8-1-2024

Residential Street Trees and Cardiovascular Disease Among Urban-Dwelling Mexican Adults

Christine Campbell
Walden University

Walden University

College of Health Sciences and Public Policy

This is to certify that the doctoral dissertation by

Christine Campbell

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Harrison Ndetan, Committee Chairperson, Public Health Faculty
Dr. Howell Sasser, Committee Member, Public Health Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
2024

Abstract

Residential Street Trees and Cardiovascular Disease Among Urban-Dwelling Mexican Adults

by

Christine Campbell

MS, Duke University, 2001

BA, Smith College, 1996

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Public Health

Walden University

August 2024

Abstract

Cardiovascular diseases (CVDs) are a significant public health burden in Mexico despite national efforts to address traditional risk factors. With growing evidence that elements of nature can improve physical and mental health of people living in cities, this quantitative epidemiological study of secondary data examined the relationship between the presence of street trees in Mexican metropolitan areas and self-reported CVD in adults over age 40. The integrated socio-environmental model of health and well-being provided the conceptual framework for the study. A secondary data analysis was performed using combined individual health data from Mexico's 2012 National Health and Nutrition Survey and environmental data from other governmental sources. Each analysis adjusted for different subsets of known individual and environmental risk factors. Results based on data from 10,798 adults living in urban neighborhoods of Mexico showed a marked trend of reduced likelihood of CVD prevalence as the number of streets with street trees increased, although this finding was not statistically significant after controlling for individual- and household-level factors (adjusted odds ratio [*AOR*] = 0.84, 95% confidence interval [CI] = [0.56, 1.28], $p = .43$), after controlling for neighborhood- and municipality-level factors (*AOR* [95% CI] = 0.95 [0.59, 1.54], $p = .83$), and after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors (*AOR* [95% CI] = 0.87 [0.55, 1.38], $p = 0.56$). Findings may be relevant to public health practitioners, urban planners, and political leaders who could employ street tree planting to promote health equity and reduce CVD prevalence in cities, thereby contributing to meaningful social change for Mexico's urbanizing population.

Residential Street Trees and Cardiovascular Disease Among Urban-Dwelling Mexican Adults

by

Christine Campbell

MS, Duke University, 2001

BA, Smith College, 1996

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Public Health

Walden University

August 2024

Dedication

Being from the East Coast of the United States, trees have always been an integral part of the landscape and fabric of my life. Whether I was in the foothills of the Appalachian Mountains, the suburbs of an Alabama steel city, or a western Massachusetts college town, the towering poplar, oak, maple, and sycamore trees were essential elements in creating a sense of community and belonging. This background made my first visit to my husband's homeland in central Mexico a surprisingly different experience.

As our bus traveled out of Mexico City and later into heart of Puebla City, I was struck by the absence of trees along the city streets. I took note of the thin layer of brown haze that hung over the cities and wondered about the experience of people living in some of these neighborhoods. Some of the places that we passed along the bus route were not designed to optimize the mental or physical health of their residents. On the other hand, when there are trees lining the streets, that is where you will find pedestrians seeking to avoid the intense sun. Food vendors set up under trees and the shade provided by their branches. At dusk, sitting under the Indian laurels in the Zócalo of any Mexican city when the birds return to roost is a magical experience.

I knew from that first visit that I wanted my dissertation to contribute to making cities in Mexico healthier for the people that live in them. Therefore, this dissertation is dedicated to the people in living in Mexican cities, both in areas with street trees and nearby parks and those without. It is dedicated to the people living in cities who have created nature on their rooftops and balconies in the form of small trees growing out of discarded washing machine drums and shrubs emerging old utility buckets. Most importantly, this dissertation is dedicated to the millions of people in Mexico who have been impacted by cardiovascular disease We all deserve to live in environments that contribute to, not detract from, our health and well-being.

Acknowledgements

Earning a Ph.D. has been a lifelong goal. I started along the path in 1998 at Duke University, took a twenty-year hiatus, then began again in 2018 at Walden University. I am profoundly grateful and relieved to have completed this particular goal and to see where I can take it.

My deepest gratitude goes to my husband, Memo, for his unwavering support, patience, and pragmatism throughout this process. He stayed calm and rational during the times I became frustrated and emotional and was right beside me the whole time with both actions and words. I am grateful for the unwavering support of my parents, Charles and Alla, and for the patience of my siblings, Beth and Traber. I am also thankful that Daniel, Jesús, and Noé were in my life to help me remind me of what matters and what does not.

I have so much gratitude for the network of accomplished scientists, mentors, fellow students, and faculty that I connected with during this program and for all the friends and family that provided encouragement from the sidelines. Special thanks to Negin Iranfar, Kim Frost-Pineda, Emery Ngamasana, Laura Hale, Nato Tarkashvilli, Terry Hartley, Pat Makena, Kelcey Sihanourath, Rachel TeWinkel, Michelle Heggie, Julie James, Navor Navarro Romero, Rene Tapia, and Teresa Silva.

Lastly, I want to thank Dr. Harrison Ndetan for his guidance, support, and patience throughout my thesis journey, and Dr. Howell Sasser for helping me complete this research and grow as a scholar.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

Cardiovascular disease (CVD) is a general term encompassing several major conditions related to the circulatory system. These include coronary heart disease, cerebrovascular disease, peripheral arterial disease, thrombosis/embolism, and aortic atherosclerosis (Olvera Lopez et al., 2023; WHO, 2021). CVDs are the leading causes of death and a significant contributor to global disability, accounting for approximately 18 million (32%) of global deaths and 34.4 million years lived with disability as of 2019 (Roth et al., 2020; WHO, 2021). Heart attacks, heart failure, and strokes are among the acute events resulting from CVD, and if not fatal can result in prolonged hospitalization, physical disability, and significant economic consequences for affected individuals and their families.

Mexico is facing a potential future epidemic of CVD. Recent data indicated that more than 20.5 million individuals in Mexico (approximately 26% of the adult population) are affected by the cardiovascular conditions of myocardial infarction, atrial fibrillation, and heart failure and the major CVD risk factor of hypertension (Stevens et al., 2018). In contrast to similar middle-income countries and despite improvements in medical care, CVD-related mortality is increasing in Mexico (Arroyo-Quiroz et al., 2020; Pagan et al., 2017). Major well-known individual risk factors for CVD include poor diet, physical inactivity, dyslipidemia, hyperglycemia, high blood pressure/hypertension, obesity, and age (Arroyo-Quiroz et al., 2020; Bays et al., 2021). Over 30% of Mexican adults are estimated to have two or more of these individual risk factors, and the Mexican government and nongovernmental organizations spend millions of dollars to influence lifestyle risk factors, including diet and exercise (Mendoza-Herrera et al., 2019).

However, global evidence is accumulating that these traditional risk factors may be incomplete and overcounted (Reeves & Potter, 2023). Environmental risk factors for CVD, especially those related to living in urban areas, have been demonstrated to be significant detractors of physical and mental health (Münzel et al., 2022). Such environmental risk factors include air and noise pollution and elements of the built environment, including the absence of parks and other types of green space (Wolf & Robbins, 2015).

Green spaces are vital public spaces known to counteract some of the adverse effects of living in cities and are being explored as public health interventions to address health issues related to obesity, cardiovascular effects, mental health, and well-being (Lovell et al., 2018; WHO, 2017). In the context of WHO research on the topic, urban green spaces are defined as urban spaces covered by vegetation of any kind (WHO, 2017). Green spaces include small green space features such as street trees and roadside vegetation; green spaces not available for public access or recreational use, such as green roofs and facades or green space on private grounds; and large spaces such as parks, playgrounds, and greenways that provide various social and recreational functions (WHO, 2017). Recent research has established that green space, tree canopy, and other elements of nature in urban areas are associated with lower levels of obesity, hypertension, diabetes, and CVD and improved physical and mental health of its residents (Bhatnagar, 2017; Münzel et al., 2022). The small green space feature referred to as street trees are trees located in sidewalks, lining streets, and in public rights-of-way in cities. Street trees are of interest as a potential public health intervention because of their public accessibility and the opportunity to create everyday exposures to nature for urban residents (Lai & Kontokosta, 2019; Salmond et al., 2016).

Building on this understanding of street trees as a potential public health intervention, my research focused on urban areas in Mexico. Specifically, the current study examined whether the presence of street trees in census tracts designated as metropolitan was associated with reduced CVDs among residents. The intent was to extend general knowledge related to the potential health effects of street trees in urban areas that could be relevant to recommendations for infrastructure investments in urban and urbanizing areas within Mexico and beyond. For example, increasing the presence and distribution of street trees could serve as a tool to advance health equity and improve health outcomes for Mexican city dwellers, thereby contributing to social change.

Chapter 1 presents the background, purpose, research questions and related hypothesis statements, conceptual framework, study nature, definitions and assumptions, scope and delimitations, limitations, and potential significance to social change.

Background

CVDs and their consequences have been on the rise in Mexico. One proposed causal factor is the shifting demographic trends and the consequent aging population (Angel et al., 2017). By 2055, the median age will be 44, and almost 30% of Mexicans will be over 60 (United Nations [UN], 2022). Other factors contributing to CVD risk include lifestyle and metabolic risk factors that are high in Mexican adults and rising in Mexican adolescents (Acosta-Cázares & Escobedo-de la Peña, 2010; Terminel-Zaragoza et al., 2023). In a 2010 study, Acosta-Cázares and Escobedo-de la Peña reported that 70% of Mexican adults in the productive, preretirement age group of 45 to 64 years had at least one major CVD risk factor, and 7.2% had three or more major CVD risk factors. In contrast to other Latin American countries, Mexico remains in the growing phase of the cardiovascular health epidemic (Arroyo-Quiroz et al., 2020). Coronary heart disease excess mortality in Mexico, for example, rose 34% in men and 23% in women between 2000 and 2012 (Arroyo-Quiroz et al., 2020). The proximal causes of excess mortality are increased prevalence of diabetes, high cholesterol levels, and physical inactivity. Environmental factors are distal causes of disease via their influence on lifestyle and behavioral choices, but can also impact cardiovascular function (Arroyo-Quiroz et al., 2020; Medina et al., 2020; Mendoza-Herrera et al., 2019; Organisation for Economic Co-operation and Development [OECD], 2015a). Because environmental factors are more pronounced in dense, urban environments, the current trend of rapid urbanization has brought global attention to urban neighborhood environments and inspired research to identify factors that can exert protective effects on cardiovascular health.

Urbanization can have positive and negative effects on population health depending on how it is managed and the circumstances of an urban area. On the positive side, cities generally provide access to better educational and economic opportunities and improved housing quality (OECD, 2015b). On the negative side, residents are often exposed to the environmental stressors that are common in cities, such as air pollution, increased heat due to the urban heat island effect, traffic noise, and the absence of outdoor areas for safe physical activity (Bianconi et al., 2023; Dadvand et al., 2016; James et al., 2015). Approximately 90% of Mexico's population is expected to live in cities by 2050, making efforts to improve air quality and separate residents from pollution sources increasingly necessary (WHO, 2019). Urbanization in Mexico has resulted in a significant amount of urban sprawl and large numbers of people living in unplanned settlements on the peripheries of urban areas (OECD, 2015b). Without intentional urban planning to set land aside for green space and urban vegetation, such settlements have the potential to be stressful and pathogenic.

Cardiovascular risk factors in the urban environment include light pollution, noise pollution, and other disruptors of the natural human circadian rhythm that can increase CVD susceptibility and severity (Bhatnagar, 2017). Air pollution is a significant contributor to CVD, with some estimates that air pollution is responsible for as much as 21% of all global deaths from CVD (Landrigan et al., 2018). Other important environmental determinants of CVD risk include accessibility to infrastructure providing easy access to tobacco, alcohol, and unhealthy food choices, and inaccessibility to infrastructure providing easy access to markets selling healthy foods and facilities for physical and leisure activities (Y. Zhang et al., 2023). Of primary relevance to the current study, there is accumulating high-quality evidence that residential proximity to green space is associated with improved physical and mental health outcomes including reduced incidence and prevalence of CVD.

Green space is an umbrella term indicating different elements of the physical environment containing or comprising vegetation (L. Mitchell et al., 2011; Taylor & Hochuli, 2017). Common measures of green space in epidemiological research include the percentage of land covered by parks/open spaces, the amount of satellite-detected greenness at various buffer distances surrounding individual residences, the percentage of tree canopy, and residential tree density (Kondo et al., 2018).

Trees constitute a central feature of urban green space. Trees have environmental benefits (e.g., carbon sequestration, air pollution reduction, and atmospheric cooling) and positive influences on health outcomes (e.g., cardiovascular benefits and stress reduction; (X. Liu et al., 2022; Pataki et al., 2021; Wolf et al., 2020). Urban tree cover has been associated with reduced allostatic load from chronic stress, reduced medication sales for cardiovascular conditions, and lower CVD prevalence in high-income countries in North America and Europe (Astell-Burt & Feng, 2020; Chi et al., 2022; Egorov et al., 2020). All forms of green space represent potential strategies for large-scale interventions to improve urban health (Reeves & Potter, 2023; WHO, 2017). Recent research demonstrating that higher levels of residential greenness are associated with reduced CVD-related risk factors, CVD-related biomarkers, and lower CVD incidence, prevalence, and mortality is reviewed in Chapter 2: Literature Review

Street trees are a prominent type of tool in the urban greening toolkit. As described by Smart et al. (2020), street trees "define the space of a street, delimit the pedestrian realm, calm traffic, filter sunlight, promote visual order, soften the streetscape, and introduce beauty in the form of nature" (p. 2). There is a small body of literature devoted to the health-promoting aspects of street trees. Studied outcomes have included childhood asthma (Moreira et al., 2020), birth outcomes, nonaccidental mortality, hypertension, and various cardiometabolic conditions (Abelt & McLafferty, 2017; Lovasi et al., 2008). Most research has been conducted in high-income countries with temperate climates, leaving a significant gap in knowledge for low- and middle-income countries with different climatic and economic conditions (R. Wang et al., 2022; Wolf et al., 2020). Furthermore, very few studies have investigated street trees and cardiovascular health

(Giacinto et al., 2021; R. Wang et al., 2022). My study was designed to fill this gap in the literature on the impact of green space, specifically street trees, on CVD in the middle-income, tropical/temperate country of Mexico.

Problem Statement

Mexico faces a potential epidemic of CVD with rising prevalence and mortality rates despite efforts to address well-known individual risk factors. Heart disease affects a quarter of the Mexican population, and more than 4% of total health expenditures are estimated to be related to cardiovascular health (Richards et al., 2022; World Heart Federation, 2016). Recent research suggested that traditional risk factors may be incomplete, and environmental factors, particularly those related to living in urban areas, could play a crucial role. Urban green spaces, including street trees, have emerged as potential interventions to mitigate health issues such as obesity, CVD, and mental health concerns. Although existing literature supported the positive health effects of urban green spaces and tree cover, there was a gap in understanding the impact of street trees in the context of Mexican urban environments.

With this research, I sought to contribute to the scientific evidence on the potential health effects of street trees and recommendations for infrastructure investments in urban and urbanizing areas of Mexico. Urban greening strategies have been explored in the United States and judged to be of relatively low cost when viewed from the perspective of rising health care costs and lost productivity. Through implementation of evidence-based, cost-effective interventions that create more health-promoting (salutogenic) cities, individual lives could be positively impacted on a broad scale. Enhanced urban environments that promote health equity and improve cardiovascular outcomes may contribute to meaningful societal progress and significant social change in Mexico and similar countries.

Purpose of the Study

This quantitative study of secondary cross-sectional data was conducted to examine the relationship between street trees in urban neighborhoods of Mexico and self-reported prior diagnoses of heart attack, angina, heart failure, heart disease, and stroke among adults, taking into account known covariates and potential confounders. The research questions were iterative, first addressing the relationship between the proportions of streets within a census tract with street trees and CVD in the context of individual- and household-level factors (Research Question 1), and then addressing the relationship between street trees and CVD while adjusting for census-tract- and municipality-level environmental factors (Research Question 2). Finally, the relationship between the presence of street trees and CVD was addressed while adjusting for individual-, household-, census-tract-, and municipality-level covariates (Research Question 3).

Research Questions and Hypotheses

Three research questions and corresponding hypotheses were developed by reviewing the extant literature on elements of urban green space and the integrated socio-environmental model of health and well-being (ISEM) framework.

RQ1: Is there a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults living in those neighborhoods after controlling for individual- and household-level factors?

H_o1: There is no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors.

H_a1: There is a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors.

RQ2: Is there a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for neighborhood- and municipality-level factors?

H_o2: There is no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for neighborhood- and municipality-level factors.

H_a2: There is a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for neighborhood- and municipality-level factors.

RQ3: Is there a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual-, household-, census-tract-, and municipality-level covariates.

H_o3: There is no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors.

*H*a3: There is a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors.

Conceptual Framework and Study Variables

The ISEM was employed as the conceptual framework for the study. Like the socioecological model of health promotion (SEM) developed in the 1970s, the ISEM identifies intra-individual, neighborhood-level, social, and physical environmental factors as independently and jointly involved in an individual's health outcomes (Hayden, 2019; Olvera Alvarez, Appleton, et al., 2018). Whereas the canonical SEM focuses on the impact of multiple levels of influences on health behaviors (Pahn & Yang, 2021), the ISEM adopts a broader perspective that includes both behavioral and biological responses. The ISEM framework acknowledges that these biological and behavioral responses can have either adverse or beneficial effects depending on individuals' prior life experiences and their protective resources or innate susceptibilities to various environmental triggers. The ISEM has been employed in conceptualizing the relationship between early life stress, air pollution, inflammation, and disease in socially disadvantaged individuals (Olvera Alvarez, Kubzansky, et al., 2018) and cited in studies on how the social and physical environment interact in the social patterning of general well-being and the aging trajectory across generations (Boehm, 2021; Malecki et al., 2022). By considering positive health outcomes instead of only disease and deficit, the model provides a framework for identifying protective, restorative, and health-promoting influences.

Numerous studies have identified elements of urban green space as health-promoting factors. There are multiple mechanistic pathways by which different aspects of green space have been posited to contribute to health and well-being. Researchers have organized these potential pathways into three primary domains: (a) reducing harm (e.g., mitigation), (b) restoring capacities (e.g., restoration), and (c) building capacities (e.g., instoration; (Markevych et al., 2017; Yeager et al., 2020). The present study did not address a specific pathway of action between street trees and CVD in Mexico. Rather, it was designed to detect whether a statistically significant relationship existed while controlling for other potentially relevant factors.

Because of the known biological, psychological, and sociological factors contributing to the development of CVD (James et al., 2015), the ISEM provided a strong foundation for conceptualizing the relationship between street trees and health outcomes in this study. As discussed more thoroughly in Chapter 2, the ISEM conceptual model was employed to inform the selection of covariates (see Table 1) and the consideration of whether multilevel regression models were needed to account for similarities among people living in the same community.

Table 1

Hierarchical Structure of Covariates

Level	Variable
Individual	Age, sex, family history of infarction, hypertriglyceridemia, hypercholesterolemia, prior diabetes diagnosis, prior hypertension diagnosis, years since hypertension and diabetes diagnosis[a], prior depression diagnosis, smoking status, excessive alcohol use, body mass index (BMI)[b], current physical activity level[c], hours of sleep per night[c], education[c]
Household	Household cookstove (gas or other)
Neighborhood/census tract	Social Lag Index (SLI/GRS), altitude
Municipal	Road network density

[a] Years since diagnosis was redundant with prior diagnosis of diabetes and hypertension. Only the continuous variables of years since diagnosis were included in the final models, with 0 representing no diagnosis.

[b] There was a substantial amount of missing data for BMI, so it was removed from the final models, although sensitivity analyses indicated it was not statistically significant and it did not change the results for other variables into relevant models.

[c] Data on these variables were missing for 80% of the subpopulation and were excluded from the final analysis.

Nature of the Study

This study employed a quantitative analysis of cross-sectionally collected survey data, the design of which was guided by the ISEM framework and the availability of data on street trees in Mexico. This study made use of individual-level secondary data from the 2012 Mexican Encuesta Nacional de Salud y Nutrición (National Health and Nutrition Survey), referred to herein as ENSANUT 2012. This was a national probabilistic survey with state representation, urban and rural strata, and an oversample of marginalized households to quantify the frequency, distribution, and trends of health and nutrition conditions and their determinants in the Mexican population (Romero-Martínez et al., 2012). Although more recent surveys were available, ENSANUT 2012 was used because it contained higher resolution information about participants' residential locations and could be matched with a separate, contemporaneous data set containing street tree information in the same locations. The study sample included adults 40 years and older living in areas designated as metropolitan and for which there was residential information at the census tract level and responses to questions regarding a prior medical diagnosis of angina, heart failure, heart disease, stroke, or heart attack. The ENSANUT 2012 data sets are publicly available, as are the codebooks, questionnaires, informed consent forms, and descriptions of the sampling procedures.

The primary independent variable in all research questions was the proportion of streets with street trees along the perimeter of each city block comprising a census tract. The street tree variable was derived from a 2014 survey conducted by the Instituto Nacional de Estadística y Geografía (National Health and Nutrition Evaluation Survey [INEGI], 2014). The survey methodology involved INEGI personnel walking the perimeter of each city block and recording both he number of streets making up the perimeter and how many of those streets contained at least one street tree. These data were converted into a scale value representing the proportions of streets with street trees aggregated at the census tract (AGEB) level.

CVD-related covariates at different levels of influence were included in the analysis. At the individual level, covariates of interest included age, sex, family history of infarction, hypertriglyceridemia, hypercholesterolemia, prior diabetes diagnosis, prior hypertension diagnosis, years since hypertension and diabetes diagnosis, and prior depression diagnosis. Additional individual-level variables considered for inclusion were current smoking status, excessive alcohol use, physical activity level, average sleep per night, and the household cooking method. Neighborhood- and municipality-level factors linked to CVD were identified from existing literature on CVD, and publicly available data sets with information on neighborhood marginalization, altitude, and municipal road density were located. The rationale for the inclusion of each covariate was based on previous findings in the literature, which are described in Chapter 2. Descriptions of the data collection instruments and operationalization of the variables are provided in Chapter 3. Single-level complex samples logistic regression analyses were used for the final analyses.

Definitions

The variables, attributes, and concepts relevant to the study are organized conceptually and defined herein:

Health-Related Terms

Body mass index (BMI): A measure of obesity based on height and weight. Clinical and epidemiological data have established a connection between obesity and a diverse range of CVD. Direct effects of obesity include structural and functional adaptations of the cardiovascular system to accommodate excess body weight (Koliaki et al., 2019). Indirect effects are manifested through coexisting CVD risk factors including insulin resistance, hyperglycemia, hypertension, and dyslipidemia.

Cardiovascular disease: A general term encompassing several major conditions related to the circulatory system, including problems with blood flow to heart muscles (coronary heart disease), peripheral tissues, and the brain (cerebrovascular disease) ;

(Olvera Lopez et al., 2023; WHO, 2021). The dependent variable underlying all research questions in this study was whether respondents had been told by a medical professional that they had angina, heart failure, heart disease, stroke, or a heart attack. Although these outcomes were limited in scope due to data constraints, they represented some of the most important indicators of CVD. The same self-reported outcomes were included in versions of ENSANUT around the world (NHANES-U.S., NHANES-KOREA, China Health and Nutrition Survey).

- Angina is chest pain caused by reduced blood flow to the heart, either from vessel narrowing due to coronary heart disease and/or a blockage in the arteries that feed the heart (i.e., thrombosis).
- Infarction/heart attack is blood flow to the heart being severely reduced or blocked. The blockage is usually due to a buildup of fat, cholesterol, and other substances in the heart (coronary) arteries.
- Heart failure/cardiac insufficiency is the heart muscle not pumping blood sufficiently. Blood backs up, and fluid can build up in the lungs, causing shortness of breath.
- Stroke is the blood supply to part of the brain being interrupted or reduced, preventing brain tissue from getting oxygen and nutrients.

Green Space and Related Terms

Green infrastructure: A term historically used to describe an approach to water management involving planting trees and restoring wetlands to supplement or replace gray infrastructure such as drains and treatment plants. Types of green infrastructure include rain gardens, green roofs, infiltration planters, and tree boxes (Grabowski et al., 2022). Green infrastructure in urban areas serves a dual role of stormwater management and increasing greenness for residents.

Green space (also written as greenspace): Parts of urban environments containing elements of nature. These spaces are available for inhabitants to interact with either visually or physically and, depending on the definition, can include small and large parks, trails, road verges, median plantings, and vegetation along roadways. This study focused on trees in the public right-of-way and those that line residential streets as a distinct form of urban green space.

Greenness: The amount of green vegetation at ground level, including trees and shrubs, or various measures of greenness from satellite imagery. The Normalized Difference Vegetation Index (NDVI) is the most commonly used satellite-derived metric for measuring the relative abundance and spatial distributions of vegetation (de la Iglesia Martinez & Labib, 2023). Other indices used in the foundational literature relating green space and health were discussed by Shahtahmassebi et al. (2021). An overview is provided in Chapter 2.

Street trees: Trees located in sidewalks, lining streets, in public rights-of-way, and medians. The 2014 Characteristics of the Urban Environment survey (INEGI, 2015b) counted street trees according to the following definitions:

- A tree is a plant with a thick, woody, and elevated trunk, branched at a certain height from the ground and covered with foliage. The size is variable due to the species or to pruning to improve its appearance.

- A palm is a tree-like plant with a straight and flexible trunk and the crown formed by large plume-shaped leaves. A palm does not develop branches or trunks with wood.

Streets were counted as having at least one tree or palm tree on the edge of the road regardless of its size or who planted it. Weed-type vegetation, shrubs, and gardens were not counted, nor were trees within road medians (INEGI, 2015b).

Mexican Governmental Institutions and Data Sources

Consejo Nacional de Evaluacion de la Politica de Desarrollo Social / National Council for the Evaluation of Social Development Policy (CONEVAL): A decentralized public agency of the Mexican government that coordinates and evaluates policies, programs, and interventions related to poverty and social development. CONEVAL develops and publishes the Social Deprivation Index (SLI) and the Degree of Social Lag (GRS) scale (CONEVAL, n.d.).

La Encuesta Nacional de Salud y Nutrición / National Health and Nutrition Evaluation Survey (ENSANUT): A periodic national survey that gathers information on the health and nutrition status of the Mexican population, providing benchmarks and statistics used to inform health policies, programs, and funding (Shamah-Levy et al., 2019).

Instituto Nacional de Estadística y Geografía / National Institute of Statistics and Geography (INEGI): An autonomous governmental body responsible for collecting and disseminating information about Mexican territories, populations, and economic activities (Esparza Rios, 2017).

Geographic Terms

Área GeoEstadística Básica / Basic Geostatistical Area (AGEB): A geostatistical boundary that is analogous to a U.S. census tract developed by INEGI as part of Mexico's National System of Statistical and Geographic Information. Between 2010 and 2015, there were approximately 2.5 million demarcated AGEBs (Esparza Rios, 2017). AGEBs and other geostatistical boundaries are updated periodically to reflect population growth and new settlements. At the time of the 2020 Mexican Census, the number of AGEBs had increased to approximately 2.7 million.

Entidad Federativa / Federal Entity: The geopolitical equivalent of a U.S. state. Mexico counts 32 federal entities comprising 31 states and Mexico City (Esparza Rios, 2017).

Manzana / City Block: The smallest geostatistical unit defined by the National System of Statistical and Geographic Information and only defined for settled areas. Manzanas are analogous to U.S. census blocks and referred to as city blocks for the purposes of this study. Due to privacy concerns, data collected at this level are aggregated and published at the AGEB or municipality level (GeoAnalitica, 2020). All inhabited areas of Mexico are identified using a nested hierarchy of codes starting with the state code and ending with the manzana code.

Municipio / Municipality: Both a geostatistical and geopolitical unit, municipalities have their own president and governing bodies. There are approximately 2,500 municipalities across Mexico, encompassing metropolitan, urban, and rural localities. Municipalities are the smallest geographic boundaries that cover 100% of Mexico's land area (Esparza Rios, 2017).

Other Terms

Global South: A multidimensional term generally used to describe developing countries with lower levels of wealth, economic development, income equality, and democratic institutions than developed countries of North America, Europe, and Asia (Rigolon et al., 2018). Although the term does not strictly imply geographic location, most countries comprising the Global South are in the southern hemisphere.

Metropolitan: An INEGI classification for state capitals and localities with 100,000 or more inhabitants (INEGI, 2018).

Social Lag Index / Grado de Rezago Social (SLI/GRS): Scales that integrate information on educational attainment, access to health services, housing quality, and basic household services aggregated at either the AGEB or municipality level. Based on their SLI/GRS score, geographical units are classified on a 3-point scale of social deprivation: low, medium, and high. The SLI is updated every 5 years according to new data, and the GRS is updated every 10 years.

Urban: An INEGI classification for locations with more than 2,500 but fewer than 100,000 inhabitants that are not otherwise defined as metropolitan (INEGI, 2018).

Assumptions

A few assumptions were considered and documented. First, I assumed that participants in the ENSANUT 2012 sample recalled and responded to the survey questions accurately. Secondly, I assumed that proxy values for neighborhood street trees were accurate and reliable exposure indicators and that any bias due to the method of variable derivation was nondifferential. Third, I assumed that all relevant covariates were appropriately identified and controlled. Lastly, I assumed that the sample included in

ENSANUT 2012 had lived at their present residence for enough time to experience any benefits or stresses related to the presence or absence of street trees.

Scope and Delimitations

Using secondary data from governmental surveys conducted in Mexico between 2010 and 2017, this study addressed the research problem by testing for a statistically significant relationship between the presence of street trees and a known prior medical diagnosis of CVD in Mexican adults. Covariates at multiple levels of influence that could mask or distort the observed association between the independent and dependent variables were controlled statistically to increase internal validity and support the inference that any observed statistically significant relationship was due to the primary relationship being investigated. Health data were sourced from the 2012 ENSANUT survey, and the neighborhood-, municipality-, and regional-level data were sourced from four additional data sets with information collected between 2010 and 2017. All data were publicly available from the Mexican government, and all contained standardized geographical codes by which data sets were combined. The study sample included adults over 40 who were identified as living in metropolitan census tracts for which street tree data were available. The probabilistic sampling methodology and survey weights of the health data contributed to the generalizability of the study results to Mexico.

Limitations

Several limitations were identified prior to data access and evaluation. As a secondary data analysis, the study relied on information collected for other purposes, potentially omitting variables that could contribute to CVD development, such as air quality, proximity to high-traffic areas, and respondents’ duration of residence at their current location. The study outcome (self-reported prior diagnoses of CVD by medical professionals) was also subject to bias. Participants may have failed to recall prior diagnoses, potentially underestimating CVD prevalence. Moreover, individuals with limited health care access or those who infrequently seek medical care may have undiagnosed CVD, further contributing to an undercount. This issue is common in studies of CVD risk factors such as hypertension, as evidenced by a recent Mexican study that found that although 32.8% of adults had arterial hypertension, only 72% were aware of their condition (Palomo-Piñón et al., 2022). The definition of street tree exposure presented another limitation. The 2014 Urban Characteristics Survey measured only the presence or absence of street trees on the periphery of city blocks within a census tract. I assumed these values were representative of interior streets, which may not be accurate. These limitations should be taken into account when evaluating the study's findings and implications.

Significance

This study was designed to better understand how environmental features can impact residents' cardiovascular health, potentially leading to the identification of a strategy for local risk mitigation measures and health equity improvements. The relationships between street trees and health outcomes examined in this study are relevant both to place-based social justice and to United Nations Sustainable Goal 11.7 of "provid[ing] universal access to safe, inclusive and accessible, green and public spaces" (United Nations, 2015, p. 22). There have been studies in specific areas of Mexico examining the distribution of green spaces and street trees based on social and economic marginalization (Martínez Juárez et al., 2022; Ribeiro-Palacios et al., 2021). However, a deeper understanding of any benefits conferred by the presence of street trees in residential environments could be used by cities and municipalities to design civic projects that have multiple benefits to the community. Decisions about the green space interventions in which to invest are critical to ensuring that urban green space delivers positive health, social, and environmental outcomes.

Summary

Following this introduction, Chapter 2 provides a fuller discussion of the theoretical framework and how it relates to the research questions. Additionally, Chapter 2 provides a review of the published literature from 2016 to 2024 for the key constructs related to the current study. Chapter 3 provides a description of the methods used in the study, including details regarding the population, sampling, procedures, the instruments used for measurement, threats to validity, and the data analysis plan. Chapter 4 presents the results of the statistical analyses, including assumption testing and descriptions of the study population. The last chapter summarizes and interprets the findings in relation to existing research and in the context of the study’s limitations.

Chapter 2: Literature Review

Diseases of the heart and circulatory system are the leading causes of death and a significant contributor to global disability, accounting for approximately 18 million deaths (32% of global deaths) and 34.4 million years lived with disability as of 2019 (Roth et al., 2020; WHO, 2021). Over three quarters of CVD deaths take place in low- and middle-income countries and pose a significant economic burden via direct and indirect costs (Münzel et al., 2022). The prevalence of CVD and its related problems are rising, especially in developed countries and urban areas that have undergone changes in economic development, physical activity, and food consumption patterns (Barquera et al., 2016). Country-specific prevalence and cost estimates vary by country and its available data collection infrastructure. Consistent with global statistics, CVD is the leading cause of mortality among Mexico's population of 127 million, accounting for approximately 20% of annual deaths and 2,919 years of life lost per 100,000 population (Pan American Health Organization, 2021). Heart disease affects approximately 26% of the Mexican population, with over 30% of Mexican adults estimated to have two or more individual CVD risk factors (Mendoza-Herrera et al., 2019; World Heart Federation, 2016).

