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Green Space and Healthy Aging: Evidence from Static and Dynamic Green Space Exposure Measurements

GEO 511 Master's Thesis

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ABSTRACT

A growing body of studies indicates the positive association between green space and older adults' health and well-being. However, many studies solely rely on static residential contexts to evaluate green space exposure, overlooking the role of daily mobility. Moreover, mobility-based exposure studies often ignore travel modes, although active travel usually involves direct, immersive exposure to surrounding environments. This study analyzed GPS tracking and daily self-reported data from 60 healthy older adults who participated in the MOASIS project over 15 days in 2024. Based on GPS data, I measured individuals' static home and neighborhood and daily active-travel-based dynamic green space exposure. I evaluated the patterns of both green space exposure metrics, then compared the correlations between them. Further, I examined the association between daily well-being and dynamic green space exposure metrics. The results show that home-level and neighborhood-level static green space exposure metrics were significantly different among individuals. Activity space beyond the neighborhood and high daily trip frequency are correlated with high daily dynamic green space exposure. In addition to spatiotemporal factors, walking generated higher dynamic green space exposure than cycling. Furthermore, dynamic green space exposures were positively correlated with static neighborhood ones rather than static home-based ones. Lastly, compared with distance-weighted and time-weighted green space exposure, the total volume of dynamic green space exposure has a positive correlation with daily self-rated health. Females and those with higher income, lower education, and better general health can experience stronger well-being benefits from dynamic green space exposure. This thesis emphasizes the value of incorporating daily mobility and active travel modes into green space exposure assessment. Findings suggest that different active travel modes provide distinct levels of green space exposure. A greener neighborhood can enhance older adults' daily green space exposure. This research contributes to more nuanced green space exposure assessment and offers insights for health-promoting urban design and infrastructure development, particularly in fostering equitable, green-rich neighborhoods that support healthy aging.

Keywords: Green Space, Green Space Exposure, Healthy Aging, Older Adults, Well-being, GPS, Daily Mobility, Active Travel.

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CONTENTS

ABBREVIATIONS

Abbreviation	Definition
API	Application Programming Interface
ART	Attention Restoration Theory
AT	Active Travel
CEST	Central European Summer Time
CET	Central European Time
CV	Coefficient of Variation
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DEM	Digital Elevation Model
EMA	Ecological Momentary Assessment
EPSG	European Petroleum Survey Group
EVI	Enhanced Vegetation Index
FSO	Federal Statistical Office
GE	Green Exercise
GEE	Google Earth Engine
GPS	Global Positioning System
GVI	Green View Index
GVIF	Generalized Variance Inflation Factor
GSAR	Green Space Area Ratio
HDOP	Horizontal Dilution of Precision
ICC	Intraclass Correlation Coefficient
LiDAR	Light Detection and Ranging

Continued on next page

Abbreviation	Definition
LST	Land Surface Temperature
LULC	Land Use / Land Cover
LV95	Swiss Coordinate System (the 1995 national survey)
MOASIS	Mobility, Activity and Social Interaction Study
NDVI	Normalized Difference Vegetation Index
NO_2	Nitrogen Dioxide
PA	Physical Activity
PM	Particulate Matter
$PM_{2.5}$	Particulate Matter of Less Than 2.5
PM_{10}	Particulate Matter of Less Than 10
PP	Percentage Point
RG	Research Gap
RQ	Research Question
SATPOP	Population and Households Statistics
SAVI	Soil-Adjusted Vegetation Index
SD	Standard Deviation
SF-12	Short-Form Health Survey
SRT	Stress Reduction Theory
TGE	Total Green Space Exposure
THF	Tobler's Hiking Function
TLM	Topographic Landscape Model
TypoCH	Swiss Habitat Typology
UGCoP	Uncertain Geographic Context Problem
UDGE	Green Space Exposure per unit Distance
UN	United Nations
USA	United States of America
UTC	Universal Time Coordinated
UTGE	Green Space Exposure per unit Time
V90	90th-Percentile Speed

Continued on next page

Abbreviation	Definition
VDOP	Vertical Dilution of Precision
VHM	Vegetation Height Model
VIF	Variance Inflation Factor
WGS84	World Geodetic System 1984
WHO	World Health Organization

CHAPTER 1

INTRODUCTION

1.1 Motivation

More than 68% of the world's residents are anticipated to live in urban areas globally by 2050 (United Nations, 2018). The environment that residents interact with daily can significantly influence their health and well-being (Krefis et al., 2018). Urban nature has the potential to enhance the livability of cities by providing various biophysical ecosystem services (Shanahan et al., 2015), including air filtering, micro-climate regulation, and noise reduction (Assessment Millennium Ecosystem, 2005; Per and Sven, 1999). Green space, defined as "green in the sense of being predominantly covered with vegetation" (Heckert, 2012, p. 811), is a primary component of urban natural environments (Yu and Kwan, 2024). A growing body of studies has highlighted that green space can contribute to diverse physical, mental, and social health benefits (fig. 1.1), including increasing physical activity (PA), facilitating recovery from stress, and enhancing social contact (Huang and Lin, 2023; Jin et al., 2024; Mao et al., 2024).

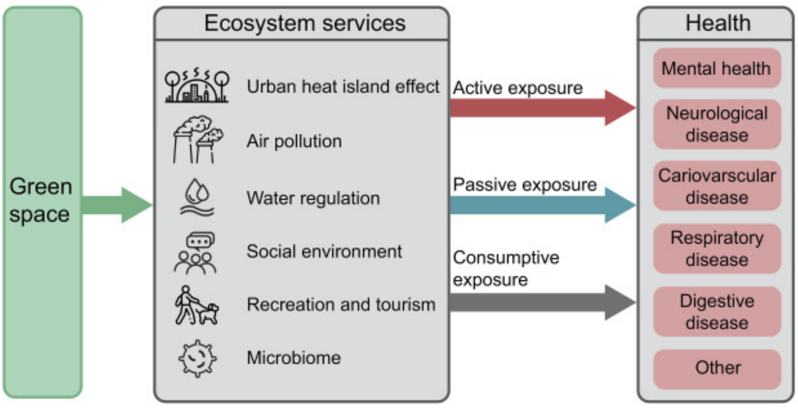


Figure 1.1: Ecosystem services provided by green spaces described in the Ecosystem Drivers, Pressures, States, Exposures, Effects, and Actions model (adapted from Chiabai et al. (2018), as cited in Chen et al. (2024, p. 2)). Exposure constitutes the critical nexus between green space and an array of health outcomes.

People's exposure is a vital linkage between green space and a wide range of health outcomes (Bowler et al., 2010b; Liu et al., 2023a). While existing research has consistently demonstrated the health benefits associated with green space exposure (Jiang et al., 2020; Yu and Kwan, 2024), these benefits are not uniformly experienced across individuals (Zheng et al., 2024b). Two key aspects contribute to this variation. First, green spaces within urban living environments are not always equitably distributed, leading to significant disparities in access and quality (James et al., 2015; Wolch et al., 2014). Urban sprawl can also exacerbate this issue by reducing the overall supply of green spaces in urban areas (Bertram and Rehdanz, 2015; Chen et al., 2025). Second, the use and perceived benefits of green spaces are influenced by socio-demographic factors such as age, gender, and income (Dadvand et al., 2012a). These factors play a crucial role in shaping the ways citizens engage with and utilize green space in everyday life (Sang et al., 2016). Consequently, health outcomes influenced by green space exposure can diverge across social groups (Remme et al., 2021).

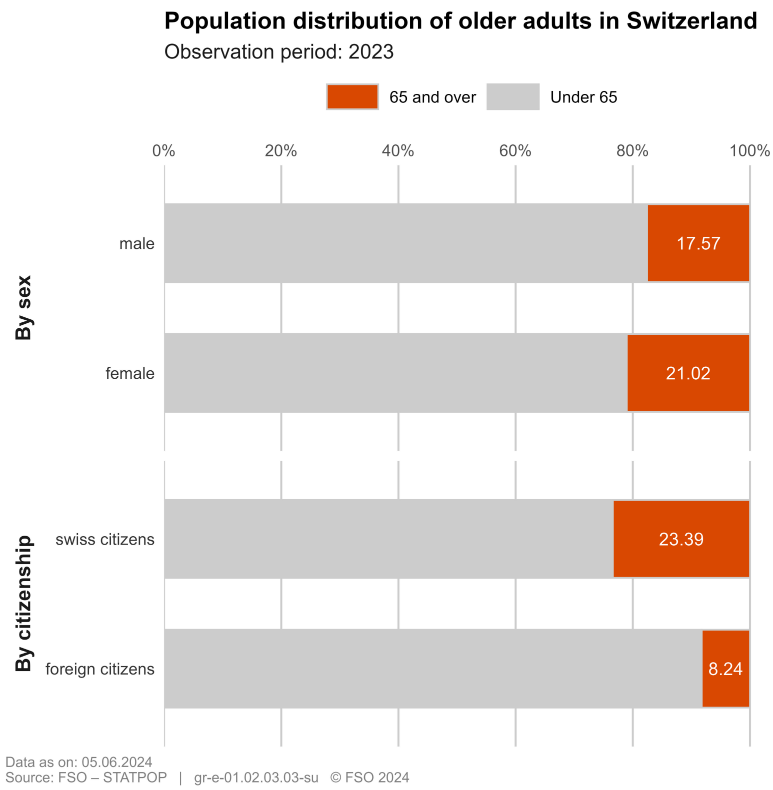


Figure 1.2: Proportion (%) of the Swiss population aged 65 and above, by sex and citizenship status (source: FSO - STATPOP). **Note:** A population is regarded as being *aging* when more than 7% of people are 65 years or older and *aged* when more than 14% of people are 65 years or older (Kasai, 2021).

Comprehending the associations of green space with the well-being and health of older adults is essential for fostering healthy aging worldwide, but particularly in post-industrial societies such as Switzerland (Phillipson, 2009). The World Health Organization (WHO) defines healthy aging as "the process of developing and maintaining the functional ability that enables well-being in older age" (World Health Organization, 2015, p. 28). With 19.6% of its population aged 65 years and over in 2024 (Federal Statistical Office, 2024), Switzerland represents a notably large share of older adults (fig. 1.2). With the population aged 65 and older projected to comprise 30% of the total population by 2060 (Lewis and Ollivaud, 2020), green space is likely to be instrumental in improving the health and well-being of older adults in Switzerland. Recent studies highlight the diverse benefits of green space exposure for healthy aging, including reductions in mortality and cardiovascular risks (Yuan et al., 2021), increased walking and other PA (Miao and Xiao, 2024; Wen et al., 2018), enhanced social interactions (Enssle and Kabisch, 2020), and improvements in mental health and overall well-being (De Keijzer et al., 2020; Zuo et al., 2024). However, most studies overlook the role of daily mobility in shaping green space exposure, leading to potential biases in estimating green space health benefits (Kwan, 2013).

Thus, it is crucial to examine the mobility patterns of older adults concerning green space using precise and comprehensive measurements (Wang et al., 2021b). Global Positioning System (GPS) technology offers a window into quantifying actual individual environmental exposure based on locations and time, viz., trajectories, of people's movements in real-world settings (Li et al., 2018; Marquet et al., 2023). Nevertheless, it is challenging to define an appropriate quantitative indicator to evaluate people's spatiotemporal green space exposure (Liu et al., 2023a; Zhang et al., 2021). Moreover, the accessibility of individual daily GPS data is often restricted due to costly acquisition and potential privacy issues (Michael et al., 2006; Wang et al., 2021b).

1.2 Aims

To address these gaps, my thesis aims to evaluate green space exposure with multiple measurements (i.e., spatial and spatiotemporal approaches with different green space metrics) from older adults' daily GPS tracking data. I will also examine the correlation between green space exposure and mental well-being for older adults, considering sociodemographic factors. These findings are expected to deliver a framework that sheds light on the positive effects of green space exposure on healthy aging in urban environments.

1.3 Structure

The remainder of this thesis is organized as follows. Chapter 2 illustrates the theoretical foundations of research on green space exposure and healthy aging, and identifies the key research gaps and questions guiding this study. Chapter 3 describes the study area and data sources. Chapter 4 details the methodological approach, including data preprocessing, sample selection, green space exposure measurements, and statistical analysis. Chapter 5 presents the primary findings, followed by a critical interpretation in chapter 6. Finally, chapter 7 synthesizes the contributions, main conclusions, limitations, and outlines directions for future research.

CHAPTER 2

THEORETICAL FRAMEWORK AND BACKGROUND

2.1 Nature Exposure

The term “exposure”, described as “contact between an agent and a target” under a certain spatiotemporal context (Zartarian et al., 1997, p. 411), has been broadly applied in epidemiology (Velentgas et al., 2013), public health (Bowler et al., 2010b), and environmental health (Paustenbach, 2000). Concerned with the risks of hazards to human health, exposure assessments in these fields estimate human exposures to environmental stressors, including toxicants (Paustenbach, 2000) and pollutants (Marquet et al., 2023; Roe et al., 2020).

With the paradigm of the eco-environment health field shifting to positive health benefits, early eco-psychological theories laid the groundwork in this field. The *biophilia hypothesis* posits that humans have an innate tendency to seek connections with nature (Kellert and Wilson, 1995; Wilson, 1986). The *stress reduction theory* (SRT) puts forward that natural scenes can reduce stress and elicit a positive affective response (Ulrich et al., 1991). Finally, the *attention restoration theory* (ART) illustrates that exposure to nature can have restorative effects and improve cognitive capacity (Kaplan and Kaplan, 1989; Kaplan, 1995).

Leveraging these theories, Bratman et al. (2019) describe the positive mental health benefits of interacting with nature as *psychological ecosystem services*. They provide a straightforward definition of *nature exposure* as "the amount of contact that an individual or population has with nature" (Bratman et al., 2019, p. 4). The pathway linking natural features to mental health is conceptualized as a simple four-step process: natural features, exposure, experience (i.e., the critical specifics of exposure through multiple sensory modalities), and mental health effects, with each component building on the preceding one. Expanding on this framework, Remme et al. (2021) demonstrate that exposure to nature can boost people's physical activity levels, which in turn contributes to positive health outcomes. They further argue that the magnitude of activity-related benefits can vary by different socioeconomic and demographic factors.

Yu et al. (2024b, p. 2) propose the framework of *exposure ecology*, articulating the concept of *ecological exposure* as "the amount (magnitude, frequency, and duration) of exposure that an individual or population has with natural ecosystems". They put forward a frame of axes, including subject-object and reality-virtual. The domain "subject-reality" under this frame focuses on the health impacts on individuals or population exposed to real natural ecosystems. With significant enhancements in technical means (e.g., street view images and deep learning technologies) and data acquisition (e.g., portable GPS devices), recent studies on this interface have gradually shifted from static to dynamic exposure assessment (Pearson et al., 2024; Wang et al., 2021a).

2.2 Green Space and Health

Green space is a vital component of the natural environment in urban areas (Hunter et al., 2019; Yu and Kwan, 2024). Mounting evidence suggests that green space can foster physical, mental, and social health benefits, including improved birth outcomes; lower cardiovascular disease prevalence and mortality; reduced psychiatric morbidity; and enhanced social contact (James et al., 2015). Markevych et al. (2017) summarize that green space can promote health and well-being under three potential mechanisms: mitigation, restoration, and instoration (fig. 2.1).

2.2.1 Mitigation

Mitigation (reducing harm) involves reducing the harmful effects of environmental stressors such as heat, noise, and air pollution (Markevych et al., 2017).

Reducing exposure to heat: Green space can reduce land surface temperature (LST) on site and in adjacent areas (Aram et al., 2019). Such thermal comforts can promote human health and well-being especially during heat stress episodes (Bowler et al., 2010a). For instance, in a survey study conducted in Italy and the United Kingdom in July 2006 (the hottest month of the year), Lafortezza et al. (2009) found that longer and more frequent visits to green spaces were associated with higher perceived psychological and physical benefits and well-being status.

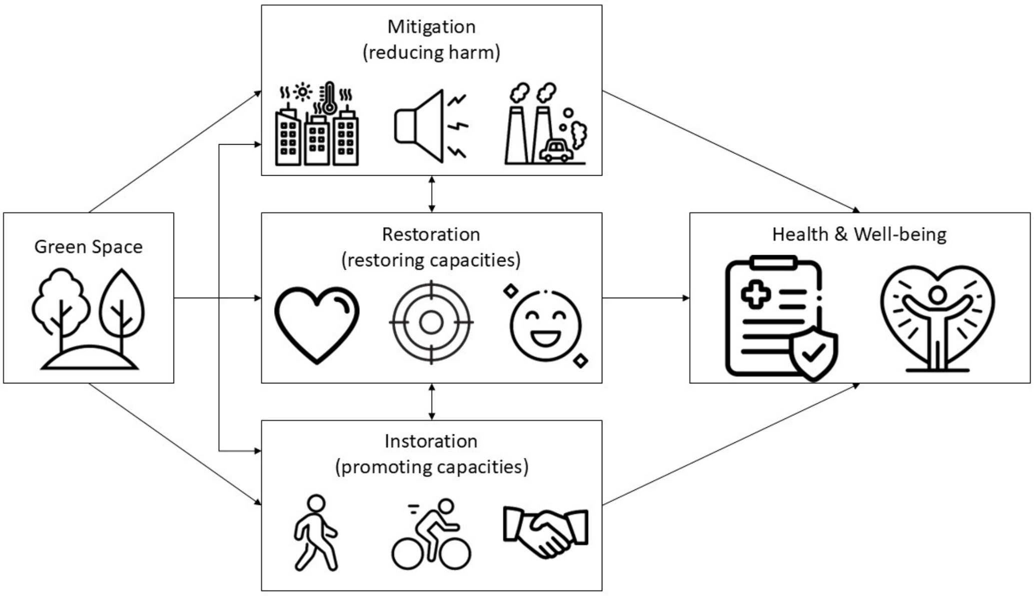


Figure 2.1: Three domains of pathways linking green space to positive health outcomes, including mitigation, restoration, and instoration. Arrows indicate theoretical influence patterns, whereby specific pathways within each domain can exert effects on one or more pathways in the remaining domains (adapted from Markevych et al. (2017, p. 302) and Yu et al. (2024b, p. 5)). Resource of icons: https://www.freepik.com/.

Reducing exposure to noise: Green space can reduce noise exposure and also acts as a psychological buffer that dampens stress responses to noise (Dzhambov and Dimitrova, 2015). Accordingly, noise may mediate the association between green space and mental health (Markevych et al., 2017). For example, Astell-Burt et al. (2013) found that residents of greener neighborhoods had lower odds of short sleep. Similarly, Van Renterghem and Botteldooren (2016) reported that visible greenery from the living room was associated with lower noise annoyance. These findings suggest that green space can confer benefits at both the physical and perceptual levels in mitigating noise.

Reducing exposure to air pollution: Air pollution can be lower in and around green space because major emission sources are absent and vegetation removes pollutants via deposition (e.g., particulate matter (PM) of less than 10 μm (PM_{10}) and ozone) (Markevych et al., 2017). Consistent with these pathways, Dadvand et al. (2012b) found that higher residential greenness was associated with lower indoor and outdoor $PM_{2.5}$ (PM of less than 2.5 μm) among pregnant women and with more time spent outdoors at home (i.e., in the area around the home). Similarly, Dadvand et al. (2015) reported that decreased air pollution partially mediated the association between residential greenness and children's cognitive development.

2.2.2 Restoration

Restoration (restoring capacities) refers to the process of replenishing depleted capacities, including managing stress, improving affect, and revitalizing attention, as described by SRT and ART. This restorative process enables individuals to accrue health benefits (Yu et al., 2024b). Research in this domain examines whether encounters with green space coincide with reduced physiological arousal and more positive self-reported affect, as well as improved sustained attention and broader executive functioning (Markevych et al., 2017).

Some field experiments have explored the restoration effects of green space. For instance, Simkin et al. (2020) demonstrated that activities such as sitting or walking in urban forests produced greater restorative outcomes. Likewise, taking in the forest atmosphere can have positive physiological effects, including lower concentrations of cortisol and blood pressure, greater parasympathetic nerve activity, and reduced sympathetic nerve activity (Park et al., 2010). Observational studies also provide supporting evidence. Van den Berg et al. (2010) reported that the associations between stressful life events and both the number of health complaints and perceived general health were significantly moderated by the amount of green space near respondents' homes. Similarly, an online survey study by Jiang et al. (2020) indicated that greater daily exposure to trees was related to better health outcomes. In a longitudinal study, Alcock et al. (2015) found that greater broadleaf and grassland cover was linked to lower odds of psychiatric caseness in rural England.

2.2.3 Instoration

Instoration (promoting capacities) refers to constructing capacities and resilience to face further threats to health (Beute et al., 2023). Two main dimensions fall under this pathway: (1) promoting physical activities (PA) and (2) enhancing social cohesion.

Promoting PA: PA usually underpins physical and mental health, and green space can provide safe, convenient, and attractive settings for PA (Yu et al., 2024b). PA conducted in green space (viz., green exercise, GE) may benefit dwellers more than in other (e.g., indoor) settings (Biddle and Mutrie, 2007; Thompson Coon et al., 2011). Consistent with this, Kondo et al. (2018) found that greater green space exposure corresponded to higher-level self-reported PA. PA also may mediate the pathway from green space to physical and mental health (Markevych et al., 2017). For example, De Vries et al. (2013) showed that PA in public/green spaces mediated the effect of streetscape greenery on several well-being outcomes.

Enhancing social cohesion: Social cohesion means the sense of trust, mutual respect, and safety among neighbors, along with the belief that they are willing to offer assistance when needed (Markevych et al., 2017). Green space may supply a setting for social interactions, which is likely to enhance social cohesion (Sugiyama et al., 2008; Yu and Kwan, 2024). Theoretically, community-level social interaction and cohesion are associated with health and well-being (Hartig et al., 2014). Recent studies also showed that social cohesion can be an intermediary between green space and mental health and well-being (Mao et al., 2024; Sugiyama et al., 2008).

2.3 Green Space and Healthy Aging

Green space can benefit health for all age groups, but such benefits can be particularly important for older population groups, given the aging of societies (Benton et al., 2021; World Health Organization, WHO Regional Office for Europe., 2016; Lee et al., 2015). Furthermore, compared with younger groups, older adults are, on average, less mobile and occupy smaller activity spaces (Rantanen et al., 2012), making their proximal green space more consequential for daily exposure. Calogiuri et al. (2016) found that weekly GE was more common in older adults than younger adults. Moreover, older adults are more likely to perceive higher aesthetic value in green spaces and report greater related well-being than younger adults (Sang et al., 2016). Thus, green space in older adults' direct living environment can be vital to support their needs and enhance their health and well-being (Douglas et al., 2017; Kemperman and Timmermans, 2014).

2.3.1 Physical Health and Well-being

Green space can provide high-quality outdoor environments for physical activities (Bedimo-Rung et al., 2005; Douglas et al., 2017). A growing body of research suggests that, in older adults, green space is associated with improved physical well-being and health. From a field experiment, Kabisch et al. (2021) reported that visits to green spaces with higher naturalness were associated with better cardiovascular health among adults aged 55 to 70. Herbolsheimer et al. (2020) conducted a cross-sectional telephone survey and found that available parks were positively correlated with walking time for transportation among older adults in Metro Portland (USA) and Metro Vancouver (Canada). Likewise, Lau et al. (2021) indicated that longer green space exposure was positively correlated with perceived physical well-being in older adults based on an on-site survey.

