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Transportation and Land Use Planning for Healthy Cities

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Abstract

Healthy cities provide physical and mental health benefits to citizens. To promote scientific transportation and land use planning for healthy cities, robust geospatial methods are required. This thesis introduces two new geospatial methods to facilitate healthy transportation and land use planning. First, to help healthy land use planning, a new analytical framework for identifying green space deserts based on various walking distance thresholds is introduced. This method is particularly useful in low-middle-income countries in the Global South where guidelines for proper walking distance thresholds to green spaces are missing. Second, to aid healthy transportation planning, a new measure of transit-based accessibility is proposed to incorporate transit users' exposure to extreme weather events. This measure will enhance the preparedness of our society and transportation systems for climate change. Together, the two geospatial methods developed in this thesis will guide informed policymaking efforts to make our world more liveable, sustainable, and healthier.

Keywords

Healthy Cities, Land Use, Transportation, Planning, Urban Green Space, Public Transit, Public Health

Summary for Lay Audience

Healthy cities prioritize public health through various means such as providing accessible green spaces, promoting physical activity, and minimizing negative health outcomes for citizens. This research highlights the importance of scientific and evidence-based land use and transportation planning as a key strategy in fostering healthy cities. By contributing to the ongoing challenges of healthy city development this thesis introduces two geospatial methods to advance healthy land use and transportation planning, aligning with the objectives of creating healthy cities. First, in order to help healthy land use planning, a new analytical framework for identifying urban green space deserts and oases based on various walking distance thresholds is introduced. This new method is particularly useful in low- and middle-income countries in the Global South where well-established guidelines for proper walking distance thresholds to urban green space are missing. This method will also help us understand the inequalities in green space distribution in the cities of the Global South. Second, to aid healthy transportation planning, a new measure of transit-based accessibility is proposed to incorporate public transit users' exposure to extreme weather events such as extreme heat or cold. This new accessibility measure will enhance the resilience and preparedness of our society and transportation systems under climate change. Together, these two newly developed methods serve as strategic tools to support the creation of healthier cities, emphasizing the importance of evidence-based and healthy planning in achieving positive public health outcomes and making our world more livable, sustainable, and healthier.

Co-Authorship Statement

This thesis is presented in an integrated article format with two related studies. Each integrated article has been published or submitted for publication in a peer-reviewed journal.

Chapter 2: Ahmed, N., Lee, J., Liu, D., Kan, Z., & Wang, J. (2023). Identifying urban green space deserts by considering different walking distance thresholds for healthy and socially equitable city planning in the Global South. *Urban Forestry & Urban Greening*, 89, 128123. (Published) DOI: https://doi.org/10.1016/j.ufug.2023.128123

Chapter 2 was written by Naser Ahmed with Dr. Jinhyung Lee, Dr. Dong Liu, Dr. Zihan Kan, and Dr. Jinfei Wang. Naser Ahmed conceptualized the paper and developed the methodology, performed the analysis, and wrote the first draft, and is the first author. Dr. Lee supervised the project, was involved in conceptualizing and developing the methodology, and contributed to editing the manuscript. Dr. Liu was involved in conceptualization, formal analysis, and reviewing the paper. Dr. Kan was involved in conceptualization, formal analysis, and reviewing the paper. Dr. Wang supervised the project, was involved in co-conceptualizing the methodology and contributed to reviewing and editing the manuscript.

Chapter 3: Ahmed, N., Lee, J., Liu, L., Kim, J., Jang, K. M., Wang. J. (2023). The cost of climate change: A general cost function approach for incorporating extreme weather exposure into public transit accessibility., Computers, Environment and Urban Systems, Elsevier (Under Review)

Chapter 3 was written by Naser Ahmed with Dr. Jinhyung Lee, Dr. Luyu Liu, Dr. Junghwan Kim, Dr. Kee Moon Jang, and Dr. Jinfei Wang. Naser Ahmed conceptualized the paper and developed the methodology, conducted the analysis, and wrote the first draft, and is the first author. Dr. Lee supervised the project, was involved in conceptualizing and developing the methodology, and contributed to editing the manuscript. Dr. Liu was involved in conceptualization, formal analysis, and reviewing the paper. Dr. Kim was involved in conceptualization, formal analysis, and reviewing the paper. Dr. Jang was involved in conceptualization, formal analysis, and reviewing the paper. Dr. Wang supervised the project, was involved in co-conceptualizing the methodology and contributed to reviewing and editing the manuscript.

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List of Abbreviations

Artificial Neural Network	ANN
Dhaka North City Corporation	DNCC
Dhaka South City Corporation	DSCC
Dhaka Transport Co-ordination Authority	DTCA
Dissemination Block	DB
Dissemination Area	DA
General Transit Feed Specification	GTFS
Land Surface Temperature	LST
Land Use and Land Cover	LULC
Low- and Middle-Income Countries	LMICs
Manitoba	MB
Maximum Likelihood Classification	MLC
Moderate Resolution Imaging Spectroradiometer	MODIS
Normalized Difference Vegetation Index	NDVI
Open Street Map	OSM
Operational Land Imager	OLI
Per Capita Green Space	PCG
Rajdhani Unnayan Kartripakkha	RAJUK
Random Forest	RF
Support Vector Machine	SVM
Sustainable Development Goals	SDGs
Thermal Infrared Sensor	TIRS
Top of Atmosphere	TOA
Total Degree Minutes	TDM
Urban Green Space	UGS

Chapter 1

1. Introduction

1.1 Research context

A healthy city aims to provide physical and mental well-being for its citizens (Hancock & Bezold, 2017). According to the World Health Organization (WHO), a healthy city cannot be determined based on a particular health status; instead, it involves an ongoing effort to improve the health outcomes of residents by enhancing both the physical and social environment of the city (WHO, 2023). In addition, healthy cities take proactive measures in battling the negative consequences of climate change (Bentley, 2007). Promoting healthy cities demands the application of scientific, evidence-based approaches, which include the integration of urban and transport planning, environment, and health (Nieuwenhuijsen, 2020). As a result, introducing various measures of healthy city goals has received significant attention among urban planners and practitioners in recent years (Bafarsat and Sharifi et al., 2024).

Climate change is leading to serious health issues in urban areas (Paavola, 2017; Louse and Hess, 2008; Haines et al., 2006). The increase in greenhouse gas (GHG) emissions from power, industry, transportation, and domestic aviation, combined with a reliance on non-renewable energy sources, is driving long-term changes in the climate (Liu et al. 2023 Alterations in weather patterns due to climate change are resulting in more frequent and severe extreme weather events, such as heatwaves (Brown, 2020), unpredictable winters (Jalili et al. 2010), sudden flooding (Brobstert, 2003), and wildfires (Halofsky et al. 2020) all of which can impact urban areas (Banholzer et al., 2014). These, in turn, can lead to a rise in illnesses associated with heat, cold, and respiratory problems, which is straining healthcare systems already grappling with the impacts of climate change on disease patterns (Mora et al., 2022). Consequently, there has been a notable uptick in various health-related ailments within cities in recent years (Patz et al., 2003), including asthma, diarrhea, skin diseases, and heat stroke (Mora et al., 2022). Furthermore, the limited availability of green spaces in cities is indirectly causing a reduction in rainfall patterns (Zhang et al. 2015), introducing new risks of waterborne diseases during floods and presenting a dual health hazard (Willems et al., 2012). What is worse is that the health effects are not the same for everyone, and marginalized communities face even greater health risks due to social and economic inequalities (Roberts, 2001).

Cities around the world are realizing the need to tackle the root causes of climate change, mainly reducing greenhouse gas emissions, and also moving toward *urban greening*-public landscaping and urban forestry projects that create mutually beneficial relationships between city dwellers and their environments (Gogilo et al., 2020; Bowler et al., 2010). Switching to renewable energy, promoting sustainable transportation, and incorporating green spaces into city planning are essential parts of a comprehensive strategy to fight climate change, protect public health, and build cities that can withstand future challenges (Fawzy et al., 2020).

For instance, green spaces offer a dual benefit by positively impacting both public health and the fight against climate change (Sturiale and Scuderi, 2019). Firstly, green spaces provide essential recreational spaces that promote physical and mental well-being (Zhou & Rana, 2012; Maas et al., 2006). Access to green spaces encourages physical activity, reducing the risk of chronic illnesses such as obesity and cardiovascular diseases (Sadler et al., 2010). Additionally, exposure to nature has proven psychological benefits, reducing stress and improving overall mental health. Beyond individual well-being, green spaces play a crucial role in mitigating and adapting to climate change. They also contribute to cooling urban environments through shade and transpiration, mitigating urban heat and thus reducing GHG emissions associated with cooling energy demand. Strategically integrating green spaces into urban planning not only fosters healthier communities but also contributes to the overall resilience of cities in the face of climate challenges.

Similarly, public transit serves as a crucial ally in the battle against climate change by significantly reducing car dependency (Hensher, 2008). Public transit systems are generally more energy-efficient, transporting larger numbers of people with fewer emissions per capita compared to individual cars (Liu et al., 2019). By promoting mass transit, cities can reduce air pollution, thereby curbing the emission of greenhouse gases. Furthermore, the integration of efficient public transit options encourages people to do more physical activities such as walking and biking. The collective impact of increased public transit use not only contributes to immediate emissions reduction but also fosters a shift towards a more sustainable and environmentally friendly urban transportation paradigm.

The importance of urban green spaces (UGS) as a part of healthy city planning has been widely acknowledged by researchers for positive health benefits and fighting climate change (Zhou & Rana, 2012; Maas et al., 2006). Consequently, how to ensure required green spaces in cities has received significant research interest. Significant efforts have been made in this regard, by understanding the accessibility, availability, and inequalities in UGS distribution (Kabisch et al., 2016; Dai, 2011, Huang et al., 2023). As research, various criteria have been proposed, including the distance at which green space should be available, the amount needed for health benefits, and the equal distribution of existing green spaces. While cities in the Global North have proposed planning and policies regarding green space provision, we found limited research related to green space distribution in the developing cities of the Global South. However, the entire planet being a global village, it is equally important to investigate the availability of green space in such cities and facilitate green space where needed. To investigate green space availability, the first step is to ensure the required green spaces for health benefits followed by the distance to it. Although there are a few thresholds regarding the quantity, a lingering question in the Global South context is the appropriate walking distance threshold due to the lack of consensus in the literature and planning guidelines. Addressing this gap, Chapter 02 of this thesis contributes to healthy land use planning by developing an analytical framework for identifying UGS deserts, and areas lacking adequate UGS availability, considering different walking distance thresholds. Moreover, this chapter investigates inequalities in green space availability.

In addition, efficient, affordable, and accessible public transit provides various benefits, including promoting physical activity through first- and last-mile walking and reducing private automobile use, consequently minimizing greenhouse gas emissions (Nieuwenhuijsen, 2020). However, the exposure of public transit users to environmental conditions, such as extreme heat, cold, and air pollution, poses health risks that have been overlooked in the literature on public transit accessibility, despite their increasing importance in the context of climate change. It is essential to investigate whether such environmental exposures disproportionately affect marginalized public transit users. Chapter 03 of this thesis investigates these issues by incorporating exposure to extreme weather into public transit accessibility and examining how this extreme exposure factor affects marginalized population groups.

Scientifically informed and healthy land use planning holds significant importance in fighting climate change impacts, ensuring adequate access to green spaces, and implementing transportation infrastructure that enhances walkability, bikeability, and public transit use (Barton, 2009). Similarly, evidence-based and healthy transport planning plays a crucial role in shaping urban environments that prioritize healthy mobility options (Nieuwenhuijsen, 2020). Considering the negative health impacts on pedestrians and public transit users in transportation planning allows us to deliver a healthier urban environment for citizens. However, erroneous land use and transport planning that overlooks citizens' health can lead to significant morbidity and premature mortality (Stevenson et al., 2016). For instance, a study reports that flawed land use and transport planning caused nearly 3,000 annual premature deaths in Barcelona (Mueller et al., 2017). The primary reasons were a failure to meet guidelines to facilitate required access to urban green spaces and a lack of consideration for exposure to extreme weather and pollution in the planning strategy (Mueller, Rojas-Rueda, Basagaña, Cirach, Cole-Hunter, et al., 2017).

Practical and robust geospatial methods can contribute to evidence-based, scientific, and healthy land use and transportation planning. For instance, high-resolution remote sensing data and advanced geospatial models, for example, enable planners to strategically implement healthy land use planning, particularly in evaluating the availability and accessibility of green spaces within urban landscapes. Additionally, advanced transportation models can guide planners in minimizing citizens' health risks associated with various transportation modes, such as walking, biking, and public transit, by evaluating their exposure to extreme weather and pollution during city movement.

By prioritizing sustainable urban planning through advanced geospatial techniques, healthy cities can enhance resilience against extreme weather events and climate change impacts. High resolution geospatial information on green spaces and healthier public transit systems not only promote physical and mental well-being but also serve as effective carbon sinks, absorbing greenhouse gases and mitigating urban heat. Implementing effective policies that enhance green space availability and promote eco-friendly transportation options can collectively reduce carbon emissions. By fostering healthier, more sustainable urban environments, healthy cities can effectively address climate change impacts while simultaneously improving the quality of life for their residents.

To ensure citizen's health and prepare our cities for future climate change consequences, this thesis contributes to the ongoing efforts of healthy city planning by proposing two new geospatial methods. The proposed geospatial methods in this thesis contribute to the existing literature both conceptually and methodologically by informing urban planners, local governments, and policymakers to make our world more liveable, sustainable, and healthier. Chapter 2 makes a methodological contribution to the existing literature by developing an analytical framework applicable in geographic contexts where local policies lack information on the distance people would be willing to travel to access green spaces. This chapter addresses this gap by providing a framework that can guide decision-making processes in such scenarios. On the other hand, Chapter 3 contributes both conceptually and methodologically to the fields of transportation geography and planning. Firstly, it introduces a new accessibility metric that incorporates environmental exposure as a new variable, making a conceptual contribution. Secondly, the chapter refines the existing methodology by integrating environmental exposure into the assessment of public transit accessibility.

1.2 Research objectives

This thesis develops two new geospatial methods to advance land use and transportation planning in pursuit of healthy city objectives: 1) a new analytical framework for identifying urban green space deserts by considering various walking distance thresholds (Chapter 2) and 2) a new accessibility measure that incorporates extreme weather exposure during public transit travel (Chapter 3).

The following chapters of this thesis are guided by several research objectives related to healthy land use and transportation planning and are applied to two cities located in the Global South and North. Chapter 2 which is related to healthy land use planning is applied to Dhaka, a city in a Global South developing country, Bangladesh, while Chapter 3 which proposed a healthy transportation planning approach is applied to Winnipeg, Canada, a city in the Global North.

Chapter 2 comprises three research objectives:

- To investigate whether and how the geographic distributions of limited green space areas can be sensitive to the choice of a walking distance threshold.
- To develop an analytical framework to detect areas with limited green space, regardless of various walking distance thresholds, for more reliable and accurate identification of underserved areas.
- To conduct a statistical test to examine the differences in socioeconomic characteristics between UGS desert and oasis areas.

Chapter 3 has three research objectives:

- To develop a generalized framework for measuring public transit accessibility considering exposure to extreme weather as an environmental health cost.
- To demonstrate the applicability of the proposed framework within the context of extreme cold in the city of Winnipeg, MB, Canada.
- To perform a statistical test to investigate the differences in socioeconomic characteristics between areas experiencing accessibility loss and gain.

1.3 Thesis format

This thesis is structured into four chapters, with Chapters 2 and 3 adopting an integrated article format. **Chapter 1** serves as the introduction, providing a comprehensive overview of the research context, objectives, and the overall structure of the thesis.

Chapter 2 discusses the research question concerning land use planning in cities of the Global South. It introduces a new analytical framework aimed at identifying areas with limited green space availability considering various walking distance thresholds into a single framework.

In **Chapter 3**, an improved transportation planning approach is developed that combines travel time and environmental exposure. This results in a comprehensive measure of public transit accessibility designed for the cities in the Global North.

The concluding **Chapter 4** serves to summarize key findings from the integrated articles. Additionally, it discusses the contributions of the research, acknowledges its limitations, and provides recommendations for future studies. The implications of the findings for both policy and practice are also explored in this final chapter.

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Chapter 2

2. Identifying urban green space deserts by considering different walking distance thresholds for healthy city planning in the Global South[1]

2.1 Introduction

Researchers have long discussed the importance of urban green space (UGS) in improving quality (Zhou & Rana, 2012) and positivity (Maas et al., 2006) in daily life. In addition, UGS can play significant roles in providing essential biodiversity, reducing air pollution, controlling heat island effects, improving psychological and physical health benefits, and fighting the negative consequences of climate change (Cohen-Cline et al., 2015; Liu et al., 2021; Song et al., 2021). As a result, identifying areas without an adequate level of UGS availability – UGS deserts – based on the standards provided by local governments has received significant attention among urban planners and practitioners in recent years (Kabisch et al., 2016; Sikorska et al., 2020; Xu et al., 2018; Koprowska et al., 2020; Łaszkiewicz et al., 2018).

The first step to identifying UGS deserts is to measure neighbourhood-level UGS availability – the amount of urban green space within a certain walking distance threshold from residential locations in a neighbourhood (Koprowska et al., 2020). When measuring UGS availability, a *lingering question* is which walking distance threshold (e.g., 100-meter, 300-meter, 500-meter) should be used since there is no consensus on that in the literature (Wüstemann et al., 2017; Barbosa et al., 2007). If local governments, planners, and policymakers do not provide official guidelines for walking distance thresholds, the

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[1]A version of this chapter has been published (Ahmed, N., Lee, J., Liu, D., Kan, Z., & Wang, J. (2023). Identifying urban green space deserts by considering different walking distance thresholds for healthy and socially equitable city planning in the Global South. *Urban Forestry & Urban Greening*, 89, 128123. DOI: https://doi.org/10.1016/j.ufug.2023.128123)

situation becomes worse. For instance, in low- and middle-income countries (LMIC) in the Global South where well-defined local policy guidelines for walking distance thresholds are missing, UGS availability is often evaluated by using a single ad-hoc or arbitrary walking distance threshold, which can lead to an erroneous measurement of UGS availability (Malca and Haddad 2016; Dinda et al., 2021; Song et al. 2021; Singh, 2018).

This unreliable way of detecting UGS deserts can hinder evidence-based land use planning and result in erroneous inequality evaluation regarding the UGS provision since the level of UGS availability and the geographic distribution of UGS deserts may fluctuate depending on the walking distance threshold of choice. Kabisch et al., (2016) found that the availability of UGS significantly fluctuates depending on the distance threshold of choice: 300-meter versus 500-meter, in European cities. Another issue associated with the use of a single walking distance threshold is that it may overlook individuals' heterogeneous levels of mobility. In other words, it can overlook the fact that peoples' walking distance thresholds can differ based on their willingness to walk, ability to walk, and need to reach desired UGS.

To address these limitations, this study develops an analytical framework for identifying UGS deserts by considering various walking distance thresholds. We first demonstrated how the geographic distribution of UGS deserts can be sensitive to the walking distance threshold of choice. We used high-resolution remotely sensed data for measuring the UGS availability of neighbourhoods. Further, given the variability in the spatial patterns of UGS deserts depending on the walking distance threshold used, we introduced and examined *robust UGS oases and deserts*: geographic areas with and without the UGS availability level recommended by a local government organization regardless of different walking distance thresholds used, respectively.

Specifically, this study has three interrelated research objectives:

- To investigate whether and how the geographic distributions of UGS deserts can be sensitive to the choice of a walking distance threshold.
- To develop an analytical framework that enables the detection of robust UGS deserts for more reliable and accurate identification of underserved areas.

- To conduct a statistical test comparing the socioeconomic characteristics of UGS desert and oasis areas, with the goal of investigating whether socially disadvantaged population groups are more likely to be situated in areas with limited green spaces.

From the practical standpoint, detecting robust UGS deserts and oases considering various walking distance thresholds will provide policymakers and planners with a reliable measure of UGS availability that enables better informed and evidence-based planning for promoting equitable access to UGS. This would also facilitate achieving the sustainable development goals (SDGs) towards healthy, sustainable, and resilient communities (Hak et al., 2017). More importantly, our robust UGS deserts approach can be a useful alternative for UGS availability research and planning in LMICs of the Global South where walking distance thresholds for measuring UGS availability are yet to be determined due to the lack of well-defined policy guidelines. To demonstrate this, we applied the proposed approach in Dhaka, a rapidly developing capital city of Bangladesh. Using the identified robust UGS deserts and oases, we conducted further analysis to compare the socioeconomic characteristics between these two types of areas.