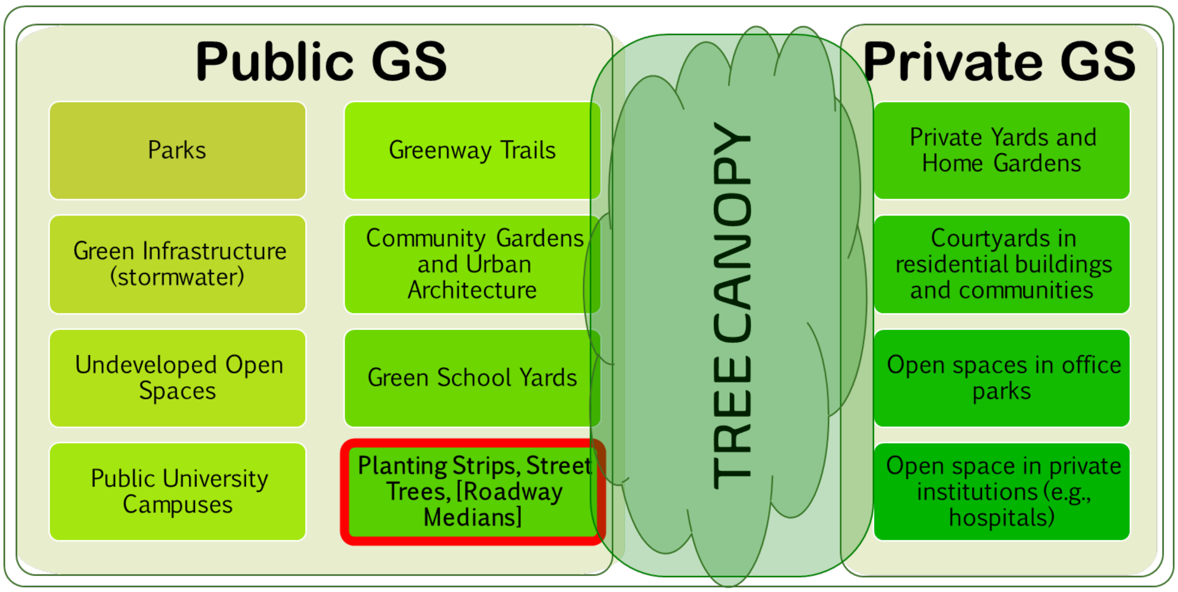
Among the countries of Latin America, Mexico has the third highest age-standardized CVD-related disability-adjusted life years lost per 100,000 people, a statistic driven by ischemic heart disease, hypertensive heart disease, and stroke (Lindstrom et al., 2022). The CVD burden in Mexico has been compared to other megacountries, or countries with populations over 100 million people (Barquera et al., 2016; Mendoza-Herrera et al., 2019). Hypercholesterolemia, hypertriglyceridemia, and obesity are the most prevalent metabolic risk factors in these megacountries, but Mexico's rates are higher than those of Nigeria, India, China, the United States, and Japan (Mendoza-Herrera et al., 2019). Unlike the United States or China where the incidence of CVD risk factors and the CVD mortality rates are higher in rural areas than in urban areas, the trend is reversed in Mexico. The rate of cardiovascular mortality is 11% higher in urban areas of Mexico than in rural ones (Martínez-Téllez et al., 2023).

Heart conditions cost Mexico billions of dollars every year in direct and indirect costs. Direct costs include expenses related to health care services, such as hospitalization, medication, diagnostic tests, and surgeries, and are thought to comprise half of expenditures (Mendoza-Herrera et al., 2019). The remaining indirect costs refer to the productivity losses resulting from premature death, disability, absenteeism from work, opportunity costs of informal care by family and friends, and lost tax revenue (Mendoza-Herrera et al., 2019; Stevens et al., 2018). A 2024 estimate put the costs of productivity losses due to chronic CVD at $11.8 billion for Mexican men and $3.7 billion for Mexican women (Guerrero-López et al., 2024). Advancements in medical treatments have improved CVD management in affluent nations of the Global North, but low-income countries and those in the Global South lack comparable physical and financial means for medical interventions. Consequently, these regions must prioritize primary prevention efforts to address CVD risk factors (Barquera et al., 2016; Mendoza-Herrera et al., 2019).

Of particular interest for the current study was the growing body of literature describing a negative relationship between CVD and elements of what is referred to as green space among people living in urban and metropolitan areas. Green space in these environments includes vegetated areas in cities, such as parks, forests, gardens, and greenways, and comprises public and private settings (Jennings et al., 2017). As discussed in more detail later in this chapter, many studies have described positive effects of green space, tree canopy, and greenness on physical and mental health. Additionally, a a small number of researchers have looked at the health benefits of street trees, a particular type of public green space. Street trees are trees located in sidewalks, lining streets, and in public rights-of-way (see Figure 1). Street trees are an essential element of streetscape design that define the space of a street, delimit the pedestrian realm, calm traffic, filter sunlight, promote visual order, soften the streetscape, and introduce beauty in the form of nature associated with enhancing the experience of living in cities (Smart et al., 2020). The presence of street trees can also influence individual behaviors such as increasing the likelihood of physical activity and providing spaces for social interactions.

Figure 1

Different Types of Urban Green Space



Note. Adapted from (Jennings et al., 2017).

The primary focus of the current study was the relationship between street trees in metropolitan administrative divisions of Mexico and self-reported CVD among adults, while controlling for established individual and environmental CVD risk factors. In the remainder of this chapter, I describe the theoretical foundations and conceptual frameworks that underpinned this study. Next, I present a historical overview of studies connecting various green space elements to CVD epidemiology and synthesize existing literature linking trees, tree canopy, and urban street trees to CVD. Finally, background information on all relevant risk factors for CVD is provided to justify the inclusion or exclusion of different covariates for the final analyses.

Literature Search Strategy

The literature search was initiated using the keywords *greenspace* or *green space*, *urban* or *city* or *cities* or *metropolitan* or *urban areas*, *street trees*, *tree cover*, *cardiovascular disease* or *CVD* or *heart* or *cardiac* or *coronary heart disease*, *population health*, *GIS*, and *public health* or *community health* in MEDLINE/PubMed, Cochrane Database of Systematic Reviews, CINAHL, APA PsycInfo, SocIndex, ScienceDirect, Academic Search, Education Source, ERIC, IEEE Xplore, Emerald Insight, and Directory of Open Access Journals. Additional searches were conducted in Google Scholar and LILACS (Latin American and Caribbean Health Science Literature) using the English-language search terms *green space*, *street trees*, *urban trees*, *health*, *cardiovascular*, and *heart disease*, and the Spanish search terms *arbolado de alineacion*, *areas verdes*, *infraestructura verde*, *arboles*, and *salud*. Because of the paucity of research focused on street trees and the publication of a study central to the study of street tree epidemiology in 2013, I restricted initial searches from 2013 to the present and identified older studies of particular interest from reference lists. Both peer-reviewed materials and sources that were not peer-reviewed were considered for their contributions and were used for reference mining. At regular intervals, forward citation searches were undertaken in Google Scholar with seminal publications to identify more recent relevant studies.

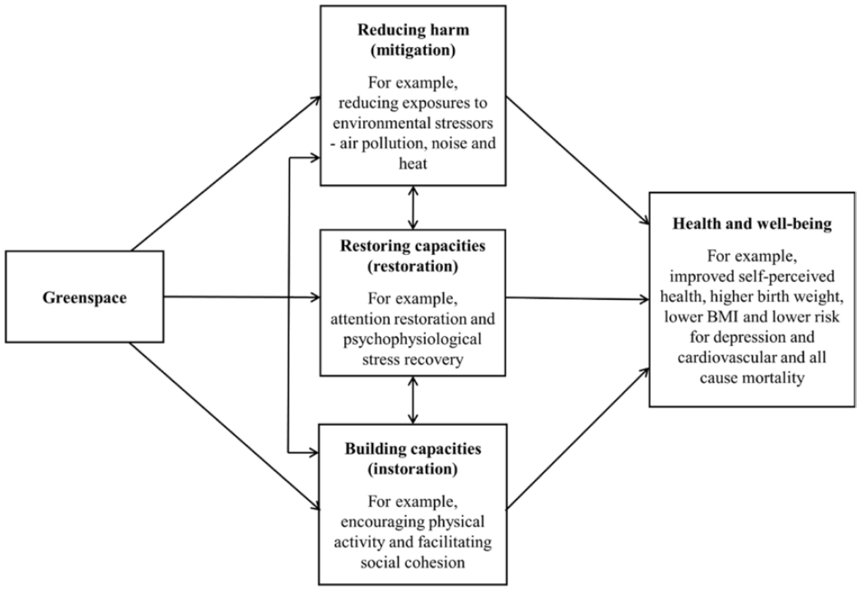
Theoretical Foundations

Several theories have been proffered to explain the mechanisms by which green space and tree cover (generally) and street trees (specifically) can impact health (Li & Zhang, 2023). These include named theories such as the conditioned restoration and toxic stress theories and nonnamed theories involving dose response, psychological well-being, and social cohesion. Kuo (2015) identified 21 plausible causal pathways from nature to health, each of which had been tied to nature contact while accounting for other factors and was empirically or theoretically tied to specific health outcomes. All pathways are generally compatible with a three-domain framework proposed by a transdisciplinary, international group of 100+ scientists who met in 2016 to review potential mechanisms underlying the relationship between greenness and health (Kuo, 2015; Markevych et al., 2017). The three domains within the framework are *reducing harm* (i.e., mitigation), *restoring capacities* (i.e., restoration), and *building capacities* (i.e., instoration).

The harm reduction/harm mitigation domain encompasses physiochemical actions in which components of urban green space reduce exposure to air pollution, noise pollution, heat, and UV radiation. The restorative domain covers pathways by which nature can improve attention, mental health, and related clinical outcomes and reduce stress. Green space can also promote health through a building capacities/health promotion/instoration domain. This refers to the capacity of nature to promote reorientation and the creation of new coping strategies (Hartig et al., 2014). Outcomes included in the instoration domain have included improved birth outcomes, increased physical activity levels, and strong social networks (see Figure 2).

Figure 2

Three Domains Linking Green Space to Positive Health Outcomes



Note. From Markevych et al. (2017, p. 8).

These three domains encompass the same four general pathways identified by Hartig et al. (2014), which are air quality, physical activity, social cohesion, and stress reduction pathways. A fourth domain, *causing harm,* was recently proposed by Marselle (2021). This domain includes negative aspects of contact with nature such as infectious and zoonotic disease exposures and increased exposure to allergens (Marselle et al., 2021). Multiple pathways within each domain have been investigated in epidemiological studies using mediation and moderation analyses.

Several studies of green space were designed with all three domains in mind. A cross-sectional study conducted in China tested whether the amount of urban green space and neighborhood walkability around homes in Beijing were associated with less coronary atherosclerosis via mechanisms involving enhanced physical activity, air pollution mitigation, or reduced psychological stress (Hu et al., 2022). In another example, Moran et al. (2021) examined the relationship between urban greenness and four mortality outcomes: life expectancy at birth and three categories of cause-specific mortality. The outcomes were selected to represent the three main domains through which green spaces are hypothesized to benefit health. Although Moran et al. (2021) initially linked cardiovascular mortality with pathways involving recreation and physical activity, they also acknowledged the potential overlap between pathways and noted that green spaces could also reduce stress. Moran et al. acknowledged using the three domains as a simplified framework to guide their analysis, but also recognized the potential for overlapping pathways and nuanced relationships between variables. The complex interplay of social, physical, and psychological factors impacting health outcomes means that multiple theoretical pathways should be considered when linking green space or street tree exposure to downstream health endpoints.

Many researchers have acknowledged the likelihood of multiple and interacting mechanisms linking green infrastructure and health, although their research focused primarily on a single mechanism or pathway. The restoration/stress reduction pathway has been examined in studies with mood evaluations before and after subjects spent time in nature using stress response testing before and after viewing different types of landscapes (An et al., 2022; Huang et al., 2020; L. Liu et al., 2022). The building capacities/health promotion pathway has been supported by research findings of improved cardiovascular function (e.g., heart rate, blood pressure, homocysteine levels) after the practice of walking in a forested area (Wolf et al., 2020). Typically grouped with other evidence of improved resilience and better health, social cohesiveness has been identified as a mediating factor between the number of green spaces and self-reported health (R. Zhang, et al., 2021). Complicating the literature and the identification of causal pathways are the inconsistencies in the literature regarding how green space is measured and whether the results using one measure of green space, or green exposures, can be transposed onto others. The literature review describes diverse ways in which green space exposure is measured and highlights research specific for measures of trees, tree canopy, and street trees.

Each of the three main domains (mitigation, restoration, instoration) have been proposed as mechanisms by which trees could have health effects. The domains and pathways outlined by Markevych et al. (2017) and Kuo (2015) are applicable to the relationship between street trees and health. Furthermore, the domains can be situated inside a broader conceptual framework, one that identifies potential feedback loops, interferences, and multilevel factors that could alter the exposure influence. The ISEM is one such framework that was helpful in conceptualizing the relationship between street trees and cardiovascular health and designing the current study (see Olvera Alvarez, Appleton, et al., 2018).

Conceptual Framework

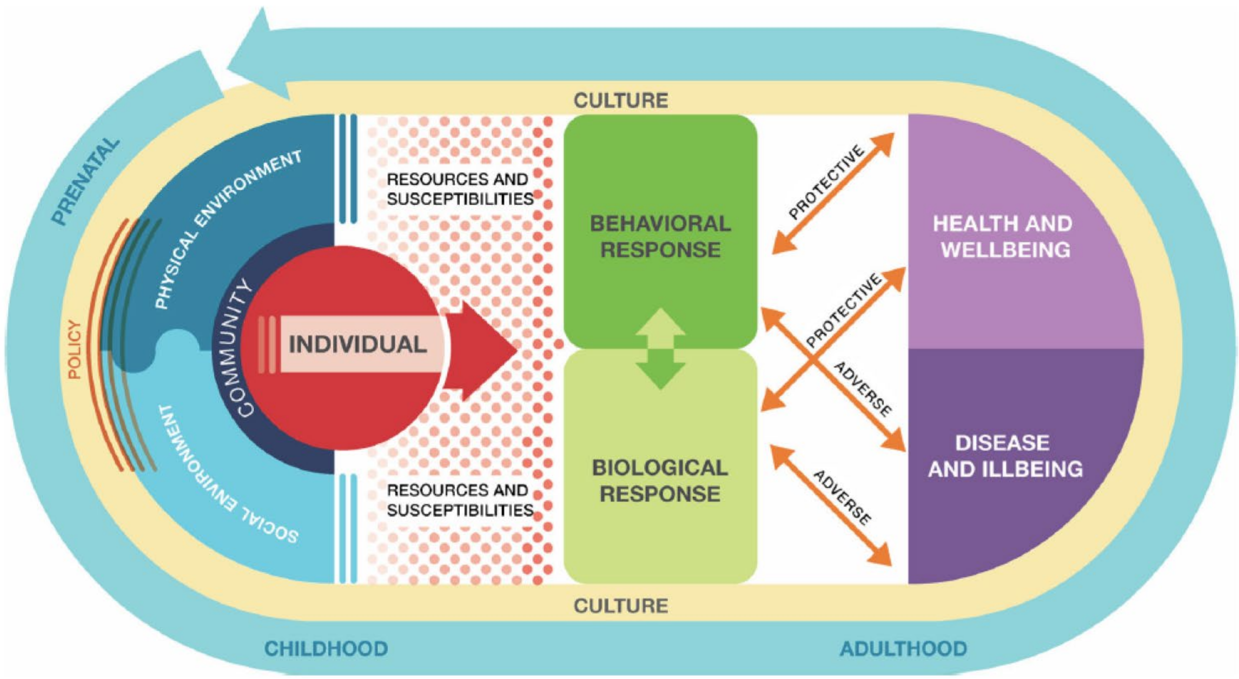
The ISEM was first proposed in 2018 by an interdisciplinary team of environmentally focused social scientists and epidemiologists who noted that environmental and social determinants of health often cooccur but that joint effects on health are likely underestimated because they are studied separately (Olvera Alvarez, Appleton, et al., 2018). The ISEM was selected for the current study because it is a comprehensive, theory-informed framework to guide future research on the joint contribution of social and environmental factors to health and well-being across the lifespan (Olvera Alvarez et al. 2018a). On its face, the ISEM appears similar to the well-established SEM (Hayden, 2019). The ISEM can be used to conceptualize the interplay among the natural environment, the social environment, and the personal environment and how the various pathways might interact to promote or damage human health. Both the SEM and the ISEM acknowledge multiple interconnected levels of influence over individual behavior and health outcomes. However, the ISEM was more appropriate for the current epidemiological investigation because it includes biological and behavioral responses to external stimuli.

The ISEM conceptual model is built upon two prior frameworks, both initially applied to birth outcomes. The first one, published in 2006, describes an environmental risk-scape in which community-level stressors and buffers of the built and social environments interact with individual-level stressors and buffers, combining to affect individual allostatic load and susceptibility to disease (Morello-Frosch & Shenassa, 2006). The second foundational framework by Tulve et al. (2016) depicted five levels of interacting influences, expanding from the individual out to the city/state/nation. Moreover, the concept of the life course was included in this model. The authors emphasized that stressors and buffers at every level are present during multiple phases of development and can change people's health trajectories (Tulve et al., 2016). Tulve et al. also explicitly discussed policy in their model because the sum of an individual's environment is shaped by many types of decisions from both governmental and corporate decision-makers.

All of the components of these earlier models are included within the ISEM (Figure 3), which is centered on the individual and the community together as a unit in the context of the physical and social environments. The physical environment includes both the built and the natural environments; the social environment comprises the connections between people and the industries around them (Yen & Syme, 1999). The social environment also includes governmental factors such as laws and regulations. Located around the edge of Figure 3, policy and cultural factors are depicted as influencing the social and physical environments and also downstream individual responses to health promoters and stressors.

Figure 3

Integrated Socio-Environmental Model of Health and Well-Being (ISEM)



Note. From Olvera Alvarez, Appleton, et al. (2018, p. 6).

While conceptualizing the research study, I applied the ISEM framework and drew from existing literature to select variables for inclusion in the statistical analyses. To isolate a potential contributory or protective role of street trees in the development of CVD, I considered the overlapping and interconnecting harm reduction, restoration, and instoration pathways and how they might function within the cultural and environmental backdrop of Mexican urban areas. At the individual level, people have an innate risk for CVD (i.e., gender, age, family history) as well as accumulated risk factors (i.e., smoking, a sedentary lifestyle) that develop over their life course. At the neighborhood and municipality levels, environments can positively or negatively affect behaviors that contribute to CVD and help buffer the effects of negative external stressors.

The ISEM provides a solid framework for this study, but the present cross-sectional study design and the available data do not and cannot include all the factors conceptualized in the model. For example, early life experiences and individuals' current social environments could impact CVD susceptibility, but neither are addressed in this study. Additionally, this study tests relationships, rather than the pathways of health and illness that were the focus of the model's creators (Olvera Alvarez, Appleton, et al., 2018; Olvera Alvarez, Kubzansky, et al., 2018). In a later review of the benefits of nature exposure, the creators of the ISEM noted that effective interventions at the individual and population levels are most informed when they account for the multiple environmental exposures that interact in direct and indirect ways to impact psychological well-being (Bratman et al., 2021). The spirit of this sentiment is applied via the multiple covariates and risk factors conceptualized in the present study and consideration of the hierarchical nature of the data in the analytical model.

Literature Review Related to Key Variables and Concepts

This section includes background information related to the key independent, dependent, and covariates. It also reviews and synthesizes the extant research linking various green space measures to CVD incidence, prevalence, and outcomes. This review is focused on literature published between 2016 and 2024, although important works published earlier are included for historical context and supporting evidence. All information is included to support the purpose and design of the present investigation.

Cardiovascular Diseases

These represent a group of disorders of the heart and blood vessels that include coronary heart disease (involving blood vessels to heart muscles), cerebrovascular disease (involving blood vessels supplying the brain), peripheral arterial disease (involving blood vessels supplying arms and legs), rheumatic heart disease (caused by bacterial rheumatic fever), congenital heart disease, and thrombosis/embolism (WHO, 2021). Myocardial infarctions (heart attacks) and cerebrovascular accidents (strokes) are consequences of CVD that account for the most significant percentages of global CVD-related death and disability around the world (Vaduganathan et al., 2022). Another symptom is angina, which is chest pain caused by reduced blood flow to the heart, either from vessel narrowing due to coronary heart disease or a blockage in the arteries that feed the heart (Mayo Clinic, 2022). The CVD-related outcomes probed in this study are self-reported angina, heart failure, heart disease, stroke, or heart attack. The same outcomes have been employed in other studies linking green space to CVD (Richardson et al., 2013; Tamosiunas et al., 2014; R. Wang et al., 2022) and are also included in multiple international versions of national health surveys similar to ENSANUT 2012. Examples of other surveys using similar endpoints are the Longitudinal Ageing Study of India, Brazil's National Health Survey (BPNS), China's National Health Survey (CNHS), and ENSANUT-Ecuador, among others (Ahmed et al., 2023; Glynn et al., 2021; Gonçalves et al., 2019; He et al., 2020; Jeong et al., 2020; Pengpid & Petlzer, 2021). These outcomes are limited to self-reported prior diagnoses, which may undercount the actual prevalence of CVD and its major risk factors (Ahmed et al., 2023; Palomo-Piñón et al., 2022). Nonetheless, self-reported diagnoses are an important and consistent indicator of CVD in the extant literature and are appropriate for this study.

The global proliferation of CVDs has been linked to a set of modifiable and nonmodifiable risk factors that are associated with behavioral, socioeconomic, environmental, physiological, and psychosocial characteristics (Keymolen & Robles Linares, 2021). Metabolic and behavioral risk factors are prominent targets of public health and medical research because, by their very definition, they are modifiable by the actions of individuals. Individual behaviors, such as excessive salt and sugar intake, smoking, and a sedentary lifestyle, contribute to CVD indirectly via their effects on metabolic risk factors, but they also can directly affect the function of the cardiovascular system.

Many elements of an individual's environment have been linked to elevated CVD risk after controlling for the known individual-level risk factors. The most well-known environmental risk factors are anthropogenic air, water, and soil pollution as well as increased heat (Franklin et al., 2015; WHO, 2022). These environmental factors are typically more pronounced in dense, urban environments.

Additional environmental factors like noise pollution, heat, light cycles, sunlight exposure, seasons, and geographic characteristics, as well as social and personal aspects of the environment, such as built environments, socioeconomic status, and social networks, can also significantly influence CVD risk (Bhatnagar, 2017; Cosselman et al., 2015). The noise and light pollution found in urban environments are known to disrupt circadian rhythms which elevates CVD risk. The urban heat island effect is the phenomenon of increased temperatures in high-density urban areas due to the amount of impervious surfaces and lack of shade (Shao & Kim, 2022; Vaduganathan et al., 2022). In susceptible individuals, increased heat in general is associated with cardiovascular mortality. In susceptible environments, increased heat can create a destructive feedback loop of increased energy consumption, altered water and air quality, and worsened environmental quality (Bhatnagar, 2017; Shao & Kim, 2022). Road and intersection density and proximity to major roads can negatively impact human physiology and the proper functioning of the circulatory system by increasing stress related to environmental noise and air pollution (Chum & O'Campo, 2015).

Urban environments also affect individual behaviors and choices. Environmental factors have a “crucial influence” on the physical and financial burden caused by CVD by dismantling healthy food systems, accelerating urbanization, and fostering sedentary, inactive lifestyles (Mendoza-Herrera et al., 2019, p. 2; Reeves & Potter, 2023). Food availability, accessibility of cigarettes and alcohol, distribution of recreational spaces, and differences in transportation services, health care resources, social interactions, and neighborhood identity have been linked to CVD outcomes through impacts on individual behaviors and metabolic risk factors such as hypertension and diabetes (Avila-Palencia et al., 2022; Bhatnagar, 2017; Chum & O'Campo, 2015).

The scientific underpinning of the present study is research which demonstrates higher levels of residential greenness are significantly associated with reduced CVD mortality (Bianconi et al., 2023; Gascon et al., 2016; X. Liu et al., 2022), lower CVD incidence and prevalence (Asri et al., 2020; H. Chen et al., 2020; T. Li et al., 2022), fewer CVD-related hospital admissions (Pereira et al., 2012), reduced incidence and prevalence CVD risk factors (Almeida et al., 2021; Knobel et al., 2021), and lower levels of CVD-related biomarkers (Iyer et al., 2022; T. Liu et al., 2021; L. Yang et al., 2021). A 2018 systematic review and meta-analysis including almost 150 observational and interventional research projects established that higher exposure to green spaces was statistically significantly associated with reduced stress biomarkers, lower heart rate, decreased diastolic blood pressure, improved cholesterol levels, enhanced heart rate variability, lower prevalence of type II diabetes, and improved self-reported health (Twohig-Bennett & Jones, 2018). Two subsequent systematic metareviews have synthesized the available literature and concluded that there are beneficial associations of green space with all-cause and stroke-specific mortality, CVD morbidity, cardiometabolic factors, and mental health (B. Yang et al., 2021; Y. Zhang et al., 2023).

Green Spaces, Greenness, and Cardiovascular Health

Medicus curat, Natura sanat morbus.

The physician heals, Nature makes well.

-Latin Proverb

Cardiovascular Mortality

Nature has long been recognized as a health agent, but the current era of green space research did not begin until the 1990s and 2000s. Initial interest was focused on the ecological benefits of green infrastructure, including stormwater management and urban heat mitigation (Nieuwenhuijsen, 2021). Soon thereafter, contact with nature and residential greenness were linked with positive outcomes for both mental and physical well-being (Hartig et al., 2014; Lee & Maheswaran, 2011).

Cardiovascular-related mortality was the endpoint of interest in early epidemiology studies of green space because of the completeness of readily available data. A string of papers published between 2008 and 2014 showed a reduction in the risk of CVD mortality in areas with higher residential greenness as assessed using either normalized difference vegetation index (NDVI) or land cover maps (discussed below) (Gascon et al., 2016). Similar reductions were not seen in all-cause mortality or lung cancer mortality. Subsequently, an inverse relationship between the amount of residential greenness and CVD mortality has been documented in at least a dozen countries. These include studies conducted in Hong Kong (Xu et al., 2017), Brazil (da Silveira & Junger, 2018), South Korea (Kim et al., 2019), Taiwan (H. Y. Lee et al., 2020), and Greece (Kasdagli et al., 2021). Although many of these studies were ecological and subject to the limitations inherent in such study designs, the findings have been reinforced using cross-sectional (United States / Yitshak-Sade et al., 2019) and longitudinal (Canada / H. Chen et al., 2020; Feng et al., 2023; Italy /Orioli et al., 2019) study designs.

A 2016 meta-analysis with pooled data from eight published studies demonstrated a statistically significant risk reduction for CVD mortality (RR = 0.96; 95% CI: 0.94, 0.97) and all-cause mortality (RR = 0.92; 95% CI: 0.87, 0.97) when greenness was measured as “high” and “low” but not when measured in 10% increments (Gascon et al., 2016). A second systematic review published in 2018 included mortality as well as stroke and coronary heart disease incidence. Although only two studies were included in the summary for cardiovascular mortality, it covered almost 4 million participants and demonstrated an odds ratio (*OR*) (95% CI) of 0.84 (0.76, 0.93; $p < 0.001$) when comparing people living in high green space versus low green space areas (Twohig-Bennett & Jones, 2018). In the same meta-analysis, positive results were found for type II diabetes and hypertension but not for stroke or coronary heart disease. More recent meta-analyses were published in 2023 by Bianconi et al. (2023); M. Liu et al. (2023); Y. Zhang et al. (2023). Increases in NDVI demonstrated an overall statistically significant protective effect of urban green for CVD, ischemic heart disease, and cerebrovascular disease mortality (Bianconi et al., 2023). Additional studies were referenced that studied different green space metrics and CVD morbidity and are discussed elsewhere in support of the premise of the present research study.

Identifying and Quantifying Green Space Exposures

The process of quantifying individual exposure to nature in epidemiological studies and determining which elements of urban nature are responsible for health benefits is challenging. Not only do different studies use different methods to measure green exposure, but they also connect those exposures to different outcomes.

A common measure in the research literature is NDVI, a remote sensing method that takes advantage of plants' unique reflectance characteristics for near infrared and red visible light. The NDVI is calculated as a ratio of reflectances in those two light bands and can differentiate between areas of high versus low vegetation. NDVI values range from -1 to 1, with values closer to 1 indicating greater amounts and healthier vegetation (Scheftic et al., 2014; Shahtahmassebi et al., 2021). Using the NDVI, individual exposures can be calculated as the percent greenness within a given radius around an address or as a percentage of an administrative land division.

Other satellite-based measures of greenness include the LAI (Leaf Area Index), SAVI (Soil-Adjusted Vegetation Index), LiDAR (Light Detection and Ranging), EVI (Enhanced Vegetation Index), and several LC/LU (Land Use/Land Cover) data sets (Shahtahmassebi et al., 2021). LC/LU maps provide spatial information on types of land cover (e.g., forests, grasslands, croplands, lakes, wetlands) or land use categories (e.g., agricultural, residential, recreational, commercial, industrial, transportation).

Both LU/LC classifications and satellite data have been used to quantify tree canopy cover, the percentage of land occupied by parks, and other natural elements. The results for tree canopy cover are of particular interest to this study, as tree canopy cover distinguishes between the greenness provided by trees versus other sources of vegetation. In urban areas, tree canopy cover reflects the amount of shade provided by trees, a feature of urban greenness known to reduce heat intensity and improve feelings of well-being (Ulmer et al., 2016; C. Zhang et al., 2022). At present, new techniques are being developed to analyze street-level greenness exposure using machine-learning and image databases such as Google Street View (Hankey et al., 2021; Larkin & Hystad, 2019; R. Wang et al., 2022).

Other measures used in the exploration of green space and health relate to the proximity, accessibility, quality, and various attributes green spaces, including of parks, open spaces, and trees versus grasses. Frequent measures in published literature are the total number of parks within an administrative area, the distance to a park entry from a known address, the frequency of visiting a public park, and proximity to space designated as a park or other open space (De Petris et al., 2021; Jennings et al., 2019). Exposure measures specific to trees are most relevant to the current study.

In head-to-head comparisons of the effects of distinct types of green space variables, measures related to tree canopy, tree diversity, or tree cover seem to outperform other measures and other types of nature in their contributions to human health. In one such example, three different green space metrics (NDVI, % tree cover, % herbaceous cover) were used to examine the differential contribution of each type of neighborhood green space to the prevalence of the CVD risk factors of obesity, abdominal obesity, and low HDL among a sample of adult Brazilians (Almeida et al., 2021). The authors concluded, “tree cover seems more relevant for cardiometabolic health than does herbaceous cover, since the former presented stronger magnitudes of associations with the studied outcomes when compared to the latter" (p. 6). In New York City, Reid et al. (2017) found higher reporting "very good" or "excellent" self-reported health for respondents with the highest, compared to the lowest, quartiles of tree density but not grass density within 1,000 m buffers.

In a small cross-sectional study of North Carolina residents, Egorov et al. investigated tree cover and biomarkers of allostatic load (2020). The group living in the highest tertile of tree cover within 500 meters of their homes was had a statistically significant 14% reduction in fifteen biomarkers indicative of allostatic load for the group versus those living in the area of the lowest tree cover. On the other hand, there was no statistical relationship between the amount of grass cover and markers of allostatic load.

Several studies have found that tree canopy percentage, but not other vegetation indexes have positive health and well-being influences. A recent analysis of data from Australia's largest ongoing study of health and aging uncovered reduced odds of both prevalent and incident social loneliness among those studied with 10% more green space or tree canopy, but increases in open grass areas were associated with increased odds of social loneliness measures (Astell-Burt et al., 2023). A separate analysis from the same data set reported that residential addresses with higher levels of tree canopy (> 30% versus 0%–9%) were associated with lower odds of incident psychological stress and poor health, whereas addresses with higher levels of open grasslands were associated with the opposite (Astell-Burt & Feng, 2019). There are publications with less clear results, such as Wu et al. (2018). In their study of census tracts in urban Wake County, NC, sudden unexpected cardiac death was inversely associated with greenway density and the percentage of forest but not with grassland, average tree canopy, near-road tree canopy, and tree canopy diversity (Wu et al., 2018). Nonetheless, a systematic review of different green space measures and various health endpoints was published in 2021 by Astell-Burt and collaborators (Nguyen et al., 2021). The conclusion, not specifically related to CVD, was that "health benefits were more consistently observed in areas with greater tree canopy, but not grassland" (p. 1).

The following sections continue to summarize the literature relating green space to CVD and then describe the research that has linked trees to human health. These findings set the stage for the present study by providing theoretical and scientific support for the hypothesis that there is a relationship between urban street trees and CVD prevalence in Mexico.

CVD Prevalence and Incidence

Research revealing a connection between CVD mortality and exposure to urban green spaces has prompted further investigation into the role of green space role in disease development. These studies have focused on CVD incidence and prevalence as key outcomes. Disease prevalence is the total number of cases of disease existing in a population . It is frequently evaluated in large, cross-sectional, and nationally representative studies such as ENSANUT 2012. In contrast, disease incidence measures the number of new cases that emerge during a specified time frame and provides insight into the rate at which a disease is developing within a population. By examining both prevalence and incidence in relation to urban green spaces, researchers have been trying to tease out the mechanisms by which environmental factors might influence CVD at different stages of its progression.

A negative statistical relationship has been documented between areas of higher greenness and incidence rates of acute myocardial infarction (Ponjoan et al., 2022)/[NDVI], (Seo et al., 2019)/[%GS area]); cerebrovascular disease/stroke (Orioli et al., 2019; Seo et al., 2019)/[%GS area]; heart failure (H. Chen et al., 2020)/[NDVI]; and ischemic heart disease (Dalton & Jones, 2020)/[%GS area]. Similarly, lower CVD prevalence has been linked to increased green space (Astell-Burt & Feng, 2020)/[%GS area and Tree Canopy Cover], (Maas et al., 2009)/[%GS area], and (T. Liu et al., 2021)/[NDVI tertiles]). Other studies found non-statistically significant or non-dose responsive positive trends in CVD prevalence related to green space measures (Astell-Burt et al., 2021; Pereira et al., 2012; Richardson et al., 2013). One study in Atlanta, GA, reported a significantly higher prevalence of COPD, coronary heart disease, and stroke in areas with greater tree canopy cover and green space access (Servadio et al., 2019). Areas with majority African American populations also had higher disease prevalence. The counterintuitive results with green space metrics are thought to result from the inability of the researchers to fully control for interactions between demographics, air quality, and green space.

