

A Computational Approach to Population-Level Mental Wellbeing Assessment in Smart Cities

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Para mi familia,

Gracias a su esfuerzo, fe y apoyo incondicional, he podido alcanzar este sueño. Este logro no es solo mío, sino un triunfo compartido, un testimonio de nuestro camino juntos y una contribución a nuestra comunidad.

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Abstract

Urban mental wellbeing has emerged as a critical public health concern as more than half of the global population now lives in cities. Environmental factors within urban settings, such as air quality, access to greenspaces, and mobility infrastructure, directly influence residents' psychological mental health outcomes. Cities worldwide struggle to systematically assess how their environmental conditions affect population-level mental wellbeing risk. Without standardized methods to measure these risks, urban planners and policymakers lack the evidence-based tools needed to prioritize resources in environmental infrastructure that could improve urban mental wellbeing for millions of urban residents. Current approaches to assessing urban mental wellbeing typically rely on clinical trials, surveys, or subjective self-reporting methods that are resource-intensive, time-consuming, and difficult to scale across different cities. Existing smart city data infrastructure captures extensive environmental information through monitoring stations, geographic databases, and transit records, yet this data remains underutilized for mental wellbeing assessment purposes. This research develops a computational framework that transforms established scientific findings about environmental exposure and urban mental wellbeing in a systematic approach using data that smart cities already collect. The computational framework focuses on three environmental contextual cues that research has consistently linked to mental wellbeing outcomes: air quality measured through PM_{2.5} concentrations, accessibility to greenspaces, and proximity to public transit infrastructure. Each contextual cue is evaluated using literature-derived thresholds that define risk levels, converting raw environmental measurements into standardized risk scores. The methodology applies these risk assessments at the administrative level across entire urban populations, then aggregates scores using population weighting to generate neighborhood-level and city-level indices. This approach produces the Urban Mental Wellbeing Index (UMWI), which provides a quantitative measure of environmental exposure risk to urban mental wellbeing. The computational framework was validated through implementation in three diverse cities: Chicago, Manchester, and Portland. These cities differ substantially in population density, geographic characteristics, climate conditions, and data infrastructure, yet the framework successfully processed data from all three contexts using consistent analytical procedures. Results demonstrated that greenspace accessibility emerged as the primary driver of overall risk variation, with near-perfect correlation to final UMWI scores. Chicago exemplified how spatial distribution matters more than aggregate provision, providing 139.2 square meters per person yet leaving 90% of residents beyond the protective 300-meter threshold for stress recovery benefits.

This research contributes a scalable, replicable methodology that smart cities can implement using their existing data infrastructure without requiring new data collection or specialized survey instruments. By converting established research findings into operational metrics, this work bridges the gap between academic knowledge about urban mental wellbeing and practical smart city applications. The computational framework provides cities with a diagnostic tool to assess their current state, identify priority areas for improvement, and monitor the effectiveness of environmental interventions over time, ultimately supporting evidence-based decisions that could improve mental wellbeing outcomes for urban populations worldwide.

Chapter 1

Introduction and Motivation

Urban citizens can feel the burdens of living in a city in their everyday life. Noise pollution disrupts sleep and raises stress levels. Lack of greenspaces limits opportunities for psychological recovery and social connection. Poor air quality affects both physical and mental health. These environmental stressors are real, measurable, and affect millions of people daily. Yet, cities lack systematic ways to measure the cumulative mental wellbeing risk these environmental factors create. Understanding this type of mental wellbeing risk would be useful, not only for urban citizens but also for policymakers and urban planners. Measuring and understanding environmental risk exposure for mental wellbeing could create opportunities for urban planners to identify priority neighborhoods, and policymakers could intentionally allocate resources based on evidence.

This thesis explores methods of measuring environmental exposure risk relevant to urban mental wellbeing using data that smart cities already collect. This research develops a computational framework that converts environmental data on air quality, greenspace accessibility, and mobility into standardized risk scores. This framework enables cross-city comparison and provides urban planners with actionable insights about population-level mental wellbeing risk.

1.1 Problem Statement

The urban mental health crisis is substantial and growing. Mental health conditions affect 970 million people worldwide, approximately one in eight individuals ([World Health Organization 2024b](#)). With 57% of the global population now living in urban areas, this means more than 550 million urban citizens experience mental health disorders. The World Health Organization states there is no “health without mental health,”¹ recognizing that mental wellbeing is fundamental to overall health and quality of life.

Urban environments create specific mental health challenges. Research consistently links urban living with elevated rates of depression, anxiety, and stress-related disorders compared to rural areas. This disparity has been documented for over 180 years, from the 1839 Copenhagen study to recent meta-analyses ([Okkels et al. 2018](#)). Specific urban characteristics directly influence psychological outcomes through measurable biological pathways. Air quality, greenspace, and mobility impact mental wellbeing in urban citizens ([Chen et al. 2018](#), [Gascon et al. 2018](#), [Wang et al. 2019](#)).

The growth of smart city data infrastructure has created unprecedented opportunities to measure these environmental exposures at population scale. Cities worldwide have invested billions ([D’Amico et al. 2020](#)) in sensor networks that continuously monitor air quality and maintain geographic databases of parks and transit systems. Open data initiatives have made much of this information publicly accessible through municipal portals that support population-level analysis without cost or specialized access agreements. However, cities lack systematic

¹<https://www.who.int/data/gho/data/major-themes/health-and-well-being>

frameworks to convert this raw environmental data into actionable mental wellbeing insights.

Data quality, availability, and accessibility vary across cities, and can pose significant challenges. Missing values, measurement errors, and temporal gaps are common in open datasets. Some cities maintain comprehensive networks while others rely on intermittent updates. Systematic methodologies must address these data quality, consistency, and spatial heterogeneity issues.

The fundamental problem: Cities collect extensive environmental data that could inform population-level mental wellbeing assessment but lack the computational frameworks to convert this data into actionable insights.

1.2 Current approaches to urban mental wellbeing assessment

Current approaches to urban mental wellbeing risk assessment fall into several categories, each with distinct limitations. Chapter 2 delivers a broader overview of current approaches. Traditional approaches for measuring mental health use clinical trials and population surveys. These approaches provide individual-level data and do not scale to population-level assessment. Thus, they can be intrusive, time-consuming, and introduce bias. Cities need population-level insights, not individual diagnoses, for urban planning decisions. Current research presents theoretical frameworks (Von Szombathely et al. 2017) that recognize that cities affect wellbeing through multiple pathways, including environmental and socioeconomic. These frameworks advance the theoretical understanding of cities and urban wellbeing yet remain conceptual and lack implementation. The gap between conceptual models and computational implementation prevents translation of research insights into planning tools. Other technological solutions (Banerjee et al. 2023) for monitoring mental health have only succeeded at small scale in pilot programs. Methods that work for small populations do not scale to city-wide assessment. Additionally, the lack of standardized approaches prevents comparative analysis and limits the replication of effective methods.

These gaps collectively define the problem space this research addresses. Current solutions provide either theoretical sophistication without operational specificity, or operational tools without transferability across contexts. What is needed is a computational framework that bridges these gaps: operationally specific enough for implementation, theoretically grounded in established research, scalable to population-level assessment, and transferable across different urban data infrastructures. The next section describes how this thesis develops such a framework.

1.3 A Computational Framework for Urban Mental Wellbeing Assessment

This thesis proposes a computational framework that converts smart city environmental data into population-level mental wellbeing risk assessments. The framework is built on the concept of contextual cues, which are measurable indicators in urban data that link to established scientific research on mental health outcomes. The approach systematically bridges the gap between environmental data collection and wellbeing assessment through a structured, replicable process.

This research focuses on three contextual cues selected based on these criteria: air quality measured through $PM_{2.5}$ concentrations, greenspace accessibility measured through proximity to parks, and mobility measured through access to public transportation. The measurements can be standardized and computed systematically across different urban contexts. These three

cues represent complementary pathways influencing mental wellbeing: air quality affects neurological function through biological mechanisms, greenspace provides stress reduction through physiological and behavioral pathways, and transit mobility enables social connectivity. Each cue demonstrates established epidemiological evidence and provides quantifiable thresholds enabling systematic risk assessment.

The computational framework follows a systematic four-component process, applied to three case study cities: Chicago (US Midwest, 2.7 million residents), Portland (US Pacific Northwest, 678,332 residents), and Manchester (UK, 2.8 million residents). These cities were selected to test framework generalizability across varying population sizes, geographic regions, and smart city data ecosystems. First, data collection and quality assessment identify relevant sources for each contextual cue and evaluate completeness and spatial coverage. Second, data processing and standardization convert heterogeneous inputs into comparable measures: monitor readings become population-weighted $PM_{2.5}$ estimates; residential locations become distance metrics to nearest parks and transit stops. Third, literature-based labeling applies research-derived thresholds to convert measurements into risk scores using [Chen et al. \(2018\)](#) for air quality, [Gascon et al. \(2018\)](#) for greenspace, and [Wang et al. \(2019\)](#) for mobility. Fourth, aggregation combines individual cue scores into the Urban Mental Wellbeing Index (UMWI) at multiple spatial scales, from addresses to neighborhoods to city-wide summaries.

Our focus in this work has been on three case-study cities and three contextual cues. However, our computational framework is developed to allow for the addition of other contextual cues and applications to other cities where appropriate data is available for use.

Our computational framework delivers several advantages over existing approaches. The computational methods operate on entire urban populations without requiring individual participation or clinical resources. Once implemented, the framework can assess hundreds of thousands of residential locations efficiently. The framework utilizes open, freely accessible data sources from existing smart city infrastructure, enabling cities to implement this methodology without building new data collection systems or requiring specialized data access agreements.

All analyses are observational, identifying associations rather than causal effects, and remain subject to measurement error and ecological inference limitations. The computational framework generates environmental exposure risk scores from literature-derived labels, which serve as population-level proxies for urban mental wellbeing risk instead of direct measures of mental health.

1.3.1 Key Terminology

This thesis uses specific terminology consistently to ensure conceptual clarity:

Urban Mental Wellbeing: Population-level mental health outcomes that result from living in city environments, distinct from individual clinical diagnosis. This includes how urban factors like air quality, greenspace access, and mobility patterns collectively influence the psychological state of urban citizens.

Computational Framework: The novel, replicable methodology developed in this thesis. It consists of the systematic processes, literature-derived thresholds, and analytical steps used to select, process, and aggregate smart city data for contextual cues into the final Urban Mental Wellbeing Risk Index (UMWI).

1.4 Aim and Research Questions

Given the absence of computational frameworks that translate smart city environmental data into population-level mental wellbeing assessments, this research aims to develop and validate a systematic methodology for environmental exposure risk assessment. The computational framework converts air quality, greenspace accessibility, and mobility data into standardized

urban mental wellbeing risk scores. These scores must be comparable across cities with different data infrastructures and actionable for evidence-based urban planning decisions. This aim is addressed through three research questions:

- RQ1** Can environmental indicators identified in the literature be operationalised as spatially explicit contextual cues for population-level urban mental wellbeing assessment using smart city data?
- RQ2** Can a computational spatial framework integrate heterogeneous environmental contextual cues to produce comparable mental wellbeing risk assessments across cities having varying spatial and data characteristics?
- RQ3** To what extent can this framework be generalised, transferred, and scaled across multiple cities with differing environmental and data infrastructures?

This research cannot replicate population-level clinical trials that establish causal relationships between environmental conditions and diagnosed mental health disorders. The computational framework assesses environmental exposure risk conditions at the population level and does not predict individual mental health outcomes or identify specific residents requiring clinical intervention. The research and computational framework exclude factors that are known to influence mental health such as demographic, socioeconomic, and individual-level factors. These factors fall outside this research’s scope. The framework assesses environmental conditions that affect population mental wellbeing, not comprehensive mental health status. Time and resource constraints limited the application of the computational framework to three case study cities: Chicago, Manchester, and Portland. While additional cities would provide broader validation, the three cities provide sufficient methodological validation while representing diverse urban contexts, data infrastructures, and geographic regions. This research prioritizes methodological development of the contextual cue framework over exhaustive city coverage. The contribution lies in demonstrating a replicable methodology for converting smart city data into mental wellbeing risk assessments, not in creating a comprehensive global database of city scores.

1.5 Publications and Outputs

This doctoral research has produced several publications and conference presentations that disseminate findings to academic and professional communities. These outputs contributed to the development and validation of the computational framework presented in this thesis.

Oteiza, T. P., Mooney, P. & Kelly, L. (2022), Smart city data in urban wellbeing estimation, in ‘2022 IEEE International Smart Cities Conference (ISC2)’, IEEE, pp. 1–4. [Oteiza et al. \(2022\)](#)

Perez Oteiza, T., Kelly, L. & Mooney, P. (2021), ‘Using contextual cues in understanding urban mental well-being’, *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 46, 85–89. [Perez Oteiza et al. \(2021\)](#)

1.6 Thesis Organisation

This thesis is organized into eight chapters designed for readability and logical progression from conceptual foundation through methodological development to empirical application and conclusions.

Chapter 1: Introduction and Motivation establishes the research context by identifying the problem of urban mental wellbeing assessment in smart cities. The chapter outlines current approaches to urban mental wellbeing assessment and introduces the proposed computational framework. Key terminology is defined, followed by the research aim and three research questions that structure the investigation. The chapter concludes with an overview of publications arising from this work and the thesis organization.

Chapter 2: Urban Mental Wellbeing and Smart Cities examines the evolution of urban mental wellbeing research and smart city development. Section 2.2 traces the origins and evolution of urban mental wellbeing research, reviewing modern frameworks that address population-level assessment. Section 2.3 evaluates measurement approaches including objective biological measures, subjective perceptual methods, and risk-based assessment frameworks, explaining why this research adopts environmental exposure risk assessment. Section 2.4 explores smart city concepts, frameworks, and data infrastructure capabilities, identifying the research gap between available smart city data and systematic urban mental wellbeing assessment applications.

Chapter 3: Contextual Cues in Smart Cities reviews the epidemiological evidence linking environmental factors to mental health outcomes. The chapter examines three environmental domains: air quality (Section 3.1), greenspace accessibility (Section 3.2), and transit mobility (Section 3.3). For each domain, the chapter presents global smart city initiatives, direct and indirect mental health mechanisms, and heterogeneous population impacts. Section 3.4 synthesizes key outcomes and establishes the quantitative thresholds that inform the computational framework’s risk classification system.

Chapter 4: Smart City Data Landscape and Selection addresses the practical challenge of dataset selection for urban wellbeing research. Section 4.1 examines smart city big data characteristics and openness challenges. Section 4.2 introduces the Smart City Data Classification and Access Framework (SCDCAF), an original framework developed in this research that evaluates smart city data through five dimensions: availability across multiple cities, data sensitivity and privacy constraints, temporal update frequency, cost and accessibility, and data provider types. The chapter demonstrates how SCDCAF guided the systematic selection of Chicago, Manchester, and Portland as case study cities.

Chapter 5: Methodology presents the methodological framework underpinning the research. Section 5.1 provides an overview of the computational framework architecture. Section 5.2 establishes the research philosophy, explaining the positivist paradigm and deductive reasoning approach. Section 5.3 details the cross-sectional research design and comparative case study justification. Section 5.4 documents the systematic evaluation criteria and methodological justification for selecting air quality, greenspace accessibility, and transit mobility as contextual cues, while explaining why other environmental factors were excluded. Section 5.5 presents the six-stage systematic city selection process. Section 5.6 describes data collection protocols for each city. Section 5.7 justifies the five-level ordinal risk scale structure using psychometric evidence. Section 5.8 outlines replication procedures enabling framework implementation in additional cities.

Chapter 6: Data Infrastructure and Analytical Methods details the technical implementation of the computational framework. Section 6.1 operationalizes the dependent variable (Urban Mental Wellbeing Risk Index) and three independent contextual cue variables, documenting literature-derived thresholds, distance calculation methods, population-weighting procedures, and control variables. For each contextual cue, the section provides step-by-step computational procedures: air quality uses z-score standardization following [Chen et al. \(2018\)](#), greenspace applies Euclidean distance calculations to park boundaries based on [Gascon et al. \(2018\)](#), and mobility measures transit stop accessibility using [Wang et al. \(2019\)](#) thresholds. Section 6.2 outlines spatial analysis techniques using Python geospatial libraries and statistical analysis strategies appropriate for comparative case studies. Section 6.3 addresses research ethics, privacy protection measures embedded in the methodological design, and beneficence

considerations.

Chapter 7: Results and Discussion presents empirical findings from applying the computational framework across Chicago, Manchester, and Portland. Sections 7.2, 7.3, and 7.4 report air quality, greenspace, and mobility results for each city, including descriptive statistics, risk score distributions, and spatial patterns. Section 7.5 compares Urban Mental Wellbeing Risk Index scores across the three cities. Section 7.6 discusses results in relation to research questions, examining city-level patterns, cross-city comparisons, theoretical and practical implications, framework consistency and transferability, and validity considerations. The chapter demonstrates how the computational framework reveals environmental risk patterns and supports evidence-guided urban planning decisions.

Chapter 8: Conclusions and Future Work consolidates research findings and evaluates contributions. Section 8.1 answers the three research questions, summarizes key empirical findings, articulates contributions to knowledge (the computational framework, UMWI, and SCDCAF), and discusses implications for urban planning practice. Section 8.2 acknowledges limitations including geographic transferability constraints, open data restrictions, external validation needs, and risk reduction measurement capabilities. Section 8.3 proposes three future research directions: integrating qualitative methods to capture lived experiences, expanding contextual cues to include ambient noise, lighting, and blue spaces, and developing an interactive web-based dashboard for broader accessibility.

Chapter 2

Urban Mental Wellbeing and Smart Cities

Rapid urbanization over the last couple of decades has led to over 50% of the global population residing in cities ([World Health Organization 2024b](#)). The rate of this growth presents significant urban planning setbacks, particularly in managing resources and, consequently, affecting citizens' wellbeing ([Xu et al. 2023](#)). Urban factors, such as noise pollution, a lack of greenspace, and harmful air pollution, have been consistently linked to everyday stressors that can worsen the risk of mental health conditions ([Bratman et al. 2019](#), [Prince et al. 2007](#)), including depression, which is one of the most common mental health disorders in the world ([Xu et al. 2023](#)).

Urban problems have led to the creation of Smart Cities. The smart city concept involves implementing advanced technology and relevant policies to improve urban life. Smart cities are capable of producing and capturing large amounts of data through sensor networks, providing valuable mobility and environmental insights. Many smart city projects and IoT frameworks have successfully met their goals of optimizing efficiency and promoting economic growth ([Sanchez et al. 2014](#)), yet they often fail to address the urban mental wellbeing concerns that their data could inform. The literature review on smart city evolution, data infrastructure, and wellbeing initiatives demonstrates the need for analytical frameworks to convert data into population-level urban mental wellbeing insights.

This research proposes contextual cues as a computational link between established scientific knowledge and smart city data infrastructure. Contextual cues are computable indicators derived from urban data sources that reflect environmental and social stressors with established links to urban mental wellbeing. The chosen three data-rich contextual cues are: air quality, greenspace access, and mobility patterns. Contextual cues are introduced and formally defined at the opening of Chapter 3, where their relationship to the urban and spatial context of this research is established. This research highlights the significant gap between the potential of smart cities and the current state of urban mental wellbeing.

Section 2.1 defines key terminology used throughout the thesis to ensure conceptual clarity and consistency. Section 2.2 provides a literature review of Urban Mental Wellbeing, detailing its historical evolution and current definitions. Section 2.3 examines measurement approaches for urban mental wellbeing, comparing objective and subjective methods, analyzing fear and perceived safety, and explaining the risk-based environmental exposure framework adopted for population-level assessment. The Smart Cities and Urban Mental Wellbeing Section 2.4 examines the evolution of smart cities and their technological infrastructure, from core concepts to data collection capabilities. It then analyzes the current state of wellbeing initiatives in smart cities and highlights the opportunity to use existing IoT data for urban mental wellbeing approaches.

2.1 Key Terminology and Definitions

This section defines key terminology used throughout the thesis to ensure conceptual clarity and consistency.

Urban Mental Wellbeing: Mental wellbeing outcomes influenced by urban environmental factors that can be measured through smart city data and contextual cues. This definition supports computational approaches that assess environmental factors affecting mental health through data-driven analysis.

Smart City: An urban area that uses data collection sensors and digital technologies to manage assets, resources, and services efficiently while improving quality of life for citizens.

Environmental Exposure Risk: The likelihood of adverse mental wellbeing outcomes based on residential exposure to environmental conditions. This research assesses environmental exposure risk as a proxy for mental wellbeing risk through quantifiable contextual cues.

Population-Level Assessment: Analysis conducted at the aggregate level across neighborhoods or cities rather than individual clinical evaluation. Population-level assessment uses address-level data with population weighting to estimate collective risk.

Risk: A measure of the probability and severity of adverse effects. In this research, risk represents the likelihood of negative mental wellbeing outcomes based on environmental exposure levels derived from literature-based thresholds.

Observational Research: Research design that identifies associations and patterns in existing data without manipulating variables or establishing causation. This thesis conducts observational analysis, meaning findings represent correlations rather than causal effects.

Urban Mental Wellbeing Index (UMWI): An original framework developed in this research that aggregates environmental exposure risk across three contextual cues to produce a population-weighted city-level assessment score ranging from 1 to 5.

Smart City Data Classification and Access Framework (SCDCAF): An original framework developed in this research that evaluates smart city datasets across five dimensions: availability, sensitivity, temporal frequency, cost, and data providers.

2.2 Urban Mental Wellbeing

Rapid global urbanization exposed the unbalanced relationship between the changing urban environment and citizens' mental health and wellbeing. Neuropsychiatric disorders represent approximately 14% of the global burden of disease, with depression and other common mental disorders creating chronic disability that significantly impacts urban populations ([Prince et al. 2007](#)). Stress is a central pathway through which urban environments influence health outcomes, with factors such as crowding, noise, and social fragmentation linked to elevated stress and reduced mental wellbeing ([Bratman et al. 2019](#), [Prince et al. 2007](#)). The focus on urban mental wellbeing empowers cities to redefine their success, rather than depending on economic measures like GDP to capture quality of life and overall wellbeing ([Diener & Seligman 2004](#), [World Health Organization 2024b](#), [Prince et al. 2007](#)). This section explores urban mental wellbeing research evolution and modern frameworks within the context of urban areas and cities, identifying implementation gaps that create opportunities for smart city data integration.

2.2.1 Defining Urban Mental Wellbeing and Mental Health

Mental health is a global priority, with 970 million people worldwide, about one in eight, experiencing a mental health disorder ([World Health Organization 2024b](#)). Given that 57% of people live in urban areas, this means that more than 550 million urban citizens are affected by mental health disorders. The World Health Organization (WHO) states that there is “no

health without mental health”.¹ As urbanization continues, this represents one of the largest modern public health crises. This impact makes understanding what constitutes mental health crucial for policymaking and urban planning.

It is essential to define key terminology that is often used interchangeably but has distinct definitions: *mental health*, *mental wellbeing*, *urban mental wellbeing*, and *quality of life*. The WHO defines mental health as “a state of mental wellbeing that enables people to cope with the stresses of life, realize their abilities, learn well, and work well, and contribute to their community.” The WHO clarifies that mental health is more than just the absence of mental disorders. Mental health represents an umbrella term that includes a full spectrum of psychological functioning and wellbeing. Mental health can be assessed at an individual level in terms of personal characteristics, genetics, and behavior. The importance of mental health meaning is particularly relevant in urban contexts, where environmental and social factors significantly influence mental health outcomes. Mental health differs from the clinical concept of mental disorders. Mental disorders such as anxiety, depression, bipolar disorder, PTSD, and schizophrenia impact cognition, emotion, and behavior (World Health Organization 2024b).

Mental wellbeing represents a related but distinct dimension compared to mental health. Currently, there is not a formal definition of mental wellbeing. In research, it is characterized as the combination of subjective experience (how one feels), psychological functioning, positive social connections, and self-realization (Mcaneney et al. 2015). Mental health and mental wellbeing are two distinct but correlated continua in populations. Mental wellbeing is measured at a population level, where environmental and social factors play key roles in determining outcomes (Mcaneney et al. 2015). Urban planning, infrastructure, and neighborhood characteristics influence mental wellbeing and can be measured to assess population-level health. Individuals with mental illness may also have positive mental wellbeing, and individuals who do not suffer from mental illness can still benefit from enhanced mental wellbeing. Quality of Life (QoL) is a broad concept that includes additional factors such as mental health. Quality of Life is often used to measure a person’s satisfaction. The WHO defines it as “an individual’s perception of their position in life in the context of the culture and value systems in which they live.” Quality of Life covers a broader range of factors, such as environmental, social, and economic conditions. Mental health is well defined, yet the specific application to urban contexts remains underdeveloped (Adams 2013). Current literature fails to standardize one definition for urban mental wellbeing. Adams (2013) and Allam & Dhunny (2019) explored urban wellbeing by incorporating subjective experiences, spatial relationships, and quality of life factors in urban environments. In this research, *urban mental wellbeing* is defined as mental wellbeing outcomes influenced by urban environmental factors that can be measured through smart city data and contextual cues (Oteiza et al. 2022). This definition supports computational approaches that can assess urban factors affecting urban mental health and wellbeing through data-driven contextual cues. These definitions focus on computational approaches to environmental factors affecting urban mental wellbeing. This targeted framework acknowledges that comprehensive urban mental health encompasses broader clinical, social, economic, and individual psychological factors that extend beyond the environmental data assessment methods examined in this research. Environmental factors affect urban mental wellbeing through two distinct pathways. Direct pathways involve biological mechanisms such as PM2.5 triggering neuroinflammation (Genc et al. 2012) or greenspace reducing cortisol levels (Ward Thompson et al. 2012). Indirect pathways involve behavioral consequences such as pollution reducing outdoor activity (Currie et al. 2009) or transit barriers limiting social interaction (Ma et al. 2021). For this research, urban mental wellbeing is operationally defined as mental wellbeing outcomes influenced by measurable urban environmental factors that can be assessed through smart city data, specifically air quality, greenspace accessibility, and transit mobility. This definition focuses on environmental determinants that are spatially distributed, objectively measurable, and actionable through urban planning interventions, acknowledging that comprehensive urban mental

¹<https://www.who.int/>

health encompasses broader clinical, social, economic, and individual factors beyond environmental exposure assessment. Chapter 3 details these mechanisms for air quality, greenspace, and mobility.

2.2.2 Origins and Evolution of Urban Mental Wellbeing Research

Urban Wellbeing can be traced back to prehistoric times. The author Milne (2017) claims that about 7 million years ago, when human lineage began biologically evolving, humans developed “hunter-gather” style communities. Humans are accustomed to having minimal to medium routine activity levels essential for survival, such as walking, climbing, lifting, etc. The modern-day sedentary human burns only one-fifth the energy than our prehistoric ancestors, who expended 3,000–5,000 kJ daily. Milne (2017) argues that building a city where a citizen can move around, walking and cycling, is a modest “evolutionary-concordant” compromise (Milne 2017).

This evolutionary mismatch between human biology and urban environments helps explain patterns that researchers have observed for centuries. Historian Edward Shorter narrates the story of a Danish medical doctor who, in 1839, surveyed priests in Copenhagen and nearby areas about the prevalence of mental illness in their parishes. The findings revealed that more individuals suffering from mental health issues resided in urban areas than in the countryside. In the city of Copenhagen, 1 in 331 inhabitants were diagnosed as mentally ill, compared to 1 in 466 inhabitants residing in the countryside (Okkels et al. 2018). In 1939, one hundred years later, a study in Chicago examined 34,864 patients with mental diseases during the period of 1922-1934. The results identified a strong link between mental illness and the city’s ecological structure, showing higher mental illness prevalence in disorganized areas whereas residential outskirts had lower rates. A recent meta-study further developed what scientists had once suspected, by pooling 25 years of all psychiatric disorders. The results confirmed that prevalence of mental illness is higher in urban areas than in rural areas, with an odds ratio of 1.21 (Okkels et al. 2018). Research from the last 180 years suggests that the divide between urban and rural mental health represents a persistent challenge rooted in fundamental mismatches between human evolution and urban design.

Early research on mental health followed a traditional medical model focusing on mental illness and pathology. The disease-centered approach prioritized treating symptoms instead of promoting wellness as seen in the 1939 study in Chicago (Okkels et al. 2018). This resulted in individual-level clinical interventions that dominated the field. Wellbeing was often implied as an “absence of disease,” and since the 2000s, the field has shifted to a holistic approach, redefining mental health to “presence of wellbeing.” In 2001, the WHO released the *Mental Health: New Understanding, New Hope* report (World Health Organization 2001), which established mental health as fundamental to overall health. The WHO also created a Quality of Life manual, which states that “quality of life per se, which has been aptly described as ‘the missing measurement in health’.” The WHO’s redefinition allowed researchers to move from illness prevalence to understanding how environmental, social, and economic factors shape wellbeing.

2.2.3 Modern Urban Mental Wellbeing Frameworks

The shift from pathology to positive wellbeing created the foundation for modern urban planning approaches that recognize cities as complex systems influencing population health through multiple environmental contextual cues. The systems perspective led to the development of numerous frameworks that now shape urban wellbeing research. This section examines three of the most widely applied frameworks that demonstrate key conceptual advances in population-level urban mental wellbeing assessment.

Systems-Based Conceptual Models

Modern urban mental wellbeing research recognizes cities as complex adaptive systems where multiple environmental contextual cues interact to influence population-level urban wellbeing. [Von Szombathely et al. \(2017\)](#) proposed a conceptual modeling approach to urban wellbeing that integrated population-level assessment approaches. The UrbWellth framework divides urban wellbeing into four interconnected sectors: Individual, Society, Morphology, Stressors. This framework has an integrated vulnerability filter system that modifies how strongly each urban factor affects mental wellbeing based on exposure, sensitivity, and adaptive capacity. The UrbWellth framework is a fitting example of the shift from single-factor analysis to multi-factor inclusion by acknowledging that urban mental wellbeing emerges from complex interactions.

Building on systems recognition, [Bai et al. \(2012\)](#) recognized the importance of viewing urban cities as multifaceted and dynamic systems that create health risks like pollution and sedentary lifestyles that extend beyond healthcare access. [Bai et al. \(2012\)](#) outlined an urban environmental model representing four evolutionary stages: poverty-driven cities, industrial cities, consumption-driven cities, and healthy eco-cities. This framework was developed through the International Council for Science (ICSU) program on Health and Wellbeing in the Changing Urban Environment and categorizes urban health risks into five types: infectious diseases, industrial pollution, lifestyle diseases, injury risks, and climate change impacts. [Bai et al. \(2012\)](#) argue that a systems approach is required in understanding the many linkages between health and wellbeing and urban environments. This framework relies on mathematical modeling and stakeholder input to address the complexity of urban wellbeing systems.

A crucial research breakthrough in urban mental wellbeing recognizes the need for population-level assessment rather than individual clinical assessment. Neighborhood deprivation can alter the impact of environmental interventions that produce different mental health outcomes across socioeconomic contexts ([Mcaneney et al. 2015](#)). The results revealed that neighborhood satisfaction significantly affects urban mental wellbeing. Residents moving from “very dissatisfied” to “very satisfied” recorded an increase of 8.75 points in wellbeing scores. This effect occurred only in higher income areas ([Mcaneney et al. 2015](#)). A sensory urbanism framework, introduced by [Adams \(2013\)](#), challenges traditional visual-focused planning by incorporating the full range of sensory experience, emphasizing the importance of the use and functionality of urban spaces.

These frameworks contribute to the theoretical understanding of environmental risk indicators relevant to urban mental wellbeing risk estimation through considering population-level approaches and recognizing multi-dimensional complexity in cities. Modern frameworks remain primarily theoretical and do not support real-time data analysis for urban planning.

Limitations of Modern Research Approaches

Modern urban mental wellbeing frameworks are a valuable foundation for city-level urban mental wellbeing risk estimation, yet crucial limitations exist in their practical approach. Established frameworks ([Von Szombathely et al. 2017](#); [Adams 2013](#); [Ala-Mantila et al. 2018](#)) rely on static data sources such as surveys, census data, and periodic clinical assessments. While these data resources are useful indicators, they are unable to capture the changes of real-time data. This lack of dynamic modeling limits policy adaptation, as updated data is often unavailable. Planners demand actionable tools, beyond conceptual models. Researchers recognize the importance of urban mental wellbeing frameworks but lack tactical implementation models. Urban mental wellbeing research encounters critical data gaps as most studies concentrate in high-income countries ([Gascon et al. 2018](#), [Hogan et al. 2016](#)). This relevance of current evidence to low- and middle-income urban contexts where most global urban growth occurs ([Bai et al. 2012](#), [Okkels et al. 2018](#), [Krefis et al. 2018](#), [Patel et al. 2018](#)). Less than 6% of the internationally accessible literature stems from low-income and middle-income countries ([Okkels et al. 2018](#)).

Summary

It is established that urban mental wellbeing research is crucial as 970 million people worldwide live with a mental health disorder ([World Health Organization 2024b](#)). Rapid urbanization has affected more than 550 million urban citizens. Understanding the distinct definitions of mental health versus mental wellbeing is essential, since urban wellbeing operates at the population level rather than individual clinical assessment. There is more than 180 years of evidence, from the 1839 Copenhagen study to recent meta-analyses. These findings indicate higher mental health risks in urban areas compared with rural areas ([Okkels et al. 2018](#)). Early urban wellbeing research focused on individual clinical treatment and shifted towards population-level assessment of urban mental wellbeing. Modern frameworks ([Von Szombathely et al. 2017](#); [Bai et al. 2012](#); [Adams 2013](#)) conceptualized cities as a complex multi-dimensional system, affecting population wellbeing through multiple environmental factors. However, these frameworks remain theoretical, relying on static data and lacking real-time analysis. Smart city technologies could help address this implementation gap by providing real-time, actionable data. Section 2.2 establishes that urban environmental conditions influence population mental wellbeing outcomes, yet traditional clinical assessment tools cannot scale to entire urban populations and modern conceptual frameworks remain theoretical without operational implementation. Section 2.3 examines this measurement challenge, comparing objective and subjective approaches before explaining why this research adopts risk-based environmental exposure assessment as the methodological foundation for population-level evaluation.

2.3 Measuring Urban Mental Wellbeing

Measuring urban mental wellbeing requires choosing between objective and subjective data, individual and population-level assessment, and diagnostic versus risk-based frameworks. Each choice carries distinct trade-offs in scalability, cost, and planning applicability. Section 2.3.1 compares objective biological measures with subjective perceptual approaches. Section 2.3.2 examines fear and perceived safety as mental wellbeing factors that cannot be objectively quantified at population scale and explores the defensible space framework by [Newman \(1996\)](#). Section 2.3.3 explains why our research adopts risk-based environmental exposure assessment. The selected approach enables population-level assessment through measurable environmental contextual cues including air quality, greenspace accessibility, and transit infrastructure without requiring individual clinical data or ongoing surveys, prioritizing scalability and planning actionability while acknowledging it cannot capture subjective lived experience.

2.3.1 Objective and Subjective Measurement Approaches

Urban mental wellbeing research employs two fundamentally different measurement approaches. Objective biological measures use biomarkers to quantify physiological stress responses. [Ward Thompson et al. \(2012\)](#) demonstrated that salivary cortisol levels varied systematically with greenspace access in deprived communities, with residents near greenspace showing lower stress patterns. [Kyriakou et al. \(2019\)](#) conducted a study on wearable physiological sensors that enable continuous monitoring of stress through galvanic skin response, heart rate variability, and skin conductance. [Bakker et al. \(2011\)](#) developed algorithms to automatically detect stress levels at work from physiological signals. These approaches produce quantifiable, comparable wellbeing data not subject to self-report bias. However, they require clinical infrastructure or wearable sensor distribution, demand ongoing technical support, and raise privacy concerns. The cost per participant limits scaling to citywide populations.

Subjective perceptual measures capture how residents experience their urban environment through self-report and participatory methods. Survey instruments such as the Happy City Index assess wellbeing and life satisfaction ([Montgomery 2015](#)), while UN Habitat Quality of

Life indices incorporate perceived environmental quality. Citizen science approaches engage residents as active participants in data collection. Willis & Nold (2022) proposed emotion data frameworks for smart city governance that systematically incorporate residents’ emotional experiences into planning decisions. Pánek (2018) developed emotional mapping methods where residents crowdsource perceptions of urban spaces, revealing spatial patterns in how different areas affect wellbeing. The SENSE project integrated quantified self technologies with citizen science to record stress experiences in neighborhoods (Chrisinger & King 2018), demonstrating that electrodermal activity levels varied spatially with proximity to specific street features and land uses. SafetiPin enables crowdsourced safety perceptions focused on lighting, visibility, and gender diversity (Viswanath & Basu 2015). Lynch (1960) established how cognitive perceptions affect wayfinding and spatial anxiety through mental mapping. These approaches capture lived experience, cultural context, and emotional responses that physiology cannot reveal. However, they require sustained participant engagement, introduce selection bias, are vulnerable to social desirability effects, and capture only temporal snapshots.

The choice between approaches involves fundamental trade-offs. Objective measures offer scalability and continuous monitoring but miss subjective experience and cultural meaning. Subjective measures capture perception and emotion but require ongoing participation and produce temporal snapshots. Ferreira (2013) argued that emotions are essential in planning practice while acknowledging the difficulty of systematizing emotional data at population scale. This research uses objective environmental data as a proxy for exposure risk rather than measuring wellbeing directly. Environmental conditions such as air quality, greenspace accessibility, and transit proximity can be measured using existing datasets and link to mental wellbeing through established epidemiological thresholds, as covered in Chapter 3. This enables population-scale assessment without clinical infrastructure or ongoing surveys, acknowledging that environmental exposure does not equal experienced wellbeing.

2.3.2 Fear, Perceived Safety, and Defensible Space

Fear of crime and perceived safety represent important dimensions of urban mental wellbeing that affect behavior, stress levels, and quality of life. Newman (1996) developed the defensible space framework demonstrating that physical design features enable residents to exert territorial control and natural surveillance over their neighborhoods. Architectural elements including sightlines, lighting, territorial markers, and spatial configuration influence perceived safety by shaping opportunities for observation and the sense of ownership residents feel toward shared spaces. Newman’s intervention studies in public housing demonstrated that physical redesign reducing anonymous public areas and clarifying territorial boundaries decreased both actual crime and fear of crime (Newman 1996). He measured objective environmental features including lighting, fencing, street patterns, and sight lines, then modified these to enable resident territorial control, demonstrating that environmental improvements reduce both crime and fear without requiring perceptual surveys. Fear of crime produces mental health consequences independent of actual victimization risk (Lorenc et al. 2012). Chronic fear elevates anxiety levels, restricts outdoor activity and social interaction, and creates environmental unpredictability that serves as a persistent stressor (Jackson & Stafford 2009). Fear-driven behavioral changes such as avoiding parks or limiting evening mobility create indirect mental health effects by reducing access to greenspace, physical activity, and social connection (Lorenc et al. 2012).

While Newman measured objective environmental features that influence perceived safety, other researchers have developed methods to directly capture residents’ subjective safety perceptions through participatory data collection. SafetiPin enables crowdsourced safety perception mapping where users rate locations based on lighting quality, visibility, crowd presence, and gender diversity (Viswanath & Basu 2015). The platform demonstrates the feasibility of collecting spatially explicit perceptual safety data, initially focused on women’s safety in Indian cities but adaptable to other contexts. Pánek (2018) developed emotional mapping techniques

where residents mark urban locations associated with feelings of safety or fear, revealing spatial patterns in perceived threat that may not correspond to objective crime statistics. [Lynch \(1960\)](#) found that urban environments that are easy to understand and navigate reduce anxiety during navigation. These approaches capture subjective safety perceptions that influence how residents experience and use urban environments.

Despite the documented importance of perceived safety for mental wellbeing, it was not selected as a contextual cue in this framework for several methodological reasons. Perceived safety is inherently subjective and requires survey instruments, participatory mapping applications, or crowdsourced data collection incompatible with the static open data approach adopted in this research. Unlike PM2.5 concentrations or greenspace distances that can be measured objectively using existing monitoring networks and geospatial datasets, perceived safety has no objective environmental threshold. Two residents at the same address may perceive radically different safety levels based on gender, age, ethnicity, prior victimization experience, and cultural background ([Pain 2000](#), [Reid & Konrad 2004](#)). Fear of crime affects demographic groups unequally ([Lorenc et al. 2012](#)). Women, ethnic minorities, and lower-income residents experience greater psychological burden from crime and the threat of victimization. Women’s fear often manifests as constant vigilance that restricts behavior and reduces wellbeing, and people with mental health problems are disproportionately likely to experience fear that substantially impacts quality of life ([Lorenc et al. 2012](#)). Perceived safety also varies temporally across time of day, seasons, and in response to specific events, requiring ongoing data collection rather than one-time assessment.

2.3.3 Risk-Based Assessment Frameworks

Risk in public health contexts refers to the probability that exposure to a hazard will result in adverse health outcomes within a defined population ([Canadian Centre for Occupational Health and Safety 2023](#)). Risk assessment frameworks translate measurable environmental exposures into population-level health estimates by applying epidemiologically established thresholds that indicate when exposure conditions elevate health vulnerability ([U.S. Environmental Protection Agency 2016](#)). These frameworks evaluate environmental conditions rather than measuring individual health status directly, enabling population-scale assessment where individual clinical evaluation proves impractical. The U.S. Environmental Protection Agency Air Quality Index ² exemplifies this approach, translating daily pollution concentrations into six risk categories from Good to Hazardous to enable public advisories based on environmental measurements rather than individual health screening. Similarly, the World Health Organization air quality guidelines define exposure thresholds above which population health risks become unacceptable, providing reference standards for policy intervention independent of clinical diagnosis ([World Health Organization 2021](#)). The EPA Guidelines for Human Exposure Assessment establish the methodological foundation for this approach, defining exposure assessment as characterizing contact between environmental agents and human populations to support risk estimation and management decisions ([U.S. Environmental Protection Agency 2016](#)).

Urban mental wellbeing research increasingly adopts risk-based frameworks because individual-level mental health measurement tools require direct survey administration or clinical interview, limiting their application to sample-based research rather than comprehensive population assessment. Tools such as the Kessler Psychological Distress Scale (K6), Warwick-Edinburgh Mental Wellbeing Scale (WEMWBS), Center for Epidemiologic Studies Depression Scale (CES-D), and General Health Questionnaire (GHQ) provide validated measures of mental health status ([McManus et al. 2016](#)) but demand individual participation that cannot scale to entire urban populations without prohibitive cost and logistical complexity. Risk assessment in mental health practice has traditionally focused on individual clinical prediction tools that screen for suicide risk, violence potential, or acute psychiatric crisis in hospital settings ([Janse van](#)

²<https://www.airnow.gov/aqi/aqi-basics/>

Rensburg & van der Wath 2020), with trained clinicians administering structured instruments to patients already receiving mental health services. Keyes et al. (2010) demonstrated that mental health status functions as a risk indicator for future mental illness in longitudinal population studies, with adults maintaining poor mental wellbeing over a 10-year period showing 6.6 times higher likelihood of developing mental illness than those maintaining good mental wellbeing. This evidence supports population-level risk classification approaches that evaluate environmental and social determinants of mental health rather than requiring individual clinical assessment. Campion (2018) advocates for public mental health approaches that address risk factors and protective factors at the population level through interventions targeting socioeconomic inequalities, environmental conditions, and community resources, emphasizing that sustainable reduction in mental disorder burden requires primary prevention strategies addressing entire populations rather than treatment of diagnosed individuals alone.

Environmental exposure risk assessment provides an appropriate framework for urban mental wellbeing measurement because epidemiological evidence has established reliable associations between measurable urban environmental conditions and population-level mental health outcomes (Bratman et al. 2019, Prince et al. 2007), as detailed in Chapter 3. Risk assessment approaches align with urban planning practice by producing spatially explicit evaluation of environmental conditions that planning interventions can address (U.S. Environmental Protection Agency 2016), while acknowledging the fundamental limitation that environmental exposure assessment cannot capture subjective lived experience or individual variation in vulnerability and resilience (Campion 2018). The risk classification approach produces environmental condition scores rather than individual mental health predictions, as individual outcomes depend on unmeasured factors including social support, genetic predisposition, prior trauma, and personal resilience (Keyes et al. 2010). Chapter 4 examines the data ecosystem required to implement this risk-based environmental exposure framework, analyzing smart city data availability, accessibility, and quality considerations that enable population-level assessment. Our research adopts this risk-based environmental exposure framework because it enables population-level urban mental wellbeing assessment through measurable environmental contextual cues that urban planning interventions can address, providing spatially explicit evidence for infrastructure decisions while maintaining scalability through open data sources.

2.4 Smart Cities and Urban Mental Wellbeing

The rapid pace of urbanization has increased complexity in planning and managing urban stressors, such as noise, pollution, and traffic. These urban stressors have a direct human consequence, affecting millions of urban mental wellbeing (Maas et al. 2009, Gascon et al. 2018, Wood et al. 2017). As a response, the concept of smart cities emerged to address urban challenges through implementing technologically advanced infrastructure (Albino et al. 2015, Nam & Pardo 2011). Although the smart city concept has primarily focused on efficiency, automation, and economic development (Moss Kanter & Litow 2009), modern smart city frameworks assign quality of life as a core component (Giffinger et al. 2007). The newly collected data can bring valuable insights regarding urban citizens' behavior, yet smart cities lack computational frameworks for measuring population-level urban mental wellbeing (Lim et al. 2019). This section examines the evolution of smart cities and their modern frameworks, the infrastructure they employ, and current wellbeing attempts, ultimately highlighting the significant urban mental wellbeing gap.

2.4.1 Evolution of the Smart City Concept

Smart Cities emerged as a solution for rapid urbanization issues, driven by the integration of advanced digital technology, interconnected network systems, and innovative governance

models. The push to improve cities accelerated after World War II (Moss Kanter & Litow 2009) as cities absorbed large populations migrating from rural regions. Urban renewal mainly focused on physical restoration of decaying buildings. The government advocated for the improvement of cities to promote economic development. In the 1960s the idea of a “Model City” was introduced to categorize one effective city. This idea encountered shortcomings as this “Model City” mainly consisted of social services rather than job opportunities, which failed to recognize the interconnected nature of urban systems (Moss Kanter & Litow 2009). Cities face many constraints: from economic pressures, inadequate public services, rising crime, and outdated infrastructure that demand extensive urban system transformation. Traditional approaches have proven insufficient, forcing civic leaders to rethink entire urban frameworks rather than implementing piecemeal solutions (Moss Kanter & Litow 2009).

Global urbanization accelerated rapidly, with cities of 1 million plus inhabitants growing from 371 in 2000 to a projected 706 by 2030. This unexpected urban expansion includes 43 megacities by 2030, where more than 10 million citizens reside. The rapid growth of urbanization creates demands on city systems to manage population growth while maintaining quality of life for residents (of Economic & Affairs 2019). Cities hold power towards the future; they impact economic growth, environmental performance, and social aspects (Albino et al. 2015, Moss Kanter & Litow 2009). Cities are responsible for producing large shares of GHG emissions, consuming between 60% to 80% of the energy worldwide (Albino et al. 2015). Cities rely on too many external resources and simultaneously are considered to be consumers of the resources (UN-Habitat 2020). This prompted governments and urban planners to consider a sustainable approach to managing cities (Albino et al. 2015). In response, cities and urban planners started researching new ways to manage the challenges, leading to the inclusion of modern technologies such as Information and Communication Technology (ICT), which evolved into Smart Cities (Albino et al. 2015, Nam & Pardo 2011).

2.4.2 Smart City Frameworks and Dimensions

To address these urban challenges, the concept of “smart cities” emerged, but what exactly makes a city “smart” requires careful definition. Researchers consciously chose the more inclusive term “smart” rather than “intelligent” to avoid elitist classification. Smartness implies that a city is self-sufficient and self-optimizing (Nam & Pardo 2011). The term “smart cities” aims to describe a city that adapts to the urban citizen’s needs and is able to provide customized solutions. Early smart city initiatives in the 2000s primarily focused on technological infrastructure and operational efficiency. Companies like IBM introduced the “smarter cities” concept (Moss Kanter & Litow 2009), which advocates for integrated information systems and cross-sector collaboration to optimize urban operations and reduce costs.

Foundational Frameworks and Dimensional Models

By 2007, researchers established smart city concepts into comprehensive frameworks. The purpose of a smart city varies by country and by city-specific priorities. Research conducted across (Nam & Pardo 2011, Albino et al. 2015) used different methods to categorize the concept of a smart city to describe the goals of a specific smart city. The creation of such categories and dimensions is viewed as part of an organic system (Nam & Pardo 2011). The interconnected relationship between categories and dimensions in a smart city is the basis of creating a smart system in cities. This smart system in a city uses the information to provide ICT and embedded infrastructures to collect adequate data, facilitate mobility, provide solutions to disasters and emergencies, monitor patterns, and now has the opportunity to improve urban citizens’ wellbeing. Given that a smart city is interconnected, researchers argue that a smart city should be managed as an organic whole, instead of focusing on how to make each category “smart” (Nam & Pardo 2011). However, these cities have evolved to contain an artificial nervous system, where the nerves represent digital telecommunication networks, the brains are smart ICTs,

the sensory organs illustrate sensors and tags, and the software depicts cognitive consciousness and knowledge. In the research of [Nam & Pardo \(2011\)](#), the dimensions can be placed into three categories: technologies, people, and community. Other research papers such as [Komninos & Sefertzi \(2009\)](#) identify four dimensions; the first one creates a knowledge-based city. The second dimension is the active use of information technology to improve urban life. The third dimension physically adds ICT to the city's infrastructure. The fourth is the combination of the other dimensions where the purpose is to connect ICT and urban people. Similarly, another research team, [Giffinger et al. \(2007\)](#), identifies four dimensions: education, industry, technical infrastructure, and participation. The Centre of Regional Science at the Vienna University of Technology used this list as a base and constructed a new list of six categories that included: Smart Economy, Smart Environment, Smart People, Smart Mobility, Smart Living, and Smart Governance. Within these categories, the following dimensions highlighted a different view: transport and ICT economics, natural resources, quality of life, and social capital. These frameworks serve as a guide for researchers and urban planners to follow a smart city concept, yet the inclusion of a new, crucial dimension "Quality of Life" revolutionized modern frameworks.

The Quality of Life Debate

The smart city framework evolution pivoted in 2011 when [Nam & Pardo \(2011\)](#) introduced their three-dimensional model, intentionally recognizing that successful smart cities require integration across technology, people, and institutions rather than focusing solely on technological solutions. A discussion among researchers arose when deciding if "Quality of life" should be considered as its own dimension as some researchers ([Nam & Pardo 2011](#)) argue that the other dimensions exist to improve the quality of life in a city as a consequence. Researchers have identified various categories and dimensions, but it is essential that the entire system remains citizen centric. Determining categories and dimensions of a smart city defines what a smart city is, but researchers have focused on describing how a city becomes smart and its overall performance. A key perspective from [Nam & Pardo \(2011\)](#) highlights the importance of the connection of these dimensions, concluding that a city becomes smart when efforts in improving human capital and IT infrastructure promote sustainable growth and enriches the quality of life of urban citizens. The focus on improving and sustaining the quality of life for urban citizens is a crucial factor. Whether it is part of the base dimensions or the effect, a smart city must consider the wellbeing of citizens. Cities and industries across the globe have set up initiatives to create and aid in building smart cities.

From Technology-Driven to Urban Mental Wellbeing Approaches

The shift from efficiency and optimization to citizen-centered approaches reflects differently across global contexts and thus varying government models and cultural priorities. Depending on where a city is located, it can have different priorities on how it approaches turning into a smart city. A study in 2021 ([Hu & Zheng 2021](#)) highlights the main differences between cities in the United States and cities in China. In this investigation, factors such as socioeconomic context, type of government, and culture-specific indicators were taken into consideration. The socioeconomic factor describes the importance of human capital as it promotes smart city advancement by taking the role of leaders but also as receivers. The governance of a smart city can have a great impact on the development of a smart city since it is the one that implements policies and initiatives ([Hu & Zheng 2021](#)). However, it is crucial for a government to be transparent and take accountability to achieve and build a sustainable smart city. In this way, the government ensures that it provides urban citizens with access to information that may have an impact on their lives ([Nam & Pardo 2011](#)). The study by [Hu & Zheng \(2021\)](#) concludes that while China and the USA have similar smart city dimensions and projects, their approaches

differ. The USA relies on citizen participation and stakeholders, while China relies on its own government to fulfill the smart projects.

2.4.3 Smart City Data Infrastructure

The rise of Internet of Things (IoT) and real-time data platforms facilitate the way smart cities collect, manage and interpret information on city insights. IoT ecosystems generate extensive continuous data streams on relevant factors that can be linked to urban mental wellbeing. Environmental stressors including air quality, noise exposure, mobility patterns, and greenspace access (Ghazal et al. 2021) are the main drivers of IoT ecosystems. Even though many smart cities have technological capabilities for data collection, most platforms lack the analytical frameworks necessary to transform factors into urban mental wellbeing risk insights.

IoT Ecosystems in Smart Cities

IoT Ecosystems in Smart Cities represent real-life urban testbeds creating an opportunity for researchers to test IoT infrastructure that encompasses management frameworks and analytical operations. The implementation of IoT Ecosystems supports the development of prospective urban services prototypes before city-wide deployment. SmartSantander (Sanchez et al. 2014) is a European smart city centralized platform in Santander, Spain. SmartSantander deployed over 20,000 sensors across four European cities: Belgrade, Guildford, Lübeck and Santander. The SmartSantander project worked with a three-tier architecture: IoT Nodes, Repeaters, and Gateways. IoT Nodes collect environmental data such as temperature, noise, air pollutants, car presence, etc. These sensors are often installed into street infrastructure such as parking sensors. The second tiers are repeaters that are integrated on high points such as streetlights and traffic lights. These devices forward IoT data via low-cost and low-power 802.15.4 protocol (Sanchez et al. 2014). This design extends network coverage and reduces individual sensors' power consumption. The third tier is gateways which aggregate all the data from the IoT nodes and repeaters and complete the task by sending all the data to central servers. This data is then displayed in a portal for administrative use. The collected data can be used for urban service applications such as parking management, enabling real-time parking occupancy, and can be viewed in an app. Citizen engagement is enabled by a Participatory Sensing service where citizens can report, share, and be notified of events happening in the city. This allows for real-time citizen forward feedback (Sanchez et al. 2014).

Technical Platforms for Smart City Data Analysis

While IoT frameworks focus on sensor deployment and data collection, various technological platforms (Puiu et al. 2016, Lecue et al. 2014, Papishev & Yarime 2021) have emerged with analytical capabilities for processing large-scale data generated by IoT. The CityPulse project started to facilitate processing and integrate large volumes of heterogeneous, real-time smart city data to assist cities and developers with creating better city services. The CityPulse framework contains an architecture with two main categories: Large-Scale Data Stream Processing Modules and Adaptive Decision Support Modules. The first category manages diverse sensor and social media data by reducing data volume, detecting events in the city, and addressing missing data values. This data is visualized on a dashboard displaying real-time and historical urban trends. The second category uses the processed data to support context-aware reasoning by monitoring data quality and dynamically adjusting data sources to maintain reliability. While the CityPulse framework is a well-rounded framework for data analytics, the CityPulse project mainly focuses on travel planning and operational efficiency rather than using the collected data to generate population-level wellbeing insights.

IBM in conjunction with the city of Dublin, Ireland developed the technological platform for smart cities: *Semantic Traffic Analytics and Reasoning for CITY* (STAR-CITY) (Lecue

et al. 2014). The STAR-CITY platform is a semantic web-based platform that integrates heterogeneous city data, historical and real-time, and various sources to assess and predict traffic conditions. Its goal is to diagnose causes and forecast congestion to support urban planning. The platform handles input from six different data sources, including journey times, road weather conditions, and real-time Dublin bus data. The core functionalities of the STAR-CITY platform entail diagnosing the causes of traffic congestion using semantic reasoning as well as forecasting traffic congestion. A website with interactive maps and relevant charts is available for urban planners and researchers to fully understand traffic trends (Lecue et al. 2014). The STAR-CITY platform successfully identifies traffic congestion causes and predicts traffic trends, yet researchers are not considering using this sophisticated platform for urban mental wellbeing applications.

The Rise of City Digital Twins

An innovative Smart City approach to simulate and process large-scale data is through the use of Digital Twins. The City Digital Twin (CDT) is a virtual representation of the characteristics and behaviors of a city. A digital copy of the city is created allowing for imaginative modeling approaches to be applied to the design of smart cities. The concept of digital twins can be used for policymaking as outlined in a case study introducing Virtual Singapore (Papyshev & Yarime 2021). The National Research Foundation of Singapore granted \$73 million, and Dassault Systèmes developed the project. The Singapore Land Authority and the Government Technology Agency acted as partners and provided static data on building geometry and the state’s greenery. The Virtual Singapore data ecosystem integrates real-time IoT system data with static infrastructure data to create a realistic 3D virtual model. Virtual Singapore incorporates underground structures adding 20 core datasets including vegetation, road networks, and waterways. The platform supports applications such as accessibility planning for useful routes for elderly and disabled citizens and simulations of urban planning regarding transport flows and new pathways. However, there are a few notable limitations of the digital twin Virtual Singapore as it excluded citizen-engagement (Papyshev & Yarime 2021). The platform also lacks a deeper integration of mobility data; it cannot realistically simulate mobility trends. Despite being one of the most recognized CDT platforms globally, Virtual Singapore lacks consideration of urban mental wellbeing applications (Papyshev & Yarime 2021).

2.4.4 Identifying the Research Gap for this work in the Literature

Evidence of the Gap through Systematic Reviews

There are several IoT ecosystems and technical platforms that support Smart city initiatives and goals. The outcomes and applications of these large-scale data processing platforms aim for optimization efficiency and economic development rather than shifting the focus on wellbeing benefits (Lim et al. 2019, Trencher & Karvonen 2019).

Lim et al. (2019) conducted a systematic review of 60 articles of the outcomes of smart cities measuring the positive and negative impact that were either observed or fully hypothetical. The impacts, for example, measured the increasing quality of life, enhancing citizen involvement, and facilitating economic development. The systematic review showed that 86% positive results were hypothetical and only 14% were observed, with only one study demonstrating observed improvement in quality of life. This reflects a systemic research imbalance that prioritizes evaluating efficiency and economic development while concepts like quality of life and citizen engagement are often not backed with evidence. The findings of these systemic reviews reinforce the need to refocus smart city research on measurable urban mental wellbeing impacts.

A different systematic review (Moustaka et al. 2018) of 204 smart cities papers revealed that technological focus dominates the discourse in a smart city. The results of the systematic review highlighted that mobility services accounted for one-third of implementations whereas wellbeing

applications represented 11.3% of implementations. The authors [Moustaka et al. \(2018\)](#) call for further integration of “citizen-centric applications and mental wellbeing indicators.” This disparity shows that while smart cities are rich in data, there are few efforts towards utilizing data streams for urban mental wellbeing applications.

Current Approaches to Urban Mental Wellbeing and Limitations

Historically, physicians and clinicians have relied on interviews and questionnaires to gather information on an individual’s wellbeing. These individual assessments can be invasive because they take people out of their normal environment as well as create risk of the interviewer setting up biased questions ([Banerjee et al. 2023](#)). Subjective assessments, recall, and hindsight biases can impact survey data. These surveys often capture data after a major event has occurred or after a person has experienced a meaningful change ([Saha et al. 2021](#)).

From a large-scale clinical studies perspective, it is time-consuming and labor-intensive, resulting in an expensive approach. Conducting large-scale clinical studies can also be socially and ethically complex and extremely hard to repeat ([Oteiza et al. 2022](#)). This gap inspired researchers ([Banerjee et al. 2023](#), [Marković et al. 2019](#), [Chakraborty et al. 2024](#)) to study several ways of detecting emotional stress mainly through observation or physical reactions. [Chakraborty et al. \(2024\)](#) developed a conceptual framework, Mind Turner, to monitor mental health conditions, including stress, using smart city infrastructure and Artificial Intelligence (AI) techniques. This framework relies on individual monitoring measuring mental health through questionnaires, facial expressions, and real-time sensor data measuring biometric data. AI techniques were applied to measure and predict mental health risks. Similarly, [Jacobson et al. \(2019\)](#) demonstrated that using digital biomarkers from wearable actigraphy sensors can predict mood disorders in a cohort of 55 participants with 89% accuracy and track symptom changes over time. Although these approaches prove the feasibility of passive, non-intrusive digital mental health monitoring, they require individual device installation and personal health data collection. This creates scalability and privacy concerns for population-level implementation. Even cities that explicitly prioritize wellbeing, such as Kashiwanoha Smart City’s health initiatives ([Trencher & Karvonen 2019](#)), struggle with population-level implementation, reaching only 2.5% of residents with advanced monitoring. Detailed analysis of these initiatives is provided in Appendix [A.1](#). The fundamental challenge is not data availability or technical capacity but rather the absence of computational frameworks that can assess wellbeing across entire urban populations.

Governance and Implementation Challenges

Many governments and policymakers have pursued smart cities transformations, yet while technological implementation advances urban efficiency, governance of smart cities remains highly unstable ([Vanolo 2014](#)). Smart cities face a “smartmentality” critique, which argues that the implementation of smart solutions is often detached from traditional democratic processes and public health initiatives. This institutional fragmentation creates complex power dynamics between private technology firms, city administrators, and urban planners. [Vanolo \(2014\)](#) argues that integrating health and wellbeing metrics into core smart city designs has yet to become standard practice. In the World Cities Report, UN-Habitat states: “The new approach to mental health must move beyond biomedical techniques and instead seek to address the social determinants of health such as improving access to urban green spaces.” However, few smart cities have developed the analytical frameworks necessary to implement this integrated approach.

Research Gap Definition

The gap between smart city data capacities and urban mental wellbeing applications presents an urgent challenge with consequential ramifications for public health (Vanolo 2014). Mental health disorders affect over 550 million urban citizens globally, with environmental factors playing a crucial role in these outcomes (World Health Organization 2024b, Gascon et al. 2018).

The COVID-19 pandemic intensified the urgency around urban mental health monitoring. Lockdowns, social distancing, and economic uncertainty disproportionately affected urban populations, leading to a documented increase in anxiety, depression, and other mental health challenges (Qiu et al. 2020). This crisis highlighted a critical need for real-time, population-level mental health intelligence. Cities that had access to monitoring of air quality, mobility trends, and greenspace usage were better positioned to understand the pandemic’s mental health impacts (Centers for Disease Control and Prevention 2024). However, the crisis revealed a core limitation: most cities lack necessary computational frameworks to convert such raw data into population-level wellbeing insights.

Research has established clear links between air quality, greenspace access, mobility options, and urban mental wellbeing (Gascon et al. 2018, Wood et al. 2017, Maas et al. 2009). Despite this, smart cities continue to prioritize operational efficiency, collecting substantial amounts of data on these factors without converting them into actionable mental health insights (Moustaka et al. 2018, Lim et al. 2019). This unexplored potential for real-time wellbeing monitoring and predictive interventions is not due to a lack of data infrastructure, but rather a fundamental analytics gap. Smart cities have already invested billions in the necessary data infrastructures, such as the extensive sensor network in a project like SmartSantander (Sanchez et al. 2014). The missing component, however, is a computational framework that can translate this environmental and mobility data into population-level urban mental wellbeing insights. This research examines the disparity between established scientific links and their computational implementation in a smart city context. By utilizing existing infrastructure, this research moves beyond efficiency and economic development to demonstrate how smart cities can move towards a human-centered approach, improving urban mental wellbeing and quality of life for urban residents. Addressing this gap requires three research questions: examining whether environmental indicators from literature can be operationalised as spatially explicit contextual cues for population-level assessment **RQ1**, developing a computational spatial framework that integrates heterogeneous environmental contextual cues to produce comparable risk assessments across cities with varying data characteristics **RQ2**, and determining the extent to which this framework can be generalised, transferred, and scaled across multiple cities with differing infrastructures **RQ3**.

The evidence presented in this section reveals a significant discrepancy between smart city conceptual and technological advances and urban mental wellbeing assessment. Current approaches to monitoring urban mental wellbeing face significant scalability limitations as demonstrated by individual-focused frameworks (Trencher & Karvonen 2019) like those in Kashiwanoha Smart City. The fundamental challenge is not data availability or technical capacity but rather the absence of computational frameworks that translate environmental data into population-level wellbeing insights. This gap represents a clear research opportunity. The convergence of urban mental wellbeing research establishing environmental determinants of population mental health (Section 2.2), risk-based assessment methodology that enables population-level evaluation without individual clinical data (Section 2.3), and existing smart city data ecosystems that already collect relevant environmental data (Section 2.4) creates the research opportunity this thesis addresses. Chapter 3 examines the specific environmental contextual cues selected for the Urban Mental Wellbeing Risk Index, detailing the epidemiological evidence linking air quality, greenspace accessibility, and transit mobility to mental health outcomes and establishing the thresholds that enable risk classification.

2.5 Conclusion

This literature review establishes the foundation for understanding urban mental wellbeing as a population-level concept that is differentiated from individual mental health diagnosis. The built environment and neighborhood factors influence mental health outcomes, as recognized by world health organizations. Urban mental wellbeing encompasses the various aspects that affect mental health: depression, anxiety, and distress at population scale.

Smart cities have invested heavily in IoT ecosystems that support continuous data collection on urban factors. Air quality sensors, GIS systems, and transport infrastructure already capture the environmental data needed for wellbeing assessment. However, most smart cities direct their technological and policy efforts toward efficiency optimization and economic growth. This focus creates a significant gap: cities collect vast amounts of environmental data but rarely apply these existing frameworks for environmental exposure risk assessment for urban mental wellbeing.

This literature review reveals how three distinct research domains converge to create the research opportunity this thesis addresses. Section 2.2 established that urban environmental conditions influence population mental wellbeing outcomes, with 180 years of evidence demonstrating higher mental health risks in urban areas and modern frameworks conceptualizing cities as complex systems affecting wellbeing through multiple environmental factors. Section 2.3 demonstrated that while individual-level clinical tools provide validated mental health measurement, they cannot scale to entire urban populations, and risk-based environmental exposure assessment frameworks offer a methodologically sound alternative that evaluates measurable environmental conditions rather than requiring individual clinical data. Section 2.4 showed that smart city data infrastructures already collect the environmental data required for population-level assessment through IoT sensor networks, air quality monitoring, GIS systems, and transport infrastructure, yet direct their capabilities toward operational efficiency rather than wellbeing applications. The convergence of these three domains reveals that the barrier to population-level urban mental wellbeing assessment is not conceptual understanding, measurement methodology, or data availability, but rather the absence of computational frameworks that operationalize existing knowledge using existing infrastructure.

