ABSTRACT

Title of Thesis: EXPLORING RISK ASSESSMENT METHODS TO EXAMINE NEUROLOGICAL RISK DUE TO AIR TOXIC EXPOSURE IN MINNESOTA

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Background

Existing research has investigated the relationships between sociodemographic characteristics and air toxic exposure in the United States. However, a few studies have examined the neurological risk from exposure to air toxics. The purpose of the study was to determine the correlation between sociodemographic variables and neurological risk due to exposure to air toxics. Also, spatial methods were used to understand the distribution of neurological risk and sociodemographic characteristics.

Methods

Air toxic neurological risk data were obtained from the United States Environmental Protection Agency's National-scale Air Toxics Assessment and sociodemographic data from the 2010-2014

American Community Survey US Census Bureau. The NATA dataset contains 24 neurotoxic air pollutants. The hazard quotient (HQ) for each air pollutant was quantified by calculating the ratio of the inhalation exposure concentration (EC) to the reference concentration (RfC). In addition, the EPA additively models the neurological risks of different pollutants (HQ) to estimate an aggregate neurological risk score (hazard index (HI)) for each census tract. We conducted statistical analysis using R and spatial analysis using ArcGIS 10.

Results

The mean cumulative neurological risk (HI) from all sources was 0.05, and all HI<1 for all tracts in Minnesota. The range of values for HI is ≤1 to >1, with >1 being the greatest harm. Percent poverty, percent without high school education and percent non-Hispanic white were weakly negatively correlated with cumulative neurological risk. In comparison, median household income, percent unemployed, percent non-Hispanic black, percent Hispanic and percent people of color were weakly positively correlated with cumulative neurological risk. The choropleth map of cumulative neurological risk showed that individuals in Minneapolis-St. Paul may be disproportionately exposed to air toxics.

Conclusions

These findings suggest that there may be an unequal distribution of neurotoxic air pollutants, especially in Minneapolis-St. Paul. Study results may inform and target public health efforts at specific locations to eliminate sociodemographic inequalities in exposure to neurotoxic air pollutants.

EXPLORING RISK ASSESSMENT METHODS TO EXAMINE NEUROLOGICAL RISK DUE TO AIR TOXIC EXPOSURE IN MINNESOTA

by

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Dedication

This is dedicated to Bartholomew A.C and Franca C. Ezeugoh, and everyone who supported me.

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List of Abbreviations

Abbreviation	Meaning
ACS	American Community Survey
AD	Alzheimer's disease
ADHD	Attention-deficit/hyperactivity disorder
AERMOD	American Meteorological Society/Environmental Protection Agency Regulatory Model
AERR	Air Emissions Reporting Rule
ALS	Amyotrophic lateral sclerosis
ALS	Amyotrophic lateral sclerosis
API	Asian/Pacific Islander
ASD	Autism spectrum disorder
ATRA	Air Toxics Risk Assessment
ATSDR	Agency for Toxic Substances and Disease Registry
CAA	Clean Air Act
CAL EPA-OEHHA	California Environmental Protection Agency Office of Environmental Health Hazard Assessment
CMAQ	Community Multiscale Air Quality
CNS	Central nervous system
EC	Exposure concentration
EIS	Emissions Inventory System
EPA	Environmental Protection Agency
HAPEM7	version 7 of the EPA Hazardous Air Pollutant Exposure Model
HAPs	Hazardous air pollutants
HD	Huntington's disease
HI	Hazard index
HOME	Home Observation for Measurement of the Environment
HQ	Hazard quotient
MACT	Maximum achievable control technology
MDH	Minnesota Department of Health
MN Tracking	Minnesota Department of Health Environmental Public Health Tracking Program
MNRISKS	Minnesota (statewide) risk screening tool
MPCA	Minnesota Pollution Control Agency
N.Ds	Neurological disorders
NAAQS	National Ambient Air Quality Standards
NATA	National-scale Air Toxics Assessment
NEI	National Emissions Inventory
PD	Parkinson's disease
RfC	Reference concentration

SATMN	Statewide air toxic monitoring network
SVOCs	Semivolatile organic compounds
TRI	Toxics Release Inventory
UFP	Ultrafine particles
VOCs	Volatile organic compounds
WMH	White matter hyperintensities

Exploring risk assessment methods to examine neurological risk due to air toxic exposure in Minnesota

Chapter 1: Introduction

1.1 Rationale

Growing scientific evidence links exposure to air toxics and an elevated risk of developing various neurological health outcomes such as Parkinson's disease and autism.[1–3] Neurological disorders are concerning because they affect people of all ages and can significantly impact their lives. As a result, racial and ethnic disparities in air toxic exposure could lead to disparities in the outcomes of neurologic diseases among exposed persons. For example, increased $PM_{2.5}$ (a neurotoxicant) exposure is associated with double the risk for Alzheimer's disease in black women than in white women.[4] Despite the documented evidence of a disproportionate burden of air toxic exposures with increased risk on populations of color or low-income persons,[5–8] there is a paucity of studies that have examined the neurological risk due to exposure to air contaminants and the related disparities in this risk for sub-populations. Besides, risk assessment methods used to examine the association between air toxic exposure and risks of unfavorable health outcomes have relied on a single pollutant approach.[5,9–11] Pollutants, however, are ubiquitous and typically exist as mixtures of different chemicals and chemical classes based on the source of emission. Thus, the cumulative risk assessment approach is preferable, especially for identifying vulnerabilities at the neighborhood level.[12] However, this method has rarely been used to investigate the neurological risks associated with air toxic exposure. Altogether, these gaps in the literature support the need to assess the relationship between neurological risks and exposure to air contaminants.

The proposed study seeks to address some of these gaps by characterizing neurological risks due to air toxic exposure in Minnesota. The cumulative neurological risk (hazard index) estimates associated with exposure to air toxics at the census tract level in Minnesota were obtained from U.S.

Environmental Protection Agency's National-scale Air Toxics Assessment (NATA) 2014 data. Additionally, the census tract is the smallest unit for which the estimated neurological risks are available from the U.S. EPA's NATA 2014 data. Subsequently, we will determine the correlation between cumulative neurological risk for air toxic exposure and sociodemographic characteristics of the Minnesotan population.

1.2 Significance

In the U.S., over 50 million people live in areas where air toxic concentrations exceed the levels for non-cancer health effects,[10] and neurological health endpoints were ranked 2nd out of 17 adverse health endpoints (after respiratory endpoints) in a cumulative risk assessment of 40 air toxics.[13,14] Thus, exposures to air toxics with neurological health endpoints have the potential to significantly impact the health of the population because they may be associated with or create vulnerability for neurological disorders (N.Ds) such as epilepsy, Alzheimer's disease and other dementias, cerebrovascular diseases including stroke, multiple sclerosis, Parkinson's disease, autism, attention-deficit/hyperactivity disorder (ADHD).[15,16] In fact, Gooch et al.,[16] estimate that about 100 million Americans were suffering from at least one of the over 1000 neurological disorders in 2011. Additionally, N.Ds are the second leading cause of death (after heart disease) and the first cause of severe long-term disability globally.[17,18] As such, exposure to air toxics with a neurological health endpoint is an emerging concern, and the related risk for individuals and populations to develop N.D needs to be quantified. Yet, few studies in the U.S. have quantified the neurological risks associated with air toxic exposure.

Quantification of the potential risks for neurological endpoints associated with exposure to air toxics requires a verified and efficient risk assessment method that is easy to understand by all stakeholders. Traditionally, risk assessment methods employ a single pollutant approach which is incapable of assessing the risks of cumulative exposures to multiple environmental stressors.[12] The single pollutant approach will be inappropriate for assessing neurological risks due to exposure to air toxics because they exist as mixtures of several chemicals and classes of chemicals. In the U.S alone, 187 air toxics have been identified as requiring attention and long-term monitoring under the 1990 Clean Air Act Amendments, while a subtotal of 30 have been recognized as urban air toxics because they are a potential threat to public health in urban areas.[19] Thus, a cumulative risk assessment approach that analyzes, characterizes, and quantifies the combined risks to human health from multiple agents or stressors is warranted in quantifying neurological risks associated with air toxic exposure. Despite the critical need to appropriately quantify and assess the association between neurological risks and air toxic exposure because of the potential for public harm, the cumulative risk assessment approach is yet to be applied in the study of this association.

Moreover, the distribution and burden of exposure to air toxics in the environment are not uniform. Disparities in air toxic exposures could translate to differential neurological risks and related disparities in health outcomes. Disproportionate air toxic exposures typically fall along racial/ethnic and socioeconomic lines and these racial/ethnic and socioeconomic factors could pose as essential vulnerability factors. These vulnerability factors need to be explored as potential predictors of exposure and neurological risks to generate necessary information that could be incor-

porated into interventions to reduce the disparities in neurological risks and exposure to air toxics. Although some studies have characterized the role of several sociodemographic measures on the association between cancer risks and exposure to air toxics, [5,11,20–22] few studies have examined the association between sociodemographic measures and disparities in cumulative neurological risks associated with exposure to air toxics.[10,23,24] Grineski and Collins investigated the relationship between neurological risk and school-level environmental inequalities in the US.[23] The authors observed that students who attended "high risk" public schools nationwide were significantly more likely to be eligible for free/reduced price meals, and Hispanic, black, or Asian/Pacific Islander (API).[23] Also, the schools with greater proportions of Hispanic, black, and API students, schools with higher enrollment, and schools located in more urban (vs. rural) counties faced greater neurological risks.[23] In addition, the schools that served the youngest students (e.g., pre-kindergarten) had increased neurological risk than schools that served older students.[23] Also, two studies have estimated neurological risk (hazard index). Young et al. estimated the mean neurological health hazard or risk of 0.07 in their study that examined differential exposure to hazardous air pollution in the United States.[25] Morello-Frosh et al. investigated the public health implications of outdoor concentrations of air toxics and health risks in California.[10] The authors estimated the neurological hazard index or risk of 0.9.[10] Crafting intervention strategies to potentially modify exposure and risk to reduce their related health effects is hampered by the lack of knowledge on the relationship between neurological risk and socioeconomic factors. The paucity of evidence-based knowledge on the impact of sociodemographic characteristics on cumulative neurological risk is detrimental to the development of cumulative risk assessment methods and effective intervention strategies. Our study seeks to address these significant knowledge gaps.

Minnesota was chosen as the study area because Minnesota is concerned about the effects of air pollution exposure on its population, particularly the elderly, the poor, children with asthma, the uninsured and people with pre-existing medical conditions.[26] Although Minnesota meets the federal quality air standards, urban communities are concerned about the effect of air toxic exposure on their health.[27] Minnesota Department of Health (MDH) Environmental Public Health Tracking Program (MN Tracking) and the Minnesota Pollution Control Agency (MPCA) jointly conducted a 2008 environmental health impact analysis for Minneapolis-St. Paul (the Twin Cities) at the zip code level.[27] They observed that exposure to PM led to approximately 2.1% of respiratory hospitalizations among residents aged 65 years and older (95% CI, 1.2-3.0) and 2.1% of child asthma hospitalizations (95% CI, 0-10.6); 0.7% of cardiovascular hospitalizations among residents aged 65 years and older (95% CI, 0.3-1.1); and 2.9% of all-ages asthma emergency department (ED) visits (95% CI, 0.8-4.9).[27] While exposure to ozone resulted in about 1.1% of all-ages premature cardiopulmonary deaths (95% CI, 0.4-1.8), 4.9% of all-ages asthma hospitalizations (95% CI, 3.0-6.7), and 3.2% of all-ages asthma ED visits (95% CI, 0-67.0).[27] Minnesota began monitoring air toxics in 1991[9] and the Minnesota Pollution Control Agency (MPCA) closely monitors air toxic exposure in the state by collecting statewide air monitoring data on air toxics at the block group level; this geographic resolution is vital for identifying disparities in exposure and changes over small areas. These monitoring sites were designed to measure air concentrations at specific point sources, collect baseline data on air toxic exposure in the Minneapolis-St. Paul metro area, and serve as a part of the statewide air toxic monitoring network (SATMN).[9] Additionally, the MCPA has a statewide risk screening tool for air toxics known as MNRISKS for estimating the risks associated with air toxic exposure. Pratt et al. conducted an assessment of air toxics in Minnesota, and observed that the highest modeled and monitored concentrations of

most air toxics were near the center of the Minneapolis-St. Paul metropolitan area.[9] Pratt et al. conducted a study to investigate the inequities in traffic and air pollution exposure and associated risks (cancer and non-cancer) in Minnesota.[28] The authors observed that populations of low socioeconomic status and non-white bear disproportionately high effects of exposure to air pollution (mainly from transportation sources) and higher risks for adverse health outcomes.[28] Our study will provide valuable information on sociodemographic disparities due to neurological risk in Minnesota and assist the state in focusing its resources on neighborhoods and locations that were identified as having air toxic levels of (neurological) concern.

1.3 Study aim and objective

The study's overall objective is to examine geographic and sociodemographic disparities in neurological risk due to air toxic exposures in Minnesota using a spatial analyses framework. Specifically, our aim is:

Aim 1: To determine the correlation between sociodemographic features of the Minnesotan population and neurological risk estimates from exposure to air toxics. *H1: Cumulative neurological risk would be positively correlated with percent non-Hispanic black, percent Hispanic, percent people of color, percent unemployed, percent with less than high school education, and percent poverty. H2: Cumulative neurological risk would be negatively correlated with percent non-Hispanic white and median household income.* Approach: We will extract the neurological risk estimates from Minnesota's air toxic exposure from US EPA NATA 2014 data and merge with several socioeconomic measures (e.g., race/ethnicity, poverty status) from the U.S. Census Bureau's American Community Survey 5-Year Estimates 2010 - 2014 for Minnesota. Subsequently, we will conduct correlation analyses to observe the association between sociodemographic

measures and cumulative neurological risk estimates. Additionally, we will create maps to visualize disparities in socioeconomic measures and neurological risk estimates individually using overlay methods.

Impact: Our findings will inform new research pathways aimed at elucidating the relationship between neurological risks and sociodemographic characteristics of the U.S. population. Characterizing sociodemographic characteristics that can influence population vulnerability and neurological risks is an essential first step to improving our knowledge of the influence of sociodemographic features on neurological risks to develop efficient interventions to reduce exposures, risks, and health disparities due to air toxic exposure in the future. Finally, understanding the links between neighborhood characteristics and air toxics exposure is crucial for developing and evaluating effective public health interventions.

Chapter 2: Literature Review

2.1 Air toxics

Air toxics are airborne pollutants which are also known as hazardous air pollutants (HAPs) are defined by the Environmental Protection Agency (EPA) as pollutants that may cause serious health effects or adverse environmental and ecological effects.[29] 187 hazardous air pollutants (HAPs) known to cause or suspected of causing cancer, respiratory, neurological, reproductive, and other severe chronic health effects have been identified by The 1990 Clean Air Act Amendments (CAA).[30] In addition, the EPA identified 30 air toxics in urban areas that represent the most significant potential health threat.[30] HAPs comprise a variety of volatile (e.g., formaldehyde, benzene, 1,3-butadiene) and semivolatile (e.g., naphthalene, polycyclic aromatic hydrocarbon (PAH) congeners, organic compounds (volatile organic compounds [VOCs] and semivolatile organic compounds [SVOCs]), and metals (e.g., arsenic, hexavalent chromium). Air toxics are emitted by various sources, which comprise mobile sources (e.g., cars, trucks and construction equipment); large or major sources (e.g., factories and power plants); smaller, or area, sources (e.g., gas stations and dry cleaners); and natural processes (biogenic VOC releases and wildfires).

U.S Environmental Protection Agency (EPA) does not regulate air toxics under the National Ambient Air Quality Standards (NAAQS); however, the EPA is mandated under the Clean Air Act (CAA) and its amendments to characterize, prioritize and address the effects of air toxic on public health and the environment.[31] The CAA mandates the EPA to set emissions standards for major sources of air toxics based on technology performance.[32] The CAA uses a phased regulatory approach to control air toxic emissions and mitigate risks from major stationary sources.[32]

The first phase focuses on emission standards based on the best performers in the industry.[32] The EPA establishes national emission regulations for major stationary sources of air toxics, which are generally referred to as the maximum achievable control technology (MACT) program, with numerical limitations that reflect available control technologies or work practice requirements.[32] The residual risk program is the second regulatory phase, which evaluates health and environmental risks and develops risk-based standards.[32] Within 8 years of MACT regulations being established, the EPA analyzes the health and environmental risks posed by sources.[32] Additionally, the CAA requires the EPA to establish new risk-based standards if substantial emission reductions are required to protect public health and safety.[32]

The U.S EPA estimates air toxic emissions using the National Emissions Inventory (NEI), which "is a comprehensive and detailed estimate of air emissions of criteria pollutants, criteria precursors, and hazardous air pollutants from air emissions sources." [33] The NEI is released every three years and built using the Emissions Inventory System (EIS) which collects data from state, local and tribal air agencies and synchronizes the data with other data sources.[33] NEI covers five major emission sources comprise: (1) point sources: large stationary facilities regulated based on the emissions thresholds set in the Air Emissions Reporting Rule (AERR) (such as electrical power plants, airports), (2) nonpoint sources: individually small in magnitude to report as point sources (such as residential heating, asphalt paving), (3) on-road sources: fuel combustion from automobiles during transportation or road-work or idling, (4) nonroad sources: lawn and garden equipment, aircraft, commercial marine vessels, (5) event sources: wildfires and prescribed burns.[33] a

critical emissions inventory that is linked to and overlaps with air emissions and NEI is the Toxics Release Inventory (TRI). TRI tracks the management of certain toxic chemicals released into the air, water or land disposal.[34]

EPA created the National-scale Air Toxics Assessment (NATA) as a screening tool for state, local and tribal air agencies and to serve as a geographical extension of the ambient air monitoring network concerning emissions of air toxics.[35] NATA is a vital decision-making tool because it helps to identify and prioritize pollutants and emission sources, identify locations of interest (such as hotspot areas) for further investigation, improve emissions inventory, inform and design air monitoring programs, improve the knowledge of health risks posed by air toxics, support communities in developing their local assessments.[35,36] The goal of NATA is to identify the air toxics that are the most significant potential concern and pose the greatest threat to public health.[36] Typically, NATA generates ambient and exposure concentrations as well as risk and hazard estimates for air toxics at the census tract level in each state.[36] NATA estimates cancer and non-cancer risk from inhalation and outdoor exposure to air pollutants.[35] NATA models air toxic concentrations and risks from a year's emission data at the census tract level.[35] EPA has completed six assessments of cancer risk estimates and non-cancer hazards, with 2014 as the sixth and most recent assessment that was released in 2018.[35] NATA data have been used by environmental epidemiologists to understand the relationship between air toxic exposure and health outcomes, such as autism spectrum disorder (ASD),[1] amyotrophic lateral sclerosis (ALS)[2]. The non-cancer hazard index for neurological risk from NATA has been used to explore the relationship between neurological health and air toxic exposure in public schools in the U.S.[37] We focused on neurological risk since neurological illnesses affect people of all ages and have long-

term consequences that are cumulative over the lifespan of an individual. It is important to note that several behavioral, genetic and environmental factors may be important influences on individual and group neurological risks.

