varying heavy metals,[134–137] are associated with mental ill-health. Environmental noise presents as another modifiable environmental exposure relevant to mental ill-health. In fact, the World Health Organization (WHO) has recognized potential negative impacts of noise on mental ill-health since 1999.[2] However, in 2018, the WHO stated that their guidelines for environmental noise[3] were not influenced by impacts on mental health, pointing to the weak body of existing evidence supporting the relationship.[5]

The current lack of consistent findings between noise exposure and mental ill-health[23–37,138,139] may be partially attributed to the inconsistencies in the noise source and time-periods of exposure. Most studies restrict noise exposure to specific sources, such as road or rail-traffic, or aircraft flyovers,[23–35,37,138,139] which may not fully capture the cumulative environmental noise to which individuals are exposed. Additionally, full-day noise exposures ($LA_{eq}24$ or LA_{den}) based on residential addresses are often used,[23,25–29,31–35,37] and may not accurately capture the true burden of individual-level noise exposure, which is dependent on spatial-temporal movements in and outside of the residence.[36,39] A few studies have attempted to eliminate this issue by specifically examining noise exposure during nighttime hours, assuming that most individuals are located in their residence during these times.[30,33,35] Nighttime noise exposure may be more impactful on mental ill-health than daytime exposure due to disturbances of sleep,[28,140–142] which may mediate the association of noise with mental ill-health.[28,108–110,116,139,143–145]

Evidence suggests that mental ill-health outcomes vary between seasons.[146–149] Some have investigated the role of environmental factors in mental ill-health seasonality. For example, seasons with higher atmospheric concentrations of ozone and $PM_{2.5}$ had significantly more emergency department visits for mental ill-health outcomes compared to seasons with lower concentrations.[150] Additionally, seasonal changes in monthly average rainfall were observed to significantly increase the likelihood of mental illness.[151] Although environmental noise likely varies by season,[152] its seasonal association with mental ill-health has not yet been studied. Moreover, disparities in mental ill-health exist by racial group and socioeconomic status,[153,154] and effect modification by race and income on the associations of environmental exposures (exposures) with mental ill-health have been observed. For instance, $PM_{2.5}$ concentration is more strongly associated with depression among individuals living in census tracts with higher population percentages of below-poverty income.[155] Additionally, greenness is less protective on anxiety and on depression among black and other non-

Hispanic individuals and among individuals with lower household income.[156] However, these potentially modifying factors have yet to be examined in the association of environmental noise with mental ill-health.

To date, investigations into the environmental noise and mental ill-health relationship among adults has been focused in Europe[23–35,37,138] or Asia[36,139] and has yet to be conducted in North America. Louisville, Kentucky presents as an ideal candidate for a US based study, given its varying contributors of environmental noise, including the Louisville Muhammad Ali International Airport (SDF) – a passenger airport and major global cargo traffic hub – five busy interstate systems, and several major roads. SDF and a large proportion of the major roadways are in or near residential areas, creating concern about the impact of environmental noise exposure on the health of the population in Louisville. Therefore, the purpose of this study is to determine the association of seasonal 5:00 PM to 9:00 AM environmental noise and mental ill-health prevalence among adults at the census-tract level in Louisville, Kentucky, and to examine for modification by several factors.

Methods and Materials

Exposure Data – Winter and Spring 16-hour Noise

Detailed descriptions of noise data are documented elsewhere (see Aim 1 manuscript). Briefly, noise data were collected in winter 2021 (January/February) and spring 2021 (April/May) at 15 sites throughout Louisville. For each collection period, noise was recorded every 10 seconds for 24 hours at each site using a

Class 1 noise meter (Type 2236, Brüel & Kjær, Naerum, Denmark). Average noise at each site was calculated for the 16-hour time-period between 5:00 PM and 9:00 AM, chosen to represent the presumed times that adults would likely be at their homes.[24,30,33,35] We estimated winter 2021 and spring 2021 16-hour noise distribution in Louisville, Kentucky using land use regression models with geographic characteristics of collection sites as covariates (e.g. normalized difference vegetation index, distance to airport flyovers, annual average road traffic, length of streams) and averaged seasonal noise by census tracts (N=190). Models resulted in satisfactory fit and prediction error, with a winter model R^2 of 0.73 and leave-one-out cross-validation (LOOCV) root mean square error (RMSE) of 2.98 decibels, and a spring model R^2 of 0.57 and a LOOCV RMSE of 5.92 decibels.

Outcome Data – Adult Mental Ill-Health Prevalence

Data for the outcome of interest were obtained from the Center for Disease Control and Prevention (CDC) 2020 *PLACES (Population Level Analysis and Community Estimates: Local Data for Better Health)* project. PLACES estimates the prevalence of 27 varying health-related measures (e.g., health status, chronic diseases, health risk behaviors, and prevention measures) across the US at multiple geographic levels, including nearly all US census tracts. To estimate the prevalence of health measures, the CDC PLACES uses a multilevel regression and poststratification approach to geographically link population demographic and socioeconomic data from Census Bureau 2010 or 2015-2019 or 2014-2018 American Community Survey (ACS) to the 2017 or 2018

Behavioral Risk Factor Surveillance System (BRFSS) health surveys,[157] which are conducted annually to willing participants above the age of 17 years using random digit dialing.[158]

The variable used for our outcome of interest, adult mental ill-health prevalence, was that of "Mental Health Not Good For ≥14 Days Among Adults Aged ≥18 Years" from CDC PLACES 2020[159] for the 190 census tracts in Louisville. This adult mental ill-health prevalence variable was derived from the 2018 BRFSS, in which participants were asked "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health *not* good," in which responses included one of the following: a number of days between 1 and 30, none, don't know/not sure, or refused to answer.[160] PLACES calculates and reports an annual crude prevalence at the census-tract level, where the numerator is the number of respondents in a census tract who answered 14 or more days in the past 30 days and the denominator is the number of all respondents in a census tract who gave a response of either none or any number of days.[159]

Covariate Data

Census-tract level data for covariates and potential confounders were obtained from 2015-2019 ACS 5-year estimates and the CDC PLACES 2020 project. Census-tract level variables obtained from the ACS 5-year estimates included, median age, median individual income, income inequality, prevalence of varying disabilities, and prevalence of male gender; white, black, or other race;

unmarried (divorced, widowed, or have never been married) individuals 25 years or older; and college-education or higher (attainment of bachelor's degree or higher) among individuals 25 years or older. Income inequality is reported as the Gini Index, which represents income dispersion across the income distribution of a census tract; with a range from 0 to 1, values closer to 0 are indicative of perfect equality, and values closer to 1 are indicative of perfect inequality.[161]

Chronic conditions, which are often associated with mental ill-health,[162] came from PLACES 2020. Prevalence estimations for arthritis, asthma, high blood pressure, cancer, high cholesterol, chronic kidney disease, chronic obstructive pulmonary disease, coronary heart disease, diabetes, obesity, and stroke, were considered for model inclusion as potential confounders. Additionally, we considered the prevalence of physical ill-health, defined by PLACES as "Physical Health Not Good For ≥14 Days." Finally, we considered health risk behavior measures such as the prevalence of insufficient sleepers (i.e., sleep less than 7 hours per night), binge drinking, current cigarette smoking, and having no leisure-time physical activity.

Statistical Analyses

Age-standardized descriptive statistics (mean and standard deviation) of census tracts were presented by tertiles of seasonal environmental noise and by tertiles of mental ill-health prevalence. To limit multicollinearity, we first reduced the number of covariates considered for statistical models. We observed strong correlations between the prevalence of specific disabilities and any disability (Supplemental Table 3A.1), and selected prevalence of any disability. Likewise, we included the physical ill-health prevalence in our statistical models because the prevalence of specific chronic conditions (except for cancer) was moderately or strongly correlated with the physical ill-health prevalence (Supplemental Table 3A.2). The population percentage of white race was selected to represent the racial distribution of census tracts as we could not include all race variables due to multicollinearity issues.

To aid in variable selection for regression modeling, directed acyclic graphs (DAGs) (Figure 3A.1) were constructed to aid in the visualization of the ecological-level relationship between environmental noise and mental ill-health prevalence. The current DAGs do not imply causation, particularly given the ecologic nature of this study. Rather, they demonstrate the ways in which the exposure, the outcome, and population characteristics may be related ecologically. According to the DAGs, potential confounders of the association between seasonal environmental noise and mental ill-health prevalence within the population were age, race, marital status, education level, income, income inequality, disability, and chronic conditions. Therefore, the following variables were selected to be tested in modeling: median age; population percentages of white race, unmarried, and college-educated; median individual income; income inequality; prevalence of any disability; and prevalence of physical ill-health.

To determine the association of a one-decibel increase in seasonal noise with mental ill-health prevalence, we utilized multivariable linear regression, with winter or spring 16-hour environmental noise as the continuous exposure and mental ill-health prevalence as the outcome. The above covariates were added into the model one at a time to assess how each variable altered the strength of the association between noise and mental ill-health prevalence. Final models were achieved once the addition of further covariates did not change materially the seasonal noise β coefficient. The performance of final models was determined by R^2 values and condition indexes greater than 30 indicated the presence of multicollinearity.

We assessed effect modification for several variables using the fully adjusted model. Based on extant literature describing their potential to modify environmental effects on mental health outcomes, variables of interest were median individual income,[35,156,163] population percentage of college-educated,[26,155,164] population percentage of white race,[156,165] and physical ill-health prevalence.[155,156] These variables were dichotomized based on their median to create a low and high group. To test for effect modification of a variable of interest, an interaction variable was included in the final models. Although insufficient sleep prevalence was not utilized as a confounder, we additionally assessed effect modification by insufficient sleep prevalence based on prior findings that sleep disturbance may be important in the association of noise and mental ill-health.[28,140–142] During analysis of effect modification by insufficient sleep prevalence, a dichotomized insufficient sleep prevalence variable, along with an interaction variable with noise, was added to the model. The Wald X^2 p-value was used to determine whether the strength of the associations between groups differed significantly. When resulting beta coefficients of effect modification analysis were incongruous with the expected direction, we additionally conducted a sensitivity analysis in which highly influential census tracts, determined by a Cooks D greater than 1, were removed from analysis. Further, median and IQR noise levels were calculated for each group to describe the noise distribution within categories of the effect modifier. We plotted the adjusted linear regression models to display the modified prediction of mental ill-health prevalence from noise levels between census tract groups of effect modifiers (only one plot shown). All statistical analyses were performed using SAS Software (version 9.4).

Results

Tertiles of winter 16-hour (Figure 3A.2) and spring 16-hour environmental noise (Figure 3A.3) are displayed for Louisville census tracts (N=190). The mean winter noise across Louisville census tracts was 54.84 decibels (SD=2.89). For spring noise, the mean was 56.91 decibels (SD=4.26). The mean mental ill-health prevalence of census tracts was 16.24% (SD=4.12%; Figure 3A.4).

Table 3A.1 displays median age-adjusted characteristics of census tracts by tertiles of winter and spring 16-hour environmental noise, and by tertiles of mental ill-health prevalence. Census tracts with louder seasonal noise had a higher mental ill-health prevalence. Additionally, census tracts in high tertiles of seasonal noise and mental ill-health prevalence generally had a younger, less white and more black, and less college-educated population, compared to census tracts in low or moderate tertiles. Furthermore, these noisier census tracts had populations with higher percentages of unmarried, disabled (except hearing disabled), chronically ill for most conditions (except cancer), and physically unhealthy populations compared to census tracts in low or moderate noise tertiles. Census tracts that were louder and had higher prevalence of mental ill-health also had higher prevalences of insufficient sleepers, current cigarette smokers, and physical inactivity, but lower prevalences of binge drinkers. The distribution of the male population did not differ across tertiles of seasonal noise nor tertiles of mental ill-health prevalence.

Results of regression modeling are shown in Table 3A.2. In crude models a one-decibel increase in winter noise was significantly associated with a higher prevalence of mental ill-health by 0.84 percentage points (winter noise β=0.84, 95% CI: 0.68, 1.00), while a one-decibel increase in spring noise was significantly associated with higher mental ill-health prevalence by 0.68 percentage points (spring noise β=0.68, 95% CI: 0.58, 0.78). Confounders retained in modeling were census-tract level median age; population percentages of white race, unmarried, and college-educated; median individual income; income inequality; and prevalence of physical ill-health. After all adjustments, louder winter and spring noise by one-decibel increase was significantly associated with higher mental ill-health prevalence by 0.09 and 0.07 percentage points, respectively (winter noise β=0.09, 95% CI: 0.01, 0.16; spring noise β=0.07, 95% CI: 0.02, 0.13). Final models for both seasons of noise had an R^2 value of 0.94, indicating that the model was explaining most of the variation in mental ill-health prevalence. The winter model had a condition index of 109.29, while the spring model had a condition index of 91.22; these values indicate that multicollinearity was present in both final models. However, multicollinearity inflates the standard errors of covariates, which can lead to a potential lack of significance of beta estimates; since the beta estimates in the final models were highly significant, the effects of multicollinearity did not appear to be an issue of major concern.

Table 3A.3 shows the results for effect modification by income, race, education, insufficient sleep, and physical ill-health. Median individual income was observed as a significant effect modifier for winter noise ($p_{interaction}<0.001$), with louder winter noise by one decibel being significantly associated with higher mental ill-health prevalence by 0.14 percentage points among low-income census tracts (β=0.14, 95% CI: 0.07, 0.22). Conversely, louder winter noise by one decibel was significantly associated with lower mental ill-health prevalence by 0.15 percentage points among high-income census tracts (β=-0.15, 95% CI: -0.28, -0.02). However, after removing one highly influential census tract (Cooks D>1), this association was no longer significant in high-income census tracts (β=-0.10, 95% CI: -0.21, 0.01), but remained significant in low-income census tracts (β=0.12, 95% CI: 0.05, 0.19; $p_{interaction}<0.001$). Figure 3A.5 displays how the differing associations by low or high median individual income changes predicted prevalence of mental ill-health from noise level. The association between winter noise and mental ill-health prevalence was significantly positive in census tracts with low population percentages of white race (β=0.23, 95% CI: 0.14, 0.32) but null in census tracts with high population percentages of white race (β=0.06, 95% CI: -0.04, 0.16), with less white census tracts having a winter noise association with mental ill-health prevalence that is nearly four-times that of more white census tracts ($p_{interaction}$=0.003). Further, louder winter noise was associated with higher mental ill-health prevalence among census tracts with higher prevalence of people with insufficient sleep (β=0.14, 95% CI: 0.06, 0.21), but louder winter noise was associated with lower mental ill-health prevalence in census tracts with lower insufficient sleep prevalence (β=-0.13, 95% CI: -0.24, -0.02; $p_{interaction}$<0.001). Upon removal of the highly influential census tract, the association in census tracts with low insufficient sleep prevalence were no longer significant (β=-0.09, 95% CI: -0.19, 0.01), but remained significant in census tracts with high insufficient sleep prevalence (β=0.12, 95% CI: 0.05, 0.18; $p_{interaction}$<0.001). For winter noise, there was no statistically significant effect modification by population percentage of college-educated ($p_{interaction}$=0.615) nor physical ill-health prevalence ($p_{interaction}$=0.067).

The association for spring noise with mental ill-health prevalence differed significantly by median individual income ($p_{interaction}$<0.001), with low-income census tracts having a significantly positive association (β=0.12, 95% CI: 0.06, 0.17) and high-income census tracts having a significantly inverse association (β=-0.17, 95% CI: -0.28, -0.06). These associations were attenuated after removing a highly influential census tract but remained significant (low-income β=0.09, 95% CI: 0.05, 0.14; high-income β=-0.12, 95% CI: -0.22, -0.02; $p_{interaction}$<0.001). Louder spring noise was associated with higher mental ill-health prevalence among census tracts with greater prevalence of insufficient sleepers (β=0.09, 95% CI: 0.04, 0.14) but lower mental ill-health prevalence among census tracts with lower insufficient sleep prevalence (β=-0.14, 95% CI: -0.24, -0.03; $p_{interaction}$<0.001). Removal of the highly influential census tract attenuated these associations, but significance was still observed (low insufficient sleep prevalence β=-0.10, 95% CI: -0.19, -0.01; high insufficient sleep prevalence β=0.08, 95% CI: 0.03, 0.12; $p_{interaction}$<0.001). The associations of spring noise and mental ill-health prevalence did not differ significantly by population percentage of white race ($p_{interaction}$=0.406), population percentage of college-educated ($p_{interaction}$=0.138), nor physical ill-health prevalence ($p_{interaction}$=0.087).

Discussion

The current study examined the census-tract level association between 5:00 PM to 9:00 AM winter and spring total environmental noise with the mental ill-health prevalence among adults in Louisville, Kentucky. After adjusting for several confounders, we observed that census tracts with louder winter and louder spring nighttime/early morning environmental noise had higher prevalence of mental ill-health, and the associations between noise and mental ill-health prevalence were similar between seasons. Louder winter and louder spring noise by five decibels were associated with a 0.71 and 0.59 percentage point higher prevalence of mental ill-health, respectively. Furthermore, the associations of winter and spring noise with mental ill-health prevalence were stronger in census tracts with lower median individual income, higher prevalence of insufficient sleepers, and lower population percentages of white race.

Winter and spring noise had similar strengths of association with mental ill-health prevalence. Although others have not assessed seasonality of the association, our findings of louder noise being associated with increased mental ill-health prevalence are congruous with other studies.[25,27,29,36,37] However, we investigated total environmental noise rather than source-specific noise.[25,27,29,37] Our results are similar to those reported in Ma et al., who investigated individual-level total environmental noise in association with mental ill-health in a cohort of 117 participants, and reported that mental health was significantly lower with louder 24-hour noise.[36] We further defined environmental noise to specific hours during which adults would likely be at their residences. Other studies have utilized nighttime noise[30,33,35] and observed significant associations between louder noise and worse mental ill-health outcomes.[33,35] Our investigation of *total* environmental noise during *nighttime*-inclusive hours may be more appropriate for the association with adult mental ill-health than those that use source-specific or residence-based 24-hour estimates of noise, which do not represent true exposures to noise if individuals are exposed to other sources of noise or are not in their homes at all hours.

We observed nonsignificant effect modification by population percentage of college-educated and physical ill-health prevalence on the association of noise with mental ill-health prevalence, which are concordant with findings of others.[24,29] However, we did observe significant effect modification by prevalence of insufficient sleepers, with louder winter and spring noise being associated with higher mental ill-health prevalence among census tracts with higher insufficient sleep prevalence. Nighttime noise exposure may cause sleep disturbances[28,111–113,140,141,166,167] that can contribute to the development of mental ill-health,[108,109,115,116,168] and it is widely proposed that sleep may mediate the environmental noise and mental ill-health relationship.[28,108–110,116,139,143–145] Although the current study was not conducive to assessment of mediation by insufficient sleep prevalence, our findings provide further evidence that sleep may be a potentially important factor in the association between environmental noise and mental ill-health, and future studies should seek to expound potential mediation by sleep.

Further, we observed that louder winter and spring noise was associated with higher prevalence of mental ill-health among census tracts with low median individual income and louder winter noise was associated with higher prevalence of mental ill-health among census tracts with lower population percentages of white race. Moreover, we observed louder distributions of winter and spring noise among census tracts with larger non-white and lower income populations, and the disproportionate exposure of noise may contribute to larger allostatic load and higher likelihoods of mental ill-health,[107–117] especially since populations of black, Indigenous, and people of color (BIPOC) and lower-income disproportionately experience additional stressors of social determinants of health (e.g., housing, violence, economic instability, systemic racism).[118,119] Our findings indicate that BIPOC and low-income communities in Louisville, KY may have disproportionately louder environmental noise exposures, which may explain non-linear associations between environmental noise and mental ill-health prevalence as we observed in our study (Figure 3A.6). Others who have explored non-linearity of the relationship between environmental noise and mental ill-health outcomes[23,26,31,32] do not account for potential effect modification by population subgroups that may be disproportionately exposed to loud environmental noise, and thus have disproportionate mental ill-health outcomes. Future investigations should consider effect modification by socioeconomic factors and their potential for exposures to louder environmental noise.

For both winter and spring noise, we observed that louder noise was associated with lower mental ill-health prevalence among census tracts with higher insufficient sleep prevalence, and among census tracts with lower median individual income. These peculiar observations may simply be due chance. Alternatively, the inverse association may be due to the sources contributing to louder noise within these census tracts; natural sources, such as bird song or running water, may have a protective association with mental ill-health.[169–173] The distribution of natural and unnatural noise may also explain the effect modification observed by other factors (i.e., socioeconomic status and sleep), as natural noise sources are more desirable,[174] more expensive,[175] more relaxing,[176] and less harmful for sleep[177] than unnatural noise sources. However, among the high-income census tracts, greenness was lower in louder tertiles of winter and spring noise (mean(SD) winter NDVI by increasing tertiles of winter noise: 0.17 (0.02), 0.15 (0.02), 0.13 (0.03); mean(SD) spring NDVI by increasing tertiles of spring noise: 0.35 (0.03), 0.30 (0.02), 0.27 (0.03); winter and spring p-value<0.001). Future investigations should seek to explicate the distributions of natural and unnatural noise and the potentially varied associations with mental ill-health.

Limitations and Strengths

First, the study was ecological, and the ecologic fallacy limits the interpretation of findings. For example, we do not know the noise exposure, mental ill-health status, or risk factor characteristics of individuals. As such, we cannot infer an individual-level association between environmental noise exposure and adult mental ill-health. Next, this study lacks temporality between the exposure and the outcome, and the findings should not be interpreted as necessarily causative. Additionally, mental ill-health prevalence, estimated by CDC PLACES, represents self-reported experiences of “stress, depression, and problems with emotions,”[160] which may lack ample specificity and misclassify *clinically* mentally healthy individuals as “mentally ill,” overestimating true prevalence of mental ill-health. As such, effect estimates may be biased toward the null, and interpretation of findings may underestimate the true association between environmental noise and mental ill-health prevalence. Finally, although there were 190 census tracts included in analysis, noise estimates were derived from models built from collections at only 15 sites on different days due to the constraints of time and resources; the inherent limitations of the noise estimates may have contributed to exposure measurement error, and the findings of the current study may be due to chance. Additional testing sites and/or co-occurring testing may provide a better estimate for seasonal 5:00 PM to 9:00 AM environmental noise; however noise models resulted in acceptable levels of error (see Aim 1 manuscript).

Despite the limitations, the current study has several strengths. Notably, to best represent true noise exposure, we utilized total environmental noise restricted to hours in which adults would likely be home, which included hours during which most individuals are home or at sleep. We also investigated potential seasonal differences of associations between environmental noise and mental ill-health. Through data-linkage, our estimations of association were adjusted for multiple confounders, including various socioeconomic, demographic, and health characteristics of census tract populations. Further, we investigated potential effect modification by two previously uninvestigated factors – income and race – and the widely proposed potential mediator of insufficient sleep, and our findings indicate their importance in explicating the relationship between environmental noise and mental ill-health. Finally, our results add to the collective understanding of the environmental noise and mental ill-health relationship among adults, particularly in North America.

Conclusion

The current study observed that mental ill-health prevalence in Louisville, Kentucky was significantly higher, albeit with small estimates, in census tracts with louder winter and spring 5:00 PM to 9:00 AM total environmental noise, and associations were stronger among census tracts with low median income and lower prevalence of white population. We underscore sleep as a potentially important factor of the relationship between environmental noise and mental ill-health and display a need for further investigation of the potential mediation by sleep. Further, we propose that combined effects of socioeconomic status with noise exposure may explain inconsistency of findings among similar investigations and call for future analyses to consider these potentially modifying factors. To effectively understand the true relationship between environmental noise exposure and adult mental ill-health, longitudinal individual-level research is required.