We organized the remainder of the paper as follows: the second section contains a literature review on UGS availability studies, and section three describes the study area and data. The methodology used in the study is presented in section four. Sections five, six, and seven demonstrate the result, discussion, and conclusion, respectively.

2.2 Background

2.2.1 Definition of UGS

UGS is usually defined as any type of vegetation (e.g., forest cover, trees, parks, residential gardens, playgrounds, grassland, and any other natural areas) that exists within city boundaries whether they are formal or informal green space (Dallimer et al., 2011; Dinda et al., 2021; Kloek et al., 2013; Wang et al., 2018). However, in many existing studies (Kabisch et al., 2016; Koprowska et al., 2018; Xu et al., 2018; Fan et al., 2017; Liu et al., 2021), only formal UGS such as designated public parks and/or playgrounds is considered when measuring UGS availability and accessibility, which undermines the importance of informal UGS (e.g., road and railway greenspace, rooftop, or residential green space). For instance, Sikorska et al. (2020) identified the equal importance of formal and informal green spaces for tackling negative health outcomes. To this end, we considered both formal and informal UGS to evaluate UGS availability in this study.

2.2.2 UGS availability standards

UGS availability refers to the presence or existence of green spaces located within a specific walking distance threshold from residential areas in urban settings (Biernacka et al. 2020; Kabisch et al., 2016). It is important to note that UGS availability should not be conflated with accessibility. While certain green spaces may be available, it does not necessarily imply that they are physically accessible due to factors such as being non-public, fenced, or potentially unsafe during nighttime (Kabisch et al., 2016).

Existing studies have employed different standards in terms of adequate UGS availability levels, recognizing domestic policy guidelines. For instance, Kabisch et al., (2016) used a per capita green space (PCG) of 2 ha for investigating whether European cities satisfy the given PCG threshold or not. On the contrary, due to the lack of articulated policies regarding the minimum required green space availability level, studies conducted in developing cities such as Kolkata, India (Dinda et al., 2021), and Bathinda, India (Singh, 2018), used 9 m^2 per capita. In terms of the desired level of UGS availability, we used a PCG value of 3.48 m^2/person. This metric was chosen based on the guidelines provided by the local planning organization Rajdhani Unnayan Kartripakkha (RAJUK) in Dhaka, as outlined in the Dhaka Structure plan (2016-2035) (RAJUK, 2015).

2.2.3 Motivation: Walking distance thresholds used in UGS availability studies

Previous UGS availability research has used various walking distance thresholds to either reflect local policy contexts or based on arbitrary decisions. Some studies (Dinda et al., 2021; Singh, 2018) did not even consider people's mobility and instead evaluated UGS availability only within their residential neighbourhoods. **Table 2.1** summarizes various walking distance thresholds used in the literature.

Table 2-1: Walking distance thresholds used in previous UGS availability studies.

Previous studies	Distance threshold used	Geographic context
Wüstemann et al., (2017)	500 meters	Schwerin and Bergisch Gladbach, Germany
Kabisch et al., (2016)	300 and 500 meters	Berlin, Germany and Lodz, Poland
Sikorska et al., (2020)	300 meters	Warsaw and Lodz, Poland
Xu et al., (2018)	300 meters	Munich, Germany
Koprowska et al., (2020)	1000 meters	Lodz, Poland
Koprowska et al., (2018)	300 meters	Lodz, Poland
Łaszkiewicz et al., (2018)	300 meters	Lodz, Poland
Dinda et al., (2021)	No distance used	Kolkata, India
Singh, (2018)	No distance used	Bathinda, India

For example, Wüstemann et al., (2017) used a 500 meters buffer around the centroid of the grid cell/household to quantify green space availability in German cities. Kabisch et al., (2016) evaluated UGS availability for two European cities (Berlin, Germany and Lodz, Poland) by using two distance thresholds (300 and 500 meters) around green and forest areas. Sikorska et al., (2020) examined the contribution of informal UGS in alleviating disparities in UGS availability for children and the elderly using a 300 meters distance from each resident's location. Similarly, Xu et al., (2018) also used a maximum of 300 meters distance around the selected green spaces and all settlement areas for demonstrating the influence of urban spatial structure on UGS availability. The interlinkage between urban sprawl and UGS availability was investigated by Koprowska et al., (2020), where a 1,000 meters buffer around the household address point was used for the analysis. A relationship between noise exposure and UGS availability using a 300 meters buffer around household location was investigated by Koprowska et al., (2018).

Based on the studies consulted it is evident that there is no consensus or uniform rule regarding the appropriate distance threshold for measuring UGS availability (Wüstemann et al., 2017). Relying solely on a single ad-hoc distance threshold can lead to unreliable identification of UGS deserts since the magnitude of UGS availability can vary depending on the chosen threshold. Such an approach can hinder evidence-based land use planning and result in inaccurate evaluations of UGS provision within urban areas.

This can be especially true in low- and middle-income countries (LMICs) in the Global South. In these regions, well-defined local policy guidelines for walking distance thresholds are often lack, leading to UGS availability assessments based on singular, ad-hoc, or arbitrary walking distance thresholds. Such assessment can be misleading. Moreover, relying solely on a single distance threshold might overlook the fact that individuals can have different walking distance thresholds based on their willingness, ability, and need to access desired UGS. To tackle these issues, this study introduces a new analytical framework that integrates various walking distance thresholds to measure UGS availability more accurately and identify UGS desert areas with greater reliability.

2.3 Study area and Data

2.3.1 Study area

Dhaka, the largest city in Bangladesh, is situated at the centre of the country and is home to approximately 6.9 million residents according to the Population & Housing Census Bangladesh 2011 (BBS, 2014). It is located at the coordinates 23°46’ N and 90°23’ E in South Asia, as depicted in **Figure 2-1**. The city is divided into two city corporations: the

Dhaka South City Corporation (DSCC) with 56 Wards, and the Dhaka North City Corporation (DNCC) with 36 Wards, as shown in **Figure 2-1**. In recent decades, Dhaka has undergone rapid urbanization, which has led to the loss of urban green spaces, playgrounds, and wetlands (Buyantuyev & Wu, 2010). This unplanned and rapid expansion has resulted in a disregard for the equitable distribution of green spaces, making Dhaka a prime example of the challenges faced by developing cities in the Global South. For these reasons, Dhaka was selected as an example study area to investigate the geographic distribution of UGS deserts and oases in such cities of the Global South.

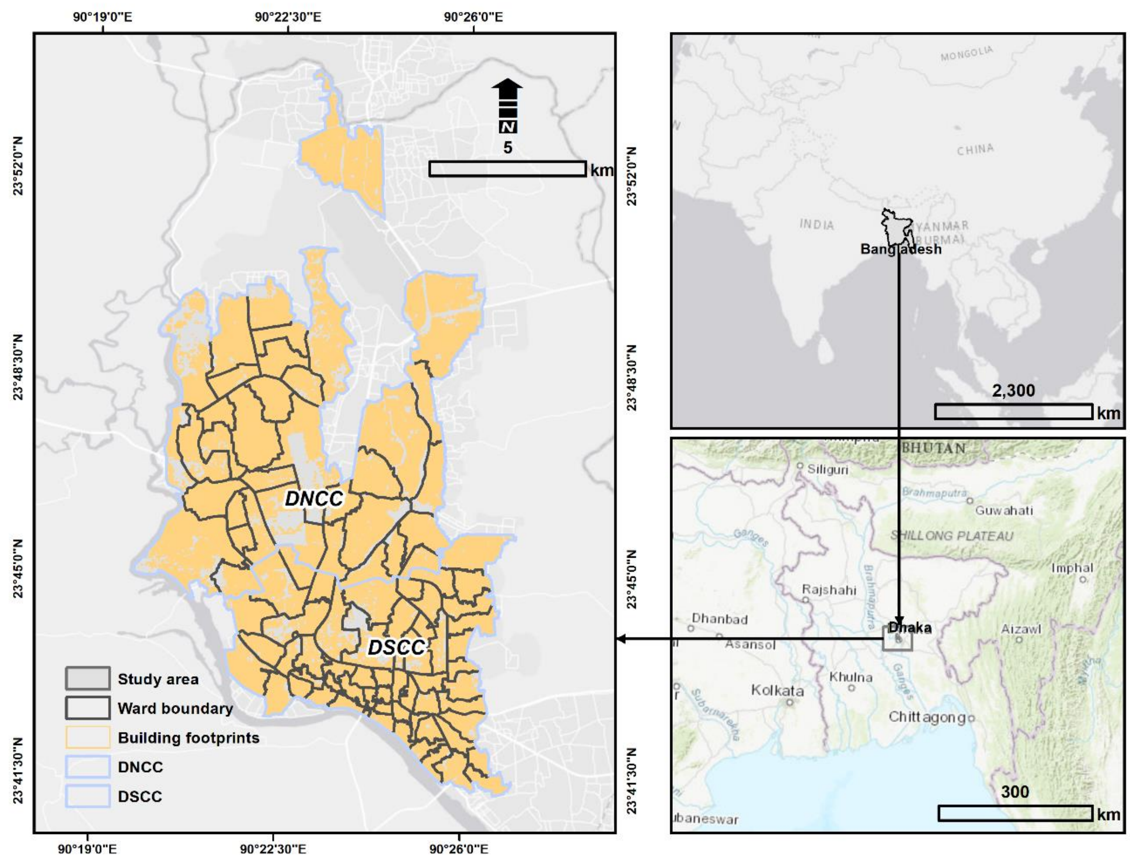

Figure 2-1: A map of study areas.

2.3.2 Data sources

Table 2-2 presents an overview of the datasets used in this study. To create the UGS dataset, we classified high-resolution satellite images (RapidEye at 5-meter resolution) from RapidEye (2011). We applied two criteria for selecting the images: 1) minimum cloud coverage and 2) leaf-on-season (i.e., April with abundant leafage) to separate the variability of vegetation reflectance from other land use and land cover (LULC) components. We also utilized high-resolution Google Earth images to enhance the accuracy of LULC classification by manually checking the selected LULC features (Lisle, 2006).

Socioeconomic information was obtained from the Population & Housing Census Bangladesh for 2011 (BBS 2014). The spatial unit of analysis considered for the study was the Ward. In the context of the current study areas, Ward is the smallest administrative unit with socioeconomic and population information available. While utilizing a unit smaller than the Ward might have offered a more detailed and nuanced understanding, finer-resolution spatial units with population data were not available. Additionally, the socioeconomic variables employed in this study were also exclusively available at the Ward level. Building footprints data used as residential locations for the UGS availability analysis was also obtained from the Population & Housing Census Bangladesh for 2011 (BBS 2014).

Lastly, we used road network data obtained from the Dhaka Transport Co-ordination Authority (DTCA) for the year 2014 to create a street network dataset for network buffer analysis. Since road network data for 2011 was unavailable, we used the road network data for 2014, which is the closest year to the other datasets used in this study.

Table 2-2: Datasets used in this study.

Data	Sources	Year
Urban green space	RapidEye (planet.com)	2011
Administrative boundary (Ward)	Dhaka South City Corporation (dscc.gov.bd)	2011
Building footprints	Population & Housing Census Bangladesh (bbs.gov.bd)	2011
Road network	Dhaka Transport Co-ordination Authority (dtca.portal.gov.bd)	2014
Dependent population, unemployment, literacy, and homeless population	Population & Housing Census Bangladesh (bbs.gov.bd)	2011

2.4 Methods

2.4.1 Robust UGS deserts and oases analysis

In this section, we describe analytical procedures for identifying robust UGS deserts and oases. There are four steps listed below and **Figure 2-2** illustrates these analytical steps in a flow chart.

- **Step 1**: Extract UGS data from high-resolution remote sensing images.
- **Step 2**: Measure UGS availability based on each of three walking distance thresholds: 100-meter, 300-meter, and 500-meter.
- **Step 3**: Classify neighbourhoods into UGS deserts and oases based on each walking distance threshold.
- **Step 4**: Identify robust UGS deserts and oases by synthesizing three UGS deserts and oases maps based on the three walking distance thresholds.

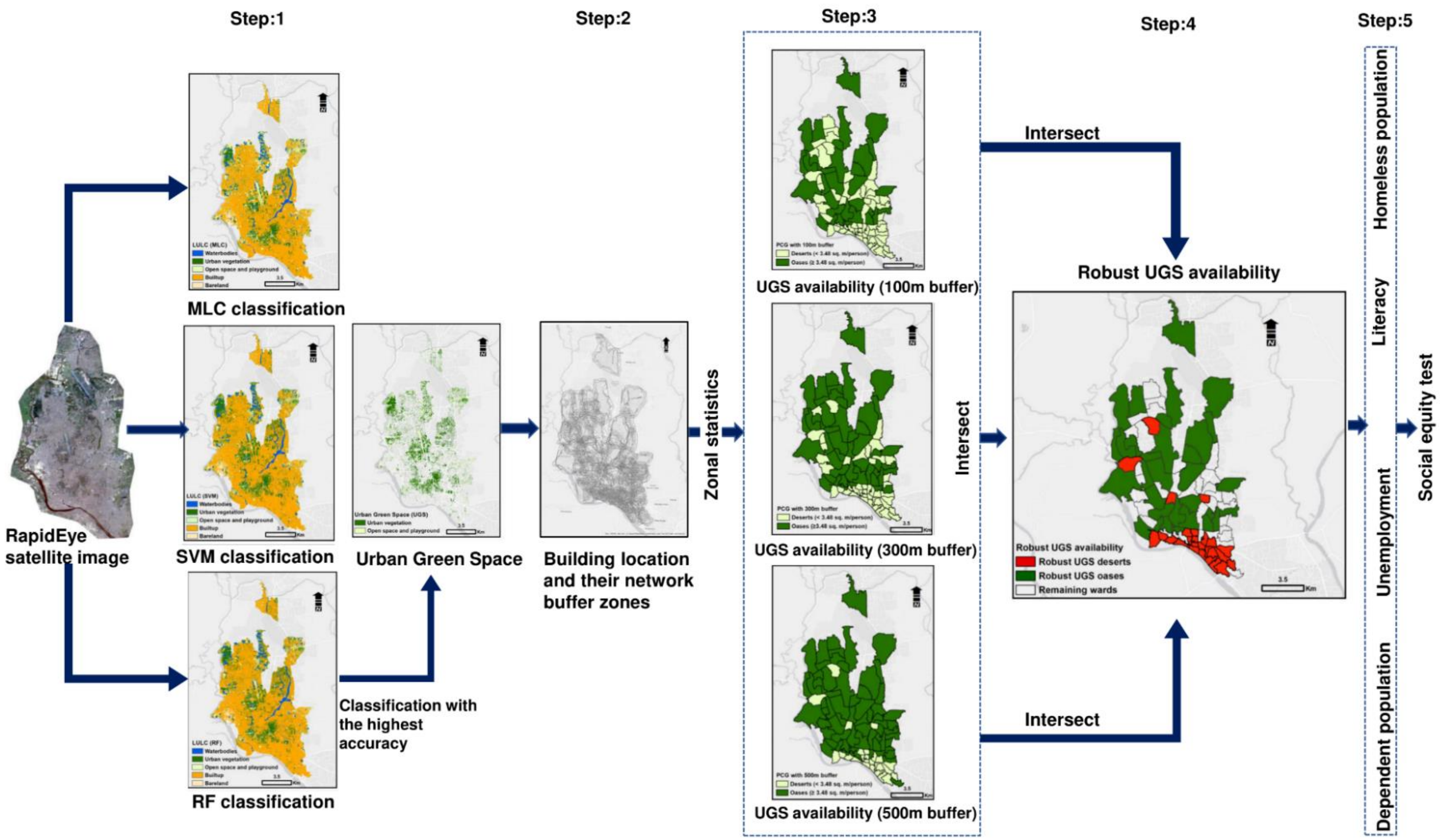

Figure 2-2: A methodological flowchart of this study.

In Step 1, we extracted UGS data from high resolution remote sensing data. Due to the absence of readily available UGS data, we derived UGS information from high-resolution satellite imagery. So far, various studies extracted green space information by classifying remotely sensed data. When classifying satellite imageries for detecting UGS, various approaches have been reported in the literature such as object-based classification (e.g., Degerickx et al., 2020; W. Zhou & Troy, 2008), support vector machine (SVM) (Zhu & Woodcock, 2014), decision tree (Park et al., 2012), artificial neural network (ANN) (Dinda et al., 2021), maximum likelihood classification (MLC) (Dennis et al., 2018; Ghosh et al., 2019), Bayesian hierarchical model (Ludwig et al., 2021), and Random Forest (RF) (Huang et al., 2021; Kuang et al., 2021; Li et al., 2020). However, the urban environment consists of complex features and there are imitations that no model can rectify perfectly (Phiri & Morgenroth, 2017; Zeng et al., 2019). Therefore, we compared three well-established methods: 1) maximum likelihood classification (MLC), 2) support vector machine (SVM), and 3) random forest (RF), in terms of their performance for detecting UGS and chose one with the highest accuracy performance.

MLC is widely accepted for its efficient parametric classification based on Bayes' theorem of probability density functions (Otukei & Blaschke, 2010). The second approach we applied in this study is a non-parametric machine learning approach, namely SVM. Unlike MLC which follows various distributions including Gaussian distribution, SVM is neither based on Gaussian distribution nor sensitive to the highest trends (Zeng et al., 2019). Another advantage of SVM is that it can perform better despite having a limited number of training samples (Shih et al., 2019). Similarly, RF is another common supervised machine learning algorithm that can create multiple decision trees that perform better than a single tree and generate the classification based on the means of voting. As it selects the average vote of multiple trees, this ensemble model can reduce the problem of overfitting.

There are several steps to extract UGS data based on satellite images. First, we used RapidEye imagery (RapidEye, 2011) with 5-meter spatial resolution. RapidEye products have already been corrected for sensor artifacts and transformed to Top of Atmosphere (TOA) (at-sensor) radiance, thus, no further correction is required. To classify the entire study area at once, we combined multiple tiles into a single tile using the Mosaic to New

Raster tool in ArcGIS. Subsequently, we created training samples for each LULC class in order to train our models. We selected five commonly recognized urban features for urban areas, including 1) urban vegetation, 2) water bodies, 3) built-up, 4) open space and playground, and 5) bare land, and created training samples by utilizing Google Earth Pro version 7.3. Using the generated training samples, we trained our selected models in ArcGIS version 10.8. Then, we classified the imagery using three selected classification methods.

Finally, we assessed the performance of each method for detecting UGS via a confusion matrix. A confusion matrix can reveal each model's performance by generating the user's accuracy, producer's accuracy, overall accuracy, and Kappa Coefficient. Samples for accuracy assessment are prepared by using Google Earth imageries. We generated around 500 samples using stratified sampling techniques in ArcGIS 10.8 for each classification method. There is no standard for many points should be considered for accuracy assessment, however, 500 random samples are recommended by the ArcGIS toolset (ESRI. 2020). Based on this evaluation, a classification method with the highest accuracy is selected and used for further analysis.

In LULC classification, user's accuracy, producer's accuracy, and overall accuracy are metrics used to assess the performance of a classification model. User's accuracy measures the likelihood that a pixel classified as a specific class by the model actually belongs to that class. Producer's accuracy, on the other hand, measures the model's ability to correctly identify all the pixels belonging to a specific class. Overall accuracy represents the proportion of correctly classified pixels in the entire image, providing a general measure of the model's performance across all classes. The Kappa coefficient is a statistical measure that evaluates the agreement between the observed classification and a randomly expected classification, correcting for chance agreement. It considers both omission and commission errors and provides a robust assessment of classification accuracy. A kappa coefficient of 1 indicates perfect agreement, 0 represents agreement equivalent to chance, and negative values suggest agreement worse than chance.

In Step 2, we measured UGS availability based on each walking distance threshold. To quantify the UGS availability, we used the per-capita green space (PCG) metric, a ratio between the total size of UGS accessible given a walking distance threshold (e.g., 100-meter, 300-meter, 500-meter) for each Ward and its total population as shown in **Equation 2-1**:

$$PCG_{w,d} = \frac{UGS_{w,d}}{P_w} \tag{2-1}$$

where, $PCG_{w,d}$ is the per-capita green space value for a Ward w given a walking distance threshold of d, $UGS_{w,d}$ is the total size of UGS reachable given the walking distance threshold for the Ward, and P_w is the total population of the Ward w.

