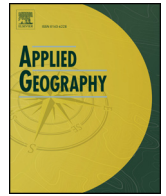




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Dynamic cities: Location-based accessibility modelling as a function of time

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ABSTRACT

The concept of *accessibility* – the potential of opportunities for interaction – binds together the key physical components of urban structure: people, transport and social activity locations. Most often these components are dynamic in nature and hence the accessibility landscape changes in space and time based on people's mobilities and the temporality of the transport network and activity locations (e.g. services). Person-based accessibility approaches have been successful in incorporating time and space in the analyses and models. Still, the more broadly applied location-based accessibility modelling approaches have, on the other hand, often been static/atemporal in their nature. Here, we present a conceptual framework of dynamic location-based accessibility modelling that captures the dynamic temporality of all three accessibility components. Furthermore, we empirically test the proposed framework using novel data sources and tools. We demonstrate the impact of temporal aspects in accessibility modelling with two examples: by investigating food accessibility and its spatial equity. Our case study demonstrates how the conventional static location-based accessibility models tend to overestimate the access of people to potential opportunities. The proposed framework is universally applicable beyond the urban context, from local to global scale and on different temporal scales and multimodal transport systems. It also bridges the gap between location-based accessibility and person-based accessibility research.

1. Introduction

The UN has projected that the amount of people living in urban areas will rise from the 54% at present to 66% by 2050 (UN, 2014, 2015). Our cities are forming an ever more complex global network society (Castells, 2000) that is steered by the flows of people, products, waste, money and data (Urry, 2007). This reshaping of mobile urban societies is influencing not only the daily lives of citizens (Cresswell & Merriman, 2011) and the dynamic structures of cities (Batty, 1971), but also the global economy and urban hierarchies (Sassen, 1991). The rapidly urbanizing world is challenged by a myriad of environmental and social problems. A comprehensive understanding of the dynamics of cities from spatial, temporal and social perspectives is needed to be able to plan sustainable and liveable cities, and to mitigate social challenges such as socio-spatial inequality, public health, segregation and aging.

Spatial accessibility is one of the key conceptual and methodological tools for examining and modelling urban patterns and processes (Bertolini, le Clercq, & Kapoen, 2005; Geurs, Krizek, & Reggiani, 2012).

The concept of accessibility binds together the key components of an urban structure: people, mobility and social activities, and makes it possible to have a functional view of urban structures and processes. In general, spatial accessibility describes “the potential of opportunities for interaction” (Hansen, 1959). However, the concepts of access and accessibility are slippery notions that have many definitions (Gould, 1969; Penchansky & Thomas, 1981). The conceptualization and operationalization varies substantially depending on whether accessibility is examined from a location-based (also referred to as place-based) or a person-based perspective. Also, the applied approach for measuring accessibility (constraint-, attraction-, or benefit-oriented), the complexity of modelling (e.g. social, economic, and environmental components), the measure of network distance (time, distance, CO₂ load or trip quality, e.g. Banister, 2011) as well as the broader research context influences how (and what) accessibility is examined (Geurs & van Wee, 2004; Miller, 2005). Overall, defining accessibility and developing methods to measure accessibility has improved over time and continues to be an ongoing effort (van Wee, 2016).

Accessibility has become an important analytical approach and the

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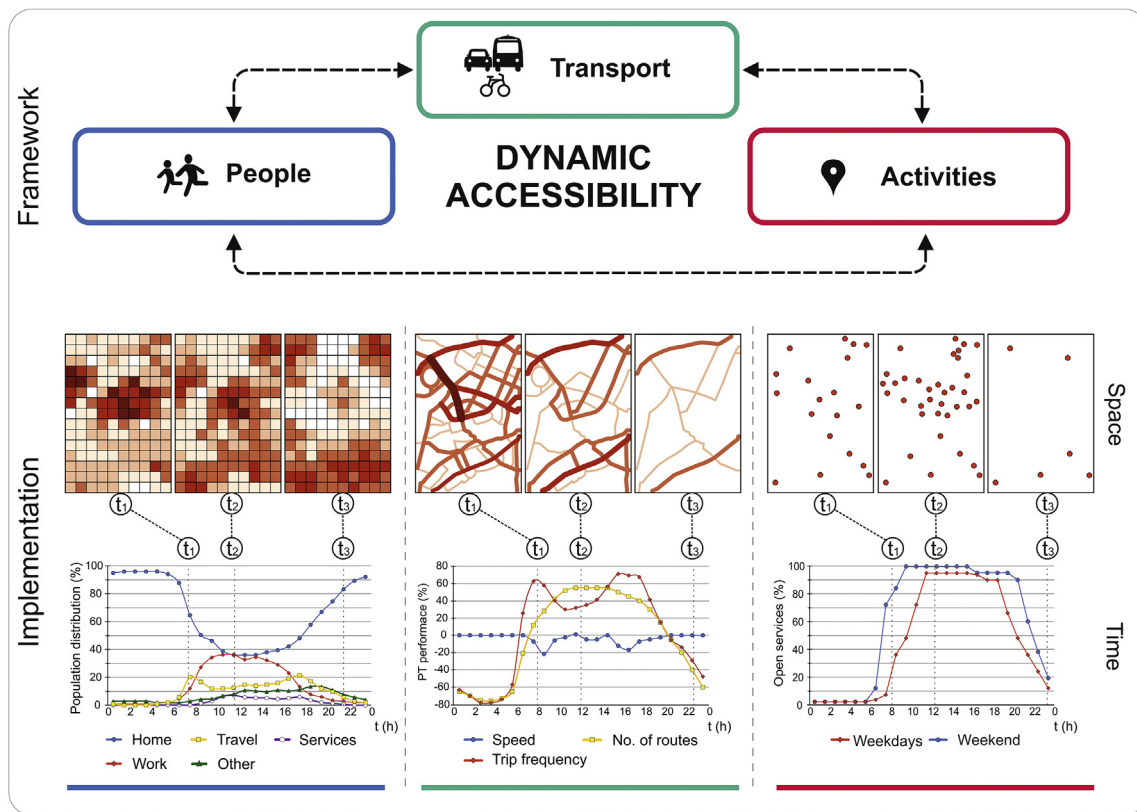