2.2 NATA's estimation of neurological risk

NATA used these steps to produce the 2014 final assessment: compile national emissions inventory (2014 NEI), estimate ambient concentrations of air toxics across the U.S, estimate population exposures, and characterize potential public health risks from inhalation.[36] NATA's emission data are from the 2014 NEI version 2 and is the bedrock of NATA's air quality modeling.[36] NEI emissions and meteorological data are incorporated in the American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD) atmospheric dispersion model and the Community Multiscale Air Quality (CMAQ) photochemical model.[36] All NATA air toxics are modeled using AERMOD, and CMAQ is used for a list of 52 air toxics that are incorporated into CMAQ multipollutant version 5.2.[36] For hazardous air pollutants (HAPs) generated subsequently in the atmosphere (i.e., secondary pollutants, e.g., formaldehyde, acetaldehyde, and acrolein), CMAQ offers overall mass, chemistry, and formation. In contrast, AERMOD provides spatial granularity and more comprehensive source attribution.[36] Also, CMAQ provides biogenic and fire concentrations because these source emission categories are not run in AERMOD.[36]

Annual average concentrations generated through the models (CMAQ and AERMOD) are used to estimate census tract-level concentrations of all modeled air toxics.[36] In addition, the HAPEM7 (version 7 of the EPA Hazardous Air Pollutant Exposure Model) exposure model is

used to account for human activity patterns and develop exposure concentrations (ECs) for each census tract in the country. HAPEM 7 is a screening-level exposure model that calculates inhalation ECs based on ambient-pollutant levels.[36] Finally, census tract-level risks are estimated by using health benchmark data and the ECs.[36]

Following EPA risk assessment methodologies (hazard identification and dose-response assessment), the EPA conducts a toxicity assessment to identify and quantify the negative health impacts of chemical exposure.[36] The results of this toxicity assessment are known as toxicity values, which are combined with exposure estimates to characterize health risks for exposed populations.[36] NATA's toxicity values are numerical expressions that indicate the likelihood of adverse health effects given a predicted concentration and duration of exposure.[36] To evaluate the potential for neurological adverse health effects, chronic dose-response data were used to estimate a threshold that is the EC (exposure concentration) in the air at which neurological adverse health effects are assumed to be unlikely (i.e., the RfC (reference concentration)).[36] In an air toxics risk assessment, the potential for neurological effects is quantified by calculating the ratio of the inhalation EC to the RfC. This ratio is referred to as the hazard quotient (HQ). It is represented as:

$HQ_{ij} = EC_{ij}/RfC_J$ ……Equation 1

Where:

HQ_{ij} = Hazard quotient for pollutant j in census tract i, unitless

EC_{ij} = Exposure air concentration ($\mu g/m^3$) of pollutant j in census tract i (estimate of long-term inhalation exposure concentration for a specific air toxic,in units of mg/m^3)

RfC_j = Reference concentration ($\mu g/m^3$) for pollutant j (the corresponding reference concentration for that air toxic, in units of mg/m^3)

Exposures at or below the RfC (i.e., HQs of 1 or less) are unlikely to have harmful health effects for a specific air toxicant. As exposures rise above the RfC (i.e., HQs rise above 1), the risk of deleterious effects also rises. On the other hand, the HQ should not be construed as a likelihood of negative neurological consequences. HQ >1 simply states whether (and by how much) a certain exposure concentration exceeds the RfC. This could indicate that if exposures exceed RfC, the risk of neurological adverse effects increases.

Neurological risks for multiple air toxics were estimated by summing chronic neurological HQs for individual air toxics. The result is a hazard index (HI), which is defined as a sum of HQs for individual air toxics that affect the nervous system. The HI is referred to as the neurological risk in the study. The equation below is used to estimate HI from inhalation of multiple air toxics:

$HI_i = \Sigma_j HQ_{ij} = HQ_1 + HQ_2 + \ldots. + HQ_i$ …….Equation 2

Where:

HI_i = Hazard index at census tract i (sum of the hazard quotients for all pollutants in census tract i), unitless

HQ_{ij} = Hazard quotient for each air toxic with neurological health endpoint emitted at census tract I, unitless

A HI score of less than or equal to 1 implies that the exposure is unlikely to cause neurological harm. A HI value larger than one does not mean a risk of adverse neurological effects and should not be construed as the occurrence of neurological adverse effects. This could mean that the risk of neurological effects increases.

2.3 Reference concentrations (RfCs)

A reference concentration is "an estimate of a continuous inhalation exposure over a 70-year lifetime that is thought to be without an appreciable risk of adverse health effects over a lifetime." [36] Reference concentrations are intended to protect known sensitive populations or subgroups, such as children, asthmatics and the elderly.[36,38,39] The RfC values are obtained by reviewing a health-effects database (such as the Integrated Risk Information System (IRIS) from the U.S. Environmental Protection Agency (EPA), U.S. Department of Health and Human Services, Agency for Toxic Substances and Disease Registry (ATSDR), California Environmental Protection Agency Office of Environmental Health Hazard Assessment (CAL EPA-OEHHA), US EPA Health Effects Assessment Summary Tables for a chemical and identifying the most sensitive and relevant (neurological) endpoint principal study or studies showing that endpoint.[36]

2.4 Risk assessment methods used in NATA

EPA used a risk-based methodology which is the general risk assessment framework in NATA and has developed a three-volume Air Toxics Risk Assessment (ATRA) Reference Library[40] which is a reference for those conducting air toxics risk assessments.[36] This library contains information on the core principles of risk-based assessment for air toxics, application of these principles in various situations and strategies for risk reduction at the local level.[36,41] The purpose of a human health air toxics risk assessment is to understand the public health risks associated with exposures to air toxics from various sources of interest.[36] The EPA's risk assessment has three phases: problem formulation, analysis and risk characterization.[36]

The first phase is problem formulation, which includes an initial and systematic planning and scoping activities as well as the problem identification, which leads to the creation of a conceptual model.[36] This is a critical phase and influences EPA's decisions on methods, models and data sources to use in the assessment.[36] The planning process ensures that the developed objectives are met, resources are efficiently utilized and the project is successful.[36] This planning and the scoping process is critical in determining "the scope of the risk assessment, the level of detail and documentation, trade-offs between depth and breadth in the analysis, quality assurance and quality control requirements, analytical approaches to be used (modeling vs monitoring), and the staffing and monitoring resources to commit." [36] The problem formulation phase leads to the development of the conceptual model and the analysis plan.[36] The conceptual model is a guide and describes the human health risks associated with air toxic exposure.[36]

Analysis is the second phase in which risk assessment methods are used to evaluate the problem and comprise exposure assessment and toxicity assessment (comprise hazard identification and dose-response assessment).[36] The purpose of an exposure assessment is to identify the potentially exposed population, the air toxics of concern, exposure pathways and routes, and quantify exposure.[36] The exposure assessment refines the conceptual model and is the analytical step where the magnitude, frequency and duration of air toxic exposures are quantified.[36] Toxicity assessment is used to determine the types of adverse health effects linked to exposure to the air toxic of concern and the relationship between exposure and response to the exposure of various dosages of the air toxic of concern.[36] Toxicity assessment comprises hazard identification and dose-response assessment. The process of determining adverse health outcomes from exposure to air toxics, which includes the nature and strength of the evidence of causation, as well as the circumstances

in which these health endpoints occur (e.g., inhalation vs. ingestion, acute vs. chronic), is known as hazard identification.[36] Dose-response relationship quantifies the association between the dose of the air toxic and the incidence of adverse health effects in the exposed population.[36] Models are used to predict the dose-response relationship and derive the toxicity values used in risk characterization.[36]

Risk characterization is the third phase, which is a synthesis of the exposure and toxicity assessment results to characterize health risks for the scenario given in the first phase.[36] Basically, this phase produces numbers that denote the likelihood that the exposure to the air toxic of potential concern result in an adverse health outcome.[36] This process entails a thorough uncertainty analysis for each step of the risk assessment to understand better which aspects of the assessment are uncertain, the magnitude and direction of the effect that the various uncertainties have on the risk estimates.[36] The risk assessor's expert judgment is reflected in the uncertainty analysis.[36] A written report containing all of the analyses performed to quantify exposure, identify toxicity values, characterize risk, and assess and present uncertainty is the end product of risk assessment.[36]

2.5 Air toxics and neuro-pathology

Exposure to air toxics at sufficient concentrations and duration may increase the risk of experiencing adverse health outcomes, such as neurological disorders. Although emerging evidence suggests that chronic exposure to air toxics can affect brain functioning and lead to neurological health outcomes, exposure to neurological air toxics has rarely been investigated.[37] While ingestion has been considered the predominant way of neurotoxicant exposure, and inhalation is a common, essential, and more toxic mode of exposure. Exposure to air toxics via inhalation has

far-reaching consequences. Inhaled air toxics such as ultrafine particles (UFP) can be deposited in the pulmonary alveolar regions of the lung, where they can cross the alveolocapillary barrier to access the pulmonary interstitium and cross endothelial cells into blood circulation, affecting other organs such as the brain and nervous system.[42,43] Also, air toxics can be deposited in the nasal cavity, which can be translocated to the brain.[44,45] Exposures to air toxic adversely affect the brain and nervous system through inflammation and oxidative stress.[46] Inhaled air toxics damage the body's natural barriers and enter the body, triggering an innate immune response that involves proteins known as cytokines (which are found in the blood and cerebrospinal fluids).[47] These cytokines result in swelling of tissues and the release of cytotoxic substances from immune cells and trigger the synthesis of additional cytokines. This causes neuroinflammation in the brain and results in widespread neural tissue loss and damage. Cytokines are linked to the development of white matter hyperintensities (WMH) which are regions of demyelinated neurons in the brain that have a deleterious impact on synaptic capabilities and are linked with cognitive deficits. In addition, neuroinflammation could be aggravated by increased peripheral inflammation and macrophage activation, which could increase the permeability of the blood-brain barrier, thereby allowing the movement of activated macrophage, pathogens and other foreign bodies into the central nervous system (CNS).[48] Ultimately, exposure to air toxic can lead to cognitive deficiencies via neuroinflammation and cell loss, and damage to myelin and neural functioning.[49] Apart from causing oxidative stress, the toxicity of neurotoxicants such as metals is due to the ability to substitute various polyvalent cations, such as calcium that serve as charge carriers, intermediaries in catalyzed reactions, or as structural elements in the maintenance of protein conformation.[50]

2.6 Air toxics and neurological disorders

Emerging evidence has shown that there is a link between air toxic exposure and neurological disorders, which could be neurodevelopmental or neurodegenerative. Neurodevelopmental disorders are a group of conditions that manifest early in development and are characterized by developmental deficiencies that result in impairments of personal, social, academic or occupational functioning.[51] These disorders comprise autism spectrum disorder (ASD), intellectual disability, communication disorders, attention deficit hyperactivity disorder (ADHD), neurodevelopmental motor disorders and specific learning disorders.[51] Neurodegenerative disorders are disorders in which the neurological system deteriorates gradually and irreversibly. Examples of late-onset neurodegenerative disorders are Alzheimer's disease (AD), Parkinson's disease (PD), Huntington's disease (HD) and Amyotrophic lateral sclerosis (ALS).

There is mounting scientific evidence on the relationship between neurodevelopmental disorders and exposure to air toxics.[1,2,52–54] Ehrenstein et al. investigated the risks for autism in children due to in utero exposure to air toxics.[52] The study used data from 4 air toxic monitoring stations (collecting 24-hour integrated samples every 12 days at each monitoring site) in Los Angeles County, which the California Air Resources Board maintained. Participants' addresses were geocoded and the distance from the participant's address to each monitoring station was determined. Participants were assigned pollutants (24 air toxics) values based on the measurements taken at the nearest monitoring station. The authors observed that after adjusting for maternal age, race/ethnicity, nativity, education, insurance type, maternal birthplace, parity, child sex, and birth year; there were increased autism risks per interquartile-range increase in average concentrations

during pregnancy of several correlated toxics mostly loading on one factor, including 1,3-butadiene (OR=1.59 [95% CI=1.18–2.15]), meta/para-xylene (1.51 [1.26–182]), other aromatic solvents, lead (1.49 [1.23–1.81]), perchloroethylene (1.40 [1.09–1.80]), and formaldehyde (1.34 [1.17–1.52]).[52] Talbott et al. also conducted a case-control study to examine the relationship between exposure to 30 neurotoxic air pollutants (as modeled by NATA) and the risk of developing autism spectrum disorder (ASD) using geocoded participants' addresses and 2005 NATA data.[55] The authors determined that exposure to chromium and styrene significantly increased the risk of ASD after adjusting for the mother's age, race, education, smoking, child's year of birth and child's sex.[55] Kalkbrenner et al. examined the relationship between perinatal air toxics with ASD and associated quantitative traits in high-risk multiplex families.[54] Individuals from the Autism Genetic Resource Exchange (AGRE), a volunteer research repository of families from around the United States with two or more siblings diagnosed with ASD, were used in the study (multiplex families). Air toxic data (for 155 pollutants) from NATA were linked to participants' birth year and address during the pregnancy. Also, three outcome measures were used to assess autism: an ASD diagnosis, a continuous measure of the broader autism phenotype among cases and controls using the Social Responsiveness Scale (SRS), and a measure of the severity of autism symptoms only among those who met diagnostic criteria for ASD using the Calibrated Severity Score (CSS). The results revealed that Propionaldehyde, methyl tert-butyl ether (MTBE), bromoform, 1,4-dioxane, dibenzofurans, and glycol ethers were positively associated with ASD diagnosis, while 1,4-dichlorobenzene, 4,4′-methylene diphenyl diisocyanate (MDI), benzidine, and ethyl carbamate (urethane) were inversely associated with ASD diagnosis.[54] These associations were still observed after adjustment in two-pollutant models. Carbon disul-

fide and chlorobenzene were positively associated with autism severity. In contrast, 1,4-dichlorobenzene was negatively associated, and there were no observed associations with SRS.[54] Kalkbrenner et al. conducted a screening analysis of air toxics and ASD using a prevalent case-control design in North Carolina and West Virginia.[53] Participants were assigned individual perinatal exposures based on the 1996 air toxic data (35 pollutants) from NATA corresponding to the census tract of their residential address from their birth certificate. The authors observed elevated OR estimates for methylene chloride (OR = 1.4 [95% CI = 0.7-2.5]), quinoline (1.4 [1.0-2.2]), and styrene (1.8 [1.0-3.1]).[53] Roberts and colleagues used a case-control design to examine the relationship between perinatal exposure to air toxics and ASD.[56] Participants' were assigned air toxic measurements from NATA (1990, 1996, 1999 and 2002) closest to their birth year. The results showed that perinatal exposures (highest vs lowest quintile) of diesel (2.0 [1.0–4.0]), lead (1.6 [1.1-2.3]), manganese (1.5 [1.1-2.2]), mercury (2.0 [1.2-3.3]), methylene chloride (1.8 [1.2-2.7]) and an overall measure of metals (1.5 [1.0-2.3]) were significantly associated with ASD.[56]

Dellefratte and colleagues investigated the joint association between early exposure to common air toxics (benzene, toluene, ethylbenzene, and xylene (BTEX)) and material hardship on teacher-assessed ADHD-suggestive behaviors in a nationally representative sample of children enrolled in kindergarten.[57] Participants were from the Early Childhood Longitudinal Study Birth Cohort (ECLS-B) and participants' BTEX exposures were estimated using 2002 NATA data. The results showed that after adjusting for covariates, there were increased odds of displaying ADHD-suggestive behaviors in children who had both high-level exposure to BTEX and in those experiencing material hardship (odds ratio 1.54, 95% CI 1.12, 2.11, and OR 2.12, 95% CI 1.25, 3.59, respectively). These associations were stronger when the study population was restricted to

children living in urban areas OR 1.83 95% CI (1.23, 2.73) for BTEX exposure and material hardship exposure OR 2.44 95% CI (1.33, 4.49).[57] Stingone et al. examined the relationship between early-life exposure to BTEX compounds and the use of academic support services (which was defined as the use of early intervention programming) later in childhood.[58] Exposure to BTEX pollutants was assigned to participants from 1996 NATA data. The results showed that children with higher exposure to one or more BTEX pollutants were more likely to use academic support services than children with lower exposure levels.[58] Also, children with higher levels of exposure to one or more BTEX pollutants have a slightly increased hazard of using academic support services compared to children born in areas with lower levels of exposure.[58] Dickerson et al. used 1999 NATA data to examine if the lead, mercury and arsenic ambient air concentrations were associated with ASD prevalence among 8-year-old children of the Autism and Developmental Disabilities Monitoring (ADDM) Network.[59] The results showed that after adjusting for confounders, census tracts with air lead concentrations in the highest quartile had a significantly higher prevalence of ASD compared to census tracts with air levels of lead in the lowest quartile (prevalence ratio (PR) = 1.36; 95% CI: 1.18, 1.57).[59] Also, census tracts with mercury levels above the 75th percentile (>1.7 ng/m^3) and arsenic levels below the 75th percentile (≤0.13 ng/m^3) had a significantly higher prevalence of ASD (adjusted RR = 1.20; 95%% CI: 1.03, 1.40) than census tracts with arsenic, lead, and mercury levels below the 75th percentile.[60] Lett et al. investigated the joint association of isophorone exposure (an ambient air marker of industrial pollution) and social factors on early cognitive skills in an urban cohort of children.[61] Exposure levels were assigned to the Early Childhood Longitudinal Study participants using 2002 NATA. The low quality home learning environment was used as a marker of social factors, which was assessed with a modified version of the Home Observation for Measurement

of the Environment (HOME) Inventory, and standardized math assessment scores were used as a measure or proxy of early cognitive skills. The authors observed that after adjusting for confounders, children who lived in areas with ambient isophorone in the upper quintile of exposure (>0.49 ng/m^3) had lower math scores than their less exposed peers (-1.63, 95% CI: −2.91, −0.34).[61] Also, children with lower HOME scores (at or below 9 out of 12) had lower math scores that were 1.20 points lower than children with better HOME scores (-1.20, 95% CI: −2.30, −0.10).[61] Stingone et al. examined the effects of prenatal exposure to both diesel particulate matter (PM) and perchloroethylene on academic outcomes later in childhood.[62] Exposure levels were assigned to participants using 1996 NATA based on the census tract which corresponds to the address on their birth records. The authors observed that children exposed to the highest levels of both diesel PM and perchloroethylene had math scores that were about 6% lower than children exposed to lower levels of both pollutants.[62]