Specifically, our UGS availability calculation involves several steps. First, using building locations (as a proxy for residential locations) in each Ward as origins, we created network buffers based on a walking distance threshold (say 100 meters). For example, **Figure 2-3** illustrates an example of network buffer zones around building footprint centroids of Ward 56 (South) for three walking distance thresholds. Next, we quantified the total size of UGS included within the 100-meter network buffers, which is $UGS_{w,100-meter}$ in **Equation 2-1**. This is divided by Ward's total population, and the resulting value is used as the final UGS availability measure with the walking distance threshold of 100-meter. We repeated this for other walking distance thresholds (e.g., 300 meters, 500 meters).

To account for edge effects (Fortney et al. 2000), we considered UGS outside the city boundary as well. The edge effect refers to a scenario in which analysts overlook the possibility of individuals travelling beyond their neighbourhood or city boundaries to enjoy green spaces or other services/resources if they are within an acceptable travel distance or time. To address these edge effects in this study, green spaces that are located within the specified walking distance (e.g., 100 meter) from the resident's location but fall beyond the Ward or city boundary was also included to measure UGS availability. In other words, we assumed that individuals are willing to travel beyond the city boundary to access UGS if it is located within a reasonable walking distance from their residences.

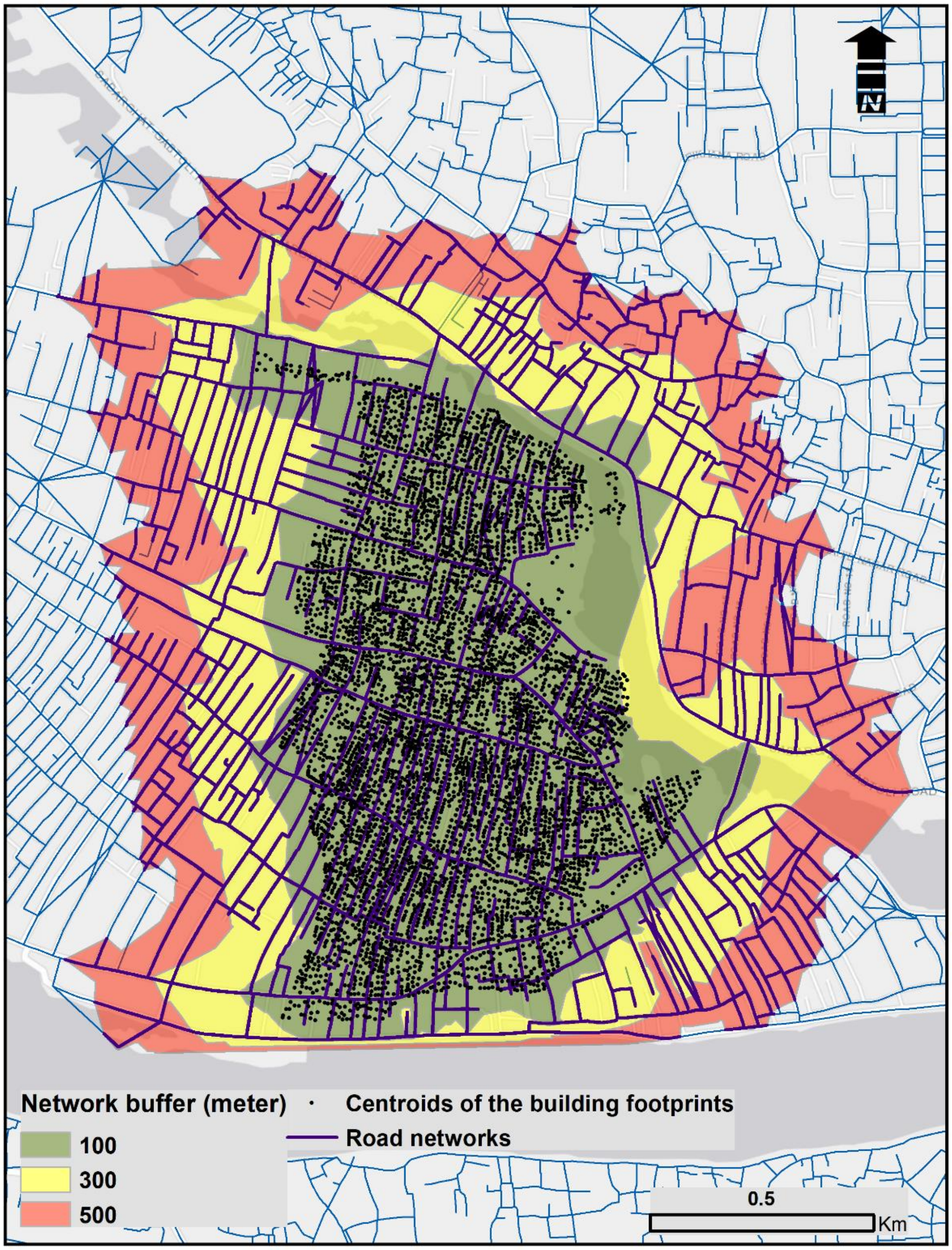

Figure 2-3: An example of network buffer zones around building footprint centroids of Ward 56 (South) for three walking distance thresholds.

In Step 3, we classified neighbourhoods into UGS deserts and oases. We classified neighbourhoods into two categories, UGS deserts and UGS oases depending on their UGS availability based on each walking distance threshold (e.g., 100-meter, 300-meter, 500-meter). UGS deserts are geographic areas where the PCG value is less than the local government's 3.48 m^2 per person standard while UGS oases are neighbourhoods that satisfy or exceed this standard. We used this classification method for each walking distance threshold and created three maps of UGS deserts and oases as a basis for identifying robust UGS deserts and oases in the next section.

In Step 4, we identified *robust UGS deserts* and *oases*. We used intersected set theory to identify robust UGS deserts and oases by intersecting the three maps of UGS deserts and oases based on the 100-, 300-, and 500-meter walking distance threshold generated in the previous step. **Figure 2-2** describes this process. As shown in **Figure 2-2**, the resulting robust UGS oases and deserts are geographic areas with and without the UGS availability level recommended by the local planning organization regardless of different walking distance thresholds used, respectively. This robust method with the intersected set theory in mathematics has also been used in other domains and applications such as analytical time geography (Lee & Miller, 2020) and equity analysis of public transit accessibility (Lee & Kim, 2023).

2.4.2 Examining inequality and socioeconomic characteristics of UGS deserts and oases

Gini index for exploring inequality of UGS availability within robust UGS deserts and oases

To examine and compare the inequality in UGS availability between the robust UGS deserts and oases areas identified in section 4.1, we employed the Gini index. This index provides an overview of the inequality in the distribution of PCGs. This widely used and effective measure of inequality is easily interpretable through the use of Lorenz curves (Cheng et al., 2020; Lucas et al., 2016; Lee and Kim, 2023; Chen et al., 2020). A Gini index value of 1 denotes perfect inequality, while a value of 0 indicates complete equality.

In this study, we performed an inequality analysis by applying the Gini index to the average PCG values across three walking distance thresholds within the identified robust UGS deserts and oases Wards in section 4.1. This approach enabled us to understand and contrast the inequality levels between the robust UGS deserts and oases.

T-test for exploring differences in socioeconomic characteristics between robust UGS deserts and oases

Furthermore, to test if there are statistically significant differences in socio-economic and demographic variables between robust UGS desert and oasis areas identified in section 4.1, we employed Welch's T-test and a nonparametric Mann-Whitney U-test due to the normal or non-normal distribution of these values (as verified by the Shapiro-Wilk test) and the relatively small number of samples.

To understand the socio-economic characteristics of UGS deserts and oases, researchers have utilized a variety of variables. Among the most popular are income (Xu et al. 2018; Nesbitt et al. 2019), unemployment (Xu et al. 2018), elderly population (Xu et al. 2018; Huang et al. 2023), children (Xu et al. 2018; Huang et al. 2023), disability (Lasky et al. 2023), race (Nesbitt et al. 2019; Heckert 2012; Heckert and Rosan 2016; Huang et al. 2023; Liu et al. 2021), education (Nesbitt et al. 2019), housing prices (Xu et al. 2018; Rao et al. 2022), and homelessness (Kaprowska et al. 2020). Although we acknowledge the importance of each variable in understanding the characteristics of UGS deserts, including all variables in the current study was not possible due to limited data availability in the study area (Dhaka, Bangladesh), which is a typical scenario in low- and middle-income countries of the Global South. An overview of the variables used in this study is presented in Table 2-3.

Table 2-3: Variables used for understanding the socioeconomic characteristics of UGS deserts and oases areas

Variables	Rationale
Unemployment (Xu et al. 2018)	To understand association between green space accessibility and unemployment rate
Elderly population (Xu et al. 2018; Huang et al. 2023)	To promote safe, inclusive, and accessible public green space
Children (Xu et al. 2018; Huang et al. 2023)	To promote safe, inclusive, and accessible public green space
Education attainment level (Nesbitt et al. 2019)	To understand association between green space accessibility and education attainment level
Homelessness (Kaprowska et al. 2020)	To understand association between green space accessibility and homelessness

Specifically, we tested if there are statistically significant differences between robust UGS deserts and oases with respect to four census variables: 1) dependents, 2) unemployed individuals, 3) those with low literacy, and 4) homeless people. In this study, dependents are individuals who are either not eligible to work or are retired and dependent on other working family members. We focused on children under 14 and the elderly over 60 years of age. The unemployed population are individuals who are not attending school, eligible to work, but unable to obtain a job. Literacy is defined as the ability to write. The homeless population is defined as individuals without a permanent residence who spend their nights in unconventional and temporary places, such as railway stations, bus terminals, parks, mosques, footpaths, etc. We used R to conduct statistical analysis and visualize the outcomes for the four selected variables used in the study.

2.5 Results

2.5.1 Robust UGS deserts and oases analysis results

Classification model selection results and geographic distribution of UGS in Dhaka

In this study, three supervised classification methods were used to derive UGS from the best-performing method. **Figure 2-4** displays LULC maps of Dhaka based on the three methods. The accuracy assessment of three classification models: Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), and Random Forest (RF), based on 500 random samples revealed acceptable results (overall accuracy > 80% and kappa coefficient > 0.7) for all classification methods as shown in **Table 2-3**. Given that the RF model outperformed the SVM and MLC in terms of accuracy performance, RF is selected as a final classification model for generating the UGS dataset.

Table 2-4: LULC classification results based on three models: MLC, SVM, and RF.

Classification method		**MLC**	**SVM**	**RF**
LULC class				
Waterbodies	Area (km^2)	3.55	4.24	4.92
	Area (%)	2.89	3.45	4.00
Urban vegetation	Area (km^2)	19.12	17.53	20.62
	Area (%)	15.56	14.26	16.78
Open space and playground	Area (km^2)	17.47	8.95	9.15
	Area (%)	14.22	7.28	7.44
Built-up	Area (km^2)	80.34	88.98	86.24
	Area (%)	65.38	72.40	70.17
Bare land	Area (km^2)	2.40	3.20	1.97
	Area (%)	1.95	2.60	1.60
Overall accuracy (%)		0.83	0.89	0.90
Kappa coefficient		0.74	0.82	0.83

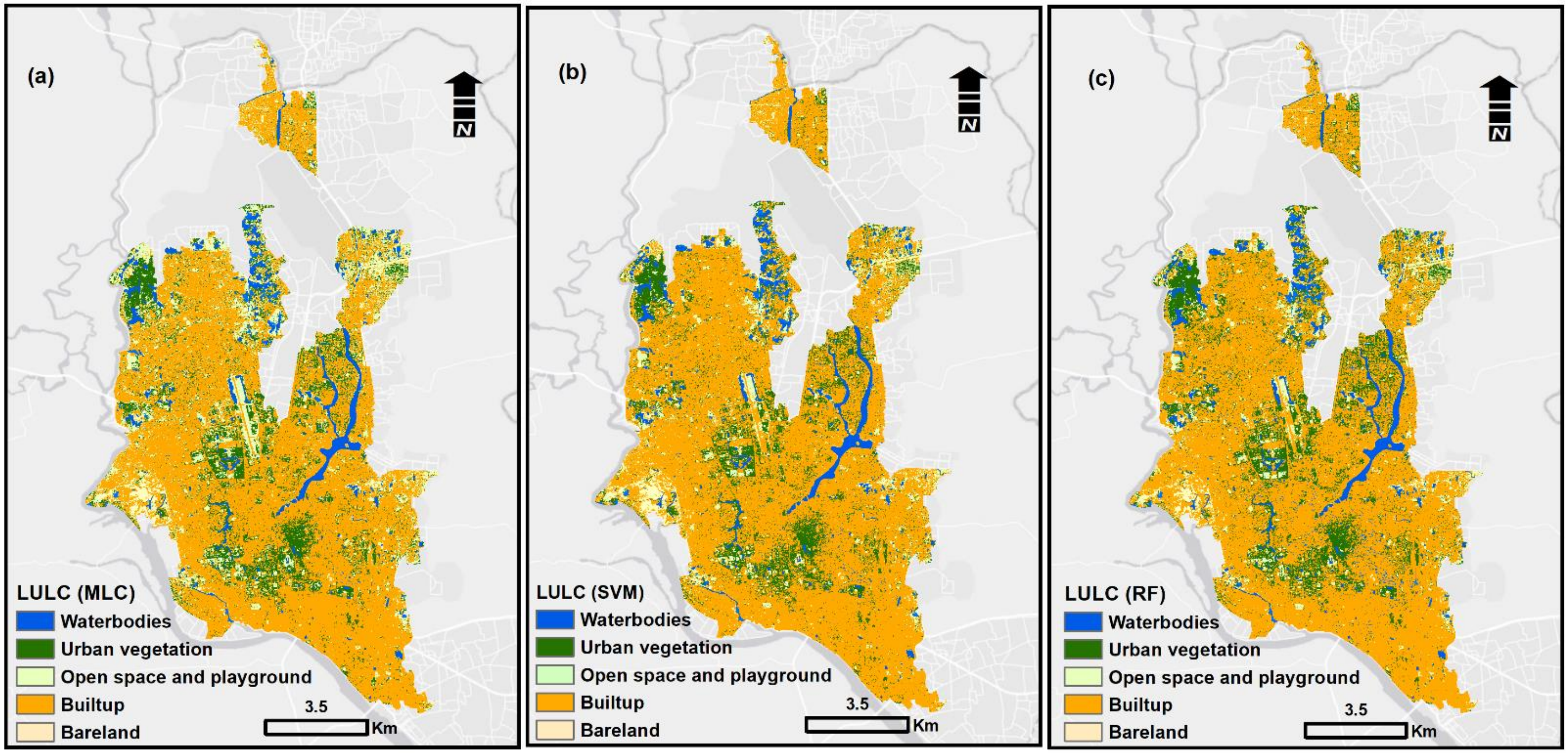

Figure 2-4: LULC maps of the study area using (a) Maximum Likelihood Classification, (b) Support Vector Machine, and (c) Random Forest method.

Figure 2-5 presents the UGS data generated by the RF model. Our analysis indicated a limited presence of UGS in Dhaka, as seen in **Figure 2-5 (b)**. We also found that UGS in Dhaka is clustered in a few Wards, with most of the Wards with higher UGS availability belonging to the Dhaka North City Corporation (DNCC), as illustrated in **Figure 2-5 (b)**. On the contrary, there is a shortage of UGS availability in the Dhaka South City Corporation (DSCC). These areas with insufficient UGS availability in the southern part of the city have been affected by rapid population growth and the absence of an urban policy regarding UGS provision in the past, leading to encroachment of this essential urban resource during the development process.

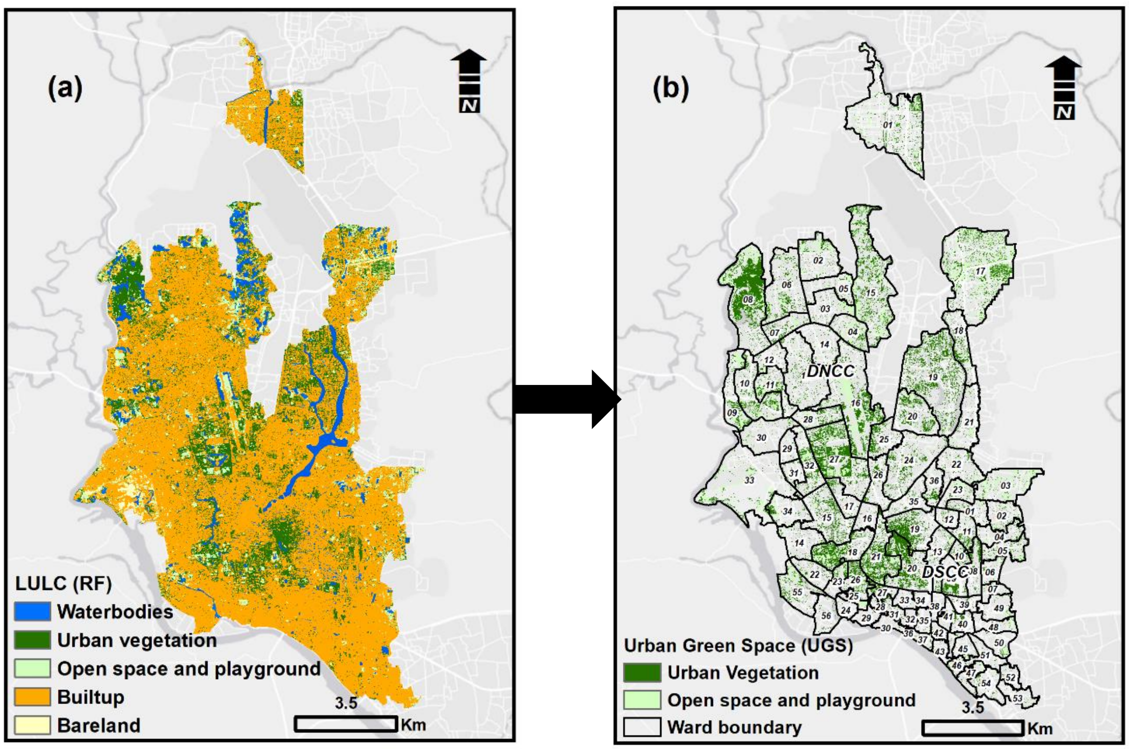

Figure 2-5: Final UGS dataset generated by the RF model.

Maps of UGS deserts and oases for three types of walking distance thresholds

Figure 2-6 shows that UGS availability (i.e., PCG) gradually increases with higher walking distance thresholds used. **Figure 2-6 (a)** displays the PCG within a 100-meter walking distance, which reveals limited green space availability in most Wards. Many neighbourhoods do not meet the local government's minimum cutoff value for a healthy urban life, which is a PCG of 3.48 m^2 per person. UGS availability slightly improves with the 300-meter walking distance, but many neighbourhoods still fail to meet the minimum standard (see **Figure 2-6 (b)**). **Figure 2-6 (c)** shows the PCG at the Ward level with the maximum walking distance threshold (500 meters) used in this study. As the walking distance increased, the UGS availability continued to improve.

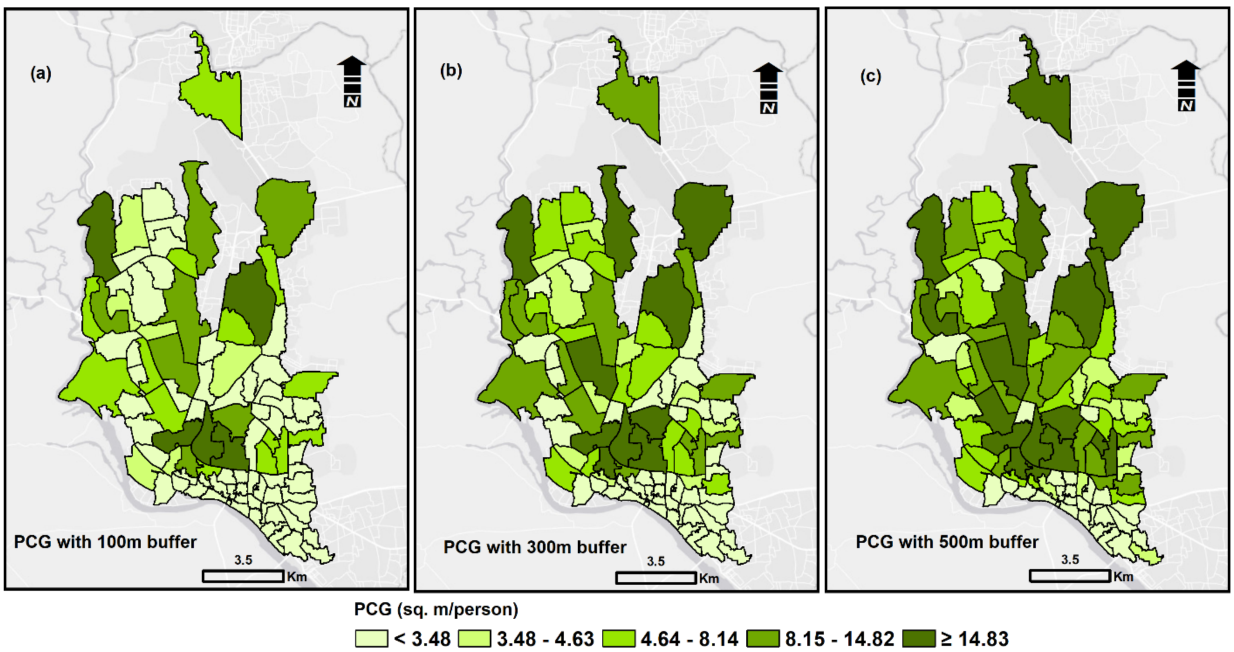

Figure 2-6: UGS availability based on a walking distance threshold of (a) 100-meter, (b) 300-meter, and (c) 500-meter.

