The built environment in which we live, work, and play largely affects various aspects of our health. Three health aspects were studied in more detail in this thesis, and these are associated with the built environment in different ways. First, perceived and objective characteristics of the built environment may encourage or discourage people to be physically active. Second, accessibility to primary health care is largely influenced by the road network and the distribution of both the population and health care facilities. Third, the environment where people live and their individual travel patterns both have a major influence on their exposure to air pollution.

However, studies examining the relationship between the built environment and these health aspects have several shortcomings. Often solely traditional methods are used to obtain data, the capabilities of geospatial data and analyses are often insufficiently exploited, and frequently individual travel patterns are neglected.

To overcome these shortcomings, the aim of this thesis is to examine the relationship between the built environment and health by incorporating individual travel patterns, and using both existing and new geospatial data sources and analyses implemented in a GIS.

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GEOSPATIAL DATA AND ANALYSES TO EXAMINE THE RELATIONSHIP BETWEEN THE BUILT ENVIRONMENT AND HEALTH

BART DEWULF

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Geospatial data and analyses to examine the relationship between the built environment and health

Bart Dewulf

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GEOSPATIAL DATA AND ANALYSES TO EXAMINE THE RELATIONSHIP BETWEEN THE BUILT ENVIRONMENT AND HEALTH

THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR IN SCIENCES: GEOGRAPHY

RUIMTELIJKE DATA EN ANALYSES OM DE RELATIE TUSSEN DE BEBOUWDE OMGEVING EN GEZONDHEID TE BESTUDEREN

PROEFSCHRIFT INGEDIEND TOT HET BEHALEN VAN DE GRAAD VAN
DOCTOR IN DE WETENSCHAPPEN: GEOGRAFIE

BART DEWULF

GHENT 2016

It always seems impossible until it's done.

Nelson Mandela

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During the last four years of my life, I have experienced some major life-changing events. Not only did Bieke and myself–together with a lot of help of family and friends–renovate our house to become our home, also I got married to the best woman one can imagine. Besides these personal changes, completing a PhD research has been a challenging journey with this dissertation as a satisfying result.

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Bart Dewulf
November 2016

Summary

In recent years, there has been a growing interest in understanding the different determinants of health. Besides personal characteristics, the built environment is an important determinant from a policy perspective, offering the possibility of a long-term influence on health for a large population group. The built environment in which we live, work, and play largely affects various aspects of our health, such as: physical activity, exposure to air pollution, accessibility to health care, and contact with green environments. Examples of built environment characteristics influencing these health aspects are the land use pattern, the road network density, and the spatial distribution of facilities (e.g. primary health care physicians).

Three health aspects–particularly important in developed countries–were examined in this thesis, to study the relationship between the built environment and health in various contexts. We selected physical activity, accessibility to primary health care, and exposure to air pollution, as a plethora of studies have shown that they are of high importance for creating healthy communities and people. Being physically active, having a good accessibility to primary health care, and not being exposed to high air pollution concentrations all have positive short- and long-term health effects. These three health aspects are associated with the built environment in different ways. First, perceived and objective characteristics of the built environment may encourage or discourage people to be physically active. Second, accessibility to primary health care is largely influenced by the road network and the distribution of both the population and health care facilities. Third, the environment where people live and their individual travel patterns both have a major influence on their exposure to air pollution.

However, studies examining the relationship between the built environment and these health aspects have several shortcomings. First, often solely traditional methods (e.g. questionnaires) are used to obtain data, such as physical activity levels or built environment characteristics, which may lead to subjective and biased measures. Second, the geographical aspect of the relationship is often overlooked, insufficiently exploiting the capabilities of geospatial data and analyses. Third, frequently only the residential neighbourhood is considered when studying the impact of the built environment on the

exposure to air pollution or greenness, without incorporating individual travel patterns. These shortcomings introduce two geographical problems: the Modifiable Areal Unit Problem when using different sized or shaped areal units, and the Uncertain Geographical Context Problem when neglecting the actual context where people spend their time. Because of these shortcomings, the resulting associations might be inaccurate, possibly misinforming policy makers trying to improve health by altering the built environment.

To overcome these shortcomings, the aim of this thesis is to examine the relationship between the built environment and health by incorporating individual travel patterns, and using both existing and new geospatial data sources and analyses. From this general aim, two more specific research objectives are formulated. The first objective is to apply existing geospatial analyses to study the relationship between the built environment and health. The second objective is to additionally incorporate individual travel patterns when examining this relationship, using both existing and new geospatial data sources.

For the first objective, geospatial analyses were implemented in a Geographic Information System (GIS) to check the correspondence between objective and perceived built environment characteristics and to calculate advanced measures of accessibility to primary health care. It was found that perceived characteristics do not correspond well with objectively determined characteristics, and that this correspondence is influenced by one's physical activity. Also, GIS was deemed very useful in calculating advanced measures of accessibility incorporating factors ignored in traditional measures. Using geospatial analyses in GIS can thus lead to a better understanding of the relationship between the built environment and health. However, depending on the method used (objective or perceived measures of the built environment, or different accessibility measures) the results can differ significantly.

To meet the second objective, individual travel patterns were obtained–using either Global Positioning System (GPS) data combined with accelerometer data, or mobile phone network data–to measure where people are mostly physically active and to calculate their exposure to air pollution. It was found that people are more physically active in green areas than in non-green areas. Furthermore, the exposure to air pollution is significantly different when individual travel patterns were incorporated rather than

only taking into account the home location. These results show how incorporating individual travel patterns can contribute to a better insight in the relationship between the built environment and health, not possible when only considering the residential location.

This thesis has shown that the use of various geospatial data sources and analyses implemented in a GIS, combined with other data sources, offers interesting insights into the relationship between the built environment and health, difficult to obtain using traditional methods. With each data source and analysis having its own strengths and weaknesses, researchers and policy makers should make a choice based on their research questions and available resources. The presented geospatial data sources and analyses also have large potential in other health-related research domains, and technological advances may further improve these techniques in the future.

Samenvatting

De laatste jaren wordt er gestreefd naar een beter begrip van de verschillende factoren die onze gezondheid beïnvloeden. Naast persoonlijke kenmerken is ook de bebouwde omgeving een belangrijke factor voor beleidsmakers, die hen de mogelijkheid biedt om de gezondheid van een grote bevolkingsgroep op lange termijn te beïnvloeden. De bebouwde omgeving waarin we wonen, werken en ons ontspannen heeft een grote invloed op verschillende gezondheidsaspecten, zoals de fysieke activiteit, de blootstelling aan luchtvervuiling, de bereikbaarheid van gezondheidszorg en het contact met groene gebieden. Enkele kenmerken van de bebouwde omgeving die deze gezondheidsaspecten beïnvloeden zijn het landgebruik, de dichtheid van het wegennetwerk en de ruimtelijke spreiding van faciliteiten (bv. huisartsen).

Drie specifieke gezondheidsaspecten – vooral van belang in ontwikkelde landen – werden grondiger bestudeerd in deze thesis om zo de relatie tussen de bebouwde omgeving en gezondheid in verschillende contexten te onderzoeken. We weerhielden fysieke activiteit, bereikbaarheid van gezondheidszorg en blootstelling aan luchtvervuiling omdat verschillende studies hun belang aantoonden bij het creëren van een gezonde bevolking. Voldoende fysieke activiteit, een goede bereikbaarheid van gezondheidszorg en weinig blootstelling aan luchtvervuiling hebben positieve gezondheidseffecten op zowel korte als lange termijn. Deze drie gezondheidsaspecten zijn op verschillende manieren geassocieerd met de bebouwde omgeving. Ten eerste kunnen gepercipieerde en objectieve kenmerken van de bebouwde omgeving mensen aan- of ontmoedigen om fysiek actief te zijn. Ten tweede is bereikbaarheid in grote mate afhankelijk van het wegennetwerk en de verdeling van zowel de bevolking als de faciliteiten die gezondheidszorg aanbieden. Ten derde beïnvloeden de omgeving waar mensen wonen en hun individuele verplaatsingspatronen hun blootstelling aan luchtvervuiling.

Vaak lijden studies die de relatie tussen de bebouwde omgeving en gezondheidsaspecten onderzoeken echter aan verschillende tekortkomingen. Ten eerste worden regelmatig enkel traditionele methoden (bv. enquêtes) gebruikt om data betreffende fysieke activiteit en de bebouwde omgeving te verzamelen, wat aanleiding kan geven tot

subjectieve en/of foutieve waarden. Ten tweede wordt het geografische aspect van de relatie tussen de bebouwde omgeving en gezondheid vaak over het hoofd gezien, waardoor de mogelijkheden van ruimtelijke data en analyses niet ten volle worden benut. Ten derde wordt dikwijls enkel de woonlocatie in rekening gebracht bij het bestuderen van de impact van de bebouwde omgeving op de blootstelling aan luchtvervuiling of het contact met groene gebieden, zonder rekening te houden met individuele verplaatsingspatronen. Deze tekortkomingen leiden tot twee geografische problemen: enerzijds het probleem van de schaalbaarheid van ruimtelijke eenheden (*Modifiable Areal Unit Problem*) wanneer ruimtelijke eenheden van verschillende vorm of grootte gebruikt worden, en anderzijds het probleem van de onzekere geografische context (*Uncertain Geographical Context Problem*) wanneer de werkelijke locatie waar mensen tijd spenderen niet in rekening wordt gebracht. Door deze tekortkomingen kunnen de verkregen relaties onnauwkeurig zijn, waardoor beleidsmakers die de gezondheid van de bevolking proberen te verbeteren door de bebouwde omgeving aan te passen mogelijk verkeerd geïnformeerd worden.

Om die redenen heeft deze thesis als doel de relatie tussen de bebouwde omgeving en gezondheid te bestuderen rekening houdend met individuele verplaatsingspatronen en gebruik makend van zowel bestaande als nieuwe ruimtelijke data en analyses. Dit leidde tot de volgende twee specifieke doelstellingen. De eerste is om via bestaande ruimtelijke analyses de relatie tussen de bebouwde omgeving en gezondheid te bestuderen. De tweede doelstelling bestaat erin om bijkomend individuele verplaatsingspatronen in rekening te brengen bij het bestuderen van deze relatie, door gebruik te maken van zowel bestaande als nieuwe ruimtelijke databronnen.

Om de eerste doelstelling te bereiken werden ruimtelijke analyses geïmplementeerd in een geografisch informatiesysteem (GIS) om enerzijds de relatie tussen objectieve en gepercipieerde kenmerken van de bebouwde omgeving te controleren en anderzijds geavanceerde bereikbaarheidsmaten te berekenen. Hieruit bleek dat gepercipieerde omgevingskenmerken niet goed overeenkomen met objectief bepaalde kenmerken en dat deze relatie beïnvloed wordt door de hoeveelheid fysieke activiteit. GIS bleek bovendien heel nuttig om geavanceerde bereikbaarheidsmaten te berekenen die rekening houden met factoren die vaak genegeerd worden bij traditionele maten. Gebruik makend van ruimtelijke analyses in een GIS kan de relatie tussen de bebouwde omgeving en gezondheid verder uitgediept worden. Belangrijk hierbij is dat afhankelijk van de methode (objectieve of gepercipieerde omgevingskenmerken, of verschillende bereikbaarheidsmaten) het resultaat significant verschillend kan zijn.

Om de tweede doelstelling te realiseren, werd er gebruik gemaakt van twee databronnen met individuele verplaatsingspatronen, namelijk *Global Positioning System* (GPS)-gegevens gecombineerd met accelerometerdata, en gsm-netwerkdata. Hieruit werd afgeleid waar mensen het meest fysiek actief zijn en wat hun blootstelling tot luchtvervuiling is. Zo bleek dat mensen fysiek actiever zijn in groene gebieden dan in niet-groene gebieden. Tevens is de blootstelling aan luchtvervuiling significant verschillend wanneer individuele verplaatsingspatronen in rekening gebracht worden en niet louter de woonlocatie. Deze resultaten tonen aan hoe het in rekening brengen van verplaatsingspatronen kan bijdragen tot een beter begrip van de relatie tussen de bebouwde omgeving en gezondheid, iets wat niet mogelijk is wanneer enkel de woonomgeving in rekening wordt gebracht.

Als besluit kunnen we stellen dat dit doctoraat aantoont dat het gebruik van verschillende ruimtelijke databronnen en analyses geïmplementeerd in een GIS en gecombineerd met andere databronnen tot interessante inzichten kan leiden wat betreft de relatie tussen de bebouwde omgeving en gezondheid. Dergelijke inzichten zijn moeilijk te verkrijgen wanneer louter traditionele methoden gebruikt worden. Iedere databron en analyse heeft zijn eigen sterktes en zwaktes, waardoor onderzoekers en beleidsmakers een keuze moeten maken op basis van hun onderzoeksvragen en de beschikbare middelen. De voorgestelde ruimtelijke databronnen en analyses hebben tevens een groot potentieel in andere gezondheidsgerelateerde onderzoeksdomeinen. Technologische vernieuwingen kunnen deze technieken in de toekomst ongetwijfeld nog verder verbeteren.

1

Scope objectives and outline

1.1 Introduction

The main purpose of this thesis is to examine the relationship between the built environment and health, how this relationship is influenced by people's individual travel patterns, and how geospatial data and analyses can help to further understand this.

The built environment in which we live, work, and play largely affects our health. As early as in 400 BC, Hippocrates conceptualised the influence of place on health, explaining how places oriented differently towards the sun and the wind are characterised by distinct health conditions (Hippocrates, n.d.). Later, during the industrialisation in the 1800s and 1900s, epidemic diseases such as cholera and tuberculosis were linked with poor housing conditions and the distribution and/or use of polluted water pumps (Rosen, 1985; Snow, 1855). Even now, worldwide, there is a multitude of health issues related to the built environment. Some actual examples that illustrate the association between the built environment and health-related aspects–particularly important in developed countries–are: industrial activities might have a negative impact on drinking and recreational water quality, the built environment may be designed to promote walking and cycling activities, the place we live or the route we take to work may impact our exposure to air pollution, the spatial distribution of hospitals and physicians influences the accessibility to health care, the accessibility to healthy eating facilities differs significantly from place to place, and an urban design where green areas are well incorporated might improve mental health. Not only does the built environment influence health, personal characteristics (e.g. gender, socio-economic status, or one's attitude and preferences) may moderate this relationship (Barton & Grant, 2006).

However, when studying the relationship between the built environment and certain health aspects, in recent scientific work, often traditional methods (e.g. questionnaires) were used, the capabilities of geospatial analyses were insufficiently exploited, and/or individual travel patterns were neglected, leading to inaccurate results and possibly misinforming policy makers. In this thesis, we try to bridge these gaps by studying the relationship between the built environment and health using existing and new geospatial data and analyses, and analysing the influence of individual travel patterns.

The following section will describe the built environment and how it is related to different health aspects (1.2). Next, the problem statement of the current research on this topic will be described, together with two fundamental geographical issues that are often referred to in this context (1.3). Finally, the research objectives of this PhD research will be formulated and an outline of the thesis will be presented (1.4), as well as a list of publications included in this thesis (1.5).

1.2 The built environment and its relationship with different health aspects

The built environment is defined as "*the totality of the following elements: land use patterns; the distribution across space of activities and the buildings that house them; the transportation system, the physical infrastructure of roads, sidewalks, bike paths, etc., as well as the service this system provides; and urban design, the arrangement and appearance of the physical elements in a community*" (Handy, Boarnet, Ewing, & Killingsworth, 2002, p. 65). Researchers in the field of urban design and planning have mainly studied how the design of the built environment affects travel behaviour, both motorised and non-motorised (Handy et al., 2002; Southworth, 2005). Consequently, a new research field emerged when health researchers examined the impact of the built environment on physical activity (PA) (Sallis, Frank, Saelens, & Kraft, 2004) and other health outcomes, such as the exposure to air pollution, water quality, mental health, and the accessibility to health services and healthy eating facilities (Srinivasan, O'Fallon, & Dearry, 2003).

From a policy perspective, the built environment is an important factor that decision-makers can change to improve health (Frank, Kavage, & Devlin, 2012). In contrast to personal and psycho-social characteristics, built environment characteristics reach a large number of people and initiate long-term changes on health (Gebel, Bauman, &

Petticrew, 2007; Ghekiere, Vanwolleghem, Van Cauwenberg, Cardon, & Deforche, 2015). The relationship between the built environment and health has been a hot topic in scientific research for several years (Frank et al., 2012) and several special issues have been published on this topic (Boarnet, 2007; Jackson, 2003; Killingsworth, Earp, & Moore, 2003; Timmermans, Kemperman, & van den Berg, 2016). This growing knowledge of the relationship between the built environment and health is therefore observed in several health-promoting policy programmes in developed countries. Examples of such programmes are: Healthy People 2020 (Office of Disease Prevention and Health Promotion, 2016) and Urban Design 4 Health (Frank, 2016) in the US, the 7th Environment Action Programme (European Environment Agency, 2013) in the EU, and the service Environment & Health (Department of Environment, Nature and Energy, 2016) in Flanders.

In this thesis, three health aspects–particularly important in developed countries–are studied more thoroughly, to examine the relationship and use the proposed geospatial data and analyses in various contexts. The following three aspects of the relationship between the built environment and health were selected: PA (1.2.1), accessibility to primary health care (1.2.2), and the exposure to air pollution (1.2.3). The selection of these three aspects grew naturally during the PhD research, when appropriate datasets became available or a research question emerged from reading research papers or discussions with colleagues or promotors, always considering the main goal of the thesis: use existing and new geospatial data and analyses to examine the relationship between the built environment and health. We specifically selected these three aspects, because they are recurring in most of the aforementioned special issues (ibid.). Several researchers have identified these health aspects for being strongly influenced by the built environment and of high importance for creating healthy communities and people (Frank et al., 2012; Srinivasan et al., 2003). In this thesis, it is studied how characteristics of the built environment are related with PA, how using different methods influences the calculated accessibility to health care, and how being in contact with different environments affects the exposure to air pollution. In the Belgian context, these three aspects are important because of the general low amounts of PA and following health problems, the use of crude measures of health care accessibility, and the high exposure to air pollution (Bauman et al., 2009; IRCEL CELINE, 2015; RIZIV, 2013). The research in this thesis focuses both on adults (18 years and older), to obtain a broad view on the relationship between the built environment and health, and on late middle-aged adults (58–65 years), since this age cohort is on the brink of retirement or recently retired and thus has varying time-activity patterns interesting for this research, and is associated with higher health risks.

1.2.1 PHYSICAL ACTIVITY

PA is defined as "*bodily movements produced by skeletal muscles that result in energy expenditure*" (Caspersen, Powell, & Christenson, 1985, p. 126) and is often classified into occupational, household-related, transport-related, and leisure time PA (Sallis et al., 2006). Sedentary behaviour is not a synonym for physical inactivity, nor is it the opposite of PA: people may perform sufficient amounts of PA, but can still spend the rest of the time being sedentary (Owen et al., 2011). Examples of sedentary behaviour are: watching television, driving a car, sitting during meals, using a computer, and reading.

Doing regular PA (approximately 150 minutes of moderate-to-vigorous PA (MVPA)–more than 1,952 accelerometer counts per minute–per week for adults) has several positive short- and long-term effects on health (Department of Health, 2004; Freedson, Melanson, & Sirard, 1998; Garber et al., 2011; Haskell et al., 2007; Pate, Pratt, Blair, & Haskell, 1995; U.S. Department of Health and Human Services, 1996; Warburton, Nicol, & Bredin, 2006). PA plays a significant role in weight management and it lowers blood pressure (U.S. Department of Health and Human Services, 1996). Sufficient amounts of PA and less sedentary behaviour are associated with a decreased risk for several chronic diseases (e.g. cardiovascular diseases), obesity, some types of cancer, premature deaths, and lower mortality, resulting in lower economic costs (Andersen, 2003; Department of Health, 2004; Dishman, Washburn, & Heath, 2004; Hamilton, Healy, Dunstan, Theodore, & Owen, 2012; Healy et al., 2008; Katzmarzyk, Church, Craig, & Bouchard, 2009).

Although the benefits of PA are well-known, a significant part of the population living in developed countries does not meet the minimal guidelines to achieve health benefits (U.S. Department of Health and Human Services, 2008; WHO, 2010). In Belgium, self-report data from the Belgian Health Survey indicates that 36% of all people aged 15 and older reaches the recommended amount of at least 30 minutes MVPA, whereas in the age group of 55 to 64 year olds only 32% reaches this recommendation (Drieskens, 2014). To promote PA (and similarly reduce sedentary behaviour), it is important to have insight in the determinants that facilitate higher levels of PA. It is common to integrate the different determinants of PA in an ecological model (Sallis, Owen, & Fisher, 2008). Four levels have been identified as contributors to explain PA: personal, social, environmental, and policy (Bauman et al., 2012). In this thesis, we will focus on the personal and environmental determinants, although the other are sometimes intertwined within these two.

Several personal characteristics have been identified as determinants of PA. Older, overweight, lower-educated, female, overweight adults tend to be less physically active than their counterparts (Allen & Vella, 2015; Bauman & Bull, 2007; Oliveira-Brochado, Oliveira-Brochado, & Brito, 2010). Psychological characteristics have also been associated with PA: self-efficacy (the confidence in being active on a regular basis), attitude towards PA, and perceived benefits are positively linked with PA in adults (De Bourdeaudhuij, Teixeira, Cardon, & Deforche, 2005; Oliveira-Brochado et al., 2010). Additionally, social factors, such as social support, are positively linked with PA in adults (De Bourdeaudhuij et al., 2005; Oliveira-Brochado et al., 2010).

Next to personal characteristics, built environment attributes have been identified as important determinants of PA. Since 2002, an extensive amount of research articles and reviews on this topic has been published (Ding & Gebel, 2012). Several attributes of the built environment (e.g. walkability, access to public transport, land use mix, aesthetics, vegetation, and population density) are linked with PA in adults (Grasser, Van Dyck, Titze, & Stronegger, 2013; Owen, Humpel, Leslie, Bauman, & Sallis, 2004; Saelens & Handy, 2008; Wang, Chau, Ng, & Leung, 2016). Specifically for Belgian adults, a positive relationship was found between neighbourhood socio-economic status and walkability, and higher levels of PA (Van Dyck et al., 2010). A recent review showed that for European adults mainly the walkability of the built environment and access to shops/services/work are positively related with PA (Van Holle et al., 2012). Additionally, it was found that transportation PA was more often related to the built environment than recreational PA (Van Holle et al., 2012). Both living in an area with a higher availability of green areas (e.g. parks) and spending more time in green areas can lead to higher amounts of PA in adults (Shores & West, 2010; Van Holle et al., 2012; Van Holle et al., 2014). Also, when PA occurs in green areas, it can have more positive effects on both physical (e.g. less exposure to pollution) and mental (e.g. wellbeing) health (Coombes, Sluijs, & Jones, 2013; Fan, Das, & Chen, 2011; Frumkin, 2001; Mackay & Neill, 2010; St Leger, 2003; Sugiyama, Leslie, Giles-Corti, & Owen, 2008; Thompson Coon et al., 2011).

These built environment attributes can be assessed in either an objective or perceived manner. The EnRG (Environmental Research framework for weight Gain prevention) is a theoretical framework on the influence of both objective and perceived measures of the built environment on health-related behaviour (Kremers et al., 2006). It provides a dual-process view, considering both direct and indirect–via cognitive mediators (e.g. attitude)–influences, moderated by various person- and behaviour-related factors. Objective attributes are the actual measured or calculated characteristics of the built environment, while perceived attributes are subjective characteristics interpreted by participants. The perception of the built environment depends on various personal characteristics, such as age, gender and PA itself (Lackey & Kaczynski, 2009; McCormack, Cerin, & Leslie, 2008). The fact that PA influences the perception of the built environment, creates a mutual relationship between the built environment and health. Both objective and perceived attributes do not necessarily coincide and may therefore relate differently with PA behaviour. For example, while the objective availability of pertinent destinations in a neighbourhood may be high, a person's perceived availability can be low due to the fact that a person may not be aware of all feasible destinations in her/his neighbourhood (Mondschein, Blumenberg, & Taylor, 2010). While previous studies have identified associations between perceived attributes of the built environment and PA (Gebel, Bauman, & Owen, 2009; Hoehner, Brennan Ramirez, Elliott, Handy, & Brownson, 2005; Kirtland et al., 2003; Lackey & Kaczynski, 2009; McCormack et al., 2008; Sugiyama, Leslie, Giles-Corti, & Owen, 2009), these perceptions are not necessarily precise representations of the actual objective built environment (Blacksher & Lovasi, 2012; Cerin, Macfarlane, Ko, & Chan, 2007; Golledge & Stimson, 1997; Macintyre & Macdonald, 2008). Understanding how these two measures deviate from each other and which factors cause this, provides information on how people perceive their environment, which is useful for policy makers, e.g. to increase active transport by adapting the actual availability of certain facilities or by improving the perception of the environment (Gebel, Bauman, Sugiyama, & Owen, 2011; Jáuregui et al., 2016). More research in how the objective and perceived built environment are correlated is therefore important to gain a more complete insight in the relationship between the built environment and health.

1.2.2 ACCESSIBILITY TO PRIMARY HEALTH CARE

Good accessibility to primary health care facilitates population health, and is considered a fundamental right (Guagliardo, 2004). Since good primary health care can prevent or reduce unnecessary expensive speciality care (P. R. Lee, 1995), ensuring equal accessibility to primary care for those in equal need is of major concern to public health policy makers, service providers, researchers, and consumers alike. In this thesis, the focus is on general practitioners often working in private practices or medical centres, who–in Belgium–administer first line, primary care and–when necessary–refer patients to specialists or the hospital. Despite the general good accessibility to primary health care services in Belgium, improvements can still be made (Gerkens & Merkur, 2010). A main problem in Belgium is that crude measures of health care accessibility are used to award financial assistance to physicians settling in shortage areas (RIZIV, 2013).

However, measuring whether or not accessibility to health care is achieved is difficult, because there is no straight definition of accessibility (Aday & Andersen, 1974; Ansari, 2007; Gulzar, 1999; Rogers & Pencheon, 1999). The main problem is that its original term 'access' is both a noun and a verb (Guagliardo, 2004; McGrail, 2012). The former deals with the actual use of health care services, while the latter focuses on the aggregated supply of available health care in an area and thus deals with the potential use of services. Both can be further subdivided into spatial and non-spatial accessibility. Non-spatial accessibility can be categorised into three dimensions: affordability (cost of health care), acceptability (health service compliance and satisfaction), and accommodation (appropriateness and suitability of health services) (Aday & Andersen, 1974; Joseph & Phillips, 1984; Neutens, 2015; Penchansky & Thomas, 1981). In this thesis, the main focus is on spatial accessibility, which consists of two dimensions: availability (the number and spatial distribution of health care providers and the population) and proximity (travel impedance between patients and providers) (Joseph & Phillips, 1984; Neutens, 2015; Penchansky & Thomas, 1981). When additionally the amount of time available for travel and activity participation, and travel speeds are considered, the term space-time accessibility can be used (Burns, 1979; Hägerstrand, 1970).

When defining spatial accessibility–further referred to as accessibility–the two spatial dimensions need to be measured together (Guagliardo, 2004; McGrail & Humphreys, 2009). High availability of health care providers does not assure high accessibility, because it depends on the proximity of the population to these health care providers. The other way round, high proximity does not assure high accessibility, because it depends on the size of the population competing for the available providers. Health care providers and the population are spatially distributed and their distributions do not always match (Luo, 2004). The distribution of physicians can be linked with the threshold (the minimum number of patients needed to maintain the facility) and range (the maximum distance people are prepared to travel for health care) of Christaller's classic central place theory (Smith, 1979). The spatial barriers between the population and health providers contribute to lower health care use and a decreased uptake of preventive services, which may lead to poorer health outcomes (Neutens, 2015).

1.2.3 Exposure to air pollution

Air pollution is defined as "*contamination of the indoor or outdoor environment by any chemical, physical, or biological agent that modifies the natural characteristics of the atmosphere*" (WHO, 2016). There are several pollutants which have major health impacts, for example: particulate matter (PM), carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_2), and sulphur dioxide (SO_2). Sources of air pollution are multiple, but traffic-related air pollution is identified as the highest (approximately 60%) contributor in developed countries (Brugge, Durant, & Rioux, 2007; Knibbs, Cole-Hunter, & Morawska, 2011; Mcdonald, 2012; Weichenthal et al., 2011). Despite an improvement of the air quality in Belgium during the last decade (except NO_2 which tends to increase), respectively 21 and 97% of the population is still exposed to yearly averaged PM_{10} and $PM_{2.5}$ concentrations higher than health-based limit values (Fierens, 2010; IRCEL CELINE, 2015).

Being exposed to, and consequently inhaling, air pollution can have severe acute and chronic health impacts, such as respiratory and cardiovascular diseases (Beelen et al., 2014; Brook et al., 2010; Brugge et al., 2007; Gehring et al., 2013; HEI, 2010; Peters et al., 2004; Pope III & Dockery, 2006; Riediker et al., 2004; WHO, 2003). This was accepted already in the 1970s and 1980s, largely because of increases in morbidity and mortality after extreme air pollution episodes (Pope III & Dockery, 2006). In the 1990s, several studies concluded that even low air pollution concentrations can have substantial health effects (Pope III & Dockery, 2006).

As explained earlier, the built environment may influence individual behaviour. For example, the built environment may generate more walking behaviour and less motorised trips, resulting in lower air pollution concentrations (Frank, Schmid, Sallis, Chapman, & Saelens, 2005). More importantly, people are not only a source of air pollution, but are also exposed to air pollution. The location where people live, work, play, etc. influences their exposure to air pollution because of spatially and temporally varying air pollution concentrations. Several studies have indicated that residing in areas with higher long-term air pollution concentrations, increases the risk for cardiovascular morbidity and mortality (Brook et al., 2010). However, since a fair amount of time is spent away from the home location (e.g. transport, work, recreation), people's individual travel patterns also play an important role in their exposure to air pollution. Mainly spending time near roads (e.g. because of commuting) leads to a higher exposure to air pollution (Knibbs et al., 2011).

1.3 Problem statement

Past research studying the aforementioned relationship between the built environment and these three health aspects has several shortcomings, which may lead to deriving erroneous associations between the built environment and health, possibly misinforming policy makers trying to improve health by influencing the built environment. First, in studies examining the impact of the built environment on PA, measures of PA were sometimes obtained merely using questionnaires, leading to subjective and possibly biased measures (1.3.1). Second, the capabilities of geospatial analyses were not sufficiently exploited, both for delineating neighbourhoods and calculating accessibility (1.3.2). Third, individual travel patterns were often not taken into account when studying the impact of the built environment on health (e.g. contact with green environments, exposure to air pollution) (1.3.3).

Because of these shortcomings, two well-known geographical problems may occur when studying the relationship between the built environment and health: the Uncertain Geographical Context Problem (UGCoP) and the Modifiable Areal Unit Problem (MAUP).

The UGCoP, first documented by Kwan (2012), relates to the spatial and temporal uncertainty about the actual settings (e.g. home, work) that exert contextual influence on health behaviour (e.g. PA, exposure to air pollution) (Kwan, 2012). Not only the actual built environment people have contact with, but also their social context (e.g. friends and family) can influence their behaviour. This problem is characterised by an uncertainty in the exact geographic area having a direct influence on health behaviour, and the timing and duration individuals are exposed to these contextual influences (Dunton, Almanza, Jerrett, Wolch, & Pentz, 2014). The UGCoP may be the underlying cause for many of the inconsistencies found in research studying the influence of the built environment on health (Black & Macinko, 2008; Inagami, Cohen, & Finch, 2007; Wilks, Besson, Lindroos, & Ekelund, 2011).

The MAUP, acknowledged in 1984, is a well-known fundamental problem in geography, that arises in studies examining the effects of area-based attributes on individual behaviour and health (Openshaw, 1984). The MAUP states that the geographical scale of the studied units and different configurations of units of the same size can affect the obtained results. In health-related research, this problem mainly comes forth when studying the impact of the neighbourhood on individual behaviour (here PA) and other health outcomes (e.g. exposure to air pollution or accessibility to health care) (Flowerdew, Manley, & Sabel, 2008; Houston, 2014; Parenteau & Sawada, 2011). Often the residential location is the base unit of study, but changing this unit may alter the results significantly.

1.3.1 Misjudging physical activity using questionnaires

Often merely questionnaires (e.g. activity diaries) are used to assess the amount of sedentary behaviour or PA performed (Chaudhury, Campo, Michael, & Mahmood, 2015; Coombes, Jones, & Hillsdon, 2010; Hillsdon, Panter, Foster, & Jones, 2006; Lachowycz & Jones, 2011; H. Lee et al., 2015). The International Physical Activity

Questionnaire (IPAQ) is often used to define the amount of PA performed during a week (IPAQ, 2014). An advantage of using self-reported measures is that additional personal information (e.g. gender, income, BMI) and information on the domain-specificity of sedentary behaviour and PA (transport, recreation, household, or occupation) can be obtained.

However, the relative agreement between IPAQ and accelerometer-based PA is only small-to-moderate ($r = 0.05 - 0.37$) and is moderated by various sociodemographic factors (e.g. age, gender, weight, and education) (Cerin et al., 2016). Additionally, perceptions about behaviour are susceptible to recall bias and misclassification error (Almanza, Jerrett, Dunton, Seto, & Pentz, 2012), and it is difficult to classify PA in different PA levels (light, moderate, or vigorous) using questionnaires, and respondents often tend to over-report PA (Lee et al., 2011). There may also be inconsistency in the data between different population groups, influenced by language or literacy.

To obtain more accurate measures of PA, objective measuring devices (e.g. heart rate monitors, pedometers, or accelerometers) could be used. However, these lack domain-specific information on the performed PA. It should be noted that both perceived and objective measures supplement each other in informing the researcher on the actual PA (Kelly, Fitzsimons, & Baker, 2016).

1.3.2 Insufficiently exploiting the capabilities of geospatial analyses

Mainly in health practice and policy, but also in previous research, the capabilities of geospatial analyses were often insufficiently exploited when examining the relationship between the built environment and certain health aspects.

Characteristics of the built environment were often determined using questionnaires. It is important to consider the perceived characteristics of the built environment to take someone's full context into account when studying the relationship between the built environment and individual behaviour (cf. the UGCoP). It can happen that these perceived characteristics have a bigger influence on individual behaviour than objective characteristics. A questionnaire that was often used to assess people's perceptions of the built environment in health-related studies is the Neighbourhood Environment

Walkability Scale (NEWS) (Cerin, Saelens, Sallis, & Frank, 2002). The NEWS questionnaire–of which test-retest reliability and construct validity has been established–measures the following built environment characteristics: residential density, land use mix, street connectivity, aesthetics, crime safety, availability and quality of walking and cycling facilities, and availability of PA equipment at home (Saelens, Sallis, Black, & Chen, 2003). The advantage of using a questionnaire is that the participants report characteristics on the area they consider their neighbourhood (Schipperijn, Ejstrud, & Troelsen, 2013). However, these perceived characteristics can be difficult to define by participants and they may be interpreted differently between participants. Also, increased PA may lead to better perceptions of the neighbourhood, which may in turn lead to increased PA, unravelling the directionality of the relationship (Hajna, Dasgupta, Halparin, & Ross, 2013). Also, these perceived characteristics were sometimes solely used, without considering objective characteristics of the built environment (Cerin et al., 2002; De Bourdeaudhuij, Sallis, & Saelens, 2003; Reimers, Mess, Bucksch, Jekauc, & Woll, 2013; Saelens et al., 2003; Spittaels et al., 2010; Sugiyama et al., 2009). Both objective and perceived measures of the built environment may however be related differently with health, and therefore it is important to consider them both.

Second, when built environment characteristics were objectively calculated, often the area around the home location (the residential neighbourhood) was used as a base unit. Two reviews have shown that research studying the impact of the built environment on health outcomes defined the residential neighbourhood as either the surrounding administrative unit (e.g. census tract) or as a circular buffer around the residential location (Feng, Glass, Curriero, Stewart, & Schwartz, 2010; Jilcott, Evenson, Laraia, & Ammerman, 2007; Leal & Chaix, 2011; Van Dyck et al., 2010). Selecting an appropriate neighbourhood, both from a conceptual and mathematical perspective, is crucial (Schipperijn et al., 2013). It is however difficult to determine the 'right' neighbourhood to perform analyses on (Voigtländer, Razum, & Berger, 2013). Using a different unit to study the influence on individual behaviour may significantly alter the obtained results, an issue raised in the MAUP (Haynes, Jones, Reading, Daras, & Emond, 2008; James et al., 2014; Mitra & Buliung, 2012).

A third way in which the capabilities of geospatial analyses were insufficiently exploited, is when calculating accessibility to health care. In past research, three approaches have dominated measures of accessibility: physician-to-population ratios (PPR), distance/time to the nearest health provider, and gravity models (Guagliardo, 2004; Langford & Higgs, 2006). PPRs are usually calculated with zonal data, which is based on administrative boundaries that are considered impermeable. As a result, interaction across borders is not sufficiently taken into consideration (Guagliardo, 2004; Joseph & Phillips, 1984). Also, persons residing in the same administrative unit are assigned equal levels of accessibility, and the accessibility measures therefore do not provide a robust description of how access to health care is distributed among the population (Kwan & Weber, 2008; Neutens, 2015). Also, PPRs assume equal accessibility to physicians irrespective of where people live in that unit, which is obviously not the case (Higgs, 2004; Wan, Zou, & Sternberg, 2012). Again, using a different zonation may significantly alter the results, as stated in the MAUP. Distance/time to the nearest provider, a second measure of accessibility, does not capture full accessibility, because it is often observed that people bypass the nearest physician when there are multiple available (Fryer et al., 1999; Hyndman, D'Arcy, Holman, & Pritchard, 2003; Martin & Williams, 1992; McGrail, 2012). For these two measures, only limited Geographic Information System (GIS) tools are needed. Gravity models try to represent the potential interaction between any population point and all health care providers within a reasonable distance, assuming decreasing potential interaction with increasing distance (Guagliardo, 2004). A major caveat of this method is that the used distance-decay function is difficult to determine (Guagliardo, 2004; Joseph & Phillips, 1984; Luo & Wang, 2003; McGrail & Humphreys, 2009).

1.3.3 Neglecting individual travel patterns

In research studying the relationship between the built environment and various health aspects, often only the residential neighbourhood was taken into account. This is the case for studies examining how the built environment influences PA or other health outcomes (Grasser et al., 2013; Leal & Chaix, 2011; Van Dyck et al., 2010), as well as for studies calculating the exposure to air pollution (Brunekreef et al., 2009; Dons et al., 2011; Jerrett et al., 2013; Pope III, Ezzati, & Dockery, 2009; Tenailleau, Mauny, Joly, François, & Bernard, 2015). However, because of individual travel patterns, people are in contact with other areas, with characteristics other than at their home location. Their home location might thus not represent the actual area that has an influence on the health outcome (here PA and the exposure to air pollution), an issue raised in the UGCoP.

Given that approximately 60% of daily PA occurs away from the home location (Troped, Wilson, Matthews, Cromley, & Melly, 2010), the residential neighbourhood may only partially explain PA behaviour. Also, someone's individual travel patterns throughout the day may result in different exposure to and inhalation of air pollution (de Nazelle et al., 2013). Disregarding individual time-activity patterns can thus lead to incomplete or incorrect associations between the built environment and PA, and bias in air pollution exposure assessments, possibly misinforming policy makers.