The studies described up to this point have included ecological, cross-sectional, and longitudinal cohort studies. Additionally, experimental and quasi-experimental studies are valuable in establishing a cause-and-effect relationship between independent exposure variables and outcomes.

Experimental and Quasi-Experimental Studies on Greenness and Cardiovascular Health

Experimental studies are those in which the investigators manipulate exposure to a stressor or protective factor in randomly assigned research subjects and look for a change. Quasi-experimental studies are those in which similar populations of people are exposed to different stressors or protective factors by chance, giving researchers an opportunity to look for differences between exposed and nonexposed groups. Both types of these studies have been conducted and both support the role of green spaces and nature-based interventions in improved cardiovascular health outcomes.

In a 2022 systematic review summarizing the impact of green spaces or greenness on cardiovascular health and cancer-related outcomes, Bikomeye et al. (2022) identified four types of interventions that demonstrated a beneficial effect on blood pressures, heart rate variability, or CVD-related biomarkers. Two experimental studies in Japan used “forest bathing” as an intervention to reduce stress-related feelings (i.e., stress and depression) or physiological responses to stress (e.g., blood pressure, inflammatory and CVD-related biomarkers) (Mao et al., 2012; Morita et al., 2007). In both studies, therapeutic effects on mood, hypertension, or inflammation were noted and the authors suggested that exposure to nature could be used to decrease the risk of psychosocial stress-related diseases. In a more recent study, L. Yang et al. (2021) recruited 39 participants in Hong Kong and tracked weekly exposure to green space, air pollution, and the physical activities of individual participants using personal tracking devices. After accounting for factors such as sex, income, occupation, physical activities, dietary intake, noise, and air pollution, noteworthy inverse relationships were identified between exposure to high levels of greenness and cardiorespiratory biomarkers. These included significant decreases in total cholesterol (–21.6% per interquartile range rise in NDVI), low-density lipoprotein (–14.9%), glucose (–11.2%), and high-sensitivity C-reactive protein (–41.3%) (L. Yang et al., 2021).

Other experimental studies have used nature-based images to see if they can partially ameliorate stress responses measured as skin conductance, heart rate, salivary cortisol, or eye movement analysis. In one set of studies, participants were exposed to a social or mental stressor in a laboratory situation and then shown images or videos of urban scenes with various levels of greenery and tree cover density (Jiang et al., 2014; L. Liu et al., 2022; X. Wang et al., 2016). Comparisons of stress recovery responses indicated that images with higher levels of greenness and tree cover had the most positive effects on stress recovery, whereas buildings and pavement had either neutral or negative effects. In another set of studies, participants were shown images of urban streetscapes and subsequently asked to rate their perceived affect from a validated positive and negative affect schedule (Navarrete-Hernandez & Laffan, 2023). An 8% increase in green coverage in a photo was associated with a 0.23 increase in positive affect on a ten-point scale. Furthermore, green coverage positively impacted nine of ten queried emotions, and negatively impacted all ten of the negative emotions covered in the scale. Notably, there was a threshold of approximately 16% green coverage in a photo before changes in affective states were detected and a leveling off at high levels of green coverage.

Quasi-experimental research has been harnessed to provide important insights into the benefits of urban nature. Several studies have used the devastation of U.S. ash trees due to the spread of the Emerald Ash Borer (EAB) that started in 2002 as an opportunity to examine social and physical health effects after neighborhood tree loss. An invasive beetle, the EAB kills nearly all ash trees that it infects and has devastated U.S. ash trees since it was first detected in the United States in 2002. In one study using data from before and after tree loss, a significant and positive relationship between tree loss and four types of crime was uncovered (Kondo et al., 2017). In another study, tree loss was associated with a “negative and persistent relationship” in daily outdoor leisure time (Jones, 2016, p. 49). Most notably, Donovan et al. (2013) established a significant link between tree loss and increased cardiovascular mortality.

Urban Trees and Various Health Outcomes

In 2013, Donovan published the results of a quasi-experimental ecological study that estimated the relationship between the presence of the EAB and county-level mortality in 15 U.S. states. Controlling for a wide range of demographic covariates, Donovan et al. revealed an increase in mortality related to cardiovascular and lower-respiratory-tract illness, but not accidental mortality, in counties infested with the EAB (Donovan et al., 2013). The magnitude of this effect was greater the longer the EAB had been in the county and in counties with a greater percentage of tree canopy from ash trees. For example, the estimated marginal effect of the EAB on CVD-related mortality after one year of infestation was 9.7 additional deaths per year per 100,000 adults (95% CI: 1.8, 17.6) and after six years of infestation, the effects had increased to 38.6 additional deaths per year per 100,000 adults (95% CI: 23.6, 53.6) (Donovan et al., 2013). Jones (2023) suggested that a possible, but not exclusive, mechanism of action of this deforestation was a reduction in physical activity outside. Another team of researchers described increased subjective well-being scores among Australian urban residents with a tree in front of their home Ordóñez Barona et al. (2024). These changes in well-being scores was partially mediated by prior feelings of relatedness to nature.

Donovan and colleagues extended their study of the effect of EAB-related tree loss and health outcomes using individual-level outcome data from the Women's Health Initiative, one of the largest longitudinal studies of women's health undertaken in the United States (Donovan et al., 2015). In their 2015 follow-up study, Donovan et al. compared these individual health outcomes with data indicating the years since EAB was first detected in an individual's county of residence (Donovan et al., 2015). Living in a county infested with EAB versus no EAB was associated with a 41% increased risk of CVD (hazard ratio [*HR*] = 1.4; 95% CI: 1.4, 1.5). CVD was defined as acute myocardial infarction requiring overnight hospitalization, silent myocardial infarction determined from electrocardiogram, stroke, or coronary heart disease-related death. The association was unchanged when the analysis was limited to metropolitan areas. The association between years of EAB infestation and CVD risk was somewhat attenuated when the analysis was restricted to EAB-infested counties only (*HR* = 1.3, 95% CI:1.2, 1.3) (Donovan et al., 2015). As discussed previously, both Donovan studies support the conclusion that tree cover, rather than other measures of green space, has a protective role in maintaining cardiovascular health. Although neither study was designed to investigate the mechanism of action, both studies provided a springboard for later researchers designing studies to understand which features of urban greenness are most impactful and why.

More recently, Donovan et al. (2022) assessed the impact of 30 years of tree planting by an environmental nonprofit on non-accidental, cardiovascular, lower respiratory, and accidental mortality in Portland, Oregon. With geolocated data on mortality from the Oregon Health Authority and a corresponding data set with the number, date, and location of new trees, the authors estimated linear mixed models of mortality rate with the tree planting data, census tract random effects, and potentially confounding census tract-level sociodemographic drivers of mortality (Donovan et al., 2022). There was a statistically significant negative association between the number of trees planted in the past 15 years and CVD and respiratory mortality, with the mean number of trees planted per year (11.7) associated with an annual reduction of 5.0 CVD deaths (95% CI: 1.9, 8.0). Further analysis showed only a weak association between tree planting and lower respiratory deaths and no relationship with accidental mortality. Their results both support the linkage between street trees and CVD and unique methods to measure tree exposure.

A body of research has identified associations between urban trees and all three positive health domains (i.e., harm reduction, restoration, and instoration) of the theoretical framework linking green space to health. Harm reduction has been demonstrated via urban forests' known ability to mitigate air pollution and urban heat and to reduce extreme heat events (Graham et al., 2016; Nowak et al., 2018; Y. Yang et al., 2023). The extent of tree canopy cover is negatively correlated with heat-related emergency calls, decreases in pedestrian falls, fewer suicide attempts, improved self-reported general health, improved healthy aging scores, and lower individual and county-level Medicare health care costs, (Becker et al., 2019; John et al., 2023; S. Lee et al., 2023; S. Lee et al., 2022; Ulmer et al., 2016; Van Den Eeden et al., 2022). Van den Eeden et al. noted that the health benefits conferred by green exposure are "likely through effects across multiple organ systems and chronic diseases" such that a dependent variable of health care costs "can be considered a measure of the systemic impact of green cover on health" (p.7).

The proposed restorative and instorative capabilities of urban trees and tree canopy have been demonstrated by the studies with mental health outcomes, reduced crime and aggression, and improved general health and health perceptions. Restoration indicates the experience of a psychological and/or physiological recovery process" (Joye & van der Berg, 2013, p. 58); instoration refers to "perceptions of restorative potential and outcomes without a prior stress intervention" (Korpela & Ratcliffe, 2021, p. 1). Instoration, in particular, is thought to build the capacity to withstand the negative impacts of stressful events (Joye & van der Berg, 2013). In Brussels, higher tree crown volume was associated with lower medication sales for medications commonly prescribed for mood disorders (Chi et al., 2022). In London and in Leipzig, decreases in antidepressant prescriptions have been reported in areas of higher street tree density (Marselle et al., 2020; Taylor et al., 2015). Kardan et al. (2015) found that having ten more trees in an Ontario, Canada, city block improved personal health perceptions comparable to being seven years younger and improved residents' cardiometabolic profiles.

Urban Trees and CVD

The cardiometabolic profile in the Kardan et al. (2015) study was a summation of the following seven variables: the presence of the risk factors hypertension, high blood glucose, obesity, high cholesterol, and diabetes, as well as a a prior diagnosis of myocardial infarction, heart disease, and stroke. These CVD risk factors and related diagnoses have not only been linked to NDVI levels, park proximity, and land cover percentages, they have also specifically been connected to urban trees and tree canopy, providing evidentiary support for the premise of the present research study. For example, Moreira et al. (2020) reported that 10,000 more street trees within regional government boundaries encompassing an individual's residence (trees in sidewalks, street islands and roundabouts and not those in squares, parks, reserves, and private areas) was associated with a lower odds of hypertension (*OR* = 0.94; 95% CI: 0.88, 0.99). At smaller 300 m buffer distances, this association was not significant. Other green space variables such as tree canopy cover and district-level green space showed nonsignificant tendencies towards negative ORs. In a longitudinal study of nearly 50,000 older Australians, Astell-Burt and Feng (2020) reported that areas with ≥ 30% tree canopy (compared with 0–9%) exhibited lower odds of incident diabetes (*OR* = 0.69, 95% CI: 0.55, 0.86), incident hypertension (*OR* = 0.83, 95% CI: 0.72, 0.95) and incident CVD (*OR* = 0.78, 95% CI: 0.65, 0.94). Notably, these health benefits were consistently associated with higher tree canopy cover but not with higher total green space in the Sydney, Wollongong, and Newcastle study areas.

Research by Alkhatib et al. (2021) in Palestinian occupied territory demonstrated that residents in areas with the lowest quartile of non-crop mixed trees (about 2.8% of total land) had twice the likelihood of chronic illness compared to those in the third quartile (about 9% of total land). Only the green space variables had a significant association with chronic illness, not factors like living in refugee camps or under Israeli versus Palestinian governance (Alkhatib et al., 2021). When analyzed as a continuous variable, each 1% increase in non-crop mixed trees corresponded to a 4% decrease in chronic illness odds (*OR* = 0.96). In a separate longitudinal study in China, Zhou et al. (2023) found that higher levels of residential greenness, tree coverage, and the ratio of trees to shrublands/grassland were inversely associated with peripheral overweight/obesity and central obesity, both significant risk factors for CVD.

In Brussels, a quartile increase in tree crown volume was linked with a 25% decrease in CVD medication sales (Chi et al., 2022). Another ecological study conducted in Tampa, FL, demonstrated that tree density showed a significant inverse association with respiratory and cardiovascular hospitalizations, but percent tree canopy cover showed a nonsignificant inverse association (Jennings et al., 2019). Conversely, no significant association was found between heart attack or hypertension prevalence and percent tree canopy cover in an ecological study of Texas metro areas (Tarar et al., 2015).

The bulk of the evidence points to the potential for increased green space in general, and an increased presence of trees in general, to positively impact cardiovascular health. The purpose for this study was to extend the current research related to street trees. To isolate the potential effects of the presence of street trees, the analyses controlled for the effects of the CVD risk factors. The most notable risk factors, both individual and environmental, are described below.

Costs of Urban Greening Strategies

Recent studies in the United States have highlighted the substantial economic benefits of urban greening strategies in relation to health outcomes. A study conducted in Philadelphia projected that reaching a 30% tree canopy goal by 2030 would yield annual health-related benefits of USD 3.8 billion (Konijnendijk et al., 2023). In Portland, OR, a group studying an urban tree planning initiative estimated that planting just one tree in each of the city's 140 census tracts would generate USD 14.2 million in annual benefits from deaths averted based on the U.S. Environmental Protection Agency value of a statistical life (Donovan et al., 2022). The annual maintenance cost for these 140 trees would be less than $15,000 per tree, a relatively low cost when viewed from the perspective of health care costs and lost productivity. These findings underscore the significant return on investment that urban greening initiatives can offer in terms of public health and economic benefits.

Behavioral, Metabolic, and Environmental Risk Factors for CVD

Individual-Level Risk Factors

Age. CVD is often thought of as a disease of older individuals, and aging is an important factor contributing to cardiovascular decline. Over time, accumulated oxidative stress, inflammation, tissue degradation, and imbalances in circulating factors can cause functional changes in cardiac activity (Rodgers et al., 2019). Furthermore, the incidence of many of the important metabolic risk factors for CVD, such as BMI and central obesity, hypertension, diabetes, high fasting plasma glucose levels, and altered blood lipid levels also increase with age (Acosta-Cázares & Escobedo-de la Peña, 2010; Vaduganathan et al., 2022). The lifetime risk of developing CVD is similar for men and women, although there are notable differences in age-specific rates of CVD diagnoses and mortality. Men typically manifest CVD at an earlier age than women, but after age 60, the incidence rates for CVD among women increase and prevalence approaches parity (Peters et al., 2019).

Among adults in the United States, the odds of reporting CVD is four to ten times higher for individuals 40–59 years of age than for those under 40 (Abdalla et al., 2020).

The odds of CVD for those over 60 years old is 15 to 30 times higher than for those under 40. Age is such an important factor in the risk of CVD that comparisons between countries and across time are nearly universally reported using age standardization (Dávila-Cervantes, 2020; Rittiphairoj et al., 2022). Mexico is currently at the cusp of a dramatic demographic transition, with the median age expected to rise from 28 to 42 by 2050 and the proportion of people 65 and older tripling to 20.2% (Angel et al., 2017). Therefore, age should not only be controlled for in the study analysis, but the aging of the population should also be taken into account when contemplating the future burden of CVD in Mexico.

Sex. Some of the observed gender differences in incidence rates have been hypothesized to result from protective effects of estrogen in women (Sophie et al., 2017). Sex is differentially linked to other prominent risk factors for CVD, including obesity (more common in women) and diabetes (more common in men) (Rodgers et al., 2019). Sex is nearly universally included as a covariate in the body of research that associates residential green space with cardiovascular outcomes.

Family History of CVD or Myocardial Infarction. Family history of CVD is a known risk factor for CVD, although it is unclear the extent to which family history is meaningful for traditional ages of diagnosis versus being relevant only for premature CVD, or diagnosis before age 50 (Bittencourt, 2018). Furthermore, because families often share habits such as diet and smoking, it can be challenging to disentangle the specific contribution of family behaviors versus genetics. A 10-year prospective multiethnic cohort study in the United States found that individuals with a known family history of heart disease had increased hazard ratios, ranging from 1.3 to 1.6, for various forms of heart disease compared to those without a family history (Patel et al., 2018).

Hypertension. Hypertension is a condition in which the pressure in arteries is high and the heart needs to work harder to move blood through the body. Normal blood pressure is close to 120/80 mm Hg. The clinical definition of hypertension is systolic blood pressure over 130 mm Hg and diastolic blood pressure over 80 mm Hg. Continual pumping of the heart against these elevated blood pressures can lead to conditions such as heart failure, arterial and venous wall damage, heart valve disease, and atrial fibrillation (Fuchs & Whelton, 2020). Labeled as a metabolic risk factor, hypertension has been identified as the single largest risk factor for CVD and its prevalence increases with age. According to Yusuf et al. (2020), hypertension is responsible for 22.3% of the population-attributable fraction (PAF) of incident CVD and accounts for the largest proportion of disability-adjusted life years lost in Latin America (Lindstrom et al., 2022). The PAF of abdominal obesity, tobacco use, high cholesterol, poor diet, diabetes, household air pollution, and low education were each estimated by the same research team to be between 5 and 10% for CVD (Yusuf et al., 2020). The remaining major risk factors, including alcohol use, physical activity, and depression, were assessed to contribute less than 5% of the PAF for CVD.

In high- and middle-income countries, the hazard ratio for incident CVD between those with and without hypertension ranges from 1.5 to 2.1 (Ruilope et al., 2017). In Latin American countries, generally up to 40% of the population is affected by hypertension, with estimates in Mexico from ENSANUT 2012 being 26% affected women and 31% affected men in the adult population (Ruilope et al., 2017). By some estimates, at least half of CVD-related mortality in Mexicans 50 years and older is attributable to suboptimal blood pressure levels (Cortés-Hernández et al., 2014).

Obesity. The WHO and other health organizations recognize obesity as a major public health concern due to its link with various chronic diseases, including CVD (OECD, 2017). Numerous studies have shown a strong association between obesity and an increased risk of developing various cardiovascular conditions such as coronary artery disease, heart failure, stroke, and hypertension (Escobedo-de la Peña et al., 2021). Mexico and Poland are two countries in which obesity has the greatest impact on health by reducing life expectancy by 4.2 years and 3.9 years, respectively (OECD, n.d.). As of 2017, Mexico had the highest obesity prevalence (32.4%) among people aged 15–74 years in OECD countries and ranked fourth in childhood obesity (OECD, 2017). Some of the mechanisms by which obesity affects healthy physiological functioning and cardiovascular health are listed below and discussed independently in other subsections.

- metabolic changes which contribute to atherosclerosis
- low-grade inflammation contributing to the development and progression of atherosclerosis
- overactivation of the renin-angiotensin-aldosterone system leading to hypertension
- an imbalance of lipid levels leading to dyslipidemia
- type 2 diabetes
- structural and functional changes in the heart
- sleep apnea

- physical inactivity

Smoking. Extensive epidemiological research has established smoking as a significant preventable factor in the development and progression of heart disease (Gallucci et al., 2020). Although precise mechanisms have not yet been completely elucidated, it is known that smoking affects endothelial function via inflammatory and oxidative processes within the vascular wall. In 2010, Acosta-Cázares & Escobedo-de la Peña identified smoking as the most prevalent cardiovascular risk factor in men within the Mexican Social Security health care system (31.9%). Since 2010, smoking rates have decreased to approximately 25% among males and 8.2% among females, with nondaily smoking being slightly more prevalent than daily smoking (Sreeramareddy & Aye, 2021). Smoking rates in Mexico demonstrate a declining trend with age, which is encouraging (Acosta-Cázares & Escobedo-de la Peña, 2010). However, negative atherosclerotic changes may have already occurred in those who formerly smoked.

In Mexico, the current prevalence of smoking is 16% (Rojas-Martínez et al., 2021). Additionally, a total of 20.5% have arterial hypertension, and almost 80% of adults are classified as overweight or obese (Rojas-Martínez et al., 2021).

Hypercholesterolemia/Hypertriglyceridemia. Hypercholesterolemia is the condition of having a blood level of cholesterol greater than 190 mg/dl, greater than 160 mg/ml with one other CVD risk factor, or greater than 130 mg/dl with two other cardiovascular risk factors (Ibrahim et al., 2022). Similarly, hypertriglyceridemia is a blood lipid disorder in which circulating triglyceride levels are elevated above 200 mg/dl (Karanchi et al., 2023). People with high cholesterol or high triglycerides are at a higher risk of adverse cardiac events, including stroke, heart disease, and peripheral artery disease due to blood hyperviscosity and the aging of important blood vessels. The prevalence of hypercholesterolemia and hypertriglyceridemia is higher among Mexican adults, 43.6% and 31.5%, respectively, than in the high-development countries of Japan and the United States (Mendoza-Herrera et al., 2019). Depending on moderating factors, the hazard ratio (HR) of incident CVD is approximately 1.5 to two times higher for people with high lipid levels than those who do not.

Diabetes. As with obesity, the relationship between diabetes (type II) and CVD is complex. Though much of the excess CVD risk in diabetics stems from well-known factors, diabetes-related vascular dysfunction also plays a role. This dysfunction is influenced by changes in visceral adiposity, insulin resistance, and alterations in hormones, lipids, and inflammatory cytokines (Cannatà et al., 2017; Martín-Timón et al., 2014). Over the past 12 years, the reported adult diabetes prevalence in Mexico has been approximately 15%, one of the highest in the OECD and trending upwards (López Sánchez et al., 2022; OECD, 2015b). Notably, Mexico also has a higher prevalence of early onset type 2 diabetes compared to other OECD countries, with 23.8% for ages 40–59 and 5.9% for ages 20–39, versus the OECD averages of 8.9% and 1.7%, respectively (Bello-Chavolla et al., 2022; OECD, 2015b). Early onset of diabetes has important implications for long-term health status and may result in greater social and health care needs over extended periods.

Alcohol Intake. There is a complicated relationship between alcohol consumption and CVD incidence and outcomes. On the one hand, there is some evidence that moderate levels of alcohol consumption exert a protective effect on cardiometabolic risk among middle-aged adults, particularly those without multiple other risk factors

(Yoon et al., 2020). On the other hand, excessive alcohol consumption of 60g or more (≥ 6 drinks) results in myocardial toxicity and cumulative cardiovascular damage and dysfunction (Fernández-Solà, 2015; Piano et al., 2017). Research by Wannamethee et al. (2015) identified that regular consumption of five drinks per day increased heart failure among men.

Depression. A link between depression and CVD has been established for more than three decades, with evidence from diverse populations and from countries of all levels of economic development (Rajan et al., 2020). Not only this, the relative risk of depressive symptoms and incident CVD is twice as high in urban versus rural areas across 7 different geographical regions and in countries at all economic levels (Rajan et al., 2020). The hypothetical biological pathway linking depression and CVD involves stress hormones and elevated inflammatory cytokines (Ryder & Cohen, 2021). This pathway supported by research with evidence that green space and tree canopy is associated with reduced stress and depressive symptoms in urban areas (Jimenez et al., 2021). Depression may be more than a risk factor, but also a mediating or moderating factor affecting the relationship between green space and disease (R. Zhang, et al., 2021).

Physical Activity. Physical activity is well-established to be inversely related to CVD incidence, prevalence, and mortality (Shakoor et al., 2023). Regular physical activity substantially lowers the risk of experiencing the cardiovascular events that are of interest for this research (Aune et al., 2021). Moderate physical activity is associated with a 5% to 15% reduced relative risk of developing various forms of CVD compared with inactivity (Aune et al., 2021; Chomistek et al., 2018). Evidence also supports the idea that physical activity plays a pivotal role in reducing the incidence of hypertension, hypercholesterolemia, metabolic syndrome, weight gain, and diabetes in a curvilinear dose-dependent manner (Shakoor et al., 2023; U.S. Department of Health Human Services, 2018).

Physical activity has been proposed to be a primary mediating factor between green space exposures and measures of CVD, but the results have been inconclusive (Dalton & Jones, 2020). A 10-year Australia cohort study showed a weak mediating effect in which increased physical activity among those with higher access to public open spaces was linked with lower cumulative risk scores based on metabolic syndrome biomarkers (Paquet et al., 2013). On the other hand, Richardson et al. (2013) and T. Liu et al. (2021) did not find a statistically significant mediating effect of physical activity levels between area-level green space and a diagnosis of CVD or between NDVI-defined greenness levels and the presence of hypertension, coronary heart disease, or stroke.

According to previously published ENSANUT data, the prevalence of physical inactivity in Mexico rose from 13.4% to 19.4% between 2006 and 2012 and stayed relatively stable between 2012 and 2018 (Medina et al., 2013; Medina et al., 2021). As a reference, the prevalence of physical inactivity was 25.3% in the United States in 2020, ranging from 17.7% (Colorado) to 49.4% (Puerto Rico) (U.S. Department of Health and Human Services, 2022).

Hours of Sleep per Night. In 2022, the American Heart Association (AHA) added sleep health to its list of significant factors needed for cardiovascular health. Supported by numerous epidemiological studies, the AHA recommended 7 to 9 hours of sleep daily for optimal cardiovascular health for adults (AHA, 2022). Insufficient and poor-quality sleep has been found to interfere with numerous physiological functions, including previously described conditions such as hypertension, glucose sensitivity, and obesity. Even controlling for confounders that could affect both sleep duration and cardiovascular health (e.g., age, depressive mood, alcohol consumption), findings still favor a pathogenic contribution of inadequate sleep to CVD (Covassin & Singh, 2016; Mentzelou et al., 2023).

Household-Level Risk Factors

The most well-known environmental risk factors are anthropogenic air, water, and soil pollution (Franklin et al., 2015; WHO, 2022). The term *air pollution* describes a complex mixture of small particles (particulate matter [PM]) and various gaseous pollutants such as ozone, nitrogen, and sulfur dioxide (Mannucci, 2023). Airborne PM consists of a diverse mix of aerosols that differ in size and composition and are generally classified by size—course, PM_{10} (2.5–10 μm), fine ($PM_{2.5}$ < 2.5 μm), or ultrafine ($PM_{0.1}$ < 0.1 μm) (Franklin et al., 2015). Air pollution includes the environmental air that individuals breathe outside their homes and the ambient air they are exposed to inside their homes. Vehicle emissions, construction activities, and industrial combustion are among the primary sources of PM outside the home, and residential wood burning is a major PM source inside the home (Fatmi & Coggon, 2016). In particular, PM_{10} and $PM_{2.5}$ are commonly associated with increased CVD-related hospitalization and mortality (Franklin et al., 2015) and current epidemiological evidence points to a 2 to 4-fold increased risk of coronary heart disease from indoor burning fuels for cooking and heating (Fatmi & Coggon, 2016),

Census Tract and Municipality-Level Risk Factors

Socioeconomic Status/Social Deprivation Index. Neighborhood socioeconomic status has been identified as a significant risk factor for CVD. Individuals with low socioeconomic status (SES) and those residing in disadvantaged neighborhoods face an higher odds of CVD and poorer outcomes due to a combination of biological, behavioral, and psychosocial risk factors (Coughlin & Young, 2020; Perner et al., 2022; Roux et al., 2001; Sundquist et al., 2004). The interplay of limited resources, inadequate health care infrastructure, and variations in lifestyle and living conditions contributes to the higher prevalence of cardiovascular risk factors in these populations (Schultz et al., 2018). Although the specific dynamics may differ between more and less developed countries, neighborhood socioeconomic status remains an important consideration in understanding cardiovascular health outcomes.

Elevation. Epidemiological data related to living at high altitudes is conflicting and is highly dependent upon the population and the distribution and prevalence of other risk factors (Mallet et al., 2021). While short-term visits to high altitudes can stress the circulatory system of people from low altitudes, long-term exposure to high altitude has been found to be protective against cardiovascular mortality in some populations and not in others (Bhatnagar, 2017; Mallet et al., 2021). Despite not having specific information on how high altitude affects cardiovascular risk in the Mexican population, it is appropriate to include residential altitudes in the analysis to control for its potential unknown positive or negative effects.

Road Density. Residential proximity to heavily trafficked roads has been linked to a myriad of diseases, including CVD, respiratory health, and cancer. Road traffic is a major contributor to ambient air pollution in urban areas. Multiple studies have demonstrated that most of the risk comes from living within 50 m of highly trafficked roads, with exposure to air pollution being lower the further away from roads. Some of this information comes from an ecological study conducted in Malaysia (Kwan et al., 2021) 20-year longitudinal study conducted in Canada (Cakmak et al., 2019), and a 2-year longitudinal study conducted in the United States (Kan et al., 2008).

Mexico's Street Tree Data Set

The current study was the first application of the INEGI 2014 Characteristics of the Urban Environment survey to a specific health outcome and the first to concentrate on the health effects of street trees (*arboles lineales*). Although previous studies in Mexico have assessed street tree distribution and developed methodologies for estimating water needs, none have directly examined health outcomes using this data set (Martínez Juárez et al., 2022; Mayen Huerta, 2021; Wessolek & Kluge, 2021). To date, the only published study using the INEGI street tree data was an exploratory analysis on urban environment quality during COVID-19 confinement in Tijuana (Ordóñez Barba, 2021). On the other hand, ENSANUT is a well-established national health survey that provides essential data on public health and policymaking in Mexico (Medina et al., 2020; Medina et al., 2013; Rojas-Martínez et al., 2021; Shamah-Levy et al., 2019). The present study leverages the distinct information of the INEGI 2014 Characteristics of the Urban Environment survey with the ENSANUT 2012 data set to address unique research questions about the relationship between street trees and CVD in Mexico.

Summary and Conclusions

CVD is the leading cause of mortality in Mexico and is a substantial contributor to morbidity and health care costs. Continued public health efforts to address known modifiable metabolic and behavioral risk factors are appropriate, but environmental factors in urban settings should also be leveraged to reduce CVD and its risk factors. The interconnectedness among individuals, their environments, their health behaviors, and, ultimately, their state of health or disease, is a central concept in the conceptual framework for this study, the ISEM. In particular, features of the urban environment that are increasingly being studied and recognized as important for health are the amount and accessibility of proximate green spaces. Street trees represent a type of green space and existing evidence supports their contribution to health. Street trees are integral elements of urban design that could also influence individual behaviors, such as physical activity, and counteract some of the physical and psychological stresses of urban living. The present study examined the relationship between street trees in urban Mexico and self-reported CVD among adults over 40, considering other known individual and environmental factors contributing to CVD.

Chapter 3: Research Method

The purpose of this quantitative study of secondary data was to examine the relationship between street trees in urban neighborhoods of Mexico and CVD among adults living in those neighborhoods, while adjusting for individual and environmental factors that contribute to the development of CVD. This chapter provides the rationale for the study design and the statistical methodology. This chapter also provides the details of each survey from which the data were sourced, including the target population, sampling procedures, and variable operationalization. Data screening procedures to identify missing data and assess data suitability are described, as are potential threats to validity and ethical considerations.

Research Design and Rationale

This study was a secondary data analysis using information from several publicly available national data sets from the Mexican government. Individual-level data, including self-reported prior diagnosis of CVD and related risk factors, were sourced from ENSANUT 2012, a probabilistic and representative national health survey conducted in 2011 and 2012. Census tract- and municipality-level data providing information on elements of the local environment came from the INEGI Characteristics of the Urban Environment Survey (2010), the CONEVAL Social Lag Index (2010), a CEDRUS 2017 road density data set (2017), and the INEGI Catalog of General Integration of Localities (CIGEL, 2010).

The study integrated individual-level data from various ENSANUT 2012 data sets using household and household member codes. Environmental data were linked to individuals through a shared geospatial linking variable across all data sets. The analysis included only households with geographic information at the census tract (AGEB) level, allowing for matching with environmental data. Data collection occurred between 2010 and 2014 with one exception: Municipality-level road density data used as a proxy for air quality came from 2017 due to lack of earlier information. Although more recent ENSANUT surveys were available from INEGI, the 2012 version was chosen for this study because it provided information on residential census tracts. In contrast, recent surveys share only participants' municipalities, thereby limiting the granularity of geographic analysis.

Logistic regression models were developed to estimate the odds of self-reporting a prior medical diagnosis of a cardiovascular-related health event as a function of the proportion of city block boundary streets within census tracts with a least one street trees. Based on published research, the original expectation was that multilevel logistic regression models would be required to align with established methodologies in the field of green space research and to address clustering effects. Therefore, both single-level and multilevel models were considered for the analysis, taking into account limitations of the statistical program and the need to address the variability inherent in the sampling method. As described later in this chapter and in Chapter 4, intercept-only models were used to determine whether clustering was present in the outcome variable and whether multilevel modeling techniques were required. The final analyses were conducted using single-level logistic regression models that accounted for the multistate sampling plan of the primary data set.

Research Questions and Hypotheses

Three research questions and corresponding hypotheses were developed by reviewing the extant literature on elements of urban green space and the conceptual framework:

RQ1: Is there a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors?

H_o1: There is no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors.

H_a1: There is a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors.

RQ2: Is there a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for neighborhood- and municipality-level factors?

H_o2: There is no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for neighborhood- and municipality-level factors.

H_a2: There is a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for neighborhood- and municipality-level factors.

RQ3: Is there a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors?

H_o3: There is no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors.

H_a3: There is a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors.

Study Population

The population of interest for this study was adults 40 years and above who lived in census tracts categorized as *metropolitan* by INEGI at the time of the study. Metropolitan municipalities are defined by INEGI as those that are part of state capitals and areas with 100,000 or more inhabitants; *urban* municipalities are defined as having more than 2,500 inhabitants but fewer than 100,000 inhabitants and are not otherwise defined as metropolitan (INEGI, 2015a). My study sample originally included urban-designated census tracts. As described in Chapter 4, I later determined that the metropolitan census tracts better represented the large urban centers that I am interested in and limited the study sample. The sample was further limited to those who could be linked with street tree data.

My study focused on the metropolitan population due to an interest in urban health improvement and because research indicated that green space health relationships differ between urban and rural areas (Hongsheng et al., 2017; Maas et al., 2006; Vienneau et al., 2017). Adults over 40 were selected as the target group because CVD risks and incidence begin to increase in the fifth decade of life, with a sharp rise between ages 55 and 65 (Hajar, 2017). Participants under 40 with a previous diagnosis of CVD were assumed to have different risk factor profiles and a higher likelihood of inherited predispositions unrelated to standard individual and environmental factors.

Data Sources and Methodologies

Data from five independent sources were merged for the analysis, with place-based data assembled from four national surveys being linked to individual respondents in ENSANUT 2012 using codes established by INEGI's National Geostatistical Framework.

Introduction to Mexico's Geostatistical Framework

The United Mexican States are organized into three levels of disaggregation, called Geostatistical Areas (*Áreas Geoestadísticas*). These levels correspond to the state/federal entity, municipality, and census-tract/basic levels (i.e., *Área Geoestadística Básica/AGEB* in Spanish). AGEBs are referenced as census tracts for the purposes of this study. Census tracts are the smallest aggregation unit of federally available data and are classified as urban or rural by their locality. In urban localities, these census tracts comprise between 1 and 50 units called manzanas, referred to as city blocks for the purposes of this study. City blocks are delimited by streets, avenues, walkways, or other features that are easy to identify and whose use is defined as residential, industrial, services, or commercial (INEGI, 2019).