Figure 2-7 shows the varying geographic distribution of UGS deserts and oases based on each walking distance threshold used: a) 100-meter, b) 300-meter, and c) 500-meter. When using a 100-meter walking distance threshold (**Figure 2-7 (a)**), 32 neighbourhoods were identified as UGS oases and 60 areas were classified as UGS deserts. With a 300-meter walking distance, the number of deserts decreased slightly (**Figure 2-7 (b)**), and this trend continued as the distance increased to 500 meters (**Figure 2-7 (c)**). This clearly demonstrates that the geographic distribution of UGS deserts is sensitive to the choice of walking distance threshold, which can result in unreliable and inaccurate identification of UGS deserts.

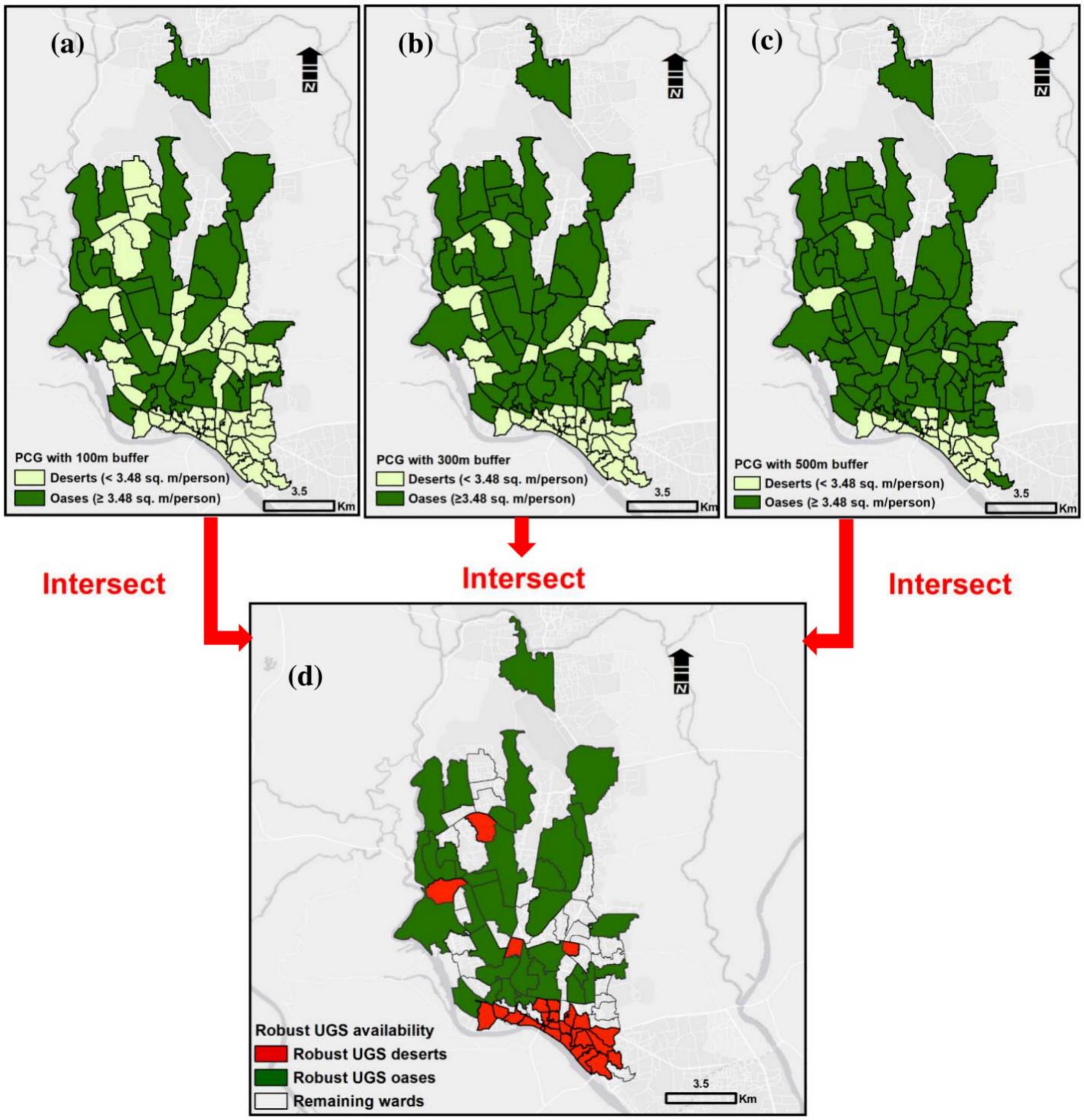

Figure 2-7: A map of (d) robust UGS deserts and oases which is the intersection of UGS availability maps based on a walking distance threshold of (a) 100-meter, (b) 300-meter, and (c) 500-meter.

Robust UGS deserts and oases analysis results

Figure 2-7 (d) presents the map of robust UGS deserts and oases which is the intersection of **Figures 2-7(a), 2-7(b)**, and 2-**7(c)**. The robust UGS availability approach identified 32 robust oases and 26 robust desert locations that remain consistent across all walking distance thresholds used. The robust UGS deserts were primarily situated in the southern part of the study area, which falls under the jurisdiction of the Dhaka South City Corporation (DSCC). The results of our robust UGS deserts analysis indicate that these regions show persistent low UGS supply levels compared to their high demand (i.e., population), regardless of walking distance thresholds used. These areas are in dire need of future attention and investment to meet the minimum standard for a healthy urban environment.

2.5.2 Inequality analysis results and socioeconomic characteristics of UGS deserts and oases

The results of UGS availability inequality analysis

Figure 2-8 presents the Gini index values for robust UGS deserts and oases and the corresponding Lorenz curves. The Lorenz curve depicts the cumulative distribution of Wards on the horizontal axis against the cumulative distribution of the indicator (e.g., averaged PCG value of three walking distance thresholds) on the vertical axis. The Gini coefficient is calculated as the ratio of the area between the equal distribution line and the Lorenz curve to the area under the triangle formed by the equal distribution line, the horizontal axis, and the vertical axis.

The Gini index for robust UGS deserts is 0.21, indicating a lower level of inequality compared to robust UGS oases, which have a Gini coefficient of 0.29. Interestingly, this suggests that the PCG distribution in robust UGS oases is less even, although these areas boast a wealth of UGS availability. Put another way, while they are abundant in terms of UGS availability, ironically there is greater inequality and disparity in UGS availability among robust UGS oases neighbourhoods.

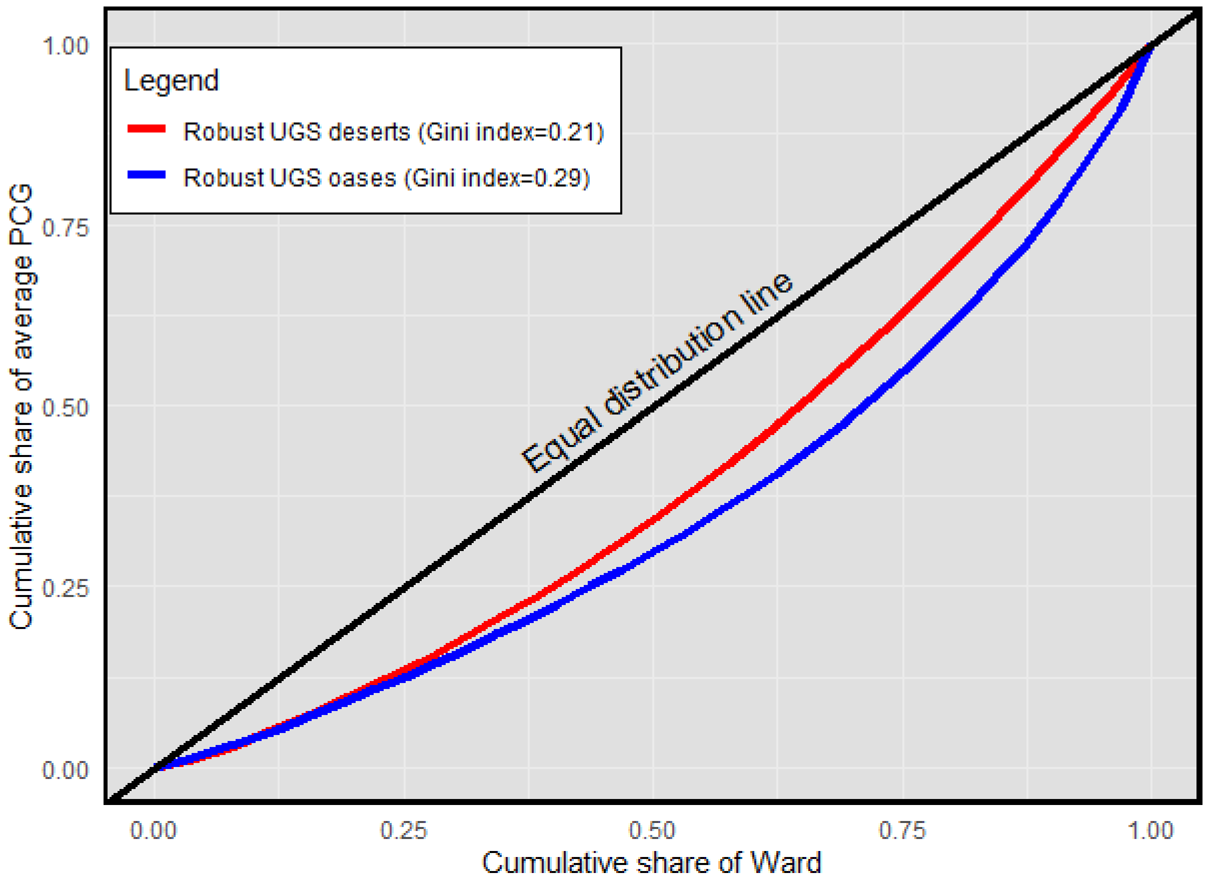

Figure 2-8: Lorenz curves of robust UGS deserts and oases.

Findings on socioeconomic differences between UGS deserts and oases

To examine the differences in socioeconomic characteristics of UGS desert and oasis areas in Dhaka, we performed Welch's T-test and Mann-Whitney U-test using the identified robust UGS deserts and oases in the previous section 5.1. **Figure 2-9** displays the geographic distributions of the four census variables used in this analysis: a) dependent population, b) unemployment, c) literacy, and d) homeless population. **Figure 2-10** shows boxplots of these variables for robust UGS deserts (red) and oases (green) neighbourhoods. **Table 2-4** presents the results of Welch's T-test and Mann-Whitney U-test.

We found statistically significant differences between robust UGS deserts and oases when it comes to the dependent population and literacy variables. Robust UGS deserts had a higher proportion of dependent populations (robust deserts: average of 30.05%, robust oases: average of 28%). Conversely, robust UGS oases were found to have a higher proportion of literate individuals. These differences were statistically significant with a p-value of less than 10% as presented in **Table 2-4**.

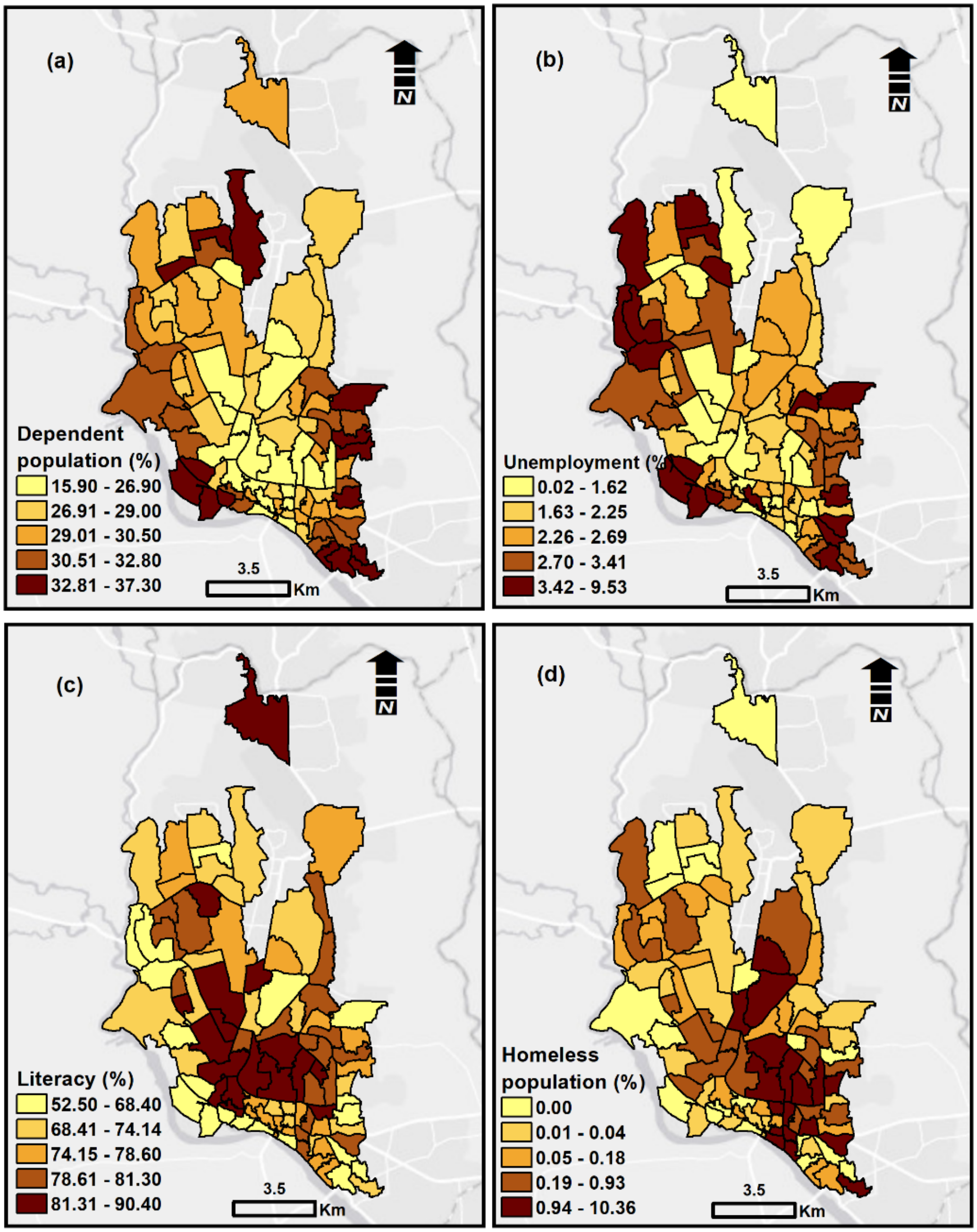

Figure 2-9: Maps of (a) dependent population, (b) unemployment, (c) literacy, and (d) homeless population in Dhaka.

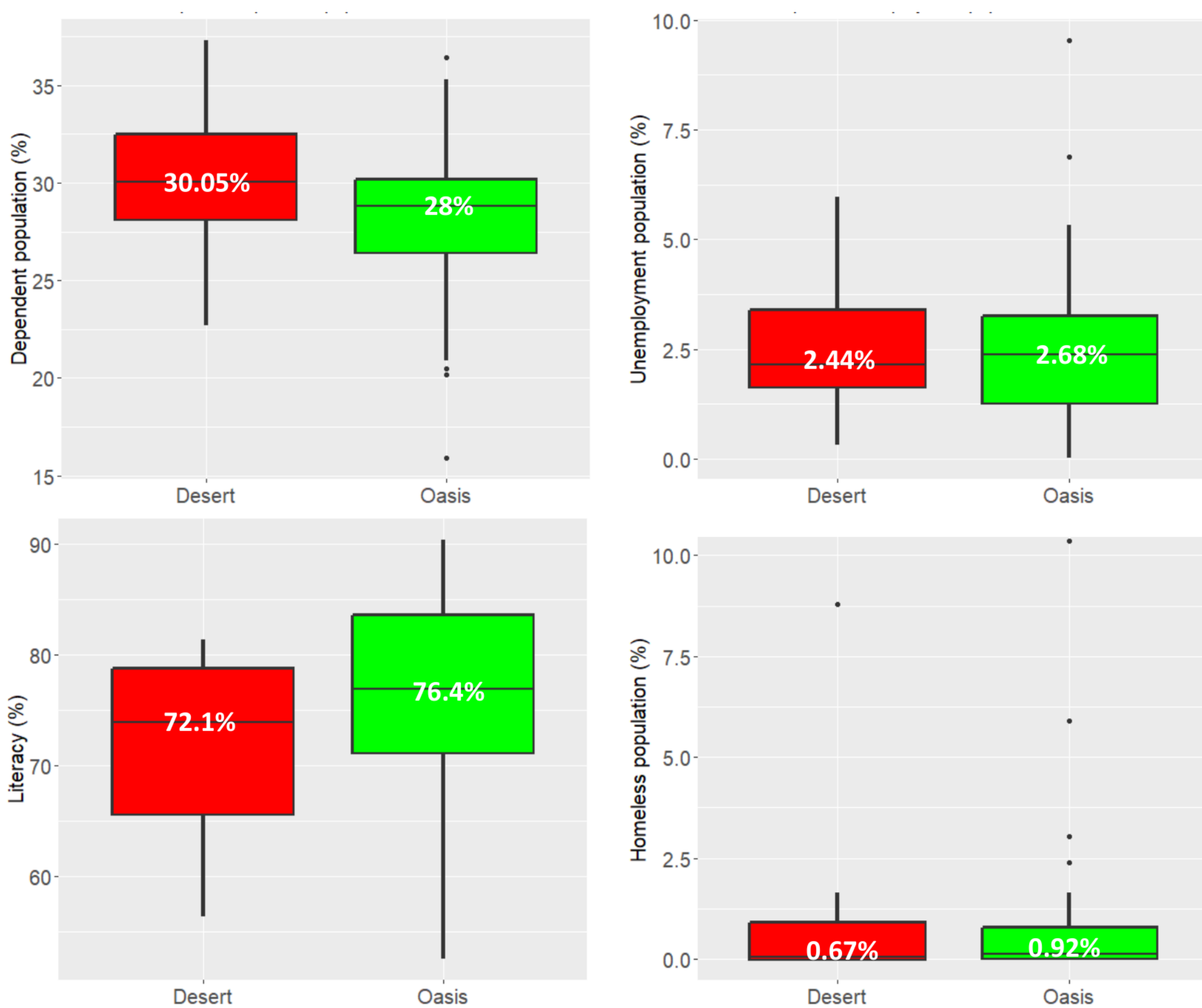

Figure 2-10: Boxplots of socio-economic variables in robust UGS deserts (red) and oases (green): dependent population, unemployment, literacy, and homeless population.

Table 2-5: T-test results.