1.4 Research objectives and outline of the thesis

To obtain more accurate results on the relationship between the built environment and health and correctly inform policy makers, it is important for researchers examining this relationship to accurately measure PA, taking more advantage of geospatial analyses, and consider the real context that might influence people's behaviour (e.g. PA) or exposure to air pollution by incorporating individual travel patterns. Integrating these techniques in future research may thus lead to more (and more accurate) policy recommendations. Therefore, the overall aim of this thesis is to examine the relationship between the built environment and different health aspects, applying both existing and new geospatial data and analyses, and address the issues raised in the MAUP and UGCoP. The specific research objectives can be described as:

> **Objective 1**: Demonstrate how existing geospatial analyses can be used to examine the relationship between the built environment and health in this field of research.
>
> **Objective 2**: Incorporate individual travel patterns to study the relationship between the built environment and health, using both existing and new geospatial data sources.

The general outline of this PhD thesis is illustrated in Figure 1.1.

Chapter 2 provides an overview of the state-of-the-art in assessing the relationship between the built environment and different health aspects. The chapter describes the current state-of-the-art concerning both data sources and techniques available to overcome the issues mentioned in the problem statement.

Chapters 3 to *7* are the original research articles of this PhD, which are published in international peer-reviewed journals. In these different studies, several topics (e.g. physical activity and the built environment, accessibility to primary health care, visiting green areas, and exposure to air pollution) are studied to gain a broad view on the relationship between the built environment and health, each contributing to the above mentioned research objectives. There can be some overlap between the different chapters, because these were written as independent publications.

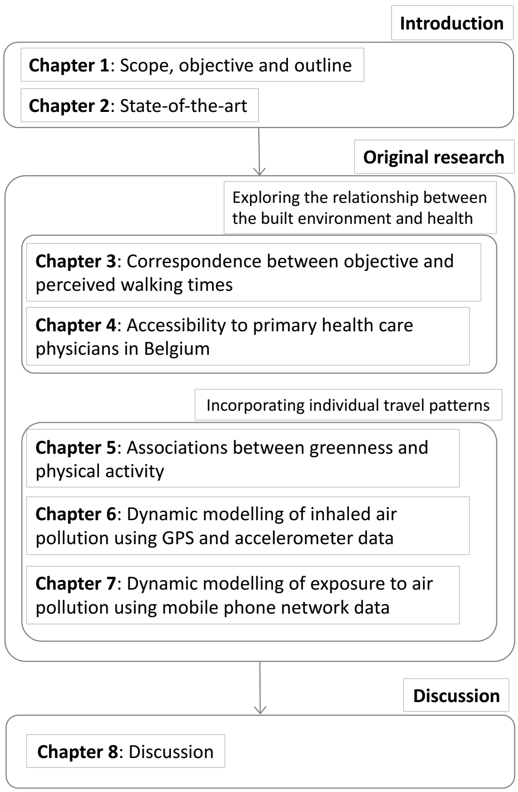

Figure 1.1: Outline of the thesis.

In *chapters 3* and *4*, different geospatial analyses are used to examine the relationship between the built environment and health, and are thus linked to objective 1. In *chapter 3*, published in *International Journal of Health Geographics*, it is studied how good the perception (obtained using a questionnaire) of one specific built environment characteristic (i.e. walking time) corresponds with the objective measure calculated in GIS, and how this is influenced by various factors (e.g. PA), for 1,164 adults (18 years and older) living in Ghent, Belgium. In *chapter 4*, published in *BMC Family Practice*, various traditional methods to calculate accessibility to primary health care in Belgium are discussed and compared with the more advanced Enhanced 2-Step Floating Catchment Area (E2SFCA) method.

In *chapters 5* to *7*, individual travel patterns are taken into account for examining the relationship between the built environment and health, using both existing and new geospatial data sources, and are thus directly linked to objective 2. *Chapter 5*, published in *Geospatial Health*, focuses on how the greenness of the environment has an effect on health (here PA), studying the actual time-activity patterns of 180 late middle-aged adults (58–65 years) living in Ghent, Belgium, collected using GPS and accelerometer data, and overlaying this with land-use data. The influence of individual travel patterns on the exposure to and inhalation of air pollution (largely determined by the built environment) is discussed, using GPS and accelerometer data of the same 180 late middle-aged adults in *chapter 6*, published in *Journal of Transport and Health*, and using mobile phone network data of approximately 5 million Belgian people in *chapter 7*, published in *International Journal of Health Geographics*. The combined use of GPS and accelerometer data, and especially using mobile phone network data is innovative for calculating the exposure to air pollution.

The questionnaire and accelerometer data from the 1,164 adults–used in *chapter 3*–were collected as part of the Belgian Environmental Physical Activity Study (BEPAS), which is part of the International Physical Activity and the Environment Network (IPEN; funded by the National Institutes of Health and National Cancer Institute, 2009–2012). The GPS and accelerometer data from the 180 late middle-aged adults–used in *chapters 5* and *6*–were collected as part of the post-doc research of dr. Veerle Van Holle. These datasets were available through a collaboration between our Department of Geography and the Department of Movement and Sports Sciences, both part of Ghent University.

The greenness data was received from the Flemish Institute for Technological Research (*Vlaams Instituut voor Technologisch Onderzoek*; VITO), the air pollution concentration data from Belgian Interregional Environment Agency, and the mobile phone network data from Proximus. The other data used is obtained from various other sources and is listed in Table 8.1.

Chapter 8 provides the general discussion and main conclusions of this dissertation, together with some general strengths and limitations, implications for practice, and avenues for future work.

Figure 1.2 shows how the different research articles from *chapters 3* to *7* are situated within the general relationship between the built environment and health, using a mindmap.

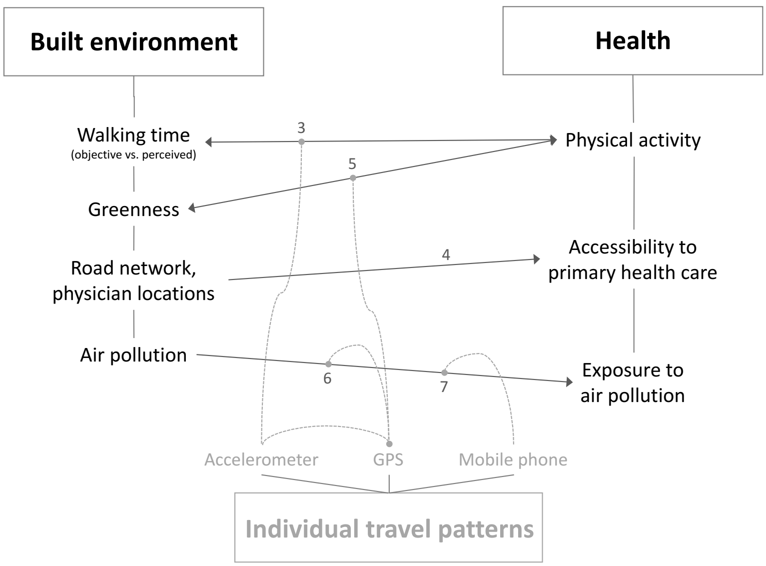

Figure 1.2: Mindmap to illustrate how the research articles from *chapters 3* to *7* are situated within the general relationship between the built environment and the three studied health aspects.

1.5 Publications included in the thesis

Dewulf, B., Neutens, T., Van Dyck, D., de Bourdeaudhuij, I., Van de Weghe, N. (2012). Correspondence between objective and perceived walking times to urban destinations: Influence of physical activity, neighbourhood walkability, and socio-demographics. *International Journal of Health Geographics, 11*(43), 10p. IF 2015: 2.27.

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2

State-of-the-art in examining the relationship between the built environment and health

This chapter gives an overview of some traditional and more advanced geospatial data sources and analyses that are available to examine the relationship between the built environment and different health aspects.

To overcome the shortcomings and issues described in *chapter 1*, several options are available. First, accelerometers can be used to objectively measure someone's physical activity (PA) (2.1). Second, more advanced geospatial analyses can be used in a threefold way: to objectively calculate characteristics of the built environment (instead of using questionnaires), to make a more accurate delineation of the neighbourhood, and to calculate advanced accessibility measures (2.2). Third, individual travel patterns can be taken into account to incorporate the actual context where people spend their time, to better understand where they are mostly physically active and to be able to calculate more dynamic measures of air pollution exposure (2.3). Applying these improvements also limits the issues of the Modifiable Areal Unit Problem (MAUP) and the Uncertain Geographical Context Problem (UGCoP).

2.1 Measuring physical activity objectively

Determining PA is challenging because movements are often sporadic. To obtain more accurate and objective measures of the amount of PA performed, accelerometers can be used. Other devices are also available, for example heart rate monitors (J. S. Duncan, Badland, & Schofield, 2009), but the association between the number of accelerations and PA has been studied more extensively and therefore accelerometers are often preferred (Pruitt et al., 2010). Other techniques are also available to measure energy expenditure (EE), such as calorimetry, metabolic equivalent, and the doubly layered water technique (Hills, Mokhtar, & Byrne, 2014). Both PA and EE are often considered synonymous, but it is important to know that PA is considered as behaviour, which results in EE and should thus be assessed using different approaches. In this thesis, the focus is on PA, since we also want to study e.g. duration and intensity, not possible using EE.

An accelerometer is an advanced pedometer, which logs the amount of accelerations in one or three directions (side-to-side: X; forward and backward: Y; and up and down: Z) per time interval (e.g. 15 or 60 seconds), often for a period of four to ten consecutive days in this type of research (Trost & O'Neil, 2014). Accelerometers have been shown to be valid and reliable tools to measure PA (Copeland & Esliger, 2009; Pruitt et al., 2010). Because the devices are small (approximately 5 x 3 x 1.5 cm), light (approximately 40 g) and non-invasive, they are well-tolerated by the participants. The uniaxial GT1M and the triaxial Actigraph GT3X+ (Actigraph LLC, n.d.) are currently the most frequently used accelerometers and have received considerable research attention (Trost, Way, & Okely, 2006). Currently, the ActivPAL accelerometer is considered as the golden standard in objectively determining physical activity and sedentary behaviour, as it is also able to detect someone's posture (e.g. standing, sitting), because it is placed on the upper leg (Kozey-Keadle, Libertine, Lyden, Staudenmayer, & Freedson, 2011). Standalone accelerometers are predominantly asked to be worn at the hip or wrist, compared to wearing it in a backpack or around the ankle (Trost & O'Neil, 2014). When worn at the hip, the most accurate results are obtained (Kamada, Shiroma, Harris, & Lee, 2016; Rosenberger et al., 2014). A disadvantage of this placement, as well as the backpack or wrist placement, is that only little accelerations are registered when cycling, despite being physically active (Hansen, Kolle, Dyrstad, Holme, & Anderssen, 2012; Montoye, 1996). Despite its lower accuracy, there has been a growing interest in wrist-worn accelerometers because of the higher acceptability leading to a higher wear time (Quante et al., 2015). Also, the increasing popularity of wrist-worn accelerometers aimed at consumers (e.g. Fitbit) offers a potential new data source for objectively measuring PA.

As an alternative to standalone devices, built-in accelerometers in smartphones can also be used (de Nazelle et al., 2013), but these offer less accurate results since a phone is often worn at different positions (e.g. hand, pants pocket, or handbag) and some population groups may be difficult to reach (e.g. children and older adults) (Guidoux et al., 2014).

The advantage of using objective measures of PA is that respondents cannot over-report their activity time, and recall and misclassification errors are brought to a minimum (Evenson, Catellier, Gill, Ondrak, & McMurray, 2008). Also, the PA of respondents is logged automatically without disturbing them, except to explain them how and where to wear it. However, crucial information is needed when reporting the validity and reliability of objective (and perceived) measures, since PA is not a single, unidimensional construct, but is characterised by different domains, dimensions, correlates, and determinants (e.g. transport or recreation, total movement or only walking bouts, type of PA, with who, intensity, and duration) (Kelly, Fitzsimons, & Baker, 2016). The Edinburgh Validity and Reliability Framework provides a strategy for combining research methods and analyses to find out how valid and reliable measures of PA are (Kelly et al., 2016).

2.2 Exploiting the capabilities of geospatial analyses

Geospatial analyses can be easily implemented in a Geographic Information System (GIS): a piece of software that enables to input, store, manipulate, analyse, and visualise spatial information (Higgs, 2004). In a GIS, data is structured in different layers, with each layer containing information on a single feature (e.g. road network, locations of health care facilities, park locations, or air pollution concentration). The analytical power of GIS holds tremendous value for health researchers and policy makers in uncovering the relationship between the built environment and health (Butler, Ambs, Reedy, & Bowles, 2011). "*GIS uses sophisticated databases and software to analyse data by location, revealing hidden patterns, relationships and trends that may not be apparent in spreadsheets or through the use of the standard statistical packages from epidemiology or the social sciences*" (Leslie et al., 2007, pp. 113–114). For a brief overview of GIS and the applications in health science, we refer to other work (Schipperijn, Ejstrud, & Troelsen, 2013).

GIS can be used to visualise various data sources (e.g. air pollution data, land use data, or primary care physician locations). In addition, GIS also holds a large potential in geographically analysing the data (on their own or combined with each other). Some examples of geospatial analyses are: shortest path along the network, area calculation, buffer creation, and calculating spatial statistics. In the following paragraphs, it is explained in what other ways GIS can contribute in examining the relationship between the built environment and health.

2.2.1 Characteristics of the built environment

Although we acknowledge the importance of incorporating perceived characteristics of the built environment, these may be difficult to define by participants, interpreted differently between participants, or influenced by the participants' PA. Hence, it is important to consider objective measures–next to self-reported measures–of the built environment.

Therefore, a first use of GIS is to calculate objective measures of the built environment using geospatial analyses (e.g. overlay, network analysis, density calculation), extensively proven to be useful in earlier studies (Carlson et al., 2012; D'Haese, Van Dyck, De Bourdeaudhuij, Deforche, & Cardon, 2014; Houston, 2014; James et al., 2014; King et al., 2011; Leslie et al., 2007; Loon, Frank, Nettlefold, & Naylor, 2014; Lovasi et al., 2008; Marshall, Piatkowski, & Garrick, 2014). Examples of such objective characteristics are: residential density, street network connectivity, land use mix, and accessibility or distance/time to certain destinations (e.g. school, park, shop) (Brownson, Hoehner, Day, Forsyth, & Sallis, 2009). With GIS, the obtained measures are more objective, accurate, and reliable. Earlier research showed high correlations between GIS-derived measures of the built environment and measures obtained via on-field audits from experts, indicating that these GIS-derived measures can be used instead of labour and cost-intensive audits (Hajna, Dasgupta, Halparin, & Ross, 2013). However, sometimes on-field audit data from experts is needed because GIS data on more micro-level environmental features might not exist.

2.2.2 Neighbourhood delineation

Second, characteristics of the built environment are often calculated within the administrative unit (often census tract or municipality) of the participant's residential location, but researchers have identified neighbourhoods in various ways, making comparisons across studies difficult (Schipperijn et al., 2013). The advantage of using administrative units to define a neighbourhood is that often other (e.g. socio-economic) data is available from these units. However, these boundaries are not always relevant for the health outcome studied, they might not represent the actual context someone is exposed to, and administrative units are often varying in size making comparisons less straightforward (Schipperijn et al., 2013).

With GIS, it is easy to improve this by calculating a buffer around the participant's home location. One must be aware of the issues raised in the MAUP, when differently sized or shaped buffers are used. The easiest method is to calculate a circular buffer, but since GIS are often already used to calculate these buffers, it is only a small step to incorporate the road network to calculate street network buffers (Oliver, Schuurman, & Hall, 2007). This way, a more veracious measure of the area influencing someone's behaviour can be obtained (Leal & Chaix, 2011; Oliver et al., 2007), and the issues of the UGCoP are thus limited. To further eliminate the UGCoP, additionally the work or school location–or other important destinations–could be considered. Also, the actual locations (determined e.g. using GPS data) where people were could be used, for example within a certain distance from the home location, thus looking at someone's activity space (Perchoux, Chaix, Cummins, & Kestens, 2013; Villanueva et al., 2012; Zenk et al., 2012). Another approach would be to ask the participants what they see as their neighbourhood, as this might be differently related with health behaviour than the objectively determined neighbourhoods (Chaix, Merlo, Evans, Leal, & Havard, 2009).

It is important for health researchers to be aware of how the chosen neighbourhood influences the results, and care should therefore be taken to choose the 'right' neighbourhood (Schipperijn et al., 2013).

2.2.3 Advanced accessibility measures

Third, with GIS it is easy to calculate advanced accessibility measures, which overcome the limitations of the basic measures (e.g. PPR and distance to nearest provider). "*There is now a wide recognition of the value of GIS in mapping the spatial distribution of health care needs and utilisation, monitoring and evaluating the socio-spatial repercussions of health policy actions, determining optimal health service locations and disentangling the* *relationships between disparities in accessibility and health outcomes*" (Neutens, 2015, p. 14).

A more advanced method than the traditional measures to calculate accessibility is the Enhanced 2-Step Floating Catchment Area (E2SFCA) method (Langford & Higgs, 2006; Langford, 2012; Luo & Qi, 2009; McGrail, 2012). This method combines overlay and buffer analyses in GIS using geolocated data on primary health care locations and the road network (if a network catchment/buffer is used). The E2SFCA method controls for capacity restrictions, local competition between health care providers, cross-border primary care-seeking behaviour, and distance decay of accessibility within these borders (Luo & Wang, 2003; Neutens, 2015). The most significant strength of the E2SFCA method is that "*no fixed geographic or administrative boundaries are used, but instead floating catchments which overlap, enabling the measurement of real-life healthcare access behaviour with unrestricted utilisation*" (McGrail, 2012, p. 2).

2.3 Incorporating individual travel patterns

Incorporating individual travel patterns is important to better understand in which areas people spend their time. This leads to more accurate results in both studying the influence of the built environment on individual behaviour (in our case PA) and air pollution exposure assessments, the two cases previously described where often only the home location is considered. This largely constrains the UGCoP as this way the actual built environment context influencing individual behaviour and exposure is taken into account (Houston, 2014).

There is a multitude of geospatial data sources available to determine individual travel patterns. In past research often questionnaire-based methods are used to deduce individual travel patterns, using for example travel diaries. Alternatively, mathematical models of travel patterns are sometimes used. Currently, there is a growing pervasiveness of various location-acquisition technologies leading to large spatiotemporal datasets (Giannotti & Nanni, 2007). Global Positioning System (GPS) and mobile phone network data are two techniques used in this thesis. There are however also other techniques available to obtain individual travel pattern data.

2.3.1 Travel diaries and transport models

A first method to determine individual travel patterns, often used in national travel surveys, is to use travel diaries (questionnaires), on paper, by phone, or on computer. An advantage of travel diaries is that the transport mode, destination, and purpose can be identified accurately, as well as the accompaniment and participant perceptions (Mavoa, Witten, McCreanor, & O'Sullivan, 2012), similar to using questionnaires to measure PA (activity diaries). Major disadvantages of this approach are the large non-response rate (Wilson, 2004), non-representative sample (Murakami, 2008), high costs (Stopher & Greaves, 2007), and limited temporal resolution (Maas, Sterkenburg, Vries, & Pierik, 2013). Also, similar as with activity diaries, recall errors (when, how, with whom, and along which route the trip was made) may occur. Finally, using travel diaries, often only the start and end location of a trip is known. The actual route can be questioned in the travel diary, but recall may be difficult with complex routes (Stopher, FitzGerald, & Zhang, 2008).

The base information from travel diaries (e.g. residential location, working hours, household activity pattern and its scheduling, opening hours, and choice behaviour) can be used to build transport models to estimate the spatiotemporal behaviour of individuals. Such models often use the activity-based approach to predict which, where, when, for how long, with whom, and with which transport mode activities are conducted (Beckx et al., 2009). More information on the activity-based modelling framework can be found elsewhere (Mcnally & Rindt, 2007). Some examples of such models are: the Built Environment Stochastic Spatial Temporal Exposure (BESSTE) model for Orange County, North Carolina, US (de Nazelle, 2007), A Learning-Based Transportation Oriented Simulation System (ALBATROSS) for the Netherlands (Arentze & Timmermans, 2004), the Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS (FEATHERS) for Flanders and Brussels (Belgium) (Bellemans, Janssens, Wets, Arentze, & Timmermans, 2010). An advantage of using models is that they can be used without disturbing participants and without high costs of additional infrastructure. Also, they provide information within a short time period, and, more importantly, they can predict travel patterns for the future. However, real-world travel patterns are so complex that they are difficult to accurately determine using models (Arentze & Timmermans, 2004).

2.3.2 Global Positioning Systems

As early as in 1995–when the system became fully operational for the public–it was suggested that GPS could be used to locate and monitor vehicles for research-purposes (Zito, D'Este, & Taylor, 1995). In respectively 1999 and 2001, it was suggested to improve or eliminate travel survey data by gathering individual travel patterns using GPS data (Murakami & Wagner, 1999; Wolf, Guensler, & Bachman, 2001). Several studies have demonstrated the valuable use of GPS in health-related research (Kerr, Duncan, & Schipperijn, 2011; Krenn et al., 2011; Maas et al., 2013). GPS data have already shown their added value in air pollution exposure assessments (Bekö et al., 2015; de Nazelle et al., 2013; Dons et al., 2011; Steinle, Reis, & Sabel, 2013), and in other studies examining the relationship between the built environment and health (Kerr et al., 2012; Krenn et al., 2011).

With GPS data, a more detailed time-activity pattern can be obtained than when using travel diaries (Duncan, Badland, & Mummery, 2009; Houston, Ong, Jaimes, & Winer, 2011; Stopher & Speisser, 2011), therefore reducing the spatial and temporal uncertainty in the actual areas that exert contextual influences on individual behaviour and health, reducing the issue stated in the UGCoP (Boruff, Nathan, & Nijënstein, 2012; James et al., 2014; Jankowska, Schipperijn, & Kerr, 2015; Madsen, Schipperijn, Christiansen, Nielsen, & Troelsen, 2014; Zenk et al., 2012). Major advantage of GPS data is that origin, destination and route are automatically collected, both in space and time, without troubling the respondent. GPS devices estimate their location (latitude, longitude, and the altitude relative to standardised sea level) by triangulating their position using signals from satellites orbiting the earth. The position is determined by calculating the difference in time between when a satellite signal was sent to when it was received. More information on the obtained accuracy of the GPS devices has been described earlier (Duncan et al., 2009), but it has been shown that GPS offers location data accurate enough for assessing human behaviour (Schutz & Chambaz, 1997; Witte & Wilson, 2004). Possible errors in GPS data are: the initialisation period when powering on the device leading to no data in this period, cluttered data when the device is indoors, and signal reflection and/or blocking because of buildings (e.g. in urban canyons) and natural structures (Kerr et al., 2011; Maas et al., 2013; Schipperijn et al., 2014).

GPS devices have evolved over time, from large devices to small portable devices (passive tracking; i.e. data must be downloaded to a computer), and now even built-in devices on smartphones accessed through an application (active tracking is possible because of the available internet connection). Advantage of a built-in GPS tracker in a smartphone is that participants only have to install an application instead of carrying a standalone device with them, which limits the time needed to collect the data from participants (de Nazelle et al., 2013). A disadvantage of such applications is that they drain the battery of the smartphone (Montini, Prost, Schrammel, Rieser-Schüssler, & Axhausen, 2015). Using standalone devices requires informing the participant about the use of the device, and costs more than using an application, therefore leading to a smaller study sample than possible using an app. The spatial accuracy of a standalone device is however higher than a smartphone app, making a standalone device currently the most chosen method for GPS tracking (Montini et al., 2015; Zandbergen, 2009).

In contrast to travel diaries, GPS data only consists of location data. Additional information on transport mode and purpose is not directly available. GPS data can be combined with data from travel diaries to obtain additional information on participant perceptions, trip purpose, transport mode, and accompaniment (Mavoa et al., 2012). Combining these two data sources is however difficult, with manual matching offering the best results, but with high labour costs. Sequence alignment might offer a more cost-efficient method to match the two data sources (Mavoa et al., 2012). There are also methods to derive trip purpose and transport mode using only GPS data (Prins et al., 2014; Wolf et al., 2001). When the speed is calculated, the transport mode can be derived using predefined (average and maximum) speed classes. Trip purpose can be derived by combining the GPS data with land use data, offering information on the trip destination (e.g. residential, industrial, or commercial).

When GPS data is combined with accelerometer data, the exact location of people can be linked with their objectively measured PA, which has proven useful in several earlier studies (Almanza, Jerrett, Dunton, Seto, & Pentz, 2012; Cooper et al., 2010; Kang, Moudon, Hurvitz, Reichley, & Saelens, 2013; Klinker, Schipperijn, Toftager, Kerr, &

Troelsen, 2015; Lachowycz, Jones, Page, Wheeler, & Cooper, 2012; McCrorie, Fenton, & Ellaway, 2014; Oliver et al., 2007; Oreskovic, Blossom, Field, Chiang, & Jonathan, 2012; Prins et al., 2014; Wheeler, Cooper, Page, & Jago, 2010). This way, the transport mode can also be specified more accurately, since each transport mode is characterised by certain acceleration patterns (Troped et al., 2008). An often used online tool is the Personal Activity Location Measurement System (PALMS), where GPS and accelerometer data can be combined together with for example heart monitor data, erroneous data can be removed, and important stop locations and trips can be identified (PALMS, 2015).

2.3.3 Mobile phone network

Location data can also be obtained from mobile phone network data (or passive mobile positioning data), which originates from radio waves from the mobile phone network to trace the location of mobile phones using the network. The phone switches to the Base Transceiver Station (BTS) with the strongest radio coverage, which is often the closest one. This way, an approximate location of the mobile phone user is available. Major advantages of this method are that it is non-intrusive and that a large study sample (often several millions of users) can be tracked. A disadvantage is that the spatial resolution of the location data depends on the density of BTSs, and that because of varying signal strengths mobile phones can connect to BTSs further than the closest one. Also, major measures must be taken to preserve people's privacy, since people can be tracked without knowing.

This method has been used in previous research mainly to analyse population densities (de Jonge, Van Pelt, & Roos, 2012; Deville et al., 2014; Ratti, Frenchman, Pulselli, & Williams, 2006), in tourism (Ahas, Aasa, Roose, Mark, & Silm, 2008; Asakura & Iryo, 2007; Kuusik, Nilbe, Mehine, & Ahas, 2014), and mobility (Ahas, Silm, Järv, Saluveer, & Tiru, 2010; Alexander, Jiang, Murga, & Gonz, 2015; Calabrese, Ferrari, & Blondel, 2014; Calabrese, Lorenzo, Liang, & Carlo, 2011; Widhalm, Yang, Ulm, Athavale, & Gonz, 2015). To our knowledge, only one study has used mobile phone network data to calculate the exposure to air pollution (Gariazzo, Pelliccioni, & Bolignano, 2016).

2.3.4 Other tracking technologies

A disadvantage of GPS data is that indoor positioning is unavailable or largely inaccurate. There are similar methods available to track individuals when indoors, using technologies available on mobile phones. Examples of this are Bluetooth and Wi-Fi. Bluetooth has previously been successfully used to track the location of crowds at mass events (Versichele, Neutens, Delafontaine, & Van de Weghe, 2012) or to track tourists in a certain area (Versichele et al., 2014). Wi-Fi has shown promising results to detect the location of people indoors (Zhou et al., 2014; Zhou, Qiu, Xu, Tian, & Wu, 2016). Another tracking technique currently tested, is to identify and track people using cameras. This method has a wide application in security surveillance, and now gets to the attention of researchers studying human movement behaviour (Liu, Liu, Zhang, Zhu, & Chen, 2015; Sugandi, Kim, Kooi Tan, & Ishikawa, 2009). These various tracking technologies can also be used outdoors, but they require the set-up of sensors to acquire the location of mobile devices within this sensor network, and are therefore limited in tracking people over large areas (Gartner, 2014).

Several of the proposed geospatial data sources and analyses were used in the different studies performed for this thesis, to examine the relationship between the built environment and different health aspects. Accelerometers were used to objectively PA, advanced GIS-based analyses were used in a threefold way (define built environment characteristics, delineate neighbourhoods, and calculate accessibility), and individual travel patterns were incorporated based on GPS and mobile phone network data. In Table 8.2, an overview of these geospatial data sources and analyses is given, which is useful in future research and for policy makers to choose the IDEAL data source or analysis, depending on for example the research question, available time, and budget.

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3

Correspondence between objective and perceived walking times

Adapted from: Dewulf, B., Neutens, T., Van Dyck, D., de Bourdeaudhuij, I., Van de Weghe, N. (2012). Correspondence between objective and perceived walking times to urban destinations: Influence of physical activity, neighbourhood walkability, and socio-demographics. *International Journal of Health Geographics, 11*(43), 10p.

3.1 Abstract

Doing regular physical activity has positive effects on health. Several built environmental factors are identified as important correlates of physical activity. However, there seems to be a difference between perceived and objective measures of the built environment. This study examines the influence of physical activity, neighbourhood walkability, and socio-demographic characteristics on the correspondence between self-reported and objectively measured walking time to urban destinations of adults in the city of Ghent (Belgium). Previously collected survey data was used from 1,164 respondents in the city of Ghent who reported walking times to various closest destinations in the neighbourhood of residence. These were compared with corresponding walking times that were objectively measured through geographical information systems. Physical activity was recorded over a 7-day period using accelerometers. Neighbourhood walkability was assessed on the basis of residential density, connectivity, and land-use mix. We observed a relatively poor agreement between objective and perceived walking times. Stronger agreements were noted amongst the most physically active group, while

low-level walkers tended to overestimate walking time. Surprisingly, however, people residing in a low-walkable neighbourhood underestimated walking times more frequently relative to those in high-walkable neighbourhoods. Researchers investigating the influence of built environmental attributes on physical activity behaviour should thus be cautious when using only self-reported built environmental data, since these are a priori influenced by physical activity levels and various socio-demographic factors.

3.2 Background

3.2.1 Introduction

Doing regular moderate-to-vigorous physical activity (MVPA) has several positive short- and long-term effects on health (Haskell et al., 2007; Pate, Pratt, Blair, & Haskell, 1995; U.S. Department of Health and Human Services, 1996; Warburton, Nicol, & Bredin, 2006). In 2008, approximately 31% of the global adult world population was not active enough to obtain these positive health effects (World Health Organization, 2010). Being insufficiently active is associated with an increased risk for several chronic diseases, like cardiovascular diseases, type 2 diabetes, obesity and some types of cancers (Andersen, 2003; Department of Health, 2004; Dishman, Washburn, & Heath, 2004). Overall, being insufficiently active is related to premature deaths, resulting in heavy economic costs (Andersen, 2003; Department of Health, 2004). No changes in activity levels have been observed, and obesity rates and sedentary activities have increased during the last decade for example in North America and Australia, despite efforts that seek to encourage physical activity (PA) (Bauman & Bull, 2007).

It is therefore important to develop insight in the correlates of PA and to develop a comprehensive population-based approach in promoting PA instead of an individual approach, which is the case nowadays (Bauman & Bull, 2007; Bauman, Sallis, Dzewaltowski, & Owen, 2002; Owen et al., 2011; Sallis & Owen, 1998; Van Holle et al., 2012). Next to personal, cultural, and socio-economical factors, built environmental attributes have been identified as important correlates of PA. A bourgeoning number of studies have offered compelling evidence that the built environment influences people's propensity to engage in physically active pursuits (Owen, Humpel, Leslie, Bauman, & Sallis, 2004; Saelens & Handy, 2008; Saelens, Sallis, Black, & Chen, 2003; Saelens, Sallis, & Frank, 2003; Sallis et al., 2009; Van Dyck et al., 2010; Van Holle et al., 2012). For example, Humpel et al. found a positive relationship between accessibility and aesthetic attributes with PA in several reviewed articles (Humpel, Owen, & Leslie, 2002). In another review article, Saelens et al., for their part, identified 14 studies where an association between several neighbourhood attributes (e.g. accessibility, land use mix, access to public transport, and population density) and PA occurred (Saelens, Sallis, Black, et al., 2003). In a related study, Saelens et al. concluded that people living in high walkable neighbourhoods in San Diego, California (US) engaged in approximately 52 more minutes of PA during a week compared to their counterparts living in low walkable neighbourhoods (Saelens, Sallis, & Frank, 2003). Likewise, Owen et al. reviewed 18 articles and observed that several built environmental attributes (i.e. aesthetics, walking facilities, accessibility, and traffic perceptions) are linked with walking behaviour (Owen et al., 2004).

However, these built environmental attributes can be assessed in either an objective or perceived manner. Objective built environmental attributes are measured using detailed georeferenced data by means of geographical information systems (GIS), while perceived attributes stem from self-reports in the form of surveys or questionnaires. Both types of attributes do not necessarily coincide and therefore may relate differently with physical activity behaviour. For example, while objective availability of pertinent destinations in a neighbourhood may be high, a person's perceived availability can be low due to the fact that a person may not be aware of all feasible destinations in her/his neighbourhood (Kwan & Hong, 1998; Mondschein, Blumenberg, & Taylor, 2010). A decreased environmental awareness may in turn lead to a lower propensity to walk in that neighbourhood, although the objective availability of destinations suggests otherwise. People process and store information about their environment according to their own attitudes, motivations, and preferences. These perceptions are not necessarily precise representations of the actual objective built environment (Blacksher & Lovasi, 2012; Golledge, 1991). Incorporating both objective measures and perceptions of residents in research is important, as the impact of the objective built environment on health depends on human perceptions, motivation, and deliberation (Blacksher & Lovasi, 2012).

In response to this potential discrepancy between the objective and perceived built environment, several studies have scrutinised the concordance between objective and perceived built environmental attributes, such as accessibility, walkability, dwelling density, street connectivity, land use mix, and retail density. Cerin et al., for example, observed moderate to high correspondence between objective and perceived access to services, ease of walking, street connectivity, and walkability, whereas Ball et al. found only a poor agreement between perceived and objective availability of PA facilities (Ball et al., 2008; Cerin, Leslie, Owen, & Bauman, 2007). Additionally, Ball et al. noticed a greater mismatch between objective and perceived availability of PA facilities for less active people (Ball et al., 2008). However, they only examined whether or not certain facilities lie within a buffer zone around respondents' location of residence (i.e. availability), but did not investigate distances to these facilities (i.e. accessibility). In a similar vein, Gebel et al. observed a fair overall agreement between objective and perceived measures for dwelling density, intersection density, land use mix, and retail area (Gebel, Bauman, & Owen, 2009). They found that less active people are more likely to misperceive the walkability of their neighbourhood. The reason for this is that more active people walk more in their neighbourhood, resulting in a better awareness of the built environment (Cohen & Weatherford, 1980; Golledge & Stimson, 1997; Thorndyke, 1982). Gebel et al. additionally found that male, higher educated, normal weighted, older people from high walkable neighbourhoods make more correct estimations of built environmental attributes (Gebel et al., 2009).

3.2.2 Related work

Instead of examining previously mentioned built environmental attributes, this paper studies the agreement between objective and perceived walking times from respondents' residences to different locations. Only few studies examined the agreement between objective and perceived walking distances/times to date. Jilcott et al. and Macintyre et al., for example, observed a fair agreement between objective and perceived walking distances to parks, gyms, and schools, while McCormack et al. and Lackey & Kaczynski noticed only a poor agreement for these destinations (Jilcott, Evenson, Laraia, & Ammerman, 2007; Lackey & Kaczynski, 2009; Macintyre & Macdonald, 2008; McCormack, Cerin, & Leslie, 2008). Besides general agreement, some studies also studied the degree of underestimation or overestimation. In both Jilcott et al. and McCormack et al., it was concluded that on average the perceived walking distance to several destinations is greater than the objective walking distance, presumably because people can be unaware of the existence certain close facilities (Jilcott et al., 2007; McCormack et al., 2008). An overestimation of walking distance in self-reported data was also identified in many earlier studies (Canter & Tagg, 1975; Gatrell, 1983; Golledge & Stimson, 1997; Walmsley & Jenkins, 1992).

The agreement between objective and perceived walking distances/times can depend on several factors, with PA having the strongest influence. Because of greater environmental exposure and concomitant locational awareness, active people not only have a better perception of the previously mentioned attributes such as walkability and connectivity, but they can also make more accurate estimates of walking distances/times (Lackey & Kaczynski, 2009; McCormack et al., 2008). Regarding shops, McCormack et al. found that less active people overestimate the distance in comparison to their active counterparts (McCormack et al., 2008). Looking at distances to parks, Lackey & Kaczynski concluded that people who did at least some park-based PA can more accurately appraise walking distances, since they experience more intimate and slow speed interaction with the places resulting in better distance estimates (Cohen & Weatherford, 1980; Humpel et al., 2002; Kirtland et al., 2003; Lackey & Kaczynski, 2009; Mondschein et al., 2010; Thorndyke, 1982). However, reasoning also works the other way around: people with a good mental map of the built environment might be more likely to be physically active, because they are more familiar with the local environment. However, to date, no literature was found to substantiate this direction of causation. Next to PA, other factors have also been tested. McCormack et al. observed, for instance, that people from high walkable neighbourhoods in Adelaide (Australia) overestimated distances to several destinations (McCormack et al., 2008). Also, it has been pointed out that people overestimate short and well-known routes and underestimate long and less-known routes (Canter & Tagg, 1975; Cervero & Radisch, 1996; Frank, Engelke, & Schmid, 2003; Golledge & Stimson, 1997). Considering other socio-demographic variables, Lackey & Kaczynski concluded that younger, high educated, and normal weighted people have higher odds of achieving a match between objective and perceived proximity to parks in Ontario (Canada) (Lackey & Kaczynski, 2009).

This study seeks to add to the knowledge base surrounding the above discussion by bringing additional evidence to the fore that sheds new light on the differential effects of objective and perceived access to urban destinations on physical activity.

The first objective is to analyse the agreement between objective and perceived walking times for residents from the city of Ghent. This is done by comparing objective and perceived walking times from one's residence to different facilities (e.g. bakery, restaurant, and swimming pool etc.). The second objective is to test whether or not this agreement depends on PA, neighbourhood walkability, gender, educational level, body mass index (BMI), and age. It will be determined whether the degree of underestimation or overestimation differs depending on the previously mentioned factors.

3.3 Methods

3.3.1 Participants and procedures

For this study, data was used from the Belgian Environmental Physical Activity Study (BEPAS), conducted between May 2007 and September 2008 in the city of Ghent (237,000 inhabitants, 156.18 km^2, and 1,468 inhabitants/km^2). An equal number of respondents were selected from 24 neighbourhoods, containing one to five adjacent statistical sectors. Statistical sectors are the smallest units for which demographical data is available. An equal proportion of neighbourhoods with high/low walkability (explained later) and high/low socio-economic status (SES) based on neighbourhood level income data was selected. This means that six neighbourhoods are high walkable/high SES, six are high walkable/low SES, six are low walkable/high SES, and six are low walkable/low SES. From each neighbourhood, 250 adults aged 18–66 were randomly selected by the Public Service of Ghent. Two to six days after receiving an informational letter on the study, home visits were made to potential participants, until 50 participants in each neighbourhood agreed to participate in the study. Overall response rate was 58% (2069 possible participants found at home, of which 1,200 were willing to participate). From these participants, 1,164 had datasets that could be used for this study. For a more detailed description of the procedures, the reader is referred to Van Dyck et al. (Van Dyck et al., 2010).