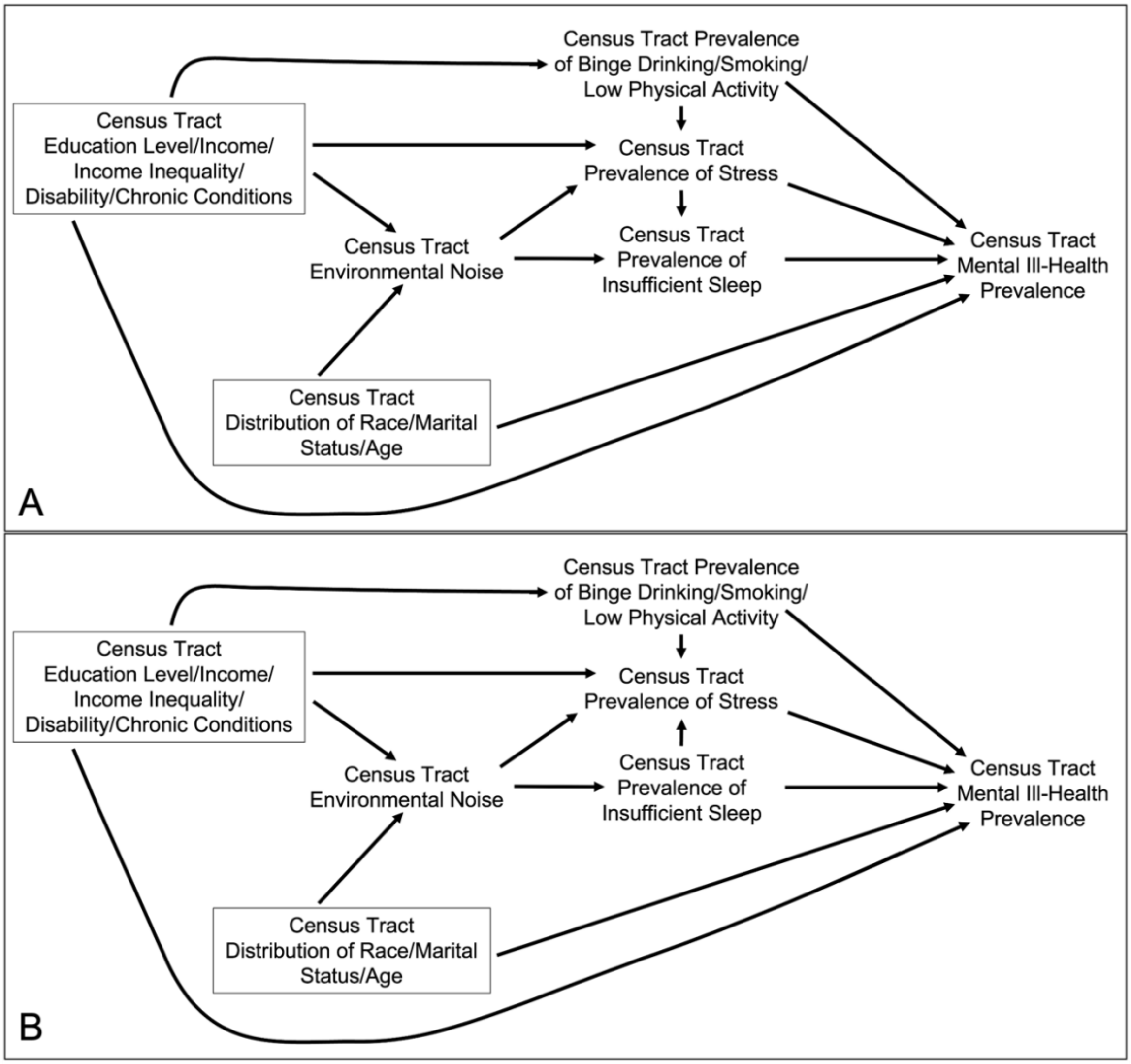

Figure 3A.01: Directed acyclic graphs of the association between census-tract level environmental noise and census-tract level mental ill-health prevalence. The relationship between sleep and stress may be bidirectional. Therefore, DAG A shows represents sleep as dependent on stress levels, and DAG B represents stress as dependent on sleep.

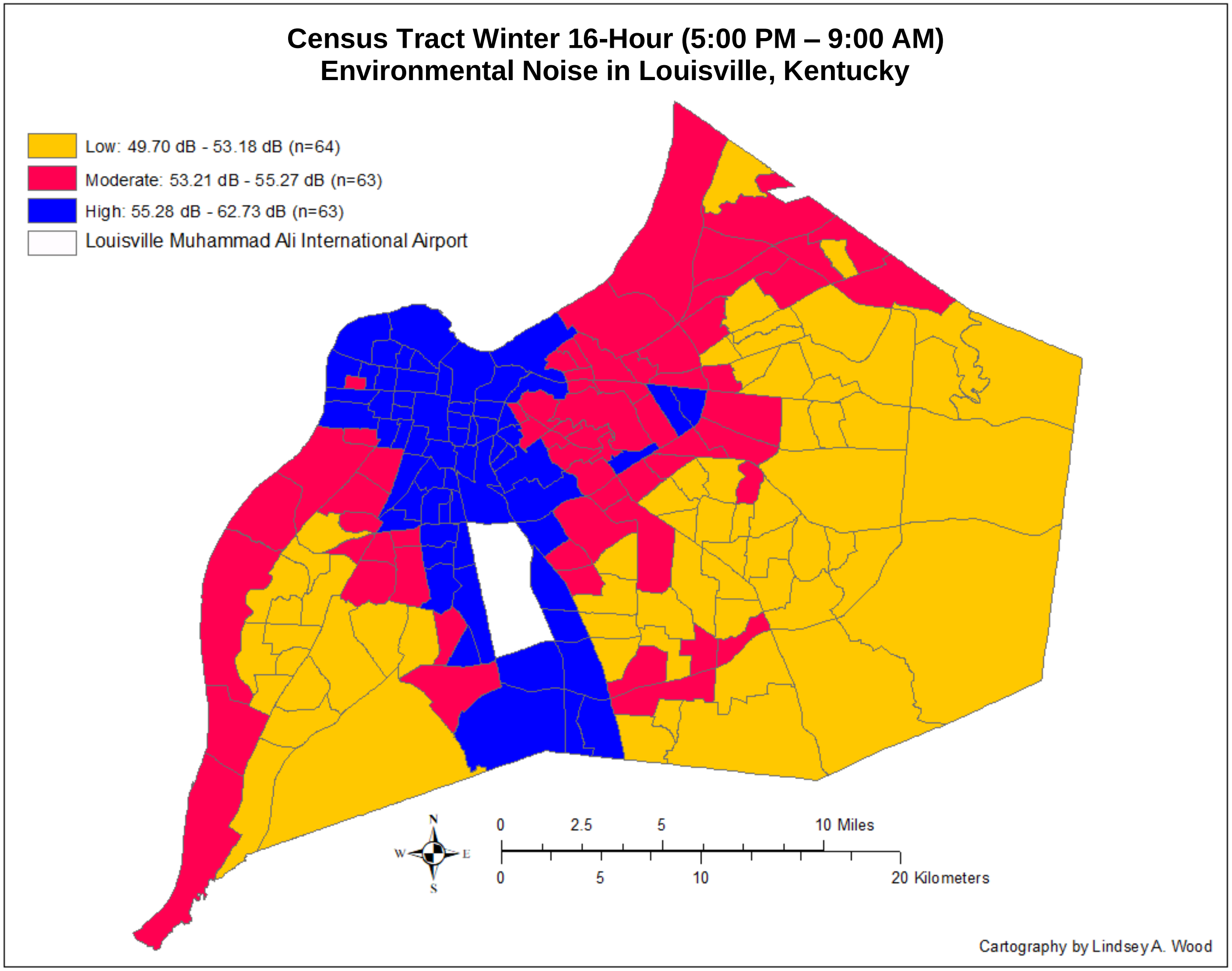

Figure 3A.2: Census-tract level winter 16-hour (5:00 PM – 9:00 AM) environmental noise in Louisville, KY.

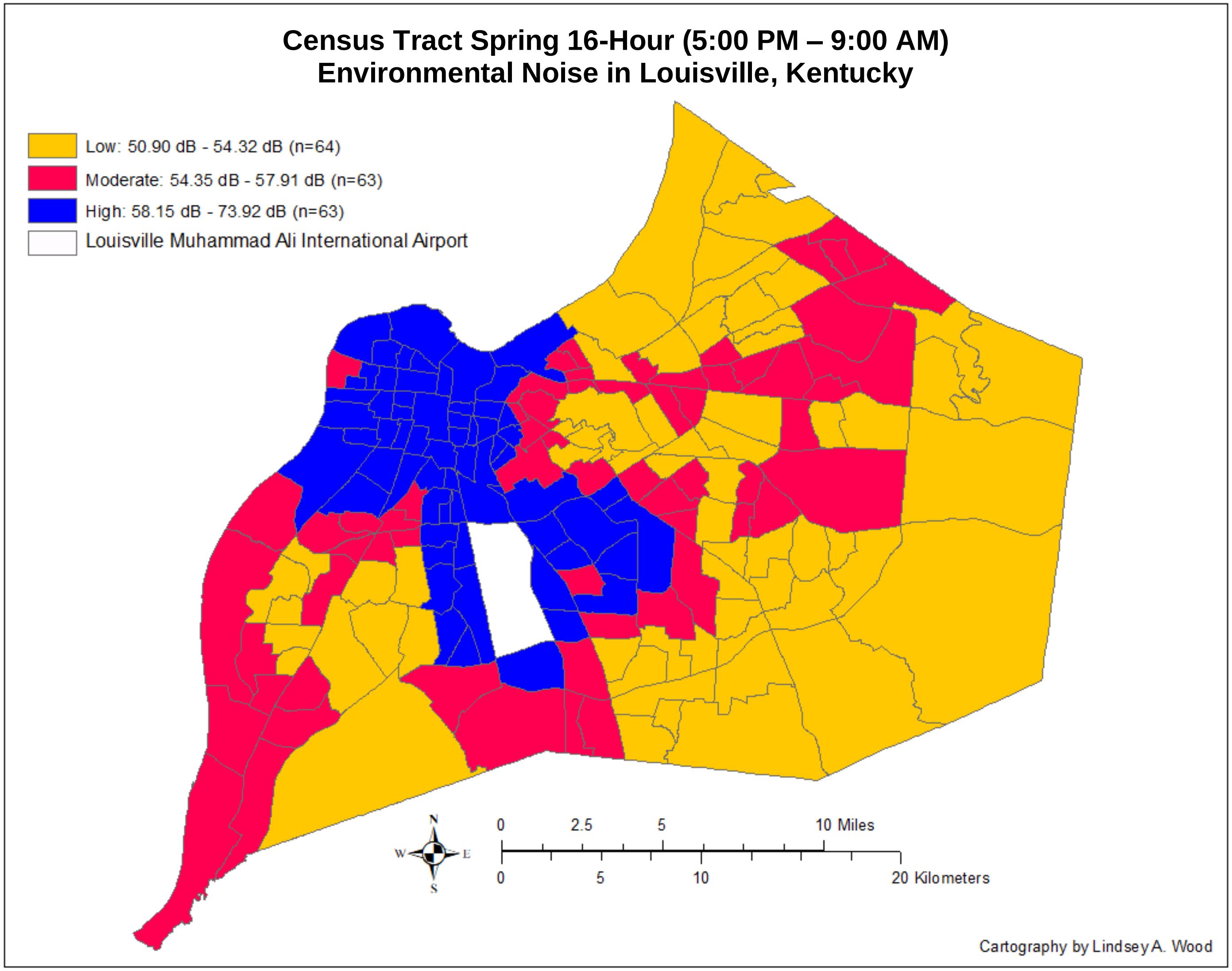

Figure 3A.3: Census-tract level spring 16-hour (5:00 PM – 9:00 AM) environmental noise in Louisville, KY.

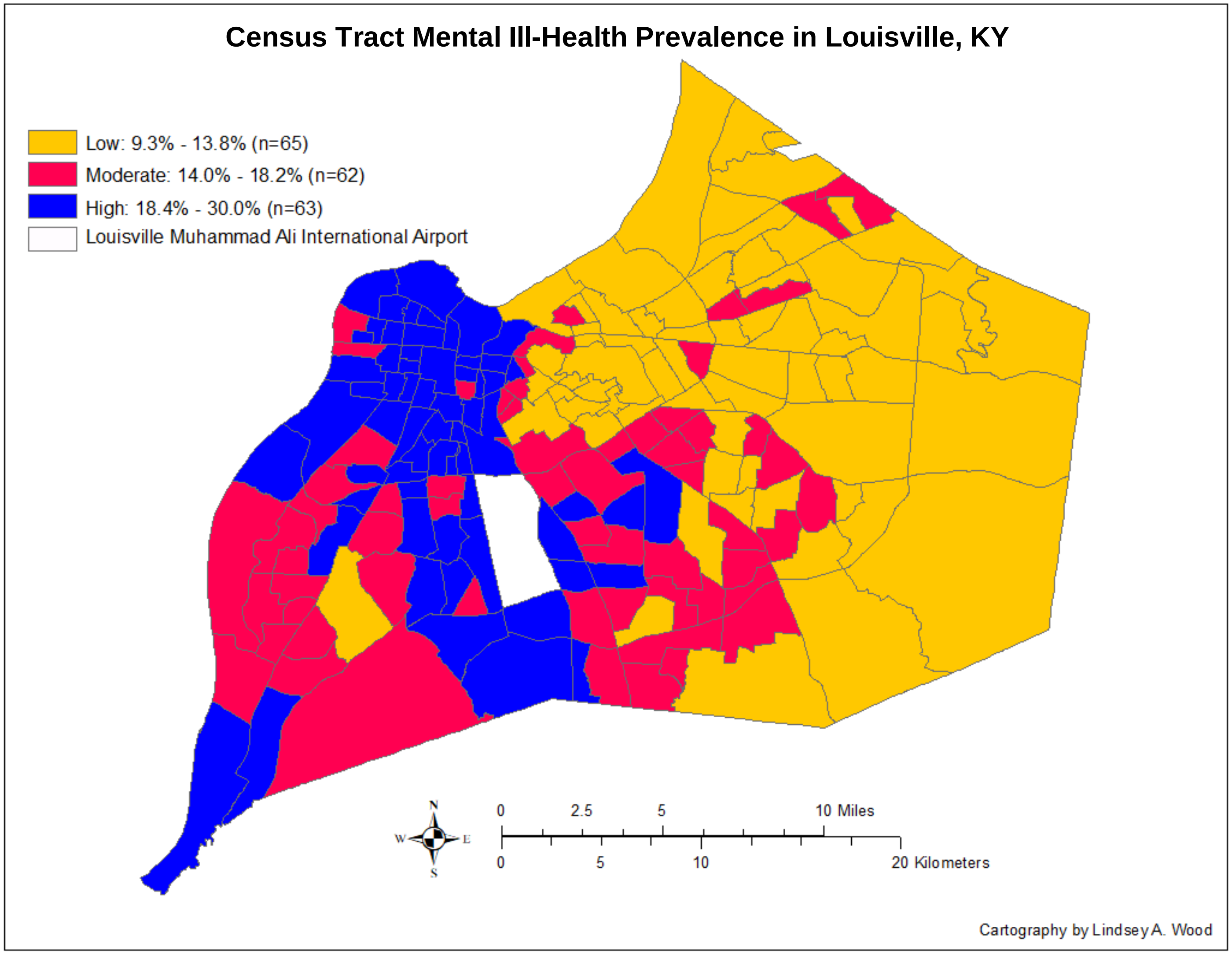

Figure 3A.4: Census tract mental ill-health prevalence in Louisville, KY.

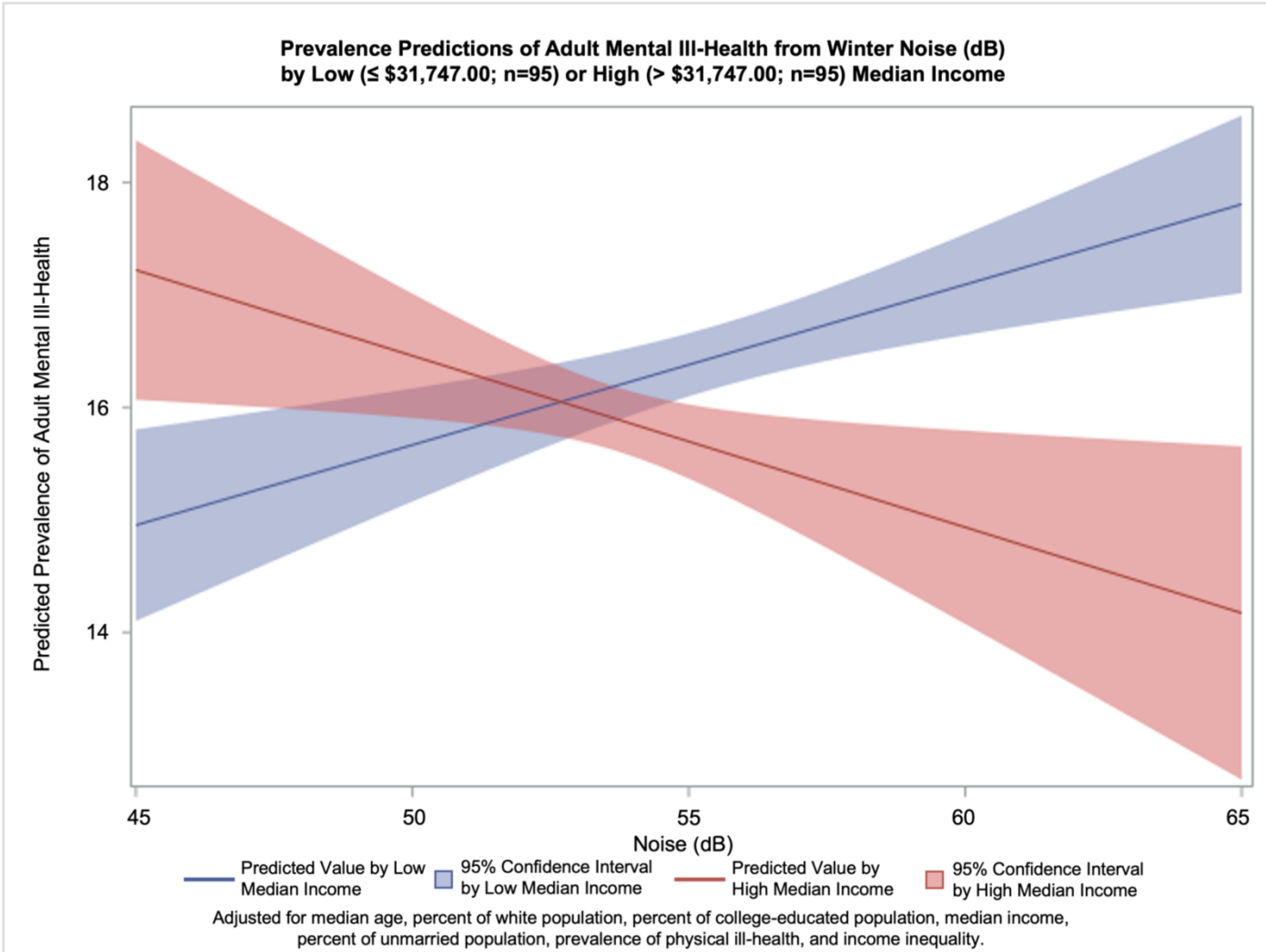

Figure 3A.5: Effect modification of the association between winter environmental noise and mental ill-health prevalence by census tract median individual income.

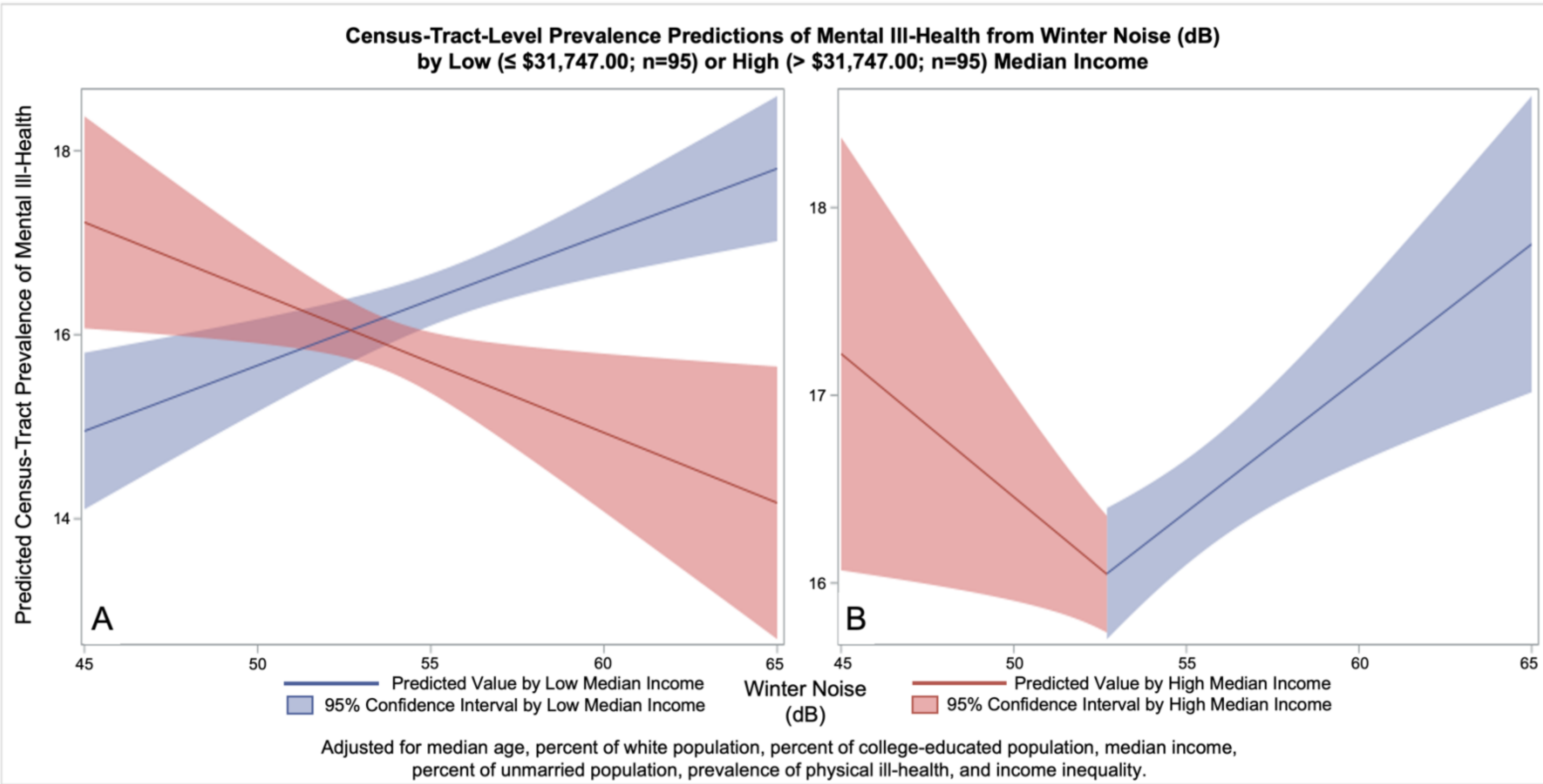

Figure 3A.6: Effect modification may explain non-linearity of the association between winter environmental noise and mental ill-health prevalence.

Graph A displays predictions and 95% confidence intervals of census-tract level mental ill-health prevalence from nighttime winter noise levels among census tracts with low and high median individual income. The plotted estimation lines intersect at 52.7 dB, which is roughly representative of the point at which winter noise levels begin to differ between low- (median=55.58 dB, IQR: 53.35 dB – 58.51 dB) and high-income (median=53.21 dB, IQR: 52.32 dB – 54.28 dB) census tracts. Graph B illustrates how restricting data to winter noise levels representative of the distributions within low- and high-income census tracts (i.e., low-income tracts restricted to winter noise levels above the intersection and high-income tracts restricted to winter noise levels below the intersection) results in an apparent non-linear association between winter noise and mental ill-health prevalence. For modification of the association of winter noise and mental ill-health prevalence by percentage of white population, and for modification of the association between spring noise and mental ill-health by median income, similar observations of non-linearity can be made when restricting data to represent noise distribution between categories.

Tabe 3A.1: Age-standardized characteristics* of census tracts in Louisville, KY by tertiles of winter and spring 16-hour (5:00 PM – 9:00 AM) environmental noise and by tertiles of mental ill-health prevalence (N=190).

	Average Winter Noise			Average Spring Noise			Mental Ill-Health Prevalence		
	Low (49.70 – 53.18 dB) (n=64)	Moderate (53.21 – 55.27 dB) (n=63)	High (55.28 – 62.73 dB) (n=63)	Low (50.90 – 54.32 dB) (n=64)	Moderate (54.35 – 57.91 dB) (n=63)	High (58.15 – 73.92 dB) (n=63)	Low (9.3 – 13.8%) (n=65)	Moderate (14.0 – 18.2%) (n=62)	High (18.40 – 30.0%) (n=63)
Mental Ill-Health Prevalence	14.41 (1.79)	15.04 (2.58)	19.23 (2.66)	13.61 (1.80)	15.56 (2.36)	19.61 (2.31)			
Median Age, years[a]	40.28 (5.34)	39.90 (5.63)	35.33 (5.70)	42.28 (5.23)	37.73 (4.48)	35.47 (6.01)	42.68 (5.43)	38.08 (3.73)	34.64 (5.55)
Male	48.69 (1.88)	48.19 (2.50)	48.33 (3.81)	48.31 (1.87)	49.28 (2.10)	47.85 (3.89)	48.60 (1.96)	49.07 (2.23)	48.08 (3.91)
Race									
White	78.36 (9.81)	74.45 (15.72)	56.69 (23.62)	84.14 (5.75)	75.62 (13.27)	49.68 (23.06)	85.04 (6.88)	73.09 (13.89)	52.15 (21.71)
Black	15.03 (9.00)	18.92 (15.45)	37.21 (24.03)	10.26 (5.18)	17.11 (12.44)	43.90 (23.84)	8.14 (4.59)	20.49 (13.91)	41.52 (22.26)
Other	1.30 (1.46)	0.88 (0.91)	0.77 (0.74)	0.61 (0.63)	1.29 (1.47)	0.97 (0.83)	1.08 (1.62)	1.23 (1.18)	0.98 (0.89)
Not Currently Married	49.51 (6.96)	56.08 (8.61)	71.54 (7.77)	47.06 (6.71)	57.50 (7.22)	72.16 (7.69)	47.23 (7.72)	57.50 (6.31)	72.17 (8.02)
College-Educated	33.57 (11.60)	39.14 (17.52)	20.86 (12.20)	40.79 (14.90)	33.57 (15.04)	18.17 (10.56)	53.49 (10.14)	25.53 (8.01)	12.22 (6.26)
Median Individual Income	$36,726.06 ($6,348.09)	$35,168.70 ($8,076.81)	$23,733.48 ($6,127.53)	$39,308.09 ($7,313.79)	$33,263.10 ($6,119.82)	$22,430.17 ($5,248.86)	$43,130.14 ($5,898.07)	$31,459.71 ($3,127.87)	$20,167.89 ($3,217.87)
Income Inequality (Gini Index)	0.38 (0.04)	0.43 (0.05)	0.44 (0.04)	0.40 (0.04)	0.40 (0.04)	0.44 (0.05)	0.42 (0.04)	0.38 (0.04)	0.44 (0.04)

Tabe 3A.1: Age-standardized characteristics* of census tracts in Louisville, KY by tertiles of winter and spring 16-hour (5:00 PM – 9:00 AM) environmental noise and by tertiles of mental ill-health prevalence (N=190).