Several research gaps emerge from this literature review:

1. **Computational Framework Gap:** Lack of computational spatial frameworks that integrate heterogeneous environmental contextual cues to produce comparable mental wellbeing risk assessments across cities. [RQ2](#)
2. **Population-level Assessment Gap:** Absence of scalable approaches for environmental risk assessment across entire urban populations.
3. **Smart City Integration Gap:** Disconnect between smart cities' extensive environmental data collection capabilities and their application to urban mental wellbeing assessment.
4. **Data Translation Gap:** Absence of methods to operationalise environmental indicators identified in literature as spatially explicit contextual cues for population-level urban mental wellbeing assessment. [RQ1](#)
5. **Scalability Implementation Gap:** Current wellbeing initiatives face significant scalability limitations, with unclear potential for generalisability, transferability, and scaling across multiple cities with differing infrastructures. [RQ3](#)

This research addresses these gaps by proposing contextual cues as measurable, data-rich pathways that link smart city data to environmental exposure risk assessment for urban mental wellbeing. Chapter 3 examines the specific contextual cues selected for this research: air quality, greenspace access, and mobility patterns. These three indicators were chosen because they offer

robust scientific evidence linking them to mental health outcomes while utilizing data sources already available in smart city infrastructure.

Chapter 3

Contextual Cues in Smart Cities

Urban environmental factors affecting mental health have been studied through various methodological approaches. Traditional epidemiological research relies on survey-based assessments linking self-reported environmental exposures to mental health outcomes (Gascon et al. 2018, Wang et al. 2019). Clinical studies measure biological markers (cortisol levels, cardiovascular stress) in response to controlled environmental conditions (Ward Thompson et al. 2012). Geographic information systems (GIS) enable spatial analysis linking residential locations to environmental features, though typically examining single exposures in isolation (Gascon et al. 2018). These established methods provide the empirical foundation demonstrating associations between specific environmental conditions and mental health outcomes. Environmental factors influence mental health through both direct and indirect pathways. Direct pathways involve biological mechanisms where environmental exposures trigger physiological responses, such as air pollution causing neuroinflammation or greenspace exposure reducing cortisol levels. Indirect pathways operate through behavioral changes and access barriers, such as fear of crime restricting park usage or transit limitations reducing social connection opportunities. However, existing approaches lack systematic frameworks for converting heterogeneous smart city data streams into comparable, multi-dimensional environmental assessments at population scale. This research addresses that gap through the computational approach of contextual cues.

The term *contextual cues* as used throughout this thesis is an original adaptation introduced in this research. The concept originates in cognitive and environmental psychology, where contextual cues refer to information encoded in an environment that influences perception, behaviour, and emotional state (Perez Oteiza et al. 2021). In this research, the term is adapted and extended to an urban and spatial context. *Contextual cues* are defined here as spatially explicit, computable quantities derived from smart city data sources that represent environmental conditions with established links to population-level urban mental wellbeing. Unlike general environmental indicators, contextual cues in this research must satisfy three criteria: they must be measurable using existing smart city data infrastructure, they must have quantifiable thresholds grounded in peer-reviewed epidemiological literature, and they must be spatially distributed across urban environments to enable population-level assessment at residential address level. In doing so, it connects the computational processing of smart city data with the epidemiological evidence linking environmental exposures to mental health outcomes.

Urban living often exposes citizens to environmental stressors such as noise, overcrowding, substandard housing, poor neighborhood conditions, environmental degradation, and traffic congestion (Bilotta et al. 2018). These stressors can be recognised as contextual cues and vary in their computational demands. Traffic congestion can be quantified using traffic flow datasets, while others, such as neighborhood quality, need the integration of multiple data sources. Similarly, air quality as a contextual cue requires a calculation of several different air quality indicators related to public health, including fine particulate matter (PM_{2.5}) and nitrogen dioxide (NO₂).

For this research, contextual cues are selected based on their established links to urban men-

tal wellbeing and the availability of relevant, data-rich sources in urban settings (Perez Oteiza et al. 2021). While considerable literature supports the association between various urban systems and mental health, this study focuses on three specific contextual cues: Air Quality, Greenspaces, and Mobility. These elements represent crucial aspects of urban life and additionally offer robust datasets, enabling a detailed examination of their impact on mental wellbeing. This chapter addresses RQ1 by examining whether environmental indicators identified in the literature can be operationalised as spatially explicit contextual cues for population-level urban mental wellbeing assessment using smart city data.

3.1 Literature on Air Quality

Air quality is a critical component of urban wellbeing, influencing not only physical health but also mental health (Kahn 2006a). The challenges posed by rapid urbanization, industrial activity, and vehicular emissions have worsened air quality globally, with pollutants like PM_{2.5} playing a significant role in heightening mental health disorders such as anxiety and depression (Chan & Yao 2008, Kelly & Fussell 2015). These issues create pressure in the context of smart cities, where their focus on innovation and technology uniquely positions them to address these challenges.

Section 3.1.1 examines these challenges in depth. It begins with an analysis of global policies and responses to air pollution followed by Section 3.1.2, an exploration of direct biological and indirect mechanisms through which air pollution impacts mental health. The section also delves into adaptive behavioral responses and examines disparities across demographic groups.

3.1.1 Global Responses to Urban Air Pollution: Policies and Initiatives

Over the years, the population of cities worldwide has surged, leading to increased urban density. This population density, in conjunction with increased industrial activities and vehicular traffic, has significantly deteriorated urban air quality. The concentration of pollutants in cities seriously challenges environmental sustainability and public health (Kahn 2006b). The deterioration in air quality shows as an excess concentration of various contaminants including carbon monoxide (CO), carbon dioxide (CO₂), nitrogen oxides (NO_x), ozone (O₃), and ambient particulate matter of varying aerodynamic diameters (PM₁₀ and PM_{2.5}) (Gładka et al. 2018).

Cities across the globe are struggling with the challenge of escalating air pollution and are facing the detrimental consequences of deteriorating air quality. The European Environment Agency (EEA) reported that 96% of urban citizens experience exposure to levels of ambient particulate matter that exceed the health-based guidelines set by the World Health Organization (WHO) (European Environment Agency 2025). The WHO has associated ambient air pollution with 4.2 million premature deaths annually. Additionally, the EEA states that over 1,200 underage individuals die annually from air pollution in European cities. Moreover, declining air quality disproportionately burdens low- and middle-income countries, where 89% of these premature deaths occur, with the majority recorded in the South-East Asia and Western Pacific regions (World Health Organization 2024a).

Research into hazardous air pollutants like PM_{2.5} commenced only after 2003 in China, despite the country's population having experienced massive growth since the 1990s. China's rapidly expanding economy and industrial developments have fostered numerous megacities. This urban growth has led to increased energy consumption, resulting in higher emissions of air pollutants and more frequent days of poor air quality in these cities (Chan & Yao 2008). He et al. (2001) reported that in two of China's largest cities, Beijing and Shanghai, concentrations of PM_{2.5} exceed the World Health Organization's guidelines by tenfold and sixfold, respectively. China's major cities exemplify how urban growth and industrial activities are driving severe air

quality issues, demanding robust governmental action (Chan & Yao 2008). Singapore’s response to the 2013 smoke haze caused by wildfires in Sumatra, Indonesia, provides a model of effective crisis management (Velasco & Rastan 2015). Singapore practiced transparent governance through making data public, which exemplifies proactive air quality and public health management. The full case study on Singapore and Sumatra can be found in Appendix A.2.

World organizations like the WHO, the United Nations, and the European Environment Agency have publicly responded and set out initiatives to target this worldwide issue (World Health Organization 2024a, European Environment Agency 2025, United Nations Environment Programme n.d.). The WHO advocates for policies across multiple sectors, including industry, transport, and urban planning. In the industrial sector, stakeholders’ direct efforts toward minimizing smokestack emissions by implementing cleaner technologies. For transportation, world organizations emphasize adopting clean energy sources and enhancing rapid urban transit systems. In urban development, initiatives focus on designing greener and more compact cities, thus increasing energy efficiency (World Health Organization 2024a).

The European Environment Agency supports the European Union’s Ambient Air Quality Directives, which establish standards for twelve pollutants aligned with the World Health Organization’s air quality guidelines (European Environment Agency 2025). This initiative encouraged the European Union to establish a network of over 4,000 air quality monitors across Europe, enabling reliable air quality data collection. Furthermore, the European Commission has introduced the Zero Pollution Action Plan, specifically targeting reductions in $PM_{2.5}$ concentrations to decrease the risk of premature deaths by 55% (European Commission n.d.).

Research has consistently shown that air pollution has serious impacts on both the physical and mental health of urban citizens (Kelly & Fussell 2015). Modern-day pollutants, such as PM_{10} and $PM_{2.5}$, which are ambient particulate matter particles with diameters of less than 10 μm and 2.5 μm respectively, are approximately 30 times narrower than human hair (Kelly & Fussell 2015). $PM_{2.5}$ particles, despite their microscopic diameters, have large surface areas. This enables them to carry a significant toxic load (Xing et al. 2016). These particles can bypass the body’s natural filters, making them easily inhalable and capable of reaching the lungs (Karagulian et al. 2015). PM primarily consists of sulfates, nitrates, ammonia, sodium chloride, black carbon, mineral dust, and water (World Health Organization 2021).

Karagulian et al. (2015) conducted a literature review on ambient particulate matter and identified the primary contributors to $PM_{2.5}$ emissions: 25% from traffic-related emissions such as exhaust and tire wear, 15% from industrial activities including oil combustion and coal burning in power plants, and 20% from domestic fuel burning as well as the cause of fires. Ambient particulate matter is considered the most reliable indicator of health risks associated with air pollution. The World Health Organization (WHO) reports that ambient air pollution in urban environments leads to elevated concentrations of fine ambient particulate matter, which in turn is associated with a higher prevalence of strokes, cardiovascular diseases, lung cancer, and both acute and chronic respiratory disorders (World Health Organization 2024a).

3.1.2 Air Quality Effect on Urban Mental Health

There is extensive research on the effects of polluted air on the physical health of urban citizens. Recently, however, a new and less explored area of study has emerged, focusing on the impacts of poor air quality on the urban mental wellbeing of urban citizens. Current literature has extensively examined the harmful consequences of poor air quality, particularly $PM_{2.5}$. These pollutants can lead to mortality from both short-term and long-term exposure (Brook et al. 2010).

Air pollution and particulate matter ($PM_{2.5}$) impact mental health through two key pathways: primary mechanisms, involving direct channels, and secondary mechanisms, encompassing indirect channels and adaptive responses. Research also considers human adaptive responses and the heterogeneous effects of air pollution on mental health. This overview can be seen in

Mechanisms of Impact: Air Pollution (PM_{2.5}) and Mental Wellbeing

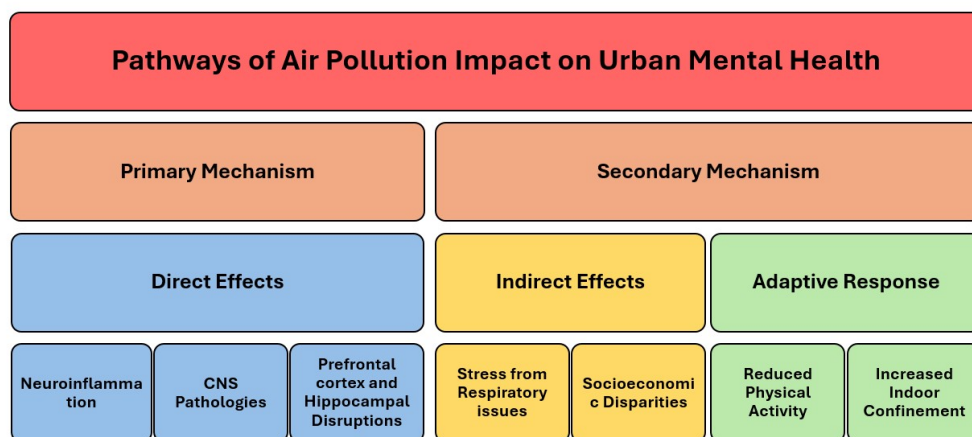


Figure 3.1: PM_{2.5} Exposure Pathways Affecting Mental Health

Figure 3.1, where we visualized the various pathways through which poor air pollution can affect urban mental health. This section explores the effects of air pollution, specifically PM_{2.5}, on urban mental health through various mechanisms and outlines the specific research findings that quantify these effects.

3.1.3 Direct Effects

The direct channels through which PM_{2.5} particles affect urban mental health are intrinsically connected to the biological and physiological responses of the human body. The effects of PM_{2.5} can be traced back to the cellular and molecular level, as they are found to be a mixture of solid particles and liquid droplets suspended in the air. Due to their miniature size, PM_{2.5} can travel through the respiratory systems, including the olfactory bulb, reaching critical areas of the body such as the lungs and vascular system, and impacting the brain. Specifically, the inhalation of these particles predominantly affects the brain and nervous system, thereby influencing mental health (Genc et al. 2012). This occurs through mechanisms such as oxidative stress and systemic inflammation, both of which are known to contribute significantly to mental health disorders like depression and anxiety. This section explores how PM_{2.5} directly influences the central nervous system, potentially leading to a variety of neurological and cognitive outcomes.

Current literature on environmental neurotoxicology (Genc et al. 2012, Gładka et al. 2018, Ventriglio et al. 2020, Yang et al. 2021a, Tzivian et al. 2015, Chen et al. 2018) relies on the findings of (Block & Calderón-Garcidueñas 2009, Calderón-Garcidueñas et al. 2015) to emphasize the direct detrimental effects of PM_{2.5} air pollution on human brain chemistry. PM_{2.5} particles affect mental health through two primary pathways. First, particles enter through the nasal pathway and reach the brain directly via the olfactory bulb, triggering neuroinflammation and oxidative stress (Genc et al. 2012). Second, particles enter through the lungs, causing respiratory inflammation that leads to systemic inflammation. This systemic response compromises the blood-brain barrier, allowing inflammatory agents to affect brain chemistry. Both pathways disrupt neural functioning and increase the risk of mental health disorders, including depression and anxiety (Gładka et al. 2018).

3.1.4 Indirect Channels and Adaptive Responses

Air pollution impacts urban mental health through direct biological effects and secondary mechanisms, including indirect channels and adaptive responses. Indirect channels involve the physiological and psychological consequences of pollution-induced conditions, including respiratory and cardiovascular illnesses, which heighten anxiety and stress symptoms (Power et al. 2015, Chen et al. 2018). Adaptive responses, on the other hand, refer to behavioral changes, such as reduced physical activity and increased indoor confinement, which can limit outdoor activities and social interaction, making urban residents more vulnerable to mental health issues (Currie et al. 2009, Taylor et al. 1985).

Indirect Channels

PM_{2.5} exposure is strongly associated with respiratory and cardiac conditions, which may act as intermediaries affecting mental health. Studies have found that symptoms like respiratory inflammation and cardiovascular stress can contribute to anxiety and stress (Power et al. 2015, Mehta et al. 2021). Dysfunctional breathing and impaired cardiac performance resulting from these conditions can lead to mental illness through physiological reactions, such as altered oxygenation, which worsens psychological distress (Chen et al. 2018). The fear, stress, and uncertainty surrounding air pollution's health effects can further contribute to mental health challenges. For example, individuals may experience heightened anxiety due to the misinterpretation of respiratory or cardiac symptoms as severe or life-threatening (Chen et al. 2018). These psychological responses to pollution-related stressors highlight how air pollution indirectly affects urban mental wellbeing, even in the absence of physical illness.

Adaptive Responses

Currie et al. (2009) finds that individuals limit their time outdoors during periods of high pollution, which reduces opportunities for outdoor exercise and other physical activities that help alleviate mental illness (Taylor et al. 1985, Glenister 1996, Beebe et al. 2005). This behavioral adjustment has measurable consequences. Chen et al. (2018) analysis reveals that a 1 µg/m³ increase in PM_{2.5} concentrations decreases the probability of exercising by 0.49%, or 1.05% of the mean. Similarly, exercise frequency decreases by 0.0068 times per week (0.28% of the mean), while weekly exercise duration drops by 0.0448 hours (1.33% of the mean). The reduction in physical activity not only limits physical health benefits but also negatively affects mental health. Physical exercise is a well-documented contributor to stress reduction and improved mood (Brenes 2003). When air pollution restricts access to outdoor spaces, it creates an additional barrier to maintaining mental wellbeing. These indirect effects highlight how air pollution deepens vulnerabilities in urban populations by limiting their physical and social coping mechanisms. However, the impact of air pollution is not uniformly experienced and varies significantly based on demographic, socioeconomic, and cultural factors.

3.1.5 Heterogeneous Impacts of Air Pollution on Mental Health

With the global rise of smart cities, each urban environment adapts to its unique blend of environmental, governmental, and cultural factors. These contextual variations result in diverse experiences of the effects of air pollution on urban citizens. According to Hu et al. (2021), the effects of such environmental disparities are highly disproportionate, shaped significantly by demographic factors and cultural differences. Hu et al. (2021) examined the varied impacts of air pollution on mental health across demographic and socioeconomic groups, using data from 51 countries spanning 2010 to 2017. The analysis revealed significant effects on depression, with the impact on happiness and anxiety varying according to income levels. Notably, factors such as income, education, and population density exacerbated these disparities. The findings also

indicate that while physical health mediates some effects, significant disparities persist. This reinforces the need for urgent, targeted public health policies to address these inequities.

Similarly, research by [Zhang et al. \(2017\)](#) reveals that air pollution’s impact on happiness and mental health varies by gender and age, with young adults experiencing more significant effects than older adults. The study attributes this disparity to several key factors including young adults being less accustomed to poor air quality, spending more time outdoors, and being more aware of air quality issues through widespread access to smartphones and the internet. The research ([Zhang et al. 2017](#)) further emphasizes that air pollution disproportionately affects vulnerable populations, including those with lower income, less education, and outdoor workers, who are more exposed. Wealthier individuals often mitigate the impact with measures like air purifiers, while individuals with limited education face harsher consequences.

Summary

Section 3.1 explores the impact of urban air quality on mental health in the context of smart cities. It highlights how increased urbanization, industrial activities, and vehicular emissions have worsened air pollution globally. Specific pollutants like $PM_{2.5}$ are emphasized for their adverse effects on both physical and mental health, contributing to disorders like depression and anxiety through direct biological mechanisms (e.g., neuroinflammation) and indirect pathways (e.g., stress from respiratory issues) ([Block & Calderón-Garcidueñas 2009](#)). Additionally, this section explains how demographic and socioeconomic factors influence the severity of the impacts of air pollution, highlighting the necessity of multi-faceted solutions in smart cities ([Hu et al. 2021](#)). Addressing these challenges requires a comprehensive and integrated approach that incorporates technological, infrastructural, and policy innovations.

This includes integrating IoT sensors and AI analytics that provide real-time data, enabling rapid decision-making for both policymakers and citizens ([Singh et al. 2021](#)). Implementing greenspaces, including urban forests and green roofs, reduces pollution and enhances urban quality of life ([Rowe 2011](#)). Furthermore, AI-driven traffic management systems adapt in real time to minimize congestion and vehicle emissions ([Bigazzi & Rouleau 2017](#)). Together, these innovative approaches contribute to enhancing urban sustainability and significantly improving the quality of life in smart cities. Research shows $PM_{2.5}$ affects anxiety and depression through two pathways: direct neuroinflammation and indirect effects like respiratory problems and reduced outdoor activity. $PM_{2.5}$ data offers continuous, real-time measurements from urban sensor networks, making it ideal for predictive modeling in this research.

3.2 Literature on Greenspaces

The concept of greenspaces as essential urban infrastructure has evolved significantly over a century. Frederick Law Olmsted, a landscape architect from the late 1800s and early 1900s, argued that urban green areas should give people access to nature’s benefits. He believed parks should be linked together and connected to the neighborhoods around them ([Csepely-Knorr 2010](#)). This foundational thinking gained renewed momentum when greenspaces began emerging as a formal concept in the late 1990s, with the “greenway movement” in North America bringing these ideas into focus for a wider range of professionals. Urban planners, landscape artists, environmental groups, ecologists, and politicians all began paying attention to this concept, with [Benedict & McMahon \(2002\)](#) work acting as catalysts for the expansion of greenspace planning ([Mell 2017](#)). During this period, greenways began to be understood to address the physical and psychological challenges that come with urbanization, including cultural and social pressures ([de Vries 2021](#)).

This evolution in understanding has led to the recognition that greenspaces is not just a luxury but a necessity in urban areas. Like other essential infrastructure, it requires proper planning, design, and funding ([de Vries 2021](#)). [McEwen \(2007\)](#) explains that “human beings

are prone to prolonged periods of elevated activity of the same systems which help us survive more acute challenges. This prolonged elevation may be due to anxiety; to constant exposure to adverse environments involving such irritants as noise, pollution, and interpersonal conflict; and to changes in lifestyle and health-related behaviors that result from being under chronic stress” (McEwen 2007). While urban environments and air pollution contribute to this chronic stress activation, research demonstrates that greenspaces can provide a counterbalance by triggering restorative biological responses that help regulate these overactive stress systems.

For this research, greenspaces refer to publicly accessible urban areas with significant vegetation coverage, including parks, gardens, tree-lined streets, urban forests, and recreational green areas. This definition excludes private gardens, golf courses, and other restricted-access green areas, focusing instead on spaces that contribute to community mental wellbeing through direct public use and visual exposure.

This section is organized as follows: Section 3.2.1 presents global smart cities initiatives and the global response to urban greenspace integration, explaining the different approaches of governmental institutes followed by case studies for a deeper understanding. This is followed by Section 3.2.2 the impacts of greenspace on mental health, describing the direct impact, which focuses on biological responses, and the indirect impact, which focuses on behavioral and social responses. Lastly, in Section 3.2.3 we examine the socioeconomic and demographic impacts that are seen in cities due to greenspace impacts.

3.2.1 Global Smart Cities Initiatives: Greenspaces and Urban Mental Wellbeing

As urban areas continue to expand, the strategic integration of greenspaces has become a vital element of smart city initiatives worldwide. Public greenspaces promote urban sustainability, public health, and urban wellbeing. The correlation between accessing urban public greenspace and improved mental health is well supported by extensive research. People visit parks for a variety of reasons, including physical activity, relaxation, and social interaction. These greenspaces provide opportunities for exercise, community gatherings, educational programs, and pet-friendly activities. Additionally, parks host both private and public events, fostering community engagement and cultural activities. By supporting a wide range of recreational activities, urban parks contribute significantly to the physical and mental wellbeing of urban citizens (Henderson 2013).

Parks not only serve as recreational spaces but also provide significant environmental benefits. They contribute to air and water purification, mitigate noise and wind pollution, and support biodiversity by offering habitats for various plant and animal species (Henderson 2013). Through these ecological functions, urban greenspaces play a crucial role in enhancing environmental sustainability while simultaneously improving the wellbeing of urban citizens. Studies by Douglas (2012), Nutsford et al. (2013), and Houlden et al. (2019) demonstrate that interaction with urban greenspaces fosters reduced stress, improved mood, and enhanced quality of life. Despite these well-documented benefits, urban greenspace development is often overshadowed by other priorities in urban planning (Torres et al. 2018). The rapid growth of urban populations, expected to reach 68% by 2050, further complicates this as densification policies can jeopardize greenspace development (The Global Goals n.d.). Studies show that in places like South and East Europe, urban greenspace development falls short of urban expansion, with significant losses reported between 2006 and 2012 (Aalbers et al. 2019).

Despite their known benefits for public health and social wellbeing, the provision and distribution of urban greenspaces remain inadequate in many cities, highlighting the need for more equitable distribution to enhance accessibility (Nesbitt et al. 2019). Cities demonstrate varied approaches to greenspace integration with different outcomes for urban mental wellbeing. Singapore, recognized as a “city in a garden,” has strategically maximized limited land area through small urban parks and extensive tree coverage, supported by significant government

investment (Sabri et al. 2023). In contrast, Amsterdam faces distribution inequities where immigrant and low-income communities often have fewer and lower-quality greenspaces, leading to poorer health outcomes (De Haas et al. 2021). To address these disparities, Amsterdam doubled its investment in green projects to €20 million, prioritizing urban nature as essential for public wellbeing. Cases like this have led world organizations to further develop global greenspace targets. Detailed discussion on Amsterdam and Singapore’s greenspace approach is detailed in Appendix A.4 and Appendix A.3.

The United Nations’ Target 11.7 aims for universal access to safe, inclusive, and accessible greenspaces by 2030 (The Global Goals n.d.). The WHO emphasizes the significance of integrating greenspaces into urban health strategies through a comprehensive 91-page report. The report covers greenspace metrics, physical and psychological advantages, socio-demographic impacts, and provides a toolkit for data analysis. This initiative targets public health specialists and policymakers by promoting systematic approaches to quantifying and monitoring urban greenspace access. As detailed in the report, it aims to support evidence-based decision-making to enhance urban health and sustainability through the integration of greenspaces (WHO Regional Office for Europe 2016).

The 2020 *World Happiness Report*, Chapter 5, titled “How Environmental Quality Affects Our Happiness,” explores the positive impacts of greenspaces on urban health, including mental wellbeing. It highlights direct effects, such as stress reduction, and indirect effects, like improved social interaction (Kaplan 2001). The report emphasizes that the visibility and accessibility of greenspaces significantly enhance urban residents’ happiness and health, demonstrating the critical role of environmental quality in greenspaces in promoting urban wellbeing. Global initiatives set by world organizations have significantly influenced individual countries to translate policies into practice.

3.2.2 Impact of Greenspace on Urban Mental Wellbeing

This section reviews methodological approaches used in recent literature to study the mental health impacts of greenspace in urban settings. It focuses on how researchers define and operationalize greenspace exposure, the tools, and data sources they employ, and the mechanisms they examine when linking greenspace to psychological outcomes. These methodological strategies form the foundation for the data-driven approach adopted in this thesis, as discussed in Chapter 4.

Greenspaces play a critical role in promoting urban mental wellbeing in cities. A growing body of evidence shows that access to and interaction with nature can reduce stress, anxiety, and depressive symptoms, while also fostering psychological resilience, emotional regulation, and overall wellbeing (Maas et al. 2009, Beyer et al. 2014, Bratman et al. 2015). These benefits have been observed across multiple demographic and socio-economic groups and are especially pronounced in densely populated cities with limited green infrastructure (Jennings et al. 2017, Maas et al. 2009, WHO Regional Office for Europe 2016, Kabisch et al. 2015).

In exploring the relationship between greenspace and urban mental health, researchers have used a wide variety of methodological approaches. These range from satellite-derived indices of vegetation coverage to network-based proximity models, to subjective assessments of green space quality (Gascon et al. 2018, de Vries 2021, Houlden et al. 2019, WHO Regional Office for Europe 2016). Outcomes have also varied, from self-reported stress and depression to biological markers and even neuroimaging data (Bratman et al. 2015). Understanding these methodologies is essential not only for interpreting the current literature but also for situating the methodological choices made in this research.

Biological and Psychological Mechanisms

Direct Effects

Exposure and interaction with greenspaces can have a direct impact on the mental wellbeing of a person. Direct impact measures the biological impact it has on a person's brain and body. [Ulrich et al. \(1991\)](#) psychoevolutionary model proposes that greenspaces trigger immediate, unconsciously initiated physiological responses that aid in stress recovery. In a study from 1991, [Ulrich et al. \(1991\)](#) measured how quickly people recovered from stress after viewing a stressor film, comparing recovery in natural versus urban environments. Using physiological measurements, the study demonstrated that stress recovery was quicker in natural environments, occurring within 5–7 minutes, while urban settings never achieved full recovery. [Ulrich et al. \(1991\)](#)'s research demonstrates a connection between greenspace exposure and better urban mental wellbeing.

Taking this as a foundation, and base research, [Ward Thompson et al. \(2012\)](#) expanded on this research by examining the biological effects via psychoneuroendocrine mechanisms, a study that explains how psychological experiences affect the nervous system and hormone endocrine systems, and how these biological responses can result in changes in behavior and mental health. Within psychoneuroendocrine mechanisms, focus is placed on the hypothalamic–pituitary–adrenal axis (HPA), a complex neuroendocrine system comprising the hypothalamus, pituitary gland, and adrenal glands. This system acts as a bridge between the brain and the body's hormone production. This system regulates cortisol secretion and controls stress responses, along with multiple body processes including digestion, immune responses, mood, and energy storage ([McEwen 2007](#)). Dysregulation of the HPA axis is associated with a range of disease outcomes ([McEwen 2007](#)) and can manifest in various mental health problems.

Research ([Ward Thompson et al. 2012](#)) demonstrates that both elevated levels of cortisol and abnormally low levels of cortisol, known as hypocortisolemia, can lead to depression. The key factor is maintaining a balanced cortisol level and avoiding disruption of the normal diurnal cortisol pattern, the healthy rhythm where cortisol is high in the mornings, up to 20 nmol/l, and naturally declines throughout the day down to 1 nmol/l while sleeping ([Ward Thompson et al. 2012](#)). When this cortisol slope becomes flat, whether at high or low levels, it signifies HPA axis dysfunction. This dysfunction creates chronic stress, which increases the risk for mental health disorders such as depression and post-traumatic stress disorder (PTSD) ([Ward Thompson et al. 2012](#)). Greenspace exposure directly modulates the HPA axis stress response system, resulting in healthier cortisol rhythms and improved stress resilience ([Herman et al. 2016](#), [Ward Thompson et al. 2012](#)). This biological pathway demonstrates how environmental factors create measurable physiological changes that can be monitored through urban data systems.

In a study in 2012, [Ward Thompson et al. \(2012\)](#) used cortisol as a biomarker of stress since it shows sensitivity to activities in natural environments. In contrast to other controlled studies, [Ward Thompson et al. \(2012\)](#) examined cortisol patterns throughout the day for people in their normal daily routines. They measured diurnal cortisol patterns because these daily rhythms provide a more realistic picture of chronic stress than single-point measurements, showing how environmental stressors affect people over time in their everyday lives. The study ([Ward Thompson et al. 2012](#)) also used the wellbeing score (SWEMWBS) to measure physical activity.

From the 25 participants in the study, the percentage of greenspace varied by postcode and ranged from 14% to 74%. The results show that people living in areas with a higher percentage of greenspace have better cortisol patterns throughout the day. This demonstrates a significant positive correlation between cortisol slope and the percentage of greenspace [Ward Thompson et al. \(2012\)](#). Specifically, the results show that with every 1% increase of greenspace, cortisol slope increases by 0.07%, that promotes a steeper slope which is linked to healthier stress regulation. The study also found a significant negative correlation between self-reported stress and greenspace percentage, indicating that for every 1% increase in greenspace percentage, self-reported stress decreased by 0.14 units ([Ward Thompson et al. 2012](#)). Additionally, there was a positive correlation between cortisol slope and wellbeing scores, demonstrating that healthier cortisol patterns were linked to better overall wellbeing. Participants with less greenspace

access showed flatter cortisol slopes, indicating HPA axis dysfunction like patterns seen in chronic stress conditions. In contrast, participants living in areas with higher percentages of greenspace showed steeper cortisol slopes, suggesting they were more resilient to the negative effects of urban deprivation and stress (Ward Thompson et al. 2012).

Neuroimaging studies (Bratman et al. 2015) have identified specific brain regions where greenspace exposure creates measurable changes in neural activity. Bratman et al. (2015) conducted a randomized controlled trial using functional magnetic resonance imaging (fMRI) to examine how nature exposure affects brain function in 38 healthy urban residents. Participants were assigned to take 90-minute walks through either a natural grassland-and-oak park or along a busy urban street, with brain activity measured using arterial spin labeling before and after exposure. The results revealed that participants who walked in nature showed significantly decreased neural activity in the subgenual prefrontal cortex (sgPFC), measured via cerebral blood flow changes (Bratman et al. 2015). The sgPFC is a critical brain region connected to depression, rumination, and maladaptive self-referential thinking patterns. Participants who took the urban route did not show such neural changes, with sgPFC activity remaining elevated. Accompanying psychological measures confirmed that nature walkers also reported reduced rumination scores, establishing both objective neural and subjective psychological changes (Bratman et al. 2015).

The sgPFC connects directly to the HPA axis through established neural pathways linking prefrontal regions to hypothalamic stress centers (Urry et al. 2006). Hyperactivity in this region contributes to HPA axis dysregulation and abnormal cortisol patterns observed in depression. These neuroimaging findings suggest that nature exposure helps regulate this unstable brain region, potentially interrupting the cycle of rumination and stress hormone dysregulation identified in the Ward Thompson et al. (2012) cortisol studies. Supporting evidence from Sudimac et al. (2022) demonstrates that one-hour nature walks also decreased amygdala activity using a similar fMRI methodology. The coordinated changes across sgPFC and amygdala regions suggest that greenspace exposure creates systematic modifications in interconnected brain networks involved in stress processing and emotional regulation (Bratman et al. 2015).

Indirect Effects

While direct biological pathways demonstrate immediate physiological responses to greenspace exposure, indirect mechanisms explain how greenspaces influence mental health through behavioral and social changes. Research identifies three primary indirect pathways: physical activity promotion, social cohesion enhancement, and environmental buffering effects (Gascon et al. 2016, de Vries 2021).

Physical Activity

Urban residents who are living near greenspaces feel more encouraged to do physical activity, which can help improve mental health. A study conducted by van den Berg et al. (2017) found that longer time spent in greenspaces increases outdoor activity and improves mental health by lowering stress. Greenspaces provide accessible venues for exercise, walking, cycling, and recreational activities without requiring paid facilities or distant travel (de Vries 2021). White et al. (2019) demonstrated that spending at least 120 minutes per week in nature was significantly associated with better health and wellbeing. Physical activity in greenspaces triggers endorphin release, reduces cortisol levels, and promotes neuroplasticity in brain regions associated with mood regulation, creating a pathway to the direct HPA axis effects described earlier (Gascon et al. 2016).

Social Cohesion and Community Connection

Greenspaces serve as natural gathering places that foster social interactions and strengthen community bonds. Maas et al. (2009) found that people living in areas with less greenspace

reported increased feelings of loneliness and perceived shortage of social support. The research shows that social interactions in greenspaces contribute to these mental health benefits. [Kuo \(2015\)](#) demonstrated that greenspace enhances social cohesion, which improves mental health. [Sugiyama et al. \(2008\)](#) showed that perceived greenness was linked to better mental health, with social interactions helping explain this connection. [Peters et al. \(2010\)](#) found that urban parks actively stimulate social cohesion by providing meeting opportunities that help build local communities and neighborhood connections.

Environmental Buffering Effects

Greenspaces provide environmental benefits that indirectly support mental health by reducing urban stressors. Trees and vegetation filter air pollutants, reduce noise levels, moderate temperature extremes, and create more pleasant sensory environments ([Alvarsson et al. 2010](#)). These environmental improvements reduce the chronic stress that comes with urban living. [Kardan et al. \(2015\)](#) found that higher tree canopy coverage was associated with fewer antidepressant prescriptions, independent of income and education levels, suggesting that environmental buffering contributes to mental health beyond socioeconomic factors.

Greenspace Measurement Approaches

Current research identifies several methodological approaches for measuring greenspace exposure in urban environments. These approaches are categorized into four main types: availability, access and proximity, visibility, and perceived quality ([Gascon et al. 2018](#)). Each measurement strategy offers a distinct lens to examine the relationship between urban greenspace and mental health outcomes.

These exposure types are not mutually exclusive; they are often used in combination and are chosen based on the availability of data, the scale of the study, and the research question being addressed. In the literature, these greenspace metrics are frequently linked to specific mental health outcomes such as depression, anxiety, stress, or mental wellbeing through a variety of behavioral pathways including stress reduction, physical activity, social cohesion, and environmental buffering. The following subsections provide an overview of each measurement category and its role in greenspace and mental health research.

a. Availability Availability is defined as the percentage of greenspace in each area or neighborhood in a city. This is typically measured using the Normalized Difference Vegetation Index (NDVI), based on how vegetation reflects red and near-infrared light differently than other surfaces ([Weier & Herring 2000](#)). NDVI is commonly used to measure green availability around residential addresses within specific buffer zones, such as 100 m, 300 m, or 500 m ([Labib et al. 2020](#)). This ties in with the use of buffer zones more broadly, where researchers define a central point—most commonly a residential postcode or the center of a neighborhood—and calculate the total square meters of greenspace within that radius ([Houlden et al. 2019](#)). Some studies also use Urban Tree Canopy (UTC) as an alternative to NDVI. Instead of measuring the percentage of all vegetation, tree canopy analysis focuses specifically on the percentage of land area covered by trees ([Kardan et al. 2015](#)).

These methods rely on spatial data and are typically analyzed using GIS, remote sensing, or satellite imagery. This approach makes it possible to consistently measure greenspace across large cities over time. However, availability alone does not guarantee accessibility or quality, which are explored in the next subsections.

b. Access and Proximity The access and proximity method measures the distance from a given point in space, commonly a residential address or the center of a buffer within a neighborhood, to the nearest greenspace. This distance is calculated using either Euclidean

distance (a straight-line measure) or network-based distance, which considers the actual layout of roads and walking paths (Labib et al. 2020). Researchers often use buffer zones such as 100 m, 300 m, or 500 m to estimate how much greenspace exists within a person’s immediate surroundings (Labib et al. 2020, Nutsford et al. 2013).

In addition to buffer zones, some studies use set distance thresholds, such as 300 m or 3 km, to represent a practical walking distance from a residence to a greenspace (Nutsford et al. 2013). This approach relies on spatial and quantitative data and is usually implemented using GIS tools. It considers the effort required by urban residents to physically access greenspaces and reflects a more functional understanding of how greenspace exposure occurs in daily life.

Research by Gascon et al. (2018) provides important evidence for optimal buffer distances in greenspace connections to mental health and wellbeing. Their systematic review found that greenspace within 300 m [OR (95% CI) = 0.83 (0.67, 1.03)] was associated with 17% reduced odds of self-reported mental health disorders or medication use, while 500 m buffers [OR (95% CI) = 0.84 (0.69, 1.04)] showed 16% reduced odds. Both distances demonstrated protective effects that were almost statistically significant, indicating consistent mental health benefits from accessible greenspace. While the study clarifies that there is no preference between the 300 m buffer versus the 500 m buffer, both buffers show evidence of significant wellbeing benefits. Gascon et al. (2018) buffer distance findings provide evidence-based parameters for greenspace proximity analysis, making them ideal for spatial modeling as described in Chapters 5 and 6. Meta-analyses indicate that greenspace exposure is associated with lower physiological stress, reflected in a statistically significant reduction in salivary cortisol levels (−0.06, 95% CI: −0.07 to −0.04). This biomarker evidence suggests that greenspace may improve population wellbeing through stress-buffering mechanisms, complementing epidemiological findings on reduced odds of chronic disease (Twohig-Bennett & Jones 2018).

c. Visibility The visibility of greenspace is the citizen’s experience of perceiving or seeing greenery, regardless of physical accessibility or use. Compared to accessibility and availability, visibility focuses on the visual experience of greenspaces, what urban residents see from their homes, workplaces, or as they pass by during daily life (Labib et al. 2020). This form of exposure can create a sense of connection to nature even without physical contact. Researchers such as Beyer et al. (2014) measure visibility through a combination of NDVI values and self-reported perceptions of neighborhood greenness. Their study found that higher perceived greenness was associated with lower levels of depression and stress, with particularly strong effects among women.

Furthermore, Larkin & Hystad (2019) introduced the Green View Index (GVI), derived from Google Street View images, to quantify visible greenspace at eye level. This street-level approach is considered more representative of everyday human experience compared to top-down satellite data. Larkin & Hystad (2019) also proposed the GVI:NDVI ratio to quantify the proportion of vertical greenspace, such as tree coverage, offering more detailed insight into the types of greenery people are exposed to (Larkin & Hystad 2019). Recent studies suggest that daily visual exposure to nature, even without direct interaction, contributes positively to mental health by promoting psychological restoration, reducing stress, and enhancing subjective wellbeing. This perspective helps frame greenspace as a multisensory, layered experience embedded in urban life (Neale et al. 2021).

d. Perceived Quality Perceived quality refers to the subjective evaluation by residents on their experience in greenspaces, based on factors such as maintenance, safety, usability, and aesthetic appeal. This approach captures the lived experience of urban residents and how they emotionally or practically engage with green areas. This type of measurement is typically collected through resident surveys or community audits, focusing on elements like cleanliness, lighting, safety, and overall comfort (Labib et al. 2020). Although subjective, perceived quality is increasingly recognized as critical for understanding greenspace’s role in promoting mental

and physical wellbeing. This is particularly relevant in cases where spaces are technically available but underutilized due to neglect or perceived risk.

Researchers often integrate subjective perceptions with objective indicators (e.g., GIS-based land use, NDVI) to build a more realistic picture of greenspace impact. For example, [Cleary et al. \(2019\)](#) found that changes in perceptions of greenspace significantly affect improvements in mental wellbeing over time. Similarly, [Wang et al. \(2019\)](#) reported that perceived greenspace quality, particularly in terms of safety, recreational usability, and aesthetics, had stronger associations with mental health than greenspace quantity. This highlights the vital role of lived experience in greenspace utility.

3.2.3 Heterogeneous Impacts of Greenspace on Mental Health

The importance of greenspaces in urban cities is recognized by many lawmakers, urban planners, and governments. With growing bodies of research focusing on the effects of greenspace on urban citizens, smart cities have started to find accessible ways for their urban residents to be able to experience greenspaces. However, in most cases a smart city is only an extension of an already established city. This means that there are districts, neighborhoods, and people who have different experiences depending on where they live in the city. Some urban citizens have greater benefits than others, depending on socioeconomic background, race, ethnicity, gender, and age.

In the context of urban greenspaces in smart cities, research by [Browning & Rigolon \(2018\)](#) has found that there is significant variation in greenspace benefits across different populations. Their analysis of 496 U.S. cities revealed that income, race, and ethnicity significantly influence the greenspace-mental health relationship, with low-income communities and communities of color experiencing both reduced access to quality greenspaces and diminished health benefits when access is available. Additionally, research by [Huang et al. \(2023\)](#) found that factors such as income, education, and neighborhood characteristics make these disparities worse.

A study by [Heo & Bell \(2023\)](#) shows that areas with higher percentages of low-income and lower-education populations had reduced access to most types of greenspaces, with some metrics showing decreases of up to 7.3% in greenspace availability as socioeconomic disadvantage increased. Similarly, research reveals that greenspace impacts vary by gender. [Roe et al. \(2013\)](#) conducted a cortisol study in deprived Scottish communities, comparing women and men's stress responses to greenspace. In low-percentage greenspace neighborhoods, women experienced significantly more chronic stress than men, showing hypocortisolemia with low and flat cortisol slopes throughout the day. In high greenspace neighborhoods, these gender disparities disappeared. [Roe et al. \(2013\)](#) explain: "High green space levels therefore appear to offer some degree of stress buffering in this socially disadvantaged population, reducing or moderating the differences in stress levels perceived in men and women compared with those living with low green space." ([Roe et al. 2013](#))

These disparities show that creating more greenspaces is not enough. Governments, urban planners, and policymakers must ensure that greenspace benefits reach all urban residents, regardless of income, race, gender, or neighborhood. Without addressing these inequities, greenspace initiatives may worsen existing health disparities instead of reducing them.

Summary

Section 3.2.2 explores the impact of greenspaces on urban mental wellbeing in the context of smart cities. The rapid growth of urban populations, expected to reach 68% by 2050, has led to higher densification that affects greenspace integration. Despite well-documented benefits for public health and urban mental wellbeing, many cities still lack adequate greenspace provision and equitable distribution ([Bratman et al. 2019](#)). This creates accessibility challenges that prevent all urban residents from benefiting equally from greenspaces, which conflicts with the

United Nations' Target 11.7 ([The Global Goals n.d.](#)) goal of universal access to safe, inclusive greenspaces by 2030.

Research demonstrates that greenspace accessibility and availability can significantly improve urban mental wellbeing by reducing depression, stress, and rumination through both direct biological pathways and indirect behavioral mechanisms. The evidence shows measurable effects on cortisol regulation, neural activity, physical activity levels, and social cohesion ([Ward Thompson et al. 2012](#)). However, demographic and socioeconomic factors create unequal access patterns, with low-income communities and communities of color experiencing reduced benefits ([Huang et al. 2023](#)). This reinforces the need for comprehensive, equitable greenspace policies that consider both quantity and quality in smart city planning approaches.

3.3 Literature on Mobility

In just over a century, global vehicle production grew from 181,000 in 1910 to 94 million in 2023, while urban populations surged past 50% globally ([Mirovic et al. 2024](#)). This rapid transformation created transportation systems optimized for vehicle efficiency rather than human experience, causing significant decline in urban wellbeing for citizens through congestion, unreliable service, and safety concerns. Today, only 49.5% of urban residents worldwide have convenient access to public transport, highlighting mobility inequities that directly impact urban mental wellbeing ([United Nations 2021](#)). With growing recognition that traditional approaches are insufficient, cities are shifting toward smart mobility in response to these challenges. In this context, mobility refers to the forms urban citizens travel through a city, such as active modes like cycling and walking, public transit networks, and vehicle-based transportation. Smart mobility is widely recognized as a core pillar of smart city development ([Albino et al. 2015](#)).

Depending on the context, researchers have shared distinct definitions of smart mobility. [Albino et al. \(2015\)](#) describe Smart Mobility as “the use of Information and Communication Technology in modern transport technologies to improve urban traffic,” while the [Eurostat \(Statistical Office of the European Communities\) \(2025\)](#) defines smart mobility as “an agglomeration of diverse technologies that enhance the sustainability of transport systems in a safer, smarter, and greener way.” ([Nam & Pardo 2011](#)) emphasize human connection through “technologies, people, and community,” where smart mobility connects “ICT and urban people.” One common description of smart mobility is the integration of information and communication technologies (ICT) with traditional transportation systems. A common goal for smart mobility is to improve commute time and reduce emissions while improving user experience ([Salcedo 2024](#)). Smart mobility prioritizes public transportation options but requires systems to be affordable, efficient, and accessible ([Salcedo 2024](#)).

Within the concept of smart mobility, [Biyık et al. \(2021\)](#) propose four core components as the definition. The first core component is Intelligent Transport Systems (ITS), which integrate advanced interconnected communication and information technology into transportation infrastructure for data collection, storage, and processing. This allows experts to plan and integrate smart mobility policies and initiatives. The second core component of smart mobility is open data and open-source technology, referring to data that is freely available for the public to access, use, and share alongside open-source software ready for public use. This allows for mass data collection and analysis to study real-time transit connectivity. Valuable knowledge can be retrieved from the process of open data that aids policymaking and decision-making. The third core component of smart mobility is big-data applications, where visualization and trend analysis are used to address commuters' needs and wellbeing by monitoring traffic control and delays. Big data applications in mobility have provided solutions for traffic control and routing. The final and fourth core component of smart mobility proposed by [Biyık et al. \(2021\)](#) is citizen engagement, promoting the inclusion of urban citizens' input and experience to empower relevant decision-making. This creates an opportunity to promote community governance within

cities and neighborhoods with a significant impact on decision-making and urban planning. However, citizen engagement is still considered expensive, time-consuming, and complicated.

Innovative smart frameworks are needed to measure urban wellbeing and smart mobility for smart cities. [Biancuzzi et al. \(2024\)](#) explain that smart mobility creates value across six key dimensions: flexibility and efficiency, sustainability, safety, satisfaction, image, and addressing implementation problems ([Biancuzzi et al. 2024](#)). Notable smart mobility applications include street light control systems, smart parking solutions, and intelligent road traffic management systems ([Faria et al. 2017](#)). Quantitative research by [Garau et al. \(2016\)](#) demonstrates that smart mobility performance can be measured through six key variables: public transport systems, cycle lanes, bike sharing, car sharing, private mobility support systems, and public transport support systems ([Garau et al. 2016](#)). Cities with multi-mode transportation options and high implementation of technology consistently score better in smart mobility performance ([Garau et al. 2016](#)). The mental health implications of smart mobility extend beyond efficiency improvements. Focusing on addressing mobility challenges such as congestion, time delays, and inconsistency, smart mobility can be a solution to transportation-related stress ([Novaco et al. 1990](#)). However, implementation differs dramatically across urban contexts, creating varied outcomes depending on technological capacity, infrastructure investment, and cultural integration.

The following section is organized as follows: First, Section [3.3.1](#) smart mobility initiatives are presented on a global scale, outlining solutions from cities, governments, and research institutions. Section [3.3.2](#) the impact of mobility on urban wellbeing is analyzed through primary and secondary pathways describing the immediate physiological and psychological effects and indirect impacts through behavioral and social changes. Lastly, heterogeneous impacts of mobility across populations are examined to reveal how transportation inequities affect various socioeconomic and demographic groups of urban citizens.

3.3.1 Global Smart Cities Initiatives: Smart Mobility Solutions for Urban Wellbeing

In Britain, the average worker spends over 139 hours per year commuting, equivalent to 19 standard working days ([Lyons & Chatterjee 2008](#)). Urban citizens invest valuable time in transportation, with direct implications for work-life balance and overall wellbeing. Cities are facing immense pressure to integrate smart mobility systems to combat logistical and social challenges, while also considering negative environmental and wellbeing impacts ([Müller-Eie & Kosmidis 2023](#)). Mobility can have a significant impact on urban wellbeing by generating higher risk in stress, depression, and declining quality of life. Only 50% of urban citizens have access to public transportation ([Barrington-Leigh 2020](#)), creating mobility inequities that directly impact urban mental wellbeing through increased stress and social isolation. Cities worldwide recognize the importance of smart mobility in smart city development, implementing sensor networks to monitor traffic flows, optimize route efficiency, and reduce commuting impedance ([Nam & Pardo 2011](#)). The United Nations set in motion international mobility initiatives through establishing the UN Sustainable Development Goal 11.2 ([The Global Goals n.d.](#)), which aims to provide “access to safe, affordable, accessible and sustainable transport systems for all” by 2030. This UN goal considers vulnerable citizens such as women, children, persons with disabilities, and the elderly. The United Nations recognizes that sustainable transport promotes economic growth and environmental protection, positively impacting social equity, health, resilience of cities, and urban-rural links.

The European Union has set forward this initiative through the 2024 TEN-T Regulation, requiring 431 urban nodes to adopt Sustainable Urban Mobility Plans by 2027 ([European Parliament and of the Council 2024](#)) that prioritize quality of life while maintaining efficiency metrics. To ensure that the goals are met, the TEN-T Regulation mandates consistent data collection on urban mobility indicators. This policy framework recognizes that sustainable

mobility systems must be safe, accessible, inclusive, and affordable. The European Commission supports the integration of urban wellbeing considerations into smart city mobility planning (Eurostat (Statistical Office of the European Communities) 2025). Cities and companies across Europe and North America are implementing diverse smart mobility initiatives that demonstrate their focus on urban wellbeing. IBM’s smart mobility partnership with Dublin uses innovative methods to analyze urban traffic through the STAR-CITY (Semantic Traffic Analytics and Reasoning for CITY) platform (Lecue et al. 2014). This platform aggregates heterogeneous real-time data from static or dynamic sensors and delivers contextual analysis, diagnosis, exploration, and prediction of traffic anomalies (Lecue et al. 2014). STAR-CITY generates semantic data that identify “congested segments” and “unusual vehicle delays,” allowing proactive decision-making that reduces commuting impedance and the risk of stress. STAR-CITY’s success in Dublin led to deployment across four cities: Bologna, Miami, and Rio de Janeiro, supporting that STAR-CITY is scalable to any city within sensor data contexts. Similarly, SmartSantander in Santander, Spain provides one of the most comprehensive examples, deploying IoT sensors across urban scenarios including traffic monitoring, environmental sensing, and public transportation, with mobility support through devices on buses and citizen smartphones for participatory sensing (Sanchez et al. 2014).

In Canada, the iCity project¹ at the University of Toronto demonstrates a smart city initiative that focuses on urban mobility analytics, integrating large-scale data from traffic patterns, public transportation usage, and travel behavior to better assist transportation infrastructure decisions. These initiatives illustrate how cities are focusing on making mobility efficient and sustainable. Global mobility initiatives demonstrate varied outcomes depending on infrastructure investment and governance stability. Tokyo’s systematic development over decades, including 500 billion Yen in rail infrastructure and real-time traffic management systems, creates predictable, reliable transportation that reduces commuting stress (Wolniak & Grebski 2023). Mexico City, despite implementing innovative solutions like ECOBICI bike-share and integrated mobility apps, faces infrastructure challenges where only 9% of Metro budget goes to maintenance, creating the uncertainty and delays that trigger stress responses (Salcedo 2024). This infrastructure disparity illustrates that technological solutions alone cannot guarantee mental health benefits, underscoring that smart mobility requires sustained investment and stable governance to create the predictable systems that support urban wellbeing. Detailed case exploration of Mexico City can be found in Appendix A.5.

While these initiatives bring benefits like predictability and operational optimization, they do not show that the urban wellbeing of citizens is ensured. When efficiency is prioritized over urban wellbeing, the quality of life of citizens is compromised. Cities must design transportation systems that support urban mental wellbeing alongside operational efficiency, ensuring that daily mobility experiences enhance rather than diminish citizen mental health. Balancing technological innovation and citizen wellbeing in smart mobility highlights a critical challenge in smart city development, requiring new methods that integrate citizens’ mental health considerations into mobility planning and data analysis.

3.3.2 Impact of Mobility on Urban Mental Wellbeing

The researcher Novaco et al., led one of the first empirical studies to consider commuting as an environmental stressor through the community psychology lens. In 1979, Novaco et al. introduced the *commuting impedance theory*, a foundational framework connecting commuting behavior with mental health (later cited by Wang et al. 2019). The impedance theory explains the difficulty people experience moving between their origin and destination. This framework aims to quantify commuting “difficulty,” where the degree of impedance is defined by both commuting distance and time measured between origin and destination. When urban residents repeatedly encounter barriers such as delayed public transit, traffic congestion, or inadequate

¹<http://icity.utoronto.ca/>

infrastructure, these daily frustrations accumulate into chronic stress patterns that trigger the same HPA axis dysfunction observed in other urban stressors.

The [Novaco et al. \(1979\)](#) study examined 100 industrial workers and measured stress effects across three domains: physiological responses including blood pressure and heart rate, psychological outcomes through mood scales measuring tension, irritability, and impatience, and behavioral effects through cognitive task performance using digit-symbol tests and puzzle-solving to assess frustration tolerance. The results demonstrate a linear dose-response relationship between higher impedance and higher blood pressure, negative mood, and reduced frustration tolerance. In 1990, [Novaco et al. \(1990\)](#) expanded the impedance theory by introducing two dimensions of commuting stress: physical impedance (PI) measures distance and time of the commute, and subjective impedance (SI) measures the perceived commuting constraints through a 17-item questionnaire. Physical and subjective impedance showed overlapping but distinct effects. PI predicted physical health and job satisfaction; SI affected the evening's home mood satisfaction. The study brought a new advancement demonstrating that people's perception of their commute (SI) does not always equal objective conditions (PI). Some drivers in objectively difficult conditions reported low stress, while others in easy conditions experienced high stress. This 1990 study supports both direct and indirect pathways through which mobility impacts urban mental wellbeing.

Almost twenty years later, [Novaco & Gonzalez \(2009\)](#) further developed the impedance theory by examining multiple stress mechanisms: perceived control, predictability and variability, time urgency, and loss of autonomy. These stress dimensions demonstrated that mental health impacts manifest through commuting-related stress, causing mood disturbance, irritability, fatigue, and lower psychological wellbeing. Longer and more congested commutes affect physical health through higher blood pressure and elevated cortisol levels. Both physical and subjective impedance create stress through the frustration of failing to achieve the task. This chronic stress and emotional strain impair concentration and memory retention while increasing accident risk. The 2011 study revealed that under specific conditions such as quiet routes and reduced congestion, commuting can serve a restorative purpose. Some commuters reported that structured commute time provides a transitional buffer between work and family settings. The authors argued for including mental health considerations in urban transportation policy, moving beyond economic efficiency toward urban wellbeing priorities.

[Novaco et al. \(1979\)](#) established the foundation for measuring commuting and mobility impacts on urban mental wellbeing. Various recent mobility researchers have applied [Novaco et al. \(1990\)](#) impedance theory to explore deeper connections between transportation and psychological outcomes. This section examines the primary mechanism through direct channels showing how commuting physiologically affects urban citizens, and the secondary mechanism through indirect channels demonstrating how commuting impacts behavioral patterns and lifestyle factors.

Primary Mechanism: Direct Channels

There are direct pathways through which mobility can affect the urban wellbeing of a citizen, causing direct and immediate effects on physiological and psychological responses in the human body. [Wang et al. \(2019\)](#) examined eleven Latin American cities and the total commuting time across all commuting modes. The research concludes that every ten additional minutes of commuting time across all modes causes a 0.5% higher probability of depression. Lack of transit stops within a ten-minute walk from home creates measurable increases in depression risk. These precise relationships provide the foundation for developing predictive models that can identify areas where transportation improvements would yield the greatest mental health benefits. Additionally, [Wang et al. \(2019\)](#) found that unpredictable delay, rather than predictable congestion, results in a 0.8% higher probability of screening positively for depression every ten additional minutes of traffic delay. The unpredictable delays and loss of control activate stress

response through the frustration pathway described in the impedance theory (Novaco et al. 1979), where mental stress is caused by the feeling of failing to achieve expected travel time.

A different study by Chen et al. (2024) examined burnout risk in Taiwanese healthcare workers across various commuting times. The results revealed a critical threshold: healthcare workers commuting over 50 minutes scored 4.21 points higher on the burnout scale compared to those with shorter commutes ($B = 4.21$, $p = 0.015$). This 50-minute threshold represents a tipping point in which commuting transitions from manageable daily stress to chronic exhaustion. Notably, the study also found that short commutes between ten to forty minutes showed a protective effect against work-related burnout, suggesting that brief travel periods may provide beneficial transition time between home and work. In the context of extreme commuting time, research by Lyons & Chatterjee (2008) reveals that one in twenty-five workers commutes over 100 km and one in ten workers commutes over two hours daily. This can be considered extreme commuting. This further adds to the risk of chronic stress and declining urban wellbeing.

A study by Evans & Wener (2006) examined the physiological stress rail commuters face during long-distance travel. The study compared salivary cortisol levels at the end of morning commutes versus weekend baseline measurements, finding significant cortisol elevations ($B = 0.010$, $p < .01$). This provides direct evidence that commuting duration activates the HPA axis through the same biological pathways observed in air pollution and reduced greenspace exposure. In this research, Evans & Wener (2006) identified a linear dose-response relationship, demonstrating that stress increases consistently from 45 to 180 minutes of commuting. Every minute of commuting adds to the stress burden. Additionally, Evans & Wener (2006) observed a decline in motivation after the morning commute, finding poorer task persistence, which is defined as the “spillover effect.”

Indirect Effects

Mobility impacts mental health through secondary mechanisms, where transportation patterns create indirect changes in physical health, social connections, and behaviors that subsequently affect urban mental wellbeing. The physical manifestations of commuting patterns are noted in research by Chen et al. (2024), where neck and shoulder pain serve as a significant mediating factor between long rail commuting times over 50 minutes, representing 19.48% of residual effects. Furthermore, healthcare workers that commute more than 50 minutes are at high risk of developing musculoskeletal pain.

In a systematic review, Norgate et al. (2020) identified multiple indirect health impacts among public transport commuters, including reduced sleep quality, increased sickness rates, and self-rated health complaints. While these physical impacts accumulate, transportation also affects health through activity levels. The study from Saleh (2024) confirms that compared to driving, public transportation increases physical and cognitive health through physical activity, noting that over two-thirds of riders walk to their public transit stops. Yet, physical activity does not fully cover the remaining negative impacts of commuting. Research on cycling for transportation (Ma et al. 2021) found that “physical activity level does not fully mediate the effects,” indicating that sustainable transport modes provide additional mental health benefits through greenspace exposure and reduced driving stress. However, these benefits are at risk if commuters are exposed to air pollution and social isolation that induce chronic stress. Supporting the importance of commute quality, van Hooff (2015) found that workers who encountered stressful delays showed impaired recovery status regardless of commuting time. This is tied to the impedance theory (Novaco et al. 1979) and the spillover effect, extending the consequences beyond the commute itself. This creates a cycle of accumulating stress, depriving workers of adequate recovery and mental health resources.

3.3.3 Heterogeneous Impacts of Mobility on Mental Health

Mobility impacts vary dramatically across populations, with some groups experiencing disproportionate mental health burdens from transportation stress. The strongest evidence points to gender disparities. [Feng & Boyle \(2014\)](#) report that 26% of women experience distress in commutes over one hour compared to 17% of men. This discrepancy persists in shorter commutes under 30 minutes, where 21% of women report distress compared to 14% of men. These effects amplify dramatically when considering family responsibilities. Women with children face 2.6 times greater risk of mental distress when commuting 60 minutes or more compared to women without children who commute less than 30 minutes. Women are more likely to manage childcare coordination and added household responsibilities that add to transport stress ([Feng & Boyle 2014](#)). Women also experience heightened vulnerability to harassment and violence during transit use. The [United Nations \(2021\)](#) found that six in ten women in major Latin American cities report physical harassment while using transport systems, with safety concerns varying by transport mode and directly influencing modal choice.

Disparities also extend to socioeconomic, demographic, and infrastructure access. [Saleh \(2024\)](#) reports that 24% of Black households lack car ownership compared to only 7% of white households, highlighting the importance of public transportation access. Women, young adults, low-income workers, individuals with disabilities, and elderly populations show higher dependence on public transportation, making transit access essential for reducing health disparities ([Feng & Boyle 2014](#)). No transit stop within a ten-minute walk corresponds to a higher depression risk, emphasizing the need for accessible public transportation ([Wang et al. 2019](#)). [Ahmed et al. \(2008\)](#) define transportation equity as “distribution of impacts and degree to which that distribution is fair.” Understanding these disparities enables targeted transportation interventions and public policy that address urban mental health equity rather than assuming universal solutions.

Analysis from the Victoria Transport Policy Institute ² demonstrates that communities with high-quality public transport show significantly reduced car dependency, leading to increased physical fitness, improved mental health, reduced traffic crashes, decreased pollution emissions, and enhanced access to medical care and healthy food options. This crucial evidence supports cities implementing smart mobility systems that cater to urban citizens to further consider urban wellbeing and quality of life.

Summary

Smart mobility promises to revolutionize urban transportation through technological innovation ([Albino et al. 2015](#)). Yet while cities advance in technological capabilities, consideration of citizen mental health consistently falls behind. Global initiatives and case studies further prove that technological innovation alone does not guarantee improved urban wellbeing ([Müller-Eie & Kosmidis 2023](#)). Balanced approaches that prioritize human experience along with operational efficiency create successful smart mobility integration in smart cities. While there is a push from global organizations like the UN to make mobility accessible for all ([United Nations 2021](#)), some cities struggle to adapt depending on governance, funding, and cultural integration. Case studies from Tokyo, Japan and Mexico City, Mexico show contrasting approaches to smart mobility implementation. Tokyo’s 500 billion Yen investment and reliable governance create the predictable, safe systems that reduce transportation stress ([Wolniak & Grebski 2023](#)), while Mexico City’s 9% maintenance budget and infrastructure deficits generate the uncertainty and delays that trigger depression risk. Technology alone is not enough; smart mobility requires sustained investment, governance stability, and cultural integration. This infrastructure disparity directly translates into different mental health outcomes. [Novaco et al. \(1990\)](#) impedance theory reveals how commuting challenges impact urban wellbeing through stress-induced expe-

²<https://www.vtpi.org/>

riences. The evidence reveals consistent biological pathways through which urban environments influence urban mental wellbeing. Air quality affects mental health through direct neuroinflammation and HPA axis activation (Block & Calderón-Garcidueñas 2009), with PM_{2.5} providing continuous measurement opportunities. Greenspace exposure modulates the same stress systems through sgPFC regulation and indirect behavioral changes (Bratman et al. 2015, Ward Thompson et al. 2012), while mobility patterns create measurable cortisol responses that follow predictable dose-response relationships (Evans & Wener 2006). Research demonstrates that every additional ten minutes of commuting increases depression risk by 0.5% (Wang et al. 2019). Smart mobility must prioritize predictability to reduce commuter stress. This impact disproportionately affects 26% of women compared to 17% of men due to safety concerns and family responsibilities (Feng & Boyle 2014, United Nations 2021). Cities must develop long-term mobility plans that integrate real-time data systems like Dublin’s STAR-CITY platform (Lecue et al. 2014) that reduces commuting uncertainty. Additionally, cities should follow proposals like Garau et al. (2016) six-dimensional framework for balanced implementation.

The future of urban mobility depends on cities designing transportation systems that enhance rather than diminish citizen mental health. Smart mobility is a key factor in shaping urban mental wellbeing and enhancing quality of life (Nam & Pardo 2011). Alongside contextual cues such as air quality and greenspace, smart mobility serves as a strong measurable contextual cue within the urban mental wellbeing framework.

3.4 Key Outcomes and Discussion

The three contextual cues examined in this review demonstrate complementary mechanisms that strengthen their collective utility for environmental exposure risk affecting urban mental wellbeing. Air quality, greenspace access, and mobility availability operate through overlapping biological pathways while offering distinct measurement opportunities. All three domains activate the HPA axis stress response system: PM_{2.5} exposure triggers direct neuroinflammation (Block & Calderón-Garcidueñas 2009, Genc et al. 2012), lack of greenspace reduces natural stress buffering through sgPFC regulation (Bratman et al. 2015, Urry et al. 2006), and commuting impedance creates predictable cortisol elevation following dose-response relationships (McEwen 2007, Evans & Wener 2006).

The selection as contextual cues is validated by the shared stress pathways, while their different data sources, air quality sensors, GIS systems, and transport infrastructure, enable comprehensive population-level assessment (Block & Calderón-Garcidueñas 2009, Herman et al. 2016). The contextual cues also demonstrate interconnected effects: green infrastructure helps mitigate air pollution impacts, accessible public transport increases greenspace utilization, and air quality affects active mobility choices. This interconnected nature makes the chosen contextual cues valuable for computational frameworks, as they provide multiple data streams that can cross-validate and strengthen overall urban wellbeing assessment accuracy. We generated a table 3.1 that summarizes key literature findings that provide empirical evidence for each contextual cue, including air quality, greenspace, and mobility, along with their exposure metrics, mental health outcomes, and measurement tools used across studies.