Clark-Reyna et al. investigated the relationship between health status, residential air toxics risk estimates and grade point averages (GPA) among a representative sample of 4th and 5th graders in El Paso, Texas.[63] Risk estimates (respiratory and diesel particulate matter risk) were assigned to participants using 2005 NATA based on the census block where the child's residential address was located. The results revealed that the participant's health status was positively and significantly associated with GPA (β= 0.035, $p<0.0001$).[63] Also, respiratory and diesel PM risks (β=-0.023, $p<0.004$ and β=-0.021, $p<0.009$ respectively) were significantly and negatively associated with GPA.[63] Grineski and colleagues examined the associations between hazardous air pollutants (HAPs) and individual performance of children in reading, math and science.[64] Participants were from the Early Childhood Longitudinal Study, Kindergarten Cohort, 2011 (ECLS-K:2011). Risk

estimates (lifetime cancer risk) were assigned to participants using 2011 NATA based on the census tract where the participants' addresses were located. Reading (β=-0.016; p 0.05), science (β=-0.046; p 0.001), and math (β =-0.024; p 0.001) were all found to have statistically significant negative relationships with the risk estimates.[64]

Aging is linked to a wide range of clinical and pathological problems known as neurodegenerative disorders and has been identified as a risk factor for neurodegenerative disorders. Emerging evidence shows that an aging brain could be susceptible to neurotoxicants, and studies have been published that provide scientific evidence on the relationship between neurodegenerative disorders and exposure to air toxics.[2,65,66] Malek et al. conducted a case-control study to examine the relationship between residential exposure to 35 suspected neurotoxic hazardous air pollutants and the development of sporadic amyotrophic lateral sclerosis (ALS).[2] The study linked geocoded participants' addresses by census tract to U.S. Environmental Protection Agency's (EPA) National-Scale Air Toxics Assessment (NATA) data for 1999, 2002, and 2005 to determine historical exposure. The authors categorized neurotoxic hazardous air pollutants (HAPs) based on their structures into metals, aromatic solvents, organic/chlorinated solvents, other HAPs and pesticides. After controlling for education, smoking, and other exposure groups (outpatient hospital controls and population-based controls), the authors discovered that exposure to aromatic solvents significantly increased the odds of ALS among cases compared to controls in 2002 (OR = 5.03, 95% CI: 1.29, 19.53) and 1999 (OR = 4.27, 95% CI: 1.09, 16.79). Kirrane et al. examined the associations between Parkinson's disease (PD) and exposure to ambient ozone and $PM_{2.5}$ in North Carolina and Iowa among participants in the Agricultural Health Study.[65] Exposure to the air pollutants were assigned to participants based on their residential addresses using USEPA Air

Quality System (AQS) and Community Multiscale Air Quality Model (CMAQ). The results showed positive associations of PD with ozone (OR=1.39; 95% CI: 0.98, 1.98) and $PM_{2.5}$ (OR=1.34; 95% CI: 0.93, 1.93) in North Carolina but not in Iowa.[65] Liu and colleagues used a nested case-control study to examine the associations between long-term residential exposures to particulate matter (PM_{10} and $PM_{2.5}$) and nitrogen dioxide (NO_2) and the risk of PD.[67] Participants were from the PAGE study within a large prospective National Institutes of Health (NIH)-AARP, (formerly known as the American Association of Retired Persons) Diet and Health Study. Exposure levels were assigned to participants based on their addresses using EPA Air Quality System Data Mart. The results showed that high exposure PM_{10} was associated with an increased risk of PD among women (OR=1.65, 95% CI: 1.11,2.45) but not among men (OR = 0.92; 95% CI: 0.73, 1.14).[67] Also, there was an increased risk of PD among never smokers (OR=1.29, 95% CI: 0.94,1.76) associated with exposure to the highest quintile of $PM_{2.5}$ levels.[67] Gatto et al. investigated cross-sectional associations between residential exposures of O_3, $PM_{2.5}$ and NO_2, global cognition and six domains of cognitive function among healthy, cognitively intact middle-aged and older adults in the greater Los Angeles area, California.[66] Exposure levels were assigned based on the participant's residential address using measurements from EPA AQS. The results indicated that increasing $PM_{2.5}$ exposure was significantly associated with lower verbal learning ($\beta = -0.32$ per $10\mu g/m^3$ $PM_{2.5}$, 95% CI: −0.63, $p = 0.00$).[66] Also, exposure to NO_2 >20 ppb was not significantly associated with lower logical memory ($\beta = -0.62$, 95% CI = −1.35, 0.11; $p = 0.095$) compared to exposure ≤10 ppb.[66] In addition, O_3 exposures above 49 ppb were associated with lower executive function ($\beta = -0.66$, 95% CI = −1.35, 0.03; $p = 0.059$).[66] While, mid-range O_3 exposure (34–49 ppb) was also associated with a higher logical memory factor score, which appeared to be driven by the effect in women ($\beta = 0.46$, 95%

CI = 0.09, 0.83) and in adults aged 60 and older (β = 0.51, 95% CI = 0.11, 0.91).[66] Ailshire and colleagues investigated the relationship between exposure to ambient $PM_{2.5}$ and cognitive function among non-Hispanic white and black men and women aged 55 and older from the Americans' Changing Lives (ACL) study.[68] $PM_{2.5}$ exposure levels were assigned to participants based on their census tract from data obtained from EPA AQS. Cognitive function was assessed with a serial 3's subtraction test to measure working memory and recall of the date, day of the week, and name of the president and vice-president to measure orientation. The results indicated that participants who lived in areas with higher exposure to $PM_{2.5}$ had an error rate of 1.5 times greater than those exposed to lower $PM_{2.5}$ levels(IRR = 1.53, 95% CI: 1.02–2.30).[68]

2.7 Sociodemographic disparities and air toxic exposures

Disparities in risks and health outcomes associated with air toxic exposure are not uniformly distributed in populations. Exposure to air toxics can lead to health disparities attributed to individual-level and community-level vulnerability.[12,69,70] Scientific evidence has indicated that health disparities occur due to individual-level vulnerabilities because research shows that people of color and low-income individuals are often disproportionately impacted by adverse health effects due to air toxic exposure.[6,22] Also, at the community-level vulnerability, social and economic characteristics of residential areas tend to be associated with air toxic exposures and various health risks and outcomes. For instance, Gary and colleagues found that socioeconomic status (SES) and race/ethnicity were associated with $PM_{2.5}$ and O_3 exposures when they examined the racial and socioeconomic disparities in air pollution across North Carolina.[71] The results indicated that lower SES and a higher proportion of people of color were associated with higher concentrations of annual average $PM_{2.5}$, while lower SES and a higher proportion of people of color

were associated with lower concentrations of annual O_3.[71] Perlin et al. observed that African Americans were more likely to be of low income and reside near industrial emission sources.[72] Grineski et al. observed that census block groups that had lower neighborhood socioeconomic status, greater proportions of Latina immigrants and greater proportions of renters were exposed to higher concentrations of criteria air pollutants (NO_x, CO and O_3).[73]

Sociodemographic variables have been used to understand the disparities in exposures, risks, and health. Sociodemographic variables about race/ethnicity and socioeconomic status from the U.S Census Bureau data that have been used in existing research comprise: percent Hispanic, percent African American, percent non-white (inclusive of all races except non-Hispanic whites), percent home ownership, per capita income, median household (HH) income, percent poverty, percent unemployment, percent of homes built pre-1950, percent without a high school (HS) education, percent unemployed and percent urban area.[5,6,11,21,74]

Emerging research indicates that sociodemographic and geographic disparities exist in cancer risk due to exposure to air toxic. Apelberg et al. used 1996 NATA data and determined that the census tracts with a higher percentage of African Americans (3 times) and lower socioeconomic positions (10 to 100 times more likely) experienced increased cancer risk because of exposure to air toxics in Maryland.[75] Additionally, James et al. used cancer risk estimates for Cancer alley, LA from 2005 NATA data to show that individuals in low-income census tracts (12% more) and those in black-dominant tracts (16% more) experienced greater cumulative cancer risk than those in high-income and white-dominant tracts.[22] Wilson et al. indicated that a greater number of high cancer risk census tracts were found in tracts with higher percent poverty (3.6 times), homes

built pre-1950s (5.2 times), percent non-white (3.7 times), percent Hispanic (2.1 times) and in urban areas (17.8 times) in South Carolina.[76] Ekenga et al. observed that census tracts with higher percent non-white residents (18.5 times), percent African American (17.4 times), percent poverty (12 times), percent unemployment (3.4 times) and percent without high school education (2.8 times) were more likely to be identified as air toxic hot spots (at 99% significance level).[21] Collins et al. observed that census block groups with the highest proportion of Hispanics (3.6 times), the lowest proportion of non-Hispanic whites (2.71 times), lowest median household income (9.67 times), the highest proportion of people greater than 25 years without high school education (5 times), the highest proportion of percent income below the poverty level (7.67 times), a higher proportion of renter occupied rental units (10 times), the highest proportion of percent greater than 64 years (5 times), the highest proportion of female-headed households (6.75 times) were more likely to be identified among the high cancer risk census block groups.[74] Altogether, these results consistently show that census tracts with a higher percentage of people of color experience greater cancer risks because of exposure to air toxics than those with a lower percentage of people of color.

Although there is scientific evidence of socioeconomic and geographic disparities in health risks, including cancer risks due to air toxic exposure,[20,75–77] only one study[23] has examined these disparities based on the neurological risk associated with exposure to air toxics. Grineski and Collins examined social and geographic disparities to 24 air neurotoxicants in U.S. public schools using USEPA NATA 2011 data.[37] The authors showed that EPA region 5 (including Minnesota) has 16.5% of high-risk schools in the region with the third-highest levels of air neurotoxicants.[23]

Also, schools with an increased number of children of color, children in the earliest grades (elementary schools), and schools in urban counties are more likely to experience higher neurotoxicant risk.[23]

Chapter 3: Methods

We examined socioeconomic disparities in estimated neurological risk from air toxics in Minnesota. We obtained modeled neurological risk estimates from the U.S. EPA's 2014 NATA data and linked them to socioeconomic and racial characteristics from the 2010 – 2014 ACS 5-year U.S. The census tract was chosen as the unit of analysis to determine the relationship between Minnesota's economic and racial makeup and neurological risk from exposure to air toxics. Additionally, the census tract is the smallest unit for which the estimated cumulative neurological risks are available from the U.S. EPA's NATA 2014 data.

3.1 Study area: Minnesota

Minnesota is the 12th largest state (land area 79,626.7 square miles), [78] in the upper Midwestern of the United States and a part of North America's Great Lakes Region.[79] Minnesota shares a water border with Michigan, and to the east, a land and water border with Wisconsin. Also, it shares a border with Iowa to the south, North and South Dakota to the west, and Canada (Ontario and Manitoba) to the north.[79] The 2020 U.S. Census revealed that, as of April 1, 2020, Minnesota had a population of 5,706,494.[80,81] 50.2% of the people are female, 23.1% are under 18 years, and 16.3% are 65 years and above.[80] 83.8% of the population are white, while 79.1% are white alone.[80] Black or African Americans account for 7%, 5.6% are Hispanic or Latino, 1.4% are American Indian and Alaska Native, 5.2% are Asian alone, and 0.1% are Native Hawaiian and

other Pacific Islander alone.[80] Also, Minnesota has 1,338 census tracts, 4,111 block groups, and 259,777 blocks.[78]

3.2 National Scale Air Toxics Assessment (NATA)

The NATA dataset includes all air toxics or hazardous air pollutants (HAPs), which have carcinogenic, neurological, developmental, respiratory, immunological, and reproductive adverse health effects. Our data was focused on air toxics with neurological health effects. There are 24 neurotoxicants which are in the NATA dataset (as shown in Table 1): 1,1,1-Trichloroethane, 2,4-Dinitrotoluene, Acrylamide, Allyl Chloride, Benzidine, Calcium Cyanamide, Carbon Disulfide, Carbonyl Sulfide, Cresol/Cresylic Acid, Cyanide Compounds, Dichlorvos, Ethylene Oxide, Hexachloroethane, Hexane, Lead Compounds, Manganese Compounds, Mercury Compounds, Methyl Chloride (Chloromethane), Selenium Compounds, Styrene, Tetrachloroethylene, Toluene, Trichloroethylene, and Xylenes. The EPA additively models the neurological risks of different pollutants (hazard quotient – Equation 1) to estimate an aggregate neurological risk score (hazard index – Equation 2) for each census tract (as shown and discussed under NATA's estimation of neurological risk in chapter 2). The EPA suggests adding the exposure risk estimates for each chemical known to affect the same target organ (e.g., the nervous system in this case) to compute a cumulative exposure risk score, given the significant degree of uncertainty surrounding non-additive interactions between chemicals. The neurological risk estimates were determined based on the concentration of each pollutant to which people are exposed and each chemical's reference concentration (i.e., the amount of toxicity below which long-term exposure to the general population is not expected to result in adverse effects). These estimates reflect neurological risk due to

chronic inhalation exposure to air toxics.[36] The variable used in this study is cumulative neurological risk, which includes neurological risks associated with inhalation exposure to air toxics released by the different emission sources. In the NATA dataset, there are five different emission sources: (1) on-road, (2) nonroad, (3) major or point, (4) area or non-point, and (5) background sources. In addition, the USEPA's NATA dataset includes neurological risk estimates for each source and a total neurological risk estimated as the sum of the risks from all the emission sources. Currently, the NATA is publicly available and is a widely used secondary data source for a spatially explicit characterization of air toxic exposure and risk in the U.S.

Table 1. Description of the 24 neurotoxicants contained in the NATA dataset

Air toxicants	Noncancer chronic air reference	Reference concentration (mg/m^3)	Reference concentration (ug/m^3)	Human or animal study	Critical health endpoints
1,1,1 -Trichloroethane	IRIS	5		rat	Performance on neurobehavioral tests
	CAL OEHHA		400		Nervous system
2,4-Dinitrotoluene	IRIS	n/a			Neurotoxicity
Acrylamide	IRIS	0.006	6	rat	Degenerative nerve changes
Allyl Chloride	IRIS	0.001	1	rabbit	Functional and histological peripheral neurotoxicity
Benzidine	IRIS	n/a			
Calcium Cyanamide		n/a			
Carbon Disulfide	IRIS	0.70		Occupational study	Peripheral nervous system dysfunction
	CAL EPA		800		Nervous system
Carbonyl Sulfide	CAL OEHHA		10		Nervous system
Cresol/Cresylic Acid	IRIS				
	CAL EPA		600		Nervous system
Cyanide Compounds	IRIS		0.8		Nervous system
Dichlorvos	IRIS	0.0005		rat	Decreased brain cholinesterase activity
Ethylene Oxide	CAL EPA		30		Nervous system
Hexachloroethane	IRIS		30		Neurotoxicity (tremors and ruffled pelt)
Hexane		0.70	700	rat	Peripheral neuropathy (decreased MCV at 12 weeks)
Lead Compounds	NAAQS		0.15		Nervous system

Manganese Compounds	MDH HRV		0.2		Nervous system
Mercury Compounds	IRIS	0.0003	0.3	Occupational study	Hand tremor; increases in memory disturbances; slight subjective and objective evidence of autonomic dysfunction
Methyl Chloride (Chloromethane)	IRIS	0.09		mouse	Cerebellar lesions
Selenium Compounds	CAL EPA		20		Nervous system
Styrene	IRIS	1		Occupational study	CNS effects
Tetrachloroethylene	IRIS	0.04		Human	Neurotoxicity
Toluene	IRIS	5		Human (Occupational study)	Neurological effects in occupationally-exposed workers
Trichloroethylene	IRIS	0.02		rat, mice	Nervous system
Xylenes	IRIS	0.1		rat	Impaired motor coordination (decreased rotarod performance)

Integrated Risk Information System (IRIS) from U.S. Environmental Protection Agency (EPA), California Environmental Protection Agency Office of Environmental Health Hazard Assessment (CAL EPA-OEHHA), Minnesota Department of Health Health Risk Values (MDH HRV)

3.3 Census Data - Socioeconomic Measures

We obtained the U.S. Census 2010-2014 data for Minnesota. Socioeconomic measures including income, wealth, poverty and education indicators were considered because of prior use in previous studies assessing air toxic exposure, risk, and health outcomes.[75,76,82] Specifically, we used percent non-Hispanic white, percent Hispanic, percent non-Hispanic black or African American, percent people of color (inclusive of all races except non-Hispanic whites), median household (H.H.), income, percent poverty, percent unemployed, and percent without a high school (H.S.) education (data was obtained from data.census.gov and accessed 1 December 2021).