	Average Winter Noise			Average Spring Noise			Mental Ill-Health Prevalence		
	Low (49.70 – 53.18 dB) (n=64)	Moderate (53.21 – 55.27 dB) (n=63)	High (55.28 – 62.73 dB) (n=63)	Low (50.90 – 54.32 dB) (n=64)	Moderate (54.35 – 57.91 dB) (n=63)	High (58.15 – 73.92 dB) (n=63)	Low (9.3 – 13.8%) (n=65)	Moderate (14.0 – 18.2%) (n=62)	High (18.40 – 30.0%) (n=63)
Prevalence of Disability									
Any	12.28 (2.52)	12.89 (4.29)	18.80 (4.86)	12.19 (2.56)	13.37 (3.84)	18.70 (4.98)	10.32 (2.12)	13.56 (2.25)	20.63 4.85)
Hearing	3.53 (1.00)	3.24 (1.12)	3.19 (1.23)	3.54 (0.98)	3.17 (1.08)	3.09 (1.26)	3.34 (0.81)	2.89 (0.99)	3.82 1.47)
Visual	1.92 (0.72)	2.21 (1.23)	3.33 (1.36)	1.82 (0.71)	2.30 (1.05)	3.44 (1.43)	1.60 (0.65)	2.10 (0.77)	3.96 (1.47)
Cognitive	4.61 (1.39)	5.26 (2.57)	9.61 (3.12)	4.60 (1.49)	5.43 (2.29)	9.45 (3.12)	3.82 (1.20)	5.73 (1.53)	10.16 3.24)
Ambulatory	6.91 (1.73)	7.43 (3.21)	11.60 (3.90)	6.83 (1.85)	7.63 (2.94)	11.56 (3.94)	5.35 (1.57)	7.70 (1.74)	13.06 3.72)
Self-care	2.58 (0.93)	2.55 (1.16)	4.09 (1.63)	2.45 (0.88)	2.85 (1.19)	3.86 (1.60)	2.07 (0.88)	2.92 (1.00)	4.24 (1.51)
Independent Living	5.85 (1.55)	5.63 (2.29)	9.38 (3.17)	5.81 (1.71)	6.02 (2.26)	9.17 (3.25)	4.46 (1.40)	6.55 (1.77)	10.23 (2.94)
Prevalence of Physical Ill-Health	12.18 (1.67)	13.02 (2.82)	17.35 (3.17)	11.56 (1.53)	13.29 (2.54)	17.90 (2.86)	10.23 (0.74)	13.47 (1.50)	19.21 (2.03)
Prevalence of Chronic Conditions									
Arthritis	28.29 (2.17)	28.64 (3.07)	30.85 (3.72)	28.39 (2.28)	28.60 (2.91)	31.16 (3.75)	27.26 (2.48)	28.72 (2.78)	32.24 3.18)
Asthma	10.08 (0.67)	10.47 (1.17)	12.32 (1.42)	9.77 (0.60)	10.53 (1.00)	12.60 (1.27)	9.27 (0.28)	10.66 (0.60)	12.97 1.00)

Tabe 3A.1: Age-standardized characteristics* of census tracts in Louisville, KY by tertiles of winter and spring 16-hour (5:00 PM – 9:00 AM) environmental noise and by tertiles of mental ill-health prevalence (N=190).

	Average Winter Noise			Average Spring Noise			Mental Ill-Health Prevalence		
	Low (49.70 – 53.18 dB) (n=64)	Moderate (53.21 – 55.27 dB) (n=63)	High (55.28 – 62.73 dB) (n=63)	Low (50.90 – 54.32 dB) (n=64)	Moderate (54.35 – 57.91 dB) (n=63)	High (58.15 – 73.92 dB) (n=63)	Low (9.3 – 13.8%) (n=65)	Moderate (14.0 – 18.2%) (n=62)	High (18.40 – 30.0%) (n=63)
Cancer[b]	7.35 (0.82)	7.21 (0.92)	6.39 (0.92)	7.68 (0.96)	7.10 (0.80)	6.23 (0.89)	7.80 (0.95)	6.98 (0.76)	6.22 (0.81)
Coronary Heart Disease[c]	6.96 (0.91)	7.33 (1.30)	8.77 (1.55)	6.91 (0.95)	7.35 (1.21)	8.97 (1.52)	6.41 (0.82)	7.38 (1.06)	9.51 1.26)
COPD[d]	8.39 (1.30)	8.76 (2.00)	11.52 (2.15)	8.00 (1.25)	9.10 (1.92)	11.75 (1.97)	6.91 (0.74)	9.24 (1.17)	12.87 1.47)
Diabetes	10.76 (1.42)	11.78 (2.82)	15.76 (4.03)	10.31 (1.20)	11.50 (2.29)	16.68 (3.85)	9.50 (0.95)	11.75 (2.21)	17.26 (3.18)
High Blood Pressure	36.50 (2.47)	37.62 (4.72)	42.86 (6.25)	36.06 2.47)	37.14 (3.97)	44.19 (6.13)	34.87 (2.66)	37.72 (4.03)	44.71 (5.32)
High Cholesterol[e]	34.64 (1.73)	34.50 (2.13)	35.23 (2.56)	34.95 (1.87)	34.46 (2.09)	35.29 (2.57)	34.34 (2.10)	34.48 (2.05)	35.92 (2.40)
Chronic Kidney Disease	2.75 (0.31)	2.98 (0.55)	3.74 (0.79)	2.69 (0.30)	2.93 (0.46)	3.89 (0.77)	2.55 (0.25)	2.93 (0.45)	4.02 0.64)
Obesity	30.47 (2.31)	31.72 (4.26)	38.11 (5.26)	29.28 (2.05)	31.76 (3.41)	39.46 (4.76)	27.61 (1.05)	32.34 (2.46)	40.56 (3.74)
Stroke	2.99 (0.46)	3.33 (0.87)	4.62 (1.26)	2.87 (0.41)	3.28 (0.72)	4.86 (1.22)	2.60 (0.31)	3.34 (0.69)	5.06 (1.02)
Health Behaviors									
Insufficient Sleep[f]	37.60 (2.13)	38.46 (3.62)	43.81 (4.12)	36.36 (2.05)	38.64 (2.85)	44.94 (3.68)	34.89 (1.27)	39.45 (1.96)	45.64 (2.90)

Tabe 3A.1: Age-standardized characteristics* of census tracts in Louisville, KY by tertiles of winter and spring 16-hour (5:00 PM – 9:00 AM) environmental noise and by tertiles of mental ill-health prevalence (N=190).

	Average Winter Noise			Average Spring Noise			Mental Ill-Health Prevalence		
	Low (49.70 – 53.18 dB) (n=64)	Moderate (53.21 – 55.27 dB) (n=63)	High (55.28 – 62.73 dB) (n=63)	Low (50.90 – 54.32 dB) (n=64)	Moderate (54.35 – 57.91 dB) (n=63)	High (58.15 – 73.92 dB) (n=63)	Low (9.3 – 13.8%) (n=65)	Moderate (14.0 – 18.2%) (n=62)	High (18.40 – 30.0%) (n=63)
Binge Drinking	18.83 (1.17)	18.08 (1.98)	16.36 (2.44)	18.86 (1.28)	18.50 (1.68)	15.79 (2.39)	19.14 (1.33)	18.60 (1.67)	15.45 (1.95)
Current Smoking	21.38 (3.40)	21.96 (5.02)	29.53 (4.73)	19.79 (3.58)	23.15 (4.52)	30.22 (4.06)	16.78 (1.68)	24.05 (1.86)	32.70 (2.67)
No Leisure-Time Physical Activity	26.35 (3.45)	27.78 (5.89)	36.26 (6.10)	24.72 (3.22)	28.39 (5.03)	37.68 (5.47)	21.94 (1.69)	29.23 (3.06)	39.91 (3.63)

*Values are mean (SD) and are standardized to the median age distribution of census tracts.

[a]Value is not age adjusted

[b]Not including skin cancers

[c]Includes angina

[d]Chronic obstructive pulmonary disease; includes emphysema and chronic bronchitis

[e]Among those who have been screened in the past 5 years coronary heart disease

[f]<7 hours per night

Table 3A.2: Beta coefficients for a one-decibel increase in winter and spring 16-hour (5:00 PM – 9:00 AM) environmental noise on mental ill-health prevalence in various models.

Model	Beta Coefficient	95% Confidence Interval	p-value
Winter Noise			
Crude	0.84	0.68, 1.00	<0.001
Model 1	0.58	0.43, 0.72	<0.001
Model 2	0.51	0.38, 0.64	<0.001
Model 3	0.43	0.34, 0.51	<0.001
Model 4	0.29	0.20, 0.38	<0.001
Model 5	0.26	0.16, 0.36	<0.001
Model 6	0.10	0.03, 0.18	0.009
Model 7	0.09	0.01, 0.16	0.021
Spring Noise			
Crude	0.68	0.58, 0.78	<0.001
Model 1	0.50	0.41, 0.60	<0.001
Model 2	0.41	0.31, 0.51	<0.001
Model 3	0.33	0.26, 0.39	<0.001
Model 4	0.22	0.15, 0.29	<0.001
Model 5	0.20	0.13, 0.27	<0.001
Model 6	0.08	0.02, 0.13	0.005
Model 7	0.07	0.02, 0.13	0.007

The Crude model includes only noise.
Model 1 includes the Crude model plus median age.
Model 2 includes Model 1 plus population percentage of white race.
Model 3 includes Model 2 plus population percentage of college education.
Model 4 includes Model 3 plus median individual income.
Model 5 includes Model 4 plus population percentage of unmarried.
Model 6 includes Model 5 plus physical ill-health prevalence.
Model 7 includes 6 plus income inequality.

Table 3A.3: Effect modification of the association of a one-decibel increase in winter or spring 16-hour (5:00 PM – 9:00 AM) environmental noise and the mental ill-health prevalence using Model 7.

Effect Modifier	Beta Coefficient for Noise	95% Confidence Interval	Median Noise [IQR] (dB)	Wald X^2 p-value
Winter Noise				
Median Individual Income				<0.001
≤ $31,747.00 (n=95)	0.14	0.07, 0.22	55.58 [53.35-58.51]	
> $31,747.00 (n=95)	-0.15	-0.28, -0.02	53.21 [52.32-54.28]	
Population Percentage of College Education				0.615
≤ 25.50% (n=95)	0.06	-0.03, 0.14	55.27 [53.18-57.73]	
> 25.50% (n=95)	0.09	-0.02, 0.19	53.61 [52.42-54.56]	
Population Percentage of White Race				0.003
≤ 78.00% (n=95)	0.23	0.14, 0.32	55.10 [53.16-57.10]	
> 78.00% (n=95)	0.06	-0.04, 0.16	53.61 [52.35-54.76]	
Physical Ill-Health Prevalence				0.067
≤ 13.00% (n=96)	0.07	-0.10, 0.23	53.31 [52.30-54.29]	
> 13.00% (n=94)	0.22	0.12, 0.33	55.55 [53.35-58.34]	
Insufficient Sleep Prevalence				<0.001
≤ 38.60% (n=97)	-0.13	-0.24, -0.02	53.29 [52.32-54.31]	
> 38.60% (n=93)	0.14	0.06, 0.21	55.53 [51.47-58.34]	
Spring Noise				
Median Individual Income				<0.001
≤ $31,747.00 (n=95)	0.12	0.06, 0.17	60.02 [55.81-62.32]	
> $31,747.00 (n=95)	-0.17	-0.28, -0.06	54.21 [53.05-55.07]	
Population Percentage of College Education				0.138
≤ 25.50% (n=95)	0.03	-0.03, 0.09	58.33 [54.68-61.68]	
> 25.50% (n=95)	0.10	0.02, 0.18	54.57 [53.43-55.67]	
Population Percentage of White Race				0.406
≤ 78.00% (n=95)	0.09	0.03, 0.16	58.29 [54.80-61.68]	
> 78.00% (n=95)	0.05	-0.03, 0.14	54.23 [53.24-55.76]	
Physical Ill-Health Prevalence				0.087
≤ 13.00% (n=96)	0.06	-0.07, 0.18	54.16 [53.02-55.04]	
> 13.00% (n=94)	0.17	0.10, 0.24	59.59 [55.89-61.86]	
Insufficient Sleep Prevalence				<0.001
≤ 38.60% (n=97)	-0.14	-0.24, -0.03	54.23 [53.24-55.11]	
> 38.60% (n=93)	0.09	0.04, 0.14	60.02 [55.89-62.32]	

Model covariates include median age, population percentage of white race, population percentage of college education, median individual income, population percentage of unmarried, physical ill-health prevalence, income inequality, and noise*binary effect modifier. For analysis of effect modification by insufficient sleep prevalence, a binary insufficient sleep prevalence variable was included in the model along with an interaction term with noise.

Supplemental Table 3A.1: Pearson correlation coefficients between census-tract level prevalence of varying disabilities (N=190).

	Any	Hearing	Visual	Cognitive	Ambulatory	Self-care	Independent Living
Any	1						
Hearing	R=0.49 p<0.01	1					
Visual	R=0.75 p<0.01	R=0.38 p<0.01	1				
Cognitive	R=0.90 p<0.01	R=0.33 p<0.01	R=0.67 p<0.01	1			
Ambulatory	R=0.94 p<0.01	R=0.47 p<0.01	R=0.71 p<0.01	R=0.81 p<0.01	1		
Self-care	R=0.69 p<0.01	R=0.42 p<0.01	R=0.55 p<0.01	R=0.63 p<0.01	R=0.74 p<0.01	1	
Independent Living	R=0.84 p<0.01	R=0.46 p<0.01	R=0.62 p<0.01	R=0.78 p<0.01	R=0.83 p<0.01	R=0.77 p<0.01	1

Supplemental Table 3A.2: Pearson correlation coefficients between census-tract level physical ill-health prevalence and prevalence of varying chronic conditions (N=190).

	Physical Ill-Health	Arthritis	Asthma	Cancer	Chronic Heart Disease	COPD	Diabetes	High Blood Pressure	High Cholesterol	Chronic Kidney Disease	Obesity	Stroke
Physical Ill-Health	1											
Arthritis	R=0.70 p<0.01	1										
Asthma	R=0.94 p<0.01	R=0.52 p <0.01	1									
Cancer	R=-0.33 p<0.01	R=0.42 p<0.01	R=-0.52 p<0.01	1								
Chronic Heart Disease	R=0.85 p<0.01	R=0.93 p<0.01	R=0.67 p<0.01	R=0.18 p<0.01	1							
COPD	R=0.98 p<0.01	R=0.77 p<0.01	R=0.86 p<0.01	R=-0.19 p<0.01	R=0.91 p<0.01	1						
Diabetes	R=0.92 p<0.01	R=0.80 p<0.01	R=0.88 p<0.01	R=-0.14 p=0.05	R=0.87 p<0.01	R=0.86 p<0.01	1					
High Blood Pressure	R=0.82 p<0.01	R=0.89 p<0.01	R=0.76 p<0.01	R=0.08 p=0.26	R=0.88 p<0.01	R=0.79 p<0.01	R=0.96 p<0.01	1				
High Cholesterol	R=0.42 p<0.01	R=0.91 p<0.01	R=0.17 p=0.02	R=0.67 p<0.01	R=0.77 p<0.01	R=0.53 p<0.01	R=0.53 p<0.01	R=0.68 p<0.01	1			
Chronic Kidney Disease	R=0.89 p<0.01	R=0.86 p<0.01	R=0.82 p<0.01	R=-0.02 p=0.83	R=0.93 p<0.01	R=0.87 p<0.01	R=0.98 p<0.01	R=0.96 p<0.01	R=0.60 p<0.01	1		
Obesity	R=0.95 p<0.01	R=0.60 p<0.01	R=0.97 p<0.01	R=-0.46 p<0.01	R=0.72 p <0.01	R=0.86 p<0.01	R=0.93 p<0.01	R=0.83 p <0.01	R=0.27 p<0.01	R=0.87 p<0.01	1	
Stroke	R=0.91 p<0.01	R=0.82 p<0.01	R=0.87 p<0.01	R=-0.10 p=0.17	R=0.90 p<0.01	R=0.88 p<0.01	R=0.99 p<0.01	R=0.96 p<0.01	R=0.55 p<0.01	R=0.99 p<0.01	R=0.91 p<0.01	1

Supplemental Table 3A.3: Average NDVI in Louisville, KY by tertiles of winter and spring 16-hour (5:00 PM – 9:00 AM) environmental noise in high-income census tracts. (N=95).

	Average Winter Noise			Average Spring Noise		
	Low (49.70 – 52.65 dB) (n=32)	Moderate (52.66 – 54.04 dB) (n=32)	High (54.13 – 60.32 dB) (n=31)	Low (50.90 – 53.55 dB) (n=32)	Moderate (53.57 – 54.79 dB) (n=32)	High (54.80 – 62.11 dB) (n=31)
Greenness by season (NDVI)	0.17 (0.02)	0.15 (0.02)	0.13 (0.03)	0.35 (0.03)	0.30 (0.02)	0.27 (0.03)

Average NDVI for census tracts was calculated from Landsat8 images obtained from the United States Geological Survey. Winter NDVI was representative of January 6th, 2020, with a cloud coverage of 6.09%. Spring NDVI was representative of August 17th, 2020, with a cloud coverage of 1.05%.

The Kruskal Wallis test was used to compare distributions of winter NDVI in tertiles of winter noise due to the non-normal distribution of winter NDVI.

An ANOVA test was used to compare distributions of spring NDVI in tertiles of spring noise.

AIM 3B. THE ASSOCIATION OF ENVIRONMENTAL NOISE WITH DEPRESSION IN SOUTH LOUISVILLE NEIGHBORHOODS[d]

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Acknowledgments:
The University of Louisville Center for Integrative Health Sciences NIEHS P30 ES030283 (ND), University of Louisville Superfund Research Center NIEHS P42 ES023716 (LW, RY, JT, TS, SS, RK, AB), and University of Louisville Green Heart Louisville Project NIEHS R01 ES029846 (LW, RY, JT, RK, AB) supported researchers on this project.

Competing Financial Interests Declaration:
The authors declare that they have no actual or potential competing financial interests.

Introduction

Depression is a complex psychiatric disease characterized by sad or anxious mood, lack of interest in pleasurable activities, feelings of hopelessness, and decreased energy, among others.[178] Depression may be present in other mood disorders, such as bipolar disorder, seasonal affective disorder, and dysthymia.[178] The World Health Organization (WHO) estimates that depressive disorders are the third leading global cause of years lived with disability,[179] and 9.7% of adults in the United States experienced a depressive disorder between 2001 and 2003.[180] Depressive disorders are multi-causal,[181–184] with no single factor contributing to its development. However, environmental noise exposure contributes to sleep disturbance[28,108–110,116,139,143–145] or stress response[107–117] that may influence the development of depression.

Several studies reported significant associations between louder environmental noise and increased prevalence[23,25,27] and incidence[37] of depression. However, noise exposure estimates were generally defined as source-specific noise, such as aircraft nosie,[23] road-traffic noise,[23,27] rail-traffic noise,[23] or some combination of the three,[25,37] which may not be fully representative of the totality of environmental noise exposures. Additionally, noise exposures were mostly defined by full-day exposures at specific locations,[23,25,27] which likely does not represent full-day noise exposures, which are based on the spatial-temporal movements of individuals.[36,39] Other studies reported no associations between noise exposures and depression.[26,31–33] The inconsistent findings throughout the literature may be partially due to inconsistencies in defining depression, which include diagnosed depressive disorders,[23,25] varying questionnaires that assess depression,[25–27] emergency admissions for depression,[37] and anti-depressant medication use.[31–33]

Depression disparities exist amongst genders,[185–187] and some have reported stronger associations between environmental noise and depression among women compared to men.[27] Disparities of depression also exist by racial[188,189] and income groups,[190,191] but analysis of effect modification by race and income have yet to be examined in the association of environmental noise with depression. The association between environmental noise exposure and depression may differ by levels of sleep disturbance or stress, however only one study has reported on modification by sleep[32] where no modification was observed, and stress has yet to be investigated. Further, studies on the association of environmental noise and depression among adults have been predominately conducted in Europe.[23,25–27,31–33,37] Just one study, with the specific population of women and the hazard of post-partum depression, has been conducted in Montreal, Canada.[192]

Louisville, Kentucky is a strong candidate for a US based study, given the presence of several environmental noise sources, such as an international and large cargo airport (SDF), five interstates, and several railways. Particularly, South Louisville neighborhoods are in close proximity to all three of these major noise polluters, and the noise produced in these neighborhoods may be contributing to depression among the South Louisville population. Therefore, the purpose of this study is to determine the association of depression and environmental noise during 5:00 PM to 9:00 AM, chosen to represent the times during which most adults would be at home,[30,33,35] among adults in South Louisville, Kentucky and to examine whether the association differs by gender, race, income, sleep, and stress.

Methods and Materials

Study Population and Outcome Data

Green Heart Louisville (GHL) and its health study – Health, Environment, and Action in Louisville (HEAL) – is a non-randomized clinical trial aimed to assess an intervention of added greenery and its effects on cardiovascular health in South Louisville communities. Baseline enrollment of participants occurred in the summers of 2018 and 2019. Eligibility criteria to participate in HEAL included being between 25 and 70 years of age, not being part of a vulnerable population (e.g., incarcerated, paroled, or pregnant individuals), and having no pre-existing cancers or blood disorders. At enrollment, all participants (N=735) completed an extensive questionnaire on health history and behaviors and a physical health exam that included assessment of blood pressure, height, weight, lung capacity, and collection of toenail, blood, and urine samples.

Included in the questionnaire was the Patient Health Questionnaire 9 (PHQ-9), which is a validated assessment for depression severity.[193] Participants were asked a series of nine questions regarding depressive symptoms within the last two weeks, to which they responded with a 4-point Likert scale of “not at all” [0], “several days” [1], “more than half the days” [2], or “nearly every day” [3].

Points are summed to range between 0 and 27, where scores of 0 – 4 represent none/minimal depression, 5 – 9 represents mild depression, 10 – 14 represents moderate depression, 15 – 19 represents moderately severe depression, and 20 – 27 represents severe depression. Of the 735 HEAL participants, 11 had missing values for one of the nine PHQ-9 questions and were excluded from analysis, resulting in a final sample of 724 participants. For the current study, PHQ-9 scores were treated dichotomously, where scores of 5 or greater indicated the presence of depression (n=312) and those of 4 or lower indicated the absence of depression (n=412).[193,194] Further, those who reported taking any medication used for treating depression were additionally considered as having depression (n=52), resulting in 364 individuals with depression, and 360 without depression.

Exposure Data – Spring 16-hour Noise

Detailed descriptions of noise data are documented elsewhere (see Aim 1 manuscript). Briefly, noise data were collected at 15 sites in Louisville during April/May 2021. At each site, noise levels were recorded every 10 seconds for 24 hours using a Class 1 noise meter (Type 2236, Brüel & Kjær, Naerum, Denmark), and the average noise was calculated for the 16-hour time-period between 5:00 PM and 9:00 AM, chosen to represent the presumed times that adults would likely be at their homes.[24,30,33,35] The spring 2021 noise distribution in Louisville was estimated via land use regression (LUR) modeling, which included geographic characteristics of collection sites as covariates (e.g. normalized difference vegetation index, distance to airport flyovers, annual average road traffic, length of streams). The resulting LUR model had satisfactory fit and prediction error, with an R^2 of 0.57 and a leave-one-out cross-validation (LOOCV) root mean square error (RMSE) of 5.92 decibels. Using ArcGIS 10.7.1, individual-level 16-hour noise exposure was extracted at the geocoded residential addresses of participants at enrollment.

Covariate Data

Covariate data from the HEAL participants included age (in years), gender (male or female), race (white, black, or other), Hispanic ethnicity, household income (less than $20,000, $20,000-44,999, $45,000-64,999, $65,000 or more, and missing), education level (associate degree or lower or bachelor's degree or higher), perception of general health (excellent or very good, good, fair or poor, and missing), number of chronic conditions, physical activity (none, low intensity at least once per week, moderate intensity 1-4 times per week, or moderate intensity at least 5 times per week or high intensity at least once per week, and missing), cigarette smoking status (never, ever – at least 100 cigarettes in lifetime, current, and missing), alcohol risk level based on the Alcohol Use Disorder Identification Test (AUDIT; no risk, low risk, risky to severe, and missing),[195] marijuana use (never, current – less than a month ago, former – more than a month ago, and missing), and stress level in tertiles (and missing) of the Perceived Stress Scale (PSS).[196,197] Additionally, census-tract level prevalence of insufficient sleep (≤7 hours per night) was obtained from CDC PLACES and assigned to the census tract of each participant's residential address.

Statistical Analyses

Age-adjusted characteristics of the 724 participants were calculated by exposures of <57.0, 57.0 – <60.0, 60.0 – <63.0, and ≥63.0 decibels of 16-hour noise levels and depression status. Multivariable logistic regression was utilized to estimate odds ratios (OR) and 95% confidence intervals (95% CI) of depression (yes/no) in relation to 16-hour noise exposure, assessed continuously and by categories of <57.0, 57.0 – <60.0, 60.0 – <63.0, and ≥63.0 decibels. Covariates that were considered confounders or associated with depression in descriptive analyses were entered into the model in groups to determine their effect on the strength of the association between noise and depression. Final models were assessed for goodness of fit by a Hosmer-Lemeshow p-value>0.05. Effect modification by gender, race, income, census-tract level prevalence of insufficient sleep, and perceived stress level was assessed using the fully adjusted models. For dichotomous effect modification variables, an interaction term with continuous noise was included in the model and significance was determined by the Wald X^2 test. For categorical variables, dummy variables were created for each category and interaction terms with noise were created with each dummy variable, and significance was determined by the Likelihood Ratio Test. For analysis of effect modification by income and stress levels, those with missing income or stress data were removed from the sample, leaving sample sizes of 688 and 720, respectively.