Table 3.1: Summary of Literature Findings for Contextual Cues of Urban Mental Wellbeing

(a) Air Quality (PM_{2.5}) and Greenspace Contextual Cues

Contextual Cue	Author / Year	Key Finding	Exposure / Measurement	Outcome	Measurement Tool
Air Quality (PM _{2.5})	Chen et al. (2018)	A 1 SD rise in PM _{2.5} increases likelihood of mental illness by 6.67 percentage points.	PM _{2.5} (1 SD increment over past month)	Mental illness (depression, anxiety, distress)	Kessler Psychological Distress Scale (K6)
Air Quality (PM _{2.5} , 30 days)	Pun et al. (2017)	Every 5 $\mu\text{g}/\text{m}^3$ increase over 30 days raises odds of depressive symptoms by 20% (OR=1.20, 95% CI: 1.08–1.33).	PM _{2.5} , 30-day average	Moderate-to-severe depression	CESD-11
Air Quality (PM _{2.5} , 180 days)	Pun et al. (2017)	Every 5 $\mu\text{g}/\text{m}^3$ increase over 180 days linked to 55% higher odds of anxiety (OR=1.55, 95% CI: 1.31–1.85).	PM _{2.5} , 180-day average	Moderate-to-severe anxiety	HADS-A
Greenspace	Gascon et al. (2018)	Access to greenspace within 300 m reduces odds of depression (OR=0.18, 95% CI: 0.06–0.58).	Residential greenness (NDVI, 100–500 m buffers)	Depression, anxiety	Logistic regression
Greenspace	Ward Thompson et al. (2012)	Each 1% increase in greenspace linked to 0.07% steeper cortisol slope and 0.14 lower stress score.	Percentage greenspace in neighborhood	Stress, well-being	Cortisol biomarker+ PSS

(b) Mobility Contextual Cue

Contextual Cue	Author / Year	Key Finding	Exposure / Measurement	Outcome	Measurement Tool
Mobility (commute time)	Wang et al. (2019)	Every additional 10 min of commuting linked to 0.5% higher depression probability.	Commute duration (minutes)	Depression	Depression screening
Mobility (commute delay)	Wang et al. (2019)	Every 10 min of delay (congestion) increases depression probability by 0.8%.	Commute delay (minutes)	Depression	Depression screening
Mobility (transit access)	Wang et al. (2019)	No transit stop within a 10-min walk increases depression risk by 4.8% (95% CI: 0.171–0.507).	Distance to nearest transit stop	Depression	Depression screening

Chapter 3 directly addresses **RQ1**: *Can environmental indicators identified in the literature be operationalised as spatially explicit contextual cues for population-level urban mental wellbeing assessment using smart city data?* The three contextual cues examined in this chapter were selected because they offer both robust scientific evidence (Gascon et al. 2018, Wang et al. 2019, Chen et al. 2018) linking them to mental health outcomes and rich data sources already available in smart city infrastructure (Puiu et al. 2016, Sanchez et al. 2014). The systematic conversion operates through three principles: quantifiable exposure thresholds, literature backing the urban mental wellbeing connection, and smart city data infrastructure. Each contextual cue links environmental exposure to mental health through established biological mechanisms (McEwen 2007, Block & Calderón-Garcidueñas 2009). The conversion follows a replicable pattern. The literature review establishes environmental factors and biological mechanisms. Epidemiological studies quantify exposure thresholds through validated methods (Gascon et al.

2018, [Chen et al. 2018](#), [Wang et al. 2019](#)). These thresholds become operational criteria measurable through smart city data. The computational framework applies standardized processing methods and threshold-based labeling to generate population-level risk scores, as detailed in Chapter 5. The data required to measure these environmental exposures already exist in smart city infrastructure, which supports population-level assessment without additional investment. Air quality networks, GIS platforms, and transit databases were originally developed for operational management rather than urban mental wellbeing research ([Lim et al. 2019](#), [Moustaka et al. 2018](#)). The computational framework repurposes this existing infrastructure for environmental exposure risk assessment using literature-validated thresholds. The operationalization of these contextual cues requires systematic evaluation of smart city data sources. Chapter 4 presents the data selection framework that guided dataset identification and city case study selection for this research.

Chapter 4

Smart City Data Landscape and Selection

Urban mental wellbeing assessment through contextual cues requires systematic evaluation of available smart city data sources. Researchers and data scientists need smart city data for urban studies, yet choosing among the plethora of datasets becomes a modern-day challenge. Smart cities produce data from various sources for different purposes. However, not all smart city data is suitable or accessible for environmental exposure risk relevant to urban wellbeing research, and the current approaches lack selection criteria.

This chapter establishes the foundation for dataset selection by examining smart city data characteristics and developing evaluation criteria that balance research validity with practical accessibility constraints. The contextual cue selection is based on two parts: data must be practically obtainable and be scientifically valid by connecting to mental health literature. This chapter focuses on the first part: examining existing data through the Smart City Data Classification and Access Framework (SCDCAF), an original framework developed in this research. The SCDCAF framework evaluates smart city data through five dimensions: data availability across multiple cities, data sensitivity, temporal data, cost of obtaining data, and data providers. These five key dimensions provide systematic evaluation criteria that determine data suitability for urban wellbeing research. By applying SCDCAF to assess smart city data landscapes, this framework guided the selection of Chicago, Manchester, and Portland as case studies based on their alignment with optimal data availability, accessibility, and research feasibility requirements. SCDCAF is presented in this before the computational methodology to establish the fundamental data requirements and evaluation criteria that inform the city selection process in Chapter 5 and the data infrastructure implementation in Chapter 6.

This chapter begins with Section 4.1, where the big data landscape is examined including smart city big data characteristics and openness challenges. Section 4.2 presents SCDCAF, detailing each evaluation dimension from an urban wellbeing risk perspective. A discussion is provided with multi-level relationships and dependencies through identifying trade-offs between dimensions. The framework establishes the analytical foundation for the specific dataset selections and city case studies presented in Chapter 5.

4.1 Smart City Data Landscapes

Smart cities' growth was a direct effect of technical advancement in the past years. City governmental departments and private agencies have invested in generating and gathering data. This has created a plethora of data. Digital transformation has moved city services online; transparency initiatives require public data sharing, and daily urban operations now depend on constant information flows. The increasing volume of smart city data creates pressure on city representatives to consolidate, organize, and manage these diverse data streams effectively (Lnenicka et al. 2024). This data explosion requires systematic approaches to transform raw information into actionable insights, enabling efficient data exchange, sharing, and reuse. Without

proper organization and management, the wealth of available smart city data becomes overwhelming rather than helpful for addressing sustainable development needs (Lnenicka et al. 2024). Understanding the characteristics of this smart city data is essential for developing effective management frameworks. Specifically, the integration of big data analytics and machine learning algorithms is crucial for extracting meaningful patterns from this voluminous and diverse data, enabling the development of predictive and descriptive models for smart city applications, including those focused on urban mental health (Cesario 2023).

4.1.1 Big Data Characteristics

Governments use big data to support the development and sustainability of smart cities around the world. The integration of big data in smart cities allows smart city frameworks to develop under their key characteristics, governance, mobility, quality of life, and Internet of Things (IoT) (Al Nuaimi et al. 2015). Big data has become a fundamental driver of modern technological advancement. Big data refers to datasets that exceed the capacity of traditional data processing applications due to their volume, velocity, and variety (Ishwarappa & Anuradha 2015). In 2025, big data will reach 181 zettabytes in volume; to put that into perspective, that is equivalent to storing 250 billion DVDs. The massive growth in data volume originates from IoT devices, real-time data processing, and cloud-based storage (Taylor 2025). Individual big datasets, typically measured in terabytes and petabytes, originate from diverse sources including search queries, health records, social network interactions, traffic flows, and weather changes (Sagiroglu & Sinanc 2013, Ishwarappa & Anuradha 2015, Kumar & Singh 2019). Yet, current big data literature reveals a gap highlighting the lack of urban wellbeing risk estimation approaches.

In smart city contexts, these data characteristics create specific challenges and opportunities. The evolution of sensor technology and networks has made it feasible for smart cities to integrate them in a cost-effective and scalable way. Sensors provide both static baseline awareness and dynamic real-time monitoring of city conditions. This shift enables continuous, real-time awareness of the city's state, replacing the limitations of traditional, periodic manual inspections that offer only snapshots in time (Hancke et al. 2013). Examples in smart cities include air quality monitoring stations, water and electricity meters, CCTV, mobile phone GPS, and traffic flow sensors, all feeding into centralized systems for analysis. However, traditional big data collection and analysis produce generic data frameworks that may not fully capture the unique data requirements of environmental risk relevant to urban wellbeing risk estimation research. This gap underscores the need for developing new evaluation criteria specifically designed to assess smart city data's suitability for urban mental wellbeing research, leading to the framework presented in this chapter.

4.1.2 The 5Vs of Big Data

The complexity of smart city big data can be understood through five key characteristics that represent both challenges and opportunities in transforming heterogeneous, large-scale datasets into computational insights for assessing urban mental wellbeing. Volume describes the massive scale of data, measured in terabytes and petabytes, generated by billions of continuous sensor streams, transactions, and healthcare files (Sagiroglu & Sinanc 2013, Ishwarappa & Anuradha 2015). Velocity refers to the speed at which data is created, processed, and analyzed, which holds value when used as it is produced and is critical for urban wellbeing risk estimation where mental health impacts arise from short-term exposures like air pollution fluctuations (Sagiroglu & Sinanc 2013). Variety captures the diversity of data types and formats, including structured, semi-structured, and unstructured data from various sources, making it difficult to harmonize smart city data and extract consistent contextual cues (Ishwarappa & Anuradha 2015, Sagiroglu & Sinanc 2013). Veracity concerns the reliability, accuracy, and quality of data, where high volumes often include incorrect data, nulls, and missing values that can lead to inaccurate or

incomplete urban wellbeing risk estimation (Ishwarappa & Anuradha 2015). Value represents the actionable insights and benefits extracted from big data analysis, which in this research lies in converting raw smart city data into contextual cues for urban wellbeing risk estimation (Ishwarappa & Anuradha 2015). Additional to technical characteristics, how smart city data is accessed and shared fundamentally shapes its utility for wellbeing research.

4.1.3 Smart City Data Openness

Smart cities generate vast amounts of data, but how this data is managed and shared determines its value for urban planning and citizen wellbeing. Effective data management in smart cities relies on understanding different approaches to smart city data platforms, primarily distinguishing between closed and open data, each impacting value generation distinctly (Gupta et al. 2020). Closed data platforms are managed and solely controlled by city authorities so data can increase organizational value, for example, by enhancing security or operational efficiency through surveillance data generated by CCTV cameras (Gupta et al. 2020). In contrast, open data platforms allow the public to access, modify, and share data.

The movement toward open data has accelerated significantly in recent years. In 2004, the Open Knowledge Foundation (OKF)¹ established principles for fair and sustainable distribution of knowledge, promoting open data communities. In 2009–2010, the United States and United Kingdom became one of the first nations to make their data public via *data.gov* and *data.gov.uk*, allowing access to one of the largest repositories of open data collected by governments (Neves et al. 2020). Shortly after, many European countries and major cities across the world adopted the open data approach. Since then, open data portals can be found available in regional and district levels (Neves et al. 2020). In contrast, geo-blocking has become more prominent in the last decade (Shanahan & Bezuidenhout 2022), as governments intentionally block access to websites and data depending on the geographical location.

Openness in a smart city context aims to reinforce citizen engagement, foster co-creation, and collective intelligence (Neves et al. 2020). Maintaining data open for researchers, policymakers, and urban planners promotes crucial pathways not only for economic and cultural growth (Neves et al. 2020) but also creates opportunities for enhanced urban wellbeing risk estimation, as demonstrated by (Oteiza et al. 2022). Gupta et al. (2020) refer to open data platforms as “more collaborative models of smart city governance that emphasize a role for city governments in the curation and management of data assets to support a city’s strategic priorities.” Tools like city dashboards, data portals, and datastores (centralized data repositories) often provide these open and free datasets (Gupta et al. 2020).

Despite these benefits, significant challenges remain in implementing effective open data systems. Smart city data platforms face challenges such as the misalignment of vendor–government needs, interoperability issues, and complex data transformation processes (e.g., data cleaning, integration, or harmonization) (Gupta et al. 2020). Furthermore, the effective implementation of useful open data is hindered by limitations like a lack of infrastructure and a failure to fully grasp the value of certain data. Consequently, governments often supply data based on availability rather than public demand. This discrepancy can lead to a significant misalignment between open data initiatives and smart city goals, ultimately causing a disconnection between public needs and governmental efforts (Neves et al. 2020).

¹<https://okfn.org/en/>

4.2 Smart City Data Classification and Access Framework (SCDCAF)

Existing big data frameworks focus primarily on technical properties (volume, velocity, variety, veracity, value) without addressing practical accessibility constraints for population-level mental wellbeing research (Kitchin 2014, Hashem et al. 2015). Smart city data management frameworks emphasize interoperability standards (International Organization for Standardization 2018) or technical architectures (Zanella et al. 2014) but do not evaluate whether datasets meet urban wellbeing research requirements such as cross-city availability for comparative analysis, appropriate temporal resolution for environmental exposure assessment, or ethical accessibility for privacy-sensitive research. While some frameworks address data quality dimensions (Batini et al. 2009), none provide systematic evaluation criteria integrating availability, sensitivity, temporal frequency, cost, and provider characteristics for population health applications. This gap necessitated the development of SCDCAF.

Smart city data for wellbeing research must be evaluated across multiple dimensions to determine its suitability and accessibility. This section presents the SCDCAF framework visualized in Figure 4.1. SCDCAF assesses datasets based on five key criteria: availability across cities, data sensitivity levels, temporal update frequency, access costs, and data provider considerations. This framework guides the selection of appropriate datasets for contextual cue analysis by identifying which smart city data sources are both scientifically suitable and practically accessible for wellbeing research. The SCDCAF framework prioritizes open, freely accessible data to enable scalable and reproducible urban wellbeing risk estimation across different cities and research contexts.

The five SCDCAF dimensions interact to determine dataset suitability for urban wellbeing research. Data availability establishes the baseline pool of candidate datasets, filtering for sources accessible across multiple cities to enable comparative analysis. Data sensitivity then determines ethical feasibility, distinguishing publicly accessible environmental data from restricted health records. Temporal frequency interacts with both availability and research design, where higher update frequencies (daily air quality readings) support dynamic exposure assessment while lower frequencies (annual census data) limit temporal resolution. Cost considerations intersect with availability and sensitivity, as highly sensitive or rare datasets often require fee-based access that constrains scalability. Data provider characteristics compound these relationships, where government sources typically offer free access to low-sensitivity data with varying temporal frequencies, while private platforms control high-sensitivity data through restrictive commercial models. These interdependencies mean that optimal dataset selection requires balancing trade-offs across all five dimensions rather than maximizing any single criterion. For population-level urban wellbeing research, this framework prioritizes Level 1-2 availability combined with low sensitivity and free access to enable replicable comparative analysis across diverse cities.

4.2.1 Data Availability and Accessibility

Data availability refers to how widely a dataset can be found across different smart cities globally. In Figure 4.1, the availability spectrum depicts three levels, from rare data availability to common data availability. Some smart cities and governing bodies have different priorities and resources which reflect on what datasets are available (Shanahan & Bezuidenhout 2022). Data availability shows significant bias toward high-income countries (Shanahan & Bezuidenhout 2022). Additionally, some smart cities are practicing openness while others are still adapting, leading to a lack of available data open for the public. Data may exist but remain inaccessible due to restricted access policies.

Availability levels directly impact urban mental wellbeing research quality. Higher availabil-

Smart City Data Classification and Access Framework (SCDCAF)

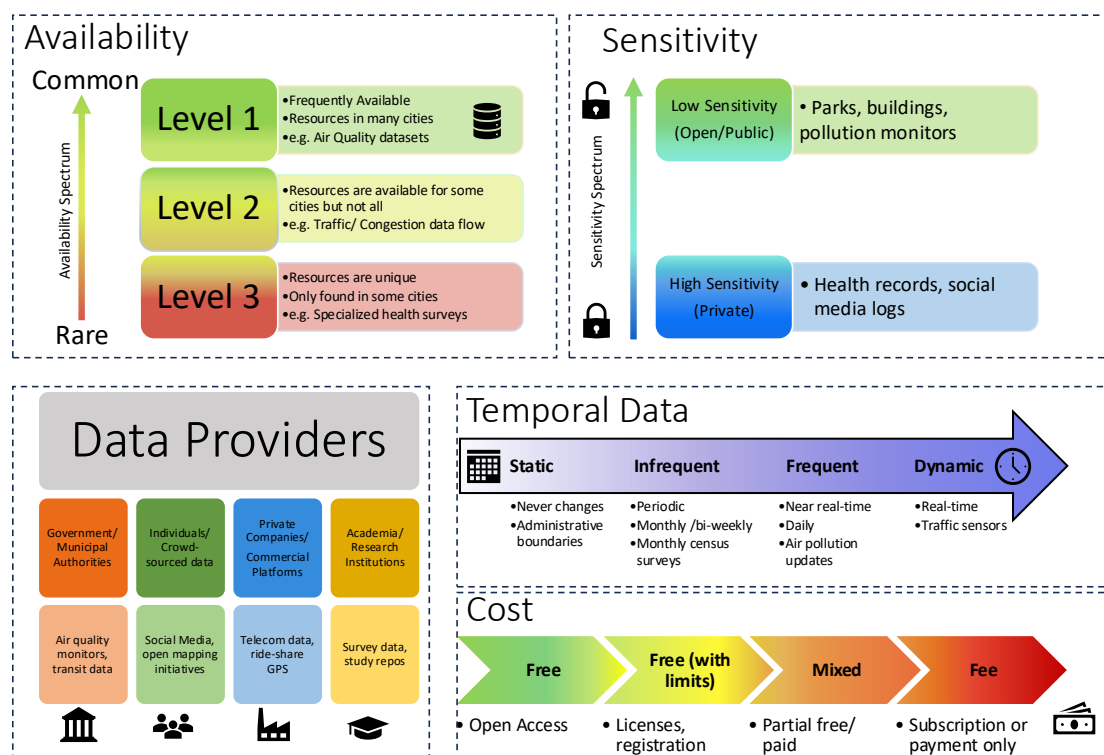


Figure 4.1: Smart City Data Classification and Access Framework (SCDCAF): This framework assesses smart city datasets across five categories to determine their suitability for contextual cue development.

ity enables comparative analysis across multiple cities, while rare datasets limit research scope and generalizability. When datasets like detailed traffic flow data are Level 2, meaning they are selectively available across regions, comparative wellbeing assessment between cities becomes challenging due to inconsistent data presence.

Level 1 represents the most common data availability and describes data that is frequently available across various cities, such as air quality data and geographic neighborhood boundaries. This level enables broad comparative studies across multiple urban contexts.

Level 2 refers to data that is selectively available in smart cities. This can be due to regions such as the European Union creating standardized data strategies across the continent, but the same data availability may not be found in the rest of the world. This dataset can refer to detailed geographical data such as transit stops or building addresses. Level 2 availability limits geographic scope and requires targeted city selection for research.

Level 3 describes data that is rare to see across different smart cities. This can include data such as custom sensor networks or limited projects across one or two cities. Level 3 data restrict research to case studies or pilot validation rather than broad comparative analysis.

4.2.2 Data Sensitivity and Access Models

Data sensitivity refers to privacy levels of data that can range from highly sensitive data to low sensitivity data. In SCDCAF, the spectrum runs from low-sensitivity public datasets to high-sensitivity private datasets.

Low Sensitivity (Open/Public): Includes non-personal datasets such as parks, building footprints, and pollution monitors. These are generally more accessible and ethically straightforward.

High Sensitivity (Private/Restricted): Includes datasets such as health records, telecom logs, and social media traces. These pose challenges around privacy, legality, and ethics.

Governments have created laws to protect highly sensitive data, for example in Europe their GDPR laws establish strict rules on collecting, sharing, and keeping personal information. The USA has similar laws through the Health Insurance Portability and Accountability Act (HIPAA) that focus on keeping individuals' health information private. This has led to the creation of data anonymization, pseudonymization, ethical guidelines, and data governance frameworks.

The Data Sensitivity category helps assess datasets for contextual cues. Low-sensitive and open data is more feasible for this research due to easier accessibility and avoids privacy issues that direct health data collection creates. This research emphasizes that urban mental wellbeing estimation will be conducted using contextual cues rather than direct health records, to maintain individual privacy and adhere to ethical considerations. While highly sensitive data remains inaccessible for this research, even low-sensitive data has varying access requirements. Many open data platforms require data sharing agreements, while others restrict access to verified researchers.

4.2.3 Temporal Data Categories

The Temporal Data category refers to the update frequency characteristics of datasets. The four temporal data categories are defined based on their update frequency, from static, infrequent, frequent to dynamic data. Update frequency is a crucial aspect of data selection for contextual cues as it can provide different insights into urban wellbeing risk estimation.

Static data almost never changes and rarely requires updates, such as administrative boundaries in a city. This type of data gives a stable estimation of urban wellbeing risk that remains consistent across time periods.

Infrequent data updates are data that are updated monthly or biweekly such as census data. The benefit of this data update is that it is good for long-term trend analysis, policy

evaluation, or baseline assessments.

Frequent data updates are data that are generated daily, such as daily air quality levels. This data is useful for tracking evolving trends or responding to short-term events.

Dynamic data updates refer to data that is real-time and provides continuous data updates such as traffic sensors. For example, real-time traffic congestion data may be able to identify specific hours that urban wellbeing is at risk due to congestion, which is important for immediate crisis detection or monitoring sudden changes (Miranda et al. 2024).

The choice of update frequency directly impacts the type of wellbeing insights that can be extracted and the research questions that can be addressed through contextual cue analysis.

4.2.4 Cost Considerations and Data Access Strategy

The Cost category highlights that access to datasets may involve financial barriers, particularly for commercial datasets or organizations that operate on a cost-recovery or profit-driven model. There are four categories representing the spectrum from free to paid:

Free (Open Access): Fully public, e.g., government open data portals.

Free (with limitations): Requires registration or licenses. The California Department of Transportation requires both registration and an application to access its traffic datasets.

Mixed: Some open datasets but restrictions for detailed ones.

Fee-based access: ArcGIS Online represents the Fee model, as they require a subscription to download and use geographic data.

Implications for wellbeing research are significant. Free and open access datasets reduce barriers, enable scalable research, and foster interdisciplinary collaboration, ultimately allowing for broader validation and innovation. Conversely, datasets that require substantial fees pose risks for equity and inclusion in research, limiting opportunities for early-career scholars or institutions with restricted funding. High-cost access can therefore skew the landscape of wellbeing research toward well-funded organizations, creating imbalances in who can contribute knowledge and shape policy.

4.2.5 Data Providers

There are distinct categories of actors that create, collect, and share smart city data. In this framework, four principal data providers were identified: government and municipal authorities, individuals and crowdsourcing communities, private companies and commercial platforms, and academic and research institutions.

Government and municipal authorities generate administrative datasets and collect sensor-based information from city infrastructure. The strengths of this data include its official status, domain-specific comprehensiveness, and policy relevance. However, limitations arise from bureaucratic access procedures, fragmented data silos, and temporal latency that reduce timeliness.

Individuals and crowdsourcing initiatives contribute societal data that is often open-source and public. A key example is OpenStreetMap, where volunteers collaboratively build a global open-source map. The strengths of this type of data lie in its volume, diversity, and dynamic updating, while the weaknesses include bias, inconsistency, noise, and privacy concerns.

Private companies and commercial platforms produce highly specialized datasets, including telecommunications records, ride-share GPS traces, and social media logs. These datasets provide granularity and advanced analytical value, but are often constrained by their proprietary nature, cost barriers, and ethical considerations related to surveillance and profit-driven control.

Academic and research institutions typically focus on survey data, experimental studies, and small-scale data collection efforts. While these datasets may lack scale, they often

provide methodological rigor, contextual insights, and theory-driven approaches that complement other data providers.

Identifying data providers is important because it enables researchers to categorize and triangulate diverse sources, creating a more rounded and reliable basis for analysis. Cross-sectoral collaborations and data partnerships among these providers are increasingly recognized as essential for advancing holistic smart city initiatives, particularly those addressing complex challenges such as urban wellbeing risk estimation.

4.3 Discussion

The SCDCAF framework reveals that dataset selection for urban wellbeing risk research involves measurable trade-offs across availability, sensitivity, temporal resolution, cost, and data provider characteristics. These categories do not operate independently; rather, they create interdependent relationships that require strategic decision-making when building contextual cue datasets. The trade-offs and interdependencies create a guide for researchers and data scientists to navigate selecting data for contextual cue development. The reality of current research and data accessibility favors high-income countries, which creates additional constraints when making these strategic choices ([Shanahan & Bezuidenhout 2022](#)).

Application of SCDCAF criteria to potential case study cities identified Chicago, Manchester, and Portland as optimal sites. All three cities achieved Level 1-2 availability across required datasets, maintained low-sensitivity open data portals, provided temporal frequency suitable for contextual cue analysis, and required no access fees. Alternative cities such as Dublin, Berlin, and Mexico City were excluded due to data gaps and temporal limitations.

Multi-level Relationships

Level 1 (common) datasets often align with free or open access models, which are present in cities that have widespread open data initiatives, such as Portland, USA. In contrast, Level 3 (rare) datasets often require fee-based access since they represent unique data for specific purposes. This research focuses on broad comparative analysis through the application of population-level urban wellbeing risk estimation across cities. Accordingly, this study prioritizes Level 1–2 datasets. In contrast, researchers who require specialized and rare data must consider budget constraints.

Temporal frequency directly affects the other evaluation categories. When datasets are commonly available like air quality levels, temporal differences become manageable through standard harmonization practices. Common coding practices make temporal differences feasible when the variation is small. For example, researchers can calculate monthly averages from daily air quality levels to achieve temporal consistency across cities. This relationship between temporal data and availability depends on research goals, and in this research such minor differences made it feasible to consider most datasets across various smart cities. However, larger temporal differences create significant harmonization challenges. For instance, yearly air quality averages cannot be converted to monthly data when monthly resolution is required for the analysis.

Data provider characteristics compound these dimensional relationships, influencing availability, cost, and sensitivity simultaneously. Data sourced by governments can cover all aspects of the sensitivity spectrum. Governments handle highly sensitive data, such as health records, while also being the primary source for public data such as park boundaries. Private companies mainly control highly sensitive data through restrictive commercial models. Academia often bridges these extremes by providing sample case studies through partnerships. Crowdsourced or individual data is often low sensitivity, representing data collected through experience, like documenting a new park. While crowdsourced data supports government–citizen relationships,

the lack of quality control mechanisms means this data may contain errors or inconsistencies.

The optimal dataset for this research in estimating population-level urban mental wellbeing requires a balance across all five categories, rather than maximizing a single category. For example, Level 2 data with low-sensitive characteristics and free access requiring only registration may provide better value for this research than Level 1 availability combined with highly sensitive data and infrequent updates. SCDCAF encourages systematic evaluation rather than single-criterion selection. For this research, prioritizing high availability, low-sensitivity, and free access created the most scalable research opportunities, enabling replication across various smart cities. Datasets with restricted access may add analytical value but ultimately compromise methodology replication and scalability.

4.4 Conclusion

Chapter 4 establishes a systematic approach to evaluating smart city data for urban wellbeing risk research. This chapter examined big data landscapes to understand the volume, velocity, variety, veracity, and value challenges that smart cities face when managing diverse data streams for research purposes. The classification framework, Smart City Data Classification and Access Framework (SCDCAF), evaluates smart city data across five main dimensions: availability, sensitivity, temporal frequency, cost considerations, and data providers. This framework serves as a guide for researchers and data scientists to consider data trade-offs based on their research goals. The analysis of this framework revealed that the dimensions interact and influence each other. Effective dataset selection requires a balanced consideration across each dimension rather than maximizing a single dimension. For population-level urban wellbeing risk research and implementation, Level 1–2 commonly available data combined with low sensitivity, and free or limited restriction access is prioritized. This approach enables comparative analysis across multiple cities while avoiding the resource constraints and ethical complications associated with highly sensitive or expensive datasets.

SCDCAF's core contribution makes explicit the data trade-offs that researchers encounter when building contextual cue datasets. The framework shows how temporal frequency creates cascading effects across cost and provider categories, how data provider characteristics compound accessibility challenges, and how availability levels fundamentally determine research scope and generalizability. The framework provides the analytical foundation for dataset selection and city case study development presented in Chapter 5. By systematically evaluating data sources through SCDCAF dimensions, the research can proceed with transparent, justified choices that balance scientific validity with practical constraints.

Chapter 5

Methodology

This chapter presents the methodological framework for assessing environmental exposure risk to urban mental wellbeing through environmental contextual cues derived from smart city data. The research follows a positivist philosophy, applying deductive reasoning to assess environmental exposures against literature-derived thresholds within a cross-sectional design that captures population-level risk patterns across three cities in 2024. Chapter 2 reviewed urban mental health literature, Chapter 3 established epidemiological evidence linking environmental exposures to mental health outcomes through quantifiable thresholds, and Chapter 4 introduced the Smart City Data Classification and Access Framework (SCDCAF) evaluating data availability for population-level assessment.

This chapter details the complete methodological approach across eight major sections. Section 5.1 provides an overview of the computational framework architecture. Section 5.2 establishes the research philosophy and epistemological foundation supporting the quantitative, deductive approach. Section 5.3 presents the research design, including the cross-sectional strategy and comparative case study justification. Section 5.4 documents the systematic evaluation criteria and justification for selecting air quality, greenspace accessibility, and transit mobility as contextual cues. Section 5.5 details the systematic city selection process from 300 global open data portals to three case study cities: Chicago, Manchester, and Portland. Section 5.6 describes data collection protocols and quality validation procedures. Section 5.7 presents the literature-based labeling methodology for converting environmental measurements into risk scores, and Section 5.8 outlines replication procedures enabling framework implementation in additional cities meeting SCDCAF data availability criteria.

5.1 Computational Framework Overview

The computational framework, as seen in Figure 5.1, addresses a critical gap: smart cities collect extensive environmental data but lack systematic methods to translate this data into mental wellbeing insights. The computational framework follows five stages. First, the Smart City Data Classification and Access Framework (SCDCAF) evaluates candidate cities across five dimensions to determine data infrastructure suitability (Chapter 4). Second, contextual cues are selected based on epidemiological evidence linking environmental exposures to mental health outcomes. Third, smart city data is collected from cities meeting SCDCAF criteria. Fourth, the data processing and risk assessment pipeline applies systematic procedures such as data quality validation, geospatial processing, and risk scoring using thresholds from [Chen et al. \(2018\)](#), [Gascon et al. \(2018\)](#), and [Wang et al. \(2019\)](#). Fifth, the framework aggregates contextual cue scores into the Urban Mental Wellbeing Risk Index (UMWI), a single 1.0 to 5.0 metric enabling cross-city comparison. Application to Chicago, Manchester, and Portland demonstrates the framework's capacity to convert diverse smart city data into comparable risk assessments. Any city meeting SCDCAF criteria can replicate this methodology, transforming

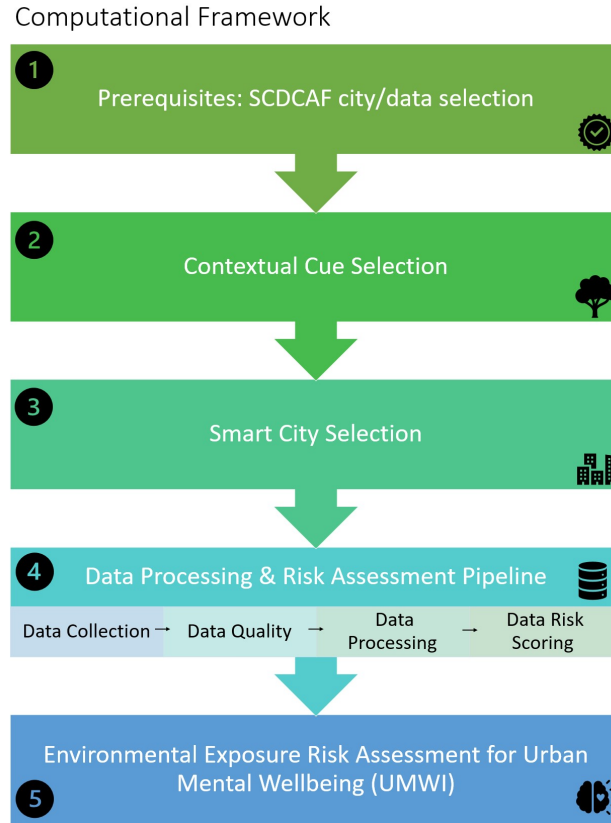


Figure 5.1: Computational framework for environmental exposure risk assessment for urban mental wellbeing.

epidemiological research into operational planning tools.

5.2 Research Methodology and Philosophy

5.2.1 Research Paradigm and Epistemology

The research methodology adopts a positivist epistemological approach (Park et al. 2020), which assumes that factors affecting urban mental wellbeing are objective and measurable phenomena. By treating $\text{PM}_{2.5}$ concentrations, greenspace distances, and mobility accessibility as objective environmental conditions that exist independently of individual perceptions, the computational framework can operate entirely on open municipal datasets without requiring subjective mental health measures or clinical data collection. This epistemological choice is fundamental because it enables cities to assess environmental risk using only the data infrastructure they already possess; air quality measurements, GIS databases, and transit records. This makes the framework both scalable and replicable across urban contexts (Park et al. 2020).

Air quality monitoring stations collect $\text{PM}_{2.5}$ concentrations which pose an environmental exposure risk for urban citizens. Similarly, distances from residential addresses to eligible greenspaces and to transit stops are computed in GIS. These environmental conditions create exposure risks that affect physiological and psychological processes through documented biological mechanisms (Gascon et al. 2018, Wang et al. 2019), regardless of individual awareness of these relationships. Findings from meta-analyses and large-scale studies provide evidence of predictable patterns that can be used for assessment systems such as spatial buffers and thresholds. The validated relationships facilitate the development of literature-based labeling systems for each contextual cue.

5.2.2 Justification for using Deductive Reasoning

Deductive Reasoning Justification

The research methodology follows deductive reasoning to build a fixed, literature-based computational framework. This approach is supported by well-documented research findings, presented in Chapter 3, to create systematic procedures for testing the relationship in new urban contexts using standardized measurement and labeling. Three primary research findings support the theoretical foundation for the computational framework: [Chen et al. \(2018\)](#) demonstrated that one standard deviation increase in PM_{2.5} concentrations over the past month increases severe mental illness probability by 6.67 percentage points, measured using the Kessler Psychological Distress Scale (K6). This research establishes monthly PM_{2.5} exposure windows as operational metrics for air quality risk assessment, with standard deviation increases serving as quantitative thresholds for risk categorization. [Gascon et al. \(2018\)](#) found that access to major greenspaces (≥ 0.5 hectares) within 300 meters was associated with substantially lower odds of depression (OR=0.18, 95% CI: 0.06–0.58), with protective effects also observed at 500-meter buffers (OR $\approx$ 0.84). These findings provide specific spatial criteria for greenspace accessibility assessment: minimum park sizes of 0.5 hectares and proximity thresholds of 300 meters for optimal protective effects, with measurable benefits extending to 500-meter distances. [Wang et al. \(2019\)](#) established that not having a formal or informal transit stop within a 10-minute walk was associated with a 4.8% increased probability of screening positively for depressive symptoms (coefficient 0.339, 95% CI: [0.171, 0.507]). This research provides operational definitions for transit accessibility assessment using 10-minute walking distances as threshold criteria for identifying areas with elevated depression risk.

The deductive approach produces three attainments (operational research objectives established through literature review): A1, A2, and A3, which are assessed across Chicago, Manchester, and Portland using address-level data as population proxies and thresholds from literature.

A1: Urban areas that have higher monthly PM_{2.5} variability should demonstrate higher environmental exposure risk scores compared to areas with more stable air quality.

A2: Residential addresses within 300 meters of eligible greenspaces (≥ 0.5 hectares) should show lower environmental exposure risk scores compared to addresses with limited greenspace access.

A3: Residential addresses that cannot access a transit stop within a 10-minute walk should show higher environmental exposure risk scores compared to addresses with closer transit access.

The deductive framework applies literature findings as standardized rules for exposure risk classification. For example, monthly PM_{2.5} exposure windows are adapted from [Chen et al. \(2018\)](#), 300-meter buffers to greenspaces ≥ 0.5 hectares follow [Gascon et al. \(2018\)](#), and 10-minute walking distances to transit stops are based on [Wang et al. \(2019\)](#). Each of these contextual cues is systematically converted into risk labels ranging from 1 to 5. The computational framework processes every address using an identical approach to label air quality exposure risk, greenspace accessibility, and transit proximity based on the three literature facts. Individual contextual cue labels combine through a standardized weighting process to output a total environmental exposure risk score for each address. The standardization for the computational framework ensures consistent application on different cities and therefore data formats.

Quantitative Methodological Selection

This research applies quantitative research methods as it uses numerical and spatial data collected from open source. In this research the aim is to reduce bias by using already existing databases to reach valuable conclusions. To be specific, this research applies spatial analysis to establish the technical foundation for implementing the literature-based labeling system across large urban populations. Geographic Information Systems (GIS) are used to calculate distances,

buffer zones, and accessibility patterns, and can adapt to different geographical contexts while maintaining precision. Spatial analysis also incorporates population-weighting procedures that consider variation in residential density and demographic distribution across neighborhoods.

The literature-based labeling system converts established research findings and facts into classification labels that represent the environmental exposure risk assessment without subjective interpretation. Environmental exposures are categorized into risk levels on a 1–5 ordinal scale, using research-derived thresholds as objective criteria. The five-level structure is supported by psychometric evidence that scales with five to seven categories optimize measurement precision (Preston & Colman 2000, Revilla et al. 2014, Pontin et al. 2013), as detailed in Section 5.7. The scale offers enough granularity for policy applications while remaining simple to implement. Full justification for the five-level scale and risk construction methodology is detailed in Section 2.3.3. A literature-validated scale ensures meaningful exposure categories, allowing for cross-city risk comparisons and the creation of city-level summary scores. The quantitative-deductive approach fits well into this research as it allows for a replicable process which supports the application of the computational framework in other cities. Standardized data requirements, processing steps, and validation criteria enable municipal planners to implement the computational framework with commonly available technical resources and open data.

All analysis are observational, identifying associations rather than causal effects, and remain subject to measurement error and ecological inference limitations. The computational framework generates environmental exposure risk scores from literature-derived labels, which serve as population-level proxies for urban mental wellbeing risk instead of direct measures of mental health. This design supports evidence-based urban planning while recognizing the constraints of observational environmental assessment.

5.3 Research Design

This research uses a cross-sectional design approach to assess environmental exposure risk to estimate urban mental wellbeing risk across three cities at a single time point. The cross-sectional approach aligns with the research objectives of developing a computational framework for current-state urban mental wellbeing risk assessment, rather than tracking individual mental health trajectories over time. The design provides population-level records of environmental exposure risk patterns that are relevant for urban planning policy decisions. Government and public-health planners require current assessments of environmental risk factors to allocate resources for pressing infrastructure enhancements and environmental policy. In contrast, longitudinal tracking of individual urban citizens does not directly meet these policy needs, since planning decisions address population-level exposures rather than personal health outcomes.

Additionally, the cross-sectional design supports development of the computational framework by enabling deductive assessment of environmental exposures against established thresholds from research on PM_{2.5}, greenspace proximity, and transit accessibility impacts on urban mental wellbeing, as outlined in Section 5.2.2. It allows comparison of environmental exposure risk patterns in Chicago, Manchester, and Portland without relying on multi-year data collection, which can be influenced by changes in air quality policies or changing urban infrastructure. This approach enables scalable implementation in other qualifying cities with the use of a replicable methodology. This methodology only utilizes open datasets, avoiding the need for specialized survey infrastructure that can vary across different cities. The framework’s scalability allows deployment in data-ready cities, supporting the study’s contribution to building widely applicable urban mental wellbeing assessment tools.

Comparative Case Study Approach

In this research, urban addresses are used as analytical units that represent urban citizens across the three case study cities. This address-based approach for population-level analysis aligns with the positivist epistemological framework established in Section 5.2.1 by treating environmental exposure as objective, which is a measurable natural phenomenon that exists outside the subject's perception.

Additionally, population-level assessment is possible while protecting individuals' privacy and maintaining a scalable integration for the case study cities. The study contains 815,343 addresses across three cities: Chicago (400,320 addresses), Manchester (71,741 addresses), and Portland (343,282 addresses). Residential address points function as representation for population, allowing environmental exposure estimation without direct participant contact or personal health data. The computational framework integrates census population and household counts at the ZIP Code or borough level to support the address-based, population-level assessment. An address-based approach facilitates integration of sources with different spatial resolutions and update cycles. Environmental monitoring data, greenspaces, transit infrastructure, and census small-area statistics are harmonized and spatially joined to the address points using spatial buffers for proximity analysis and temporal alignment procedures, detailed in Chapter 6.

The three-city design tests framework performance across distinct development patterns, regulatory environments, and geographies. The population size differs across Chicago, Manchester, and Portland which tests framework scalability from medium-sized cities to major metropolitan cities. This range supports the framework's adaptability across cities with different population densities and geographic contexts. The comparative approach fosters cross-validation of the literature-based labeling system across diverse cultural and political contexts.

5.4 Contextual Cue Selection

Contextual cues are computable quantities derived from urban data sources that reflect environmental conditions with established links to mental wellbeing outcomes. The selection of contextual cues for the Urban Mental Wellbeing Risk Index applied systematic evaluation criteria to ensure selected indicators could support robust, generalizable, and scalable population-level assessment. This section documents the evaluation criteria and justification for selecting air quality, greenspace accessibility, and transit mobility as the contextual cues used in this research.

5.4.1 Selection Criteria Framework

The Urban Mental Wellbeing Risk Index required contextual cues representing environmental conditions with established links to mental wellbeing outcomes. Drawing on urban environmental health research reviewed in Chapter 2, seven environmental factors were identified with documented mental health associations: air quality (PM2.5 exposure), greenspace accessibility, public transit infrastructure, noise pollution, blue space access, traffic congestion, and commuting time. Three systematic criteria guided evaluation of these candidates to ensure selected indicators could support robust cross-city comparative assessment (Table 5.1).

Criterion 1: Epidemiological Evidence Base. The candidate cue must demonstrate established associations between environmental exposure and mental health outcomes documented in peer-reviewed epidemiological research. The evidence base must include quantifiable mental health outcomes such as depression diagnosis, anxiety symptoms, or psychological distress scores linked to measurable environmental exposures.

Criterion 2: Quantifiable Exposure Threshold. The candidate cue must provide a quantifiable exposure threshold or distance metric enabling binary or categorical risk classification at the residential address level. Thresholds could derive from regulatory standards (WHO

air quality guidelines), epidemiologically derived protective distances (greenspace proximity thresholds from dose-response studies), or accessibility metrics with documented mental health effects (transit stop proximity distances). The threshold must enable address-level classification as protective or risk based on residential location, excluding environmental factors with well-established mental health associations but lacking operational thresholds for population-level assessment.

Criterion 3: SCDCAF Data Availability. The candidate cue must demonstrate Level 1-2 data availability as defined by SCDCAF evaluation criteria in Chapter 4, indicating that required datasets exist in open or accessible formats with appropriate spatial resolution, temporal coverage, and documented quality standards across multiple smart city contexts. This criterion required data sources supporting address-level assessment without prohibitive access restrictions, cost barriers, or sensitivity classifications that would prevent population-level implementation. Data availability was assessed through examination of open data portals across the 25 candidate cities identified in Section 5.5.1.

Table 5.1 presents the systematic evaluation of seven candidate contextual cues against the three selection criteria. Air quality, greenspace accessibility, and transit mobility met all three criteria. Noise pollution demonstrated strong evidence and operational thresholds but failed Criterion 3 due to insufficient spatial monitoring coverage across candidate cities. Blue space met technical selection criteria but greenspace was prioritized to maintain three contextual cues while ensuring variety across environmental exposure types. Traffic congestion failed Criterion 2 due to lack of stable residential exposure thresholds, as congestion represents a temporal rather than spatial characteristic. Commuting time failed Criterion 3 as address-level assessment requires individual travel pattern data unavailable through open smart city datasets.

Table 5.1: Systematic Evaluation of Candidate Contextual Cues

Candidate Cue	Criterion 1: Evidence	Criterion 2: Threshold	Criterion 3: Data Availability	Selected?
Air Quality (PM2.5)	Chen et al. (2018)	10 $\mu\text{g}/\text{m}^3$ threshold	Level 1: Monitoring networks	Yes
Greenspace Access	Gascon et al. (2018)	300m-500m distance	Level 1-2: GIS park data	Yes
Transit Mobility	Wang et al. (2019)	850m accessibility	Level 1: Stop coordinates	Yes
Noise Pollution	Clark & Paunovic (2018)	WHO 55 dB limit	Limited coverage	No
Blue Space Access	Gascon et al. (2018)	Distance thresholds proposed	Prioritized greenspace	No
Traffic Congestion	Wang et al. (2019)	No residential threshold	Flow data insufficient	No
Commuting Time	Wang et al. (2019)	Time thresholds exist	Individual data required	No

5.4.2 Selected Contextual Cues: Methodological Justification

Air Quality (PM2.5) met all three selection criteria with strong empirical support and comprehensive data availability. [Chen et al. \(2018\)](#) established 10 $\mu\text{g}/\text{m}^3$ annual mean PM2.5 as the threshold above which mental health risk increases through neuroinflammation and HPA axis dysregulation (detailed in Chapter 3.1.2). Air quality monitoring networks in smart cities provide continuous hourly PM2.5 measurements through regulatory compliance infrastructure,

meeting SCDCAF Level 1 availability with documented spatial coverage, temporal frequency, and quality assurance protocols enabling address-level exposure assessment.

Greenspace Accessibility demonstrated robust evidence across all criteria with strong epidemiological support and comprehensive municipal data availability. [Gascon et al. \(2018\)](#) conducted a systematic review and meta-analysis establishing that residential proximity to greenspace within 300 meters provides protective mental health benefits, with effects diminishing beyond 500 meters, providing operational distance thresholds for binary risk classification. The protective mechanisms operate through cortisol reduction, autonomic nervous system regulation, and behavioral pathways facilitating physical activity and social interaction (Chapter 3.2.2). Municipal GIS systems document park boundaries with polygon geometries enabling precise residential distance calculations, meeting SCDCAF Level 1-2 availability across smart city open data portals with consistent spatial resolution and update frequencies.

Transit Mobility satisfied all selection criteria through documented accessibility thresholds and comprehensive transit authority data availability. [Wang et al. \(2019\)](#) established that public transit access within 850 meters reduces depression risk by enabling mobility, social connection, and resource access, particularly for non-drivers and lower-income populations (Chapter 3.3.2). Transit authority datasets provide stop coordinates across bus, rail, and light rail systems with comprehensive spatial coverage, meeting SCDCAF Level 1 availability requirements without access restrictions or cost barriers.

5.4.3 Excluded Contextual Cues: Methodological Constraints

Four candidate contextual cues were excluded due to data availability limitations, threshold operationalization challenges, or strategic prioritization to maintain framework focus on three complementary environmental exposures.

Noise Pollution demonstrated established mental health associations through stress pathways and sleep disruption ([Clark & Paunovic 2018](#)), with WHO regulatory thresholds defining harmful exposure levels (55 dB daytime). However, comprehensive spatial noise assessment requires extensive monitoring networks beyond standard smart city infrastructure. Data availability assessment across the 25 candidate cities revealed that most municipalities provide either noise complaint data or limited monitoring station coverage insufficient for address-level population assessment, failing SCDCAF Criterion 3. The sparse spatial coverage and inconsistent measurement protocols prevented systematic address-level risk classification across case study cities.

Blue Space Access demonstrated emerging mental health evidence ([Gascon et al. 2018](#)), with protective distance thresholds proposed in the literature. However, empirical findings remain inconsistent, with some studies showing borderline significant protective effects ([Gascon et al. 2018](#)) while others find no associations. Greenspace accessibility was prioritized to maintain three contextual cues while ensuring variety across environmental exposure types. Greenspace demonstrated stronger evidence from systematic reviews and meta-analyses ([Gascon et al. 2018](#)) and provided more comprehensive data availability across candidate cities, as municipal park systems are more consistently documented in GIS datasets than water body access points.

Traffic Congestion demonstrated mental health associations through stress pathways documented in commuting research ([Wang et al. 2019](#)), yet lacked standardized residential exposure thresholds enabling address-level risk classification. Traffic flow data exists in smart city infrastructure through sensor networks and GPS-based platforms, yet translating dynamic congestion patterns into stable residential risk classifications proved methodologically complex. Congestion represents a temporal rather than spatial exposure characteristic, requiring time-weighted exposure models incompatible with the static address-level assessment approach, failing Criterion 2.

Commuting Time showed documented mental health effects, with longer commuting du-

ration associated with increased depression risk (Wang et al. 2019). Epidemiologically derived time-distance thresholds exist in the literature. However, address-level commuting exposure assessment requires individual-level travel pattern data unavailable through open smart city datasets. While aggregate commuting statistics exist in census data, individual commuting routes and durations require mobility tracking or survey data incompatible with the open data approach adopted in this research, failing Criterion 3.

Final Selection Rationale

Air quality, greenspace accessibility, and transit mobility were selected as the contextual cues for the computational framework because they satisfied all three selection criteria. The three cues represent complementary pathways influencing mental wellbeing: biological mechanisms through PM2.5-induced neuroinflammation, physiological stress reduction through greenspace-mediated cortisol regulation, and social determinants through transit-enabled connectivity and resource access. The selected cues rely on environmental characteristics consistently documented across smart city open data portals, enabling cross-city comparative assessment without requiring specialized monitoring networks, restricted datasets, or individual behavioral data.

The exclusion of noise pollution and blue space access reflects pragmatic data availability constraints rather than dismissal of their mental health importance. Chapter 3 details the epidemiological evidence, exposure thresholds, biological mechanisms, and literature-based labeling methodology for each selected contextual cue. With contextual cues established, the systematic city selection process identified case study cities meeting data availability requirements for all three environmental indicators (Section 5.5).

5.5 Case Study City Selection and Justification

5.5.1 Systematic City Selection Process

The city selection process began with a comprehensive survey of global open data portals to identify candidate cities with potential smart city data infrastructure. The Open Knowledge Foundation’s DataPortals.org registry (Open Knowledge Foundation 2024) provided a systematic starting point, listing approximately 300 open data portals worldwide. From this global registry, the initial filtering prioritized English-speaking cities in North America and Europe to ensure consistent interpretation of data documentation, metadata standards, and administrative terminology. This language criterion served as a practical accessibility constraint necessary for accurate data evaluation. The 25 cities retained after this filter were selected based on evidence of established open data portals with documented environmental datasets, while deliberately excluding megacities such as Los Angeles and New York to avoid computational complications associated with processing datasets exceeding several million addresses.

The candidate pool was systematically filtered through six progressive stages, each applying objective data availability criteria documented in Table 5.2:

- **Stage 1 - Air Quality Monitoring:** Required comprehensive air quality monitoring infrastructure with at least three active PM2.5 monitoring stations providing continuous data over 12 months or more. Most cities fell short at this stage, either lacking sufficient monitoring station density or providing only intermittent data, reducing the pool to 12 cities.
- **Stage 2 - Greenspace Data:** Filtered for greenspace data availability, specifically GIS polygon geometries meeting the 0.5-hectare minimum threshold established by Gascon et al. (2018), leaving 9 cities.

- **Stage 3 - Transit Data:** Verified transit data comprehensiveness across all formal public transportation modes, reducing to 7 cities.
- **Stage 4 - Residential Address Points:** Confirmed residential address point availability with sufficient spatial resolution for population-level analysis. Address point datasets proved particularly restrictive, as many cities either restricted access or provided only aggregated spatial data unsuitable for residential-level analysis, yielding 5 cities.
- **Stage 5 - Administrative Boundaries:** Ensured administrative boundary data with census population counts enabling weighted aggregation. Cities excluded at this stage typically provided census data through web interfaces or interactive dashboards without straightforward download mechanisms required for computational analysis, leaving 4 cities.
- **Stage 6 - Geographic Diversity:** Prioritized geographic diversity to test framework generalizability across different regional contexts, resulting in the final three cities spanning two continents and diverse urban characteristics.

Chicago, Portland, and Manchester emerged as the cities meeting all methodological requirements while providing geographic and contextual diversity. Each filtering stage applied transparent, reproducible criteria that future researchers could replicate when implementing the framework in new cities.

5.5.2 SCDCAF-Guided Selection Criteria

SCDCAF explored in Chapter 4 guided city selection by defining what constitutes 'available' data for urban mental wellbeing research. The framework assesses whether data sources meet practical and methodological requirements for population-level contextual cue analysis, distinguishing between data that exists versus data that supports scalable comparative assessment.

Case study selection applied SCDCAF evaluation criteria through systematic data ecosystem assessment. Cities needed to demonstrate Level 1-2 availability across multiple contextual cue domains, offer predominantly low-sensitivity open datasets, provide frequent temporal updates for environmental monitoring, and maintain free or limited-restriction access models. The selection followed an exploratory discovery process where SCDCAF-defined availability guided decisions, with preference for medium and major sized cities, avoiding megacities, for faster analysis. Cities were then systematically explored through municipal, city or state open data portals, commercial platforms, and government census data. Cities demonstrating strong data coverage in one contextual cue category, for example air quality, were further investigated for complementary datasets for greenspace and mobility data. This exploratory process identified Chicago, Portland, and Manchester as providing the most comprehensive data coverage across all required categories, enabling robust cross-city comparative analysis. Each city provided enough data to cover contextual cues and supporting data for complete analysis, presented in Table 5.3.

Table 5.3 presents SCDCAF-guided criteria that ensure the selected cities could support environmental exposure assessment for urban mental wellbeing estimation while maintaining methodological consistency across different urban contexts. The availability of complete datasets across all three cities allows for cross-validation of the literature-based labeling approach and assessment of framework generalizability.

Chicago Selection Criteria

Chicago City was selected based on comprehensive data availability across all required categories and its suitability as a major metropolitan test case for appropriate computational framework scalability. The city of Chicago, located in Illinois, USA, has 2.7 million residents across

Table 5.2: Systematic City Selection Process: From 300 Global Cities to 3 Case Studies

Stage	Criterion	Cities Re- maining	Rationale
Initial	Global open data portal registry (DataPortals.org)	300	Comprehensive survey of global open data infrastructure
Filter 1	English-speaking cities (North America, Europe) with established open data portals; excluded megacities	25	Practical accessibility; avoided computational complications with datasets exceeding millions of addresses
Stage 1	Air quality: 3+ PM2.5 stations, 12+ months continuous data	12	Most cities lacked sufficient monitoring density or continuous data
Stage 2	Greenspace: GIS polygons with 0.5+ hectare parks	9	Excluded cities lacking detailed park geometry data
Stage 3	Transit: Stop coordinates across all public transport modes	7	Excluded cities with incomplete transit datasets
Stage 4	Residential address points with adequate spatial resolution	5	Address data often restricted or spatially aggregated
Stage 5	Administrative boundaries with census population data (downloadable format)	4	Many cities provided census data only through web interfaces without download capability
Stage 6	Geographic diversity preference	3	Framework generalizability testing across regional contexts
Final	Chicago, Portland, Manchester	3	US Midwest + Pacific Northwest + UK; comprehensive data coverage

77 community areas and 60 zip codes¹. The city covers 60,000 hectares with 3,000 hectares designated as city park greenspace. The CTA network includes 146 rail stations, providing comprehensive transit accessibility data². Chicago is a major city in the United States, still its data is manageable compared to megacities such as Los Angeles and New York City where population exceeds 10 million residents. Chicago’s data characteristics complement Manchester and Portland, providing city scale diversity while maintaining methodological consistency across the three-city comparative framework. Chicago met SCDCAF requirements with comprehensive data coverage across all contextual cues and extensive temporal coverage, making it suitable as a large metropolitan test case. Chicago has launched several smart city projects, from smart grid implementations with advanced metering infrastructure to sensor networks for intelligent transportation systems³. These smart city initiatives highlight Chicago’s effort towards a data-driven city which facilitates the integration of this framework.

¹<https://www.chicago.gov/city/en/about/facts.html>

²<https://www.transitchicago.com/>

³<https://www.chicago.gov/city/en/progs/env/smart-grid-for-a-smart-chicago.html>

Table 5.3: Required Datasets by Category for Case Study Selection (referenced in Table 5.2)

Data Category	Requirements	Preferred Format	Purpose	SCDAF Dimensions Preferability
Air Quality	PM _{2.5} pollution data with hourly measurements	Time series data, CSV	Contextual cue analysis	Level 1 Availability, Low Sensitivity, Frequent Temporal
Greenspace	City parks, public greenspaces	Geospatial, CSV	Contextual cue analysis	Level 1 Availability, Low Sensitivity, Infrequent Temporal
Mobility	Transit stops; traffic data preferred when available	Geospatial, CSV	Contextual cue analysis	Level 1 Availability, Low Sensitivity, Infrequent Temporal
Address Data	Residential addresses or filterable general addresses	Spatial and point coordinates	Population-level analysis	Level 1 Availability, Low Sensitivity, Static Temporal
Spatial Boundaries	City, neighborhood, or zip code boundaries	Geospatial polygons	Geographic aggregation	Level 1 Availability, Low Sensitivity, Static Temporal, Government provided
Demographics	Census population counts by geographic area	Tabular, CSV	Population-level analysis	Level 1 Availability, Low Sensitivity, Static Temporal (yearly), Government provided

Manchester Selection Criteria

The Greater Manchester area was selected because it met the data selection criteria, and it adds location variety. Greater Manchester is a combined authority area in the United Kingdom, with a population of 2,867,769 and consists of 10 metropolitan districts and boroughs namely, Bolton, Bury, Manchester, Oldham, Rochdale, Salford, Stockport, Tameside, Trafford and Wigan. Greater Manchester covers 500 square miles and is connected via tram and bus routes through the Metrolink network ⁴. Greater Manchester has adopted a Digital Strategy (2021–2026) to implement technology-driven goals across four key areas: smart people, digital places, future prosperity, and sustainable resilience. The strategy integrates digital systems in urban planning and ensures that data is managed responsibly through ethical frameworks while supporting the city’s 2038 zero-carbon target ⁵.

Portland Selection Criteria

Portland was selected as a case study site because it met all requirements for data collection across contextual cues and provided additional datasets for analysis. The City of Portland, located in Oregon, covers approximately 134 square miles (85,760 acres) and has a population of 678,332 residents, divided into 32 zip codes and 94 neighborhoods. Portland’s smaller population size offers contrasting scenario for testing compared to Chicago and Manchester. Portland is characterized by its strong greenspace system, including neighborhood parks, urban squares, and large natural reserves such as Forest Park, and it maintains a multimodal public transport network of buses and light rail ⁶. Portland established smart city governance projects through the Smart City PDX program, which focuses on digital equity, data privacy, and responsible AI use. The city has established comprehensive data governance policies and launched workgroups to ensure transparent algorithmic systems. These policies, combined with the city’s open-data ecosystem, provide suitable conditions for testing the framework in a mid-sized U.S. city. Portland’s data characteristics complement Chicago’s and Manchester and are a suitable fit for the computational framework.

Multi-City Validation Logic

The framework is applied across three cities in different geographic contexts to test generalizability. Chicago (2.7 million residents), Portland (678,332 residents), and Manchester (2.8 million residents) represent varying urban development patterns, population densities, and geographic regions spanning the US and UK. Each city has implemented different smart city initiatives tailored to local needs, from Chicago’s infrastructure sensors to Portland’s digital equity focus to Manchester’s digital strategy. Cross-validation of the literature-based labeling approach in application to these diverse cities validates the framework’s methodological consistency. The framework is designed for replication in any city meeting SCDAF data availability criteria, enabling scalable urban mental wellbeing assessment.

5.6 Data Collection Methods

This research utilizes open data sources as the foundation for data collection across all three case study cities, supporting methodological transparency, and addressing practical limitations in large-scale urban analysis. Open data enables direct replication since datasets from Chicago’s Open Data Portal, Portland’s PortlandMaps platform, and the UK’s Ordnance Survey Data Hub are publicly accessible, addressing gaps in urban mental wellbeing research where private

⁴<https://fireknowledge.co.uk/gmfrs/about-greater-manchester/>

⁵<https://www.manchester.gov.uk>

⁶https://www.portland.gov/sites/default/files/2020-01/urb_form_complete_web_1009.pdf

data cannot be independently validated. The widespread adoption of open data portals, with 41 US states, 51 US cities, over 47 countries, and 125 regional portals globally maintaining dedicated platforms, means the computational framework can potentially extend to hundreds of additional cities without specialized access agreements or cost restrictions. Population-level environmental exposure assessment requires extensive spatial and temporal datasets that would be prohibitively expensive and time-consuming through traditional survey methods. A comprehensive survey achieving the same geographic coverage as this study’s 815,343 addresses across three cities would require substantial funding and time for survey design, administration, and quality control, while open data provides higher temporal and spatial resolution at no direct cost.

5.6.1 Chicago Data Collection

Primary Data Portal: The Chicago Open Portal (COP) ⁷ offers human and machine-readable data across 16 distinct categories totaling 1924 available datasets. Categories include administration and finance, buildings, community, education, environment, ethics, events, FOIA, facilities and geo boundaries, health and human services, historic preservations, parks and recreation, public safety, sanitation, service requests, and transportation. Data formats include CSV files, GIS shapefiles, JSON, and PDF documentation. Key datasets obtained through this portal included greenspace boundaries, transit stops, traffic monitoring data, building footprints, and administrative boundaries. Greenspace data collection retrieved park boundaries information through COP and included detailed attribute information on park types, amenities, and accessibility features. Additionally, transit infrastructure data for Chicago was obtained from the COP which includes CTA bus and rail station locations.

Air Quality: The United States Environmental Protection Agency provides pre-generated standardized data files on multiple air quality pollutants including daily PM_{2.5} data. This data file covers the whole united states, with option to select city limits. The year ranges from 1990 to the current year, 2025. The Illinois Environmental Protection Agency provided additional PM_{2.5} daily averages. ⁸

Address and Census Data: The Cook County open-data portal ⁹ facilitated the address point data. The Chicago Health Atlas ¹⁰ provides Chicago city census data including population and households per ZIP codes and community areas. Building footprint data, acquired from the Chicago Open Portal, provided additional spatial context necessary for address filtering procedures.

Chicago meets SCDCAF requirements across all evaluation criteria with particularly strong dataset diversity. Air quality data reaches Level 2 availability through EPA monitoring with hourly PM_{2.5} measurements spanning 1990-2025. Greenspace data achieves Level 1 availability via GIS datasets from the Chicago Open Portal, while transit data reaches Level 1 availability through CTA network covering 146 rail stations. The city maintains low-sensitivity data throughout, using aggregated spatial information that enables population-level analysis without individual identification. Data updates align with research needs, hourly air quality monitoring, regular transit infrastructure updates, and periodic greenspace boundary revisions. Chicago’s open data policies provide unrestricted access to 1,924 datasets across 16 categories, supporting both academic research and public use without licensing barriers. All datasets demonstrated strong spatial coverage across Chicago and temporal compatibility enabling analysis across the three contextual cues. The data from the various sources are updated frequently and is available publicly at the time of this research.

⁷<https://data.cityofchicago.org/>

⁸<http://www.epa.state.il.us/air/pm25/index.html>

⁹<https://hub-cookcountyil.opendata.arcgis.com/>

¹⁰<https://chicagohealthatlas.org/>

5.6.2 Manchester Data Collection

Primary Data Portal: The Ordnance Survey (OS) Data Hub ¹¹ offers free access, premium fee-based access, and public sector workers. The OS Data Hub provides 27 total free open datasets with 7 distinct categories: geological, greenspaces, height, identifiers, lookups, mapping, and networks. Key datasets retrieved from this data hub were greenspaces, area boundaries, open map pointers, and UPRN post codes. The OS also provided important sites and building data used for additional address filtering procedures.

Air Quality data: Air Quality England provides validated monitoring data for PM_{2.5} from nine stations across Greater Manchester. The data is available in hourly CSV format through the Air Quality England portal ¹²

Mobility data: The UK Government's open data portal provides geospatial data on Greater Manchester Metrolink stops and rail stations. The dataset is available at ¹³

Census data: The UK Office for National Statistics provides a service, Nomi ¹⁴, that publishes statistics from census data. For this research, key datasets that were extracted are population counts and household counts by district boroughs.

Greater Manchester's datasets align with SCDCAF requirements across all contextual cues. Air quality data reaches Level 1 availability through nine monitoring stations providing hourly PM_{2.5} measurements. Ordnance Survey Open Greenspace data covers public parks and gardens across the ten boroughs at Level 1 availability with low sensitivity. ONS census data provides population, and household counts at borough and district levels, also at Level 1 availability. Address data from OS Open UPRN reaches Level 2 availability because it includes all addressable locations rather than residential-only classifications, requiring additional filtering. The city's data coverage meets SCDCAF requirements for population-level contextual cue analysis.

5.6.3 Portland Data Collection

Primary Data Portal: The PortlandMaps Open Data ¹⁵ portal, powered by ArcGIS, serves as the city's central data sharing platform. The portal contains 12 categories including 358 datasets: boundaries, capital projects, planning and development, zoning, environment, public safety, important places, property, transportation, utilities, miscellaneous, and American Rescue Plan Act data. Key datasets for this research include parks and greenspaces, residential addresses with pre-applied filtering, city and neighborhoods boundaries, and traffic count data.

Air Quality: PM_{2.5} concentrations are sourced from the EPA's Air Quality System ¹⁶, providing consistent measurement standards across all case study cities. EPA's air quality data spans from 1999 to 2025, with filtering capabilities for administrative boundaries. The dataset includes hourly measurements from multiple monitoring stations, enabling robust temporal analysis for 2024. An additional PM_{2.5} dataset from the Oregon Department of Environmental Quality ¹⁷ was included for additional monitor addition.