2.3.2 Social Interaction and Social Contacts

Social interaction becomes particularly important in later life, as retirement, role transitions, age-related loss, and mobility limitations can shrink daily networks (Kemperman et al., 2019). Among older adults, greater social connection is linked to better physical health, mental health, and psychological well-being (Yung et al., 2016; Sugiyama and Thompson, 2006; Zhou et al., 2020). Green space can provide accessible venues for everyday encounters, enhancing social connectedness (Bedimo-Rung et al., 2005). For instance, Yung et al. (2016) found that park features enabling social connection and mobility were strongly correlated with older users' satisfaction, indicating that green space can promote social contact in later life. Similarly, Kemperman and Timmermans (2014) argued that higher levels of greenness were associated with more social contact among aging neighbors.

2.3.3 Mental Health and Well-being

Emerging evidence suggests that green space is associated with improved mental health and well-being among older adults. Luo et al. (2024) found in a field experiment that greenery in residential open spaces was linked to lower emotional arousal. In a cohort study, Astell-Burt and Feng (2019) reported that exposure to tree canopy was associated with a lower incidence of psychological distress. Similarly, an on-site questionnaire survey by Lau et al. (2021) indicated that longer green space exposure was linked to better perceived mental well-being of adults aged above 60. Moreover, using GPS tracking and momentary questionnaires, Han et al. (nd) demonstrated that higher greenness was associated with a lower negative affect in older adults.

2.4 Green Space Exposure Measurements

Measuring green space exposure is the primary challenge in evaluating the health impact of green space (Yu and Kwan, 2024). A crucial preliminary step is to delineate the *features* of green space before attempting to assess exposure (Neuenschwander et al., 2014). Specifically, according to Liu et al. (2023a), green space features can be described through attributes and components. *Attributes* usually encompass areal size and type (e.g., parks, forests, trees, grassland, meadows, public squares, etc.) for individual green space. Parks and vegetation (predominantly forests and trees) are the most examined attributes in recent studies (Liu et al., 2023a; Roe et al., 2020). At a regional scale, attributes contain the number, density, connectivity, and canopy coverage percentage of green space patches, encompassing not only parks and forests but also other forms of greenery (e.g., grassland). *Components* of green space include amenities such as facilities for physical activities, wildlife, individual trees that exhibit seasonal variations, and diverse vegetation structures across a region (Duan et al., 2024).

Assessments of green space exposure based on static geographical contexts, such as residential or workplace locations, are categorized as *static green space exposure* (see details in section 2.4.1). However, limiting assessment to one or a few static locations is overly simplistic relative to individuals' time-varying activity spaces (Kwan, 2012; Yu and Kwan, 2024). In contrast, *dynamic green space exposure* reflects individuals' interactions with green space based on their daily mobility and activities, accounting for both spatial and temporal dimensions (Kwan, 2013; Xie et al., 2023). This approach provides a more nuanced and comprehensive understanding of how people engage with green space in their everyday lives, extending beyond the limitations of static exposure assessments (see details in section 2.4.2).

2.4.1 Static Green Space Exposure

Integrated with the framework of green justice (fig. 2.2), static green space exposure is usually measured by three indicators: availability, accessibility, and visibility (Labib et al., 2020; Łaszkiewicz et al., 2018; Xie et al., 2023; Yoo et al., 2022).

Availability refers to the physical quantity of green space within a certain spatial unit (Bratman et al., 2019). The normalized difference vegetation index (NDVI) is applied broadly in many studies to quantify the availability of green space (Kondo et al., 2018; Marquet et al., 2023; Zhou and Wang, 2011). Similar metrics from remote sensing data contain the soil-adjusted vegetation index (SAVI) and the enhanced vegetation index (EVI) (Markevych et al., 2017). Land use/land cover (LULC) and Light Detection and Ranging (LiDAR) data are also important data sources for availability estimation (Liu et al., 2023a; Xie et al., 2023). Quantitative indicators of availability include the tree density, the percentage of tree canopy

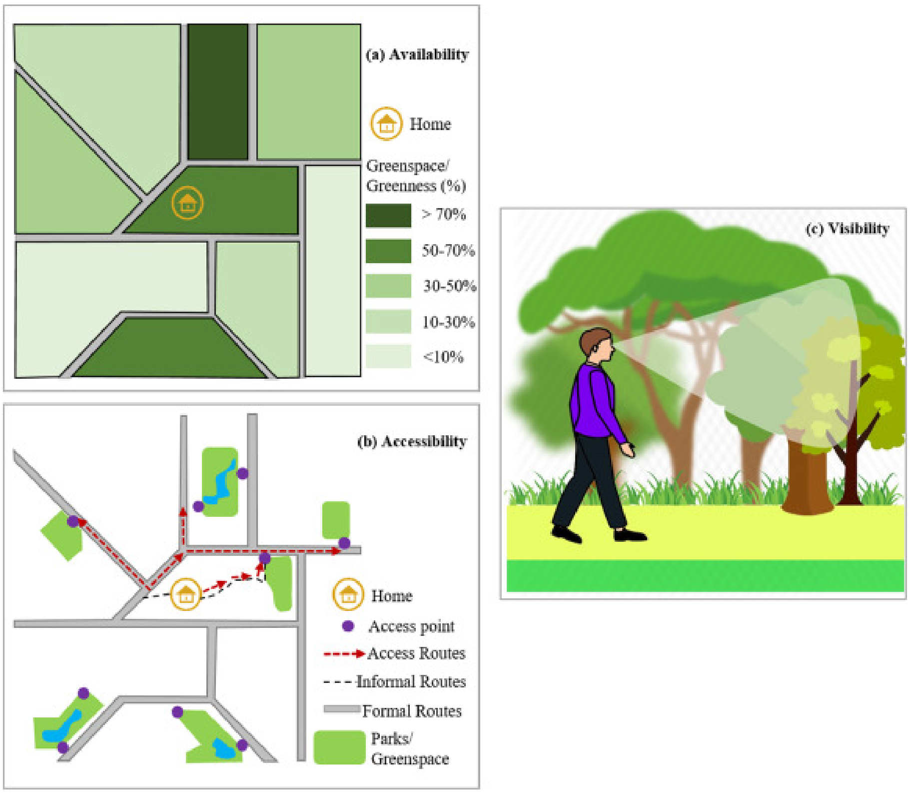


Figure 2.2: Three domains of static green space exposure indicators (from Labib et al. (2020, p. 5)): **(a) availability** (physical amount of green space), **(b) accessibility** (spatial proximity of green space to locations of interest), and **(c) visibility** (the amount of greenness that can be seen visually from a particular location of interest).

area, and the green space area ratio (GSAR) (De Keijzer et al., 2020; Kabisch et al., 2016; Schmid et al., 2024; Yu and Kwan, 2024).

Accessibility refers to the ease with which a person can reach relevant sites, in this case, green space (Geurs and Van Wee, 2004; Kwan, 1998). Accessibility estimation considers the spatial proximity, temporal constraints, or the effects of traffic restrictions on people's ability to visit green space (Liu et al., 2021; Wu et al., 2019). Accessibility is usually estimated in combination with availability metrics (Labib et al., 2020). Measures here include the shortest distance or travel time to the nearest green space, GSAR, NDVI, or other quantified indicators within a specific spatiotemporal context (e.g., from home to green space, within 10 minutes), usually based on buffer and network analysis (Liu et al., 2023a; Wang et al., 2021b; Xie et al., 2023).

Visibility refers to the perceived greenery within an individual's visual field. In recent years, it is usually calculated by the pixel ratio of vegetation (Green View Index, GVI) identified in street view images fetched or sampled from an Application Programming Interface (API) of a service such as Google Street View (Jiang et al., 2020; Wang et al., 2021a; Xie et al., 2023). GVI has been used extensively to capture human-scale greenery as experienced on streets or pathways, which differs from the broader overhead, birds-eye measurements provided by satellite data (Jiang et al., 2020; Wang et al., 2021a; Zhai and Baran, 2016).

2.4.2 Dynamic Green Space Exposure

Static green exposure is crucial in evaluating the health impact of green space because it reflects the environmental effects in people's daily dominant activity places, including residences, workplaces, and recreational places (Wang et al., 2021b). However, people may experience exposure to green space while traveling their daily routes outside these primary places (Kwan, 2012). Static green space exposure neglects people's actual spatiotemporal mobility context (Hasanzadeh et al., 2019; Kwan, 2013), which cannot sufficiently reflect how people interact with green space in reality.

GPS tracking can assess the actual exposure of individuals embedded with environmental and contextual features (Li et al., 2018; Pearson et al., 2024). Many studies use GPS-enabled devices or mobile phones with GPS sensors to assess individual-level dynamic green space exposure (Xie et al., 2023; Yoo and Roberts, 2022). For example, Marquet et al. (2023) estimated daily average exposure as mean NDVI within a 20-m buffer around GPS fixes. Other work computes cumulative dynamic green space exposure: Yu and Kwan (2024) calculated NDVI along travel routes using a 100-m street-network buffer, and Wang et al. (2021a) derived exposure from the GVI for each walking and cycling trip. Beyond GPS traces, some studies also use travel surveys to acquire self-reported mobility paths for assessing dynamic green space exposure (Wang et al., 2021b).

2.4.3 Linkages between Green Space Exposure Measurements

The comparison between static and dynamic green space exposure offers a lens into the patterns and motivations behind residents' daily interactions with green space. Nevertheless, recent studies have produced conflicting findings. Wang et al. (2021b) reported no significant association between green space exposure metrics between working places and daily mobility paths. Xie et al. (2023) found static green space exposure at workplaces positively aligned with commuters' daily dynamic green space exposure. Likewise, Marquet et al. (2023) illustrated that there was no significant difference between dynamic and static green space exposures among seniors. Wang et al. (2021a), however, suggested that working in environments with limited green space led to compensatory dynamic green space exposure.

2.5 Research Gaps

Several research gaps (RGs) were identified as a result of the literature review.

General RG

Lack of evidence from older adults' daily lives.

Recent work has begun to examine the relationship between dynamic and static green space exposure at the individual level (Wang et al., 2021a; Xie et al., 2023; Yoo and Roberts, 2022; Zheng et al., 2024a). Still, most studies include multiple demographic groups or focus on commuters, with limited attention to older adults. Meanwhile, substantial evidence links residential greenness to better mental health and well-being in later life (De Keijzer et al., 2020). Yet, much of this evidence comes from surveys (Kemperman and Timmermans, 2014; Yang et al., 2022; Zhou et al., 2020) and field experiments (Luo et al., 2024), with little focus on older adults' daily mobility and real-world environmental contexts. There is a clear need for studies that, in older adults, jointly measure dynamic and static green space exposure from their daily lives.

RG 1

Lack of attention on vegetation.

The term "green space" is defined inconsistently across studies (Taylor and Hochuli, 2017). This heterogeneity in definitions can underlie attributes of green spaces, introducing biases into green space exposure measurements.

With respect to static green space exposure measurements, accessibility is often operationalized via proximity (e.g., minimum travel time estimation) to urban parks (Xie et al., 2023), but this proxy may not reflect static exposure to natural land cover (Jarvis et al., 2020). As a result, the contribution of non-park vegetation remains unclear. Emphasizing static green space exposure derived from LULC vegetation data is warranted.

RG 2

Lack of attention on active travel.

Active travel (human-powered modes such as walking and cycling) improves human health by increasing physical activity (Doorley et al., 2015). Such health benefits are substantial for maintaining overall mobility and well-being among older adults (Yang et al., 2018).

Accordingly, individual accessibility to green space for older adults should be evaluated considering active travel modes. Furthermore, active-travel green space accessibility should produce an age-sensitive estimation: for older adults, their active-travel mobility depends strongly on the travel environment (Duim et al., 2017), and typical speeds are lower due to age-related declines in physical capacity (Bendall et al., 1989; Vlakveld et al., 2015), implying distinct accessibility needs. Topography (e.g., slope, elevation) is therefore incorporated into green space accessibility estimation (Weiss et al., 2018).

Also, most studies estimating dynamic green space exposure do not distinguish travel modes (Marquet et al., 2023; Yu and Kwan, 2024; Zheng et al., 2024a). However, active travel (walking or cycling) generally entails more intense and direct environmental exposure than passive transport (traveling in vehicles). Travel mode detection should therefore be integrated into dynamic green space exposure assessment, with a focus on active trips.

RG 3

Unknown daily mental well-being outcomes.

Yu and Kwan (2024) reported that, within a 4-hour window, streetview-based dynamic green space exposure was correlated with lower momentary stress. Relationships between dynamic green space exposure and daily subjective well-being are rarely examined. While Marquet et al. (2023) compared dynamic with static green space exposure in older adults, their analysis stopped at exposure metrics. Consequently, how dynamic green space exposure influences older adults' daily well-being remains an open question.

2.6 Research Questions

Addressing the above research gaps, and using data from the MOASIS study (Röcke et al., 2023), this thesis sets out to answer the following three research questions (RQs):

RQ 1

What are the levels and patterns of green space exposure among older adults during the study period?

RQ 2

To what extent are dynamic and static measures of green space exposure correlated among older adults?

RQ 3

How strongly is mental well-being among older adults associated with different indices of green space exposure?

CHAPTER 3

STUDY AREA AND DATA

This chapter describes the study area and the data utilized in this thesis. Figure 3.1 shows the schematic representation of each (sub)section and their relationships in this chapter.

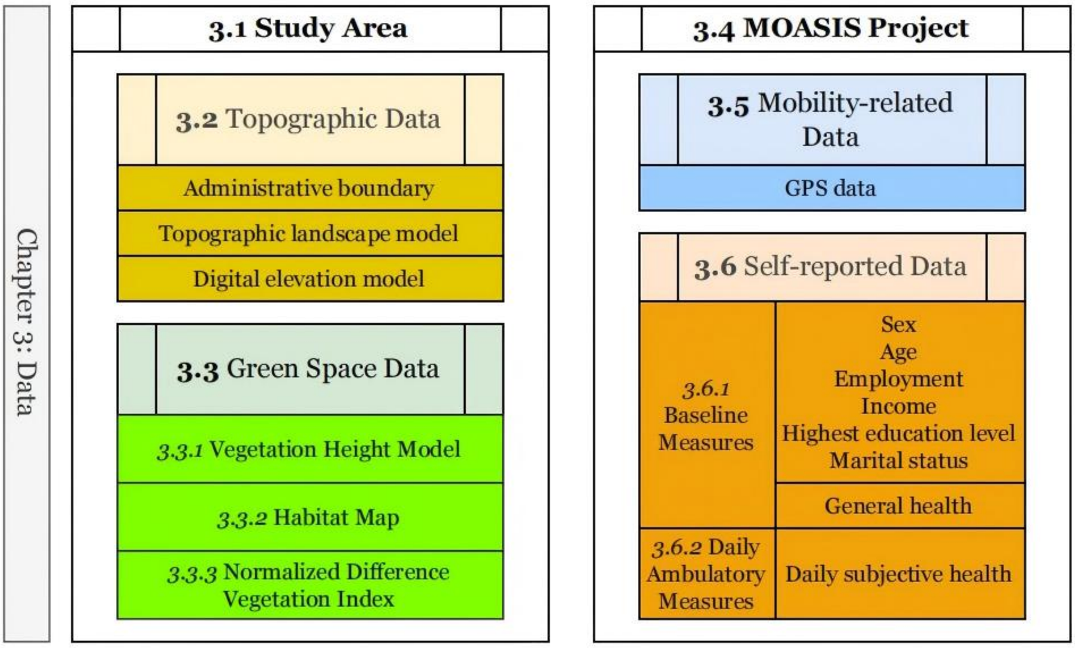


Figure 3.1: Diagram of data used in this study. **X.X** represents section numbers, and *X.X.X* indicates subsection numbers.

3.1 Study Area

The Canton of Zurich, Switzerland (Figure 3.2) is the study area of this thesis. This canton is the most populous among the 26 Swiss cantons, with a population of 1,579,967 residents (Federal Statistical Office, 2024). It covers 1729 km^2 (Federal Statistical Office, 2021) and features a mix of urban, periurban, but also major rural

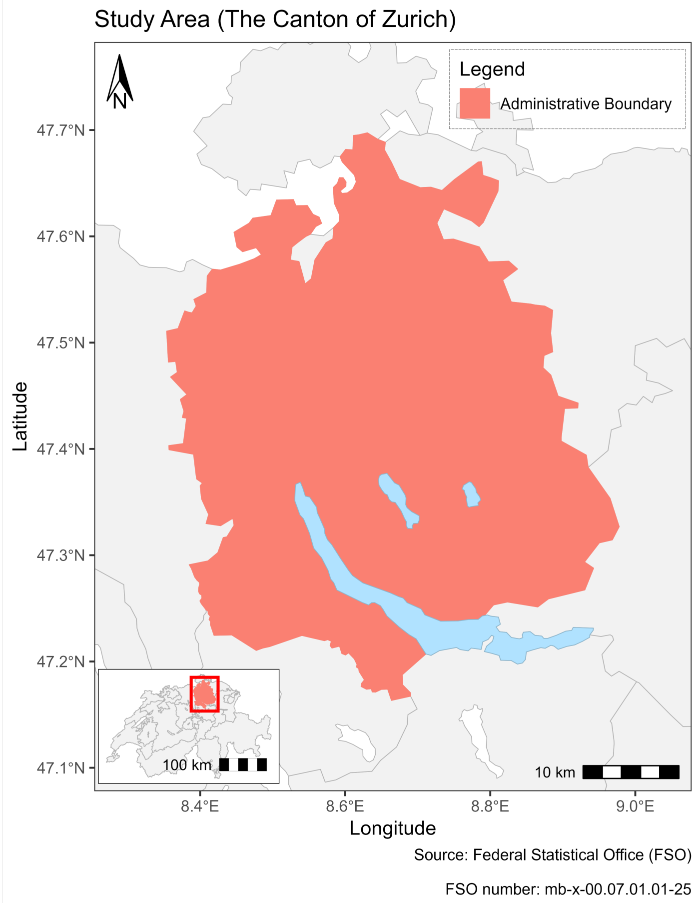


Figure 3.2: Study Area. Canton of Zurich, Switzerland. Source: ThemaKart map boundaries - Set 2025, FSO.

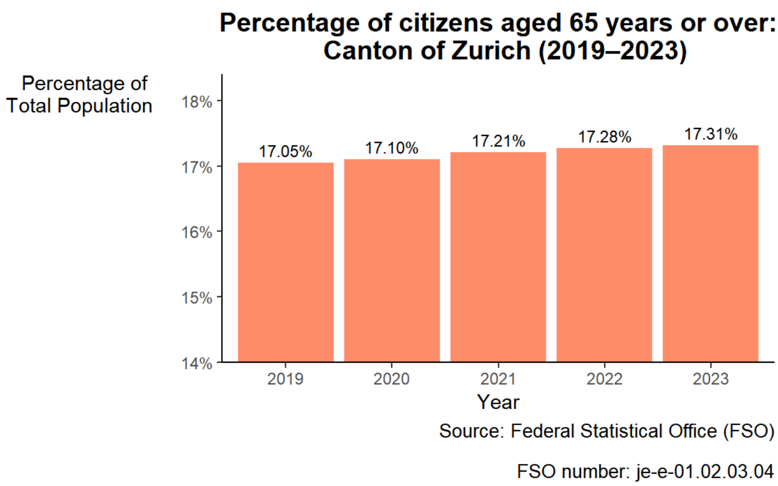


Figure 3.3: Share of residents aged 65 years and over in the Canton of Zurich from 2019 through 2023 (source: FSO). The proportion of senior citizens in the Canton has increased modestly in recent years, reaching 17.31% in 2023. **Note:** A population is considered *aged* when more than 14% of people are 65 years or older (Kasai, 2021).

areas. Over the past few years, green space in the canton has been under pressure due to ongoing urbanization and increasing population (Marcelo et al., 2022). Furthermore, with the proportion of older adults exceeding 14% (Kasai, 2021), the canton has qualified as an aged society in recent years (Figure 3.3). Thus, green space dynamics and demographic shift make the Canton of Zurich an ideal case study for assessing how green space can promote healthy aging.

3.2 Topographic Data

Three topographic data sets were used for this study: the administrative boundary, the topographic landscape model (TLM), and the digital elevation model (DEM) of the study area. All data were obtained as open data products from swisstopo, the Swiss national mapping agency.

The administrative boundary of the study area is from swissTLMRegio[1], which contains two-dimensional vector data. The boundary here was used for (1) clipping and integrating all spatial datasets to the study area extent, (2) visualization in subsequent chapters, and (3) home and life space detection (see details in subsection 4.2.2).

The topographic landscape model (TLM) is obtained from SwissTLM3D[2]. This data set includes roads and rail tracks with their geometries and categories. Because the focus of this study was on active travel, walking and cycling road segments would ideally be isolated. However, SwissTLM3D does not encode legal or physical pedestrian/cyclist access across the full road network (Morelle et al., 2019). I therefore retained all road segments within the study area, except all highway-related segments (Table 3.1), because use of highways by pedestrians and cyclists is prohibited.

The digital elevation model (DEM) is taken from SwissALTI3D [3], a digital terrain model with 0.5 m resolution over the study area. Because the road linestrings were converted to two-dimensional vectors for segmentation, the DEM was used to recover precise elevations at the start and end of each road segment. The road segments with elevation data were utilized for individual accessibility estimation under a travel mode with a time limit, regarding topographic factors (see details

[1] https://www.swisstopo.admin.ch/en/landscape-model-swisstlmregio, accessed on 28 February 2025

[2] https://www.swisstopo.admin.ch/en/landscape-model-swisstlm3d, accessed on 28 February 2025

[3] https://www.swisstopo.admin.ch/en/height-model-swissalti3d, accessed on 28 February 2025

Table 3.1: Description of highway-related road segments (source: Objektkatalog swissTLM3D 2.2). The column *Wertebereich* (meaning: type) shows the original text of road types in German; the column *Type* represents the attribute of road segemnts translated in English via DeepL. With the assumption that these roads are not transitable for pedestrians and cyclists, they were removed from the road network in active-travel accessibility estimation.

GDB-code	Wertebereich	Type
0	Ausfahrt	Exit
1	Einfahrt	Driveway
2	Autobahn	Highway
3	Raststaette	Rest Stop
4	Verbindung	Connection
5	Zufahrt	Access Road
6	Dienstzufahrt	Service Entrance
21	Autostrasse	Motorway

in subsection 4.3.2).

3.3 Green Space Data

To address natural landscape features (vegetation) as the vital attribute of green space, three green space datasets were included (Table 3.2). The vegetation height model (VHM) and the habitat map were utilized for static green space exposure measurements. Similarly, the normalized difference vegetation index (NDVI) was used for dynamic green space exposure assessments. Following Roberts and Helbich (2021), I restricted the growing vegetation season in Europe, namely May to September 2024, as the study period. During that period, vegetation indices were stable and relevant to daily exposure, reducing bias induced by spring or winter phenology.

3.3.1 Vegetation Height Model

Vegetation height models (VHMs) capture the vertical structure of vegetation that matters for shade and screening (Ma et al., 2023). This data was generated based on stereo aerial images for Switzerland with a 1-meter spatial resolution (Ginzler, 2021). The current VHM (2023) was clipped within the administrative boundary

Table 3.2: Description of green space data in this study.

Data	Description	Spatial resolution	Usage	Source
Vegetation Height Model	Average vegetation height for each cell	1 m	Static home-based green space exposure	(Ginzler, 2021)
Habitat Map	Habitat class (land cover type) of each polygon	1 m	Static neighborhood green space exposure	(Price et al., 2024)
NDVI	NDVI for each cell	30 m	Dynamic green space exposure	(Gorelick et al., 2017)

of the study area and utilized as the home-based green space metric in this study.

