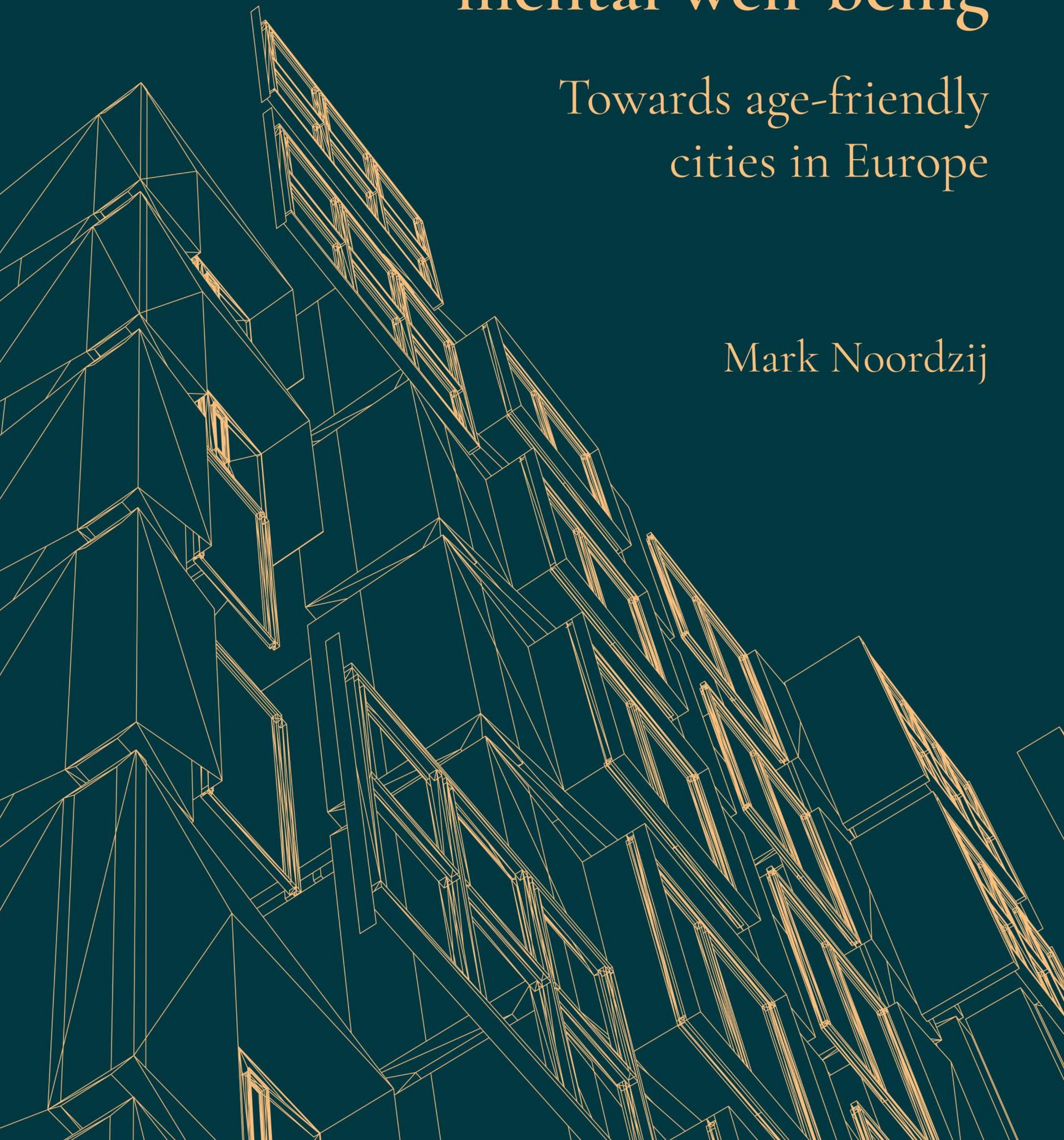
Urban environments, physical activity, and mental well-being

Towards age-friendly cities in Europe



Mark Noordzij

Urban environments, physical activity, and mental well-being

Towards age-friendly cities in Europe

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Urban environments, physical activity, and mental well-being. Towards age-friendly cities in Europe.
Doctoral thesis, Erasmus Univsersity Rotterdam

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Urban Environments, Physical Activity, and Mental Well-being
Towards age-friendly cities in Europe

De stedelijke leefomgeving, fysieke activiteit en mentaal welzijn
Op weg naar leeftijdsvriendelijke steden in Europa

Thesis

to obtain the degree of Doctor from the
Erasmus University Rotterdam
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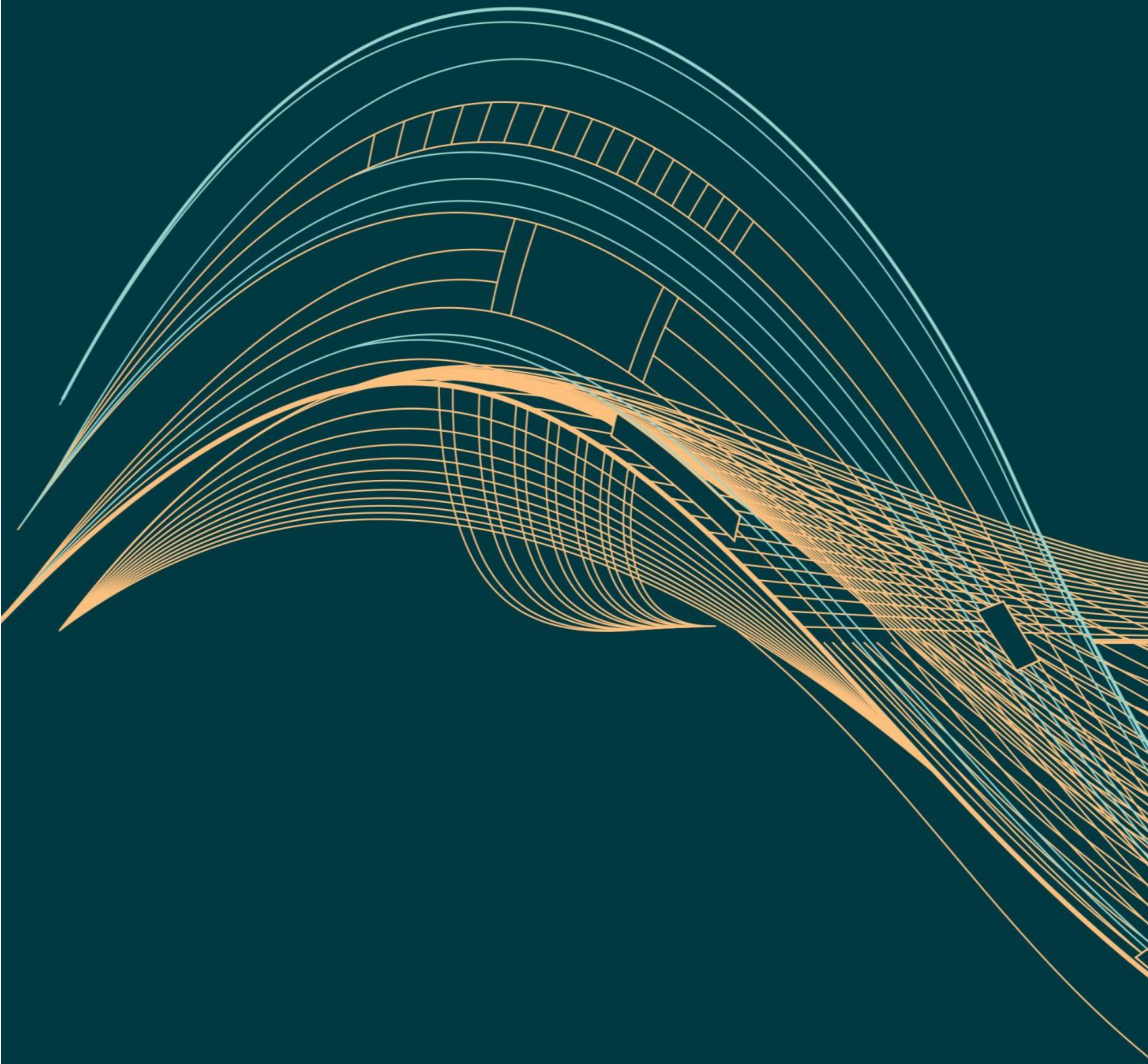
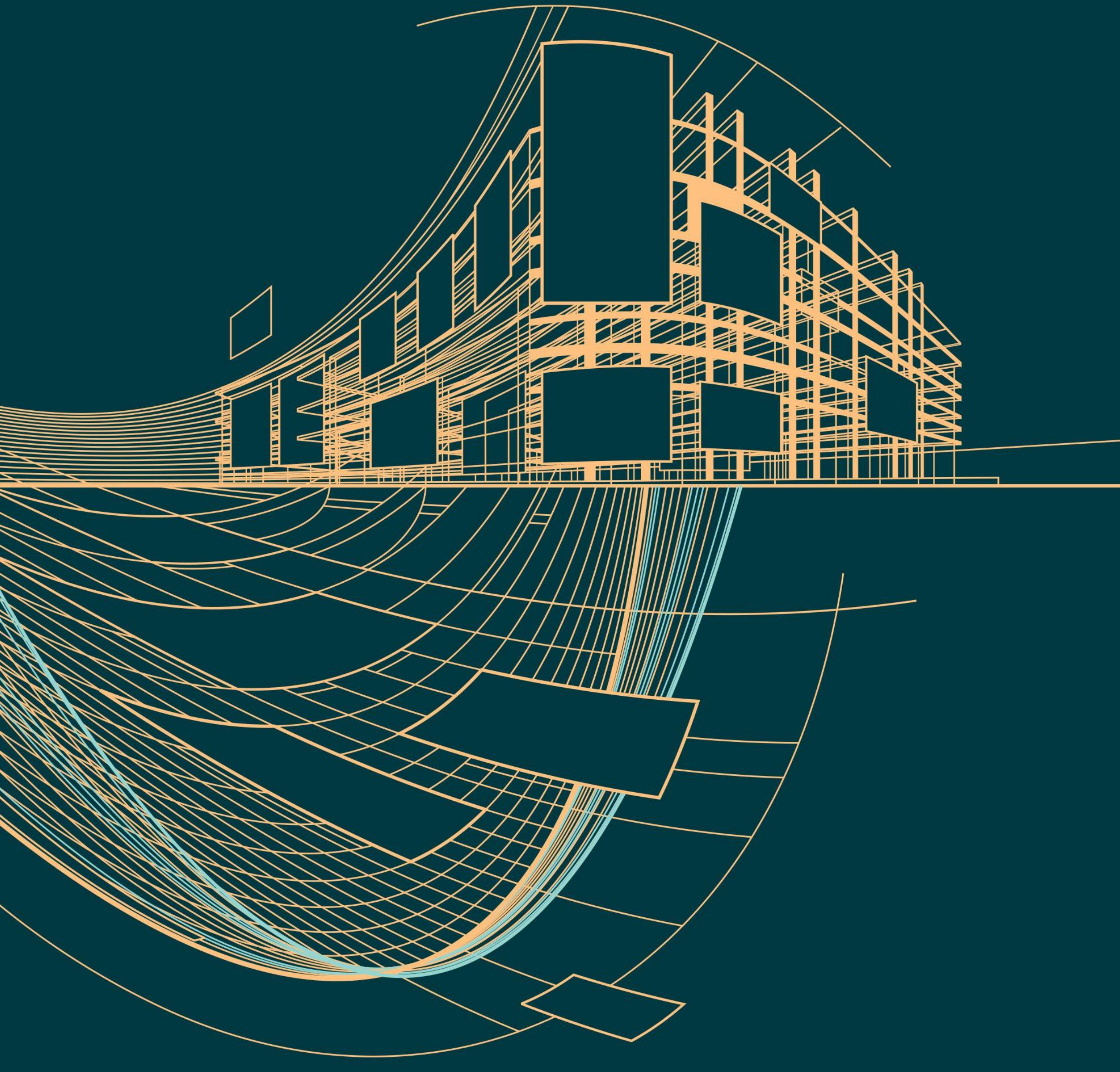


Introduction



1

Introduction

The linkages between space, place, and health have been the subject of many studies in recent years [1-2]. Such studies often emphasize 'place' or 'context' as an important factor impacting health in urban environments, and have contributed to what is now collectively known as health geography: research concerned with showing that "place matters" with regards to health, disease and health care [3]. However, linking individual and population level health to place, context, and the environment is not a new phenomenon [4-6]. Its lineage can be traced as far back as Hippocrates who stated that: *"You will find, as a general rule, that the constitutions and habits of a people follow the nature of the land where they live [7]."* For years, the relationship between health, space, and place was the domain of medical geography. This sub-category of human geography was mainly concerned with human-environment interactions and the influence of such interactions on health [8]. Over the last decades, this sub-domain of geography shifted from a 'confusing sub-variety' to a recognized and distinct research field with a new name: *health geography* [3].

While some consider the difference between medical and health geography to be purely semantics, most refer to the name change as indicative of a change in subject matter. Health geography moved away from concerns with disease and the interests of the medical world in favor of an increased interest in well-being and broader social models of health and health care [3]. The general consensus therefore is that health geography broke away from a concern with biomedical aspects of health and embraced a broader and more social model of health [9]. Health geography has also become a more prominent topic in scientific journals, books, and reports. For example, the World Health

Organization (WHO) has published a number of reports in recent years on how to improve urban environments for health, well-being, and healthy aging [10-11], and journals such as *Health & Place* focus entirely on: "*the study of all aspects of health and health care in which place or location matters* [12]."

A few key factors have to be examined in order to better understand the rise of health geography and what it entails. In 1963, geographer Ian Burton published a paper titled '*The quantitative revolution and theoretical geography*' [13]. In it he explored an intensely mathematical approach to geography that can be likened to that of social physics [14]. Following the natural sciences, geographers turned their focus towards finding general scientific laws and models that would explain and predict spatial patterns. Burton's paper illustrates a geography where space is almost entirely mathematized, eliminating many traditional regional or descriptive approaches in the process. This approach to geography became known as the *spatial analysis* and was highly influential in the academic geography of the 1950s and 1960s. Within this mathematical geography there was very little room for a contextual approach. However, by the time health geography came into its own as a discipline, a major change had taken place within geography and the broader social sciences. Human geography had moved from just spatial analytics towards a more post-modernist version of geography, advocating a spatial revolution in scientific thinking that became known as the *spatial turn in social science*. Books such as *The Production of Space* [15], *Social Relations and Spatial Structures* [16], and *Postmodern Geographies: The Reassertion of Space in Critical Social Theory* [17], invited geographers to study the role of space and place in social processes. It was argued that social phenomena could not be viewed outside of their spatial contexts and this led to a resurgence of concepts such as localities and regions [18].

According to geographers of the spatial turn, space was not a reflection of the social world, but a constitutive element of it [19]. They advocated the integration of spatial thinking into the broader social sciences by advocating more holistic approaches. Influential geographers such as David Harvey and Doreen Massey argued that the relation between space and human behavior could not be captured and predicted within mathematical models alone. Space was not just a static backdrop that existed independently of any objects or relations, but it was a relational and relative concept that was as much influenced by the social as the social was influenced by it [20-23]. This shift in spatial thinking paved the way for health geography by (re-)opening the door to more contextual approaches that considered the role of space in social and health processes.

At the same time, however, arguments remain on how much of the health variability between individuals can be attributed to differences in their environments. For example, while many studies conclude that the environment has a quantitatively measurable impact on health, the observed effects are oftentimes relatively minor when compared to 'traditional' individual-level explanations of health variation [24]. The root cause of this problem – also known as *the composition versus context debate* – remains open for discussion. It could be due to methodological shortcomings, but the question remains if methodological limitations are a sufficient explanation in and by themselves. There is a growing sense among both researchers and policy makers that purely individual-based explanations of variations in health are insufficient, and that characteristics of the groups or contexts to which individuals belong need to be considered as well. Within this emerging paradigm, the residential area of the individual has emerged as the *de facto* context as it possesses both physical and social attributes that could potentially affect health and well-being [25]. This branch of research has been commonly labelled as *neighborhood research*.

Neighborhood studies usually link various exposure measures on a certain geographical scale to individual-level health-related outcomes. Many of such studies consist of secondary data analyses of individual-level data from health studies linked to census data, based on the residential addresses of study participants. Census areas or existing administrative neighborhoods are commonly used to proxy the specific neighborhood's physical or social features that are hypothesized to be etiologically relevant to the health outcome being studied [25]. Within this domain of neighborhood research, particular attention has been paid to urban neighborhoods. The city has become an important site of research for health geographers looking to test hypotheses on how the environment relates to health and well-being. A number of different trends can be identified that have contributed to the rise of the city as an important research site for health geographers. First, the aforementioned spatial turn helped to create more awareness for the role of space and place in social processes, and it led to more integration of spatial perspectives into other social sciences. Second, rapid urbanization has led the way to general acceptance of the *Urban Age Thesis*. Described in numerous United Nations (UN) reports, this thesis states that: "*In 2008 [..] for the first time in history, more than half [of the] human population will be living in urban areas* [26]." The urban age thesis is today repeated regularly as a reference point for researchers and policy makers concerned with justifying the city as a site of research and policy making. Much like the notion of modernization in the 1960s and that of globalization in the 1980s and 1990s, the Urban Age Thesis can be considered as an all-encompassing framing device to contextualize the importance of research questions [27]. Third, the basic nature of 'cityness' has become more differentiated, polymorphic, variegated and multiscalar [28]. Contemporary cities cannot be understood as a singular worldwide phenomenon and therefore require multi-tiered approaches and research methodologies that do justice to the differences between urban environments across the world. Questions of external validity – how do results of a North-American city translate to a European one? – have led to more investment in research to better understand urban dynamics across different geographical territories.

Where the *Urban Age Thesis* provides health-geographical research with a geographical frame of reference, a second frame of reference is that of ageing. In 2017 around 13% of the world's population was estimated to be aged 60 years or older. This part of the population is growing at an annual rate of about 3% and is projected to grow to an estimated 22% in 2050 [29]. A substantial part of this ageing population lives in cities, which leads to public health challenges, such as a higher risk of mental disorders resulting in impairments in social functioning [30]. In 2006, the WHO therefore launched an initiative targeting the health of older urban residents: the *Age-friendly City* [31]. At the same time, many questions still remain on how the urban environment relates to health and well-being of ageing individuals. Some of these questions are methodological ones, while others are of a more ontological or etiological nature. In a 2016 review, professor Ana Diez Roux – a leading researcher in the field of health geography – concluded that *"the jury is still out on [questions regarding the effects of neighborhood factors on health], and some may argue that given discordant findings in the literature, little consensus has been reached* [32]."

Within the context of this thesis, we will therefore first explore two topics to gain a better understanding of how the urban environment might relate to health and well-being. First, we will try to answer a vital question: "*What makes a city?*" Second, we will explore some of the empirical literature on how cities and health might relate. We will conclude this chapter with the introduction of the research questions of this thesis.

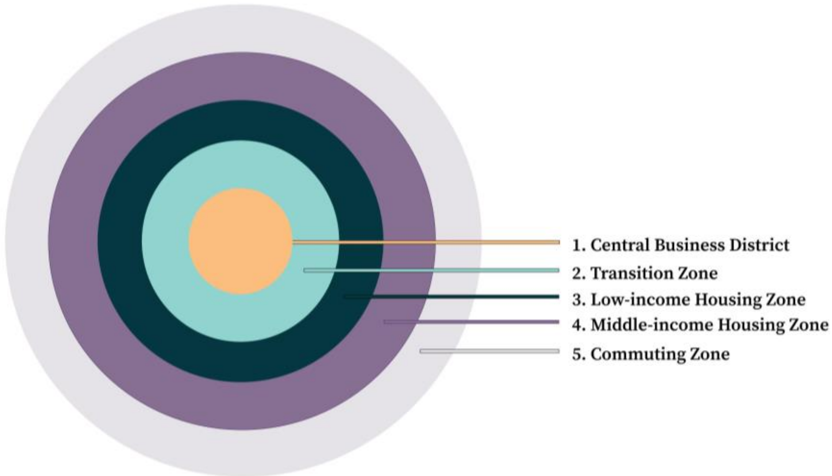
1.1 What makes a city?

'What makes a city?' Most of us probably feel like we have a reasonable grasp of what makes some places cities, while others are villages or rural areas. The city is often defined through a series of explicit or implied geographical contrasts. Urban versus rural, core versus periphery, densely versus sparsely populated. Across otherwise divergent methodological and epistemological traditions, many studies involving the city rest upon an underlying assumption that the city represents a particular type of spatial configuration that can be defined only in contrast to other, different configurations that lay outside of its formal boundaries [33]. Probably the most famous description of this city comes in the form of Burgess' classic concentric rings diagram from the 1920s (Figure 1.1). In this diagram the city is defined as a series of bounded and delineated rings that stretch out from a geometrically positioned center towards suburban areas and ultimately an empty horizon. Burgess' model incorporates five distinct zones:

1. Central Business District (CBD): the traditional city center, where employment is located and where infrastructure converges;
2. Transition Zone: the zone where many industrial activities are located to take advantage of the CBD;
3. Low-Income Housing Zone: a zone that is gradually converted to other uses by the expansion of the Transition Zone, and which contains the cheapest housing;
4. Middle-Income Zone: residential zone for the working class and those that move away from the low-income housing zone. It has the advantage of being close to zones 1 and 2;
5. Commuting Zone: another residential zone with higher quality housing, but also longer commuting times.

[34-35]

Figure 1.1: A visual representation of the Concentric Zone Model by Edward W. Burgess



Burgess based his model on empirical observations of American cities, – most notably 1920s Chicago – but it has been applied to describe cities worldwide. The model assumes a relationship between the socio-economic status of households and their distance from the CBD: the further away from the CBD, the better and more expensive the housing becomes. This amounts to a decidedly horizontal interpretation of the city. Burgess' city was an extended landscape on which the spaces of different settlement types were juxtaposed, with some amount of coherence within them. The city's different zones were assumed to be bounded, contiguous, and non-overlapping. The urban, suburban, and rural zones were known to shift over time – the transition zone could expand towards the low-income housing zone – but the spaces themselves were viewed as discreet, distinct, and universal. They were defined based on specific features, were geographically separated from each other, and were observable in some form in all cities around the world [33].

Burgess' horizontal demarcation of the city became an integral part of urban studies, serving as an epistemological bedrock for many studies that involved the city as a research site. Nowadays, its assumptions are often challenged by researchers, but its basic principles are still firmly implanted in the (geographical) subconsciousness. A recent example of the pervasiveness of Burgess' principles can be found in the aforementioned *Urban Age Thesis*. This thesis follows a long tradition of urban-demographical research, dating back to the 1950s, and its core principle relies on some sort of division of what is urban and what is not. It presents a dualism between urban and non-urban areas, and between urban and non-urban populations. According to the *Urban Age Thesis,* the dynamic of this dualism would shift towards urban areas in 2008. While the *Urban Age discourse* is commonly presented as a set of empirical claims about urban demographics, it is based on a very 'Burgess-like' theoretical framework. It divides the indivisible insofar as it treats urban and rural areas as fundamentally distinct [27]. Burgess' city therefore becomes a horizontal container of sorts: delineated and decidedly different from the rural hinterland. While such a distinction is useful for demographical purposes, it is not without its flaws. Urban and rural areas do not operate in a vacuum, independent of each other, and it is very much debatable if a hard border exists that divides the two. Furthermore, it can be argued that such a representation of urban and rural landscapes is generalized to the point of meaninglessness as both states refer to extremely heterogeneous conditions that in reality rarely manifest as such.

Many of the criticisms of the Urban Age Thesis reflect the criticisms of Burgess' model, which was criticized for being overly simplistic, and its underlying theory of human ecology inherently flawed. Over the years numerous alternative conceptualizations of the city have been formulated in response to Burgess' model. Many of these models focus on a more vertical positioning of different scales within a dynamic, multitiered geographical configuration. Within these *vertical approaches,* the city is a geographical scale that is embedded within other scales, such as the region or the nation. From the individual's home environment, through the neighborhood to a (polynuclear) city-region, *scale* becomes a vital part of analyzing socio-spatial and economic relations.

Within vertical conceptualizations of the city, urban areas are defined less as bounded containers, and more as sets of socio-spatial relations embedded within a dynamically evolving whole. The city is no longer defined by its boundedness, but by its positionality within a broader, multiscalar framework. Such conceptualizations work well within the context of geographical information systems (GIS), where data consists of multiple, often overlapping, layers. The concept of scale then becomes an integral part of answering the question: '*What makes a city?'* Within this intellectual tradition, scale is understood to be socially produced and malleable [36]. In other words, geographical scales are formed with specific goals in mind. This means that any scalar hierarchy has a historical geography and is malleable by definition. This notion of scale provided researchers with a powerful conceptual tool to compare and analyze different geographical areas and the changing geographies of urbanization.

The malleability of geographical scales was also central to the argument provided by Stan Openshaw in his influential work on the *Modifiable Areal Unit Problem* (MAUP) [37]. Building on the early work of Gehlke and Biehl (1934), the essence of MAUP is that analytical results for the same data in the same study area can be different if aggregated in different ways [38-39]. MAUP is often described as having two effects: a zonation effect and a scale effect. The zonation – or aggregation – effect shows that major differences may be found based on how a study area is divided up, even at the same scale [37]. The scale effect of MAUP is concerned with how analytical results differ depending on the size of the geographical units used. Correlations could, for example, be more pronounced for bigger geographical units.

While MAUP is primarily a geographical-statistical problem, other researchers have focused on other implications of zoning and scale issues that arise when we turn to the urban environment as a site for research. Mei-Po Kwan's *Uncertain Geographic Context Problem* (UGCoP) is concerned with how and when spatial features exert contextual influences on individuals [40]. The UGCoP is concerned with both the spatial uncertainty in the representation of geographical areas as well as temporal uncertainty. If, for example, we want to analyze the influence of some area-level contextual exposure on individuals, it is essential that we know when and how long the individuals were exposed to said exposure. The UGCoP also argues that if we truly want to measure the effect of a contextual area-level exposure, we need to be mindful of how well the geographical delineation of the area represents the experienced reality. UGCoP therefore is not only a statistical problem, but also an ontological one. It provides a view of urban space that is very much scalar and relational: concerned with how the delineation of geographical scales relates to individual's experiences.

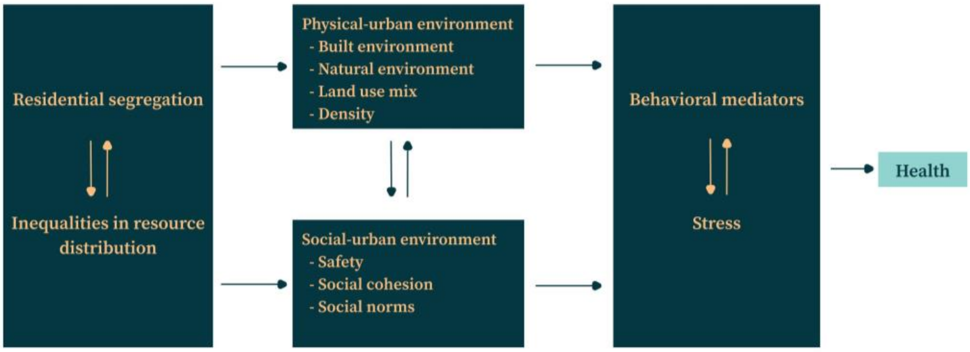
When we circle back to the original question of this paragraph, we have to conclude that there is no definitive answer to the question: '*What makes a city?*' Multiple approaches can be identified that either view the city as a horizontal patchwork of different zones or as a vertical 'slice' that is part of both larger and smaller scales embedded within a dynamically evolving whole. Problems as MAUP and UGCoP show that geographical scales and areas are not a pre-emptive given, but very much the result of specific processes and associated choices. Measures of the urban environment are malleable and as much socially produced as contested. When we use geographical units to analyze the urban environment we have to be aware of these different perspectives and the potential problems.

1.2 Cities and health

With no definitive answer to the question what makes a city, it makes logical sense to conclude that there is also no definitive answer to the question how *the* city relates to health. To explore potential health effects of urban environments, therefore means that we have to explore how certain parts of the complex puzzle of what makes a city, can relate to health-related outcomes. A distinction that is commonly used within health geography to better understand how urban environments can relate to health, is to define urban-environmental exposures as part of the *physical* or *social* urban environment. The physical urban environment often includes features of built environments, such as land use patterns, density, and access to destinations. Factors of social urban environments are often discussed as being relevant to pathways linking cities to health, but are notoriously harder to measure. Studies linking social-urban factors to health outcomes are therefore less common than those linking physical-urban factors to health outcomes. Social-urban factors that are hypothesized to be relevant to health include social norms, social cohesion and related constructs, and safety.

While the distinction between physical and social factors is useful for research purposes, in reality they often intertwine. For example, a physical-environmental exposure, such as the amount of green spaces in the residential environment, could be related to health, but this relation could be the result of the social function that parks can have. Nonetheless, the distinction between the physical and social urban environment can help to get a better understanding how different parts of the urban environment relate to different health outcomes. Figure 1.2 offers a schematic summary of some of the different processes that can contribute to health and how they might interact. This figure offers a simplified version of complex, intertwined relations that combine to form the urban environment, but it helps us to conceptualize how parts of the urban environment may relate to health. For example, processes of residential segregation might lead to less access to parks for residents of one urban area compared to residents from another area. This may affect behavior, such as walking or cycling, which in turn can influence overall health. This model assumes that there are interactions between its parts, such as between the physical and social urban environment. Physical-environmental characteristics such as the quality of public spaces can affect the nature of social interactions between residents. Behavioral and stress processes operating at the individual level are also dynamically related. For example, some behaviors such as physical activity can buffer the adverse effects of stress, while stress can in turn can influence other behaviors [41]. Of course, many more factors and interactions could be conceptualized, but this schematic overview helps us to gain some understanding of how the different parts of the urban environment relate to each other and to health.

Figure 1.2: A schematic representation of the possible interactions between different urban-environmental factors and health



Based on Diez Roux et al. (2010) [25].

Within the context of this thesis, the focus will be on the physical-urban environment, and how (parts of) it relate to health and health-related behavior. The choice for the physical environment is based on a number of different reasons. First, there is a solid body of research on how the physical-urban environment relates to health, but a lot of questions remain on the nature of this relation. Second, advances in geospatial technologies, data quality, and data availability have made it possible to more accurately capture the individual's residential environment and convert it to meaningful exposures.

Third, an influx of researchers from different backgrounds has brought a lot of (methodological) innovation to the field, which can help to gain a better understanding of how physical-urban characteristics might relate to health. Finally, the physical environment is often considered as a relevant domain by policy makers as they can influence it relatively well through policy. We will explore these topics in more depth in the next paragraph.

1.3 Physical-urban characteristics and health

Studies of how physical-environmental characteristics can relate to health can generally be categorized by the class of outcomes studied. A distinction that is commonly made is that between *physical health outcomes* and *mental health outcomes*. Physical health outcomes often include – but are not limited to – behaviors of diet and physical activity and related health outcomes of obesity, diabetes, and hypertension. Mental health outcomes include levels of stress and anxiety, depression, or mental well-being [42]. Similar to the debate around urban-environmental exposures, the distinction between physical and mental health is up for discussion. For example, access to more green spaces could relate to better mental health and more physical activity; outcomes that in turn can reinforce each other as more physical activity by itself is also related to better mental health. Untangling how the physical-urban environment can relate to health has therefore commonly involved studying specific relations and hypotheses that are grounded in theory or empirical observations. One of these specific study fields is the study of how nature and green spaces can relate to stress, depression, and general mental well-being. Psychoevolutionary theories developed in the 1990s suggest that natural environments can have restorative effects on mental health [43-46]. Both Ulrich's *stress reduction theory* and Kaplan's *attention restoration theory* specify an antecedent condition from which an individual needs restoration. Nature and natural environments can aid with this restoration as they can reduce stress by evoking positive emotions (stress reduction) or can act as a means to recover from directed attention fatigue (attention restoration).

The theorized positive effects of natural environments on mental health have been studied by many different researchers within the environment-health domain. Such studies range from the impact of the presence of potted plants in study rooms on mood and cognitive performance [47] to the effects of moving to greener or less green neighborhoods [48]. Generally, research in this domain assumes that an individual that spends time in an environment with a comparatively high restorative quality (i.e. a greener environment) will realize greater mental health benefits compared to when the same individual would have spent that time in an environment with less restorative qualities [49]. However, the results of many of these studies are mixed. Some experimental or laboratory studies have found evidence of positive effects in line with the stress reduction and attention restoration theories [50-51], but others report no findings or even findings inverse of those expected [52-53]. This is especially true in the context of urban environments, where the evidence of long-term mental health benefits of green spaces appears to be inconsistent at best [54-55]. Such inconsistencies are not limited to just green spaces and mental health, but can be found in much of the health-geographical literature. A particularly striking example comes from multiple German studies on green spaces and childhood allergies. In one study area, increasing greenness was positively associated with childhood allergies, while in another area the associations were inverted, despite the use of identical epidemiological methods [56]. Similar patterns of inconsistency can also be observed in studies with different exposures. One exposure class commonly linked to health outcomes is that of *built environment measures* or *BEMs*. BEMs represent parts of the environment that are man-made, such as traffic intersections, cycling paths, or varying land uses, and are commonly linked to health and health-related outcomes, such as physical activity. For example, a systematic review found moderate-to-strong evidence of positive associations between land use mix and older adults' total walking [57], but other studies find that such associations can vary quite substantially [58-59].

Explanations of why results of health-geographical studies tend to show many inconsistencies can be broadly categorized as being *epidemiological* or *geographical* in nature. Epidemiological explanations tend to focus on research techniques, statistical practices, and etiological concerns. One of the most common, and valid, complaints about health-geographical studies, is that there is a severe lack of longitudinal studies and an overrepresentation of cross-sectional studies [60-61]. While good cross-sectional study designs can lead to valuable insights, they cannot assess temporality, and therefore cannot establish causality. Many cross-sectional studies adjust for confounding factors, but it remains unclear which factors should be included. Selection bias also remains a serious issue. Study participants may choose to live in specific areas based on lifestyle preferences and socioeconomic factors [62]. For example, a physically active person may deliberately choose to live in an area that facilitates physical activity, therefore potentially inflating the relationship between the environmental exposure and physical activity outcome.

Geographical explanations tend to focus more on geographical conceptualizations and the definition of geographical exposures. The aforementioned MAUP and UGCoP offer prime examples of how geographical definitions of environmental exposures can influence study findings. Very little consensus exists on how individuals' environmental exposures should be defined. For example, if we return to the topic of green spaces in the residential environment, basically no consensus exists on how green spaces in the residential environment should be measured or defined. In nearly all health-geographical studies, the term '*green space exposure*' implies the presence of some form of green in the residential environment [10, 63]. However, no definition exists of what such an exposure should measure. Should it consist of all green spaces in a specified area, even if they are very small? Or should it only contain those that are publicly accessible? Similar questions can be asked about what data should be used to measure such exposures. Some studies advocate the use of satellite imagery to construct a *Normalized Difference Vegetation Index* (NDVI), which reflects the light-absorbing capacity of vegetation. Other studies use land use data of varying spatial scales to define green areas [10]. Finally, a lot of debate exists on how the individual's residential environment should be defined. Multiple studies have demonstrated that different buffer techniques and buffer sizes can lead to substantial differences in observed associations [59, 64-66].

Different solutions for these problems have been proposed. Recent research agenda's and review studies all advocate the application of different study designs that make better use of natural variation that exists within the data [60-61, 63]. Longitudinal cohort studies in which participants can be tracked through space and time offer particularly promising prospects. Such studies offer a number of important advancements over cross-sectional study designs. As participants can be tracked, longitudinal cohort studies enable researchers to answer different questions. For example, is a change in exposure over time the result of a change in the environment or is it due to a residential relocation? Recent methodological advancements that have made their way into health geography, enable researchers to exploit this spatio-temporal character of longitudinal cohort studies. Statistical techniques as fixed effects modelling allow researchers to investigate how changes in exposures over time relate to changes in the outcome, providing more insight in how the environmental changes can contribute to health [67-68]. Another technique to potentially improve results from health-geographical studies is to increase variation in exposure. Many health-geographical studies are limited to one city or a handful of cities in one country. However, it is not unlikely that urban environments within one country are relatively similar, which raises concerns of external validity. For example, a recent European-wide study concluded that associations between green space exposures and mortality were more pronounced in Western-European cities [69]. These results raise the question if more variation in exposure could lead to different study results.

The aim of this thesis is to explore variation in urban environments and how it relates to physical activity and mental well-being. Two types of variation in physical-urban environmental exposures are explored: variation between different urban environments, and variation within urban environments over time. We aim to accomplish this goal by using variation that exists both within and between different urban environments. This results in the following research aims:

- **Research aim 1:** To explore variation in physical urban-environmental exposures between cities and within cities over time.
- **Research aim 2:** To explore how physical urban-environmental exposure measures can be harmonized and applied within health research.
- **Research aim 3:** To investigate the extent to which variation in urban physical-environmental exposures between cities or over time relates to mental health and walking and cycling.

Chapter 2 explores the variation in physical urban-environmental exposures both between European cities and within cities over time. Chapter 3 details how urban-environmental exposures can be harmonized. Chapters 4-7 explore the associations between urban physical-environmental exposures measures and health outcomes. Chapter 4 investigates the associations between green space levels in the residential environment and subjective health and well-being in different European cities. Chapter 5 investigates the longitudinal associations between green space levels in the residential environment and mental health, while chapter 6 investigates the longitudinal associations between green space levels in the residential environment and walking and cycling outcomes. Chapter 7 investigates the longitudinal associations between land use mix in the residential environment and walking and cycling outcomes. Chapter 8 concludes with a discussion of the age-friendly city.

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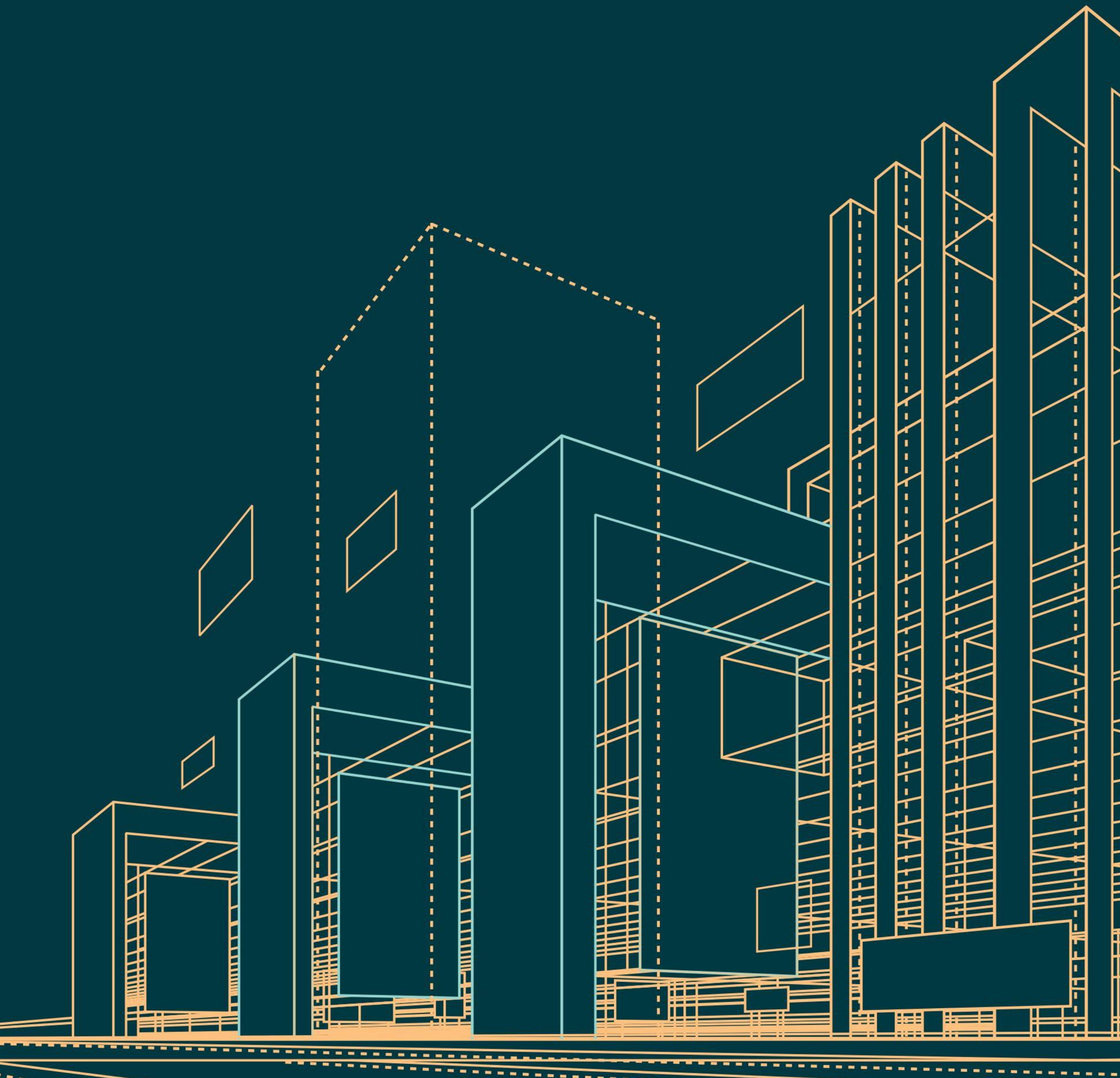

Exploring variation in urban environments and developing a database for health research

2

Variation in urban environments in European cities

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European Union Technical Report

2.1 Introduction

A large number of studies have shown that substantial variations in health outcomes exist across populations living in different urban environments [1-3]. Such studies use quantitative methods to incorporate multiple levels of analysis – from the individual to the socio-urban context – to account for the effect of living in a certain urban environment. Paradoxically however, a large majority of these studies have been conducted within single cities, limiting opportunities to examine how urban characteristics that vary between cities can influence health and behavior both within and between cities. Only a handful of studies exist that have examined associations between urban-environmental factors and health outcomes across different cities and different socio-urban contexts. A recent study examining the associations between urban green spaces and mortality across different European regions concluded that the associations differed between macro-European regions with the effects being more pronounced in Western-European cities [4]. Such studies warrant caution against generalizing findings from studies conducted in one city to another. Furthermore, they suggest that variation between urban-environmental contexts can play an important role in defining the health-environment relationship within an urban setting.

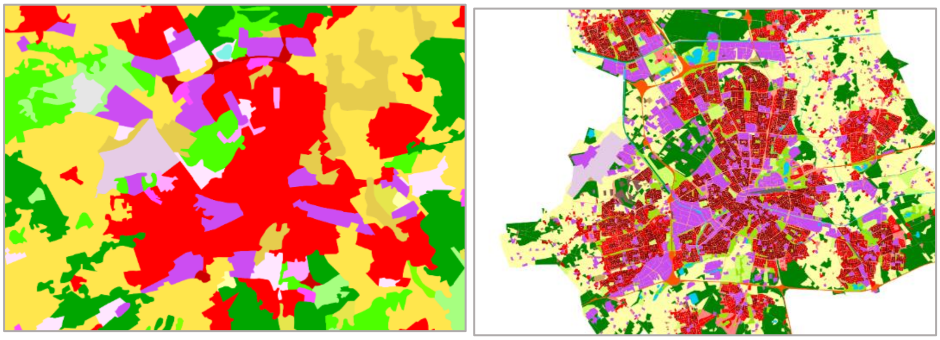
Quantifying variation in urban-environmental characteristics is, however, not an easy task. When quantifying such characteristics not only the characteristics themselves must be considered, but also the spatial scale at which to quantify them. Within the public health literature, a distinction is commonly made between social-environmental characteristics (i.e. the average neighborhood income) and physical-environmental characteristics (i.e. the amount of parks in the neighborhood). Even as this distinction has its limits – can the amount of parks be viewed independently of the social function they facilitate? – it is useful to discern various elements that make-up the urban setting. Physical-environmental urban characteristics commonly include such characteristics as green spaces, street connectivity, land use mix, or air pollution. These environmental characteristics are commonly linked to health outcomes, such as physical activity or mental well-being. The general idea behind such studies is that varying levels of exposure to these urban characteristics can be related to varying levels of health outcomes. For example, neighborhoods with more public parks may be more inviting to walk and therefore a higher number of parks may be associated with more walking. It is assumed that the amount of physical-environmental exposure varies enough that individuals with different levels of exposure can be compared to each other. In general, two approaches can be distinguished. The first approach makes use of variation between individuals exposed to different levels of the exposure of interest. In the example of parks and walking, such a study would assume that individuals living in different parts of the city are exposed to different amounts of green spaces. A second approach is to consider changes within the exposure over time. For example, if a new park is built in a specific neighborhood, is that associated with an increase in walking? This approach assumes that changes in the urban environment occur over time. A distinction can therefore be made between methodological approaches that consider effects *between* different units of analysis (e.g. individuals, neighborhoods) and those that consider changes *within* the units of analyses. What both approaches have in common is that they assume that environmental differences are inherent to city settings; either between the units of analysis or as a result of changes over time. If such differences exist, it is interesting to compare them both between and within cities and to determine if combining different urban environments can possible lead to more variation in environmental exposure.

For this exploration of the variation in physical-environmental urban characteristics, we selected three characteristics to be included: *urban green spaces* (1), *residential density* (2), and *land use mix* (3). These characteristics were all selected based on their potential relevance for health outcomes. Urban green spaces are one of the most commonly researched urban physical-environmental characteristics within the domain of public health research. They are believed to be related to both physical and mental health through a number of different pathways, such as physical activity, attention restoration, and stress reduction [5]. Residential density is an important measure representing urban sprawl, and its health-related effects are an important topic in public health research [6-8]. Land use details the amount of land allocated to a specific function (e.g. residential area). Land use mix is the level of homogeneity between the different types of land uses within a defined area and is commonly used as a proxy measure for overall variation. As such it is commonly linked to health behaviors such as walking and cycling [8-10].

2.1.1 Data sources

To compare the variation in urban-environmental characteristics within European cities, we identified data sources that were available for multiple cities and multiple time-points: the CORINE Land Cover (CLC) dataset, and the Urban Atlas (UA) dataset [11-12]. Both the CLC and UA databases are EU-wide topographical datasets that detail land coverage on different geographical scales and are maintained by the Copernicus Land Monitoring Service. CLC and UA are meant to be used in tandem, with CLC offering an EU-wide coverage on a high geographical scale (i.e. less detailed), while UA offers data on a lower geographical scale (i.e. more detailed), but limited to urban agglomerations with at least 100.000 residents.

Figure 2.1: A comparison between CLC and UA data for the city of Eindhoven, The Netherlands



CLC data offers less detail, but is available for the entire EU. UA data is more detailed, but only available for cities with at least 100.000 inhabitants.

The CLC and UA data were used to compute the land use mix and urban green space measures. The scale of the measures was set to the municipal level to enable comparisons between cities. The residential density measures were based on address databases of each city, again limited to the municipal scale level. These databases contained all addresses within the city border with x and y coordinates.

2.2 Urban green spaces

2.2.1 Developing an indicator of urban green spaces

Within the context of an increasingly urbanizing world, contact with natural environments may play an important role in improving mental and physical health. In order to assess the variation in urban green space levels between different European cities, an indicator of green space on a municipal level was developed. This indicator was based on the UA dataset and was available for two time-points: 2006 and 2012. The indicator was developed for the MINDMAP cities Amsterdam, Eindhoven (The Netherlands), Liberec (Czech Republic), and Paris (France). Two main types of relevant green spaces were identified based on the classifications within the UA data: green urban areas (1), and forest areas (2). For each city, the total amount of both types of green spaces was calculated (in hectares), as well as the percentage of green spaces of the total municipal area. A count measure of the number of green spaces was also calculated. The differences in green space measures between 2006 and 2012 were calculated to give an overview of the changes in green spaces over time.

2.2.2 Results

Amsterdam, The Netherlands
In general, the total area size of green spaces in Amsterdam is relatively low with less than 10% of the total land use of the city allocated to green spaces. Amsterdam therefore ranks the lowest in the relative amount of green space areas among the cities considered in this comparison. The green spaces in the city consist mostly of green urban areas and very few forest areas (90% versus 10% for 2012). Negative changes over time were observed for the forest category with a small decrease in the total area size of forest areas within the

city boundaries (Map & Table 2.2.1). The total area size of green urban areas increased slightly over time, but decreased relative to the total land use area. Amsterdam is the only city in this comparison where the number of green spaces increased slightly between 2006 and 2012 (Table 2.2.5), indicating that more new green spaces were added than removed.

Eindhoven, The Netherlands

The city of Eindhoven is a relatively green city with around 16% of its total land use area consisting of green spaces (Map and Table 2.2.2). Compared to Amsterdam, Eindhoven has more forest areas with 60% of the total green space areas allocated to forests in 2012. The changes in the total area size of green spaces consist of deceases in both green space categories, with a notable decrease of 54 hectares in the total forest area within the municipal boundaries. Furthermore, there appears to have been a number of changes over time with several green spaces being removed or added between 2006 and 2012 (Map 2.2.2 and Table 2.2.5). Overall, almost double the amount of green spaces was removed between 2006 and 2012 compared to those that were added during this time period.