Mobility data: TriMet provides geospatial data on transit stops, covering both bus routes and the light rail and tram system. The dataset is available through the TriMet developer portal ¹⁸

Census and Demographic Data: The U.S. Census Bureau provides population data through 3425 demographic datasets, including population by neighborhoods, household num-

¹¹<https://osdatahub.os.uk/data/downloads/open>

¹²<https://www.airqualityengland.co.uk/>

¹³(<https://www.data.gov.uk/dataset/8faea7ee-eb7d-43dd-b1d4-f01aac4c44d3/metrolink-and-rail-stations>)

¹⁴<https://www.nomisweb.co.uk/>

¹⁵<https://gis-pdx.opendata.arcgis.com/>

¹⁶<http://www.epa.state.il.us/air/pm25/index.html>

¹⁷<https://aqi.oregon.gov/>

¹⁸<https://developer.trimet.org/gis/>

bers, and socioeconomic indicators necessary for contextualizing environmental exposure patterns.¹⁹

Portland’s data ecosystem demonstrates strong performance across all SCDCAF evaluation criteria. The city achieves Level 2 availability for air quality data through EPA monitoring stations, Level 1 for greenspace data via comprehensive GIS datasets, and Level 1 for transit data through TriMet’s open data initiatives. Data sensitivity remains predominantly at the low-sensitivity level, with spatially aggregated information that protects individual privacy while enabling population-level analysis. Temporal frequency meets research requirements with hourly air quality updates, frequently updated transit stop data, and semi-annual greenspace updates. Access restrictions are minimal, with most datasets available under open licenses that support academic research and public use.

5.6.4 Data Collection Protocols

Data discovery employed consistent search strategies across all three cities to ensure comparable dataset identification. The initial search phase used standardized Google queries combining “open data portal” with each city name to locate primary data sources. This approach successfully identified direct portal access for Chicago and Portland. However, Manchester’s fragmented structure required broader UK-wide searches.

File format standardization was evident across cities with each city offering CSV, shapefile, GeoJSON file formats. The coordinate system is addressed based on city location to consider environmental characteristics, yet all coordinate systems are set to meters for consistency. Authentication requirements varied substantially across cities and data types. Chicago, Portland, and Manchester portals provided anonymous access to chosen datasets with an option to create an account.

Data validation implemented multi-stage quality checks adapted to each dataset type. Initial validation confirmed successful downloads through file size and format verification. Spatial data validation considered boundary containment checks to guarantee coordinates exist within calculated city limits to ensure the right study area is being used. Air quality data validation applied EPA range checks ($(0\text{--}500\text{ }\mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$) to identify data outliers. Temporal validation assessed the monitoring records for continuous gaps in hourly and daily data to ensure reliable coverage. Distance calculations were verified to confirm that all measurements were made in meters by checking coordinate reference system transformations. All air quality monitoring stations across the three cities maintained data completeness above 85% for the study period. This ensures reliable temporal coverage for annual risk score calculations. Chicago’s city-wide completion is at 94.8%, Manchester’s is at 95.7%, and Portland’s is at 100%.

The data collection methodology includes replication procedures designed for framework replication in additional cities with open data portals. Python scripts were used for data loading, pre-processing and analysis since they have reliable libraries and functions to deal with geospatial data through the pandas library and the extension of geopandas. Data loading was customized for each city, as the structure and attributes of available datasets differed across sources. Some datasets require additional preprocessing, such as selecting only relevant columns or joining multiple files. All raw datasets were downloaded to cloud storage and then loaded into Python scripts for analysis. A README file documenting dataset URLs, search keywords, and preprocessing steps was included through the GitHub link, in Appendix B, to the main repository to support reproducibility.

¹⁹https://data.census.gov/profile/Portland_city;_Oregon?g=160XX00US4159000

5.7 Risk Score Construction and Justification

5.7.1 Risk as Assessment Framework

This framework adopts risk as the primary assessment construct rather than direct wellbeing measurement or health indices. As discussed in Section 2.3.3, risk-based assessment aligns with the epidemiological evidence base where [Chen et al. \(2018\)](#), [Gascon et al. \(2018\)](#), and [Wang et al. \(2019\)](#) frame environmental exposures through protective and harmful thresholds rather than continuous wellbeing scales. Environmental health research consistently operationalizes mental health outcomes as risk probabilities such as increased odds of depression, elevated likelihood of psychological distress, or protective effects against anxiety symptoms ([Bratman et al. 2019](#)).

The risk framework enables binary classification at literature-derived thresholds. Air quality research establishes PM2.5 concentrations above 10 $\mu\text{g}/\text{m}^3$ as increasing mental health risk ([Chen et al. 2018](#)), greenspace research identifies 300-meter proximity as protective ([Gascon et al. 2018](#)), and transit research defines 850-meter accessibility as the threshold beyond which depression risk increases ([Wang et al. 2019](#)). These threshold-based findings translate directly into risk classifications, whereas continuous wellbeing scales would require additional assumptions about dose-response linearity outside empirically tested ranges.

Risk-based assessment supports the computational framework’s policy application objectives by identifying which neighborhoods face elevated environmental exposure risk, which populations lack protective infrastructure access, and where environmental improvements would reduce mental health vulnerability. This approach has precedent in environmental health assessment, including the Globally Harmonized System’s hazard classification for chemical risks and health impact assessments for climate change adaptation strategies.

5.7.2 Five-Level Ordinal Scale Justification

The Urban Mental Wellbeing Risk Index (UMWI) employs a five-level ordinal scale (1 = Very Low Risk, 2 = Low Risk, 3 = Moderate Risk, 4 = High Risk, 5 = Very High Risk) to classify environmental exposure risk at the residential address level. This five-point structure balances methodological requirements for meaningful discrimination between risk categories with practical constraints on threshold operationalization from epidemiological literature.

Psychometric research on optimal response scale granularity provides evidence supporting five-level categorization. [Preston & Colman \(2000\)](#) demonstrated through empirical comparison of scales ranging from 2 to 11 response categories that reliability and validity increase from two-point to seven-point scales, with test-retest reliability highest for scales with 7 to 10 response categories and diminishing returns beyond this range. Their findings indicated that scales with fewer than five response categories performed poorly across multiple validity and discriminating power indices, while scales with five to seven categories optimized measurement precision without exceeding respondents’ cognitive capacity for meaningful discrimination. [Revilla et al. \(2014\)](#) found that five-point scales yielded significantly higher measurement quality than longer scales with seven or eleven response categories. Research on wellbeing measurement instruments has found that five-point scales improve data quality, internal consistency, and discriminant validity compared to four-point scales ([Pontin et al. 2013](#)).

The five-level structure accommodates the discrete thresholds documented in environmental health literature while avoiding false precision. Air quality assessment divides PM2.5 z-score distributions into quintiles reflecting standard deviation ranges ([Chen et al. 2018](#)). Greenspace assessment operates through three primary distance categories (0-300m protective, 300-500m transitional, 500m+ elevated risk) derived from [Gascon et al. \(2018\)](#), which map naturally onto a five-point scale with additional granularity for extreme exposures. Transit accessibility functions as a binary threshold at 850 meters ([Wang et al. 2019](#)), which converts to risk scores

through protective (1-2) and harmful (4-5) endpoints with a moderate midpoint (3) for transitional distances. The five-point scale enabled assignment of a middle category (Level 3) to addresses where one or more contextual cues reached or marginally exceeded literature-derived thresholds, distinguishing these transitional cases from addresses with clearly protective (Levels 1-2) or clearly harmful (Levels 4-5) environmental profiles. A three-level scale would collapse meaningful distinctions documented in the literature, particularly for air quality where dose-response relationships demonstrate graded effects across PM2.5 exposure ranges. In contrast, scales exceeding seven levels would introduce artificial precision unsupported by epidemiological evidence, as the underlying research establishes discrete protective and harmful thresholds rather than continuous linear relationships across all exposure ranges.

5.7.3 Risk Level Operational Definitions

Each risk level represents a distinct environmental exposure profile based on literature-derived thresholds applied to individual contextual cues. At the address level, contextual cue scores (1-5) reflect exposure to air quality, greenspace accessibility, and transit mobility. These individual scores aggregate into the Urban Mental Wellbeing Risk Index (UMWI) through population-weighted means, producing a city-level composite score ranging from 1.0 to 5.0, further explanation in Chapter 6.

Level 1 (Very Low Risk) represents residential locations meeting all protective criteria across contextual cues. Air quality consistently below harmful thresholds with minimal variability, greenspace accessibility within 300 meters of eligible parks, and transit stops accessible within 850 meters.

Level 2 (Low Risk) represents residential locations meeting most protective criteria with minor deviations. Air quality slightly elevated but below harmful thresholds, greenspace access within 300-500 meters (transitional protective range), or transit accessibility marginally beyond optimal distance.

Level 3 (Moderate Risk) marks the critical threshold where protective conditions transition to elevated risk. This represents the inflection point documented in epidemiological literature where PM2.5 approaches +1 standard deviation above city mean ([Chen et al. 2018](#)), greenspace access beyond 500 meters where protective effects substantially diminish ([Gascon et al. 2018](#)), or transit accessibility exceeding the 850-meter walking threshold ([Wang et al. 2019](#)).

Level 4 (High Risk) represents residential locations exceeding harmful thresholds for one or more contextual cues. Air quality substantially above population mean exposure levels, greenspace access beyond 800 meters (minimal protective effects), or no transit accessibility within comfortable walking distance.

Level 5 (Very High Risk) represents residential locations exceeding harmful thresholds across multiple contextual cues simultaneously. Combination of elevated PM2.5 exposure, severely limited greenspace access, and absent transit infrastructure.

When aggregated to city level through population-weighted means, the UMWI maintains this five-level interpretation on a continuous 1.0-5.0 scale. Table 6.1 in Section 6.1.1 presents the specific score ranges and burden interpretations for the normalized city-level index. This standardized metric enables cross-city comparison while maintaining interpretability for local planning decisions, with scores above 3.0 indicating cities where populations face elevated environmental exposure risk requiring systematic intervention.

5.8 Framework Replication for New Cities

The computational framework is designed for replication in cities with appropriate data infrastructure, most likely found in smart cities, as discussed in Chapter 3. Table 5.2 documents

the systematic filtering criteria applied during case study selection, while Table 5.3 specifies the complete dataset requirements and SCDCAF dimension preferences that prospective cities must satisfy. Successful implementation requires systematic data collection, first by identifying regional open data portals. Air quality monitoring infrastructure requires the presence of a minimum of 3–5 active stations with continuous monthly $\text{PM}_{2.5}$ data spanning 12 months or more. Verification of GIS data availability includes confirming the presence of geocodable residential address points, greenspace polygon geometries for applying the 0.5-hectare threshold, and coordinate data for transit stops across all formal public transportation modes. Due to data formats differing across cities, Python collection scripts need to be adapted to each city-level data model and coordinate system while maintaining a consistent literature-based labeling framework.

For new city implementations, validation starts with cross-referencing results against the Chicago, Manchester, and Portland baselines to detect potential data quality issues. Further validation includes verifying distance accuracy through spot-checks, confirming that literature-based thresholds apply to the new context, and reviewing data completeness to identify temporal gaps. The computational framework’s modular design allows iterative refinement as cities have unique constraints and adaptation needs. Documenting city-specific processing decisions contributes to the framework’s continued development and its applicability across diverse smart cities.

5.9 Conclusion

This chapter established the methodological approach for assessing environmental exposure risk through literature-validated thresholds and smart city data. The positivist philosophy treats environmental factors as objective, measurable phenomena affecting mental health through documented biological mechanisms. The deductive framework converts three established research findings (Chen et al.; Gascon et al.; Wang et al.) into operational thresholds that standardize risk assessment across different urban contexts. The cross-sectional design captures current environmental risk patterns across Chicago, Manchester, and Portland using population-level address data. Chapter 6 details the technical implementation, presenting the data collection methods, quality assessment procedures, and analytical techniques that operationalize this framework into executable processes for environmental exposure risk assessment.

Chapter 6

Data Infrastructure and Analytical Methods

Chapter 6 implements the computational framework introduced in Chapter 5, through open data infrastructure and standardized analytical methods that convert environmental indicators into population-level urban mental wellbeing risk scores. The chapter prioritizes methodological transparency to ensure complete replicability, explaining how publicly available open data from Chicago, Manchester, and Portland serve as framework inputs. This research introduces the Urban Mental Wellbeing Risk Index (UMWI) as an original contribution to urban mental wellbeing assessment methodology. The UMWI represents a novel computational framework developed through this research to aggregate multiple environmental contextual cues into a single population-level risk metric. Section 6.1 defines the dependent variable (UMWI) and three independent contextual cue variables (air quality, greenspace accessibility, transit mobility), documenting the literature-derived thresholds, distance calculation methods, population-weighting procedures, and control variables that operationalize environmental exposure risk assessment at the address and city levels. Section 6.2 outlines the analytical framework for spatial analysis, covering both the spatial analysis techniques and the statistical strategy used to interpret the results. Section 6.3 addresses research ethics and data privacy considerations.

6.1 Variable Definition and Operationalization

6.1.1 Dependent Variable: Urban Mental Wellbeing Risk Index (UMWI)

The dependent variable is the Urban Mental Wellbeing Risk Index (UMWI), a normalized index summarizing environmental risk to mental wellbeing based on environmental stressors, represented by contextual cues in this research: air quality, greenspace, and mobility. This metric serves as a proxy for potential mental wellbeing risk, reflecting environmental exposure burden rather than individual clinical diagnosis. The UMWI measures environmental risk to mental wellbeing. Lower index scores indicate stronger protective conditions and higher wellbeing potential, while higher scores indicate greater environmental burden and elevated mental health risk. The UMWI employs a five-level ordinal scale (1 = Very Low Risk, 2 = Low Risk, 3 = Moderate Risk, 4 = High Risk, 5 = Very High Risk) at the address level, with methodological justification for this scale structure provided in Section 5.7.2. The normalized Urban Mental Wellbeing Risk Index is a continuous variable ranging from 1.0 to 5.0. The three contextual cue scores (each ranging from 1-5) are summed (producing a 3-15 range), then linearly transformed using the formula shown below. This normalization preserves the cumulative burden while producing a metric directly comparable to individual cue scales. The risk score aggregates three equally weighted contextual cues, each cue contributing equally to the cumulative burden. Equal weighting is applied because current evidence does not provide sufficient research

on weighing the relative contributions or interactive effects of the contextual cues. Air quality, greenspace, and transit accessibility each represent distinct but complementary pathways to mental health impact, all three causing biological stress, as explained in Chapter 3. Equal weighting acknowledges each contextual cue’s impact on mental health equally and creates a transparent composite index.

$$\text{Cumulative Score}_{\text{City}} = \text{Air Quality Score} + \text{Greenspace Score} + \text{Mobility Score}$$

$$\text{UMWI}_{\text{City}} = 1 + \left(\frac{\text{Cumulative Score}_{\text{City}} - 3}{12} \right) \times 4$$

Risk category thresholds are defined at approximately one-point intervals to create five distinct burden levels, as seen in Table 6.1.

Table 6.1: Urban Mental Wellbeing Risk Index (UMWI) Normalized Score Interpretation

Normalized Score Range	Risk Level	Interpretation
$1 \leq x < 2$	Very Low Risk	Minimal exposure burden: environmental conditions consistently score at or near the lowest risk levels, indicating strong protective factors across all contextual cues.
$2 \leq x < 3$	Low Risk Burden	Light environmental stress: conditions remain well below critical thresholds, with most cues providing protective conditions or minimal stress exposure.
$3 \leq x < 4$	Elevated Risk Burden	The critical transition burden: the normalized cumulative burden has crossed the 3.0 threshold, indicating consistent failure to maintain protective environmental conditions across multiple domains.
$4 \leq x < 5$	High Risk Burden	Severe environmental stress: the normalized score reflects multiple contextual cues substantially exceeding documented harm or deprivation thresholds.
5.0	Very High Risk Burden	Extreme environmental stress: all contextual cues are at maximum risk, representing pervasive environmental deprivation.

Since the normalized UMWI is a continuous variable, this approach ensures that cities scoring 3.0 or above are unambiguously classified as having crossed critical environmental thresholds, simplifying interpretation for urban planners and policymakers. Individual contextual cue scores help identify specific improvement areas, while the cumulative UMWI captures the total environmental burden. This approach also supports cross-city comparison, which can help planners understand their own context better. The outcome of this process is a final dataset in which each city receives one aggregated PM_{2.5} score, one greenspace accessibility score, one transit accessibility score, and one overall Urban Mental Wellbeing Risk Index score.

6.1.2 Independent Variables: Contextual Cues

Literature thresholds are converted into operational rules that structure data processing and risk categorization. [Chen et al. \(2018\)](#) monthly PM_{2.5} windows function as temporal aggregation criteria to standardize air quality measurements across monitoring networks and reporting

schedules. [Gascon et al. \(2018\)](#) spatial thresholds of 300-meter buffers and 0.5-hectare minimum sizes define parameters for greenspace accessibility calculations in GIS. Because network walking data are unavailable, [Wang et al. \(2019\)](#) thresholds are implemented as an 850-meter spatial cutoff by converting a 10-minute walk to average distance for measuring transit accessibility. These operational metrics allow consistent application of literature-based criteria while adjusting to differences in urban context and data availability.

The contextual cues represent specific and measurable environmental inputs that previous research has linked to mental health outcomes. Each cue is quantified using the standardized 1–5 labeling system developed in this study, based on scientifically validated thresholds such as one standard deviation above the mean for PM_{2.5}, distance cutoffs of 300 and 500 meters for greenspace access and 850-meter threshold for transit access. A general representation of the risk scale can be seen in Table 6.2. This general scale applies to each contextual cue exposure risk assessment. Each contextual cue is mapped onto the same 1-5 structure, indicating the transition point between protective and harmful exposure conditions. Each contextual cue final score can be interpreted using Table 6.2. A score of 1 represents low exposure risk and 5 equals very high exposure risk and score 3 is elevated risk that represents the critical inflection point.

Table 6.2: General 1–5 Risk Labeling for Contextual Cues

Score	Risk Level	General Description
$1 \leq x < 2$	Very Low Risk	Conditions represent maximum protective factors or minimal hazardous exposure; significantly better than average.
$2 \leq x < 3$	Low Risk	Conditions are protected and below the average risk level; maintains generally good exposure or accessibility.
$3 \leq x < 4$	Elevated Risk	At or beyond literature-documented thresholds where protection ends or harm begins; the threshold transition from protected to at-risk.
$4 \leq x < 5$	High Risk	Substantially beyond protective thresholds and/or deep into the range of documented harm or deprivation.
$x = 5$	Very High Risk	Conditions represent severe, extreme exposure or deprivation; significantly exceed all documented harm thresholds.

Air Quality Contextual Cue

The air quality contextual cue captures atmospheric air pollution exposure that affects mental health through neuroinflammatory pathways. The air pollutant, (PM_{2.5} was chosen because its particles size ($< 2.5 \mu\text{m}$) is minuscule) enough that it penetrates deep into lungs, crosses into the bloodstream, and reach the brain triggering neuroinflammation ([Genc et al. 2012](#)). This cue represents the invisible but chronic environmental stressor that degrades cognitive function and impacts mental health in urban populations. The full literature review of air quality and PM_{2.5} pollutant can be found in Chapter 3.

[Chen et al. \(2018\)](#) found that one standard deviation increase in PM_{2.5} increases severe mental illness probability by 6.67 percentage points. Their study measured 30-day average PM_{2.5} exposure and assessed psychological distress using the Kessler-6 screening scale, with a K6 score of more than 13, indicating serious distress. The 6.67 percentage point change represents absolute probability increase, if baseline risk is 10%, one standard deviation increase raises it to 16.67%. ([Chen et al. 2018](#)) standardized PM_{2.5} so the unit is one standard deviation

(1 SD) of that 30-day mean within the study sample. The 30-day average window better reflects sustained exposure since it smooths day-to-day spikes compared to a single 24-hour reading. This temporal aggregation also aligns with monthly air quality reporting schedules that are shared with the public. [Chen et al. \(2018\)](#) results for this study provide a quantitative anchor: a precise pollution threshold that translates environmental exposure into mental health risk.

Air Quality Contextual Cue was operationalized as an independent variable through the calculation of 30-day average concentrations of fine particulate matter (PM_{2.5}). The transformation of raw monitoring data into a standardized 1–5 risk score followed a fixed procedure designed to align with the mental health risk thresholds reported in [Chen et al. \(2018\)](#). This relationship serves as the empirical basis for defining discrete risk thresholds in the computational framework. The operationalization of the Air Quality Contextual Cue follows a 5-step process:

Step 1: Defining the Local City Baseline

For each case study city, a fixed reference distribution was established. All 30-day average PM_{2.5} measurements collected from monitoring stations within the city across the full study period (2024) were combined to calculate a citywide mean (μ_{City}) and standard deviation (σ_{City}). These parameters formed the stable baseline against which all subsequent monthly averages were standardized.

City Mean (μ_{City}): This average becomes the zero-point or baseline against which every current monthly reading is compared to calculate its risk score.

$$\mu_{\text{City}} = \frac{\sum_{i=1}^N \text{PM}_{2.5,i}}{N}$$

where i represents a single 30-day PM_{2.5} average reading and N is the total number of such readings within the city during the study period.

City Standard Deviation (σ_{City}): The σ_{City} represents the definitive measure of the city’s historical volatility and indicates the PM_{2.5} concentration value that constitutes a +1 standard deviation change away from the citywide mean.

$$\sigma_{\text{City}} = \sqrt{\frac{\sum_{i=1}^N (\text{PM}_{2.5,i} - \mu_{\text{City}})^2}{N - 1}}$$

where i represents a single 30-day PM_{2.5} average reading and N is the total number of readings used to calculate the citywide distribution.

Step 2: Monthly Risk Scoring at the Monitor Level

To measure the air quality risk associated with each monitoring location, monthly PM_{2.5} concentrations were standardized against the city’s long-term baseline. This step translates raw pollution values into comparable relative scores that express how unusual or extreme each month’s air quality is within the city’s historical context. By converting every 30-day average into a standardized z-score, monthly readings from different monitors and seasons can be directly compared on the same scale. The z-score quantifies how far a given month’s PM_{2.5} level deviates from the citywide mean, measured in units of standard deviation. A positive z-score indicates above-average pollution (higher risk), while a negative z-score indicates cleaner-than-average air (lower risk). This normalization ensures that local air quality performance is assessed relative to each city’s typical conditions rather than absolute pollution levels. This aligns with the computational framework’s objective of identifying internal variation in environmental risk.

For each monitoring station and month:

1. A 30-day mean PM_{2.5} value was calculated.
2. Each value was standardized to a z-score using the city's fixed baseline:

$$Z = \frac{\text{PM}_{2.5, \text{Monthly}} - \mu_{\text{City}}}{\sigma_{\text{City}}}$$

where $\text{PM}_{2.5, \text{Monthly}}$ represents the 30-day mean PM_{2.5} concentration for a specific month, μ_{City} is the citywide mean, and σ_{City} is the citywide standard deviation.

Step 3: Air quality risk score classification

Z-scores were classified into discrete ordinal risk categories (1 to 5). Table 6.3 lists the thresholds used to convert standardized z-scores into ordinal risk levels. Thresholds are centred on the +1 SD level, reflecting the effect reported by Chen et al. (2018). Scores express relative environmental risk for spatial planning, not individual clinical prediction.

Table 6.3: Air Quality Contextual Cue Thresholds

Score	Risk level	Z-score threshold	Interpretation
1	Very low risk	$Z \leq -1.0$	Well below typical exposure; minimal pollution burden.
2	Low risk	$-1.0 < Z \leq 0.0$	Below-average exposure; relatively clean air.
3	Elevated risk	$0.0 < Z \leq +1.0$	Baseline exposure approaching the threshold reported by Chen et al. (2018).
4	High risk	$+1.0 < Z \leq +1.5$	Documented harm threshold: +1 SD linked to a 6.67 percentage point higher probability of severe distress (Chen et al. 2018).
5	Very high risk	$Z > +1.5$	Severe pollution change; substantially exceeds the harm threshold.

Step 4: Annual Address-Level Risk Scores

Each residential address was linked to the nearest PM_{2.5} monitor using GIS spatial joining. This produced a continuous value (e.g., 3.42) representing the chronic air quality risk experienced by each address during the study year. This annual address-level risk score was then used to calculate a single representative city-level score in Step 5. The twelve monthly risk scores from that monitor were averaged to generate the annual address score:

$$\text{AnnualAddressScore} = \frac{\sum_{i=1}^{12} \text{RiskScore}_i}{12}$$

where i represents each month (1 through 12), and RiskScore_i is the monthly risk score (1–5) for month i .

Step 5: City-Level PM_{2.5} Cue Score

To obtain a citywide measure, Annual Address Scores were aggregated across all addresses within the city. Population weighting was applied so that scores reflected the distribution of residents rather than the density of address points alone. The resulting population-weighted average risk score represented the city's Air Quality Contextual Cue Score and was subsequently integrated with greenspace and transit cues in the cumulative Urban Mental Wellbeing Risk Index.

Population Weighting:

$$\text{CityPM}_{2.5}\text{Score} = \frac{\sum_{j=1}^M (\text{AnnualAddressScore}_j \times \text{Population}_j)}{\sum_{j=1}^M \text{Population}_j}$$

where j represents each spatial unit (address cluster defined by ZIP code, neighborhood, or borough boundaries), M is the total number of spatial units in the city, RiskScore_j is the contextual cue score (1–5) for that unit, and Population_j is the number of people living in that unit.

The air quality score translates abstract statistical findings into a practical policy tool. Instead of stating that high $\text{PM}_{2.5}$ levels are harmful, the framework quantifies this relationship: when pollution exceeds one standard deviation above the local average, roughly seven additional people out of every hundred are expected to experience serious psychological distress (Chen et al. 2018). This transforms the indicator into a meaningful performance measure for local policymakers and urban planners. By referencing each city’s own baseline, the score functions as a localized warning system. Rather than reporting a raw value such as $\text{PM}_{2.5} = 15 \mu\text{g}/\text{m}^3$, which offers little context, the score expresses how unusual and risky that concentration is for that specific city. For example, if a $15 \mu\text{g}/\text{m}^3$ reading corresponds to a Score 4 in Manchester, policymakers can immediately recognize under-performance relative to the city’s typical conditions and understand that this environmental lapse contributes to measurable mental health risk among residents.

The operationalization of the Air Quality Contextual Cue assumes monitoring station measurement represents nearby residential exposure, which may exclude specific local $\text{PM}_{2.5}$ variations such as near busy highways and factories. Additionally, a constraint is that individual time-activity patterns such as, an urban resident’s indoor time, commuting routes, and workplace exposure, are not measured. Despite these constraints, monthly averages from regulatory monitoring stations provide the most reliable and spatially comprehensive exposure estimates available for population-level analysis across Chicago, Manchester, and Portland.

Greenspace Contextual Cue

Greenspace accessibility represents the opportunity for urban citizens to access restorative environments that mitigate stress through contact with nature. Exposure to greenspace triggers immediate, unconscious psychological responses that aid in stress recovery. This type of exposure to nature directly modulates the Hypothalamic Pituitary Adrenal (HPA) axis which regulates the hormone cortisol. This leads to healthier cortisol rhythms that promote stress resilience, whereas low access disrupts cortisol regulation and causes chronic stress. This cue represents a visible environmental stress reliever that when absent, can heighten citizens’ urban mental wellbeing stress.

Gascon et al. (2018) found protective associations between major greenspace accessibility and depression risk, with odds ratio varying by distance threshold. Urban residents within 300 meters of greenspace had $\text{OR} = 0.18$, meaning they had 82% lower odds of depression compared to residents living farther away. The methodology utilizes this finding to establish a strong protective effect and set the threshold for the “Very low risk” category (Score 1: 300 m) in the computational framework. At a threshold of 500 meters, the $\text{OR} \approx 0.84$ which meant that urban residents had 16% lower odds of experiencing depression risk. The study defined qualifying greenspaces as parks or green areas ≥ 0.5 hectares ($5,000 \text{ m}^2$), excluding small pocket parks. The protective effect diminishes with distance, suggesting that both passive exposure (viewing greenery) and active use (visiting parks) contribute to mental health benefits through stress reduction and attention restoration.

The greenspace Contextual Cue was operationalized as an independent variable by calculating accessibility using Euclidean distances between residential address points and the nearest qualifying park boundaries. Parks qualified when they met the minimum 0.5-hectare thresh-

old and were open for public use. A strict 0.5-hectare minimum was applied because larger greenspaces provide key environmental qualities such as tree coverage, biodiversity, and quiet zones that support stress recovery and attention restoration. Smaller parks may also offer benefits but generally lack the spatial and ecological conditions needed for measurable mental health improvement. This follows the eligibility criteria used by [Gascon et al. \(2018\)](#) Spatial coding tools, such as GeoPandas, were used to calculate distances, producing a continuous distance measure in meters for each address in the dataset. The Euclidean, straight-line distance approximates walking accessibility, although it may overestimate access where barriers such as highways or fences exist, or underestimate access where pedestrian networks provide shortcuts.

Step 1: Distance Calculation and Data Preparation

The Greenspace Contextual Cue serves as a protective factor where a higher risk score (5) indicates higher environmental deprivation and thus higher mental wellbeing risk. The greenspace accessibility contextual cue follows a 3-step process:

Address Identification: Identify all residential address points within the city boundaries.

Greenspace Boundary: Use GIS software to define the boundaries of all eligible greenspaces (≥ 0.5 ha).

Distance Metric: Calculate the Euclidean, straight-line distance ($D_{\text{Greenspace}}$) in meters from each residential address point to the nearest boundary of an eligible greenspace with weighted population. $D_{\text{Greenspace}}$ is the input for the 1–5 risk classification.

$$D_{\text{Greenspace}} = \min \left(\sqrt{(x_P - x_G)^2 + (y_P - y_G)^2} \right)$$

where (x_P, y_P) are the address coordinates and (x_G, y_G) are the greenspace boundary coordinates.

Step 2: Distance-to-Risk Score Classification

The measured distance for each address is directly classified into a 1–5 ordinal risk score using the fixed spatial thresholds as seen in Table 6.4. This step assigns risk status based on measured distance to the restorative environment. An address is considered to have greenspace access if the shortest distance to the park boundary is within a given threshold of 300 m or 500 m.

Table 6.4: Greenspace Contextual Cue Thresholds

Score	Risk Level	Distance to Greenspace	Literature Basis
1	Very low risk	≤ 300 m	OR ≈ 0.18 (82% lower odds of depression), establishing a strong protective effect.
2	Low risk	301–500 m	OR ≈ 0.84 (16% lower odds); distance still within the protective effect range.
3	Elevated risk	501–800 m	Protective effect size substantially diminishes beyond 500 m; limited protection.
4	High risk	801–1100 m	Beyond the primary effective range; minimal protective benefit.
5	Very high risk	>1100 m	Outside the effective buffer distance, considered no protective effect.

Step 3: City-Level Greenspace Contextual Cue Score

The final city score represents a population-weighted exposure risk for the entire urban area. The goal of this step is to transform all the individual address scores into a single, representative population-weighted average for the entire city. This score is then used in the final Urban Mental Wellbeing Risk Index. The city-level greenspaces cue is the population-weighted mean of cluster-level risk scores that ensures the metric reflects the distribution of residents rather than the distribution of addresses.

Following the same population weighting procedure described for the Air Quality cue, the city-level greenspace score is calculated as:

$$\text{CityGreenspaceScore} = \frac{\sum_{j=1}^M (\text{AddressRiskScore}_j \times \text{Population}_j)}{\sum_{j=1}^M \text{Population}_j}$$

where j represents each spatial unit (address cluster defined by administrative boundaries), M is the total number of spatial units in the city, RiskScore_j is the contextual cue score (1–5) for that unit, and Population_j is the number of people living in that unit.

The Greenspace Score translates spatial accessibility evidence into a quantifiable urban performance metric that diagnoses environmental inequality. Instead of simply noting that access to parks benefits wellbeing, the framework quantifies the severity of deprivation by linking specific distances to established mental health outcomes. This system operationalizes an accessibility gradient that planners can map and compare across neighborhoods. By using the city’s own greenspace distribution, the score functions as a spatial equity diagnostic tool: a high-risk score (4 or 5) in a district immediately signals that large populations are living outside the effective 500-meter buffer, indicating areas where infrastructure failure directly contributes to a heightened risk of chronic mental stress. This shifts greenspace planning from abstract ideals to data-driven performance monitoring.

Although the 300-meter buffer and 0.5-hectare minimum size are supported by international recommendations and were associated with significant outcomes in [Gascon et al. \(2018\)](#), the evidence does not yet establish a definitive optimal buffer size for policy application. Further longitudinal research is needed to clarify how greenspace exposure and characteristics contribute to mental health outcomes. In this framework, the reported distance effects are used to construct a graded classification scale for Scores 1 and 2, rather than to define a universal policy threshold. The odds ratios reported in the literature are based on individual-level data, while the labels in this study serve as population-level proxies.

Mobility Contextual Cue: Transit Accessibility

The Mobility Contextual Cue operationalizes transit accessibility as a core spatial determinant of social connection and autonomy ([Wang et al. 2019](#)). Its absence or unreliability creates commuting impedance and transport-related stress ([Novaco et al. 1990](#)), increasing the likelihood of screening positively for depressive symptoms ([Wang et al. 2019](#), [Novaco et al. 1990](#)). Longer commuting times contribute to chronic stress by elevating cortisol levels. Since commuting stress follows a linear dose–response relationship, each additional minute of travel adds incrementally to the overall stress burden ([Evans & Wener 2006](#)).

[Wang et al. \(2019\)](#) found that urban citizens without a formal or informal transit stop within a 10-minute walking distance from their home had a 4.8% higher probability of screening positively for depressive symptoms (coefficient = 0.339, 95% CI [0.171, 0.507]). The 10-minute threshold serves as an empirically validated cutoff between protective and risk conditions for urban mental wellbeing. The study measured depressive symptoms using a standardized screening scale, CESD-10, where participants scoring 10 or higher were categorized as positive for the depression screen. The lack of transit stop access serves as a social-environmental stressor that reduces daily autonomy ([Wang et al. 2019](#)).

The mobility contextual cue converts Wang et al. (2019) findings into measurable spatial accessibility metrics using open transit datasets. In this analysis, all formal public transport stops such as bus, tram, metro, and rail are included to capture realistic mobility options within each city. Informal stops are excluded since there are no formal datasets. Since network-based walking data were unavailable, Euclidean distance calculations were applied, acknowledging that this approach may overestimate accessibility in areas where physical barriers exist. The operationalization to calculate the transit accessibility risk score is divided into three core steps.

Step 1: Distance Calculations

Address Identification: Identify all residential address points within the city boundaries.

Transit Stop Data: Utilize GIS data for all formal transit stops within the city limits.

Time-to-Distance Conversion: The 10-minute walk threshold is operationalized as a distance metric. Using a standard urban planning speed of 5 km/h (≈ 83.3 m/min), the critical threshold distance is set at approximately 850 meters.

Distance Metric: Calculate the Euclidean distance (D_{Transit}) in meters from each residential address point to the nearest transit stop. This calculation will be used for the risk scoring index.

$$D_{\text{Transit}} = \min \left(\sqrt{(x_P - x_T)^2 + (y_P - y_T)^2} \right)$$

where x_P, y_P are the address coordinates and x_T, y_T are the nearest transit stop coordinates.

Step 2: Distance-to-Risk Score Classification

Once all distances were calculated, each residential address was assigned a discrete ordinal risk score based on its proximity to the nearest transit stop. Each address receives a risk label (1–5) according to its distance from the nearest transit stop (D_{Transit}), as illustrated in Table 6.5. These thresholds align with Wang et al. (2019), which identifies 850 m (a 10-minute walk) as the comfortable walking distance for routine transit use.

Table 6.5: Mobility Accessibility Cue (Wang et al., 2019)

Score	Risk Level	Distance to Transit Stop	Literature Basis
1	Very low risk	≤ 400 m (5-min walk)	Well below the typical 10-minute maximum threshold; signifies strong accessibility.
2	Low risk	401–850 m	Within typical walking distance for transit; good accessibility.
3	Elevated risk	851–1000 m	Wang et al. (2019): The absence of transit within 10 minutes elevates depression risk. This is the critical threshold.
4	High risk	1001–1500 m	Beyond the established protective 10-minute threshold; signifies weak accessibility and increased barrier to use.
5	Very high risk	>1500 m	Substantially outside the reasonable walking distance for regular transit use; effectively no accessible transit service.

Step 3: Aggregation and City-Level Computation

Each address-level risk score is aggregated into a population-weighted city average, following the same equation applied to the air quality and greenspace contextual cues:

$$\text{CityMobilityScore} = \frac{\sum_{j=1}^M (\text{MobilityRiskScore}_j \times \text{Population}_j)}{\sum_{j=1}^M \text{Population}_j}$$

where j represents each spatial unit (address cluster defined by administrative code boundaries), M is the total number of spatial units in the city, RiskScore_j is the contextual cue score (1–5) for that unit, and Population_j is the number of people living in that unit.

The population-weighted average of the individual risk scores is calculated across the entire city. This continuous value, between 1.0–5.0, becomes the city’s single Mobility Contextual Cue Score used in the final Urban Mental Wellbeing Risk Index.

The transit accessibility score translates urban mental wellbeing research into a practical planning performance metric. Instead of simply stating that limited transit access increases depression risk, the framework quantifies this relationship spatially by identifying where residents are most disconnected from reliable transit. For instance, a district averaging a Score 4 indicates that many residents live beyond the 850-meter threshold, reflecting reduced mobility autonomy and greater vulnerability to social isolation. By referencing each city’s unique transit geography, the score operates as a localized diagnostic tool. Planners can use it to target infrastructure investments, identify underserved neighborhoods, and monitor accessibility improvements over time. The indicator directly links transport equity to urban mental wellbeing, transforming abstract mobility data into actionable urban health insight. Detailed implementation procedures for calculating these contextual cue scores, including data preprocessing, spatial analysis workflows, and computational validation steps, are presented in Section 6.2.

6.1.3 Control Variables

Control variables account for factors that may influence the relationship between environmental contextual cues and urban mental wellbeing risk. These variables are managed through methodological design choices rather than discrete scoring. Geographic standardization, population weighting, and temporal aggregation protocols isolate the relationship between the three focal environmental cues and mental wellbeing risk.

Geographic Location

Geographic location is controlled through standardized spatial reference systems for each city: Chicago uses NAD83 / Illinois State Plane, Manchester uses British National Grid (EPSG:27700), and Portland uses NAD83 / Oregon North. These projections preserve distance accuracy in meters for Euclidean calculations of greenspace and mobility. Cities have different latitudes, climates, and topographic contexts that influence baseline environmental conditions. By calculating risk scores relative to city-specific baselines, such as the z-score approach for the air quality contextual cue, the framework accounts for this specific geographic variation. A Score 4 in Manchester, for example, reflects conditions unusually poor for Manchester’s typical environment, not an absolute global threshold. This localized referencing prevents geographic bias where cities with naturally different climates would be unfairly penalized or rewarded.

Urban Density Indicators

This research implements population weighting to control urban density by considering household numbers per administrative boundary. Administrative boundaries serve as the spatial clus-

tering unit: addresses within each administrative boundary are grouped and weighted by that administrative boundary’s population count. Higher-density areas concentrate more residents near environmental stressors but may provide better transit access and compact greenspace networks. The city-level contextual cue score calculation gives addresses with higher resident counts a proportionally greater weight. A high-risk monitor in a sparsely populated industrial district contributes less to the city’s overall $PM_{2.5}$ score than a moderate-risk monitor surrounded by dense residential neighborhoods.

Temporal Factors

The computational framework aligns all environmental data to the most current condition for 2025. However, air quality data ($PM_{2.5}$) uses the full 2024 annual dataset to include all twelve months. Monthly $PM_{2.5}$ averages are aggregated to form annual means that capture long-term exposure patterns while smoothing short-term seasonal fluctuations. Greenspace and transit accessibility remain structurally stable, as park boundaries and transit stop locations show minimal change month to month. This stability allows 2025 spatial datasets to be effectively compared with the 2024 air quality baseline. By combining 2024 and 2025 data into one aligned snapshot, the cross-sectional design ensures that all cities are compared under the same temporal conditions.

6.2 Data Analysis Methods

6.2.1 Spatial Analysis Techniques

Spatial analysis used Python 3.9.6-based geospatial libraries. GeoPandas 1.0.1 handled vector geometries that included address points, park boundaries, transit stops, air quality monitor locations, and city boundaries. The SciPy library provided the `cKDTree` algorithm, which allows for efficient nearest-neighbor distance calculations across large address datasets. Consistent coordinate systems were applied to all spatial data to ensure accurate distance calculations. Depending on location, each city’s datasets were reprojected to meter-based coordinate systems: Chicago adapted to NAD83 – Illinois State Plane (EPSG:3436), Manchester aligned with the British National Grid (EPSG:27700), and Portland used NAD83 – Oregon North (EPSG:6554). Projected coordinate systems maintain accurate Euclidean calculations, whereas geographic coordinate systems based on latitude and longitude distort spatial relationships as latitude changes. Throughout the spatial analysis, coordinate systems were verified to ensure consistency.

Proximity Distance Analysis Calculation

To measure distances between address points and contextual cues, a three-step standardized procedure was applied. Step 1 extracts the x and y coordinates of address points and the feature coordinates of contextual cues from their geometries, storing them in NumPy arrays. Step 2 handles spatial indexing by building a k -dimensional tree (KD-Tree) from the target feature coordinates using SciPy’s `cKDTree` function. This function conducts efficient nearest-neighbor searches in logarithmic time, avoiding the computational cost of using nested loops. The `cKDTree` function significantly reduced computation time when calculating distances for large datasets containing more than 100,000 entries. Step 3 identified the nearest contextual cue for each address and returned the Euclidean distance in meters, producing a one-to-one mapping where every address received a single distance value to its closest qualifying contextual cue.

Spatial Joins and Administrative Aggregation

A study area was defined using ZIP code, borough boundaries, and neighborhoods. A spatial join using a `within` predicate was applied to the raw address data to include only the points located within the study area. For address data without residential filtering (Chicago and Manchester), spatial filtering was conducted by joining building data indicating whether an address could have residential units or be a commercial unit. Once every address was assigned a risk score, all the data were aggregated. All address points within a given neighborhood, ZIP code, or boundary polygon were grouped together.

Residential address filtering applied city-specific methodologies based on available data structures. Chicago used building footprint data to filter Cook County addresses, retaining addresses in buildings with unit counts greater than zero (confirmed residential) and addresses without building matches that were likely single-family homes, while removing addresses in buildings with zero units (confirmed non-residential). Manchester excluded UPRNs matching Ordnance Survey's Important Buildings or Functional Sites categories. Portland's PortlandMaps portal provides pre-filtered residential addresses, eliminating additional processing. These filtering methods ensured distance calculations reflected residential exposure patterns.

6.2.2 Statistical Analysis Strategy

Descriptive Analysis

Descriptive statistics summarize environmental risk distributions across multiple spatial scales. For each address, the average distance to the nearest parks, transit stops, and PM_{2.5} monitors describe typical exposure levels. The standard deviation indicates variability in environmental exposure. Median values represent a more stable central tendency, minimizing the influence of outliers. The minimum and maximum values indicate the range of environmental conditions a given address can experience within each city.

Frequency distributions show the count and percentage of addresses assigned to each risk category (Scores 1–5). These distributions highlight how many residents in each city face elevated environmental exposure risk for urban mental wellbeing. Cumulative distribution curves display the proportion of addresses that meet specific accessibility thresholds. This allows direct comparison to literature benchmarks of 300 m for greenspace [Gascon et al. \(2018\)](#) and 850 m for transit access [Wang et al. \(2019\)](#). The percentile breakdowns (10th, 25th, 50th, 75th, 90th) reveal the spatial disparity that the city average might conceal. For instance, the 90th percentile distance to greenspace shows how far the most underserved 10% of addresses must travel to reach a park.

Cross-City Comparison Approach

Cities have different baseline environmental conditions due to geography, climate, and infrastructure. Chicago, Manchester, and Portland have distinct pollution profiles, greenspace distributions, and transit network densities. Comparing raw measurements would conflate these baseline differences with performance differences. The computational framework addresses this through applying relative scoring: air quality z-scores reference each city's own pollution distribution, while distance-based scores for greenspace and mobility rely on universal thresholds drawn from current literature (Tables [6.4](#) and [6.5](#)). This hybrid approach allows cross-city comparison while accounting for local conditions.

Contextual Cue Profiling

Correlation analysis and descriptive statistics were used to profile the contextual cues and compare their relative variability across the three cities. This analysis indicates which cues

were most stable, which varied most widely, and which had the strongest influence on the final UMWI score. Finally, the proportion of cities with scores exceeding the critical risk threshold of the score 3.0 was noted to show which contextual cues have the most extensive challenges across the case study cities.

Correlation Analysis

A Pearson correlation analysis measured the strength and direction of linear relationships between the three contextual cue scores and the UMWI. The correlation matrix shows whether cities that perform poorly on one contextual cue, such as air quality, also perform poorly on others like greenspace or mobility, or whether these contextual cues vary independently across cities. This analysis also quantifies the correlation between each cue and the UMWI to identify which contextual cue is the strongest influence on the overall urban mental wellbeing risk. The small sample size ($N = 3$) means these correlations serve as descriptive measures rather than statistically generalizable inferences. These patterns indicate whether urban planning efforts should focus on broad, integrated interventions or targeted strategies addressing specific environmental domains.

Pairwise City Comparisons

Pairwise comparison quantifies the differences between each city pair (Chicago–Manchester, Chicago–Portland, Manchester–Portland) by calculating the differences in their UMWI and individual contextual cue scores. The pairwise analysis identifies the specific contextual cue most responsible for variation in overall urban mental wellbeing risk, which reveals whether a large UMWI gap between two cities results from one dominant contextual cue, such as greenspace disparity, or from more balanced differences across all three contextual cues.

Sensitivity Analysis

A sensitivity analysis was conducted to validate the internal consistency of the model. The analysis increased each of the three cue scores by one point and recalculated UMWI to measure how much the overall score changed. This increment test measured how a one-point improvement in any single contextual cue would affect overall urban mental wellbeing risk.

WHO Compliance Assessment

The framework measures WHO guideline compliance to provide policy-relevant benchmarks for air quality and greenspace provision. WHO (2021) guidelines set an annual average $\text{PM}_{2.5}$ limit of $5.0 \mu\text{g}/\text{m}^3$, the threshold below which health risks are minimized. The computational framework calculates citywide annual $\text{PM}_{2.5}$ averages and assesses monitor-level compliance to identify whether cities meet this international standard and quantify excess pollution levels requiring intervention [World Health Organization \(2021\)](#). For greenspace, WHO recommends urban citizens have access to greenspace within 300 m of their residence, aligning with the [Gascon et al. \(2018\)](#) threshold used in the framework’s risk labeling. WHO establishes two greenspace provision standards: a minimum of 9 m^2 per capita representing the baseline threshold for urban health, and an ideal standard of 50 m^2 per capita for optimal wellbeing outcomes. Applying these compliance metrics complements the 1–5 scoring system by providing internationally recognized reference points. Cities can use WHO compliance status alongside contextual cue scores to communicate environmental quality to the public and track progress toward healthier cities.

6.3 Research Ethics

6.3.1 Ethical Framework

This research uses publicly accessible open data provided through governmental portals. The use of these sources adheres to all relevant data-sharing and ethical compliance standards. All datasets used in this study were obtained through official open data channels, including the Chicago Data Portal, Manchester City Council’s open data platform, UK Government Data Service, Portland’s PortlandMaps system, United States Census Bureau, and U.S. states’ air quality monitoring services. Each data source explicitly allows academic research use under its respective open data license.

The computational framework follows a transparent methodology to support reproducibility. Sufficient detail is provided for reproducibility and integration of the computational framework. This information can be found throughout Chapter 5, including research design, data collection, threshold tables, and formulas. Additional guidance for integration of new cities into the computational framework is outlined in Section 5.8. The Python scripts, found in the GitHub link ¹ in Appendix B follow consistent naming conventions, include inline comments, and generate terminal logs that output analysis steps. This approach guarantees external examination and detection of potential errors.

Privacy Protection Measures

The computational framework incorporates privacy protection measures through methodology design rather than post-hoc anonymization. The aim of this computational framework is to measure environmental exposure risk for urban mental wellbeing risk, not medical mental health outcomes, thus eliminating the need for personal health information. Therefore, no individual-level mental health data are collected, assessed, or analyzed. The methodological choice of using address-level data to represent geographical location ensures that individuals cannot be identified.

Residential address points indicate building locations and do not contain any data on residents’ identity, demographics, or mental health status. Each address point is used for proximity calculation to the nearest contextual cue, then later grouped into administrative units for population-weighted calculation. Population-level aggregation and city-level scores protect individual privacy by not reporting individual-level results.

Since this research follows a cross-sectional design, environmental conditions and urban mental wellbeing risk are captured at a single point in time (2024). This means address points are not followed over time, an additional safeguard for urban residents’ privacy.

6.3.2 Beneficence and Non-Maleficence

Research Benefits

The primary benefit of this research is the creation of evidence-based tools for urban planning decisions that affect urban residents’ mental wellbeing. Policy makers and city planners invest in environmental infrastructure such as parks, public transit, and air quality monitoring without systematically assessing urban mental wellbeing risk. The computational framework transforms literature findings about environmental risk into actionable metrics representing the risk level of urban mental wellbeing for contextual cues and overall city status. Policy development gains empirical support through quantified risk scores.

Decision-makers can take informed actions on future investments and planning. For instance, if a city has a low risk score for air quality and a high risk score for greenspace ac-

¹<https://github.com/tzirath/ThesisComputationalFramework>

cessibility, planners can prioritize greenspace infrastructure, knowing there is higher risk of worsening mental wellbeing outcomes. With the computational framework as a tool, planners can explore administrative-level risk scores to identify which neighborhood, ZIP code, or borough requires more attention. If policy makers apply this framework and invest in parks or expand transit stops, urban residents may experience reduced environmental stress and improved urban mental wellbeing, ultimately benefiting public health.

Risk Mitigation

This computational framework design prevents harm to individuals. Since no personal information is collected or reported, there are no risks of privacy breaches, discrimination, or stigmatization. Urban residents living in high-risk areas cannot be identified from the outputs, as the results represent aggregated administrative- and city-level summaries across large populations.

This research acknowledges that high-risk areas may face multiple socioeconomic challenges beyond environmental factors, potentially increasing stigmatization risks. To mitigate this, contextual cue scores are presented as continuous measures (range 1.0–5.0), acknowledging that environmental quality exists on a spectrum rather than binary classifications. The computational framework presents risk scores as opportunities for public health improvement and resource allocation, not as negative judgments of neighborhood or city quality. Therefore, the framework is intended for responsible use by urban planners and scientists with appropriate technical capacity to interpret results correctly. Individual urban residents' actual mental health depends on various factors beyond environmental exposure, including social support, economic security, healthcare access, and personal experiences. This research does not aim to oversimplify the relationship between contextual cue scores and mental health outcomes, which would mislead policymakers and the public about urban mental wellbeing determinants. The ethical use of this computational framework requires a commitment to improving conditions rather than using environmental deficiencies to justify gentrification or displacement.

6.4 Conclusion

Chapter 6 established the methodological foundation for assessing urban mental wellbeing risk through environmental exposure measurement. The computational framework converts open data for each contextual cue into standardized risk scores. The data collection strategy prioritizes open governmental sources across Chicago, Manchester, and Portland, ensuring replicability without specialized access agreements. The framework operationalizes three contextual cues into standardized 1–5 risk scores. Air quality scores derive from $PM_{2.5}$ monitoring data using z-score standardization based on each city's annual baseline following [Chen et al. \(2018\)](#). Greenspace and mobility scores calculate Euclidean distance from residential addresses to the nearest park or transit stop, classified using thresholds from [Gascon et al. \(2018\)](#) and [Wang et al. \(2019\)](#). Population-weighted aggregation enables city-level assessment of environmental exposure risk related to urban mental wellbeing. The final Urban Mental Wellbeing Index (UMWI) combines individual cue scores into a single composite score, producing comparable assessments across cities. Spatial analysis used Python libraries such as GeoPandas and SciPy for geometry processing, distance calculations, and administrative aggregation. The statistical strategy applied descriptive and correlational methods appropriate for small comparative studies. Privacy protection was embedded in methodological design choices: address points represent locations without identifying individuals, population-level aggregation prevents personal data exposure, and the cross-sectional design avoids longitudinal tracking. Chapter 7 presents the empirical findings generated through this framework, analyzing urban mental wellbeing risk patterns across Chicago, Manchester, and Portland.

Chapter 7

Results and Discussion

This chapter presents the results of the computational framework’s application and discussion in Chicago, Manchester, and Portland, addressing two research questions. **RQ2** examines whether a computational spatial framework can integrate heterogeneous environmental contextual cues to produce comparable mental wellbeing risk assessments across cities with varying spatial and data characteristics. **RQ3** explores the extent to which this framework can be generalised, transferred, and scaled across multiple cities with differing environmental and data infrastructures. The analysis evaluates three contextual cues: air quality, greenspace accessibility, and mobility, aggregating them into the Urban Mental Wellbeing Risk Index (UMWI).

This chapter presents objective findings for air quality 7.2, greenspace 7.3, mobility 7.4, and the aggregated Urban Mental Wellbeing Risk Index 7.5. Each subsection follows a consistent structure: city-level scores, geographic unit analysis, and World Health Organisation (WHO) compliance status. Section 7.6 interprets these findings. Section 7.6.2 examines individual city profiles, identifying primary risk drivers and specific challenges. Additionally, Section 7.6.2 provides a discussion on cross-city comparisons, addressing **RQ2** by demonstrating whether the framework converts diverse data infrastructures into comparable assessments. Section 7.6.3 discusses theoretical and practical implications for urban policy and research. Section 7.6.4 addresses **RQ3**, analyzing the extent to which the framework demonstrates transferability and scalability for adoption by other cities. The chapter concludes with validity assessment in Section 7.6.5.

7.1 Results

Figure 7.1 presents city-level contextual cue scores across all three cities. The following subsections examine each contextual cue in detail, analyzing patterns at city and ZIP code/borough/neighborhood levels. Section 7.2 presents air quality results, Section 7.3 examines greenspace accessibility, Section 7.4 evaluates mobility, and Section 7.5 presents the Urban Mental Wellbeing Risk Index (UMWI).

7.2 Air Quality Results

The air quality contextual cue applies Chen et al. (2018) z-score method to monthly PM_{2.5} data from each city’s monitoring network. Table 7.1 presents the city-level scores and baseline parameters. Portland has the lowest baseline exposure (4.52 $\mu\text{g}/\text{m}^3$). Chicago and Manchester have similar score ranges (2.59 and 2.86), while Portland’s score is 2.46.

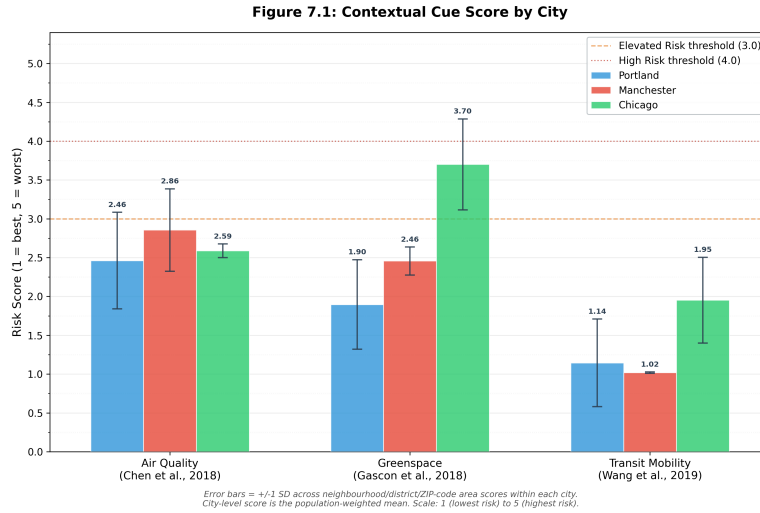


Figure 7.1: Contextual Cue Score by City.

Table 7.1: City Air Quality Scores and Parameters

City	Score	μ ($\mu\text{g}/\text{m}^3$)	σ ($\mu\text{g}/\text{m}^3$)	WHO Compliant
Chicago	2.59	$7.88 \mu\text{g}/\text{m}^3$	$1.59 \mu\text{g}/\text{m}^3$	No
Manchester	2.86	$7.76 \mu\text{g}/\text{m}^3$	$1.13 \mu\text{g}/\text{m}^3$	No
Portland	2.46	$4.52 \mu\text{g}/\text{m}^3$	$1.63 \mu\text{g}/\text{m}^3$	Yes

7.2.1 Chicago Air Quality

Chicago City-level Analysis

The air quality assessment for Chicago uses $\text{PM}_{2.5}$ data from seven monitoring stations across the metropolitan area from January 1 to December 31, 2024. Monthly averages were standardized using [Chen et al. \(2018\)](#) z-score method to calculate risk scores for 533,839 addresses distributed across 58 ZIP codes. The population for Chicago is 2,797,595, according to the 2024 US Census data.

Table 7.2: Chicago Air Quality City Score and Baseline Parameters

Metric	Value
City Air Quality Score	2.59
Total Addresses	533,839
Total Population	2,797,595
City Baseline (μ)	$7.88 \mu\text{g}/\text{m}^3$
City Std Dev (σ)	$1.59 \mu\text{g}/\text{m}^3$
+1 SD Threshold (Chen)	$9.46 \mu\text{g}/\text{m}^3$
Mean Annual Score (unweighted)	2.62
Difference (weighted - unweighted)	0.030

Chicago’s population-weighted city score of 2.59 represents the category “Low Risk” (Table 7.2), with a baseline concentration of $7.88 \mu\text{g}/\text{m}^3$. The monthly distribution (Table 7.3) shows 51.2% of monitor months in low-risk categories (1–2), 32.1% at elevated risk (3) and 16.6% in high-risk categories (4–5).

Table 7.3: Chicago Monthly Risk Score Distribution

Risk Score	Risk Level	Number of Months	Percentage
1	Very Low Risk	15	17.9%
2	Low Risk	28	33.3%
3	Elevated Risk	27	32.1%
4	High Risk	7	8.3%
5	Very High Risk	7	8.3%

(Figure 7.2) shows monthly z-scores across the seven monitors in Chicago throughout 2024. January-February: Chicago-Springfield, Schiller Park, and Alsip exceeded +1 SD. March-June: Most monitors recorded values below the baseline. July: Chicago-ComEd and Schiller Park exceeded +1 SD. (Figure 7.3) shows the distribution of the scores in 533,839 addresses.

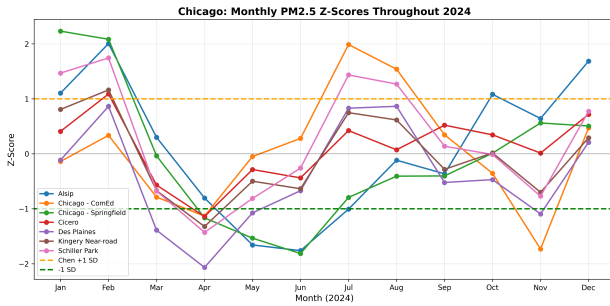
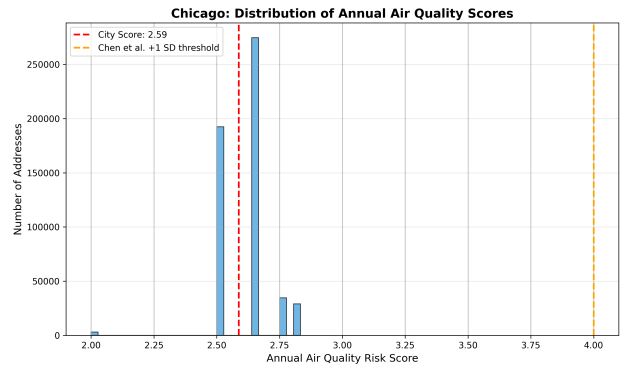
Figure 7.2: Monthly PM_{2.5} z-scores in 2024.

Figure 7.3: Address-level risk score distribution.

Chicago Monitor-level Analysis

Table 7.4 presents annual monitor scores and address assignments. Schiller Park recorded the highest score (2.83), with 29,100 addresses. Des Plaines recorded the lowest (2.00), covering 3,178 addresses. Figure 7.4 maps address-level scores and monitor locations.

Chicago Air Quality Risk: Address-Level Scores and Monitor Locations

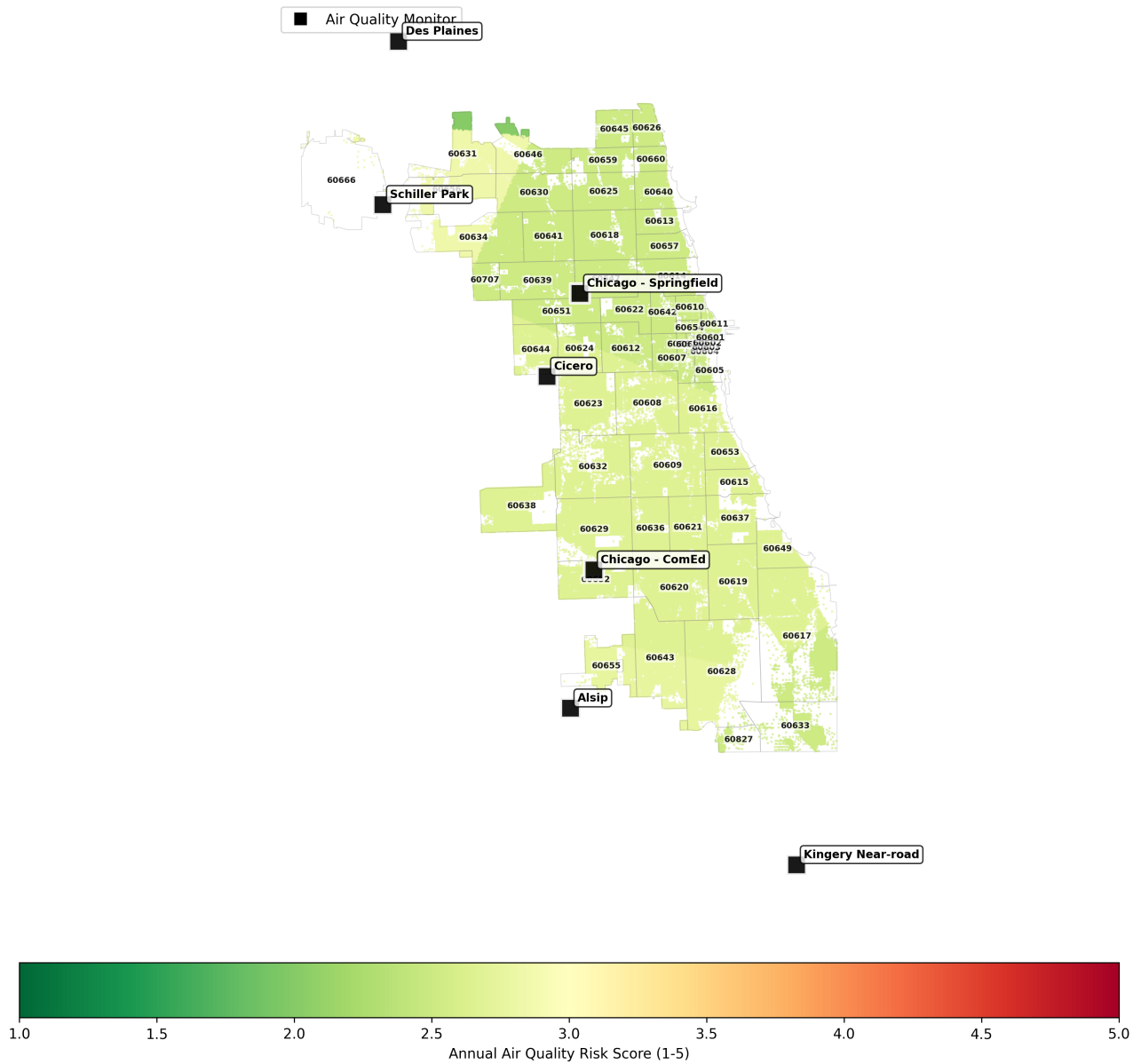


Figure 7.4: Chicago address-level air quality risk scores and monitor locations

Chicago ZIP-level Analysis

Table 7.4: Top 10 Priority ZIP Codes for Air Quality Intervention

Rank	ZIP Code	Mean AQ Score	Population	Address Count
49	60649	2.67	48,171	6,099
50	60652	2.67	40,898	12,777
51	60636	2.67	34,800	14,287
52	60637	2.67	53,555	7,961
53	60653	2.67	33,146	5,667
54	60638	2.67	56,928	17,039
55	60628	2.71	62,832	26,216
56	60643	2.71	47,831	19,658
57	60655	2.74	27,837	10,402
58	60656	2.83	28,474	6,851

Figure 7.5 maps the spatial distribution of air quality scores across Chicago’s 58 ZIP codes. Mean air quality scores were aggregated to ZIP code boundaries for administrative reference. All ZIP codes recorded mean scores below 4.0. The ten highest-scoring ZIP codes collectively house 449,783 residents (16.1% of Chicago’s population). ZIP 60656 recorded the highest mean air quality score of 2.83. Detailed ZIP-level rankings are provided in Appendix C.1.1.