3.3.2 Habitat Map

The Habitat Map of Switzerland maps the habitat types at 1 m spatial resolution (Price et al., 2024). The map encoded habitat polygons in a hierarchical structure according to the Swiss Habitat Typology (TypoCH) (Delarze et al., 2008). The current habitat map (v1.1, 2024) was clipped within the administrative boundary of the study area and utilized as the neighborhood green space metric, restricted to land cover components (TypoCH first-level classes).

3.3.3 Normalized Difference Vegetation Index

Normalized difference vegetation index (NDVI) has been widely applied in recent dynamic green space exposure studies (Marquet et al., 2023; Yoo and Roberts, 2022; Yu and Kwan, 2024). The NDVI product used here was derived from the Landsat8 Operational Land Imager and Thermal Infrared Sensor at a spatial resolution of 30 m and obtained from the Google Earth Engine (GEE) platform (Gorelick et al., 2017).

To minimize the effects of clouds, I utilized the GEE cloud score algorithm (Google Earth Engine, 2024) before calculating the NDVI. The image collection was filtered to the study area and the study period. Only scenes with total cloud cover ≤40% were retained. Surface reflectance bands were rescaled to reflectance units. The

QA_PIXEL band was used to identify cloud and cloud-shadow pixels via bit-wise flagging. A supplemental threshold on the blue band (reflectance ≥0.2) further screened remaining bright artifacts. All masked pixels were excluded from subsequent data acquisition.

For preprocessed cloud-free images, the NDVI at each cell was calculated as in Equation 3.1:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{3.1}$$

Where NIR is Band 5, and RED is Band 4 in Landsat8. The NDVI value varies between -1 and 1. The higher the value, the higher the density of green vegetation.

The code for image acquisition and NDVI calculation described in this subsection is available at the GEE link[4].

3.4 MOASIS Project

The mobility-related data used in this study is based on a larger project named MOASIS (Mobility, Activity and Social Interaction Study), which deals with mobility at older age (Röcke et al., 2023). The project recruited older adults aged 65 years or older with no clinically relevant cognitive impairments or depressive symptoms. In 2024, recruitment used snowball sampling from April to November. 118 participants aged 65 and above enrolled for a 15-day ambulatory assessment phase; 113 of them completed the entire protocol. This study period largely aligns with the vegetation growing season in Europe (May to September), which supports the green space domain of this thesis. The data collected by the MOASIS study used in this thesis comprise mobility-related data, described in section 3.5, and sociodemographic and subjective well-being data, described in section 3.6.

3.5 Mobility-related Data

Mobility-related data from older adults were collected with a custom wearable sensor, *uTrail*, which includes a GPS sensor sampling at 1 s intervals (Fastrax UC530) (Fillekes et al., 2019c). Participants wore the device on the waist daily during their

[4] The boundary of Canton Zurich in this code is same as in section 3.2.

waking hours for a 15-day sampling period, removing it only for recharging over night. Each GPS fix recorded latitude, longitude, and a timestamp in Coordinated Universal Time (UTC). Although the logger also stored other attributes, such as speed, altitude, HDOP (Horizontal Dilution of Precision), VDOP (Vertical Dilution of Precision), only coordinates (latitude and longitude) and timestamps were used for analysis. The GPS preprocessing pipeline was subsequently delineated in Chapter 4.

3.6 Self-reported Data

Two self-reported data sets were used in this study. Sociodemographic characteristics and self-reported health were collected from the baseline assessment through an online survey; daily well-being data were collected from a daily evening questionnaire during the 15-day sampling period. Table B.1 indicates how these variables were measured.

3.6.1 Baseline Measures

Participants completed a baseline survey containing an array of web-based questions at the beginning of the study period. Sociodemographic and physical health measures from the baseline assessment were utilized in this study. Specifically, sociodemographic measures contained conventional measures such as sex, age, marital status, etc. Physical health was evaluated using the Short-Form Health Survey (SF-12) (Lawton and Brody, 1969; Ware et al., 1996).

3.6.2 Daily Ambulatory Measures

Over the entire ambulatory assessment phase of 15 days, participants received seven smartphone prompts per day for brief experience sampling. In this study, daily subjective well-being was evaluated solely from the evening survey (the 7th daily measurement, prompted at 21:00-21:15 (in HH-MM)), which captured a retrospective appraisal of the entire day. Responses from daytime (1st to 6th) experience-sampling prompts were not included in this study.

CHAPTER 4

METHODOLOGY

4.1 Conceptualization

Figure 4.1 shows the workflow of this study. Data processing and analysis were conducted in R 4.4.1 (R Core Team, 2024) and RStudio 2024.12.1+563 (Posit team, 2025). Table C.1 shows the details of R packages and their usage in the thesis.

4.2 Data Preprocessing Pipeline

Figure 4.2 describes the sample selection of this study. Each step with its criteria is explained throughout this section. There were 118 participants aged 65 years or older who attended the MOASIS study in 2024; 113 of them finished all assessments with data available for analysis. The data preprocessing pipeline started with the GPS data, then integrated the GPS data with the daily subjective well-being data.

4.2.1 GPS Validity and Preprocessing

For GPS data, coordinates were projected from WGS84 (EPSG: 4326) to the Swiss national coordinate reference system LV95 (EPSG: 2056); timestamps were converted from UTC to Swiss time (Central European Time (CET); Central European Summer Time (CEST)) by applying the Europe/Berlin time-zone offset. Participants' GPS data were partitioned into person-days using a midnight (00:00:00, in HH:MM:SS) cut-point. After this daily segmentation, the dataset comprised 1709 person-days of GPS data.

To ensure the GPS quality of person-days, I maintained person-days with a minimum of 12 hours of GPS time coverage. This threshold can ensure that GPS data

Figure 4.1: Workflow of this thesis as described in Chapters 3 and 4. *Note:* X.Y represents the corresponding section, X.Y.Z the relative subsection. The colors of subsections and related measurements in Chapter 4 correspond to the scheme in Chapter 3 to show which dataset(s) were used for measurements.

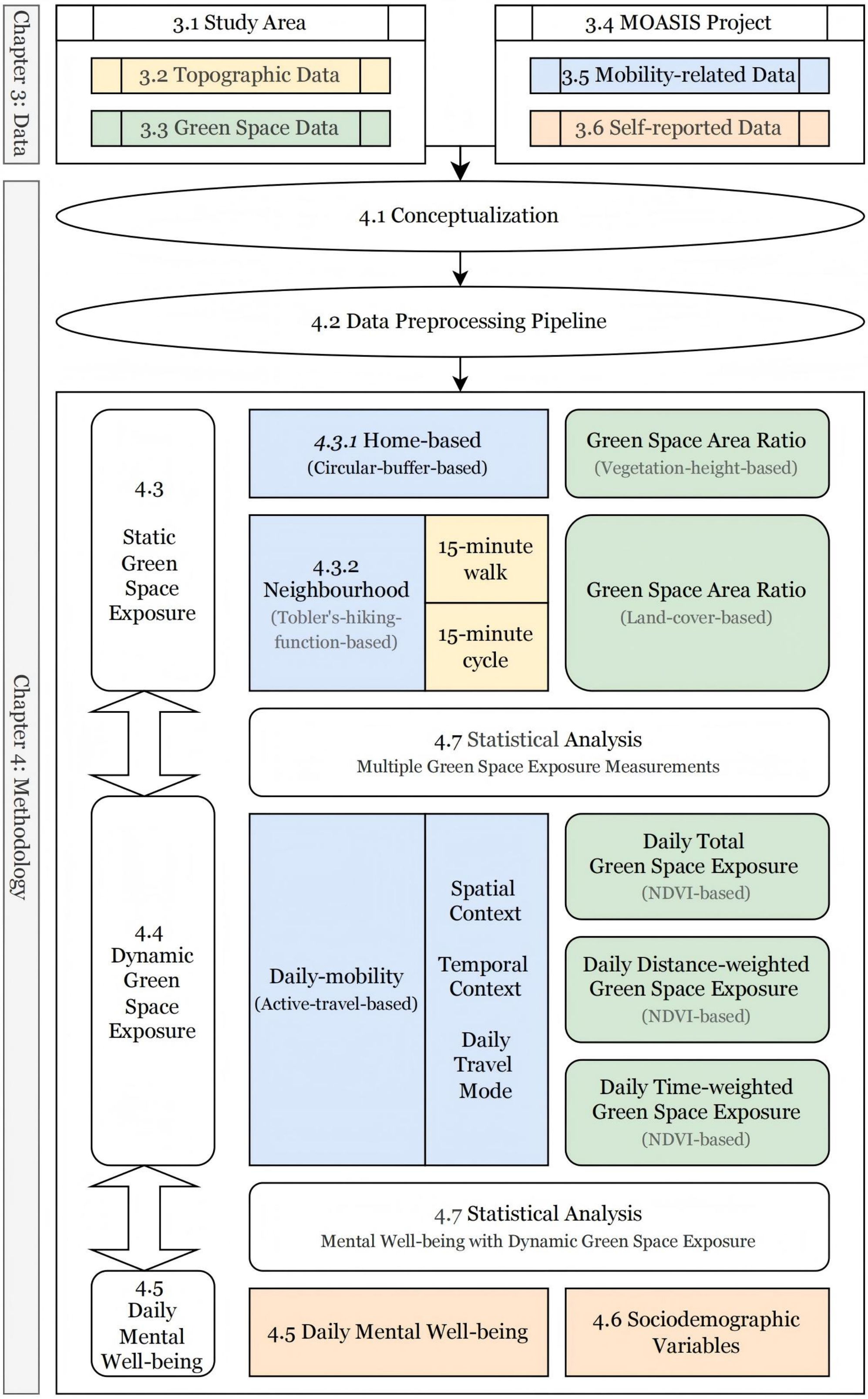
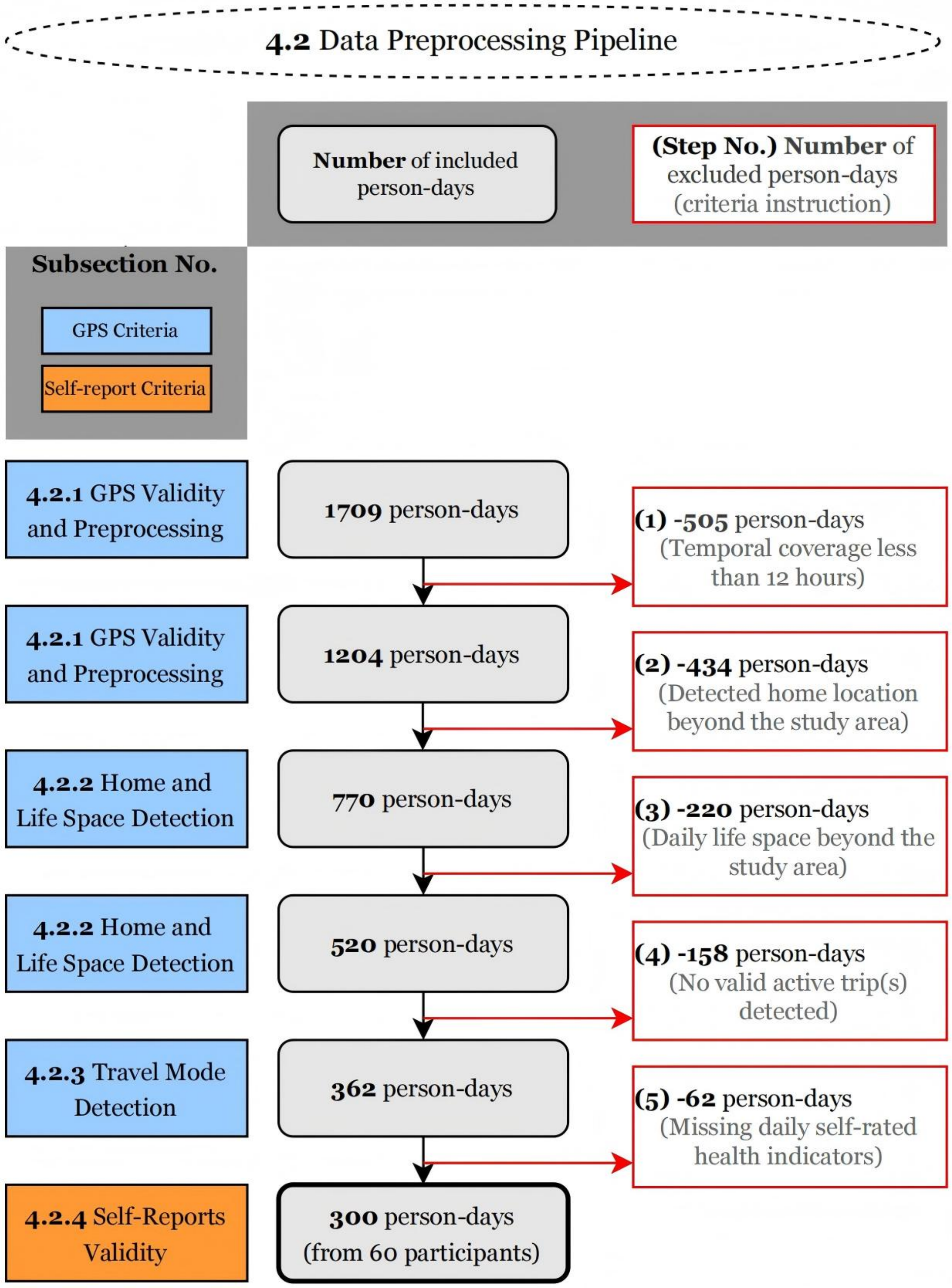


Figure 4.2: Workflow of sample selection. Color-filled boxes show the subsections and relative data, with blue for GPS data and orange for self-reported data. Gray-filled boxes with rounded corners show the number of remaining person-days for each selection step, while the number of excluded person-days and applied criteria are shown in the red boxes.



reliably reflect individuals' daily mobility (Fillekes et al., 2019c; Yu and Kwan, 2024). A 03:00:00 (HH:MM:SS) cut-point was further applied to minimize the effects of short cross-midnight sampling in daily temporal coverage calculation (Fillekes et al., 2019a). This criterion excluded 505 person-days with GPS time coverage below 12 hours, yielding 1204 valid person-days (Step 1, fig. 4.2).

To denoise GPS fixes, speed outliers were detected and excluded. After calculating the speed between two consecutive GPS fixes in the unit of km/h, I applied an iterative denoising procedure on each person-day's GPS trajectory (Fillekes et al., 2019a): for each iteration, the speed between consecutive fixes was calculated, and segments exceeding 250 km/h — the maximum train speed in Switzerland (Swiss federal authorities, 2024) — were flagged as outliers and then removed. The process was repeated until the proportion of outliers per person-day converged to a stable value.

4.2.2 Home and Life Space Detection

Computing home location is a prerequisite for measuring static green space exposure and mobility indicators. I used the denoised GPS data to infer home locations for each participant. Building on the approach of Fillekes et al. (2019b) and Fillekes et al. (2019c), I applied the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm to the third and last GPS fixes of each person-day, using a neighborhood radius of 60 m and a minimum-points threshold of 3 (Ester et al., 1996). The first two GPS fixes of each person-day were dropped to avoid inaccurate positioning that might occur at device reactivation. Clusters were represented as polygons. I retained the two largest-area polygons as candidate home clusters. For each participant, I counted all GPS fixes across all person-days that fell within the polygon. The home location was assigned to the polygon centroid (i.e., the mean projected coordinate) of the candidate cluster whose fix count exceeded the other by at least two fixes. If this criterion was not met, or neither candidate cluster contained any GPS fixes, home detection was deemed ambiguous, and that participant was excluded from analyses.

After home detection, 97 out of 98 participants had valid home locations; 62 out of 97 home locations were within the study area. Thus, 434 person-days were excluded due to detected home locations outside the study area (Step 2, fig. 4.2), with 770 person-days left. In addition, I restricted activity spaces (all GPS fixes of a person-day) to the study area (Fillekes et al., 2019c). I assumed that mobility within this life space level can reflect a typical day of older adults. 520 person-days were retained from those same 62 participants (Step 3, fig. 4.2).

4.2.3 Travel Mode Detection

Considering active travel usually involves physical activities and direct, immersive connections with green space, only person-days with valid active-travel trips were utilized for dynamic green space exposure measurements (Doorley et al., 2015; Wang et al., 2021a). There were three steps to extract person-days with valid active trips using GPS fixes: (1) stop-move segmentation, (2) travel mode detection, and (3) valid exposure extraction.

Stop-move segmentation. Following the stop-move segmentation algorithm by Montoliu et al. (2013), which has been applied in recent MOASIS studies (Fillekes et al., 2019a,b,c), person–day GPS trajectories were further split at large gaps: a chunk was first identified when the inter-fix time exceeded 1 hour or the step length exceeded 300 meters. Within each chunk, starting at the first fix, subsequent fixes were accumulated while all remained within a 150-meter radius of that start point; if the resulting duration was ≥ 5 minutes, the segment was labeled a *stop*, otherwise *too short*. Segments labeled *too short* were treated as move segments for subsequent steps (Vanwolleghem et al., 2016). Consecutive stops were first merged when separated by moves lasting ≤ 3 minutes, and were subsequently merged if the inter-stop time gap was < 1 hour and the median-to-median distance was ≤ 150 meters. Each stop was represented by the median projected coordinates of its fixes and by its arrival and departure timestamps.

Travel mode detection. In line with Carlson et al. (2015) and Vanwolleghem et al. (2016), I classified each "move" segment by its 90th-percentile speed (v90) against two thresholds. Segments with v90 ≥ 25 km/h were labeled passive (i.e., motorized) transport and those < 25 km/h active (i.e., non-motorized) transport. Within the active class I further sub-labeled walking when v90 < 10 km/h versus cycling for 10 ≤v90 ≤ 25 km/h. Finally, any single active segment flanked by passive segments (a passive–active–passive pattern) was relabeled as passive and merged with the adjacent passive stages into one continuous passive segment (Schuessler and Axhausen, 2009). This post-processing step reduced spurious mode switches caused by brief speed drops from congestion or traffic fluctuations.

Valid exposure extraction. A valid exposure was defined as a trip in detected active travel modes with either a minimum distance of 300 meters (Yoo et al., 2020) or a minimum duration of 3 minutes (Lee and Kwan, 2019). After this extraction, 362 person-days from 62 participants with valid exposure(s) were retained, finalizing the GPS sample for subsequent integration with self-reported measures (Step 4, fig. 4.2).

4.2.4 Self-Reports Validity

To examine the correlation between daily mental well-being and daily dynamic green space exposure metrics, only person-days with the complete evening assessment were retained. Applying this criterion, 62 person-days without evening assessments were excluded from the sample (Step 5, fig. 4.2). Finally, 300 days from 60 participants (Mean = 5, SD = 2.99) were utilized for analysis. As days per participant were highly imbalanced (CV (coefficient of variation) = 0.6), I did not consider intra-individual heterogeneity via random or fixed effects in this study.

4.3 Static Green Space Exposure

After home detection, two green space exposure metrics were calculated using the green space area ratio (GSAR) based on the detected home location at different life space levels: (1) home-based and (2) neighborhood.

GSAR is the ratio of green space area to the total area of a certain zone z (Yu et al., 2024a), as given in eq. (4.1):

$$\mathrm{GSAR}_z^{(\%)} = \frac{A_{\mathrm{green},\,z}}{A_{\mathrm{total},\,z}} \times 100 \tag{4.1}$$

4.3.1 Home-based Static Green Space Exposure

Home-based static green space exposure was calculated as GSAR within a 50-meter-radius buffer around the detected home location. Using the VHM introduced in Section 3.3.1, the green space here was defined as the cells with a vegetation height ≥ 5 cm (Eggimann, 2022).

4.3.2 Neighborhood Static Green Space Exposure

Neighborhood static green space exposure was assessed as GSAR in areas reachable within 15 minutes of walking and cycling, respectively, from participants' home locations. Three classes of habitat were defined as green space at the neighborhood level: (1) class 4: grasslands, (2) class 5: woodland edges, tall herb communities, shrubs, and (3) class 6: forests (Price et al., 2023). The detailed groups within each class of green space are reported in Table A.1. The computation of 15-minute walking/cycling reachable areas from home locations is described below.

The neighborhood zones (15-minute walking/cycling reachable areas from home locations) were delineated by isochrone polygons. Isochrones are lines of equal travel time (O'Sullivan et al., 2000). An isochrone map can visualize the area accessible from a certain location, given a certain travel mode (and thus travel speed) considering the restrictions of the road network (Dovey et al., 2017).

With the focus of this study on active travel, topographic factors should be considered when assessing individual accessibility (Valls and Clua, 2023). Given that, Tobler's Hiking Function (THF) was used to estimate the reachable areas in a walking travel mode (Tobler, 1993), with eq. (4.2):

$$
\begin{aligned}
W_{walking} &= 6\, e^{-3.5\left|\frac{dh}{dx}+0.05\right|} \\
\frac{dh}{dx} &= S = \tan\theta
\end{aligned}
\tag{4.2}
$$

where $W_{walking}$ is the walking speed [km/h], dh is the elevation difference, dx is the distance, S is the slope, and θ is the angle of slope (inclination). Equation (4.2) was used for walking estimation. Based on that, I used an adjusted base speed (25 km/h instead of 6 km/h) for cycling estimation (Monteiro et al., 2023), with eq. (4.3):

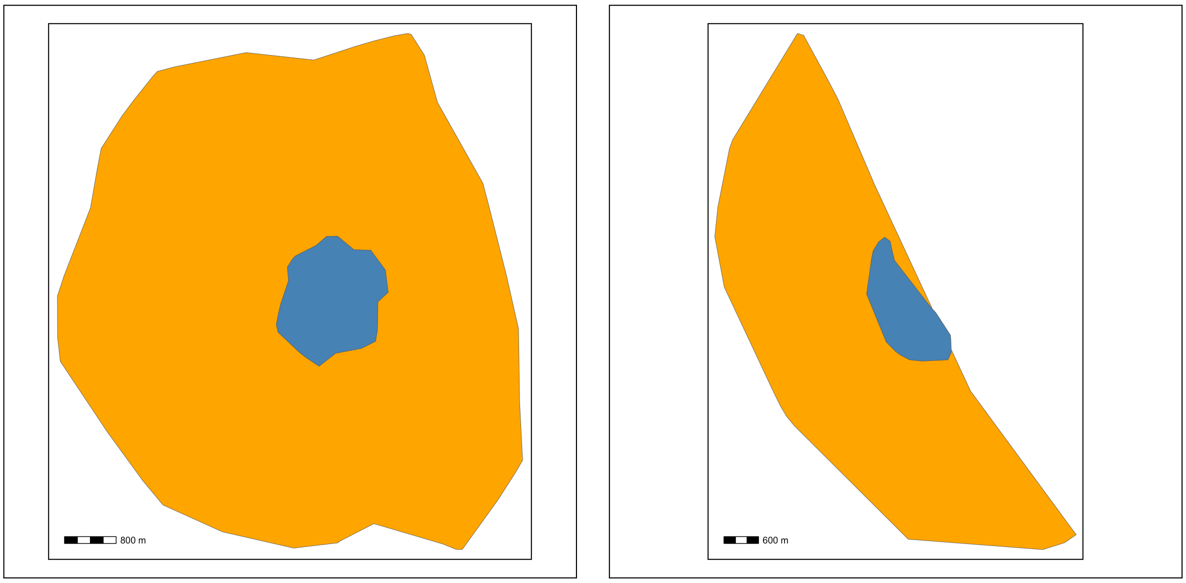
$$
\begin{aligned}
W_{cycling} &= 25\, e^{-3.5\left|\frac{dh}{dx}+0.05\right|} \\
\frac{dh}{dx} &= S = \tan\theta
\end{aligned}
\tag{4.3}
$$

where $W_{cycling}$ is the cycling speed [km/h], dh is the elevation difference, dx is the distance, S is the slope, and θ is the angle of slope (inclination).