Map 2.2.1: Changes in green spaces between 2006 and 2012 in Amsterdam, The Netherlands

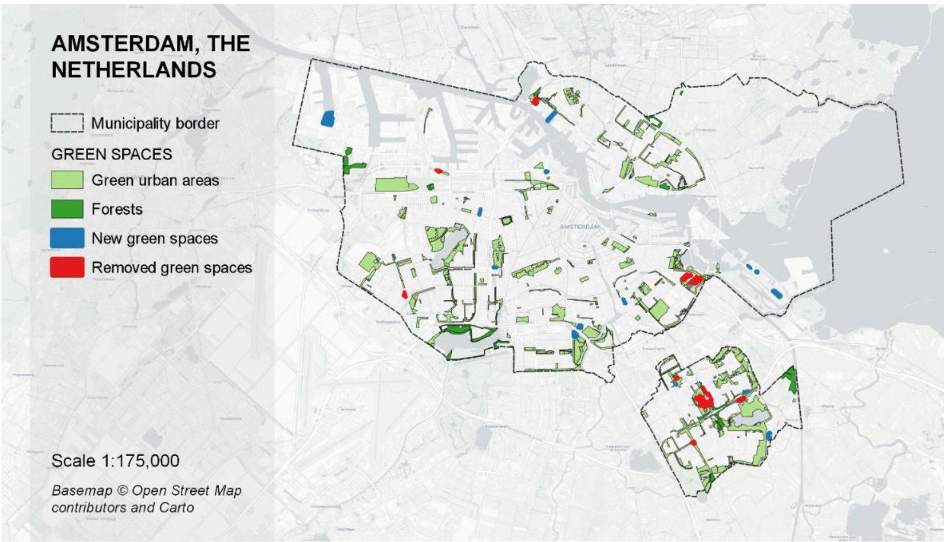


Table 2.2.1: Total amount of green space in hectares and as a percentage of the total land use in 2006 and 2012 in Amsterdam, The Netherlands

	2006	**2012**	**+/-**
Total amount of green urban areas, hectares	1886	1509	+23
Relative amount of green urban areas, %	7.6	6.9	-0.7
Total amount of forest areas, hectares	203	175	-28
Relative amount of forest areas, %	1.0	0.8	-0.2

Map 2.2.2: Changes in green spaces between 2006 and 2012 in Eindhoven, The Netherlands

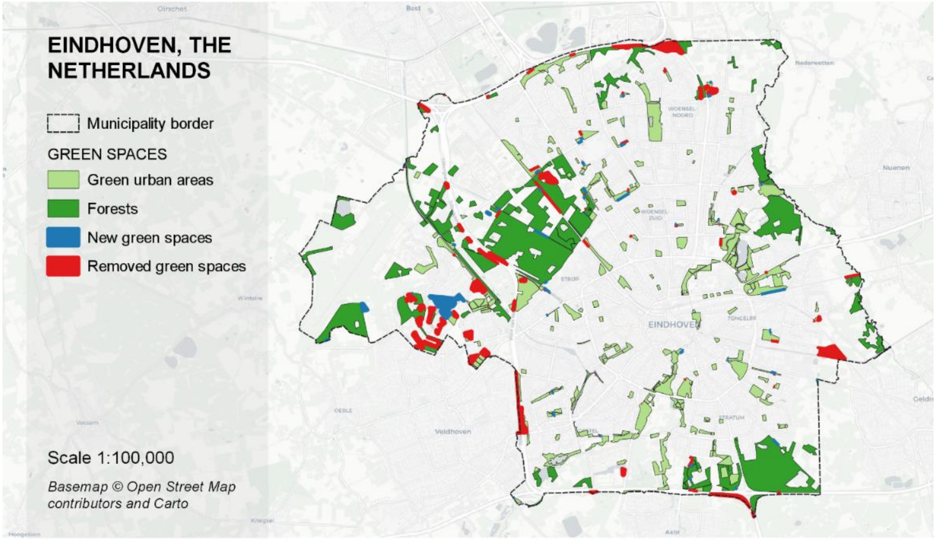


Table 2.2.2: Total amount of green space in hectares and as a percentage of the total land use in 2006 and 2012 in Eindhoven, The Netherlands

	2006	**2012**	**+/-**
Total amount of green urban areas, hectares	574	569	-5
Relative amount of green urban areas, %	6.5	6.4	-0.1
Total amount of forest areas, hectares	907	853	-54
Relative amount of forest areas, %	10.2	9.6	-0.6

Liberec, Czech Republic

Liberec is the greenest city included in this comparison with almost half of the land use area within the municipality borders consisting of green spaces. 44% of the municipal area is covered in forest, which is mostly the result of large forest areas near its borders. The city has seen a relatively modest reduction in both green urban and forest areas between 2006 and 2012. The number of green spaces was also reduced with more green spaces being removed than added between 2006 and 2012 (Table 2.2.5).

Paris, France

Paris is the city with the highest relative amount of green urban areas included in this comparison with it being the only city with more than 10% of its total land use area allocated to green urban areas (Table 2.2.4). In terms of total green spaces, it is most comparable with Eindhoven with both cities averaging around 15% green space. The changes in the area size of both green space categories appear to be relatively small with a slight decrease in area size for both green space categories. The number of green spaces was reduced between 2006 and 2012 with exactly double the number of green spaces being removed than added (Table 2.2.5).

Map 2.2.3: Changes in green spaces between 2006 and 2012 in Liberec, Czech Republic

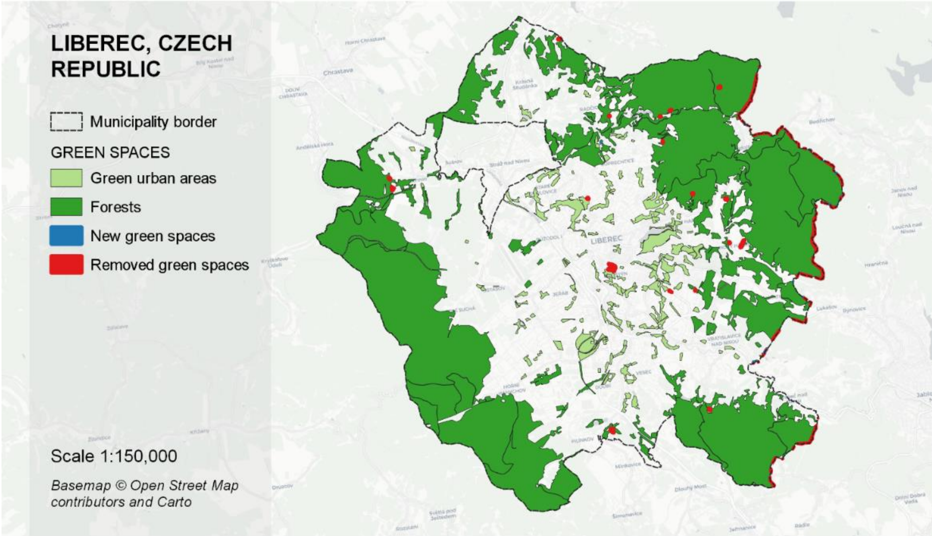


Table 2.2.3: Total amount of green space in hectares and as a percentage of the total land use in 2006 and 2012 in Liberec, Czech Republic

	2006	2012	+/-
Total amount of green urban areas, hectares	384	380	-4
Relative amount of green urban areas, %	3.6	3.6	0
Total amount of forest areas, hectares	4736	4715	-21
Relative amount of forest areas, %	44.7	44.5	-0.2

Map 2.2.4: Changes in green spaces between 2006 and 2012 in Paris, France

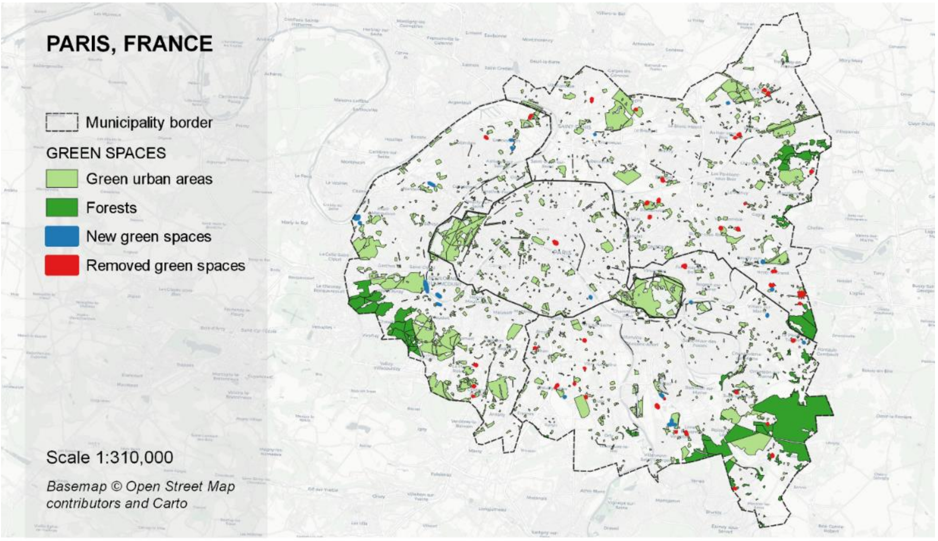


Table 2.2.4: Total amount of green space in hectares and as a percentage of the total land use in 2006 and 2012 in Paris, France

	2006	**2012**	**+/-**
Total amount of green urban areas, hectares	8034	8020	-14
Relative amount of green urban areas, %	10.5	10.5	0
Total amount of forest areas, hectares	3342	3337	-5
Relative amount of forest areas, %	4.4	4.4	0

Table 2.2.5: Total number of green spaces in 2012 and changes in the number of green spaces between 2006 and 2012

Green space added and removed between 2006 and 2012, count	Total	Added	Removed	+/-
Amsterdam, The Netherlands	471	16	14	+2
Eindhoven, The Netherlands	325	58	101	-43
Liberec, Czech Republic	281	35	80	-45
Paris, France	1823	21	42	-21

2.2.3 Discussion

Based on the green space indicators in this comparison, it can be concluded that there is quite some variation in green space levels between different European cities, and that there is some variation over time in green space levels. Of the cities considered, Amsterdam has the lowest overall amount of green spaces with 7.7% of its total land use area dedicated to green spaces in 2012 compared to 48.1% for Liberec (Table 2.2.6). Considerable differences exist in the amount of green spaces per subtype (green urban areas or forests). Larger, more metropolitan areas, such as Amsterdam and Paris, have very low levels of forests areas, but relatively more green urban areas, which is especially true for Paris. In terms of total land use areas dedicated to green spaces in 2012, Paris and Eindhoven appear relatively comparable with 14.9% and 16.0% of green space coverage. However, in Eindhoven 9.6% of this coverage is forests while for Paris this is 4.4%. A second conclusion from this comparison therefore has to be that while cities can have similar levels of total green space coverage, this coverage can differ per subtype. Some evidence suggests that different types of green spaces can impact health outcomes in different ways [13]. It would therefore be good practice to consider not only total green space coverage, but also coverage of specific types of green spaces.

Table 2.2.6: Total amount of green space in hectares and as a percentage of the total land use in 2006 and 2012

	2006		2012	
	Hectares	%	Hectares	%
Amsterdam, The Netherlands	2089	8.6	1684	7.7
Eindhoven, The Netherlands	1481	16.7	1422	16.0
Liberec, Czech Republic	5120	48.3	5095	48.1
Paris, France	11376	14.9	11357	14.9

The number of green spaces in each city and how that number changes over time also warrants the inclusion of different types of green space measurements (Table 2.2.5). Liberec has the most relative green space coverage of all cities, but has the lowest number of green spaces. On average, Liberec's green spaces are larger than those in the other cities (Table 2.2.7). A change in the number of green spaces might therefore be more consequential in Liberec when compared to Amsterdam, where the average size of a green space is much smaller. However, Amsterdam has the overall lowest green space coverage, so the argument could also be made that the removal of a green space in Amsterdam would impact health outcomes more severely compared to Liberec.

Table 2.2.7: Mean and median green space sizes in 2012 in hectares

	Mean	Median
Amsterdam, The Netherlands	3.6	1.4
Eindhoven, The Netherlands	4.4	1.5
Liberec, Czech Republic	18.1	2.0
Paris, France	6.2	1.2

Based on this exploration of green spaces on a municipal level, including multiple measures of green spaces would be highly advised. Different green space measures represent different aspects of the physical-urban environment and therefore careful consideration should be given to how the green space measure relates to the outcome of interest. Furthermore, there are substantial differences in green space levels between different cities. Including measurements from multiple cities therefore has the potential to increase variation in environmental exposure. These results also warrants some caution against generalizing findings linking green spaces to health outcomes from one city to another as the differences in green space levels, as well as the make-up of those green space measures, can vary. Some exploratory evidence suggests that the associations between green space exposures and health outcomes can vary substantially between different European regions [4]. Including multiple cities from preferably different European regions should therefore be considered good practice; especially in cross-sectional study designs.

The changes in green spaces over time appear to be relatively limited when the total area size of green spaces is considered. However, when considering the changes ipso facto, there appears to be more variability. Green spaces are both added and removed over time, resulting in quite some changes and a net decrease in the number of green spaces for three of the four cities. These changes can be particularly useful to study how a change in green space exposure over time can relate to health outcomes. For example, the city of Eindhoven saw a negative change of 54 hectares or 6% of the total forest area between 2006 and 2012, as well as a relatively high amount of green spaces removed in this time period. These changes make it plausible to assume that a sizable amount of the population of Eindhoven would be impacted by a change in green space exposure over time, because a green space gets removed or added in their residential environment. These changes may not be visible in the total amount of green space area on the municipal level, but may be visible on a smaller scale. The geographical scale chosen for the calculation of exposure measures can therefore impact individual exposures. Careful consideration should therefore be given to the geographical scale of green space exposure calculations. This is especially relevant for research that considers changes over time, where geographical scales should be comparable in order to accurately represent actual changes in green space exposure over time that are not the result of changes in geographical boundaries.

More geographical research may provide more insight into the processes that determine how green cities can be. For example, Amsterdam might not have much space left to add new green spaces when compared to Eindhoven, which results in less changes over time. Conversely, specific policy priorities may also limit room for green spaces to be added. This potentially impacts how green spaces relate to health outcomes as the relative impact of a change in green spaces may be experienced differently between populations from different cities. For example, a 1% reduction in green space may lead to a less pronounced effect in a very green city as Liberec when compared to Amsterdam, but represents a higher absolute amount. Finally, it is important to consider the time frame of the expected changes. By default the physical-urban environment does not seem very susceptible to large changes in short time periods. Expanding the time frame considered, may aid in observing more changes and therefore increasing variation in exposure.

2.3 Residential density

2.3.1 Developing an indicator of residential density

Residential density is a measure that represents urban sprawl and how spread-out residents of cities are across the available space. Instinctively, dense environments are thought of as urban and, as such, are often juxtaposed against less dense towns or rural villages. It is therefore commonly considered to be one of the concepts reached for when asked: what makes a city [15]? In recent years, density and compact city building have been advocated as economically and environmentally smart ways to improve urban environments. Dense and compact cities could allegedly lower carbon emissions, promote and agglomerate job creation, and increase walking and cycling [7, 16-18]. Density has therefore become the next-in-line in studies that look at more composite measures of urban environments and how they relate to health outcomes. In the same way as land use mix can be thought of as a more broad, encompassing measure compared to looking at just green spaces, density can be thought of as a broader measure of urban form.

However, like land use mix, density has no pre-given topography making it hard to measure. Despite the tendency to conflate density with centrality, density can take on numerous forms; both physical and social. Density can be considered as a topological or networked phenomenon connecting spaces in ways that have consequences for other spaces [15]. It can take on physical forms, such as dense infrastructure networks or dense housing, or it can take on more social forms, such as density of jobs or services. Urban density as it is most often considered in health research relates to the (relative) amount of residents within a geographical area, the distribution of these residents among set area, the amount of (residential) addresses in a geographical area, or a combination of all of these [6]. For this exploration, density will be defined as the amount of addresses within the municipal borders. This choice was driven by the aim to generate a meaningful comparison between different cities. By using address databases, a measure of residential density was developed on a geographical scale that was equal for all cities. The address databases contain all addresses within the city borders with x and y coordinates, which were subsequently imported into a geographical information system (GIS) and converted to a raster grid with 1 by 1 centimeter cells. The residential density was measured as the amount of addresses within a 50 meter radius of the individual cells.

The city-level densities were subsequently converted to heatmaps that show the density of addresses on a yellow-orange-red color continuum. Two heatmaps were made for each city: one representing the distribution of the density *within* the city, and one with the densities as compared *between* the different cities. In order to generate informative heatmaps, the residential density data was grouped into different classes. For the first heatmap a continuous classification was used that best represented the density within the specific city. This classification uses a cut-off point of 98% which means that the highest value of the classification covers 98% of all density values in that city. For example, for Paris this value was 11.8. This means that 98% of the density values in Paris are between 0 and 11.8. This classification ensures that the heatmap gives a good overview of how different densities are spread across the city. The second heatmap of each pair uses a different classification that is comparable between the cities. All density values were grouped into classes with a difference of 5 points. 5 classes were made, spanning a range between 0 – 20 with five-point intervals. This classification might not be appropriate for each city individually, but enables a comparison between different cities as the classes are equal.

To generate a comparable measure of residential density between different cities, address databases with all addresses within the municipal borders were used. Address databases are one of the components of the European INSPIRE directive, which establishes a data infrastructure for the collection and distribution of spatial information in the European Union [19]. As such, address databases are available via the INSPIRE network. As the INSPIRE directive is still a work in progress, address data availability was limited. The aim was to match the data years for the address data as closely as possible. For Amsterdam and Eindhoven, data from 2018 was used. For Paris data from 2017 was used and for Liberec data from 2015.

2.3.2 Results

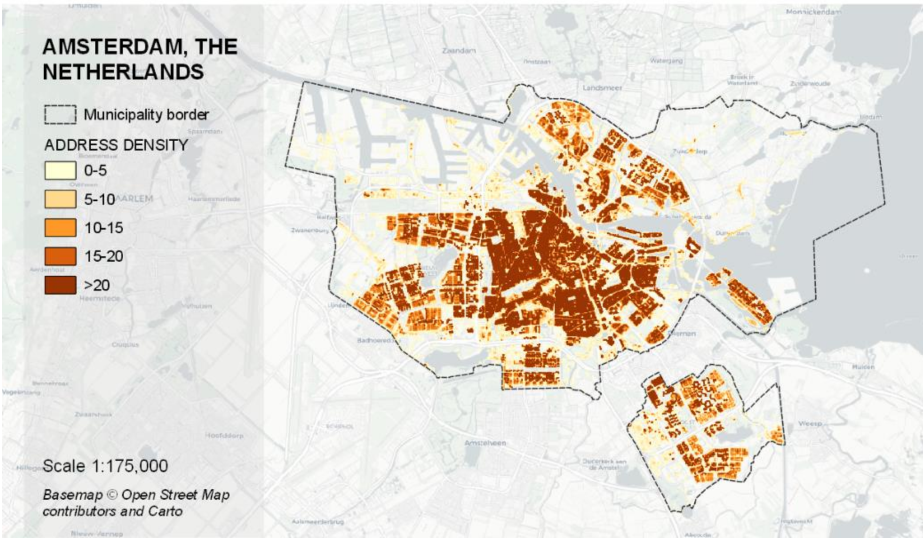
Amsterdam, The Netherlands

Amsterdam has the highest residential density of the cities in this comparison. 98% of the grid cells have between 0 and 74.1 addresses within a 50 meter radius. The mean density is 17 with a standard deviation of 26. This is especially high when compared to the other cities in the comparison. For example, Paris – the other capital city in this comparison – has a 98% cut-off value of 11.8 and a mean density of 3.9. The geographical spread of Amsterdam's density follows a classic concentric design where the densest areas are concentrated in or around the city center with density decreasing near the edges.

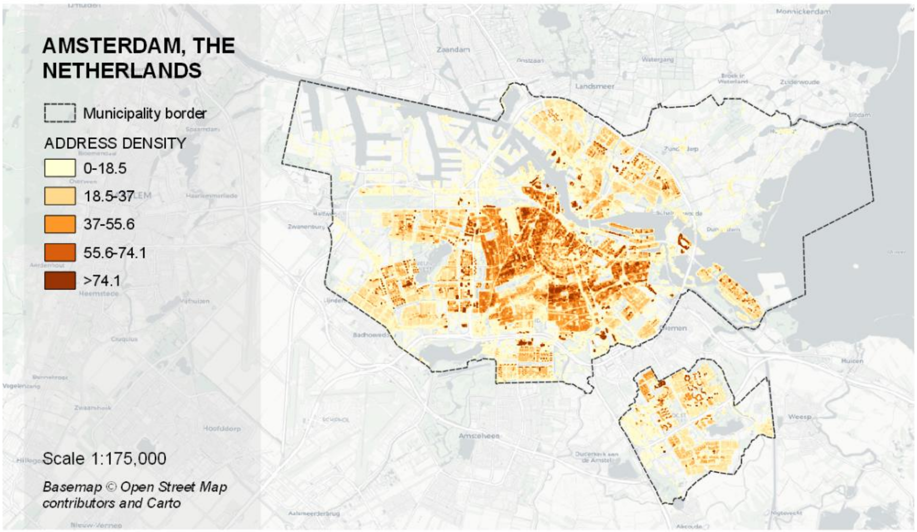
Eindhoven, The Netherlands

Eindhoven has a much lower 98% cut-off compared to Amsterdam, but with a value of 22.4 it is still relatively high compared to the other European cities. It has a mean density of 5 and a standard deviation of 8. As with Amsterdam, the densest areas are located in or near the city center, but Eindhoven's densities appear to be more spread-out with small pockets of very dense areas near the southern and northern municipal borders.

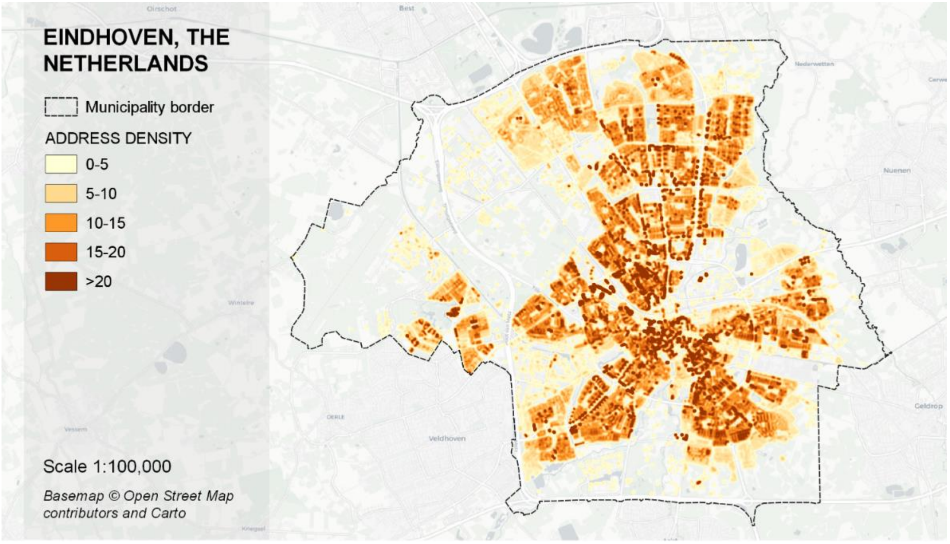
Map 2.3.1: Address density in 2018 in Amsterdam, The Netherlands using a harmonized classification



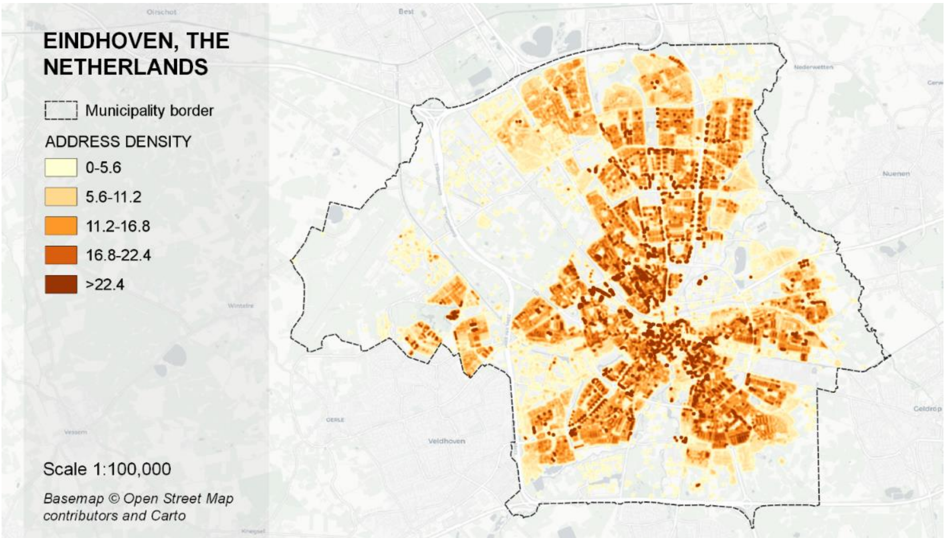
Map 2.3.2: Address density in 2018 in Amsterdam, The Netherlands using a city-specific classification



Map 2.3.3: Address density in 2018 in Eindhoven, The Netherlands using a harmonized classification



Map 2.3.4: Address density in 2018 in Eindhoven, The Netherlands using a city-specific classification



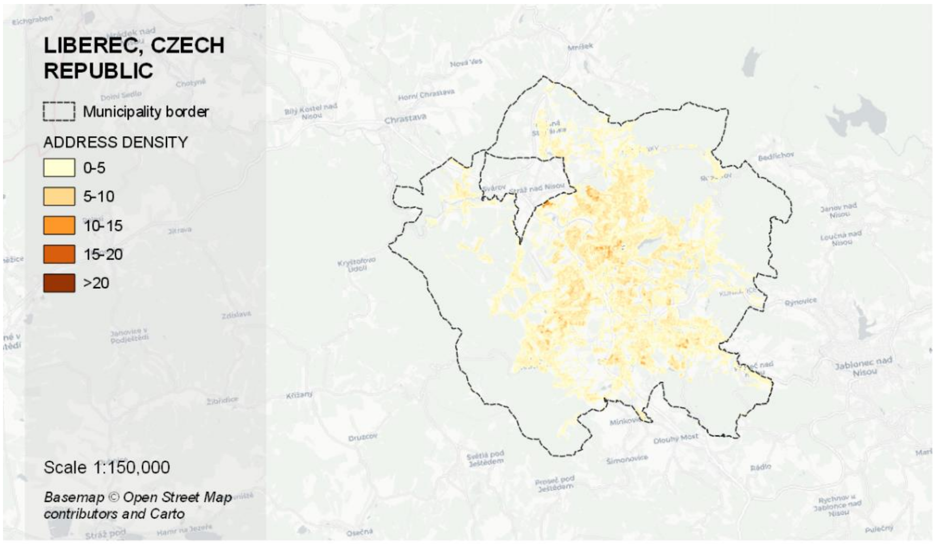
Liberec, Czech Republic

Liberec has the lowest density of the cities in this comparison with an average density of 1.2 addresses and a standard deviation of 1.3. Its 98% cut-off value of 4 is lower than the means of Amsterdam and Eindhoven. Compared to the Dutch cities, the pattern of dense areas appear to be more evenly spread-out across the inhabited areas.

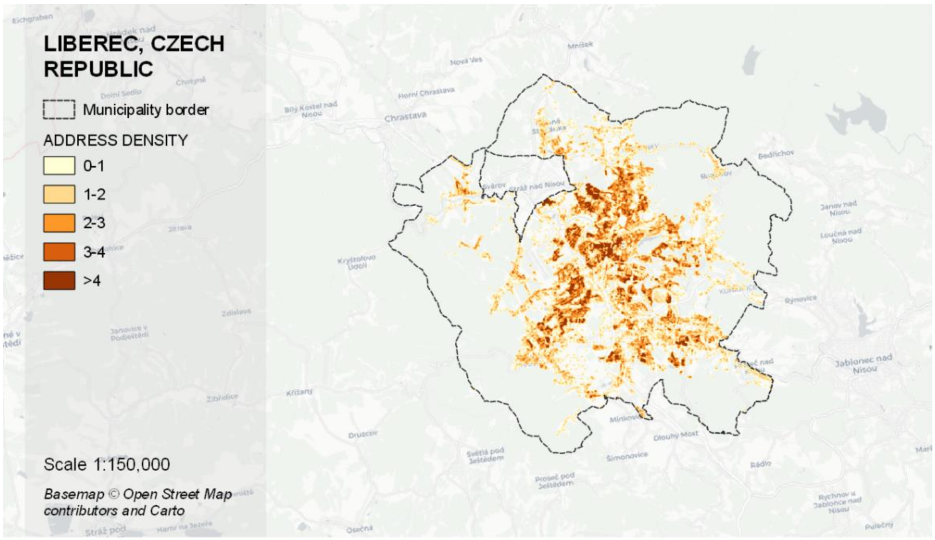
Paris, France

Paris has an average density of 3.9 with a standard deviation of 3.5, and a 98% cut-off value of 11.4. Compared to both Amsterdam and Eindhoven, the average density in Paris is much lower. For example its densest areas would only be considered to be moderately dense in Eindhoven. Paris' density is also more evenly spread across its metropolitan area, with no clear concentric design evident.

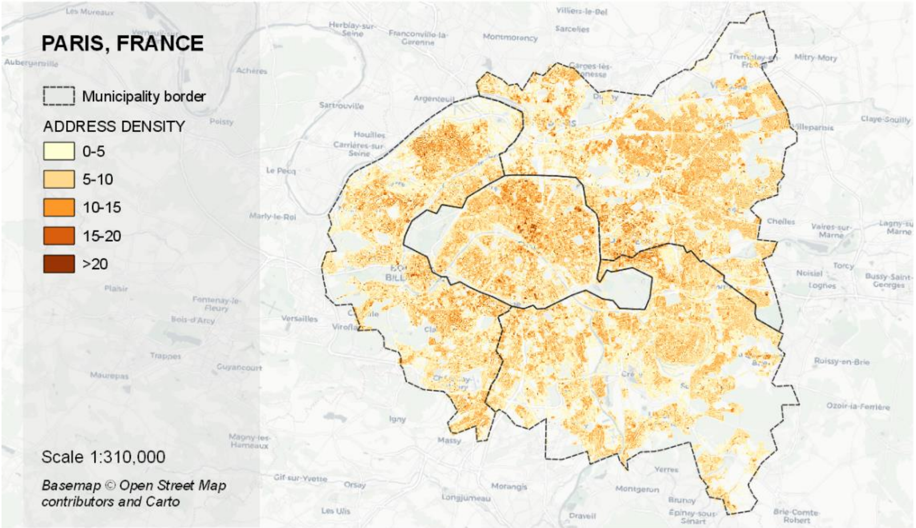
Map 2.3.5: Address density in 2015 in Liberec, Czech Republic using a harmonized classification



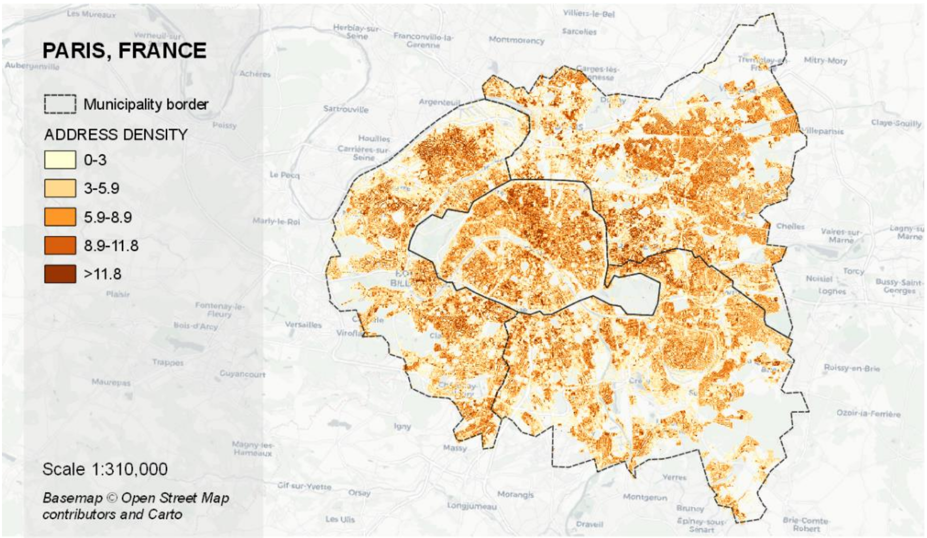
Map 2.3.6: Address density in 2015 in Liberec, Czech Republic using a city-specific classification



Map 2.3.7: Address density in 2017 in Paris, France using a harmonized classification



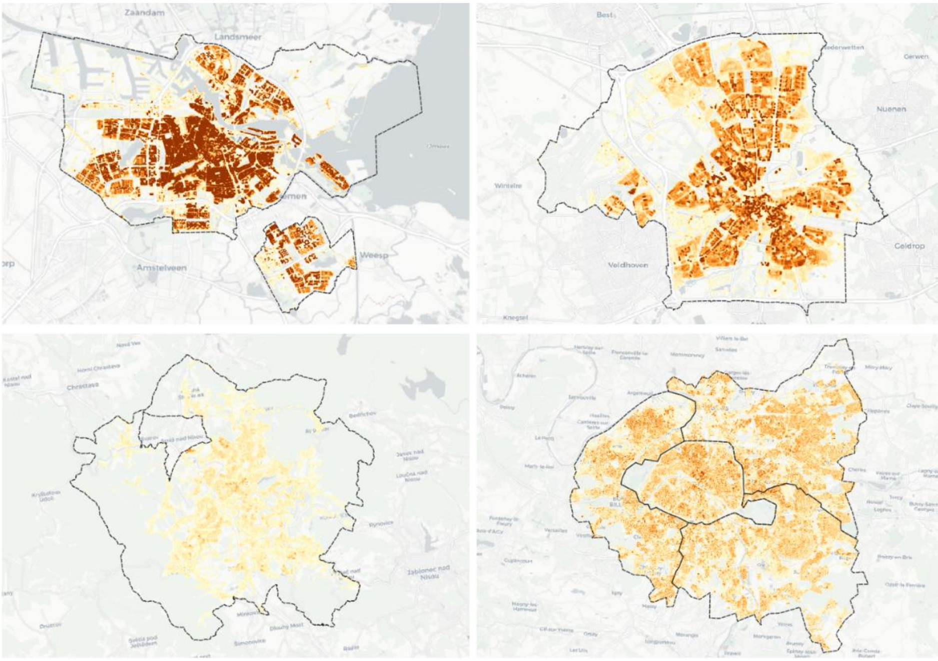
Map 2.3.8: Address density in 207 in Paris, France using a city-specific classification



2.3.3 Discussion

Based on the density measures presented in this comparison, it can be concluded that there is substantial variation in residential density between different European cities (Map 2.3.9). On average, the density is highest in the Dutch cities Amsterdam and Eindhoven, where even the mean values are higher than 98% of the density values of the Czech city Liberec. Furthermore, it appears that the densities are spread-out more evenly in Liberec and Paris, as compared to the Dutch cities, where the densities are the highest in or near the city center.

Map 2.3.9: Address density in Amsterdam, Eindhoven, Liberec, and Paris using a harmonized classification



By calculating residential densities using a cell-based raster, it is possible to calculate density values on a very detailed scale and to calculate densities that are comparable between different cities. The detail level is especially important when residential density is concerned as large variations can exist within a very small geographical area. For example, one street might consist of multiple low density housing blocks, while the next street has multiple high density apartment blocks. On a higher geographical level, these densities may level out to an average that would not do the variation justice. As with the previous measure of green spaces, the geographical scale of the measure plays an important role in defining the exposure. The resulting heatmaps give important insight into where dense areas are located in a city compared to other areas within that same city, as well as how the density between cities compare to each other.

As discussed in the brief introduction on the concept of density, density can take on many forms; both social and physical. The density indicator discussed in this chapter only gives insight into one specific type of density: the density of addresses. This density measure can be considered to be a proxy measure of residential density as it shows how many addresses are located in a specific geographical area. However, it contains no information on the amount of residents that live at each address and therefore lacks the social dimension of a more traditional population density measure. This does mean that it is less sensitive to privacy concerns. When health outcomes are considered, residential density is an important (proxy) exposure measure as it represents how many people live together in a specific geographical space. However, not much is known on potential health effects of other density types, such as infrastructural density or the density of jobs. When considering density as topological or networked, it is likely that different types of densities influence each other. For example, increasing residential density could lead to increased infrastructural density leading to possible multiplier effects when health outcomes are considered. Different variations of urban density each come with their own strengths and weaknesses and therefore should therefore be considered as complementary.

2.4 Land use mix

2.4.1 Developing an indicator of land use mix

Land use mix represents how evenly different types of land use are distributed within a specified area. Within urban environments, mixing different types of land uses within close proximity is thought to lead to complementarity with each land use type enhancing the utility of its partners. Potential benefits are believed to include the promotion of active travel, reducing private vehicle use, increasing the viability of different modes of transportation, and building a sense of place [20]. Within public health research, land use mix is often used as a proxy measure for destinations and overall variation within the urban environment. Areas with a variety of interesting and complementary destinations are thought to encourage active travel modes with associated health benefits.

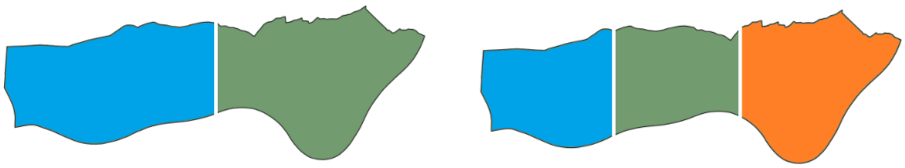
A commonly used indicator for land use mix is the entropy score pioneered by mathematician Claude E. Shannon in his 1948 book *A Mathematical Theory of Communication*, and adapted for public health research by Frank & Pivo in 1994 [21]. As a measure, it accounts for the relative percentages of a number of distinct land uses within a specified area. The term "entropy" refers to a statistical mechanic where two bodies of fluid will naturally mix and integrate over time. The land use mix entropy score therefore represents a value of mixture with higher scores corresponding to higher levels of mixing.

The land use mix entropy score can be calculated using the following formula:

$$LUM = -\frac{\left[\sum_{j=1}^{N} p^j \ln(p^j)\right]}{\ln(N)}$$

whereby LUM is an entropy score with a value between 0 and 1, p^j is the percentage of each land use type j of the total area, and N the total amount of land use classes. The calculated entropy value represents a measure of heterogeneity, whereby 1 represents a perfect mix of land use classes and 0 no mix of classes. As the land use mix entropy measure represents the amount of heterogeneity between land use classes, the specification of the total amount of classes in each area – denoted in the formula by N – becomes an integral part. For example, consider two hypothetical neighborhoods A en B (Figure 2.4.1). Neighborhood A consists of two types of land use (i.e. residential areas and green spaces), while neighborhood B consists of three types of land uses (i.e. residential areas, green spaces, and commercial areas). Assuming that the total amount of land use classes available is three ($N = 3$), neighborhood A should have an entropy score <1, while neighborhood B's entropy score would equal 1, indicating perfect mix. In this example, N is set to a fixed value (3) that represents the total amount of available land use classes.

Figure 2.4.1: Two hypothetical neighborhoods representing a land use mix of 50% - 50% (A) and 33% - 33% - 33% (B)



A B

Now consider the same two neighborhoods, but let N denote the amount of actually available land use classes in the neighborhood. Specifying N in this way would lead to a value of 2 for neighborhood A and a value of 3 for neighborhood B. The entropy score of both neighborhoods would be 1 in this example, indicating a perfect land use mix for both.

While an argument can be made that setting N to vary across neighborhoods leads to an overestimation of land use mix [22], the definition of N ultimately comes down to a conceptual question: do we expect that a perfect mix of all defined land use classes influences our outcome of choice? Or do we think that only the amount of heterogeneity – unconditional of the amount of different types of land uses in the area – is the most important factor? As the goal of this chapter is to compare urban characteristics between different European cities, the choice was made to set N to a fixed number of classes. As the same dataset is used for all cities, setting N to a fixed number of classes enables a valid comparison between the different urban environments. The land use mix in this chapter therefore represents how mixed different urban environments are when compared to an optimal mix were every land use class is evenly represented.

For the MINDMAP project, land use categories relevant for mental well-being were defined based on the original classification present in the UA dataset (Table 2.4.1). As with the previous indicators, the land use mix calculation was limited to the municipal areas of each city.

Table 2.4.1: Land use classifications within the MINDMAP project compared to the original classifications as present in the Urban Atlas dataset

Land use category	Urban atlas classification
1. Built areas	Continuous urban fabric (S.L. : > 80%) Discontinuous dense urban fabric (S.L. : 50% - 80%) Discontinuous low density urban fabric (S.L. : 10% - 30%) Discontinuous medium density urban fabric (S.L. : 30% - 50%) Discontinuous very low density urban fabric (S.L. : < 10%)
2. Industrial & commercial	Industrial, commercial, public, military and private units
3. Infrastructure	Fast transit roads and associated land Other roads and associated land Railways and associated land
4. Ports	Airports Port areas
5. Green urban areas	Green urban areas
6. Facilities	Sports and leisure facilities
7. Agriculture	Arable land (annual crops)
8. Other natural areas	Forests

	Herbaceous vegetation associations (natural grassland, moors...) Open spaces with little or no vegetation (beaches, dunes, bare rocks) Pastures
9. Blue spaces	Water Wetlands
10. Other	Construction sites Isolated structures Land without current use Mineral extraction and dump sites

2.4.2 Results

The land use mix indicator on a city level was calculated for the MINDMAP cities *Amsterdam, Eindhoven* (The Netherlands), *Liberec* (Czech Republic), and *Paris* (France). For the calculations only the UA data was used as it provides the most detailed classification of land use classes. The indicator was calculated for 2006 and 2012 with the exception of Liberec were only data for 2006 was available. All data was limited to the area within the municipal borders.

Amsterdam, The Netherlands

Amsterdam has a high amount of land use mix with an entropy value of 0.88 for both 2006 and 2012 (Table 2.4.2). As a port city, it is a relatively blue city with 25% of its land use dedicated to blue spaces in 2006. The built areas and industrial & commercial areas have expanded between 2006 and 2012, while the agricultural land uses see the largest drop. The amount of changes is limited, however, which is to be expected as changes to the entire land use mix in a municipality would acquire large shifts in land use allocations. Specific types of land use are clustered in certain parts of the municipal area. The built areas correspond closely to the residential density presented in the previous paragraphs. The municipality also has a relatively high amount of agricultural land uses, but most of them are clustered in the northeastern part of the municipality. So while the total land use mix on a municipal level is very mixed, it would be reasonable to assume that this can differ greatly between different geographical scales.

Table 2.4.2: Land use in 2006 and 2012 in Amsterdam, The Netherlands

Land use category	**% of total area 2006**	**% of total area 2012**	**Change**
1. Built areas	19.9	20.5	+0.6
2. Industrial & commercial	7.8	8.9	+1.1
3. Infrastructure	10.4	10.5	+0.1
4. Ports	5.5	5.7	+0.2
5. Green urban areas	6.8	6.9	+0.1
6. Facilities	4.2	4.4	+0.2
7. Agriculture	16.7	15.4	-1.3
8. Other natural areas	0.9	0.9	-
9. Blue spaces	25.0	24.6	-0.4
10. Other	2.6	2.1	-0.5
Total land use mix	**0.876**	**0.877**	**+0.001**

Eindhoven, The Netherlands

With an entropy score of 0.86, Eindhoven also has a high amount of land use mix (Table 2.4.3). Compared to Amsterdam, it has a comparatively high amount of other natural areas, which contain forests and natural landscapes. This increase has most likely come at the expense of agricultural land uses which see a large drop between 2006 and 2012.

Table 2.4.3: Land use in 2006 and 2012 in Eindhoven, The Netherlands

Land use category	% of total area 2006	% of total area 2012	Change
1. Built areas	27.3	26.4	-0.9
2. Industrial & commercial	17.9	17.8	-0.1
3. Infrastructure	12.3	12.4	+0.1
4. Ports	3.4	3.3	-0.1
5. Green urban areas	6.5	6.1	-0.4
6. Facilities	4.0	3.8	-0.2
7. Agriculture	15.2	8.1	-7.1
8. Other natural areas	10.2	18.6	+8.4
9. Blue spaces	1.3	1.3	-
10. Other	1.9	2.1	+0.2
Total land use mix	**0.864**	**0.860**	**-0.004**

Liberec, Czech Republic

Liberec has a relatively low land use mix with a value of 0.68 (Table 2.4.4). This comparatively low overall mix is the result of a large amount of natural areas that total almost 45% of the total land use. As with Amsterdam, it is likely that the land use mix will differ greatly between different geographical scales as certain land uses are concentrated in certain areas of the municipality.

Table 2.4.4: Land use in 2006 in Liberec, Czech Republic

Land use category	**% of total area 2006**
1. Built areas	17.3
2. Industrial & commercial	6.5
3. Infrastructure	4.5
4. Ports	-
5. Green urban areas	3.6
6. Facilities	1.6
7. Agriculture	20.0
8. Other natural areas	44.7
9. Blue spaces	0.2
10. Other	1.5
Total land use mix	**0.681**

Paris, France

Paris is the only city in this comparison that sees a noticeable change in land use mix between 2006 and 2012 with its overall mix dropping from 0.73 in 2006 to 0.70 in 2012. Built areas make-up the largest part of the municipality and have also seen the largest increase between 2006 and 2012. (Table 2.4.5). This increase appears to come at the cose of industrial & commercial land uses which have dropped with a comparable amount. Other noticeable changes are an increase in green urban areas and a decrease in agricultural areas of around the same amount.

Table 2.4.5: Land use in 2006 and 2012 in Paris, France

Land use category	% of total area 2006	% of total area 2012	Change
1. Built areas	41.5	43.7	+2.2
2. Industrial & commercial	18.4	15.9	-2.5
3. Infrastructure	13.2	13.8	+0.6
4. Ports	2.9	3.0	-0.1
5. Green urban areas	9.1	11.0	+1.9
6. Facilities	4.0	4.1	+0.1
7. Agriculture	3.6	1.6	-2.0
8. Other natural areas	4.4	3.7	-0.7
9. Blue spaces	2.0	2.1	+0.1
10. Other	1.0	1.1	+0.1
Total land use mix	**0.726**	**0.704**	**-0.022**

2.4.3 Discussion

Based on the data on land use mix on a municipal level, it can be concluded that there is some variation in land use mix between different European cities, but that changes between 2006 and 2012 within each city are limited (Table 2.4.5). The land use mix calculated in this comparison is based on data on the municipal level. This data gives a good overview of how different land uses are distributed within cities, but this methodology of calculating land use mix is very susceptible to the geographical scale at which it is calculated. The total land use mix is calculated based on the formula described in paragraph 2.4.1. This formula accounts for the proportion of each land use within a specified area (i.e. the total municipality). However, the land use maps show that different land uses are not evenly spread across the municipal areas. It is therefore likely that when the same calculations would be performed on a different geographical scale – for example a neighborhood scale – that they would produce different results based on where the neighborhood is located. This measure of land use mix therefore seems to be susceptible to the scale at which it is calculated. When using land use mix measures in empirical research, it is therefore important to consider the geographical scale of the exposure in relation to the outcome. For example, if the outcome of interest is walking a smaller scale might be more relevant.

Table 2.4.5: Land use mix in 2006 and 2012 in different European cities

	Land use mix 2006	**Land use mix 2012**	**Change**
Amsterdam, The Netherlands	0.876	0.877	+0.001
Eindhoven, The Netherlands	0.864	0.860	-0.004
Liberec, Czech Republic	0.681	-	-
Paris, France	0.726	0.704	-0.022

The land use mix measures calculated in this chapter are based on 10 land use classes that were defined based on their relevance for mental well-being. The entropy measure represents the amount of mix that exists between all these classes. However, optimal mix between *all* classes might not always be a desired outcome. For example, some classes might not be relevant to the research question or the outcome of an empirical study. When we consider walking as an outcome, land uses as green spaces and facilities might be positively related to the outcome, but industrial or port areas may be negatively related to the outcome. The land use entropy score captures the mix between all of these classes, but does not account for how individual classes relate to the outcome of interest. The entropy measure is therefore very much a measure of heterogeneity. The key assumption is that an optimal mix of *all* classes is desirable. It is also possible to exclude some classes from this mix, because they are not relevant to the outcome, but this would lead to a fundamentally different research question: how does the mix of *desired* land use classes relate to the outcome? Both research questions are valid and interesting, but they are fundamentally different. Defining the research question of interest and its relation to the type of land use mix, is therefore an essential part of any study that uses land use mix as a measure of exposure.

