Dissertation

Geostatistical Modeling of Built Environment Characteristics of Urban Moveability

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Abstract

Physical inactivity among other behaviors such as smoking, alcohol consumption, and an unhealthy diet, is considered as a major risk factor for non-communicable diseases, for example cardiovascular diseases or obesity. In particular, technological developments and environmental changes led to a decrease of physical activity in daily life. In the last two decades, the investigation of factors influencing physical activity more and more focused on characteristics of the built environment and identified opportunities as well as barriers for physical activity. The walkability concept was established to investigate the association between the built environment and physical activity. This research starts from a walkability index that combines urban measures for residential density, land use mix, and street connectivity.

The walkability index was mainly used to investigate neighborhoods that support physical activity with regard to active transport of adults in everyday life. Moreover, studies were mainly conducted in regions of the U.S. and Australia which have a different urban and suburban structure compared to Europe. In this thesis, the walkability concept was expanded by built environment characteristics that might affect physical activity in European children. The IDEFICS study (Identification and prevention of Dietary- and lifestyle-induced health EFfects In Children and infantS) gave the opportunity to investigate the association between urban measures of the built environment and objectively measured physical activity in children based on accelerometry data. Moderate-to-vigorous physical activity (MVPA) was assessed in 400 2- to 9.9-year old children living in one German study region that was selected for a pilot study. Spatial data were collected and processed in order to assess walkability measures and recreational facilities. Based on these data a new concept was introduced to capture opportunities for physical activity in the neighborhood of children, called moveability index.

Spatial and individual-level data were linked using two approaches; administrative areas such as districts and sub-districts, and ego-centered network-dependent neighborhoods. The latter are calculated based on a distance from the place of residence using the footpath-network. The spatial context in which built environment characteristics are assumed to affect the behavior of residents is recently discussed in the literature which was accounted for in the spatial analyses of this thesis using different spatial scales and neighborhood contexts.

Based on these neighborhoods, different methods to assess point characteristics were compared. Commonly used methods to estimate urban measures do not account for spatial variation within urban neighborhoods and might be improved by a more complex geostatistical modeling of point characteristics. Kernel intensity measures estimate the parameter of an inhomogeneous point process and lead to a smoothed estimation of the intensity, i.e.

the availability, of urban point characteristics. The kernel approach depends on the choice of a bandwidth as a smoothing parameter. Point characteristics were assessed within administrative areas as well as in ego-centered neighborhoods comparing different methods for bandwidth selection. Methods for bandwidth selection such as isotropic and anisotropic cross-validation as well as the use of an adaptive bandwidth, that adjust the assessment with regard to underlying information on residential density, were used to investigate the association between the built environment and physical activity in children.

In the German study region, the availability of parks and playgrounds was particularly associated with MVPA in children. Ego-centered neighborhoods with distances from 750 m up to 1.250 m were found to capture the neighborhood of these children. Moreover, the use of kernel intensity measures based on an anisotropic bandwidth to assess the availability of point characteristics performed better compared to the commonly used simple intensity.

Overall, the availability of public open spaces within well-connected residential areas might positively affect physical activity in children. However, perceived neighborhood safety of the parents is an important moderator that restricts the use of their neighborhood and reduces physical activity of children. Future studies combine GPS and accelerometry data to better capture the space-time behavior of children in order to assess the moveability index particularly within large urban study regions. The moveability index allows to rate urban neighborhoods with regard to their opportunities for physical activity and to give recommendations for city planners and public health stakeholders promoting healthy living in children.

Zusammenfassung

Körperliche Inaktivität steht neben anderem Risikoverhalten wie Rauchen, Alkoholkonsum und schlechte Ernährung als wichtiger Einflussfaktor für Zivilisationskrankheiten wie Herz-Kreislauferkrankungen und Fettleibigkeit im Fokus der aktuellen Gesundheitsforschung. Vor allem die veränderte Lebensumwelt der letzten Jahrzehnte hat zu einer Reduktion von körperlicher Aktivität in der Bevölkerung geführt. Die Untersuchung möglicher Einflussfaktoren auf körperliche Aktivität fokussierte sich in den letzten Jahrzehnten immer stärker auf den Einfluss der bebauten Lebensumwelt, wodurch sowohl Möglichkeiten als auch Barrieren für körperliche Aktivität identifiziert wurden. Für die Erfassung von Einflussfaktoren der bebauten Nachbarschaft hat sich das Walkability Konzept etabliert, das urbane Maße wie Einwohnerdichte, Landnutzungsmischung und die Wegekonnektivität zu einem Index kombiniert, um den Einfluss auf leichte und moderate körperliche Aktivität von Anwohnern zu untersuchen.

Der Walkability Index wurde bisher eingesetzt, um bewegungsfreundliche Nachbarschaften mit Blick auf das Bewegungsverhalten von Erwachsenen im Alltag zu untersuchen. Die bisher durchgeführten Studien basieren außerdem auf urbanen und suburbanen Regionen in den USA und Australien, die sich stark von europäischen Regionen unterscheiden. In der vorliegenden Dissertation wurde das Walkability Konzept um urbane Charakteristika erweitert, die das Bewegungsverhalten von Kindern beeinflussen können. Die IDEFICS-Studie (Identification and prevention of Dietary- and lifestyle-induced health EFfects In Children and infantS) bot die Möglichkeit, den Zusammenhang von Maßen der bebauten Umgebung und dem Bewegungsverhalten von Kindern basierend auf Akzelerometerdaten zu untersuchen. Moderate bis intensive körperliche Aktivität (moderate-to-vigorous physical activity, MVPA) wurde bei 400 2- bis 9.9-jährigen Kindern in einer deutschen Studienregion erfasst, die als Pilotregion ausgewählt wurde. Räumliche Daten wurden verarbeitet, um urbane Charakteristika des Walkability Konzepts und Merkmale, die Möglichkeiten für körperliche Aktivität in der Freizeit bieten, zu erfassen. Darauf aufbauend wurde ein neuer Index für urbane Bewegungsfreundlichkeit (urban moveability) für Kinder entwickelt.

Die Verknüpfung von räumlichen und individuellen Daten erfolgte über zwei verschiedene Ansätze: Zum einen durch administrative Einheiten wie Stadtbezirke und zum anderen durch individuelle Nachbarschaften. Letztere werden abhängig vom Fußwegenetzwerk durch eine vorgegebene Distanz ausgehend vom Wohnort erzeugt. Der genaue räumliche Kontext, in dem urbane Merkmale das Bewegungsverhalten von Anwohnern beeinflussen, wird in der Literatur intensiv diskutiert und wurde unter Verwendung von verschiedenen Skalenniveaus und Nachbarschaften bei der Untersuchung berücksichtigt.

Auf Basis dieser Nachbarschaften wurden verschiedene Methoden zu Erfassung von Punktmerkmalen verglichen. Die bisher verwendeten Methoden zur Schätzung urbaner Maße berücksichtigen nicht die Heterogenität in urbanen Nachbarschaften und können durch eine komplexere räumliche Modellierung der urbanen Charakteristika verbessert werden. Kernintensitätsschätzer basieren auf einem so genannten inhomogenen Punktprozess und glätten die Schätzung der Intensität, also die Verfügbarkeit, von urbanen Punktcharakteristika in Abhängigkeit der Bandweite der Kernfunktion als Glättungsparameter. Die Erfassung von urbanen Punktmerkmalen wurde sowohl in administrativen Einheiten als auch in individuellen Nachbarschaften unter Berücksichtigung verschiedener Modellierungsansätze zur Bestimmung der Bandweite verglichen. Dabei wurden Methoden zur Kreuzvalidierung von isotropen, anisotropen bzw. adaptiven Bandweiten eingesetzt, die die Schätzung abhängig von zu Grunde liegender Information über Einwohnerdichte anpassen, und deren Einfluss auf den Zusammenhang von urbaner Umgebung und Bewegungsverhalten von Kindern untersucht.

Mit Blick auf das Bewegungsverhalten von Kindern aus der deutschen Studienregion zeigten im Vergleich vor allem die Verfügbarkeit von Parks und Spielplätzen einen positiven Einfluss auf moderate bis intensive körperliche Aktivität von Kindern. Dabei wurde deutlich, dass netzwerkabhängige Nachbarschaften basierend auf Distanzen von 750 m und 1.250 m die Nachbarschaft von Kindern widerspiegeln und die Modellierung einer anisotropen Bandweite für die Kerndichteschätzung der Intensität bzw. der Verfügbarkeit von urbanen Charakteristika anderen Schätzmethoden überlegen ist.

Insgesamt zeigte sich, dass die Verfügbarkeit von gestalteten öffentlichen Freiflächen in Wohnquartieren das Bewegungsverhalten von Kindern positiv beeinflussen kann. Dabei können jedoch subjektive Sicherheitsbedenken der Eltern einen wesentlichen Einfluss auf das Bewegungsverhalten bzw. den Bewegungsradius der Kinder haben und deren körperliche Aktivität stark einschränken. Durch die gemeinsame Erfassung von GPS- und Akzelerometerdaten kann das räumlich-zeitliche Verhalten von Kindern und Familien besser erfasst, und so der Moveability Index als Instrument zur Erfassung der Bewegungsfreundlichkeit einer Umgebung vor allem in größeren urbanen Studienregionen untersucht werden. Eine Bewertung von Nachbarschaften durch den Moveability index würde es erlauben, Quartiere hinsichtlich ihrer Bewegungsförderung genauer einzuschätzen und so Empfehlungen für Stadtplaner und Akteure der Gesundheitsförderung zu geben.

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1. Introduction

Physical activity is one major determinant of lifestyle-related non-communicable diseases such as cardiovascular diseases, diabetes, and obesity. Insufficient physical activity has been found to be an important risk factor of all-cause mortality, besides smoking, alcohol consumption and unhealthy diet (Kvaavik et al., 2010), and to be responsible for 6% to 10% of major non-communicable diseases (Lee et al., 2012). A meta-analysis revealed that active transport alone such as walking and cycling reduces the risk for all-cause mortality adjusted for other physical activity(Kelly et al., 2014). Whereas early research of correlates or determinants of physical activity and active transport in particular mostly focused on individual-level behavior, in the last two decades studies were launched to consider opportunities and barriers in the social and physical environment (Andrews et al., 2012; Bauman et al., 2012; Ding and Gebel, 2012; Sallis et al., 2012). These studies particularly account for the fact that changes in technology, lifestyle, transportation and urbanized built environments have led to a vast decrease of physical activity, especially in industrialized countries (Huybrechts et al., 2009; Sallis, 2009).

The urbanized built environment is a result of humankind's efforts to shape their environment, to improve daily routine and to increase their quality of life. In return, the built environment shaped the physical behavior of residents by offering opportunities for active transport and recreational physical activity or creating barriers that reduce the need for physical activity in everyday life (Forsyth et al., 2007; Sallis, 2009). This problem is evident mainly in the U.S. and especially in the Western parts of the U.S., where suburban sprawl has been promoted as the new standard of housing over the last century. Suburban areas are characterized as low-density, monofunctional and car-dependent neighborhoods, i.e. inhabited by a low number of residents per km^2. The design of suburban sprawl induced a dispersal of living, working, and services. It offers limited opportunities for walking and cycling, since destinations of everyday life are located outside of the suburban sprawl, thereby necessitating car-use (Hall, 1996; Cervero and Kockelman, 1997; Krizek, 2003b; Montgomery, 2013). Besides other risk behaviors and technological advancement, the dispersal of the urban built environment and car-dependency are the main drivers of physical inactivity (Sallis et al., 2012).

Due to this relationship, the public health burden increased and research of environmental risk factors, which was primarily conducted in the U.S., commenced to identify characteristics and elements of the built environment that are related to physical activity (Cervero and Kockelman, 1997; Krizek, 2003a; Frank et al., 2005; Sallis, 2009). Public health and urban planning institutions started to collaborate and considered built environment characteristics from urban development as factors that particularly influence active travel modes such as walking and cycling in everyday life (Krizek et al., 2004; Sallis, 2009; Kent and Thompson, 2014). The 3D's, i.e. residential **density**, **diversity** of destinations, and pedestrian friendly street **design**, were considered as basic concept (Cervero and Kockelman, 1997). These were expanded by different characteristics to investigate specific research questions regarding, for instance, leisure time activity (Klinker et al., 2014) or public transport (Freeman et al., 2013).

To measure built environment characteristics that represent opportunities or barriers of physical activity in the neighborhoods of residents, two main approaches are used. The first comprises multiple questionnaires that were developed to assess perceived built environment characteristics (Millington et al., 2009), esthetics of streets (Bethlehem et al., 2014), or recreational areas (Gidlow et al., 2012) via field surveys. One example is the widely-used Neighborhood Environment Walkability Scale (NEWS) which consists of items considering the density of living, availability of destinations for utilitarian purposes, as well as items regarding street design that also account for neighborhood safety (Cerin et al., 2006; Tappe et al., 2013). The second approach results from the combination of technological advancements in computing power and the availability of high-quality spatial data which allow the use of Geographic Informations Systems (GIS) to collect, manage and objectively measure built environment characteristics (Thornton et al., 2011; Kwan, 2012a; Schipperijn et al., 2013; Buck and Tkaczick, 2014). Based on the concept of the 3D's, GIS-based urban measures such as residential density, land use mix, and street connectivity were established and found to have an effect on physical activity, particularly on walking for transport in adults (Frank et al., 2005; Lee and Moudon, 2006; Owen et al., 2007; Brownson et al., 2009; Van Dyck et al., 2010; Sundquist et al., 2011). In detail, dense neighborhoods that enclose short and well-connected footpaths to multiple and diverse destinations were identified to provide more opportunities for physical activity in terms of active transport compared to suburban neighborhoods (Owen et al., 2007; Forsyth et al., 2007; Brownson et al., 2009; Ding and Gebel, 2012; Freeman et al., 2013). Hence, these three urban measures, residential density, land use mix, and street connectivity, emerged to form the walkability concept. Due to their mutual correlation these measures were combined to build the first walkability index that formed the basis of further research mainly conducted in the U.S. and in Australia (Frank et al., 2005; Sallis, 2009; Kerr et al., 2013; De Bourdeaudhuij et al., 2015). To specify the walkability of neighborhoods and include information on additional characteristics different measures for built environment characteristics, such as the commercial floor area ratio (Frank et al., 2010), density of specific destinations (Witten et al., 2012), or availability of public transit (Freeman et al., 2013) were added to the index.

Different versions of the walkability index have been investigated, mostly regarding active transport, i.e. walking, in adults. However, effects of the built environment on leisure time physical activity were rarely taken into account. For instance, Witten et al. (2012) found associations between street connectivity or destination density and active travel as well as leisure time physical activity. Besides the focus on a different domain of physical activity, the walkability index has hardly been investigated with regard to physical activity in children and adolescents. In a recent review, Ding et al. (2011) found only few articles that investigated associations of GIS-based walkability measures with objectively measured physical activity in children. Findings are less clear compared to the evidence in adults (D'Haese et al., 2011, 2014; Frank et al., 2012; Buck et al., 2015c; Casey et al., 2014). Time spent outdoors and in recreational space has, however, been reported to be the main factor to increase physical activity in children (Roemmich et al., 2006; Holt et al., 2009; Cooper et al., 2010). This implies that the walkability concept applied so far is not sufficient to capture opportunities for children to be physically active. Thus, the walkability concept needs to be expanded by incorporating built environment characteristics that are related to leisure time physical activity in children, for example the availability of public open spaces and playgrounds (Krizek et al., 2004; Fyhri and Hjorthol, 2009), such that it captures the playability or the moveability of a neighborhood (Buck et al., 2015c).

Moreover, the spatial scale and the definition of the neighborhood are crucial for the investigation of the association between environmental exposure and physical behavior within the neighborhood, because assumptions on the spatial context in which built environment characteristics influence physical activity also influence the strength of this association (Spielman and Yoo, 2009; Chaix et al., 2010; Feng et al., 2010; Leal and Chaix, 2011; Casey et al., 2014). The walkability index is mostly calculated within administrative areas of cities (Leal and Chaix, 2011). This is, however, known to induce spatial misclassification of urban measures and the behavior of residents (Duncan et al., 2014; Vallée et al., 2014) as well as problems of scaling and zoning, which are also known as the Modifiable Area Unit Problem (MAUP) (Houston, 2014). Administrative areas are artificially drawn and do not necessarily enclose spatial movement and activity locations of residents (Perchoux et al., 2013). Limitations by means of scaling and zoning could be resolved by using ego-centered neighborhood buffers around the place of residence or a place of interest for individual behavior (Frank et al., 2005; Chaix et al., 2010). However, only few studies used ego-centered neighborhoods and buffer sizes were chosen differently, thereby hindering a comparison of the results presented in the literature (Feng et al., 2010; Leal and Chaix, 2011).

From a methodological point of view, walkability measures might also be improved by using more complex geostatistical methods. In particular, point characteristics such as intersections, public transit stations, or public open spaces are commonly measured using a simple intensity approach, i.e. number per area, which does not account for variation within the neighborhood area (Maroko et al., 2009; Buck et al., 2011; Diggle, 2013). Kernel approaches are widely used for cluster detection and may also improve the assessment of the availability of public transit or public open spaces by means of intensity measures (Maroko et al., 2009; Buck et al., 2011; Diggle, 2013). Following the idea of a smoothing average, the kernel intensity is calculated as the weighted sum of points within a chosen bandwidth around a point of observation. However, the performance of kernel estimators strongly depends on the choice of the bandwidth as a smoothing parameter (Scott, 1992). Different cross-validation techniques are applied to model circular and elliptical bivariate bandwidths that could enhance the assessment of the availability of point characteristics in the built environment. Moreover, adaptive bandwidths, that are discussed with regard to cluster detection, might be used in order to adjust a kernel intensity estimator by the underlying residential density (Carlos et al., 2010).

1.1. Aim of the thesis

This thesis focuses on the objective assessment of the built environment and GIS-based urban measures to investigate the association between built environment characteristics and physical activity in children. The IDEFICS study (Identification and prevention of dietary- and lifestyle-induced health effects in children and infants) provides a unique opportunity to investigate this association particularly in European children. The IDEFICS study is a multicenter study that was conducted from 2006 to 2012 and that collected anthropometrical, medial, socio-demographical, and behavioral data of 16,228 2- to 9.9-year old children from eight European countries including Germany. In the IDEFICS study, accelerometers were provided to a subsample of participating children in order to objectively measure physical activity. One German study region was selected to conduct a substudy on the influence of the built environment on physical activity behavior of children. This substudy pursued three major aims

1) First, to evaluate the performance of kernel intensity measures and various approaches for bandwidth selection to improve the assessment of point characteristics compared to the simple intensity method.

2) Second, to investigate the association of walkability measures in children and to identify additional characteristics of the built environment in order to expand the walkability concept to a moveability concept that should be appropriate to capture opportunities for physical activity in children.

3) Third, to construct a moveability index that is able to assess opportunities for physical activity in the built environment of children; and to investigate the influence of different spatial scales and concepts of the designated neighborhoods on the moveability index and its association with physical activity.

1.2. Structure of the thesis

The research on built environment characteristics of urban moveability and their effect on physical activity in children is presented in seven chapters. The first three chapters of the thesis (Chapters 2 - 4) summarize the scientific background of environmental research with respect to the aims of the thesis. Chapter 2 provides a summary on GIS-based urban measures of built environment characteristics that are related to physical activity and highlights which characteristics should be considered to capture opportunities for leisure time activities in children. Chapter 3 describes measures of built environment characteristics such as the simple intensity and kernel intensity approaches that build on geostatistical theory of point processes. Kernel intensity measures are discussed with regard to a more flexibly estimation of the availability of point characteristics based on cross-validation techniques for bandwidth selection. Chapter 4 summarizes the recent discussion in the literature about the conceptualization of the neighborhood context and the spatial scale that both determine where to measure built environment characteristics with regard to physical activity behavior of residents in space and time.

The last three chapters (Chapters 5 - 7) describe the spatial analyses that have been conducted to achieve the aims of the thesis. The analyses are comprised in the referred articles to which I contributed as first author and that were published in or recently submitted to epidemiological journals with peer-review (see Appendix B). Chapter 5 introduces the IDEFICS study that provided individual-level data, particularly on objectively measured physical activity, and describes data sources as well as the processing of spatial data. The realization of the aims of the thesis is presented in Chapter 6 in terms of the development of the moveability index in line with spatial analyses, that evaluate methodological improvements as well as associations between the built environment and physical activity. The thesis concludes with a critical appraisal of the findings in Chapter 7 illustrating future perspectives on new measurements and methods that will become state of the art in the investigation of individual behavior and environmental exposure.

1.3. Acknowledgments

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2. Built environment characteristics and urban measures

In the last decades, characteristics of the built environment were identified that provide opportunities or barriers for physical activity. Based on spatial data, characteristics were objectively assessed using urban measures to investigate their association with various end-points such as physical activity levels, active travel, or obesity (Brownson et al., 2009; Sallis, 2009; Durand et al., 2011; McCormack and Shiell, 2011; Ding and Gebel, 2012).

This chapter provides a narrative overview of built environment characteristics that are used to calculate common GIS-based urban measures. Eventually, the walkability concept is introduced and the expansion of existing indices to capture additional characteristics of the built environment is described. A detailed systematic review of the assessment of the objective built environment is provided by Brownson et al. (2009) and an overview of the conceptualization and historical development in assessing "physical activity environments" was published by Sallis (2009). Urban measures and walkability indices are based on the operationalization of neighborhoods which is crucial in assessing the built environment. For this reason, the determination of neighborhoods is described in Chapter 4 in more detail although the major concepts are applied in the following.

2.1. The walkability concept

City planners in the early 1980s started to investigate built environment characteristics such as land use or transportation system and their relation to travel behavior, while health researchers only focused on the distance to and availability of recreational space related to leisure time physical activity (Sallis, 2009). Cervero and Kockelman (1997) first introduced the idea of walkability mentioned as the 3D's: **density**, **diversity**, and **design**. Residential **density**, land use **diversity**, and pedestrian-oriented **design** were considered as key components that affect walking and cycling in residents (Cervero and Kockelman, 1997; Sallis, 2009). Built environment characteristics and urban measures to be used to assess these components were not specified in the concept of the 3D's (Lee and Moudon, 2006), but emerged in further research based on the concept of Cervero and Kockelman (1997). In the field of urban planning and public health, characteristics and measures correlated with active travel were identified from a variety of variables (Brownson et al., 2009; Sallis, 2009; McCormack and Shiell, 2011; Ding and Gebel, 2012) that will be described in the following paragraph.

2.1.1. Street network

Being active in urban environments mainly results from the need of everyday trips to destinations such as the workplace, the school, or commercial destinations, and from the decision to use active travel modes. This can be influenced by the availability of streets and main roads, of footpaths beside the streets, or additional bike lanes. Streets and main roads clearly offer the opportunity for car use. Thus, the availability of footpaths and bike lanes as well as short routes are important to increase active travel such as walking or cycling (Giles-Corti et al., 2009; D'Haese et al., 2011; Wong et al., 2011).

The choice of different routes is commonly assessed by the amount of intersections of the network of footpaths or bike lanes. Neighborhoods with a high number of intersections offer multiple and short ways within the neighborhood and encourage active travel, whereas a small number of intersections point out that the neighborhood only includes long single routes which are more likely to increase car use (Lee and Moudon, 2006; Berrigan et al., 2010; Winters et al., 2010; Wong et al., 2011). The intersection density ID is calculated as the number of 3-way and 4-way intersections per neighborhood area and is commonly used as a measure of street connectivity in the recent literature (Frank et al., 2005; Brownson et al., 2009; Van Dyck et al., 2011; Frank et al., 2010; Freeman et al., 2013; Chaix et al., 2014; Glazier et al., 2014).

In addition to the intersection density, multiple measures and indices were also considered (Brownson et al., 2009) such as the density of street segments, i.e. segments of footpaths between intersections, ratios of nodes (intersections and dead-ends) and links (street segments) (Chaix et al., 2014), as well as so called α- or γ-indices that quantify the possible amount of links based on the number of nodes (Berrigan et al., 2010).

The choice for active travel in urban environments is also supported by the availability of public transit (Edwards, 2008; Freeman et al., 2013), which has been assessed by the number of public transit stations or services, i.e. bus lines or subway routes, per neighborhood in recent studies (Freeman et al., 2013). Detailed descriptions and comparisons of measures with regard to the street network can be found in Brownson et al. (2009); Berrigan et al. (2010) and Wong et al. (2011).

2.1.2. Land use

The decision to walk or cycle in an urban environment does not only depend on the availability of sidewalks or the street connectivity, but also on the number and the diversity of everyday life destinations such as schools, workplaces, shopping opportunities, or services within walking or cycling distance (Frank et al., 2005; Lee and Moudon, 2006). Single destinations near the home location encourage residents to walk or cycle a short trip to one destination, whereas various destinations offer the opportunity to combine multiple trips from home and between destinations to longer tours in the neighborhood via active travel modes (Krizek, 2003b).

Geographical data on land use offer an easy way to assess the diversity or the availability of destinations in urban areas, which, however, strongly depends on the quality of commercial or municipal databases. Typically, land use types such as residential, commercial, recreational, or industrial are processed to characterize the study area with regard to the diversity of destinations. Complex measures based on the proportion of these land use types per neighborhood are employed to either assess the diversity or dissimilarity of land use (Lee and Moudon, 2006; Frank et al., 2007b; Brownson et al., 2009). Predominantly, the diversity of land use types, i.e. the land use mix LUM, is assessed by the entropy formula based on the proportions $p_{A_j,l}, l = 1, \ldots, L$, of land use types l in neighborhoods $A_j, j = 1, \ldots, m$, with $\sum_{l=1}^{L} p_{A_j,l} = 1$ defined as

$$H(p)_{A_j} = -\frac{1}{\ln(L)} \sum_{l=1}^{L} p_{A_j,l} \cdot \ln(p_{A_j,l}) \tag{2.1}$$

(Frank et al., 2005; Lee and Moudon, 2006; Frank et al., 2007b; Ding et al., 2011; Van Dyck et al., 2011; Frank et al., 2010; Glazier et al., 2014). The entropy $H(p)$ provides values between 0 and 1, where 0 describes homogeneity, i.e. only one land use type dominates the neighborhood, and 1 means heterogeneity, i.e. all land use types are evenly distributed (Frank et al., 2005; Buck et al., 2011; Buck and Tkaczick, 2014).

In addition, a more specific measure of commercial land use is applied to describe the car dependency of urban neighborhoods (Badland et al., 2009; Frank et al., 2010; Freeman et al., 2013). The retail floor area ratio FAR is based on the retail floor area that is actually used for commercial purpose. This area is divided by the official commercial area to obtain the FAR that is used to assess the amount of commercial land use designated for parking space. Commercial areas without any parking space show ratios close to 1, whereas a lower ratio indicates that a certain amount of parking space is offered to reach commercial destinations in this neighborhood predominantly by car (Frank et al., 2010).

Assessing the diversity of destinations, land use types, and particularly the retail floor area ratio strongly depends on the availability of high-quality data on land use types and commercial sites. Since commercial or municipal databases as well as sources for geographical data differ, many studies implemented slightly different measures to assess e.g. land use mix or diversity of destinations. A detailed overview is provided by Brownson et al. (2009).

2.1.3. Residential density

The availability of short routes and a high mix of destinations within an urban region imply a certain amount of residents and are, in fact, induced by the number of residents in a neighborhood to warrant the supply of residents through retailers and services. Thus, a high number of residents creates a critical mass, where at a certain threshold synergy effects on the street network and land use result in a neighborhood that might support active travel (Lee and Moudon, 2006; Forsyth et al., 2007).

Residential density RD illustrates one of the main urban measures in the literature of built environment research (Frank et al., 2005, 2007b,a, 2010; Ding et al., 2011; Van Dyck et al., 2011; Glazier et al., 2014) and is genuinely measured as number of residents per neighborhood area. The number of residents in urban regions is typically provided in census districts and different aggregation levels are used to assess the residential density in specific neighborhoods, which are listed in Brownson et al. (2009) and also compared by Forsyth et al. (2007).

Residential density is highly correlated with land use mix and street connectivity. Therefore, it is discussed that residential density can be seen only as a proxy for other dimensions of the built environment that tend to affect physical activity such as diversity and street design, or even individual-level dimensions of socio-economic status or safety perceptions (Forsyth et al., 2007). Residents of highly populated neighborhoods, for instance, could have similar preferences for walkable areas and show similar activity levels, which confounds the association between residential density and walking. Isolated effects of residential density were identified in some studies, though different measurements of physical activity as an outcome and uncontrolled confounding hinder a comparison of studies. Recently, Glazier et al. (2014) investigated residential density and land use mix and found strong associations with transport behavior. "High residential density and availability of destinations tended to coexist spatially; similarly, the absence of density and destinations also tended to occur together. Relatively few areas had only high density without many destinations or vice versa." (Glazier et al., 2014).

2.1.4. Walkability indices

The three main components, i.e. the 3D's: ID, LUM, and RD, show a high degree of mutual correlation (Cervero and Kockelman, 1997) as a "function of their inherent synergy in creating a walkable urban environment" (Frank et al., 2005). Neighborhoods with high residential density tend to show higher land use mix and higher street connectivity than neighborhoods with low residential density. Thus, urban measures of the 3D's induce estimation problems in regression models due to multicollinearity which can be solved by combining them to a walkability index as a compound measure of the built environment (Krizek, 2003a; Frank et al., 2005). In detail, urban measures are standardized as z-scores based on the mean and standard deviation of urban measures per neighborhood (Frank et al., 2005; Buck et al., 2011; Buck and Tkaczick, 2014). For instance, the intersection density ID_{A_j} calculated per neighborhood $A_j, j = 1, \dots, m$, is standardized as

$$z(ID_{A_j}) = \frac{ID_{A_j} - M(ID)}{S(ID)} \tag{2.2}$$

using the mean

$$M(ID) = \frac{1}{m}\sum_{j=1}^{m} ID_{A_j} \tag{2.3}$$

and the standard deviation

$$S(ID) = \sqrt{\frac{1}{m-1}\sum_{j=1}^{m}(ID_{A_j} - M(ID))^2}. \tag{2.4}$$

Then, standardized z-scores of each component, $z(ID_{A_j}), z(LUM_{A_j})$, and $z(RD_{A_j})$, are summed up to a walkability index per neighborhood A_j. This index was first introduced by Frank et al. (2005) and further extended by adding the standardized retail floor area ratio $z(FAR_{A_j})$ (Frank et al., 2007b, 2010). The walkability index is for instance used in the International Physical Environment Network (IPEN) to harmonize the objective assessment of the built environment[1] in twelve countries (Kerr et al., 2013; De Bourdeaudhuij et al., 2015).

Minor differences in the construction of the index result from different weightings of single components. For example, Frank et al. (2005) used a weight of 6 for the z-score of land use mix $z(LUM_{A_j})$ based on their study data "which was found to have the greatest explanatory power of the variation in the valid number of minutes of moderate activity per day" (Frank et al., 2005). The weight was omitted in a later version of the index (Frank et al., 2007b), but with regard to another study sample, a weight of 2 for the standardized intersection density $z(ID_{A_j})$ was then used (Frank et al., 2010). This version of the walkability index is eventually applied as a standardized measure of the built environment in IPEN studies (Kerr et al., 2013).

Mayne et al. (2013) investigated differences in the three-dimensional index based on $z(ID_{A_j})$, $z(LUM_{A_j})$, and $z(RD_{A_j})$ and the four-dimensional walkability index that also includes the retail floor area ratio $z(FAR_{A_j})$, since spatial data on commercial land use was only available in 5.3% of the considered census districts. Comparable associations between both indices and walking frequency were found and both indices were strongly correlated (Mayne et al., 2013). Thus, the three-dimensional walkability index seems to be sufficient to assess opportunities for walking in urban neighborhoods, if data on the retail floor area are not available.

Freeman et al. (2013) applied an unweighted version of the four-dimensional index in New York City. By adding the standardized density of public transit stations, i.e. subway and

[1] `http://www.ipenproject.org/methods_gis.html`, [18.05.2015]

bus stations, the index was adapted accounting for a major characteristic of this metropolitan area, the public transit, that is strongly related to active travel and walking frequency (Edwards, 2008; Freeman et al., 2013). This study particularly highlighted the potential of extending the walkability concept to capture multiple characteristics of the built environment with regard to specific outcomes of physical activity such as walking to work or to school and leisure time activities.

2.2. Recreational facilities and urban greenness

Leisure time activities represent another dimension of physical activity. Obviously, parks, green spaces, and recreational facilities such as sports clubs or sports fields are characteristics of the built environment that affect leisure time physical activity (Roemmich et al., 2006; Holt et al., 2009; Billaudeau et al., 2011; Charreire et al., 2012; Casey et al., 2014). It is therefore of importance to capture the availability, proximity, and accessibility to green spaces or recreational facilities. Considering land use data, a simple measure of the availability of parks and green spaces is provided by the size of recreational space within a neighborhood or the percentage of recreational area per neighborhood area (Roemmich et al., 2006; King et al., 2012; Charreire et al., 2012; Chaix et al., 2014).

Another approach is to put the areal information aside and to consider parks, green spaces, and recreational facilities as points. Availability and proximity of points can then be assessed based on density measures, such as the number of points per area (Brownson et al., 2009; Maroko et al., 2009; Reyer et al., 2014). Particularly, Maroko et al. (2009) recommended to use a kernel intensity approach (see Section 3.1.2) to assess the mean availability of parks. Reyer et al. (2014) considered a distance weighted approach to assess the number of public open spaces. Here, the weighted mean number of parks and green spaces was measured as number within a certain area, where points get lower weights the farther away they are from the location of interest (Reyer et al., 2014). Billaudeau et al. (2011) conducted a thorough analysis of the availability of different types of sports facilities such as tennis courts, swimming pools, soccer fields, etc. using the kernel intensity of point characteristics (Billaudeau et al., 2011).

2.3. Neighborhood safety

Beside the four main components that are used to assess opportunities for physical activity in the urban environment, one of the most important characteristics is the safety of the urban neighborhood. Two domains of neighborhood safety are relevant, namely traffic safety and safety from crime. Both domains are associated with active travel particularly in children and are assessed as parental perception of traffic safety or fear of crime (Weir et al., 2006; Lorenc et al., 2008; Panter et al., 2010). To objectively assess neighborhood safety, built environment characteristics such as traffic lights, illumination of parks, or speed limits are rarely considered (Brownson et al., 2009). Objective assessment of neighborhood safety depends on a sufficient level of detail that needs to be available in spatial data, though the availability differs between data sources, municipalities, and countries. However, perceived traffic safety or fear of crime showed stronger associations with active travel than objective safety measures, particularly in children. Thus, perceived safety should be considered as individual-level confounder for the association of objectively assessed built environment characteristics and physical activity levels (Timperio, 2004; Weir et al., 2006; Panter et al., 2010).

3. Geostatistical modeling of point characteristics

The availability of point characteristics in the built environment of children is commonly assessed using a simple intensity approach (Frank et al., 2005; Brownson et al., 2009). Due to the stationary assumption of the simple intensity, this approach does not account for the varying urban environment within a neighborhood or study area (Maroko et al., 2009; Buck et al., 2011). In this chapter, point characteristics in the built environment are modeled by means of point processes to derive the kernel intensity function. In addition, methods for isotropic and anisotropic bandwidth selection are presented in order to estimate the intensity of points within a study area (Scott, 1992; Illian et al., 2008; Diggle, 2013).

3.1. Point processes

The observation of points $s_i, i = 1, \dots, n$, within subsets $A \subset W$ of a study area $W \subset \mathbb{R}^2$ is statistically modeled as a Poisson point process (PPP) $N(A)$ with the following two properties (Illian et al., 2008):

1) The number of points $N(A)$ in any bounded area A follows a Poisson distribution, i.e. $N(A) \sim Poi(\lambda\nu(A))$ with $\mathrm{E}[N(A)] = \lambda\nu(A)$,

2) The number of points $N(A_j)$ in j disjoint areas $A_j \subset W, j = 1, \dots, m$, of a study area W represent j stochastically independent random variables.

The proof of property 1) can be found in Stoyan et al. (1987). It is based on the Bernoulli probability of the occurrence of one point within an area which is extended via the Binomial distribution, that considers a finite number of points, to the Poisson distribution that allows to observe an infinite number of points in the study area. Property 2) then obviously follows from the properties of a Poisson distribution (Ambartzumjan et al., 1993). The intensity λ characterizes the PPP and allows to infer the availability of point characteristics such as intersections, public transit stations, and public open spaces. In general, this is done assuming a homogeneous point process (Section 3.1.1). The inference of point availability can, however, be improved by inhomogeneous modeling of $N(A)$ (Section 3.1.2).

3.1.1. Homogeneous point processes

Based on properties 1) and 2), stated above, a homogeneous PPP assumes a constant intensity function $\lambda(s) \equiv \lambda$ which is motion-invariant and does not depend on any location $s \in A \subset$

$W, s \in \mathbb{R}^2$. A motion-invariant intensity is described as stationary and isotropic, i.e. the distribution does not change neither through a translation nor a rotation of the point process (Illian et al., 2008).

Let $\#_{s_i}(A) = \{s_i \in A | s_i \in \mathbb{R}^2, i = 1, \ldots, n\}$ be the number of points s_i that are located in area A and let $\nu(A)$ be the size of area A. Then the canonical estimator of the intensity λ is given as

$$\widehat{\lambda} = \frac{\#_{s_i}(A)}{\nu(A)}. \tag{3.1}$$

The stationary intensity estimator $\widehat{\lambda}$ of a homogeneous PPP represents the commonly used approach to assess the availability of public open spaces or the intersection density in the recent literature (Frank et al., 2005; Brownson et al., 2009; Maroko et al., 2009; Frank et al., 2010). The intensity function averages over larger areas and does not provide information on clusters within the area. To be more specific, the stationary assumption does not account for the variation of spatial information in urban environments and thus can not be recommended to assess the availability of point characteristics (Schabenberger and Gotway, 2005; Maroko et al., 2009; Buck et al., 2011).

3.1.2. Inhomogeneous point processes

To improve the assessment of the availability of point characteristics, an inhomogeneous PPP might be considered which is characterized by a Poisson distribution based on an intensity measure Λ. Then, instead of property 1), the number of points $N(A)$ in an area A is assumed to be Poisson distributed with $N(A) \sim Poi(\Lambda(A))$ and

$$\mathrm{E}[N(A)] = \Lambda(A) = \int_A \lambda(s)\, ds, \tag{3.2}$$

where $\lambda(s)$ denotes the inhomogeneous intensity function at location $s \in W$ (Stoyan et al., 1987; Schabenberger and Gotway, 2005). Property 2) again follows from the Poisson distribution (Stoyan et al., 1987).

Equation 3.2 is used to estimate the intensity of the process, since it represents the mean number of points and does not integrate to 1 in terms of a probability density function (Diggle, 2013). Nevertheless, the approach is often named kernel density in the literature on environmental research (Brownson et al., 2009; Maroko et al., 2009).

The inhomogeneous intensity function $\lambda(s)$ is estimated by means of a kernel estimator which originates from the numeric approximation of the cumulative distribution function (Scott, 1992). The two-dimensional kernel intensity function $\widehat{\lambda}(s)$ is given as

$$\widehat{\lambda}(s) = \frac{w_{|\mathbb{H}|,s}}{|\mathbb{H}|} \sum_{i=1}^{n} \mathbb{K}(\mathbb{H}^{-1}|s - s_i|), \tag{3.3}$$

where $\mathbb{H}$ is a two dimensional positive definite bandwidth matrix, i.e. the smoothing parameter that determines the kernel function $\mathbb{K}$; $w_{|\mathbb{H}|,s}$ represents an edge correction factor that is used when s is close to the border of W such hat the circle $B_{\mathbb{H}}(s)$ partially falls outside of W (Schabenberger and Gotway, 2005; Møller and Waagepetersen, 2007; Illian et al., 2008). For each point of observation $s \in \mathbb{W} \subset R^2$, the inhomogeneous intensity $\lambda(s)$ is calculated as the sum of points $s_i \in W$ that are located within the bandwidth $\mathbb{H}$. The kernel function weights each point s_i depending on its distance $|s - s_i|$ from the point of observation, where a greater distance induces a lower weight. The weight is zero for observations that fall outside the bandwidth (Silverman, 1986; Schabenberger and Gotway, 2005; Buck et al., 2011).

The Performance of a kernel estimate mainly depends on the choice of the bandwidth as a smoothing parameter, while the choice of the kernel function only plays a minor role. A conservative recommendation is to choose a smooth, clearly unimodal kernel that is symmetric about the origin (Scott, 1992). In this thesis, a two dimensional Gaussian kernel function $\mathbb{K}(x) = \varphi(x)$, i.e. the probability density function of the standard normal distribution $\mathcal{N}(0,1)$, is applied, since it is widely used, it has convenient statistical properties, and it only shows slightly less efficiency compared to the Epanechnikov kernel, which is optimal if the mean square error (MSE) is used as criterion (Silverman, 1986; Scott, 1992).

The bivariate Gaussian kernel function $\mathbb{K}(x) = \varphi(x)$ uses the covariance matrix $\mathbb{H} = \mathbf{\Sigma}$ and reshapes the formula of the kernel intensity estimator to

$$\widehat{\lambda}(s) = \frac{w_{|\mathbf{\Sigma}|,s}}{|\mathbf{\Sigma}|} \sum_{i=1}^{n} \mathbb{K}\left(|s - s_i|^T \mathbf{\Sigma}^{-1} |s - s_i|\right). \tag{3.4}$$

This formula is equivalent to using $\mathbb{K} = f(x)$, where f denotes the probability density function of a bivariate normal distribution $\mathcal{N}(0,\mathbf{\Sigma})$ and $\mathbb{H} = \mathbb{I}$, where $\mathbb{I}$ denotes the identity matrix (Scott, 1992; Buck et al., 2015b). Obviously, $\varphi(x)$ satisfies the required properties of a kernel function such as

1) radial symmetry,
2) representing a probability density,
3) $\varphi(0) = 1$.