Chicago Air Quality Risk by ZIP Code

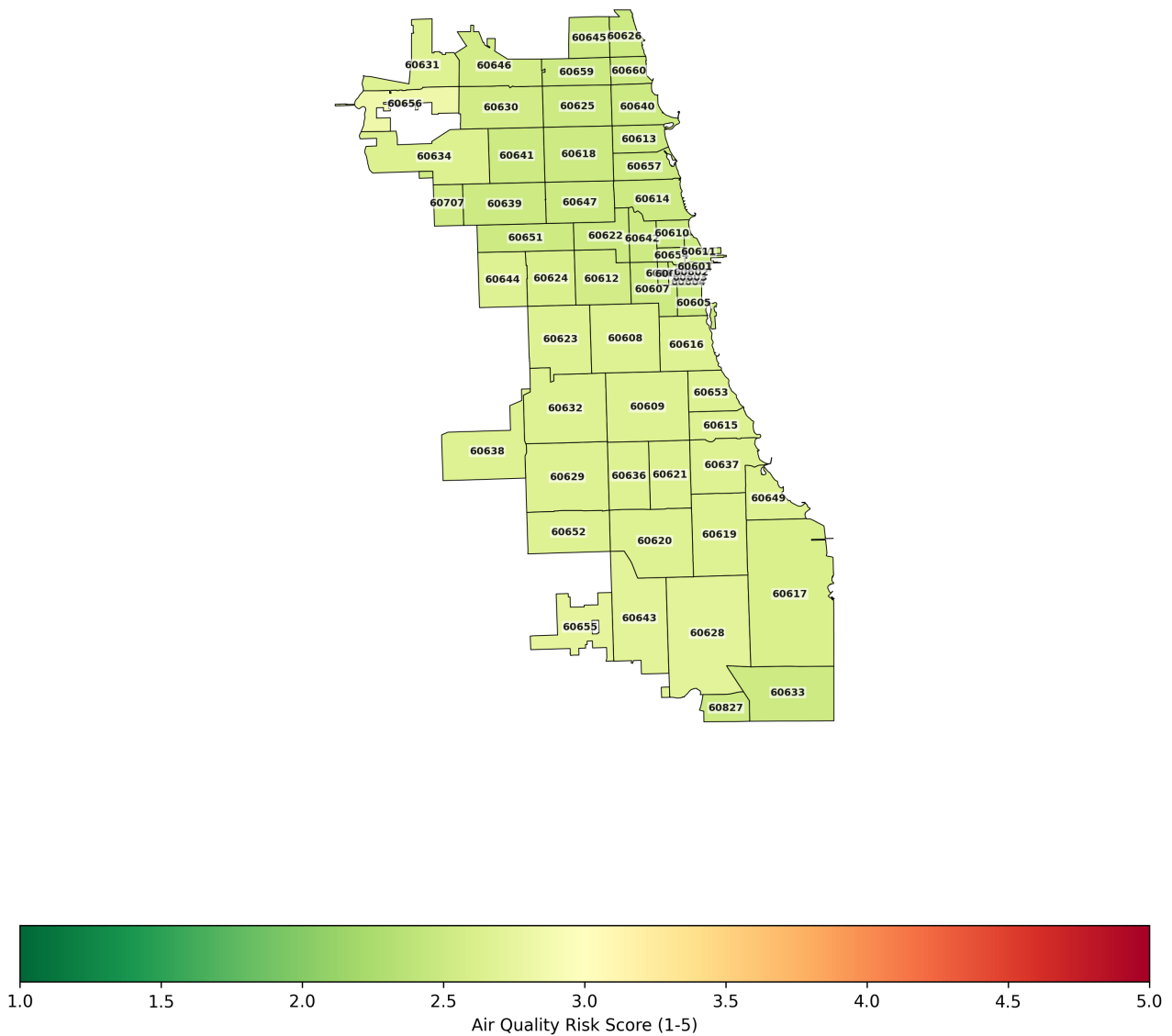


Figure 7.5: Chicago ZIP-level air quality risk scores and population distribution

Chicago WHO 2021 Compliance Analysis

The WHO (2021) air quality guidelines establish $5.0 \mu\text{g}/\text{m}^3$ as the annual average limit for $\text{PM}_{2.5}$ exposure. Chicago's citywide annual average of $7.88 \mu\text{g}/\text{m}^3$ exceeds the WHO guideline by $2.88 \mu\text{g}/\text{m}^3$, representing a 55% exceedance (Table 7.5). None of the seven monitoring stations are compliant (Figure 7.6), with annual averages ranging from $7.26 \mu\text{g}/\text{m}^3$ to $8.25 \mu\text{g}/\text{m}^3$.

Table 7.5: Chicago WHO 2021 PM_{2.5} Compliance Status

Metric	Value
WHO Annual Limit	5.00 $\mu\text{g}/\text{m}^3$
Chicago Annual Average	7.88 $\mu\text{g}/\text{m}^3$
Compliance Status	Non-Compliant
Excess PM _{2.5}	2.88 $\mu\text{g}/\text{m}^3$
Compliant Monitors	0 / 7
Total Monitors	7

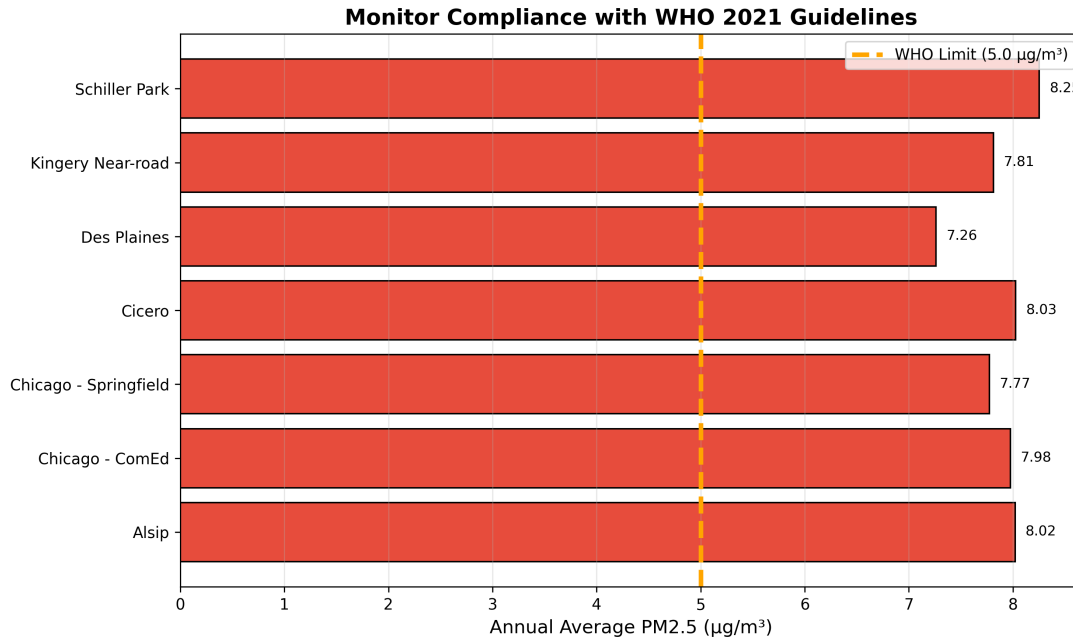


Figure 7.6: Chicago Monitor Compliance with WHO 2021 PM_{2.5} Guidelines

7.2.2 Manchester Air Quality

Manchester City-level Analysis

The air quality assessment for Manchester uses PM_{2.5} data from seven monitoring stations across Greater Manchester from January 1, 2024, to December 31, 2024. The total population for Greater Manchester is 3,009,664 according to the UK Census (2024). Monthly averages were standardized using [Chen et al. \(2018\)](#) z-score method to calculate risk scores for 61,796 addresses distributed across ten metropolitan boroughs. Table 7.6 reports Manchester’s city-level metrics. The population-weighted city score of 2.86 corresponds to “Low Risk” environmental exposure from PM_{2.5}, with a baseline concentration of 7.76 $\mu\text{g}/\text{m}^3$ and a standard deviation of 1.13 $\mu\text{g}/\text{m}^3$. The weighted–unweighted difference is 0.007.

Table 7.6: Manchester City Score and Baseline Parameters

Metric	Value
City Air Quality Score	2.86
Total Addresses	61,796
Total Population	3,009,664
City Baseline (μ)	7.76 $\mu\text{g}/\text{m}^3$
City Standard Deviation (σ)	1.13 $\mu\text{g}/\text{m}^3$
+1 SD Threshold (Chen)	8.89 $\mu\text{g}/\text{m}^3$
Mean Annual Score (Unweighted)	2.86
Difference (Weighted – Unweighted)	0.007

Table 7.7 presents the distribution of monthly air quality risk scores. The results indicate that 45.2% of monitor-months were in low-risk categories (1–2), 40.5% were at elevated risk (3), and 14.2% were in high-risk categories (4–5).

Table 7.7: Manchester Monthly Risk Score Distribution

Risk Score	Risk Level	Number of Months	Percentage
1	Very Low Risk	17	20.2%
2	Low Risk	21	25.0%
3	Elevated Risk	34	40.5%
4	High Risk	6	7.1%
5	Very High Risk	6	7.1%

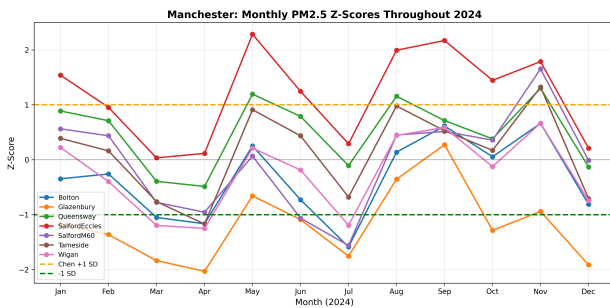
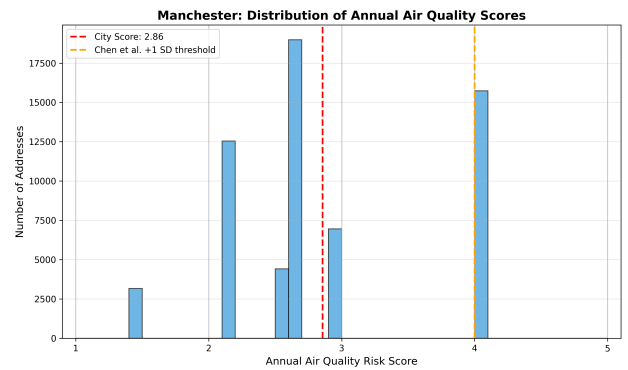
Figure 7.7: Manchester monthly $\text{PM}_{2.5}$ z-scores throughout 2024.

Figure 7.8: Manchester annual address-level air quality score distribution.

Figure 7.7 shows the monthly variation of the z-score. Figure 7.8 shows the distribution of annual air quality scores across all 61,796 Manchester addresses. The largest concentration lies between scores 2–3, representing 30.4% (18,759 addresses), followed by score 4, representing 25.5% (15,733 addresses).

Manchester Monitor-Level Analysis

Table 7.8 presents Manchester’s monitor-level air quality scores. SalfordEccles recorded the

highest score (4.00), serving 15,733 addresses and exceeding the +1 SD [Chen et al. \(2018\)](#) threshold. Glazenbury showed the lowest score (1.42), covering 3,167 addresses. Scores ranged from 1.42 to 4.00, indicating a 2.58-point spread across the seven monitoring sites. Figure 7.9 maps the monitoring stations and their surrounding address-level risk scores.

Table 7.8: Manchester Air Quality Scores by Monitor

Monitor Name	Annual AQ Score	Addresses Assigned
Bolton	2.17	6,811
Glazenbury	1.42	3,167
Queensway	2.92	6,959
SalfordEccles	4.00	15,733
SalfordM60	2.58	4,418
Tameside	2.67	18,979
Wigan	2.17	5,729

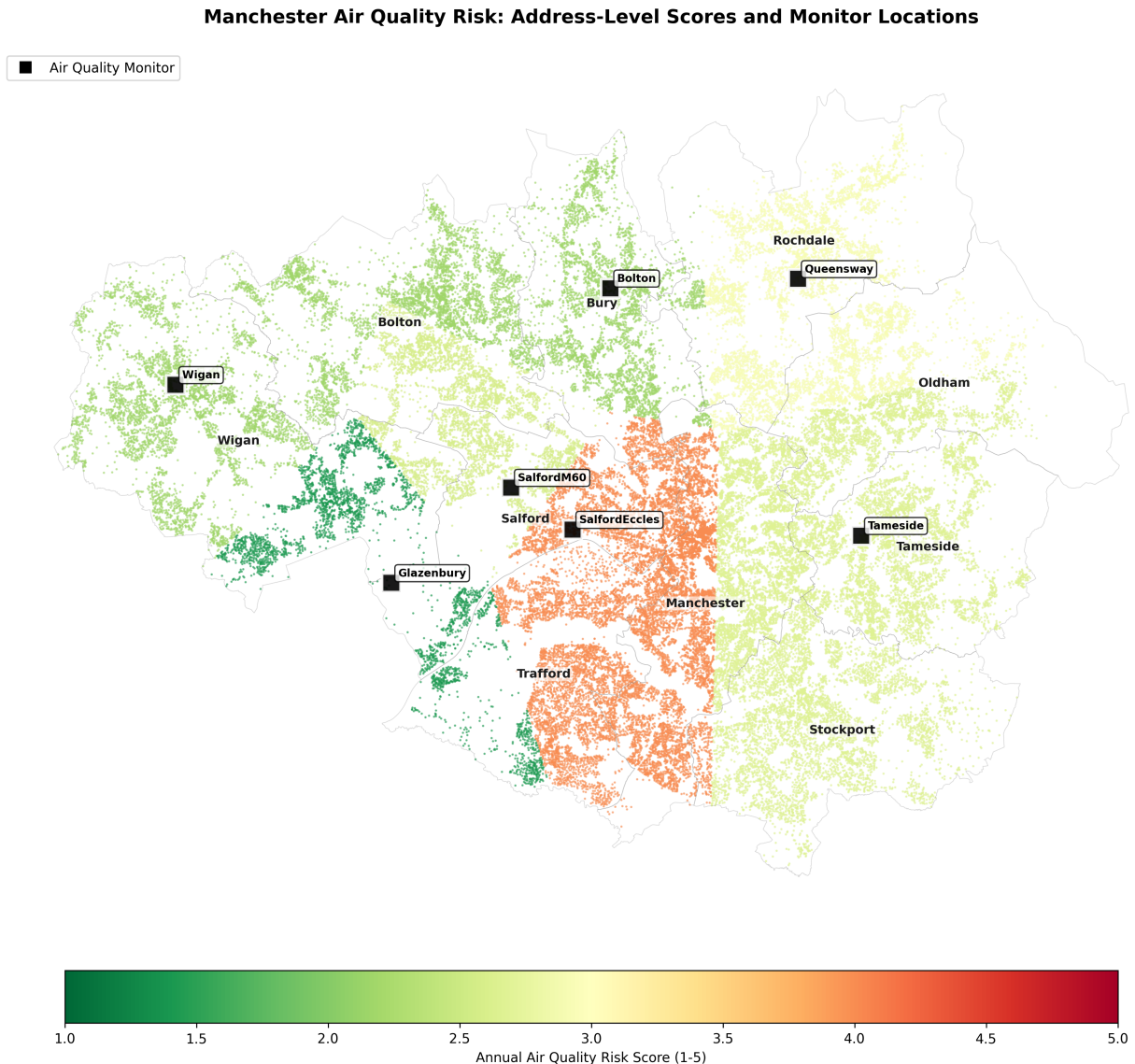


Figure 7.9: Manchester address-level air quality scores and monitor locations

Manchester Borough-Level Analysis.

Figure 7.10 maps borough-level air quality risk scores across Greater Manchester, showing spatial variation from 1.98 (Wigan) to 3.68 (Trafford). The three highest-scoring boroughs (Table 7.9) are Trafford (3.68), Manchester (3.39), and Salford (3.36). These centrally and southerly located areas collectively house 1,125,043 residents (37.4% of Greater Manchester’s population). The lowest-scoring boroughs are Wigan (1.98), Bolton (2.30), and Bury (2.41). Detailed borough-level rankings are provided in Appendix C.1.2.

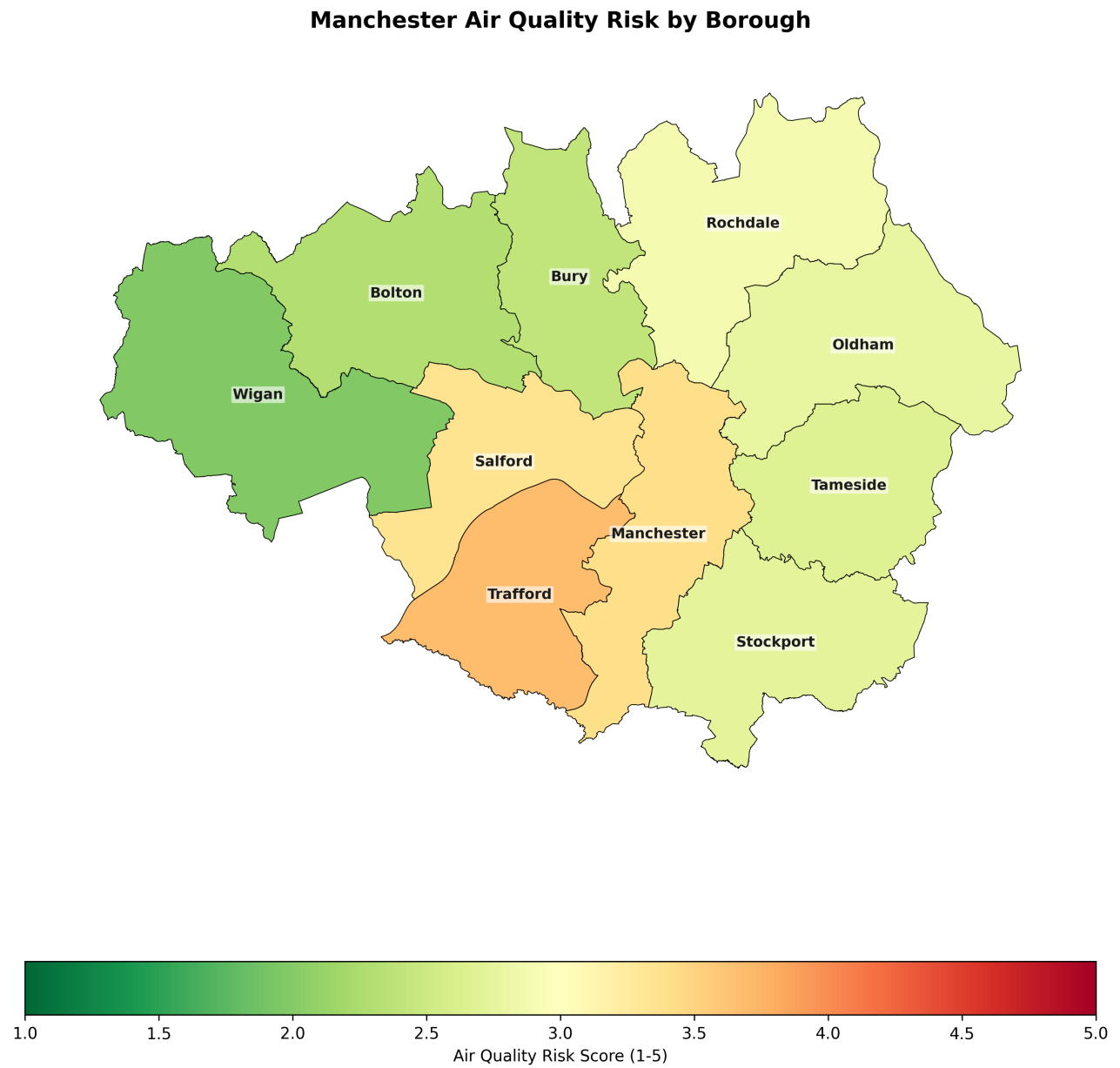


Figure 7.10: Manchester air quality risk by borough

Table 7.9: Manchester top 10 priority boroughs for air quality intervention

Rank	Borough	Mean AQ Score	Population	Address Count
1	Wigan Borough (B)	1.98	344,922	6,827
2	Bolton Borough (B)	2.30	310,085	6,298
3	Bury Borough (B)	2.41	198,921	4,305
4	Tameside Borough (B)	2.67	239,643	5,239
5	Stockport Borough (B)	2.72	303,929	5,991
6	Oldham Borough (B)	2.77	251,560	4,986
7	Rochdale Borough (B)	2.88	235,561	4,945
8	Salford Borough (B)	3.36	294,348	5,663
9	Manchester Borough (B)	3.39	589,670	11,827
10	Trafford Borough (B)	3.68	241,025	5,715

Manchester WHO 2021 Compliance Analysis.

The WHO (2021) air quality guidelines establish $5.0 \mu\text{g}/\text{m}^3$ as the annual average limit for $\text{PM}_{2.5}$ exposure. Table 7.10 shows that Manchester’s citywide annual average of $7.76 \mu\text{g}/\text{m}^3$ exceeds this guideline by $2.76 \mu\text{g}/\text{m}^3$, representing a 55% exceedance. Figure 7.11 displays monitor performance relative to the WHO threshold. None of the seven monitoring stations meet WHO compliance.

Table 7.10: Manchester WHO 2021 $\text{PM}_{2.5}$ Compliance Status

Metric	Value
WHO Annual Limit	$5.00 \mu\text{g}/\text{m}^3$
Manchester Annual Average	$7.76 \mu\text{g}/\text{m}^3$
Compliance Status	NON-COMPLIANT
Excess $\text{PM}_{2.5}$	$2.76 \mu\text{g}/\text{m}^3$
Compliant Monitors	0 / 7
Total Monitors	7

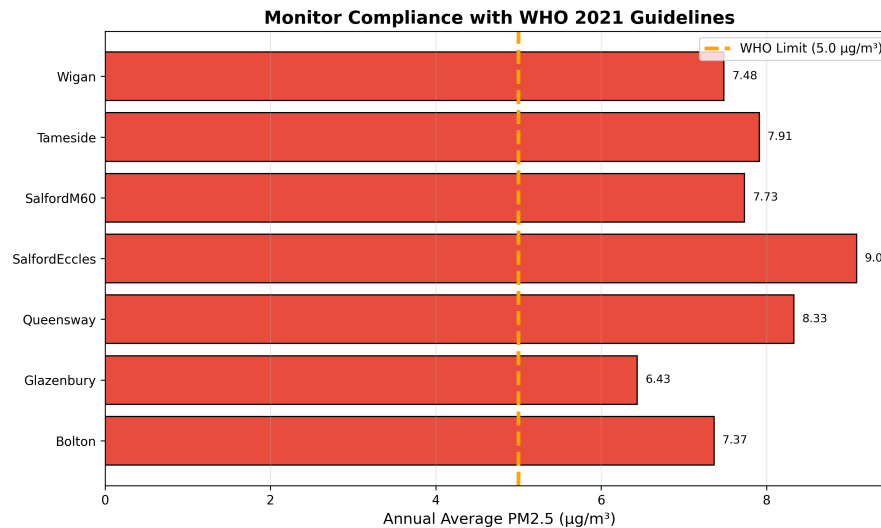


Figure 7.11: Manchester Monitor Compliance with WHO Guidelines PM_{2.5}

7.2.3 Portland Air Quality

Portland City-Level Assessment

The air quality assessment for Portland uses PM_{2.5} data from nine monitoring stations across the city of Portland from January 01, 2024, to December 31, 2024. Monthly averages were standardized using [Chen et al. \(2018\)](#) z-score method to calculate risk scores for 331,764 addresses distributed across 98 neighborhoods. The total population for Portland is 678,332 according to the 2024 US Census data.

Table 7.11: Portland City Score and Baseline Parameters

Metric	Value
City Air Quality Score	2.46
Total Addresses	331,764
Total Population	678,332
City Baseline (μ)	4.52 $\mu\text{g}/\text{m}^3$
City Std Dev (σ)	1.63 $\mu\text{g}/\text{m}^3$
+1 SD Threshold (Chen)	6.15 $\mu\text{g}/\text{m}^3$
Mean Annual Score (unweighted)	2.38
Difference (weighted - unweighted)	0.08

Table 7.11 summarizes the Portland city-level statistics for PM_{2.5} assessment, with a population-weighted city score of 2.46 which is associated with a “Low Risk” environmental exposure from PM_{2.5}. The baseline concentration is 4.52 $\mu\text{g}/\text{m}^3$, and the standard deviation of 1.63 $\mu\text{g}/\text{m}^3$. The difference between weighted and unweighted scores is 0.08.

The monthly distribution, as seen in Table 7.12, shows 57.40% of monitor-months fell in low-risk categories (Scores 1–2), with 24.10% at elevated risk and 18.50% in high-risk categories. Figure 7.12 shows monthly z-scores for Portland monitors throughout 2024.

Figure 7.13 shows the address-level distribution. The largest cluster appears at Score 1.75 (91,704 addresses, 27.70%), with secondary concentrations at 2.25–2.50. 7,638 addresses (2.30%) scored above 3.00.

Table 7.12: Portland Monthly Risk Score Distribution

Risk Score	Risk Level	Number of Months	Percentage
1	Very Low Risk	15	13.90%
2	Low Risk	47	43.50%
3	Elevated Risk	26	24.10%
4	High Risk	7	6.50%
5	Very High Risk	13	12.00%

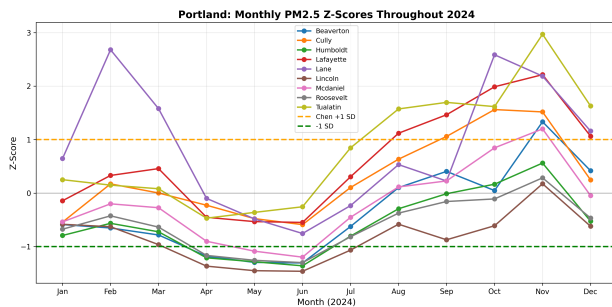
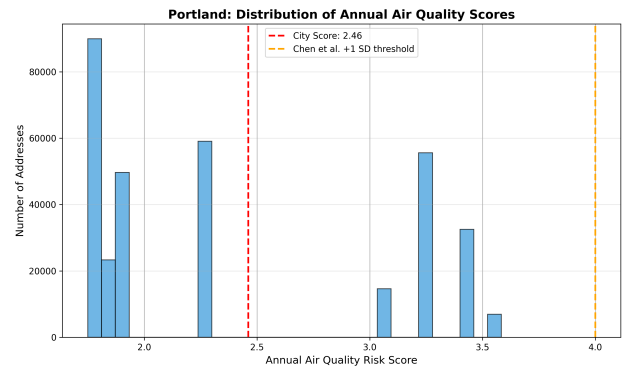
Figure 7.12: Portland Monthly PM_{2.5} Z-Score Timeline

Figure 7.13: Portland Annual Score Distribution by Addresses

Portland Monitor-Level Analysis

Table 7.13 displays that Tualatin recorded the highest score (3.58) housing 6,955 addresses, while Lincoln showed the lowest (1.75) serving 89,925 addresses. Scores ranged from 1.75 to 3.58; a 1.83-point spread. Figure 7.14 illustrates the address-level score and the monitors.

Table 7.13: Portland Air Quality Scores by Monitor

Monitor Name	Annual AQ Score	Addresses Assigned
Beaverton	2.25	1,779
Cully	3.08	14,604
Humboldt	1.92	49,677
Lafayette	3.25	55,616
Lane	3.42	32,558
Lincoln	1.75	89,925
McDaniel	2.25	57,295
Roosevelt	1.83	23,355
Tualatin	3.58	6,955

Portland Air Quality Risk: Address-Level Scores and Monitor Locations

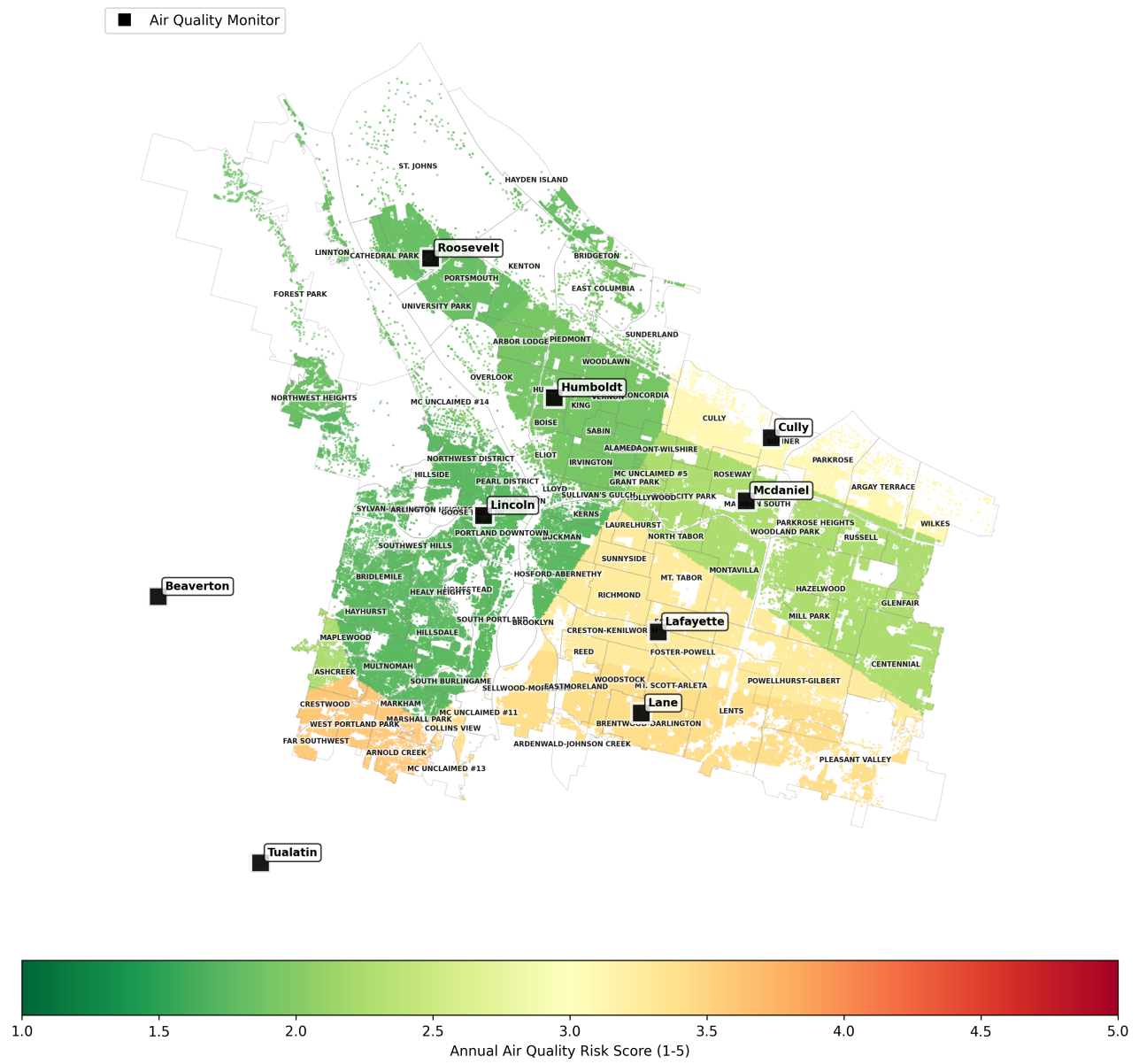


Figure 7.14: Portland Address-Level Scores and Monitor Locations

Portland Neighborhood-Level Analysis

Table 7.14 records the ten highest-scoring neighborhoods (3.37–3.58) home to 69,104 residents (10.20% of Portland’s population). Figure 7.15 illustrates this spatial pattern; green areas (scores 1.50–2.50) concentrate in northwest and north-central Portland, while yellow-orange zones (scores 2.50–3.60) appear in eastern and southeastern neighborhoods. Detailed neighborhood-level rankings are provided in Appendix C.1.3.

Table 7.14: Portland Top 10 Priority Neighborhoods

Rank	Neighborhood	Mean AQ Score	Population	Address Count
85	MT. SCOTT-ARLETA	3.37	8,037	3,749
86	PLEASANT VALLEY	3.38	13,409	4,623
87	SELLWOOD-MORELAND	3.41	13,940	7,311
88	EASTMORELAND	3.41	5,252	1,693
89	ARDENWALD-JOHNSON CREEK	3.42	4,706	378
90	BRENTWOOD-DARLINGTON	3.42	13,536	5,871
91	CRESTWOOD	3.56	2,575	1,049
92	ARNOLD CREEK	3.58	3,108	1,203
93	WEST PORTLAND PARK	3.58	4,080	2,116
94	FAR SOUTHWEST	3.58	1,461	725

Portland Air Quality Risk by Neighborhood

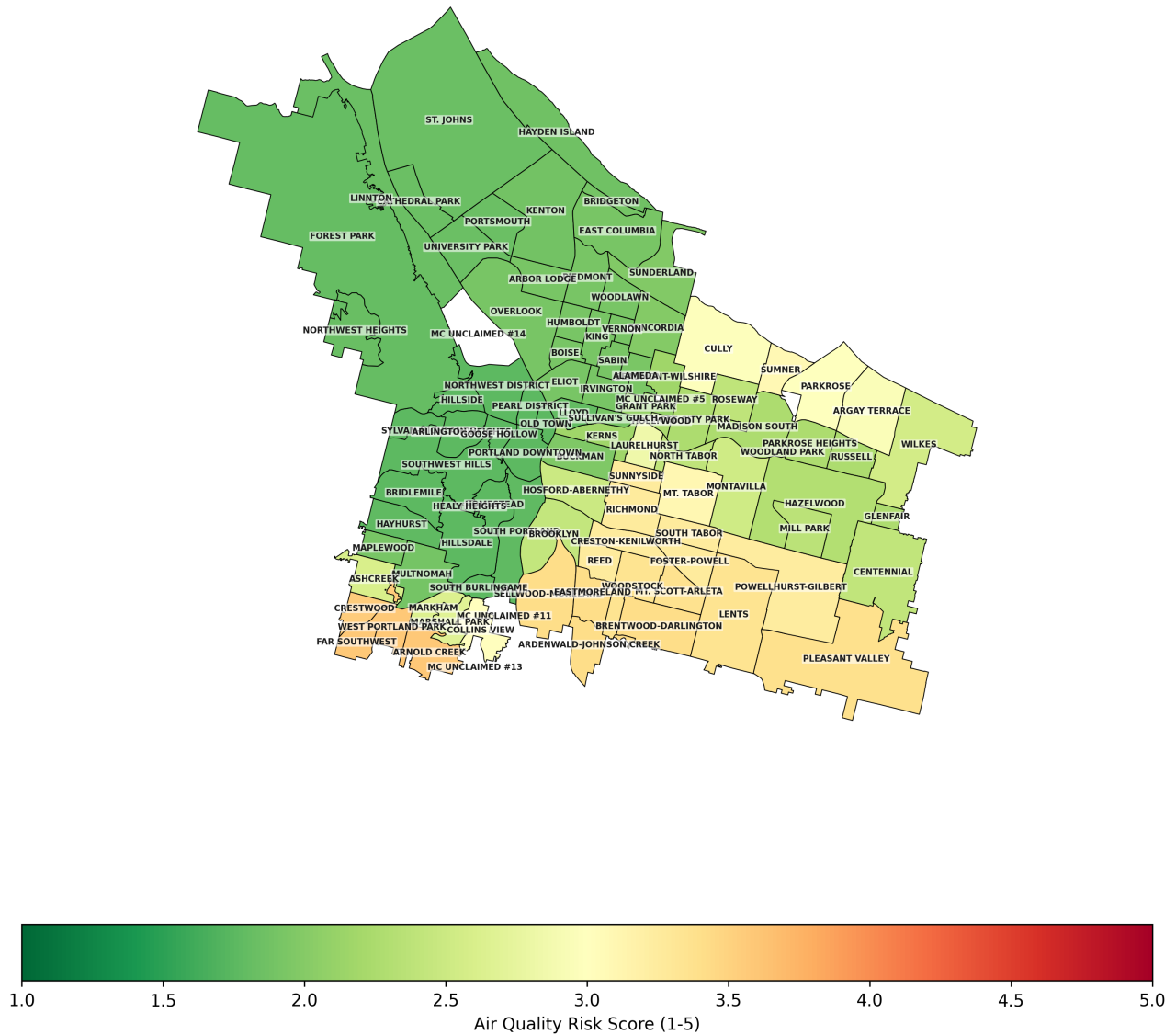


Figure 7.15: Portland Air Quality Risk by Neighborhood

Portland WHO 2021 Compliance Analysis

Portland’s citywide average ($4.52 \mu\text{g}/\text{m}^3$) met the WHO compliance, falling $0.48 \mu\text{g}/\text{m}^3$ below the $5.00 \mu\text{g}/\text{m}^3$ threshold, as seen in Table 7.15. This is illustrated in Figure 7.16, where six of nine monitors are compliant.

Table 7.15: Portland WHO 2021 Compliance Status

WHO Annual Limit	$5.00 \mu\text{g}/\text{m}^3$
Portland Annual Average	$4.52 \mu\text{g}/\text{m}^3$
Compliance Status	COMPLIANT
Excess $\text{PM}_{2.5}$	N/A
Compliant Monitors	6 / 9
Total Monitors	9

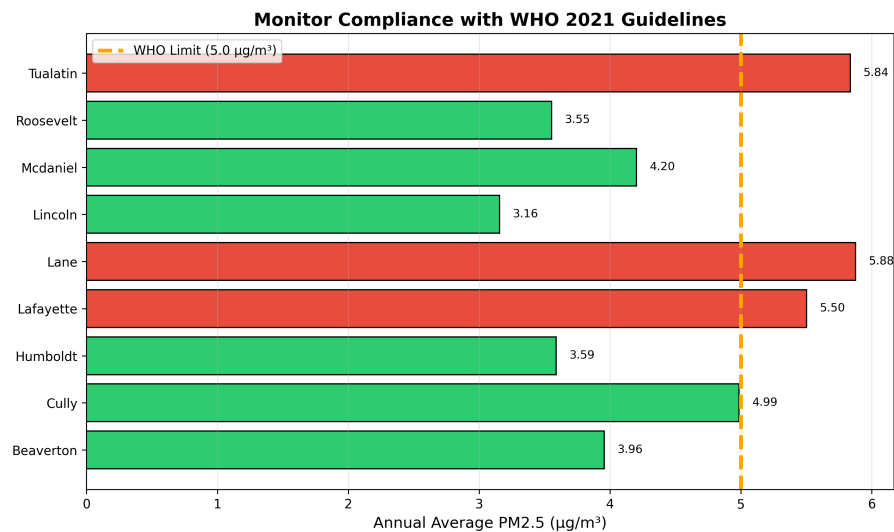


Figure 7.16: Portland Monitor Compliance with WHO 2021 Guidelines

7.3 Greenspace

The greenspace accessibility contextual cue applies [Gascon et al. \(2018\)](#) distance-based methodology to evaluate proximity to eligible parks (≥ 0.5 hectares). Distance calculations use the framework’s 300 m optimal threshold (OR=0.18, 82% reduction in depression risk) and 500 m protective distance (OR0.84, 16% reduction). Table 7.16 presents city-level scores and coverage statistics across all three cities.

Table 7.16: City Greenspace Scores and Coverage Parameters

City	Score	Mean Distance (m)	300m Coverage	500m Coverage	WHO Rating
Chicago	3.70	1201.50	9.80%	19.70%	Excellent
Manchester	2.46	560.30	31.40%	54.50%	Adequate
Portland	1.90	373.90	43.60%	73.40%	Excellent

7.3.1 Chicago Greenspace

Chicago City-Level Assessment

The greenspace accessibility assessment for Chicago analyzed proximity to eligible parks (≥ 0.5 hectares) using [Gascon et al. \(2018\)](#) distance-based methodology. Analysis covered 533,839 addresses across Chicago's 58 ZIP codes, using distance thresholds of 300 m (optimal, OR=0.18) and 500 m (protective, OR=0.84). Of 617 total parks, 606 met the size threshold (≥ 0.5 ha), with 11 parks (1.80%) excluded. Chicago's population-weighted greenspace score of 3.70 is associated with an elevated risk category (Table 7.17). 9.80% of addresses (52,555) fall within the optimal 300 m threshold, while 19.70% (104,971) are within protective distance (≤ 500 m). The mean distance to the nearest eligible park is 1201.50 m, with a median of 1066.50 m.

Table 7.17: Chicago Greenspace City Score and Coverage

Metric	Value
City Greenspace Score	3.70
Total Addresses	533,839
Total Population	2,797,595
Mean Distance (m)	1201.50
Median Distance (m)	1066.50
Addresses ≤ 300 m	52,555
Addresses ≤ 300 m (%)	9.80%
Addresses ≤ 500 m	104,971
Addresses ≤ 500 m (%)	19.70%
Mean Risk Score (unweighted)	3.83
Difference (weighted - unweighted)	0.13

According to Table 7.18, 19.60% of addresses scored in low-risk categories (1–2), while 80.30% scored in elevated or high-risk categories (3–5). 257,493 addresses (48.20%) exceeded 1100 m, the very high-risk threshold. Figure 7.17 illustrates the distance distribution of addresses to eligible greenspaces.

Table 7.18: Chicago Greenspace Risk Score Distribution

Risk Score	Risk Level	Distance Range	Number of Addresses	Percentage
1	Very Low Risk	≤ 300 m	52,555	9.80%
2	Low Risk	301–500m	52,416	9.80%
3	Elevated Risk	501–800m	87,316	16.40%
4	High Risk	801–1100m	84,059	15.70%
5	Very High Risk	>1100 m	257,493	48.20%

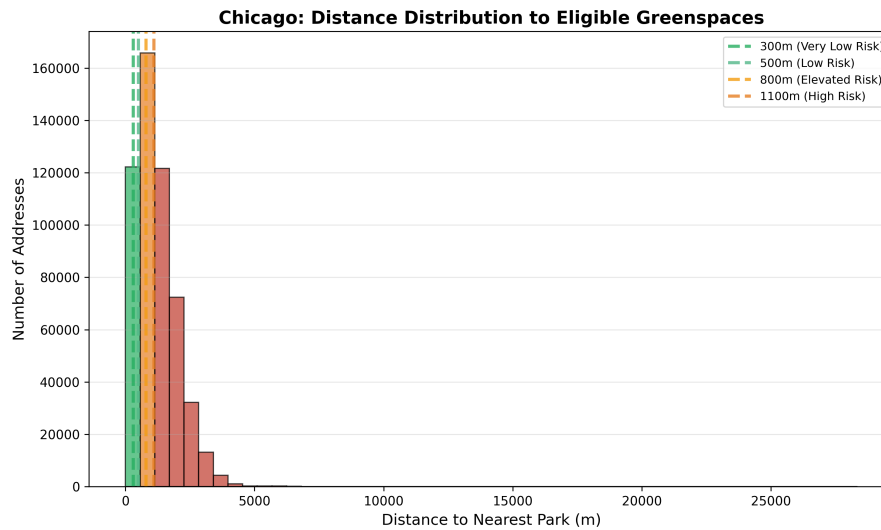


Figure 7.17: Chicago Distance Distribution to Eligible Greenspaces

Chicago ZIP-Level Analysis

Table 7.19 documents the ten ZIP codes with scores 4.20–4.98 collectively housing 519,875 residents (18.60% of Chicago’s population). ZIP 60606 shows the highest risk (4.98), with a mean distance of 1934.67 m. ZIP 60707 (4.67, 1978.05 m) and ZIP 60656 (4.54, 2348.72 m) also show high-risk scores. Northwest ZIP 60634 (4.47, 1828.73 m) houses 75,694 residents. This spatial pattern is mapped in Figure 7.18. Detailed ZIP-level rankings are provided in Appendix C.2.1.

Table 7.19: Chicago Top 10 Priority ZIP Codes for Greenspace Intervention

Rank	ZIP Code	Mean Risk Score	Population	Address Count	Mean Distance (m)	Median Distance (m)	Min Distance (m)	Max Distance (m)
49	60641	4.20	69,354	13,285	1303.17	1292.93	18.60	2935.29
50	60655	4.20	27,837	10,402	1603.41	1437.19	45.26	6588.04
51	60652	4.20	40,898	12,777	1389.67	1349.22	27.55	3809.49
52	60629	4.22	114,453	24,412	1581.02	1480.44	49.35	4222.59
53	60654	4.23	23,890	473	1456.61	1299.99	9.12	3090.32
54	60632	4.39	92,237	17,892	1643.95	1532.18	16.82	4848.88
55	60634	4.47	75,694	19,374	1828.73	1803.72	19.54	9020.94
56	60656	4.54	28,474	6,851	2348.72	2159.48	31.39	9876.17
57	60707	4.67	43,241	4,383	1978.05	1963.97	24.34	4085.63
58	60606	4.98	3,797	80	1934.67	1873.95	901.24	2759.38

Chicago Greenspace Risk by ZIP Code

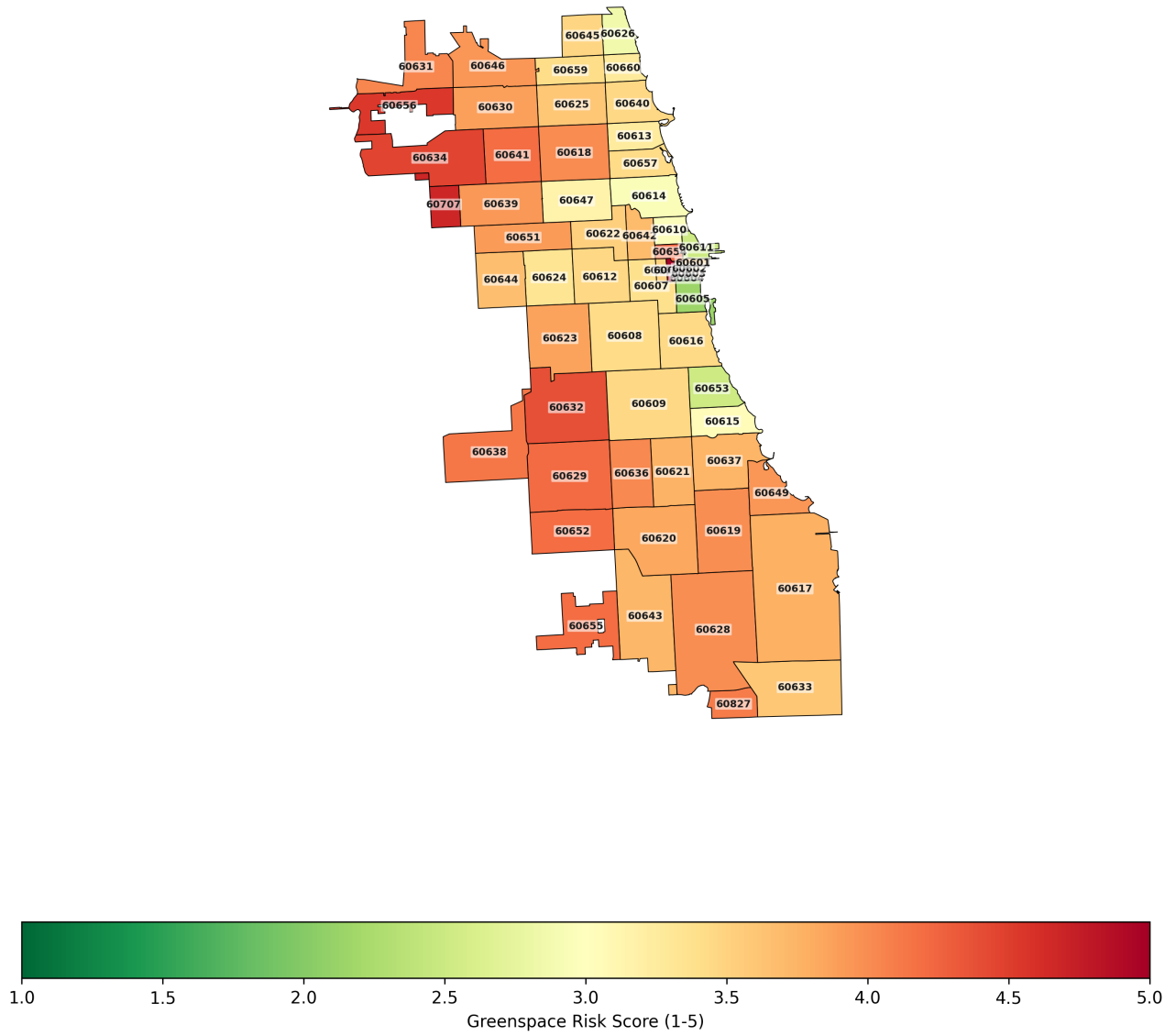


Figure 7.18: Chicago Greenspace Risk by ZIP Code

Chicago: Greenspace Risk Score (1-5)

- ZIP Code Boundaries
- Eligible Parks (≥ 0.5 ha)
- Score 1: Very Low Risk (≤ 300 m)
- Score 2: Low Risk (301-500m)
- Score 3: Elevated Risk (501-800m)
- Score 4: High Risk (801-1100m)
- Score 5: Very High Risk (> 1100 m)

The map shows the distribution of risk scores across Chicago's ZIP codes. The legend indicates that risk scores range from 1 (Very Low Risk) to 5 (Very High Risk). The map also shows the locations of eligible parks (≥ 0.5 ha) in dark green. The map is color-coded by risk score: Score 1 (Very Low Risk) is light green, Score 2 (Low Risk) is medium green, Score 3 (Elevated Risk) is yellow, Score 4 (High Risk) is orange, and Score 5 (Very High Risk) is red. The map shows a high concentration of high-risk areas (Scores 4 and 5) in the central and southern parts of the city, particularly in the areas around the Loop and the South Loop. The northern parts of the city generally show lower risk scores (Scores 1 and 2). The map also shows the locations of eligible parks, which are concentrated in the central and southern parts of the city, particularly in the areas around the Loop and the South Loop.

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Chicago WHO Compliance

Chicago provides 139.20 m² of greenspace per person, exceeding the WHO ideal standard of 50 m²/person by 178% (Table 7.20). The city’s provision is 1447% above the WHO minimum (9 m²/person).

Table 7.20: Chicago WHO Greenspace Provision

Metric	Value
Current Provision (m ² per person)	139.20
WHO Minimum Standard	9.00
WHO Ideal Standard	50.00
Status vs Minimum	MEETS WHO MINIMUM
Status vs Ideal	EXCEEDS WHO IDEAL
Deficit to Minimum (ha)	0.00
Gap to Ideal (ha)	0.00

7.3.2 Manchester Greenspace

Manchester City-level Analysis

The greenspace accessibility assessment for Manchester analyzed proximity to eligible parks (≥ 0.5 hectares) using [Gascon et al. \(2018\)](#) distance-based methodology. Analysis covered 61,796 addresses across Manchester’s 10 metropolitan boroughs, using distance thresholds of 300m (optimal, OR=0.18) and 500m (protective, OR $\approx$ 0.84). Of 533 total parks, 374 met the size threshold (≥ 0.5 ha), with 159 parks (29.80%) excluded. Manchester’s population-weighted greenspace score of 2.46 is associated with an “Low Risk” category (Table 7.21). 31.40% of addresses (19,379) fall within the optimal 300m threshold, while 54.50% (33,671) are within protective distance (≤ 500 m). The mean distance to nearest eligible park is 560.30 meters, with a median of 459.20 meters. Figure 7.20 illustrates the distance distribution to greenspace.

Table 7.21: Manchester Greenspace City Score and Coverage

Metric	Value
City Greenspace Score	2.46
Total Addresses	61,796
Total Population	3,009,664
Mean Distance (m)	560.30
Median Distance (m)	459.20
Addresses ≤ 300 m	19,379
Addresses ≤ 300 m (%)	31.40%
Addresses ≤ 500 m	33,671
Addresses ≤ 500 m (%)	54.50%
Mean Risk Score (unweighted)	2.46
Difference (weighted – unweighted)	0.00

Table 7.22: Manchester Greenspace Risk Score Distribution

Risk_Score	Risk_Level	Distance_Range	Number_of_Addresses	Percentage
1	Very Low Risk	$\leq 300\text{m}$	19,379	31.40%
2	Low Risk	301–500m	14,292	23.10%
3	Elevated Risk	501–800m	14,654	23.70%
4	High Risk	801–1100m	7,235	11.70%
5	Very High Risk	$>1100\text{m}$	6,236	10.10%

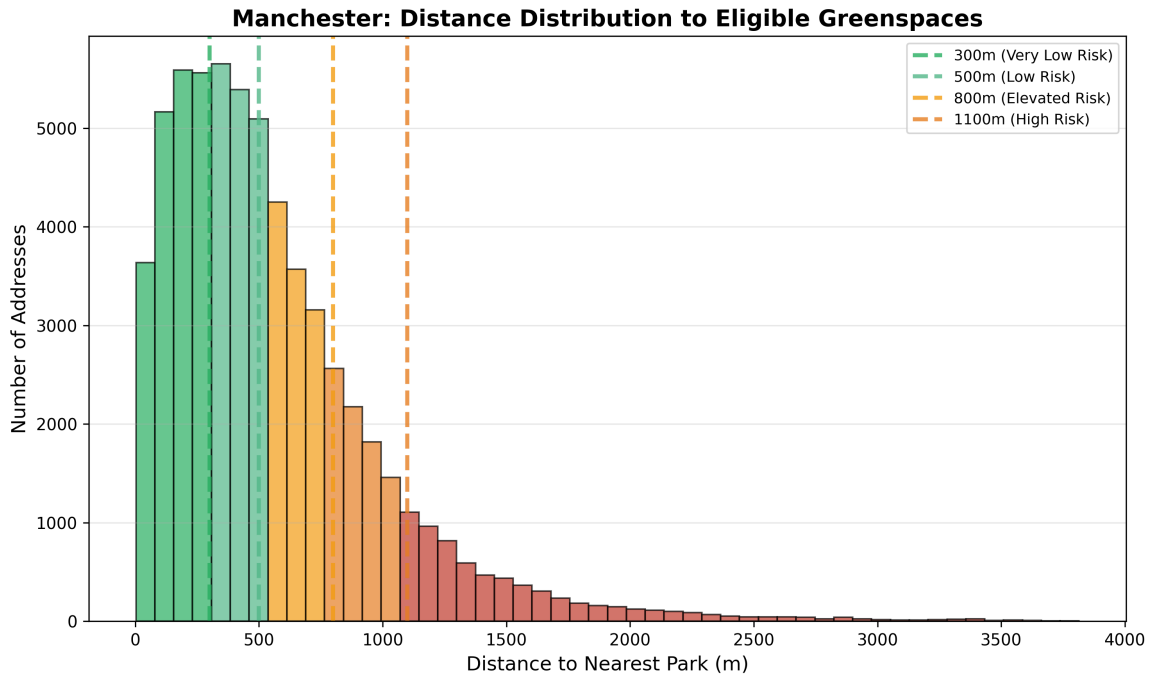


Figure 7.20: Manchester Distance Distribution to Eligible Greenspaces

Manchester Borough-Level Analysis

The five highest-scoring boroughs (scores 2.56–2.70) collectively house 1,336,661 residents (44.40% of Greater Manchester’s population) (Table 7.23). Trafford recorded the highest score (2.70), with a mean distance of 631.00 meters. Oldham (2.69, 640.92m) and Tameside (2.64, 654.98m) also show elevated-risk scores. Bolton houses 310,085 residents, the largest population among the five boroughs. Figure 7.21 depicts neighborhood risk scores in Greater Manchester. Detailed borough-level rankings are provided in Appendix C.2.2.

Table 7.23: Manchester Top 5 Highest-Scoring Boroughs

Boroughs 6–8						
Rank	Borough	Mean Risk Score	Population	Address Count	Mean Distance (m)	Median Distance (m)
6	Bolton Borough (B)	2.56	310,085	6,298	615.24	474.84
7	Salford Borough (B)	2.60	294,348	5,663	582.20	519.54
8	Tameside Borough (B)	2.64	239,643	5,239	654.98	509.11

Boroughs 9–10						
Rank	Borough	Mean Risk Score	Mean Distance (m)	Median Distance (m)	Min Distance (m)	Max Distance (m)
9	Oldham Borough (B)	2.69	640.92	523.59	3.51	3,518.34
10	Trafford Borough (B)	2.70	630.99	534.72	7.34	2,997.76

Manchester Greenspace Risk by Borough

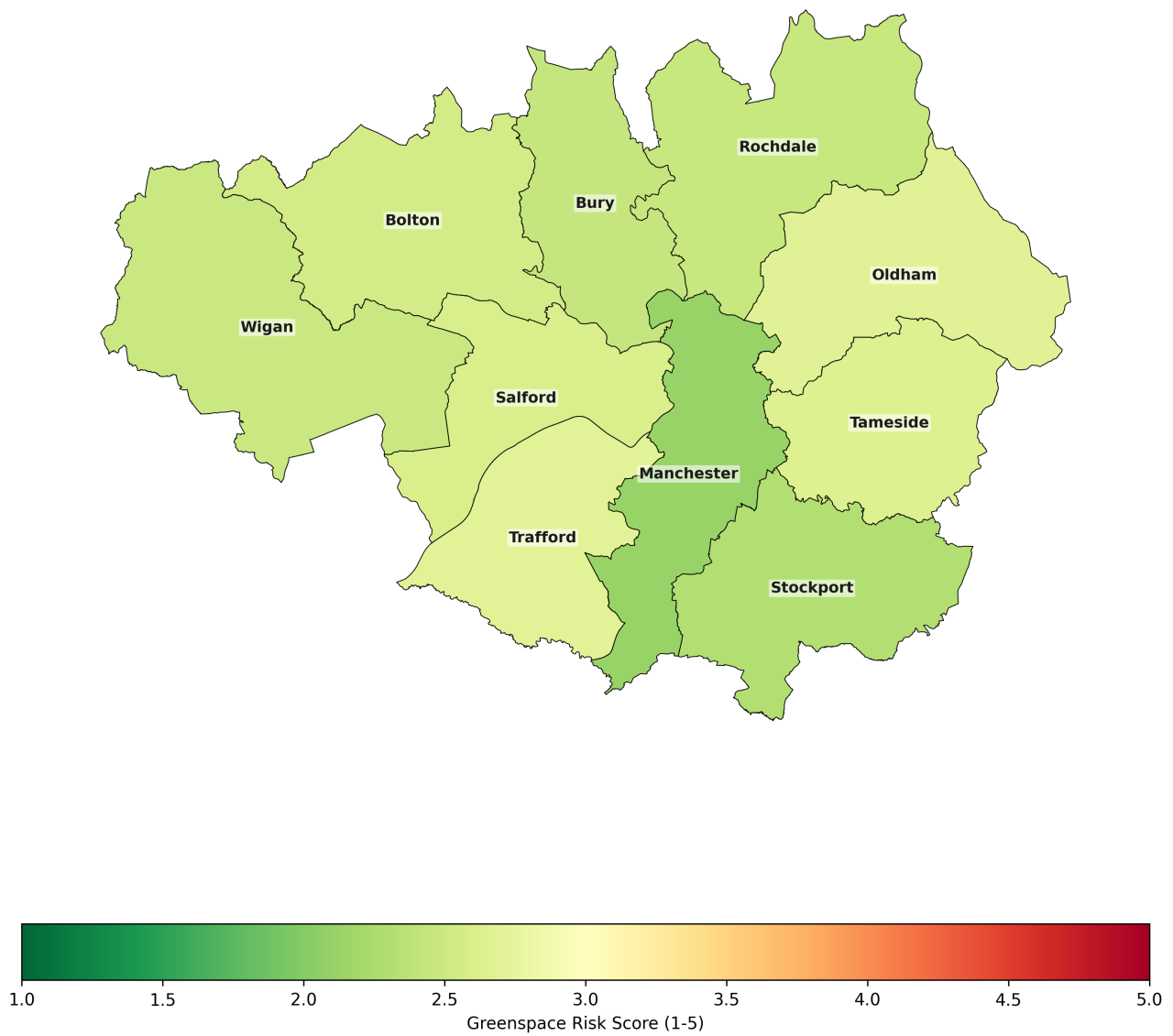


Figure 7.21: Manchester Greenspace Risk by Borough

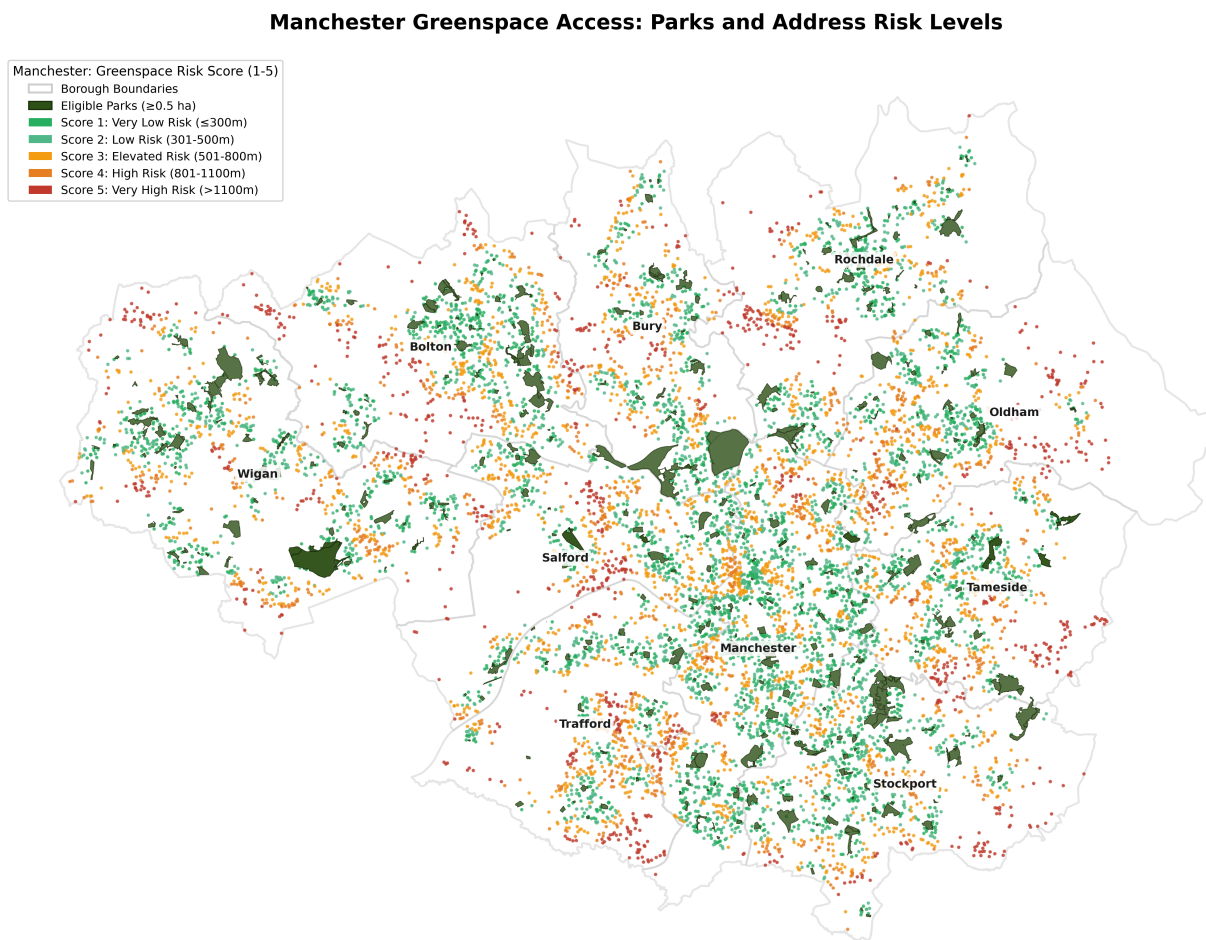


Figure 7.22: Manchester Greenspace Access: Parks and Address Risk Levels

Manchester WHO Compliance

Manchester provides 15.30 m² of greenspace per person, exceeding the WHO minimum standard of 9 m²/person by 70% (Table 7.24). The city falls below the WHO ideal standard of 50 m²/person, requiring an additional 10,435.20 hectares to reach the ideal threshold.

Table 7.24: Manchester WHO Greenspace Provision

Metric	Value
Current Provision (m ² per person)	15.30
WHO Minimum Standard	9
WHO Ideal Standard	50
Status vs Minimum	MEETS WHO MINIMUM
Status vs Ideal	BELOW WHO IDEAL
Deficit to Minimum (ha)	0
Gap to Ideal (ha)	10,435.20

7.3.3 Portland Greenspace

Portland City-level analysis

The greenspace accessibility assessment for Portland analyzed proximity to eligible parks (≥ 0.5 hectares) using [Gascon et al. \(2018\)](#) distance-based methodology. Analysis covered 331,764 addresses across Portland’s 98 neighborhoods, using distance thresholds of 300 m (optimal, OR=0.18) and 500 m (protective, OR $\approx$ 0.84). Of 317 total parks, 229 met the size threshold (≥ 0.5 ha), with 88 parks (27.8%) excluded. Portland’s population-weighted greenspace score of 1.90 is categorized as “Very Low Risk” (Table 7.25). 43.6% of addresses (144,787) fall within the optimal 300 m threshold, while 73.4% (243,510) are within protective distance (≤ 500 m). The mean distance to nearest eligible park is 373.90 m, with a median of 338.30 m. Table 7.26 reports that 73.4% of addresses achieved low-risk access (Scores 1–2), while 26.6% fell into elevated or high-risk categories (Scores 3–5). 3,241 addresses (1.0%) exceeded 1100 m, the very high-risk threshold.

Table 7.25: Portland Greenspace City Score and Coverage

Metric	Value
City Greenspace Score	1.90
Total Addresses	331,764
Total Population	678,332
Mean Distance (m)	373.90
Median Distance (m)	338.30
Addresses ≤ 300 m	144,787
Addresses ≤ 300 m (%)	43.60%
Addresses ≤ 500 m	243,510
Addresses ≤ 500 m (%)	73.40%
Mean Risk Score (unweighted)	1.89
Difference (weighted – unweighted)	0.00

Figure 7.23 shows the distribution peaks between 250–400 m, with 243,510 addresses (73.4%) within 500 m. 17,659 addresses (5.3%) exceed 800 m, and 3,241 (1.0%) fall beyond 1100 m.