With TLM and DEM introduced in section 3.2, a three-dimensional undirected road network was generated in a 10-meter resolution (edge length) with vertices and edges by `sfnetworks` (van der Meer et al., 2024). Three main steps were executed: (1) I first clipped the network to a circular buffer (radius: base speed × time budget) based on the detected home location to limit the reachable area under a constant speed without topography to improve the efficiency of the following calculations. (2) For the clipped road network, I assigned each edge a baseline travel time (edge length divided by mode-specific base speed). Using travel time for each edge as weights, the nodes reachable from the home location in the clipped network within time budget can be generated using `tidygraph::node_distance_from()` using Dijkstra's algorithm (Dijkstra, 2022; Pedersen, 2024). Nodes within the time budget were deemed reachable. Subsequently, I extracted the corresponding shortest paths as candidate paths from the home to all reachable nodes with `sfnetworks::st_network_paths()` and retained the induced set of edges. (3) Then, along each candidate path, I recalculated the travel time of each edge under THF and the cumulative travel time from the home location. Once the cumulative travel time reached the time budget (15 minutes), the reachable nodes were extracted along each path. If not, all nodes along the path were retained and extracted.

Finally, all extracted nodes were combined and converted to a concave hull using the *sf::st_concave_hull*() in `sf` with alpha as 0.6 (Pebesma and Bivand, 2023; Pebesma, 2018). The pseudocode of this approach was illustrated in Algorithm 1. Figure 4.3 shows two examples of isochrone maps.

Figure 4.3: Two example isochrone maps of 15-minute walking (sky blue) and cycling (orange) reachable areas from the home location used in this study. The shape and area of isochrone polygons can be influenced by topographic factors (e.g., slopes, road network structures, etc.) around individuals' home locations. In the left example, the reachable areas (unit: km^2) were 2.45 for walking and 45.32 for cycling. The shape of both isochrone polygons is nearly round. In the right example, however, the reachable areas (unit: km^2) were 1.71 for walking and 24.57 for cycling. The shape of both isochrone polygons is a half moon. *Note*: home locations, coordinates, and participant IDs are anonymized.



4.4 Dynamic Green Space Exposure

For cloud-free images processed as described in section 3.3.3, negative NDVI pixels (indicative of non-vegetation) were masked as zero prior to analysis to prevent distortion of NDVI values (Yu and Kwan, 2024).

Trip-level dynamic green space exposure. Valid active trips extracted according to section 4.2.3 were used to compute dynamic green space exposure. For each trip, GPS fixes were temporally matched to the closest preprocessed NDVI image (nearest date). For each trip with k GPS fixes, I computed at each fix i the mean NDVI within a 50m circular buffer q. Considering each trip with trip duration T_{tot} (minutes) and total trip distance D_{tot} (meters), I defined three trip–level indices: (1) total green space exposure (TGE), (2) green space exposure per unit time (UTGE), and (3) green space exposure per unit distance (UDGE).

$$\text{TGE}_{\text{trip}} = \sum_{i=1}^{k} q_i, \tag{4.4}$$

$$\text{UTGE}_{\text{trip}} = \frac{\text{TGE}_{\text{trip}}}{T_{\text{tot}}} \quad \text{(per minute)}, \tag{4.5}$$

$$\text{UDGE}_{\text{trip}} = \frac{\text{TGE}_{\text{trip}}}{D_{\text{tot}}} \quad \text{(per meter)}. \tag{4.6}$$

where T_{tot} is the total travel duration for each trip, and D_{tot} is the total travel dis-

Algorithm 1 THF-based T-Minute Walking/Cycling Reachable Area

Input: home H; graph $G = (V, E)$ with geometry and Z; mode $m \in \{\textsc{walk}, \textsc{cycle}\}$; T (min)
Output: polygon of area reachable within T
$v_0 \leftarrow 6$ if $m = \textsc{walk}$ else 28 (km/h); $T_s \leftarrow 60T$
(1) Spatial prefilter: constant speed without topographic factors
$r \leftarrow (v_0/3.6)\,T_s$ ▷ meters
$G' \leftarrow G \cap \mathrm{Buffer}(H, r)$ ▷ clip graph to circle
(2) Base pass: constant speed under the road network
for $e \in E(G')$ **do**
    $w_e^0 \leftarrow \ell_e/(v_0/3.6)$ ▷ seconds
end for
Run Dijkstra from H with weights w_e^0
Keep shortest-path tree $\mathcal{P}_0$ to nodes with $\tau_0 \le T_s$ and frontier edges
(3) Refine on paths: slope-aware speed
$S \leftarrow \varnothing$
for path $p \in \mathcal{P}_0$ from H **do**
    $t \leftarrow 0$
    for edge $e = (u, v)$ along p **do**
        $s_e \leftarrow \frac{Z(v)-Z(u)}{\ell_e}$
        $v_e \leftarrow \left(v_0\, e^{-3.5|s_e+0.05|}\right)/3.6$ ▷ m/s
        $\Delta t \leftarrow \ell_e/v_e$
        if $t + \Delta t \le T_s$ **then**
            add full e to S; $t \leftarrow t + \Delta t$
        else
            add prefix of e at fraction $f = (T_s - t)/\Delta t$ to S; **break**
        end if
    end for
end for
(3) Isochrone
Dissolve S to nodes, polygonize, then apply ConcaveHull $\rightarrow$ isochrone polygon

tance for each trip.

Daily dynamic green space exposure. For each person-day, three trip-level green space exposure indices were aggregated into a daily level. For person p on day d, $\mathcal{T}_{p,d}$ denotes that day's set of active trips. The following metrics were used to measure daily dynamic green space exposure:

$$\mathrm{TGE}_{p,d} = \sum_{t \in \mathcal{T}_{p,d}} \mathrm{TGE}_{\mathrm{trip},t}, \tag{4.7}$$

$$\mathrm{UTGE}_{p,d} = \sum_{t \in \mathcal{T}_{p,d}} \mathrm{UTGE}_{\mathrm{trip},t}, \tag{4.8}$$

$$\mathrm{UDGE}_{p,d} = \sum_{t \in \mathcal{T}_{p,d}} \mathrm{UDGE}_{\mathrm{trip},t}. \tag{4.9}$$

All computations for dynamic green space exposure above were repeated with alternative buffer radii (30, 100, 300, and 500 meters) to ascertain the robustness of the results (Browning and Lee, 2017; Yoo and Roberts, 2022; Yu and Kwan, 2024).

Daily mobility indicators aggregation. Five daily mobility indicators considering diverse contexts were derived from active trip(s) for each person-day, labeled from (a) to (e) in table 4.2.

Spatial Context. For each active trip, I computed a trip-level mean distance to home as the average distance from each GPS fix in the trip to the detected home location. Consequently, for each person–day, I computed a daily mean distance to home as the average of that day's trip-level means. To classify spatial mobility, I defined (a) neighborhood by dichotomizing the person–day values at the sample median of the daily mean distance to home: person–days with values ≤ median were labeled (a.1) within-neighborhood, and those > median were labeled (a.2) beyond-neighborhood.

Temporal Contexts. According to recent dynamic green space exposure studies (Xie et al., 2023; Yoo and Roberts, 2022), three mobility indicators in temporal contexts were defined at the person-day level as: (b) travel time: the time band (HH:MM:SS) with the longest travel duration ((b.1) 06:00:00-11:59:59, morning; (b.2) 12:00:00-17:59:59, afternoon; (b.3) others, evening), (c) trip frequency—(c.1) high or (c.2) low via median split of trips per person-day (≤ median = low), and (d) weekday (whether a person-day was on (d.1) a weekday or (d.2) the weekend).

Travel Mode. Finally, (e) daily travel mode was stratified by mode(s) from all trip(s) into three classifications: (e.1) cycle only, (e.2) cycle and walk, and (e.3) walk only.

Table 4.2: Mobility aggregation from trip level to daily level.

Daily Mobility Indicators	Description	Factors
Spatial Context		
(a) Neighborhood	By median of "mean distance to home" of all trips for a person-day	(1) Within (2) Beyond
Temporal Context		
(b) Travel Time	The daytime period with the longest travel duration for a person-day	(1) Morning (2) Afternoon (3) Evening
(c) Trip Frequency	By median of the count of trips for a person-day	(1) High (2) Low
(d) Weekday	Weekday or weekend for a person-day	(1) Weekday (2) Weekend
Travel Mode		
(e) Daily Travel Mode	The aggregation of all trips for a person-day	(1) Cycle only (2) Cycle and walk (3) Walk only

4.5 Daily Mental Well-being

Daily subjective health was utilized as the daily mental well-being variable, evaluated through a question on a 7-point Likert scale in the evening assessment. Respondents were asked, "*How would you rate your health today* (range from 1 [Very bad] to 7 [Very good])?" This indicator is considered valid and reliable, which can measure overall health status for older adults (Benyamini et al., 2003; Schüz et al., 2011).

4.6 Sociodemographic Variables

According to studies examining relationships between green space and mental outcomes (Lyshol and Johansen, 2024; Yu and Kwan, 2024), I included the following variables as sociodemographic covariates:

- *sex*: male vs female;
- *age*: chronological age in years;
- *highest education level*: reclassified to (1) less than secondary, (2) secondary, and (3) tertiary, according to the international standard classification of education in the Swiss context (Faeh et al., 2010; Schneider, 2013);
- *individual monthly net income*: classified as low ($\leqslant$ 4,000 CHF), medium (4,001–8,000 CHF), and high ($\geqslant$ 8,000 CHF);
- *employment*: retired vs part-time employment;
- *marital status*: categorized as long-term or registered relationships (long-term relationships and married) vs others (single, widowed, or divorced);
- *general health*: assessed using a question from the SF-12: "*In general, would you say your health is…*" on a five-point Likert scale (1 = poor to 5 = excellent) (Lawton and Brody, 1969; Ware et al., 1996).

4.7 Statistical Analysis

To answer RQ1, I began with descriptive statistics to summarize the characteristics of multiple green space exposure metrics. Static metrics were defined at the individual level, whereas dynamic metrics were computed at the person-day level. For subsequent person-day analyses, each participant's static exposure value was aggregated to all of their days, so that every person-day inherited the same static value for that participant. I adopted this time-invariant specification because the green space data (VHM and the habitat map) used to derive static exposure cannot resolve day-to-day changes within the 15-day activity sampling window used in the MOASIS study, and thus cannot provide a dynamic residential context aligned with the person-day data.

To comprehend the patterns of green space exposure, I began with static ones. First, I dichotomized each metric (home-based, 15-minute walking, and 15-minute-cycling GSAR) at the individuals' sample median and compared the low vs. high groups using the Wilcoxon rank–sum (Mann–Whitney) test. The significant difference confirmed the validity of the low and high static green space exposure grouping for subsequent analyses. Second, regarding the uncertain geographic context problem (UGCoP) in the three residential contexts within participants (Kwan, 2012), I used a repeated measures analysis of variance (rmANOVA) to determine if the mean exposure levels differed significantly across these three residential contexts. Given that daily mobility indicators were aggregated into groups, I used the Kruskal–Wallis test to compare the distributions of daily dynamic green space exposure metrics across mobility-indicator groups.

Finally, the reliability of person-day TGE across different buffer sizes (30 m, 50 m, 100 m, 300 m, 500 m) was assessed using the Intraclass Correlation Coefficient (ICC). I quantified agreement between person-day TGE computed with alternative buffer radii by calculating two intraclass correlations for each pairwise comparison with 50-meter-radius values as the reference: absolute agreement, ICC(A,1), and consistency, ICC(C,1), both with 95% confidence intervals (Jimenez et al., 2022; McGraw and Wong, 1996). Because at a person-day level, UTGE and ULGE were normalizations of TGE by the same denominators: trip duration and trip distance, these denominators were independent from the buffer radius. The impact of buffer choice was consistent across all three green space indices for each person-day. Consequently, the evaluation of the buffer-radius agreement for TGE was considered adequate.

To address RQ2, I employed a daily (person-day) frame for analysis. Given that all green space exposure metrics were continuous variables, the Pearson correlation coefficient was applied to examine the correlation between dynamic and static green space exposure metrics. I applied multivariate linear regression models at the person–day level with dynamic green space exposure as the outcome, including static green space exposure and mobility indicators as predictors to estimate their adjusted associations in Equation 4.10:

$$\begin{aligned} &Dynamic\ Green\ Space\ Exposure_{pd} = \\ &a_0 + a_1 Static\ Green\ Space\ Exposure_{pd} + a_2 Mobility\ Indicators_{pd} + \epsilon \end{aligned} \tag{4.10}$$

where p represents the person (individual), d the study day, and ϵ the error of the model.

To answer RQ3, the Spearman rank correlation coefficient was used to examine the association between daily self-rated health (an ordinal variable) and daily dynamic green space exposure metrics. In accordance with the preceding analysis, individual sociodemographic factors were aggregated to the person–day panel. Using sociodemographic contexts as covariates, multivariate linear regression models were utilized for analysis as expressed in Equation 4.11:

$$\begin{aligned} &Daily\ Subjective\ Health_{pd} = \\ &b_0 + b_1 Dynamic\ Green\ Space\ Exposure_{pd} + b_2 Covariate_{pd} + \epsilon \end{aligned} \tag{4.11}$$

where p denotes the person (individual), d the study day, and ϵ the error of the model.

CHAPTER 5

RESULTS

5.1 Descriptive Statistics

Table 5.1 displays the sociodemographic characteristics of the participants. The average age of the participants was 76.15 (SD = 5.13) years. Above half of the participants were female (61.67%). Most of the participants were retired (85%). Approximately half of the participants (45%) were classified within the medium income group. Slightly more than half (53.33%) of the participants were married or had a long-term partnership. Of all the participants, 53.34% possessed a tertiary level of education. The overwhelming majority of participants (95%) reported experiencing good or better general health. Sociodemographic characteristics from the original questionnaires including all 113 MOASIS participants are presented in table B.2. Person-day distributions closely matched participant-level distributions (max absolute difference 11.3 percentage points (pp) in marital status, all others ≤ 5.3 pp). Given that these characteristics were inherently constant over the sampling period, I propagated them to each person-day as covariates.

5.2 Green Space Exposure Metrics

5.2.1 Static Green Space Exposure Metrics

Descriptive statistics of the individuals' static green space exposure variables are presented in table 5.2, with table 5.3 showing the comparison between high and low static green space exposure metrics grouped by median value under the Wilcoxon rank–sum test. The results indicate that there were significant differences among all static green space exposure metrics. This participant-level grouping was then propagated to the person-day dataset. Each person-day observation was assigned to the static green space group (low or high) of its corresponding participant.

Table 5.1: Sociodemographic characteristics of the participants.

Variables	Description	Number (Proportion) of People (N=60)	Number (Proportion) of Days (N=300)
Gender	Male	23 (38.33%)	112 (37.33%)
	Female	37 (61.67%)	188 (62.67%)
Age	65–74	24 (40.00%)	134 (44.67%)
	75–84	31 (51.67%)	148 (49.33%)
	⩾ 85	5 (8.33%)	18 (6.00%)
Employment	Part-time employment	9 (15.00%)	44 (14.67%)
	Retired	51 (85.00%)	256 (85.33%)
Individual monthly net income	Low (⩽ 4,000 CHF)	21 (35.00%)	90 (30.00%)
	Medium (4,001 – 8,000 CHF)	27 (45.00%)	142 (47.33%)
	High (⩾ 8,000 CHF)	16 (26.67%)	88 (29.33%)
Education	Less than secondary	3 (5.00%)	12 (4.00%)
	Secondary	23 (38.33%)	113 (37.67%)
	Tertiary	32 (53.34%)	171 (57.00%)
	Missing data	2 (3.33%)	4 (1.33%)
Marital status	Long-term or registered partnership	32 (53.33%)	194 (64.67%)
	Others	28 (46.67%)	106 (35.33%)
General health	Fair	3 (5.00%)	17 (5.67%)
	Good	18 (30.00%)	76 (25.33%)
	Very good	31 (51.67%)	151 (50.33%)
	Excellent	8 (13.33%)	56 (18.67%)

Figure 5.1 presents the comparison of static green space exposure between three residential contexts under rmANOVA. It revealed a significant main effect of spatial context on static green space exposure ($F(1.68, 99.38) = 29.07$, $p < .0001$). The large effect size ($\eta_g^2 = .17$) indicated that static green space exposure metrics under the three residential contexts were significantly different for the participants.

5.2.2 Dynamic Green Space Exposure Metrics

Table 5.2 presents descriptive statistics for daily dynamic green space exposure. The metrics exhibit a highly skewed distribution and considerable variability across

Table 5.2: Descriptive statistics of multiple green space exposure metrics.

Variables	N	Min	Max	Mean	SD
Static					
Home-based GSAR (%)	60	17.88	71.99	46.43	11.47
15-minute-walking GSAR (%)	60	16.96	74.70	48.50	11.36
15-minute-cycling GSAR (%)	60	43.02	73.78	57.27	8.40
Dynamic					
Total Volume (TGE)	300	0.00	9786.30	1121.20	1717.45
Distance-weighted (UDGE)	300	0.00	16.93	1.09	1.61
Time-weighted (UTGE)	300	0.00	488.40	86.78	78.35

Table 5.3: Differences in low and high static green space exposure metrics under Wilcoxon rank–sum test.

Variables	Group	Mean (SD)	P-value and significance
GSAR (%) (home)	Low (n = 30)	37.70 (1.43)	<0.001***
	High (n = 30)	55.16 (1.28)	
GSAR (%) (15-minute walk)	Low (n = 30)	39.32 (1.33)	<0.001***
	High (n = 30)	57.66 (1.08)	
GSAR (%) (15-minute cycle)	Low (n = 30)	49.80 (0.66)	<0.001***
	High (n = 30)	64.75 (0.70)	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

person-days.

Table 5.4 provides the outcomes of the Kruskal-Wallis test comparing daily dynamic green space exposure across mobility-indicator groups, with detailed comparison plots in appendix D. Specifically, I found significant between-group differences for three indicators: (1) beyond-neighborhood person-days had higher median dynamic green space exposure than within-neighborhood person-days; (2) dynamic green space exposure metrics in high-frequency person-days exceeded low-frequency person-days; and (3) person-days including walking (walking only,

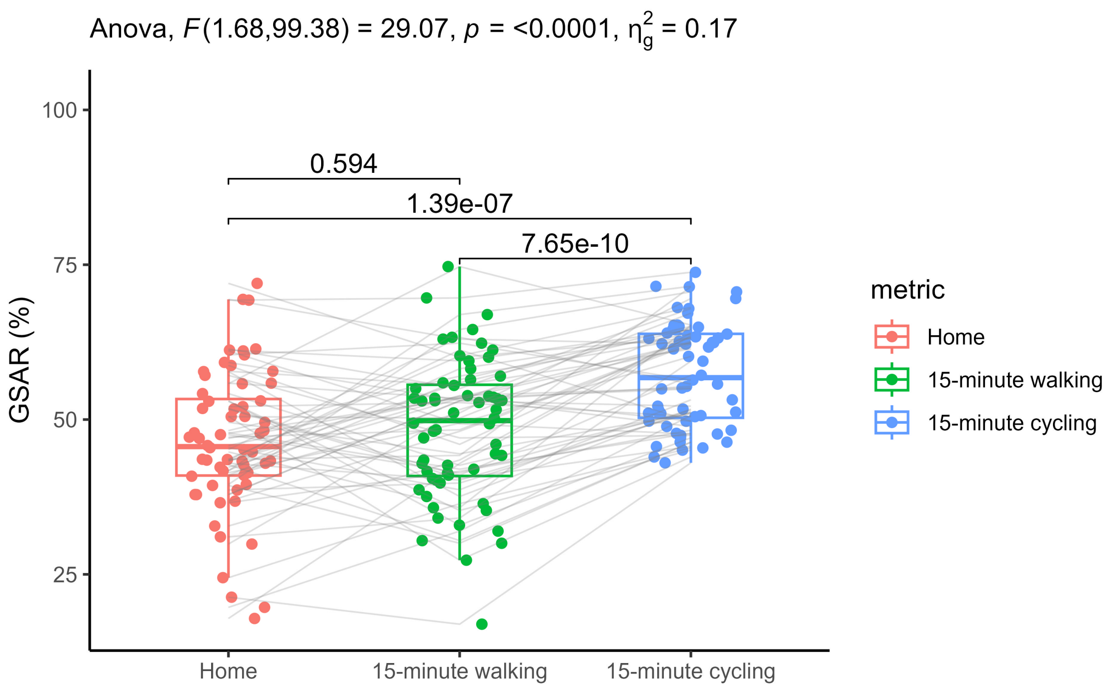


Figure 5.1: Static green space exposure metrics (GSAR, %) across spatial contexts: *Home* (50 m buffer), *15-minute walking* (THF isochrone), and *15-minute cycling* (THF isochrone with adjusted speed). Boxes show medians and interquartile ranges; points are participants (persons) ($N = 60$); grey lines connect the same participant across contexts. A repeated-measures ANOVA showed a main effect of context, $F(1.68, 99.38) = 29.07$, $p < 0.0001$, $\eta^2_g = 0.17$. Bonferroni-adjusted paired tests indicated *cycling* > *home* ($p = 1.39 \times 10^{-7}$) and *cycling* > *walking* ($p = 7.65 \times 10^{-10}$), whereas *walking* ≈ *home* ($p = 0.594$).

walking and cycling) showed higher exposure than cycling-only person-days. In contrast, dynamic green space exposure metrics did not differ markedly between weekdays and weekends, and no pronounced differences were detected across travel time categories.

Table 5.5 presents the results of the pairwise ICC analysis comparing various buffer sizes to the 50-meter-radius reference. Absolute agreement (ICC(A,1)) and consistency (ICC(C,1)) were excellent (ICC > 0.9) for all buffer pairs, indicating that all buffers produced nearly identical TGE values. Thus, dynamic green space exposure metrics were robust to various buffer-radius choices.

Table 5.4: The statistical results of mobility contextual differences in dynamic green space exposure patterns under Kruskal-Wallis test.

Variables	**TGE (median)**	**Sig. (p)**	**UTGE (median)**	**Sig. (p)**	**UDGE (median)**	**Sig. (p)**
Spatial Context						
Neighborhood (median of daily mean distance to home: 528.90 m)		0.000***		0.000***		0.000***
Within (n = 149)	280.95		43.24		0.50	
Beyond (n = 151)	957.39		80.38		0.81	
Temporal Contexts						
Trip Frequency (median of daily trip frequency: 2)		0.000***		0.000***		0.000***
Low (n = 168)	192.26		35.01		0.32	
High (n = 132)	1093.07		127.83		1.34	
Travel Time		0.72		0.47		0.17
Morning (n = 137)	499.48		64.99		0.57	
Afternoon (n = 133)	458.70		63.29		0.69	
Evening (n = 30)	635.13		68.00		0.53	
Weekend		0.79		0.68		0.34
True (n = 78)	378.44		62.19		0.34	
False (n = 222)	502.33		64.93		0.63	
Travel Mode						
Daily Travel Mode		0.000***		0.000***		0.000***
Cycle & walk (n = 110)	898.73		105.49		1.05	
Cycle only (n = 100)	191.31		34.68		0.23	
Walk only (n = 90)	667.88		58.13		0.93	

Sig.: significance.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.3 Associations between Green Space Exposure Metrics

Pearson correlations among the green space exposure metrics are reported in table 5.6. Neighborhood-level static green space exposure metrics were positively associated with dynamic green space exposure metrics (minimum rρ = 0.18, all p < 0.001). By contrast, home-based static exposure showed little correspondence with dynamic exposure: correlations were not statistically significant for any dynamic metric except the distance-weighted measure, which was weak but signifi-

Table 5.5: Intraclass correlations comparing TGE at other-size buffers to a 50-meter-radius reference. ICC(A,1) = two–way random-effects, absolute agreement; ICC(C,1) = two–way mixed-effects, consistency. Each row reports the ICC between the listed buffer and the 50 m buffer.