3.4 Statistical Analysis

We downloaded the 2014 NATA data (from https://www.epa.gov/national-air-toxics-assessment/2014-nata-assessment-results#nationwide and accessed 1 December 2021) and racial/socioeconomic data from the U.S. Census 2010-2014 estimates as Excel spreadsheets and the census

2010 tiger shapefile for Minnesota (shapefile was obtained from https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2010.html and accessed 1 December 2021). NATA 2014 and 2010-2014 U.S. Census data were merged using FIPS codes. Data linking, management and statistical analysis were performed in R and mapped using ArcGIS version 10. We calculated summary descriptive statistics to show the distribution of demographic characteristics and estimated neurological risk from air toxics among the census tracts in Minnesota. We conducted a correlation analysis between neurological risk estimates from each emission source and census tract level demographic characteristics as continuous variables to determine the linear association's strength and direction. These correlations allowed us to observe the linear relationship between different sources of neurological risk regarding their relationship with sociodemographic factors.

3.5 Spatial Analysis

We created choropleth maps and graduated symbology of sociodemographic measures of the population and cumulative neurological risk estimates in Minnesota, respectively. Disparity and correlational maps were created by overlaying sociodemographic measures individually as graduated symbols on choropleth maps of cumulative neurological risk for clarity. Finally, we excluded red and green colors from our maps to make them color blind adaptive.

Chapter 4: Results

The distribution of the hazard quotients for the 24 neurotoxicants in the EPA dataset are shown in Table 2. 13 of the 24 neurotoxicants had maximum values greater than 0, while 8 of them had minimum values greater than 0. The maximum values of the hazard quotients ranged from 0.0002 to 0.0475. Cyanide compounds had the highest mean value of 0.0142 (minimum = 0.0001 and maximum = 0.0475) and toluene had the lowest mean value of 0.0002 (minimum = 0 and maximum = 0.0004). Methyl Chloride (Chloromethane) had the largest minimum value of 0.0057. Cyanide compounds, tetrachloroethylene and trichloroethylene had the lowest minimum value of 0.0001.

The distribution of sociodemographic variables and cumulative neurological risk estimates from air toxics by emission source categories for Minnesota are summarized in Table 3. The mean percent non-Hispanic white, percent non-Hispanic black and percent Hispanic account for 81.8%, 5.6%, and 5.1% of the population. 18.2% of Minnesotans were people of color. The mean percent of the population without a high school education was 15.3% and 2.2% were un-employed. The state's mean poverty rate was 23.3%.

The mean cumulative neurological risk or hazard index from all sources was ~ 0.05. The estimated mean cumulative neurological risk from area sources (~0.03) was higher than the mean cumulative neurological risk from all other sources (major, on-road, nonroad and background). Also, the lowest mean cumulative neurological risk was from background sources (0.000004). Furthermore, the variation in cumulative neurological risk between the 5th and 95th percentiles of all sources reflected a wide range in risk (~0.02 and ~0.11, respectively), while nonroad sources demonstrated a smaller range in risk (0.0007 and 0.0036, respectively). The neurological risk from all sources, area sources and major sources increased progressively from the 5th percentile to the 95th percentile as shown in Figure 1.

Table 2. Distribution of the hazard quotients for the 24 neurotoxicants contained in the NATA dataset

		Hazard Quotient		
Air toxicants	**CAS RN**	**Mean**	**Minimum**	**Maximum**
1,1,1 -Trichloroethane	71-55-6	0	0	0
2,4-Dinitrotoluene	121-14-2	0	0	0
Acrylamide	79-06-1	0	0	0.0017
Allyl Chloride	107-05-1	0	0	0
Benzidine	92-87-5	0	0	0
Calcium Cyanamide		0	0	0
Carbon Disulfide	75-15-0	0	0	0
Carbonyl Sulfide	463-58-1	0	0	0
Cresol/Cresylic Acid	1319-77-3	0	0	0.0002
Cyanide Compounds		0.0142	0.0001	0.0475
Dichlorvos	62-73-7	0	0	0
Ethylene Oxide	75-21-8	0	0	0.0011
Hexachloroethane	67-72-1	0	0	0
Hexane	110-54-3	0.0003	0	0.0139
Lead Compounds	7439-92-1	0.0017	0.0002	0.038
Manganese Compounds		0.0011	0.0002	0.0254
Mercury Compounds	7439-97-6	0.0039	0.0022	0.0146

Methyl Chloride (Chloro-methane)	74-87-3	0.0113	0.0057	0.0349
Selenium Compounds	0-01-9	0	0	0
Styrene	100-42-5	0	0	0
Tetrachloroethylene	127-18-4	0.0005	0.0001	0.011
Toluene	108-88-3	0.0002	0	0.0004
Trichloroethylene	79-01-6	0.0106	0.0001	0.3457
Xylenes	1330-20-7	0.0045	0.0003	0.0144

Table 3. Distribution of demographic characteristics (2010-2014) and estimated neurological risk from air toxics among Minnesota census tracts (n = 1338 tracts)

Characteristic	**Mean**	**SD**	**Min**	**Max**	**5th**	**25th**	**50th**	**75th**	**95th**
Median household income (US$)	61979	23504.2	12255	177727	32306	46341	56708	73430	108265
Percent poverty	23.3	8.3	3.7	61.4	11.1	17.3	23.0	28.2	38.3
Percent without high school educa-tion	15.3	10.7	0.0	70.8	0.0	7.4	13.9	20.6	35.6
Percent unemployed	2.2	1.1	0.3	10.6	0.8	1.4	1.9	2.7	4.3
Percent Non-Hispanic white	81.8	18.5	2.6	99.6	36.0	76.7	88.2	94.6	97.8
Percent Non-Hispanic black	5.6	9.6	0.0	76.2	0.0	0.3	1.6	6.5	24.4
Percent Hispanic	5.0	6.5	0.0	59.5	0.3	1.3	2.8	6.1	17.8
Percent people of color	18.2	18.5	0.4	97.4	2.2	5.4	11.8	23.4	64.0
Neurological risk									
All sources	0.0483	0.0345	0.0161	0.4239	0.0185	0.0234	0.0377	0.0733	0.1083
Major or point sources	0.0144	0.0183	0.0001	0.3558	0.0013	0.0036	0.0097	0.0189	0.0396
Area or non-point sources	0.0311	0.0169	0.0026	0.0631	0.0123	0.0171	0.0244	0.0476	0.0605
On-road sources	0.0034	0.0025	0.0002	0.0105	0.0004	0.0009	0.0030	0.0056	0.0074
Nonroad sources	0.0022	0.0011	0.0003	0.0160	0.0007	0.0013	0.0024	0.0030	0.0036
Background sources	0.000004								

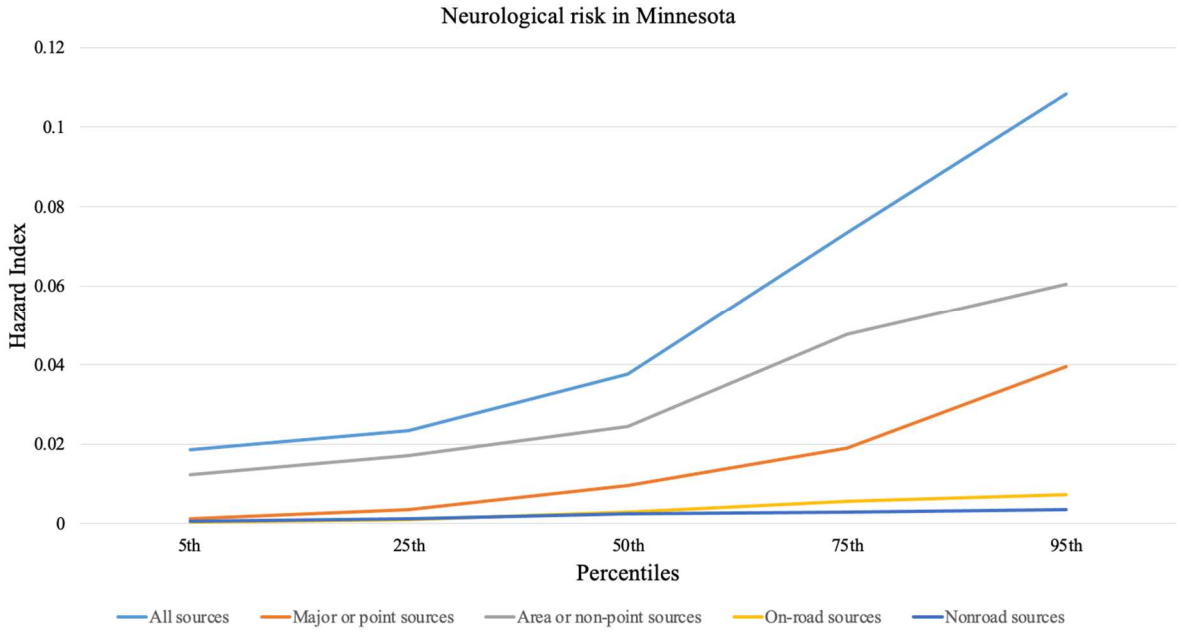

Figure 1. Neurological risk values at selected percentiles for Minnesota

The first step in investigating relationships between sociodemographic variables and exposure to air toxics was to conduct a correlation analysis. The correlation values between cumulative neurological risk by source and sociodemographic variables are displayed in Table 2. Race-related variables (percent non-Hispanic white (-0.18), people of color (0.18), percent non-Hispanic Black (0.17) and percent Hispanic (0.10)) had higher correlation values with cumulative neurological risk from all sources than other sociodemographic characteristics. Median household income, percent unemployed, percent non-Hispanic black, percent Hispanic and percent people of color were weakly positively correlated with cumulative neurological risk from the different source categories. Percent poverty, percent without high school education and percent non-Hispanic white were weakly negatively correlated with cumulative neurological risk from the different source emission categories.

Table 4. Correlation between NATA neurological risk and sociodemographic characteristics (2010-2014) in Minnesota (n 1338 = tracts)

	Median household income (US$)	Percent poverty	Percent without high school education	Percent unemployed	Percent non-Hispanic white	Percent non-Hispanic black	Percent Hispanic	Percent people of color
Neurological risk								
All sources	0.15****	-0.15****	-0.08**	0.12****	-0.18****	0.17****	0.10***	0.18****
Major or point sources	0.07**	-0.06*	-0.06*	0.09***	-0.13****	0.11****	0.08**	0.13****
Area or non-point sources	0.18****	-0.20****	-0.08**	0.13****	-0.19****	0.19****	0.10***	0.19****
On-road sources	0.21****	-0.20****	-0.08**	0.11****	-0.17****	0.17****	0.09***	0.17****
Nonroad sources	0.21****	-0.17****	-0.07*	0.08**	-0.14****	0.14****	0.07**	0.14****
Background sources	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

***p<0.05, **p<0.01, ***p<0.001, ****p<0.00001**

The neurological risk from nonroad sources had a higher correlation value with median household income (0.21) than other sociodemographic characteristics. Also, the correlation between the neurological risk from on-road sources and median household income was 0.21. The neurological risk for area sources had higher correlation values with race/ethnicity-related variables than the other source emission categories. The correlation of percent non-Hispanic white, percent non-Hispanic black, percent Hispanic and percent people of color were -0.19, 0.19, 0.10 and 0.19, respectively, with cumulative neurological risk from area sources. Overall, we observed a weak correlation which was statistically significant between cumulative neurological risk and the various sociodemographic variables.

The spatial distributions of cumulative neurological risk and sociodemographic characteristics are displayed in Figures 1to 8. The choropleth map showing the distribution percent non-Hispanic white (Figure 2) indicates the population is majorly white with about greater than 70.9% accounting for the population that self-identify as white. Map showing the distribution of percent

non-Hispanic Black population (Figure 3) reveals that the black or African American population (9.11% to 76.20%) are concentrated in certain parts of Minnesota. Also, the map showing the distribution of percent of the population that identify as Hispanic (Figure 4) also indicates that Hispanics (7.71% to 59.5%) are concentrated in certain areas of the state. In addition, the map showing the distribution of the percent of the population that identifies as people of color (Figure 5) shows that people of color (29.31% to 97.40%) are concentrated in certain parts of Minnesota.

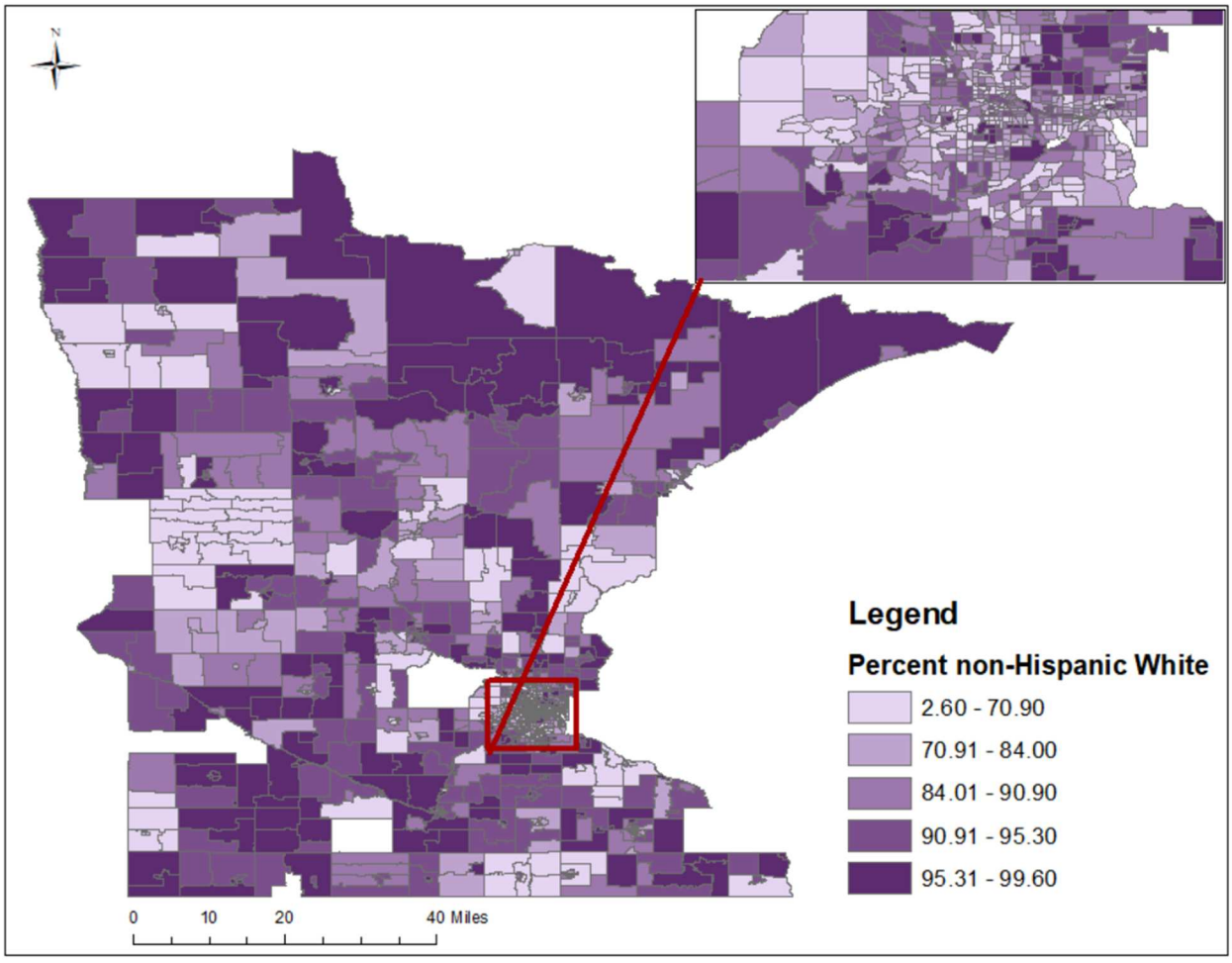

Figure 2. Map showing the distribution of percent non-Hispanic white in Minnesota (with an insert showing the Minneapolis-St. Paul area)

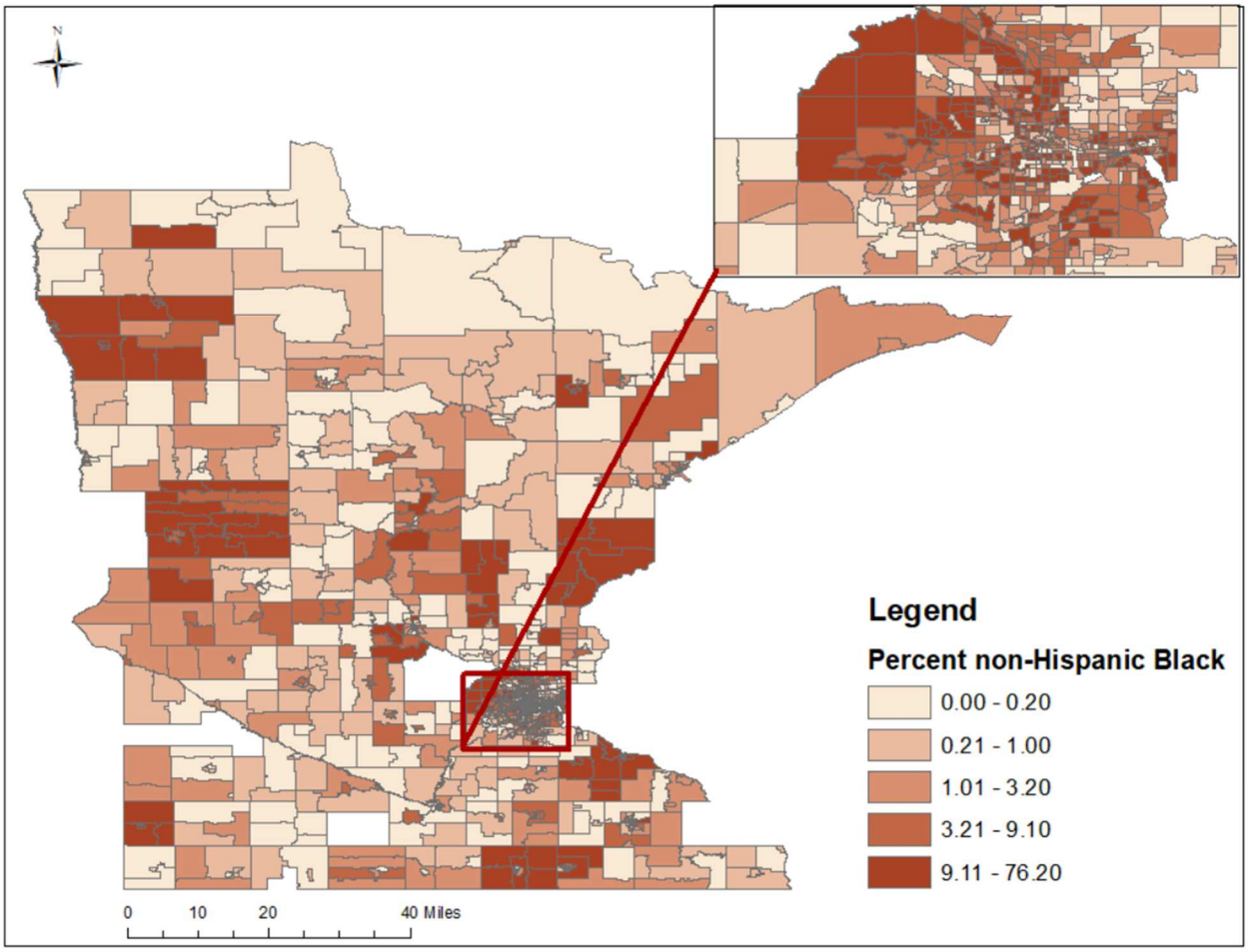

Figure 3. Map showing the distribution of percent non-Hispanic black in Minnesota (with an insert showing the Minneapolis-St. Paul area)