Fig. 1. The conceptual framework for a dynamic location-based accessibility modelling (top), where all three basic components of spatial accessibility (people, transport and activities) vary as a function of time. The implementation of the framework (bottom) is an illustration of our case study, exemplifying the variation of accessibility in space and time to grocery stores in Helsinki, taking into account all the three accessibility components within a 24-h timeframe. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

existing literature is rich in applications (van Wee, 2016). From a location-based modelling perspective, accessibility has been used as a tool to understand the compactness, functioning, sustainability and equity of the urban form and to identify likely centres of social interaction. Examples range from analysing transport network efficiency and land use strategies (Benenson, Martens, Rofé, & Kwartler, 2011; Geurs & van Eck, 2003; Gutiérrez & García-Palomares, 2008; Kujala, Weckström, Mladenović, & Saramäki, 2018; Vandenbulcke, Steenberghen, & Thomas, 2009) to the economic performance of a city (Chin & Foong, 2006; Salas-Olmedo, García-Alonso, & Gutiérrez, 2016). Accessibility has also been applied to understand the social and environmental justice (Farrington & Farrington, 2005; Laatikainen, Tenkanen, Kyttä, & Toivonen, 2015; Wolch, Byrne, & Newell, 2014) and the spatial equity in urban areas (Dai & Wang, 2011; Lucas, van Wee, & Maat, 2016; Talen & Anselin, 1998; Van Wee & Geurs, 2011). Recently, more applications are being linked to public health (Neutens, 2015; Tenkanen, Saarsalmi, Järv, Salonen, & Toivonen, 2016; Widener, Farber, Neutens, & Horner, 2015), wellbeing and the quality of life of urban dwellers (Casas, 2007; Lowe & Mosby, 2016; Serag El Din, Shalaby, Farouh, & Elariane, 2013).

While the concept of spatial accessibility is inherently related to time, as it determines access to, and the use of desired social opportunities, the time dimension has to date been poorly incorporated into spatial accessibility modelling (Kwan, 2013). Despite advances in time-dependent person-based accessibility modelling (see, e.g. Neutens, Delafontaine, Schwanen, & Weghe, 2012; Widener et al., 2015), still most of the location-based accessibility models rely entirely or partially on an atemporal view of access (Chen et al., 2017; Lucas et al., 2016). Such “sedentary” models presume that people are at home, and that both transport supply and the opportunities for activities of social practices are fixed in time. However, neglecting the temporal dynamics of cities and the mobility of inhabitants (Schönfelder & Axhausen,

2010) may lead to biased or even misleading conclusions in accessibility models (Neutens et al., 2012; Tenkanen et al., 2016).

One factor limiting the full incorporation of the time dimension into a location-based accessibility modelling has been the lack of temporally sensitive spatial data. In recent years, however, suitable data sources for modelling have gradually emerged. For example, General Transit Feed Specification (GTFS) data is providing temporal data on public transport, and platforms like Foursquare or Yelp on the activity locations of people (Dewulf et al., 2015; Tenkanen et al., 2016; Widener et al., 2015). Still, even in the case of partially dynamic location-based accessibility studies, there is often a lack of information on the actual whereabouts of people in time (see, e.g. Widener et al., 2017). Such information would be needed to facilitate dynamic accessibility modelling instead of using static census data. However, the widespread use of mobile communication technologies and the emerging big data revolution are providing additional data sources (e.g. mobile phone or social media data) to reveal dynamic locations of people (Chen et al., 2018; Kitchin, 2014; Moya-Gómez, Salas-Olmedo, García-Palomares, & Gutiérrez, 2017). The latter is needed for applying fully dynamic accessibility modelling.

In this paper, we aim to contribute to the conceptual development of location-based accessibility research by proposing a generic conceptual framework of dynamic location-based accessibility modelling, where all three of the core components of accessibility (people, transport, and activity locations) are considered as a function of time. Furthermore, we exemplify the proposed framework by investigating urban food accessibility. This example was chosen because food is one of the basic physiological needs for everyone, and because the social inequality of accessing food stores from the spatial accessibility perspective often depends on time (Fransen et al., 2015; Stepniak & Goliszek, 2017). We take advantage of novel data sources (GTFS, mobile phone data,

OpenStreetMap) and test systematically: 1) how different components of the dynamic accessibility model are affected by time; 2) to what extent a fully dynamic accessibility model differs from a static model; and 3) how temporal dynamics in accessibility influence the measures of spatial equity. Finally, we discuss the pros and cons of dynamic accessibility modelling and identify potential data sources for the implementation of dynamic accessibility models.

2. Dynamic accessibility modelling as a generic conceptual framework

2.1. Components of dynamic accessibility

Given that everything in our world takes place in inherently inter-related space-time, it is evident that accessibility is inherently both a *spatial* and a *temporal* phenomenon. We acknowledge the conceptual idea of a person-based space-time accessibility modelling (Hägerstrand, 1970; Miller, 1991; Neutens, Schwanen, Witlox, & De Maeyer, 2010; Pirie, 1979) and apply it to a location-based accessibility modelling framework. The generic conceptual framework of dynamic location-based accessibility modelling consists of three components – *people*, *transport*, *activities* – which all occur in and are shaped by inter-dependent spatial and temporal dimensions (Fig. 1).