2.5 Discussion and conclusions

Empirical studies linking urban-environmental exposures to health outcomes commonly rely on some form of variation in environmental exposures between the units of analyses. It is often assumed that sufficient variation exists between the units of analyses; either within neighborhoods or within cities. Potential strategies to increase this variation are to include multiple cities – that preferably differ from each other in the exposure of interest – or to include multiple measurements taken at different time-points. This chapter aimed to provide more insight into this variation by examining three commonly used exposure measures that represent a part of the physical-urban environment: green spaces, residential density, and land use mix. Environmental exposures based on these characteristics were calculated for four European cities from the MINDMAP project and two time points: Amsterdam, The Netherlands; Eindhoven, The Netherlands; Liberec, Czech Republic; Paris, France. European data from the Urban Atlas was used to calculate environmental exposures for the years 2006 and 2012. These measures were calculated on the municipal level to provide more insight into how these cities can be compared on these commonly used exposure measures.

Based on the exploration of these environmental exposures on a municipal level, it can be concluded that some degree of variation exists between different cities and over time. When the strategy is to increase variation in exposure, it is important to select urban environments that are suited for the research question. For example, if the research question relates to green space exposure – and the strategy is to maximize variation in exposure – careful attention has to be paid to the selection of cities. Eindhoven and Paris, while very different cities in a lot of respects, share very similar overall green space levels with 16.0% and 14.9% in 2012 respectively. If maximizing variation in exposure is the goal, it would make more sense to include Amsterdam and Liberec, whose green space levels are much further apart.

It can also be concluded that large variation in exposures exists *within* each city. For example, Liberec has a relatively high amount of green spaces with around 48% of its total municipal area dedicated to some sort of green space. However, as the maps in this chapter show, much of the green space is located near the borders of the municipality. The higher green space levels may therefore not necessarily translate to individual observations. For example, if all respondents live near the city center it is likely that their green space measurements would differ much from respondents living in Amsterdam. So while the general idea of increasing variation in exposure by including multiple urban environments seems sound, it remains to be seen whether this actually translates to more variation in individual exposures.

While variation within cities over time appears to be more limited than variation between cities, some changes were observed. These measurements over time are, however, very much reliant on data quality and harmonization. The UA dataset is a high quality dataset that uses detailed land use polygons based on satellite imagery. These polygons get categorized as a specific land use based on certain criteria and cut-off values described in the data manual. However, each polygon can only be given one value even if it may house several different uses or functions. For example, an apartment complex with shops on the ground floor can only be classified as one of either categories. This is an issue that plagues land use data in general and is not specific to the Urban Atlas data. It does, however, warrants caution on the importance of data quality. The larger the scale of the data, the more pronounced the problem will become as the polygons get larger and the overall image less detailed.

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3

MINDMAP: establishing an integrated database infrastructure for research in ageing, mental well-being, and the urban environment

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Abstract

Background

Urbanization and ageing have important implications for public mental health and well-being. Cities pose major challenges for older citizens, but also offer opportunities to develop, test, and implement policies, services, infrastructure, and interventions that promote mental well-being. The MINDMAP project aims to identify the opportunities and challenges posed by urban environmental characteristics for the promotion and management of mental well-being and cognitive function of older individuals.

Methods

MINDMAP aims to achieve its research objectives by bringing together longitudinal studies from 11 countries covering over 35 cities linked to databases of area-level environmental exposures and social and urban policy indicators. The infrastructure supporting integration of this data will allow multiple MINDMAP investigators to safely and remotely co-analyse individual-level and area-level data.

Individual-level data is derived from baseline and follow-up measurements of ten participating cohort studies and provides information on mental well-being outcomes, sociodemographic variables, health behaviour characteristics, social factors, measures of frailty, physical function indicators, and chronic conditions, as well as blood derived clinical biochemistry-based biomarkers and genetic biomarkers. Area-level information on physical environment characteristics (e.g. green spaces, transportation), socioeconomic and sociodemographic characteristics (e.g. neighbourhood income, residential segregation, residential density), and social environment characteristics (e.g. social cohesion, criminality) and national and urban social policies is derived from publically available sources such as geoportals and administrative databases.

The linkage, harmonization, and analysis of data from different sources are being carried out using piloted tools to optimize the validity of the research results and transparency of the methodology.

Discussion

MINDMAP is a novel research collaboration that is combining population-based cohort data with publicly available datasets not typically used for ageing and mental well-being research. Integration of various data sources and observational units into a single platform will help to explain the differences in ageing-related mental and cognitive disorders both within as well as between cities in Europe, the US, Canada, and Russia and to assess the causal pathways and interactions between the urban environment and the individual determinants of mental well-being and cognitive ageing in older adults.

3.1 Background

From 1990 to 2010, the burden of mental ill-health increased by 38%, an increase mostly attributable to population ageing [1]. Mental disorders in old age lead to impairments in the ability to function socially, decreased quality of life, and increased risk of health problems and comorbidities. Poor mental well-being in later life carries significant social and economic impacts on families and societies, imposing a substantial burden on health and social care services [1]. Mental disorders associated with ageing, therefore, have become a key priority for public health policy and prevention.

Today, over 70% of Europeans and over 80% of North Americans reside in cities [2]. While urbanization is expected to increase in these regions over the coming decades, there is limited understanding of the critical contribution of the urban environment to mental well-being in ageing societies. Cities pose major challenges for older citizens, but also offer opportunities to develop, test, and implement policies, services, infrastructure, and interventions that promote mental well-being. The MINDMAP project, building on a novel database infrastructure, aims to identify the opportunities and challenges posed by urban environmental characteristics for the promotion and management of mental well-being and cognitive function of older individuals.

Funded from 2016 to 2020 by the Horizon2020 programme of the European Commission, MINDMAP aims to achieve its research objectives by bringing together ten longitudinal studies from eight European countries, the United States (US), Canada and Russia (in total over 35 cities of different sizes) linked to databases of area-level environmental exposures and social and urban policy indicators. Linking micro- (i.e. individual), meso- (i.e. neighbourhood), and macro- (i.e. city or national) level data enables MINDMAP to investigate the causal pathways and multi-level interactions between characteristics of the urban environment and the behavioural, social, and biological determinants of mental well-being and cognitive function in older adults. Compared to studies based on a single country or city, integrating data from cohort studies in multiple cities offers many advantages for research exploring the impact of the urban environment on mental well-being. Harmonizing information across international cohort studies and combining them with data from different sources (physical, social and socioeconomic environmental characteristics, policy indicators) allows examining contextual determinants of variation in mental well-being across different populations and exploring the impact of neighbourhood, urban, and national policies for the prevention of mental disorders in older people. Furthermore, integrating data increases sample sizes and statistical power necessary to identify high-risk population subgroups, study relatively rare health conditions, unravel causal pathways and explore interactions between risk factors. Finally, and potentially most relevant for studies investigating environmental influences on health, integrating data from different geographical locations increases the variation in environmental characteristics and policies that influence mental well-being and cognitive function both within as well as between cities.

The MINDMAP database infrastructure will support these research objectives by integrating data from multiple sources and providing investigators with a platform to analyse it. The infrastructure will allow multiple MINDMAP investigators to safely and remotely co-analyse data from multiple sources and across different populations. Integration of different data sources will facilitate analyses exploring the importance of individual- and area-level determinants of mental well-being and cognitive function.

3.2 Methods/Design

Participating institutions and cohort studies

Research centres and longitudinal cohort studies from across Europe and North America are involved in the MINDMAP consortium. Thirteen research teams with a wide range of expertise are contributing to the MINDMAP project (see Additional file 1). MINDMAP also brings together ten ongoing longitudinal ageing cohort studies from eight European countries, the US, Canada, and Russia (Table 1). The European cohort studies appropriately cover urban areas in all regions including North, Central, Southern, and Eastern Europe (Fig. 1).

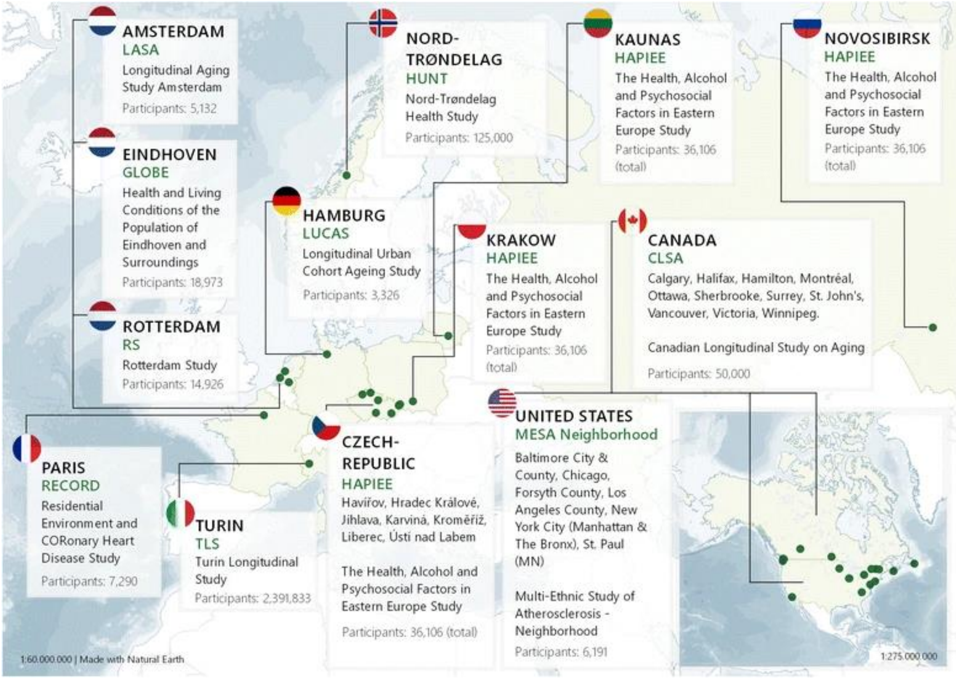
Several cohort studies additionally include more rural areas, which will be useful for comparative purposes.

Table 1: Overview of MINDMAP participating cohort studies

Name	Type of study	Number of participants	Country	Main study locations	Baseline	Last follow-up
Canadian Longitudinal Study on Aging (CLSA) [34]	Cohort	50,000	Canada	Victoria Vancouver Surrey Calgary Winnipeg Hamilton Ottawa Montréal Sherbrooke Halifax St. John's	2008	Ongoing (until 2018)
Health and Living Conditions of the Population of Eindhoven and Surroundings (Gezondheid en Levens Omstandigheden Bevolking Eindhoven en omstreken; GLOBE) [35]	Cohort	18,973	Netherlands	Eindhoven and surroundings	1991	2016
The Health, Alcohol and Psychosocial Factors in Eastern Europe Study (HAPIEE) [36]	Cohort	36,106	Russia Poland Lithuania Czech Republic	Novosibirsk Krakow Kaunas Hradec Kralove Jihlava Karvina Kromeriz Liberec Usti nad Labem	2002	2015
Nord-Trøndelag Health Study (HUNT) [37]	Cohort	125,000	Norway	Nord-Trøndelag county	1984	2008

Longitudinal Aging Study Amsterdam (LASA) [38]	Cohort	5132	Nether-lands	West (including Amsterdam) East (including Zwolle) South (including Oss)	1992	2014
Longitudinal Urban Cohort Ageing Study (LUCAS) [39]	Cohort	3326	German y	Hamburg	2000	2017
Multi-Ethnic Study of Atherosclerosis – Neighbourhood (MESA Neighbourhood) [7]	Cohort	6191	United States of America	Forsyth County (NC), Northern Manhattan & the Bronx (NY), Baltimore City & Baltimore County (MD), St. Paul (MN), Chicago (IL), Los Angeles County (CA)	2000	2012
Residential Environment and CORonary Heart Disease Study (RECORD) [40]	Cohort	7290	France	Paris	2007	2015
Rotterdam Study (RS) [41]	Cohort	14,926	Nether-lands	Rotterdam (Ommoord)	1989	Ongoing (until 2020)
Turin Longitudinal Study (TLS) [42]	Registry based cohort	2,391,833	Italy	Turin	1971	2015

Figure 1: Overview of participating MINDMAP studies and their geographical locations



Variables and data sources

MINDMAP is integrating data from numerous sources for different observational units. Individual-level data collected by longitudinal ageing studies will be combined with area-level urban characteristics and local and national policy indicators. Additional file 2 provides a visual representation of the structure of the MINDMAP project, including all work-packages and their relation to the different data presented below. A detailed overview of data used in the MINDMAP project is provided in Additional file 3. The selection of variables was based on scientific literature and a draft conceptual model on the influence of environmental factors on mental well-being and cognitive function that is being developed by MINDMAP investigators.

Individual-level data

The MINDMAP consortium makes use of baseline and follow-up data collected by 10 participating studies.

Mental health, mental well-being and cognitive function

The main outcomes of interest within the MINDMAP project are indicators of mental health, mental well-being, and cognitive function. These indicators are measured in the cohort studies at multiple times through questionnaires, interviews, and cognitive tests and include variables covering life satisfaction, quality of life, depression and depressive symptoms, cognitive functioning, anxiety, and loneliness.

Individual-level determinants, mediators and confounders

MINDMAP-participating cohort studies have also collected detailed measures of sociodemographic variables, health behaviour characteristics, social factors, as well as measures of frailty and physical function indicators, and chronic conditions (multi-morbidities). An important feature of the MINDMAP studies is the collection of repeated measurement of determinants of mental well-being and cognitive function in cohort studies of urban residents. Several studies also have information available on blood derived clinical biochemistry-based biomarkers and genetic biomarkers.

Area-level data

Area-level information on physical environment characteristics (e.g. green spaces, transportation), socioeconomic and sociodemographic characteristics (e.g. neighbourhood income, residential segregation, residential density), and social environment characteristics (e.g. social cohesion, criminality) and national and urban social policies is derived from publicly available resources.

Physical environmental characteristics

Geospatial data is being collected from existing data portals, and city-specific contacts across the MINDMAP study sites. In the European Union, publicly available spatial information has drastically improved thanks to INSPIRE [3], a 2007 European Directive that establishes a data infrastructure for the collection and distribution of spatial information in the European Union. The European Data Portal [4] was systematically reviewed for all files containing items relevant to mental well-being or intermediary factors for all countries and cities of the participating European cohort studies. In addition, using the European Data Portal, relevant national, regional, and local data portals were identified and are systematically searched for relevant data that is not yet catalogued on the European Data Portal.

Harmonized high-resolution land use data, road infrastructure files, and residential address databases of the general population over the study territory were obtained for all European MINDMAP cities. For its land use data, MINDMAP extracted data from the European Urban Atlas [5]. This data is derived from satellite imagery and consists of 21 distinct categories, which capture a city's land use (including public green areas). This data is being used to calculate individual 'greenness' exposure. In combination with the infrastructure information, measures such as nearest road network distance to urban green spaces are also being calculated. Point data of all residential addresses is used to determine population density. Information on facilities, transportation, and pollution have been obtained for a subset of cities from local and national data portals and are used to derive measures such as exposure to pollutants, access to public transport and availability of facilities.

The CLSA is part of the Canadian Urban Environmental Health Research Consortium (CANUE), a pan-Canadian initiative which is gathering and developing measures of environmental characteristics such as greenness, walkability, air pollution, and socioeconomic conditions for every neighbourhood across Canada [6]. As they become available, environmental characteristics developed within CANUE will be linked to CLSA cohort data. For our US cohort study, we will use the area-level geospatial data collected within the MESA neighbourhood study, which was specifically designed to study environmental influences on health [7].

Socioeconomic, sociodemographic and social environmental characteristics

Area level variables on neighbourhood socioeconomic measures (e.g. average income, proportion of rental housing), sociodemographic composition (e.g. proportion of older people, residential segregation), and social interaction indicators (e.g. proxies of social cohesion, criminality) are also being derived from publicly available sources such as the local and national statistics agencies and local governments.

National and local policies

Data on national and subnational policies that range from proximal to more distal influences on the mental well-being of older people in an urban environment has been collected within the MINDMAP project to evaluate the effects of public policies on mental well-being outcomes. Existing, cross-city and cross-national databases such as the Social Insurance Entitlements Dataset (SIED) [8], the Labour Market Reforms (LABREF) database [9], the Eurostat databases [10], and the OECD Long Term Care database [11] were the principal sources for social policies such as old age pensions and social care. Urban policy indicators, such as transportation affordability and accessibility indicators, were collected for each MINDMAP city from the Eurostat Urban Audit database [12] and the OECD Metropolitan Indicators database [13]. Mental health policy indicators, such as mental health system governance, resources and services were collected at the national level for European countries from the Eurostat Health Indicators database and the European Health for All database [14], and for all countries from the WHO Mental Health Atlas Country Profiles [15] and from two OECD data sources [16, 17]. MINDMAP aims to collate such policy data for the past 30 years, and earlier, when applicable. When longitudinal data was not available, we collected the latest available cross-sectional data. In addition, data has been collected on local mental health promotion and prevention policies through interviews with experts in MINDMAP cities [18].

The MINDMAP process

To support cross-national research on ageing, mental well-being and the urban environment, the MINDMAP consortium adapted harmonization guidelines and software applications developed by Maelstrom Research [19, 20]. These tools have been employed under similar collaborative health research projects such as BioSHaRE [21], InterConnect [22], and the Canadian Partnership for Tomorrow Project [23]. Seven consecutives actions are being undertaken to establish an integrated database infrastructure allowing analyses of individual- and area-level data for research in ageing, mental well-being, and the urban environment (Fig. 2).

Figure 2: Step-by-step process to establish the MINDMAP integrated database infrastructure

Define research questions

As a first step, MINDMAP consortium investigators identified a number of research questions addressing the variation in mental well-being and disorders in old age, both within cities as well as between cities and exploring how environments and policies at different levels might influence mental well-being in later life. Table 2 shows main research questions to be answered with the integrated database infrastructure. In addition, more detailed domain-specific research questions were defined, to be explored by each work package (Additional file 2).

Table 2: Main MINDMAP research questions to be answered with the integrated database infrastructure

1. How do variations across cities in mental well-being and cognitive outcomes in later life relate to urban environments, and how do they impact on co-morbidities?
2. How does the urban environment modify genetics and biomarkers as a potential mechanism through which features of the urban environment contribute to psychopathology in later life?
3. How do urban environmental characteristics influence mental well-being and cognitive outcomes in later life by shaping lifestyle behaviours?
4. How do psychosocial urban determinants influence mental well-being in later life?
5. How do 'health-in-all' and mental health prevention policies impact the mental well-being of older urban residents?

Document metadata

The design of participating studies and the data they collect were documented on a web-based platform [24]. This platform includes a search and query interface allowing MINDMAP investigators to quickly and easily identify studies collecting data items required to answer specific research questions. Questionnaires, standard operating procedures, and data dictionaries were also documented within the platform so that heterogeneity of data collection instruments could be properly assessed. Area-level urban characteristics as well as local and national policies of interest are also being documented.

Develop data sharing and publication guidelines

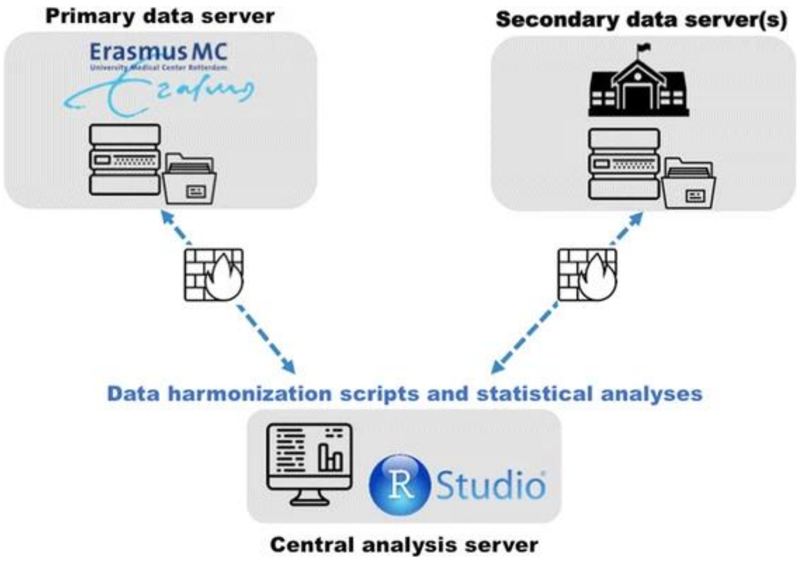
In order to establish basic governing principles for the consortium, MINDMAP principal investigators drafted guidelines covering access and usage of cohort study data and publication of results. First, each cohort study's regular data access procedures will be respected, including the submission of access applications and obtainment of all required approvals from ethical review boards. Second, only data relevant to answer MINDMAP research questions is being requested. Third, after receiving all necessary approvals, these subsets of cohort study data will be hosted on firewall-protected servers. Participating studies were given the option of transferring a subset of their data to the coordinating centre's (Erasmus MC) server or installing a local server at their home institution. Fourth, the MINDMAP coordinating team and cohort representatives will review each manuscript proposal. At this point, cohort representatives will need to confirm that they agree to the use of their data for a given manuscript, and will be able to opt-out if they wish. Lastly, a publication agreement was adopted to describe the authorship and acknowledgement guidelines relevant to work generated in connection with MINDMAP.

Put in place IT infrastructure

Given potential restrictions related to sharing of individual-level data, a distributed database infrastructure was put in place to support data harmonization and cross-study analyses (Fig. 3). As such, a primary data server was installed at Erasmus Medical Centre in Rotterdam (the MINDMAP coordinating centre) to host datasets from studies whose policies allow the physical transfer of data to a third party. Cohort studies with more restrictive data sharing rules were given the option of installing secondary data servers in their own institution, which would be remotely accessible via encrypted connections (using HTTPS). Finally, a central analysis server running Rstudio

[25] was set up and allows authenticated MINDMAP staff and investigators to securely access firewall-protected data on the primary and secondary data servers (see step 7 below).

Figure 3: MINDMAP database infrastructure



Harmonize cohort data

MINDMAP research teams were assigned specific domains of information to harmonize across all MINDMAP cohort studies. Assignment of data harmonization work was based on the expertise of the investigators at participating institutions. University College London is responsible for mental well-being and cognitive outcomes harmonization, Vrije Universiteit Amsterdam (VU) University Medical Centre was assigned social factors and perceived environment variables harmonization, Erasmus Medical Centre, in collaboration with McGill University Health Centre, is harmonizing socioeconomic variables, multi-morbidities and health behaviours variables.

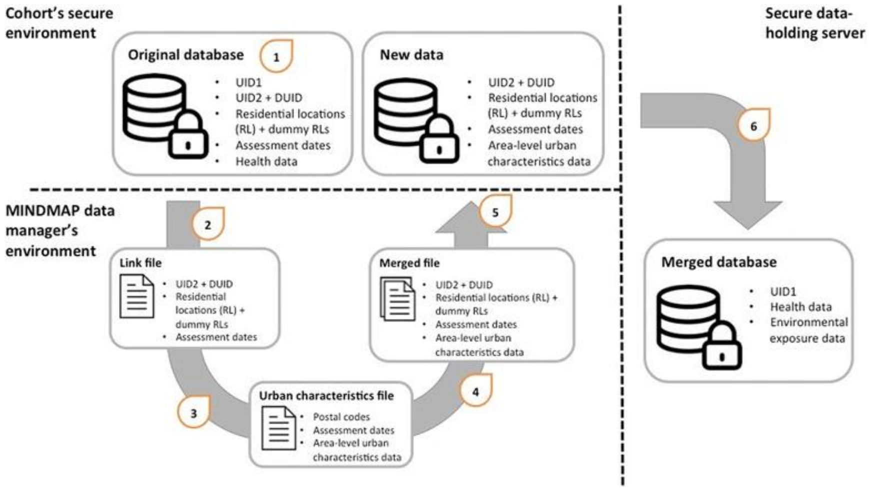
Finally, biomarker data is harmonized by McMaster University (for details on the domains of information, see Additional file 3).

Research teams began by reviewing the variables collected by each cohort study and related documentation (e.g. questionnaire(s), standard operating procedures, data dictionaries) for their assigned domain, and identifying missing information or highlighting unclear variable definitions, codes, or values. Targeted variables for harmonization are then defined (e.g. current cigarette consumption — categorical: yes (coded as 1) or no (coded as 0); pack-years of smoking — continuous variable) and documented in a central MINDMAP GitHub repository. The choice and specific definitions of targeted variables is determined by the research questions that they will help to address and the actual data collected by each cohort. Once defined, the potential for each cohort to generate target variables is assessed. Next, data harmonizers develop data transformation scripts to generate common-format variables in Rstudio [25] on the password protected central analysis server. Decisions made and harmonization scripts applied for each study-specific dataset are documented using cohort-specific Rmarkdown documents [26] in the publicly-accessible MINDMAP GitHub repository, thereby making data transformation decisions open and transparent. Lastly, quality control checks are conducted on harmonized variables by comparing the distribution and counts of harmonized datasets to the data originally collected by each study.

Link area-level data

Addresses and postal codes of cohort participants will be used to link urban environmental characteristics and policy data (i.e. area-level data) to harmonized cohort data (Fig. 4). Given that the utilization of residential locations in research projects compromises study participants' privacy, the georeferenced information will be blinded in a step-by-step process. Firstly, the cohort data manager will generate new unique identifiers (UID2) for all individuals in cohort studies along with dummy (i.e. random) identifiers (DUID) and residential locations (home address or postal code) for approximately 5% of the total cohort study's sample (more if preferred). Second, a Link file containing UID2 and residential locations (RL) as well DUID and dummy RLs will be sent to the MINDMAP data manager. Third, MINDMAP will prepare a clearly documented Urban characteristics file to be merged with the Link file. Fourth, the Link file and Environmental exposures file will be merged into the Merged file using residential locations and dates of assessment. The resulting dataset is then sent back to the data manager of the cohort study who deletes all addresses. Lastly, the merged data is made available through the data infrastructure (either on the primary data server or a secondary data server).

Figure 4: MINDMAP data linkage process



Co-analyse integrated data

Using a web browser and secure internet connection, authenticated MINDMAP researchers can login to the central analysis server outlined in step four and conduct on-demand statistical analyses on geographically distributed firewall-protected databases using the Rstudio web interface. While some studies have given permission for individual-level data to be analysed by MINDMAP investigators, others have restricted data access to aggregate-level information. For all analyses that include cohort studies prohibiting the use of individual-level data, the DataSHIELD approach is used [27, 28]. Under DataSHIELD, analysis requests are sent from the central analysis computer to the harmonized data held on the data servers. Computation is done simultaneously but in parallel on each data server linked by non-disclosive summary statistics. Individual-level cohort data thereby stay on their respective data server described in step four above.

Unlike experimental data, in our observational design, exposure to environmental and individual risk factors cannot be assumed to be randomly assigned [29, 30]. This is a challenge for research on the impact of the urban environment on health. To minimize risks of bias as much as possible with the available data, MINDMAP will capitalise on recent advances in causal inference and causal mediation methods, particularly derived from econometric and policy evaluation [29]. Because of the impossibility to randomize many of the key environmental determinants of mental well-being, quasi-experimental approaches applied to longitudinal data will provide the basis for the identification of causal effects. These techniques will include instrumental variables, regression discontinuity, and difference-in-differences approaches [31], which exploit naturally occurring changes in the environment, including policy reforms, to identify their causal effect on mental well-being. For example, the introduction of the free bus pass in England in 2006, a transportation policy, has been linked to increased physical activity and reduced obesity [32, 33]. Similar evaluations could be carried for the impact of policy reforms in the domains of housing, which affect the living arrangements of older people; pension policies, which influence the financial well-being of urban older dwellers; mental health promotion programmes that target the mental health of older people in cities; and environmental policies that affect access to outdoor and meeting spaces, lightening and walkability. MINDMAP will aim to implement policy evaluation studies to examine how some of these policies affecting older people living in MINDMAP cities may influence their mental health, with the aim of identifying transferrable lessons.

3.3 Discussion

The MINDMAP project aims to identify the opportunities and challenges posed by the urban environment for the promotion of mental well-being and cognitive function in later life. MINDMAP aims to achieve its research objectives by bringing together longitudinal studies from 11 countries covering over 35 cities linked to databases of area-level environmental exposures and social and urban policy indicators. The infrastructure supporting integration of this data will allow multiple MINDMAP investigators to safely and remotely co-analyse individual-level and area-level data through a single platform.

The MINDMAP project has several important strengths. Integrating data from cohort studies in multiple cities and across various exposure or policy databases allows examining the role of contextual determinants on variations in mental well-being across different populations. It also increases variations across these contextual determinants and it raises sample sizes and statistical power and, because the data is pooled from different regions and jurisdictions, allows exploring the effect of policy on mental well-being. The harmonization approach and tools that are employed by the project have been methodically developed by Maelstrom Research [19, 20] and put to use in similar research collaborations [21,22,23]. These tools and approaches have been adapted to accommodate the specific needs of the MINDMAP project and ensure that all aspects of the harmonization project are carried out in a uniform, open, and methodical way to optimize the validity of the research results and transparency of the methodology. Moreover, the research teams contributing to the project bring a wide range of experiences and expertise that complement each other.

The integration of different data sources from different countries also present several challenges. Firstly, different questions and scales have been used within the participating cohort studies to measure similar underlying concepts. For some measures, harmonizing across the cohort studies is relatively straightforward (e.g. simple algorithmic transformations or calibrations). However, for measures such as mental well-being outcomes, this process is more complex, requiring the application of statistical modelling (e.g. standardization, latent variable or multiple imputation) [11]. Further, in many instances not all variables can be harmonized and constructed for all participating studies, because this might compromise the quality of the constructed variables. Secondly, all environmental data needs to be methodically checked for accuracy, completeness (e.g. missing roads), and geocoding or projection errors (e.g. a road is projected next to the real location of the road) to ensure the validity of the data. Furthermore, there is often a lack of historical data due to rapid changes in geographical information system (GIS) techniques and the tendency to only publish the most recent data by many of the sources publishing geospatial data. Extensive efforts are therefore needed to obtain high quality historical measures of environmental exposures. Thirdly, linking environmental data to cohort data can lead to privacy concerns when not dealt with properly. To prevent this, we developed a process to link the environmental data to cohort data that protects participant privacy by isolating residential addresses from privacy sensitive health data. Finally, integrating data from 10 longitudinal studies requires extensive coordination. Streamlining this process while respecting each study's guidelines and regulations necessitates considerable time investments and meticulous planning.

MINDMAP is a novel research collaboration which is combining population-based cohort data with publicly available datasets not typically used for ageing and mental well-being research. Integration of various data sources and observational units into a single platform will facilitate multilevel analyses exploring the influence of individual- and area-level determinants of mental well-being. In the end, this infrastructure will help to explain the differences in ageing-related mental and cognitive disorders both within as well as between cities around the world and assess the causal pathways and interactions between the urban environment and the individual determinants of mental well-being and cognitive ageing in older adults.

3.4 Abbreviations

CANUE: Canadian urban environmental health research consortium
CLSA: Canadian longitudinal study on ageing
DUID: Dummy unique identifier
GIS: Geographical information system
GLOB: Health and living conditions of the population of eindhoven and surroundings (Gezondheid en levens omstandigheden bevolking eindhoven en omstreken)
HAPIEE: The health, alcohol and psychosocial factors in eastern Europe study
HUNT: Nord-trøndelag health study (Helseundersøkelsen i Nord-Trøndelag)
LABREF: Labour market reforms
LASA: Longitudinal aging study Amsterdam
LUCAS: Longitudinal urban cohort ageing study
MESA: Multi-ethnic study of atherosclerosis
RECORD: Residential environment and CORonary heart disease study
RL: Residential locations
RS: Rotterdam study
SIED: Social insurance entitlements dataset
TLS: Turin longitudinal study
UID1: Unique identifier — original
UID2: Unique identifier — new
US: United States (of America)
VU: Vrije Universiteit Amsterdam

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Appendices

Annex 1: MINDMAP research teams

The Department of Public Health from the Erasmus MC in Rotterdam is a leading centre of public health research both within the Netherlands, and internationally and it is the coordinating centre of the MINDMAP project. They have extensive experience with large European comparative studies and they are experts on environmental influences on health and health behaviour.

The Department of Global Health and Social Medicine from King's College London in the United Kingdom, has world-leading expertise on global ageing, understanding the long-run impact of macro-economic shocks on the health of older people, and examining the health impact of social policies using longitudinal surveys and registry data.

Maelstrom Research from Research Institute of the McGill University Health Center in Montreal, Canada, is a leading expert on retrospective data harmonization and integration across studies. The methods developed by Maelstrom Research are applied and further improved within the MINDMAP project.

The Department of Social Policy from the London School of Economics and Political Science, in the United Kingdom, contributes unique knowledge on ageing research from a social perspective and can help to bridge the gap between research and policy.

The Population Research Unit from the University of Helsinki in Finland has wide-ranging experience with linking registry data, comparative studies, and areas effects on health.

The Department of Epidemiology and Public Health from University College London in the United Kingdom provides unique insight into understanding the determinants of health in Central and Eastern Europe and the former Soviet Union, in partnership with local investigators of the HAPIEE project in the Czech Republic, Russia, Poland and Lithuania.

The Department of Public Health and Nursing from the Norwegian University of Science and Technology offers vast expertise in large population studies and gene-environment interactions that benefit the MINDMAP project.

The Department of Epidemiology and Biostatistics from the VU University Medical Center is a leading centre of epidemiology of ageing and has a particular strong expertise on the social determinants of ageing.

INSERM, the French National Institute of Health and Medical Research in Paris is a work-leading institute on neighbourhood socioeconomic disparities in health and how multiple facets of the neighbourhood environment can influence health.

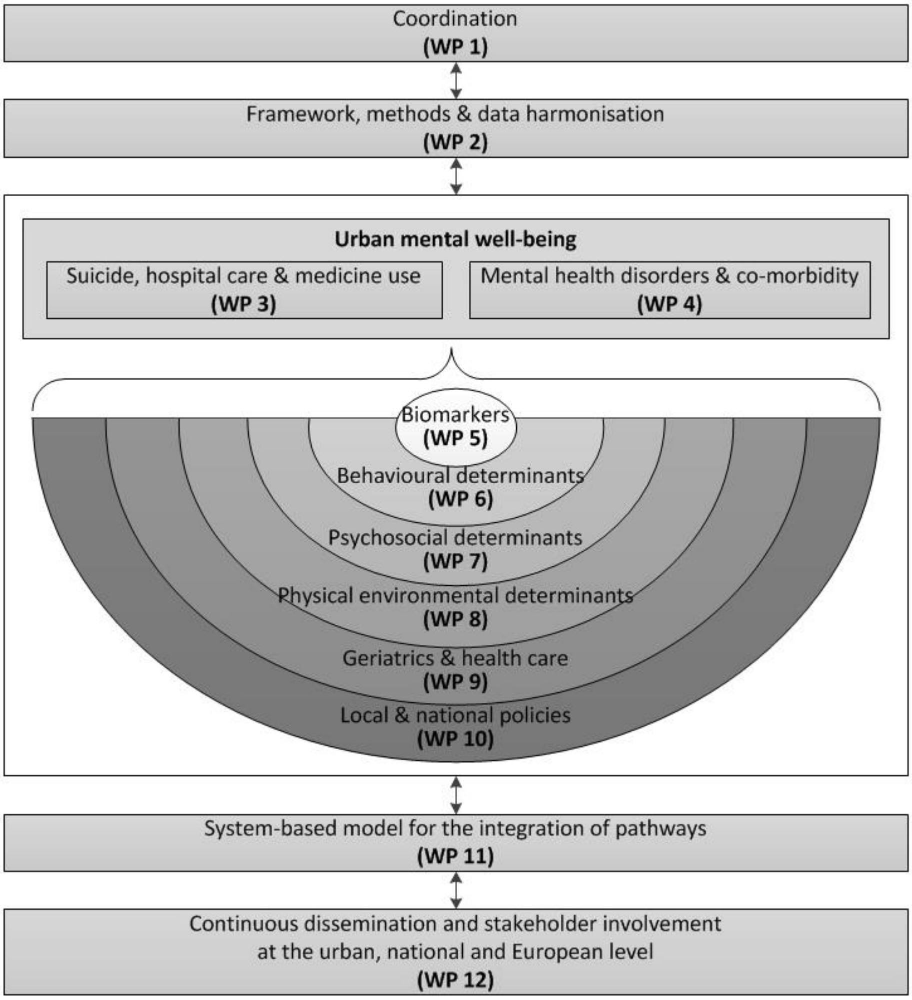
The Geriatrics Research Department at the Albertinen-Haus and the University of Hamburg are experts in geriatrics and functional ability within ageing population.

The Department of Clinical Epidemiology and Biostatistics at McMaster University in Hamilton, Canada has great knowledge on geroscience; the science to understand the processes of aging from cell to society.

The Drexel University Dornsife School of Public Health in in Philadelphia, Pennsylvania carries out world-leading research on social epidemiology by using novel methods in public health including agent based modelling.

The Regional Epidemiology Unit ASL TO3 liaised with the University of Turin in Italy has a wide expertise in the engagement of stakeholders at national and European level and in strategic communication with policy makers. They will help to valorise the results of the MINDMAP project.

Annex 2: Structure of the MINDMAP project



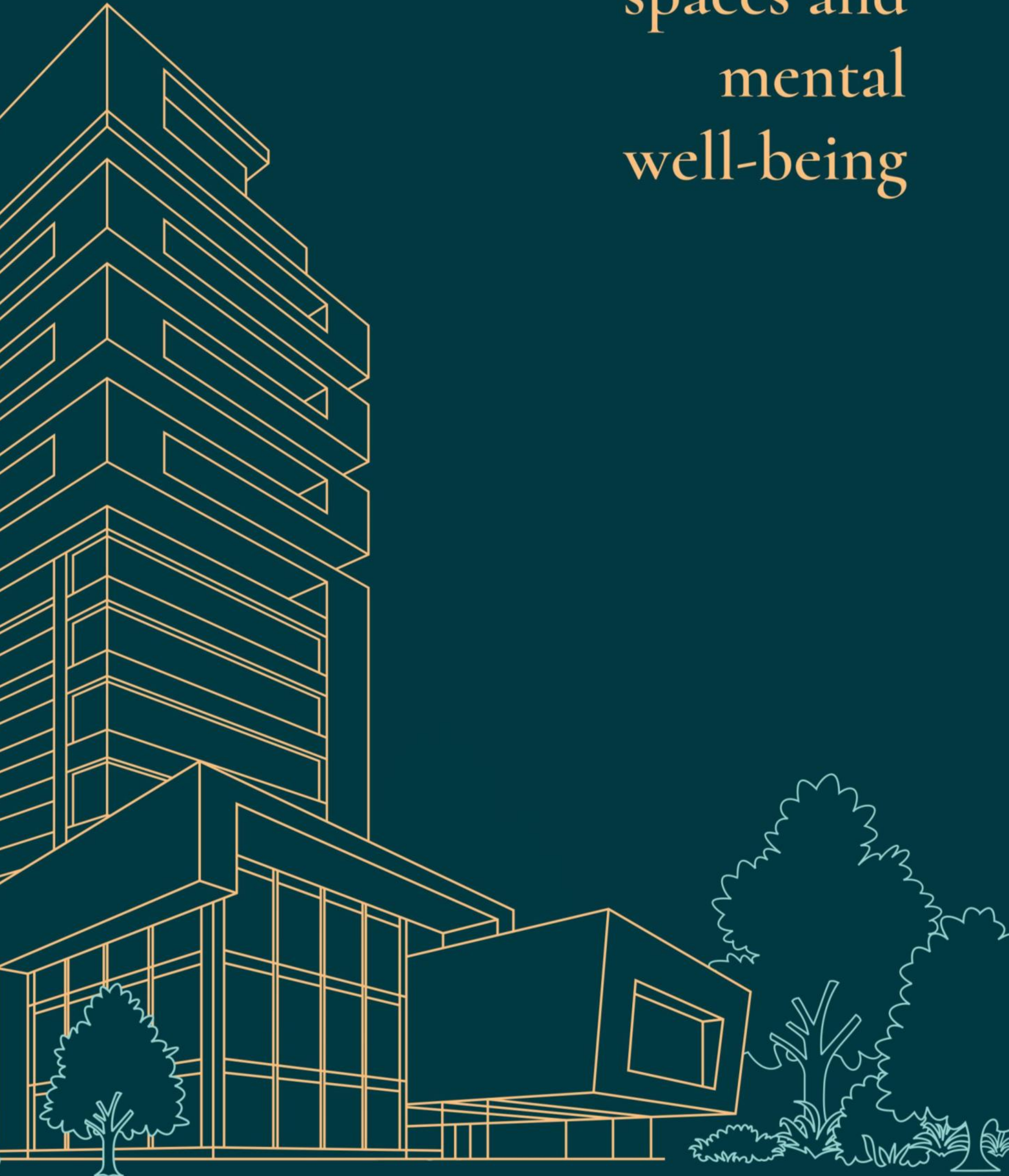
Note: WP = Work Package

Annex 3: Overview of data

Domain	Subdomains	Source	Level of measurement
Mental health, well-being and cognitive outcomes	Life satisfaction, quality of life, depression and depressive symptoms, cognitive functioning, anxiety, loneliness	Cohort self-report and measurements	Individual
Sociodemograph ic variables	Age, sex, employment and retirement status, education, income, marital status, household structure	Cohort self-report and administrative data	Individual
Health behaviours	Alcohol consumption, tobacco use, diet and nutrition, physical activity, sleep quality	Cohort self-report	Individual
Social factors	Social and community support, social participation, social inclusion, major life event, home ownership	Cohort self-report and administrative data	Individual
Perception of urban environment	General neighbourhood safety, social trust, crime, social cohesion, deprivation	Cohort self-report	Individual
Other health outcomes (multi-morbidities)	Hypertension, Angina, myocardial infarction, stroke, BMI, perception of health, disability, medication use	Cohort self-report and measurements	Individual
Biomarkers and genetics	Genetics, inflammatory markers, neuroendocrine markers, blood lipids, glucose, vitamins	Cohort biological samples	Individual
Built environment	Density, land use, infrastructure (roads, walking and cycling paths)	European Environmental Agency, national and subnational data portals	Small area

Local services	Public transportation proximity, (healthcare) facilities	National and subnational data portals	Small area
Pollution	Air pollution, noise pollution	National and subnational data portals	Small area
Neighbourhood socioeconomic position	Average neighbourhood income, proportion of rental houses, neighbourhood unemployment	National and subnational statistical agencies	Small area
Neighbourhood composition	Age composition, gender composition, residential segregation	National and subnational statistical agencies	Small area
Social-interaction indicators	Social cohesion, criminality	National and subnational statistical agencies & governments	Small area
Social policy indicators	Old age pensions, employment protections, housing & social care	Swedish Institute for Social Research Social Insurance Entitlements Dataset (SIED), European Commission Labour Market Reforms Database (LABREF), European Commission Eurostat Databases, OECD Long Term Care Database	National
Urban policy indicators	Urban form, green spaces, transportation	OECD Metropolitan Indicators Database, European Commission Eurostat Urban Audit Database	City
Mental health policy indicators	Mental health system governance, resources & services, health insurances, promotion & prevention	World Health Organization Mental Health Atlas Country Profiles, World Health Organization European Office, European Health Information Gateway, Health for All Database, European Commission Eurostat Database, OECD Health Systems Characteristics Survey, OECD Health Statistics	National

Urban green spaces and mental well-being



4

Green spaces, subjective health and depressed affect in middle-aged and older adults: a cross-country comparison of four European cohorts

Noordzij, J.M., Beenackers, M.A., Oude Groeniger, J., Timmermans, E., Chaix, B., Doiron, D., Huisman, M., Motoc, I., Ruiz, M., Wissa, R., Avendano, M., & Van Lenthe, F.J. (2021).

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Abstract

Background

Studies on associations between urban green space and mental health have yielded mixed results. This study examines associations of green space exposures with subjective health and depressed affect of middle-aged and older adults in four European cohorts.

Methods

Data came from four Western-European and Central-European ageing cohorts harmonised as part of the Mindmap project, comprising 16 189 adults with an average age of 50–71 years. Green space exposure was based on the distance to the nearest green space and the amount of green space within 800 m buffers around residential addresses. Cohort-specific and one-step individual participant data (IPD) meta-analyses were used to examine associations of green space exposures with subjective health and depressed affect.

Results

The amount of green spaces within 800 m buffers was lowest for Residential Environment and CORonary heart Disease (Paris, 15.0 hectares) and highest for Health, Alcohol and Psychosocial factors In Eastern Europe (Czech Republic, 35.9 hectares). IPD analyses indicated no evidence of an association between the distance to the nearest green space and depressed affect (OR 0.98, 95% CI 0.96 to 1.00) or good self-rated health (OR 1.01, 95% CI 0.99 to 1.02). Likewise, the amount of green space within 800 m buffers did not predict depressed affect (OR 0.98, 95% CI 0.96 to 1.00) or good self-rated health (OR 1.01, 95% CI 0.99 to 1.02). Findings were consistent across all cohorts.

Conclusions

Data from four European ageing cohorts provide no support for the hypothesis that green space exposure is associated with subjective health or depressed affect. While longitudinal evidence is required, these findings suggest that green space may be less important for older urban residents.

4.1 Introduction

Within the context of an increasingly urbanising world, contact with natural environments may play an important role in improving subjective health and mental well-being. A recent review by WHO concluded that that there are many public health benefits of urban green spaces for the general population [1]. Evidence suggests that urban green spaces may be linked to less chronic stress and favourable lifestyle factors, such as increased levels of physical activity, [1-2] which strongly predict physical and mental health. Other studies have shown that individuals living in urban areas with more green space have a reduced level of stress and improved well-being compared with those with poorer availability of green space [3-4]. Furthermore, psychoevolutionary theories suggest that mental health can be influenced through restorative functions of natural environments [5-6]. Yet, empirical studies on the association between green spaces and health have yielded mixed findings. While some cross-sectional [7-9] and some longitudinal studies [4, 10] have reported associations, other studies have failed to reproduce these results or reported associations opposite to those expected [11-13]. Most of these studies tend to rely on data from only one city or several cities within one country, limiting variation in exposure. In addition, very few studies have examined whether the hypothesised benefits of green space exposure also apply to middle-aged and older adults. Some empirical studies have shown that emotional well-being might improve with age as symptoms of depression decline [14]. As a result, ageing may be associated with greater emotional stability. In this context, the positive associations between green spaces and mental well-being may be different for middle-aged and older adults compared with younger adults. Furthermore, it has been theorised that older adults may be particularly susceptible to characteristics of the residential environment as they are likely to spend more time closer to home than younger adults [15].

Only a handful of studies has examined the association between green space and health outcomes across different regions or countries. A recent study concluded that associations between green space exposures and mortality differed between macro-European regions and that the effects were more pronounced in Western-European cities [16]. However, this study used aggregated exposure data at the city level, implying substantial measurement error. This leads to a second problem commonly associated with studies linking green space exposures to health outcomes: a lack of consistency in defining exposure measures. Markevych et al [17] identified this lack of consistency noting that in epidemiological studies, green space exposure generally implies the presence of some form of green space near the home, but a standardised definition for even this 'simple' exposure proxy does not exist. Green space exposure is commonly defined at the neighbourhood level. These neighbourhoods can consist of census tracts or postal code areas, or more detailed individual-level exposures, such as 'crow-fly' or network buffers around the residential address [18]. Census tract data are generally easy to obtain for multiple cities, and are therefore commonly used in studies that compare multiple cities within one country [19-20]. However, census areas are often the result from arbitrarily defined boundaries used to aggregate continuous spatial features [18, 21-22]. More sophisticated individual-level buffers that offer improvements by considering the individual's actual location are often limited to single cities or several cities within one country, but potentially offer useful benefits for international comparisons.

This study uses individual-level green space exposure data linked to harmonised outcomes from four cohorts in ten cities across three European countries to examine the association of green space with subjective health and depressed affect in older age. By applying common exposure data and individual buffers, we reduce measurement error and maximise variation in green space exposure across multiple cohorts. We fist analyse data for each cohort separately and then pool data for all cohorts using one-step individual participant data (IPD) meta-analysis. To our knowledge, this is the first study to use harmonised data from ageing cohorts across different cities and countries, linked to detailed individual-level data on green exposure using identical buffers.

4.2 Methods

Data

Data were obtained from four cohort studies in the Mindmap project, which brings together longitudinal studies from multiple European countries, Canada and Russia and offers an integrated database structure for analysing harmonised data from these cohorts [23]. Data from four ageing cohorts in the Mindmap Harmonised Dataset V.2.01 release were used: Longitudinal Ageing Study Amsterdam (LASA), Health and Living Conditions of the Population of Eindhoven and Surroundings (GLOBE), Residential Environment and CORonary heart Disease (RECORD) and Health, Alcohol and Psychosocial factors In Eastern Europe (HAPIEE). These cohorts were chosen because of the availability of harmonized exposure and outcome measures. LASA is a longitudinal population-based study of the predictors and consequences of ageing in the Netherlands [24]. The 2005 LASA I and LASA II samples of participants residing in the cities of Amsterdam, Zwolle and surrounding areas were selected for the analyses. The GLOBE study is a prospective cohort study on the role of living conditions for health in the Dutch city of Eindhoven and surrounding areas. The 2004 sample of GLOBE participants was selected for the analyses [25]. The RECORD study was established in 2007 to investigate environmental determinants of territorial disparities in health in the Paris metropolitan areas [26]. Data from 2007 were used for these analyses. The HAPIEE study is a cohort study that assesses the effects of dietary factors, alcohol consumption and psychosocial factors on the health of men and women aged 45–69 years in four countries of Central and Eastern Europe [27]. The 2006 sample of HAPIEE participants from the Czech Republic was used for the analyses. More details on the selection of respondents can be found in online supplemental file 3.