Additionally, we conducted a sensitivity analysis using the fully adjusted model with three other definitions of depression: PHQ-9 ≥5 only (n of depression events=312), PHQ-9 ≥10[198–200] (n of depression events=140), and PHQ-9 ≥10 or use of anti-depressant medication (n of depression events=232). Effect modification analysis was also assessed using the secondary depression outcomes. All statistical analyses were performed using SAS Software (version 9.4).

Results

Figure 3B.1 displays the distribution of noise exposure in Louisville and in the GHL study area. Noise in Louisville ranged between 47.73 and 80.16 decibels, whereas noise within the GHL study area ranged between 53.13 and 66.43 decibels. Figure 3B.2 displays the noise distribution in the GHL study area and the population density of HEAL participants. HEAL participants were more densely distributed in louder areas than in quieter areas. Overall, the mean (SD) 16-hour environmental noise exposure of HEAL participants was 59.50 (2.75) decibels, with a minimum exposure of 54.40 decibels and a maximum of 66.16 decibels.

Table 3B.1 displays the age-adjusted characteristics of participants by <57.0, 57.0 – <60.0, 60.0 – <63.0, and ≥63.0 decibels of 16-hour noise and depression status. Relationships between noise levels and characteristics were not always consistent. Individuals with the loudest noise exposures were similar to those with the quietest noise exposures in terms of age and number of chronic conditions. However, compared to those with the quietest noise exposures, those exposed to the loudest noise were more likely to be depressed, males, black or other race, and Hispanic; to have lower income, lower education, lower general health, less physical activity, risky to severe alcohol use, and never used marijuana; to reside in census tracts with low prevalence of insufficient sleepers and to experience higher stress levels; but less likely to be a current cigarette smoker. Those who had depression were similar in age and Hispanic ethnicity to those without depression. However, relative to those without depression, depressed individuals were more likely to be female, white race, a current smoker, and a current marijuana user; to have lower income, lower education, lower general health, more chronic conditions, less physical activity, and no alcohol use risk; to reside in census tracts with high prevalence of insufficient sleepers and to experience higher stress levels.

Logistic regression modeling results are shown in Table 3B.2. In the crude model, louder continuous noise by one decibel was associated with higher odds of depression by 3%, however this association was not statistically significant (OR=1.03, 95% CI: 0.98, 1.09). After adjustments for age, gender, race, education, income, self-perceived health, number of chronic conditions, cigarette smoking status, alcohol risk, marijuana use, physical activity, stress levels, and prevalence of insufficient sleep prevalence of residence census tract, louder continuous noise by one decibel was not associated with higher odds of depression (OR=1.05, 95% CI: 0.97, 1.14). The Hosmer-Lemeshow test p-value was 0.836, indicating that the model was of good fit. In the fully adjusted model (model 8) and compared to those exposed to <57.0 decibels, exposure to noise levels between 57.0 and <60.0 decibels was associated with 1.83-times higher odds of depression; those exposed to 60.0 to <63.0 decibels did not have higher odds of depression; and those with noise exposures of ≥63 decibels had 2.15-times higher odds of depression (OR for 57.0 – <60.0 dB=1.83, 95% CI: 1.06, 3.18; OR for 60 – <63 dB=1.44, 95% CI: 0.79, 2.60; OR for ≥63 dB=2.15, 95% CI: 1.00, 4.64; p_{global}=0.098). The categorical noise model was deemed to be of good fit, with a Hosmer-Lemeshow test p-value of 0.637.

Table 3B.3 displays the findings of effect modification. For all variables, no significant effect modification was observed (all X^2 or LRT $p_{interaction}$>0.05). However, there is a suggestion of one-decibel louder noise being associated with 10% higher odds of depression among those with lower stress levels (OR=1.10, 95% CI: 1.00, 1.22), but not among those with higher stress levels (OR=0.99, 95% CI: 0.90, 1.10). Also, one-decibel louder noise was associated with 12% higher odds of depression among those residing in census tracts with lower prevalence of insufficient sleepers (OR=1.12, 95% CI: 1.00, 1.25), but not among those residing in census tracts with higher prevalence of insufficient sleepers (OR=0.99, 95% CI: 0.91, 1.09).

Results of sensitivity analyses are shown in Supplemental Table 3B.1. Overall, sensitivity analyses resulted in null findings; louder noise had no association with odds of the additional depression outcomes. Similarly, effect modification analysis using the sensitivity depression outcomes reflected the findings of the main results (shown in Supplemental Table 3B.2). Interestingly, when using the most severe outcome of depression (PHQ-9 ≥10 or anti-depressant use), louder noise is still suggested to be associated with higher odds of depression by 12% among those with low levels of stress (OR=1.12, 95% CI: 1.00, 1.26). Compared to the main depression outcome, all additional depression outcomes had fewer events and findings were more likely to be null.

Discussion

The current study found no association between one-decibel louder 16-hour environmental noise and depression among adults in South Louisville, Kentucky; however, those with noise exposures of 57.0 – <60.0 decibels and those exposed to ≥63.0 decibels had higher odds of depression than those with the quietest noise exposures (i.e., <54 dB). Further, odds of depression from louder noise was not modified by gender, race, nor income, but there was suggestive modification by census-tract level prevalence of insufficient sleep and individual stress levels, with those in lower insufficient sleep prevalence census tracts and those with lower stress levels had higher odds of depression in relation to one-decibel louder noise.

Our findings are similar to others who have found null relationships between louder environmental noise and depression.[23,26,31–33] Particularly, Seidler et al. observed inverted-U-shaped associations of categorical aircraft noise and railway noise with depressive disorders.[23] However, the Seidler et al. study may have lacked large-enough samples in the loudest noise groups, such that the ability to detect potential significance in associations was hindered. As such, future work should strive for larger samples, particularly in the loudest exposure groups, to compare results observed in the current study.

Further, we observed no significant effect modification of the association between environmental noise and depression by gender (X^2 $p_{interaction}$=0.080), which is congruent with several others.[23,26,27,33] Based on our previous findings (see Aim 3A manuscript), we assessed for effect modification by race and income, which have not yet been investigated, and did not detect significant modifications by race LRT $p_{interaction}$=0.805) and income (quartile LRT $p_{interaction}$=0.825; dichotomous X^2 $p_{interaction}$=0.840). Our null findings may be a consequence of the limited spatial variability of the study area.

Okokon et al. reported no significant effect modification by sleep disturbance on the association between road-traffic noise and anti-depressant use.[32] However, we observed a suggestive association between environmental noise and depression among those residing in census tracts with lower prevalence of insufficient sleepers (OR=1.12, 95% CI: 1.00, 1.25), as well as among those with lower stress levels (OR=1.10, 95% CI: 1.00, 1.22). These findings indicate that environmental noise exposure may be most harmful for depression among individuals who do not experience sleep problems or stressful daily lives; high-stress[201,202] or sleep-disturbed[168,203,204] individuals are more prone to depression than low-stress or non-sleep-disturbed individuals, such that the additional stressor and disturbance of environmental noise may be negligible to likelihood of depression. However, higher powered analyses are needed to determine the true modifications by sleep and/or stress, and longitudinal studies are required to determine the widely-proposed[28,107–117,139,143–145] mediation by these two factors.

Limitations and Strengths

There are a few limitations of the current study, as well as strengths. First, the noise model used to estimate noise exposure was built using data from 15 collection sites, which may have produced measurement error of the noise exposure and the null observed associations, as well as the suggestive effect modification findings, may be due to chance. However, the noise estimate data had acceptable levels of inter-rater reliability (intra-class correlation coefficient=0.857, n=2 sites, 4 samples; see Aim 1 manuscript) and the noise model resulted in acceptable levels of prediction error (leave-one-out cross-validation root-mean square error=5.92 dB; see Aim 1 manuscript). Further, the HEAL cohort study may not be fully representative of the Louisville area, as the study area is located near the international airport, a major noise source, and contains little spatial variability (mean noise=59.50 dB, SD=2.75 dB) relative to all of Louisville (census tract mean noise=56.91 dB, SD=4.26 dB); as such, variability in individual environmental noise exposures may be too low to detect a true association. Lack of variability in exposures increases the standard errors of parameter estimates and widens the confidence intervals of effect estimates; larger sample sizes or greater variability in the exposure are needed to obtain higher precision in estimating associations. Moreover, individual noise exposure is dependent on the spatial-temporal movements of individuals,[36,39] which were not accounted for in the current study. The use of GPS data from study participants, potentially collected through smart phone data, would aid in reducing exposure measurement error and potentially increase exposure variability, thereby increasing the confidence in effect estimates.[205,206] Additionally, the HEAL study lacked detailed data on income, which may have contributed to the non-linear associations observed in categorical model. Finally, the current study was a cross-sectional analysis that lacked temporality between noise exposure (collected in 2021) and participant data (collected in 2018 or 2019), and causation should not be inferred from effect estimates. To better explicate potential causative effects of noise exposure on depression, future work should seek to achieve longitudinal analyses with exposure-outcome temporality.

Despite the limitations, there are strengths of the current study. The GHL study area includes demographically diverse neighborhoods, and data contained variation in socioeconomic and demographic characteristics. HEAL surveys were reviewed for completion and/or administered by interviewers, which minimized the amount of missing data. Further, data from HEAL participants were robust, and models were adjusted for many important demographics and behavioral confounders that have not been widely adjusted for in past literature,[23,25–27,31] such as smoking status, alcohol intake, and physical activity. Although data on participants' sleep were not available, we were able to include residential census-tract level insufficient sleep prevalence through data linkage to CDC PLACES. Additionally, we defined the presence of depression with PHQ-9 scores and anti-depressant medication use, that captured participants who would not have been exhibiting depressive symptoms at enrollment due to effective medication. We addressed misclassification of the outcome through additional depression definitions for more severe depression used in sensitivity analyses. Finally, the current study adds to the overall understanding of the association between total environmental noise with depression by contributing analysis of a US-based population.

Conclusion

The current study observed a suggestive association between louder total environmental noise and odds of depression among adults in South Louisville, Kentucky, particularly those exposed to ≥63 decibels of total environmental noise. Additionally, there was suggestive effect modification by census-tract-level prevalence of insufficient sleep and by individual-level stress, in which those in lower insufficient sleep prevalence tracts and those with lower stress levels had higher odds of depression from louder environmental noise. Further studies with increased power, exposure variability, and longitudinal follow-up are needed to determine the true association between environmental noise and incidence of depression.

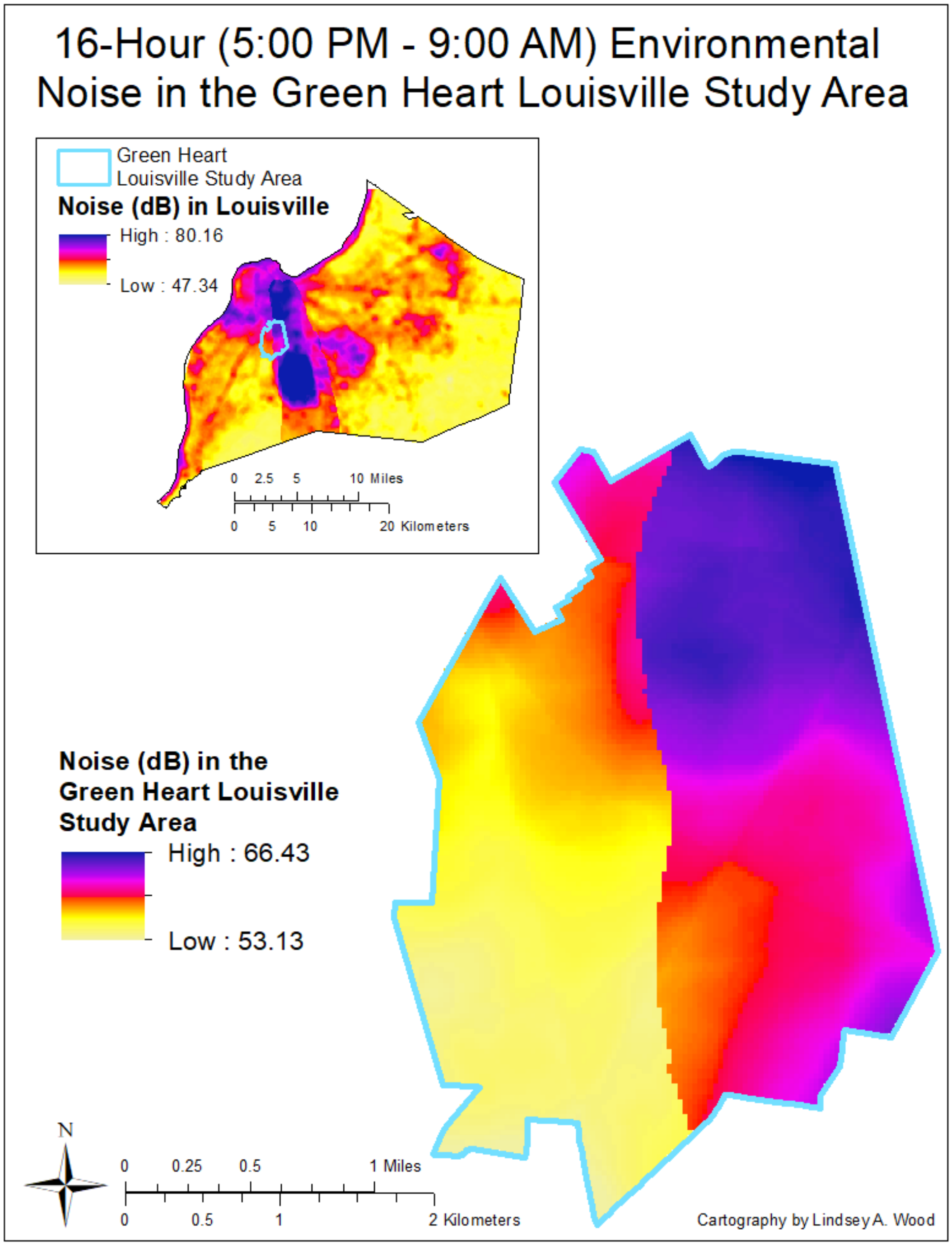

Figure 3B.1: 16-hour (5:00 PM – 9:00 AM) environmental noise in the Green Heart Louisville study area.

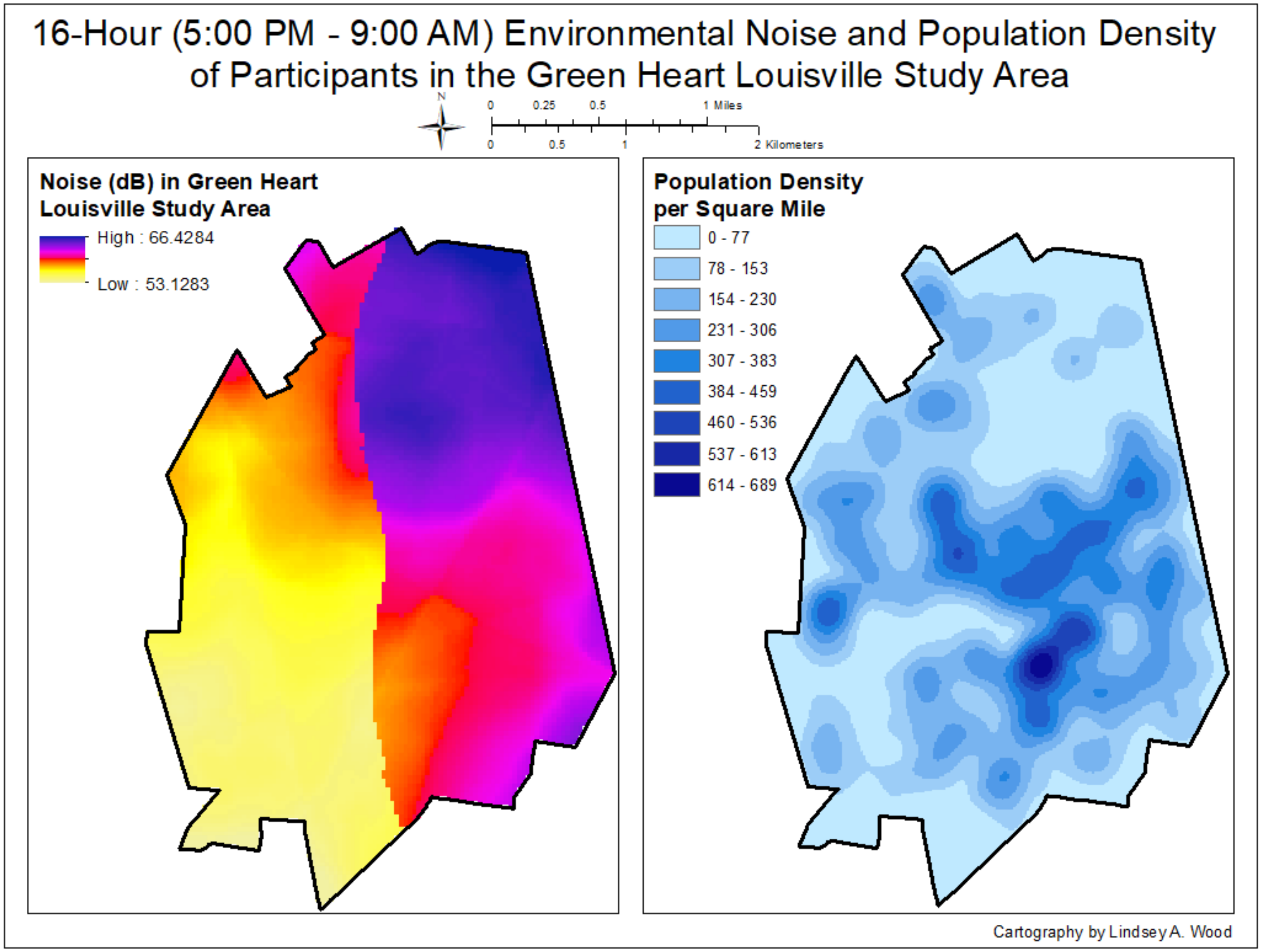

Figure 3B.2: 16-hour (5:00 PM – 9:00 AM) environmental noise and population density of participants in the Green Heart Louisville study area.

Table 3B.1: Age-adjusted descriptive characteristics by spring 16-hour noise (5:00 PM – 9:00 AM) exposure levels and depression (N=724).

	Spring 16-hour (5:00 PM – 9:00 AM) Noise				Depression (PHQ-9 ≥ 5 or anti-depressant medication use)	
	< 57.0 dB (n=160)	57.0 – < 60.0 dB (n=231)	60.0 – < 63.0 dB (n=256)	≥ 63.0 dB (n=77)	No (n=360)	Yes (n=364)
Depression, %(n)	49.04 (78)	50.73 (117)	47.70 (122)	57.29 (44)		
Age*	49.52 (12.67)	50.16 (12.90)	49.20 (12.32)	48.68 (12.96)	49.39 (13.11)	49.64 (12.16)
Male, %(n)	35.73 (57)	45.09 (104)	36.61 (94)	47.14 (36)	47.51 (171)	30.42 (111)
Race, %(n)						
White	72.89 (117)	86.93 (201)	79.48 (203)	63.54 (49)	76.43 (275)	78.43 (285)
Black	22.65 (36)	10.17 (23)	15.08 (39)	28.91 (22)	19.41 (70)	15.90 (58)
Other	4.45 (7)	2.90 (7)	5.44 (14)	7.55 (6)	4.15 (15)	5.68 (21)
Non-Hispanic, %(n)	97.27 (156)	98.72 (227)	96.47 (247)	93.12 (71)	96.59 (347)	96.22 (349)
Household Income, %(n)						
Less than $20,000	22.41 (36)	20.15 (47)	18.00 (46)	38.28 (29)	17.11 (62)	29.08 (106)
$20,000-44,999	36.06 (58)	23.28 (54)	28.51 (73)	21.09 (16)	25.69 (92)	31.43 (114)
$45,000-64,999	19.25 (31)	19.41 (45)	23.94 (61)	19.27 (15)	25.91 (93)	17.07 (62)
$65,000 or more	13.94 (22)	30.90 (71)	25.99 (67)	14.06 (11)	26.27 (95)	18.50 (67)
Missing	8.33 (13)	6.26 (14)	3.56 (9)	7.29 (6)	5.02 (18)	3.91 (14)
Education Level, %(n)						
Less than High school degree	10.20 (16)	8.43 (19)	6.41 (16)	16.15 (12)	7.80 (28)	10.94 (40)
High school graduate or GED	26.53 (42)	23.94 (55)	19.58 (50)	26.30 (20)	23.06 (83)	21.28 (77)
Some college, 2-yr degree, or certificate	47.75 (76)	30.59 (71)	36.86 (94)	38.02 (29)	37.11 (134)	42.43 (154)
Bachelors degree	10.78 (17)	16.90 (39)	20.88 (53)	11.46 (9)	16.14 (58)	14.34 (52)

Table 3B.1: Age-adjusted descriptive characteristics by spring 16-hour noise (5:00 PM – 9:00 AM) exposure levels and depression (N=724).

	Spring 16-hour (5:00 PM – 9:00 AM) Noise				Depression (PHQ-9 ≥ 5 or anti-depressant medication use)	
	< 57.0 dB (n=160)	57.0 – < 60.0 dB (n=231)	60.0 – < 63.0 dB (n=256)	≥ 63.0 dB (n=77)	No (n=360)	Yes (n=364)
Graduate degree	4.45 (7)	19.68 (45)	16.05 (41)	8.07 (6)	15.71 (57)	10.11 (37)
Missing	0.29 (0)	0.46 (1)	0.22 (1)	0.00 (0)	0.18 (1)	0.90 (3)
General Health[a], %(n)						
Excellent or very good	36.73 (59)	40.41 (93)	34.99 (90)	35.94 (28)	48.04 (173)	23.03 (84)
Good	40.71 (65)	42.23 (98)	46.76 (120)	33.59 (26)	44.31 (160)	44.12 (161)
Fair or poor	22.56 (36)	16.67 (39)	18.25 (47)	30.47 (23)	7.38 (27)	32.85 (120)
Missing	0.00 (0)	0.70 (2)	0.00 (0)	0.00 (0)	0.27 (1)	0.00 (0)
Number of Chronic Conditions[b]	1.57 (1.07)	1.20 (1.06)	1.27 (1.21)	1.40 (0.78)	0.96 (1.08)	1.64 (1.38)
Physical Activity[c], %(n)						
None	42.91 (69)	39.29 (91)	35.89 (92)	39.32 (30)	29.57 (106)	49.51 (180)
Low intensity at least once per week	23.66 (38)	22.78 (53)	22.17 (57)	32.55 (25)	27.73 (100)	21.07 (77)
Moderate intensity 1-4 times per week	18.63 (30)	21.62 (50)	25.56 (65)	17.71 (14)	23.81 (86)	17.94 (65)
Moderate intensity at least 5 times per week or High intensity at least once per week	13.36 (21)	15.97 (37)	14.58 (37)	8.85 (7)	17.31 (62)	10.32 (38)
Missing	1.44 (2)	0.35 (1)	1.80 (5)	1.56 (1)	1.58 (6)	1.16 (4)
Smoking Status, %(n)						
Never	36.78 (59)	45.82 (106)	51.91 (133)	37.76 (29)	55.82 (201)	37.65 (137)
Ever	16.91 (27)	22.93 (53)	15.44 (40)	25.52 (20)	17.92 (65)	21.02 (77)

Table 3B.1: Age-adjusted descriptive characteristics by spring 16-hour noise (5:00 PM – 9:00 AM) exposure levels and depression (N=724).

	Spring 16-hour (5:00 PM – 9:00 AM) Noise				Depression (PHQ-9 ≥ 5 or anti-depressant medication use)	
	< 57.0 dB (n=160)	57.0 – < 60.0 dB (n=231)	60.0 – < 63.0 dB (n=256)	≥ 63.0 dB (n=77)	No (n=360)	Yes (n=364)
Current	41.57 (67)	28.46 (66)	29.88 (76)	35.68 (27)	22.76 (82)	39.33 (143)
Missing	4.74 (8)	2.78 (6)	2.77 (7)	1.04 (1)	3.49 (13)	2.00 (7)
Alcohol Risk Level[d], %(n)						
No risk	35.30 (56)	32.44 (75)	34.67 (89)	41.15 (32)	33.50 (121)	36.21 (132)
Low risk	46.65 (75)	39.13 (90)	34.70 (89)	36.46 (28)	40.05 (144)	36.15 (132)
Risky to Severe	14.08 (23)	25.64 (59)	26.35 (67)	21.35 (16)	22.95 (83)	23.16 (84)
Missing	3.98 (6)	2.78 (6)	4.28 (11)	1.04 (1)	3.49 (13)	4.48 (16)
Marijuana Use, %(n)						
Never	57.57 (92)	53.52 (124)	64.25 (164)	65.63 (51)	66.19 (238)	55.45 (202)
Currently	17.67 (28)	20.53 (47)	17.93 (46)	19.01 (15)	14.40 (52)	20.91 (76)
Former	17.24 (28)	20.88 (48)	14.90 (38)	10.68 (8)	15.08 (54)	18.09 (66)
Missing	7.52 (12)	5.07 (12)	2.92 (7)	4.69 (4)	4.33 (16)	5.56 (20)
Insufficient Sleep Prevalence of Residence Census Tract, %(n)						
Low: 40.1% – 42.7%	93.52 (127)	93.19 (190)	96.07 (209)	98.79 (68)	37.60 (135)	26.26 (96)
Moderate: 42.8% –43.5%	1.83 (2)	3.01 (6)	1.65 (4)	0.00 (0)	35.05 (126)	39.56 (144)
High: 43.6% – 49.1%	2.66 (4)	3.28 (7)	1.78 (4)	0.00 (0)	27.34 (98)	34.18 (124)
Stress Level[e], %(n)						
Tertile 1: PSS ≤ 11	36.35 (58)	41.03 (95)	38.08 (97)	35.94 (28)	57.44 (207)	15.52 (56)

Table 3B.1: Age-adjusted descriptive characteristics by spring 16-hour noise (5:00 PM – 9:00 AM) exposure levels and depression (N=724).