Table 7.26: Portland Greenspace Risk Score Distribution

Risk Score	Risk Level	Distance Range (m)	Number of Addresses	Percentage
1	Very Low Risk	≤ 300	144,787	43.60%
2	Low Risk	301–500	98,723	29.80%
3	Elevated Risk	501–800	70,595	21.30%
4	High Risk	801–1100	14,418	4.30%
5	Very High Risk	>1100	3,241	1.00%

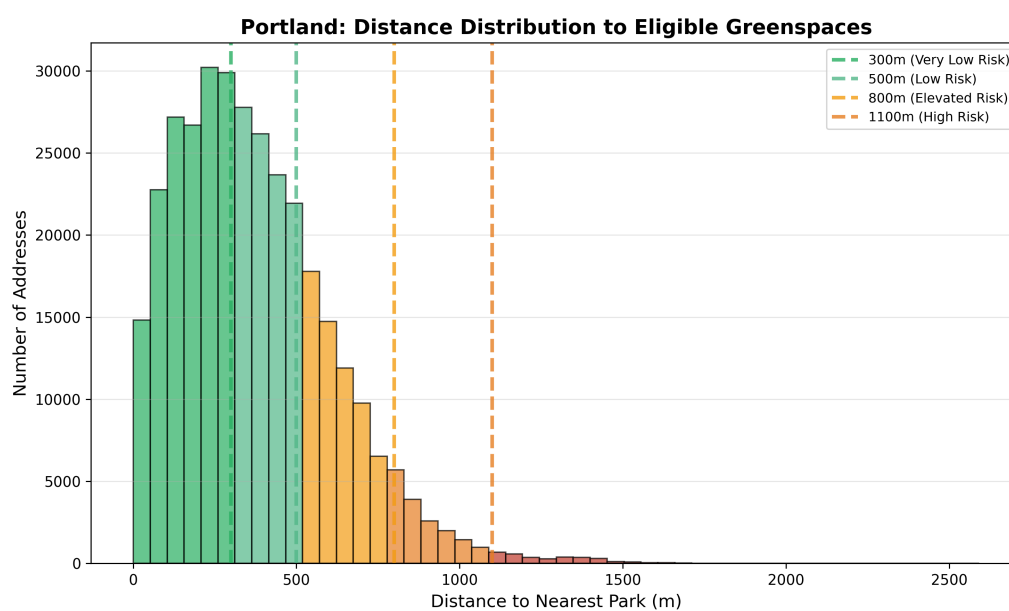


Figure 7.23: Portland Distance Distribution to Eligible Greenspaces

Portland Neighborhood-Level Analysis

The ten neighborhoods with highest-scoring greenspace access (scores 2.68–3.82) collectively house 44,322 residents (6.5% of Portland’s population) (Table 7.27). SUNDERLAND shows the highest risk (3.82), with a mean distance of 951.78 m. PARKROSE (3.47, 801.41 m) and SUMNER (3.36, 761.00 m) have higher risk scores than the city median. Figure 7.24 maps this spatial pattern. Green shading dominates northwest, southwest, and eastern Portland. Yellow-orange areas appear in northeast (PARKROSE, SUNDERLAND) and central areas (SYLVAN-HIGHLANDS, SUMNER). Figure 7.25 depicts eligible parks (229 parks ≥ 0.5 ha, shown as dark green) creating extensive coverage across Forest Park and northwest Portland. Detailed neighborhood-level rankings are provided in Appendix C.2.3.

Table 7.27: Portland Top 10 Priority Neighborhoods for Greenspace Intervention

Rank	Neighborhood	Mean Risk Score	Population	Address Count	Mean Distance (m)	Median Distance (m)	Min Distance (m)	Max Distance (m)
85	RICHMOND	2.68	13,508	6,608	574.69	577.55	13.55	1,072.30
86	HOLLYWOOD	2.73	2,248	1,541	573.92	592.78	168.19	875.77
87	FOREST PARK	2.74	3,027	818	693.98	498.83	15.56	2,368.92
88	HAYDEN ISLAND	2.96	3,000	4,781	672.01	688.51	6.51	1,671.53
89	IRVINGTON	3.02	8,852	4,426	657.13	673.90	13.79	1,113.25
90	ARNOLD CREEK	3.08	3,108	1,203	719.51	693.50	22.15	1,609.12
91	SYLVAN-HIGHLANDS	3.27	1,472	908	759.34	871.08	10.58	1,701.47
92	SUMNER	3.36	2,116	1,097	760.96	791.67	41.35	1,070.36
93	PARKROSE	3.47	6,253	3,110	801.41	843.77	39.12	1,290.58
94	SUNDERLAND	3.82	738	791	951.78	1,152.71	37.94	1,625.53

Portland Greenspace Risk by Neighborhood

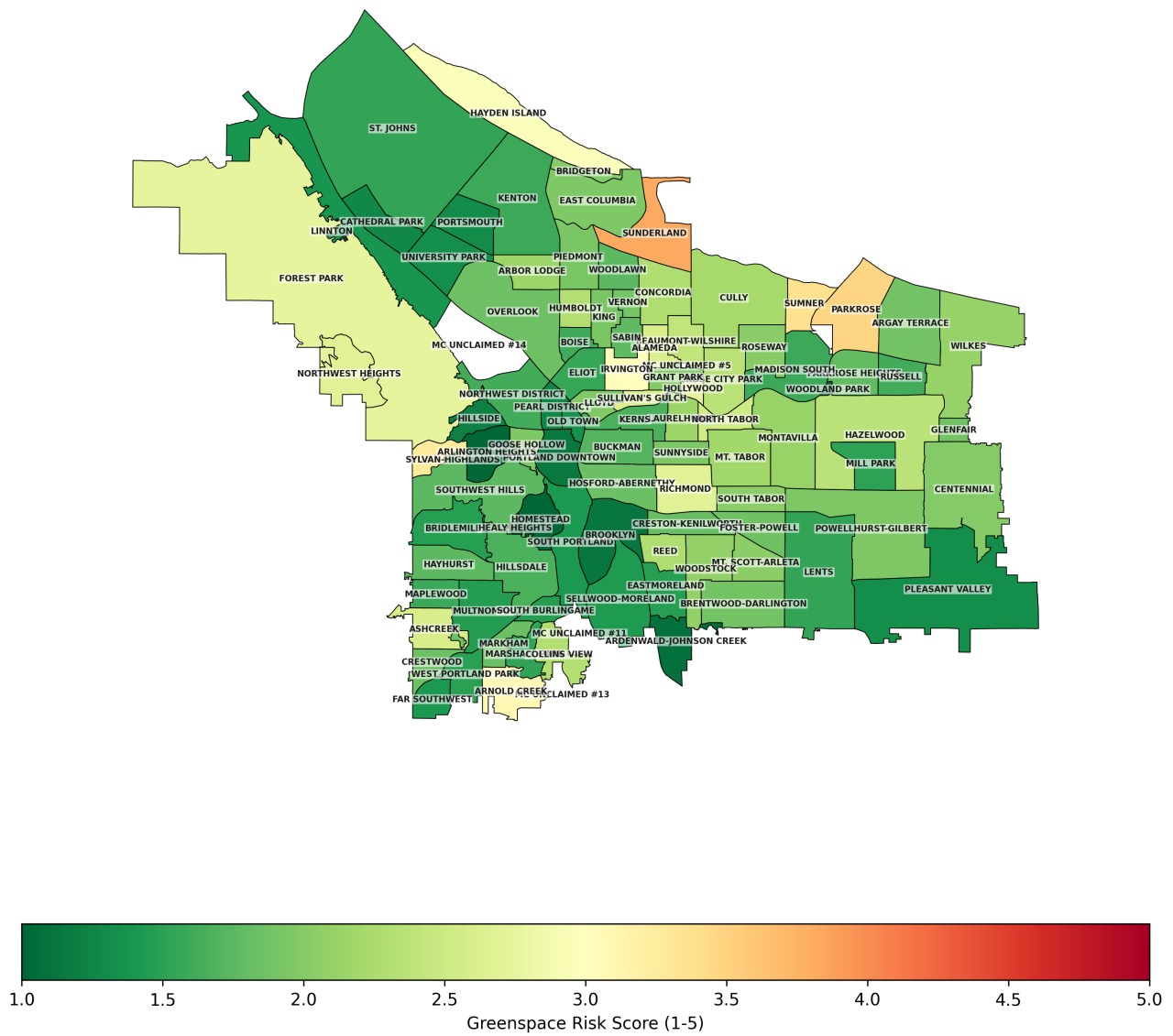


Figure 7.24: Portland Greenspace Risk by Neighborhood

Portland Greenspace Access: Parks and Address Risk Levels

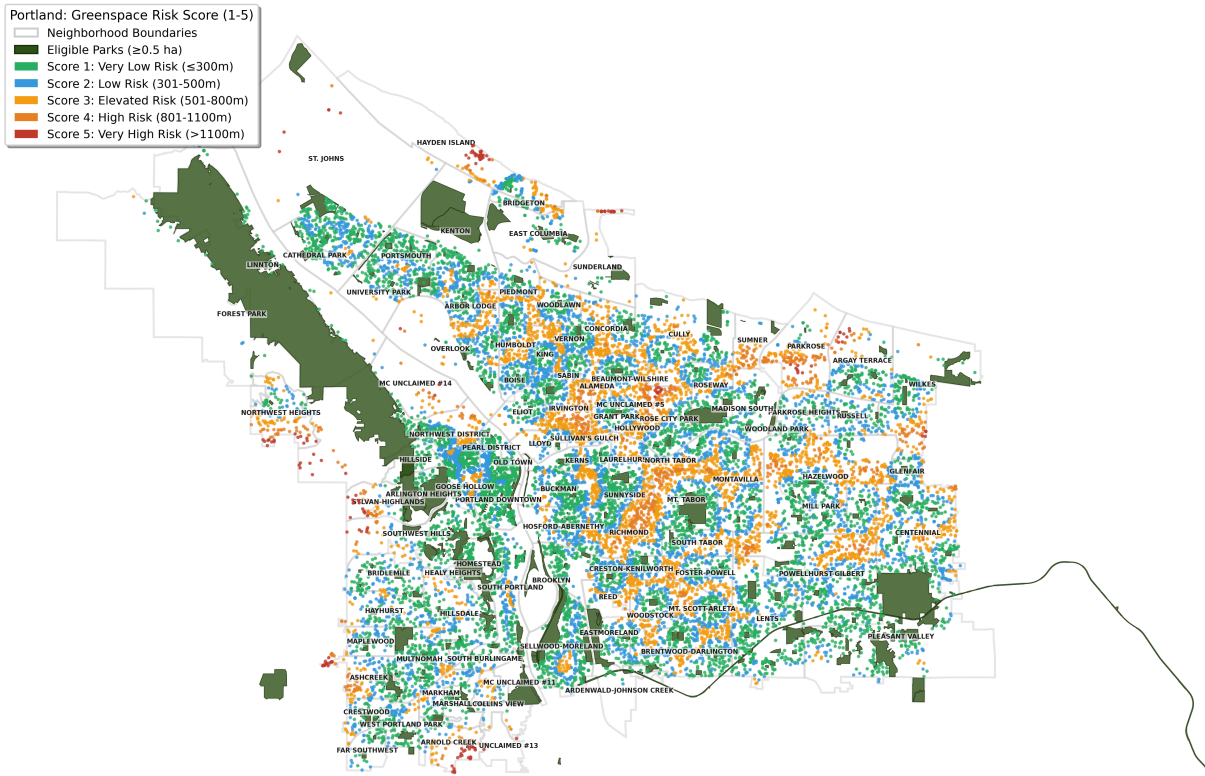


Figure 7.25: Portland Greenspace Access: Parks and Address Risk Levels

Portland WHO Compliance

The WHO Urban Green Space Indicator establishes 9 m² per person as the minimum standard and 50 m² per person as the ideal standard, calculated by dividing total eligible park area by city population. Portland provides 73.10 m² of greenspace per person, exceeding the WHO ideal standard of 50 m²/person by 46% (Table 7.28). The city's provision is 712% above the WHO minimum (9 m²/person).

Table 7.28: Portland WHO Greenspace Provision

Metric	Value
Current Provision (m ² per person)	73.10
WHO Minimum Standard	9.00
WHO Ideal Standard	50.00
Status vs Minimum	MEETS WHO MINIMUM
Status vs Ideal	EXCEEDS WHO IDEAL
Deficit to Minimum (ha)	0.00
Gap to Ideal (ha)	0.00

7.4 Mobility

The mobility contextual cue applies Wang et al. (2019) distance-based transit accessibility methodology to evaluate proximity to public transportation access points. Distance calculations

use the 850-meter threshold established by Wang et al. (2019) which represents a 10-minute walking distance (protective, OR=0.77). Table 7.29 presents city-level scores and transit coverage statistics across all three cities.

Table 7.29: City Mobility Scores and Transit Coverage Parameters

City	Score	Mean Distance (m)	850m Coverage (%)	Transit Stop Count	Transit Type
Chicago	1.95	677.10	73.60	10,905	CTA rail and bus
Manchester	1.02	119.70	99.80	21,296	Metrolink, bus and rail
Portland	1.14	209.00	98.30	6,344	TriMet bus and light rail

7.4.1 Chicago Mobility

Chicago City-level analysis

The transit accessibility assessment for Chicago analyzed proximity to public transit stops using Wang et al. (2019) distance-based methodology. Analysis covered 533,839 addresses across Chicago’s 58 ZIP codes, using distance thresholds of 850 m (protective, OR=0.77). The transit network includes 10,760 bus stops and 145 rail stops, totaling 10,905 transit points. Chicago’s population-weighted mobility score of 1.95 places it in the “Very Low Risk” category (Table 7.30). 73.6% of addresses scored in low-risk categories (1–2), while 26.4% scored in elevated or high-risk categories (3–5). 35,672 addresses (6.7%) exceeded 1500 m, the very high-risk threshold (Table 7.31). Figure 7.26 illustrates the distance distribution to transit stops.

Table 7.30: Chicago Mobility City Score and Coverage

Metric	Value
City Mobility Score	1.95
Total Addresses	533,839
Total Population	2,797,595
Mean Distance (m)	677.10
Median Distance (m)	519.40
Addresses $\leq$ 850m	392,972
Addresses $\leq$ 850m (%)	73.60%
Mean Risk Score (unweighted)	2.08
Difference (weighted – unweighted)	0.13

Table 7.31: Chicago Mobility Risk Score Distribution

Risk Score	Risk Level	Distance Range (m)	Number of Addresses	Percentage
1	Very Low Risk	$\leq$ 400	192,487	36.10%
2	Low Risk	401–850	200,485	37.60%
3	Elevated Risk	851–1200	81,043	15.20%
4	High Risk	1201–1500	24,152	4.50%
5	Very High Risk	$>$ 1500	35,672	6.70%

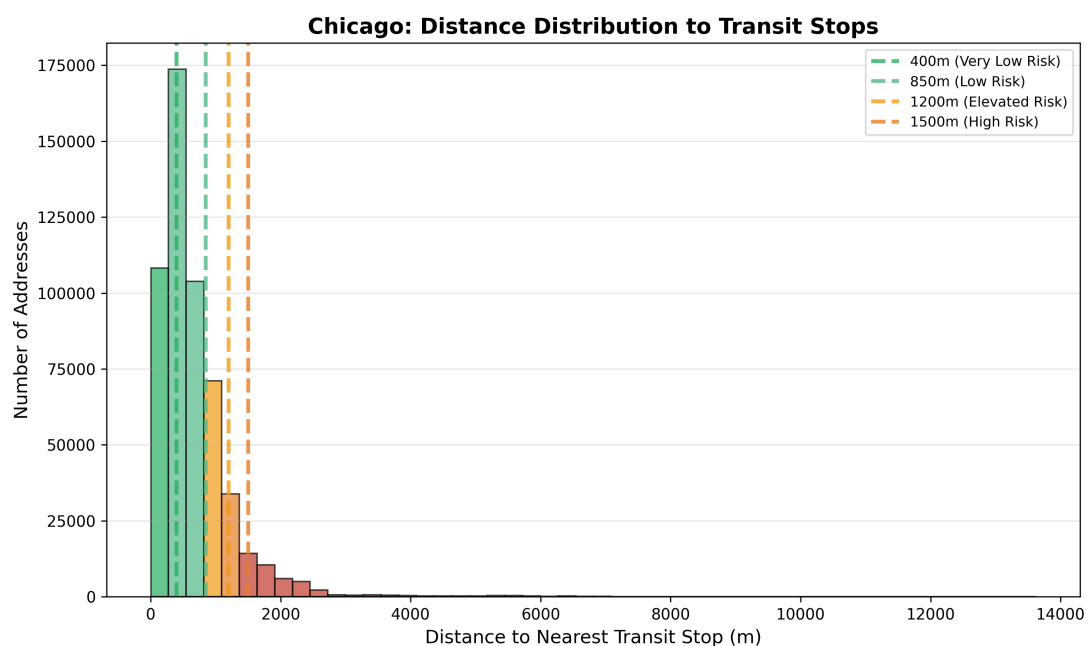


Figure 7.26: Chicago Distance Distribution to Transit Stops

Chicago ZIP-level analysis

The ten highest-scoring ZIP codes (scores 2.51–3.56) collectively house 341,578 residents (12.2% of Chicago’s population). ZIP 60827 recorded the highest score (3.56), with a mean distance of 1601.30 m. ZIP 60631 (3.26, 1519.60 m) and ZIP 60633 (3.05, 1805.70 m) also show elevated-risk scores. ZIP 60638 houses 56,928 residents, the largest population among the ten ZIP codes. Figure 7.27 maps the spatial pattern by ZIP code. Detailed ZIP-level rankings are provided in Appendix C.3.1.

Table 7.32: Chicago Top 10 Highest-Scoring ZIP Codes

Rank	ZIP Code	Mean Risk Score	Population	Address Count	Mean Distance (m)	Median Distance (m)	Min Distance (m)	Max Distance (m)
49	60707	2.51	43,241	4,383	846.34	710.46	28.26	2590.85
50	60638	2.55	56,928	17,039	850.41	609.06	29.53	2643.91
51	60643	2.68	47,831	19,658	910.63	772.62	19.27	2616.13
52	60655	2.81	27,837	10,402	985.89	840.28	45.34	4762.24
53	60646	2.88	28,383	9,282	1001.04	884.47	50.73	2879.58
54	60656	2.93	28,474	6,851	1155.18	883.64	47.86	5587.08
55	60652	2.94	40,898	12,777	1021.05	891.07	38.98	2628.42
56	60633	3.05	13,359	4,682	1805.73	854.89	41.88	7213.26
57	60631	3.26	29,691	9,078	1519.64	1085.08	34.76	5841.87
58	60827	3.56	24,936	1,015	1601.33	1250.40	37.81	4319.12

Figure 7.28 maps transit stops (purple dots) forming a dense network across Chicago. Green and blue address clusters (scores 1–2) appear along major transit corridors, representing 73.6% of addresses within protective distance. Orange and red dots (scores 3–5) scatter beyond the dense transit network.

Chicago Transit Accessibility Risk by ZIP Code

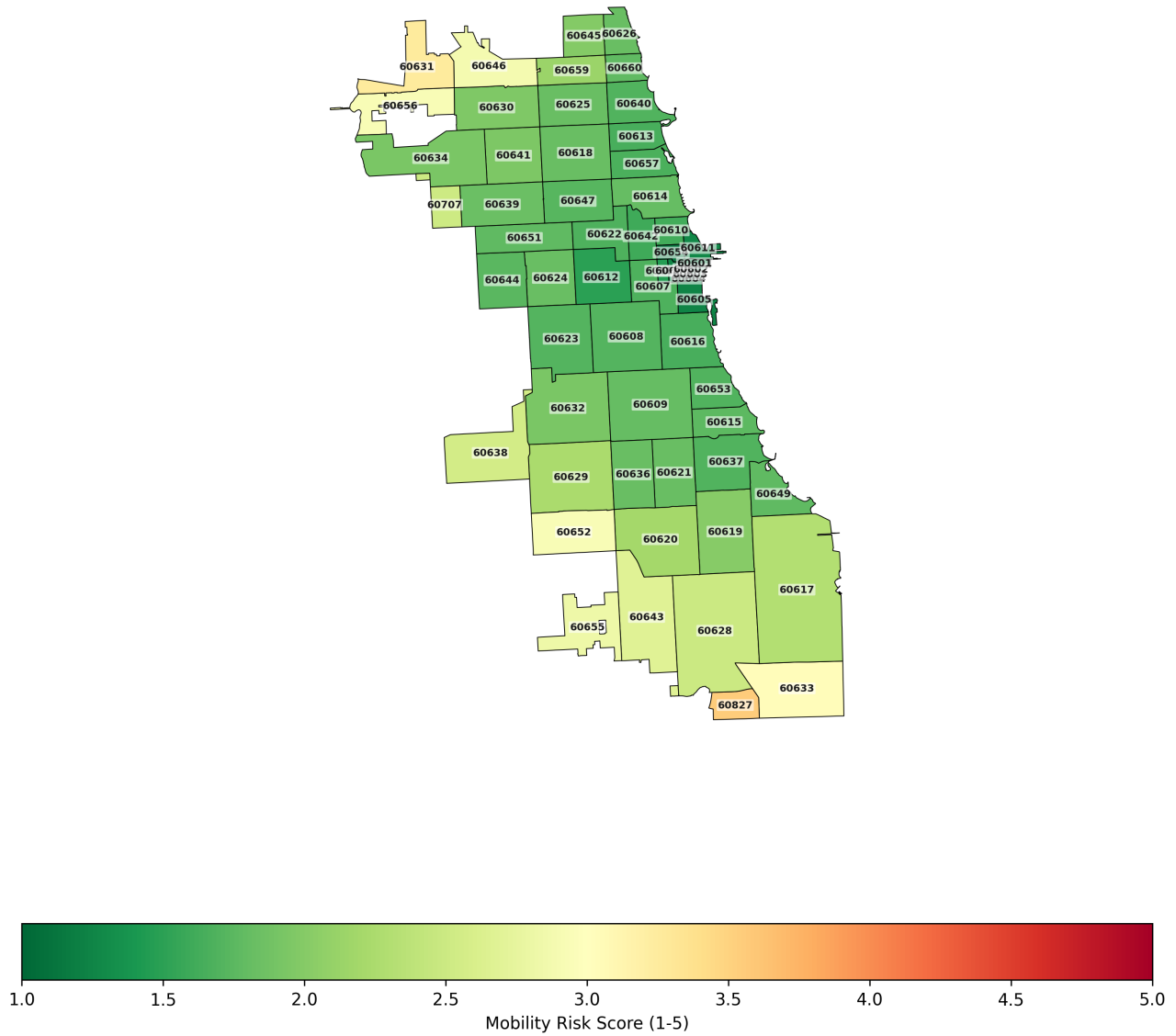


Figure 7.27: Chicago Transit Accessibility Risk by ZIP Code

Chicago Transit Access: Stops and Address Risk Levels

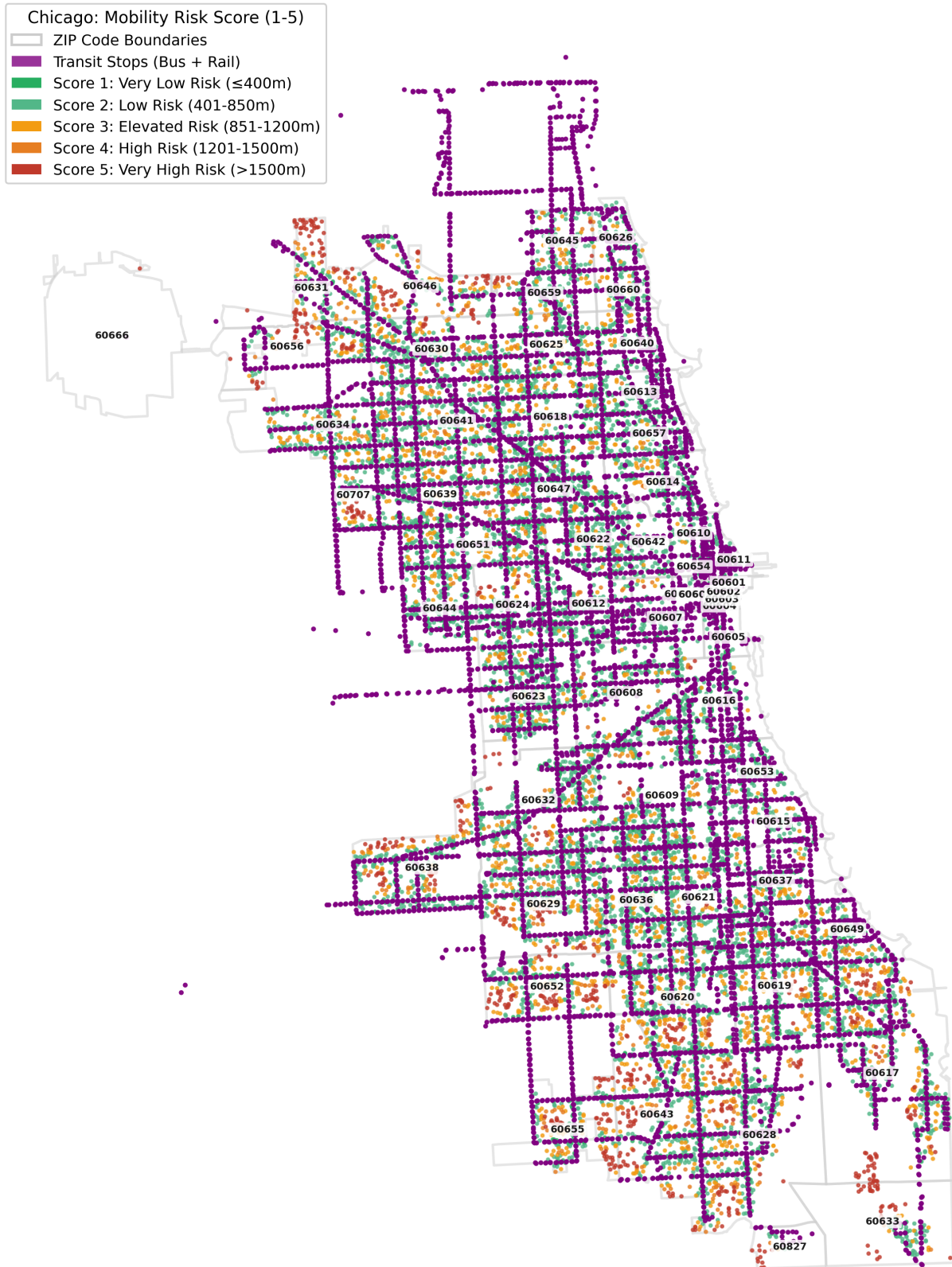


Figure 7.28: Chicago Transit Access: Stops and Address Risk Levels

7.4.2 Manchester Mobility

Manchester City-level analysis

The transit accessibility assessment for Manchester analyzed proximity to public transit stops using Wang et al. (2019) distance-based methodology. Analysis covered 61,796 addresses across Manchester’s 10 metropolitan boroughs, using distance thresholds of 850 m (protective, OR=0.77). The transit network includes 21,106 bus stops and 190 metro/tram stops, totaling 21,296 transit points. Manchester’s population-weighted mobility score of 1.02 falls in the “Very Low Risk” category (Table 7.33). 99.80% of addresses scored in low-risk categories (1–2), while 0.20% scored in elevated or high-risk categories (3–5). 33 addresses (0.10%) exceeded 1500 m, the very high-risk threshold (Table 7.34). Figure 7.29 illustrates this distance distribution to transit stops.

Table 7.33: Manchester Mobility City Score and Coverage

Metric	Value
City Mobility Score	1.02
Total Addresses	61,796
Total Population	3,009,664
Mean Distance (m)	119.70
Median Distance (m)	98.40
Addresses ≤ 850 m	61,687
Addresses ≤ 850 m (%)	99.80%
Mean Risk Score (unweighted)	1.02
Difference (weighted – unweighted)	0.00

Table 7.34: Manchester Mobility Risk Score Distribution

Risk_Score	Risk_Level	Distance_Range (m)	Number_of_Addresses	Percentage
1	Very Low Risk	≤ 400	60,878	98.50%
2	Low Risk	401–850	809	1.30%
3	Elevated Risk	851–1200	59	0.10%
4	High Risk	1201–1500	17	0.00%
5	Very High Risk	> 1500	33	0.10%

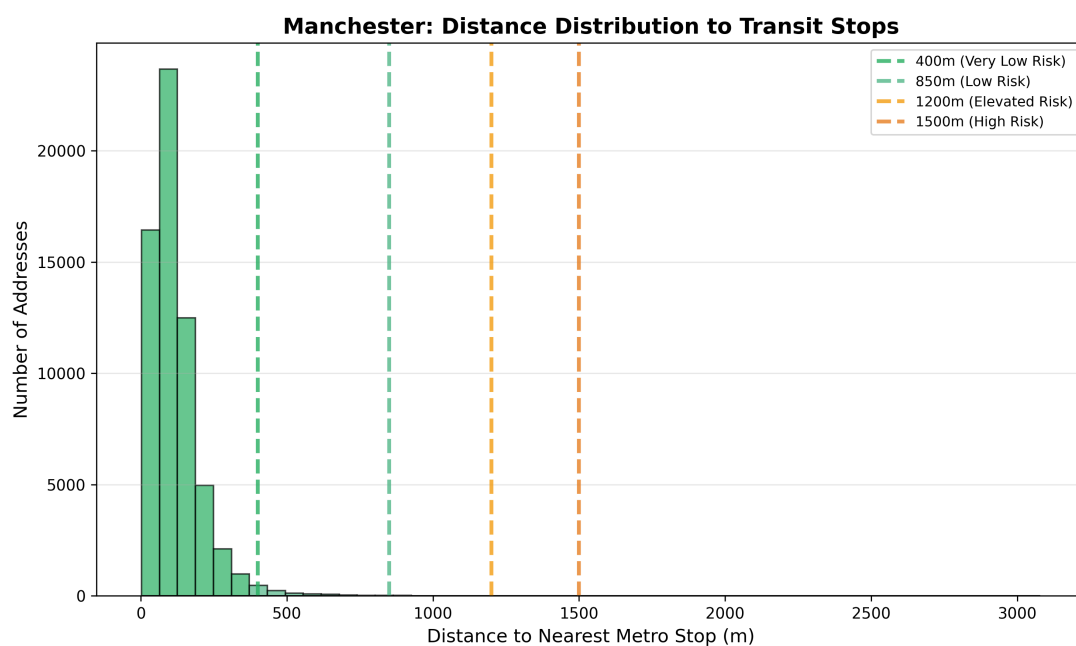


Figure 7.29: Manchester Distance Distribution to Transit Stops

Manchester Borough-Level Analysis

The five highest-scoring boroughs (scores 1.02–1.03) collectively house 1,452,205 residents (48.30% of Greater Manchester’s population) (Table 7.35). Figure 7.30 illustrates the risk score for each borough. Detailed borough-level rankings are provided in Appendix C.3.2.

Table 7.35: Manchester Top 5 Highest-Scoring Boroughs

Rank	Borough	Mean_Risk_Score	Population	Address_Count	Mean_Distance_m	Median_Distance_m	Min_Distance_m / Max_Distance_m
6	Bolton Borough (B)	1.02	310,085	6,298	122.01	97.69	3.10 / 1,903.58
7	Salford Borough (B)	1.02	294,348	5,663	124.56	101.83	5.88 / 3,079.04
8	Bury Borough (B)	1.02	198,921	4,305	122.75	97.82	6.56 / 1,280.22
9	Stockport Borough (B)	1.03	303,929	5,991	134.65	109.55	3.03 / 1,107.54
10	Wigan Borough (B)	1.03	344,922	6,827	132.66	105.18	2.41 / 2,806.96

As seen in Figure 7.31, transit stops (purple dots, 21,296 stops including 21,106 bus and 190 metro/tram) form a dense network across Greater Manchester. Purple and green address clusters (scores 1–2) appear throughout the metropolitan area, representing 99.80% of addresses within protective distance.

Manchester Transit Accessibility Risk by Borough

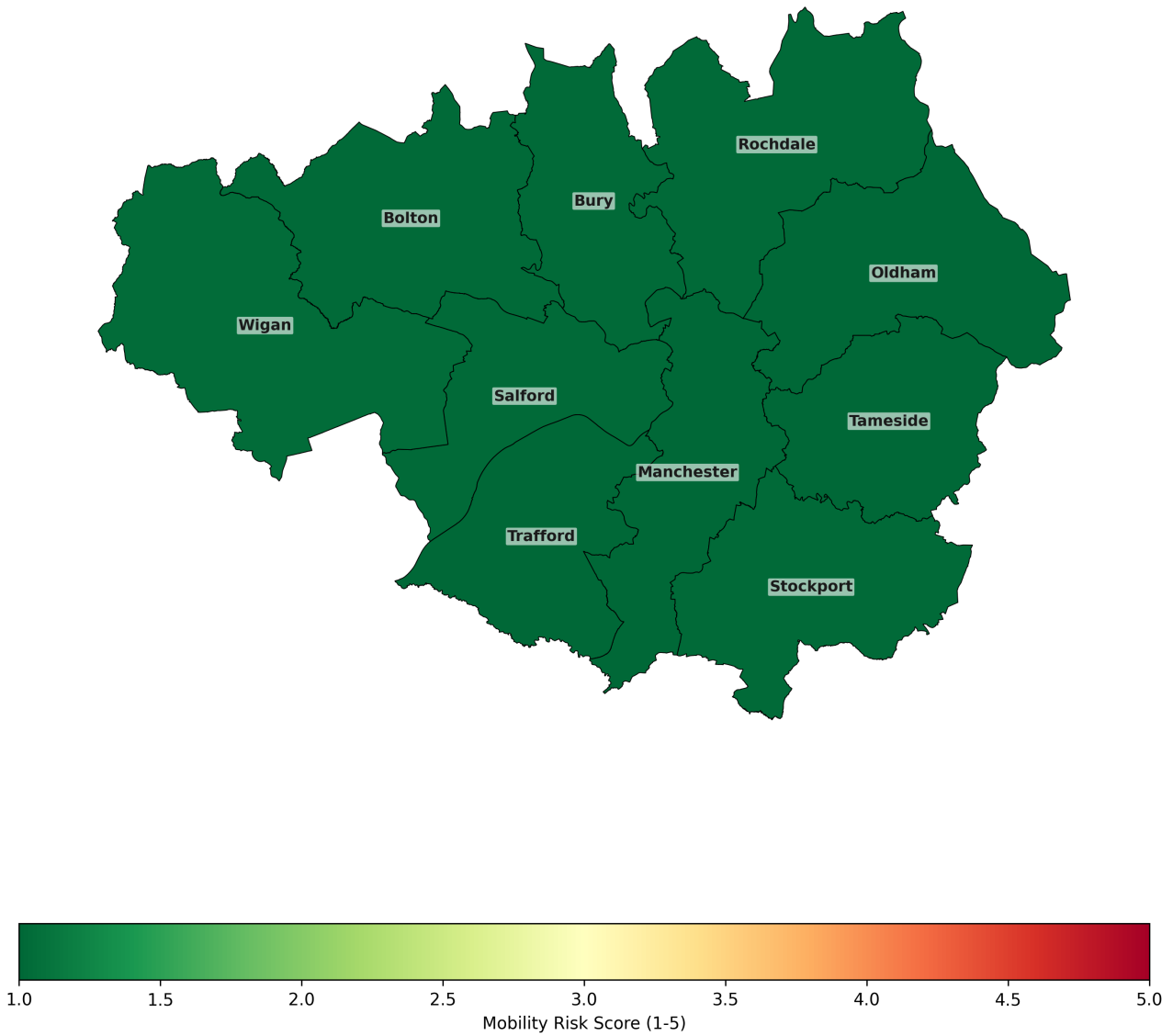


Figure 7.30: Manchester Transit Accessibility Risk by Borough

Manchester Transit Access: Stops and Address Risk Levels

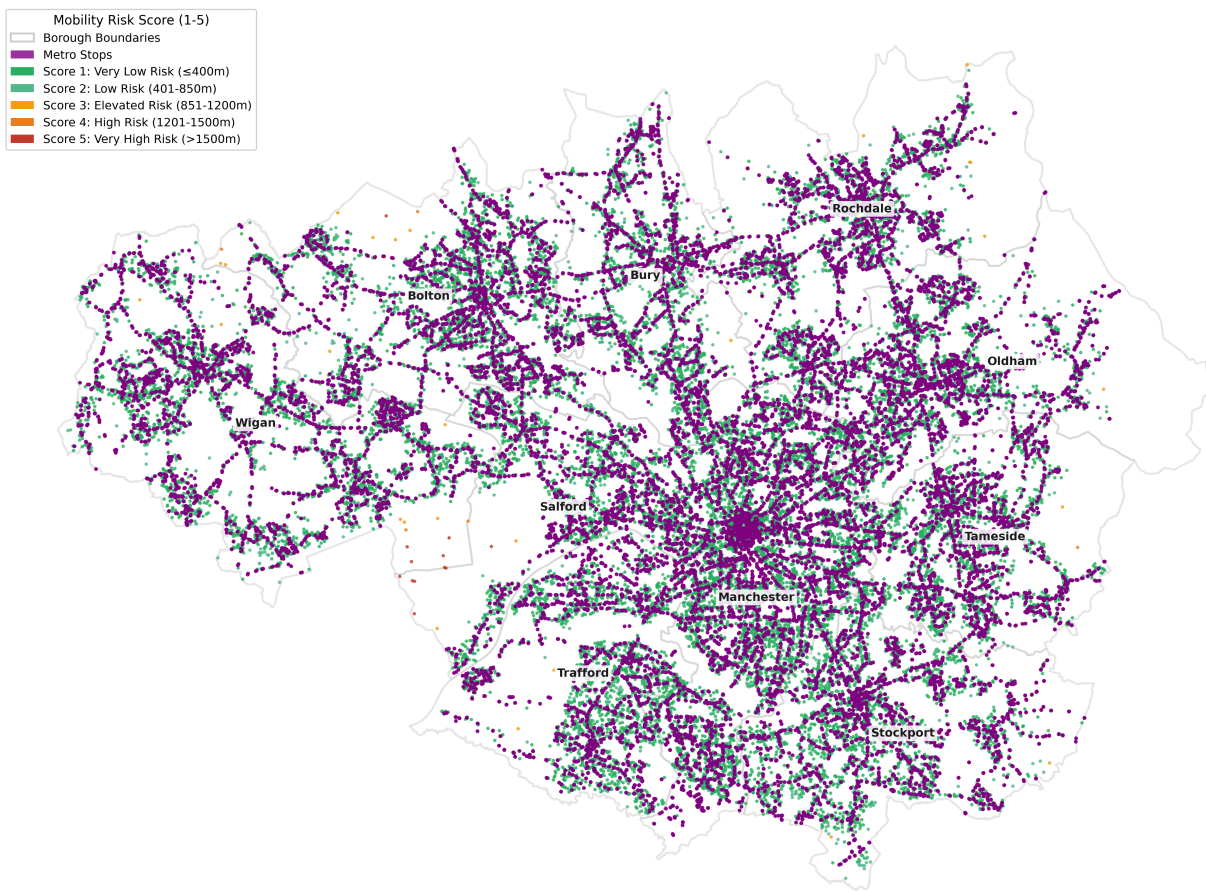


Figure 7.31: Manchester Transit Access: Stops and Address Risk Levels

7.4.3 Portland Mobility

Portland City-level analysis

The transit accessibility assessment for Portland analyzed proximity to public transit stops using Wang et al. (2019) distance-based methodology. Analysis covered 331,764 addresses across Portland’s 98 neighborhoods, using distance thresholds of 850 m (protective, OR=0.77). The transit network includes 6,103 bus stops and 161 rail stops, plus 80 other transit points (street-car, commuter rail), totaling 6,344 transit stops. Portland’s population-weighted mobility score of 1.14 represents “Very Low Risk” (Table 7.36). Table 7.37 shows that 98.40% of addresses scored in low-risk categories (1–2), while 1.60% scored in elevated or high-risk categories (3–5). 4,062 addresses (1.20%) exceeded 1500 m, the very high-risk threshold. Figure 7.32 illustrates the distance distribution to Portland transit stops.

Table 7.36: Portland Mobility City Score and Coverage

Metric	Value
City Mobility Score	1.14
Total Addresses	331,764
Total Population	678,332
Mean Distance (m)	209.00
Median Distance (m)	145.20
Addresses $\leq 850\text{m}$	326,274
Addresses $\leq 850\text{m}$ (%)	98.30%
Mean Risk Score (unweighted)	1.13
Difference (weighted – unweighted)	0.02

Table 7.37: Portland Mobility Risk Score Distribution

Risk Score	Risk Level	Distance Range (m)	Number of Addresses	Percentage
1	Very Low Risk	≤ 400	303,874	91.60%
2	Low Risk	401–850	22,400	6.80%
3	Elevated Risk	851–1000	625	0.20%
4	High Risk	1001–1500	803	0.20%
5	Very High Risk	>1500	4,062	1.20%

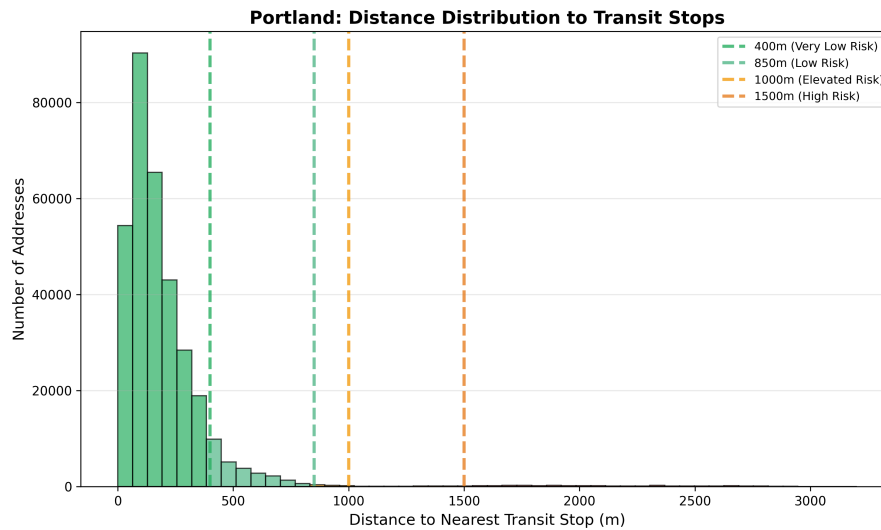


Figure 7.32: Portland Distance Distribution to Transit Stops

Portland Neighborhood-Level Analysis

Table 7.38 presents the ten highest-scoring neighborhoods (scores 1.38–4.93) that collectively house 39,140 residents (5.80% of Portland’s population). NORTHWEST HEIGHTS recorded the highest score (4.93), with a mean distance of 2142.10 m. Figure 7.33 illustrates the risk score per neighborhood. Detailed neighborhood-level rankings are provided in Appendix C.3.3.

Table 7.38: Portland Top 10 Highest-Scoring Neighborhoods

Rank	Neighborhood	Mean Risk Score	Population	Address Count	Mean Distance (m)	Median Distance (m)	Min Distance (m)	Max Distance (m)
85	MARKHAM	1.38	2,617	1,141	364.26	342.36	16.82	821.79
86	SYLVAN-HIGHLANDS	1.52	1,472	908	401.69	412.10	25.11	805.54
87	EAST COLUMBIA	1.53	2,205	1,260	360.82	309.45	13.91	1,050.64
88	EASTMORELAND	1.59	5,252	1,693	432.14	460.05	13.49	836.59
89	SUNDERLAND	1.71	738	791	519.67	638.48	13.45	1,262.94
90	HAYDEN ISLAND	1.78	3,000	4,781	543.45	544.11	28.93	1,166.73
91	MARSHALL PARK	2.08	1,493	642	598.69	593.86	27.19	1,090.72
92	PLEASANT VALLEY	2.35	13,409	4,623	736.44	388.88	1.84	3,107.01
93	FOREST PARK	4.44	3,027	818	1,979.18	2,131.69	137.39	3,201.50
94	NORTHWEST HEIGHTS	4.93	5,927	2,645	2,142.14	2,127.00	1,141.48	2,969.99

Figure 7.34 depicts transit stops (purple dots, 6,344 stops) across Portland. Green and blue address clusters (scores 1–2) appear throughout central, northern, and eastern areas. Red and dark red dots (scores 4–5) appear in FOREST PARK and NORTHWEST HEIGHTS.

Portland Transit Accessibility Risk by Neighborhood

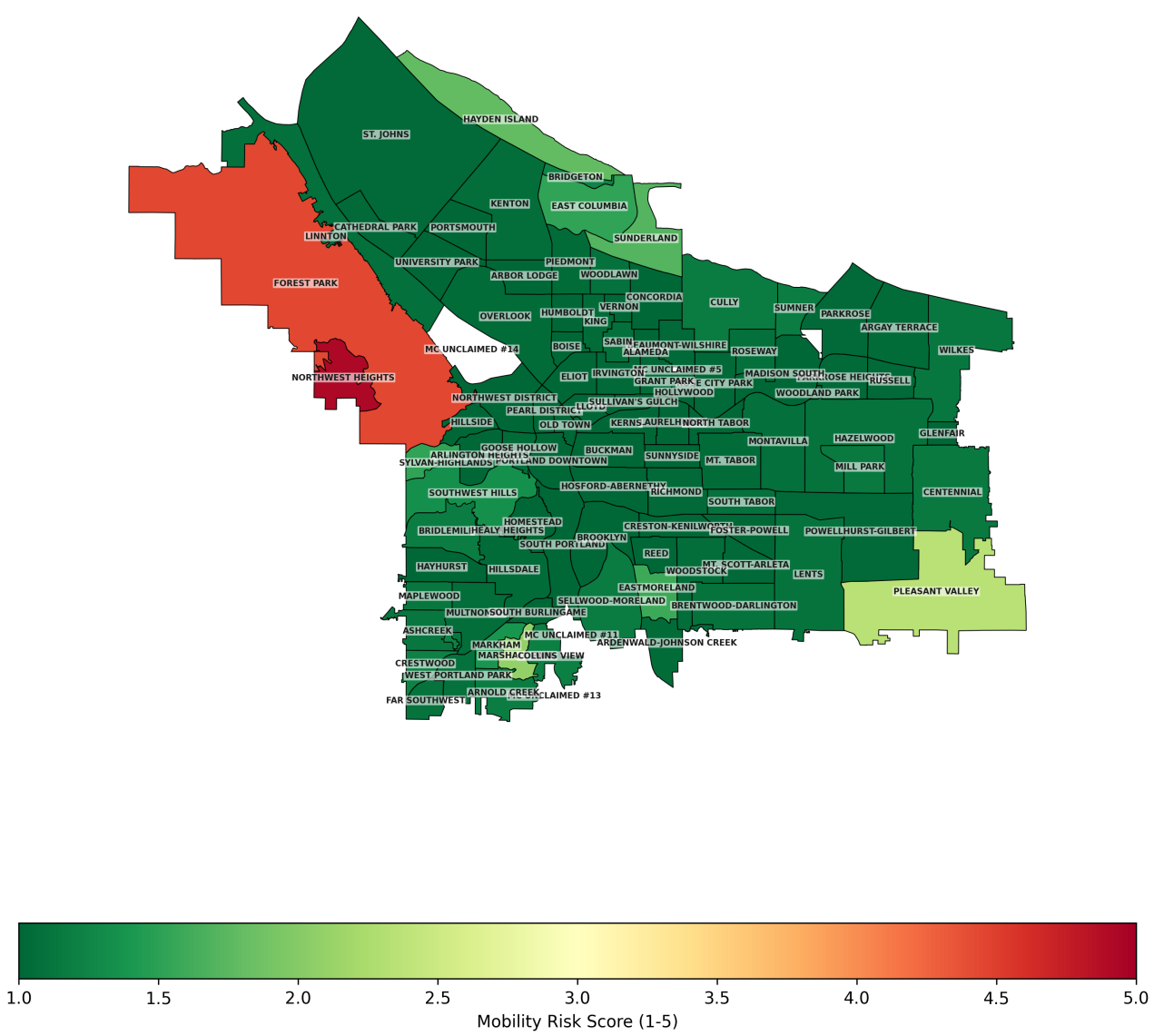


Figure 7.33: Portland Transit Accessibility Risk by Neighborhood

Portland Transit Access: Stops and Address Risk Levels

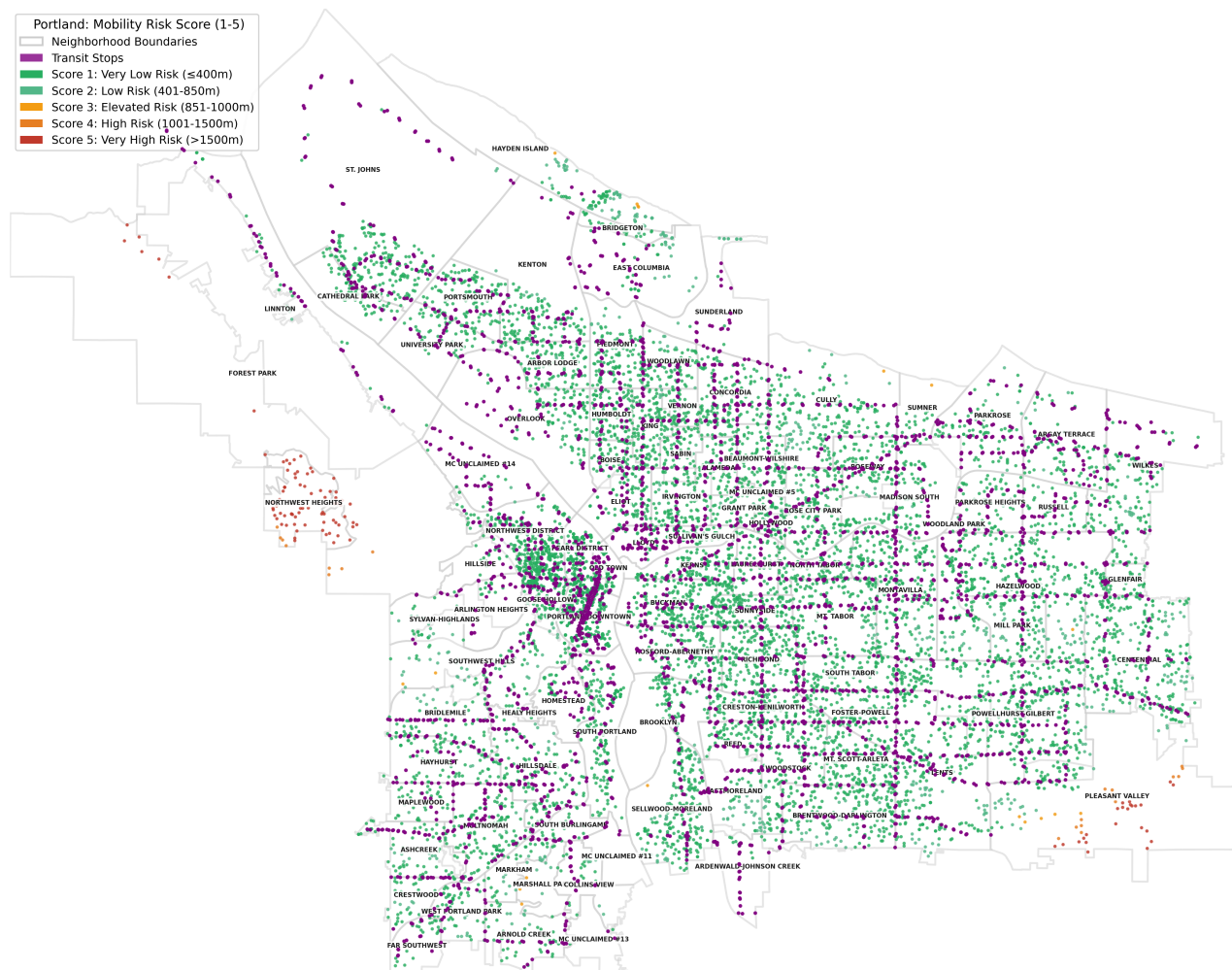


Figure 7.34: Portland Transit Access: Stops and Address Risk Levels

7.5 Urban Mental Wellbeing Risk Index (UMWI) Cross-City Comparisons

The Urban Mental Wellbeing Risk Index aggregates the three contextual cue scores into a single population-weighted measure of environmental exposure risk to urban mental wellbeing risk. Table 7.39 presents the final UMWI scores and component breakdowns for all three cities.

Table 7.39: City-Level UMWI Scores and Risk Categories

City	Air Quality	Greenspace	Mobility	Cumulative Score	UMWI	Risk Category
Chicago	2.59	3.70	1.95	8.24	2.75	Low Risk
Manchester	2.86	2.46	1.02	6.33	2.11	Low Risk
Portland	2.46	1.90	1.14	5.50	1.83	Very Low Risk

Portland recorded the lowest UMWI score (1.83). Manchester recorded a UMWI of 2.11. Chicago recorded the highest UMWI (2.75), with greenspace accessibility exceeding the elevated risk threshold of 3.00.

Correlation Analysis

Figure 7.35 shows the correlation matrix between contextual cues and UMWI. Correlations: Greenspace–Mobility ($r = 0.91$), UMWI–Greenspace ($r = 1.00$), UMWI–Mobility ($r = 0.91$), Air Quality–Mobility ($r = -0.32$), Air Quality–UMWI ($r = 0.10$).

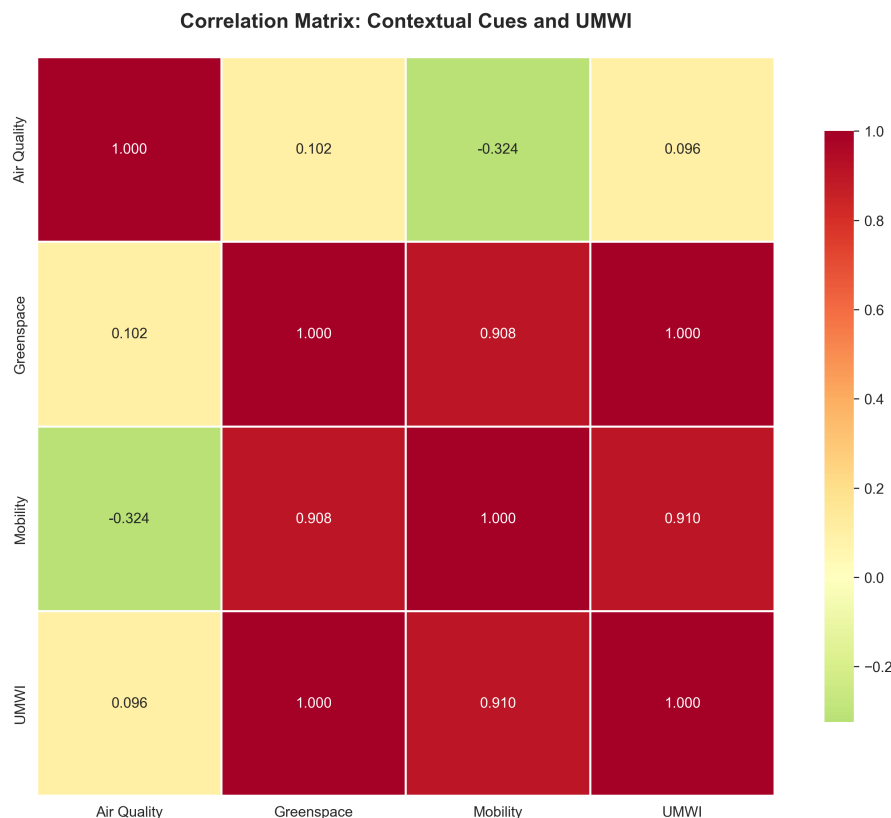


Figure 7.35: Correlation matrix for contextual cues and UMWI

Sensitivity Analysis

Table 7.40 shows the sensitivity analysis, measuring UMWI change when each contextual cue increases by one point while holding others constant. All three cities show sensitivity

coefficients of approximately 0.33–0.34 across contextual cues. A one-point increase in any contextual cue produces a 0.33-point increase in the final UMWI score.

Table 7.40: UMWI Sensitivity to Individual Contextual Cues

City	Base UMWI	AQ Sensitivity	GS Sensitivity	Mobility Sensitivity
Chicago	2.75	0.33	0.33	0.33
Manchester	2.11	0.33	0.33	0.33
Portland	1.83	0.34	0.34	0.34

Pairwise City Comparison

Table 7.41 presents pairwise differences between cities across UMWI and individual contextual cues. The Chicago–Portland comparison shows the largest UMWI gap (0.92 points). The greenspace difference (1.80 points) is the largest component difference. The Chicago–Manchester comparison shows a 0.66-point UMWI difference. Manchester and Portland show the smallest UMWI difference (0.28 points).

Table 7.41: Pairwise UMWI and Contextual Cue Differences

Comparison	UMWI Diff	AQ Diff	GS Diff	Mobility Diff
Chicago vs Manchester	0.64	-0.27	1.24	0.93
Chicago vs Portland	0.92	0.13	1.80	0.81
Manchester vs Portland	0.28	0.39	0.56	-0.13

7.6 Overall Discussion of Results

In this section, the results are discussed in three ways: City-Level Discussion (7.6.1) examines individual city profiles and risk patterns within Chicago, Manchester, and Portland. Cross-City Discussion (7.6.2) compares contextual cue performance across the three cities to identify common patterns and differences. UMWI Cross-City Discussion analyzes the overall Urban Mental Wellbeing Risk Index scores to evaluate framework effectiveness and transferability.

7.6.1 City-Level Discussion

Chicago

Chicago reveals a gap between greenspace quantity and accessibility. Despite exceeding WHO provision standards seven times (Section 7.3), the city’s elevated greenspace risk score (3.70) reflects that fewer than one in ten addresses are within the optimal 300-meter threshold documented by Gascon et al. (2018) for depression risk reduction. This demonstrates how aggregate metrics can mask spatial inequality in environmental exposure. Large parks like Lincoln Park strengthen aggregate metrics yet leave many residential neighborhoods in greenspace deserts. This gap between quantity and accessibility reveals why only relying on WHO provision metrics fails to assess environmental exposure risk for urban mental wellbeing at the population level. The city lies in a transitional zone for air quality (2.59); Chicago exceeded WHO guidelines (Section 7.2). While mobility represents a relative strength (1.95) compared to its significant greenspace challenges, the notable percentage (26.4%) of residents facing poor access still contributes to the city’s overall environmental burden.

Chicago’s final UMWI score of 2.75 places just 0.25 points below the elevated risk threshold. Chicago operates at the limit of documented urban mental wellbeing zones, where seasonal air

quality spikes or loss of greenspace can pose an elevated environmental exposure risk for urban residents' mental wellbeing.

Manchester

The city's standout strength is its mobility (Score: 1.02, "Very Low Risk"), characterized by near-universal transit access (Section 7.2) and noticeable equity across all boroughs. This extensive transit network likely protects most residents from mobility-related psychological distress. Greenspace accessibility is generally acceptable (Score: 2.46, "Low Risk"), with over half of addresses within protective distances and relatively low spatial variation. However, Manchester only meets the minimum WHO provision standard, and a substantial portion of addresses (45.5%) remain beyond evidence-based thresholds. This suggests that there are opportunities to improve both the quantity and proximity of parks, particularly for the 10.1% of addresses facing severe deprivation (>1100 m). Manchester's air quality score (2.86) is the highest among the three cities, with over one-quarter of addresses served by a monitor at the [Chen et al. \(2018\)](#) harm threshold (Section 7.2), indicating concentrated exposure risk requiring targeted intervention. Manchester significantly exceeds WHO 2021 guidelines, suggesting the city must address air quality not only at the borough level but also citywide.

Manchester presents an intermediate environmental risk profile with a final UMWI score of 2.11 ("Low Risk"). While the city avoids elevated mental health risk thresholds, its environmental profile reveals uneven protection; exceptional transit accessibility (99.8% coverage) contrasts with limited greenspace distribution (only 31.4% within optimal distance) and the highest air quality burden among the three cities studied.

Portland

Portland demonstrates that greenspace, air quality, and mobility infrastructure are not competing priorities but can be achieved simultaneously through strategic urban planning. The strong performance is driven by transit accessibility (Score: 1.14), which reaches 98.3% of residents within protective distance. The greenspace score of 1.90 reflects both WHO ideal compliance ($73.1\text{ m}^2/\text{person}$) and optimal proximity, with 43.6% of addresses within 300 m where [Gascon et al. \(2018\)](#) documented an 82% depression risk reduction. Air quality performance (2.46) achieves WHO compliance at $4.52\text{ }\mu\text{g}/\text{m}^3$. However, three of the nine monitors failed WHO compliance, primarily in the southern parts of the city, and significant temporal fluctuations indicate periods of potentially elevated risk.

Portland emerges as the city with the lowest overall environmental risk, achieving a final UMWI score of 1.83 ("Very Low Risk"). Portland's environment protects rather than threatens mental wellbeing, positioning residents within thresholds where stress buffering and depression risk reduction are empirically documented.

7.6.2 Cross-City Discussion

Cross-City Comparison

The primary driver differentiating these overall scores, as confirmed by the correlation analysis, is greenspace accessibility Figure 7.35. Chicago provides 139.2 m^2 per person, nearly double Portland's $73.1\text{ m}^2/\text{person}$, yet achieves less than one-quarter of Portland's optimal accessibility (9.8% vs. 43.6% within 300 m). Manchester occupies an intermediate position with $15.3\text{ m}^2/\text{person}$, exceeding WHO minimums by 70% yet delivering optimal access to only 31.4% of residents. The computational framework reveals that spatial distribution, not aggregate quantity, determines whether greenspace translates into urban mental wellbeing protection.

Mobility is a relative strength across all cities; Chicago (1.95), Manchester (1.02), and Portland (1.14) are categorized as "Very Low Risk." Yet, over a quarter of Chicago's addresses

fall beyond the protective 850 m threshold, indicating substantial gaps in transit coverage.

The air quality contextual cue presents similar scores across the three cities (Chicago: 2.59, Manchester: 2.86, Portland: 2.46) yet hides crucial spatial differences. Chicago exhibits relatively uniform air quality across its ZIP codes, suggesting a need for citywide reduction strategies, whereas Manchester displays significant spatial variation between boroughs, indicating potential benefits from targeted interventions in specific high-risk zones like Salford. These comparisons highlight the strength of the computational framework’s approach, which combines relative baseline and absolute (WHO) benchmarks to capture environmental performance across diverse cities.

UMWI Cross-City Discussion

The final Urban Mental Wellbeing Risk Index (UMWI) scores reveal distinct environmental exposure risks for the three cities, with Chicago presenting the highest risk (2.75), followed by Manchester (2.11), and Portland exhibiting the lowest overall risk (1.83). While none of the cities cross the “Elevated Risk” threshold, Chicago is the closest to this limit.

The correlation analysis explains the factors driving these differences. The primary determinant of the overall risk variation observed in this three-city sample is greenspace, with a near-perfect positive correlation ($r = 1.00$). Mobility also shows a strong positive correlation ($r = 0.91$), which implies that better transit access is significantly associated with lower overall environmental exposure risk. The strong positive correlation between greenspace and mobility scores ($r = 0.91$) is also noteworthy, potentially suggesting that cities with better greenspace planning also tend to invest more effectively in transit infrastructure, or vice versa. In contrast, air quality has a minimal correlation ($r = 0.10$) and weak associations with other contextual cues. This means that the air quality contextual cue reflects limited variation across the three cities studied. The negative correlation between air quality and mobility ($r = -0.32$) potentially reflects urban development patterns where transit-dense areas experience higher traffic-related pollution, though this relationship requires further research.

The sensitivity analysis confirms that the equal weighting scheme (one-third weight per contextual cue) functions as designed. All three cities show sensitivity coefficients of approximately 0.33–0.34, meaning a one-point increase in any single contextual cue produces a 0.33-point increase in final UMWI. The pairwise comparisons provide specific quantitative evidence supporting these findings. The largest overall UMWI gap is between Chicago and Portland (0.92 points), attributed to the difference in their greenspace scores (1.80 points). Similarly, the greenspace difference (1.24 points) is the largest factor separating Chicago and Manchester. The Portland–Manchester UMWI difference of 0.28 points suggests both cities have similar environmental profiles despite different strengths and weaknesses.

The UMWI successfully aggregates three distinct contextual cues into a single interpretable metric while preserving the component-level detail necessary for targeted intervention. The computational framework’s ability to process Chicago, Manchester, and Portland’s heterogeneous data infrastructures into comparable environmental exposure risk scores answers **RQ2**: smart city environmental data can be systematically converted into population-level mental wellbeing assessments across diverse urban contexts.

7.6.3 Theoretical and Practical Implications

This research aimed to develop a computational framework that enables cities to implement evidence-guided decision making to improve mental wellbeing by translating evidence-based distance thresholds into operational metrics that cities can implement through existing smart city infrastructure. Current research has documented associations between environmental exposures and mental health outcomes (see Chapter 3; (Gascon et al. 2018, Chen et al. 2018,

Wang et al. 2019)), but lacked systematic methods for population-level risk assessment across multiple contextual cues. This research addresses that gap by demonstrating the feasibility and value of this computational framework.

The strong correlation between poor greenspace accessibility and higher UMWI scores, particularly evident in Chicago, empirically reinforces the research highlighted by Gascon et al. (2018) linking proximity to mental health protection. Similarly, the generally strong performance on mobility across cities aligns with Wang et al. (2019) findings on the protective effect of transit access. Critically, this research extends the literature by demonstrating the primacy of greenspace accessibility as the key differentiator of overall environmental exposure risk in this specific cross-city comparison, a finding often overlooked when contextual cues are studied separately.

The computational framework provides a standardized, replicable methodology for converting raw data (PM_{2.5} readings, park polygons, transit stop points) from varying infrastructures into comparable risk scores. The resulting UMWI serves as a novel benchmarking tool, allowing cities to assess their mental wellbeing risk performance. This supports the potential for existing municipal data infrastructure to enable proactive public mental health initiatives.

The computational framework offers direct implications for urban policy and planning. First, it provides a powerful diagnostic tool for identifying both citywide environmental priorities and specific high-risk geographic areas that require targeted intervention. For example, the results clearly indicate that Chicago should prioritize improving greenspace accessibility systematically, while Manchester might focus on targeted air quality improvements in specific boroughs like Salford. Second, the results suggest that cities may need both targeted programs to address local inequalities and broader strategies to meet international health standards. The framework thus achieves the stated research aim by converting existing environmental monitoring data into evidence-guided intelligence. Cities can justify resource allocation through reference to empirical urban mental health thresholds rather than political priorities or subjective judgment. Chicago's results demonstrate this capability, despite exceeding WHO provision standards by 178%, only 9.8% of residents access protective greenspace proximity documented by Gascon et al. (2018), providing clear evidence-based rationale for prioritizing distributed park creation over expanding existing facilities.

7.6.4 Framework Consistency and Transferability

This research directly addresses how the computational framework can be transferred and scaled for implementation by other cities, aligning with RQ3. The consistent and successful application across the diverse cities of Chicago, Manchester, and Portland provides strong evidence for the framework's robustness and transferability. The core methodology, such as distance calculation, literature-based thresholds, score labeling, and population weighting, was applied consistently across cities despite differences in data infrastructure and spatial units.

The framework demonstrated scalability from Portland (678,332 residents) to Chicago (2,797,595), successfully processing the 300 m greenspace and 850 m mobility thresholds across varied urban forms. Manchester's boroughs, Chicago's ZIP codes, and Portland's neighborhood boundaries all supported population weighting without adjustment, confirming the framework's adaptability to diverse administrative geographies.

The key to this transferability lies in combining standardized analytical procedures with adaptability to local data realities, facilitated through common open data formats. This demonstrated consistency supports the framework's scalability. Cities possessing the necessary baseline data infrastructure, as outlined by the SCDCAF criteria in Chapter 4, can adopt this methodology. The computational framework thus offers a practical pathway for converting existing smart city environmental data into actionable insights for public mental health. This provides the opportunity for cities worldwide to systematically assess and address environmen-

tal risks impacting urban mental wellbeing.