Mexico's 32 states/federal entities are each represented by a two-digit code from 01 to 32. Within each of these entities are municipalities represented by three-digit codes. Municipality limits are permanent and mostly coincide with the political-administrative limits of the municipality. Census tracts are the next smallest geostatistical unit and are assigned a key composed of three numbers, a hyphen, and another number or letter, totaling four digits. A four-digit key encodes city blocks.

ENSANUT 2012

Background

ENSANUT 2012 was a national survey with a complex probabilistic design, a multistage survey process, and comprehensive coverage designed to support inferences about health and nutrition conditions, program coverage, and population access to health services in Mexico. The original sample included Mexicans of all ages from 55,008 households. In each household, an adult age 20 years or more was selected to respond to the individual questionnaires that included sociodemographic and health information (Romero-Martínez et al., 2012). The response rate obtained in the households was 87%. Data collection for ENSANUT 2012 occurred between November 2011 and May 2012. Nine data collection instruments covering both health and nutrition endpoints were used for the adult sample and are publicly available from the INEGI website in 13 unique data sets. These files were: 1. Seguridad_alimentaria (food insecurity); 2. Nutricion_distr_alimentos (nutrition distribution); 3. Datos_sangre_capilar (blood draw details); 4. Datos_sangre_presion (blood pressure details); 5. paf_adultos_adole_2012 (physical activity); 6. psangre_adulto_mayor (hemoglobin measuresments-adults); 7. psangre_mujeres (hemoglobin measuresments-women); 8. Pantro_adultos (anthropometrics); 9. Hogar_integrantes; (household member IDs); 10. Adultos (Individual Health Questionnaire); 11. folio_vivienda (household codes); 12. Hogar_hogar (household details); 13. Base_med_gluc (glucose levels). The primary data set was the “Adultos” file with responses to individual health questions.

Sampling Frame

The sampling frame for ENSANUT 2012 was constructed based on information from prior housing and census counts from 2005 to 2010 and included the Mexican population living in inhabited private homes. Census tracts were the primary sampling unit (Romero-Martínez et al., 2012). Dwellings were sampled proportional to the urban/rural distribution of dwellings in each state. Households with the greatest social deprivation (also referred to as marginalization) were oversampled (Instituto Nacional de Salud Pública, 2012; Romero-Martínez et al., 2012). The strengths of this nationally representative probabilistic sampling methodology were its potential for generalizability, reduced bias, enhanced precision, attention to social disparities, policy relevance, and comparability to ENSANUT surveys conducted across different years.

Seven strata were formed in each state/federal entity to accomplish the desired population representation:

- metropolitan/higher social deprivation
- metropolitan/lower social deprivation
- urban/higher social deprivation
- urban/lower social deprivation

- rural/higher social deprivation
- rural/lower social deprivation
- newly created localities

For the urban and metropolitan strata, households were identified in stages. In the first sampling stage, 1,440 dwellings were selected and distributed across the seven sampling strata in a number proportional to the size of the stratum. Primary sampling units were selected as the following groups: census tracts per stratum with a probability proportional to the total number of dwellings. In the second stage, six city blocks were chosen for each selected census tract with a probability proportional to their size. In the last stage, six dwellings were chosen in each of the selected city blocks by systematic sampling with random start-up; the selection of dwellings in the blocks was carried out in the field among those dwellings that appeared to be inhabited. Only the census tract information of a participant is available in the publicly available data.

Units of Analysis

A total of 1,728 households, defined as a "group of people, related by some kinship or not, who usually sleep in a dwelling under the same roof, and benefiting from a common income contributed by one or more members of the household" (Romero-Martínez et al., 2012, p. S334) were sampled in each state/federal entity. Adults were defined as those 20 years and older.

Recruitment, Participation, and Data Collection

Within each household and whenever the household composition permitted, at least one adult and one or two health service users were selected using simple random sampling. The application of household and individual questionnaires was completed first, and anthropometric measurements, blood pressure measurements, and blood sampling were completed later for a subset of the initial survey respondents.

Data Access

Data for ENSANUT 2012 were publicly available for download on the INEGI website along with study documentation including codebooks, questionnaires, informed consent forms, and descriptions of the sampling procedures (INEGI, 2015a).

Ethical Procedures

In accordance with the provisions of Articles 13 and 16 of Mexican General Health Law regulations on health research, the identity and privacy of individual participants in ENSANUT 2012 are protected, and continued management and publication of any data has been and will be accomplished under observance of the principles of confidentiality. The Research Ethics Committee of the National Institute of Public Health of Mexico was responsible for the review and approval of all informed consent forms used during the survey. The process for retrieving the de-identified study data adhered to the ethical and procedural guidelines stipulated by the Walden University IRB (Approval #: 02-05-24-1000349).

2014 Characteristics of the Urban Environment Survey

Background

Starting with the 1950 decennial census, the Mexican government began collecting information related to the human habitat, or housing information, to provide inputs for the design, implementation, and evaluation of public policies to improve living conditions in Mexico (INEGI, 2015b). In 2010, the research scope was expanded to capture information on the neighborhood environment in which the homes and the population are located, with separate survey instruments for urban and rural localities. The Characteristics of the Urban Environment Survey was updated in 2014 to capture information on road infrastructure, benches and public lighting, sidewalks and pedestrian pathways, types of areas available for public commerce, and the presence of trees and ornamental plants (*árboles o plantas de ornato*) along roadsides (INEGI, 2015b).

Units of Analysis

The observation units for the 2014 Characteristics of the Urban Environment Survey were manzanas (city blocks).

Data Collection Procedures

The survey objective was to collect data for all urban and metropolitan inhabited localities across Mexico. No sampling strategy was employed. The survey data were collected by direct observation of survey personnel who started in the northwest corner of each city block and walked the perimeter in a clockwise manner until returning to the starting point. A total of 16 features for each urban unit of analysis were assessed for almost 5 million roads demarcating the boundaries of approximately 1.2 million city blocks (INEGI, 2015b).

Data Access

Data and documentation for the 2014 Characteristics of the Urban Environment Survey were publicly available for download on the INEGI website (INEGI, 2015a).

Ethical Procedures

This data set did not include human subjects or other sensitive data that necessitated ethical review. However, the process for retrieving study data adhered to the ethical and procedural guidelines stipulated by the Walden University IRB.

CONEVAL Social Lag Index/Grado de Rezago Social

Background on SLI/GRS

Mexico's Social Lag Index is based on the United Nations Human Development Index (Martínez-García et al., 2021). It is a measure that summarizes aggregate indicators of access to some of the social rights of people and their assets across four dimensions: education, health services access, the quality of the home, and basic services in the house (CONEVAL, 2023). The stated purpose of the SLI has been to identify priority areas in Mexico for social development and public policy efforts. However, researchers have also used the SLI to investigate the relationship between social and economic indicators and health endpoints (Martínez-García et al., 2021).

CONEVAL creates estimates of social lag every 5 years at the state/federal entity and municipality levels. An expanded version of the SLI, the Degree of Social Resilience (GRS), at the urban census tract level was created in 2010 and 2020 using information from Mexico's decennial census. The variables used to estimate social lag described in Table 2. For the purposes of this study, I refer to the social lag variable used in this study as SLI/GRS.

Table 2

Variables Used to Estimate Social Lag

Associated indicator	Variables for the estimation of social lag (SLI) (municipality and town, 2010*)	Variables for the estimation of social lag (GRS) (Census tract level, 2010*)
	Total variables: 11	Total variables: 14
Educational lag	Illiterate population aged 15 years and over	Illiterate population aged 15 years and over
	Out-of-school population aged 6-14	Out-of-school population aged 6-14
	Population aged 15 and over with incomplete primary education	Population aged 15 and over with incomplete primary education
		Population aged 15 to 24 years who do not attend school
Access to health services	Population not entitled to health services	Population not entitled to health services
Quality and spaces of the house	Homes with dirt floors	Homes with dirt floors
		People living in overcrowded conditions
Basic services in the house	Homes that do not have a toilet or toilet	Homes that do not have a toilet or toilet
	Homes that do not have piped water from the public network	Homes that do not have piped water from the public network
	Homes that do not have drainage	Homes that do not have drainage
	Homes that do not have electricity	Homes that do not have electricity
Income (household assets)	Homes that do not have a washing machine	Homes that do not have a washing machine

* Variables are represented by percentages

Units of Analysis

The unit of analysis was the census tract.

Variable

In the 2010 classification of SLI/GRS, census tracts were classified as low, medium, and high social risk.

Data Access

Data and data documentation are publicly available for download on the CONEVAL website.

Ethical Procedures

This data set did not include human subjects or other sensitive data that necessitated ethical review beyond the Walden IRB requirements for a secondary data analysis.

CEDRUS Road Density in Mexican Municipalities

Background

INEGI maintains a database of roads throughout Mexico, from major highways and roadways to pedestrian pathways and alleyways. The Center for the Study of Regional Development and Urban Sustainability (CEDRUS) applied INEGI data to calculate road density and road network density for each municipality across Mexico. Their purpose for creating these indicators was two-fold: (a) to rank municipalities on connectivity and infrastructure available for economic activity, and (b) for administrative awareness at all levels of government of the potential economic and human resource needs to manage and maintain road infrastructure (CEDRUS, 2019). The density of the road network within a municipality was a proxy for the relative level of transportation-related air pollution to which residents within the municipality may have been exposed.

Unit of Analysis

The unit of analysis in this data set was a municipality. Density values were calculated for road density (length of roads in km/area in square kilometers) and road network density (length of road network in km/area in square kilometers) from 2017 INEGI data.

Data Access

Data were available in CSV format from the Center for the Study of Regional Development and Urban Sustainability (CEDRUS, 2019).

Ethical Procedures

This data set did not include human subjects or other sensitive data that necessitated ethical review. However, the process for retrieving study data adhered to the ethical and procedural guidelines stipulated by the Walden University IRB.

INEGI Catalog of General Integration of Localities (CIGEL)

Background

The Catalog of General Integration of Localities (Catálogo de Integración General e Localidades) is a regularly updated publication from INEGI used to ensure homogeneity of the names, codes, and data of Mexico's geostatistical divisions that are referenced by different institutions across the government (Instituto Nacional de Estadística y Geografía, 2015c). The 2010 Catalog of General Integration of Localities is linked to the 2010 General Census of Population and Housing.

Unit of Analysis

CIGEL 2010 contains over 192,000 data points at the census tract level, including location name and code, rural or urban status, latitude, longitude, and altitude, among other information.

Data Access

Data for CIGEL 2010 were publicly available for download on the INEGI website.

Ethical Procedures

This data set did not include human subjects or other sensitive data that necessitated ethical review beyond the Walden IRB requirements for a secondary data analysis.

Procedures for Matching Place-Based Data to Individual Data

The geographic location of every subject in this study was identified by a 13-digit variable ("GEOCODE") derived from state, municipality, locality, and census tract codes. The original state, municipality, and locality information were preserved in the final data set.

GEOCODE = STATE (00) + MUNICIPALITY (000) + LOCALITY (0000) + CENSUS TRACT (0000).

Table 3 presents examples of geographic coding from the INEGI 2014 Urban Characteristics Survey. The first row uniquely identifies city block #20 in census tract #0257 within Aguascalientes state (01), the Calvillo municipality (003), and the Ojocaliente (0055) locality. The second two rows represent city blocks #43 and #45 in census tract #0079 within the same state, municipality, and locality. The same geostatistical framework was used for households and household members in ENSANUT 2012. To match individuals with street tree data, the city block level 2014 Characteristics of the Urban Environment Survey was aggregated at the census tract level and matched to participant locations using the derived GEOCODE variable.

Table 3

Geographic Coding From the 2014 Characteristics of the Urban Environment Survey

State/federal entity		Municipality		Locality		Census tract (AGEB)	City block (Manzana)	Derived GEOCODE
Code	Name	Code	Name	Code	Name			
01	Aguascalientes	003	Calvillo	0055	Ojocaliente	0257	20	0100300550257
01	Aguascalientes	003	Calvillo	0055	Ojocaliente	0079	43	0100300550257
01	Aguascalientes	003	Calvillo	0055	Ojocaliente	0079	45	0100300550079

Identification and Operationalization of Study Variables

Based on the literature review presented in Chapter 2, factors significantly related to CVD development were identified alongside the primary exposure variable of street trees. These included individual, household, neighborhood, and municipal characteristics. The first two types of variables were sourced from ENSANUT 2012; the latter were from the other four data sets previously discussed. All data were merged into the final data set using the 13-digit GEOCODES.

Dependent Variable

The dependent variable underlying all research questions was an individual's self-reported prior medical diagnosis of CVD. In the 2012 ENSANUT data set, respondents were asked, "Has a medical professional told you that you have [angina, heart failure, heart disease, stroke, had a heart attack]?" and to which they responded either "Yes" or "No" for each of these conditions. The study CVD variable was derived from these data into a binary categorical variable coded "1" if a respondent answered "yes" for any of these five conditions and "0" if all responses were negative. Table 4 provides an overview of all the variables described in this section.

Independent Variables

The primary independent variable underlying all research questions was the proportion of streets with street trees within individuals' residential neighborhoods. This was a census tract-level variable sourced from the 2014 Characteristics of the Urban Environment Survey. City block-level data were available in the survey but was aggregated at the census tract level to match the geospatial resolution of participants' addresses in ENSANUT 2012.

The 2014 Characteristics of the Urban Environment Survey report used an aggregated variable at the census tract level to describe the extent that the boundary streets within a census tract contained street trees: all streets, some streets, no streets. However, city block-level data were available in the underlying data sets and used to create a derived variable that represented the proportion of boundary streets within a census tract with street trees (Equation 1). The total number of streets with street trees was divided by the sum of the total number of streets evaluated per census tract. Streets with missing data were ignored when calculating the denominator. It is important to note that this data did not include information on the quantity of trees per street, only their presence or absence. Additionally, the survey was limited to the streets defining the block boundaries, not interior streets.

Equation 1

The following equation was used to derive the independent variable representing street trees:

$$Proportion\ of\ Street\ Trees\ per\ AGEB = \frac{\sum_{All\ manzanas} Streets\ with\ Street\ Trees}{\sum_{All\ manzanas} Total\ Streets}$$

During the survey, city blocks were categorized as either typical, a housing complex, or unspecified. Only manzanas classified as typical were used in the final analysis because the environmental characteristics were not assessed for housing complexes or the unspecified block types.

Individual- and Household-Level Covariates

Individual-level contributors to the development of CVD include physiological and behavioral factors (Table 4). Following the theoretical framework of the ISEM, these variables reflect individual resources and susceptibilities that result in adverse or protective behavioral and biological responses. Whereas some of these variables were used in their original form, others were recoded for the final analyses. For example, most comorbidities and behavioral risk factors were represented as binary variables in which zero represented the absence of the risk factor and one represented its presence.

Age and Hours of Sleep Per Night. Interval level scale variables, represented in years and hours, respectively.

Sex. Response categories for gender were “male” and “female” and were coded as “0” and “1,” respectively.

Diagnosis of Diabetes, Hypertension, or Depression. These three variables were initially presented as binary categorical variables in ENSANUT coded as 1 for “yes” and 2 for “no.” Each wase recoded as 0 for “no” and 1 for “yes”.

Years Since Diagnosis of Diabetes or Hypertension. Published evidence indicates that the risk of developing CVD increases with the duration of having diabetes or hypertension (de Jong et al., 2022; Zheng et al., 2022). Participants who responded “yes” to a prior diagnosis of hypertension or diabetes were asked the follow-up question, “How many years since their diagnosis?” A new variable was constructed from the original scale data, with 0 indicating “no diagnosis” and all other numbers representing years and fractions of years since diagnosis.

Family History of Infarction. ENSANUT 2012 included two questions regarding family history of infarction, “Did your mother have an infarction?” and “Did your father have an infarction?” The presence of family history was derived from these two variables into a single binary categorical variable coded “1” if a respondent answered “yes” to either question or “0” if both responses were negative.

Excessive Alcohol Use. All participants in ENSANUT 2012 were asked their frequency of drinking any alcohol and their frequency of heavy drinking (defined as five or more drinks in a single sitting for men and four or more for women). The twelve response options ranged from 1 (“daily”) to 12 (“never”). For this analysis, I identified heavy drinkers as those who consume more than 5 (males) or 4 (females) drinks during a single occasion once a week or more frequently. The original ENSANUT responses of “1,” “2,” “3,” and “4” were recoded into a single category represented by “1,” and the rest were coded as “0”.

High Triglycerides or High Cholesterol. Adults in ENSANUT 2012 were next asked whether they had ever had their blood cholesterol or triglyceride levels tested. Those who responded positively were then asked whether the test was positive or negative. The responses for both questions were combined into a single variable in which 0 represented “normal triglycerides (cholesterol) level,” 1 represented “high triglycerides (cholesterol) level”, and 2 represented “not tested”.

Obesity. Information on BMI was collected on two separate occasions. In one data set (Physical Activity), BMI was coded into one of four categories, “underweight,” “normal,” overweight,” or obese.” In the other data set (Obesity), two additional obese categories were available and were recoded have four categories. The data sets were merged to minimize missing data.

WHO Physical Activity Level. Level of physical activity information was collected for only a subset of ENSANUT 2012 participants. Activity levels were coded as “0” for “inactive,” “1” for “moderately active,” and “2” for “active.”

Smoking. The smoking variable originally had six categories that included whether the individual had consumed more than 100 cigarettes in their lifetime. Due to cell size consideration, the final variable had four categories that only described current smoking frequency. Those who indicated they had never smoked were coded as “0,” those who had previously smoked but were currently not smoking coded as “1,” those with a current smoking frequency of monthly or less were coded as “2,” and those reporting their smoking frequency of as “daily” or “weekly” were coded as “3.”

Stove Type. Information about the participant’s home was collected, including what type of cookstove was used. There were five response options, including “gas stove," closed oven with chimney," and "open flame or stove without chimney or exhaust hood." As the latter is linked to indoor air pollution, a dichotomous variable to indicate cooking with an unvented open flame or not was created with gas stove as "0" and all other responses as "1".

Census Tract- and Municipality-Level Covariates

SLI/GRS. As described previously, census tracts were classified as low ("1"), medium ("2"), and high ("3") social risk.

Altitude. A scale variable calculated as the height above mean sea level at the centroid of the census tract.

Road Density. The density of roads within a municipality could provide information on the potential level of transportation-related air pollution to which residents may be exposed. Road network density was calculated as the length of road network in km/area of the municipality in km^2 and included in a CEDRUS data set as "DENSRED."

Table 4

Overview of Variables

Purpose	Level	Information	Variable type	Coding
Outcome	Individual	Prior CVD diagnosis	Binary categorical	0 = No; 1 = Yes
Exposure	Census tract	Proportion of streets with trees	Scale	From 0 to 1
Covariate	Individual	Age	Scale	40+
Covariate	Individual	Sex	Binary categorical	0 = Male; 1=Female
Covariate	Individual	Prior hypertension diagnosis	Binary categorical	0 = No; 1 = Yes
Covariate	Individual	Prior diabetes diagnosis	Binary categorical	0 = No; 1 = Yes
Covariate	Individual	Prior depression diagnosis	Binary categorical	0 = No; 1 = Yes
Covariate	Individual	Family history of infarction	Binary categorical	0 = No; 1 = Yes
Covariate	Individual	Excessive alcohol use	Binary categorical	0 = No; 1 = Yes
Covariate	Individual	High triglycerides	Nominal	0 = No; 1 = Yes; 3 = Never tested
Covariate	Individual	High cholesterol	Nominal	0 = No; 1 = Yes; 3 = Never tested
Covariate	Individual	Obesity	Ordinal	0 = Underweight, 1 = Normal; 2 = Overweight; 4=Obese
Covariate	Individual	Hypertension-years since diagnosis	Scale	(0 = No diagnosis)
Covariate	Individual	Diabetes-years since diagnosis	Scale	(0 = No diagnosis)
Covariate	Individual	Smoking status	Ordinal	0 = Never smoked; 1 = Not currently smoking; 2 = Currently smoking monthly to yearly; 3 = Currently smoking weekly or daily
Covariate	Individual	Physical activity level	Ordinal	0 = inactive; 1 =moderate activity; 2 = active
Covariate	Individual	Hours of sleep/night	Scale	5 to 9

Purpose	Level	Information	Variable type	Coding
Covariate	Household	Cookstove-gas stove	Binary categorical	0 = Yes; 1 = All others
Covariate	Census tract	Social lag index/GRS	Nominal	1 = Low; 2 = Medium; 3 = High
Covariate	Census tract	Altitude (m)	Scale	0 to 3560
Covariate	Municipality	Road network density (km2)	Scale	0.0 to 2.02

Data Analysis Plan

Statistical Model

Logistic regression models were developed to estimate the odds of self-reporting a prior medical diagnosis of a cardiovascular-related health event as a function of the proportion of boundary streets within census tracts with at least one street tree. Logistic regression models allow one to predict membership in one of the two outcome categories using a generalized linear model (GLM) and a link function that relates the expected value of the dependent variable to the linear predictor variables in the model (Warner, 2012). The link function transforms the probabilities of each categorical outcome from a bounded scale (0 to 1) to an unbounded continuous scale ($-\infty$ to $+\infty$) (Heck et al., 2012). Once transformed, the relationship between the predictors and the dependent variables can be modeled linearly. The GLM for a logistic regression equation can be written to reflect probabilities of Y (dependent variable) being 1 given X (independent variable) under the null hypothesis (H_0) and the alternative hypothesis (H_1) where β represents the regression coefficient for each independent variable (Equation 2).

Equation 2

$$Probability\ (Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_n X_n)}}$$

The primary outcome of a logistic regression equation is the odds ratio, which is calculated from the probabilities of Y = 1 and Y = 0 based on changes in predictor variables.

The probability of the dependent variable Y being "1" given X under the null hypothesis (H_o) and the alternative hypothesis (H_a) will be calculated using the logistic function for each research question. The simplified equation logistic function is demonstrated in Equation 3 where $\beta 0$ is the constant term, β_x is the coefficient for the x^{th} independent variable, and *e* is the base of the natural logarithm.

Equation 3

$$\text{Predicted Probability of CVD as } 1 = \hat{Y_i} = \frac{e^{(\beta 0 + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 \ldots)}}{1 + e^{-(\beta 0 + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 \ldots)}}$$

The predicted probability of an event can then be converted into an odds ratio that represents the change in the odds of the dependent variable being 1 (having CVD) for a one-unit change in the independent variable (Equation 4).

Equation 4

$$Odds(Y = 1) \mid X1, X2, X3, \ldots = \frac{P(Y = 1 \mid X1, X2, X3, \ldots)}{1 - P(Y = 1 \mid X1, X2, X3, \ldots)}$$

Basic assumptions of a logistic regression are that the dependent variable is a dichotomous nominal variable, the sample size is adequate, there is a linear relationship between the continuous independent variables and the log transformation of the dependent variable, there is no multicollinearity, no significant outliers or leverage points, and there is independence of observations for the dependent variable. Laerd Statistics recommends bare minimum of 15 cases per independent variable, although some sources recommend as high as 50 cases per independent variable (Laerd Statistics, 2017b).

The complex sampling procedures of ENSANUT 2012 result in census tract- and municipality-level variables being shared among respondents, thereby violating the assumption of independence. Groups of people living in the same area may be subject to external influences that could impact the relationship between individual predictors and the outcome. Therefore, multilevel logistic regression models were considered for all research questions. Multilevel models, also known as hierarchical logistic regression models or mixed-effects logistic regression models, account for the clustering of subjects within higher-level units when estimating the effect of subject and cluster characteristics on subject outcomes (Austin & Merlo, 2017; Diez-Roux, 2000). Using a traditional single-level regression model on data subject to cluster effects increases the risk of Type I errors because the statistical model incorrectly assumes that any variability is solely due to individual differences and not influenced by the within-cluster correlations (Guo & Zhao, 2000; Sommet & Morselli, 2017). When standard errors $(\sigma/\sqrt{n})$ are calculated assuming independence, when in fact there is correlation within clusters, the standard errors are underestimated (Sommet & Morselli, 2017). Multilevel modeling of cross-sectional data is a common statistical technique used by researchers to probe cardiometabolic health benefits of green spaces (Astell-Burt & Feng, 2020; R. Wang et al., 2022). Other techniques used in the published literature to account for clustering have included the evaluation of spatial autocorrelation using Moran's I statistic or marginal models using generalized estimating equations (Diez-Roux, 2000; B. Wang et al., 2022). Multilevel modeling techniques often provide more precise estimates for hierarchical data than traditional logistic regression models (Austin & Merlo, 2017; Goldstein et al., 2002).

Multilevel logistic regression analysis incorporates the assumptions of single-level regression while introducing additional requirements. A key requirement is the presence of sufficient clusters to accurately calculate intergroup variability, which typically results in a larger sample size to detect relationships of interest. Most texts suggest that 50 is the minimum number of clusters required (Heck et al., 2012; Maas & Hox, 2005). Another crucial assumption in multilevel modeling is the correct specification of the model to appropriately distribute variances across and between levels (Leyland & Groenewegen, 2020). Based on the hypotheses and research questions for this study, a *random intercepts model* was used to test for clustering effects. For a Level-2 explanatory variable (street trees), a random intercepts model assumes a consistent effect of street trees on the response variable (presence of CVD) across all clusters, while allowing for variation in the baseline levels of the response variable between clusters (Leyland & Groenewegen, 2020). Conversely, a *random slopes model* does not assume a consistent relationship between variables across groups and allows the explanatory variable to have a different effect for each group (Pillinger, n.d.). Given that the research questions in this study hypothesize a stable relationship between variables while controlling for Level 2 clustering, a random effects model focusing on the interpretation of the fixed effects was tested following the steps recommended by Heck et al. (2012) and Sommet and Morselli (2017).

No correction for multiple statistical tests was planned for this analysis. Methods such as the Bonferroni correction are used to address the potential for Type I errors (concluding that a significant difference is present when it is not) as the number of statistical tests increases (Hollestein et al., 2021). According to a 2014 review by Armstrong, no correction for multiple statistical testing is recommended “if the study is restricted to a small number of planned comparisons” or if “it is the results of the individual tests that are important” (Armstrong, 2014, p. 505).

Data Screening and Cleaning

Data were screened, cleaned, and transformed prior to merging data sets and then reviewed for accuracy of data entry, variable specification, the extent of missing values, and the presence of outliers or potential high-leverage observations. Data distributions were examined to determine whether they are appropriate for the intended analysis and derived variables were created following the merging of all data into the final data set.

Handling of Data Inconsistencies/Missing Data

Inconsistent or missing data are an expected complication of a secondary data analysis and must be handled carefully and intentionally. Missing data can reduce statistical power to detect a departure of the data from the null hypothesis (Kang, 2013). Depending on which data are missing and whether data are missing at random versus missing due to systemic differences in individuals, missing data can also cause bias in parameter estimation and reduce representativeness (Kang, 2013). It was known prior to analysis that the sampling methodology and questionnaire administration of ENSANUT 2012 would result in some key covariates with a substantial amount of missing data.

Generally accepted options for addressing missing data are to 1) remove cases with missing data from the analysis (listwise deletion); 2) remove the variable with a high proportion of missing data from the model; 3) impute missing data using an appropriate imputation method. Imputation methods mentioned in recent literature include mean substitution, regression imputation, multiple imputation, maximum likelihood, hot deck, cold deck, and nearest neighbor methods, among others (Kang, 2013; Pandey et al., 2021). Chapter 4 describes the results and outcomes of the missing data analysis.

Power Calculation

G*Power is a computational tool developed by German statisticians to compute statistical power for many test families (Faul et al., 2009). Statistical power calculations for multilevel models can be more complex than single-level models, but the limiting factor is typically the Level 2 group sizes (Maas & Hox, 2005). Based on the published sampling strategy and number of participants surveyed in ENSANUT 2012, there were expected to be a sufficient number of clusters (> 1,000 Level 2 clusters with 20 respondents per cluster) such that a power analysis for a single-level logistic regression would be appropriate (Romero-Martínez, 2012; Romero-Martínez et al., 2012).

The selected test family was “z tests,” the selected test was “logistic regression,” and the type of power analysis was “A priori: Compute required sample size – given alpha, power, and effect size.” CVD prevalence was expected to be between five and 15 percent (Sánchez Velasco et al., 2014). The other assumptions that were used in the a priori power calculations are in Table 5. The results of the sample size calculation indicated that 12,542 participants would be sufficient to achieve 80% power with a two-tailed hypothesis test at an alpha value of 0.05.

Table 5

Input Parameters for the a Priori Power Calculation

Input parameter	Purpose	Entry	Rationale
Tails	Establish a threshold for significance	Two-tailed	A two-tailed test is suitable for a general alternative hypothesis, like "X is related to Y," without a directional distinction.
$Pr(Y = 1 \mid X = 1)\ H_o$	Probability of Y = 1, when the main IV is at its mean	0.15	Based on extant literature
Effect size (*OR)*	Difference to be detected	0.75	Based on extant literature, a small effect size was selected.
Alpha error prob	specific α	0.05	Standard
Power (1- β error prob)	specific β	0.80	Standard
R^2 other X	Accounting for variability in the main predictor due to other covariates	0	"R^2 other X" is the expected R^2 value between main predictor and other covariates. Individual-level covariates do not influence the value of the main predictor variable, so this was entered as 0.
X distribution	The distribution of the X variable	Normal	
X parameter μ	The population mean of variable X	0.6	
X parameter σ	The population standard deviation of variable X	0.3	
Output parameter	**Purpose**	**Entry**	**Rationale**
Critical Z	Determining statistical significance in hypothesis testing	-1.96	
Actual power	Calculated power	0.80	Statistical power of 0.8 indicates an 80% chance of finding a statistically significant difference if one exists (i.e., not making a Type II error).
Total sample size		12,542	Number of participants required to detect a statistically significant difference based on selected parameters.

Data Weighting

The complex multistage sampling design necessitated consideration of, and correction for, the types of individuals being sampled with unequal probabilities. In the case of ENSANUT 2012, primary sampling units designated as low SLI/GRS were oversampled to ensure sufficient information was gathered for this vulnerable population. The resulting systematic differences between the composition of the sample and the composition of the underlying population would result in different estimates with weighted and unweighted data. This issue was corrected using case-weighting procedures as provided by the ENSANUT 2012 research team:

```
*CSPLAN ANALYSIS*
/PLAN FILE= 'varianzas.csaplan'
/PLANVARS ANALYSISWEIGHT= pondeh
/PRINT PLAN
/DESIGN STRATA= est_var CLUSTER= code_upm
/ESTIMATOR TYPE=WR.
```

(Romero-Martínez, 2012, p. 13)

Each ENSANUT 2012 data set had its own case weighting calculations so that they could be analyzed independently. When merging files with different weighting variables, it was recommended to merge into the data set with the fewest missing values, which was “Adultos” in this analysis (see Romero-Martínez, 2012).

Software

Microsoft Excel for Microsoft 365 MSO (Version 2310) was used for elements of data screening and data cleaning and the remainder of the analysis employed IBM SPSS Statistics (Version 29.0.1.0).

Statistical Plan to Address Research Questions

Descriptive Statistics

Summary statistics for categorical and scale data were prepared for the overall sample and for those with and without CVD, independently. Summaries of continuous data were created for the sample to reflect the number of nonmissing values, median, mean, standard deviation (*SD*), minimum, and maximum as well as lower and upper quartiles. Sample summaries for categories were done using frequencies, percentages, and extent of nonmissing values. These results reflect unweighted data and provide information as to the completeness of the final data set. Due to the probabilistic nature of the study design, national population estimates were calculated using weighting techniques and the SPSS Complex Samples Analysis tools.

Inferential Statistics

Inferential statistics were used to address each of the three research questions. Adjusted odds ratios with 95% confidence intervals were calculated that described the relationship between street trees and CVD while accounting for the covariates. All inferential statistics were conducted using the SPSS Complex Samples Analysis tool to account for the sampling strategy.

Threats to Validity

Several potential threats to external validity were considered, including those caused by sampling bias, temporal validity, and latent interaction effects. The probabilistic nature of the ENSANUT sampling procedures mitigated the sampling bias threat. The risk of temporal validity was partially mitigated by using the most recently available data to address the research questions and by diligently looking for relevant data collected within the same approximate time.

Internal validity refers to the degree to which the observed effects in a study can be attributed to the independent variable of interest rather than to other factors of the individual or the environment. This was partially mitigated by controlling for factors that may also have a significant relationship with CVD prevalence. Minimizing missing data also helped improve internal validity. Additional threats and study limitations are discussed in Chapter 5.

Ethical Procedures

This study used publicly available, deidentified individual-level secondary data collected with ethical oversight and informed consent. Additionally, INEGI suppressed potentially sensitive data when there were fewer than three units of analysis in a given territorial demarcation, such as a municipality or census tract. Walden University IRB approval was requested and granted (approval number: 02-05-24-1000349) prior to accessing the data.

Summary

This chapter presents details of the research design and rationale for this research study, which evaluated the relationship between neighborhood street trees and a prior diagnosis of CVD. The target population, the sample and sampling strategy for ENSANUT 2012 and other source data sets, procedures for recruitment and procedures for data collection, and operationalization of variables were described. The data analysis, data cleaning, and data management plans were summarized, as were potential threats to validity and ethical procedures. The results are presented in Chapter 4 and a discussion of these results in the context of external research and the study's limitations is presented in Chapter 5.

Chapter 4: Presentation of Results

This study focused on examining the association between street trees in metropolitan areas of Mexico and the prevalence of CVD among adults over 40 living in those areas. Chapter 4 is organized into sections that describe the creation of the final data set, the assessment of missing values, the testing of statistical assumptions, and the results of the analyses Descriptive statistics are presented as *n*, the number of respondents from the data set contributing to the population-level results, national population estimates (*NPE)*, and population proportions with standard error (*SE*). Descriptive statistics for continuous variables included estimated means (*SE*) and 95% confidence intervals of the mean. The results of three complex samples logistic regression analyses used to probe the relationships between the independent variable and CVD are displayed as crude and adjusted odds ratios with 95% confidence intervals. The three research questions focused on the relationship between the number of streets with street trees and CVD in the context of individual- and household-level factors (Research Question 1); census tract- and municipality-level environmental factors (Research Question 2); and individual-, household-, census tract-, and municipality-level factors (Research Question 3). The results are presented relative to the null and alternative hypotheses for each research question.