3.3.2 MEASURES

3.3.2.1 PERCEIVED WALKING TIMES

As part of a questionnaire assessing perceived built environmental attributes in the neighbourhood (Neighbourhood Environmental Walkability Scale (NEWS)), respondents were asked to estimate walking times to various closest destinations: supermarket, bakery, butchery, clothes shop, post office, library, primary school, restaurant, bank, video shop, pharmacy, bus or tram stop, and swimming pool (Cerin et al., 2007; De Bourdeaudhuij, Sallis, & Saelens, 2003; Saelens, Sallis, Black, et al., 2003). Response options included: 1–5min, 5–10min, 11–20min, 21–30min, and more than 30 minutes. Previously, it has been shown that this NEWS survey has strong reliability and validity (Saelens, Sallis, & Frank, 2003)s. In the remainder of the paper, this self-reported walking time will be referred to as the perceived walking time.

3.3.2.2 OBJECTIVE WALKING TIMES

Objective walking times to the closest facilities were calculated in ArcGIS 9.0™ using Network Analyst. This was done by calculating the shortest route from residents' home locations (available from the survey) to different types of destinations (available from a large and detailed inventory from 2009 of urban destinations in the city of Ghent). A GIS street network layer of routes available for walking, including exclusive pedestrian paths, is used in this analysis. These walkable paths are exported from the Large-Scale Reference Base (in Dutch: GRB, Grootschalig Referentiebestand), which is a highly accurate (20 cm) geographical database with information about various characteristics of roads, buildings, railways, water areas, and parcels and will soon be available (*erratum: as of the end of 2013 it is complete*) for the whole of Flanders (Agentschap voor Geografische Informatie Vlaanderen, 2011). Computed shortest distances were transformed into walking times by dividing them by an average walking speed. Average walking speeds were differentiated by gender and age according to Bohannon (Bohannon, 1997). Bohannon calculated these average comfortable speeds from 230 healthy individuals (see Table 3.1).

Following McCormack et al., 0.3 km/h was subtracted from the average speeds to correct for stopping at crossings and for turning (McCormack et al., 2008). The calculated walking times were then grouped into the same categories as those available in the NEWS questionnaire (i.e. 1–5min, 6–10min, 11–20min, 21–30min, and >30min) in order to be able to compare these to the self-reported walking times.

Table 3.1: Average corrected walking speeds (km/h), based on the results of Bohannon (Bohannon, 1997), from a sample of 230 individuals and corrected according to the results of McCormack et al. (McCormack, Cerin, and Leslie, 2008).

Age group	*Male*	*Female*
18–30	4.71	4.77
31–40	4.95	4.79
41–50	4.96	4.71
51–60	4.71	4.72
61–70	4.59	4.37
>70	4.49	4.28

3.3.2.3 Physical activity

In order to estimate the level of PA, participants were asked to wear an accelerometer (model 7164, Computer Science Application) for seven consecutive days. Accelerometers have proven to be a valid and reliable instrument for PA assessment in adults (Melanson & Freedson, 1995; Welk, Schaben, & Morrow, 2004). The accelerometers were set to measure the number of accelerations per minute. 1,952 to 5,724 accelerations per minute correspond with moderate PA, and >5,724 accelerations per minute correspond with vigorous PA (Freedson, Melanson, & Sirard, 1998). Only data from participants with at least 10 hours wear time for at least four days (including at least one weekend day) were included in the study. From the raw data, the average time of moderate-to-vigorous physical activity (MVPA) per day was calculated. To dichotomise this variable, the health norm was used, which is recommended by several organisations (Department of Health and Ageing, 1999; Department of Health, 2004; U.S. Department of Health and Human Services, 1996; World Health Organization, 2003). The American College of Sports Medicine also recommends this health norm (Garber et al., 2011). It stipulates that adults with at least 30 minutes of MVPA per day, for at least five days per week are physically active enough to take advantage of health benefits. Adults who do not reach this threshold are considered physically insufficiently active.

3.3.2.4 Neighbourhood walkability

Neighbourhood walkability indicates "*the extent to which characteristics of the built environment and land use are conducive to walking for leisure, exercise or recreation, to access services, or to travel to work*" (Leslie et al., 2007, p. 112). Using a GIS, a neighbourhood walkability index was constructed on the basis of three built environmental variables: street connectivity, residential density, and land use mix (Saelens, Sallis, Black, et al., 2003). These built environmental variables were obtained from the Service for Environmental Planning in Ghent. A more detailed description on how this neighbourhood walkability is calculated can be found in Van Dyck et al. (Van Dyck et al., 2010).

3.3.2.5 Socio-demographic variables

From the survey, different personal and socio-demographic factors were obtained, including gender, educational level (higher education (i.e. college or university degree) or not), BMI (≥25: overweight or <25: normal weight), and age (dichotomised to 18–45 and >45 years).

3.3.3 Analyses

3.3.3.1 Objective 1: Agreement between objective and perceived walking time

The first objective of this study is to examine the degree of agreement between objective and perceived walking times. To test whether the difference between objective and perceived walking times is significant, a Wilcoxon t-test was used. This was done for the separate destinations as well as for all destinations together. To calculate average (objective and perceived) walking times, the time categories were transferred to the mean value. Also the total proportion of underestimations, correct estimations, and overestimations was calculated for all destinations using cross tabs. Correct estimations occur when the perceived walking time class is the same as the objective walking time class. Underestimations and overestimations occur when the perceived walking time class is respectively lower and higher than the objective walking time class.

3.3.3.2 Objective 2: Relation between different factors (PA, neighbourhood walkability, gender, educational level, BMI, and age) and degree of agreement

The second objective of this study is to assess the relation between different factors and the degree of agreement between objective and perceived walking times. To assess the odds of achieving a match (i.e. objective and perceived walking time are in the same category) in relation to the different factors, a logistic regression model was constructed. In this logistic regression, the odds ratios of making a correct estimation were calculated, depending on the different factors. If the 95% confidence interval does not include the null value 1, the selected part of the respondents (depending on the factor) has higher/lower odds of achieving a match. For factors found to be significant, the proportion of people making an underestimation, correct estimation or overestimation was calculated again, but now for the two ends of the factor (e.g. active and insufficiently active people) for all destinations separately. The proportion of underestimations, correct estimations, and overestimations were also calculated for the other factors, for all destinations combined. The logistic regression was repeated to assess the odds of making an underestimation or overestimation.

3.4 Results

3.4.1 Descriptive statistics

In Table 3.2 the descriptive statistics of the study sample are given. The sample contains slightly more active than insufficiently active respondents. The number of people from high and low walkable neighbourhoods is almost equal. There are more females than males in the sample. The majority of the sample has a higher education and normal weight and there are approximately 10% more 18–45 year olds in comparison with 46–66 year olds.

Table 3.2: Descriptive statistics (n=1,164).

Characteristic	*N*	%
PA[a]		
Insufficiently active	560	48.1
Active	604	51.9
Gender		
Male	558	47.9
Female	606	52.1
Educational level		
No higher education	450	38.7
Higher education	701	60.2
Missing	13	1.1
BMI[b]		
Normal weight	705	60.6
Overweight	418	35.9
Missing	41	3.5
Age		
18–45 years	646	55.5
46–66 years	518	44.5
Neighbourhood walkability		
Low	583	50.1
High	581	49.9

[a] Physical activity

[b] Body mass index

3.4.2 Objective 1: Agreement between objective and perceived walking time

The percentage of participants with available perceived walking time data was calculated (Table 3.3). It can be inferred that these percentages are very high and vary only slightly between different destinations. Table 3.3 also shows the average objective and perceived walking times for all destinations combined and for all destinations separately. Clothes shops, post offices, libraries, video shops, and swimming pools are on average located farthest from the respondents, while bus or tram stops tend to be present closest to the respondents' home location. In addition, Table 3.3 shows the average difference between perceived and objective walking times. It is clear from Wilcoxon's test that for all but two destinations (i.e. post office and library), participants significantly overestimate the objective walking time. The absolute average difference is greatest for supermarkets, clothes shops, and restaurants. For post offices there is a significant underestimation of objective walking time.

Table 3.3: Average objective and perceived walking times, average differences, underestimations, correct estimations, and overestimations.

Destination	*Respondents for whom perceived walking time was available (%)*	*Average objective walking time (min)**	*Average perceived walking time (min)**	*Average difference (min)*	*Under-estimation (%)*	*Correct estimation (%)*	*Over-estimation (%)*
All destinations	97.2	13	16	3**	13.9	52.2	33.9
Bus or tram stop	99.5	3	4	1**	2.6	83.2	14.2
Restaurant	98.9	6	13	7**	6.9	39.1	54.0
Primary school	98.0	8	12	4**	12.0	47.2	40.8
Bakery	99.2	8	9	1**	15.3	63.8	20.9
Pharmacy	99.1	8	10	2**	5.8	66.5	27.7
Supermarket	99.3	9	17	8**	7.1	27.7	65.2
Butchery	99.3	10	11	1**	14.3	55.2	30.5
Bank	99.2	10	14	4**	8.7	50.0	41.3
Clothes shop	98.5	16	22	6**	10.9	42.8	46.3
Video shop	97.2	18	20	2**	18.4	56.0	25.6
Post office	99.3	21	20	-1**	28.3	50.3	21.4
Library	98.8	24	23	-1	29.5	45.5	25.0
Swimming pool	98.7	24	26	2**	20.4	51.5	28.1

* Time category midpoints were used to calculated average values

** $p<0.001$ from Wilcoxon t-test

From this average difference, no further information about the proportions of underestimations, correct estimations or overestimations can be deduced. Therefore, cross tabs were made with the objective and perceived walking times from all destinations combined and separately. From these cross tabs, the total proportion of people making an underestimation, correct estimation and overestimation were calculated. This can be found in the final three columns of Table 3.3. On average, for all destinations combined, 52.2% of the respondents made a correct estimation, 13.9% made an underestimation, and 33.9% made an overestimation. The largest proportion of correct estimations is found for bakeries, butcheries, video shops, pharmacies, and bus or tram stops. Most underestimations are found for post offices, libraries, and swimming pools. These are typically the destinations, which are generally located farthest away from the location of residence. Overestimations are most prominent for supermarkets, clothes shops, and restaurants.

3.4.3 Objective 2: Relation between different factors (PA, neighbourhood walkability, gender, educational level, BMI, and age) and degree of agreement

Table 3.4 depicts the results of a logistic regression, performed to assess the relation between different factors and the degree of agreement between objective and perceived walking times. PA is the only significant predictor of the degree of agreement (OR=1.138), suggesting that active people have higher odds of achieving a match between objective and perceived walking times.

Table 3.4: Logistic regression to test the relation between different factors and the degree of agreement between objective and perceived walking times.

Factor (concerning category)	*Odds Ratio*	*95% Confidence Interval*
PA[a] (active)	1.138*	1.068–1.214
Gender (female)	0.972	0.911–1.036
Educational level (higher education)	1.010	0.945–1.078
BMI[b] (overweight)	0.965	0.902–1.032
Age (>45 years)	1.054	0.989–1.124
Neighbourhood walkability (high)	0.992	0.931–1.058

* $p<0.05$ from the logistic regression

[a] Physical activity

[b] Body mass index

The logistic regression only tells us something about the degree of agreement, but it does not give any information about whether walking times are underestimated or overestimated. Hence, Figure 3.1 shows the proportion of both active and insufficiently active people making an underestimation, correct estimation, and overestimation. For all destinations combined, it can be observed that active people make more correct estimations than insufficiently active people, which aligns with the results from the logistic regression. In addition, active people make more underestimations than insufficiently active people and insufficiently active people make more overestimations than active people.

For all destinations separately (except for post offices, libraries, primary schools, and swimming pools) active people make more correct estimations than insufficiently active people. For butcheries, post offices, libraries, banks, and swimming pools active people make more underestimations than insufficiently active people. The overall result is that for all destinations insufficiently active respondents make more overestimations than active people.

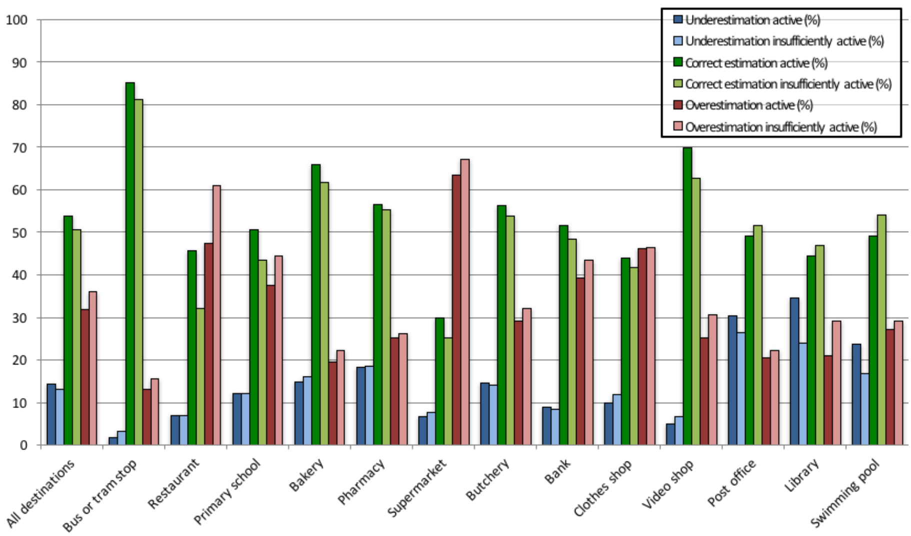

Figure 3.1: Proportion of underestimations, correct estimations, and overestimations, for active and insufficiently active people.

As can be seen in Table 3.4, no significant results were obtained for the other factors from the logistic regression. But since the logistic regression only estimates the odds ratios of achieving a match, the proportion of underestimations, correct estimations, and overestimations were additionally calculated for the other factors for all destinations combined. The results are summarised in Table 3.5. Significant results from the additional logistic regression are marked with an *. It can be inferred that male, normal weight, younger people make significantly more underestimations and significantly less overestimations than their female, overweight, older counterparts. Also, people from a low walkable neighbourhood make almost 5% more underestimations than people from a high walkable neighbourhood. In addition, people from a high walkable neighbourhood make almost 5% more overestimations than people from a low walkable neighbourhood.

Table 3.5: Proportion of underestimations, correct estimations, and overestimations, for active and insufficiently active people.

Factor		*Under-estimation (%)*	*Correct estimation (%)*	*Over-estimation (%)*
PA[a]	Insufficiently active	13.2*	50.6*	36.1*
	Active	14.4*	53.7*	31.9*
Gender	Male	14.4*	52.6	32.9*
	Female	13.3*	51.9	34.9*
Educational level	No higher education	13.6	52.3	34.1
	Higher education	14.0	52.2	33.8
BMI[b]	Normal weight	14.5*	52.5	33.0*
	Overweight	13.0*	51.6	35.4*
Age	≤45j	15.0*	51.6	33.4
	>45j	12.3*	53.0	34.7
Neighbourhood walkability	Low	16.2*	52.3	31.5*
	High	11.5*	52.1	36.4*

[a] Physical activity

[b] Body mass index

* $p<0.05$ from the logistic regression

3.5 Discussion

3.5.1 Objective 1: Agreement between objective and perceived walking time

The first objective of the study was to examine the agreement between objective and perceived walking times to various closest destinations. This agreement was found to be relatively poor: on average 52.2% of the respondents made a correct estimation. This finding aligns with Macintyre et al. and Jilcott et al., who respectively found a correspondence of 62.0% and 60.9% (Jilcott et al., 2007; Macintyre & Macdonald, 2008). However, the observed agreement strongly differs from that of Lackey & Kaczynski (17.9%) and McCormack et al. (11.4%) (Lackey & Kaczynski, 2009; McCormack et al., 2008). However, it ought to be noted that it is difficult to compare with the studies of Macintyre et al. and Lackey & Kaczynski since they have only studied perceived and objective access to parks by verifying whether there is a park within 750 m from one's residence or not (Lackey & Kaczynski, 2009; Macintyre & Macdonald, 2008). Furthermore, in our study, 33.9% of the respondents tended to overestimate the objective walking time. This general overestimation was also found in earlier studies as mentioned in the specific literature review and may be explained by the fact that people can be unaware of certain close facilities (Jilcott et al., 2007).

More specifically, when separate destinations are considered, the furthest destinations (swimming pools, libraries, post offices, and video shops) have the largest proportion of underestimations. This is similar to the results of McCormack et al., where the two farthest destinations (libraries and post offices) also represented the largest amount of underestimations (McCormack et al., 2008). Also in accordance with McCormack et al., the walking time to supermarkets is overestimated most (McCormack et al., 2008). Proffitt et al. mention a possible explanation for this: it has been shown that carrying heavy bags requires more physical effort, which results in distance overestimations (Proffitt, Stefanucci, Banton, & Epstein, 2003). Additionally, people often go shopping by car to prevent carrying heavy bags or to make sure that frozen goods do not melt. The use of motorised transport causes less interaction with the environment (Mondschein et al., 2010), resulting in more overestimations (Cohen & Weatherford, 1980; Golledge & Stimson, 1997; Thorndyke, 1982). Another possible explanation for the overestimation of walking time to supermarkets is that small (often foreign) shops are also included in the data, although people may not patronise these shops as frequently as larger shops. Walking times to destinations that are most common (bakeries, butcheries, pharmacies, and bus or tram stops) are most often estimated correct. Also walking times to video shops and swimming pools are estimated rather well, probably because only few of these facilities exist which are therefore well known.

3.5.2 Objective 2: Relation between different factors (PA, neighbourhood walkability, gender, educational level, BMI, and age) and degree of agreement

As mentioned in the introduction, it has previously been shown that active people can better estimate walking distances/time because of their greater exposure and awareness resulting from more intense interaction with the environment (Cohen & Weatherford, 1980; Humpel et al., 2002; Kirtland et al., 2003; Lackey & Kaczynski, 2009; McCormack et al., 2008; Thorndyke, 1982). The logistic regression carried out in this paper showed that active people actually have higher odds (OR=1.138) of achieving a match between objective and perceived walking distances. Detailed analyses showed that active people make 3.1% more correct estimations than insufficiently active people. While McCormack et al. observed that insufficiently active people overestimate only the distance to shops, this paper found that insufficiently active people overestimate walking times to all destinations (McCormack et al., 2008). More specifically, insufficiently active people make 4.2% more overestimations than active people. Additionally, active people make 1.2% more underestimations than insufficiently active people.

Since an earlier study in Ghent showed that people from high walkable neighbourhoods tend to be more active than people from low walkable neighbourhoods (Van Dyck et al., 2010), it was expected that people from high walkable neighbourhoods would make more underestimations, whereas people from low walkable neighbourhoods would make more overestimations. However, our results showed that there is almost no difference in the proportion of correct estimations between high and low walkable neighbourhoods and that residents of low walkable neighbourhoods make more underestimations, while those of high walkable neighbourhoods make more overestimations. There may be two explanations for this. First, the higher degree of overestimations of distance can be explained by the presence of more intersections in high walkable neighbourhoods (Cohen & Weatherford, 1980; Sadalla & Magel, 1980; Sadalla & Staplin, 1980). Second, routes to destinations in high walkable neighbourhoods are often relatively short and it has been shown earlier that short and well-known routes are more often overestimated, whereas long and unknown routes are more often underestimated (Canter & Tagg, 1975; Cervero & Radisch, 1996; Frank et al., 2003; Golledge & Stimson, 1997).

For the other demographic variables (gender, educational level, BMI, and age) no significant results were found in Macintyre et al. and Lackey & Kaczynski (Lackey & Kaczynski, 2009; Macintyre & Macdonald, 2008). This coincides with the results of this study, since these factors had no significant influence on the odds of making a correct estimation. However, results of this paper show that male, normal weighted, younger people make more underestimations and less overestimations, than female, overweighed, older people. These results are as expected, because male, normal weighted, and younger people are more active (Trost, Owen, Bauman, Sallis, & Brown, 2002).

3.5.3 STUDY STRENGTHS AND LIMITATIONS

This study has several strengths. First, it is to our knowledge the first study in European mainland about the effect of physical activity behaviour on travel time estimations and on associations between objective and perceived walking distances to destinations. Other studies concerning the relationship between the built environment and PA are mainly North American and Australian. Previous studies were conducted, among others, in South Carolina (US), North Carolina (US), Glasgow (UK), Adelaide (Australia), and Ontario (Canada) (Jilcott et al., 2007; Kirtland et al., 2003; Lackey & Kaczynski, 2009; Macintyre & Macdonald, 2008; McCormack et al., 2008). Second, the sample of 1,164 respondents used in this study is larger than that of many other similar studies: 86 in McCormack et al., 199 in Jilcott et al., 574 in Lackey & Kaczynski, and 658 in Macintyre et al. (Jilcott et al., 2007; Lackey & Kaczynski, 2009; Macintyre & Macdonald, 2008; McCormack et al., 2008). Only in Kirtland et al. a similar number of participants (1,112) were studied (Kirtland et al., 2003). Third, more types of destinations are taken into consideration: 13 in contrast with 1 to 9 in the previously mentioned studies. Fourth, as in Jilcott et al., this study uses accelerometer data to estimate PA, which is more objective compared to the self-reported data used in many previous studies including Kirtland et al., McCormack et al., Macintyre et al., and Lackey & Kaczynski (Jilcott et al., 2007; Kirtland et al., 2003; Lackey & Kaczynski, 2009; Macintyre & Macdonald, 2008; McCormack et al., 2008). Fifth, body mass index (BMI) has been taken up as an explanatory variable in this study, which is not the case in the other five similar studies (ibid.). Sixth, in contrast to prior work, walking time is used instead of walking distance. The advantage of this is that walking speeds, and thus walking time–in contrast to walking distance–can be differentiated according to gender and age (Bohannon, 1997).

Apart from the many advantages our study has over similar studies, there are also limitations. First, it is possible that people do not know the closest facility of a particular type simply because they are unaware of it. Incorporating the time that respondents have lived in their neighbourhood might help to gain insights in this effect. Second, the questionnaire (NEWS) used for this study uses predefined categories to estimate the perceived walking time to various closest destinations. The reason for this is to minimise errors, because it can be hard to estimate walking times with a precision of one minute. However, because of these categories, short objective walking times cannot be underestimated and long objective walking times cannot be overestimated. Third, in choosing routes, people are often driven by sense of safety, attractiveness and complexity of the built environment, and emotional responses (Briggs, 1973; Gatrell, 1983; Golledge & Stimson, 1997; Owen et al., 2004; Saelens, Sallis, & Frank, 2003), and therefore do not necessarily take the shortest route possible. Future studies comparing objective and perceived walking times should therefore include the actual routes, possibly making use of the GPS technology, and compare these with the objective and perceived shortest routes.

3.6 CONCLUSIONS

While in the past several studies used perceived walking times or distances as a substitute for actual walking times as a measure for access to different facilities (Hawthorne & Kwan, 2012; Sugiyama, Leslie, Giles-Corti, & Owen, 2009), this study has shown that these perceived walking times/distances are often an overestimation of the objective walking times/distances. Future studies should keep this poor correspondence in mind, as well as the fact that when only using self-reported walking times, the results can be influenced by physical activity and other variables. In general, people overestimate walking times, but physically insufficiently active people in particular make even more overestimations, probably because of their inadequate mental map resulting from lower interaction and experience with their residential neighbourhood. By overestimating walking times, people can be discouraged to walk and might end up being insufficiently active. These vicious circle effects should make policy makers aware that in order to promote physical activity, one should not only look at the objective neighbourhood characteristics but also at how people of socio-demographic segments and with different PA levels may perceive these. It is important for policymakers to appreciate that by influencing people's perception, one can change PA behaviour without adjusting the built environment itself.

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4

Accessibility to primary health care physicians in Belgium

Adapted from: Dewulf, B., Neutens, T., De Weerdt, Y., Van de Weghe, N. (2013) Accessibility to primary health care in Belgium: An evaluation of policies awarding financial assistance in shortage areas. *BMC Family Practice, 14*(122), 13p.

4.1 Abstract

In many countries, financial assistance is awarded to physicians who settle in an area that is designated as a shortage area to prevent unequal accessibility to primary health care. Today, however, policy makers use fairly basic methods to define health care accessibility, with physician-to-population ratios (PPRs) within predefined administrative boundaries being overwhelmingly favoured. Our purpose is to verify whether these basic methods are accurate enough for adequately designating medical shortage areas and explore how these perform relative to more advanced GIS-based methods. Using a geographical information system (GIS), we conduct a nation-wide study of accessibility to primary care physicians in Belgium using four different methods: PPR, distance to closest physician, cumulative opportunity, and floating catchment area (FCA) methods. The official method used by policy makers in Belgium (calculating PPR per physician zone) offers only a crude representation of health care accessibility, especially because large contiguous areas (physician zones) are considered. We found substantial differences in the number and spatial distribution of medical shortage areas when applying different methods. The assessment of spatial health care accessibility and

concomitant policy initiatives are affected by and dependent on the methodology used. The major disadvantage of PPR methods is its aggregated approach, masking subtle local variations. Some GIS methods overcome this issue, but have limitations in terms of conceptualisation of physician interaction and distance decay. Conceptually, the enhanced 2-step floating catchment area (E2SFCA) method, an advanced FCA method, was found to be most appropriate for supporting areal health care policies, since this method is able to calculate accessibility at a small scale (e.g. census tracts), takes interaction between physicians into account, and considers distance decay. While at present in health care research methodological differences and modifiable areal unit problems have remained largely overlooked, this manuscript shows that these aspects have a significant influence on the insights obtained. Hence, it is important for policy makers to ascertain to what extent their policy evaluations hold under different scales of analysis and when different methods are used.

4.2 INTRODUCTION

Primary health care is the first line of defence for a population and can prevent or reduce unnecessary, expensive speciality care (Lee, 1995; Luo & Qi, 2009; Luo, 2004). Hence, accessibility to primary health care is considered a fundamental right and an important facilitator of overall population health.

Ensuring equal accessibility to primary care for those in equal need has long been of concern to public health policy makers, service providers, researchers, and consumers alike. Various countries have implemented incentive health programmes to redress spatial gaps in service provision. In the US, for instance, the federal government spends over one billion dollars a year on programmes (e.g. National Health Service Corps Program) that seek to improve accessibility to health care by, among others, offering financial support to health care professionals, who serve shortage areas (GAO: United Stated General Accounting Office, 1995; Luo & Qi, 2009). Likewise, in Belgium, the *'Rijksinstituut voor Ziekte- en Invaliditeitsverzekering'* (RIZIV; 'National Institute for Disease and Invalidity Insurance') has an incentive programme, called Impulseo I, which awards 20,000 euros to physicians who settle in a physician zone–consisting of multiple municipalities–with a low physician-to-population ratio; that is, less than 90 physicians/100,000 inhabitants, or both less than 120 physicians/100,000 inhabitants and less than 125 inhabitants/km^2 (RIZIV, 2013).

While medical deficits determined on the basis of zonal physician-to-population ratios can be derived easily from a simple spread sheet, they may–if not complemented by a more in-depth spatial analysis–generate only crude and even misleading insights into the health provision landscape. Such a spatial analysis can be achieved by using geographical information systems (GIS) that enable to input, store, manipulate, analyse, and visualise spatial information (Higgs, 2004). The analytical power of GIS holds tremendous value for public health reformers in uncovering and mapping socio-spatial disparities in health care accessibility, and monitoring the impact of policy initiatives aimed at reducing these (Langford & Higgs, 2006; Nettleton, Pass, Walters, & White, 2006). However, it is regrettable to observe with Joyce that "*despite GIS having applications in fields as diverse as engineering and anthropology, the potential of GIS has yet to be fully exploited in health settings*" (Joyce, 2009, p. 831). Policy decisions in Belgium–and elsewhere–are based on rather crude definitions of what constitutes accessibility, disregarding the full diversity of sophisticated indicators that have been proposed in the academic literature.

In this paper, we examine the validity of the Belgian policy directives regarding financial support for physicians using different GIS-based methods to designate underserved areas of primary health care. The general aim is to evaluate to what extent spatial health care accessibility and concomitant policy initiatives are affected by and depend on the method and scale of analysis used. This general aim unfolds into two specific objectives. The first objective is to statistically analyse the results from four different GIS methods using cross tabs and compare these with current practice in Belgium. The second objective is to perform an analysis of the spatial distribution of shortage areas.

4.3 BACKGROUND

Health care accessibility can be classified into two categories: revealed accessibility and potential accessibility (Joseph & Phillips, 1984; Phillips, 1990; Thouez, Bodson, & Joseph, 1988). The former deals with the actual use of health care services, while the latter focuses on the aggregated supply of available health care in an area and thus the potential use of services. Both can be further subdivided into spatial and non-spatial accessibility. Spatial accessibility is based on spatial factors, including the distribution of primary health care providers (supply; in Belgium mostly self-employed physicians) and population (demand), and the distance/time between supply and demand (Aday & Andersen, 1974). Non-spatial accessibility is based on non-spatial factors such as socio-economic factors, the health status of the population, and people's knowledge about the health care system (Aday & Andersen, 1974; Joseph & Phillips, 1984). It is essential toward any effective government intervention programme to identify where potential shortage areas are located (Guagliardo, 2004; Luo, 2004). In this paper, we will focus on potential spatial accessibility (henceforth briefly referred to as accessibility).

To calculate primary health care accessibility in general and physician shortage areas in particular, various methods can be used. Basic methods include distance/time (Euclidean, Manhattan, or network) to the nearest physician, the average distance/time to a certain number of physicians, and cumulative opportunity (which is calculated as the number of physicians within a certain distance/time) (Apparicio, Abdelmajid, Riva, & Shearmur, 2008; Talen, 2003). However, these methods give only a rough estimation of accessibility. Distance to the nearest provider for example does not capture full accessibility, because it is often observed that people bypass the nearest service when there is more than one service to choose from (Fryer et al., 1999; Goodman et al., 1999; Hyndman, D'Arcy, Holman, & Pritchard, 2003; Martin & Williams, 1992; McGrail, 2012). Cumulative opportunity does not take interaction between population and physicians, and competition between physicians into consideration (Fryer et al., 1999; McGrail, 2012).

Physicians co-exist in a network of overlapping catchments, and people are free to choose health care wherever and from whomever. Therefore, physicians compete for the population's use of their services (McGrail, 2012). Some methods are based on PPRs to measure accessibility in a predefined area, as is the case in Impulseo I. The advantage of these methods is that they are easy to implement (no GIS tools needed) and comprehend. In spite of this, traditional PPRs have several limitations (Kleinman & Makuc, 1983; McGrail & Humphreys, 2009a; Wing & Reynolds, 1988). First of all, PPRs are usually calculated with zonal data, which are based on administrative boundaries (e.g. municipalities). In Impulseo I, PPRs are calculated per physician zone, which have a median area of 86.53 km^2 with a median population of 36,613. When using administrative zones boundaries are considered impermeable and as a result, the interaction across borders is not sufficiently taken into consideration (Guagliardo, 2004; Joseph & Phillips, 1984). Second, the physical separation with physicians is not equal for all inhabitants residing in the same zone, which causes accessibility to vary within that zone (Guagliardo, 2004; Wan, Zou, & Sternberg, 2012). Nonetheless, the PPR method assumes equal accessibility to services irrespective of where individuals live within the zone (Higgs, 2004). Calculating PPRs within administrative borders can hence strongly influence the results when working on a different scale level, which constitutes a well-known source of statistical bias in geography termed the modifiable areal unit problem (MAUP) (Openshaw, 1984). MAUP generally occurs when point-based measures of spatial phenomena are aggregated into districts.

A method that partly overcomes both limitations is the 2-step floating catchment area (2SFCA) method, developed by Luo & Wang and based on the spatial decomposition idea by Radke & Mu (Luo & Wang, 2003; Radke & Mu, 2000). In this method, a circle (catchment) of some reasonable radius (matched on the road network) centred on the census tract centroid is used as the basic unit instead of using a predefined administrative boundary to calculate PPRs.

Because catchments are used instead of administrative borders, crossing of borders is now possible. This can be seen in Figure 4.1, where an example of a catchment from a centroid of a census tract (in casu 'Rekencentrum' in Ghent) is shown. This catchment is strongly related with the road network and intersects with the census tract boundaries. The catchment radius is defined as the maximum distance/time along the road network, where all physicians are deemed accessible and equally proximate to that particular population (centred at the census tract centroid). The catchment that is hereby formed floats from census tract centroid to census tract centroid, hence the name of the method. This way, shortage areas with PPRs lower than a predefined value can be defined.

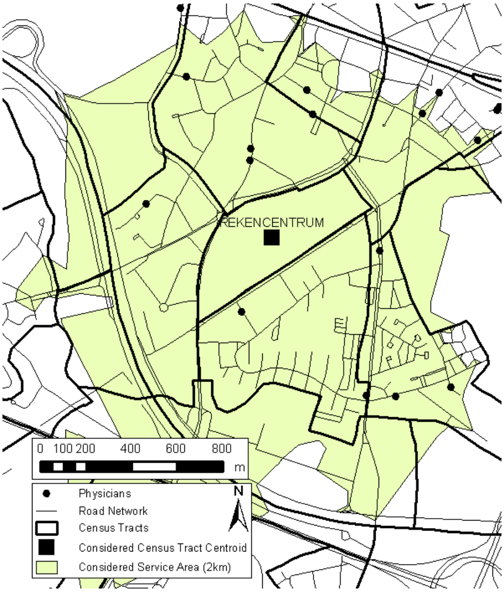

Figure 4.1: Example of a service area around a census tract centroid, showing the alignment with the road network and the intersection with the census tract boundaries.

The PPR per census tract centroid is calculated in two steps. In the first step, the PPR is first calculated on each physician location, using equation 4.1. In the second step, the PPR is calculated per census tract centroid by summating all PPRs from step one, using equation 4.2. Doing so, the method considers interaction between population and physicians (Higgs, 2004; McGrail, 2012).

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} P_k} \qquad \text{(eq. 4.1)}$$

$$A_i = \sum_j R_j \qquad \text{(eq. 4.2)}$$

where R_j is the PPR at physician location j, S_j is the number of physicians at location j, P_k is the population of census tract k whose centroid falls within the physician catchments (that is, $d_{kj} \leq d_0$), d_{kj} is the travel distance between k and j, d_0 is the travel distance radius of the catchment, and A_i represents the accessibility at census tract i to physicians.

In the 2SFCA method, the assumption of equal accessibility within the catchment and no accessibility outside stands (McGrail & Humphreys, 2009a; Yang, Goerge, & Mullner, 2006). The enhanced 2-step floating catchment area (E2SFCA) method overcomes this by applying a distance decay function (Luo & Qi, 2009). Each catchment is divided into multiple sub catchments, which receive varying weights defined by a weight function, which can be adjusted depending on the type or importance of a service. Equations 4.1 and 4.2 are hereby transformed into equations 4.3 and 4.4. By doing this, it is accepted that services that are closer to the census tract centroid are more accessible. The use of this function is required when working across large geographies, which is often the case for health policies at national level (Luo & Qi, 2009).

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \leq D_r\}} P_k W_r} \qquad \text{(eq. 4.3)}$$

$$A_i = \sum_j R_j W_r \qquad \text{(eq. 4.4)}$$

where W_r is the distance weight for the r-th travel time zone defined by the distance decay weight function capturing the distance decay of accessibility to physician j.

This E2SFCA method is now considered the standard FCA method, and is used in a variety of studies (Langford, 2012; Luo & Qi, 2009; Ngui & Apparicio, 2011). McGrail suggests to use a variable catchment size function, depending on the population type (urban or rural) and service (McGrail, 2012). The reason for this is that rural populations are generally more accustomed to travel further to a service location, and urban populations will mostly access services in a closer proximity because service locations are densely located. However, since in Belgium differences between urban and rural populations are not as big as in, say, Australia or North America, such function will not be applied here.

FCA-based methods have the advantage of calculating accessibility on a much smaller scale than is feasible with traditional PPRs (McGrail & Humphreys, 2009a).

4.4 DATA AND METHODS

4.4.1 DATA

The study area of the paper is the whole country of Belgium (see Figure 4.2), with a population of approximately 10.8 million inhabitants on an area of 30,528 km^2. Belgium is divided into 161 physician zones (median area: 86.53 km^2, median population: 36,613), 589 municipalities (median area: 40.10 km^2, median population: 11,702), and 19,781 census tracts (median area: 0.51 km^2, median population: 310). A physician zone collects physicians who are active in a contiguous geographic area that consists of one or more municipalities, or is part of a municipality in the large agglomerations of Antwerp, Brussels, Ghent, and Liège. Population data per census tract of the year 2011 were used, together with the geocoded addresses of all active physicians (in total, 10,353) in Belgium in that same year. Physicians are considered active when they have at least 500 patient contacts per year, which is concurrent with the official definition of Impulseo I. In order to calculate shortest paths between physicians and census tracts centroids, and subsequently define service areas we have used a transportation network shapefile (TeleAtlas MultiNet®), consisting of a detailed topological representation of the Belgian road network.

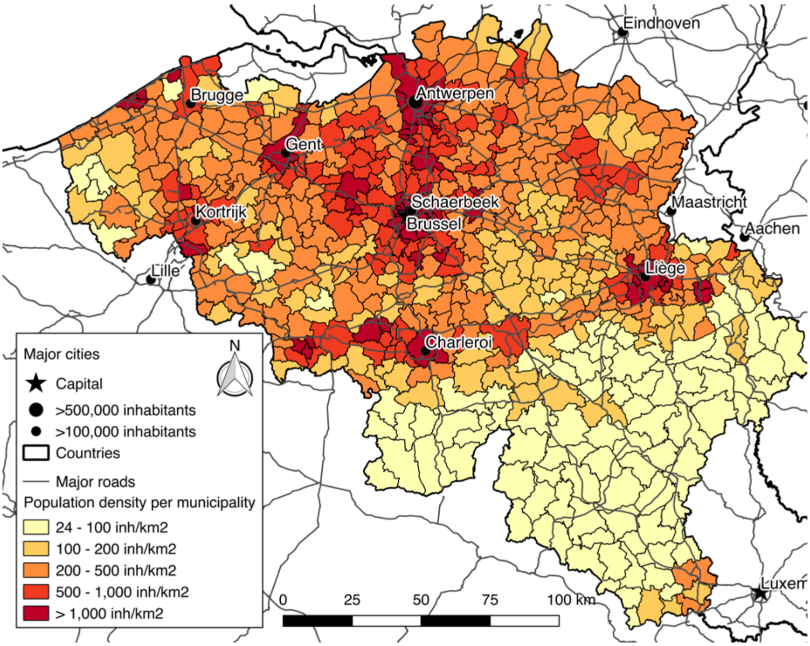

Figure 4.2: Study area indicating Belgium and its neighbouring countries, the major motorways, and the population density per municipality.