Variable	Type	Mean	P-value
Dependent population (%)	Robust Oasis	28.01	0.056*
	Robust Desert	30.05	
Unemployment (%)	Robust Oasis	2.68	0.784
	Robust Desert	2.44	
Literacy (%)	Robust Oasis	76.43	0.052*
	Robust Desert	72.17	
Homeless population (%)	Robust Oasis	0.92	0.311
	Robust Desert	0.67	

Note: P-values marked in bold demonstrate the variables are statistically significant. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

2.6 Discussion

The use of arbitrary walking distance thresholds can result in unreliable and inaccurate UGS desert identification, which is often the case in LMIC countries in the Global South. To address this limitation, we introduced the concept of robust UGS oases and deserts, which are geographic areas with and without the recommended per capita green space (PCG) level by a local organization regardless of different walking distance thresholds used. During the application of this robust approach, we considered both network buffer and edge effects to measure urban green space availability more rigorously. We demonstrated the utility of the proposed robust UGS deserts framework in the city of Dhaka, Bangladesh.

This study found that the spatial patterns of UGS deserts and oases are sensitive to different walking distance thresholds used. These findings are consistent with Kabisch et al., (2016) where the study demonstrated the quantity of green spaces increases with an increased distance threshold. Therefore, the use of an ad-hoc, arbitrary, not well-informed walking distance threshold can lead to inaccurate identification of UGS deserts. Robust UGS deserts approach can be a possible solution for this. We also found that socioeconomically disadvantaged populations are disproportionately located in robust UGS desert areas. This is consistent with previous research that shows low-income populations tend to live in areas with limited UGS availability (Astell-Burt et al., 2014; Williams et al., 2020; Barbosa et al., 2007; Wu et al., 2020; Liu et al., 2022). For instance, Astell-Burt et al., (2014) concluded that green space availability was substantively lower in regions with a higher percentage of low-income residents. Similarly, Williams et al. (2020) found that disparities among socioeconomic subgroups are significantly intensified when accessing safe parks, with racial/ethnic minorities and low-income communities experiencing greater disadvantages. Therefore, we argue that policymakers and planners in Dhaka should carefully reconsider their UGS provision strategy to ensure that the required amount of UGS is provided across the city and to reduce the gaps in terms of UGS distribution. Given the limited physical space to create new green spaces in Dhaka, policymakers may consider informal vegetation, such as rooftop vegetation, as a potential solution. Studies have shown that informal green spaces, including rooftops, play an important role in improving the quality of life in urban areas (Sikorska et al., 2020). Rooftops have also been identified as a potential alternative for tree plantations, which can help alleviate the UGS desert situation in Dhaka (Safayet et al., 2017; Rahman and Zhang, 2018).

2.7 Conclusion

This study highlights the limitations of using arbitrary walking distance thresholds for identifying urban green space (UGS) deserts, particularly in low- and middle-income countries (LMICs) in the Global South. To address this issue, the concept of robust UGS oases and deserts, based on various walking distance thresholds, was introduced.

The utility of the proposed robust UGS deserts framework was demonstrated by using the city of Dhaka, Bangladesh, as an example. The example study revealed that the spatial patterns of UGS deserts and oases vary depending on the walking distance thresholds used, emphasizing the need for a well-informed approach. The findings also revealed statistically significant differences among various population groups in UGS deserts and oases, with socially disadvantaged population groups more likely to be predominant in UGS deserts.

The proposed robust UGS deserts approach based on various walking distance thresholds offers a more rigorous and reliable method for decision-making. This is particularly useful in the absence of clear guidelines for walking distance thresholds, a situation commonly observed in low- and middle-income countries. Ultimately, this research contributes to the development of urban policies aimed at fostering healthy cities, enhancing UGS provision, and helping our cities prepare for future climate change.

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Chapter 3

3. The cost of climate change: A general cost function approach for incorporating extreme weather exposure into public transit accessibility

3.1 Introduction

Public transit offers an affordable and sustainable mode of transportation for urban populations to access opportunities (e.g., jobs, education) (Palm & Farber, 2020; Sanchez et al., 2004), resources (e.g., food) (Widener et al., 2015), and services (e.g., healthcare) (Lee & Miller, 2018). In particular, transit is often a lifeline mobility option for socio-economically underprivileged populations who would otherwise have limited accessibility to desired destinations (Allen et al., 2023; Sanchez et al., 2004). However, as public transit journeys often include first- and last-mile walking (e.g., from home to the nearest transit stop) and waiting at initial and transfer stations, transit users are more likely to be exposed to severe environmental conditions, such as extreme heat, extreme cold, and air pollution, which can have adverse short- and long-term effects on their health outcomes, such as heat stroke and other respiratory diseases (Broadbent et al., 2020; Hoehne et al., 2018).

Climate change is increasing the frequency and intensity of extreme weather events; this makes public transit users, many of whom are from marginalized and vulnerable communities and are captive transit users because they do not own private vehicles, more susceptible to heat-related (e.g., heat exhaustion, heat stroke) (Fraser and Chester 2017; Karner, Hondula, and Vanos 2015), cold-related (e.g., hypothermia, frostbite) (Antunes et al., 2017), and respiratory (e.g., asthma, emphysema) (Van Ryswyk et al., 2021) illnesses. This increased vulnerability can exacerbate social and environmental injustice within urban areas. Therefore, there is an urgent need for a public transit accessibility measure that captures and incorporates environmental health costs (e.g., extreme weather exposure) during transit travels to better understand the equity landscape of these environmental risks.

This will guide evidence-based planning and policy efforts toward creating healthy, equitable, and resilient cities in the face of climate change.

However, environmental health costs have been largely overlooked in the literature on public transit accessibility, despite its increasing importance in the context of climate change. Several previous studies (Fraser and Chester 2017; Karner, Hondula, and Vanos 2015; Lyu et al. 2018; Rosenthal et al. 2022; Dzyuban et al. 2021) have focused on measuring exposure, vulnerability, and risks faced by transit and active transport users *per se*. Nevertheless, there have been limited efforts to explicitly incorporate these environmental health costs into public transit accessibility measures. Overlooking the environmental health cost of transit trips can lead to two methodological problems—unrealistic estimation of the true "cost" that passengers experience, and eventually the inaccurate measurement of accessibility. This not only hinders targeted interventions to improve accessibility for transit-dependent populations but also imposes an additional burden on them. Therefore, there is a need to develop a transit-based accessibility measure that moves beyond travel time and monetary costs to integrate environmental health costs to make transit accessibility measures ready for climate change.

In light of this context, this paper develops a general cost function approach for integrating environmental health costs, such as extreme weather exposure, into public transit accessibility measures. We will demonstrate the utility and applicability of the proposed method using an example study that incorporates transit users' extreme cold exposure into accessibility measures in the city of Winnipeg, MB, Canada. Also, we will perform a statistical test to investigate the differences in socioeconomic characteristics between areas experiencing accessibility loss and gain due to the inclusion of environmental health costs. Although our study focuses on exposure to cold as a case study, the general cost function approach that is proposed by this study can be applied to other environmental exposure factors, such as extreme heat, natural hazards (e.g., urban flooding, heavy precipitation and wind), and air pollution. The proposed method can be a more realistic and practical measurement of public transit accessibility, particularly in the context of climate change and aggravating extreme weather events (e.g., heatwaves, polar vortex, cold air outbreaks, cold wave).

The remainder of the paper is organized as follows. The second section provides background on measuring accessibility by cost and introduces previous public transit research in the context of climate change. Section three describes the methodology. The detailed analysis procedure and the findings of the example study are presented in section four. Finally, section five offers the discussion and conclusion of this study.

3.2 Background

3.2.1 Accessibility by cost and dual accessibility measures

Accessibility refers to the ease of reaching destinations and opportunities or characteristics of places in terms of how easily they can be reached by population (Geurs & van Wee, 2004; Neutens et al., 2010). Various approaches have been developed to effectively measure accessibility, and one way to broadly categorize these measures is by classifying them into *primal* or *dual* measures of accessibility (Wu & Levinson, 2020).

Primal accessibility quantifies the number of opportunities, such as jobs, that can be reached within a fixed travel cost, whether in terms of time (e.g., 30 minutes), distance (e.g., 5 kilometres), or monetary value (e.g., an hourly wage). A fundamental and widely used primal accessibility measure, as introduced by Hansen (1959), calculates the number of opportunities accessible within a given time limit, often referred to as the cumulative-opportunity measure (El-Geneidy & Levinson, 2007). On the other hand, *dual* accessibility is a measure of the travel costs for accessing a fixed number of opportunities (Cui & Levinson, 2020). For example, dual accessibility measures can be time, distance, or monetary costs required to reach a fixed number of healthcare, job, and food resources. Unlike primal accessibility, which focuses on the number of opportunities, the dual measure becomes more relevant in situations where the cost of travel to an opportunity or location is more crucial than the number of opportunities available (Cui & Levinson, 2020).

Travel time/distance is a common and well-established type of cost when computing dual accessibility measures (Batty, 2009). In simpler terms, this time-based dual measure of transit accessibility computes the temporal duration to physically reach destinations, where lower travel time indicates higher accessibility. For instance, Allen & Farber, (2021) measured transit accessibility as the one-way travel time by public transit to the nearest food bank in minutes from locations across Toronto. Similarly, travel time of various travel modes (e.g., walking, automobile, public transit) was used as an indicator for determining accessibility to grocery stores (Widener, 2017). Monetary costs are another popular type of cost for measuring dual and primal transit-based accessibility measures that have received considerable recent research interest (Currie 2004; Herszenhut et al., 2022; El-Geneidy et al., 2016; Liu & Kwan, 2020).

A largely neglected but critical type of cost when measuring public transit accessibility is environmental health costs associated with transit journeys, including riders' exposure to negative environmental externalities such as extreme weather events, air pollution, and urban flooding. Similar to travel time/distance and monetary costs, environmental health costs also might act as barriers for transit users to access destinations (Tétreault et al., 2018). Disregarding environmental health costs when it comes to measuring accessibility can lead to erroneous and unrealistic measurement of accessibility especially in the context of climate change and global warming.

3.2.2 General cost function approaches in accessibility research

A generalized cost function approach, in the context of accessibility, refers to a framework that combines multiple types of costs associated with travel into an integrated dual accessibility measure (Bocarejo & Oviedo, 2012; El-Geneidy et al., 2016; Kim & Lee, 2019; Liu & Kwan, 2020). Common costs included are travel time, monetary cost, comfort, and environmental cost. Common costs included are travel time (Allen & Farber, 2021), monetary cost (El-Geneidy et al., 2016), and safety (Cui & Levinson, 2018).

The generalized cost function approach has been actively used in the literature on public transit accessibility. For instance, (Bocarejo & Oviedo , 2012) introduced and used a generalized cost function approach that integrates travel time cost and monetary cost (e.g., the percentage of income spent on transportation) to evaluate the impacts of different transport policies (e.g., changes in the transit fare structure) in Bogota. Currie (2004) assessed the geographical distribution of transport needs and compared this with the distribution of public transport service quality using a generalized travel cost approach, which incorporated both travel time and travel fare. In this approach, travel time was converted into monetary values based on hourly wage and travel fare using the local currency in Hobart, Australia. Furthermore, Ford et al. (2015) developed a tool for measuring transit accessibility that considered a generalized cost approach, including both time and travel fares, however, the fare component was based on a flat rate (e.g., average price/km). Similarly, El-Geneidy et al. (2016) proposed a generalized cost function combining travel time and monetary cost (or transit fare) to compare the transit accessibility between socially disadvantaged neighbourhoods and remaining neighbourhoods. In general, they proposed two approaches, first, calculating the number of opportunities within the travel cost threshold which is a combination of transit fares and travel time converted to monetary value (i.e., hourly wage), and second, calculating travel cost by combining travel time and transit fares which is converted to time (i.e., hourly wage).

In summary, we observe that the components of the generalized cost approach for public transit accessibility measurement predominantly revolve around travel time and monetary costs, while the significance of environmental health costs (e.g., exposure to extreme heat and cold) associated with transit trips has been largely overlooked. The purpose of this research is to address this gap.

3.2.3 Measuring extreme weather exposure during transit travels

Given the negative impacts of climate change, research on assessing extreme weather exposure during public transit travels is growing. These assessments cover a wide range of scenarios, with a major focus on evaluating the extreme heat exposure experienced by transit riders (Dzyuban et al. 2021; Fraser and Chester 2017; Karner et al. 2015; Kuras et al. 2017; Rosenthal et al. 2022; Lanza and Durand 2021; Miao et al. 2019; Sami and Keith

2023; Hoehne et al. 2022). For example, Fraser and Chester (2017) evaluated the heat vulnerability of transit riders by considering the time spent on first-mile walking (e.g., from home to the nearest transit stop) and waiting time at the initial stop. However, evaluating heat exposure based solely on the duration of exposure can be erroneous because it overlooks the intensity (i.e., temperature) of exposure. To address this issue, Karner et al. (2015) developed a method that estimates the heat exposure of non-motorized travellers by taking into account both duration and intensity of exposure. However, still, relatively limited attention has been paid to explicitly incorporate these extreme weather exposures into the measures of public transit accessibility. Our research aims to fill this gap using the methods described in section 3.1.

3.3 Methods

3.3.1 A generalized cost function approach

This study proposes a generalized cost function approach that combines travel time cost and environmental health cost (e.g., extreme weather exposure) into an integrated measure of dual accessibility. **Figure 3-1** illustrates the idea of the generalized cost function approach in this study. In our framework, environmental health cost arising from extreme weather exposure is estimated based on a simple yet practical concept: the amount of time a transit passenger spends in adverse environmental conditions (e.g., extreme heat, cold) while accessing (e.g., walking, biking to) the transit stop, waiting at transit stops, walking/biking between two transit stops for transfer, and last-mile walking/biking to the final destination as illustrated in **Figure 3-1**. In this context, the more time spent in such conditions, the higher the environmental health cost. We consider both the intensity and duration of exposure to extreme weather when estimating environmental health costs.

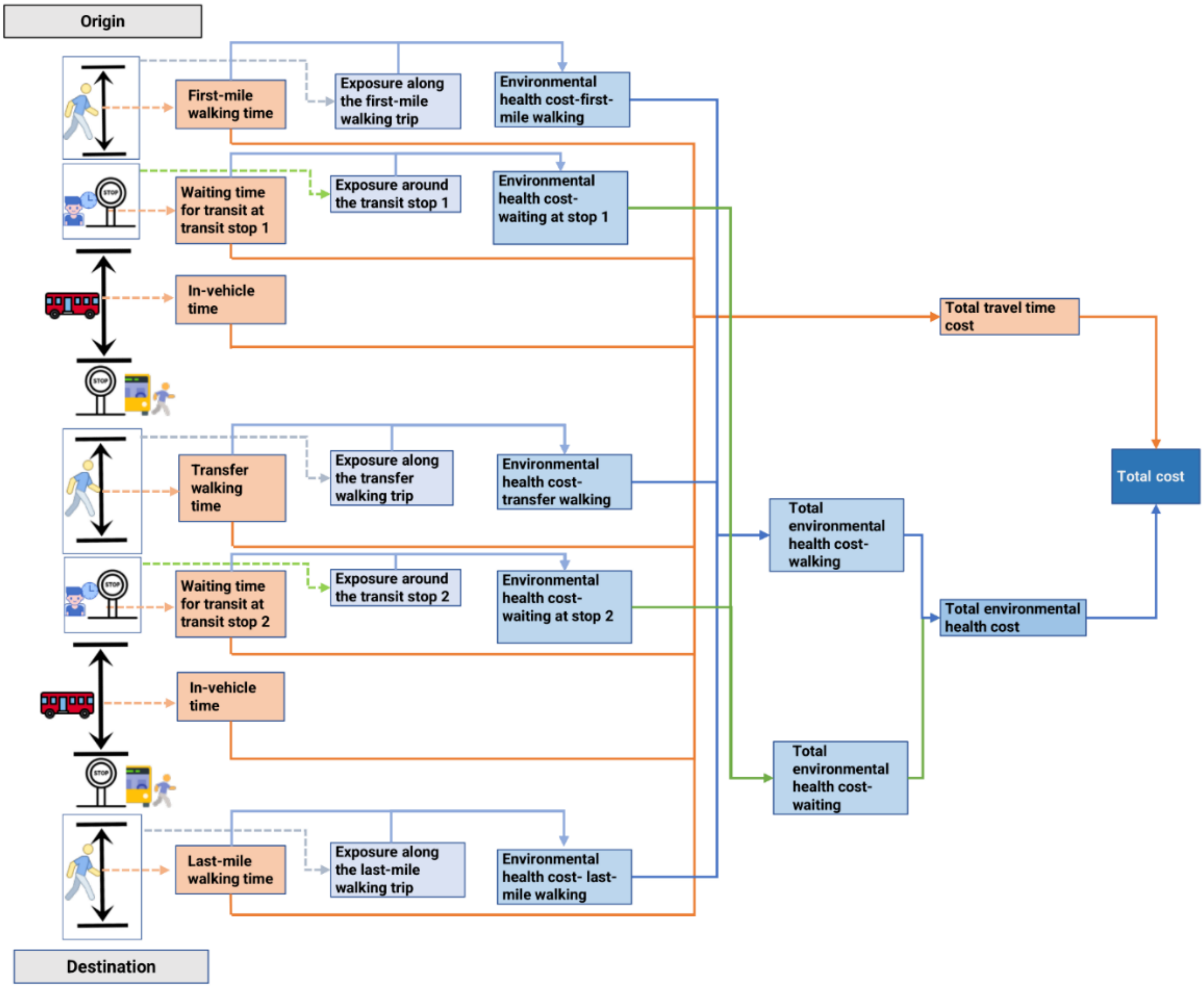

Figure 3-1: A graphical illustration of the generalized cost function approach that combines travel time cost and environmental health cost associated with public transit trips. (Icon sources: icons8.com)

The generalized cost function framework in this study combines travel time cost and environmental health cost using a weighted sum approach like **Equation 3-1**:

$$C_i = \left(\delta_t \frac{\overline{t_{ij}}}{max_{i \in I}\,\overline{t_{ij}}}\right) + \left(\delta_e \frac{\overline{e_{ij}}}{max_{i \in I}\,\overline{e_{ij}}}\right)\ \forall i \in \mathrm{I} \tag{3-1}$$

Here, C_i represents the generalized total cost for origin i (e.g., centroid of a neighbourhood), $\overline{t_{ij}}$ denotes the average total transit travel time from origin i to a fixed number of destinations j (e.g., three nearest healthcare facilities), $\overline{e_{ij}}$ is the average environmental health cost for origin i when travelling to a fixed number of destinations j, and I is the set of origin locations. max $\overline{t_{ij}}$ and max $\overline{e_{ij}}$ are the maximum value within their respective category in a study area. δ_t and δ_e reflect the importance of travel time cost $\overline{t_{ij}}$ and environmental health cost $\overline{e_{ij}}$, respectively and where $\delta_t + \delta_e$ equals 1.

It is worth noting that unlike travel time and fares, which can be directly converted into comparable units either in time or money (El-Geneidy et al., 2016, Currie 2004; Ford et al., 2015), environmental health cost and travel time cost can be challenging to be equated or translated into a common unit. To address this issue, we normalize each component by dividing it by the maximum value within its respective category as shown in **Equation 3-1**. The normalized travel time cost and environmental health cost are then combined into the total integrated cost metric. To enhance the interpretability and comparability, we further perform min-max normalization on the integrated cost (**Equation 3-2**), thereby scaling the values to a standard range. This step facilitates a more straightforward communication of the cost metrics and helps the comparative analysis across different scenarios such as accessibility only based on travel time cost versus environmental health cost (Dony et al., 2015). **Equation 3-2** is specified as:

$$\widetilde{C_i} = \frac{C_i - min_{i \in I} C_i}{max_{i \in I}\, C_i - min_{i \in I} C_i}\ \forall i \in \mathrm{I} \tag{3-2}$$

where $\widetilde{C_i}$ is the normalized integrated total cost for origin i. $\widetilde{C_i}$ redistributes all the cost values between 0 and 1. The following two sections will provide more detailed explanations of how to compute travel time costs and estimate environmental health costs.

3.3.2 Travel time cost

To calculate the travel time cost component within the proposed generalized cost function approach, the initial step involves the computation of the total transit travel time from the origin to a fixed number (e.g., nearest, three nearest) of destinations, which is also known as *dual* measures of accessibility (Cui & Levinson, 2020). Total transit travel time consists of a series of time segments that encapsulate the entire transit journey as shown in **Equation 3-3**:

$$t_{ij} = t_{ij}^{walking} + t_{ij}^{waiting} + t_{ij}^{in-vehicle} \tag{3-3}$$

where t_{ij} represents the total transit travel time from an origin i to a destination j. It encompasses all segments of a comprehensive transit journey from an origin i to a destination j, including:

- $t_{ij}^{walking}$: the walking time to reach the departure transit stop, the time spent walking during transfers between stops, and the last-mile walking time after alighting from the transit. Other first- and last-mile mobility options such as bikes, e-bikes, e-scooters, and smart mobility devices can also be considered.
- $t_{ij}^{waiting}$: the waiting time at the initial stop and at intermediate stops.