Data Access and Final Data Set Construction

This study was a secondary data analysis of ENSANUT 2012 adult self-reported health data combined with secondary data of participants' residential census tracts and municipalities. ENSANUT 2012 was a cross-sectional representative survey of the Mexican population using a probabilistic population-based survey with a multistage and stratified sampling design. A complex samples analysis plan was created and applied to the entire data set, with the descriptive statistics and regression models including only adults 40 and older living in census tracts designated as metropolitan. The process of assembling the final data set was captured in a contemporaneous data analysis activities log and an output file that included the syntax used to create, rename, recode, and relabel data along with the merge file commands. The systematic series of steps in the process is outlined in the following subsections.

Neighborhood- and Municipality-Level Data

Data set creation commenced with the assembly of a single file for the Characteristics of the Urban Environment survey data from 32 state-specific files. Unique 13-digit census tract identification numbers were created by combining Mexico's standardized state, municipality, locality, and census tract codes provided in the data files. Unnecessary variables were removed from the data set prior to being exported to Microsoft Excel in order to use pivot tables and formulas to derive the variable representing street trees. The goal was to calculate the primary exposure variable for each census tract based on data originally collected at the city block level.The primary independent variable, Propor_Trees_NM, represented the proportions of city block-delimiting streets within a census tract with at least one street tree. The denominator included only the number of assessed streets that had available data. The resulting place-based data set contained 53,594 census tracts. The street tree variable was uniformly distributed between 0 and 1 with a large mode at 0.

After data cleaning activities and the creation of the common GEOCODE identifier, municipality-level road network density data and census tract-level altitude and

SLI/GRS scores were merged with the street tree data. The final place-based data set included 46,404 census tracts with complete information and 53,583 census tracts missing only the SLI/GRS data.

Individual-Level Data

Most of the ENSANUT 2012 data were from the Adultos data set and were originally coded according to the analysis plan presented in Chapter 3. Information for BMI, activity level, and average hours of sleep per night variables came from the Anthropometrics file. Furthermore, small amounts of missing data for cholesterol, triglycerides, diabetes, and hypertension in the Adultos data set were supplemented with data from the Anthropometrics file. Cookstove information was sourced from the Household data set. The Household Members file was the source of additional demographic information including marital and employment status.

Residential Location Data

A file containing census-tract level residential information for each household was created by creating a file with the GEOCODE variable from five combined ENSANUT data sets (Nutrition, Food Security, Blood Pressure, Blood Analysis, and Physical Activity). The GEOCODE was matched to the primary data set using unique six-digit subject identifiers comprising a four-digit household code and a two-digit respondent code. Adding the GEOCODE variable allowed for matching individual- and place-based data.

Final Data Set

The place-based data were merged with the individual-level data using the common GEOCODE variable. Of the 46,277 individuals in the final data set, 29,232 were matched with the street trees and other place-based information. Most unmatched individuals were from rural areas, which were not covered in the 2014 Characteristics of the Urban Environment survey. Furthermore, it became apparent that the census tracts designated as urban were not appropriate for inclusion in the current study. A visual review of these census tracts and further research on how tracts were classified revealed that the urban designation by INEGI was more administrative than descriptive. These tracts were often found in small to medium-size cities near farmland, did not represent the study population of interest, and were excluded from the analysis.

A recoded version of the final data set was created for use with the complex samples analysis tool in SPSS. The default CSLOGISTIC procedure does not have the option to change the reference category for an independent factor from the default (highest) when calculating parameter estimates (IBM, 2021). The recoded data set established the desired reference category as the highest rather than lowest value. A complex samples analysis plan was created using the information for each weighting variable (strata, cluster, and weight) as provided by INEGI.

Statistical Assumptions

Statistical modeling of binary outcome data is subject to several assumptions regarding the underlying data. As described by Warner (2012) and Laerd Statistics (2017a), requirements for a binary logistic regression include (a) a dichotomous outcome variable with mutually exclusive and exhaustive categories; (b) one or more independent variables, which can be continuous or categorical; (c) independence of observations; (d) a linear relationship between any continuous independent variables and the logit transformation of the dependent variable; (e) a correctly specified model with all relevant predictors and no irrelevant predictors; and (f) no extreme outliers or multicollinearity for scale data and an expected number of cases of five for each pair of categorical predictor variables.

Dichotomous Outcome Variable

This assumption was met.

One or More Independent Continuous or Categorical Variables

This assumption was met.

Statistically Independent Outcomes

The sampling strategy raised the possibility that the outcome (CVD prevalence) could have statistically linked outcomes dependent on their location and independent of the primary predictor variables. The initial plan to use multilevel logistic regression was predicated on the idea that there would be heterogeneity between predictors and the outcome across different clusters (higher-level units) due to differences in the properties of clusters and that using a traditional single-level regression model would increase the risk of Type I errors.

An unconditional (no predictors) generalized linear mixed model was used to examine the extent of variability of CVD prevalence across Level 2 clusters (Heck et al., 2012). Random effects were specified as random intercepts. The random intercept model allowed each cluster to have a different prevalence but assumed that the relationships between independent variable and dependent variables would be consistent across clusters (Theobald, 2018).

Three different models were run, each using a different clustering unit (i.e., census tract, municipality, and federal entity). The multiple models addressed some of the uncertainty and model convergence errors of the first model using census tract-based clusters. The intercept coefficient, or the predicted odds of having CVD versus not having CVD, was consistent regardless of the clustering unit. The value used to determine whether a multilevel model was necessary was the estimate for intercept variances across sampling clusters (Heck et al., 2012). The variance in the intercept across the census tract clusters was extremely small at 2.222×10^{-10} and had insufficient variation to calculate standard error and significance (see Table 6). The models with other clustering units also demonstrated negligible random effect covariance, and the interclass correlation coefficients were all 0.004 or smaller. The results from these analyses indicated that greater than 99.5% of the variability in CVD outcomes occurred within, rather than between, each cluster.

Table 6

Random Effect Covariance of Different Level 2 Clusters

Clustering unit	Random effect covariance	*p* value	Intraclass correlation coefficient
Census tract[a],	1.23×10^{-10}	.	0.000
Municipality	0.035	.061	0.003
State	0.043	.024	0.004

[a] The model included the following warning in SPSS: This parameter is redundant.

Currently, multilevel effects cannot be modeled when conducting a complex samples analysis in SPSS (Heck et al., 2012). Therefore, the results indicating that multilevel models were not necessary for accurate estimations of variation across clusters alleviated concerns about using the complex samples analysis tool in SPSS.

Linear Relationship Between the Continuous Predictor Variables and the Log Odds of the Dependent Variable

The linearity of continuous variables with respect to the logit of the dependent variable was assessed via the Box-Tidwell (1962) procedure in both the full data set and the subsample of interest. An interaction term was created between the original and the natural log of each continuous variable (i.e., age, altitude, the proportion of nonmissing streets with street trees, and road density). These were included in a simple binary logistic regression model alongside the original variables to predict CVD prevalence.

All variables except one demonstrated linearity with the dependent variable's logit according to the parameters of the Box-Tidwell test. The *p* value for the age interaction term was .02, indicating a violation of the null hypothesis that the relationship between the logit of the dependent variable and the continuous predictor variables is linear (i.e., the interaction term is not significantly different from zero). However, after a Bonferroni correction was applied to address the increased possibility of Type I errors with multiple comparisons, all continuous independent variables were found to be linearly related to the logit of the dependent variable. The Box-Tidwell procedure was repeated to check the linearity assumption for the continuous predictor variables in each of the logistic regression models addressing research questions. There were no violations of the assumption with or without Bonferroni corrections.

Correct Model Specification

A correctly specified model is one that contains all relevant predictors and necessary transformations, no irrelevant or redundant predictors, and accounts for data structure (Leyland & Groenewegen, 2020). As described in Chapter 3, scientific evidence and the theoretical framework of the ISEM model were utilized to identify important predictors of CVD and to support their inclusion in the final statistical models. Chapter 5 discusses the limitations of these final models, including the potential for omitted variable bias. Correct model specification also requires that the data be transformed to match the requirements of the model and that there is no multicollinearity between continuous variables. The former was unnecessary for this analysis, and the latter was confirmed during exploratory analysis.

Absence of Outliers and Multicollinearity of Independent Continuous Variables and Sufficient Expected Cases in Each Cell of Categorical Variables

Continuous Variables

Multicollinearity and the presence of outliers were tested for the four continuous predictor variables in the subpopulation of interest. A correlation revealed weak but statistically significant correlations between several continuous variables. No outliers were detected for the street tree and altitude variables. Univariate outliers were detected for the age and road network density variables. A simple binary logistic regression regressing CVD on these variables revealed no outlying residuals or unusual leverage points. Therefore, no action was taken to remove any age or road network density outliers or transform the variables.

Categorical Variables

I tested for expected cell sizes and statistical significance between all combinations of categorical predictor variables. A series of bivariate chi-squared tests demonstrated that many of the covariates were statistically significantly correlated, and that there were several instances of small sample sizes. To solve these problems, categories of BMI and smoking status were reduced and "NS/NR" ("*no sabe/no responde*") for the cholesterol and triglyceride variables were reset to "missing" and excluded from the analysis.

Missing Values

A missing values analysis was conducted to determine the extent and potential impact of missing data. The maximum sample size for the study was limited by the availability of self-reported CVD status and the availability of street tree data. A total of 590 respondents (5.2%) had no street tree data, making the maximum sample size 10,798 assuming these respondents were not missing other data. The variables with significant levels of missing data were BMI (26% missing), hours of sleep per night (81% missing), and physical activity level (81% missing). Further information on these variables and the rationale for how these variables were handled for the final analyses is described in the following sections.

Sleep

Sleep information was available for only 2,158 adults 40 and older living in metropolitan census tracts. To inform the decision of how to best address the missing data, several analyses using unweighted data were conducted to examine the relationship between hours of sleep and self-reported CVD. Among all adults regardless of age or urbanicity status, there was a statistically significant relationship between sleep/activity level and self-reported CVD (χ^2 [4, 10,062] = 17.84, p < .001). The proportion with CVD among those getting fewer than 5 hours of sleep was statistically significantly higher than those getting 8 hours or more (p = .03). This relationship did not hold when limiting the data to only those 40 or older (χ^2 [4, 5,110] = 2.53, p = .64) or those over 40 living in metropolitan areas (χ^2 [4, 2,157] = 3.26, p = .52). Because of the dramatic reduction in sample size if this variable was to be included in the final analysis and the apparent lack of relationship with CVD in the subsample, this variable was removed from the final analyses.

Activity Level

Physical activity information was available for only 2,155 adults 40 and older living in metropolitan census tracts. The relation between self-reported activity levels (inactive, moderately active, active) and CVD was significant for adults 20 and older in the entire unweighted data set (χ^2 [2, 10,058] = 8.04, p < .02) and for all adults over 40 (χ^2 [2, 5,108] = 7.93, p = .02). The statistical difference was between the “inactive” and “active” categories (p = .02) and did not include “moderately active.”

On the other hand, there was no significant relationship between activity level and CVD for adults in the study subpopulation (χ^2 [2, 2,154] = 3.02, p = .22), even though CVD is more prevalent in metro areas (9.1%) than in other areas (between 6.9% and 8.4%) and despite a higher proportion of metropolitan residents reporting inactivity (21.1%) than residents of other areas (14.3% to 19.5%). These results suggest heterogeneity in the relationship between activity level and CVD activity, with additional factors in play in metropolitan areas. Because of this inconsistency and the lack of relationship in my subpopulation, this covariate was excluded from the final analyses to maintain a larger sample size.

Obesity

BMI information was available for only 81% (8,430) of adults. Although there was a statistically significant relationship between BMI category and CVD in the total sample (χ^2 [3, 35,154] = 22.14, $p < .001$) and all adults over 40 (χ^2 [3, 19,551] = 9.17, $p = .03$), in adults over 40 living in metropolitan areas, there was no statistically significant relationship between BMI and CVD outcome (χ^2 [3, 8,418] = 5.79, $p = .12$). The lack of association between BMI and CVD led to the decision to remove BMI from primary analysis and to conduct sensitivity analyses for RQ1 and RQ3 including only the 8,430 survey respondents with valid BMI values.

Sampling Strata

The entire data set contained data for 46,277 adults twenty and over. These individuals were distributed across 155 sampling strata and 1,620 sampling units. A total of 11,388 individuals met the study inclusion criteria of living in a metropolitan-coded census tract and being 40 years or older. The study sample was distributed over 50 sampling strata and 800 sampling units. Valid tree data at the census tract level were available for 44 strata (756 sampling units) within which the 10,798 respondents that met the inclusion criteria for this study resided.

Descriptive Statistics

The total number of people in the study sample represented an estimated 20.8 million adults. Women slightly outnumbered the men (53.9% vs. 46.1%), and the mean age was 55.0 (95% CI: 54.6, 55.4). A majority resided in the states of Mexico, Jalisco, Nuevo Leon, Veracruz, and the Distrito Federal, where some of Mexico’s largest urban centers are located (data not shown). National population estimates for demographic characteristics of the study sample are included in Table 7. Population summary statistics of the variables included in the analysis are displayed in Table 8.

Table 7

National Population Estimates for Demographic Characteristics

Characteristic/variable	*n*	NPE	% [*SE*]
Gender			
Male	4,780	9,572,042	46.1 [0.8]
Female	6,608	11,196,902	53.9 [0.8]
Self-identifies as Indigenous			
No	1,961	3,276,897	15.8 [0.8]
Yes	9,427	17,492,047	84.2 [0.8]
Education			
None or preschool	1,018	1,618,121	7.8 [0.5]
Elementary	4,346	7,456,140	35.9 [0.9]
Secondary	2,252	4,556,884	21.9 [0.7]
High school or baccalaureate	1,113	2,275,968	11.0 [0.5]
Technical or commercial studies	972	1,829,442	8.8 [0.4]
Bachelor's degree	1,504	2,704,046	13.0 [0.7]
Postgraduate	183	328,343	1.6 [0.3]
Marital status			
Single	1,029	1,697,127	8.2 [0.4]
Unmarried partner	1,317	2,554,650	12.3 [0.6]
Married	6,122	12,215,015	58.8 [0.7]
Separated	978	1,430,298	6.9 [0.4]
Divorced	398	562,955	2.7 [0.2]
Widowed	1,544	2,308,899	11.1 [0.5]
Employment status			
Working	5,681	10,739,968	51.7 [0.8]
Not currently working	77	163,161	0.8 [0.1]
Looking for work	217	413,299	2.0 [0.2]
Retired	1,113	1,878,556	9.0 [0.5]
Student	14	18,355	0.1 [0.0]

Characteristic/variable	*n*	NPE	% [*SE*]
Maintains household	3,617	6,286,949	30.3 [0.7]
Unable to work/disability	353	692,787	3.3 [0.3]
Other	316	575,869	2.8 [0.2]
Street tree data available			
No	590	3.1	3.1 [0.7]
Yes	10,798	96.9	96.9 [0.7]

Note. n = sample size; NPE = national population estimate; *SE* = standard error.

Table 8

National Population Estimates for CVD-Related Risk Factors

Variable	*n*	NPE	% [SE]
Prior CVD diagnosis			
No	10,347	18,747,624	90.3 [0.4]
Yes	1,032	2,008,804	9.7 [0.4]
Family history of infarction			
No	8,014	14,265,792	71.8 [0.8]
Yes	2,008	3,927,549	19.8 [0.7]
NS/NR for at least one parent	958	1,671,048	8.4 [0.5]
Prior hypertension diagnosis[a]			
Negative	8,212	14,870,951	71.6 [0.7]
Positive	3,176	5,897,993	28.4 [0.7]
Cholesterol status			
Normal	5,422	9,478,010	46.0 [0.8]
High	2,713	5,437,570	26.4 [0.8]
Not tested	3,176	5,689,509	27.6 [0.8]
Prior diabetes diagnosis [b]			
No	9,313	16,870,380	81.2 [0.5]
Yes	2,075	3,898,564	18.8 [0.5]
Prior depression diagnosis			
No	9,845	17,696,654	85.2 [0.6]
Yes	1,543	3,072,289	14.8 [0.6]
Excessive alcohol use			
No	10,647	19,258,761	92.7 [0.5]
Yes	741	1,510,183	7.3 [0.5]
Triglycerides status			
Normal	5,434	9,544,573	46.8 [0.9]
High	1,976	4,068,534	20.0 [0.7]
Not tested	3,799	6,776,263	33.2 [0.9]

Variable	*n*	NPE	% [SE]
BMI			
Underweight/normal	1,996	3,622,324	23.7 [0.8]
Overweight	3,265	6,028,872	39.4 [0.9]
Obese	3,164	5,660,695	37.0 [0.9]
Smoking status			
Never	5,483	9,035,678	43.5 [0.8]
Smoking daily to weekly	1,679	3,606,961	17.4 [0.6]
Smoking monthly to yearly	527	1,085,629	5.2 [0.4]
Not currently smoking	3,696	7,034,788	33.9 [0.8]
Physical activity level			
Inactive	454	707,956	19.1 [1.3]
Moderate active	284	554,541	14.9 [1.2]
Active	1,417	2,447,245	66.0 [1.6]
Hours of sleep/night			
<= 5	192	331,486	8.9 [1.0]
6	416	739,879	19.9 [1.4]
7	507	850,498	22.9 [1.4]
8	750	1,350,413	36.3 [1.6]
>= 9	293	444,162	12.0 [0.9]
Cookstove			
Gas stove	10,928	20,227,823	97.4 [0.3]
All others	460	541,121	2.6 [0.3]

Note. BMI = body mass index; n = sample size; NPE = national population estimate; NS/NR = no sabe/no responde (Spanish: do not know/does not answer); *SE* = standard error.

[a] The duration of diabetes diagnosis was available for 2,060 individuals. *M* = 10.4 years (95% CI: 9.7, 11.2); range: 0.8–71.

[b] The duration of hypertension diagnosis was available for 2,060 individuals. *M* = 9.1 years (95% CI: 8.8, 9.5); range:0.8–84.

Research Questions

Baseline (Unadjusted Model)

A single-level complex samples logistic regression analysis was conducted to examine the relationship between street trees and self-reported history of CVD in the subpopulation of adults over 40 living in metropolitan areas of Mexico. This model serves as a reference for subsequent analyses and does not include any adjustments for individual or environmental risk factors. The weighted count for the analysis was 20,115,385 individuals, with 9.8% having self-reported a prior diagnosis of CVD.

The overall model was not statistically significant, Wald $\chi^2(1, n = 924) = 0.184$, $p = .67$, signifying that the model did not significantly improve the prediction of CVD beyond the intercept-only model. In this unadjusted model, the proportion of manzana-delimiting streets with trees had no statistically significant relationship with CVD (unadjusted $OR = 1.09$, 95% CI: 0.74, 1.60).

In the models addressing RQ1, RQ2, and RQ3, covariates were incorporated into the statistical analyses. These three research questions aimed to investigate the relationship between street trees and CVD while controlling for different sets of established CVD risk factors. The alpha level for all analyses was set at 0.05.

Research Question 1: Adjustment for Individual- and Household-Level Factors

RQ1 queried whether there was a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors. The hypothesis statements were as follows:

*H_o*1: There is no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors.

*H_a*1: There is a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors.

This logistic regression model was statistically significant (Wald $\chi^2(17, 907) = 13.64$, $p = < .001$) and explained between 5.3% (Cox & Snell R^2) and 11.7% (Nagelkerke R^2) of the variance in reporting a prior diagnosis of CVD. The adjusted odds ratio (*AOR*) for CVD related to the primary street trees independent variable was 0.84 (95% CI: 0.56, 1.28; $p = .43$) with the inclusion of individual- and household-level covariates. The results hint at a potential protective influence of street trees against CVD, despite the association not achieving statistical significance in the analysis.

Several factors exhibited statistically significant associations with CVD and contributed to its predictive model. These key variables included: age (*AOR* = 1.031; $p = < 0.001$), known parental history of CVD (*AOR* =1.412 ; $p = .016$), ever diagnosis of depression (*AOR* = 1.953; $p < 0.001$), use of a cook stove other than gas (*AOR* = 0.367; $p = .009$), and duration of hypertension diagnosis (*AOR* = 1.043; $p = < 0.001$) and triglycerides levels (*AOR* = 1.501; $p = .027$) (Table 9). To examine potential indirect effects, a second model was constructed (results not presented) that incorporated only the six variables that achieved statistical significance in the primary analysis. This focused model looked at whether the nonsignificant variables from the initial model indirectly influenced the outcome through their relationships with the statistically significant predictors. Other than a slight decrease in the pseudo-R^2 values, there were no differences in the overall results of the model (Wald $\chi^2(7, 917) = 27.315$, $p < 0.001$) or in the statistical relationship between street trees and CVD. A decision was made to keep all variables in the final models for each research question due to their theoretical importance and relationships with other covariates.

A sensitivity analysis was conducted that included BMI as a marker for obesity. This model was statistically significant (Wald $\chi^2(19, 905) = 12.42$, $p < 0.001$) but with a reduced sample size and a slight increase in the proportion of variance in explained by the model (to 5.8% and 12.4% according to Cox & Snell R^2 and Nagelkerke R^2, respectively). There was no change in the relationship between the street tree variable and CVD (*AOR* [95% CI] = 0.83 [0.53, 1.30], $p = .41$).

Without considering any covariates, an increase in street trees in the baseline model was associated with a nonsignificant 9% increase in the odds of CVD. After controlling for individual- and household-level covariates, the *AOR* suggested a 16% lower likelihood of CVD in areas as the proportion of streets with street trees increase. Nonetheless, there was insufficient evidence for RQ1 to reject the null hypothesis of no relationship between the presence of street trees and CVD while adjusting for individual- and household-level contributors to CVD.

Table 9

RQ1: Parameter Estimates With Individual- and Household-Level Factors

Variable	Category (where applicable)	Crude		Adjusted	
		OR (95% CI)	*p* value	*OR* (95% CI)	*p* value
Proportions of streets with street tree(s)		1.09 (0.74, 1.60)	.67	0.84 (0.56, 1.28)	.43
Age (year)		1.04 (1.03, 1.05)	< .001	1.03 (1.02, 1.04)	< .001
Hypertension duration (years; 0 = no diagnosis)		1.06 (1.05, 1.07)	< .001	1.04 (1.03, 1.06)	< .001
Diabetes duration (years; 0 = no diagnosis)		1.04 (1.03, 1.05)	< .001	1.01 (0.99, 1.03)	.37
Family history of infarction	No	REF	-	REF	-
	Yes	1.62 (1.27, 2.07)	< .001	1.41 (1.07, 1.87)	.02
	NS/NR for at least 1 parent	1.22 (0.90, 1.67)	.21	0.93 (0.66, 1.23)	.67
Sex	Male	REF	-	REF	-
	Female	1.22 (1.0, 1.48)	.052	1.0 (0.76, 1.31)	.98
Cholesterol	Normal	REF	-	REF	-
	High	1.34 (1.07, 1.67)	< .001	1.01 (0.69, 1.46)	.97
	Not tested	0.50 (0.37, 0.68)	< .001	0.92 (0.51, 1.68)	.79
Triglycerides	Normal	REF	-	REF	-
	High	1.67 (1.29, 2.16)	< .001	1.5 (0.99, 2.27)	.06
	Not tested	0.52 (0.40, 0.67)	< .001	0.67 (0.39, 1.14)	.14
Prior depression diagnosis	No	REF	-	REF	-
	Yes	2.14 (1.74, 2.76)	< .001	1.95 (1.43, 2.66)	< .001
Excessive alcohol use	No	REF	-	REF	-
	Yes	0.62 (0.42, 0.92)	.02	0.66 (0.41, 1.07)	.09

Variable	Category (where applicable)	Crude		Adjusted	
		OR (95% CI)	*p* value	*OR* (95% CI)	*p* value
Smoking status	Never smoked	REF	-	REF	-
	Not currently smoking	1.26 (1.00, 1.57)	.05	1.16 (0.88, 1.52)	.30
	Smoking monthly to yearly	0.72 (0.40, 1.31)	.28	1.08 (0.59, 2.00)	.80
	Smoking daily to weekly	0.77 (0.54, 1.08)	.13	0.98, (0.66, 1.45)	.93
Cooking stove	Gas stove	REF	-	REF	-
	All others	0.32 (0.17, 0.61)	< .001	0.37 (0.17, 0.78)	.01

Note. All factors used in the computation were fixed at the reference category (i.e., never, normal, negative). The reference for cookstove was gas stove and the reference gender was male. The covariates were set at the sample mean values.

Research Question 2: Adjustment for Neighborhood- and Municipality-Level Factors

In RQ2, I asked whether there was a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for neighborhood- and municipality-level factors. The hypothesis statements were as follows:

H_o2: There is no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for neighborhood- and municipality-level factors.

H_a2: There is a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for neighborhood- and municipality-level factors.

The logistic regression model was not statistically significant (Wald $\chi^2(5, 916) = 1.11$, $p = .36$ (Table 10). Inclusion of environmental factors that could impact CVD did not appreciably change the relationship between street trees and CVD, although the point estimate for the OR changed from slightly positive to a slightly negative (*AOR* [95% CI] = 0.95 [0.59, 1.54], $p = .83$).

Table 10

RQ2: Parameter Estimates With Neighborhood- and Municipality-Level Factors

Variable	Category (where applicable)	Crude		Adjusted	
		OR (95% CI)	*p* value	*OR* (95% CI)	*p* value
Proportions of streets with street tree(s)		1.09 (0.74, 1.60)	.67	0.95 (0.59, 1.54)	.83
Road network density		1.06 (0.97, 1.17)	.21	1.10 (0.97, 1.24)	.13
Altitude		1.0 (1.0, 1.0)	.60	1.0 (1.0, 1.0)	.20
SLI/GRS	Low	REF	-	REF	-
	Medium	0.81 (0.61, 1.08)	.15	0.81 (0.58, 1.13)	.21
	High	0.92 (0.36, 2.38)	.86	0.68 (0.25, 1.87)	.45

These results for RQ2 provided insufficient evidence to reject the null hypothesis of no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD after controlling for neighborhood- and municipal-level potential factors.

Research Question 3: Adjustment for all Individual-, Household-, Neighborhood- and Municipality-Level Factors

RQ3 asked whether there was a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors. The related hypothesis statements were as follows:

> H_o3: There is no relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors.
>
> H_a3: There is a relationship between the presence of street trees in urban neighborhoods of Mexico and CVD among adults over 40 living in those neighborhoods after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors.

The logistic regression model for RQ3 was statistically significant (Wald $\chi^2(21, 900) = 11.38$, $p < 0.001$). The model was similar to that of RQ1. It explained between 5.4% (Cox and Snell R^2) and 11.8% (Nagelkerke R^2) of the variance in reporting a prior diagnosis of CVD. As found previously, there was nonsignificant inverse relationship between street trees and self-reported prior diagnosis of CVD (*AOR* [95% CI] = 0.87 [0.55, 1.17], $p = .56$; Table 11). The same individual-level variables (parental history of infarction, prior diagnosis of depression, use of a cook stove other than gas, age, prior diagnosis of hypertension, and triglycerides levels) contributed significantly to the model. The addition of BMI in a separate sensitivity analysis did not impact the relationships between variables, including that of street trees and CVD (*AOR* [95% CI] = 0.88 [0.54, 1.44], $p = .62$). There was insufficient evidence in this study to reject the null hypothesis of no relationship between the presence of street trees and CVD after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors.

Table 11

RQ3: Parameter Estimates With Individual-, Household-, Neighborhood-, and Municipality-Level Factors

Variable	Category (where applicable)	Crude		Adjusted	
		OR (95% CI)	*p* value	*OR* (95% CI)	*p* value
Proportions of streets with street tree(s)		1.09 (0.74, 1.60)	.67	0.87 (0.55, 1.38)	.56
Age (year)		1.04 (1.03, 1.05)	< .001	1.03 (1.02, 1.04)	<0.001
Hypertension duration (years; 0 = no diagnosis)		1.06 (1.05, 1.07)	< .001	1.04 (1.03, 1.06)	< .001
Diabetes duration (years; 0 = no diagnosis)		1.04 (1.03, 1.05)	< .001	1.01 (0.99, 1.03)	.37
Road network density		1.06 (0.97, 1.17)	.21	1.03 (0.90, 1.17)	.68
Altitude		1.0 (1.0, 1.0)	.60	1.0 (1.0, 1.0)	.15
Family history of infarction	No	REF	-	REF	-
	Yes	1.62 (1.27, 2.07)	< .001	1.41 (1.07, 1.87)	.02
	NS/NR for at least 1 parent	1.22 (0.90, 1.67)	.21	0.93 (0.66, 1.23)	.67
Sex	Male	REF	-	REF	-
	Female	1.22 (1.0, 1.48)	.05	1.0 (0.76, 1.31)	.98
Cholesterol	Normal	REF	-	REF	-
	High	1.34 (1.07, 1.67)	< .001	1.0 (0.69, 1.45)	1.0
	Not tested	0.50 (0.37, 0.68)	< .001	0.93 (0.51, 1.69)	.81
Triglycerides	Normal	REF	-	REF	-
	High	1.67 (1.29, 2.16)	< .001	1.53 (1.01, 2.32)	.05
	Not tested	0.52 (0.40, 0.67)	< .001	0.67 (0.40, 1.14)	.14
Depression	No	REF	-	REF	-
	Yes	2.14 (1.74, 2.76)	< .001	1.97 (1.45, 2.69)	<0.001
Excessive alcohol	No	REF	-	REF	-
	Yes	0.62 (0.42, 0.92)	.02	0.65 (0.40, 1.05)	.08

Variable	Category (where applicable)	Crude		Adjusted	
		OR (95% CI)	*p* value	*OR* (95% CI)	*p* value
Smoking status	Never smoked	REF	-	REF	-
	Not currently smoking	1.26 (1.00, 1.57)	.05	1.16 (0.88, 1.53)	.28
	Smoking monthly to yearly	0.72 (0.40, 1.31)	.28	1.10 (0.60, 2.04)	.75
	Smoking daily to weekly	0.77 (0.54, 1.08)	.13	1.00 (0.67, 1.49)	1.0
Cooking stove	Gas stove	REF	-	REF	-
	All others	0.32 (0.17, 0.61)	< .001	0.36 (0.17, 0.77)	.01
SLI/GRS	Low	REF	-	REF	-
	Medium	0.81 (0.61, 1.08)	.15	1.02 (0.73, 1.42)	.93
	High	0.92 (0.36, 2.38)	.86	1.07 (0.34, 3.39)	.91

Note. All factors used in the computation were fixed at the reference category (i.e., never, normal, negative) or the lowest value (i.e., social risk = low). The reference for cookstove was gas stove and the reference gender was male. The covariates were set at the sample mean values.

Summary

In this quantitative study, the relationship between a derived variable representing the level of street trees within a census tract and CVD was examined while adjusting for CVD-related covariates at multiple levels of influence. These levels included individual health and risk factor data from ENSANUT 2012 and census tract and municipality information from other sources. Because of the multistage probabilistic sampling plan employed by ENSANUT 2012, a complex samples adjustment to the variance structure was used to generate population estimates of adjusted odds ratios and 95% confidence intervals for the study subpopulation: adults over 40 living in metropolitan areas of Mexico. For all three research questions, there was insufficient evidence to reject the null hypothesis of no relationship between the primary independent variable of street tree proportions. Chapter 5 provides an interpretation of these findings, a discussion of study limitations, and recommendations for future research.

Chapter 5: Discussion, Conclusions, and Recommendations

The intent of this quantitative epidemiological study with secondary cross-sectional data was to determine whether there was a relationship between street trees and self-reported CVD diagnoses in metropolitan areas of Mexico. Such a relationship could be exploited to make environmental changes in metropolitan areas to reduce the increasing prevalence of CVD and its consequences. Three iterative research questions were constructed, each adjusting for different combinations of individual and environmental risk factors using logistic regression analyses. The data were analyzed first to determine whether multilevel modeling techniques were needed to account for cluster effects on the dependent variable. No cluster effects were identified. Subsequently, the analyses were conducted using single-level models and appropriate weighting techniques to account for the ENSANUT 2012 complex sampling plan.

No statistically significant relationship between street trees and CVD prevalence was identified in either a univariate analysis or in the three multivariate regression analyses addressing the research questions. However, the results showed a marked trend of reduced likelihood of CVD prevalence among adults who lived in urban neighborhoods of Mexico as the number of streets with street trees increased, after controlling for individual- and household-level factors (*AOR* [95% CI]) = 0.84 [0.56, 1.28], $p = .43$), after controlling for neighborhood- and municipality-level factors (0.95 [0.59, 1.54], $p = .83$), and after controlling for individual- and household-level factors and adjusting for neighborhood- and municipality-level factors (0.87 [0.55, 1.38], $p = 0.56$). The unadjusted model implied that street trees were associated with a higher risk of CVD (1.09 [0.74, 1.60]), but in the statistically significant adjusted models for RQ1 and

RQ3, the relationship changed and suggested possible protective effect of street trees on CVD risk.

The covariates of age, depression, triglycerides, hypertension, parental history of myocardial infarction, and household cookstove explained approximately 12% of the variation in reporting a prior CVD diagnosis. The remaining factors did not demonstrate a statistically significant relationship. The inclusion of covariates highlights the importance of considering confounding variables in epidemiological studies, but also provides an opportunity for future work to further isolate the impact, if any, of street trees on human health.

Interpretation of the Findings

Street trees have been recognized as a form of urban green space that could positively impact the physical and mental health of people living in cities. Street trees are being considered as a cost-efficient intervention for CVD-related mortality in urban environments (Giacinto et al., 2021). The present study employed a unique data set from Mexico in which characteristics of the streets delimiting city blocks were assessed and classified as having or not having street trees. With my interest in public health risks in Mexico, I was able to combine the street tree data from the 2014 Characteristics of the Urban Environment study with individual-level health outcome information from the ENSANUT 2012. I was unable to reject the null hypothesis that there is no relationship between the proportion of street trees along the block-delimiting roads in individuals' census tract and a prior medical diagnosis of CVD when controlling for covariates at multiple levels of influence. However, these findings should be regarded in the context of recent research on street trees and the study's limitations.