4.4.2 METHODS

All calculations were performed in ArcGIS 9.3™. Four types of methods to measure accessibility were selected on the basis of their frequent use in health studies: (i) PPR, (ii) distance to closest physician(s), (iii) cumulative opportunity, and (iv) floating catchment area (FCA) methods. To explore the scale effect of the MAUP, different spatial units of analysis were used: physician zone, municipality, and census tract.

First, PPRs were calculated per physician zone (which is also done in the official Impulseo I method) and per municipality. PPRs have not been calculated per census tract, simply because a lot of census tracts contain no physicians (which would yield a PPR of zero), while in fact there is a physician located in its proximity (e.g. in one of the adjacent tracts). This is often referred to as the small population problem.

Second, basic GIS methods expressing physical separation between population and physicians were calculated per census tract, including distance to the nearest physician, and mean distance to the nearest three physicians. This last method was included, because people often bypass the nearest physician (Fryer et al., 1999; Hyndman et al., 2003).

Third, cumulative opportunity was calculated per census tract as the number of physicians within a certain distance from its centroid. These thresholds are often arbitrary and difficult to select. Based on previous studies (Apparicio et al., 2008; Higgs, 2004), we have used buffers of 5 and 10 km.

Finally, two types of FCA-based methods were computed per census tract. It is noted that calculating FCA measures per census tract is meaningful because in FCA methods, crossing administrative borders, including those with zero physicians, is possible (Apparicio et al., 2008). This spatial smoothing effect thus solves the small population problem (Wang, 2012). Based on prior work and in analogy with the cumulative opportunity metric, the 2SFCA was performed with a catchment of 5 and 10 km (Apparicio et al., 2008; Higgs, 2004). Following McGrail, in the E2SFCA, we used the following slow step-decay function: 1, 0.80, 0.55, and 0.15, respectively for the catchments 1 km, 2 km, 5 km, and 10 km (McGrail, 2012). A slow step-decay function is preferred to a fast step-decay function, because in the context of Belgium physicians located outside the 1 km catchment not necessarily have a low accessibility.

To implement the accessibility measures above, distances and car travel times were calculated along the street network. This was done by using the Network Analyst

Extension of ArcGIS 9.3™. However, like Apparicio (Apparicio et al., 2008), we found a strong positive correlation between both the shortest network distance and car travel time (two-tailed Pearson $r = 0.949$, $p < 0.001$), and therefore in this paper we only elucidate the results using network distances. Also, network distances are preferred because we did not want to presuppose the transport mode used to get to a physician by using mode-specific speeds for calculating travel time (Apparicio et al., 2008; Dewulf, Neutens, Van Dyck, De Bourdeaudhuij, & Van de Weghe, 2012; Luo, 2004).

Impulseo I defines the following criteria to determine whether an area is underserved: (i) PPR <90 physicians/100,000 inhabitants, or (ii) <120 physicians/100,000 inhabitants and population density <125 inhabitants/km^2. For the FCA based methods (2SFCA, and E2SFCA), we have used the same criteria, but without criterion (ii). This is because population density is already indirectly incorporated in the FCA methods as it accounts for the fact that people compete for physicians (and vice versa). For average distance to the (three) closest physician(s) and cumulative opportunity within 5 and 10 km, the same number of census tracts as resulting from the official Impulseo I method (i.e. PPR per physician zone) have been designated as shortage area. This means that a threshold distance and cumulative opportunity value had to be set, with all census tracts having an accessibility value above/below this threshold being designated as underserved.

The different methods will be tested on correlation using a two-tailed Pearson test in SPSS Statistics 21™. The methods that did not exhibit high mutual correlation will then be compared with each other and with the official Impulseo I method using a large cross tab and by visualising the spatial data in maps. To accomplish the second objective, i.e. the detailed spatial analysis of the conceptually most advanced method (E2SFCA method), a geographical analysis will be performed.

4.5 RESULTS

4.5.1 STATISTICAL ANALYSIS

Table 4.1 shows the results from a two-tailed Pearson correlation test, indicating the correlation coefficient and its significance. It can be observed that there is a strong and significant correlation (0.739) between the distance methods (Dist1 and Dist3). In addition, there is a strong correlation (0.653) between the cumulative opportunity methods (Cum5 and Cum10). A moderate to strong correlation is noted among the different FCA methods (2SFCA5, 2SFCA10, and E2SFCA). The E2SFCA method in particular has a rather strong correlation with the other FCA-based methods. It should also be noted that the correlation between different methods is rather weak (mostly lower than 0.4). Based on the outcome of this correlation analysis, we have selected four specific methods (one per method group) for further analysis: PPR per municipality (PPR_Mun), distance to three closest physicians (Dist3), cumulative opportunity within 10 km (Cum10), and the E2SFCA method.

Table 4.1: Results from the two-tailed Pearson correlation test.

Method	*PPR_Phys*[1]	*PPR_Mun*[2]	*Dist1*[3]	*Dist3*[4]	*Cum5*[5]	*Cum10*[6]	*2SFCA5*[7]	*2SFCA10*[8]	*E2SFCA*[9]
PPR_Phys[1]	1*								
PPR_Mun[2]	0.396*	1*							
Dist1[3]	0.176*	0.110*	1*						
Dist3[4]	0.203*	0.122*	0.739*	1*					
Cum5[5]	0.269*	0.152*	0.410*	0.543*	1*				
Cum10[6]	0.321*	0.121*	0.355*	0.457*	0.653*	1*			
2SFCA5[7]	0.169*	0.277*	0.201*	0.218*	0.244*	0.045*	1*		
2SFCA10[8]	0.207*	0.215*	0.149*	0.155*	0.145*	0.190*	0.199*	1*	
E2SFCA[8]	0.192*	0.267*	0.341*	0.367*	0.310*	0.131*	0.597*	0.488*	1*

* Correlation is significant at the 0.01 level.

[1]: physician-to-population ratio per physician zone; [2]: physician-to-population ratio per municipality; [3]: mean distance to nearest physician; [4]: mean distance to nearest physician; [5]: cumulative opportunity within a 5km network buffer; [6]: cumulative opportunity within a 10 km network buffer; [7]: 2-step floating catchment area method with a catchment of 5 km; [8]: 2-step floating catchment area method with a catchment of 10 km; [9]: enhanced 2-step floating catchment area method.

The results of these methods will be compared mutually as well as against the official Impulseo I method (that is PPR per physician zone; PPR_Phys) using a cross tab (Table 4.2), showing the number (Count) and percentage (Table %) of underserved census tracts per method.

Table 4.2 shows that in total 8,157 census tracts (41.2% of all census tracts) are underserved and should thus receive financial assistance, when using the official Impulseo I method (PPR_Phys). In contrast, when using the first selected method (PPR_Mun) 9,498 census tracts (48.0%) are identified as shortage areas (Table 4.2). In total, 5,841 census tracts (29.5%, compared to 41.2% from the official method) are in both methods consistently classified as underserved, while 7,967 census tracts (40.3%, compared to 58.8% from the official method) are in both methods consistently not identified as shortage areas. This PPR_Mun method is most similar to the official PPR_Phys method, simply because both are based on calculating PPRs.

The second alternative method (Dist3) consists of calculating the average distance to the three closest physicians. The average value of all average distances from each census tract centroid to the closest three physicians for the whole of Belgium is 2,045 m. In order to identify the same amount (8,157) of underserved census tracts as in the official Impulseo I method, a threshold value (1,878 m) was determined so that exactly 8,157 census tracts had a value higher than this threshold and were thus classified as underserved. Table 4.2 shows that 4,335 census tracts (21.9%/41.2%) are shortage areas in both methods (Dist3 and PPR_Phys). It can also be deduced that 61.3% (39.4% + 21.9%) of all census tracts were in both the official PPR_Phys and the Dist3 method classified consistently, while in 38.6% (19.3% + 19.3%) of all census tracts there are inconsistent evaluations as to whether or not financial assistance should be awarded.

For the third method (Cum10), we calculated the number of physicians within 10 km for all census tracts, and considered the 8,157 census tracts with the lowest number of physicians within 10 km. We found 8,215 census tracts with less than 58 physicians within 10 km. Following Table 4.2, 4,928 census tracts (24.9%/41.2%) are identified as shortage areas in both methods (official and Cum10 method). 67.0% (42.1% + 24.9%) of all census tracts are assessed consistently in both methods, while 32.9%/58.8% (16.6% + 16.3%) are different.

Finally, when using the E2SFCA method, 8,968 census tracts (45.3%) are considered underserved and 10,813 (54.7%) are not (see Table 4.2). In 4,629 census tracts (23.4%/41.2%) financial assistance is awarded in both methods (official and E2SFCA method) and in 7,285 (36.8%/58.8%) not. Also, 60.2% (36.8% + 23.4%) of all census tracts are equally identified in both methods (official and E2SFCA method) and 39.7% (21.9% + 17.8%) are different.

Table 4.2: Cross tab showing the comparison between the official Impulseo I method and the four selected methods.

			PPR_Phys[1]		*PPR_Mun*[2]		*Dist3*[3]		*Cum10*[4]		*E2SFCA*[5]	
			No shortage area	*Shortage area*	*No shortage area*	*Shortage area*	*No shortage area*	*Shortage area*	*No shortage area*	*Shortage area*	*No shortage area*	*Shortage area*
PPR_Phys[1]	*No shortage area*	Count	11,624	0								
		Table %	58.8%	0%								
	Shortage area	Count	0	8,157								
		Table %	0%	41.2%								
PPR_Mun[2]	*No shortage area*	Count	7,967	2,316	10,283	0						
		Table %	40.3%	11.7%	52,0%	0%						
	Shortage area	Count	3,657	5,841	0	9,498						
		Table %	18.5%	29.5%	0%	48,0%						
Dist3[3]	*No shortage area*	Count	7,802	3,822	6,635	4,989	11,624	0				
		Table %	39.4%	19.3%	33.5%	25.2%	58.8%	0%				
	Shortage area	Count	3,822	4,335	3,648	4,509	0	8,157				
		Table %	19.3%	21.9%	18.4%	22.8%	0%	41.2%				
Cum10[4]	*No shortage area*	Count	8,337	3,229	6,601	4,965	8,991	2,575	11,566	0		
		Table %	42.1%	16.3%	33.4%	25.1%	45.5%	13.0%	58.5%	0%		
	Shortage area	Count	3,287	4,928	3,682	4,533	2,633	5,582	0	8,215		
		Table %	16.6%	24.9%	18.6%	22.9%	13.3%	28.2%	0%	41.5%		
E2SFCA[5]	*No shortage area*	Count	7,285	3,528	6,935	3,878	8,135	2,678	6,957	3,856	10,813	0
		Table %	36.8%	17.8%	35.1%	19.6%	41.1%	13.5%	35.2%	19.5%	54.7%	0%
	Shortage area	Count	4,339	4,629	3,348	5,62	3,489	5,479	4,609	4,359	0	8,968
		Table %	21.9%	23.4%	16.9%	28.4%	17.6%	27.7%	23.3%	22,0%	0%	45.3%

[1]: physician-to-population ratio per physician zone; [2]: physician-to-population ratio per municipality; [3]: mean distance to nearest 3 physicians; [4]: cumulative opportunity within a 10 km network buffer; [5]: enhanced 2-step floating catchment area method.

The results of the four methods can also be visually represented in maps. Figure 4.3 and Figure 4.4 show the spatial distribution of census tracts that are considered as shortage areas in Belgium, for the official Impulseo I method as well as the four selected methods. Additionally, Table 4.3 provides some general numbers for each of these methods. The table summarises the percentage of census tracts that are underserved, but also shows the percentage of underserved area and population. In order to illustrate the potential financial implications of methodological choices, the last column indicates the money that would have to be awarded per year assuming an increase of one physician per 10 underserved census tracts per year.

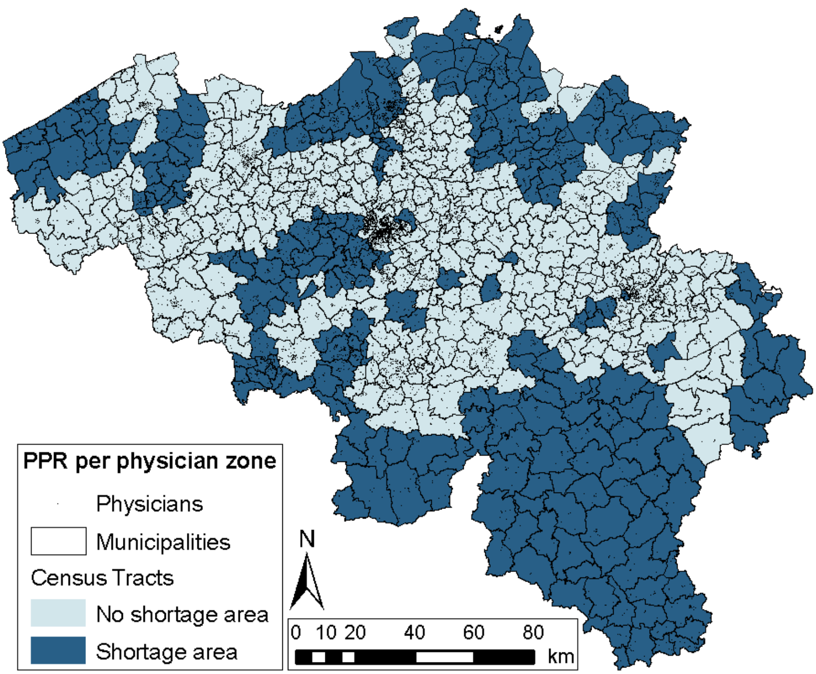

Figure 4.3: Map showing which census tracts are considered shortage areas, using the official Impulseo I method (PPR per physician zone), additionally indicating the location of all physicians.

Table 4.3: Percentage of underserved census tracts, area, and population, and amount of money needed for the official and the four selected methods.

Method	*Census tracts underserved (%)*	*Area underserved (%)*	*Population underserved (%)*	*Amount of money needed per year[a] (€)*
PPR_Phys[1]	41.2	51.9	35.3	16,314,000
PPR_Mun[2]	48.0	51.2	47.7	18,996,000
Dist3[3]	41.2	66.3	17.1	16,314,000
Cum10[4]	41.5	62.5	23.1	16,430,000
E2SFCA[5]	45.3	60.2	33.1	17,936,000

[a] Assuming one new physician per 10 underserved census tracts per year.

[1]: physician-to-population ratio per physician zone; [2]: physician-to-population ratio per municipality; [3]: mean distance to nearest 3 physicians; [4]: cumulative opportunity within a 10 km network buffer; [5]: enhanced 2-step floating catchment area method.

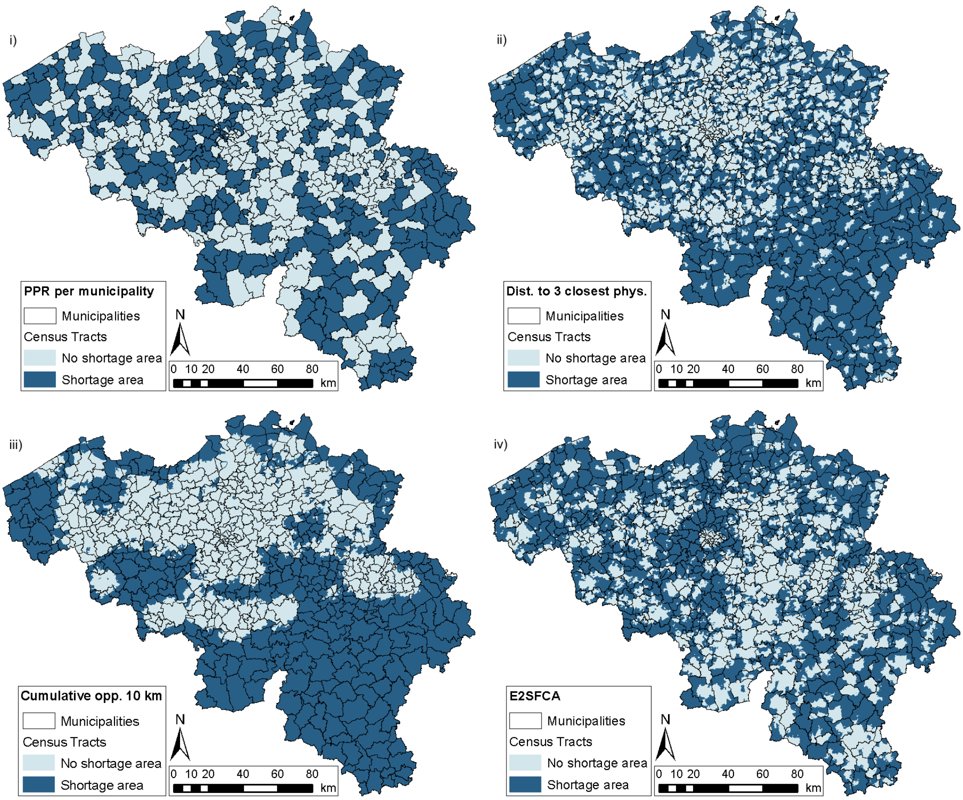

Figure 4.4: Map showing which census tracts are considered underserved, using the (i) PPR per municipality, (ii) distance to three closest physicians, (iii) cumulative opportunity within 10 km, and (iv) E2SFCA method.

In the official PPR_Phys method, the analysis is performed per physician zone. These cover large areas, and therefore the zones where financial assistance is given or not are large contiguous areas (Figure 4.3). As mentioned earlier, 41.2% of all census tracts are underserved, which coincides with 51.9% of the total area and 35.3% of the total population of Belgium (Table 4.3). Assuming one new physician per 10 underserved census tracts per year, an amount of €16.3 million would be needed each year, which is the lowest amount of money of all selected methods.

When using the PPR_Mun method, and identifying shortage areas with the same criterion as in the official Impulseo I method but on the scale of municipalities, the ascription of financial assistance is now much more geographically diversified (Figure 4.4). Also, more census tracts are underserved (48.0%; see Table 4.3), resulting in a higher amount of money needed (almost €19 million). Approximately the same percentage of area is seen as shortage area (51.2%), but 47.7% of the population lives within these census tracts, which means that with this PPR_Mun method, census tracts with higher population densities are selected.

With the Dist3 method, the spatial distribution of census tracts where financial assistance should be given is striking. Here, shortage areas are mainly located outside city centres (Figure 4.4). The reason for this is the increasing distance to physicians outside city centres, because physicians are mainly located in city centres. From Table 4.3, this can also be deduced, because with the same percentage of census tracts as with the official PPR_Phys method (41.2%), an area of 66.3% and a population of only 17.1% is considered underserved.

It can be inferred from Figure 4.4 that with the Cum10 method, mainly physicians that settle in rural areas receive financial assistance. However, the geographical spread is much more clustered than with the Dist3 method and mainly in Wallonia physicians receive financial assistance. As with the previous method, a similar pattern is visible in Table 4.3: a large area of 60.2%, but only 23.1% of the population is underserved.

With the E2SFCA method, again a different spatial result is obtained (Figure 4.4). Now, mainly suburban and rural regions are underserved. With this method, 45.3% of census tracts are seen as shortage area, resulting in an amount of almost €18 million needed.

Now, approximately the same percentage of population (33.1%), but a larger area (60.2%) is identified as underserved.

4.5.2 DETAILED SPATIAL ANALYSIS

In this section, the official Impulseo I method (PPR per physician zone) is geographically compared in more detail with the method that is conceptually most advanced and often used in recent studies: the E2SFCA method. Figure 4.5 shows all census tracts, divided in four classes, depending on whether or not the census tract is considered a shortage area in both methods.

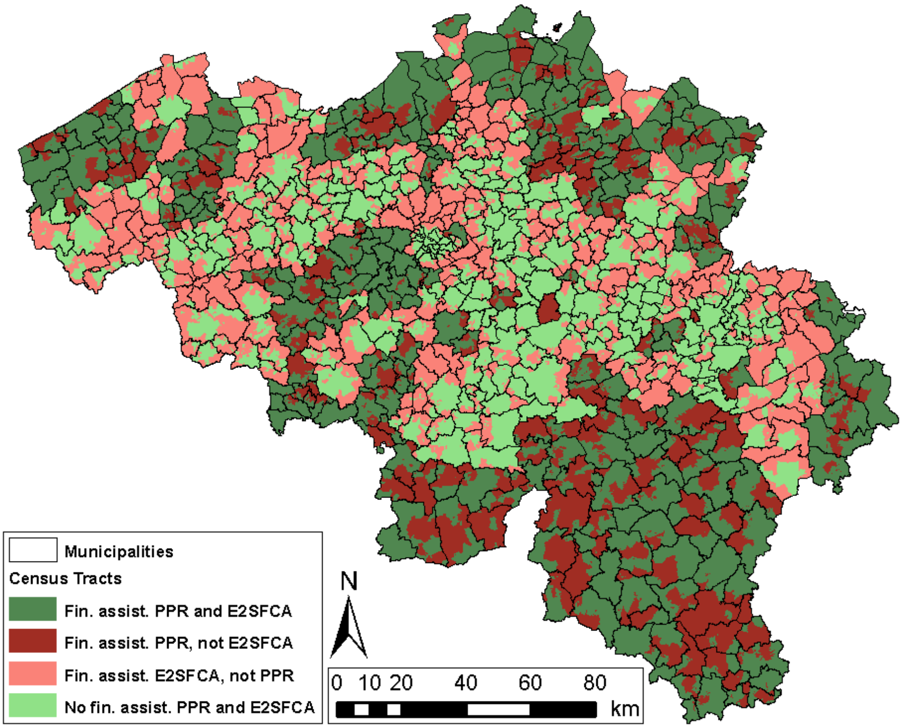

Figure 4.5: Detailed geographic analysis between Impulseo I and the E2SFCA method, with classes: 'Fin. assist. for PPR and E2SFCA', 'Fin. assist. for PPR, but not for E2SFCA', 'Fin. assist. for E2SFCA, but not for PPR', and 'No fin. assist. for PPR and E2SFCA'.

The two classes represented in green ('Financial assistance for PPR and E2SFCA' and 'No financial assistance for PPR and E2SFCA') indicate the census tracts that are in both methods consistently classified as underserved/overserved. Underserved areas occur mainly in the periphery of the country, while overserved areas are mostly located in the central part of the country.

More important from a policy perspective is class ‘Financial assistance for PPR, but not for E2SFCA’. In the southern part of Belgium, many areas where physicians receive financial assistance by the official Impulseo I method would not have been identified as underserved on the basis of the E2SFCA method. Class ‘Financial assistance for E2SFCA, but not for PPR’ is also interesting for policy makers as these represent locations where currently no financial assistance is awarded while it might be appropriate. Mainly rural and suburban regions occur in this class.

4.6 Discussion

4.6.1 General discussion

Whether or not financial assistance should be awarded to physicians strongly depends on the selected method and spatial unit of analysis. Policy makers often define shortage areas by calculating PPR per physician zone, for the simple reason that it is an easy calculation and offers a readily understandable measure of accessibility. The advantage of this method is that it considers both the number of physicians and the population within the zone. However, it only offers a very crude representation of accessibility to primary health care because physician zones cover too large geographic areas (Kleinman & Makuc, 1983; McGrail & Humphreys, 2009b; Wing & Reynolds, 1988). Therefore, it cannot detect local variations in accessibility.

When calculating PPR per municipality, we observe slightly more underserved census tracts. This means that when using physician zones, some municipalities are not identified as shortage areas, while in fact they should be. There are however also some municipalities that are considered underserved, while they should not be. There can nevertheless be variations at an even smaller scale (e.g. census tracts), which cannot be detected using this method. Another disadvantage of this method is that interaction across borders is not sufficiently taken into account (Guagliardo, 2004; Joseph & Phillips, 1984).

Other basic GIS methods (Dist1, Dist3, Cum5, and Cum10) are solely based on the supply (physicians), while the demand (population) is not accounted for. The results show that when using the Dist3 method, only few census tracts maintain their status as shortage area. The Cum10 method provides a result that coincides more with the official method, because both are based on the number of physicians.

FCA-based methods have the advantage of the small geographical scale of analysis at the level of census tracts, and taking interaction between population and physicians into account. From the FCA-based methods, the E2SFCA method is preferred because it accounts for distance decay by using a weight function (Higgs, 2004; Luo & Qi, 2009). The use of this method results in more shortage census tracts compared to the official Impulseo I method. However, only 51.6% of these census tracts were originally indicated as shortage areas. This means that 48.4% of all census tracts should be seen as shortage areas, while now they are not. When geographically comparing the results of the official Impulseo I method (PPR per physician zone) with the results of the E2SFCA method, the ascription of financial assistance is very different. Despite high population densities, urban areas are mostly not identified as shortage areas because of a dense concentration of physicians. Rural and suburban areas are often considered as shortage areas because physician accessibility is low. When using the official Impulseo I method, this pattern is less pronounced, because extreme values are filtered out. This aligns with the findings of Apparicio and McGrail, who found that most accessibility problems occur in suburban areas, with low population density and mostly non-residential land use (Apparicio et al., 2008; McGrail, 2012). Interestingly, however, the defined shortage areas follow the distribution of physicians much better when using the E2SFCA method.

The total number of census tracts where financial assistance should be awarded when a physician settles there is slightly higher with the E2SFCA method, so more money would be needed to invest in helping underserved areas. However, approximately the same population (33.1%) and a much bigger area (60.2%) is reached. Therefore, we would advise policy makers to use this method in future evaluations of accessibility to primary health care, because it aligns better with the actual distribution of physicians. In this way, and according to the spatial analysis, the current policy in Belgium could be adjusted towards a more area-oriented approach.

Additionally, we want to propose a different way of awarding financial assistance to physicians settling in shortage areas. Now, shortage areas are defined based on a sharp threshold (PPR <90 physicians/100,000 inhabitants). Alternatively, one could vary the financial award in function of the magnitude of shortage (see Figure 4.6 for an example). The higher the shortage, the higher the award a physician receives when settling there. Doing so, unequal accessibility to primary health care would possibly be conquered even more effectively, since more underserved areas would have a higher attraction to physicians.

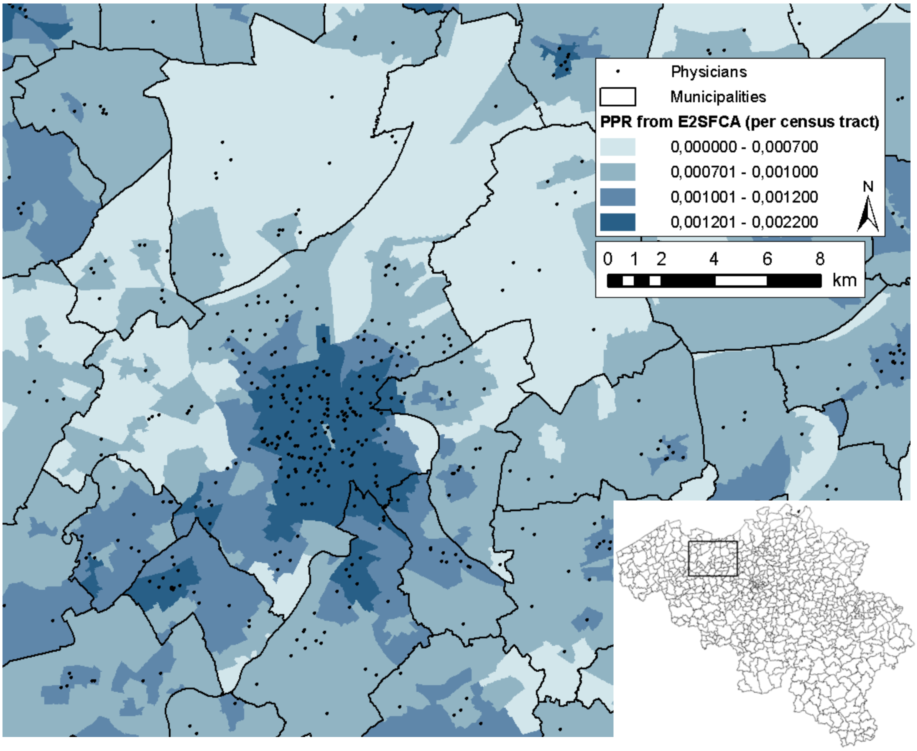

Figure 4.6: Choropleth map of the area around Ghent showing the PPR calculated with the E2SFCA method.

4.6.2 STUDY STRENGTHS AND LIMITATIONS

This study has several strengths. First, most previous studies using FCA-based methods use the centroid of the municipality where physicians live as physician location (Guagliardo, 2004; Luo & Qi, 2009; Luo & Wang, 2003; Luo, 2004), whereas we use the exact location of physicians, leading to more accurate estimations of accessibility and reducing the influence of the MAUP.

Second, distance in this study has been considered following the street network, instead of following a straight line. In many studies (e.g. (Apparicio et al., 2008; Luo, 2004)) the lack of using street network data is considered a major limitation.

Third, the study area (Belgium) is larger and more populated relative to other applications of FCA-based methods in the context of accessibility to primary care. Our study area measures 30,528 km^2 and has 10.8 million inhabitants, whereas in other studies the spatial coverage was limited to 19,774 km^2 and 3.8 million inhabitants (nine counties in central Texas, USA; (Wan et al., 2012)), 14,331 km^2 and 1.6 million (9 counties surrounding DeKalb in northern Illinois, USA; (Luo & Qi, 2009; Luo, 2004)), 4,258 km^2 and 3.4 million (Montreal census metropolitan area, Canada; (Apparicio et al., 2008)), 499 km^2 and 1.9 million (island of Montreal, Canada; (Ngui & Apparicio, 2011)), and 177 km^2 and 601,000 (Washington DC, USA; (Guagliardo, 2004)). Two studies have bigger study areas, but a lower population: 230,000 km^2 and 1.5 million inhabitants (rural Victoria, Australia; (McGrail & Humphreys, 2009b)), and 227,000 km^2 and 5.5 million inhabitants (Victoria, Australia; (McGrail, 2012)).

Fourth, the proposed study adds to the spatial coverage of evidence by spatially complementing existing studies that have been carried out primarily in North America (e.g. (Apparicio et al., 2008; Guagliardo, 2004; Luo & Qi, 2009; Luo, 2004; Ngui & Apparicio, 2011; Wan et al., 2012)) and Australia (e.g. (McGrail & Humphreys, 2009b; McGrail, 2012)) with evidence from Europe.

Fifth, previous studies (ibid.) are all regional, while ours is nation-wide. A disadvantage of a regional study is that there can occur edge effects, because people can also go to a physician in a neighbouring region (Luo, 2004). Our nation-wide study limits this, because it is less likely that inhabitants of Belgium will go to a doctor in a neighbouring country. Small edge effects can still occur within Belgium however. Belgium is separated in two regions with different languages, which implies that people prefer to go to a physician that speaks their native language. It was however difficult to control for this, because the language of physician and aggregated population was not known and there is a lot of bilingualism along the borders between the two regions. Also, with our nation-wide study, we can link our results with the conducted policy of the entire country to check whether the policy decisions correspond with the scientific results.

However, this study also has some limitations, most of which constitute interesting avenues for future work. First, accessibility is considered from the home location. However, people can also access primary health care from their working location, which can influence accessibility (Kwan, 2009; Neutens, Delafontaine, Scott, & De Maeyer, 2012; Salze et al., 2011). Nevertheless, in Belgium people shall probably be inclined to go to a physician in their residential neighbourhood whom they are familiar with, rather than searching for a physician near their work location.

Second, according to some studies, the size of the catchment should vary depending on whether it is urban or rural (Luo & Qi, 2009; McGrail & Humphreys, 2009b; Yang et al., 2006). Despite the small differences between urban and rural populations in Belgium, adding a varying catchment size function (larger catchment sizes for rural populations) could improve the results.

Third, the population per census tract is now centred at its centroid. This is more accurate than looking at a scale level of a municipality or physician zone, but still is an approximation of reality. To improve this, one could consider each home location as a population location, from where accessibility is calculated. However, such data is often not available because of privacy issues and the calculation would be very computationally intensive.

Fourth, various socio-economic factors can also influence accessibility to primary health care (Luo & Wang, 2003). Several studies have considered such factors as financial barriers, car-ownership, and educational level (Joseph & Phillips, 1984; Khan, 1992; Kirby & Kaneda, 2005; Meade & Emsch, 2010; Prentice, 2006; Van der Heyden, Demarest, Tafforeau, & Van Oyen, 2003). Also, data about the actual use of health services could provide information about revealed accessibility, instead of potential accessibility what is studied now. However, collecting this data is expensive (Luo, 2004), definitely at the scale of our study. Socio-economic attributes of physicians (e.g. ethnicity, gender, age) could also provide interesting information. This could however be incorporated in future research. Gender could be accounted for since the sex of a physician is known to be a barrier for certain population groups (e.g., young women (Young, Dobson, & Byles, 2000)). Age could be dealt with because it will enable to identify and anticipate future shortage areas (i.e. areas that are likely to become underserved because of ageing physicians). Some other factors could also be incorporated in future research concerning this topic: e.g. the fact that physicians can also visit patients, visiting hours of physicians, average visit length which can vary per physicians, and congestion problems along the road network.

4.7 CONCLUSIONS

Because of the simplicity of basic PPR methods, policy makers often use these to award financial assistance to shortage areas considering primary health care accessibility. Despite the fact that the PPR takes both supply and demand into consideration, a major disadvantage is its aggregated approach and the lack to detect local variations in accessibility, which arises because of local clustering and dispersion in the physician distribution.

Other GIS-based methods (e.g. distance to closest physician, cumulative opportunity, FCA-based methods) overcome this by not taking any boundaries into consideration. The E2SFCA method takes interaction between population and physicians into account, and considers distance decay by applying a weight function (which can be adjusted depending on the type or importance of a service). This method can however also be used to define accessibility to other services, e.g. dentists, post offices, hospitals, and schools. Network data is more and more accessible, and the effective use of network analysis software makes it possible to easily use more advanced GIS methods.

This manuscript has clearly shown that a different method and scale of analysis provides different results, not only in the total number of census tracts that are underserved, but also in the geographical spread. Currently, health policy makers often neglect the importance of these aspects in accessibility analyses. As a consequence, the distribution of financial incentives to prevent unequal spatial accessibility to primary health care may be biased.

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5

Associations between greenness and physical activity

Adapted from: Dewulf, B., Neutens, T., Van Dyck, D., de Bourdeaudhuij, I., Broekx, S., Beckx, C., Van de Weghe, N. (2016). Associations between greenness and physical activity amongst late middle-aged adults. *Geospatial Health, 11*(411), 225–232.

5.1 Abstract

Physical activity is an important facilitator for health and wellbeing, especially for late middle-aged adults, who are more susceptible to cardiovascular diseases. Physical activity performed in green areas is supposed to be particularly beneficial, so we studied whether or not late middle-aged adults are more active in green areas than in non-green areas and how this is influenced by personal characteristics and the level of neighbourhood greenness. We tracked 180 late middle-aged (58–65 years) adults using global positioning system (GPS) and accelerometer data to know whether and where they were sedentary or active. These data were combined with information on land use to obtain information on the greenness of sedentary and active hotspots. We found that late middle-aged adults are more physically active when spending more time in green areas than in non-green areas. Spending more time at home and in non-green areas was found to be associated with more sedentary behaviour. Time spent in non-green areas was found to be related to more moderate-to-vigorous physical activity (MVPA) for males and to less MVPA for females. The positive association between time spent in green areas together with MVPA was the strongest for highly educated people and for

those living in a green neighbourhood. This study shows that the combined use of GPS and accelerometer data facilitates understanding of where people are sedentary or physically active, information that can help policy makers encourage activity in this age cohort.

5.2 INTRODUCTION

Aging is often associated with physical frailty and increased health problems (Rockwood et al. 2004; Landi et al. 2010). With increasing life expectancy and an expected increased number of middle-aged (45–65 years) and older adults (≥ 65 years) in the future, health care costs are expected to rise globally (Department of Health, 2004; Organization for Economic Cooperation and Development, 2006). Sufficient physical activity and limited sedentary behaviour can prevent certain diseases, especially in middle-aged and older adults who are more susceptible to e.g. cardiovascular diseases than younger people (Nicol and Bredin, 2006; Cavill et al., 2008; U.S. Department of Health and Human Services, 2008; King and Guralnik, 2010; Warburton et al., 2010; Hamilton et al., 2012).

Theoretically, late middle-aged adults (58–65 years) have more leisure time to spend on recreational physical activity (PA) or active transport than younger adults and could thus be more physically active or spend more time away from home (Banister and Bowling, 2004). However, with increasing age people seem to spend more time at home (Kerr et al., 2012), their sedentary behaviour increases (Clark et al., 2014; Ortlieb et al., 2014), and they are less physically active (Bauman and Bull, 2007; Troiano et al., 2008; Ortlieb et al., 2014). In most developed countries, 60 to 70% of adults aged 65 and more do not reach 150 minutes of moderate-to-vigorous PA (MVPA) per week, which is recommended to benefit positive health effects (Services and U.S. Department of Health and Human Services, 1996; WHO, 2010).

The presence of green areas can have a positive impact on achieving these health effects. Several publications demonstrate that a higher availability of accessible green spaces is associated with a higher amount of PA (Van Cauwenberg et al., 2011; Van Holle et al., 2012; Van Holle et al., 2014). On the other hand, when PA occurs in green areas (e.g. parks), it can have positive effects on both physical (e.g. less exposure to pollution) and mental (e.g. wellbeing) health (Frumkin, 2001; St Leger, 2003; Thompson et al., 2011;

Sugiyama et al., 2008; Mackay and Neill, 2010; Fan et al., 2011). It has also been demonstrated that performing PA in non-green areas, especially alongside urban roads, increases inhalation levels and hence exposure to air pollution (Int Panis et al., 2010). Providing a sufficient amount of accessible green areas in urban areas is potentially a cost effective way to improve health and wellbeing. However, the relationships between greenness and health are complex and further exploration is needed. The research presented here explores the link between PA levels of late middle-aged adults and the presence of green areas. Not only do we focus on where PA mainly takes place as this significantly influences health impacts, but also on the general relationship between the amount of available greenness and the level of PA.

To better understand time-activity patterns and PA of late middle-aged adults, it is important to know if and where they are mostly active. Global positioning system (GPS) devices in combination with accelerometers have been previously used to analyse the location-specific PA in children (Elgethun et al., 2003; Oreskovic et al., 2012; Lachowycz et al. 2012; Almanza et al., 2012; Coombes, Sluijs and Jones, 2013). Knowing where people are can give insights into their exposure to different attributes of the environment (e.g. air pollution, noise, greenness) and related health effects (Seeger et al., 2007; Dons et al., 2013; Dewulf et al., 2015; Bekö et al., 2015). Knowing where people are physically active (in terms of location or greenness) can also provide policy makers with insights into people's needs.