- $t_{ij}^{in-vehicle}$: the in-vehicle (e.g., bus, light rail) travel time.

It is worthwhile to note that not all transit journeys are as complicated as the one described above, which includes transfers. In reality, transit trips can involve simpler sequences, typically comprising only first-mile walking, a single waiting period, in-vehicle travel time, and last-mile walking to the destination. Nevertheless, we have accounted for the possibility of complex transit travels to ensure comprehensive modelling.

3.3.3 Environmental health cost

We use the concept of *total degree minutes* (TDM) (Hondula et al., 2021; Karner et al., 2015) to estimate the environmental health costs associated with the out-of-vehicle segments of a transit journey, specifically the walking and waiting components. TDM is calculated by multiplying travel time with temperature. Karner et al. (2015) utilized this TDM metric to quantify travellers' exposure to extreme heat during non-motorized and active travels and explore the associations between heat-related vulnerability and socio-economic variables in the San Francisco Bay Area.

Based on this concept of TDM, environmental health costs attributed to walking $e_{ij}^{walking}$ from an origin i to a destination j is estimated based on **Equation 3-4**:

$$e_{ij}^{walking} = \sum_{k=1}^{n} t_k m_k \tag{3-4}$$

where t_k is the time duration, in minutes, spent on each walking segment k, m_k is the average exposure level (i.e., temperature) experienced along the walking segment k, and *n* is a positive integer representing the number of walking segments.

Similarly, environmental health costs also attributed to waiting $e_{ij}^{waiting}$ from an origin i to a destination j can be estimated using **Equation 3-5**:

$$e_{ij}^{waiting} = \sum_{g=1}^{n} t_g m_g \tag{3-5}$$

where t_g is the time duration, in minutes, spent on each waiting segment g, m_g is the average exposure level (i.e., temperature) experienced during waiting, and n is a positive integer representing the number of waiting stops.

Finally, we derive the total out-of-vehicle environmental health cost e_{ij} by summing the environmental health costs for both walking and waiting based on the **Equation 3-6**:

$$e_{ij} = e_{ij}^{walking} + e_{ij}^{waiting} \tag{3-6}$$

where, $e_{ij}^{walking}$ and $e_{ij}^{waiting}$ represent the environmental health costs incurred during walking and waiting, respectively.

3.3.4 Interpretation of the total integrated cost

The general cost function approach creates a total integrated cost that ranges between 0 and 1. In this context, values closer to 0 represent lower costs (i.e., higher accessibility), while a value of 1 indicates the highest cost (i.e., the lowest accessibility).

3.4 Application: Incorporating extreme cold exposure into accessibility by public transit

In this section, we demonstrate the applicability and utility of the methods we developed in the previous section. Although the developed framework can be used to integrate environmental health costs due to exposure to various extreme climatic events (e.g., extreme heat, air pollution, urban flooding), we apply it to the case of incorporating extreme cold exposure into public transit accessibility in the city of Winnipeg, MB, Canada, as an example. This section describes the study area, dataset used, analysis procedure and findings of the example study.

3.4.1 Study area

The study area for this example analysis is the city of Winnipeg, located in the province of Manitoba (MB), Canada (**Figure 3-2**). Winnipeg serves as the capital city of Manitoba and is characterized by a diverse urban landscape and a unique set of climatic challenges. According to the most recent available data, Winnipeg has a total population of approximately 749,607 people, making it the major urban centre of the province (Statistics Canada, 2023). The city is known for its relatively high population density, with an estimated 1623.3 people residing per square kilometre (Statistics Canada, 2023). Winnipeg's public transit system plays an important role in the daily lives of its residents with 9.17% of people commuting to work using public transit compared to other modes of transportation (Statistics Canada, 2023). The transit system comprises 87 bus routes and an extensive network of 5170 bus stops, which provide essential transportation services to the city's residents (Winnipeg Transit, 2023).

A distinctive aspect of Winnipeg that profoundly influences its public transit system and overall urban life is the extreme cold weather conditions experienced during the winter months. The city is well-known for its harsh and frigid winters, characterized by sub-zero temperatures, heavy snowfall, and icy conditions. For instance, in January, which is the coldest month in Winnipeg, the average temperature ranges between -21 and -11 degrees

Celsius (https://climate.weather.gc.ca/). These extreme cold weather conditions can significantly impact the accessibility and usability of the public transit system, as well as the overall mobility and well-being of the city's residents. For these reasons, the city of Winnipeg was selected as a meaningful example study area to investigate the applicability of the proposed approach.

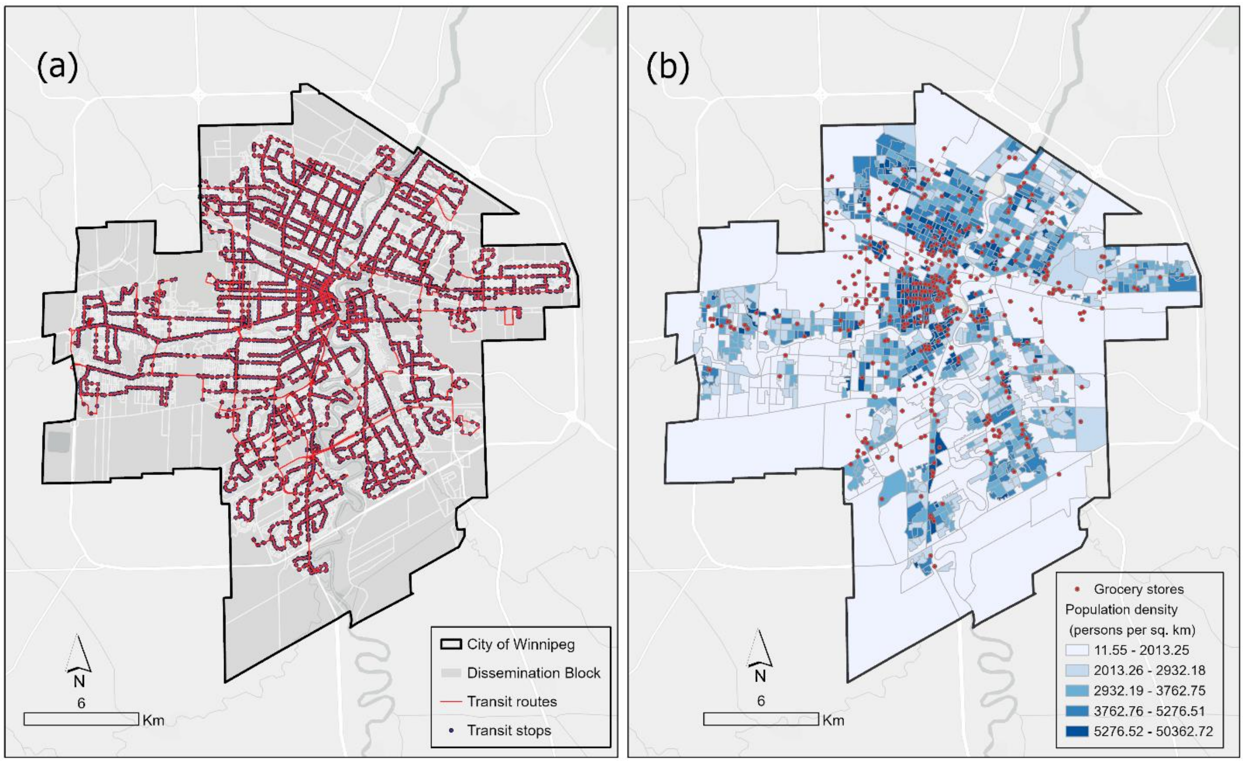

Figure 3-2: Maps of the study area: a) the public transit network in the city of Winnipeg, and b) the locations of food resources and population density in the study area.

3.4.2 Data

We use a variety of datasets including remote sensing data for extracting temperature, transportation data, origin and destination information, and socioeconomic variables. We begin our analysis by obtaining the boundary for the city of Winnipeg from the Winnipeg open data portal (data.winnipeg.ca/), which serves as the geographic boundary of our study area.

Satellite data

To estimate the temperature, which is the basis of environmental health cost analysis, we use Landsat 8 satellite imageries, an open-source product obtained from USGS Earth Explorer (https://earthexplorer.usgs.gov/) (USGS, 2023) which consists of two science instruments—the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). The thermal bands (Band 10 and 11) are commonly used for the analysis of urban surface temperature. We obtained satellite imagery with minimum cloud coverage for January 2022, which is usually the coldest month in the study area. While we acknowledge that land surface temperature may not directly substitute for the air temperature (i.e., known as air temperature derived from local meteorological stations), we use it as a proxy due to the limited coverage of weather stations in the region (Environment Canada, 2023). In addition, LST has advantages in obtaining higher spatial resolution temperature information compared to the data acquired from limited local meteorological stations (Braun & Fraser, 2022).

Transportation data

For our transit analysis, we utilize the General Transit Feed Specification (GTFS) with detailed transit operational information (Google, 2023). GTFS datasets are standardized formats for transit agencies to release information (e.g., locations of stops) about the transit services available and the schedules (Google, 2023). We obtained the GTFS data for Winnipeg in the winter season from Open Mobility Data (https://transitfeeds.com/). For the sidewalk information, we used Open Street Map (OSM) (Open Street Map, 2023) data obtained from BBBike (https://extract.bbbike.org/).

Origin and destination data

Our analysis uses the Dissemination Block (DB) as the spatial unit for accessibility analysis, with the centroids of DBs serving as the trip origins for the accessibility analysis.

As for the destinations, we consider the locations of food resources for demonstration purposes. We obtained DB information from Statistics Canada (https://www.statcan.gc.ca/) (Statistics Canada, 2023) and locations of food resources from SafeGraph (https://www.safegraph.com/) (SafeGraph, 2023), both for the year 2021. The food resources data used in this study include general merchandise stores (e.g., Walmart) and grocery stores (e.g., Sobeys) based on the "top_category" information in the SafeGraph's Canadian Places dataset. A limitation worth noting is that convenience stores (e.g., 7-Eleven) are also classified as grocery stores within the SafeGraph dataset. While convenience stores do offer some food resources, we recognize that classifying them as grocery stores does not align with the literature.

Socioeconomic information

In preparation for exploring the socioeconomic characteristics of areas experiencing accessibility loss and gain, we aggregate the accessibility analysis results from the Dissemination Block (DB) level to the larger Dissemination Area (DA) level. This allows us to utilize detailed socioeconomic information available only at the DA level. We acquired socioeconomic information from Statistics Canada (www.statcan.gc.ca) for the year 2021. We collected six socioeconomic variables: 1) average household income (CA$) in 2020, 2) percentage of visible minorities, 3) percentage of immigrants from 2011 to 2021, 4) percentage of people with a bachelor’s degree or higher, 5) unemployment rate, and 6) percentage of people who use public transit for their work commute. An overview of the variables used in this study is presented in Table 2-1.

Table 3-1: Variables used for understanding the socioeconomic characteristics of areas with accessibility loss and gain

Variables	**Rationale**
Income (El-Geneidy et al., 2016; Lee and Kim 2023; Griffin and Sener 2016; Pereira 2019; Karner et al. 2024)	To understand association between public transit accessibility and income level
Visible minorities (Lee and Kim 2023; Javanmard et al. 2023; Palm et al. 2020; Liu and Shalaby 2023)	To understand association between public transit accessibility and visible minority population group
Immigrants (Palm et al. 2020; Barajas et al 2018)	To understand association between public transit accessibility and immigrants
Educational qualifications (Lee and Kim 2023)	To understand association between public transit accessibility and education attainment level
Unemployment (Lee and Kim 2023)	To understand association between public transit accessibility and unemployment rate

3.5 Analysis

In this section, we describe the analytical procedures for measuring public transit accessibility by incorporating the environmental health cost through the generalized cost function framework. There are four steps. First, we estimate land surface temperature using remote sensing images. Next, we compute the detailed transit travel time to the destinations. Third, we calculate the total cost using the generalized cost function approach that combines travel time cost and environmental health cost. Lastly, we examine the differences in socioeconomic characteristics between areas experiencing accessibility loss and those experiencing gain due to the inclusion of environmental health costs. For the accessibility and inequality analysis, we used R (R, 2023), and for deriving land surface temperature, we used QGIS version 3.32 (QGIS, 2023).

3.5.1 Estimating land surface temperature

Algorithms have been developed to estimate land surface temperature (LST) from the thermal infrared sensors (TIRS) of satellite images, including the mono-window algorithm (Qin et al., 2001), single-channel algorithm (Jimenez-Munoz et al., 2014; Jiménez-Munoz & Sobrino, 2003), and the split-window algorithm (Sobrino et al., 1993). Among these methods, the split-window algorithm stands out as the most popular and robust approach (Käfer et al., 2020). The split-window algorithm utilizes two thermal bands: bands 10 and 11, for LST estimation. However, it is important to note that the data provider USGS EarthExplorer recommends users refrain from relying on band 11 data in quantitative analysis of the TIRS data, such as the use of split window techniques for retrieval of surface temperature values (Landsat 8 (L8) Data Users Handbook, 2019). The mono-window algorithm requires a single thermal band along with atmospheric water vapour and near-surface air temperature data at the time of image capture, which can be challenging to obtain for large study areas with limited weather station coverage.

Consequently, we opt for the single-channel algorithm that needs only one thermal band (Jimenez-Munoz et al., 2014; Jiménez-Munoz & Sobrino, 2003) and does not require the aforementioned atmospheric information. This algorithm can be expressed using **Equation 3-7**:

$$T_s(k) = \gamma \left[\frac{1}{\varepsilon}(\psi_1 L_{sen} + \psi_2) + \psi_3\right] + \delta \tag{3-7}$$

where T_s is the land surface temperature in Kelvin, which is later converted to degree Celsius; ε is the surface emissivity; L_{sen} is the top of atmosphere (TOA) radiance; γ and δ are two parameters defined as follows (**Equations 3-8** and 3-**9**):

$$\gamma = \frac{{T_{sen}}^2}{b_\gamma L_{sen}} \tag{3-8}$$

$$\delta = T_{sen} - \frac{{T_{sen}}^2}{b_\gamma} \tag{3-9}$$

where, T_{sen} is the at-sensor brightness temperature, calculated using **Equation 3-10**, and b_γ can be determined as $c\ /\ \lambda$; here c is the Planck radiation constant and λ is wavelength.

$$T_{sen} = \frac{k_2}{\ln\left(\frac{k_1}{L_\lambda} + 1\right)} \tag{3-10}$$

Here in **Equation 3-10**, L_λ is the TOA radiance of the TIR band obtainable using **Equation 3-11** below, and k_1 and k_2 are thermal conversion constants.

$$L_\lambda = M_L Q_{cal} + A_L \tag{3-11}$$

In **Equation 3-11**, M_L is the band-specific multiplicative rescaling factor and $A_L$is band-specific additive rescaling factor, both available in the image metadata; Q_{cal} is the calibrated pixel digital number.

The atmospheric correction functions ψ_1, ψ_2, and ψ_3 in **Equation 3-7** can be expressed using the following **Equation 3-12**:

$$\psi_1 = \frac{1}{\tau};\ \psi_2 = -L_{\downarrow} - \frac{L_{\uparrow}}{\tau};\ \psi_3 = L_{\downarrow} \tag{3-12}$$

Here, τ is the atmospheric transmission, $L_{\uparrow}$ and $L_{\downarrow}$ are the atmospheric upwelling and downwelling radiance, respectively, obtainable from the Atmospheric Correction Parameter Calculator developed by NASA (https://atmcorr.gsfc.nasa.gov/).

Finally, surface emissivity ε in **Equation 3-7** can be computed using the normalized difference vegetation index (NDVI) threshold method proposed by (Sobrino et al., 2008). With the estimated NDVI value, we observed an NDVI value ranges between 0 to 0.2 which reflects the bare land, soil, or impervious surface. Therefore, we employed the following **Equation 3-13** for deriving surface emissivity suggested by (Sobrino et al., 2008):

$$\varepsilon = a_i \rho_{red} + b_i \tag{3-13}$$

where, ρ_{red} is the red band reflectance, and a_i and b_i are parameters derived from an empirical relationship between the red band reflectance and Moderate Resolution Imaging Spectroradiometer (MODIS) emissivity library (Yu et al., 2014).

3.5.2 Computing detailed transit travel time

We utilize an open-source transportation analysis package called *r5r*, developed by Pereira et al., (2021) to compute transit-based travel time. This R package computes a travel time matrix when users provide a schedule-aware transit network dataset in GTFS format. Within the *r5r* package, we used the "detailed itineraries" function that provides detailed trip information between origin-destination pairs (r5r, 2023). The output includes the access, egress, waiting and in-vehicle time in each trip, as well as some info such as the distance travelled, the routes used and the geometry of each leg.

One notable advantage of this "detailed itineraries" function within the *r5r* package is its flexibility. It allows users to configure various parameters, such as origin and destination details, mode types, departure time, maximum walking time, maximum trip duration, and more. In our analysis, we employ a maximum walking time of 17 minutes for each walking segment. This duration was initially derived as a 1000-meter distance and converted into minutes using the default walking speed of 3.6 km/hour, as specified by the r5r package. This 1000-meter threshold has been commonly utilized in previous research focused on public transit-based accessibility. (Pereira et al., 2021; Pönkänen, 2022.; Tomasiello et al., 2023). We also set the maximum trip duration to the default value of two hours. To align our analysis with a satellite image acquired at 11:22 AM on January 24, 2022, we calculate detailed travel times for 11 AM departure time using a time window of 30 minutes. Within the 30-minute time window, a minimum travel time for each origin-destination pair for each minute departure time (e.g., 11:01, 11:02, 11:03 AM) based on the fastest paths, is used for further cost analysis.

Our dataset consists of an extensive 4,148,408 origin-destination pairs: 8024 origins (i.e., centroids of DBs) × 517 destinations (e.g., locations of food resources). We narrow our focus to identify the three nearest food resources for each origin. This step enables us to retain detailed transit travel time information specifically for the three closest food resources and use these for further dual accessibility analysis. It is important to note that our study also accounts for occasions when walking is the fastest mode to reach the destination. In these specific cases, waiting and exposure around the transit stops are not included in the cost analysis.

For illustrative purposes, **Figure 3-3a** presents the geographic patterns of walking and in-vehicle segments from detailed itineraries from all dissemination blocks to their three nearest food resources. Meanwhile, **Figure 3-3b** showcases a close-up view of a detailed itinerary from a specific DB to its three nearest food resources. Using these geo-located, detailed itinerary data, we generate buffers for each walking segment to compute the surface temperature along the walking segments. For this analysis, we use a buffer size of 30 meters to maintain consistency with the resolution of the satellite image. Although the original pixel size of the thermal band in Landsat 8 imagery is 100 meters, we resample it to 30 meters to match the resolution of the red band. This resampling is necessary because both bands are used in estimating emissivity as well as land surface temperature. For estimating the environmental health costs of walking and waiting segments based on **Equations 4** and **5**, we use the absolute value of temperature, where higher values indicate greater exposure levels.

Although the "detailed itinerary function" provides waiting time for each transit trip, it does not provide information about which stop the waiting time is associated with. To address this issue, we first detect the starting point of each in-vehicle trip leg and then search for the closest transit stop from that starting point and assign it with the associated waiting time accordingly. With the identified transit stops for each waiting time, we create buffers around the stops, which will be used as a basis for estimating travellers' exposure to extreme cold weather while waiting for the next bus.