Since $\mathbf{\Sigma}$ denotes the standard deviation in φ, which is often used as $\mathbf{\Sigma} = \sigma\mathbb{I}$, the weights are determined differently by the Gaussian kernel compared to other kernel functions. The asymptotic tails of the density will not produce a weight of zero, though for computational reasons, the weights are set to zero for e.g. $|s - s_i| > 3 \cdot \sigma$. With regard to the use of an isotropic Gaussian kernel the standard deviation is calculated as $\sigma = h/2$ to provide about the same range of the bandwidth in which $|s - s_i|$ is accounted for with regard to other kernel functions (Baddeley and Turner, 2005). Please note, the radial symmetry of $\varphi(x)$ is only hold for isotropic bandwidths $\mathbf{\Sigma} = \sigma \cdot \mathbb{I}$ which only depend on the distance $|s - s_i| \leq \sigma$, but not on the direction of $|s - s_i| \in \mathbb{R}^2$. An anisotropic bandwidth results from using the covariance matrix $\mathbf{\Sigma}$ which produces more elliptical kernel estimates and is discussed below.

3.2. Bandwidth selection

Choosing the smoothing parameter to calculate the kernel intensity is the most important part of the kernel approach. A large bandwidth smooths the resulting intensity surface and reduces the variance, but it increases the bias of $\widehat{\lambda}(s)$. In contrast a small bandwidth will reduce the bias and provide detailed information on clusters, but the variance of $\widehat{\lambda}(s)$ increases. This is commonly known as the variance-bias trade-off (Silverman, 1986; Illian et al., 2008; Buck et al., 2015b). To overcome this trade-off and to optimize the estimation of $\lambda(s)$, bias and variance are combined to the mean square error

$$\text{MSE}\left(\lambda(s)\right) = \text{Var}\left(\lambda(s)\right) + \text{Bias}\left(\lambda(s)\right)^2, \tag{3.5}$$

which should be minimized depending on $\lambda(s)$ (Scott, 1992). Cross-validation methods selecting the bandwidth parameter that are presented below are implemented in packages of the R-software (R Core Team, 2015) for spatial analyses, *spatstat* (Baddeley and Turner, 2005), or multivariate density estimation, *ks* (Duong, 2014). Instead of the computation of $\widehat{\lambda}(s)$ on the innumerable space in $\mathbb{R}^2$, the study area W is divided in adjacent cells $c_{(x,y)}$, with $W = \biguplus_x \biguplus_y c_{(x,y)}$, of a certain extent, for example 10×10 meters. Then $\widehat{\lambda}(c_{x,y})$ is calculated as a discrete approximation to $\widehat{\lambda}(s)$.

3.2.1. Isotropy

In the isotropic case the smoothing parameter $\mathbb{H} = h\mathbb{I}$ or $\mathbf{\Sigma} = \sigma\mathbb{I}$, respectively, does not depend on the direction of $|s - s_i|$ (Scott, 1992). In general, the bias for $\widehat{\lambda}(s)$ is then given as

$$\text{Bias}\left(\widehat{\lambda}(s)\right) = \frac{h^2}{2}\left(\nabla^2\lambda(s)\right) \tag{3.6}$$

and the variance as

$$\text{Var}\left(\widehat{\lambda}(s)\right) = \frac{\lambda(s)}{nh^2}\int_{\mathbb{R}^2} \mathbb{K}(s)\,ds. \tag{3.7}$$

Clearly, the trade-off is determined by the smoothing parameter h that appears in the first term of both formulas. Another difficulty to determine the optimal bandwidth h that minimizes the MSE is the unknown intensity function and their derivates in the bias and the variance formula, respectively.

A good estimate of the intensity $\lambda(s)$ using a bandwidth selection based on the MSE criterion was proposed by Diggle (1985). Assuming a stationary estimate of

$$\widehat{\lambda}_h(s) = \frac{N(B_h(s))}{\pi h^2}, \tag{3.8}$$

where $N(B_h(s))$ denotes the number of points s_i that fall in a circle $B_h(s)$ around s and $\nu(B_h(s)) = \pi h^2$. Due to the assumed stationary, $\lambda(s) = \lambda(0)$ and MSE(h) is given as

$$\text{MSE}(h) = \text{E}_h \left[\text{Var}_N \left(\frac{N(B_h(0))}{\pi h^2} \right) + \left(\text{E} \left(\frac{N(B_h(0)}{\pi h^2} \right) - \lambda(0) \right)^2 \right] \tag{3.9}$$

The smoothing parameter h that minimizes MSE(h) is determined by cross-validation (see Berman and Diggle, 1989; and Diggle, 2013).

3.2.2. Anisotropy

In the anisotropic case, the smoothing parameter is chosen as a covariance matrix $\mathbb{H} = \mathbf{\Sigma}$ of the Gaussian kernel function to model the kernel function depending on the direction of $|s - s_i|$ and to obtain elliptical kernel functions. Considering the anisotropy of spatial processes, i.e. random fields, is common using interpolation methods such as Kriging, where the semivariogram, i.e. the variance of a random field, is modeled depending on the direction of the process. For instance, interpolating rainfall intensity is strongly influenced by the position of mountain ranges that induce directional differences in the variation of the rainfall. The theoretical background of random fields and spatial interpolation with regard to anisotropy is provided by Chiles and Delfiner (2009).

Topographic features such as rivers, valleys or motorways fundamentally shape the urban environment and should be accounted for when assessing the availability of point characteristics. Thus, modeling anisotropic kernel functions might improve the assessment of the availability of point characteristics, that is influenced by the townscape (Buck et al., 2015b). To perform a data-driven selection of a bandwidth matrix $\mathbb{H}$, Chacón and Duong (2014) considered the derivate of a kernel density

$$\mathcal{D}\widehat{\lambda}(s) = \frac{1}{n} \sum_{i=1}^{n} \mathcal{D}\varphi_{\mathbb{H}}(|s - s_i|) \tag{3.10}$$

and used a derivate estimator of $\mathbb{H}$ based on the mean integrated squared error

$$\text{MISE}(\mathbb{H}) = \text{E} \int ||\mathcal{D}\widehat{\lambda}_{\mathbb{H}}(s) - \mathcal{D}\lambda(s)||^2 \, ds. \tag{3.11}$$

Cross-validation is again used to determine $\mathbb{H}$ (Bowman, 1984). Chacón and Duong (2014) present three estimators of MISE($\mathbb{H}$), the least-squares and smoothed least-squares estimators, as well as a plug-in estimator.

3.2.3. Adaptive bandwidths

Bandwidths are commonly selected by a data-driven method based on the realization of the point process itself. However, considering varying background information of the point process such as the residential density within an urban study area to adjust the estimation of the availability of point characteristics might be promising (Carlos et al., 2010; Shi, 2010). Using adaptive bandwidths is already discussed for modeling spatial risks, i.e. disease clustering, and is also applicable to assess the availability of point characteristics in terms of a kernel intensity (Carlos et al., 2010).

In particular, the availability of public open spaces, public transit stations, and the intersection density strongly correlate with residential density. Clusters of these point characteristics that are identified via kernel intensity might be caused by the number of residents in the neighborhood (Buck et al., 2015b). For example, densely populated areas are more likely to include a high number of public open spaces or public transit stations. A kernel intensity measure that is adjusted for residential density might thus enhance the assessment of the availability by, for instance, capturing areas that provide more or less public open spaces than it is sufficient for the number of residents living within the area.

To adjust a kernel intensity measure by adapting the bandwidth over varying background information, Shi (2010) proposed a bandwidth $h(p,s)$ that depends on the underlying residential density p at location $s \in \mathbb{R}^2$. A simple linear adjustment of the bandwidth used in Equation 3.2 can be modeled as

$$\tilde{h}(p,s) = \frac{h}{p(s)} \tag{3.12}$$

in the isotropic case and as

$$\tilde{\mathbb{H}}(p,s) = \frac{1}{p(s)} \cdot \mathbb{H} \tag{3.13}$$

in the anisotropic case, where h and $\mathbb{H}$, respectively, are pilot bandwidths that are determined prior to the adjustment. Then, the bandwidth will be decreased for densely populated areas and increased for sparsely populated areas by the factor $p(s)$, respectively (Carlos et al., 2010; Buck et al., 2015b). More details on adaptive bandwidths and a case study focusing on spatial risk assessment are provided by Shi (2010).

4. Spatial scale and the definition of neighborhoods

The conceptualization of the spatial context, in which built environment characteristics are assumed to affect individual behavior, i.e. the neighborhood, is an important step to be taken in assessing the influence of the built environment. Within the determined neighborhood urban measures are calculated and linked with individual-level information via the geographical localization of study participants, i.e. place of residence, workplace, or school (Leal and Chaix, 2011; Vallée et al., 2014). By this, the definition of the neighborhood affects the association of built environment characteristics and behavioral outcomes (Spielman and Yoo, 2009; Leal and Chaix, 2011; James et al., 2014; Vallée et al., 2014) and does not necessarily capture the spatial behavior of residents (Kwan, 2012b). This chapter describes two major concepts of neighborhoods, administrative areas and ego-centered neighborhoods, and discusses strengths and limitations of both concepts to assess environmental exposure and individual behavior in urban environments.

4.1. Administrative areas

Administrative areas are a disjoint partition of the geographical area ranging from the national level, i.e. federal states and municipalities, to districts and sub-districts within a city. These areas are used to provide statistics on their inhabitants and lead municipal governance as well as urban planning (Buck and Tkaczick, 2014). The majority of studies in environmental research are conducted based on administrative areas such as zip code areas or census tracts (Leal and Chaix, 2011), although these imply two major drawbacks.

First, administrative areas are artificially defined and their delineation does not necessarily include the spatial pattern of residential behavior (Leal and Chaix, 2011), which was described as the container effect (Maroko et al., 2009). Urban measures, for example the number of public open spaces per neighborhood area, are assigned to residents that live in the respective area. However, built environment characteristics of outside the border of a neighborhood might also influence the behavior of residents (Maroko et al., 2009; Buck et al., 2011). Hence, administrative areas do not represent the true link between individual behavior and environmental exposure (Leal and Chaix, 2011; Vallée et al., 2014) and bias exposure estimates of proximity measures (Duncan et al., 2014).

Second, the geographical size of administrative areas differ within countries as well as between countries. Census tracts in the US or zip code areas in the UK are defined as having about the same number of residents, but not the same size. Moreover, the association between urban measures and the behavior of residents, that is found on one scale, might not be found on a higher scale, due to an averaging effect of the neighborhood size (Duncan et al., 2014). This problem is described as the modifiable areal unit problem (MAUP) (Kwan and Weber, 2008; Kwan, 2012b; Houston, 2014) meaning that, for example, a positive association between public open spaces and cycling might be revealed based on sub-districts, but not with regard to districts in the same study area.

To account for different sizes of administrative areas, Duncan et al. (2010) rescaled land use mix LUM (see Section 2.1.2) with regard to the smallest geographical size of the areas under study. The size of each area was divided by the size of the smallest area and this ratio was used to rescale values of LUM of the corresponding administrative areas. However, the rescaling approach does not solve the MAUP with regard to changes in scale and results based on census blocks can differ from results based on census tracts. Chaix et al. (2005), for instance, included measures of adjacent and surrounding census districts to calculate a distance-weighted mean of the socio-economic level and to overcome the MAUP. Here, the socio-economic level of a considered census district was adjusted by the socio-economic value of surrounding census districts multiplied by a weight that will decrease the farther away census districts are located. Maroko et al. (2009) also used a distance-weighted approach modeling public open spaces as inhomogeneous point process and recommended the use of a kernel intensity to account for environmental information around the census districts particularly with regard to the availability of public open spaces. Artificially defined areas that are used to assess the availability of public open spaces do not capture the geographical distance to the place of residence, which is illustrated in Figure 4.1. Although these approaches improve the assessment of built environment characteristics using administrative areas, fixed boundaries and non-overlapping areas do not capture the behavior of residents in the study area.

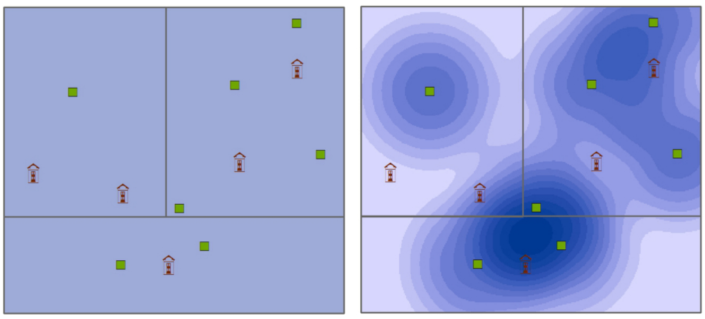

Figure 4.1.: Container effect of administrative neighborhoods. Left: based on artificial areas, the availability to public open spaces (green square) is incorrectly assigned to residents (houses). Right: kernel intensity methods can improve the assessment of public open space availability (Buck and Tkaczick, 2014)

4.2. Ego-centered neighborhoods

Ego-centered neighborhoods are based on the exact location of the place of residence and capture environmental exposure on the individual level (Frank et al., 2005; Kwan and Weber, 2008; Chaix et al., 2009). Neighborhoods are constructed as a buffer around the place of residence based on a pre-defined distance. The distance is applied either to determine a circular buffer based on the euclidian distance as the radius or to calculate a street-network buffer, where the neighborhood is determined by the area that can be reached from the place of residence in the respective distance depending on the street network (Buck and Tkaczick, 2014).

Buffer distance is commonly determined by assuming a 10 to 15 minute walk in order to capture the area that residents are most likely to reach conveniently by walking (Brownson et al., 2009). Only few studies used ego-centered neighborhoods with either circular or network-dependent buffers (Leal and Chaix, 2011) and these studies considered different distances to determine the spatial scale. Recent reviews, for instance, found distances ranging from 400 m to 3.2 km (Brownson et al., 2009; Casey et al., 2014) or from 100 m to 4.8 km (Leal and Chaix, 2011).

It was assumed that the best buffer distance that captures the environmental exposure in line with residential behavior can be determined via the best model fit of regression analyses. However, a simulation study found that the resulting distance does often not reflect the true spatial context of exposure, since the model fit is influenced by undetected environmental and individual-level variability (Spielman and Yoo, 2009). The association of built environment characteristics and the behavior of residents is strongly influenced by the choice of the buffer distance and it is recommended to conduct sensitivity analyses and report the results with regard to different buffer sizes (Brownson et al., 2009; Leal and Chaix, 2011). Moreover, Chaix et al. (2009, 2010) argued that the place of residence is not sufficient to capture individual behavior, but buffers around the school or workplace should be additionally considered.

4.3. Uncertain geographic context

The spatial behavior of study participants is often determined for the whole study sample, although individual-level characteristics such as age and sex (Kerr et al., 2007), preference of active or passive travel (Frank et al., 2007b), life stage (Christiansen et al., 2014), or perception of the environment (Adams et al., 2013) confound the association between built environment characteristics and individual behavior.

Overall, individual-level variability in the spatial behavior of residents contributes to the uncertainty of the spatial context in which built environment characteristics, i.e. the exposure, should be assessed. Kwan (2012b) discussed this so-called Uncertain Geographic Context Problem (UGCoP). For example, older adults or disabled persons interact with a smaller neighborhood area or might perceive different barriers with regard to neighborhood safety compared to younger adults. Moreover, children and adolescents are often influenced by parental supervision that can restrict the range of their spatial behavior (Chaix et al., 2009; Spielman and Yoo, 2009; Kwan, 2012b). To account for individual-level differences, Adams et al. (2013) and Christiansen et al. (2014) conducted a latent class analysis to derive factors that describe similarities in the study sample and correct the association between built environment characteristics and active transport.

New approaches and technologies have recently been considered in order to capture the heterogeneity of individual behavior and particularly the interaction of residents with their environment. Assessing the perceived and objectively measured neighborhood based on reported activity locations as well as modeling the space-time behavior using GPS are promising approaches that are discussed in Chaix et al. (2009), Kwan (2012a), Perchoux et al. (2013), and Chaix et al. (2014). These approaches will be outlined in the discussion (see Chapter 7).

5. Spatial and individual-level data

5.1. The IDEFICS study

This research is based on the IDEFICS study (Identification and prevention of Dietary- and lifestyle-induced health EFfects In Children and infantS), which is a longitudinal, multi-center, population-based study that was conducted to investigate lifestyle-related diseases in children and infants and to develop, implement and evaluate programs for primary prevention of childhood obesity (Ahrens et al., 2006).

The IDEFICS study was funded by the 6th EU Framework Programme and took place between August 2006 and March 2012. The baseline survey was conducted from September 2007 until June 2008 in eight European countries (Belgium, Cyprus, Estonia, Germany, Hungary, Italy, Spain, and Sweden) and resulted in an overall sample of 16,228 children between 2 and 9.9 years of age with at least available data on age, sex, weight, and height (Ahrens et al., 2011). All children participated in an exhaustive examination program which among others included parental questionnaires on lifestyle habits, socio-economic status and medical history. Physical examinations such as anthropometric measurements of the children were performed, and samples of blood, saliva, and urine were taken. In particular, accelerometer devices were provided to a subsample of children objectively measure physical activity levels. About 40% of all children delivered valid accelerometer measurements. All measurements were taken according to a standardized study protocol in all eight countries of the IDEFICS study.

In each country, the participating centers obtained ethical approval from the local ethics committees. Parents provided written informed consent for all examinations. Each child was informed orally about the measurements by field workers and asked for his/her consent immediately before the examination. Further details on the study design and different measurements can be found in Ahrens et al. (2006, 2011) and first results of the survey are described in Ahrens et al. (2014). The IDEFICS study investigated a bunch of potential risk factors of childhood obesity, where my research was focused on the assessment of the built environment and its influence on children's physical activity as one of the major risk factors of obesity. For this purpose, a pilot study was conducted in one German study region of the IDEFICS study. The development of the statistical methodology to investigate this research question was funded by the German Research Foundation (DFG) under grant PI 345/7-1.

5.2. Pilot study region

Urban moveability was modeled in one German study region of the IDEFICS study, named Delmenhorst, located in Lower Saxony. The city of Delmenhorst covers an area of about 62 km^2 and is characterized by a small river from south-east to north as well as an urban core surrounded by slightly suburban residential areas and agricultural areas near the border (see Figure 5.1). In line with the baseline survey of the IDEFICS study, residential statistics were considered for 2008, where Delmenhorst had about 77,300 residents. The city is organized into eleven districts and 43 sub-districts[1]. In Delmenhorst, overall 1,179 children participated in the baseline survey of whom 736 were school children (6- to 9.9-year-old) with 49.1% girls and 443 were pre-school children (2- to <6-year-old) with 48.5% girls.

5.2.1. Spatial data

Three different types of spatial data, i.e. points, lines, and polygons, can be processed using a geographic information system (GIS) which allows to georeference geometric features in space according to a specific projection of coordinates (Buck and Tkaczick, 2014). Spatial data on built environment characteristics were collected via three different channels: officially used administrative data, open source databases, and manually referenced data. Spatial data were processed and managed in *ArcGIS 10.0 & 10.1*[2], respectively.

Administrative data on land use were obtained from the Official Topographic-Cartographic Information System (Amtliches Topographisch-Kartographische Informationssystem - ATKIS) from the land registry office of Lower Saxony. Land use data were provided as adjacent polygons including a vast number of attributes defining their exact use. Objects, e.g. settlement, traffic, or vegetation, are subdivided by attributes, for instance car traffic, or rail traffic (object: traffic), as well as residential area or areas of mixed use (object: settlement)[3]. Polygon data were condensed based on these attributes to obtain land use data with regard to six different types such as residential, commercial, industrial & agricultural, recreational, and miscellaneous. Data on residential density as well as the delineation of the city border, districts and sub-districts were provided by the municipality of Delmenhorst.

Since administrative data on the street network were provided as polygons which are difficult to process, I used data from the OpenStreetMap-project (OSM)[4] which features streets, footpaths, cycleways etc. as line data. OSM follows the wiki-concept, where everyone is enabled to collaborate, to collect spatial data, and to store it based on a fixed categorization and attribution of types and the data are provided as open source. The wiki-concept more

[1] Census data 2009: Facts and Figures from the city of Delmenhorst, Service of Urban Development and Statistics, 31.12.2009 ("Zahlenspiegel 2009: Daten und Fakten aus der Stadt Delmenhorst, Fachdienst Stadtentwicklung und Statistik, Stand 31.12.2009")

[2] ESRI 2011. ArcGIS Desktop: Release 10.1 Redlands, CA: Environmental Systems Research Institute.

[3] `http://www.atkis.de/dstinfo/dstinfo2.dst_gliederung`, [01.07.2014]

[4] `www.openstreetmap.org` - Open Data Commons Open Database License (ODbL)

or less is capable to standardize data collection, but OSM data might be less valid than administrative data. However the current database, particularly in countries such as U.S., UK, and Germany, shows high quality and validity compared to administrative data (Sehra et al., 2014; Buck and Tkaczick, 2014). To obtain a footpath-network, I used spatial data on the street network, i.e. line data, and reduced the data based on attributes, i.e. lines with attributes such as highways, major roads, railways etc. were excluded. Since the validity of footpath information based on the OSM-data could not be guaranteed, I used administrative data on footpaths (polygons) provided by the municipal geospatial information system (Kommunales Raumbezogenes Informationssystem (KRIS)) of Delmenhorst to validate and manually supplement missing line data.

Public transit stations as well as recreational facilities were manually georeferenced. According to addresses or images, these locations were edited as points in the study area based on land use data, street network data, and satellite image data. A map of the public transit network was provided by the website of the public transit company. Lists of sports facilities, i.e. sports fields and sports halls, were obtained from the local municipality and addresses of parks and playgrounds from the civil service for green space and nature conservation of Delmenhorst (Buck et al., 2011). In addition, parks and green spaces, for instance in and around apartment housing areas, were georeferenced based on imagery data, i.e. accessible or open source satellite images. Later, these areas were visited and validated via field survey to exclude non-accessible or wrongly edited locations (Buck et al., 2015c). Spatial data of all built environment characteristics in the study area of Delmenhorst are displayed in Figure 5.1.

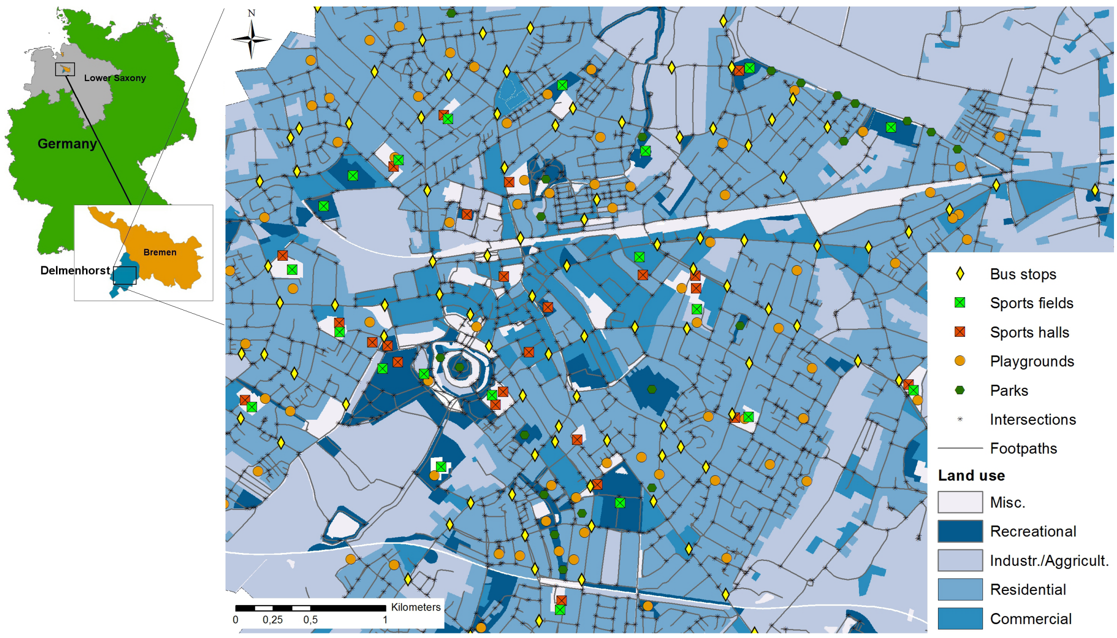

Figure 5.1.: Spatial data of built environment characteristics used to model the moveability concept in one German IDEFICS study area Delmenhorst, Lower Saxony

5.2.2. Spatial link

Environmental and individual-level variables had to be linked using geographical information of the individual-level data such as address data or the assigned area of living. In the IDEFICS study, the study design did not allow to use address data and no consent was given to process addresses into coordinates for the use in spatial analyses because of data protection regulations. The first approach to link environmental variables with data of the IDEFICS survey therefore considered school catchment areas. During the baseline survey school children were recruited within their schools and school catchment areas represent the area in which each child has to visit the public school. Thus, I first focused only on 6- to 9.9-year-old school children who visited those 14 public schools that took part in the baseline survey (Buck et al., 2011). Environmental variables that were calculated in school catchment areas were linked to children who visited these schools. However, school catchment areas are artificially defined and thus induce limitations that were previously described (see Section 4.1). Moreover, school catchment areas at the border of the study region include larger agricultural areas that inhabit only few residents and are less likely to include characteristics that influence physical activity levels of all children living in these areas.

To apply ego-centered neighborhoods and to improve the spatial analyses (see Section 4.2), I proposed a spatial blurring to anonymize the address information. The blurring was implemented based on a Gaussian error that was introduced by Cassa et al. (2006) with regard to spatial cluster analyses and disease mapping. In particular, the variance of the Gaussian error was determined in relation to the underlying residential density. In order to attain a certain threshold of k-anonymity, i.e. the number of residents such that a participant cannot be re-identified, the variance was lower for higher residential density and vice versa. A simulation study was conducted to investigate differences in the walkability index according to Freeman et al. (2013) when using original addresses compared to their blurred counterparts. The spatial blurring shifted the coordinates only about 50 to 100 m and differences in walkability indices turned out to be relatively small particularly for highly populated areas (Buck et al., 2015a). Since the use of blurred addresses was allowed by the responsible office for data protection of Lower Saxony, ego-centered network-dependent neighborhoods could be applied for all 2- to 9.9-year-old children for the analyses on a micro-level while ensuring data protection requirements (see Appendix B.4). Network-dependent neighborhoods cover the area that can be reached from the place of residence within a certain distance using the street network. In order to account for variation of the results depending on spatial scale (Chaix et al., 2010; Leal and Chaix, 2011) (see Section 4.2), I established ego-centered network-dependent neighborhoods based on six different network distances from 500 m up to 2 km using the *network analyst* in *ArcGIS 10.0* (see Figure 5.2 and Appendix B.5)

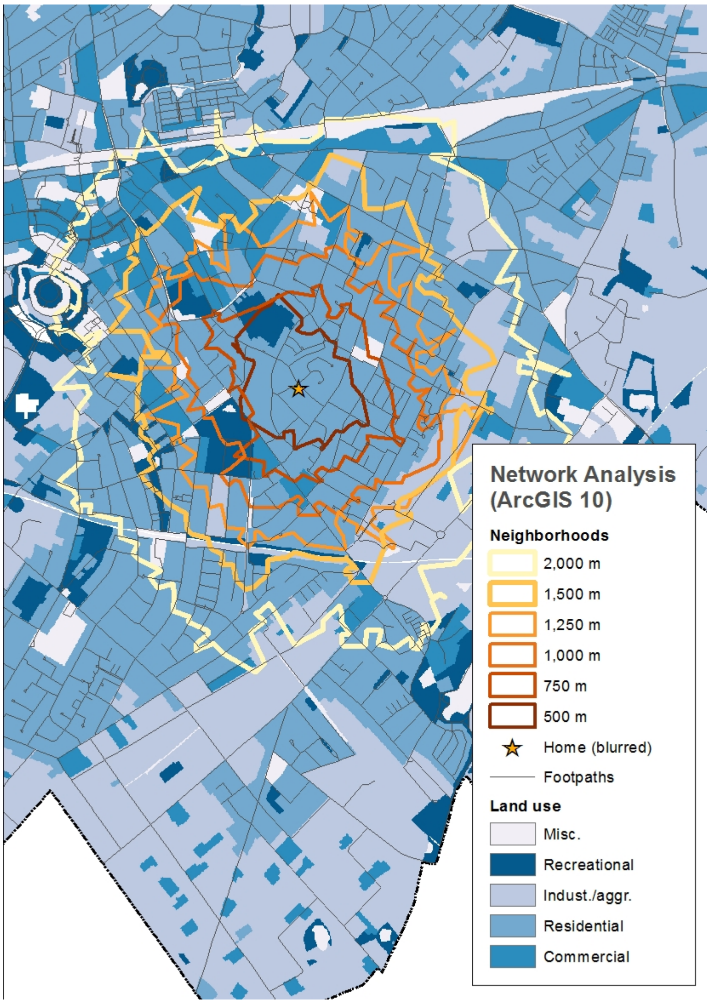

Figure 5.2.: Ego-centered network-dependent neighborhoods derived for six different network-distances from a place of residence (blurred coordinates) in the study area of Delmenhorst, Lower Saxony (Buck et al., 2015b)

5.3. Individual-level variables

Various individual-level variables, such as age, sex, z-scores of body mass index (BMI) according to Cole and Lobstein (2012), parental education in terms of the ISCED scale (Schneider, 2013), and safety concerns of parents were considered to adjust regression analyses investigating the association between built environment characteristics and physical activity measurements. Children with missing information due to item non-response were excluded from the analysis, i.e. a complete-case analysis was conducted. Besides the macro-level analyses, that used data on reported physical activity in 596 6- to 9.9-year-old school children (Buck et al., 2011), the sample size of further analyses was restricted by the number of available accelerometer measurements that were collected in 460 (39%) of the 1,179 children living in the study area Delmenhorst. In addition, missing values in parental questionnaires lead to further exclusions. Finally, 400 2- to 9.9-year-old children were included in the analyses investigating the association between built environment characteristics and objectively measured physical activity. Exclusion criteria and study characteristics are provided in Buck et al. (2015c,b) (see Appendix B.3 and B.5).

5.3.1. Physical activity levels

To objectively assess physical activity, children were asked to wear an uniaxial accelerometer (ActiTrainer or GT1M)[5] on the right hip during waking hours (Ahrens et al., 2011). About 40% of participants of the baseline survey provided valid measurements that were defined as having at least three days including one weekday and one weekend day of measurement with at least 8 hours of weartime after the exclusion of 20 minutes of consecutive zeros, i.e. non-wearing time (Konstabel et al., 2014). The devices collected average counts within 15 seconds epochs. Intensities of physical activity were defined as light (LPA), moderate (MPA), and vigorous (VPA) physical activity levels based on cut-off points according to Evenson et al. (2008). Moderate-to-vigorous physical activity (MVPA) was considered as outcome variable for the regression analyses. Season of accelerometry assessment and valid weartime could have influenced the results on physical activity levels and were considered as adjusting variables. A detailed overview of the processing of accelerometry data, the discussion on minimum requirements for valid measurements, and objectively measured physical activity levels in the IDEFICS study are provided by Konstabel et al. (2014). Physical activity levels of children living in the considered study region are presented in Table 5.1. Overall, valid weartime did not differ between age groups and sex, but boys showed higher levels of MPA and VPA compared to girls and higher MPA and VPA levels were found in schol children compared to pre-school children.

5.3.2. Safety concerns

As previously described, objective measurements of neighborhood safety are difficult to identify and showed less evidence than perceived measures of neighborhood safety (see Section 2.3). Environmental characteristics and items assessing the perceived environment were not in the focus of the IDEFICS study. Thus only two statements on safety concerns, that could restrict physical activity of children and that might be caused by environmental perception, were included in the parental questionnaire and were considered as confounding variables in the regression analyses:

1) I restrict my child's outdoor activities for safety reasons.
2) I don't like to let my child walk/cycle to kindergarten, pre-school or school for safety reasons.

[5] Actigraph, LLC, Pensacola, FL, USA

Table 5.1.: Objectively measured physical activity levels of 2- to 9.9-year-old children and valid weartime based on accelerometry measurements from one German study region of the IDEFICS study, Delmenhorst, Lower Saxony

	MPA		VPA		MVPA		Valid weartime (h)	
	Mean(std)	range	Mean(std)	range	Mean(std)	range	Mean(std)	range
All children (n=400)								
	45.0(16.2)	11 - 100	15.3(8.9)	0 - 53	60.3(23.1)	12 - 144	11.5(1.2)	8 - 16
Boys (n=194)	49.5(16.6)	12 - 100	16.8(9.7)	2 - 51	66.3(24.5)	15 - 144	11.5(1.3)	8 - 16
Girls (n=206)	40.9(14.6)	11 - 91	13.8(7.8)	0 - 53	54.7(20.2)	12 - 114	11.4(1.2)	8 - 16
Pre-school children (n=100)								
	43.4(17.0)	11 - 95	12.3(7.3)	1 - 39	55.7(22.9)	12 - 114	11.1(1.1)	8 - 14
Boys (n=57)	45.4(16.5)	12 - 95	12.6(7.9)	2 - 39	58.0(23.0)	15 - 111	11.3(1.1)	8 - 14
Girls (n=43)	40.7(17.6)	11 - 91	11.9(6.3)	1 - 28	52.6(22.7)	12 - 114	10.9(1.0)	8 - 13
School children (n=300)								
	45.6(15.9)	12 - 100	16.2(9.2)	0 - 53	61.8(23.0)	13 - 144	11.6(1.3)	8 - 16
Boys (n=137)	51.2(16.5)	19 - 100	18.6(9.9)	3 - 51	69.7(24.3)	22 - 144	11.7(1.4)	8 - 16
Girls (n=163)	40.9(13.8)	12 - 86	14.3(8.1)	0 - 53	55.2(19.5)	13 - 112	11.5(1.2)	9 - 16

Intensity levels of physical activity in minutes per day according to the cut-off points of Evenson et al. (2008)

Parents could agree or disagree on both questions on a four point Likert scale. Parents who agreed or moderately agreed on at least one question were categorized as having safety concerns with regard to outdoor physical activity of their child. In the sample of 400 children parents of 37.8% of the children reported safety concerns with a higher proportion in pre-school children (46%) than in school children (35%) (Buck et al., 2015c).

6. Urban moveability

This chapter summarizes the spatial analyses that were conducted in order to accomplish the aims of the thesis. The articles that were published in epidemiological journals are presented in Appendix B. Urban measures of point characteristics were calculated using kernel intensity estimators based on different approaches for bandwidth selection (see Section 3). Multiple point characteristics such as playgrounds, parks, sports facilities, and green spaces were included in the analyses to capture opportunities for leisure time physical activity in the neighborhood of children. Kernel intensity methods as well as point characteristics were compared by investigating the association between the resulting urban measure and moderate-to-vigorous physical activity (MVPA). The regression analyses were adjusted for individual-level variables (see Section 6.1). The comparison of intensity measures depends on built environment characteristics and vice versa. The choice of the method to assess the urban measure influences the resulting association between the considered built environment characteristics and MVPA. In contrast, the performance of kernel intensity measures depends on the considered built environment characteristics. Thus, both, measures and characteristics were simultaneously investigated, but the results are separately reported below. I will first present potential methodological improvements by using kernel intensity measures followed by the investigation of point characteristics that will be included in the moveability index.

6.1. Statistical analyses

The association between urban measures and MVPA in the final sample of 400 2- to 9.9-year-old children was analyzed using a log-gamma regression model. Prior to the inclusion of environmental variables, the association between individual-level variables and MVPA was investigated. Since the distribution of MVPA was highly skewed, a log-gamma regression was applied. Individual-level factors and confounder of the association between the built environment and MVPA were considered such as age, BMI z-scores, parental education and parental safety concerns, as well as season and valid weartime of accelerometer measurements. Results of individual-level factors are presented in Table 6.1 stratified by age group and sex (see B.5 and Buck et al., 2015b). In school children BMI z-score was associated with MVPA, but this association could only be confirmed in school girls in the stratified analyses. In particular safety concerns showed an association with MVPA in the full sample of pre-school children and when stratified by sex. It could also be seen from the unstratified analysis that MVPA was significantly reduced in children whose parents had safety concerns although this result did not hold true for pre-school boys alone (Buck et al., 2015c,b).

Table 6.1.: Results of the basic log-gamma regression model investigating individual-level factors on MVPA in children (Buck et al., 2015b)

Individual-level Variables	$\exp\left(\hat{\beta}\right)$	p-value	$\exp\left(\hat{\beta}\right)$	p-value	$\exp\left(\hat{\beta}\right)$	p-value
	School children All (n=300) AIC=2,707.1		Boys (n=137) AIC=1,260.1		Girls (n=163) AIC=1,433.2	
Age	0.97	0.30	0.96	0.30	0.99	0.81
BMI z-score[a]	0.95	0.028	0.98	0.61	0.94	0.031
Valid weartime	1.04	0.022	1.05	0.041	1.02	0.39
Season (ref: winter/autumn)	1.17	0.001	1.19	0.011	1.14	0.042
Safety concerns (ref: no)	0.99	0.79	1.02	0.76	0.94	0.29
Low ISCED (ref:medium)	0.95	0.38	0.90	0.18	1.04	0.59
High ISCED (ref:medium)	1.01	0.88	1.00	0.96	1.05	0.54
	Pre-school children All (n=100) AIC=893.0		Boys (n=57) AIC=519.5		Girls (n=43) AIC=386.6	
Age	1.28	<0.001	1.24	0.008	1.33	0.001
BMI z-score[a]	1.03	0.46	1.04	0.34	1.02	0.70
Valid weartime	1.00	0.99	1.03	0.65	0.97	0.67
Season (ref: winter/autumn)	0.99	0.93	1.07	0.62	0.91	0.49
Safety concerns (ref:no)	0.86	0.044	0.95	0.68	0.75	0.019
Low ISCED (ref: medium)	1.12	0.33	1.18	0.28	1.04	0.85
High ISCED (ref: medium)	1.12	0.29	1.03	0.81	1.22	0.26

a: according to Cole and Lobstein (2012)

6.2. Evaluation of intensity measures

In the first step of this research presented here the simple intensity was compared with a kernel intensity measure based on a fixed and manually selected bandwidth (Buck et al., 2011). Number of intersections (ID) and number of destinations (DD), i.e. public open spaces and sports facilities, were calculated per size of disjoint school catchment areas $A_j, j = 1, \ldots, 14$, (see Section 5.2.2) and compared to the mean intensity value $\widehat{\Lambda}$ of intersections, ID_Λ, and destinations DD_Λ according to Equation 3.2 and 3.3. A comparison of both methods showed that in densely populated areas, the simple intensity overestimated ID and DD, while in sparsely populated areas, it underestimated both measures compared to the mean kernel intensity ID_Λ and DD_Λ, respectively (see Appendix B.1). Figure 6.1 illustrates the use of simple intensity and kernel intensity $\widehat{\lambda}(s)$ within sub-districts and shows another advantage of the kernel intensity measure. The estimation of the simple intensity is limited to the use of sub-districts and adjacent sub-districts show large differences in their intensity estimate. In comparison, the kernel intensity $\widehat{\lambda}(s)$ (see Equation 3.3) does not depend on the choice of the neighborhood and leads to a smoothed intensity estimation.

Besides the intensity to assess the availability of destinations, the distance to public open spaces or sports facilities was also investigated with regard to physical activity in children (see Section 2.2). The distance (in meter) to parks, playgrounds, and green spaces was calculated

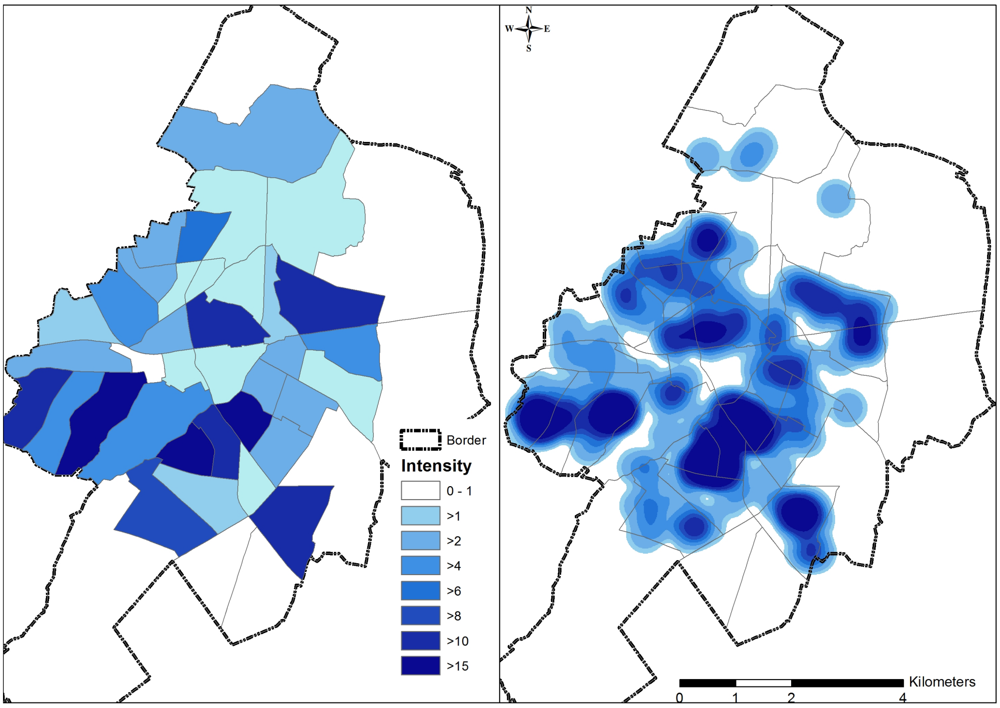

Figure 6.1.: Comparison of public open space density in the study area Delmenhorst based on the simple intensity (left) and kernel intensity measure (right)

via network analysis in *ArcGIS 10*[1] and used as environmental variable within the log-gamma regression model (see Section 6.1). In addition, all publicly accessible destinations were combined and the distance to public open spaces was also considered. Results are presented in Table 6.2 showing that the distance to the nearest destination does not affect physical activity in children neither in the full sample nor stratified by age groups and sex (results not published). Thus, further analyses are focused on the assessment of the availability of destinations based on kernel intensity measures.