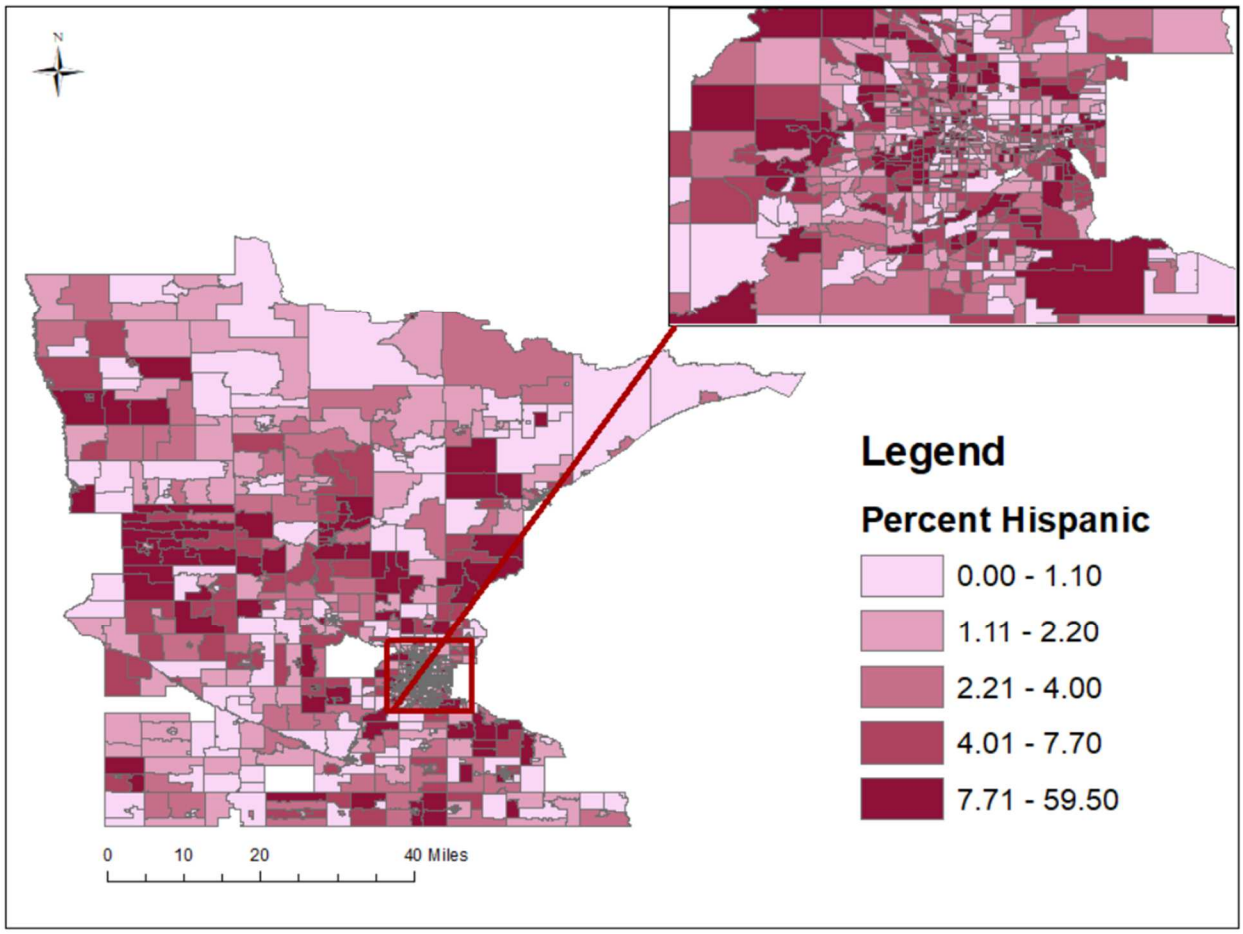

Figure 4. Map showing the distribution of percent Hispanic in Minnesota (with an insert showing the Minneapolis-St. Paul area)

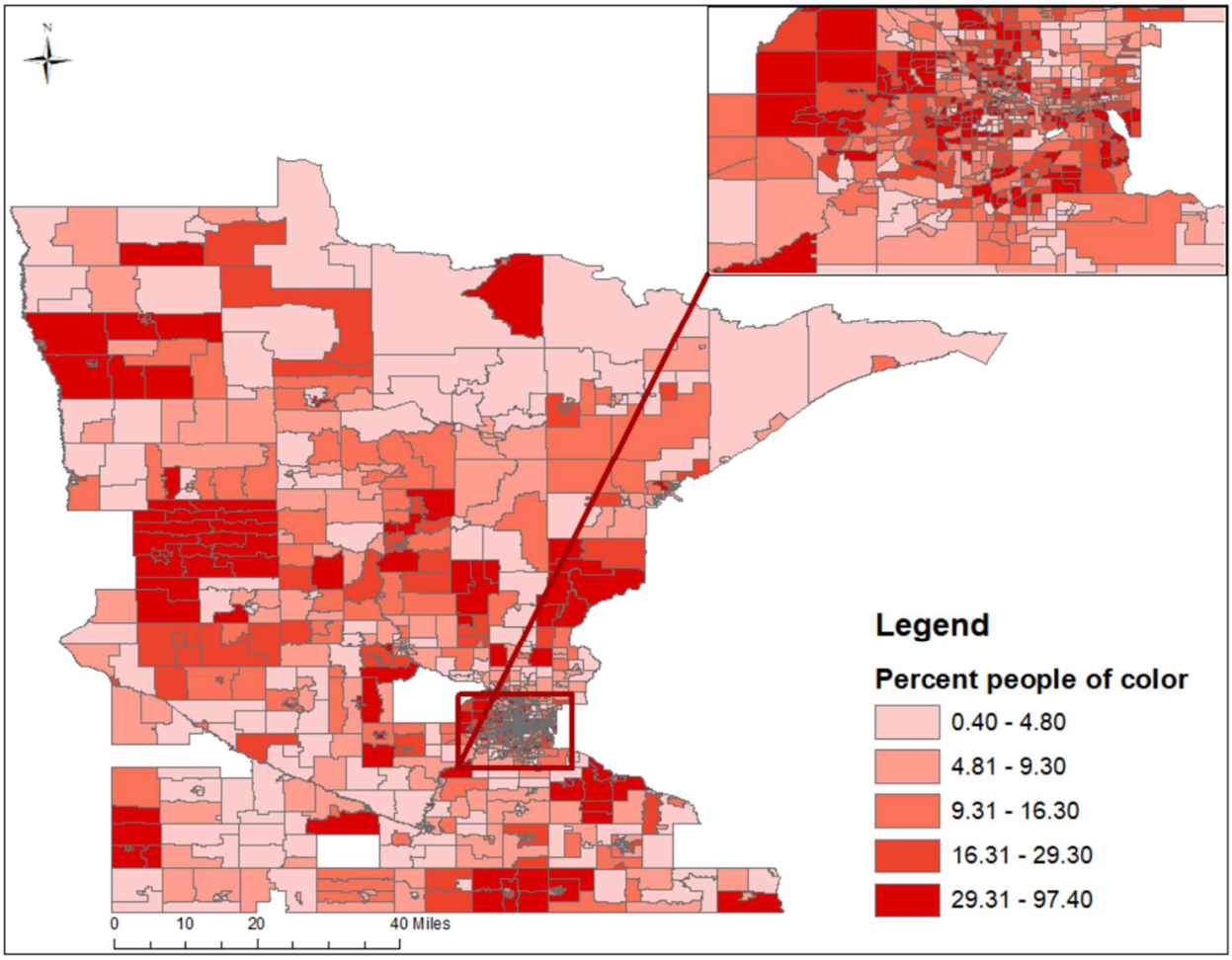

Figure 5. Map showing the distribution of percent people of color in Minnesota (with an insert showing the Minneapolis-St. Paul area)

The choropleth map showing the distribution of the median household income ($) in Minnesota (Figure 6) reveals that a larger proportion of the state has median household incomes greater than $52,500. The distribution of the percent of the unemployed population is shown in Figure 7, which shows that some census tracts have greater than 3.11% of the population unemployed. Figure 8 shows the distribution of percent poverty in Minnesota, which reveals that census tracts with greater than 21.01% percent poverty are scattered across the state. The distribution of the percent of the population with less than high school education (Figure 9) shows that census tracts

with greater than 22.70% of the population with less than high school education are concentrated in the northern part of Minnesota.

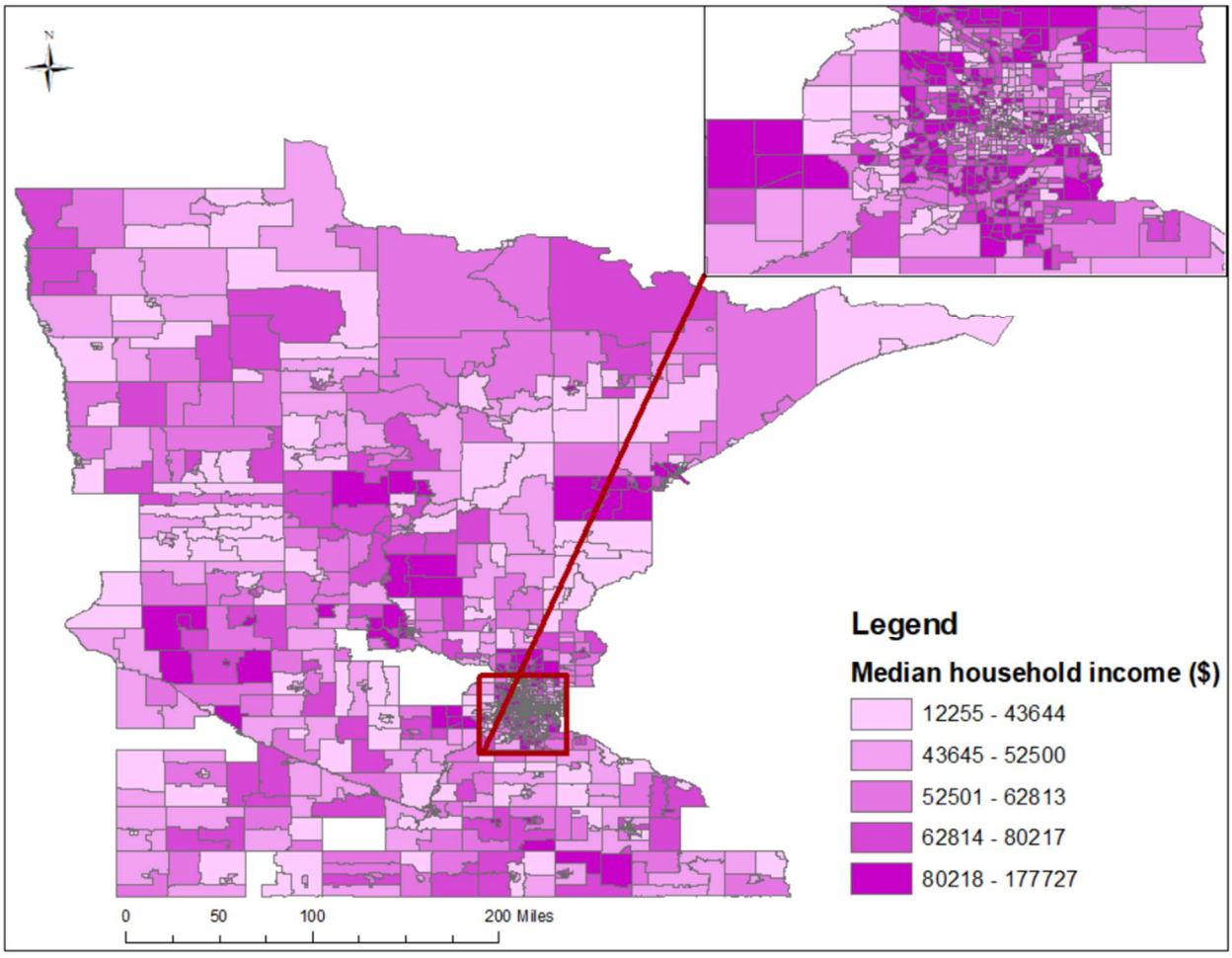

Figure 6. Map showing the distribution of median household income ($) in Minnesota (with an insert showing the Minneapolis-St. Paul area)

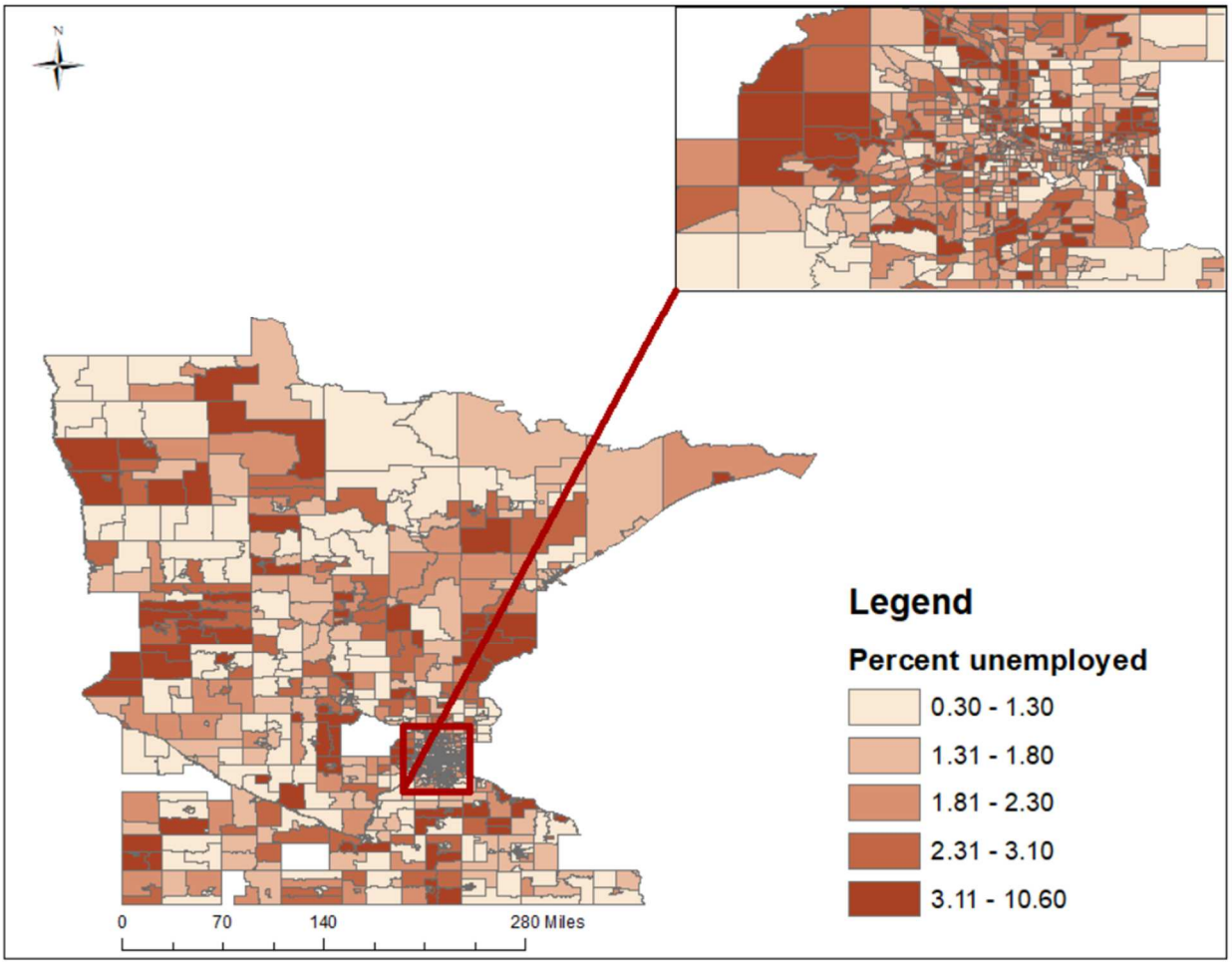

Figure 7. Map showing the distribution of percent of the population that is unemployed in Minnesota (with an insert showing the Minneapolis-St. Paul area)