Exposure to green space

Geocoded respondent addresses were linked to environmental exposures as part of the Mindmap database infrastructure [23]. Environmental exposure data were obtained from the Urban Atlas (UA) dataset. The UA is supported by the European Environment Agency and provides pan-European comparable land use and land cover data for urban areas [28]. Land classification data were used to determine categories of green space relevant for subjective health and well-being. A category comprising all relevant green spaces (total green spaces) was used as the main exposure category. This category consisted of publicly accessible green urban areas and forest areas. More details on the green space categorisation can be found in online supplemental file 1. The straight-line distance from the participant's residential address to the nearest point on the boundary of a green space was measured for each participant (in metres) using geographical software package QGIS [29]. These distances were transformed to a 100 m scale to improve interpretation. Data on the amount of green space (in hectares) were calculated using Euclidian buffers of 800 m with sensitivity analyses performed on 400 m and 1000 m buffers. The amount of green space in buffers was transformed to a 10 hectares scale to improve interpretation. Cohort data for each cohort were linked to environmental exposure data from the nearest available UA wave (figure 1).

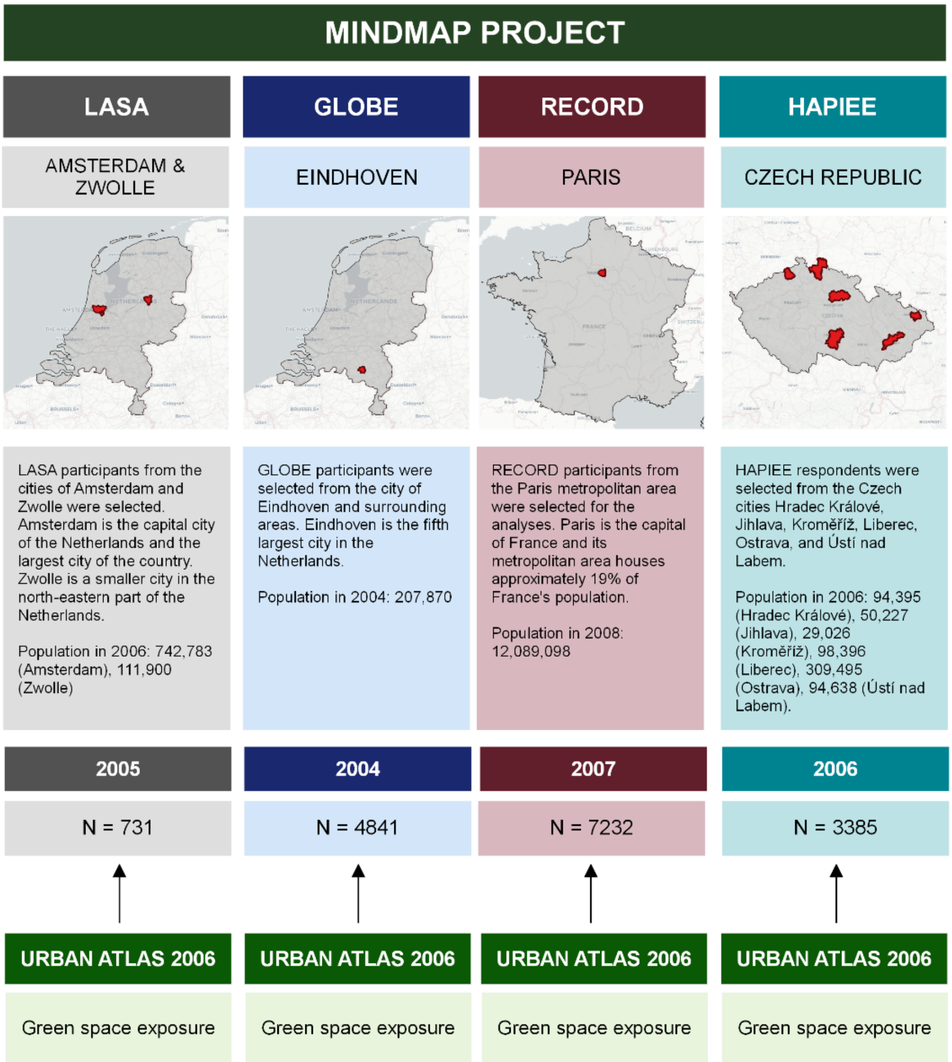
Subjective health and depressed affect

Two measures of subjective health and well-being were available for all four cohorts within the Mindmap data release V.2.01. These included a self-reported indicator on depressed affect based on whether a participant felt sad, downhearted or blue (hereafter named 'depressed affect'), and a dichotomous indicator of self-rated health of the participant, indicating good versus less than good health. Additionally, two subjective health and well-being outcomes that were only available for at least two cohorts were used for sensitivity analyses. These included an indicator of whether the participant had elevated psychological distress symptoms in accordance with the scale-specific threshold of psychological distress score, and an indicator of whether the participant had elevated depressive symptoms in accordance with the scale-specific threshold of depressive symptom score. More information on the harmonisation of the outcome variables can be found in online supplemental file 1.

Statistical analysis

Modified Poisson regression models [30] were used to estimate whether green space was associated with subjective health and depressed affect. These models included the relevant exposure and outcome measures as well as harmonised individual indicators: age, gender, employment status, retirement status, partner status (currently living with a partner) and postsecondary education as measured using the International Standard Classification of Education (ISCED) . Second, we applied a one-step IPD meta-analysis. IPD meta-analyses aim to collect, check, and reanalyse individual-level data from multiple studies addressing a particular research question and can therefore be considered the gold-standard approach to evidence synthesis [31]. We used a one-stage method that models the individual data from all studies simultaneously by pooling the data and using a hierarchical model that accounts for the clustering of participants within cohorts [32-33]. All analyses were performed using R-studio and the Mindmap data infrastructure [23, 34].

Figure 1: Overview of the MINDMAP project and the cohorts involved in this study



Basemap: Open street map contributors & CARTO. Countries: Natural Earth Data. GLOBE, Health and Living Conditions of the Population of Eindhoven and Surroundings; HAPIEE, Health, Alcohol and Psychosocial factors In Eastern Europe; LASA, Longitudinal Ageing Study Amsterdam; RECORD, Residential Environment and CORonary heart Disease.

4.3 Results

All study cohorts consist of middle-aged and older adults with the mean age ranging from 50 (RECORD) to 71 years (LASA) (table 1). On average, the distance to the nearest green space ranged from 142 m (HAPIEE) to 267 m (RECORD). The amount of green spaces within 800 m buffers was lowest for RECORD (15.0 hectares) and highest for HAPIEE (35.9 hectares). More details on the green space exposures can be found in online supplemental file 2. Depressed affect ranged from 3.4% (LASA) to 15.2% (RECORD), and while the prevalence of good self-rated health ranged from 55.1% (HAPIEE) to 82.4% (GLOBE).

Table 1: Description of the study sample for each cohort

	LASA n = 731	**GLOBE** n = 4841	**RECORD** n = 7232	**HAPIEE** n = 3385
Exposures	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**
Distance to nearest green space, meters	255 (268)	192 (155)	267 (220)	142 (139)
Amount of green space within 800-meter buffers, hectares	17.4 (16.1)	21.9 (16.9)	15.0 (18.3)	35.9 (22.7)
Outcomes	%	%	%	%
Depressed affect	3.4%	6.7%	15.2%	13.1%
Good self-rated health	63.9%	82.4%	52.9%	55.1%
Individual characteristics				
Age, mean (SD)	71 (9)	55 (15)	50 (12)	62 (7)
Male, %	47%	48%	66%	46%

Highest level of education completed, %				
Upper secondary or less (ISCED 0-3)	80%	71%	50%	85%
Post-secondary non-tertiary education or more (ISCED 4-8)	20%	29%	50%	15%
Employment status, %				
Currently not in paid employment	82%	55%	39%	52%
Currently in paid employment	18%	45%	61%	48%
Retirement status, %				
Currently not in retirement	81%	69%	82%	35%
Currently in retirement	19%	31%	18%	65%
Partner status, %				
Currently not married or living with partner	36%	21%	36%	24%
Currently married or living with partner	64%	79%	64%	76%

Table 2 summarises results from the modified Poisson models for each cohort separately. The distance to the nearest green space was not associated with any of the outcomes in any of the cohorts. Sensitivity analyses were performed for probable caseness of depression and psychological distress, which were not available for all cohorts; estimates yielded very similar results (online supplemental file 2).

Table 2: Modified Poisson regression models regressing subjective health and depressed affect on the distance to the nearest green space

	LASA	GLOBE	RECORD	HAPIEE
Adjusted model*	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**
Distance to nearest green space (per 100m.)				
Depressed Affect	0.99 (0.81 – 1.12)	1.01 (0.94 – 1.08)	0.97 (0.95 – 1.00)	0.98 (0.91 – 1.04)
Good self-rated health	1.01 (0.97 – 1.04)	1.00 (0.98 – 1.02)	1.01 (0.99 – 1.03)	0.99 (0.96 – 1.02)

*adjusted for age, gender, employment, retirement status, post-secondary education, and partner status.

The amount of green space in 800 m buffers was not associated with subjective health or depressed affect (table 3). Sensitivity analyses performed on both smaller and larger buffer sizes as well as other outcomes showed similar associations (online supplemental file 2).

Table 3: Modified Poisson regression models regressing subjective health and depressed affect on the amount of green space within 800 m buffers around the residential address

	LASA	GLOBE	RECORD	HAPIEE
Adjusted model*	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**
Amount of green space within 800-meter buffers (per 10 hectares)				
Depressed Affect	1.01 (0.77 – 1.27)	0.98 (0.91 – 1.05)	1.01 (0.98 – 1.04)	1.01 (0.97 – 1.05)
Good self-rated health	1.00 (0.95 – 1.06)	1.01 (0.99 – 1.03)	1.00 (0.98 – 1.02)	1.01 (0.99 – 1.03)

*adjusted for age, gender, employment, retirement status, post-secondary education, and partner status.

One-step IPD analyses that combined all cohorts yielded no evidence of associations of green space exposures with subjective health and depressed affect (table 4).

Table 4: One-step IPD analyses regressing subjective health and depressed affect on the distance to the nearest green space and on the amount of green space within 800 m buffers, adjusted for cohort

	Pooled dataset
Adjusted model*	**RR (95% CI)**
Distance to nearest green space (per 100m)	
Depressed Affect	0.98 (0.96 – 1.00)
Good self-rated health	1.01 (0.99 – 1.02)
Amount of green space within 800-meter buffers (per 10 hectares)	
Depressed Affect	1.00 (0.98 – 1.03)
Good self-rated health	1.00 (0.99 – 1.01)

*adjusted for age, gender, employment, retirement status, post-secondary education, partner status, and study.

4.4 Discussion

In the present study, we found no evidence of cross-sectional associations of green space exposures with subjective health, depressed affect and other measures of depressive symptoms. This finding appeared quite consistent across four cohorts with diverse settings and levels of exposure to green space. Studies conducted on the effect of green spaces on health outcomes tend to rely on data from only one city or one country, limiting variation as well as generalisability. Our study addressed this issue by including data from ten cities across four cohorts from three countries. The results for the Dutch cohorts are in line with other studies conducted in the Netherlands. For example, a study conducted in Maastricht, The Netherlands did not find associations between green spaces and self-rated health [35]. A previous study using data from eight Dutch cohorts—including the LASA cohort—found some inconsistent associations between green space and a prevalence of depression [19]. A previous study using the GLOBE data used very similar green space exposures, and found inconsistent associations between distance to the nearest green space and a more detailed measure of mental health [36].

Inconsistent findings are not new in the literature on urban green spaces and health and extend beyond the Dutch context [10, 37]. While a number of reviews and meta-analyses conclude that urban green spaces can be beneficial for subjective health and well-being, other studies find no associations or even report associations opposite to those expected [11-13]. This could be the result of variation in methodological approaches and the measurement of green spaces. In nearly all epidemiological studies, green space exposures are defined as the presence of some form of green space in the residential environment, but some studies make use of census data or postal code areas to define green space exposure, while others make use of buffers; either circular 'crow fly' or network-based ones. Multiple studies have shown these differences in defining green space exposures can result in variation in associations [21, 37]. Variation in geographical units and scales used to define the exposures could mask consistencies that may actually exist between different studies.

There are multiple possible interpretations for the findings of this study. First, the lack of associations in the present study may suggest that urban green space exposures have a limited influence on individuals' subjective perceptions of their own health and mental well-being. Prior studies have focused on the impact of green spaces on outcomes such as physical activity, which may be critical for physical health outcomes, but their influence on mental health in older age may be less marked. Second, findings may also indicate that other, non-measured aspects of green spaces, such as their quality and design, might still be associated with health outcomes and be more important than the presence of green space in the residential environment. For example, a Dutch study showed that specific characteristics of green spaces, such as their size and quality, may influence the effect of green spaces on multiple outcomes

[38]. Likewise, evidence from the UK also suggests that variations in 'ecological quality', that is, habitat diversity and ecological functions, may determine whether green spaces have psychological restorative benefits to residents [39]. Third, the impact of green spaces on subjective and mental health may be contingent on other, possibly intertwining, factors not measured in our study. For example, green spaces may only bring benefits if they influence risk factors associated with subjective and mental well-being, such as social interactions or exposure to harmful environmental stressors. For example, Pietilä et al [40] found that exposure to green spaces was associated with self-rated health, but the mechanisms that explain this association were different for suburbs compared with more urban residential areas [40].

Aside from methodological limitations, these findings raise the possibility that green space might not be associated with the health of middle-aged and older adults. Some earlier studies have also failed to find consistent evidence that a change in green space exposure in a relatively green city improves health [35, 41]. A possible explanation for these findings might be found in what is labelled the paradox of ageing: empirical studies show that emotional well-being trends to improve with older age, while symptoms of depression decline as individuals get older [14]. While the explanation of this age pattern is not fully understood, life span development theories, such as the socioemotional selectivity theory, suggest that older people may attach greater importance to finding emotional meaning and less importance to other goals [42]. As a result, ageing may be associated with more positive emotions and greater emotional stability. In this context, green spaces may become less important for older people as they become less goal oriented and more focused on the regulation of emotional states. More research that explores this hypothesis is warranted.

4.5 Strengths and limitations

The current study aims to add to the literature on the health benefits of urban green spaces by using a cross-country perspective to investigate if green spaces in the residential environment are related to subjective health and depressed affect in Western and Central European cities. Some limitations of our study should be considered. We were not able to control for other urban-environmental factors, such as residential density or neighbourhood socioeconomic status, because either these data were not available for all cities or we were not able to harmonise the data on the same spatial scale as our exposure data (ie, 800 m buffers). One of the strengths of this study is that all data are harmonised across the cohorts, enabling a valid cross-country comparison. Introducing other environmental data on different geographical scales would not only weaken this comparison, but would also introduce biases associated with the spatial configuration of neighbourhoods, the overlap of varying spatial extends and other issues of spatial misclassification [19].

The green space data used in this study were limited to publicly accessible green spaces, such as parks and forests. These areas represent green spaces that policy makers can influence as opposed to private green spaces. However, it should be noted that the exclusion of private green spaces can potentially bias our results as they may provide functions similar to public green spaces (eg, views of nature). The green space measures in this study are based on individual-level buffers and distances around the residential address. While we consider this a strength of our study as not many studies that use data from different cities in multiple countries use such specific measures, it has to be noted that our study uses straight-line distances and so-called 'Crow-fly' buffers. These measures do not take accessibility of green spaces into account as there may be a physical barrier preventing access. We could not investigate whether differences exist between respondents that had recently moved to the address compared with those that already resided at the address for a longer period of time. The data collection waves of the included studies had a maximum of 2 years mismatch with the green space data. An important assumption therefore is that the green space measures used, remained relatively constant over 2 years. A violation of this assumption may slightly bias our findings in an unpredictable direction. However, a previous study using similar exposure data and health outcomes from the GLOBE cohort, found that the majority of respondents had no, or very small changes, in green space exposure over a period of 10 years [36]. Finally, as this is a cross-sectional study, we do not know whether the participants' health status preceded or proceeded the exposure to green space.

We were able to control for a number of relevant individual characteristics, such as employment and education, but not all of these characteristics were available for all cohorts. For example, data on household income had to be excluded from the analyses as it was not available for the HAPIEE cohorts and contained a relatively large number of missing values in the GLOBE cohort. We conducted additional analyses with only the LASA and RECORD cohorts that included data on household income, but these yielded very similar results to those presented here. For the HAPIEE cohort we had to resort to using the post-secondary education from the baseline data wave (2002) as this variable was not available for the wave that was used in the analyses (2006). However, it is unlikely that this has influenced the results as education status rarely changes in middle-aged and older adults. The Mindmap project makes use of retrospective harmonisation of cohort data, which means that study variables are harmonised after they have been collected. While this is a great way to make comparisons between cohorts possible, it does inherently come with the limitation that some detail is lost in the harmonisation. For example, the LASA wave used in this study only contained data on early retirement, while the other cohorts included data on general retirement status. Such harmonisation choices lead to an inevitable loss in sensitivity in covariates as well as in the outcomes. Furthermore, while the harmonisation makes a comparison of the associations possible, prevalences might not be comparable. This, however, is unlikely to be a major issue when comparing associations between variables across cohorts. More prospective harmonisation would alleviate these limitations and therefore make more comparisons between cohorts possible.

4.6 Conclusion

The present study did not find evidence of associations of green space exposures with subjective health and depressed affect in middle-aged and older adults. A possible interpretation is that distance to or amount of green space near the home may not be the most important feature for subjective health and mental well-being, but that other factors, such as the quality of green space, may be more important. However, results also suggest that green spaces may be only weak predictors of subjective health and mental well-being in older people, who may benefit less from the proximity to green spaces than other age groups. More research using longitudinal data and examining confounding is needed to better understand how green spaces and subjective health and mental well-being relate.

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Appendices

Appendix 1: More information on the harmonization of the outcome variables and the cohort data selection

Supplementary table 1: More details on the harmonization of the outcome variables

Main outcomes

	LASA	GLOBE	RECORD	HAPIEE
Self-rated health	Dichotomous indicator of self-assessed health of the participant, indicating good versus less than good health. Based on an original categorization of very good, good, moderate, sometimes good, sometimes bad, and bad self-rated health.	Dichotomous indicator of self-assessed health of the participant, indicating good versus less than good health. Based on an original categorization of excellent, very good, good, fair and poor self-rated health.	Dichotomous indicator of self-assessed health of the participant, indicating good versus less than good health. Based on a score between 0 (terrible) and 10 (excellent) self-rated health, with all scores >7 labeled as good.	Dichotomous indicator of self-assessed health of the participant, indicating good versus less than good health. Based on an original categorization of very good, good, average, poor and very poor self-rated health.

Feels sad, downhearted or blue	Based on a 4-point ('rarely or none of the time', 'some or a little of the time', 'occasionally or a moderate amount of time', 'most or all of the time') item response to "I felt sad" from the CES-D scale, 20-item version. Participants who responded 'occasionally or a moderate amount of time' or 'most or all of the time' were defined as feeling sad, downhearted or blue.	Based on a 6-point ('all of the time', 'most of the time', 'a good bit of the time', 'some of the time', 'a little of the time', 'none of the time') item response to "How much of the time during the past 4 weeks, have you felt downhearted and blue?" from the MHI-5 scale. Participants who responded 'all of the time' to 'a good bit of the time' were defined as feeling sad, downhearted or blue.	Based on a yes/no item response to "I feel sad at present" from the QD2A depression scale.	Based on a 4-point ('less than 1 day', '1-2 days', '3-4 days', '5-7 days') item response to "I felt sad" from the CES-D scale, 20-item version. Participants who responded '3-4 days' or '5-7 days' were defined as feeling sad, downhearted or blue.

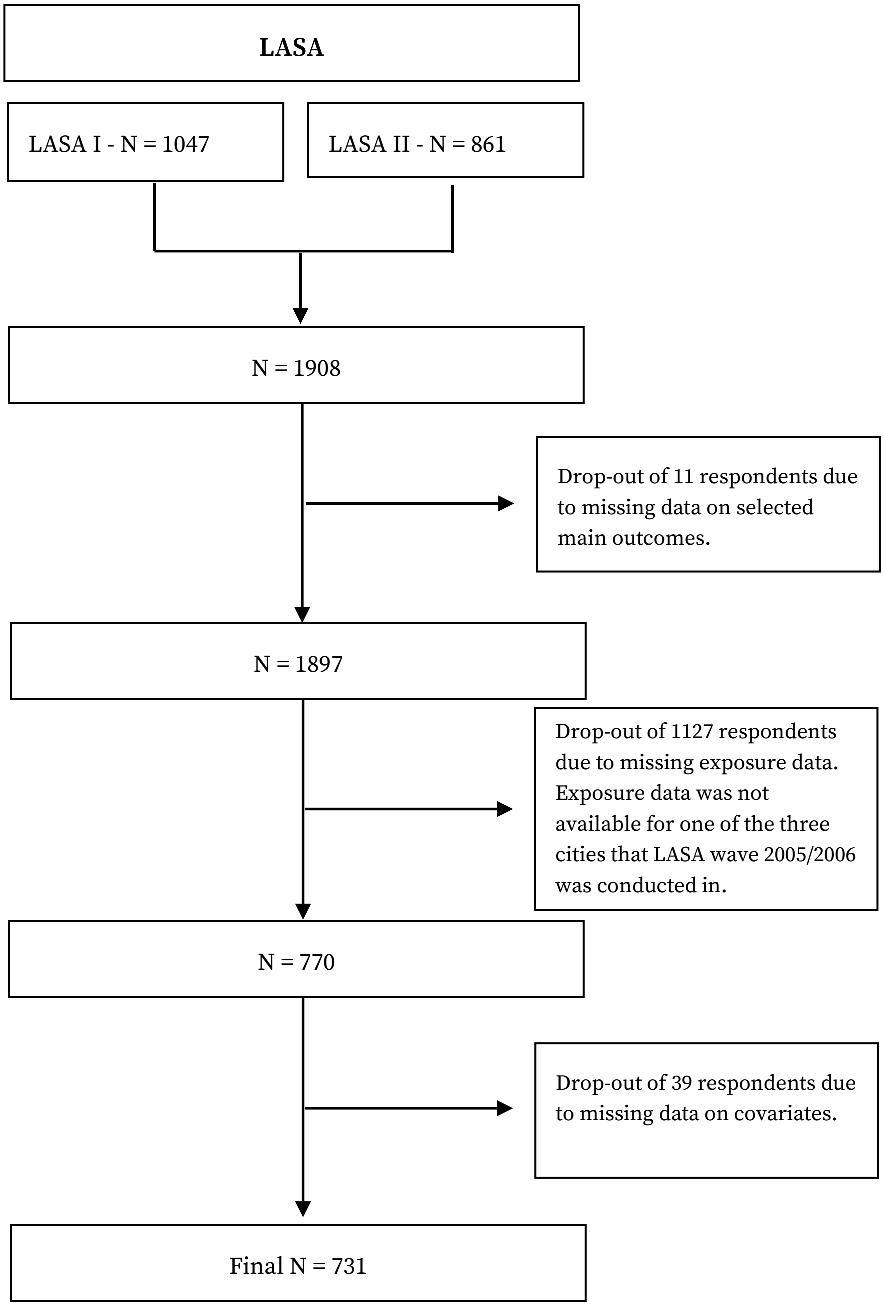
Additional outcomes*

	LASA	GLOBE	RECORD	HAPIEE
Probable caseness of depression	Participants with CESD-20 scores of 16 or higher (out of a possible 60) were defined as cases as per the scale-specific threshold [1].	n.a.	Participants with QD2A depression scores of 7 or higher (out of a possible 13) were defined as cases as per the scale-specific threshold [2].	Participants with CESD-20 scores of 16 or higher (out of a possible 60) were defined as cases as per the scale-specific threshold [1].

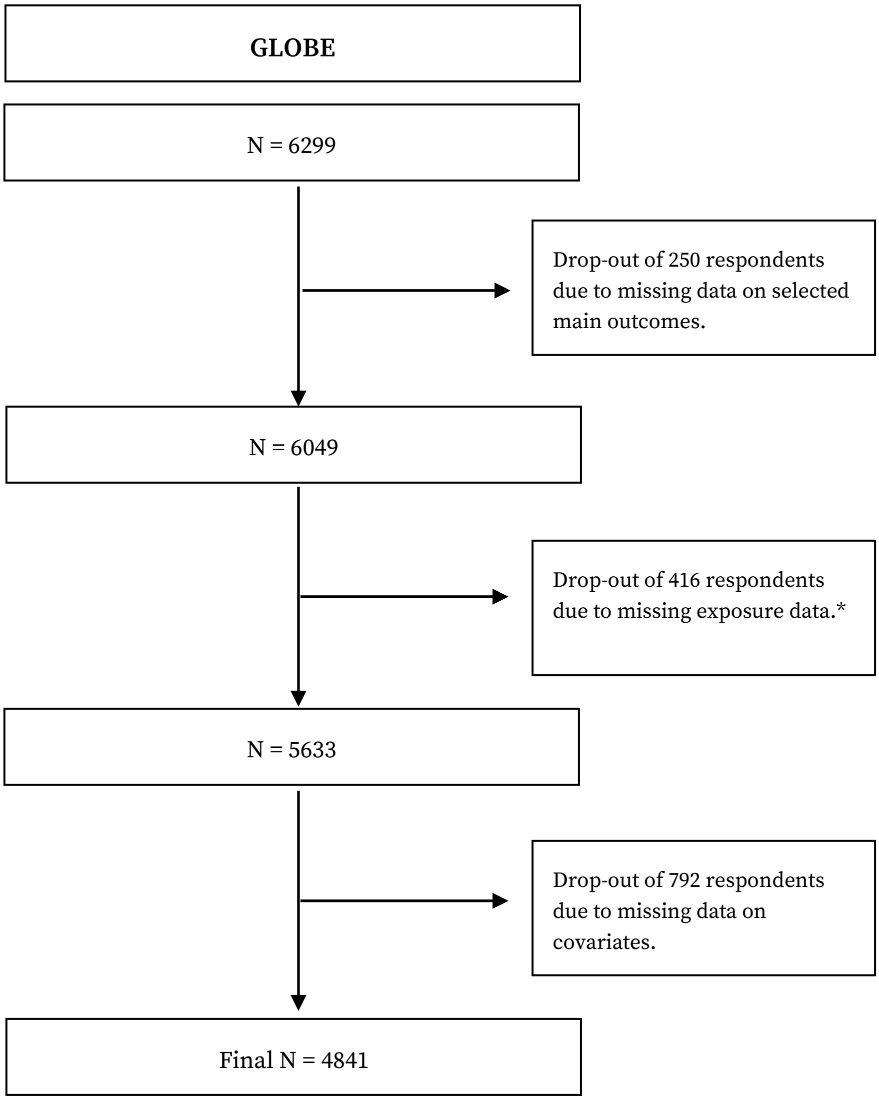
Probable caseness of psychological distress	The MHI-2 scores (2-12) in LASA were transformed to a scale ranging from 0 to 100. As there is no established cut-off score for the MHI-2, participants whose scores ranged from 50 to 100 were classified as cases.	The MHI-4 scores (4-24) in GLOBE were transformed to a scale ranging from 0 to 100. As there is no established cut-off score for the MHI-4, participants whose scores ranged from 50 to 100 were classified as cases.	n.a.	n.a.

*additional outcomes were only used for sensitivity analyses.

Supplementary figure 1: selection of LASA respondents

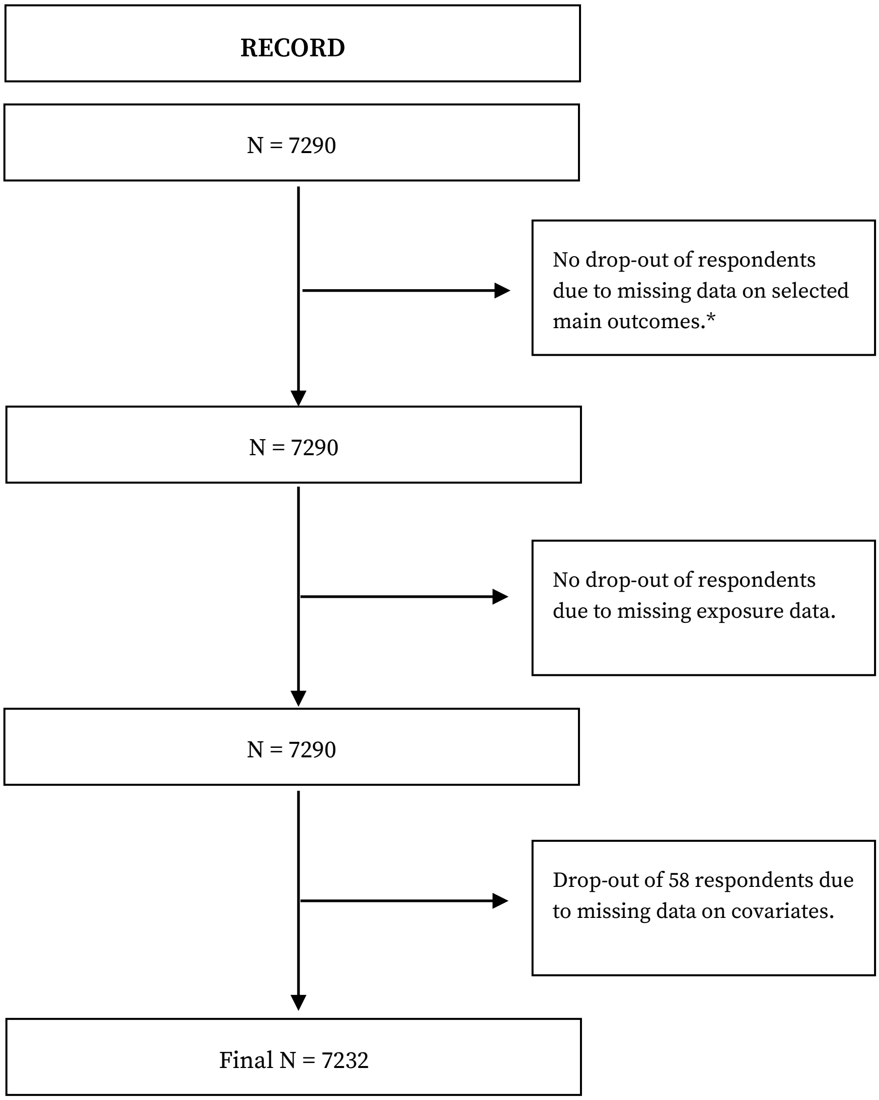


Supplementary figure 2: selection of GLOBE respondents



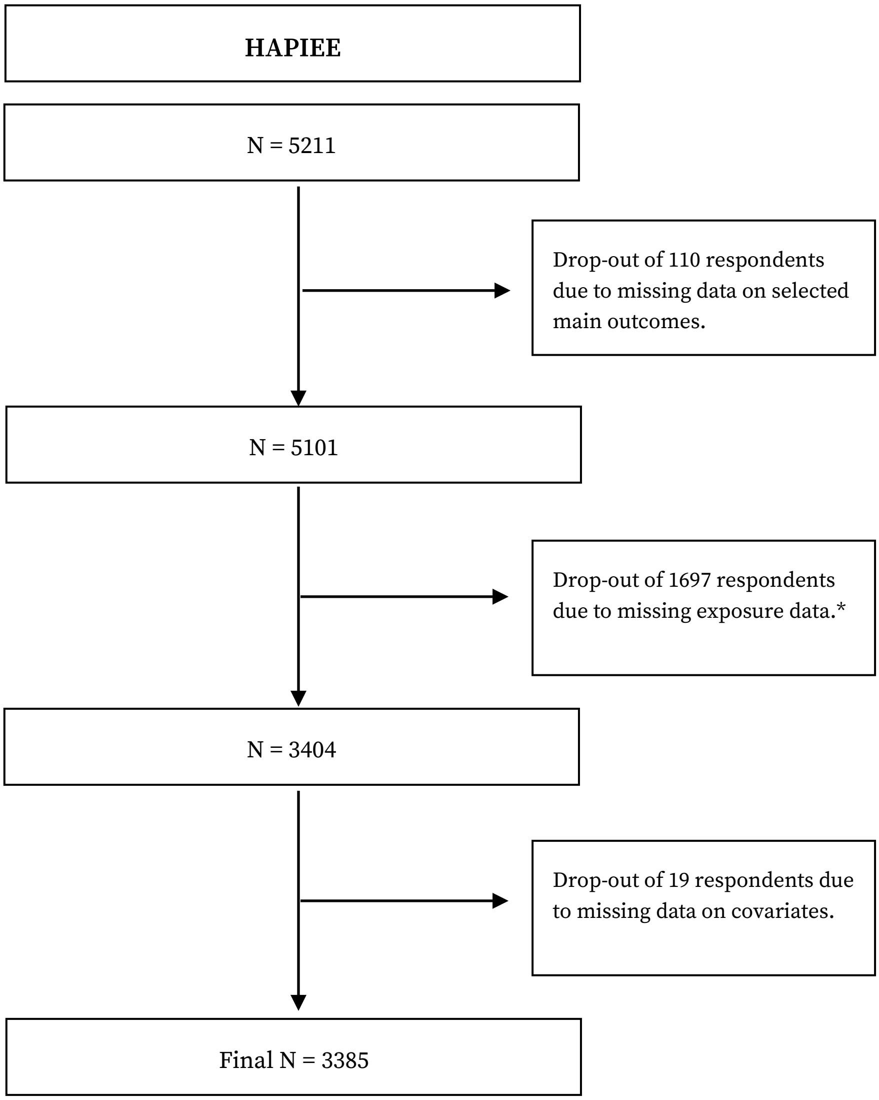
*GLOBE respondents living outside of the Eindhoven area were excluded.

Supplementary figure 3: selection of RECORD respondents



*Selected RECORD wave was the baseline wave of the study.

Supplementary figure 4: selection of HAPIEE respondents



*Exposure data was not available for cities in the HAPIEE Czech cohort with <100,000 inhabitants.

Appendix 2: More information on the green space exposure data

Supplementary table 2: More details on the green space exposures for each cohort

Distance to the nearest green space (m)

LASA										
Mean (sd)	255 (268)									
Min – max (m)	0 – 2100									
Distribution (percentiles)	**0-10**	**10-20**	**20-30**	**30-40**	**40-50**	**50-60**	**60-70**	**70-80**	**80-90**	**90-100**
	0-40	40-77	77-107	107-143	143-180	180-236	236-289	289-363	363-549	549-2100
GLOBE										
Mean (sd)	255 (268)									
Min – max (m)	0 – 2100									
Distribution (percentiles)	**0-10**	**10-20**	**20-30**	**30-40**	**40-50**	**50-60**	**60-70**	**70-80**	**80-90**	**90-100**
	0-38	38-68	68-99	99-129	129-159	159-195	195-240	240-297	297-381	381-1528
RECORD										
Mean (sd)	255 (268)									
Min – max (m)	0 – 2100									
Distribution (percentiles)	**0-10**	**10-20**	**20-30**	**30-40**	**40-50**	**50-60**	**60-70**	**70-80**	**80-90**	**90-100**
	0-50	50-93	93-136	136-178	178-220	220-264	264-322	322-397	397-539	539-1629

HAPIEE										
Mean (sd)	255 (268)									
Min – max (m)	0 – 2100									
Distribution (percentiles)	**0-10**	**10-20**	**20-30**	**30-40**	**40-50**	**50-60**	**60-70**	**70-80**	**80-90**	**90-100**
	0-19	19-35	35-58	58-80	80-107	107-135	135-172	172-218	218-298	298-1167

Amount of green space in 800 meter buffers (ha)*

LASA										
Mean (sd)	17.4 (16.1)									
Min – max (m)	0 – 104.8									
Distribution (percentiles)	**0-10**	**10-20**	**20-30**	**30-40**	**40-50**	**50-60**	**60-70**	**70-80**	**80-90**	**90-100**
	0-1.2	1.2-2.9	2.9-6.1	6.1-9.1	9.1-12.0	12.0-18.4	18.4-24.1	24.1-29.6	29.6-38.1	38.1-104.8
GLOBE										
Mean (sd)	21.9 (16.9)									
Min – max (m)	0 – 130.6									
Distribution (percentiles)	**0-10**	**10-20**	**20-30**	**30-40**	**40-50**	**50-60**	**60-70**	**70-80**	**80-90**	**90-100**
	0-5.9	5.9-9.2	9.2-11.9	11.9-14.6	14.6-17.8	17.8-21.8	21.8-25.8	25.8-31.0	31.0-41.0	41.0-130.6

RECORD										
Mean (sd)	15.0 (18.3)									
Min – max (m)	0 – 189.3									
Distribution (percentiles)	**0-10**	**10-20**	**20-30**	**30-40**	**40-50**	**50-60**	**60-70**	**70-80**	**80-90**	**90-100**
	0-1.6	1.6-3.6	3.6-5.1	5.1-6.6	6.6-8.7	8.7-10.9	10.9-14.4	14.4-22.0	22.0-38.0	38.0-189.3
HAPIEE										
Mean (sd)	35.9 (22.7)									
Min – max (m)	0 – 166.0									
Distribution (percentiles)	**0-10**	**10-20**	**20-30**	**30-40**	**40-50**	**50-60**	**60-70**	**70-80**	**80-90**	**90-100**
	0-11.2	11.2-16.0	16.0-20.6	20.6-27.0	27.0-32.1	32.1-38.7	38.7-44.4	44.4-51.3	51.3-65.6	65.6-166.0

*the total area size of an 800-meter buffer is approximately 201 hectares. A decrease or increase of 10 hectares corresponds to approximately 5% of the total buffer size.

Appendix 3: Sensitivity analyses

Supplementary table 3: Descriptive statistics of the additional subjective health and well-being outcomes for each cohort

	LASA Mean (SD)	GLOBE Mean (SD)	RECORD Mean (SD)	HAPIEE Mean (SD)
Probable caseness of depression, % (n)	15.3% (112)	n.a.	7.7% (558)	11.1% (377)
Probable caseness of psychological distress, % (n)	17.8% (130)	8.7% (419)	n.a.	n.a.

*additional outcomes were only used for sensitivity analyses.

Supplementary table 4: Modified Poisson regression models regressing the probable caseness of depression and psychological distress on the distance to the nearest green space

	LASA	GLOBE	RECORD	HAPIEE
Adjusted model*	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**
Distance to nearest green space (per 100m.)				
Probable caseness of depression	1.02 (0.95 – 1.08)	n.a.	0.98 (0.94 – 1.01)	1.00 (0.93 – 1.08)

Probable caseness of psychological distress	1.04 (0.98 – 1.10)	0.97 (0.91 – 1.03)	n.a.	n.a.

*adjusted for age, gender, employment, retirement status, post-secondary education, and partner status.

Supplementary table 5: Modified Poisson regression models regressing the probable caseness of depression and psychological distress on the amount of green space within 800-meter buffers

	LASA	**GLOBE**	**RECORD**	**HAPIEE**
Adjusted model*	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**
Amount of green space within 800-meter buffers (per 10 hectares)				
Probable caseness of depression	1.02 (0.92 – 1.15)	n.a.	1.00 (0.96 – 1.05)	0.99 (0.95 – 1.04)
Probable caseness of psychological distress	1.02 (0.91 – 1.13)	0.98 (0.92 – 1.03)	n.a.	n.a.

*adjusted for age, gender, employment, retirement status, post-secondary education, and partner status.

Supplementary table 6: Modified Poisson regression models regressing subjective health and well-being outcomes on the amount of green spaces in 400 and 1000 meter buffers

	LASA	**GLOBE**	**RECORD**	**HAPIEE**
Adjusted model*	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**	**RR (95% CI)**
Amount of green space within 400-meter buffers (per 10 hectares)				
Depressed affect	1.10 (0.42 – 2.44)	0.93 (0.73 – 1.18)	1.06 (0.92 – 1.21)	1.01 (0.87 – 1.17)
Good self-rated health	0.99 (0.80 – 1.21)	1.03 (0.97 – 1.10)	1.00 (0.94 – 1.06)	1.03 (0.96 – 1.11)
Amount of green space within 1000-meter buffers (per 10 hectares)				
Depressed affect	0.95 (0.78 – 1.13)	0.99 (0.94 – 1.03)	1.01 (0.99 – 1.03)	1.01 (0.98 – 1.04)
Good self-rated health	1.00 (0.96 – 1.04)	1.00 (0.99 – 1.02)	1.00 (0.99 – 1.01)	1.00 (0.99 – 1.02)

*adjusted for age, gender, employment, retirement status, post-secondary education, and partner status.

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5

Effect of changes in green spaces on mental health in older adults: a fixed effects analysis

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Abstract

Background

Urban green spaces have been linked to different health benefits, but longitudinal studies on the effect of green spaces on mental health are sparse and evidence often inconclusive. Our objective was to study the effect of changes in green spaces in the residential environment on changes in mental health using data with 10 years of follow-up (2004–2014).

Methods

Data from 3175 Dutch adults were linked to accessibility and availability measures of green spaces at three time points (2004/2011/2014). Mental health was measured with the Mental Health Inventory-5. Fixed effects analyses were performed to assess the effect of changes in green spaces on mental health.

Results

Cross-sectional analysis of baseline data showed significant associations between Euclidean distances to the nearest green space and mental health, with an increase of 100 m correlating with a lower mental health score of approximately 0.5 (95% CI −0.87 to −0.12) on a 0–100 scale. Fixed effects models showed no evidence for associations between changes in green spaces and changes in mental health both for the entire sample as well as for those that did not relocate during follow-up.

Conclusions

Despite observed cross-sectional correlations between the accessibility of green space in the residential environment and mental health, no evidence was found for an association between changes in green spaces and changes in mental health. If mental health and green spaces are indeed causally linked, then changes in green spaces in the Eindhoven area between 2004 and 2014 are not enough to produce a significant effect.

5.1 Introduction

From 1990 to 2010, the burden of mental health increased by 38%, an increase mostly attributable to population growth and ageing. Major depressive disorder, a common mental disorder in older age, is the leading cause of disability-adjusted life years (DALYs) and the fourth leading contributor to the global burden of disease worldwide [1]. Mental disorders in old age lead to impairments in the ability to function socially, decreased quality of life, and increased risk of health problems and comorbidities. They carry substantial social and economic impacts on families and societies, imposing a burden on health and social care services [1]. Decades of research have documented the higher risk of mental disorders among those living in urban versus rural areas [2]. Global urbanisation trends have led to more and more people living in cities, with urbanisation affecting the whole world [3]. This situation of planetary urbanisation means that the urban environment has become a key site for the implementation of prevention and early identification policies on the trajectories of ageing and mental well-being.

Within the context of an increasingly urbanising world, contact with natural environments may play an important role in improving mental health. A review by the WHO indicated mental health as being one of the most important factors influenced by urban green spaces [4]. Other studies have shown that individuals living in urban areas with more green space have a reduced level of stress and improved well-being compared with controls with poorer availability of green space [5-6]. However, the mechanisms linking green spaces to mental health appear to be complex, leading to much discussion on underlying pathways. Psychoevolutionary theories suggest that mental health can be influenced through restorative functions of natural environments. Views of, or interaction with, nature can reduce stress, [7-8] or involuntary attention given to stimuli from nature can aid in performing cognitively demanding tasks [9-10]. Other mechanisms include green spaces supporting physical activity, stimulating social interactions and reducing exposure to harmful environmental stressors [11-12].

While a substantial number of studies present significant associations between green spaces and mental health, they are often based on cross-sectional data [13]. Thus, causality cannot be established, putting into question whether increasing the amount of green spaces leads to better mental health. The evidence of long-term mental health benefits of urban green spaces seems to be inconsistent at best, as many studies are hampered by weak statistical associations, or failure to exclude confounding, bias or reverse causality [14-15]. Longitudinal studies that do assess how green space and mental health relate over time provide evidence that the impact of green spaces on mental health can vary across the life course, [16] or find little to no impact at all [17]. This further raises questions about the strength and robustness of cross-sectional findings relating mental health to green spaces.

An attractive method to address these concerns comes with the use of fixed effects models that rely on within-individual changes. This method eliminates the effects of time-invariant confounding variables as long as they remain stable over time (ie, they are 'fixed') [18]. A UK study that used this approach found that 'respondents in areas with more green space experienced significantly lower mental distress and significantly higher well-being' [6]. However, a complicating factor of these models is that the method requires multiple measurements. While individual-level longitudinal outcome data are becoming increasingly available, individual-level longitudinal exposure data are still rare. Longitudinal studies therefore commonly rely on neighbourhood-level data or small-area statistics and link those exposures to individual-level outcomes [6]. The problems associated with such linkages have been described in detail [19-20]. The present study, however, is able to circumvent these problems by using a harmonised, longitudinal geographical information system (GIS) database to generate individual-level green space exposure data. Using individual-level exposures helps to circumvent methodological problems of area-level data and will strengthen the evidence base of the effects of green spaces on mental health. To the best of our knowledge, no studies to date exist that use fixed effects models to investigate how green space and mental health of older adults relate over time using both individual-level exposures and outcomes.

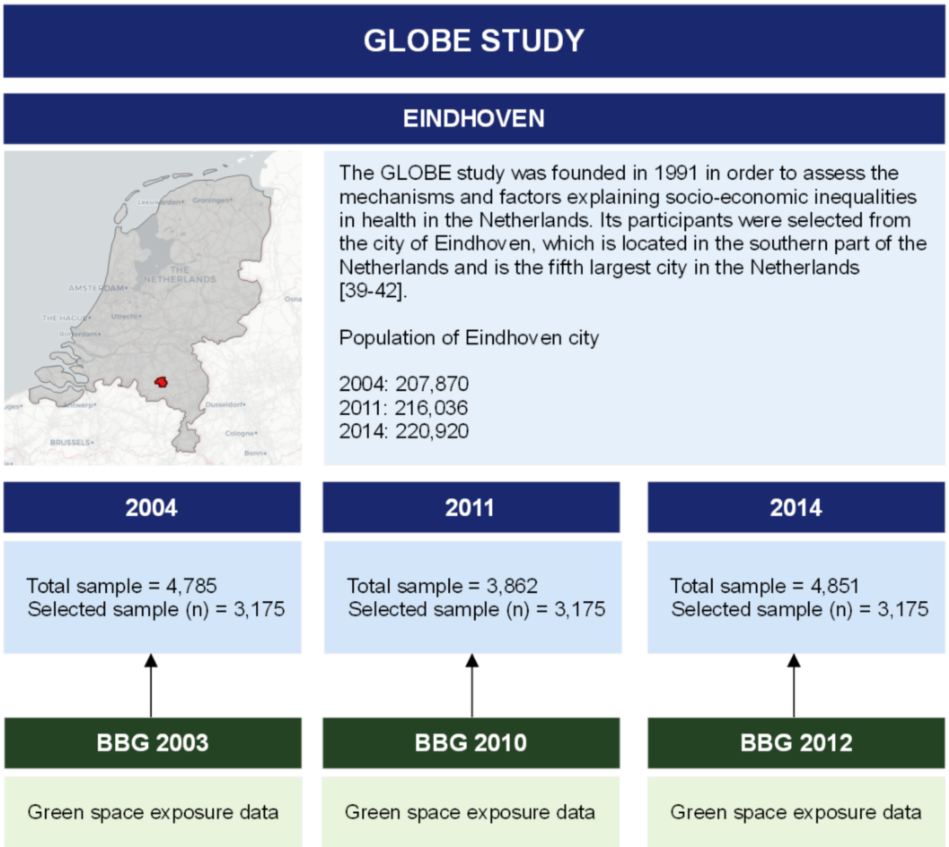
Our present study links individual urban green space exposures to mental health outcomes from cohort data with 10 years of follow-up. We first describe group-level associations deduced from a cross-sectional analysis of the baseline data. Second, we explore within-subject changes with a fixed effects model. Lastly, we estimate within-subject changes among participants who did not relocate during follow-up. Sensitivity analyses were performed using random effects models that explore variation between individuals, and on data on the amount of green space within the residential environment.

5.2 Methods

Study population

Data were obtained from GLOBE (Gezondheid en Levens Omstandigheden van de Bevolking van Eindhoven en omstreken), a prospective cohort study on the role of living conditions for health in the Netherlands. The 2004 sample of GLOBE participants was selected for the analyses (n=4785) with follow-up data collected for the years 2011 and 2014 (figure 1). The sample consisted mainly of older adults living in the city of Eindhoven and surrounding areas. Additional details of the GLOBE study can be found elsewhere [21]. The residential addresses of these respondents were geocoded using the geographical software package QGIS22 and a geocoding plug-in developed by the Dutch National Spatial Data Infrastructure 'Publieke Dienstverlening Op de Kaart' (PDOK) [23]. To maintain respondent privacy, addresses were extracted and geocoded using a process previously described [24-25]. Additional questionnaires were administered in 2011 and 2014. Respondents who only participated in 1 year were excluded (33%), resulting in a final sample of 3175 respondents. Movement to different addresses between follow-up years was recorded.