There are numerous factors influencing both PA itself and the association between greenness, location (i.e. at home, in the neighbourhood or further away) and PA, which need to be known to further promote PA. Several personal characteristics are correlates of PA. Males with a higher income and normal weight tend to be more physically active than their counterparts (Bauman and Bull, 2007; Ortlieb et al., 2014). For older adults, 'being confident to be physically active and having social support' is positively correlated with PA, while 'feeling too old' has an adverse effect (Bauman and Bull, 2007; Carlson et al., 2012). Next to personal characteristics, the relation of neighbourhood built environment factors and PA has been widely studied in the past, mainly showing that people living in highly 'walkable' neighbourhoods tend to be more physically active (Berke et al., 2007; Frank et al., 2010; King et al., 2011; Van Holle et al., 2014; Marshall et al., 2014; Marquet and Miralles-Guasch, 2015). However, a study based on a national survey on Canadian adults reports that there is a positive association between neighbourhood greenness in a 500 m buffer around the home location and leisure-time PA (McMorris et al., 2015). Research on the influence of greenness on PA in late middle-aged adults is however limited, and there is hitherto no research on how neighbourhood greenness impacts the time spent active in green areas. In general, specific research on late middle-aged adults is relatively uncommon (especially in Europe) and does often not include objective measures of PA (Berke et al., 2007; Kaczynski et al., 2008; Lovasi et al., 2008; Shigematsu et al., 2009; Frank et al., 2010; McMorris et al., 2015) or shows inconsistent results (Berke et al. 2007; Lovasi et al. 2008; Frank et al. 2010; King et al. 2011; Carlson et al. 2012; Van Holle et al. 2014).

To our knowledge, research on the influence of personal characteristics and neighbourhood greenness on the association between greenness, location and PA in late middle-aged adults in Europe is unprecedented. We also feel that the use of detailed GPS and accelerometer data in this line of research can offer new insights. The main goal of this study is to reach an understanding where late middle-aged adults are mostly physically active in terms of location (home/neighbourhood/further) and in relation to greenness. Secondly, the influence of several personal characteristics, such as gender, working status, body mass index (BMI) and diploma as well as neighbourhood greenness has been studied with respect to PA and its association with greenness and location.

5.3 Materials and methods

5.3.1 Participants and procedures

We used data from 180 community-dwelling late middle-aged adults selected from a systematic random sample. Participants were all between 59 and 65 years old, working or retired, and live in Ghent, a medium-sized city (156.2 km^2; 250,000 inhabitants) (Stad Gent, 2014) in Belgium. In order to participate, individuals had to meet three criteria: 1) understand and speak Dutch; 2) live independently; and 3) be able to walk a couple of hundred metres without severe physical restrictions. The home address for each participant was available. They were all visited at home and asked to wear a GPS device (Qstarz BT-Q1000X from Qstarz International, Taipei, Taiwan) and an accelerometer (Actigraph GT3X, GT3X+, or GT1M, from ActiGraph, Fort Walton Beach, USA), a valid and reliable tool for objectively measuring PA levels (Melanson and Freedson, 1995;

Copeland and Esliger, 2009; Pruitt et al., 2010). The instruments were worn at waist height for a week. The participants entered the required information on PA for different purposes (home, work, transport, and recreation) in the international PA questionnaire: the 'long past seven days' version (IPAQ, 2014). They also provided information regarding several personal characteristics: e.g. gender, working status, height and weight (from which the BMI was calculated), and diploma.

5.3.2 DATA COLLECTION AND ANALYSIS

5.3.2.1 GLOBAL POSITIONING SYSTEM AND ACCELEROMETER DATA

GPS and accelerometer data were captured during the participants' waking hours. GPS data were collected at a 15 seconds time interval, between February 22nd 2013 and April 5th 2013 resulting in a raw dataset of 5,672,590 points. Additionally, participants were equipped with an accelerometer, which showed the number of accelerations per 15 seconds. GPS and accelerometer data were linked using the 'personal activity and location measurement system' (PALMS) (Demchak et al., 2012; PALMS, 2015) enabling us to know the number of accelerometer counts for each GPS point, from which each participant's PA level was calculated based on the Freedson cut-off points (Freedson et al., 1998) as shown in Table 5.1.

Because distinction between car and bike movement (especially in the city centre where they have similar speeds) is difficult, the ‘vehicle’ PA level will only be studied in the first part of the manuscript (sections 3.1 and 3.2). In the current study, we only took into account data points where people are either sedentary or active. Data points showing non-wearing time and erroneous ones were omitted from the dataset, resulting in 3,019,491 valid (wearing) data points (53.2% of the original dataset).

Table 5.1: Estimated physical activities based accelerometer counts.

Accelerometer data (counts per minute)	*Type of defined physical activity*	*Activity*
> 60 minutes zero	Non-instrument wearing/sleeping*	Non-defined; not measured
0–100	Sedentary	Reading, watching TV, eating, desk work
0–100 (speed >5 km/h)	Vehicle-related	In transport (car/tram etc.), biking
101–1,951	LPA[1]	Standing (e.g. ironing, washing up and other household tasks), low-speed walking
1,952–100,000	MVPA[2]	Walking, running
> 100,000	Error*	N.A.

[1]Light physical activity;

[2]Moderate-to-vigorous physical activity;

*removed from the dataset.

5.3.2.2 LOCATION CALCULATION

For each data point, the network distance to each participant's home address was calculated in ArcGIS 10.0™ using Network Analyst (ESRI, 2011). Based on this distance, the following movement classification was made:

- 0 to 50 m: at the home location;
- 51–1,000 m: in the neighbourhood;
- > 1,000 m: outside the neighbourhood.

We used a distance of 50 m for the home location including the yard, since too little movement can cause noise in the GPS data. A distance of 1,000 m coincides with a 10–15 minute walk and is internationally used as the neighbourhood boundary (Frank et al., 2005; Lovasi et al., 2008; Oliver et al., 2007; Bauman and Bull 2007; Boruff et al., 2012).

5.3.2.3 GREENNESS CALCULATION

A 10-m resolution land use map containing 48 classes of the Flanders and Brussels region was used to calculate the greenness of each location using ArcGIS 10.0™ (Van Esch et al., 2011). This map was developed by the Flemish Institute for Technological Research (*Vlaams Instituut voor Technologisch Onderzoek* (VITO); Boeretang 200, BE-2400 Mol) and combines the CORINE land cover, detailed parcel data, a biological appreciation map (*Biologische WaarderingsKaart*) and others. The following land use classes were considered as 'green': agriculture, grassland, forest, swamp, heath land and coastal dune as well as park, recreation and sport terrains. The other classes were considered as 'non-green' land uses (e.g. residential, commercial, industrial, roads). While a further distinction could be made between e.g. natural/built green areas and commercial/residential non-green ones, in this exploratory study we made a dichotomist distinction to offer a first view on the association between greenness and PA.

5.3.2.4 Average values per person

To analyse the association of greenness and location with PA per person and to study the influence of personal characteristics on this association, the point dataset was summarised to obtain average values per person. The following values were calculated using pgAdmin™ (a PostgreSQL administration and management tool; PostgreSQL Global Development Group, 2015): hours of PA levels (sedentary, vehicle, light PA (LPA), MVPA) per day, hours in green/non-green areas per day, hours at home/neighbourhood/further per day, hours of PA levels in green/non-green per day, hours of PA levels at home/neighbourhood/further per day. Only participants with at least 6 hours of valid accelerometer data per day and at least 4 valid days were included in the analyses. As a result, we maintained 138 (76.7%) participants of the initial 180, with respect to whom full further analyses were done.

5.3.2.5 Neighbourhood greenness

The neighbourhood greenness was calculated in a network buffer (only using 'walkable' roads) of 1,000 m around each participant’s home location using ArcGIS 10.0™, and expressed as the percentage green land use cells of all cells. Data on the road network (TeleAtlas MultiNet®; Tele Atlas, 2015) was used to define the walkable roads.

5.3.3 Geographical and statistical analyses

Geographical and visual analyses were performed in QGIS 2.8™ (QGIS Develoment Team, 2015). Statistical analyses were done using SPSS Statistics 22™ (IBM Corp., 2013). The association between greenness, location and PA per GPS data point ($n =$

3,019,491) was tested for significance using an independent-samples t-test (after successfully testing the data for normality). The averaged data per person ($n = 138$) were examined by performing a linear regression analysis to study the associations of greenness and location with PA (again, after successfully testing the data for normality). To examine whether these associations are similar in different socio-demographic subgroup, stratified linear regression analyses were conducted.

5.4 Results

This section presents first some general descriptive statistics about the population sample. The second part describes analyses of the 3,019,491 valid data points to detect where the late middle-aged adults ($n = 180$) are mostly active. The third part deals with the analyses based on the data per person ($n = 138$) and has to do with the association between greenness, the distance from home and PA level per person and includes an analysis of the influence of several personal characteristics and neighbourhood greenness.

5.4.1 General descriptive statistics

General descriptive statistics of the 180 participants are presented in Table 5.2. The majority of the sample was non-smoking, had a higher education, was retired and had a partner. The mean age was 61.7 years and the mean body mass index (BMI) = 26.0. The sample contains slightly more women than men.

From all valid data points ($n = 3{,}019{,}491$) it is clear that the participants were mainly sedentary (65.5%), followed by LPA (24.0%), vehicle (5.8%) and MVPA (4.7%). Table 5.3 shows the distribution of valid data points for both greenness and location. The data points referring to the participants' whereabouts mainly pointed at non-green land use classes (residential, commercial, or other industrial) compared to green land use classes (forest, recreation, park, grassland, agriculture). Additionally, it was found that late middle-aged adults spent most of their time at the home location rather than anywhere else.

Table 5.2: General descriptive statistics of the study sample.

Parameter	*Sample (n=180)*
Age (mean [5%–95%][1])	61.7 [58.0–65.0]
BMI[2] (mean [5%–95%][1])	26.0 [20.6–32.4]
Gender (% male)	47.8
Smoking (% not smoking)	90.0
Working/retired (% working)	23.3
Marital status (%)	
Married	67.8
Living together	7.8
Single	4.4
Divorced	14.4
Widow(er)	5.6
Education (%)	
Primary school	7.2
Secondary school	40.0
Higher/university	52.2
Missing	0.6

[1]Confidence interval

[2]Body mass index

Table 5.3: Distribution of valid data points (n=3,019,491) with regard to greenness/non-greenness and location.

	Non-green area	*Green area*	*Total*
Home (< 50 m)	1,618,459 (53.6%)	12,931 (0.4%)	1,631,390 (54.0%)
Neighbourhood (50–1,000 m)	441,267 (14.6%)	30,605 (1.0%)	471,872 (15.6%)
Further away (> 1000 m)	852,484 (28.2%)	63,745 (2.1%)	916,229 (30.3%)
Total	2,912,210 (96.4%)	108,281 (3.6%)	3,019,491 (100%)

5.4.2 Where are late middle-aged adults mostly active?

5.4.2.1 Geographical and visual analyses

In Figure 5.1, data points from one specific green area as an example (the *'Citadel'* park) are visualised for all participants, indicating the PA level. One can see that in this green area MVPA (probably mainly walking) was done along the walking trails. At certain locations, we observed some LPA and sedentary behaviour as well, mainly near certain points of interest (in the Southwest a statue with benches, in the Northeast a pond with benches). This type of pattern was also observed at other green locations.

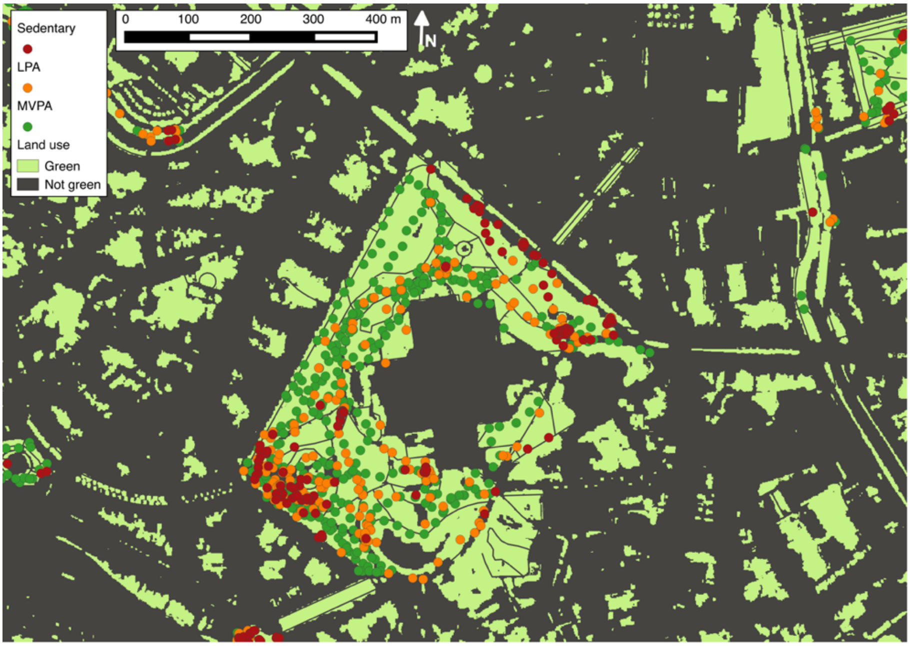

Figure 5.1: Visualization of the collected GPS and accelerometer data in a green area (*Citadel Park* in Ghent, Belgium).

5.4.2.2 Associations of greenness, location, and PA per data point

Figure 5.2 visualises the PA levels depending on the location and greenness of the data points, summed to 100% for greenness. We did not consider the home location (> 50 m) here, since this is a mainly non-green area, where this analysis would be purposeless. In the neighbourhood, the participants were mainly sedentary and performed LPA. Outside the neighbourhood we observed less sedentary behaviour ($p < 0.05$) in favour of more time spent in the vehicle ($p < 0.001$) and more MVPA ($p < 0.001$). LPA was approximately the same in the neighbourhood and further, and mainly involved walking at a slow pace.

Taking greenness into account, sedentary time was found to be much higher in non-green areas than in green areas ($p < 0.01$). There is generally more vehicle use ($p < 0.01$) in green areas, because green areas are often located outside city centres and car use is higher there. LPA ($p < 0.05$) but more striking MPVA ($p < 0.001$) was significantly higher in green areas than in non-green areas.

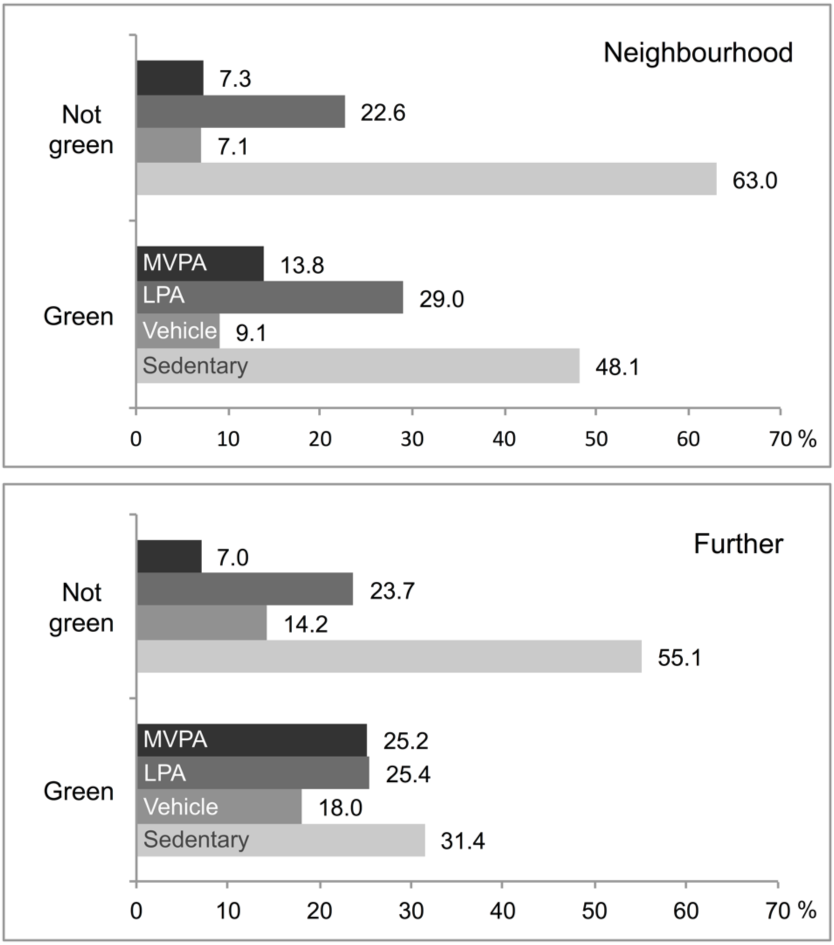

Figure 5.2: Percentages of the type of physical activity at of all valid points dependent on greenness and location.

5.4.3 Individual greenness/location/PA association and the influence of personal characteristics and neighbourhood greenness

5.4.3.1 Descriptive statistics

Table 5.4 shows some additional general descriptive statistics of the participants ($n = 138$), concerning greenness, location and PA. Each participant had an average of 12.0 hours of data per day (non-wearing time and sleeping excluded) for on average 6.6 days. Only 30 minutes per day was spent in green areas, 6.7 hours are spent at the home location, almost 2 hours in the neighbourhood and more than 3 hours further away (the histogram of the time spent further away shows a large peak between from 1 to 5 hours, and a smaller peak from 6 to 9 hours). Almost 8 hours is spent being sedentary, and approximately 2.8 hours per day is spent being active (LPA and MVPA).

Table 5.4: Descriptive statistics of the study sample (n = 138) concerning greenness, location, and physical activity.

Parameter	*Hours per day (mean [5%–95%][1])*
Valid days	6.6 [5.0–8.0] (days)
Data	12.0 [8.8–14.8]
Greenness	
Non-green	11.6 [8.4–14.4]
Green	0.4 [0.0–1.7]
Location	
Home	6.7 [0.0–12.0]
Neighbourhood	1.8 [0.1–10.3]
Further	3.4 [0.6–9.4]
Physical activity	
Sedentary	7.9 [5.2–10.4]
Vehicle	0.6 [0.1–1.3]
LPA[2]	2.3 [1.3–3.6]
MVPA[3]	0.5 [0.1–1.3]

[1]Confidence interval

[2]Light physical activity

[3]Moderate-to-vigorous physical activity

The results indicate that 70% of the late middle-aged adults are sedentary for more than 7 hours per day and 35% does not reach the 21.4 minutes of MVPA per day (or 150 minutes per week) to benefit positive health effects.

5.4.3.2 Associations of greenness, location, and PA per person

We performed a linear regression analysis to study the association of greenness and location (i.e. being at home) with PA and found some significant results (Table 5.5). More time spent in non-green areas was associated with more hours of sedentary behaviour and LPA, while more time in green areas was associated with less sedentary behaviour and more hours of MVPA. More time spent at home was also associated with more sedentary behaviour and LPA.

Table 5.5: Results of linear regression analysis between greenness, location, and physical activity.

Independent variable	– dependent variable	$\boldsymbol{\beta}$[1]
Hours in non-green area	– hours of sedentary behaviour	0.80***
Hours in non-green area	– hours of LPA[2]	0.47***
Hours in non-green area	– hours of MVPA[3]	0.10
Hours in green area	– hours of sedentary behaviour	-0.16*
Hours in green area	– hours of LPA	0.02
Hours in green area	– hours of MVPA	0.17*
Hours at home	– hours of sedentary behaviour	0.33***
Hours at home	– hours of LPA	0.37***
Hours at home	– hours of MVPA	0.03

[1]Standardized β regression coefficient

[2] Light physical activity

[3] Moderate-to-vigorous physical activity

*p <0.05; **p <0.01; ***p <0.001

5.4.3.3 Influence of personal characteristics and neighbourhood greenness

Table 5.6 shows of our analysis whether the association of greenness and location with PA differs depending on various personal characteristics (gender, working status, BMI, and educational level).

Table 5.6: Results of the stratified linear regression analysis.

	Gender		*Working status*		*BMI*		*Diploma*		*Neighbourhood greenness*	
Indep. var. - dep. var. (hours in/of)	β_{male}	β_{female}	$\beta_{retired}$	$\beta_{working}$	β_{normal}	β_{high}	β_{low}	β_{high}	β_{not}	β_{green}
Non-green - sed. beh.	0.86***	0.73***	0.82***	0.70***	0.78***	0.82***	0.79***	0.84***	0.81***	0.75***
Non-green - LPA	0.50***	0.52***	0.48***	0.46**	0.44**	0.50***	0.56***	0.41***	0.48***	0.46***
Non-green - MVPA	0.31**	-0.27*	0.13	-0.06	0.01	0.17	0.11	0.07	0.07	0.18
Green - sed. beh.	-0.20*	-0.14	-0.22*	0.64	-0.30*	-0.03	-0.36**	0.05	-0.18	-0.03
Green - LPA	0.24**	-0.13	0.04	-0.06	-0.17	0.16	-0.04	0.06	0.01	0.09
Green - MVPA	0.26*	0.15*	0.19*	0.14*	0.23*	0.14*	0.10*	0.30**	0.07	0.31**
At home - sed. beh.	0.30**	0.37**	0.50***	-0.23	0.28*	0.38**	0.45***	0.24*	0.40**	0.24*
At home - LPA	0.36**	0.38***	0.40***	0.36*	0.41**	0.35**	0.34**	0.42***	0.36**	0.35**
At home - MVPA	-0.10	0.14	0.02	0.08	0.04	0.03	0.04	0.04	0.08	-0.00

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

The positive associations between the time spent in non-green areas and time being sedentary or in LPA were comparable for the different subgroups. The association between time spent in non-green areas and time in MVPA was positive for males, i.e. more time spent in non-green areas was related to more MVPA, and negative for females, i.e. more time in non-green was related to less MVPA.

The negative association between time spent in green areas and sedentary time was only significant for male, retired participants with a normal BMI and lower education. The positive association between time spent in green areas and LPA was only significant for men, and the association between time spent in green areas and MVPA was the strongest for highly educated people and those living in a green neighbourhood. The positive association between the time spent at home and sedentary behaviour was strongest for retired participants. The association between the time spent at home and doing LPA is comparable in the different subgroups.

5.5 DISCUSSION

Previous research has shown that being active in green areas has a positive effect both on physical and mental health (Dewulf et al., 2016; Frumkin, 2001; St Leger, 2003; Thompson Coon et al., 2011). This study demonstrates that late middle-aged adults spend an average of 30 minutes per day in green areas, and when more time is spent there, people are more active compared to their behaviour in non-green areas. This suggests that availability of green areas lead to higher amounts of PA. The knowledge of the link between greenness and PA hotspots is important for policy makers wishing to stimulate PA. Nevertheless, there will always be a large proportion of PA occurring in non-green areas (e.g. in city centres). Being physically active in these non-green areas does not necessarily imply a negative health impact, but small green features could be introduced to improve people's wellbeing. However, spending more time at home is associated with more sedentary behaviour, and with more time spent at home with increasing age (Kerr et al., 2012), a vicious circle is established that could thus lead to more sedentary behaviour and related health risks (Clark et al., 2014; Ortlieb et al., 2014).

Our results of the influence of various characteristics on the association between greenness, location and PA indicate that the association between the time spent in non-green and MVPA is positive for males and negative for females. This means that more time spent in non-green areas is related to more MVPA for males, while to less MVPA for females. The positive association between the time spent in green areas and MVPA is strongest for highly educated people and for those living in a green neighbourhood, indicating that living in a green neighbourhood leads to more PA when time is spent in green areas, which coincides with the findings by McMorris et al. (2015). In contrast to previous studies (Berke et al., 2007; Frank et al., 2010; King et al., 2011; Marquet & Miralles-Guasch, 2015; Marshall et al., 2014; Van Holle et al., 2014), on the other hand, living in a non-green neighbourhood was not found to be associated with more PA and less sedentary behaviour. The positive association between the time spent at home and sedentary behaviour was found to be the strongest for retired participants, indicating that once retired the time spent at home is often linked with sedentary behaviour. It would be interesting to study the association between greenness in the home neighbourhood and PA (and more specifically PA in green areas) further in different age groups.

Our study has several strengths compared with similar studies. First, this research is the first to study the association between greenness, location and PA with respect to late middle-aged adults in Europe. Second, most studies are only based on self-reported PA values (Berke et al., 2007; Frank et al., 2010; Kaczynski et al., 2008; Lovasi et al., 2008;

Shigematsu et al., 2009), while we used accelerometer-based PA, which offers more objective values. This made it possible to attribute PA levels to each GPS data point, which cannot be done when using only self-reported data, where for example only binary data (participant walked or did not walk today) is extracted (Clark et al., 2014). Third, the combined use with GPS data offers detailed insights in where active behaviour is done (Duncan, Badland, & Mummery, 2009; Kerr et al., 2012; Oreskovic et al., 2012; Troped, Wilson, Matthews, Cromley, & Melly, 2010). In contrast to previous studies, where only the home neighbourhood is considered, we additionally gathered information on the specific context of where PA is carried out.

Although our approach had also limitations, they open up interesting avenues for future work. First and foremost, we already described the difficulty to detect bicycle use (Hansen, Kolle, Dyrstad, Holme, & Anderssen, 2012) when deriving PA levels from accelerometer data. We considered both bike and car use as 'vehicle', therefore losing some active data when people are biking. In future work, mode-detection algorithms could be used to detect transport modes. However, for the specific research results reported here, the loss of information must be deemed limited as only 5.8% of the entire dataset was considered 'vehicle'-related. Second, in this cross-sectional study it was not possible to extract causal relationships. One must therefore be careful when interpreting the results, because it is not given that the greenness of the area is the cause of a higher PA activity. Future studies should focus on longitudinal research to detect whether or not changes are causal, and occasional or persistent. In this way, the effect of introducing green areas (using natural experiments) on PA levels can be studied (Bauman & Bull, 2007). Third, the data were collected in March, possibly influencing space-time activity patterns of some participants because of the weather (e.g. low temperatures, snow). Future research should incorporate weather characteristics (e.g. temperature, rain, wind speed) to account for this. Fourth, future studies on this topic should try to incorporate socio-economic status (e.g. income, education) indicators, to analyse its possible correlation with 'walkability' and greenness and potential influence on the association of greenness, location and PA. Finally, we considered agriculture as a green area. Despite the fact that moving through these areas is associated with positive health effects, this can possibly affect our results since such trips can also be functional trips. For example, people living in a rural neighbourhood are likely to spend more time in green areas because they automatically pass through green areas when moving. This could be reduced in future research by filtering the trips per goal. Related to this final limitation, a more detailed distinction could be made between natural (e.g. forest, coastal dune, grassland) and built green areas (e.g. park, sport terrain), in future work considering the possibility that they could be differently related to PA.

5.6 Conclusions

The combined use of GPS and accelerometer data can help detecting where people are sedentary or physically active. Knowing where people are mainly physically active should encourage policy makers to increase activity in this age cohort. Despite the fact that the observed population spends little time in green areas, higher levels of PA are reached in green areas. As this is the first research studying the association between greenness, location and PA, and the influence of several characteristics on this relationship, our results are useful in updating the current knowledge on PA in late middle-aged adults. However, more research is needed to better understand where and why late middle-aged adults are physically activity or sedentary.

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6

Dynamic modelling of inhaled air pollution using GPS and accelerometer data

Adapted from: Dewulf, B., Neutens, T., Van Dyck, D., de Bourdeaudhuij, I., Int Panis, L., Beckx, C., Van de Weghe, N. (2016). Dynamic assessment of inhaled air pollution using GPS and accelerometer data. *Journal of Transport & Health, 3*(1), 114-123.

6.1 Abstract

Exposure to air pollution can have severe health impacts, especially for the elderly. To estimate the inhaled dose of air pollution, traditionally only the air pollution concentration at the home location is considered, without incorporating individual travel behaviour and physical activity. This can lead to bias in health impact assessment and epidemiological studies, possibly underestimating exposure to air pollution and misinforming policy makers. Our paper addresses this issue using accurate 7-day GPS and accelerometer data on 180 participants aged between 58 and 65 living in Ghent (Belgium). NO_2 concentration for Belgium is available from a land-use regression model. Three methods are used to calculate the inhaled dose of NO_2. The first method is the traditional static method, using only the NO_2 concentration at the home location. The second method incorporates travel behaviour using GPS data, thus looking at the NO_2 concentration at the exact location of the participant. The third method additionally incorporates accelerometer data and estimates the transport mode used and physical activity to calculate the ventilation rate. When incorporating geographical location, differences in inhaled dose of NO_2 depend on the NO_2 concentration at the home

location and the individual travel behaviour. When additionally incorporating ventilation rate, the inhaled dose of NO_2 increases by more than 12%. In addition to comparing these three methods with each other, the influence of transport mode is tested. Cycling is associated with increased inhaled doses of NO_2 relative to other modes. It is important for health impact assessment and epidemiological studies to incorporate individual travel behaviour and physical activity to measure the inhaled dose of air pollution, and this can be done accurately using GPS and accelerometer data.

6.2 Introduction

There is a large body of evidence indicating that exposure to air pollution causes various acute and chronic health effects, such as respiratory and cardiovascular diseases (Beelen et al., 2014; Brook et al., 2010; Brugge, Durant, & Rioux, 2007; Gehring et al., 2013; HEI, 2010; Peters et al., 2004; Pope III & Dockery, 2006; Riediker et al., 2004; WHO, 2003). Several pollutants are identified as culprits of negative health effects, such as black carbon (BC), particulate matter (PM), and nitrogen dioxide (NO_2). In our study, we focus on NO_2, a pollutant that can cause an increase in pulmonary morbidity, a worsening of obstructive lung disease and a higher susceptibility to airway infections (Blomberg et al., 1997; Cesaroni et al., 2014; WHO, 2003). An additional focus of this article is on late middle-aged adults (age 58 to 65 years), since this is a vulnerable group concerning health impacts of air pollution and has a growing share of the population (Bentayeb et al., 2012; Schwartz, 1999).

The majority of current health impact assessment and epidemiological studies examines exposure to air pollution by solely considering air pollution concentrations at the respondent's home location (Brunekreef et al., 2009; Jerrett et al., 2013). Such static approaches that do not take individual travel behaviour into account may give rise to biased exposure assessments and may misinform policy makers. Not only do people have certain activities during the day, their travel behaviour also varies between days. It has been shown that people's individual travel behaviour has a major influence on exposure to air pollution (Beckx et al., 2009; Dons et al., 2011; Setton, 2011).

To obtain better and more dynamic estimates of inhaled dose of air pollution, more detailed information on travel behaviour is needed. This can be obtained by using an activity-based transport model (Beckx et al., 2009; Dhondt et al., 2012; Fecht, Beale, & Briggs, 2014), travel diaries or Global Positioning Systems (GPS) data (Houston, Ong, Jaimes, & Winer, 2011). Using more accurate travel behaviour data, someone's geographical location can be incorporated to calculate the inhaled dose of air pollution more dynamically. Compared with the static approach in which only air pollution at a person's home location is accounted for, incorporating activity patterns and travel behaviour may lead to an increase in estimated exposure to air pollution (Dhondt et al., 2012).

Not only the location where people are, but also their physical activity (PA) has a major influence on the inhaled dose of air pollution. A high physical activity implies a high ventilation rate and thus a higher inhaled dose, but performing physical activity while being exposed to air pollution can also cause intermediary health effects like acute pulmonary effects, e.g. temporary decreases in lung function, acute cardiovascular effects (Bos, De Boever, Int Panis, & Meeusen, 2014; Strak et al., 2010; Weichenthal et al., 2011). Despite the fact that the relationship between PA and ventilation rate is uncertain because of complex lung physiology (EPA, 2011), incorporating ventilation rate can result in more detailed values of inhaled dose.

Research combining both individual travel behaviour data and detailed physical activity or ventilation rate data, to improve the estimation of exposure to air pollution, is fairly limited (de Nazelle et al., 2013; Hu, Wang, Rahman, & Sivaraman, 2014; Int Panis et al., 2010). De Nazelle et al. (2013) showed that using a smartphone app to track geographic location and physical activity could considerably alter exposure estimates. Hu et al. (2014), for their part, found significant differences in inhaled dose of CO taking ventilation rate into account (driving 186 μg/h, cycling 396 μg/h, and jogging 600 μg/h), compared to an equal inhaled dose of 156 μg/h when not incorporating ventilation rate. Finally, Int Panis et al. (2010) showed that bicycle users inhale 4.3 times more air pollution than car drivers because of a higher ventilation rate.

This paper will contribute to the above strand of literature considering both travel behaviour (geographical location) and physical activity (and the resulting ventilation rate) to model the inhaled dose of air pollution. Our study seeks to bring additional evidence on how the combined use of GPS and accelerometer data can offer more detailed estimations of the inhaled dose of air pollution. To overcome the limitations of previous studies, we use a large sample of 180 late middle-aged adults using accurate standalone GPS and accelerometer devices, collecting data from an entire week. Three methods are used to calculate the inhaled dose of NO_2. The first method is the traditional static approach that only considers the NO_2 concentration at the home location and will serve as a benchmark. The second method takes individual travel behaviour into account, by considering the outdoor NO_2 concentration at the exact location where the participants are located. The third method additionally takes transport mode and physical activity into account, to make a better estimation of the inhaled dose by incorporating the ventilation rate. This paper has two specific objectives. The first and main objective of this study is to compare the inhaled dose from these three methods. The second objective is to check whether or not transport mode affects the inhaled dose.

6.3 Material and methods

6.3.1 Data

For this study we used data of 180 adults, aged between 58 and 65 years, living in Ghent, a medium-sized city (247,941 inhabitants in 2012; Stad Gent, 2012) in Belgium. This age group contains both working and retired people. The participants were selected from a systematic random sample. In order to recruit a sufficient number of participants, the Public Service of Ghent selected a random sample of 7,500 58–65 year old adults from the municipal register. An information letter with the purpose of the study was sent by postal mail, with the announcement of the visit of a trained interviewer during the subsequent two weeks. Approximately one week after sending the letters, all selected late middle-aged adults were visited at home. The general descriptive statistics of the participants can be found in Table 6.1.

7-day GPS data were collected with a Qstarz BT-Q1000X, at 15 seconds time interval, between February 22nd 2013 and April 5th 2013, resulting in a dataset of 5,811,375 points. Despite the fact that the participants live in Ghent, the GPS points are spread over the entire country. For 89.2% of the GPS data, 6 or more satellites were used to calculate the position, indicating a high accuracy. Additionally, participants wore an accelerometer Actigraph GT3X, GT3X+, or GT1M collecting a ‘count’ value giving an indication of the energy expenditure of the participant.

The NO_2 concentration data (in µg/m^3) for the entire country of Belgium is available from the Land Use Regression model RIO-IFDM-MIMOSA4 (Residual Interpolation optimised for Ozone - Immission Frequency Distribution Model - *Milieu Model Stad Antwerpen*, Antwerp City Environmental Model) from VITO (*Vlaams Instituut voor Technologisch Onderzoek*, Flemish Institute for Technological Research). This model combines air quality measurements and land use (RIO), meteorology (IFDM), and vehicle fleet and COPERT4 emission functions (MIMOSA4) to obtain high-resolution (10m) air quality maps (Lefebvre et al., 2013). We used the average NO_2 concentration for the entire study period, because using hourly values severely increases the computational burden. The NO_2 concentration in Belgium varies from 5 to 91 µg/m^3 and in the Ghent municipality from 16 to 66 µg/m^3.

Table 6.1: General descriptive statistics of participants (n=180).

Parameter	Sample
Sex (%)	
Female	52.8
Male	47.2
Age (mean)	61.7
Education (%)	
Lower (technical and vocational)	47.8
Higher (general and higher)	51.7
Missing	0.6
Employment status (%)	
Working	23.9
Retired	76.1
Body mass index (mean)	26.0
Smoking (%)	
No	90.6
Yes	9.4
Marital status (%)	
Without partner	23.9
With partner	76.1

6.3.2 DATA PROCESSING

GPS and accelerometer data are linked to each other using PALMS (Personal Activity and Location Measurement System; Demchak et al., 2012; PALMS, 2015). Figure 6.1

schematically shows how the ventilation rate was calculated. The transportation mode is defined based on an existing speed profile (Reddy et al., 2010) to discriminate between walking (including vigorous walking and jogging), cycling and driving (car or public transport). The ventilation rate is calculated based on transport mode and physical activity (from the accelerometer counts). Despite the fact that being stationary is not a transport mode, it is however included in the analysis. When stationary or walking, physical activity is defined based on the number of accelerometer counts (Freedson, Melanson, & Sirard, 1998), from which a ventilation rate is calculated (Allan & Richardson, 1998), as indicated in

Table 6.2. Because accelerometer devices detect little activity when riding a bike, this method cannot be used for the transport mode cycling. Therefore, often a constant factor is used to calculate the ventilation rate relative to sedentary behaviour (Bernmark, Wiktorin, Svartengren, Lewné, & Aberg, 2006; O'Donoghue, Gill, McKevitt, & Broderick, 2007; Rank, Folke, & Jespersen, 2001; Zuurbier, Hoek, van den Hazel, & Brunekreef, 2009). A better alternative is to use cycling speed as a proxy to calculate ventilation rate, using equation 6.1 (McNabola, Broderick, & Gill, 2007). For driving (car and public transport), we assume that physical activity levels are similar to sedentary behaviour. Additionally, the ventilation rate was adjusted for gender using equations 6.2 and 6.3, based on Allan and Richardson (1998).

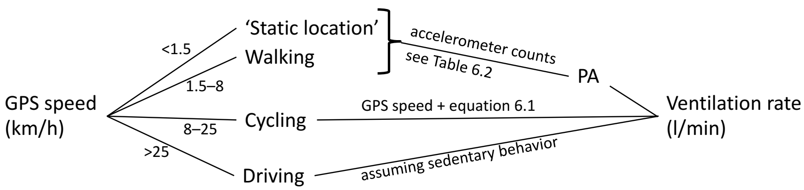

Figure 6.1: Schematic representation of ventilation rate calculation.

$$VR_{cycle} = 3.55/1.61 \times v - 5.85 \quad \text{(eq. 6.1; McNabola et al., 2007)}$$
$$VR_{male} = 0.0079 \times VR^2 + 0.94 \times VR \quad \text{(eq. 6.2; Allan \& Richardson, 1998)}$$
$$VR_{female} = 0.0071 \times VR^2 + 0.75 \times VR \quad \text{(eq. 6.3; Allan \& Richardson, 1998)}$$

with VR the ventilation rate (in l/min), and v cycling speed (in km/h).

Table 6.2: Physical activity and ventilation rate (l/min) for stationary and walking based on the number of accelerometer counts.

Accelerometer counts (per 15 s)	*Physical activity*[1]	*Ventilation rate*[2] *(l/min)*
< 25	Sedentary	7.5
25–488	Light physical activity	10.4
488–1431	Moderate physical activity	14.7
1431–2375	Heavy physical activity	27.6
> 2375	Very heavy physical activity	54.3

[1]: Based on Freedson et al. (1998).

[2]: Based on Allan and Richardson (1998).

Next, the NO_2 concentration was spatially joined with each GPS point using PostGIS. Points outside the Belgian borders, with no pollution data available, were removed from the dataset. This way, 5,730,887 data points remained, which is 98.6% of the original dataset.