The first core component of dynamic accessibility – *people* – is related to the needs and abilities of individuals regarding their socio-economic factors, values, preferences, attitudes, prejudices and habits that influence one's opportunities to access certain transport modes and activities (Geurs & van Wee, 2004). This is directly related to what type of activities people are performing, and where and when the given activities are conducted. Thus, it is important to know how individuals are spatially distributed in relation to the activity locations. In location-based accessibility modelling, the spatial distribution of people has so far been regarded as the most static as it is commonly derived from residential areas (Tenkanen et al., 2016; Widener et al., 2017), despite the critiques against the assumption of home-based journeys in transport research generally (Naess, 2006).

Certainly, home is one of the most important locations in our daily lives (Vilhelmson & Thulin, 2008), yet people are not spatially fixed to their homes as accessibility research predominantly presupposes (Schönfelder & Axhausen, 2010). People from different socio-economic groups conduct different social activities (e.g. sleep, work, and conduct leisure activities) at certain places and at certain times with certain activity sequences resulting in a dynamic spatial distribution of people in hourly, daily, weekly, monthly and yearly temporal patterns (Deville et al., 2014; Järv, Muurisepp, Ahas, Derudder, & Witlox, 2015; Schönfelder & Axhausen, 2010). Thus, the dynamic (also referred to as ambient) population – the actual whereabouts of people (e.g. by different social group) in time – need to be considered for modelling more realistic accessibility.

The second core component of dynamic accessibility – *transport* – allows people to move from an origin to a desired destination location. The transport component comprises the spatial outcome of the transport system, including different modes of travel (walk, bicycle, private car, public transport). The “cost” that it takes to move from one place to another is most often measured in time or distance (Banister, 2011), but also measures of CO₂, monetary value, or the quality of a trip have been used as measures of the cost of moving between places (Lahtinen, Salonen, & Toivonen, 2013; Salonen, Tenkanen, Heikinheimo, & Toivonen, 2016). Different modes of transport and different measures of cost have different sensitivities to temporal changes (Tenkanen et al., 2016). At a small temporal granularity (24 h, a week), the public transport (PT) supply is generally the most dependent on time, as the availability and density of lines and routes changes (Salonen & Toivonen, 2013), influencing travel times and experiences. For a private car, the day of the week and hour of the day (e.g. peak hours) do not necessarily change the distances, but can significantly affect travel

times and experience, as actual travel speeds vary from free flow to congested situations (Dewulf et al., 2015; Yiannakoulis, Bland, & Svenson, 2013). Furthermore, the time and effort spent on finding a parking space and reaching a desired destination depend on timing. For non-motorised transport (walking, cycling), differences between individuals are generally greater than temporal variation, and the CO₂ burden is always roughly the same. Temporality becomes very important, however, when the inspection is expanded over seasons: depending on the latitude, biking can be much more challenging in winter than in summer conditions (Noland, Smart, & Guo, 2016).

The third core component of dynamic accessibility – *activities* – comprises all the possible activity opportunities in order to perform social practices that people desire, or are bound to conduct, such as going to work and school, meeting people, obtaining services, attending events, or discovering desired places. Potential activity locations for possible social opportunities are determined by the spatial distribution of given activity locations as well as their temporal availability – operating hours of the day, weekday schedule as well as the seasonal schedule (Delafontaine, Neutens, Schwanen, & Weghe, 2011; Tenkanen et al., 2016; Widener et al., 2017).

2.2. From components to dynamic modelling

Integrating the dynamics of each component into accessibility models allows inspection of dynamic location-based accessibility landscapes. In mathematical terms (Equation (1)), the framework of dynamic accessibility DA can be defined as:

$$DA = \int (P T A)_{st} \quad (1)$$

where P refers to the people component, i.e. the spatial distribution of people as origins from where they depart, T refers to the transport component, i.e. the spatial distribution of the transport system supply allowing people to reach desired destinations with a certain cost, and A refers to the activities component, i.e. the spatial distribution of opportunities for activities as destination locations for desired social practices in space *s* and time *t*. Certainly, the implementation of a fully dynamic accessibility model depends on what accessibility is being modelled, and what kind of time perspective it is feasible to include. The proposed framework also allows one to consider more complex modelling by considering the clustering of activities of people and their trip chaining, if the given data is available.

The given framework stems from ideas of a person-based accessibility modelling where the time dimension is already well-adopted and many advanced time-dependent methods are developed, such as individual space-time accessibility (Lee & Miller, 2018; Neutens et al., 2012; Widener et al., 2015). In recent years, also activity- and trip-based transport simulation modelling has been applied for assessing accessibility (Bellemans et al., 2010; Horni, Nagel, & Axhausen, 2016; Ziemke, Joubert, & Nagel, 2017). However, the vast popularity of location-based accessibility modelling among scholars and practitioners lies in its generic nature and simplistic use. With our proposed framework, we take location-based accessibility modelling one step closer to a person- (activity)-based accessibility modelling framework – we combine the strength of place-based accessibility with time-dependent spatial modelling.

3. Demonstrating the framework: data and methods

We demonstrate the applicability of the proposed framework in practice by presenting an empirical study on urban food accessibility over a 24-h period in Tallinn, the rapidly transforming post-Soviet capital city of Estonia (Sjöberg & Tammaru, 1999).