	Spring 16-hour (5:00 PM – 9:00 AM) Noise				Depression (PHQ-9 ≥ 5 or anti-depressant medication use)	
	< 57.0 dB (n=160)	57.0 – < 60.0 dB (n=231)	60.0 – < 63.0 dB (n=256)	≥ 63.0 dB (n=77)	No (n=360)	Yes (n=364)
Tertile 2: PSS 12-18	31.47 (50)	29.74 (69)	34.41 (88)	30.47 (23)	33.81 (122)	34.45 (125)
Tertile 3: PSS ≥ 19	31.32 (50)	29.23 (68)	26.53 (68)	33.59 (26)	8.24 (30)	49.58 (180)
Missing	0.86 (1)	0.00 (0)	0.97 (2)	0.00 (0)	0.51 (2)	0.45 (2)

Values are means(SD) or medians(IQR) for continuous variables; %(n) for categorical variables, and are standardized to the age distribution of the study population.

[*] Value is not age adjusted

[a] Self-reported perception

[b] Includes cardiovascular disease, chronic obstructive pulmonary disease, chronic kidney failure, type 2 diabetes, HIV/AIDS, chronic inflammatory or autoimmune disease, and hyperlipidemia.

[c] More than 10 minutes each time

[d] Alcohol Use Disorders Identification Test (AUDIT) risk levels

[e] Tertiles based on Perceived Stress Scale (PSS) scores

Table 3B.2: Odds ratios for depression (PHQ-9 ≥ 5 or anti-depressant medication use) by a one-decibel increase and by categories of noise in various models N=724, Events: 364.

	Continuous	Categorical				
Model	OR (95% CI)	OR (95% CI) for < 57.0 dB	OR (95% CI) for 57.0 – < 60.0 dB	OR (95% CI) for 60.0 – < 63.0 dB	OR (95% CI) for ≥ 63.0 dB	p_{global}
Events/n		76/160	118/231	125/256	45/77	
Crude	1.03 (0.98, 1.09)	REF	1.15 (0.77, 1.73)	1.05 (0.71, 1.57)	1.55 (0.90, 2.69)	0.418
Model 1	1.03 (0.98, 1.09)	REF	1.18 (0.78, 1.78)	1.02 (0.68, 1.53)	0.70 (0.97, 2.99)	0.224
Model 2	1.04 (0.98, 1.10)	REF	1.29 (0.85, 1.96)	1.12 (0.74, 1.69)	1.78 (1.01, 3.14)	0.200
Model 3	1.04 (0.98, 1.10)	REF	1.34 (0.87, 2.06)	1.15 (0.76, 1.74)	1.73 (0.97, 3.09)	0.242
Model 4	1.04 (0.98, 1.10)	REF	1.49 (0.94, 2.37)	1.16 (0.74, 1.82)	1.89 (1.01, 3.52)	0.126
Model 5	1.04 (0.98, 1.11)	REF	1.64 (1.02, 2.63)	1.27 (0.80, 2.00)	2.01 (1.07, 3.77)	0.077
Model 6	1.05 (0.98, 1.12)	REF	1.67 (1.02, 2.71)	1.34 (0.83, 2.15)	2.09 (1.09, 4.00)	0.082
Model 7	1.05 (0.97, 1.12)	REF	1.73 (1.01, 2.97)	1.31 (0.77, 2.22)	2.19 (1.05, 4.55)	0.094
Model 8	1.05 (0.97, 1.14)	REF	1.83 (1.06, 3.18)	1.44 (0.79, 2.60)	2.15 (1.00, 4.64)	0.098

The Crude model includes only noise.
Model 1 includes the Crude model plus age, gender (male/female), and race (white/black/other).
Model 2 includes Model 1 plus education (associate degree or lower, bachelor's degree or higher; and missing).
Model 3 includes Model 2 plus income (<$20K, $20K – $44.9K, $45K – $64.9K, ≥$65K; and missing)
Model 4 includes Model 3 plus self-perceived health (fair or poor, good, excellent or good; and missing).
Model 5 includes Model 4 plus number of chronic conditions.
Model 6 includes Model 5 plus cigarette smoking status (never, ever, current; and missing), alcohol risk (no risk, low risk, risky to severe; and missing), marijuana use (never, current, former; and missing), physical activity (none, low intensity at least once per week, moderate intensity 1-4 times per week, moderate intensity at least 5 times per week, high intensity at least once per week; and missing).
Model 7 includes Model 6 plus stress levels (tertile 1: PSS ≤11, tertile 2: PSS 12-18, tertile 3: PSS ≥19; and missing).
Model 8 includes Model 7 plus prevalence of insufficient sleep prevalence of residence census tract (low, moderate, or high).

Table 3B.3: Effect modification of the association between noise and odds of depression using Model 8,* N=724.

Effect Modifier	Events/n	OR (95% CI)	$p_{interaction}$
Gender			0.080
Male	112/283	1.00 (0.91, 1.10)	
Female	252/441	0.88 (0.71, 1.09)	
Race			0.805
White	285/562	1.07 (0.97, 1.17)	
Black	58/125	1.03 (0.89, 1.19)	
Other	21/37	0.97 (0.70, 1.35)	
Income[a]			0.825
≤ \$20K	107/168	1.12 (0.97, 1.29)	
\$20K- \$44.9K	116/205	1.05 (0.92, 1.19)	
\$45K – \$64.9K	65/157	1.03 (0.88, 1.20)	
≥ \$65K	60/158	1.11 (0.93, 1.32)	
			0.840
≤ \$44.9K	223/373	1.08 (0.98, 1.19)	
≥ \$45K	125/315	1.06 (0.94, 1.20)	
Prevalence of Insufficient Sleep			0.100
40.1% - 42.8%	139/327	1.12 (1.00, 1.25)	
43.2% - 49.1%	225/397	0.99 (0.91, 1.09)	
Perceived Stress Level[b]			0.136
PSS ≤ 14	97/367	1.10 (1.00, 1.22)	
PSS > 14	265/353	0.99 (0.90, 1.10)	

*Model covariates include age, gender (male/female), race (black/other/white), education (associate degree or lower, bachelor's degree or higher; and missing), income (<\$20K, \$20K – \$44.9K, \$45K – \$64.9K, ≥\$65K; and missing), self-perceived health (fair or poor, good, excellent or good; and missing), number of chronic conditions, cigarette smoking status (never, ever, current; and missing), alcohol risk (no risk, low risk, risky to severe; and missing), marijuana use (never, current, former; and missing), physical activity (none, low intensity at least once per week, moderate intensity 1-4 times per week, moderate intensity at least 5 times per week, high intensity at least once per week; and missing), stress levels (tertile 1: PSS ≤11, tertile 2: PSS 12-18, tertile 3: PSS ≥19; and missing), and prevalence of insufficient sleep prevalence of residence census tract (low, moderate, or high).
[a]N=688, those with missing data for income were excluded.
[b]N=720, those with missing data for PSS were excluded.

Supplemental Table 3B.1: Odds ratios for varying depression outcomes by a one-decibel increase and by categories of noise using Model 8,* N=724.

	Continuous	Categorical				
Outcome	OR (95% CI)	OR (95% CI) for < 57.0 dB	OR (95% CI) for 57.0 – < 60.0 dB	OR (95% CI) for 60.0 – < 63.0 dB	OR (95% CI) for ≥ 63.0 dB	p_{global}
PHQ-9 ≥ 5	1.04 (0.96, 1.13)	REF	1.54 (0.86, 2.77)	1.35 (0.72, 2.52)	1.86 (0.85, 4.10)	0.362
Events/n	312/724	67/160	97/231	108/256	40/77	
PHQ-9 ≥ 10	1.04 (0.95, 1.15)	REF	1.32 (0.63, 2.78)	1.95 (0.87, 4.34)	1.24 (0.78, 3.22)	0.411
Events/n	140/724	30/160	44/231	50/256	16/77	
PHQ-9 ≥ 10 or anti-depressant medication use	1.04 (0.96, 1.12)	REF	1.66 (0.94, 2.90)	1.46 (0.80, 2.68)	1.51 (0.72, 3.21)	0.352
Events/n	232/724	48/160	80/231	79/256	25/77	

Models include age, gender (male/female), race (white/black/other), education (associate degree or lower, bachelor's degree or higher; and missing), income (<$20K, $20K – $44.9K, $45K – $64.9K, ≥$65K; and missing), self-perceived health (fair or poor, good, excellent or good; and missing), number of chronic conditions, cigarette smoking status (never, ever, current; and missing), alcohol risk (no risk, low risk, risky to severe; and missing), marijuana use (never, current, former; and missing), physical activity (none, low intensity at least once per week, moderate intensity 1-4 times per week, moderate intensity at least 5 times per week, high intensity at least once per week; and missing), stress levels (tertile 1: PSS ≤11, tertile 2: PSS 12-18, tertile 3: PSS ≥19; and missing), and prevalence of insufficient sleep prevalence of residence census tract (low, moderate, or high).

Supplemental Table 3B.2: Effect modification of the association of noise and odds of depression using Model 8* and various depression outcomes, N=724.

		PHQ-9 ≥ 5, Events: 312			PHQ-9 ≥ 10, Events:140			PHQ-9 ≥ 10 or anti-depressant medication use, Events: 232		
Effect Modifier	n	Events	OR (95% CI)	$p_{interaction}$	Events	OR (95% CI)	$p_{interaction}$	Events	OR (95% CI)	$p_{interaction}$
Gender				0.229			0.397			0.323
Male	283	97	1.01 (0.92, 1.11)		44	1.07 (0.96, 1.20)		70	1.01 (0.92, 1.11)	
Female	441	215	0.92 (0.74, 1.14)		96	1.17 (0.89, 1.53)		162	0.94 (0.76, 1.16)	
Race				0.717			0.575			0.468
White	562	239	1.06 (0.97, 1.17)		110	1.05 (0.94, 1.18)		191	1.04 (0.95, 1.14)	
Black	125	52	1.01 (0.87, 1.17)		19	1.08 (0.88, 1.32)		27	1.06 (0.91, 1.25)	
Other	37	21	0.95 (0.68, 1.33)		11	0.88 (0.62, 1.24)		14	0.86 (0.63, 1.18)	
Income[a]				0.729			0.790			0.983
≤ $20K	168	96	1.10 (0.95, 1.28)		52	1.04 (0.89, 1.21)		72	1.03 (0.90, 1.18)	
$20K- $44.9K	205	106	1.06 (0.93, 1.22)		49	1.10 (0.95, 1.28)		70	1.06 (0.93, 1.20)	
$45K – $64.9K	157	52	0.98 (0.84, 1.15)		18	0.96 (0.77, 1.21)		39	1.02 (0.87, 1.20)	
≥ $65K	158	44	1.08 (0.89, 1.31)		12	1.06 (0.86, 1.47)		39	1.06 (0.88, 1.28)	
				0.448			0.481			0.908
≤ $44.9K	373	202	1.08 (0.98, 1.19)		101	1.07 (0.95, 1.20)		142	1.05 (0.95, 1.15)	
≥ $45K	315	96	1.02 (0.90, 1.15)		30	0.99 (0.82, 1.19)		78	1.04 (0.92, 1.17)	
Prevalence of Insufficient Sleep				0.070			0.361			0.419
40.1% - 42.8%	327	112	1.14 (1.01, 1.28)		46	0.98 (0.84, 1.15)		91	0.99 (0.88, 1.10)	
43.2% - 49.1%	397	200	0.99 (0.90, 1.09)		94	1.07 (0.96, 1.20)		141	1.05 (0.96, 1.14)	
Perceived Stress Level[b]				0.946			NA			0.079
PSS ≤ 14	367	63	1.04 (0.93, 1.16)		7	NA		56	1.12 (1.00, 1.26)	
PSS > 14	353	247	1.03 (0.94, 1.14)		131	NA		174	0.99 (0.90, 1.08)	

*Model covariates include age, gender (male/female), race (black/other/white), education (associate degree or lower, bachelor's degree or higher; and missing), income (<$20K, $20K – $44.9K, $45K – $64.9K, ≥$65K; and missing), self-perceived health (fair or poor, good, excellent or good; and missing), number of chronic conditions, cigarette smoking status (never, ever, current; and missing), alcohol risk (no risk, low risk, risky to severe; and missing), marijuana use (never, current, former; and missing), physical activity (none, low intensity at least once per week, moderate intensity 1-4 times per week, moderate intensity at least 5 times per week, high intensity at least once per week; and missing), stress levels (tertile 1: PSS ≤11, tertile 2: PSS 12-18, tertile 3: PSS ≥19; and missing), and prevalence of insufficient sleep prevalence of residence census tract (low, moderate, or high).

[a]N=688, those with missing data for income were excluded.

[b]N=720, those with missing data for PSS were excluded.

NA: Model resulted in non-convergence due to small number of observations in stratified analysis.

DISCUSSION

The current dissertation aimed to determine the association of environmental noise with multiple psychological outcomes in Louisville, Kentucky. Specifically, this study estimated total environmental noise throughout Louisville during two seasons and four specific time-periods (Aim 1), and assessed the association of environmental noise with standardized testing scores of elementary schools (Aim 2) and with mental ill-health and depression among adults (Aim 3). The key findings are discussed below.

AIM 1: Develop and validate multiple noise models of Louisville using land-use regression (LUR) methodology.

Before understanding how environmental noise is associated with health outcomes, it is important to understand the spatial distribution of environmental noise, itself. We collected noise data at 15 sites throughout Louisville and utilized LUR methodology to estimate seasonal environmental noise distributions during multiple time periods. Given the small sample of which to build LUR models upon, we adapted conventionally-practiced LUR methodologies that rely heavily on statistical testing[44,56,57,59,60,63] to include prior-proposed manual modifications of predictor variables,[57] as well as further expansions of modifications to include *a priori* knowledge of noise mechanics. Consistent predictors of noise across both seasons and all time periods were the distance to the 60-decibel Noise Exposure Map (NEM) contours and greenness (Normalized Difference Vegetation Index; NDVI). Other important predictors were traffic volume and length of streams, as both were retained in several models, although with varying strengths of association. Overall, environmental noise was loudest in downtown, West, and South ends of Louisville, with the spring season being louder than the winter season.

AIM 2: Determine the association of spring school (7-hour) and at-home (17-hour) noise estimates on standardized testing scores at the school-level.

Prior work has identified associations between environmental noise exposure and standardized testing scores of primary and elementary school-children.[19–22,102] However, total environmental noise exposure is rarely assessed,[19,102] and the potential varying effects of school versus at-home noise is not yet understood. We estimated the individual associations of school noise (7-hour) and at-home noise (17-hour) with standardized testing scores for several subjects, and we observed no association between neither 7-hour nor 17-hour environmental noise with Math, Reading, or combined Math or Reading standardized testing scores. However, our findings suggest that certain socioeconomic and demographic characteristics of student populations, such as race distribution and participation in free and reduced lunch, as well as economic characteristics of the surrounding school neighborhood, can modify the strength of association between louder noise and lower testing scores.

AIM 3: Determine the association of winter and spring 16-hour (5:00 PM – 9:00 AM) noise estimates on adult mental ill-health parameters.

SUBAIM 3A: Examine the association of seasonal environmental noise estimates with census-tract level prevalence of adult mental ill-health using the CDC PLACES Study.

The association between varying source-specific environmental noise exposures and varying definitions of mental ill-health have been widely studied, albeit with inconsistent findings,[23–37,138,139] and without investigation of seasonality of associations and potential effect modification by socioeconomic factors. We examined the associations of winter and spring 5:00 PM to 9:00 AM environmental noise with the census-tract level prevalence of mental ill-health prevalence among adults. After adjusting for several important confounders, we observed similar associations between seasons, in that louder environmental noise was associated with higher prevalence of mental ill-health. However, the associations of seasonal environmental noise with mental ill-health prevalence were modified by census-tract level socioeconomic and health behavioral characteristics, with the strongest associations among census tracts with lower median individual income, lower population percentages of white race, and higher prevalence of insufficient sleepers. It is important to note that respondents of the Behavioral Risk Factor Surveillance Survey (BRFSS), the data source used to derive prevalence estimates of mental ill-health used in Aim 3A, are most likely to be those who experience fewer life stressors, such as those who are white or who have higher incomes.

SUBAIM 3B: Determine the association of spring environmental noise on depression status in participants from the Green Heart Louisville cohort.

Environmental noise in association with depression among adults has been commonly observed;[23,25,27,37] however, source-specific or 24-hour estimates of noise are utilized, and analysis of modification by socioeconomic and behavioral factors are not investigated. We examined the association of 16-hour (5:00 PM to 9:00 AM) total environmental noise with odds of depression among adults in South Louisville, Kentucky. We observed no association between one-decibel louder 16-hour environmental noise and odds of depression but did observe that those with noise exposures of 57.0 – <60.0 decibels and those exposed to ≥63.0 decibels had higher odds of depression than those with <57.0 decibels of noise exposure. Our findings also suggest modification by stress and sleep, as those with lower stress levels and those in lower insufficient sleep prevalence census tracts had higher odds of depression in relation to one-decibel louder noise.

Implications for Future Work

The current work has several strengths and limitations that have been discussed in the prior manuscripts. Here, we will focus on general limitations of the current body of literature as a whole that have not been mentioned prior. We believe that consideration of these limitations in future works will strengthen the understanding of environmental noise exposure as it relates to psychological health outcomes.

With most environmental exposures, a paradigm exists in which adverse health outcomes are results of the exposure making entry into the human body and making some physical alteration to a structure or function, and many of these biological mechanisms are well-known, such as radon and lung cancer or particulate matter and cardiovascular/respiratory health. This paradigm applies to noise exposure in relation to hearing loss and tinnitus, where sound vibrations physically alter the structure and function of the auditory system. However, in relation to non-auditory adverse health outcomes, noise is distinguishable from other environmental exposures in that this paradigm is not applicable. As such, subjective sensitivity to noise perceived and interpreted by individuals – like annoyance,[32,108,139,142,145,207–222] sleep-disturbance,[28,108–112,116,139,140,143–145,167,209,210,223,224] or chronic stress response[107–117,207–209,225–230] – is likely integral in possible biological pathways through which environmental noise exposure is related to psychological outcomes.

The subjectivity of these potential mediators contributes to the convoluted nature of studying the relationship between environmental noise and psychological outcomes. Exposure measurement error becomes a particular concern; whether an individual finds a certain loudness or source of noise to be “annoying” or “disturbing” would greatly influence findings. For instance, some may find chirping crickets to be soothing, while others may be kept awake by them. Future work should consider these subjective differences of "good" versus "bad" noise sources to further specify noise exposure definitions.

In future studies of noise exposure and psychological outcomes, it is imperative that longitudinal analysis occur. Little of the current literature is longitudinal in nature,[14,26,29,35] which contributes to the lack of evidence supporting a causal relationship between environmental noise and psychological health outcomes. To be the most beneficial, longitudinal analyses should include the above considerations, as well as specific mental health diagnoses and cognitive functions. Further, noise exposures should account for spatial-temporal movements of individuals, which could be achieved using GPS data from smart phones. Alternatively, recent work has investigated the use of a smartphone app, developed by the National Institute for Occupational Safety and Health (NIOSH), to monitor noise exposure levels with success.[231] With some improvements, the same features could be implemented in cohort studies, which would automatically account for spatial-temporal movements of individuals with relative ease and affordability.

Broader Conclusions

In Aim 2, we observed that louder environmental noise was more strongly associated with lower standardized testing scores for some subjects among schools with more children from families with higher income. These findings suggest that noise exposure is least harmful for non-white and lower-income students, who may experience louder at-home noise than white or higher-income students, whether by social-cultural differences – such as multi-generational living arrangements or having higher household composition – or by simply living in neighborhoods with louder environmental noise. If children from louder homes have become accustomed to loud environmental noise, then children with quieter homes, like higher-income or white students, may be more negatively affected by louder school noise. Alternatively, lower-income or non-white children may have extenuating stressors, such as experiences of discrimination and contributing to up-keep of the household, that may hinder academic success such that further hinderances from noise exposure are negligible.

It is not unknown that impoverished and people of color are particularly at risk of mental ill-health due to societal stressors that increase allostatic load. These populations are often caught in a cycle of environmental health disparities, where their socioeconomic status determines their residential options and neighborhood characteristics, thereby determining their environmental exposures and their health outcomes, which contributes to the maintenance of lesser quality social determinants of health. Aim 3A of this dissertation highlights that the association between environmental noise and census-tract level prevalence of mental ill-health was modified by race and income, with stronger associations among lower-income census tracts and less white-populated census tracts. Although this is an important finding on its own, it is also important to recognize that these areas in Louisville are also the areas with the loudest noise distributions. We cannot ignore the presence of structural and systemic racism and classism in Louisville, which segregates our most vulnerable communities and contributes to the proliferation of environmental health disparities. The Aim 3B population is essentially a microcosm of the average Louisville community. As identified in Aim 3A, areas in Louisville that were most negatively impacted by environmental noise were those that had median *individual* incomes of $31,747.00 or less, white populations of 78% or less, and sleep insufficiency prevalence of 38.6% or higher; the Aim 3B population comparatively had a median *household* income of $45,000.00 or less, 77.6% of participants were white, and all participants lived in census tracts with sleep insufficiency prevalence of 40.1% or higher. In this population, we observed that louder environmental noise was more strongly associated with odds of depression among those with low stress levels and among those living in census tracts of low insufficient sleep prevalence, suggesting that noise is more harmful for low-stress and non-sleep-deprived adults. These particular individuals may have low-enough allostatic loads that any additional increase in, what is already loud, noise exposure is detrimental for their mental health. The mental health of individuals with larger allostatic loads in these louder-exposed populations is seemingly unaffected by any additional loudness.

Public Health Significance

The findings from these aims suggest effect modification by factors related to stress (i.e. income, race, and stress), but in opposite directions; at the ecological level (Aim 3A), environmental noise was most strongly associated with mental ill-health in areas with larger non-white and lower-income populations, while at the individual-level (Aim 3B), noise was most strongly associated with higher odds of depression among individuals with lower stress levels. It is possible that the findings in Aim 3A are being driven by the individuals living within these louder, less-white, lower income areas, such as those who are white or who have higher incomes, since the source of mental health data for Aim 3A are obtained from the BRFSS respondents. This theory is supported by the findings of Aim 2, where the testing scores of schools with more high-income children were most negatively impacted by louder environmental noise. This is not to say that high-income/white/low-stress individuals are the individuals that public health interventions and policies should focus on, but rather to emphasize that structural and systemic racism and classism is good for no one. Whether louder environmental noise is only harmful for the most advantaged individuals among the most disadvantaged populations is irrelevant; if, as much of the evidence suggests, environmental noise is harmful for multiple facets of health, it is enough that Louisville's loudest communities are majority non-white and lower income to justify public health significance. Especially since any environmental noise mitigation would be implemented at the neighborhood level.

Of note, elementary school children who attend schools within these areas are subject to the loudest exposures of environmental noise during school hours. Several studies have observed that louder noise contributes to impairments of various cognitive skills, such as reading comprehension,[13,15,16,101,227] memory,[17,101] and attention.[227] It is particularly concerning that Kentucky has no regulatory guidelines on noise mitigation for school buildings. Under Kentucky

Revised Statutes (KRS) 156.160 and 162.060, the State Board for Elementary and Secondary Education are delegated to regulate the construction and planning of all state school buildings. As such, the Kentucky Administrative Regulations (KAR) Title 702, Chapter 4, Regulation 170 developed a planning guide for facility programming and construction criteria of school buildings. The guide is outdated by nearly three decades (effective March 1995) and provides little guidance on limiting environmental noise exposures of schools, with the only mention of noise being that classrooms and instructional units should be located such that they are “shielded from noise-producing activities or functions.”[232] It is well overdue for Kentucky law-makers and/or Kentucky executive agencies to update facilities planning to include evidence-based interventions for noise exposure, which could be as simple as upgrading window units to double-glazed windows that effectively reduce noise[233] or replacing current insulation to noise-mitigating insulation.[234]

Along these lines, the Louisville Regional Airport Authority (LRAA), in partnership with the Federal Aviation Administration (FAA), has provided funding for noise-blocking home improvements – including windows, doors, and ventilation systems – for eligible homes surrounding the Louisville International Airport (SDF); to be eligible, a home must be located within the 65-decibel Noise Exposure Map contour of SDF. Although this project, called the Quieter Homes Project, is an admirable initiative and should be celebrated, not all those exposed to harmful levels of aircraft noise will be eligible, considering that the World Health Organization (WHO) recommends that aircraft noise to be below a 24-

hour average of 45 decibels and below a nightly average of 40 decibels.[3] However, legislative action could fill in the gaps unreached by this project.