Radius of circular buffer (m)	ICC(A,1)		ICC(C,1)	
	Value	95% CI	Value	95% CI
30	1.00***	[1.00, 1.00]	1.000***	[1.00, 1.00]
100	1.00***	[1.00, 1.00]	1.000***	[1.00, 1.00]
300	0.99***	[0.99, 1.00]	0.99***	[0.99, 0.99]
500	0.99***	[0.99, 1.00]	0.99***	[0.99, 0.99]

ICC < 0.5 poor, 0.5–0.75 fair, 0.75–0.9 good, > 0.9 excellent.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

cant (rρ = 0.13, p < 0.01).

Table 5.6: Results of correlation test: green space exposure variables.

Variable	GSAR (home)	GSAR (15-min walking)	GSAR (15-min cycling)	UTGE	UDGE	TGE
Static						
Home						
GSAR (home)	1.00					
Neighborhood						
GSAR (15-min walking)	0.49***	1.00				
GSAR (15-min cycling)	0.18**	0.67***	1.00			
Dynamic						
UTGE	0.03	0.21***	0.22***	1.00		
UDGE	0.13*	0.22***	0.23***	0.70***	1.00	
TGE	-0.09	0.18***	0.24***	0.75***	0.47***	1.00

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed t-test).

I analyzed day-level dynamic green space exposure (TGE, UTGE, UDGE) using multivariate linear regression with static exposure and mobility indicators as predictors. Because mobility indicators were modeled as categorical groups, I likewise dichotomized static exposure at the sample median (low vs high, according to table 5.3) to avoid overdispersion. Subsequently, only mobility that showed between-group differences (neighborhood, trip frequency, and daily travel mode table 5.4) were included in the regression analysis along with the static green space exposure.

Results of linear regression analysis are reported in table 5.7. Models 1–3 included all static exposure groups (home-based, 15-min walking, 15-min cycling) with

Table 5.7: Regression on dynamic green space exposure under static green space exposure and mobility indicators.

	(1)	(2)	(3)	(4)	(5)	(6)
	TGE	UTGE	UDGE	TGE	UTGE	UDGE
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Static Green Space Exposure Group						
Home-based (reference: low)	−539.6**	−7.80	−0.04			
	(164.70)	(6.12)	(0.19)			
15-minute walk (reference: low)	391.70*	20.33**	0.41*	399.00*	20.44**	0.41*
	(180.9)	(6.73)	(0.17)	(189.00)	(6.75)	(0.17)
15-minute cycling (reference: low)	520.9**	26.60***	0.59***	502.90**	26.32***	0.59***
	(181.5)	(6.75)	(0.17)	(189.40)	(6.76)	(0.17)
Mobility Indicator Groups						
Spatial Context						
Neighborhood (reference: beyond neighborhood)	686.70***	9.07	0.03			
	(169.30)	(6.29)	(0.16)			
Temporal Context						
Trip Frequency (reference: low)	1374.6***	98.77***	1.26***	1604.60***	101.86***	1.27***
	(195.20)	(7.26)	(0.19)	(198.00)	(7.07)	(0.18)
Daily Travel Mode						
(reference: cycle only)						
Walk only	722.70***	28.27***	1.15***	692.10**	27.76***	1.15***
	(210.80)	(7.84)	(0.20)	(218.00)	(7.78)	(0.20)
Walk and Cycle	255.70	28.65***	0.51*	211.60	28.00***	0.51*
	(223.90)	(8.33)	(0.21)	(233.40)	(8.33)	(0.21)
R2	0.34	0.56	0.31	0.28	0.56	0.31
R2 Adj.	0.33	0.55	0.29	0.27	0.55	0.29
RMSE	1409	53.83	1643	1472	74.08	26.32

[a] SE: standard error in parentheses
[b] + p <0.1, * p <0.05, ** p <0.01, *** p <0.001

neighborhood, trip frequency and daily travel mode as mobility indicators. After estimating these full models for the three dynamic outcomes, I dropped home-based static green space exposure and the neighborhood group and retained only predictors that were consistently significant across all outcomes. Models 4–6, therefore, report the reduced specification using the remaining static exposure and mobility predictors, with the same reference categories as in Models 1–3. Generalized variance inflation factors (GVIF ≤ 1.42) suggest that multicollinearity is not serious among the predictors among all six models. Across models, the R^2 and adjusted R^2 ranged from 0.27 to 0.56, indicating moderate explanatory power. Under the assumption that other predictors remain constant, person-days with higher neighborhood static green space exposure (15-min walking or cycling reachable areas) showed consistently higher dynamic exposure metrics. In the mobility contexts, dynamic green space exposure was higher on person-days with high trip frequency and walking.

5.4 Associations between Well-being and Dynamic Green Space Exposure

The Spearman rank correlation coefficient was used to assess correlations between daily subjective health and dynamic green space exposure metrics (table 5.8). Only daily total green space exposure shows a significant positive correlation (rSP = 0.17, $p < 0.01$) with daily subjective health. To further examine the effects of sociodemographic factors on daily subjective well-being, later models used other person-day sociodemographic features as independent variables, with the daily total green space exposure in dynamic green space exposure metrics as the covariate.

Table 5.8: Association between daily dynamic green space exposure and daily subjective health.

	Daily subjective health	
	Spearman r	P-value and significance
Total green space exposure	**0.17**	**0.003****
Distance-weighted green space exposure	-0.01	0.92
Time-weighted green space exposure	0.06	0.28

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table 5.9 shows the associations of daily subjective health with daily total green space exposure and sociodemographic factors. Model 7 included all sociodemographic factors, which indicates that age, employment, and marital status have nonsignificant associations with daily subjective well-being. Given that, Model 8 only considered the significant sociodemographic factors determined from Model 7. Variance inflation factors (VIF ≤ 1.52) suggest that multicollinearity is not serious among the predictors in Models 8 and 9. The overall fitting effect of both models was deemed moderate ($R^2 = 0.48$–0.49; adjusted $R^2 = 0.47$). Outcomes from both Model 8 and Model 9 reveal that female sex (compared with male), higher income, and better baseline general health were positively associated with daily subjective health, whereas education showed a negative coefficient. These estimates reflect conditional associations holding other covariates constant.

Table 5.9: Regression of daily subjective health on dynamic green space exposure and sociodemographic characteristics.

	(7)	(8)
	Daily subjective health	Daily subjective health
	Coef. (SE)	Coef. (SE)
Dynamic Green Space Exposure		
Daily total green space exposure	0.00 (0.00)	0.00* (0.00)
Sociodemographic Contexts		
Gender (female)	**0.23*** (0.10)	**0.24*** (0.09)
Income	**0.40***** (0.07)	**0.38***** (0.07)
Education	**-0.15**** (0.05)	**-0.13**** (0.05)
General Health	**0.72***** (0.06)	**0.74***** (0.05)
Age	0.00 (0.01)	
Employment	–0.10 (0.07)	
Marital Status (long-term or registered partnership)	0.06 (0.10)	
Intercept	0.96 (0.95)	0.21 (0.30)
R2	0.49	0.48
R2 Adj.	0.47	0.47
RMSE	0.73	0.73

[a] SE: standard error in parentheses
[b] * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

CHAPTER 6

DISCUSSION

This chapter offers a synopsis of the primary findings and their critical interpretation. There are three main components in this chapter to address each RQ, with section 6.1 and section 6.2 covering green space exposure patterns (RQ1), section 6.3 devoted to the association between dynamic and static green space exposure metrics (RQ2), and section 6.4 discussing the relationship between daily mental well-being and dynamic green space exposure (RQ3).

6.1 Residential Static Green Space Exposure

My results showed that home-adjacent (50-meter circular buffer) and neighborhood (areas reachable within 15 minutes of walking and cycling) static green space exposure metrics can diverge substantially, consistent with the UGCoP: residential green space exposure estimates vary with spatial contexts (Kwan, 2012). Similar scale-dependent differences were reported in prior work about older adults, that spatial context in neighborhood green space measurements may influence the health outcomes (Yoo et al., 2024). Thus, home and neighborhood can be different residential contexts regarding static green space exposure measurements.

6.2 Mobility Factors Influencing Daily Dynamic Green Space Exposure

Different buffer sizes did not show significant impacts on daily dynamic green space exposure in this study, despite the potential influence of spatial scale sensitivity suggested by previous literature (Markevych et al., 2017). Thus, I further discuss the effects of daily mobility indicators on dynamic green space exposure in three aspects: (1) spatial, (2) temporal, and (3) travel-mode context(s). The following subsections will discuss each aspect accordingly.

6.2.1 Spatial Context

In the spatial context, I found a "compensatory" exposure pattern: the older adults in the MOASIS sample can generate a higher green space exposure when they are beyond (compared to within) their neighborhoods. The neighborhood threshold in this study was 528.90 meters. This finding accords with recent dynamic green space exposure studies that employees may compensate for green space exposure by traveling farther from their workplaces, rather than to nearby places (Wang et al., 2021a; Xie et al., 2023). A potential explanation for "compensatory" exposure in older adults may be found in their travel patterns. Hirsch et al. (2016) reported that compared with older adults' close neighborhood (400 or 800-meter circular buffer), their GPS-based activity places had a higher destination density and diversity. Given that, the MOASIS older adults may perceive environments outside their immediate neighborhood as more attractive. Consequently, they are more likely to undertake active trips beyond their neighborhood that are longer in time or distance, increasing their dynamic green space exposure.

6.2.2 Temporal Contexts

Regarding temporal contexts, my first finding is that high travel frequency can enhance dynamic green space exposure. A plausible explanation is the high baseline greenness of the study area (the Canton of Zurich), with 29.1% forest and 1.4% woodland cover (Federal Statistical Office, 2016). In such a context, more frequent trips readily translate to greater cumulative green space exposure. This finding aligns with Xie et al. (2023), who found a positive association between trip frequency and total green space exposure. My operationalization of 'trip intensity' differs, however: I defined low trip frequency as ≤ 2 trips. Whereas Xie et al. (2023) dichotomized frequency as 1 trip (low) versus 2 trips (high) to reflect commuters' typical workday travel patterns. This distinction underscores the importance of sample selection and threshold choices in dynamic green space exposure assessment.

In addition, my results revealed no significant differences in daily dynamic green space exposure across different travel time periods (morning, afternoon, evening) or between weekdays and weekends. This finding contrasts with studies of younger commuters, which found significant variations based on temporal patterns (Xie et al., 2023; Yoo and Roberts, 2022; Zheng et al., 2024a). A key factor explaining this inconsistency is likely the age profile of our sample (adults aged 65 or older), with 85% fully retired (Table 5.1). Unlike working-age commuters, older adults often have more flexible schedules, leading to weaker temporal structuring of their mobility (Pasanen et al., 2021). For instance, retirees' physical activity patterns often do not differ between weekdays and weekends (Pasanen et al., 2021). Older adults' daily trips can be distributed across a wider time interval compared with younger adults (Shen et al., 2017). This relative lack of time constraints may effectively diminish the temporal contrasts in dynamic green space exposure observed in aging populations.

6.2.3 Travel-Mode Context

A particularly novel finding of this study is that travel mode significantly influences the magnitude of daily dynamic green space exposure, with walking generating higher exposure levels than cycling. While most dynamic exposure assessments incorporate spatial and temporal constraints, the role of travel mode has been largely overlooked. For instance, Wang et al. (2021a) incorporated both walking and cycling trips but did not differentiate between them.

My findings can be well-supported by principles of environmental exposure science. For instance, Adams et al. (2016) found that the cycling trip dose was significantly lower than the walking trip dose of $PM_{2.5}$. Similarly, Mainka et al. (2025) reported that the NO_2 dose normalized by distance for walking was significantly higher compared to cycling.

A potential explanation for this effect is travel speed. The dynamic green space exposure metrics used in this study reflected cumulative exposure during active trips. Holding spatiotemporal factors constant, slower-speed travel extends time spent in a given environment and therefore increases cumulative green space exposure. Consequently, walking can facilitate a higher accumulation of green space exposure than the faster mode of cycling.

6.3 Associations between Dynamic and Static Green Space Exposure

My results indicate a positive correlation between daily dynamic green space exposure and static residential exposure for the older adults in the MOASIS sample. This accords with prior work (Wang et al., 2021b; Yoo and Roberts, 2022) and with Marquet et al. (2023), who—using NDVI and focusing on older adults—also found higher average daily dynamic exposure in greener home neighborhoods. Two potential mechanisms, related to the active-travel-based measurement in this study, may explain this correlation. First, an age-related mobility pattern is likely a key factor. Older adults tend to undertake a higher proportion of home-based (start from home) walking trips compared to younger groups (Watson et al., 2021). This pattern may also apply to older adults' cycling trips. Consequently, greater residential greenness directly elevates the greenness encountered during daily travel.

Second, the well-established link between neighborhood greenery and increased physical activity (Douglas et al., 2017) is also relevant for older adults (De Keijzer et al., 2020). Higher residential greenness may encourage more frequent or longer active trips within the neighborhood. Therefore, a greener residential environment not only provides exposure but also promotes the very behaviors that lead to greater daily dynamic green space exposure in this population. Together, these mechanisms suggest that residential greenness can promote higher dynamic exposure among older adults.

However, no significant correlation was found between home-level static exposure and dynamic exposure. This suggests that these metrics capture fundamentally different aspects of the green space exposure. As discussed in section 6.1, static exposure can vary significantly between the home location and the broader neighborhood. Thus, a weak correlation between home-level static and dynamic exposure is plausible.

6.4 Daily Well-being and Dynamic Green Space Exposure

6.4.1 Mental Outcomes from Dynamic Green Space Exposure

My results suggest a potentially beneficial impact of dynamic green space exposure on the mental well-being of older adults in our sample. In the domain of evaluating mental outcomes from dynamic green space exposure, however, this finding was inconsistent with recent studies. For instance, Yu and Kwan (2024) concluded that mental stress was negatively correlated with distance-weighted dynamic green space exposure but not significantly associated with total volume green space exposure. Similarly, Liu et al. (2023b) indicated that dynamic green space exposure can be positive to overall health but not significant. Apart from potential differences in study contexts (Hong Kong vs. the Canton of Zurich), several key methodological differences may explain this discrepancy. First, the sample composition differs critically; this study focused exclusively on older adults, whereas the compared studies included general populations. Second, they employed different green space representations (GVI and log-scaled NDVI) for dynamic measurements. Third, the temporal alignment of measures may be decisive. This study used a daily frame for both dynamic green space exposure and well-being assessment, but they used mental indicators with different temporal intervals (e.g., a 4-hour exposure window versus a single questionnaire). Fourth, active-travel-based dynamic green space exposure in this study may provide a nuanced exposure assessment for individuals, which can capture health and well-being outcomes from green space exposure better than ones that ignore travel modes.

6.4.2 Green Space and Healthy Aging

Within the domain of green space and healthy aging, the positive association between daily subjective health and dynamic green space exposure identified in this study aligns with a growing body of evidence linking green space to improved mental health and well-being in older adults (Astell-Burt and Feng, 2019; Han et al., nd; Lau et al., 2021; Luo et al., 2024). This finding may also help resolve an inconsistency in the literature. While Zhou et al. (2020) found no significant direct relationship between NDVI-based neighborhood greenness and mental health among older adults, this study suggests that the dynamic exposure accrued during active travel may be the crucial mechanism.

In this study, dynamic green space exposure was evaluated based on older adults' active trips. This active-travel-based metric potentially captures the synergistic effects of physical activity and green space exposure—simultaneously engaging the theoretical pathways of instoration (through activity) and restoration (through green space contact) (Markevych et al., 2017). Consequently, this study adds a critical nuance to previous MOASIS project findings. Where Luo et al. (2023) found that mere active-travel duration was insignificant for daily well-being, my results imply that the environmental quality of that travel (i.e., its green space exposure) is a key factor. This suggests that greener active travel routes may be more impactful for day-to-day well-being than active travel time or distance alone.

Finally, this study underscores that an individual's general health is a vital factor in mediating green space benefits, which accords with Lyshol and Johansen (2024). Given the mixed evidence surrounding other sociodemographic characteristics (Pun et al., 2018; Yoo et al., 2024), future research should prioritize unraveling the complex interplay between these factors and dynamic green space exposure to better understand for whom these benefits are most potent.

CHAPTER 7

CONCLUSION

7.1 Contributions

This work contributes to the existing body of knowledge by providing new insights into evaluating mobility-based green space exposure considering different active travel modes. The results from this study support that green space can benefit older adults' health and well-being. Neighborhood green space might be a key investment for cities that want to create a positive influence on healthy aging. This study has made several contributions:

- A comprehensive pipeline for GPS data processing in dynamic green space exposure analysis.
- A workflow of green space exposure measurements focusing on natural landscape (vegetation).
- A novel THF-based isochrone polygon generation method using road segment data and taking into account topography (DEM, TLM).
- Integration of dynamic green space exposure measurements with detected active trips.
- Exploration of the effects of daily mobility on dynamic green space exposure metrics, including spatiotemporal and travel-mode factors.
- Evaluation of the association between mental well-being and dynamic green space exposure metrics at a daily level, regarding sociodemographic characteristics.

7.2 Main Findings

There are three main findings in this thesis: (1) daily travel mode can influence daily dynamic green space exposure of older adults (as represented by the MOASIS sample); (2) dynamic green space exposure is positively associated with the static neighborhood-level green space exposure rather than the one at home-level; (3) daily self-rated health is positively correlated with the total volume of dynamic green space exposure, but not with distance-weighted and time-weighted measures.

With respect to the research questions, the findings can be summarized as follows.

RQ 1

What are the levels and patterns of green space exposure among older adults during the study period?

> The static green space exposure metrics under different residential (home and neighborhood) contexts were significantly different among individuals. Among the metrics, the high and low static green space exposure metrics grouped by the median value were significantly different.
>
> The daily dynamic green space exposure metrics were influenced by several mobility factors. High trip frequency (compared with low), activity space beyond the neighborhood (compared with within), and daily travel with walking (compared with cycling only) can significantly improve dynamic green space exposure. However, there was no significant difference in dynamic green space exposure with respect to daily dominant travel time or between weekdays and weekends.

RQ 2

To what extent are dynamic and static measures of green space exposure correlated among older adults?

> Daily active-travel-based dynamic green space exposure was positively correlated with neighborhood static ones (reachable areas within 15-minute walking or cycling). However, there was no significant relationship between the dynamic and static home-based (50-meter circular buffer) green space exposure.

RQ 3

How strongly is mental well-being among older adults associated with different indices of green space exposure?

> The results show that daily total green space exposure was positively associated with daily self-rated health, while daily green space exposure metrics standardized by travel time or distance did not show a significant correlation. Specifically, females, people with higher income, lower education, and better general health could be associated with better self-rated health.

7.3 Limitations

This study has several limitations. Although this study used sampling data from older adults living in the Canton of Zurich, the *sample* may not be representative of the Swiss aging population. Selection bias is likely because the MOASIS eligibility criteria—Mini-Mental State Examination (MMSE) ≥ 27 and the ability to use a smartphone and the uTrail sensor—tend to exclude older adults with cognitive impairment or decline, limited digital literacy, or other functional limitations. Also, the results in this study may also not be applicable to other demographic groups (adolescents, youth, etc.).

Regarding *static green space exposure*, I operationalized green space quantitatively using VHM and LULC data. I did not include subjective measures (e.g., individuals' preferences or perceived quality) in this study. Although I delineated individuals' walking and cycling reachable areas with time and topographic constraints, the algorithm may not reflect the travel strategy in older adults' daily lives.

Considering *dynamic green space exposure*, I used a rule-based approach to detect travel modes primarily based on the speed threshold applied to segmented GPS trajectories. The detected travel modes were not externally validated. Dynamic green space exposure was derived solely from NDVI, which may differ from visual exposure (GVI) used in recent green space exposure studies.

Finally, *mental well-being outcomes* were examined using correlation analysis, which identifies associations rather than causal effects. The mechanisms and contextual factors linking green space exposure to older adults' mental well-being remain unclear. Moreover, I used a single daily indicator of mental well-being, which may limit measurement precision and construct validity.

7.4 Outlook

Using GPS and self-reported data of older adults from the MOASIS study (Röcke et al., 2023), this thesis evaluated dynamic and static residential green space exposure and mental well-being outcomes with vegetation as a focus. Further studies should consider the roles of other components in individuals' daily green space exposure assessments, including biodiversity, soundscape, amenities, etc. In addition to direct green space exposure during traveling, other forms of green space exposure (e.g., virtual, visual, etc.) should be emphasized in further research. The results in this thesis also highlight that sociodemographic context is vital in green space exposure assessments. Given that, cross-sectional comparison can be essential. Finally, considering the interconnected pathways linking green space to health, additional studies are warranted to explore causal linkages between green space exposure and health outcomes. Collectively, a more holistic and nuanced understanding of these complex interactions is essential for promoting health benefits towards healthy aging, but also for informing public health strategies targeting other age groups.

BIBLIOGRAPHY

Adams, M. D., Yiannakoulias, N., and Kanaroglou, P. S. (2016). Air pollution exposure: An activity pattern approach for active transportation. *Atmospheric Environment*, 140:52–59.

Alcock, I., White, M., Lovell, R., Higgins, S. L., Osborne, N., Husk, K., and Wheeler, B. (2015). What accounts for 'England's green and pleasant land'? A panel data analysis of mental health and land cover types in rural England. *Landscape and Urban Planning*, 142:38–46.

Appelhans, T., Detsch, F., Reudenbach, C., and Woellauer, S. (2023). *mapview: Interactive Viewing of Spatial Data in R*. R package version 2.11.2.

Aram, F., García, E. H., Solgi, E., and Mansournia, S. (2019). Urban green space cooling effect in cities. *Heliyon*, 5(4).

Assessment Millennium Ecosystem (2005). *ECOSYSTEMS AND HUMAN WELL-BEING: WETLANDS AND WATE*. World Resources Institute.

Astell-Burt, T. and Feng, X. (2019). Association of Urban Green Space With Mental Health and General Health Among Adults in Australia. *JAMA network open*, 2(7):e198209.

Astell-Burt, T., Feng, X., and Kolt, G. S. (2013). Does access to neighbourhood green space promote a healthy duration of sleep? Novel findings from a cross-sectional study of 259 319 Australians. *BMJ Open*, 3(8):e003094.

Bedimo-Rung, A. L., Mowen, A. J., and Cohen, D. A. (2005). The significance of parks to physical activity and public health: A conceptual model. *American Journal of Preventive Medicine*, 28(2):159–168.

Bendall, M., Bassey, E., and Pearson, M. (1989). Factors Affecting Walking Speed of Elderly People. *Age and Ageing*, 18(5):327–332.