Table 6.2.: Association of distance to nearest recreational facility and MVPA in children stratified by age groups and sex

	All (n=400)		Pre-school children (n=100)				School children (n=300)			
			Boys (n=53)		Girls (n=47)		Boys (n=137)		Girls (n=163)	
	$\hat{\beta}$	p-value	$\hat{\beta}$	p-value	$\hat{\beta}$	p-value	$\hat{\beta}$	p-value	$\hat{\beta}$	p-value
Distance to (per 1 km)										
Playgrounds	0.022	0.73	0.004	0.99	-0.149	0.65	0.085	0.37	-0.019	0.84
Parks	-0.057	0.27	0.135	0.40	0.233	0.23	-0.078	0.35	-0.103	0.19
Green space	-0.059	0.89	0.094	0.42	0.101	0.57	-0.062	0.34	-0.026	0.68
Public open spaces	-0.042	0.64	0.059	0.79	-0.180	0.71	0.071	0.61	-0.105	0.41

Mainly three point characteristics were considered and assessed based on kernel intensity measures in more detail. Urban measures of public open spaces, i.e. parks and playgrounds,

[1]ESRI 2011. ArcGIS Desktop: Release 10.1 Redlands, CA: Environmental Systems Research Institute.

intersections, and public transit stations, were calculated based on the bivariate Gaussian kernel estimator (see Section 3.4) exploiting various methods for bandwidth selection compared to the simple intensity measure:

1) a fixed bandwidth σ_f that was determined by visual inspection of resulting kernel intensities,

2) a univariate and isotropic bandwidth σ_{CV} selected by cross-validation of the MSE (see Section 3.2.1),

3) a bivariate and anisotropic bandwidth matrix $\mathbf{\Sigma}_{lscv}$ selected by least squares cross-validation of the MISE (see Section 3.2.2).

In addition, the fixed and cross-validated bandwidths were considered as pilot bandwidths $\tilde{\sigma}_f, \tilde{\sigma}_{CV}$ as well as $\tilde{\Sigma}_{lscv}$ for selecting an appropriate adaptive bandwidth (see Section 3.2.3). The three bandwidths were adjusted by multiplyication with an adaptive factor to derive their corresponding adaptive versions as shown for the fixed bandwidth below:

$$\tilde{\sigma}_f = \frac{2{,}000}{RD_{A_j}} \cdot \sigma_f = \frac{2{,}000 \cdot km^2}{\#residents} \cdot \sigma_f, \tag{6.1}$$

where RD_A denotes the number of residents per km^2 in ego-centered neighborhoods A_j of $j = 1, \ldots, 400$ children (Buck et al., 2015b). The value of 2,000 was approximately the mean residential density in the study area. If the residential density was smaller than 2,000, the pilot bandwidth was reduced by the corresponding factor and vice versa (Buck et al., 2015b).

Kernel intensity measures were compared for various spatial scales, i.e. distances of ego-centered network-dependent neighborhoods A_j, to simultaneously investigate the effect of intensity measures and spatial scales on the association between built environment characteristics and MVPA in children. Figure 6.2 illustrates the pattern of results, i.e. effect estimates and p-values over differing network distance that was used to calculate network-dependent neighborhoods for the estimation of kernel intensity measures.

This analysis revealed that the simple intensity is strongly influenced by the choice of the network distance which results in different effect sizes and thus also in differen p-values. This may lead to different conclusions on the association between built environment characteristics and MVPA in children. In contrast, the anisotropic bandwidth was almost not affected by the choice of the network distance and was thus used for the moveability index. The anisotropic adaptive bandwidth that also accounted for the underlying residential density performed similarly to the non-adaptive version, but showed higher variation in the results for the differing network distances (see Appendix B.5). Thus, the adaptive anisotropic bandwidth was also chosen for the subsequent spatial analyses. Figure 6.3 shows the resulting kernel intensity surfaces for the adaptive and non-adaptive anisotropic bandwidth with regard to public open spaces. Figures depicting the resulting intensity surfaces of the remaining point characteristics, intersections and public transit stations are provided in Appendix A.1.

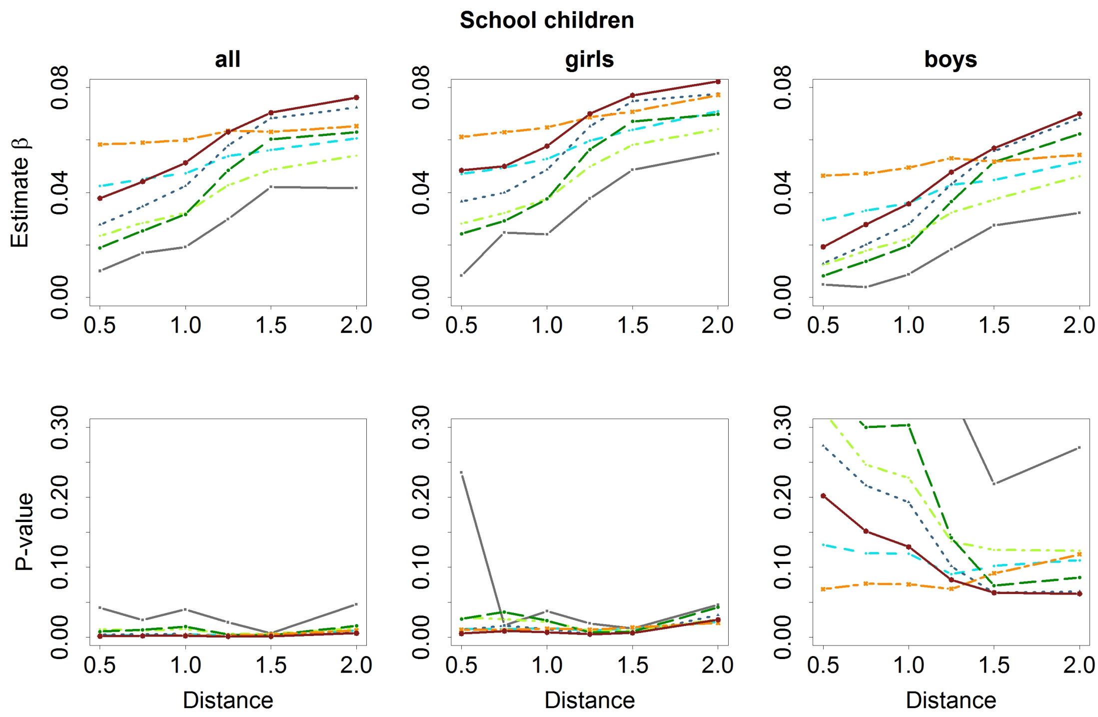

Figure 6.2.: Comparison of urban measures based on a kernel intensity measure using different methods for bandwidth selection. Strengths of the association and p-values are depicted for varying spatial scales of ego-centered neighborhoods (Buck et al., 2015b).

6.3. Walkability and moveability measures

In a second step of my research, point characteristics were considered to expand the walkability concept with regard to built environment characteristics that support physical activity in children. Urban measures of the walkability index were applied as described in Section 2.1 in the study region of Delmenhorst and their association with physical activity was investigated. Walkability measures such as residential density, land use mix, and street connectivity were calculated within school catchment areas (Buck et al., 2011) and were further investigated by micro-level analyses (Buck et al., 2015c). These were conducted using ego-centered neighborhoods based on the anonymized place of residence (see Section 5.2.2 and B.4). Information on residential density RD was provided within sub-districts and had to be rescaled as a weighted mean within school catchment areas that overlapped and intersected with multiple sub-districts (see Section 2.1.3). Land use mix (LUM) was calculated based on the commonly used entropy formula (see Section 2.1.2) and street connectivity, i.e. intersection density, was calculated using a kernel intensity (see Section 3.1.2). To facilitate the comparison of urban measures, these were standardized into z-scores and included in a multilevel log-gamma regression that accounted for clustering of physical activity within school catchment areas. In these analyses, level of urbanity was measured on the sum of the z-scores of residential density and land use mix. Table 6.3 presents the association between walkability measures as well as mean intensity of different destinations and MVPA in school children. Within school catchment areas, associations between walkability measures and MVPA (not published) as well as reported physical activity (Buck et al., 2011) were found. Only green spaces showed no association with physical activity in children.

Table 6.3.: Macro-level association between urban measures in school catchment areas and MVPA in 300 school children based on a log-gamma regression

	Estimate ($\widehat{\beta}$)	p-value
z-scores of		
Mean intensity of playgrounds	1.17	0.004
Mean intensity of sports facilities	1.25	0.002
Mean intensity of green spaces	1.12	0.17
Mean intensity of destination	1.25	0.002
Street connectivity	1.26	<0.001
Level of urbanity	1.22	0.02

Further analyses were conducted on a micro-level, i.e. using ego-centered neighborhoods , to explore whether findings from the macro-level can be confirmed on the micro-level. Sports facilities were, however, excluded from these analyses, since the use of sports facilities depends on club membership which restricts the accessibility of these locations to a certain extent. Micro-level analyses are published in Buck et al. (2015c) and in this paper particularly the association between MVPA and publicly accessible recreational facilities such as parks, playgrounds, and green spaces or a combination of these three was investigated. Green spaces were defined as areas being not under public responsibility and larger than 100 m^2. They are often located near residential areas, in particular apartment housing areas and might also provide opportunities for physical activity in the neighborhood of children. The study revealed a positive association of walkability measures such as street connectivity, residential density, and public transit density. However, the association between and MVPA turned out to be negative in all children and in the stratified models for pre-school children and school children as well as for boys and girls in both age groups, respectively. Green spaces did not show any association with MVPA (see Appendix B.3). Hence, the availability of public open spaces, i.e. parks and playgrounds, was considered for the construction of the moveability index accounting for the negative influence of land use mix on urban moveability.

6.4. Construction of a moveability index

Based on the findings of the presented analyses a moveability index was constructed to assess the built environment of children with respect to opportunities for physical activity. To be more specific, I considered the following urban measures of built environment characteristics within ego-centered neighborhoods:

1) Residential density RD based on the information in sub-districts. For each neighborhood, the overlapping areas of sub-districts within the neighborhood are divided by the total area of the corresponding sub-districts to derive weights for the calculation of the mean residential density.

2) Land use mix LUM was calculated using the entropy formula (see Section 2.1.2).

3) Street connectivity was measured in terms of intersection intensity ID.

4) Availability of public transit stations PT as well as

5) Availability of public open spaces POS, i.e. parks and playgrounds, was also measured using the mean kernel intensity per neighborhood A_m.

For the last three point characteristics of the moveability concept, the mean kernel intensity, for example $ID_{\Lambda(h)}$, was calculated using an anisotropic bandwidth considering the adaptive $\tilde{\Sigma}$ and the non-adaptive version Σ. Analogously, $PT_{\Lambda(\Sigma)}$ and $POS_{\Lambda(\Sigma)}$ as well as $PT_{\Lambda(\tilde{\Sigma})}$ and $POS_{\Lambda(\tilde{\Sigma})}$ were calculated. Each urban measure was standardized to a z-score (see Section 2.1.4) using the mean and standard deviation of urban measures per neighborhood $A_j, j = 1, \ldots, 400$, in order to combine them in the so-called moveability index

$$MOV_{\Sigma} = z(RD) - z(LUM) + z(ID_{\Lambda(\Sigma)}) + z(PT_{\Lambda(\Sigma)}) + z(POS_{\Lambda(\Sigma)}) \tag{6.2}$$

based on the non-adaptive anisotropic bandwidth and

$$MOV_{\tilde{\Sigma}} = z(RD) - z(LUM) + z(ID_{\Lambda(\tilde{\Sigma})}) + z(PT_{\Lambda(\tilde{\Sigma})}) + z(POS_{\Lambda(\tilde{\Sigma})}) \tag{6.3}$$

based on the adaptive anisotropic bandwidth. In addition, both versions of the moveability index were calculated within raster cells, which are depicted in Figure 6.4. Based on the non-adaptive intensity measures, the index shows clusters of higher values within the study area, while based on the adaptive bandwidth, the values of the moveability index are adjusted by the underlying residential density.

6.5. Associations of the built environment and physical activity in children

The moveability index and its component were included in the log-gamma regression model (see Section 6.1) to investigate the association between urban moveability and MVPA in 400 children. Again different network-distances of ego-centered neighborhoods were used for the calculation of urban measures. Figure 6.5 shows the patterns of effect estimates, p-values, and goodness of fit by means of the Akaike Information Criterion (AIC). The moveability index showed a significant positive association with MVPA that was stable over the different spatial scales. In the stratified models, strength of the association was higher in girls and lower in boys compared to the complete sample. Moreover, the association was significant only in girls. Goodness of fit only slightly changed depending on the network distance. In pre-school children (see Figure A.3) effect estimates were slightly smaller than in school children, but stable over different network-distances. In contrast to the stratified analysis in school children, the association was stronger in pre-school boys than in pre-school girls. However, in pre-school children the association between the moveability index and MVPA was not significant. The associations between the various components of the moveability index and MVPA in school-children and pre-school children are shown in Appendix A.2.

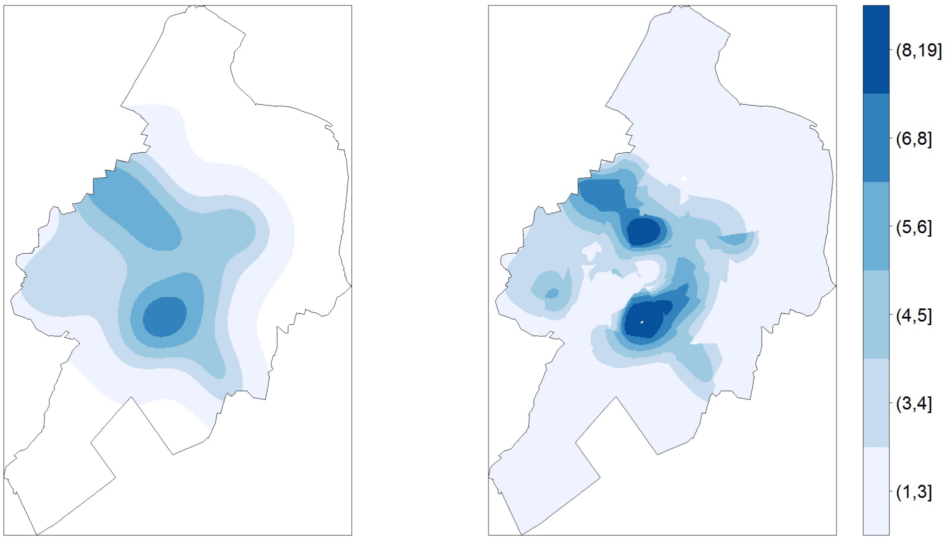

Figure 6.3.: Anisotropic kernel intensity of public open spaces in the study area of Delmenhorst based on adaptive (right) and non-adaptive (left) bandwidths

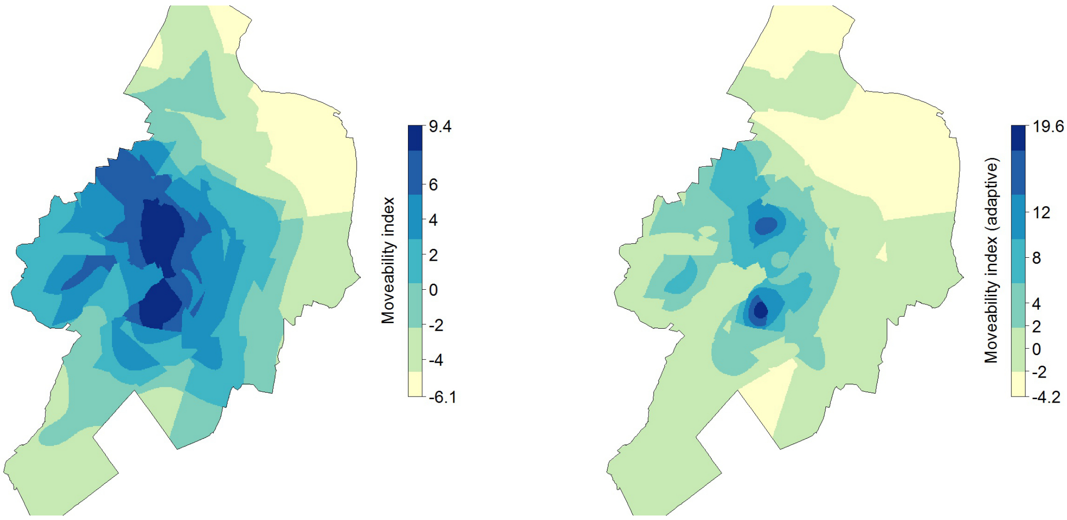

Figure 6.4.: Raster image of the moveability index in the German study region of the IDEFICS study based on adaptive (right) and non-adaptive (left) anisotropic kernel intensity measures

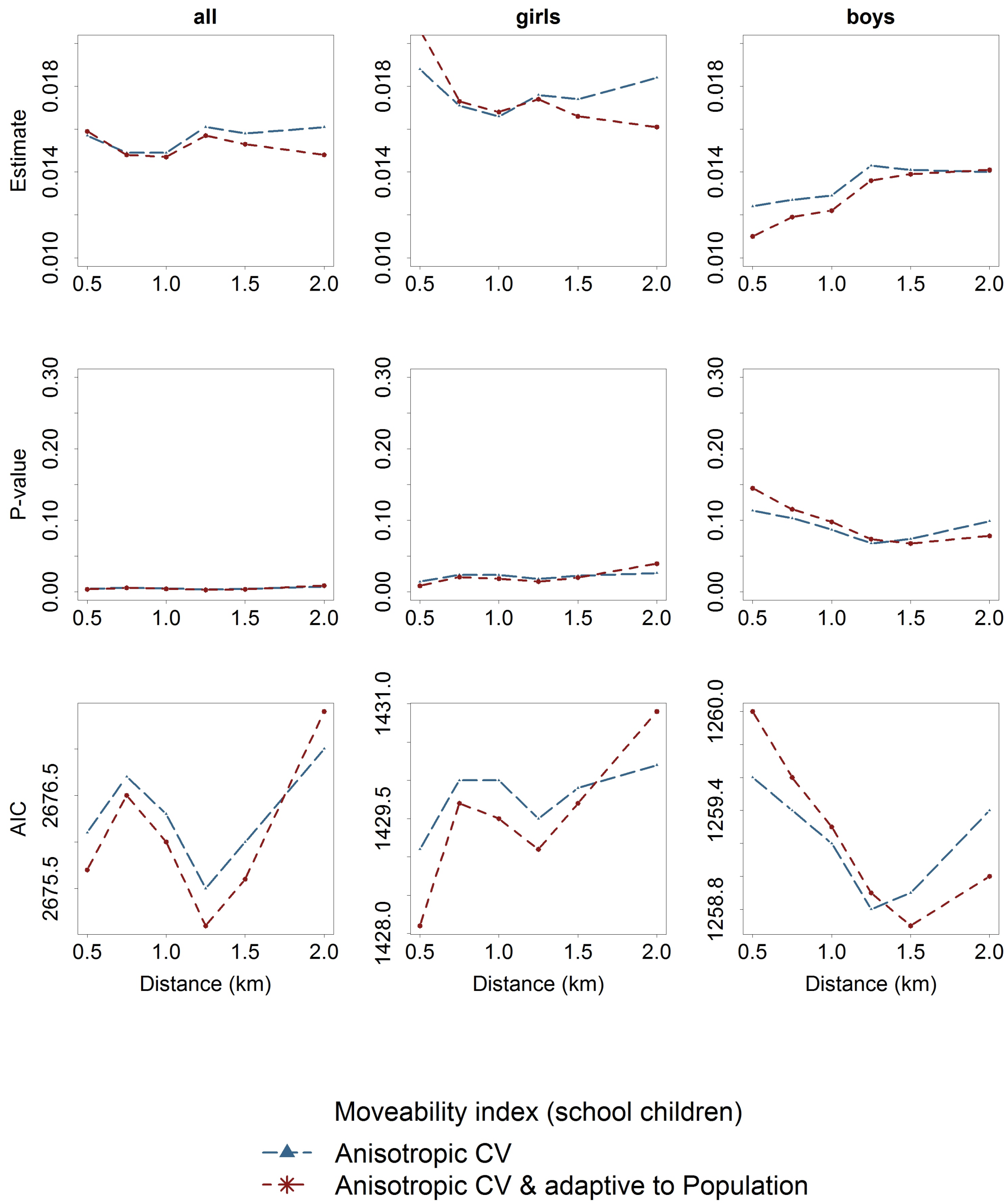

Figure 6.5.: Association between the moveability index and MVPA in school children based for differing spatial scales on adaptive and non-adaptive anisotropic intensity measures

7. Discussion and future perspectives

The present thesis builds the bridge between sound statistical theory and an important application in public health by presenting spatial analyses of built environment characteristics that offer opportunities for active transport and leisure time activities in children. Kernel intensity methods were used to assess the availability of point characteristics in order to improve urban measures and construct moveability concept (Buck et al., 2015c). The moveability index that was developed based on these findings and on the methodological improvements identified neighborhoods that support physical activity in children. In particular, data-driven methods such as the anisotropic kernel intensity could be applied to overcome commonly known limitations in the assessment of urban measures (Buck et al., 2015b). Overall, the analyses of the moveability index revealed that residential areas with a low diversity of land use and with sufficient public open spaces designed for recreational purposes provide a neighborhood that promotes physical activity in children (Buck et al., 2015c). Thus, the moveability index that was introduced in this thesis provides a useful GIS-based tool to evaluate urban neighborhoods with regard to their opportunities for physical activity in children. This highlights the importance of sound and innovative geostatistical methods that are able to enhance the modeling of exposure variables in environmental research. The index might support urban planners and public health stakeholders in creating healthy environments to counteract the lack of physical activity by providing evidence for environmental interventions and identify necessary changes in the urban built environment (Durand et al., 2011).

In the research of built environment characteristics the *modifiable area unit problem* (MAUP) (Houston, 2014) is induced by the use of the simple intensity method and a fixed conceptualization of the neighborhood, which are both often combined in the investigation of built environment characteristics and physical activity (Chaix et al., 2009; Maroko et al., 2009; Buck et al., 2011; Vallée et al., 2014; Buck et al., 2015b). The zoning scheme or the spatial scale of the neighborhood influences the association between urban measures and physical activity and the simple intensity measure strongly depends on the conceptualization of the neighborhood (Buck et al., 2015b). Moreover, administrative areas do not capture the true spatial behavior of residents, which was already discussed as *container effect* (Maroko et al., 2009) or *constant size neighborhood trap* (Vallée et al., 2014).

The simple intensity, which is often used in administrative areas, does not account for the variation of the built environment and, hence, variation in the availability of point characteristics within the area (Buck et al., 2011). A more flexible method is provided by the kernel intensity to asses the availability of point characteristics and investigate their association with physical activity behavior in urban space (Buck et al., 2015c,b). Maroko et al. (2009)

and Houston (2014) recommended kernel intensity measures to assess the availability of and proximity to point characteristics within administrative areas. Leal and Chaix (2011) also recommended ego-centered neighborhoods that focus on the environment around the individual place of residence. However, ego-centered neighborhoods are based on a chosen distance that is differently used in the literature to determine the spatial scale. Again, differences in the spatial scale do have an unknown effect on the association between urban measures and physical activity and sensitivity analyses with regard to neighborhood scale are recommended (Chaix et al., 2009; Leal and Chaix, 2011). Besides the sensitivity analyses that cope with the MAUP, Kwan (2012b) also highlighted the need to consider differences in the study sample due to individual-level differences of the social environment, individual perceptions of the built environment, and preferences to use the environment.

I considered various methods for the bandwidth selection to compare methodological improvements of kernel intensity measures in more detail. The use of a kernel intensity based on an anisotropic cross-validated bandwidth was found to capture point characteristics best (Buck et al., 2011, 2015b) by also accounting for the variation within administrative areas. Furthermore, the anisotropic kernel intensity showed a better performance compared to the simple intensity. The strength of the association between urban measures and MVPA in children was simultaneously investigated where it's dependance on the neighborhood distance and on different types of kernel intensity measures stratified by age groups and sex was of particular interest (Buck et al., 2015c,b). The anisotropic kernel intensity showed stable results and stronger associations compared to the simple intensity which lead to strongly differing results depending on the spatial scale (Buck et al., 2015b). Stratified analyses did not indicate differences in the neighborhood context of boys and girls or pre-school children and school children. Similar associations between urban measures and especially between the moveability index and MVPA were found for different network distances from 750 m up to 1,250 m in pre-school and school children. Significantly positive associations between the moveability index and MVPA were found in school children, but this association was less pronounced in pre-school children. However, stratified by sex the association was mainly found in school girls and pre-school girls, but less pronounced in school boys and pre-school boys.

7.1. Strengths and limitations

Some limitations of the presented spatial analyses have to be discussed. First, the sample of children who participated in the IDEFICS study was slightly biased with regard to socio-economic status of the parents. About 60% had high educational levels or high household income. Also the sample of pre-school children was considerably small and might have underpowered the analyses. However, findings revealed that parental safety concerns affected MVPA levels in pre-school children whose physical activity behavior may also be more dependent on the behavior of their parents (Tappe et al., 2013).

In addition, the spatial analyses were based on a relatively small study area. Larger urban areas, i.e. cities with more than 100,000 residents, provide higher environmental variability that is needed to evaluate the association between the built environment and physical activity. In larger urban areas, however, performance of kernel intensity measures might deviate from the results presented in this thesis. This possible drawback may be resolved by using adaptive bandwidths that account for varying background information such as residential density.

Strengths of the presented studies are the use of objectively measured physical activity in children and objectively measured built environment characteristics, although, accelerometer measurements were taken over the whole day and the derived physical activity levels were thus not restricted to outdoor activities which are influenced by built environment characteristics (Chaix et al., 2009; Kwan, 2012b). Another strength resulted from the spatial blurring which allowed to apply ego-centered neighborhoods around the anonymized place of residence that improved the spatial link between environmental information (Buck et al., 2015a).

7.2. Future perspectives

The investigation of urban moveability and its association with physical activity in children will be expanded in the future. In the framework of the IDEFICS study it is envisaged to conduct further analyses in other European regions, for example in Sweden and Italy. Furthermore, two follow-up surveys were conducted, the latter of which was conducted in 2013 and 2014 as part of the I.Family project that is funded by the 7th EU Framework Programme including children who already participated in surveys of the IDEFICS study. The IDEFICS / I.Family cohort allows to investigate longitudinal effects of the moveability index on MVPA in children accounting for changes in the environment through relocation (Sahlqvist et al., 2013; Knuiman et al., 2014). Up to now longitudinal analyses are rarely conducted, but necessary to investigate the causal relationship between the built environment and physical activity in children or adolescents with regard to changes of physical activity behavior over the early stages of the life course (Leal and Chaix, 2011).

Moreover, in the I.Family study measurements of the global positioning system (GPS) and accelerometry will be collected in a subsample and combined using the time stamp to specify environmental exposure of participants and cluster spatial mobility of family members (Kerr et al., 2011). Recent studies combined measurements of GPS and accelerometry (Cooper et al., 2010; Chaix et al., 2014; Wheeler et al., 2010) which enables to allocate the behavior in space and time (Kwan, 2012b,a). Accelerometer measurements are then restricted to assess outdoor physical activity that might be directly influenced by built environment characteristics. In addition, ego-centered neighborhoods can be improved by GPS-measurements (Perchoux et al., 2013). These neighborhoods are usually determined radially around the place of residence. However, based on preferred locations for everyday life purposes, the individual neighborhood that is reached by walking might strongly differ from the radial concept. Moreover, the distance that is suitable to walk differs individually and induces unknown geographic context in spatial analyses, which was extensively discussed by Kwan (2012b).

The association between the built environment and physical activity behavior of residents is strongly influenced by perceptions and individual-level characteristics as well as environmental confounder. In particular, a mismatch between the perceived and the objectively measured built environment was identified which influenced the association between the built environment and physical activity (Frank et al., 2007b; Gebel et al., 2011; van Lenthe and Kamphuis, 2011). Recent studies account for, both, the perceived environment and the objectively measured environment (Scott et al., 2007; Van Dyck et al., 2011; Strath et al., 2012). The perceived environment and the preference to use it are important confounder for the association between the objectively measured environment and physical activity. To overcome this mismatch, latent class analyses were recently used to comprise and include multiple individual-level information in spatial analyses (Adams et al., 2013; Christiansen et al., 2014). For example, Adams et al. (2013) used a latent class analysis to comprise items of a questionnaire on the perceived environment into four main components. Christiansen et al. (2014) investigated differences in the spatial behavior, i.e. distance and range of active transportation, and identified life stages based on multiple individual-level information.

Based on web-GIS applications, GPS-measurements or interviews, different methods to individually specify the neighborhood and its use in more detail were tested in various studies. On the one hand, GPS-measurements were used to identify activity spaces, areas, or activity locations, i.e. points, that are usually visited by each individual (Perchoux et al., 2013). On the other hand, study participants were asked for their activity locations that were visited within a specific time period using questionnaires (Vallée et al., 2014) or web-GIS applications (Robinson and Oreskovic, 2013) to delineate the neighborhood area. Advancements in computing technologies and particular the use of smartphones make it feasible to assess the surrounding of participants through a number of sensors. This allows to specify their behavior in space and time and to evaluate the use of the built environment as well as its influence on residential behavior. (Kerr et al., 2011; Kwan, 2012a).

The moveability index also showed that the walkability concept can be expanded to capture the influence of the built environment on multiple domains of physical activity such as active transport and leisure time activities in different life stages. Considering publicly designed recreational facilities such as parks and playgrounds as well as sports facilities allows a broader view on urban opportunities for physical activity that should be investigated with regard to adolescents, adults, and older adults (Krizek et al., 2004; Giles-Corti et al., 2009; Ding et al., 2011; Oreskovic et al., 2015).

Summarizing, the moveability concept could be used to counteract the public health burden that is influenced by built environment barriers on two levels. On the policy-level the moveability index may support the collaboration of urban planning and health promotion by identifying places for interventions and evidence for the most-effective support for healthy living in the environment (Kent and Thompson, 2014). On the individual-level, the moveability index might enable residents to choose their neighborhood according to their preference. In addition, the graphical representation might provide information on nearest opportunities for PA such as recreational space or sports clubs. For example, the *walkscore* (`www.walkscore.com`, Carr et al., 2010) is implemented and publicly available via web-GIS and includes real estate information based on the preferred neighborhood. However, the walkscore only accounts for the diversity of destinations and is limited to the data quality of the web-GIS.

Besides the focus on physical activity promotion through the environment, different aspects of the built environment are also important for wellbeing (Kent and Thompson, 2014), social cohesion and social support (Panter et al., 2010) which are also influenced by places, experiences and cultural background (Andrews et al., 2012). Eventually, multiple characteristics of the built environment might be considered to assess the *liveability* of an urban neighborhood by developing a liveability index (Giles-Corti et al., 2014; Badland et al., 2014). In particular, geostaticsial modeling of built environment characteristics that was presented in this thesis may be generalized to be applied with regard to the various aspects of the built environment that increase the quality of life in urban environments.

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A. Figures

A.1. Intensity measures of point characteristics

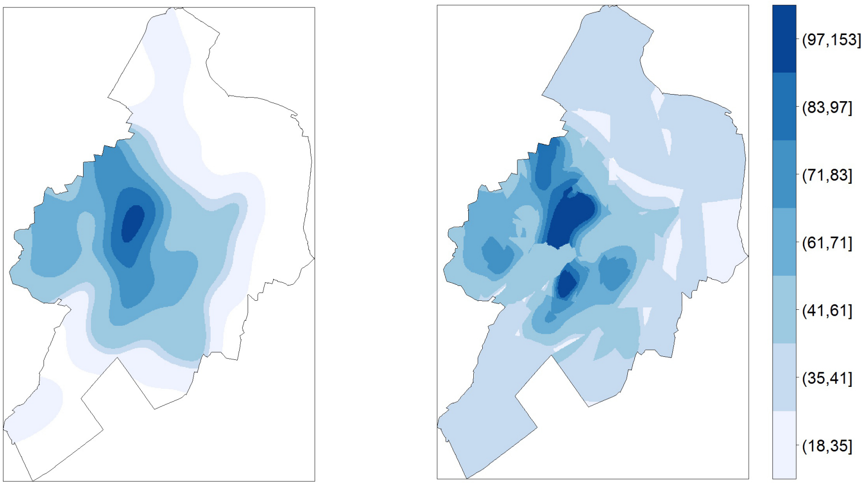

Figure A.1.: Anisotropic kernel intensity surface of intersections in the study area of Delmenhorst based on adaptive (right) and non-adaptive (left) bandwidths

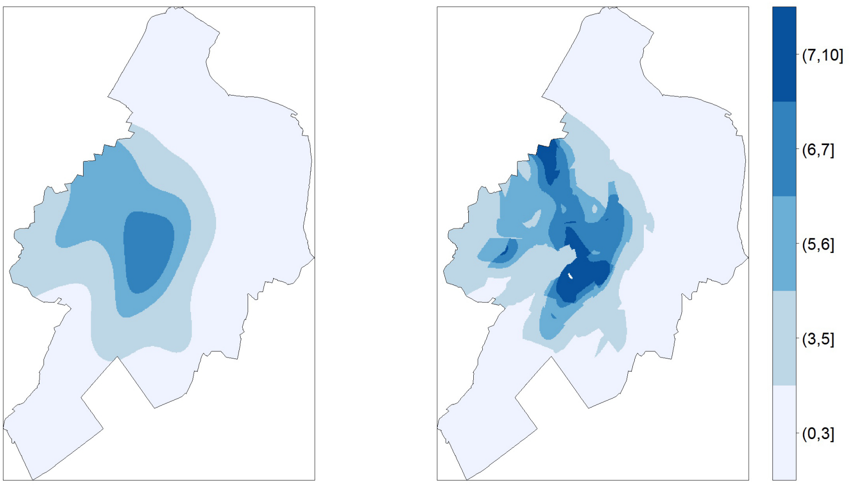

Figure A.2.: Anisotropic kernel intensity surface of public transit stations in the study area of Delmenhorst based on adaptive (right) and non-adaptive (left) bandwidths

A.2. Results of urban measures of the moveability concept

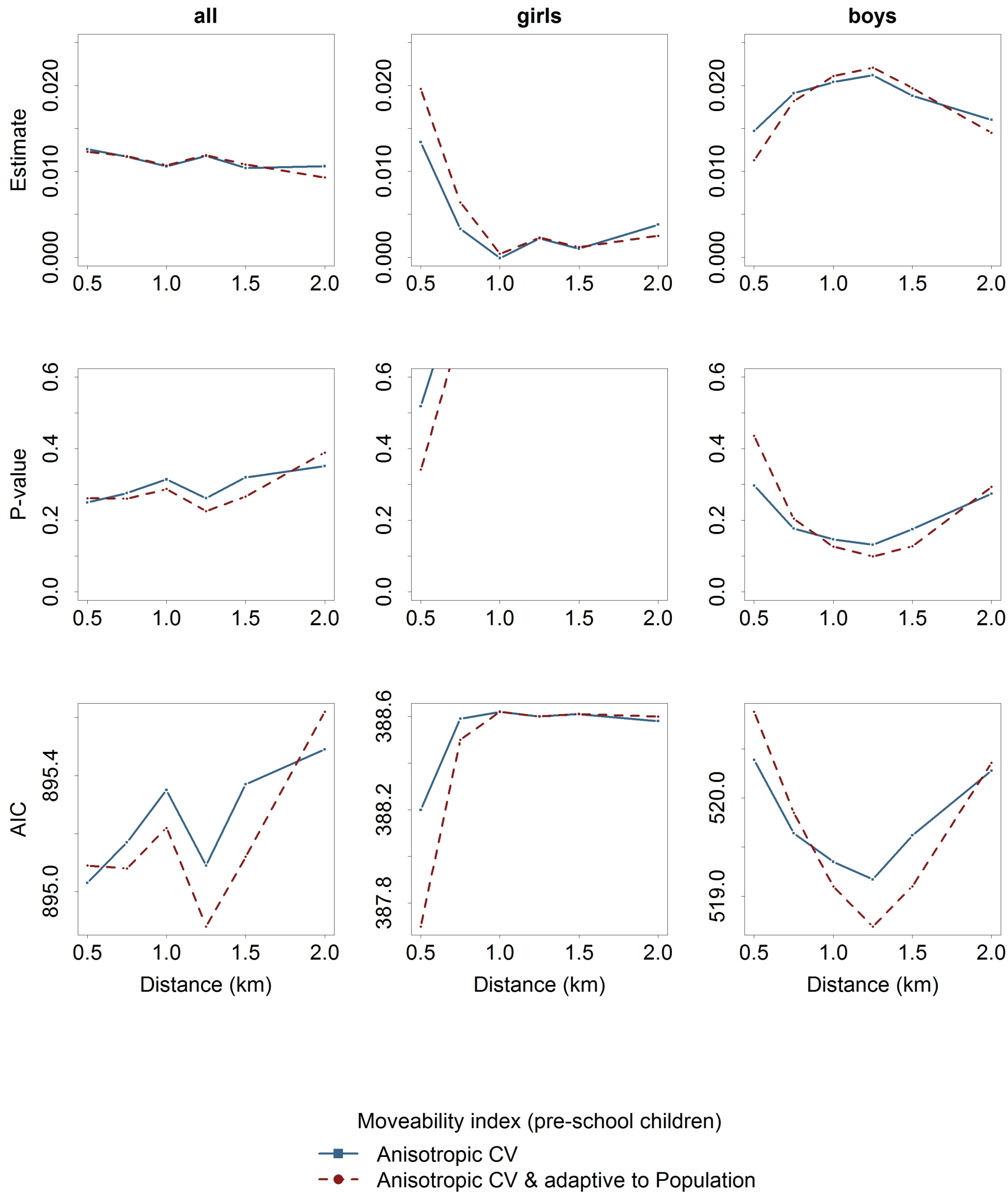

Figure A.3.: Association between the moveability index and MVPA for differing spatial scales in pre-school children based on adaptive and non-adaptive anisotropic intensity measures

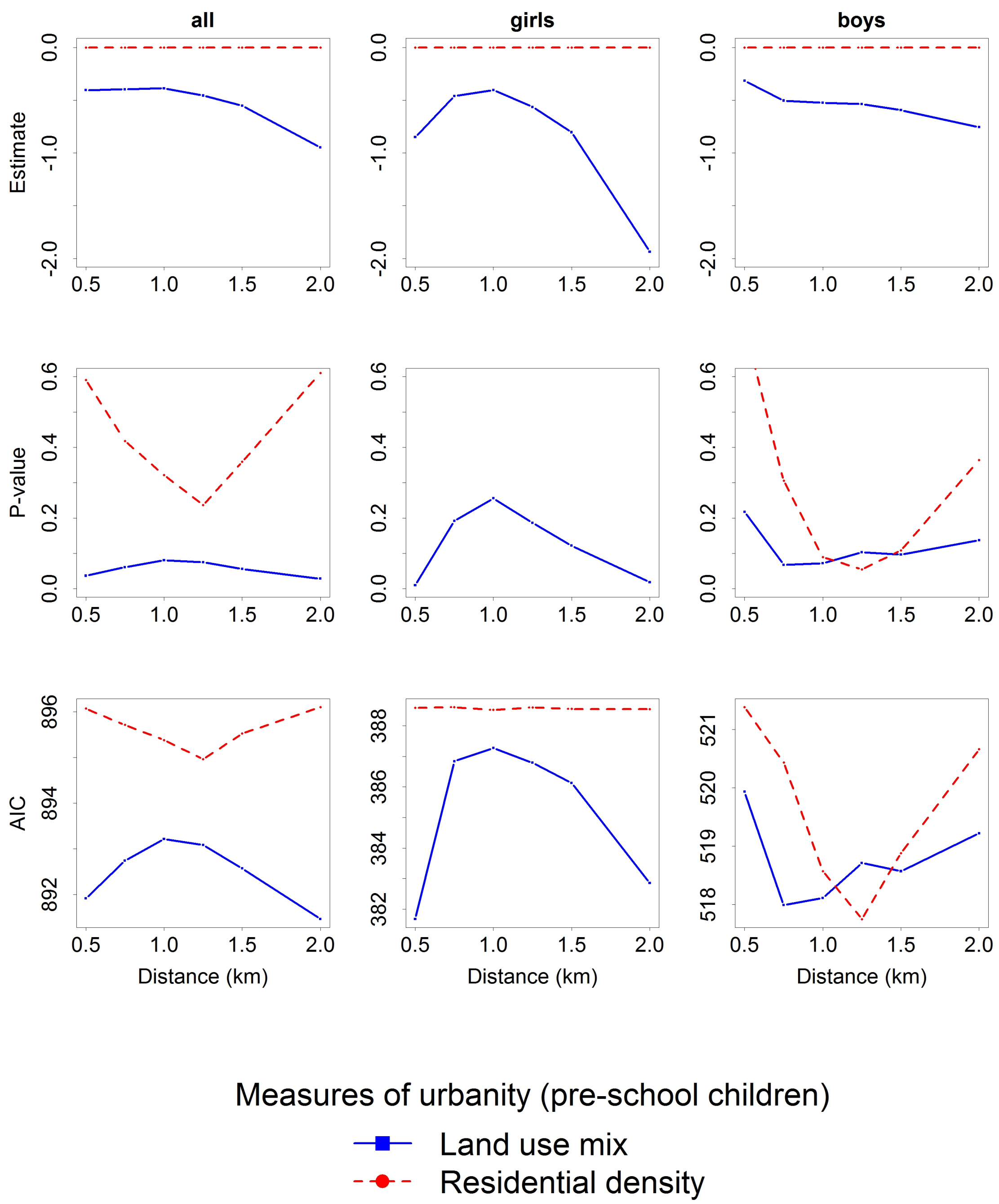

Figure A.4.: Association between urbanity measures and MVPA in pre-school children for differing spatial scales