The published literature on street trees is varied. A large number of studies described associations between street trees and improved health outcomes, although the outcomes could vary within the same study depending on how exposures were defined and calculated. Marselle et al. (2020) reported a lower rate of antidepressant prescriptions among adults living close to a higher density of street trees in Leipzig, with a statistically significant association for individuals of low socioeconomic status. Moreira et al. (2020) used a local inventory of street trees in São Paulo, Brazil, and described a negative association between the number of street trees per regional government boundaries and hypertension (*OR* = 0.94; 95% CI: 0.88, 0.99). However, in the same study, no such association was seen when smaller geographic units were used. The *OR* for hypertension using 300-meter buffers around residential addresses was 1.06 (95% CI: 0.9, 1.13) and 0.99 (0.94, 1.04) when district boundaries were used. The Moriera et al. study also provided an example of statistical associations changing with different combinations of covariates. In the logistic regression models using the 300-meter exposure buffer, there was a positive association when age, sex, race, and education level were included as covariates, but no statistical association was found when adjusting for age, sex, race, education, smoking, BMI, excessive alcohol use, salt consumption, physical activity, dyslipidemia, and diabetes. The São Paulo study provided a good example of how sensitive statistical associations between street trees and health endpoints can be to the methods of calculating exposures and the effects of other influences on the health endpoint of interest.

In a study using individual health data, land use information, and political boundaries in occupied Palestinian territory, (Alkhatib et al., 2021) constructed a series of multilevel regression analysis using the diagnosis of a chronic illness as the dependent variable. The proportion of mixed trees, but not crop trees or open space, was associated with a reduced odds of a chronic disease diagnoses (*OR* = 0.96; 95% CI: 0.95, 0.97) when controlling for age, sex, education, employment, marital status, refugee status, health insurance, years of residence, household car ownership, and household assets index. Furthermore, the negative effects of living in a refugee camp were also attenuated when the green space variables were added to the model.

In an innovative application of artificial intelligence and deep learning models, Z. Chen et al. (2024) recently published their work in which features of the built environment were extracted from Google Street View images and assessed in relation to prevalence of coronary heart disease in seven U.S. cities. Chen et al. were able to isolate trees visible from the road as a built environment feature and calculate a measure of level of exposure. The number of trees visible from the roadside was negatively associated with coronary heart disease at the census tract level. The trees detected using Google Street View were not necessarily street trees because many trees that were counted were on private property. However, the Chen et al. study added to evidence correlating the presence of trees along roadsides, whether on public or private property, to improved cardiovascular health outcomes. The results from my analyses imply the same trend may be true in Mexico, but my data were insufficient to make strong conclusions.

During my process of data exploration, I detected a relationship between the neighborhood SLI/GRS score and the proportion of streets with trees at the census block level (data not shown). This aligns with literature on the inequitable distribution of green space (Fernández-Álvarez, 2017; Mitchell & Popham, 2008). Beyond distributional equity and spatial justice, this finding suggests the potential of street trees for equigenesis—health equality through targeted interventions addressing social determinants of health. Green space interventions have been shown to improve health outcomes for disadvantaged individuals (Markevych et al., 2017; Marselle et al., 2020; Moran et al., 2021; Sarkar, 2017). For instance, Moran et al. (2021) found that area-level greenness moderated the relationship between education and mortality in Latin American cities. In China, the extent of trees visible from roadways was inversely associated with kidney failure, with greater benefits for lower income individuals (R. Wang et al., 2023). The potential of green space, including street trees, to narrow health inequities in Mexico is a topic worthy of further exploration.

An unexpected relationship that was unrelated to the primary independent variable of street trees was the strength of the negative relationship between the use of cookstoves other than natural gas and CVD. This variable was included to indicate indoor air pollution because of combustion from wood-fired stoves. The present results indicated that using cookstoves other than gas served as a protective factor for CVD. This contradicts the current evidence that using propane or natural gas for cooking rather than solid biomass fuels substantially lowers the risk of multiple health outcomes, including various cardiovascular events (Mitter et al., 2016; Puzzolo et al., 2024). It is unclear whether this was a spurious result from the small proportion of respondents using home cooking methods other than gas stoves (< 3%) or whether it was evidence of a link between propane cookstoves and CVD. In sensitivity analyses in which cookstove was removed from the regression models, the Nagelkerke R^2 was reduced slightly, but there was minimal impact on the results related to street trees and CVD. The lack of statistically significant results regarding the effect of street trees on CVD outcomes from the present study should be interpreted in the context of the study's numerous limitations, both those that were known prior to study initiation and those that were revealed during the analysis. Statistical power and issues with the measure of street tree exposure preclude this study from providing solid evidence to the body of work on the public health implications of street trees.

Limitations of the Study

This research was subject to internal and external threats to validity. This section extends the discussion from Chapter 1 on potential limitations and incorporates additional comments based on the observed results.

Statistical Power

A post hoc investigation of statistical power was conducted using G*Power 3.1 to determine whether my sample size was sufficient to detect a meaningful relationship between street trees and CVD. The assumptions used in the power calculation were that 15% of the population would have CVD and that approximately 12,500 individuals would be needed to achieve 80% power to detect a 25% change in odds of being diagnosed with a CVD. The mean proportion of street trees was set at 0.6, and the standard deviation was set at 0.3. These calculations were repeated using the actual sample size and other values taken from the results. With a sample size of 10,228, a CVD prevalence of 8.6%, an odds ratio indicating only a 13% change, and actual values for the street tree data, the statistical power achieved for Research Question 3 was only 17.1%. The results for the other models were +/- 5% for statistical power achieved. In short, one of primary limitations of the study was that it was not sufficiently powered to detect the effect of interest.

Several problems with the initial assumptions were revealed following initial data exploration. First, CVD was much less prevalent than initially assumed. Prior estimates placed the prevalence of CVD as high as 26% in the general Mexican adult population and 39% among people with diabetes receiving medical care from private health providers (Arenas-León et al., 2023; Mendoza-Herrera et al., 2019). The actual prevalence was 9.1% in metropolitan areas. Such a low disease prevalence has an impact on the number of subjects that are needed to detect a statistical association. After I retained all other inputs for the a priori sample size calculation except disease prevalence, the sample size jumped from 12,542 to 19,181 to achieve 80% power.

Second, the impact of street trees on CVD was overestimated in the initial power calculations. Rather than a 25% difference in CVD resulting from street tree exposure, the results suggested the maximum difference would be 14%. At the conclusion of the study when actual statistical power of 22% was calculated, it was apparent that the a priori assumptions regarding CVD prevalence and the expected contribution of street trees to that prevalence were inaccurate.

Predicted Versus Actual Sample Size

During initial data exploration and visualization of urban and metropolitan census, it became evident that the administrative designation of urban by INEGI did not align with the type of densely populated urban environment in which I was interested. Many INEGI-designated urban census tracts bordered farmland or undeveloped countryside, and the proportion of missing street data in these tracts was higher than in the metropolitan tracts (18% vs. 6% missing data, respectively). For these reasons, the study population was restricted to those living in metropolitan areas. The anticipated sample size of approximately 15,000 respondents was reduced to 11,388, and then further reduced due to missing data.

Measurement Error Related to Street Trees

A key concern in this study was potential measurement error in street tree data. In environmental epidemiology studies, it is difficult to quantify an individual's level of exposure to the health-related environmental factor of interest. There are challenges in estimating the exposure variable and the uncertainty around the extent of exposure to the estimated variable based on individuals' daily movements and residential history. This study's unique data set presented additional challenges in measuring street trees. The final variable used was a derived variable representing the proportion of block-delimiting streets with at least one street tree.

The likelihood of measurement error in the street tree data was not fully appreciated without examining maps of census tracts, their constituent city blocks, and the method of data collection and aggregation. INEGI representatives collected data at the city block level, with official reports designating each census tract into one of three categories: All streets that delimit the city blocks within have street trees, some streets that delimit the city blocks within have trees, and no streets that delimit the city blocks within have street trees (INEGI, 2014). Rather than using these data, I accessed the underlying block-level data to create a derived variable based on the proportions of streets within a census tract with street trees. The purpose was to create a higher resolution measure of street trees than INEGI provided, but it also had complications.

This aggregation method did not account for shared borders between block-delimiting streets within a census tract, potentially leading to double-counting. Although there is no reason to believe that this process would cause systemic over- or undercounting of street trees, the probability is increased that the value representing the extent of street tree coverage in an area does not accurately reflect actual numbers. I have not yet identified a method for checking the extent of over- or undercounting, but this challenge is discussed in the recommendations section.

Model Specification

A common limitation in nonexperimental secondary data research is the potential omission of essential variables affecting the outcome. Using the ISEM conceptual framework and recent research literature on contributors to CVD, I identified and incorporated as many known CVD contributors as possible from ENSANUT 2012 and the other data sets. However, not all variables had easily accessible, publicly available data, and all the known risk factors for CVD did not contribute meaningfully to the statistical models when included. These factors included smoking, a prior diagnosis of diabetes, road network density, and altitude. The statistically significant models in this study showed very low pseudo-R^2 values (< 0.15), indicating that over 85% of the variability in CVD diagnosis was attributable to unidentified variables. Any potential relationship between street trees and CVD could have been masked by the effects of these unidentified covariates. Sleep, physical activity, hours of sleep per night, and BMI are positive contributors to CVD in the literature, but in univariate analyses with CVD, they were not statistically significant. Other factors with a known influence on CVD were not included in my statistical models because of the lack of accessible information. These include more detailed information on diet, air pollution levels, and salt intake.

Other Limitations

Recall bias is a significant challenge in survey data, potentially leading to underreporting of medical history and risk factors. I encountered discrepancies between self-reported data and published estimates, exemplified by the difference in excessive alcohol consumption rates (7% in this study versus > 40% in a national survey on addictive behaviors; (Instituto Nacional de Salud Pública, 2008). The alcohol consumption variable did not achieve statistical significance in my models ($p = .08$), possibly due to underreporting. Although it is important to acknowledge the limitations of the covariates included in the analysis, a different, larger, and more representative set of covariates would not necessarily overcome the limitations inherent in the calculation of the street tree variable. On the other hand, additional covariates might be able to reduce the sample size needed to detect an effect.

Recommendations

The most significant limitation of this study involved the external validity of the street tree data, making this an essential target for future studies involving these data. Geographic Information Systems (GIS) could be employed in future studies to estimate census tract-level street tree data. These systems include ArcGIS, Maptitude, Latapult and Govpilot and are regularly by state and local governments for city planning, utility and asset management, and emergency preparedness. In environmental epidemiology, ArcGIS has been employed for proximity analysis of contaminant sources, documenting unequal distribution of environmental burdens, and modeling future environmental risks

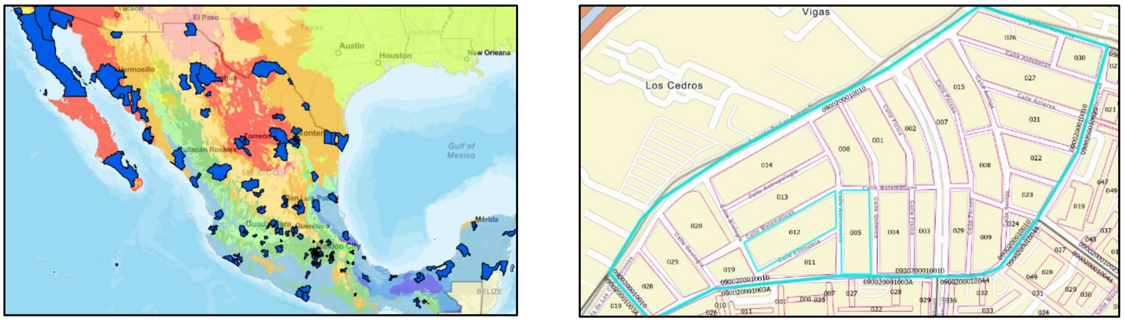
(Nuckols et al., 2004; Sayyed et al., 2024). Thousands of high-resolution geographic files are available on ArcGIS online, wherein locations and their geographic boundaries are linked with data tables. Furthermore, multiple data sets can be linked via either their map coordinates or via identifiers in the underlying data tables and used for geoprocessing and spatial analysis.

ArcGIS Online provides public access to detailed maps of Mexico, including federal, municipal, census tract, and city block levels. I downloaded several data sets to test whether tested whether ArcGIS could be used to account for shared boundaries within census tracts or to provide previously unavailable covariate data. Figure 4a and Figure 4b are examples of maps generated in ArcGIS Pro with data from Mexico. Figure 4a demonstrates the boundaries of metropolitan municipalities (blue) included in my final statistical models. The underlying color layer shows climates zones (Beck et al., 2018). The light-blue outlined area in Figure 4b depicts the boundaries of census tract 0901000010010 in Mexico City, and the pink lines demarcate the 30 city blocks within. Advanced geoprocessing tools in ArcGIS could potentially improve the accuracy of street tree proportion estimates by accounting for contiguous city blocks within census tracts. Future analyses could also incorporate remote-sensed data on weather, tree cover, greenness (NDVI), and air pollution.

Figure 4

Boundary Maps Demonstrating Municipalities, Census Tracts, and City Blocks

a *b*



Note. The climate zones overlapping with the municipalities where the study sample resided included Desert, Cold Semi-Arid, Cold Subtropical Highland / Subpolar Oceanic, Hot Desert, Hot Semi-Arid, Hot-Summer Mediterranean, Humid Subtropical, Subtropical Highland or Temperate Oceanic with Dry Winters, Temperate Oceanic, Tropical Monsoon, Tropical Rainforest, Tropical Savanna, Tundra, Warm Oceanic / Humid Subtropical, and Warm-Summer Mediterranean.

Part of the research gap identified at the initiation of the study was to examine the influence of street trees on health in a country with arid climate zones, as most research focuses on temperate zones in the Global North. However, climate zones were not included as a factor in this study because of the absence of an accessible data set. After locating data from Beck et al. (2018) available on ArcGIS online, I was able to identify the 15 climate zones represented in my study. Future analyses could incorporate this information and improved measurements of green space exposures. Future studies could also use verified health data such as laboratory results or medical records and consider the timing of diagnoses relative to characteristics or changes of the external environment.

Implications

The potential link between street trees and other forms of urban green space and CVD prevalence has implications for positive social change at various levels. At the individual and familial level, tree-lined streets can promote physical activity, reduce stress, and enhance overall well-being. At the local community and policy level, incorporating different types of green space in urban planning could achieve benefits for general public health and community well-being.

Although this study did not find a statistically significant association between street trees and reduced CVD, the results were intriguing and emphasize the need for further research into environmental health interventions. Promoting the multifaceted benefits of green spaces can lead to positive social change by enhancing individual health, supporting family well-being, fostering healthier organizational cultures, and informing policies that prioritize public health through environmental sustainability.

Conclusion

In summary, this quantitative epidemiological study examined the potential link between street trees and self-reported CVD in Mexican adults living in metropolitan census tract using secondary, cross-sectional data. Complex samples logistic regression analysis were conducted that accounted for different combinations of individual and environmental risk factors. The analyses did not yield sufficient evidence to reject the null hypothesis of no significant relationship between street trees and CVD, and a significant relationship between street trees and CVD could not be established. However, the results showed a marked trend of reduced likelihood of CVD prevalence among adults who lived in urban neighborhoods of Mexico as the number of streets with street trees increased, although this finding was not statistically significant after controlling for individual- and household-level factors. The study's post hoc analyses revealed that the sample size was underpowered (<30%), and it is possible that with a larger sample size, statistically significant results might be observed. Similarly, adding other covariates could help isolate the effect of street trees on the outcome. The results warrant further investigation into street trees' potential protective effect on CVD. Future studies addressing the main limitations of this research may yield more definitive conclusions about the relationship between street trees and cardiovascular health in urban environments.

The investigation into the health benefits of green spaces in urban areas remains a vital area of research. As urban areas continue to grow and CVD rates rise, environmental interventions like street tree planting can be a valuable component of public health strategies. The results of this study implying a protective effect of street trees on CVD make the addition of street trees to urban landscapes a potentially powerful strategy to affect social change via improved health outcomes. The on-going urbanization of Mexico's population and expected aging of the population underscore the need for continued research on the multifaceted approaches to mitigate the increasing burden of CVD. By integrating street tree planting into urban planning and public health initiatives, cities may be able to create more resilient, healthier communities.

References

Abdalla, S. M., Yu, S., & Galea, S. (2020). Trends in cardiovascular disease prevalence by income level in the United States. *JAMA Network Open*, *3*(9), Article e2018150. https://doi.org/10.0.3.233/jamanetworkopen.2020.18150

Abelt, K., & McLafferty, S. (2017). Green streets: Urban green and birth outcomes. *International Journal of Environmental Research and Public Health*, *14*(7), Article 771. https://doi.org/10.3390/ijerph14070771

Acosta-Cázares, B., & Escobedo-de la Peña, J. (2010). High burden of cardiovascular disease risk factors in Mexico: An epidemic of ischemic heart disease that may be on its way? *American Heart Journal*, *160*(2), 230–236. https://doi.org/10.1016/j.ahj.2010.05.016

Ahmed, W., Muhammad, T., Maurya, C., & Akhtar, S. N. (2023). Prevalence and factors associated with undiagnosed and uncontrolled heart disease: A study based on self-reported chronic heart disease and symptom-based angina pectoris among middle-aged and older Indian adults. *PLoS ONE*, *18*(6), Article e0287455. https://doi.org/10.1371/journal.pone.0287455

Alkhatib, A. M., Olsen, J. R., & Mitchell, R. (2021). Contextual influences on chronic illness: A multi-level analysis in the twin cities of Ramallah and Al Bireh in the occupied Palestinian Territory. *Health and Place*, *72*. https://doi.org/10.1016/j.healthplace.2021.102677

Almeida, L. F. F., Barreto, S. M., Souza, R. C. F. d., Cardoso, L. d. O., & Giatti, L. (2021). Neighborhood greenspace and cardiometabolic risk factors: Cross-sectional and longitudinal analysis in ELSA-Brasil participants. *Health and Place*, *72*, Article 102699. https://doi.org/10.1016/j.healthplace.2021.102699

American Heart Association. (2022). *American Heart Association adds sleep to cardiovascular health checklist.* https://newsroom.heart.org/news/american-heart-association-adds-sleep-to-cardiovascular-health-checklist

An, C., Liu, J., Liu, Q., Liu, Y., Fan, X., & Hu, Y. (2022). How perceived sensory dimensions of forest park are associated with stress restoration in Beijing? *International Journal of Environmental Research and Public Health*, *19*(2). https://doi.org/10.3390/ijerph19020883

Angel, J. L., Vega, W., & López-Ortega, M. (2017). Aging in Mexico: Population trends and emerging issues. *Gerontologist*, *57*(2), 153–162. https://doi.org/10.1093/geront/gnw136

Arenas-León, J. L., Morales-Villegas, E. C., Cardona-Muñoz, E. G., Alcocer-Gamba, M. A., Ramirez-Contreras, J. P., Contreras-Sandoval, A. Y., & González-Galvez, G. (2023). A cross-sectional study on the prevalence of cardiovascular disease in elderly patients with long-term type 2 diabetes mellitus mainly attended in private clinics in Mexico. The CAPTURE study. *Diabetology & Metabolic Syndrome*, *15*(1), Article 258. https://doi.org/10.1186/s13098-023-01231-6

Armstrong, R. A. (2014). When to use the Bonferroni correction. *Ophthalmic and Physiological Optics*, *34*(5), 502–508. https://doi.org/10.1111/opo.12131

Arroyo-Quiroz, C., O'Flaherty, M., Guzman-Castillo, M., Capewell, S., Chuquiure-Valenzuela, E., Jerjes-Sanchez, C., & Barrientos-Gutierrez, T. (2020). Explaining the increment in coronary heart disease mortality in Mexico between 2000 and 2012. *PLoS ONE*, *15*(12), Article e0242930.

https://doi.org/10.1371/journal.pone.0242930

Asri, A. K., Yu, C.-P., Pan, W.-C., Guo, Y. L., Su, H.-J., Lung, S.-C. C., Wu, C.-D., & Spengler, J. D. (2020). Global greenness in relation to reducing the burden of cardiovascular diseases: Ischemic heart disease and stroke. *Environmental Research Letters*, *15*(12), Article 124003. https://doi.org/10.1088/1748-9326/abbbaf

Astell-Burt, T., & Feng, X. (2019). Association of urban green space with mental health and general health among adults in Australia. *JAMA Network Open*, *2*(7), Article e198209. https://doi.org/10.1001/jamanetworkopen.2019.8209

Astell-Burt, T., & Feng, X. (2020). Urban green space, tree canopy and prevention of cardiometabolic diseases: A multilevel longitudinal study of 46,786 Australians. *International Journal of Epidemiology*, *49*(3), 926–933. https://doi.org/10.1093/ije/dyz239

Astell-Burt, T., Navakatikyan, M. A., Walsan, R., Davis, W., Figtree, G., Arnolda, L., & Feng, X. (2021). Green space and cardiovascular health in people with type 2 diabetes. *Health and Place*, *69*, Article 102554. https://doi.org/10.1016/j.healthplace.2021.102554

Astell-Burt, T., Walsan, R., Davis, W., & Feng, X. (2023). What types of green space disrupt a lonelygenic environment? A cohort study. *Social Psychiatry and Psychiatric Epidemiology*, *58*(5), 745–755. https://doi.org/10.1007/s00127-022-02381-0

Aune, D., Schlesinger, S., Leitzmann, M. F., Tonstad, S., Norat, T., Riboli, E., & Vatten, L. J. (2021). Physical activity and the risk of heart failure: A systematic review and dose–response meta-analysis of prospective studies. *European Journal of Epidemiology*, *36*(4), 367–381. https://doi.org/10.1007/s10654-020-00693-6

Austin, P. C., & Merlo, J. (2017). Intermediate and advanced topics in multilevel logistic regression analysis. *Statistics in Medicine*, *36*(20), 3257–3277. https://doi.org/10.1002/sim.7336

Avila-Palencia, I., Rodri-guez, D. A., Miranda, J. J., Moore, K., Gouveia, N., Moran, M. R., Caiaffa, W. T., & Diez Roux, A. V. (2022). Associations of urban environment features with hypertension and blood pressure across 230 Latin American cities. *Environmental Health Perspectives*, *130*(2), Article 027010. https://doi.org/10.1289/EHP7870

Barquera, S., Pedroza-Tobias, A., & Medina, C. (2016). Cardiovascular diseases in mega-countries: The challenges of the nutrition, physical activity and epidemiologic transitions, and the double burden of disease. *Current Opinion in Lipidology*, *27*(4), 329–344. https://doi.org/10.1097/MOL.0000000000000320

Bays, H. E., Taub, P. R., Epstein, E., Michos, E. D., Ferraro, R. A., Bailey, A. L., Kelli, H. M., Ferdinand, K. C., Echols, M. R., Weintraub, H., Bostrom, J., Johnson, H. M., Hoppe, K. K., Shapiro, M. D., German, C. A., Virani, S. S., Hussain, A., Ballantyne, C. M., Agha, A. M., & Toth, P. P. (2021). Ten things to know about ten cardiovascular disease risk factors. *American Journal of Preventive Cardiology*, *5*, Article 100149. https://doi.org/10.1016/j.ajpc.2021.100149

Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., & Wood, E. F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific data*, *5*(1), Article 180214.

https://doi.org/10.1038/sdata.2018.214

Becker, D. A., Browning, M. H. E. M., Kuo, M., & Van Den Eeden, S. K. (2019). Is green land cover associated with less health care spending? Promising findings from county-level Medicare spending in the continental United States. *Urban Forestry and Urban Greening*, *41*, 39–47. https://doi.org/10.1016/j.ufug.2019.02.012

Bello-Chavolla, O. Y., Antonio-Villa, N. E., Fermín-Martínez, C. A., Fernández-Chirino, L., Vargas-Vázquez, A., Ramírez-García, D., Basile-Alvarez, M. R., Hoyos-Lázaro, A. E., Carrillo-Larco, R. M., Wexler, D. J., Manne-Goehler, J., & Seiglie, J. A. (2022). Diabetes-related excess mortality in Mexico: A comparative analysis of national death registries between 2017–2019 and 2020. *Diabetes Care*, *45*(12), 2957–2966. https://doi.org/10.2337/dc22-0616

Bhatnagar, A. (2017). Environmental determinants of cardiovascular disease. *Circulation Research*, *121*(2), 162–180. https://doi.org/10.1161/circresaha.117.306458

Bianconi, A., Longo, G., Coa, A., Fiore, M., & Gori, D. (2023). Impacts of urban green on cardiovascular and cerebrovascular diseases—A systematic review and meta-analysis. *International Journal of Environmental Research and Public Health*, *20*, Article 5966. https://doi.org/10.3390/ijerph20115966

Bikomeye, J. C., Balza, J. S., Kwarteng, J. L., Beyer, A. M., & Beyer, K. M. (2022). The impact of greenspace or nature-based interventions on cardiovascular health or cancer-related outcomes: A systematic review of experimental studies. *PLoS ONE*, *17*(11), Article e0276517. https://doi.org/10.1371/journal.pone.0276517

Bittencourt, M. S. (2018). Family history of cardiovascular disease: How detailed should it be? *Mayo Clinic Proceedings*, *93*(9), 1167–1168. https://doi.org/10.1016/j.mayocp.2018.01.014

Boehm, J. K. (2021). Positive psychological well-being and cardiovascular disease: Exploring mechanistic and developmental pathways. *Social and Personality Psychology Compass*, *15*(6), Article e12599. https://doi.org/10.1111/spc3.12599

Box, G. E. P., & Tidwell, P. W. (1962). Transformation of the independent variables. *Technometrics*, *4*, 531–550.

Bratman, G. N., Olvera-Alvarez, H. A., & Gross, J. J. (2021). The affective benefits of nature exposure. *Social and Personality Psychology Compass*, *15*(8), Article e12630. https://doi.org/10.1111/spc3.12630

Cakmak, S., Hebbern, C., Vanos, J., Crouse, D. L., & Tjepkema, M. (2019). Exposure to traffic and mortality risk in the 1991-2011 Canadian Census Health and Environment Cohort (CanCHEC). *Environment International*, *124*, 16–24. https://doi.org/10.1016/j.envint.2018.12.045

Cannatà, A., Marcon, G., Cimmino, G., Camparini, L., Ciucci, G., Sinagra, G., & Loffredo, F. S. (2017). Role of circulating factors in cardiac aging. *Journal of Thoracic Disease*, *9*(Suppl 1), S17–S29. https://doi.org/10.21037/jtd.2017.03.95

CEDRUS. (2019). *Densidad de carreteras y redes viales en los municipios de México [Density of roads and road networks in Mexican municipalities]*. Centro de Estudios del Desarrollo Regional y Urbano Sustentable. https://cedrus-unam.blogspot.com/2019/05/densidad-de-carreteras-y-redes-viales.html

Chen, H., Burnett Richard, T., Bai, L., Kwong Jeffrey, C., Crouse Dan, L., Lavigne, E., Goldberg Mark, S., Copes, R., Benmarhnia, T., Ilango Sindana, D., van

Donkelaar, A., Martin Randall, V., & Hystad, P. (2020). Residential greenness and cardiovascular disease incidence, readmission, and mortality. *Environmental Health Perspectives*, *128*(8), Article 087005. https://doi.org/10.1289/EHP6161

Chen, Z., Dazard, J.-E., Khalifa, Y., Motairek, I., Al-Kindi, S., & Rajagopalan, S. (2024). Artificial intelligence–based assessment of built environment from Google Street View and coronary artery disease prevalence. *European Heart Journal*, *45*(17), 1540–1549. https://doi.org/10.1093/eurheartj/ehae158

Chi, D., Aerts, R., Van Nieuwenhuyse, A., Bauwelinck, M., Demoury, C., Plusquin, M., Nawrot, T. S., Casas, L., & Somers, B. (2022). Residential exposure to urban trees and medication sales for mood disorders and cardiovascular disease in Brussels, Belgium: An ecological study. *Environmental Health Perspectives*, *130*(5), Article 57003. https://doi.org/10.1289/EHP9924

Chomistek, A. K., Cook, N. R., Rimm, E. B., Ridker, P. M., Buring, J. E., & Lee, I. M. (2018). Physical activity and incident cardiovascular disease in women: Is the relation modified by level of global cardiovascular risk? *Journal of the American Heart Association*, *7*(12), Article e008234. https://doi.org/10.1161/JAHA.117.008234

Chum, A., & O'Campo, P. (2015). Cross-sectional associations between residential environmental exposures and cardiovascular diseases. *BMC Public Health*, *15*, Article 438. https://doi.org/10.1186/s12889-015-1788-0

CONEVAL (El Consejo Nacional de Evaluacion de la Politica de Desarrollo Social). (n.d.). *What is social lag? (¿Que es el resago social?)*. CONEVAL. https://www.coneval.org.mx/Medicion/IRS/Paginas/Que-es-el-indice-de-rezago-social.aspx

Cortés-Hernández, D. E., Lundelin, K. J., Picazzo-Palencia, E., de la Cruz, J. J., Sánchez, J. J., & Banegas, J. R. (2014). The burden of blood-pressure-related cardiovascular mortality in Mexico. *International Journal of Hypertension*, *2014*, Article 427684. https://doi.org/10.1155/2014/427684

Cosselman, K. E., Navas-Acien, A., & Kaufman, J. D. (2015). Environmental factors in cardiovascular disease. *Nature Reviews Cardiology*, *12*(11), 627–642. https://doi.org/10.1038/nrcardio.2015.152

Coughlin, S. S., & Young, L. (2020). Social determinants of myocardial infarction risk and survival: A systematic review. *European Journal of Cardiovascular Research*, *1*(1). https://doi.org/10.31487/j.ejcr.2020.01.02

Covassin, N., & Singh, P. (2016). Sleep duration and cardiovascular disease risk: Epidemiologic and experimental evidence. *Sleep Medicine Clinics*, *11*(1), 81–89. https://doi.org/10.1016/j.jsmc.2015.10.007

da Silveira, I. H., & Junger, W. L. (2018). Green spaces and mortality due to cardiovascular diseases in the city of Rio de Janeiro. *Revista de Saúde Pública* *52*(49). https://doi.org/10.11606/S1518-8787.2018052000290

Dadvand, P., Bartoll, X., Basagaña, X., Dalmau-Bueno, A., Martinez, D., Ambros, A., Cirach, M., Triguero-Mas, M., Gascon, M., Borrell, C., & Nieuwenhuijsen, M. J. (2016). Green spaces and general health: Roles of mental health status, social support, and physical activity. *Environment International*, *91*, 161–167. https://doi.org/10.1016/j.envint.2016.02.029

Dalton, A. M., & Jones, A. P. (2020). Residential neighbourhood greenspace is associated with reduced risk of cardiovascular disease: A prospective cohort study. *PLoS ONE*, *15*(1), Article e0226524. https://doi.org/10.1371/journal.pone.0226524

Dávila-Cervantes, C. A. (2020). Cardiovascular disease in Mexico 1990–2017: Secondary data analysis from the Global Burden of Disease study. *International Journal of Public Health*, *65*(5), 661–671. https://doi.org/10.1007/s00038-020-01377-4

de Jong, M., Woodward, M., & Peters, S. A. E. (2022). Duration of diabetes and the risk of major cardiovascular events in women and men: A prospective cohort study of UK Biobank participants. *Diabetes Research and Clinical Practice*, *188*, Article 109899. https://doi.org/10.1016/j.diabres.2022.109899

de la Iglesia Martinez, A., & Labib, S. (2023). Demystifying normalized difference vegetation index (NDVI) for greenness exposure assessments and policy interventions in urban greening. *Environmental Research*, *220*, Article 115155. https://doi.org/10.1016/j.envres.2022.115155

De Petris, S., Squillacioti, G., Bono, R., & Borgogno-Mondino, E. (2021). Geomatics and epidemiology: Associating oxidative stress and greenness in urban areas. *Environmental Research*, *197*, Article 110999. https://doi.org/10.1016/j.envres.2021.110999

Diez-Roux, A. V. (2000). Multilevel analysis in public health research. *Annual Review of Public Health*, *21*(1), 171–192. https://doi.org/10.1146/annurev.publhealth.21.1.171

Donovan, G. H., Butry, D. T., Michael, Y. L., Prestemon, J. P., Liebhold, A. M., Gatziolis, D., & Mao, M. Y. (2013). The relationship between trees and human health: Evidence from the spread of the emerald ash borer. *American Journal of Preventive Medicine*, *44*(2), 139–145. https://doi.org/10.1016/j.amepre.2012.09.066

Donovan, G. H., Michael, Y. L., Gatziolis, D., Prestemon, J. P., & Whitsel, E. A. (2015). Is tree loss associated with cardiovascular-disease risk in the Women's Health Initiative? A natural experiment. *Health and Place*, *36*, 1–7. https://doi.org/10.1016/j.healthplace.2015.08.007

Donovan, G. H., Prestemon, J. P., Gatziolis, D., Michael, Y. L., Kaminski, A. R., & Dadvand, P. (2022). The association between tree planting and mortality: A natural experiment and cost-benefit analysis. *Environment International*, *170*, Article 107609. https://doi.org/10.1016/j.envint.2022.107609

Egorov, A. I., Griffin, S. M., Converse, R. R., Styles, J. N., Klein, E., Scott, J., Sams, E. A., Hudgens, E. E., & Wade, T. J. (2020). Greater tree cover near residence is associated with reduced allostatic load in residents of central North Carolina. *Environmental Research*, *186*, Article 109435. https://doi.org/10.1016/j.envres.2020.109435

El Consejo Nacional de Evaluacion de la Politica de Desarrollo Social. (2023). *Medición de la pobreza: ¿Qué es el Rezago Social Indice? [Measuring poverty: What is the Social Lag Index?]*. CONEVAL. https://www.coneval.org.mx/Medicion/IRS/Paginas/Que-es-el-indice-de-rezago-social.aspx

Escobedo-de la Peña, J., Rascón-Pacheco, R. A., Ascencio-Montiel, I. d. J., González-

Figueroa, E., Fernández-Gárate, J. E., Medina-Gómez, O. S., Borja-Bustamante, P., Santillán-Oropeza, J. A., & Borja-Aburto, V. H. (2021). Hypertension, diabetes and obesity, major risk factors for death in patients with COVID-19 in Mexico. *Archives of Medical Research*, *52*(4), 443–449. https://doi.org/10.1016/j.arcmed.2020.12.002

Esparza Rios, L. G. (2017). *National geostatistical framework, as an example of success in Mexico for the linking of statistical and geographic information*. https://unece.org/fileadmin/DAM/stats/documents/ece/ces/ge.58/2017/mtg3/Paper_MGNVinculaIEIG-30Ago2017EnglishV2__1_.pdf

Fatmi, Z., & Coggon, D. (2016). Coronary heart disease and household air pollution from use of solid fuel: A systematic review. *British Medical Bulletin*, *118*(1), 91–109. https://doi.org/10.1093/bmb/ldw015

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/doi.org/10.3758/BRM.41.4.1149

Feng, X., Navakatikyan, M. A., Toms, R., & Astell-Burt, T. (2023). Leafier communities, healthier hearts: An Australian cohort study of 104,725 adults tracking cardiovascular events and mortality across 10 years of linked health data. *Heart, Lung and Circulation*, *32*(1), 105–113. https://doi.org/10.1016/j.hlc.2022.10.018

Fernández-Álvarez, R. (2017). Distribución inequitativa del espacio público verde en la Ciudad de México: un caso de injusticia ambiental. [Inequitable distribution of green public space in the Mexico City: An environmental injustice case].