Benton, J. S., Cotterill, S., Anderson, J., Macintyre, V. G., Gittins, M., Dennis, M., Lindley, S. J., and French, D. P. (2021). Impact of a low-cost urban green space intervention on wellbeing behaviours in older adults: A natural experimental study. *Wellbeing, Space and Society*, 2:100029.

Benyamini, Y., Leventhal, E. A., and Leventhal, H. (2003). Elderly people's ratings of the importance of health-related factors to their self-assessments of health. *Social Science & Medicine*, 56(8):1661–1667.

Bertram, C. and Rehdanz, K. (2015). The role of urban green space for human well-being. *Ecological Economics*, 120:139–152.

Beute, F., Marselle, M. R., Olszewska-Guizzo, A., Andreucci, M., Lammel, A., Davies, Z. G., Glanville, J., Keune, H., O'Brien, L., Remmen, R., et al. (2023). How do different types and characteristics of green space impact mental health? A scoping review. *People and Nature*, 5(6):1839–1876.

Biddle, S. and Mutrie, N. (2007). *Psychology of Physical Activity Determinants, Well-Being and Interventions*. Routledge.

Bowler, D. E., Buyung-Ali, L., Knight, T. M., and Pullin, A. S. (2010a). Urban greening to cool towns and cities: A systematic review of the empirical evidence. *Landscape and Urban Planning*, 97(3):147–155.

Bowler, D. E., Buyung-Ali, L. M., Knight, T. M., and Pullin, A. S. (2010b). A systematic review of evidence for the added benefits to health of exposure to natural environments. *BMC Public Health*, 10:1–10.

Bratman, G. N., Anderson, C. B., Berman, M. G., Cochran, B., De Vries, S., Flanders, J., Folke, C., Frumkin, H., Gross, J. J., Hartig, T., et al. (2019). Nature and mental health: An ecosystem service perspective. *Science Advances*, 5(7):eaax0903.

Browning, M. and Lee, K. (2017). Within What Distance Does "Greenness" Best Predict Physical Health? A Systematic Review of Articles with GIS Buffer Analyses across the Lifespan. *International Journal of Environmental Research and Public Health*, 14(7):675.

Calogiuri, G., Patil, G. G., and Aamodt, G. (2016). Is Green Exercise for All? A Descriptive Study of Green Exercise Habits and Promoting Factors in Adult Norwegians. *International Journal of Environmental Research and Public Health*, 13(11):1165.

Carlson, J. A., Saelens, B. E., Kerr, J., Schipperijn, J., Conway, T. L., Frank, L. D., Chapman, J. E., Glanz, K., Cain, K. L., and Sallis, J. F. (2015). Association between neighborhood walkability and GPS-measured walking, bicycling and vehicle time in adolescents. *Health & Place*, 32:1–7.

Chen, J., Li, H., Luo, S., Su, D., Xie, J., Zang, T., and Kinoshita, T. (2024). Estimating changes in inequality of ecosystem services provided by green exposure: From a human health perspective. *Science of The Total Environment*, 908:168265.

Chen, Y., La Rosa, D., and Yue, W. (2025). Does urban sprawl lessen green space exposure? Evidence from chinese cities. *Landscape and Urban Planning*, 257.

Chiabai, A., Quiroga, S., Martinez-Juarez, P., Higgins, S., and Taylor, T. (2018). The nexus between climate change, ecosystem services and human health: Towards a conceptual framework. *Science of The Total Environment*, 635:1191–1204.

Dadvand, P., de Nazelle, A., Figueras, F., Basagana, X., Su, J., Amoly, E., Jerrett, M., Vrijheid, M., Sunyer, J., and Nieuwenhuijsen, M. J. (2012a). Green space, health inequality and pregnancy. *Environment International*, 40:110–115.

Dadvand, P., de Nazelle, A., Triguero-Mas, M., Schembari, A., Cirach, M., Amoly, E., Figueras, F., Basagaña, X., Ostro, B., and Nieuwenhuijsen, M. (2012b). Surrounding Greenness and Exposure to Air Pollution During Pregnancy: An Analysis of Personal Monitoring Data. *Environmental Health Perspectives*, 120(9):1286–1290.

Dadvand, P., Nieuwenhuijsen, M. J., Esnaola, M., Forns, J., Basagaña, X., Alvarez-Pedrerol, M., Rivas, I., López-Vicente, M., De Castro Pascual, M., Su, J., et al. (2015). Green spaces and cognitive development in primary schoolchildren. *Proceedings of the national academy of sciences*, 112(26):7937–7942.

De Keijzer, C., Bauwelinck, M., and Dadvand, P. (2020). Long-Term Exposure to Residential Greenspace and Healthy Ageing: a Systematic Review. *Current Environmental Health Reports*, 7:65–88.

De Vries, S., Van Dillen, S. M., Groenewegen, P. P., and Spreeuwenberg, P. (2013). Streetscape greenery and health: Stress, social cohesion and physical activity as mediators. *Social Science & Medicine*, 94:26–33.

Delarze, R., Gonseth, Y., and Galland, P. (2008). *Lebensräume der Schweiz*. Ott Bern, Switzerland.

Dijkstra, E. W. (2022). A Note on Two Problems in Connexion with Graphs. In *Edsger Wybe Dijkstra: his life, work, and legacy*, pages 287–290.

Doorley, R., Pakrashi, V., and Ghosh, B. (2015). Quantifying the Health Impacts of Active Travel: Assessment of Methodologies. *Transport Reviews*, 35(5):559–582.

Douglas, O., Lennon, M., and Scott, M. (2017). Green space benefits for health and well-being: A life-course approach for urban planning, design and management. *Cities*, 66:53–62.

Dovey, K., Woodcock, I., and Pike, L. (2017). Isochrone Mapping of Urban Transport: Car-dependency, Mode-choice and Design Research. *Planning Practice & Research*, 32(4):402–416.

Duan, Y., Bai, H., Yang, L., Li, S., and Zhu, Q. (2024). Impact of seasonal changes in urban green spaces with diverse vegetation structures on college students' physical and mental health. *Scientific Reports*, 14(1):16277.

Duim, E., Lebrão, M. L., and Antunes, J. L. F. (2017). Walking speed of older people and pedestrian crossing time. *Journal of Transport & Health*, 5:70–76.

Dunnington, D. (2023). *ggspatial: Spatial Data Framework for ggplot2*. R package version 1.1.9.

Dzhambov, A. M. and Dimitrova, D. D. (2015). Green spaces and environmental noise perception. *Urban Forestry & Urban Greening*, 14(4):1000–1008.

Eggimann, S. (2022). Expanding urban green space with superblocks. *Land Use Policy*, 117:106111.

Enssle, F. and Kabisch, N. (2020). Urban green spaces for the social interaction, health and well-being of older people— An integrated view of urban ecosystem services and socio-environmental justice. *Environmental Science & Policy*, 109:36–44.

Ester, M., Kriegel, H.-P., Sander, J., Xu, X., et al. (1996). A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In *kdd*, volume 96, pages 226–231.

Faeh, D., Bopp, M., and Group, S. N. C. S. (2010). Educational inequalities in mortality and associated risk factors: German-versus French-speaking Switzerland. *BMC Public Health*, 10(1):567.

Federal Statistical Office (2016). Land use and land cover. https://www.bfs.admin.ch/bfs/en/home/statistics/territory-environment/land-use-cover.html. [Accessed 13-08-2025].

Federal Statistical Office (2021). Arealstatistik land cover - kantone und grossregionen nach 6 hauptbereichen. https://www.bfs.admin.ch/bfs/en/home/statistics/territory-environment/land-use-cover/unproductive-areas.assetdetail.19805731.html. [Accessed 30-07-2025].

Federal Statistical Office (2024). Permanent resident population by age and dependency ratio, in 2024. https://www.bfs.admin.ch/bfs/en/home/statistics/population/effectif-change/age.html. [Accessed 26-07-2025].

Federal Statistical Office (2024). Structure of the permanent resident population by canton, 2010-2023. https://www.bfs.admin.ch/bfs/en/home/statistics/population.assetdetail.32229047.html. [Accessed 30-07-2025].

Fillekes, M. P., Giannouli, E., Kim, E.-K., Zijlstra, W., and Weibel, R. (2019a). Towards a comprehensive set of GPS-based indicators reflecting the multidimensional nature of daily mobility for applications in health and aging research. *International Journal of Health Geographics*, 18(1):17.

Fillekes, M. P., Kim, E.-K., Trumpf, R., Zijlstra, W., Giannouli, E., and Weibel, R. (2019b). Assessing Older Adults' Daily Mobility: A Comparison of GPS-Derived and Self-Reported Mobility Indicators. *Sensors*, 19(20):4551.

Fillekes, M. P., Röcke, C., Katana, M., and Weibel, R. (2019c). Self-reported versus GPS-derived indicators of daily mobility in a sample of healthy older adults. *Social Science & Medicine*, 220:193–202.

Geurs, K. T. and Van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography*, 12(2):127–140.

Ginzler, C. (2021). Vegetation Height Model NFI.

Google Earth Engine (2024). Landsat Algorithms — developers.google.com. https://developers.google.com/earth-engine/guides/landsat. [Accessed 30-07-2025].

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202:18–27.

Grolemund, G. and Wickham, H. (2011). Dates and times made easy with lubridate. *Journal of Statistical Software*, 40(3):1–25.

Hahsler, M., Piekenbrock, M., and Doran, D. (2019). dbscan: Fast density-based clustering with R. *Journal of Statistical Software*, 91(1):1–30.

Han, C., Weibel, R., Luo, M., Röcke, C., and Fu, C. (n.d.). Tracking older adults' everyday audio-visual life to explore the impact of green space and soundscape on well-being. in preparation.

Hartig, T., Mitchell, R., De Vries, S., and Frumkin, H. (2014). Nature and Health. *Annual Review of Public Health*, 35(1):207–228.

Hasanzadeh, K., Heinonen, J., Ala-Mantila, S., Czepkiewicz, M., Kyttä, M., and Ottelin, J. (2019). Beyond geometries of activity spaces: A holistic study of daily travel patterns, individual characteristics, and perceived wellbeing in Helsinki metropolitan area. *Journal of Transport and Land Use*, 12(1):149–177.

Heckert, M. (2012). Access and Equity in Greenspace Provision: A Comparison of Methods to Assess the Impacts of Greening Vacant Land. *Transactions in GIS*, 17(6):808–827.

Henry, L. and Wickham, H. (2024). *rlang: Functions for Base Types and Core R and 'Tidyverse' Features*. R package version 1.1.4.

Herbolsheimer, F., Mahmood, A., Michael, Y. L., and Chaudhury, H. (2020). Everyday Walking Among Older Adults and the Neighborhood Built Environment: A Comparison Between Two Cities in North America. *Frontiers in Public Health*, 8:564533.

Hester, J. and Bryan, J. (2024). *glue: Interpreted String Literals*. R package version 1.7.0.

Hester, J., Wickham, H., and Csárdi, G. (2024). *fs: Cross-Platform File System Operations Based on 'libuv'*. R package version 1.6.4.

Hijmans, R. J. (2024). *terra: Spatial Data Analysis*. R package version 1.7-78.

Hirsch, J. A., Winters, M., Ashe, M. C., Clarke, P. J., and McKay, H. A. (2016). Destinations That Older Adults Experience Within Their GPS Activity Spaces: Relation to Objectively Measured Physical Activity. *Environment and Behavior*, 48(1):55–77.

Huang, W. and Lin, G. (2023). The relationship between urban green space and social health of individuals: A scoping review. *Urban Forestry & Urban Greening*, 85:127969.

Hunter, R. F., Cleland, C., Cleary, A., Droomers, M., Wheeler, B. W., Sinnett, D., Nieuwenhuijsen, M. J., and Braubach, M. (2019). Environmental, health, wellbeing, social and equity effects of urban green space interventions: A meta-narrative evidence synthesis. *Environment International*, 130:104923.

James, P., Banay, R. F., Hart, J. E., and Laden, F. (2015). A Review of the Health Benefits of Greenness. *Current Epidemiology Reports*, 2(2):131–142.

Jarvis, I., Gergel, S., Koehoorn, M., and van den Bosch, M. (2020). Greenspace access does not correspond to nature exposure: Measures of urban natural space with implications for health research. *Landscape and Urban Planning*, 194:103686.

Jiang, X., Larsen, L., and Sullivan, W. (2020). Connections Between Daily Greenness Exposure and Health Outcomes. *International Journal of Environmental Research and Public Health*, 17(11):3965.

Jimenez, R. B., Lane, K. J., Hutyra, L. R., and Fabian, M. P. (2022). Spatial resolution of Normalized Difference Vegetation Index and greenness exposure misclassification in an urban cohort. *Journal of Exposure Science & Environmental Epidemiology*, 32(2):213–222.

Jin, Y., Yu, Z., Yang, G., Yao, X., Hu, M., Remme, R. P., van Bodegom, P. M., Morpurgo, J., Huang, Y., Wang, J., and Cui, S. (2024). Quantifying physiological health efficiency and benefit threshold of greenspace exposure in typical urban landscapes. *Environmental Pollution*, 362:124726.

Kabisch, N., Püffel, C., Masztalerz, O., Hemmerling, J., and Kraemer, R. (2021). Physiological and psychological effects of visits to different urban green and street environments in older people: A field experiment in a dense inner-city area. *Landscape and Urban Planning*, 207:103998.

Kabisch, N., Strohbach, M., Haase, D., and Kronenberg, J. (2016). Urban green space availability in European cities. *Ecological Indicators*, 70:586–596.

Kaplan, R. and Kaplan, S. (1989). *The Experience of Nature: A Psychological Perspective*. Cambridge university press.

Kaplan, S. (1995). The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology*, 15(3):169–182.

Kasai, T. (2021). Preparing for population ageing in the Western Pacific Region. *THE LANCET Regional Health–Western Pacific*, 6.

Kassambara, A. (2023). *ggpubr: 'ggplot2' Based Publication Ready Plots*. R package version 0.6.0.

Kellert, S. R. and Wilson, E. O. (1995). The Biophilia Hypothesis.

Kemperman, A. and Timmermans, H. (2014). Green spaces in the direct living environment and social contacts of the aging population. *Landscape and Urban Planning*, 129:44–54.

Kemperman, A., van den Berg, P., Weijs-Perrée, M., and Uijtdewillegen, K. (2019). Loneliness of Older adults: Social Network and the Living Environment. *International Journal of Environmental Research and Public Health*, 16(3):406.

Kondo, M. C., Fluehr, J. M., McKeon, T., and Branas, C. C. (2018). Urban Green Space and Its Impact on Human Health. *International Journal of Environmental Research and Public Health*, 15(3):445.

Krefis, A., Augustin, M., Schlünzen, K., Oßenbrügge, J., and Augustin, J. (2018). How Does the Urban Environment Affect Health and Well-being? a Systematic Review. *Urban Science*, 2(1).

Kwan, M.-P. (1998). Space-Time and Integral Measures of Individual Accessibility: A Comparative Analysis Using a Point-based Framework. *Geographical Analysis*, 30(3):191–216.

Kwan, M.-P. (2012). The Uncertain Geographic Context Problem. *Annals of the Association of American Geographers*, 102(5):958–968.

Kwan, M.-P. (2013). Beyond Space (as we knew it): Toward Temporally Integrated Geographies of Segregation, Health, and Accessibility: Space–Time Integration in Geography and Giscience. *Annals of the Association of American Geographers*, 103(5):1078–1086.

Labib, S., Lindley, S., and Huck, J. J. (2020). Spatial dimensions of the influence of urban green-blue spaces on human health: A systematic review. *Environmental Research*, 180:108869.

Lafortezza, R., Carrus, G., Sanesi, G., and Davies, C. (2009). Benefits and well-being perceived by people visiting green spaces in periods of heat stress. *Urban Forestry & Urban Greening*, 8(2):97–108.

Łaszkiewicz, E., Kronenberg, J., and Marcińczak, S. (2018). Attached to or bound to a place? The impact of green space availability on residential duration: The environmental justice perspective. *Ecosystem Services*, 30:309–317.

Lau, K. K.-L., Yung, C. C.-Y., and Tan, Z. (2021). Usage and perception of urban green space of older adults in the high-density city of Hong Kong. *Urban Forestry & Urban Greening*, 64:127251.

Lawton, M. P. and Brody, E. M. (1969). Assessment of older people: self-maintaining and instrumental activities of daily living. *The Gerontologist*.

Lee, A. C. K., Jordan, H. C., and Horsley, J. (2015). Value of urban green spaces in promoting healthy living and wellbeing: prospects for planning. *Risk Management and Healthcare Policy*, pages 131–137.

Lee, K. and Kwan, M.-P. (2019). The Effects of GPS-Based Buffer Size on the Association between Travel Modes and Environmental Contexts. *ISPRS International Journal of Geo-Information*, 8(11):514.

Lewis, C. and Ollivaud, P. (2020). Policies for Switzerland's ageing society. OECD Economics Department Working Papers 1600, Organisation for Economic Co-operation and Development, Paris.

Li, D., Deal, B., Zhou, X., Slavenas, M., and Sullivan, W. C. (2018). Moving beyond the neighborhood: Daily exposure to nature and adolescents' mood. *Landscape and Urban Planning*, 173:33–43.

Liu, D., Kwan, M.-P., and Kan, Z. (2021). Analysis of urban green space accessibility and distribution inequity in the City of Chicago. *Urban Forestry & Urban Greening*, 59:127029.

Liu, Y., Kwan, M.-P., Wong, M. S., and Yu, C. (2023a). Current methods for evaluating people's exposure to green space: A scoping review. *Social Science & Medicine*, page 116303.

Liu, Y., Kwan, M.-P., and Yu, C. (2023b). The uncertain geographic context problem (UGCoP) in measuring people's exposure to green space using the integrated 3S approach. *Urban Forestry & Urban Greening*, 85:127972.

Luo, M., Kim, E.-K., Weibel, R., Martin, M., and Röcke, C. (2023). GPS-Derived Daily Mobility and Daily Well-Being in Community-Dwelling Older Adults. *Gerontology*, 69(7):875–887.

Luo, W., Chen, C., Li, H., and Hou, Y. (2024). How do residential open spaces influence the older adults' emotions: A field experiment using wearable sensors. *Landscape and Urban Planning*, 251:105152.

Lyshol, H. and Johansen, R. (2024). The association of access to green space with low mental distress and general health in older adults: a cross-sectional study. *BMC Geriatrics*, 24(1):329.

Ma, Q., Lin, J., Ju, Y., Li, W., Liang, L., and Guo, Q. (2023). Individual structure mapping over six million trees for new york City USA. *Scientific Data*, 10(1):102.

Mainka, A., Nocoń, W., Malinowska, A., Pfajfer, J., Komisarczyk, E., Góra, D., and Wargocki, P. (2025). Exposure to No2 and PM2. 5 While Commuting: Utility of Low-Cost Sensor. *Applied Sciences*, 15(11):5965.

Mao, Y., Xia, T., Hu, F., Chen, D., He, Y., Bi, X., Zhang, Y., Cao, L., Yan, J., Hu, J., Ren, Y., Xu, H., Zhang, J., and Zhang, L. (2024). The greener the living environment, the better the health? Examining the effects of multiple green exposure metrics on physical activity and health among young students. *Environmental Research*, 250:118520.

Marcelo, G.-T., Constance, B., Joseph, M., Kay, A., David, Z., Maarten, V. S., and Adrienne, G.-R. (2022). Do we have enough recreational spaces during pandemics? An answer based on the analysis of individual mobility patterns in Switzerland. *Landscape and Urban Planning*, 221:104373.

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

Marquet, O., Tello-Barsocchini, J., Couto-Trigo, D., Gomez-Varo, I., and Maciejewska, M. (2023). Comparison of static and dynamic exposures to air pollution, noise, and greenness among seniors living in compact-city environments. *International Journal of Health Geographics*, 22(1):3.

McGraw, K. O. and Wong, S. P. (1996). Forming inferences about some intraclass correlation coefficients. *Psychological Methods*, 1(1):30.

McLean, M. W. (2014). Straightforward bibliography management in R using the RefManageR package.

Miao, S. and Xiao, Y. (2024). Exploring the spatial trade-off effects of green space on older people's physical inactivity: Evidence from shanghai. *Landscape and Urban Planning*, 251.

Michael, K., McNamee, A., and Michael, M. G. (2006). The Emerging Ethics of Humancentric GPS Tracking and Monitoring. In *2006 International Conference on Mobile Business*, pages 34–34. IEEE.

Monteiro, J., Sousa, N., Natividade-Jesus, E., and Coutinho-Rodrigues, J. (2023). The Potential Impact of Cycling on Urban Transport Energy and Modal Share: A GIS-Based Methodology. *International Journal of Geo-Information*, 12(2):48.

Montoliu, R., Blom, J., and Gatica-Perez, D. (2013). Discovering places of interest in everyday life from smartphone data. *Multimedia Tools and Applications*, 62(1):179–207.

Morelle, K., Buchecker, M., Kienast, F., and Tobias, S. (2019). Nearby outdoor recreation modelling: An agent-based approach. *Urban Forestry & Urban Greening*, 40:286–298.

Müller, K. (2020). *here: A Simpler Way to Find Your Files*. R package version 1.0.1.

Neuenschwander, N., Hayek, U. W., and Grêt-Regamey, A. (2014). Integrating an urban green space typology into procedural 3D visualization for collaborative planning. *Computers, Environment and Urban Systems*, 48:99–110.

O'Sullivan, D., Morrison, A., and Shearer, J. (2000). Using desktop GIS for the investigation of accessibility by public transport: an isochrone approach. *International Journal of Geographical Information Science*, 14(1):85–104.

Park, B. J., Tsunetsugu, Y., Kasetani, T., Kagawa, T., and Miyazaki, Y. (2010). The physiological effects of Shinrin-yoku (taking in the forest atmosphere or forest bathing): evidence from field experiments in 24 forests across Japan. *Environmental Health and Preventive Medicine*, 15(1):18–26.

Pasanen, S., Halonen, J. I., Pulakka, A., Kestens, Y., Thierry, B., Brondeel, R., Pentti, J., Vahtera, J., Leskinen, T., and Stenholm, S. (2021). Contexts of sedentary time and physical activity among ageing workers and recent retirees: cross-sectional GPS and accelerometer study. *BMJ Open*, 11(5):e042600.

Paustenbach, D. J. (2000). THE PRACTICE OF EXPOSURE ASSESSMENT: A STATE-OF-THE-ART REVIEW. *Journal of Toxicology and Environmental Health Part B: Critical Reviews*, 3(3):179–291.

Pearson, A. L., Tribby, C., Brown, C. D., Yang, J.-A., Pfeiffer, K., and Jankowska, M. M. (2024). Systematic review of best practices for GPS data usage, processing, and linkage in health, exposure science and environmental context research. *BMJ Open*, 14(2):e077036.

Pebesma, E. (2018). Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal*, 10(1):439–446.

Pebesma, E. and Bivand, R. (2023). *Spatial Data Science: With applications in R*. Chapman and Hall/CRC.

Pebesma, E., Mailund, T., and Hiebert, J. (2016). Measurement units in R. *R Journal*, 8(2):486–494.

Pedersen, T. L. (2024). *tidygraph: A Tidy API for Graph Manipulation*. R package version 1.3.1.

Per, B. and Sven, H. (1999). Ecosystem services in urban areas. *Ecological Economics*, 29(2):293–301.

Phillipson, C. (2009). *Social Welfare, Aging, and Globalization in a Post-industrial Society*, pages 57–70. Springer New York, New York, NY.