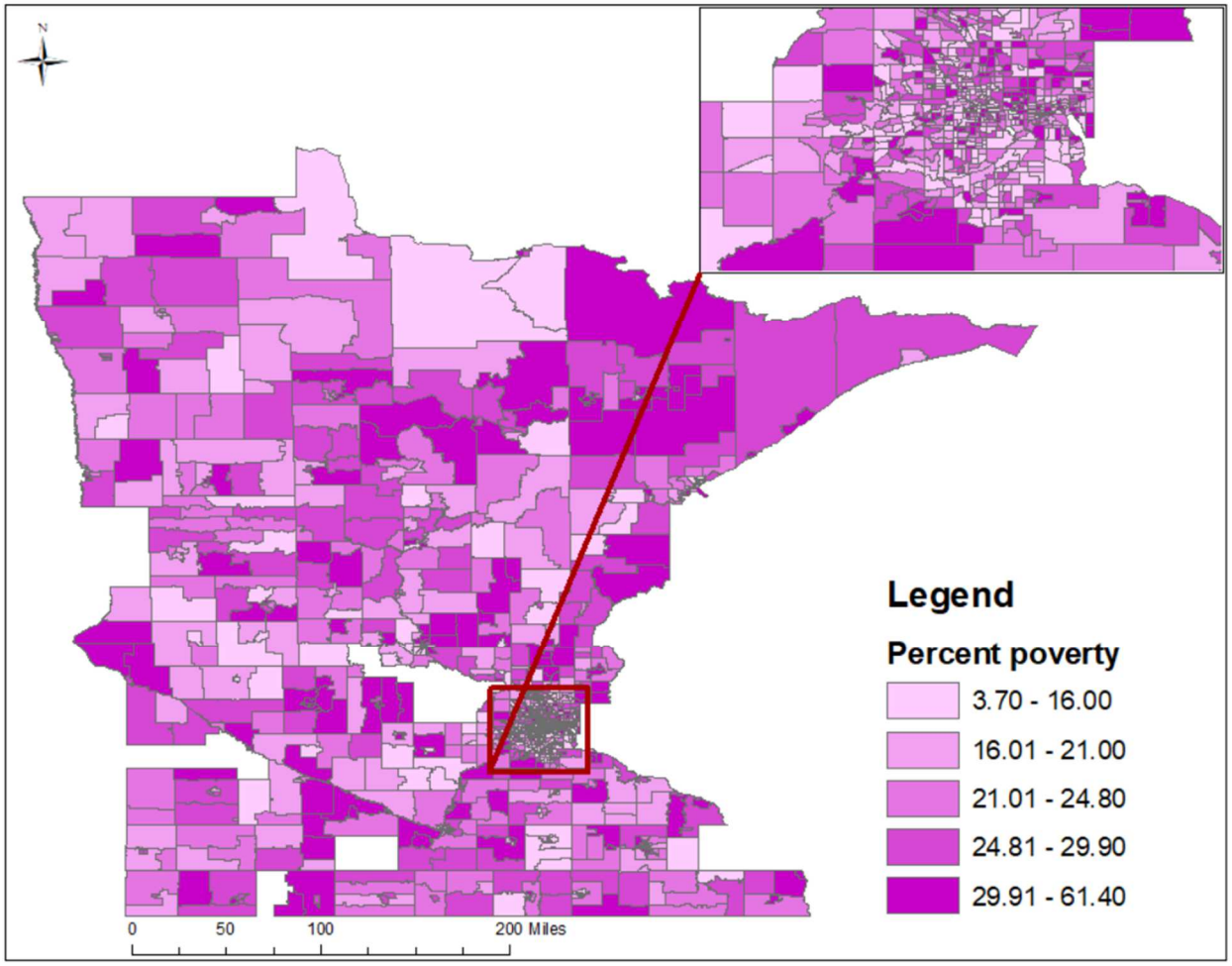

Figure 8. Map showing the distribution of percent poverty in Minnesota

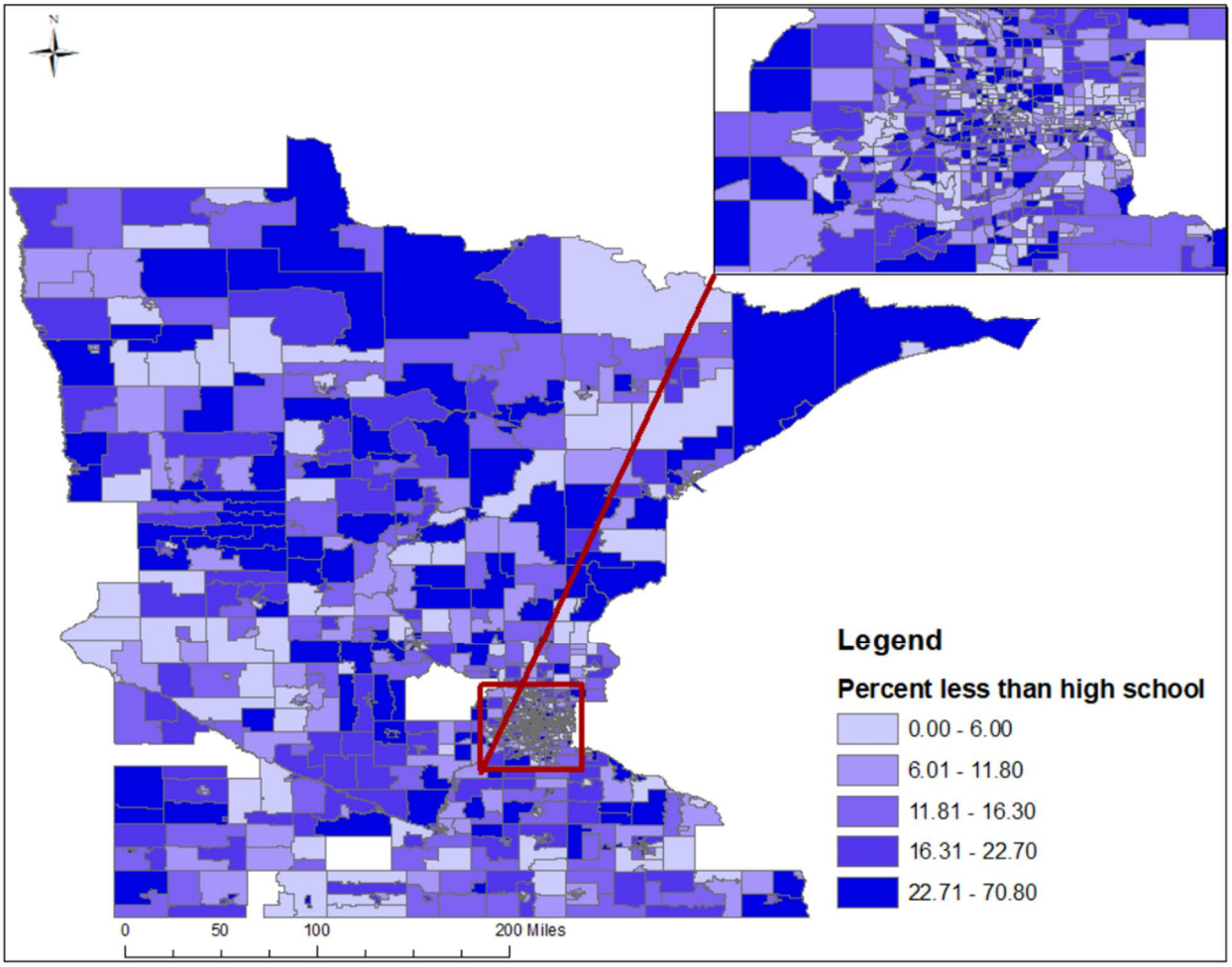

Figure 9. Map showing the distribution of percent of the population with less than high school education in Minnesota (with an insert showing the Minneapolis-St. Paul area)

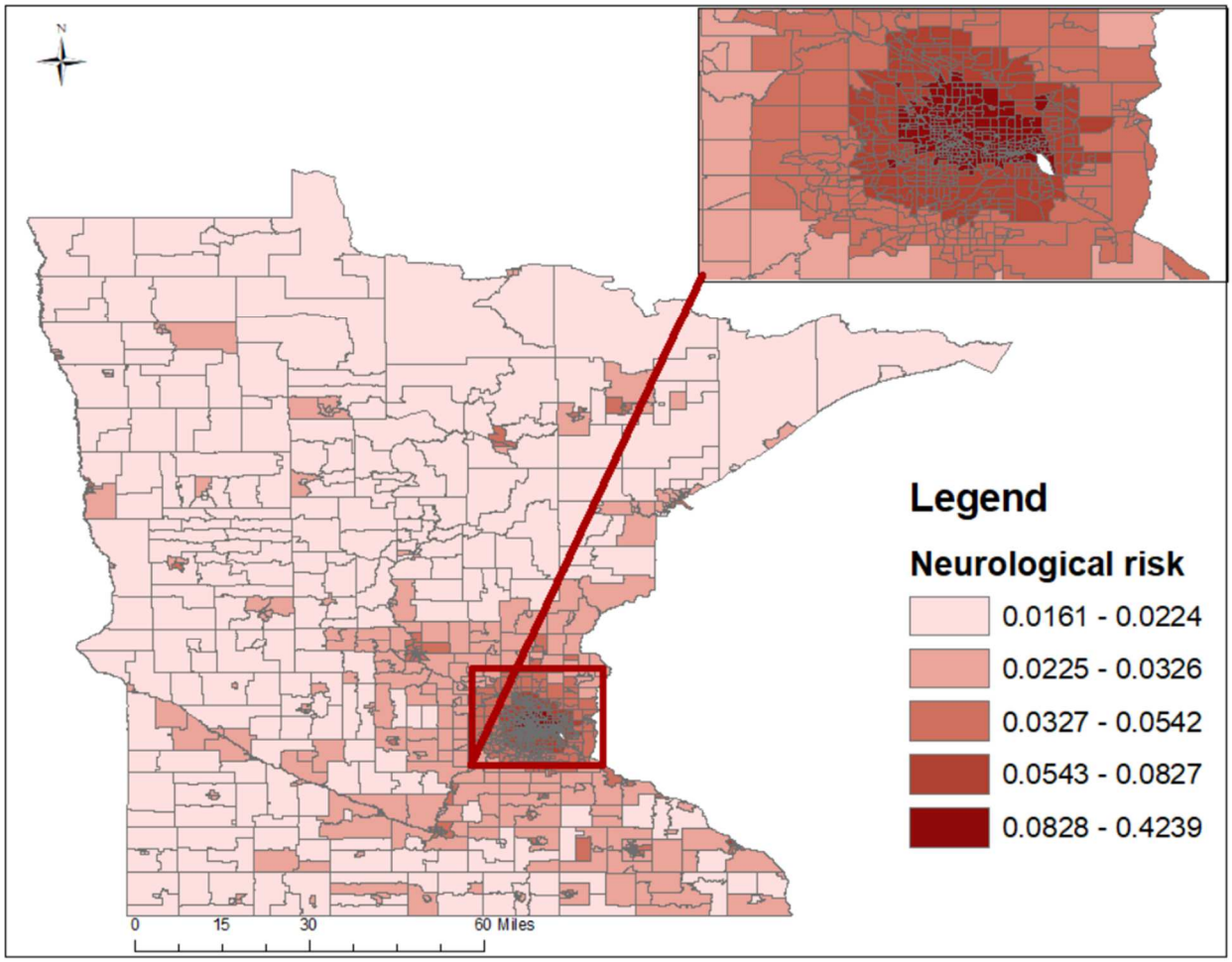

Figure 10. Map of the distribution of cumulative neurological risk in Minnesota (with an insert showing the Minneapolis-St. Paul area)

The map showing the distribution of cumulative neurological risk in Minnesota (Figure 10) shows that the cumulative neurological risk is greatest in the south-eastern part of Minnesota (Minneapolis-St. Paul area). It is observed that the highest values of neurological risk are at the center of this cluster. The map showing the cumulative neurological risk and percent people of color (Figure 11) shows that the census tracts with higher neurological risks (in the south-eastern part of the state) have greater than 16.30% of the population as people of color. Figure 12 shows the map of cumulative neurological risk and percent non-Hispanic white. Figure 13 displays a

map of cumulative neurological risk and percent non-Hispanic black. Figure 14 shows the map of cumulative neurological risk and percent Hispanic. Figures 15, 16, 17 and 18 are maps that show cumulative neurological risk and percent poverty, median household income, percent less than high school education and percent unemployed respectively.

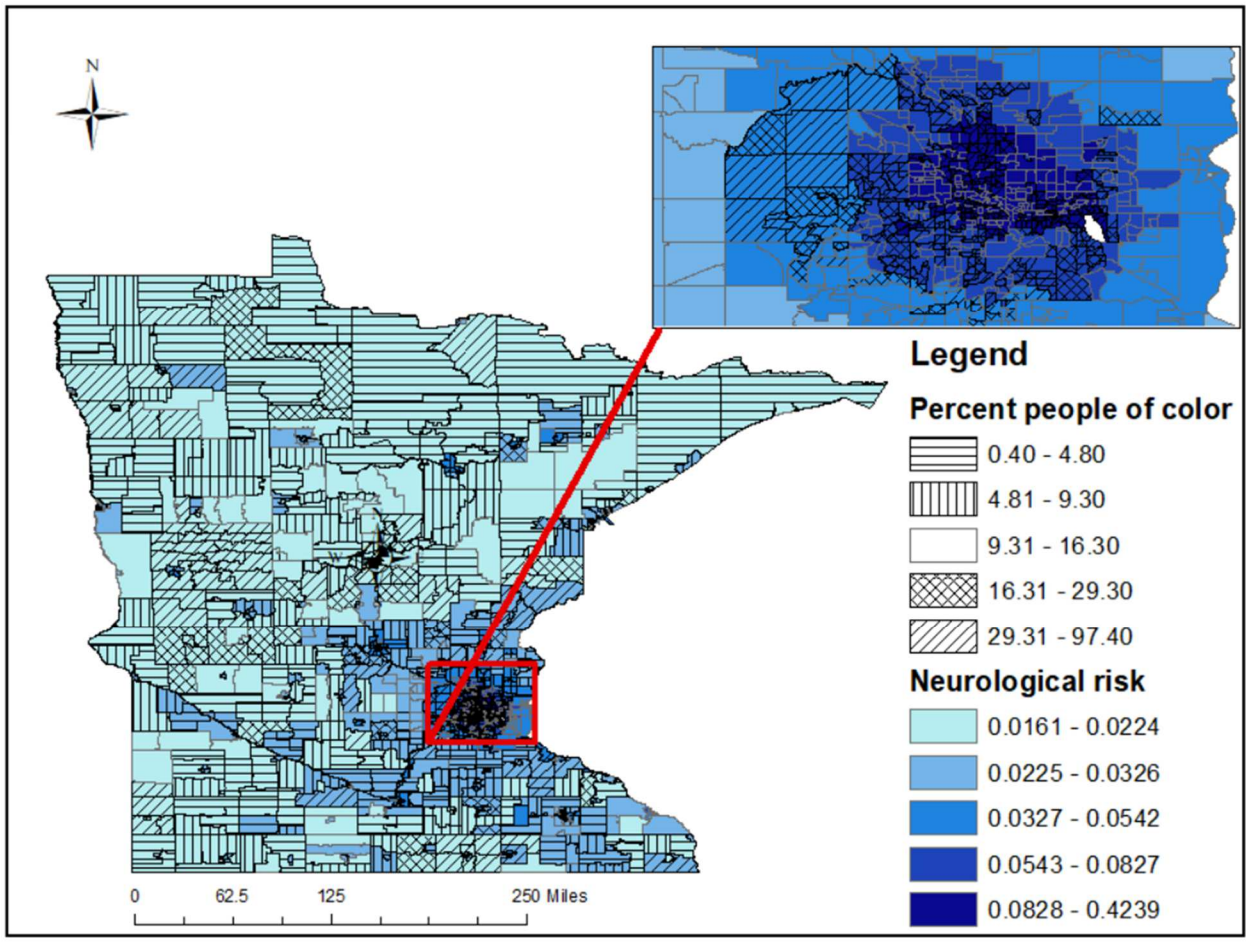

Figure 11. Map of the distribution of cumulative neurological risk and percent people of color in Minnesota (with an insert showing the Minneapolis-St. Paul area)

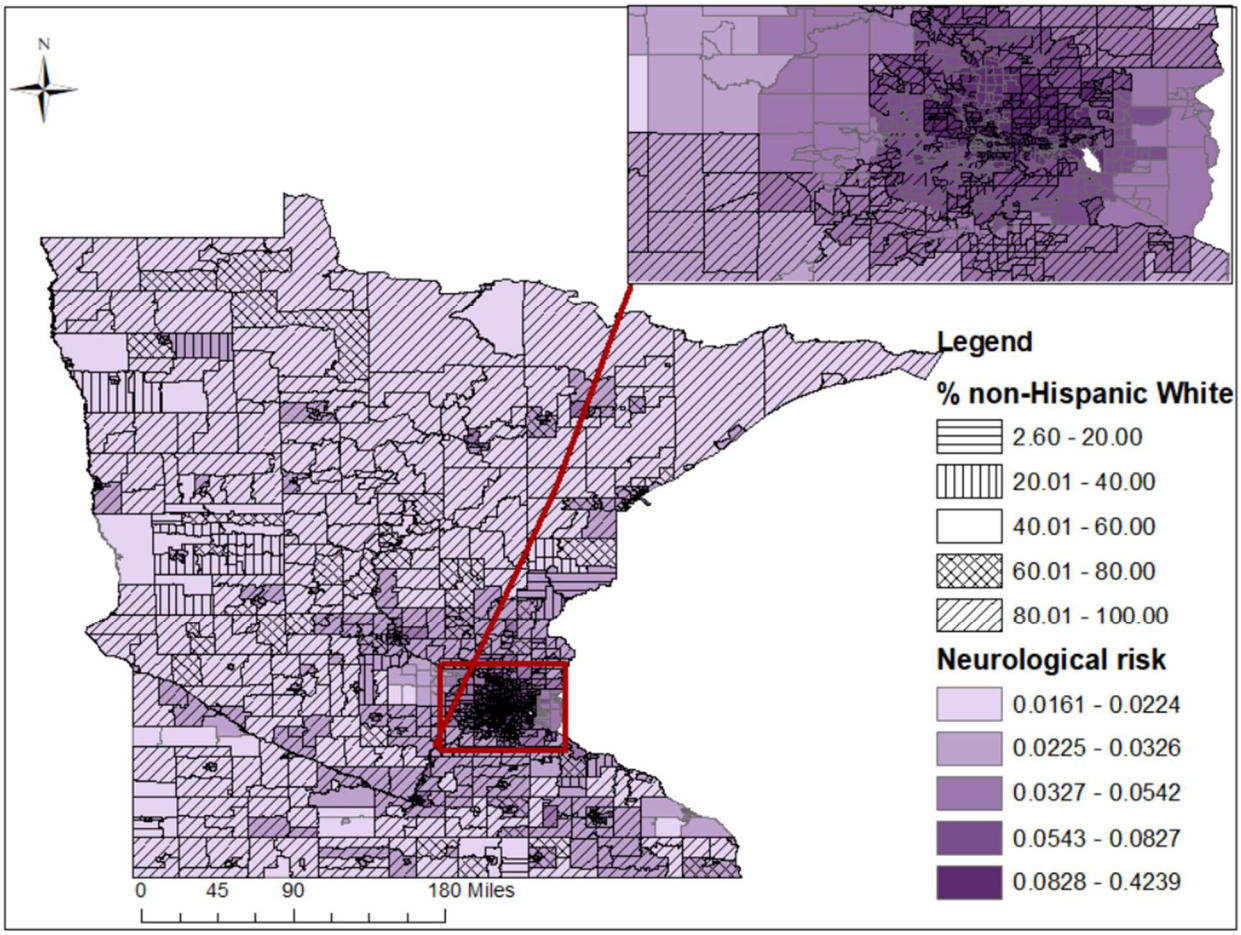

Figure 12. Map showing the distribution of cumulative neurological risk and percent non-Hispanic white in Minnesota (with an insert showing the Minneapolis-St. Paul area)