3.1. Mobile phone data as one proxy for people

This study employed a set of one-month anonymized mobile phone call detail records (CDRs) collected by the largest mobile network operator in Estonia in March 2015. Whenever a mobile subscriber used a phone within the city of Tallinn, the anonymous user ID, time of the call, and the location of the user at base station level was recorded. The inherent uneven spatial resolution bias of CDR data is minimized using a multi-temporal function-based dasymetric interpolation method (see, e.g. Järv, Tenkanen, & Toivonen, 2017). Here, the CDR-based estimate of the number of people per antenna is allocated to $500\text{ m} \times 500\text{ m}$ statistical grid cells suitable for accessibility modelling for each hour of a day. For more details, see [Supplementary Information S1](#). We consider the relative distribution of hourly CDR data as a proxy for population distribution by grid cells ([Supplementary Information S2](#)). The allocated locations of people at given hour of the day are the departure locations (the centroids of grid cells) from which the travel times to the closest open grocery store are calculated.

3.2. Temporally sensitive transport supply and service network data

We use grocery stores in Tallinn as the destination activity locations. Data for grocery store addresses and opening hours were derived from the websites of the stores in March 2016. Addresses were further geocoded into target points. We use open-access General Transit Feed Specification (GTFS) data to retrieve up-to-date routes and schedules for public transport (PT), and select Wednesday 16th March 2015 to represent working day schedules. OpenStreetMap road network data is used to calculate the walking parts of a PT journey by setting the walking speed to 70 m per minute (4.2 km/h). For short travel distances, walking is used as a travel mode, if that is faster than reaching the destination by PT. We calculate the travel times from the centroids of 500 m statistical grid cells. We apply an advanced door-to-door approach for the travel time measurements, where all parts of the journey, including walking and possible transfer and waiting times, are taken into account (Salonen & Toivonen, 2013).

We apply a freely available open source accessibility tool *localroute.js* (www.github.com/HSLdevcom/localroute) to calculate the fastest routes between origin and destination by PT and walking based on a modified version of Dijkstra's algorithm (Järvi, Salonen, Saarsalmi, Tenkanen, & Toivonen, 2014). The fastest routes for every hour of the day are calculated from the centroids of each statistical grid cell to the nearest open grocery store at a given time. Since departure times may affect travel times due to varying schedules of PT, we select the fastest route based on a set of routes with 5 different departure times for each hour (e.g. departures 12:01, 12:04, 12:09, 12:11 for 12 o'clock) according to the Golomb ruler (Bloom & Golomb, 1977). The developed codes and tools for the applied methods are openly available at GitHub (<http://www.github.com/AccessibilityRG/DYNAMO>).

3.3. Modelling dynamic accessibility

Accessibility can be measured in various ways. However, travel time is often used as a tangible measure of accessibility in providing a surrogate for the easiness of reaching these opportunities (Bertolini et al., 2005; Frank, Bradley, Kavage, Chapman, & Lawton, 2007). Hence, we measure accessibility as travel time between origins (locations of people) and destinations (available activity locations) for each hour of the day.

In total, we apply five different accessibility models (see [Table 1](#)). We first calculate the static accessibility model, where all three accessibility components are atemporal (model 1): we consider the PT network and schedule of a morning peak hour at 7:00–7:59 a.m. as a benchmark indicator in line with other studies (El-Geneidy et al., 2016); the distribution of population is derived from population register data; and all grocery stores are considered to be open. Then, we

Table 1

Different scenarios applied to demonstrate the impact of time on different components of fully dynamic accessibility model.

	People	Transport	Activity locations
Model 1	Static	Static	Static
Model 2	Dynamic	Static	Static
Model 3	Static	Dynamic	Static
Model 4	Static	Static	Dynamic
Model 5	Dynamic	Dynamic	Dynamic

include temporal data into each accessibility component at the time, resulting in three partially dynamic accessibility models (models 2–4). Finally, the model 5 is fully dynamic accessibility model where we consider time in all the three components of accessibility.

3.4. Spatial equity measure

The final aspect is to demonstrate how the fully integrated time dimension in accessibility modelling influences the measures of spatial equity, which has rarely been studied from the temporal perspective using a systematic approach (Stępnik & Goliszek, 2017). The Gini coefficient (GC) is a widely used indicator of social equity (Gini, 1936), and often used also in relation to accessibility as an indicator for spatial equity (see Lucas et al., 2016 for an overview). Here, GC is used to evaluate the spatial equity of accessibility to grocery stores as GC is calculated for each hour of the day by comparing the ratio of the area between the Lorenz curves (accessible population) and the line of perfect equality, which assumes uniform accessibility among all people. The Lorenz curve represents the rank-ordered cumulative share of population with access to stores.

4. Demonstrating the framework: results

4.1. Implementing dynamic accessibility - case of food accessibility

The baseline for our analysis is a conventional static accessibility model without incorporating time into any of the three components: the location of people is derived from register-based home locations; the transport network is based on one snapshot of a public transport schedule; and all grocery stores are assumed to be open. According to the static model ([Fig. 2A](#)), some 82% of people in the case study area reach the closest grocery store within 10 min by public transport.

The effect of incorporating time into each of the three accessibility components separately is shown in [Fig. 2](#). From the model considering the hourly variation in population distribution as the only dynamic component (with the other two components being static), some 70–77% of people reach their closest grocery store within 10 min depending on the hour of the day ([Fig. 2B](#)). By considering the hourly variation in public transport supply (routes and schedules) as the only dynamic component in the model, the outcome shows no significant temporal changes in accessibility, since the model assumes that all stores are open and people stay at home ([Fig. 2C](#)). The model considering the hourly variation in activity locations (i.e. the availability of grocery stores) as the only dynamic component reveals a clear influence of time – the availability of destination locations affects clearly the spatial accessibility in time ([Fig. 2D](#)). According to the latter model, some 82% of people reach their closest grocery store within 10 min at a day time (9 a.m.–10 p.m.) while at other times accessibility is more limited due to fewer grocery stores being open.