Posit team (2025). *RStudio: Integrated Development Environment for R*. Posit Software, PBC, Boston, MA.

Price, B., Huber, N., Nussbaumer, A., and Ginzler, C. (2023). The Habitat Map of Switzerland: A Remote Sensing, Composite Approach for a High Spatial and Thematic Resolution Product. *Remote Sensing*, 15(3):643.

Price, B., Kolecka, N., Huber, N., Rüetschi, M., Nussbaumer, A., and Ginzler, C. (2024). The Habitat Map of Switzerland v1_1 2024.

Pun, V. C., Manjourides, J., and Suh, H. H. (2018). Association of neighborhood greenness with self-perceived stress, depression and anxiety symptoms in older U.S adults. *Environmental Health*, 17(1):39.

R Core Team (2024). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Rantanen, T., Portegijs, E., Viljanen, A., Eronen, J., Saajanaho, M., Tsai, L.-T., Kauppinen, M., Palonen, E.-M., Sipilä, S., Iwarsson, S., et al. (2012). Individual and environmental factors underlying life space of older people–study protocol and design of a cohort study on life-space mobility in old age (LISPE). *BMC Public Health*, 12(1):1018.

Remme, R. P., Frumkin, H., Guerry, A. D., King, A. C., Mandle, L., Sarabu, C., Bratman, G. N., Giles-Corti, B., Hamel, P., Han, B., Hicks, J. L., James, P., Lawler, J. J., Lindahl, T., Liu, H., Lu, Y., Oosterbroek, B., Paudel, B., Sallis, J. F., Schipperijn, J., Sosic, R., de Vries, S., Wheeler, B. W., Wood, S. A., Wu, T., and Daily, G. C. (2021). An ecosystem service perspective on urban nature, physical activity, and health. *Proceedings of the National Academy of Sciences*, 118(22).

Roberts, H. and Helbich, M. (2021). Multiple environmental exposures along daily mobility paths and depressive symptoms: A smartphone-based tracking study. *Environment International*, 156:106635.

Robin Lovelace and Richard Ellison (2018). stplanr: A Package for Transport Planning. *The R Journal*, 10(2):10.

Röcke, C., Luo, M., Bereuter, P., Katana, M., Fillekes, M., Gehriger, V., Sofios, A., Martin, M., and Weibel, R. (2023). Charting everyday activities in later life: Study protocol of the mobility, activity, and social interactions study (MOASIS). *Frontiers in Psychology*, 13:1011177.

Roe, J., Mondschein, A., Neale, C., Barnes, L., Boukhechba, M., and Lopez, S. (2020). The Urban Built Environment, Walking and Mental Health Outcomes Among Older Adults: A Pilot Study. *Frontiers in Public Health*, 8:575946.

Sang, Å. O., Knez, I., Gunnarsson, B., and Hedblom, M. (2016). The effects of naturalness, gender, and age on how urban green space is perceived and used. *Urban Forestry & Urban Greening*, 18:268–276.

Schmid, F. B., Hersperger, A. M., Grêt-Regamey, A., and Kienast, F. (2024). Effects of different land-use planning instruments on urban shrub and tree canopy cover in Zurich, Switzerland. *Urban Forestry & Urban Greening*, 94:128272.

Schneider, S. L. (2013). The international standard classification of education 2011. In *Class and stratification analysis*, pages 365–379. Emerald Group Publishing Limited.

Schuessler, N. and Axhausen, K. W. (2009). Processing Raw Data from Global Positioning Systems without Additional Information. *Transportation Research Record*, 2105(1):28–36.

Schüz, B., Wurm, S., Schöllgen, I., and Tesch-Römer, C. (2011). What do people include when they self-rate their health? Differential associations according to health status in community-dwelling older adults. *Quality of Life Research*, 20(10):1573–1580.

Shanahan, D. F., Fuller, R. A., Bush, R., Lin, B. B., and Gaston, K. J. (2015). The Health Benefits of Urban Nature: How Much Do We Need? *BioScience*, 65(5):476–485.

Shen, S., Koech, W., Feng, J., Rice, T. M., and Zhu, M. (2017). A cross-sectional study of travel patterns of older adults in the USA during 2015: implications for mobility and traffic safety. *BMJ Open*, 7(8):e015780.

Simkin, J., Ojala, A., and Tyrväinen, L. (2020). Restorative effects of mature and young commercial forests, pristine old-growth forest and urban recreation forest-A field experiment. *Urban Forestry & Urban Greening*, 48:126567.

Sugiyama, T., Leslie, E., Giles-Corti, B., and Owen, N. (2008). Associations of neighbourhood greenness with physical and mental health: do walking, social coherence and local social interaction explain the relationships? *Journal of Epidemiology & Community Health*, 62(5):e9–e9.

Sugiyama, T. and Thompson, C. W. (2006). Environmental Support for Outdoor Activities and Older People's Quality of Life. *Journal of Housing for the Elderly*, 19(3-4):167–185.

Swiss federal authorities (2024). Transport — aboutswitzerland.eda.admin.ch. https://www.aboutswitzerland.eda.admin.ch/en/transport. [Accessed 19-08-2025].

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

Thompson Coon, J., Boddy, K., Stein, K., Whear, R., Barton, J., and Depledge, M. H. (2011). Does Participating in Physical Activity in Outdoor Natural Environments Have a Greater Effect on Physical and Mental Wellbeing than Physical Activity Indoors? A Systematic Review. *Environmental Science & Technology*, 45(5):1761–1772.

Tobler, W. (1993). Three presentations on geographical analysis and modeling.

Ulrich, R. S., Simons, R. F., Losito, B. D., Fiorito, E., Miles, M. A., and Zelson, M. (1991). Stress recovery during exposure to natural and urban environments. *Journal of Environmental Psychology*, 11(3):201–230.

United Nations (2018). Revision of World Urbanization Prospects. *Population Division-United Nations*.

Valls, F. and Clua, Á. (2023). Modeling Barcelona sidewalks: A high resolution urban scale assessment of the geometric attributes of the walkable network. *PLOS One*, 18(7):e0284630.

Van den Berg, A. E., Maas, J., Verheij, R. A., and Groenewegen, P. P. (2010). Green space as a buffer between stressful life events and health. *Social Science & Medicine*, 70(8):1203–1210.

van der Meer, L., Abad, L., Gilardi, A., and Lovelace, R. (2024). *sfnetworks: Tidy Geospatial Networks*. R package version 0.6.5.

Van Renterghem, T. and Botteldooren, D. (2016). View on outdoor vegetation reduces noise annoyance for dwellers near busy roads. *Landscape and Urban Planning*, 148:203–215.

Vanwolleghem, G., Schipperijn, J., Gheysen, F., Cardon, G., De Bourdeaudhuij, I., and Van Dyck, D. (2016). Children's GPS-determined versus self-reported transport in leisure time and associations with parental perceptions of the neighborhood environment. *International Journal of Health Geographics*, 15(1):16.

Velentgas, P., Dreyer, N. A., Nourjah, P., Smith, S. R., and Torchia, M. M. (2013). Developing a Protocol for Observational Comparative Effectiveness Research.

Vlakveld, W. P., Twisk, D., Christoph, M., Boele, M., Sikkema, R., Remy, R., and Schwab, A. L. (2015). Speed choice and mental workload of elderly cyclists on e-bikes in simple and complex traffic situations: A field experiment. *Accident Analysis & Prevention*, 74:97–106.

Wang, B., Xu, T., Gao, H., Ta, N., Chai, Y., and Wu, J. (2021a). Can daily mobility alleviate green inequality from living and working environments? *Landscape and Urban Planning*, 214:104179.

Wang, R., Feng, Z., Pearce, J., Zhou, S., Zhang, L., and Liu, Y. (2021b). Dynamic greenspace exposure and residents' mental health in Guangzhou, china: From over-head to eye-level perspective, from quantity to quality. *Landscape and Urban Planning*, 215.

Ware, J. E., Kosinski, M., and Keller, S. D. (1996). A 12-Item Short-form Health Survey Construction of Scales and Preliminary Tests of Reliability and Validity. *Medical Care*, 34(3):220–233.

Watson, K. B., Whitfield, G. P., Bricka, S., and Carlson, S. A. (2021). Purpose-Based Walking Trips by Duration, Distance, and Select Characteristics, 2017 National Household Travel Survey. *Journal of Physical Activity and Health*, 18(S1):S86–S93.

Weiss, D. J., Nelson, A., Gibson, H., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., et al. (2018). A global map of travel time to cities to assess inequalities in accessibility in 2015. *Nature*, 553(7688):333–336.

Wen, C., Albert, C., and Von Haaren, C. (2018). The elderly in green spaces: Exploring requirements and preferences concerning nature-based recreation. *Sustainable Cities and Society*, 38:582–593.

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York.

Wickham, H. (2023). *forcats: Tools for Working with Categorical Variables (Factors)*. R package version 1.0.0, https://github.com/tidyverse/forcats.

Wickham, H., François, R., Henry, L., Müller, K., and Vaughan, D. (2023). *dplyr: A Grammar of Data Manipulation*. R package version 1.1.4.

Wickham, H. and Henry, L. (2023). *purrr: Functional Programming Tools*. R package version 1.0.2.

Wickham, H., Hester, J., and Bryan, J. (2024a). *readr: Read Rectangular Text Data*. R package version 2.1.5.

Wickham, H., Vaughan, D., and Girlich, M. (2024b). *tidyr: Tidy Messy Data*. R package version 1.3.1.

Wilson, E. O. (1986). *Biophilia*. Harvard university press.

Wolch, J. R., Byrne, J., and Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landscape and Urban Planning*, 125:234–244.

World Health Organization (2015). *World Report on Ageing and Health*. World Health Organization.

World Health Organization, WHO Regional Office for Europe. (2016). Urban green spaces and health. In *Urban green spaces and health*.

Wu, X., Lu, Y., Lin, Y., and Yang, Y. (2019). Measuring the Destination Accessibility of Cycling Transfer Trips in Metro Station Areas: A Big Data Approach. *International Journal of Environmental Research and Public Health*, 16(15):2641.

Xie, X., Zhou, H., and Gou, Z. (2023). Dynamic real-time individual green space exposure indices and the relationship with static green space exposure indices: A study in Shenzhen. *Ecological Indicators*, 154:110557.

Yang, Y., Sasaki, K., Cheng, L., and Tao, S. (2022). Does the built environment matter for active travel among older adults: Insights from Chiba City, Japan. *Journal of Transport Geography*, 101:103338.

Yang, Y., Xu, Y., Rodriguez, D. A., Michael, Y., and Zhang, H. (2018). Active travel, public transportation use, and daily transport among older adults: The association of built environment. *Journal of Transport & Health*, 9:288–298.

Yoo, E.-H., Min, J.-Y., Choi, B.-Y., Ryoo, S.-W., Min, K.-B., and Roberts, J. E. (2024). Spatiotemporal variability of the association between greenspace exposure and depression in older adults in South Korea. *BMC Public Health*, 24(1):2556.

Yoo, E.-H. and Roberts, J. E. (2022). Static home-based versus dynamic mobility-based assessments of exposure to urban green space. *Urban Forestry & Urban Greening*, 70:127528.

Yoo, E.-H., Roberts, J. E., Eum, Y., Li, X., and Konty, K. (2022). Exposure to urban green space may both promote and harm mental health in socially vulnerable neighborhoods: A neighborhood-scale analysis in new york city. *Environmental Research*, 204:112292.

Yoo, E.-H., Roberts, J. E., Eum, Y., and Shi, Y. (2020). Quality of hybrid location data drawn from GPS-enabled mobile phones: Does it matter? *Transactions in GIS*, 24(2):462–482.

Yu, C. and Kwan, M.-P. (2024). Dynamic greenspace exposure, individual mental health status and momentary stress level: A study using multiple greenspace measurements. *Health & Place*, 86:103213.

Yu, C., Kwan, M.-P., and Liu, Y. (2024a). Assessing momentary stress responses to dynamic real-time greenspace exposure: Unveiling algorithmic uncertainty and the temporality of exposure context. *Social Science & Medicine*, 363:117411.

Yu, Z., Yang, G., Lin, T., Zhao, B., Xu, Y., Yao, X., Ma, W., Vejre, H., and Jiang, B. (2024b). Exposure Ecology Drives a Unified Understanding of the Nexus of (Urban) Natural Ecosystem, Ecological Exposure, and Health. *Ecosystem Health and Sustainability*, 10:0165.

Yuan, Y., Huang, F., Lin, F., Zhu, P., and Zhu, P. (2021). Green space exposure on mortality and cardiovascular outcomes in older adults: a systematic review and meta-analysis of observational studies. *Aging Clinical and Experimental Research*, 33(7):1783–1797.

Yung, E. H., Conejos, S., and Chan, E. H. (2016). Social needs of the elderly and active aging in public open spaces in urban renewal. *Cities*, 52:114–122.

Zartarian, V., Ott, W. R., and Duan, N. (1997). A QUANTITATIVE DEFINITION OF EXPOSURE AND RELATED CONCEPTS. *Journal of Exposure Analysis and Environmental Epidemiology*, 7(4):411.

Zhai, Y. and Baran, P. K. (2016). Do configurational attributes matter in context of urban parks? Park pathway configurational attributes and senior walking. *Landscape and Urban Planning*, 148:188–202.

Zhang, L., Tan, P. Y., and Richards, D. (2021). Relative importance of quantitative and qualitative aspects of urban green spaces in promoting health. *Landscape and Urban Planning*, 213:104131.

Zheng, L., Kwan, M.-P., Liu, Y., Liu, D., Huang, J., and Kan, Z. (2024a). How mobility pattern shapes the association between static green space and dynamic green space exposure. *Environmental Research*, 258:119499.

Zheng, Y., Lin, T., Hamm, N. A. S., Liu, J., Zhou, T., Geng, H., Zhang, J., Ye, H., Zhang, G., Wang, X., and Chen, T. (2024b). Quantitative evaluation of urban green exposure and its impact on human health: A case study on the 3-30-300 green space rule. *Science of The Total Environment*, 924:171461.

Zhou, X. and Wang, Y.-C. (2011). Spatial–temporal dynamics of urban green space in response to rapid urbanization and greening policies. *Landscape and Urban Planning*, 100(3):268–277.

Zhou, Y., Yuan, Y., Chen, Y., and Lai, S. (2020). Association Pathways Between Neighborhood Greenspaces and the Physical and Mental Health of Older Adults—A Cross-Sectional Study in Guangzhou, China. *Frontiers in Public Health*, 8:551453.

Zuo, W., Cheng, B., Feng, X., and Zhuang, X. (2024). Relationship between urban green space and mental health in older adults: mediating role of relative deprivation, physical activity, and social trust. *Frontiers in Public Health*, 12:1442560.

APPENDIX A: GREEN SPACE DEFINITION

Table A.1: Definition of green space used in this thesis (from (Price et al., 2023, Table 1)).

TypoCH	Class	Group	TypoCH Name
4	4	-	Grasslands
4.0	4	40	Re-seeded and heavily fertilised grasslands (re-seeded grasslands)
4.1	4	41	Pioneer vegetation on rocky surfaces
4.2	4	42	Dry grasslands
4.3	4	43	Nutrient-poor alpine and subalpine grasslands (alpine/subalpine grasslands)
4.4	4	44	Snowbed communities
4.5	4	45	Nutrient-rich pastures and meadows
4.6	4	46	Fallow grasslands
5	5	-	Woodland edges, tall herb communities, shrubs
5.1	5	51	Herbaceous fringes
5.2	5	52	Forest clearings
5.3	5	53	Shrubs, bushes, hedges
5.4	5	54	Dry dwarf shrub heaths
6	6	-	Forests
6.0	6	60	Plantations and trees outside forest
6.1	6	61	Swamp forests
6.2	6	62	Beech forests
6.3	6	63	Other deciduous forests
6.4	6	64	Thermophilic pine forests
6.5	6	65	Bog forests
6.6	6	66	High-altitude coniferous forests

APPENDIX B: QUESTIONNAIRES AND ORIGINAL DATA DISTRIBUTION IN THE MOASIS STUDY

Table B.1: Self-reported variables with their items (German & English) from the original questionnaires.

Variable	Item (German)	Item (English)
Baseline questionnaire		
Sociodemographic Variables		
Sex	• Männlich • Weiblich • Divers	• Male • Female • Diverse
Age	Chronologisches Alter	Chronological Age
Employment	Sind Sie gegenwärtig… • Voll erwerbstätig (1) • Teilzeit erwerbstätig (2) an ____ Stunden pro Woche • Arbeitslos (3) • Im Ruhestand (4) • Hausfrau / -mann (5)	Are you present… • Fully employed (1) • Part-time employment (2) at ____ hours per week • Unemployed (3) • Retired (4) • Housewife / - husband (5)

Table B.1 (*continued*)

Variable	**Item (German)**	**Item (English)**
Income	In welchem Bereich der folgenden Einkommensgruppen liegen Ihre eigenen monatlichen Netto-Einkünfte? • Bis 3′000 Fr. (1) • 3′001 bis 4′000 Fr. (2) • 4′001 bis 6′000 Fr. (3) • 6′001 bis 8′000 Fr. (4) • 8′001 bis 12′000 Fr. (5) • Mehr als 12′000 Fr. (6)	In which area of the following income groups are your own monthly net incomes? • Up to 3′000 Fr. (1) • 3′001 to 4′000 Fr. (2) • 4′001 to 6′000 Fr. (3) • 6′001 to 8′000 Fr. (4) • 8′001 to 12′000 Fr. (5) • More than 12′000 Fr. (6)
Education	Höchster Schulabschluss • Keine Schul- oder Berufsbildung (1) • Primarschule (2) • Obligatorische Schule (Sekundar-/ Real-/ Bezirksschule oder Untergymnasium) (3) • Berufslehre oder Vollzeit-Berufsschule (4) • Maturität (5) • Höhere Fach- oder Berufsausbildung (Meisterdiplom, Höhere Fachprüfung) (6) • Höhere Fachschule (HF) (7) • Fachhochschule (FH) (8) • Universität (9)	Highest school diploma • No education or training (1) • Primary school (2) • Compulsory school (Secondary / Real / District School or Lower Grammar School) (3) • Apprenticeship or full-time vocational school (4) • Matura (5) • Higher technical or vocational training (master's diploma, advanced technical examination) (6) • Higher Technical College (HF) (7) • University of Applied Sciences (FH) (8) • University (9)

Table B.1 (continued)

Variable	**Item (German)**	**Item (English)**
Marital status	Familienstand • Ledig (1) • Langjährige Partnerschaft (2) • Verheiratet / eingetragene Partnerschaft (3) • Geschieden (4) • Verwitwet (5)	Marital status • Single (1) • Long-term partnership (2) • Married / registered partnership (3) • Divorced (4) • Widowed (5)
Subjective Well-being		
General health	Wie würden Sie Ihren momentanen Gesundheitszustand einschätzen? • Mangelhaft (1) • Weniger gut (2) • Gut (3) • Sehr gut (4) • Ausgezeichnet (5)	In general, would you say your health is... • Poor (1) • Fair (2) • Good (3) • Very good (4) • Excellent (5)
Daily questionnaire		
Evening assessment		
Subjective health	Wie würden Sie Ihren heutigen Gesundheitszustand einschätzen? • Sehr schlecht (1) • Schlecht (2) • Leicht schlecht (3) • Fair (4) • Leicht gut (5) • Gut (6) • Sehr gut (7)	How would you rate your health today? • Very bad (1) • Bad (2) • Slightly bad (3) • Neutral (4) • Slightly good (5) • Good (6) • Very good (7)

Table B.2: Demographic and socioeconomic characteristics of participants (original data from the dataset).

Variables	**Description**	**Number (Proportion) of People (N = 60)**	**Number (Proportion) of Days (N = 300)**
Gender	Male	23 (38.33%)	112 (37.33%)
	Female	37 (61.67%)	188 (62.67%)
Age	65–74	24 (40.00%)	134 (44.67%)
	75–84	31 (51.67%)	148 (49.33%)
	$\geqslant$ 85	5 (8.33%)	18 (6.00%)
Employment	Part-time employment	9 (15.00%)	44 (14.67%)
	Retired	51 (85.00%)	256 (85.33%)
Individual monthly net income	$\leqslant$ 3,000 CHF	12 (20.00%)	52 (17.33%)
	3,001–4,000 CHF	9 (15.00%)	38 (12.67%)
	4,001–6,000 CHF	16 (26.67%)	88 (29.33%)
	6,001–8,000 CHF	11 (18.33%)	54 (18.00%)
	8,001–12,000 CHF	10 (16.67%)	62 (20.67%)
	$\geqslant$ 12,000 CHF	2 (3.33%)	6 (2.00%)
Education	Compulsory school	3 (5.00%)	12 (4.00%)
	Apprenticeship or full-time vocational school	13 (21.67%)	68 (22.67%)
	Higher technical or vocational training	10 (16.67%)	45 (15.00%)
	Higher technical college	1 (1.67%)	1 (0.33%)
	University of applied sciences	10 (16.67%)	56 (18.67%)
	University	21 (35.00%)	114 (38.00%)
	Missing data	2 (3.33%)	4 (1.33%)
Marital status	Single	4 (6.67%)	10 (3.33%)
	Long-term partnership	6 (10.00%)	43 (14.33%)
	Married / registered partnership	26 (43.33%)	151 (50.33%)
	Divorced	16 (26.67%)	68 (22.67%)

Continued on next page

Table B.2 (*continued*)

Variables	**Description**	**Number (Proportion) of People (N = 60)**	**Number (Proportion) of Days (N = 300)**
	Widowed	8 (13.33%)	28 (9.33%)
General health	Fair	3 (5.00%)	17 (5.67%)
	Good	18 (30.00%)	76 (25.33%)
	Very good	31 (51.67%)	151 (50.33%)
	Excellent	8 (13.33%)	56 (18.67%)

APPENDIX C: USED R PACKAGES

Packages	Version	Usage	References
base	4.4.1	statistical analysis	(R Core Team, 2024)
dbscan	1.2.0	dbscan algorithm	(Hahsler et al., 2019)
dplyr	1.1.4	data manipulation	(Wickham et al., 2023)
forcats	1.0.0	categorical variable operation	(Wickham, 2023)
fs	1.6.4	file operation	(Hester et al., 2024)
ggplot2	3.5.2	map and data visualization	(Wickham, 2016)
ggpubr	0.6.0	correlation analysis and plotting	(Kassambara, 2023)
ggspatial	1.1.10	spatial data visualization	(Dunnington, 2023)
glue	1.7.0	text operation	(Hester and Bryan, 2024)
here	1.0.1	file path operation	(Müller, 2020)
lubridate	1.9.3	temporal data operation	(Grolemund and Wickham, 2011)
mapview	2.11.2	spatial data visualization	(Appelhans et al., 2023)
purrr	1.1.3	functional programming	(Wickham and Henry, 2023)
RefManageR	1.4.0	bibliographic reference operation	(McLean, 2014)
rlang	1.1.4	string operation	(Henry and Wickham, 2024)
readr	2.1.5	data import	(Wickham et al., 2024a)
sf	1.0.16	spatial object operation[5]	(Pebesma and Bivand, 2023; Pebesma, 2018)
sfnetworks	0.6.5	sfnetworks operation	(van der Meer et al., 2024)
stplanr	1.2.2	road segments operation	(Robin Lovelace and Richard Ellison, 2018)
terra	1.7.78	raster data operation	(Hijmans, 2024)
tidygraph	1.3.1	graph (nodes and edges) operation	(Pedersen, 2024)
tidyr	1.3.1	dataframe operation	(Wickham et al., 2024b)
units	0.8.5	unit operation	(Pebesma et al., 2016)

Table C.1: R packages used in this thesis.