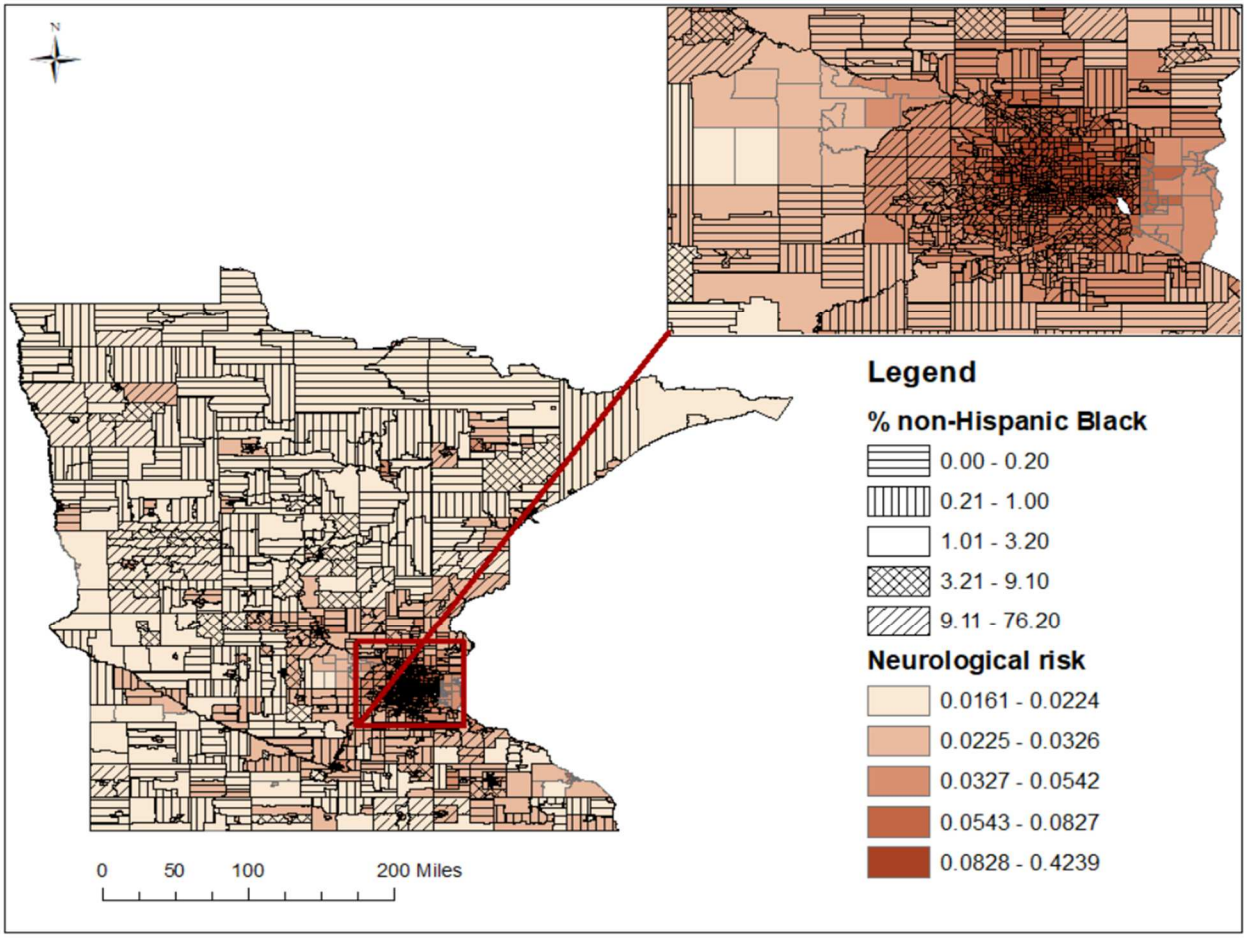

Figure 13. Map showing the distribution of cumulative neurological risk and percent non-Hispanic Black in Minnesota (with an insert showing the Minneapolis-St. Paul area)

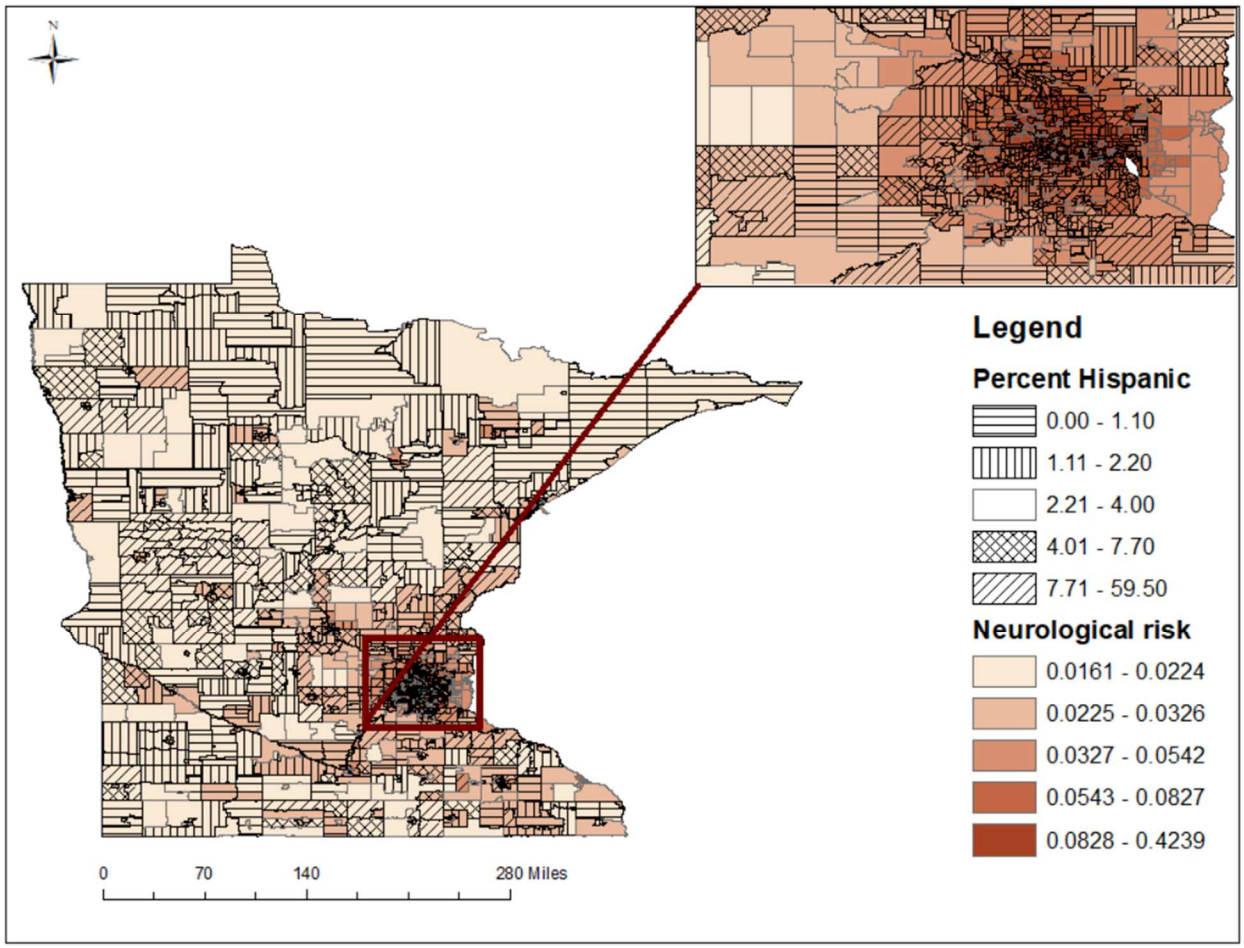

Figure 14. Map showing the distribution of cumulative neurological risk and percent Hispanic in Minnesota (with an insert showing the Minneapolis-St. Paul area)

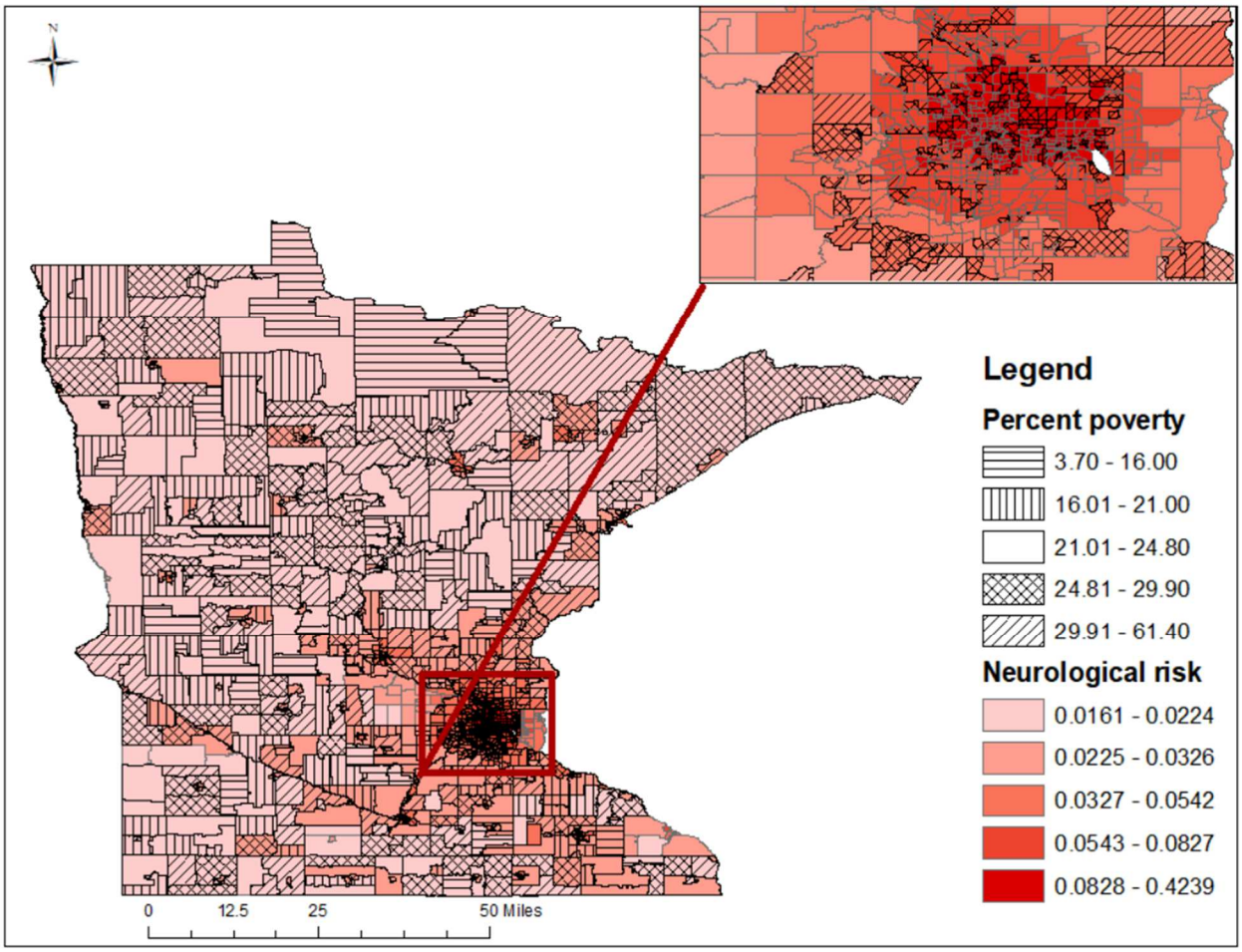

Figure 15. Map showing the distribution of cumulative neurological risk and percent poverty in Minnesota (with an insert showing the Minneapolis-St. Paul area)

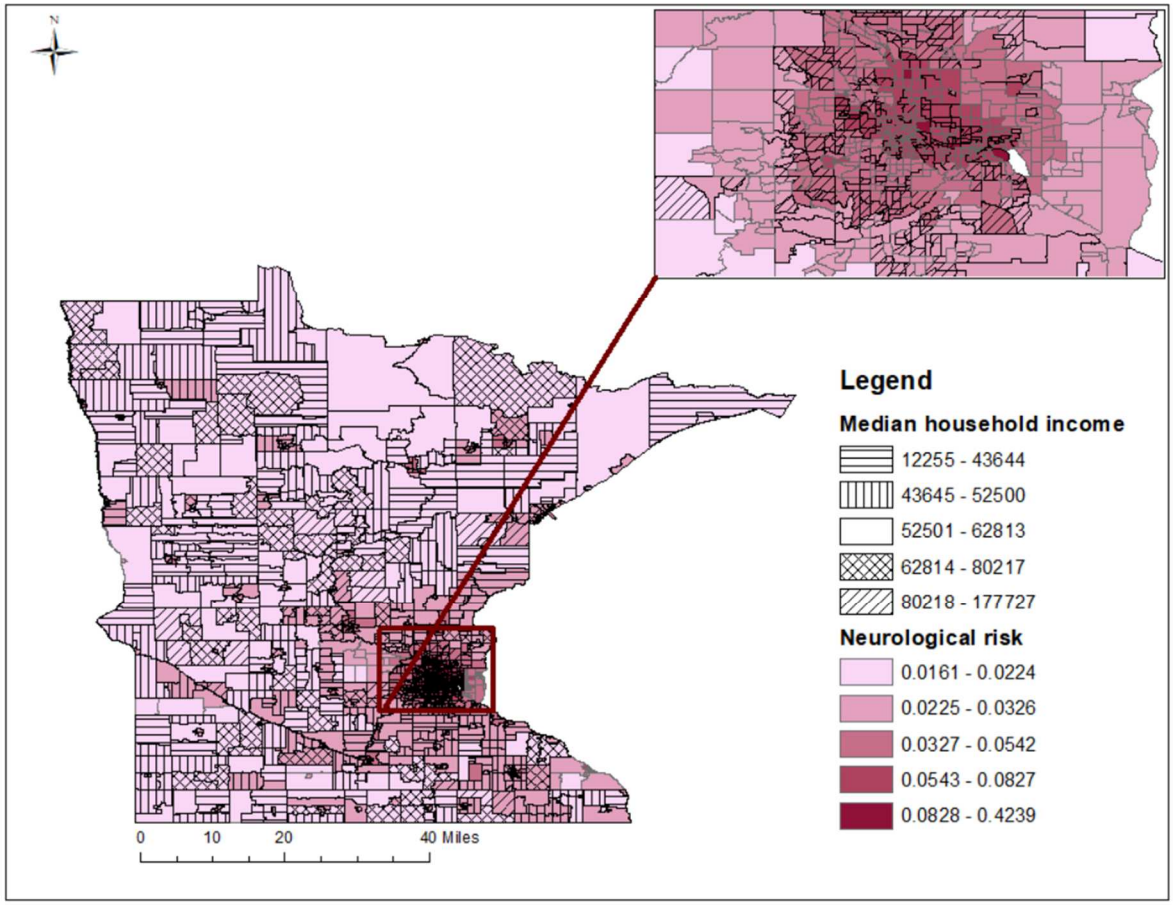

Figure 16. Maps of the distribution of cumulative neurological risk and median household income ($) in Minnesota (with an insert showing the Minneapolis-St. Paul area)