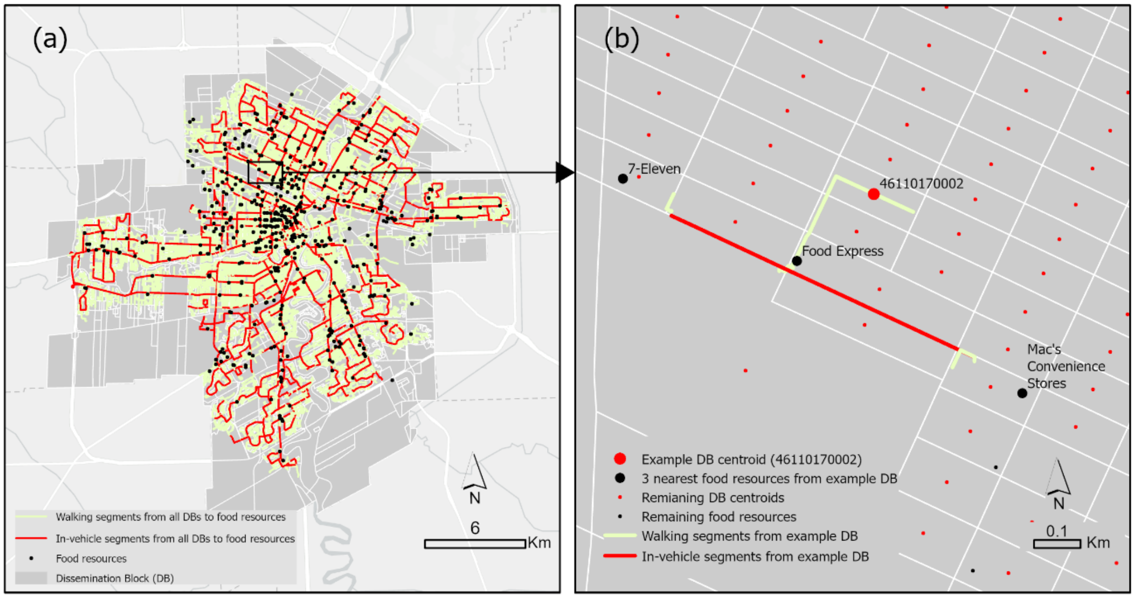

Figure 3-3: Geographic patterns of detailed itineraries between origin-destination pairs: a) walking and in-vehicle segments from detailed itineraries from all dissemination blocks to their three nearest food resources and b) a close-up view of a detailed itinerary from a specific DB to its three nearest food resources.

3.5.3 Cost and dual accessibility analysis

Using the generalized cost function framework (**Equation 3-1**), we compute the total cost by combining travel time cost and environmental health cost (i.e., extreme cold exposure). Due to the asymmetric distributions of travel time cost and environmental health cost, we implement a natural logarithm transformation to each cost component before calculating the total cost. We further calculate the normalized total cost using **Equation 3-2** to facilitate scenario analysis for examining the impacts of overlooking or considering environmental health costs with different weighting schemes. We have three scenarios as described below:

- **Scenario 1**: Measuring accessibility based on travel time cost only (δ_e =0 and $\delta_t = 1$).

- **Scenario 2**: Measuring accessibility based on environmental health cost only (δ_e =1 and $\delta_t = 0$).
- **Scenario 3**: Measuring accessibility with equal weighting ($\delta_e = \delta_t$), which is a dual measure of accessibility based on the total cost.

3.5.4 Exploring socioeconomic characteristics of areas experiencing accessibility loss and gain

Using the resulting total integrated costs obtained in section 4.3.3., we categorize neighbourhoods into two groups: those experiencing increased costs (i.e., decrease in accessibility) and those experiencing decreased costs (i.e., increase in accessibility) by comparing Scenario 1 (baseline) and 3 results. We then examine whether differences in socio-economic and demographic variables between the two types of neighbourhoods are statistically significant using a nonparametric Mann-Whitney U-test. The purpose of this analysis is to examine whether individuals with low income (El-Geneidy et al., 2016; Lee and Kim 2023; Giffin and Sener 2016; Pereira 2019; Karner et al. 2024), those from visible minority backgrounds (Lee and Kim 2023; Javanmard et al. 2023; Palm et al. 2020; Liu and Shalaby 2023), immigrants (Palm et al. 2020; Barajas et al 2018), individuals with limited educational qualifications (Lee and Kim 2023), and those facing unemployment (Lee and Kim 2023) are disproportionately located in areas with accessibility loss due to the inclusion of environmental health costs.. We use the Mann-Whitney U-test due to the asymmetrical distribution of the variables as verified by the Shapiro-Wilk test. The outcomes from the Mann-Whitney U-test can reveal how the increased cost (i.e., decrease in accessibility), arising from the inclusion of environmental health costs (i.e., exposure to extreme cold weather), affects socially disadvantaged population groups.

3.6 Results

3.6.1 Spatial patterns of land surface temperature

Figure 3-4 presents the spatial pattern of land surface temperature (LST) in Winnipeg, classified using quantile classification schemes, as derived from Landsat 8 data, which is used as the basis of environmental health cost estimation in this study. In **Figure 3-4a**, the temperature ranges from -16.78°C to -7.78°C across the city of Winnipeg, revealing a noticeable trend where urban areas experience relatively milder cold, while suburban regions display colder conditions. Notably, the city's central core stands out as areas with less severe cold. This can be attributed to the prevalent land use pattern characterized by extensive concrete and asphalt surfaces (Herb et al., 2008). **Figures 3-4b** and 3-**4c** further show the temperature patterns along the walking segments of a transit journey and around transit stops, respectively, reflecting the similar trends observed in **Figure 3-4a**, with colder temperatures prevalent in the outskirts of the city. This spatial variance in LST highlights the significant variability in temperature across space, which suggests overlooking these heterogeneous temperatures and corresponding environmental health costs could lead to erroneous and misleading measurements of public transit accessibility.

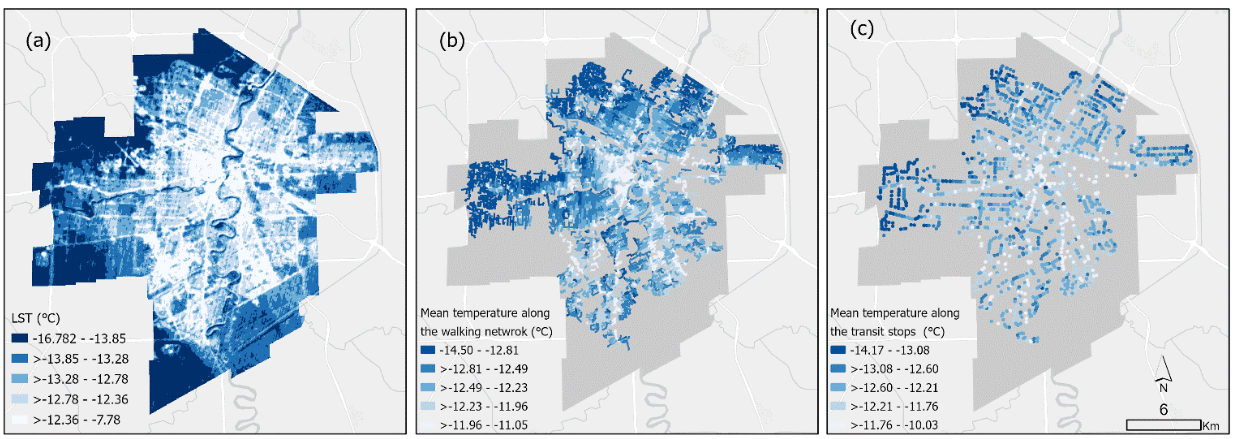

Figure 3-4: Spatial patterns of land surface temperature: a) overview, b) temperature along the walking network, and c) temperature around the transit stops.

3.6.2 Geographic patterns of detailed transit travel time

Figure 3-5 provides the analysis results of average transit travel times to the three nearest food resources. Specifically, **Figure 3-5a** illustrates the total travel time, **Figure 3-5b** represents walking time, **Figure 3-5c** depicts waiting time, and **Figure 3-5d** shows in-vehicle time. In terms of total travel time, which ranges from 1.56 minutes to 37.46 minutes, the central city area stands out with significantly lower travel times. On average, residents living near downtown experience travel times of less than 6.73 minutes, while those residing farther away endure significantly longer transit times (**Figure 3-5a**). This trend also extends to the walking portion of a transit journey with residents near the downtown experiencing shorter walking times whereas those living farther away face longer walking times (**Figure 3-5b**). It is important to note that during extreme weather events (i.e., extreme cold and heat), longer walking times can pose a significant health risk to transit riders (Fraser and Chester 2017). When considering waiting time, we observe the majority of neighbourhoods in Winnipeg experience an average waiting time of less than 1.9 minutes when accessing food resources via transit (**Figure 3-5c**). Similarly, the in-vehicle time segment shows that most neighbourhoods experience in-vehicle times averaging below 4.3 minutes for trips to the three nearest food resources (**Figure 3-5d**).

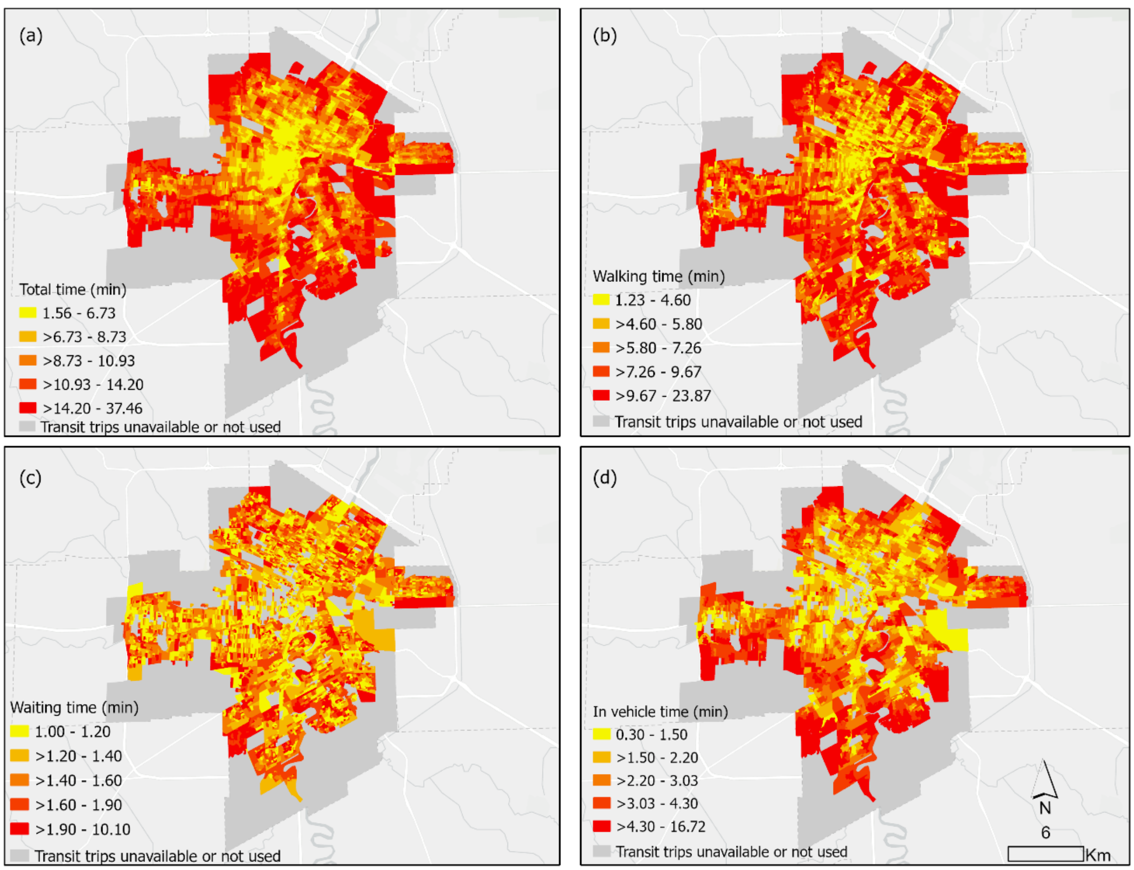

Figure 3-5: Spatial patterns of transit travel time: a) total transit travel time, b) walking time, c) waiting time, and d) in-vehicle time.

3.6.3 Cost and dual accessibility analysis results

Figure 3-6 presents the outcomes of the cost and dual accessibility analysis based on three scenarios: Scenario 1) cost/accessibility based on travel time only (**Figure 3-6a**), Scenario 2) cost/accessibility based on environmental health cost only (**Figure 3-6b**), and Scenario 3) total integrated cost (**Figure 3-6c**). All of these figures are presented with the same classification and colour scheme for a fair comparison.

A consistent trend emerges across all cost metrics: lower costs (i.e., higher accessibility) are observed near the downtown area, while costs tend to increase for neighbourhoods located farther from downtown. For example, in **Figure 3-6a**, when considering travel time only, the downtown area exhibits very low costs, which aligns with the findings from the travel time analysis in **Figure 3-5a**. In **Figure 3-6b**, we focus on Scenario 2. **Figure 3-6b** shows a similar trend with lower costs near the downtown area. However, there is a slight increase in cost near downtown and a minor decrease in areas farther from downtown compared to Scenario 1 results (**Figure 3-6a**).

Figure 3-6c presents the results of Scenario 3 analysis based on the total integrated cost with an equal weight of travel time cost and environmental health cost. **Figure 6c** generally mirrors the trends observed in **Figures 3-6a** and 3-**6b**. However, when compared to Scenario 1 results (**Figure 3-6a**), we notice changes in the total integrated cost, particularly in the downtown and northeast parts of the study area. This is due to the inclusion of environmental health cost, which is heterogeneous across space as shown in **Figure 3-4**.

To further confirm these changes, we analyze the relative change in cost by comparing Scenario 1 and 3 results (**Figure 3-7a**). This analysis reveals both increases and decreases in cost, confirming the influence of environmental health costs on accessibility analysis. We also classified neighbourhoods into increased cost (i.e., decreased dual accessibility) and decreased cost (i.e., increased dual accessibility) categories (**Figure 3-7b**) for a clearer comparison. **Figure 3-7b** suggests that a considerable number of neighbourhoods (i.e., 44%) experience increased costs, which are spatially randomly distributed across the study area.

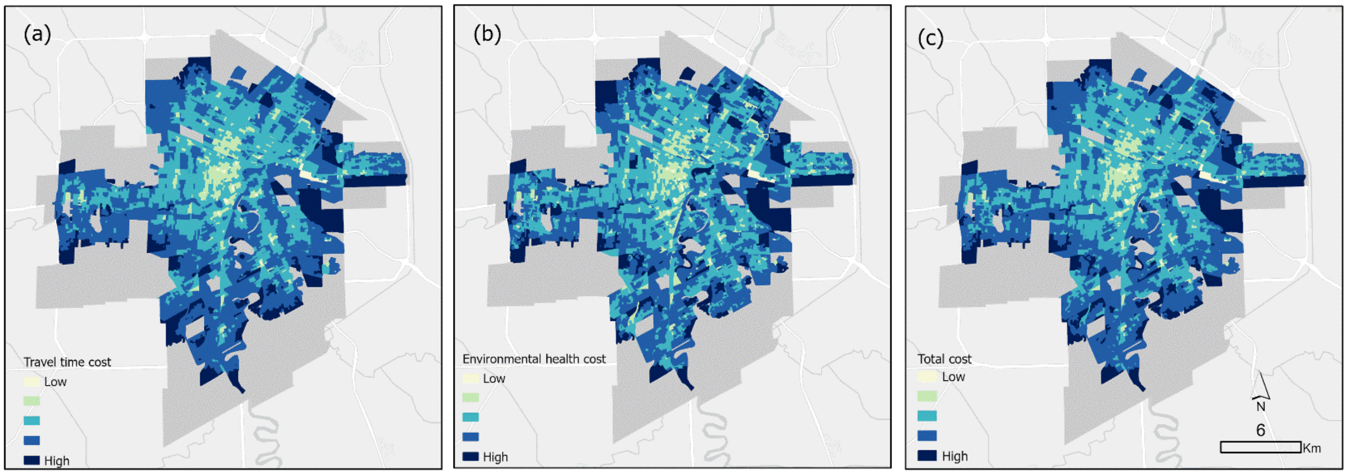

Figure 3-6: Cost analysis results: a) travel time as a cost (Scenario 1), b) environmental health as a cost (Scenario 2), and c) total cost incorporating travel time and environmental health costs (Scenario 3).

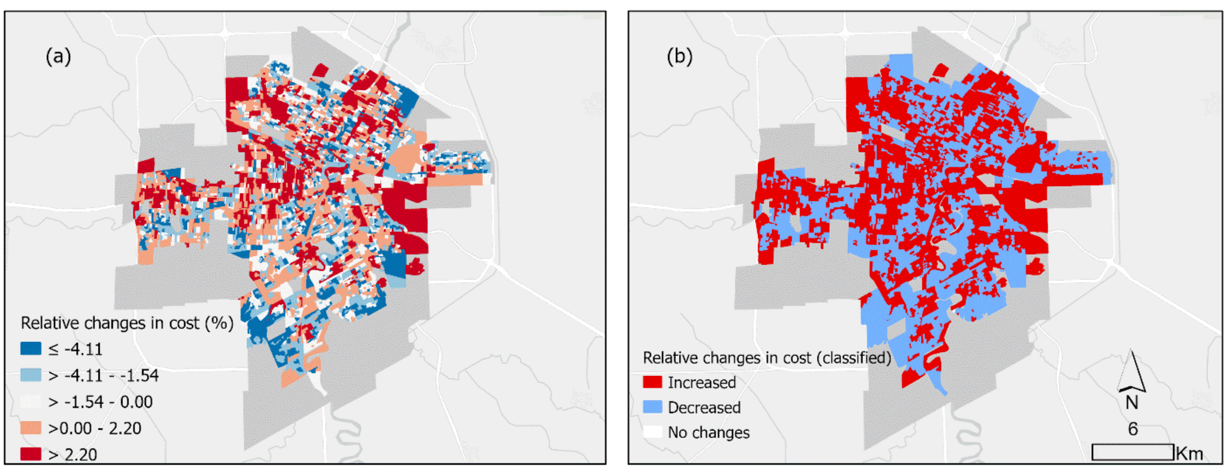

Figure 3-7: Relative changes in costs due to the inclusion of environmental health costs (Scenario 1 versus Scenario 3): a) relative changes (%) and b) neighbourhoods with increased or decreased costs.

3.6.4 Findings on socioeconomic characteristics of areas with accessibility loss and gain

This section reveals whether there are statistically significant differences in socioeconomic characteristics between two types of neighbourhoods: 1) increased costs (i.e., decrease in accessibility) and 2) decreased costs (i.e., increase in accessibility), identified from the previous section.

Figure 3-8 shows boxplots of these variables for neighbourhoods classified under increased or decreased cost categories. **Table 3-1** presents Mann-Whitney U-test results.

We found statistically significant disparities across all socioeconomic variables between neighbourhoods experiencing increased and decreased costs. For instance, in neighbourhoods experiencing increased costs, we observed a higher proportion (a median of 9.09%) of the population using public transit for commuting to job places who are often marginalized individuals, as opposed to the 7.29% in neighbourhoods with decreased costs. A similar pattern emerges for variables such as the percentage of unemployment rates, visible minorities, and recent immigrants, with a notably higher concentration of these demographic groups residing in neighbourhoods facing increased costs (i.e., decreased accessibility). Additionally, neighbourhoods subject to increased costs tend to exhibit lower average household incomes (a median of $44,000). As for the education attainment level, neighbourhoods with increased costs show a lower proportion of people with a college degree or higher.

The Mann-Whitney U-tests confirm the statistically significant differences, indicating that areas experiencing accessibility loss are generally associated with socioeconomically disadvantaged residential areas with higher proportions of public transit users, visible minorities, recent immigrants, unemployed individuals, as well as lower household income and education levels.