One potential legislative solution could focus on one of the largest and loudest sources of environmental noise in Louisville: the United Parcel Service (UPS). In 2021, the UPS world port, located at SDF, operated an average of 387 in- and out-bound flights daily,[68] most of which are arriving or departing during the night hours; a total of 260 UPS flights were operated from 10:00 PM on August 10, 2021 to 7:00 AM on August 11, 2021.[46] In 2008, UPS became the first airline in the United States to meet the Stage III noise standards for aircrafts and the only airline to meet the Stage IV noise standards set by the International Civil Aviation Organization of the United Nations.[235] However, UPS reported in 2020 that policymakers and government officials still expected "innovative solutions to…noise…pollution" from the company.[236] Despite making considerable donations to the Louisville area – with over $500,000 donated in 2020 to non-profits in Kentucky and surrounding states for COVID-19 relief[237] and $5 billion to University of Louisville athletics in 2019[238] – the company has yet to provide any direct funding for noise-mitigation efforts to Louisville residents that are the most exposed to the company's noise pollution. Regulations aimed at limiting the allowed number of nighttime flights and calls of action for UPS to make donations to noise-mitigation efforts with each nighttime flyover could accomplish implementation of interventions in the loudest Louisville neighborhoods.

In the age of striving to achieve health equity, it must not be forgotten that environmental equity is inherent to attaining health equity. Although it is important to focus on individual fish in the river, it is equally as important to move upstream and determine what parts of the river itself are contributing to harming the fish. Regarding noise pollution, there are yet to be enacted policies aimed at limiting exposures. Such action could contribute to breaking the cycle of environmental health disparities in Louisville, and our river depends on it.

REFERENCES

1. Theakston F, World Health Organization, editors. Burden of disease from environmental noise: quantification of healthy life years lost in Europe. Copenhagen: World Health Organization, Regional Office for Europe; 2011. 106 p.

2. Berglund, Birgitta, Lindvall, Thomas, Schwela, Dietrich H & World Health Organization. Occupational and Environmental Health Team. (1999). Guidelines for community noise. World Health Organization. https://apps.who.int/iris/handle/10665/66217.

3. World Health Organization. Environmental noise guidelines for the European Region [Internet]. 2018 [cited 2022 Jan 11]. Available from: http://www.euro.who.int/__data/assets/pdf_file/0008/383921/noise-guidelines-eng.pdf?ua=1

4. Clark C, Paunovic K. WHO Environmental Noise Guidelines for the European Region: A Systematic Review on Environmental Noise and Cognition. Int J Environ Res Public Health. 2018;15.

5. Clark C, Paunovic K. WHO Environmental Noise Guidelines for the European Region: A Systematic Review on Environmental Noise and

Quality of Life, Wellbeing and Mental Health. Int J Environ Res Public Health. 2018;15.

6. Haines MM, Stansfeld SA, Job RF, Berglund B, Head J. Chronic aircraft noise exposure, stress responses, mental health and cognitive performance in school children. Psychol Med. 2001;31:265–77.

7. Stansfeld SA, Berglund B, Clark C, Lopez-Barrio I, Fischer P, Ohrström E, et al. Aircraft and road traffic noise and children's cognition and health: a cross-national study. Lancet Lond Engl. 2005;365:1942–9.

8. Hygge S, Evans GW, Bullinger M. A Prospective Study of Some Effects of Aircraft Noise on Cognitive Performance in Schoolchildren. Psychol Sci. 2002;13:469–74.

9. Haines MM, Stansfeld SA, Brentnall S, Head J, Berry B, Jiggins M, et al. The West London Schools Study: the effects of chronic aircraft noise exposure on child health. Psychol Med. 2001;31:1385–96.

10. Matsui T, Stansfeld S, Haines M, Head J. Children's cognition and aircraft noise exposure at home--the West London Schools Study. Noise Health. 2004;7:49–58.

11. Haines MM, Stansfeld SA, Job RF, Berglund B, Head J. A follow-up study of effects of chronic aircraft noise exposure on child stress responses and cognition. Int J Epidemiol. 2001;30:839–45.

12. Seabi J, Cockcroft K, Goldschagg P, Greyling M. The impact of aircraft noise exposure on South African children's reading comprehension: The moderating effect of home language. Noise Health. 2012;14:244–52.

13. Seabi J, Cockcroft K, Goldschagg P, Greyling M. A prospective follow-up study of the effects of chronic aircraft noise exposure on learners' reading comprehension in South Africa. J Expo Sci Environ Epidemiol. 2015;25:84–8.

14. Clark C, Head J, Stansfeld SA. Longitudinal effects of aircraft noise exposure on children's health and cognition: A six-year follow-up of the UK RANCH cohort. J Environ Psychol. 2013;35:1–9.

15. Clark C, Martin R, van Kempen E, Alfred T, Head J, Davies HW, et al. Exposure-effect relations between aircraft and road traffic noise exposure at school and reading comprehension: the RANCH project. Am J Epidemiol. 2006;163:27–37.

16. Papanikolaou M, Skenteris N, Piperakis SM. Effect of external classroom noise on schoolchildren's reading and mathematics performance: correlation of noise levels and gender. Int J Adolesc Med Health. 2015;27:25–9.

17. Matheson M, Clark C, Martin R, van Kempen E, Haines M, Barrio IL, et al. The effects of road traffic and aircraft noise exposure on children's episodic memory: the RANCH project. Noise Health. 2010;12:244–54.

18. Weyde KV, Krog NH, Oftedal B, Magnus P, Øverland S, Stansfeld S, et al. Road traffic noise and children's inattention. Environ Health Glob Access Sci Source. 2017;16:127.

19. Pujol S, Levain JP, Houot H, Petit R, Berthillier M, Defrance J, et al. Association between ambient noise exposure and school performance of children living in an urban area: a cross-sectional population-based study. J Urban Health Bull N Y Acad Med. 2014;91:256–71.

20. Haines MM, Stansfeld SA, Head J, Job RFS. Multilevel modelling of aircraft noise on performance tests in schools around Heathrow Airport London. J Epidemiol Community Health. 2002;56:139–44.

21. Eagan ME, Anderson G, Nicholas B, Horonjeff R, Tivnan T. Relation between Aircraft Noise Reduction in Schools and Standardized Test Scores. Washington, DC, USA: Federal Interagency Committee on Aviation Noise (FICAN); 2004 p. 7.

22. Shield BM, Dockrell JE. The effects of environmental and classroom noise on the academic attainments of primary school children. J Acoust Soc Am. 2008;123:133–44.

23. Seidler A, Hegewald J, Seidler AL, Schubert M, Wagner M, Dröge P, et al. Association between aircraft, road and railway traffic noise and depression in a large case-control study based on secondary data. Environ Res. 2017;152:263–71.

24. Wright DM, Newell K, Maguire A, O'Reilly D. Aircraft noise and self-assessed mental health around a regional urban airport: a population based record linkage study. Environ Health Glob Access Sci Source. 2018;17:74.

25. Generaal E, Timmermans EJ, Dekkers JEC, Smit JH, Penninx BWJH. Not urbanization level but socioeconomic, physical and social neighbourhood characteristics are associated with presence and severity of depressive and anxiety disorders. Psychol Med. 2019;49:149–61.

26. Orban E, McDonald K, Sutcliffe R, Hoffmann B, Fuks KB, Dragano N, et al. Residential Road Traffic Noise and High Depressive Symptoms after Five Years of Follow-up: Results from the Heinz Nixdorf Recall Study. Environ Health Perspect. 2016;124:578–85.

27. Leijssen JB, Snijder MB, Timmermans EJ, Generaal E, Stronks K, Kunst AE. The association between road traffic noise and depressed mood among different ethnic and socioeconomic groups. The HELIUS study. Int J Hyg Environ Health. 2019;222:221–9.

28. Sygna K, Aasvang GM, Aamodt G, Oftedal B, Krog NH. Road traffic noise, sleep and mental health. Environ Res. 2014;131:17–24.

29. Roswall N, Høgh V, Envold-Bidstrup P, Raaschou-Nielsen O, Ketzel M, Overvad K, et al. Residential exposure to traffic noise and health-related quality of life--a population-based study. PloS One. 2015;10:e0120199.

30. Baudin C, Lefèvre M, Champelovier P, Lambert J, Laumon B, Evrard AS. Aircraft Noise and Psychological Ill-Health: The Results of a Cross-Sectional Study in France. Int J Environ Res Public Health. 2018;15:1642.

31. Klompmaker JO, Hoek G, Bloemsma LD, Wijga AH, van den Brink C, Brunekreef B, et al. Associations of combined exposures to surrounding green, air pollution and traffic noise on mental health. Environ Int. 2019;129:525–37.

32. Okokon EO, Yli-Tuomi T, Turunen AW, Tiittanen P, Juutilainen J, Lanki T. Traffic noise, noise annoyance and psychotropic medication use. Environ Int. 2018;119:287–94.

33. Floud S, Vigna-Taglianti F, Hansell A, Blangiardo M, Houthuijs D, Breugelmans O, et al. Medication use in relation to noise from aircraft and road traffic in six European countries: results of the HYENA study. Occup Environ Med. 2011;68:518–24.

34. Halonen JI, Lanki T, Yli-Tuomi T, Turunen AW, Pentti J, Kivimäki M, et al. Associations of traffic noise with self-rated health and psychotropic medication use. Scand J Work Environ Health. 2014;40:235–43.

35. Bocquier A, Cortaredona S, Boutin C, David A, Bigot A, Sciortino V, et al. Is exposure to night-time traffic noise a risk factor for purchase of anxiolytic–hypnotic medication? A cohort study. Eur J Public Health. 2013;24:298–303.

36. Ma J, Li C, Kwan MP, Kou L, Chai Y. Assessing personal noise exposure and its relationship with mental health in Beijing based on individuals' space-time behavior. Environ Int. 2020;139:105737.

37. Díaz J, López-Bueno JA, López-Ossorio JJ, Gónzález JL, Sánchez F, Linares C. Short-term effects of traffic noise on suicides and emergency hospital admissions due to anxiety and depression in Madrid (Spain). Sci Total Environ. 2020;710:136315.

38. Borghans L, Golsteyn BHH, Heckman JJ, Humphries JE. What grades and achievement tests measure. Proc Natl Acad Sci. 2016;113:13354–9.

39. Tonne C, Milà C, Fecht D, Alvarez M, Gulliver J, Smith J, et al. Socioeconomic and ethnic inequalities in exposure to air and noise pollution in London. Environ Int. 2018;115:170–9.

40. Biel R, Danieli C, Shekarrizfard M, Minet L, Abrahamowicz M, Baumgartner J, et al. Acute cardiovascular health effects in a panel study of personal exposure to traffic-related air pollutants and noise in Toronto, Canada. Sci Rep. 2020;10:16703.

41. El Aarbaoui T, Méline J, Brondeel R, Chaix B. Short-term association between personal exposure to noise and heart rate variability: The RECORD MultiSensor Study. Environ Pollut. 2017;231:703–11.

42. Hoek G, Beelen R, de Hoogh K, Vienneau D, Gulliver J, Fischer P, et al. A review of land-use regression models to assess spatial variation of outdoor air pollution. Atmos Environ. 2008;42:7561–78.

43. Harouvi O, Ben-Elia E, Factor R, de Hoogh K, Kloog I. Noise estimation model development using high-resolution transportation and land use regression. J Expo Sci Environ Epidemiol. 2018;28:559–67.

44. Aguilera I, Foraster M, Basagaña X, Corradi E, Deltell A, Morelli X, et al. Application of land use regression modelling to assess the spatial distribution of road traffic noise in three European cities. J Expo Sci Environ Epidemiol. 2015;25:97–105.

45. Xie D, Liu Y, Chen J. Mapping Urban Environmental Noise: A Land Use Regression Method. Environ Sci Technol. 2011;45:7358–64.

46. Flightradar24. Live Flight Tracker - Real-Time Flight Tracker Map [Internet]. Flightradar24. [cited 2021 Aug 10]. Available from: https://www.flightradar24.com/data/airports/sdf

47. Illinois Department of Transportation. Highway Traffic Noise Assessment Manual [Internet]. Springfield, Illinois; 2017. Available from: http://www.idot.illinois.gov/Assets/uploads/files/Doing-Business/Manuals-Guides-&-Handbooks/Highways/Design-and-Environment/Environment/Highway%20Traffic%20Noise%20Assessment%20Manual%202017.pdf

48. Accountability, Research and Systems Improvement. Jefferson County Public Schools 2018-19 Accountable K-PREP Reading and Mathematics [Internet]. 2019 [cited 2020 Dec 2]. Available from: https://assessment.jefferson.kyschools.us/publicdatasets/pdf/2020/jcpsdbk35.pdf

49. Centers for Disease Control and Prevention. BRFSS Prevalence & Trends Data [Internet]. 2019 [cited 2020 Dec 2]. Available from: https://nccd.cdc.gov/BRFSSPrevalence/rdPage.aspx?rdReport=DPH_BRFSS.ExploreByLocation&rdProcessAction=&SaveFileGenerated=1&irbLocationType=States&islLocation=21&islState=&islCounty=&islClass=CLASS20&islTopic=TOPIC71&islYear=2019&hidLocationType=States&hidLocation=21&hidClass=CLASS20&hidTopic=TOPIC71&hidTopicName=Healthy+Days&hidYear=2019&irbShowFootnotes=Show&rdICL-iclIndicators=_PHYS14D%2c_MENT14D&iclIndicators_rdExpandedCollapsedHistory=&iclIndicators=_PHYS14D%2c_MENT14D&hidPreviouslySelectedIndicators=&DashboardColumnCount=2&rdShowElementHistory=divTopicUpdating%3dHide%2cislTopic%3dShow%2cdivYearUpdating%3dHide%2cislYear%3dShow%2c&rdScrollX=0&rdScrollY=242&rdRnd=31461

50. 500 Cities: Local Data for Better Health [Internet]. Centers for Disease Control and Prevention; 2019 Apr [cited 2020 Oct 19]. Available from: https://www.cdc.gov/500cities/definitions/health-outcomes.htm

51. Albert DG, Decato SN. Acoustic and seismic ambient noise measurements in urban and rural areas. Appl Acoust. 2017;119:135–43.

52. Kempen E van, Casas M, Pershagen G, Foraster M. WHO Environmental Noise Guidelines for the European Region: A Systematic Review on Environmental Noise and Cardiovascular and Metabolic Effects: A Summary. Int J Environ Res Public Health. 2018;15:E379.

53. Nieuwenhuijsen MJ, Ristovska G, Dadvand P. WHO Environmental Noise Guidelines for the European Region: A Systematic Review on Environmental Noise and Adverse Birth Outcomes. Int J Environ Res Public Health. 2017;14:E1252.

54. Śliwińska-Kowalska M, Zaborowski K. WHO Environmental Noise Guidelines for the European Region: A Systematic Review on Environmental Noise and Permanent Hearing Loss and Tinnitus. Int J Environ Res Public Health. 2017;14:E1139.

55. Guski R, Schreckenberg D, Schuemer R. WHO Environmental Noise Guidelines for the European Region: A Systematic Review on Environmental Noise and Annoyance. Int J Environ Res Public Health. 2017;14:1539.

56. Alam MS, Corcoran L, King EA, McNabola A, Pilla F. Modelling of intra-urban variability of prevailing ambient noise at different temporal resolution. Noise Mapp. 2017;4:20–44.

57. Fallah-Shorshani M, Minet L, Liu R, Plante C, Goudreau S, Oiamo T, et al. Capturing the spatial variability of noise levels based on a short-term monitoring campaign and comparing noise surfaces against personal exposures collected through a panel study. Environ Res. 2018;167:662–72.

58. Goudreau S, Plante C, Fournier M, Brand A, Roche Y, Smargiassi A. Estimation of Spatial Variations in Urban Noise Levels with a Land Use Regression Model. Environ Pollut. 2014;3.

59. Ragettli MS, Goudreau S, Plante C, Fournier M, Hatzopoulou M, Perron S, et al. Statistical modeling of the spatial variability of environmental noise levels in Montreal, Canada, using noise measurements and land use characteristics. J Expo Sci Environ Epidemiol. 2016;26:597–605.

60. Sieber C, Ragettli MS, Brink M, Toyib O, Baatjies R, Saucy A, et al. Land Use Regression Modeling of Outdoor Noise Exposure in Informal Settlements in Western Cape, South Africa. Int J Environ Res Public Health. 2017;14.

61. Ryu H, Park IK, Chun BS, Chang SI. Spatial statistical analysis of the effects of urban form indicators on road-traffic noise exposure of a city in South Korea. Appl Acoust. 2017;115:93–100.

62. Wang VS, Lo EW, Liang CH, Chao KP, Bao BY, Chang TY. Temporal and spatial variations in road traffic noise for different frequency components in metropolitan Taichung, Taiwan. Environ Pollut. 2016;219:174–81.

63. Chang TY, Liang CH, Wu CF, Chang LT. Application of land-use regression models to estimate sound pressure levels and frequency components of road traffic noise in Taichung, Taiwan. Environ Int. 2019;131:104959.

64. Daigle GA, Embleton TFW, Piercy JE. Propagation of sound in the presence of gradients and turbulence near the ground. J Acoust Soc Am. 1986;79:613–27.

65. Traffic Monitoring Guide [Internet]. U.S. Department of Transportation, Federal Highway Administration; [cited 2021 Aug 11] p. 1–30. Available from: https://www.fhwa.dot.gov/policyinformation/tmguide/tmg_fhwa_pl_17_003.pdf

66. Louisville Muhammad Ali International Airport. Reports & Statistics [Internet]. Reports & Statistics. [cited 2021 Aug 10]. Available from: https://www.flylouisville.com/corporate/reports-statistics/

67. Airports Council International. ACI reveals top 20 airports for passenger traffic, cargo, and aircraft movements [Internet]. ACI reveals top 20 airports for passenger traffic, cargo, and aircraft movements. 2020 [cited 2021 Aug 10]. Available from: https://aci.aero/news/2020/05/19/aci-reveals-top-20-airports-for-passenger-traffic-cargo-and-aircraft-movements/

68. United Parcel Service. UPS Air Operations Facts [Internet]. 2021 Feb [cited 2021 Aug 10] p. 2. Available from:

https://about.ups.com/content/dam/upsstories/assets/fact-sheets/airlines-fact-sheets/Air%20Operations%20Facts_021221.pdf

69. INRIX. Global Traffic Scorecard [Internet]. Inrix. 2019 [cited 2022 Jan 11]. Available from: https://inrix.com/scorecard/

70. Kentucky Transportation Cabinet. KYTC Traffic Count Reporting System [Internet]. [cited 2021 Aug 31]. Available from: https://datamart.kytc.ky.gov/EDSB_SOLUTIONS/CTS/

71. Nicolas J, Berry J -L., Daigle GA. Propagation of sound above a finite layer of snow. J Acoust Soc Am. 1985;77:67–73.

72. Traffic Monitoring Guide [Internet]. U.S. Department of Transportation, Federal Highway Administration; [cited 2021 Aug 11] p. 1–5, 1–6, 1–7. Available from: https://www.fhwa.dot.gov/policyinformation/tmguide/tmg_fhwa_pl_17_003.pdf

73. NPC Library: Aviation Noise Effects [Internet]. [cited 2021 Aug 10]. Available from: https://www.nonoise.org/library/ane/ane.htm#sect2.4.2

74. ESPA - LSRD [Internet]. [cited 2021 Jul 4]. Available from: https://espa.cr.usgs.gov/index/

75. EarthExplorer [Internet]. [cited 2021 Jul 4]. Available from: https://earthexplorer.usgs.gov/

76. United States Geological Survey. NDVI, the Foundation for Remote Sensing Phenology [Internet]. [cited 2021 Aug 11]. Available from: https://www.usgs.gov/core-science-systems/eros/phenology/science/ndvi-foundation-remote-sensing-phenology?qt-science_center_objects=0#qt-science_center_objects

77. Landsat Normalized Difference Vegetation Index [Internet]. [cited 2021 Jul 4]. Available from: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-normalized-difference-vegetation-index?qt-science_support_page_related_con=0#qt-science_support_page_related_con

78. Integrated Environmental Health Impact Assessment System. Land use regression modelling: air pollution in Great Britain | Integrated Environmental Health Impact Assessment System [Internet]. [cited 2020 Nov 30]. Available from: http://www.integrated-assessment.eu/eu/guidebook/land_use_regression_modelling_air_pollution_great_britain.html

79. Documenting Kentucky's path to recovery from the coronavirus (COVID-19) pandemic, 2020-2021 [Internet]. Ballotpedia. [cited 2021 Aug 31]. Available from: https://ballotpedia.org/Documenting_Kentucky%27s_path_to_recovery_from_the_coronavirus_(COVID-19)_pandemic,_2020-2021

80. Pishue B. 2021 INRIX Global Traffic Scorecard. INRIX; 2021.

81. Paige Mitchell. Speed and Road Traffic Noise [Internet]. UK Noise Association; 2009 Dec [cited 2021 Oct 14] p. 20. Available from: http://www.ukna.org.uk/uploads/4/1/4/5/41458009/speed_and_road_traffic_noise.pdf

82. San Francisco General Plan :: Environmental Protection [Internet]. [cited 2020 Mar 10]. Available from: https://generalplan.sfplanning.org/I6_Environmental_Protection.htm#ENV_TRA

83. Geraghty D, O'Mahony M. Investigating the temporal variability of noise in an urban environment. Int J Sustain Built Environ. 2016;5:34–45.

84. Basagaña X, Rivera M, Aguilera I, Agis D, Bouso L, Elosua R, et al. Effect of the number of measurement sites on land use regression models in estimating local air pollution. Atmos Environ. 2012;54:634–42.

85. Harvey PD. Domains of cognition and their assessment. Dialogues Clin Neurosci. 2019;21:227–37.

86. Batty GD, Mortensen EL, Nybo Andersen AM, Osler M. Childhood intelligence in relation to adult coronary heart disease and stroke risk: evidence from a Danish birth cohort study. Paediatr Perinat Epidemiol. 2005;19:452–9.

87. Barnett JH, McDougall F, Xu MK, Croudace TJ, Richards M, Jones PB. Childhood cognitive function and adult psychopathology: associations with

psychotic and non-psychotic symptoms in the general population. Br J Psychiatry J Ment Sci. 2012;201:124–30.

88. Batty GD, Mortensen EL, Osler M. Childhood IQ in relation to later psychiatric disorder: evidence from a Danish birth cohort study. Br J Psychiatry J Ment Sci. 2005;187:180–1.

89. Koenen KC, Moffitt TE, Roberts AL, Martin LT, Kubzansky L, Harrington H, et al. Childhood IQ and adult mental disorders: a test of the cognitive reserve hypothesis. Am J Psychiatry. 2009;166:50–7.

90. Dobson KG, Schmidt LA, Saigal S, Boyle MH, Van Lieshout RJ. Childhood cognition and lifetime risk of major depressive disorder in extremely low birth weight and normal birth weight adults. J Dev Orig Health Dis. 2016;7:574–80.

91. Lu K, Nicholas JM, Collins JD, James SN, Parker TD, Lane CA, et al. Cognition at age 70: Life course predictors and associations with brain pathologies. Neurology. 2019;93:e2144–56.

92. Russ TC, Hannah J, Batty GD, Booth CC, Deary IJ, Starr JM. Childhood Cognitive Ability and Incident Dementia: The 1932 Scottish Mental Survey Cohort into their 10th Decade. Epidemiology. 2017;28:361–4.

93. Batty GD, Deary IJ, Schoon I, Emslie C, Hunt K, Gale CR. Childhood mental ability and adult alcohol intake and alcohol problems: the 1970 British cohort study. Am J Public Health. 2008;98:2237–43.

94. Batty GD, Deary IJ, Schoon I, Gale CR. Childhood Mental Ability in Relation to Food Intake and Physical Activity in Adulthood: The 1970 British Cohort Study. Pediatrics. 2007;119:e38–45.

95. Heckman JJ, Masterov DV. The Productivity Argument for Investing in Young Children. Rev Agric Econ. 2007;29:446–93.

96. Heckman JJ, Lochner LJ, Todd PE. Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond [Internet]. National Bureau of Economic Research; 2005 Aug [cited 2022 Apr 16]. (Working Paper Series). Report No.: 11544. Available from: https://www.nber.org/papers/w11544

97. Shearer DL, Mulvihill BA, Klerman LV, Wallander JL, Hovinga ME, Redden DT. Association of early childbearing and low cognitive ability. Perspect Sex Reprod Health. 2002;34:236–43.

98. Waldfogel J, Han WJ, Brooks-Gunn J. The Effects of Early Maternal Employment on Child Cognitive Development. Demography. 2002;39:369–92.

99. Chetty R, Friedman JN, Rockoff JE. Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood. Am Econ Rev. 2014;104:2633–79.

100. Chetty R, Friedman JN, Hilger N, Saez E, Schanzenbach DW, Yagan D. How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star *. Q J Econ. 2011;126:1593–660.

101. Stansfeld SA, Berglund B, Clark C, Lopez-Barrio I, Fischer P, Öhrström E, et al. Aircraft and road traffic noise and children's cognition and health: a cross-national study. 2005;365:8.

102. Sharp BH, Connor TL, McLaughlin D, Clark C, Stansfeld SA, Hervey J, et al. Assessing Aircraft Noise Conditions Affecting Student Learning, Volume 1: Final Report [Internet]. Washington, D.C.: Transportation Research Board; 2014 [cited 2022 Apr 16]. Available from: https://www.nap.edu/catalog/22433

103. Jefferson County Public Schools. District Data [Internet]. [cited 2022 Jun 1]. Available from: https://www.jefferson.kyschools.us/node/1181/

104. Jefferson County Public Schools. School Profile Pages [Internet]. [cited 2022 Apr 1]. Available from: https://www.jefferson.kyschools.us/schools/school-profile-pages

105. Rothwell J. Housing Costs, Zoning, and Access to High- Scoring Schools. 2012;31.

106. Morsy L, Rothstein R. Toxic stress and children's outcomes. :33.

107. Babisch W. The Noise/Stress Concept, Risk Assessment and Research Needs. Noise Health. 2002;4:1–11.

108. Rylander R. Noise, Stress and Annoyance. Noise Vib Worldw. 2006;37:9–13.

109. Hahad O, Prochaska JH, Daiber A, Münzel T. Environmental Noise-Induced Effects on Stress Hormones, Oxidative Stress, and Vascular Dysfunction: Key Factors in the Relationship between Cerebrocardiovascular and Psychological Disorders. Oxid Med Cell Longev. 2019;2019:1–13.