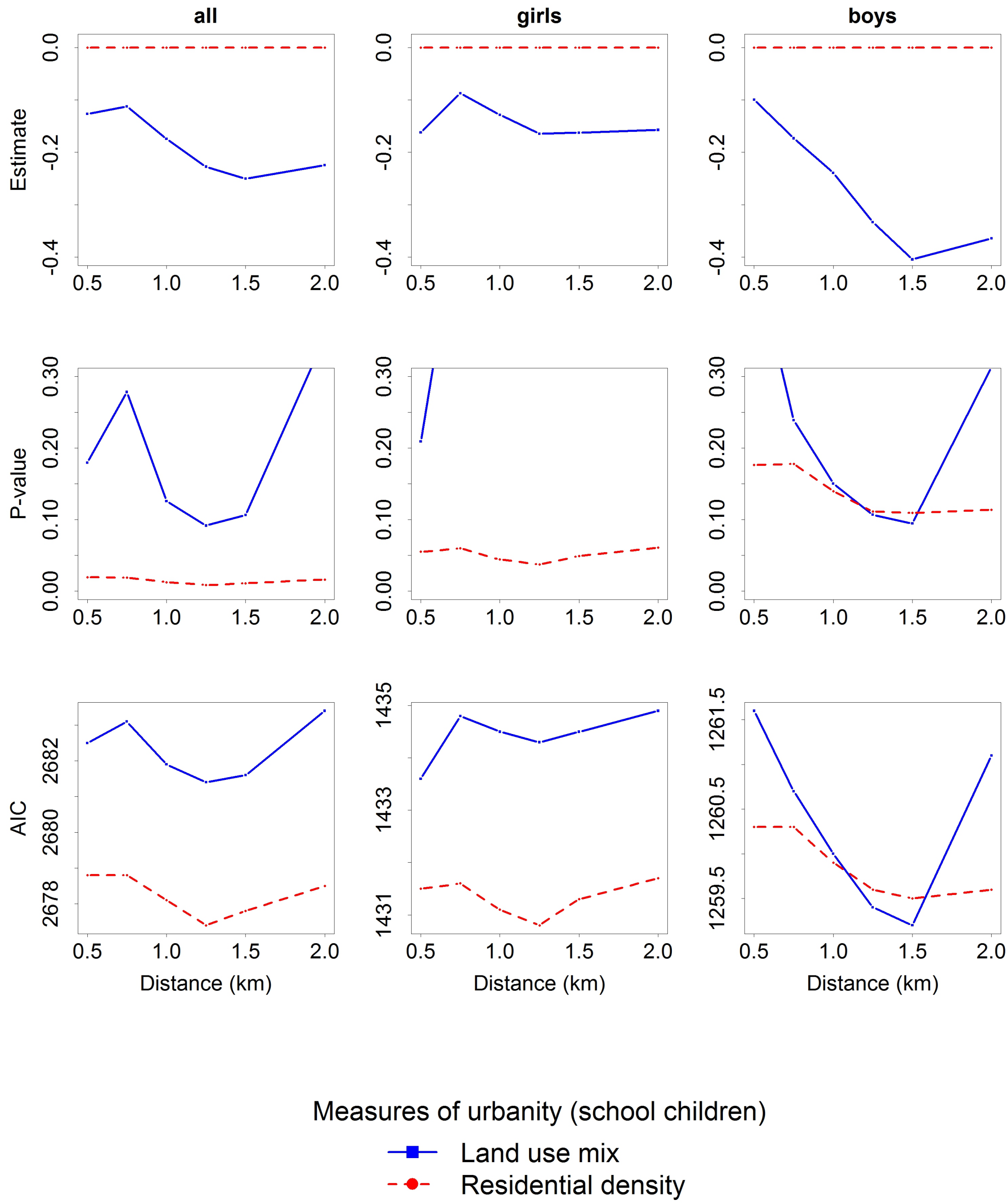

Figure A.5.: Association between urbanity measures and MVPA in school children for differing spatial scales

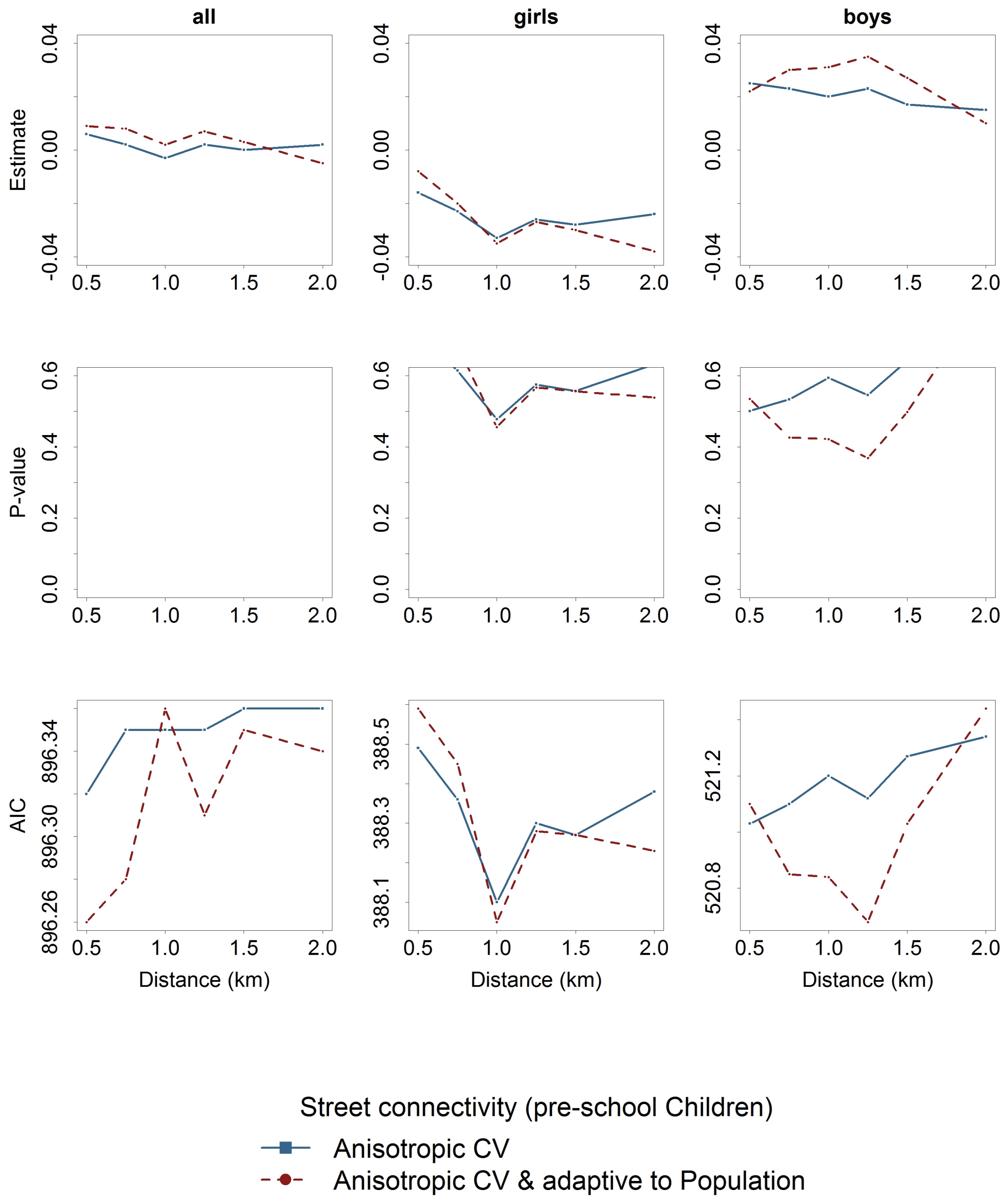

Figure A.6.: Association between street connectivity and MVPA in pre-school children for differing spatial scales based on adaptive and non-adaptive anisotropic intensity measures

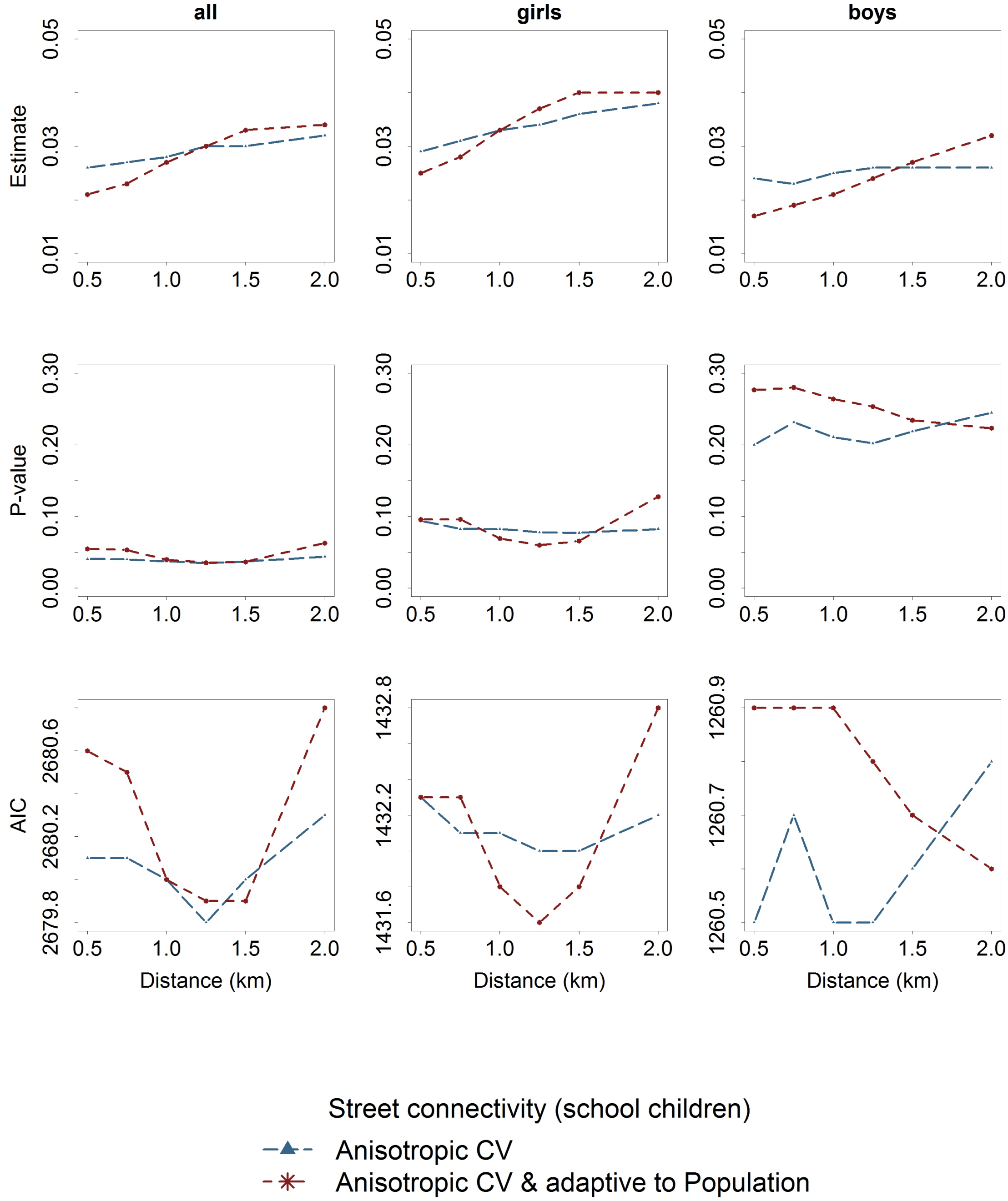

Figure A.7.: Association between street connectivity and MVPA in school children for differing spatial scales based on adaptive and non-adaptive anisotropic intensity measures

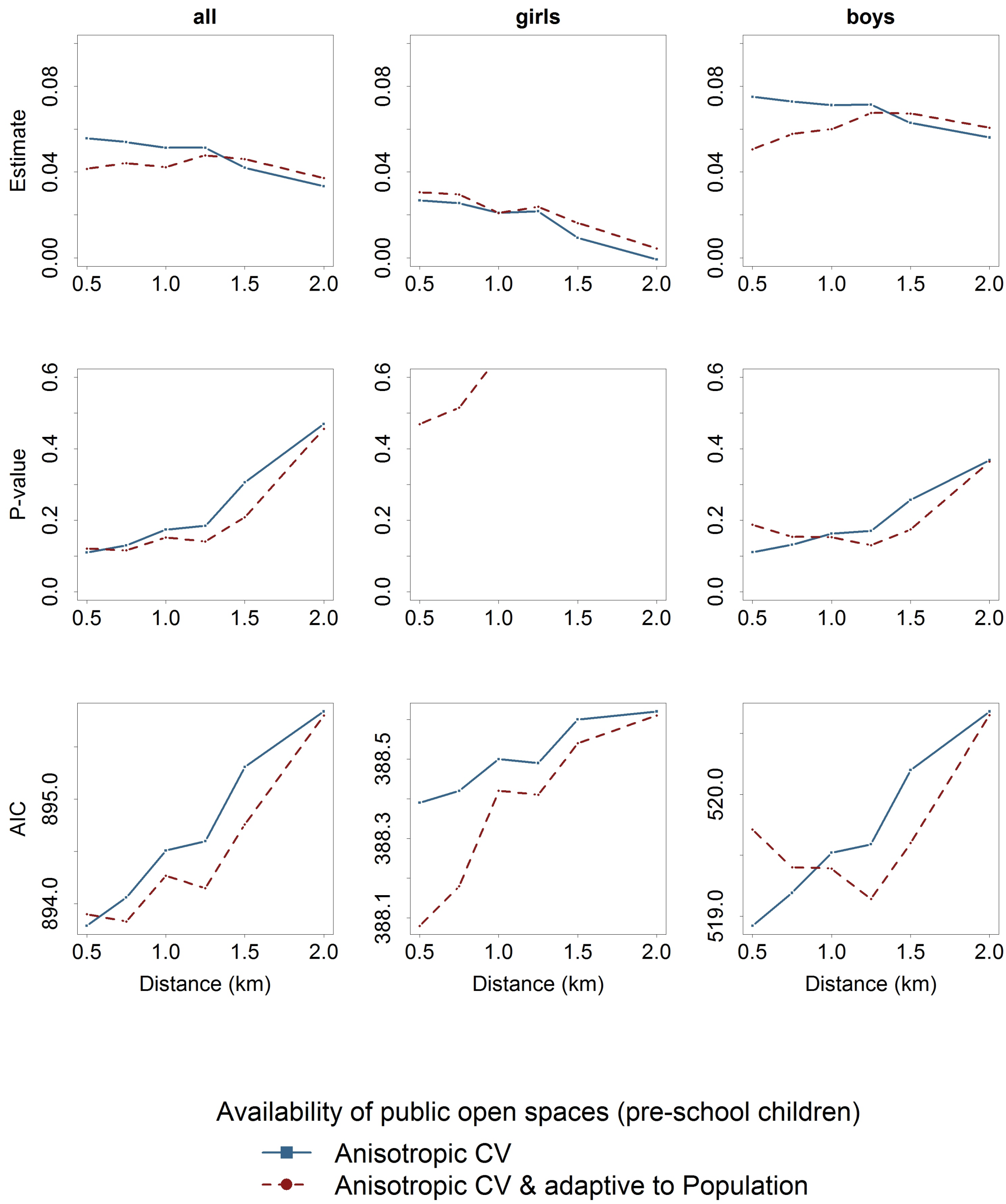

Figure A.8.: Association between public open space and MVPA availability in pre-school children for differing spatial scales based on adaptive and non-adaptive anisotropic intensity measures

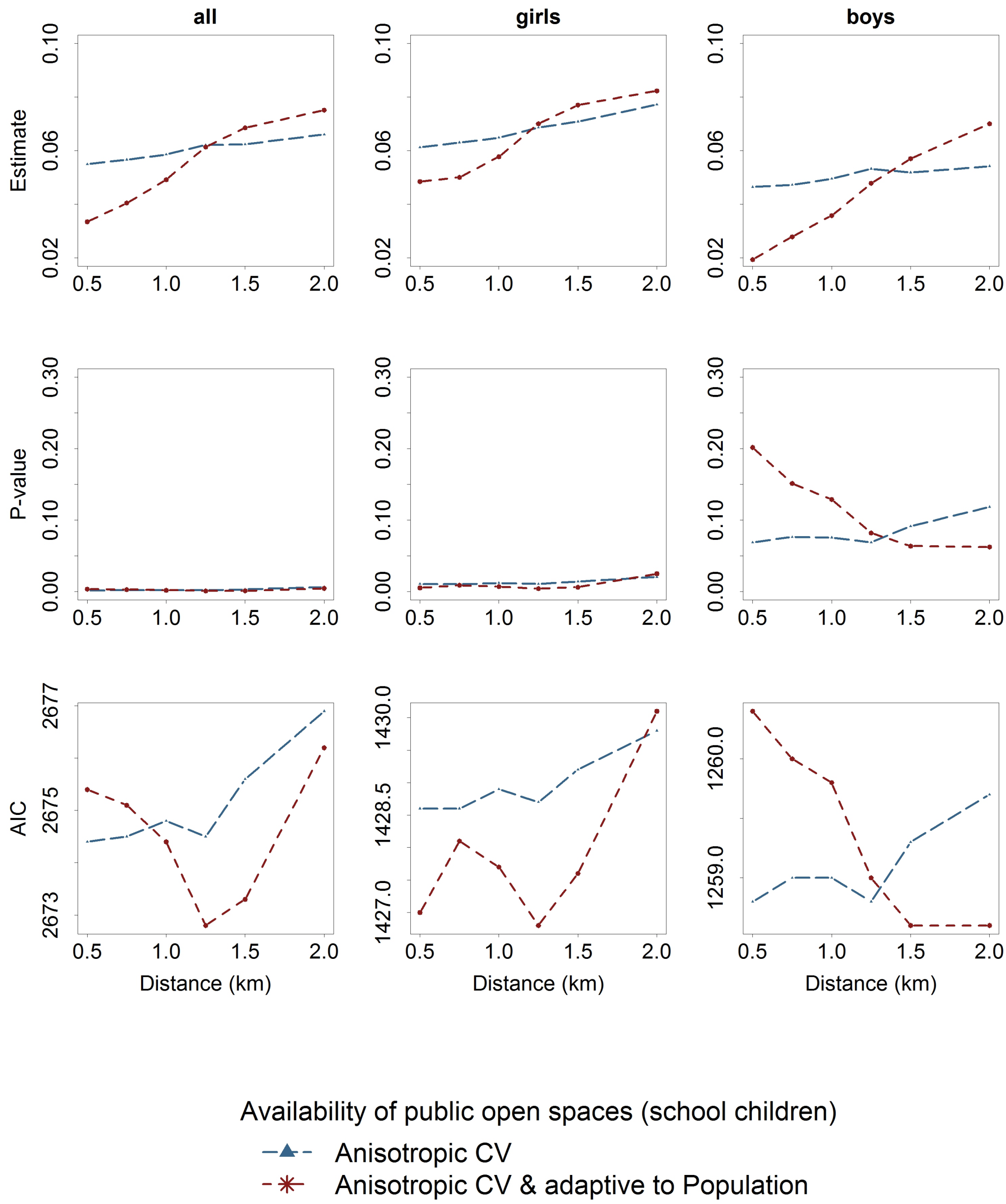

Figure A.9.: Association between public open space availability and MVPA in school children for differing spatial scales based on adaptive and non-adaptive anisotropic intensity measures

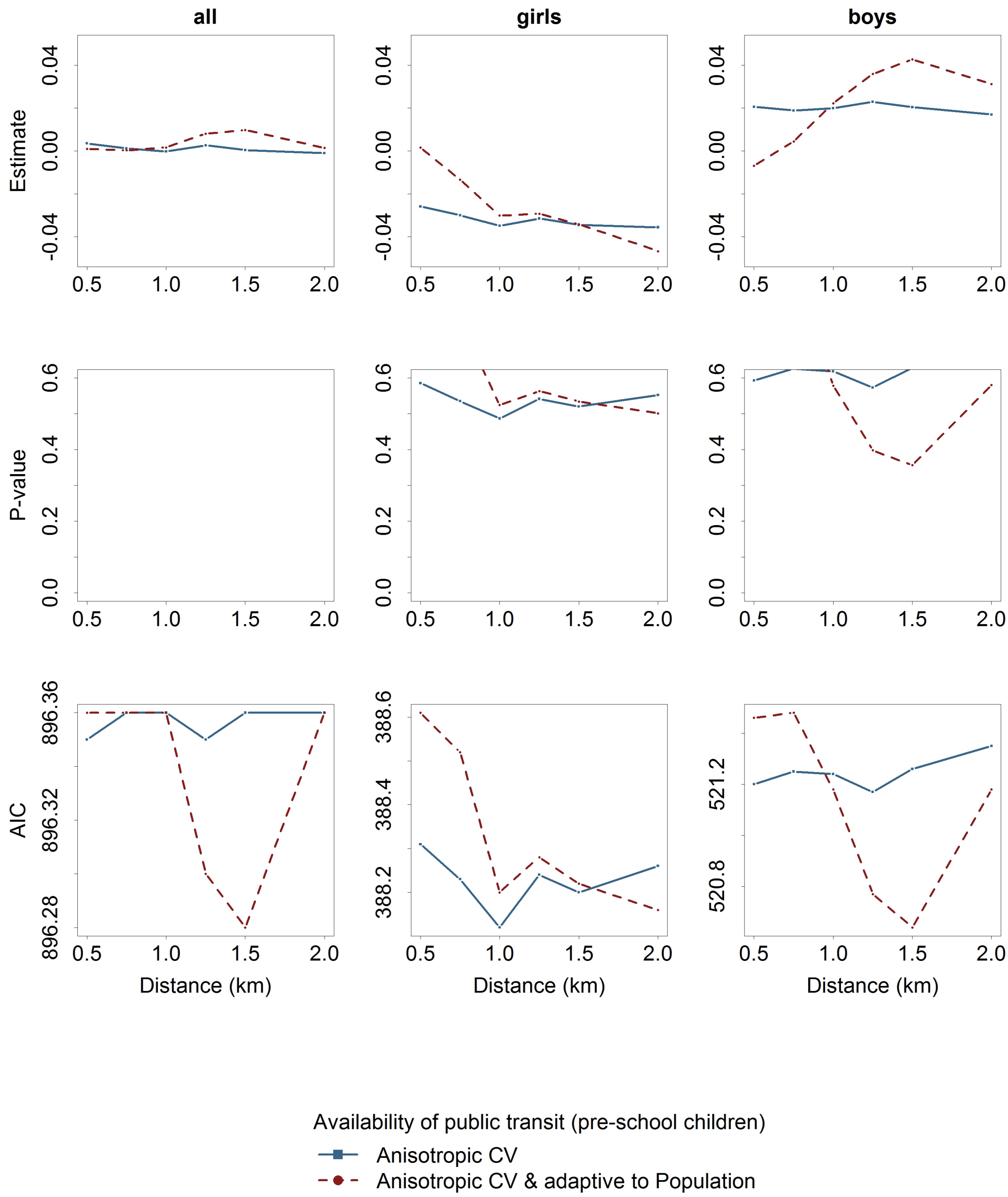

Figure A.10.: Association between public transit availability and MVPA in pre-school children for differing spatial scales based on adaptive and non-adaptive anisotropic intensity measures

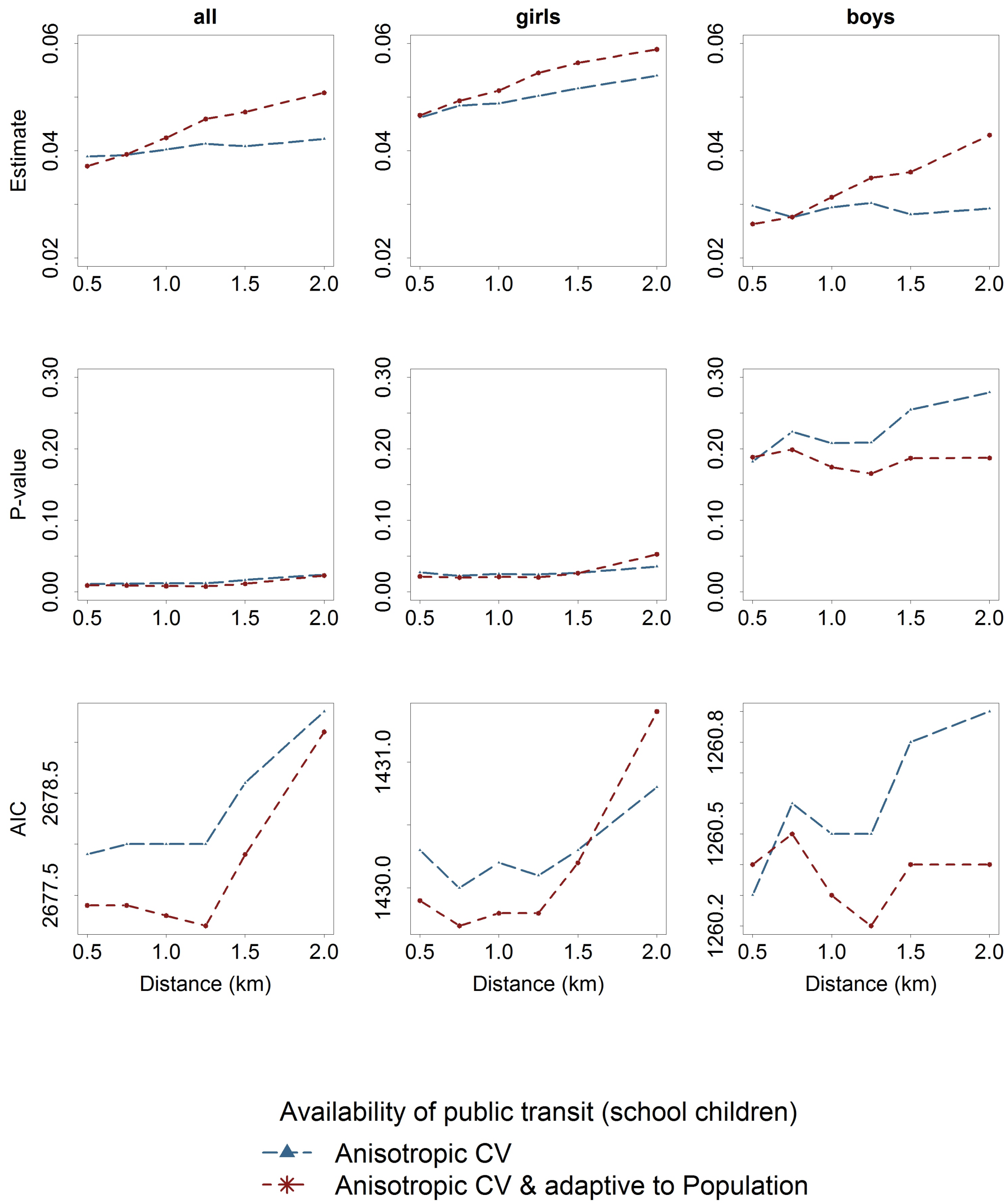

Figure A.11.: Association between public transit availability and MVPA in school children for differing spatial scales based on adaptive and non-adaptive anisotropic intensity measures

B. Publications

B.1. Development and application of a moveability index to quantify possibilities for physical activity in the built environment of children

This study describes the geostatistical modeling of urban characteristics based on Poisson point processes and presents the first approach of combining urban measures into a moveability index which was published in the peer-reviewed journal *Health & Place* (Impact Factor of 2011: 2.67) (Buck et al., 2011).

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Development and application of a moveability index to quantify possibilities for physical activity in the built environment of children

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ABSTRACT

Several studies show that urban forms are environmental correlates of physical activity. Most of these studies used data based on questionnaires while only a few used geographic information systems (GIS) to objectively assess urban forms. Based on GIS data, we applied a kernel density method to measure urban forms and combined these measures to a moveability index to assess the opportunities for physical activity in the German intervention region of the IDEFICS study. In this proof-of-principal analysis, we linked the moveability index with physical activity data obtained from the baseline survey of the IDEFICS study. Regression analyses revealed a modest but significant impact of the built environment on the physical activity of 596 school children in the study region, supporting the potential application of the moveability index.

1. Background

Characteristics of the built environment do have an impact on the physical activity (PA) of residents, but there are great disparities in the design of studies related to the physical environment. On the one hand, different field surveys (Millington et al., 2009) or questionnaires (De Bourdeaudhuij et al., 2003; Cerin et al., 2006, 2007; Spittaels et al., 2010) that provide perceived data on urban forms were used depending on the study area and the country in which the study was conducted. On the other hand, geographic information systems (GIS) were used to collect geodata on aspects of the built environment and to objectively assess urban forms with measures for distance, density or diversity. In this respect, indices were developed that combine measures of urban forms to reflect the impact of the built environment on PA in one single value (Krizek, 2003; Rodriguez et al., 2006; Owen et al., 2007; Leslie et al., 2007), but these measures were mostly averaged regionally on a large scale, although they are combined with individual level data (Frank et al., 2005).

In particular, Frank et al. (2005, 2010) developed the concept of walkability using GIS to objectively assess urban forms for studies of the physical environment. The walkability is assessed using measures of urban form that characterize possibilities for walking using individual pedestrian catchment areas within a 1 km buffer zone. Compared to this definition of an individual home environment in GIS-based studies, Lee et al. (2008) used buffer zones with a radius of 0.25 mile (approx 400 m) to assess walking suitability around schools and Oreskovic et al. (2009) implemented also 400 m buffer zones based on the distance an average adult can walk in 5 min. However, in some studies, individual pedestrian catchment areas were substituted by census districts (Leslie et al., 2007; Owen et al., 2007) which is the so-called "container approach" (Maroko et al., 2009). This approach is based on the simple density to measure the accessibility to urban forms, i.e. the accessibility is measured by the number of urban elements within a particular geographic unit of aggregation (e.g. census tracts) (Maroko et al., 2009). This method is worth discussing and may be improved using more refined geostatistical methods which are described below.

Additionally, physical environment studies that use objective measures of urban form calculated in GIS are mostly examined in the US (Frank et al., 2005, 2010; Evenson et al., 2009) or Australia (Leslie et al., 2007; Owen et al., 2007), but rarely in Europe (Bringolf-Isler et al., 2008; Panter and Jones, 2008). Findings from

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these physical environment studies cannot be adapted in a straightforward manner, because (1) the environments in the US and Australia differ from urban areas in many European towns and cities (Millington et al., 2009) and (2) built environments do have a different impact on PA across different countries (Sallis et al., 2009).

Finally, physical environment studies mainly focus on the impact on the PA of adults. Considering particular urban forms like intersections and sidewalks, there is a strong evidence for their impact on the PA of adults. However, whether there exists a comparable association in children has not been sufficiently examined. Some recently published studies showed evidence that some urban forms may influence PA with regard to transportation or recreation in children (Panter et al., 2008; Jones et al., 2009), but studies that use objective measures based on GIS are lacking.

Therefore the aim of this pilot study was to investigate the impact of the built environment in a European context, using Germany as the pilot area, on the PA of children, This was achieved by adapting the concept of walkability from Frank et al. (2005, 2010) which was developed for adults and included recreational facilities offering possibilities for PA particularly for children.

This paper aims to address three main objectives. First, we describe the density and diversity as measures of urban form that are used to objectively assess opportunities for PA. Second, we propose a process that combines several dimensions of urban forms to a moveability index in order to measure opportunities for PA of children in urban areas. Finally, statistical analyses are performed to investigate the practicability of the moveability index linking the index with selected self-reported questionnaire information on travel mode and leisure time PA using data collected within the IDEFICS (Identification and prevention of Dietary- and lifestyle-induced health EFfects in Children and infantS) study.

2. Methods

We also conducted a review of physical environment studies to identify objectively assessed and perceived urban forms that showed evidence of being environmental correlates of PA. Urban forms are presented in categories that were used to derive urban form features (for an overview see Table 1).

2.1. Street connectivity

Street connectivity comprises measures characterizing the urban infrastructure within the neighborhood environment. Studies using GIS to assess the urban environment, in general, only intersections are considered to describe the connectivity of the street network (Frank et al., 2005, 2007; Schlossberg et al., 2006; Kerr et al., 2007; Leslie et al., 2007; Owen et al., 2007; Holt et al., 2008). As a result, intersection density was positively associated with weekly frequency of walking for transport in adults (Frank et al., 2005, 2007; Owen et al., 2007) and active travel mode of children on their way to school (Schlossberg et al., 2006; Kerr et al., 2007; Holt et al., 2008).

Other studies using questionnaires or field surveys also showed associations between sidewalks (De Bourdeaudhuij et al., 2003, 2005; Sallis et al., 2009), bikeways, and public transit stations (Sallis et al., 2009) and reported PA of residents. Higher levels of PA in adults were found in neighborhoods whose residents reported a higher availability of sidewalks (De Bourdeaudhuij et al., 2003, 2005). Particularly, Edwards (2008) found that using public transit was associated with walking 8.3 more minutes per day on average in adults.

Since the considered urban forms that were used to assess the street network differ from one study to another, we included all four urban forms, i.e. sidewalks, bikeways, intersections, and public transit stations, in our street connectivity feature to cover all possibilities for PA.

2.2. Destination density

Environmental correlates of recreational PA are destinations like parks, playgrounds, and sports facilities that impact on the PA of residents. Studies showed that higher levels of PA in children were reported, if such destinations were located in the neighborhood (Davison and Lawson, 2006; Frank et al., 2007; Kerr et al., 2007; Scott et al., 2007; Black and Macinko, 2008). For example, the PA of children was positively associated with the proportion of green space (DeVries et al., 2007) or access to parks and recreational facilities (Roemmich et al., 2006). In a sample of English adults, it was also shown that those who reported five sessions of activity per week tended to live closer to sports facilities than their less active counterparts (Panter and Jones, 2008). Furthermore, Giles-Corti et al. (2005) showed for adults that the use of public open space for physical recreation was positively associated with accessibility to public open space.

Therefore, the destination density feature includes public playgrounds, sports facilities, and parks and green spaces to account for recreational areas where children can be physically active.

2.3. Level of urbanization

Characteristics like land use and number of residents or dwellings, respectively, are associated with the infrastructure and the number and variety of destinations within urban areas. Therefore, we derived the urban form feature called 'level of urbanization' including both urban forms that influence the walkability and the possibilities

Table 1
Description of the considered urban forms, the resulting measures of urban form as well as the urban form features including abbreviations.

Urban form feature	Abbr.	Description	Urban forms	Measures	Abbr.
Street connectivity	*SC*	Characterizes the infrastructure of the built environment. Higher density values of urban forms reflect a connected infrastructure for pedestrians and cyclists	Sidewalks Bikeways Intersections Public transit stops	Density	*WD* *BD* *ID* *TD*
Destination density	*DD*	Characterizes the accessibility to facilities that provide possibilities for PA. Higher density of urban forms provide more possibilities for PA in the neighborhood	Public playgrounds Sports facilities Parks/green space	Density	*PD* *FD* *GD*
Level of urbanization	*LU*	Characterizes the urbanity. Areas with high residential or dwelling density and diverse land use types are considered as urban	Residents/dwellings Land use types	Density Diversity	*RD* *LM*

for PA within urban areas (Cervero and Kockelman, 1997) consistently used in physical environment studies (De Bourdeaudhuij et al., 2005; Frank et al., 2005, 2007; Rodriguez et al., 2006; Owen et al., 2007; Black and Macinko, 2008) involving adults primarily. Land use mix and residential density were related to overall PA in adults (De Bourdeaudhuij et al., 2003). For example, Kerr et al. (2007) reported that both measures were related to higher walking percentages in young individuals.

2.4. Geostatistical methods

To objectively assess urban forms, we adapted and revised existing methods. In previous research, a simple density method was commonly used to characterize accessibility of urban elements, particularly to assess intersection density (Krizek, 2003; Kerr et al., 2007; Leslie et al., 2007; Owen et al., 2007). Here, the density of urban elements was measured as the number of elements divided by the size of an area, which was mainly a census district. This is also called the "container approach" (Maroko et al., 2009) which has three major limitations: (1) The simple density is a descriptive measure that depends on the chosen geographical unit: Zip code areas or census tracts were commonly used, but do not reflect the real environment of the residents. For example, parks and playgrounds which were assessed within a census tract may also be used by residents living in adjacent census tracts. However, the simple density would only count parks and playgrounds as accessible for residents living in the same census tract (Maroko et al., 2009). (2) Additionally, simple density does not provide any information about clusters of parks and playgrounds for example within the chosen geographical unit. (3) Areas, for instance zip code areas, strongly vary in areal size making it difficult to compare the availability of parks and playgrounds between areas. Even if the number of parks and playgrounds are scaled by the size of the area, the number of residents may also vary within a large zip code area.

Therefore, we used the kernel density method to assess the accessibility of elements of an urban form within the study area. This method is based on the weighted sum of urban elements within a chosen bandwidth for each point of the study area. In mathematical terms the kernel density $\lambda(s)$ of an observation point $s \subset W$ of the study area $W \subset \mathbb{R}^2$ is expressed as

$$\lambda(s) = \frac{1}{h^2} \sum_{i=1}^{n} \mathbb{K}\left(\frac{|s-s_i|}{h}\right), \quad (1)$$

where s_i, $i = 1, \ldots, n$, are n urban elements of an urban form within the study area and $\mathbb{K}$ is a kernel function that depends on the bandwidth h. For each observation point $s \subset W$ the distance $|s-s_i|$ to each point of interest s_i is calculated and standardized by the bandwith h. This ratio is used in the kernel function $\mathbb{K}$ to produce weights depending on the distance $|s-s_i|$. The farther away an urban element s_i is located from an observation point $s \in W$, the lower is the weight given by the function $\mathbb{K}$. For each distance that is greater than the bandwith h, the weight produced by the kernel function is zero (Schabenberger and Gotway, 2005).

To calculate the kernel density of urban elements in ArcGIS 9.3[2] we used a cell size of 2 m × 2 m which are used as observation points s_i for the whole study area and the bandwidth of the kernel function was set to $h = 1$ km to obtain an appropriate distance for the accessibility of urban elements. The *kernel density tool* of the *spatial analyst* in ArcGIS uses a quadratic kernel function $\mathbb{K}$ (Silverman, 1986) and provides the kernel density estimation of *point layers* as well as *line layers*. The *kernel density tool* then calculates the weighted sum of urban elements for each cell within the study area and produces a *raster layer* that is independent from census tracts or zip codes. On the one hand, the mean kernel density can be calculated for districts, subdistricts, etc. using the *zonal statistic tool* that calculates the mean kernel density value per area. On the other hand, survey data of residents whose house was located within a cell can be directly compared to the kernel density values that are calculated for this cell.

We used the kernel density method with a bandwith of 1 km to calculate the density of sidewalks (*WD*), bikeways (*BD*), intersections (*ID*), public transit stations (*TD*), public playgrounds (*PD*), sports facilities (*FD*), and parks and green spaces (*GD*).

It was not always possible based on the available information to calculate the residential density (*RD*) using the kernel density method. If the number of residents is provided for cells, the data can be converted to a *point layer* which in turn can be used by the *kernel density tool*. Other options for data sources could include dwellings or households per cell. In general, the number of residents is available for districts or subdistricts and can only be transformed in a simple density using the number of residents per km^2 within an area. In both cases we used the term residential density (*RD*).

To assess the diversity of land use, called land use mix (*LM*), we used the entropy:

$$H(p) = -\frac{1}{\ln(K)} \sum_{k=1}^{K} p_k \cdot \ln(p_k) \quad (2)$$

of proportions $p_k, k = 1, \ldots, K$, of land use types with $\sum_{k=1}^{K} p_k = 1$ which is commonly used in the recent literature (Krizek, 2003; Frank et al., 2005, 2010; Leslie et al., 2007). $H(p)$ gives a value between 0 and 1, with 0 characterizing homogeneity (only one land use type exists within the area) and 1 characterizing heterogeneity (all land use types are evenly distributed). Within ArcGIS, we derived a raster layer including six land use types (residential, commercial, industrial, agricultural, recreational, and miscellaneous) and used the *tabulate area tool* in ArcGIS to calculated the proportions of each land use type within an area. Using the entropy formula, we then calculated the land use mix (*LM*) for the area.

2.5. Development of the index

The nine measures of urban form (see abbreviations in Table 1) were difficult to compare. For example, we observed more intersections than public playgrounds. Therefore, we built *z*-scores (Frank et al., 2005, 2010) that make the measures of urban form comparable. For instance, for L values $v_l, l = 1, \ldots, L$, of a measure of an urban form within a study area that was divided in L subareas, we calculated the mean M_v^L and the standard deviation SD_v^L of these L values. Then, for the value v_l of the l-th subarea, $l = 1, \ldots, L$, we obtained the individual *z*-score as

$$z(v_l) = \frac{v_l - M_v^L}{\mathrm{SD}_v^L}, \quad l = 1, \ldots, L. \quad (3)$$

Measures of urban form best represent the possibilities for PA best when they are appropriately combined. In addition, the correlation coefficients between measures if urban form are assumed to be relatively high (Krizek, 2003). Therefore, we combined the measures of urban form to three urban form features, the street connectivity, the destination density, and the level of urbanization, e.g. for the l-th subarea, as follows:

$$SC_l = \frac{1}{4}(z(WD_l) + z(BD_l) + z(ID_l) + z(TD_l)) \quad (4)$$

$$DD_l = \frac{1}{3}(z(PD_l) + z(FD_l) + z(GD_l)) \quad (5)$$

$$LU_l = \frac{1}{2}(z(RD_l) + z(LM_l)). \quad (6)$$

[2] ESRI (Ed.) (2001–2008), What is ArcGIS 9.3?

Finally, a moveability index (MI) for the l-th area was calculated as the mean of the three urban form features:

$$MI_l = \frac{1}{3}(SC_l + DD_l + LU_l), \quad l = 1, \ldots, L. \tag{7}$$

3. Application of the index

We applied the moveability index to the German intervention region of the IDEFICS study. We compared the survey data on PA and travel mode of school children with the measures of urban form, the urban form features, and the moveability index, respectively. Regression analyses were carried out to investigate the impact of the built environment on PA in children.