6.3.3 Data analyses

Knowing the ventilation rate and the NO_2 concentration, the inhaled dose of NO_2 was calculated using three methods. In this manuscript, we use the term 'inhaled dose' for the inhaled concentration of air pollution, without incorporating the exhaled concentration. The first method calculated the inhaled dose statically, using only the air quality at the home location and using a sedentary breathing rate (equation 6.4). The second method is more dynamic, since it takes individual travel behaviour into account using GPS data. Here, the NO_2 concentration at each GPS location and a sedentary ventilation rate are used (equation 6.5). The third method is similar to the second one, but now the calculated ventilation rate, based on transportation mode and physical activity, at each individual GPS point is used (equation 6.6). Figure 6.2 illustrates this overlay of GPS points with the calculated ventilation rate value on a base map of NO_2 concentration, from a typical location in Ghent. The inhaled dose was calculated per 15 seconds and transformed to a value in μg/h. Subsequently, average values for NO_2 concentration, ventilation rate and inhaled dose were calculated per person.

$$Inhaled\ dose_1 = C_{home} \times VR_{sedentary} \quad \text{(eq. 6.4)}$$

$$Inhaled\ dose_2 = \sum_{i=0}^{all\ GPS\ points} C_i \times VR_{sedentary} \quad \text{(eq. 6.5)}$$

$$Inhaled\ dose_3 = \sum_{i=0}^{all\ GPS\ points} C_i \times VR_i \quad \text{(eq. 6.6)}$$

with C_{home} the NO_2 concentration (in µg/m^3) at the home location, C_i is the NO_2 concentration (in µg/m^3) on GPS point i, and VR the ventilation rate (transformed from l/min to m^3/15s) associated with sedentary behaviour or on GPS point i.

The averaged data per person was statistically analysed using IMB SPSS Statistics 22. To check for significant differences between the mean inhaled doses of the three methods, a paired-samples t-test was performed on all data points. An independent-samples t-test was used on all data points to check for significant differences between the mean inhaled doses from the dynamic method for different transport modes (after successfully testing the data for normality). Statistical significance was set at $p < 0.05$.

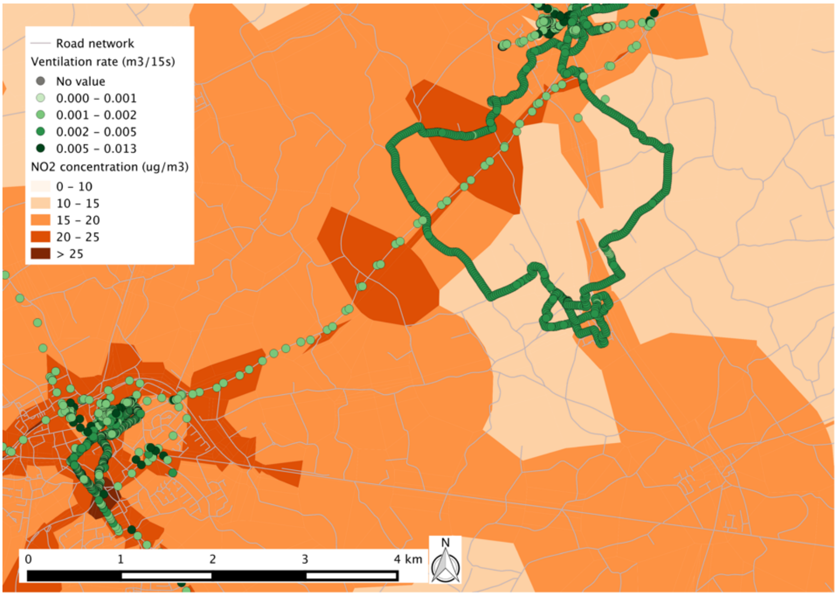

Figure 6.2: Map illustrating the overlay of GPS points with the calculated ventilation rate on base map with NO_2 concentration, from a random location in Ghent.

6.4 RESULTS

This section is divided into two parts following the study objectives. First, the three methods used to calculate the inhaled dose of NO_2 are compared with each other. Second, the influence of the transport mode on inhaled dose of NO_2 is tested.

6.4.1 STATIC VS. DYNAMIC MEASUREMENTS OF INHALED DOSE

The mean NO_2 concentration and mean inhaled dose of NO_2 per person were calculated with the three methods and are presented in Table 6.3. The differences are small, but all values are significantly different from each other ($p < 0.001$), based on a paired-samples t-test. Figure 6.3 shows the mean inhaled dose of NO_2 per person (data shown on participant's home location) using method 3. Large differences in inhaled dose of NO_2 can be observed, not linked with the underlying NO_2 concentration, indicating that the inhaled dose also largely depends on the travel behaviour and ventilation rate.

Table 6.3: Mean NO_2 concentration and mean inhaled dose of NO_2 per person calculated with the three different methods.

Method	*Mean NO_2 concentration ($\mu g/m^3$) [σ_x]*	*Mean inhaled dose of NO_2 ($\mu g/h$) [σ_x]*
1: NO_2 concentration at the home location	29.38 [5.56]	11.12 [2.36]
2: NO_2 concentration at each GPS point	28.87 [4.89]	10.93 [2.23]
3: NO_2 concentration and ventilation rate at each GPS point	28.87 [4.89]	12.33 [2.67]

By incorporating the GPS location of participants (comparing method 1 and 2), the mean inhaled dose of NO_2 decreases with 0.19 μg/h (1.74%). To better visualise the disparity between the first two methods, Figure 6.4a shows the mean inhaled dose calculated with method 2 minus the inhaled dose calculated with method 1. About half of the participants (48%) has a lower inhaled dose of NO_2 using method 2, compared to method 1. The other half (52%) has a higher inhaled dose, thus leading to the small mean difference between method 1 and 2. Despite the small average difference between the two methods, individual differences are not to be neglected. There is a significant

Pearson correlation ($r = 0.44, p < 0.001$) between the NO_2 concentration at the home location and the difference in inhaled NO_2 between method 1 and 2.

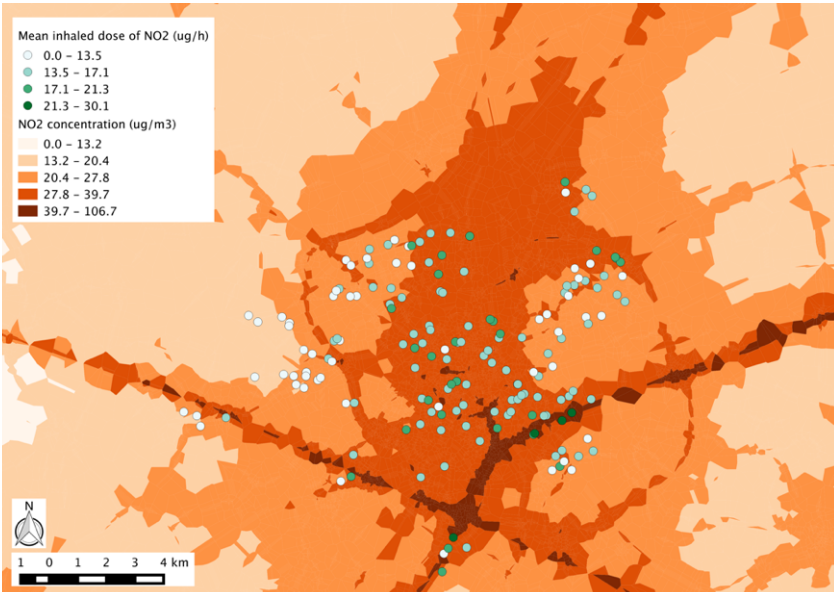

Figure 6.3: Mean inhaled dose of NO_2 per person using method 3, as an overlay on the NO_2 concentration.

When additionally including ventilation rate based on transport mode and accelerometer counts (method 3) the inhaled dose of NO_2 increases by 1.40 µg/h (12.81%) compared to method 2. Figure 6.4b shows the mean inhaled dose calculated with method 3 minus the inhaled dose calculated with method 2. Almost all (97.8%) participants have an increase in inhaled dose.

6.4.2 Influence of transport mode on inhaled dose

For this analysis, we use method 3 since this method uses values of NO_2 concentration and ventilation rate at each GPS point. To investigate the influence of transport mode on the inhaled dose, we first look at the NO_2 concentration and the ventilation rate in function of transport mode. Figure 6.5a and Figure 6.5b show this visually using boxplots, and in Table 6.4 the mean values are presented.

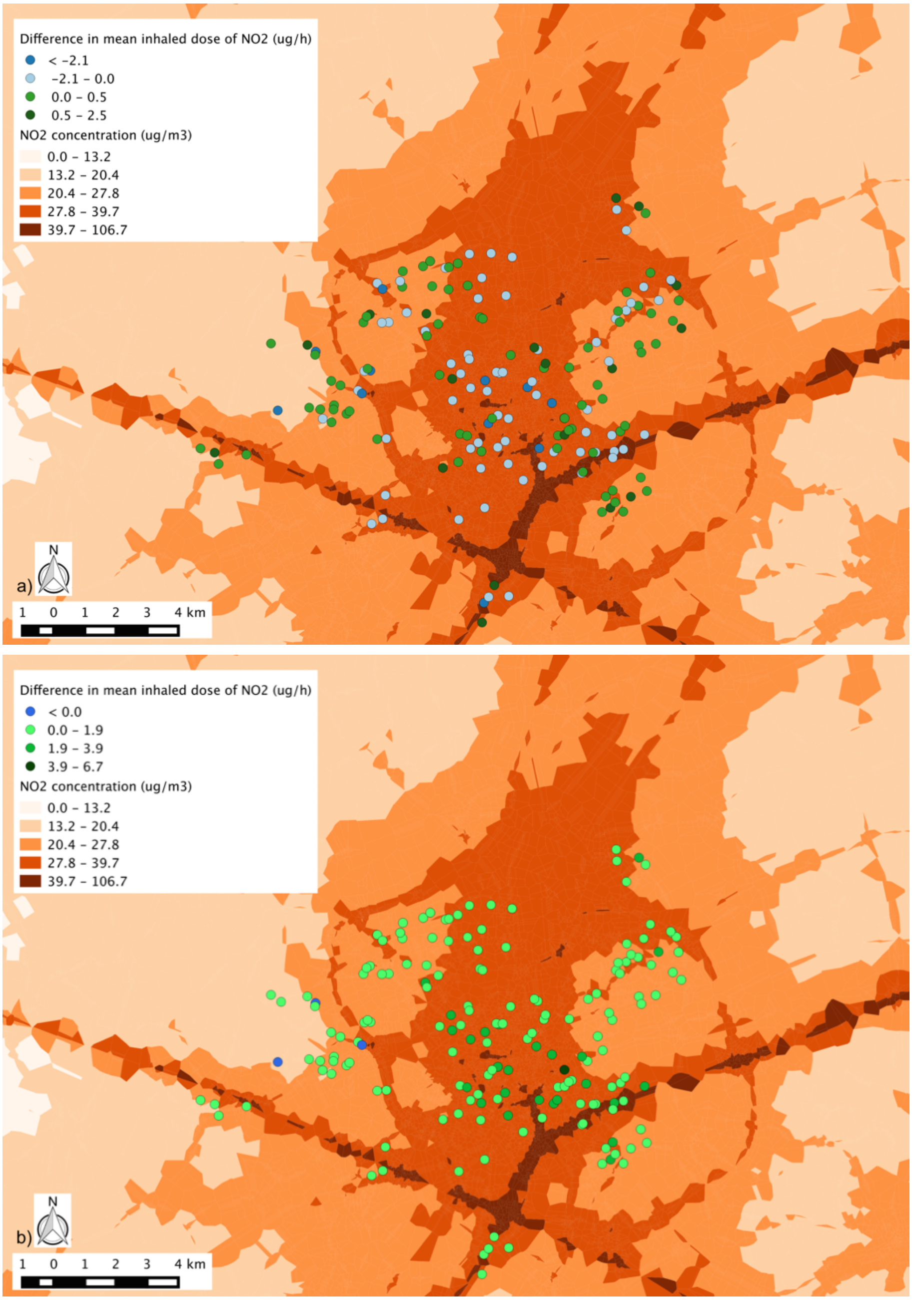

Figure 6.4: Difference in mean inhaled dose of NO_2, between method 1 and method 2 (a; 'method 2' minus 'method 1') and between method 2 and method 3 (b; 'method 3' minus 'method 2').

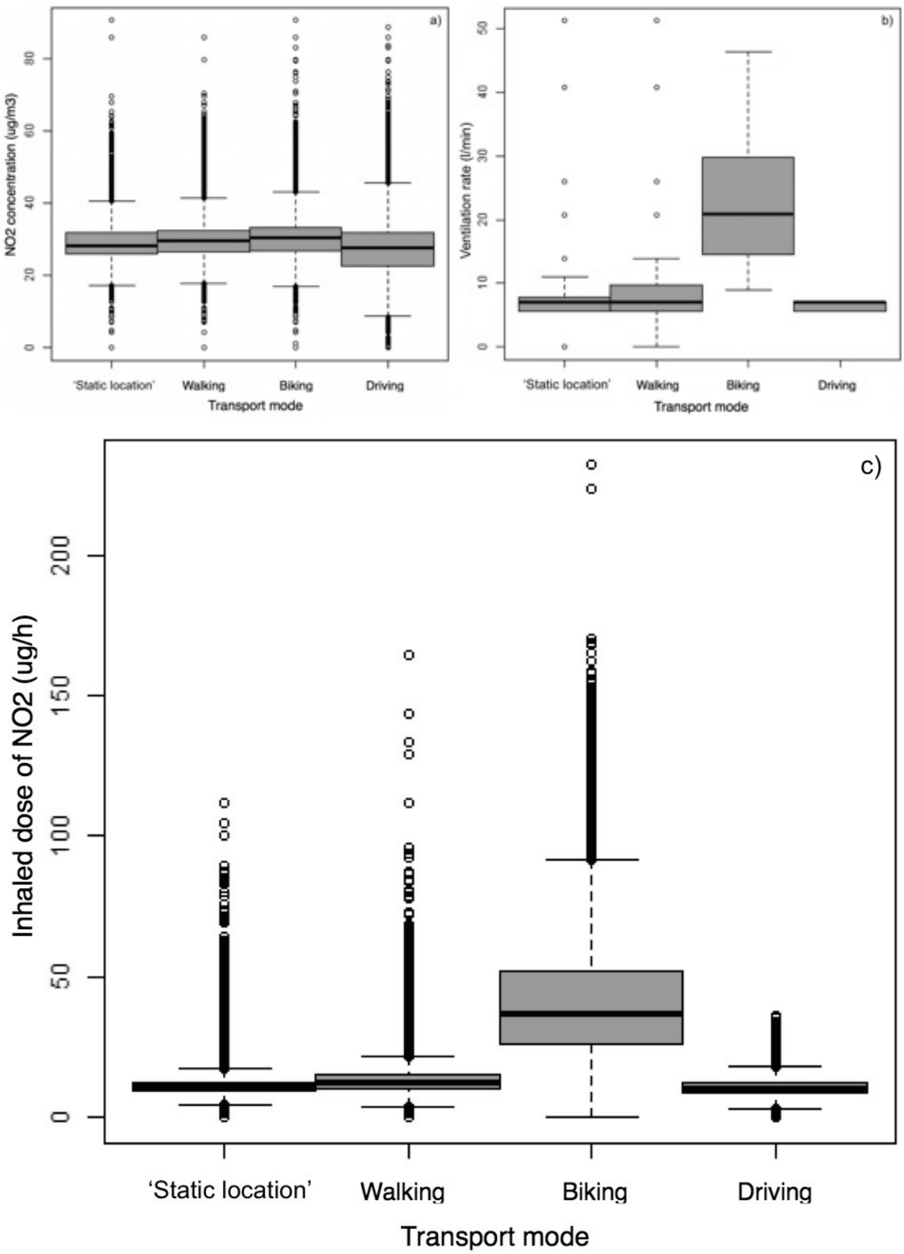

Figure 6.5: Boxplots showing a) NO_2 concentration (µg/m3), b) ventilation rate (l/min), and c) inhaled dose of NO_2 (µg/h) as a function of transport mode.

Table 6.4: Mean value of NO_2 concentration, ventilation rate, and inhaled dose of NO_2, for each transport mode.

Transport mode	*NO_2 concentration ($\mu g/m^3$)*	*Ventilation rate (l/min)*	*Inhaled dose of NO_2 ($\mu g/h$)*
Stationary	28.8	7.08	11.5
Walking	29.6	7.96	13.4
Cycling	30.0	22.72	40.6
Driving	27.4	6.40	10.6

The average NO_2 concentration is similar for the different transport modes. For stationary behaviour (i.e. when GPS speed is lower than 1.5 km/h) a sedentary ventilation rate is used, but now the accelerometer counts are taken into consideration, and therefore ventilation rate here is slightly higher than for driving. The ventilation rate is again higher for walking, but cycling has the highest ventilation rate. Combining the ventilation rate and the NO_2 concentration leads to the inhaled dose of NO2, calculated per hour (Figure 6.5c and Table 6.4). The high ventilation rate for cycling results in an inhaled dose of 40.6 µg/h, which is significantly larger ($p < 0.001$) than the three other transport modes ranging between 10.6 and 13.4 µg/h.

To further investigate the relationship between transport mode and inhaled dose of NO_2, we calculated the proportion that each transport mode contributes to the total amount of inhaled NO_2. Table 6.5 shows the percentage of data points linked with each transport mode. The high percentage for stationary behaviour has various reasons. First, people are sleeping, and thus stationary, for approximately 8 hours per day. Second, older people are often less active than their younger counterparts and thus more sedentary. Combining this percentage with the mean inhaled dose results in a weighted inhaled dose contribution for each transport mode, shown in Table 6.5. Despite the fact that the inhaled dose for cycling is large, due to its small proportion in the data points, the weighted inhaled dose of NO_2 for cycling is fairly small. When combining the number of data points with the inhaled dose, we obtain the total inhaled NO_2 per transport mode for all participants combined (Table 6.5). Again it is clear that due to the small percentage of cycling in the dataset, the total inhaled NO_2 for cycling is relatively small in this elderly population.

Table 6.5: Number and percentage of data points, weighted inhaled dose of NO_2 and total inhaled dose of NO_2 for all data points, per transport mode.

Transport mode	*Data points*	*Percentage*	*Average weighted inhaled dose of NO_2 per day ($\mu g/h$)*	*Total inhaled dose of NO_2 per day (g)*
Stationary	4,776,956	83.4	9.6	229
Walking	737,751	12.9	1.7	41
Cycling	92,593	1.6	0.6	16
Driving	123,587	2.2	0.2	5

6.5 DISCUSSION

6.5.1 STATIC VS. DYNAMIC MEASUREMENT OF INHALED DOSE

The influence of individual travel behaviour on the inhaled dose of air pollution is often neglected (Brunekreef et al., 2009), but recent studies indicate that this is of high importance in estimating air pollution exposure and inhalation (Beckx et al., 2009; Dons et al., 2011; Setton, 2011). Following our study, we can support that it is important in exposure assessments to incorporate both location and ventilation rate when calculating the inhaled dose of air pollution. Using GPS and accelerometer data offers accurate data to use in health impact assessment and epidemiological studies.

Comparing method 1, only looking at the home location, with method 2, incorporating GPS location, we observe a mean decrease of 1.74% of inhaled dose of NO_2. This small difference originates from the fact that people living in highly polluted areas often visit cleaner areas and thus undergo a decrease in inhaled dose when incorporating their GPS location, and people living in less polluted areas often visit more polluted areas and therefore increase their inhaled dose. Additionally, individual travel behaviour has a large influence on the inhaled dose of NO_2. The average difference is small, but the average absolute value of the individual differences is important (this is called exposure misclassification and biases effects estimates).

When additionally incorporating the ventilation rate in method 3 (based on the transport mode and physical activity), there is a 12.81% increase in inhaled dose. This means that, on average, the actual ventilation rate is higher than the sedentary ventilation rate. Using this dynamic method, we obtain a mean value per person of 12.33 μg/h. Per day, that is 29 μg of inhaled NO_2 that is not dealt with when using the static method.

6.5.2 Influence of transport mode on inhaled dose

Our results show that cycling leads to a 4 times higher inhaled dose of NO_2, compared to the other transport modes, which is similar to the results of Int Panis et al. (2010) and Hu et al. (2014), who respectively found that bicycle users inhale 4.3 and 2 times more air pollution than car drivers. Other studies also support the statement that being physically active could lead to a higher inhaled dose of air pollution (Mills et al., 2007; Weichenthal et al., 2011). However, the proportion of cycling in our dataset is limited and therefore has a small influence on the total amount of NO_2 inhaled. However, in other age cohorts, where the proportion of walking and cycling is higher, the total inhaled dose of NO_2 for these transport modes will also be higher.

Also, the positive influence of being physically active, especially for the elderly, cannot be underestimated (de Hartog, Boogaard, Nijland, & Hoek, 2011; Pate, Pratt, Blair, & Haskell, 1995; Warburton, Nicol, & Bredin, 2006). Hence, it is vital that older people are physically active (e.g. by walking or cycling), but preferable in areas outside the city or in parks where the concentration of air pollution is low.

6.5.3 Strengths and limitations

Our study has several strengths over other similar studies, estimating the inhaled dose of air pollution using GPS and accelerometer data. First, using modelled air pollution concentrations offers nation-wide data on a detailed geographical scale (Beckx et al., 2009; Dhondt et al., 2012) and is less costly to generate than personal measurements (Dons, Van Poppel, Kochan, Wets, & Int Panis, 2014). Second, in contrast to for example Dons et al. (2014) and Fecht et al. (2014) who used simulated travel behaviour, we used actual data measured with GPS. Third, the sample size largely exceeds those of de Nazelle et al. (2013) and Hu et al. (2014). Not only did we study 180 randomly selected persons, we also collected and used data from a full 7-day period. De Nazelle et al. (2013) only studied 31 predominantly female, high-educated people during one day and Hu et al. (2014) only had an initial experimental sample of 3 participants studied on one particular route. Fourth, the innovative aspect of these two studies is the fact they use smartphone to collect data. This method has the potential to reach a very large study group, however using built-in GPS devices limits mobile phone battery life and thus limits data collection. We used accurate standalone GPS and accelerometer devices to measure geographical location and physical activity, every 15 seconds.

Apart from these strengths, this study also has limitations that create interesting avenues for future work. First, using GPS, one could also retrieve information about the indoor/outdoor status based on the number of satellites in view. With this information, the exposure to air pollution could be further adjusted, since a recent study stated that outdoor environments account for only 5% of the daily exposure to ultrafine particles (Bekö et al., 2015). However, indoor air quality is very complex and previous studies show inconsistent results (EPA, 2011; Goyal, Khare, & Prashant, 2012). Therefore, more research is needed to shed light on indoor air quality assessments. Additionally, more research is needed on exposure to air pollution inside motorised vehicles, depending on ventilation parameters, to make a more accurate distinction between sedentary behaviour and driving (Hudda & Fruin, 2013; Riediker, Williams, Devlin, Griggs, & Bromberg, 2003). Second, we used the average NO_2 concentration for the entire study period because of computational limitations. However, air pollution concentration can vary significantly during the day and between days. Therefore, we hope to be able to use hourly values in the future, to make better estimations of the inhaled dose of polluted air. Doing so, the inhaled dose calculated with the dynamic method could increase even more, because in those periods when air pollution concentration is highest (peak commute times), people are more likely to be active. The average value used now can however provide a first insight into the influence of individual travel behaviour and physical activity on the inhaled dose of NO_2. Third, we used a cohort of late middle-aged adults, of which 76.1% are reported as retired. This study group is characterised with specific travel behaviour and results can therefore not be extrapolated tot other groups. The difference with other age cohorts should be further studied in the future. Fourth, it has been shown earlier that it is difficult to define transport modes, cycling in particular (Butte, Ekelund, & Westerterp, 2012). In this study, we defined transport mode based on speed measured by GPS. Future work should however combine GPS and accelerometer data to define the transport mode used (Troped et al., 2008). Nonetheless, with the increasing use of electrically assisted bicycles (e-bikes), especially by older adults, defining physical activity for bicycle users becomes increasingly difficult, because less physical activity is required at higher speed levels.

6.6 CONCLUSIONS

This study has shown that it is important for epidemiological studies and exposure assessments, especially those relying on modelled exposure values, to incorporate individual travel behaviour and physical activity to estimate the inhaled dose of air pollution. This can be done using accurate GPS and accelerometer data. The change in inhaled dose of NO_2 when using GPS data depends on the NO_2 concentration at the home location and individual travel behaviour. However, when incorporating accelerometer data to estimate the ventilation rate, an increase of over 12% in inhaled dose of NO_2 is observed compared to the traditionally used static method. Cycling is associated with the highest inhaled dose of NO_2, mainly because of higher ventilation rate. Cycling and other active transport modes should be encouraged to increase physical activity. However, air pollution concentration should be reduced to limit negative health impacts.

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7

DYNAMIC MODELLING OF EXPOSURE TO AIR POLLUTION USING MOBILE PHONE NETWORK DATA

Adapted from: Dewulf, B., Neutens, T., Lefebvre, W., Seynaeve, G., Vanpoucke, C., Beckx, C., Van de Weghe, N. (2016). Dynamic assessment of exposure to air pollution using mobile phone data. *International Journal of Health Geographics, 15*(14), 14p.

7.1 ABSTRACT

Exposure to air pollution can have major health impacts, such as respiratory and cardiovascular diseases. Traditionally, only the air pollution concentration at the home location is taken into account in health impact assessments and epidemiological studies. Neglecting individual travel patterns can lead to a bias in air pollution exposure assessments. In this work, we present a novel approach to calculate the daily exposure to air pollution using mobile phone data of approximately 5 million mobile phone users living in Belgium. At present, this data is collected and stored by telecom operators mainly for management of the mobile network. Yet it represents a major source of information in the study of human mobility. We calculate the exposure to NO_2 using two approaches: assuming people stay at home the entire day (traditional static approach), and incorporating individual travel patterns using their location inferred from their use of the mobile phone network (dynamic approach). The mean exposure to NO_2 increases with 1.27 μg/m^3 (4.3%) during the week and with 0.12 μg/m^3 (0.4%) during the weekend when incorporating individual travel patterns. During the week, mostly people living in municipalities surrounding larger cities experience the highest

increase in NO_2 exposure when incorporating their travel patterns, probably because most of them work in these larger cities with higher NO_2 concentrations. It is relevant for health impact assessments and epidemiological studies to incorporate individual travel patterns in estimating air pollution exposure. Mobile phone data is a promising data source to determine individual travel patterns, because of the advantages (e.g. low costs, large sample size, passive data collection) compared to travel surveys, GPS, and smartphone data (i.e. data captured by applications on smartphones).

7.2 BACKGROUND

A large body of evidence indicates that exposure to air pollution causes various acute and chronic health effects, such as respiratory and cardiovascular diseases (Beelen et al., 2014; Brook et al., 2010; Brugge, Durant, & Rioux, 2007; Gehring et al., 2013; HEI, 2010; Peters et al., 2004; Pope III & Dockery, 2006; Riediker et al., 2004; WHO, 2003). Approximately 2 million deaths worldwide are caused by air pollution annually (WHO, 2013). Mainly black carbon (BC), particulate matter (PM), and nitrogen dioxide (NO_2) are identified as culprits of negative health effects.

Current health impact assessments and epidemiological studies examining exposure to air pollution often only take the air pollution concentration at the home location into account (Bell, Ebisu, & Belanger, 2007; Brunekreef et al., 2009; Cesaroni, Badaloni, Porta, Forastiere, & Perucci, 2008; Hoek, Brunekreef, Goldbohm, Fischer, & Brandt, 2002; Huynh, Woodruff, Parker, & Schoendorf, 2006; Jerrett et al., 2013; Tenailleau, Mauny, Joly, François, & Bernard, 2015). Such static approach does not incorporate individual travel patterns and may lead to a bias in exposure and health assessments (Beckx et al., 2009; Dons et al., 2011; Dons, Van Poppel, Kochan, Wets, & Int Panis, 2014; Setton, 2011; Steinle, Reis, & Sabel, 2013; Valero et al., 2009).

Detailed information on travel patterns is thus needed to obtain more dynamic estimates of the exposure to air pollution. Previous research showed an increase in exposure to air pollution by incorporating individual travel patterns (Dhondt et al., 2012), but the outcome depends on the air pollution concentration at the home location (Dewulf et al., 2016). To assess individual travel patterns, often self-reported household travel surveys are used (Stopher & Greaves, 2007). Major disadvantages of this approach are the large non-response rate (Wilson, 2004), non-representative samples (Murakami, 2008), and high costs (Stopher & Greaves, 2007). Alternatively, mathematical models of travel patterns can be used (Beckx et al., 2009; Dhondt et al., 2012; Fecht, Beale, & Briggs, 2014). This approach allows to draw more quantitative conclusions from a larger population size, but results are however only valid for situations similar to those for which their initial parameters were estimated. More recently, Global Positioning Systems (GPS) (Dewulf et al., 2016; Houston, Ong, Jaimes, & Winer, 2011) or smartphone data (de Nazelle et al., 2013; Su, Jerrett, Meng, Pickett, & Ritz, 2015) were used to provide detailed information on people's travel patterns. However, data collection with GPS or smartphone devices is often intensive for both researchers and participants, expensive and only a limited number of people can be tracked.

To overcome the limitations of travel surveys, travel models and GPS/smartphone data, mobile phone data can be used to derive information on individual travel patterns. At present, this kind of data is collected and stored by telecom operators mainly for management of the mobile network. However, it represents a major source of information in the study of human mobility. This data is continuously available, does not need additional costs to collect, and is often available for millions of phone users. With over 6 billion mobile subscriptions globally and a growing awareness of telecom operators of the potential, this data source offers a wide range of applications and research possibilities (Calabrese, Ferrari, & Blondel, 2014). However, the number of studies published with such data is limited up to now because of privacy issues and problems accessing the data (Ahas, Silm, Järv, Saluveer, & Tiru, 2010). Previous studies using this type of data mostly analyse population densities (de Jonge, Van Pelt, & Roos, 2012; Deville et al., 2014; Ratti, Frenchman, Pulselli, & Williams, 2006), tourism (Ahas, Aasa, Roose, Mark, & Silm, 2008; Kuusik, Nilbe, Mehine, & Ahas, 2014), and mobility (Ahas et al., 2010; Alexander, Jiang, Murga, & Gonz, 2015; Calabrese et al., 2014; Calabrese, Lorenzo, Liang, & Carlo, 2011; Chen, Bian, & Ma, 2014; de Jonge et al., 2012; Pappalardo, Simini, Rinzivillo, Pedreschi, & Giannotti, 2015; Widhalm, Yang, Ulm, Athavale, & Gonz, 2015). To our knowledge, no studies have used mobile phone data to dynamically estimate the exposure to air pollution.

This research will add knowledge to the existing strand of literature by calculating the exposure to air pollution using mobile phone data of more than 5 million people in

Belgium. Our main objective is to bring evidence on how this innovative, underused data source can offer more dynamic estimations of the exposure to air pollution. Further, we explore how using daily averaged and hourly air pollution concentrations influences the results.

7.3 METHODS

7.3.1 DATA

7.3.1.1 MOBILE PHONE DATA

Mobile phone data (or passive mobile positioning data) is based on signalling information that is exchanged between mobile devices and the mobile network. When using the mobile network, there is a flow of signalling information between the device and the mobile network. The mobile device switches to the antenna with the strongest radio coverage, which is typically the closest one. The signalling messages contain an indication of the antenna in use.

The data used for this study is available from probes installed in the Proximus network, which capture this information. We have data available from more than 4,000 antennae sites. On each antenna site there are typically three or four antennae, delivering network coverage in diverged directions. As sites can be equipped with 2G, 3G and 4G technologies in different frequency bands, we make abstraction of the different technologies and group all cells that are co-located on the same antenna site and cover the same sector to considerably reduce complexity. This leads to more than 10,000 macro cells covering the entire country of Belgium. The mobile phone location is thus available at the precision of these macro cells, with each cell having its own, unique geographical coverage area and identity code. Figure 7.1 shows the antennae with the associated macro cells for the region of Ghent, overlaid on the road network. Because of the higher capacity needs, macro cells are smaller in urban areas and larger in rural areas. Figure 7.2 shows a histogram of the area of the macro cells. Some macro cells are larger than 10 km^2 (with a maximum of 49 km^2), but 50% of them have an area smaller than 2 km^2.

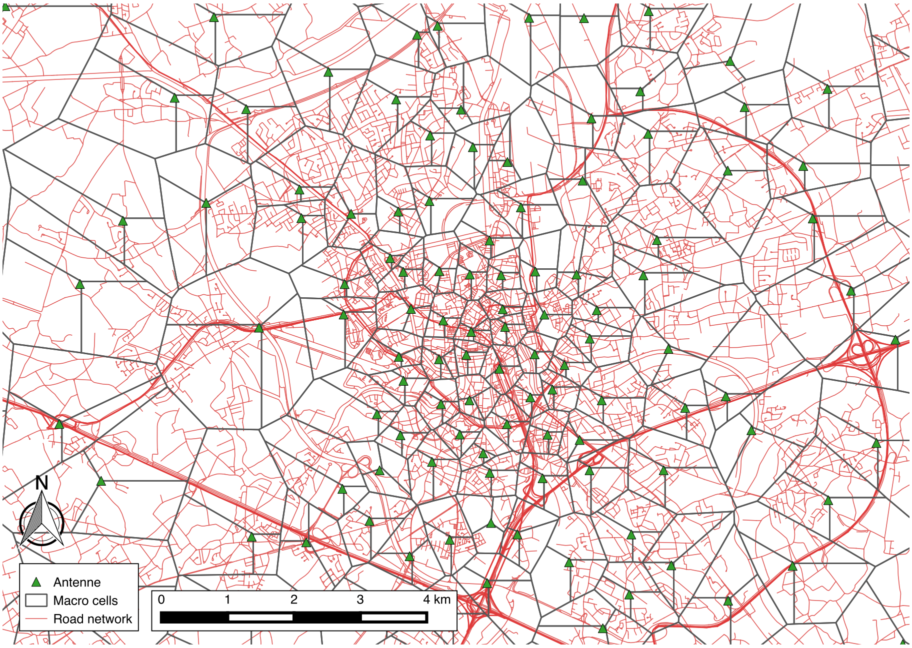


Figure 7.1: Map showing the macro cells of the region of Ghent, overlaid on the road network.

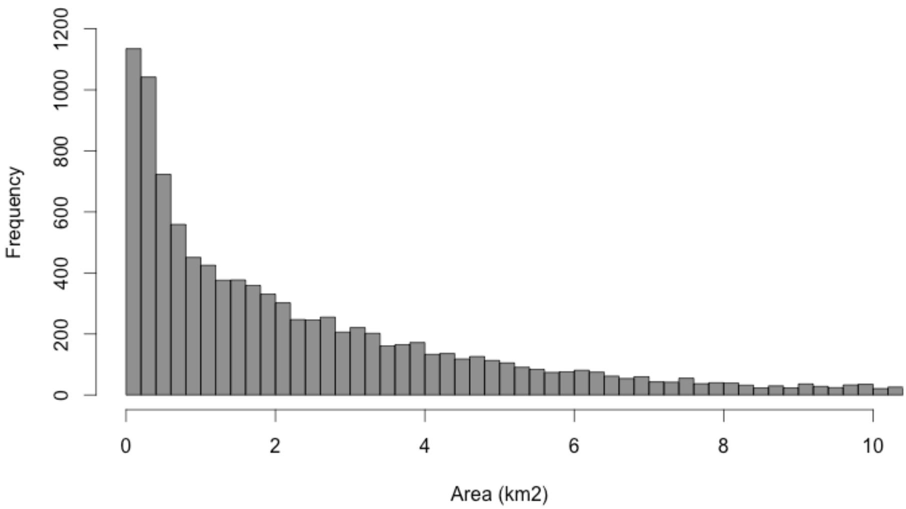


Figure 7.2: Histogram showing the area (km²) of the macro cells.

Data is collected from more than 5 million users of the Proximus network, which are representative for the Belgian population (Proximus, 2015). In Belgium, Proximus has a market share of about 41%, which is higher than the other Belgian telecom operators:

Mobistar (27%), Telenet (14%), Base (11%), and others (7%) (Smart Business Strategies, 2014).

The network probing system collects from all active users. Each data point consists of an anonymised user ID, the date and time of the transaction, the cell where the transaction occurred, and the transaction type. The following transaction types are possible: a) turning on and off the phone; b) setting up, maintaining and terminating calls; c) sending and receiving text messages; d) setting up, maintaining and terminating data sessions; e) location update (when changing from location area; a location area is a group of cells of which there are approximately 65 in the Proximus network); f) periodic location update (automatic update every three hours when there is no activity). For this study, we used mobile phone data for both one week and one weekend day: Thursday October 8 and Saturday October 11 2015. Because of regulation terms we had limited access to the data, but these two days were chosen to be as representative as possible, in terms of weather conditions for the time of the year, and travel behaviour (e.g. no holidays). No data of the home location was available due to privacy issues. Therefore, we used the location of the users at 4 am as a proxy for their home location (hereafter called reference location), since it is assumed most of the people are at home at that time.

Privacy issues of using mobile phone network data are a major concern of phone owners, telecom operators, researchers, and the general public. Because of this, no personal information is linked to the mobile phone data, and IDs that can link directly to individuals are removed. Individual exposure measures were aggregated to postal code level for mapping purposes.

7.3.1.2 Air pollution data

We focus on NO_2, an understudied pollutant that can cause an increase in pulmonary morbidity, a worsening of obstructive lung disease, and a higher susceptibility to airway infections (Blomberg et al., 1997; Cesaroni et al., 2014; WHO, 2003). Hourly NO_2 concentration data (in $\mu g/m^3$) for Belgium was provided by the coupled RIO-IFDM model (Lefebvre et al., 2013). This model couples the land use regression model RIO, the road emissions model MIMOSA4 (considering COPERT4 emission functions, vehicle fleet and vehicle counts), and the Gaussian plume model IFDM. The latter is used to incorporate large concentration variations close to the major air pollution sources, such as roads and point sources. The model has been validated extensively for the discussed region (Lefebvre et al., 2013; VMM & VITO, 2013). Hourly air quality measurements are provided by the Belgian Interregional Environment Agency (IRCEL, 2015).

In line with the mobile phone data, NO_2 concentration patterns in Belgium were modelled during two days. NO_2 concentration levels varied from 3 to 63 $\mu g/m^3$ on the weekday (Thursday October 8 2015) and from 5 to 54 $\mu g/m^3$ on the weekend day (Saturday October 11 2015). Figure 7.3 shows the mean NO_2 concentration for the entire country of Belgium, for both Thursday October 8 and Saturday October 11 2015.

7.3.2 Data processing

Mobile phone data are collected and stored by the telecom operator, mainly for management of the mobile network and technical operations. Because each user in the mobile network has a different mobile activity, the temporal resolution of the data varies. The last known position (cell) of each user was used at a temporal resolution of 15 minutes. We assume that when there is no new data point within 15 minutes the user is at the same location as before. As an example, Figure 7.4 shows the user density (number of users per cell divided by the cell area) of Thursday October 8 2015 at 12 am UTC.

Proximus has 5,574,000 active customers (Leroy et al., 2015). Active customers are customers who have made or received at least one call, or sent or received at least one message in the last three months, or if at least one data connection has been made on the last month. From the initial dataset, users are omitted if:

- they are international users;
- their data relate to machine-to-machine transactions (e.g. car kits; to avoid duplicate data);
- their travel patterns exceed the borders of Belgium during the selected days (no air pollution concentration available);
- they have no known position from 1:00 until 4:00 in the morning (necessary to derive the reference location).

This results in a dataset of 3,465,917 users on the weekday and 3,495,453 on the weekend day.