Table 3-2 Mann-Whitney U-test results

Variables	Median		P-values
	Neighbourhoods with increased cost (decreased accessibility)	**Neighbourhoods with decreased cost (increased accessibility)**	
Public transit to work (%)	9.09	7.29	**<0.001**
Unemployment rate (%)	9.1	8.2	**0.001**
Visible minority (%)	28.02	22.39	**<0.001**
Recent immigrants (2011-2021) (%)	9.61	7.18	**<0.001**
Average household income ($)	44000	46800	**<0.001**
Have a bachelor's degree or higher (%)	24.44	27.13	**0.02**

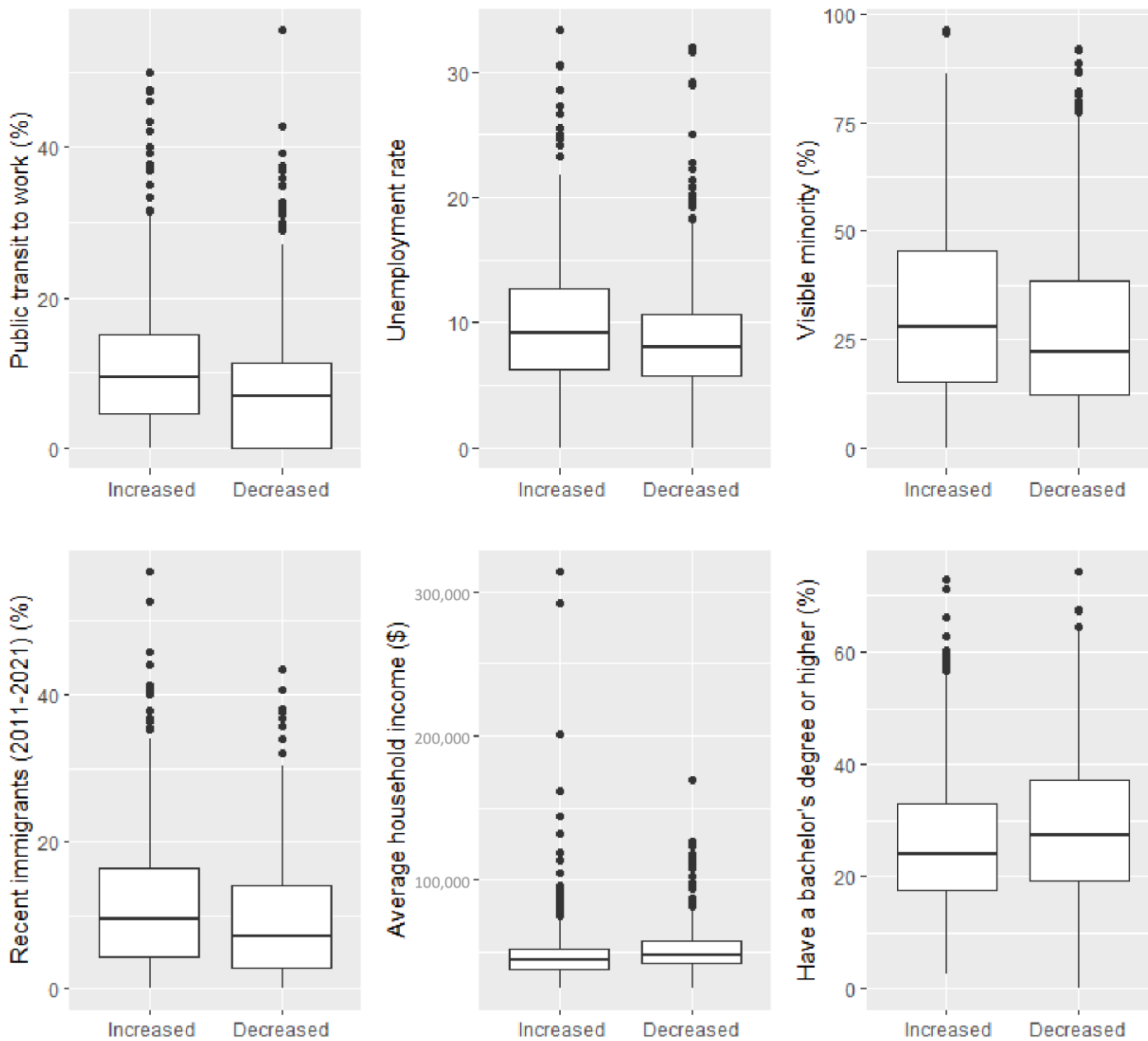

Figure 3-8: Box plots of six socioeconomic variables for the DAs where cost increased or decreased due to the inclusion of environmental health cost (Scenario 1 versus 3).

3.7 Discussion and conclusion

This paper introduced a general cost function approach that combines travel time and environmental health costs into an integrated measure of dual accessibility: a measure of the travel costs of accessing a fixed number of destinations. In this study, we define environmental health costs as the exposure of transit users to extreme environmental conditions, such as extreme cold or heat, which can cause adverse health outcomes. The proposed general cost function approach is versatile and can be applied to addressing exposure to various extreme environmental conditions such as extreme heat, cold, air pollution, and urban flooding. However, we recommend being cautious when applying this approach to weather extremes other than extreme heat or cold because different types of exposure might involve varying sensitivities and behaviours (e.g., linear vs exponential increase of exposure impacts). To demonstrate the utility of our approach, we conducted an example study that incorporates transit users' extreme cold exposure into accessibility measures in the city of Winnipeg, MB, Canada. Additionally, we also explored whether the increase in costs (i.e., decrease in accessibility) arising from the inclusion of environmental health costs disproportionately affects socially disadvantaged population groups.

Overall, the findings of the example study highlight notable differences in the spatial patterns of accessibility across three scenarios: 1) measuring accessibility based on travel time cost only, 2) measuring accessibility based on environmental health cost only, and 3) measuring accessibility with equal weighting of travel time and environmental health cost, which is a dual measure of accessibility based on the total cost. These findings confirm that disregarding environmental health costs can lead to an inaccurate estimation of the actual costs associated with accessing urban opportunities and resources. Additionally, we observed that an increase in costs (i.e., a decrease in accessibility) disproportionately affects socioeconomically marginalized populations.

Therefore, we recommend that policymakers and planners give careful consideration to environmental health costs when evaluating public transit accessibility, particularly in the context of anticipated climate change impacts. For example, by enhancing transit infrastructure (e.g., shelters, heaters) to improve user comfort during extreme weather conditions, we can mitigate the health risks and associated costs for transit riders exposed to harsh environmental conditions. The general cost function approach introduced in this paper has the potential to enhance the practicality of transit-based accessibility measures, thus leading to better preparedness for climate change implications. By using this method, planners and policymakers could gain valuable insights to shape development strategies that effectively balance social and environmental sustainability in the face of climate change.

In the next phase of our research, we aim to expand the scope of our study to encompass various environmental exposures, including but not limited to extreme heat, air pollution, and urban flooding in cities around the world. As we grapple with the current and future challenges of climate change, the framework developed in this paper can serve as a guide for evidence-based planning and policymaking efforts for healthy and resilient cities.

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Chapter 4

4. Conclusions

4.1 Summary of Thesis

Healthy City is an ongoing process that prioritizes public health through various key initiatives which primarily involve improving the quality of citizens' lives (Haslauer et al., 2015). In the recent decade, climate change poses significant health challenges in cities. The consequences include a surge in climate-related diseases, such as heat and cold related illnesses, and respiratory diseases (Patz and Olson, 2006).

Recognizing the need to address climate change root causes, cities worldwide are focusing on reducing greenhouse gas emissions and embracing urban greening initiatives (Mihavlov et al., 2020; Fryd et al., 2011). Renewable energy adoption, sustainable transportation promotion, and green space integration into urban planning form a comprehensive strategy to combat climate change, protect public health, and enhance city resilience.

Green spaces play a dual role, positively impacting public health and climate change mitigation. They provide recreational spaces, promoting physical and mental well-being, while also absorbing carbon dioxide and contributing to urban cooling. Public transit, as a crucial element in climate change mitigation, reduces car dependency, curbing emissions and encouraging physical activities like walking and biking. This thesis focuses on identifying limited green space availability areas (Liu et al. 2021; Dai et al. 2011; Xu et al., 2018) in the cities of Global South and understanding the exposure to extreme weather during public transit use (Dzyuban et al. 2021; Fraser and Chester 2017; Karner et al. 2015; Kuras et al. 2017; Rosenthal et al. 2022; Lanza and Durand 2021; Miao et al. 2019; Sami and Keith 2023; Hoehne et al. 2022).

The thesis proposes two new geospatial methods to advance land use and transportation planning for healthy cities: an analytical framework for identifying urban green space deserts and a new accessibility measure considering extreme weather exposure during public transit travel. Chapter 2 focuses on understanding the sensitivity of green space distribution to walking distance thresholds, developing a reliable analytical framework, conducting an inequality analysis and investigating socioeconomic characteristics of UGS desert areas in the context of Global South cities. Chapter 3 developed a generalized framework for measuring public transit accessibility, applying it to extreme cold conditions in Winnipeg, Canada, and exploring its impact on socially disadvantaged groups.

This thesis contributes to healthy city planning by proposing practical geospatial methods to inform urban planners, local governments, and policymakers. By addressing the importance of green spaces, public transit, and scientifically informed planning in fighting ongoing climate change impacts, this thesis aims to create more liveable, sustainable, and healthier urban environments globally.

4.1.1 Chapter 2 summary

Urban green space (UGS) has several health benefits. Ensuring adequate and equitable access to UGS is a prerequisite for a healthy city. Citizen-centred land use planning can satisfy this requirement. Evidence-based land use planning includes quantifying the availability of green spaces based on the guidelines provided by local governments. For instance, a standard walking distance is often used as an important criterion for measuring UGS availability. However, in low- and middle-income countries (LMICs) in the Global South where well-defined local policy guidelines for walking distance thresholds are missing for UGS availability evaluations, UGS availability is often evaluated by using a single ad-hoc or arbitrary walking distance threshold. Accurate detection of UGS availability will enable policymakers and planners' evidence-based land use planning. A lingering question in the research on UGS availability in the Global South is which walking distance threshold should be used due to the absence of consensus on that in the literature and planning guidelines. The second chapter of this thesis answers that question by developing an analytical framework for identifying UGS deserts – areas without adequate UGS availability levels – considering various walking distance thresholds.

We first demonstrate how geographic distributions of UGS deserts can change depending on different walking distance thresholds (e.g., 100, 300, 500 meters) of choice. Unreliable and inaccurate detection of UGS deserts can hinder evidence-based land use planning for promoting healthy cities and result in erroneous inequality evaluation. To overcome this limitation, we introduce and examine robust UGS oases and deserts: geographic areas with and without the per capita green space (PCG) level recommended by a local government regardless of different walking distance thresholds used, respectively. With the identified robust UGS deserts and oases, we further examined whether there are the statistically significant differences in socioeconomic characteristics between UGS desert and oases areas.

This study found that the spatial patterns of UGS deserts and oases are sensitive to different walking distance thresholds used. Therefore, the use of an ad-hoc, arbitrary, not well-informed walking distance threshold can lead to inaccurate identification of UGS deserts. Robust UGS deserts approach can be a possible solution for this. We also found that socioeconomically disadvantaged populations are disproportionately located in robust UGS desert areas. The robust UGS deserts approach enables more reliable and informed land use planning to enhance UGS availability and its equality, thereby facilitating an optimal development of methodology that supports healthy city objectives.

4.1.2 Chapter 3 summary

In the Global North, cities prioritize personal automobiles, discouraging active transportation and public transit. While transit use can encourage physical activity, it exposes users to extreme environmental conditions during out-of-vehicle segments. Such exposure can be considered as environmental health costs because exposure to weather extremes can lead to adverse health outcomes. Even worse, climate change is increasing the intensity and frequency of extreme weather events. In this context, how can we make public transit accessibility measures ready for climate change? Chapter 3 answers the question by developing a methodology which is a general cost function approach combining travel time and environmental health costs into an integrated measure of dual accessibility: a measure of the travel costs of accessing a fixed number of destinations.

To demonstrate the utility of the proposed method, we carry out an example study that incorporates transit passengers' extreme cold exposure into accessibility measures in the city of Winnipeg, Manitoba, Canada. Further, we examined the differences in socioeconomic characteristics of areas with accessibility loss and gain to investigate whether the increase in total integrated costs (i.e., decrease in accessibility) due to the inclusion of environmental health costs disproportionately affects areas with higher proportions of socially disadvantaged population groups.

Overall, the findings of the example study highlight notable differences in the spatial patterns of accessibility when environmental exposures were integrated to measure accessibility. These findings confirm that disregarding environmental health exposures can lead to an inaccurate estimation of accessibility and may pose additional burdens on citizens. Additionally, we observed that a decrease in accessibility disproportionately affects socioeconomically marginalized populations. The proposed method enables a more realistic and practical transportation planning approach to evaluate public transit accessibility under climate change; thereby, improving the readiness and resilience of our society and transport systems for future challenges align with healthy city objectives.

4.2 Limitations and recommendations

Chapter 2 has several limitations. First, due to the absence of information on the building type (e.g., residential, office, industrial), we included all buildings in the analysis. However, analysis only based on residential location can produce more accurate results in future studies. Second, the UGS distribution data were obtained using satellite image classification, which may be less reliable than information directly obtained from city officials. While satellite image classification is a commonly used method to obtain UGS data, it may not always capture the most accurate information since its performance can be influenced by weather conditions or other factors that affect image quality. Furthermore, it is important to acknowledge that the remote sensing approach utilized in this study neither differentiates between public and private green spaces nor considers different impacts and attractions of distinct green space types. Given the lack of reliable information on green spaces in Dhaka, which is a common challenge in low- and middle-income countries, remote sensing classification was employed as the best available alternative. However, it should be noted that this approach only allowed us to calculate UGS availability, rather than accessibility, as it focused solely on quantifying the amount of green space without providing insights into its physical accessibility to the public due to possible restrictions (e.g., private, unsafe, etc.). With more information collected from surveys/interviews and higher resolution spatiotemporal datasets, future research could undertake more nuanced studies to examine the availability of specific types of UGS and evaluate their impacts on people's physical and mental health. Lastly, we also acknowledge that the quantitative measures of UGS availability in this study may not resonate with local residents' perceptions of their UGS availability. A future study examining the consistency between the objective and subjective measures of UGS availability through the surveys/interviews would make the analysis more robust and citizen-centred.

Despite the limitations, our proposed approach for detecting robust UGS deserts offers a more rigorous and reliable method for decision-making in enhancing UGS provision, promoting equality, and ultimately supporting the development of urban policies for healthier and more equitable cities. In light of this, we suggest several future research agendas and recommendations that we encourage researchers and practitioners to consider. 1) Test multiple walking distance thresholds: It is recommended to use multiple walking distance thresholds when identifying UGS deserts. Relying on a single threshold may lead to erroneous measurements of UGS availability as demonstrated in this study. 2) Use network buffers: Future studies should adopt network buffer analysis instead of Euclidean buffer approaches. Utilizing network buffers would enable a more accurate assessment of UGS availability along the walking networks. 3) Consult local planning and community guidelines: When setting up a standard for UGS availability analysis, it is important to consider local planning and community guidelines. For instance, in Dhaka, the recommended guideline is to have at least 3.48 m^2 of green space per person. However, this might differ in other countries. 4) Consider edge effects: To accurately measure UGS availability, it is recommended to consider the edge effect. This approach can account for UGS availability beyond the city boundary if green spaces fall within a desired walking distance. 5) Evaluate inequality: It is crucial to conduct inequality tests to determine whether underserved and vulnerable communities have limited access to green spaces.

Investigating the disparities in UGS availability for these communities is an important aspect of promoting equitable access to green spaces within urban areas.

Chapter 3 also has a few limitations. First of all, while this chapter contributes conceptually and methodologically to making accessibility measures adaptable to climate change, we acknowledge a weakness in our new accessibility metric from an applicability standpoint. Essentially, the proposed accessibility index becomes unitless when we combine travel time and environmental health costs into a generalized cost. We understand that this generalized cost might not be intuitive for planners and policymakers to comprehend and implement in practice. The Winnipeg case study has limitations as well. First, for estimating exposure to weather extremes, we relied on land surface temperature derived from remotely sensed data. While we recognize that surface temperature does not directly equate to air temperature, we opted to use it as a proxy (Li, 2021). This decision was driven by the limited coverage of weather stations in the study area, whereas land surface temperature (LST) provides temperature data at a much higher spatial resolution. However, there remain some uncertainties regarding the LST. In a winter-time scenario, air temperature may provide a closer estimate of the experienced temperature of individuals using transit and while available at only coarse spatial scales, it is available on an hourly temporal time scale. However, due to time constraints, it was not possible to investigate the spatiotemporal variability in temperature between LST and air temperature or the relative sensitivity to the use of air temperature in place of LST. Future studies can adopt a sensitivity test to address these issues. To achieve a more realistic and accurate estimation of exposure, our future research will use a more appropriate indicator of human exposure to cold or heat. This will be based on mean radiant temperatures using an urban 3D model through SOlar and LongWave Environmental Irradiance Geometry (SOLWEIG) modelling (Lindberg et al., 2008). Second, this paper considers the simple assumption of environmental exposure and overlooks the complex impacts of environmental exposure on health outcomes (e.g., time-lagged, frequency, recency) (Kwan, 2018). Third, we acknowledge that our analysis overlooked the temporal (e.g., monthly) variability of cold exposure. Instead, we relied on temperature data from a single day at a specific time—11:22 AM on January 24th, 2022—due to the availability of Landsat 8 satellite imagery on a 16-day cycle. To account for monthly variations in cold exposure, future research can use temperature data from a couple of days in other winter months such as December 7th/23rd or February 9th/25th based on the 16-day cycle to perform the analysis. For examining variations at higher temporal resolutions like daily and hourly, future research can utilize SOLWEIG (Lindberg et al., 2008) or more comprehensive urban canopy layer numerical models (Leroyer et al. 2018) or through advanced technologies such as unmanned aerial vehicles (UAVs) or drones to obtain local temperature data at finer spatio-temporal resolutions . These data would enable future studies to investigate the temporal variability of weather exposure and examine its impacts on the results of accessibility inequality analysis. For studies spanning a longer time frame (e.g., an entire year), it is important to consider the varying impacts of different temperature levels on accessibility. For instance, while extreme hot or cold weather during summer or winter seasons may affect access, milder or warmer temperatures during the spring or fall seasons might not have the same impacts. Investigating how different temperature levels affect access in different ways is an important direction for future research. Additionally, it is crucial to consider the extremity of high (e.g., 30 °C) versus low (e.g., -20 °C) temperatures. Geographic contexts should also be taken into account as the same temperature might be perceived differently across the world. For example, a temperature of 30 degrees Celsius might be perceived as manageable in regions accustomed to high heat such as the Middle East where such temperatures are common and infrastructures like buildings and public spaces are designed to cope with the heat. Conversely, in cooler climates such as the west coast (e.g., Vancouver) of Canada, the same temperature could lead to significant discomfort, health risks, and increased energy consumption for cooling because these regions are less adapted to handling such heat in terms of infrastructure and public awareness. Also, we overlooked the variation in individuals' sensitivity to cold weather and instead assumed that everyone places equal importance on travel time and weather exposure as part of their travel costs, which is unrealistic. Future research should conduct sensitivity analysis using various weighting schemes (e.g., 0.3 vs. 0.7, 0.4 vs. 0.6, 0.6 vs. 0.4, 0.7 vs. 0.3) to account for interpersonal variability. Ideally, the design of these weighting schemes should be informed by the literature on the range of interpersonal variation in response to cold weather and/or empirical data such as surveys or interviews with public transit users. For our travel time analysis, we relied on static GTFS data that assumes transit operates perfectly on time without any delays or service interruptions. However, real-world public transit services can be far from this ideal. They frequently encounter uncertainties like delays, early arrivals, detours, and pass-ups. Ignoring these variabilities can result in inaccurate public transit accessibility measures (Liu et al., 2023) and even erroneous evaluation of inequalities in transit-based accessibility (Lee and Kim, 2023). Also, the travel time analysis in this paper adopts a default walking speed of 3.6 km/hour. However, walking speed can be significantly influenced by various factors such as inclement weather, snow presence on sidewalks, and individuals' walking abilities (e.g., young adults vs. elderly). Addressing these will make future analysis more realistic. Lastly, for future analysis, factors that can mitigate extreme weather exposure should be also taken into account. For instance, incorporating information on whether a bus stop is sheltered would be beneficial. Deep learning methods using Google streetview images can be used as an efficient approach for obtaining bus shelter information (Kim et al., 2024). Furthermore, future research might consider the presence of vegetation and green spaces along the walking paths and near the transit stops when estimating transit users' environmental exposure. This approach would offer a more realistic understanding of weather exposure during public transit travel.

4.3 Conclusions

Healthy cities prioritize citizens' well-being through healthy urban planning and design that promotes physical and mental health. In addition, healthy cities take proactive measures to tackle the negative consequences of climate change. Promoting healthy cities demands the application of scientific, evidence-based approaches, which include effective and healthy land use and transportation planning. This thesis introduces two new geospatial methods to facilitate healthy transportation and land use planning. Chapter 02 develops an analytical framework for identifying regions with limited green space in the Global South. Chapter 03 introduces a new accessibility method by integrating extreme weather exposure into public transit accessibility assessments for Global North. Both studies demonstrate their applicability in their respective study regions. The proposed methods offer insights and tools for researchers, policymakers, and urban planners striving to achieve desirable healthy objectives. By emphasizing the importance of evidence-based and healthy land use and transportation planning, this work contributes to the broader discussion on sustainable healthy city development.

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