Figure 1: Study overview of the GLOBE study (Gezondheid en Levens Omstandigheden van de Bevolking van Eindhoven en omstreken) and the Eindhoven area.



Basemap: Open street map contributors & CARTO. Countries: Natural Earth Data. GLOBE, Health and Living Conditions of the Population of Eindhoven and Surroundings. BBG, Bestand BodemGebruik.

Exposure measures of green space

Exposure measures of this study were obtained using the data set 'Bestand Bodemgebruik' (BBG), which is maintained by Statistics Netherlands [26]. The BBG database is a harmonised data set based on 'Top10NL' digital 1:10 000 topographic maps provided by the Dutch mapping agency Kadaster [27]. The harmonisation of the BBG data ensures that observed changes are representative of actual changes in the environment and not related to changes in GIS processing or methodology. Extensive land classification data were used to locate categories of green spaces based on previous research in the Netherlands using similar data [28] (online supplementary appendix 1). The classifications were subsequently divided into four categories: (1) green spaces, (2) green and blue spaces, (3) green and agricultural spaces, and (4) green, blue and agricultural spaces. Accessibility measures were calculated as the Euclidean distance from the participant's residential address to the nearest point on the boundary of a green space for each participant at each time point using QGIS. Availability of green space was calculated based on the amount of green spaces within the Euclidean buffers of 300 m, 500 m and 1000 m around the residential address. Sensitivity analyses were performed on respondents from Eindhoven inner city and respondents from the Eindhoven city region (figure 1). GLOBE cohort data from each wave were linked to geographical data from the preceding year, keeping in line with an appropriate chronology of exposure preceding outcome (figure 1). Unfortunately, BBG data were not available for 2013, so 2014 outcome data were linked to exposure data from 2012.

Outcome measures of mental health

Mental health was assessed using the five-item version of the 'mental health inventory' (MHI-5). MHI-5 is a validated questionnaire that asks respondents how their mental health was over the last 4 weeks [29-30]. It consists of the following five questions: (1) 'Have you felt so down in the dumps that nothing could cheer you up?', (2) 'Have you felt downhearted and blue?', (3) 'Have you been a happy person?', (4) 'Have you been a very nervous person?', and (5)

‘Have you felt calm and peaceful?’. Each question has six possible responses ranging from ‘all the time’ to ‘none of the time’; the third and fifth questions were reverse-coded. A total mental health score was calculated by taking the mean of the five items and transforming it to 100-point scale to improve interpretation (a higher score indicates better mental health) [29-30]. Cronbach’s alpha for the MHI-5 scale was 0.85. Participants had to answer at least three out of five questions to be included.

Covariates

Marital status (married/partnership, not married, divorced, widowed), annual household income (monthly; <€1200, €1200–€1800, €1800–€2600, >€2600) and employment status (employed, unemployed, retired, non-employed) were included as relevant time-varying confounders. All covariates were measured at all three time points, capturing changes that occurred in the 10-year period. Time-invariant characteristics (as measured in 2004) that were included in the cross-sectional analyses include age, gender (male, female), place of birth (the Netherlands, elsewhere) and education classified using the International Standard Classification of Education (ISCED) (lowest=ISCED 0–1, low=ISCED 2, middle=ISCED 3–4, high=ISCED 5–7) [31].

Statistical analyses

Missing data on covariates were handled via multiple imputation using data on the variables listed above, as well as self-rated health (excellent, very good, good, fair, poor), smoking (yes, no), home ownership (rental, owner), financial stress (no, some, yes) and body mass index [32]. Missing data ranged from 0% on the exposures to 36% on income (online supplementary appendix 3). First, cross-sectional analyses were performed on baseline data from 2004. Associations between exposure and outcome were explored with linear regression models adjusted for age, age squared, gender, place of birth, education, marital status, income and employment. Second, fixed effects models were used to estimate the relationship between within-person changes in the distance to the nearest green space and within-person changes in mental health. Two fixed effects models were applied: a linear regression model controlling for time only, and an adjusted model with additional controls for time-varying characteristics of marital status, employment and income. The following model was used for the analyses:

$$MentalHealth_{it} = \mu_t + \beta_1 GreenSpace_{it} + \beta_2 x_{it} + \alpha_i + \epsilon_{it}$$

whereby $MentalHealth_{it}$ indicates the total mental health score for individual i at time t, μ_t accounts for time effects that are fixed for all individuals, $GreenSpace_{it}$ represents the green space exposure measure (i.e. the distance to the nearest green space or the area within the designated buffer), x_{it} is a vector of time-varying control regressors, α_i controls for time-invariant personal characteristics, while ϵ_{it} is the error term. The fixed effects analyses were performed first on all available data, and second on data restricted to participants who did not relocate during follow-up. Robust SEs were used to account for non-independence clustering at the individual level. Sensitivity analyses were performed using random effects models that explore variation between individuals. All analyses were performed using Stata V.15 [33].

5.3 Results

At baseline (2004; table 1) the mean age was 53 years, and 55.5% of the participants were women. On average, the total mental health score of respondents was 73.2 on a 0–100 scale. The distance to the nearest green space ranged from 163 m to 193 m on average between different green space categories. The amount of green space ranged from an average amount of 3.46 hectares in the smallest buffer (300 m) to 47.75 hectares in the largest (1000 m).

Table 1: Description of the study population at baseline (2004, n=3175)

Variables	Mean (SD) / %
Exposures	
Distance to nearest green space, meters	193 (139)
Distance to nearest green or blue space, meters	186 (136)
Distance to nearest green or agricultural space, meters	169 (129)
Distance to nearest green, blue, or agricultural space, meters	164 (126)
Amount of green spaces within 300m buffers, hectares	3.46 (3.01)
Amount of green spaces within 500m buffers, hectares	9.66 (7.70)
Amount of green spaces within 1000m buffers, hectares	47.75 (27.61)
Outcome	
Total mental health score (MHI5)	73.2 (15.7)
Time-fixed characteristics	
Male, %	44.5
Born in The Netherlands, %	93.0
Educational level	
High, %	31.3
Middle, %	24.7
Low, %	35.1
Lowest, %	8.9
Time-varying characteristics	
Age, mean(SD)	53 (13)
Marital status	

Married/partnership, %	75.6
Unmarried, %	12.1
Divorced, %	6.9
Widowed, %	5.4
Employment	
Employed, %	50.3
Unemployed, %	7.4
Retired, %	25.7
Non-employed, %	16.6
Household income	
<€1200, %	10.4
€1200-1800, %	20.1
€1800-2600, %	27.9
€2600-4000, %	29.1
>€4000, %	12.5

Linear regression models applied to cross-sectional data from 2004 showed significant associations between the distance to the nearest green space and the total mental health score for all green space categories (table 2). On average, the total mental health score declined with 0.49 (95% CI −0.87 to −0.12) to 0.55 (95% CI −0.96 to −0.13) points when the distance to the nearest green space was extended by 100 m. Sensitivity analyses showed that these results were only observed among respondents within the suburban areas and not among respondents within the inner city (online supplementary appendix 2). Applied random effects models showed similar effect directions, but effect sizes were attenuated greatly (online supplementary appendix 2). The amount of green space in hectares within buffers was not significantly associated with the total mental health score (table 2).

Table 2: Linear regression models regressing total mental health on the distance to the nearest green, blue and agricultural spaces using cross-sectional data from 2004 (n=3175)*

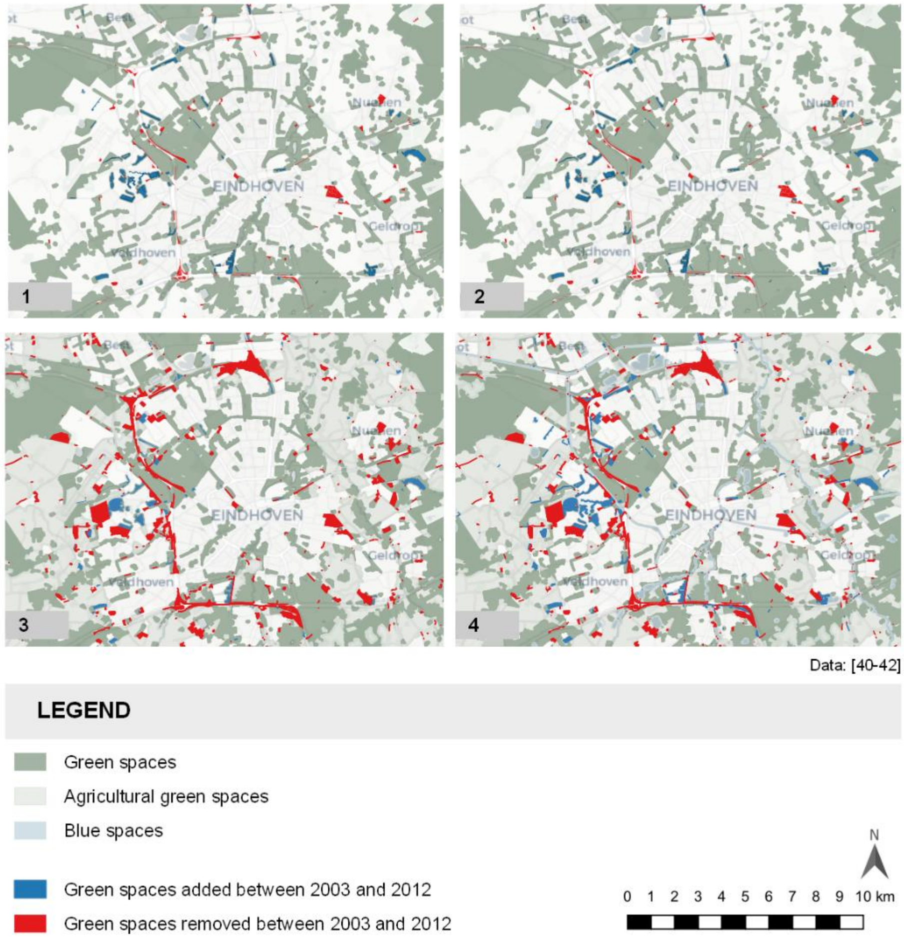
Name	β	95% CI	P value
Distance to nearest green space (100m)			
Total Mental Health Score	-0.584	-0.965 to -0.204	0.003
Distance to nearest green or blue space (100m)			
Total Mental Health Score	-0.584	-0.965 to -0.204	0.030
Distance to nearest green or agricultural green space (100m)			
Total Mental Health Score	-0.445	-0.960 to -0.134	0.030
Distance to nearest green, blue or agricultural green space (100m)			
Total Mental Health Score	-0.547	-0.960 to -0.134	0.010
Amount of green spaces within 300m buffers (hectares)			
Total Mental Health Score	0.120	-0.071 to 0.311	0.219
Amount of green spaces within 500m buffers (hectares)			
Total Mental Health Score	0.055	-0.012 to 0.123	0.109
Amount of green spaces within 1000m buffers (hectares)			
Total Mental Health Score	0.017	-0.002 to 0.036	0.079

*adjusted for age, age squared, sex, country of birth, education, marital status, income, and employment.

Green space changes and within-person changes

Changes in distances to and amount of green spaces were observed over the 2003–2012 period (figure 2). Within-person changes were also observed, consisting of both increases and decreases of the total mental health score over time (table 3). It appears that more green spaces have been removed than added over this time period, resulting in more increases in the distance to the nearest green space than decreases.

Figure 2: Changes in (A) green, (B) green and blue, (C) green and agricultural, and (D) green, blue and agricultural green spaces in the Eindhoven city region between 2003 and 2012.



Basemap: Open street map contributors & CARTO. GLOBE, Health and Living Conditions of the Population of Eindhoven and Surroundings. BBG, Bestand BodemGebruik.

Table 3: Within-person changes in green space and mental health between 2004 and 2014

	Decrease		No change		Increase	
All participants (n = 7269 person observations)	**Mean**	**n**	**Mean**	**n**	**Mean**	**n**
Distance to nearest green space (m)	-131	923	0	5379	137	967
Distance to nearest green or blue space (m)	-128	847	0	5374	119	1048
Distance to nearest green or agricultural space (m)	-130	925	0	5332	133	1012
Distance to nearest green blue or agricultural space (m)	-125	55	0	5338	116	1076
Amount of green spaces within 300m buffers (hectares)	-1.58	965	0	3496	1.57	942
Amount of green spaces within 500m buffers (hectares)	-3.19	1824	0	3324	2.92	1827
Amount of green spaces within 1000m buffers (hectares)	-8.61	2801	0	1690	7.34	2766
Total mental health score	-11.9	2.955	0	1078	11.9	2808
	Decrease		**No change**		**Increase**	
Participants that did not relocate (n = 6160 person observations)	**Mean**	**n**	**Mean**	**n**	**Mean**	**n**
Distance to nearest green space (m)	-109	466	0	5182	121	512
Distance to nearest green or blue space (m)	-106	382	0	5167	103	611
Distance to nearest green or agricultural space (m)	-107	472	0	5132	121	566
Distance to nearest green blue or agricultural space (m)	-102	390	0	5131	103	639

Amount of green spaces within 300m buffers (hectares)	-1.06	668	0	3376	1.11	668
Amount of green spaces within 500m buffers (hectares)	-2.04	1335	0	3232	1.97	1379
Amount of green spaces within 1000m buffers (hectares)	-5.45	2229	0	1669	4.63	2253
Total mental health score	-11.8	2483	0	940	11.7	2349

Fixed effects analyses

Fixed effects analyses in the total sample resulted in non-significant associations between changes in the distance to green space categories and changes in the mental health score, both for the total sample as well as for those that did not relocate during follow-up (table 4). Analyses were also performed on changes in the amount of green space within buffers and changes in mental health, but the associations were close to null (table 4). Analyses on subgroups of respondents within the city of Eindhoven and respondents within surrounding areas did not alter the results (online supplementary appendix 2).

Table 4: Fixed effects linear regression models regressing changes in mental health on changes in green, blue and agricultural spaces using data from 2004, 2011 and 2014 (n=8194 person observations)

	Unadjusted			**Adjusted***		
Total sample (n = 8194 person observations)	**β**	**95% CI**	**P value**	**β**	**95% CI**	**P value**
Distance to nearest green space (m) Total mental health score	0.18	-0.28 to 0.64	0.447	0.17	-0.28 to 0.63	0.460
Distance to nearest green or blue space (m) Total mental health scores	0.15	-0.30 to 0.61	0.517	0.16	-0.29 to 0.61	0.486
Distance to nearest green or agricultural space (m) Total mental health score	0.35	-0.16 to 0.85	0.183	0.33	-0.17 to 0.84	0.193
Distance to nearest green blue or agricultural space (m) Total mental health score	0.31	-0.18 to 0.81	0.215	0.32	-0.17 to 0.81	0.200
Amount of green spaces within 300m buffers (hectares) Total mental health score	0.06	-0.25 to 0.36	0.715	0.06	-0.25 to 0.36	0.716
Amount of green spaces within 500m buffers (hectares) Total mental health score	0.01	-0.10 to 0.11	0.923	0.00	-0.11 to 0.11	0.989
Amount of green spaces within 1000m buffers (hectares) Total mental health score	0.00	-0.03 to 0.03	0.943	0.00	-0.03 to 0.03	0.894

	Unadjusted			Adjusted*		
Non-movers (n = 4449 person observations)	**β**	**95% CI**	**P value**	**β**	**95% CI**	**P value**
Distance to nearest green space (m) Total mental health score	-0.40	-2.37 to 1.56	0.687	-0.36	-2.30 to 1.58	0.715
Distance to nearest green or blue space (m) Total mental health scores	-0.28	-1.95 to 1.40	0.745	-0.25	-1.92 to 1.43	0.772
Distance to nearest green or agricultural space (m) Total mental health score	-0.74	-2.89 to 1.65	0.502	-0.69	-2.83 to 1.45	0.526
Distance to nearest green blue or agricultural space (m) Total mental health score	-0.26	-2.18 to 1.65	0.789	-0.22	-2.15 to 1.70	0.819
Amount of green spaces within 300m buffers (hectares) Total mental health score	0.25	-0.71 to 1.22	0.606	0.29	-0.69 to 1.26	0.567
Amount of green spaces within 500m buffers (hectares) Total mental health score	0.19	-0.45 to 0.84	0.557	0.21	-0.42 to 0.83	0.518
Amount of green spaces within 1000m buffers (hectares) Total mental health score	0.05	-0.10 to 0.19	0.526	0.05	-0.10 to 0.19	0.526

*adjusted for time-varying confounders marital status, income, and employment.

5.4 Discussion

In this study we have linked longitudinal individual-level green space exposure data to mental health outcomes using a fixed effects approach. The present study provides evidence that the accessibility of green space is correlated with mental health, but that changes in green spaces observed during the 10-year follow-up did not lead to significant changes in mental health. The literature on this topic offers mixed results regarding the role of urban green spaces on mental health, due to variation in methodological approaches and the measurement of green spaces [34-35]. Alcock et al [34] found that individuals who moved to a greener area experienced significantly better mental health while controlling for time-invariant individual-level heterogeneity and other area-level and individual-level effects within a fixed effects framework. Our study investigated the effect of a change in green space among those who did not move and found no statistically significant effects. White et al [6] investigated the effect of green spaces on both well-being and mental distress using a fixed effects framework and found small but significant effects for both. We were not able to replicate these results, which may be due to methodological differences. Where White et al [6] focused on the availability of green space defined as the percentage of green land cover within small areas, our study focused on both the accessibility and availability of green spaces within the residential environment. Analyses performed on the availability of green spaces defined as the amount of green spaces within 300/500/1000 m buffers around residential addresses did not lead to statistically significant effects in the longitudinal analyses. We did not find evidence of a change in the amount of green space within the residential environment leading to a change in mental health.

If mental health and green spaces are causally linked, then changes in green spaces in the Eindhoven area between 2004 and 2014 are not enough to produce a significant effect. Extending the follow-up of our study may mitigate this issue as we are more likely to observe changes in green spaces. However, this may also dilute the potential effect of green spaces on mental health as some of the processes believed to generate changes in mental health as a result of green space exposure may take a short time to exhibit [36]. The current study holds value for policy makers as well, as it reflects the actual changes in the environment in the Eindhoven area between 2004 and 2014. Whereas current policies are often targeted at increasing green spaces in urban areas, our study found that overall there appeared to be as much if not more negative changes in green spaces (ie, green spaces actual changes, our analyses provide evidence that if mental health and green spaces are causally linked, then changes in green spaces in the Eindhoven area between 2004 and 2014 are not enough to produce a significant effect. More research is needed that combines the strengths of both random and fixed effects models in order to gain more insight into potential causal effects of green spaces on mental health.

The choice of land use data as the source of our exposure data was mainly based on its policy relevance, as our focus was to determine if a decrease or increase in urban green spaces could lead to better or worse mental health. Policies on urban green spaces are commonly based on land use data sets, as green space land use data represent parks and larger plots of green space that are accessible to residents. For example, the Accessible Natural Greenspace Standard, developed by Natural England, states that all residents, wherever they reside, should live within 300 m from the nearest green area [38]. The European common indicator of local public open areas is not specifically focused on green spaces, but uses similar land use data as its basis. However, land use data do not capture fine-grained vegetation that other sources such as the Normalised Difference Vegetation Index capture [4]. These fine-grained vegetation covers may be especially relevant for pathways considering stress reduction and attention restoration. Future research exploring pathways and underlying mechanisms between green spaces and mental health is needed. Different theorised mechanisms, such as green spaces supporting physical activity, stimulating social interactions and reducing exposure to harmful environmental stressors, may be intertwined and the direction of proposed effects is often unclear [39]. Mediation analysis could be a valuable tool in assessing these different pathways.

One final point to consider is the specific context of our study and its external validity. The city of Eindhoven is considered to be one of the greener cities in the Netherlands compared with other large Dutch cities. As Dutch cities are considered to be very compact and dense, the spatial context of this study might not be generalisable to other cities [40]. More research is needed that compares the effects of green spaces on mental health across different spatial contexts. Furthermore, the exposure measures in our present study were based on the residential environment, which means we were not able to control for time spent away from this residential environment. Home and neighbourhood environments are considered to be important places of ageing and a relevant spatial context for older adults [41]. However, studies that adapt an approach where participants are tracked during the day using Global Positioning Systems (GPS) could potentially lead to more insights into how green space and mental health relate [42-43].

5.5 Conclusions

The introduction of more green spaces in urban settings has been widely endorsed as a method to improve both physical and mental health. While our present study finds statistically significant cross-sectional associations between accessibility to four different types of green spaces and mental health, we did not find evidence of a change in green spaces leading to a change in mental health. This has specific policy implications as gaining more insights into before-and-after effects of environmental changes has great practical relevance in public health policy. If mental health and green spaces are indeed causally linked, then changes in green spaces in the Eindhoven area between 2004 and 2014 are not enough to produce a significant effect.

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Appendices

Appendix 1: More information on the BBG database and land use classification

The TOP10NL dataset is the official, national topographical representation of the Netherlands and is maintained by the Dutch mapping agency ‘Kadaster’. Statistics Netherlands converts this topographical data to land use data and publishes the resulting files as open source GIS data. The ‘Bestand Bodemgebruik’ (BBG) is the collection of these files. The BBG dataset is generally updated every two to four years depending on funding sources and research needs. The most recent dataset is distributed by Statistics Netherlands and is reposited in the Dutch National Georegister. Historical files are distributed by the Netherlands institute for permanent access to digital research resources. These files are available through their Data Archiving and Networked Services (DANS). This platform aims to make digital research data and related outputs findable, accessible, interoperable and reusable. All historical BBG files are available through this platform free of charge.

Supplementary table 1: Green space classifications based on the land use classification of the BBG dataset

Green space categories	**Corresponding BBG classifications**
1. Green spaces	Parks Allotment gardens Dry open terrain Recreational Areas
2. Green and blue spaces	Parks Allotment gardens Dry open terrain Recreational Areas Lakes Estuaries Rivers Backwaters Wet open terrain
3. Green and agricultural spaces	Parks Allotment gardens Dry open terrain Recreational Areas Agricultural areas
4. Green, blue, and agricultural spaces	Parks Allotment gardens Dry open terrain Recreational Areas Lakes Estuaries Rivers Backwaters Wet open terrain Agricultural areas

Supplementary table 2: Complete land use classification of the BBG dataset as translated by the authors

Category	Lower bounds (hectares)	Description
1. Traffic areas		
10.	-	Railway areas
11.	-	Road traffic areas
12.	1	Airports
2. Built environment		
20.	1	Residential areas
21.	1	Retail areas
22.	1	Public facility areas
23.	1	Social-cultural facility areas
24.	1	Business areas
3. Semi-built-up areas		
30.	1	Dumping grounds
31.	0.1	Junkyards
32.	0.1	Cemeteries
33.	0.5	Quarries
34.	1	Building sites
35.	1	Other
4. Recreational areas		
40.	1	Parks
41.	0.5	Sports areas
42.	0.1	Allotment gardens
43.	1	Recreational areas

44.	1	Extended stay recreational areas
5. Agricultural areas		
50.	1	Greenhouses
51.	1	General agricultural areas
6. Forests and natural areas		
60.	1	Forests
61.	1	Open terrain (dry)
62.	1	Open terrain (wet)
7. Backwaters		
70.	-	Lakes: IJsselmeer and Markermeer
71.	-	Closed estuaries
72.	-	Rivers: Rhine and Maas
73.	-	Border lakes
74.	1	Water reservoirs
75.	1	Recreational backwaters
76.	1	Water used for mineral extraction
77.	1	Sludge fields
78.	1	Other backwaters
8. Open waters		
80.	-	Specific open waters: Waddenzee, Eems, Dollard
81.	-	Specific open waters: Oosterschelde
82.	-	Specific open waters: Westerschelde
83.	-	North Sea
9. Borders		
90.	-	Country borders

Appendix 2: Sensitivity analyses

Table 1: Linear regression models regressing total mental health on the distance to the nearest green, blue, and agricultural spaces using cross-sectional data from 2004 restricted to respondents within the suburban areas surrounding Eindhoven city (n=1,210)*

	β	95% CI	P value
Distance to nearest green space (100m)			
Total Mental Health Score	-0.818	-1.364 to -0.272	0.003
Distance to nearest green or blue space (100m)			
Total Mental Health Score	-0.647	-1.203 to -0.091	0.023
Distance to nearest green or agricultural green space (100m)			
Total Mental Health Score	-1.028	-1.731 to -0.326	0.004
Distance to nearest green, blue or agricultural green space (100m)			
Total Mental Health Score	-1.003	-1.713 to -0.293	0.006

*adjusted for age, age squared, sex, country of birth, education, marital status, income, and employment.

Table 2: Linear regression models regressing total mental health on the distance to the nearest green, blue, and agricultural spaces using cross-sectional data from 2004 restricted to respondents within the city of Eindhoven (n=1,910)*

	β	95% CI	P value
Distance to nearest green space (100m)			
Total Mental Health Score	-0.147	-0.576 to 0.281	0.500
Distance to nearest green or blue space (100m)			
Total Mental Health Score	-0.273	-0.714 to 0.169	0.226
Distance to nearest green or agricultural green space (100m)			
Total Mental Health Score	-0.076	-0.516 to 0.363	0.734
Distance to nearest green, blue or agricultural green space (100m)			
Total Mental Health Score	-0.203	-0.655 to 0.250	0.380

*adjusted for age, age squared, sex, country of birth, education, marital status, income, and employment.

Table 3: Linear regression models regressing total mental health on the distance to the nearest green, blue, and agricultural spaces using cross-sectional data from 2011 (n=2,710)*

	β	95% CI	P value
Distance to nearest green space (100m)			
Total Mental Health Score	-0.080	-0.468 to 0.308	0.686
Distance to nearest green or blue space (100m)			
Total Mental Health Score	-0.056	-0.455 to 0.343	0.783
Distance to nearest green or agricultural green space (100m)			
Total Mental Health Score	-0.149	-0.561 to 0.263	0.479
Distance to nearest green, blue or agricultural green space (100m)			
Total Mental Health Score	-0.130	-0.556 to 0.297	0.550

*adjusted for age, age squared, sex, country of birth, education, marital status, income, and employment.

Table 4: Linear regression models regressing total mental health on the distance to the nearest green, blue, and agricultural spaces using cross-sectional data from 2014 (n=2,309)*

	β	**95% CI**	**P value**
Distance to nearest green space (100m)			
Total Mental Health Score	-0.122	-0.551 to 0.306	0.576
Distance to nearest green or blue space (100m)			
Total Mental Health Score	-0.075	-0.517 to 0.367	0.738
Distance to nearest green or agricultural green space (100m)			
Total Mental Health Score	-0.153	-0.605 to 0.299	0.507
Distance to nearest green, blue or agricultural green space (100m)			
Total Mental Health Score	-0.077	-0.547 to 0.393	0.747

*adjusted for age, age squared, sex, country of birth, education, marital status, income, and employment.

Table 5: Random effects linear regression models regressing total mental health on the distance to the nearest green, blue, and agricultural spaces using longitudinal data from 2004, 2011, and 2014 (N=8,194 person observations)

	Unadjusted			**Adjusted***		
	β	**95% CI**	**P value**	**β**	**95% CI**	**P value**
Distance to nearest green space (m) Total mental health score	-0.24	-0.51 to 0.03	0.086	-0.17	-0.43 to 0.09	0.193
Distance to nearest green or blue space (m) Total mental health scores	-0.27	-0.55 to 0.00	0.054	-0.19	-0.45 to 0.08	0.169
Distance to nearest green or agricultural space (m) Total mental health score	-0.25	-0.54 to 0.05	0.097	-0.14	-0.42 to 0.14	0.326
Distance to nearest green blue or agricultural space (m) Total mental health score	-0.28	-0.58 to 0.01	0.062	-0.15	-0.44 to 0.14	0.300

*adjusted for age, age squared, sex, ethnicity, education, marital status, income, and employment

Table 6: Fixed effects linear regression models regressing changes in mental health on changes in green, blue, and agricultural spaces using data from 2004, 2011 and 2014 restricted to respondents within the suburban areas surrounding Eindhoven city (N = 2,036 person observations)

	Unadjusted			**Adjusted***		
	β	**95% CI**	**P value**	**β**	**95% CI**	**P value**
Distance to nearest green space (m) Total mental health score	0.54	-0.43 to 1.52	0.275	0.54	-0.42 to 1.49	0.269
Distance to nearest green or blue space (m) Total mental health scores	0.60	-0.33 to 1.54	0.205	0.60	-0.31 to 1.51	0.197
Distance to nearest green or agricultural space (m) Total mental health score	0.41	-0.80 to 1.77	0.503	0.45	-0.74 to 1.64	0.458
Distance to nearest green blue or agricultural space (m) Total mental health score	0.61	-0.56 to 1.77	0.305	0.64	-0.51 to 1.78	0.273

*adjusted for marital status, income, and employment

Table 7: Fixed effects linear regression models regressing changes in mental health on changes in green, blue, and agricultural spaces using data from 2004, 2011 and 2014 restricted to respondents within the city of Eindhoven (N = 3,600 person observations)

	Unadjusted			**Adjusted***		
	β	**95% CI**	**P value**	**β**	**95% CI**	**P value**
Distance to nearest green space (m) Total mental health score	0.33	-0.47 to 1.14	0.419	0.23	-0.57 to 1.03	0.569
Distance to nearest green or blue space (m) Total mental health scores	0.07	-0.71 to 0.86	0.854	0.00	-0.79 to 0.78	0.997
Distance to nearest green or agricultural space (m) Total mental health score	0.24	-0.57 to 1.06	0.559	0.16	-0.65 to 0.96	0.703
Distance to nearest green blue or agricultural space (m) Total mental health score	0.03	-0.77 to 0.83	0.942	-0.03	-0.82 to 0.76	0.939

*adjusted for marital status, income, and employment

Table 8: Duration of residence in the current neighbourhood in 2004 (n = 3,175)

Duration of residence (years)	Frequency	%	Cumulative
1	151	4.74	4.74
2	161	5.05	9.79
3	143	4.49	14.27
4	175	5.49	19.76
5	168	5.27	25.03
6	131	4.11	29.14
7	122	3.83	32.97
8	111	3.48	36.45
9	78	2.45	38.90
10	130	4.08	42.97
11	70	2.20	45.17
12	80	2.51	47.68
13	67	2.10	49.78
14	73	2.29	52.07
15	115	3.61	55.68
>15	1400	44.32	100

Table 9: Fixed effects linear regression models regressing changes in mental health on changes in green, blue, and agricultural spaces using data from 2004, 2011 and 2014 restricted to respondents who lived in the same neighbourhood for a maximum of 5 years (N = 2,003 person observations)

	Unadjusted			Adjusted*		
Duration of Residence <5 years	**β**	**95% CI**	**P value**	**β**	**95% CI**	**P value**
Distance to nearest green space (m) Total mental health score	0.00	-0.76 to 0.75	0.996	0.53	-0.42 to 1.49	0.269

*adjusted for marital status, income, and employment

Table 10: Fixed effects linear regression models regressing changes in mental health on changes in green, blue, and agricultural spaces using data from 2004, 2011 and 2014 restricted to respondents who lived in the same neighbourhood for more than 5 years (N = 6,187 person observations)

	Unadjusted			Adjusted*		
Duration of Residence >5 years	**β**	**95% CI**	**P value**	**β**	**95% CI**	**P value**
Distance to nearest green space (m) Total mental health score	0.31	-0.27 to 0.90	0.294	0.54	-0.42 to 1.49	0.269

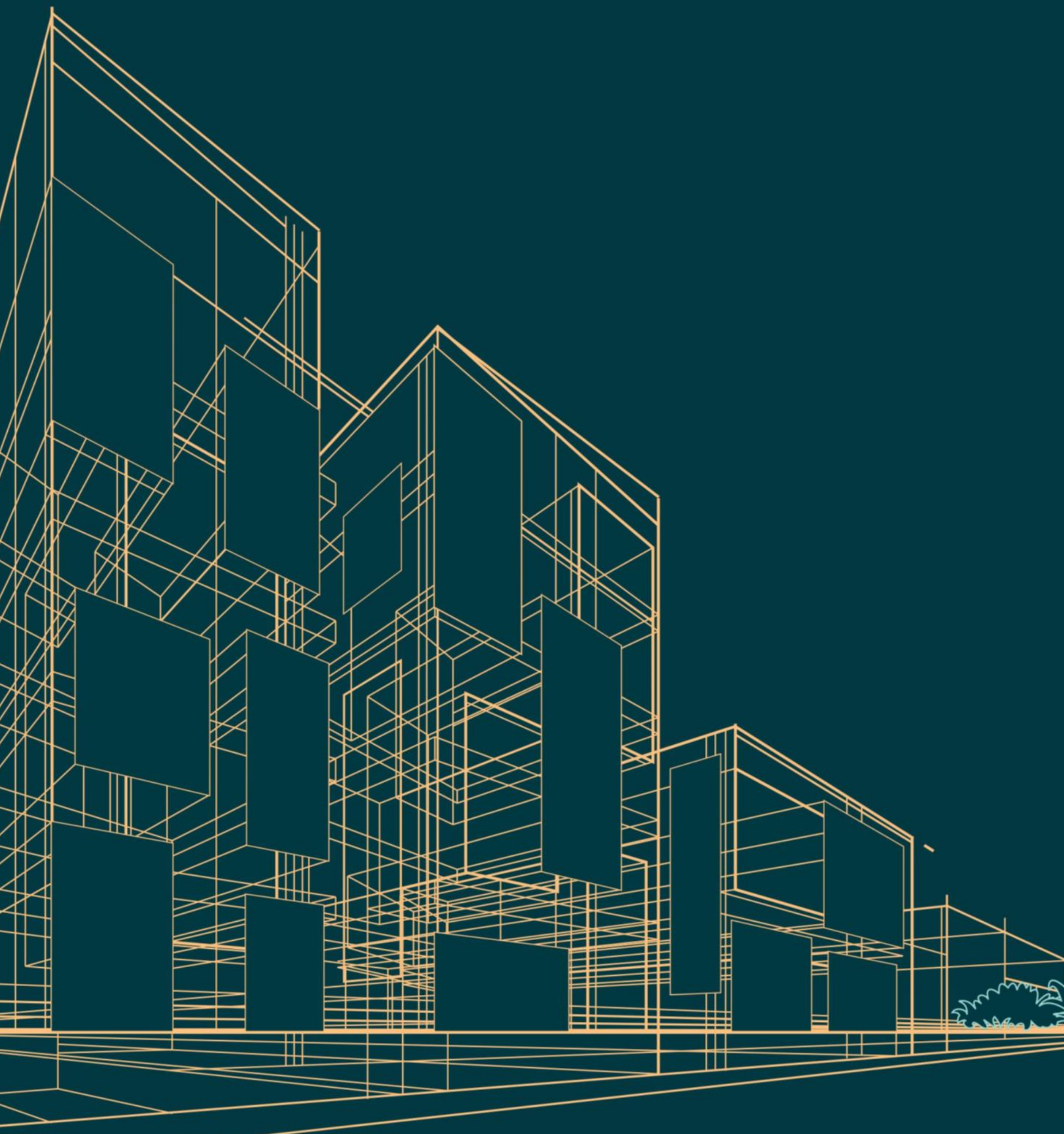
*adjusted for marital status, income, and employment

Appendix 3: Missing data

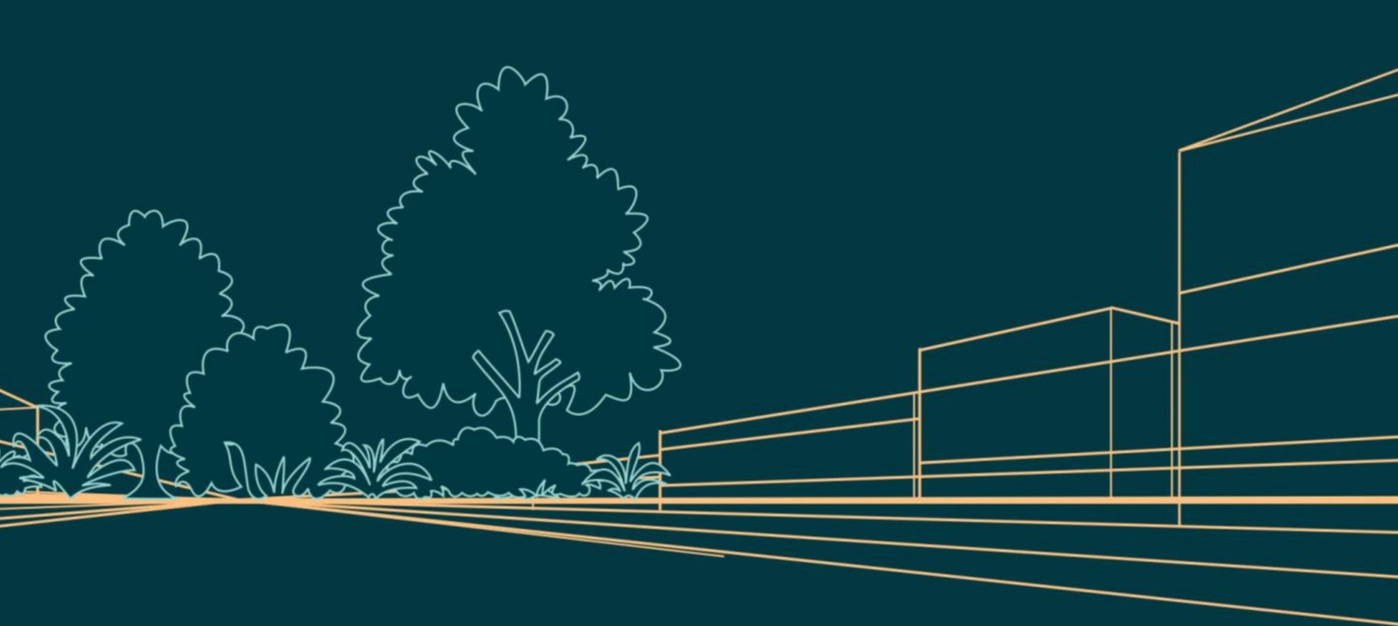
Table 11: Missing data

Variable	Missing	Total	% Missing
Age			
2004	33	3,175	1.0
2011	211	3,175	11.1
2014	838	3,175	26
BMI			
2004	63	3,175	2
2011	418	3,175	13
2014	881	3,175	27.4
Education			
2004	155	3,175	4.8
2011	501	3,175	15.6
2014	864	3,175	26.8
Employment			
2004	215	3,175	6.7
2011	482	3,175	15
2014	936	3,175	29.1
Financial stress			
2004	47	3,175	1.5
2011	395	3,175	12.3
2014	915	3,175	28.4
Gender			
2004	0	3,175	0
2011	0	3,175	0
2014	0	3,175	0

Home			
ownership	17	3,175	0.5
2004	378	3,175	11.7
2011	896	3,175	27.8
2014			
Income			
2004	69	3,175	2.1
2011	751	3,175	23.3
2014	1,170	3,175	36.3
Marital status			
2004	54	3,175	1.7
2011	353	3,175	11
2014	848	3,175	26.3
Self-rated health			
2004	75	3,175	2.3
2011	508	3,175	15.8
2014	858	3,175	26.6
Smoking			
2004	204	3,175	6.3
2011	416	3,175	12.9
2014	863	3,175	26.8



The urban environment and physical activity



6

Longitudinal effects of urban green space on walking and cycling: A fixed effects analysis

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Abstract

This study examined whether changes in green space within the living environment were associated with changes in walking and cycling frequencies in a cohort of 3,220 Dutch adults between 2004, 2011 and 2014. Data on self-reported weekly time spent walking and cycling for active commute and leisure were linked to geographic information system (GIS) measures of total green areas within 1000 m buffer zones around each participant's home address, and distance to the nearest green space. First, cross-sectional linear regression models showed no statistically significant associations between green space measures and walking and cycling. Second, fixed effects (FE) models were used to analyze whether changes in green space were associated with changes in walking and cycling, using longitudinal data from respondents who did not relocate over time. As distance to the nearest green area increased by 100 m, individuals spent 22.76 fewer (95% CI: - 39.92, - 5.60) minutes walking for leisure per week and 3.21 more (95% CI: 0.46, 5.96) minutes walking for active commute. Changes in distance to green space were not significantly related to changes in cycling measures. No clear associations between changes in green areas within 1000 m buffers and changes in walking and cycling were observed. Overall, there was weak evidence of an effect of changes in green space area on changes in walking, and no evidence for cycling.

6.1 Background

The urban landscape can shape human activity and offer avenues for health promotion. Current trends in overconsumption and sedentary lifestyles contribute to the prevalence of non-communicable diseases (NCDs), accounting for 70% of deaths worldwide and inflicting strain on health, societal, and economic systems. Increased physical activity (PA) is cited as a top priority intervention in curbing the detrimental effects of chronic disease [1] by increasing longevity and protecting against cardiovascular diseases, site-specific cancers, type 2 diabetes, obesity, osteoporosis, metabolic syndrome, and high blood cholesterol [2-3]. While many public health efforts focus on conscious behavior change to increase PA, the built environment has been shown to have an effective role in encouraging activity [4-6]. A spatial analysis of residential vicinities can inform public policies on how best to influence the health of a population.

Walking is recognized among the most common, acceptable, and accessible forms of physical activity across different age groups, gender, and ethnicities [7]. Along with cycling, it can be used for commute and leisure purposes to habitually increase daily energy expenditure and improve health [8]. The Netherlands offers a unique case study given the high prevalence of commuter walking and cycling, with 25% of all journeys being travelled by bicycle [9]. Given a cultural predisposition to an active commute, what stimulates or demotivates Dutch adults to walk or cycle? More importantly, how can cities spatially adapt to further increase activity on a population level?

Emerging socio-ecological approaches have focused on the importance of the built environment in shaping health and behavior. Studies often cite street connectivity, land use mix, neighborhood safety, traffic, access to facilities and parks, landscape, and others, as relevant aspects of an active commute [10]. However, unlike countries been conducted, the Netherlands offers a pedestrian and cyclist friendly infrastructure featuring extensive cycling rights of way, bicycle lanes and parking, and educational training for cyclists and motorists [11]. Exploring other characteristics, such as the availability of green space, may therefore prove more fruitful in decoding the health-place relationship.

Increased green space has been associated with reduced adult mortality [12], improved social capital, and lower stress [13-14]. A recent report by the World Health Organization (WHO) lists pathways linking green space to a multitude of health outcomes [15], and positive associations have been shown between the quantity and quality of urban green areas in relation to small-area life expectancy [16]. A review by Hartig et al. details varying and mixed effects on active and leisure transport [17]. In terms of accessibility and usage, an increase in distance to green space is linked with a decline in its use [18]. In addition, quality features and facilities might carry more importance in determining whether residents utilize green areas [19].

While some cross-sectional analyses tout significant associations between green space and PA [20-21] they cannot assess a temporal relationship between exposure and outcome. Thus, causality cannot be established, putting in question the strength and robustness of these observations. Many studies do adjust for confounding factors, but it remains unclear which factors should be included to effectively account for selection [12]. Individuals may choose to live in certain neighborhoods based on lifestyle preferences, environmental considerations, and economic or social factors. The deliberate choice of a physically active person to live in a neighborhood with more green space, for instance, will inflate the association observed between the environment and physical activity in a cross-sectional study. Statistical methods to account for these concerns exist, but have not been widely applied, and the complex nature and interacting features of environmental factors, health, and other variables make it difficult to extricate underlying mechanisms [15]. A few studies explore the effects of longitudinal changes in the built environment [22-25] and specifically green space [26-28] on physical activity measures, but none over a substantial time period with the use of historical green space data and specific, continuous measures of activity such as walking and cycling. Our study offers a unique approach by analyzing longitudinal data with fixed effects (FE) models that rely on within-individual changes to control for confounding. FE models can allow researchers to estimate causal effects from panel data without the need to measure all possible characteristics, as long as these factors do not change over time (i.e. they are "fixed"). This effectively reduces the burden of confounding, and controls for selection effects [29]. To the extent that an individual's choice to select into a neighborhood and potential confounding factors do not change over time (i.e. to the extent that they can be considered to be "fixed effects"), the FE approach is well suited to observe unbiased effects. Moreover, gaining ground on before-and-after effects of environmental change has greater practical relevance in public health policy. While traditional studies describe associations that exist in a moment, FE analyses can strengthen the basis for causal inference by considering whether a change in green space may lead to a change in physical activity. Ultimately, causal evidence may be a cause for action.

This paper aims to decode causal relationships between green space and frequency of walking and cycling by linking comprehensive GIS measures of green space area and proximity to physical activity outcomes from cohort data with 10 years of follow-up. We first describe group-level associations deduced from a cross-sectional analysis. Next, we explore within-subject changes with a fixed effects model. Lastly, we estimate within-subject changes among participants that did not relocate during follow-up.

6.2. Methods

6.2.1. Study population

Data was obtained from GLOBE, a prospective cohort study on socioeconomic health inequalities in the Netherlands. The study surveyed adults living in the city of Eindhoven and surrounding areas, a sample representative of the Netherlands as a whole in terms of age, gender, and level of education. Baseline health questionnaires were distributed in 1991 to a random sample of 27,070 individuals aged 15–75 years old, with an overall response rate of 70.1%. The postal questionnaires assessed health, material, behavioral, psychological, and environmental factors indicative of socioeconomic and health disparities. Additional details of the Dutch GLOBE study can be found elsewhere [30]. The

2004 sample of GLOBE participants representative of the source population of residents aged 25–75 years who resided in Eindhoven and surroundings were selected for the analyses (N = 4,758). Additional questionnaires were administered in 2011 and 2014 (but not in intermediate years). Given that fixed-effects analyses require at least two measurements, respondents who only participated in one year were excluded (30%), resulting in a sample of 3,340 respondents. Analyses were restricted to individuals who resided in Eindhoven and surrounding municipalities at the waves they participated in, and who could be successfully geocoded, resulting in a final sample of 3,220 participants of which 62.8% had measures for all three waves (2004: N = 3,220; 2011: N = 2,884; 2014: N = 2,382).

6.2.2. Outcome measures of walking and cycling

Self-reported measures of walking and cycling were assessed using the validated SQUASH (Short Questionnaire to Assess Health enhancing physical activity), a tool created by the Dutch National Institute of Public Health and the Environment to measure habitual physical activity levels in an adult population. This simple questionnaire offers a reliable evaluation of physical activity in large populations [31]. Participants reported average number of days per week, and hours and minutes per day, spent walking and cycling as part of an active commute and for leisure purposes. Following SQUASH-guidelines, it was assumed that all participants who filled in hours or minutes per week, but omitted ‘days per week,’ had been active for at least one day. Further, if the number of days was provided without a corresponding time frequency, the median minutes per day of all respondents was substituted, and a final measure of minutes per week was computed. Variables were recoded into separate measures for walking and cycling for active commute, and leisure, as well as total frequencies.

6.2.3. Exposure measures of green space

The main explanatory variables used included the total area of green space in the living environment, and distance to the nearest green space. GLOBE cohort data from the 2004 and 2011 waves was linked with geographical data from 2003 and 2010 respectively, keeping in line with an appropriate chronology of exposure preceding outcome measures. The 2014 GLOBE cohort data was linked with 2012 geographical data as 2013 geographical data was not available. Respondent addresses were geocoded using geographical software package QGIS and a geocoding plug-in developed by the Dutch National Spatial Data Infrastructure (PDOK) [32-33]. To maintain respondent privacy, addresses were extracted and geo-coded using a process previously described [34-35]. In total, 98% of addresses were successfully geo-coded. Movement to a different address between follow-up years was recorded.

Historical geographic data of Eindhoven and surrounding areas was obtained from the Dutch dataset 'Bestand Bodemgebruik' (BBG), created by Statistics Netherlands (CBS). The BBG is a harmonized dataset based on "Top10NL" digital 1:10,000 topographic maps provided by Dutch mapping agency Kadaster, and is available as free, open source GIS files. Each BBG data release is based on the most recently available topographical data from that year. Furthermore, whenever a new wave of the BBG data is released, all previous data waves are updated using the most recent processing techniques. The time-varying exposure variables of green space were calculated at each wave. The harmonization of the BBG data ensures that observed changes in green spaces are representative of actual changes in the built environment and not related to changes in GIS processing.

Extensive land classification data was used to locate categories of green spaces relevant to walking and cycling, including parks, sports areas, allotment gardens, recreational areas, agricultural land, forests, and dry and wet open terrain. The absolute distance from the participant's home to the nearest point on the boundary of a green space was measured and recorded for each participant at each time point in QGIS. The total area of green space was calculated within an Euclidian buffer of 1000 m (area 314.16 ha) from geo-coded addresses using QGIS. This buffer represents a large enough area around the home suitable for physical activity, roughly equivalent to 15–20 min of walking and is comparable to measures in previous research [15, 36-39]. A review analyzing GIS buffer measures of green space suggests that larger buffers better predict physical health than smaller ones [40], informing our selection of a 1000 m buffer to measure potential effects on both walking and cycling.