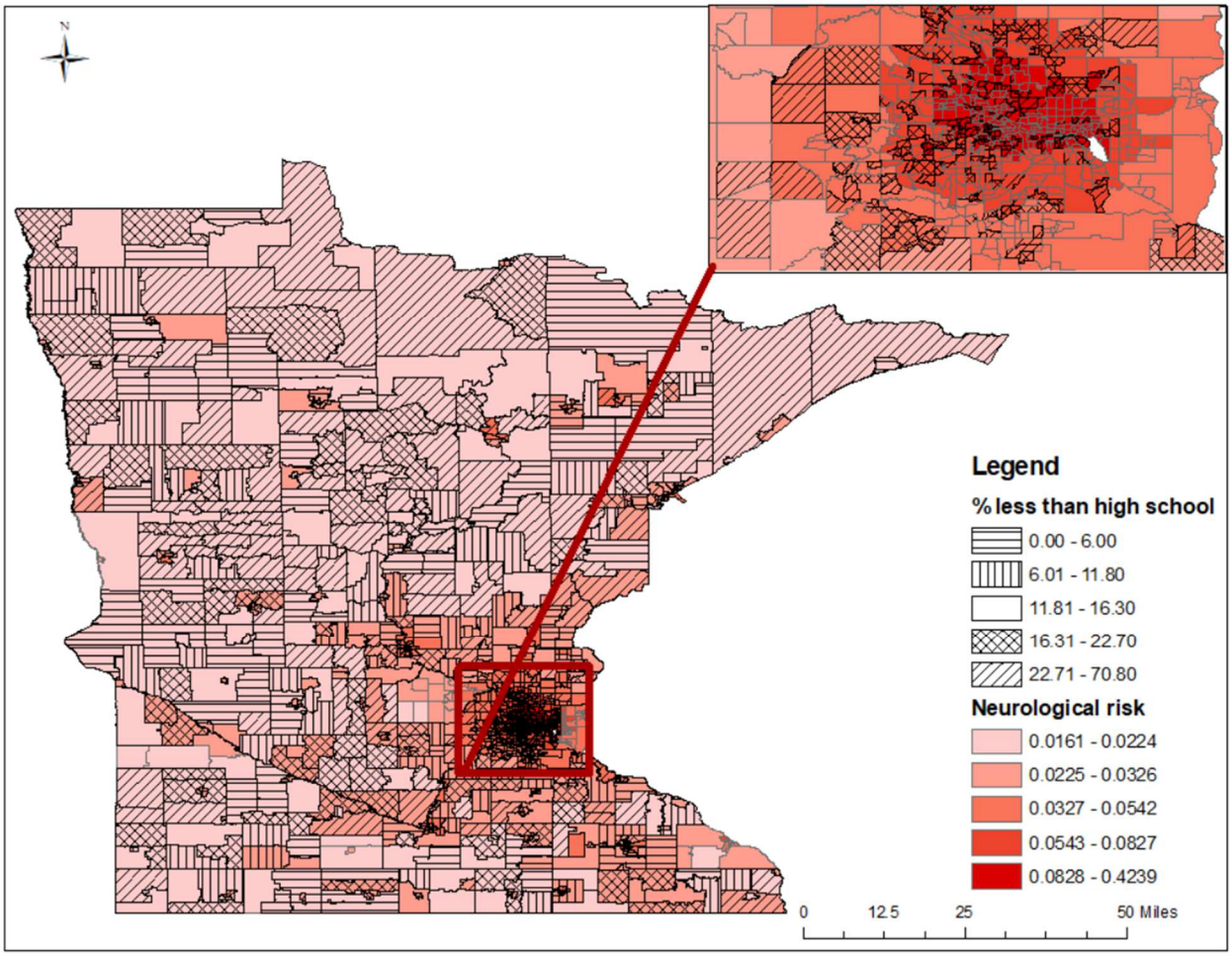

Figure 17. Maps of the distribution of cumulative neurological risk and percent with less than high school education in Minnesota (with an insert showing the Minneapolis-St. Paul area)

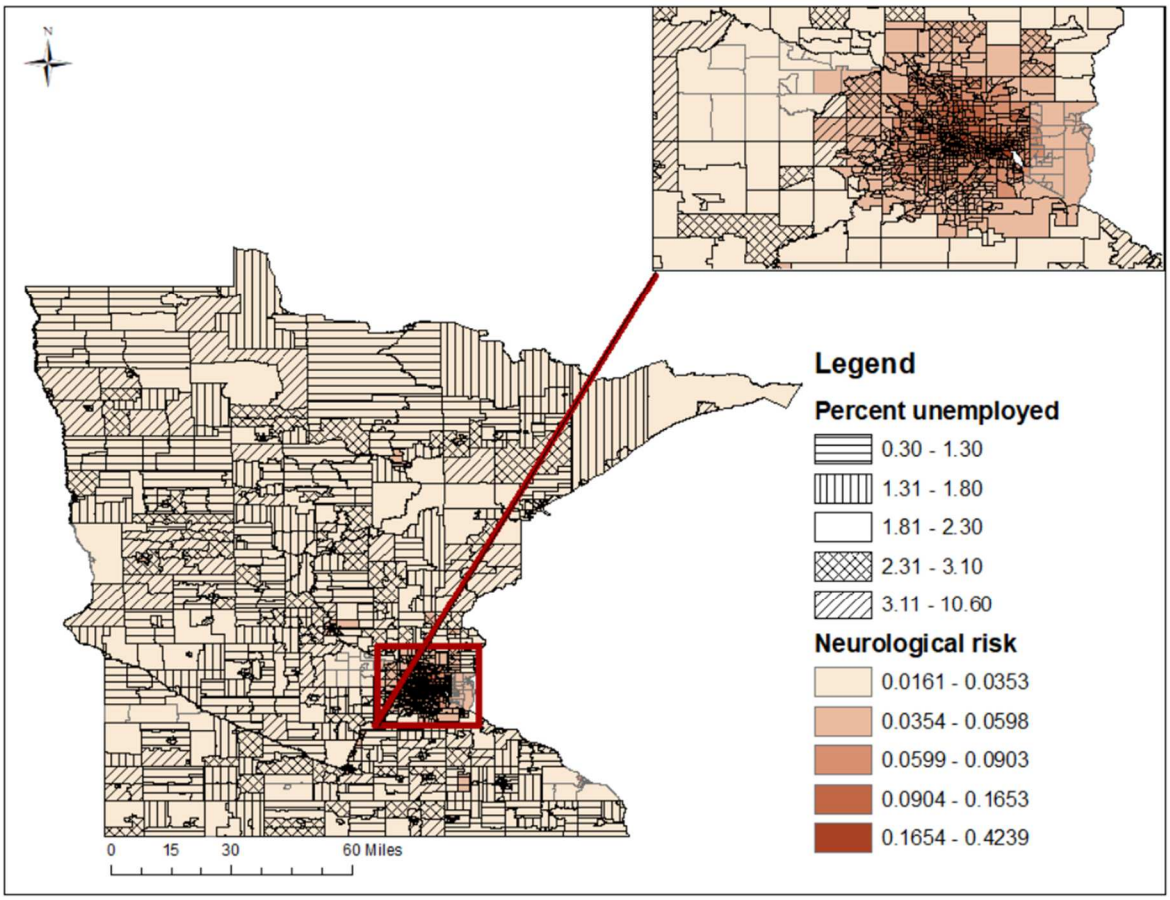

Figure 18. Map showing the distribution of cumulative neurological risk and percent unemployed in Minnesota (with an insert showing the Minneapolis-St. Paul area)

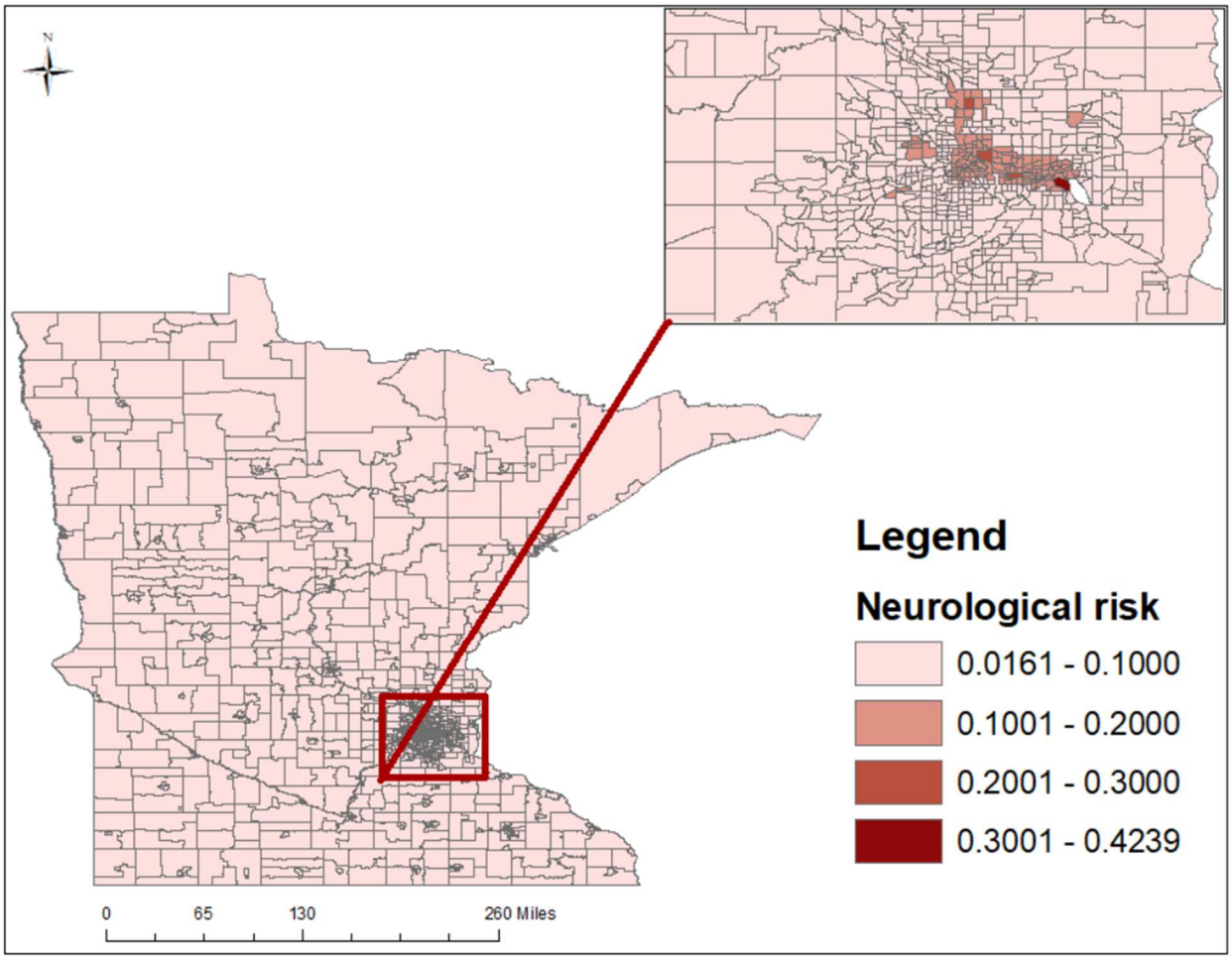

Figure 19. Map showing the distribution of cumulative neurological risk (considering the hazard index >0.1) in Minnesota (with an insert showing the Minneapolis-St. Paul area)

A map showing the distribution of cumulative neurological risk in Minnesota (Figure 19) which considers the neurological (risk) hazard index as >0.1 rather than >1 was created. Kortenkamp and Koch[83] in their paper titled "Refined reference doses and new procedures for phthalate mixture risk assessment focused on male developmental toxicity" proposed using a hazard index of 0.1-0.2 as a benchmark for interpreting phthalate mixture risk assessments. This proposal to revise the hazard index benchmark could be applicable to air toxics with neurological health endpoints. This proposed idea is due to uncertainties (such as the number of chemicals used in the

risk assessment, uncertainty factors used in calculating reference doses, bias during the estimation of HI) and feedback from the scientific community. The cumulative neurological risk for all the census tracts in our study were less than 1. However, air toxics (HAPs) are a group of 187 compounds that include arsenic, lead, cadmium, pollutant gases, solvents, and pesticides, many of which are deemed to have no safe level of exposure.[84] In addition, neurological health endpoints affect individuals of different ages and its impacts can last throughout an individual's life course. Therefore, we should consider the suggestion from Kortenkamp and Koch[83] and reduce the hazard index for air toxics with neurological health endpoints to 0.1-0.2.

Chapter 5: Discussion

Our study investigated the correlation between sociodemographic characteristics and neurological risk due to air toxic exposure in Minnesota. The mean neurological risk from all sources was ~0.05 and the mean neurological risk from point sources was ~0.01. In addition, the mean neurological risk from area sources, on-road sources and nonroad sources was 0.0311, 0.0034 and 0.0022 respectively. Also, the variation in neurological risk between the 5th and 95th percentiles ranged from 0.0185 to 0.1083 for all sources, 0.013 to 0.0396 for point sources, 0.0123 to 0.0605 for area sources, 0.0034 to 0.0074 for on-road sources and 0.0007 to 0.0036 for nonroad sources. We observed that census-tract measures of median household income, percent unemployed, percent non-Hispanic black, percent Hispanic and percent people of color were positively correlated with neurological risk. However, the correlation values obtained for neurological risk and percent without high school education show little or no correlation. In contrast, characteristics such as poverty, percent with less than high school education, and percent non-Hispanic white were weakly negatively correlated with cumulative neurological risk. The findings show some sociodemographic and geographic differences in neurological risk due to air toxic exposure, which may have severe implications for the health of Minnesotans.

Overall, we observed that sociodemographic factors were weakly correlated with estimated cumulative neurological risks. The correlation results could mean that the neurological risk increases in census tracts with high median household income, percent non-Hispanic black, percent Hispanic and percent people of color. Also, the results could mean that neurological risk in-

creases in tracts with lower percent poverty, percent without high school education, percent unemployed and percent non-Hispanic white. The largest correlation value observed was 0.21 for neurological risk from on-road sources and median household income and the neurological risk from nonroad sources and median household income (both relationships were positively correlated). This could mean that census tracts that have a larger number of (on-road and nonroad) emission sources may be predominantly found in tracts with high median household incomes than tracts with lower median household incomes. Our findings showed that neurological risk from area and on-road sources had a stronger correlation value of -0.20 with percent poverty compared to other emission source categories. Also, nonroad sources had a correlation value of -0.17 with percent poverty. These results could mean that locations that produce these emissions (area, on-road and nonroad sources) may be more common in communities or census tracts with a lower percent of poverty.

The mean cumulative neurological risk in our study (~0.05–using the 2014 NATA data) for Minnesota is higher than the mean neurological risk of 0.07 for the United States obtained by Young et al.[24] Young et al. used the 2005 NATA data to assess differential exposure to HAP respiratory, neurological and cancer hazard related to the Townsend Index of Socioeconomic Deprivation (TSI) in the U.S.[24] Morello-Frosch et al. used EPA's Cumulative Exposure Project (CEP) 1990 data to characterize the exposure to air toxics in California.[10] Morello-Frosch et al. observed that the mean neurological risk was 0.9 (median = 0.6, minimum = 0.4 and maximum = 14) higher than the mean neurological risk of ~0.05 in our study.[10] The minimum value for neurological risk from all sources in our study was 0.0161 and the maximum value was 0.4239.

Extant literature has provided scientific evidence about sociodemographic disparities in air toxic and air pollution exposures.[5,6,11,20,21,23] Sociodemographic disparities in neurological risk were not evenly distributed for all emission categories in Minnesota. The correlation results show that on-road and nonroad sources had larger correlation values of 0.21 (positive correlation) with median household income. This trend agrees with Pratt et al.[28] that transportation sources appear to be a major source of disparities. Also, individuals on the lower end of the socioeconomic spectrum and minorities are disproportionately exposed to air pollution and are at higher risk for adverse health outcomes in Minnesota. The map showing the distribution of the cumulative neurological risk was consistent with Pratt et al.[9] who observed the highest concentrations of 1,3-butadiene (an air toxic) and the highest excess lifetime inhalation cancer risk at the center of the Minneapolis-St. Paul metro area (the south-eastern part of the state on our map).

5.1 Limitations

There are several limitations to the study. NATA data was used to examine neurological risk at the census tract level across Minnesota, but we could not account for individual-level exposures to air toxic in the state. Also, NATA does not consider all potential exposure pathways to air toxics (such as dermal contact and ingestion) but includes risks due to inhalation of air toxics. The addition of other exposure pathways to the assessment (NATA) would probably increase the estimated health risks. Also, NATA data reflects air toxics emitted outdoors but not indoors, and it does not consider air toxics released into water or soil.

Furthermore, NATA does not include all air toxics to which people may be exposed, and it only estimates the neurological risk associated with a limited number of air toxics. Also, NATA does

not consider all potential sources and exposure pathways of neurotoxic air pollutants. In addition, EPA risk assessment models were used to estimate NATA neurological risks which were not based on any human neurological disease data. Neurological risks were estimated for a limited number of air toxics (n = 24) which does not allow for a thorough estimate of neurological risk from all potential air toxics, including indoor pollutants.

Our study was cross-sectional in nature, and although we observed correlations between socio-demographic factors and neurological risk due to air toxic exposure, we cannot infer causality from this data. Sociodemographic information from census data from 2010 to 2014 was merged with NATA data from 2014, which may lead to overestimating or underestimating neurological risk among our study population. This study focused on estimated neurological risk and did not examine the relationship between estimated neurological risk, the incidence or prevalence of any neurological disorders, and mortality due to any neurological disorder in Minnesota. Neurological diseases are multifactorial in nature, and risk factors comprise age, family history of neurological diseases, genetic disorders, etc.

5.2 Strengths

This study is the first to investigate the relationship between neurological risk due to air toxic exposure and sociodemographic characteristics in Minnesota. Identifying census tracts with neurological air toxic levels of concern in the state is an important step. It would assist Minnesota and MPCA in utilizing site-specific air toxic monitoring programs and local-scale (such as block-group level) assessments that could provide refined and localized data that are fundamental to developing risk-reduction efforts to improve the lives of Minnesotans.

5.3 Policy implications and future research

Our study provides a significant contribution because it has improved the understanding and knowledge of neurological risk from air toxic exposure in Minnesota. Our findings are significant and critical for developing policies and interventions to reduce and eliminate sociodemographic inequities and neurological risks due to air toxic emissions and exposure. Our findings support the promotion and evaluation of measures targeted at reducing air toxic emissions and neurological risks, besides highlighting local areas of concern within Minnesota. Although, the values of neurological risk obtained through the hazard index were <1, suggesting that there may not be a need for further action. Kortemkamp and Koch's proposal to consider using a hazard index of 0.1-0.2 for phthalate mixtures should be considered and applicable to air toxic risk assessments.[83] Typically, air toxics occur as mixtures and the uncertainty factors used to estimate the reference concentrations of most of the air toxics in the study were from animal studies.

Future research should consider using MPCA's statewide risk screening tool (MNRISKS) which estimates concentrations and risks at the block group level. The use of MNRISKS may be instrumental in providing information on the relationship between neurological risk and sociodemographic variables in Minneapolis-St. Paul. Future studies should consider residential segregation in the analyses, and the results may provide critical information that could be useful in developing and implementing strategies to address air toxic exposure disparities in Minnesota. In addition, future research should consider using source-apportionment studies and local air toxic monitoring data, which will help identify and prioritize source compounds. Also, this step may reveal neighborhood-level spatial variability of air toxic exposure at a granular level. In addition to

quantifying disproportionate exposures, these methodologies could be applied to exposure assessments for future epidemiologic studies of air toxics and health outcomes.

5.4 Conclusion

There are inequities in the distribution of neurological risk from air toxics in Minnesota, with sociodemographic factors including median household income, unemployment, being African American, Hispanic, or a person of color being linked to increased risk. Future research is needed to identify priority sources of air toxic pollutants and inform public health activities to reduce socioeconomic disparities in exposure to air toxics.

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