[Fig. 2E](#) presents a full dynamic model where all three components are temporally sensitive. The overall hourly pattern shows how spatial accessibility is influenced by time. From a city level, differences in accessibility vary slightly from 9 a.m. to 9 p.m. and on average 74% of people reach the closest grocery store within 10 min. Differences do occur from late night until early morning; for example, at 10 p.m. only



Fig. 2. A step-wise incorporation of time into accessibility modelling in case of Tallinn. Lines indicate the share of people reaching the closest grocery store by hour of the day, based on a fully static accessibility model (A), a model with only dynamic population component (B), a model with only dynamic transport component (C), a model with only dynamic activity locations (e.g. stores), and a model with fully dynamic accessibility components (E). Figure E includes the line for the static model as a baseline to compare the influence of time on food accessibility. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

39% of people reach the closest grocery store within 10 min, while at 8 a.m. some 65% of people reach them accordingly. During the night, access to a grocery store is limited given the lack of public transport supply and fewer grocery stores being open.

At a local scale, the temporal variation of access to a grocery store in the case of travel time is evident within a city (Fig. 3). Dynamic accessibility reveals how travel time to the closest grocery store varies in space regarding the transport system supply and potentially available activity locations (i.e. grocery stores) at a given hour of the day

(Supplementary Information S3).

4.2. Dynamic vs. static accessibility model

At a city level, differences between the static and dynamic accessibility models are evident – a static accessibility model tends generally to overestimate people’s access to a grocery store, and particularly from late evening until the morning hours (Fig. 2E). At local (grid cell level), differences between the static and dynamic models depend on time of

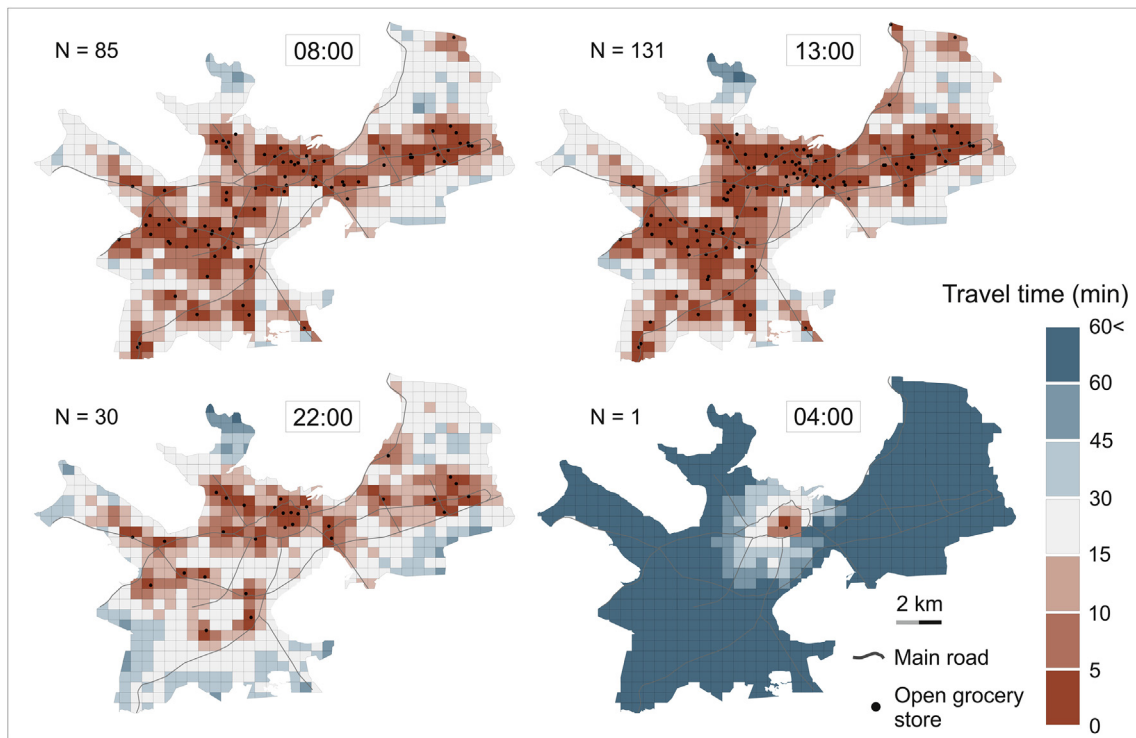


Fig. 3. Spatial variation of travel times to the closest grocery store by grid cell level at four different time periods of the day. N indicates the number of open grocery stores at a given time. The variation of food accessibility in Tallinn for the whole 24-h time frame as an animation is available at GitHub (<http://www.github.com/AccessibilityRG/DYNAMO>). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