Economía, Sociedad y Territorio, *17*(54), 399–428. https://doi.org/10.22136/est002017697

Fernández-Solà, J. (2015). Cardiovascular risks and benefits of moderate and heavy alcohol consumption. *Nature Reviews Cardiology*, *12*(10), 576–587. https://doi.org/10.1038/nrcardio.2015.91

Franklin, B. A., Brook, R., & Arden Pope, C. (2015). Air pollution and cardiovascular disease. *Current Problems in Cardiology*, *40*(5), 207–238. https://doi.org/10.1016/j.cpcardiol.2015.01.003

Fuchs, F. D., & Whelton, P. K. (2020). High blood pressure and cardiovascular disease. *Hypertension*, *75*(2), 285–292. https://doi.org/10.1161/HYPERTENSIONAHA.119.14240

Gallucci, G., Tartarone, A., Lerose, R., Lalinga, A. V., & Capobianco, A. M. (2020). Cardiovascular risk of smoking and benefits of smoking cessation. *Journal of Thoracic Disease*, *12*(7), 3866–3876. https://doi.org/10.21037/jtd.2020.02.47

Gascon, M., Triguero-Mas, M., Martínez, D., Dadvand, P., Rojas-Rueda, D., Plasència, A., & Nieuwenhuijsen, M. J. (2016). Residential green spaces and mortality: A systematic review. *Environment International*, *86*, 60–67. https://doi.org/10.1016/j.envint.2015.10.013

GeoAnalitica. (2020). *The quick guide to Mexico Censo AGEBs and manzanas*. GeoAnalitica. https://geoanalitica.com/the-quick-guide-to-mexico-censo-agebs-and-manzanas/

Giacinto, J. J., Fricker, G. A., Ritter, M., Yost, J., & Doremus, J. (2021). Urban forest biodiversity and cardiovascular disease: Potential health benefits from California's street trees. *PLoS ONE*, *16*(11), Article e0254973. https://doi.org/10.1371/journal.pone.0254973

Glynn, P. A., Ning, H., Bavishi, A., Freaney, P. M., Shah, S., Yancy, C. W., Lloyd-Jones, D. M., & Khan, S. S. (2021). Heart failure risk distribution and trends in the United States population, NHANES 1999-2016. *American Journal of Medicine*, *134*(3), e153–e164. https://doi.org/10.1016/j.amjmed.2020.07.025

Goldstein, H., Browne, W., & Rasbash, J. (2002). Partitioning variation in multilevel models. *Understanding Statistics*, *1*(4), 223–231. https://doi.org/10.1207/S15328031US0104_02

Gonçalves, R. P. F., Haikal, D. S. A., Freitas, M. I. d. F., Machado, Í. E., & Malta, D. C. (2019). Diagnóstico médico autorreferido de doença cardíaca e fatores de risco associados: Pesquisa Nacional de Saúde. [Self-reported physician diagnosis of heart disease and associated risk factors: National Health Survey]. *Revista Brasileira de Epidemiologia*, *22*. https://doi.org/10.1590/1980-549720190016.supl.2

Grabowski, Z. J., McPhearson, T., Matsler, A. M., Groffman, P., & Pickett, S. T. (2022). What is green infrastructure? A study of definitions in US city planning. *Frontiers in Ecology and the Environment*, *20*(3), 152–160. https://doi.org/10.1002/fee.2445

Graham, D. A., Vanos, J. K., Kenny, N. A., & Brown, R. D. (2016). The relationship between neighbourhood tree canopy cover and heat-related ambulance calls during extreme heat events in Toronto, Canada. *Urban Forestry and Urban Greening*, *20*, 180–186. https://doi.org/10.1016/j.ufug.2016.08.005

Guerrero-López, C. M., Serván-Mori, E., Jan, S., Downey, L., Heredia-Pi, I., Orozco-Núñez, E., Muradás-Troitiño, M. C., & Norton, R. (2024). Gender disparities in lost productivity resulting from non-communicable diseases in Mexico, 2005-2021. *Journal of Global Health*, *14*, Article 04121. https://doi.org/10.7189/jogh.14.04121

Guo, G., & Zhao, H. (2000). Multilevel modeling for binary data. *Annual Review of Sociology*, *26*(1), 441–462. https://doi.org/10.1146/annurev.soc.26.1.441

Hajar, R. (2017). Risk factors for coronary artery disease: Historical perspectives. *Heart Views*, *18*(3), 109–114. https://doi.org/10.4103/heartviews.Heartviews_106_17

Hankey, S., Zhang, W., Le, H. T. K., Hystad, P., & James, P. (2021). Predicting bicycling and walking traffic using street view imagery and destination data. *Transportation Research: Part D*, *90*. https://doi.org/10.1016/j.trd.2020.102651

Hartig, T., Mitchell, R., de Vries, S., & Frumkin, H. (2014). Nature and health. *Annual Review of Public Health*, *35*(1), 207–228. https://doi.org/10.1146/annurev-publhealth-032013-182443

Hayden, J. (2019). *Introduction to health behavior theory* (3rd ed.). Jones & Bartlett Learning.

He, H., Pan, L., Cui, Z., Sun, J., Yu, C., Cao, Y., Wang, Y., & Shan, G. (2020). Smoking prevalence, patterns, and cessation among adults in Hebei province, central China: Implications from China National Health Survey (CNHS). *Frontiers in Public Health*, *8*. https://doi.org/10.3389/fpubh.2020.00177

Heck, R. H., Thomas, S., & Tabata, L. (2012). *Multilevel modeling of categorical outcomes using IBM SPSS*. Routledge.

Hollestein, L. M., Lo, S. N., Leonardi-Bee, J., Rosset, S., Shomron, N., Couturier, D. L., & Gran, S. (2021). MULTIPLE ways to correct for MULTIPLE comparisons in MULTIPLE types of studies. *British Journal of Dermatology*, *185*(6), 1081–1083. https://doi.org/10.1111/bjd.20600

Hongsheng, C., Ye, L., Zhenjun, Z., & Zhigang, L. (2017). Does where you live matter to your health? Investigating factors that influence the self-rated health of urban and rural Chinese residents: evidence drawn from Chinese General Social Survey data. *Health & Quality of Life Outcomes*, *15*, 1–11. https://doi.org/10.1186/s12955-017-0658-0

Hu, H. B., Hou, Z. H., Huang, C. H., LaMonte, M. J., Wang, M., & Lu, B. (2022). Associations of exposure to residential green space and neighborhood walkability with coronary atherosclerosis in Chinese adults. *Environmental Pollution*, *292*(A), Article 118347. https://doi.org/10.1016/j.envpol.2021.118347

Huang, Q., Yang, M., Jane, H.-a., Li, S., & Bauer, N. (2020). Trees, grass, or concrete? The effects of different types of environments on stress reduction. *Landscape and Urban Planning*, *193*, Article 103654. https://doi.org/10.1016/j.landurbplan.2019.103654

IBM. (2021). IBM SPSS Complex Samples 29. https://www.ibm.com/docs/en/SSLVMB_29.0.0/pdf/IBM_SPSS_Complex_Samples.pdf

Ibrahim, M. A., Asuka, E., Jialal, I., & Corcione, J. (2022). Hypercholesterolemia (Nursing). In *StatPearls* StatPearls Publishing.

Instituto Nacional de Estadística y Geografía. (2015a). *Características de las localidades* *y del entorno urbano 2014. [Characteristics of localities and all urban environments 2014].* https://www.inegi.org.mx/programas/cleu/2014/

Instituto Nacional de Estadística y Geografía. (2015b). *Características del entorno urbano 2014: Síntesis metodológica y conceptual. [Characteristics of the Urban Environment 2014: Methodological and conceptual synthesis]*. Aguascalientes, Aguascalientes Retrieved from https://www.inegi.org.mx/contenidos/productos/prod_serv/contenidos/espanol/bvinegi/productos/nueva_estruc/702825078867.pdf

Instituto Nacional de Estadística y Geografía. (2015c). Catálogo único de claves de áreas geoestadísticas estatales, municipales y localidades. [Unique catalog of keys for state, municipal and local geostatistical areas]. *Consulta y descarga.* https://www.inegi.org.mx/app/ageeml/

Instituto Nacional de Estadística y Geografía. (2018). *Delimitación de las zonas metropolitanas de México 2015. [Delimitation of the metropolitan areas of Mexico 2015]*.

Instituto Nacional de Estadística y Geografía. (2019). *Encuesta Nacional Agropecuaria (ENA 2019): Manual de Cartografía Geoestadística [National Agricultural Survey (ENA 2019): Geostatistical cartography manual]*. Instituto Nacional de Estadística y Geografía Retrieved from https://www.inegi.org.mx/rnm/index.php/catalog/607/download/18173

Instituto Nacional de Estadística y Geografía (INEGI). (2014). *Síntesis metodológica y conceptual de la infraestructura y características del entorno urbano del Censo de Población y Vivienda 2010 [Methodological and conceptual synthesis of the* *infrastructure and characteristics of the urban environment of the Population and Housing Census]*.

Instituto Nacional de Salud Pública. (2008). *Encuesta Nacional de Adicciones 2008. [National Addition Survey 2008]*. Cuernavaca, MEX Retrieved from http://www.conadic.salud.gob.mx/pdfs/ena08/ENA08_NACIONAL.pdf

Instituto Nacional de Salud Pública. (2012). *Encuesta Nacional de Salud y Nutrición 2012: Aspectos Metholốgicos. [National Survey of Health and Nutrition 2012: Methodological aspects]*. Cuernavaca, MEX

Iyer, H. S., Hart, J. E., James, P., Elliott, E. G., DeVille, N. V., Holmes, M. D., De Vivo, I., Mucci, L. A., Laden, F., & Rebbeck, T. R. (2022). Impact of neighborhood socioeconomic status, income segregation, and greenness on blood biomarkers of inflammation. *Environment International*, *162*, Article 107164. https://doi.org/10.1016/j.envint.2022.107164

James, P., Banay, R. F., Hart, J. E., & Laden, F. (2015). A review of the health benefits of greenness. *Current Epidemiology Reports*, *2*(2), 131–142. https://doi.org/10.1007/s40471-015-0043-7

Jennings, V., Floyd, M. F., Shanahan, D., Coutts, C., & Sinykin, A. (2017). Emerging issues in urban ecology: Implications for research, social justice, human health, and well-being. *Population and Environment*, *39*(1). https://doi.org/10.1007/s11111-017-0276-0

Jennings, V., Gragg, R. S., 3rd, Brown, C. P., Hartel, D., Kuehler, E., Sinykin, A., Johnson, E., & Kondo, M. (2019). Structural characteristics of tree cover and the association with cardiovascular and respiratory health in Tampa, FL. *Journal of*

Urban Health, *96*(5), 669–681. https://doi.org/10.1007/s11524-019-00380-2

Jeong, J., Yun, S.-m., Kim, M., & Koh, Y. H. (2020). Association of blood cadmium with cardiovascular disease in Korea: From the Korea National Health and Nutrition Examination Survey 2008–2013 and 2016. *International Journal of Environmental Research and Public Health*, *17*, Article 6288. https://doi.org/10.3390/ijerph17176288

Jiang, B., Chang, C.-Y., & Sullivan, W. C. (2014). A dose of nature: Tree cover, stress reduction, and gender differences. *Landscape and Urban Planning*, *132*, 26–36. https://doi.org/10.1016/j.landurbplan.2014.08.005

Jimenez, M. P., DeVille, N. V., Elliott, E. G., Schiff, J. E., Wilt, G. E., Hart, J. E., & James, P. (2021). Associations between nature exposure and health: A review of the evidence. *International Journal of Environmental Research and Public Health*, *18*, Article 4790. https://doi.org/10.3390/ijerph18094790

John, E. E., Astell-Burt, T., Yu, P., Brennan-Horley, C., & Feng, X. (2023). Green space type and healthy ageing in place: An Australian longitudinal study. *Urban Forestry and Urban Greening*, *84*, Article 127903. https://doi.org/10.1016/j.ufug.2023.127903

Jones, B. A. (2016). Work more and play less? Time use impacts of changing ecosystem services: The case of the invasive emerald ash borer. *Ecological Economics*, *124*, 49–58. https://doi.org/10.1016/j.ecolecon.2016.02.003

Jones, B. A. (2023). Can invasive species lead to sedentary behavior? The time use and obesity impacts of a forest-attacking pest. *Journal of Environmental Economics and Management*, *119*, Article 102800.

https://doi.org/10.1016/j.jeem.2023.102800

Joye, Y., & van der Berg, A. E. (2013). *Environmental psychology: An introduction*. Wiley-Blackwell.

Kan, H., Heiss, G., Rose, K. M., Whitsel, E. A., Lurmann, F., & London, S. J. (2008). Prospective analysis of traffic exposure as a risk factor for incident coronary heart disease: the Atherosclerosis Risk in Communities (ARIC) study. *Environmental Health Perspectives*, *116*(11), 1463–1468. https://doi.org/10.1289/ehp.11290

Kang, H. (2013). The prevention and handling of the missing data. *Korean Journal of Anesthesiology*, *64*(5), 402–406 https://doi.org/10.4097/kjae.2013.64.5.402

Karanchi, H., Muppidi, V., & Wyne, K. (2023). *Hypertriglyceridemia*. StatPearls Publishing LLC.

Kardan, O., Gozdyra, P., Misic, B., Moola, F., Palmer, L. J., Paus, T., & Berman, M. G. (2015). Neighborhood greenspace and health in a large urban center. *Scientific Reports*, *5*, Article 11610. https://doi.org/10.1038/srep11610

Kasdagli, M.-I., Katsouyanni, K., de Hoogh, K., Lagiou, P., & Samoli, E. (2021). Associations of air pollution and greenness with mortality in Greece: An ecological study. *Environmental Research*, *196*, Article 110348. https://doi.org/10.1016/j.envres.2020.110348

Keymolen, D. L., & Robles Linares, S. C. G. (2021). Factores de riesgo cardiovascular y condiciones socioeconómicas y sociodemográficas en México, 2000 - 2018. [Cardiovascular risk factors and socioeconomic and sociodemographic conditions in Mexico, 2000 - 2018]. *Población y Salud en Mesoamérica*, *18*(2), 63–93. https://doi.org/10.15517/psm.v18i2.41748

Kim, S., Kim, H., & Lee, J. T. (2019). Interactions between ambient air particles and greenness on cause-specific mortality in seven Korean metropolitan cities, 2008-2016. *International Journal of Environmental Research and Public Health*, *16*(10), Article 1866. https://doi.org/10.3390/ijerph16101866

Knobel, P., Kondo, M., Maneja, R., Zhao, Y., Dadvand, P., & Schinasi, L. H. (2021). Associations of objective and perceived greenness measures with cardiovascular risk factors in Philadelphia, PA: A spatial analysis. *Environmental Research*, *197*, Article 110990. https://doi.org/10.1016/j.envres.2021.110990

Koliaki, C., Liatis, S., & Kokkinos, A. (2019). Obesity and cardiovascular disease: Revisiting an old relationship. *Metabolism*, *92*, 98–107. https://doi.org/10.1016/j.metabol.2018.10.011

Kondo, M. C., Fluehr, J. M., McKeon, T., & Branas, C. C. (2018). Urban green space and its impact on human health. *International Journal of Environmental Research and Public Health*, *15*(3), Article 445. https://doi.org/10.3390/ijerph15030445

Kondo, M. C., Han, S., Donovan, G. H., & MacDonald, J. M. (2017). The association between urban trees and crime: Evidence from the spread of the emerald ash borer in Cincinnati. *Landscape and Urban Planning*, *157*, 193–199. https://doi.org/10.1016/j.landurbplan.2016.07.003

Konijnendijk, C., Devkota, D., Mansourian, S., & Wildburger, C. (2023). *Forests and trees for human health: Pathways, impacts, challenges, and response options. A global assessment project.* International Union of Forest Research Organizations (IUFRO).

Korpela, K., & Ratcliffe, E. (2021). Which is primary: Preference or perceived instoration? *Journal of Environmental Psychology*, *75*, Article 101617. https://doi.org/10.1016/j.jenvp.2021.101617

Kuo, M. (2015). How might contact with nature promote human health? Promising mechanisms and a possible central pathway. *Frontiers in Psychology*, *6*, Article 1093. https://doi.org/10.3389/fpsyg.2015.01093

Kwan, S. C., Ismail, R., Ismail, N. H., & Mohamed, N. (2021). An ecological study of the relationship between urban built environment and cardiovascular hospital admissions (2004-2016) in an Asian developing country. *Social Science & Medicine*, *276*, Article 113868. https://doi.org/10.1016/j.socscimed.2021.113868

Laerd Statistics. (2017a). Binomial logistic regression using SPSS Statistics. *Statistical Tutorials and Software Guides*. https://statistics.laerd.com

Laerd Statistics. (2017b). *Binominal logistic regression using SPSS statistics*. https://statistics.laerd.com/

Lai, Y., & Kontokosta, C. E. (2019). The impact of urban street tree species on air quality and respiratory illness: A spatial analysis of large-scale, high-resolution urban data. *Health and Place*, *56*, 80–87. https://doi.org/10.1016/j.healthplace.2019.01.016

Landrigan, P. J., Fuller, R., Acosta, N. J. R., Adeyi, O., Arnold, R., Basu, N., Baldé, A. B., Bertollini, R., Bose-O'Reilly, S., Boufford, J. I., Breysse, P. N., Chiles, T., Mahidol, C., Coll-Seck, A. M., Cropper, M. L., Fobil, J., Fuster, V., Greenstone, M., Haines, A., . . . Zhong, M. (2018). The Lancet Commission on pollution and health. *Lancet*, *391*(10119), 462–512. https://doi.org/10.1016/S0140-6736(17)32345-0

Larkin, A., & Hystad, P. (2019). Evaluating street view exposure measures of visible green space for health research. *Journal of Exposure Science and Environmental Epidemiology*, *29*(4), 447–456. https://doi.org/10.1038/s41370-018-0017-1

Lee, A. C., & Maheswaran, R. (2011). The health benefits of urban green spaces: A review of the evidence. *Journal of Public Health*, *33*(2), 212–222. https://doi.org/10.1093/pubmed/fdq068

Lee, H. Y., Wu, C. D., Chang, Y. T., Chern, Y. R., Lung, S. C., Su, H. J., & Pan, W. C. (2020). Association between surrounding greenness and mortality: An ecological study in Taiwan. *International Journal of Environmental Research and Public Health*, *17*, Article 4525. https://doi.org/10.3390/ijerph17124525

Lee, S., Lee, R. J., & Scherr, S. (2023). How tree canopy cover can reduce urban suicide attempts: A geospatial analysis of the moderating role of area deprivation. *Landscape and Urban Planning*, *230*, Article 104606. https://doi.org/10.1016/j.landurbplan.2022.104606

Lee, S., Ye, X., Nam, J. W., & Zhang, K. (2022). The association between tree canopy cover over streets and elderly pedestrian falls: A health disparity study in urban areas. *Social Science & Medicine*, *306*, Article 115169. https://doi.org/10.1016/j.socscimed.2022.115169

Leyland, A. H., & Groenewegen, P. P. (2020). *Multilevel modelling for public health and health services research: health in context*. Springer Nature.

Li, H., & Zhang, G. (2023). How can plant-enriched natural environments benefit human health: A narrative review of relevant theories. *International Journal of Environmental Health Research*, 1–14.

https://doi.org/10.1080/09603123.2023.2170990

Li, T., Yu, Z., Xu, L., Wu, Y., Yu, L., Yang, Z., Shen, P., Lin, H., Shui, L., Tang, M., Jin, M., Chen, K., & Wang, J. (2022). Residential greenness, air pollution, and incident ischemic heart disease: A prospective cohort study in China. *Science of the Total Environment*, *838*, Article 155881. https://doi.org/10.1016/j.scitotenv.2022.155881

Lindstrom, M., DeCleene, N., Dorsey, H., Fuster, V., Johnson Catherine, O., LeGrand Kate, E., Mensah George, A., Razo, C., Stark, B., Varieur Turco, J., & Roth Gregory, A. (2022). Global Burden of Cardiovascular Diseases and Risks Collaboration, 1990-2021. *Journal of the American College of Cardiology*, *80*(25), 2372–2425. https://doi.org/10.1016/j.jacc.2022.11.001

Liu, L., Qu, H., Ma, Y., Wang, K., & Qu, H. (2022). Restorative benefits of urban green space: Physiological, psychological restoration and eye movement analysis. *Journal of Environmental Management*, *301*, Article 113930. https://doi.org/10.1016/j.jenvman.2021.113930

Liu, M., Meijer, P., Lam, T. M., Timmermans, E. J., Grobbee, D. E., Beulens, J. W. J., Vaartjes, I., & Lakerveld, J. (2023). The built environment and cardiovascular disease: An umbrella review and meta-meta-analysis. *European Journal of Preventive Cardiology*. https://doi.org/10.1093/eurjpc/zwad241

Liu, T., Cai, B., Peng, W., Xiao, L., Shi, H., Wu, X., Gao, H., & Jia, X. (2021). Association of neighborhood greenness exposure with cardiovascular diseases and biomarkers. *International Journal of Hygiene and Environmental Health*, *234*, Article 113738. https://doi.org/10.1016/j.ijheh.2021.113738

Liu, X. X., Ma, X. L., Huang, W. Z., Luo, Y. N., He, C. J., Zhong, X. M., Dadvand, P., Browning, M., Li, L., Zou, X. G., Dong, G. H., & Yang, B. Y. (2022). Green space and cardiovascular disease: A systematic review with meta-analysis. *Environmental Pollution*, *301*, Article 118990. https://doi.org/10.1016/j.envpol.2022.118990

López Sánchez, G. F., López-Bueno, R., Villaseñor-Mora, C., & Pardhan, S. (2022). Comparison of diabetes mellitus risk factors in Mexico in 2003 and 2014. *Frontiers in Nutrition*, *9*, Article 894904. https://doi.org/10.3389/fnut.2022.894904

Lovasi, G. S., Quinn, J. W., Neckerman, K. M., Perzanowski, M. S., & Rundle, A. (2008). Children living in areas with more street trees have lower prevalence of asthma. *Journal of Epidemiology and Community Health*, *62*(7), 647–649. https://doi.org/10.1136/jech.2007.071894

Lovell, R., Depledge, M., & Maxwell, S. (2018). *Health and the natural environment: A review of evidence, policy, practice and opportunities for the future*. https://beyondgreenspace.files.wordpress.com/2018/09/health-and-the-natural-environment_full-report.pdf

Maas, C. J., & Hox, J. J. (2005). Sufficient sample sizes for multilevel modeling. *Methodology*, *1*(3), 86–92.

Maas, J., Verheij, R. A., de Vries, S., Spreeuwenberg, P., Schellevis, F. G., & Groenewegen, P. P. (2009). Morbidity is related to a green living environment. *Journal of Epidemiology and Community Health*, *63*(12), 967–973. https://doi.org/10.1136/jech.2008.079038

Maas, J., Verheij, R. A., Groenewegen, P. P., de Vries, S., & Spreeuwenberg, P. (2006). Green space, urbanity, and health: How strong is the relation? *Journal of Epidemiology and Community Health*, *60*(7), 587–592. https://doi.org/10.1136/jech.2005.043125

Malecki, K. M. C., Andersen, J. K., Geller, A. M., Harry, G. J., Jackson, C. L., James, K. A., Miller, G. W., & Ottinger, M. A. (2022). Integrating environment and aging research: Opportunities for synergy and acceleration. *Frontiers in Aging Neuroscience*, *14*, Article 824921. https://doi.org/10.3389/fnagi.2022.824921

Mallet, R. T., Burtscher, J., Richalet, J. P., Millet, G. P., & Burtscher, M. (2021). Impact of high altitude on cardiovascular health: Current perspectives. *Vascular Health and Risk Management*, *17*, 317-335. https://doi.org/10.2147/vhrm.S294121

Mannucci, P. M. (2023). Air pollution, cardiovascular disease and urban greening: An ecological blueprint. *European Journal of Preventive Cardiology*, *132*, 1707–1724.

Mao, G.-X., Cao, Y.-B., Lan, X.-G., He, Z.-H., Chen, Z.-M., Wang, Y.-Z., Hu, X.-L., Lv, Y.-D., Wang, G.-F., & Yan, J. (2012). Therapeutic effect of forest bathing on human hypertension in the elderly. *Journal of Cardiology 60*(6), 495–502. https://doi.org/10.1016/j.jjcc.2012.08.003

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., de Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M. J., Lupp, G., Richardson, E. A., Astell-Burt, T., Dimitrova, D., Feng, X., Sadeh, M., Standl, M., Heinrich, J., & Fuertes, E. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research*, *158*, 301–317. https://doi.org/10.1016/j.envres.2017.06.028

Marselle, M. R., Bowler, D. E., Watzema, J., Eichenberg, D., Kirsten, T., & Bonn, A. (2020). Urban street tree biodiversity and antidepressant prescriptions. *Scientific Reports*, *10*(1), Article 22445. https://doi.org/10.1038/s41598-020-79924-5

Marselle, M. R., Hartig, T., Cox, D. T. C., de Bell, S., Knapp, S., Lindley, S., Triguero-Mas, M., Böhning-Gaese, K., Braubach, M., Cook, P. A., de Vries, S., Heintz-Buschart, A., Hofmann, M., Irvine, K. N., Kabisch, N., Kolek, F., Kraemer, R., Markevych, I., Martens, D., . . . Bonn, A. (2021). Pathways linking biodiversity to human health: A conceptual framework. *Environment International*, *150*, Article 106420. https://doi.org/10.1016/j.envint.2021.106420

Martín-Timón, I., Sevillano-Collantes, C., Segura-Galindo, A., & Del Cañizo-Gómez, F. J. (2014). Type 2 diabetes and cardiovascular disease: Have all risk factors the same strength? *World Journal of Diabetes*, *5*(4), 444–470. https://doi.org/10.4239/wjd.v5.i4.444

Martínez-García, M., Gutiérrez-Esparza, G. O., Roblero-Godinez, J. C., Marín-Pérez, D. V., Montes-Ruiz, C. L., Vallejo, M., & Hernández-Lemus, E. (2021). Cardiovascular risk factors and social development index. *Frontiers in Cardiovascular Medicine*, *8*, 631747, Article 631747. https://doi.org/10.3389/fcvm.2021.631747

Martínez-Téllez, D. B., Martínez-Calderón, E. E., Esquivel-Ferriño, P. C., Cantú-Cardenas, L. G., & González-Santiago, O. (2023). Mortality in residents of the urban and rural areas of Mexico, 2002-2019. *Rural Remote Health*, *23*(4), Article 7833. https://doi.org/10.22605/rrh7833

Martínez Juárez, G., Rodríguez Trejo, D. A., Granados Sánchez, D., Mohedano Caballero, L., & Villanueva Morales, A. (2022). Description of the linear trees of Puebla City by degree of marginalization and street. *Revista mexicana de ciencias forestales*, *13*(70), 85–111. https://doi.org/10.29298/rmcf.v13i70.830

Mayo Clinic. (2022). *Angina*. Mayo Clinic. (https://www.mayoclinic.org/diseases-conditions/angina/symptoms-causes/syc-20369373)

Medina, C., Coxson, P., Penko, J., Janssen, I., Bautista-Arredondo, S., Barquera, S., & Bibbins-Domingo, K. (2020). Cardiovascular and diabetes burden attributable to physical inactivity in Mexico. *Cardiovascular Diabetology*, *19*(1), Article 99. https://doi.org/10.1186/s12933-020-01050-3

Medina, C., Janssen, I., Campos, I., & Barquera, S. (2013). Physical inactivity prevalence and trends among Mexican adults: Results from the National Health and Nutrition Survey (ENSANUT) 2006 and 2012. *BMC Public Health*, *13*(1), Article 1063. https://doi.org/10.1186/1471-2458-13-1063

Medina, C., Jáuregui, A., Hernández, C., Shamah, T., & Barquera, S. (2021). Physical inactivity and sitting time prevalence and trends in Mexican adults: Results from three national surveys. *PLoS ONE*, *16*(7), Article e0253137. https://doi.org/10.1371/journal.pone.0253137

Mendoza-Herrera, K., Pedroza-Tobías, A., Hernández-Alcaraz, C., Ávila-Burgos, L., Aguilar-Salinas, C. A., & Barquera, S. (2019). Attributable burden and expenditure of cardiovascular diseases and associated risk factors in Mexico and other selected mega-countries. *International Journal of Environmental Research and Public Health*, *16*(20), Article 4041. https://doi.org/10.3390/ijerph16204041

Mentzelou, M., Papadopoulou, S. K., Papandreou, D., Spanoudaki, M., Dakanalis, A., Vasios, G. K., Voulgaridou, G., Pavlidou, E., Mantzorou, M., & Giaginis, C. (2023). Evaluating the relationship between circadian rhythms and sleep, metabolic and cardiovascular disorders: Current clinical evidence in human studies. *Metabolites*, *13*(3), Article 370. https://doi.org/10.3390/metabo13030370

Mitchell, R., Astell-Burt, T., & Richardson, E. A. (2011). A comparison of green space indicators for epidemiological research. *Journal of Epidemiology and Community Health*, *65*(10), 853–858. https://doi.org/10.1136/jech.2010.119172

Mitchell, R., & Popham, F. (2008). Effect of exposure to natural environment on health inequalities: An observational population study. *Lancet*, *372*(9650), 1655–1660. https://doi.org/10.1016/S0140-6736(08)61689-X

Mitter, S. S., Vedanthan, R., Islami, F., Pourshams, A., Khademi, H., Kamangar, F., Abnet, C. C., Dawsey, S. M., Pharoah, P. D., Brennan, P., Fuster, V., Boffetta, P., & Malekzadeh, R. (2016). Household fuel use and cardiovascular disease mortality: Golestan Cohort Study. *Circulation*, *133*(24), 2360–2369. https://doi.org/10.1161/circulationaha.115.020288

Moran, M. R., Bilal, U., Dronova, I., Ju, Y., Gouveia, N., Caiaffa, W. T., Friche, A. A. L., Moore, K., Miranda, J. J., & Rodríguez, D. A. (2021). The equigenic effect of greenness on the association between education with life expectancy and mortality in 28 large Latin American cities. *Health and Place*, *72*, Article 102703. https://doi.org/10.1016/j.healthplace.2021.102703

Moreira, T. C. L., Polizel, J. L., Santos, I. d. S., Silva Filho, D. F., Bensenor, I., Lotufo, P. A., & Mauad, T. (2020). Green spaces, land cover, street trees and hypertension in the megacity of São Paulo. *International Journal of Environmental Research and Public Health*, *17*(3), Article 725. https://doi.org/10.3390/ijerph17030725

Morello-Frosch, R., & Shenassa, E. R. (2006). The environmental “riskscape” and social inequality: Implications for explaining maternal and child health disparities. *Environmental Health Perspectives*, *114*(8), 4. https://doi.org/https://doi.org/10.1289/ehp.8930

Morita, E., Fukuda, S., Nagano, J., Hamajima, N., Yamamoto, H., Iwai, Y., Nakashima, T., Ohira, H., & Shirakawa, T. (2007). Psychological effects of forest environments on healthy adults: Shinrin-yoku (forest-air bathing, walking) as a possible method of stress reduction. *Public Health*, *121*(1), 54–63. https://doi.org/10.1016/j.puhe.2006.05.024

Münzel, T., Hahad, O., Sørensen, M., Lelieveld, J., Duerr, G. D., Nieuwenhuijsen, M., & Daiber, A. (2022). Environmental risk factors and cardiovascular diseases: A comprehensive expert review. *Cardiovascular Research*, *118*(14), 2880–2902. https://doi.org/10.1093/cvr/cvab316

Navarrete-Hernandez, P., & Laffan, K. (2023). The impact of small-scale green infrastructure on the affective wellbeing associated with urban sites. *Scientific Reports*, *13*(1), Article 9687. https://doi.org/10.1038/s41598-023-35804-2

Nguyen, P.-Y., Astell-Burt, T., Rahimi-Ardabili, H., & Feng, X. (2021). Green space quality and health: A systematic review. *International Journal of Environmental Research and Public Health*, *18*(21), Article 11028. https://doi.org/10.3390/ijerph182111028

Nieuwenhuijsen, M. J. (2021). Green infrastructure and health. *Annual Review of Public Health*, *42*(1), 317-328. https://doi.org/10.1146/annurev-publhealth-090419-102511

Nowak, D. J., Hirabayashi, S., Doyle, M., McGovern, M., & Pasher, J. (2018). Air pollution removal by urban forests in Canada and its effect on air quality and human health. *Urban Forestry and Urban Greening*, *29*, 40–48. https://doi.org/10.1016/j.ufug.2017.10.019

Nuckols, J. R., Ward, M. H., & Jarup, L. (2004). Using geographic information systems for exposure assessment in environmental epidemiology studies. *Environmental Health Perspectives*, *112*(9), 1007–1015. https://doi.org/10.1289/ehp.6738