3.1. The IDEFICS study

The collection of geographical data and the calculation of a moveability index were done for the German intervention region of the IDEFICS study which is an Integrated Project within the Sixth Framework Programme of the European Commission. The IDEFICS study is a multicenter survey population-based cohort study that investigates the etiology of selected diet- and lifestyle-related diseases and develops as well as evaluates strategies for primary prevention in more than 16,000 from 2- to 10-year-old children in eight European countries (Bammann et al., 2007; Ahrens et al., 2011). The moveability index was linked with the survey data of the IDEFICS cohort which is described in detail by Ahrens et al. (2011). In Germany, the baseline survey (T0) was conducted from October 2007 to May 2008 and included the assessment of dietary habits, social, environmental and family factors, as well as PA, and anthropometric indices (Ahrens et al., 2006; Bammann et al., 2006).

3.2. Study area

The German intervention region of the IDEFICS study is Delmenhorst,[3] Lower Saxony, Germany, with an area of 62.36 km^2 and about 77,300 residents. The city of Delmenhorst includes urban areas in the center as well as rural areas in the outskirts.

The objective assessment of the built environment of children required great efforts in data management. The urban forms mentioned above were collected in digitized and non-digitized form for the city of Delmenhorst, Lower Saxony, in 2007 and 2008. These were georeferenced within ArcGIS 9.3 to calculate urban form features and the moveability index.

3.3. Survey data

Data management was based on the AK5 (official map, scale 1:5000) as a reference layer bought from the land registry office of Lower Saxony. The map contains information such as parcels and parcel identification numbers, political borders, different classes of buildings, land use types, and street names. In addition, we obtained boundaries of districts and subdistricts, including the number of residents, as well as primary school catchment areas and a list of primary schools as geodata from the municipality of Delmenhorst.

Using the reference layer, we derived land use types, green spaces, public playgrounds, and sport facilities. The civil service for green space and nature conservation of Delmenhorst provided a list of public playgrounds and sport facilities which we used to validate the derived data. The municipal geospatial information system (Kommunales Raumbezogenes Informationssystem (KRIS)) of Delmenhorst provided a complete dataset of sidewalks and bikeways from which we derived intersection data. Finally, we added a layer of bus stops derived from the map of the company responsible for public transportation in Delmenhorst. Fig. 1 shows the study area Delmenhorst including all geodata which we used to derive the moveability index.

For reasons of data privacy, we were not allowed to use individual addresses to create individual pedestrian catchment areas as previously conducted by Frank et al. (2005, 2010). Therefore, we used the school catchment areas as a proxy for the home environment to link the data of 596 primary school children with the moveability index. In addition to age and sex of the children as well as the ISCED-level of the parents (International Standard Classification of Education) as a proxy for the socio-economic status (SES), we assessed the PA of children as reported by their parents using the following questions: 'How does your child usually get to/from kindergarten, pre-school or school?' (by foot, by bike, by bus, by car), 'How much time does your child usually spend per day at a park, playground or outdoor recreation area (e.g. swimming pool, zoo or amusement park)?' (0 min, 1–15 min, 16–30 min, 31–60 min, over 60 min), 'Think for a moment about a typical weekday for your child in the last month. How much time would you say your child spends playing outdoors on a typical weekday/weekend day?', 'How much time does he/she spend doing sport in a sports club per week?'. Recruitment took place between September 2007 and May 2008 (Ahrens et al., 2011).

Mean time of outdoor PA was calculated using the response to the question regarding time that the child spent outdoors on a typical weekday and on a typical weekend day, as well as the weekly time the child did sports in a sports club. The dichotomous variable about leisure time PA, answered in 482 children, was based on the question 'How much time does your child usually spend per day at a park, playground, or outdoor recreation area?'. If the parents' answer was 'over 60 min', the child was categorized as active in leisure time, otherwise as inactive.

BMI was measured and overweight and obesity were defined using age- and sex-specific cut-off values according to Cole et al. (2000). Descriptive characteristics of the sample are presented in Table 2. Mean age was 7.6 ± 0.8 and mean BMI was 16.6 ± 2.4. A higher proportion of girls was overweight and obese (22.0%) compared to boys (13.6%). The proportion of families with an ISCED-level for one parent of at least three was 56.7%.

Because school catchment areas in the outskirts were twice as large as in the inner city and included large agricultural areas (see Fig. 1), we implemented a dichotomous variable to account for urban (inner city) areas and non-urban areas that include agricultural land use. Thus, six out of 14 school catchment areas were classified as non-urban.

3.4. Calculation of the index

Using the *kernel density tool*, we calculated the mean kernel density of intersections, public transit stations, sidewalks, and bikeways as well as parks and green spaces, public playgrounds, and sport facilities for six school catchment areas. Since the residential density was only provided as number of residents per subdistrict, we could not calculate the dwelling density using the kernel density method. Therefore we derived a layer that contained the number of residents per km^2 from the layer of subdistricts mentioned above. Using the *tabulate area tool*, we calculated the size of the subdistricts within each school catchment area and then the residential density per school catchment

[3] Census data 2009: Facts and Figures from the city of Delmenhorst, Service of Urban Development and Statistics, 31.12.2009 ("Zahlenspiegel 2009: Daten und Fakten aus der Stadt Delmenhorst, Fachdienst Stadtentwicklung und Statistik, Stand 31.12.2009").

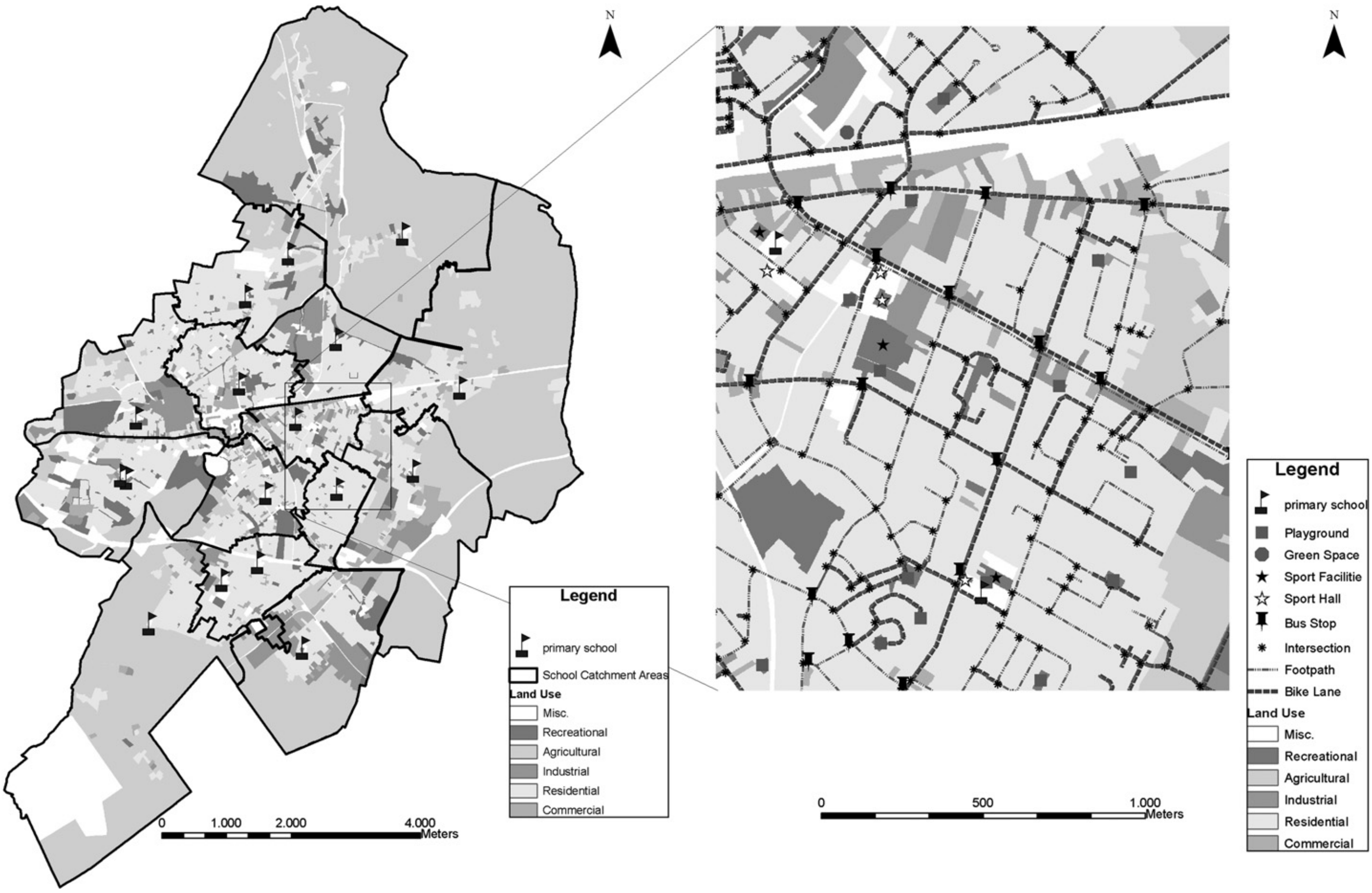

Fig. 1. Geodata of all urban forms in the study area Delmenhorst that were accounted for in the construction of a moveability index.

Table 2
Descriptive statistics for the sample of primary school children in Delmenhorst.

Characteristics	Boys		Girls		Overall	
	Sample size	(%)	Sample size	(%)	Sample size	(%)
	296	(49.7)	300	(50.3)	596	(100)
Age						
6	15	(5.1)	23	(7.7)	38	(6.4)
7	118	(39.9)	104	(34.7)	222	(37.3)
8	121	(40.9)	130	(43.3)	251	(42.1)
9–10	42	(14.2)	43	(14.3)	85	(14.4)
Underweight/normal-weight[a]	256	(86.5)	234	(78.0)	490	(82.2)
Overweight[a]	28	(9.5)	49	(16.3)	77	(12.9)
Obese[a]	12	(4.1)	17	(5.7)	29	(4.9)
ISCED[b] of parents						
Both parents up to level 2	124	(41.9)	134	(44.7)	258	(43.3)
One parent with level 3 or higher	172	(58.1)	166	(55.3)	338	(56.7)

Level 2 relates to lower secondary education and level 3 relates to higher secondary education.

[a] According to Cole et al. (2000).
[b] ISCED (International Standard Classification of Education).

area, based on the number of residents per subdistricts. Land use mix was calculated using the entropy per school catchment areas. Using all measures of urban form, we derived the urban form features and the moveability index per school catchment area as previously described.

We additionally compared the measures of urban form using the simple density method with those obtained from the kernel density method. Therefore, for each school catchment area, we calculated the density of intersections, green spaces, playgrounds, and sport facilities as counts per km^2 and the density of sidewalks and bikeways as counts of km's per km^2. Using these measures, we also derived the moveability index per school catchment area.

3.5. Statistical analyses

Descriptive statistics of measures of urban form and urban form features were calculated comparing school catchment areas with high vs. low moveability index (high: z-score ≥ 0, low: z-score < 0).

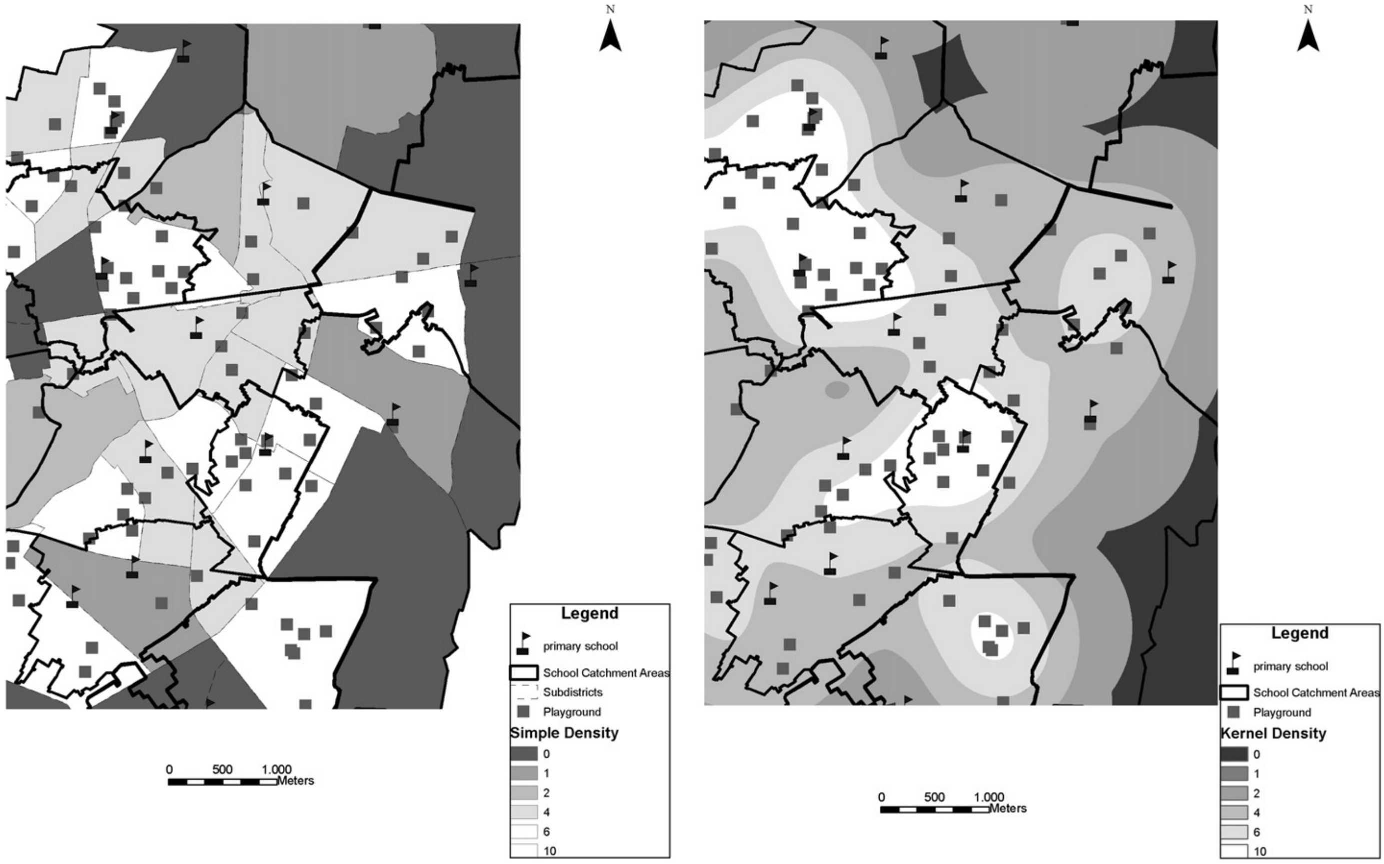

Fig. 2. Kernel density measures of four urban forms, parks, playgrounds, bikeways, and intersections within the study area. The mean of the kernel density raster per school catchment area represents the corresponding measure of urban form.

Further percentages/means of travel mode variables and PA in areas with high vs. low moveability were calculated.

The impact of the built environment on measures of PA was investigated using multilevel logistic and multilevel lognormal regression models accounting for a cluster effect within two levels, namely urban and non-urban areas on the first level and school catchment areas on the second level (Brown and Prescott, 2006). Dichotomous variables of travel mode to school (by foot, by bike, by bus, by car) and leisure time activity as well as log-transformed hours of PA per day were considered as dependent variables.

We considered as independent variables the corresponding measure of urban form and the urban form feature related to travel mode. Consequently, we examined the impact of sidewalk density on walking to school, bikeway density on cycling to school, public transit density on bus use, and street connectivity on car use. We separately examined the effect of the destination density and the moveability index on reported leisure time activity and reported hours of total PA.

Regression models were also adjusted for age, sex, and the ISCED-level of the parents. With regard to travel mode, distance to school was also considered as a confounder. In case of missing values, a complete case analysis was performed resulting in slightly smaller sample sizes for the adjusted models. For the multilevel logistic regression models, odds ratios (OR) (with 95% confidence intervals) were estimated and effects of continuous variables were assessed as one unit offsets from the mean. In the lognormal regression model the influence on the reported PA (h/day) was estimated. All statistical analyses were performed using SAS 9.2.[4]

[4] PROC GLIMMIX; SAS version 9.2, SAS Institute Inc, Cary, NC.

4. Results

Overall we calculated a moveability index for 14 school catchment areas of the study area. Survey data of school children were available for 11 school catchment areas. To visualize the measures of urban form, Fig. 2 shows some examples of kernel density measures of parks, playgrounds, bikeways, and intersections.

Descriptive statistics of urban form variables are presented in Table 3. The mean residential density was 2057 res./km^2 ranging from 398 to 4444 res./km^2 and the mean land use mix, i.e. the entropy value, was 0.72 (range from 0.33 to 0.88). Seven out of 11 areas were classified as areas with high moveability, where 68.1% of our sample lived. Five areas were classified as non-urban due to agricultural land use.

Percentages of walking and cycling did not differ between high moveability areas and low moveability areas, but the percentages of children using the bus were higher in areas with high moveability. Mean hours of PA and percentages of active children were higher in areas of high moveability.

In Table 4 mean values of the urban form features showed differences between the simple density method and the kernel density method. With regard to urban and non-urban areas, the kernel density method gave higher values for urban areas than the simple density method, whereas for non-urban areas this trend was reversed and these differences were more pronounced for the destination density feature.

Results of the logistic regression analyses for the travel mode of children to school (model 1 to model 4) are presented in Table 5. No impact of the corresponding measure of urban form on travel mode was observed. This held true for the non-adjusted as well as the adjusted models. For all travel modes, only distance to school was a significant confounder.

Table 3
Descriptive statistics of measures of urban form, urban form features as well as travel mode and PA.

	All		High moveability (z-score ≥ 0)		Low moveability (z-score < 0)	
Statistics	Mean ± SD		Mean ± SD		Mean ± SD	
Number of areas	11		7		4	
Urban forms						
Residential density (residents/km^2)	2057 ± 1288		2838 ± 862		680 ± 356	
Land use mix (entropy)	0.67 ± 0.15		0.71 ± 0.11		0.59 ± 0.20	
Level of urbanization	0.11 ± 0.70		0.51 ± 0.30		−0.61 ± 0.63	
Street connectivity	−0.03 ± 0.92		0.54 ± 0.55		−1.05 ± 0.27	
Destination density	−0.03 ± 0.82		0.49 ± 0.47		−0.95 ± 0.26	
Statistics	n	%	n	%	n	%
Sample size	596	100.0	406	68.1	190	31.9
Travel mode to school						
Walking	404	67.8	276	68.0	128	67.4
Cycling	68	11.4	31	7.6	37	19.5
By bus	34	5.7	28	6.9	6	3.2
By car	183	30.7	131	32.3	52	27.4
Highly active in leisure time	230	38.6	159	39.2	71	37.4
Statistics	n	Mean ± SD	n	Mean ± SD	n	Mean ± SD
Outdoor PA (h/day)	596	2.6 ± 1.9	406	2.7 ± 2.1	190	2.5 ± 1.5
Distance to school (km)	555	1.7 ± 0.9	377	1.7 ± 0.9	178	1.7 ± 0.9

Table 4
Mean and standard deviation of destination density and street connectivity calculated with the simple density method and the kernel density method, as well as the difference of both urban form features for urban and non-urban school catchment areas.

Urban forms	No. areas	Simple density Mean ± std	Kernel density Mean ± std	Difference[a] Mean ± std
Destination density	14	0.00 ± 0.81	0.00 ± 0.88	0.00 ± 0.16
Urban	8	0.54 ± 0.56	0.62 ± 0.49	−0.09 ± 0.16
Non-urban	6	−0.71 ± 0.46	−0.83 ± 0.49	0.11 ± 0.09
Street connectivity	14	0.00 ± 0.97	0.00 ± 0.98	0.00 ± 0.14
Urban	8	0.67 ± 0.59	0.71 ± 0.52	−0.04 ± 0.17
Non-urban	6	−0.90 ± 0.52	−0.95 ± 0.49	0.05 ± 0.04

[a] Difference = Simple density method − Kernel density method.

As presented in Table 6, neither the destination density (model 5) nor the moveability index (model 6) showed an influence on leisure time activity. In both adjusted models, age and ISCED-level of the parents revealed significant effects on leisure time activity.

Table 7 summarizes the results of the lognormal regression models investigating the impact of the destination density and the moveability index on the reported PA in children, respectively. Parameter estimates of model 7 and model 8 showed a significant positive effect of the destination density and of the moveability index on PA in children even after adjustment. In both adjusted models, sex and the ISCED-level of the parents were significant confounders.

5. Discussion

The comparison of the simple density method and the kernel density method revealed differences between the two methods. With regard to non-urban areas which were relatively large and did not provide many points of interest, the simple density method produced higher values than the kernel density, whereas in urban areas values of the simple density were lower than kernel density values. This may be due to the fact that on the one hand the simple density method does not account for local variation within an area and on the other hand, the kernel density method does not require a partition of the study area for its application. Taking this into account, we conclude that with regard to block level analyses, the simple density overestimates the point density in large areas and underestimates the point density in small areas.

To illustrate the improvement achieved by using a kernel density, Fig. 3 compares values of the simple density per subdistricts with values of the kernel density within the study area. Obviously the simple density shows different values between adjacent subdistricts, although they do not represent the real neighborhood of residents.

The pilot application of the moveability index and the underlying measures of urban form and urban form features revealed only small effects of the built environment on PA and the travel mode of children. These findings correspond to previous findings from physical environment studies (De Bourdeaudhuij et al., 2003, 2005; Frank et al., 2005; Kerr et al., 2007; Owen et al., 2007; Holt et al., 2008; Van Dyck et al., 2009). The strongest predictor on the individual level for all travel modes was distance to school which was also found by Schlossberg et al. (2005, 2006) and Frank et al. (2007). A short distance to school was the main predictor for walking, whereas longer distances to school resulted in cycling as the active travel mode. The highest positive associations between travel mode and distance to school were found for bus use and car use. The overall percentage of children walking to school was clearly higher than reported by Schlossberg et al. (2005) which supports cultural differences between European settings and settings in the US (Van Dyck et al., 2009) and has to be considered in future research of the physical environment.

With regard to leisure time activity of children, the destination density as well as the moveability index showed a positive impact on the percentage of children who spent on average more than 60 min per day at a recreational area. Considering the reported overall PA, the destination density as well as the moveability index showed the same effect. This indicates that measures of recreational destinations could present the main factors influencing the PA in children. Overall, the destination density and the moveability index turned out to be positive predictors of PA. Compared to

Table 5
Logistic regression results on travel mode to school, presenting estimated odds ratios (OR) and 95% confidence intervals (CI) for non-adjusted ($n=596$) and adjusted ($n=513$) models.

Dependent variable	Model 1 (Walking)		Model 2 (Cycling)	
	Non-adj. OR (CI)	Adj. OR (CI)	Non-adj. OR (CI)	Adj. OR (CI)
Independent variables	Footpath density		Bikeway density	
	1.24 (0.85, 1.81)	1.37 (0.88, 2.14)	0.63 (0.40, 1.00)	0.65 (0.41, 1.05)
Confounders				
Sex (ref: male)		0.92 (0.57, 1.47)		1.64 (0.95, 2.83)
Age		1.08 (0.79, 1.46)		1.18 (0.83, 1.68)
ISCED-level (ref: low)		1.02 (0.62, 1.68)		0.78 (0.45, 1.38)
Distance to school		0.17 (0.12, 0.24)		1.56 (1.18, 2.04)
Dependent variables	Model 3 (By bus)		Model 4 (By car)	
	Non-adj. OR (CI)	Adj. OR (CI)	Non-adj. OR (CI)	Adj. OR (CI)
Independent variables	Transit stop density		Street connectivity	
	0.67 (0.20, 2.29)	0.67 (0.19, 2.42)	0.98 (0.71, 1.36)	1.04 (0.81, 1.32)
Confounders				
Sex (ref: male)		1.54 (0.68, 3.50)		0.85 (0.57, 1.25)
Age		1.13 (0.67,1.89)		0.79 (0.61, 1.01)
ISCED-level (ref: low)		1.04 (0.45, 2.43)		0.96 (0.64, 1.44)
Distance to school		3.03 (2.04, 4.50)		2.61 (2.06, 3.31)

Table 6
Logistic regression results on leisure time activity, presenting estimated odds ratios (OR) and 95% confidence intervals (CI) for non-adjusted and adjusted models ($n=482$).

Dependent variable	Model 5 (leisure active)		Model 6 (leisure active)	
	Non-adj. OR (CI)	Adj. OR (CI)	Non-adj. OR (CI)	Adj. OR (CI)
Independent variables	Destination density		Moveability index	
	1.24 (0.97, 1.58)	1.19 (0.94, 1.52)	1.22 (0.95, 1.56)	1.18 (0.93, 1.49)
Confounders				
Sex (ref: male)		0.81 (0.56, 1.17)		0.81 (0.56, 1.17)
Age		1.28 (1.01, 1.62)		1.27 (1.01, 1.62)
ISCED-level (ref: low)		0.52 (0.36, 0.77)		0.52 (0.35, 0.76)

Table 7
Results of the parameter estimation for predictors on PA using non-adjusted ($n=596$) and adjusted ($n=536$) lognormal regression models.

Parameter	$\hat{\beta}$	Standard error	*p*-Value	Parameter	$\hat{\beta}$	Standard error	*p*-Value
Model 7: PA (h/day) regressed on the destination density							
Non-adjusted				Adjusted			
Intercept	0.90	0.096	0.068	Intercept	0.59	0.304	0.304
DD	0.19	0.069	0.006	*DD*	0.17	0.074	0.023
				Age	0.06	0.037	0.090
				Sex (ref: male)	−0.16	0.057	0.005
				ISCED (ref: low)	−0.14	0.061	0.018
Model 8: PA (h/day) regressed on the moveability index							
Non-adjusted				Adjusted			
Intercept	0.89	0.095	0.068	Intercept	0.58	0.304	0.307
MI	0.18	0.074	0.014	*MI*	0.16	0.077	0.038
				Age	0.06	0.037	0.089
				Sex (ref: male)	−0.16	0.057	0.004
				ISCED (ref: low)	−0.15	0.061	0.017

the percentage of leisure time activity predicted by the destination density, age was no predictor of PA, but sex was a negative predictor with lower PA in girls than in boys which is a well known sex-specific effect on PA in children (Scott et al., 2007).

Although the findings of these regression analyses revealed potentially exciting effects of the built environment on PA in children, this represents only a pilot study aimed at exploring the feasibility of our concept of environmental moveability. From a

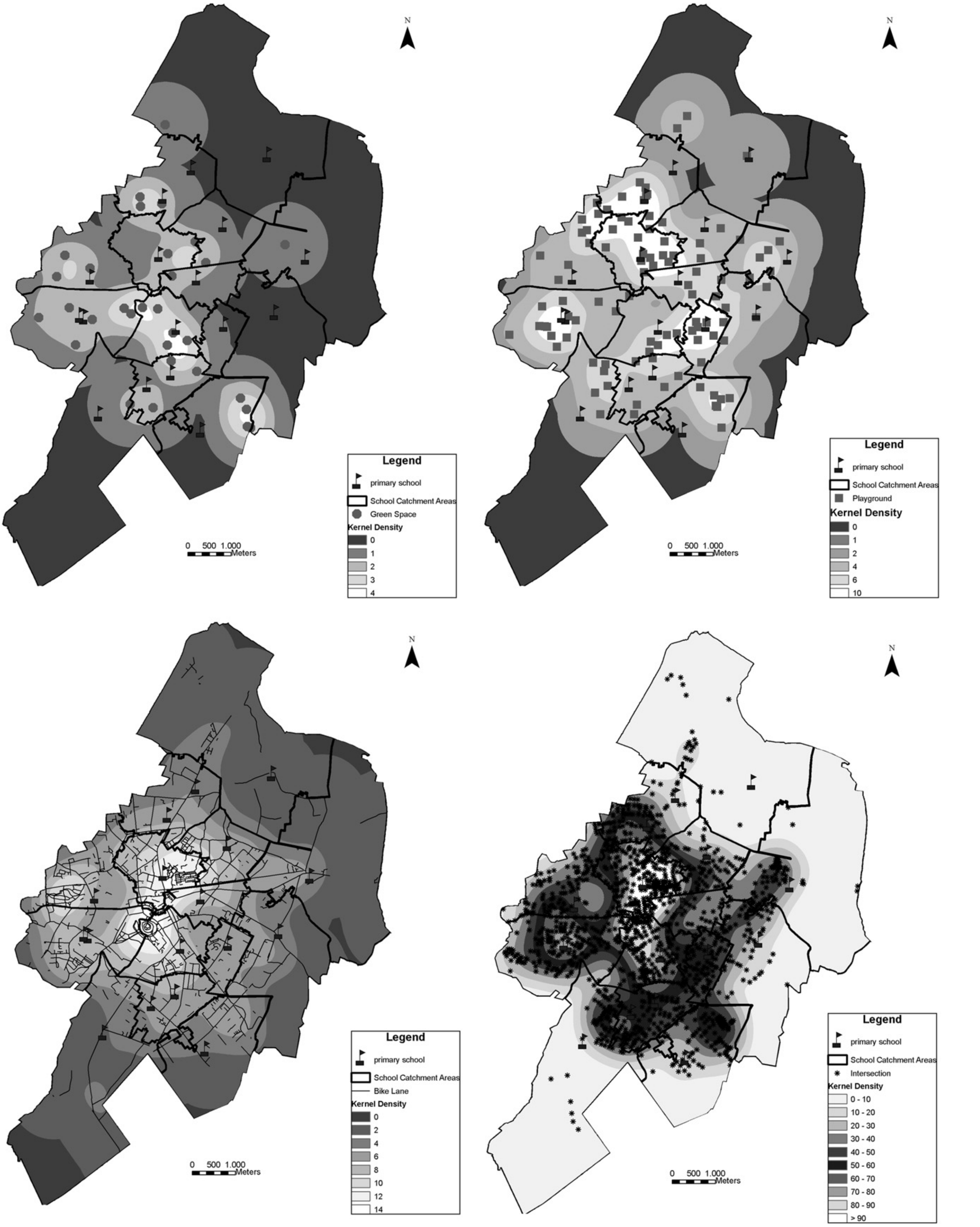

Fig. 3. Comparison of the simple density method (left) with the kernel density method (right) which shows smoothed values, independent of any spatial classification.

methodological point of view, we were able to improve the assessment of urban forms with regards to the problems of the "container approach" using the kernel density method. The kernel density revealed clusters of urban elements within larger areas and was calculated independently from a spatial classification. Correlation coefficients between measures of urban form were relatively high, which underlined the need to combine multiple measures to one single value with regard to estimation problems caused by interactions between the measures of urban form and spatial multicollinearity (Frank et al., 2005). The classification of areas providing low or high moveability was useful and the moveability index measured all possibilities for PA that we had defined. Additionally, the classification showed that infrastructure characteristics may differ from the accessibility of recreational areas. For instance, a school catchment area that showed a high street connectivity but low land use mix due to the dominance of residential areas and little destination density, was classified as a low moveability area in contrast to an area that was located in the inner city showing a high land use mix and more recreational areas.

Limitations to the study have to be noticed. Due to the school catchment areas that we used to calculate the mean kernel density of urban elements, we calculated the moveability index for large areas and regionally averaged the measured impact of the built environment on PA. Additionally, self-reported measures of PA have limited validity (Frank et al., 2005) and should be replaced by objective measures of PA such as accelerometry (Welk, 2002). Another drawback which received only little attention in physical environment studies is the quality of urban forms. The density only reflects the accessibility of urban forms which is a quantitative measure. Regarding parks and playgrounds as well as sidewalks and bikeways, neither their dimension nor aesthetical aspects and attractiveness are, until now, incorporated into the measures of urban form. All identified limitations will be considered in future methodological studies on the moveability index to emerge from our group.

6. Conclusion

Overall, the moveability index was useful in assessing urban possibilities for PA in children. Measures of urban forms were derived by the kernel density method and improved the assessment of urban forms with regard to the ‘‘container approach’’. This pilot study has successfully illustrated the impact, albeit small, of the built environment on PA in children in the selected study region but not on the percentages of active travel modes to school. However, the index has the potential to be improved with regard to urban forms and quality aspects by including geostatistical methods. Additionally, school catchment areas should be replaced by individual buffer zones or small and standardized districts. Therefore, methods like spatial randomization of addresses that allow implementation of individual buffer zones while ensuring data privacy will also be considered in the future. Following this, the kernel density method would need to be compared to the simple density method on a small-scaled level.

Main objective of our research is to improve the introduced method and to investigate the performance of a modified moveability index using subsamples of the IDEFICS cohort from three European survey centers. The greater sample size and the inclusion of different areas of assessment will then allow the inclusion of accelerometer data collected within the IDEFICS study to objectively assess the PA of children. This development ought to give more insight into individual and particularly environmental determinants of PA in children.

Acknowledgments

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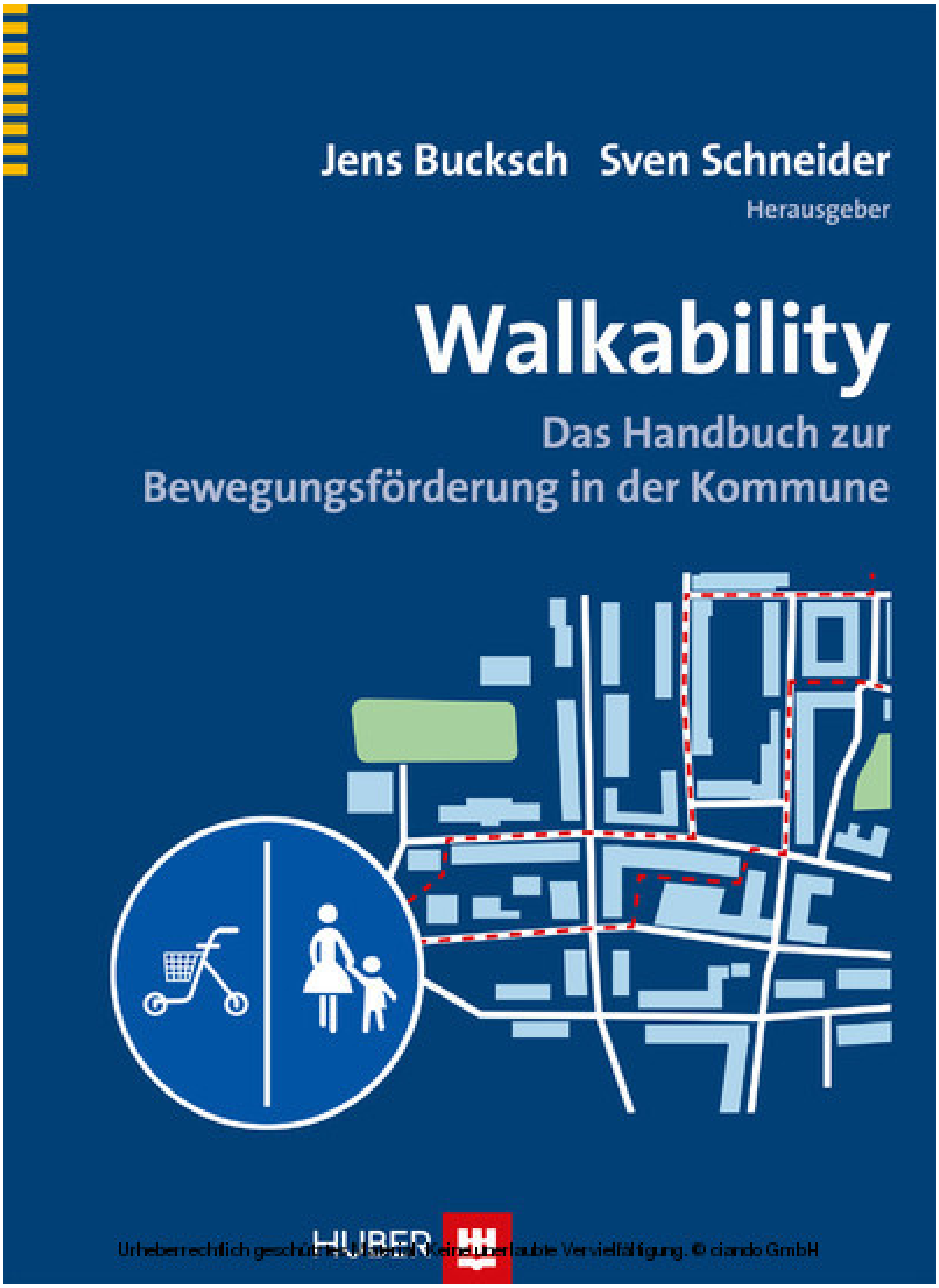
B.2. Book chapter: Geographische Informationssysteme

The book chapter *Geographische Informationssysteme* (Geographical Information Systems) was published in "Walkability - Das Handbuch zur Bewegungsförderung in der Kommune" (Walkability - a hand book of community-based physical activity promotion) (Buck and Tkaczick, 2014). This book introduces the walkability concept considering different fields of resarch and provides overviews of different methods to assess built environment characteristics that promote physical activity. The book chapter comprises methodological aspects of built environment assessment and calculation of GIS-based urban measures, introduces the walkability index, and discusses limitations and challenges in the calculation of urban measures. Overall, this book provides an introduction in the walkability concept and built environment research in German language encouraging this field of research on a national level.


Jens Bucksch Sven Schneider
Herausgeber
Walkability
Das Handbuch zur
Bewegungsförderung in der Kommune
HUBER

B.3. Objective measures of the built environment and physical activity in children: From walkability to moveability

This article presents the first results regarding the association between accelerometer-based physical activity of children and the moveability index and its components in one study region of the IDEFICS study. The article was published in the *Journal of Urban Health* (Impact Factor 2014: 1.90) (Buck et al., 2015c).

Journal of Urban Health: Bulletin of the New York Academy of Medicine
doi:10.1007/s11524-014-9915-2

Objective Measures of the Built Environment and Physical Activity in Children: From Walkability to Moveability

Christoph Buck, Tobias Tkaczick, Yannis Pitsiladis, Ilse De Bourdehaudhuij, Lucia Reisch, Wolfgang Ahrens, and Iris Pigeot

ABSTRACT *Features of the built environment that may influence physical activity (PA) levels are commonly captured using a so-called walkability index. Since such indices typically describe opportunities for walking in everyday life of adults, they might not be applicable to assess urban opportunities for PA in children. Particularly, the spatial availability of recreational facilities may have an impact on PA in children and should be additionally considered. We linked individual data of 400 2- to 9-year-old children recruited in the European IDEFICS study to geographic data of one German study region, based on individual network-dependent neighborhoods. Environmental features of the walkability concept and the availability of recreational facilities, i.e. playgrounds, green spaces, and parks, were measured. Relevant features were combined to a moveability index that should capture urban opportunities for PA in children. A gamma log-regression model was used to model linear and non-linear effects of individual variables on accelerometer-based moderate-to-vigorous physical activity (MVPA) stratified by pre-school children (<6 years) and school children (≥6 years). Single environmental features and the resulting indices were separately included into the model to investigate the effect of each variable on MVPA. In school children, commonly used features such as residential density* $\left(\widehat{\beta} = 0.5\cdot10^{-4}, p = 0.02\right)$*, intersection density* $\left(\widehat{\beta} = 0.003, p = 0.04\right)$*, and public transit density* $\left(\widehat{\beta} = 0.037, p = 0.01\right)$ *showed a positive effect on MVPA, while land use mix revealed a negative effect on MVPA* $\left(\widehat{\beta} = -0.173, p = 0.13\right)$*. In particular, playground density* $\left(\widehat{\beta} = 0.048, p = 0.01\right)$ *and density of public open spaces, i.e., playgrounds and parks combined* $\left(\widehat{\beta} = 0.040, p = 0.01\right)$*, showed positive effects on MVPA. However, availability of green spaces showed no effect on MVPA. Different moveability indices were constructed based on the walkability index accounting for the negative impact of land use mix. Moveability indices showed also strong effects on MVPA in school children for both components, expanded by*

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playground density $\left(\widehat{\beta} = 0.014, p = 0.008\right)$ *or by public open space density* $\left(\widehat{\beta} = 0.014, p = 0.007\right)$ *, but no effects of urban measures and moveability indices were found in pre-school children. The final moveability indices capture relevant opportunities for PA in school children. Particularly, availability of public open spaces seems to be a strong predictor of MVPA. Future studies involving children should consider quantitative assessment of public recreational facilities in larger cities or urban sprawls in order to investigate the influence of the moveability on childhood PA in a broader sample.*

KEYWORDS *Accelerometry, Built environment, Children, IDEFICS study, Moderate-to-vigorous physical activity, Walkability*

INTRODUCTION

Features of the built environment can positively influence physical activity (PA) levels in adults and are commonly assessed using objective measures such as residential density, land use mix, and street connectivity.[1,2] To assess the overall walkability of urban areas, these measures are typically combined to a so-called walkability index which captures possibilities for PA through walking in everyday life of adults.[1,3] Moreover, the walkability index can be extended to capture additional features for instance using public transit density to capture the impact of public transit on reported PA in adults.[4]

Most previous studies employing the walkability index were conducted in the USA and Australia, where environmental features and transport mode choices significantly differ from those in Europe and Germany, in particular.[5] Moreover, studies of the walkability concept focused on physical activity in adults and it is not evident that urban measures of the walkability index assess built environment characteristics that influence PA in children. With regard to children, some studies showed that walkability measures are applicable to investigate the effect of the built environment on PA,[6,7] but other findings strongly differ and found no effect of walkability on PA.[8]

Hence, the idea to extend the walkability index and to create indices to assess the playability or the moveability of the urban environment has recently been discussed.[8–11] Since the walkability index does not capture recreational facilities that reflect opportunities for PA in children in leisure time, additional features of the built environment that have particular relevance for children and adolescents have to be studied.[6] Particularly, time spent outdoors for example on green spaces can positively influence moderate-to-vigorous physical activity (MVPA) in children[12,13] and the spatial availability of recreational facilities such as playgrounds and parks is an important aspect of the built environment in the neighborhood that influences PA in children.[14–16]

A moveability index that is based on the walkability index and extended by additional components such as the density of recreational facilities or playgrounds possibly allows to investigate the effect of the built environment on PA in children.[8,10,11] In a previous study, we investigated the built environment on a macro-level in a German study region and found a small but significant influence of features such as playground density, residential density, and intersection density on reported PA of school children. We developed a first moveability index considering all types of recreational facilities to extend the walkability index and also found small effects of the moveability index on reported PA of school children.[11] However, it is unclear if only specific recreational facilities should be considered for extending the walkability index and if the walkability index itself can be used without changes in the original components.[10,11]

To investigate the impact of the built environment on PA levels in children, we use data from the IDEFICS study (Identification and prevention of Dietary- and lifestyle-induced health EFfects In Children and infantS) of one German study region \cite{Ahrens10tic}. In detail, we investigate the influence of common walkability measures and different types of recreational areas such as playgrounds, green spaces, and parks within individual network-dependent neighborhoods[3] to extend the walkability index to a *moveability index* and analyze the effect of the built environment on accelerometer-based MVPA of pre-school and primary school children.