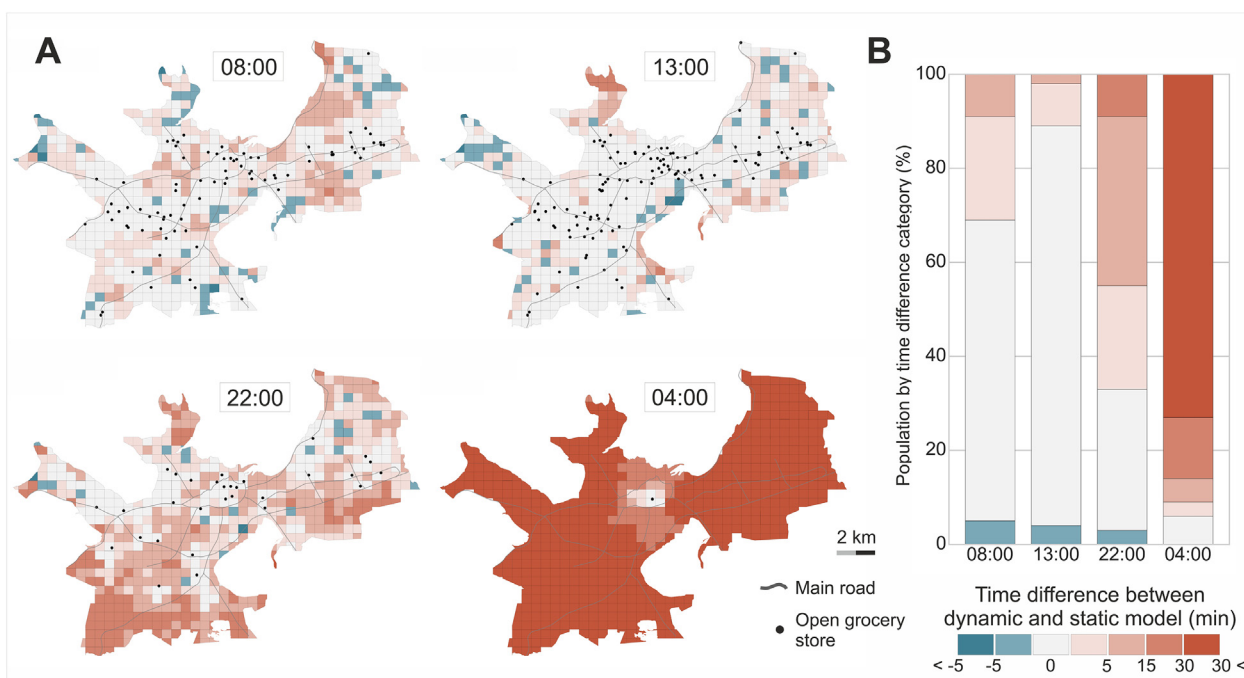


Fig. 4. Comparison between the fully dynamic accessibility model and the static accessibility model. The maps (A) show differences in travel time to the closest grocery store between the two models at different times of the day (A). The graphs (B) show the population in Tallinn aggregated to given travel time difference categories. In both cases, red indicates more minutes of travel according to the dynamic model compared to the static model, whereas blue indicates shorter travel times in the dynamic model compared to the static model. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the day (Fig. 4A). In particular, grid cells located further away from open grocery stores tend to have more significant differences in travel time.

According to the dynamic accessibility model, the travel time to the closest store is at least 5 min longer for 9% of the population in the morning (8 a.m.) than in the case of the static model (Fig. 4B). At 1 p.m., differences in travel time between the two models for reaching the stores are less evident (up to 5 min), although given differences influence some 15% of population. During the day (from 9 a.m. to 5 p.m.), the latter share remains between 12 and 19% (Supplementary Information S4). Overall, only for a marginal share of the population (3–6%), travel times are faster according to the dynamic model than with the static model.

In the late evening (10 p.m.), the dynamic model indicates that travel time to the closest store takes at least 5 min longer than the static model for up to 45% of the population. After 11 p.m., when most of the stores are closed in the study area, some 65% of the population have at least 15 min longer travel times to the closest grocery store, and 13% of them would need to travel more than 30 min compared to the static model. The differences are the biggest at 4 a.m., when only one grocery store is open. The static model completely overestimates accessibility, as it assumes a normal public transport supply and that all grocery stores are open.

When looking at the accessibility of each store separately, the difference between the two models is highly case-specific, as it depends on the two other components of accessibility – transport supply and whereabouts of people. For example, the static model clearly underestimates the accessibility of grocery stores located in the city centre, whereas the accessibility estimation may be equal or overestimated in the outer parts of the city (Supplementary Information S5).

4.3. Impact of time on spatial equity

As a final step, we assessed the variations in travel times to grocery stores and spatial equity to access stores by each hour of the day

(Fig. 5). According to the dynamic accessibility model, the variation in accessing the closest grocery store by public transport in Tallinn shows that during the day, travel times are rather stable within the city, but from the late evening until morning times significant spatial variations occur in accessing the stores. Interestingly, however, the hourly variation of Gini coefficients (GC), indicates the highest level of spatial equity in food accessibility among the population, especially during the night, whereas there is more inequity during the day. Hence, the level of spatial equity is lowest during the day (GC between 0.6 and 0.8) when travel times are shorter, but there is more spatial variation in them. The spatial equity is the highest (GC between 0.3 and 0.5) during the early morning hours (3–7 a.m.). This, however, relates to the fact that during this period the service accessibility is equally poor for most residents of Tallinn.

5. Discussion

In this study, we have proposed a conceptual framework for modelling dynamic accessibility landscapes taking into account the three dynamic components of accessibility – people, transport and activity locations. Our practical presentation of the framework stems from the recent studies acknowledging the importance of incorporating the temporal dimension in location-based accessibility modelling, and the potential of novel big data sources to enable dynamic analyses of people (Ahas, Silm, Järv, Saluveer, & Tiru, 2010; Chen et al., 2018; Kitchin, 2014), networks (Kujala et al., 2018) and services (Moya-Gómez et al., 2017). We combine these aspects to present a fully dynamic accessibility modelling framework. Below, we discuss 1) the empirical findings obtained, 2) the data sources, and 3) the importance and challenges of the conceptual framework.