6.2.4. Covariates

Marital status (married/partnership, not married, divorced, widowed), annual household income (monthly; <€1200, €1200–1800, €1800–2600, >€2600) employment status (employed, unemployed, retired, non-employed), smoking status (current, former, or never smoker), and self-rated health (excellent, very good, good, fair, poor) were included as relevant time-varying confounders that may play a role in physical activity outcomes. All covariates were measured at all time points, capturing changes that occurred in the ten-year period. Time-invariant characteristics (measured in 2004) included in the cross-sectional analyses were age, gender (male, female), birthplace (Netherlands, elsewhere), and education (lowest = ISCED 0–1, low = ISCED 2, middle = ISCED 3–4, high = ISCED 5–7).

6.2.5. Statistical analysis

Missing data on covariates (missingness ranged from 0% [gender and age] to 7% [employment], and up to 26% for household income in 2014) were handled via multiple imputation (M = 20) using all variables listed above and several other variables, such as educational level, place of birth, marital status, smoking status, and self-rated health. Outcome variables were not imputed (10.5% missing on walking/cycling for active commute, 7.0% missing on walking/cycling for leisure, 13.1% missing on total walking/cycling). No missing data were present on the exposures (i.e. GIS-measures could be calculated for all geocoded participants).

First, cross-sectional analyses were performed separately on data from 2004 on the full sample of 3,220 participants. Associations between exposure and outcome were explored with linear regression models adjusted for age, age squared, gender, birthplace, education, marital status, income, employment, smoking, and self-rated health. Second, fixed effects (FE) models (using data from 2004, 2011 and 2014) were used to estimate the relationship between within-person change in urban green areas in the living environment, and within-person change in walking and cycling outcomes on data restricted to participants who did not relocate during follow-up (N = 2,850). An FE analysis controls for potential confounders that do not change over time, but vary between individuals, such as gender, place of birth, and highest level of education. Provided that changes are observed, the FE model is able to capture to what extent changes in green space exposure between time-points is related to changes in walking and cycling frequencies between time-points. Two FE models were applied: a linear regression model controlling for time only, and an adjusted model with additional controls for time-varying characteristics of marital status, employment, income, smoking, and self-rated health. The following model was used for the analyses:

$$Walking/cycling_{it} = \mu_t + \beta_1 GreenSpace_{it} + \beta_2 x_{it} + \alpha_i + \epsilon_{it}$$

where $Walking/cycling_{it}$ indicates the walking/cycling frequency for individual i at time t, $green\ space_{it}$ represents the green space area within separate buffer zones or distance to nearest green space, x_{it} is a vector of time-varying control regressors, and ϵ_{it} is the error term. μ_t accounts for time effects that are fixed for all individuals, while α_i controls for time-invariant personal characteristics. Robust standard errors were used to account for non-independence clustering at the individual level. Analyses were performed using STATA 13 [41].

6.3. Results

6.3.1. Sample characteristics

Participant demographic characteristics are presented in Table 1. The final sample consisted of 3,220 adults of mostly Dutch origin residing in Eindhoven and surrounding areas. The mean follow-up time was 9.2 years. The baseline mean age in 2004 was 53 years; 56% of the participants were women. A little over half of all respondents completed a middle-to-high level of education. On average, respondents walked for 160 min per week and cycled for 150 min per week, spending 66% more time on leisure travel as compared to active travel to work or school. In 2004, respondents resided an average distance of 193 m from the nearest green space. Participants were surrounded by an average green area of 47.6 ha (15%) within a 1000 m buffer around their home address.

Table 1: Description of the study population in 2004 (n = 3,220).

Variables	Mean (SD) / %
Exposures	
Distance to green space (m)	193 (139)
Green space within a 1000m buffer (ha)	47.6 (27.7)
Walking and cycling (min/week)	
Walking for transport	13 (59)
Cycling for transport	39 (87)
Walking for leisure	147 (198)
Cycling for leisure	110 (170)
Walking and cycling for transport	52 (111)
Walking and cycling for leisure	257 (282)
Total walking	160 (211)
Total cycling	150 (198)
Total walking and cycling	310 (309)
Time-fixed characteristics	
Age, mean (SD)	53 (13)
Male, %	44
Born in The Netherlands, %	93
Educational level	
High, %	31
Middle, %	25

Low, %	35
Lowest, %	9
Time-varying characteristics	
Marital status	
Married/partnership, %	76
Unmarried, %	12
Divorced, %	7
Widowed, %	5
Employment	
Employed, %	50
Unemployed, %	7
Retired, %	26
Non-employed, %	17
Smoking status	
Never smoked, %	42
Former smoker, %	38
Current smoker, %	20
Household income per month	
<€1200, %	33
€1200-1800, %	29
€1800-2600, %	25
€2600-4000, %	13
Self-rated health	
Excellent, %	8
Very good, %	22
Good, %	55
Fair, %	14
Poor, %	1

6.3.2. Cross-sectional analyses

Linear regression models applied to cross-sectional data in 2004 showed non-significant and negligible associations between distance to green space and time spent walking and cycling, as shown in Table 2. Similarly, the area of green space was not significantly associated with outcome measures, and results showed wide confidence intervals.

Table 2: Linear regression models regressing walking and cycling measures (in minutes per week) on green space using cross-sectional data from 2004 (n = 3,220).

	β	**95% CI**		**p-value**
Distance to nearest green space (100m)				
Walking for transport	0.32	-1.16	1.79	0.674
Cycling for transport	-0.23	-2.33	1.87	0.828
Walking for leisure	0.65	-4.33	5.64	0.797
Cycling for leisure	-2.92	-7.09	1.25	0.169
Walking and cycling for transport	0.08	-2.63	2.80	0.952
Walking and cycling for leisure	-2.27	-9.17	4.64	0.519
Total walking	0.90	-4.43	6.23	0.740
Total cycling	-3.39	-8.37	1.60	0.183
Total walking and cycling	-2.48	-10.20	5.23	0.528
Green space within 1000m buffer (ha)				
Walking for transport	-4.84	-12.25	2.57	0.201
Cycling for transport	8.49	-2.08	19.05	0.115
Walking for leisure	6.59	-18.28	31.45	0.603
Cycling for leisure	3.13	-17.66	23.92	0.768
Walking and cycling for transport	3.65	-10.03	17.32	0.601
Walking and cycling for leisure	9.72	-24.71	44.15	0.580
Total walking	2.07	-24.54	28.67	0.879

Total cycling	11.07	-13.80	35.94	0.383
Total walking and cycling	13.14	-25.33	51.61	0.503

*adjusted for age, age squared, sex, birthplace, education, marital status, income, employment, smoking and self-rated health.

6.3.3. Within-person changes

Within-person changes were observed for all exposures and outcomes, consisting of both increases and decreases in measures over time (Table 3). For the green space measures, about two-thirds of the 6,158 available person observations exhibited changes in distance to nearest green space and changes in green area within a 1000 m buffer. For walking and cycling outcomes, changes were particularly small for active commute measures, with only 14% and 30% of within-person changes over time for walking and cycling, respectively. For leisure walking and cycling, changes were considerably more frequent (81% and 74% respectively). There was an average positive change in total walking and cycling (increase of 16.84 min per week). Average time spent on leisure activities increased by 19.84 min per week, whereas total active commute measures saw a decrease by 2.68 min per week.

Table 3: Within-person changes in green space and walking and cycling between 2004, 2011 and 2014.

Participants that did not relocate between years (N=6,158 person observations)	Decrease Mean (N)	No Change Mean (N)	Increase Mean (N)	Average change Mean (N)
Distance to nearest GS (m)	-23.34 (N=2166)	0 (N=1846)	28.76 (N=2146)	1.81 (N=6158)
1000m buffer (ha)	-5.45 (N=2228)	0 (N=1668)	4.78 (N=2262)	-0.22 (N=6158)
Walking for active commute	-127.74 (N=386)	0 (N=4697)	147.04 (N=395)	1.60 (N=5478)
Cycling for active commute	-132.79 (N=902)	0 (N=3834)	129.85 (N=742)	-4.28 (N=5478)
Walking for leisure	-174.04 (N=2097)	0 (N=1099)	176.65 (N=2519)	14.00 (N=5715)
Cycling for leisure	-155.42 (N=2058)	0 (N=1492)	163.14 (N=2165)	5.83 (N=5715)
Total active commute	-150.02 (N=1072)	0 (N=3484)	158.52 (N=922)	-2.68 (N=5478)
Total leisure	-225.44 (N=2410)	0 (N=457)	230.57 (N=2848)	19.84 (N=5715)
Total walking	-180.11 (N=2009)	0 (N=940)	185.05 (N=2374)	14.55 (N=5323)
Total cycling	-173.27 (N=2064)	0 (N=1196)	179.27 (N=2063)	2.29 (N=5323)
Total walking and cycling	-239.42 (N=2349)	0 (N=354)	248.88 (N=2620)	16.84 (N=5323)

6.3.4. Fixed effects analyses

Table 4 presents results from fixed effects regression analyses using only data from respondents who did not relocate between years. An increase of 100 m in distance to the nearest green space was related to more walking for commute (β 3.21, 95% CI 0.46, 5.96), and less walking for leisure (β - 22.76, 95% CI - 39.92, - 5.60) and total walking (β - 21.37, 95% CI - 38.87, - 3.88). Greater distance was related to less time spent walking and cycling (β - 22.36, 95% CI - 46.19, 1.48), but confidence intervals included the null. Walking for commute decreased with each additional hectare of green space in the 1000 m buffer (β - 33.84, 95% CI - 67.90, 0.23). Meanwhile, increases in green space area seemed to be associated with additional minutes spent walking for leisure (β 58.42, 95% CI - 74.22, 191.06), but confidence intervals included the null. When combined, the measure of total walking minutes was not significantly related to the area of green space in the 1000 m buffer (β 39.46, 95% CI - 98.22, 177.14). Minutes spent cycling, and combined measures of all outcomes, were also not significantly related to green space.

Table 4: Fixed effects linear regression models regressing changes in walking and cycling measures (in minutes per week) on changes in green space using data from 2004, 2011 and 2014 and restricted to participants who did not relocate during follow-up (n = 6,158 person observations).

	Crude model				**Adjusted model***			
	β	**95% CI**		**p**	**β**	**95% CI**		**p**
Distance to nearest GS (100m)								
Walking for active commute	3.42	0.68	6.15	0.014	3.21	0.46	5.96	0.022
Cycling for active commute	-2.92	-8.06	2.22	0.265	-2.08	-7.21	3.05	0.427
Walking for leisure	-20.78	-38.19	-3.37	0.019	-22.76	-39.92	-5.60	0.009

Cycling for leisure	3.43	-12.44	19.31	0.671	2.22	-13.50	17.93	0.782
Total active commute	0.50	-5.36	6.35	0.868	1.13	-4.72	6.98	0.705
Total leisure	-17.34	-41.70	7.01	0.163	-20.55	-44.22	3.13	0.089
Total walking	-19.30	-37.02	-1.57	0.033	-21.37	-38.87	-3.88	0.017
Total cycling	-1.03	-17.10	15.04	0.900	-0.98	-16.89	14.92	0.904
Total walking and cycling	-20.33	-44.46	3.80	0.099	-22.36	-46.19	1.48	0.066
1000m buffer (ha)								
Walking for active commute	-32.99	-67.10	1.12	0.058	-33.84	-67.90	0.23	0.052
Cycling for active commute	8.64	-49.29	66.57	0.770	10.30	-45.88	66.48	0.719
Walking for leisure	50.08	-82.40	182.57	0.459	58.42	-74.22	191.06	0.388
Cycling for leisure	-51.84	-164.76	61.08	0.368	-50.22	-162.04	61.60	0.379
Total active commute	-24.35	-92.57	43.87	0.484	-23.54	-89.79	42.71	0.486
Total leisure	-1.76	-174.74	171.22	0.984	8.20	-163.26	179.66	0.925
Total walking	30.67	-106.83	168.16	0.662	39.46	-98.22	177.14	0.574
Total cycling	-40.34	-162.07	81.38	0.516	-38.64	-160.18	82.90	0.533
Total walking and cycling	-9.68	-188.70	169.35	0.916	0.82	-178.84	180.48	0.993

*adjusted for marital status, income, employment, smoking and self-rated health.

6.4. Discussion

This study examined whether changes in green space within the living environment were associated with changes in walking and cycling frequencies over a ten-year period. An initial cross-sectional analysis of baseline data did not show significant associations between green space proximity and the amount of green space within the living environment, and weekly walking and cycling. Fixed effects analysis restricted to participants that did not relocate during follow-up suggested that as distance to the nearest green area increased, individuals decreased their walking frequency, with no relation to changes in cycling measures. No clear associations between changes in green areas within 1000 m buffers and changes in walking and cycling were observed. There was weak evidence overall of an effect of changes in green space area on changes in walking, and no evidence for cycling.

Urban green space has widely been endorsed with health-promoting benefits, with positive associations found between nearby parks and overall health and physical activity [42]. Recent policy frameworks, notably the United Nations' Habitat III New Urban Agenda, also support the greening of urban areas as a means toward physical and mental health promotion [42]. However, literature offers mixed results regarding the role of urban green space on physical activity due to variation in methodological approaches, measurement of physical activity [19], and the characterization of relevant green space [43-44]. The current study is one of few longitudinal analyses which models estimated effects of green space change on the most common, and accessible forms of physical activity: walking and cycling. It fills an important methodological gap by aiming to interpret the relationship between health and place in a way that has more potential for evidence-based action.

Our baseline analysis found weak, non-significant associations between green space and activity levels, which is comparable to findings of Maas et al. (2008) [37]. In contrast, the longitudinal fixed effects analysis among participants that did not relocate during follow-up showed that changes in residential proximity to green space significantly impacted walking frequency; an increase of 100 m to the nearest green space resulted in 21 fewer minutes per week spent walking overall, 23 fewer minutes of leisure walking, but 3 additional minutes walking for commute. Previous research has shown that green space within walking distance of the home generally supports human health [45], while parks located further away are not as likely to be used [46]. While no official cut-off distance is supported by empirical evidence, Annerstedt van den Bosch et al. have proposed a guideline of 1 ha within a 300 m absolute distance to the nearest green space as a green space indicator for public health [47]. Other studies also cite distance as a key determinant of green space use, with 100–300 m appearing as the threshold beyond which a decline in use is observed [18]. Our findings suggest that introducing green space closer to one's residence can encourage people to spend more time walking for leisure, but not as part of their commute. Green space closer to the home may deter individuals from walking to work or school, and instead encourage cycling or driving. This observed effect may also relate to the cohort demographic and nature of the activity; members of an ageing cohort gradually enter retirement, thus eliminating the necessity of walking to work, and this in turn can skew the FE model to produce significant results.

Whereas walking seemed to be affected by changes in green space, cycling was not. Moreover, in relation to the changes in green area in 1000 m buffer, no significant associations were observed for total measures of walking and cycling. This lack of significant associations suggests that additional factors may be more important for physical activity than changes in green space. Walking and cycling can depend on personal preferences and constraints. An aging generation will likely be faced with different demands, for example, familial obligations such as caring for grandchildren. The mechanisms linking walking and cycling to green space availability are also likely influenced by other factors in the home environment. For instance, factors such as crime, safety, deprivation, social interaction, road safety, and particularly a pedestrian and cyclist friendly urban environment in the Netherlands, may affect whether or not people walk or cycle in nearby green areas, and may have limited or tempered any effects of changes in green space on changes in activity. This may be particularly pronounced for cycling, considering the wide availability and use of bike lanes in The Netherlands [48-51]. Furthermore, the choice of buffer sizes in measuring total area of green space may play a role in the strength and significance of the results.

6.4.1. Strengths and limitations

The original contribution of this study is the multi-methodological approach and use of detailed GIS data, enabling the linkage of changes in environment and behavior. Much of previous research has relied on wider scale, neighborhood or city-level data that does not accurately depict within-subject changes in exposure. The data provided by the BBG allowed for precise calculations of total green space area and identification of actual changes over time that are not affected by changes in GIS processing. Euclidian buffers around respondents' homes aided in reducing spatial misclassification faced by other indicators, such as neighborhood boundaries [52], and the choice of a 1000 m buffer was comparable to other studies. Further, data from the GLOBE study offered detailed measures of personal characteristics that were used to control for time-varying confounding. The use of multiple outcomes based on a validated questionnaire offered insight into how specific activities are affected by factors in the environment, discerning between commuting and leisure activities, and modes of walking and cycling.

A main limitation of this study is the low within-person variability in walking and cycling for active commute, which restricts the statistical efficiency of a fixed-effects analysis. Although FE analyses are better able to infer causality, they are dependent on observable changes in exposure and outcome measures. The current FE models may have not been able to depict significant relationships due to limited changes observed in the sample population. Further, baseline characteristics reflect a generally active, healthy, and affluent sample of individuals, which may influence how they react to changes in the built environment. For instance, aspects such as car ownership, or the propensity for an active lifestyle, can minimize the impact of de-greening a neighborhood. In addition, around one quarter of missing baseline data on household income was imputed, with implications for biased effect estimates if data was not missing at random. Our statistical model assumes no correlation of attrition and missingness to unmeasured, time-varying characteristics in the study sample, but, if violated, this correlation may have biased the results. In addition, the assumption that the residuals of the linear regression model are normally distributed was violated in the cross-sectional analysis for the active commute measures. However, using negative binomial regression models did not change the findings. Moreover, the fixed effects models did not suffer from this limitation (changes in walking and cycling were mostly normally distributed). We therefore reported results from the linear regression models only.

Self-reported measures of walking and cycling, though based on a validated questionnaire, are subject to recall bias if older participants struggle to provide accurate measures of physical activity. In addition, while our GIS data offered an accurate measure of existing green space, there is no evidence for the actual use or even awareness of these green areas by participants. Similarly, the nearest green space to an individual's home address may not be perceived as such, given its size or functionality, and Euclidian distances may not reflect the travel routes taken by participants.

6.4.2. Future research

To better understand environmental influences on walking and cycling, prospective studies should incorporate both individual and social factors that may affect outcomes, such as self-efficacy, attitude, or social support [53]. Neighborhood level factors of safety and deprivation may confound the effect of green space on physical activity, and should be considered in future research. While our study focused on adults of mostly Dutch origin, the inclusion of youth and non-Dutch residents would offer a more representative group of green space users. Objective measures of walking and cycling, through the use of accelerometers or GPS trackers, might strengthen the validity of outcome values. Additional green space indicators, such as network distance, can be used to better evaluate the use of green space, reflecting likely routes of access. Similarly, the number of green spaces present within a residential area, and a specification of the types of changes occurring in green space, may provide a more robust analysis. Testing for interaction would assess the cumulative effects that multiple factors may have on physical activity. Finally, conducting similar studies in diverse geographic settings on large study samples would help build a solid foundation of evidence generalizable to a wider population.

6.5. Conclusions

The methods used to study relationships between place and health greatly shape the foundation of knowledge that exists in this field. Our approach separately compared group-level associations, and individual within-person effects, of green space on walking and cycling, leveraging longitudinal data to strengthen the basis for causal inference. Our results indicate that walking, and particularly leisure walking, decreases as green spaces are moved further from one's residence. However, local green space alone may not significantly affect physical activity. Replicating our approach on larger, diverse study samples with more variability across time would strengthen the reliability of these findings, or introduce different patterns of effect. Future research should aim to identify aspects of the quality and quantity of changes required in the built environment to improve physical activity, which can steer urban planning and policy efforts and ultimately guide the prevention of chronic disease in an increasingly urbanized world.

Abbreviations

FE	Fixed effects
GIS	Geographic Information System
GLOBE	Gezondheid en LevensOmstandigheden Bevolking Eindhoven en omstreken
ISCED	International Standard Classification of Education NCD Non-communicable disease
PA	Physical activity
SQUASH	Short Questionnaire to Assess Health enhancing physical activity
WHO	World Health Organization

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7

Land use mix and physical activity in middle-aged and older adults: a longitudinal study examining changes in land use mix in two Dutch cohorts

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Abstract

Background

With urbanization and aging increasing in coming decades, societies face the challenge of keeping aging populations active. Land use mix (LUM) has been associated with cycling and walking, but whether changes in LUM relate to changes in cycling/walking is less known.

Objectives

Our objective was to study the effect of LUM on cycling/walking in two Dutch aging cohorts using data with 10 years of follow-up.

Methods

Data from 1183 respondents from the Health and Living Conditions of the Population of Eindhoven and Surroundings (GLOBE) study and 918 respondents from the Longitudinal Aging Study Amsterdam (LASA) were linked to LUM in 1000-m sausage network buffers at three time-points. Cycling/walking outcomes were harmonized to include average minutes spent cycling/walking per week. Data was pooled and limited to respondents that did not relocate between follow-up waves. Associations between LUM and cycling/walking were estimated using a Random Effects Within-Between (REWB) model that allows for the estimation of both within and between effects. Sensitivity analyses were performed on smaller (500-m) and larger (1600-m) buffers.

Results

We found evidence of between-individual associations of LUM in 1000-m buffers and walking (β: 11.10, 95% CI: 0.08; 21.12), but no evidence of within-associations in 1000-m buffers. Sensitivity analyses using 500-m buffers showed similar between-associations, but negative within-associations (β: -35.67, 95% CI: − 68.85; − 2.49). We did not find evidence of between-individual associations of LUM in any buffer size and cycling, but did find evidence of negative within-associations between LUM in 1600-m buffers and cycling (β: -7.49, 95% CI: − 14.31; − 0.66).

Discussion

Our study found evidence of positive associations between LUM and average walking time, but also some evidence of negative associations between a change in LUM and cycling/walking. LUM appears to be related to cycling/walking, but the effect of changes in LUM on cycling/walking is unclear.

7.1 Introduction

In the coming decades, the global population of older adults is projected to increase substantially [1]. As older age is often associated with physical frailty, sustaining good physical functioning is essential. Physical inactivity has been identified as the fourth leading risk factor for global mortality [2] and increasing physical activity (PA) has been marked as a top priority intervention to reduce death rates of noncommunicable diseases [3]. Regular PA contributes to several beneficial health effects for older adults, such as lower risk of cardiovascular disease, diabetes, and cognitive decline [4]. To promote PA among older adults, it is important to foster residential environments that encourage PA as older adults might be especially susceptible to residential factors that discourage an active lifestyle, due to a decline in overall mobility and comparatively more time spent in the neighborhood [5, 6]. Multiple studies have shown positive associations between PA and measures of urban form, such as urban green spaces, public open spaces, residential density, and land use mix [7–9]. Changes in the built environment, such as increased investment in green spaces and pedestrian and cycling infrastructure, as well as transforming cities towards more compact, mixed-used environments can potentially aid in promoting PA [8, 10]. Furthermore, modification of the built environment for health-related purposes could gain more traction in the coming years as a co-benefit of structural urban changes, such as climate control efforts.

One commonly studied physical-environmental exposure with regards to PA is that of land use mix (LUM). LUM represents how evenly different types of land uses are distributed within a specified area [11]. Mixed-use areas contain a variety of different land uses and are believed to encourage PA because they include a larger number of destinations [12, 13]. A systematic review on the neighborhood environment and active travel in older adults found moderate-to-strong evidence of positive associations between LUM and older adults' total walking [6], while a recent study from Finland found strong evidence in support of the hypothesis that increasing neighborhood density, mixed land use, and access networks may enhance regular walking and cycling [14]. However, much of the evidence linking varying land uses to PA is cross-sectional, which makes it difficult to establish a causal relationship. Many studies adjust for confounding factors, but it remains unclear which factors should be included. Furthermore, selection bias remains an issue as individuals may choose to live in areas based on lifestyle preferences and socioeconomic factors [15]. A physically active person may deliberately choose to live in a PA friendly area, inflating the possible relation between LUM and PA.

Various methods have been applied to account for these methodological shortcomings, such as adjustments for proxy indicators of preferences, as well as applying fixed effects (FE) models that control for time-invariant characteristics, assuming that they remain stable over time. A few studies to date exist that apply such models to analyze how environmental factors relate to PA, but the results are inconclusive. A study conducted in Brisbane, Australia found that any walking for transport versus no walking for transport was increased in association with LUM, but minutes walking per week was not [12], while a Dutch study found weak evidence of associations between changes in green space areas and changes in walking in middle-aged and older adults, but no evidence for cycling [16]. While FE models provide valuable tools for assessing the effects of temporal changes, they disregard between-individual variability. As the method solely relies on within-individual changes, it might not be the best fit for LUM measures, as it is debatable how much LUM changes over time. The primary alternative – the random effects (RE) model – makes use of between-individual variability, but in turn does not remove the effects of time-invariant causes, and assumes that the unmeasured causes are uncorrelated with measured causes. The latter is often a difficult assumption to make and, if violated, will result in omitted-variable bias [17]. Methods exist that combine elements of both RE and FE models and take "the best of both worlds [17]." These models go by different names, such as random effects between-within models (REWB), Mundlak models, or simply hybrid models, and make use of centering of all individual units around their means [18, 19]. Such models can be of great value for research considering the impact of LUM on PA as they not only explore the differences between individuals, but also how a change in LUM might influence a change in PA. However, these models have only been scarcely applied within the public health domain [19].

Further complicating the evidence in the field of environment-PA research is a lack of consistency in both geographic units and scale used to define the residential environment [20, 21]. To quantify environmental exposures, researchers traditionally relied on neighborhood level data, such as pre-existing administrative units. A more refined method that is especially relevant for PA comes with the use of network buffers that define buffers as areas accessible via a street network. The "sausage" or "line-based" buffering method selects roads within a certain distance of the individual and creates a buffer around these roads by a set distance (e.g. 25 m). This ensures that only those features that are directly accessible from the street network are selected. This method has the key advantage that it is based directly on the road network where people travel [21, 22]. Sausage buffers therefore offer an attractive alternative to more traditional Euclidian buffers – especially when PA is concerned – as these buffers represent areas that are actually accessible via the road network.

Our study uses sausage buffers to define LUM within the individual's residential environment and links these data to cycling and walking outcomes. We linked data from two Dutch cohorts with 7 to 10 years of follow-up to a harmonized land use dataset, and explored both within-person and between-person associations of LUM on cycling/walking using a REWB model.

7.2 Methods

Study population

Data were obtained from two longitudinal cohort studies on aging in the Netherlands that are participating in the MINDMAP project [23]: the Health and Living Conditions of the Population of Eindhoven and Surroundings (GLOBE) study, and the Longitudinal Aging Study Amsterdam (LASA). The GLOBE study is a prospective cohort study on the role of living conditions for health in the Netherlands [24]. The 2004 sample of GLOBE participants who resided in the city of Eindhoven and surrounding areas was selected for the analyses (n = 4775) with follow-up data collected for the years 2011 and 2014. The LASA study is a longitudinal population based study of the predictors and consequences of aging in the Netherlands [25]. The 2005/2006 LASA sample of participants who resided in the cities of Amsterdam, Zwolle, and Oss and their surrounding areas was selected for the analyses (n = 2165) with follow-up data collected for the years 2008/2009 and 2011/2012. The residential addresses of these respondents were geocoded using geographical software package QGIS [26] and a geocoding plug-in developed by the Dutch National Spatial Data Infrastructure (PDOK) [27]. To maintain respondent privacy, addresses were extracted and geocoded using a process previously described [23, 28]. Respondents whose addresses could not be geocoded, who did not participate in all three data collection waves, or who moved outside of the study area of the respective cohorts were excluded. The sample was limited to respondents that did not relocate during follow-up waves, resulting in a final sample of 1183 respondents aged 26 to 85 for GLOBE and 918 respondents aged 57 to 93 for LASA. Sensitivity analyses were performed on the total sample including respondents that moved between follow-up waves (Supplementary File 1).

Land use exposure measures

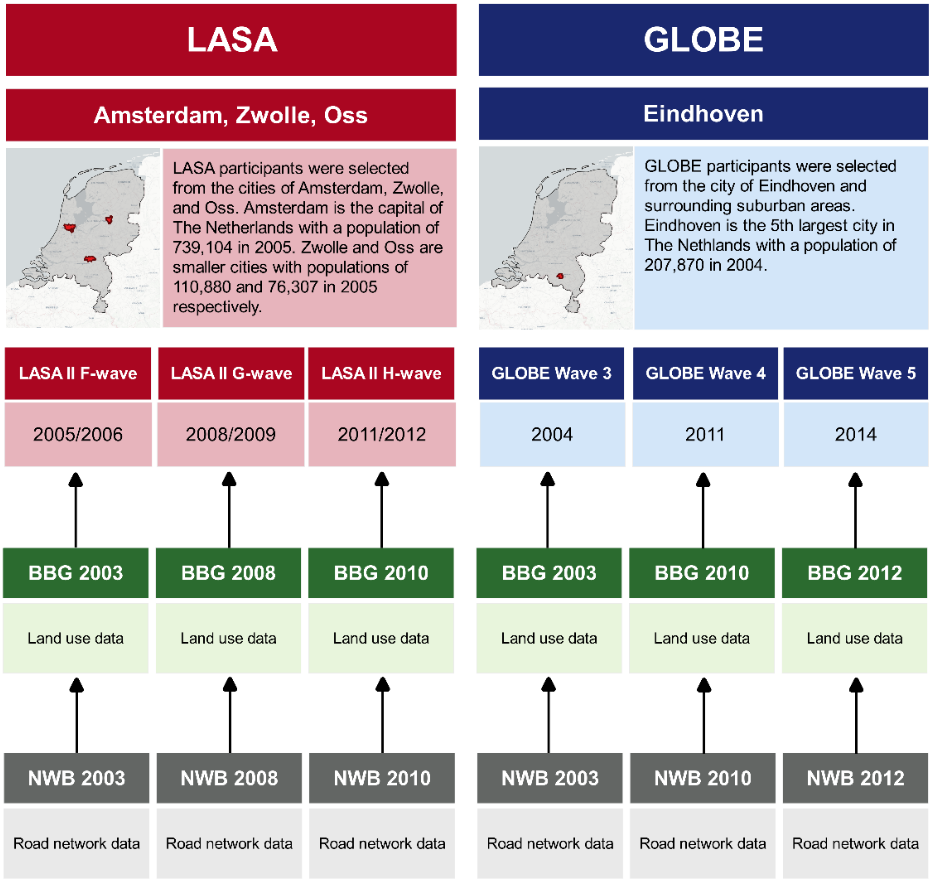
Exposure measures were obtained using the dataset 'Bestand Bodemgebruik' (BBG) which is maintained by Statistics Netherlands [29]. The BBG database is a harmonized dataset based on 'Top10NL' digital 1:10,000 topographic maps provided by the Dutch mapping agency Kadaster [30]. The harmonization of the BBG data ensures that observed changes are representative of actual changes in the environment and not related to changes in GIS processing or methodology. The total land use data was grouped into 11 land use categories based on the relevance for cycling and walking. More details on the land use classification can be found in Supplementary File 2. LUM was calculated using network buffers of 1000m as the main exposure with additional buffers of 500 and 1600m for sensitivity analyses. The Dutch 'Nationaal Wegenbestand' (NWB) database [31] was used for the calculation of the network buffers. The NWB is an open source database with all publicly available roads in the

Netherlands with either a street name or a road number. Roads that are not available to pedestrians and cyclists, such as highways, were excluded to provide an accurate estimation of reachable destinations. Sausage buffers were created using line buffers with a radius of 25m [22, 32]. Land use mix was calculated for all buffer sizes using the following entropy formula:

$$LUM = -\frac{\left[\sum_{j=1}^{N} p^j \ln\left(p^j\right)\right]}{\ln\left(N\right)}$$

whereby LUM is an entropy score with a value between 0 and 1, p^j the percentage of each land use class j of the total buffer area, and N the total amount of land use classes. The calculated entropy value represents a measure of heterogeneity, whereby 1 represents a perfect mix of land use classes and 0 no mix of classes [33]. N was set to 11 LUM classes to avoid measurement bias and to improve comparability of the changes in LUM over time [34]. The LUM entropy score was transformed in the analyses to represent a 10% change in LUM to improve interpretation. Cohort data from each wave was linked to both NWB and BBG data from a preceding year, keeping in line with an appropriate chronology of exposure preceding outcome (Fig. 1). LUM exposure data was calculated for all respondents in the final sample. Outcome measures of walking and cycling Walking and cycling outcomes were assessed using self-reported time spent walking and cycling and defined as average minutes spent walking and cycling per week. GLOBE uses the Short Questionnaire to Assess Health enhancing physical activity (SQUASH) tool, which was created by the Dutch National Institute of Public Health and the Environment to measure habitual physical activity levels in an adult population [35]. In accordance with the SQUASH guidelines, it was assumed that participants who filled-in hours or minutes per week, but omitted 'days per week,' had been active for at least 1 day. If the number of days was provided without a corresponding time frequency, the median minutes per day of all respondents was substituted. LASA uses the LASA Physical Activity Questionnaire (LAPAQ), which asks respondent how often and for how long they engaged in various activities, including walking and cycling in the last 2 weeks. LAPAQ has been validated against 7-day physical activity diaries and 7-day pedometer counts in a subsample of LASA participants [36]. A final measure of average minutes per week was computed for both cohorts.

Figure 1: Overview of the land use measures and the cohorts included in this study.



Basemap: Open street map contributors & CARTO. Countries: Natural Earth Data. LASA, Longitudinal Ageing Study Amsterdam. GLOBE, Health and Living Conditions of the Population of Eindhoven and Surroundings.

Covariates

Time-invariant characteristics (as measured at baseline) that were included in the analyses include sex (male, female), and education as measured using the International Standard Classification of Education (lowest = ISCED 0–1, low = ISCED 2, middle = ISCED 3–4, high = ISCED 5–7) [37]. Education was considered to be time-invariant because of the relatively old age of the cohorts. Age, marital status (married/partnership, not married, divorced, widowed), household income (monthly; <€1200, €1200–1800, €1800–2600, >€2600), and employment status (employed, non-employed) were included as relevant time-varying confounders. All time-varying covariates for both studies were measured at all three time points, capturing changes that occurred during follow-up. Missing data on covariates were handled via multiple imputation using the covariates listed above as well as self-rated health (excellent, very good, good, fair, poor), smoking (yes, no), and BMI. Only the covariates education, income, and employment (GLOBE), and income and employment (LASA) had missing values, ranging from 2 to 11% for GLOBE and 5–12% for LASA.

Statistical analyses

The imputed data of both cohorts was pooled, enabling us to observe more changes in the environment as well as increasing variation in environmental exposure, therefore strengthening both the between- and within-analyses. The analyses were restricted to non-movers to limit selection effects. Sensitivity analyses were performed on data from the separate cohorts as well as on the total sample including those who had moved between data collection waves (Supplementary File 1). We constructed a random effects within-between (REWB) model to conduct the analyses. This model decomposes the time-varying LUM variable into individual-specific means (between-individual estimates) and deviations from those individual-specific means (within-individual estimates). The estimated between-individual regression coefficient represents how the exposure across all participant-observations is related to the outcome, and the within-individual coefficient represents how variation in exposure around the individual's mean level is related to the outcomes. In addition, the model can include both time-varying and time-invariant covariates. A random intercept is added to account for the dependence of multiple measurements for each participant. The following model was used for the analyses:

$$PA_{it} = \beta_0 + \beta_{1W}(x_{it} - \bar{x}_i) + \beta_{2B}\bar{x}_i + \beta_3 Z_i + \beta_4 \gamma_i + (v_i + \epsilon_{it})$$

whereby PA_{it} indicates the PA outcome for individual i at time t, and x_{it} is the time-varying land use mix variable. The relationship between x_{it} and PA_{it} is decomposed into two parts with β_{1W} representing the average within effect and β_{2B} the between effect. β_3 represents the effects of time-invariant measures Z_i, and β_4 represents the effects of time-varying measures γ_i. v_i is the model's random effect for individuals I, and ϵ_{it} are the model's level-1 residuals. More details on the modelling approach can be found in Supplementary File 3. All analyses were performed using R [38].

7.3 Results

Both cohorts consist of middle-aged and older adults with the mean age ranging from 53 (GLOBE) to 69 years (LASA) at baseline (Table 1). The respondents had an average LUM entropy score of 0.30 (GLOBE) or 0.24 (LASA) on a scale from 0 to 1. Both the average cycling and walking time was higher for GLOBE with 177 min spent cycling per week and 176 min walking compared to 76 min of cycling and 169 min of walking for LASA. Within-individual changes in LUM were observed for approximately 44% of all person-observations (Table 2). The observed changes consisted of both decreases and increases in the LUM which corresponded to an average 5% decrease and an average 3% increase.

Table 1: Description of the baseline study samples for GLOBE and LASA

	GLOBE n = 1,183 Mean (SD)	LASA n = 918 Mean (SD)	POOLED n = 2,101 Mean (SD)
Exposure			
Land use mix in 1000-meter buffers, entropy score	0.30 (0.06)	0.24 (0.09)	0.30 (0.07)
Outcomes			
Average cycling time per week, minutes	177 (240)	76 (111)	133 (201)
Average walking time per week, minutes	176 (248)	169 (226)	173 (239)
Individual characteristics			
Time-invariant characteristics			
Male, %	48%	44%	46%
Education, %			
Lower secondary or less (ISCED 0-2)	21%	44%	31%
Upper secondary (ISCED 3)	19%	16%	18%
Post-secondary non-tertiary education or short-cycle tertiary education (ISCED 4,5)	25%	19%	22%
Bachelor, master, doctoral, or equivalent (ISCED 6,7,8)	35%	21%	29%
Time-varying characteristics			
Age, mean (SD)	56 (12)	68 (8)	60 (12)
Employment status, %			
Currently in paid employment	51%	21%	39%

Currently not in paid employment	49%	79%	61%
Income, %			
< €1200	8%	17%	12%
€1200 - €1800	24%	32%	27%
€1800 - €2600	32%	51%	40%
> €2600	36%	n.a.*	21%*
Marital status, %			
Married or registered partnership	80%	69%	75%
Never married	9%	6%	8%
Divorced	6%	6%	6%
Widowed	5%	19%	11%

*the highest income class for LASA consists of respondents with an income of > €2270.

Table 2: Within-individual changes in land use mix in 1000-m buffers and average cycling and walking time per week between 2004and 2014 using pooled data from respondents that did not relocate during follow-up

	Decrease		**No Change**		**Increase**	
n = 6,303 person-observations	Mean	n	Mean	n	Mean	n
Exposure						
Land use mix in 1000-meter buffers	-0.05	942	0	3513	0.03	1848
Outcomes						
Average cycling time per week (minutes)	-120	2974	0	1157	159	2172
Average walking time per week (minutes)	-182	2635	0	905	180	2763

Within-individual changes were also observed for both outcomes with approximately 18% (cycling) and 14% (walking) reporting no change in the average amount of minutes spent walking/cycling per week. REWB models provided no evidence of within or between associations between LUM in 1000-m buffers and the average time spent cycling (Table 3). Sensitivity analyses conducted on 1600-m buffers provided no evidence of between-associations, but did provide evidence of a negative association between a within-individual change in LUM and average time spent cycling (β: -7.49, 95% CI: − 14.31; − 0.66) (Supplementary File 1, Table 5). These results suggest that a 10% change in LUM in 1600-m buffers is associated with a decrease in cycling time per week of 7.49 min.

REWB models modelling the average time walking showed evidence of positive between-individual associations between average LUM in 1000-m buffers and the average walking time (β: 11.10, 95% CI: 0.08; 21.12), indicating that a 10% change in LUM in 1000-m buffers is associated with an increase of minutes walked per week of 11.10 min. Sensitivity analyses conducted using 500-m buffers showed similar between-individual associations, but also negative within-individual associations (β: -35.67, 95% CI: − 68.85; − 2.49) (Supplementary File 1, Table 9), suggesting that a 10% change in LUM in 500-m buffers is negatively associated with average time spent walking per week.

Table 3: Within and between associations of land use mix in 1000-m buffers and average minutes cycling and walking per week using pooled data on respondents that did not relocate during follow-up

n = 6,303 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	-5.55	-17.17 ; 6.07	0.349
Average walking time per week (minutes)	0.75	-14.31 ; 15.80	0.922
	Between effects		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	5.06	-4.91 ; 15.04	0.320
Average walking time per week (minutes)	11.10	0.08 ; 22.12	0.048

*adjusted for study, time-invariant individual characteristics sex and education, and time-varying characteristics age, employment, income, and marital status.

7.4 Discussion

In the present study, we found evidence of between-individual associations of land use mix in 1000-m buffers and the average walking time per week. We also found comparable between-associations in the smaller 500-m buffers, adding to the robustness of these results. We did not find evidence of within-individual associations between LUM in 1000-m buffers and walking nor did we find evidence of within- or between-individual associations between LUM in 1000-m buffers and cycling. We did find evidence of a negative within-effect on cycling in larger 1600-m buffers, and evidence of a negative within-effect on walking in 500-m buffers.

The 1000-m network buffer is a commonly used exposure measure in PA research as it is believed to be a reasonable distance that people can walk [12]. The associations that we found for this buffer are in line with other studies on this subject. For example, a recent study using the GLOBE data found no evidence of within-associations of green spaces in 1000-m buffers on cycling and walking outcomes [16]. Our study also found no evidence of within-associations between a change in LUM in 1000-m buffers and cycling/walking. These findings raise questions if the observed changes in the 1000-m buffers are large enough to observe a change in cycling/walking. A recent study conducted in Eindhoven, The Netherlands that used similar environmental exposures in 1000-m buffers concluded that it did not find evidence for a change in green space exposure being related to a change in mental health [39]. This study did find some evidence of cross-sectional between-individual associations, and argued that there may have been too few observed changes in the environmental exposure in 1000-m buffers. A study conducted in Brisbane, Australia in adults aged 40 to 60 found that results of estimates from random effects models indicated positive associations between any walking for transport and an increase in LUM of 10%, which is in line with the between-associations that we observed for walking [12]. This Australian study also found positive, if less pronounced, within-individual associations. While our study did not observe within-associations for our main exposure buffers, we did observe within-associations for the smaller 500-m buffers, but these were the inverse of the between associations.

Several issues may contribute to the explanation of the negative within-individual associations in our sensitivity analyses. It is important to note that little consensus exists about what buffer sizes to use when analyzing how LUM and cycling/walking relate, with other studies reporting both smaller and larger buffers [40]. Furthermore, a recent systematic review on the physical environment and active travel in older adults concluded that not much is known about the optimal mix and number of destination types that might promote active travel in this age group [6]. Several studies have concluded that associations between environmental exposures and health outcomes can vary greatly based on the size and type of the buffers used ("crow-fly" Euclidian buffers or network buffers) [21]. Some explanation might therefore be found in the definition of our exposure measures. A study conducted in the Netherlands among older adults found a mean distance of 1997m for cycling trips and 1101m for walking trips [41]. As both the GLOBE and LASA cohorts include a large proportion of older adults, we included a larger buffers of 1600m (one mile) in our sensitivity analyses. The 1600-m buffer is another commonly used buffer and can be especially relevant for cycling as larger distances can be covered compared to walking. We also included a smaller buffer of 500m in our sensitivity analyses to test whether LUM in this smaller buffer was associated with walking. This is especially important in a population of primarily older adults as their physical functioning might deteriorate over time, confining their PA to a smaller area. However, the results for the larger and smaller buffer sizes were contrary to what we expected based on the existing literature. For example, a study conducted in Perth, Australia in middle-aged adults found that an increase in access to destinations in the residential environment was associated with taking-up cycling, providing evidence that changes in the built environment may support the uptake of cycling among formerly non-cycling adults [42]. Our study did not find evidence that a change in LUM in the residential environment is associated with time spent cycling in our main exposure buffers of 1000m and some evidence of negative associations between LUM and cycling in larger 1600-m buffers (Supplementary File 1, Table 5). Explanations for these results may be found in age differences between the studies, cultural differences between cycling in The Netherlands and Australia, but also in the definition of the exposure and the mechanisms between LUM and cycling outcomes. Whereas the study in Perth included respondents that moved to a new residential neighborhood, our study specifically only included respondents that did not relocate during follow-up. The within-changes are therefore indicative of changes in the residential environment and not the result of moving to a different residential environment. Different mechanisms may therefore be at play when compared to the effect that moving to a different neighborhood can have. As our study provides mixed results, more research is needed that explores how changes in the residential environment relate to cycling/walking. This is not only an important question from a scientific point of view, but also from a policy perspective as it provides policy makers with more insights how a change in the environment might relate to a change in cycling/walking. More longitudinal research on this topic is therefore urgently needed; a call that has been echoed by other authors in the field in recent years [43].

7.5 Strengths & limitations

The present study adds to the literature on how the residential environment relates to cycling and walking by using data from two Dutch cohorts with 10 years of follow-up and linking this data to harmonized LUM exposures. By pooling data from two Dutch cohorts, we were able to both increase variation in environmental exposures as well as increase the statistical power of our analyses. Our study provides more evidence on how LUM and cycling/walking relate, by considering the effects of changes in LUM on cycling/walking in a Dutch socio-spatial context where cycling is a big part of everyday life, and for cities that are already very compact compared to those in other countries such as Australia or the United States. Evidence from such countries suggests that a move towards more compact cities with a mixed-use environment can have a positive effect on cycling and walking, but there is little evidence from cities that are already very compact and dense such as the ones in this study [13].

Our study also fills an important methodological gap by exploring both between-individual and within-individual associations of LUM on cycling/walking. By applying the REWB framework to longitudinal data of respondents that did not relocate during follow-up, we gain more insight into how different levels of LUM affect cycling/walking and how a change in LUM can potentially influence the average cycling and walking time. The REWB model retains the advantages of the standard FE model, but also incorporates between-individual variation, while allowing to control for measured time-invariant confounders. By retaining the virtues of the standard FE approach, it helps to infer potential causal relationships between changes in LUM and cycling/walking that have more potential for evidence-based action [19]. It also helps to answer a relevant (policy) question: is a change in LUM in the residential environment associated with a change in cycling/walking? As most of the research on LUM and cycling/walking is cross-sectional, answering this question can broaden the understanding of potential causal pathways between LUM and PA.

The use of sausage network buffers offers numerous improvements over more traditional Euclidian or "crowfly" buffers that do not consider if the street network allows or prevents access to specific locations. A study comparing different buffer types for PA research concluded that the sausage buffer method remains the most defensible method for creating network buffers as it increases both comparability and repeatability [21]. By including multiple individual-specific network buffers and by excluding roads that are not accessible to pedestrians and cyclists, we aimed to provide an accurate exposure measure that ensures that only those features that are accessible from the road network are included. By applying the buffers to a harmonized land use dataset, we ensured that changes observed in the data are representative of actual changes in the environment and not the result of changes in data processing of GIS methodology.

Our study also has some limitations to consider. First, while individual-level network buffers offer great improvements in measuring exposure compared to more traditional neighborhoods, we were not able to control for other urban-environmental and social-urban factors, such as residential density, safety, or neighborhood socio-economic status. A study conducted in Amsterdam, The Netherlands found evidence that neighborhood safety was associated with cycling [44]. As we used individual-specific network buffers, we were not able to control for such effects in our analyses. Secondly, we were also not able to control for time spent away from the residential environment. However, it has been theorized that older adults may be particularly susceptible to environmental factors in the residential environment as they are likely to spend more time closer to home than younger adults [5]. Thirdly, all cohort waves are separated by 3 years with the exception of GLOBE waves 3 and 4, which are separated by 7 years (Fig. 1). This longer follow-up period could potentially influence physical functioning and cycling/walking time. As our study population has a large proportion of older adults, decay of physical functioning during follow-up could negatively impact cycling and walking time, possibly influencing the within-individuals estimates. Finally, in order to pool the data from both cohorts, variables had to be retrospectively harmonized, which means that study variables are harmonized after they have been collected. While retrospective harmonization is a good way to make comparisons between cohorts possible, it does inherently come with the limitation that some detail is lost in the process. For example, income classes in both cohorts did not match well and therefore had to be generalized in order to be comparable. Harmonization choices like these inevitably lead to a loss in sensitivity and specificity of the data. More prospective harmonization would alleviate these limitations and therefore make better comparisons between cohorts possible.

7.6 Conclusions

The present study found evidence of between-individual associations of land use mix in the residential environment and the average walking time per week, as well as some evidence of negative within-associations between land use mix and the average cycling/walking time in respondents that did not move to a different residential address during follow-up. These findings advocate the use of research methods that combine both between- and within-individual analyses in order to gain more understanding of how land use mix in the residential environment can relate to cycling/walking. More longitudinal research is needed to explore how changes in land use mix over time can influence cycling and walking outcomes.