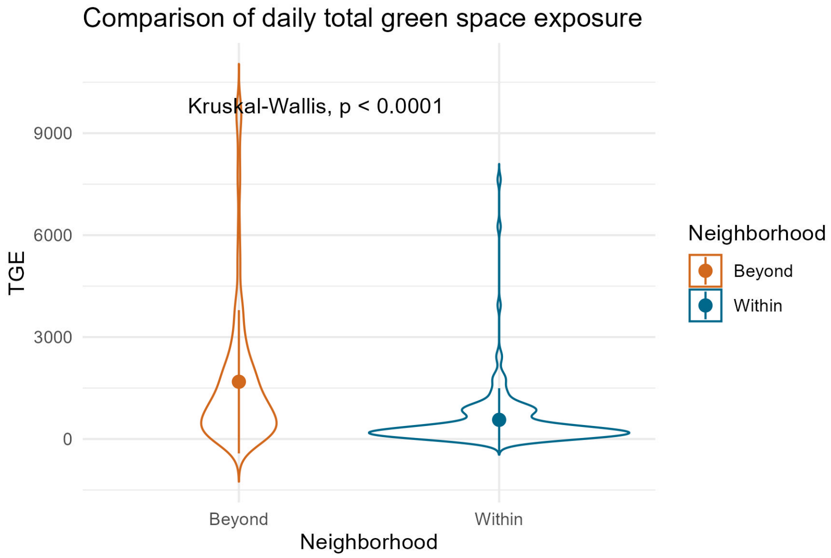
[5] For isochrone generation, the `alpha` in `sf::st_concave_hull()` is 0.6.

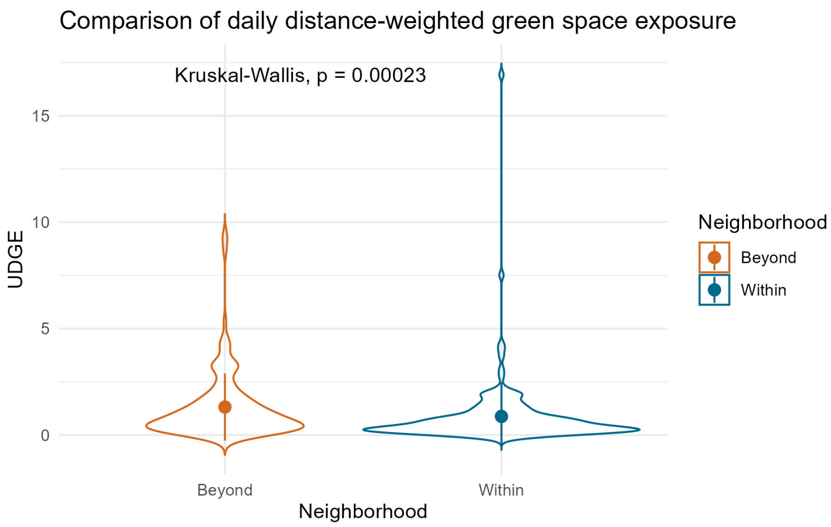
APPENDIX D: SUPPLEMENTARY DATA

Table D.1: Index of comparison plots in this appendix. For each dynamic green space exposure metric and each mobility indicator, a violin plot is used to show the data distribution of each variable, with the mean (dot) and the error limit (vertical line across the dot, defined by the standard deviation). For mobility indicators with three variables (i.e., travel time and daily travel mode), the p-value under the Wilcoxon rank sum (Mann–Whitney) test for each paired group is also labeled.

Mobility Indicator (variables)	**Figure Index**
Spatial Context	
Neighborhood (within, beyond)	Figure D.1
Temporal Contexts	
Trip Frequency (low, high)	Figure D.2
Travel Time (morning, afternoon, evening)	Figure D.3
Weekend (true, false)	Figure D.4
Travel Mode	
Daily Travel Mode (cycle only, walk and cycle, walk only)	Figure D.5

Figure D.1: Comparison of dynamic green space exposure metrics between neighborhood (threshold: $\leq$ 528.90 meters (daily mean distance to home) as "within", otherwise "beyond") groups. The plots are listed in the order of: TGE (daily total green space exposure), UDGE (daily distance-weighted green space exposure), and UTGE (daily time-weighted green space exposure), from top to bottom.





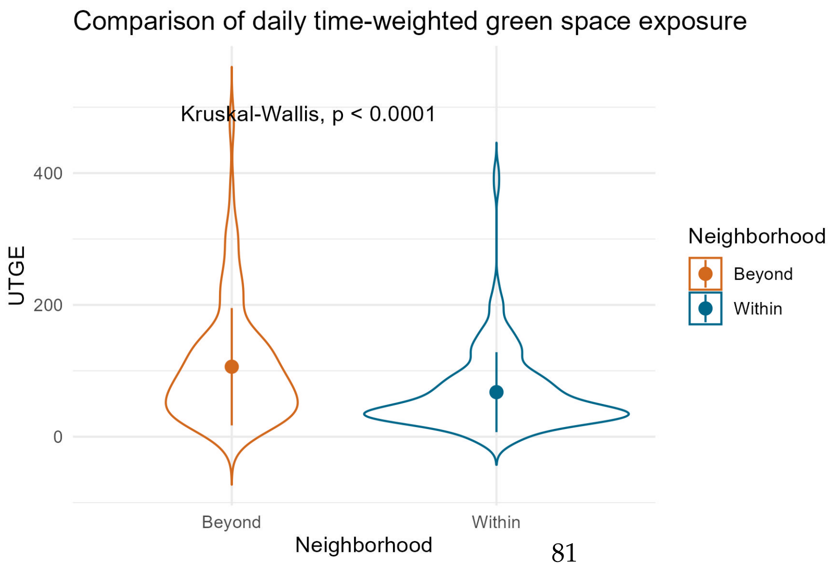


Figure D.2: Comparison of dynamic green space exposure metrics between trip-frequency (threshold: daily trip count ≤ 2 as "low", otherwise "high") groups. The plots are listed in the order of: TGE (daily total green space exposure), UDGE (daily distance-weighted green space exposure), and UTGE (daily time-weighted green space exposure), from top to bottom.

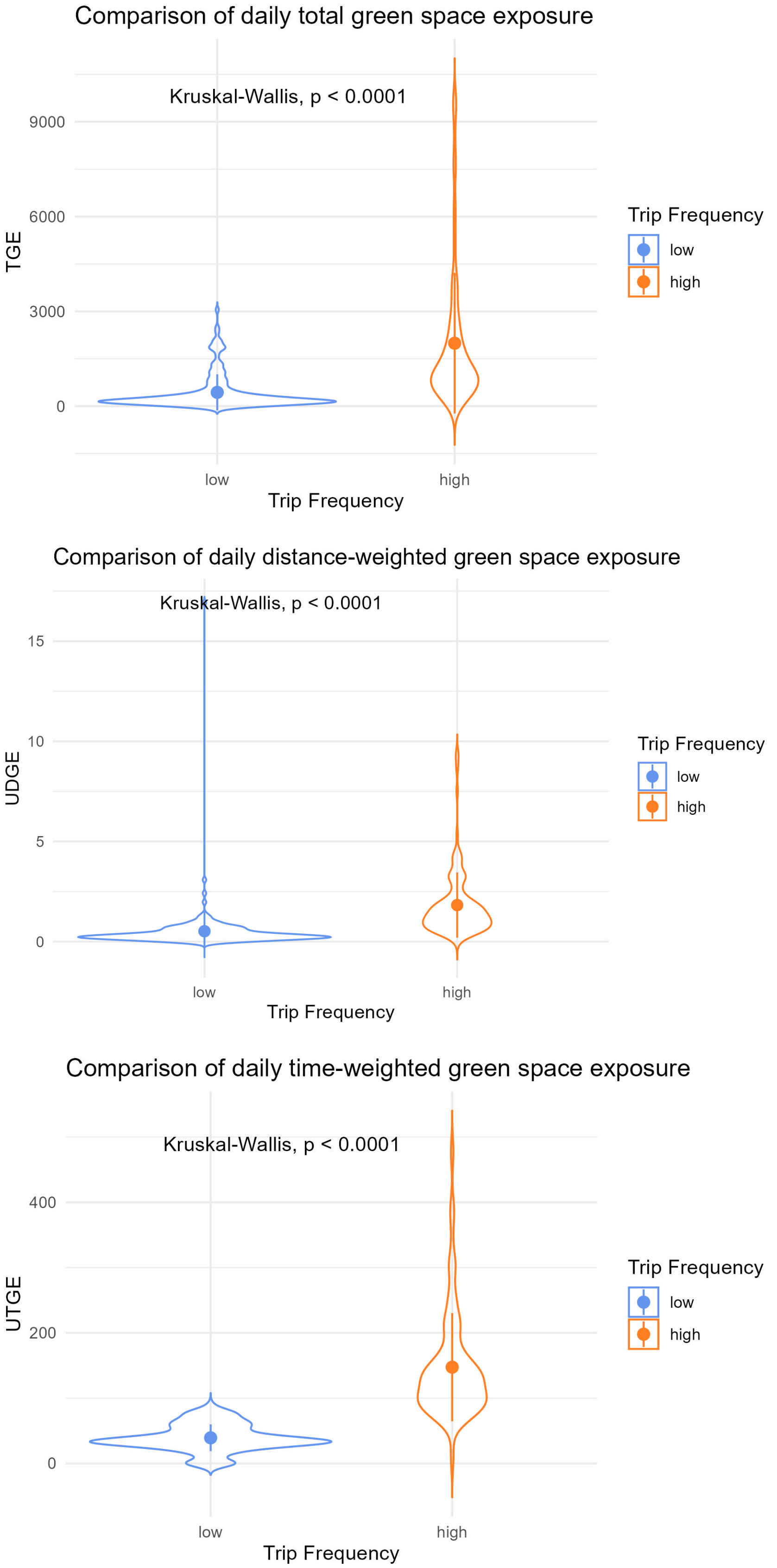


Figure D.3: Comparison of dynamic green space exposure metrics between travel-time groups. The plots are listed in the order of: TGE (daily total green space exposure), UDGE (daily distance-weighted green space exposure), and UTGE (daily time-weighted green space exposure), from top to bottom.

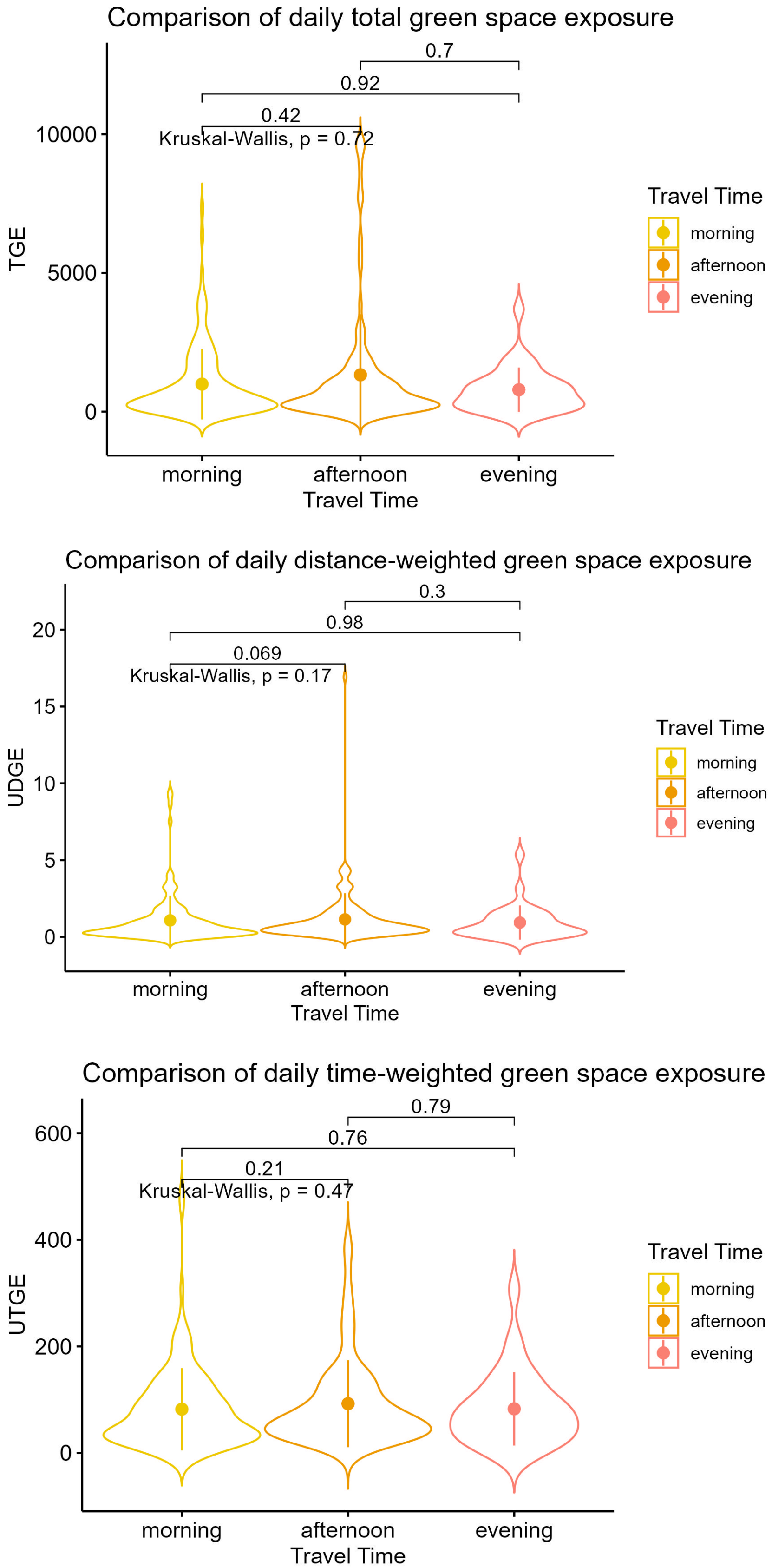
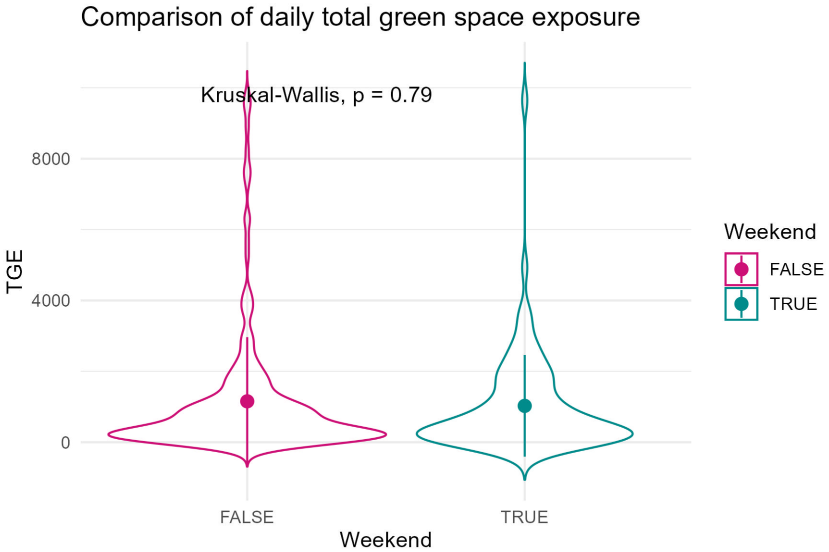
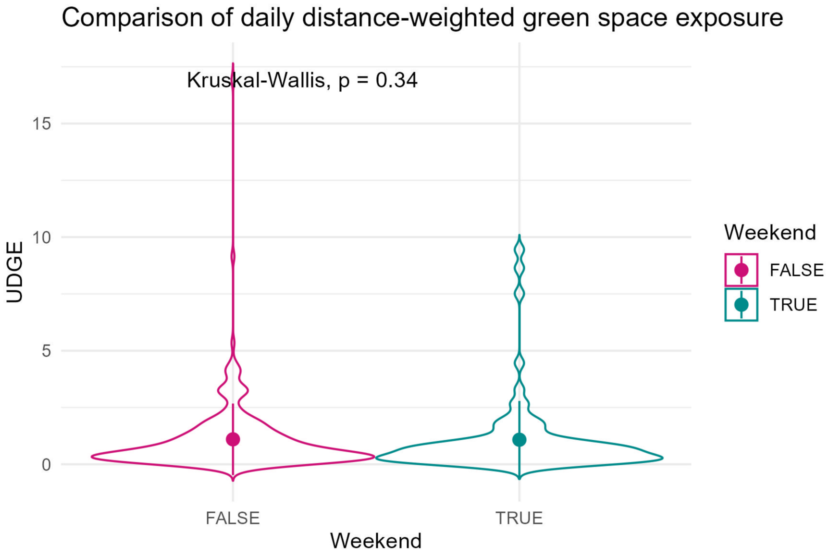


Figure D.4: Comparison of dynamic green space exposure metrics between weekday and weekend groups. The plots are listed in the order of: TGE (daily total green space exposure), UDGE (daily distance-weighted green space exposure), and UTGE (daily time-weighted green space exposure), from top to bottom.





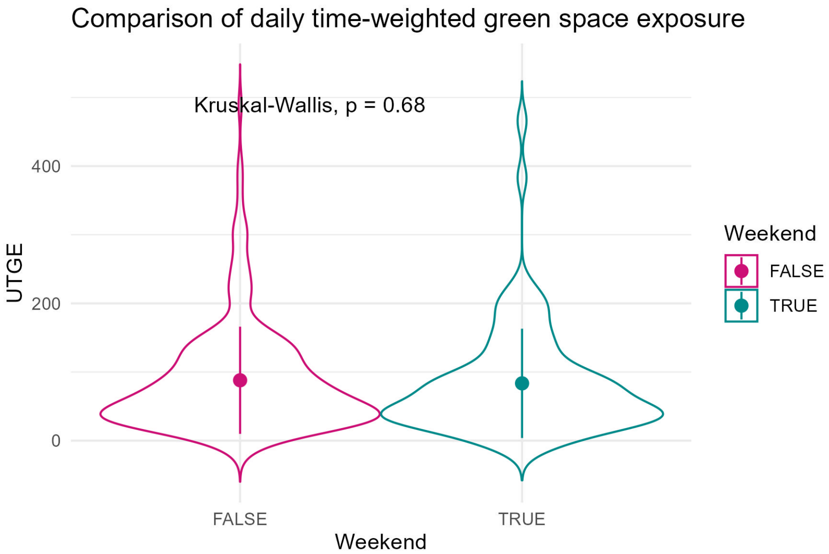
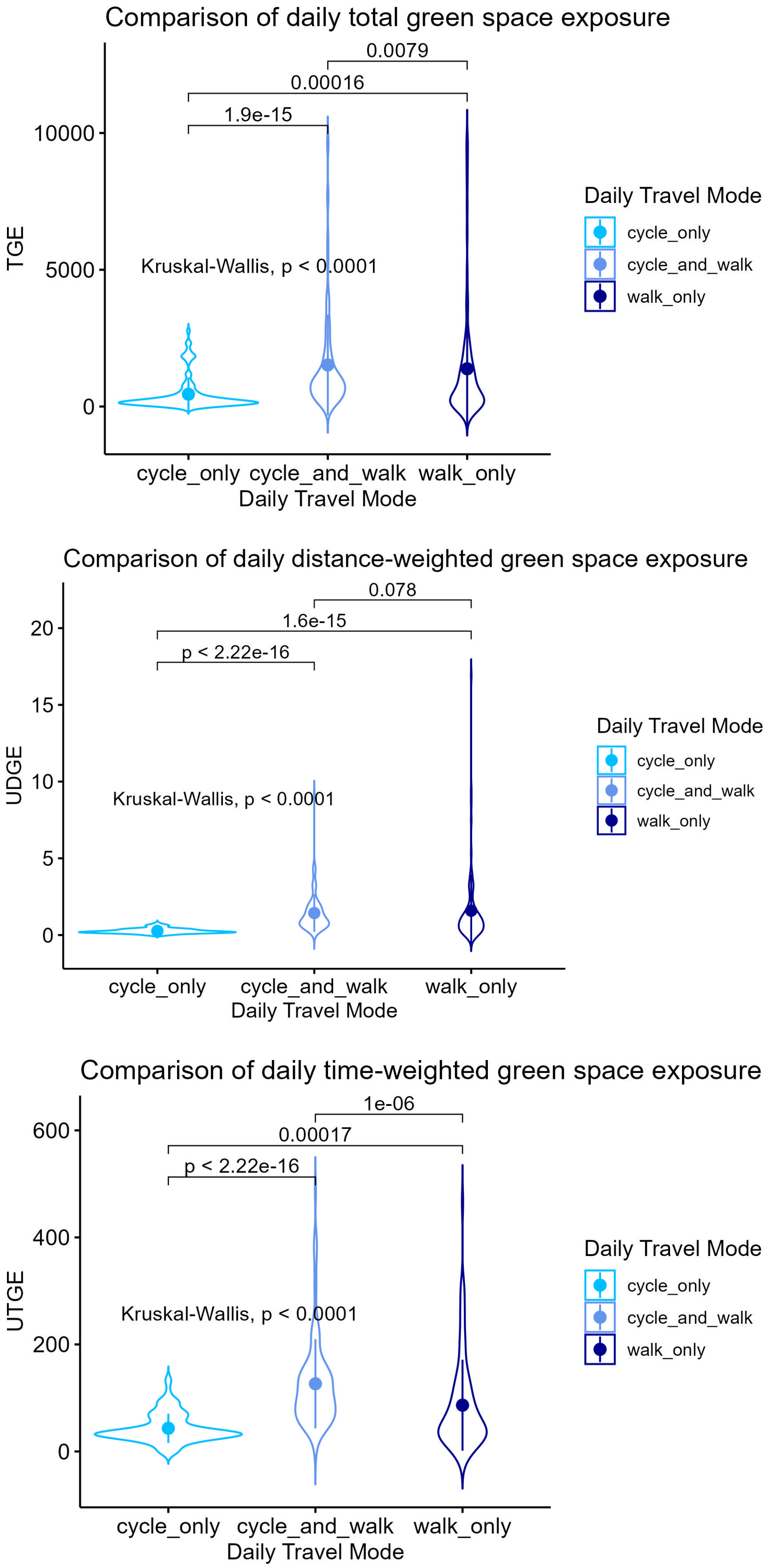


Figure D.5: Comparison of dynamic green space exposure metrics between daily-travel-mode groups. The plots are listed in the order of: TGE (daily total green space exposure), UDGE (daily distance-weighted green space exposure), and UTGE (daily time-weighted green space exposure), from top to bottom.



PERSONAL DECLARATION

I declare that the submitted thesis is the result of my independent work. All external sources are explicitly acknowledged in the thesis.

I further declare that the following generative AI tools were used during the development of the work: OpenAI's ChatGPT[6] for brainstorming and code debugging (JavaScript via Google Earth Engine, LaTeX, and R), and DeepL for translation[7] (from German to English) and embellishment[8].

I am aware that I bear full responsibility for the adoption and results of the AI-generated outputs I used. I also declare that all use of generative AI is fully disclosed. I acknowledge that work that violates the principles set out in this declaration of authenticity may have legal and disciplinary consequences.

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Date: 29.08.2025

Place: Zürich, Switzerland

[6] https://chatgpt.com/
[7] https://www.deepl.com/en/translator
[8] https://www.deepl.com/en/write