5.1. Lessons learnt from the empirical tests

Our empirical example on multi-temporal food accessibility demonstrates how temporally sensitive modelling of spatial accessibility

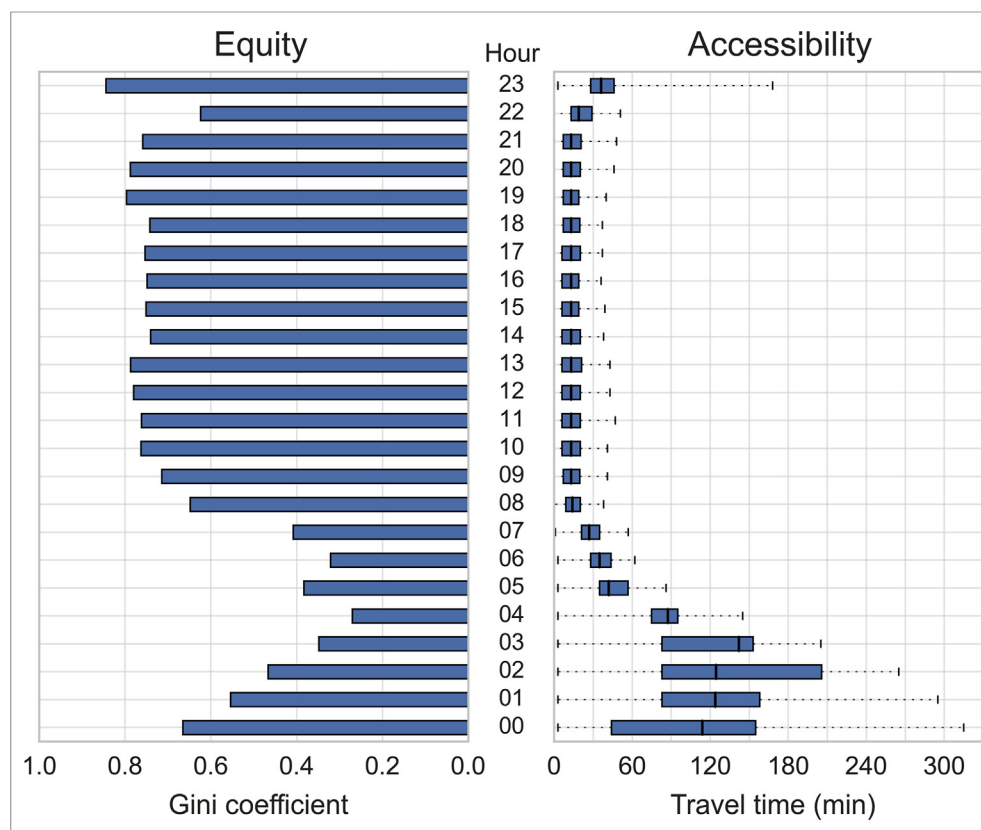


Fig. 5. Hourly variations of both accessibility and spatial equity in case of access to grocery stores. The studied spatial units are divided into quartiles based on travel time to the closest open grocery store by public transport as an indicator of accessibility (right). Gini coefficients indicate the level of spatial equity in reaching groceries among the population (left) in Tallinn.

may differ from the more traditional static modelling. Taking into account simultaneously the dynamic population distribution, changing transport supply and activity opportunities at a given time of the day will provide more realistic modelling results. As shown by our example, conventional static modelling has a risk of overestimating (or underestimating in some cases) the access of people to activity opportunities. As in our example, the most influential accessibility component tends to be the activities of social practices if they have strict opening hours, like the availability of stores.

Also, our findings suggest that understanding spatio-temporal disparities of spatial equity is a relevant issue to consider in social equity research. This is certainly relevant for 24-h urban societies where activity practices are mixed in terms of the time of day (Glorieux, Mestdag, & Minnen, 2008; Hubers, Schwanen, & Dijst, 2008). For example, even if the issue of accessing groceries during the night is a reality for only a relatively marginal social group, it is a matter of social and spatial justice, and the right to the city (Soja, 2010). Our findings show that social equity regarding opportunities for people in space is not static either and depends on time. Certainly, the importance of temporal variation and the most important component of dynamic accessibility is context-specific, and the findings may depend on the study context (see e.g. Widener et al., 2017).

5.2. Data sources for dynamic location-based accessibility modelling

Data availability has been a key limiting factor for developing temporally sensitive location-based accessibility modelling. Fortunately, the gradual emergence of various temporally sensitive spatial data sources which are suitable for dynamic accessibility modelling is mitigating this limitation (Chen et al., 2018; Moya-Gómez et al., 2017) (Table 2).

Until now, the most significant limitation has been the lack of data revealing the dynamic population distribution. Information on dynamic population can be acquired from mobile devices, either doing the

collection actively using GPS positioning (e.g. Wolf, Schönfelder, Samaga, Oliveira, & Axhausen, 2004) or passively, based on mobile phone CDR data (e.g. Ahas et al., 2010). Also, other pervasive geo-located data such as location-based sensors, smart card transactions (e.g. transit, bank, and customer cards) and geo-located social media data are promising sources to reveal population dynamics (Table 2). Access to such detailed population data can, however, be a challenge.

Similar big data sources can also be used to generate meaningful, temporally sensitive information on activity locations as destinations in accessibility models. Several websites and platforms provide information on the locations and opening hours of services, while some services (e.g. Google Places) can also provide information on the volume of the service usage. Location-based social networks and social media platforms provide another good source of information on service locations. Certainly, the best source for the destinations is specific to the case study. While social media sources and service catalogues work well for commercial services and leisure time activities, workplaces or educational institutes (as destinations for accessibility analyses) would best be found on public registries.