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Appendices

Appendix 1: Sensitivity analyses

Individual cohorts

Supplementary table 1: Within and between associations of land use mix in 1000-meter buffers and average minutes cycling and walking per week for the total GLOBE cohort

n = 4645 person observations	**Within effects**		
REWB model*	β	95% CI	p-value
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	-6.42	-20.75 ; 7.92	0.380
Average walking time per week (minutes)	-1.57	-16.68 ; 13.53	0.838
	Between effects		
REWB model*	β	95% CI	p-value
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	7.41	-9.70 ; 24.52	0.396
Average walking time per week (minutes)	10.13	-5.25 ; 25.51	0.197

*adjusted for time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Supplementary table 2: Within and between associations of land use mix in 1000-meter buffers and average minutes cycling and walking per week for the total LASA cohort

n = 3342 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	-0.40	-10.88 ; 10.07	0.940
Average walking time per week (minutes)	8.81	-8.46 ; 26.08	0.317
	Between effects		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	3.85	-1.98 ; 9.68	0.196
Average walking time per week (minutes)	15.74	4.07 ; 27.42	0.008

*adjusted for time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Total sample including movers

Supplementary table 3: Within and between associations of land use mix in 1000-meter buffers and average minutes cycling and walking per week using the total sample of pooled data

n = 7998 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	-2.62	-12.12 ; 6.88	0.589
Average walking time per week (minutes)	2.15	-9.26 ; 13.55	0.712
	Between effects		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	5.18	-3.55 ; 13.90	0.245
Average walking time per week (minutes)	13.80	4.37 ; 23.23	0.004

*adjusted for time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Supplementary table 4: Within-individual changes in land use mix in 500- and 1600-meter buffers using pooled data from respondents that did not relocate during follow-up

	Decrease		No Change		Increase	
n = 6303 person-observations	**Mean**	**N**	**Mean**	**N**	**Mean**	**N**
Exposure						
Land use mix in 500-meter buffers	-0.02	833	0	3779	0.03	1691
Land use mix in 1600-meter buffers	-0.01	860	0	3097	0.05	2346

Supplementary table 5: Within and between associations of land use mix in 1600-meter buffers and average minutes cycling per week using pooled data on respondents that did not relocate during follow-up

n = 6285 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1600-meter buffers			
Average cycling time per week (minutes)	-7.49	-14.31 ; -0.66	0.032
	Between effects		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1600-meter buffers			
Average cycling time per week (minutes)	3.57	-5.41 ; 12.55	0.436

*adjusted for study, time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Supplementary table 6: Within and between associations of land use mix in 1600-meter buffers and average minutes cycling per week using the total sample of pooled data

n = 7998 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1600-meter buffers			
Average cycling time per week (minutes)	-2.12	-8.18 ; 3.94	0.493
	Between effects		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1600-meter buffers			
Average cycling time per week (minutes)	4.30	-4.63 ; 12.23	0.288

*adjusted for study, time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Supplementary table 7: Within and between associations of land use mix in 1600-meter buffers and average minutes cycling per week for respondents that did not relocate during follow-up for the GLOBE cohort

n = 3531 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1600-meter buffers			
Average cycling time per week (minutes)	-6.89	-16.41 ; 2.62	0.155
	Between effects		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1600-meter buffers			
Average cycling time per week (minutes)	3.06	-14.67 ; 20.79	0.735

*adjusted for study, time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Supplementary table 8: Within and between associations of land use mix in 1600-meter buffers and average minutes cycling per week for respondents that did not relocate during follow-up for the LASA cohort

n = 2754 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1600-meter buffers			
Average cycling time per week (minutes)	-10.66	-18.73 ; -2.60	0.010
	Between effects		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1600-meter buffers			
Average cycling time per week (minutes)	2.75	-2.85 ; 8.35	0.336

*adjusted for study, time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Supplementary table 9: Within and between associations of land use mix in 500-meter buffers and average minutes walking per week using pooled data on respondents that did not relocate during follow-up

n = 6285 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 500-meter buffers			
Average walking time per week (minutes)	-35.67	-68.85 ; -2.49	0.035
	Between effects		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 1600-meter buffers			
Average walking time per week (minutes)	11.39	-0.28 ; 23.05	0.056

*adjusted for study, time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Supplementary table 10: Within and between associations of land use mix in 500-meter buffers and average minutes walking per week using the total sample of pooled data

n = 7998 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 500-meter buffers Average walking time per week (minutes)	-4.16	-22.94 ; 14.62	0.664
	Between effects		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 500-meter buffers Average walking time per week (minutes)	10.90	0.89 ; 20.91	0.033

*adjusted for study, time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Supplementary table 11: Within and between associations of land use mix in 500-meter buffers and average minutes cycling per week for respondents that did not relocate during follow-up for the GLOBE cohort

n = 3531 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 500-meter buffers			
Average walking time per week (minutes)	-28.45	-72.76 ; 15.86	0.208
	Between effects		
REWB model*	**B**	**95% CI**	**p-value**
Land use mix in 500-meter buffers			
Average walking time per week (minutes)	-2.65	-22.55 ; 16.95	0.791

*adjusted for study, time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Supplementary table 12: Within and between associations of land use mix in 500-meter buffers and average minutes cycling per week for respondents that did not relocate during follow-up for the LASA cohort

n = 2754 person observations	**Within effects**		
REWB model*	**β**	**95% CI**	**p-value**
Land use mix in 500-meter buffers			
Average walking time per week (minutes)	-40.23	-90.75 ; 10.28	0.119
	Between effects		
REWB model*	**B**	**95% CI**	**p-value**
Land use mix in 500-meter buffers			
Average walking time per week (minutes)	20.66	6.54 ; 34.78	0.004

*adjusted for study, time-invariant individual characteristics gender and education, and time-varying characteristics age, employment, income, and marital status.

Appendix 2: More information on the BBG database and land use classification

The TOP10NL dataset is the official, national topographical representation of the Netherlands and is maintained by the Dutch mapping agency 'Kadaster'. Statistics Netherlands converts this topographical data to land use data and publishes the resulting files as open source GIS data. The 'Bestand Bodemgebruik' (BBG) is the collection of these files. The BBG dataset is generally updated every two to four years depending on funding sources and research needs. The most recent dataset is distributed by Statistics Netherlands and is reposited in the Dutch National Georegister. Historical files are distributed by the Netherlands institute for permanent access to digital research resources. These files are available through their Data Archiving and Networked Services (DANS). This platform aims to make digital research data and related outputs findable, accessible, interoperable and reusable. All historical BBG files are available through this platform free of charge.

The land use categories used in the analyses (supplementary table 13) were based on the original classification of the BBG data (supplementary table 14). The categories were formed based on their potential relevance for walking and cycling. The spatial context of the cities included in the cohorts was taken into consideration in the selection of the land use categories. For example, the GLOBE cohort includes the city of Eindhoven and its more suburban surrounding areas. Therefore, agricultural areas were included as they might be relevant for cycling. The blue spaces category contains recreational water, such as canals and small lakes, which is especially relevant for the city of Amsterdam (LASA cohort).

Supplementary table 13: Green space classifications based on the land use classification of the BBG dataset

Green space categories	Corresponding BBG classifications
1. Green spaces	Parks Allotment gardens Dry open terrain Recreational Areas
2. Green and blue spaces	Parks Allotment gardens Dry open terrain Recreational Areas Lakes Estuaries Rivers Backwaters Wet open terrain
3. Green and agricultural spaces	Parks Allotment gardens Dry open terrain Recreational Areas Agricultural areas
4. Green, blue, and agricultural spaces	Parks Allotment gardens Dry open terrain Recreational Areas Lakes Estuaries Rivers Backwaters Wet open terrain Agricultural areas

Supplementary table 14: Complete land use classification of the BBG dataset as translated by the authors

Category	Lower bounds (hectares)	Description
1. Traffic areas		
10.	-	Railway areas
11.	-	Road traffic areas
12.	1	Airports
2. Built environment		
20.	1	Residential areas
21.	1	Retail areas
22.	1	Public facility areas
23.	1	Social-cultural facility areas
24.	1	Business areas
3. Semi-built-up areas		
30.	1	Dumping grounds
31.	0.1	Junkyards
32.	0.1	Cemeteries
33.	0.5	Quarries
34.	1	Building sites
35.	1	Other
4. Recreational areas		
40.	1	Parks
41.	0.5	Sports areas
42.	0.1	Allotment gardens
43.	1	Recreational areas
44.	1	Extended stay recreational areas
5. Agricultural areas		

50.	1	Greenhouses
51.	1	General agricultural areas
6. Forests and natural areas		
60.	1	Forests
61.	1	Open terrain (dry)
62.	1	Open terrain (wet)
7. Backwaters		
70.	-	Lakes: IJsselmeer and Markermeer
71.	-	Closed estuaries
72.	-	Rivers: Rhine and Maas
73.	-	Border lakes
74.	1	Water reservoirs
75.	1	Recreational backwaters
76.	1	Water used for mineral extraction
77.	1	Sludge fields
78.	1	Other backwaters
8. Open waters		
80.	-	Specific open waters: Waddenzee, Eems, Dollard
81.	-	Specific open waters: Oosterschelde
82.	-	Specific open waters: Westerschelde
83.	-	North Sea
9. Borders		
90.	-	Country borders

Appendix 3: More information on the random effects within-between model

The random effects within-between model (REWB) goes by a variety of different names, such as the Mundlak model or hybrid model. The models used in our analyses are based on the work of Bell et al. (2019) and Lüdecke (2019) [1-2].

Bell et al. (2019) describe a number of different REWBs with increasing degrees of complexity. They first present a general model (1) based on panel data example, where individuals i (level 2) are measured on multiple occasions t (level 1). This model is followed-up by a simplified model (2), that assumes homogeneous effects across level-2 entities. This is the model we have used for our analyses and which is presented in the main text.

Lüdecke (2019) has published a helpful article on how to apply the models presented by Bell et al. (2019) in statistical analyses using R. We used the lme4-package to specify our model parameters and to estimate the between and within effects based on the "simple" model as presented by Bell et al. (2019). We highly recommend Lüdecke's guide for more information on how to specify REWB models in R.

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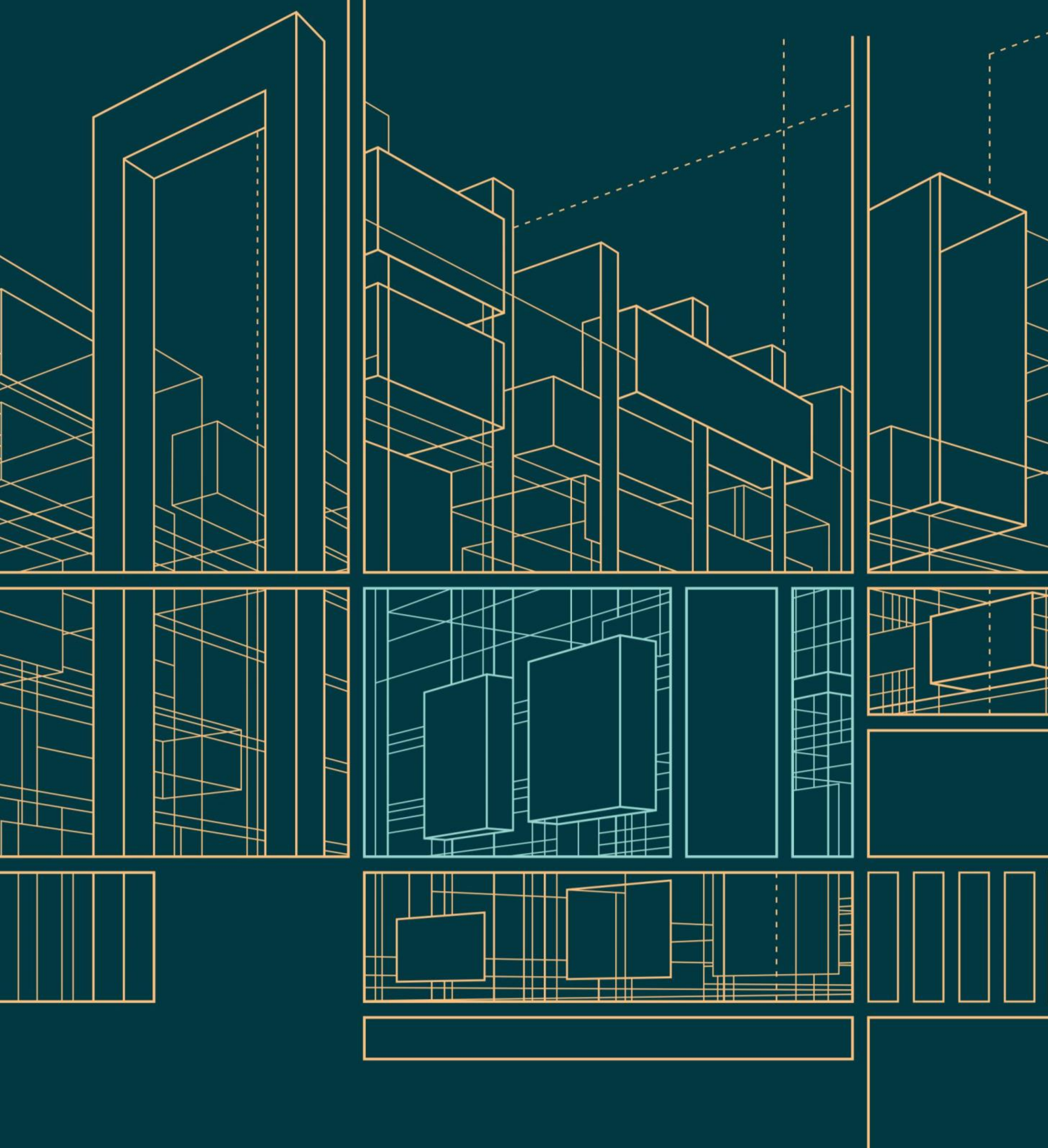
Developing age-friendly cities



8

Age-friendly cities: challenges for future research

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The development of age-friendly cities and communities has become an important area of work in the fields of public health, ageing and public policy. This development reflects several larger trends including the complexity of demographic change and the recognition of the role of the environment in healthy ageing [1].

In 2017, there were an estimated 962 million people aged 60 years or older worldwide, that is, around 13% of the global population. This part of the population is growing at an annual rate of about 3% and further growth is almost inevitable [1]. An increasing part of this population lives in cities, where the combination of urbanization and ageing leads to new public health challenges, such as a higher risk of mental disorders, resulting in impairments in the ability to function socially [2]. However, while cities pose major challenges for older citizens, they also offer opportunities for the implementation of policies and interventions that promote public health. In 2006, the World Health Organization (WHO) initiated a programme specifically targeting the health of urban residents aged 60 years and older, linking the challenges of urbanization and ageing. This collaborative programme aimed to identify which features of the built and social urban environment are essential in creating sustainable and supportive environments for older residents, and culminated in the publication of the Age-friendly city guide in 2006 [3]. An age-friendly city was defined as a place that encourages active ageing by optimizing opportunities for health, participation and security to enhance quality of life as people age [3]. Starting with 33 cities, WHO built on the guide by launching the Global Network for Age-friendly Cities and Communities in 2010, currently consisting of more than 500 cities where more than 155 million people live.

The network has reached several of the guide's objectives, such as generating greater recognition of the implications of population ageing on urban planning and involving stakeholders at multiple governmental levels [4]. At the same time, some of the network's limitations must be considered, as age-friendly initiativesoften compete with wider objectives associated with economic growth and development [1]. Furthermore, exchange between the age-friendly city movement and related debates in urban geography, sociology and other social sciences remains limited. This gap is most notable around research on structural urban changes, such as the rise of global cities, widening socioeconomic inequalities, and the impact of rural migration.

With increasing population ageing and urbanization, the development of age-friendly environments is a topic that demands the attention of both researchers and policy-makers. Two approaches hold the potential to move age-friendly city research forward: integration of determinants of ageing at multiple levels and the dynamics of urban environments.

8.1 Determinants of ageing

The guide [3] reflects on then-current scientific developments by including determinants of active ageing into its model, such as social determinants and the built environment. These determinants have become the focus of researchers looking at different factors that contribute to the age-friendliness of cities. A review of age-friendly city research concluded that most studies can be ranked on a set of axes ranging from physical to social environment on one axis, to bottom-up to top-down governance on the other [5]. Most studies reviewed look either at outcomes that define the age-friendly city or at processes associated with age-friendly cities.

A recent publication builds on these findings by exploring the prevalence of the tendency "to focus on the characteristics of ageing individuals and their immediate milieu, while paying little attention to the interaction between the micro-individual traits and the macrolevel workings [6]." However, we argue that the understanding of micro-individual traits is the beginning of age-friendly city research and not the endpoint. The layers of the sociospatial world are nested within one another: the household, the neighborhood, the city and so on. The age-friendly city is uniquely positioned to improve our understanding of how these layers interact with one another and how the combined impact of these mechanisms influences ageing individuals. Assessing the combined effects of different micro and macro processes on ageing could provide valuable information on how to better adapt to the challenges of urban ageing.

An example of how micro and macro processes are intertwined in the age-friendly city context is that of the prioritization of working-age families in urban renewal processes. This prioritization marginalizes older people from urban renewal, which implicitly creates a cultural bias towards age-segregated residential landscapes [7]. Micro levels such as the individual's home environment cannot be explained adequately without considering such macro-level processes and the role they play in shaping the immediate home environment.

While many studies investigate micro-level indicators of age-friendly cities, such as accessibility or individual safety, relatively few studies investigate how large socioeconomic and sociospatial developments impact ageing communities and the cities they live in. An example is the seesaw effect between urban greenness and urban density: both an increase in the amount of urban green areas and the development of more compact cities have been linked to better health [8]. What if increasing urban density leads to a reduction in the amount of urban green spaces? Will there still be a net benefit to public health? Considering how these concepts work together is important to determine how they influence health. Untangling such relational effects requires an integrated approach that considers both micro and macro levels, and therefore require the synthesizing of multiple topic areas and indicators from the guide to assess their combined effects.

As with many other public health challenges, a systems approach may be a promising strategy to analyze such effects. Two sample research questions exemplify this integration of cross-level interactions. First, what multilevel processes of sociospatial transformation are driving urban change and how do these forces impact the health of ageing urban populations? Second, how can we use system-based approaches to simulate the effect of prevention and early identification policies specific to urban environments on the trajectories of ageing and well-being? To answer these questions, engaging in current debates in the fields of urban geography and complex system science is necessary and can provide new perspectives.

8.2 Dynamics of urban environments

A second important approach to consider relates to the temporal character of urban environments. Cities are dynamic and constantly evolving [9], but this dynamic character is often neglected in age-friendly city research, as most existing research commonly applies a static lens that assumes that the individual's needs and capacities can be based on their current location. Temporal characteristics such as neighborhood stability or the longevity of an individual's residence in a specific place are essential dimensions to understand how environmental changes affect ageing individuals. Age-friendly city research would therefore benefit from more longitudinal or experimental study designs that account for this dynamic character [10].

An example is the effect of lifecourse neighborhood exposures on health. The life-course perspective informs understanding of how at later periods in life, health is affected by earlier experiences. This perspective also draws attention to historical circumstances and periods that are vital in shaping people and places [11]. Tracking the individual's personal geography through time will not only allow to improve measures of exposure, but also chart the socioeconomic trajectories of the places they inhabit. This trajectory is especially relevant for older individuals who by default have a more substantial life-course history, and the effects of their history may therefore be more pronounced than in younger individuals.

Two sample research questions are relevant to this approach. First, how are life-course histories of ageing individuals connected to the sociospatial histories of urban environments, and how does this combined effect influence health? Second, how do individual space-time constraints and temporal rhythms of activities affect health and health behavior in ageing urban populations? Answering these questions will not only contribute to a better understanding of how the space-time of individuals and places relate to current health, but will also provide better insight on how age-friendly developments are influenced or limited by other historical urban developments. Building the evidence base this way will provide both researchers and policy-makers with tools to better design age-friendly communities.

The public health challenges of ageing and urbanization are likely to intensify in the coming decades. Age-friendly cities still hold potential for both researchers and policy-makers. This potential should be further explored as the age-friendly city will never be an achieved condition, but an offer of an open horizon to work towards sustainable and age-friendly environments.

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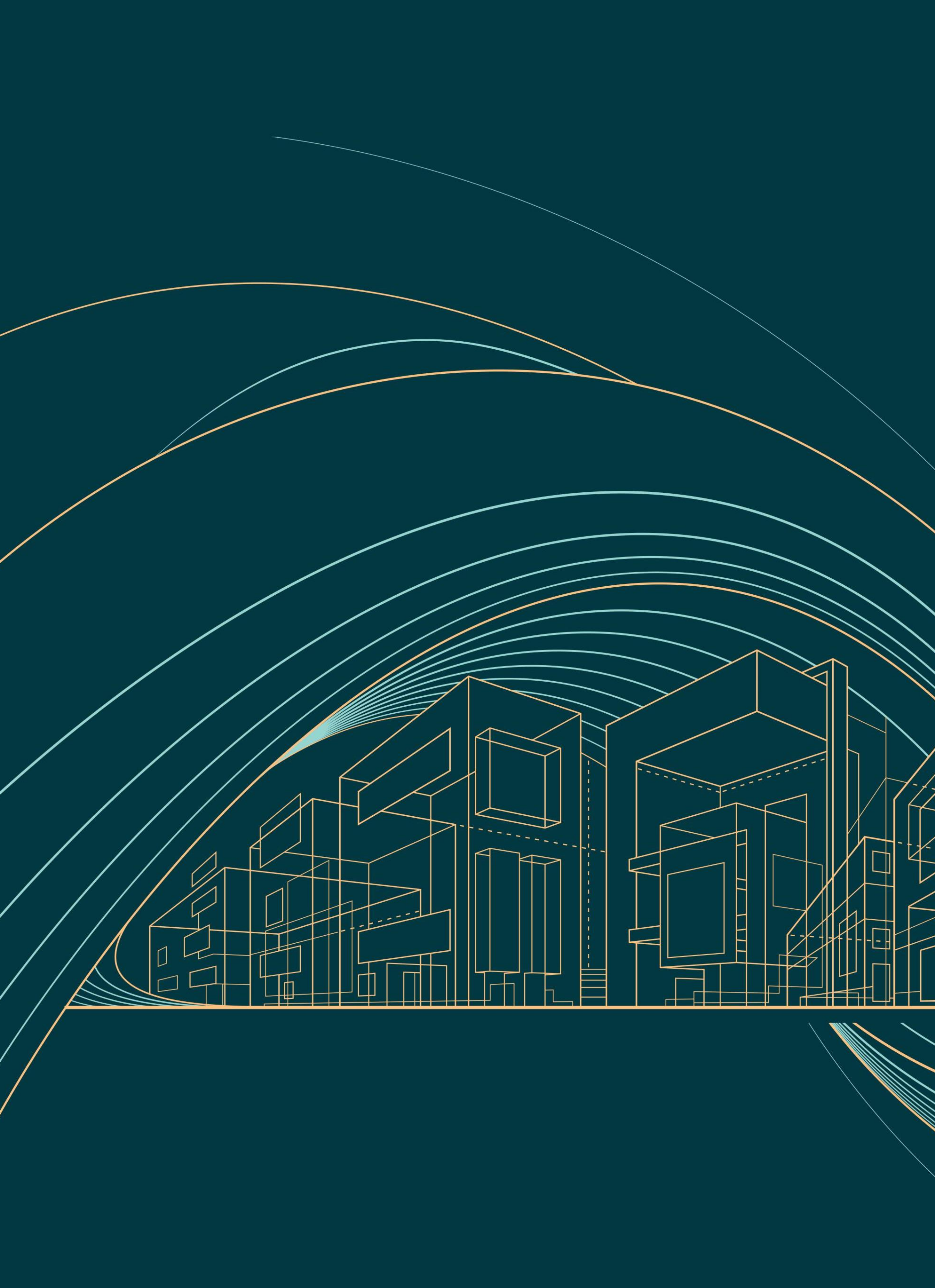
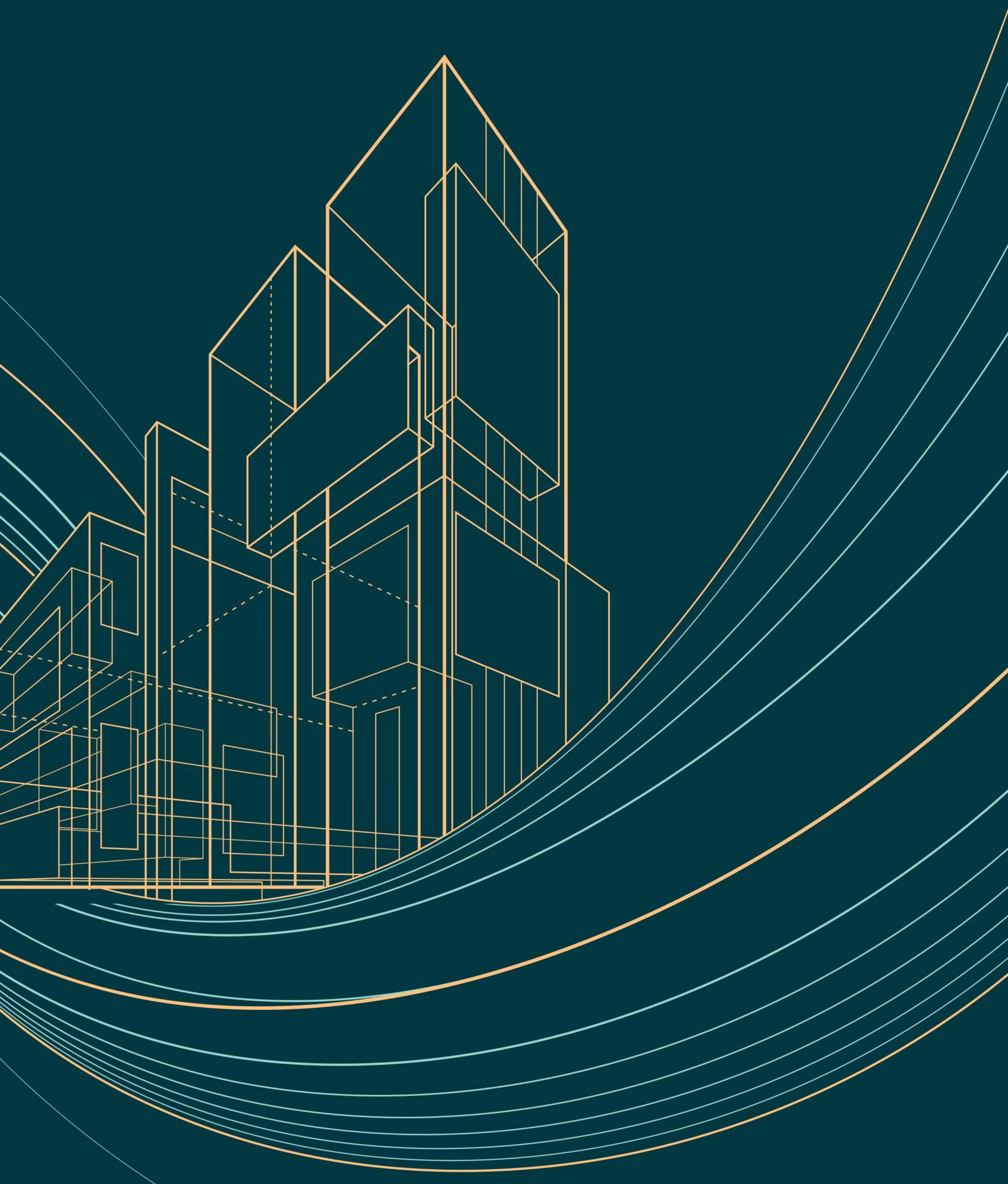


Discussion



9

Discussion

This thesis aimed to explore variation in urban environments and how it relates to physical activity and mental well-being. The discussion starts with a summary of the main findings and how they relate to the research aims presented in Chapter 1. It will conclude with a discussion of the methodological considerations of the studies presented in this thesis, and how they might have influenced the results, and a number of research and policy implications.

9.1 Main findings

- **Research aim 1:** To explore variation in physical urban-environmental exposures between cities and within cities over time.

Empirical studies linking urban-environmental exposures to health outcomes rely on some amount of variation in exposure between the units of analyses (e.g. individuals). Two potential strategies to increase this variation are to include multiple neighborhoods or cities with different levels of exposure, or to include multiple measurements taken over time. Strategy one necessitates that sufficient variation exists between urban environments, while strategy two necessitates that enough changes over time are observed. Furthermore, both strategies rely on harmonized data to make sure that observed differences – either between cities or over time – are indicative of actual changes and not the result of changes in data collection or processing. Chapter 2 explored variation between cities and within cities over time by examining three key urban-environmental exposure measures: (1) *urban green spaces* , (2) *residential density*, and (3) *land use mix*. These exposure measures were calculated for four European cities that were part of the MINDMAP project, and two years: 2006 and 2012. Based on the exploration, it can be concluded that variation exists both between cities as well as within cities over time. The degree to which variation exists between cities or within cities over time, depends on the type of exposure. For example, land use mix differs quite strongly between cities, but is more stable over time. Changes in environmental exposures over time are more dependent on the spatial scale at which they are measured as changes can be concentrated in one area of a city. Green spaces may be clustered in one part of the city, while land use mix might be more evenly distributed. Therefore careful consideration has to be given to how the research topic of interest is distributed in a city.

- **Research aim 2:** To explore how physical urban-environmental exposure measures can be harmonized and applied within health research.

Measurement of exposures over time heavily depends on the availability of harmonized longitudinal data of sufficient quality. Observed changes over time have to be the result of changes in the environment and not of changes in data processing or the applied methodology. This is especially important for any GIS-based measures as small changes in data processing can lead to substantial changes in calculated exposure measures. Chapter 2 exemplified the importance of this by comparing land use data that was based on the same source data, but is processed differently.

The MINDMAP project – described in Chapter 3 – developed a data harmonization protocol to enable data from multiple cohort studies from different cities to be harmonized and analyzed. The project combined this population-based cohort data with publicly available (GIS) datasets not typically used for ageing and mental well-being research. It integrated this data within one research platform, enabling researchers to investigate how urban-environmental characteristics relate to health and well-being between and within cities in Europe, and Canada. The integration of data from cohort studies from multiple countries and cities, allows researchers to investigate the role of contextual determinants on variations in health and well-being across different populations. While the general idea of increasing variation in exposure to specific urban-environmental characteristics by including multiple cities appears to be sound, using these data within a research context is a challenging tasks that requires a lot of harmonization work. The MINDMAP project integrated high-resolution spatial datasets into a research framework that also includes validated and harmonized measures of mental health and well-being. The resulting MINDMAP data platform enables researcher to examine how urban-environmental exposures relate to health outcomes between different cities. This infrastructure will help to explain differences in mental well-being both between cities and within cities over time, and will aid researchers in assessing the pathways and interactions between the urban environment and the individual determinants of mental well-being.

- **Research aim 3:** To investigate the extent to which variation in urban physical-environmental exposures between cities or over time relates to mental health and walking and cycling.

To answer research aim three, we will first discuss the result of the cross-sectional analyses reported in this thesis before discussing the results of the longitudinal analyses. Chapter 4 used data from multiple European cities to analyze how green space exposures in the residential environment relate to depressed affect and self-rated health. This study aimed to improve variation in exposure by including respondents from multiple cities across Europe. This study analyzed data from four Western-European and Central-European ageing cohorts, comprising 16,189 adults from nine different cities with an average age of 50–71 years. Harmonized individual-level exposure measures of green space availability and accessibility in the residential environment were linked to self-rated health, and depressed affect outcomes. No evidence was found of cross- sectional associations of green space exposures with subjective health, depressed affect, and other measures of depressive symptoms. This finding appeared quite consistent across four cohorts with diverse settings and levels of exposure to green space.

Chapter 5 used harmonized individual-level green space exposures to explore associations between green space levels in the residential environment and mental health. Linear regression models applied to cross-sectional data from 2004 for the city of Eindhoven and surrounding areas showed significant associations between the distance to the nearest green space and mental health, but no evidence of association between the amount of green spaces and mental health. On average, the total mental health score declined with 0.49 points on a 0-100 scale when the distance to the nearest green space was extended by 100 meters. The study described in Chapter 6 used similar exposure measures for the Eindhoven area and linked these to walking and cycling outcomes. The cross-sectional results from this study did not show significant associations between green space availability and accessibility in the residential environment and weekly walking and cycling.

The cross-sectional results from Chapters 4, 5, and 6 provide some evidence of associations between the accessibility of green space in the residential environment and mental health, but no evidence of associations with depressed affect and self-rated health, or walking and cycling. These results are in line with the general literature on the topic of urban green spaces and health, which is troubled by inconsistent and often inconclusive findings [1]. In Chapter 5, 6, and 7 we therefore also explored longitudinal relations between green space, land use mix, and mental health, and walking and cycling. Chapters 5, and 6 used data from multiple measurements to analyze how changes in green space exposures over time relate to changes in mental health, and walking and cycling outcomes in the city of Eindhoven and surrounding areas. Changes in green space exposures observed during the 10- year follow-up did not relate to significant changes in mental health. These results were observed for both the total sample as well as for respondents that did not move to a different residential location during the follow-up period. Chapter 6 provided some evidence for associations between changes in green space accessibility and changes in walking outcomes. As distance to the nearest green space increased with 100 meters, overall walking time per week decreased with 21 minutes. These results were observed among respondents that did not relocate to a different residential location during follow-up waves. Due to the harmonized green space exposures that were used in these studies, it can be concluded that the observed changes in green space exposures are the result of actual changes in the residential environment, and not the result of changes in data processing.

Chapter 7 examined the associations between land use mix in the residential environment and walking and cycling outcomes. Data from two Dutch cohorts spanning four cities was measured at three time points. Land use mix was calculated within network buffers of varying sizes around respondents' residential addresses. This study provided some evidence of between-individual associations of land use mix in 1000-meter buffers and the average walking time per week. On average, individuals with 10% more land use mix within 1000-meter buffers, spent 11 more minutes walking per week (95% CI: 0.08; 21.12). Similar associations were also observed for smaller buffers of 500 meters (β: 11.39, 95% CI: -0.28; 23.05) However, the study did not provide evidence that a change in the land use mix was associated with a change in time spent walking per week. Similarly, it did not provide evidence of associations between land use mix in 1000-meter buffers and time spent cycling per week. Complicating these results are the analyses performed on smaller and larger buffers. The 1000-meter network buffer is a commonly used exposure measure in health-geographical research as it is often regarded as a reasonable distance that people can walk. However, very little consensus exists on what buffer sizes best represent the residential environment. For the 500-meter buffers, negative within-individual associations between land use mix and time spent walking per week were observed. These results suggest that an increase of 10% in the land use mix is negatively associated with time spent walking. Similar negative within-individual associations for land use mix and cycling in the 1600-meter buffers were observed. Again, as these analyses were restricted to respondents that did not relocate during follow-up, and the exposure data was harmonized, these changes represent actual changes in the environment. The results from Chapter 7 therefore suggest that land use mix in

the residential environment is associated with time spent cycling and walking per week, but the exact nature of these associations remains unclear. Several methodological factors may contribute to these varying results, which are explored in more detail in the section on methodological considerations.
The studies described in Chapters 4 - 7 offer mixed results on how urban-environmental exposures are related to mental health and walking and cycling outcomes. While some cross-sectional associations between green space exposures and mental health for the Eindhoven region were observed, similar associations for walking and cycling outcomes were not. Associations between self-rated health and depressed affects outcomes were also not observed. The studies in Chapters 5, 6, and 7 applied a longitudinal design to deepen our understanding of these cross-sectional results. These studies made use of the fixed effects (FE) framework, which was expanded for Chapter 7 to also include a random effects (RE) component. This framework alleviates the effects of time-invariant confounding variables as long as they remain stable over time. While Chapter 6 found some evidence of a positive relation between a change in the distance to the nearest green space and a change in time spent walking, Chapter 5 did not find evidence of a similar relation for mental health. The implications of these results and our interpretation will be discussed separately.

9.2 Interpretation of the findings

In our studies on green spaces in the residential environment, we found some cross-sectional evidence of associations between green space exposure measures and mental health. However, our study on the associations between green space exposures and subjective health, depressed affect, and other measures of depressive symptoms, yielded no evidence that a larger amount of green spaces in the residential neighborhood is related to better health or well-being. These inconsistent results raise the question if urban green spaces are important for health and well-being or that we should focus our attention elsewhere. The lack of associations may suggest that green spaces in the residential environment have a limited influence on subjective perceptions of individuals' mental health or behavioral choices. The impact of green spaces on mental health may be contingent on other factors both within and outside individuals that we did not measure. For example, more green spaces in the area might only bring mental health benefits if they influence risk factors associated with mental health, such as social interactions. We also have to consider that potential effects of green spaces in the residential area on mental health or behavior might not be equal for the entire population. It could be that the effect differs across specific subgroups of the population. For example, a part of the population might walk or cycle independent of whether their residential area is green or not. Increasing green spaces in the area might therefore not have an effect on this part of the population. The same may be true for a subgroup of the population that will never walk or cycle. Increasing the amount of residential green spaces will likely not have an effect on this part of the population either. This raises the question if the general population is best suited to measure effects of green spaces on health and behavior. It could be that we should focus our efforts more on those parts of the population that might be receptive to a change in the environment. The elderly might be an example of such a subgroup as they are likely to spend more time in the residential environment compared to the general population. However, they should be 'sufficiently old' as our research in middle-aged and older adults did not provide evidence of differing effects for this subgroup.

The relatively small changes in green space exposures over time could also contribute to the limited findings. Not much is known about how large changes in green space exposures should be to generate a positive, measurable effect on health and behavior on a population level. A study conducted in The Netherlands suggested that there are critical values at which green space benefits operate [2]. According to the authors, the greatest mental health benefits of green spaces may be realized in areas with a proportion of green space of over 79% [2]. Individuals' residential areas should therefore be very green to observe positive mental health effects. Individual-level studies might not be best suited to examine such relationships. The study described in Chapter 4 included cities with varying degrees of 'greenness': Amsterdam had a green space level of 7.7% compared to 14.9% for Paris (Chapter 2). However, these city-wide green space levels do not necessarily translate to comparable differences between individuals living in those cities. The respondents from the LASA study from Amsterdam had 17.4 hectares of green space within a 800-meter buffer around their home address (8.7%) compared to 15.0 hectares for respondents from the Paris' RECORD study (7.5%) (Chapter 4). Further complicating this disparate relation is the observation that objective green space measures – as presented in this thesis – do not necessarily align with how residents perceive green space in their residential environment. A study from Sugiyama et al. found that individuals who perceived their neighborhood as very green had higher odds of better mental health compared to those who perceived their neighborhood as least green [3]. Perception of green space levels might therefore be important as well further complicating the relation as it is plausible that residents of a relatively green neighborhood in a very 'non-green' or 'grey' city perceive their neighborhood as very green, while residents of a neighborhood with similar objective levels of green space living in a greener city, might perceive their neighborhood as less green. It would therefore be beneficial to include different types of measurements of green spaces, such as measures that compare neighborhood green space levels to city-level averages as well as measures of how residents perceive the greenness of their neighborhood.

Finally, it is plausible that green space exposures in the residential neighborhood are non-linearly related with health and behavior outcomes. The aforementioned study by Helbich et al. (2018) used an ecological Bayesian geoadditive quantile regression approach to analyze how green space exposures relate to antidepressant prescription rates [2]. Their results suggest that green space exposure was overall inversely and non-linearly associated with the outcome, and that the associations differed across the quantiles. There appeared to be a threshold of 28% at which green space provides mental health benefits, but the largest health gains occur within the highest quintile. These findings suggest that small increases in green space exposure might not be enough to generate sufficient mental health benefits. The mean green space exposure in all of our studies did not reach 28% green space coverage in any buffer size. It is plausible that, in order for the level of green space in the residential area to have a measurable effect on mental health, it has to be much larger than it was in our studies. This furthers the argument to focus more research on specific subgroups instead of the general population. Does green space exposure relate to better mental health in a very green residential settings? And, consequently, does increasing the green space levels in such neighborhoods relate to mental health gains? Answering these questions might be more relevant than focusing research on the general population.

The limitations of retrospective data harmonization

One of the aims of the MINDMAP project was to harmonize data from multiple cohort studies in order to analyze how the urban environment relates to mental health across different urban contexts. A rigorous harmonization process involving multiple teams of experts was put in place to achieve this aim (Chapter 3). The harmonization of MINDMAP data was retrospective: variables were harmonized after the data were collected. MINDMAP data were processed using a common format for all cohorts, allowing co-analysis of data across different studies. This processing is vital to ensure content equivalence across studies and to reduce bias due to methodological differences between studies. While much care and thought was put into this retrospective harmonization, it invariably leads to loss of some quality and specificity, because of major differences between the studies. Methods for population sampling and participant follow-up, data formats and collection, and content varied extensively across the different cohorts [4]. The data available within the MINDMAP data infrastructure enable researchers to leverage existing cohort data to address research questions that are difficult to answer in studies that use data from one city. The MINDMAP data infrastructure allows researchers to include research populations from diverse urban environments across multiple countries, to study how differences between countries or cities can influence mental health and well-being outcomes. It can therefore be an important tool in collaborative research projects.

MINDMAP dataset 2.0 (April 2020) included 2.841 harmonized variables from 30 cohort waves or data collection events across six cohorts [4]. While the breath of information across multiple cohort studies is undoubtedly one of the main strengths of the project, it is also the cause of some limitations. Not all core variables could be harmonized across all cohort-specific datasets. Furthermore, because variable measurements can vary across cohorts, harmonization in some cases had to resort to the lowest common denominator. For example, a five item scale on self-reported health had to be reduced to a dichotomous ‘good or less than good’ variable in order to be compatible with data from as many cohorts as possible. These decisions were made with great care and were documented in detail. Multiple harmonization groups with a wide range of expertise contributed to the harmonization process to achieve the best possible results. However, this method invariably leads to some loss in data quality and/or specificity.

This problem was addressed using two different approaches. For the research conducted for Chapter 4, the decision was made to include data from four different cohorts with data collection across ten cities, comprising a total population sample of 16.189 adults. The strategy was to include data from these four cohorts in order to improve variation and statistical power. However, this approach led to a loss in specificity. As is detailed in Chapter 4, some variables such as retirement status were not comparable across all cohorts and therefore had to be dropped. For the research described in Chapter 7, the strategy was to use data from two cohorts that were more comparable in terms of available variables and data structure. This strategy meant that we were able to apply advanced statistical methods that make use of repeated measurements over time. The downside of this strategy was that the analyses were limited to two cohorts within the same country, comprising a research population of 2.101 adults. The utility of the MINDMAP data and data infrastructure will therefore have to be examined for each potential research question. Both the strengths and limitations of the data and data infrastructure will have to be considered in this process.

9.3 Methodological considerations

When interpreting the results and findings presented in this thesis, there are several methodological concerns that must be considered. Many study-specific methodological strengths and limitations have already been discussed within the relevant Chapters, but there are a number of more general and overarching limitations to consider.

Questions of scale

In the introduction, we introduced the concept of geographical scale as both horizontal and vertical (Chapter 1). Conceptualizing scale as horizontal allows for multiple spaces to coexist. A space can be viewed as a container of sorts, such as a neighborhood or an urban zone. These containers can be compared and contrasted to each other. Vertical conceptualizations of scale emphasize how different layers of space are stacked and embedded within each other within a multitiered configuration. For example, a park can be part of a larger natural area, but in itself may also contain smaller areas, such as playgrounds. Within this thesis we applied a mostly horizontal conceptualization of scale. A horizontal approach to geographical scales lends itself well to population-based studies, as reasonably objective measures can be calculated for large numbers of individuals. In Chapters 4-6 we calculated urban-environmental exposures using individual buffers of increasing sizes (i.e. 400/800/1600 meters). These buffers were used to calculate exposures for each individual. In Chapter 5 and 6 we calculated changes in the amount of green space within each individual's buffers. Using this approach meant that we were able to determine how a change in the amount of green space within the individual's residential environment could relate to a change in outcomes. This approach helps to answer a very relevant question: how much 'greener' does an individual's residential environment need to become in order to benefit health? However, this approach does not consider changes on a vertical scale. For example, while the amount of green space within an individual's buffer could increase over time, we did not consider changes in green space levels outside this specific buffer. What if the amount of green space within an individual's residential buffer increased, but overall green space levels in the city declined? Would this individual still perceive this change as positive, because the amount of green space in their direct residential environment increased? Or would they view it as negative as the city-level greenness declined? In Chapter 5 and 6 we observed that, on a municipal scale, overall levels of greenness declined for the city of Eindhoven and surrounding areas. For individuals we found both decreases and increases in the amount of green space, but it is unknown how these changes are perceived within a context of overall decreasing levels of greenness.

The approach presented in this thesis has the advantage that it enables us to better represent the individual's residential environment and lessen the impact of methodological concerns, such as the Modifiable Areal Unit Problem (MAUP) [5]. However, it does not consider how contextual influences at different geographical scales might intertwine. Factors such as neighborhood deprivation or neighborhood safety can be very relevant confounders for studies linking urban-environmental exposures to health outcomes. If such factors are to be integrated within the approach presented in this thesis, they have to be measured in a comparable way. This leads to concerns about the overlap of different spatial extents and the integration of different spatial scales. If safety is calculated on a census neighborhood level, but the amount of green space is based on individual-level buffers, spatial scales differ. Linking such area-level factors to exposures based on individual buffers, is challenging because it can lead to a patchwork of different scales that might not overlap (figure 9.1). The example detailed in figure 9.1 shows respondent 'individual I' whose residential address is represented by the red dot. This individual gets assigned some environmental exposure based on buffer 'B'. Data on potentially relevant confounders is available on a neighborhood level, but linking the value of neighborhood 'N' to individual 'I' would lead to a misrepresentation. The exposure buffer of individual 'I' crosses four different neighborhoods and has a different spatial scale compared to neighborhood 'N'. Linking the data of neighborhood 'N' to individual 'I' would therefore not be accurate.

For Chapters 5 and 6, individual-level exposures to urban-environmental characteristics were calculated. As these exposures were calculated for each study participant individually, we were not able to calculate potentially relevant area-level confounders due to these scalar issues. Resolving these scalar issues asks for a better understanding of what the spatial scale of an individual's neighborhood is and what it is not. Some work has been done to better understand what comprises the individual's neighborhood. For example, Prins et al. (2014) used GPS data to determine the average walking and cycling distances of elderly [6]. Much methodological work has also been done to derive methods to account for these issues. Of particular interest is the development of Geographical Ecological Momentary Assessments (GEMAs), which we will discuss in more detail in the paragraphs on the implications of our studies for future research.

Figure 9.1: An example of the difficulties of combining individual exposure measures with existing data on a neighborhood level

Traditional neighborhood approaches that use existing (census) neighborhood data often do allow for the use of area-level data. Within such studies, areal-level factors can be added to the analyses alongside individual-level factors potentially strengthening the analyses. However, these approaches face their own set of methodological challenges, such as the aforementioned MAUP and other challenges that are well documented [7-8]. The integration between both approaches appears to be limited. On one hand, health geographers are hard at work finding innovative ways to more accurately measure exposure to environmental determinants. The sausage buffers applied in Chapter 7 is an example of how a more developed approach to measuring environmental exposure can aid in developing a better representation of actual exposures [5]. While geographical advancements in how to measure environmental exposures are undoubtedly useful, they do little to mitigate concerns over how to integrate contextual area-level factors outside the individual into the analyses. Within this context, it becomes increasingly important to consider not just the right method for a specific research question, but also what assumptions and conceptualizations lie at the foundation of the preferred method. We will therefore discuss how specific conceptualizations of space and the role of time in these conceptualizations might impact how we approach different research questions regarding the urban environment and health.

Questions of space

In Chapters 4-6 one of the main exposure measures was the distance to the nearest green area. This distance was calculated in absolute terms: it was the Euclidian or straight-line distance from a point to the edge of a polygon. The choice for Euclidian distances was made based on comparability: many studies that investigate how green spaces and health relate, use Euclidian distances to calculate exposures to green spaces. In Chapter 7, we iterated on this approach by using a road network to generate buffers that more accurately represent the exposure area. Both approaches are rooted in a Newtonian conceptualization of space. Newtonian space exists independent of objects or relations and serves as a framework. It allows distances and scales to be measured without ambiguity: we know what is big and what is small, and what is close to what [9].

This conceptualization of space gives the concept analytical fixity as distances between objects can be calculated, and objects can be ordered based on such calculations. While such measures can provide valuable information, it is debatable if spatial distances are the most relevant urban-environmental exposures. Is the distance to a green space – even if it is calculated in the most precise way possible – the most relevant measure to represent an urban-environmental exposure?

A number of arguments have been made that a Newtonian conceptualization of space is not necessarily the best representation of spatial relations. The concept of relative space – also known as Einsteinian space – is based on the assumption that space can only be defined in relation to the objects or processes that are being considered [10]. The spatial frame that is chosen depends on what is relativized and by whom [11-12]. Instead of classifying observations within a spatial framework, the framework depends on the observations. This relative space can be especially relevant when discussing the movement of people, goods, services or information, because such movements take money, time, and energy to overcome a physical distance [13]. The distance to the nearest green space could also be based on the effort needed to reach a green area. Applying such a framework would mean that the nearest green space is not necessarily the one that is the closest in terms of absolute distance. Rather, the nearest green space would be the one that requires the least amount of effort to reach. Considering a green space as an relational object instead of a fixed physical space, would also ask for a different research approach or methodology. Thinking of space in relational terms has become popular among geographers in the last decades; especially among those concerned with issues of scale, region and bordering (see for example [14-17]). Relational thinkers often consider space as a social-relational construct in constant transformation [18]. A more relational approach to green spaces would, for example, consider the relations between the green space and its users. A number of studies have shown that such factors of green spaces might be more important when health outcomes are considered compared to physical distances [19-20].