110. van den Bosch M, Meyer-Lindenberg A. Environmental Exposures and Depression: Biological Mechanisms and Epidemiological Evidence. Annu Rev Public Health. 2019;40:239–59.

111. Maschke C, Breinl S, Grimm R, Ising H. The influence of nocturnal aircraft noise on sleep and on catecholamine secretion. Schriftenr Ver Wasser Boden Lufthyg. 1993;88:395–407.

112. Schmidt FP, Basner M, Kröger G, Weck S, Schnorbus B, Muttray A, et al. Effect of nighttime aircraft noise exposure on endothelial function and stress hormone release in healthy adults. Eur Heart J. 2013;34:3508–3514a.

113. Spreng M. Noise induced nocturnal cortisol secretion and tolerable overhead flights. Noise Health. 2004;6:35–47.

114. Jafari Z, Kolb BE, Mohajerani MH. Chronic traffic noise stress accelerates brain impairment and cognitive decline in mice. Exp Neurol. 2018;308:1–12.

115. Samson J, Sheeladevi R, Ravindran R, Senthilvelan M. Stress response in rat brain after different durations of noise exposure. Neurosci Res. 2007;57:143–7.

116. Slavich GM, Irwin MR. From stress to inflammation and major depressive disorder: a social signal transduction theory of depression. Psychol Bull. 2014;140:774–815.

117. Lupien SJ, Juster RP, Raymond C, Marin MF. The effects of chronic stress on the human brain: From neurotoxicity, to vulnerability, to opportunity. Front Neuroendocrinol. 2018;49:91–105.

118. Stress and Health Disparities: Contexts, Mechanisms, and Interventions Among Racial/Ethnic Minority and Low Socioeconomic Status Populations: (500202018-001) [Internet]. American Psychological Association; 2017 [cited 2022 Jan 18]. Available from: http://doi.apa.org/get-pe-doi.cfm?doi=10.1037/e500202018-001

119. Burris S, Kawachi I, Sarat A. Integrating law and social epidemiology. J Law Med Ethics J Am Soc Law Med Ethics. 2002;30:510–21.

120. Mental Illness [Internet]. National Institute of Mental Health (NIMH). [cited 2022 Jan 10]. Available from: https://www.nimh.nih.gov/health/statistics/mental-illness

121. Clark LA, Cuthbert B, Lewis-Fernández R, Narrow WE, Reed GM. Three Approaches to Understanding and Classifying Mental Disorder: ICD-11, DSM-5, and the National Institute of Mental Health's Research Domain Criteria (RDoC). Psychol Sci Public Interest. 2017;18:72–145.

122. Golembiewski JA. The Designed Environment and How it Affects Brain Morphology and Mental Health. HERD Health Environ Res Des J. 2016;9:161–71.

123. Ochodo C, Ndetei DM, Moturi WN, Otieno JO. External built residential environment characteristics that affect mental health of adults. J Urban Health Bull N Y Acad Med. 2014;91:908–27.

124. Qiu Y, Liu Y, Liu Y, Li Z. Exploring the Linkage between the Neighborhood Environment and Mental Health in Guangzhou, China. Int J Environ Res Public Health. 2019;16:E3206.

125. Melis G, Gelormino E, Marra G, Ferracin E, Costa G. The Effects of the Urban Built Environment on Mental Health: A Cohort Study in a Large Northern Italian City. Int J Environ Res Public Health. 2015;12:14898–915.

126. Cohen-Cline H, Turkheimer E, Duncan GE. Access to green space, physical activity and mental health: a twin study. J Epidemiol Community Health. 2015;69:523–9.

127. de Vries S, Ten Have M, van Dorsselaer S, van Wezep M, Hermans T, de Graaf R. Local availability of green and blue space and prevalence of

common mental disorders in the Netherlands. BJPsych Open. 2016;2:366–72.

128. Nutsford D, Pearson AL, Kingham S. An ecological study investigating the association between access to urban green space and mental health. Public Health. 2013;127:1005–11.

129. Wood LA, Tomlinson MM, Pfeiffer JA, Walker KL, Keith RJ, Smith T, et al. Time spent outdoors and sleep normality: A preliminary investigation. Popul Med. 2021;3:7.

130. Hu Q, Feng Y, Xu M. Are There Heterogeneous Impacts of Air Pollution on Mental Health? Front Public Health. 2021;9:780022.

131. Braithwaite I, Shuo Zhang, Kirkbride JB, Osborn DPJ, Hayes JF. Air Pollution (Particulate Matter) Exposure and Associations with Depression, Anxiety, Bipolar, Psychosis and Suicide Risk: A Systematic Review and Meta-Analysis. Environ Health Perspect. 2019;127:126002–1.

132. Wei F, Yu Z, Zhang X, Wu M, Wang J, Shui L, et al. Long-term exposure to ambient air pollution and incidence of depression: A population-based cohort study in China. Sci Total Environ. 2022;804:149986.

133. Ma Y, Wang W, Li Z, Si Y, Wang J, Chen L, et al. Short-term exposure to ambient air pollution and risk of daily hospital admissions for anxiety in China: A multicity study. J Hazard Mater. 2022;424:127535.

134. Ayuso-Álvarez A, Simón L, Nuñez O, Rodríguez-Blázquez C, Martín-Méndez I, Bel-Lán A, et al. Association between heavy metals and metalloids in topsoil and mental health in the adult population of Spain. Environ Res. 2019;179:108784.

135. Reuben A, Schaefer JD, Moffitt TE, Broadbent J, Harrington H, Houts RM, et al. Association of Childhood Lead Exposure With Adult Personality Traits and Lifelong Mental Health. JAMA Psychiatry. 2019;76:418–25.

136. Bouchard M, Bellinger DC, Weuve J, Matthews-Bellinger J, Gilman SE, Wright RO, et al. Blood lead levels and major depressive disorder, panic disorder, and generalized anxiety disorder in U.S. young adults. Arch Gen Psychiatry. 2009;66:1313–9.

137. Fujino Y, Guo X, Liu J, You L, Miyatake M, Yoshimura T. Mental health burden amongst inhabitants of an arsenic-affected area in Inner Mongolia, China. Soc Sci Med. 2004;59:1969–73.

138. Generaal E, Hoogendijk EO, Stam M, Henke CE, Rutters F, Oosterman M, et al. Neighbourhood characteristics and prevalence and severity of depression: pooled analysis of eight Dutch cohort studies. Br J Psychiatry J Ment Sci. 2019;215:468–75.

139. Yoon JH, Won JU, Lee W, Jung PK, Roh J. Occupational noise annoyance linked to depressive symptoms and suicidal ideation: a result from nationwide survey of Korea. PloS One. 2014;9:e105321.

140. Rudolph KE, Shev A, Paksarian D, Merikangas KR, Mennitt DJ, James P, et al. Environmental noise and sleep and mental health outcomes in a nationally representative sample of urban US adolescents. Environ Epidemiol Phila Pa. 2019;3:e056.

141. Basner M, Glatz C, Griefahn B, Penzel T, Samel A. Aircraft noise: effects on macro- and microstructure of sleep. Sleep Med. 2008;9:382–7.

142. Nivison ME, Endresen IM. An analysis of relationships among environmental noise, annoyance and sensitivity to noise, and the consequences for health and sleep. J Behav Med. 1993;16:257–76.

143. Muzet A. Environmental noise, sleep and health. Sleep Med Rev. 2007;11:135–42.

144. Halperin D. Environmental noise and sleep disturbances: A threat to health? Sleep Sci. 2014;7:209–12.

145. Eze IC, Foraster M, Schaffner E, Vienneau D, Pieren R, Imboden M, et al. Incidence of depression in relation to transportation noise exposure and noise annoyance in the SAPALDIA study. Environ Int. 2020;144:106014.

146. Clarke M, Moran P, Keogh F, Morris M, Kinsella A, Larkin C, et al. Seasonal influences on admissions for affective disorder and schizophrenia in Ireland: a comparison of first and readmissions. Eur Psychiatry J Assoc Eur Psychiatr. 1999;14:251–5.

147. Fellinger M, Waldhör T, Serretti A, Hinterbuchinger B, Pruckner N, König D, et al. Seasonality in Major Depressive Disorder: Effect of Sex and Age. J Affect Disord. 2022;296:111–6.

148. Kasper S, Wehr TA, Bartko JJ, Gaist PA, Rosenthal NE. Epidemiological findings of seasonal changes in mood and behavior. A telephone survey of Montgomery County, Maryland. Arch Gen Psychiatry. 1989;46:823–33.

149. Morken G, Lilleeng S, Linaker OM. Seasonal variation in suicides and in admissions to hospital for mania and depression. J Affect Disord. 2002;69:39–45.

150. Nguyen AM, Malig BJ, Basu R. The association between ozone and fine particles and mental health-related emergency department visits in California, 2005-2013. PloS One. 2021;16:e0249675.

151. O'Hare C, O'Sullivan V, Flood S, Kenny RA. Seasonal and meteorological associations with depressive symptoms in older adults: A geo-epidemiological study. J Affect Disord. 2016;191:172–9.

152. Munir S, Khan S, Nazneen S, Ahmad SS. Temporal and seasonal variations of noise pollution in urban zones: a case study in Pakistan. Environ Sci Pollut Res Int. 2021;28:29581–9.

153. Anglin DM, Lui F. Racial microaggressions and major discriminatory events explain ethnoracial differences in psychotic experiences. Schizophr Res. 2021;S0920-9964(21)00421-7.

154. Pimentel Maldonado DA, Eusebio JR, Amezcua L, Vasileiou ES, Mowry EM, Hemond CC, et al. The impact of socioeconomic status on mental health and health-seeking behavior across race and ethnicity in a large multiple sclerosis cohort. Mult Scler Relat Disord. 2021;58:103451.

155. Pun VC, Manjourides J, Suh H. Association of Ambient Air Pollution with Depressive and Anxiety Symptoms in Older Adults: Results from the NSHAP Study. Environ Health Perspect. 2017;125:342–8.

156. Pun VC, Manjourides J, Suh HH. Association of neighborhood greenness with self-perceived stress, depression and anxiety symptoms in older U.S adults. Environ Health. 2018;17:39.

157. CDC. PLACES Methodology [Internet]. Centers for Disease Control and Prevention. 2021 [cited 2021 Oct 19]. Available from: https://www.cdc.gov/places/methodology/index.html

158. CDC - BRFSS - BRFSS Frequently Asked Questions (FAQs) [Internet]. 2019 [cited 2021 Dec 27]. Available from: https://www.cdc.gov/brfss/about/brfss_faq.htm

159. Health Status | PLACES: Local Data for Better Health | CDC [Internet]. 2021 [cited 2021 Oct 19]. Available from: https://www.cdc.gov/places/measure-definitions/health-status/index.html

160. Centers for Disease Control and Prevention (CDC). Behavioral Risk Factor Surveillance System Survey Questionnaire. Atlanta, Georgia: U.S.

Department of Health and Human Services, Centers for Disease Control and Prevention, 2018.

161. Bureau UC. Gini Index [Internet]. Census.gov. [cited 2021 Oct 19]. Available from: https://www.census.gov/topics/income-poverty/income-inequality/about/metrics/gini-index.html

162. Onyeka IN, Maguire A, Ross E, O'Reilly D. Does physical ill-health increase the risk of suicide? A census-based follow-up study of over 1 million people. Epidemiol Psychiatr Sci. 2020;29:e140.

163. Franklin M, Yin X, McConnell R, Fruin S. Association of the Built Environment With Childhood Psychosocial Stress. JAMA Netw Open. 2020;3:e2017634.

164. van den Berg M, van Poppel M, van Kamp I, Andrusaityte S, Balseviciene B, Cirach M, et al. Visiting green space is associated with mental health and vitality: A cross-sectional study in four european cities. Health Place. 2016;38:8–15.

165. Pun VC, Manjourides J, Suh HH. Close proximity to roadway and urbanicity associated with mental ill-health in older adults. Sci Total Environ. 2019;658:854–60.

166. Poulsen AH, Raaschou-Nielsen O, Peña A, Hahmann AN, Nordsborg RB, Ketzel M, et al. Impact of Long-Term Exposure to Wind Turbine Noise on

Redemption of Sleep Medication and Antidepressants: A Nationwide Cohort Study. Environ Health Perspect. 2019;127:37005.

167. Pirrera S, De Valck E, Cluydts R. Nocturnal road traffic noise: A review on its assessment and consequences on sleep and health. Environ Int. 2010;36:492–8.

168. Tsuno N, Ritchie K. Sleep and Depression. J Clin Psychiatry. 2005;16.

169. Franco LS, Shanahan DF, Fuller RA. A Review of the Benefits of Nature Experiences: More Than Meets the Eye. Int J Environ Res Public Health. 2017;14:864.

170. Alvarsson JJ, Wiens S, Nilsson ME. Stress recovery during exposure to nature sound and environmental noise. Int J Environ Res Public Health. 2010;7:1036–46.

171. Aghaie B, Rejeh N, Heravi-Karimooi M, Ebadi A, Moradian ST, Vaismoradi M, et al. Effect of nature-based sound therapy on agitation and anxiety in coronary artery bypass graft patients during the weaning of mechanical ventilation: A randomised clinical trial. Int J Nurs Stud. 2014;51:526–38.

172. Ratcliffe E. Sound and Soundscape in Restorative Natural Environments: A Narrative Literature Review. Front Psychol. 2021;12:570563.

173. Cox DTC, Shanahan DF, Hudson HL, Plummer KE, Siriwardena GM, Fuller RA, et al. Doses of Neighborhood Nature: The Benefits for Mental Health of Living with Nature. BioScience. 2017;biw173.

174. Carles JL, Barrio IL, de Lucio JV. Sound influence on landscape values. Landsc Urban Plan. 1999;43:191–200.

175. Gerrish E, Watkins SL. The relationship between urban forests and income: A meta-analysis. Landsc Urban Plan. 2018;170:293–308.

176. Gould van Praag CD, Garfinkel SN, Sparasci O, Mees A, Philippides AO, Ware M, et al. Mind-wandering and alterations to default mode network connectivity when listening to naturalistic versus artificial sounds. Sci Rep. 2017;7:45273.

177. Nasari M, Ghezeljeh TN, Haghani H. Effects of nature sounds on sleep quality among patients hospitalized in coronary care units: A randomized controlled clinical trial. Nurs Midwifery Stud. 2018;7:18.

178. National Institute of Mental Health (NIMH). Depression [Internet]. [cited 2022 May 28]. Available from: https://www.nimh.nih.gov/health/topics/depression

179. James SL, Abate D, Abate KH, Abay SM, Abbafati C, Abbasi N, et al. Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories,

1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. The Lancet. 2018;392:1789–858.

180. National Institute of Mental Health (NIMH). Any Mood Disorder [Internet]. [cited 2022 May 28]. Available from: https://www.nimh.nih.gov/health/statistics/any-mood-disorder

181. Otte C, Gold SM, Penninx BW, Pariante CM, Etkin A, Fava M, et al. Major depressive disorder. Nat Rev Dis Primer. 2016;2:16065.

182. Kessler RC. The Costs of Depression. Psychiatr Clin North Am. 2012;35:1–14.

183. Geschwind DH, Flint J. Genetics and genomics of psychiatric disease. Science. 2015;349:1489–94.

184. Kempton MJ, Salvador Z, Munafò MR, Geddes JR, Simmons A, Frangou S, et al. Structural neuroimaging studies in major depressive disorder. Meta-analysis and comparison with bipolar disorder. Arch Gen Psychiatry. 2011;68:675–90.

185. Platt JM, Bates L, Jager J, McLaughlin KA, Keyes KM. Is the US Gender Gap in Depression Changing Over Time? A Meta-Regression. Am J Epidemiol. 2021;190:1190–206.

186. Parker G, Brotchie H. Gender differences in depression. Int Rev Psychiatry Abingdon Engl. 2010;22:429–36.

187. Hyde JS, Mezulis AH. Gender Differences in Depression: Biological, Affective, Cognitive, and Sociocultural Factors. Harv Rev Psychiatry. 2020;28:4–13.

188. Dunlop DD, Song J, Lyons JS, Manheim LM, Chang RW. Racial/Ethnic Differences in Rates of Depression Among Preretirement Adults. Am J Public Health. 2003;93:1945–52.

189. Bailey RK, Mokonogho J, Kumar A. Racial and ethnic differences in depression: current perspectives. Neuropsychiatr Dis Treat. 2019;15:603–9.

190. Sareen J, Afifi TO, McMillan KA, Asmundson GJG. Relationship Between Household Income and Mental Disorders: Findings From a Population-Based Longitudinal Study. Arch Gen Psychiatry. 2011;68:419–27.

191. Lorant V, Deliège D, Eaton W, Robert A, Philippot P, Ansseau M. Socioeconomic inequalities in depression: a meta-analysis. Am J Epidemiol. 2003;157:98–112.

192. He S, Smargiassi A, Low N, Bilodeau-Bertrand M, Ayoub A, Auger N. Residential noise exposure and the longitudinal risk of hospitalization for depression after pregnancy: Postpartum and beyond. Environ Res. 2019;170:26–32.

193. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. J Gen Intern Med. 2001;16:606–13.

194. Ghazisaeedi M, Mahmoodi H, Arpaci I, Mehrdar S, Barzegari S. Validity, Reliability, and Optimal Cut-off Scores of the WHO-5, PHQ-9, and PHQ-2 to Screen Depression Among University Students in Iran. Int J Ment Health Addict [Internet]. 2021 [cited 2022 May 30]; Available from: http://link.springer.com/10.1007/s11469-021-00483-5

195. Johnson JA, Lee A, Vinson D, Seale JP. Use of AUDIT-based measures to identify unhealthy alcohol use and alcohol dependence in primary care: a validation study. Alcohol Clin Exp Res. 2013;37 Suppl 1:E253-259.

196. Cohen S, Kamarck T, Mermelstein R. A global measure of perceived stress. J Health Soc Behav. 1983;24:385–96.

197. Cohen S. Perceived stress in a probability sample of the United States. In: The social psychology of health. Thousand Oaks, CA, US: Sage Publications, Inc; 1988. p. 31–67. (The Claremont Symposium on Applied Social Psychology).

198. Kroenke K, Spitzer RL, Williams JBW, Löwe B. The Patient Health Questionnaire Somatic, Anxiety, and Depressive Symptom Scales: a systematic review. Gen Hosp Psychiatry. 2010;32:345–59.

199. Manea L, Gilbody S, McMillan D. Optimal cut-off score for diagnosing depression with the Patient Health Questionnaire (PHQ-9): a meta-analysis. CMAJ. 2012;184:E191–6.

200. Manea L, Gilbody S, McMillan D. A diagnostic meta-analysis of the Patient Health Questionnaire-9 (PHQ-9) algorithm scoring method as a screen for depression. Gen Hosp Psychiatry. 2015;37:67–75.

201. Hammen C. Risk Factors for Depression: An Autobiographical Review. Annu Rev Clin Psychol. 2018;14:1–28.

202. Cruz-Pereira JS, Rea K, Nolan YM, O'Leary OF, Dinan TG, Cryan JF. Depression's Unholy Trinity: Dysregulated Stress, Immunity, and the Microbiome. Annu Rev Psychol. 2020;71:49–78.

203. Murphy MJ, Peterson MJ. Sleep Disturbances in Depression. Sleep Med Clin. 2015;10:17–23.

204. Fang H, Tu S, Sheng J, Shao A. Depression in sleep disturbance: A review on a bidirectional relationship, mechanisms and treatment. J Cell Mol Med. 2019;23:2324–32.

205. Dias D, Tchepel O. Spatial and Temporal Dynamics in Air Pollution Exposure Assessment. Int J Environ Res Public Health. 2018;15:558.

206. Jankowska MM, Schipperijn J, Kerr J. A Framework for Using GPS Data in Physical Activity and Sedentary Behavior Studies. Exerc Sport Sci Rev. 2015;43:48–56.

207. Jensen HAR, Rasmussen B, Ekholm O. Neighbour and traffic noise annoyance: a nationwide study of associated mental health and perceived stress. Eur J Public Health. 2018;28:1050–5.

208. Rylander R. Physiological aspects of noise-induced stress and annoyance. J Sound Vib. 2004;277:471–8.

209. Westman JC, Walterst JR. Noise and stress: a comprehensive approach. Environ Health Perspect. 1981;19.

210. Lercher P, Kofler WW. Behavioral and health responses associated with road traffic noise exposure along alpine through-traffic routes. Sci Total Environ. 1996;189–190:85–9.

211. Alimohammadi I, Kanrash FA, Abolghasemi J, Vosoughi S, Rahmani K, Chalak MH. Relationship Between Noise Annoyance and Cognitive Performance in Automotive Workers Exposed to Chronic Noise. J UOEH. 2019;41:375–85.

212. Alimohammadi I, Sandrock S, Gohari MR. The effects of low frequency noise on mental performance and annoyance. Environ Monit Assess. 2013;185:7043–51.

213. Dzhambov A, Tilov B, Makakova-Tilova D, Dimitrova D, Dzhambov AM, Dimitrova DD. Pathways and contingencies linking road traffic noise to annoyance, noise sensitivity, and mental Ill-Health. Noise Health. 2019;21:248–57.

214. Hammersen F, Niemann H, Hoebel J. Environmental Noise Annoyance and Mental Health in Adults: Findings from the Cross-Sectional German Health Update (GEDA) Study 2012. Int J Environ Res Public Health. 2016;13.

215. Jensen HAR, Rasmussen B, Ekholm O. Neighbour noise annoyance is associated with various mental and physical health symptoms: results from a nationwide study among individuals living in multi-storey housing. BMC Public Health. 2019;19:1508.

216. Melamed S, Luz J, Green MS. Noise exposure, noise annoyance and their relation to psychological distress, accident and sickness absence among blue-collar workers--the Cordis Study. Isr J Med Sci. 1992;28:629–35.

217. Onchang R, Hawker DW. Community noise exposure and annoyance, activity interference, and academic achievement among university students. Noise Health. 2018;20:69–76.

218. Reijneveld SA. The impact of the Amsterdam aircraft disaster on reported annoyance by aircraft noise and on psychiatric disorders. Int J Epidemiol. 1994;23:333–40.

219. Schreckenberg D, Griefahn B, Meis M. The associations between noise sensitivity, reported physical and mental health, perceived environmental quality, and noise annoyance. Noise Health. 2010;12:7–16.

220. van Kempen E, van Kamp I, Nilsson M, Lammers J, Emmen H, Clark C, et al. The role of annoyance in the relation between transportation noise and children's health and cognition. J Acoust Soc Am. 2010;128:2817–28.

221. Wothge J, Belke C, Möhler U, Guski R, Schreckenberg D. The Combined Effects of Aircraft and Road Traffic Noise and Aircraft and Railway Noise on Noise Annoyance-An Analysis in the Context of the Joint Research Initiative NORAH. Int J Environ Res Public Health. 2017;14.

222. Beutel ME, Jünger C, Klein EM, Wild P, Lackner K, Blettner M, et al. Noise Annoyance Is Associated with Depression and Anxiety in the General Population- The Contribution of Aircraft Noise. PloS One. 2016;11:e0155357.

223. Basner M. Nocturnal aircraft noise exposure increases objectively assessed daytime sleepiness. Somnologie - Schlafforschung Schlafmed. 2008;12:110–7.

224. Basner M, Glatz C, Griefahn B, Penzel T, Samel A. Aircraft noise: effects on macro- and microstructure of sleep. Sleep Med. 2008;9:382–7.

225. Evans GW, Bullinger M, Hygge S. Chronic Noise Exposure and Physiological Response: A Prospective Study of Children Living Under Environmental Stress. Psychol Sci. 1998;9:75–7.

226. Evans GW, Hygge S, Bullinger M. Chronic Noise and Psychological Stress. Psychol Sci. 1995;6:333–8.

227. Haines MM, Stansfeld SA, Job RFS, Berglund B, Head J. Chronic aircraft noise exposure, stress responses, mental health and cognitive performance in school children. Psychol Med. 2001;31:265–77.

228. Maschke C, Rupp T, Hecht K. The influence of stressors on biochemical reactions--a review of present scientific findings with noise. Int J Hyg Environ Health. 2000;203:45–53.

229. Ventriglio A, Bellomo A, di Gioia I, Di Sabatino D, Favale D, De Berardis D, et al. Environmental pollution and mental health: a narrative review of literature. CNS Spectr. 2021;26:51–61.

230. Waye KP, Bengtsson J, Rylander R, Hucklebridge F, Evans P, Clow A. Low frequency noise enhances cortisol among noise sensitive subjects during work performance. Life Sci. 2002;70:745–58.

231. Jacobs N, Roberts B, Reamer H, Mathis C, Gaffney S, Neitzel R. Noise exposures in different community settings measured by traditional dosimeter and smartphone app. Appl Acoust. 2020;167:107408.

232. 702 KAR 4:170 - Facility Programming and Construction Criteria Planning Guide [Internet]. Kentucky Department of Education, Division of Facilities Managemnet; 1995 Mar [cited 2022 Feb 4]. Available from: https://education.ky.gov/districts/fac/Documents/Facility%20Programming%20and%20Construction%20Criteria%20Planning%20Guide%203%206%2015.pdf

233. Lee HM, Hua Y, Wang Z, Lim KM, Lee HP. A review of the application of active noise control technologies on windows: Challenges and limitations. Appl Acoust. 2021;174:107753.