In many cities, information on transport is collected at a very detailed level. Traffic flows and road network speed can be derived from vehicle navigation data, floating car data, mobile applications and location-based sensors (Table 2). Public transport routes and schedules may be obtained from open-access data sources such as General Transit Feed Specification (GTFS) and OpenStreetMap (OSM). These sources can generally be used to gain at least rough average estimates on travel times with different modes of transport. More detailed estimates of e.g. door-to-door travel times with a private car (including parking) may be more difficult to obtain (Salonen & Toivonen, 2013). Our example used travel time as the network measure to calculate accessibility. In some other cases, the physical distance, price of travelling or route quality/experience might be more important. Then, also the sources of relevant information would be different.

Table 2

Examples of potential data sources for dynamic accessibility modelling given the three core components of accessibility, in comparison to data sources of static accessibility modelling.

	Temporal dimension	Spatial dimension	Data sources	References
People	Static	predefined locations	Registers and databases (e.g. census, population register)	
	Dynamic	<i>De facto</i> locations in time	Active mobile devices (GPS, mobile positioning) Passive mobile devices (mobile phone CDR data) Location-based sensors (WiFi, Bluetooth) Smart card transactions (transit, bank, customer cards) Geo-located social media	Ahas, Aasa, et al. (2010) and Ahas, Silm, et al. (2010); Wolf et al. (2004); Ahas, Aasa, et al. (2010) and Ahas, Silm, et al. (2010); Deville et al. (2014); Järv et al. (2015); Diao, Zhu, Ferreira, and Ratti (2016); Reades, Calabrese, and Ratti (2009) Bhaskar and Chung (2013); Lei and Church (2010) Ma, Wu, Wang, Chen, and Liu (2013); Long and Thill (2015) Hawelka et al. (2014); Steiger, Westerholt, Resch, and Zipf (2015)
Transport	Static	predefined routes	Transport network with speed limits (e.g. national road network)	
	Dynamic	<i>De facto</i> routes by travel mode in time	Private car: Online navigation services Car navigator data Floating car GPS-data Location-based services Public transport: GTFS data Online journey planners Cycling and walking: OpenStreetMap, Mobile sports applications	Páez, Moniruzzaman, Bourbonnais, and Morency (2013) Moya-Gómez and García-Palomares (2015) Dewulf et al. (2015); Tenkanen et al. (2016) Wang, Wei, He, Gong, and Wang (2014) El-Geneidy et al. (2016); Widener et al. (2015); Kujala et al. (2018); Lee and Miller (2018) Salonen and Toivonen (2013); Djurhuus, Sten Hansen, Aadahl, and Glümer (2016) Zielstra and Hochmair (2011) Sainio, Westerholm, and Oksanen (2015)
Activities	Static	predefined locations	Register-based data (e.g. enterprise register)	
	Dynamic	<i>De facto</i> locations given the availability in time	Service websites Geo-located social media Location-based social networks (Foursquare; Google Places, Yelp)	Delafontaine et al. (2011); Tenkanen et al. (2016) Dunkel (2015) Noulas, Scellato, Mascolo, and Pontil (2011)

5.3. Considerations of the conceptual framework

The temporal aspect has long been considered as a fundamental characteristic in spatial accessibility when attempting to understand urban structures, social processes and phenomena for planning and developing urban societies (Kwan, 2013; Urry, 2007). Without considering temporality, we may end up making decisions based on unrealistic or false information regarding e.g. spatial structure, sustainable mobility or social equity in terms of service provision.

The proposed framework is generic and applicable regardless of the study setting. Hence, it is not limited only to the examination of 24-h urban food accessibility for the entire population by public transport, as we demonstrated. Conceptually, dynamic location-based accessibility modelling is applicable similarly for both urban and rural settings, for spatial scales from neighbourhood to global level, for different time scales from hourly to yearly, and for various measures of network distance (time, physical distance, cost, quality, or CO₂ emissions). Furthermore, the framework can be used for more sophisticated accessibility modelling. It could be used, for example, when studying multimodal transport systems (private car, public transport, walking, cycling, air and marine traffic) for transport supply, and modelling the more complex demand of people by considering socio-economic subgroups.

Making fully dynamic accessibility models, however, requires more input data, efficient computing resources and more advanced analyses. Hence, each case study needs careful consideration of how, and to what extent to apply the framework. For example, for examining school accessibility on foot, the conventional static model works well in most cases – schools do not compete with opening hours, the origin for the trip is obtained from residential registry data as children go to school from home, and the characteristics of travel (time, effort and distance)

tend to be the same regardless of the hour of the day or weekday. Only seasonality due to climate conditions may influence travel.

The dynamic location-based accessibility modelling framework allows one to consider the clustering of activities of people and their mobility. Hence, it is a step forward in bridging the gap between a mainstream location-based accessibility and a person- (activity-) based accessibility modelling – allowing the incorporation of time into the three components of accessibility and the activity travel behaviour of population at an aggregated level. However, the focus of the two approaches remains different, as they focus on accessibility from different perspectives. Location-based accessibility modelling aims to provide a general overview of spatial accessibility landscapes as realistically as possible, without detailed input on individual activity-travel behaviour as in person-based modelling.

In conclusion, this study provides a solid starting point for advancing fully dynamic location-based accessibility modelling by proposing a generic framework and exemplifying its applicability in practice, and identifying a set of potential temporally-sensitive data sources.

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Appendix A. Supplementary information

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