Olvera Alvarez, H. A., Appleton, A. A., Fuller, C. H., Belcourt, A., & Kubzansky, L. D. (2018). An integrated socio-environmental model of health and well-being: A conceptual framework exploring the joint contribution of environmental and social exposures to health and disease over the life span. *Current Environmental Health Reports*, *5*(2), 233–243. https://doi.org/10.1007/s40572-018-0191-2

Olvera Alvarez, H. A., Kubzansky, L. D., Campen, M. J., & Slavich, G. M. (2018). Early life stress, air pollution, inflammation, and disease: An integrative review and immunologic model of social-environmental adversity and lifespan health. *Neuroscience and Biobehavioral Reviews*, *92*, 226–242. https://doi.org/10.1016/j.neubiorev.2018.06.002

Olvera Lopez, E., Ballard, B. D., & Jan, A. (2023). Cardiovascular disease. [Updated 2022 Aug 8]. *StatPearls*. https://www.ncbi.nlm.nih.gov/books/NBK535419/

Ordóñez Barba, G. (2021). Tijuana ante el confinamiento social impuesto por la COVID

19: habitabilidad de las viviendas, entorno urbano y condiciones económicas de los hogares. [Tijuana in the face of social confinement imposed by COVID 19: Habitability of homes, urban environment and economic conditions of homes]. *Espiral Estudios sobre Estado y Sociedad*, *27*(78-79). https://doi.org/10.32870/eees.v28i78-79.7209

Ordóñez Barona, C., Kendal, D., Davern, M., & Conway, T. (2024). Having a tree in front of one's home is associated with greater subjective wellbeing in adult residents in Melbourne, Australia, and Toronto, Canada. *Environmental Research*, *250*, Article 118445. https://doi.org/10.1016/j.envres.2024.118445

Organisation for Economic Co-operation and Development. (2015a). *Cardiovascular disease and diabetes: Policies for better health and quality of care*. http://www.oecd.org/health/cardiovasculardisease-and-diabetes-policies-for-better-healthand-quality-of-care-9789264233010-en.htm

Organisation for Economic Co-operation and Development. (2015b). Mexico: Transforming urban policy and housing finance. *OECD Urban Policy Reviews*. https://doi.org/10.1787/9789264227293-en

Organisation for Economic Co-operation and Development. (n.d.). *The economic burden of obesity*. https://www.oecd-ilibrary.org/sites/67450d67-en/1/2/3/index.html?itemId=/content/publication/67450d67-en&_csp_=77ac5dad9f2cb67b4d2e46c9fc814aa4&itemIGO=oecd&itemContentType=book#section-d1e7058

Organization for Economic Cooperation and Development. (2017). *Obesity Update 2017*. https://www.oecd.org/els/health-systems/Obesity-Update-2017.pdf

Orioli, R., Antonucci, C., Scortichini, M., Cerza, F., Marando, F., Ancona, C., Manes, F., Davoli, M., Michelozzi, P., Forastiere, F., & Cesaroni, G. (2019). Exposure to residential greenness as a predictor of cause-specific mortality and stroke incidence in the Rome Longitudinal Study. *Environmental Health Perspectives*, *127*(2), Article 027002. https://doi.org/10.1289/EHP2854

Pagan, E., Chatenoud, L., Rodriguez, T., Bosetti, C., Levi, F., Malvezzi, M., La Vecchia, C., Negri, E., & Bertuccio, P. (2017). Comparison of trends in mortality from coronary heart and cerebrovascular diseases in North and South America: 1980 to 2013. *American Journal of Cardiology*, *119*(6), 862–871. https://doi.org/10.1016/j.amjcard.2016.11.040

Pahn, J., & Yang, Y. (2021). Factors associated with cardiovascular disease prevention behavior among office workers based on an ecological model. *SAGE Open*, *11*(1), 1–9. https://doi.org/10.1177/21582440211004163

Palomo-Piñón, S., Antonio-Villa, N. E., García-Cortés, L. R., Álvarez-Aguilar, C., González-Palomo, E., Bertadillo-Mendoza, O. M., Figueroa-Suárez, M. E., Vargas-Hernández, F., Herrera-Olvera, I. G., Cruz-Toledo, J. E., Cruz-Arce, M. A., Serafín-Méndez, B., Muñoz-Cortés, G., & Morfin-Macias, C. J. (2022). Prevalence and characterization of undiagnosed arterial hypertension in the eastern zone of Mexico. *Journal of Clinical Hypertension*, *24*(2), 131–139. https://doi.org/10.1111/jch.14414

Pan American Health Organization. (2021). *ENLACE Data Portal. Cardiovascular disease burden in the Region of the Americas, 2000-2019*. https://www.paho.org/en/enlace/cardiovascular-disease-burden

Pandey, A. K., Singh, G. N., Bhattacharyya, D., Ali, A. Q., Al-Thubaiti, S., & Yakout, H. A. (2021). Some classes of logarithmic-type imputation techniques for handling missing data. *Computational Intelligence and Neuroscience*, *2021*, Article 8593261. https://doi.org/10.1155/2021/8593261

Paquet, C., Orschulok, T. P., Coffee, N. T., Howard, N. J., Hugo, G., Taylor, A. W., Adams, R. J., & Daniel, M. (2013). Are accessibility and characteristics of public open spaces associated with a better cardiometabolic health? *Landscape and Urban Planning*, *118*, 70–78. https://doi.org/10.1016/j.landurbplan.2012.11.011

Pataki, D. E., Alberti, M., Cadenasso, M. L., Felson, A. J., McDonnell, M. J., Pincetl, S., Pouyat, R. V., Setälä, H., & Whitlow, T. H. (2021). The benefits and limits of urban tree planting for environmental and human health. *Frontiers in Ecology and Evolution*, *9*, Article 603757. https://doi.org/10.3389/fevo.2021.603757

Patel, J., Al Rifai, M., Scheuner, M. T., Shea, S., Blumenthal, R. S., Nasir, K., Blaha, M. J., & McEvoy, J. W. (2018). Basic vs more complex definitions of family history in the prediction of coronary heart disease: The multi-ethnic study of atherosclerosis. *Mayo Clinic Proceedings*, *93*(9), 1213–1223. https://doi.org/10.1016/j.mayocp.2018.01.014

Pengpid, S., & Petlzer, K. (2021). Prevalence and correlates of self-reported cardiovascular diseases among a nationally representative population-based sample of adults in Ecuador in 2018. *Vascular Health and Risk Management*, *17*, 195–202. https://doi.org/10.2147/VHRM.S299272

Pereira, G., Foster, S., Martin, K., Christian, H., Boruff, B. J., Knuiman, M., & Giles-Corti, B. (2012). The association between neighborhood greenness and cardiovascular disease: An observational study. *BMC Public Health*, *12*(1), Article 466. https://doi.org/10.1186/1471-2458-12-466

Perner, M. S., Alazraqui, M., & Amorim, L. D. (2022). Social inequalities between neighborhoods and cardiovascular disease: A multilevel analysis in a Latin American city. *Ciência & Saúde Coletiva*, *27*, 2597–2608. https://doi.org/10.1590/1413-81232022277.21662021

Peters, S. A. E., Muntner, P., & Woodward, M. (2019). Sex differences in the prevalence of, and trends in, cardiovascular risk factors, treatment, and control in the United States, 2001 to 2016. *Circulation*, *139*(8), 1025–1035. https://doi.org/10.1161/circulationaha.118.035550

Piano, M. R., Mazzuco, A., Kang, M., & Phillips, S. A. (2017). Cardiovascular consequences of binge drinking: An integrative review with implications for advocacy, policy, and research. *Alcohol Clinical Experimental Research*, *41*(3), 487–496. https://doi.org/10.1111/acer.13329

Pillinger, R. (n.d.). *Random slope models*. University of Bristol Centre for Multilevel Modeling. Retrieved Dec. 20, 2023 from https://www.bristol.ac.uk/cmm/learning/videos/random-slopes.html#:~:text=The%20random%20slopes%20model,-So%20what's%20the&text=Well%2C%20unlike%20a%20random%20intercept,different%20effect%20for%20each%20group.

Ponjoan, A., Blanch, J., Alves-Cabratosa, L., Martí-Lluch, R., Comas-Cufí, M., Cirach, M., Nieuwenhuijsen, M., Garcia-Gil, M. d. M., & Ramos, R. (2022). Impact of residential greenness on myocardial infarction in the population with diabetes: A sex-dependent association? *Environmental Research*, *205*, Article 112449. https://doi.org/10.1016/j.envres.2021.112449

Puzzolo, E., Fleeman, N., Lorenzetti, F., Rubinstein, F., Li, Y., Xing, R., Shen, G., Nix, E., Maden, M., Bresnahan, R., Duarte, R., Abebe, L., Lewis, J., Williams, K. N., Adahir-Rohani, H., & Pope, D. (2024). Estimated health effects from domestic use of gaseous fuels for cooking and heating in high-income, middle-income, and low-income countries: A systematic review and meta-analyses. *Lancet Respiratory Medicine*, *12*(4), 281–293. https://doi.org/10.1016/S2213-2600(23)00427-7

Rajan, S., McKee, M., Rangarajan, S., Bangdiwala, S., Rosengren, A., Gupta, R., Kutty, V. R., Wielgosz, A., Lear, S., AlHabib, K. F., Co, H. U., Lopez-Jaramillo, P., Avezum, A., Seron, P., Oguz, A., Kruger, I. M., Diaz, R., Nafiza, M. N., Chifamba, J., . . . Yusuf, S. (2020). Association of symptoms of depression with cardiovascular disease and mortality in low-, middle-, and high-income countries. *JAMA Psychiatry*, *77*(10), 1052–1063. https://doi.org/10.1001/jamapsychiatry.2020.1351

Reeves, F., & Potter, B. J. (2023). Toward a cardio-environmental risk model: Environmental determinants of cardiovascular disease. *Canadian Journal of Cardiology*, *39*(9), 1166–1181. https://doi.org/10.1016/j.cjca.2023.06.419

Reid, C. E., Clougherty, J. E., Shmool, J. L. C., & Kubzansky, L. D. (2017). Is all urban green space the same? A comparison of the health benefits of trees and grass in New York City. *International Journal of Environmental Research and Public Health*, *14*(11), Article 1411. https://doi.org/10.3390/ijerph14111411

Ribeiro-Palacios, M., Soria Yañez, K., & Morales Gómez, C. A. (2021). Inequalities in the quality and governance of urban, public green spaces, evidence from deprived neighborhoods in Queretaro, Mexico. *Environmental Justice*, *14*(1), 1–7. https://doi.org/10.1089/env.2020.0031

Richards, D. R., Belcher, R. N., Carrasco, L. R., Edwards, P. J., Fatichi, S., Hamel, P., Masoudi, M., McDonnell, M. J., Peleg, N., & Stanley, M. C. (2022). Global variation in contributions to human well-being from urban vegetation ecosystem services. *One Earth*, *5*(5), 522–533. https://doi.org/10.1016/j.oneear.2022.04.006

Richardson, E. A., Pearce, J., Mitchell, R., & Kingham, S. (2013). Role of physical activity in the relationship between urban green space and health. *Public Health*, *127*(4), 318–324. https://doi.org/10.1016/j.puhe.2013.01.004

Rigolon, A., Browning, M. H. E. M., Lee, K., & Shin, S. (2018). Access to urban green space in cities of the Global South: A systematic literature review. *Urban Science*, *2*(3), Article 67. https://doi.org/10.3390/urbansci2030067

Rittiphairoj, T., Reilly, A., Reddy, C. L., Barrenho, E., Colombo, F., & Atun, R. (2022). *The state of cardiovascular disease in G20+ countries*. Health Systems Innovation Lab-Harvard University.

Rodgers, J. L., Jones, J., Bolleddu, S. I., Vanthenapalli, S., Rodgers, L. E., Shah, K., Karia, K., & Panguluri, S. K. (2019). Cardiovascular risks associated with gender and aging. *Journal of Cardiovascular Development and Disease*, *6*(2). https://doi.org/10.3390/jcdd6020019

Rojas-Martínez, R., Aguilar-Salinas, C. A., Romero-Martínez, M., Castro-Porras, L., Gómez-Velasco, D., & Mehta, R. (2021). Trends in the prevalence of metabolic syndrome and its components in Mexican adults, 2006-2018. *Salud Pública de México 63*(6), 713–724. https://doi.org/10.21149/12835

Romero-Martínez, M. (2012). *Guía para el análisis de la ENSANUT 2012. [ENSANUT 2012 Analysis Guide]* Cuernavaca, MOR, Instituto Nacional de Salud Pública.

Romero-Martínez, M., Franco-Núñez, A., Cuevas-Nasu, L., Gutierrez, J.-P., & Rivera-Dommarco, J. (2012). Encuesta Nacional de Salud y Nutrición 2012: Diseño y cobertura. (National Health and Nutrition Survey 2012: Design and coverage]. *Salud Publica Mex*, *55*, S332–S340. https://doi.org/10.21149/spm.v55s2.5132

Roth, G. A., Mensah, G. A., Johnson, C. O., Addolorato, G., Ammirati, E., Baddour, L. M., Barengo, N. C., Beaton, A. Z., Benjamin, E. J., Benziger, C. P., Bonny, A., Brauer, M., Brodmann, M., Cahill, T. J., Carapetis, J., Catapano, A. L., Chugh, S. S., Cooper, L. T., Coresh, J., . . . Fuster, V. (2020). Global burden of cardiovascular diseases and risk factors, 1990–2019: Update from the GBD 2019 study. *Journal of the American College of Cardiology*, *76*(25), 2982–3021. https://doi.org/10.1016/j.jacc.2020.11.010

Roux, A. V. D., Merkin, S. S., Arnett, D., Chambless, L., Massing, M., Nieto, F. J., Sorlie, P., Szklo, M., Tyroler, H. A., & Watson, R. L. (2001). Neighborhood of residence and incidence of coronary heart disease. *New England Journal of Medicine*, *345*(2), 99–106. https://doi.org/10.1056/NEJM200107123450205

Ruilope, L. M., Chagas, A. C., Brandão, A. A., Gómez-Berroterán, R., Alcalá, J. J., Paris, J. V., & Cerda, J. J. (2017). Hypertension in Latin America: Current perspectives on trends and characteristics. *Hipertensión y Riesgo Vascular*, *34*(1), 50–56. https://doi.org/10.1016/j.hipert.2016.11.005

Ryder, A. L., & Cohen, B. E. (2021). Evidence for depression and anxiety as risk factors for heart disease and stroke: Implications for primary care. *Family Practice*, *38*(3), 365–367. https://doi.org/10.1093/fampra/cmab031

Salmond, J. A., Tadaki, M., Vardoulakis, S., Arbuthnott, K., Coutts, A., Demuzere, M., Dirks, K. N., Heaviside, C., Lim, S., Macintyre, H., McInnes, R. N., & Wheeler, B. W. (2016). Health and climate related ecosystem services provided by street trees in the urban environment. *Environmental Health*, *15*(36), 95–111. https://doi.org/10.1186/s12940-016-0103-6

Sánchez Velasco, L., Barbosa, J. M., & Arias V., S. A. (2014). Morbilidad cardiovascular por autoreporte y su asociación con factores biopsicosociales, Tolima, Colombia. [Self-reported cardiovascular morbidity and its association with biopsychosocial factors, Tolima, Colombia]. *Revista Facultad Nacional de Salud Pública*, *32*, 80–87. https://doi.org/10.17533/udea.rfnsp.13628

Sarkar, C. (2017). Residential greenness and adiposity: Findings from the UK Biobank. *Environment International*, *106*, 1–10. https://doi.org/10.1016/j.envint.2017.05.016

Sayyed, T. K., Ovienmhada, U., Kashani, M., Vohra, K., Kerr, G. H., O'Donnell, C., Harris, M. H., Gladson, L., Titus, A. R., & Adamo, S. B. (2024). Satellite data for environmental justice: A scoping review of the literature in the United States. *Environmental Research Letters*, *19*(3), Article 033001. https://doi.org/10.1088/1748-9326/ad1fa4

Scheftic, W., Zeng, X., Broxton, P., & Brunke, M. (2014). Intercomparison of seven NDVI products over the United States and Mexico. *Remote Sensing*, *6*(2), 1057–

1084. https://doi.org/10.3390/rs6021057

Schultz, W. M., Kelli, H. M., Lisko, J. C., Varghese, T., Shen, J., Sandesara, P., Quyyumi, A. A., Taylor, H. A., Gulati, M., & Harold, J. G. (2018). Socioeconomic status and cardiovascular outcomes: Challenges and interventions. *Circulation*, *137*(20), 2166–2178. https://doi.org/10.1161/CIRCULATIONAHA.117.029652.

Seo, S., Choi, S., Kim, K., Kim, S. M., & Park, S. M. (2019). Association between urban green space and the risk of cardiovascular disease: A longitudinal study in seven Korean metropolitan areas. *Environment International*, *125*, 51–57. https://doi.org/10.1016/j.envint.2019.01.038

Servadio, J. L., Lawal, A. S., Davis, T., Bates, J., Russell, A. G., Ramaswami, A., Convertino, M., & Botchwey, N. (2019). Demographic inequities in health outcomes and air pollution exposure in the Atlanta area and its relationship to urban infrastructure. *Journal of Urban Health*, *96*(2), 219–234. https://doi.org/10.1007/s11524-018-0318-7

Shahtahmassebi, A. R., Li, C., Fan, Y., Wu, Y., lin, Y., Gan, M., Wang, K., Malik, A., & Blackburn, G. A. (2021). Remote sensing of urban green spaces: A review. *Urban Forestry and Urban Greening*, *57*, Article 126946. https://doi.org/10.1016/j.ufug.2020.126946

Shakoor, H., Platat, C., Ali, H. I., Ismail, L. C., Al Dhaheri, A. S., Bosevski, M., Apostolopoulos, V., & Stojanovska, L. (2023). The benefits of physical activity in middle-aged individuals for cardiovascular disease outcomes. *Maturitas*, *168*, 49–52. https://doi.org/10.1016/j.maturitas.2022.11.002

Shamah-Levy, T., Romero-Martínez, M., Cuevas-Nasu, L., Méndez Gómez-Humaran, I., Antonio Avila-Arcos, M., & Rivera-Dommarco, J. A. (2019). The Mexican National Health and Nutrition Survey as a basis for public policy planning: overweight and obesity. *Nutrients*, *11*, Article 1727. https://doi.org/10.3390/nu11081727

Shao, H., & Kim, G. (2022). A comprehensive review of different types of green infrastructure to mitigate urban heat islands: Progress, functions, and benefits. *Land*, *11*(10), Article 1792. https://doi.org/10.3390/land11101792

Smart, N., Eisenman, T. S., & Karvonen, A. (2020). Street tree density and distribution: An international analysis of five capital cities. *Frontiers in Ecology and Evolution*, *8*, Article 562646. https://doi.org/10.3389/fevo.2020.562646

Sommet, N., & Morselli, D. (2017). Keep calm and learn multilevel logistic modeling: A simplified three-step procedure using Stata, R, Mplus, and SPSS. *International Review of Social Psychology*, *30*(1), 203–301. https://doi.org/10.5334/irsp.90

Sophie, H. B., Sanne, A. E. P., & Mark, W. (2017). Sex differences in coronary heart disease and stroke mortality: A global assessment of the effect of ageing between 1980 and 2010. *BMJ Global Health*, *2*(2), Article e000298. https://doi.org/10.1136/bmjgh-2017-000298

Sreeramareddy, C. T., & Aye, S. N. (2021). Changes in adult smoking behaviours in ten global adult tobacco survey (GATS) countries during 2008–2018: A test of 'hardening' hypothesis'. *BMC Public Health*, *21*(1), Article 1209. https://doi.org/10.1186/s12889-021-11201-0

Stevens, B., Pezzullo, L., Verdian, L., Tomlinson, J., Estrada-Aguilar, C., George, A., &

Verdejo-Paris, J. (2018). The economic burden of hypertension, heart failure, myocardial infarction, and atrial fibrillation in Mexico. *Archivos de Cardiología de México*, *88*(3), 4. https://doi.org/https://doi.org/10.1016/j.acmx.2018.03.004

Stevens, B., Pezzullo, L., Verdian, L., Tomlinson, J., Estrada-Aguilar, C., George, A., & Verdejo-París, J. (2018). The economic burden of hypertension, heart failure, myocardial infarction, and atrial fibrillation in Mexico. *Archivos de Cardiología de México*, *88*(3), 241–244. https://doi.org/10.1016/j.acmx.2018.03.004

Sundquist, K., Winkleby, M., Ahlén, H., & Johansson, S.-E. (2004). Neighborhood socioeconomic environment and incidence of coronary heart disease: A follow-up study of 25,319 women and men in Sweden. *American Journal of Epidemiology*, *159*(7), 655–662. https://doi.org/10.1093/aje/kwh096

Tamosiunas, A., Grazuleviciene, R., Luksiene, D., Dedele, A., Reklaitiene, R., Baceviciene, M., Vencloviene, J., Bernotiene, G., Radisauskas, R., Malinauskiene, V., Milinaviciene, E., Bobak, M., Peasey, A., & Nieuwenhuijsen, M. J. (2014). Accessibility and use of urban green spaces, and cardiovascular health: Findings from a Kaunas cohort study. *Environmental Health*, *13*(1), 1–11. https://doi.org/10.1186/1476-069X-13-20

Tarar, G., Etheredge, C. L., McFarland, A., Snelgrove, A., Waliczek, T. M., & Zajicek, J. M. (2015). The effect of urban tree canopy cover and vegetation levels on incidence of stress-related illnesses in humans in metropolitan statistical areas of Texas. *HortTechnology*, *25*(1), 76–84. https://doi.org/10.21273/horttech.25.1.76

Taylor, L., & Hochuli, D. F. (2017). Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning*, *158*, 25–38.

https://doi.org/10.1016/j.landurbplan.2016.09.024

Taylor, M. S., Wheeler, B. W., White, M. P., Economou, T., & Osborne, N. J. (2015). Research note: Urban street tree density and antidepressant prescription rates—A cross-sectional study in London, UK. *Landscape and Urban Planning*, *136*, 174–179. https://doi.org/10.1016/j.landurbplan.2014.12.005

Terminel-Zaragoza, R., Angulo-Urías, M., de Jesús Toledo-Domínguez, I., Quintero-Portillo, H., Bojórquez-Díaz, C. I., Ulloa-Mercado, G., Gortares-Moroyoqui, P., Arias-Gastélum, M., Legarreta-Muela, F., & Rentería-Mexía, A. (2023). Low prevalence of ideal levels in cardiovascular behavior metrics among Mexican adolescents. *BMC Public Health*, *23*(1), Article 1125. https://doi.org/10.1186/s12889-023-15959-3

Theobald, E. (2018). Students are rarely independent: When, why, and how to use random effects in discipline-based education research. *CBE—Life Sciences Education*, *17*, 1–12. https://doi.org/10.1187/cbe.17-12-0280

Tulve, N., Ruiz, J., Lichtveld, K., Darney, S., & Quackenboss, J. (2016). Development of a conceptual framework depicting a child's total (built, natural, social) environment in order to optimize health and well-being. *Journal of Environmental Health Sciences*, *2*(2), 1-8.

Twohig-Bennett, C., & Jones, A. (2018). The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes. *Environmental Research*, *166*, 628–637. https://doi.org/10.1016/j.envres.2018.06.030

U.S. Department of Health and Human Services. (2022, January 20, 2022). *CDC releases* *updated maps of America's high levels of inactivity* https://www.cdc.gov/media/releases/2022/p0120-inactivity-map.html

U.S. Department of Health Human Services. (2018). 2018 Physical activity guidelines advisory committee scientific report. https://health.gov/sites/default/files/2019-09/PAG_Advisory_Committee_Report.pdf

Ulmer, J. M., Wolf, K. L., Backman, D. R., Tretheway, R. L., Blain, C. J. A., O'Neil-Dunne, J. P. M., & Frank, L. D. (2016). Multiple health benefits of urban tree canopy: The mounting evidence for a green prescription. *Health and Place*, *42*, 54–62. https://doi.org/10.1016/j.healthplace.2016.08.011

United Nations. (2015). Transforming our world: The 2030 agenda for sustainable development. Resolution adopted by the General Assembly on 25 September 2015. *42809*, 1–13. https://sdgs.un.org/publications/transforming-our-world-2030-agenda-sustainable-development-17981

United Nations. (2022). *World Population Prospects 2022*. United Nations, Department of Economic and Social Affairs, Population Division. https://population.un.org/wpp/Graphs/Probabilistic/PopPerc/60plus/484

Vaduganathan, M., Mensah, G., A., Turco, J. V., Fuster, V., & Roth, G. A. (2022). The global burden of cardiovascular diseases and risk: A compass for future health. *Journal of the American College of Cardiology*, *80*(25), 2361–2371. https://doi.org/10.1016/j.jacc.2022.11.005

Van Den Eeden, S. K., Browning, M. H., Becker, D. A., Shan, J., Alexeeff, S. E., Ray, G. T., Quesenberry, C. P., & Kuo, M. (2022). Association between residential green cover and direct healthcare costs in Northern California: An individual level analysis of 5 million persons. *Environment International*, *163*, Article 107174. https://doi.org/10.1016/j.envint.2022.107174

Vienneau, D., de Hoogh, K., Faeh, D., Kaufmann, M., Wunderli, J. M., & Röösli, M. (2017). More than clean air and tranquillity: Residential green is independently associated with decreasing mortality. *Environment International*, *108*, 176–184. https://doi.org/10.1016/j.envint.2017.08.012

Wang, B., Gu, K., Dong, D., Fang, Y., & Tang, L. (2022). Analysis of spatial distribution of CVD and multiple environmental factors in urban residents. *Computational Intelligence and Neuroscience*, *2022*, Article 9799054. https://doi.org/10.1155/2022/9799054

Wang, R., Dong, G., Cao, M., Zhou, Y., & Dong, G.-H. (2023). Exploring "equigenesis" in the associations between green space and kidney health among middle-aged and older adults using street view data. *Innovation in Aging*, *8*(1). https://doi.org/10.1093/geroni/igad130

Wang, R., Dong, P., Dong, G., Xiao, X., Huang, J., Yang, L., Yu, Y., & Dong, G.-H. (2022). Exploring the impacts of street-level greenspace on stroke and cardiovascular diseases in Chinese adults. *Ecotoxicology and Environmental Safety*, *243*. https://doi.org/10.1016/j.ecoenv.2022.113974

Wang, X., Rodiek, S., Wu, C., Chen, Y., & Li, Y. (2016). Stress recovery and restorative effects of viewing different urban park scenes in Shanghai, China. *Urban Forestry and Urban Greening*, *15*, 112–122. https://doi.org/10.1016/j.ufug.2015.12.003

Wannamethee, S. G., Whincup, P. H., Lennon, L., Papacosta, O., & Shaper, A. G. (2015).

Alcohol consumption and risk of incident heart failure in older men: A prospective cohort study. *Open Heart*, *2*(1), Article e000266. https://doi.org/10.1136/openhrt-2015-000266

Warner, R. M. (2012). *Applied Statistics: From bivariate through multivariate techniques* (2nd ed.). Sage Publications.

Wessolek, G., & Kluge, B. (2021). Predicting water supply and evapotranspiration of street trees using hydro-pedo-transfer functions (HPTFs). *Forests*, *12*, Article 1010. https://doi.org/10.3390/f12081010

Wolf, K. L., Lam, S. T., McKeen, J. K., Richardson, G. R. A., van den Bosch, M., & Bardekjian, A. C. (2020). Urban trees and human health: A scoping review. *International Journal of Environmental Research and Public Health*, *17*(12), Article 17124371. https://doi.org/10.3390/ijerph17124371

Wolf, K. L., & Robbins, A. S. T. (2015). Metro nature, environmental health, and economic value. *Environmental Health Perspectives*, *123*(5), 390–398. https://doi.org/10.1289/ehp.1408216

World Health Organization. (2017). *Urban green space interventions and health: A review of impacts and effectiveness*. WHO Regional Office for Europe.

World Health Organization. (2019). *Cities: a 'cause of and solution to' climate change. Climate and Environment*. https://news.un.org/en/story/2019/09/1046662

World Health Organization. (2021). *Cardiovascular diseases (CVDs)*. World Health Organization. https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

World Health Organization. (2022). *Exposure and health impacts of air pollution*. World

Health Organization. https://www.who.int/teams/environment-climate-change-and-health/air-quality-and-health/health-impacts/exposure-air-pollution

World Heart Federation. (2016). *Cost of heart disease in Latin America tops $30bn* https://world-heart-federation.org/wp-content/uploads/2017/05/WHF_Economics_Release_Final.pdf

Wu, J., Rappazzo, K. M., Simpson, R. J., Joodi, G., Pursell, I. W., Mounsey, J. P., Cascio, W. E., & Jackson, L. E. (2018). Exploring links between greenspace and sudden unexpected death: A spatial analysis. *Environment International*, *113*, 114–121. https://doi.org/10.1016/j.envint.2018.01.021

Xu, L., Ren, C., Yuan, C., Nichol, J. E., & Goggins, W. B. (2017). An ecological study of the association between area-level green space and adult mortality in Hong Kong. *Climate*, *5*(3), 1–11. https://doi.org/10.3390/cli5030055

Yang, B. Y., Zhao, T., Hu, L. X., Browning, M., Heinrich, J., Dharmage, S. C., Jalaludin, B., Knibbs, L. D., Liu, X. X., Luo, Y. N., James, P., Li, S., Huang, W. Z., Chen, G., Zeng, X. W., Hu, L. W., Yu, Y., & Dong, G. H. (2021). Greenspace and human health: An umbrella review. *Innovation*, *2*(4), Article 100164. https://doi.org/10.1016/j.xinn.2021.100164

Yang, L., Chan, K. L., Yuen, J. W. M., Wong, F. K. Y., Han, L., Ho, H. C., Chang, K. K. P., Ho, Y. S., Siu, J. Y.-M., Tian, L., & Wong, M. S. (2021). Effects of urban green space on cardiovascular and respiratory biomarkers in Chinese adults: Panel study using digital tracking devices. *JMIR Cardio*, *5*(2), Article e31316. https://doi.org/10.2196/31316

Yang, Y., Xu, Y., Duan, Y., Zhang, S., Zhang, Y., & Xie, Y. (2023). How can trees protect us from air pollution and urban heat? Associations and pathways at the neighborhood scale. *Landscape and Urban Planning*, *236*, 104779. https://doi.org/10.1016/j.landurbplan.2023.104779

Yeager, R. A., Smith, T. R., & Bhatnagar, A. (2020). Green environments and cardiovascular health. *Trends in Cardiovascular Medicine*, *30*(4), 241–246. https://doi.org/10.1016/j.tcm.2019.06.005

Yen, I. H., & Syme, S. L. (1999). The Social Environment and Health: A Discussion of the Epidemiologic Literature. *Annual Review of Public Health*, *20*(1), 287-308. https://doi.org/10.1146/annurev.publhealth.20.1.287

Yitshak-Sade, M., James, P., Kloog, I., Hart, J. E., Schwartz, J. D., Laden, F., Lane, K. J., Fabian, M. P., Fong, K. C., & Zanobetti, A. (2019). Neighborhood greenness attenuates the adverse effect of PM(2.5) on cardiovascular mortality in neighborhoods of lower socioeconomic status. *International Journal of Environmental Research and Public Health*, *16*(5), Article 814. https://doi.org/10.3390/ijerph16050814

Yoon, S.-J., Jung, J.-G., Lee, S., Kim, J.-S., Ahn, S.-k., Shin, E.-S., Jang, J.-E., & Lim, S.-H. (2020). The protective effect of alcohol consumption on the incidence of cardiovascular diseases: Is it real? A systematic review and meta-analysis of studies conducted in community settings. *BMC Public Health*, *20*(1), Article 90. https://doi.org/10.1186/s12889-019-7820-z

Yusuf, S., Joseph, P., Rangarajan, S., Islam, S., Mente, A., Hystad, P., Brauer, M., Kutty, V. R., Gupta, R., & Wielgosz, A. (2020). Modifiable risk factors, cardiovascular disease, and mortality in 155 722 individuals from 21 high-income, middle-income, and low-income countries (PURE): A prospective cohort study. *Lancet*, *395*(10226), 795–808. https://doi.org/10.1016/S0140-6736(19)32008-2.

Zhang, C., Wang, C., Chen, C., Tao, L., Jin, J., Wang, Z., & Jia, B. (2022). Effects of tree canopy on psychological distress: A repeated cross-sectional study before and during the COVID-19 epidemic. *Environmental Research*, *203*, Article 111795. https://doi.org/10.1016/j.envres.2021.111795

Zhang, R., Liu, S., Li, M., He, X., & Zhou, C. (2021). The effect of high-density built environments on elderly individuals' physical health: A cross-sectional study in Guangzhou, China. *International Journal of Environmental Research and Public Health*, *18*(19), Article 10250. https://doi.org/10.3390/ijerph181910250

Zhang, R., Zhang, C. Q., & Rhodes, R. E. (2021). The pathways linking objectively-measured greenspace exposure and mental health: A systematic review of observational studies. *Environmental Research*, *198*, Article 111233. https://doi.org/10.1016/j.envres.2021.111233

Zhang, Y., Liu, N., Li, Y., Long, Y., Baumgartner, J., Adamkiewicz, G., Bhalla, K., Rodriguez, J., & Gemmell, E. (2023). Neighborhood infrastructure-related risk factors and non-communicable diseases: A systematic meta-review. *Environmental Health*, *22*, Article 2. https://doi.org/10.1186/s12940-022-00955-8

Zheng, Y., Gao, X., Jia, H. Y., Li, F. R., & Ye, H. (2022). Influence of hypertension duration and blood pressure levels on cardiovascular disease and all-cause mortality: A large prospective cohort study. *Frontiers in Cardiovascular Medicine*, *9*, Article 948707. https://doi.org/10.3389/fcvm.2022.948707

Zhou, W., Wang, Q., Kadier, A., Wang, W., Zhou, F., Li, R., & Ling, L. (2023). The role of residential greenness levels, green land cover types and diversity in overweight/obesity among older adults: A cohort study. *Environmental Research*, *217*, Article 114854. https://doi.org/10.1016/j.envres.2022.114854