234. Zhu X, Kim BJ, Wang Q, Wu Q. Recent Advances in the Sound Insulation Properties of Bio-based Materials. BioResources. 2014;9:1764–86.

235. 2010 UPS Corporate Sustainability Report [Internet]. United Parcel Service, Inc.; [cited 2022 Jun 24]. Available from: https://about.ups.com/content/dam/upsstories/assets/reporting/2010-UPS-Corporate-Sustainability-Report.pdf

236. 2020 UPS GRI Content Index [Internet]. United Parcel Service, Inc.; 2021 Aug [cited 2022 Jun 21]. Available from: https://about.ups.com/content/dam/upsstories/assets/reporting/sustainability-2021/2020_UPS_GRI_Content_Index_081921v2.pdf

237. UPS Donates Nearly $500,000 In New Funding To Kentucky, Indiana, Ohio Nonprofits, University Of Louisville For Coronavirus Relief [Internet]. [cited 2022 Jun 21]. Available from: https://aviationbenefits.org/newswire/2020/07/ups-donates-nearly-500-000-in-new-funding-to-kentucky-indiana-ohio-nonprofits-university-of-louisville-for-coronavirus-relief/

238. UPS donates $5 million to Louisville athletics [Internet]. [cited 2022 Jun 21]. Available from: https://www.courier-

journal.com/story/sports/college/louisville/2019/02/22/louisville-athletics-gets-5-million-dollar-donation-ups/2947605002/

CURRICULUM VITA

Lindsey A. Wood
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EDUCATION

University of Louisville, School of Public Health and Information Sciences, Department of Epidemiology and Population Health, Louisville, Kentucky

Ph.D. Epidemiology | 2022
Dissertation: "Environmental noise exposure and its association with elementary standardized testing scores and adult mental ill-health in Louisville, Kentucky"
Chair: Natalie C. DuPré, Sc.D., Assistant Professor of Epidemiology

M.S. Epidemiology | 2019
Thesis: "Probability of conception after fertility counseling and the effects of sexually transmitted infection on pregnancy and the time to pregnancy in the LOUSSI study: a multiple method analysis"
Chair: Kira C. Taylor, Ph.D., Associate Professor of Epidemiology

Southern Arkansas University, College of Science and Engineering, Magnolia, Arkansas

B.S. Pre-Health Biology | 2017
Minor: Chemistry
Cum Laude

RELATED EXPERIENCE

Graduate Research Assistant, Superfund Trainee | April 2018 – Present
University of Louisville Superfund Research Center, Envirome Institute
University of Louisville Departments of Communication, Epidemiology, School of Medicine
Drs. Joy Hart, Kandi Walker, and Aruni Bhatnagar
Grant: Srivastava, S. (PI), Bhatnagar, A. (Co-I), Heberle, L. (Co-I), O'Toole, T. (Co-I), McClain, C. J. (Co-I), Nantz M. H. (Co-I), Rai, S. N. (Co-I), Turner, J. R. (Co-I), Hein, D. (Co-I) et al. Superfund Research Center (Environmental

Exposure and Metabolic Disease). National Institute of Environmental Health Sciences; $7,280,928 for 2017-2021.
Superfund Research Translation Core Description: A promotion of increasing the awareness of affected communities on exposure risk and its health effects as well as translation of study findings to affected communities and stakeholders. Assisted with communication study findings to stakeholder groups and developed and employed multiple methods of communicating information. Superfund Project 1 – VOCs and cardiometabolic disease.
Cardiometabolic Injury Description: An environmental health study aimed to evaluate the effects of VOCs on various adverse human health outcomes at the Superfund site in Louisville, KY. Assisted with health study data collection, including survey design and administration, consenting participants, and data entry. Supported participant recruitment via community events and door-to-door initiatives.

Graduate Research Assistant | April 2018 – Present
University of Louisville Envirome Institute, Green Heart Louisville
University of Louisville Departments of Communication, Epidemiology, School of Medicine
Drs. Joy Hart and Kandi Walker
Grant: Bhatnagar, A. (PI), Keith, R. (Co-I), DeFilippis, A. (Co-I), O'Toole, T. (Co-I), Hart, J. L. (Co-I), Walker, K. L. (Co-I), et al. Green Heart Louisville (Urban Greenness and Cardiovascular Health). National Institute of Environmental Health Sciences; $2,614,648 for 2018-2023.
Green Heart Louisville Description: An environmental community health study examining the relationships between community greenness, air quality and other environmental factors, and many facets of human health. Participated in all phases of community engagement, collaborated with project partners and research team leads, facilitated relationships with community members and organizations, built ongoing relationships for multiyear project, led community meetings and presentations, assisted in primary health data collection of participants in person at several study visits, and recruited and retained study participants through several novel methods.

Graduate Research Assistant | August 2020 – Present
University of Louisville, American Heart Association VAPERACE Center
University of Louisville Departments of Communication, Epidemiology, School of Medicine
Drs. Joy Hart and Kandi Walker
Grant: Hamburg, N., Wu, J., Blaha, M. (PIs), et al. Rapidly Advancing Discovery to Arrest the Outbreak of Youth Vaping (VAPERACE). (Hart and Walker, PIs, Community Engagement and Research Translation Core; Hart and Walker, Co-Is, Project 3—Cessation of Nicotine Vaping in Youth). American Heart Association; $6,650,000 for 2020-2022.
VAPERACE Description: A research center aiming to better understand the youth perspective on anti-vaping campaigns with a long-term goal of

implementing anti-vaping initiatives led by the Youth Advisory Council (YAC). Participated in YAC engagement and research translation of the vaping epidemic among youth. Led discussions with the YAC and translated the youth perspective to leading researchers. Assisted the YAC in building anti-vaping campaigns targeted towards youth. Managed and created content for all VAPERACE social media accounts.

Adjunct Professor | August 2021 – May 2022
Southern Arkansas University, Department of Biology
Courses: Biological Concepts of Public Health (Fall 2021). Health Care and Public Health Policy (Spring 2022).
Description: Provided 3 hours of synchronous online instruction per week to roughly 15 undergraduate students per term. Designed syllabi, course structure, lecture materials, homework assignments, quizzes, and exams. Facilitated discussions regarding supplemental reading materials relevant to the course topics.

Field Researcher | February 2020 – April 2020
Goodman Research Group, The National Aeronautics and Space Administration (NASA)
Dr. Janet Smith
Discover Exoplanets Description: An interactive community exhibit designed to educate children and adults on exoplanets. Surveyed visitors on their enjoyment and general feelings towards the exhibit, conducted observations on interactions with the exhibit, and reported data Goodman Research Group to help NASA understand community engagement with the exhibit.

Graduate Research Volunteer | August 2018 – August 2019
University of Louisville, Department of Epidemiology and Population Health
Dr. Kira Taylor
Louisville Tobacco Smoke Exposure, Genetic Susceptibility, and Infertility Study Description: A clinical-based study assessing the relationship between NAT2 acetylator type, smoking status, and fertility outcomes. Assisted in primary data collection of 6 month follow up via phone and email, created data sets, and analyzed data as relevant to thesis project.

PUBLICATIONS

Wood, L. A., Agbonlahor, O., Tomlinson, M. M., Kerstiens, S., Vincent, K., McLeish, A. C., Walker, K. L., & Hart, J. L. (2022, May). *Readability of online e-cigarette cessation Information.* Article accepted for publication to Tobacco Induced Diseases.

Agbonlahor, O., Vincent, K., **Wood, L. A.**, Tomlinson, M. M., Kerstiens, S., Clarke, J., McLeish, A. C., Walker, K. L., & Hart, J. L. (2022, May). *Readability of online information on nature and mental health*. Manuscript submitted for publication.

McLeish, A. C., Hart, J. L., **Wood, L. A.**, & Walker, K. L. (2022, May). *Differences in young adults' perceptions of e-cigarettes by history of use*. Manuscript submitted for publication.

Groom, A. L., Vu, TH. T., Landry, R. L., Kesh, A., Hart, J. L., Walker, K. L., **Wood, L. A.**, Robertson, R. M., & Payne, T. J. (2021, June). *The influence of friends on teen vaping: a mixed-methods approach.* Article published in the International Journal of Environmental Research and Public Health.

Pfeiffer, J. A., Hart, J. L., **Wood, L. A.**, Bhatnagar, A., Keith, R. J., Yeager, R. A., Smith, T., Tomlinson, M. M., Gilkey, D., Kerstiens, S., Gao, H., Srivastava, S., & Walker, K. L., (2021, June). *The importance of urban planning: Views of greenness and open space is reversely associated with self-reported views and depressive symptoms.* Article published in Population Medicine.

Wood, L. A., Tomlinson, M. M., Pfeiffer, J. A., Walker, K. L., Keith, R. J., Smith, T. R., Yeager, R. A., Bhatnagar, A., Kerstiens, S., Gilkey, D., Gao, H., Srivastava, S., & Hart, J. L. (2021, March). *Time spent outdoors and sleep normality: A preliminary investigation.* Article published in Population Medicine.

Hart, J.L., **Wood, L. A.**, & Walker, K. L. (2021, January). *Managing uncertainty in the face of certain dangers.* Article published in Medical Sciences Forum.

Hart, J. L., Ridner, S. L., **Wood, L. A.**, Walker, K. L., Groom, A., Kesh, A., Landry, R. L., Payne, T. J., Ma, J. Z., Robertson, R. M., Hart, P. E., Giachello, A. L., & Vu, TH. T. (2020, November). *Associations between tobacco use patterns and demographic characteristics of sexual minority and heterosexual youth: Results from a nationwide online survey.* Article published in Tobacco Prevention & Cessation.

Mattingly, D. T., Hart, J. L., **Wood, L. A.**, & Walker, K. L. (2020, July). *Sociodemographic differences in single, dual, and poly tobacco use among Appalachian youth.* Article published in Tobacco Prevention & Cessation.

Ridner, S. L., Ma, J. Z., Walker, K. L., Vu, T. T., Groom, A., Landry, R. L., Kesh, A., Robertson, R.M., Payne, T. J., Giachello, A. L., **Wood, L. A.**, & Hart, J. L. (2019, December). *Cigarettes smoking, ENDS use and dual-use among a national sample of lesbians, gays and bisexuals.* Article published in Tobacco Prevention & Cessation.

PRESENTATIONS

Wood, L. A., Gaskins, J., Taylor, K. C., Guinn, B., Yeager, R., & DuPré, N. C. (2022, June). *The association between environmental noise and prevalence of mental ill-health was modified by neighborhood income and race in Jefferson County, Kentucky.* Paper presented at the annual meeting of the Society for Epidemiologic Research, Chicago, Illinois.

Wood, L. A., Gaskins, J., Taylor, K. C., Guinn, B., Yeager, R., & DuPré, N. C. (2022, April). *Modification of the relationship between environmental noise and prevalence of mental ill-health by neighborhood income and race in*

Louisville, Kentucky. Paper presented at the 74th annual meeting of the Kentucky Public Health Association, Bowling Green, Kentucky.

Walker, K. L., McLeish, A. C., **Wood, L. A.**, Agbonlahor, O., Tomlinson, M. M., Vincent, K. A., Kerstiens, S., & Hart, J. L. (2022, March). *An end to ENDS: Youth-led initiatives.* Paper presented at the 28th annual meeting of the Society for Research on Nicotine and Tobacco, Baltimore, Maryland.

McLeish, A. C., Hart, J. L., **Wood, L. A.**, & Walker, K. L. (2022, March). *Internalizing symptoms and affective vulnerability in e-cigarette users and non-users.* Paper presented at the 28th annual meeting of the Society for Research on Nicotine and Tobacco, Baltimore, Maryland.

McLeish, A. C., Walker, K. L., **Wood, L. A.**, & Hart, J. L. (2022, March). *Impact of the COVID-19 pandemic on vaping among college student e-cigarette users.* Paper presented at the 28th annual meeting of the Society for Research on Nicotine and Tobacco, Baltimore, Maryland.

Wood, L. A., Agbonlahor, O., Tomlinson, M. M., Kerstiens, S., Vincent, K., McLeish, A. C., Walker, K. L., & Hart, Joy L. (2022, March). *Readability of vaping information on the web*. Paper presented at the 28th annual meeting of the Society for Research on Nicotine and Tobacco, Baltimore, Maryland.

McLeish, A. C., Hart, J. L., **Wood, L. A.**, & Walker, K. L. (2022, March). *Emotion dysregulation and vaping expectancies among college student e-cigarette users*. Paper presented at the 28th annual meeting of the Society for Research on Nicotine and Tobacco, Baltimore, Maryland.

Wood, L. A., Gaskins, J., Taylor, K. C., Guinn, B., & DuPré, N. C. (2021, August). *Winter and spring noise in relation to the prevalence of mental ill-health in adults: A census-tract level ecological study in Jefferson County, Kentucky.* Paper presented at the annual meeting of Research!Louisville, Louisville, Kentucky.

Kinison, W. T., Owolabi, U. S., **Wood, L. A.**, McLeish, A. C., Walker, K. L., Hart, J. L., Bhatnagar, A., & Keith, R. J. (2021, October). *The effect of the SARS-CoV-2 pandemic on tobacco use patterns in a longitudinal community sample.* Paper presented at the annual meeting of Research!Louisville, Louisville, Kentucky.

McLeish, A. C., Hart, J. L., **Wood, L. A.**, & Walker, K. L. (2021, October). *How much do college students really know about e-cigarettes?* Paper presented at the annual meeting of the NIH Tobacco Regulatory Science Conference, Bethesda, Maryland. Electronic conference due to COVID-19 pandemic.

McLeish, A. C., Hart, J. L., **Wood, L. A.**, & Walker, K. L. (2021, October). *Internalizing symptoms and affective vulnerability in e-cigarette users and non-users.* Paper presented at the annual meeting of the NIH Tobacco Regulatory Science Conference, Bethesda, Maryland. Electronic conference due to COVID-19 pandemic.

Wood, L. A., Agbonlahor, O., Tomlinson, M. M., Kerstiens, S., McLeish, A. C., Walker, K. L., & Hart, J. L. (2021, October). *Readability of online vaping information: Assessing messages to teens and parents.* Paper presented at the annual meeting of the NIH Tobacco Regulatory Science Conference, Bethesda, Maryland. Electronic conference due to COVID-19 pandemic.

Walker, K. L., McLeish, A. C., **Wood, L. A.**, & Hart, J. L. (2021, October). *Vape gods, Vape lords, and fiends: The language of vaping.* Paper presented at the annual meeting of the NIH Tobacco Regulatory Science Conference, Bethesda, Maryland. Electronic conference due to COVID-19 pandemic.

Wood, L. A., Tomlinson, M. M., Kerstiens, S., Agbonlahor, O., Vincent, K., Clarke, J., McLeish, A., Walker, K. L., & Hart, J. L. (2021, September). *Communication and community engagement: Green Heart Louisville's youth Art and Literature Showcase (presentation of the 2020-2021 K-12 student work).* Paper presented at annual meeting of the Kentucky Communication Association, Highland Heights, KY.

Vincent, K., Werner, A., Agbonlahor, O., **Wood, L. A.**, Tomlinson, M. M., Kerstiens, S., Kramer, A., Clarke, J., McLeish, A. C., Walker, K. L., & Hart, J. L. (2021, September). *Youth Vaping: Seeing through the clouds.* Paper presented at annual meeting of the Kentucky Communication Association, Highland Heights, KY.

Wood, L. A., Yeager, R., Guinn, B., Taylor, K. C., Gaskins, J., Loehr, M., Turner, J., & DuPré, N. C. (2021, August). *Land-use regression estimation of cumulative environmental noise exposure in Jefferson County, Kentucky.* Paper presented at the annual meeting of the International Society for Environmental Epidemiology, New York City, New York. Electronic conference due to COVID-19 pandemic.

Wood, L. A., Gilkey, D., Tomlinson, M., Pfeiffer, J., & Hart, J. L. (2021, April). *The color of hope: Evergreen (and deciduous).* Paper presented at the annual meeting of the Southern States Communication Association. Electronic conference due to COVID-19 pandemic.

Hart, J. L., Patel, J., Baldwin, J. N., Walker, K. L., **Wood, L. A.**, & Smith, T. R. (2021, February). *Youth, vaping, and anti-vaping initiatives.* Paper presented at the annual meeting of the Society for Research on Nicotine and Tobacco. Electronic conference due to COVID-19 pandemic.

McLeish, A.C., **Wood, L. A.**, Walker, K. L., & Hart, J. L. (2021, February). *Differences in young adults' perceptions of e-cigarettes by history of use.* Paper presented at the annual meeting of the Society for Research on Nicotine and Tobacco. Electronic conference due to COVID-19 pandemic.

Hart, J.L., **Wood, L. A.**, & Walker, K. L. (2021, January). *Managing uncertainty in the face of certain dangers.* Paper presented at the 3rd International Electronic Conference on Environmental Research and Public Health — Public Health Issues in the Context of the COVID-19 Pandemic. Electronic conference due to COVID-19 pandemic.

Ali, T., Oladipupo, I., **Wood, L. A.**, Torres, S., Bohler, H., Pagidas, K., Chiang, J., Gentry, A., & Taylor, K. C. (2020, December). *Active smoking and environmental tobacco smoke exposure with pregnancy outcomes among females seeking fertility care.* Paper accepted at The Society for Pediatric and Perinatal Epidemiologic Research annual conference, Boston, Massachusetts. Conference cancelled due to COVID-19 pandemic.

Wood, L. A., Tomlinson, M. M., Gilkey, D., Pfeiffer, J. A., Kerstiens, S. Hart, J. L. Walker, K. L., & Bhatnagar, A. (2020, December). *Pandemic possibilities: The heart of the matter.* Paper presented at the Superfund Research Program annual meeting, College Station, Texas. Electronic conference due to COVID-19 pandemic.

McLeish, A.C., **Wood, L. A.**, Walker, K. L., & Hart, J. L. (2020, October). *Differences in young adults' perceptions of e-cigarettes by history of use.* Paper presented at the annual NIH Tobacco Regulatory Science Conference, Bethesda, Maryland.

Hart, J. L., Walker, K. L., **Wood, L. A.**, Kerstiens, S., Gilkey, D., Tomlinson, M. M. & Pfeiffer, J. (2020, September). *Communication and community engagement: Green Heart Louisville's youth Art and Literature Showcase.* Paper accepted for presentation at the annual meeting of the Kentucky Communication Association. Conference cancelled due to COVID-19 pandemic.

Wood, L. A., Gaskins, J., Wallis, A., Ali, T., Oladipupo, I., & Taylor, K. C. (2020, March). *The association of sexually transmitted infections with pregnancy in the LOUSSI Study*. Paper presented at the Kentucky Public Health Association annual conference, Covington, Kentucky. Electronic conference due to COVID-19 pandemic.

Wood, L. A., Walker, K. L., Pfeiffer, J., Gilkey, D., Hart, J. L., & Bhatnagar, A. (2019, November). *Collaborative initiatives with urban youth and young adults: The heart of the matter.* Paper presented at the Superfund Research Program annual meeting, Seattle, Washington.

Hart, J. L., **Wood, L.**, Pfeiffer, J., Gilkey, D., Zachary, A., & Walker, K. L. (2019, November). *Relational dialectics in community-rooted research and partnerships.* Paper presented at the 2nd International Electronic Conference on Environmental Health Sciences.

Ridner, S. L., Ma, J. Z., Walker, K. L., Vu, T-H. T., Groom, A., Landry, R. L., Kesh, A., Robertson, R. M., Payne, T. J., Giachello, A. L., **Wood, L. A.**, & Hart, J. L. (2019, October). *Cigarette, ENDS, and dual use among a national sample of lesbians, gays, and bisexuals.* Paper presented at the NIH Tobacco Regulatory Science Conference, Bethesda, Maryland.

Cahill, M., Farley, G., Ali, T., Bohler, H., Oladipupo, I., **Wood, L.**, & Taylor, K. C. (2019, September). *The association between polycystic ovarian syndrome and the probability of conception in women undergoing fertility counseling.* Paper presented at the annual meeting of Research!Louisville, Louisville, Kentucky.

Wood, L. A., Hart, J. L., Walker, K. L., & Ridner, S. L. (2019, September). *Tobacco messaging to and tobacco use among LGBT-identifying groups.* Paper presented at the annual meeting of the Kentucky Communication Association, Cadiz, Kentucky.

Wood, L. A., Pfeiffer, J., Gilkey, D., Zachary, A., Tompkins, L. K., Kerstiens, S., Walker, K. L., & Hart, J. L. (2019, September). *Blurring borders, breaking boundaries: Classroom and community collaborations.* Paper presented at the annual meeting of the Kentucky Communication Association, Cadiz, Kentucky.

Hart, J. L., Tompkins, L. K., Pfeiffer, J., **Wood, L.**, Zachary, A., Carter, S., Gilkey, D., Mattingly, D., Thornsbury, A., & Walker, K. L. (2019, April). *Growing*

together: Community engagement and student involvement. Paper presented at the annual meeting of the Southern States Communication Association, Montgomery, Alabama.

Tompkins, L. K., Pfeiffer, J., **Wood, L.**, Zachary, A., Walker, K. L., & Hart, J. L. (2019, April). *Translating research for community members: Learning partnerships and change mechanisms*. Paper presented at the annual meeting of the Southern States Communication Association, Montgomery, Alabama.

Tompkins, L. K., Sears, C. G., Lee, A. S., Smith, C., Siu, A., Pfeiffer, J., **Wood, L.**, Zachary, A., Walker, K. L., & Hart, J. L. (2019, April). *Engaging communities, engaging change: Rural middle and high school youth and tobacco products.* Paper presented at the annual meeting of the Southern States Communication Association, Montgomery, Alabama.

Hart, J. L., Heberle, L., Walker, K. L., Tompkins, L. K., Wheeler, J., Pfeiffer, J., **Wood, L.**, Gilkey, D., Zachary, A., & Bhatnagar, A. (2018, November). *UofL Superfund Research Center: Communicating and engaging across disciplinary, professional, and institutional boundaries.* Paper presented at the Superfund Research Program annual meeting, Sacramento, California.

Noa de la Paz, M., Thornsbury, A., Carter, S., Tompkins, L. K., **Wood, L.**, Zachary, A., Pfeiffer, J., Gilkey, D., Walker, K. L., & Hart, J. L. (2018, November). *Community collaborations: Building partnerships and scientific understanding.* Paper presented at the annual meeting of the Ohio Valley Society of Toxicology, Louisville, Kentucky.

Hart, J. L., Walker, K. L, Tompkins, L. K., Zachary, A., **Wood, L.**, Mattingly, D. T., Gilkey, D., Carter, S., Thornsbury, A., & Pfeiffer, J. (2018, September). *Environmental health: Engaging a community in research, partnership, and practice.* Paper presented at the annual meeting of the Kentucky Communication Association, Prestonsburg, Kentucky.

RELATED SKILLS

- Statistical analysis with SAS programming
- Geographic analysis with ArcGIS
- Scientific writing and preparation of manuscripts
- Community engagement
- Collaboration and teamwork
- Study design
- Research translation
- Public speaking and presenting
- Health study participant recruitment
- Independent learning of complex topics
- Management of research teams
- Exposure assessment
- Teaching

PROFESSIONAL WORKSHOPS

Intro to Spatial Analysis & GIS for Spatial Epidemiology in R, Society for Epidemiologic Research; June 14, 2022

An Introduction to R for Epidemiologists, Society for Epidemiologic Research; May 13, 2022

Quality Matters, Applying the QM Rubric (APPQMR); February 3, 2022

Texas A&M Superfund Research Center, Disaster Research Training Workshop; December 17-18, 2018

Texas A&M Engineering Extension Service in cooperation with the Department of Homeland Security, FEMA: AWR-160-W WMD/Terrorism Awareness for Emergency Responders; October 15, 2018

U.S. Department of Homeland Security, FEMA: IS-00800.c National Response Framework, An Introduction; October 8, 2018

U.S. Department of Homeland Security, FEMA: IS-00200.b ICS for Single Resources and Initial Action Incident, ICS-200; October 8, 2018

QPR Institute, QPR Suicide Prevention Gatekeeper Certificate; September 9-15, 2018

U.S. Department of Homeland Security, FEMA: IS-00100.c Introduction to Incident Command System, ICS-100; August 10, 2018

U.S. Department of Homeland Security, FEMA: IS-00700.a National Incident Management System (NIMS) And Introduction; October 31, 2017

VOLUNTEER EFFORTS

Volunteered during local COVID-19 vaccination administration conducted by Louisville Metro Public Health and Wellness. Screened patients for qualification of vaccination including relevant sensitive health information and completed vaccination documentation for LMPHW and vaccination cards for patients; January 2021

Volunteered during the COVID-19 pandemic response conducted by Louisville Metro Public Health and Wellness. Worked as a case investigator which consisted of calling newly reported COVID-19 cases, collecting relevant data from cases, data matching from health facilities, and reporting all data to the Centers for Disease Control and Prevention; April 2020

Volunteered during an Epi-Aid conducted by the Centers for Disease Control and Prevention and the Kentucky Department for Public Health. Interviewed community members and first responders about their exposures to a natural gas pipeline explosion and health following the explosion; September 2019

HONORS AND AWARDS

Outstanding Student Epidemiology Poster, 2022 Kentucky Public Health Association Annual Conference; April 2022

Public Health Emergency Preparedness and Response: Outstanding Response as a member of the 2019 Lincoln County Pipeline Explosion CDC Interview Team, Medical Reserve Corps, Kentucky Department of Public Health, and the Centers for Disease Control and Prevention; October 2019

REFERENCES

Dr. Joy Hart
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