7.6.5 Framework Validity

The computational framework requires rigid validation to confirm that it accurately measures environmental exposure risk as a proxy for potential urban mental wellbeing outcomes. This section uses five methods for validation: external validity across diverse cities, criterion validity against established benchmarks, internal validity through sensitivity analysis, face validity through score interpretation, and construct validity through theoretical alignment.

External Validity

The computational framework was applied across three cities with distinct characteristics to test generalizability. Chicago represents a large and dense American metropolis with industrial activity affecting PM_{2.5} levels. Manchester exemplifies a post-industrial British city with major focus on greenspace and transit mobility. Portland demonstrates strong environmental urban planning for a smaller American city. These cities differ in population density, with Chicago at 4,613 per km², Manchester at 4,716, and Portland at 1,839. Observing consistent patterns across different city contexts demonstrates the computational framework’s robustness and supports replication in new smart cities.

Criterion Validity

Each contextual cue threshold was validated against established literature benchmarks to ensure that the framework accurately represents documented risk levels. The computational framework uses standard deviation increases above the mean to measure air quality exposure risk following [Chen et al. \(2018\)](#). For greenspace accessibility, a 300 m and 500 m proximity threshold and 0.5-hectare minimum size criterion were derived from [Gascon et al. \(2018\)](#), linking depression risk reduction to specific spatial patterns. The 0.5-hectare minimum ensures that greenspaces are large enough to provide measurable wellbeing benefits. Transit accessibility uses an 850 m threshold, aligned with [Wang et al. \(2019\)](#), representing a 10-minute walking distance associated with lower mental distress.

Internal Validity

Sensitivity analysis, as explained in Section 6.5.2, confirmed that each contextual cue contributes $\beta = 0.33/0.34$ to the UMWI score. This equal weighting reflects the theoretical position that air quality, greenspace access, and mobility each represent independent pathways to mental wellbeing outcomes. The computational framework applies consistent measurement protocols across all cities to reduce subjective bias. Distance calculations used identical Euclidean formulas in appropriate projected coordinate systems. PM_{2.5} aggregation followed identical monthly averaging procedures across cities; greenspace eligibility applied a consistent 0.5-hectare minimum size; and transit stop identification combined all eligible formal transit stops.

Face Validity

The computational framework successfully differentiated cities with known environmental quality differences. Portland’s UMWI score (1.83) reflects WHO-compliant air quality (4.52 $\mu\text{g}/\text{m}^3$), strong greenspace accessibility (43.6% within 300 m), and comprehensive transit (98.3% coverage). Chicago’s score (2.75) captures documented challenges where 80.3% of residents lack greenspace access despite abundant provision (139.2 m²/person), validating the framework’s ability to detect inequality masked by aggregate metrics. Manchester’s intermediate score (2.11) appropriately reflects exceptional transit (99.8%) combined with elevated air quality burden (7.76 $\mu\text{g}/\text{m}^3$) and moderate greenspace access (31.4% within 300 m).

Construct Validity

The UMWI construct validity is supported by three principles. First, thresholds derive from studies by [Chen et al. \(2018\)](#), [Gascon et al. \(2018\)](#), [Wang et al. \(2019\)](#) that measure mental health outcomes using validated instruments (K6, CESD-10). This ensures that risk categories correspond to evidence-based impacts. Second, air quality, greenspace, and mobility were selected based on robust epidemiological evidence of significant mental health relationships, as discussed in [Chapter 3](#). Third, the 1–5 ordinal scale provides nuanced assessment, avoiding binary classifications and detecting subtle environmental exposure differences that influence population-level mental wellbeing.

7.7 Conclusion

The computational framework successfully converted heterogeneous environmental data across Chicago, Manchester, and Portland into comparable risk assessments ([RQ2](#)). The Urban Mental Wellbeing Risk Index revealed greenspace accessibility as the primary driver of overall risk differences, with spatial distribution proving more critical than aggregate quantity. Chicago’s elevated UMWI score (2.75) despite superior provision demonstrates how the framework detects inequality masked by aggregate metrics. The consistent application across cities with diverse data infrastructures, administrative geographies, and population scales confirms transferability ([RQ3](#)). The five-method validity assessment demonstrates that the framework accurately measures environmental exposure risk for mental wellbeing outcomes. [Chapter 8](#) synthesizes these findings into conclusions and recommendations, outlining data infrastructure requirements and policy applications for cities adopting this methodology.

Chapter 8

Conclusions and Future work

This final chapter consolidates the research findings and situates them within broader smart city and urban wellbeing contexts. Section 8.1 presents conclusions by revisiting the three research questions, discussing key empirical findings, outlining contributions to knowledge, and examining implications for urban planning practice. Section 8.2 outlines limitations presented in this research. Section 8.3 identifies future research directions that would extend the computational framework’s capabilities, improve its methodological rigor, and support wider adoption across diverse urban contexts.

8.1 Conclusions

This research addressed a fundamental gap in smart city applications: cities collect extensive environmental data but lack systematic frameworks to convert this information into population-level mental wellbeing assessments. The thesis developed and validated a computational framework that transforms air quality, greenspace accessibility, and mobility data into standardized risk scores. This computational framework provides urban planners and policymakers with actionable insights for evidence-based decision making.

8.1.1 Answering the Research Questions

The three research questions guided this work from the literature foundation through implementation to transferability assessment. Each question received clear answers through systematic investigation.

RQ1: Can environmental indicators identified in the literature be operationalised as spatially explicit contextual cues for population-level urban mental wellbeing assessment using smart city data?

Yes. The literature review in Chapter 3 established strong empirical foundations for all three selected contextual cues. Air quality research documents clear dose-response relationships between PM2.5 exposure and mental health outcomes through neuroinflammation pathways. Greenspace studies demonstrate measurable protective effects based on proximity thresholds. Mobility research quantifies the depression risk associated with limited transit access. These relationships operate through shared biological mechanisms, particularly the HPA axis stress response system. The convergence on common stress pathways validates using these three factors together as integrated measures of environmental burden. The literature provided specific quantitative thresholds that enabled operational implementation: [Chen et al. \(2018\)](#) z-score method for air quality, [Gascon et al. \(2018\)](#) distance-based categories for greenspace, and [Wang et al. \(2019\)](#) transit accessibility metrics for mobility.

RQ2: Can a computational spatial framework integrate heterogeneous environmental contextual cues to produce comparable mental wellbeing risk assessments across cities having varying

spatial and data characteristics?

The computational framework successfully converted heterogeneous smart city data into comparable assessments across Chicago, Manchester, and Portland. These cities differ substantially in population size, geographic context, administrative structures, and data collection methods. Chicago represents a large and dense city in the north of United States. Manchester offered a European mid-city context. Portland supplied mid-sized city characteristics with strong environmental policy emphasis. Despite these differences, the computational framework maintained methodological consistency through four key design features. The Smart City Data Classification and Access Framework, presented in Chapter 4, provided systematic criteria for evaluating data readiness. This enabled transparent assessment of what each city could support rather than forcing uniform data requirements. Second, the processing pipeline adapted to local characteristics while preserving core methodology. Cities using different spatial units or monitoring frequencies could still apply the same literature-based thresholds. Third, population-weighted aggregation enabled comparison across different administrative geographies. Fourth, the 1.0 to 5.0 risk score scale provided intuitive interpretation while supporting statistical analysis.

The resulting Urban Mental Wellbeing Risk Index successfully aggregated the three contextual cues into single comparable metrics. Portland achieved the lowest overall risk at 1.83. Manchester scored 2.11. Chicago reached 2.75, indicating an elevated environmental burden. These scores enabled meaningful comparisons while respecting each city's unique characteristics.

RQ3: To what extent can this framework be generalised, transferred, and scaled across multiple cities with differing environmental and data infrastructures?

The computational framework demonstrates clear transferability through its successful application across three diverse urban contexts. The methodology relies exclusively on open data sources that many cities already collect. Air quality monitoring, GIS databases of parks, and transit system locations represent standard smart city infrastructure. Cities do not need to build new collection systems. Implementation requirements are well defined in Chapter 6. Cities need air quality monitoring data with temporal coverage, spatial datasets of greenspaces and transit infrastructure, and residential address or population distribution information. The SCDCAF criteria help cities assess their readiness. The computational framework documentation provides step-by-step procedures for data processing, quality assessment, threshold application, and aggregation. Python libraries for spatial analysis are freely available and widely used in urban planning contexts.

Scalability spans population sizes from Portland's 678,332 residents to Chicago's 2.7 million. The address-based approach handles hundreds of thousands of locations efficiently. Computation time remains manageable on standard hardware. The computational framework scales from neighborhood-level analysis to city-wide assessment through hierarchical aggregation. This multi-scale capability supports different planning needs, from targeted interventions in high-risk areas to comprehensive city benchmarking.

8.1.2 Key Empirical Findings

Greenspace accessibility emerged as the primary driver of overall risk variation. Correlation analysis showed greenspace scores correlating at $r=1.00$ with the final UMWI across the three cities. This near-perfect relationship indicates that greenspace accessibility explains more variation in overall environmental risk than air quality or mobility. The finding elevates greenspace from one environmental factor among many to the critical differentiator in urban mental wellbeing risk.

Spatial distribution matters more than aggregate quantity. Chicago provides 139.2 square meters of greenspace per person, exceeding the WHO ideal by 178%. Yet Chicago received an elevated risk score of 3.70 for greenspace accessibility because only 9.80% of addresses fell

within the protective 300-meter threshold. The city’s large parks serve specific populations while leaving many neighborhoods beyond walking distance of stress recovery benefits. This finding demonstrates that traditional provision metrics based on total area per capita can mask severe accessibility problems. The computational framework’s distance-based approach reveals inequality that aggregate statistics hide.

Air quality challenges persist across cities. Chicago averaged $7.88 \mu\text{g}/\text{m}^3$ annual PM_{2.5} and Manchester reached $7.76 \mu\text{g}/\text{m}^3$, both substantially exceeding the WHO 2021 guideline of $5.0 \mu\text{g}/\text{m}^3$. Only Portland achieved WHO compliance at $4.52 \mu\text{g}/\text{m}^3$. The computational framework revealed spatial patterns within cities. Manchester’s Salford borough reached 4.0 on the risk scale, indicating the highest documented concern level. Chicago showed more uniform exposure across ZIP codes. These patterns inform different intervention strategies. Manchester needs targeted action in specific boroughs while Chicago requires city-wide air quality improvements.

Mobility infrastructure showed strong performance in major cities. Chicago achieved a 1.95 mobility score with 73.6% of addresses within protective transit distance. Manchester reached 1.02 with 99.8% coverage. These scores indicate that both cities have successfully built transit networks that support population mental wellbeing. Portland scored 1.14, also demonstrating strong transit infrastructure. The findings suggest that transit investment provides clear returns for population-level stress reduction.

8.1.3 Contributions to Knowledge

This research makes several contributions that advance both smart city applications and urban mental wellbeing assessment methodology.

Primary contribution: the contextual cue computational framework. The thesis introduces contextual cues as operational bridges between environmental data and mental health research. Previous approaches either remained theoretical or addressed single factors in isolation. The framework demonstrates how to systematically convert multiple data streams into integrated risk assessment. The approach is replicable, requiring only clear documentation of literature sources, threshold selection rationale, and aggregation rules. Other researchers can validate, extend, or challenge the methodology because all decisions are transparent and justified.

Secondary contribution: Urban Mental Wellbeing Risk Index (UMWI). The UMWI is the specific index produced by applying the computational framework to air quality, greenspace accessibility, and transit mobility contextual cues. The UMWI aggregates these three environmental domains into a single population-level risk metric, providing cities with a standardized assessment tool. The UMWI scores for Chicago, Manchester, and Portland establish reference points for other cities implementing the framework.

Supporting contribution: Smart City Data Classification and Access Framework (SCDCAF). This research developed SCDCAF to address the absence of systematic data evaluation criteria for smart city research in regards to urban mental wellbeing. Existing frameworks focus on technical interoperability but do not provide practical selection guidance for researchers constrained by open data availability and privacy considerations. SCDCAF evaluates datasets across five dimensions (availability, sensitivity, temporal frequency, cost, data providers), enabling systematic city selection through transparent, reproducible filtering stages.

Technical contribution: literature-based labeling. The computational framework grounds risk classifications in empirical research rather than arbitrary thresholds. [Chen et al. \(2018\)](#) findings on PM_{2.5} impacts, [Gascon et al. \(2018\)](#) greenspace distance effects, and [Wang et al. \(2019\)](#) transit accessibility relationships provide quantitative bases for score categories. This evidence-based approach maintains clear connections between measurements and documented mental health outcomes. Policy makers can trace risk scores back to specific studies,

supporting resource allocation decisions with scientific evidence.

Practical contribution: open data utilization. The framework demonstrates that cities can assess population mental wellbeing risk using data they already collect. This finding has significant implications for implementation barriers. Cities do not need to conduct expensive surveys, build new monitoring networks, or purchase commercial data. The methodology works with standard municipal data sources, making it accessible to cities with varying resource levels. This accessibility supports wider adoption and knowledge sharing across the urban planning community.

Empirical contribution: cross-city comparative baseline. The thesis provides a novel approach to standardize environmental mental wellbeing risk comparison across major cities using identical methodology. Future applications can situate their results within this growing comparative database.

These contributions advance the thesis aim of developing a computational framework that enables cities to implement evidence-guided decision-making to improve mental wellbeing.

8.1.4 Implications for Urban Planning

The research findings reveal tangible opportunities for cities to transform environmental planning into direct urban mental wellbeing interventions. The computational framework enables a fundamental opportunity to implement evidence-guided decision making.

The computational framework provides urban planners with immediate practical applications that shift environmental planning toward measurable mental health outcomes. The most fundamental change involves moving greenspace planning from quantity metrics to accessibility assessment. Residents need parks within 300 meters to access stress recovery benefits regularly. Instead of calculating the total park area per capita, planners can use the computational framework UMWI output to identify what areas require more attention. Small, distributed parks provide greater mental health benefits than large, distant ones. Greenspace risk scores provide quantitative justification for pocket park investments and greenway development in high-risk areas. Policy makers can prioritize funding by showing which areas score close to or above 3.0 and would benefit most from an intervention. This supports equitable distribution of environmental improvements with quantitative evidence.

Similarly, the computational framework enables integration of risk scores into urban development reviews. Planners could use these scores to assess how proposed projects affect neighborhood wellbeing. For instance, a development that removes greenspace or transit access in a high-priority area would require recalculating neighborhood scores and adjusting designs to reduce negative impacts or include compensatory improvements. Regular monitoring completes the operational cycle. Annual reporting should present UMWI scores alongside traditional indicators, positioning mental wellbeing as a standard planning outcome rather than an aspirational goal. Through this process, the computational framework evolves from a research tool into an operational planning instrument, giving cities a consistent method to assess environmental mental wellbeing risk, prioritize investments, coordinate interventions, and demonstrate accountability for population-level wellbeing outcomes.

8.1.5 Broader Context

This research contributes to the growing recognition that smart cities must serve human wellbeing beyond operational efficiency. Early smart city projects focused on optimizing traffic flow, reducing energy consumption, and improving service delivery. These goals remain important but represent incomplete visions of urban success. The data infrastructure built for efficiency optimization can serve population mental wellbeing when appropriate analytical frameworks exist. The computational framework demonstrates one pathway for human-centered smart city development. Environmental monitoring data collected primarily for regulatory compliance

and operational management, gains new purposes when connected to mental health evidence. This repurposing does not require new technology investments. It requires different analytical perspectives and interdisciplinary connections between environmental monitoring, public health research, and urban planning.

The framework also addresses equity concerns in smart city development. Technology deployments can exacerbate inequalities when benefits concentrate in affluent areas or when implementation costs limit access. This framework uses open data that represents entire urban populations. Risk assessments cover all neighborhoods, not just those with resources for custom studies. The methodology makes population-level environmental assessment accessible to cities regardless of budget, supporting more equitable urban planning.

8.2 Limitations

The framework assesses population-level environmental exposure risk, not individual clinical mental health status. This design choice enables scalable, non-intrusive monitoring using existing data infrastructure rather than resource-intensive clinical assessments. The framework targets actionable environmental conditions that urban planners can modify (air quality, greenspace, and transit) rather than attempting comprehensive mental health assessment across all contributing factors including demographic and socioeconomic variables.

Section 8.2.1 addresses the Western cultural bias in the three-city case study sample and the need for testing framework transferability across diverse geographic and cultural contexts. Section 8.2.2 examines how the deliberate reliance on open data enables methodological accessibility while restricting access to commercial datasets that could improve precision. Section 8.2.3 discusses the absence of independent external validation by researchers or practitioners applying the framework in their own smart cities. Section 8.2.4 acknowledges that the framework quantifies current risk but does not predict how specific interventions might reduce environmental exposure burden over time.

8.2.1 Geographic and Cultural Transferability

The three-city case study sample provided sufficient diversity in population size, geographic context, and data infrastructure to validate framework transferability. Chicago, Manchester, and Portland revealed the core implementation challenges and demonstrated replicability across different urban contexts. However, all three cities are located in Western cultural contexts, specifically Anglo-Saxon settings in the United States and United Kingdom. This geographic limitation raises questions about whether the framework implements primarily Western principles of what constitutes urban mental wellbeing. Cultural differences in how mental health is conceptualized, experienced, and prioritized may mean that the selected environmental contextual cues reflect Western urban planning values rather than universal determinants of mental wellbeing (Patel et al. 2018). For example, concepts of personal greenspace access or individualized mobility may carry different significance in cultures with stronger communal orientations or different built environment traditions. While the literature review drew evidence from geographically diverse contexts including research conducted in China (Chen et al. 2018, Zhang et al. 2017, Yang et al. 2021b, Wang et al. 2021), Latin America (Wang et al. 2019, Salcedo 2024, Leo et al. 2017), Singapore (Henderson 2013), and Japan (Derdouri & Osaragi 2025), high-income Western countries remain overrepresented in the evidence base. Future research should test framework transferability across diverse cultural and geographic settings to assess whether the selected contextual cues and operationalized thresholds appropriately reflect non-Western cultural understandings of mental wellbeing and urban environmental quality.

8.2.2 Open Data Constraint

The deliberate reliance on open data ensures methodological accessibility and replicability, but restricts access to commercial or licensed datasets that could improve precision and coverage. Research resources did not permit acquisition of proprietary datasets. Cities purchasing proprietary data for their own administrative use would likely achieve better results through higher-quality address classifications, more granular spatial resolution, continuous real-time monitoring infrastructure, premium air quality networks, proprietary transit ridership data, and high-resolution greenspace inventories unavailable in public repositories. Commercial datasets often provide cleaner residential classifications, reducing the filtering procedures required in this research to distinguish residential from commercial properties. Data quality varied across cities, requiring adapted filtering procedures. Chicago's address data and Manchester's UPRN dataset include non-residential properties, necessitating filtering using building footprints to approximate residential populations. While restricted-access datasets would provide cleaner classifications, the research deliberately used open data to ensure methodology accessibility. The filtering procedures developed enable framework application in cities without premium data access, supporting widely adoptable implementation.

8.2.3 External Validation

The framework has been designed for reproducibility and this research documents the systematic city selection process, contextual cue justification, and computational procedures enabling independent implementation. However, the framework has not yet undergone external validation where researchers or practitioners outside this study apply it independently to their own urban contexts. External validation would test whether the documented procedures support independent replication, whether the framework produces consistent results when implemented by different analysts, and whether cities find the outputs actionable for planning decisions. Ideally, this would involve urban planners or researchers beyond Chicago, Manchester, and Portland using the framework to assess their own environmental risk profiles or incorporating framework outputs as evidence in official planning reports. Real-world application would reveal implementation challenges not apparent in the original case studies and demonstrate whether the framework successfully translates from research methodology to practical planning tool. Given additional time and resources, external validation studies could be conducted in partnership with municipal planning departments or academic collaborators in diverse urban settings, strengthening confidence in the framework's reliability and practical utility.

8.2.4 Risk Reduction Measurement

The framework quantifies current environmental exposure risk but does not measure how specific interventions might reduce that risk over time. Cities implementing the framework would receive clear assessments of their current air quality, greenspace accessibility, and transit mobility risk levels, but the methodology does not predict how proposed improvements would affect future scores. For example, if a city with high greenspace risk (Score 4) plans to create five new parks in underserved neighborhoods, the framework cannot estimate the resulting risk reduction without recalculating scores after implementation. This limitation means planners cannot use the framework to model intervention scenarios or compare the relative effectiveness of different investment strategies before committing resources. Ideally, cities adopting this framework would want to track whether infrastructure investments successfully reduced environmental risk burden. A city improving air quality monitoring, expanding park networks, or extending transit routes would need to reapply the complete computational framework using updated data to observe whether risk scores decreased, requiring the same data collection and processing effort as the initial assessment. Given additional time and resources, scenario modeling capabilities could be developed to estimate risk score changes from proposed interventions,

enabling planners to evaluate options before implementation. This could also facilitate the generation of future data scenarios where potential interventions in a city are realized in simulated data that could be used in the framework to investigate the change in risk.

8.3 Future work

8.3.1 Future Work Proposal 1:

This thesis investigates the application of data science principles to smart cities and urban mental health, emphasizing the use of data and technology to assess mental wellbeing. The research that has been presented relies on existent smart city data. There are numerous limitations to using data from open-source sites. The quality of datasets varies across different open-source datahubs due to inconsistent data collection methods. Different cities and organizations may gather data differently and face unique challenges, such as technical limitations, resource constraints, or varying priorities. These factors can further impact the quality, completeness, and accuracy of the collected data.

While this thesis focuses on the application of data science principles to assess environmental risk for urban mental wellbeing within smart cities, using predominantly quantitative methods and existing smart city data, future work proposes a complementary qualitative approach. Although the development of quantitative methods to estimate urban mental wellbeing is innovative, integrating qualitative research can provide deeper insights by capturing the lived experiences and perceptions of urban citizens. The proposed future research would transition from relying solely on preexisting data extracted from open-source databases to actively collecting primary data through methods such as questionnaires, focus groups, and case studies. This shift would enable a more nuanced understanding of urban mental wellbeing, directly informed by the perspectives of those living in smart cities. Through the proposed research questions, this project aims to explore the experience of urban citizens and the effect of smart city policies and initiatives. As well as determining the gravity of each contextual cue.

The proposed project for future work, would consider the following research questions:

1. How do citizens of smart cities perceive the impact of contextual cues on their mental wellbeing?
2. Do citizens of smart cities notice a change in their mental wellbeing when cities improve quality of life?

In [Addas \(2023\)](#) and [Weimann et al. \(2019\)](#), researchers incorporated qualitative methods to explore the impact of urban greenspaces on quality of life and health. Through in-depth interviews, focus groups, case studies, and observations, the study provided rich, contextual insights into how greenspaces are perceived and utilized by residents, and how they integrate with smart city designs. Case studies offered practical examples of successful green space integration, and observations documented how these spaces impact daily life. These qualitative insights not only enrich the understanding of greenspaces' effects but also complement quantitative data by providing a deeper context for the observed trends.

In this future work project, the proposed data collection methodology includes questionnaires, focus groups, and case studies, which are described as follows:

Questionnaires: Would follow the standards from previous research methods. Both Addas and Weimann chose to have a mix of open-ended questions to capture the natural experience of a candidate and a close ended question for metrics purposes. In this case, the questionnaire would be used to collect data from urban citizens to determine if they notice a change of mental health based on certain contextual cues.

Focus Groups: These will facilitate discussions among urban citizens to gather diverse perspectives on the impact of smart city policies and initiatives on mental wellbeing.

Case Studies: These will provide detailed examples of how contextual cues, such as air quality, urban greenspaces, and transportation, affect mental health in real-life scenarios.

The contextual cues that will be considered in this future work proposal will align with this thesis and will mainly focus on: air quality, greenspaces, and transportation. These contextual cues represent the three categories that are most studied in the smart city realm.

In conclusion, while this thesis has advanced the use of data science to explore urban mental health through existing smart city data, future research will enhance these findings by integrating qualitative methods. By incorporating primary data collection through questionnaires, focus groups, and case studies, this future work aims to provide deeper insights into how contextual cues and smart city policies affect mental wellbeing. This comprehensive approach will offer a richer understanding of urban mental wellbeing and inform more effective, citizen-centered smart city initiatives.

8.3.2 Future Work Proposal 2: Contextual Cues Expansion

This thesis established a computational framework using three environmental contextual cues: air quality, greenspace accessibility, and mobility. These factors represent well-documented pathways through which urban environments affect mental wellbeing. However, additional environmental stressors with established mental health links remain unexplored. Future research should expand the framework by developing methodologies for extracting and operationalizing additional contextual cues from smart city data.

Three promising contextual cues for computational framework expansion include ambient noise, smart lighting, and blue spaces. Ambient noise pollution shows clear links to sleep disruption, stress activation, and cognitive impairment (Topf 2000). Smart cities deploy noise monitoring sensors that could support noise-based risk assessment. Omar et al. (2022) document how inadequate lighting increases anxiety and restricts mobility, affecting perceived and actual safety. This impact disproportionately affects women, who experience significantly higher safety concerns in poorly lit areas (Roberts 2016). Smart lighting systems already collect data on illumination levels, coverage, and operational status. Blue spaces, proximity to water bodies like rivers, lakes, and coastlines, provide protective mental health effects (Gascon et al. 2018). Coastal cities and those with significant waterways could benefit from incorporating blue space accessibility as a fourth contextual cue.

The proposed research question for this study:

1. Can ambient noise, smart lighting, and blue space accessibility be operationalization as contextual cues with literature-derived thresholds comparable to air quality, greenspace, and mobility?

The proposed research would address the following objectives:

Establish evidence-based thresholds: Review literature linking each proposed contextual cue to mental health outcomes and identify quantitative thresholds enabling operational risk scoring comparable to Chen et al. (2018) for air quality or Gascon et al. (2018) for greenspace.

Assess data availability using SCDCAF criteria: Apply the Smart City Data Classification and Access Framework to evaluate which cities maintain adequate monitoring infrastructure, spatial datasets, and temporal coverage for each new contextual cue.

Develop extraction and processing methodologies: Create standardized procedures for converting raw data into contextual cue scores: frequency-weighted noise measurements

accounting for duration and timing, spatial lighting coverage with illumination thresholds, and distance-based blue space accessibility metrics.

Validate expanded framework: Test new contextual cues in cities with appropriate data infrastructure and compare expanded UMWI scores against original three-cue assessments to evaluate whether additional cues improve accuracy or reveal new disparities.

The expanded framework would provide urban planners with more complete environmental risk assessment, revealing additional intervention opportunities beyond air quality, greenspace, and mobility improvements.

8.3.3 Future Work Proposal 3: Interactive Decision Support Dashboard

The computational framework currently produces risk scores and statistical summaries designed for academics and urban planners who are familiar with spatial data analysis. Future development should create an interactive web-based dashboard that makes framework outputs accessible to diverse user groups including urban planners, policymakers, and the public. This decision support tool would transform static assessments into dynamic exploration and scenario planning capabilities. Governments would have the opportunity to practice transparency and accountability.

The proposed research question for this study:

1. How can the computational framework be translated into an interactive web-based interface that makes environmental mental wellbeing risk assessment accessible to non-technical audiences?

The Dublin Dashboard¹ demonstrates effective smart city data visualization, enabling users to examine performance metrics, compare regions, view real-time data, and download datasets for analysis. A similar approach for the UMWI Dashboard would make environmental mental wellbeing risk assessment accessible to non-technical audiences. The dashboard infrastructure would support a growing network of qualifying smart cities, creating a collaborative platform for knowledge sharing and best practice identification. The UMWI dashboard would focus on three development objectives:

Design interactive map visualization: Create web-based interface displaying UMWI and individual contextual cue scores across administrative boundaries and city level.

Create multi-city comparison interface: As additional cities implement the framework, build comparison tools showing relative performance.

Develop scenario modeling capabilities: Build tools enabling planners to test proposed interventions. Users could input changes like new park locations, transit line extensions, or air quality policies that would recalculate the risk scores.

8.4 Closing summary

This research addressed a fundamental gap between smart city data collection capabilities and population-level mental wellbeing assessment. The computational framework successfully converts environmental data on air quality, greenspace accessibility, and mobility into standardized Urban Mental Wellbeing Risk Index scores for Chicago, Manchester, and Portland. This thesis demonstrated that existing literature provides strong foundations for operational contextual

¹<https://smartdublin.ie/dublin-dashboard/>

cues, that heterogeneous data can be systematically converted into comparable risk scores, and that the framework transfers effectively across diverse urban contexts. Key findings revealed greenspace accessibility as the primary driver of overall risk variation and demonstrated that spatial distribution matters more than aggregate provision for mental health benefits. The framework provides urban planners with actionable tools for evidence-based resource allocation, integrated environmental planning, and continuous monitoring. Future research directions include expanding to additional contextual cues such as ambient noise and smart lighting, developing interactive web-based dashboards for diverse stakeholders, and integrating qualitative methods to capture lived experiences. The computational framework moves environmental exposure risk assessment for urban mental wellbeing from conceptual aspirations to operational reality, enabling evidence-based environmental planning for population mental health.

References

- Aalbers, C., Kamphorst, D. & Langers, F. (2019), 'Fourteen local governance initiatives in greenspace in urban areas in the netherlands. discourses, success and failure factors, and the perspectives of local authorities', Urban Forestry & Urban Greening **42**, 82–99.
URL: <https://www.sciencedirect.com/science/article/pii/S1618866718307052>
- Adams, M. (2013), Quality of Urban Spaces and Wellbeing, John Wiley & Sons, Ltd, chapter 10, pp. 1–21.
URL: <https://onlinelibrary.wiley.com/doi/abs/10.1002/9781118539415.wbwell064>
- Addas, A. (2023), 'Influence of urban greenspaces on quality of life and health with smart city design', Land **12**(5).
URL: <https://www.mdpi.com/2073-445X/12/5/960>
- Ahmed, Q. I., Lu, H. & Ye, S. (2008), 'Urban transportation and equity, a case study of beijing and karachi', Transportation Research Part A, Policy and Practice **42**(1), 125–139.
URL: <https://www.sciencedirect.com/science/article/pii/S0965856407000559>
- Al Nuaimi, E., Al Neyadi, H., Mohamed, N. & Al-Jaroodi, J. (2015), 'Applications of big data to smart cities', Journal of Internet Services and Applications **6**(1), 1–15.
- Ala-Mantila, S., Heinonen, J., Junnila, S. & Saarsalmi, P. (2018), 'Spatial nature of urban well-being', Regional Studies **52**(7), 959–973.
URL: <https://doi.org/10.1080/00343404.2017.1360485>
- Albino, V., Berardi, U. & Dangelico, R. (2015), 'Smart cities: Definitions, dimensions, performance, and initiatives', Journal of Urban Technology **22**, 2015.
- Allam, Z. & Dhunny, Z. A. (2019), 'On big data, artificial intelligence and smart cities', Cities **89**, 80–91.
- Alvarsson, J. J., Wiens, S. & Nilsson, M. E. (2010), 'Stress recovery during exposure to nature sound and environmental noise', International Journal of Environmental Research and Public Health **7**(3), 1036–1046.
- Auger, T. (2013), Living in a Garden: The Greening of Singapore, Editions Didier Millet, Singapore.
- Authority, U. R. (1986), 'Urban redevelopment authority'.
- Bai, X., Nath, I., Capon, A., Hasan, N. & Jaron, D. (2012), 'Health and wellbeing in the changing urban environment: complex challenges, scientific responses, and the way forward', Current Opinion in Environmental Sustainability **4**(4), 465–472. Human settlements and industrial systems.
URL: <https://www.sciencedirect.com/science/article/pii/S1877343512001169>

- Bakker, J., Pechenizkiy, M. & Sidorova, N. (2011), What's your current stress level? detection of stress patterns from gsr sensor data, in '2011 IEEE 11th International Conference on Data Mining Workshops', pp. 573–580.
- Balikçi, S., Giezen, M. & Arundel, R. (2022), 'The paradox of planning the compact and green city: analyzing land-use change in amsterdam and brussels', Journal of Environmental Planning and Management **65**(13), 2387–2411.
- Banerjee, J., Mahmud, M. & Brown, D. (2023), 'Heart Rate Variability-Based Mental Stress Detection: An Explainable Machine Learning Approach', SN Computer Science **4**(176).
URL: <https://doi.org/10.1007/s42979-022-01605-z>
- Barrington-Leigh, C. P. (2020), How Environmental Quality Affects Our Happiness, in J. F. Helliwell, R. Layard, J. Sachs & J.-E. De Neve, eds, 'World Happiness Report 2020', Sustainable Development Solutions Network, chapter 5.
URL: <https://worldhappiness.report/ed/2020/how-environmental-quality-affects-our-happiness/>
- Batini, C., Cappiello, C., Francalanci, C. & Maurino, A. (2009), 'Methodologies for data quality assessment and improvement', ACM Comput. Surv. **41**(3).
- Beebe, L. H., Tian, L., Morris, N., Goodwin, A., Allen, S. S. & Kuldau, J. (2005), 'Effects of exercise on mental and physical health parameters of persons with schizophrenia', Issues in Mental Health Nursing **26**(6), 661–676.
URL: <https://doi.org/10.1080/01612840590959551>
- Benedict, M. A. & McMahon, E. T. (2002), 'Green Infrastructure: Smart Conservation for the 21st Century', Renewable Resources Journal **20**(3), 12–17.
- Beyer, K. M., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F. J. & Malecki, K. M. (2014), 'Exposure to neighborhood green space and mental health: evidence from the survey of the health of Wisconsin', International Journal of Environmental Research and Public Health **11**(3), 3453–3472.
URL: <https://doi.org/10.3390/ijerph110303453>
- Biancuzzi, H., Massaro, M. & Bagnoli, C. (2024), 'Smart mobility in venice: An ecosystem perspective', Journal of Cleaner Production **434**, 140096.
URL: <https://www.sciencedirect.com/science/article/pii/S0959652623042543>
- Bigazzi, A. Y. & Rouleau, M. (2017), 'Can traffic management strategies improve urban air quality? a review of the evidence', Journal of Transport & Health **7**, 111–124.
URL: <https://www.sciencedirect.com/science/article/pii/S2214140517301330>
- Bilotta, E., Vaid, U. & Evans, G. W. (2018), Environmental Stress, John Wiley & Sons, Ltd, chapter 4, pp. 36–44.
URL: <https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119241072.ch4>
- Block, M. L. & Calderón-Garcidueñas, L. (2009), 'Air pollution: mechanisms of neuroinflammation and CNS disease', Trends in Neurosciences **32**(9), 506–516.
- Bratman, G., Hamilton, J., Hahn, K., Daily, G. & Gross, J. (2015), 'Nature experience reduces rumination and subgenual prefrontal cortex activation', Proceedings of the National Academy of Sciences of the United States of America **112**(28), 8567–8572.
URL: <https://doi.org/10.1073/pnas.1510459112>

- Bratman, G. N., Anderson, C. B., Berman, M. G., Cochran, B., De Vries, S., Flanders, J., Folke, C., Frumkin, H., Gross, J. J., Hartig, T. et al. (2019), 'Nature and mental health: An ecosystem service perspective', Science advances **5**(7), eaax0903.
- Brenes, G. A. (2003), 'Anxiety and chronic obstructive pulmonary disease: prevalence, impact, and treatment', Psychosomatic Medicine **65**(6), 963–970.
URL: <https://doi.org/10.1097/01.psy.0000097339.75789.81>
- Brook, R. D., Rajagopalan, S., Pope, C. A., r., Brook, J. R., Bhatnagar, A., Diez-Roux, A. V., Holguin, F., Hong, Y., Luepker, R. V., Mittleman, M. A., Peters, A., Siscovick, D., Smith, S. C., J., Whitsel, L., Kaufman, J. D. & American Heart Association Council on Epidemiology and Prevention, Council on the Kidney in Cardiovascular Disease, and Council on Nutrition, Physical Activity and Metabolism (2010), 'Particulate matter air pollution and cardiovascular disease: An update to the scientific statement from the American Heart Association', Circulation **121**(21), 2331–2378.
URL: <https://doi.org/10.1161/CIR.0b013e3181dbee1>
- Browning, M. & Rigolon, A. (2018), 'Do Income, Race and Ethnicity, and Sprawl Influence the Greenspace-Human Health Link in City-Level Analyses? Findings from 496 Cities in the United States', International Journal of Environmental Research and Public Health **15**(7), 1541.
- Bıyık, C., Abareshi, A., Paz, A., Ruiz, R. A., Battarra, R., Rogers, C. D. & Lizarraga, C. (2021), 'Smart mobility adoption: A review of the literature', Journal of Open Innovation: Technology, Market, and Complexity **7**(2), 146.
URL: <https://www.sciencedirect.com/science/article/pii/S2199853122009155>
- Calderón-Garcidueñas, L., Calderón-Garcidueñas, A., Torres-Jardón, R., Avila-Ramírez, J., Kulesza, R. & Angiulli, A. (2015), 'Air pollution and your brain: what do you need to know right now', Primary Health Care Research & Development **16**(4), 329–345.
- Campion, J. (2018), 'Public mental health: Key challenges and opportunities', BJPsych International **15**(3), 51–54.
- Canadian Centre for Occupational Health and Safety (2023), 'Hazard and risk'.
URL: https://www.ccohs.ca/oshanswers/hsprograms/hazard/hazard_risk.html
- Centers for Disease Control and Prevention (2024), 'Social Determinants of Health', https://www.cdc.gov/public-health-gateway/php/about/social-determinants-of-health.html#cdc_program_profile_program_impact-how-sdoh-impacts-lives. Accessed on: 2025-10-30.
- Cesario, E. (2023), 'Big data analytics and smart cities: applications, challenges, and opportunities', Frontiers in Big Data **Volume 6 - 2023**.
URL: <https://www.frontiersin.org/journals/big-data/articles/10.3389/fdata.2023.1149402>
- Chakraborty, A., Banerjee, J. S., Bhadra, R., Dutta, A., Ganguly, S., Das, D., Kundu, S., Mahmud, M. & Saha, G. (2024), 'A framework of intelligent mental health monitoring in smart cities and societies', IETE Journal of Research **70**(2), 1328–1341.
URL: <https://doi.org/10.1080/03772063.2023.2171918>
- Chan, C. K. & Yao, X. (2008), 'Air pollution in mega cities in china', Atmospheric Environment **42**(1), 1–42.
URL: <https://www.sciencedirect.com/science/article/pii/S1352231007007911>

- Chatziioannou, I., Alvarez-Icaza, L. & Bakogiannis, E. (2020), ‘A structural analysis method for the promotion of mexico city ´ s integral plan of mobility’, *Cogent Engineering* **7**(1), 1759395.
- Chen, S., Oliva, P. & Zhang, P. (2018), Air pollution and mental health: Evidence from china, Working Paper 24686, National Bureau of Economic Research.
URL: <http://www.nber.org/papers/w24686>
- Chen, Y. H., Lin, J. J., Yang, C. W. & et al. (2024), ‘The effect of commuting time on burnout: the mediation effect of musculoskeletal pain’, *BMC Health Services Research* **24**(468).
URL: <https://doi.org/10.1186/s12913-024-10908-1>
- Chrisinger, B. W. & King, A. C. (2018), ‘Stress experiences in neighborhood and social environments (sense): a pilot study to integrate the quantified self with citizen science to improve the built environment and health’, *International Journal of Health Geographics* **17**(1), 17.
- Clark, C. & Paunovic, K. (2018), ‘WHO environmental noise guidelines for the European Region: A systematic review on environmental noise and quality of life, wellbeing and mental health’, *International Journal of Environmental Research and Public Health* **15**(11), 2400.
- Cleary, A., Roiko, A., Burton, N. W., Fielding, K. S., Murray, Z. & Turrell, G. (2019), ‘Changes in perceptions of urban green space are related to changes in psychological well-being: Cross-sectional and longitudinal study of mid-aged urban residents’, *Health & Place* **59**, 102201.
URL: <https://www.sciencedirect.com/science/article/pii/S1353829218307998>
- Csepely-Knorr, L. (2010), Frederick Law Olmsted’s Public Parks, Parkways and their influence on the Continent, in ‘Proceedings of the Fábos Conference on Landscape and Greenway Planning’, Vol. 3, pp. 671–678.
URL: <https://openpublishing.library.umass.edu/fabos/vol3/iss1/80>
- Currie, J., Neidell, M. & Schmieder, J. F. (2009), ‘Air pollution and infant health: Lessons from New Jersey’, *Journal of Health Economics* **28**(3), 688–703.
URL: <https://doi.org/10.1016/j.jhealeco.2009.02.001>
- D’Amico, G., L’Abbate, P., Liao, W., Yigitcanlar, T. & Ioppolo, G. (2020), ‘Understanding Sensor Cities Insights from Technology Giant Company Driven Smart Urbanism Practices’, *Sensors (Basel)* **20**(16), 4391.
URL: <https://www.mdpi.com/1424-8220/20/16/4391>
- De Haas, W., Hassink, J. & Stuiver, M. (2021), ‘The role of urban green space in promoting inclusion: Experiences from the netherlands’, *Frontiers in Environmental Science* **Volume 9 - 2021**.
URL: <https://www.frontiersin.org/journals/environmental-science/articles/10.3389/fenvs.2021.618198>
- de Vries, G. (2021), Green infrastructures in amsterdam: A case study on the governance challenges of green infrastructure implementation, Master’s thesis, University of Utrech.
- Derdouri, A. & Osaragi, T. (2025), ‘A complex network analysis of urban human mobility in tokyo’, *Travel Behaviour and Society* **40**, 101020.
- Diener, E. & Seligman, M. E. (2004), ‘Beyond money: Toward an economy of well-being’, *Psychological science in the public interest* **5**(1), 1–31.
- Douglas, I. (2012), ‘Urban ecology and urban ecosystems: understanding the links to human health and well-being’, *Current Opinion in Environmental Sustainability* **4**(4), 385–392. Human settlements and industrial systems.
URL: <https://www.sciencedirect.com/science/article/pii/S1877343512000966>

- European Commission (n.d.), ‘Zero Pollution Action Plan’, https://environment.ec.europa.eu/strategy/zero-pollution-action-plan_en. Accessed on: 2025-10-10.
- European Environment Agency (2025), ‘Air pollution’, <https://www.eea.europa.eu/en/topics/in-depth/air-pollution?activeTab=fa515f0c-9ab0-493c-b4cd-58a32dfaae0a>. Accessed on: 2025-6-30.
- European Parliament and of the Council (2024), Regulation (eu) 2024/1679 of the european parliament and of the council of 13 june 2024 on union guidelines for the development of the trans-european transport network, amending regulations (eu) 2021/1153 and (eu) no 913/2010 and repealing regulation (eu) no 1315/2013 (text with eea relevance), Technical Report OJ L, 2024/1679, Publications Office of the European Union. ELI: <http://data.europa.eu/eli/reg/2024/1679/oj>.
URL: <http://data.europa.eu/eli/reg/2024/1679/oj>
- Eurostat (Statistical Office of the European Communities) (2025), Key figures on European transport: 2024 edition, Publications Office of the European Union, Luxembourg.
URL: <https://ec.europa.eu/eurostat/web/products-key-figures/w/ks-01-25-057>
- Evans, G. & Wener, R. (2006), ‘Rail commuting duration and passenger stress’, Health Psychology **25**(3), 408–412.
- Faria, R., Brito, L., Baras, K. & Silva, J. (2017), Smart mobility: A survey, in ‘2017 International Conference on Internet of Things for the Global Community (IoTGC)’, pp. 1–8.
- Feng, Z. & Boyle, P. (2014), ‘Do Long Journeys to Work Have Adverse Effects on Mental Health?’, Environment and Behavior **46**(5), 609–625.
URL: <https://doi.org/10.1177/0013916512472053>
- Ferreira, A. (2013), ‘Emotions in planning practice: a critical review and a suggestion for future developments based on mindfulness’, The Town Planning Review **84**(6), 703–719.
URL: <https://www.jstor.org/stable/24579219>
- Garau, C., Masala, F. & Pinna, F. (2016), ‘Cagliari and smart urban mobility: Analysis and comparison’, Cities **56**, 35–46.
URL: <https://www.sciencedirect.com/science/article/pii/S026427511630021X>
- Gascon, M., Sánchez-Benavides, G., Dadvand, P., Martínez, D., Gramunt, N., Gotsens, X., Cirach, M., Vert, C., Molinuevo, J. L., Crous-Bou, M. & Nieuwenhuijsen, M. (2018), ‘Long-term exposure to residential green and blue spaces and anxiety and depression in adults: A cross-sectional study’, Environmental Research **162**, 231–239.
URL: <https://www.sciencedirect.com/science/article/pii/S0013935118300124>
- 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.
URL: <https://www.sciencedirect.com/science/article/pii/S0160412015300799>
- Genc, S., Zadeoglulari, Z., Fuss, S. H. & Genc, K. (2012), ‘The adverse effects of air pollution on the nervous system’, Journal of Toxicology **2012**, 782462.
- Ghazal, T. M., Hasan, M. K., Alshurideh, M. T., Alzoubi, H. M., Ahmad, M., Akbar, S. S., Al Kurdi, B. & Akour, I. A. (2021), ‘IoT for smart cities: Machine learning approaches in smart healthcare—a review’, Future Internet **13**(8).
URL: <https://www.mdpi.com/1999-5903/13/8/218>

- Giffinger, R., Fertner, C., Kramar, H., Kalasek, R., Pichler-Milanović, N. & Meijers, E. (2007), 'Smart cities: Ranking of european medium-sized cities. vienna, austria: Centre of regional science (srf), vienna university of technology', [www. smart-cities. eu/download/smart cities final report. pdf](http://www.smart-cities.eu/download/smart%20cities%20final%20report.pdf) .
- Gładka, A., Rymaszewska, J. & Zatoński, T. (2018), 'Impact of air pollution on depression and suicide', *International journal of occupational medicine and environmental health* **31**(6), 711–721.
- Glenister, D. (1996), 'Exercise and mental health: a review', *Journal of the Royal Society of Health* **116**(1), 7–13.
- Gupta, A., Panagiotopoulos, P. & Bowen, F. (2020), 'An orchestration approach to smart city data ecosystems', *Technological Forecasting and Social Change* **153**, 119929.
URL: <https://www.sciencedirect.com/science/article/pii/S0040162519312314>
- Haaland, C. & van den Bosch, C. K. (2015), 'Challenges and strategies for urban green-space planning in cities undergoing densification: A review', *Urban Forestry Urban Greening* **14**(4), 760–771.
URL: <https://www.sciencedirect.com/science/article/pii/S161886671500103X>
- Hancke, G. P., Silva, B. D. C. e. & Hancke, Jr., G. P. (2013), 'The role of advanced sensing in smart cities', *Sensors* **13**(1), 393–425.
URL: <https://www.mdpi.com/1424-8220/13/1/393>
- Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A. & Khan, S. U. (2015), 'The rise of “big data” on cloud computing: Review and open research issues', *Information Systems* **47**, 98–115.
- He, K., Yang, F., Ma, Y., Zhang, Q., Yao, X., Chan, C. K., Cadle, S., Chan, T. & Mulawa, P. (2001), 'The characteristics of pm2.5 in beijing, china', *Atmospheric Environment* **35**(29), 4959–4970.
URL: <https://www.sciencedirect.com/science/article/pii/S1352231001003016>
- Henderson, J. C. (2013), 'Urban parks and green spaces in Singapore', *Managing Leisure* **18**(3), 213–225.
URL: <https://doi.org/10.1080/13606719.2013.796181>
- Heo, S. & Bell, M. L. (2023), 'Investigation on urban greenspace in relation to sociodemographic factors and health inequity based on different greenspace metrics in 3 US urban communities', *Journal of Exposure Science & Environmental Epidemiology* **33**, 218–228.
URL: <https://doi.org/10.1038/s41370-022-00468-z>
- Herman, J. P., McKlveen, J. M., Ghosal, S., Kopp, B., Wulsin, A., Makinson, R., Scheimann, J. & Myers, B. (2016), 'Regulation of the Hypothalamic-Pituitary-Adrenocortical Stress Response', *Comprehensive Physiology* **6**(2), 603–621.
- Hogan, M., Leyden, K., Conway, R., Goldberg, A., Walsh, D. & McKenna-Plumley, P. (2016), 'Happiness and health across the lifespan in five major cities: The impact of place and government performance', *Social Science & Medicine* **162**, 168–176.
- Houlden, V., Porto de Albuquerque, J., Weich, S. & Jarvis, S. (2019), 'A spatial analysis of proximate greenspace and mental wellbeing in london', *Applied Geography* **109**, 102036.
URL: <https://www.sciencedirect.com/science/article/pii/S0143622818312384>
- Hu, Q., Feng, Y. & Xu, M. (2021), 'Are there heterogeneous impacts of air pollution on mental health?', *Frontiers in Public Health* **9**.

- Hu, Q. & Zheng, Y. (2021), 'Smart city initiatives: A comparative study of american and chinese cities', *Journal of Urban Affairs* **43**(4), 504–525.
URL: <https://doi.org/10.1080/07352166.2019.1694413>
- Huang, Z., Guo, Y., Chan, K. L. & Lau, K. K. L. (2023), 'Socioeconomic and racial/ethnic disparities in greenspace availability and accessibility and their relationship with mental health: A systematic review', *Journal of Environmental Management* **329**, 117066.
- International Organization for Standardization (2018), Iso 37120:2018 sustainable cities and communities – indicators for city services and quality of life, Technical report, ISO. Edition 2, Stage 90.92.
URL: <https://www.iso.org/standard/68498.html>
- Ishwarappa & Anuradha, J. (2015), 'A brief introduction on big data 5vs characteristics and hadoop technology', *Procedia Computer Science* **48**, 319–324. International Conference on Computer, Communication and Convergence (ICCC 2015).
URL: <https://www.sciencedirect.com/science/article/pii/S1877050915006973>
- Jackson, J. & Stafford, M. (2009), 'Public health and fear of crime: A prospective cohort study', *British Journal of Criminology - BRIT J CRIMINOL* **49**.
- Jacobson, N. C., Weingarden, H. & Wilhelm, S. (2019), 'Using digital phenotyping to accurately detect depression severity', *The Journal of nervous and mental disease* **207**(10), 893–896.
- Janse van Rensburg, E. & van der Wath, A. (2020), 'Risk assessment in mental health practice: An integrative review', *Issues in Mental Health Nursing* **41**(11), 995–1003.
- Jennings, V., Baptiste, A. K., Osborne Jelks, N. & Skeete, R. (2017), 'Urban Green Space and the Pursuit of Health Equity in Parts of the United States', *International Journal of Environmental Research and Public Health* **14**(11), 1432.
- Kabisch, N., Qureshi, S. & Haase, D. (2015), 'Human–environment interactions in urban green spaces — a systematic review of contemporary issues and prospects for future research', *Environmental Impact Assessment Review* **50**, 25–34.
URL: <https://www.sciencedirect.com/science/article/pii/S0195925514000754>
- Kahn, M. E. (2006a), Air pollution in cities, in R. J. Arnott & D. P. McMillen, eds, 'A Companion to Urban Economics', Blackwell Publishing, pp. 502–514.
URL: <https://doi.org/10.1002/9780470996225.ch29>
- Kahn, M. E. (2006b), 'Air pollution in cities', *A Companion to Urban Economics* pp. 502–514.
- Kaplan, R. (2001), 'The nature of the view from home: Psychological benefits', *Environment and behavior* **33**(4), 507–542.
- Karagulian, F., Belis, C. A., Dora, C. F. C., Prüss-Ustün, A. M., Bonjour, S., Adair-Rohani, H. & Amann, M. (2015), 'Contributions to cities' ambient particulate matter (pm): A systematic review of local source contributions at global level', *Atmospheric Environment* **120**, 475–483.
URL: <https://www.sciencedirect.com/science/article/pii/S1352231015303320>
- Kardan, O., Gozdyra, P., Misic, B. & et al. (2015), 'Neighborhood greenspace and health in a large urban center', *Scientific Reports* **5**, 11610.
URL: <https://doi.org/10.1038/srep11610>
- Kelly, F. & Fussell, J. (2015), 'Air pollution and public health: emerging hazards and improved understanding of risk', *Environmental Geochemistry and Health* **37**, 631–649.
URL: <https://doi.org/10.1007/s10653-015-9720-1>

- Keyes, C. L. M., Dhingra, S. S. & Simoes, E. J. (2010), 'Change in level of positive mental health as a predictor of future risk of mental illness', American Journal of Public Health **100**(12), 2366–2371.
- Kitchin, R. (2014), The Data Revolution: Big Data, Open Data, Data Infrastructures & Their Consequences, SAGE Publications Ltd.
- Komninos, N. & Sefertzi, E. (2009), 'Intelligent cities: R&d offshoring, web 2.0 product development and globalization of innovation systems', Second Knowledge Cities Summit **2009**.
- Krefis, A. C., Augustin, M., Schlünzen, K. H., Oßenbrügge, J. & Augustin, J. (2018), 'How does the urban environment affect health and well-being? a systematic review', Urban Science **2**(1).
URL: <https://www.mdpi.com/2413-8851/2/1/21>
- Kumar, S. & Singh, M. (2019), 'Big data analytics for healthcare industry: impact, applications, and tools', Big Data Mining and Analytics **2**(1), 48–57.
- Kuo, M. (2015), 'How might contact with nature promote human health? promising mechanisms and a possible central pathway', Frontiers in Psychology **Volume 6 - 2015**.
URL: <https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2015.01093>
- Kyriakou, K., Resch, B., Sagl, G., Petutschnig, A., Werner, C., Niederseer, D., Liedlgruber, M., Wilhelm, F. H., Osborne, T. & Pykett, J. (2019), 'Detecting moments of stress from measurements of wearable physiological sensors', Sensors **19**(17), 3805.
- Labib, S., Lindley, S. & Huck, J. J. (2020), 'Spatial dimensions of the influence of urban green-blue spaces on human health: A systematic review', Environmental Research **180**, 108869.
URL: <https://www.sciencedirect.com/science/article/pii/S0013935119306668>
- Larkin, A. & Hystad, P. (2019), 'Evaluating street view exposure measures of visible green space for health research', Journal of Exposure Science & Environmental Epidemiology **29**(4), 447–456.
URL: <https://doi.org/10.1038/s41370-018-0017-1>
- Lecue, F., Tucker, R., Tallevi-Diotalle, S., Nair, R., Gkoufas, Y., Liguori, G., Borioni, M., Rademaker, A. & Barbosa, L. (2014), Semantic traffic diagnosis with star-city: Architecture and lessons learned from deployment in dublin, bologna, miami and rio, in 'Semantic Traffic Diagnosis with STAR-CITY: Architecture and Lessons Learned from Deployment in Dublin, Bologna, Miami and Rio', pp. 292–307.
- Leo, A., Morillón, D. & Silva, R. (2017), 'Review and analysis of urban mobility strategies in mexico', Case studies on transport policy **5**(2), 299–305.
- Lim, Y., Edelenbos, J. & Gianoli, A. (2019), 'Identifying the results of smart city development: Findings from systematic literature review', Cities **95**, 102397.
URL: <https://www.sciencedirect.com/science/article/pii/S0264275118314161>
- Lnenicka, M., Nikiforova, A., Clarinval, A., Luterek, M., Rudmark, D., Neumaier, S., Kević, K. & Rodríguez Bolívar, M. P. (2024), 'Sustainable open data ecosystems in smart cities: A platform theory-based analysis of 19 european cities', Cities **148**, 104851.
URL: <https://www.sciencedirect.com/science/article/pii/S0264275124000659>
- Lorenc, T., Clayton, S., Neary, D., Whitehead, M., Petticrew, M., Thomson, H., Cummins, S., Sowden, A. & Renton, A. (2012), 'Crime, fear of crime, environment, and mental health and wellbeing: Mapping review of theories and causal pathways', Health & Place **18**(4), 757–765.

- Lynch, K. (1960), The Image of the City, The MIT Press, Cambridge, MA.
- Lyons, G. & Chatterjee, K. (2008), ‘A Human Perspective on the Daily Commute: Costs, Benefits and Trade-offs’, Transport Reviews **28**(2), 181–198.
URL: <https://doi.org/10.1080/01441640701559484>
- Ma, L., Ye, R. & Wang, H. (2021), ‘Exploring the causal effects of bicycling for transportation on mental health’, Transportation Research Part D: Transport and Environment **93**, 102773.
- 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 & Community Health **63**(12), 967–973.
- 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 & community health **60**(7), 587–592.
- Marković, D., Vujičić, D., Stojić, D., Jovanović, v., Pešović, U. & Randić, S. (2019), Monitoring system based on IoT sensor data with complex event processing and artificial neural networks for patients stress detection, in ‘2019 18th International Symposium INFOTEH-JAHORINA (INFOTEH)’, IEEE, pp. 1–6.
- Mcaneney, H., Tully, M., Hunter, R., Kouvonen, A., Veal, P., Stevenson, M. & Kee, F. (2015), ‘Individual factors and perceived community characteristics in relation to mental health and mental well-being’, BMC Public Health **15**.
- McEwen, B. S. (2007), ‘Physiology and neurobiology of stress and adaptation: central role of the brain’, Physiological Reviews **87**(3), 873–904.
URL: <https://doi.org/10.1152/physrev.00041.2006>
- McManus, S., Bebbington, P., Jenkins, R. & Brugha, T. (2016), Mental health and wellbeing in England: Adult psychiatric morbidity survey 2014, Technical report, NHS Digital, Leeds. Accredited official statistics.
- Mehta, U., Dey, S., Chowdhury, S., Ghosh, S., Hart, J. E. & Kurpad, A. (2021), ‘The Association Between Ambient PM2.5 Exposure and Anemia Outcomes Among Children Under Five Years of Age in India’, Environmental Epidemiology **5**(1), e125.
- Mell, I. C. (2017), ‘Green infrastructure: reflections on past, present and future praxis’, Landscape Research **42**(2), 135–145.
URL: <https://doi.org/10.1080/01426397.2016.1250875>
- Milne, G. (2017), ‘A conceptual approach to urban wellbeing from a human evolution perspective’, Preprints .
URL: <https://doi.org/10.20944/preprints201712.0041.v1>
- Ministerie van Economische Zaken (2014), ‘Natuurlijk verder: Rijksnatuurvisie 2014’.
URL: <https://www.rijksoverheid.nl/documenten/rapporten/2014/04/01/rijksnatuurvisie-2014>
- Miranda, R., Alves, C., Sousa, R., Chaves, A., Montenegro, L., Peixoto, H., Durães, D., Machado, R., Abelha, A., Novais, P. & Machado, J. (2024), ‘Revolutionising the quality of life: The role of real-time sensing in smart cities’, Electronics **13**(3).
URL: <https://www.mdpi.com/2079-9292/13/3/550>
- Mirovic, V., Mitrović Simić, J., Milicic, M. & Ruskic, N. (2024), ‘Smart mobility in smart cities’, JTTTP - JOURNAL OF TRAFFIC AND TRANSPORT THEORY AND PRACTICE **13**.

- Montgomery, C. (2015), Happy City: Transforming Our Lives Through Urban Design, Penguin Books, London, UK.
- Moss Kanter, R. & Litow, S. S. (2009), Informed and interconnected: A manifesto for smarter cities, Working Paper 09-141, Harvard Business School General Management Unit.
- Moustaka, V., Vakali, A. & Anthopoulos, L. G. (2018), ‘A systematic review for smart city data analytics’, ACM Comput. Surv. **51**(5).
URL: <https://doi.org/10.1145/3239566>
- Müller-Eie, D. & Kosmidis, I. (2023), ‘Sustainable mobility in smart cities: a document study of mobility initiatives of mid-sized Nordic smart cities’, European Transport Research Review **15**, 36.
URL: <https://doi.org/10.1186/s12544-023-00610-4>
- Nam, T. & Pardo, T. A. (2011), Conceptualizing smart city with dimensions of technology, people, and institutions, in ‘Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times’, Association for Computing Machinery, New York, NY, USA, p. 282–291.
URL: <https://doi.org/10.1145/2037556.2037602>
- Neale, C., Lopez, S. & Roe, J. (2021), ‘Psychological Restoration and the Effect of People in Nature and Urban Scenes: A Laboratory Experiment’, Sustainability **13**(11), 6464.
URL: <https://doi.org/10.3390/su13116464>
- Nesbitt, L., Meitner, M. J., Girling, C., Sheppard, S. R. & Lu, Y. (2019), ‘Who has access to urban vegetation? a spatial analysis of distributional green equity in 10 us cities’, Landscape and Urban Planning **181**, 51–79.
URL: <https://www.sciencedirect.com/science/article/pii/S0169204618307710>
- Neves, F. T., de Castro Neto, M. & Aparicio, M. (2020), ‘The impacts of open data initiatives on smart cities: A framework for evaluation and monitoring’, Cities **106**, 102860.
URL: <https://www.sciencedirect.com/science/article/pii/S0264275120312087>
- Newman, O. (1996), Creating defensible space, Technical report, U.S. Department of Housing and Urban Development, Office of Policy Development and Research, Washington, DC. Contract No. DU100C000005967. Contractor: Institute for Community Design Analysis; Center for Urban Policy Research, Rutgers University.
- Norgate, S. H., Cooper-Ryan, A. M., Lavin, S., Stonier, C. & Cooper, C. L. (2020), ‘The impact of public transport on the health of work commuters: a systematic review’, Health Psychology Review **14**(2), 325–344.
URL: <https://doi.org/10.1080/17437199.2019.1618723>
- Novaco, R., Stokols, D. & Milanesi, L. (1990), ‘Objective and subjective dimensions of travel impedance as determinants of commuting stress’, American Journal of Community Psychology **18**(2), 231–257.
- Novaco, R. W. & Gonzalez, O. I. (2009), Commuting and well-being, in Y. Amichai-Hamburger, ed., ‘Technology and Psychological Well-Being’, Cambridge University Press, chapter 7, pp. 174–205.
- Novaco, R. W., Stokols, D., Campbell, J. & Stokols, J. (1979), ‘Transportation, stress, and community psychology’, American journal of community psychology **7**(4), 361–380.

- Nutsford, D., Pearson, A. & Kingham, S. (2013), 'An ecological study investigating the association between access to urban green space and mental health', Public Health **127**(11), 1005–1011.
URL: <https://www.sciencedirect.com/science/article/pii/S0033350613002862>
- of Economic, U. N. D. & Affairs, S. (2019), World Urbanization Prospects: The 2018 Revision, United Nations.
URL: <https://www.un-ilibrary.org/content/books/9789210043144>
- Okkels, N., Kristiansen, C. B., Munk-Jørgensen, P. & Sartorius, N. (2018), 'Urban mental health: challenges and perspectives', Current Opinion in Psychiatry **31**(3), 258–264.
URL: <https://doi.org/10.1097/YCO.0000000000000413>
- Omar, A., AlMaeeni, S., Attia, H., Takruri, M., Altunaiji, A., Sanduleanu, M., Shubair, R., Ashhab, M. S., Al Ali, M. & Al Hebsi, G. (2022), 'Smart City: Recent Advances in Intelligent Street Lighting Systems Based on IoT', Journal of Sensors **2022**, 5249187.
URL: <https://doi.org/10.1155/2022/5249187>
- Open Knowledge Foundation (2024), 'Dataportals.org: A comprehensive list of open data portals from around the world'.
URL: <https://dataportals.org>
- Oteiza, T. P., Mooney, P. & Kelly, L. (2022), Smart city data in urban wellbeing estimation, in '2022 IEEE International Smart Cities Conference (ISC2)', IEEE, pp. 1–4.
- Pain, R. (2000), 'Place, social relations and the fear of crime: a review', Progress in Human Geography **24**(3), 365–387.
- Papyshev, G. & Yarime, M. (2021), 'Exploring city digital twins as policy tools: A task-based approach to generating synthetic data on urban mobility', Data & Policy **3**, e16.
- Park, Y. S., Konge, L. & Artino, A. R. J. (2020), 'The Positivism Paradigm of Research', Academic Medicine **95**(5), 690–694.
- Patel, V., Saxena, S., Lund, C., Thornicroft, G., Baingana, F., Bolton, P., Chisholm, D., Collins, P. Y., Cooper, J. L., Eaton, J., Herrman, H., Herzallah, M. M., Huang, Y., Jordans, M. J. D., Kleinman, A., Medina-Mora, M. E., Morgan, E., Niaz, U., Omigbodun, O., Prince, M. & Unützer, J. (2018), 'The Lancet Commission on global mental health and sustainable development', Lancet (London, England) **392**(10157), 1553–1598.
URL: [https://doi.org/10.1016/S0140-6736\(18\)31612-X](https://doi.org/10.1016/S0140-6736(18)31612-X)
- Perez Oteiza, T., Kelly, L. & Mooney, P. (2021), 'Using contextual cues in understanding urban mental well-being', The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences **46**, 85–89.
- Peters, K., Elands, B. & Buijs, A. (2010), 'Social interactions in urban parks: Stimulating social cohesion?', Urban Forestry & Urban Greening **9**(2), 93–100. Special section on "Forest recreation and nature tourism".
URL: <https://www.sciencedirect.com/science/article/pii/S1618866709000855>
- Pontin, E., Schwannauer, M., Tai, S. & Kinderman, P. (2013), 'A UK validation of a general measure of subjective well-being: the modified BBC subjective well-being scale (BBC-SWB)', Health and Quality of Life Outcomes **11**, 150.