METHODS

IDEFICS Study

We assessed features of the built environment in one German study region, the city of Delmenhorst, and linked these to individual data obtained from 400 2- to 9-year-old children that were collected during the baseline survey of the IDEFICS study, which took place between September 2007 and May 2008.[17] Delmenhorst is located in Lower Saxony, Germany and covers an area of about 62 km^2 with about 77,300 residents in 2008. The IDEFICS study is a European multicenter study that was conducted from 2006 to 2012 to investigate the etiology of lifestyle- and nutrition-related diseases and disorders in 16,228 2-to 9-year-old children from eight European countries.[18] Measurements included anthropometry, food intake, PA, and other lifestyle factors.[17]

Individual data included body mass index (BMI), accelerometer measurements, and education of parents assessed by the International Standard Classification of Education (ISCED). Reported safety concerns of the parents that restricted PA of the children were identified using two items derived from the parental questionnaire, “I restrict my child’s outdoor activities for safety reasons.”, and “I don’t like to let my child walk/cycle to kindergarten, pre-school or school for safety reasons.” to which parents could agree or disagree.

Environmental Data

Geographic data on land use and number of residents within the study region were provided by the land registry office of Lower Saxony. Geographic line data of the footpath network were obtained from the OpenStreetMap project and validated using data of the municipal geospatial information system (Kommunales Raumbezogenes Informationssystem (KRIS)) of the city of Delmenhorst. Bus stops and recreational facilities, i.e., playgrounds, and parks, were digitalized based on available maps and lists provided by the public transit company and the civil service for green space of Delmenhorst, respectively. Mainly, playgrounds and parks, that are under responsibility of the municipality, are considered with regard to opportunities for leisure time PA \cite{Roemmich06aoa,holt09npa}. Geographic data of these features can easily be obtained from public authorities, though these data do not capture all accessible opportunities for PA in an urban environment. Other green spaces, particularly in apartment housing areas that are not under public responsibility, could provide the same opportunities for PA in leisure time as public open spaces. Based on land use maps and imagery data provided in *ArcGIS 10.0*,* we assessed and digitalized green spaces that were larger than 100 m^2 and located in or adjacent to residential areas but that were not defined as public. We ensured the accessibility of recreational facilities and green spaces via field surveys resulting in 103 playgrounds, 45 park areas, and 103 green spaces that were considered as points in our analyses. We processed and digitalized geographic data in *ArcGIS 10.0*.

Study Data

In our study region, Delmenhorst, 1,179 children participated in the baseline survey of the IDEFICS study.[17] Due to budgetary constraints, accelerometer devices were not available for all children. A random sample of children was asked to wear an accelerometer device of whom 460 children agreed. Anonymized address coordinates of these children were geocoded within the study area of whom we excluded 34 children who lived in the rural peripheral area of Delmenhorst to focus on children living in an urban environment. Due to missing values of questionnaire information, 26 children were additionally excluded resulting in a total sample of 400 2- to 9-year-old children. Age- and sex-specific BMI z-scores and categories for overweight and obesity were calculated according to Cole and Lobstein.[19] Accelerometer measurements of 15 s epochs covered at least three consecutive days with at least 8 h of valid weartime each after exclusion of all intervals of at least 30 min of consecutive zeros. MVPA was defined using the cutoff value of 2,298 counts per minute (cpm) that was proposed by Evenson.[20] In addition, we considered hours of valid weartime and the season of accelerometer measurement as a confounder. Assessments that took place in September 2007 and from March to May 2008 were categorized as spring/summer and measurements from October 2007 until February 2008 were categorized as autumn/winter where the majority of the assessments took place (70.5 %). The categorization of the seasonal variable was also verified based on mean temperature per month.†

Moveability Indices

We calculated objective measures of the built environment within individual network-dependent neighborhoods based on a distance of 1 km per child, i.e., the neighborhood captures an area that can be reached within 1 km around the home location depending on the street network.[3] Due to data protection requirements, it was not allowed to use the exact address coordinates to calculate individual neighborhoods. Therefore, we proposed a spatial blurring based on a Gaussian error that was inversely proportional to the underlying residential density.[21,22] According to Cassa et al.[22], the anonymization of address data using a Gaussian error only slightly affects spatial cluster analyses. In our analyses, the spatial blurring shifted the coordinates by about 50 to 100 m on average and a simulation study showed only small differences of walkability measures after spatial blurring.[21] We conducted the network analyses using the *network analyst* in *ArcGIS 10.0* and calculated the spatial blurring in *R* 3.0.1[23] using the *rnorm* function.

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*ESRI 2011. ArcGIS Desktop:Release 10. Redlands, CA: Environmental Systems Research Institute.

*http://www.wetteronline.de/wetterdaten/delmenhorst

In each individual 1-km network-dependent neighborhood, we constructed two versions of a walkability index first including residential density, i.e., number of residents per km^2, land use mix, calculated as the entropy of land use types, and intersection density which assesses the street connectivity,[1,3] and second an extended index that also comprises the density of public transit stations.[4] In recent studies, the retail floor area, i.e., the ratio of retail floor area to retail land use area, has also been used to describe the car dependency of commercial areas that is associated with car use in adults.[1,4] However, data on retail floor areas were not available in our study region, and since we focused on opportunities for PA in children, we did not consider the retail floor area ratio in the index construction. We calculated intersection density and public transit density as number of points per area based on the simple density approach.[2,3] For the construction of both walkability indices, we standardized all measures using z-scores. Indices were constructed as non-weighted sums of z-scores of (1) three measures, i.e., residential density, land use mix, and intersection density,[1] and (2) four measures, i.e., residential density, land use mix, intersection density, and additionally public transit density.[4]

We accounted for urban opportunities for leisure time PA in children by constructing an extended walkability index and calculated the intensity of all point characteristics such as intersections, public transit stations, and midpoints of recreational areas based on a kernel approach which was already used in previous analyses.[11] To assess point patterns in a varying urban environment, the use of a kernel approach is recommended to assess the intensity, i.e., availability, of a point process.[11,24] For each cell of a 2×2 m raster, the intensity is the weighted sum of point characteristics, where the weights depend on the distance from the point of observation and decrease for an increasing distance based on a Gaussian kernel.[25,26] We then calculated environmental variables of point characteristics as mean intensity, i.e., number per km^2, of cells per neighborhood. The mean intensity of points such as recreational facilities, public transit stations, and intersections serves as our density measure. Figure 1 exemplarily illustrates the playground density in the study region calculated by the kernel approach.

Eventually, we constructed three different moveability indices to account for different types of recreational facilities and added the standardized z-score of the mean intensity of (1) only playgrounds, (2) playgrounds and parks, called public open spaces, and (3) all playgrounds, parks, and green spaces, which we named open spaces.

To illustrate the spatial distribution of the built environment measures, we calculated the four-dimensional walkability index and the moveability index that includes public open spaces based on z-scores of raster cells within the study area (Fig. 2).

We calculated all environmental variables with the *spatstat* package[25] in the statistical software *R* 3.0.1.[23] Particularly, we implemented the kernel density approach using the *density.ppp* function in the spatstat package (version 1.31.1) that is based on a Gaussian kernel and a fixed bandwidth of σ=500 m.

Statistical Analyses

We first performed descriptive analyses stratified by pre-school and school children to reveal potential differences in environmental variables. In a second step, we investigated the influence of environmental variables on MVPA. For this purpose, we calculated a gamma log-regression model as a basic model without any environmental variables and considered linear and non-linear effects of continuous

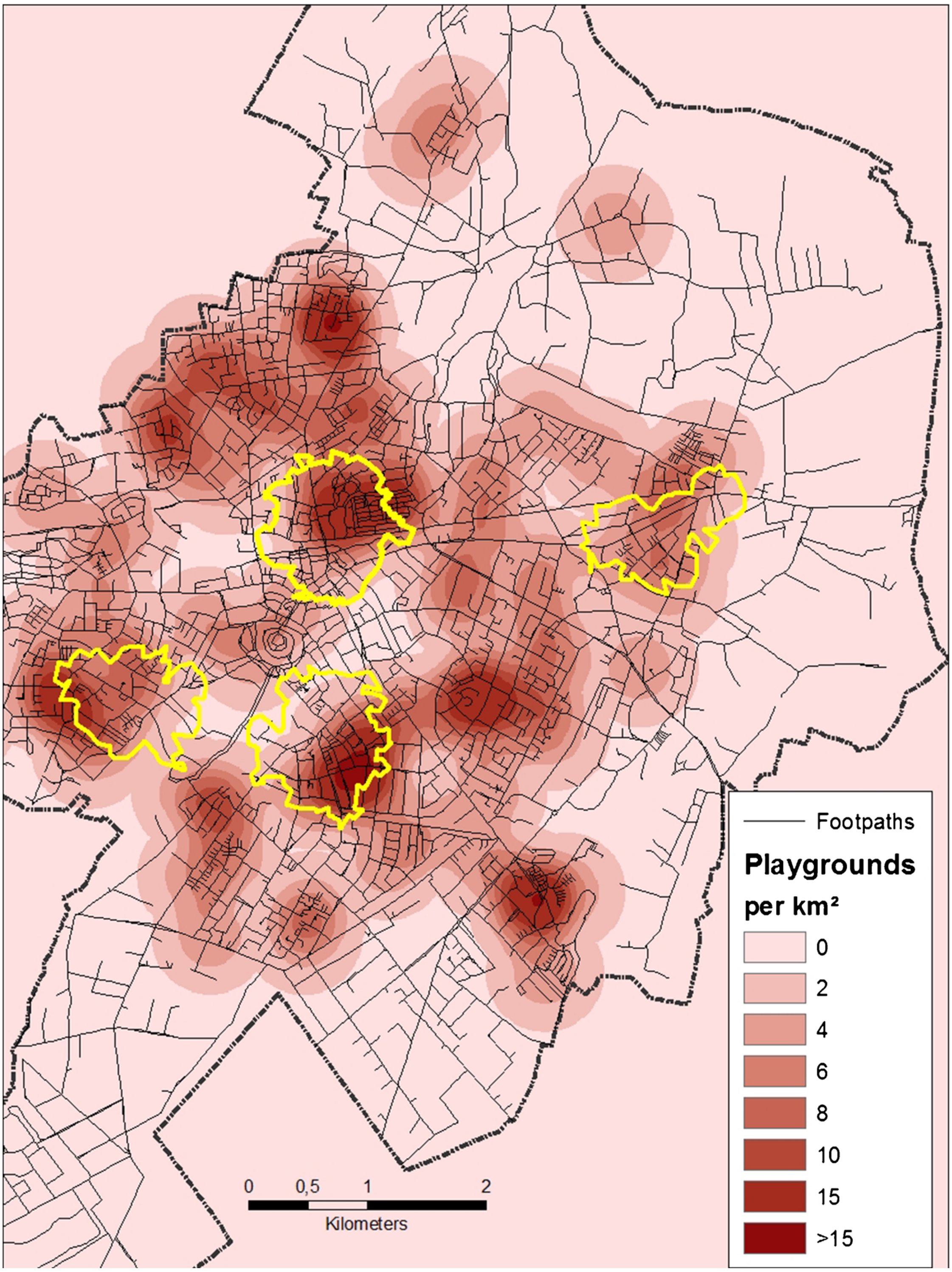

FIG. 1 Density of playgrounds as number per km^2 assessing the availability within individual neighborhoods. As an example, four individual neighborhoods are depicted in yellow.

variables such as age and BMI *z*-score as well as single effects of categorial variables, e.g. sex or education level, to optimize the goodness of fit based on Akaike's information criterion (AIC). We stratified each model by pre-school children including 2 to <6 years old (25 %) and school children from 6 to 9 years old. Please note that the estimated effects are derived from a cross-sectional study and should therefore not be interpreted as causal. To be more specific, we modeled age as

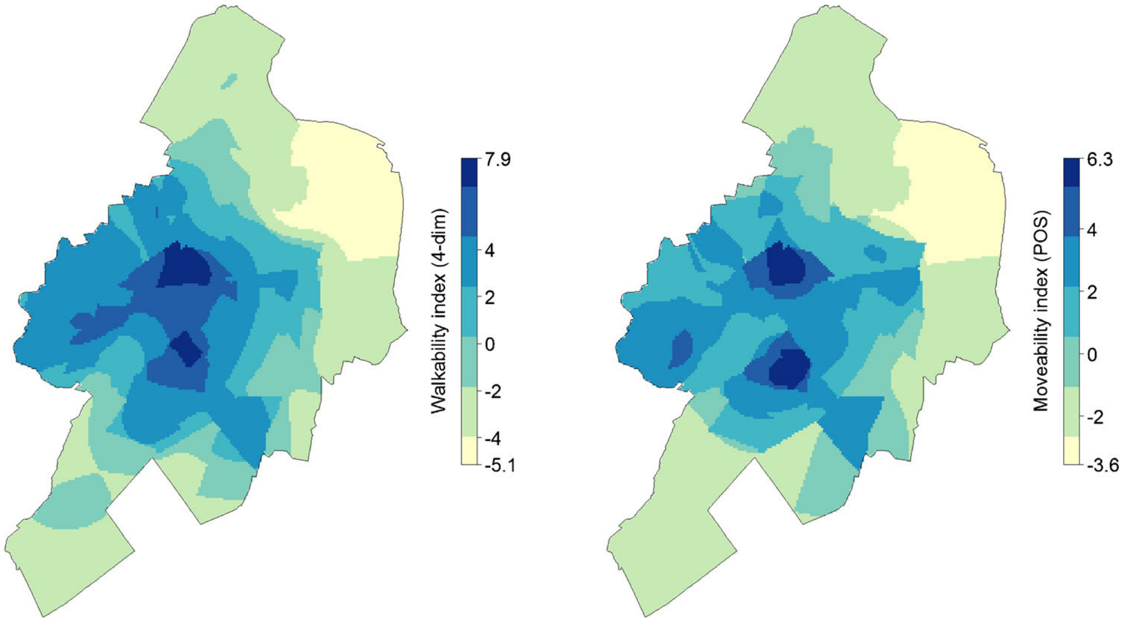

FIG. 2 Raster values of the walkability index including four dimensions (*left*) and the moveability index including public open space density (*right*) in the study area of Delmenhorst.

a linear and a quadratic term to account for a known plateau effect of age, but due to the small age range, the linear and quadratic term for age were not considered in the stratified models. The basic model was also adjusted for sex, BMI *z*-score, education level of parents, valid weartime of accelerometer devices, and season of assessment. Then, we separately included environmental variables as single environmental features and the indices into the basic model to investigate the effect of each environmental variable on children's MVPA (two-sided test at α=0.05). Statistical analyses were performed using *SAS 9.2* and the *glimmix* procedure,* in particular.

RESULTS

Overall, 16.3 % of the children were overweight or obese and mean MVPA was 60.2 min per day with lower mean MVPA in pre-school than in school children (55.4 min/day vs. 61.8 min/day). Mean age was 6.7 years, and overall 51.8 % were girls. Characteristics of the study sample are presented in Table 1 for all children and stratified by pre-school and school children.

Table 2 presents descriptive statistics stratified by pre-school and school children. Mean intensity of recreational facilities was about the same for playgrounds and green spaces with higher variability in green spaces, but maximum intensity was highest for green spaces with 11.7 areas per km^2. Parks showed a low availability per neighborhood with 0.9 parks per km^2 on average ranging from 0 to only 2.6. Overall, environmental variables and indices showed about the same mean and standard deviation in both pre-schoolers and school children.

Results for the basic model that only included individual variables are presented in Table 3. In all children, age showed a positive plateau effect on MVPA as a combination of the linear and the quadratic term $\left(\widehat{\beta}_{\text{age}} = 0.367, p{<}0.001; \widehat{\beta}_{\text{age}^2} = -0.027, p{<}0.001\right)$. In school children, girls were less active with significantly lower levels of MVPA

*PROC GLIMMIX; SAS version 9.2, SAS Institute Inc, Cary, NC

TABLE 1 Characteristics of the study sample in the study region, Delmenhorst, Germany

N (%)	All		Pre-school children		School children	
Sample size	400	(100)	100	(25.0)	300	(75.0)
Weight status[a]						
Thinness	27	(6.8)	11	(11.0)	16	(5.3)
Normal weight	308	(77.0)	79	(79.0)	229	(76.3)
Overweight	47	(11.8)	6	(6.0)	41	(13.7)
Obesity	18	(4.5)	4	(4.0)	14	(4.7)
ISCED level[b]						
Low	80	(20.0)	12	(12.0)	68	(22.7)
High	320	(80.0)	88	(88.0)	232	(77.3)
Safety concerns of parents						
No	249	(62.3)	54	(54.0)	195	(65.0)
Yes	151	(37.8)	46	(46.0)	105	(35.0)
Season of MVPA assessment						
Autumn/winter	282	(70.5)	69	(69.0)	213	(71.0)
Spring/summer	118	(29.5)	31	(31.0)	87	(29.0)
Mean (SD)						
MVPA (min/day)	60.2	(23.1)	55.4	(22.8)	61.8	(23.0)
Age	6.7	(1.7)	4.2	(0.8)	7.5	(0.8)
BMI *z*-score[a]	0.32	(1.1)	0.02	(1.1)	0.4	(1.0)
Valid weartime (h)[c]	11.5	(1.2)	11.1	(1.0)	11.6	(1.3)

[a]According to Cole and Lobstein[19]

[b]Max. ISCED level of both parents, low: level 1 and 2 relates to lower secondary education and less

[c]Weartime of accelerometers after exclusion of 30 min of consecutive zeros

$\left(\hat{\beta} = -0.216, p<0.001\right)$ and BMI *z*-score showed a negative effect on MVPA $\left(\hat{\beta} = -0.037, p = 0.08\right)$,but in pre-school children, the effect of BMI *z*-score was reverse $\left(\hat{\beta} = 0.036, p = 0.37\right)$ and no difference between boys and girls was found. Higher levels of MVPA were observed in spring and summer months $\left(\hat{\beta} = 0.156, p<0.001\right)$ in both pre-schoolers and school children. In particular, the negative effect of safety concerns of parents was more pronounced in pre-school children $\left(\hat{\beta} = -0.136, p = 0.11\right)$ than in school children $\left(\hat{\beta} = -0.027, p = 0.52\right)$.

The estimated effects of all environmental variables are summarized in Table 4. In school children, playground density $\left(\hat{\beta} = 0.048, p = 0.01\right)$ and density of public open spaces, i.e., playgrounds and parks combined $\left(\hat{\beta} = 0.040, p = 0.01\right)$, revealed a positive effect on MVPA, but no effect was found for green space density and density of open spaces that also included green spaces $\left(\hat{\beta} = 0.005, p = 0.39\right)$. Particularly, including playground density or public open space density revealed the best goodness of fit (see AIC in Table 4).

Furthermore, positive effects on MVPA of school children were found for public transit density $\left(\hat{\beta} = 0.037, p = 0.01\right)$, intersection density $\left(\hat{\beta} = 0.003, p = 0.04\right)$,

TABLE 2 Descriptive statistics of environmental variables stratified by age groups

Mean (SD) min/max						
Environmental variables	all		pre-school children		School children	
Residents per km^2	2535 (884)	211/4173	2587 (757)	596/3940	2517 (919)	211/4173
Land use mix	0.63 (0.18)	0/0.98	0.63 (0.18)	0/0.98	0.64 (0.18)	0/0.98
Playgrounds per km^2	3.3 (1.1)	0.3/5.6	3.3 (0.9)	1.0/5.4	3.3 (1.1)	0.3/5.6
Green spaces per km^2	2.7 (2.8)	0/11.7	3.2 (3.1)	0.1/11.7	2.6 (2.7)	0/11.7
Parks per km^2	0.9 (0.5)	0/2.6	0.8 (0.5)	0/2.1	0.9 (0.6)	0/2.6
Intersections per km^2	59.3 (15.3)	20.8/91.1	59.6 (13.9)	24.2/86.6	59.2 (15.7)	20.8/91.1
Public transit stops per km^2	4.6 (1.4)	1.0/7.0	4.6 (1.4)	1.2/7.0	4.6 (1.4)	1.0/6.9
Walkability index (three-dimensions)[a]	−0.07 (1.8)	−4.9/5.6	−0.00 (1.5)	−3.4/3.5	−0.09 (1.9)	−4.9/5.6
Walkability index (four-dimensions)[a]	−0.07 (2.5)	−6.8/6.8	0.08 (2.2)	−5.0/4.7	−0.12 (2.6)	−6.8/6.8
Moveability index (incl. playgrounds)	−0.09 (3.8)	−9.8/9.0	0.07 (3.5)	−8.7/9.0	−0.14 (4.0)	−9.8/8.9
Moveability index (incl. POS)[b]	−0.09 (3.8)	−10.0/8.4	0.07 (3.5)	−8.7/8.4	−0.14 (4.0)	−10.0/8.4
Moveability index (incl. OS)[c]	−0.12 (3.7)	−9.2/7.1	0.13 (3.5)	−8.5/6.8	−0.20 (3.7)	−9.2/7.1

[a]Excluding retail floor area ratio[1,4]

[b]Public open spaces: playgrounds and parks

[c]Open spaces: playgrounds, parks, and green spaces

and residential density $\left(\widehat{\beta} = 0.5{\cdot}10^{-4}, p = 0.02\right)$, while land use mix showed a negative effect on MVPA $\left(\widehat{\beta} = -0.173, p = 0.13\right)$. Thus, we constructed the final moveability indices based on the unweighted sum of standardized z-scores of residential density, public transit density, intersections density, and density of recreational facilities minus the z-score of land use mix. All three versions of a moveability index showed significantly positive effects on MVPA (Table 4), and the strongest effect was found including density of public open spaces $\left(\widehat{\beta} = 0.014, p = 0.007\right)$. In particular, goodness of fit was best including playground density or public open space density (see Table 4). However, no effects of walkability indices or moveability indices on MVPA were found in pre-school children, though in both pre-school and school children, goodness of fit slightly improved using the moveability indices compared to the walkability indices. Environmental variables showed the same effect in the overall sample, but in pre-school children, effects were smaller and not statistically significant compared to school children.

DISCUSSION

Based on our results of the micro-level analyses, the extension of the walkability index to a moveability index seems to be an appropriate approach to investigate opportunities for PA, particularly in school children. Environmental features that

TABLE 3 Basic log-gamma regression model including all factors influencing MVPA without environmental variables in all children and stratified for age groups

	All		Pre-school children		School children	
	(n=400, AIC=3569)		(n=100, AIC=907.1)		(n=300, AIC=2679)	
Variable	β	p value	β	p value	β	p value
Age	0.367	*<0.001*				
Age^2	−0.027	*<0.001*				
BMI z-score[a]	−0.019	0.27	0.036	0.37	−0.037	0.08
Sex (ref: male)	−0.187	*<0.001*	−0.067	0.44	−0.216	*<0.001*
Valid weartime (h)[b]	0.028	0.07	0.058	0.18	0.032	0.06
ISCED[c] (ref: low)	0.016	0.73	−0.057	0.67	0.048	0.34
Season (ref: autumn/winter)	0.156	*<0.001*	0.217	*0.01*	0.151	*0.001*
Safety concerns (ref: no)	−0.043	0.25	−0.136	0.11	−0.027	0.52

[a]According to Cole and Lobstein[19]

[b]Weartime of accelerometers after exclusion of 30 min of consecutive zeros

[c]Max. ISCED level of both parents, low: level 1 and 2 relates to lower secondary education and less

were used to construct walkability indices such as residential density, intersection density, and public transit density showed a positive effect on MVPA. However, land use mix was found to influence PA negatively which was the only observation that is in contrast to findings in adults.[3,1,4] Thus, the construction of the moveability index was based on the sum of z-scores of residential density, intersection density, and public transit density according to the walkability indices,[3,4] but land use mix was substracted.

Adding information about the spatial availability of opportunities for PA in leisure time and taking into account the negative influence of land use mix on MVPA provided a feasible index that can be used to predict MVPA levels particularly in school children. Overall, neighborhoods characterized by a high moveability index (index value >0) provided more opportunities for PA in children that resulted in higher amounts of MVPA (results not shown). These neighborhoods were mainly residential providing single or apartment housing with low values of land use mix and included more public recreational facilities. Moreover, these neighborhoods were particularly not located in or adjacent to the center of the city, whereas in adults, high-walkable neighborhoods are mainly located in the city center providing highly connected walking facilities and a mix of different land use types.[1,4]

Furthermore, the density of public open space, i.e., playgrounds and parks, showed a positive impact on MVPA in children as found previously.[14,16] Considering different types of recreational facilities, our analyses revealed that mainly public open spaces such as playgrounds and parks need to be considered as opportunities for PA, but the spatial availability of non-public green spaces did not seem to influence physical activity levels neither in pre-school children nor in school children.

The assessment of green spaces based on imagery and land use data, particularly within high-populated areas, was more laborious than assessing parks and playgrounds that were provided by the municipality and that could be digitalized using listed addresses or street names. Moreover, in our analyses, green spaces did not turn out as an environmental factor explaining MVPA in pre-school and primary school children. Thus, in the setting that we investigated, it seems to be

TABLE 4 Influence of environmental variables and indices on MVPA separately calculated using the basic log-gamma regression model adjusted for non-environmental factors in all children and stratified for age groups

	All (n=400)			Pre-school children (n=100)			School children (n=300)		
Variable	β	p value	AIC	β	p value	AIC	β	p value	AIC
Playground density	0.053	*0.002*	3561	0.061	0.17	907.1	0.048	*0.01*	2674
Green space density	0.003	0.62	3571	0.004	0.82	909.0	−0.001	0.87	2681
Park density	0.048	0.18	3569	0.074	0.38	908.3	0.032	0.43	2681
Public open space density[a]	0.045	*0.002*	3561	0.051	0.14	906.9	0.040	*0.01*	2675
Open space density[b]	0.008	0.14	3569	0.006	0.56	908.7	0.005	0.39	2680
Intersection density	0.002	0.09	3568	0.001	0.70	908.9	0.003	*0.04*	2677
Public transit density	0.030	*0.02*	3566	0.019	0.52	908.7	0.037	*0.01*	2675
Residential density	0.00005	*0.01*	3565	0.00006	0.28	907.9	0.00005	*0.02*	2676
Land use mix	−0.197	*0.049*	3567	−0.155	0.50	908.6	−0.173	0.13	2679
Walkability index (three-dimensions)[c]	0.008	0.45	3570	0.002	0.93	909.1	0.013	0.26	2680
Walkability index (four-dimensions)[c]	0.010	0.20	3569	0.005	0.81	909.0	0.013	0.13	2679
Moveability index (incl. playgrounds)	0.013	*0.005*	3563	0.012	0.29	908.0	*0.014*	0.008	2674
Moveability index (incl. POS)[a]	0.014	*0.004*	3562	0.013	0.28	907.9	0.014	*0.007*	2674
Moveability index (incl. OS)[b]	0.013	*0.009*	3564	0.010	0.37	908.3	0.014	*0.015*	2675

[a]Public open spaces: playgrounds and parks

[b]Open spaces: playgrounds, parks, and green spaces

[c]Excluding retail floor area ratio[1,4]

sufficient to consider availability of playgrounds or parks to assess the moveability of urban neighborhoods.[14] Previous studies in adolescents suggested that this association is different and parks are the main public open spaces that provide opportunities for PA in leisure time for this age group.[16] For example, Wheeler et al.[12] found based on GPS and accelerometry data of children that particularly in boys, high intensity PA is more likely when located on parks. Since in our study the moveability index including public open space density, i.e., number of playgrounds and parks, was also a strong predictor of MVPA, this index may present a compromise providing a tool to assess opportunities for PA in both children and adolescents.

Due to the large proportion of school children, effects of environmental variables were similar in the overall sample compared to our findings in school children. However, in pre-school children, effects of environmental variables on MVPA were smaller and not significant. The reduced sample size of pre-school children may have been too small to detect effects of playground and park density or moveability indices which were slightly smaller than in school children. Moreover, parents of pre-school children showed higher percentage of safety concerns, and the effect on MVPA was more pronounced compared to school children. Hence, the contribution of environmental moveability and particularly effects of the transport network on PA levels in young children seem to be mediated by parental safety perceptions which were also observed in recent studies.[27,28] Since independent mobility increases with age,[27] the effect of environmental variables such as intersection density and public transit density can also be observed in older children of our study.

Some limitations have to be considered. Primarily, the study sample was slightly biased including more children whose parents had high education levels (65.0 %) or high household income (62.1 %). Moreover, the reported results may be influenced by the spatial blurring that had to be conducted to use anonymized individual address coordinates, although we found that the Gaussian blurring does only slightly affect environmental analyses. With regard to the recent literature, strengths of our study are the use of objective measurements of environmental variables based on geographic data as well as of objectively measured PA of study participants using accelerometry. Furthermore, the link of individual data to geographic data based on individual network-dependent neighborhoods allowed to assess all opportunities around a child's home, instead of averaging values in larger districts or artificial areas.[3] The use of the kernel approach improved the assessment of point patterns as it was described previously.[11] However, the kernel density was implemented based on a fixed bandwidth. Therefore, possible methodological improvements such as the use of cross-validation to choose an optimal bandwidth or the use of an adaptive bandwidth to consider environmental variability in the underlying residential density[29] have to be investigated.

Besides multiple determinants of physical activity in children that exist on the individual level, our study supports the evidence that physical activity of children is also influenced by built environment characteristics. Well-designed public open spaces and particularly playgrounds offer opportunities for children to be physically active in addition to sport activities that are promoted in schools or kindergartens. Moreover, safely designed public open spaces might also reduce parental concerns. This would encourage children to have more leisure time outdoor activities and increase their independent mobility. Public health practitioners and health policy makers should therefore consider urban planning as an additional discipline that needs to be involved in the promotion of a healthy environment for children providing safe and well-designed public open spaces in the urban neighborhood of children.

CONCLUSION

The moveability index turned out to be a useful tool to capture opportunities for PA on a micro-level in the urban neighborhood of school children in everyday life. Environmental features showed a significant effect on PA levels in children and could be combined to a moveability index. Moreover, availability of public open space and particularly playgrounds were positive predictors while other features that were commonly used to build the walkability index showed similar effects on PA levels for school children as for adults, except for land use mix. However, studies involving larger study areas, e.g. major cities or urban sprawls, as well as the assessment of regions in other countries are needed to further generalize these findings by quantitatively assessing recreational facilities. To also consider PA in leisure time of adults or adolescents, recreational facilities such as fitness centers or sports clubs should also be used to adapt the index in the same way as it was presented in our study. In addition, questionnaires assessing the perceived environment and its influence on PA levels may still be useful to identify motivational factors and to gain more insight into the association of the environment and the PA behavior of residents, besides objective measures of the urban neighborhood. In the long run, a validated quantitative moveability index may offer a valuable tool for urban planners to assess the communities where children live. Safe and well-designed public open spaces may encourage children to be more physically active and create a healthy environment to counteract the worrying lack of physical activity.

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B.4. Anonymisation of address coordinates for microlevel analyses of the built environment: A simulation study

This simulation study investigates the effect of a spatial blurring method on the assessment of walkability measures. The spatial blurring had to be implemented to allow a micro-level analysis of address coordinates while ensuring data protection requirements. The article was recently published in *BMJ Open* (Impact Factor 2014: 2.27) (Buck et al., 2015a).

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Anonymisation of address coordinates for microlevel analyses of the built environment: a simulation study

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ABSTRACT

Background: Data privacy is a major concern in spatial epidemiology because exact residential locations or parts of participants' addresses such as street or zip codes are used to perform geospatial analyses. To overcome this concern, different levels of aggregation such as census districts or zip code areas are mainly used, though any spatial aggregation leads to a loss of spatial variability. For the assessment of urban opportunities for physical activity that was conducted in the IDEFICS (Identification and prevention of dietary- and lifestyle-induced health effects in children and infants) study, macrolevel analyses were performed, but the use of exact residential addresses for micro-level analyses was not permitted by the responsible office for data protection. We therefore implemented a spatial blurring to anonymise address coordinates depending on the underlying population density.
Methods: We added a standard Gaussian distributed error to individual address coordinates with the variance σ^2 depending on the population density and on the chosen k-anonymity. 1000 random point locations were generated and repeatedly blurred 100 times to obtain anonymised locations. For each location 1 km network-dependent neighbourhoods were used to calculate walkability indices. Indices of blurred locations were compared to indices based on their sampling origins to determine the effect of spatial blurring on the assessment of the built environment.
Results: Spatial blurring decreased with increasing population density. Similarly, mean differences in walkability indices also decreased with increasing population density. In particular for densely-populated areas with at least 1500 residents per km², differences between blurred locations and their sampling origins were small and did not affect the assessment of the built environment after spatial blurring.
Conclusions: This approach allowed the investigation of the built environment at a microlevel using individual network-dependent neighbourhoods, while ensuring data protection requirements. Minor influence of spatial blurring on the assessment of walkability was found that slightly affected the assessment of the built environment in sparsely-populated areas.

Strengths and limitations of this study

- Spatial blurring only induces small differences in values of the walkability index between blurred locations and their origins.
- Impact of spatial blurring on the association between walkability and physical activity could not be investigated.
- The use of a large simulated data set enabled us to identify differences in the walkability index and to calculate the k-anonymity of blurred points.

BACKGROUND

Data privacy is a major issue in conducting epidemiological studies. In spatial epidemiology, data protection becomes an even more important concern, since the exact residential location or parts of participants' address information such as street names or zip codes are used to perform geospatial analyses.[1 2] To overcome this concern different levels of aggregation such as census districts or zip code areas are mainly used for spatial analyses of disease patterns or to assess the built environment in the neighbourhood of participants.[1 3] Any administrative division, however, leads to a loss of spatial variability and the use of address proxies based on centroids of aggregated areas induces large positional discrepancies.[3–5] Considering built environment research, the use of ego-centred neighbourhoods based on the home address of participants is recommended to assess environmental exposure of the built environment on a microlevel and to investigate its influence on physical activity of residents.[6–8]

Complementary to the overall examination programme of the IDEFICS study (Identification and prevention of dietary- induced and lifestyle-induced health effects in children and infants),[9] we performed environmental analyses in German study regions using geographic information systems (GIS) to investigate the impact of the built environment on the physical activity of children.[10] The IDEFICS study was conducted from 2006 to 2012 as a longitudinal multicentre study examining 16 228 children aged 2–9 years from eight European countries at baseline to investigate the aetiology of lifestyle-related and nutrition-related diseases.[9] In one German study region, pilot analyses of the built environment were conducted on a macrolevel considering school catchment areas as aggregation level to assess the living environment of participating children.[10]

Linking individual and environmental data based on administrative areas has two main disadvantages. First, the use of school catchment areas, which are defined by the municipality, reduces the variability of environmental variables of participants, for example, by calculating average values of these variables in oftentimes large areas.[6] Second, administrative areas are artificially defined and as such do not necessarily reflect individual characteristics or patterns in physical behaviour. Adjacent school catchment areas, for instance, may capture the living environment of children living near schools, but children living at the border of one area may be influenced by characteristics of an adjacent area, which is referred to as the container effect.[4] Hence, assessing the environment of participants based on their exact home address provides the best information on the individual living environment. Such an approach may also overcome the modifiable area unit problem which results from artificial areas and varying sizes of aggregation levels.[7] In the IDEFICS study, however, the use of exact address coordinates of participants was not permitted by the office for data protection of Lower Saxony, which was responsible for the two German study regions.

We therefore considered a geomasking approach to anonymise address data of participants in the German study regions of the IDEFICS study, which provides a simple method to blur participants' address coordinates by adding a standard Gaussian error.[2 11] According to Cassa *et al*,[11] this approach only slightly affects cluster detection based on spatial scan statistics, but it is not clear how the assessment of built environment measures is affected.[6 8] Thus, we calculated the walkability index according to Freeman *et al*[12] in ego-centred network-dependent neighbourhoods around randomly generated point locations and their repeatedly blurred counterparts. Differences between the value of the index based on sampling origins and based on blurred locations were considered to assess whether this approach has an effect on walkability measures. Hence, the simulation study was conducted to investigate the effect of spatial blurring on walkability measures that are calculated on a microlevel while ensuring data protection requirements.

METHODS

Spatial blurring

Implementing a fixed standard Gaussian error in a varying urban environment does not provide a proper disturbance that prevents the reidentification of addresses of participants' home with regard to k-anonymity, where one participant should not be reidentified from at least k−1 individuals.[11 13 14] For example, a fixed disturbance value used for one study region possibly allows to reidentify participants in sparsely-populated subdistricts, because anonymised addresses may be located close to less than k residents. In densely-populated subdistricts of the study area, such a disturbance value may be too large and could be reduced while still preventing reidentification of participants within k residents.[11]

To consider the variability of population density within a study region, we implemented a procedure to anonymise given coordinates $a_i=(b_i, c_i)$, $a_i \in R^2$, of participants $i=1,\ldots,n$ on a surface $W \subset R^2$. In detail, we added a spatial blurring $S_i=(X_i, Y_i)$ based on independent Gaussian distributed errors $X_i, Y_i \sim \mathcal{N}(0, \sigma_i^2)$ for both components to obtain the anonymised coordinates $a_i + S_i=(b_i + X_i, c_i + Y_i)$, where $S_i \sim \mathcal{N}(0, \sigma_i^2 I_2)$ and I_2 is the two-dimensional identity matrix. Anonymised coordinates $a_i + S_i$ are located in a $3\sigma_i$ circle around the original address coordinates with probability of about 99.7%, due to the Gaussian distribution. Hence, we considered the area $|B|=9\sigma_i^2\pi$ to define the degree of anonymisation using the expected age-specific number k_σ of residents that provides k-anonymity given as $k_\sigma=|B|\, p_A RD_A$, where RD_A is the number of residents per km² and $p_A \in [0, 1]$ is the age-specific percentage of residents in a given subdistrict $A \subset W$. Based on the parameter of k-anonymity k_σ, we derived the variance σ_i^2 of the spatial blurring as being inversely proportional to the underlying population density $p_A \cdot RD_A$ of the specific age group as

$$\sigma_i^2(A) = \frac{k_\sigma}{9\pi \cdot p_A \cdot RD_A}.$$

In summary, the variance of the Gaussian error will be calculated for any coordinate based on the underlying population density of the considered age group and the chosen k-anonymity. The blurring is then induced by the inverse Gaussian distribution with mean value of zero and the given variance and is added to the original coordinates. Coordinates in densely-populated areas will be blurred less, and vice versa.

Built environment measures

Spatial data on land use and population density were provided by the land registry office of Lower Saxony. Data on footpath network were obtained from the OpenStreetMap project (http://www.openstreetmap.org) and validated using official data. Additionally, bus stops were digitalised based on available maps and lists provided by the public transit company.[10] *ArcGIS 10.0* (ESRI 2011. ArcGIS Desktop: Release 10. Redlands) was used to process and digitalise spatial data as well as to generate random locations within the study region.

The walkability index was calculated based on ego-centred network-dependent neighbourhoods capturing an area that can be reached within 1 km based on the street network.[6 8] For both, circular and network-dependent neighbourhoods, the appropriate size of buffers that should be used to assess built environment measures is still discussed in the literature. Commonly used buffer distances range from 400 to 3200 m and are mainly defined according to walking distances.[7] Thus, we determined the distance of 1 km based on a 10 to 15 min walking distance. Network-dependent neighbourhoods around blurred points and their origins were calculated using the *network analyst*-tool in *ArcGIS 10.0*.

Walkability measures were calculated within these ego-centred neighbourhoods using the *spatstat*-package (1.33.0)[15] in *R* (3.0.1):[16]

- Number of residents per km^2,
- Land use mix based on the entropy of land use types,
- Number of intersections per area to assess the street connectivity,
- And number of bus stops per area to assess public transit density.

To standardise all four measures, z-scores of each variable were calculated based on mean and SD of walkability measures determined separately for sampling origins and for each blurring step. Z-scores of all four measures were then summed up to the walkability index according to Freeman *et al*.[12] Thus, the walkability score is a standardised non-dimensional score with mean value 0 and a SD of 4 based on the four standardised components.

Study data

We focussed our analyses of the built environment on one German survey region of the IDEFICS study to validate the approach of spatial blurring.[10] For this purpose, we thus considered built environment measures that were assessed in the city of Delmenhorst, Lower Saxony, which covers an area of about 62 km² with about 77 300 residents. The baseline survey of the IDEFICS study was conducted in 2007/2008 and geographical data were assessed for the same year.[9]

We generated 1000 random locations i=1, … , 1000, based on the underlying population density of the age-group that was eligible for the IDEFICS study within subdistricts in the study area of Delmenhorst which are presented in figure 1. We performed the spatial blurring based on the presented approach using data on residential density and the age-specific percentage of children below the age of 12 per subdistricts. These data were provided by the municipality of Delmenhorst. Randomly generated sampling origins i=1, … , 1000 were repeatedly blurred 100 times, j=1, … , 100, based on the underlying age-specific population density $p_A \cdot RD_A$ and a given k-anonymity k_σ using the *spatstat*-package (1.33.0) and the *sp*-package (1.0–13) in R (3.0.1).