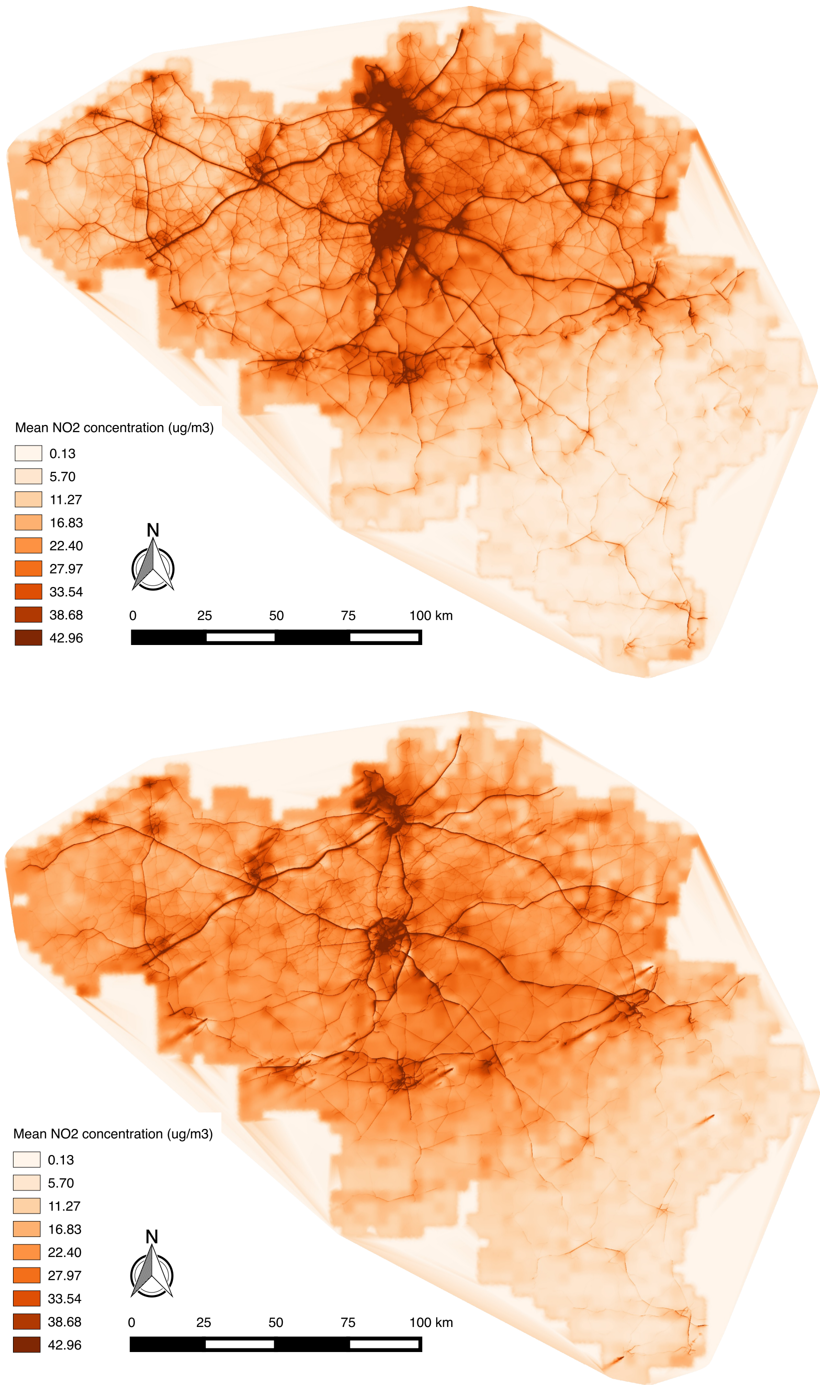


Figure 7.3: Map showing the mean NO_2 concentration for the entire country of Belgium, for both Thursday October 8 and Saturday October 11 2015.

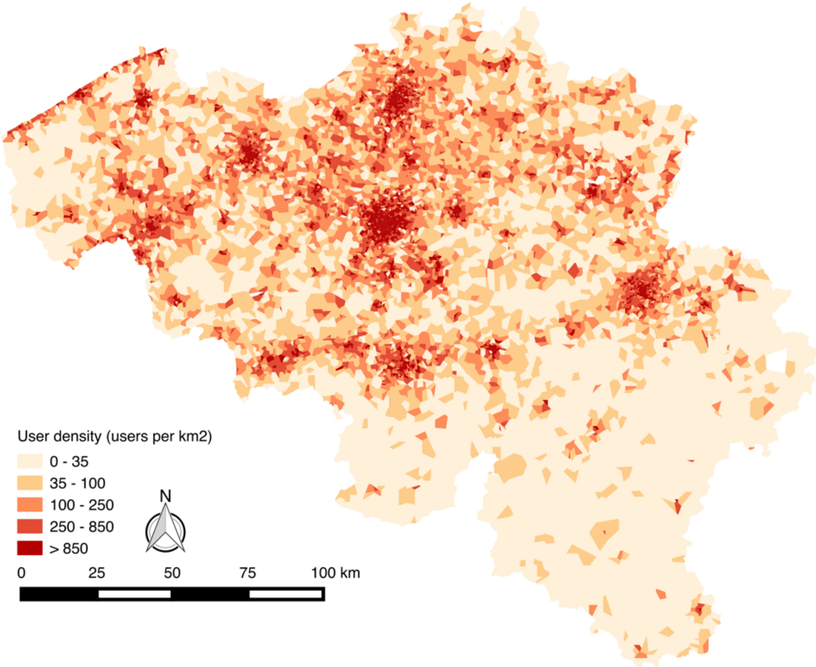


Figure 7.4: User density per cell on October 8 2015 at 12 am UTC.

The point dataset of the NO_2 concentration is triangulated to a 50x50 m grid, using the SAGA 'gridding triangulation tool' in QGIS. Following, we calculate the average NO_2 concentration per cell using the SAGA 'grid statistics for polygons tool' in QGIS to combine this with the location data. The mean NO_2 concentration per cell is 29.36 $\mu g/m^3$ on the weekday and 27.32 $\mu g/m^3$ on the weekend day, with a mean standard deviation per cell of respectively 3.62 $\mu g/m^3$ and 2.73 $\mu g/m^3$.

The location of the users is combined with the air pollution concentration, to calculate the exposure to air pollution. The air pollution data is in Coordinated Universal Time (UTC), and the mobile phone data is in local time (UTC+1). Therefore, we have an overlap of 23 hours (92 quarters) per day, and are thus able to combine the datasets from 0 am UTC to 11 pm UTC. The exposure to NO_2 is calculated using either a static or dynamic location. For the static approach, we use the cell where the user is at 4 am UTC as their reference location. For the dynamic approach, we use the exact cell where the user is, at a temporal resolution of 15 minutes. Additionally, we use the NO_2 concentration per cell in two different ways. We either use the hourly concentration or the daily averaged concentration per cell. This results in four possible average air pollution concentrations each user is exposed to during the day.

7.3.3 DATA ANALYSES

First, having these four average air pollution exposure values for two days, we check what the influence of using hourly air pollution concentrations (hour) is on the exposure to air pollution, compared to using the daily average air pollution concentration (day). Second, we compare the effect of using the reference location of the user (static) with taking into account the actual location of the user (dynamic) on the calculated exposure to air pollution. Third, this comparison is also analysed geographically.

The data was statistically analysed using R 3.2.2™. To check for significant differences between the approaches, paired-samples t-tests (hour vs. daily averaged air pollution concentration, static vs. dynamic approach, week vs. weekend days) were performed. The data does not have to be tested for normality, because of the large sample size (Altman & Bland, 1995). Statistical significance was set at $p < 0.05$. Geographical analyses were performed in QGIS 2.12™. Averages of individual exposure values were calculated per municipality and visualised using choropleth maps.

7.4 RESULTS

To gain insight into the origin of the four average values per user, Figure 7.5 shows the exposure to NO_2 during the weekday for a random user, calculated statically and dynamically, with both hourly and daily averaged NO_2 concentrations. Using hourly NO_2 concentrations leads to a higher level of detail of the exposure to air pollution. However, since we calculate the average exposure to air pollution per day, this has limited effects on the results. It is also clear that taking into account actual travel patterns (instead of assuming the person stays at the reference location) leads to a different exposure to air pollution. In this case, the person spends time in cells with a higher NO_2 concentration than at his or her reference location.

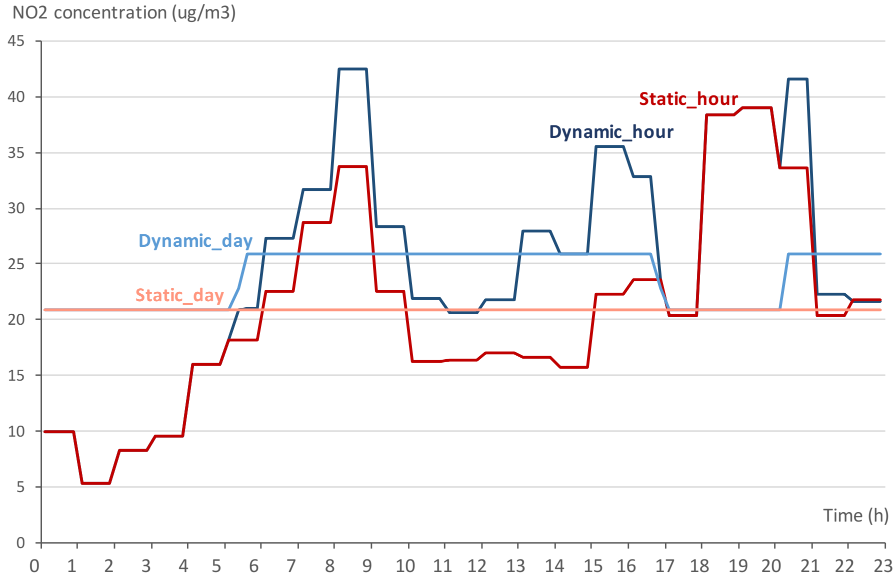


Figure 7.5: Exposure to NO_2 during the weekday for a random user, using the four different approaches (static_hour, dynamic_hour, static_day, dynamic_day).

The mean NO_2 exposure per person was calculated statically and dynamically, using hourly NO_2 concentration values for both the week and weekend day, and is presented in Table 7.1. The significance of the differences was tested using multiple paired-samples t-tests (daily averaged vs. hourly NO_2 concentrations, static vs. dynamic, week vs. weekend).

Table 7.1: Mean exposure to NO_2 per person, calculated statically and dynamically, using hourly and daily averaged NO_2 concentrations, for both the weekday (n=3,465,917) and weekend day (n=3,495,453).

Method	*Mean NO_2 exposure ($\mu g/m^3$) [σ_x]*			
	Weekday		*Weekend day*	
	NO_2 per hour	*NO_2 per day*	*NO_2 per hour*	*NO_2 per day*
Static	29.69 [12.03]	29.69 [12.03]	27.47 [8.58]	27.47 [8.58]
Dynamic	30.96 [11.26]	30.83 [11.25]	27.59 [7.99]	27.57 [8.01]
Difference	1.27 [5.02]	1.14 [4.43]	0.12 [2.82]	0.10 [2.41]

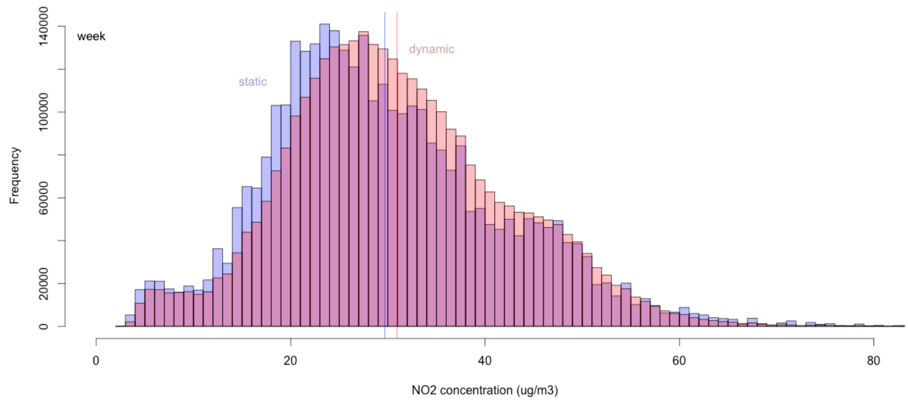
7.4.1 COMPARISON OF USING HOURLY OR DAILY AVERAGED AIR POLLUTION CONCENTRATIONS

From Table 7.1, we observe practically no difference in the mean NO_2 exposure calculated with hourly and daily averaged NO_2 concentrations for the static approach, which is expected. For the dynamic approach, we observe a small significant difference ($p < 0.001$) only during the week. Here, the calculated NO_2 exposure is 0.13 $\mu g/m^3$ (0.4%) higher when using hourly values compared to when using daily averaged values.

7.4.2 COMPARISON OF THE STATIC AND DYNAMIC CALCULATION OF THE EXPOSURE TO AIR POLLUTION FOR A WEEK AND WEEKEND DAY

To compare the static with the dynamic approach, we will only consider the values calculated with the hourly NO_2 concentrations, since this way the highest level of detail is obtained.

Table 7.1 shows that by incorporating individual travel patterns (dynamic), the mean exposure to NO_2 increases with 1.27 $\mu g/m^3$ (4.3%) on the weekday and with 0.12 $\mu g/m^3$ (0.4%) on the weekend day, compared to assuming the person stays at the reference location (static). These values are all significantly different from each other ($p < 0.001$). Figure 7.6 combines the static and dynamic approach for the two days in a histogram. It is clear that during the week, there are more users who experience an increase in exposure to NO_2. During the weekend, the values are more central and the increase in NO_2 exposure is less pronounced. During the week, 12.4% of the users have no change, 54.5% have an increase, and 33.1% have a decrease. During the weekend, 20.1% have no change, 43.3% have an increase, and 36.6% have a decrease.



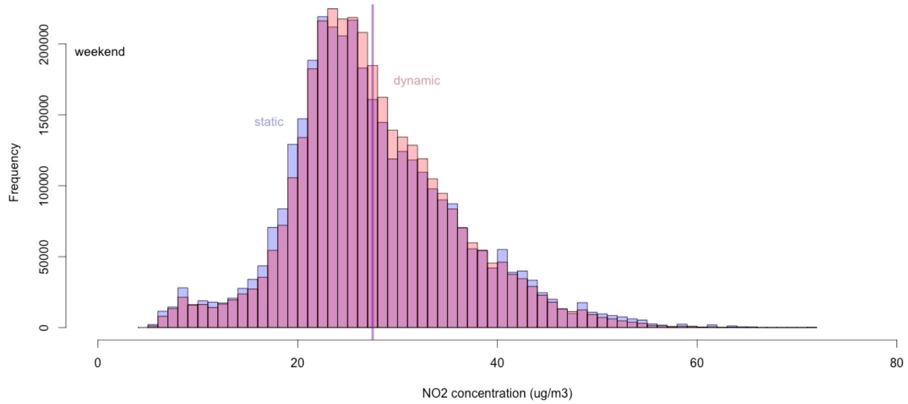


Figure 7.6: Histogram of the average NO_2 concentration that the users are exposed to using the static and dynamic approach, for the week (n=3,465,917) and weekend day (n=3,495,453), including the mean reference line for both approaches.

Figure 7.7 shows a scatterplot of the exposure to NO_2 calculated statically and dynamically, for both the week and weekend day. During the week, it is clear that users with a low NO_2 exposure calculated statically (thus with a low average NO_2 concentration at the reference location) experience a strong increase in NO_2 exposure when dynamically calculated (indicated in blue), a pattern that is less pronounced during the weekend. This is also true the other way around: users with high NO_2 concentrations at the reference location experience a decrease in NO_2 exposure when their travel patterns are considered (indicated in green), which is also observed during the weekend.

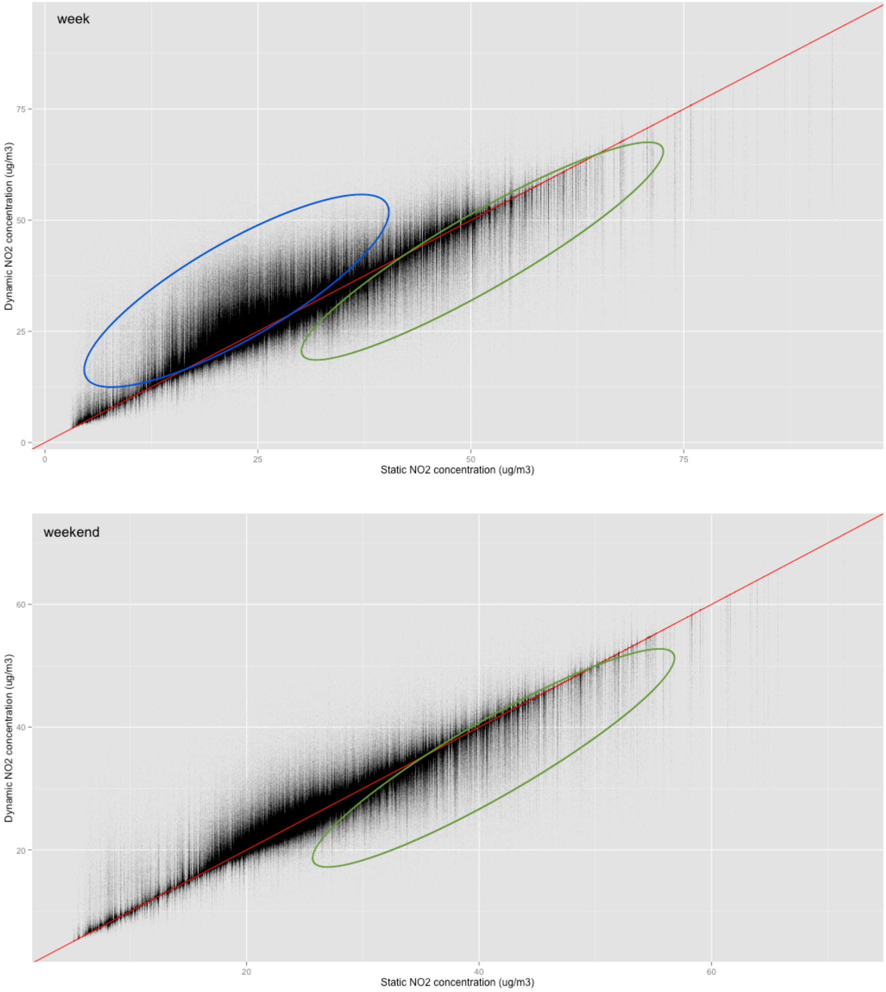


Figure 7.7: Scatterplot of the exposure to NO_2 calculated with the static and the dynamic approach, for the week (n=3,465,917) and weekend day (n=3,495,453).

7.4.3 GEOGRAPHICALLY ANALYSING THE COMPARISON BETWEEN THE STATIC AND DYNAMIC CALCULATION OF THE EXPOSURE TO AIR POLLUTION

Next to these statistical analyses, we also performed geographical analyses on the comparison between the static and dynamic approach to calculate the NO_2 exposure. Here, again only hourly NO_2 concentrations were used in the calculations.

Figure 7.8 shows the average exposure to NO_2 per municipality, for both the week and weekend day, calculated statically and dynamically with hourly NO_2 concentrations.

Figure 7.9 shows the difference between the average exposure to NO_2 calculated with the static and dynamic approach (dynamic minus static), using hourly NO_2 concentrations, per municipality for both the week and weekend day. During the week, there is a large increase mostly in the municipalities surrounding larger cities (Brussels, Antwerp, Ghent) and a decrease in these larger cities. During the weekend we observe a similar pattern, but with lower increases and more decreases in the difference between the static and dynamic approach.

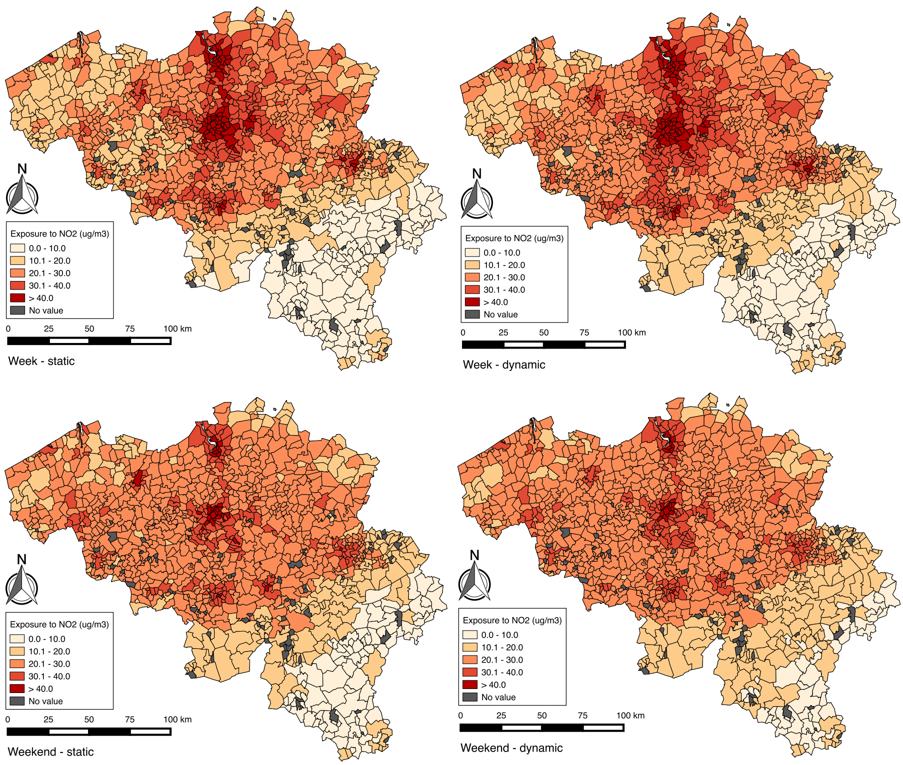
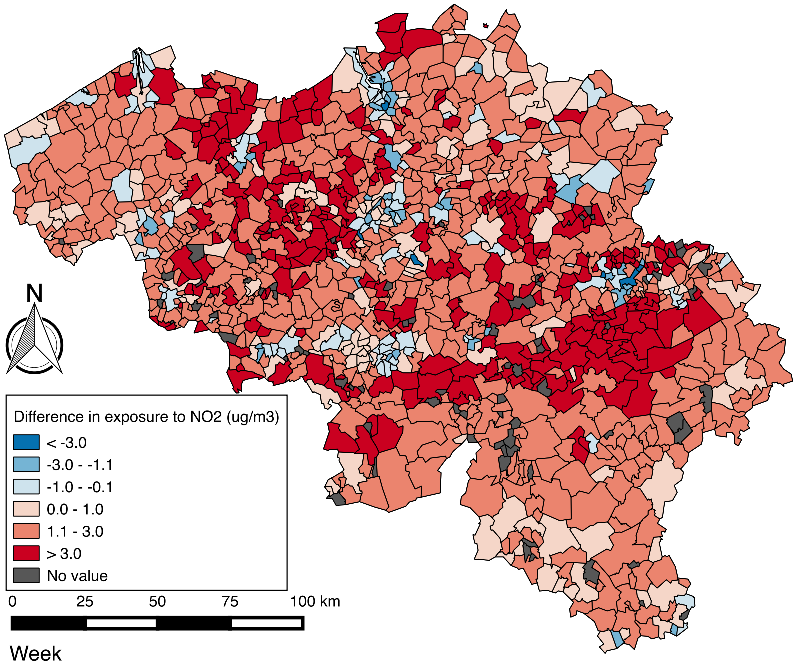


Figure 7.8: Maps of Belgium, showing the statically and dynamically calculated exposure to NO_2, for the week (n=3,465,917) and weekend day (n=3,495,453).



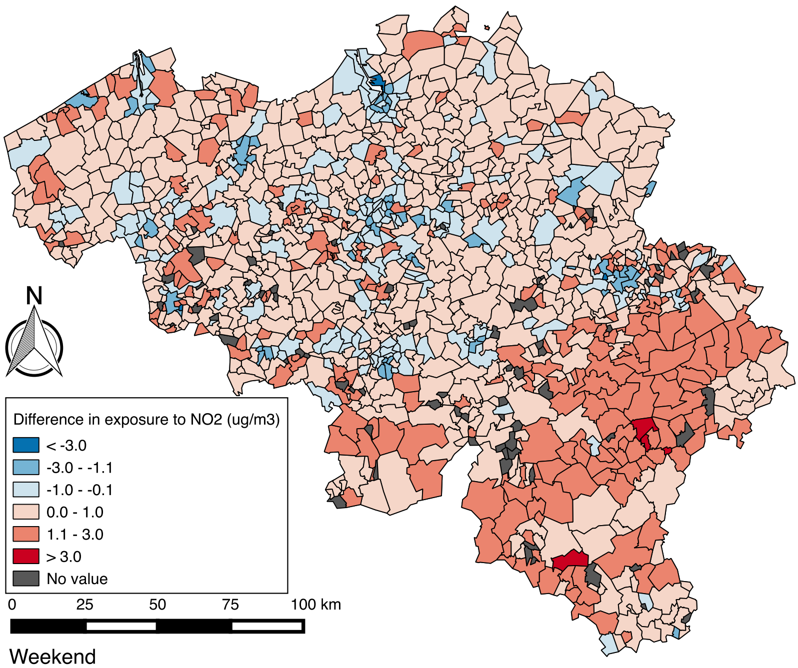


Figure 7.9: Maps of Belgium showing the difference between the statically and dynamically (dynamic minus static) calculated exposure to NO_2, for both the week (n=3,465,917) and weekend day (n=3,495,453).

7.5 DISCUSSION

7.5.1 GENERAL DISCUSSION

First, our study shows that using daily averaged instead of hourly NO_2 concentrations leads to only a 0.4% decrease in dynamically calculated exposure to NO_2 in our analyses. If hourly data is available, it is preferred to use it (Beckx et al., 2009; de Nazelle et al., 2013). If, however, no detailed hourly NO_2 concentration data is available, the impact will be limited.

Second, our study supports the findings of several recent studies stating the importance of incorporating individual travel patterns in estimating air pollution exposure (Beckx et al., 2009; Dewulf et al., 2016; Dons et al., 2011; Setton, 2011; Steinle et al., 2013; Valero et al., 2009), an issue sometimes overlooked (Brunekreef et al., 2009). Mobile phone data makes it possible to estimate individual travel patterns to use in health impact assessments and epidemiological studies. We observe a mean increase in NO_2 exposure of 4.3% during the weekday and 0.4% during the weekend day when incorporating individual travel patterns, which means that current health impact assessments underestimate the exposure to NO_2 and the related acute and chronic health effects. These increases were also found in previous research, where integrating time-activity information lead to a 1.2% increase air pollution exposure than when assuming people are always at their home location (Dhondt et al., 2012). We observed an increase or decrease in NO_2 exposure for respectively 54.5% and 33.1% of the users because of their travel patterns during the week. In the weekend, respectively 43.3% and 36.6% of the users experience an increase or decrease in exposure. Thus, people tend to make more trips to areas that are less polluted than their reference location in the weekend than during the week. During the week, people living in areas with a low NO_2 concentration undergo an increase in NO_2 exposure because of their travel patterns (going to work in a more polluted area) whereas people living in highly polluted areas undergo a decrease in NO_2 exposure, which is similar to our previous study (Dewulf et al., 2016).

Third, concerning the geographical analysis, our study reports that people living near Brussels are most exposed to NO_2 both during the week and the weekend, because of the highest density of air pollution sources (industry and roads), and Brussels being one of the most congested cities in Europe (FOD Mobiliteit en Vervoer, 2013; OECD, 2013). People living in the south of Belgium are least exposed to NO_2. Mainly people from municipalities around larger cities experience an increase in exposure to air pollution during the week because of their travel patterns (going to work in these cities). The average difference for people living in these cities is negative since people working in the city do not experience any change and people working outside the city experience a decrease in NO_2 exposure. During the weekend, we observe lower increases and more decreases in NO_2 exposure because of individual travel patterns, because during the weekend people tend to visit more areas with lower air pollution concentrations than at the reference location. In more rural areas (e.g. the south of Belgium) there is an increase in NO_2 exposure during the weekend when incorporating travel patterns, because every trip people living in this area make leads to an increased NO_2 exposure due to the low air pollution concentration at people's reference location.

7.5.2 Strengths and limitations

This study has several strengths compared to similar studies. First, to our knowledge, this is the first study that combines mobile phone data with air pollution concentration data to dynamically estimate the exposure to air pollution. Using mobile phone data has several advantages above GPS data or questionnaires: no additional costs have to be made to collect the data, a very large number of people can be traced because of the wide adoption of the mobile phone, the data collection is passive so people are not disturbed and does not influence the battery of their mobile devices, and they are tracked without them knowing so they don't change their normal behaviour. Numerous practical applications can be developed based on the presented method, both for individual as on a community level. Policy makers can for example be interested to follow-up the average population exposure indicator or to assess the impact of a policy measure such as on the exposure. However, it is not easy to access mobile phone data. Concerning privacy issues, good agreement with the telecom operator is needed, as well as a clear understanding of the data use (Ahas et al., 2008; Calabrese et al., 2014). A second strength of the current study involves the type of location data that were used. Previous studies using mobile phone data only collected a location when users made a phone call or sent a text message. In our study, we additionally locate users when turning the phone on or off, during a data session, when changing location area, or when periodically updating the location area by the telecom operator. This approach significantly improves the spatial accuracy of all the users but also includes relevant information on non-frequent callers in the population. Third, using modelled air pollution concentrations instead of personal measurements offers nation-wide data on a detailed geographical scale (Beckx et al., 2009; Dhondt et al., 2012) and is easier to generate than personal measurements (Dons et al., 2014). Fourth, we used both the hourly and daily averaged NO_2 concentrations in contrast to our previous research (Dewulf et al., 2016), making a comparative analysis possible. Using daily averaged values does not alter the results extremely, since we calculated daily exposure values. It is however preferred to use the hourly values when available, to obtain more accurate results.

Apart from these strengths, this study also has some limitations that open up interesting avenues for future work. First, we only used air pollution concentration and individual travel data for two days. Despite the fact that these days were chosen to be as representative as possible, it would be better to use more data, e.g. for an entire week, month or even year. Also, in order to assess the associated health impacts, more data is required. Second, following the privacy issues of mobile phone data, it is difficult to combine this data with personal sociodemographic variables or other semantic information (e.g. transport purpose and trip mode), which limits the analysis possibilities. Future research could try to deduce the sociodemographic characteristics from the most likely living place (possible to determine using long-term location data) to get an idea of the socioeconomic status of the users. These privacy issues could be addressed by using privacy-enhancing technologies (Giannotti & Pedreschi, 2008). One possible solution is to slightly obfuscate the location of the user, while keeping enough information to perform satisfying analyses (Wightman, Coronell, Jabba, Jimeno, & Labrador, 2011). Another possibility is that telecom providers could ask for an opt-in consent from their customers to make use of their location data for scientific research and try to build a trust relationship with them, and build services where customers benefit from. Third, since we had no information on the user's home location, we used the location at 4 am as a proxy for their home location (and use it as reference location). A better solution would be to use mobile phone data from a longer period (e.g. one month), to make a more accurate estimate of the most likely living location. Fourth, the spatial resolution of mobile phone data is limited to that of the used cells, which is low compared to the spatial accuracy of GPS data. Because of this low spatial resolution, local differences in air pollution concentration (e.g. near roads) may not be taken into account. This might mean that the exposure to air pollution is probably even higher because of people spending time in traffic (Dons et al., 2011). On the other hand, the pollution concentration gradients in the rural areas, where the macro cell size is larger, are in general very small. As a result, smaller rural macro cells, if available, would not increase the accuracy of our results. The spatial resolution of the data could be increased by applying triangulation (Alexander et al., 2015; Ratti et al., 2006).

7.6 CONCLUSIONS

Hourly air pollution concentrations are preferably used over daily averages to maximise the level of detail when combining air pollution with individual travel patterns. This study shows that for epidemiological studies and exposure assessments, it is relevant to incorporate individual travel patterns to estimate the exposure to air pollution. The change in exposure to air pollution depends on the air pollution concentration at the reference location and someone's individual travel patterns, but on average we found an increase of 4.3% in the exposure to NO_2 during the week and 0.4% during the weekend. People living in and near large cities are most exposed to NO_2. However, people from other areas experience a higher increase in NO_2 exposure when taking their travel patterns into account. Mainly people living in municipalities surrounding larger cities have an increase in NO_2 exposure because they work in these cities. Aside from privacy issues, we strongly believe that using mobile phone data has several advantages (e.g. low costs, large sample, passive data collection) over travel surveys, GPS, and smartphone data. Especially for air pollution research the applications of using mobile phone data are numerous. Policy makers can use this information to assess the impact of air pollution on the population. Also, they can analyse the impact of a certain policy measure or occurring events (e.g. festivals, strikes) on the individual travel patterns and assess the associated impacts on exposure to air pollution. Mobile phone data is therefore a promising data source for air pollution research.

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8

Discussion

The research described in this thesis examined the relationship between the built environment and three health aspects, how this relationship is influenced by people's individual travel patterns, and how geospatial data and analyses can help to further understand this. This final chapter starts with a summary of the main findings of the different studies described in *chapters 3* to *7* (8.1). Next, an overall discussion and conclusion across these studies are given (8.2). Further, general strengths and limitations are provided (8.3), as well as implications for practice (8.4). Finally, some possibilities for future research are formulated (8.5).

8.1 What this dissertation adds: summary of the main research findings

Chapters 3 and *4* were devoted to explore the **first research objective**: demonstrate how existing geospatial analyses can be used to explore the relationship between the built environment and health. We studied how perceived measures of the built environment correspond with objectively calculated Geographic Information System (GIS)-based measures, and how geospatial analyses, implemented in GIS, can be used to calculate advanced measures of accessibility.

In *chapter 3*, one specific characteristic of the built environment (as an example of built environment characteristics influencing health) was studied: walking time to various destinations (e.g. supermarket, restaurant, swimming pool) in the residential neighbourhood. The perceived–self-reported–measure was determined using a questionnaire on 1,164 adults aged 18–66 years living in Ghent, Belgium, while the objective measure was calculated as the shortest road network distance using GIS. It was found that perceived walking times to various destinations do not coincide well with objectively calculated walking times: only 52.2% of the participants made a correct estimation (i.e. the perceived walking time class is the same as the objective walking time class, using 5-minute class widths). Walking time to closer, well-known destinations, such as bus stops and bakeries, were more often correctly estimated. Additionally, it was found that individual health (here with physical activity (PA) as a proxy for the individual health status, objectively measured using accelerometers) influences this correspondence. Physically more active adults tended to make more correct and underestimations of walking time, while physically less active adults made more overestimations. Reason for this might be the greater interaction with and awareness of the neighbourhood in the physically more active group. Another possible reason is that less active adults making these overestimations walk slower than the speeds used in the study. This could not be verified since no Global Positioning System (GPS) data was available for these participants, but future research could answer this question by using GPS data to obtain the actual used route and walking speed. Using GPS tracks also overcomes the problem that certain walking paths might not be included in the street network dataset. It could also be inferred that male, normal weight, younger adults made significantly more underestimations and significantly less overestimations than their female, overweight, older counterparts.

In *chapter 4*, advanced measures of accessibility to primary health care physicians in Belgium were calculated in a GIS and compared with traditional, often-used measures. Three traditional measures were calculated: physician-to-population ratio (PPR; the official method used by policy makers in Belgium to award financial assistance to physicians settling in shortage areas), distance to closest physician, and cumulative opportunity (the number of physicians within a certain distance). These were compared with the more advanced Enhanced 2-Step Floating Catchment Area (E2SFCA) method. The major disadvantage of the PPR method is its aggregated approach because it is calculated within administrative borders. The other two traditional GIS methods overcome this issue, but have limitations in terms of conceptualisation of physician interaction and distance decay. Conceptually, the E2SFCA method was found to be most appropriate for supporting areal health care policies, since this method is able to calculate accessibility at a small scale (e.g. census tracts), takes competition between physicians and interaction between the population and physicians into account, and considers distance decay. We found substantial differences in the defined shortage areas using the different accessibility measures. Not only the amount of shortage areas was strongly different, but also their spatial distribution differed significantly.

The **second research objective** was to study how individual travel patterns alter the relationship between the built environment and health, using both existing and new geospatial data sources. In *chapters 5* to *7*, we measured individual travel behaviour using both conventional (GPS) and new (mobile phone network) geospatial data sources and incorporated this information when calculating health-related measures (PA in green environments and the exposure to air pollution).

In *chapter 5*, we tested how the greenness of the environment influences PA, objectively measured using accelerometers. We studied if 180 late middle-aged adults (58–65 years) living in Ghent, are more physically active in green areas than in non-green areas. Additionally, it was tested how this is influenced by personal characteristics and residential neighbourhood greenness. The whereabouts of the participants were determined using GPS data, and were combined with land use data. The neighbourhood greenness was determined within a road network buffer around the home location, instead of using a circular buffer, to obtain a more veracious measure of the area influencing the participants' behaviour. We found that, for late middle aged adults, PA is significantly higher in green areas than in non-green areas. More specifically, when more time is spent in green areas, people spend less time being sedentary and are more physically active. Spending more time at home and in non-green areas was found to be associated with more sedentary behaviour. The results were slightly different between subgroups based on personal characteristics (gender, working status, BMI, educational level). Men have a positive association between the time spent in non-green areas and performing MVPA, while women have a negative association. Also, people living in green neighbourhoods have a stronger association between the time spent in green areas and performing MVPA, although they do not necessarily perform more PA in general.

In *chapters 6* and *7*, we examined how individual travel patterns influence the exposure to and inhalation of air pollution (here: nitrogen dioxide; NO_2). This exercise was done using two travel data sources: GPS and accelerometer data of the same 180 late middle-aged adults from *chapter 5* on the one hand (*chapter 6*) and mobile phone network data of more than 5 million mobile phone users in Belgium on the other (*chapter 7*). Three important conclusions resulted from *chapter 6*. First, we found that the inhalation of air pollution for late middle-aged adults is significantly different when incorporating individual travel patterns, compared to only considering the home location. Second, when the ventilation rate–based on the number of accelerations–was incorporated, the amount of inhaled air pollution increased with more than 12%. Third, the transport mode cycling was associated with the highest inhaled doses of air pollution, compared to being stationary and other transport modes (walking and driving), mainly because of the higher ventilation rate when cycling. From *chapter 7*, we can conclude that incorporating individual travel patterns leads to an average increase in the exposure to air pollution, compared to considering only the home location. This increase was 4.3% during the week and 0.4% during the weekend. During the week, mostly people living in municipalities surrounding larger cities experienced the highest increase in NO_2 exposure when incorporating their travel patterns, because most of them work in these larger cities with higher NO_2 concentrations. Although the average difference between only considering the home location and additionally incorporating individual travel patterns might be relatively small (mean = 1.27 / 0.12 $\mu g/m^3$ for week and weekend days) and might have limited health impacts, the individual difference for certain people can however be much higher (σ_x = 5.02 / 2.82 $\mu g/m^3$ for week and weekend days), and might be overlooked when only considering the home location.

In order to perform the analyses associated with the aforementioned research articles, different data sources were used and are presented in Table 8.1.