- Power, M. C., Kioumourtzoglou, M. A., Hart, J. E., Okereke, O. I., Laden, F. & Weisskopf, M. G. (2015), 'The relation between past exposure to fine particulate air pollution and prevalent anxiety: observational cohort study', BMJ (Clinical research ed.) **350**, h1111.
URL: <https://doi.org/10.1136/bmj.h1111>
- Preston, C. C. & Colman, A. M. (2000), 'Optimal number of response categories in rating scales: reliability, validity, discriminating power, and respondent preferences', Acta Psychologica **104**(1), 1–15.
- Prince, M., Patel, V., Saxena, S., Maj, M., Maselko, J., Phillips, M. R. & Rahman, A. (2007), 'No health without mental health', The Lancet **370**(9590), 859–877.
- Puiu, D., Barnaghi, P., Tönjes, R., Kümper, D., Ali, M. I., Mileo, A., Xavier Parreira, J., Fischer, M., Kolozali, S., Farajidavar, N., Gao, F., Iggena, T., Pham, T.-L., Nechifor, C.-S., Puschmann, D. & Fernandes, J. (2016), 'Citypulse: Large scale data analytics framework for smart cities', IEEE Access **4**, 1086–1108.
- Pánek, J. (2018), 'Emotional maps: Participatory crowdsourcing of citizens' perceptions of their urban environment', Cartographic Perspectives **91**, 17–29.
- Qiu, J., Shen, B., Zhao, M., Wang, Z., Xie, B. & Xu, Y. (2020), 'A nationwide survey of psychological distress among chinese people in the covid-19 epidemic: implications and policy recommendations', General Psychiatry **33**(2), e100213. Erratum in: General Psychiatry. 2020 Apr 27;33(2):e100213corr1. doi: 10.1136/gpsych-2020-100213corr1.
URL: <https://doi.org/10.1136/gpsych-2020-100213>
- Reid, L. W. & Konrad, M. (2004), 'The gender gap in fear: Assessing the interactive effects of gender and perceived risk on fear of crime', Sociological Spectrum **24**(4), 399–425.
- Revilla, M. A., Saris, W. E. & Krosnick, J. A. (2014), 'Choosing the number of categories in agree–disagree scales', Sociological Methods & Research **43**(1), 73–97.
- Roberts, M. (2016), Gender, fear and the night-time city, in 'Fair shared cities', Routledge, pp. 49–64.
- Roe, J. J., Thompson, C. W., Aspinall, P. A. & et al. (2013), 'Green space and stress: evidence from cortisol measures in deprived urban communities', International Journal of Environmental Research and Public Health **10**(9), 4086–4103.
- Rowe, D. B. (2011), 'Green roofs as a means of pollution abatement', Environmental Pollution **159**(8), 2100–2110. Selected papers from the conference Urban Environmental Pollution: Overcoming Obstacles to Sustainability and Quality of Life (UEP2010), 20–23 June 2010, Boston, USA.
URL: <https://www.sciencedirect.com/science/article/pii/S0269749110004859>
- Sabri, S. A., Ponrahono, Z., Bakar, A. & Aziz, F. (2023), 'Comparative analysis of open green spaces policies in enhancing urban resilience to climate change through small urban parks in malaysia and singapore', Chemical Engineering Transactions **106**, 211–216.
- Sagiroglu, S. & Sinanc, D. (2013), Big data: A review, in '2013 International Conference on Collaboration Technologies and Systems (CTS)', pp. 42–47.
- Saha, K., Seybolt, J., Mattingly, S. M., Aledavood, T., Konjeti, C., Martinez, G. J., Grover, T., Mark, G. & De Choudhury, M. (2021), What life events are disclosed on social media, how, when, and by whom?, in 'Proceedings of the 2021 CHI conference on human factors in computing systems', pp. 1–22.

- Salcedo, J. (2024), 'Smart metropolis? mexico city's ongoing transformation.', Brown Journal of World Affairs **31**(1).
- Saleh, N. (2024), 'Taking public transit improves mental and physical health', <https://www.mdlinx.com/article/taking-public-transit-improves-mental-and-physical-health/3NtHFpS9fCquX2uI0qzwS8>. Accessed on: 2025-10-30.
- Sanchez, L., Muñoz, L., Galache, J. A., Sotres, P., Santana, J. R., Gutierrez, V., Ramdhany, R., Gluhak, A., Krco, S., Theodoridis, E. et al. (2014), 'Smartsantander: Iot experimentation over a smart city testbed', Computer Networks **61**, 217–238.
- Shanahan, H. & Bezuidenhout, L. (2022), 'Rethinking the A in FAIR Data: Issues of Data Access and Accessibility in Research', Frontiers in Research Metrics and Analytics **7**.
URL: <https://www.frontiersin.org/journals/research-metrics-and-analytics/articles/10.3389/frma.2022.912456>
- Singh, D., Dahiya, M., Kumar, R. & Nanda, C. (2021), 'Sensors and systems for air quality assessment monitoring and management: A review', Journal of Environmental Management **289**, 112510.
URL: <https://www.sciencedirect.com/science/article/pii/S0301479721005727>
- Sudimac, S., Sale, V. & Kühn, S. (2022), 'How nature nurtures: Amygdala activity decreases as the result of a one-hour walk in nature', Molecular Psychiatry **27**, 4446–4452.
URL: <https://doi.org/10.1038/s41380-022-01720-6>
- Sugiyama, T., Leslie, E., Giles-Corti, B. & Owen, N. (2008), 'Associations of neighbourhood greenness with physical and mental health: do walking, social coherence and local social interaction explain the relationships?', Journal of Epidemiology and Community Health **62**(5), e9–e9.
- Taylor, C. B., Sallis, J. F. & Needle, R. (1985), 'The relation of physical activity and exercise to mental health', Public Health Reports **100**(2), 195–202.
- Taylor, P. (2025), 'Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2023, with forecasts from 2024 to 2028', <https://www.statista.com/statistics/871513/worldwide-data-created/>. Accessed on: 2025-10-30.
- The Global Goals (n.d.), 'Goal 11: Sustainable Cities and Communities', <https://globalgoals.org/goals/11-sustainable-cities-and-communities/>. Accessed on: 2025-10-30.
- Topf, M. (2000), 'Hospital noise pollution: an environmental stress model to guide research and clinical interventions', Journal of Advanced Nursing **31**(3), 520–528.
URL: <https://doi.org/10.1046/j.1365-2648.2000.01307.x>
- Torres, A. C., Prévot, A.-C. & Nadot, S. (2018), 'Small but powerful: The importance of french community gardens for residents', Landscape and Urban Planning **180**, 5–14.
URL: <https://www.sciencedirect.com/science/article/pii/S0169204618307382>
- Trencher, G. & Karvonen, A. (2019), 'Stretching “smart”: advancing health and well-being through the smart city agenda', Local Environment **24**(7), 610–627.
- 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.
URL: <https://www.sciencedirect.com/science/article/pii/S0013935118303323>

- Tzivian, L., Winkler, A., Dlugaj, M., Schikowski, T., Vossoughi, M., Fuks, K., Weinmayr, G. & Hoffmann, B. (2015), 'Effect of long-term outdoor air pollution and noise on cognitive and psychological functions in adults', International journal of hygiene and environmental health **218**(1), 1–11.
- Ulrich, R. S., Simons, R. F., Losito, B. D., Fiorito, E., Miles, M. A. & Zelson, M. (1991), 'Stress recovery during exposure to natural and urban environments', Journal of Environmental Psychology **11**(3), 201–230.
URL: <https://www.sciencedirect.com/science/article/pii/S0272494405801847>
- UN-Habitat (2020), World Cities Report 2020: The Value of Sustainable Urbanization, UN-Habitat.
- United Nations (2021), Sustainable transport, sustainable development: Interagency report for second Global Sustainable Transport Conference, Technical report, United Nations Department of Economic and Social Affairs, New York.
URL: https://sdgs.un.org/sites/default/files/2021-10/Transportation%20Report%202021_FullReport_Dig
- United Nations Environment Programme (n.d.), 'Air quality management', <https://www.unep.org/topics/air/air-quality-management>. Accessed on: 2025-10-30.
- Urry, H. L., van Reekum, C. M., Johnstone, T., Kalin, N. H., Thurow, M. E., Schaefer, H. S., Jackson, C. A., Frye, C. J., Greischar, L. L., Alexander, A. L. & Davidson, R. J. (2006), 'Amygdala and ventromedial prefrontal cortex are inversely coupled during regulation of negative affect and predict the diurnal pattern of cortisol secretion among older adults', The Journal of Neuroscience: The Official Journal of the Society for Neuroscience **26**(16), 4415–4425.
URL: <https://doi.org/10.1523/JNEUROSCI.3215-05.2006>
- U.S. Environmental Protection Agency (2016), Guidelines for human exposure assessment, Technical Report EPA/100/B-16/001, U.S. Environmental Protection Agency, Risk Assessment Forum, Washington, DC.
- van den Berg, M., van Poppel, M., Smith, G., Triguero-Mas, M., Andrusaityte, S., van Kamp, I., van Mechelen, W., Gidlow, C., Gražulevičiene, R., Nieuwenhuijsen, M. J., Kruize, H. & Maas, J. (2017), 'Does time spent on visits to green space mediate the associations between the level of residential greenness and mental health?', Urban Forestry & Urban Greening **25**, 94–102.
URL: <https://www.sciencedirect.com/science/article/pii/S1618866716304691>
- van Hooff, M. L. (2015), 'The daily commute from work to home: Examining employees' experiences in relation to their recovery status', Stress and Health **31**(2), 124–137.
- Vanolo, A. (2014), 'Smartmentality: The smart city as disciplinary strategy', Urban Studies **51**(5), 883–898.
URL: <https://doi.org/10.1177/0042098013494427>
- Velasco, E. & Rastan, S. (2015), 'Air quality in singapore during the 2013 smoke-haze episode over the strait of malacca: Lessons learned', Sustainable Cities and Society **17**.
- Ventriglio, A., Bellomo, A., di Gioia, I., Di Sabatino, D., Favale, D., De Berardis, D. & Cianconi, P. (2020), 'Environmental pollution and mental health: a narrative review of literature', CNS Spectrums **26**(1), 51–61.
- Viswanath, K. & Basu, A. (2015), 'Safetipin: an innovative mobile app to collect data on women's safety in Indian cities', Gender & Development **23**(1), 45–60.

- Von Szombathely, M., Albrecht, M., Antanaskovic, D., Augustin, J., Augustin, M., Bechtel, B., Bürk, T., Fischereit, J., Grawe, D., Hoffmann, P., Kaveckis, G., Krefis, A. C., Oßenbrügge, J., Scheffran, J. & Schlünzen, K. H. (2017), 'A conceptual modeling approach to health-related urban well-being', *Urban Science* **1**(2).
URL: <https://www.mdpi.com/2413-8851/1/2/17>
- Wang, R., Feng, Z., Pearce, J., Liu, Y. & Dong, G. (2021), 'Are greenspace quantity and quality associated with mental health through different mechanisms in guangzhou, china: A comparison study using street view data', *Environmental Pollution* **290**, 117976.
- Wang, X., Rodríguez, D. A., Sarmiento, O. L. & Guaje, O. (2019), 'Commute patterns and depression: Evidence from eleven latin american cities', *Journal of Transport & Health* **14**, 100607.
- Ward Thompson, C., Roe, J., Aspinall, P., Mitchell, R., Clow, A. & Miller, D. (2012), 'More green space is linked to less stress in deprived communities: Evidence from salivary cortisol patterns', *Landscape and Urban Planning* **105**(3), 221–229.
URL: <https://www.sciencedirect.com/science/article/pii/S0169204611003665>
- Weier, J. & Herring, D. (2000), 'Measuring Vegetation (NDVI & EVI)', <https://earthobservatory.nasa.gov/features/MeasuringVegetation>. Accessed on: 2025-10-30.
- Weimann, H., Björk, J. & Håkansson, C. (2019), 'Experiences of the urban green local environment as a factor for well-being among adults: An exploratory qualitative study in southern sweden', *International Journal of Environmental Research and Public Health* **16**(14).
URL: <https://www.mdpi.com/1660-4601/16/14/2464>
- White, M. P., Alcock, I., Grellier, J., Wheeler, B. W., Hartig, T., Warber, S. L., Bone, A., Depledge, M. H. & Fleming, L. E. (2019), 'Spending at least 120 minutes a week in nature is associated with good health and wellbeing', *Scientific Reports* **9**(1), 7730.
URL: <https://doi.org/10.1038/s41598-019-44097-3>
- WHO Regional Office for Europe (2016), Urban green spaces and health: A review of evidence, Technical Report WHO/EURO:2016-3352-43111-60341, WHO Regional Office for Europe, Copenhagen.
- Willis, K. S. & Nold, C. (2022), 'Sense and the city: An emotion data framework for smart city governance', *Journal of Urban Management* **11**(2), 142–152.
- Wolniak, R. & Grebski, W. (2023), 'Smart mobility in smart city–singapore and tokyo comparison', *Zeszyty Naukowe. Organizacja i Zarządzanie/Politechnika Śląska* pp. 751–770.
- Wood, L., Hooper, P., Foster, S. & Bull, F. (2017), 'Public greenspaces and positive mental health–investigating the relationship between access, quantity and types of parks and mental wellbeing', *Health & place* **48**, 63–71.
- World Health Organization (2001), *The World Health Report 2001: Mental Health: New Understanding, New Hope*, World Health Organization, Geneva, Switzerland.
URL: <https://www.who.int/whr/2001/en/>
- World Health Organization (2021), 'What are the WHO air quality guidelines?', <https://www.who.int/news-room/feature-stories/detail/what-are-the-who-air-quality-guidelines>.
- World Health Organization (2024a), 'Ambient (outdoor) air pollution', [https://www.who.int/news-room/fact-sheets/detail/ambient-\(outdoor\)-air-quality-and-health](https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health). Accessed on: 2025-10-30.

- World Health Organization (2024b), Mental disorders: Key facts, World Health Organization. Available at: <https://www.who.int/news-room/fact-sheets/detail/mental-disorders>, Accessed: September 9, 2025.
- Xing, Y. F., Xu, Y. H., Shi, M. H. & Lian, Y. X. (2016), ‘The impact of PM_{2.5} on the human respiratory system’, Journal of Thoracic Disease **8**(1), E69–E74.
URL: <https://pubmed.ncbi.nlm.nih.gov/26904255/>
- Xu, C., Miao, L., Turner, D. & DeRubeis, R. (2023), ‘Urbanicity and depression: A global meta-analysis’, Journal of Affective Disorders **340**, 299–311.
- Yang, Z., Song, Q., Li, J., Zhang, Y., Yuan, X.-C., Wang, W. & Yu, Q. (2021a), ‘Air pollution and mental health: The moderator effect of health behaviors’, Environmental Research Letters **16**(4), 044005.
- Yang, Z., Song, Q., Li, J., Zhang, Y., Yuan, X.-C., Wang, W. & Yu, Q. (2021b), ‘Air pollution and mental health: the moderator effect of health behaviors’, Environmental Research Letters **16**(4), 044005.
- Zanella, A., Bui, N., Castellani, A., Vangelista, L. & Zorzi, M. (2014), ‘Internet of things for smart cities’, IEEE Internet of Things Journal **1**(1), 22–32.
- Zhang, X., Zhang, X. & Chen, X. (2017), ‘Happiness in the air: How does a dirty sky affect mental health and subjective well-being?’, Journal of Environmental Economics and Management **85**, 81–94.

Appendix A

Smart City Case Studies

A.1 Kashiwanoha City: How They Improved Wellbeing

The city of Kashiwanoha in Japan represents one of the few successful examples of a smart city purposefully prioritizing urban health and wellbeing while balancing economic and technological goals. Mitsui Fudosan developed this initiative, offering a \$73 million investment serving more than 6000 residents ([Trencher & Karvonen 2019](#)). The city implemented three prolonged smart health strategy stages between 2012-2015: technology and monitoring, education and community, and behavioral incentives. Through the first stage, 150 residents received a wearable device and digital scales to track biometrics and body weight. Participants had access to a digital platform to view their stats, and this resulted in a 34% increase in exercise time and better sleep quality. In the second stage, education was encouraged through providing free of charge health centers, where over 2000 residents registered ([Trencher & Karvonen 2019](#)). Additionally, the city of Kashiwanoha created a digital health diary for young mothers to provide tailored educational content and communication with the government. The third stage of developing a healthy smart city focused on motivating behavioral change in residents by creating community competition and gamification of health metrics. With the distribution of 1000 pedometers, a point-based reward system for daily walking was introduced with the ability to redeem points for store purchases (Monthly maximum of 600 points equivalent to USD5). The measured outcomes revealed a positive impact on health, community building, and improved citizen-government communication. The main challenges of this smart city implementation in Kashiwanoha reveal scalability limitations. Only 2.5% of the city's population got advanced monitoring and the other 17% of citizens received basic pedometers, and only 10% of pedometer users regularly engaged with the reward system ([Trencher & Karvonen 2019](#)). Additionally, residents showed reluctance to pay for continued services once free trials ended, highlighting commercialization barriers for individual monitoring approaches ([Trencher & Karvonen 2019](#)). The case study of Kashiwanoha Smart City highlights policy gaps to make wellbeing a core dimension rather than a side effect.

A.2 Air Quality: Singapore and Sumatra, Indonesia

Singapore's response to the 2013 smoke haze caused by wildfires in Sumatra, Indonesia, provides a model of effective crisis management ([Velasco & Rastan 2015](#)). The extreme pollution event in Singapore, where $PM_{2.5}$ concentrations soared to $310 \mu g/m^3$, more than 12 times the WHO guidelines, triggered public demand for timely, transparent air quality data. In response, within 10 months, the Singaporean government began releasing daily hourly $PM_{2.5}$ data and distributed more than four million dust masks ([Velasco & Rastan 2015](#)). In addition, the government partnered with media outlets to release widespread public health warnings, urging residents to remain indoors. This coordinated effort exemplifies proactive air quality and public

health management (Velasco & Rastan 2015).

A.3 Singapore: Successes in Greenspace Integration

Singapore, acknowledged as a city-state model of greenspace excellence, has effectively utilized its limited land area to integrate substantial greenspaces (Haaland & van den Bosch 2015). Recognized as the "city in a garden," Singapore has strategically used small urban parks, green roofs, and extensive tree coverage, enhancing its reputation as a thriving smart city (Sabri et al. 2023). This successful integration is largely attributed to significant government investments in greenspaces, aimed at improving the quality of life for its urban residents Sabri et al. (2023). Singapore has a comprehensive urban planning program guided by a Concept Plan, which outlines the city's development over a 40 to 50-year period. The latest version aims to achieve five core objectives: fostering economic growth, enhancing the living environment, promoting an inclusive society, ensuring sustainability in Singapore, and creating a sense of belonging for its residents (Henderson 2013). The Urban Redevelopment Authority (URA) ¹ has committed to implementing the 2008 Leisure Plan, which aims to expand the park connector network to 360 km, three times its original length, establish a 150 km round-island route for walking, jogging, and cycling, and increase greenspaces from 3,300 to 4,200 hectares, introducing more parks with greater diversity (Authority 1986). Similarly, The Singapore Green Plan 2030 ² aligns its vision with the United Nations' 17 sustainability goals, including environmental and wellbeing goals.

Since the 1960s, the focused efforts on urban greening have quadrupled tree cover from 10% to 47% and created over 1,000 parks and gardens. (Sabri et al. 2023). Singapore established the National Parks Board (NParks) to oversee the regulation and management of urban greenspaces. The nation has nearly met its goal of providing 0.8 hectares of greenspace per 1,000 people, currently offering 0.78 hectares. Such accomplishments are particularly remarkable given the challenges of Singapore's rapid population growth and limited land resources. During the COVID-19 pandemic, observed a significant increase in the use of greenspaces in Singapore, as residents turned to these areas to cope, resulting in a noticeable rise in visits. Beyond government-led efforts, community participation has played a crucial role in maintaining Singapore's parks, as demonstrated in the book *Living in a Garden* by Auger (2013) highlights the community efforts involved in maintaining Singapore's parks. It also features user profiles of key individuals dedicated to conserving greenspaces. This sustained focus not only enhances urban livability but also ensures that greenspaces continue to play a critical role in the city's resilience and public health strategies.

A.4 Amsterdam: Challenges of Limited Greenspaces

Government involvement in greenspace management in Amsterdam dates to the late 19th century, but it significantly increased after World War II due to rising public demand (de Vries 2021). In 2000, the policy document *Nature for People, People for Nature* (Natuur voor mensen, Mensen voor natuur) was introduced, emphasizing the experiential and practical value of greenery. This policy aimed to bring nature closer to urban citizens, reinforcing the idea that access to greenspaces improves wellbeing (Ministerie van Economische Zaken 2014). In 2014, the Ministry of Economic Affairs introduced the *Nature Vision*, a national policy guiding green and nature policies until 2025 (Ministerie van Economische Zaken 2014). This vision represented a major shift in perspective, positioning nature as the center of society, not just in designated natural areas. This initiative recognized that integrating greenspaces enhances both urban

¹<https://www.ura.gov.sg/Corporate>

²<https://www.greenplan.gov.sg/>

wellbeing and environmental sustainability. Greenspaces help cool the city, absorb pollutants, and enhance the overall attractiveness of urban environments (Ministerie van Economische Zaken 2014). In 2019, the Dutch Ministry of Agriculture, Nature, and Food Quality introduced a new legal framework to enhance urban greenery. The policy focuses on strengthening agreements for green space implementation, improving existing urban green conditions, and expanding greening policies by integrating biodiversity and natural capital into urban planning. It also emphasizes collaboration among municipalities, provinces, regional water authorities, and stakeholders to address climate adaptation and water management challenges. Public support for green policies has historically been weak (Ministerie van Economische Zaken 2014). In a small, densely populated country like the Netherlands, conflicting land-use priorities are inevitable, and in some cases, strict conservation regulations have led to significant societal pressure (Ministerie van Economische Zaken 2014).

To address the challenges of high population density and greenspace accessibility, Amsterdam has adopted compact city policies that prioritize the planned densification, ensuring densification happens in already existing urban areas. and expansion of urban greenery. The city has implemented several key policies to ensure that greenspaces remain an integral part of urban development. In the research of Balikçi et al. (2022) a comparative case study between Amsterdam and Brussels was conducted, comparing government policies. Compared to Amsterdam, Brussels, did not focus on planned densification,

The ‘Main Structure Greenspace’ (Hoofdgroenstructuur) policy provides legal protection for key green areas, preventing urban development from encroaching on vital natural spaces. Additionally, the Amsterdam Standard for Social Services, Greenspace, and Play Facilities mandates that new residential projects include a minimum greenspace provision per inhabitant, reinforcing the city’s commitment to equitable access to urban greenery. These policies have helped manage densification pressures, limiting greenspace loss to 4.7% between 2003 and 2016, significantly lower than in other European cities. Balikçi et al. (2022)

Additionally, the focus on protecting greenspaces has made it difficult to integrate. The technical complexity of green policy tools has further hindered their effectiveness, contributing to public misunderstanding, frustration, and resistance. As a result, green initiatives are often perceived as bureaucratic obstacles rather than essential components of sustainable urban development (Ministerie van Economische Zaken 2014). In Amsterdam, access to greenspaces is not equally distributed, with immigrant and low-income communities often having fewer and lower-quality greenspaces (De Haas et al. 2021). This disparity limits their ability to fully benefit from the environmental and wellbeing advantages that greenspaces provide, leading to poorer health (Maas et al. 2006).

To address public resistance, provincial governments have been given responsibilities for nature and greenspaces policy, ensuring that decision-making remains closer to local communities and better aligned with societal needs. Greenspaces are increasingly recognized for their role in enhancing mental wellbeing and creating a healthier urban environment. Access to greenspace promotes calm, reduces stress, and improves quality of life. Recognizing these benefits, Amsterdam has doubled its investment in green projects to €20 million, prioritizing urban nature as an essential element for public wellbeing³.

A.5 Mexico City: A Megacity’s Smart Mobility Evolution

Mexico City stands as one of the world’s largest megacities, with over 22.3 million inhabitants making it the sixth most populous city globally (Salcedo 2024). Rapid urbanization has created immense pressure on the city’s transportation infrastructure, requiring innovative solutions to accommodate the mobility needs of millions of residents. In just 9 years, from 2004 to 2013, vehicle ownership has increased 96% (Leo et al. 2017). Only 15% of transport comes from

³<https://onderzoek.amsterdam.nl/>

private vehicles, 26% is non-motorized, and 57% of citizens use public transportation (Chatziioannou et al. 2020). Mexico City began building the metro system in 1969, during periods of economic constraints and government instability. This resulted in urbanization outpacing infrastructure development (Leo et al. 2017). The city operates one of Latin America's most extensive public transit networks, featuring 12 Metro lines, 5 Bus Rapid Transit (BRT) lines, and over 316 kilometers of bike lanes (Leo et al. 2017, Salcedo 2024). This infrastructure supports approximately 17 million daily trips across various modes including subway, metro bus, trolley bus, light rail, and last-mile mobility systems. The city also facilitated a multi-modal transport card to encourage micro-mobility. In 2020, Mexico made it a constitutional law ⁴ stating that mobility is a right for citizens "under conditions of safety, accessibility, efficiency, sustainability, quality, inclusion and equality." Mexico enacted this constitutional amendment due to 16,000 annual road traffic deaths. The law prioritizes vulnerable citizens, pedestrians, and cyclists. Additionally, Mexico City integrated ECOBICI, the first public bike-share in Latin America (Leo et al. 2017). The city has implemented several smart mobility solutions, including an integrated mobility app providing real-time information and the ECOBICI system, which has grown to serve 55,000 registered users with 2,565 bikes across the city (Leo et al. 2017). Despite the legal commitment, the system struggles to meet the enormous demand generated by the metropolitan area's population, often facing overcrowding. Much of the infrastructure, particularly the Metro system, is now over 50 years old and requires substantial maintenance. In 2021, only 9% of the Metro's total budget was allocated for maintenance and repairs, with 101 out of 390 trains out of operation Salcedo (2024). A 3D model of Mexico City revealed that the urban growth shows to be dispersed, distant and disconnected connected to a disproportionate, fragmented, and unplanned urban expansion (Chatziioannou et al. 2020). This fragmented growth pattern explains why there are large, developed areas without proper infrastructure and formal planning.

Salcedo (2024) notes, developing countries like Mexico face difficulties in implementing long-term sustainable growth plans due to short political cycles and limited budgets, leaving little space for the significant investments needed to transform into smart cities. While similar to Tokyo, the metro has a designated wagon for women and children, gender-based harassment is prominent and 77.5% of people experience street insecurities, which significantly impacts people's willingness to walk to transit stops and use public transportation. The infrastructure challenges, risk of safety, and lack of funding translate to a low quality of public transportation harming the quality of life of Mexico city's citizens. Mexico City's experience illustrates both the potential and limitations of smart mobility transformation in developing contexts. This insight offers valuable lessons about the importance of legal frameworks, citizen safety, and sustained investment in aging infrastructure for other megacities pursuing similar transitions.

⁴<https://www.wri.org/outcomes/mexico-adds-fundamental-right-mobility-its-constitution>

Appendix B

External Links

The GitHub repository can be found <https://github.com/tzirath/ThesisComputationalFramework>¹. This contains all python scripts and README file for replication of the computational framework.

¹<https://github.com/tzirath/ThesisComputationalFramework>

Appendix C

Results

C.1 Air Quality

C.1.1 Chicago Air Quality: Ranked ZIP-Level Scores

Table C.1: Chicago Air Quality: Ranked ZIP-Level Scores

Rank	ZIP Code	Mean AQ Score	Population	Address Count
1	60601	2.50	15,814	77
2	60602	2.50	1,261	12
3	60603	2.50	1,288	10
4	60604	2.50	897	49
5	60605	2.50	34,071	647
6	60606	2.50	3,797	80
7	60611	2.50	38,456	425
8	60610	2.50	43,794	1,963
9	60614	2.50	73,173	7,521
10	60613	2.50	53,048	4,115
11	60622	2.50	55,075	8,170
12	60633	2.50	13,359	4,682
13	60625	2.50	76,525	10,139
14	60626	2.50	50,548	3,447
15	60618	2.50	90,316	15,930
16	60642	2.50	21,687	3,023
17	60654	2.50	23,890	473
18	60660	2.50	42,534	3,030
19	60645	2.50	48,356	6,193
20	60647	2.50	85,631	13,174
21	60639	2.50	89,543	14,508
22	60661	2.50	11,987	290
23	60659	2.50	40,579	5,715
24	60657	2.50	72,316	6,363
25	60641	2.50	69,354	13,285
26	60640	2.50	65,941	4,753
27	60827	2.50	24,936	1,015
28	60607	2.50	31,816	2,672
29	60651	2.51	62,819	12,257

Continued on next page

Table C.1 – continued from previous page

Rank	ZIP Code	Mean AQ Score	Population	Address Count
30	60707	2.54	43,241	4,383
31	60630	2.55	54,064	14,165
32	60612	2.56	34,402	9,101
33	60646	2.56	28,383	9,282
34	60624	2.62	37,547	9,303
35	60617	2.62	77,270	28,320
36	60634	2.65	75,694	19,374
37	60644	2.66	47,239	8,794
38	60616	2.66	54,013	6,964
39	60631	2.66	29,691	9,078
40	60608	2.66	75,770	13,248
41	60609	2.67	65,770	17,777
42	60632	2.67	92,237	17,892
43	60629	2.67	114,453	24,412
44	60623	2.67	87,649	16,028
45	60620	2.67	66,514	19,825
46	60619	2.67	63,303	18,841
47	60621	2.67	29,570	12,466
48	60615	2.67	43,502	3,526
49	60649	2.67	48,171	6,099
50	60652	2.67	40,898	12,777
51	60636	2.67	34,800	14,287
52	60637	2.67	53,555	7,961
53	60653	2.67	33,146	5,667
54	60638	2.67	56,928	17,039
55	60628	2.71	62,832	26,216
56	60643	2.71	47,831	19,658
57	60655	2.74	27,837	10,402
58	60656	2.83	28,474	6,851

C.1.2 Manchester Air Quality: Ranked Borough-Level Scores

Table C.2: Manchester Air Quality: Ranked Borough-Level Scores

Rank	Borough	Mean AQ Score	Population	Address Count
1	Wigan District (B)	1.98	344,922	6,827
2	Bolton District (B)	2.30	310,085	6,298
3	Bury District (B)	2.41	198,921	4,305
4	Tameside District (B)	2.67	239,643	5,239
5	Stockport District (B)	2.72	303,929	5,991
6	Oldham District (B)	2.77	251,560	4,986
7	Rochdale District (B)	2.88	235,561	4,945
8	Salford District (B)	3.36	294,348	5,663
9	Manchester District (B)	3.39	589,670	11,827
10	Trafford District (B)	3.68	241,025	5,715

C.1.3 Portland Air Quality: Ranked Neighborhood-Level Scores

Table C.3: Portland Air Quality: Ranked Neighborhood-Level Scores

Rank	Neighborhood	Mean AQ Score	Population	Address Count
1	ARLINGTON HEIGHTS	1.75	813	332
2	BRIDLEMILE	1.75	5,940	2,698
3	GOOSE HOLLOW	1.75	7,333	5,279
4	OLD TOWN	1.75	4,159	3,055
5	HOMESTEAD	1.75	8,251	1,386
6	HILLSIDE	1.75	2,405	1,325
7	HILLSDALE	1.75	8,355	4,046
8	HEALY HEIGHTS	1.75	227	91
9	SOUTHWEST HILLS	1.75	8,527	3,993
10	SYLVAN-HIGHLANDS	1.75	1,472	908
11	PORTLAND DOWNTOWN	1.75	14,127	15,724
12	PEARL DISTRICT	1.75	11,019	7,458
13	NORTHWEST DISTRICT	1.75	18,319	12,932
14	SOUTH BURLINGAME	1.76	1,839	842
15	HAYHURST	1.77	5,649	2,626
16	SOUTH PORTLAND	1.77	8,251	6,836
17	LLOYD	1.78	2,665	1,990
18	FOREST PARK	1.80	3,027	818
19	NORTHWEST HEIGHTS	1.82	5,927	2,645
20	PORTSMOUTH	1.83	10,149	3,984
21	UNIVERSITY PARK	1.83	7,005	2,172
22	CATHEDRAL PARK	1.83	4,130	2,228
23	LINNTON	1.83	784	866
24	ST. JOHNS	1.83	12,843	6,138
25	HAYDEN ISLAND	1.87	3,000	4,781
26	KENTON	1.88	8,088	3,895
27	BRIDGETON	1.89	996	1,254
28	MULTNOMAH	1.90	8,395	4,928
29	ELIOT	1.91	5,514	3,076
30	ARBOR LODGE	1.91	6,946	3,127
31	OVERLOOK	1.91	7,229	3,607
32	EAST COLUMBIA	1.92	2,205	1,260
33	SULLIVAN'S GULCH	1.92	4,073	2,422
34	VERNON	1.92	2,932	1,478
35	HUMBOLDT	1.92	5,513	2,967
36	PIEDMONT	1.92	7,033	3,448
37	WOODLAWN	1.92	5,145	2,530
38	KING	1.92	6,775	3,500
39	SABIN	1.92	4,438	1,967
40	IRVINGTON	1.92	8,852	4,426
41	BOISE	1.92	4,660	2,351
42	MAPLEWOOD	1.92	2,821	1,142
43	ALAMEDA	1.92	5,455	2,140
44	BUCKMAN	1.96	11,151	7,552
45	SUNDERLAND	1.98	738	791

Continued on next page

Table C.3 – continued from previous page

Rank	Neighborhood	Mean AQ Score	Population	Address Count
46	CONCORDIA	1.99	10,238	4,699
47	GRANT PARK	2.10	4,139	1,723
48	KERNS	2.16	6,958	4,525
49	BEAUMONT-WILSHIRE	2.16	6,080	2,633
50	ROSE CITY PARK	2.25	9,604	4,338
51	PARKROSE HEIGHTS	2.25	6,171	2,646
52	HOLLYWOOD	2.25	2,248	1,541
53	GLENFAIR	2.25	3,663	1,425
54	WOODLAND PARK	2.25	254	104
55	RUSSELL	2.25	3,241	1,291
56	MADISON SOUTH	2.26	7,208	3,403
57	HAZELWOOD	2.31	26,653	11,787
58	MILL PARK	2.37	9,123	3,690
59	ROSEWAY	2.40	6,725	3,226
60	NORTH TABOR	2.40	5,506	3,088
61	CENTENNIAL	2.41	26,449	9,836
62	BROOKLYN	2.43	3,916	2,371
63	HOSFORD-ABERNETHY	2.49	7,713	4,756
64	MONTAVILLA	2.53	16,942	8,108
65	WILKES	2.55	9,297	4,245
66	ASHCREEK	2.60	4,692	2,064
67	MARKHAM	2.63	2,617	1,141
68	MARSHALL PARK	2.67	1,493	642
69	LAURELHURST	2.83	4,878	1,933
70	ARGAY TERRACE	2.94	6,285	3,065
71	CULLY	2.97	13,339	6,463
72	PARKROSE	3.00	6,253	3,110
73	COLLINS VIEW	3.01	3,265	939
74	SUMNER	3.08	2,116	1,097
75	MT. TABOR	3.10	10,751	5,125
76	POWELLHURST-GILBERT	3.24	33,070	12,802
77	SUNNYSIDE	3.25	8,251	4,565
78	CRESTON-KENILWORTH	3.25	9,046	4,391
79	RICHMOND	3.25	13,508	6,608
80	SOUTH TABOR	3.25	6,633	3,012
81	FOSTER-POWELL	3.25	7,827	3,659
82	REED	3.26	4,734	2,214
83	WOODSTOCK	3.35	9,931	4,515
84	LENTS	3.36	22,236	8,978
85	MT. SCOTT-ARLETA	3.37	8,037	3,749
86	PLEASANT VALLEY	3.38	13,409	4,623
87	SELLWOOD-MORELAND	3.41	13,940	7,311
88	EASTMORELAND	3.41	5,252	1,693
89	ARDENWALD-JOHNSON CREEK	3.42	4,706	378
90	BRENTWOOD-DARLINGTON	3.42	13,536	5,871
91	CRESTWOOD	3.56	2,575	1,049
92	ARNOLD CREEK	3.58	3,108	1,203
93	WEST PORTLAND PARK	3.58	4,080	2,116

Continued on next page

Table C.3 – continued from previous page

Rank	Neighborhood	Mean AQ Score	Population	Address Count
94	FAR SOUTHWEST	3.58	1,461	725

C.2 Greenspace

C.2.1 Chicago Greenspace: Ranked ZIP-Level Scores

Table C.4: Chicago Greenspace: Ranked ZIP-Level Scores

Rank	ZIP	Mean Risk	Population	Addresses	Mean (m)	Median (m)	Min (m)	Max (m)
1	60604	1.76	897	49	363.88	283.80	40.21	1,424.71
2	60605	2.15	34,071	647	446.27	421.90	19.15	1,279.86
3	60653	2.51	33,146	5,667	545.68	492.21	11.03	1,695.76
4	60611	2.52	38,456	425	570.97	480.15	32.90	2,056.17
5	60626	2.85	50,548	3,447	662.25	592.31	11.49	1,969.83
6	60614	2.94	73,173	7,521	683.33	639.67	19.25	2,344.50
7	60610	2.96	43,794	1,963	691.26	609.40	23.69	1,771.38
8	60615	3.03	43,502	3,526	736.79	644.48	11.42	2,543.47
9	60647	3.17	85,631	13,174	786.03	715.80	1.59	2,375.56
10	60613	3.25	53,048	4,115	764.87	751.67	6.06	1,698.11
11	60660	3.27	42,534	3,030	771.79	768.51	21.11	1,937.53
12	60624	3.33	37,547	9,303	852.67	777.27	10.89	2,658.66
13	60607	3.39	31,816	2,672	955.62	867.19	2.79	3,009.67
14	60603	3.40	1,288	10	1,004.34	897.54	265.46	1,908.09
15	60659	3.42	40,579	5,715	883.65	804.55	4.92	2,542.99
16	60602	3.42	1,261	12	1,076.20	852.45	77.32	2,673.71
17	60608	3.43	75,770	13,248	918.66	820.83	4.38	2,974.05
18	60657	3.43	72,316	6,363	838.19	801.47	3.23	2,011.54
19	60616	3.45	54,013	6,964	863.29	822.25	8.86	2,318.09
20	60640	3.45	65,941	4,753	843.60	806.70	28.68	2,191.47
21	60612	3.47	34,402	9,101	907.25	841.87	16.93	2,497.12
22	60609	3.47	65,770	17,777	916.68	841.01	14.71	3,550.74
23	60645	3.48	48,356	6,193	907.50	869.26	18.53	2,362.04
24	60661	3.51	11,987	290	846.89	856.34	39.39	1,604.02
25	60622	3.52	55,075	8,170	877.43	865.31	9.41	2,099.85
26	60601	3.58	15,814	77	1,384.29	1,325.59	41.62	2,915.22
27	60625	3.61	76,525	10,139	994.77	924.64	7.15	2,920.23
28	60633	3.61	13,359	4,682	1,088.58	930.21	15.94	5,634.71
29	60644	3.67	47,239	8,794	1,005.90	925.11	46.79	3,531.02
30	60642	3.70	21,687	3,023	1,043.42	957.25	39.31	2,761.09
31	60643	3.73	47,831	19,658	1,159.20	1,004.28	8.65	3,854.13
32	60637	3.74	53,555	7,961	1,209.59	1,024.07	19.88	3,465.35
33	60621	3.76	29,570	12,466	1,061.54	981.49	1.40	3,085.62
34	60617	3.78	77,270	28,320	1,087.64	1,049.91	9.68	4,752.75
35	60620	3.84	66,514	19,825	1,091.68	1,041.49	9.56	3,787.28
36	60623	3.86	87,649	16,028	1,286.76	1,094.83	16.54	4,414.88
37	60630	3.88	54,064	14,165	1,120.90	1,073.11	16.57	2,829.85
38	60651	3.92	62,819	12,257	1,140.23	1,056.32	30.22	3,489.70
39	60639	3.94	89,543	14,508	1,167.19	1,109.49	34.68	2,889.33
40	60649	3.94	48,171	6,099	1,231.37	1,135.08	28.42	3,065.46
41	60646	3.95	28,383	9,282	1,249.09	1,224.64	10.79	3,287.71
42	60619	3.99	63,303	18,841	1,264.62	1,170.83	12.00	3,421.12
43	60628	4.00	62,832	26,216	1,339.26	1,263.00	9.76	4,815.63
44	60618	4.00	90,316	15,930	1,243.09	1,196.19	12.73	3,499.85
45	60636	4.02	34,800	14,287	1,229.27	1,162.23	28.51	3,776.29
46	60631	4.05	29,691	9,078	1,335.75	1,236.05	35.76	4,960.11
47	60827	4.10	24,936	1,015	1,621.82	1,472.42	63.00	4,460.71
48	60638	4.13	56,928	17,039	1,501.24	1,367.18	17.13	4,760.52
49	60641	4.20	69,354	13,285	1,303.17	1,292.93	18.60	2,935.29
50	60655	4.20	27,837	10,402	1,603.40	1,437.19	45.26	6,588.04
51	60652	4.20	40,898	12,777	1,389.67	1,349.22	27.55	3,809.48
52	60629	4.22	114,453	24,412	1,581.02	1,480.44	49.35	4,222.59
53	60654	4.23	23,890	473	1,456.61	1,299.99	9.12	3,090.32
54	60632	4.39	92,237	17,892	1,643.95	1,532.18	16.82	4,848.88
55	60634	4.47	75,694	19,374	1,828.73	1,803.72	19.54	9,020.93
56	60656	4.54	28,474	6,851	2,348.72	2,159.48	31.39	9,876.17
57	60707	4.67	43,241	4,383	1,978.05	1,963.96	24.34	4,085.63
58	60606	4.98	3,797	80	1,934.67	1,873.95	901.24	2,759.38

C.2.2 Manchester Greenspace: Ranked Borough-Level Scores

Table C.5: Manchester Greenspace: Ranked Borough-Level Scores

Rank	Borough	Mean Risk	Population	Addresses	Mean (m)	Median (m)	Min (m)	Max (m)
1	Manchester District (B)	2.12	589,670	11,827	433.74	400.87	3.18	3,045.75
2	Stockport District (B)	2.30	303,929	5,991	524.48	408.41	2.85	3,626.58
3	Bury District (B)	2.45	198,921	4,305	539.82	449.84	9.37	2,712.50
4	Rochdale District (B)	2.46	235,561	4,945	568.94	444.74	5.81	3,142.70
5	Wigan District (B)	2.48	344,922	6,827	558.23	457.84	5.71	3,215.54
6	Bolton District (B)	2.56	310,085	6,298	615.24	474.84	6.10	3,169.60
7	Salford District (B)	2.60	294,348	5,663	582.20	519.54	10.53	3,288.30
8	Tameside District (B)	2.64	239,643	5,239	654.98	509.11	8.93	3,814.59
9	Oldham District (B)	2.69	251,560	4,986	640.92	523.59	3.51	3,518.34
10	Trafford District (B)	2.70	241,025	5,715	630.99	534.72	7.34	2,997.76

C.2.3 Portland Greenspace: Ranked Neighborhood-Level Scores

Table C.6: Portland Greenspace: Ranked Neighborhood-Level Scores

Rank	Neighborhood	Mean Risk	Population	Addresses	Mean (m)	Median (m)	Min (m)	Max (m)
1	HOMESTEAD	1.00	8251	1386	111.20	95.57	4.80	309.15
2	ARLINGTON HEIGHTS	1.00	813	332	107.73	93.82	6.57	300.40
3	WOODLAND PARK	1.02	254	104	186.78	188.15	86.87	304.99
4	ARDENWALD-JOHNSON CREEK	1.07	4706	378	117.23	93.21	11.53	414.76
5	HEALY HEIGHTS	1.08	227	91	182.86	184.74	35.17	401.29
6	BROOKLYN	1.14	3916	2371	193.63	178.79	7.71	734.40
7	PORTLAND DOWNTOWN	1.15	14127	15724	187.60	188.61	2.03	491.73
8	HILLSIDE	1.21	2405	1325	195.69	168.47	12.90	446.11
9	PEARL DISTRICT	1.26	11019	7458	222.81	213.72	14.65	481.15
10	CATHEDRAL PARK	1.27	4130	2228	214.94	195.58	6.22	565.85
11	PORTSMOUTH	1.31	10149	3984	215.28	187.57	10.58	595.84
12	UNIVERSITY PARK	1.32	7005	2172	228.47	217.85	15.10	664.97
13	PLEASANT VALLEY	1.32	13409	4623	212.59	183.61	0.74	904.43
14	OLD TOWN	1.35	4159	3055	244.67	241.52	32.91	480.75
15	LINNTON	1.39	784	866	222.70	134.04	4.65	1175.68
16	FAR SOUTHWEST	1.41	1461	725	244.80	256.85	11.98	515.17
17	SOUTH PORTLAND	1.42	8251	6836	237.44	224.94	8.35	561.78
18	SELLWOOD-MORELAND	1.43	13940	7311	254.51	232.14	4.53	709.83
19	MULTNOMAH	1.46	8395	4928	257.07	231.13	6.51	711.45
20	SOUTH BURLINGAME	1.47	1839	842	263.54	256.43	13.45	565.68
21	BRIDLEMILE	1.47	5940	2698	266.31	253.52	11.26	779.34
22	EASTMORELAND	1.47	5252	1693	265.59	260.19	10.52	850.32
23	WEST PORTLAND PARK	1.50	4080	2116	263.78	233.83	11.89	648.01
24	MILL PARK	1.51	9123	3690	276.69	260.04	9.95	681.93
25	MARSHALL PARK	1.52	1493	642	270.00	248.06	12.65	666.43
26	LENTS	1.54	22236	8978	279.05	254.15	4.02	850.07
27	ST. JOHNS	1.54	12843	6138	289.82	249.21	8.69	2592.01
28	ELIOT	1.55	5514	3076	294.38	275.92	9.06	737.02
29	KENTON	1.58	8088	3895	298.61	283.62	12.93	753.00
30	MADISON SOUTH	1.59	7208	3403	293.65	242.35	11.16	902.67
31	MAPLEWOOD	1.59	2821	1142	302.78	303.24	14.38	789.37
32	BOISE	1.60	4660	2351	307.47	325.89	25.68	553.45
33	RUSSELL	1.61	3241	1291	309.66	315.84	8.52	628.58
34	NORTHWEST DISTRICT	1.62	18319	12932	308.21	291.36	5.84	1081.18
35	HILLSDALE	1.66	8355	4046	313.06	306.89	8.09	703.71
36	KERNS	1.67	6958	4525	316.18	314.30	7.60	672.14
37	BUCKMAN	1.72	11151	7552	330.55	299.73	7.77	731.42
38	SOUTHWEST HILLS	1.75	8527	3993	334.33	238.35	8.68	1622.95
39	HAYHURST	1.76	5649	2626	345.28	335.27	24.73	1082.98
40	WOODLAWN	1.77	5145	2530	334.79	348.06	15.58	721.75
41	SABIN	1.78	4438	1967	343.44	331.72	7.86	838.36
42	PARKROSE HEIGHTS	1.79	6171	2646	348.93	344.19	13.49	752.56
43	CRESTON-KENILWORTH	1.82	9046	4391	361.36	350.13	12.92	849.73
44	HOSFORD-ABERNETHY	1.83	7713	4756	352.79	360.31	23.97	697.19
45	MARKHAM	1.84	2617	1141	359.09	368.65	25.56	645.17
46	CRESTWOOD	1.84	2575	1049	349.30	354.99	15.11	797.74
47	OVERLOOK	1.85	7229	3607	360.49	351.57	8.25	1210.04
48	FOSTER-POWELL	1.87	7827	3659	364.52	357.81	13.06	790.94
49	GLENFAIR	1.88	3663	1425	367.36	402.64	12.38	587.60

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Table C.6 – continued from previous page

Rank	Neighborhood	Mean Risk	Population	Addresses	Mean (m)	Median (m)	Min (m)	Max (m)
50	BRENTWOOD-DARLINGTON	1.89	13536	5871	362.81	378.94	0.78	737.52
51	ARGAY TERRACE	1.89	6285	3065	375.01	342.06	15.39	1295.12
52	VERNON	1.90	2932	1478	375.47	391.19	24.20	733.20
53	PIEDMONT	1.93	7033	3448	372.37	383.61	26.33	784.44
54	KING	1.94	6775	3500	393.54	384.80	20.23	855.72
55	SUNNYSIDE	1.94	8251	4565	396.30	333.72	23.67	1047.98
56	POWELLHURST-GILBERT	1.95	33070	12802	390.29	348.81	5.22	1008.41
57	GOOSE HOLLOW	1.95	7333	5279	391.54	434.55	4.02	685.03
58	EAST COLUMBIA	1.96	2205	1260	377.43	433.27	8.11	825.95
59	LLOYD	1.98	2665	1990	407.97	422.57	32.85	759.63
60	CENTENNIAL	1.99	26449	9836	389.11	388.10	0.74	963.78
61	GRANT PARK	2.00	4139	1723	400.84	385.69	15.03	875.77
62	BRIDGETON	2.01	996	1254	415.60	387.34	17.37	845.81
63	ROSEWAY	2.02	6725	3226	398.89	406.55	17.28	853.92
64	SOUTH TABOR	2.03	6633	3012	407.67	424.77	9.14	797.04
65	MT. SCOTT-ARLETA	2.05	8037	3749	410.57	411.47	18.24	892.39
66	WOODSTOCK	2.09	9931	4515	417.45	436.97	9.12	800.89
67	WILKES	2.10	9297	4245	431.03	360.95	10.12	1189.58
68	MONTAVILLA	2.11	16942	8108	421.21	425.72	12.76	914.43
69	ARBOR LODGE	2.15	6946	3127	431.62	456.70	17.33	843.84
70	LAURELHURST	2.15	4878	1933	433.62	429.95	25.22	911.71
71	MT. TABOR	2.17	10751	5125	447.71	402.77	7.77	1045.47
72	CULLY	2.21	13339	6463	451.04	458.29	16.18	1133.52
73	CONCORDIA	2.28	10238	4699	467.73	488.99	10.60	837.34
74	REED	2.28	4734	2214	454.51	476.23	25.92	854.57
75	COLLINS VIEW	2.31	3265	939	476.26	488.18	35.67	1077.27
76	HUMBOLDT	2.31	5513	2967	479.81	485.76	34.63	822.24
77	ROSE CITY PARK	2.34	9604	4338	493.05	435.41	10.63	1242.79
78	HAZELWOOD	2.37	26653	11787	495.00	501.15	10.11	1098.92
79	BEAUMONT-WILSHIRE	2.42	6080	2633	507.26	502.35	19.11	1073.06
80	NORTH TABOR	2.52	5506	3088	530.20	519.40	28.28	851.42
81	ASHCREEK	2.58	4692	2064	566.95	494.05	7.54	1322.63
82	ALAMEDA	2.59	5455	2140	547.35	532.47	34.25	1014.38
83	SULLIVAN'S GULCH	2.60	4073	2422	550.65	559.72	32.85	879.39
84	NORTHWEST HEIGHTS	2.67	5927	2645	579.20	555.76	20.03	1505.46
85	RICHMOND	2.68	13508	6608	574.69	577.55	13.55	1072.30
86	HOLLYWOOD	2.73	2248	1541	573.92	592.78	168.19	875.77
87	FOREST PARK	2.74	3027	818	693.98	498.83	15.56	2368.92
88	HAYDEN ISLAND	2.96	3000	4781	672.01	688.51	6.51	1671.53
89	IRVINGTON	3.02	8852	4426	657.13	673.90	13.79	1113.25
90	ARNOLD CREEK	3.08	3108	1203	719.51	693.50	22.15	1609.12
91	SYLVAN-HIGHLANDS	3.27	1472	908	759.34	871.08	10.58	1701.47
92	SUMNER	3.36	2116	1097	760.96	791.67	41.35	1070.36
93	PARKROSE	3.47	6253	3110	801.41	843.77	39.12	1290.58
94	SUNDERLAND	3.82	738	791	951.78	1152.70	37.94	1625.53

C.3 Mobility

C.3.1 Chicago Mobility: Ranked ZIP-Level Scores

Table C.7: Chicago Mobility: Ranked ZIP-Level Scores

Rank	ZIP	Mean Risk	Population	Addresses	Mean (m)	Median (m)	Min (m)	Max (m)
1	60604	1.00	897	49	242.28	274.75	53.09	378.14
2	60654	1.14	23890	473	249.76	208.43	24.62	897.93
3	60602	1.17	1261	12	269.24	241.58	153.30	470.01
4	60601	1.18	15814	77	262.83	211.86	32.20	1108.21
5	60603	1.20	1288	10	291.16	224.57	169.59	652.91
6	60605	1.24	34071	647	311.64	283.28	17.36	1467.03
7	60606	1.26	3797	80	315.28	245.68	30.43	834.47
8	60611	1.28	38456	425	305.84	309.09	18.63	782.70
9	60661	1.46	11987	290	381.05	344.37	44.57	1003.59
10	60612	1.49	34402	9101	400.01	358.14	19.26	1328.56
11	60642	1.61	21687	3023	457.50	424.22	20.44	1384.77
12	60610	1.62	43794	1963	457.48	383.59	15.82	1297.00
13	60613	1.65	53048	4115	475.92	421.42	6.78	1312.77
14	60616	1.65	54013	6964	463.96	404.59	8.81	2201.59
15	60657	1.67	72316	6363	476.56	432.40	5.13	1262.74

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Table C.7 – continued from previous page

Rank	ZIP	Mean Risk	Population	Addresses	Mean (m)	Median (m)	Min (m)	Max (m)
16	60607	1.68	31816	2672	483.38	392.37	19.07	2153.92
17	60622	1.69	55075	8170	487.84	439.66	27.67	1243.04
18	60637	1.69	53555	7961	490.05	419.08	22.36	1727.62
19	60640	1.70	65941	4753	491.29	426.69	15.63	2080.84
20	60653	1.70	33146	5667	503.33	437.90	20.61	1427.34
21	60623	1.71	87649	16028	494.37	427.51	25.21	1949.30
22	60608	1.71	75770	13248	499.23	443.65	7.10	1875.86
23	60647	1.73	85631	13174	508.02	439.90	29.71	1356.60
24	60644	1.75	47239	8794	508.50	439.90	27.03	1374.78
25	60615	1.75	43502	3526	521.04	476.73	16.68	1355.33
26	60651	1.77	62819	12257	520.47	449.29	20.42	1343.50
27	60649	1.77	48171	6099	525.70	449.85	8.54	1353.21
28	60660	1.78	42534	3030	529.65	464.96	33.90	1384.82
29	60609	1.80	65770	17777	525.23	441.16	8.44	2492.82
30	60614	1.80	73173	7521	528.66	465.84	22.67	1478.39
31	60636	1.82	34800	14287	537.24	491.61	3.31	1313.49
32	60624	1.82	37547	9303	528.65	411.16	12.84	2449.36
33	60618	1.82	90316	15930	541.13	471.59	11.94	1331.32
34	60625	1.82	76525	10139	537.76	467.24	15.17	1917.38
35	60621	1.82	29570	12466	535.45	444.38	8.07	1898.77
36	60626	1.83	50548	3447	548.25	473.66	44.22	1932.52
37	60639	1.84	89543	14508	548.84	472.51	37.76	1334.86
38	60634	1.93	75694	19374	584.87	517.07	28.44	4437.80
39	60632	1.93	92237	17892	581.94	483.41	15.77	2667.01
40	60641	1.94	69354	13285	584.53	519.44	29.49	1312.28
41	60630	1.96	54064	14165	596.13	539.45	9.18	2564.70
42	60645	1.99	48356	6193	609.45	530.67	27.58	2005.64
43	60619	2.00	63303	18841	620.45	522.00	12.70	2561.94
44	60659	2.13	40579	5715	673.59	554.80	30.03	2508.99
45	60620	2.19	66514	19825	683.41	571.40	33.45	2543.98
46	60629	2.25	114453	24412	717.67	580.26	7.38	2758.49
47	60617	2.31	77270	28320	912.11	566.30	26.15	7428.44
48	60628	2.49	62832	26216	827.31	668.20	5.32	5079.06
49	60707	2.51	43241	4383	846.34	710.46	28.26	2590.85
50	60638	2.55	56928	17039	850.41	609.06	29.53	2643.91
51	60643	2.68	47831	19658	910.63	772.62	19.27	2616.13
52	60655	2.81	27837	10402	985.89	840.28	45.34	4762.24
53	60646	2.88	28383	9282	1001.04	884.47	50.73	2879.58
54	60656	2.93	28474	6851	1155.18	883.64	47.86	5587.08
55	60652	2.94	40898	12777	1021.05	891.07	38.98	2628.42
56	60633	3.05	13359	4682	1805.73	854.89	41.88	7213.26
57	60631	3.26	29691	9078	1519.64	1085.08	34.76	5841.87
58	60827	3.56	24936	1015	1601.33	1250.40	37.81	4319.12

C.3.2 Manchester Mobility: Ranked Borough-Level Scores

Table C.8: Manchester Mobility: Ranked Borough-Level Scores

Rank	Borough	Mean Risk	Population	Addresses	Mean Dist. (m)	Median Dist. (m)	Min–Max (m)
1	Manchester District (B)	1.00	589,670	11,827	105.89	93.37	4.70–820.32
2	Oldham District (B)	1.01	251,560	4,986	109.29	91.57	4.57–1,433.54
3	Tameside District (B)	1.01	239,643	5,239	111.21	90.69	2.99–1,365.37
4	Trafford District (B)	1.02	241,025	5,715	131.79	113.74	6.03–1,012.56
5	Rochdale District (B)	1.02	235,561	4,945	111.56	88.68	5.93–1,485.75
6	Bolton District (B)	1.02	310,085	6,298	122.01	97.69	3.10–1,903.58
7	Salford District (B)	1.02	294,348	5,663	124.56	101.83	5.88–3,079.04
8	Bury District (B)	1.02	198,921	4,305	122.75	97.82	6.56–1,280.22
9	Stockport District (B)	1.03	303,929	5,991	134.65	109.55	3.03–1,107.54
10	Wigan District (B)	1.03	344,922	6,827	132.66	105.18	2.41–2,806.96

C.3.3 Portland Mobility: Ranked Neighborhood-Level Scores

Table C.9: Portland Mobility: Ranked Neighborhood-Level Scores

Rank	Neighborhood	Mean Risk	Population	Addresses	Mean Dist. (m)	Median Dist. (m)	Min–Max (m)
1	BUCKMAN	1.00	11,151	7,552	128.34	118.88	6.00–364.36
2	BOISE	1.00	4,660	2,351	113.65	100.92	7.32–314.86
3	ELIOT	1.00	5,514	3,076	117.99	109.35	8.53–399.07
4	LLOYD	1.00	2,665	1,990	71.73	58.61	10.28–200.12
5	KERNS	1.00	6,958	4,525	132.94	113.74	5.32–381.30
6	HOLLYWOOD	1.00	2,248	1,541	103.34	86.63	7.13–388.62
7	HUMBOLDT	1.00	5,513	2,967	126.91	127.44	4.74–294.69
8	HOMESTEAD	1.00	8,251	1,386	122.01	104.94	15.37–396.00
9	OLD TOWN	1.00	4,159	3,055	75.64	63.07	9.63–167.84
10	SUNNYSIDE	1.00	8,251	4,565	139.95	132.18	6.41–343.86
11	PORTLAND DOWNTOWN	1.00	14,127	15,724	82.10	69.44	6.32–308.57
12	WOODLAND PARK	1.00	254	104	112.16	110.96	15.55–212.68
13	SULLIVAN'S GULCH	1.00	4,073	2,422	114.15	86.16	14.59–358.32
14	PEARL DISTRICT	1.00	11,019	7,458	92.29	92.20	7.04–266.37
15	SOUTH PORTLAND	1.00	8,251	6,836	156.36	156.07	9.32–411.86
16	REED	1.00	4,734	2,214	133.41	120.52	13.42–404.40
17	UNIVERSITY PARK	1.00	7,005	2,172	177.73	169.20	8.58–410.34
18	NORTHWEST DISTRICT	1.00	18,319	12,932	106.93	99.96	6.08–429.96
19	LAURELHURST	1.00	4,878	1,933	145.13	127.43	7.96–400.66
20	VERNON	1.00	2,932	1,478	146.83	122.51	7.05–416.15
21	FOSTER-POWELL	1.00	7,827	3,659	171.44	153.91	9.67–405.69
22	SOUTH BURLINGAME	1.00	1,839	842	153.90	144.41	12.92–400.77
23	CRESTON-KENILWORTH	1.00	9,046	4,391	154.81	137.61	6.37–424.14
24	ARLINGTON HEIGHTS	1.00	813	332	132.16	118.93	12.75–406.90
25	HOSFORD-ABERNETHY	1.00	7,713	4,756	161.18	150.39	6.30–423.97
26	CONCORDIA	1.00	10,238	4,699	149.73	130.45	3.29–410.02
27	ALAMEDA	1.00	5,455	2,140	165.35	145.35	5.29–424.71
28	PORTSMOUTH	1.01	10,149	3,984	167.51	155.28	5.75–436.43
29	GLENFAIR	1.01	3,663	1,425	160.68	136.23	14.02–411.75
30	ARBOR LODGE	1.01	6,946	3,127	187.17	174.75	8.09–433.47
31	HILLSIDE	1.01	2,405	1,325	123.23	105.36	15.18–729.04
32	MADISON SOUTH	1.01	7,208	3,403	193.29	175.27	10.33–520.75
33	HEALY HEIGHTS	1.01	227	91	171.33	163.07	23.90–414.01
34	NORTH TABOR	1.01	5,506	3,088	134.26	100.20	4.33–411.88
35	HAYHURST	1.01	5,649	2,626	164.39	152.77	0.17–481.02
36	BROOKLYN	1.02	3,916	2,371	160.67	144.82	7.14–677.19
37	BEAUMONT-WILSHIRE	1.02	6,080	2,633	181.42	164.10	10.78–454.50
38	RICHMOND	1.02	13,508	6,608	173.38	160.05	4.09–456.84
39	RUSSELL	1.02	3,241	1,291	174.96	159.98	16.48–500.50
40	PARKROSE	1.03	6,253	3,110	159.04	139.71	4.03–543.45
41	ST. JOHNS	1.03	12,843	6,138	184.02	167.50	8.03–1,281.22
42	MT. SCOTT-ARLETA	1.03	8,037	3,749	189.92	168.82	3.54–421.42
43	ROSE CITY PARK	1.03	9,604	4,338	176.58	155.66	9.18–492.43
44	PARKROSE HEIGHTS	1.03	6,171	2,646	184.19	169.97	6.49–497.14
45	POWELLHURST-GILBERT	1.03	33,070	12,802	182.43	161.62	1.84–711.09
46	IRVINGTON	1.03	8,852	4,426	184.23	172.49	5.29–454.93
47	CATHEDRAL PARK	1.03	4,130	2,228	195.81	188.64	6.23–608.10
48	HILLSDALE	1.03	8,355	4,046	152.52	124.50	6.90–644.92
49	ARGAY TERRACE	1.03	6,285	3,065	154.91	134.48	1.61–552.29
50	GOOSE HOLLOW	1.04	7,333	5,279	108.92	83.82	0.40–564.63
51	ARDENWALD-JOHNSON CREEK	1.04	4,706	378	210.26	218.01	16.37–513.26
52	OVERLOOK	1.04	7,229	3,607	200.51	188.85	6.15–634.29
53	GRANT PARK	1.04	4,139	1,723	199.72	188.41	18.15–453.55
54	KING	1.04	6,775	3,500	168.72	147.75	4.58–452.23
55	MT. TABOR	1.04	10,751	5,125	170.48	153.66	3.54–626.59
56	PIEDMONT	1.04	7,033	3,448	170.24	146.45	1.30–620.38
57	KENTON	1.05	8,088	3,895	189.17	167.90	4.79–1,114.10
58	MULTNOMAH	1.06	8,395	4,928	173.58	142.52	7.40–508.45
59	WOODSTOCK	1.06	9,931	4,515	177.58	151.43	3.07–527.11
60	MONTAVILLA	1.06	16,942	8,108	185.16	154.03	6.59–642.83
61	LINNTON	1.07	784	866	196.38	193.80	14.02–2,233.11
62	SABIN	1.07	4,438	1,967	194.43	168.74	10.24–517.42
63	ROSEWAY	1.07	6,725	3,226	195.23	161.61	11.20–685.18
64	SOUTH TABOR	1.08	6,633	3,012	206.34	188.25	2.02–493.37
65	WOODLAWN	1.08	5,145	2,530	203.33	180.93	5.81–684.91
66	WEST PORTLAND PARK	1.09	4,080	2,116	182.16	158.22	11.98–565.72
67	FAR SOUTHWEST	1.10	1,461	725	192.60	168.98	17.48–609.25
68	LENTS	1.10	22,236	8,978	215.06	184.28	7.33–862.64
69	HAZELWOOD	1.10	26,653	11,787	211.24	172.71	2.94–855.73
70	BRENTWOOD-DARLINGTON	1.11	13,536	5,871	223.37	189.57	6.35–673.74
71	ASHCREEK	1.13	4,692	2,064	212.43	185.22	16.15–590.55
72	WILKES	1.13	9,297	4,245	235.65	205.06	4.28–826.99
73	MAPLEWOOD	1.14	2,821	1,142	214.19	168.64	16.17–620.13
74	MILL PARK	1.14	9,123	3,690	230.98	204.05	2.03–733.06
75	CENTENNIAL	1.15	26,449	9,836	240.42	213.85	10.39–1,184.26
76	CULLY	1.16	13,339	6,463	242.54	200.76	4.47–1,003.50
77	SELLWOOD-MORELAND	1.17	13,940	7,311	237.55	201.07	7.61–907.39
78	ARNOLD CREEK	1.17	3,108	1,203	244.95	196.31	14.24–949.50
79	SUMNER	1.18	2,116	1,097	230.20	177.43	14.21–933.53
80	BRIDLEMILE	1.19	5,940	2,698	234.40	156.00	11.46–991.19
81	COLLINS VIEW	1.19	3,265	939	247.86	219.60	16.87–645.97
82	CRESTWOOD	1.23	2,575	1,049	277.55	255.47	18.27–663.46
83	BRIDGETON	1.24	996	1,254	300.58	270.06	34.03–629.96
84	SOUTHWEST HILLS	1.34	8,527	3,993	318.35	277.44	13.52–1,068.83
85	MARKHAM	1.38	2,617	1,141	364.26	342.36	16.82–821.79
86	SYLVAN-HIGHLANDS	1.52	1,472	908	401.69	412.10	25.11–805.54
87	EAST COLUMBIA	1.53	2,205	1,260	360.82	309.45	13.91–1,050.64
88	EASTMORELAND	1.59	5,252	1,693	432.14	460.05	13.49–836.59
89	SUNDERLAND	1.71	738	791	519.67	638.48	13.45–1,262.94
90	HAYDEN ISLAND	1.78	3,000	4,781	543.45	544.11	28.93–1,166.73
91	MARSHALL PARK	2.08	1,493	642	598.69	593.86	27.19–1,090.72
92	PLEASANT VALLEY	2.35	13,409	4,623	736.44	388.88	1.84–3,107.01
93	FOREST PARK	4.44	3,027	818	1,979.18	2,131.69	137.39–3,201.50
94	NORTHWEST HEIGHTS	4.93	5,927	2,645	2,142.14	2,127.00	1,141.48–2,970.00