With regard to statistics of aggregated areas, thresholds for k-anonymity of 5 or 10 are commonly used to prevent the reidentification of participants.[13 14] However, determining k-anonymity for spatial analyses leads to a trade-off between geomasking of addresses and resulting k-anonymity, which has significant computational challenges.[14 17] To identify the best approach that provides a compromise between geomasking and k-anonymity, we blurred sampling origins considering values of k_σ=10, 15 as a parameter for the blurring variance σ_i^2. By this, we assumed that our virtual participants should not be reidentified among 10 and 15 residents of the same age group, respectively. We chose values greater than k=5 as parameter for k-anonymity, since shifting original addresses of participants through spatial blurring can result in anonymised locations that fall into sparsely-populated areas where common thresholds of k-anonymity may not be fulfilled anymore. We therefore calculated the observed k-anonymity $\hat{k}_{i,j}$ of blurred locations j=1, … , 100 and origins i =1, … , 1000 for each parameter k_σ based on the underlying age-specific population density within $3\sigma_i$ circles and evaluated if the observed k-anonymity $\hat{k}_{i,j}$ did not fall under a threshold of k=5.

Statistical analyses

To investigate the variation of the simulated blurring, mean, SD, and range of the simulated blurring $|s_i|=\sqrt{x_i^2+y_i^2}$ were calculated for each sampling origin. Additionally, the mean, SD, and range of $\hat{k}_{i,j}$ of blurred locations were also calculated for each sampling origin. Spatial blurring and $\hat{k}_{i,j}$ were depicted depending on the underlying population density. The walkability index was calculated based on ego-centred neighbourhoods of 1000 sampling origins i and of 100 000 blurred locations j. Owing to the spatial blurring, locations fell outside the study area and neighbourhoods could not be calculated for 480 (k_σ=10) and 476 (k_σ=15) blurred locations. Differences in values of the walkability index between blurred locations and their related origins were calculated to assess changes in the index that were induced by spatial blurring. For each sampling origin i mean differences of walkability indices of blurred locations j to the related origin were calculated and displayed depending on the underlying population density. All statistics were calculated in *SAS 9.3* (SAS Institute Inc., Cary, North Carolina, USA).

RESULTS

Figure 2 presents statistics of the simulated blurring $|s_i|$ and the resulting $\hat{k}_{i,j}$ compared to the initial σ_i and the threshold of k=5, respectively. Mean shift of $|s_i|$ is close to the initial variance σ_i for both values of k_σ. Spatial blurring induced higher values of about 200–500 m for areas with less than 1000 residents per km² (k_σ=10) and for areas with less than 1500 residents per km² (k_σ=15), respectively. Accordingly, mean and maximum shift $|s_i|$ decreased for densely-populated areas with more than 1500 residents per km². The maximum shift $|s_i|$ showed values of 150 m (k_σ=10) or 200 m (k_σ=15) at most, while mean $|s_i|$ decreased from 48 to 32 m (k_σ=10) and 58 to 39 m (k_σ=15) (figure 2, top). Summing up, for both values of k-anonymity the mean and maximum shift decreased with increasing residential density. Assuming a higher value of k-anonymity (k_σ=15), that is a participant

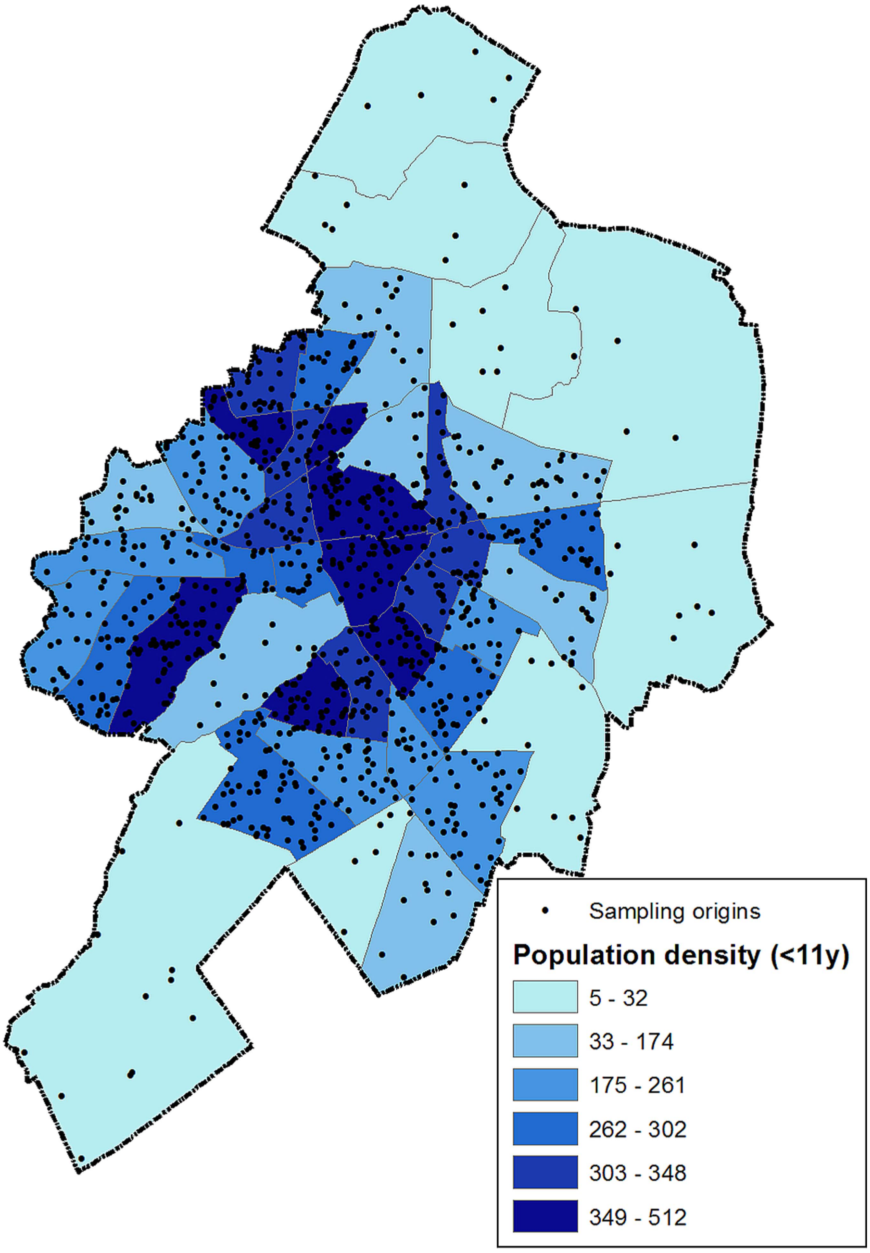

Figure 1 Distribution of random points and age-specific population density of subdistricts in the study region Delmenhorst, Germany.

cannot be reidentified from at least 15 residents, the shift of the coordinates was slightly higher compared to the lower value of k-anonymity.

Mean observed k-anonymity $\hat{k}_{i,j}$ leveled off at the chosen parameter k_σ. On the basis of higher value of k-anonymity k_σ=15, the observed $\hat{k}_{i,j}$ was higher than based on the lower value k_σ=10 (figure 2, bottom). For both parameters, the observed k-anonymity $\hat{k}_{i,j}$ showed values below the threshold of k=5 and even reached zero. Overall, the observed k-anonymity $\hat{k}_{i,j}$ fell below k=5 for 4.3% (k_σ=10) and 1.2% (k_σ=15) of blurred address locations, respectively. In other words, on average the assumed parameter of k-anonymity was met. However, assuming the less restrictive k-anonymity (k_σ=10 compared to k_σ=15), the blurred coordinates were more likely to be reidentified from less than five residents after spatial blurring.

Values of walkability indices of 1000 original locations i showed mean and SD of $0.92 \cdot 10^{-15}$ and 2.9 and ranged from −10.5 to 6.6. Figure 3 shows mean differences in the walkability indices between blurred locations j and their related sampling origins i depending on the underlying population density RD_A. Each dot shows the mean difference between the walkability index based on the neighbourhood of the sampling origin and walkability indices based on the neighbourhoods of 100 blurred locations of this origin. For both values of k-anonymity k_σ, the mean difference strongly decreased for a higher population density and did not exceed a value of 1 for at least 1000 residents per km² with only some exceptions. Summarising, it became obvious that the walkability index remained rather stable when shifting the address coordinates in densely-populated areas

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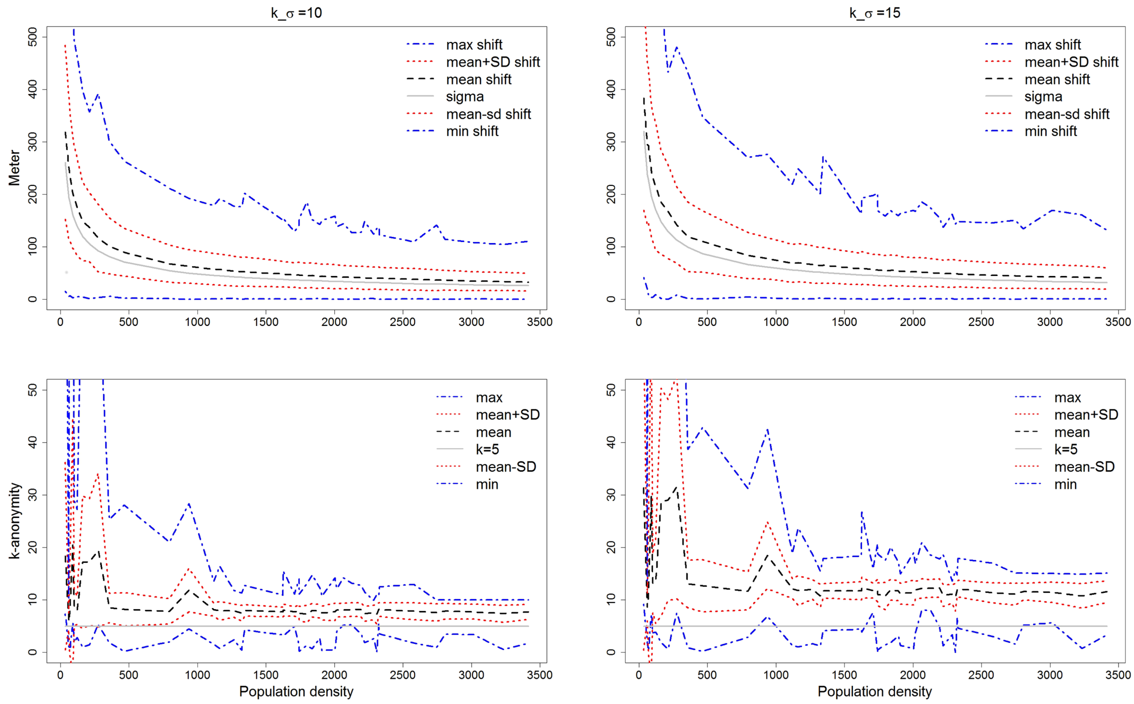

Figure 2 SD σ_i of the spatial blurring $|S_i|$ and summary statistics of the simulated spatial blurring $|s_i|$ (top) and of resulting $\hat{k}_{i,j}$ (bottom) depending on the underlying population density RD_A and two parameters k_σ=10, 15.

whereas it showed some more variability in sparsely-populated areas. For the more restrictive k-anonymity, a slightly higher difference between the walkability indices based on the blurred locations and the original location was observed.

DISCUSSION

The simulated spatial blurring that we conducted was based on randomly generated locations. In densely-populated areas, it resulted in only small shifts for most original locations. Owing to the population-dependent σ_i, the blurred points were rather strongly shifted in sparsely-populated areas, but the shift was less than 50 m on average for densely-populated areas with at least 1500 residents per km². Apparently, a stronger shift was observed for k_σ=15 than for k_σ=10, whereas for k_σ=15 the resulting k-anonymity $\hat{k}_{i,j}$ fell under the threshold of k=5 only in 1.2% of blurred locations.

Mean differences between walkability indices based on blurred points and on their related sampling origins showed similar patterns. For sparsely-populated areas, spatial blurring in most cases had a stronger impact on the walkability index. However, for blurred locations in densely-populated areas with at least 1000 residents per km², spatial blurring only led to differences in the walkability index of about 0.5–1 at most for both values of k_σ=10, 15. Compared to the range of the walkability index of original locations, these differences were acceptable and only slightly affected the assessment of built environment measures. On the basis of this approach, the use of anonymised individual coordinates of the home address was allowed by the office for data protection of Lower Saxony. In summary, we can

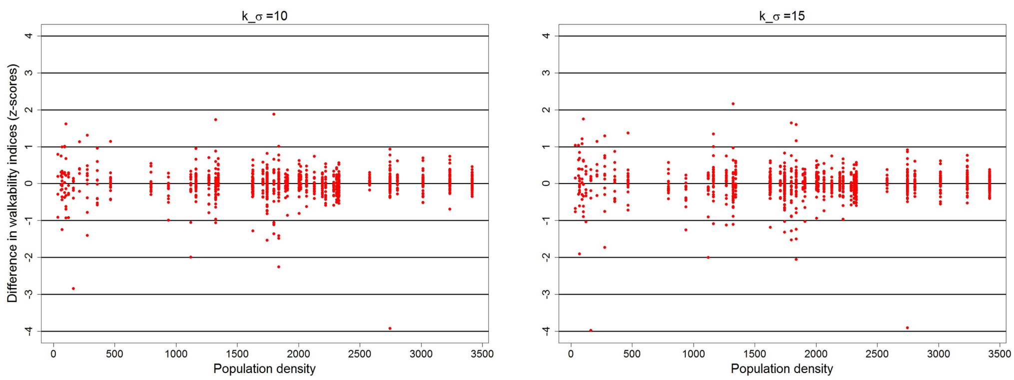

Figure 3 Mean difference in walkability indices between original coordinates and blurred coordinates (dots) depending on the underlying population density RD_A for parameters k_σ=10, 15.

therefore recommend k_σ=15 as a reasonable compromise between an acceptable shift and k-anonymity. Based on the SD of walkability measures in our study, a difference of 0.5 is equivalent to 17% of the SD. In larger study regions with higher variation in built environment characteristics, the walkability index can show a higher range, as for example in Freeman *et al*,[12] where the index showed values from −7.9 to 11.7. Thus, the effect of spatial blurring might be even lower depending on the size and environmental variability of the study area.

Our findings concerning the assessment of built environment measures are similar to the results of Cassa *et al*[11] who showed that the spatial blurring only slightly affected cluster detection analyses. However, some limitations have to be discussed. Cassa *et al*[18] deduced a vulnerability of spatial blurring which may enable adversaries to reidentify individuals based on the mean coordinates of multiple anonymised versions of the original data. Deriving ego-centred neighbourhoods based on address coordinates, that were only blurred once, should reduce the risk of reidentification of study participants.

Sparsely-populated areas, such as parts in the centre of the study area, induced larger changes in the walkability index if these areas were adjacent to densely-populated areas. Different approaches, such as the donut method,[19] may reduce the geomasking error and should restrict effects of sparsely-populated areas within or at the edge of the study area as long as thresholds for k-anonymity are maintained.

Using a large simulated data set is the major strength of our study, since the knowledge about the origins and the outcome of our approach enabled us to identify the difference in the walkability index and to calculate the k-anonymity of blurred points. Repeating the spatial blurring multiple times for one origin also controlled for the variation in our results.

However, consequences for real study samples have to be further investigated. In the IDEFICS study, the majority of the participating children lived in urban and densely-populated areas of the study region.[10] Thus, the spatial blurring should not affect the investigation of the built environment in the majority of the study sample. Rural and sparsely-populated areas may have an effect on the assessment of the built environment, due to the changes in walkability indices of blurred locations that were found in our analyses. Excluding participants that live in areas with less than 1000 residents per km² should ensure that spatial blurring does not lead to an undesired bias in the walkability index. However, the association of physical activity and built environment might then again be affected due to differences in the physical behaviour between residents of urban and rural neighbourhoods. Thus, the exclusion of participants in sparsely-populated areas still needs to be further investigated.

Eventually, we only inferred the effect of spatial blurring on the assessment of built environment measures, but not on the association between physical activity levels of residents and walkability in their neighbourhood. Thus, further analyses based on data of participants whose addresses are allowed to be used in spatial analyses are necessary to determine the effect of spatial blurring on the association between built environment and physical activity levels.

Taking the strengths and limitations into account, the effect of spatial blurring on built environment measures and on the walkability index was found to be relatively small. This supports the feasibility of the presented geomasking approach for densely-populated areas with at least 1000 residents per km². The use of point locations to assess the built environment on a micro-level is a strong advantage compared to the use of administrative areas and may compensate both, the disadvantages of spatial blurring and of a potential exclusion bias of participants that live in sparsely-populated areas.[7 8] Investigating the association between physical activity levels of residents and the walkability of their neighbourhood, we may therefore conclude that a small change in the walkability index may only slightly influence the assessment of built environment measures.

CONCLUSION

The presented approach allows to assess the built environment on a microlevel while ensuring data protection requirements. It facilitates to determine the urban neighbourhood of each participant using ego-centred network-dependent neighbourhoods based on anonymised address coordinates. Small differences were found in the walkability index which should only slightly affect further assessment of the built environment. As a result of the spatial blurring, available individual contact details, such as address information, can be used to assess environmental exposure combining individual and environmental data on a microlevel while ensuring data protection requirements.

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Contributors IP, SD, and CB conceptualised the research question and the geospatial analyses and interpreted the results. IP and CB discussed the results with the responsible office for data protection. CB conducted the analyses and wrote the manuscript and SD and IP reviewed the manuscript. All authors approved the final manuscript for publication.

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B.5. Assessing opportunities for physical activity in the built environment of children: Interrelation between kernel density and neighborhood scale

This article describes the impact of the spatial scale of neighborhoods and of different methods for bandwidth selection on the association between built environment characteristics and physical activity based on data of the IDEFICS study. The manuscript was still under review by the *International Journal of Health Geographics* when defending this thesis, and accepted before publishing the thesis.

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RESEARCH

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Assessing opportunities for physical activity in the built environment of children: interrelation between kernel density and neighborhood scale

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Abstract

Background: Built environment studies provide broad evidence that urban characteristics influence physical activity (PA). However, findings are still difficult to compare, due to inconsistent measures assessing urban point characteristics and varying definitions of spatial scale. Both were found to influence the strength of the association between the built environment and PA.

Methods: We simultaneously evaluated the effect of kernel approaches and network-distances to investigate the association between urban characteristics and physical activity depending on spatial scale and intensity measure. We assessed urban measures of point characteristics such as intersections, public transit stations, and public open spaces in ego-centered network-dependent neighborhoods based on geographical data of one German study region of the IDEFICS study. We calculated point intensities using the simple intensity and kernel approaches based on fixed bandwidths, cross-validated bandwidths including isotropic and anisotropic kernel functions and considering adaptive bandwidths that adjust for residential density. We distinguished six network-distances from 500 m up to 2 km to calculate each intensity measure. A log-gamma regression model was used to investigate the effect of each urban measure on moderate-to-vigorous physical activity (MVPA) of 400 2- to 9.9-year old children who participated in the IDEFICS study. Models were stratified by sex and age groups, i.e. pre-school children (2 to <6 years) and school children (6–9.9 years), and were adjusted for age, body mass index (BMI), education and safety concerns of parents, season and valid weartime of accelerometers.

Results: Association between intensity measures and MVPA strongly differed by network-distance, with stronger effects found for larger network-distances. Simple intensity revealed smaller effect estimates and smaller goodness-of-fit compared to kernel approaches. Smallest variation in effect estimates over network-distances was found for kernel intensity measures based on isotropic and anisotropic cross-validated bandwidth selection.

Conclusion: We found a strong variation in the association between the built environment and PA of children based on the choice of intensity measure and network-distance. Kernel intensity measures provided stable results over various scales and improved the assessment compared to the simple intensity measure. Considering different spatial scales and kernel intensity methods might reduce methodological limitations in assessing opportunities for PA in the built environment.

Keywords: Active living, Adaptive bandwidth, IDEFICS study , Moveability, Spatial scale, Urban neighborhood, Walkability

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Background

There is broad evidence that environmental opportunities in the urban neighborhood can positively affect health outcomes such as obesity, hypertension, and other cardiometabolic risk factors by promoting physical activity (PA) of residents [1–4]. However, findings regarding the association between the built environment and PA are still difficult to compare or pool [1, 4, 5]. In particular, differences in the results are induced by varying definitions of neighborhood scale and an inconsistent use of urban measures to assess the built environment [3–7]. In the last decade, the assessment of built environment characteristics that identified walkable and health promoting neighborhoods shifted more and more to the application of objective measures based on spatial data using a variety of methods [6–9]. However, the definition of the geographical context, i.e. the neighborhood of individuals, differs throughout many studies [1, 6, 10].

An important step to assess the built environment is the definition of the spatial context, i.e. the neighborhood scale, in which the built environment is assumed to affect the individual [1, 4, 10–13]. Most of the studies that investigated the built environment relied on pre-defined administrative areas [1], though these are known to induce bias and spatial misclassification of neighborhoods. First, spatial movement and behavior of an individual is not bound to artificially defined areas. Assigning spatial information in one district to residents that are more attracted to adjacent districts might lead to a misclassification of urban measures, which was previously described as the container effect [14]. Second, the size and proportion of e.g. census districts or zip codes induce differing results due to changes in spatial scales, which is commonly known as the modifiable areal unit problem (MAUP) [13, 15].

Ego-centered neighborhoods [10, 16] that assess built environment characteristics based on a pre-defined distance around the place of residence can avoid the MAUP as well as the container effect and seem to be suitable to assess urban measures [8, 9, 15]. However, studies that used ego-centered neighborhoods did not use the same distance to determine individual network-dependent neighborhoods in which built environment measures were assessed. Since the neighborhood distance influences study results, discrepancies in the use of spatial scale hinder a comparison of the findings reported in the literature [5, 11]. Recent reviews of built environment factors that focussed on either PA [6], cardiometabolic risk factors [1], or obesity [4] found multiple ranges applied for ego-centered neighborhoods and discussed contradictory results and varying definitions of spatial scale. Brownson et al. [6], for instance, found studies using ego-centered neighborhoods that ranged from 500 m up to 3.2 km (up to 2 miles) and that were mostly determined by assuming a 10 min walk. Casey et al. [4] as well as Leal and Chaix [1] found some studies that used ego-centered neighborhoods with euclidian or network-based distances which, however, ranged from 400 m to 5 km [4] or from 100 m to 4.8 km [1]. Only few of these studies considered the effect of neighborhood scale on their results [4].

In addition, studies often used a fixed neighborhood distance for the assessment of the built environment in general, though the spatial context of the association between the built environment and PA might differ by age groups, sex, or other individual level characteristics [12]. Older adults, for example, or disabled persons might interact with a quite small neighborhood compared to younger and healthier adults [13]. Boone-Heinonen et al. [17] evaluated urban measures using buffer distances from 1 to 8.05 km and found the strongest association between urban characteristics and PA in different network-distances depending on the considered urban characteristic. Overall, a broad definition of the spatial context in which point characteristics should be assessed to capture the exposure of the built environment induces an uncertainty that adds to the methodological gap in the recent literature. This gap was particularly discussed as the Uncertain Geographic Context Problem (UGCoP) by Kwan [13].

Another difficulty in comparing studies of the built environment is caused by the choice of the geostatistical method [6, 14] and the fact that different measurements were found to affect the association between the built environment and PA [18]. The appropriate assessment of the built environment depends on a thorough modeling of point characteristics. The simple intensity approach that calculates urban measures as number per area of the chosen neighborhood is commonly used, but it is based on the assumption of a non-varying mean of point characteristics in the study area [19]. Since urban environments show strong spatial variation in built environment characteristics, an inhomogeneous intensity measure is recommended [14, 19, 20]. The inhomogeneous intensity assesses urban point characteristics by a smoothed intensity surface in terms of a weighted average that is calculated independently from a specific delineation of neighborhoods. In a previous study, we found an association between the built environment and PA levels in children on a macro-level. Here, urban measures were calculated based on a kernel approach within administrative areas, where the kernel intensity of point characteristics improved the assessment compared to the simple intensity [19]. In further research, we also used the kernel intensity on a micro-level and found it to be a useful method to asses built environment characteristics in ego-centered neighborhoods compared to the simple intensity [21].

However, the kernel approach is mainly determined by the choice of the bandwidth [20]. Commonly, a fixed bandwidth is used to estimate the inhomogeneous point intensity, though the choice of the optimal bandwidth as a smoothing parameter is difficult due to a trade-off between bias and variance of the kernel estimator. A data-driven choice of the bandwidth based on cross-validation might improve the intensity measure compared to a pre-defined value [22].

Using bandwidths adaptive to a varying background information of the study area may enhance the kernel intensity measure in urban environments [23, 24]. A fixed bandwidth does not account for the underlying residential density that directly influences, for example, the availability of public open spaces or intersections. A kernel intensity measure based on a bandwidth adaptive to the residential density might be able to identify and quantify true hot spots that reflect the availability or density of point characteristics adjusted for space and population [23]. Shi [24] discussed the use of an adaptive bandwidth with regard to the use of kernel intensity measures in disease mapping. Considering the inhomogeneous background that is present in a varying urban environment, an adaptive bandwidth that depends on the underlying residential density might improve the assessment of environmental exposure [23].

The present study was conducted to simultaneously evaluate two important components of built environment research. First, the simple intensity and kernel intensity measures were used to assess three point characteristics such as intersections, public transit stations, and public open spaces. In particular, cross-validated and adaptive bandwidths that depend on the underlying residential density were considered to improve kernel intensity measures. Second, the influence of the neighborhood scale on the association between built environment characteristics and habitual PA in children was investigated. Urban measures were assessed in different network-distances. Analyses of the association between urban measures and PA levels were stratified by sex and age groups. Overall the study aimed to identify the influence of varying spatial scales and sex- and age-specific neighborhoods as well as a suitable method to assess point characteristics.

Methods

Study data

Our analysis is based on data of the Identification and prevention of Dietary- and lifestyle-induced health EFfects In Children and infantS study (IDEFICS) [25]. The IDEFICS study is a European multicenter study that was conducted from 2006 to 2012 to investigate the etiology of lifestyle- and nutrition-related diseases and disorders in 16,228 2-to 9.9-year-old children at baseline from eight European countries [26]. We used data of 448 children that lived in one German study region, Delmenhorst, Lower Saxony, and took part in the baseline survey in 2007 and 2008. The study region Delmenhorst is about 62 km^2 large and had about 77,300 residents in 2008.

PA was assessed based on accelerometer devices using 15 s epochs. We considered accelerometer measurements of 448 children who wore the devices for at least three consecutive days including one weekend day with at least 8 h of valid weartime each after exclusion of intervals of at least 30 min of consecutive zeros [27]. We excluded 24 children who lived in the rural peripheral area of the municipality, since we focused on children living in an urban environment. Additionally, 24 children were excluded due to missing values in questionnaire information, which resulted in a total sample of 400 2- to 9.9-year-old children. Age- and sex-specific BMI z-scores and categories for overweight and obesity were calculated according to Cole and Lobstein [28]. Our sample included slightly more girls (n = 231, 51.6 %) than boys and 75 % were school children (n = 300) aged 6–9.9 years.

Moderate-to-vigorous physical activity (MVPA) was defined using the cut-off value of 2298 counts per minute (cpm) according to Evenson [29]. In addition we considered hours of valid weartime and the season of accelerometer measurement as confounder. Seasons of assessment were categorized to spring/summer, if the accelerometer device was worn in September 2007 and between March and May 2008, and to autumn/winter, if assessment took place between October 2007 to February 2008. Moreover, education and qualification of parents were classified according to the International Standard Classification of Education (ISCED) [30]. We collapsed ISCED-levels into three categories, i.e. low (lower secondary education and less), medium (upper and post-secondary education), and high (tertiary education). Reported safety concerns of the parents that might have restricted children's PA were identified using two items of the parental questionnaire, 'I restrict my child's outdoor activities for safety reasons', and 'I don't like to let my child walk/cycle to kindergarten, pre-school or school for safety reasons.' to which parents could agree or disagree on a four point Likert-scale. Agreement and disagreement on one of these statements was condensed to a binary variable for parental safety concerns.

Environmental data

We collected and processed spatial data of the city of Delmenhorst based on land registry data and open source data which was described previously [19, 21]. In particular, we derived the street network utilizing data of the OpenStreetMap-Project[1] (OSM). Spatial data of point characteristics such as the street network, i.e. intersections, public transit stations, and public open spaces, such as playgrounds, parks, and public green spaces of the German study region Delmenhorst were considered for the calculation of urban measures in different neighborhood distances. Environmental data were processed and managed in *ArcGIS 10.1*[2].

Neighborhood distance

For each participant, ego-centered network-dependent neighborhoods were derived based on the place of residence and the street network. To capture opportunities of the built environment in differing neighborhood contexts [12, 17], we considered six different network-distances, i.e. 500 m, 750 m, 1, 1.25, 1.5, and 2 km, for which we calculated urban measures of point characteristics. Figure 1 illustrates the extent of neighborhoods based on the six chosen network-distances from a hypothetical place of residence.

Exact address coordinates could not be used as place of residence to calculate ego-centered neighborhoods, due to data protection requirements. Therefore, we used a spatial blurring based on a Gaussian error that was inversely proportional to the underlying residential density [31, 32]. In a previous simulation, spatial blurring turned out to shift original coordinates by about 50 to 100 m in densely-populated areas and to induce only small differences of walkability measures [31].

We calculated network-dependent neighborhoods using the *network analyst* in *ArcGIS 10.1* based on the blurred coordinates and conducted spatial blurring in *R* 3.1.0 [33] using the *rnorm* function.

Urban measures

Point characteristics of the built environment, i.e. public open spaces, intersections, and public transit stations, were modeled as Poisson point processes (PPP) [20, 22] and assessed using different intensity measures. Considering a homogeneous PPP, where it is assumed that the number of points have a constant mean over neighborhoods A of the study area $W \subset \mathbb{R}^2, A \subset W$, we first assessed the availability of point characteristics by the simple intensity $\hat{\lambda}_A$, of neighborhood A, i.e. as number of points $\#s_i, i = 1, \ldots, n$, per area $\nu(A)$

$$\hat{\lambda}_A = \frac{\#s_i \in A}{\nu(A)}.$$

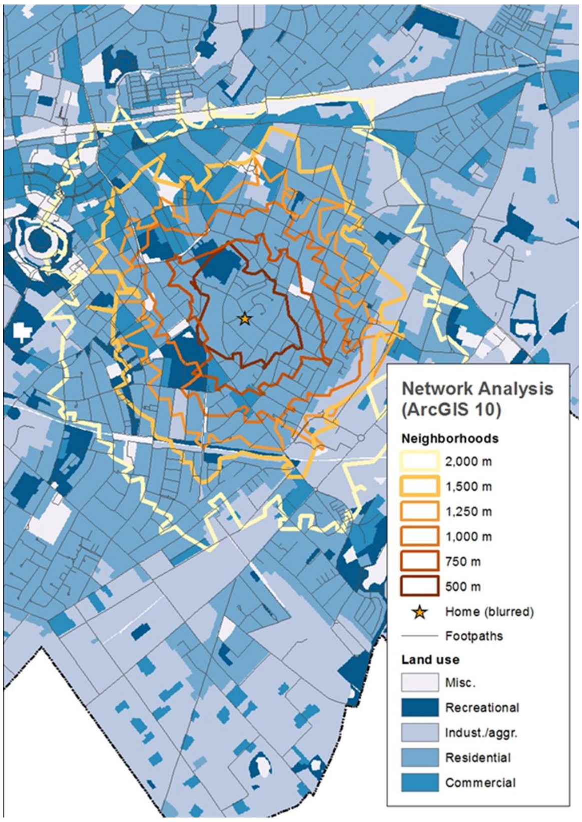

Fig. 1 Ego-centered neighborhoods using six different network-distances based on a hypothetical place of residence in the study area Delmenhorst

In a previous study, we emphasized that the assessment of built environment characteristics in adjacent districts can be improved by kernel intensity approaches. We modeled point characteristics as an inhomogeneous PPP $\mathrm{N}(A) \sim \mathrm{Poi}(\Lambda_A)$ with $\Lambda_A = \int_A \lambda(s)\, ds$ to evaluate if kernel density approaches also improve the assessment based on ego-centered neighborhoods. Thus, we inferred the availability of point characteristics using an inhomogeneous intensity measure

$$\hat{\lambda}(s) = \frac{w_{|\Sigma|,s}}{|\Sigma|} \sum_{i=1}^{n} \mathbb{K}\left(|s - s_i|^T \Sigma^{-1} |s - s_i|\right),$$

where Σ is the covariance matrix, i.e. bandwidth, of the two-dimensional Gaussian kernel function $\mathbb{K}$ and $w_{|\Sigma|,s}$ is an edge-correction factor [19, 22, 34]. For a given neighborhood A the mean Λ_A of the inhomogeneous intensity $\hat{\lambda}(s)$ for $s_i \in A$ is calculated. The choice of an adequate bandwidth is crucial when using a kernel density. A very small bandwidth will result in an undersmoothed intensity surface that manifests a large amount of single peaks, while a very large bandwidth will induce an

[1] http://www.openstreetmap.org—Open Data Commons Open Database License (ODbL).

[2] ESRI 2011. ArcGIS Desktop: Release 10.1 Redlands, CA: Environmental Systems Research Institute.

oversmoothed intensity where less variation is visualized by the intensity surface [22, 34]. This dilemma is referred to as the well-known bias-variance trade-off [35].

First, we chose a fixed bandwidth of $\sigma_f = 500$ m of the Gaussian kernel function with regard to the isotropic case of $\Sigma = \sigma\mathbb{I}$. The fixed bandwidth σ_f was determined by visual screening of resulting intensity surfaces based on different values for σ_f. Second, we specified a cross-validated bandwidth σ_{CV} that was calculated by minimizing the mean square error (MSE) to choose the optimal bandwidth based on the available data of point characteristics [20, 36]. Both approaches still assume an isotropic, i.e. circular, kernel function that expands by the same distance in each direction and thus implies that point characteristics can be available in all directions. However, topographic features of the landscape can shape the built environment and can lead to a more elliptical townscape. Point characteristics might then also appear more likely according to the shape of the urban region. Modeling anisotropy is very common conducting spatial interpolation, i.e. kriging [37], and might also improve intensity measures of PPP. As a third kernel intensity measure, we therefore considered an anisotropic cross-validated bandwidth Σ_{lscv} that allows to model an elliptical Gaussian kernel. This bandwidth is characterized by a covariance matrix Σ that is calculated based on a least-square cross-validation [38].

Urban measures of point characteristics strongly correlate with residential density, since the spatial distribution of e.g. intersections, public transit stations, and public open spaces is particularly influenced by the number of residents that live in a certain neighborhood. Considering the spatial availability of, e.g., public open spaces, intensity measures only capture the availability per area. Hence, hot spots or clusters of public open spaces are inevitably identified where public open spaces are built according to the number of residents. Adaptive bandwidths allow to adjust the kernel intensity measure by the number of residents and smoothen the assessment of point characteristics [23, 24]. To change bandwidths depending on the underlying residential density $R_A = \#residents/km^2$, we multiplied the adjustment factor $(2000/R_A)$ with the three pilot bandwidths σ_f, σ_{CV}, and Σ_{lscv} and defined adaptive bandwidths as

$$\tilde{\sigma}_f = \frac{2000}{R_A} \cdot \sigma_f = \frac{2000 \cdot km^2}{\#residents} \cdot \sigma_f$$

and $\tilde{\sigma}_{CV}$ as well as $\tilde{\Sigma}_{lscv}$ accordingly. We used a pilot residential density, here 2000 residents per km^2, for which the pilot bandwidth remains unchanged. In areas with higher residential density, the factor reduces the pilot bandwidth and in areas with lower residential density, the factor increases the pilot bandwidth.

The seven intensity measures, i.e. the simple intensity $\hat{\lambda}_A$ and kernel intensities based on the bandwidths $\sigma_f, \tilde{\sigma}_f, \sigma_{CV}, \tilde{\sigma}_{CV}, \Sigma_{lscv}$, and $\tilde{\Sigma}_{lscv}$ were applied to calculate the mean intensity of point characteristics within six ego-centered network-dependent neighborhoods using the distances, 500, 750, 1000, 1250, 1500, and 2000 m (Fig. 1). Intensity surfaces of all six kernel intensities of public open spaces in the study area are illustrated in Fig. 2.

Urban measures were calulated using the *spatstat*-package 1-37-0 [34] in *R* 3.1.2 [33]. In detail, the MSE cross-validation was implemented using the *bw.diggle* function in *spatstat* and the least-square cross-validation was conducted using the *Hlscv* function in the *ks*-package 1.9.3 [39].

Statistical analyses

Mean and standard deviation (SD) of individual-level variables were calculated stratified for sex and age groups. In addition, we calculated mean and SD of intensity measures based on 400 addresses considering each intensity measure and each network-distance. We calculated gamma-log-regression models to identify the effect of neighborhood distance and intensity measure on the association between urban measures and children's habitual MVPA of children. For this purpose, we considered average minutes per day as a measure of habitual PA [27].

We first investigated the effect of individual-level variables such as age, sex, BMI z-score, ISCED level and safety issues of parents, as well as season and valid weartime of accelerometer measurements on habitual MVPA. These models are referred to as basic models in the following. Due to the skewness of the distribution and the large range of values of MVPA, we considered gamma distribution and a log-link function in our regression model. To account for differences in MVPA between boys and girls as well as pre-school children and school, which were previously identified [21], we stratified all models by age groups and by sex. As a sensitivity analysis, we also allowed for a finer age stratification to investigate the robustness of our results with respect to age strata. In addition, the performance of intensity measures and the neighborhood scale was investigated using a multi-level model that consideres daily MVPA accounting for clustering of repeated measurements nested within individuals (2679 days in 400 children).

Environmental variables, i.e. mean intensity of points per neighborhood for each type of measure based on each distance, were then separately included in the basic models. Patterns of beta estimates, p values, and goodness of fit based on the Akaike Information Criteria (AIC) of the corresponding model, were depicted by distance separately for different types of methods. Statistical

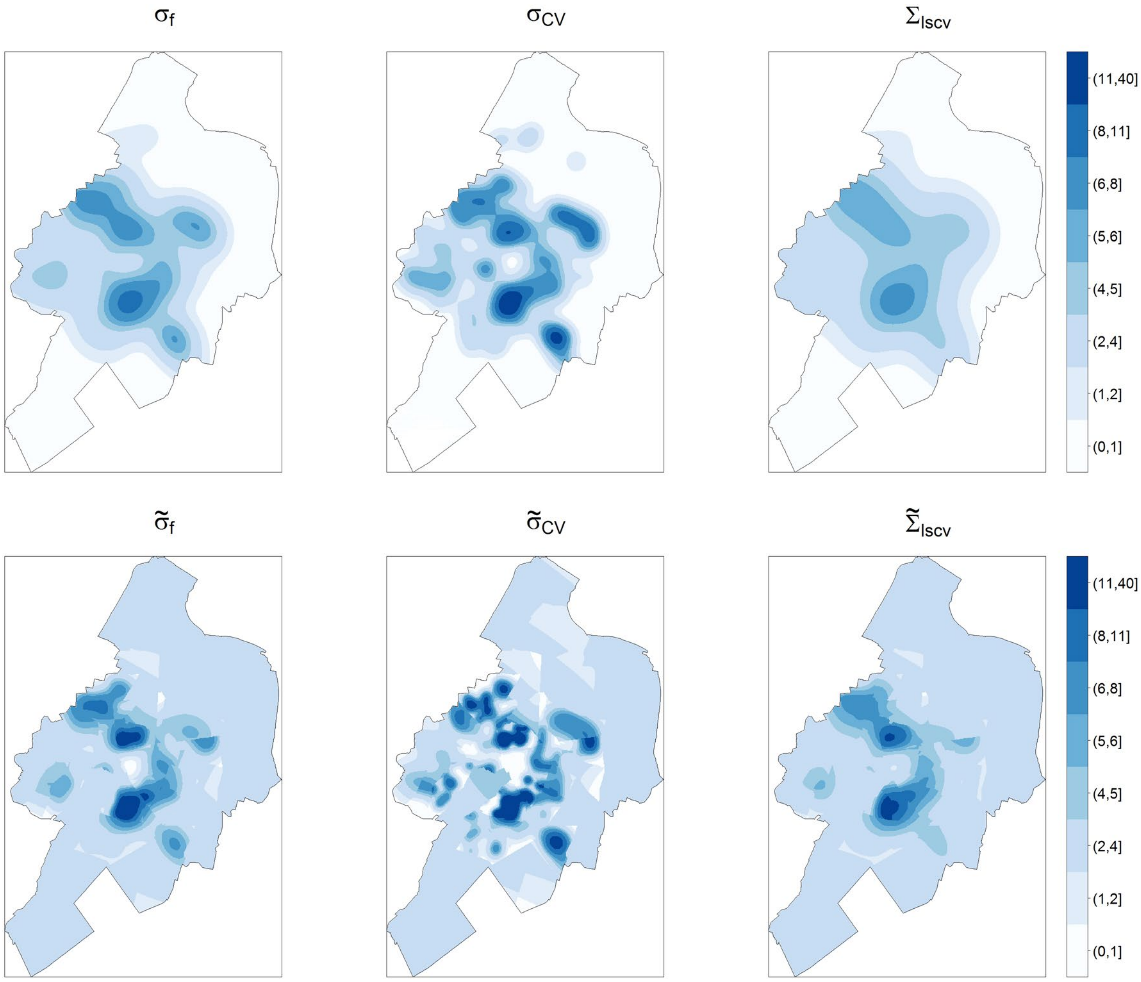

Fig. 2 Kernel intensity surfaces based on different approaches of bandwidth selection considering a fixed (*left*), cross-validated (*middle*), or anisotropic cross-validate bandwidth (*right*), as well as a factor (*bottom*) adaptive to the underlying residential density

analyses were conducted in *SAS 9.3* (SAS Institute Inc., Cary, NC, USA) and regression models were calculated using the *glimmix* procedure.