How space is conceptualized has implications for the results presented in this thesis. It is hard to imagine space as something that exists as a framework in the complete absence of any physical objects or events, but it is equally hard to view space as just an abstract way to think about objects. The fact that we found null results in most of the fixed effects analyses presented in Chapters 5 and 6 cannot be viewed independently of how the spatial relation between green spaces and the respondents was conceptualized. It raises the question if Euclidian distance or green space are size in the residential environment, is the best way to measure spatial relations between individuals and green spaces. For example, would it be better to measure distance to the nearest green space in time or effort spent reaching that space? Or should we be measuring more relational and less 'objective' aspects of green spaces, such as their perceived quality and aesthetics? The results presented in this thesis imply that when mental health and well-being, and walking and cycling are concerned, distance to the nearest green space and the area size of green spaces in the residential environment might not be the best representations of the spatial relation between individuals and green spaces.

Questions of time

Apart from ensuring a proper chronology where exposure proceeds outcome, not enough attention is given to the role of time within health geography. Returning to our research on green spaces, we know that a park is close to an individual, but not if or how much time this individual spends in said park. This 'blind spot' has been criticized by authors, such as Mei-Po Kwan who introduced the *Uncertain Geographical Context Problem* (UGCoP) [8]. According to Kwan, researchers commonly assume that if a green space is close to an individual, that individual experiences some contextual influence from it. However, researchers do not know this with certainty unless it is measured. Furthermore, they also do not know how strong this influence is and how it might differ between individuals. The same holds true for measurements of changes over time. Within the fixed effects framework, only the change 'as is' is used in the analyses. For example, a change from 50 square meters to 100 square meters of green space is equal to a change from 700 to 750 square meters. In both cases, the change is +50 square meters, but the perception of this change could be very different. In Chapter 7, we therefore expanded on the fixed effects framework by also analyzing differences between individuals. Applying this method helps to alleviate some of the concerns of the fixed effects method, but does not address more fundamental problems on the role of time in health-geographical research.

In a 2013 article, Kwan offers two specific critiques on the lack of integration of time in health-geographical studies [21]:

- Most individuals move around during the day and therefore come under the influence of various neighborhood contexts outside of their home neighborhoods.
- Individuals move around over time between different residential locations.

When interpreting the results presented in this thesis, we therefore have to consider how temporality might have influenced the results. The study samples in our research consisted of middle-aged and older adults. There is some evidence that these age groups spend relatively more time in the residential neighborhood compared to other age groups [22]. However, when considering the results of the analyses, we have to account for the fact that we do not know how much time individual respondents have been exposed to an environmental factor. The results only tell more about the potential effects that changes in the residential environment can have on health outcomes. They do not tell if such effects – if they exist – are equally distributed among all residents or if they are stronger for residents who spend comparatively more time close to home.

The fixed effects method is ideally suited to analyzing changes over time within individuals. However, changes can be the result of either a change in the residential environment or the result of moving to a different residential location. To account for individuals moving between residential locations over time, we created subgroups in our analyses of so-called 'movers' and 'non-movers'. By focusing on the non-movers, we gained more insight into how a change in the residential environment relates to changes in the outcomes. The results for movers were also reported, but were not further investigated. Changes due to moving to a different residential location are likely not comparable to changes that are not the result of moving. Furthermore, the fixed effects method controls for unmeasured confounders as long as they remain stable over time. When someone moves to a different residential location, it is likely that a number of these unmeasured confounders would also change, diminishing this strength of the fixed effects method. Finally, the results from movers also contain less policy relevance as they do not inform policy makers of how a change in the environment might impact health outcomes.

The results presented in this thesis should therefore be interpreted based on their relevance for policy. Because we do not know the time spent in a certain green area, we cannot comment on differences in exposure levels of individuals. However, policy decisions have to be made on a neighborhood or city level and these results can be valuable for the decision making process. As changes to public spaces are likely to have an impact on residents that live in the area, these results can help to answer the question of what might happen to health if we change the residential environment.

9.4 Policy implications

With urbanization levels likely to increase in the coming decades, cities will become the home of many more people. Decisions about the urban environment will affect the health and well-being of an increasingly large number of citizens. The World Health Organization (WHO) therefore recommends: '*placing health and health equity at the heart of [city] governance and planning* [23].' In order to face this challenge, many municipalities and governmental organizations in the Netherlands have introduced *Prevention Agreements* (Preventieakkoorden) that detail how to 'turn the tide' and positively impact the health and well-being of urban residents. Furthermore, a large systemic change in urban planning in the Netherlands – known collectively as the *Environment and Planning Act* (Omgevingswet) – is set to introduce new ways for integrated urban planning with a prominent role for health and well-being. This new planning system will become the backbone of urban development and planning in the Netherlands and will be of great impact on policies across multiple policy domains. The new *Environment and Planning Act* consists of three tiers (figure 9.2). The *Environment and Planning Act* (Omgevingswet) details the framework, the *Environmental Strategy* (Omgevingsvisie) future developments, and the *Environmental Plan* (Omgevingsplan) all rules and guidelines. The *Environmental Strategies* provide a great opportunity to integrate health and well-being goals into spatial planning. One of the stated goals of the *National Environmental Strategy* (NOVI) is to ensure that by 2050 the environment will 'seduce' residents to live a healthy lifestyle [24]. Municipalities are encouraged to incorporate this goal in their local environmental strategies.

Figure 9.2: The structure of the new Environment and Planning Act

Adapted from Noordzij et al. (2021) [25].

An analysis conducted in 2020 of all then available environmental strategies showed that 44% of those strategies stated that one of their goals was to create a living environment that facilitates sports and healthy behavior [25]. Improving green space levels was commonly named as an important way to achieve this goal. However, the question remains whether general availability of more green spaces is the most important factor when health and well-being outcomes are concerned. Within this thesis, green space exposures were defined as either the area size of green spaces within a certain distance from the residential address or the distance to the nearest green space. The studies in this thesis provided limited evidence that a change in either measure was related to better mental health or to more walking and cycling. While increasing the general amount of green areas could be a useful tool for reaching other policy goals, such as limiting the effects of climate change, the studies presented in this thesis imply that increasing general green space levels is not a ‘one size fits all’ answer to growing health problems within cities. However, not much is known about how much green space is needed for it to have a positive effect on health outcomes. There is a large amount of cross-sectional and some longitudinal evidence that green spaces in the residential environment are related to health outcomes [26-28]. It is possible that the green space levels observed in the studies presented in this thesis were too low to observe a positive effect on health outcomes. One question that therefore needs to be answered is how green residential areas will need to become to contribute to better health and well-being. Not much is known about what the optimum amount of green space should be from a health perspective. Does such an optimum exist? Is it worthwhile to encourage policies that can lead to small changes in the amount of green spaces? Or are (very) large increases needed?

It is possible that positive health effects of green spaces only manifest when residential areas become ‘sufficiently’ green. Research conducted in the Netherlands, suggests that these green space levels should be at least 28%, but preferably 79% or more to be beneficial to mental health [2]. A study by Klompmaker et al. (2018) found the most beneficial effects of residential green space coverage on being overweight and physical activity levels for green space levels exceeding 65% in 1000-meter buffers [29]. In comparison, the mean green space level in Eindhoven and surrounding areas was 15% (SD: 9%) for 1000-meter buffers (Chapter 5 & 6). The Eindhoven area is considered to be relatively green (Chapter 2), but even for this region green space levels did not come close to the levels recommended by Helbich et al. (2018) or Klompmaker et al. (2018) [2, 29]. It is therefore possible that the observed green space levels were not high enough and changes in green space exposures too small. If policy makers want to utilize green spaces as a policy tool to improve health and well-being, it could very well be that green space levels would have to be drastically increased to have a positive, lasting effect on health and well-being.

Drastically increasing green space levels might not always be a valid policy approach as more green spaces will often come at the cost of other facilities or amenities in a neighborhood. A second strategy to utilize green spaces as a tool for better health and well-being could therefore be to not only consider general availability, but also other aspects of green spaces. Green space quality, aesthetics, or the social function of green spaces, might be as important as general availability [19]. While one neighborhood might benefit from more green spaces, another neighborhood might benefit more from increasing access to existing green spaces or improving their quality. Furthermore, there is a small but growing evidence base that shows that variation in ecological quality of green spaces (e.g. number of species, integrity of ecological processes) may influence the link between green space exposures and health and well-being outcomes. Wood et al. (2018) suggest that the restorative effects of green spaces is predicted by their biodiversity [20]. Increasing biodiversity is also beneficial for fighting climate change and therefore presents a good opportunity for the type of synergy that the *Environment and Planning Act* envisions.

The answer to the question of how to utilize green spaces as a policy tool for healthier cities has to be found in either drastically increasing green space levels or improving other aspects of green spaces, such as their (ecological) quality. The finding that general green space availability measures might not be the most important factor when health outcomes are concerned also has implications for how research on green spaces and health is commonly conducted. These implications will be discussed in the remainder of this discussion.

9.5 Implications for future research

As stated in the introduction of this thesis, one of the goals of this thesis was to increase variation in exposure to better understand the relationship between physical-environmental exposures and health outcomes. The approach to increase this variation was to expand the research by including data from multiple cities, and to include multiple measurements over time. The approach presented in this thesis can be classified as a population-based approach: it uses relatively large population samples and exposure measures that vary both between cities and over time. This approach has a number of advantages – as detailed in this discussion – but one to highlight is that it generates insight into how the physical urban environment relates to health outcomes on a population level and over time. This approach is therefore very policy relevant as policy is usually not made on an individual level. Longitudinal evidence linking green space exposures to health outcomes is rare, and not much is known about the time interval required to observe large enough changes. The studies presented in Chapters 5 and 6 observed some changes in green space exposures over a 10-year time period, but it remains unclear if these observed changes were large enough. Expanding the longitudinal framework presented in these studies to include a longer time period might lead to more observed changes, and therefore to more insight into how these changes might impact health outcomes over a longer period of time.

Another approach to the same question could be to shorten the time interval at which potential effects are observed. The *Geographical Ecological Momentary Assessment* or GEMA approach combines geographical data from smartphones or GPS devices with data from *Ecological Momentary Assessments* (EMAs). EMAs consist of data from real-time self-reports of behaviors, contexts, emotional states, beliefs, attitudes, and perceptions [30]. GEMAs combine GPS-based location data with EMAs to assess built environment exposures along GPS routes, and subjective perceptions of the environment. GEMAs therefore rely on intensive monitoring of study participants over a set period of time [31]. The GEMA approach has a number of benefits that might be worthwhile to explore. First, static measures of environmental exposures based on the residential area of individuals, treats individuals as if they are permanently exposed to those exposures. A better assessment of exposures over time is needed to determine if and when individuals are exposed to environmental factors. As the name implies, EMAs are very much reliant on measuring something 'in the moment'. This means that the GEMA approach allows researchers to know exactly when and for how long a study participant has been exposed to an environmental factor. This could be especially relevant for mental well-being as most of the evidence available on how environmental exposures can influence stress is based laboratory experiments or short controlled experiments [32]. Second, GEMAs give more insight into the activity spaces of individuals, which can fall outside of the boundaries of statistical neighborhoods or residential areas [6, 32]. They can therefore more accurately capture individual's neighborhoods or activity spaces.

Study designs using the GEMA framework may therefore help to gain a better understanding of how factors in the individual's environment may relate to health and health-related outcomes. However, this framework comes with its own set of limitations. Privacy is an immediate concern as it is critical to establish strict rules for the management and use of data and to protect it from unauthorized access. Furthermore, data has to be processed in a secure way to ensure that identification of study participants is not possible. Methodological concerns also exist, such as the Hawthorne effect, where participants modify their behavioral routines due to the study protocol. Finally, studies using this protocol address temporal changes within a (very) short time interval. They do not enable us to gain more insight into the mid-long to long term effect of, for example, living in a greener neighborhood. Compared to population-based approach applied in this thesis, the GEMA approach is especially relevant for small individual-level changes, such as how a road diversion can impact walking. A population-based approach is more relevant when changes on both a larger spatial and temporal scale are concerned. Where the GEMA approach considers a very short time scale, the population-based approach considers long-term changes over multiple years or even decades. Both approaches therefore have their own strengths and weaknesses and it is worthwhile to consider how both can complement each other.

If green cities are good for health, are less green cities bad for health?
This thesis presents a number of studies conducted in the Eindhoven region (Chapters 5-7). Within Chapters 5 and 6 we observed an overall decrease in green space levels in the Eindhoven region. This was an unusual observation in itself as our hypothesis was that the area had become 'greener' over time. A substantial part of the research population, therefore, experienced a negative

change in the amount of green spaces in the residential area, indicating that they had less green space within their residential environment in 2014 compared to 2004. The number of respondents with a decrease in green space measurements over time was about equal to those with an increase in green space measurements between 2004 and 2014. Other studies conducted in the Netherlands observed similar declines in green space levels. For example, a study conducted in Zaanstad, The Netherlands, observed a decline in green spaces from 39% of total land use in 2003 to 32% of total land use in 2016 [33]. In in a time where governments and policy makers aim for more green spaces in cities, it is concerning to note that the overall greenness in both the Eindhoven area and Zaanstad declined over time. While the results presented in this thesis do not provide a definitive answer to the question if more green spaces lead to better health, these observations raise the question if less green spaces are bad for health.

The fixed effects models that were used in these studies rely on the assumption that the effects of variables are symmetric. These models assume that an increase in a variable has the same effect on the outcome as a decrease, but in the opposite direction. Almost all health-geographical studies on green spaces and health, operate on the assumption that an increase in green spaces is good for health, but very little is known about the potential health effects of a decrease in green spaces in the residential environment. Is this effect symmetrical? Does a 10% decrease in green space lead to an adverse effect on health that is comparable to the positive effect of a 10% increase? To the best of our knowledge, no research currently exists that aims to answer this question. Furthermore, this issue not only effects research on green spaces and health, but effects many domains of social-scientific research [34]. Numerous methods have been developed to test asymmetric hypotheses, but almost all of these methods rely on cross-sectional data [35]. Allison (2019) outlines a method for asymmetric fixed effects analyses, based on the work of York & Light (2017) [36-37]. This method operates on the same basis of a general fixed effects method, and can be applied to longitudinal data. It has been applied in some economic and econometric studies, but not within health-geographical research to date. Applying such models to gain more insight into potential effects of decreases in green space levels on health would provide important knowledge that is currently lacking.

When considering the implications of the research presented in this thesis it is important to question how the physical environment relates to health and well-being. On the one hand, the research presented in this thesis provides limited evidence of a population-level relation between green spaces, and mental health and walking and cycling, and no conclusive evidence that a change in green space levels is associated with a change in health outcomes. Reflecting on other research, it could be that measurable population-level advantages only apply when neighborhoods become very green. It could also be that other factors than the general availability green spaces are more important. Furthermore, the overall green space levels in the Eindhoven region declined between 2004 and 2014. Decreasing green space levels do not only potentially negatively impact health, but also have negative impacts on other domains, such as climate control efforts or biodiversity. More monitoring of how green space levels change over time is needed if we want to gain a better understanding of how urban green space levels might impact health on a population level. So while the urban environment appears to be a potent context for the implementation of policies directed at improving health and well-being, a more comprehensive understanding of how the environment relates to individual health and well-being is needed.

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Summary

In 2017, there were an estimated 962 million people aged 60 years or older worldwide, accounting for around 13% of the total population. This part of the population is growing at an annual rate of about 3% and increasingly lives in cities. The combination of urbanization and ageing can lead to new public health challenges, such as a higher risk of mental disorders and physical inactivity, but can also offer opportunities for the implementation of policies and interventions that promote public health. The city has therefore become a key site for the implementation of prevention and early identification policies on the trajectories of ageing and mental well-being. However, the implementation of such policies requires a good understanding of how the urban environment relates to health and well-being.

Empirical studies linking urban-environmental exposures to health outcomes rely on some amount of variation in exposure measures between the units of analysis. Variation in exposure levels can be the result of variation *between* urban environments, such as different neighborhoods, or variation *within* urban environments over time. However, many studies linking urban-environmental exposures to health-related outcomes are often limited to just one city or one, cross-sectional, measurement. Potential strategies to increase variation are to include multiple cities from different countries or to include multiple measurements taken over time. The aim of this thesis was to explore the variation in urban environments and how it relates to physical activity and mental well-being by using data from different European cities. The overall aim of this thesis was further detailed in three, more specific, research aims:

- **Research aim 1**: To explore variation in physical urban-environmental exposures between cities and within cities over time.
- **Research aim 2**: To explore how physical urban-environmental exposure measures can be harmonized and applied within health research.
- **Research aim 3**: To investigate the extent to which variation in urban physical-environmental exposures between cities or over time relates to mental health and walking and cycling.

The studies presented in this thesis use data harmonized within the MINDMAP project. The MINDMAP project aimed to identify the opportunities and challenges posed by the urban environment for the promotion of mental health and well-being of middle-aged and older adults. Within the MINDMAP project, a data harmonization protocol was developed to enable data from multiple cohort studies from different cities to be harmonized and analyzed. The project combined this population-based cohort data with spatial datasets and integrated these data within one research platform. This enabled researchers to investigate how urban-environmental characteristics relate to health and well-being between and within cities in Europe, and Canada.

The aim of this thesis necessitates that sufficient variation exists between urban environments or that enough changes over time within cities are observed. Chapter 2 therefore explored variation between cities and within cities over time by examining three key urban-environmental exposure measures: (1) *urban green spaces,* (2) *residential density,* and (3) *land use mix.* The degree to which variation exists between cities or within cities over time, depends on the type of exposure studied. For example, land use mix differs quite strongly between cities, but is more stable over time. Variation in environmental exposures over time is more dependent on the spatial scale at which it is measured as changes can be concentrated in one area of a city. Green spaces may be clustered in one part of the city, while land use mix might be more evenly distributed.

While the general idea of increasing variation in exposure by including multiple cities appears to be sound, using these data within a research context is a challenging task that requires a lot of harmonization work. The MINDMAP project as described in Chapter 3 integrated high-resolution spatial datasets into a research framework that also includes validated and harmonized measures of mental health and well-being. The resulting MINDMAP data platform enabled us to examine how urban-environmental exposures relate to health outcomes between different cities. This infrastructure enabled research to explain differences in mental well-being both between cities and within cities over time, and in assessing the pathways and interactions between the urban environment and the individual determinants of mental well-being. Chapter 4 used data from the MINDMAP project to analyze how the availability and accessibility of green spaces in the residential environment relates to depressed affect and self-assessed health for residents of multiple European cities. This study analyzed data from four Western-European and Central-European ageing cohorts, comprising 16,189 adults from nine different cities aged between 50 and 71 years old. No evidence was found of cross-sectional associations of green space exposures with subjective health, depressed affect, and other measures of depressive symptoms. These findings appeared quite consistent across four cohorts with diverse settings and levels of exposure to green space. Chapter 5 used harmonized individual-level green space exposures to explore associations between green space levels in the residential environment and mental health. Linear regression models applied to cross-sectional data from 2004 for the city of Eindhoven and surrounding areas showed significant associations between the distance to the nearest green space and mental health, but no evidence of associations between the amount of green space and mental health. The study described in Chapter 6 used similar exposure measures for the Eindhoven area and linked these to walking and cycling outcomes. The cross-sectional results from this study did not show significant associations between green space availability and accessibility in the residential environment and weekly walking and cycling.

The cross-sectional results from Chapters 4, 5, and 6 provide some evidence of associations between the accessibility of green space in the residential environment and mental health and well-being, but no evidence of associations with depressed affect and self-assessed health, or walking and cycling. In Chapter 5 and 6 we also explored longitudinal associations between green spaces, mental health, and walking and cycling. Chapters 5 and 6 used data from multiple measurements to analyze how changes in green space exposures over time relate to changes in mental health, and walking and cycling outcomes in the city of Eindhoven and surrounding areas. Changes in green space exposures observed during the 10-year follow-up did not relate to significant changes in mental health. These results were observed for both the total sample as well as for respondents that did not move to a different residential location during the follow-up period. Chapter 6 provided some evidence for associations between changes in green space accessibility and changes in walking outcomes. As distance to the nearest green space increased with 100 meters, overall walking time per week decreased with 21 minutes. These results were observed among respondents that did not relocate to a different residential location during follow-up waves. Due to the harmonized green space exposures that were used in these studies, it can be concluded that the observed changes in green space exposures are the result of actual changes in the residential environment, and not the result of changes in data processing.

Chapter 7 examined the associations between land use mix in the residential environment and walking and cycling outcomes. Data from two Dutch cohorts spanning four cities and measured at three time points were used. Land use mix was calculated within network buffers of varying sizes around respondents' residential addresses. This study provided some evidence of between-individual associations of land use mix in 1000-meter buffers and the average walking time per week. On average, individuals with 10% more land use mix within 1000-meter buffers, spent 11 more minutes walking per week. Similar associations were also observed for smaller buffers of 500 meters. However, the study did not provide evidence that a change in the land use mix was associated with a change in time spent walking per week. Similarly, it did not provide evidence of associations between land use mix in 1000-meter buffers and time spent cycling per week. The results from Chapter 7 therefore suggest that land use mix in the residential environment is associated with time spent walking per week, but the exact nature of these associations remains unclear.

The studies described in Chapters 4 - 7 offer mixed results on how urban-environmental exposures are related to mental health and walking and cycling outcomes. The mixed results raise the question if urban green spaces are important for health and well-being or that we should focus our attention elsewhere. The lack of associations may suggest that green spaces in the residential environment have a limited influence on subjective perceptions of individuals' mental health or behavioral choices. The impact of green spaces on mental health may be contingent on other factors both within and outside individuals that we did not measure. For example, more green spaces in the area might only bring mental health benefits if they influence risk factors associated with mental health, such as social interactions. We also have to consider that potential effects of green spaces in the residential area on mental health or behavior might not be equal for the entire population. The relatively small changes in green space exposures over time could also contribute to the limited findings. Not much is known about how large changes in green space exposures should be to generate a positive, measurable effect on health and behavior on a population level. Furthermore, the results from Chapter 5 and 6 show that overall green space levels in the Eindhoven region declined between 2004 and 2014. Decreasing green space levels do not only potentially negatively impact health, but also have negative impacts on other domains, such as climate control efforts or biodiversity.

Finally, it is plausible that green space exposures in the residential neighborhood are non-linearly related with health and behavior outcomes. A threshold might exist at which point green spaces provide mental health benefits. Small increases in green space exposure might not be enough to generate sufficient mental health benefits if they remain under such a threshold. It is plausible that, in order for the level of green space in the residential area to have a measurable effect on mental health, it has to be much larger than it was in the studies presented in this thesis.

The work presented in this thesis aligns with the ambition of cities to become more 'age-friendly'. In 2006, the *World Health Organization* (WHO) developed the concept of *Age-friendly Cities* to identify which features of the built and social urban environment are essential in creating sustainable and supportive environments for older residents. Trends of urbanization and ageing are likely to further converge and increase in the coming decades, providing both challenges and opportunities for policy makers to ensure healthy ageing for older urban residents. Chapter 8 discusses the potential for the development of *age-friendly cities* and current challenges, such as the prioritization of working-age families in urban renewal processes, and the tendency to assume that the individual's needs and capacities can be based on their current location.

Chapter 9 concludes this thesis with discussing the interpretation of the findings presented in this thesis, a number of methodological considerations, and the policy and research implications. The introduction of the *Environment and Planning Act* (in Dutch 'Omgevingswet') in the Netherlands offers policy makers a unique opportunity to integrate health and well-being into urban planning. The *National Environmental Strategy* (NOVI) details its goal to ensure that by 2050 the environment will "seduce" residents to live a healthy lifestyle. One commonly cited way to achieve this goal is to utilize green spaces as a policy tool towards healthier cities. The research presented in this thesis provides limited evidence of population-level associations between green spaces, and mental health and walking and cycling, and no conclusive evidence that a change in green space levels is associated with a change in health outcomes. Reflecting on other research, it could be that measurable population-level advantages only apply when neighborhoods become very green. It could also be that other factors than the general availability green spaces are more important, such as accessibility of green spaces. The answer to the question of how to create healthier cities using green spaces therefore likely lies in either drastically increasing green space levels or improving other aspects of green spaces, such as their (ecological) quality. More monitoring of how green space levels change over time is needed if we want to gain a better understanding of how urban green space levels might impact health on a population level. So while the urban environment appears to be a potent context for the implementation of policies directed at improving health and well-being, a more comprehensive understanding of how the environment relates to individual health and well-being is needed.

Samenvatting

In 2017 was naar schatting 13% van de totale wereldbevolking 60 jaar of ouder, wat overeenkomt met ongeveer 962 miljoen mensen. Het aandeel 60+'ers stijgt naar verwachting de komende jaren met gemiddeld 3%. Bovendien woont een steeds groter deel van deze bevolkingsgroep in steden. De combinatie van vergrijzing van de wereldbevolking en verdere verstedelijking leidt tot nieuwe gezondheidsuitdagingen. Zo hebben oudere stadsbewoners een hogere kans op psychische ziekten en bewegen ze vaak onvoldoende. De verdergaande verstedelijking en vergrijzing bieden echter ook kansen voor de implementatie van interventies of beleid gericht op het bevorderen van de publieke gezondheid. Deze combinatie van factoren heeft eraan bijgedragen dat de stad steeds belangrijker is geworden als plek om preventiebeleid of beleid gericht op het actief houden van een ouder wordende bevolking te implementeren. Om dit effectief te kunnen doen, is echter gedegen kennis nodig van hoe de stedelijke leefomgeving van invloed kan zijn op gezondheid en welzijn.

Empirische studies die onderzoeken hoe blootstelling aan verschillende stedelijke omgevingsfactoren van invloed kan zijn op gezondheidsuitkomsten, maken vaak gebruik van een zekere mate van variatie in de omgevingsfactoren. De variatie in omgevingsfactoren kan het gevolg zijn van variatie *tussen* verschillende stedelijke leefomgevingen of het gevolg van *veranderingen binnen omgevingen over tijd*. Veel studies naar dit onderwerp worden echter beperkt tot één stad of één meetmoment. Dit beperkt de variatie in de omgevingsfactoren die gementen worden. Er bestaan verschillende strategieën om deze variatie te vergroten. Zo kan variatie vergroot worden door verschillende buurten binnen steden met elkaar te vergelijken of door meerdere metingen van omgevingsfactoren over de tijd te benutten. Het onderzoek dat beschreven wordt in dit proefschrift is opgezet om de variatie in omgevingskenmerken te benutten om zo meer te leren over de relatie tussen stedelijke omgevingskenmerken en gezondheid.

Het doel van dit proefschrift was om te onderzoeken hoe de variatie in stedelijke omgevingskenmerken van invloed is op beweeggedrag en mentaal welzijn binnen verschillende Europese steden. Dit onderzoeksdoel is uitgewerkt in drie specifieke onderzoeksdoelen:

- **Onderzoeksdoel 1**: Het onderzoeken en beschouwen van de variatie in fysieke omgevingskenmerken tussen verschillende steden en binnen steden over de tijd.
- **Onderzoeksdoel 2:** Het onderzoeken hoe fysieke, stedelijke omgevingskenmerken berekend en geharmoniseerd kunnen worden en hoe deze kenmerken toegepast kunnen worden binnen gezondheidsonderzoek.
- **Onderzoeksdoel 3:** Het onderzoeken van de mate waarin variatie in fysieke omgevingskenmerken van verschillende steden en binnen steden over tijd zich verhouden tot mentale gezondheid, wandelen en fietsen.

De studies die opgenomen zijn in dit proefschrift maken gebruik van data die geharmoniseerd zijn binnen het MINDMAP-project. Het MINDMAP-project had als doel om te onderzoeken welke kansen en uitdagingen stedelijke leefomgevingen bieden voor het bevorderen van mentale gezondheid en mentaal welzijn van oudere volwassenen. Voor het MINDMAP-project is een harmonisatieprotocol opgesteld, waarmee data van verschillende cohortstudies uit verschillende steden geharmoniseerd kon worden. In het project zijn data van verschillende cohortstudies samengevoegd met ruimtelijke omgevingsdata binnen een dataplatform. Met behulp van dit platform kon onderzoek gedaan worden naar hoe stedelijke omgevingsfactoren van invloed zijn op gezondheid en welzijn binnen Europese en Canadese steden.

Voor het behalen van het onderzoeksdoel van dit proefschrift is het nodig dat er voldoende variatie in stedelijke omgevingskenmerken bestaat tussen steden en/of over de tijd. In hoofdstuk 2 is daarom beschreven wat de variatie in omgevingskenmerken tussen verschillende steden is en hoe deze kenmerken veranderen over de tijd. Hiervoor werd gekeken naar drie belangrijke stedelijke omgevingskenmerken, te weten: (1) *stedelijk groen*, (2) *omgevingsdichtheid* en (3) de *verdeling van het landgebruik*. De mate waarin er variatie in stedelijke omgevingskenmerken bestaat, is voornamelijk afhankelijk van welk kenmerk onderzocht wordt. Zo verschilt de verdeling van landgebruik aanzienlijk tussen verschillende steden, maar zijn veranderingen in de verdeling van het landgebruik over tijd relatief beperkt. Variatie in stedelijke omgevingskenmerken is bovendien sterk afhankelijk van de ruimtelijke schaal waarop de kenmerken gemeten worden. Zo kunnen omgevingskenmerken geconcentreerd zijn in bepaalde stadsdelen of buurten. Stedelijk groen kan bijvoorbeeld geclusterd zijn in enkele grote parken, terwijl de verdeling van het landgebruik als geheel gelijkmatiger is.

De uitkomsten beschreven in hoofdstuk 2 gaven aanwijzingen dat het vergroten van variatie in omgevingskenmerken door data van meerdere steden te combineren een kansrijke methode is. Om deze data te kunnen gebruiken in een onderzoekscontext moest echter een belangrijke en uitdagende harmonisatieslag gemaakt worden. Binnen het MINDMAP-project, dat in detail in hoofdstuk 3 is beschreven, zijn meerdere ruimtelijke datasets van hoge kwaliteit in een dataplatform geïntegreerd. Bovendien bevat dit dataplatform ook gevalideerde en geharmoniseerde gezondheidsdata over mentale gezondheid en mentaal welzijn. Dit MINDMAP-dataplatform maakte het mogelijk om onderzoek te doen naar hoe stedelijke omgevingskenmerken samenhangen met gezondheidsuitkomsten voor verschillende steden en over de tijd. Bovendien kan het platform onderzoekers helpen om de interacties tussen de stedelijke leefomgeving en individuele determinanten van gezondheid beter in kaart te brengen.

Het onderzoek dat beschreven is in hoofdstuk 4 maakte gebruik van data van het MINDMAP-dataplatform om te analyseren hoe de aanwezigheid en bereikbaarheid van groen in de woonomgeving zich verhoudt tot het hebben van depressieve gevoelens en zelfgerapporteerde gezondheid voor bewoners van meerdere Europese steden. Binnen deze studie werden data van vier Centraal- en West-Europese gezondheidscohorten geanalyseerd. In totaal bestond de onderzoekspopulatie uit 16.189 volwassenen in de leeftijd van 50 tot en met 71 jaar verdeeld over negen steden. De analyses leverden geen overtuigend bewijs op van cross-sectionele associaties tussen groen in de leefomgeving en zelfgerapporteerde gezondheid, het hebben van depressieve gevoelens en andere uitkomstmaten gerelateerd aan depressiviteit. Deze resultaten waren consistent voor alle cohorten, ondanks de verschillen in ruimtelijke structuur van de onderzochte steden.

Voor het onderzoek beschreven in hoofdstuk 5 is gebruik gemaakt van geharmoniseerde omgevingsdata van groen in de woonomgeving om te onderzoeken wat de associaties zijn tussen de hoeveelheid groen in de directe woonomgeving en mentale gezondheid. Met behulp van lineaire regressiemodellen is voor Eindhoven en omgeving onderzocht wat de cross-sectionele verbanden tussen groen en mentale gezondheid waren met behulp van data uit 2004. Uit deze modellen kwamen significante verbanden naar voren tussen de afstand tot het dichtstbijzijnde groen en mentale gezondheid, maar geen verbanden tussen de hoeveelheid groen in de woonomgeving (in hectare) en mentale gezondheid. De studie omschreven in hoofdstuk 6 maakte gebruik van vergelijkbare omgevingsdata voor Eindhoven en omgeving en vergelijkbare statistische modellen om te onderzoeken wat de verbanden tussen groen in de woonomgeving en de hoeveelheid wandelen en fietsen waren. Deze studie vond geen cross-sectionele verbanden tussen zowel de afstand tot het dichtstbijzijnde groen als de hoeveelheid groen in de woonomgeving met de hoeveelheid wandelen en fietsen per week.

De cross-sectionele resultaten beschreven in de hoofdstukken 4, 5 en 6 geven een gemengd beeld. Enerzijds zijn in deze studies associaties gevonden tussen groen in de woonomgeving en mentale gezondheid, maar anderzijds geen associaties tussen groen en het hebben van depressieve gevoelens, zelfgerapporteerde gezondheid, of wandelen en fietsen. In hoofdstuk 5 en 6 zijn de analyses daarom uitgebreid met longitudinale analyses die onderzochten wat de longitudinale verbanden tussen groen en mentale gezondheid en tussen groen en wandelen en fietsen waren. De onderzoeken beschreven in de hoofdstukken 5 en 6 maakten gebruik van data die op meerdere momenten gemeten waren om zo te kunnen analyseren hoe veranderingen in groen in de woonomgeving over een periode van 10 jaar van invloed kunnen zijn op veranderingen in mentale gezondheid en wandelen en fietsen voor Eindhoven en omgeving. De studie beschreven in hoofdstuk 5 leverde geen bewijs op van associaties tussen veranderingen in groen in de leefomgeving en veranderingen in mentale gezondheid. Dit gold zowel voor bewoners die niet verhuisd waren, als voor bewoners die wel verhuisd waren tijdens de opvolgperiode van 10 jaar. De studie beschreven in hoofdstuk 6 leverde wel bewijs op van associaties tussen veranderingen in groen in de woonomgeving en veranderingen in de hoeveelheid wandelen en fietsen per week. Een toename van 100 meter tot het dichtstbijzijnde groen hield verband met een afname van 21 minuten wandelen per week. Deze resultaten golden voor bewoners die niet waren verhuisd tijdens de onderzoeksperiode van 10 jaar. Vanwege de geharmoniseerde omgevingsdata die gebruikt zijn in deze studie, kan geconcludeerd worden dat de geobserveerde veranderingen in groen het gevolg zijn van daadwerkelijke veranderingen in de omgeving en bijvoorbeeld niet van wisselingen in hoe de data zijn verzameld of bewerkt.

Het onderzoek beschreven in hoofdstuk 7 ging in op de vraag of er verbanden zijn tussen de mate van landgebruik in verschillende steden en wandelen en fietsen. Voor deze studie werden data gebruikt van twee Nederlandse cohortstudies uit vier steden gemeten op drie tijdsmomenten. De functiemix van het landgebruik werd berekend door middel van netwerkbuffers rond de woonadressen van de respondenten. De resultaten van deze studie toonden aan dat er een verband is tussen de mate van functiemix in buffers van 1.000 meter en het gemiddelde aantal minuten wandelen per week. Respondenten met 10 procent meer landgebruikmix binnen de buffer van 1.000 meter wandelden gemiddeld 11 minuten per week meer. Vergelijkbare associaties werden ook gevonden voor kleinere buffers van 500 meter. Een verandering over tijd in landgebruikmix hield echter geen verband met de hoeveelheid wandelen per week. Tevens werd er in deze studie geen verband gevonden tussen de landgebruikmix in buffers van 1.000 meter en de hoeveelheid fietsen per week. De resultaten beschreven in hoofdstuk 7 suggereren dus dat de mate van landgebruikmix in de woonomgeving verband kan houden met hoeveel er gewandeld wordt, maar het blijft onduidelijk of een verandering in mix ook verband houdt met een verandering in de hoeveelheid wandelen.

De studies omschreven in de hoofdstukken 4 tot en met 7 laten gemengde resultaten zien over hoe stedelijke omgevingskenmerken van invloed zijn op mentale gezondheid, wandelen en fietsen. Deze gemengde resultaten roepen de vraag op of groen in de woonomgeving belangrijk is voor de gezondheid en het welzijn van bewoners of dat we onze aandacht beter op andere thema's kunnen richten. De gemengde resultaten kunnen de suggestie wekken dat groen in de woonomgeving slechts in beperkte mate van belang is voor gedragskeuzes en mentaal welzijn. Het is waarschijnlijk dat de impact van groen in de woonomgeving op mentaal welzijn mede afhankelijk is van andere factoren. Dit kunnen zowel individuele factoren als factoren in de leefomgeving zijn. Zo kan het zijn dat meer groen in de woonomgeving alleen een positief effect heeft op mentaal welzijn als het een effect heeft op bepaalde risicofactoren voor mentale gezondheid, zoals (een gebrek aan) sociale interacties. Het kan ook zijn dat het effect van groen in de woonomgeving op mentaal welzijn of gedragskeuzes niet gelijk verdeeld is over de gehele populatie. Bovendien kan de relatief kleine omvang van de veranderingen in groen over de tijd ook een factor zijn. Er is vanuit onderzoek nog niet veel bekend over hoeveel groener een woonomgeving moet worden om een positief, meetbaar effect te hebben op gezondheid en gedrag op populatieniveau. Daarnaast laten de resultaten uit hoofdstukken 5 en 6 zien dat het groenniveau in de woonomgeving van Eindhoven en omgeving tussen 2004 en 2014 is afgenomen. Deze afname is niet alleen potentieel negatief voor de gezondheid, maar kan ook een negatief effect hebben op andere domeinen, zoals klimaatvraagstukken of biodiversiteit.

Als laatste is het goed om te benoemen dat het plausibel is dat het effect van groen in de leefomgeving wellicht niet lineair verband houdt met gezondheidsuitkomsten en gedragskeuzes. Er kan bijvoorbeeld een drempelwaarde zijn, waaraan voldaan moet worden voordat groen een meetbaar effect op gezondheid heeft. Kleine stapjes in vergroening kunnen daarom niet voldoende zijn voor mentaal welzijn als het groenniveau in de woonomgeving onder een drempelwaarde blijft. Dit maakt het plausibel dat het groenniveau veel groter moet zijn dan in de studies beschreven in dit proefschrift om een meetbaar verschil in de gezondheidsuitkomsten te verwezenlijken.

De studies in dit proefschrift zijn in lijn met de ambities van steden om 'leeftijdsvriendelijker' te worden. In 2006 heeft de Wereldgezondheidsorganisatie (WHO) het concept van de *leeftijdsvriendelijke stad* ontwikkeld. Het doel van deze ontwikkeling was om te identificeren welke factoren van de fysieke en sociale leefomgeving essentieel zijn voor het vormgeven van duurzame en ondersteunende leefomgevingen voor ouderen. De verdere toename van verstedelijking en vergrijzing in de komende decennia bieden beleidsmakers zowel uitdagingen als kansen om steden zo in te richten dat ze bijdragen aan gezond oud worden in de stad. Hoofdstuk 8 gaat in op het potentieel van de leeftijdsvriendelijke stad en uitdagingen, zoals het prioriteit geven aan andere doelgroepen in stedenbouwkundige processen en de tendens om aan te nemen dat je de wensen en voorkeuren van individuen kunt aflezen aan de locatie waar ze op dat moment wonen.

Dit proefschrift sluit af met hoofdstuk 9, waarin de resultaten worden geïnterpreteerd en bediscussieerd. Bovendien worden in dit hoofdstuk enkele methodologische overwegingen besproken en worden de implicaties van dit onderzoek besproken. De introductie van de *Omgevingswet* in Nederland presenteert beleidsmakers een unieke kans om gezondheid en welzijn te verankeren in stedenbouwkundige en planologische processen. In de *Nationale Omgevingsvisie* (NOVI) staat het doel dat in 2050 de omgeving bewoners moet verleiden om een gezonde levensstijl te hanteren. Een belangrijke manier om dit te bewerkstelligen is volgens de NOVI het vergroenen van de omgeving. Het onderzoek dat in dit proefschrift wordt gepresenteerd draagt slechts beperkt bewijs aan voor associaties tussen groen, mentale gezondheid en wandelen en fietsen en geen definitief bewijs dat een verandering in het groenniveau geassocieerd is met een verandering in gezondheid. Zo zou het kunnen dat de voordelen van groen in de woonomgeving op populatieniveau alleen meetbaar zijn als de woonomgeving zeer groen wordt. Het zou ook kunnen dat andere factoren dan de algemene hoeveelheid groen in de woonomgeving belangrijker zijn, zoals de toegankelijkheid van groen. Het antwoord op de vraag hoe stedelijke leefomgevingen gezonder ingericht kunnen worden met behulp van groen ligt dus waarschijnlijk in het drastisch vergroenen van steden en/of het verbeteren van andere aspecten van groen, zoals de toegankelijkheid en ecologische kwaliteit. Meer monitoring of steden groener worden is hiervoor van belang.

Concluderend kan dus gesteld worden dat de stedelijke leefomgeving veel potentie kent voor de implementatie van beleid gericht op het bevorderen van gezondheid en welzijn, maar dat een meer kennis en inzicht nodig is hoe de stedelijke leefomgeving zich verhoudt tot individuele gezondheid en individueel welzijn.

Dankwoord

Ondanks dat er slechts één auteur op de kaft van dit proefschrift staat, schrijf je een proefschrift nooit alleen. Frank, Mariëlle en Joost: jullie wil ik als eerste hartelijk bedanken voor alle hulp bij het tot stand komen van dit proefschrift. Frank, ontzettend bedankt voor je hulp, het meedenken, de goede overleggen, je kritische blik en de kansen die je me hebt gegeven. Je had het vertrouwen om in 2016 een jonge sociaalgeograaf aan te nemen, die nog nooit van het woord 'cohortstudie' had gehoord. Mede dankzij jouw begeleiding leerde ik de sociale epidemiologie kennen en steeds beter begrijpen en heb ik dit proefschrift succesvol af kunnen ronden.

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Alle collega's van de afdeling *Maatschappelijke Gezondheidszorg* wil ik heel erg bedanken en dan met name ook de collega's van *Sociale Epidemiologie*. Ik kijk

met veel plezier terug op onze samenwerking, maar ook de gezellige sectie-uitjes en lunches.

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Soms kunnen dingen raar lopen. Toen Mariëlle, Joost en ik in 2019 werden gevraagd om een presentatie te geven op een studiedag van het *Mulier Instituut*, had ik nooit gedacht dat ik daar een pitch zou geven voor mijn toekomstige werkgever. Ik had nog nooit van het *MI* gehoord, maar raakte enthousiast door de leuke mensen die ik die dag sprak en de fijne sfeer die er hing. Toen ik in 2020 op zoek ging naar een nieuwe baan was de keuze snel gemaakt. Inmiddels werk ik met veel plezier al bijna drie jaar bij het *MI* en wil ik jullie bedanken dat jullie mij de tijd en ruimte hebben gegeven om dit proefschrift af te maken naast mijn werk.

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Lieve Ingrid, bedankt voor al je steun de afgelopen jaren en ik houd van je!

Curriculum Vitae

Mark Noordzij werd geboren op 8 september 1990 te Schiedam. In 2007 haalde hij zijn gymnasiumdiploma aan het Groen van Prinsterercollege te Vlaardingen. In 2013 behaalde hij zijn bachelordiploma *Sociale Geografie & Planologie* aan de Universiteit Utrecht gevolgd door zijn masterdimploma *Sociale Geografie* aan de Universiteit Utrecht in 2015. Zijn afstudeerdonderzoek richtte zich op het regiovormingsproces van de Amsterdamse Westas en de rol van ruimtelijke identiteiten in dit proces. In 2016 startte hij zijn promotieonderzoek bij de afdeling Maatschappelijke Gezondheidszorg van het Erasmus Medisch Centrum. Daar deed hij onderzoek naar de verbanden tussen de stedelijke leefomgeving, bewegen, en (mentale) gezondheid. Zijn promotieonderzoek was onderdeel van het MINDMAP-project: een internationale studie waarin verschillende stedelijke leefomgevingen met elkaar vergeleken werden om meer inzicht te krijgen in hoe de omgeving van invloed is op mentaal welzijn en mentale gezondheid. Zijn promotieonderzoek resulteerde in dit proefschrift. Sinds 2020 werkt hij voor het Mulier Instituut waar hij onderzoek doet naar vraagstukken die bewegen, sport en de leefomgeving aan elkaar verbinden.

Mark Noordzij was born on September 8th 1990 in Schiedam, The Netherlands. In 2007, he completed his secondary school at the Groen van Prinstererlyceum in Vlaardingen, The Netherlands. In 2013, he obtained his bachelor degree in *Human Geography & Spatial Planning* from Utrecht University followed by his master degree in *Human Geography* in 2015. For his master thesis he researched regional development in the Amsterdam Westas region. In 2016, he started his PhD at the Department of Public Health of the Erasmus University Medical Center. The topic of his PhD project was on how different urban environments affect mental health and physical activity. His thesis was part of the MINDMAP project: an international study desgined to compare different urban environments and their impacts on mental health and mental well-being. This thesis is the result of this PhD project. He currently works at the

Mulier Institute, where he works on research connecting urban development to physical activity and active transport.

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1. Noordzij, J. M., Beenackers, M. A., Groeniger, J. O., Timmermans, E. J., Motoc, I., Huisman, M., & van Lenthe, F. J. (2021). Land use mix and physical activity in middle-aged and older adults: a longitudinal study examining changes in land use mix in two Dutch cohorts. International Journal of Behavioral Nutrition and Physical Activity, 18(1), 29. https://doi.org/10.1186/s12966-021-01083-1.
2. Timmermans, E. J., Visser, M., Wagtendonk, A. J., Noordzij, J. M., & Lakerveld, J. (2021). Associations of changes in neighbourhood walkability with changes in walking activity in older adults: a fixed effects analysis. BMC Public Health, 21(1), 1323. https://doi.org/10.1186/s12889-021-11368-6.
3. Noordzij, J. M., Beenackers, M. A., Oude Groeniger, J., Timmermans, E., Chaix, B., Doiron, D., Huisman, M., Motoc, I., Ruiz, M., Wissa, R., Avendano, M., & Van Lenthe, F. J. (2021). Green spaces, subjective health and depressed affect in middle-aged and older adults: A cross-country comparison of four European cohorts. Journal of Epidemiology and Community Health, 75(5), 470–476. https://doi.org/10.1136/jech-2020-214257.
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7. Wey, T. W., Doiron, D., Wissa, R., Fabre, G., Motoc, I., Noordzij, J. M., Ruiz, M., Timmermans, E., Van Lenthe, F. J., Bobak, M., Chaix, B.,

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8. Hogendorf, M., Oude Groeniger, J., Noordzij, J. M., Beenackers, M. A., & van Lenthe, F. J. (2019). Longitudinal effects of urban green space on walking and cycling: A fixed effects analysis. In Health & Place (p. 102264). https://doi.org/https://doi.org/10.1016/j.healthplace.2019.102264.
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PhD Portfolio

PhD Student: J.M. Noordzij
Erasmus University Rotterdam
Faculty: Erasmus MC
Department: Public Health
PhD period: 2016 – 2020
Promotor: Prof.dr. F.J. van Lenthe
Co-promotor: Dr. M.A. Beenackers

Activity	**EC TS**	**Date**
Courses		
Netherlands Institute for Health Sciences (NIHES)		
Principles of research in medicine & epidemiology	0.7	2016
Introduction to data-analysis	1	2016
Methods of public health research	0.7	2016
Social epidemiology	0.7	2016
Logistic Regression	1.4	2017
Causal Mediation Analysis	1.4	2017
Erasmus Medisch Centrum		
Scientific Integrity	0.3	2017
Utrecht University		
Introduction to Complex Systems	1.5	2017
Datacamp		
Introduction to R	0.5	2017
Seminars, workshops & symposia		
Career Events, Erasmus MC, Department of Public Health	0.3	2017 – 2020
KNAW Masterclass Food Environments	0.3	2019
KNAW Matchmaking event urban green spaces & health	0.3	2019
MINDMAP EU Horizon 2020, first workshop on the MINDMAP conceptual model including one presentation.	1.5	2016

MINDMAP EU Horizon 2020, second workshop on the conceptual model	0.5	2018
MINDMAP EU Horizon 2020, yearly project meeting. Participation and one presentation.	1.5	2018
MINDMAP EU Horizon 2020, yearly project meeting. Participation and two presentations.	2	2019
MINDMAP EU Horizon 2020, yearly project meeting	1.5	2020
MINDMAP EU Horizon 2020 symposium Rotterdam. Presentation at the MINDMAP symposium in Rotterdam.	0.5	2020
Mulier Institute, presentation on urban green spaces and mental health	0.3	2019
Rotterdam Kennisfestival 2018. Participation.	0.3	2018
Rotterdam Kennisfestival 2019. Participation and Walkshop.	0.5	2019
Seminars Centre for effective public health in the larger Rotterdam area (CEPHIR)	1	2017 - 2020
Seminars Department of Public Health, Erasmus MC	12	2016 - 2020
Seminars Social Epidemiology, Erasmus MC	2	2016 - 2020
Teaching		
Erasmus MC, Department of Public Health, Community projects	4	2018 – 2019
Netherlands School of Public & Occupational Health (NSPOH), teaching the course 'Big data gebruiken in public health onderzoek'	1	2019 – 2020
Other activities		
Organization Public health 50 years	0.5	2019 - 2020
Reviewing manuscripts for Public Health Nutrition.	0.2	2020