8.2 Overall discussion and conclusions

The problem statement explained in *chapter 1* pointed out three issues recurring in studies on the relationship between the built environment and certain health aspects. First, sometimes PA is measured using questionnaires, leading to subjective and possibly biased measures. Second, both for delineating neighbourhoods and calculating accessibility, often the capabilities of geospatial analyses are insufficiently exploited. Third, when studying the impact of the built environment on several health aspects (e.g. contact with green environments, exposure to air pollution), individual travel patterns are often not taken into account. This section points out how the different studies from *chapters 3* to *7* overcome these issues.

8.2.1 Measuring physical activity objectively

Measuring PA objectively, as done in *chapters 3*, *5*, and *6*, was deemed useful. First and foremost, using accelerometers leads to accurate, valid, and reliable measures of PA at a high temporal resolution (Melanson & Freedson, 1995; Welk, Schaben, & Morrow, 2004). Second, from these detailed measures, it is possible to classify PA in predefined classes (e.g. light or moderate-to-vigorous PA). With questionnaires, it is difficult to obtain such detailed classifications, as for participants these classes are vague and can be interpreted differently. Third, over-reports because of social desirability are avoided (Rzewnicki, Vanden Auweele, & De Bourdeaudhuij, 2003; Sallis & Saelens, 2000).

However, a limitation of (Actigraph) accelerometers–often worn at the hip–is that sedentary behaviour may be overestimated, for example when standing or cycling (Healy et al., 2012). An alternative is the activPAL accelerometer attached to the upper leg and uses an inclinometer, which is thus capable of detecting whether or not the participant is standing, sitting, or cycling (Kozey-Keadle, Libertine, Lyden, Staudenmayer, & Freedson, 2011).

Also, because merely accelerometers are used to assess PA, the obtained measures lack domain-specific information (Aadland & Ylvis, 2015). Therefore, in *chapters 3* and *5* we miss valuable information on whether the PA is transport-, recreational-, household-, or occupation-related. In *chapter 3*, it may be that adults engaging in more transport-related PA are better at estimating walking times. In *chapter 5*, it may be that spending time in green might be related to higher levels of MVPA, because recreational PA is stimulated. However, destinations (e.g. shops, offices) are located further in green areas, which may result in discouraging transport-related PA (Van Dyck et al., 2012). Aggregating different PA domains might obscure the obtained relationships between the built environment and PA (Van Cauwenberg et al., 2011). It is therefore recommended to use a combination of accelerometers and self-reported measures to obtain a more exhaustive measure of PA (Lubans et al., 2011). The choice of measure is influenced by various factors, such as affordability, participant acceptability, age of participants, and sample size (Hills, Mokhtar, & Byrne, 2014).

Table 8.1: Overview of the data sources used in this thesis.

Data	*Data type*	*Attributes*	*Count*	*Area covered*	*Period*	*Source*
Physical activity (PA)						
International Physical Activity Questionnaire (IPAQ)	Questionnaire (perceived measure)	Amount of PA, purpose (e.g. work, recreation)	180 late middle-aged adults (58–65 years)	/	7 days 2013	Department of Movement and Sports Sciences, Ghent University, post-doc dr. Veerle Van Holle
Accelerometer a. CSA 7164 b. Actigraph GT3X, GT3X+, GT1M	Tabular (can be linked with GPS based on timestamp)	Accelerations per a. 60 s b. 15 s	a. 1,164 adults (18–66 years) b. 180 late middle-aged adults (58–65 years)	/	4 to 10 consecutive days a. 2007–2008 b. 2013	Department of Movement and Sports Sciences, Ghent University a. BEPAS b. post-doc dr. Veerle Van Holle
Built environment characteristics						
Neighbourhood Environmental Walkability Scale (NEWS)	Questionnaire (perceived measure)	Walking time to destinations (min)	1,164 adults (18–66 years)	24 neighbourhoods in Ghent, Belgium	2007–2008	Department of Movement and Sports Sciences, Ghent University
Land use	Raster 10m resolution	48 classes	/	Belgium	2013	VITO
Air pollution	Vector point	NO_2 concentration ($\mu g/m^3$)	616,615	Belgium	2014–2015	RIO-IFDM-MIMOSA4 (IRCEL)
Road network TeleAtlas MultiNet	Vector line	Max speed, number of lanes, walkable, etc.	670,191 segments	Belgium	2013–2015	TeleAtlas

Parks	Vector polygon	Name	116	Ghent, Belgium	2012	Ghent city council
Urban destinations (shops, restaurants, etc.)	Vector point	/	2,301	Ghent, Belgium	2009	Ghent city council
Bus and tram stops	Vector point	Type (bus, tram)	37,711	Flanders, Belgium	2012	De Lijn
Bus and tram routes	Vector line	Type (bus, tram), name, etc.	3,765	Flanders, Belgium	2012	De Lijn
Train stations	Vector point	Name	415	Flanders, Belgium	2012	NMBS
Primary health care facilities	Vector point	/	14,194	Belgium	2012	RIZIV
Municipalities	Vector polygon	Population count	589	Belgium	2012	Statistics Belgium, NGI
Census tracts	Vector polygon	Population count	19,781	Belgium	2012	Statistics Belgium, NGI
Individual travel patterns						
GPS Qstarz BT-Q1000X	Vector point	Lat-lon-location, number of satellites, etc.	180 late middle-aged adults (58–65 years), 5,672,590 data points	Mostly within Belgium	2013	Department of Movement and Sports Sciences, Ghent University
Mobile phone network	Vector polygon (> 5 million users of the mobile phone network)	Population count	10,421	Belgium	2015	Proximus

Also, because only limited PA is detected with accelerometers when people are cycling, the total amount of PA can be underestimated (Hansen, Kolle, Dyrstad, Holme, & Anderssen, 2012). The increasing popularity of e-bikes, also in older age groups, increases the complexity of this problem. A possible solution is to determine the used transport mode, not based on the amount of accelerations, but based on the GPS speed, as done in earlier studies (Prins et al., 2014; Wolf, Guensler, & Bachman, 2001) and in our study explained in *chapter 6*. A second possibility is to determine the transport mode using a combination of GPS and accelerometer data, as explained later (8.5).

Often–even recent–studies merely use questionnaires (e.g. travel diaries) to determine PA. Such questionnaires may however generate inaccurate measures, and the participants may have difficulties in recalling the performed activities. Accelerometers log the participants' activities automatically at a high temporal resolution, offering an objective, accurate, and valid alternative to questionnaires, however lacking domain-specific information. In future research, preferably a combination of self-reported and objectively determined measures of PA are used to obtain an exhaustive representation of PA. Knowing which factors influence this correspondence may offer additional information on how people perceive their environment, leading to knowledge for policy makers on how to increase active behaviour.

8.2.1 Exploiting the capabilities of geospatial analyses

First, geospatial analyses were deemed useful for calculating objective measures of the built environment. In *chapter 3*, we calculated the objective walking time to various urban destinations along a walkable road network to compare with perceived walking times. Our result of 52.2% of the participants making a correct estimation coincides with earlier findings of about 60% correspondence (Jilcott, Evenson, Laraia, & Ammerman, 2007; Macintyre & Macdonald, 2008). Also, our result of more active people making more correct estimations of walking times because of higher awareness of the environment corresponds with earlier findings (McCormack, Cerin, & Leslie, 2008). One should be aware of this poor correspondence between objective and perceived characteristics of the built environment when examining the relationship between the built environment and health, as using either one of them may lead to different results. It is important to know that both objective and perceived measures of the built environment may be related differently with PA or other health outcomes (Arvidsson, Kawakami, Ohlsson, & Sundquist, 2012). Future research should include the effect of PA as a moderator, when studying the relationship between perceived measures of the built environment and health, since the results are a priori influenced by health (here PA). Because we used an average walking speed per gender and age group, some uncertainty remains in knowing the actual walking time since the actual walking speed of the participants is unknown. It may therefore be that physically more active people actually walk faster than less active people, and thus do not necessarily make overestimations of the walking time. Additionally, it is not known if the perceived walking time is that one to the closest facility–it may happen that people don't know the closest one–potentially leading to uncertain results. A possibility to overcome both problems is to use GPS data to determine the actual walking speed and route taken.

Second, built environment characteristics are often calculated within a neighbourhood buffer, frequently the administrative unit or a circular buffer around the home location. In *chapter 5*, we calculated a network buffer around the home location to determine the greenness of the home neighbourhood, by calculating zonal statistics. Additionally, the walkability of each neighbourhood was calculated using GIS, based on other spatial parameters (residential density, street connectivity, and land use mix). In *chapters 5* to *7*, we determined the land use and/or air pollution concentration for each (GPS or mobile phone network data) location point. Considering where people actually were, offers a more veracious measure of the actual context people are exposed to, thus limiting the issue raised by the Uncertain Geographical Context Problem (UGCoP). However, one should keep in mind that using other shaped or sized buffers to examine the influence of the built environment on health can largely affect the results, cf. the Modifiable Areal Unit Problem (MAUP). This remains an important issue, because it is difficult to identify which criteria are most effective in defining zones relevant to health: "*maximum equality of size, compactness of shape, homogeneity in social composition, or accordance with natural boundaries*" (Flowerdew, Manley, & Sabel, 2008, p. 1241).

Third, geospatial analyses were used to calculate advanced measures of accessibility. A method often used by policy makers determines the physician-to-population ratio (PPR) within a predefined area. Despite being a geographical measure, this ratio is often calculated within a simple spreadsheet and does not incorporate any advanced geospatial analyses. There is a multitude of geospatial analyses available in GIS to calculate accessibility to health care providers–or other facilities–more accurately. In *chapter 4*, we tested various methods to calculate accessibility, leading to significantly different results. The E2SFCA method is conceptually the best to calculate accessibility, since this method incorporates border crossing, competition between physicians, interaction between population and physicians, and distance decay. The E2SFCA methods limits the MAUP (because constant distances are used to calculate catchments) and the UGCoP (because network buffers are used). However, there are several possibilities to further limit the MAUP and UGCoP, and these will be pointed out in the section on future research possibilities (8.5). Also, as will be explained in the limitations section (8.3.2), the E2SFCA method has some other drawbacks.

By using a road network or GPS-based buffer instead of a circular buffer to define the context people are exposed to, and by using more advanced measures to calculate accessibility, the MAUP is reduced both mathematically by maximising homogeneity within each area and conceptually by choosing the neighbourhood unit based on the specific health outcome in focus (Schipperijn, Ejstrud, & Troelsen, 2013). However, using for example different road network buffer sizes, may influence the results, indicating that the MAUP may still occur.

A fourth use of geospatial analyses implemented in GIS is when incorporating individual travel patterns as explained further (8.2.2). This travel data was overlaid with highly detailed land use data (Van Esch, Poelmans, Engelen, & Uljee, 2011) and modelled air pollution data (Beckx et al., 2009; Dhondt et al., 2012; Lefebvre et al., 2013) available for the entire country. The combination of GPS locations with a detailed land use map in *chapter 5* has shown to be fruitful in determining where people spend their time. Since no travel diaries were used, such land use data can offer–be it limited–domain-specific information of individual travel behaviour. In a number of earlier studies, individual travel behaviour measured with GPS devices has been combined with personal air pollution monitors (Steinle, Reis, & Sabel, 2013). Although this offers detailed spatial and temporal information about the actual exposure to air pollution, this leads to high investments needed. Therefore, we chose to use modelled air pollution data instead, offering the possibility to perform this analysis on an existing GPS dataset. Additionally, when using mobile phone network data, modelled air pollution data is effective, since it is available over extended areas and for any time period. In *chapter 6*, we only used daily averaged air pollution concentrations, whereas in *chapter 7*, we used both hourly and daily averaged air pollution concentrations to examine the influence of the temporal resolution on the obtained results. The results did not differ significantly when daily averaged air pollution concentrations are used instead of hourly values.

In previous research, the geographical aspect of the relationship between the built environment and health is often overlooked. Our research shows that geospatial data and analyses have a lot of capabilities in gaining more geographical insights in this relationship, for example when defining objective built environment characteristics, delineating a more veracious neighbourhood, calculating accessibility using advanced measures, or combining accurate travel data with other data sources.

8.2.2 Incorporating individual travel patterns

To incorporate the actual context where people spend their time, we defined individual travel patterns using two geospatial data sources: GPS data in *chapters 5* and *6*, and mobile phone network data in *chapter 7*. We chose not to use modelled travel patterns because of the uncertainty still existing within these (Arentze & Timmermans, 2004), neither did we use other technologies (e.g. Bluetooth) because of the problem to track people over large areas (Gartner, 2014). Compared to travel diaries, GPS and mobile phone network data are available at a very high temporal resolution, making them particularly suitable for measuring individual travel behaviour. This way, the actual area where people spend their time–influencing their behaviour–and are physically active is known, thus limiting the problem raised by the UGCoP.

We used standalone GPS devices to obtain a high spatial resolution and to avoid battery drainage problems occurring when using smartphone applications (Montini, Prost, Schrammel, Rieser-Schüssler, & Axhausen, 2015; Zandbergen, 2009). With standalone devices, the participants need to be informed on how to use and wear the device. Also, the initial purchase cost for this method is relatively high, and therefore only a limited amount of participants can be tracked depending on the funds available. Despite this, using GPS to define individual travel behaviour was particularly suitable for our research, and offered significant results with 180 participants. Combining GPS data with accelerometer data, for example using the online tool Physical Activity Measurement Location System (PALMS, 2015), offers information on where people are mostly physically active or sedentary, an approach already shown to be valuable (Quigg, Gray, Reeder, Holt, & Waters, 2010; Stopher & Speisser, 2011; Troped et al., 2008). This way, we were able to detect if people are more active in green areas (*chapter 5*) and to determine the ventilation rate influencing the inhalation of air pollution (*chapter 6*). The combined use of GPS and accelerometer data is an accurate geospatial data source to use in health impact assessments and other health-related studies, proving its growing popularity in health research (Kerr, Duncan, & Schipperijn, 2011; Krenn et al., 2011). When using GPS devices, whether or not combined with accelerometer data, it is important to use standardised procedures in terms of device selection, GPS settings, data cleaning, data processing, and implementation of the data in GIS to obtain valuable data (Kerr et al., 2011; Maas, Sterkenburg, Vries, & Pierik, 2013).

In *chapter 5* we incorporated travel patterns to examine if people are more active in green environments than in non-green environments. The combination of GPS data with detailed land use data offers information on the trip destinations. This can offer an alternative to travel diaries to obtain domain-specific information. When combined with accelerometer data, the link between greenness (or other land uses) and PA is easily obtained, which is useful for policy makers trying to improve PA. Our results were similar to previous studies (Shores & West, 2010; Wheeler, Cooper, Page, & Jago, 2010), showing increased PA in green areas.

As an alternative to GPS data, in *chapter 7* we used mobile phone network data to determine people's individual travel behaviour and calculate their exposure to air pollution. The main advantage of using mobile phone network data–compared with GPS data–is that small efforts are needed to generate this data since people are passively tracked. The exposure to air pollution can therefore be assessed for a large-scale population. However, a decent agreement with a mobile phone network provider is necessary. In our study, we were able to use the individual travel behaviour–be it at a lower spatial detail than GPS data–of more than 3 million users, which is much larger than the study sample that can be obtained using GPS. Privacy issues of using mobile phone network data are however a major concern of phone owners, operators, researchers, and the general public. Because of this, no personal information was linked to the mobile phone data and data records that could potentially be linked directly to individuals were removed.

The combination of individual travel patterns with air pollution data leads to interesting insights in the exposure to and inhalation of air pollution (*chapters 6* and *7*). Both with GPS and mobile phone network data, incorporating individual travel patterns can lead to both decreases and increases in exposure to air pollution, compared to only considering the home location, similar as in other studies (Beckx et al., 2009; Dons et al., 2011; Gariazzo, Pelliccioni, & Bolignano, 2016; Setton, 2011). The change depends on the air pollution concentration at the home location and the individual travel pattern, depending on for example where the working location is situated. Since it was previously shown that being physically active can lead to higher inhaled doses of air pollution (Mills et al., 2007; Weichenthal et al., 2011), the combined use of GPS and accelerometer data also showed its value here.

Frequently only the residential neighbourhood is considered when studying the impact of the built environment on for example exposure to air pollution or greenness, despite the fact that a large amount of time is spent away from home. This thesis shows that incorporating individual travel patterns–using either GPS or mobile phone network data–combined with other geospatial data sources may lead to further insights in the relationship between the built environment and health.

8.3 Strengths and limitations

Next to the strengths and limitations applicable within each original research paper, there are some general strengths and limitations overarching the different studies.

8.3.1 Strengths

A first strength of this thesis is that we explored different topics in health research (PA, accessibility to health care, contact with green environments, and exposure to air pollution) to study how geospatial data and analyses, and incorporating individual travel patterns can provide more insights in the relationship between the built environment and health. We used various advanced geospatial data and analyses (e.g. mobile phone network data, GIS analyses), each having its own strengths (e.g. high accuracy, passive tracking). This offers alternatives to researchers and policy makers examining this relationship, leading to accurate insights difficult to obtain using traditional methods.

Second, some of the performed analyses were implemented in a scripting environment (Matlab, R, or PostgreSQL with the PostGIS extension). This way, personally adjusted or created analyses can be implemented without being limited to a finite set of predefined functions. Also, the analyses can be coded in a way that they are automated instead of manually repeating multiple analyses. The raw scripts can be found at: github.com/dewulfbart/PhD-Bart-Dewulf. These scripts are not standalone executables, but can be used when similar data is available.

Third, when possible, we performed the analyses on the entire country of Belgium, while similar studies often consider a single city or region (Apparicio, Abdelmajid, Riva, & Shearmur, 2008; Gariazzo et al., 2016; Guagliardo, 2004; Luo & Qi, 2009; Luo, 2004; Ngui & Apparicio, 2011; Wan, Zou, & Sternberg, 2012). This way, the entire national context is considered and edge effects are minimised. Such studies are particularly useful for policy makers to make nation-wide policy decisions supported by scientific research. Some of the studies were also the first to be conducted in Europe, adding evidence to existing studies mainly carried out in North America and Australia.

A fourth strength is that when incorporating individual travel patterns for studying the change in exposure to air pollution, we used two different methods (GPS and mobile phone network data), exploiting the advantages of both methods and using different study samples. With GPS data we were able to detect individual travel patterns at a high spatial accuracy, whereas with mobile phone network data we collected travel behaviour for a large study sample. In both cases, this led to the same outcome: the exposure to air pollution largely depends on the air pollution concentration at the home location and the individual travel behaviour.

8.3.2 LIMITATIONS

First, some of the results about the influence of the home neighbourhood on health might be influenced by residential self-selection. The problem of residential self-selection is that physically more active people will self-select their residential location based on their preferences and may therefore choose to live in areas with, for example, a higher walkability (Cao, Handy, & Mokhtarian, 2006). This potentially generates a high correlation between walkability and PA, not directly caused by the built environment characteristics.

Second, although the E2SFCA method is brought forward as conceptually the best method to calculate accessibility, it still has some drawbacks. The main problem of the E2SFCA is that the obtained measure is difficult to interpret because of the used distance decay and weights. An improvement for this method would be to implement varying buffer sizes for population subgroups or different regions (e.g. smaller buffer sizes in more densely populated areas) (McGrail & Humphreys, 2014; McGrail, 2012). Three fundamental shortcomings of the E2SFCA have recently been identified: i) the measure is static, not allowing for travel time, supply and demand to vary over time, ii) populations that fall within the overlay of several catchments are counted multiple times, and iii) spatial bias occurs because the demand for health care is often modelled using a single spatial proxy point (e.g. the centre of an administrative unit) (Neutens, 2015). Additionally, catchments may change during the day, e.g. because of changing travel times due to congestion, possibly leading to issues mentioned in the MAUP. Because these catchments can change over time, monitoring change in health outcomes becomes difficult. Also, the UGCoP may still arise when using the E2SFCA, because individual travel patterns are neglected. Additionally, the specific context of primary health care may impact the usability of the obtained accessibility measures. For example, next to the income and education, the age of the population in a certain area will largely influence the demand for health care, as in Belgium the number of visits to primary health care providers increases from 2 per year for 15-24 year olds to 8 per year for people older than 75 years (Drieskens, 2014). Also, more research is needed to understand the reason why people choose a specific physician; this depends on the context and might affect the usefulness of certain measures: do people choose the closest physician from their home location, do they rely on experiences from people they know, or are there other factors at play?

Third, in *chapter 5* we used a stratified linear regression analysis to study how the relationship between the time spent in certain areas (green, non-green, at home) and PA differs depending on various personal characteristics (e.g. gender, working status).

However, this only offers an indication of possible differing results. To find out whether or not the results differ significantly between subgroups interaction effects should be examined. Additionally, a possibility would have been to use a multivariate regression (general linear model) to take the possible mutual dependence between the independent variables into consideration.

A fourth limitation also occurs in *chapter 5*, where the relationship between the built environment (greenness) and behaviour (PA) was studied using individual GPS points. However, because of self-selection, this type of neighbourhood delineation is less useful (e.g. people wanting to visit a green area to be physically active will likely find a green area).

Fifth, to determine the transport mode, we only considered the GPS speed, leading to a rough estimate. We did not use accelerometer data because only little activity is registered when cycling, making this particular transport mode difficult to distinguish from driving (e.g. car, bus), especially in city centres where their speeds are similar. However, for our research, this problem is limited as only 5.8% of the GPS dataset contained 'vehicle'-like speeds (cycling and driving). There are however more advanced methods available to make a more accurate estimation of the transport mode, which will be explained in a following section (8.5).

A sixth limitation of this thesis is that for the studies using GPS and accelerometer data, we used a cohort of late middle-aged adults (58–65 years), of which 76.1% are reported as retired. This age group is characterised with specific travel behaviour and it is therefore difficult to extrapolate the results to other age groups. The difference with other age cohorts should be further studied in the future. Additionally, it is questionable if the used cut-off points to classify the accelerometer counts into different PA classes (sedentary, LPA, MVPA) are valid. A recent study proposes that different cut-off points should be used depending on the age of the participants, because the intensity of certain activities can differ substantially depending on the age (Van Holle, De Bourdeaudhuij, Deforche, Van Cauwenberg, & Van Dyck, 2015). Instead of using the Freedson cut-off points, which are supposed to be applicable for all adults, but were tested on a sample with a mean age of 25 ± 4 years (Freedson, Melanson, & Sirard, 1998), the Copeland & Esliger cut-off points could be used, which are based on a sample of older adults with a mean age of 70 ± 4 years (Copeland & Esliger, 2009). However, the choice of cut-off points remains arbitrary and future researchers should be aware of this issue.

Seventh, during a significant amount of time, people are indoors (e.g. in buildings or cars) and are thus exposed to other air pollution concentrations than modelled outdoor concentrations, which has been used in *chapters 6* and *7*. We assume that indoor air pollution concentrations are, in absence of a filtering mechanism and the presence of major indoor sources (e.g. heating), linked–with a lag–to the outdoor pollution at that location. This relationship is however inconclusive and may vary between pollutants (Avery et al., 2010; Montagne et al., 2014). Though, for NO_2 it has been shown that LUR models significantly predict individual exposure (Montagne et al., 2013). It would be interesting to further study how well modelled air pollution concentrations model individual (and indoor) air pollution exposures more in detail, using individual exposure devices.

8.4 Implications for practice

8.4.1 Applying the results within the policy

As many health issues (e.g. obesity because of physical inactivity, a large exposure to air pollution, and little contact with green areas) remain prevalent in developed countries, the findings of this thesis are of great importance for policy makers. It is clear that studying the relationship between the built environment and different health aspects, using geospatial data and analyses, and incorporating individual travel patterns can help policy makers in understanding how they can improve the health of their residents. Therefore, they can use similar data sources and analyses to explore this relationship in their area of interest. In the next section (8.4.2), we list the most important advantages and disadvantages of the methods used methods in this thesis, to inform future researchers and policy makers. In the following paragraphs, we list some more specific implications for practice.

First and foremost, the main contribution of this thesis is in advancing methods to examine the relationship between the built environment and several health aspects. Building on the proposed geospatial data and analyses, more–and more accurate–policy recommendations will follow from future research.

Second, we learned that the built environment largely affects people's PA. Policy makers and urban planners may design communities or cities in a way that PA is increased, for example by enhancing walking and cycling instead of taking the car. It should however be noted that different built environment characteristics might be related to different PA domains or PA types (e.g. walking or cycling) (Gray, Zimmerman, & Rimmer, 2012; Hoedl, Titze, & Oja, 2010). As we saw, this increased activity may however result in a larger exposure to air pollution when this occurs in areas with a high air pollution concentration. Therefore, PA should be increased primarily in areas with lower air pollution concentrations, together with a general decrease of the air pollution concentration. However, the benefits of being physically active outweigh the risks of a higher exposure to air pollution, except in extreme air pollution conditions (Tainio et al., 2016). Furthermore, compared to recreational PA, increasing transport-related PA may be more achievable because it is more easily integrated into daily life, and it may have additional benefits when adopted by large groups (e.g. decreasing air pollution emissions and traffic congestion). Additionally, it is important to know where PA actually takes place (e.g. in green areas or not). The combined use of GPS and accelerometer data can help in detecting where people are sedentary or physically active. Also, mobile phone network data can offer insights in the travel behaviour of a large sample of the population, without the need of additional devices.

Third, both objective and perceived walking times to various destinations–as an example of a built environment characteristic–may (differently) influence someone's health behaviour and the correspondence between the two is influenced by various factors (e.g. socio-economic status), as shown in earlier work (Ma, 2014). To promote PA or other health-related issues, the built environment could be altered. Also, someone's perception may change when the built environment is altered. Additionally, someone's perception could be influenced, without adjusting the environment itself, using psychosocial programmes. When considering PA, this improved perception may result in even more PA, possibly starting a vicious circle effect. Depending on the feasibility of altering the environment itself or the available budget, one of the two approaches can be used. Ideally, multidimensional interventions–combining psychosocial programmes with built environment alterations–are particularly beneficial since the benefits of both approaches are combined (Van Dyck, 2012).

Fourth, to calculate the accessibility to health care–and by extension other measures–policy makers should know that different results can be obtained when using different methods. We observed that changing the unit of study may have a large impact on the results, cf. the MAUP. Hence, it is important for policy makers and researchers to ascertain to what extent their policy evaluations hold under different scales of analysis and using different methods. It is key that policy makers are consistent in the used areas (size, shape, and method) to limit the MAUP. Further, when possible, social differences (e.g. language barriers, divergent health needs, mobility issues) within the study units should be incorporated since these may have an influence on the accessibility of certain social groups at the micro-level; for example, using the Gini coefficient (Neutens, 2015). It is also important to overcome the UGCoP by considering the most appropriate context of people when studying the impact of the environment on health; for example, by considering both the home and work (or school) location, incorporating individual travel patterns, and considering individual factors influencing the demand for health care (e.g. age, income, and education) (Kwan, 2013).

Fifth, it is important to incorporate individual travel behaviour, for example when calculating the exposure to air pollution, instead of only considering the home location. Studying individual travel patterns over a longer period may help policy makers to assess the impact of a policy measure or occurring events (e.g. festivals or strikes) on health (e.g. air pollution or the contact with green areas).

Finally, linking individual travel patterns with other geospatial data might also be useful for companies offering their users services to track their travel patterns. Examples of this are Nike, Runkeeper, and Strava, companies offering apps to track runs and walks, and inform their users with the energy expenditure from an activity. When this location data is combined with air pollution and greenness data, the users could be informed with the amount of air pollution or greenness they were exposed to during their activity, having an impact on their health. This way, people could choose to follow routes where they are less exposed to air pollution or have more contact with greenness. Also, in moments when air pollution is peaking (e.g. during busy hours or bad weather conditions), users could be informed not to run in particular areas. The focus should however be on promoting PA (e.g. active transport), and not on scaring people to be physically active.

8.4.2 Selecting the appropriate method for further research and in policy

We can conclude from this thesis that geospatial data and geospatial analyses implemented in GIS are very useful in health research in general and in objectively studying the relationship between the built environment and certain health aspects in particular.

For the different studied topics, multiple data sources and analyses can be used. Built environment characteristics can be obtained from questionnaires or measured objectively (in circular, network, or GPS-based buffers). Similarly, the amount of PA can be obtained from a questionnaire or can be measured objectively using accelerometers. The accessibility to certain facilities can either be calculated using non-spatial data or using more advanced GIS-based methods. The exposure to green areas and/or air pollution can be calculated statically in a GIS using only the home location or dynamically using individual travel patterns measured with GPS or mobile phone network data. Based on the work performed in this thesis, we made an overview (Table 8.2) of the available data sources and analyses with their advantages and disadvantages. This provides useful information for future research and for policy makers, to determine which data source or analysis to use depending on the research question and available resources (budget and time).

8.5 What this dissertation could not add: possibilities for future research

This thesis showed that geospatial data and analyses can contribute in examining the relationship between the built environment and different health aspects. Additionally, we showed that incorporating individual travel patterns may impact the results. There are however several possibilities to further explore this relationship between the built environment and health, both in Geography and Health & Movement Sciences. In Geography, the future lies in optimising existing methods and creating new ones, using new techniques to collect data, and using databases and scripting techniques to analyse big data. In Health & Movement Sciences, the main aim is to incorporate these geospatial data and analyses in current and future research.

Table 8.2: Overview of available data sources and analyses.

	General information	*Advantages*	*Disadvantages*
Geospatial data sources			
PA using questionnaires	Often used: International Physical Activity Questionnaire (IPAQ), Global Physical Activity Questionnaire (GPAQ).	Domain-specific information (transport, recreation, household, occupation).	Susceptible to recall bias and over-reporting.
PA using objective devices	Several devices (accelerometer, smartphone app, heart rate monitor) possible depending on preference, budget, and study group. Smartphone app: less accurate, but cheap. Heart rate monitor: high threshold for participants to use adequately. Often accelerometers (diverse features: battery life, memory, accuracy) measuring accelerations in 3 axes are used, worn at the hip.	Possibility to measure at different time intervals (e.g. 15 or 60 s), depending on wanted detail. - Objective (no over-reports or recall errors) - Respiratory rate can be derived	- No domain-specific information - Detecting cycling, swimming, and upper-body exercise is difficult
Built environment characteristics using questionnaires	Often used: Neighbourhood Environment Walkability Scale (NEWS).	Information on what people see as their neighbourhood.	Perceptions might differ between people.
Built environment characteristics using GIS	Often calculated in a buffer around the home location.	Several buffers (circular, network, GPS-based) possible.	Difficult to determine what is the 'right' neighbourhood.
Travel patterns using questionnaires (travel diaries)	Often on paper, but also by phone and on computer.	Additional information (transport mode, accompaniment, actual destination, purpose) available.	- Large non-response rate - Non-representative sample - Limited temporal resolution - Only info on start and end point, not on the route taken - High costs for collecting and analysing the data
Travel patterns using GPS	Available as standalone device (different types with different features: e.g. battery life, memory,	- High spatial and temporal detail (depending on the device)	- High costs when large sample - Limited time period

	accuracy) or smartphone app (participants do not need to carry an additional device, but is less accurate and problem of battery drainage).	- Possibility to combine with socio-demographic information, since mostly participants are visited to advise them on the use of the device	- No info of trip purpose and transport mode - Possible errors because of slow connectivity or physical structures - Important to do proper data cleaning (e.g. remove cluttered data because of being indoors)
Travel patterns using mobile phone network	Spatial resolution depends on the density of Base Transceiver Stations (BTSs).	- Passive technique (without disturbing participants) - Large study sample size - Long time period possible - No additional sensor network needs to be put up	- Good agreement with mobile phone network provider needed - Privacy issues - Some age or social groups might be underrepresented - Limited socio-demographic user data
Travel patterns using models	Can predict which, where, when, for how long, with whom, and with which transport mode activities are conducted.	- Passive technique (without disturbing participants) - Low costs (no additional infrastructure needed) - Future predictions	- Base information needed - Difficult to obtain accurate results because of the high complexity of the real-world
Geospatial analyses			
General GIS analyses	Different data sources (travel patterns, municipalities, land use, air pollution concentration) can be combined, analysed, and/or visualised.	- Variety of analyses available (e.g. network closest distance, buffer, overlay) - Can be implemented in an off-the-shelf GIS, or in a scripting environment	Expertise needed.

Calculating accessibility with FCA method	Different methods available (physician-to-population ratio, distance to closest, cumulative opportunity), but preferably Floating Catchment Area (FCA) methods.	Conceptually the best method.	Expertise needed.
Combining GPS with accelerometer data	Using date/time-stamp of both data sources. Can be done in a scripting environment or using existing tools: for example Personal Activity Location Measurement System (PALMS) (PALMS, 2015), where also other devices (e.g. heart rate monitor) can be incorporated and additional parameters (e.g. indoor/outdoor status, transport mode, stop locations, trips) can be calculated.	Can be used to define transport mode.	/

First, the data sources used to define the individual travel patterns (GPS and mobile phone network data) can also be applied in other research domains (e.g. exposure to noise or sunlight, or contact with unhealthy eating facilities). Geospatial data and analyses implemented in GIS have a large potential in health-related studies. A lot of research has been conducted on the relationship between the built environment and health during the past ten years. Future research "*should address a range of spatial scales–from buildings to metropolitan areas–and a range of health outcomes–not only physical activity but also mental health, respiratory health, neurodevelopment among others–*"and "*public health and design professionals must recognise those at greater risk and with the greatest need for intervention and focus accordingly*" (Jackson, Dannenberg, & Frumkin, 2013, p. 1543).

Second, the use of GPS data to determine the area where people spend their time can be expanded. Instead of using individual GPS points to detect the participants' location, GPS-based activity buffers could be calculated, for example using a minimum convex polygon (Rundle et al., 2016). From this delineated buffer zonal characteristics can be calculated, better representing the neighbourhood than administrative or network buffers, which is difficult when using individual GPS points (Schipperijn et al., 2013). It should however be noted that using such GPS-based buffers are particularly useful for studying the relationship between the built environment and actual exposure (e.g. to air pollution), but care is needed when using this to study the relationship between the built environment and behaviour (e.g. PA) because of self-selection. A possible solution would be to only consider the GPS points located in a 1 km buffer around the home and work location of a participant.

Third, it was not possible to extract causal relationships in *chapter 5*, because a cross-sectional study was conducted. Future studies should focus on longitudinal research or–more ideally–natural experiments to investigate if built environment alterations induce behaviour changes and whether or not these changes are occasional or persistent. Natural experiments could also have great value in the other studied topics, for example to check if residents' perceptions can be improved, to study if introducing green areas has a positive effect on PA, or to examine if introducing health care facilities at certain locations improves accessibility to health care.

Fourth, as mentioned earlier, the transport mode can be defined more accurately than we did using only GPS based speeds. Future work should try to combine GPS and accelerometer data to define the used transport mode. A possible method is to detect trips from the raw dataset, using the GPS speed (average and/or maximum) and accelerometer counts, as each transport mode is characterised with certain values. Next, the transport mode (e.g. walking, running, cycling, car, motorcycle, bus, or train) per trip can be identified using a predefined function (Troped et al., 2008) or using a Bayesian belief network (Feng & Timmermans, 2013). Nonetheless, with the increasing use of electrically assisted bicycles (e-bikes)–especially by older adults–defining PA for cyclists becomes increasingly difficult because less physical activity is required at higher speed levels. As heart rate monitors placed around the wrist–which are less obtrusive than those placed around the chest–are becoming increasingly popular, these could be used to calculate PA as an alternative to accelerometers. However, more research is needed to model the relationship between heart rate and PA for different subgroups (e.g. gender, age). GPS and accelerometer data could also be overlaid with land use data to improve transport mode estimations, for example based on the proximity of public transport stops, and the vicinity of railway tracks and walking trails.

Fifth, some of the research conducted can be further expanded by incorporating more personal characteristics, such as the socio-economic status. We addressed the issue raised in the UGCoP by incorporating the spatial context people are exposed to. However, in future research also the social context (e.g. interaction with friends) could be incorporated to gain more insight in how social factors influence different health aspects.

Sixth, with the increasing battery life of smartphones, apps could be used instead of standalone devices to collect the participants' location or PA. This way, the cost of collecting data becomes less of a problem and a larger study sample could be reached. Also, real-time data collection is possible (active tracking) and live feedback from participants can be asked when smartphones are connected to the internet, leading to new research possibilities (Maas et al., 2013). An example of such a smartphone app is Mobile Teen, where PA is objectively measured using the mobile phone's built in motion sensor, combined with self-report surveys to collect information on the type, purpose, and context of the activity (Dunton et al., 2014). The growing interest of the Quantified

Self movement (i.e. the self-monitoring of e.g. weight, PA, caloric intake, and sleep quality using wearable sensors such as Fitbit or Apple Watch) indicates that such big data is not only interesting for researchers, but also for people wanting to quantify their everyday life (Singer, 2011).

Seventh, the accessibility measures described in *chapter 4* can be further improved. The E2SFCA method has been examined recently and several suggestions have been made to further improve this measure (Neutens, 2015). In a more 'ideal' accessibility measure temporal metrics such as individual travel patterns or the opening hours of the facilities should be more integrated. Additionally, measures should be more person-based and non-spatial factors (e.g. income, age, language barriers) should be taken into account. However, often only data per administrative unit–and not per individual–is available. Then, it is important to acknowledge and–if possible–consider social differences within these units, for example using the Gini coefficient (Neutens, 2015). However, more work is needed to develop more dynamic and individualised conceptualisations of health care accessibility.

Finally, other innovative techniques could be used to analyse individual travel data, to explore the relationship between the built environment and health on a next level. A first possibility is to use the Sequence Alignment Method (SAM) to discover interesting patterns in visited destinations or to detect (de)similarities between different sequences of visits (Delafontaine, Versichele, Neutens, & Van de Weghe, 2012; Shoval & Isaacson, 2007). A second option is to use the Continuous Spatio-Temporal Model (CSTM) to perform analyses and create visualisations at multiple temporal and spatial resolutions (Van de Weghe, De Roo, Qiang, & Versichele, 2014). While these methods have been explored in a variety of research subjects (e.g. market analysis and bioinformatics), they could also be implemented in health-related studies using big datasets of individual travel patterns.

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Curriculum vitae

Bart Dewulf was born on May 26, 1987 in Ieper. In 2005, he finished high school at Vrij Technisch Instituut in Ieper. He finished his education in physical geography at University of Leuven in 2010, while going on Erasmus to Lund University. After successfully finishing his teacher training at University of Leuven in 2011, he started working as a research assistant at the Department of Geography at Ghent University. In the same year, he received a doctoral grant from the Flemish Fund for Scientific Research (FWO) and the Flemish Institute for Technological Research (VITO) and became a PhD student.

Bart has participated in several international conferences and has published several papers in international journals in health-related geography, which are included in this thesis.

One additional publication was written during the course of this PhD. In this research, geospatial data, analyses, and visualizations were used to study transport flows and congestion. However, this manuscript is not included in the thesis, because it does not fit within the health-related scope of this thesis.

Dewulf, B., Neutens, T., Vanlommel, M., Logghe, S., De Maeyer, P., Witlox, F., De Weerdt, Y., Van de Weghe, N. (2014) Examining commuting patterns using Floating Car Data and circular statistics: Exploring the use of new methods and visualizations to study travel times. *Journal of Transport Geography*, *48*, 41-51.