Results

Table 1 presents descriptive statistics of the study sample. Overall MVPA levels were higher in school children (61.9 min/day) than in pre-school children (55.8 min/day) with higher values in boys (school boys 69.8, pre-school boys 58.1) than in girls (school girls 55.3, pre-school girls 52.7). Girls showed slightly higher mean values of BMI z-score compared to boys (see Table 1). Safety concerns of parents were less reported in school children (35 %) than in pre-school children (47 %) and differed between boys (38.5 %) and girls (58.1 %) only in pre-school children.

Table 2 shows mean and SD of intensity measures of three point characteristics depending on the considered network-distance. Mean and SD of the simple intensity were higher compared to kernel-based intensity measures with regard to all three point characteristics. Moreover, the simple intensity measure showed more pronounced differences in mean and SD between network-distances with smaller SD for larger network-distance. In contrast, kernel-based intensity measures showed more similar mean values between different types of measures and network-distances, but SD was also smaller for larger network-distances (Table 2).

Results of the basic models are presented in Table 3. In school children BMI z-score was associated with MVPA ($\exp(\hat{\beta}) = 0.95$, $p = 0.028$), but stratified by sex this association was only found in school girls ($\exp(\hat{\beta}) = 0.94$, $p = 0.031$). Season and valid weartime were positively associated with MVPA in school children as well as in school boys and school girls in the stratified analyses.

Table 1 Descriptive statistics of individuel-level variables in the study sample stratified by age groups and sex

Variables	Mean (SD)/N (%)		
	School children		
	All (n = 300)	**Boys (n = 137)**	**Girls (n = 163)**
MVPA (min/day)	61.9 (23.0)	69.8 (24.3)	55.3 (19.5)
Age	7.5 (0.8)	7.5 (0.8)	7.5 (0.8)
BMI z-score[a]	0.42 (1.0)	0.29 (1.0)	0.52 (1.1)
Valid weartime	11.6 (1.3)	11.7 (1.4)	11.5 (1.2)
ISCED level (%)			
Low	69 (23.0)	28 (20.4)	41 (25.2)
Medium	168 (56.0)	81 (59.1)	87 (53.4)
High	63 (21.0)	28 (20.4)	35 (21.5)
Safety concerns of parents (%)			
No	194 (64.7)	87 (63.5)	107 (65.6)
Yes	106 (35.3)	50 (36.5)	56 (34.4)
Season of assessment (%)			
Autumn/winter	213 (71.0)	97 (70.8)	116 (71.2)
Spring/summer	87 (29.0)	40 (29.2)	47 (28.8)
	Pre-school children		
	All (n = 100)	**Boys (n = 57)**	**Girls (n = 43)**
MVPA (min/day)	55.8 (22.9)	58.1 (23.0)	52.7 (22.7)
Age	4.2 (0.8)	4.2 (0.8)	4.2 (0.9)
BMI z-score[a]	0.03 (1.1)	–0.10 (1.1)	0.19 (1.2)
Valid weartime	11.1 (1.1)	11.3 (1.1)	10.9 (1.0)
ISCED level (%)			
Low	13 (13.0)	10 (17.5)	3 (7.0)
Medium	72 (72.0)	37 (64.9)	35 (81.4)
High	15 (15)	10 (17.5)	5 (11.6)
Safety concerns of parents (%)			
No	53 (53.0)	35 (61.4)	18 (41.9)
Yes	47 (47.0)	22 (38.6)	25 (58.1)
Season of assessment (%)			
Autumn/winter	70 (70.0)	42 (73.7)	28 (65.1)
Spring/summer	30 (30.0)	15 (26.3)	15 (34.9)

[a] According to Cole and Lobstein [28]

Safety concerns showed no significant association in school children and in the stratified samples. Effects of safety concerns were more pronounced in school girls ($\exp(\hat{\beta}) = 0.94$, $p = 0.29$) than in school boys ($\exp(\hat{\beta}) = 1.02$, $p = 0.76$). In pre-school children, age showed a significant association with MVPA in the full sample and stratified by sex. Here, children of parents with safety issues showed significantly reduced MVPA ($\exp(\hat{\beta}) = 0.86$, $p = 0.044$). In the stratified analyses, this result was found in pre-school girls ($\exp(\hat{\beta}) = 0.75$, $p = 0.019$), but not in pre-school boys ($\exp(\hat{\beta}) = 0.95$, $p = 0.68$).

Patterns of results of the log-gamma-regression models by network-distance and intensity measures in school children are presented in Figs. 3, 4 and 5 distinguishing between point characteristics. Additional files 1, 2 and 3 are available as supplemental material presenting the patterns of results in pre-school children.

The association between intensity of public open spaces and MVPA in school children strongly differed depending on the considered network-distance of neighborhood or intensity measure (Fig. 3). For larger network-distances the association was found to be stronger, with larger effect estimates in school girls than in school boys. p values showed that the association was significant in school children based on all network-distances and intensity measures. In school girls this picture only slightly changed, but in school boys p values strongly

Table 2 Mean and standard deviation (SD) of intensity of intersections, public transit stations, and public open spaces in the neighborhood of 400 children depending on network-distance and intensity measures that were used for assessment

Mean (SD)	Network-distances 500 m	750 m	1 km	1.25 km	1.5 km	2 km
Intensity measures						
Intersections						
Simple intensity	70.0 (26.3)	66.0 (20.5)	68.1 (16.8)	62.5 (16.4)	61.2 (15.8)	58.9 (14.5)
Fixed BW σ_f	59.8 (16.2)	59.2 (15.9)	59.4 (15.2)	58.3 (15.0)	57.7 (14.6)	56.6 (13.7)
Fixed and adaptive BW $\tilde{\sigma}_f$	62.4 (18.4)	61.6 (16.9)	61.7 (15.4)	60.6 (14.2)	60.3 (13.2)	59.5 (11.4)
MSE CV σ_{CV}	65.7 (21.4)	63.4 (18.5)	64.0 (16.2)	60.9 (15.8)	59.9 (15.2)	58.2 (14.4)
MSE CV and adaptive $\tilde{\sigma}_{CV}$	66.6 (21.8)	64.6 (18.0)	65.1 (15.8)	63.1 (14.5)	62.4 (13.6)	61.4 (12.0)
Anisotropic CV Σ_{lscv}	59.3 (16.0)	58.8 (15.7)	59.0 (15.0)	58.0 (14.8)	57.5 (14.4)	56.4 (13.5)
Anisotropic CV and adaptive $\tilde{\Sigma}_{lscv}$	62.1 (18.3)	61.3 (16.8)	61.4 (15.4)	60.4 (14.2)	60.0 (13.1)	59.2 (11.4)
Public transit stations						
Simple intensity	5.8 (3.3)	5.5 (2.4)	5.7 (2.0)	5.0 (1.7)	4.9 (1.6)	4.6 (1.3)
Fixed BW σ_f	4.6 (1.5)	4.6 (1.5)	4.6 (1.4)	4.5 (1.4)	4.5 (1.3)	4.3 (1.2)
Fixed and adaptive BW $\tilde{\sigma}_f$	4.9 (1.6)	4.8 (1.5)	4.9 (1.4)	4.8 (1.3)	4.7 (1.2)	4.7 (1.0)
MSE CV σ_{CV}	4.7 (1.6)	4.6 (1.5)	4.7 (1.5)	4.5 (1.4)	4.5 (1.3)	4.4 (1.2)
MSE CV and adaptive $\tilde{\sigma}_{CV}$	4.9 (1.7)	4.9 (1.5)	4.9 (1.4)	4.8 (1.3)	4.8 (1.2)	4.7 (1.0)
Anisotropic CV Σ_{lscv}	4.4 (1.4)	4.3 (1.4)	4.4 (1.3)	4.3 (1.3)	4.3 (1.3)	4.2 (1.1)
Anisotropic CV and adaptive $\tilde{\Sigma}_{lscv}$	4.7 (1.5)	4.6 (1.4)	4.7 (1.3)	4.6 (1.2)	4.6 (1.1)	4.5 (0.9)
Public open spaces						
Simple intensity	4.9 (4.2)	4.2 (2.8)	4.4 (2.2)	4.0 (1.6)	3.9 (1.4)	3.7 (1.1)
Fixed BW σ_f	4.1 (1.5)	4.1 (1.4)	4.1 (1.3)	4.0 (1.2)	3.9 (1.1)	3.8 (0.9)
Fixed BW and adaptive $\tilde{\sigma}_f$	4.6 (2.2)	4.4 (1.8)	4.4 (1.5)	4.3 (1.2)	4.3 (1.1)	4.2 (0.8)
MSE CV σ_{CV}	4.5 (2.2)	4.3 (1.9)	4.3 (1.6)	4.1 (1.4)	4.0 (1.3)	3.9 (1.0)
MSE CV and adaptive $\tilde{\sigma}_{CV}$	4.9 (2.9)	4.7 (2.1)	4.6 (1.7)	4.5 (1.3)	4.4 (1.1)	4.3 (0.8)
Anisotropic CV Σ_{lscv}	3.9 (1.2)	3.9 (1.2)	3.9 (1.1)	3.8 (1.0)	3.8 (1.0)	3.7 (0.9)
Anisotropic CV and adaptive $\tilde{\Sigma}_{lscv}$	4.3 (1.8)	4.3 (1.5)	4.2 (1.3)	4.2 (1.2)	4.1 (1.0)	4.1 (0.8)

BW bandwidth, *MSE* mean-square error, *CV* cross-validation

differed and no significant association was found. Goodness of fit only slightly differed with less variation in school boys than in school girls.

Considering the intensity measures, the simple intensity showed the smallest effect estimates and the largest values in AIC, i.e. lowest goodness of fit. In particular,

Table 3 Results of the basic log-gamma regression model investigating individual-level factors on MVPA

Individual-level variables	$\exp(\hat{\beta})$	*p* value	$\exp(\hat{\beta})$	*p* value	$\exp(\hat{\beta})$	*p* value
	School children					
	All (n = 300)		**Boys (n = 137)**		**Girls (n = 163)**	
	AIC = 2707.1		**AIC = 1260.1**		**AIC = 1433.2**	
Age	0.97	0.30	0.96	0.30	0.99	0.81
BMI z-score[a]	0.95	0.028	0.98	0.61	0.94	0.031
Valid weartime	1.04	0.022	1.05	0.041	1.02	0.39
Season (ref: winter/autumn)	1.17	0.001	1.19	0.011	1.14	0.042
Safety concerns (ref: no)	0.99	0.79	1.02	0.76	0.94	0.29
Low ISCED (ref: medium)	0.95	0.38	0.90	0.18	1.04	0.59
High ISCED (ref: medium)	1.01	0.88	1.00	0.96	1.05	0.54
	Pre-school children					
	All (n = 100)		**Boys (n = 57)**		**Girls (n = 43)**	
	AIC = 893.0		**AIC = 519.5**		**AIC = 386.6**	
Age	1.28	<0.001	1.24	0.008	1.33	0.001
BMI z-score[a]	1.03	0.46	1.04	0.34	1.02	0.70
Valid weartime	1.00	0.99	1.03	0.65	0.97	0.67
Season (ref: winter/autumn)	0.99	0.93	1.07	0.62	0.91	0.49
Safety concerns (ref: no)	0.86	0.044	0.95	0.68	0.75	0.019
Low ISCED (ref: medium)	1.12	0.33	1.18	0.28	1.04	0.85
High ISCED (ref: medium)	1.12	0.29	1.03	0.81	1.22	0.26

[a] According to Cole and Lobstein [28]

effect estimates based on the anisotropic bandwidth Σ_{lscv} showed almost no variation over network-distances followed by the adaptive version $\tilde{\Sigma}_{lscv}$. The smallest AIC, i.e. best goodness of fit, was also found for $\tilde{\Sigma}_{lscv}$ based on a network-distance of about 1250 m in school children and school girls. In school boys goodness of fit was best using a network-distance of 2 km (Fig. 3).

Figure 4 presents patterns of results of the association between intersection intensity and MVPA in school children. Again, for larger network-distances the association was found to be stronger with larger effect estimates in school girls than in school boys. *p* values also showed significant associations in school children and in school girls from a network-distance of 1250 m and more, but not in school boys. Goodness of fit slightly differed by network-distance and intensity measure considered.

Overall, intensity measures differed less for intersection intensity than with regard to public open spaces. The anisotropic bandwidth Σ_{lscv} and the fixed bandwidth σ_f showed the smallest variation in the effect estimates over network-distances. In all samples, goodness of fit of simple intensity measures differed ranging from the largest to the smallest AIC. The smallest AIC was observed for a network-distance of 1.5 km (Fig. 4).

Figure 5 depicts the results with regard to public transit stations which showed a similar pattern. Here, the intensity measures differed less for increasing network-distance in school children. Public transit intensity also revealed significant associations with MVPA in school children and also in school girls based on all types of measures and network-distances, but not in school boys. Three intensity measures (σ_f, σ_{CV}, Σ_{lscv}) showed almost no variation in effect estimates over different network-distances (Fig. 5).

Additional files 1 and 2 present pattern of results of the three considered point characteristics based on the sample of pre-school children. Effect estimates again differed based on the considered network-distance, but showed less variation with respect to kernel intensity measures. Particularly in pre-school boys and pre-school girls, effect estimates decreased for larger network-distance. Overall, *p* values differed strongly by intensity measure and network-distance, but no significant association was found with one exception. A significant but small association between public transit density and MVPA was found in pre-school boys based on the simple intensity using a network-distance of 500 m (Additional file 3).

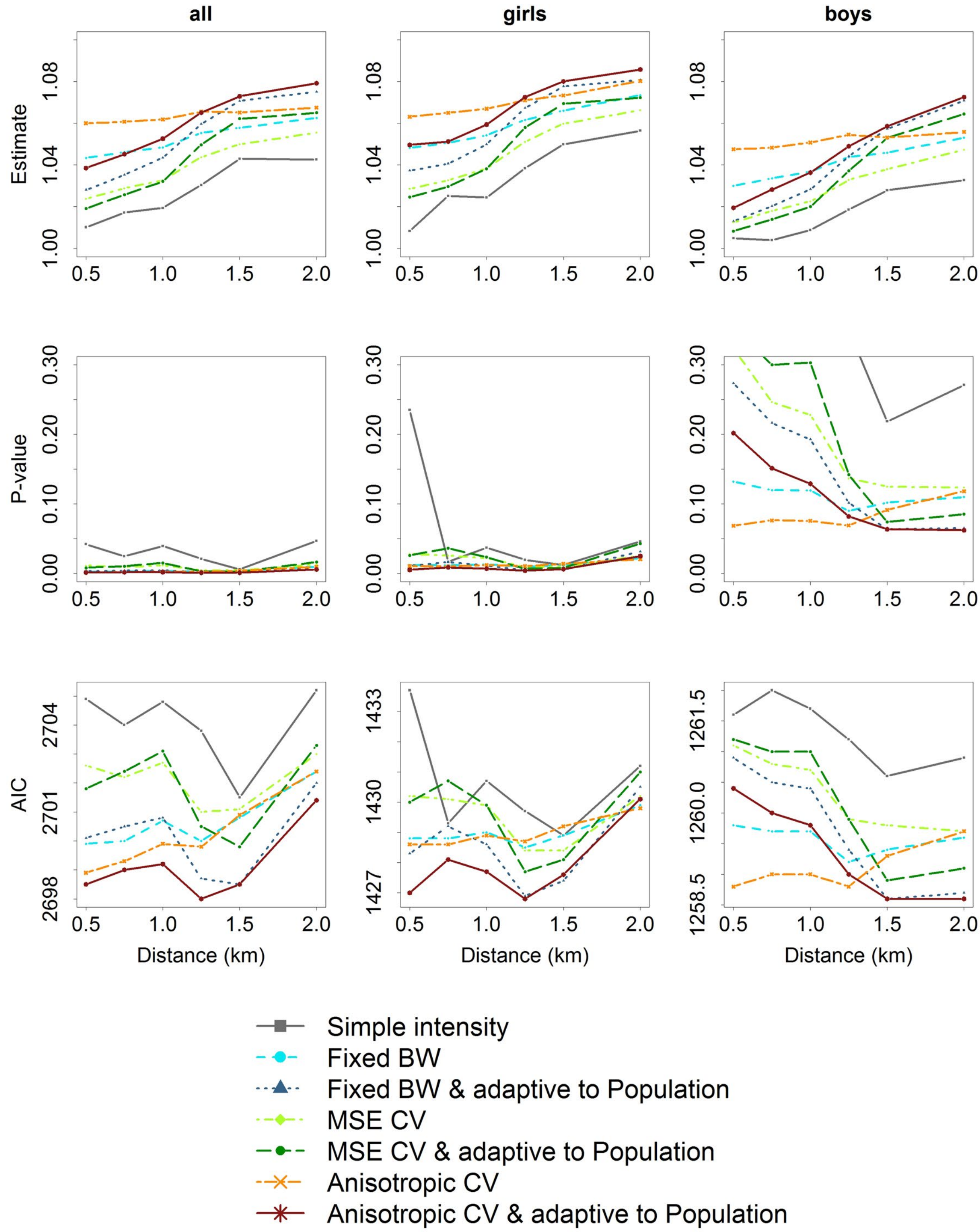

Fig. 3 Patterns of effects (*top row*), *p* values (*middle row*), and goodness of fit (AIC) (*bottom row*) of gamma-log-regression models depending on network-distance of neighborhood and intensity measures of public open spaces in school children (*left column*), school girls (*middle column*), and school boys (*right column*)

Discussion

Our results showed that the availability of public open spaces, street connectivity and the availability of public transit were positively associated with habitual PA in school children as it was previously shown [17, 21]. However, stratified results revealed the supportiveness of

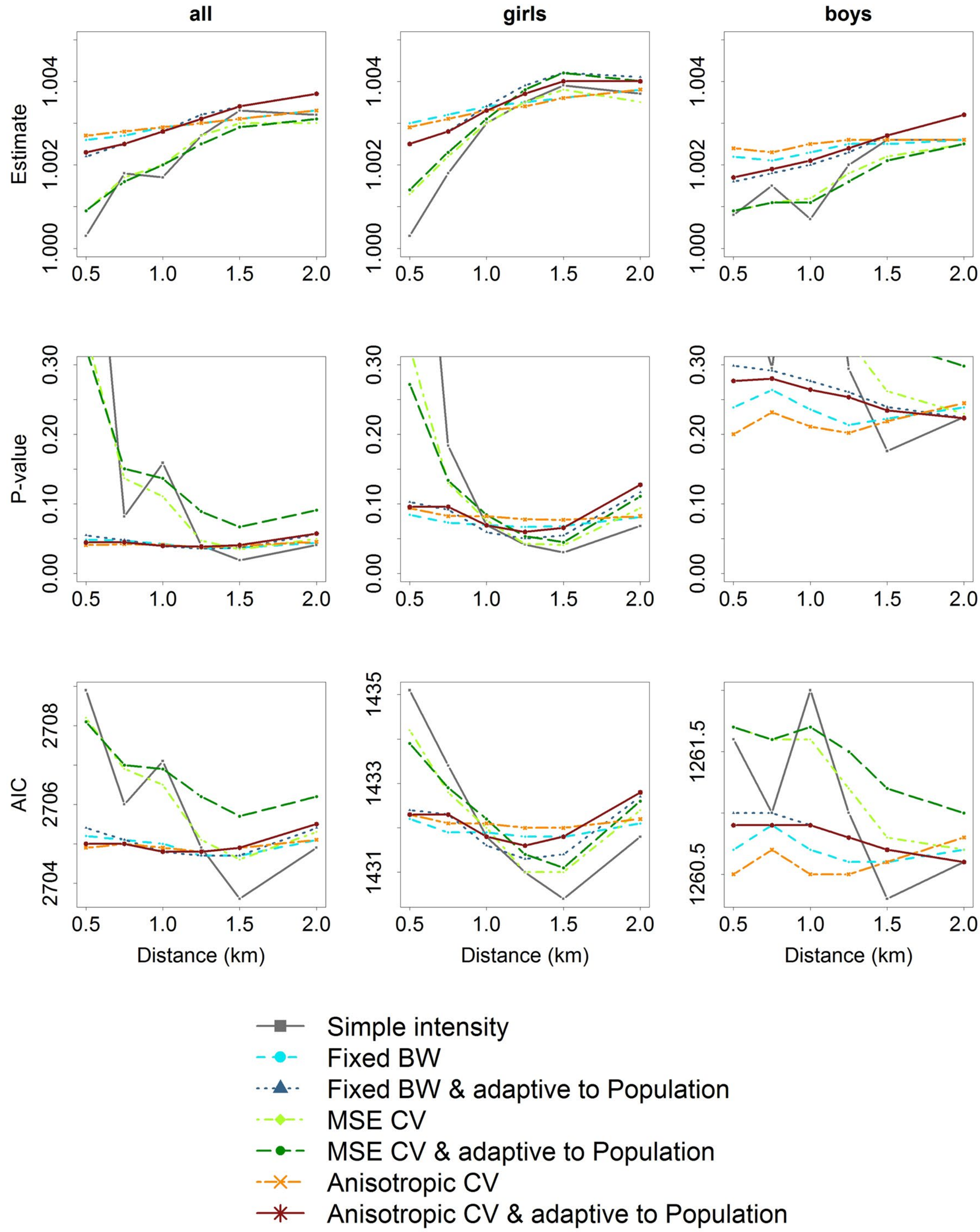

Fig. 4 Patterns of effects (*top row*), *p* values (*middle row*), and goodness of fit (AIC) (*bottom row*) of gamma-log-regression models depending on network-distance of neighborhood and intensity measures of intersections in school children (*left column*), school girls (*middle column*), and school boys (*right column*)

the built environment mainly in school girls, but not in school boys. Comparable associations of public open spaces were found in pre-school children, though street connectivity and availability of public transit showed no association with MVPA. In school children, stable results were found within a network-distance from 750 m up to

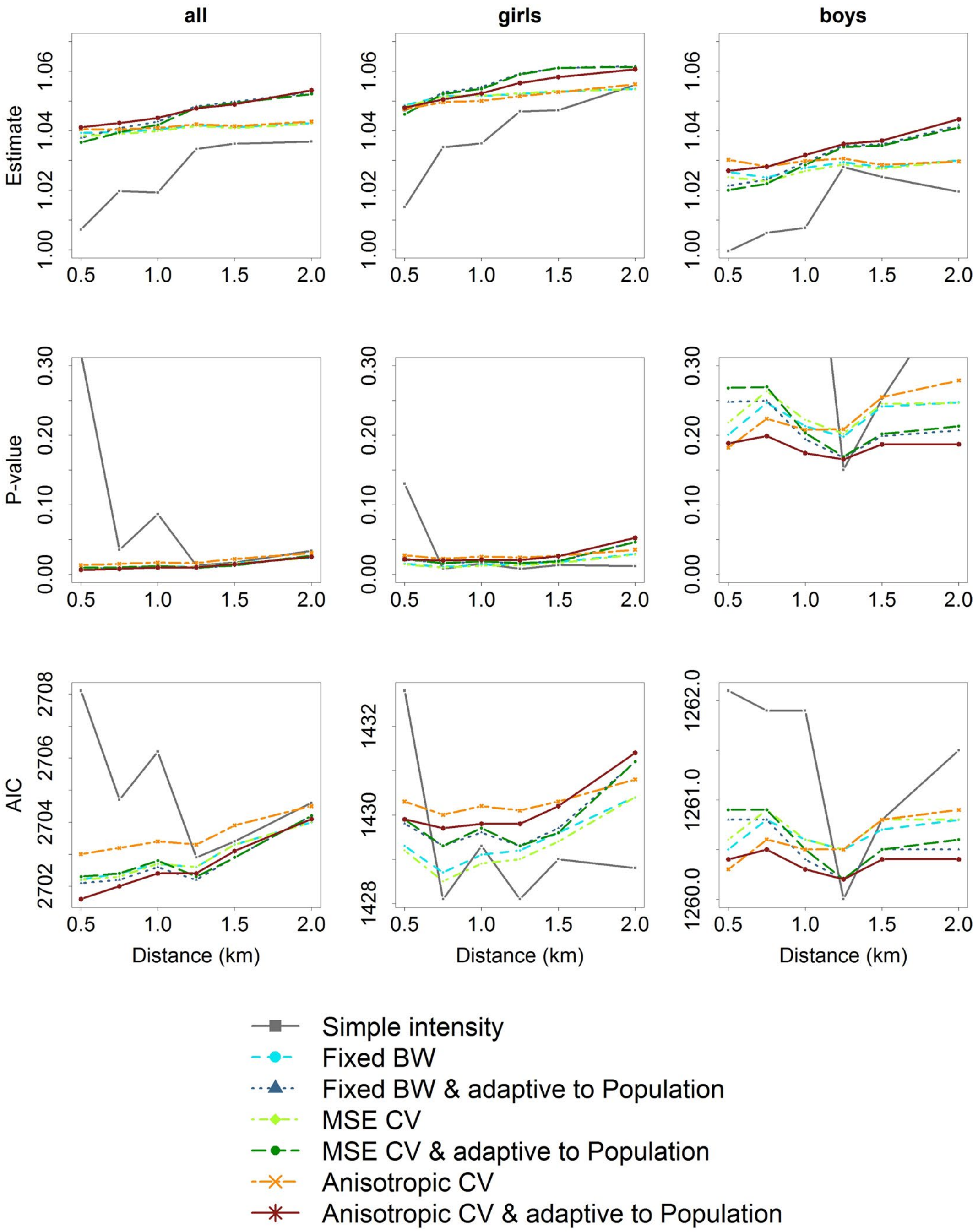

Fig. 5 Patterns of effects (*top row*), *p* values (*middle row*), and goodness of fit (AIC) (*bottom row*) of gamma-log-regression models depending on network-distance of neighborhood and intensity measures of public transit stations in school children (*left column*), school girls (*middle column*), and school boys (*right column*)

1.5 km using kernel intensity measures based on cross-validated bandwidths.

In pre-school children, effect estimates showed no association between street connectivity or availability of public transit and MVPA, but associations were found for availability of public open spaces which are similar to the association between public open spaces and MVPA in school children. Stable results were found for smaller neighborhood distances from 500 m up to 1 km, where data-driven methods again showed almost the same effect estimates over different network-distances compared to the simple intensity.

Results of the association between MVPA and urban measures based on the simple intensity, which was often used in recent publications [6, 8, 9] varied strongly by network-distance. Effect estimates of urban measures based on kernel intensity measures with cross-validated bandwidths were found to be more stable over differing network-distances. Notably, in school children, effect estimates and *p* values of urban measures based on the anisotropic cross-validated bandwidth were almost not affected by the choice of the network-distance with regard to all three point characteristics. Thus, using an anisotropic covariance matrix via cross-validation allows a more flexible modeling of the intensity and may also account for topographic features that shape the built environment and thus influence the appearance of point characteristics.

Additionally, we evaluated kernel intensity measures based on adaptive bandwidths that depend on the underlying residential density [23]. Assessing the association between point characteristics and MVPA based on an adaptive bandwidth revealed small variation in effect estimates and *p* values over network-distances from 1 to 1.5 km. Compared to the simple intensity, the anisotropic adaptive bandwidth, particularly, showed consistently larger effect estimates and smaller *p* values and showed less variation over network-distances in school children with minor disparities between school boys and school girls. The simple intensity only accounts for point characteristics within the defined neighborhood and points are either assigned or not [40]. Kernel intensity measures reduced the variance of the intensity measure compared to the simple intensity and considered point characteristics outside a defined neighborhood weighted by distance to provide a smoothed average of the availability of point characteristics within the study area. Thus, data-driven approaches might be more appropriate to assess built environment characteristics within the home neighborhood with less impact on results due to the use of different buffer distances.

In our study, goodness of fit showed only minor variation and the small differences in the AIC did not allow to identify an optimal approach or an optimal network-distance. Spielman and Yoo [12] conducted a simulation study and found that goodness of fit is not adequate to identify the optimal spatial scale in which the built environment might be assessed. For example, differences found in the spatial extent of boys and girls based on goodness of fit cannot be used to explain their spatial behavior. Thus, our choice of an appropriate intensity measure and spatial scale was based on overall performance and consistency of results. Due to the differing patterns of our results, we strongly recommend sensitivity analyses using different neighborhood scales to evaluate the consistency of the results. In a recent review, Leal and Chaix [1] emphasized the need to analyze the association between environmental exposure and health outcomes conducting more detailed analyses. Ego-centered neighborhoods should be considered and analyzed on different scales, i.e. network-distances, as to detect a possible bias in the results through sensitivity analyses and to identify comparable associations [1, 11]. Thus, our results are in line with recent discussions on the definition of the spatial context and the methodological bias [1, 10, 12, 13, 15, 40, 41].

As mentioned above, we conducted two types of sensitivity analyses (results not shown), first using a refined categorization of age groups for the stratified analyses and second considering multi-level regression to account for daily variation in the MVPA measurements. Analyses stratified by four age groups (2 to <4 , 4 to <6 , 6 to <8 , and 8 to 9.9 years) and by sex were conducted to reveal possible differences in the results between the study subgroups. Compared to the presented results, similar associations of built environment characteristics and MVPA were found and kernel intensity measures also showed more stable results compared to the simple intensity in the refined age groups. However, the small sample size in each stratum was considered too small to provide reliable results. Effect estimates and *p* values of the multi-level models differed as expected, due to the higher variability of intra-personal measurements and the larger sample size. However, performance of kernel intensity measures was similar providing more stable results over differing neighborhood scales particularly by using the anisotropic bandwidth.

Differences in the association between built environment characteristics and MVPA were identified between pre-school and school children as well as between boys and girls. Parental safety concerns were found to influence MVPA in pre-school children, especially in pre-school girls. Thus, pre-school children might experience a relatively small home neighborhood in which the availability of public open spaces or street connectivity might influence their outdoor PA that is more likely to be restricted by their parents than PA in school children. However, comparing results between pre-school and school children is limited by the small sample size for pre-school children that reduced the power of our analyses. Differences in the association of public open space intensity and street connectivity between girls and boys might be explained by including more context-specific information, e.g. sports activities in the school environment or participation in sports club outside the home neighborhood. This might be resolved in our forthcoming analyses within the framework of the I.Family study (http://www.ifamilystudy.eu) where we will employ GPS-devices.

Combined GPS- and accelerometer measurements allow to assess context-specific PA patterns [40, 42, 43] or to individualize the definition of spatial context and neighborhood scale [15] to overcome the uncertain geographic context problem [13]. In our study the association between habitual PA in children and environmental characteristics within the home neighborhood was considered, though sports activities within the school environment or destinations outside the home neighborhood might add to the overall PA [43, 44]. Results indicate that the availability of public open spaces and street connectivity within the home environment substantially contribute to overall PA of children, as it was shown in the literature [43, 45]. However, GPS-measurements allow to investigate the association between built environment characteristics and PA by generating individual activity spaces [42, 46] which do not necessarily focus on the home environment, but can also cover other environments such as the school or work environment [1]. Moreover, GPS-measurements integrated in new technologies and databases allow to combine continuous environmental variables with precise measurements of behavior and exposure on the same spatial and temporal scale [47].

Beside the methodological bias, it is important to conceptualize the spatial context considering physical or behavioral differences in the study population [1, 12, 13]. With regard to differences in PA levels and the use of the built environment, we stratified our analyses according to age groups and sex, which is suitable for a small age range. However, defining population subgroups only by simple categories such as age or sex hides multiple individual-level factors that influence PA levels and the way the built environment is perceived or used [1, 13]. In particular, self-selection factors can affect, for example, the choice of living in a walkable area, due to the preference of active travel [48] and should be considered. Similarities in the study population with regard to individual behavior, self-selection, life stages, or the perception of the environment could be addressed through latent class analyses as it was conducted by Christiansen et al. [48] and Adams et al. [49].

Some limitations in our study have to be addressed. First, results of the association might be affected by the spatial blurring that was necessary to use address coordinates, though minor effects of the spatial blurring were observed with regard to the assessment of urban measures [31]. Second, parents with medium or high educational levels were overrepresented in our study. In addition, most of the accelerometer measurements took place in autumn and winter time. Both might have also affected our results.

The major strength of our study is the use of objective measurements for the outcome on the one hand and for the environmental exposure on the other hand.

Conclusion

Considering the differences in the results of our study that are induced by the choice of intensity measure and network-distance, we found a strong variation in the association between the built environment and PA of children induced by neighborhood scale. Moreover, differences of results depending on sex and age groups as well as point characteristics revealed the possibility for false conclusions if subgroup analyses are not conducted. Taking account of important subgroups within a study sample turned out to be crucial to investigate the association between the built environment and PA levels.

Using kernel intensity measures and particularly adaptive bandwidths provided more flexibility in modeling urban measures and improved the assessment compared to the simple intensity measure by showing stable results over various spatial scales. Thus, data-driven methods might reduce methodological limitations that typically occur when assessing opportunities for PA in the built environment.

Additional files

Additional file 1: Patterns of effects (*top row*), *p* values (*middle row*), and goodness of fit (AIC)(*bottom row*) of gamma-log-regression models depending on network-distance of neighborhoodand intensity measures of public open spaces in pre-school children (*left column*), pre-school girls(*middle column*), and pre-school boys (*right column*).

Additional file 2: Patterns of effects (*top row*), *p* values (*middle row*), and goodness of fit (AIC)(*bottom row*) of gamma-log-regression models depending on network-distance of neighborhoodand intensity measures of intersections in pre-school children (*left column*), pre-school girls(*middle column*), and pre-school boys (*right column*).

Additional file 3: Patterns of effects (*top row*), *p* values (*middle row*), and goodness of fit (AIC)(*bottom row*) of gamma-log-regression models depending on network-distance of neighborhoodand intensity measures of public transit stations in pre-school children (*left column*), pre-school-girls (*middle column*), and pre-school boys (*right column*).

Authors' contributions

IP was responsible for the conceptualization and the design of the environmental analyses within the IDEFICS study. CB and TK conceptualized the geostatistical modeling. CB and TT collected and processed geographical data. KK processed accelerometer data. CB conducted the statistical analyses and wrote the manuscript. All authors have contributed to the final manuscript. All authors read and approved the final manuscript.

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Competing interests
The authors declare that they have no competing interests.

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C. Curriculum Vitae

Curriculum Vitae Christoph Buck

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Educational background

June 2002	General qualification for university entrance (Abitur) at the Altes Gymnasium Bremen
Aug 2002 – June 2003	Alternative civilian service (protestant Zion Church, Bremen)
Oct 2003	Academic studies of Mathematics at the University of Bremen
Dez 2008	Diploma in Mathematics (grade: very good)

Professional Career

Since Apr 2009	Research Associate at Leibniz Institute for Prevention Research and Epidemiology – BIPS GmbH (formerly: ZWE BIPS, University of Bremen)

Membership in scientific associations

German Society of Epidemiology (DGEpi)

German Region of the International Biometric Society

List of publications:

Publications in scientific journals with peer-review

1. Buck C, Dreger S, Pigeot I (2015). Anonymisation of address coordinates for micro-level analyses of the built environment: A simulation study. *BMJ Open* **5**(3):e006481.

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Publications without peer-review

1. Buck C (2014). Bewegungsfreundliche Merkmale im urbanen Raum [Walkable characteristics in the urban environment]. *IPP Info* **10**(12):9-11.

2. Buck C, Pigeot I (2011). Quantifying environmental opportunities for physical activity in children: A pilot application. *WHO Collaborating Centre for Housing and Health Newsletter* (10):3-5.

Book chapters

1. Bödeker M, Buck C, Bucksch J, Schmidt A, Schneider S (2014). Werkstattgespräch: Grenzen und offene Fragen zum Walkability-Konzept [Workshop Discussion: Barriers and unresolved Issues]. In: Bucksch J, Schneider S (Eds.). Walkability - Das Handbuch zur Bewegungsförderung in der Kommune [Walkability - a hand book of community-based physical activity promotion]. Bern: Hans Huber: 301-320.

2. Buck C, Tkaczick T (2014). Geographische Informationssysteme [Geographical Information Systems]. In: Bucksch J, Schneider S (Eds.). Walkability - Das Handbuch zur Bewegungsförderung in der Kommune [Walkability - a hand book of community-based physical activity promotion]. Bern: Hans Huber: 165-178.

Selected presentations at scientific meetings/conferences

1. Buck C, Dreger S, Pigeot I. Verrauschung von Adressdaten zur Verwendung in der räumlichen Epidemiologie [Anonymization of address data for spatial epidemiology]. 10. Annual Meeting of the German Society for Epidemiology (DGEpi), 30. September-2. October 2015, Potsdam, Germany

2. Buck C, Kneib T, Tkaczick T, Konstabel K, Pigeot I. Interrelation of kernel density methods and neighborhood context in the assessment of environmental opportunities for physical activity in children. 14th Annual Meeting of the International Society of Behavioral Nutrition and Physical Activity (ISBNPA), 3-6 June 2015, Edinburgh, United Kingdom.

3. Buck C, Kneib T, Tkaczick T, Konstabel K, Pigeot I. Assessing spatial availability of urban point characteristics to explain physical activity in children: Evaluation of kernel approaches and neighborhood. 60. Biometric Colloquium of the German region of the international Biometric Society (IBS-DR), 10.-13. March 2014, Bremen, Germany.

4. Buck C, Pitsiladis Y, Pigeot I, on behalf of the IDEFICS consortium. How the built environment influences physical activity in children. 12th Annual Meeting of the International Society of Behavioral Nutrition and Physical Activity (ISBNPA), IDEFICS-Symposium: "Physical Activity in Small Children - Assessment, Determinants, Health Outcomes and Methodological Challenges," 22-25 May 2013, Ghent, Belgium.

5. Buck C, Börnhorst C, Pohlabeln H, Lanfer A, Hebestreit A, Huybrechts I, Pala V, Reisch L, Pigeot I, on behalf of the IDEFICS consortium. Does environmental food supply influence junk food consumption of school children? First results of the IDEFICS study. 8th International Conference on Diet and Activity Methods (ICDAM), 14-17 May 2012, Rome, Italy.

6. Buck C, Pohlabeln H, De Bourdeaudhuij I, Pitsiladis Y, Reisch L, Pigeot I. Urban opportunities for physical activity in children. Development and application of a moveability index. 11th Annual Meeting of the International Society for Behavioral Nutrition and Physical Activity (ISBNPA), 23-26 May 2012, Austin, USA.

7. Buck C, Pohlabeln H, De Bourdeaudhuij I, Reisch L, Pigeot I. Messung von Bewegungsmöglichkeiten in der urbanen Lebensumwelt von Kindern [Assessment of opportunities for physical activity in the environment of children]. 7th Annual Meeting of the German Society for Epidemiology (DGEpi), 26.-29. September 2012, Regensburg.

8. Buck C. Development and application of a moveability index to assess the opportunities for physical activity in the neighborhood environment of children. Sahlgrenska School of Public Health and Community Medicine, 6 May 2011, Gothenberg, Sweden.

9. Buck C. Geographic Information System: Assessing the urban environment of children. Intensivkurs "Tools Targeted on Obesity Intervention and Prevention Strategies for Efficient and Sustained Implementation" (TOOLTIPS) in the Framework of the Erasmus "Lifelong Learning Programme" of the EU, February 21 – March 7, 2010, Grundlsee, Austria.

10. Buck C, Pohlabeln H, Pigeot I. Entwicklung eines Walkability-Index zur Quantifizierung der Bewegungsmöglichkeiten in urbaner Umgebung [Development of a walkability index to assess opportunities for physical activity in the urban envionrment]. Workshop "Health Geography - Geographische Methoden in Epidemiologie und Versorgungsforschung" [Geographical methods in epidemiology and care research] of the working group Health Geography of the German Society for Epidemiology (DGEpi), 25. Juni 2010, München, Germany.

Invited presentations at scientific meetings/conferences

1. Buck C. Micro-level analysis of urban opportunities for physical activity in children: A comparison of measurements and neighbourhoods. Zentrum für interdisziplinäre Forschung (ZiF) Workshop "Defining Neighbourhoods to Measure Contextual Effects on Inequalities: Large or Small? Pre-defined or Self-defined?", 2-4 June 2014, Bielefeld, Germany.

2. Buck C, Tkaczick T. Geoinformationssysteme und ihre Potenziale für die Bewegungs- und Gesundheitsförderung [Geoinformation systems and their potential for physical activity and health promotion]. 4th Symposium of the center for phyiscal activity promotion of North Rhine-Westphalia, 15. November 2012, Düsseldorf, Germany.

3. Buck C, Pohlabeln H, Pigeot I. Charakterisierung des bebauten Wohnumfeldes mit Hilfe von GIS am Beispiel der IDEFICS-Studie [Characterization oft he built environment using GIS exemplarily for the IDEFICS study]. Workshop of the joint working group „environmental medicine, exposure- and risk evaluation "Umweltmedizin, Expositions- und Risikoabschätzungen" of the DGEpi, DGSMP and GMDS, 31. March - 1. April 2011, Hannover, Germany.

Posters at scientific meetings/conferences

1. Buck C, Pigeot I. Methoden zur Untersuchung von urbanen Bewegungsmöglichkeiten: Definition von individuellen Nachbarschaften und adaptive Kernintensitäten [Methods to investigate urban moveability: Definition of individual-level neighborhoods and adaptive kernel intensities]. 10. Annual Meeting of the German Society for Epidemiology (DGEpi), 30. September-2. October 2015, Potsdam, Germany.

2. Pigeot I, Buck C, Pohlabeln H, Huybrechts I, Pitsiladis Y, De Bourdeaudhuij I, Reisch LA, on behalf of the IDEFICS consortium. Development and application of a moveability index to quantify possibilities for physical activity in the built environment of children. 3rd North American Congress of Epidemiology, 21-24 June 2011, Montreal, Canada.